Univerzitet Crne Gore
EKONOMSKI FAKULTET PODGORICA

UCG
Univerzitet Crne Gore

Broj: 01/978

Podgorica, 24.04.2023.godine

UNIVERZITET CRNE GORE
-Odboru za doktorske studije i Senatu-

PODGORICA

Predmet: Materijal za sjednicu Odbora i Senata

Poštovani,

U skladu sa članom 38. Pravila doktorskih studija, dostavljamo Vam materijal za narednu sjednicu Odbora za doktorske studije, odnoso Senata Univerziteta Crne Gore i to:

-Ispunjenost uslova doktoranda (obrazac D2) sa propratnom dokumentacijom za mr Sunčicu Rogić.

DEKAN
Jocović
Prof.dr Mijat Jocović

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UNIVERZITET CRNE GORE
EKONOMSKI FAKULTET PODGORICA
DOKTORSKE STUDIJE
Br. 01/972
Podgorica, 20.04.2023.god.

Na osnovu čl. 64. Statuta Univerziteta Crne Gore, a u vezi člana 38. i 41. Pravila doktorskih studija Vijeće Ekonomskog fakulteta je na sjednici održanoj 20.04.2023.godine donijelo

ODLUKU

1. Utvrđuje se da su ispunjeni uslovi iz Pravila doktorskih studija za dalji rad na doktorskoj disertaciji **„Prediktivni modeli odlučivanja u direktnom marketingu bazirani na Support Vector Machine metodi“** doktoranda **mr Sunčice Rogić** .
2. Predlaže se Odboru za doktorske studije i Senatu UCG da formira Komisiju za ocjenu doktorske disertacije **„Prediktivni modeli odlučivanja u direktnom marketingu bazirani na Support Vector Machine metodi“** doktoranda **mr Sunčice Rogić** u sastavu:
   - Dr Ljiljana Kašćelan, redovni profesor, Ekonomski fakultet Podgorica, Univerzitet Crne Gore, mentor;
   - Dr Boban Melović, redovni profesor, Ekonomski fakultet Podgorica, Univerzitet Crne Gore, član;
   - Dr Ivan Luković, redovni profesor, Fakultet organizacionih nauka, Univerzitet u Beogradu, Republika Srbija, član.
3. Odluka se dostavlja Centru za doktorske studije UCG na dalji postupak.

OBRAZLOŽENJE

Doktorand **mr Sunčica Rogić** je uradila doktorsku disertaciju **„Prediktivni modeli odlučivanja u direktnom marketingu bazirani na Support Vector Machine metodi“,** nakon čega je Komisiji za doktorske studije podnijela zahtjev za formiranje Komisije za ocjenu doktorske disertacije.
Komisija za doktorske studije je, nakon razmatranja dokumentacije, predložila Vijeću fakulteta da donese Odluku kojom predlaže Senatu UCG formiranje Komisije za ocjenu doktorske disertacije **„Prediktivni modeli odlučivanja u direktnom marketingu bazirani na Support Vector Machine metodi“** doktoranda **mr Sunčice Rogić**.

Na osnovu izloženog odlučeno je kao u dispozitivu.

DEKAN
Prof.dr Mijat Jocović

DOSTAVLJENO:
-a/a
-referentu doktorskih studija,
-Centru za doktorske studije.

FACULTY of ECONOMICS PODGORICA

IEP
EUA-Institutional Evaluation Programme
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Crna Gora
UNIVERZITET CRNE GORE
EKONOMSKI FAKULTET
Broj 01/553
Podgorica, 6.3.2023 god.

UNIVERZITET CRNE GORE

EKONOMSKI FAKULTET

Komisiji za doktorske studije

Predmet: Saglasnost mentora sa tekstom disertacije

Ovom izjavom dajem svoju saglasnost sa tekstom doktroske disertacije doktoranda Sunčice Rogić, koji je predala Studentskoj službi Ekonomskog fakulteta dana 06.03.2023. godine.

Podgorica, 06.03.2023.

Mentor
Prof. dr Ljiljana Kašćelan

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969
27/04/23

ISPUNJENOST USLOVA DOKTORANDA

OPŠTI PODACI O DOKTORANDU			
Titula, ime, ime roditelja, prezime	mr Sunčica Rogić		
Fakultet	Ekonomski fakultet Univerziteta Crne Gore – Podgorica		
Studijski program	Doktorske studije ekonomije		
Broj indeksa	2/18		
NAZIV DOKTORSKE DISERTACIJE			
Na službenom jeziku	Prediktivni modeli odlučivanja u direktnom marketingu bazirani na Support Vector Machine metodi		
Na engleskom jeziku	Predictive decision support models in direct marketing based on Support Vector Machine method		
Naučna oblast	Poslovna inteligencija u ekonomiji		
MENTOR/MENTORI			
Mentor	Prof. dr Ljiljana Kašćelan, redovni profesor	Univerzitet Crne Gore, Ekonomski fakultet Podgorica, Crna Gora	Računarske nauke
KOMISIJA ZA PREGLED I OCJENU DOKTORSKE DISERTACIJE			
Prof. dr Ivan Luković, redovni profesor		Univerzitet u Beogradu, Fakultet organizacionih nauka	Računarske nauke
Prof. dr Ljiljana Kašćelan, redovni profesor		Univerzitet Crne Gore, Ekonomski fakultet Podgorica, Crna Gora	Računarske nauke
Prof. dr Boban Melović, redovni profesor		Univerzitet Crne Gore, Ekonomski fakultet Podgorica, Crna Gora	Marketing i biznis

Datum značajni za ocjenu doktorske disertacije	
Sjednica Senata na kojoj je data saglasnost na ocjenu teme i kandidata	12.03.2020.
Dostavljanja doktorske disertacije organizacionoj jedinici i saglasnost mentora	06.03.2023.
Sjednica Vijeća organizacione jedinice na kojoj je dat prijedlog za imenovanje komisija za pregled i ocjenu doktorske disertacije	20.04.2023.

ISPUNJENOST USLOVA DOKTORANDA
U skladu sa članom 38 pravila doktorskih studija, kandidatkinja je dio istraživanja vezanih za doktorsku disertaciju publikovala u časopisima sa **(SCI/SCIE/SSCI/A&HCI)** liste kao prvi autor.

Spisak radova doktoranda iz oblasti doktorskih studija koje je publikovao u časopisu sa SCIE liste.

1. **Rogić, S.**, & Kašćelan, L. (2021). *Class balancing in customer segments classification using support vector machine rule extraction and ensemble learning.* Computer Science and Information Systems, 18(3), 893-925.

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Obrazloženje mentora o korišćenju doktorske disertacije u publikovanim radovima

Prema Pravilima doktorskih studija, kandidatkinja je objavila dva rada iz doktorskog istraživanja u časopisima sa SCI/SSCI liste, „*Class balancing in customer segments classification using support vector machine rule extraction and ensemble learning*" i "*Customer Response Model in Direct Marketing: Solving the Problem of Unbalanced Dataset with a Balanced Support Vector Machine*". S tim u vezi, kandidatkinja je ispunila sve neophodne uslove za naredni korak u proceduri doktorskih studija – imenovanje Komisije za pregled i ocjenu doktorske disertacije.

Datum i ovjera (pečat i potpis odgovorne osobe)

U Podgorici,

20.04.2023

DEKAN

prof. dr Mijat Jocović

MP

Prilog dokumenta sadrži:

1. Potvrdu o predaji doktorske disertacije organizacionoj jedinici
2. Odluku o imenovanju komisije za pregled i ocjenu doktorske disertacije
3. Kopiju rada publikovanog u časopisu sa odgovarajuće liste
4. Biografiju i bibliografiju kandidata
5. Biografiju i bibliografiju članova komisije za pregled i ocjenu doktorske disertacije sa potvrdom o izboru u odgovarajuće akademsko zvanje i potvrdom da barem jedan član komisije nije u radnom odnosu na Univerzitetu Crne Gore

Univerzitet Crne Gore
EKONOMSKI FAKULTET PODGORICA

UCG
Univerzitet Crne Gore

Na osnovu službene evidencije i dokumentacije Ekonomskog fakulteta u Podgorici, izdaje se

POTVRDA

o predaji doktorske disertacije na dalji postupak

Doktorand: ***mr Sunčica Rogić***

Naziv doktorske disertacije: ***„Prediktivni modeli odlučivanja u direktnom marketingu bazirani na Support Vector Machine metodi“***

Datum predaje: 06.03.2023.godine

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Class Balancing in Customer Segments Classification Using Support Vector Machine Rule Extraction and Ensemble Learning

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Abstract. An objective and data-based market segmentation is a precondition for efficient targeting in direct marketing campaigns. The role of customer segments classification in direct marketing is to predict the segment of most valuable customers who is likely to respond to a campaign based on previous purchasing behavior. A good-performing predictive model can significantly increase revenue, but also, reduce unnecessary marketing campaign costs. As this segment of customers is generally the smallest, most classification methods lead to misclassification of the minor class. To overcome this problem, this paper proposes a class balancing approach based on Support Vector Machine-Rule Extraction (SVM-RE) and ensemble learning. Additionally, this approach allows for rule extraction, which can describe and explain different customer segments. Using a customer base from a company's direct marketing campaigns, the proposed approach is compared to other data balancing methods in terms of overall prediction accuracy, recall and precision for the minor class, as well as profitability of the campaign. It was found that the method performs better than other compared class balancing methods in terms of all mentioned criteria. Finally, the results confirm the superiority of the ensemble SVM method as a preprocessor, which effectively balances data in the process of customer segments classification.

Keywords: direct marketing, customer classification, class imbalance, SVM-Rule Extraction, ensemble.

1. Introduction

Direct marketing allows for direct communication with potential customers through various media, such as e-mail, catalogs, social media and the like. It is consumer-oriented, message is sent directly to consumers and, at the same time, it's a "call to action". One of the key issues of this type of marketing is the accurate identification of potential and current customers who will most likely respond to a campaign, i.e. targeting specific customers from an existing database as well as new potential leads. Usually, the customer targeting methods are split up in the literature into segmentation and scoring methods [1, 2]. Segmentation methods, using appropriate explanatory variables, partition the customers into homogenous segments regarding the anticipated response to a direct marketing campaign [3, 4]. Thus, the promotional offers and materials are distributed to such customer segments with highest expected probability of response. On the other hand, scoring methods are used in the customer response models [5, 6], by assigning certain scores to customers, based on the predicted likelihood of the response to the campaign. It is important to state that high probability of response to the campaign does not certainly imply high profits. Hence, methods for customer profitability prediction are included in some of the most important scoring methods [7–10].

Segmentation methods, which are most commonly applied in direct marketing, split a customer data set using Recency, Frequency and Monetary (RFM) attributes [11]. They are based on various techniques, ranging from the simplest cross-tabulation technique, to more complex weighted techniques [4, 12]. These techniques generally require a subjective assessment for the necessary parameters. For this reason, data mining methods, such as K-means or Artificial Neural Network (ANN) clustering, can give more objective results for RFM customer segmentation [13–15].

Recently, classification data mining methods have become very popular, as they can enable the prediction to which segment the customer belongs to, based on the characteristics of the customer [15, 16]. Since the most valuable customer segment is usually the smallest, there is a problem of class imbalance. This problem in most classification methods leads to bias toward small classes and most often to their misclassification [17, 18]. If this problem is ignored, most classification algorithms will not identify the most valuable customer segment at all, or will identify a very small number of customers within that segment, which may lead to an unprofitable campaign.

There are methods in the literature that overcome the class imbalance problem in different ways [19–21]. The main disadvantage of the most commonly used under-sampling method, is that it ignores the large number of examples of the larger class, that may contain significant information for class differentiation. In order to reduce sample bias and minimize the loss of significant information, it can be combined with ensemble techniques (balanced ensemble) [18, 22]. The balanced ensemble approach involves taking random subsets of a larger class (equal in size with a smaller class) in multiple iterations and generating different classification models over those subsets whose results are eventually aggregated to give a final result. Combining multiple classifiers in this way does not only balance classes, but also increases predictive accuracy, reduces sample bias, reduces variance i.e. increases stability of results and avoids overfitting [23, 24].

The previous literature confirms that in case of class imbalance and overlapping the SVM method has a good predictive performance and can be used as a preprocessor that balances classes for other classifiers [25]. However, the SVM classifier is a "black-box", i.e. does not generate a model that can be interpreted, which is very important in the classification of customer segments in order to describe the segments. This deficiency can be solved by a hybrid approach, where the SVM is combined with rules extracting techniques (SVM-RE) [26].

Considering the advantages of the SVM-RE method and ensemble approach noted above, this paper proposes customer segments classification in direct marketing based on a combination of SVM-RE predictive classification and ensemble meta-algorithms. Also, a comparison of the defined method with the standalone data balancing ensemble methods for customer classification was made. Specifically, this study highlights three main research questions (RQ):

RQ1 - Is the ensemble SVM-RE approach adequate for the prediction of customer segments in direct marketing?

RQ2 - Given the unbalanced nature of data in customer segmentation, what is the best class balancing method (ensemble SVM-RE or one of the standalone balancing ensemble methods)?

RQ3 - Is the ensemble SVM-RE method suitable for describing, i.e. explaining segments?

Undoubtedly, the primary success factor of direct marketing predictive models is class imbalance. There are two basic approaches used in previous studies to solve this problem. The first involves modifying the classifier by associating different misclassification costs for each class [27, 28]. Another approach to requires data changes. Balancing is regulated by generating or reducing data using over-sampling or under-sampling techniques [17, 18, 22, 29, 30]. However, both approaches have some drawbacks. Classifier-changing methods require extensive knowledge about the specific learning methods [31], so it is necessary to hire an expert for practical application. With resampling methods, the challenge is removing the data without losing the information necessary to distinguish the classes, as well as knowing whether removing some data would give different results (instability of the solution). When supplementing the data, the main challenge is how to supplement the minority class while maintaining its distribution. Also, the question is what is the optimal class ratio [31]. All this makes the analysis complex in practical applications. A small number of papers for the customer classification use the ordinary SVM method [17, 32, 33], but it has been shown that it is not immune to class imbalance either [17]. The main contribution of the SVM-RE method proposed in this paper is that it automatically eliminates noise and class imbalance. By adjusting the parameters of the SVM as a data preprocessor, the boundaries between the classes are shifted so that the examples of the majority class that are closest (most similar) to the minority class join the minority class. Rule extraction from such balanced data has good classification performance for the minority class as well. The extracted rules provide a description of the segment of the most valuable customers that cannot be obtained if the misclassification of this minority class is not resolved. The performance of SVM-RE methods is further enhanced by combining with ensemble techniques.

Unlike the above-mentioned studies, which mainly use data sets from publicly available repositories, this study uses real-life data that are disordered and have more noise. On such data, the challenge of balancing and achieving good predictive performance is even greater. The final step was using the public dataset to validate the model.

The practical implications of this paper relate to the more accurate and objective planning of direct marketing campaigns, as well as gaining deeper insight into different customer segments, which may lead to more precise targeting and increased profits.

The paper is organized as follows: The second section gives an overview of related papers. Section three shows the proposed methodology, and the fourth section presents the results of the empirical test, which are further discussed in the fifth section. Finally, the sixth section contains concluding remarks.

2. Literature Review

This section provides an overview of previous research related to the customer segmentation and the problem of class balancing in direct marketing.

2.1. SVM Rule Extraction Method

For linearly inseparable classes, Vapnik[34] proposed a SVM method that maps data (viewed as n-dimensional vectors) from the original space into a larger dimension space (feature space), where the classes can be separated by means of a hyperplane. Finding such a hyperplane is realized by minimizing the distance between its end position (so that the gap between the classes i.e. the margin is greater) and the closest points (support vectors). Instead of an explicit mapping function in a larger dimension space, a kernel function is used, which allows calculating the scalar product of the vectors (i.e. the distance of the support vector from the hyperplane) in the original space (kernel trick). Various kernel functions can be used, but Radial Basis Function (RBF) which was used in this paper, is applied most often [35]:

$$K(x_i,x_j) = \exp(-\gamma||x_i-x_j||^2) \quad (1)$$

The SVM algorithm, therefore, strives to maximize the margin in feature space, which boils down to the convex optimization i.e. quadratic programming problem in the original space (2):

$$max_{\alpha_i} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \, \alpha_j \, y_i y_j \, K\left(x_i, x_j\right) \quad (2)$$

$$\sum_{i=1}^{n} y_i \alpha_i = 0$$

$$0 \leq \alpha_i \leq C , \quad i = 1, \ldots, n$$

where K is kernel function, αi are Lagrange multipliers, n is the number of training examples and C is a parameter, which is adjusted to trade off margin maximization against classification error minimization.

The training of the SVM classifier comes to the selection of the optimized values of the gamma parameter for the RBF kernel, and parameter C, which represents the boundary for the margin, i.e. empty space between classes. Selecting lower values for parameter C reduces over-fitting and increases the generality of the SVM model, i.e. its predictive performance.

In addition to solving the problem of linear inseparability of classes, the advantage of this method is that, in the case of class imbalance, it exhibits better predictive performance than the standard methods, such as logistic regression [25]. The literature confirms that the SVM can successfully remove the noise, i.e. class overlapping from data. Namely, the parameter C can be set so that a number of examples of a larger class, which are close to the example of a lower class (which means that they are similar), are declared as examples of the lower class. For this reason, the SVM can be used as a preprocessor that balances and purifies data, thus providing higher classification accuracy [25, 36].

However, the SVM does not generate an interpretable model, which is usually very important in application. This problem has been solved in the literature by means of rule extraction techniques that enable generating the rules from the SVM results [26, 37]. According to Barakat and Bradley [26] SVM-RE techniques are grouped into two categories: those based on the components of the SVM model, and those that do not use the internal structure of the SVM model, but draw the rules from the SVM output. When the SVM model is interpreted, or SVM is used as a data preprocessor, authors recommend techniques from the second group because they provide more understandable rules. In line with this recommendation, our research uses rule extraction from SVM output. Namely, customer targeting rules are derived from SVM output using a classification Decision Tree (DT) method [38].

The DT method divides the data set by attributes values, so that subgroups contain as many examples of one class as possible, i.e. their impurity is minimized. The criterion by which division is made (measure of quality of division) can be information gain [39], gain index [40], gini index [41], or accuracy of the whole tree. The attributes that provide the best division according to the given criterion are chosen. During the inductive division, a tree-shaped model is formed. The path from the root to the leaves defines if-then classification rules in the terms of the predictive attributes (tree nodes). The complexity and accuracy of the generated model depends on the depth of the tree, the minimum size of the node by which the division can be made (the number of examples in its subgroup), the leaf size, and the defined minimum gain achieved by the node division. The smaller the depth, the larger the minimum size for the split, the larger the leaf size and the higher minimum gain, lead to a less complex tree, but also a tree with smaller accuracy.

SVM rule extraction is not a new method in literature and it was applied in some previous economic studies [36, 38, 42], but for the topic of direct marketing, i.e., to solve the problem of the minor class of the most valuable customers in customer classification, it is applied for the first time in our research in this way.

2.2. Ensemble Methods

Ensemble methods use more learning algorithms to achieve better predictive performance than can be achieved with any of these learning algorithms alone.

There are several different ensemble methods. Thus, Bootstrap Aggregating [43] or shortened Bagging, constructs subsets of the training set using bootstrapping, which implies that the same example can be re-selected in the next iteration (sampling with replacement). The subsets thus obtained generate predictive models whose results are aggregated (the result for which most models voted is taken). If bootstrapping from a larger class takes as many instances as there are in a smaller class, then it is a case of balanced Bagging. Unlike Bagging, which generates samples and models simultaneously, Adaptive Boosting [44] generates the following sample and model based on previous results. Specifically, the succeeding sampling is more likely to select those examples that were previously incorrectly classified because they were given more weight. The result is obtained by weighting, i.e. based on the weight attached to the models depending on their accuracy. Random Forest [45] is an ensemble method that combines Bagging with a random selection of predictors. Each sample generates a forest of DTs that take random subsets of predictors, i.e., a random forest of DTs is generated.

Ensemble methods have been used in some previous studies in direct marketing. Hence, Gupta A. and Gupta G. [46] have compared neural networks and Random Forest to predict clients' response to a term deposit offered at a Portuguese bank. Their findings show that Random Forest performs better. Instead of boosting one learning algorithm, Lessmann et al. [47] proposed an ensemble approach that combines multiple different learning algorithms (decision trees, SVM, random forest, logistic regression, etc.) to create predictive marketing models, such as customer response prediction, profit scoring and churn prediction. In aggregating the results to evaluate the best models, they included profit maximization in addition to predictive model performance. The results showed that this ensemble approach outperformed standalone models in terms of profit. Lawi et al. [30] have combined Adaptive Boosting with SVM and achieved better predictive performance compared to ordinary SVM. In the approach proposed in this study, Bagging was combined with SVM to improve data preprocessing performance, i.e. to eliminate class overlapping, and balanced Bagging with the DT classifier is used to further help solve the problem of class imbalance and ultimately improve the performance of customer classification segments as much as possible.

2.3. Customer Segmentation in Direct Marketing

Hughes [11] defined one of the most commonly used customer segmentation method in direct marketing – RFM segmentation. The RFM model is based on the database of previous customers' purchasing behavior. Recency represents the time period since the last purchase, Frequency marks the number of purchases in the stated period of time and Monetary indicates the value of all customer's purchases during that period [48]. The analysis starts by sorting the available data into five equal segments (each containing 20% of customers), according to recency. Most recent customers receive the score 5, less recent score 4 and so on, following the Pareto principle – 20% of customers account for 80% of sales [49]. Following this procedure, customers are sorted according to their frequency, within the formed quintiles, receiving scores 5 to 1, which results in a database with 25 segments, and finally, database is split according to the monetary value by scoring the customers within the defined groups, which, in turn, results in a database with 125 groups based on the RFM values [4], where the best segment will have a 555 score, and the worst will have a 111 score. However, the choice of segments to be targeted in the future marketing campaigns is subjective.

The resulting segments based on the RFM model can be further analyzed using more objective data mining techniques, taking into account the customer features, their buying behavior or product specific variables [16, 50, 51].

Cheng and Chen [16] used k-means clustering [52] for RFM segmentation. They split the data into segments of 20% each (uniform coding) and created 3, 5 and 7 clusters to test the approach. The disadvantage of this approach is that uniform coding leads to the loss of fine differences between the values of RFM attributes (e.g., customers who have 5 or 9 transactions or those whose revenue is 5000 euros or 7000 euros can be placed in the same rank). Also, the pre-assumed number of clusters does not guarantee optimal RFM segmentation.

In order to develop a set of rules for targeting customers based on their features (the region and credit debt), the authors used a rough set and LEM2 rule extraction method. The predictive attributes also include RFM attributes, aiming to achieve high accuracy rate, as clusters are already formed on the basis of RFM. Hence, extracted rules perhaps do not show some significant customer characteristics for targeting, as they may be absorbed by the effect of RFM attributes. In addition, RFM attributes are unknown for new customers, so this model cannot be used for their prediction.

Additionally, the authors in [16] exclusively used accuracy rate (the percentage of precisely predicted examples within all examples) to determine their classification performance. Since there is usually the smallest number of customers with the highest value, clusters do not contain the same number of customers. Hence, there is a problem of class imbalance in the classification, which may lead to low class precision (the percentage of precisely predicted examples within a predicted class) and / or class recall (the percentage of accurately classified examples within the actual class) for the smallest class, which is the most important customer segment in this case.

In order to overcome the shortcomings mentioned above, a new method for customer segments classification based on data mining techniques will be tested in this paper. Customer segmentation by RFM attributes will be performed automatically using a clustering algorithm instead of manual coding and sorting. Clustering will be applied to the original attributes, so that there is no loss of fine differences that arise due to their uniform coding. Instead of a priori determining the number of clusters, an objective indicator of the optimal number of clusters will be used. Predictive classification will not include RFM attributes, therefore, classification rules describing segments will be defined in terms of customer and product characteristics, which is very important for customer relationship management. In this way, it is possible to classify new customers for whom RFM attributes are not known and available. Finally, and most importantly, the proposed method aims to reduce the misclassification of the most valuable customer segment.

2.4. Class Balancing in Direct Marketing

As pointed out, a major difficulty with predictive models in direct marketing is the class imbalance problem. According to the previously mentioned Pareto principle, the segment of the most valuable customers is the smallest (about 20% of the customers), but also the most important for the success of the campaign. The response rate in a direct campaign is often less than 5%, while non-responders make up as much as 95% of the total number of customers. This leads to very unbalanced datasets for training predictive classifiers in direct marketing [17, 22, 53]. Obviously, the problem of class balancing in this area is very topical, and accordingly, much more recent research deals with methods that effectively address this problem.

According to Sun et al.[31] data-level, algorithm-level and cost-sensitive solutions were developed for the problem when using imbalanced classes in classification models. At the data level, the aim is to balance classes with resampling, while solutions include random or targeted under-sampling and over-sampling. At the algorithm level, solutions try to adapt the algorithm to strengthen small-class learning. Cost-sensitive solutions, at both the algorithm and data levels, assign higher misclassification costs to small-class examples. More recently, there have been several papers that deal with this issue [54–56].

Although resampling eliminates class imbalance, this approach has several limitations and disadvantages, such as unknown optimal class distribution, inexplicit criterion in selecting examples for removal, risk of losing information relevant to class differentiation in majority class under-sampling, and risk of overfitting when over-sampling a minority class. Algorithm-level approaches require extensive knowledge of the algorithms and application domains, while cost-sensitive approaches involve extra learning costs for exploring effective cost setups, when real cost values are not available. However, despite the mentioned shortcomings, most of these solutions are used in recent research in the field of direct marketing.

Thus, Kim et al. [17] compared the efficiency of SVM classifiers with decision tree and neural networks on highly unbalanced data sets in direct marketing. They found that only SVM doesn't have a complete misclassification of the minor class, but, that positive sensitivity is very small, which means that the class imbalance is also an issue for SVM method. With random under-sampling of majority class with a ratio of 33% (i.e. the class ratio was 2:1), all classifiers improved their performance, while SVM still outperformed the others. However, with a 1:1 class ratio, the performance of SVM model has weakened, suggesting that by removing a large number of examples of the majority class, data relevant to the learning process may be lost. In that sense, it is good to combine under-sampling with ensemble techniques so that random selection is repeated several times and the probability of significant data being completely excluded is reduced, hence some papers dealing with the class imbalance problem in direct marketing go in that direction.

For example, Kang et al. [22] suggested improving customer response models by balancing classes using clustering, under-sampling and ensemble. First, the instances belonging to the non-response class are clustered. In the next step, under-sampling is performed as part of the ensemble procedure by randomly selecting a number of representatives from each cluster, proportional to the size of the cluster, but with the total number of selected instances equal to the minor class (balanced ensemble). In this way, taking a number of representative members of the larger class is achieved and reduces the loss of information relevant to class differentiation. By performing ensemble procedure in *k* iterations, on *k* of such balanced samples, *k* classifiers are generated and their predictions are combined. The results showed that compared to random sampling methods, this approach has more stable predictive performance that decision makers can trust more.

Migueis et al. [18] compared ensemble balanced under-sampling (the EasyEnsemble algorithm that uses sampling without replacement) with an over-sampling method (the Synthetic Minority Oversampling Technique-SMOTE) for direct marketing response prediction in banking and found the EasyEnsemble method gave better results. The sampling model without replacement can compromise the independence of the classifier in the ensemble procedure because the sampling in the next step depends on the one made in the previous step.

Marinakos et al. [29] tested cluster-based under-sampling and distance-based resampling techniques for the bank customer response model (with 12% of respondents and 88% of non-respondents) with several different classifiers, such as linear discriminant analysis, logistic regression, k-Nearest Neighbor (k-NN), decision tree, neural network and SVM. The highest accuracy of the minority class classification was achieved by the combination of cluster under-sampling and k-NN. Cluster under-sampling combined with SMOTE over-sampling proved consistently well, performing across all classifiers.

Peng et al. [27] proposed a solution based on algorithm adaptation in the form of cost-sensitive learning SVM for segmenting credit card users, and showed that this solution gives better results for the smallest class of high-value users than basic SVM with random under-sampling. This approach requires extensive knowledge of the SVM method in order to include misclassifying costs.

Farquad and Bose [25]tested SVM as a class-balancing preprocessor of insurance customers data and found that when classifiers are applied to such a refined set, a much higher sensitivity is obtained i.e. the number of current examples of the minor class that the model accurately classifies. They also found that data balancing with SVM is more efficient than other balancing techniques such as 100% and 200% SMOTE over-sampling or 25% and 50% under-sampling.

In our preliminary research [57], we tested how successfully a hybrid model that combines SVM and decision trees as a rule extraction technique (SVM-DT) solves the problem of the minor class of the most valuable customers. The results showed that with this approach, the segment of the most valuable customers can be predicted with an accuracy of 77%, which is 44% better than the standalone DT. Thus, SVM as a preprocessor has effectively improved the precision of the minor class. The improvement is even higher for the percentage of existing customers who are recognized as members of the most valuable cluster. Standalone DT identified only 4% of them, while SVM-DT managed to identify 63% of such customers. Although the model performed well on a training data set (obtained by cross-validation), it was not tested on an unknown data set, so its actual predictive power was not confirmed in this study.

In a study by Djurisic et al. [58] authors tested how well SVM preprocesses data and enables CRM optimization in banks. The results showed that during the segmentation of credit card users, this method successfully resolves overlapping and unbalanced classes. In this paper either, the model was not tested on a completely unknown data set.

In previous research, in order to overcome the class imbalance problem, balanced ensemble methods in combination with different classifiers, or standalone SVM, as a preprocessor that refines class overlapping and thus balances data, were mainly tested. This paper will test combining ensemble approach and SVM to improve preprocessing performance, as well as balanced ensemble in combination with DT on such a preprocessed dataset to improve rule extraction performance from SVM output, which should ultimately lead to improved performance of customer segments classification.

3. Methodology

The primary goal of predictive customer segmentation in direct marketing is customer value prediction, which determines whether or not a customer is targeted. This section describes the methodological approach for the proposed predictive procedure.

3.1. Data

First step is collection of data on purchasing transactions from previous direct campaigns, which can include customer data (such as: gender, age, region, wealth, etc.), product data (such as: type, category, purpose, etc.), and purchasing behavior data, i.e. recency, frequency and monetary value of purchases. The data were used as a training set for the predictive model.

For the empirical testing in this paper, a data set of on-line purchasing transactions from previous direct campaigns of Sport Vision Montenegro (part of the Sport Vision system - leading sport retailer in the Balkans) was used, for the period from the beginning of September 2018 to the end of January 2019 (fall/winter season). The data set consists of 1605 records (transactions) and has the following attributes: order ID, discount, price, date, gender, product type, product gender, product category, product age and product brand. Product type represents retailer's classification of products into: footwear (sneakers, shoes, boots, etc.), apparel (t-shirts, sweatshirts, joggers, etc.) and equipment (bags, dumbbells, gloves, etc.). On the other hand, product category is another form of classification, based on activities' purpose (for example, running – for running shoes, outdoor – for hiking equipment, etc.). Product gender consists of five values: products for women, for men, for boys, for girls and unisex products. In addition, product age describes the age group that products are intended for (for babies, for kids, for adults, etc.). Finally, product brand splits the products into two major groups – A brands (retailer's distribution brands) and Licence brands (retailer's production and distribution brands) and a small group of "Other" brands. In general, A brands are well known and established sport brands, that are usually more expensive, while Licence brands are more affordable, with not as strong image and brand recognition.

The data was prepared by calculating the RFM attributes as follows: Recency as the date of the last order, Frequency as the total number of orders in the considered period and Monetary as the monetary amount spent by a customer in the considered period expressed in euros. The Recency attribute is encoded so that for 20% of the most recent dates, score 5 is assigned, the next 20% less recent dates are given score 4 and so on until score 1. Attributes Frequency and Monetary are retained in their original form. In the end, all the attributes were normalized with 0-1 range transformation. Table 1 shows the attribute distribution in the starting data set.

For the purpose of testing the predictive performance of the model, the same type of data from the year after were used, but from the same season (fall/winter), when there is a similar sales offer available for consumers. This is because of seasonality, which affects and defines type of current offer. For example, in the fall/winter season, marketing focus is on "back to school" and skiing campaigns, while during the spring/summer season, focus is on summer activities. Hence, it makes sense to only compare the performance of the same seasons and different years, while the same values of attributes are available.

The data was prepared in the same way as the training set (RFM attributes were calculated and all attributes normalized).

Table 1. Attribute distribution in the training dataset

Attribute	Statistics	Range
Order_ID		[42 ; 6278]
Cust_gend	mode = M (891), least = F (714)	F (714), M (891)
Discount	avg = 0.371 +/- 0.107	[0.000 ; 0.500]
Prod_type	mode = Footwear (784), least = Equipment (181)	Footwear (784), Equipment (181), Apparel (640)
Prod_gend	mode = For men (786), least = For girls (67)	For women (399), For boys (210), For men (786), Unisex (143), For girls (67)
Prod_categ	mode = Lifestyle (869), least = Handball (1)	Lifestyle (869), Fitness (231), Running (119), Football (70), Skiing (103), Outdoor (85), Basketball (103), Other (5), Boxing (3), Tennis (12), Accessories (2), Handball (1), Volleyball (1), Skateboarding (1)
Prod_brand	mode = A brands (853), least = Other (74)	A brands (853), Licence (678), Other (74)
Prod_age	mode = For adults (1272), least = For all (23)	For adults (1272), For babies (0-4) (62), For teens (8-14) (127), For younger kids (4-10) (121), For all (23)
R	avg = 3.143 +/- 1.353	[1.000 ; 5.000]
F	avg = 3.616 +/- 3.401	[1.000 ; 17.000]
M	avg = 100.081 +/- 78.211	[9.600 ; 352.000]

3.2. Model Training and Validation

As the first step in model development, a cluster model was generated on the training set and customer segments are identified, i.e. a Customer Value-level (CV-level) for all customers is determined.

As one of the most well-known algorithms for cluster analysis, the k-means method was mostly used for customer segmentation in direct marketing [13–16]and other clustering analysis [59, 60]. This method estimates the centroid cluster model based on the Davies-Bouldin Index (DB) [61], which ensures maximum heterogeneity between clusters and maximum homogeneity within the clusters. DB index calculates the Euclidean distance from the centroid inside and between the clusters. Better quality of clustering is indicated by lower absolute values of the DB index. This study proposes the k-means method because the optimal number of clusters can be determined based on this indicator.

CV-level defines how much the customer is valuable to the company based on purchasing behavior or belonging to the appropriate segment. Thus, the segment of customers who buy most often, who bought the most recently and from whom the largest revenue was made, represents the segment of the most valuable customers for the company. All customers who belong to that segment get the best, that is. first CV level.

In the next step, Bagging SVM is trained, as the data preprocessor. On the training dataset the CV-level is then predicted by the preprocessor. In order to obtain the purest classes possible, with less overlap, and to achieve better class balance, only those results for which more than 90% of the SVM models voted in Bagging procedure are taken, i.e. results for which Confidence is > 0.9. In this way, an under-sampled training set is obtained with a new class label predicted by Bagging SVM. The new class label defines classes that overlap less and are more balanced.

A balanced Bagging DT model is trained on this Bagging SVM output. The model is now trained on much more balanced data and the balanced ensemble meta-algorithm further helps to solve the problem of the minor class (the most valuable customer class) and improves the performance of customer segments classification. In addition, the balanced Bagging DT model extracts rules that better describe customer segments, especially the minor one. Namely, solving the problem of the minor class, significantly more rules are obtained for the most important segment of the customers.

Thus, the final model for customer segments classification was created by combining an ensemble of SVM classifiers and an ensemble of DT rule extractors, so it can be called an ensemble SVM-RE model.

By training the model, the optimal combination of model's parameters is found, which achieves maximum predictive performance. This is attained by combining Grid-Search technique with k-fold cross-validation. More specifically, a grid of possible values is defined for parameters whose combinations are tested using the k-fold cross-validation procedure with stratified sampling. The cross-validation procedure implies that the starting data set is split into subgroups, taking care that percentage of class representation in subgroups corresponds to percentages of class representation in the entire set of data. Then k-1 subsets are used for training the model (training set), while one of the subsets is used for validation, i.e., testing how this model works on an unknown set of data (validation set). The procedure is repeated k times, so that each of the subsets is a validation set. At each iteration, the parameters for classification (accuracy rate, class precision, and class recall), are calculated and finally their average value is found.

For assessment of predictive performance, overall accuracy rate, class precision and class recall are used (these indicators are explained at the end of section 2.3). In addition to predict customer segment with high accuracy, for customer targeting it is important to classify existing consumers more accurately, so class recall is an important indicator of model performance.

3.3. Model Testing

In the testing phase, to assess the accuracy of the model at the test set, the actual CV-level primarily is determined using the cluster model generated in a training phase. Then the CV-level is predicted using the trained Bagging SVM model, while the test set retains examples whose predictions have Confidence > 0.9, and the predicted CV-level now is declared as the actual class label. The trained balanced Bagging DT model is then applied to this preprocessed test set, and thus CV-level predictions are obtained.

In the testing phase, the predictive performance of the model is determined by comparing the CV-level obtained by prediction using trained models with the actual CV-level values in the test set.

3.4. Summary of Predictive Procedure

Figure 1 shows a flow diagram for the training and testing phases of the predictive procedure. The procedure was implemented using Rapid Miner.

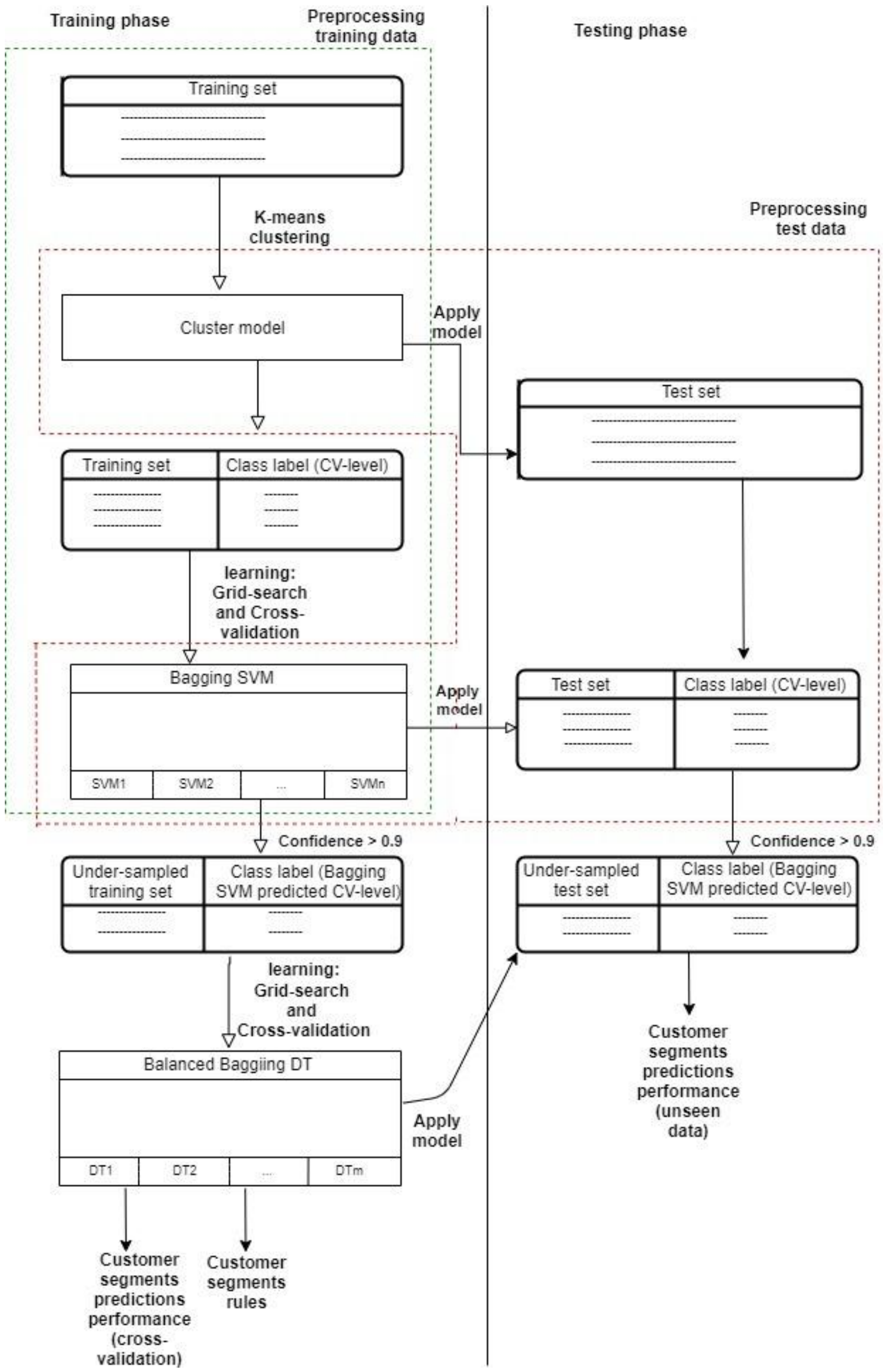

Fig. 1. Predictive procedure

4. Empirical Testing and Results

4.1. RFM Clustering of Training Data Set

By clustering the starting data set using k-means method and normalized RFM attributes, following results are obtained - shown in Table 2. It can be seen that the best DB index (minimum absolute value) is achieved for a 3-cluster model. This cluster model is shown in Table 3.

Table 2. Selection of number of clusters (parameter k) for k-means clustering

K	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
DB	-1.025	**-0.811**	-0.983	-0.958	-0.909	-1.02	-0.98	-0.976	-0.96

Table 3. Centroid Cluster model for RFM segmentation of customers

	R	**F**	**M**	**Items**
cluster_0	0.766807	0.565126	0.677733	238
cluster_1	0.735348	0.088065	0.179499	819
cluster_2	0.137318	0.101734	0.211345	548

Note: Normalized centroid values are shown (0-1 range transformation)

From Table 3, it can be seen that cluster_0 consists of the most recent, most frequent and most profitable customers (CV-Level=1), cluster_1 consists of recent, but less frequent and less profitable customers (CV-Level=2), while cluster_2 is made of non-recent customers, that are less frequent and less profitable (CV-Level=3). The most valuable customer cluster contains significantly less items than the other two clusters (238 versus 819 and 548), so the problem of class imbalance is evident.

Table 4 shows the distribution of customer frequency, recency and profitability across these CV-level segments. It can be observed that customers from the most valuable segment are recent, as well as that they have purchased on average 10 times in the considered period and their average amount of trade is around € 242. In contrast, customers from the CV-Level 3 segment, trade on average at most 3 times, with an average trading volume of around € 82.

Table 4. CV-Level customer segments

CV-Level	**Recency**	**Frequency**	**Monetary**
1	Avg: 4	Avg: 10	Avg: 241.65 €
	Min: 3	Min: 3	Min: 113.4 €
	Max: 5	Max: 17	Max: 352 €
2	Avg: 4	Avg: 2.4	Avg: 71.06 €
	Min: 3	Min: 1	Min: 9.6 €
	Max: 5	Max: 7	Max: 199.5 €
3	Avg: 1.54	Avg: 2.6	Avg: 81.96 €
	Min: 1	Min: 1	Min: 12.5 €
	Max: 2	Max: 9	Max: 239.5 €

4.2. Empirical Testing of Predictive Procedure

Training phase

In order to test proposed predictive procedure, a Bagging SVM model for the CV-level prediction obtained by initial customer clustering was first generated. Using Grid Search parameter optimization and 10-fold cross-validation, optimal combination of parameters for SVM and Bagging is defined as: SVM.C = 400.6, SVM.gamma = 200.006, Bagging.sample_ratio = 0.9, and Bagging.iterations = 10. The model then generated a CV-level prediction which is now taken as the class label of the training set.

In the next step, an under-sampled training set was made by excluding all predictions with confidence <= 0.9, i.e. those results for which only 90% of models and less voted in the Bagging SVM procedure. Table 5 shows the thus obtained new training set.

Table 5. Changes to the training set in the predictive procedure

Training set	Class label	Distribution of class label	Number of examples
Starting	CV-Level	CV-Level 1 (238) CV-Level 2 (819) CV-Level 3 (548)	1605
Obtained at the Bagging SVM output	Bagging SVM predicted CV-Level	CV-Level 1 (132) CV-Level 2 (981) CV-Level 3 (492)	1605
Under-sampled (Conf. > 0.9)	Bagging SVM predicted CV-Level	CV-Level 1 (82) CV-Level 2 (834) CV-Level 3 (360)	1276

Table 6. Results of the training phase (cross-validation performance)

Model	Accuracy	Class Recall	Class Precision
Bagging SVM[4]	61.00%	**21.01%**[1], 81.07%[2], 48.36%[3]	**50.51%**[1], 61.37%[2], 62.50%[3]
Balanced Bagging DT on Bagging SVM output[5]	88.71%	**69.51%**, 96.76%, 74.44%	**80.28%**, 87.91%, 93.38%
Standalone DT[6]	60.69%	**4.20%,** 80.34%, 55.84%	**27.78%,** 61.90%, 60.47%

[1] Class performance for CV-Level 1(most valuable customers - minor class);

[2] Class performance for CV-Level 2;

[3] Class performance for CV-Level 3 ;

[4] This model is a data preprocessor;

[5] The performance of this model is actually the performance of the final model for the customer segments classification called the ensemble SVM-RE ;

[6] Standalone DT is generated for comparison purposes.

Following that procedure, the balanced Bagging DT classifier was trained on the training set thus obtained. Grid Search and 10-fold cross-validation determined the optimal combination of parameters: Bagging.sample_ratio= 0.9, Bagging.iteration =

304, balancing_proportion: 82:500:100, split_criterion = gain_ratio, min_size_for_split = 4, min_leaf_size = 2, max_depth = 15, confidence = 0.2, min_gain = 0.01.

For the purpose of comparison, the DT standalone classifier was trained with the optimal combination of parameters: split_criterion = gini_index, min_size_for_split = 4, min_leaf_size = 16, max_depth = 15, confidence = 0.1, min_gain = 0.01.

The classification performance of the trained models are shown in Table 6.

From the Table 6, it can be noticed that the balance Bagging DT on Bagging SVM output model (hereinafter ensemble SVM-RE model) has significantly better classification performance than the standalone DT model. The standalone DT method correctly targeted only 4% of the most valuable customers, while ensemble SVM-RE successfully targeted 69% of them.

Also, all considered classification performances are better with the ensemble SVM-RE model than with DT. The class precision of the most valuable customers for DT is only 28%, which means that the company will have unnecessary campaign costs for 72% of wrongly classified customers. Precision of ensemble SVM-RE model for the class is 80%, which means that only 20% of the offers sent are likely to be unanswered. Therefore, ensemble SVM-RE will, in relation to DT, reduce the cost of the campaign. It can be concluded that, with the high overall accuracy of CV-level prediction (89%), the proposed ensemble SVM-RE method managed to solve the problem of class imbalance.

The results show that Bagging SVM as the preprocessor of data on purchase transactions eliminated noise, so that more precise classification is possible. The DT classification accuracy is increased by 28% - the accuracy for the standalone DT is 61% and for SVM-RE 89%. Mean class recall for standalone DT is 47%, and after data preprocessing and using the ensemble DT it is 80%. Mean class precision has increased from 50% to 87% after preprocessing.

Given the high cross-validation accuracy of rule extraction from the Bagging SVM output (89%), the rules validly interpret the Bagging SVM classification. Table 7 shows some of the 81 derived rules which are recognized as the most important, i.e. rules which cover a large number of examples (Support ~1% and more, except for the minor class where the minimum support is 0.3%), have high accuracy (Confidence > 80%) and good confidence in relation to overall data set (Lift > 1).

On the basis of derived rules, it can be stated that customers with CV-Level = 1 are mostly male customers, who mainly buy: basketball apparel for men from licensed brands (brands for which Sport Vision has licensed production and distribution, such as: Champion, Umbro, Lonsdale, Ellesse, Slazenger, Sergio Tacchini, etc.) and with a discount of 25% to 45%; apparel for adults – men, either for football or lifestyle category from licence brands with a discount between 25% and 35%; as well as men who purchase apparel for teens, with 25-45% discount, or equipment for women with 10-45% discount.

Customers of CV-Level = 2 are mainly women, who either mainly buy clothes from A brands (brands for which the company is a distributor, such as: Adidas, Nike, Under Armor, Reebok, Converse etc.) with a discount from 25% to 35%, or apparel from licensed brands and equipment on a discount from 25% to 45%. Additionally, women who purchase footwear for men on a 25% to 35% discount also belong to this customer segment. Male buyers in this category mainly purchase lifestyle apparel for adult men, either from licensed brands on 35% to 45% discount, or A brands from 25% to 35% discount.

CV-Level = 3 represents the group of least valuable customers. The customers belonging to this group mostly buy products on a discount larger than 45% (sale seekers). Male buyers in this category mainly buy lifestyle or equipment products from A brands. Female buyers in this segment purchase lifestyle footwear for adults from licensed brands.

Hence, with the SVM-RE ensemble, rules are obtained that explain customer segments, which is the answer to the RQ3. Also, solving the problem of the minor class provides a more efficient description of the segment of the most valuable customers with a larger number of important rules.

Table 7. Most significant classification rules derived by ensemble SVM-RE

CV-level	Rule	Confidence (>80%)	Support (>1%*)	Lift (>1)
CV-Level 1	if Discount > 45% and Prod_category = Football and Prod_age = For younger kids (4-10)	100%	0.3%	8.33
CV-Level 1	if Discount > 45% and Prod_category = Outdoor and Prod_type = Footwear and Prod_brand = Licence	100%	0.4%	8.33
CV-Level 1	if Discount ≤ 45% and Discount >>35% and Cons_gender = F and Prod_type = Apparel and Prod_brand = A brands and Prod_gender = For women	100%	0.3%	8.33
CV-Level 1	if Discount ≤ 45% and Discount > 25% and Cons_gender = M and Prod_type = Apparel and Prod_age = For adults and Prod_gender = For men and Prod_category = Basketball and Prod_brand = Licence	100%	0.4%	8.33
CV-Level 1	if Discount ≤ 35% and Discount > 25% and Cons_gender = M and Prod_type = Apparel and Prod_age = For adults and Prod_gender = For men and Prod_category = Football	100%	0.4%	8.33
CV-Level 1	if Discount ≤ 45% and Discount > 35% and Cons_gender = M and Prod_type = Apparel and Prod_age = For adults and Prod_gender = For men and Prod_category = Lifestyle and Prod_brand = A brands	100%	1%	8.33
CV-Level 1	if Discount ≤ 35% and Discount > 25% and Cons_gender = M and Prod_type = Apparel and Prod_age = For adults and Prod_gender = For men and Prod_category = Lifestyle and Prod_brand = Licence	100%	4%	8.33
CV-Level 1	if Discount ≤ 45% and Discount > 25% and Cons_gender = M and Prod_type = Apparel and Prod_age = For teens (8-14)	80%	1%	6.67
CV-Level 1	if Discount ≤ 45% and Discount > 10% and Cons_gender = M and Prod_type = Equipment and Prod_brand = Licence and Prod_gender = For women	100%	1%	8.33
CV-Level 2	if Discount > 45% and Prod_category = Skiing	86%	2%	1.17
CV-Level 2	if Discount ≤ 35% and Discount > 25% and Cons_gender = F and Prod_type = Apparel and Prod_brand = A brands	100%	6%	1.37

CV-Level 2	if Discount ≤ 45% and Discount > 25% and Cons_gender = F and Prod_type = Apparel and Prod_brand = Licence	100%	11%	1.37
CV-Level 2	if Discount ≤ 45% and Discount > 25% and Cons_gender = F and Prod_type = Equipment	94%	3%	1.29
CV-Level 2	if Discount ≤ 45% and Discount > 35% and Cons_gender = F and Prod_type = Footwear	98%	7%	1.34
CV-Level 2	if Discount ≤ 35% and Discount > 25% and Cons_gender = F and Prod_type = Footwear and Prod_gender = For men	100%	2%	1.37
CV-Level 2	if Discount ≤ 45% and Discount > 35% and Cons_gender = M and Prod_type = Apparel and Prod_age = For adults and Prod_gender = For men and Prod_category = Lifestyle and Prod_brand = Licence	100%	4%	1.37
CV-Level 2	if Discount ≤ 35% and Discount > 25% and Cons_gender = M and Prod_type = Apparel and Prod_age = For adults and Prod_gender = For men and Prod_category = Lifestyle and Prod_brand = A brands	100%	3%	1.37
CV-Level 2	if Discount ≤ 45% and Discount > 10% and Cons_gender = M and Prod_type = Footwear and Prod_age = For adults and Prod_category = Lifestyle	100%	8%	1.37
CV-Level 3	if Discount > 45% and Prod_category = Basketball	88%	1%	5.83
CV-Level 3	if Discount > 45% and Prod_category = Fitness and Cons_gender = M and Prod_brand = A brands	100%	1%	6.67
CV-Level 3	if Discount > 45% and Prod_category = Lifestyle and Prod_brand = A brands and Cons_gender = M	95%	3%	6.33
CV-Level 3	if Discount > 45% and Prod_category = Lifestyle and Prod_brand = Licence and Prod_age = For adults and Prod_type = Apparel and Prod_gender = For men	100%	1%	6.67
CV-Level 3	if Discount > 45% and Prod_category = Lifestyle and Prod_brand = Licence and Prod_age = For adults and Prod_type = Footwear and Cons_gender = F	100%	1%	6.67
CV-Level 3	if Discount > 45%and Prod_category = Running and Prod_brand = A brands	91%	2%	6.06
CV-Level 3	if Discount ≤ 25% and Discount > 10% and Cons_gender = M and Prod_type = Apparel and Prod_gender = For men	100%	1%	6.67

*note: the criteria for "Support" for chosen rules is ~1% and more, except for the minor class where the minimum support is 0.3%

Testing Phase

In order to determine the predictive performance of the model on the test set, the test set was clustered using a cluster model generated in the training phase (see Figure 1). In this way, each user is assigned an appropriate CV-level to be used to determine predictive performance in the test phase.

The next step is to preprocess the test set using a Bagging SVM trained in the training phase, as well as under-sampling the test set taking examples with a class label voted by more than 90% of the SVM models during the bagging procedure (see Figure 1). The characteristics of the test set before and after preprocessing are shown in Table 8.

Table 8. Changes to the test set in the testing phase

Test set	Class label	Distribution of class label	Number of examples
Starting	CV-Level	CV-Level 1 (286) CV-Level 2 (2906) CV-Level 3 (2027)	5219
Obtained at the Bagging SVM output	Bagging SVM predicted CV-Level	CV-Level 1 (491) CV-Level 2 (3399) CV-Level 3 (1329)	5219
Under-sampled (Conf. > 0.9)	Bagging SVM predicted CV-Level	CV-Level 1 (406) CV-Level 2 (3155) CV-Level 3 (1043)	4604

It is noted that the Bagging SVM complemented the first minor segment so that it has 491 instances after data preprocessing. In addition, this preprocessor has cleared overlaps between segments so that future classification is as accurate as possible.After under-sampling, the trained ensemble SVM-RE model was applied to this test data set and the results shown in Table 9 were obtained.

Table 9. Performance of ensemble SVM-RE model on unseen data

Model	Accuracy	Class Recall	Class Precision
Ensemble SVM-RE	85.79%	**93.84%**[1], 84.44%[2], 86.77%[3]	**79.38%**[1], 94.57%[2], 69.24%[3]

[1] Class performance for CV-Level 1 (most valuable customers - minor class);[2] Class performance for CV-Level 2; [3] Class performance for CV-Level 3;

From the table above it can be seen that the overall accuracy of the ensemble SVM-RE model on unseen data is 85.79% which is good, compared to cross-validation accuracy of 88.71%. Apart from maintaining similar overall accuracy as in model validation, the unknown data also shows good performance for the minor class (class precision of about 80% and class recall of about 94%), which is the most important because the existing and predicted potential most valuable customers are precisely identified.

The ensemble SVM-RE model targets a total of 480 most valuable customers for the campaign. Of these, 381 most valuable customers were correctly targeted (94% of all such customers in the test set) and 99 customers were missed. So about 80% of the offers sent are potentially profitable while for 20% could be in vain (see the confusion matrix shown in Table A1 in the Appendix).

So, as a result of the test phase, it can be concluded that the proposed ensemble SVM-RE model is a quality predictor for CV-level, i.e. adequate model for customer segment classification, so the answer to the RQ1 is positive.

4.3. Comparison with Other Class Balancing Methods

Due to the comparison of the proposed ensemble SVM-DT model with standalone ensemble models, with respect to the efficiency of solving the minor class problem, a combination of DT classifiers with different balanced ensemble techniques were tested. First, on the starting training dataset, a Balanced Bagging DT model was generated with parameters: Bagging.sample_ratio = 0.7, Bagging.iterations = 108, balancing_proportion: 238: 238: 238, criterion = gain_ratio, min_size_for_split = 4, min_leaf_size = 2, max_depth = 15, confidence = 0.2, min_gain = 0.01. Then a balanced AdaBoost DT model with parameters: Ada-Boost.iterations = 3001, balancing_proportion: 238: 238: 238, criterion = gain_ratio, min_size_for_split = 4, min_leaf_size = 2, max_depth = 15, confidence = 0.2, min_gain = 0.01, and finally a balanced Random Forest model with parameters: RandomForest.sample_ratio = 1.0, Random.Forest.iterations = 75, balancing_proportion: 238: 238: 238, criterion = gain_ratio, max_depth = 10, are generated. The optimal parameters were determined using Grid Search and 10-fold cross-validation.

The performance of the class balancing models are shown in Table 10.

Table 10. Classification performance of standalone balanced ensemble models

Model	Accuracy	Class Recall	Class Precision
		Cross-validation performance	
Balanced Bagging DT	56.69%	**44.12%**[1], 51.28%[2], 70.26%[3]	**34.20%**[1], 68.74%[2], 56.04%[3]
Balanced AdaBoost DT	55.32%	**41.60%**, 64.22%, 57.30%	**30.43%**, 69.44%, 57.46%
Balanced RandomForest	51.03%	**53.36%,** 41.76%, 63.87%	**28.93%**, 69.94%, 51.70%
		Performance on test set (unseen data)	
Balanced Bagging DT	49.55%	**26.22%**, 43.53%, 61.47%	**8.35%** , 66.20%, 51.70%
Balanced AdaBoost DT	46.14%	**35.66%**, 46.73, 46.77%	**7.53%**, 65.48%, 52.93%
Balanced RandomForest	44.51%	**34.62%,** 37.89%, 55.40%	**7.12%,** 67.01%, 51.37%

[1] Class performance for CV-level 1 (most valuable customers - minor class);[2] Class performance for CV-level 2; [3] Class performance for CV-level 3

Comparing the results of ensemble SVM-RE method from Table 6 with the standalone balanced ensemble methods Bagging DT, AdaBoost DT and Random Forest in Table 10, it can be concluded that this method outperforms their capabilities in terms of class balancing i.e. solutions to minor class problems. Namely, while for the ensemble SVM-DT the recall and precision for minor class were 69.51% and 80.28% respectively, the best recall of the minor class was achieved by Random Forest (53.36%) and the best precision for the minor class by balanced Bagging DT (34.20%). Also, the maximum overall accuracy of standalone balanced ensemble models (55.69%) is significantly smaller than the ensemble SVM-DT model (88.71%). When comparing the results at the test set (Table 9), the superiority of the ensemble SVM-RE models is even more pronounced.

Finally, it can be concluded that SVM, in combination with the Bagging ensemble meta-algorithm more effectively solves class imbalance problems than other methods used for this purpose.

4.4. Comparison by Profitability Criterion

For model comparisons in terms of the potentially achievable maximum profit from a campaign based on the minor class prediction (i.e. the segment of the most valuable customers), Table 11 shows the calculation of this indicator individually by models. The profit indicator is calculated by the formula (3):

$$Profit = True\ Predicted * R - (True\ Predicted + False\ Predicted) * C \qquad (3)$$

where are: *True Predicted* - number of model's true predicted customers of the most valuable segment; *R*- potential single customer revenue from a campaign; *False Predicted* - number of model's false predicted customers of the most valuable segment; and *C*-estimated campaign cost per single customer.

Table 11. Model comparison by potentially earnable campaign profit

Model	True Predicted[1]	False Predicted[2]	Revenues[3]	Costs[4]	Profit[5]
SVM-RE[6]	150	44	36300	194	36106
Ensemble SVM-RE	165	41	39930	206	39724
Balanced Bagging DT	105	202	25410	307	25103
Balanced AdaBoost DT	126	288	30492	414	30078
Balanced Random Forest	127	312	30734	439	30295

[1]Number of true predicted customers of the most valuable segment
[2] Number of false predicted customers of the most valuable segment
[3] True Predicted *Potential Single Customer Revenue (€ 242)
[4] (True Predicted+False Predicted) * Estimated Single Customer Campaign Cost (€ 1)
[5] Revenues-Costs
[6] Results for standalone SVM-RE are taken from [57]

Potential revenue is assumed to be average revenue generated in previous campaigns at the most valuable segment level (€ 242, see Table 4), while the estimated cost per campaign per customer is € 1. The number of correctly predicted and incorrectly predicted members of the most valuable customer segment is given in proportion to the participation of this class in the initial training set (since the training set obtained at the Bagging SVM output is under-sampled).

Based on the calculation in the table above, it is observed that the maximum profit can be expected based on the ensemble SVM-RE prediction. The improvement of the standalone SVM-RE method by the ensemble meta-algorithm may lead to an increase in profit in campaign for € 3618. From the standalone balanced ensemble method, the highest expected profit of € 30295 is achieved with the RandomForest prediction, which is € 9429 less than the expected profit with the ensemble SVM-RE prediction.

Thus, it can be concluded that the proposed ensemble SVM-RE model out-performs other considered models by profitability criterion. Note that the advantages of the ensemble SVM-RE method according to this criterion would be even more pronounced if the comparison was done on unseen data. Since the predictive accuracy on unseen data was not tested in [57], we compared the cross-validation performance of the models.

Taking into account the comparison according to the criterion of predictive performance from the previous section, as well as based on the criterion of profitability, ensemble SVM-RE is a better class balancing method than other considered methods, which is the answer to the RQ2.

4.5. Validation of the method by testing on a public dataset

Method was also tested on a publicly available *Customer_transaction_dataset*, available on *Kaggle* data science repository (available at: https://www.kaggle.com/archit9406/customer-transaction-dataset), which consists of data regarding cycling equipment sales. The data contains 20,000 sales transactions for 3,500 customers in the period from January to December 2017. The data were refined due to missing values, leaving 19765 items in the set, which were divided into training set (70%) and test set (30%). Recency was calculated based on the date of transactions, Monetary based on the total transactions value, and Frequency as the number of transactions in this period, the same way as in the original dataset. The distribution of these and pre-existing attributes in this dataset is shown in Table A2 in Appendix.

Data were first clustered based on RFM attributes and 3 clusters were obtained as the optimal solution (minimum DB index = -0.879) (Table 12).

Table 12. Centroid Cluster Model for the public dataset

	Recency	**Frequency**	**Monetary**	**Items**
Cluster 0	0.668	0.302	0.282	4264.000
Cluster 1	0.969	0.623	0.549	7034.000
Cluster 2	1.000	0.347	0.301	8467.000

Note: Normalized centroid values are shown (0-1 range transformation)

Cluster 1 of the most valuable customers (CV-Level = 1) contains 7034 items, cluster 2 of the medium valuable customers (CV-Level = 2) has 8467 items, while cluster 0 of the least valuable customers (CV-Level = 3) in this case is the smallest and has 4264 customers. Obviously, the problem of unbalanced classes is also present here.

Repeating the same predictive procedure defined in Figure 1, in the training phase by cross-validation and the test phase by testing on an unknown dataset, the results shown in Table 13 were obtained.

Table 13. Predictive performance of the models for the public dataset

Model	Parameters	Cross-Validation Performance	Test Performance
Bagging SVM	SVM.gamma = 0.0325	accuracy: 46.15%	accuracy: 47.29%
	SVM. C = 1000.0	class recall: 21.94%[1], 44.25%[2], 59.93%[3]	class recall: 23.69%[1], 46.16%[2], 60.12%[3]
	Bagging.iterations = 10	class precis.: 33.87%, 46.65%, 49.12%	class precis.: 37.04%, 47.56%, 49.85%
	Bagging.sample_ratio = 0.8		
Ensemble SVM-RE	DT.criterion = gain_ratio	accuracy: **88.69%**	**accuracy: 90.32%**
	DT.min_size_for_split = 4		
	DT.minimal_leaf_size = 2		
	DT.maximal_depth = 15	class recall: **61.61%,** 85.50%, 93.74%	class recall: **70.07%**, 86.67%, 94.55%
	DT.confidence = 0.1		
	DT.minimal_gain = 0.01		
	Bagging.sample_ratio = 0.9	class precis.: 74.24%, 88.71%, 90.03%	class precis.: 72.03%, 91.57%, 91.41%
	Bagging.iterations = 100 Bagging.Balancig_proportion: 435:1000:2000		
Standalone DT	DT.criterion = gain_ratio	accuracy: **43.01%**	**accuracy: 43.08%**
	DT.min_size_for_split = 4		
	DT.minimal_leaf_size = 2	class recall: **0.50%,** 0.35%, 99.87%	class recall: **0.55%**, 0.33%, 100%
	DT.maximal_depth = 15		
	DT.confidence = 0.1	class precis.: 78.95%, 80.95%, 42.90%	class precis.: 100%, 100%, 42.94%
	DT.minimal_gain = 0.01		

[1] Class performance for CV-Level 3 (minor class); [2] Class performance for CV-Level 1; [3] Class performance for CV-Level 2

The data in the table above indicate that the Ensemble SVM-RE successfully solved the problem of incorrect classification of the minor class on this data set as well. On the training and test set, standalone DT completely misclassified the best customers (class recall is only about 0.3%) and the worst customers (class recall about 0.5%), and the overall accuracy of the model is about 43%. The accuracy of the Ensemble SVM-RE model on unknown data is about 90%, class recall for the best customers about 87% and for the least valuable cluster about 70%. Bagging SVM has a class recall below 50%, not only for the minor (least valuable) class, but also for the non-minor most valuable class. This means that in this data set, besides the problem of the minor class, the problem of class overlap (noise) also exists, which Bagging SVM preprocessor has solved successfully.

5. Discussion

The proposed model aimed to test several improvements of existing methods for predictive classification of customers in direct marketing, such as objective segmentation of customers with an indicator for the optimal number of clusters, description of segments in terms of customer characteristics and products, prediction of value for new customers with unknown purchasing behavior, and finally and most importantly, the reduction of misclassification for the segment of the most valuable customers, i.e. solution of class imbalance problem.

Unlike some previous studies that use hard coding of RFM attributes, sorting based on coded values and subjective selection of segments for the campaign [4, 11, 12], this study suggests a more sophisticated and objective data mining technique - k-means clustering, which achieves segmentation algorithmically using the measure of Euclidean distance, in order to provide maximum similarity within segments and difference between segments. Instead of uniform coding of RFM attributes, which does not treat the customer individually, but identifies them with the group to which they belong, which is a characteristic of many previous studies [13, 14, 16], clustering by un-coded attributes is proposed in this study, because there are numerous values with which the algorithm for clustering works smoothly. This prevents the loss of important information at the level of each individual customer, that may distinguish them from others. Unlike the method proposed in [16], which involves subjective evaluation and testing of the best number of clusters, our method determines the optimal number of clusters objectively based on the DB index, which significantly simplifies the procedure and ensures the accuracy of the model.

Classical RFM segmentation involves the prediction of future customer behavior based only on these three attributes, and is not applicable to the prospecting for new customers because transaction information is not available [4]. In [16], sophisticated data mining techniques are used during customer segmentation, but in addition to customer characteristics, RFM attributes are included as predictive attributes, so the proposed model cannot be used for new customers for whom these attributes are unknown. In our study, only product data and customer characteristics are used as predictive attributes, as it is expected to obtain predictive rules with more suitable information for targeting the potential customers [51].

Furthermore, for predictive customer classification, this study suggests the SVM-RE method in combination with ensemble techniques that enhance the predictive power of the model. The results showed that the SVM ensemble efficiently preprocesses the data, i.e. resolves the noise and class imbalance. First, by moving the margin to the nearest (and therefore most similar) examples of the larger class and classifying them into the smaller class, SVM resolves the noise in the data, i.e. class overlapping and complements the minor class with the most relevant examples. Then, by pooling the results of multiple SVMs in the ensemble procedure, the instances that join the minor class are identified more precisely (the example joins the class that has been voted the most by the SVM model). And in the end, taking only the results for which more than 90% of the SVM models voted, representatives of the classes most likely to belong to the class are selected, i.e. those that are farthest from each other and between which the margin is the widest, leading to maximum separation of classes. Applying a balanced DT ensemble for rule extraction from such pre-processed data set (SVM-RE ensemble) misclassification rate of the most valuable customer segment is reduced by 66%, which is a much better result than the result obtained in [58], where using standalone SVM preprocessor and standalone DT rule extractor this misclassification rate was reduced by 37%.

For the test set, ensemble SVM-RE method achieved Balanced Correction Rate (BCR) (rooted product of class recall of all classes) of 83%, which is 15% better than the best achieved in [22] by applying under-sampling based on clustering and ensemble techniques. Comparing the best class recall of minority class (88%), obtained in [29] using cluster-based under-sampling and k-NN classifiers, with the result achieved by our method (94%), the superiority of our model is obvious. Additionally, the class recall for majority class in [29] is low (63%), while with our method for the other two larger classes it is above 84%. In [17] the best achieved class recall for minority class is 73%, for dataset with moderate degree of class imbalance, and with random under-sampling for class ratio of 2:1, using SVM classifier, which is again lower than our score of about 94% on the test set.

Apart from the proven efficiency, automatic class balancing using the SVM-RE ensemble is less complex for practical application (there are no unknowns regarding the choice of examples to be removed, choice of optimal class ratio, etc.) compared to resampling techniques in similar studies in direct marketing [17, 18, 22, 29, 30]. Balancing the data in this way offers a stable solution that does not suffer from the sampling bias and overfitting that can occur due to resampling [31].

The ensemble SVM-RE method had a misclassification of the most valuable customer segment of about 6% at the test set, which is an excellent result. A similar result, i.e. a misclassification rate of 4% was achieved in [27], where a method based on adapting the SVM algorithm by introducing cost-sensitive learning and random under-sampling was used. However, the advantage of our method is that its application in practice does not require extensive knowledge of the SVM method required for its adaptation.

Comparing the results of standalone SVM-RE method from [57]and the ensemble SVM-RE, it can be seen that the ensemble approach was able to improve overall accuracy by 2.98%, recall for minor class by 6.81%, as well as precision for minor class by 2.83%. While these improvements seem small, considering that identifying the most valuable customers has improved by about 7% and their prediction by about 3%, it can bring about a big increase in the profits generated by the campaign (see Table 11). It should be borne in mind that once an accurately selected or predicted high-profit customer can generate more revenue in a campaign than all other customers combined. Additionally, method was not tested in unseen data in [57], hence, its true predictive power remained unexplored.

The method was additionally tested on a publicly available data set where its superiority was confirmed. The overall accuracy of classification on unknown data was improved from 43% (held by standalone DT) to 90%. The SVM-RE ensemble method at the test set had a misclassification of the most valuable customer segment of about 13%, unlike the standalone DT which had a misclassification of as much as 97% due to the overlap of this segment with the middle value customer segment. As for the problem of the minor class, i.e. least valuable customers in this case, the SVM ensemble reduced its misclassification error from 94.5% to 29% on unknown data. Thus, the method successfully solved the problem of imbalance and class overlap on the validation data set as well.

Contributions to theory/knowledge/literature

Given the above comparison and the highlighted advantages of the proposed ensemble SVM-RE method in relation to previously applied methods, it can be concluded that this study contributes to the existing theory and knowledge in the field of predictive analytics in direct marketing in several ways:

1. Instead of judgment based RFM segmentation, objective k-means based RFM segmentation and estimation of the optimal number of clusters based on DB index is proposed, which simplifies the application and guarantees higher accuracy of the model.
2. Instead of classifying customers into uniformly coded groups, clustering is performed at the level of an individual customer, thus preventing the loss of significant segmentation information.
3. Instead of RFM attributes, customer and product characteristics are used as predictors, so the method can also be used to classify unknown customers.
4. Instead of resampling or adapting the learning algorithm, it is proposed to automatically balance and remove class overlaps using the ensemble SVM method, which leads to a stable solution free of sampling bias, overfitting and extensive knowledge of the learning method by marketers.
5. Instead of preprocessing data using standalone SVM, an ensemble SVM has been proposed that increases the efficiency of balancing and class separation.
6. Instead of rule extraction using the standalone classifier, this study suggests rule extraction using the DT classifier combined with a balanced ensemble meta-algorithm which gives better predictive performance, compared to using standalone DT as the rule extractor.
7. The proposed ensemble SVM-RE method has a smaller misclassification of minority class (segment of the most valuable customers) than the standalone balanced ensemble method, as well as the methods of resampling and adaptation of algorithms used in previous studies, while maintaining high overall accuracy.
8. The proposed method extracts rules that effectively describe user segments (including the smallest one with the most valuable customers, for which rules may be omitted if the minority class misclassification is not addressed). These rules are semantically richer because they contain customer and product characteristics, and are more suitable for targeting existing and new customers in the campaign.
9. Unlike most previous studies, the method is tested on a real-life data set in this study that has not been refined and specially prepared for analysis.Then, the method was validated by testing on a publicly available dataset.

Implications for practice

In addition to the theoretical contribution, the proposed method is important for practical applications and can significantly help marketers in planning direct campaigns. A very creative and innovative offer can result in a low response rate if the targeting is not done precisely, while, on the other hand, a poorly formulated and medium creative offer to the right target group can reduce, but not eliminate, the desired consumer response [62]. Therefore, understanding the preferences and needs of consumers is a more important factor in creating a campaign, than the creative process and the way of communicating the offer. In addition, business intelligence and data mining can enhance the competitive advantage for the companies in contemporary markets [63]. This is in line with the current and ongoing trend of digital transformation in companies, conducted with the aim of keeping up with the competition [64] and improving customer experience [65].

Using the proposed model, it is possible to overcome the impersonal nature of traditional marketing, as it allows companies to treat similar groups of customers in a unique way. The benefits that this model provides to practitioners are reflected through precise targeting, minimizing message waste, and more profitable campaigns. In this way, they are enabled to objectively segment the market, adapt the content to individual segments, and to build a reliable and loyal relationship with customers. In this paper, it is shown that using ensemble SVM-RE model prediction for the most valuable segment results in the highest number of true predicted customers, as well as the lowest number of false predicted customers of that segment. In that sense, this proposed model in direct marketing practice can achieve the highest profit, compared to other considered models and reduce the waste of marketing resources.

Based on the insights from this predictive model, a more elaborate segmentation strategies can be created and more effective targeting can be applied. The rules extracted from our model enable marketers to learn about their most valuable consumers, which is of high importance, having in mind that keeping the current customers is often six to ten times more cost-effective than acquiring new ones [66, 67]. Additionally, explicit rules that describe the most valuable consumers allows for acquisition of precisely those customers that are the most similar to this group, through various targeting strategies. Hence, customers from different clusters and of different value for the company can be targeted in customized and tailored promotional activities. In other words, targeting can be conducted in an objective and precise manner, which improves the profitability of each campaign, as well as the overall effectiveness of direct marketing activities.

Another advantage for the practitioners of direct marketing is the ease of use of our method. There is no need for complex resampling procedures to be carried out, since automatic data balancing is used. Also, practitioners do not have to know the details of the learning algorithm or hire additional experts for that purpose.

6. Conclusions

In this paper an efficient method for customer classification in direct marketing is designed. The presented predictive procedure implies the classification of customer clustering. Using the k-means clustering, customers are divided into segments based on their RFM attributes (past purchasing behavior). Different clusters have different customer value levels, as well as different probability of responding to a marketing campaign. Following this procedure, customer's affiliation with one of the clusters (as well as consumer's appropriate CV-level) is predicted using the ensemble SVM-RE method, using the data on the purchased products and the customer characteristics.

The results of our empirical testing indicate that the class imbalance problem can be overcome, which improves the classification of the minority, and most valuable class.

Combining multiple SVM models with an ensemble meta-algorithm can improve data preprocessing and separate customer segments more efficiently than standalone SVM. Applying balanced ensemble classifiers on such a preprocessed training set improves the predictive indicators for the smaller class and, consequently, the effectiveness of predictive segmentation (especially for the segment of the most valuable customers), as well as the chances of making greater profits in the campaign. Combining ensemble method, based on random (with replacements) under-sampling of larger classes, i.e. on bootstrapping, with SVM data preprocessing and rule extraction, balances classes better than standalone balanced ensemble methods, in customer segment classification.

The main contribution of this study is that the proposed method better deals with the problem of class imbalance that occurs when classifying customers in direct marketing, than the methods of resampling and algorithm adaptation applied in previous papers in this field. Namely, in comparison with the previous results, a smaller misclassification of the minority class (segment of high-value customers) with high overall accuracy was achieved. The class balancing procedure is automated by data preprocessing, thus overcoming the shortcomings of previously applied methods (sampling bias, overfitting, the need for extensive knowledge of learning methods). Ultimately, application is simplified.

In addition to the scientific contribution, this study is of practical importance because the proposed method can significantly help marketers to increase the efficiency and profitability of direct campaigns and to maintain good customer relations. The results of the method can help decide if existing (new) customers should be targeted in the following direct marketing campaigns, as two key elements of the customer relationship management are customer attraction and retention [68]. This method draws out and generates classification rules, which can be used in improving relationships with existing customers and targeting new potential customers, based on their characteristics and the products offered. Ultimately, the method can notably increase the campaign revenues, as well as decrease its costs.

However, this study also has several limitations and drawbacks. First, training sets with relatively small number of instances were used in this study. For a large training set, training of SVM learners, i.e. setting the appropriate parameters, requires high computation time [33]. Secondly, as a preprocessor, SVM is combined only with Bagging, although it is possible that it would balance classes better with some other ensemble technique. Third, the proposed model was tested on only one real data set, so it is unknown what the results would be on another set with a different class distribution. Fourth, as a rule extractor from the SVM ensemble of the preprocessed dataset, only a combination of Bagging and DT classifiers was tested. The bagging technique uses random under-sampling with replacement, which may be less effective than some other techniques such as cluster-based under-sampling. Thus, the question remains whether the rule extraction would yield better results with an ensemble using cluster under-sampling as in [22, 56], or by combining ordinary cluster under-sampling with different classifiers as in [22, 29], as well as by combining some other ensemble technique (e.g. Adaptive Boosting) with different classifiers similar to [30]. In the end, the success of the data mining method largely depends on the quality of the data. The data set used here includes only some customer characteristics. By including more customer attributes, clearer rules for targeting new customers can be obtained.

In future research, this method can be tested on other data sets to verify or improve its efficiency. In this study, the method was tested in the classification of customer segments where the minority class share is about 15%. It would be interesting to test its performance in the customer response model where minority class participation can be significantly lower, even below 5%.

To extract the rules from the ensemble SVM preprocessed dataset, some other ensemble techniques could be tested, such as Random Forest, as well as algorithm-level techniques. Since cluster-based under-sampling was previously confirmed in the literature as a successful class balancing technique [22, 29], a combination of this technique could be tested as a rule extractor (independently or within an ensemble procedure) with different classifiers. Also, although in this study Bagging SVM was confirmed as a preprocessor that successfully balances data from the domain of direct marketing, in future research its results could be compared with cluster-based under-sampling on the same data set. It would be useful to test whether some other ensemble technique, such as Adaptive Boosting, in combination with SVM, would pre-process better, i.e. balance the data more effectively.

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Article

Customer Response Model in Direct Marketing: Solving the Problem of Unbalanced Dataset with a Balanced Support Vector Machine

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Abstract: Customer response models have gained popularity due to their ability to significantly improve the likelihood of targeting the customers most likely to buy a product or a service. These models are built using databases of previous customers' buying decisions. However, a smaller number of customers in these databases often bought the product or service than those who did not do so, resulting in unbalanced datasets. This problem is especially significant for online marketing campaigns when the class imbalance emerges due to many website sessions. Unbalanced datasets pose a specific challenge in data-mining modelling due to the inability of most of the algorithms to capture the characteristics of the classes that are unrepresented in the dataset. This paper proposes an approach based on a combination of random undersampling and Support Vector Machine (SVM) classification applied to the unbalanced dataset to create a Balanced SVM (B-SVM) data pre-processor resulting in a dataset that is analysed with several classifiers. The experiments indicate that using the B-SVM strategy combined with classification methods increases the base models' predictive performance, indicating that the B-SVM approach efficiently pre-processes the data, correcting noise and class imbalance. Hence, companies may use the B-SVM approach to more efficiently select customers more likely to respond to a campaign.

Keywords: customer response model; support vector machine; data pre-processing; direct marketing; data mining; unbalanced data

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1. Introduction

The shift in marketing focus from a product-oriented to a consumer-oriented paradigm has been particularly rapid over the last decade due to the growing interest in business intelligence and customer relationship management (CRM). Marketing decisions play a significant role in the current customer-oriented environment, which generates the need for a simple and integrated framework for systematically managing available customer data. Since modern consumers are educated and sophisticated, a marketing strategy that meets their requirements becomes necessary [1].

One of the measures determining the success of a direct marketing campaign is the ratio of the customers who respond to the campaign, which is precisely the issue addressed by customer response models. The models for predicting these customers are based on dividing the potential customers into respondents and non-respondents, i.e., the group more likely to respond to a direct marketing campaign than the group with a lower response probability. In this regard, modelling the customer response is an important direct marketing activity. Identifying consumers with a higher response probability can reduce marketing costs and increase the campaign's profitability. The marketing resources can be specifically allocated to active customers with a high potential value to the company.

For example, the Ebedi Microfinance Bank utilised a customer response model to avert unnecessary spending that would have been incurred by sending promotional offers to non-respondents [2]. With predictive analytics, RedBalloon's total channel customer acquisition cost was reduced by 25% in less than a month [3], while Harley-Davidson increased sales in New York by 2930% [4]. Moreover, other customer-centric data-mining methods are widely and successfully used in companies such as Amazon, Netflix, and Alibaba [5].

However, the share of customers who respond to the campaign with purchases is usually small, i.e., often, the response rate in campaigns is very low, and even around 1% can be considered successful. Since the data in the customer databases are unbalanced, designing an effective response model is one of the direct marketing challenges [6].

The class imbalance problem in direct marketing is usually solved by using one of the following three approaches: data-based approaches [7,8], algorithm-based approaches [9], or cost-based approaches [10]. Namely, the data-based approach balances classes using resampling techniques; algorithm-based solutions are based on specifically modified algorithms, while cost-based approaches allocate different misclassification costs to different class examples [11]. These approaches have significant limitations. First, in the data-based approach, the resampling does not propose an optimal class distribution, and the criteria for selecting the instances for the resampling are unclear. Second, algorithm-level approaches require substantial algorithm knowledge. Third, cost-based solutions require additional learning costs and the in-depth exploration of effective cost setups.

Following the trends of direct mailing, with the development of social media and other Internet channels, and the possibility of placing campaigns on websites or social media in the form of posts and ads, a new field appeared to explore the effectiveness of these channels [12]. On the one hand, the abundance of user data available on these platforms allows for more precise selection and targeting in a direct marketing campaign to effectively identify respondents [13]. Effective marketing campaigns are especially relevant for social media since they play a significant role in brand development.

Response models for direct online campaigns involving web metrics are increasingly relevant nowadays, as indicated by newer research studies [14–16]. The problem of class imbalance is especially pronounced because the response rate is lower due to the large number of user accesses without response (website browsing, which does not end with a purchase). Even though some authors consider clicking on the offer link (website visit) as a response, only a completed purchase is considered a response in this research, leading to an extremely low response rate. Considering the importance of the respondents' prediction in the online direct marketing campaign and its efficiency, this paper proposes a customer response model based on the balanced Support Vector Machine (SVM) method. The proposed approach overcomes the abovementioned issues by using a balanced SVM as a data pre-processor, efficiently removing the noise and class overlapping while balancing the data.

It was shown in the literature that the SVM method [17] successfully resolves overlapping and unbalanced classes [18,19] by creating a hyperplane between the examples belonging to different classes, which can discriminate the class to the maximum distance, regardless of the number of instances available to learn from for any class [20]. Hence, SVM resolves data noise, i.e., class overlapping, and complements the minor class with the most relevant examples by moving the margin to the closest and thus most similar examples of the major class and categorising them into smaller classes [21]. In line with that, to balance the data and provide higher classification accuracy, SVM as a pre-processor of data was applied. In the case of extreme class imbalance, as we have in our data, the SVM is also biased towards the major class [7]. Therefore, during the training of the SVM pre-processor, the mentioned undersampling was applied, i.e., the balanced SVM was used as a pre-processor.

This research's main contribution is investigating the efficiency of balanced SVM data pre-processing on a dataset from online direct marketing campaigns with an extremely low response rate of 0.41%. A lower response rate is expected in the case of an online direct marketing campaign due to a larger number of website visits. A similar approach was shown in [20], where the authors used standalone SVM pre-processing, but on a dataset with a significantly higher response rate of 6%, as well as in [21], where the ensemble (Bagging) SVM pre-processing was used, but for a customer segmentation problem. Additionally, an advantage of this study is the inclusion of web metrics as predictors.

Considering the previously stated information, the main goal of this paper is to define a customer response model that overcomes the minor class misclassification problem. Therefore, considering the minor class problem in direct marketing databases, a balanced SVM is used as a pre-processor that refines the data, i.e., separates and balances the classes. This method has been confirmed in previous research as effective in class imbalance and linear inseparability. However, to the best of our knowledge, it is applied to improve customer response prediction for the first time in this research.

Following the above, this paper aims to give a precise answer to the following research question (RQ): Does the balanced SVM pre-processing increase the predictive performance of the customer response models?

To answer the RQ, empirical testing of the proposed method on real-world data and its validation on a publicly available dataset will be used. The real data were taken from a company that sells online sports equipment. Data from their online campaigns on social networks have been refined and prepared in a form suitable for predicting the customer's response. RapidMiner software was used for empirical testing of the proposed methods.

Following the introduction, this paper is structured as follows: a concise literature review is presented in Section 2, describing the previous research regarding customer response modelling using predictive analytics. The data and methods used in this paper are presented in Sections 3 and 4, followed by the results of the empirical testing in Sections 5 and 6. The seventh section discusses the obtained results and conclusions.

2. Literature Review

Digital marketing enables companies to reach far more potential customers over online channels for a lower cost than traditional marketing channels. Online channels also generate detailed customer data that allow the companies to shape customised and targeted messages and deliver them through various channels [22]. However, digital marketing faces the problem of an unknown conversion rate, which also existed in traditional direct mail.

In the online environment, the imbalanced data problem is even more present. For example, when potential customers visit the company website, each visit is called a session. The number of sessions that results from the completed purchase is significantly smaller than the total number of sessions [23], which causes a class imbalance. Consequently, the class imbalance problem leads to biased results of the predictive model since the model is trained using a small number of positive examples. Such biased models usually have a poor classification performance, as the model often classifies all test examples as the dominant class (e.g., negative purchase) [24].

On the other hand, developing predictive analytics, social media, and the available data make the customer response modelling process more precise. Instead of pure managerial judgment in choosing the targeted segments, decision-makers can utilise the data and analytics to identify their respondents much more efficiently while treating the class imbalance issue.

Daneshmandi and Ahmadzadeh [6] proposed a new approach to the class imbalance problem in their research. They showed a higher prediction accuracy in the hybrid ANN model obtained. To create a hybrid model, the authors applied a Bagging Neural Network (BNN) on an output of k-means clustering, then aggregated the results. The obtained sensitivity result for the hybrid model was 89%, and the area under the curve (AUC) result was 0.985, compared to the standalone BNN with a sensitivity of 55% and an AUC equal to 0.88. Hence, the authors proposed the hybrid techniques as more efficient than basic classifiers. This approach was tested on a dataset with a response rate of 19.81%.

Similarly, Asare-Frempong and Jayabalan [25] used Multilayer Perceptron Neural Network (MPNN), Decision Tree (DT), Logistic Regression (LR), and Random Forest (RF) classifiers for the prediction of the customer response to direct bank marketing. Their results highlight the predictive abilities of the RF classifier, which obtained the highest total accuracy of 86.8% and an AUC of 0.927. In their study, the obtained true positive rate was 90.2% for an imbalanced set with 11.63% respondents, which were undersampled in a 1:1 ratio before applying the models.

Kang et al. [26] designed a customer response model using clustering, balanced undersampling, and ensemble (CUE), aiming to solve the class imbalance problem of respondents, pairing it with several classification algorithms for prediction-logistic regression, multilayer perceptron neural network, k-nearest neighbour (k-NN) classification, and SVM. The authors used the undersampling method for the non-respondents from each cluster to avoid the loss of information relevant for classification, which can occur when applying random undersampling. Their CUE approach balanced respondents and non-respondents with no random undersampling, the synthetic minority oversampling technique (SMOTE), and one-sided selection. Additionally, the authors found that SVM was the best model under imbalanced circumstances. However, the authors focused on data-balancing methods and did not show the accuracy results for the respondent segment in more depth, but only an overall model accuracy.

Kim et al. [7] used three Direct Marketing Education Foundation (DMEF) datasets (1, 2, and 4) to test their approach, with response rates of 27.42%, 2.46%, and 9.42%, respectively. They applied two random undersampling rules (2:1 and 1:1) to balance the data. For the dataset with the highest class imbalance (DMEF2) without data balancing, SVM achieved the best result for sensitivity (7.3%) and total accuracy (95.3%). At the same time, DT, LR, and NN obtained 0% sensitivity, showing the main issue in classifying imbalanced data—all models were biased towards the major class. After 2:1 undersampling, SVM achieved the best classification performance with 23.8% sensitivity. At the same time, its efficiency was reduced after 1:1 undersampling, where it obtained the smallest sensitivity rate of 9.5%, compared to DT, LR, and NN with 41.1%, 56.5%, and 62.9%, respectively.

On a real-life direct marketing dataset from a Portuguese bank with an 11.2% response rate, Migueis et al. [8] applied the RF method on oversampled (SMOTE) and undersampled datasets (EasyEnsemble). The authors achieved the best results with undersampling, and the RF-AUC amounted to 0.989, in contrast to the oversampled and original dataset results of 0.945 in both cases. These results obtained by RF were compared to LR, NN, and SVM, and the RF still outperformed the other techniques. However, the undersampling significantly improved the results using RF as a classifier. In other cases, it was shown that it is not a universally suitable method for treating the class imbalance problem.

Marinakos and Daskalaki [27] tackled the class imbalance problem by comparing statistical, distance-based, induction, and Machine Learning classification algorithms, using the publicly available dataset with an 11.7% response rate to a direct marketing offer. The best performance was obtained by combining the cluster-based undersampling technique, and the k-NN true positive (TP) rate was 88%, while SVM achieved a TP rate of 71%. The authors stated that, regardless of the chosen algorithm, cluster-based undersampling and SMOTE obtained a similar result of TP $\approx$ 70%.

Farquad and Bose [20] tested SVM as a data pre-processor together with sampling techniques (100% oversampling, 200% oversampling, 25% undersampling, 50% undersampling, and SMOTE), aiming to solve the class imbalance problem, using a dataset from an insurance company with a 6% response rate. After pre-processing and replacing the target variable with SVM predictions, a modified dataset was used to train MLP, LR, and RF models. Similar to our study, the authors focused on the sensitivity metric—the proportion of TP. The results show that the proposed balancing approach improves the classification performance in every case. For example, MLP, LR, and Random Forest obtained the following sensitivity results on the original unbalanced data: 5.88%, 1.26%, and 7.14%, respectively, while, in combination with SVM pre-processing, the results were as follows:

65.31%, 63.03%, and 63.03%, respectively. This study's best performance was obtained using the 25% undersampled data in an RF model, which achieved a sensitivity of 71.01%.

Several recent papers treat this issue regarding online direct marketing campaigns and overall online purchase prediction using web log data. For instance, Lee et al. [14] explored machine learning models and potential effective data sampling methods for predicting online consumer behaviour for the visitors of a Google Merchandise Store. The authors found that the eXtreme Gradient Boosting (XGB) algorithm is most effective for predicting purchase conversion of online consumers, while oversampling with the SMOTE algorithm was shown to be the best method to solve the data imbalance issue. They obtained the following results: accuracy—74.17%, sensitivity—73.92%, and AUC—0.791. However, it is important to state that the dataset used contained data for all website visits, not just direct marketing campaigns. The conversion rate in this dataset was 2.29%.

Similarly, Chaudhuri et al. [15] used a dataset from an online e-commerce platform to predict purchasing behaviour, and they compared machine learning (ML) to deep learning (DL) 'algorithms' performance. Their results show that DL techniques (an evolved variant of Artificial Neural Networks) exhibit better performance than ML algorithms—the best model obtained an accuracy of 89%, a sensitivity of 96%, and an AUC of 0.89. However, the authors stated that the DL algorithm is significantly more resource-intensive than ML algorithms.

Pejić Bach et al. [28] used the k-means cluster analysis and the CHAID decision tree to predict churn in telecommunication. The ratio of the churned customers was 36.2%, indicating an unbalanced dataset. Therefore, the hybrid approach was used in which the customer database was first divided into homogenous clusters using demographic and behavioural attributes. Second, the clusters were analysed using chi-squared according to the churn level. Third, CHAID decision trees were developed separately for each cluster, with churn as the goal variable. The accuracy of the database was 79.5, while the sensitivity for the churned customers was only 49.5. On the other hand, when the CHAID decision tree was developed for the cluster with the highest churn ratio, the accuracy was lower than the whole database (68.7% compared to 79.5%). The sensitivity for the customers that churned was significantly improved (81.4% compared to 49.5%).

The summary of relevant papers treating customer response modelling from this section is given in Table 1, which presents the methods used in previous customer response model studies. In cases where the paper showed several methods and results, the model with the best performance was chosen.

Table 1. Class balancing in previous customer response model studies.

Author(s)	Response Rate	Method	Accuracy/Sensitivity/AUC
[26]	9.42% (DMEF4 dataset)	CUE with k-nearest neighbour classifier	84.50%/BCR-83.7%/-
[20]	6%	25% undersampling in combination with Random Forest	40.28%/71.01%/0.547
[7]	2.46%	Undersampling 2:1 in combination with SVM	95.20%/23.80%/-
[6]	19.81%	K-means clustering combined with Bagging Neural Network	96.50%/89.00%/0.985
[25]	11.63%	Balanced (undersampled) Random Forest	86.80%/90.20%/0.927
[8]	11.2%	Random Forest method on the undersampled dataset (EasyEnsemble)	-/-/0.989

Table 1. *Cont.*

Author(s)	Response Rate	Method	Accuracy/Sensitivity/AUC
[27]	11.7%	Cluster-based undersampling technique and k-NN	-/88.00%/0.900
[14]	2.29% (conversion rate)	eXtreme Gradient Boosting (XGB) with SMOTE oversampling	74.17%/73.90%/0.791
[15]		Deep learning neural network	89.00%/96.00%/0.890
[28]	36.2%	Cluster analysis in combination with CHAID decision trees	68.70%/81.40%/-

The lowest response rate in the previously used datasets was 2.29% (conversion rate) [14], while the highest was 27.42% [7], which is significantly higher than the response rate in this study.

Based on the analysis of previous research presented in Table 1, this paper's main contribution is defined as the investigation of the efficacy of balanced SVM data pre-processing on a dataset from online direct marketing campaigns with an extremely low response rate of 0.41%.

Previous research used datasets with a higher response rate, e.g., in [20], the authors employed standalone SVM pre-processing on a dataset with a substantially higher response rate of 6%, as well as in [21], where ensemble (Bagging) SVM pre-processing was used, but for a customer segmentation problem.

The inclusion of web metrics as predictors is also the benefit of our study.

3. Data

One of the main characteristics of online direct marketing campaigns is asking the customer to take a specific and quantifiable action, such as clicking on a link to a website, purchasing a product online, redeeming a discount code, etc. This feature of online direct marketing makes customer responses traceable and measurable, enabling high-volume customer databases [29]. To make these data useful, companies can build customer response models to help identify the customers who will, with high probability, respond to the following campaign. Additionally, such analyses can inform campaign profitability and help make relevant marketing decisions.

A dataset was obtained from a leading sports distributor from Montenegro for the empirical testing of the proposed customer response model.

The dataset contained e-commerce website visits from sponsored social media posts for four months, from October 2018 until January 2019. For the observed period, 9660 unique website users followed a link from a targeted Instagram or Facebook post, making them potential customers as they expressed interest in the presented offer. The total number of completed sessions was 33,662 during six online direct marketing campaigns on social media.

The final dataset resulted from merging several databases: the company's product database, Google Analytics, and Facebook Business Manager, followed by pre-processing and preparing the dataset for the customer response model analysis.

The dataset contained the following attribute groups:

- Web metrics;
- Product description data;
- Previous purchasing history data regarding RFM attributes.

A description of the attributes in this dataset is given in Table 2.

Table 2. Data description.

Attribute Name	Attribute Description
Camp_Sessions_avg	the average number of sessions in all campaigns
Camp_Avg Sess duration	the average session duration in all campaigns
Camp_Avg bounce rate	the average bounce rate for all selected campaign visits
Cons_Reg_Central	number of sessions completed from the Central region
Cons_Reg_South	number of sessions completed from the Southern region
Cons_Reg_North	number of sessions completed from the Northern region
Cons_Dev_Desktop	number of sessions completed using desktop
Cons_Dev_Mobile	number of sessions completed using a mobile device
Cons_Dev_Tablet	number of sessions completed using a tablet device
Cons_OS_Android	number of sessions completed using Android OS
Cons_OS_Ios	number of sessions completed using iOS
Cons_OS_Windows	number of sessions completed using Windows
Prod_Apparel	number of products purchased from the apparel category
Prod_Footwear	number of products purchased from the footwear category
Prod_Equipment	number of products purchased from the equipment category
Prod_Gen_For boys	number of purchased products for boys
Prod_Gen_For girls	number of purchased products for girls
Prod_Gen_For men	number of purchased products for men
Prod_Gen_For women	number of purchased products for women
Prod_Gen_unisex	number of unisex products purchased
Prod_Type_Performance	number of products purchased from the performance category
Prod_Type_Lifestyle	number of products purchased from the lifestyle category
Prod_Type_Outdoor	number of purchased products for outdoor activities
Prod_Br_A brand	number of purchased products from A-brands (higher end)
Prod_Br_Licence	number of purchased products from License brands (lower end)
Prod_Age_For adults	number of purchased products for adults
Prod_Age_For kids	number of purchased products for kids
Prod_Age_For teens	number of purchased products for teens
Prod_Age_For all	number of purchased products for all ages
Prod_Disc_ < 30%	number of purchased products on discount less than 30%
Prod_Disc_30–50%	number of purchased products on discount between 30% and 50%
R1	recency obtained by splitting the dataset into five equal parts from least to most recent transactions
R2	recency obtained by assigning numbers from 2 to 5 based on the last campaign the customer ordered from
F1	number of campaigns with orders
F2	total number of orders in all campaigns
F3	number of orders in the last observed campaign
M1	the average transaction amount in all campaigns
M2	an average amount of transactions in the last observed campaign
M3	a total sum of realised transactions

The model presented in this paper predicted whether the potential customer would respond to the campaign, using the previous purchasing history and product and web log data. Only a completed purchase was taken as a response in this customer response model.

The dataset was split into training and test datasets to conduct the predictive procedure. On average, data for visitors who spent less than 30 s in a session were excluded. The dataset consisted of the history of web and purchasing behaviour of visitors to the leading sports distributor's website, which launched six campaigns, with 33,662 sessions.

The training dataset used to train the model contained the history of web and purchasing behaviour of 9660 website visitors from Campaign 1 to Campaign 4 and an indicator of their response to the next Campaign 5 (only 40 customers directly responded to the offer, i.e., purchased in this campaign, which resulted in a response rate of only 0.41%).

The set for model validation and testing contained the same data categories as the training set for 7929 visitors from Campaign 1 to Campaign 5 and the response indicating whether a customer responded to Campaign 6 (there were 40 responses in this campaign as well), not including new visitors who first appeared in Campaign 5 or Campaign 6.

4. Methods

As can be observed from the data description, the response rate to this marketing campaign was 0.41%, which is extremely low, indicating a high level of class imbalance. To treat this problem, which disables classifying algorithms from recognising examples of the positive (minor) class, a combination of random undersampling and Support Vector Machine (SVM) classification was applied.

In its most basic form, random undersampling randomly removes the examples of the major class from the database. A 1:1 undersampling (the same number of examples as in the minor class) was conducted on the training set while generating the Balanced SVM (B-SVM) pre-processor.

The SVM method [17] effectively tries to resolve overlapping and unbalanced classes [18,19] by creating a hyperplane between the examples belonging to different classes, which can discriminate the class to the maximum distance, regardless of the number of instances available to learn from [20]. As a result, SVM eliminates data noise, i.e., class overlap, and complements the minor class with the most relevant examples by moving the margin to the closest, and hence most similar, examples of the major class and putting them into the smaller class [21]. As a result, SVM was used as a data pre-processor to balance the data and deliver greater classification accuracy. The SVM is biased towards the major class in cases of high class imbalance, as was present in the used dataset [7]. As a result, the specified undersampling was used during the training of the SVM pre-processor, i.e., balanced SVM was used as a pre-processor.

The following classifiers were tested on such pre-processed data: LR [30], Gradient Boosted Trees (GBT) [31], RF [32], k-NN [33], and DT [34].

Although the name contains the word regression, LR is a classification method. The most popular LR models have binary outcomes, and this technique involves predicting the likelihood of a discrete outcome given the input variables. The purpose of the k-nearest neighbour approach is to locate the closest neighbours of a given query point so we can apply a class label to that point. The k-NN technique assumes that comparable entities exist nearby. The DT method divides the dataset by attribute values, so subgroups contain as many instances of one class as possible. During inductive division, a model in the form of a tree is formed, based on which the method itself is named. The Gradient Boosting Trees algorithm selects the next DT model that minimises the residual error of the previous group of DT models. In this way, by minimising the residual error, subsequent models will favour the correct classification of previously misclassified cases [35].

On the other hand, the RF algorithm uses Bagging (also known as Bootstrap aggregation, where random data samples are selected in the training set so that individual data can be selected in multiple samples, then models are trained on these samples, and their outputs are aggregated) and random selection of attributes to create a larger number of decision trees in the training phase. In this regard, it represents an extension of the basic idea of individual DT classifiers in such a way as to create a larger number of classification decision trees. Thus, the last two methods combine the ensemble meta-algorithm with the DT classifier.

The applied predictive procedure is shown in Figure 1.

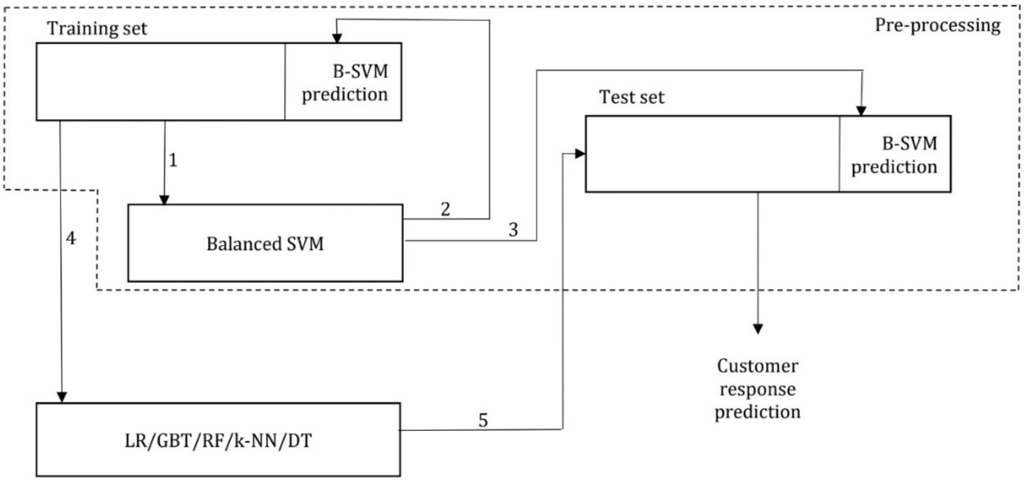

Figure 1. Predictive procedure illustration.

The proposed predictive procedure consisted of the following steps (steps 1, 2, and 3 include data pre-processing, and customer response prediction is realised in steps 4 and 5):

- Step 1—B-SVM is trained using the original imbalanced dataset. The model with the best predictive performance is obtained in the k-fold cross-validation procedure.
- Step 2—Trained B-SVM is applied to the training dataset, and its class label is replaced with B-SVM prediction. In this process, a minor class of non-respondents is supplemented with similar examples from the major (respondents) class, and class balancing is achieved.
- Step 3—Trained B-SVM is applied to the test dataset, and its class label is replaced with B-SVM prediction. This results in proclaiming customers from the test dataset who are as similar to respondents as possible.
- Step 4—Several classifiers, such as DT, LR, GBT, RF, and k-NN, are trained on the modified (balanced) dataset from Step 2. The models with the best predictive performances are chosen in k-fold cross-validation.
- Step 5—Trained classifiers are applied to the test dataset. The B-SVM prediction measures predictive performances instead of the original class label.

The model performance measures used in this paper are AUC, Accuracy, Sensitivity, and Fallout. AUC is often used in the literature to show the separability degree between classes [25,36,37]. Accuracy, Sensitivity, and Fallout were calculated using the values from the confusion matrix presented in Table 3 (equations given below the table).

$$\text{Accuracy} = (TP + TN)/(TP + FP + FN + TN) \tag{1}$$

$$\text{Sensitivity} = TP/(TP + FN) \tag{2}$$

$$\text{Fallout} = FP/(FP + TN) \tag{3}$$

Table 3. Confusion matrix.

Actual Class	Predicted Class	
	Positive (Respondent)	**Negative (Non-Respondent)**
Positive (Respondents)	True Positive (TP)	False Negative (FN)
Negative (Non-Respondents)	False Positive (FP)	True Negative (TN)

5. Results

Table 4 presents the prediction performance for all tested classifiers: LR, GBT, RF, k-NN, and DT, both before data pre-processing and balancing and after B-SVM pre-processing.

Table 4. Predictive performance of classification algorithms without and with SVM pre-processing.

Classifier	Accuracy	Sensitivity	AUC	Fallout
LR	99.23%	15.00%	0.680	0.34%
GBT	99.18%	10.00%	0.727	0.37%
RF	99.48%	0.00%	0.827	0.01%
k-NN	99.50%	0.00%	0.593	0.00%
DT	99.43%	12.50%	0.608	0.13%
B-SVM	87.15%	67.50%	0.832	12.75%
B-SVM+LR	88.21%	82.96%	0.954	11.01%
B-SVM+GBT	89.97%	83.35%	0.950	9.03%
B-SVM+RF	89.27%	75.99%	0.921	8.74%
B-SVM+k-NN	85.53%	59.15%	0.831	10.51%
B-SVM+DT	90.96%	80.54%	0.898	8.16%

Each classifier underwent cross-validation on an initial and pre-processed training set and was then applied to test data. The table shows the results obtained from the test data. When these findings are compared to the capabilities of independent classifier approaches, it is evident that this method surpasses them in class balancing or solutions to minor class problems.

Table 4 shows that sensitivity and AUC were improved across all models after data pre-processing using the B-SVM approach. For instance, RF obtained 0% sensitivity before data balancing, while B-SVM+RF obtained 75.99%. In addition, the AUC metric for some models was relatively low: 0.539 and 0.608 for k-NN and DT, respectively, which is too close to a model not being able to distinguish between the positive and negative classes efficiently. The lowest AUCs in the B-SVM models are 0.831 (B-SVM+k-NN) and 0.954 (B-SVM+LR), indicating excellent model performance.

High accuracy levels across all standalone models result from model bias towards the positive class. Hence, considering the relevance of correctly identifying those customers who will respond to a direct marketing campaign, i.e., true positives, in this study, the focus is on the sensitivity metric, not overall accuracy. From Table 4, it can be seen that Balanced SVM+GBT achieved the best performance regarding sensitivity: 83.35%. This result indicates potential improvement in future campaign profitability, as the company can precisely target a group of customers with a high probability of a response. For example, Standalone GBT would only correctly identify 10.00% of such potential customers in this dataset. Additionally, B-SVM+LR, a model with the second-best sensitivity performance, would target 82.96% of potential customers with a high response rate likelihood.

The sensitivity levels before and after data pre-processing are shown in Figure 2.

Another important metric for planning a direct marketing campaign and its budget is the fallout metric. As the fallout result shows a percentage of customers who would be targeted and not respond to the offer, it is crucial to have this metric as low as possible. Hence, Balanced SVM+DT, with a fallout metric of 8.16%, suggests that this percentage of customers would be misclassified as respondents. This is of the utmost importance to keep in mind, especially for those companies facing marketing budget restraints. This study shows that the marketing budget would be efficiently allocated.

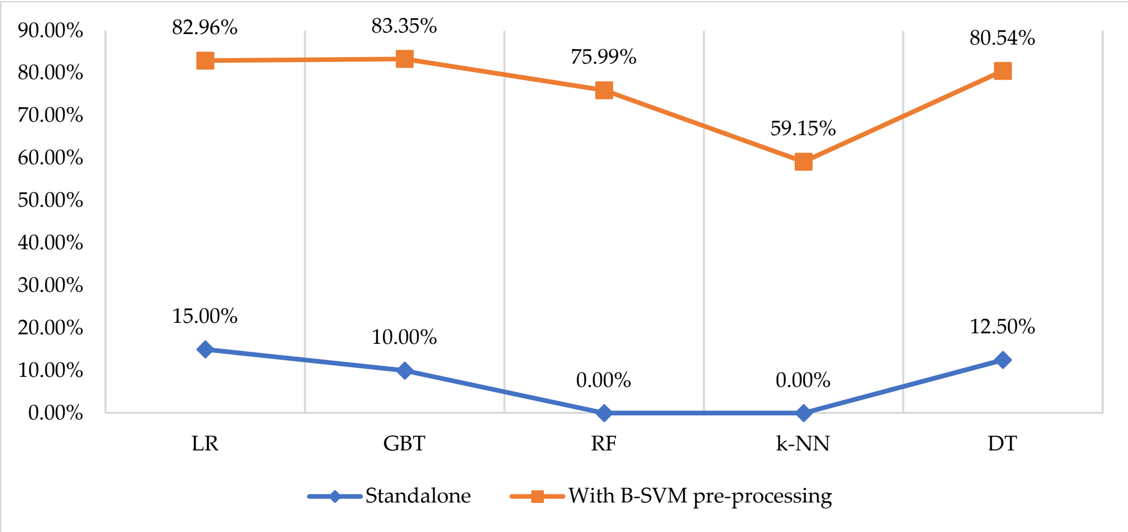

Figure 2. Sensitivity level before and after data pre-processing.

6. Model Validation on a Public Dataset

The proposed approach for customer response modelling was validated on a publicly available dataset. The dataset used for model validation was the Direct Marketing Education Foundation 3 (DMEF3).

This dataset consists of 106,284 customers' transaction data from a catalogue sales company for 12 years, from 1983 to 1995. The dataset includes customer data (ID, day and year of entry in the database, time on file), RFM attributes (number of months since last order, sales amounts and number of orders by product classes, total sales amount, dummy recency variables formed based on the number of months since the last order, and recency quantiles 1–20).

The dependent variable was the number of orders. We transformed it into binomial, i.e., the number of orders greater than or equal to 1 (respondents) was coded with 1 and non-respondents with 0.

Following the procedure from [38], the present moment was set to 1 August 1990, which resulted in training and test datasets of approximately the same size. The response to the offer in the target period was used as a dependent variable. The response rate in this dataset was 5.4%. The results are shown in Table 5. It can be observed that B-SVM leads to a significant improvement in model performances, similar to the first dataset. After the data pre-processing and balancing, the sensitivity metric amounted to 95% or over in all models. Additionally, in the case of B-SVM+GBT and B-SVM+RF, the models obtained 100% sensitivity. On the other hand, the fallout was reduced in all B-SVM models to less than 0.3%.

After pre-processing, the AUC in all tested models was close to 1, meaning that the models had a perfect ability to differentiate between the classes of respondents and non-respondents. Moreover, overall accuracy in all B-SVM models was around 99%.

In terms of obtained sensitivity metrics, the B-SVM+GBT model achieved the best performance on this dataset and the Sports Retailer dataset, presented in Table 4. The obtained sensitivity was 83.35% in the first dataset, while in the DMEF3 dataset, the model achieved 100% sensitivity. On the other hand, the weakest results were obtained using the B-SVM+k-NN for both datasets. Namely, on the Sports Retailer dataset, the sensitivity score of this model was 59.15%, while for the DMEF3 dataset, it amounted to 95.84%.

However, B-SVM pre-processing, with notable improvements across all models, proved to be a powerful technique for data balancing, and the model was successfully validated on this dataset. It has also been confirmed that advanced classifiers with an ensemble meta-algorithm give better results than classical ones on pre-processed data.

Better model performances on this dataset are due to a higher response rate. The customer database contains the purchasing behaviour history for 12 years, while the first dataset included data for several campaigns and six months. This validation has shown that this approach can be used in online and offline direct marketing campaign management.

Table 5. Predictive performance of classification algorithms without and with SVM pre-processing for the DMEF3 dataset.

Classifier	Accuracy	Sensitivity	AUC	Fallout
LR	88.72%	65.39%	0.856	3.67%
GBT	89.53%	63.56%	0.861	2.00%
RF	89.22%	60.59%	0.851	1.44%
k-NN	87.47%	62.01%	0.827	4.22%
DT	89.42%	63.66%	0.819	2.17%
B-SVM	87.30%	69.21%	0.815	6.79%
B-SVM+LR	99.88%	99.94%	1.000	0.14%
B-SVM+GBT	99.89%	100.00%	0.999	0.15%
B-SVM+RF	99.89%	100.00%	1.000	0.14%
B-SVM+k-NN	98.90%	95.84%	0.995	0.23%
B-SVM+DT	99.97%	99.87%	0.999	0.00%

7. Discussion, Implication, and Conclusions

7.1. Summary of the Research

The necessity of selecting relevant customers for efficient direct marketing has grown significantly. Saturated markets and competitive pressures lower customer response and drive marketing expenses [39]. A result of this issue requires improved response models with a finely tailored approach, allowing businesses to invest in direct marketing with proper and efficient customer selection. As the profitability of the direct marketing campaign is largely determined by the number of respondents, i.e., how many consumers respond to the placed offer, identifying target customers is one of the most significant steps in planning the campaign. The selection of potential customers must be optimised to achieve varied company objectives and maximise campaign profitability.

This research aimed to address the problem of class imbalance in customer response modelling, which is one of the most prevalent issues when using machine learning algorithms in direct marketing and campaign management. This issue is especially present for online customers, whose response rate can be very low due to the large number of website visits that do not result in a completed transaction. The balanced SVM method was used as a pre-processor to discover a solution for the severely imbalanced data.

The proposed approach for customer response modelling was designed to test whether the existing methods for customer response modelling in direct marketing (i.e., predicting customer response to a direct marketing campaign) could be improved, as well as to reduce misclassification for the respondents' segment, i.e., to propose the solution to the problem of class imbalance on a dataset with an extremely low response rate of 0.41%.

According to the results described in the preceding sections, the proposed approach exhibits excellent predictive performance. Combined with ensemble classifiers, this approach best predicts potential online buyers. The key contribution of this research is that the suggested approach better addresses the problem of class imbalance that occurs while classifying clients in direct marketing than methods presented in earlier studies. Specifically, there was a lower misclassification of the minority class than in earlier results. Moreover, data pre-processing automates the class balancing technique, and the complete application is streamlined.

The model's reliability was confirmed by applying it to data from the real world. Based on the history of purchasing behaviour from five previous campaigns, customers' response in the sixth campaign was predicted with high accuracy. Moreover, the models were validated on a different set of data from a different industry and with different data in the customer base, which confirms the robustness of the model, i.e., reliability of the proposed approach.

As customers increasingly become e-commerce users and online shoppers, decision-makers in marketing can focus on creating customised content and improving their targeting systems based on the proposed approach, which reflects the practical significance of the proposed method. With this in mind, tailored social media advertisements may be a powerful tool for connecting with customers online. With correct targeting, the process may acquire new and retain old customers.

7.2. Theoretical Implications

Comparing this paper's results with those from previous studies, it can be stated that the proposed approach surpasses the predictive performances of previous studies in customer response modelling while still working on a dataset with the smallest response rate. In the previous papers with the smallest observed response rates, Lee et al. [14] and Kim et al. [7] displayed a sensitivity level of 73.92% and 23.8%, respectively, as indicated in Table 1. The best-analysed result, achieved in a study by Asare-Frempong, and Jayabalan [25], obtained 90.2% sensitivity and 0.927 AUC with a response rate of 11.63%, using a balanced RF. Our results on the Sports Retailer dataset underperformed in the sensitivity levels with 83.35% but achieved a higher AUC of 0.950, using a B-SVM+GBT. However, the response rate in our study was significantly lower. On the DMEF3 dataset, the model achieved a sensitivity and an AUC of 100% and 0.999, respectively, outperforming all previous studies. Chaudhuri et al. [15] also obtained a high sensitivity of 96% and an AUC of 0.89. Still, there is no indication of the response (or conversion) rate in the used dataset in their paper.

This study reveals that using the B-SVM approach in conjunction with classification techniques improves the predictive ability of the models for predictive customer classification. The findings revealed that the B-SVM efficiently pre-processes the data, resolving noise and class imbalance. B-SVM reduces noise in the data, i.e., class overlapping, and complements the minor class with the most relevant instances by shifting the margin to the closest, and hence most comparable, examples of the larger class and categorising them into the smaller class of respondents. In that way, the minor class is supplemented with a group of highly probable respondents. Companies can target a wider group of potential respondents without wasting marketing budgets on a random or subjective choice.

Thus, this paper contributes in several ways to the existing literature on customer response modelling. First, a customer targeting model has been proposed that identifies respondents from the customer base and those very likely to be, recognising their similarity to respondents. Second, the proposed model had better predictive performance than models from previous studies. Third, the model was validated based on online and offline customers, which can be applied in both cases. Fourth, the possibilities of balanced SVM methods for data purification and balancing in customer response modelling with extremely low response rates have been confirmed. Fifth, the results of advanced and classical classifiers on a pre-processed dataset were compared, and the advantages of advanced ones, in this context, were empirically confirmed. Finally, due to undersampling, the time and technological complexity in the implementation of data pre-processing was reduced, and the application of the proposed method was simplified.

7.3. Managerial Implications

All models after pre-processing showed significant performance improvements. The results can be used in direct marketing decision making and campaign management to precisely and accurately target potential customers. Thus, for example, the best classifier targeted only 10% of respondents without pre-processing, and after pre-processing, as many as 83.35% of very probable respondents. This means that, under our method, 7.3 times more possible respondents were identified, leading to a significant increase in the campaign's profitability. At the same time, there were less than 10% of incorrectly targeted customers, meaning there will be little wasted campaign cost. By doing so, companies can customise the offer and target those customers with a high probability of a response, cost-effectively and profitably. Saturated markets lead to customers being targeted by numerous offers they are not interested in. Therefore, this approach can help companies target only customers who find the offer relevant.

In line with this, Stone and Jacobs [40] state that a very creative and original offer may result in a low response rate if the targeting is not done correctly. In contrast, a badly structured and moderately creative offer to the proper target group can lower, but not eliminate, the intended customer response. Hence, decision-makers in direct marketing can benefit from this approach since it allows for more accurate targeting, less message waste, and more profitable campaigns.

Predicting the response to a campaign is particularly important for creating a direct marketing strategy for all campaigns and offers individually. In this way, with information from the model, the company will allocate marketing resources to consumers with the highest probability of response. Adapting marketing activities to defined segments that differ in interests, profitability, value for the company, or other characteristics makes the overall direct marketing strategy more effective [41]. Additionally, with the development of social networks, which have made it possible to target customers more precisely than ever before, this process gains even more importance to invest marketing resources effectively. In this regard, the customers should be targeted exclusively with relevant advertisements, which could indicate that the company understands their needs and works hard towards maintaining the relationship with them. Namely, considering that some of the applied methods (such as DT, for example) at the output give explicit rules for classifying customers into respondents and non-respondents that are semantically rich and describe these segments, marketers can learn a lot from them about purchasing customer habits and can adjust the offer adequately. So, for example, if it can be seen from the rules that the respondents prefer a certain type or category of products, the following ads can be adapted following this discovery. In addition, decision-makers can recognise the characteristics of customers who are likely to be respondents and, based on them, direct the next ad to those similar to them and thus attract new customers.

Another positive aspect of our method for direct marketing practitioners is its simplicity. Because automated data balancing is employed, there is no need to perform complicated resampling operations. Furthermore, marketing managers are not required to understand the specifics of the learning algorithm or to employ extra specialists or external experts.

7.4. Limitations and Future Research Directions

However, this study also has several drawbacks and limitations. First, due to random undersampling, pre-processing of data may lead to the loss of information that is important for the model to identify respondent-like customers better. Second, the dataset used refers to a short period of several months, so the seasonality of the data was not taken into account. Moreover, the model predicts customers' behaviour after the transaction and not during the trade itself, which could be more useful in recommending or stimulating the customer.

In line with these limitations, future research could test pre-processing techniques that combine clustering of the major class, ensemble, and undersampling, similar to those in [26], to provide a more representative sample for this class and to reduce the possibility that some non-respondents similar to respondents are neglected and lost due to random undersampling. Moreover, the method should be tested on other datasets that cover a longer period and multiple campaigns to analyse the impact of data seasonality. It would be interesting to examine the possibilities of the proposed method as part of a recommendation system that would predict customer response during an online shopping session.

Additionally, other digital direct marketing strategy development aspects can be an interesting area for future research, combined with optimising the targeting process.

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CURRICULUM VITAE – BIOGRAFIJA

LIČNI PODACI

Ime i prezime:	Sunčica Rogić
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Mjesto rođenja:	Podgorica
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OBRAZOVANJE

2018 -	Doktorske studije ekonomije - Ekonomski Fakultet Podgorica, Univerzitet Crne Gore
2015 - 2018	Postdiplomske akademske studije - Ekonomski Fakultet Podgorica, Univerzitet Crne Gore (prosječna ocjena 10,00)
2011- 2015	Ekonomski Fakultet Podgorica, Univerzitet Crne Gore *smjer: Marketing* (prosječna ocjena 9,87)
2007- 2011	Srednja ekonomska škola "Mirko Vešović", Podgorica

RADNO ISKUSTVO

2018 -	Saradnik u nastavi **Ekonomski fakultet Podgorica, Univerzitet Crne Gore** oblasti: Međunarodna ekonomija, Digitalna ekonomija, Poslovna informatika, Globalizacija svjetske privrede **Primjenjene studije Menadžmenta, Ekonomski fakultet Podgorica, Univerzitet Crne Gore** oblasti: Poslovna informatika, Spoljnotrgovinsko poslovanje
2018 –	Sekretar **Stonoteniski savez Crne Gore** Honorarni angažman

2017 - 2018	Saradnik u nastavi **Ekonomski fakultet Podgorica, Univerzitet Crne Gore** oblasti: Međunarodna ekonomija, Informatika, Informacioni sistemi, Globalizacija svjetske privrede **Primjenjene studije Menadžmenta, Ekonomski fakultet Podgorica, Univerzitet Crne Gore** oblasti: Poslovna informatika, Upravljački informacioni sistemi, Elektronsko poslovanje
2016 - 2017	Saradnik u nastavi - honorarno **Ekonomski fakultet Podgorica, Univerzitet Crne Gore** oblasti: Razvoj ekonomske misli, Ekonomija, Međunarodna ekonomija, Ekonomija javnog sektora, Teorija i analiza ekonomske politike, Tržište rada **Primjenjene studije Menadžmenta, Ekonomski fakultet Podgorica, Univerzitet Crne Gore** oblast: Principi ekonomije, Poslovna informatika, Upravljački informacioni sistemi
2015 - 2016	Saradnik u nastavi **Ekonomski fakultet Podgorica, Univerzitet Crne Gore** oblasti: Marketing menadžment malog biznisa, Informacioni sistemi, Informatika i Razvoj ekonomske misli **Primjenjene studije Menadžmenta, Ekonomski fakultet Podgorica, Univerzitet Crne Gore** oblasti: Elektronsko poslovanje, Poslovna informatika i Upravljački informacioni sistemi

SPECIALIZACIJE, OBUKE I PRAKSE

- Praksa u Investiciono-razvojnom fondu, jul 2012. godine
- CEEPUS stipendija za studentsku razmjenu u Beču, WU Wien (1 semestar), 2014. godine
- COMPASS škola - vještine prezentovanja, u organizaciji Volonterskog kluba Ekonomskog fakulteta, 2015. godina.

- ERASMUS + obuka za akademsko osoblje – Freiberg University of Mining and Technology, Freiberg (Njemačka), novembar 2016.
- TRAIN obuka – „*Methodology of Scientific Research in Social Sciences*", UCG, oktobar 2016.
- ERASMUS + obuka za akademsko osoblje - University of Beira Interior, Covilha (Portugal), februar 2018.
- ERASMUS + obuka za akademsko osoblje - University of Szczecin, Szczecin (Poland), april 2018.

- ERASMUS + obuka za akademsko osoblje - University of Vigo, Vigo (Spain), jun 2018.
- ERASMUS+ mobilnost u svrhu predavanja - University of Applied Sciences Nysa, Nysa (Poland), maj 2019.
- ERASMUS+ mobilnost u svrhu predavanja - Rzeszow University of Technology, Rzeszow (Poland), mart 2020.
- ERASMUS+ mobilnost u svrhu predavanja – Alexandru Ioan Cuza University, Iasi (Romania), jun 2021.
- ERASMUS + obuka za akademsko osoblje – University of Cordoba, Cordoba (Spain)
- ERASMUS+ mobilnost u svrhu predavanja – Riga Technical University, Riga (Latvia)

OBJAVLJENI RADOVI, KONFERENCIJE I PROJEKTI

OBJAVLJENI RADOVI:

Radović, M., Rogić, S. & Cerović, B. (2017). Influence of Demographic Trends and Employment on the Financial Sustainability of the Montenegrin Pension System. Proceedings of the Faculty of Economics in East Sarajevo, Year 2017 Issue 15, 39-47.

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Djurisic, V., Rogic, S., Cerovic Smolovic, J. & Radonjic, M. (2019). Determinants of household electrical energy consumption: Evidences and suggestions with application to Montenegro. Energy

Reports, Volume 6, Supplement 3, February 2020, 209-217. SCI - https://doi.org/10.1016/j.egyr.2019.10.039

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Jaćimović, D. & Rogić, S. (2020). Montenegro: A Great Bargain between EU optimism and real Euroscepticism. In: Kaeding, M., Pollak, J. & Schmidt, P. (eds). The Future of Europe – Views from the Capitals, Palgrave Macmillan, London, 2020. https://doi.org/10.1007/978-3-030-41272-2_25 Palgrave Macmillan – Chapter

Jaćimović, D., Ivanović, M. & Rogić. S. (2020). FDI in Montenegro. In: Deichjmann, J. (ed). The Economic Geography of FDI in the Successor States of Yugoslavia: A Quarter Century after Dissolution, Springer, New York (2020) *forthcoming*. Springer – Chapter.

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Đurišić, V., Cerović Smolović, J., Mišnić, N. & Rogić, S. (2020). Analysis of public attitudes and perceptions towards renewable energy sources in Montenegro. Energy Reports, Volume 6, Supplement 6, 395-403. https://doi.org/10.1016/j.egyr.2020.08.059

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https://doi.org/10.1080/08839514.2020.1790248

Rogić, S. & Kašćelan, Lj. (2021). Class Balancing in Customer Segments Classification Using Support Vector Machine Rule Extraction and Ensemble Learning. Computer Science and Information Systems, Vol. 18, Issue 3, 893-925. https://doi.org/10.2298/CSIS200530052R

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Djukanovic, M., Rogic, S., Novicevic, L., Popovic-Bugarin, V., & Jovanovic, M. (2022, May). Application of Apriori Algorithm for CRM Improvement-Case Study from Montenegro. In Proceedings of the 2022 8th International Conference on Computer Technology Applications (pp. 48-56).

<u>KONFERENCIJE:</u>

Konferencija „Jahorinski poslovni forum 2017" - „**Uticaj demografskih faktora i zaposlenosti na finansijsku održivost penzionog sistema Crne Gore**", Jahorina, februar 2017.

Konferencija „Jahorinski poslovni forum 2018" – **„Rješavanje problema nezaposlenosti i postizanje makroekonomske stabilnosti"**, Jahorina, BIH, mart 2018.

Konferencija „Transformation Processes in Sport" – **„Sport Financing Through Gambling Revenues in Montenegro"**, Budva, Crna Gora, april 2018.

Konferencija „Sport Economics and Sport Management" - **"Analysis of the Montenegrin Model of Sport Financing"**, Beč, Austrija, maj 2018.

Konferencija „Trends in Development in Tourism and Hospitality" – „**The importance of non-technological innovations on Montenegrin Sport Tourism Offer**", Kotor, Crna Gora, oktobar 2018.

Konferencija „Sport, Physical Activity and Health: Contemporary Perspectives" – „**Importance of Loyalty to a Sport Event for the Level of Sponsorship Awareness**", Cavtat, Hrvatska, april 2019.

Konferencija „Technologies and Materials for Renewable Energy, Environment and Sustainability” – „**Determinants of household electrical energy consumption: Evidences and suggestions with application to Montenegro**”, Atina, Grčka, jun 2019.

Workshop „Modern Approaches in Data Engineering and Information System Design” – „**Customer value prediction in direct marketing using hybrid support vector machine rule extraction method**”, Bled, Slovenia, septembar 2019.

Konferencija „Sport, Physical Activity and Health: Contemporary Perspectives” – „**Testing Sponsorship Recall and Recognition after the Games of the Small States of Europe – Montenegro 2019**”, Online/Video konferencija, april 2020.

Konferencija „Technologies and Materials for Renewable Energy, Environment and Sustainability” – „**Analysis of public attitudes and perceptions toward renewable energy sources in Montenegro**”, Online/Video konferencija, jun 2020.

Konferencija „Sport, Physical Activity and Health: Contemporary Perspectives“ – „**Montenegrin Sport Associations on Social Media - Quality of Performance Assessment**”, Cavtat/Video konferencija, April 2021.

Konferencija „Analytics Without Borders” – „**Class Balancing in Customer Segments Classification Using Support Vector Machine Rule Extraction and Ensemble Learning**”, Bentley University, USA/Virtuelna konferencija, mart 2021.

Konferencija „International Conference on Marketing and Technologies 2021 (ICMarkTech21)” – „**Estimating Respondents' Profitability: Influence of RFM Attributes, Web Metrics and Product Data**”, Tenerife/online, decembar 2021.

Konferencija „International Conference on Computer Technology Applications (ICCTA2022)“ – „**Application of Apriori Algorithm for CRM Improvement - Case Study from Montenegro**“, Vienna/Online, maj 2022.

Konferencija „International Forum on Knowledge Asset Dynamics (IFKAD2022)“ – „**Data Analytics for Marketing Knowledge Advancement: a Market Segmentation Example Using Support Vector Machine**“, Lugano/online, jun 2022.

Konferencija „Computing Conference 2022“ – „**Customer Response Modeling for Direct Marketing Using Ensemble of Balanced Classifiers: Influence of Web Metrics on the Model Performance**“, London/online, jul 2022.

PROJEKTI

Marketing strategija Crnogorskog olimpijskog komiteta, COK, maj 2016.

Uticaj zaposlenosti na Fond PIO Crne Gore, Fond PIO, septembar 2016.

Promociona strategija Crnogorskog olimpijskog komiteta za Igre malih zemalja Evrope, COK, jun 2017.

Promociona strategija turizma i kulture u Bijelom Polju, TO Bijelo Polje, jul 2017.

Bilateralni projekat: Jačanje konkurentnosti kroz stimulaciju razvoja organske poljoprivrede – komparativna studija između Crne Gore i Srbije, 2016-2018.

Bilateralni projekat: **Uticaj deviznog kursa na spoljnotrgovinsku neravnotežu u uslovima krize – održivi razvoj novih zemalja članica EU i Zapadnog Balkana**, 2019-2021.

Jean Monnet Centre of Excellence: **The Challenges of the Enlargement Policy: EU Versus China's diplomacy in Western Balkans**, 2020-2023.

COST action: **CA20133 – Cross-Border Transfer and Development of Sustainable Resource Recovery Strategies Towards Zero Waste** (FFULLRECO4US) – MC member, 2021-2025.

Strategija razvoja sporta u Crnoj Gori 2022-2026, Crnogorski olimpijski komitet, novembar 2021.

COST ACTION: **Social Sciences and Humanities for Transformation and Climate Resilience (SHiFT)** – MC member, 2022-2026.

NAGRADE

- Nagrada za najbolji rad predstavljen na radionici Modern Approaches in Data Engineering and Information System Design, organizovanoj u okviru konferencije: European Conference on Advances in Databases and Information Systems (ADBIS 2019), Bled, Slovenija, septembar 2019.
- Nagrada Ekonomskog fakulteta u Podgorici za najbolje studente za sve četiri godine studija, 2012-2015. godine.
- Stipendija Ministarstva Prosvjete i sporta za najbolje studente, 2012., 2013. i 2014. god.
- Treća nagrada na konkursu Prve Banke Crne Gore na temu "*Sadašnjost i budućnost bankarskog sistema u Crnoj Gori*", održanom na konferenciji „Dani bankarstva i preduzetništva", Kolašin 2015. godine

POZNAVANJE JEZIKA

- Engleski jezik napredni nivo
- Ruski jezik srednji nivo

POZNAVANJE RADA NA RAČUNARU

- MS Office (Word, Excel, Power Point)

- Adobe Photoshop
- Rapid Miner
- Analitika društvenih mreža

OSTALE NAPOMENE

- Đak generacije Osnovne škole „Vladimir Nazor“ u Podgorici, 2007.god
- Nagrada “Luča A” nakon završene Srednje škole, 2011. god.
- Stipendija Crnogorskog Olimpijskog Komiteta za perspektivne sportiste “Perspektivni sportista – Olimpijska nada”, 2008. god.

- Učesnik konferencije “Dani bankarstva i preduzetništva” u Kolašinu, 2014. i 2015. godine
- Učesnik „Druge konferencije o nacionalnom brendiranju”, Ministarstvo ekonomije, Petrovac, septembar 2016.
- Učesnik „Treće konferencije o nacionalnom brendiranju”, Ministarstvo ekonomije, Budva, mart 2017.
- Član organizacionog odbora ASECU konferencije - “Social and Economic Impacts of Globalization and Future of European Union", Podgorica, septembar 2018.

- Član komiteta za jednakost polova Evropske stonoteniske unije
- Položen stručni ispit za rad u oblasti sporta
- Tehnički direktor stonoteniskog turnira na Igrama malih zemalja – Crna Gora 2019, Budva maj-jun 2019.
- Član stonoteniske reprezentacije Crne Gore od 2005. godine, učesnik 4 svjetska prvenstva u stonom tenisu za seniore.
- Trostruki Univerzitetski prvak u stonom tenisu (2011, 2012. i 2018)
- Licencirani trener Stonoteniskog saveza Crne Gore.
- Volonter u STK “*Golden Player*”, trener u radu sa početnicima od 2013. do 2015. godine
- Član organizacionog tima Prvog „*Montenegro Cadet Open*“ takmičenja u stonom tenisu, Budva, 2008. god.
- Vozačka dozvola “B” kategorije

Bibliografija

Naučni i stručni radovi i konferencije

Objavljeni radovi:

1. Radović, M., Rogić, S. & Cerović, B. (2017). Influence of Demographic Trends and Employment on the Financial Sustainability of the Montenegrin Pension System. Proceedings of the Faculty of Economics in East Sarajevo, Year 2017 Issue 15, 39-47.
2. Rogić, S., Radonjić, M. & Đurišić, V. (2018). Sport Financing Through the Gambling Revenues in Montenegro. Sport Mont, Vol. 16, No. 2, June 2018. SCOPUS - https://doi.org/10.26773/smj.180616
3. Đurišić, V., Rogić, S. & Radonjić, M. (2018). Role of Small and Medium Enterprises in Economic Development of Montenegro. Journal of Economic & Management Perspectives, Volume 12, Issue 4, December 2018.
4. Melović, B., Đurišić, V. & Rogić, S. (2018). Business analysis of the financial support for organic production in Montenegro – technological and organizational aspects. MATEC Web of Conferences 170. SCOPUS - https://doi.org/10.1051/matecconf/201817001001
5. Rogić, S., Đurišić, V., Radonjić, M. & Vuković, S. (2019). Importance of Loyalty to a Sport Event for the Level of Sponsorship Awareness. Sport Mont, Vol. 18, No. 2, June 2019. SCOPUS - https://doi.org/10.26773/smj.190611
6. Rogic S. & Kascelan Lj. (2019). Customer Value Prediction in Direct Marketing Using Hybrid Support Vector Machine Rule Extraction Method. In: Welzer T. et al. (eds) New Trends in Databases and Information Systems. ADBIS 2019. Communications in Computer and Information Science, vol 1064. Springer, Cham. Springer – Chapter - https://doi.org/10.1007/978-3-030-30278-8_30
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15. Đurišić, V., Cerović Smolović, J., Mišnić, N. & Rogić, S. (2020). Analysis of public attitudes and perceptions towards renewable energy sources in Montenegro. Energy Reports, Volume 6, Supplement 6, 395-403. https://doi.org/10.1016/j.egyr.2020.08.059
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Učešće na konferencijama:

1. Konferencija „Jahorinski poslovni forum 2017“ - „Uticaj demografskih faktora i zaposlenosti na finansijsku održivost penzionog sistema Crne Gore“, Jahorina, februar 2017.
2. Konferencija „Jahorinski poslovni forum 2018“ – „Rješavanje problema nezaposlenosti i postizanje makroekonomske stabilnosti“, Jahorina, BIH, mart 2018.
3. Konferencija „Transformation Processes in Sport” – „Sport Financing Through Gambling Revenues in Montenegro", Budva, Crna Gora, april 2018.
4. Konferencija „Sport Economics and Sport Management” - "Analysis of the Montenegrin Model of Sport Financing", Beč, Austrija, maj 2018.
5. Konferencija „Trends in Development in Tourism and Hospitality” – „The importance of non-technological innovations on Montenegrin Sport Tourism Offer”, Kotor, Crna Gora, oktobar 2018.
6. Konferencija „Sport, Physical Activity and Health: Contemporary Perspectives” – „Importance of Loyalty to a Sport Event for the Level of Sponsorship Awareness”, Cavtat, Hrvatska, april 2019.
7. Konferencija „Technologies and Materials for Renewable Energy, Environment and Sustainability” – „Determinants of household electrical energy consumption: Evidences and suggestions with application to Montenegro”, Atina, Grčka, jun 2019.
8. Workshop „Modern Approaches in Data Engineering and Information System Design” – „Customer value prediction in direct marketing using hybrid support vector machine rule extraction method”, Bled, Slovenia, septembar 2019.
9. Konferencija „Sport, Physical Activity and Health: Contemporary Perspectives” – „Testing Sponsorship Recall and Recognition after the Games of the Small States of Europe – Montenegro 2019”, Online/Video konferencija, april 2020.
10. Konferencija „Technologies and Materials for Renewable Energy, Environment and Sustainability” – „Analysis of public attitudes and perceptions toward renewable energy sources in Montenegro”, Online/Video konferencija, jun 2020.
11. Konferencija „Sport, Physical Activity and Health: Contemporary Perspectives“ – „Montenegrin Sport Associations on Social Media - Quality of Performance Assessment”, Cavtat/Video konferencija, april 2021.
12. Konferencija „Analytics Without Borders” – „Class Balancing in Customer Segments Classification Using Support Vector Machine Rule Extraction and Ensemble Learning”, Bentley University, USA/Virtuelna konferencija, mart 2021..
13. Konferencija „International Conference on Marketing and Technologies 2021 (ICMarkTech21)” – „Estimating Respondents' Profitability: Influence of RFM Attributes, Web Metrics and Product Data”, Tenerife/online, decembar 2021.
14. Konferencija „International Conference on Computer Technology Applications (ICCTA2022)“ – „Application of Apriori Algorithm for CRM Improvement - Case Study from Montenegro“, Vienna/Online, maj 2022.
15. Konferencija „International Forum on Knowledge Asset Dynamics (IFKAD2022)“ – „Data Analytics for Marketing Knowledge Advancement: a Market Segmentation Example Using Support Vector Machine“, Lugano/online, jun 2022.
16. Konferencija „Computing Conference 2022“ – „. Customer Response Modeling for Direct Marketing Using Ensemble of Balanced Classifiers: Influence of Web Metrics on the Model Performance“, London/online, jul 2022.

Prof. dr Ljiljana Kašćelan- Biografija sa bibliografijom

1. **Biografija**

Rođena je 30.08.1968. godine u Beranama. Osnovnu školu i gimnaziju završila je u Beranama sa odličnim uspjehom i diplomom "Luča". Studije na Prirodno-matematičkom fakultetu - odsjek Matematika, smjer Računari, Univerziteta Crne Gore, započela je 1987. godine a diplomirala 1992. godine i stekla zvanje diplomirani matematičar. Poslijediplomske studije na Elektrotehničkom fakultetu u Podgorici, smjer Računarstvo, upisala je 1992. godine. U toku studija ostvarila je prosječnu ocjenu 10. Magistarski rad pod nazivom: "Automatsko generisanje operacija nad složenim objektima" odbranila je 1996. godine na Elektrotehničkom fakultetu u Podgorici. Doktorsku disertaciju pod nazivom "Model sistema za podršku odlučivanju u sanacionom menadžmentu zasnovan na data warehouse konceptu" odbranila je 2002. godine, na Ekonomskom fakultetu Univerziteta Crne Gore.

Za saradnika u nastavi na predmetu Informatika, na Ekonomskom fakultetu u Podgorici, Univerziteta Crne Gore, primljena je 1993. godine. U zvanje asistent za predmete Informatika i Baze podataka na Ekonomskom fakultetu u Podgorici, izabrana je 1997. godine. U zvanje docent izabrana je 2003. godine a u zvanje vanredni profesor 2008. godine. U zvanje redovni profesor izabrana je 2014 godine, za predmete Informatika, Baze podataka, Poslovna informatika i Sistemi poslovne inteligencije.

Tokom bavljenja pedagoškim radom na fakultetu, pored angažovanja u nastavnoj aktivnosti, bila je angažovana kao mentor za izradu značajnog broja magistarskih i diplomskih radova. Autor je udžbenika iz oblasti poslovnih informacionih tehnologija, čiji je izdavač Univerzitet Crne Gore.

Član je međunarodnog naučnog udruženja Euro Working Group on Decision Support Systems, kao i Upravnog i Uređivačkog odbora međunarodnog časopisa ComSis koji se nalazi na SCIe . Takođe, član je Senata Unverziteta Crne Gore.

2. **Bibliografija (posljednjih 5 godina)**

Članci u indeksiranim međunarodnim časopisima (SCIe, SSCI):

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2. Biljana Rondović, **Ljiljana Kašćelan**, Vujica Lazović, Tamara Đuričković (2017): Discovering the determinants and predicting the degree of e-business diffusion using the decision tree method: evidence from Montenegro. Information Technology for Development, 12/2017 (Po 2018 latest Impact Factors (Clarivate Analytics | Journal Citation Reports | Thomson Reuters) časopis ima **IF 1,387**) **(1 citat)**

3. Jovanović M., **Kašćelan Lj.**, Joksimović M., & Kašćelan, V. (2017). „Decision Tree Analysis of Wine Consumers' Preferences: Evidence from an Emerging Market", *British Food Journal*, 119(6), ISSN 0007-070X. (Po 2018 latest Impact Factors (Clarivate Analytics | Journal Citation Reports | Thomson Reuters) časopis ima **IF 1,289**) **(2 citata)**

4. Kašćelan, V., **Kašćelan, L.**, & Novović Burić, M. (2016). A nonparametric data mining approach for risk prediction in car insurance: a case study from the Montenegrin market. *Economic Research-Ekonomska Istraživanja*, *29*(1), 545-558. (Po 2018 latest Impact

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Knjige:

1. **Kašćelan Lj.**, »Informacione tehnologije za podršku poslovnom odlučivanju«, Univerzitet Crne Gore, 2016

Poglavlja u monografijama:

1. 1. **Lj.Kašćelan**, V.Kašćelan, M. Novović Burić (2018), A Decision Tree Analysis of Real Estate Insurance Customers in the Montenegrin Market", međunarodna monografija - *Quantitative models in Economics*, Faculty of Economics of the University of Belgrade

2. **Kašćelan, Lj.**, Kašćelan, V., Novović Burić, M. (2017): Data-driven Approach as an Alternative Method for Risk Assessment in the Montenegrin Automobile Insurance Market, međunarodna monografija - *Challenges and tendencies in contemporary insurance market*, Faculty of Economics of the University of Belgrade

Članci u ostalim indeksiranim međunarodnim časopisima:

1. Jovanovic, M., Joksimovic, M., **Kascelan, L**., & Despotovic, A. (2017). Consumer attitudes to organic foods: evidence from montenegrin market. *Poljoprivreda i Sumarstvo*, *63*(1), 223.

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4. Despotović, A., Joksimović, M., **Kašćelan, L**., & Jovanović, M. (2015). Causes for depopulation of rural areas in the Municipality of Pljevlja. *Agriculture and Forestry, 61*(4), 393-407.

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1. **Kašćečan, L**., Lazović, V., Đuričković, T., & Biljana, R. (2018). Analysis of the Diffusion of E-services in Public Sector Using the Decision Tree Method. In *Proceedings of the ENTRENOVA-ENTerprise REsearch InNOVAtion Conference, Split, Croatia, 6-8 September 2018* (pp. 38-48). Zagreb: IRENET-Society for Advancing Innovation and Research in Economy. **ECONSTOR.EU**

2. Gazdić, T., & **Kašćelan, L**. (2013, May). Model of the business intelligence system for credit risk analysis. In *Information & Communication Technology Electronics & Microelectronics (MIPRO), 2013 36th International Convention on* (pp. 1155-1160). **IEEE**.

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ODLUKU
O IZBORU U ZVANJE

DR LJILJANA KAŠĆELAN bira se u akademsko zvanje **redovni profesor** Univerziteta Crne Gore za predmete: Informatika i Baze podataka, na studijskom programu Ekonomija i Poslovna informatika i Sistemi poslovne inteligencije, na studijskom programu Menadžment, na Ekonomskom fakultetu.

REKTOR

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Europass Curriculum Vitae

Lični podaci

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Pol	Muški

Radno iskustvo

Datumi: **24.09.2021. – danas Univerzitet Crne Gore**

Zanimanje ili radno mjesto: **Redovni profesor na Univerzitetu Crne Gore**

Glavni poslovi i odgovornosti: Izvodi nastavu na grupi predmeta iz naučne oblasti **Menadžment i marketing**. Predmeti na kojima je angažovan na osnovnim studijama: **Biznis, Principi marketinga** na **Ekonomskom fakultetu** u Podgorici i **Teorija menadžmenta** na **Pomorskom fakultetu** u Kotoru. Na studijskom programu **Menadžment** u Podgorici i Bijelom Polju, izvodi nastavu na predmetima **Biznis, Preduzetništvo**, **Osnovi marketinga**. Na **Postdiplomskim master studijama** Ekonomskog fakulteta angažovan je na predmetima **Brend menadžment, Strategijski marketing** i **Metrika marketinga**, dok je na master studijama na **Mašinskom fakultetu** angažovan na predmetu **Satisfakcija potrošača**. Na doktorskim studijama na Ekonomskom fakultetu angažovan na predmetu **Metrika marketinga**. Na doktorskim studijama na **Fakultetu za turizam i hotelijerstvo** izvodi predmet **Marketing istraživanje u turizmu**.

2021 -	**Član Naučnog odbora Univerziteta Crne Gore**
2019 – 2022	**Prodekan za međunarodnu saradnju**
2017 – 2022	**Član Odbora za upravljanje sistemom kvaliteta na Univerzitetu Crne Gore**
2016 – 2019	**Prodekan za nastavu**
2016 – 2019	**Predsjednik komisije za Postdiplomske studije**
2016 – 2019	**Predsjednik Komisije za kvalitet na Ekonomskom fakultetu**
2015 – 2016	**Rukovodilac akademskih studija Ekonomskog fakuleta**
2013 – 2014	**Prodekan za nastavu**
2013 – 2014	**Rukovodilac programa *Distance learning - Učenje na daljinu***
2013 – 2015	**Rukovodilac Centra za razvoj karijere na Ekonomskom fakultetu**
2013 – 2016	**Član Komisije za nastavna pitanja na Ekonomskom fakultetu**
2013 – 2014	**Predsjednik Komisije za kvalitet na Ekonomskom fakultetu**

Ime i adresa poslodavca: **Univerzitet Crne Gore, Ekonomski fakultet Podgorica**, Jovana Tomaševića 37, 81000 Podgorica, Crna Gora, www.ucg.ac.me/ef;

Datum: **27.10.2016. – 24.09.2021. Univerzitet Crne Gore – Vanredni profesor**
02.06.2011 – 27.10.2016. Univerzitet Crne Gore - Docent

Datum: **01.02.2004. – 02.06.2011. Ekonomski fakultet Podgorica, Univerzitet Crne Gore**

Zanimanje ili radno mjesto: **Saradnik u nastavi**

Glavni poslovi i odgovornosti: Na **Ekonomskom fakultetu** u Podgorici, kao saradnik u nastavi, dr Boban Melović bio je angažovan na većem broju predmeta iz oblasti marketinga i menadžmenta: **Marketing, Menadžment, Marketing malog biznisa, Razumijevanje potrošača** i **Razvoj organizacije**. Na **Studijama menadžmenta** u Podgorici bio je angažovan na predmetima **Osnovi marketinga, Istraživanje marketinga, Marketing menadžment malog biznisa, Marketing u trgovini** i **Ekonomija firme**. Na **Studijama menadžmenta** u Bijelom Polju bio je angažovan na predmetu **Osnove marketinga**. Na **Mašinskom fakultetu** u Podgorici bio je angažovan na predmetu **Marketing u saobraćaju**.

Datum	**01.02.2003. – 01.02.2004. Ekonomski fakultet Podgorica, Univerzitet Crne Gore**
Zanimanje ili radno mjesto	**Demonstrator**
Glavni poslovi i odgovornosti	Demonstrator na predmetu **Menadžment**

Obrazovanje i osposobljavanje

Datumi	**19.03.2007. - 17.12.2009.**
Naziv dodijeljene kvalifikacije	**Doktor ekonomskih nauka**
Glavni predmeti / stečene profesionalne vještine	Doktorska disertacija: **„Marketing menadžment u funkciji kreiranja brenda – primjer Crne Gore“**
Ime i vrsta organizacije pružatelja obrazovanja i osposobljavanja	Univerzitet Crne Gore, Ekonomski fakultet Podgorica
Datumi	**01.10.2003 - 13.07.2006**
Naziv dodijeljene kvalifikacije	**Magistar ekonomskih nauka**
Glavni predmeti / stečene profesionalne vještine	Postdiplomske studije - Ekonomski fakultet Beograd Smjer: **Međunarodni menadžment i marketing** Položio 10 ispita i odbranio javno dva pristupna-seminarska rada sa najvećim ocjenama. Magistarska teza**: „Strategijski značaj međunarodnog benchmarkinga za unapređenje menadžmenta i marketinga”**
Ime i vrsta organizacije pružatelja obrazovanja i osposobljavanja	Univerzitet u Beogradu, Ekonomski fakultet, Kamenička 6, 11000 Beograd, Srbija
Datumi	**01.10.1999. - 11.07.2003.**
Naziv dodijeljene kvalifikacije	**Diplomirani ekonomista**
Glavni predmeti / stečene profesionalne vještine	Prosječna ocjena na studijama 9.75. Diplomski rad: **“Uloga menadžmenta i značaj strategijskog menadžmenta u savremenom poslovanju preduzeća na primjeru preduzeća “Telekom Crne Gore” AD”**
Ime i vrsta organizacije pružatelja obrazovanja i osposobljavanja	Univerzitet Crne Gore, Ekonomski fakultet Podgorica, 81000 Podgorica, Crna Gora
Datumi	**1995. – 1999.**
Naziv dodijeljene kvalifikacije	**Srednja stručna škola Pljevlja**
Glavni predmeti / stečene profesionalne vještine	Đak generacije i dobitnik diplome ”Luča”. Učesnik većeg broja državnih i lokalnih takmičenja.
Ime i vrsta organizacije pružatelja obrazovanja i osposobljavanja	Srednja stručna škola Pljevlja, Pljevlja, Crna Gora
Datumi	**1987. – 1995.**
Naziv dodijeljene kvalifikacije	**Osnovna škola “Boško Buha“ Pljevlja**
Glavni predmeti / stečene profesionalne vještine	Đak generacije i dobitnik diplome ”Luča”. Učesnik većeg broja državnih i lokalnih takmičenja.
Ime i vrsta organizacije pružatelja obrazovanja i osposobljavanja	Osnovna škola “Boško Buha“, Pljevlja, Pljevlja, Crna Gora

Studijski boravci – (odabrano)

Prof. dr Boban Melović je obavio veći broj nekoliko specijalizacija u inostranstvu, među kojima su: Češka (2019), Poljska (2018), Univerzitet u Temišvaru (2018), Jiangnan University China (2014); Catholic University of Portugal, Lisbon (2012); Faculty of Law, ELSA, Istanbul, Turkey, (2011); Ekonomski fakultet Sarajevo (2010); Colchester, Velika Britanija (2010); Ekonomski fakultet Univerziteta u Ljubljani (2009); Royal Institute of Technology (KTH), Stocholm, Švedska (2008); Zagrebačka škola ekonomije i menadžmenta, Hrvatska (2008); RESEGE, Chisinau, Moldova (2005); FNEGE foundation, Ohrid, Makedonija (2004).

Nagrade i priznanja u toku studija

Tokom studija bio je dobitnik brojnih akademskih nagrada, među kojima se posebno ističu: redovne godišnje nagrade za najbolje studente Ekonomskog fakulteta (laureat za sve četiri godine studija), Nagrada Ministarstva prosvjete i nauke (više puta), Nagrada opštine Pljevlja, Nagrada Vojvođanske banke, Nagrada Kombinata aluminijuma Podgorica.

Dobitnik je i brojnih godišnjih stipendija: Stipendije Ekonomskog fakulteta (više puta), Stipendije Opštine Pljevlja (najbolji student opštine), "Stipendije za talentovane studente" Ministarstva prosvjete i nauke Crne Gore (više puta). Takođe, jedan je od dobitnika stipendije AtlasMont banke, koja se namijenjena najboljim studentima u Crnoj Gori. Na trećoj i četvrtoj godini studija bio je dobitnik i nagrade Univerziteta Crne Gore.

Lične osobine i kompetencije

Jezici

Samoprocjena	Razumijevanje		Govor		Pisanje
Evropski nivo	Slušanje	Čitanje	Govorna interakcija	Govorna produkcija	
Engleski	C1	C1	C1	C1	C1

(*) Common European Framework of Reference for Languages

Bibliografija, angažmani – sumarno

Autor ili koautor je četiri knjige, više poglavlja u međunarodnim monografijama i velikog broja naučnih i stručnih radova iz oblasti marketinga, menadžmenta, preduzetništva, brenda i turizma. Učestvovao na velikom broju domaćih i međunarodnih naučnih skupova. U dosadašnjoj karijeri učestvovao je u većem broju naučnih i stručnih projekata i bio član različitih ekspertskih i radnih grupa. U periodu 2012-2020. godine bio je član Centra mladih naučnika Crnogorske akademije nauka i umjetnosti (CANU). Gostujući je profesor na nekoliko fakulteta. Član međunarodne redakcije i uredništva više časopisa, te član naučnog i organizacionog odbora većeg broja naučnih konferencija. Posjeduje *WorldSkills Europe Expert Certificate*. Dvostruki je dobitnik Priznanja Univerzitata Crne Gore za postidgnute rezultate i posebne doprinose u razvoju naučno-istraživačkog rada i međunarodnog pozicioniranja (2019, 2020).

Bibilografija

Knjige studijskog karaktera:

Melović, B., Pavičić, J., Gnjidić, V., Drašković, N. (2019), ***Strategijski marketing***, Ekonomski fakultet Podgorica i Ekonomski fakultet Zagreb, ISBN 978-86-80133-73-7.

Šerić, N., **Melović, B**., Perišić, M (2019), ***Upravljanje markom u poduzetništvu - Brand management in entrepreneurship***, Redak, Hrvatska

Mitrović, S., **Melović, B.** (2017). ***Principi savremenog menadžmenta*** drugo izdanje, Univerzitet u Novom Sadu, Fakultet tehničkih nauka, Novi Sad, str. 1-533, ISBN 978-86-7892-951-39 (Univerzitetski udžbenik koji se koristi u inostranstvu i kod nas).

Mitrović, S., **Melović, B.** (2013). ***Principi savremenog menadžmenta***. Univerzitet u Novom Sadu, Fakultet tehničkih nauka, Novi Sad, str. 1-535, ISBN 978-86-7892-487-3 (Univerzitetski udžbenik koji se koristi u inostranstvu i kod nas).

Melović B., ***Međunarodni benchmarking***, Ekonomski fakultet Podgorica, ISBN 978-86-80133-41-6, 2007. godine, strana 184.

Monografije ili dio monografije

Melovic, B., & Djurisic, V. (2020). ***Women's Entrepreneurship in Montenegro***, in: Women's Entrepreneurship in Former Yugoslavia, Contributions to Management Science, pp. 83-111, Springer, Cham. ISBN 978-3-030-45252-0.

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Uvodno, objavljeno plenarno predavanje

Mitrović, S., **Melović, B.**, Nešić, A., (2015). ***„Modern approach in human resource management in organizations."*** International Scientific Conference „Corporate social responsibility and human resource management in v4 countries". Slovak University of Agriculture, Nitra, Slovakia. Faculty of Economics and Management. 4 June, 2015. ISBN 978-80-552-1432-0, pp.176-183.

Stručni radovi:

Melović B., ***„(Ne)razumijevanje marketinga u Crnoj Gori"***, časopis *Monitor*, broj 936, septembar 2008, str. 31.

Melović B., ***„Kreiranje brenda"***, časopis *„Biznis Montenegro"*, br. 3., Media System, 2008, ISSN 1800-685X, str. 88-90.

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Melović B., ***„Sport – biznis u kome svi dobijaju"***, časopis *„Biznis Montenegro"*, br. 1, Media System, novembar 2007, ISSN 1800-685X, str. 74-77.

Melović B., ***„Benchmarking vs Poslovna špijunaža“***, časopis *„Biznis Montenegro“*, br. 7., Media System, 2008, ISSN 1800-685X, str. 92-95.

Melović B., ***„Benchmarking – izazovi primjene“***, časopis *„Biznis Montenegro“*, br. 8., Media System, 2008, ISSN 1800-685X, str. 94-97.

Melović B., ***„Marketing u bankarstvu“***, časopis *„Biznis Montenegro“*, br. 9., Media System, 2008, ISSN 1800-685X, str. 90-94.

Melović B., ***„Faktori koji utiču na ponašanje korisnika bankarskih usluga“***, časopis *„Biznis Montenegro“*, br. 10., Media System, 2008, ISSN 1800-685X, str. 94-97.

Melović B., ***„Segmentacija bankarskog tržišta“***, časopis *„Biznis Montenegro“*, br. 11., Media System, 2008, ISSN 1800-685X, str. 88-90.

Melović B., ***„Marketing mix u bankarstvu“***, časopis *„Biznis Montenegro“*, br. 12., Media System, 2008, ISSN 1800-685X, str. 88-93.

Mentorstva

Na Ekonomskom fakultetu i Studijama menadžmenta u Podgorici i Bijelom Polju dr Boban Melović je bio mentor pri izradi više od velikog broja **diplomskih radova.** Takođe, do sada je bio mentor na **većeg broja magistarskih** i **specijalističkih** radova.

Gostujući profesor

ERASMUS mobilnost u studijskoj 2016/2017, 2017/2018, 2018/2019, 2019/2020, 2021/2022.

Univerzitet u Istočnom Sarajevu, Ekonomski fakultet Pale, gostujući profesor na akademskim postdiplomskim magistarskim studijama, izabran za studijske 2014/2015 (Odluka Senata UCG 08-1280/3 od 04.09.2014.); 2015/2016. godinu (Odluka Senata UCG 08-3124/1 od 23.12.2015.) i 2017/18. godinu (Odluka Senata UCG 03-2783/1 od 06.11.2017. godine).

CEEPUS gostujuci profesor na University of Novi Sad, Faculty of Technical Sciences u studijskoj 2015/16, 2016/17 i 2017/18. godini (kondenzovana nastava na predmetu *Principi inženjerskog menadžmenta* – tematska oblast: Brend menadžment), CEEPUS mreža: CIII-SK-0044-10-1516 – *Applied Economics and Management*

Faculty of Economics Skopje at St. Cyril and Methodius University - predavač na IVth International Summer School “Make A Difference - Become a Sustainable Competitive Advantage EU Leader”, Ohrid, Macedonia, 08-17.08.2015.

Organizacija naučnih skupova

Član Naučnog i Organizacionog odbora konferencije Jahorinski poslovni forum, Jahorina, 2016.
Član Naučnog odbora 2. Kongresa sportskog turizma: globalni i nacionalni izazovi sportskog turizma, Makarska, Hrvatska, 2016.
Član Naučnog odbora Međunarodnog naučnog skupa Turizam u funkciji razvoja Republike Srbije – banjski turizam u Srbiji i iskustva drugih zemalja, Univerzitet u Kragujevcu, Fakultet za hotelijerstvo i turizam u Vrnjačkoj Banji, 2016.
Član Naučnog i Organizacionog odbora konferencije Jahorinski poslovni dani, Jahorina, 2015.
Član Organizacionog odbora IV International Conference on Entrepreneurship and Innovation as Precondition for Economic Development, Podgorica, 2014.
Član Naučnog odbora konferencije Socijalni identitet u uslovima krize: problemi i rješenja, Novi Sad, 2011.
Član Organizacionog odbora konferencije Socijalni identitet u uslovima krize – zaposlenost i nezaposlenost, Novi Sad, 2012.

Rad na projektima

Pored rada sa studentima, dr Boban Melović učestvovao je u izradi jednog broja značajnih projekata i studija koje je realizovao Ekonomski fakultet, a koji su se odnosili na transformaciju i restrukturiranje preduzeća, procjenu vrijednosti imovine, izradu tenderske dokumentacije, kao i izradu biznis planova, investicionih programa i poslovnih strategija brojnih crnogorskih preduzeća, od kojih se posebno izdvajaju:

Naučno-istraživački projekti:

Erasmus+ project: ***Strengthening capacities for the implementation of dual education in Montenegro higher education (DUALMON),*** EPPKA2 - Cooperation for innovation and the exchange of good practices - Capacity Building in higher education - Structural Projects.

Bilateralni projekat: 2019-2021. ***Brendiranje organskih prehrambenih proizvoda zasnovano na principima održivog razvoja - komparativna studija između Crne Gore i Srbije*** (Univerzitet Crne Gore, Univerzitet u Novom Sadu)
Bilateralni projekat: 2019-2021. ***Impact of the exchange rate on the foreign trade imbalance in the conditions of the crisis – sustainable development of the new countries of EU and the Western Balkans***, bilateral project
Bilateralni projekat: 2016-2018. ***Jačanje konkurentnosti kroz podsticaj razvoja organske poljoprivrede - komparativna studija između Crne Gore i Srbije*** (Univerzitet Crne Gore, Univerzitet u Novom Sadu)
Bilateralni projekat: 2016-2017. ***Kauzalitet poslovnih ciklusa i strukture finansiranja preduzeća u Bosni i Hercegovini i Crnoj Gori – komparativna analiza*** (Univerzitet Crne Gore, Univerzitet "Džemal Bijedić" u Mostaru)
Međunarodni projekat 2011-2014: ***Transformacija socijalnog identiteta Srbije u uslovima krize i njen uticaj na evropske integracije***, Univerzitet u Novom Sadu, Fakultet tehničkih nauka Novi Sad, Ministarstvo nauke Republike Srbije, broj 179052, 2011-2014. godina
Bilateralni projekat: 2014-2016. ***Podizanje konkurentnosti kroz saradnju: komparativna studija o naučno-tehnološkim inovacijama u poljoprivredi, difuziji i komunikacionim sistemima između Kine i Crne Gore*** (University of Montenegro, Jiangnan University China)
Nacionalni projekat: 2012-2014. ***Konkurentnost građevinskog sektora u Crnoj Gori – uslovi, mogućnosti i pravci unapređenja***, Ministarstvo nauke Crne Gore.
Nacionalni projekat: 2009-2011. ***Primjena koncepta intelektualnog kapitala u savremenoj poslovnoj praksi***, Ekonomski fakultet Podgorica, Ministarstvo prosvjete i nauke Crne Gore.

Privredni projekti:

Marketing strategija Crnogorskog Olimpijskog Komiteta – pozicioniranje sporta kao elementa nacionalnog brenda, COK, Podgorica, 2016. godina
Biznis plan preduzeća "Open Box Studio", Podgorica 2016. godina
Pravno-finansijska analiza poslovanja FK "Sutjeska", Nikšić, 2014. godina

Investicioni elaborat za proširenje djelatnosti preduzeća „Tehnoput" DOO, Tehnoput DOO, Podgorica, 2011. godina

Biznis plan preduzeća "Primera Polis" DOO, Primera Polis, Podgorica 2011. godina

Investicioni elaborat za rekonstrukciju restorana „SPORT CAFE" – Shopping Mall „Delta", Sport Cafe, Podgorica, 2011. godina

Investicioni eleborat za modernizaciju sportske dvorane „VENOM", VENOM, Podgorica, 2010. godina

Investicioni program kompanije "Barska plovidba" AD Bar, Barska plovidba AD Bar, 2010. godine

„Ocjena efekata dosadašnje privatizacije u Crnoj Gori", Vlada Crne Gore, Podgorica, 2009. godina

„Ažuriranje procjene vrijednosti osnovnih sredstava Elektroprivrede Crne Gore", EPCG, Nikšić, 2008. godina

„Marketing istraživanje konkurentnosti poljoprivrednih proizvoda područja Bihor", BMC Podgorica, 2008. godina

„Izbor najboljeg preduzeća u Crnoj Gori 2007. godine", Direkcija za MSP, Podgorica, 2008. godina

Izrada tenderske dokumentacije AD "VEKTRA", AD Vektra, Podgorica, 2007. godina

Investicioni program štamparije "AP Print", AP Print, Podgorica, 2007. godina

Izrada tenderske dokumentacije AD "VEKTRA", AD Vektra, Podgorica, 2006. godina

"Izbor najboljeg preduzeća u Crnoj Gori 2005. godine", Direkcija za MSP, Podgorica, 2006. godina

Biznis plan AD "Marina" Bar za 2006. godinu, AD Marina Bar, 2006. godina

„Nivo razvoja i kvalitet funkcionisanja saobraćajnog sistema Crne Gore", Direkcija za puteve i Ministarstvo saobraćaja, Podgorica, 2005. godina

Marketing strategija preduzeća "Gradina Company Rožaje", Gradina Company, Rožaje, 2005 godina

Članstvo u udruženjima

Član Centra mladih naučnika Crnogorske akademije nauka i umjetnosti - CANU (2012-2020)
Član Nacionalnog partnerstva za preduzetničko učenje
Član Saveza ekonomista Crne Gore
Član Udruženja ekonomista Podgorice
Član Centra za promociju zdravlja

Ostale reference

Pored navedenih aktivnosti, u toku dosadašnjeg rada ističu se i sljedeće reference:

- Worldskills Europe Expert Certificate – Expert in Enterpreneurship representing Montenegro (2016);
- Član Savjeta za preduzetničko učenje (april 2016).
- Član Tehničkog komiteta ISME/TK 007 (predstavnik Ekonomskog fakulteta u Tehničkom komitetu ISME/TK 007 – Društvena odgovornost - Institut za standardizaciju Crne Gore, od 2014. godine)
- Član radne grupe za izradu Zakona o nacionalnom brendu (Ministarstvo ekonomije, 2015-2016.);
- Član Komisije za izbor idejno-grafičkog rješenja vizuelnog identiteta (žiga) nacionalnog brenda Crne Gore (Ministarstvo ekonomije, 2015-2016.);
- Koordinator RESICA mreže (u ime Ekonomskog fakulteta, od 2014.);
- Koordinator mreže CEEPUS za Crnu Goru: Applied Economics and Management, CIII-SK-0044 (2015/2016.);
- Član radne grupe za izradu Strategije za cjeloživotno preduzetničko učenje 2014-2019. (Ministartsvo ekonomije, Direkcija za razvoj malih i srednjih preduzeća);
- Član Nacionalnog partnerstva za preduzetničko učenje, Ministry of Economy, Directorate for development of small and medium sized enterprises;
- Član stručnog žirija Superbrands Montenegro 2015/16.;
- Konsultant Ministarstva nauke, Ministarstva prosvjete i Centra za stručno obrazovanje (od 2012.);
- Predstavnik Ekonomskog fakulteta u saradnji sa kompanijom Ernst&Young (program obrazovanja u okviru strategije za razvoj talenata "Tvoja karijera može početi ovdje“ (Ernst&Young i Zavod za zapošljavanje Crne Gore, 2014-2016.);
- Član stručnog žirija Takmičenja u rješavanju studije slučaja (Ernst&Young, 2014-2016.);
- Član međunarodne redakcije i recenzent časopisa Economics, izdavač Oikos institut, Bijeljina, Republika Srpska;
- Stalni recenzent u časopisu Zbornik radova Ekonomskog fakulteta u Istočnom Sarajevu - časopis za ekonomsku teoriju i praksu (od 2014);
- Član u Scientific council of journal Marketing of Scientific and Research Organisations, Poljska (2017);
- Recenzent u Časopisu Hotel and Tourism Management, Fakultet za turizam i hotelijerstvo, Vrnjačka Banja (2017);
- Član redakcionog odbora u časopisu Zbornik radova Ekonomskog fakulteta Brčko (od 2016);
- Savjetnik za eksterno utvrđivanje kvaliteta obrazovno-vaspitnog rada u JU Srednja ekonomska škola „Mirko Vešović“ u Podgorici (2014, 2015);
- Član Komisije za dodjelu Studentske nagrade Glavnog grada Podgorice (2013, 2014);
- Rukovodilac mentoring programa Socijalnog preduzetništva (Centar za razvoj nevladinih organizacija i Ekonomski fakultet, 2014-2015.);

Reference

Reference su dostupne na zahtjev.

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Datum / Date 24. 09. 2021

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EKONOMSKI FAKULTET
Broj 01/ 2656
Podgorica, 04.10 2021 god.

Na osnovu člana 72 stav 2 Zakona o visokom obrazovanju („Službeni list Crne Gore" br 44/14, 47/15, 40/16, 42/17, 71/17, 55/18, 3/19, 17/19, 47/19, 72/19 i 74/20) i člana 32 stav 1 tačka 9 Statuta Univerziteta Crne Gore, Senat Univerziteta Crne Gore na sjednici održanoj 24.09.2021. godine, donio je

O D L U K U
O IZBORU U ZVANJE

Dr BOBAN MELOVIĆ bira se u akademsko zvanje redovni profesor Univerziteta Crne Gore **iz oblasti Menadžment i marketing na Ekonomskom fakultetu Univerziteta Crne Gore**, na neodređeno vrijeme.

SENAT UNIVERZITETA CRNE GORE
PREDSJEDNIK

Prof. dr Vladimir Božović, rektor

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LinkedIn: https://rs.linkedin.com/in/ivan-luković-455b5b64
Date of birth: 20/12/1965 **Nationality:** Serbian

WORK EXPERIENCE

[2020 – Current]

Full Professor

University of Belgrade, Faculty of Organizational Sciences http://www.fon.bg.ac.rs/eng/

Address: Jove Ilića 154, 11000, Belgrade, Serbia
City: Belgrade
Country: Serbia
Name of unit or department: Chair of Information Systems
Business or sector: Education

[2005 – 2021]

Full Professor

University of Novi Sad, Faculty of Technical Sciences

Address: Trg Dositeja Obradovića 6, 21000, Novi Sad, Serbia
City: Novi Sad
Country: Serbia
Name of unit or department: Department of Computing and Control
Business or sector: Education

[2000 – 2006]

Associate Professor

University of Novi Sad, Faculty of Technical Sciences

[1995 – 2001]

Assistant Professor

University of Novi Sad, Faculty of Technical Sciences

[1990 – 1996]

Assistant

University of Novi Sad, Faculty of Technical Sciences

[1989 – 1991]

Programer, System Designer

ZASTAVA Arms

City: Kragujevac
Country: Serbia
Name of unit or department: Department of Informatics
Business or sector: Manufacturing

EDUCATION AND TRAINING

[1996]

Ph.D. in Computer Science

University of Novi Sad, Faculty of Technical Sciences

Address: Novi Sad, Serbia

[1989 – 1993]

M.Sc. (former Mr, 2 year degree) in Informatics

University of Belgrade, Faculty of Electrical Engineering

Address: Belgrade, Serbia

[1984 – 1990] **M.Sc. (former diploma, 5 year degree) in Informatics**

High Military and Engineering Schools, Faculty of Military and Technical Sciences

Address: Zagreb, Croatia

LANGUAGE SKILLS

Mother tongue(s): Serbian (Serbo-Croat)

Other language(s):

English

LISTENING B1 **READING** C2 **WRITING** C2

SPOKEN PRODUCTION C1 **SPOKEN INTERACTION** C1

Russian

LISTENING B1 **READING** B2 **WRITING** A2

SPOKEN PRODUCTION A1 **SPOKEN INTERACTION** A1

Macedonian

LISTENING C2 **READING** C2 **WRITING** A1

SPOKEN PRODUCTION A2 **SPOKEN INTERACTION** A2

Slovenian

LISTENING B1 **READING** B2 **WRITING** A1

SPOKEN PRODUCTION A1 **SPOKEN INTERACTION** A1

DIGITAL SKILLS

Microsoft Office | Google Drive | Outlook | Skype | LinkedIn | Power Point | Zoom | Google Docs | Internet user | Gmail | WhatsApp

Personal Skills

Decision-making | Excellent writing and verbal communication skills | Good listener and communicator | Presenting | Critical thinking | Analytical skills | Responsibility | Organizational and planning skills | Conflict resolution | Creativity | Team-work oriented | Research and analytical skills | Motivated | Flexibility | Strategic Planning | Reliability

PUBLICATIONS

[2022]

Production processes modelling within digital product manufacturing in the context of Industry 4.0

Vještica M, Dimitrieski V, Pisarić M, Kordić S, Ristić S, Luković I, "Production processes modelling within digital product manufacturing in the context of Industry 4.0", International Journal of Production Research, Taylor & Francis, London, England, United Kingdom, ISSN: 0020-7543, DOI: 10.1080/00207543.2022.2125593, 2022.

[2022] **An Approach to the Information System Conceptual Modeling based on the Form Types**

Luković I, Čeliković M, Kordić S, Vještica M, "An Approach to the Information System Conceptual Modeling based on the Form Types", in the book: Domain-Specific Conceptual Modeling: Concepts, Methods and ADOxx Tools, (Eds.) Dimitris Karagiannis, Moonkun Lee, Knut Hinkelmann, Wilfrid Utz, Springer International Publishing, Cham, Switzerland, 2022, ISBN: 978-3-030-93546-7, Vol. 1, pp. 589-614, Chapter 26, DOI: 10.1007/978-3-030-93547-4_26.

[2022] **Organizational capability for information management - do we feel a Big Data crisis?**

Luković I, "Organizational capability for information management - do we feel a Big Data crisis?", 17th Conference on Computer Science and Intelligence Systems (FedCSIS 2022), Bulgarian Academy of Sciences – Institute of Information and Communication Technologies, Sofia, Bulgaria, September 2 – 7, 2022, Keynote Talk, notified in: Anals of Computer Science and Information Systems, Vol. 30, Polish Information Processing Society, Poland and IEEE, ISSN 2300-5963, DOI: 10.15439/978-83-962423-9-6.

[2022] **Assisting Passengers on Rerouted Train Service Using Vehicle Sharing System**

Lalić M, Obrenović N, Brdar S, Luković I, Bierlaire M, "Assisting Passengers on Rerouted Train Service Using Vehicle Sharing System", International Conference on Optimization and Decision

Science (ODS 2022), Firenze, Italy, August 30 – September 2, 2022, Proceedings, SpringerNature OCS, AIRO Series.

[2022] **Lean and Agile Software Development**

Przybyłek A, Jarzębowicz A, Luković I, Ying Ng Y, "Lean and Agile Software Development", Proceedings of 6th International Conference, LASD 2022, Virtual Event, January 22, 2022, Springer, Lecture Notes in Business Information Processing LNBIP 438, ISSN 1865-1348, ISBN 978-3-030-94237-3, DOI: 10.1007/978-3-030-94238-0.

[2021]

Students' Preferences in Selection of Computer Science and Informatics Studies – A Comprehensive Empirical Case Study

Savić M, Ivanović M, Luković I, Delibašić B, Protić J, Janković D, "Students' Preferences in Selection of Computer Science and Informatics Studies – A Comprehensive Empirical Case Study", Computer Science and Information Systems (ComSIS), Consortium of Faculties of Serbia and Montenegro, Belgrade, Serbia, DOI: 10.2298/CSIS200901054S, ISSN: 1820-0214, Vol. 18, No. 1, 2021, pp. 251-283.

[2021] **Multi-Level Production Process Modeling Language**

Vještica M, Dimitrieski V, Pisarić M, Kordić S, Ristić S, Luković I, "Multi-Level Production Process Modeling Language", Journal of Computer Languages (COLA), Elsevier, DOI: 10.1016/j.cola.2021.101053, ISSN: 2590-1184, Vol. 66, No. 101053, 2021.

[2021] **Towards a Formal Specification of Production Processes Suitable for Automatic Execution**

Vještica M, Dimitrieski V, Pisarić M, Kordić S, Ristić S, Luković I, "Towards a Formal Specification of Production Processes Suitable for Automatic Execution", Open Computer Science, De Gruyter, Warsaw, Poland, ISSN: 2299-1093, DOI: 10.1515/comp-2020-0200, Vol. 11, No. 1, 2021, pp. 161-179.

[2021] **An Approach to Validation of Business-Oriented Smart Contracts Based on Process Mining**

Ivković V, Luković I, "An Approach to Validation of Business-Oriented Smart Contracts Based on Process Mining", 25th European Conference on Advances in Databases and Information Systems (ADBIS 2021), Tartu, Estonia, August 24 - 26, 2021, Proceedings New Trends in Database and Information Systems, Springer CCIS Vol. 1450, DOI: https://doi.org/10.1007/978-3-030-85082-1_27, ISSN: 1865-0929, ISBN 978-3-030-85081-4, pp. 303-309.

[2020]

C Tutor Usage in Relation to Student Achievement and Progress: A Study of Introductory Programming Courses in Portugal and Serbia

Alves L, Gajić D, Henriques P. R, Ivančević V, Ivković V, Lalić M, Luković I, Varanda Pereira M. J., Popov S, Tavares P. C, "C Tutor Usage in Relation to Student Achievement and Progress: A Study of Introductory Programming Courses in Portugal and Serbia", Computer Applications in Engineering Education, John Wiley & Sons, Inc., ISSN:1099-0542, Vol. 28, No. 5, DOI: 10.1002/cae.22278, 2020, pp. 1058-1071.

[2020]

Issues and Lessons Learned in the Development of Academic Study Programs in Data Science

Luković I, "Issues and Lessons Learned in the Development of Academic Study Programs in Data Science", 21st International Conference Data Analytics and Management in Data Intensive Domains (DAMDID 2019), Kazan Federal University, Kazan, Russia, October 15 – 18, 2019, Proceedings, Springer Nature Switzerland AG, 2020, A. Elizarov et al. (Eds.): DAMDID/RCDL 2019, CCIS 1223, DOI: 10.1007/978-3-030-51913-1_15, ISBN: 978-3-030-51912-4, pp. 227–245.

[2020]

Databases and Information Systems in the AI Era: Contributions from ADBIS, TPDL and EDA 2020 Workshops and Doctoral Consortium

Bellatreche L, Bentayeb F, Bieliková M, Boussaid O, Catania B, Ceravolo P, Demidova E, Ferrari M. H, Gomez Lopez M. T, Carmem S. H, Kordić S, Luković I, Mannocci A, Manghi P, Osborne F, Papatheodorou C, Ristić S, Sacharidis D, Romero O, Salatino A. A, Talens G, Keulen M, Vergoulis T, Zumer M. "Databases and Information Systems in the AI Era: Contributions from ADBIS, TPDL and EDA 2020 Workshops and Doctoral Consortium", 24th European Conference on Advances in Databases and Information Systems.

[2019] **Consolidation of Database Check Constraints**

Obrenović N, Luković I, Ristić S, "Consolidation of Database Check Constraints", Software and Systems Modeling, Springer, ISSN: 1619-1366, DOI: 10.1007/s10270-017-0637-2, Vol. 18, No. 3, 2019, pp. 2111-2135.

[2019]

Model Variations and Automated Refinement of Domain-Specific Modeling Languages for Robot-Motion Control

Đukic V, Popović A, Luković I, Ivančević V, "Model Variations and Automated Refinement of Domain-Specific Modeling Languages for Robot-Motion Control", Computing and Informatics (CAI), Slovak Academy of Sciences, Institute of Informatics, Bratislava, Slovakia, DOI: 10.31577/cai_2019_2_497, ISSN: 1335-9150, Vol. 38, No. 2, 2019, pp. 497-524.

[2018]

Development and Evaluation of MicroBuilder: A Model-Driven Tool for the Specification of REST Microservice Software Architectures

Terzić B, Dimitrieski V, Kordić S, Milosavljević G, Luković I, "Development and Evaluation of MicroBuilder: A Model-Driven Tool for the Specification of REST Microservice Software Architectures", Enterprise Information Systems, Taylor & Francis, ISSN: 1751-7575, DOI: 10.1080/17517575.2018.1460766, Vol. 12, No. 8-9, 2018, pp. 1034-1057.

[2018]

Extended Tuple Constraint Type as a Complex Integrity Constraint Type in XML Data Model – Definition and Enforcement

Vidaković J, Ristić S, Kordić S, Luković I, "Extended Tuple Constraint Type as a Complex Integrity Constraint Type in XML Data Model – Definition and Enforcement", Computer Science and Information Systems (ComSIS), Consortium of Faculties of Serbia and Montenegro, Belgrade, Serbia, DOI: 10.2298/CSIS180324029V, ISSN: 1820-0214, Vol. 15, No. 3, 2018, pp. 821-843.

[2018] **Formal Education in Data Science – A perspective of Serbia**

Luković I, "Formal Education in Data Science – A perspective of Serbia", 7th International Scientific Conference Technics and Informatics in Education (TIE 2018), Čačak, Serbia, May 25 – 27, 2018, Proceedings, University of Kragujevac, Faculty of Technical Sciences Čačak, ISBN: 978-86-7776-226-1, pp. 12-18.

[2017] **Development of a Database for the Common Information Model of Power Grids**

Dević S, Luković I, "Development of a Database for the Common Information Model of Power Grids", Information Technology and Control, Kaunas University of Technology (KTU), DOI: 10.5755/j01.itc.46.3.14340, ISSN 1392–124X, Vol. 46, No. 3, 2017, pp. 319-332.

[2016] **Automatic idiopathic scoliosis screening using low-cost commodity sensors**

Dimitrijević D, Obradović Đ, Nedić N, Luković I, "Automatic idiopathic scoliosis screening using low-cost commodity sensors", Journal of Intelligent & Fuzzy Systems (JIFS), IOS Press, DOI: 10.3233/JIFS-169046, ISSN 1064-1246, Vol. 31, No. 4, 2016, pp. 2073-2082.

[2015] **Using Association Rule Mining to Identify Risk Factors for Early Childhood Caries**

Ivančević V, Tušek I, Tušek J, Knežević M, , Elheshk S, Luković I, "Using Association Rule Mining to Identify Risk Factors for Early Childhood Caries", Computer Methods and Programs in Biomedicine, Elsevier, ISSN: 0169-2607, DOI: 10.1016/j.cmpb.2015.07.008, 2015, pp. 175-181.

[2015] **A DSL for Modeling Application-Specific Functionalities of Business Applications**

Popović A, Luković I, Dimitrieski V, Đukić V, "A DSL for Modeling Application-Specific Functionalities of Business Applications", Computer Languages, Systems & Structures (COMLAN), Elsevier, DOI: 10.1016/j.cl.2015.03.003, ISSN: 1477-8424, Vol. 43, 2015, pp. 69-95.

[2015]

Concepts and Evaluation of the Extended Entity-Relationship Approach to Database Design in a Multi-Paradigm Information System Modeling Tool

Dimitrieski V, Čeliković M, Aleksić S, Ristić S, Alargt A, Luković I, "Concepts and Evaluation of the Extended Entity-Relationship Approach to Database Design in a Multi-Paradigm Information System

Modeling Tool", Computer Languages, Systems & Structures (COMLAN), Elsevier, DOI: 10.1016/j.cl.2015.08.011, 2015, ISSN: 1477-8424, 2015, pp. 299-318.

[2015] **Information system software development with support for application traceability**

Đukić V, Luković I, Čerpinšek M, Kosar T, Mernik M, "Information system software development with support for application traceability", 16th International Conference on Product-Focused Software Process Improvement (PROFES 2015), December 2, 2015, Bozen-Bolzano, Italy, Proceedings: Springer International Publishing Switzerland, P. Abrahamsson et al. (Eds.): PROFES 2015, LNCS 9459, DOI: 10.1007/978-3-319-26844-6 38, ISBN: 978-3-319-26843-9, pp. 513–527.

[2014] **Key risk factors for Polish State Fire Service**

3rd Place at AAIA'14 Data Mining Competition: Key risk factors for Polish State Fire Service, organized in the scope of FedCSIS 2014 Conference: Nikolić S, Knežević M, Ivančević V, Luković I. "Building an Ensemble from a Single Naive Bayes Classifier in the Analysis of Key Risk Factors for Polish State Fire Service", FedCSIS, 1st Workshop on Complex Events and Information Modelling (CEIM 2014), September 7-10, 2014, Warsaw, Poland.

[2014] **Generic and Standard Database Constraint Meta-Models**

Ristić S, Aleksić S, Čeliković M, Luković I, "Generic and Standard Database Constraint Meta-Models", Computer Science and Information Systems (ComSIS), Consortium of Faculties of Serbia and Montenegro, Belgrade, Serbia, DOI: 10.2298/CSIS140216037R, ISSN: 1820-0214, Vol. 11, No. 2, 2014, pp. 679-696.

[2013] **DSLs in Action with Model Based Approaches to Information System Development**

Luković I, Ivančević V, Čeliković M, Aleksić S, "DSLs in Action with Model Based Approaches to Information System Development", in the book: Formal and Practical Aspects of Domain-Specific Languages: Recent Developments, (Ed.) Marjan Mernik, IGI Global, USA, 2013, ISBN: 978-1-4666-2092-6, DOI: 10.4018/978-1-4666-2092-6, pp. 502-532.

[2013] **Adaptive Testing in Programming Courses based on Educational Data Mining Techniques**

Ivančević V, Knežević M, Pušić B, Luković I, "Adaptive Testing in Programming Courses based on Educational Data Mining Techniques", in the book: Educational Data Mining: Applications and Trends, (Ed.) Alejandro Peña-Ayala, Springer, Series "Studies in Computational Intelligence", Germany, 2013, ISSN: 1860-949X, ISBN: 978-3-319-02737-1, Vol. 524, DOI: 10.1007/978-3-319-02738-8, pp. 257-287.

[2013]

Dr Warehouse - An Intelligent Software System for Epidemiological Monitoring, Prediction, and Research

Ivančević V, Knežević M, Simić M, Mandić D, Luković I. "Dr Warehouse - An Intelligent Software System for Epidemiological Monitoring, Prediction, and Research", 5th International Conference on Advances in Databases, Knowledge, and Data Applications (DBKDA 2013), January 27 - February 1, 2013, Seville, Spain, IARIA, ISBN 978-1-61208-026-0, pp. 204-210. (Best paper award)

[2013] **Meta-Modeling of Inclusion Dependency Constraints**

Ristić S, Aleksić S, Čeliković M, Luković I, "Meta-Modeling of Inclusion Dependency Constraints", 6th Balkan Conference in Informatics (BCI 2013), September 19-21, 2013, Thessaloniki, Greece, Proceedings, ACM New York, USA, DOI: 10.1145/2490257.24, ISBN: 978-1-4503-1851-8, pp. 114-121. (Best paper award).

[2013]

A Design Specification and a Server Implementation of the Inverse Referential Integrity Constraints

Aleksić S, Ristić S, Luković I, Čeliković M, "A Design Specification and a Server Implementation of the Inverse Referential Integrity Constraints", Computer Science and Information Systems (ComSIS), Consortium of Faculties of Serbia and Montenegro, Belgrade, Serbia, DOI: 10.2298/CSIS111102003A, ISSN: 1820-0214, Vol. 10, No. 1, 2013, pp. 283-320.

[2013]

Model Execution: An Approach based on extending Domain-Specific Modeling with Action Reports

Đukić V, Luković I, Popović A, Ivančević V, "Model Execution: An Approach based on extending Domain-Specific Modeling with Action Reports", Computer Science and Information Systems (ComSIS), Consortium of Faculties of Serbia and Montenegro, Belgrade, Serbia, DOI: 10.2298/CSIS121228059D, ISSN: 1820-0214, Vol. 10, No. 4, 2013, pp. 1585-1620.

[2012] **Transformations of Check Constraint PIM Specifications**

Obrenović N, Popović A, Aleksić S, Luković I, "Transformations of Check Constraint PIM Specifications", Computer and Informatics (CAI), Slovak Academy of Sciences, Institute of Informatics, Bratislava, Slovakia, ISSN: 1335-9150, Vol. 31, No. 5, 2012, pp. 1045-1079.

[2012] **A MOF based Meta-Model and a Concrete DSL Syntax of IIS*Case PIM Concepts**

Čelković M, Luković I, Aleksić S, Ivančević V, "A MOF based Meta-Model and a Concrete DSL Syntax of IIS*Case PIM Concepts", Computer Science and Information Systems (ComSIS), Consortium of Faculties of Serbia and Montenegro, Belgrade, Serbia, DOI: 10.2298/CSIS120203034C, ISSN: 1820-0214, Vol. 9, No. 3, 2012, pp. 1075-1103.

[2011] **A DSL for PIM Specifications: Design and Attribute Grammar based Implementation**

Luković I, Varanda Pereira, M. J, Oliveira N, Cruz D., Henriques, P. R., "A DSL for PIM Specifications: Design and Attribute Grammar based Implementation", Computer Science and Information Systems (ComSIS), Consortium of Faculties of Serbia and Montenegro, Belgrade, Serbia, ISSN: 1820-0214, DOI: 10.2298/CSIS101229018L, Vol. 8, No. 2, 2011, pp. 379-403.

[2010]

A Tool for Modeling Form Type Check Constraints and Complex Functionalities of Business Applications

Luković I, Popović A, Mostić J, Ristić S, "A Tool for Modeling Form Type Check Constraints and Complex Functionalities of Business Applications", Computer Science and Information Systems (ComSIS), Consortium of Faculties of Serbia and Montenegro, Belgrade, Serbia, ISSN: 1820-0214, DOI:10.2298/CSIS1002359L, Vol. 7, No. 2, 2010, pp. 359-385.

[2010] **Advances in Databases and Information Systems at the University of Novi Sad**

Ivanović M, Budimac Z, Radovanović M, Škrbić S, Luković I, Milosavljević G, "Advances in Databases and Information Systems at the University of Novi Sad", 14th East-European Conference on Advances in Databases and Information Systems (ADBIS 2010), Novi Sad, Serbia, September 20 - 24, 2010, Proceedings, University of Novi Sad, Faculty of Science, ISBN 978-86-7031-186-2, pp. 190-204.

[2009] **From the Synthesis Algorithm to the Model Driven Transformations in Database Design**

Luković I, "From the Synthesis Algorithm to the Model Driven Transformations in Database Design", 10th International Scientific Conference on Informatics (Informatics 2009), November 23-25, 2009, Herlany, Slovakia, Proceedings, Slovak Society for Applied Cybernetics and Informatics and Technical University of Košice - Faculty of Electrical Engineering and Informatics, ISBN 978-80-8086-126-1, pp. 9-18.

[2009]

Application of Information System Development Tools and Methods - Some Experiences from Industry and Research Projects in Serbia

Luković I, "Application of Information System Development Tools and Methods - Some Experiences from Industry and Research Projects in Serbia", 9th International Business Informatics Conference – 1st Symposium on Business Informatics in Central and Eastern Europe, February 25-27, 2009, Vienna, Austria, Proceedings, Austrian Computer Society and University of Vienna in cooperation with Economic University of Vienna, ISBN 978-3-85403-242-7, pp. 119-128.

[2007] **An Approach to Developing Complex Database Schemas Using Form Types**

Luković I, Mogin P, Pavićević J, Ristić S, "An Approach to Developing Complex Database Schemas Using Form Types", Software: Practice and Experience, John Wiley & Sons Inc, Hoboken, USA, ISSN: 0038-0644, DOI: 10.1002/spe.820, Vol. 37, No. 15, 2007, pp. 1621-1656.

TRAINING - SHORT COURSES AND SEMINARS

[2019] **6th International Winter School on Big Data (BigDat 2020)**

IRDTA and Marche Polytechnic University, Ancona, Italy

[2018] **Winter School on Theoretical Foundations of Computer Science**

International Black Sea University, Tbilisi, Georgia

[2005] **Intermediate Concepts of CMMI Version 1.2**

Carnegie Mellon Software Engineering Institute, Paris, France

[2005] **CMMI Version 1.2 Upgrade Training (CMMIv1.2UT)**

Carnegie Mellon Software Engineering Institute, Online.

[2004] **Introduction to Capability Maturity Model Integration (Staged and Continuous), V.1.1**

Carnegie Mellon Software Engineering Institute, Belgrade, Serbia

[1999 – 2001] **Q-4 – Quality System Internal Audits ISO 9001:2000, ISO 9001:1994**

Certificates, IIS - Research and Technology Center, Novi Sad, Serbia.

[1999] **Oracle Certified Professional Internet Application Developer R.6/6i**

RESEARCH PROJECTS

[2015 – 2019]

Development and Implementation of System for Performance Evaluation for Serbian HEIS and System (PESHES), 573820-EPP-1-2016-1-RS-EPPKA2-CBHE-SP, ERASMUS+ KA2

URL: http://peshes.ius.bg.ac.rs/, Partner Coordinator, University of Novi Sad, Serbia.

The PESHES project has wider objective improvement of management, operation and quality of higher education institutions and system in Serbia. In order to fulfil the general objective project has specific objectives to define and implement indicators and measures for performance based evaluation of higher education institutions and system as a basis for value based management in Serbian HEIs and system; Structuring and pilot implementation of the system for ranking of institutions and study programs and Introduction of performance measurement in accreditation and reaccreditation of study programs and HEIs. The project is structured as project of structural measures and project is national (Serbia). Project is under priority of "Improving management and operation of higher education institutions" in category Quality assurance processes and mechanisms.

[2013 – 2018] **COST IC1404, Multi-Paradigm Modelling for Cyber-Physical Systems (MPM4CPS)**

URL: http://www.cost.eu/domains_actions/ict/Actions/IC1404; MC Member, Serbia, and the STSM Coordinator.

The COST Action involves, supports and harmonizes the various existing national activities around CPS modelling based on Multi-Paradigm Modelling approaches. One innovative aspect of the Action is the effort of bringing together scientists and experts in Mechatronics, Smart-Cities, CPS, Software Modelling and Engineering, and Multi-Paradigm Modelling, in order to push development and implementation of state-of-the-art scientifically justified methodologies of CPS modelling in several application domains such as automotive and avionics. In order to ensure a direct impact of the scientific output, the Action is characterized by a high level of specialization and is aiming at a well defined target. Based on the joint expertise and contacts with international programmes, the Action will harmonize with the most recent developments in the USA and Canada and indeed world-wide.

[2017 – 2019] **Data Mining Based Evaluation of IT Teaching Practice in Portugal and Serbia**

Bilateral Project, Ministry of Education, Science, and Technology Development of Republic of Serbia and Foundation for Research and Technology of Republic of Portugal; University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia, and University of Minho, Braga, Portugal; Project Manager and Principal Investigator.

By automating the data mining process and integrating it into a Learning Management System (LMS), valuable information on student progress and course quality could be made available to instructors and students, which, in turn, could help to evaluate and improve the teaching process even during the semester. The proposed project is aimed at: (i) providing an LMS that would be suited to IT courses and near real-time evaluation of teaching, (ii) introducing the LMS into teaching practice in Portugal and Serbia, and (iii) using data collected within the LMS to evaluate teaching practice in the two countries. The project objectives include: (i) customizing an existing LMS to the specificities of IT courses at the university level, (ii) adding data mining capabilities to the LMS, (iii) deploying the LMS at an educational institution, (iv) testing the LMS in teaching, and (v) performing teaching evaluation based on the data collected within the LMS. The successful completion of these objectives could provide basis for the improvement of IT education in both Portugal and Serbia.

[2010 – 2019]

III-44010, Intelligent Systems for Software Product Development and Business Support based on Models

Ministry of Education and Science of Republic of Serbia; University of Novi Sad, Faculty of Technical Sciences; University of Belgrade, Faculty of Organizational Sciences; University of Kragujevac, Faculty of Economics, Faculty of Engineering, and Faculty of Science; Project Manager and Principal Investigator.

Project goals: a) Providing methodological and technological foundations for proper coupling of the organizational strategy and performances with operational processes. b) Providing a quality framework for development of software systems that will support every aspect of business, ranging from basic data and document processing, to decision making and strategic planning. c) Providing methodological, technological and organizational foundations for development of IS supporting company's business and continuously adjusting to the environment changes.

[2015 – 2017]

Self-Adapting Interface Technology for the Integration of Machines and Information Systems

Bilateral Project, Ministry of Education and Science of Republic of Serbia and DAAD Germany; University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia, and University of Leipzig, Institute for Applied Informatics (InfAI) e.V., Leipzig, Germany; Project Manager and Principal Investigator.

Project goals: a) Representation of different data formats in a uniform manner; b) Development of a mapping description language; c) Development of a transformation execution environment. d) Practical application and evaluation of the proposed approaches.

[2003 – 2007] **NPV38A, Geographic Information System of Water Resources of Serbia**

Ministry of Science and Environmental Protection and Ministry of Agriculture, Forestry and Water Resources - Republic Agency of Water, Serbia, 2004-2007, Member of the Project Team, Consultant, and Trainer.

Strategy Study of a GIS of Water Resources System of Serbia.

CONTRACTS WITH INDUSTRY

[2013 – 2018] **DOOB Innovation Studio Novi Sad, Serbia**

CTO, Consultancy service.

Technical management of the development of software products for: image acquisition, image processing, automated 3D models production, avatar generation, and the ERP information system. Building HR capacities.

[2009 – 2018] **Schneider Electric DMS Novi Sad, DMS Group, Novi Sad, Serbia**

Consultancy service.

Assistance in developing research projects in the domain of Distribution Management Systems in electricity power production. Building HR capacities.

[2008] **Strategy Study of the Information System of Clinical Center of Serbia, Belgrade**

Clinical Center of Serbia, Belgrade; University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia; Project Manager.

A Strategy Study of Information System Development, according to BSP method.

[2006] **A Manipulation and Query Language over DVDocLang Specifications**

Djukic Software Solutions, Nürnberg, Germany; Author.

A language specification for defining queries and update operations over templates, logical and implementation scripts, created by a domain-specific language for document specifications DVDocLang.

[2005] **A language for Specification of Price Rules in DVDocLang Language**

Djukic Software Solutions, Nürnberg, Germany; Author.

A language specification for defining price rules and active mechanisms for accounting prices over logical and implementation scripts, created by a domain-specific language for document specifications DVDocLang.

[2003] **Strategy Study of the Information System of Central Bank of Montenegro**

Central Bank of Montenegro, Podgorica, Serbia and Montenegro; Methodology Consultant and Member of the Project Team.

A Strategy Study of Information System Development, according to BSP method.

[2002 – 2004] **Strategy Study of the Information System DD ZGOP, Novi Sad**

Railroad Building and Maintenance Company; DD ZGOP Novi Sad, Serbia and Montenegro; IIS - Research and Technology Center, Novi Sad, Serbia and Montenegro; Methodology Consultant and Member of the Project Team.

A Strategy Study of Information System Development, according to BSP method.

[2000 – 2002] **Strategy Study of the Information System of Aviation Company ORAO Bijeljina**

Aviation Company "ORAO" (Vazduhoplovni zavod ORAO Bijeljina), Bijeljina, Bosnia and Herzegovina, 2001-2002, Methodology Consultant.

A Strategy Study of Information System Development, according to BSP method.

[1999 – 2001]

Implementation of the Quality System According to the Standard ISO 9001 in JP INFORMATIKA, Novi Sad

Municipal Computing Center of Novi Sad; IIS - Research and Technology Center, Novi Sad, Yugoslavia; Consultant.

Compatibility analysis of the current working procedures and quality system standard ISO 9001 in the scope of contracting, purchasing, development, implementation and exploitation of software and hardware systems; Recommendations for taking of working procedures into accordance with ISO 9001 standard, for contracting, purchasing, development, implementation and exploitation of software and hardware systems; Development of quality system documentation according to ISO 9001, by means of the specification of working procedures for contracting, purchasing, development, implementation and exploitation of software and hardware systems; Specifying of the elements of a common methodology for the development, implementation and exploitation of software systems in JP Informatika.

[1996 – 2002]

Reengineering and Development of the Information System of DD Hemofarm (Pharmacy Company)

Hemofarm, Vršac, Yugoslavia, Department of Informatics, consultant and trainer.

Design and integration of database schemas by means of Oracle Designer; Development of the Information System applications by means of Oracle Designer and Oracle Developer; Reverse engineering of database schema by means of Oracle Designer; Reverse engineering and reengineering methodology of current database schema; Reverse engineering of current Oracle Forms R.3 Information System applications into Oracle Developer.

[1996 – 1998]

Design of the Information System of Cutting Tool Company of Čačak (Fabrika reznog alata, Čačak)

EI - Sigraf, Niš & Cutting Tool Company, Čačak, Yugoslavia; Member of the project team, Consultant, and Trainer.

Information System Design Methodology, Consultant; Database Schema Design and Integration, Consultant; ORACLE Designer/2000 R.1.3.2, Consultant and trainer; Software System "COMMON BUSINES ENTITIES", Designer and Programmer.

[1992 – 1998] **Development of the Information System DD ZGOP, Novi Sad**

Railroad Building and Maintenance Company; DD ZGOP Novi Sad, Yugoslavia; IIS - Research and Technology Center & "Novkabel - FER", Novi Sad, Yugoslavia; Member of the Project Team, Consultant, and Trainer.

Information System Design Methodology, March 1994, Co-author; Strategy Study of The Information System, July 1994, Co-author; Internal Standards for Implementation of Integrity Rules in INGRES/KNOWLEDGE MANAGER", July 1994, Co-author; Internal Programmer's Standards and Manuals for Application Developing in INGRES/VISION by Using The Modified Template Files, December 1994, Co-author; Analysis and Design Studies of The Information System, April 1995, Co-author; Database Schema Design, Integration and Performance Tuning, 1995-1998, Consultant; Software System "STORE CONTROL", 1995-1998, Analyst, Designer and Programmer.

LECTURING

[2020 – Current] **University of Belgrade, Faculty of Organizational Sciences, Serbia**

Lecturing courses at all study levels: Databases; Information System Design; Databases 2; Software Development in Data Science; Selected Topics in Information Systems; Data Warehouses; Design of Aggregated Data Systems; Automated Design of Information Systems.

[1990 – 2021] **University of Novi Sad, Faculty of Technical Sciences, Serbia**

Lecturing courses at all study levels: Databases 1; Databases 2; Information System Engineering; Database Systems; Data Warehouse Systems; Selected Topics in Information Systems; Selected Topics in Computing; Selected Topics in Software Quality and Standardization; Introduction to Information and Financial Engineering; Business Process Automation; Fundamentals of Computer Technologies and Programming; Software Engineering; Algorithms and Data Structures; Data Structures and File Organization; etc.

[2017 – 2018] **University of Ljubljana, Faculty of Computer and Information Science, Slovenia**

Lecturing in M.Sc. course: Selected Topics in Computing and Informatics / Business Intelligence and Data Science Aspects in Practice.

[2000 – 2010]

University of Montenegro, Faculty of Science, Podgorica, Montenegro, Department of Mathematics

Lecturing courses at B.Sc. and M.Sc. levels: Software Engineering; Introduction to Information Systems; Fundamentals of File Organization; Data Structures and File Organization; Introduction to Programming and Computer Organization; Principles of Programming.

[2006 – 2008] **University of Kragujevac, Faculty of Economics, Kragujevac, Serbia**

Lecturing the course in Databases.

[2003 – 2008] **Union University, Faculty of Computing, Belgrade, Serbia**

Lecturing courses in: Information Management; Database Design; Process Improvement and CMMI.

[1991 – 2002]

University of Novi Sad, Faculty of Science, Novi Sad, Serbia, Department of Mathematics and Informatics

Lecturing the course in Databases. Assisting the course in Data Organization.

[1996 – 1998] **University of Novi Sad, Faculty of Economics, Subotica, Serbia**

Lecturing the course in Database Management Systems.

PROFESSIONAL SERVICES

[2004 – Current] **Computer Science and Information Systems (ComSIS) Journal**

Consortium of faculties and institutes of Serbia and Montenegro, URL: www.comsis.org; Chair of Managing Board, 2012 - Current; Editor-in-Chief, 2006 - 2009; Vice-Editor-in-Chief (2005, 2009 - 2021);

Note: ComSIS is included into the Thomson Reuters JCR list, with published IF from 2010.

[2022 – Current] **Chair of Study Program in Information Engineering, at M.Sc. level**

University of Belgrade, Faculty of Organizational Sciences;

Note: a new study program at M.Sc. level, introduced the first in 2022.

[2013 – 2018] **Chair of Study Program in Information Engineering, at B.Sc. and M.Sc. levels**

University of Novi Sad, Faculty of Technical Sciences, Department of Computing and Control, Novi Sad;

Note: the first study program in Data Science in a wider region.

[2011 – 2015]

Head of Department at University of Novi Sad, Faculty of Technical Sciences, Department of Computing and Control, Novi Sad

Note: >180 employees, the largest department of the faculty.

[2008 – 2012]

Vice-Head of Department at University of Novi Sad, Faculty of Technical Sciences, Department of Computing and Control, Novi Sad

[2008 – 2012] **Chair of Study Program in Computing and Control, at B.Sc. and M.Sc. levels**

University of Novi Sad, Faculty of Technical Sciences, Department of Computing and Control, Novi Sad;

Note: one of the largest study programs, with app. 1200 enrolled students.

FREE TEXT SUMMARY

Basic Info

Ivan Luković works as a Full Professor at the University of Belgrade, Faculty of Organizational Sciences, where he lectures in several Computer Science and Information Systems courses, particularly in the area of Databases, Information Systems, and Business Intelligence. His research interests are related to Database Systems, Information Systems, Software and System Engineering, Domain Specific Modeling, and Business Intelligence Systems. He is the author or co-author of over 200 papers, 5 books, and 30 industry projects and software solutions in the area. His main research interests are particularly focused on Theory of Data Models, System Design, particularly Logical and Physical Database Design, Development and Usage of MDSD / CASE tools in Software Engineering and System Design, and Domain Specific Modeling (DSM) and Languages (DSL) in System Design. In recent times, his research interests are also shifted to Business Intelligence, Data Warehouse, Big Data, OLAP, and Data Science concepts and approaches, while applications are present in Educational and Health Care Data Mining. His related research interests include also: Project Management and Quality Management in System Design, CMMI; Formal Languages and Domain Specific Languages in Software Engineering; Requirements Engineering and Process Specification; Database Management Systems – Architecture and Administration; and First Order Logic, Automatic Reasoning and Logic Programming.

He created a new set of B.Sc. and M.Sc. study programs in Information Engineering, i.e. Data Science, as well as a cluster of M.Sc. courses in High Performance Computing (HPC), at the Faculty of Technical Sciences of University of Novi Sad. The programs were accredited the first time in 2015. Currently, he is a chair of Managing Board of the Computer Science and Information Systems (ComSIS) journal, and he was one of the journal founders. Ivan Luković has served as an external referee for more than 10 journals. He is one of the founders of the Workshop on Advances in Programming Languages (WAPL), as well as a Program Chair of the Workshop on Model Driven Approaches in System Development (MDASD), both organized in the scope of FedCSIS multiconference. He is also a Program Chair of the workshop Modern Approaches in Data Engineering and Information System Design (MADEISD), organized in the scope of the ADBIS conference.

During his engagement at the Department of Computing and Control from 2004, he created and led a completely new research team, i.e. a laboratory in Data Science and Information System Design. It was a team of 15 researchers, assistant professors, Ph.D. students and research fellows. He was a supervisor of 12 already completed Ph.D. theses. He also supported his candidates in shifting to the disciplines of: graph representation and comparison of big data sets, technical space transformation approaches and frameworks, with applications in Industry 4.0, and meta modeling, etc.

УНИВЕРЗИТЕТ У БЕОГРАДУ

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Београд, 24. март 2021. године
02 Број: 61202-786/3-20
тсн

На основу чл. 75 Закона о високом образовању („Службени гласник РС", бр. 88/17, 73/18 и 67/19), чл. 43 ст. 1 тач. 23 и чл. 44 ст. 4 Статута Универзитета у Београду („Гласник Универзитета у Београду", бр. 201/18, 207/19, 213/20, 214/20 и 217/20), чл. 26 ст. 1 и ст. 2 тач. 1 Правилника о начину и поступку стицања звања и заснивања радног односа наставника Универзитета у Београду („Гласник Универзитета у Београду", бр. 200/17 и 210/19) и Правилника о минималним условима за стицање звања наставника на Универзитету у Београду („Гласник Универзитета у Београду", бр. 192/16, 195/16, 197/17, 199/17 и 203/18), а на предлог Изборног већа Факултета организационих наука, број: 05-02 бр. 4/2 од 27.1.2021. године и мишљења Већа научних области техничких наука, 02 бр. 61202-786/2-20 од 3. марта 2021. године, Сенат Универзитета, на седници одржаној 24. марта 2021. године, донео је

О Д Л У К У

БИРА СЕ др Иван Луковић за редовног професора на Универзитету у Београду – Факултет организационих наука, за ужу научну област Информациони системи.

О Б Р А З Л О Ж Е Њ Е

Факултет организационих наука („Факултет") је дана 28. октобра 2020. године, у публикацији „Послови", објавио конкурс за избор у звање редовног професора, за ужу научну област Информациони системи, због истека изборног периода.

Извештај Комисије за припрему извештаја о пријављеним кандидатима стављен је на увид јавности дана 22. децембра 2020. године, објављивањем на огласној табли и у Библиотеци Факултета.

На основу предлога Комисије за припрему извештаја о пријављеним кандидатима, Изборно веће Факултета, на седници одржаној дана 27. јануара 2021. године, донело је одлуку о утврђивању предлога да се кандидат др Иван Луковић изабере у звање редовног професора.

Факултет је дана 12. фебруара 2021. године доставио Универзитету комплетан захтев за избор у звање на прописаним обрасцима.

Универзитет је комплетну документацију коју је доставио Факултет ставио на web страницу Универзитета дана 25. фебруара 2021. године.

Веће научних области техничких наука, на седници одржаној дана 3. марта 2021. године дало је мишљење да се др Иван Луковић може изабрати у звање редовног професора.

Сенат Универзитета, на седници одржаној дана 24. марта 2021. године разматрао је захтев Факултета и утврдио да кандидат испуњава услове прописане чл. 74 и 75 Закона о високом образовању, чланом 135 Статута Универзитета у Београду, као и услове прописане Правилником о минималним условима за стицање звања наставника на Универзитету у Београду, па је донета одлука као у изреци.

ПОУКА О ПРАВНОМ ЛЕКУ:

Против ове одлуке кандидат пријављен на конкурс може изјавити жалбу Сенату Универзитета, преко Факултета. Жалба се доставља Факултету у року од 8 дана од дана достављања одлуке.

ПРЕДСЕДНИЦА СЕНАТА
РЕКТОРКА

проф. др Иванка Поповић

Доставити:
- Факултету (2)
- архиви Универзитета
- сектору 06

/

ФОН

УНИВЕРЗИТЕТ У БЕОГРАДУ
ФАКУЛТЕТ ОРГАНИЗАЦИОНИХ НАУКА

04-11 br. 16/57
22.04.2021

На основу чл. 30. - 33. Закона о раду ("Службени гласник РС" бр. 24/05.; 61/05.; 54/09.; 32/13.; 75/14.; 13/17.; 113/17.; 95/18), чл. 75. и 89. Закона о високом образовању ("Сл. гласник РС" бр. 88/2017.; 27/18.; 73/18. и 67/19.), одредби Правилника о раду Факултета (06-03 бр. 2/6-1 од 28.01.2015.) и измене и допуне (06-03 бр. 2/35 од 22.6.2015; 06-03 бр. 2/70 од 26.10.2015.; 06-03 бр. 2/51 од 14.12.2016.; 06-03 бр. 2/25 од 10.7.2019.) и члана 33. Статута Факултета (06-03 бр. 2/38 од 7.9.2018) измене и допуне (06-03 бр. 2/32 од 9.11.2020.), закључује се

УГОВОР О РАДУ

1. **Универзитет у Београду - Факултет организационих наука,** Београд, Јове Илића 154 (у даљем тексту: Факултет - Послодавац), кога заступа проф. др Милија Сукновић, декан Факултета, закључује Уговор о раду са:
   Проф. др ИВАНОМ (Славомир) ЛУКОВИЋЕМ (у даљем тексту: запослени), са пребивалиштем у **Петроварадину, општина Нови Сад, ул. Прерадовићева бр. 36.**

2. Запослени има **VIII** степен стручне спреме, стечен научни степен **доктор техничких наука (Универзитет у Новом Саду, Факултет техничких наука).**

3. Запослени ће обављати послове наставника у звању **наставник на академским студијама - редовни професор** за ужу научну област **Информациони системи** на основу предлога одлуке Изборног већа Факултета 05-02 бр. 4/2 од 27.01.2021. (седница одржана 27.01.2021.), мишљења Већа научних области техничких наука 02 бр. 61202-786/2-20 од 3.03.2021. године и одлуке Сената Универзитета 02 бр. 61202-786/3-20 од 24.03.2021.
   Послови и задаци дефинисани су Правилником о организацији и систематизацији послова на Факултету организационих наука (06-01 бр. 7/15. од 22.06.2018 и допуне 06-01 бр. 5/364 од 13.07.2018.).
   Запослени је први пут засновао радни однос на Факултету **10.05.2021. године.**

4. Запослени ће обављати послове у Београду (седишту послодавца).

5. Запослени заснива радни однос на **неодређено** време, почев од **10.05.2021**. године.

6. Запослени заснива радни однос са пуним радним временом у трајању од **40** часова недељно;
   Распоред радног времена утврђује се Правилником о раду и другим општим актима Факултета.

7. Запослени има право на одговарајућу плату - зараду, под којом се подразумева плата у смислу Закона о платама у државним органима и јавним службама, односно зарада у смислу Закона о раду.
   Запосленом се плата, односно зарада, утврђује у складу са Законом и општим актима.
   Плата - зарада запосленог се састоји од плате - зараде за обављени рад и време проведено на раду, плате - зараде по основу доприноса запосленог пословном успеху послодавца и других примања по основу радног односа у складу са општим актима.
   Плата - зарада за обављени рад и време проведено на раду састоји се од основне плате - зараде, дела плате - зараде за радни учинак и увећане плате - зараде.
   Елементи за обрачун плате - зараде, утврђени су Правилником о финансирању и обрачуну плата запослених на Факултету организационих наука 06-03 бр. 2/34 од 22.06.2015. године и Измене и допуне 06-03 бр. 2/43 од 6.12.2019. (у даљем тексту: Правилник о финансирању и обрачуну плата).

8. Новчани износ основне плате – зараде запосленог утврђује се тако што се цена рада утврђена Одлуком Владе помножи:
   - коефицијентом сложености рада за финансирање плата наставника и сарадника **30,19** (Коефицијент из Уредбе - члан 6. табела 2. Правилника о финансирању и обрачуну плата запослених на Факултету);

   - коефицијентом посла за обрачун основних плата у настави **53,13** (Коефицијент посла - члан 24. табела 4. - Правилника о финансирању и обрачуну плата запослених на Факултету)

9. Запослени има право на увећану зараду по основу времена проведеног на раду за сваку пуну годину рада остварену у радном односу на Факултету - минули рад, и у другим случајевима, право на накнаду зараде, накнаду трошкова и друга примања у складу са законом, Правилником о раду Факултета (06-03 бр. 2/6-1 од 28.01.2015.), Правилником о финансирању и обрачуну плате, Посебним колективним уговором за високо образовање и другим општим актима.

10. Плата - зарада запосленом исплаћује се у два дела и то: први део најкасније до 15. у месецу, а други део најкасније до краја месеца.

11. Запослени има право на дневни, недељни и годишњи одмор, плаћено и неплаћено одсуство, у складу са Законом, Правилником о раду Факултета, Правилником о образовању, стручном оспособљавању и усавршавању на Факултету (05-01 бр. 3/31-1 од 28.3.2014.), Посебним колективним уговором за високо образовање и другим актима.

12. Факултет је дужан да организује рад којим се обезбеђује заштита живота и здравља запосленог у складу са Законом и другим прописима.
Запослени је дужан да се придржава прописа о безбедности и заштити живота и здравља на раду.

13. Запослени и послодавац могу отказати овај уговор, под условима и у случајевима утврђеним законом.

14. Факултет може запосленом да откаже уговор о раду, ако за то постоји оправдани разлог који се односи на радну способност запосленог и његово понашање, ако учини повреду радне обавезе, не поштује радну дисциплину.
Факултет може запосленом да откаже уговор о раду на начин и по поступку утврђеним Законом, Правилником о раду и Правилима о дисциплини и понашању запослених на Факултету (06-03 бр. 2-41 од 22.06.2015.).

15. Запослени је одговоран за штету коју је на раду или у вези са радом, намерно или из крајње непажње, проузроковао Послодавцу, у складу са Правилником о раду.

16. Запослени и Послодавац прихватају да се на сва права и обавезе која нису утврђена овим уговором, примењују одговарајуће одредбе закона и општих аката.

17. Ако настане спор између Факултета и запосленог,пре покретања поступка пред надлежним судом, спорна питања се могу решавати у поступку споразумног решавања спорних питања, у складу са Законом и Правилником о раду Факултета.
Спорна питања решава арбитар, кога споразумно одређују Факултет и запослени из реда стручњака у области која је предмет спора.
Радни спорови између Факултета и запосленог могу се решавати у поступку мирног решавања радних спорова.

18. Овај уговор о раду, сачињен је у 3 (три) истоветна примерка, од којих се један примерак доставља запосленом, а два примерка задржава Факултет.

ЗАПОСЛЕНИ

ЗА ПОСЛОДАВЦА ДЕКАН ФАКУЛТЕТА
Проф. др Милија Сукновић