# Implicit bias of SGD in $L_{2}$-regularized linear DNNs: One-way jumps from high to low rank 

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## Problem setting

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- We examine the implicit bias of SGD with finite learning rate:

$$
\theta_{t+1}=(1-2 \eta \lambda) \theta_{t}-\frac{\eta}{2} \nabla_{\theta}\left(A_{i_{t} j_{t}}^{*}-A_{\theta_{t}, i_{t} j_{t}}\right)^{2} .
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## Low rank region

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- We denote the region in parameter space satisfying the conditions above by $B_{r}$.


## Main results

Theorem (Informal)
For any initialization $\theta_{0}$ and any $r \geq 0$, there exists $T$ such that

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## Lemma

For any critical point $\hat{\theta}$ in $B_{r}$, we have $\sum_{i=1}^{\operatorname{Rank} A_{\hat{\theta}}} f_{\alpha}\left(s_{i}\left(A_{\hat{\theta}}\right)^{2 / L}\right) \leq r+\epsilon_{2}$.

## Proof sketch

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(2) For any parameter $\theta_{t}$, there exists a time $T$ such that

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\mathbb{P}\left(\theta_{t+T} \in B_{r} \mid \theta_{t}\right) \geq O\left(r^{T}\right)
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## Experiments

- We observe 3 out of 4 entries of a $2 \times 2$ matrix: $\left(\begin{array}{cc}1 & * \\ \epsilon & 1\end{array}\right)$. The ground truth is the rank-1 matrix where the missing entry * is $\epsilon^{-1}$.


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Figure: Red: ratio of second to first singular value of $A_{\theta}$. Light blue: test error. Dark blue: test error after offshoots at different time with smaller $\eta$ and $\lambda$.

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## Thank you!

