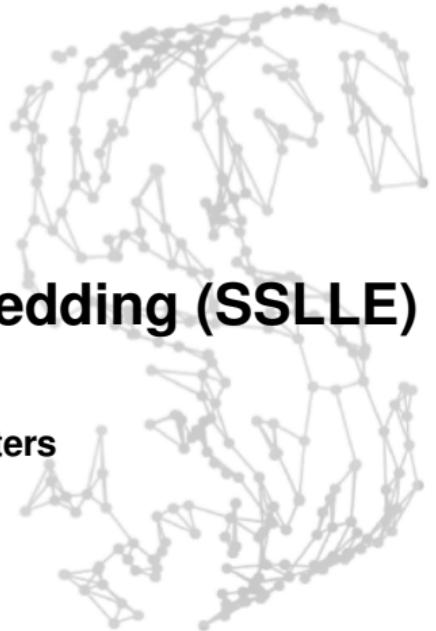


# Semi-Supervised Locally Linear Embedding (SSLLE)

Application & Sensitivity Analysis of Critical Hyperparameters



# 0 AGENDA

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- 1 Problem
- 2 Local graph-based manifold learning (LGML)
- 3 Techniques
  - 1 Unsupervised
  - 2 Semi-supervised    **SSLLE**
  - 3 Challenges
- 4 Sensitivity analysis
  - 1 Setup
  - 2 Results
- 5 Discussion

# 1 PROBLEM MANIFOLD LEARNING

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**Situation.** Rapidly increasing amount of data thanks to novel applications and data sources

**Problem.** High data dimensionality detrimental to

- Model functionality
- Interpretability
- Generalization ability

**Manifold assumption.** Data in high-dimensional observation space truly sampled from low-dimensional manifold



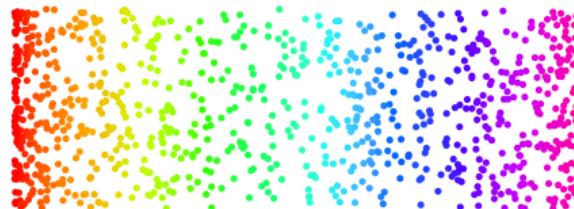
**How to find a meaningful, structure-preserving embedding?**

# 1 PROBLEM MANIFOLD LEARNING

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**Formal goal of manifold learning.**

- **Given.** Data  $\mathcal{X} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N)$ , with  $\mathbf{x}_i \in \mathbb{R}^D \forall i \in \{1, 2, \dots, N\}$  and  $N, D \in \mathbb{N}$ , supposedly lying on  $d$ -dimensional manifold  $\mathcal{M}$ 
  - $\Rightarrow \psi : \mathcal{M} \rightarrow \mathbb{R}^d$  with  $d \ll D, d \in \mathbb{N}$
  - $\Rightarrow \mathcal{X} \sim \mathcal{M} \subset \mathbb{R}^D$
- **Goal.** Find  $d$ -dimensional Euclidean representation
  - $\Rightarrow \mathcal{Y} = (\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_N)$ , with  $\mathbf{y}_i = \psi(\mathbf{x}_i) \in \mathbb{R}^d \forall i \in \{1, 2, \dots, N\}$ .



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## 2 LGML

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## 2 LGML TAXONOMY

**Landscape.** Various approaches, many of which may be translated into one another



- LEM** Laplacian eigenmaps  
**LLE** Locally linear embedding  
**HLLE** Hessian LLE  
**SSLLE** Semi-supervised LLE

## 2 LGML CONCEPT

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**Idea.** Capture intrinsic geometry, find principal axes of variability, retain most salient ones

Kernel PCA

LGML concept

LGML algorithm

Kernelization

Graph representation

Neighborhood construction

Graph functional

Matrix representation

Eigenanalysis

Eigenanalysis

Eigenanalysis

Dimensionality reduction

Dimensionality reduction

Dimensionality reduction

## 2 LGML CONCEPT

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**Graph representation.** Constructing a skeletal model of the manifold in  $\mathbb{R}^D$

**Vertices.** Given by observations

**Edges.** Present between neighboring points

- Typically,  $k$ -neighborhoods
- Edge weights determined by nearness

**Graph functional.** Belief about intrinsic manifold properties at the heart of each method

- Smoothness    LEM
- Local linearity    LLE    SSLLE
- Curviness    HLLE
- ...



**Achievements: non-linearity & locality**

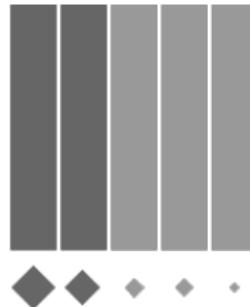
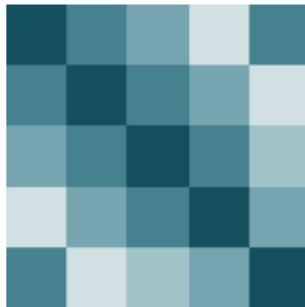
## 2 LGML CONCEPT

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**Eigenanalysis.** Finding axes of variability in intrinsic manifold structure

- Matrix representation of manifold properties
- Assessment through eigenanalysis
  - Directions of variability ⇒ eigenvectors
  - Respective degrees of variability ⇒ eigenvalues

**Dimensionality reduction.** Projection into subspace spanned by  $d$  principal eigenvectors



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# 3 TECHNIQUES

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## 3.1 UNSUPERVISED LEM

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**Proposal.** Belkin and Niyogi (2001)

**Idea.** Forcing nearby inputs to be mapped to nearby outputs

- Notion of smoothness in mapping function
- Second-order penalty on gradient

**Solution.** Eigenanalysis of graph Laplacian  $L$

- Derived from weight matrix encoding nearness of inputs
- Discrete approximation of Laplace-Beltrami operator  $\mathcal{L}(f)$
- Generalized eigenvalue problem

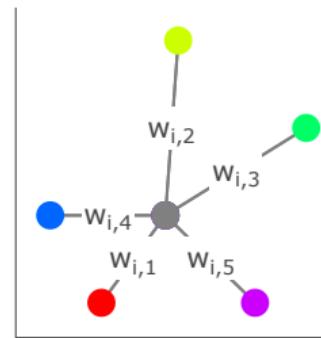
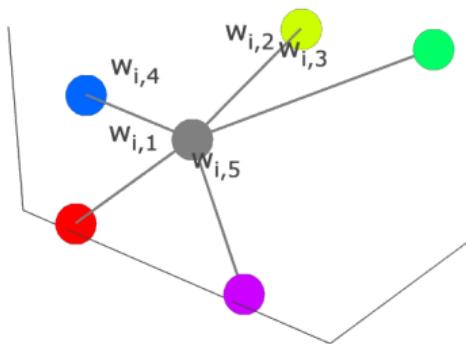
**Solution: bottom  $d + 1$  eigenvectors**

## 3.1 UNSUPERVISED LLE

**Proposal.** Roweis and Saul (2000)

**Idea.** Preserving locally linear reconstructions

- Linear reconstruction of points in  $\mathbb{R}^D$  by their neighbors
- Reconstruction weights = topological properties
- Neighborhood patches invariant to dimensionality reduction



### 3.1 UNSUPERVISED LLE

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**Reconstruction loss minimization.** Finding optimal reconstruction weights

$$\min_{\mathbf{W}} \varepsilon(\mathbf{W}) = \min_{\mathbf{W}} \sum_i \left\| \mathbf{x}_i - \sum_j w_{ij} \mathbf{x}_j \right\|^2, \quad \text{s.t. } \mathbf{1}^T \mathbf{w}_i = 1 \quad \forall i \in \{1, 2, \dots, N\} \quad (1)$$

**Embedding loss minimization.** Finding optimal embedding coordinates

$$\min_{\mathcal{Y}} \Phi(\mathcal{Y}) = \min_{\mathcal{Y}} \sum_i \left\| \mathbf{y}_i - \sum_j w_{ij} \mathbf{y}_j \right\|^2, \quad \text{s.t. } \frac{1}{N} \sum_i \mathbf{y}_i \mathbf{y}_i^T = \mathbf{I}, \quad \sum_i \mathbf{y}_i = \mathbf{0} \quad \forall i \in \{1, 2, \dots, N\} \quad (2)$$

**Eigenvalue problem.** Define  $\mathbf{E} = (\mathbf{I} - \mathbf{W})^T (\mathbf{I} - \mathbf{W})$ , such that

$$\min_{\mathcal{Y}} \text{trace}(\mathcal{Y}^T \mathbf{E} \mathcal{Y}), \quad \text{s.t. } \frac{1}{N} \mathcal{Y}^T \mathcal{Y} = \mathbf{I}, \quad \mathcal{Y}^T \mathbf{1} = \mathbf{0}. \quad (3)$$

**Solution: bottom  $d + 1$  eigenvectors**

### 3.1 UNSUPERVISED HLLE

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**Proposal.** Donoho and Grimes (2003)

**Idea.** Finding a truly linear mapping while preserving local isometry

- Notion of curviness in mapping function
- Second-order penalty on Hessian
- Strong convergence guarantees but rather complex computations

**Solution.** Eigenanalysis of empirical Hessian functional  $\mathcal{H}$

- Derived as a quadratic form of Hessian estimators in linear neighborhood patches
- Discrete approximation of continuous Hesssian functional  $\mathcal{H}(f)$
- Null space problem

**Solution: bottom  $d + 1$  eigenvectors + scaling**

## 3.2 SEMI-SUPERVISED SSLLE

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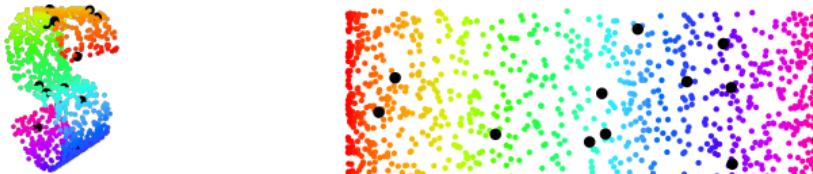
**Proposal.** Yang et al. (2006)

**Problem.** Embedding found by unsupervised methods not always meaningful

**Idea.** Improving LLE by use of prior knowledge

**Semi-supervision.** Anchoring embedding at some prior points with known coordinates

- More active than semi-supervised learning?
- Setting. Information available or to be obtained by querying the oracle
- Goal. Maximum information at little expense  $\Rightarrow$  careful choice of prior points



## 3.2 SEMI-SUPERVISED SSLLE

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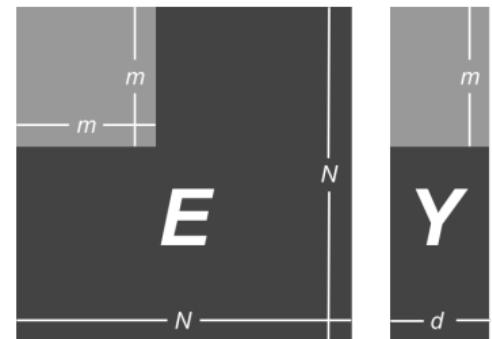
**Types of prior information.** Exact vs inexact

→ Level of confidence encoded in parameter  $\beta$

**Algorithmic impact.** Recall LLE eigenvalue problem

$$\min_{\mathcal{Y}} \text{trace}(\mathcal{Y}^T \mathbf{E} \mathcal{Y}), \quad \text{s.t. } \frac{1}{N} \mathcal{Y}^T \mathcal{Y} = \mathbf{I}, \quad \mathcal{Y}^T \mathbf{1} = \mathbf{0}.$$

⇒ Partitioning of  $\mathbf{E}$  and  $\mathcal{Y}$



## 3.2 SEMI-SUPERVISED SSLLE

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**Modified optimization problem.** Exact information

$$\min_{\mathcal{Y}_2} [\mathcal{Y}_1 \quad \mathcal{Y}_2] \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} \mathcal{Y}_1^T \\ \mathcal{Y}_2^T \end{bmatrix} \quad (4)$$

$$\Leftrightarrow \mathcal{Y}_2^T = M_{22}^{-1} M_{12} \mathcal{Y}_1^T \quad (5)$$

**Modified optimization problem.** Inexact information

$$\min_{\mathcal{Y}_1, \mathcal{Y}_2} [\mathcal{Y}_1 \quad \mathcal{Y}_2] \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} \mathcal{Y}_1^T \\ \mathcal{Y}_2^T \end{bmatrix} + \beta \left\| \mathcal{Y}_1^T - \hat{\mathcal{Y}}_1^T \right\|_F^2 \quad (6)$$

$$\Leftrightarrow \begin{bmatrix} M_{11} + \beta I & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} \mathcal{Y}_1^T \\ \mathcal{Y}_2^T \end{bmatrix} = \begin{bmatrix} \hat{\mathcal{Y}}_1^T \\ \mathbf{0} \end{bmatrix} \quad (7)$$

## 3.2 SEMI-SUPERVISED SSLLE

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**Choice of landmark points.** Basically, three options

- Pre-existing prior information  $\Rightarrow$  worst case: poor coverage
- (Uniform) random sampling
- Maximum coverage  $\Rightarrow$  minimization of condition number  $\kappa(M_{22})$



## 3.3 CHALLENGES CRITICAL PARAMETERS

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**Intrinsic dimensionality.** True sources of variability

- Considered known with availability of prior information

**Neighborhood size.** Global vs local structure

- Tunable (expensive)

**Regularization constant.** Singularity for  $D < k$

- Heuristics

**Number & location of prior points.** Utility of prior knowledge ANALYSIS

- Exploration vs labeling cost

**Noise level.** Quality of prior knowledge ANALYSIS

- How exact must prior information be?

**Confidence parameter.** Strength of belief in prior knowledge

- Rather robust

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# 4 SENSITIVITY ANALYSIS

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## 4.1 SETUP DATA

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**Data.** Two data sets,  $N = 1000$  observations each

**Swiss roll.** The standard synthetic manifold

- 1 Sample  $\mathbf{u}_1, \mathbf{u}_2 \sim U(0, 1)$  iid with  $|\mathbf{u}_1| = |\mathbf{u}_2| = N$
- 2 Compute  $\mathbf{t} = 1.5\pi(1 + 2\mathbf{u}_1)$  and  $\mathbf{s} = 21\mathbf{u}_2$
- 3  $\mathcal{X}_{\text{swiss}} = [\mathbf{x}_1 \quad \mathbf{x}_2 \quad \mathbf{x}_3] = [\mathbf{t} \cos \mathbf{t} \quad \mathbf{s} \quad \mathbf{t} \sin \mathbf{t}]$



**Incomplete tire.** Examined in Yang et al. (2006)

- 1 Sample  $\mathbf{u}_1, \mathbf{u}_2 \sim U(0, 1)$  iid with  $|\mathbf{u}_1| = |\mathbf{u}_2| = N$
- 2 Compute  $\mathbf{t} = \frac{5\pi}{3}\mathbf{u}_1$  and  $\mathbf{s} = \frac{5\pi}{3}\mathbf{u}_2$
- 3 
$$\begin{aligned}\mathcal{X}_{\text{tire}} &= [\mathbf{x}_1 \quad \mathbf{x}_2 \quad \mathbf{x}_3] \\ &= [(3 + \cos \mathbf{s}) \cos \mathbf{t} \quad (3 + \cos \mathbf{s}) \sin \mathbf{t} \quad \sin \mathbf{s}]\end{aligned}$$



## 4.1 SETUP SCENARIOS

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### Sensitivity analysis I. Landmark coverage $\times$ number of landmark points

- Landmark coverage  $\in \{\text{poor, random, maximum}\}$
- Number of landmark points  $\in \{2, 4, 6, 8, 10, 12\}$

### Sensitivity analysis II. Noise level $\times$ number of landmark points

- Simulation of inexact prior information through additive Gaussian noise
- Corruption of landmark  $\mathbf{p}$  as  $\tilde{\mathbf{p}} = \mathbf{p} + \boldsymbol{\epsilon} = (p_t, p_s) + (\epsilon_t, \epsilon_s)$   
with  $\epsilon_i \sim N(0, (\alpha \cdot s_i)^2)$  scaled by empirical variance  $s_i$ ,  $i \in \{t, s\}$
- Noise level  $\alpha \in \{0.1, 0.5, 1.0, 3.0\}$
- Number of landmark points  $\in \{2, 4, 6, 8, 10, 12\}$

## 4.1 SETUP EVALUATION

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**Evaluation criterion.**  $\text{AUC}(R_{NX})$  (Kraemer et al., 2019)

- Area under the  $R_{NX}$  curve
- Based on co-ranking matrix

**Co-ranking matrix.** Comparing distance ranks in observation & embedding spaces

- Rank distance matrices.  $(r)_{ij}^{\text{obs}}$  and  $(r)_{ij}^{\text{emb}}$
- Co-ranking matrix.  $\mathbf{Q} = (q)_{\ell m}$  with  $q_{\ell m} = |\{(i, j) : r_{ij}^{\text{emb}} = \ell \wedge r_{ij}^{\text{obs}} = m\}|$
- Interpretation.
  - 1 All non-zero entries on diagonal  $\Rightarrow$  optimal embedding
  - 2 Most non-zero entries on upper triangle  $\Rightarrow$  close points torn apart
  - 3 Most non-zero entries on lower triangle  $\Rightarrow$  faraway points collapsed

## 4.1 SETUP EVALUATION

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**Co-ranking-based metrics.** Comparing distance ranks in observation & embedding spaces

- Number of points belonging to  $k$ -neighborhood in both spaces.

$$Q_{NX}(k) = \frac{1}{kN} \sum_{\ell=1}^k \sum_{m=1}^k q_{\ell m}$$

- Adjustment for random embeddings and normalization.

$$R_{NX}(k) = \frac{(N-1)Q_{NX}(k)-k}{N-1-k}$$

**AUC measure.** Parameter-free

- $\text{AUC}(R_{NX}) = \frac{\sum_{k=1}^{N-2} R_{NX}(k)}{\sum_{k=1}^{N-2} 1/k} \in [0, 1]$

- Interpretation.

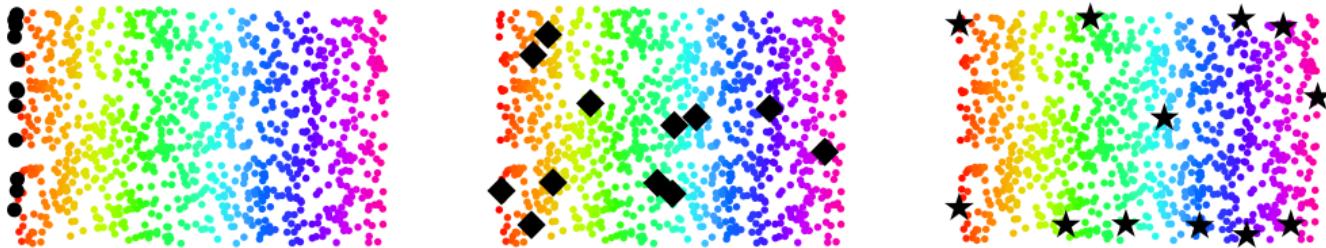
1  $\text{AUC}(R_{NX}) = 0 \Rightarrow$  random embedding

2  $\text{AUC}(R_{NX}) = 1 \Rightarrow$  optimal embedding

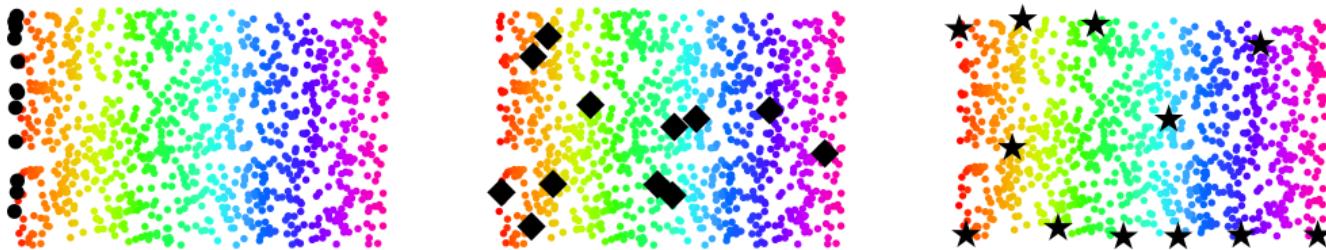
## 4.2 RESULTS SENSITIVITY ANALYSIS I

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**Key variation.** Swiss roll

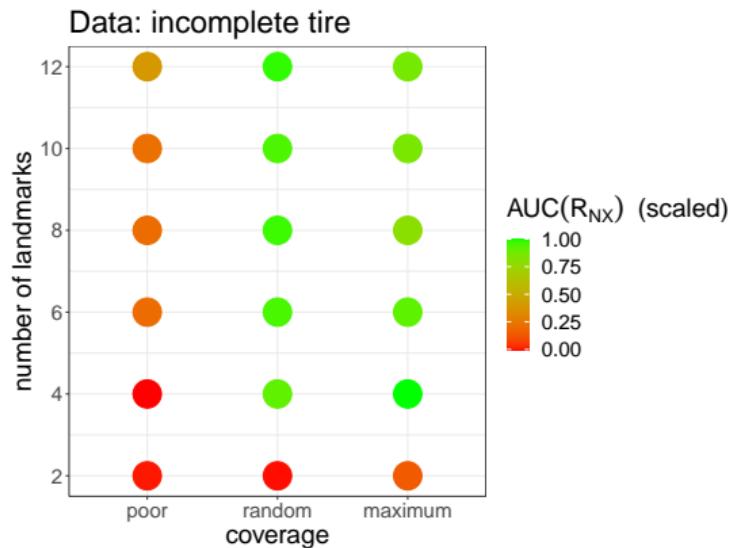
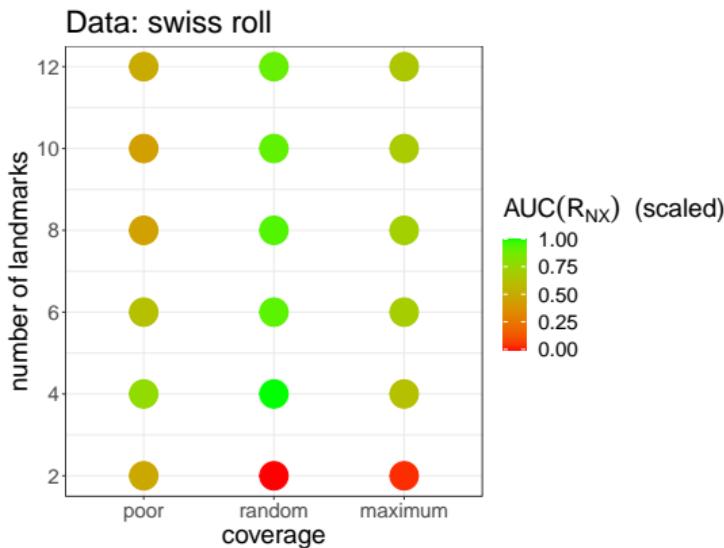


**Key variation.** Incomplete tire



## 4.2 RESULTS SENSITIVITY ANALYSIS I

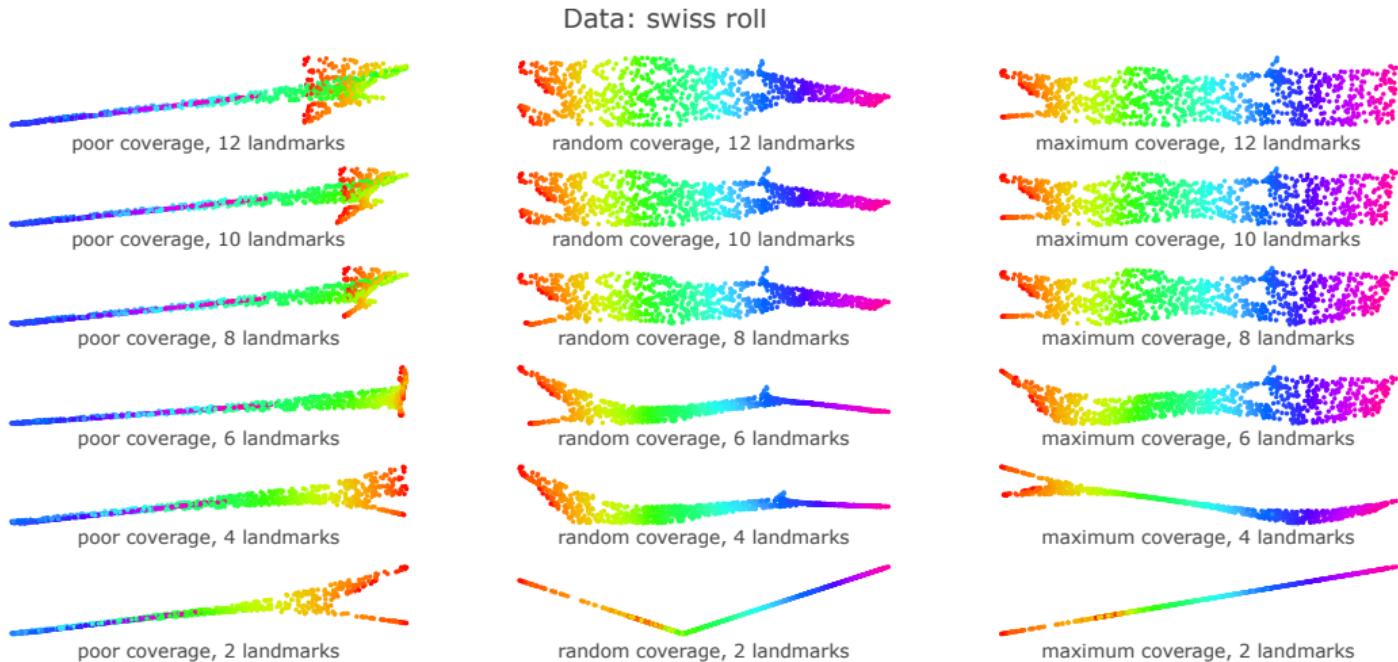
**Quantitative results.** Seemingly better performance of random coverage



AUC( $R_{NX}$ ) has been scaled to take on a minimum of 0 and maximum of 1 in both figures for better visibility of differences. Original scales. Swiss roll: AUC( $R_{NX}$ )  $\in [0.2655, 0.4086]$ , incomplete tire: AUC( $R_{NX}$ )  $\in [0.2772, 0.6231]$

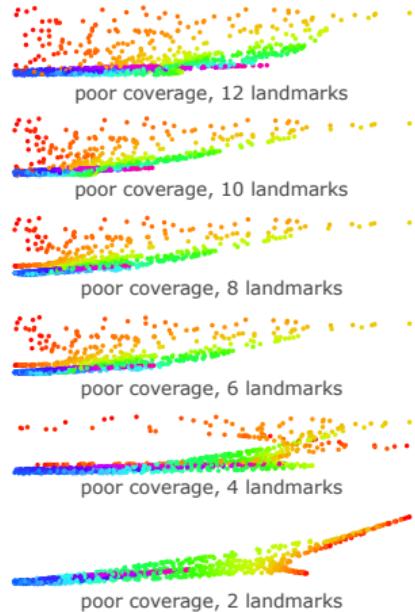
## 4.2 RESULTS SENSITIVITY ANALYSIS I

**Qualitative results.** Somewhat mixed picture

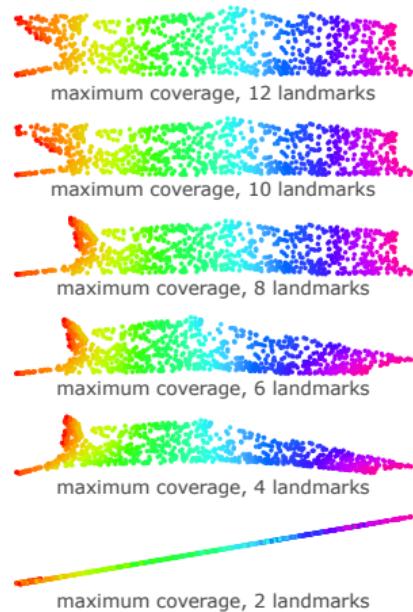
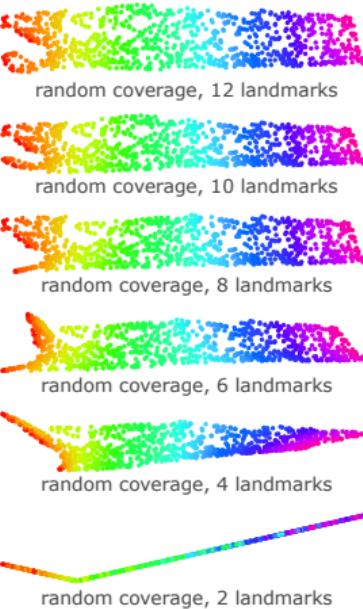


## 4.2 RESULTS SENSITIVITY ANALYSIS I

**Qualitative results.** Somewhat mixed picture



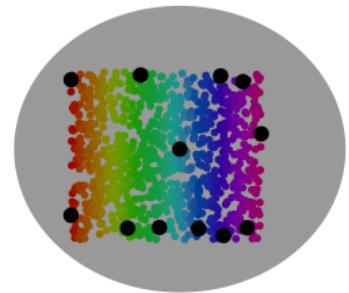
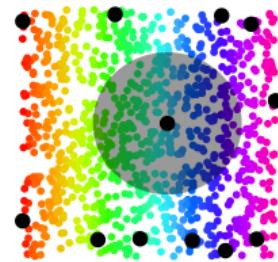
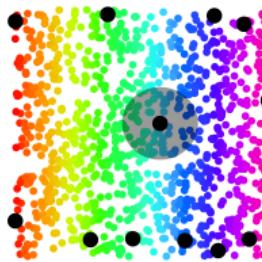
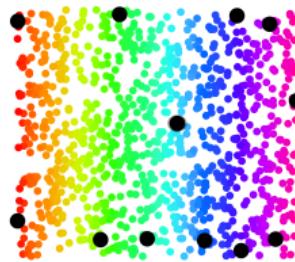
Data: incomplete tire



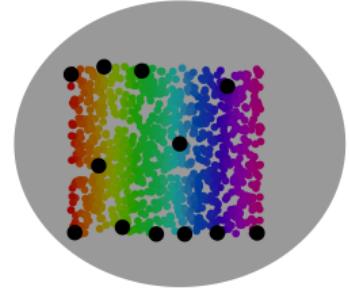
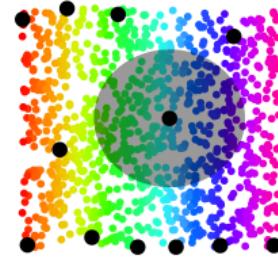
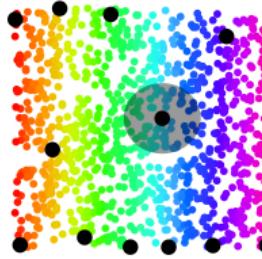
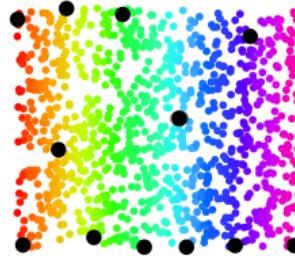
## 4.2 RESULTS SENSITIVITY ANALYSIS II

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**Key variation.** Swiss roll

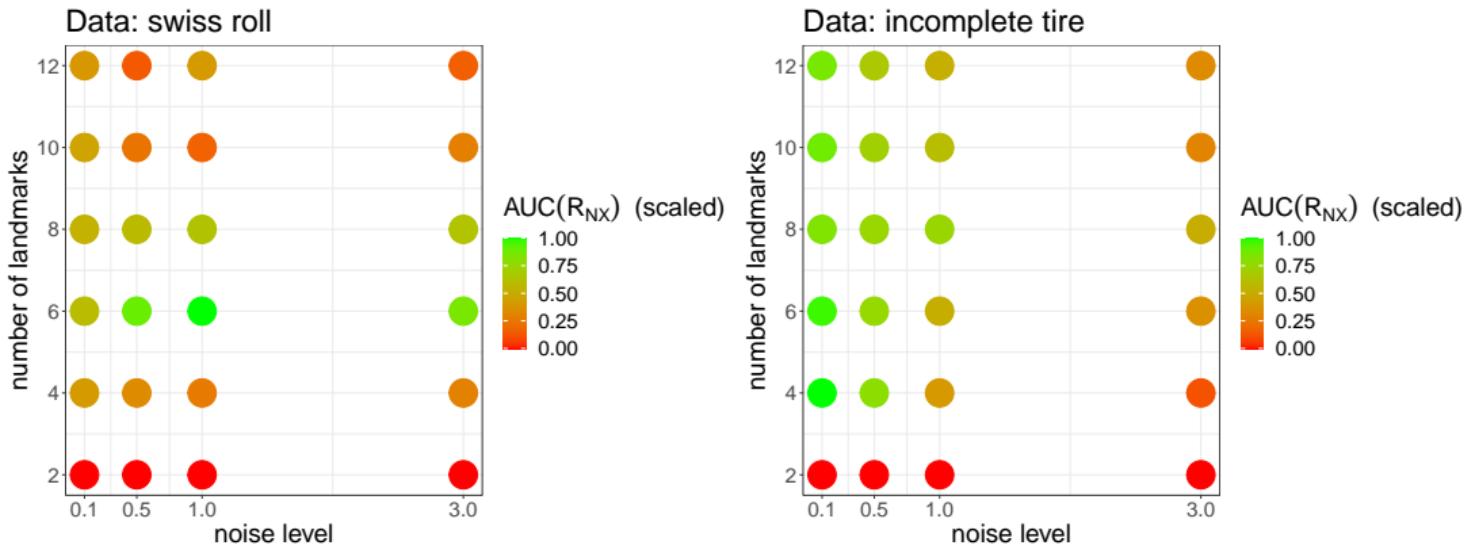


**Key variation.** Incomplete tire



## 4.2 RESULTS SENSITIVITY ANALYSIS II

**Quantitative results.** Some compensation of noise by larger number of landmarks

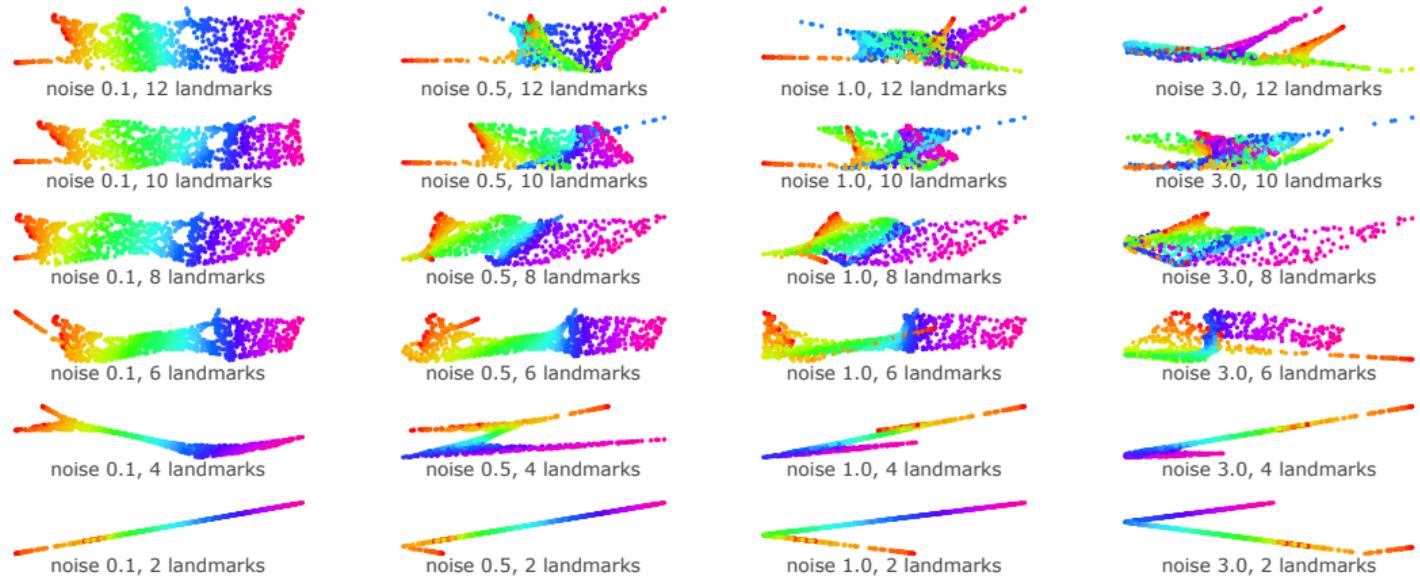


AUC( $R_{NX}$ ) has been scaled to take on a minimum of 0 and maximum of 1 in both figures for better visibility of differences. Original scales. Swiss roll: AUC( $R_{NX}$ )  $\in [0.2720, 0.4167]$ , incomplete tire: AUC( $R_{NX}$ )  $\in [0.3171, 0.6172]$

## 4.2 RESULTS SENSITIVITY ANALYSIS II

**Qualitative results.** Impact different across data sets

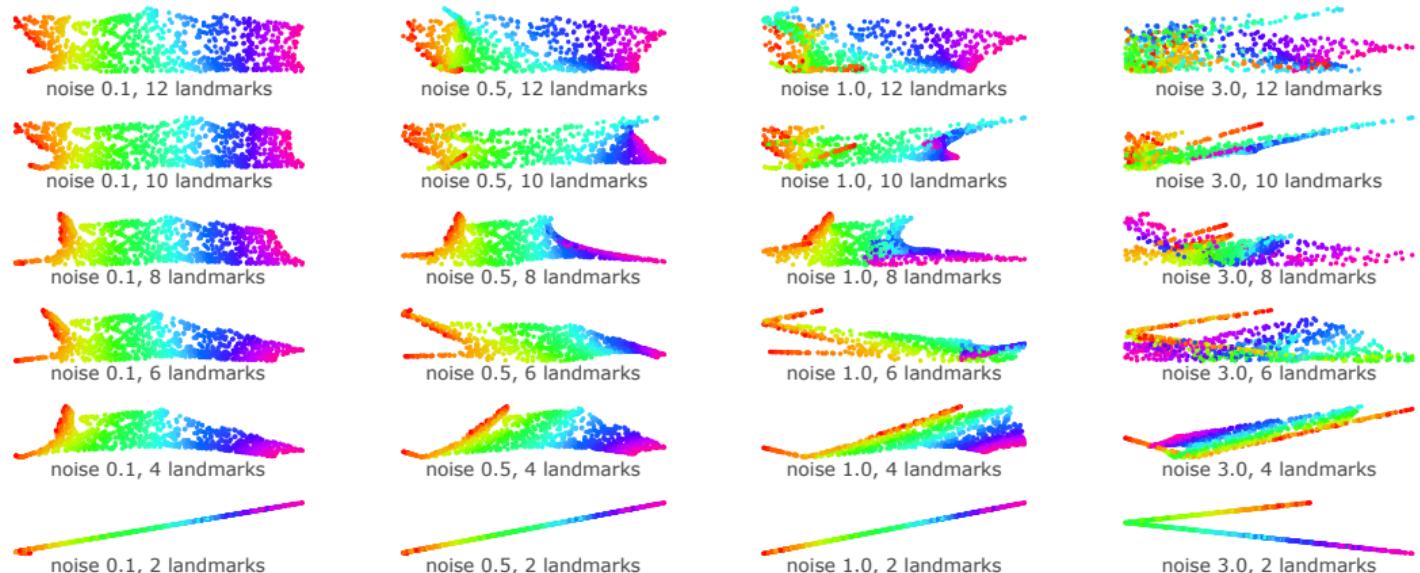
Data: swiss roll



## 4.2 RESULTS SENSITIVITY ANALYSIS II

**Qualitative results.** Impact different across data sets

Data: incomplete tire



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# 5 DISCUSSION

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## 5 DISCUSSION FOO

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woteva

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# MAIN REFERENCES

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