## Jacobi method

In numerical linear algebra, the Jacobi method (or Jacobi iterative method ${ }^{[1]}$ ) is an algorithm for determining the solutions of a diagonally dominant system of linear equations. Each diagonal element is solved for, and an approximate value is plugged in. The process is then iterated until it converges. This algorithm is a stripped-down version of the Jacobi transformation method of matrix diagonalization The method is named afterCarl Gustav Jacob Jacobi

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## Description

Let

$$
A \mathbf{x}=\mathbf{b}
$$

be a square system ofn linear equations, where:
$A=\left[\begin{array}{cccc}a_{11} & a_{12} & \cdots & a_{1 n} \\ a_{21} & a_{22} & \cdots & a_{2 n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n 1} & a_{n 2} & \cdots & a_{n n}\end{array}\right], \quad \mathbf{x}=\left[\begin{array}{c}x_{1} \\ x_{2} \\ \vdots \\ x_{n}\end{array}\right], \quad \mathbf{b}=\left[\begin{array}{c}b_{1} \\ b_{2} \\ \vdots \\ b_{n}\end{array}\right]$.
Then $A$ can be decomposed into adiagonal component $D$, and the remainder $R$ :

$$
A=D+R \quad \text { where } \quad D=\left[\begin{array}{cccc}
a_{11} & 0 & \cdots & 0 \\
0 & a_{22} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & a_{n n}
\end{array}\right] \text { and } R=\left[\begin{array}{cccc}
0 & a_{12} & \cdots & a_{1 n} \\
a_{21} & 0 & \cdots & a_{2 n} \\
\vdots & \vdots & \ddots & \vdots \\
a_{n 1} & a_{n 2} & \cdots & 0
\end{array}\right] \text {. }
$$

The solution is then obtained iteratively via

$$
\mathbf{x}^{(k+1)}=D^{-1}\left(\mathbf{b}-R \mathbf{x}^{(k)}\right),
$$

where $\mathbf{x}^{(k)}$ is the $k$ th approximation or iteration of $\mathbf{x}$ and $\mathbf{x}^{(k+1)}$ is the next or $k+1$ iteration of $\mathbf{x}$. The element-based formula is thus:

$$
x_{i}^{(k+1)}=\frac{1}{a_{i i}}\left(b_{i}-\sum_{j \neq i} a_{i j} x_{j}^{(k)}\right), \quad i=1,2, \ldots, n
$$

The computation of $x_{i}{ }^{(k+1)}$ requires each element in $\mathbf{x}^{(k)}$ except itself. Unlike the Gauss-Seidel method we can't overwrite $x_{i}{ }^{(k)}$ with $x_{i}{ }^{(k+1)}$, as that value will be needed by the rest of the computation. The minimum amount of storage is two vectors of sive

## Algorithm

Input: initial guess $x^{(0)}$ to the solution, (diagonal dominant) matrix $A$, right-hand side vector $b$, 'convergence criterion
Output: solution when convergence is reached
Comments: pseudocode based on the element-based formula above

```
k}=
While convergence not reached do
        for i := 1 step until n do
        \sigma=0
        for j := 1 step until n do
            if j # i then
                \sigma=\sigma+\mp@subsup{a}{ij}{}\mp@subsup{x}{j}{(k)}
            end
        end
        x _ { i } ^ { ( k + 1 ) } = \frac { 1 } { a _ { i i } } ( b _ { i } - \sigma )
        end
        k=k+1
iend
```

!

## Convergence

The standard convegence condition (for any iteraive method) is when thespectral radius of the iteration matrix is less than 1:

$$
\rho\left(D^{-1} R\right)<1
$$

A sufficient (but not necessary) condition for the method to converge is that the matrix $A$ is strictly or irreducibly diagonally dominant. Strict row diagonal dominance means that for each row, the absolute value of the diagonal term is greater than the sum of absolute values of other terms:

$$
\left|a_{i i}\right|>\sum_{j \neq i}\left|a_{i j}\right|
$$

The Jacobi method sometimes conveges even if these conditions are not satisfied.

## Example

A linear system of the form $A x=b$ with initial estimate $x^{(0)}$ is given by

$$
A=\left[\begin{array}{ll}
2 & 1 \\
5 & 7
\end{array}\right], b=\left[\begin{array}{l}
11 \\
13
\end{array}\right] \quad \text { and } \quad x^{(0)}=\left[\begin{array}{l}
1 \\
1
\end{array}\right]
$$

We use the equation $x^{(k+1)}=D^{-1}\left(b-R x^{(k)}\right)$, described above, to estimate $x$. First, we rewrite the equation in a more convenient form $D^{-1}\left(b-R x^{(k)}\right)=T x^{(k)}+C$, where $T=-D^{-1} R$ and $C=D^{-1} b$. Note that $R=L+U$ where $L$ and $U$ are the strictly lower and upper parts of $A$. From the known values

$$
D^{-1}=\left[\begin{array}{cc}
1 / 2 & 0 \\
0 & 1 / 7
\end{array}\right], L=\left[\begin{array}{ll}
0 & 0 \\
5 & 0
\end{array}\right] \quad \text { and } \quad U=\left[\begin{array}{ll}
0 & 1 \\
0 & 0
\end{array}\right] .
$$

we determine $T=-D^{-1}(L+U)$ as

$$
T=\left[\begin{array}{cc}
1 / 2 & 0 \\
0 & 1 / 7
\end{array}\right]\left\{\left[\begin{array}{cc}
0 & 0 \\
-5 & 0
\end{array}\right]+\left[\begin{array}{cc}
0 & -1 \\
0 & 0
\end{array}\right]\right\}=\left[\begin{array}{cc}
0 & -1 / 2 \\
-5 / 7 & 0
\end{array}\right] .
$$

Further, $C$ is found as

$$
C=\left[\begin{array}{cc}
1 / 2 & 0 \\
0 & 1 / 7
\end{array}\right]\left[\begin{array}{l}
11 \\
13
\end{array}\right]=\left[\begin{array}{l}
11 / 2 \\
13 / 7
\end{array}\right] .
$$

With $T$ and $C$ calculated, we estimate $x$ as $x^{(1)}=T x^{(0)}+C$ :

$$
x^{(1)}=\left[\begin{array}{cc}
0 & -1 / 2 \\
-5 / 7 & 0
\end{array}\right]\left[\begin{array}{l}
1 \\
1
\end{array}\right]+\left[\begin{array}{l}
11 / 2 \\
13 / 7
\end{array}\right]=\left[\begin{array}{c}
5.0 \\
8 / 7
\end{array}\right] \approx\left[\begin{array}{c}
5 \\
1.143
\end{array}\right] .
$$

The next iteration yields

$$
x^{(2)}=\left[\begin{array}{cc}
0 & -1 / 2 \\
-5 / 7 & 0
\end{array}\right]\left[\begin{array}{c}
5.0 \\
8 / 7
\end{array}\right]+\left[\begin{array}{c}
11 / 2 \\
13 / 7
\end{array}\right]=\left[\begin{array}{c}
69 / 14 \\
-12 / 7
\end{array}\right] \approx\left[\begin{array}{c}
4.929 \\
-1.714
\end{array}\right] .
$$

This process is repeated until convegence (i.e., until $\left\|A x^{(n)}-b\right\|$ is small). The solution after 25 iterations is

$$
x=\left[\begin{array}{c}
7.111 \\
-3.222
\end{array}\right]
$$

## Another example

Suppose we are given the following linear system:

$$
\begin{aligned}
10 x_{1}-x_{2}+2 x_{3} & =6 \\
-x_{1}+11 x_{2}-x_{3}+3 x_{4} & =25 \\
2 x_{1}-x_{2}+10 x_{3}-x_{4} & =-11 \\
3 x_{2}-x_{3}+8 x_{4} & =15
\end{aligned}
$$

If we choose $(0,0,0,0)$ as the initial approximation, then the first approximate solution is given by

$$
\begin{aligned}
& x_{1}=(6+0-(2 * 0)) / 10=0.6 \\
& x_{2}=(25+0-0-(3 * 0)) / 11=25 / 11=2.2727, \\
& x_{3}=(-11-(2 * 0)+0+0) / 10=-1.1, \\
& x_{4}=(15-(3 * 0)+0) / 8=1.875
\end{aligned}
$$

Using the approximations obtained, the iterative procedure is repeated until the desired accuracy has been reached. The following are the approximated solutions after five iterations.

| $x_{1}$ | $x_{2}$ | $x_{3}$ | $x_{4}$ |
| :--- | :--- | :--- | :--- |
| 0.6 | 2.27272 | -1.1 | 1.875 |
| 1.04727 | 1.7159 | -0.80522 | 0.88522 |
| 0.93263 | 2.05330 | -1.0493 | 1.13088 |
| 1.01519 | 1.95369 | -0.9681 | 0.97384 |
| 0.98899 | 2.0114 | -1.0102 | 1.02135 |

The exact solution of the system is $(1,2,-1,1)$.

## An example using Python and Numpy

The following numerical procedure simply iterates to produce the solution vector

```
import numpy as np
IITERATION_LIMIT = 1000
## initialize the matrix
A = np.array([[10., -1., 2., 0.],
                [-1., 11., -1., 3.],
# initialize the RHS vector
b = np.array([6., 25., -11., 15.])
# prints the system
iprint("System:")
'for i in range(A.shape[0]):
    row = ["{}*x{}".format (A[i, j], j + 1) for j in range(A.shape[1])]
    print(" + ".join(row), "=", b[i])
print()
'x = np.zeros_like(b)
ifor it_count in range(ITERATION_LIMIT ):
    print("Current solution:", x)
    x_new = np.zeros_like(x)
    for i in range(A.shape[0]):
        s1 = np.dot(A[i, :i], x[:i])
        s2 = np.dot(A[i, i + 1:], x[i + 1:])
        x_new[i] = (b[i] - s1 - s2) / A[i, i]
    if np.allclose(x, x_new, atol=1e-10, rtol=0.):
        break
    x = x_new
print("Solution:")
print(x)
error = np.dot(A, x) - b
!print("Error:")
print(error)
```

Produces the output:

## System:



| 'Current solution: | 0.99994242 | 2.00008477 | -1.00006833 | 1.0001085 |
| :---: | :---: | :---: | :---: | :---: |
| 'Current solution: | 1.00002214 | 1.99995896 | -0.99996916 | $0.99995967]$ |
| 'Current solution: | [ 0.99998973 | 2.00001582 | -1.00001257 | $1.00001924]$ |
| 'Current solution: | [ 1.00000409 | 1.99999268 | -0.99999444 | 0.9999925 |
| 'Current solution: | 0.99999816 | 2.00000292 | -1.0000023 | $1.00000344]$ |
| 'Current solution: | 1.00000075 | 1.99999868 | -0.99999899 | $0.99999862]$ |
| 'Current solution: | 0.99999967 | 2.00000054 | -1.00000042 | $1.00000062]$ |
| 'Current solution: | [ 1.00000014 | 1.99999976 | -0.99999982 | $0.99999975]$ |
| 'Current solution: | 0.99999994 | 2. 0000001 | -1.00000008 | $1.00000011]$ |
| 'Current solution: | [ 1.00000003 | 1.99999996 | -0.99999997 | $0.99999995]$ |
| 'Current solution: | [ 0.99999999 | 2. 00000002 | -1.00000001 | 1.00000002] |
| 'Current solution: | [ 1. | 1.99999999 | -0.99999999 | $0.99999999]$ |
| Current solution: | [ 1. 2. -1. | 1.$]$ |  |  |
| 'Solution: |  |  |  |  |
| '[ 1. 2. -1. 1.] |  |  |  |  |
| Error: |  |  |  |  |
| [ [ -2.81440107e-08 | 5.15706873 e | -08 -3.634 | 6359e-08 | $4.17092547 \mathrm{e}-08$ |

## Weighted Jacobi method

The weighted Jacobi iteration uses a paramete $\boldsymbol{\omega}$ to compute the iteration as

$$
\mathbf{x}^{(k+1)}=\omega D^{-1}\left(\mathbf{b}-R \mathbf{x}^{(k)}\right)+(1-\omega) \mathbf{x}^{(k)}
$$

with $\omega=2 / 3$ being the usual choice ${ }^{[2]}$

## Recent developments

In 2014, a refinement of the algorithm, called scheduled relaxation Jacobi (SRJ) method, was published. ${ }^{[1][3]}$ The new method employs a schedule of over- and under-relaxations and provides performance improvements for solving elliptic equations discretized on large two- and three-dimensional Cartesian grids. The described algorithm applies the well-known technique of polynomial (Chebyshev) acceleration to a problem with a known spectrum distribution that can be classified either as a multi-step method or a one-step method with a non-diagonal preconditionerHowever, none of them are Jacobi-like metheds.

Improvements published ${ }^{[4]}$ in 2015.

## See also

- Gauss-Seidel method
- Successive over-relaxation
- Iterative method § Linear systems
- Gaussian Belief Propagation
- Matrix splitting


## References

1. Johns Hopkins University(June 30, 2014). "19th century math tactic gets a makeover-and yields answers up to 200 times faster"(http://phys.org/news/2014-06-19th-century-math-tactic-makeoverand.htmIPhys.org. Douglas, Isle Of Man, United Kingdom: Omicron 巴chnology Limited. Retrieved 2014-07-01.
2. Saad, Yousef (2003). Iterative Methods for Sparse Linear Systems(2 ed.). SIAM. p. 414. ISBN 0898715342
3. Yang, Xiang; Mittal, Rajat (June 27, 2014). "\&celeration of the Jacobi iterative method by factors exceeding 100 using scheduled relaxation".Journal of Computational Physics 274: 695-708. doi:10.1016/j.jcp.2014.06.010(https:// doi.org/10.1016\%2Fj.jcp.2014.06.010.)
4. Adsuara, J. E.; Cordero-Carrión, I.; Cerdá-Durán, P, Aloy, M. A. (2015-11-11). "Scheduled Relaxation Jacobi method: improvements and applications"Journal of Computational Physics 321: 369-413. arXiv:1511.04292 (http s://arxiv.org/abs/1511.04292)б. doi:10.1016/j.jcp.2016.05.053(https://doi.org/10.1016\%2Fj.jcp.2016.05.053)

## External links

- Hazewinkel, Michiel ed. (2001) [1994],"Jacobi method", Encyclopedia of Mathematics Springer Science+Business Media B.V. / Kluwer Academic Publishers,ISBN 978-1-55608-010-4
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- Black, Noel; Moore, Shirley; and Veisstein, Eric W. "Jacobi method". MathWorld.
- Jacobi Method from wwwmath-linux.com
- Numerical matrix inversion

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