

# On the Unreasonable Effectiveness Of Single Vector Krylov for Low-Rank Approximation

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# Low-Rank Approximation

Given  $\overset{\text{PSD}}{\tilde{A}} \in \mathbb{R}^{n \times n}$ ,  $K$ ,  $\varepsilon > 0$  find ortho  $Q \in \mathbb{R}^{n \times K}$  with

$$\|A - QQ^T A\|_{F,2} \leq (1 + \varepsilon) \|A - A_K\|_{F,2}$$

Ideally,  $Q = \text{top } K \text{ eigenvectors of } A$ , so use Krylov

[Rokhlin et al. '09], [Halko et al. '11], [Drineas Ipsen '19], [Tropp '22], ...

# Block Krylov

1. Pick a start block

$$B \in \mathbb{R}^{n \times b}$$

Usually Gaussian

$b = \text{block size}$

2. Build Krylov subspace

$$Z = \text{orth}(K) = \text{orth}([B \ AB \ \dots \ A^t B])$$

Compute Ortho.  
Basis for cols of  $K$

3. Return a solution

$$Q = Z^T U_k \quad \text{where} \quad U_k = \text{top } K \text{ eigvecs of } Z^T A A^T Z$$

Runtime is  $O(n^2 b t)$ . How should we pick  $b$ ?

# How should we pick $b$ ?

1. Large block size  $b \geq K$

Rich line of work [Tropp, Halko, Martinson, Gu, Drineas, Ipsen, Woodruff, ...]

Strong theoretical results for L.R.A. specifically

Gap-Independent Convergence

[Musco Musco '15]

$$b=K, [B]_{i,j} \sim \mathcal{N}(0,1) \Rightarrow t = O\left(\frac{1}{\sqrt{\epsilon}} \log\left(\frac{n}{\epsilon}\right)\right) \text{ suffices}$$

$\tilde{O}(n^2 K \frac{1}{\sqrt{\epsilon}})$  time

Let  $g_{K \rightarrow b} = \text{gap between } K^{\text{th}} \text{ and } (b+1)^{\text{st}} \text{ eigs} = \frac{\lambda_K - \lambda_{b+1}}{\lambda_K}$

## Exponential Convergence

[Musco Musco '15]

$b \geq K, [B]_{ij} \sim N(0, 1) \Rightarrow t = O\left(\frac{1}{\sqrt{g_{K \rightarrow b}}} \log\left(\frac{n}{\epsilon}\right)\right)$  suffices

Let  $b = K+2, K+5, K+10$

$\tilde{O}(n^2 K \log \frac{1}{\epsilon})$  time

if  $g_{K \rightarrow b} \geq 0.001$

for  $b = O(K)$

# How should we pick $b$ ?

2. Small block size  $b \ll K$

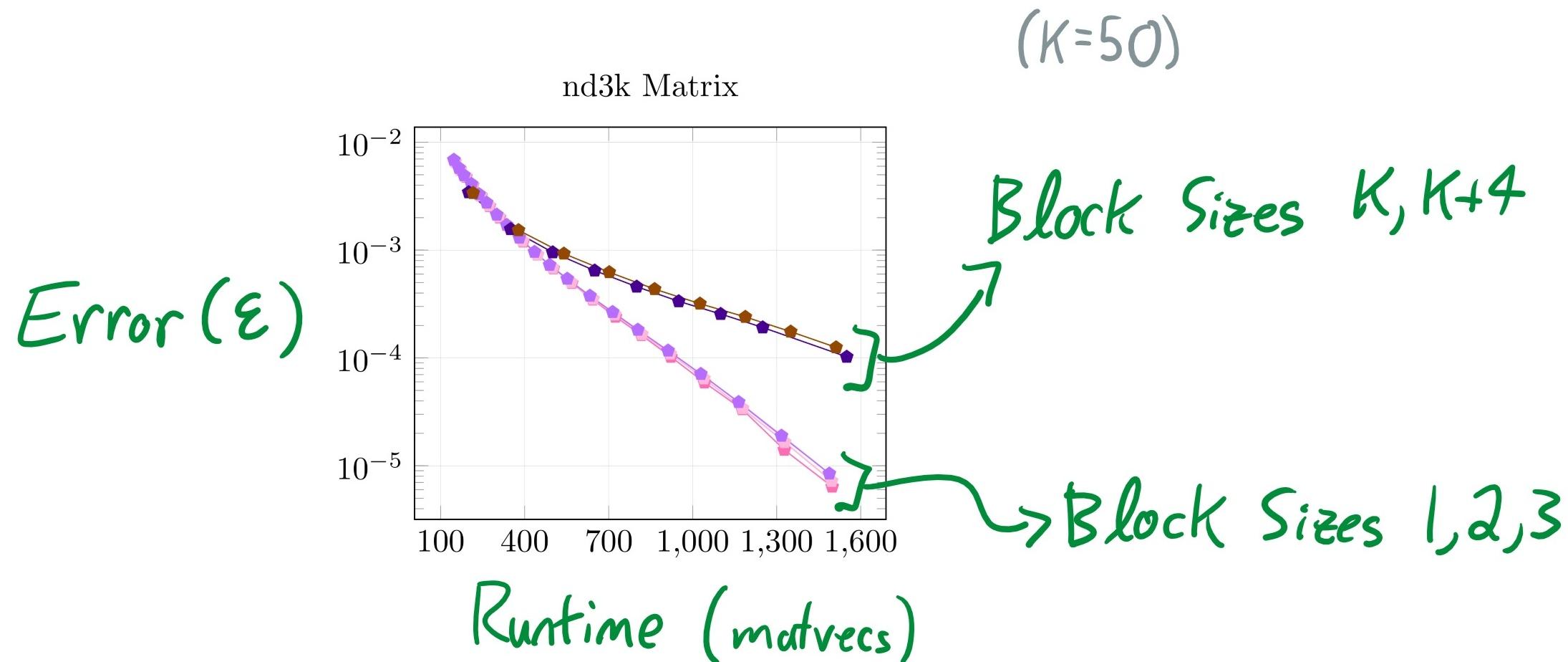
$b=1$  is called "**Single Vector Krylov**"

Applied Math suggests  $b \approx$  size of eigval clusters

Lack results\* for Low-Rank Approximation

Cannot be gap-independent

In practice,  $b=1$  often just works well



A theory/practice gap!

**When and why do small block methods  
match/outperform large block methods  
for low-rank approximation?**

Caveat: Infinite Precision

# Main Result

For all  $b \geq K$

Runtime of Single Vector Krylov

is less than

Runtime of block size  $b$  Krylov

If any  $b \geq k$  is fast, then single vector is fast

Up to log dependence on eigengaps

# Main Result (Rigorous)

Let  $g_{\min}$  = smallest gap between any of top  $K$  eigs

$$= \min_{i=1, \dots, K-1} \frac{\lambda_i - \lambda_{i+1}}{\lambda_{i+1}}$$

Then,

$b=1$  converges in  $t = O\left(\frac{K}{\sqrt{\varepsilon}} \log\left(\frac{1}{g_{\min}}\right) + \frac{1}{\sqrt{\varepsilon}} \log\left(\frac{n}{\varepsilon}\right)\right)$

For all  $\ell \geq K$ , converges in  $t = O\left(\frac{\ell}{\sqrt{g_{K \rightarrow \ell}}} \log\left(\frac{1}{g_{\min}}\right) + \frac{1}{\sqrt{g_{K \rightarrow \ell}}} \log\left(\frac{n}{\varepsilon}\right)\right)$

If some  $b \leq k$  gets exponential convergence,

$$O\left(\frac{n^2}{\sqrt{g_{K \rightarrow b}}} \cdot K \log\left(\frac{n}{\varepsilon}\right)\right) \quad \text{vs} \quad O\left(\frac{n^2}{\sqrt{g_{K \rightarrow b}}} \cdot \left(K \log\left(\frac{1}{g_{\min}}\right) + \log\left(\frac{n}{\varepsilon}\right)\right)\right)$$

Upside: separate  $K$  from  $\varepsilon$

Downside: depends on  $g_{\min}$

# Key Observation: A Silly Manipulation

Suppose  $b=I$ , so for  $\underline{x} \sim N(0, I)$

$$\mathcal{Z} = \text{orth}([\underline{x} \ A\underline{x} \ A^2\underline{x} \ \cdots \ A^t\underline{x}])$$

Now, repeat some columns

$$\begin{aligned}&= \text{orth}([\underline{x} \ A\underline{x} \ \cdots \ A^l\underline{x} \ A\underline{x} \ A^2\underline{x} \ \cdots \ A^{l+1}\underline{x} \ A^2\underline{x} \ A^3\underline{x} \ \cdots \ A^{l+2}\underline{x} \ \cdots \ A^{t-l}\underline{x} \ \cdots \ A^t\underline{x}]) \\&= \text{orth}([S_l \ S_{l+1} \ AS_l \ A^2S_l \ \cdots \ A^{t-l}S_l])\end{aligned}$$

Where  $S_l = [\underline{x} \ A\underline{x} \ \cdots \ A^l\underline{x}]$  is our **Simulated Start Block**

$b=l$  Krylov Subspace  
for  $t$  iterations  
starting from  $\underline{x} \sim \mathcal{N}(0, I)$

$\equiv$

$b=l$  Krylov Subspace  
for  $t-l$  iterations  
starting from  $S_l$

Upside: 1 iteration of single-vec = 1 iteration of block krylov

Downside:  $S_l$  is a bad starting block

$$S_l = [\underline{x} \ A\underline{x} \ \cdots A^l \underline{x}]$$

Let  $B \in \mathbb{R}^{n \times b}$  be an L-good Starting Matrix. Then,

[Musco Musco '15]

$b=K$  converges in  $O\left(\frac{1}{\sqrt{\varepsilon}} \log\left(\frac{nL}{\varepsilon}\right)\right)$  iterations

$b \geq K$  converges in  $O\left(\frac{1}{\sqrt{g_{K \rightarrow b}}} \log\left(\frac{nL}{\varepsilon}\right)\right)$  iterations

$[B]_{ij} \sim \mathcal{N}(0, 1)$  has  $L = O(nb)$

$$b=K \Rightarrow O\left(\frac{1}{\sqrt{\varepsilon}} \log\left(\frac{n}{\varepsilon}\right)\right)$$

[New Result]

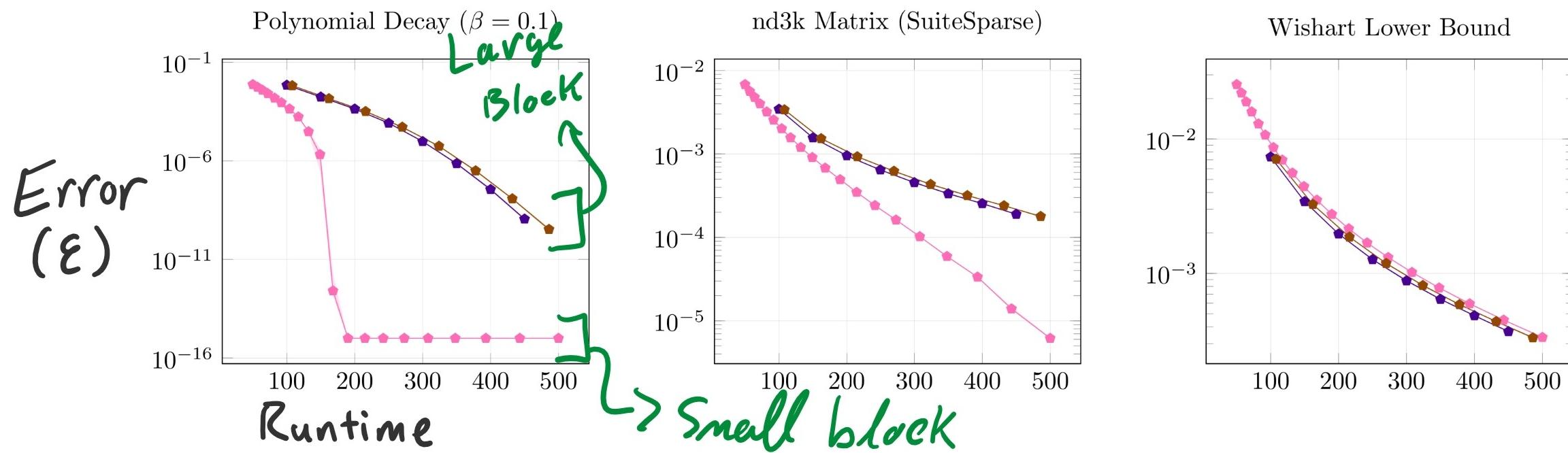
$S_l$  has  $L = O\left(\frac{n l^3}{g_{\min}^{4l}}\right)$

$$l=K \Rightarrow O\left(\frac{K}{\sqrt{\varepsilon}} \log\left(\frac{1}{g_{\min}}\right) + \frac{1}{\sqrt{\varepsilon}} \log\left(\frac{n}{\varepsilon}\right)\right)$$

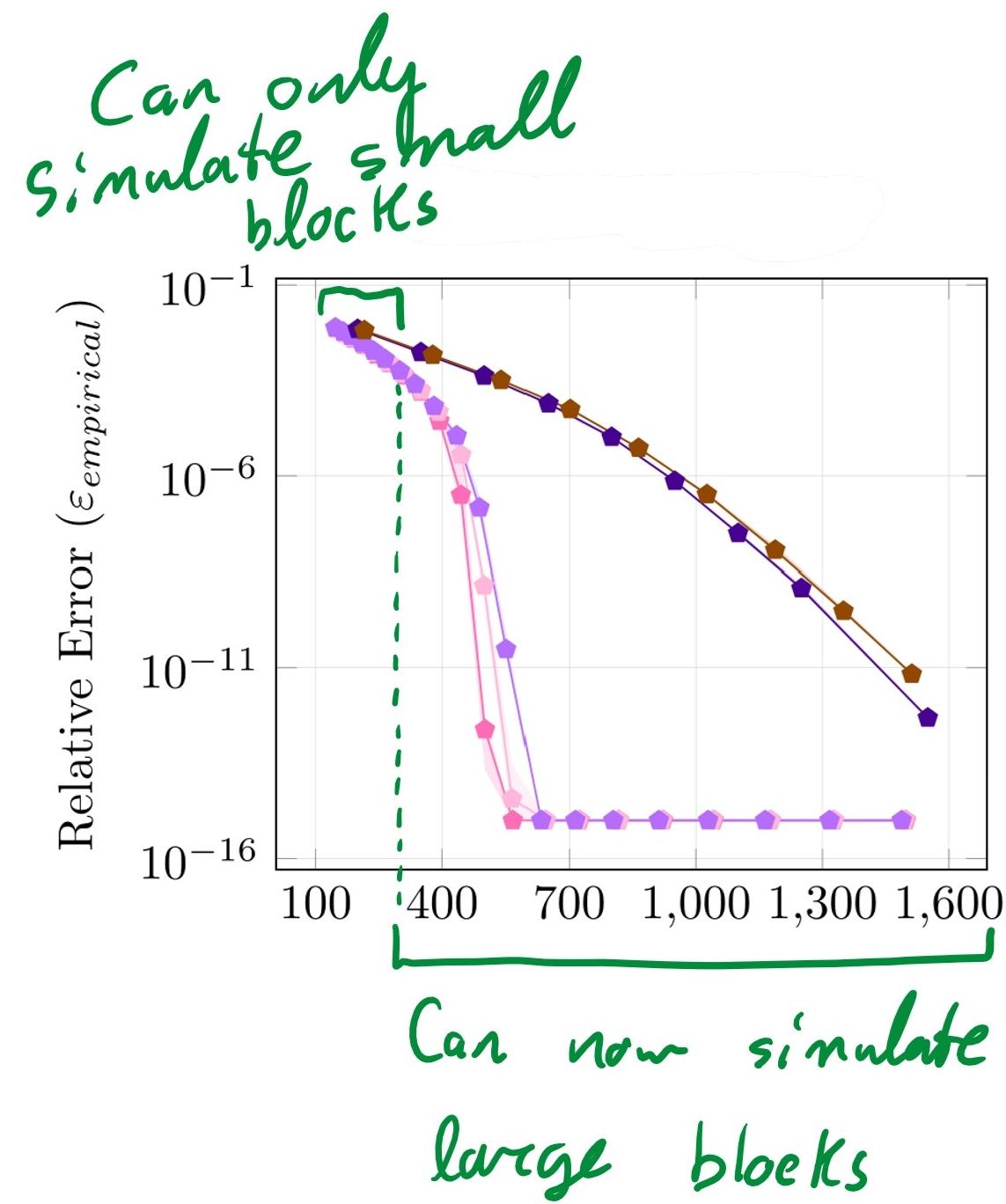
$$l \geq K \Rightarrow O\left(\frac{l}{\sqrt{g_{K \rightarrow l}}} \log\left(\frac{1}{g_{\min}}\right) + \frac{1}{\sqrt{g_{K \rightarrow l}}} \log\left(\frac{n}{\varepsilon}\right)\right)$$

*Q: When are single vector methods faster?*

*A: When some block size achieves exponential convergence.*



# Simulated blocks may explain slow-then-fast convergence



In the paper: Grab bag of more implications

- Beyond  $b=1$
- **Smoothed Analysis shatters  $\mathcal{G}_{\min}$**
- Simplify Fast-Frobenius L.R.A. [Bakshi et al. '22]
- Faster-ish Schatten-norm L.R.A
- Single Vector Subspace Iteration
- Experiments

Any questions?