

Why Single Vector Krylov is so Effective at Low-Rank Approximation

Raphael A. Meyer (New York University)

With Christopher Musco (New York University) and
Cameron Musco (University of Massachusetts Amherst)

Approximate SVD / Low Rank Approximation

- ⊙ Given $\mathbf{A} \in \mathbb{R}^{n \times d}$, target rank k , error tolerance $\varepsilon > 0$
- ⊙ Return orthonormal matrix $\mathbf{Q} \in \mathbb{R}^{n \times k}$ such that

$$|\mathbf{q}_i^\top \mathbf{A} \mathbf{A}^\top \mathbf{q}_i - \sigma_i(\mathbf{A})^2| \leq \varepsilon \sigma_i(\mathbf{A})^2$$

Algorithm from [Musco & Musco '15]:

input: Block size b . Number of iterations t .

output: Orthonormal Matrix $\mathbf{Q} \in \mathbb{R}^{n \times k}$.

- 1: Sample $\mathbf{B} \in \mathbb{R}^{n \times b}$ with i.i.d. $\mathcal{N}(0, 1)$ entries
 - 2: $\mathbf{K} = [\mathbf{B}, (\mathbf{A} \mathbf{A}^\top) \mathbf{B}, \dots, (\mathbf{A} \mathbf{A}^\top)^t \mathbf{B}]$
 - 3: Compute an orthonormal basis \mathbf{Z} for \mathbf{K}
 - 4: Compute \mathbf{U}_k , the k top left singular vectors of $\mathbf{Z}^\top \mathbf{A}$
 - 5: **return** $\mathbf{Q} = \mathbf{Z} \mathbf{U}_k$
-

Focusing on Block Size

*How should we set the **block size** b and number of iterations t ?*

In Theory,

- ⊙ Block size $b = k$ has sublinear convergence for all \mathbf{A}
- ⊙ Block size $b = k + 251$ has linear convergence if
$$\sigma_{k+251} < 0.9\sigma_k$$

In Practice,

- ⊙ Block size $b = 1$ or 2 is good

Why Single Vector Krylov is so Effective at Low-Rank Approximation?

Focusing on Block Size

*How should we set the **block size** b and number of iterations t ?*

In Theory,

- ⊙ Block size $b = k$ has sublinear convergence for all \mathbf{A}
- ⊙ Block size $b = k + 251$ has linear convergence if
$$\sigma_{k+251} < 0.9\sigma_k$$

In Practice,

- ⊙ Block size $b = 1$ or 2 is good

Why Single Vector Krylov is so Effective at Low-Rank Approximation?

Big Idea: Simulated Block Krylov

Single Vector Krylov simulates all larger-block Krylovs

To simulate block size $b = 3$, let $\mathbf{B} = [\mathbf{g} \ \mathbf{A}^2\mathbf{g} \ \mathbf{A}^4\mathbf{g}]$, then:

$$\begin{aligned} \mathbf{K} &= [\mathbf{g} \ \mathbf{A}^2\mathbf{g} \ \mathbf{A}^4\mathbf{g} \ \mathbf{A}^6\mathbf{g} \ \dots \ \mathbf{A}^{2t}\mathbf{g}] \\ &\stackrel{\text{span}}{=} \begin{bmatrix} [\mathbf{g} \ \mathbf{A}^2\mathbf{g} \ \mathbf{A}^4\mathbf{g}] & [\mathbf{A}^2\mathbf{g} \ \mathbf{A}^4\mathbf{g} \ \mathbf{A}^6\mathbf{g}] & \dots & [\mathbf{A}^{2(t-2)}\mathbf{g} \ \mathbf{A}^{2(t-1)}\mathbf{g} \ \mathbf{A}^{2t}\mathbf{g}] \end{bmatrix} \\ &= [\mathbf{B} \ \mathbf{A}^2\mathbf{B} \ \dots \ \mathbf{A}^{2(t-2)}\mathbf{B}] \end{aligned}$$

Single Vector Krylov
for t iterations



Block Size 3 Krylov
for $t - 2$ iterations
starting from \mathbf{B}

Big Idea: Simulated Block Krylov

Single Vector Krylov simulates all larger-block Krylovs

To simulate block size $b = 3$, let $\mathbf{B} = [\mathbf{g} \ \mathbf{A}^2\mathbf{g} \ \mathbf{A}^4\mathbf{g}]$, then:

$$\begin{aligned} \mathbf{K} &= [\mathbf{g} \ \mathbf{A}^2\mathbf{g} \ \mathbf{A}^4\mathbf{g} \ \mathbf{A}^6\mathbf{g} \ \dots \ \mathbf{A}^{2t}\mathbf{g}] \\ &\stackrel{\text{span}}{=} \begin{bmatrix} [\mathbf{g} \ \mathbf{A}^2\mathbf{g} \ \mathbf{A}^4\mathbf{g}] & [\mathbf{A}^2\mathbf{g} \ \mathbf{A}^4\mathbf{g} \ \mathbf{A}^6\mathbf{g}] & \dots & [\mathbf{A}^{2(t-2)}\mathbf{g} \ \mathbf{A}^{2(t-1)}\mathbf{g} \ \mathbf{A}^{2t}\mathbf{g}] \end{bmatrix} \\ &= [\mathbf{B} \ \mathbf{A}^2\mathbf{B} \ \dots \ \mathbf{A}^{2(t-2)}\mathbf{B}] \end{aligned}$$

Single Vector Krylov
for t iterations



Block Size b Krylov
for $t - b + 1$ iterations
starting from \mathbf{B}

How to Analyzed Simulated Blocks

Theorem: Initial Block isn't that Bad

Let b be the simulated block size. Let $g_{min} := \min_{i \in [b]} \frac{|\sigma_i - \sigma_{i+1}|}{\sigma_{i+1}}$.

Let \mathbf{Z} span the columns of $\mathbf{A}\mathbf{A}^T\mathbf{B}$. With probability $1 - \delta$,

$$\|\mathbf{A} - \mathbf{Z}\mathbf{Z}^T\mathbf{A}\|_F \leq O\left(\frac{d^2}{\delta g_{min}^b}\right) \|\mathbf{A} - \mathbf{A}_b\|_F$$

Proof via bounds on Legendre interpolating polynomials [Saad '80]

Via existing iterative analysis, Block Krylov depends on

$$\log\left(\frac{d^2}{\delta g_{min}^b}\right) = b \log\left(\frac{1}{g_{min}}\right) + \log\left(\frac{d}{\delta}\right)$$

Sublinear Convergence

We simulate block size $b = k$, so

$$t = O\left(\frac{k}{\sqrt{\varepsilon}} \log\left(\frac{1}{g_{min}}\right) + \frac{1}{\sqrt{\varepsilon}} \log\left(\frac{d}{\delta}\right)\right)$$

iterations suffice.

Linear Convergence

We simulate all block sizes $b \in [k + 1, t]$, so if $\sigma_b \leq 0.9\sigma_k$,

$$t = O\left(\frac{b}{\sqrt{0.1}} \log\left(\frac{1}{g_{min}}\right) + \frac{1}{\sqrt{0.1}} \log\left(\frac{d}{\delta\varepsilon}\right)\right)$$

iterations suffice.

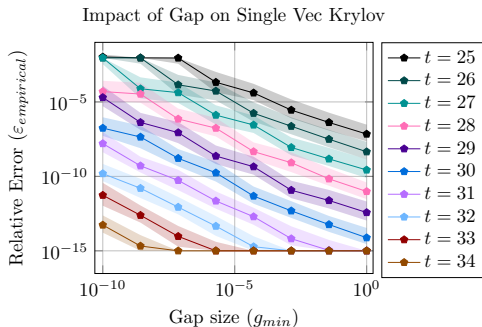
Verifying $\log\left(\frac{1}{g_{min}}\right)$

$$C_0 t = \frac{b}{\sqrt{0.1}} \log\left(\frac{1}{g_{min}}\right) + \frac{1}{\sqrt{0.1}} \log\left(\frac{1}{\varepsilon}\right)$$

Is equivalent to

$$\log(\varepsilon) = -C_1 t - b \log(g_{min})$$

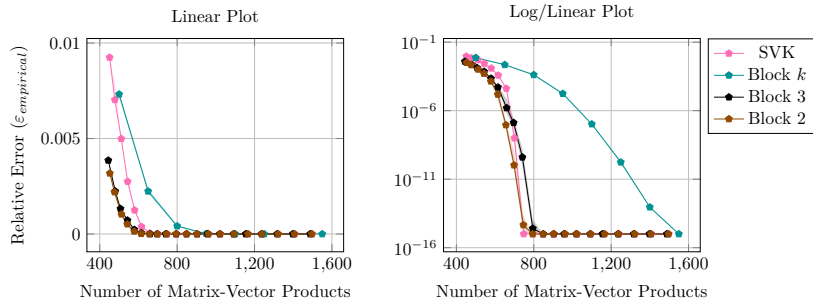
So we should see a line on a $\log(\varepsilon)/\log(g_{min})$ plot:



Small Block Sizes

- ⊙ Actually using block size 2 simulates all even block sizes
- ⊙ Robust to pairs of overlapping singular values

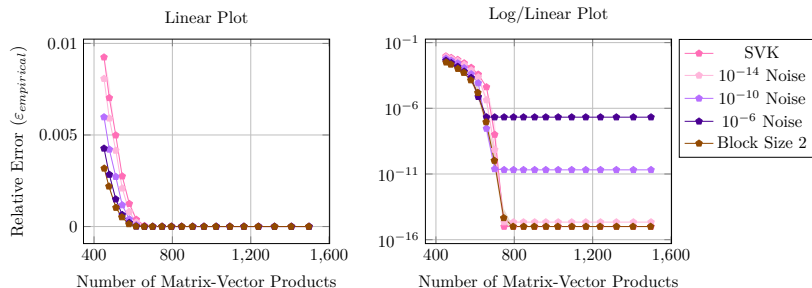
Impact of Krylov Block Size



Eigenvalue Repulsion

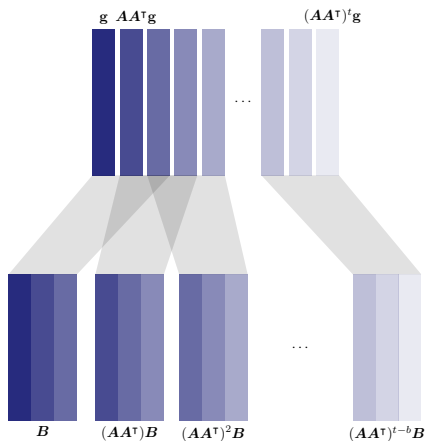
- New topic in Random Matrix Theory: Tiny Gaussian Perturbations shatter eigenvalue gaps [Nguyen et al. '17]
- $\mathbf{A} + \Delta\mathbf{G}$ has $g_{\min} \geq C_0 \left(\frac{\Delta}{d \|\mathbf{A}\|_2} \right)^{17}$
- We can tradeoff convergence and accuracy with Δ

Impact of Random Noise on Single Vec Krylov



Summary / Conclusion

1. Single Vector Krylov simulates all larger block sizes
2. Explains slow-then-fast convergence
3. Extensions to larger blocks, random perturbations



THANK
YOU