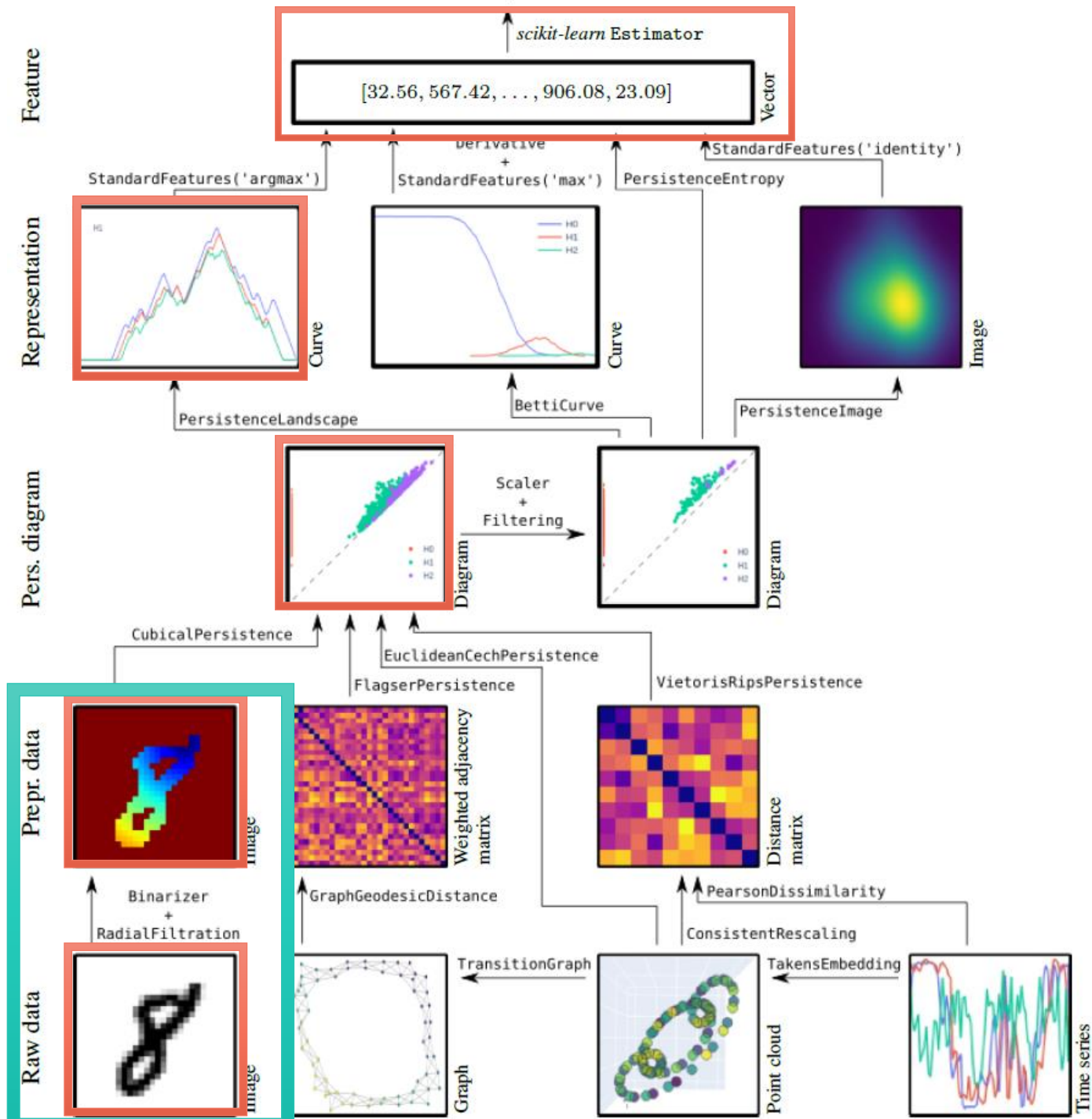

A CONVOLUTIONAL PERSISTENCE TRANSFORM

Elchanan Solomon

Duke University, informal Barcelona Campus
joint work with Paul Bendich

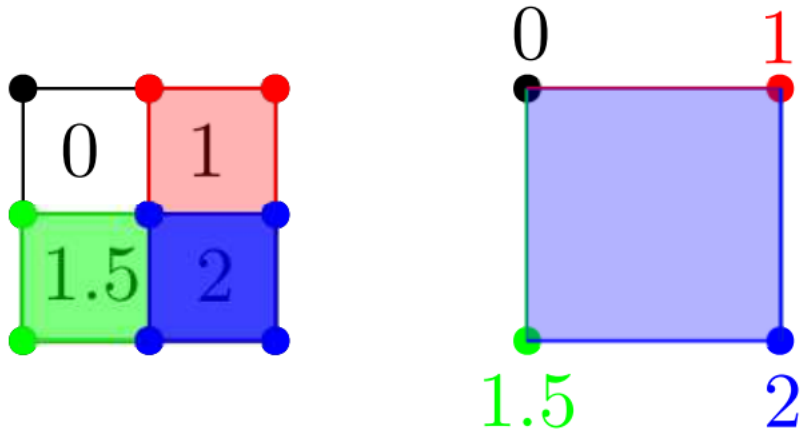
The TDA Pipeline (part of)

- Describe what this step usually consists of.
- Explain why the standard approach is limited.
- Propose a new approach.
- Prove that new approach is better.
- Try the new approach on real data and see the results.



Converting Images to Filtered Simplicial Complexes

- Represent the image grid using a cubical complex.
- Pixels are either vertices or top-dimensional cells. Pixel intensity defines a function on vertices/top-dim cells.
- Extend to the rest of the complex using lower/upper-star.
- Use Freudenthal triangulation .



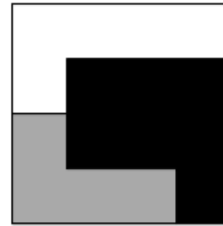
The two constructions give different but equivalent diagrams.

The Persistent Homology of Dual Digital Image Constructions

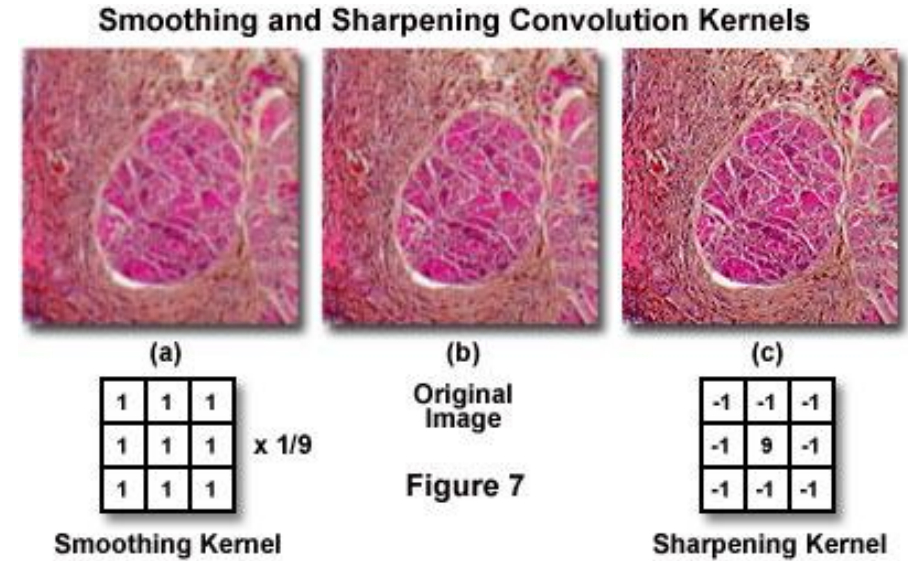
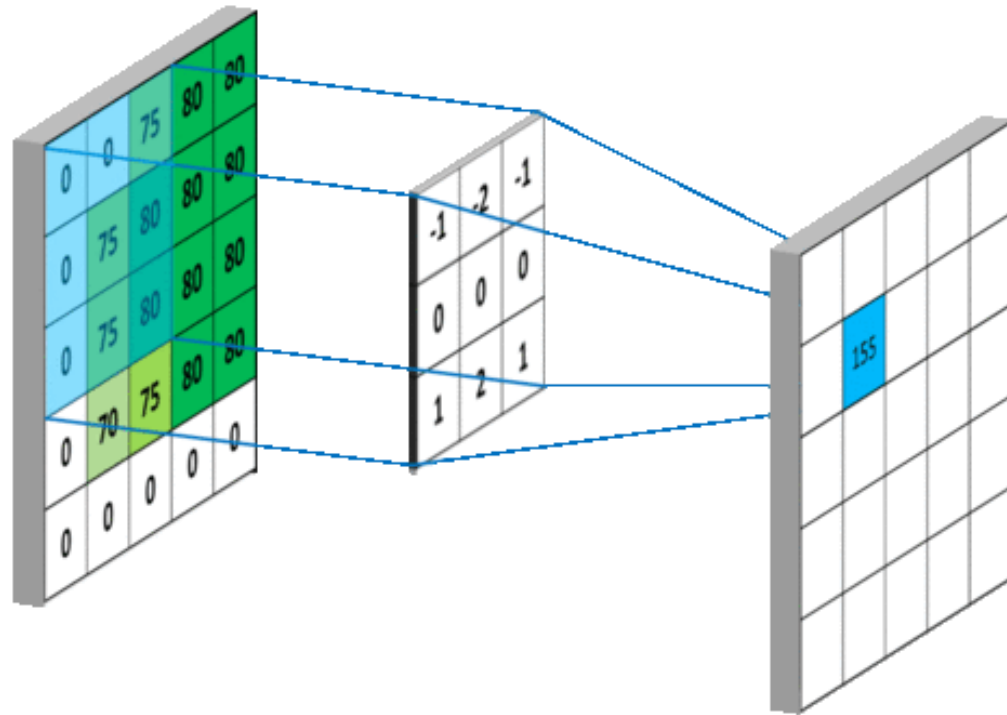
Bea Bleile¹, Adélie Garin², Teresa Heiss³, Kelly Maggs², Vanessa Robins⁴

Limitations of Image TDA (Persistence)

- Persistence is ***unstable to outliers***.
- Many different images can have the same persistence. In other words, image persistence is ***lossy / not injective***.
- Image persistence is ***not customizable***. You get a single invariant for each image, and you cannot adapt that invariant depending on the context.
- Some images need ***more preprocessing*** for topology to be useful.



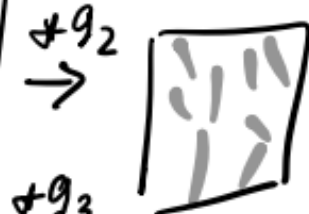
Adding an Intermediate Step: Preprocess with Convolutions



Convolutions + Persistence
=
Convolutional Persistence

convolutions

image



nera

PH

PH

PH

persistence diagrams



vec

vec

vec

vectors



summary vector



model



Prediction

yì
persistente

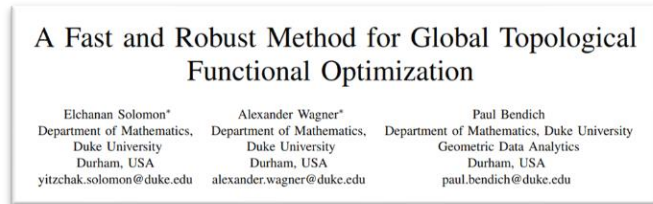
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Properties of Convolutional Persistence

- Using the right filters, convolutional persistence is **more stable to outliers**.
- A convolved image is often much smaller than the original. This greatly **speeds up** persistence computations.



- For any two images, there exists some filter that can tell them apart – meaning that convolving with that filter produces different persistence diagrams. (**injectivity**)

The Proof of Injectivity

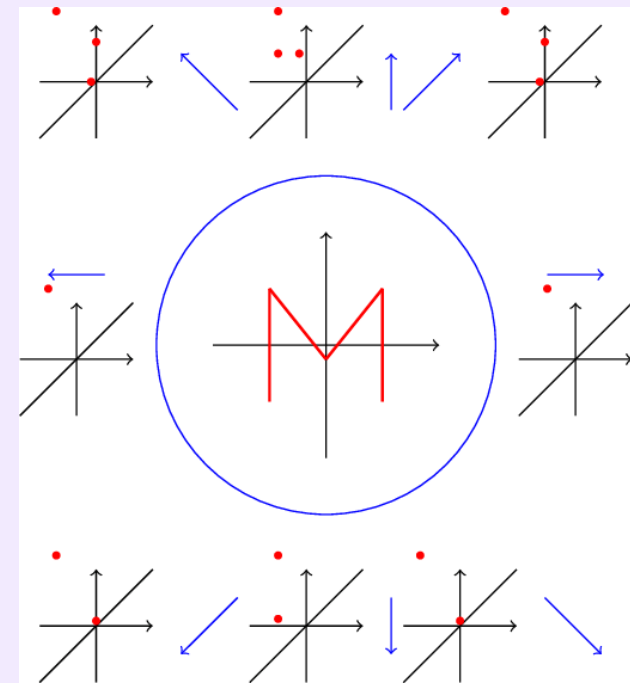
We use another construction from applied topology: the persistent homology transform.

For a vector $v \in \mathbb{S}^{d-1} \subset \mathbb{R}^d$, define the function $f_v = \langle \cdot, v \rangle$.

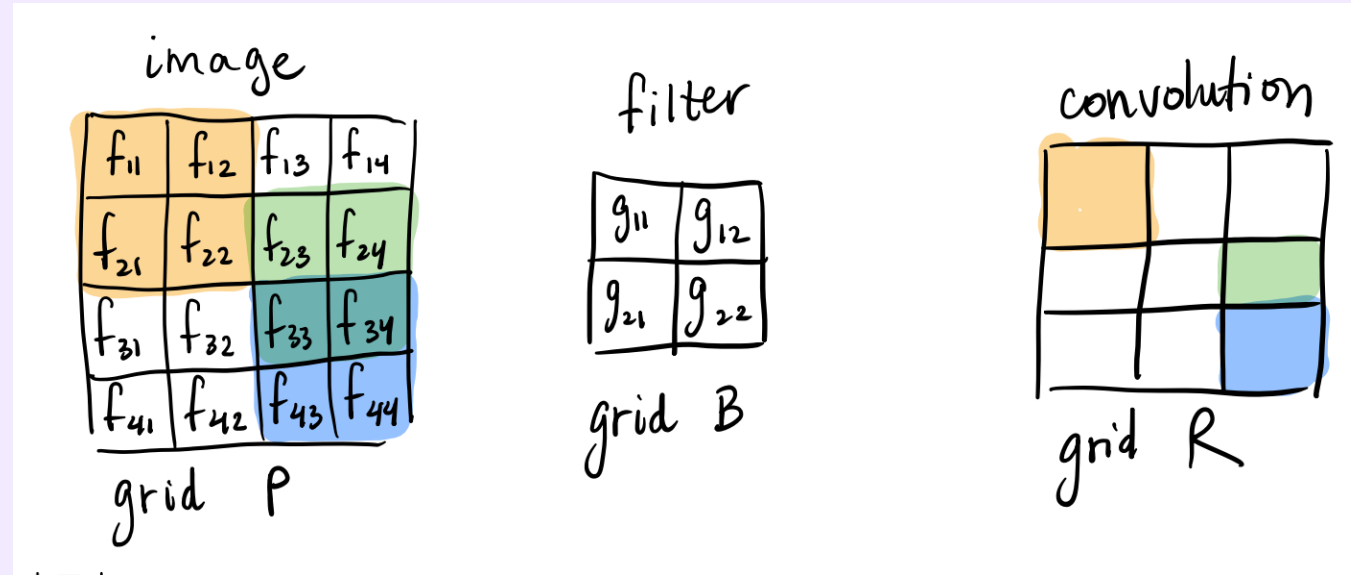
Given $X \subset \mathbb{R}^d$, define $PHT(S)$ be the function sending vectors $v \in \mathbb{S}^{d-1}$ to their corresponding persistence diagrams $PH(X, f_v)$.

Theorem (Turner, Mukherjee, Boyer, Ghrist, Levanger, Mai, Curry):

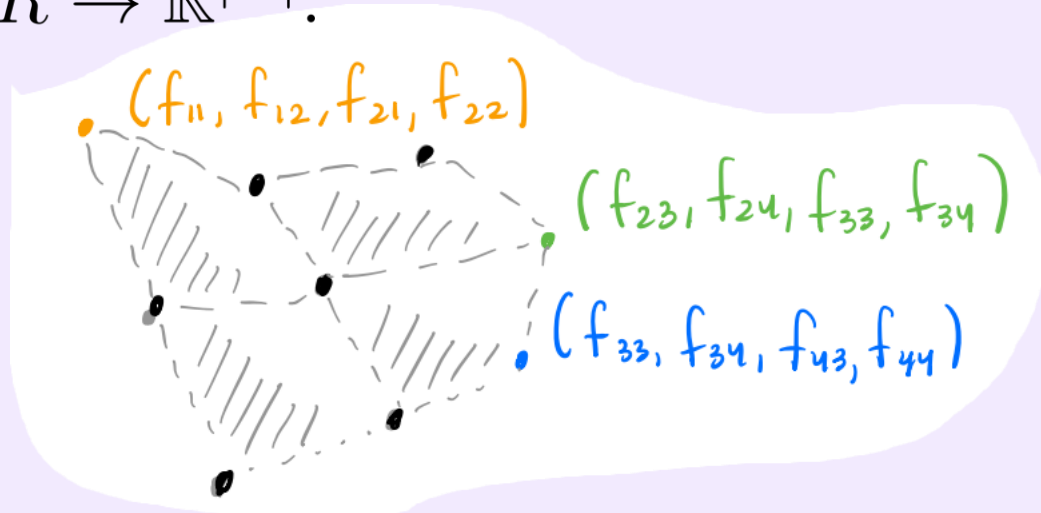
The PHT is injective, i.e. $PHT(X) = PHT(Y)$ implies $X = Y$.



Relating Convolutions and the PHT

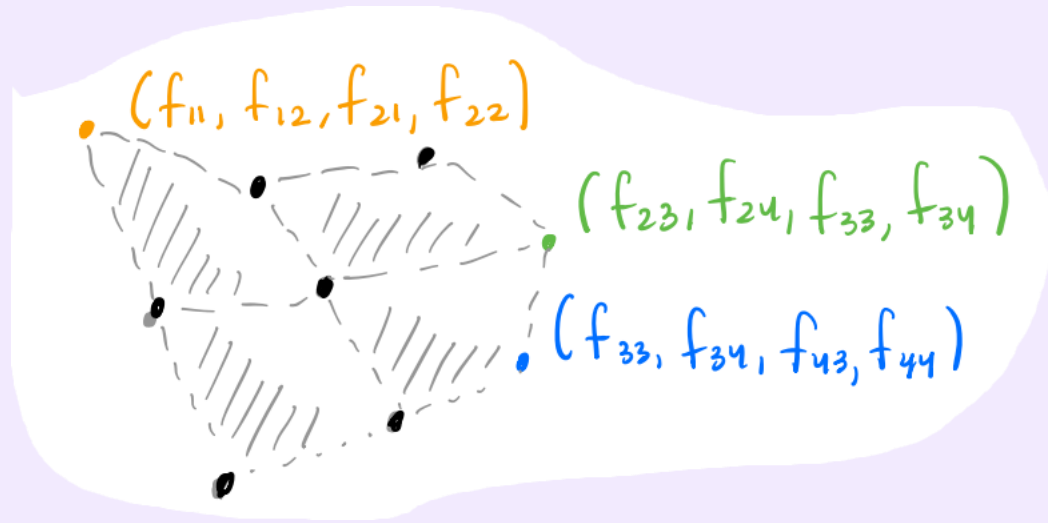


Define $\iota_f : R \rightarrow \mathbb{R}^{|B|}$:

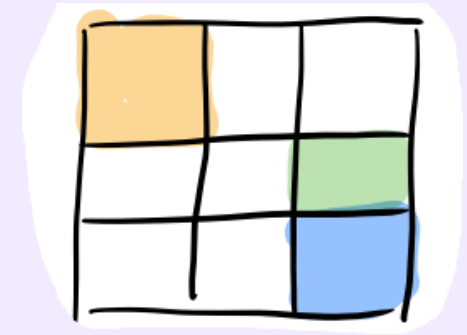


Define $\vec{g} = (g_{11}, g_{12}, g_{21}, g_{22})$.
 Observe: For a vertex $r \in R$,
 we have $(f * g)(r) = \iota_f(r) \cdot \hat{g}$.

The continuously embedded grid.



The discrete, abstract grid.



\cong
(generically)

Continuous filtration $\langle \cdot, \vec{g} \rangle$.

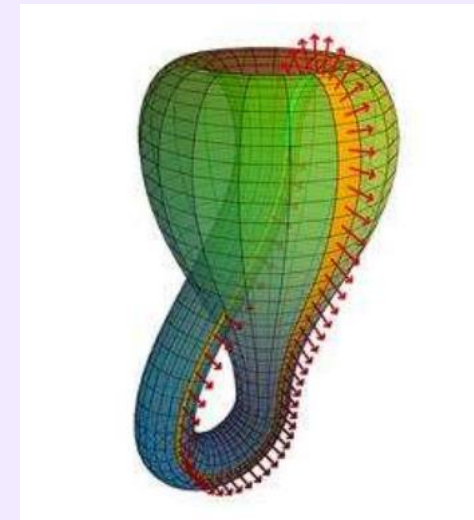
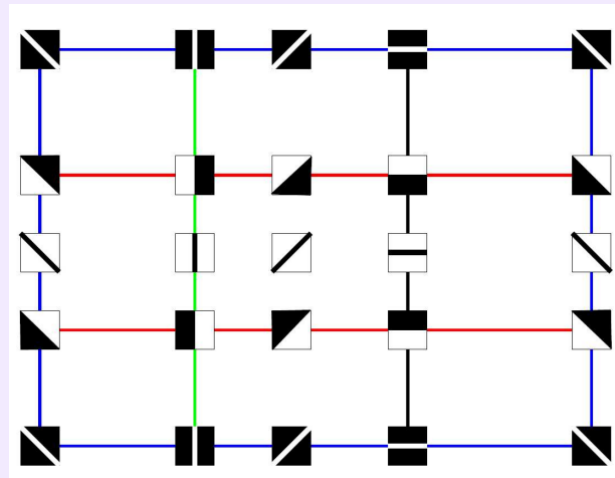
Discrete filtration $f * g$.

Due to a well-known result in persistence theory, these two filtrations, which agree on the vertex set, produce identical persistence diagrams.

$PHT(\iota_f(R))$ evaluated at \vec{g} . $=$ Convolutional persistence for filter g .

Using the embedding ι_f , convolutional persistence can be viewed as a special case of the PHT, and so inherits its injectivity properties. This can easily be generalized to high-dimensional images with multiple channels.

Important Observation: No extra information is gained by using filters that are orthogonal to the patches found in the images. In natural images, the space of patches has large codimension, significantly reducing the number of filters needed.



Convolutional Persistence Pipeline

- **Given:** collection of images.
- **Pick:** family of n filters \mathcal{G} . **Which filters?**
- For each image, **convolve** with \mathcal{G} to get n new images, and then **compute persistence**, obtaining n persistence diagrams.
- **Vectorize** the collection of diagrams. **How to vectorize?**
- Use vectors in Machine Learning **model**. **Which model?**

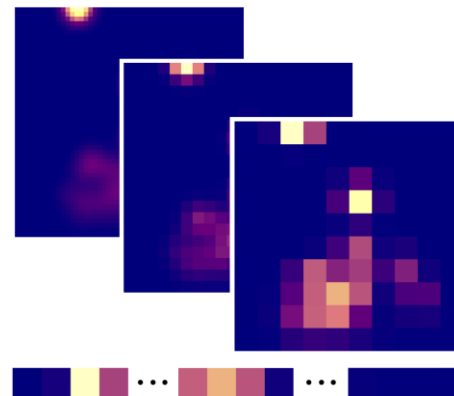
Pipeline Parameters

Filters

1. [1] – trivial filter.
2. Standard image processing filters.
3. Eigenfilters: Apply PCA to space of image patches and take random linear combinations of top eigenvectors.
4. Random filters.

Vectorizations

1. Persistence Images.
2. Total persistence.
 - A. Concatenating vectors
 - B. Averaging vectors



<https://www.math.colostate.edu/~adams/research/>

Models

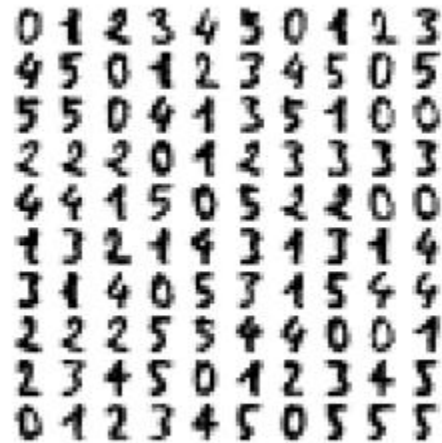
1. k-NN.
2. Boosted Tree.
3. Neural Network.

No feature engineering,
dimensionality reduction,
model tuning, etc.

Classification Tasks

UCI digits

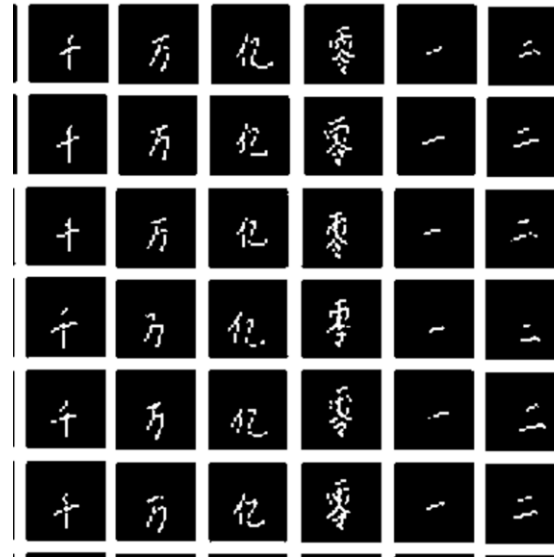
A selection from the 64-dimensional digits dataset



MNIST



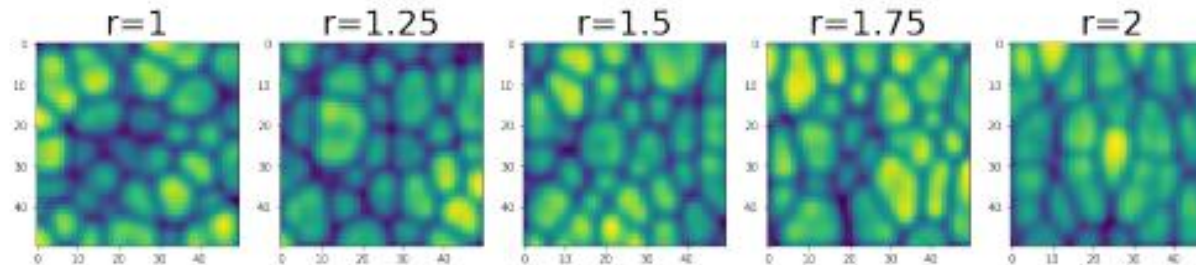
Chinese Digits



Devanagari
"MNIST"



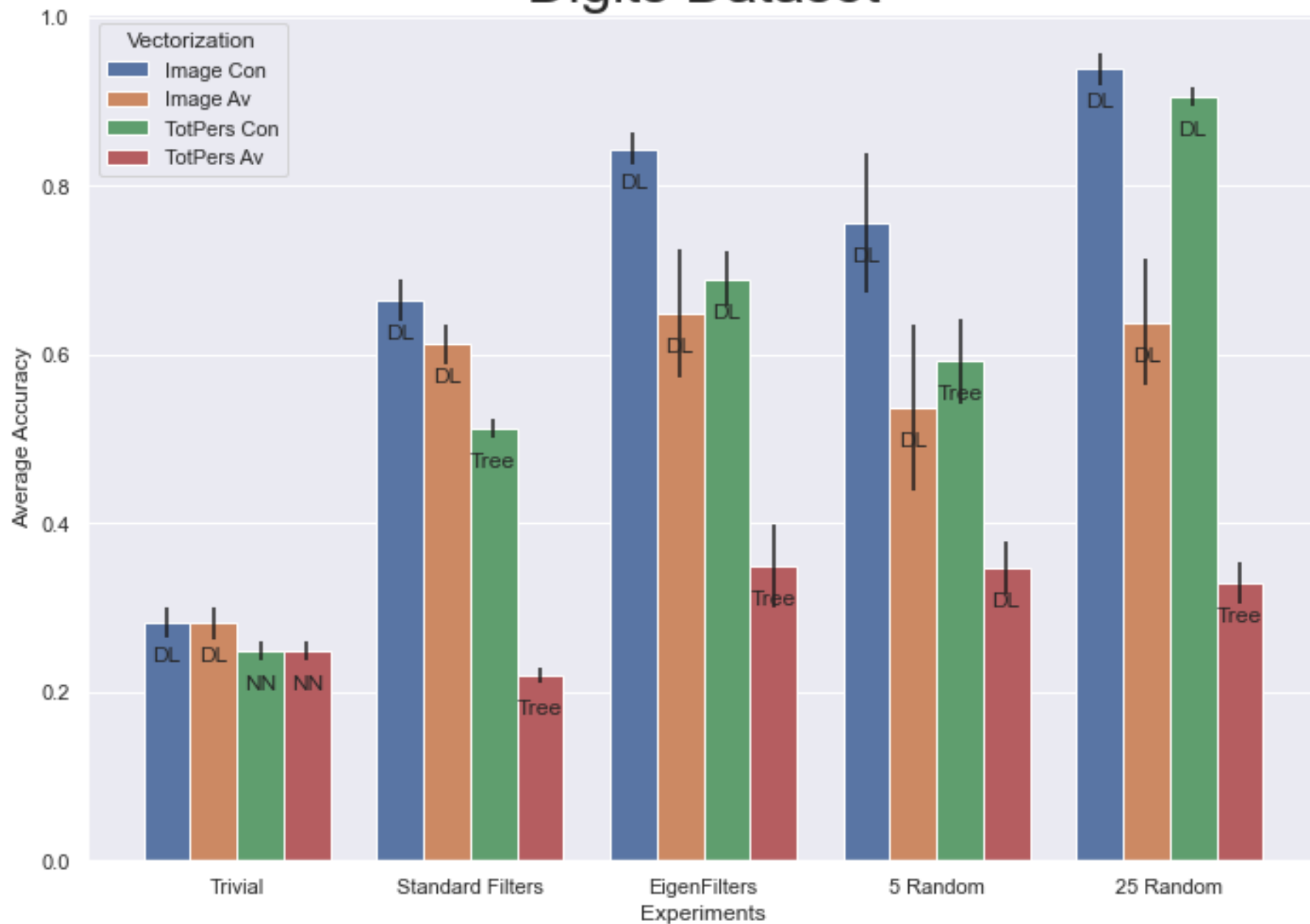
Kuramoto Sivanshinsky Examples



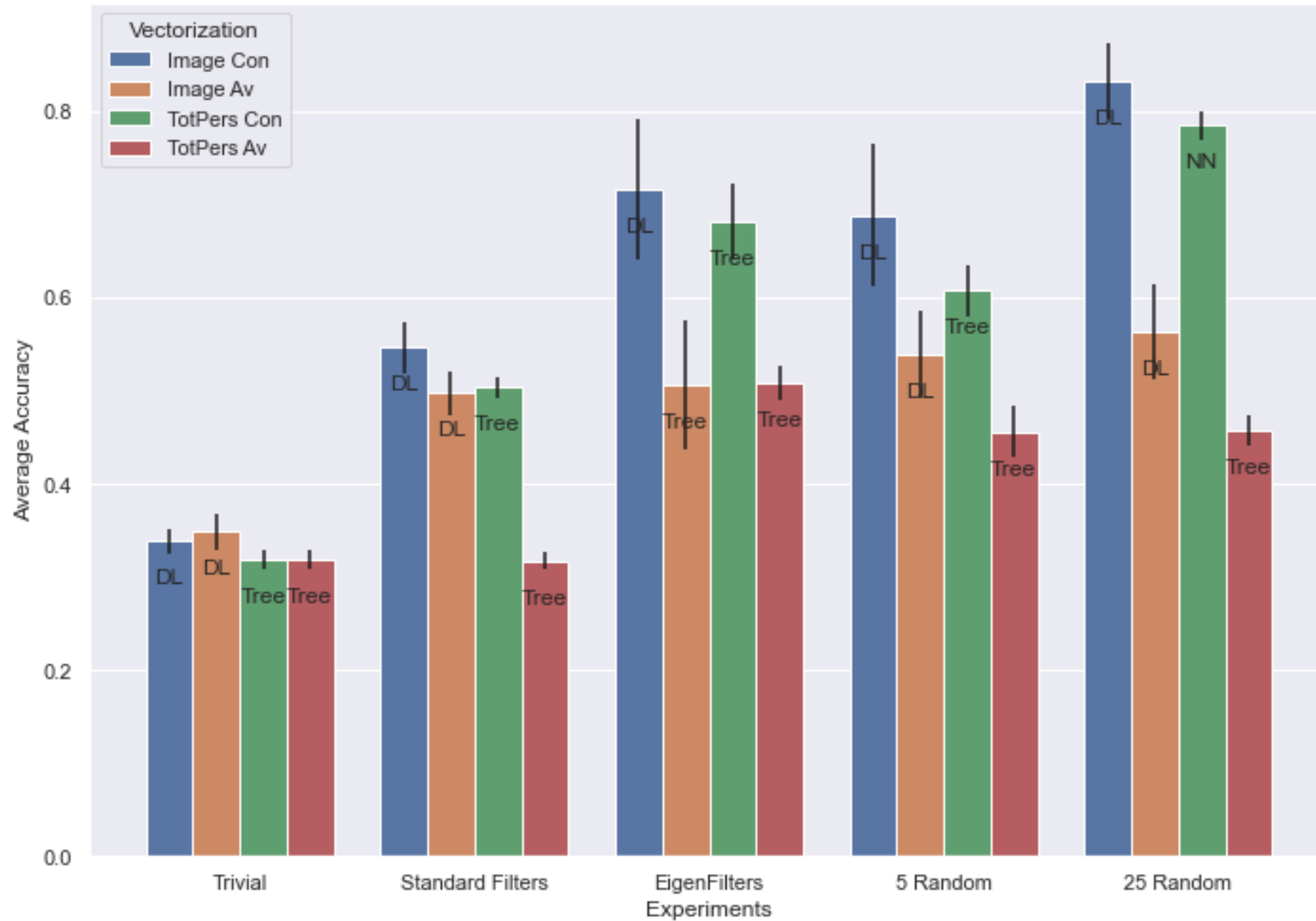
$$u_t = -\nabla^2 u - \nabla^2 \nabla^2 u + r(u_x)^2 + (u_y)^2$$

<https://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digits>
<http://yann.lecun.com/exdb/mnist/>
<https://www.kaggle.com/datasets/gpreda/chinese-mnist>
<https://www.kaggle.com/datasets/anurags397/hindi-mnist-data>

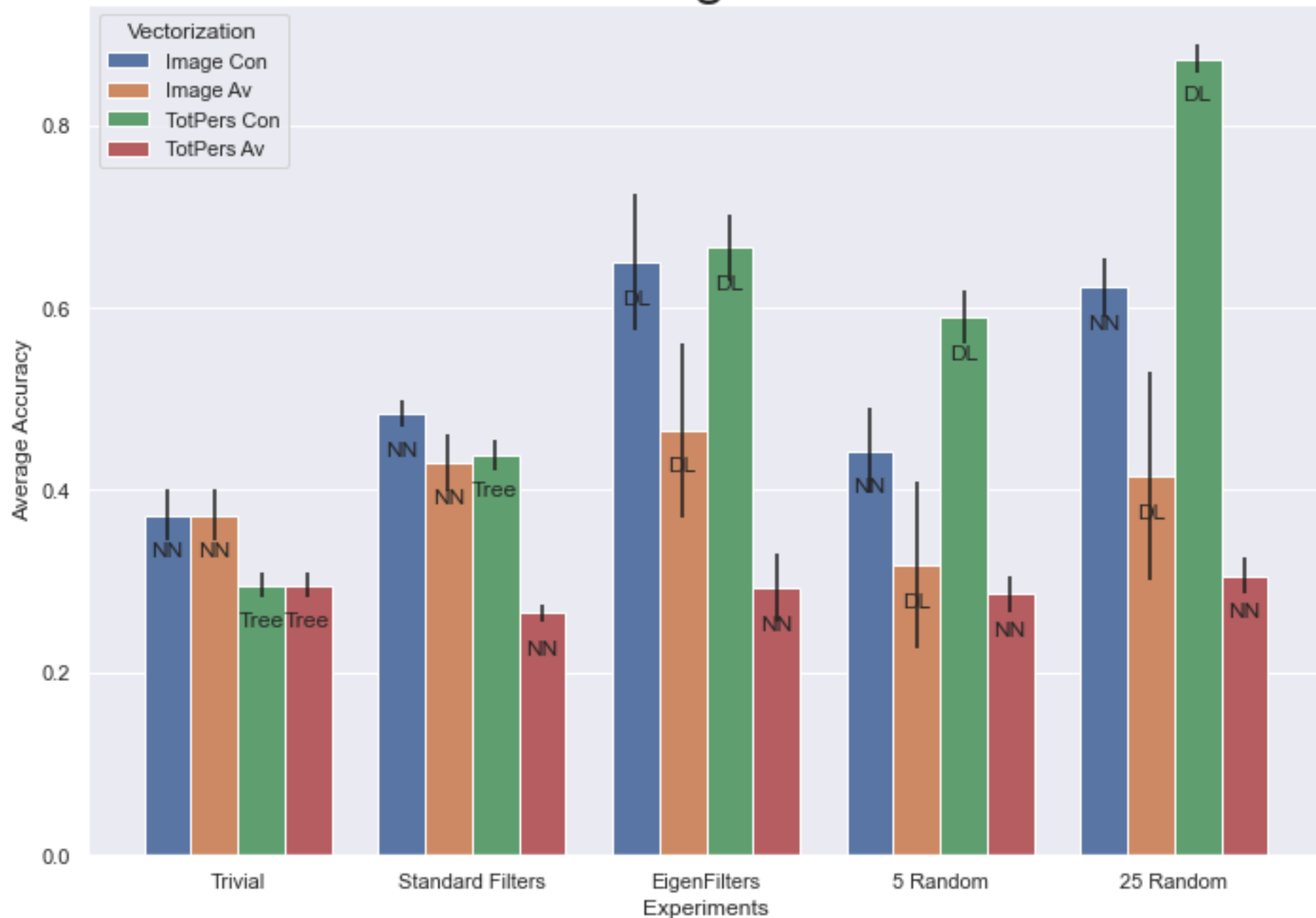
Digits Dataset



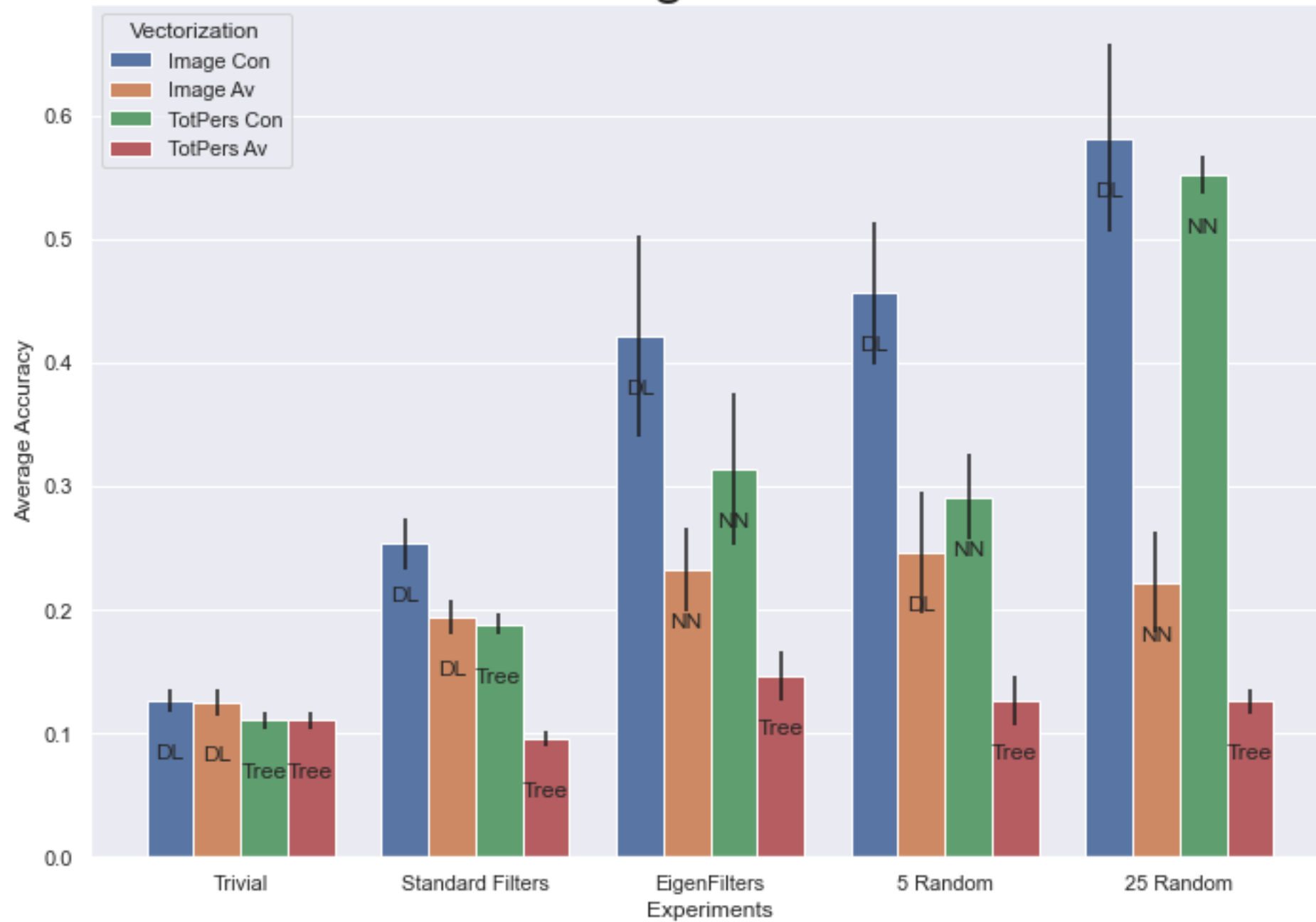
MNIST Dataset



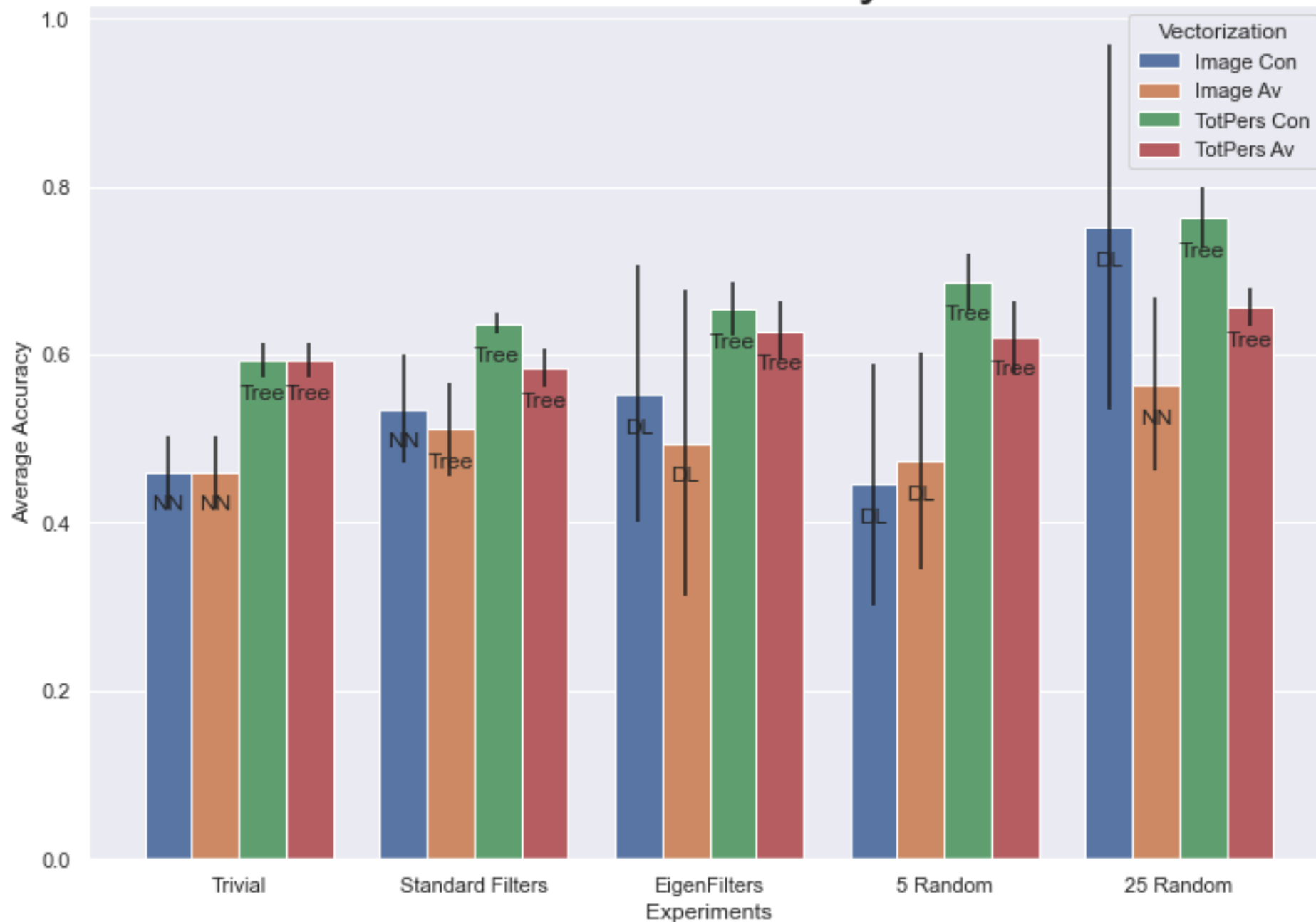
Chinese Digits Dataset



Devanagari Dataset



Kuramoto Sivashinsky Dataset



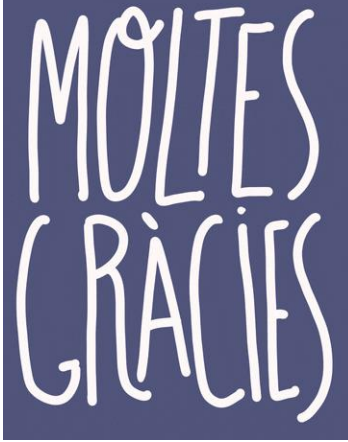
Observations

- Convolution persistence significantly **outperforms** ordinary image persistence. Concatenating vectors and using deep learning seems to give the best accuracy.
- Eigenfilters are best, but **random filters** also **work really well**.

Why?

- **Total persistence** is a very **effective** vectorization.

Why??



More questions...

- How does the filter size affect the results above?
- What happens if you use other vectorizations: Euler curves, persistence landscapes, etc. or allow learnable vectorizations?
- Can you get better accuracy scores by incorporating feature engineering and model tuning?
- Can you learn optimal filters using the training data?
- Run these experiments on more complex, higher-dimensional, or multi-channel data where topology is already known to be useful.
- There are many technical results and open questions surrounding the PHT. Can these be improved/answered for convolutional persistence?

<https://arxiv.org/abs/2208.02107>

<https://github.com/yesolomon/convpers>