Package ‘PRIMME’

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Type Package
Title Eigenvalues and Singular Values and Vectors from Large Matrices
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Description R interface to 'PRIMME' <https://www.cs.wm.edu/~andreas/software/>, a C library for computing a few eigenvalues and their corresponding eigenvectors of a real symmetric or complex Hermitian matrix, or generalized Hermitian eigenproblem. It can also compute singular values and vectors of a square or rectangular matrix. 'PRIMME' finds largest, smallest, or interior singular/eigenvalues and can use preconditioning to accelerate convergence. General description of the methods are provided in the papers Stathopoulos (2010, <doi:10.1145/1731022.1731031>) and Wu (2017, <doi:10.1137/16M1082214>). See 'citation("PRIMME")' for details.
URL https://www.cs.wm.edu/~andreas/software/
      https://github.com/primme/primme
BugReports https://github.com/primme/primme/issues
Imports Rcpp
LinkingTo Rcpp, Matrix
Suggests Matrix
SystemRequirements A POSIX system. Currently Linux and OS X are known to work. GNU make.
NeedsCompilation yes
License GPL-3
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eigs_sym

Description

Find a few eigenvalues and vectors on large, sparse Hermitian matrix

Usage

eigs_sym(
  A,
  NEig = 1,
  which = "LA",
  targetShifts = NULL,
  tol = 1e-06,
  x0 = NULL,
  ortho = NULL,
  prec = NULL,
  isreal = NULL,
  B = NULL,
  ...
)

Arguments

A symmetric/Hermitian matrix or a function with signature f(x) that returns A %*% x.

NEig number of eigenvalues and vectors to seek.

which which eigenvalues to find:
"LA" the largest (rightmost) values;
"SA" the smallest (leftmost) values;
"LM" the farthest from targetShifts;
"SM" the closest to targetShifts;
"CLT" the closest but left to targetShifts;
"CGT" the closest but greater than targetShifts;

vector of numbers the closest values to these points.

targetShifts return the closest eigenvalues to these points as indicated by target.

tol the convergence tolerance: \( \|Ax - x\lambda\| \leq tol \|A\| \).
x0 matrix whose columns are educated guesses of the eigenvectors to to find.

ortho find eigenvectors orthogonal to the space spanned by the columns of this matrix;
useful to avoid finding some eigenvalues or to find new solutions.

prec preconditioner used to accelerated the convergence; usually it is an approximation of the inverse of \( A - \sigma I \) if finding the closest eigenvalues to \( \sigma \). If it is a matrix it is used as prec \( \%\%\% \) x; otherwise it is used as prec(x).

isreal whether A \( \%\%\% \) x always returns real number and not complex.

B symmetric/Hermitian positive definite matrix or a function with signature f(x) that returns B \( \%\%\% \) x. If given, the function returns the eigenpairs of (A,B).

... other PRIMME options (see details).

Details

Optional arguments to pass to PRIMME eigensolver (see further details at [2]):

method used by the solver, one of:

"DYNAMIC" switches dynamically between DEFAULT_MIN_TIME and DEFAULT_MIN_MATVECS
"DEFAULT_MIN_TIME" best method for light matrix-vector product
"DEFAULT_MIN_MATVECS" best method for heavy matrix-vector product or preconditioner
"Arnoldi" an Arnoldi not implemented efficiently
"GD" classical block Generalized Davidson
"GD_plusK" GD+k block GD with recurrence restarting
"GD_Olsen_plusK" GD+k with approximate Olsen preconditioning
"JD_Olsen_plusK" GD+k, exact Olsen (two preconditioner applications per step)
"RQI" Rayleigh Quotient Iteration, also Inverse Iteration if targetShifts is provided
"JDQR" original block, Jacobi Davidson
"JDQMR" our block JDQMR method (similar to JDCG)
"JDQMR_ETol" slight, but efficient JDQMR modification
"STEEPEST_DESCENT" equivalent to GD(maxBlockSize,2*maxBlockSize)
"LOBPCG_OrthoBasis" equivalent to GD(neig,3*neig)+neig
"LOBPCG_OrthoBasis_Window" equivalent to GD(maxBlockSize,3*maxBlockSize)+maxBlockSize
when neig>maxBlockSize

aNorm estimation of norm-2 of A, used in convergence test (if not provided, it is estimated as the largest eigenvalue in magnitude seen).

maxBlockSize maximum block size (like in subspace iteration or LOBPCG).
printLevel  message level reporting, from 0 (no output) to 5 (show all).
locking  1, hard locking; 0, soft locking.
maxBasisSize maximum size of the search subspace.
minRestartSize minimum Ritz vectors to keep in restarting.
maxMatvecs maximum number of matrix vector multiplications.
maxit maximum number of outer iterations.
scheme the restart scheme (thick restart by default).
maxPrevRetain number of approximate eigenvectors retained from previous iteration, that are kept after restart.
robustShifts set to true to avoid stagnation.
maxInnerIterations maximum number of inner QMR iterations.
LeftQ use the locked vectors in the left projector.
LeftX use the approx. eigenvector in the left projector.
RightQ use the locked vectors in the right projector.
RightX use the approx. eigenvector in the right projector.
SkewQ use the preconditioned locked vectors in the right projector.
SkewX use the preconditioned approximate eigenvector in the right projector.
relTolBase a legacy from classical JDQR (recommend not use).
iseed an array of four numbers used as a random seed.

Value

list with the next elements
values the eigenvalues λ_i
vectors the eigenvectors x_i
rnorms the residual vector norms ∥Ax_i − λ_iBx_i∥.
stats$numMatvecs number of matrix-vector products performed
stats$numPreconds number of preconditioner applications performed
stats$elapsedTime time expended by the eigensolver
stats$timeMatvec time expended in the matrix-vector products
stats$timePrecond time expended in applying the preconditioner
stats$timeOrtho time expended in orthogonalizing
stats$estimateMinEval estimation of the smallest eigenvalue of A
stats$estimateMaxEval estimation of the largest eigenvalue of A
stats$estimateANorm estimation of the norm of A

References

See Also

eigen for computing all values; svds for computing a few singular values

Examples

A <- diag(1:10) # the eigenvalues of this matrix are 1:10 and the
eigenvectors are the columns of diag(10)
r <- eigs_sym(A, 3);
r$values # the three largest eigenvalues on diag(1:10)
r$vectors # the corresponding approximate eigenvectors
r$rnorms # the corresponding residual norms
r$stats$numMatvecs # total matrix-vector products spend

r <- eigs_sym(A, 3, 'SA') # compute the three smallest values

r <- eigs_sym(A, 3, 2.5) # compute the three closest values to 2.5

r <- eigs_sym(A, 3, 2.5, tol=1e-3); # compute the values with
r$rnorms # residual norm <= 1e-3*||A||

B <- diag(rev(1:10));
r <- eigs_sym(A, 3, B=B); # compute the 3 largest eigenpairs of
# the generalized problem (A,B)

# Build a Jacobi preconditioner (too convenient for a diagonal matrix!)
# and see how reduce the number matrix-vector products
A <- diag(1:1000) # we use a larger matrix to amplify the difference
P <- diag(diag(A) - 2.5)
eigs_sym(A, 3, 2.5, tol=1e-3)$stats$numMatvecs
eigs_sym(A, 3, 2.5, tol=1e-3, prec=P)$stats$numMatvecs

# Passing A and the preconditioner as functions
Af <- function(x) (1:100) * x; # = diag(1:100) %*% x
Pf <- function(x) x / (1:100 - 2.5); # = solve(diag(1:100 - 2.5), x)
r <- eigs_sym(Af, 3, 2.5, tol=1e-3, prec=Pf, n=100)

# Passing initial guesses
A <- diag(1:1000) # we use a larger matrix to amplify the difference
x0 <- diag(1,1000,4) + matrix(rnorm(4000), 1000, 4)/100;
eigs_sym(A, 4, "SA", tol=1e-3)$stats$numMatvecs
eigs_sym(A, 4, "SA", tol=1e-3, x0=x0)$stats$numMatvecs

# Passing orthogonal constrain, in this case, already compute eigenvectors
r <- eigs_sym(A, 4, "SA", tol=1e-3); r$values
r <- eigs_sym(A, 4, "SA", tol=1e-3, ortho=r$vectors)$values

Find a few singular values and vectors on large, sparse matrix
Description

Compute a few singular triplets from a specified region (the largest, the smallest, the closest to a point) on a matrix using PRIMME [1]. Only the matrix-vector product of the matrix is required. The used method is usually faster than a direct method (such as svd) if seeking few singular values and the matrix-vector product is cheap. For accelerating the convergence consider to use preconditioning and/or educated initial guesses.

Usage

svds(  
A,  
NSvals,  
which = "L",  
tol = 1e-06,  
u0 = NULL,  
v0 = NULL,  
orthou = NULL,  
orthov = NULL,  
prec = NULL,  
isreal = NULL,  
...  
)

Arguments

A matrix or a function with signature f(x, trans) that returns A %*% x when trans == "n" and t(Conj(A)) %*% x when trans == "c".

NSvals number of singular triplets to seek.

which which singular values to find:

"L" the largest values;

"S" the smallest values;

vector of numbers the closest values to these points.

tol a triplet (σ, u, v) is marked as converged when \( \sqrt{\|Av - \sigma u\|^2 + \|A^*u - \sigma v\|^2} \leq tol \cdot \|A\| \) is smaller than tol * ||A||, or close to the minimum tolerance that the selected method can achieve.

u0 matrix whose columns are educated guesses of the left singular vectors to find.

v0 matrix whose columns are educated guesses of the right singular vectors to find.

orthou find left singular vectors orthogonal to the space spanned by the columns of this matrix; useful to avoid finding some triplets or to find new solutions.

orthov find right singular vectors orthogonal to the space spanned by the columns of this matrix.

prec preconditioner used to accelerated the convergence; it is a named list of matrices or functions such as solve(prec[[mode]],x) or prec[[mode]](x) return an approximation of \( OP^{-1}x \), where

\[
\begin{align*}
\text{mode} & \quad OP \\
\end{align*}
\]
"AHA"  \( A^* A \)
"AAH"  \( A A^* \)
"aug"  \( [0 A; A^* 0] \)

The three values haven’t to be set. It is recommended to set “AHA” for matrices with \( \text{nrow} > \text{ncol} \); “AAH” for matrices with \( \text{nrow} < \text{ncol} \); and additionally “aug” for \( \text{tol} < 1e-8 \).

**isreal**  whether \( A \) always returns real number and not complex.

...  other PRIMME options (see details).

**Details**

Optional arguments to pass to PRIMME eigensolver (see further details at [2]):

- **aNorm** estimation of norm-2 of \( A \), used in convergence test (if not provided, it is estimated as the largest eigenvalue in magnitude seen)
- **maxBlockSize** maximum block size (like in subspace iteration or LOBPCG)
- **printLevel** message level reporting, from 0 (no output) to 5 (show all)
- **locking** 1, hard locking; 0, soft locking
- **maxBasisSize** maximum size of the search subspace
- **minRestartSize** minimum Ritz vectors to keep in restarting
- **maxMatvecs** maximum number of matrix vector multiplications
- **iseed** an array of four numbers used as a random seed
- **method** which equivalent eigenproblem to solve
  - "primme_svds_normal_equation"  \( A^* A \) or \( AA^* \)
  - "primme_svds_augmented"  \( [0 A^*; A 0] \)
  - "primme_svds_hybrid" first normal equations and then augmented (default)
- **locking** 1, hard locking; 0, soft locking
- **primmeStage1**, **primmeStage2** list with options for the first and the second stage solver; see \( \text{eigs} \_\text{sym} \)

If method is "primme_svds_normal_equation", the minimum tolerance that can be achieved is \( \|A\|\epsilon/\sigma \), where \( \epsilon \) is the machine precision. If method is "primme_svds_augmented" or "primme_svds_hybrid", the minimum tolerance is \( \|A\|\epsilon \). However it may not return triplets with singular values smaller than \( \|A\|\epsilon \).

**Value**

list with the next elements

- **d** the singular values \( \sigma_i \)
- **u** the left singular vectors \( u_i \)
- **v** the right singular vectors \( v_i \)
- **rnorms** the residual vector norms \( \sqrt{\|Av - \sigma u\|^2 + \|A^* u - \sigma v\|^2} \)
stats$numMatvecs  matrix-vector products performed
stats$numPreconds  number of preconditioner applications performed
stats$elapsedTime  time expended by the eigensolver
stats$timeMatvec  time expended in the matrix-vector products
stats$timePrecond  time expended in applying the preconditioner
stats$timeOrtho  time expended in orthogonalizing
stats$estimateANorm  estimation of the norm of A

References


See Also

svd for computing all singular triplets; eigs_sym for computing a few eigenvalues and vectors from a symmetric/Hermitian matrix.

Examples

A <- diag(1:5,10,5)  # the singular values of this matrix are 1:10 and the
                 # left and right singular vectors are the columns of
                 # diag(1,100,10) and diag(10), respectively
r <- svds(A, 3);
  r$d  # the three largest singular values on A
  r$u  # the corresponding approximate left singular vectors
  r$v  # the corresponding approximate right singular vectors
  r$nrnorms  # the corresponding residual norms
  r$stats$numMatvecs  # total matrix-vector products spend

r <- svds(A, 3, "S")  # compute the three smallest values

r <- svds(A, 3, 2.5)  # compute the three closest values to 2.5

A <- diag(1:500,500,100)  # we use a larger matrix to amplify the difference
r <- svds(A, 3, 2.5, tol=1e-3);  # compute the values with
  r$nrnorms  # residual norm <= 1e-3||A||

  # Build the diagonal squared preconditioner
  # and see how reduce the number matrix-vector products
  P <- diag(colSums(A^2))
  svds(A, 3, "S", tol=1e-3)$stats$numMatvecs
  svds(A, 3, "S", tol=1e-3, prec=list(AHA=P))$stats$numMatvecs

  # Passing A and the preconditioner as functions
  Af <- function(x,mode) if (mode == "n") A%x else crossprod(A,x);
P = colSums(A^2);
\begin{verbatim}

PAHAF <- function(x) x / P;
r <- svds(Af, 3, "S", tol=1e-3, prec=list(AHA=PAHAF), m=500, n=100)

# Passing initial guesses
v0 <- diag(1,100,4) + matrix(rnorm(400), 100, 4)/100;
svds(A, 4, "S", tol=1e-3)$stats$numMatvecs
svds(A, 4, "S", tol=1e-3, v0=v0)$stats$numMatvecs

# Passing orthogonal constrain, in this case, already compute singular vectors
r <- svds(A, 4, "S", tol=1e-3); r$d
svds(A, 4, "S", tol=1e-3, orthov=r$v)$d
\end{verbatim}
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