



PersLay: A Neural Network Layer for Persistence Diagrams and New Graph Topological Signatures

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- 1.Introduction + Related Work**
 - 2.Paper Contributions**
 - 3.Network and Training**
 - 4.Results**
 - 5.Discussion**

1. Introduction

Context: persistence diagrams are one of the main topological features, but they are difficult to use in machine learning pipeline due to the lack of structure of the space.

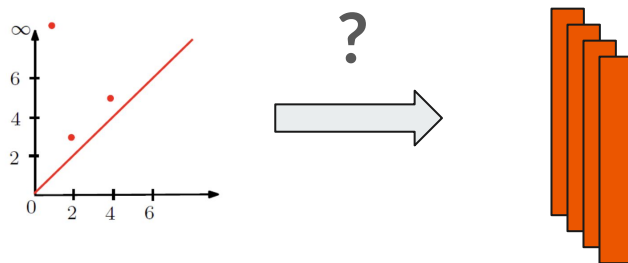
→ Solution: **vectorization** of the persistence diagrams

Related works:

- Real-valued functions on graphs
- Already existing vectorisation
- Deep Sets network [Zaheer, M., Kottur, S., Ravanbakhsh, S., Póczos, B., Salakhutdinov, R., & Smola, A.. *Deep sets.*]

Current limitations:

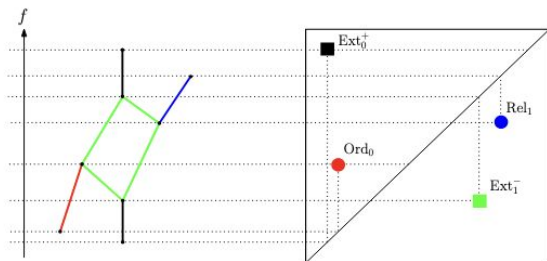
- Few trainable parameters
- Hard to know choose vectorisation for a specific task
- Kernel methods are not optimized in terms of computation times



1. Introduction

Solution proposed by the paper:

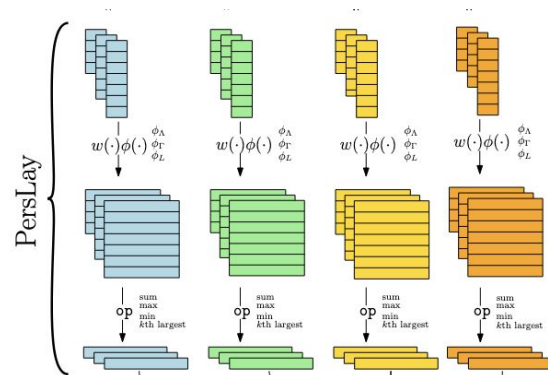
→ A framework to learn the vectorisation adapted to the task generalizing some of the vectorisation already existing.



Extended persistence diagrams

$$hks_{G,t} : \nu \mapsto \sum_{k=1}^n \exp(-t\lambda_k) \psi_k(\nu)^2$$

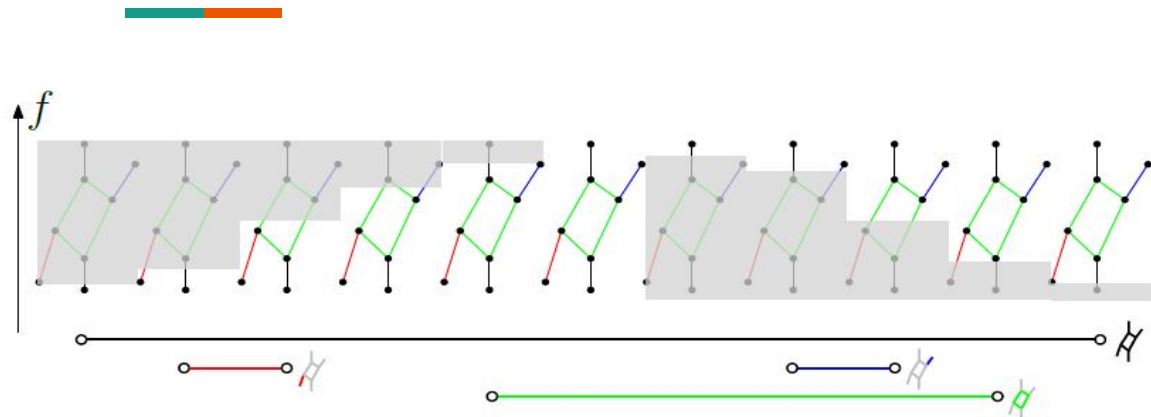
Heat kernel signatures



PersLay: a new neural network layer

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2. Extended persistence diagram



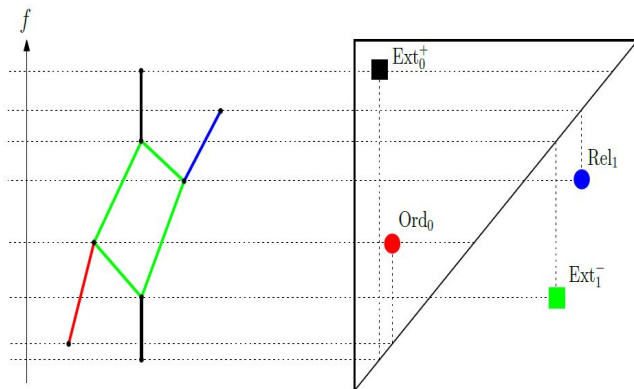
Filtration with up and sub levels

Up level :

$$[G = (V, E)][G_\alpha = (V_\alpha, E_\alpha)][V_\alpha = \{v \in V : f(v) \leq \alpha\}][E_\alpha = \{(v_1, v_2) \in E : v_1, v_2 \in V_\alpha\}]$$

Sub level :

$$[X = (V, E)][X^\alpha = \{x \in X : f(x) \geq \alpha\}][E^\alpha = \{(x_1, x_2) \in E : x_1, x_2 \in X^\alpha\}]$$



Ext_0^+ : Connected component

Ext_1^- : Loop

Ord_0 : Downward branch

Rel_1 : Upward branch

Legend with symbols

2. Heat Kernel Signatures on graphs

$$L_\omega = I - A^{-1/2}DA^{-1/2}$$

$$hks_{G,t} : \nu \mapsto \sum_{k=1}^n \exp(-t\lambda_k) \psi_k(\nu)^2$$

 λ_k

Eigenvalues of the graph Laplacian

 ψ_k

Eigenfunctions of the graph Laplacian

 t

Diffusion parameter

Property :


- Stability w.r.t graph perturbation

$$d_B(Dg(G, t), Dg(G', t)) \leq C(G, t) \|W\|_F$$

- Stability w.r.t parameter t

$$d_B(Dg(G, t), Dg(G, t')) \leq 2|t - t'|$$

2. PersLay


$$\text{PERSLAY}(\text{Dg}) := \text{op}(\{w(p) \cdot \phi(p)\}_{p \in \text{Dg}})$$

any permutation invariant
operation (sum, min...)

weight function
(learnable)

point transformation
function

Point transformation function:

Pour p un point du diagramme:

- Triangle point transformation: $\Lambda_p : t \rightarrow \max\{0, y - |t - x|\}$
- Gaussian point transformation: $\Gamma_p : t \rightarrow \exp(-\|p - t\|_2^2 / (2\sigma^2))$
- Line point transformation: $\mathbf{L}_\Delta : p \rightarrow \langle p, e_\Delta \rangle + b_\Delta$

Example with a triangle point transformation:

$$\phi : \mathbb{R}^2 \rightarrow \mathbb{R}^q$$

$$p \rightarrow \begin{matrix} \Lambda_p(t_1) \\ \Lambda_p(t_2) \\ \vdots \\ \Lambda_p(t_q) \end{matrix}$$

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3. Network

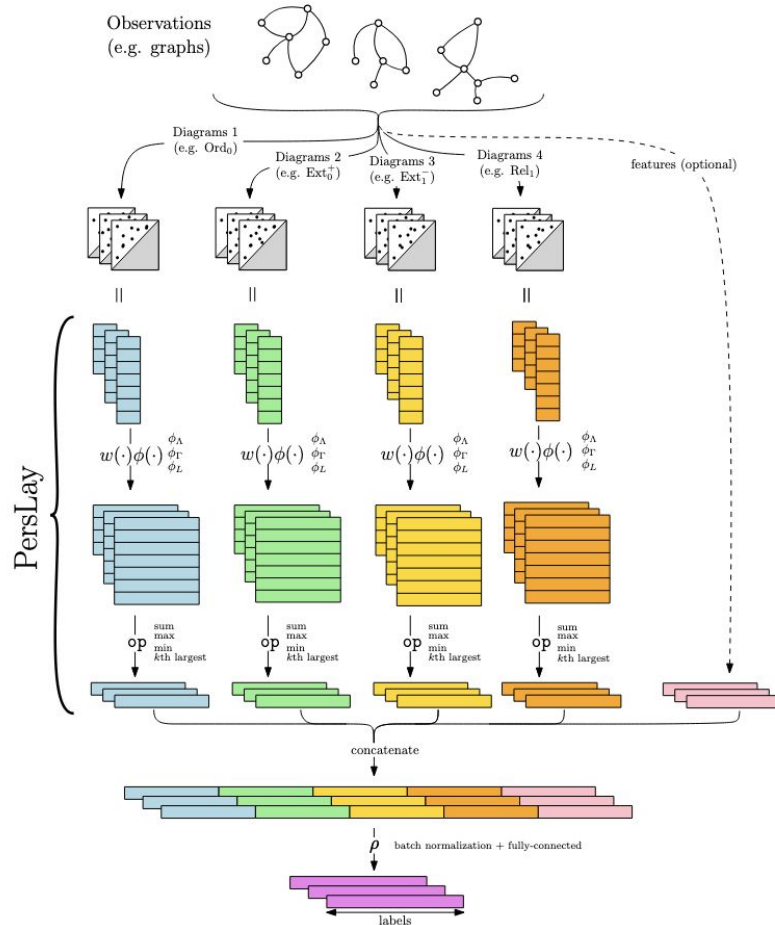
Network:

- 2 layers (PersLay + Fully connected layer)

Hyperparameters set-up:

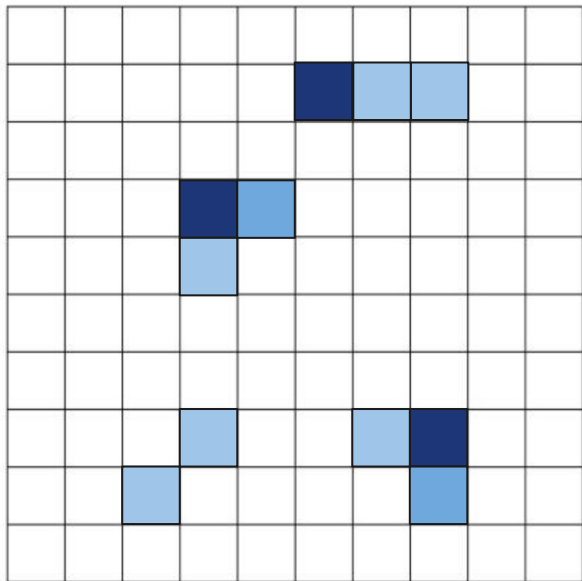
PersLay layer:

- op is the sum
- phi is the sum of the point transformation function



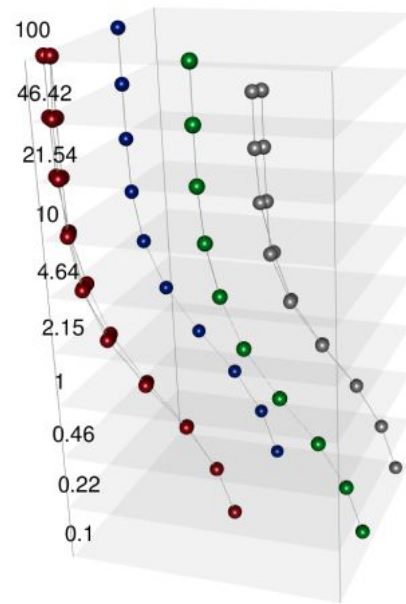
3. Choice of hyperparameters

How to set ω ?



Can we optimize t ?

The choice of t does not affect classification performance



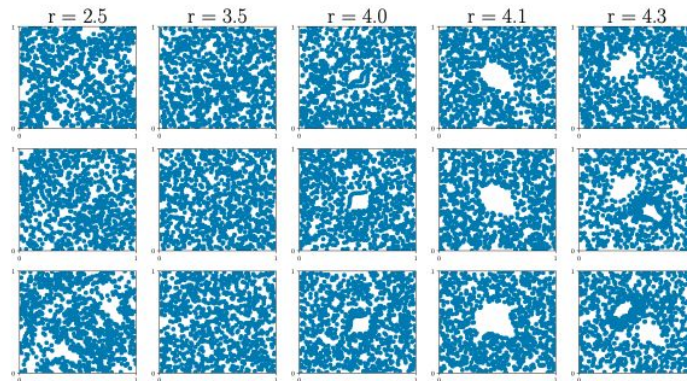
Evolution of $t \mapsto Dg(G, t)$ for one graph from the MUTAD dataset

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4. A proof of concept: Perslay results with AlphaComplex filtration

- **ORBIT5K** : Improve results compared to state-of-the-art method
- **ORBIT100K** : Capable of handling large-scale datasets where kernel method fail

Orbits generated by different choice of r :



Dataset	PSS-K	PWG-K	SW-K	PF-K	PERSLAY
ORBIT5K	72.38(± 2.4)	76.63(± 0.7)	83.6(± 0.9)	85.9(± 0.8)	87.7(± 1.0)
ORBIT100K	—	—	—	—	89.2(± 0.3)

4. Results

Ablation studies :

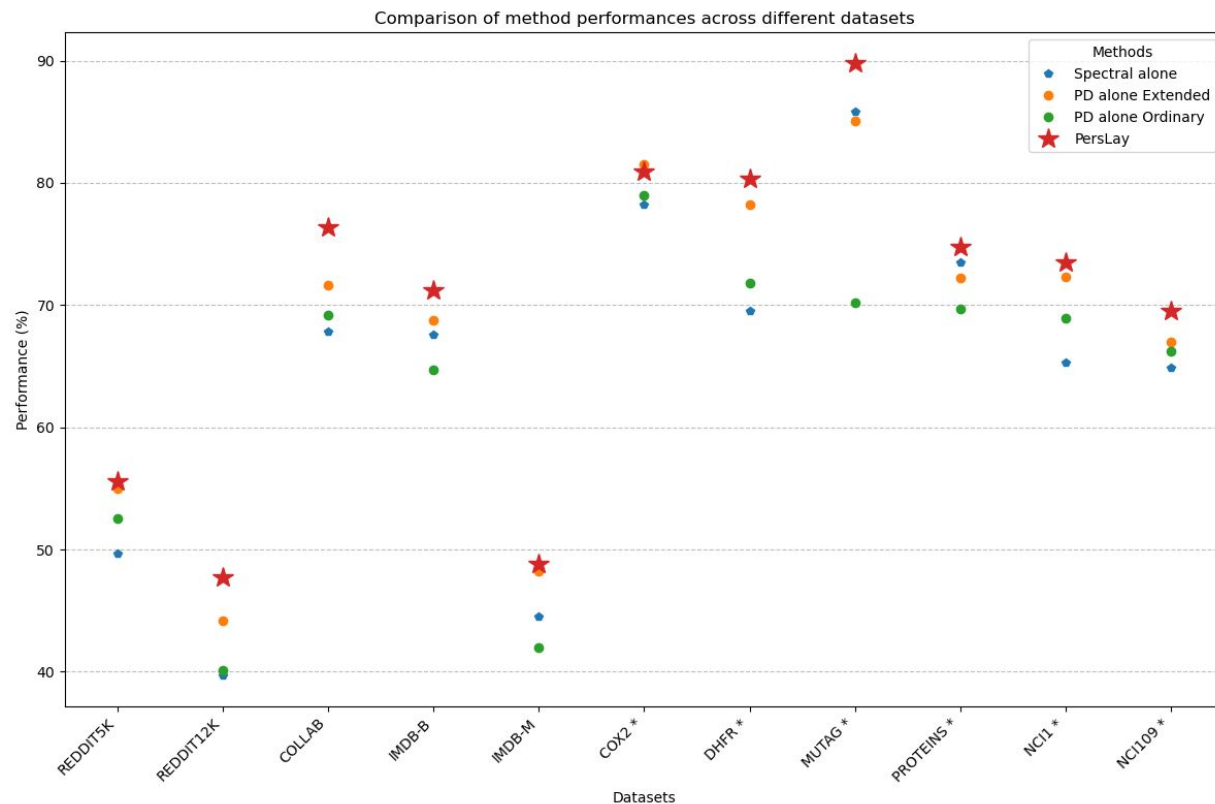
- Choice of the grid size is not a key parameter however too large grid size lead to overfitting
- The best choice of point transformation differs from one dataset to another.
- The sum permutation operator give better results

		Grid size for trainable weights $w(p)$					
		None	2×2	5×5	10×10	20×20	50×50
MUTAG	Train/Test acc (%)	92.3/88.9	91.1/88.8	91.7/89.6	92.3/ 89.9	93.7/88.3	94.1/87.7
COLLAB	Train/Test acc (%)	76.5/75.3	78.6/75.8	79.0/76.2	80.0/ 76.5	83.5/73.9	94.0/71.3

		Point transformation ϕ			Perm op	
		Gaussian	line	triangle	Sum	Max
MUTAG	Train/Test acc (%)	92.5/ 89.7	89.2/84.2	91.5/85.0	92.3/ 89.5	91.9/87.4
COLLAB	Train/Test acc (%)	79.7/75.3	79.9/ 76.1	79.4/74.7	80.0/ 76.4	78.8/75.0

4. Results

Ablation studies :



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5. Discussion



Conclusion :

- Great improvement to add the graph topology for classification
- Important value added with the extended diagram to capture loops geometry
- Vectorization with reduction of the computational cost

To go further:

- The paper focuses on graph only, an extension can be the utilisation of PersLay to other applications.

MERCI

6. Our implementation



Appendice :



The adjacency matrix A of a graph G with vertex set : $V = \{v_1, v_2, \dots, v_n\}$

$$A := (\mathbf{1}_{(v_i, v_j) \in E})_{i,j}$$

Degree matrix :
$$D_{i,j} = \sum_j A_{i,j}$$

Results - comparing to top five graphs

Dataset	SV ¹	RetGK* ²	FGSD ³	GCNN ⁴	GIN ⁵	PERSLAY	
						Mean	Max
REDDIT5K	—	56.1	47.8	52.9	57.0	55.6	56.5
REDDIT12K	—	48.7	—	46.6	—	47.7	49.1
COLLAB	—	81.0	80.0	79.6	80.1	76.4	78.0
IMDB-B	72.9	71.9	73.6	73.1	74.3	71.2	72.6
IMDB-M	50.3	47.7	52.4	50.3	52.1	48.8	52.2
COX2*	78.4	80.1	—	—	—	80.9	81.6
DHFR*	78.4	81.5	—	—	—	80.3	80.9
MUTAG*	88.3	90.3	92.1	86.7	89.0	89.8	91.5
PROTEINS*	72.6	75.8	73.4	76.3	75.9	74.8	75.9
NCI1*	71.6	84.5	79.8	78.4	82.7	73.5	74.0
NCI109*	70.5	—	78.8	—	—	69.5	70.1

Learning the weights

