

# Approximating Eigenpairs in Quantum Chemistry

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- Supported by DOE ASCI/ASAP

# Outline

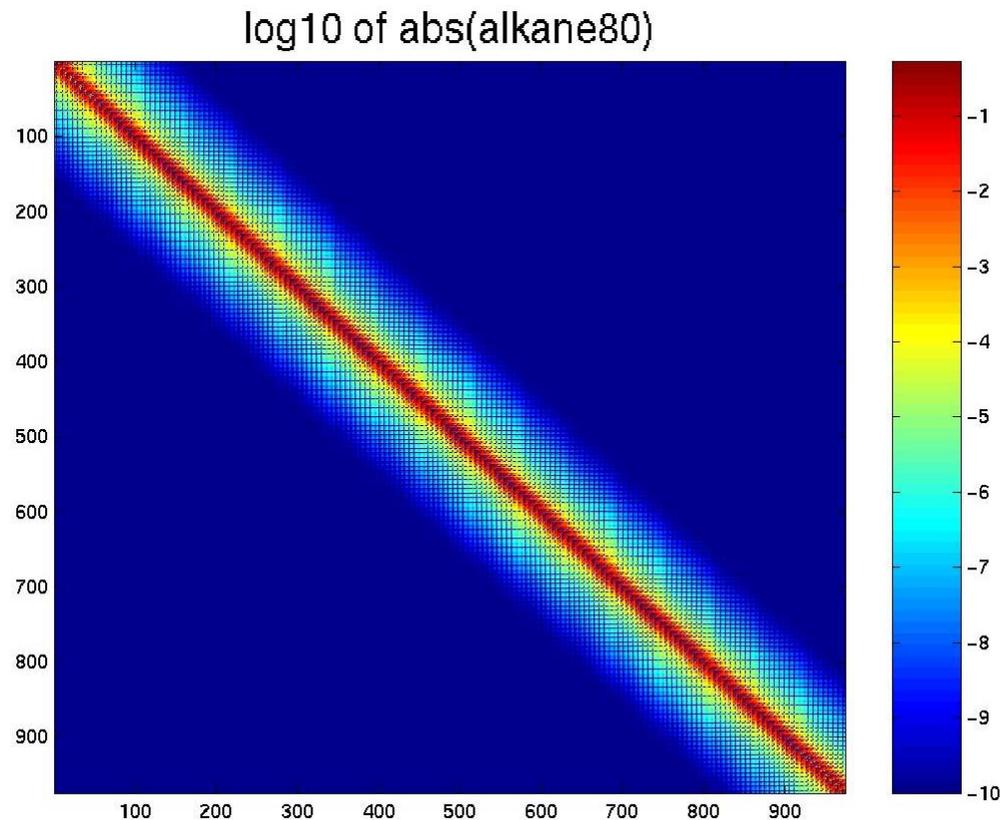


- Introduction, problem statement
- Framework: Approximation levels
- D&C (tridiagonal/block-tridiagonal)
- Analysis and experimental results
- Summary and outlook

# Introduction

# Central Problem I

- Given: Symmetric matrix  $A \in \mathbb{R}^{n \times n}$ , preferably “diagonally heavy”



# Central Problem II

- Given: Symmetric matrix  $A \in \mathbb{R}^{n \times n}$  (preferably “diagonally heavy”), tolerance parameter  $\tau$
- Wanted: *Approximate* spectral decomposition  $A \approx \hat{V} \hat{\Lambda} \hat{V}^T$ , s.t.

$$\|A - \hat{V} \hat{\Lambda} \hat{V}^T\| \leq \tau \quad \text{and} \quad \|\hat{V}^T \hat{V} - I\| \leq \varepsilon_{\text{mach}}$$

- Essentially the full spectrum required

# Application: Quantum Chemistry

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- Quantum-mechanical equations for many-electron systems (non-relativistic time-independent Schroedinger Equation)
- *Restricted Closed-Shell Hartree-Fock Approximation*
- Linearization: expand unknown molecular orbitals into finite series of basis functions

# Application: Quantum Chemistry

- Construct the *Fock matrix*  $F$  and the *Overlap matrix*  $S \Rightarrow$
- *Roothaan Equations* (nonlinear eigenvalue problem):  
$$\mathbf{F}(\mathbf{C}) \mathbf{C} = \mathbf{S} \mathbf{C} \mathbf{E}$$
- **Self-consistent-field (SCF)** procedure  $\Rightarrow$  sequence of (generalized) linear eigenproblems

# Application: Quantum Chemistry

- Objective:
  - Develop efficient *approximate* linear eigensolver for use in SCF procedure
- Desirable properties (“wish list”):
  - Variable accuracy parameter
  - Efficiency
  - Parallelization

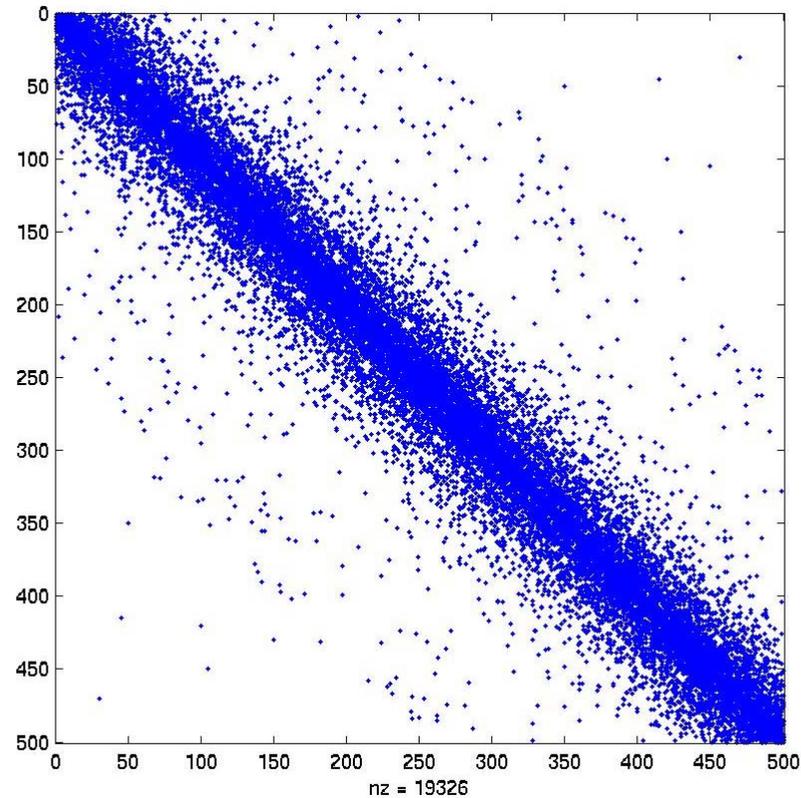
# Approximation Levels

# 3 Levels of Approximation

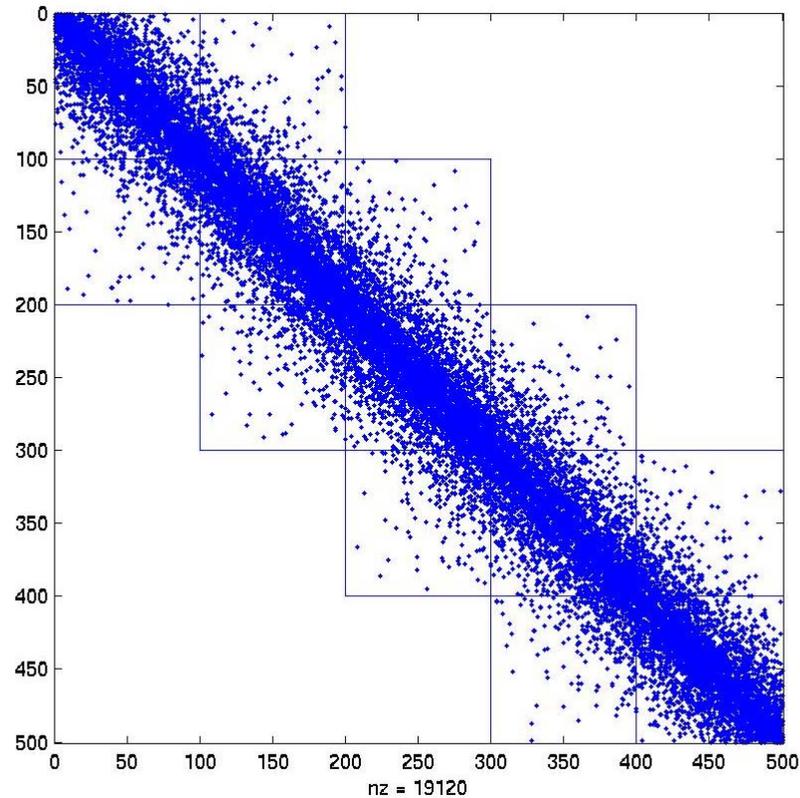
- Approximate  $A$  by a symmetric block-tridiagonal matrix  $B$ .

(thresholding, reordering, bandwidth reduction,...)

# Original Matrix

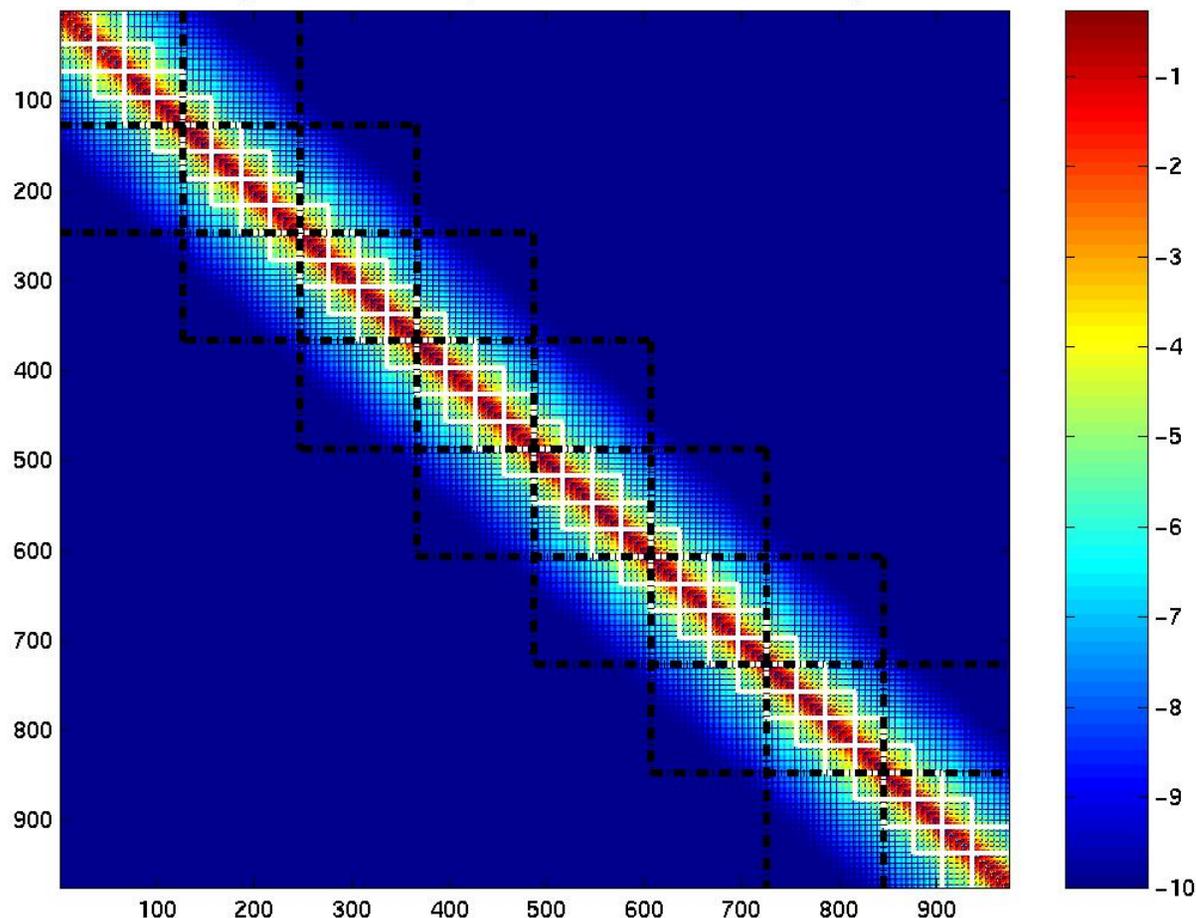


# Block-Tridiagonal Approximation B



# QC Linear Alkane: alkane80

log10 of abs(FCNDOAlkane80)



# Approximation Error I

- Error caused by thresholding and reordering can be bounded

$$|\alpha_i - \beta_i| \leq n\tau_1$$

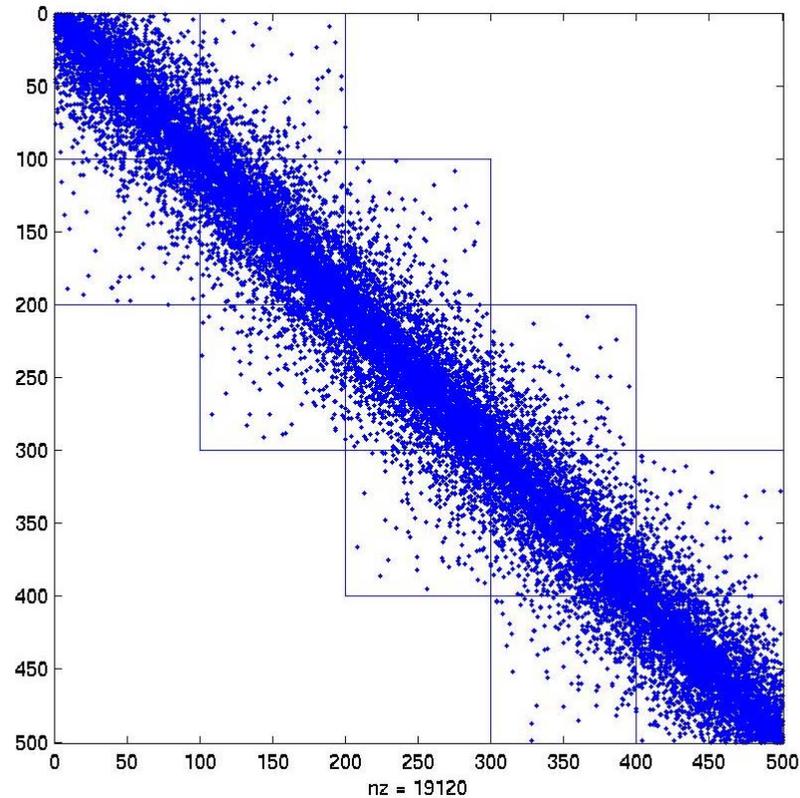
where  $\alpha_i$ ...eigenvalues of A  
 $\beta_i$ ...eigenvalues of B  
 $\tau_1$  ...thresholding tolerance

# 3 Levels of Approximation

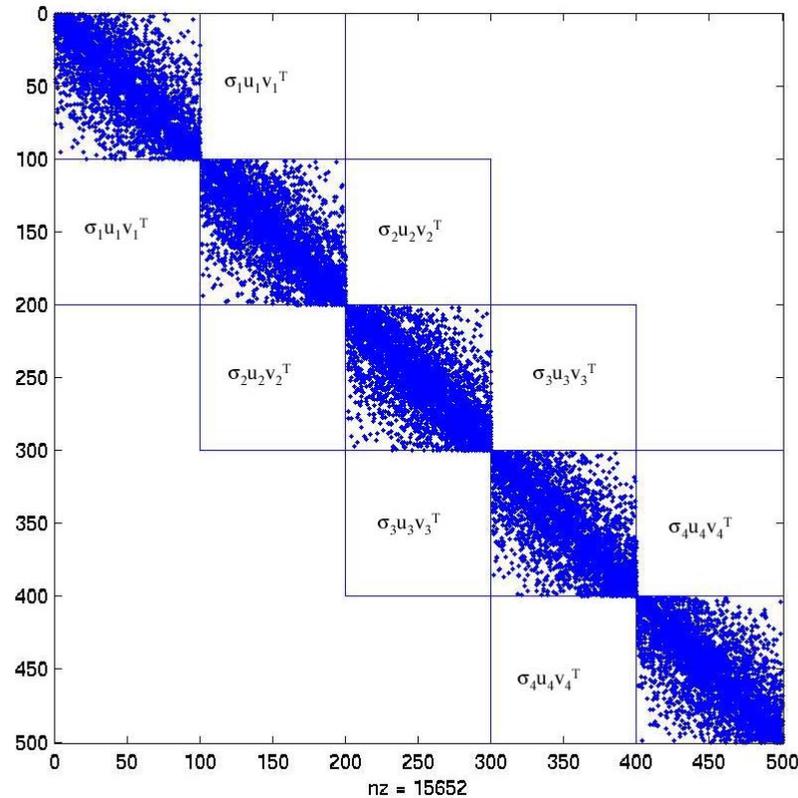
- Approximate  $A$  by a symmetric block-tridiagonal matrix  $B$ .
- Approximate the off-diagonal blocks of  $B$  by low(er) rank matrices ( $\rightarrow B'$ ).

(SVD-based rank- $r_i$  approximations)

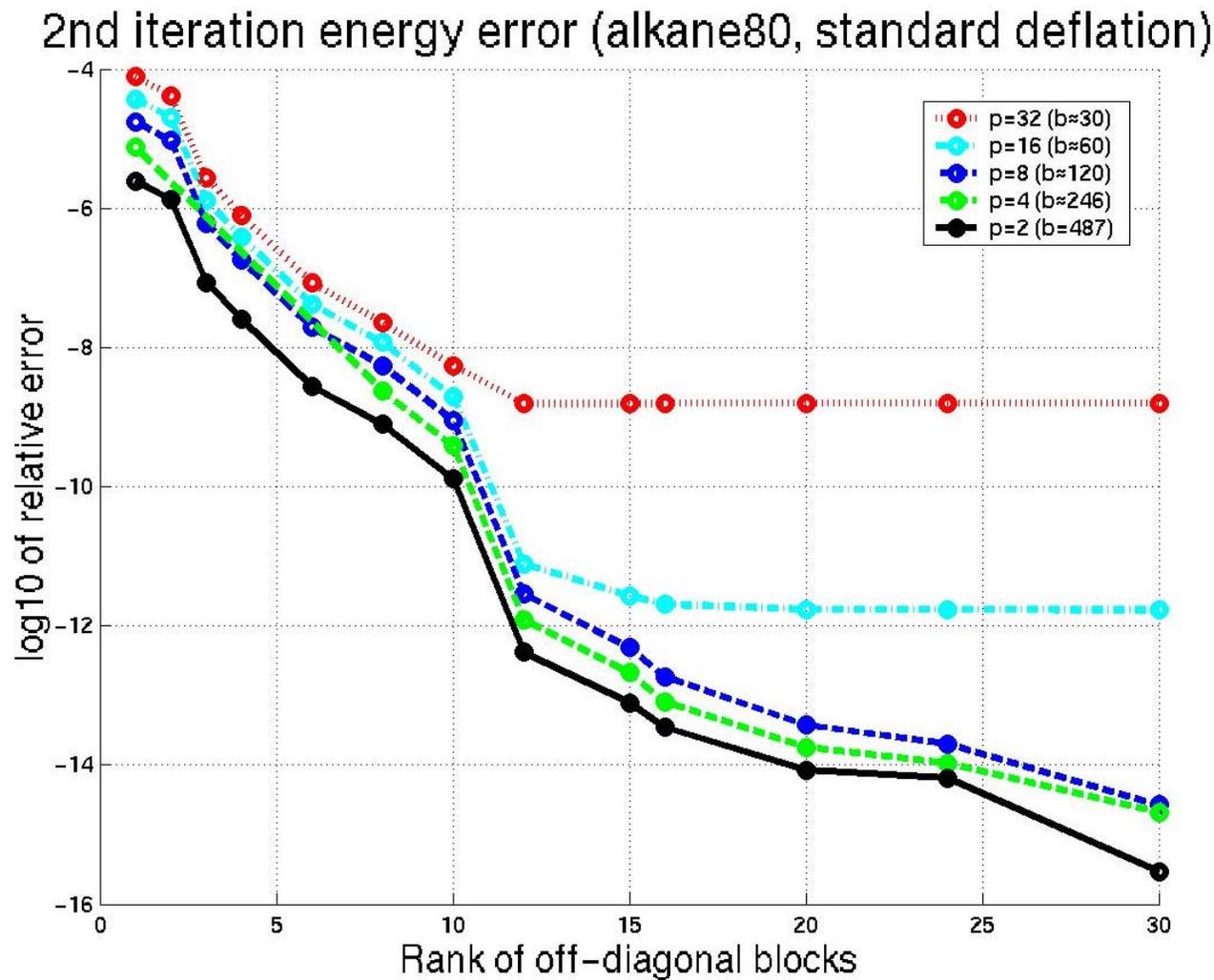
# Block-Tridiagonal Approximation B



# Rank-1 Approximation of Off-Diagonal Blocks



# Relative Errors in 2<sup>nd</sup> Iteration Energy



# Approximation Error II

- Error caused by rank approximation of off-diagonal blocks can be bounded as

$$|\beta_i - \lambda_i| \leq 2\sqrt{n} \max_{k=1,2,\dots,p-1} \sum_{j=r_k+1}^{m_k} \sigma_j^k$$

where  $\beta_i$  ... eigenvalues of B

$\lambda_i$  ... eigenvalues of B'

(approximated blocks)

$\sigma_j^k$  ... j-th singular value of the k-th subdiagonal block

# 3 Levels of Approximation

- Approximate  $A$  by a symmetric block-tridiagonal matrix  $B$ .
- Approximate the off-diagonal blocks of  $B$  by low(er) rank matrices ( $\rightarrow B'$ ).
- Apply (approximative) block divide-and-conquer algorithm to  $B'$ .

(relaxed deflation,...)

# **Divide-and-Conquer for *Tridiagonal* Problems**

[Golub (1973); Bunch et al. (1978); Cuppen (1981); Dongarra & Sorensen (1987); Gu & Eisenstat (1994/1995); Tisseur & Dongarra (1999);...]

# Divide-and-Conquer



Transform - Solve - Back-Transform

Transform - Solve - Back-Transform

Split

·  
·  
·

Transform - Solve - Back-Transform

Synthesize

# Tridiagonal Divide-and-Conquer

- Central task:  
Eigenvalues and -vectors of a  
**rank-one modification** problem

$$D + xx^T$$

with a diagonal matrix  $D$

# Deflation

$$D + xx^T$$

- **Zero component**  $x_i = 0 \Rightarrow$  corresponding eigenpair is known explicitly
- **Multiple entry**  $d_i \Rightarrow$  corresponding eigenpairs can be computed cheaply
- Problem size can be reduced (*deflated*)
- Cost for eigenvector update is reduced (block structured eigenvector matrix)

# Tridiagonal D&C

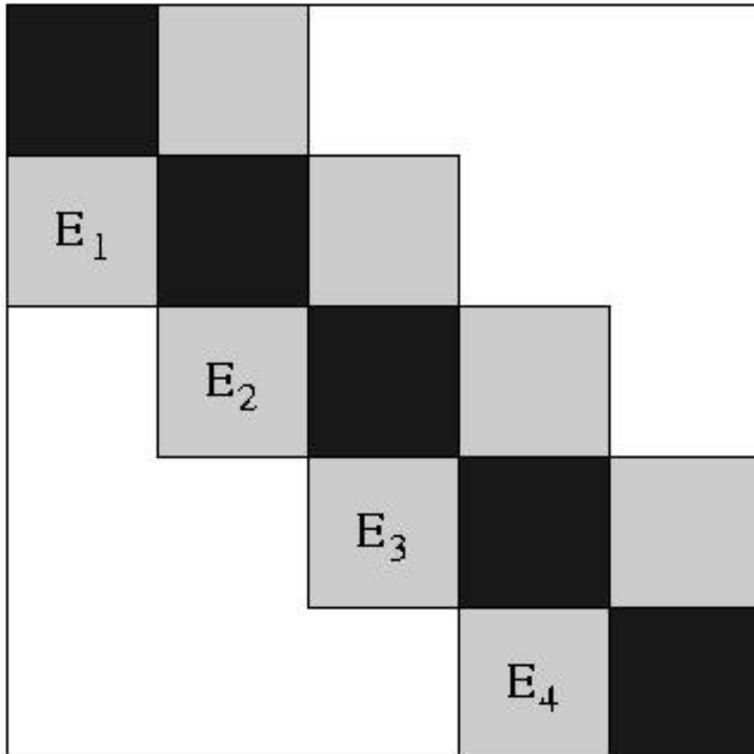
- Accumulation (multiplication) of eigenvector matrices
- Theoretical arithmetic complexity:

$$c \frac{4}{3} n^3 + O(n^2) \text{ flops}$$

- In practice often lower due to deflation
- One of the fastest algorithms available

***(Approximative)***  
**Divide-and-Conquer for**  
***Block-Tridiagonal* Matrices**

# Block-Tridiagonal D&C



- Subdivision (p blocks):
  - SVDs (off-diagonal)
  - Corrections and eigendecompositions (diagonal blocks)
- Synthesis:
  - $r_i$  rank-one modifications per off-diagonal block
  - Best merging order: lowest rank last

$$E_i = \sum_{j=1}^{r_i} \sigma_j^i u_j^i v_j^{iT}, \quad i = 1, 2, \dots, p-1$$

# Relaxed Deflation

- Standard deflation tolerance (LAPACK):

$$\tau_L := c\varepsilon \|B'\|$$

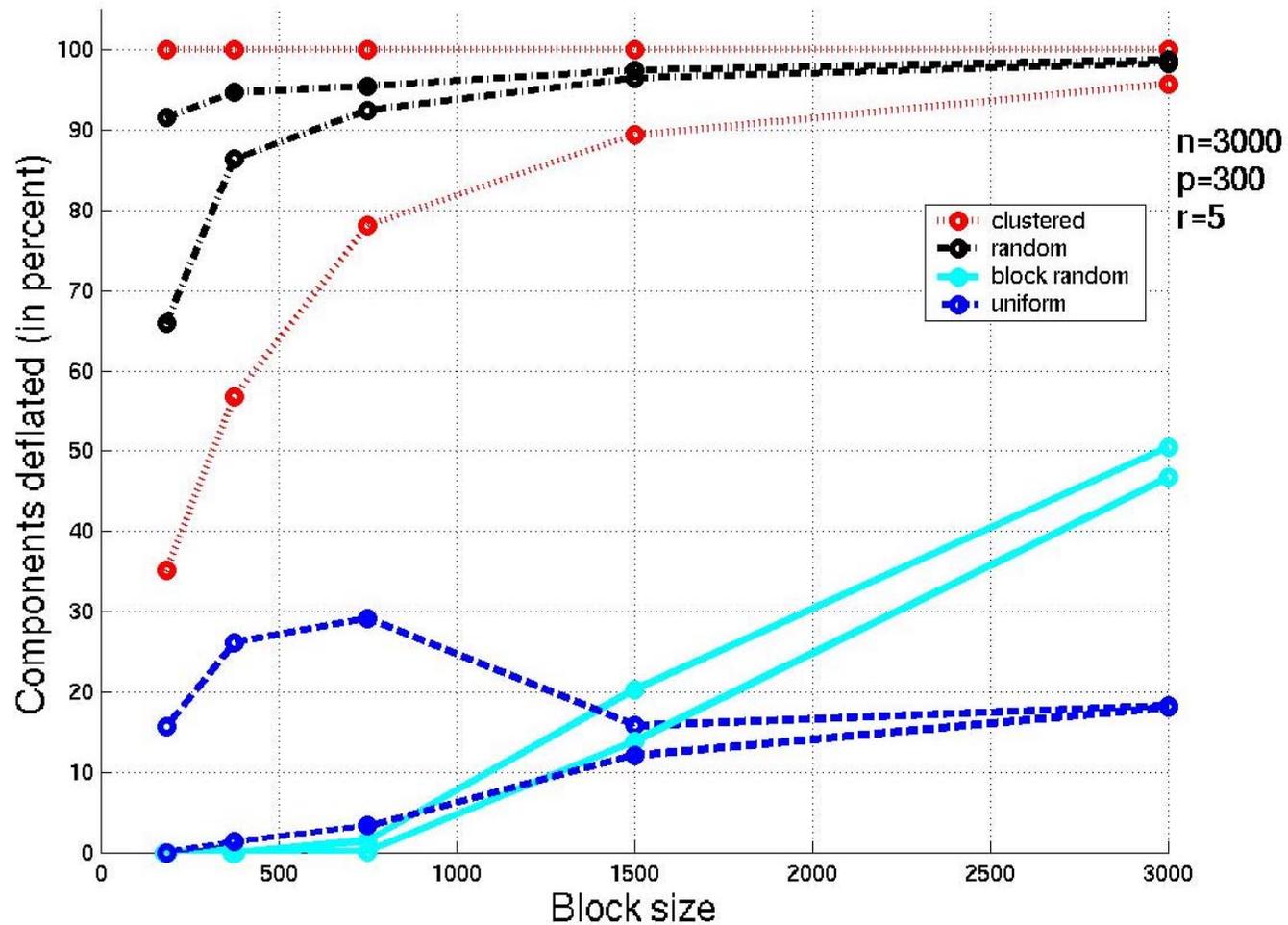
- **Relaxed deflation tolerance**  $\tau_2 < \tau_L$ 
  - Absolute eigenvalue error proportional to  $\tau_2$
  - Allows for (potentially) much more deflation
  - Significant computational savings
  - Very attractive if medium/low accuracy is sufficient

# Deflation-Experiments I

- 3 test matrices with prescribed eigenvalue distributions:
  - “clustered”: clustered around 0
  - “random”: random between -1 and 1
  - “uniform”: uniform between -1 and 1
- Additionally, “block random” matrix:
  - random diagonal blocks, off-diagonal blocks from random singular vectors

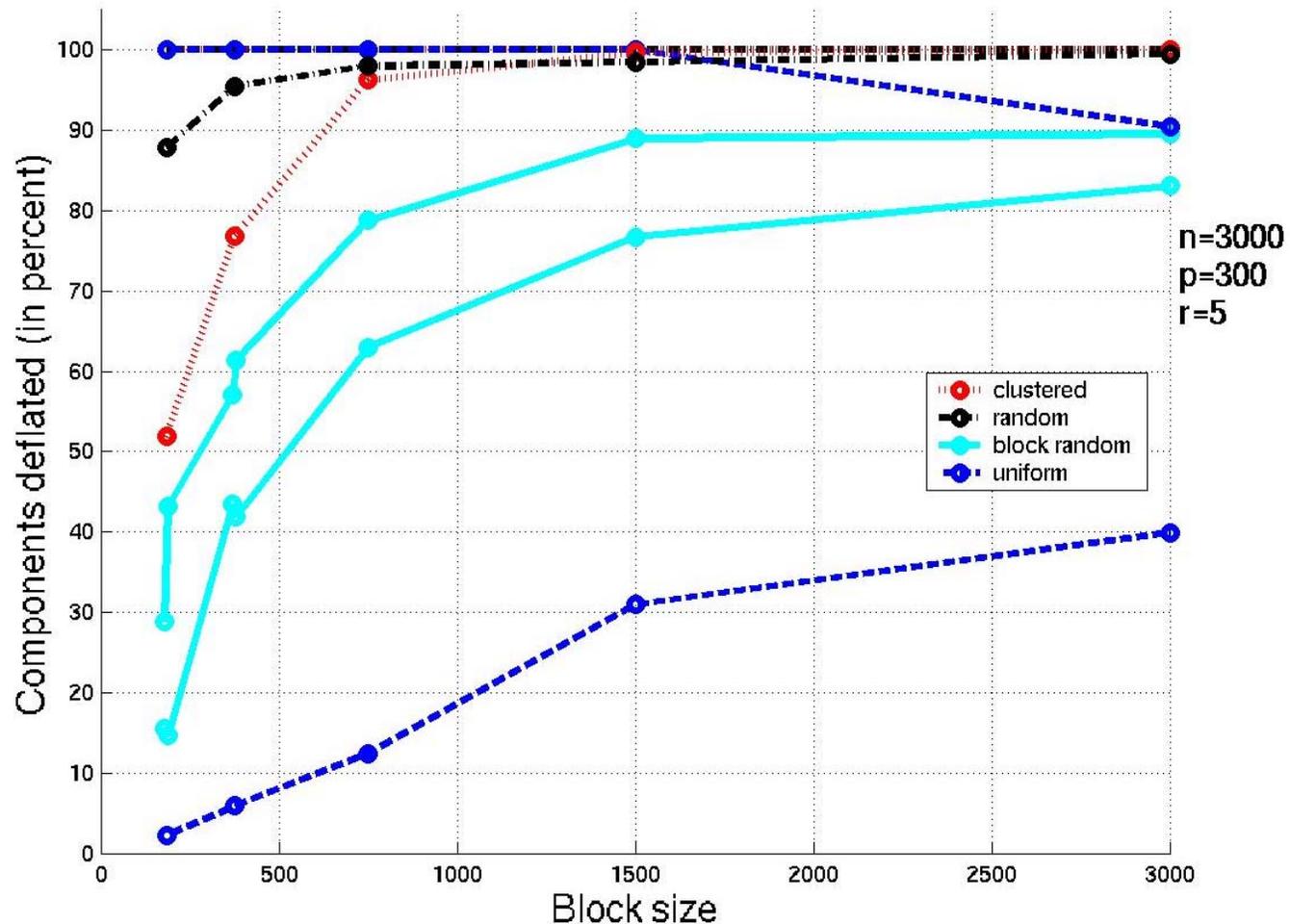
# Deflation-Experiments II

Upper and lower deflation bounds ( $\tau_2 = 1.e-10$ )



# Deflation-Experiments III

Upper and lower deflation bounds ( $\tau_2 = 1.e-4$ )



# Runtimes --

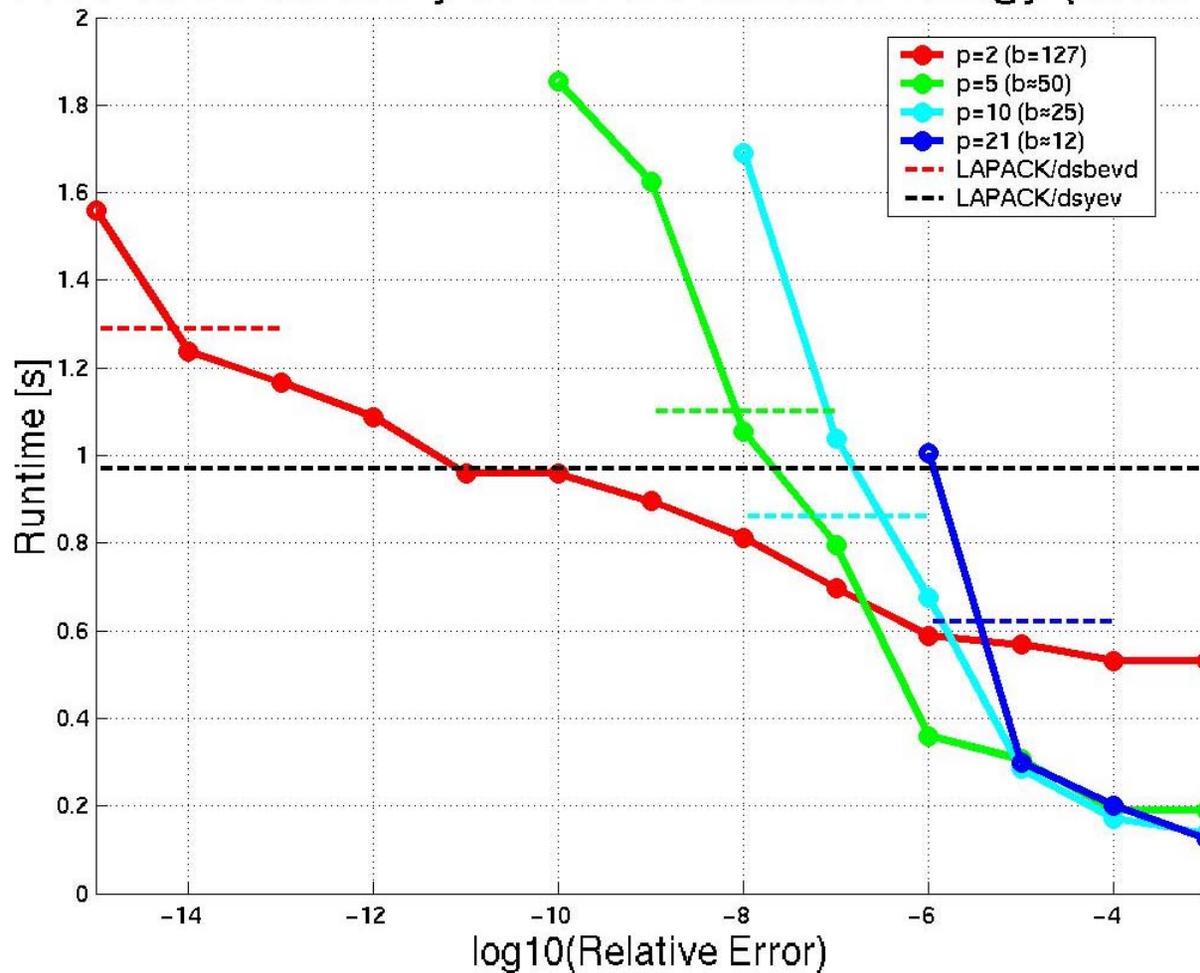
## Comparison with LAPACK

- “block random”:  $n=3000$ ,  $p=300$  ( $10 \times 10$ ), eigenvectors accumulated, times in [s]

$\tau_2$	$r_i=1$	$r_i=5$	$r_i=10$
LAPACK tolerance	30.2	942.6	2344.6
$10^{-10}$	23.1	582.6	1429.6
$10^{-6}$	17.5	229.4	498.8
$10^{-2}$	11.0	34.8	64.1
dsbevd	1501.7	1529.7	1551.4

# Runtimes -- Comparison with LAPACK

Prescribed accuracy in the 2nd iteration energy (alkane20)



# QC: SCF Procedure

Compute  $\mathbf{S}$

Determine  $\mathbf{U}$  s.t.  $\mathbf{U}^* \mathbf{S} \mathbf{U} = \mathbf{I}$

Guess  $\mathbf{C}_0$

Do  $i = 0, 1, 2, \dots$

    Compute  $\mathbf{F}(\mathbf{C}_i)$

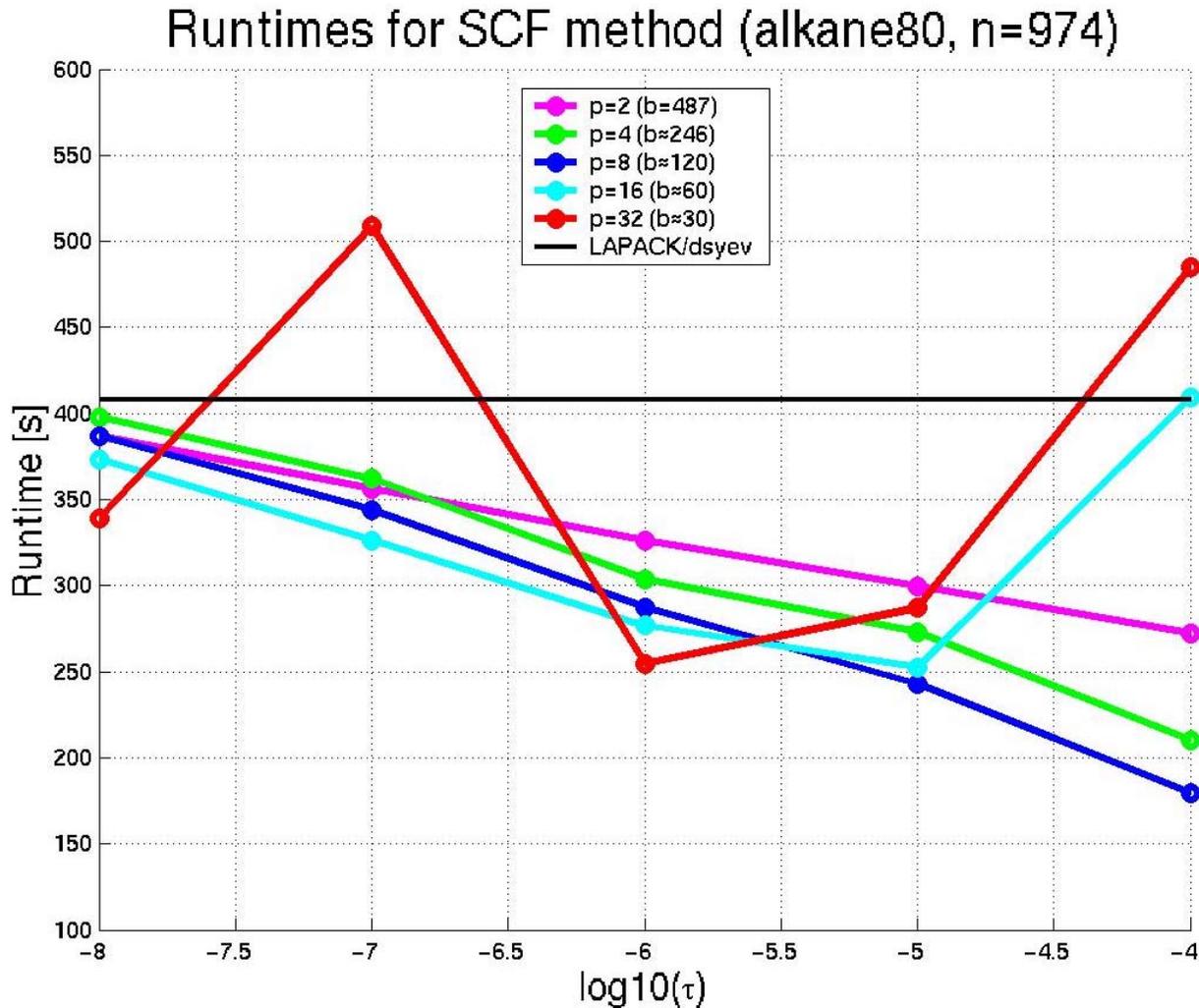
    Compute  $\mathbf{F}'_i = \mathbf{U}^* \mathbf{F}(\mathbf{C}_i) \mathbf{U}$

    Solve  $\mathbf{F}'_i \mathbf{C}'_{(i+1)} = \mathbf{C}'_{(i+1)} \mathbf{E}_{(i+1)}$  ←

    Compute  $\mathbf{C}_{(i+1)} = \mathbf{U} \mathbf{C}'_{(i+1)}$

    Check for convergence

# Runtimes -- Full SCF Procedure



# Experimental Analysis



- Efficient
  - due to good data locality (maps well onto modern memory hierarchies)
  - due to deflation
- Orders of magnitude faster than LAPACK if low accuracy requirements allow for
  - Low rank approximations
  - Large deflation tolerances

# Summary and Outlook

# Documentation



- Eigenvectors via accumulation
  - Rank-one off-diagonal approximations:  
"An Extension of the Divide-and-Conquer Method for a Class of Symmetric Block-Tridiagonal Eigenproblems", Gansterer, Ward, Muller, 2000. (submitted, also TR UT-CS-00-447)
  - Arbitrary rank off-diagonal approximations:  
"Computing Approximate Eigenpairs of Symmetric Block Tridiagonal Matrices", Gansterer, Ward, Muller, 2001. (submitted, also TR UT-CS-01-463)

# Work in Progress/ Future Work

- Alternative eigenvector computation
  - URV decomposition + postprocessing
  - Higher rank modifications, FMM
  - Newton-type approach  
[Dongarra, Moler, Wilkinson (1983)]
- Higher accuracy
  - Better block-tridiagonal/banded approximation
- Parallelization

# Future Work

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- Application to QC Problems (CalTech)
  - Utilize information from previous SCF-cycle
  - “Localization”
  - Alternative eigensolvers (Krylov-subspace methods, Jacobi-Davidson,... ?)
  - Methods for *nonlinear* eigenproblems
- Use the framework as a *preconditioner*

# More Information



<http://www.cs.utk.edu/~cape/>