



# SLISEMAP

## SUPERVISED DIMENSIONALITY REDUCTION THROUGH LOCAL EXPLANATIONS

Anton Björklund, Jarmo Mäkelä, Kai Puolamäki.

*SLISEMAP: Supervised dimensionality reduction through local explanations.*

arXiv: 2201.04455 [cs] (2022). DOI: 10.48550/arXiv.2201.04455.

<https://github.com/edahelsinki/slisemap>



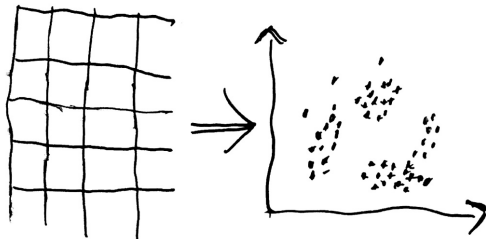
# BACKGROUND

SLISEMAP = Supervised dimensionality reduction + Local explanations



# BACKGROUND

## Dimensionality reduction



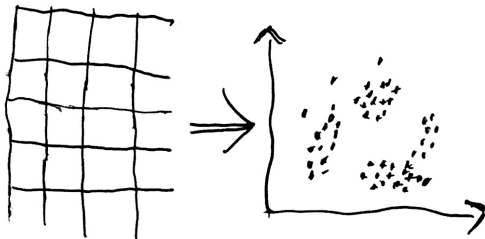
Dimensionality reduction can be used for manifold visualisation.

SLISEMAP = Supervised dimensionality reduction + Local explanations



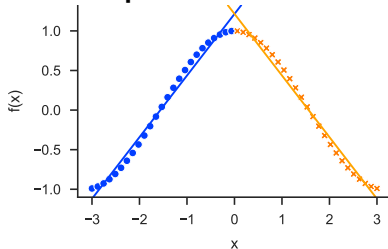
# BACKGROUND

## Dimensionality reduction



Dimensionality reduction can be used for manifold visualisation.

## Local Explanations



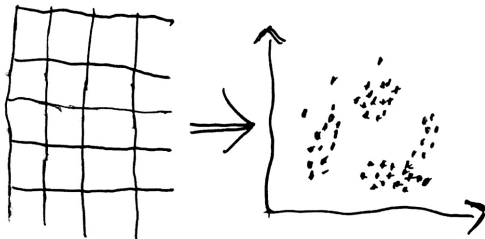
We can approximate this non-linear function with two local linear models.

SLISEMAP = Supervised dimensionality reduction + Local explanations



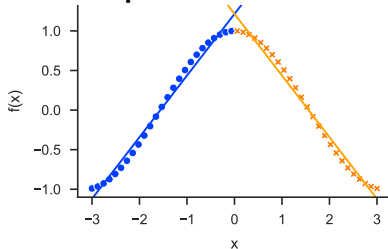
# BACKGROUND

## Dimensionality reduction



Dimensionality reduction can be used for manifold visualisation.

## Local Explanations



We can approximate this non-linear function with two local linear models.

SLISEMAP = Supervised dimensionality reduction + Local explanations

– *"Find an embedding such that data items with similar local models are next to each other".*



# PROBLEM DEFINITION

- Given a dataset of  $n$  items:  $(\mathbf{x}_1, \mathbf{y}_1), \dots, (\mathbf{x}_n, \mathbf{y}_n)$ .
- Find the embedding coordinates  $\mathbf{z}_1, \dots, \mathbf{z}_n$  and local models  $g_1, \dots, g_n$ .
- That minimises the loss:

$$\mathcal{L} = \sum_{i=1}^n \sum_{j=1}^n \frac{e^{-\|\mathbf{z}_i - \mathbf{z}_j\|_2}}{\sum_{k=1}^n e^{-\|\mathbf{z}_i - \mathbf{z}_k\|_2}} l(g_i(\mathbf{x}_j), \mathbf{y}_j)$$

- Where  $l$  is a loss function for the local models.
- Under the constraint that  $(\frac{1}{n} \sum_{i=1}^n \sum_{k=1}^d \mathbf{z}_{ik}^2)^{\frac{1}{2}} = z_{radius}$ .



# USAGE

## Installation

```
pip install slisemap
```

## Code

```
from slisemap import Slisemap
# Use Lasso regularisation
sm = Slisemap(X, y, lasso=0.01)
# Remember to optimise
sm.optimise()
# Plot the solution
sm.plot(clusters=5, bars=5,
        jitter=0.01, variables=names)
```



# USAGE

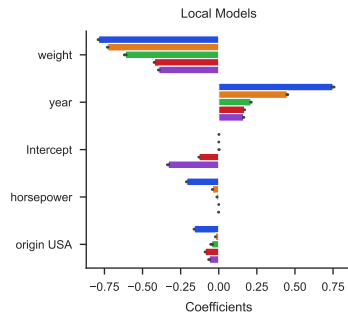
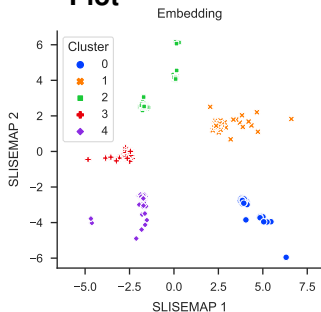
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## Plot



Cluster the local models to make them easier to read (using a dataset about cars).





# SUMMARY

SLISEMAP is a novel supervised manifold visualisation method that embeds data items into a lower-dimensional space such that the same white box model models nearby data items.

**A. Björklund, J. Mäkelä, K. Puolamäki.**

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