# Quiver Representations, Quiver Varieties and Combinatorics Bologna, May 2023 

## Quiver Representations in Topological Data Analysis (TDA)

## Steve Oudot

## References

- 1-parameter persistence theory:
O. (2015): Persistence Theory: from Quiver Representations to Data Analysis.
- Multi-parameter persistence theory:

Botnan, Lesnick (2022): An Introduction to Multi-Parameter Persistence.

- Algorithmic aspects:

Dey, Wang (2022): Computational Topology for Data Analysis.

- Statistical aspects:

Chazal, Michel (2021): An Introduction to Topological Data Analysis.

- Connection to Machine Learning:

Hensel, Moor, Rieck (2021): A Survey of Topological Machine Learning Methods.

- Software: Gudhi, PHAT, Ripser, Eirene, Persistable, ...


## Data featurization



## Data

## Features



| bag of words, word2vec |
| :--- |
| shape contexts, heat kernels |
| node2vec, Laplacian fact., rand. walks |
| dim. reduction, auto-encoders, etc. |

## Topological Data Analysis pipeline


data

invariant (barcode)

features (vectors)


## Example of application: shape segmentation

Goal: segment 3d shapes based on examples
Approach:

- train a predictor on barcodes extracted from the training shapes
- apply the predictor to barcodes extracted from the query shape

[Carrière, O., Ovsjanikov]


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Error rates (\%):

|  | TDA features | geom $/$ stat features | TDA + geom $/$ stat features |
| :--- | :---: | :---: | :---: |
| Human | 26.0 | 21.3 | $\mathbf{1 1 . 3}$ |
| Airplane | 27.4 | 18.7 | $\mathbf{9 . 3}$ |
| Ant | 7.7 | 9.7 | $\mathbf{1 . 5}$ |
| FourLeg | 27.0 | 25.6 | $\mathbf{1 5 . 8}$ |
| Octopus | 14.8 | 5.5 | $\mathbf{3 . 4}$ |
| Bird | 28.0 | 24.8 | $\mathbf{1 3 . 5}$ |
| Fish | 20.4 | 20.9 | $\mathbf{7 . 7}$ |

[Carrière, O., Ovsjanikov]

## Topological Data Analysis pipeline (again)



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## Topological Data Analysis pipeline (again)



## Filtrations

$(P, \leq)$ a poset (usually $\left(\mathbb{Z}^{d}, \leq_{\Pi}\right)$ or $\left.\left(\mathbb{R}^{d}, \leq_{\Pi}\right)\right)$
Filtration: functor $(P, \leq) \rightarrow$ Top

- typically, $F(t):=f^{-1}((-\infty, t])$ for some $P$-valued function $f$
- $F(t) \subseteq F(u)$ forall $t \leq u \in P$


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Example: offsets filtration of $X \subseteq \mathbb{R}^{n}$ :

$$
\begin{aligned}
f: & \left.\begin{array}{l}
\mathbb{R}^{n} \rightarrow P=\mathbb{R} \\
y
\end{array} \right\rvert\, \min _{x \in X}\|y-x\|_{2} \\
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- typically, $F(t):=f^{-1}((-\infty, t])$ for some $P$-valued function $f$
- $F(t) \subseteq F(u)$ forall $t \leq u \in P$
- for computational purposes, take $F: P \rightarrow$ Simp

Example: Vietoris-Rips filtration of $X \subseteq \mathbb{R}^{n}$ :

$$
f: \left\lvert\, \begin{aligned}
& 2^{X} \rightarrow P=\mathbb{R} \\
& \left\{x_{0}, \cdots, x_{k}\right\} \mapsto \max _{0 \leq i<j \leq k}\left\|x_{i}-x_{j}\right\|_{2}
\end{aligned}\right.
$$

$F(t)=$ flag complex of intersection graph

$$
\text { of } \bigcup_{x \in X} B(x, t / 2)
$$



## Other examples (any combination of the following)


density estimators

others:

- non-linear projections
- curvature measures
- PDE solutions (heat, wave)
- etc.

projections


## Topological Data Analysis pipeline (again)



## Persistence modules

$(P, \leq)$ a poset (usually $\left(\mathbb{Z}^{d}, \leq_{\Pi}\right)$ or $\left.\left(\mathbb{R}^{d}, \leq_{\Pi}\right)\right), \boldsymbol{k}$ a field
Persistence module: functor $(P, \leq) \rightarrow$ vect $_{k}$ (pointwise finite-dimensional, or pfd)

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Persistence module: functor $(P, \leq) \rightarrow$ vect $_{k}$ (pointwise finite-dimensional, or pfd)
Interval: $I \subseteq P$ that is:

$$
\begin{aligned}
& \text { - convex }(s, t \in I \Longrightarrow u \in I \forall s \leq u \leq t) \\
& \text { - connected }\left(s, t \in I \Longrightarrow \exists\left\{u_{i}\right\}_{i=0}^{r} \subseteq I \text { s.t. } s=u_{0} \leq u_{1} \geq \cdots \geq u_{r}=t\right)
\end{aligned}
$$

Interval module: indicator module $\boldsymbol{k}_{I}$ of an interval $I \subseteq P$

$$
\begin{aligned}
& \boldsymbol{k}_{I}(t)=\left\{\begin{array}{l}
\boldsymbol{k} \text { if } t \in I \\
0 \text { otherwise }
\end{array}\right. \\
& \boldsymbol{k}_{I}(s \leq t)=\left\{\begin{array}{l}
\operatorname{id}_{\boldsymbol{k}} \text { if } s, t \in I \\
0 \text { otherwise }
\end{array}\right.
\end{aligned}
$$

note: $\operatorname{End}\left(\boldsymbol{k}_{I}\right) \simeq \boldsymbol{k}$


## Persistence modules

Interval modules are described by their support:

- complete geometric descriptor
- efficient to encode (small / simple dictionary)
- readily interpretable (for data exploration)
- easy to vectorize (for Machine Learning)
- enjoy stability properties (for statistics)

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$\operatorname{note}: \operatorname{End}\left(\boldsymbol{k}_{I}\right) \simeq \boldsymbol{k}$


## 1-parameter persistence modules

discrete setting: $M: \llbracket 1, n \rrbracket \rightarrow$ vect $_{k}$



$$
k \xrightarrow{\left[\begin{array}{l}
1 \\
0
\end{array}\right]} k^{2} \xrightarrow{[01]} k \xrightarrow{\left[\begin{array}{l}
0 \\
1
\end{array}\right]} k^{2}
$$

continuous setting: $M: \mathbb{R} \rightarrow$ vect $_{\boldsymbol{k}}$


Thm [Gabriel][Auslander][Ringel][Webb][Crawley-Boevey]
For any $P \subseteq \mathbb{R}$ and any $M:(P, \leq) \rightarrow \operatorname{vect}_{\boldsymbol{k}}$ :

$$
M \simeq \bigoplus_{j \in J} \boldsymbol{k}_{I_{j}}
$$

where each $\operatorname{End}\left(\boldsymbol{k}_{I_{j}}\right)$ is local


Bar $M$

## Metric viewpoint: interleaving distance

Given $M, N:(\mathbb{R}, \leq) \rightarrow \operatorname{vect}_{k}$,

- morphism: natural transformation $M \Rightarrow N$
- isomorphism: pair of morphisms $M \stackrel{\phi}{\Rightarrow} N$ and $N \stackrel{\psi}{\Rightarrow} M$ such that:


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- $\varepsilon$-isomorphism: pair of morphisms $M \stackrel{\phi}{\Rightarrow} N[\varepsilon]$ and $N \stackrel{\psi}{\Rightarrow} M[\varepsilon]$ such that:

where $M[\varepsilon](t):=M(t+\varepsilon)$ and $\phi[\varepsilon](t):=\phi(t+\varepsilon)$
- interleaving distance: $\mathrm{d}_{i}(M, N):=\inf \{\varepsilon \mid M, N \varepsilon$-isomorphic $\}$


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- $\varepsilon$-isomorphism: pair of morphisms $M \xlongequal{\phi} N[\varepsilon]$ and $N \stackrel{\psi}{\Rightarrow} M[\varepsilon]$ such that:


$$
\begin{aligned}
& \text { Prop: } \forall f, g: X \rightarrow \mathbb{R} \\
& \qquad \mathrm{~d}_{i}(H F, H G) \leq\|f-g\|_{\infty}
\end{aligned}
$$

Thm: [Lesnick]
d stable as above $\Rightarrow \mathrm{d} \leq \mathrm{d}_{i}$
where $M[\varepsilon](t):=M(t+\varepsilon)$ and $\phi[\varepsilon](t):=\phi(t+\varepsilon)$

- interleaving distance: $\mathrm{d}_{i}(M, N):=\inf \{\varepsilon \mid M, N \varepsilon$-isomorphic $\}$


## Metric viewpoint: bottleneck distance

Given $M=\bigoplus_{a \in A} M_{a}, N=\bigoplus_{b \in B} N_{b}:(\mathbb{R}, \leq) \rightarrow \operatorname{vect}_{k}$,

- morphism: natural transformation $M \Rightarrow N$
- isomorphism: pair of morphisms $M \stackrel{\phi}{\Rightarrow} N$ and $N \stackrel{\psi}{\Rightarrow} M$ such that:

$$
\underset{\psi}{M} \underset{N}{M}
$$ bottleneck

- $\varepsilon$-isomorphism: pair of morphisms $M \stackrel{\phi}{\Rightarrow} N[\varepsilon]$ and $N \stackrel{\psi}{\Rightarrow} M[\varepsilon]$ such that:

where $M[\varepsilon](t):=M(t+\varepsilon)$ and $\phi[\varepsilon](t):=\phi(t+\varepsilon)$


## bottleneck

- bottleneck distance: $\mathrm{d}_{\mathrm{b}}(M, N):=\inf \{\varepsilon \mid M, N \varepsilon$-isomorphic $\}$


## Metric viewpoint: isometry

Given $M=\bigoplus_{a \in A} M_{a}, N=\bigoplus_{b \in B} N_{b}:(\mathbb{R}, \leq) \rightarrow \operatorname{vect}_{k}$,

- morphism: natural transformation $M \Rightarrow N$
- isomorphism: pair of morphisms $M \stackrel{\phi}{\Rightarrow} N$ and $N \stackrel{\psi}{\Rightarrow} M$ such that: bottleneck

$$
{\underset{N}{*}}_{\substack{M \\ \nu}}
$$

- $\varepsilon$-isomorphism: pair of morphisms $M \stackrel{\phi}{\Rightarrow} N[\varepsilon]$ and $N \stackrel{\psi}{\Rightarrow} M[\varepsilon]$ such that:

and $\phi, \psi$ factor through the decompositions of $M$ and $N$

Thy: $\mathrm{d}_{i}=\mathrm{d}_{\mathrm{b}}$
where $M[\varepsilon](t):=M(t+\varepsilon)$ and $\phi[\varepsilon](t):=\phi(t+\varepsilon)$

> bottleneck

- bottleneck distance: $\mathrm{d}_{\mathrm{b}}(M, N):=\inf \{\varepsilon \mid M, N \varepsilon$-isomorphic $\}$


## Wrap-up on 1-parameter persistence modules

Structure theorems

- complete classification of pfd persistence modules via their barcodes
- efficient algorithms for barcode computation


## Isometry theorem

- barcodes as complete metric invariants for persistence modules
$\rightarrow$ combinatorial algorithms for distance computation
- space of barcodes as a space of measures
$\rightarrow$ bounds on intrinsic curvature
$\rightarrow$ toolbox for statistics
$\rightarrow$ vectorizations and kernels for ML


## Multi-parameter persistence... what for?

- study joint variables (e.g. treatment efficacy vs. risk)
- increase feature sensitivity (by enhanced feature aggregation)

Thm: [Boyer, Curry, Mukherjee, Turner] [Ghrist, Levanger, Mai]
The map $X \mapsto\left\{\left.\operatorname{Bar}\langle\cdot, w\rangle\right|_{X}\right\}_{w \in \mathbb{S}^{n-1}}$ is injective on the class of compact subanalytic sets $X \subset \mathbb{R}^{n}$.

Q: can we reduce to finitely many directions using multi-parameter persistence?


## Multi-parameter persistence modules

discrete setting: $M: \llbracket 1, n \rrbracket^{d} \rightarrow$ vect $_{k}$

continuous setting: $M: \mathbb{R}^{d} \rightarrow \operatorname{vect}_{\boldsymbol{k}}$


Thm [Botnan, Crawley-Boevey]
For any poset $(P, \leq)$ and functor $M:(P, \leq) \rightarrow \operatorname{vect}_{\boldsymbol{k}}$ :

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wild-type

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Q: do non-thin indecomposables show up in applications?

non-thin summands

wild-type

## Example: two-parameter clustering

|  |  |  | * | 7th | \% | \% | - |  | - |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 碞 | ${ }^{3}$ |  | \% | 嗗 | \% | \% | 5 | 1 | - | 0 |  |
| 2- | *- |  |  | \% | * | \% | 5 | 1 | - | 1 |  |
| 8 | $\geqslant$ |  | * | 3 | 3 | 3 | 8 | 8 | - | - |  |
| \% | 2- |  | $\cdots$ | \%- | \%- | \% | 2 |  | - | 0 |  |
| 8 | $\cdots$ |  | - | \% | \% | \% |  |  | $\bigcirc$ | - |  |
|  | :- |  | :- | :- | :- | :- |  |  | 8 | 8 |  |
|  | : |  |  | E8 | :- | :- | :- | - | - 0 |  | 80 |
|  | : |  | : | : | : | :- | :- | - | :- | :- |  |
|  |  |  |  |  | : |  | : |  | : | - |  |

distance to data

## Example: two-parameter clustering


distance to data

## Example: two-parameter clustering



## Example: two-parameter clustering



Thm: [Bauer, Botnan, Oppermann, Steen]

$$
\frac{\operatorname{Fun}^{e, *}\left(\llbracket 1, n \rrbracket \times \llbracket 1, m \rrbracket, \operatorname{vect}_{\boldsymbol{k}}\right)}{\operatorname{Fun}^{e, m}\left(\llbracket 1, n \rrbracket \times \llbracket 1, m \rrbracket, \operatorname{vect}_{\boldsymbol{k}}\right)} \simeq \operatorname{Fun}\left(\llbracket 1, n \rrbracket \times \llbracket 1, m-1 \rrbracket, \operatorname{vect}_{\boldsymbol{k}}\right)
$$

## Example: two-parameter clustering



Thm: [Bauer, Botnan, Oppermann, Steen]

$$
\begin{gathered}
\text { Fun }^{e, *}\left(\llbracket 1, n \rrbracket \times \llbracket 1, m \rrbracket, \operatorname{vect}_{\boldsymbol{k}}\right) \\
\hline \operatorname{Fun}^{e, m}\left(\llbracket 1, n \rrbracket \times \llbracket 1, m \rrbracket, \operatorname{vect}_{\boldsymbol{k}}\right) \\
\simeq \operatorname{Fun}\left(\llbracket 1, n \rrbracket \times \llbracket 1, m-1 \rrbracket, \text { vect }_{\boldsymbol{k}}\right)
\end{gathered}
$$

## Incomplete invariants

Bottomline: look for incomplete invariants of persistence modules that are:

- as strong as possible ( $\mu$ stronger than $\nu$ if $\mu(M)=\mu(N) \Rightarrow \nu(M)=\nu(N)$ )
- manageable to compute (polynomial time in the input filtration size)
- stable w.r.t. perturbations of the modules in the interleaving distance $\mathrm{d}_{i}$
- interpretable in terms of the module's structure


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## Examples:

- dimension vector / Hilbert function
- rank invariant
- global rank function / generalized rank invariant
- graded Betti numbers
-...


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## The rank invariant of 1-parameter modules

$$
P=\llbracket 1,5 \rrbracket \subseteq(\mathbb{R}, \leq)
$$



$$
M: \boldsymbol{k} \xrightarrow{\binom{1}{0}} \boldsymbol{k}^{2} \xrightarrow{\left(\begin{array}{ll}
0 & 1
\end{array}\right)} \boldsymbol{k} \xrightarrow{\binom{0}{1}} \boldsymbol{k}^{2} \xrightarrow{\left(\begin{array}{ll}
1 & 0 \\
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\end{array}\right)} \boldsymbol{k}^{2}
$$

$\operatorname{Rk} M:(s \leq t) \mapsto \operatorname{rank}\left[M_{s} \rightarrow M_{t}\right]$


## The rank invariant of 1-parameter modules

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$$

$\operatorname{Rk} M=\sum_{I \in \operatorname{Bar} M} \operatorname{Rk} \boldsymbol{k}_{I}=\operatorname{Rk}\left(\bigoplus_{I \in \operatorname{Bar} M} \boldsymbol{k}_{I}\right)$
(rank invariant $\mathbb{N}$-decomposes on interval rank funcions)


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Bar $M$ :
$\operatorname{Rk} M=\sum_{I \in \operatorname{Bar} M} \operatorname{Rk} \boldsymbol{k}_{I}=\operatorname{Rk}\left(\bigoplus_{I \in \operatorname{Bar} M} \boldsymbol{k}_{I}\right)$
(unique decomposition, terms match with summands of $M$ )

$$
M \simeq \bigoplus_{I \in \operatorname{Bar} M} \boldsymbol{k}_{I} \quad(\Rightarrow \text { rank invariant is complete })
$$



## The rank invariant of 1-parameter modules

$$
P=\llbracket 1,5 \rrbracket \subseteq(\mathbb{R}, \leq)
$$


$M: \boldsymbol{k} \xrightarrow{\binom{1}{0}} \boldsymbol{k}^{2} \xrightarrow{\left(\begin{array}{ll}0 & 1\end{array}\right)} \boldsymbol{k} \xrightarrow{\binom{0}{1}} \boldsymbol{k}^{2} \xrightarrow{\left(\begin{array}{ll}1 & 0 \\ 0 & 1\end{array}\right)} \boldsymbol{k}^{2}$
$\operatorname{Rk} M=\sum_{I \in \operatorname{Bar} M} \operatorname{Rk} \boldsymbol{k}_{I}=\operatorname{Rk}\left(\bigoplus_{I \in \operatorname{Bar} M} \boldsymbol{k}_{I}\right)$
$\operatorname{mult}_{\llbracket i, j \rrbracket} \operatorname{Bar} M=\operatorname{Rk} M(i, j)-\operatorname{Rk} M(i-1, j)$

$-\operatorname{Rk} M(i, j+1)+\operatorname{Rk} M(i-1, j+1)$

## The rank invariant of multi-parameter modules

$$
P=\llbracket 1,3 \rrbracket^{2} \subseteq\left(\mathbb{R}^{2}, \leq\right)
$$

$\operatorname{Rk} M:(s \leq t) \mapsto \operatorname{rank}\left[M_{s} \rightarrow M_{t}\right]$

(rank invariant is not complete)

## The rank invariant of multi-parameter modules

$$
P=\llbracket 1,3 \rrbracket^{2} \subseteq\left(\mathbb{R}^{2}, \leq\right)
$$


(rank invariant does not $\mathbb{N}$-decompose on interval rank functions)

## The rank invariant of multi-parameter modules

$P=\llbracket 1,3 \rrbracket^{2} \subseteq\left(\mathbb{R}^{2}, \leq\right)$

(rank invariant $\mathbb{Z}$-decomposes on interval rank functions)

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## Canonical basis for the rank invariant

Hook / Upset: for $s<t \in P \cup\{\infty\}$,

$$
\begin{aligned}
& \langle s, t\langle=\{u \in P \mid s \leq u \nsupseteq t\} \\
& s^{+}=\langle s, \infty\langle
\end{aligned}
$$

$$
\xrightarrow{\mathrm{P}_{\mathrm{P}}}=\mathbb{R}^{2}
$$



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& s^{+}=\langle s, \infty\langle
\end{aligned} \quad \xrightarrow{P}=\mathbb{R}^{2} \quad l
$$



Theorem ([Botnan, Oppermann, O.]):
If $P$ is finite or an upper semi-lattice, then

$$
\left\{\operatorname{Rk} \boldsymbol{k}_{\langle i, j \backslash} \mid i<j \in P \cup\{\infty\}\right\}
$$

generates uniquely

$$
\left\{\operatorname{Rk} M \mid M: P \rightarrow \operatorname{vect}_{\boldsymbol{k}} \text { finitely presentable (fp) }\right\}
$$

via projective resolutions relative to the rank-exact structure $\mathcal{E}_{\mathrm{Rk}}$.

## The rank-exact structure

Let $\mathcal{E}_{\mathrm{Rk}}$ be the collection of short rank-exact sequences of pfd persistence modules:

$$
0 \longrightarrow A \longrightarrow B \longrightarrow C \longrightarrow 0 \quad \text { s.t. } \quad \mathrm{Rk} B=\mathrm{Rk} A+\mathrm{Rk} C
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Proposition: (follows in part from [Auslander, Solberg])

- $\mathcal{E}_{\mathrm{Rk}}$ defines the structure of an exact category on vect ${ }_{\boldsymbol{k}}^{P}$
- the indecomposable projectives relative to $\mathcal{E}_{\mathrm{Rk}}$ are the hook modules
- $P$ finite $\Longrightarrow \mid \mathcal{E}_{\mathrm{Rk}}$ has enough projectives levery $M \in \operatorname{vect}_{\boldsymbol{k}}^{P}$ has a finite projective resolution
- $P$ upper semi-lattice $\Longrightarrow \mid \mathcal{E}_{\mathrm{Rk}}^{\mathrm{fp}}$ has enough projectives every $\mathrm{fp} M \in \operatorname{Vect}_{\boldsymbol{k}}^{P}$ has a finite projective resolution


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$$

$$
[B]=[A]+[C]
$$

## Corollary:

- $P$ finite $\Longrightarrow$ the $\left[\boldsymbol{k}_{\langle i, j<}\right]$ for $i<j \in P \cup\{\infty\}$ generate $K_{0}\left(\mathcal{E}_{\mathrm{Rk}}\right)$
- $P$ upper semi-lattice $\Longrightarrow$ the $\left[\boldsymbol{k}_{\langle i, j<}\right]$ for $i<j \in P \cup\{\infty\}$ generate $K_{0}\left(\mathcal{E}_{\mathrm{Rk}}^{\mathrm{fp}}\right)$

Given a finite rank-exact projective resolution $M_{\bullet}$ of $M$ :

$$
[M]=\sum_{i=0}^{\infty}(-1)^{i}\left[M_{i}\right]
$$

## The rank-exact structure

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- In both cases, the $\left[\boldsymbol{k}_{\langle i, j<}\right]$ actually form a basis, and Rk defines
a monomorphism of abelian groups $K_{0}(\mathcal{E}) \rightarrow \mathbb{Z}^{\operatorname{Seg}(P)}$


## The rank-exact structure



## The rank-exact structure



## The rank-exact structure


identical terms cancel out in minimal rank decomposition


## Application to graph classification

- various classification tasks on molecules and social network graphs
- 5-fold evaluation ( $80 \%$ train, $20 \%$ test)


| Dataset | COX2 | DHFR | IMDB-B | IMDB-M | MUTAG | PROTEINS |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1-d barcode | $76.0(4.1)$ | $70.9(3.1)$ | $54.0(1.9)$ | $36.3(1.1)$ | $79.2(7.7)$ | $65.4(2.7)$ |
| MP-Kernel | $\mathbf{7 9 . 9 ( 1 . 8 )}$ | $\mathbf{8 1 . 7 ( 1 . 9 )}$ | $68.2(1.2)$ | $46.9(2.6)$ | $86.1(5.2)$ | $67.5(3.1)$ |
| MP-Landscapes | $79.0(3.3)$ | $79.5(2.3)$ | $71.2(2.0)$ | $46.2(2.3)$ | $84.0(6.8)$ | $65.8(3.3)$ |
| MP-Images | $77.9(2.7)$ | $80.2(2.2)$ | $71.1(2.1)$ | $46.7(2.7)$ | $85.6(7.3)$ | $67.3(3.5)$ |
| GRIL | $79.8(2.9)$ | $77.6(2.5)$ | $65.2(2.6)$ | NA | $87.8(4.2)$ | $70.9(3.1)$ |
| Rank inv. | $78.2(1.7)$ | $79.9(2.1)$ | $73.0(4.5)$ | $49.1(1.6)$ | $87.2(5.8)$ | $70.2(2.1)$ |
| Rank decomp. | $78.4(0.7)$ | $78.7(1.7)$ | $\mathbf{7 5 . 1 ( 3 . 4 )}$ | $\mathbf{5 1 . 1 ( 1 . 3 )}$ | $\mathbf{8 9 . 9 ( 4 . 3 )}$ | $\mathbf{7 3 . 9 ( 1 . 7 )}$ |
| Baseline (10-fold) | $\mathbf{8 0 . 1}$ | 81.5 | 74.3 | $\mathbf{5 2 . 4}$ | $\mathbf{9 2 . 1}$ | $\mathbf{7 6 . 3}$ |

## More on homological invariants for TDA

- Framework: dim-Hom vs. homological invariants [Blanchette, Brüstle, Hanson] https://arxiv.org/abs/2112.07632
- Computation via Koszul complexes [Chacholski et al.]
https://arxiv.org/abs/2209.05923
- Hilbert function: decomposition and stability [O., Scoccola] https://arxiv.org/abs/2112.11901
- Rank invariant: decomposition and stability [Botnan, Oppermann, O., Scoccola] https://arxiv.org/abs/2107.06800 https://arxiv.org/abs/2208.00300


## Take-home message



## Homological invariants

Definition: An additive invariant is a map $\alpha: \operatorname{Vect}_{\mathrm{fp}}^{\mathbb{R}^{d}} \rightarrow A$, with $A$ an Abelian group, such that $\alpha(M \oplus N)=\alpha(M)+\alpha(N)$ for all $M, N \in \operatorname{Vect}_{f \mathrm{f}}^{\mathbb{R}^{d}}$.

- Typical example (dim-Hom invariant): given a collection $\mathcal{I}$ of intervals,

$$
\alpha(-):=\left(\operatorname{dim} \operatorname{Hom}\left(\boldsymbol{k}_{I},-\right)\right)_{I \in \mathcal{I}} \in \mathbb{Z}^{\mathcal{I}}
$$

( $\mathcal{I}=$ positive quadrants: Hilbert function)
( $\mathcal{I}=$ hooks: dim ker invariant, or equivalently rank invariant)

## Homological invariants

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$$

- Let $\mathcal{E}_{\alpha}$ be the collection of short exact sequences $0 \rightarrow L \rightarrow M \rightarrow N \rightarrow 0$ on which $\alpha$ is additive (use the shorthand $\mathcal{E}_{\mathcal{I}}$ when $\left.\alpha=\left(\operatorname{dim} \operatorname{Hom}\left(\boldsymbol{k}_{I},-\right)\right)_{I \in \mathcal{I}}\right)$

Proposition: (follows from [Auslander, Solberg])
If $\mathcal{I}$ contains all the up-sets, then:

- $\mathcal{E}_{\mathcal{I}}$ forms an exact structure on Vect $_{f \mathrm{f}}^{\mathbb{R}^{d}}$
- the indecomposable projectives relative to $\mathcal{E}_{\mathcal{I}}$ are the $\boldsymbol{k}_{I}$ for $I \in \mathcal{I}$
- $\mathcal{E}_{\mathcal{I}}$ has enough projectives
- can do homological algebra with $\mathcal{E}_{\mathcal{I}}$


## Homological invariants

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- Let $\mathcal{E}_{\alpha}$ be the collection of short exact sequences $0 \rightarrow L \rightarrow M \rightarrow N \rightarrow 0$ on which $\alpha$ is additive (use the shorthand $\mathcal{E}_{\mathcal{I}}$ when $\left.\alpha=\left(\operatorname{dim} \operatorname{Hom}\left(\boldsymbol{k}_{I},-\right)\right)_{I \in \mathcal{I}}\right)$
- for every fp $M$ that has a finite minimal $\mathcal{E}_{\mathcal{I}}$-resolution $M_{n} \rightarrow \cdots \rightarrow M_{0} \rightarrow M$, we get a canonical decomposition:

$$
\begin{aligned}
& \quad\left(\operatorname{dim} \operatorname{Hom}\left(\boldsymbol{k}_{I}, M\right)\right)_{I \in \mathcal{I}}=\sum_{j \in \mathbb{N}}(-1)^{j}\left(\operatorname{dim} \operatorname{Hom}\left(M_{j}, M\right)\right)_{I \in \mathcal{I}} \\
& =\sum_{j \in 2 \mathbb{N}}\left(\operatorname{dim} \operatorname{Hom}\left(M_{j}, M\right)\right)_{I \in \mathcal{I}}-\sum_{j \in 2 \mathbb{N}+1}\left(\operatorname{dim} \operatorname{Hom}\left(M_{j}, M\right)\right)_{I \in \mathcal{I}}
\end{aligned}
$$

- canonical signed barcode $\left(\beta_{2 \mathbb{N}}^{\mathcal{I}}(M), \beta_{2 \mathbb{N}+1}^{\mathcal{I}}(M)\right)$ (with cancellable pairs)


## Homological invariants

Question: size of the decompositions / length of the resolutions?

- case $\mathcal{I}=\{$ up-sets $\}: \operatorname{gldim}\left(\operatorname{Vect}_{\mathrm{fp}}^{\mathbb{R}^{d}}\right)=d$ (Hilbert's Syzygy theorem)


## Homological invariants

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- case $\mathcal{I}=\{$ up-sets $\}: \operatorname{gldim}\left(\operatorname{Vect}_{f p}^{\mathbb{R}^{d}}\right)=d$ (Hilbert's Syzygy theorem)
- case $\mathcal{I}=\{$ hooks $\}:$

$$
\operatorname{gldim}^{\mathcal{E}_{\mathcal{I}}}\left(\operatorname{Vect}_{f \mathrm{f}}^{\mathbb{R}^{d}}\right)=2 d-2 \quad[\text { Botnan, Oppermann, O., Scoccola }]
$$

## Homological invariants

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- case $\mathcal{I}=\{$ hooks $\}$ :

$$
\operatorname{gldim}^{\varepsilon_{\mathcal{I}}}\left(\operatorname{Vect}_{f \mathrm{f}}^{\mathbb{R}^{d}}\right)=2 d-2 \quad \text { [Botnan, Oppermann, O., Scoccola] }
$$

- more general cases: relate $\mathcal{E}_{\mathcal{I}}$ to the usual exact structure on some alternative module category (hypothesis: $\mathbb{R}^{d}$ replaced by some finite poset $P$ ): [Blanchette, Brüstle, Hanson] consider mod $\operatorname{End}_{\boldsymbol{k} P}\left(T_{\mathcal{I}}\right)^{\mathrm{op}}$ where $T_{\mathcal{I}}=\bigoplus_{I \in \mathcal{I}} \boldsymbol{k}_{I}$

$$
\begin{aligned}
& \operatorname{add}\left(\left\{\boldsymbol{k}_{I} \mid I \in \mathcal{I}\right\}\right) \xrightarrow[\mathrm{ff}]{\operatorname{Hom}_{\boldsymbol{k} P}\left(T_{\mathcal{I}},-\right)} \operatorname{proj}\left(\bmod \operatorname{End}_{\boldsymbol{k} P}\left(T_{\mathcal{I}}\right)^{\mathrm{op}}\right) \\
& \Rightarrow \operatorname{gldim}^{\mathcal{E}_{\mathcal{I}}}(\bmod \boldsymbol{k} P) \leq \operatorname{gldim}\left(\bmod \operatorname{End}_{\boldsymbol{k} P}\left(T_{\mathcal{I}}\right)^{\mathrm{op}}\right)
\end{aligned}
$$

