



# DIAGONALIZATION OF SPARSE MATRICES

Peter Karpov, Max Planck Computing and Data Facility, Garching

<https://github.com/karpov-peter/sparse-eigensolvers-tutorial>

Meet MPCDF  
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# DIAGONALIZATION METHODS

Eigenproblem  $A\mathbf{v} = \lambda\mathbf{v}$

## Direct methods

- all or substantial part ( $>10\%$ ) of eigenpairs
- relatively small matrices (up to  $\sim 10^6$ )
- dense matrices

Software: LAPACK, ScaLAPACK, ELPA, SLATE, ...

<https://github.com/karpov-peter/elpa-tutorial>  
(Meet MPCDF, February 2024)

## Iterative methods

- small part of eigenpairs ( $\sim$ several hundreds)
- much larger matrices ( $> 10^9$ )
- (typically) sparse matrices

Software: ARPACK, SLEPc, ChASE, ...

<https://github.com/karpov-peter/sparse-eigensolvers-tutorial>  
(today)

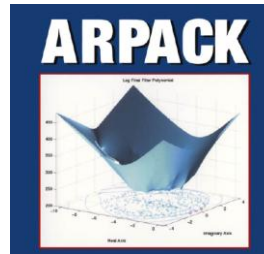
# OUTLINE

## 1. Theoretical background

- Power method
- Lanczos method (sketch)
- Matrix-free vs matrix-based methods
- Sparse matrix storage

## 2. ARPACK

- serial: Python/C/Fortran (“warmup”)
- MPI-parallel



## 3. SLEPc



## 4. Other tools and useful resources

# POWER METHOD

Finds the eigenvalue of (complex)  $n \times n$  matrix  $A$  with largest absolute value

If  $A$  is diagonalizable (i.e. there exists an invertible matrix  $P$  and diagonal matrix  $D$ :  $P^{-1}AP = D$ ),

then eigenvectors  $\mathbf{v}_i$  form a basis, so arbitrary  $\mathbf{x}_0$  can be expressed as:

$$\mathbf{x}_0 = \sum_{i=1}^n c_i \mathbf{v}_i$$

$$\mathbf{x}_1 \equiv A\mathbf{x}_0 = A \left( \sum_{i=1}^n c_i \mathbf{v}_i \right) = \sum_{i=1}^n c_i \lambda_i \mathbf{v}_i$$

...

$$\mathbf{x}_k \equiv A\mathbf{x}_{k-1} = \dots = A^k \mathbf{x}_0 = A^k \left( \sum_{i=1}^n c_i \mathbf{v}_i \right) = \sum_{i=1}^n c_i \lambda_i^k \mathbf{v}_i = \lambda_m^k \left( c_m \mathbf{v}_m + \sum_{i \neq m} c_i \left( \frac{\lambda_i}{\lambda_m} \right)^k \mathbf{v}_i \right)$$

# POWER METHOD

**Input:**  $n \times n$  matrix  $A$ , initial vector  $\mathbf{x}_0$

**Output:** Approximate dominant eigenvector  $\mathbf{v}$

```
 $\mathbf{x} \leftarrow \mathbf{x}_0 / \|\mathbf{x}_0\|$   
do  
     $\mathbf{y} \leftarrow A \cdot \mathbf{x}$   
     $\mathbf{x} \leftarrow \mathbf{y} / \|\mathbf{y}\|$   
until convergence  
 $\mathbf{v} \leftarrow \mathbf{x}$ 
```

$$\lambda \approx \frac{\mathbf{v}^T A \mathbf{v}}{\mathbf{v}^T \mathbf{v}} \quad - \quad \text{“Rayleigh quotient”}$$

Improvement: at each step build orthogonal basis  $\rightarrow$  “Krylov subspaces”  $\rightarrow$  Arnoldi/Lanczos algorithms for non-Hermitian/Hermitian matrices

# LANCZOS METHOD (SKETCH)

Let for simplicity  $\lambda_1 > \lambda_2 > \dots > \lambda_n > 0$   
(we can shift the spectrum by a constant)

Instead of just building sequence  $\mathbf{x}_0, A\mathbf{x}_0, \dots, A^k\mathbf{x}_0$   
(not orthogonal), let's orthogonalize vector  $\mathbf{x}_i$   
to all previous  $\mathbf{x}_0, \dots, \mathbf{x}_{i-1}$  each iteration.

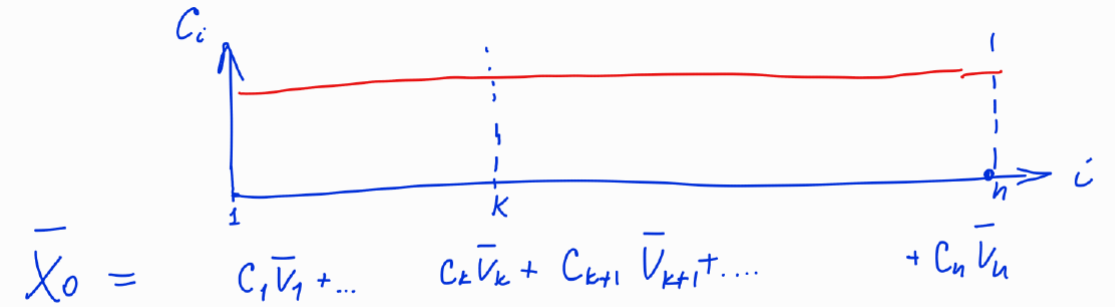
$$\mathcal{K}^{k+1}(\mathbf{x}_0) = \text{span}(\mathbf{x}_0, A\mathbf{x}_0, \dots, A^k\mathbf{x}_0)$$

Krylov subspace of dimension  $(k + 1)$

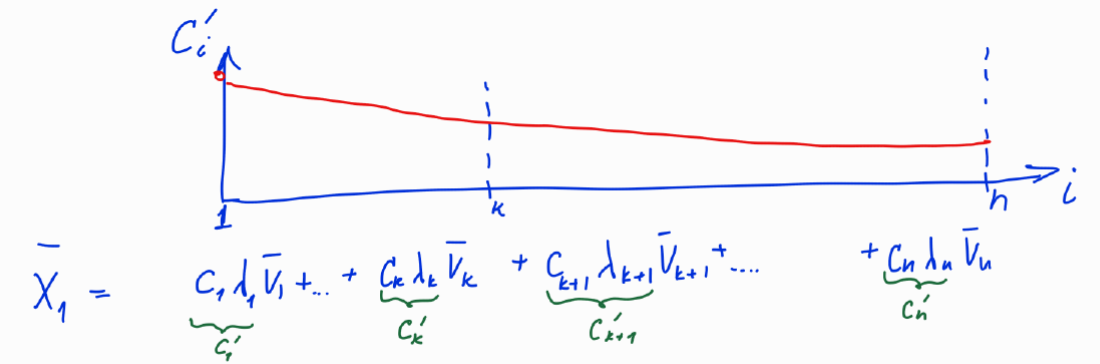
Find orthonormal basis of  $\mathcal{K}^{k+1}(\mathbf{x}_0)$ :  $\mathbf{y}_0, \mathbf{y}_1, \dots, \mathbf{y}_k$

Diagonalize small  $(k + 1) \times (k + 1)$  matrix

$$\tilde{A}_{i,j} = (\mathbf{y}_i, A\mathbf{y}_j)$$

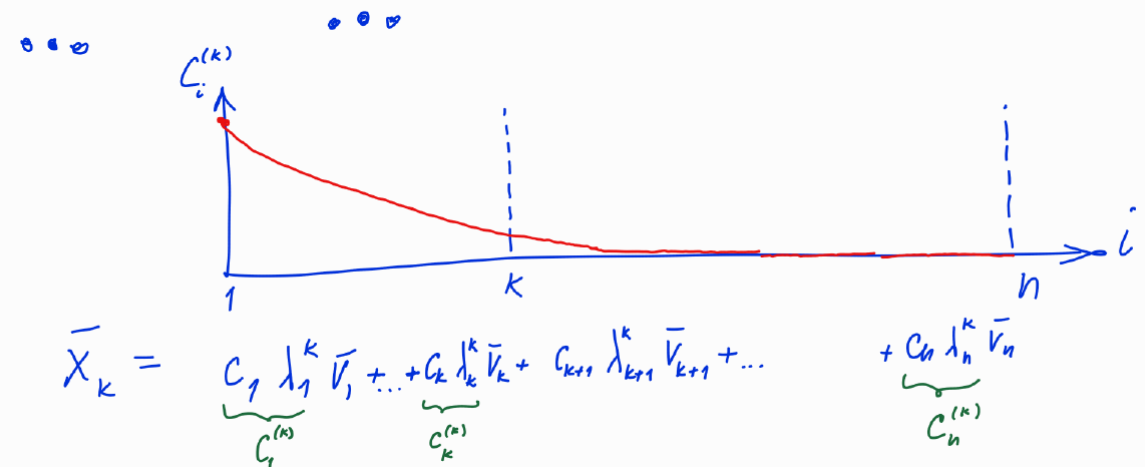


$$\bar{X}_0 = C_1 \bar{V}_1 + \dots + C_k \bar{V}_k + C_{k+1} \bar{V}_{k+1} + \dots + C_n \bar{V}_n$$



$$\bar{X}_1 = \underbrace{C_1 \lambda_1}_{C'_1} \bar{V}_1 + \dots + \underbrace{C_k \lambda_k}_{C'_k} \bar{V}_k + \underbrace{C_{k+1} \lambda_{k+1}}_{C'_{k+1}} \bar{V}_{k+1} + \dots + \underbrace{C_n \lambda_n}_{C'_n} \bar{V}_n$$

...



$$\bar{X}_k = \underbrace{C_1 \lambda_1^k}_{C_1^{(k)}} \bar{V}_1 + \dots + \underbrace{C_k \lambda_k^k}_{C_k^{(k)}} \bar{V}_k + C_{k+1} \lambda_{k+1}^k \bar{V}_{k+1} + \dots + \underbrace{C_n \lambda_n^k}_{C_n^{(k)}} \bar{V}_n$$

# MATRIX-FREE VS MATRIX-BASED ALGORITHMS

**Matrix-free algorithm:** matrix elements are not stored in memory, calculated on a fly

- Favorable for extremely large-scale problems
- Typically, we only need to know how matrix acts on a vector (matrix-vector product)

E.g. in Power method:

```
 $\mathbf{x} \leftarrow \mathbf{x}_0 / \|\mathbf{x}_0\|$   
do  
     $\mathbf{y} \leftarrow A \cdot \mathbf{x}$  // matrix-vector product – the only info about A  
     $\mathbf{x} \leftarrow \mathbf{y} / \|\mathbf{y}\|$   
until convergence  
 $\mathbf{v} \leftarrow \mathbf{x}$ 
```

**Matrix-based algorithm:** we store in memory only non-zero elements of the matrix

- Conceptually simpler (similar paradigm to dense e.g. LAPACK: matrix in memory, library function call to calculate its spectrum)

# MATRIX-BASED METHODS: SPARSE MATRIX STORAGE FORMATS

## Two classes of sparse matrix formats:

1. Allow efficient insertion of elements.

Example: “COO” format (**C**oordinate list): (row, column, value)  
(i1, j1, val1), (i2, j2, val2), ...

2. Allow efficient matrix-vector multiplication

Example: “CSR” format (**C**ompressed **S**parse **R**ow)

$$\begin{pmatrix} 10 & 20 & 0 & 0 & 0 & 0 \\ 0 & 30 & 0 & 40 & 0 & 0 \\ 0 & 0 & 50 & 60 & 70 & 0 \\ 0 & 0 & 0 & 0 & 0 & 80 \end{pmatrix}$$

$$\begin{aligned} \text{VALUE} &= [ 10 \ 20 \mid 30 \ 40 \mid 50 \ 60 \ 70 \mid 80 ] \\ \text{ROW\_INDEX} &= [ 0 \quad 2 \quad \quad 4 \quad \quad \quad 7 \quad 8 ] \\ \text{COLUMN} &= [ 0 \ 1 \ 1 \ 3 \ 2 \ 3 \ 4 \ 5 ] \end{aligned}$$

$\text{ROW\_INDEX}[i]$  = how many nonzero elements are above row  $i$

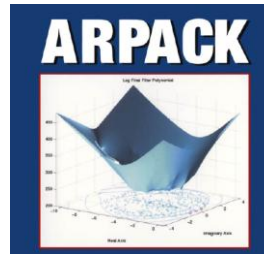


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## 3. SLEPc



## 4. Other tools and useful resources

# ARPACK

**AR**noldi **PACK**age (uses Implicitly Restarted Arnoldi/Lanczos method)

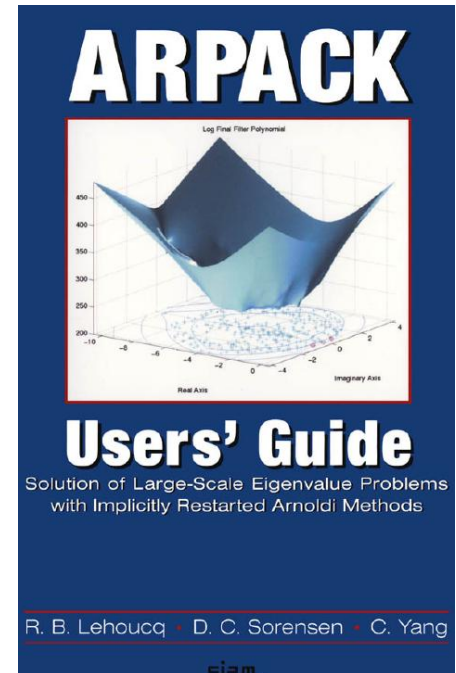
Fortran-77 library

ARPACK-NG – community-maintained version (Debian, Octave and Scilab)

<https://github.com/opencollab/arpack-ng> (includes also P\_ARPACK)

- + fast
- + MPI-parallelized (P\_ARPACK)
- + extensively tested, stable
- + matrix-free
- cumbersome Fortran-style interface
- not actively developed anymore (e.g. no GPU support)

Many packages use it under the hood: SciPy (python), Mathematica, Armadillo (C++), MATLAB, ...



# ARPACK: PYTHON

SciPy: `from scipy.linalg.sparse import eigsh`  
<https://docs.scipy.org/doc/scipy/tutorial/arpack.html>

Find eigenvalues/vectors of real/complex **sparse** matrix

1. **eigs** – for general (non-hermitian/non-symmetric)
2. **eigsh** – for **hermitian** (complex) or symmetric (real) matrices

(analogous to dense-matrix functions: `from scipy.linalg import eig, eigh`)

# ARPACK: FORTRAN / C

Routine naming convention: **pma**upd

**p** – precision:                    **s**, **d** – real **s**ingle and **d**ouble precision  
                                      **c**, **z** – complex single and double precision

**m** – matrix type:                **s**    – **s**ymmetric  
                                      **n**    – **n**on-symmetric

**a** – algorithm:                  **a**    – **A**rnoldi (Lanczos) iteration single update  
                                      **e**    – **e**igenvectors postprocessing

Example: `dsaupd`        – double symmetric Arnoldi (i.e. Lanczos) update  
          `dsaupd_c`    – same, but C-version

# ARPACK: FORTRAN / C, REVERSE COMMUNICATION INTERFACE

**Matrix-free MatVec multiplication:** input  $x$ , output  $y = Ax$

```
void myMatVec(double* x, double* y){ // Example: "1D Laplace matrix"
    int i;
    for (i = 0; i < n; i++) y[i] += 2.0*x[i]; // Main diagonal
    for (i = 0; i < n-1; i++) y[i+1] += -1.0*x[i]; // Subdiagonal
    for (i = 1; i < n; i++) y[i-1] += -1.0*x[i]; // Superdiagonal
}
```

$$\begin{bmatrix} +2 & -1 & 0 & 0 \\ -1 & +2 & -1 & 0 \\ 0 & -1 & +2 & -1 \\ 0 & 0 & -1 & +2 \end{bmatrix}$$

**Reverse communication interface:**

```
int ido = 0; // reverse communication flag; should be initialized with 0
do {
    // "double symmetric Arnoldi update"
    dsaupd_c(&ido, bmat, N, which, nev, tol, resid, ncv, V, ldv, iparam, ipntr,
            workd, workl, lworkl, &info);

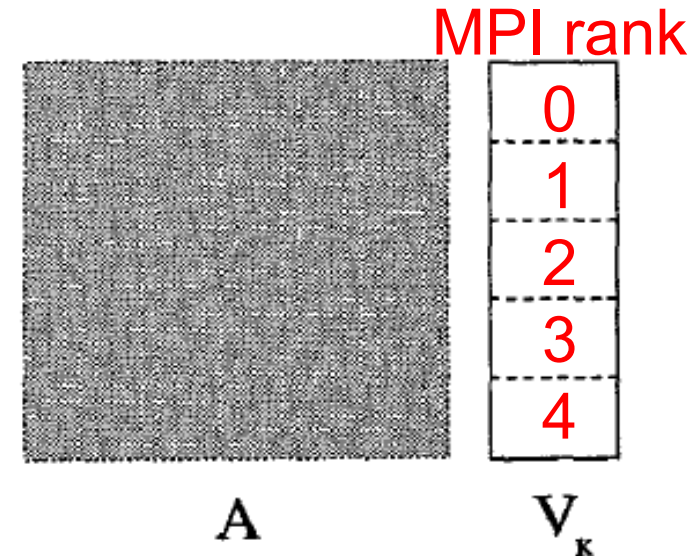
    // calculate y=Ax, where for x, y are parts of workd array
    myMatVec(&(workd[ipntr[0] - 1]), &(workd[ipntr[1] - 1]));
} while (ido == 1 || ido == -1);
```

# P\_ARPACK

Parallel **ARPACK** – MPI parallel version of ARPACK

- The parallel storage the matrix (or calculation on the fly) is up to user
- Eigenvalues are global (same on all MPI processes)
- Eigenvectors are distributed by rows

Routine naming:            ARPACK    →    P\_ARPACK  
For example:            dsaupd    →    **p**dsaupd



K. J. Maschhoff and D. C. Sorensen, P\_ARPACK: An Efficient Portable Large Scale Eigenvalue Package for Distributed Memory Parallel Architectures (1996)

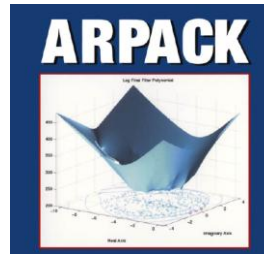
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## 4. Other tools and useful resources

Scalable Library for Eigenvalue Problem computations

Built on top of PETSc (Portable, Extensible Toolkit for Scientific computation)

- + fast
  - + MPI-parallelized
  - + GPU-support (not for all routines)
  - + both matrix-free and matrix-based
  - + many solvers under the hood
- harder to learn and incorporate in your project (but a lot of great materials for study!)



## SLEPc: TYPES OF EIGENPROBLEMS

Problem class	Model equation	Module
Linear eigenproblem	$Ax = \lambda x, \quad Ax = \lambda Bx$	EPS
Quadratic eigenproblem	$(K + \lambda C + \lambda^2 M)x = 0$	†
Polynomial eigenproblem	$(A_0 + \lambda A_1 + \dots + \lambda^d A_d)x = 0$	PEP
Nonlinear eigenproblem	$T(\lambda)x = 0$	NEP
Singular value decomp.	$Av = \sigma u$	SVD
Matrix function	$y = f(A)v$	MFN

† QEP removed in version 3.5

Source: [SLEPc tutorial](#), Jose E. Roman

# SLEPc: SOLVERS FOR LINEAR EIGENPROBLEM (“EPS MODULE”)

## 2.4 Selecting the Eigensolver

The available methods for solving the eigenvalue problems are the following:

- Basic methods (not recommended except for simple problems):
  - Power Iteration with deflation. When combined with shift-and-invert (see chapter *ST: Spectral Transformation* (page 35)), it is equivalent to the inverse iteration. Also, this solver embeds the Rayleigh Quotient iteration (RQI) by allowing variable shifts. Additionally, it provides the nonlinear inverse iteration method for the case that the problem matrix is a nonlinear operator (for this advanced usage, see `EPSPowerSetNonlinear`).
  - Subspace Iteration with Rayleigh-Ritz projection and locking.
  - Arnoldi method with explicit restart and deflation.
  - Lanczos with explicit restart, deflation, and different reorthogonalization strategies.
- **Krylov-Schur**, a variation of Arnoldi with a very effective restarting technique. In the case of symmetric problems, this is equivalent to the thick-restart Lanczos method.
- Generalized Davidson, a simple iteration based on subspace expansion with the preconditioned residual.
- Jacobi-Davidson, a preconditioned eigensolver with an effective correction equation.
- RQCG, a basic conjugate gradient iteration for the minimization of the Rayleigh quotient.
- LOBPCG, the locally-optimal block preconditioned conjugate gradient.
- CISS, a contour-integral solver that allows computing all eigenvalues in a given region.
- Lyapunov inverse iteration, to compute rightmost eigenvalues.

Source:  
Jose E. Roman et al,  
SLEPc Users Manual  
v.3.24 (2025)

## OTHER SPARSE EIGENSOLVERS (NON COMPREHENSIVE)

**Anasazi** – a C++ package within the Trilinos framework. Supports Hermitian and non-Hermitian problems, and includes block Krylov–Schur, block Davidson, LOBPCG. MPI and GPU support (through Kokkos).

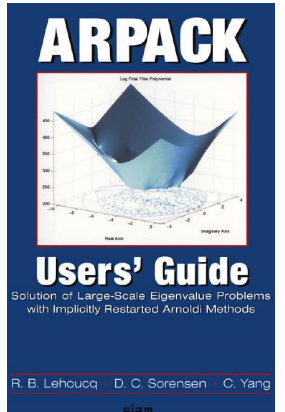
**ChASE** (Chebyshev Accelerated Subspace Eigensolver) – Chebyshev filtering and subspace iteration. Favourable when larger part of eigenspectrum is needed. MPI and GPU support.

**FEAST** – Contour-integration method. Integrates the resolvent along a contour in the complex plane to compute eigenpairs within that contour. MPI+OpenMP support.

Review of pre-2009 solvers:

V. Hernandez et al, A Survey of Software for Sparse Eigenvalue Problems, SLEPc Technical Report-6 (2009)

## RESOURCES: ARPACK



ARPACK-NG repo (many examples, both ARPACK and P\_ARPACK):

<https://github.com/opencollab/arpack-ng>

ARPACK User's guide

[http://li.mit.edu/Archive/Activities/Archive/CourseWork/Ju\\_Li/MITCourses/18.335/Doc/ARPACK/Lehoucq97.pdf](http://li.mit.edu/Archive/Activities/Archive/CourseWork/Ju_Li/MITCourses/18.335/Doc/ARPACK/Lehoucq97.pdf)

P\_ARPACK paper

<http://softlib.rice.edu/pub/CRPC-TRs/reports/CRPC-TR96659.pdf>

## RESOURCES: SLEPc

Official website (Manual, hands-on, ...)

<https://slepc.upv.es/>

Set of 10-min videotutorials

<https://slepc.upv.es/release/documentation/index.html#video-tutorials>

Need help ? <https://helpdesk.mpcdf.mpg.de/petr.karpov@mpcdf.mpg.de>