

Comparing Dimensionality Reduction Methods using Data Descriptor Landscapes

Bastian Rieck Heike Leitte

Interdisciplinary Center for Scientific Computing
Heidelberg University

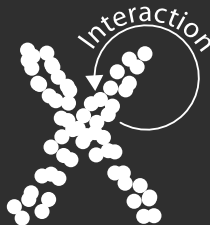


UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386



In an ideal world

Example workflow in data science



Multivariate data + Dimensionality reduction + Embedding = Insight

Disclaimer: This is *not* a definition but rather based on observing the machine learning colleagues down the hall...

An idealized metaphor



Image source: flickr user "Georg Holderied"

In practice

Opening the toolbox



Image source: flickr user "OZinOH"

In practice

Opening the toolbox



Locally linear embedding (LLE)

Image source: flickr user "OZinOH"

In practice

Opening the toolbox



Locally linear embedding (LLE)
Hessian locally linear embedding (HLLE)

Image source: flickr user "OZinOH"

In practice

Opening the toolbox



Locally linear embedding (LLE)
Hessian locally linear embedding (HLLE)
Local tangent space alignment (LTSA)

Image source: flickr user "OZinOH"

In practice

Opening the toolbox



Image source: flickr user "OZinOH"

Challenges

- 1 Choose a suitable tool.

Challenges

- 1 Choose a suitable tool.
- 2 Choose suitable parameters.

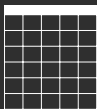
Challenges

- 1 Choose a suitable tool.
- 2 Choose suitable parameters.

How can visualization help?

Our proposed approach

Data set



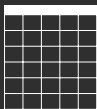
Embeddings



Data descriptors

Our proposed approach

Data set



Embeddings



Data descriptors

$$d(\text{red bar chart}, \text{yellow bar chart}) = \dots$$

$$d(\text{red bar chart}, \text{yellow bar chart}) = \dots$$

$$d(\text{red bar chart}, \text{yellow bar chart}) = \dots$$

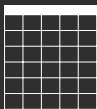
$$d(\text{red bar chart}, \text{blue bar chart}) = \dots$$

$$d(\text{red bar chart}, \text{blue bar chart}) = \dots$$

$$d(\text{red bar chart}, \text{blue bar chart}) = \dots$$

Our proposed approach

Data set



Embeddings



Data descriptors

$$d(\text{descriptor}_1, \text{descriptor}_2) = \dots$$

$$d(\text{descriptor}_1, \text{descriptor}_3) = \dots$$

$$d(\text{descriptor}_2, \text{descriptor}_3) = \dots$$

$$d(\text{descriptor}_1, \text{descriptor}_4) = \dots$$

$$d(\text{descriptor}_1, \text{descriptor}_5) = \dots$$

$$d(\text{descriptor}_2, \text{descriptor}_5) = \dots$$

Idea: If data descriptors are *close*, the properties they measure are retained.

Data descriptors

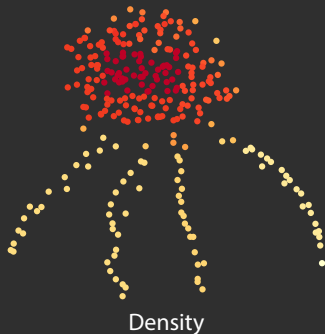
Definition & examples

Any function $f: \mathbb{D} \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$ is an admissible data descriptor. f should measure “salient properties” of a multivariate data set.

Data descriptors

Definition & examples

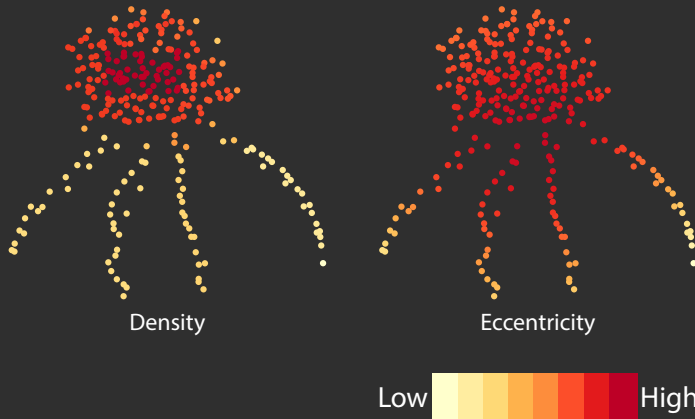
Any function $f: \mathbb{D} \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$ is an admissible data descriptor. f should measure “salient properties” of a multivariate data set.



Data descriptors

Definition & examples

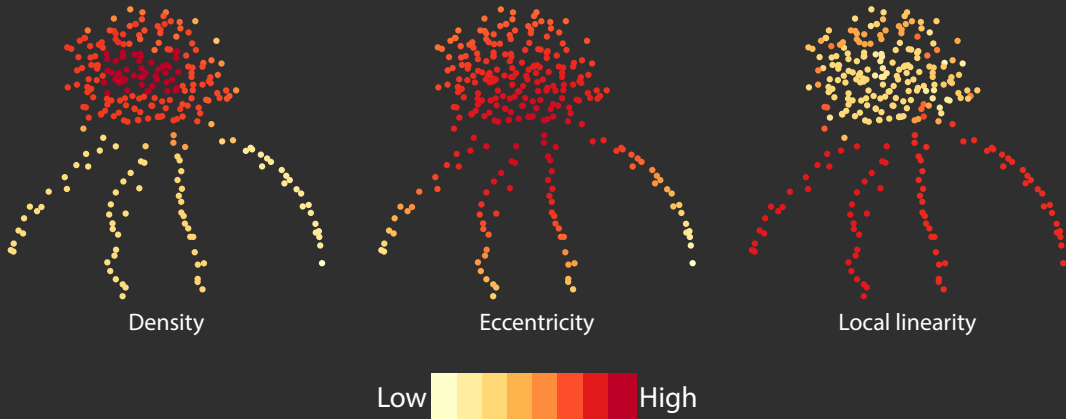
Any function $f: \mathbb{D} \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$ is an admissible data descriptor. f should measure “salient properties” of a multivariate data set.



Data descriptors

Definition & examples

Any function $f: \mathbb{D} \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$ is an admissible data descriptor. f should measure “salient properties” of a multivariate data set.



How to calculate data descriptor distances?

$$d(\text{[Histogram]}, \text{[Histogram]}) := ?$$

How to calculate data descriptor distances?

$$d(\text{[bar chart]}, \text{[bar chart]}) := ?$$

Persistent homology, because...

How to calculate data descriptor distances?

$$d(\text{[bar chart]}, \text{[bar chart]}) := ?$$

Persistent homology, because...

1 Calculation between different domains:

Original data $\mathbb{R}^n$

Embedding $\mathbb{R}^d$ ($d \ll n$)

How to calculate data descriptor distances?

$$d(\text{[bar chart]}, \text{[bar chart]}) := ?$$

Persistent homology, because...

- 1 Calculation between different domains:

Original data $\mathbb{R}^n$

Embedding $\mathbb{R}^d$ ($d \ll n$)

- 2 Invariance to some transformations.

How to calculate data descriptor distances?

$$d(\text{[bar chart]}, \text{[bar chart]}) := ?$$

Persistent homology, because...

- 1 Calculation between different domains:

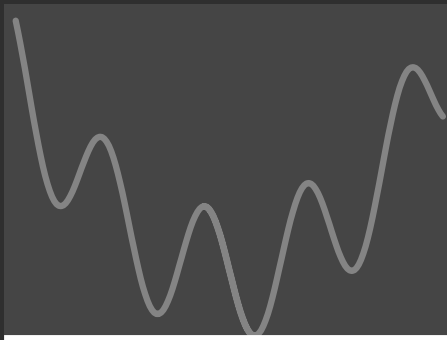
Original data $\mathbb{R}^n$

Embedding $\mathbb{R}^d$ ($d \ll n$)

- 2 Invariance to some transformations.
- 3 Robust against noise.

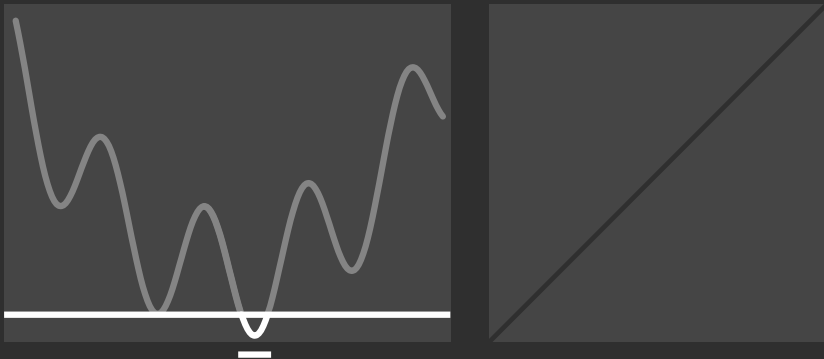
Persistent homology & persistence diagrams

One-dimensional example



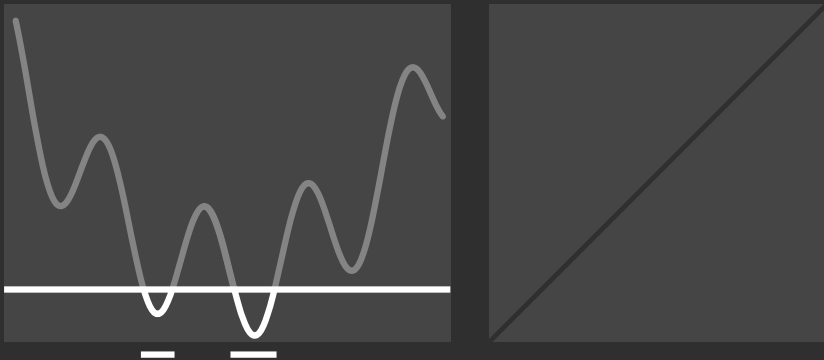
Persistent homology & persistence diagrams

One-dimensional example



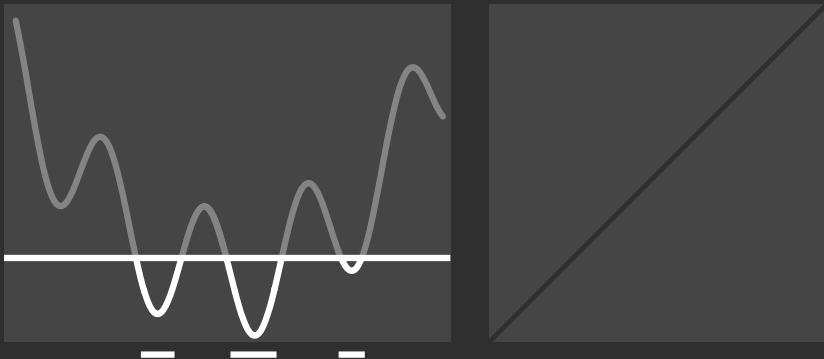
Persistent homology & persistence diagrams

One-dimensional example



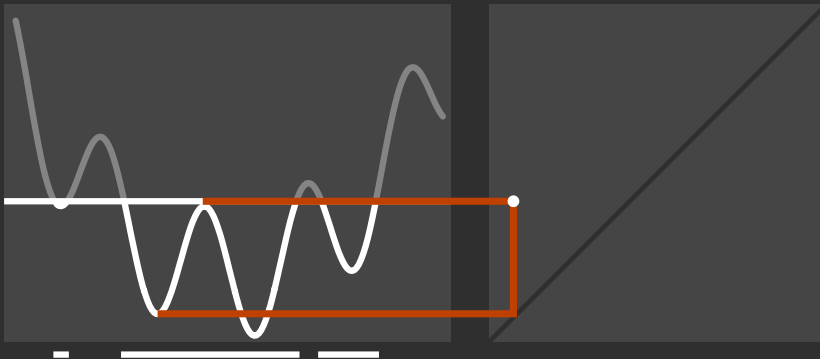
Persistent homology & persistence diagrams

One-dimensional example



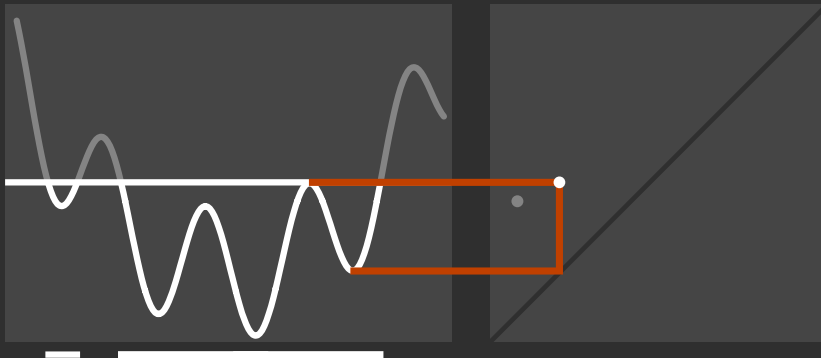
Persistent homology & persistence diagrams

One-dimensional example



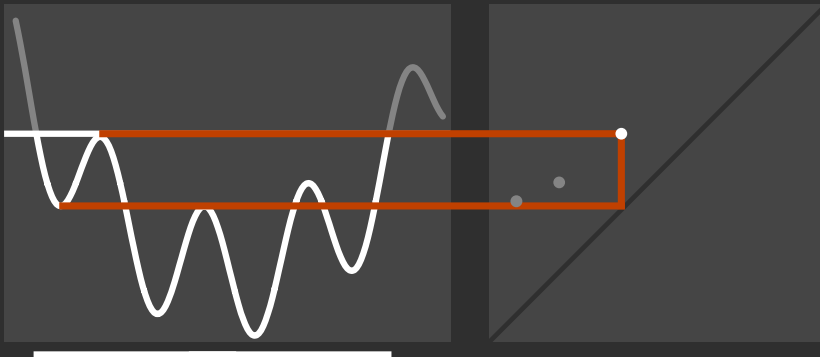
Persistent homology & persistence diagrams

One-dimensional example



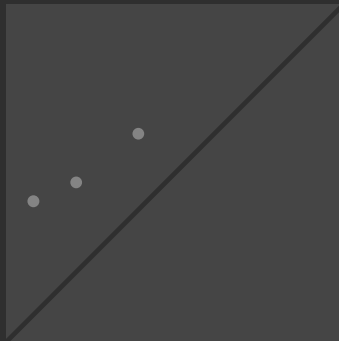
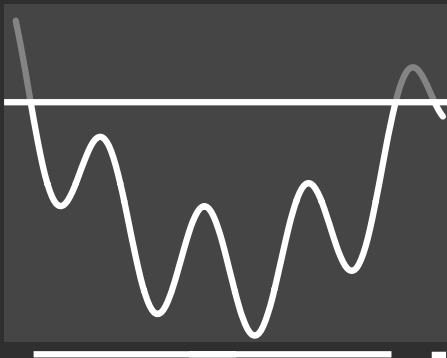
Persistent homology & persistence diagrams

One-dimensional example



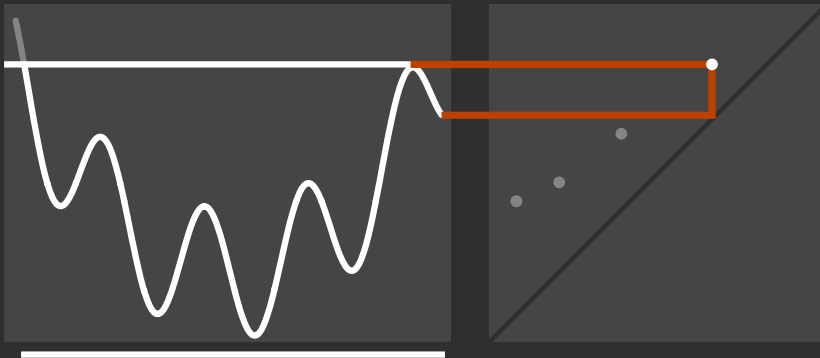
Persistent homology & persistence diagrams

One-dimensional example



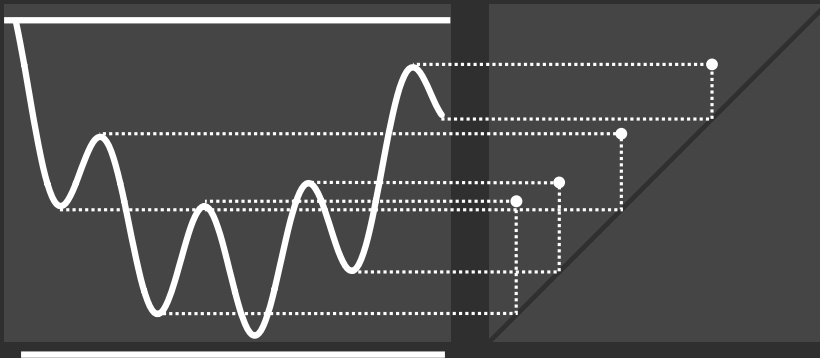
Persistent homology & persistence diagrams

One-dimensional example



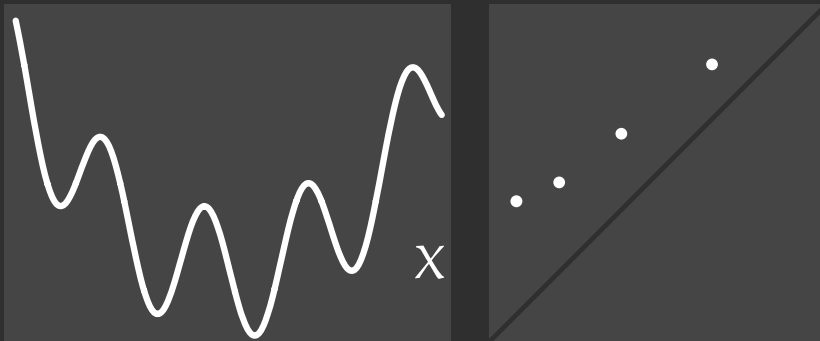
Persistent homology & persistence diagrams

One-dimensional example



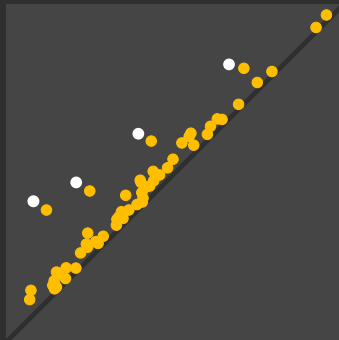
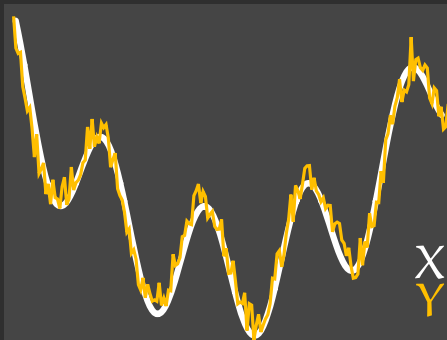
Persistent homology & persistence diagrams

Distance calculations



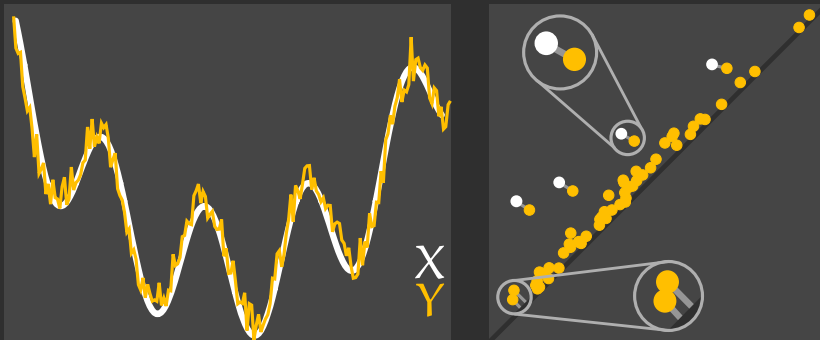
Persistent homology & persistence diagrams

Distance calculations



Persistent homology & persistence diagrams

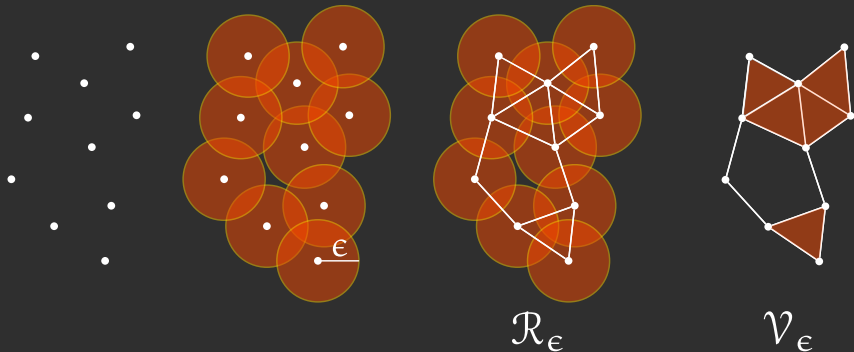
Distance calculations



$$W_2(X, Y) = \sqrt{\inf_{\eta: X \rightarrow Y} \sum_{x \in X} \|x - \eta(x)\|_\infty^2}$$

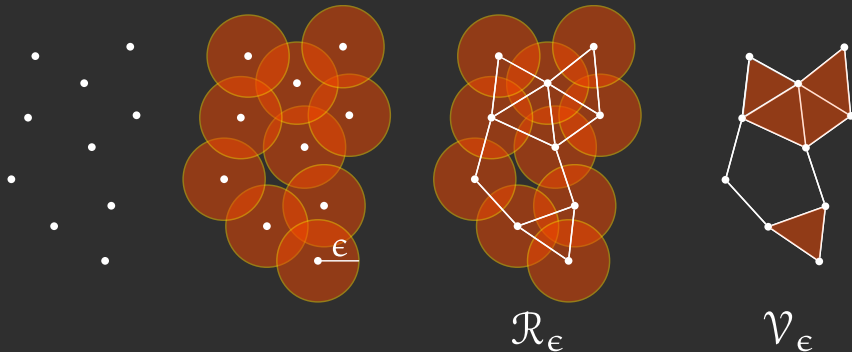
Extension to multivariate input data

Rips graphs and Vietoris–Rips complexes



Extension to multivariate input data

Rips graphs and Vietoris–Rips complexes



For $\epsilon \leq \epsilon'$, we have $\mathcal{R}_\epsilon \subseteq \mathcal{R}_{\epsilon'}$ and $\mathcal{V}_\epsilon \subseteq \mathcal{V}_{\epsilon'}$.

How to combine multiple data descriptors?



How to combine multiple data descriptors?

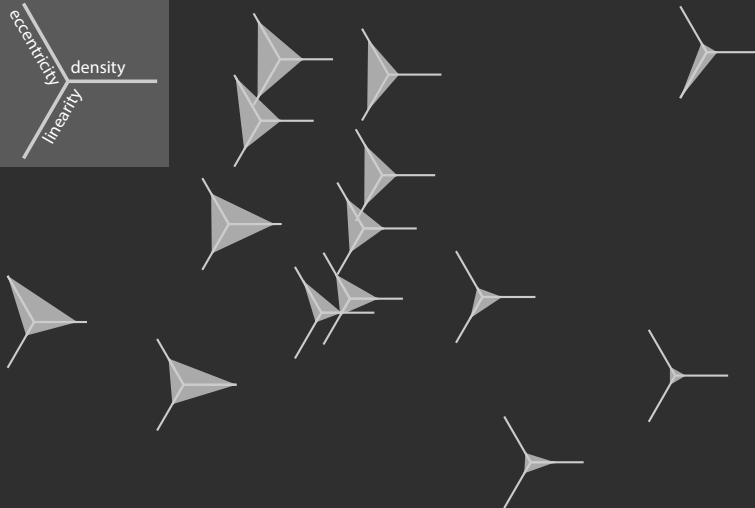


Use feature vectors as input for PCA!

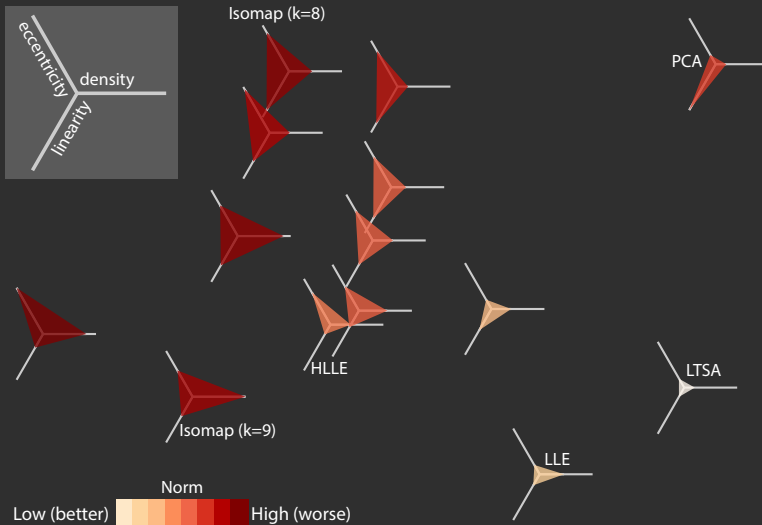
Data descriptor landscapes



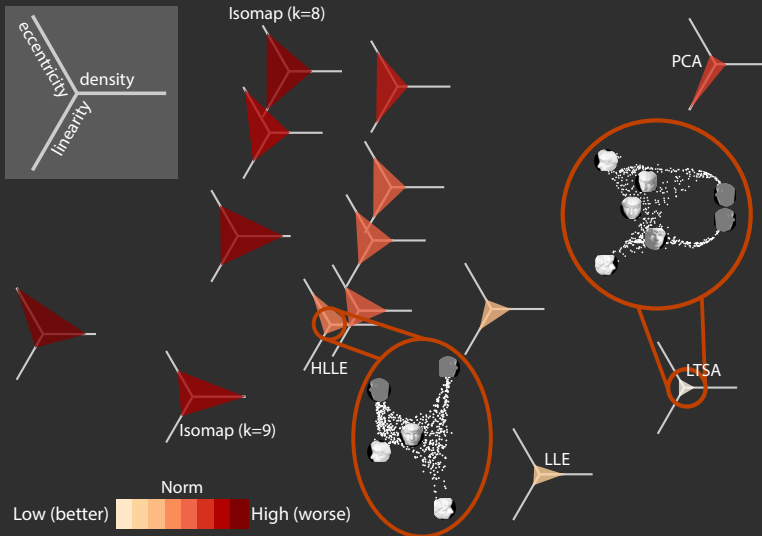
Data descriptor landscapes



Data descriptor landscapes



Data descriptor landscapes



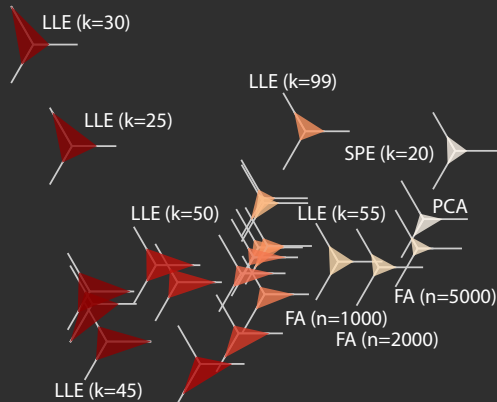
Results

Climate data

- Multivariate simulation data from *German Climate Research Centre* (DKRZ).
- Grid data from 192×96 locations with six continuous attributes over 1460 time steps.
- In total, 18432 vectors from $\mathbb{R}^6$.

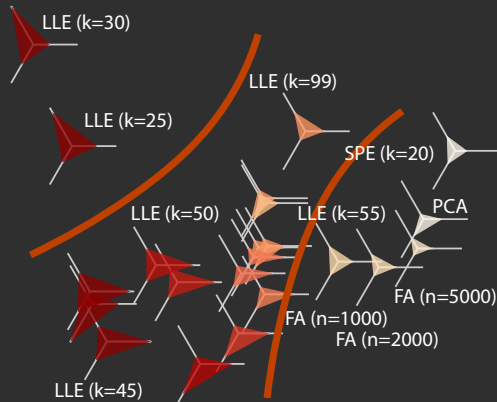
Data descriptor landscape for climate data

Linear vs. non-linear methods



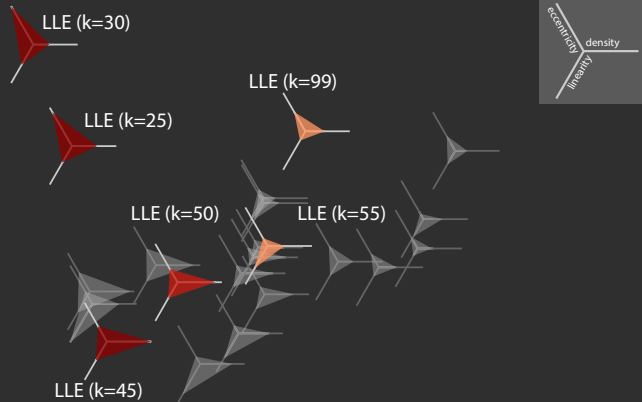
Data descriptor landscape for climate data

Linear vs. non-linear methods



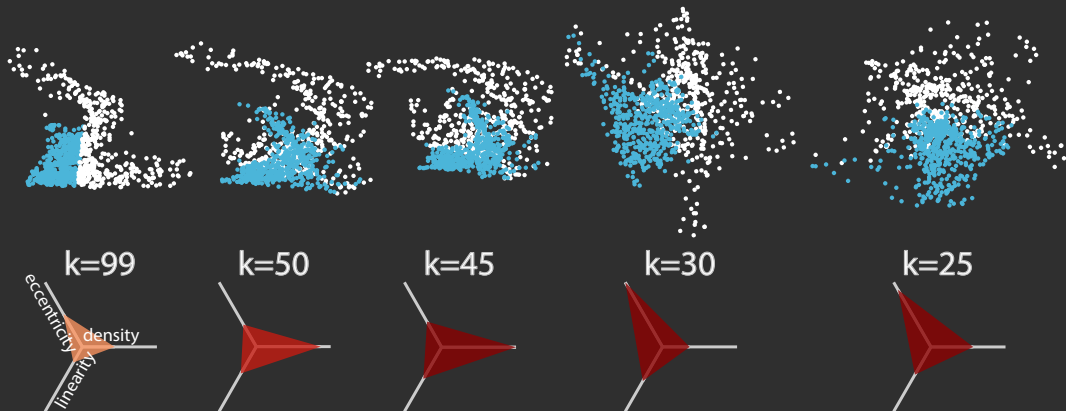
A closer look at LLE

Stability analysis

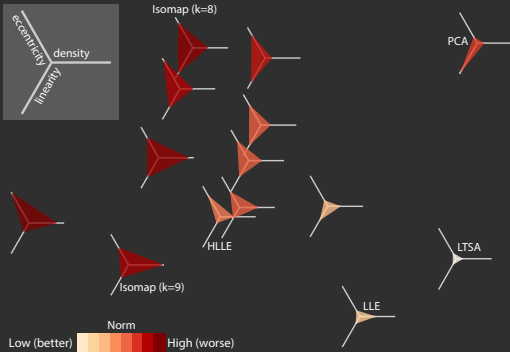


A closer look at LLE

Brushing some embeddings



Conclusion



- *Data descriptor approach:*
 - Functional description of salient properties.
 - Landscapes as a new visual metaphor for comparing multiple dimensionality reduction methods.
- Main applications: Variability and stability analysis of dimensionality reduction methods.
- Future work: Domain-specific data descriptors

Thank you for your attention!