# Nearly Optimal Bounds for Cyclic Forgetting 

Halyun Jeong ${ }^{1}$ Mark Kong ${ }^{1} \quad$ Deanna Needell ${ }^{1}$ William Swartworth ${ }^{2}$ Rachel Ward ${ }^{3}$
${ }^{1}$ University of California, Los Angeles
${ }^{2}$ Carnegie Mellon University
${ }^{3}$ University of Texas at Austin

## Overview: Our 2 main results

1. Numerical range bound: Let $\mathbb{F}=\mathbb{R}$ or $\mathbb{C}$. Let
$\mathcal{P}_{d}=\left\{\right.$ orthogonal projections in $\left.\mathbb{F}^{d}\right\}$ and let $\mathcal{P}_{d}^{T}=\prod_{t=1}^{T} \mathcal{P}_{d}$ be the Minkowski product. Then $\bigcup_{A \in \mathcal{P}_{d}^{T}} W(A)$ is a (closed, $d \in \mathbb{Z}_{\geq 1}$
filled-in) sinusoidal spiral.

- Corollary: Let $A \in \mathcal{P}_{d}^{T}$. Then $\left\|A^{m}(1-A)\right\|=O\left(\frac{T}{m}\right)$.

2. Improved bound on forgetting in continual learning

- $T$ suitably normalized datasets, at least one of rank $r_{\text {max }}$, in $\mathbb{R}^{d}$, cycled through $m$ times
- Trivial bound: 1
- Known lower bound ${ }^{1}: \Omega\left(\frac{T^{2}}{m T}\right)=\Omega\left(\frac{T}{m}\right)$
- Old upper bound ${ }^{2}:\left\{\frac{T^{2}}{\sqrt{m T}}, \frac{T^{2}\left(d-r_{\text {max }}\right)}{2 m T}\right\}$
- New upper bound: $O\left(\frac{T^{2}}{m}\right)$ with reasonable constant ${ }^{3}$

[^0]
## Review of Forgetting

- Continual learning: An ML algorithm (with parameters initialized at $\vec{w}_{0}$ ) is given a sequence $S$ of tasks to learn over, with corresponding loss functions $\mathcal{L}_{1}, \mathcal{L}_{2}, \ldots$, yielding parameter vectors $\vec{w}_{1}, \vec{w}_{2}, \ldots$ after each task
- Assuming ${ }^{4} \mathcal{L}_{t}\left(\vec{w}_{t}\right)=0$ for all $t$, forgetting after $n$th update is

$$
F_{S}(n):=\frac{1}{n} \sum_{t=1}^{n} \mathcal{L}_{t}\left(\vec{w}_{n}\right)
$$

- In words: Average loss over all previously seen tasks, evaluated at $n$th learned parameter vector.
- Each task is weighted equally, but our results generalize to weighted forgetting with weights $W_{1}, W_{2}, \cdots \in \mathbb{R}$ :

$$
\frac{1}{n} \sum_{t=1}^{n} W_{t} \mathcal{L}_{t}\left(\vec{w}_{n}\right)
$$

[^1]
## Our Setting

- Tasks are linear regression over datasets $\left(X_{t}, \overrightarrow{y_{t}}\right)$
- Loss is sum of squares error
- Datasets visited cyclically, in cycles of length $T$ : $\left(X_{1}, \overrightarrow{y_{1}}\right),\left(X_{2}, \overrightarrow{y_{2}}\right), \ldots,\left(X_{T}, \overrightarrow{y_{T}}\right),\left(X_{1}, \overrightarrow{y_{1}}\right), \ldots$
- Datasets jointly realizable ${ }^{5}$
- Learning algorithm orthogonally projects onto solution space at each step
- Only consider forgetting after a whole number of cycles $^{6}$, so forgetting becomes average loss over all datasets

[^2]
## Our Approach

Recall $\mathcal{P}_{d}=\left\{\right.$ orthogonal projections in $\left.\mathbb{F}^{d}\right\}$. Take $\mathbb{F}=\mathbb{R}$.
Previously known bounds:

- If the datasets $X_{1}, \ldots, X_{T} \subset \mathbb{R}^{d}$ are normalized ${ }^{7}$ so $\max _{t}\left\|X_{t}\right\| \leq 1$ and other suitable normalizations hold, then ${ }^{8}$

$$
F_{S}(m T) \leq \frac{T-1}{2} \max _{A \in \mathcal{P}_{d}^{T}}\left\|A^{m}(1-A)\right\|
$$

- There exists $Q \in \mathbb{R}$ such that, for any complex Hilbert space $H$, any linear map $\varphi: H \rightarrow H$, and any polynomial $f \in \mathbb{C}[z]$,

$$
\|f(\varphi)\| \leq Q \sup _{z \in W(\varphi)}|f(z)|
$$

Best known ${ }^{9}$ value of $Q$ is $1+\sqrt{2}$.

[^3]

## Proof Strategy over $\mathbb{C}$

Characterize $\bigcup_{A \in \mathcal{P}_{d}^{T}} W(A)$ : Let $S\left(\mathbb{C}^{d}\right)$ be the unit sphere. Then $d \in \mathbb{Z}_{\geq 1}$

$$
\begin{aligned}
& z \in \bigcup_{\substack{A \in \mathcal{P}_{d}^{T} \\
d \in \mathbb{Z}_{\geq 1}}} W(A) \\
& \Longleftrightarrow \exists \vec{u} \in S\left(\mathbb{C}^{d}\right), P_{1}, P_{2}, \ldots, P_{T} \in \mathcal{P}_{d}:\left\langle\vec{u}, P_{T} P_{T-1} \ldots P_{1} \vec{u}\right\rangle=z \\
& \Longleftrightarrow \exists \vec{u}_{0}, \vec{u}_{1}, \ldots, \vec{u}_{T} \in S\left(\mathbb{C}^{d}\right):\left\langle\vec{u}_{0}, \vec{u}_{T}\right\rangle\left\langle\vec{u}_{T}, \vec{u}_{T-1}\right\rangle \ldots\left\langle\vec{u}_{1}, \vec{u}_{0}\right\rangle=z
\end{aligned}
$$

so the boundary of $\bigcup_{\substack{A \in \mathcal{P}_{d}^{T} \\ d \in \mathbb{Z}_{d}}} W(A)$ is given by critical points of the $d \in \mathbb{Z}_{\geq 1}$
$\mathbb{R}$-smooth map $P:\left(S\left(\mathbb{C}^{\bar{d}}\right)\right)^{T} \rightarrow \mathbb{C}$ given by

$$
\left(\vec{u}_{0}, \vec{u}_{1}, \ldots, \vec{u}_{T}\right) \mapsto\left\langle\vec{u}_{0}, \vec{u}_{T}\right\rangle\left\langle\vec{u}_{T}, \vec{u}_{T-1}\right\rangle \ldots\left\langle\vec{u}_{1}, \vec{u}_{0}\right\rangle .
$$

Extremizers must be coplanar, so enough to consider $d=2$.
Setting derivatives of each input to be parallel + algebra gives characterization of critical points (in terms of quaternions).

## Proof strategy over $\mathbb{C}$ : Relation to quaternions

Can rephrase problem and prove result in terms of quaternions. To extremize

$$
P\left(\vec{u}_{0}, \vec{u}_{1}, \ldots, \vec{u}_{T}\right):=\left\langle\vec{u}_{0}, \vec{u}_{T}\right\rangle\left\langle\vec{u}_{T}, \vec{u}_{T-1}\right\rangle \ldots\left\langle\vec{u}_{1}, \vec{u}_{0}\right\rangle,
$$

for unit quaternions $q_{1}, \ldots, q_{T}$, set $\vec{u}_{t}=q_{t} q_{t-1} \ldots q_{1}$ and let $q_{0}=\left(q_{T} q_{T-1} \ldots q_{1}\right)^{-1}$. Then

$$
P\left(\vec{u}_{0}, \ldots, \vec{u}_{T}\right)=\mathfrak{C} q_{T} \mathfrak{C} q_{T-1} \ldots \mathfrak{C} q_{1} \mathfrak{C} q_{0}
$$

where $\mathfrak{C}$ denotes complex part.
In other words, problem is to extremize $\mathfrak{C} q_{T} \mathfrak{C} q_{T-1} \ldots \mathfrak{C} q_{1} \mathfrak{C} q_{0}$ subject to $q_{T} q_{T-1} \ldots q_{1} q_{0}=1$.
Critical points (up to certain multiplication by complex units) are when (two of the $q_{t}$ have zero complex part or):

- if $T+1$ is odd, $q_{T}=q_{T-1}=\cdots=q_{1}=q_{0}$ is a $T+1$ th quaternionic root of unity
- if $T+1$ is even, $q_{T}=q_{T-1}=\cdots=q_{1}=q_{0}$ is a $2(T+1)$ th quaternionic root of unity (where the multiplication by complex units is chosen to make their product 1 , if necessary)


## Proof Strategy over $\mathbb{R}$

For any $z \in \partial\left(\bigcup_{\substack{A \in \mathcal{P}_{d}^{T} \\ d \in \mathbb{Z}_{\geq 1}}} W(A)\right)$, Find a sequence of projections onto planes in $\mathbb{R}^{4}$ such that the extensions of these projections to $\mathbb{C}^{4}$ has an invariant copy of $\mathbb{C}^{2}$, and restricting there gives the complex projections realizing that $z$.
To do this, use the characterization of critical points to get a description of what these projections in $\mathbb{R}^{4}$ must look like.


[^0]:    ${ }^{1}$ Itay Evron et al. "How catastrophic can catastrophic forgetting be in linear regression?" In: Conference on Learning Theory. PMLR. 2022, pp. 4028-4079.
    ${ }^{2}$ lbid.
    ${ }^{3}$ Plus minor constant-factor optimizations not due to the numerical range bound

[^1]:    ${ }^{4}$ Relaxed slightly in paper

[^2]:    ${ }^{5}$ Can be relaxed slightly
    ${ }^{6}$ Can be relaxed via weighted forgetting

[^3]:    ${ }^{7}$ Alternative normalizations are possible
    ${ }^{8}$ Evron et al., "How catastrophic can catastrophic forgetting be in linear regression?"
    ${ }^{9}$ Michel Crouzeix and César Palencia. "The numerical range is a (1+2)-spectral set". In: SIAM Journal on Matrix Analysis and Applications 38.2 (2017), pp. 649-655.

