

# Oja's Algorithm for Streaming PCA: Spectral Guarantees for Sparse Matrices

William Guo (UPenn), Advisor: Erik Waingarten (UPenn)

## Background

- Principal component analysis (PCA): given a matrix  $X \in \mathbb{R}^{n \times d}$ , want to find the top eigenvector of its covariance matrix  $\frac{1}{n}X^\top X$
- Adversarial streaming setting: given arbitrary data points  $x_1, \dots, x_n$  in a stream, want to approximate  $\hat{v}_n$  s.t.  $|\langle \hat{v}_n, v_* \rangle| \approx 1$  using  $\tilde{O}(d)$  space
- Oja's algorithm: start with random unit vector  $v_0$ , updating with learning rule  $v_{i+1} = v_i + \eta x_{i+1} x_{i+1}^\top v_i$
- Want to bound performance in adversarial streams with a logarithmic spectral ratio  $R = \lambda_1 / \lambda_2 = \sigma_1 / \sigma_2$

## Algorithm

We analyze the modified version of Oja's algorithm presented in Price & Xun 2024, summarized here:

**Algorithm 1** OjaCheckingGrowth - checks if  $\eta$  is too small of a learning rate

```

Initialize  $\hat{v}_0 \leftarrow S^{d-1}$  uniformly at random
for  $i = 1$  to  $n$  do
    Perform Oja's update:  $v_{i+1} = v_i + \eta x_{i+1} x_{i+1}^\top v_i$ 
if  $\|v_n\| \leq d^{10}$  then return  $\perp$ 
else return  $\hat{v}_n$ 
    
```

**Algorithm 2** AdversarialPCA - full algorithm

```

Let  $b = O(\log nd)$  be the number of bits needed to express each matrix entry  $X_{ij}$ 
Let  $\eta_i = 2^i$ , for each  $|i| \leq O(b)$ 
Run OjaCheckingGrowth for each  $\eta_i$  in parallel; simultaneously track  $\bar{x} = \arg \max_{|x| \leq \eta_i} \|x\|$ 
Let  $i^*$  be the smallest  $i$  on which OjaCheckingGrowth outputs  $v^{(i)} \neq \perp$ 
if  $\eta^{(i^*)} \|\bar{x}\| > 1$  then return  $\frac{\bar{x}}{\|\bar{x}\|}$ 
else return  $\hat{v}^{(i^*)}$ 
    
```

## References

[1] Eric Price, Zhiyang Xun. "Spectral Guarantees for Adversarial Streaming PCA". In *FOCS*, 2024.

[2] Praneeth Kacham, David P. Woodruff. "Approximating the Top Eigenvector in Random Order Streams". In *NeurIPS*, 2024.

## Lower Bound

### Theorem (lower bound, informal)

For any sufficiently small constant  $C > 0$  and spectral ratio  $R < C \log d$ , there exists an instance on which AdversarialPCA fails to output a suitable  $\hat{v}_n$  with high probability.

**Proof Overview:** Our instance  $X \in \mathbb{R}^{n \times d}$  where  $n = R + 2$  notably includes  $R - 1$  copies of  $\frac{1}{\sqrt{R}} e_1$  immediately followed by the row  $\frac{1}{\sqrt{R}} e_1 + \frac{1}{\sqrt{R}} e_2$

$$X = \frac{1}{\sqrt{R}} \begin{pmatrix} 1 & -1 & 0 & \dots & 0 \\ 1 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 0 & 0 & \sqrt{3} & \dots & 0 \end{pmatrix}$$

- Principal component:  $e_1$  ( $x_1$  ensures symmetry of stream)
- Spectral ratio:  $\approx R/3$ ; max norm vector:  $x_{R+2}$ , uncorrelated with  $e_1$
- $|\langle v_n, e_1 \rangle| \simeq (1 + \frac{\eta}{R})^R$ ,  $|\langle v_n, e_2 \rangle| \simeq \frac{\eta}{R} (1 + \frac{\eta}{R})^R$

### Intuition:

- $\eta$  must be large enough for  $\langle v_n, e_1 \rangle$  to grow more than a factor of  $\text{poly}(d)$ , so  $\eta = \Omega(\log d)$
- Growth in direction  $e_1$  also benefits non-principal directions  $e_2$  (and then  $e_3$ ), so necessarily  $\eta < R$ .
- For sufficiently small  $R = O(\log d)$ , this is a contradiction.

Combined with the upper bound, this spectral ratio requirement is tight (up to a constant factor) for streams with row-sparsity  $s = O(1)$ .

## Upper Bound

We assume  $X = MQ^\top$ , for orthogonal  $Q \in \mathbb{R}^{d \times d}$ , and  $M \in \mathbb{R}^{n \times d}$  has at most  $s$  nonzero entries per row.

### Theorem (upper bound)

Given spectral ratio  $R = \Omega(s \log d)$ , AdversarialPCA outputs  $\hat{v}_n$  satisfying  $\langle \hat{v}_n, v_* \rangle^2 \geq 1 - O(\frac{\log d}{R})$  with high probability.

**Proof Overview:** We show the growth's "error" term is  $O(\sigma_1)$ :

$$\log \|v_n\|^2 \geq \eta \sum_{i=1}^n \langle x_i, v_{i-1} \rangle^2 \geq \frac{1}{4} \sigma_1 - \eta \sum_{i=1}^n \langle x_i, P \hat{v}_{i-1} \rangle^2$$

Here,  $P = I - v_* v_*^\top$  projects away from the principal component.

**Intuition:** Consider when each data point  $x_i$  has a nonzero contribution to only 1 non-principal direction  $w_j$ , and when  $\{1, \dots, n\}$  can be partitioned into contiguous disjoint sets  $S_j = \{i_{j-1} + 1, \dots, i_j\}$  containing the points  $x_i$  contributing to non-principal direction  $w_j$ .

We now claim  $\eta \sum_{i \in S_j} \langle x_i, P \hat{v}_{i-1} \rangle^2 \leq \sigma_2^2 \frac{\|w_j\|^2 - \|w_{j-1}\|^2}{\|w_j\|^2}$ , using that  $\langle x_i, P \hat{v}_{i-1} \rangle^2 = \langle x_i, w_j \rangle^2 \langle \hat{v}_{i-1}, w_j \rangle^2$  and that  $\langle \hat{v}_{i-1}, w_j \rangle^2$  is bounded by the fraction of growth from indices in  $S_j$  and the total growth thus far.

Since  $1 - \frac{1}{x} \leq \log x$ , summing this across all  $j$  telescopes to  $\sigma_2^2 \log \|v_n\|^2$ .

## Future Work

- Improve spectral ratio upper bound for general matrices; unclear whether  $O(\log d)$  spectral ratio is obtainable. Note Kacham & Woodruff 2024 showed  $O(\log^2 d)$  is obtainable by combining AdversarialPCA and row-norm sketching
- Extend upper/lower bounds to Oja's algorithm for top  $k$  principal components