



*Mapper can produce a topological model for fibres of failure modes.*

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**Topology in the furnace:**

**TDA as a diagnostics tool for  
process control systems.**

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*in transit* KTH → CUNY



- ❖ Early work in progress
- ❖ Collaboration with
  - Ayasdi Inc.
  - Outukumpu Stainless AB
  - KTH ITM (Industrial Engineering and Management)
- ❖ Plan: use TDA to understand, diagnose and improve industrial process control and engineering.

First approach: diagnostics on existing control systems with Mapper.

What is mapper?

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# The Mapper algorithm

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- ❖ Gurjeet Singh (2012)
- ❖ Built on a topological basic idea
- ❖ Creates intrinsic simplicial complex model of arbitrary data



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# Topological background

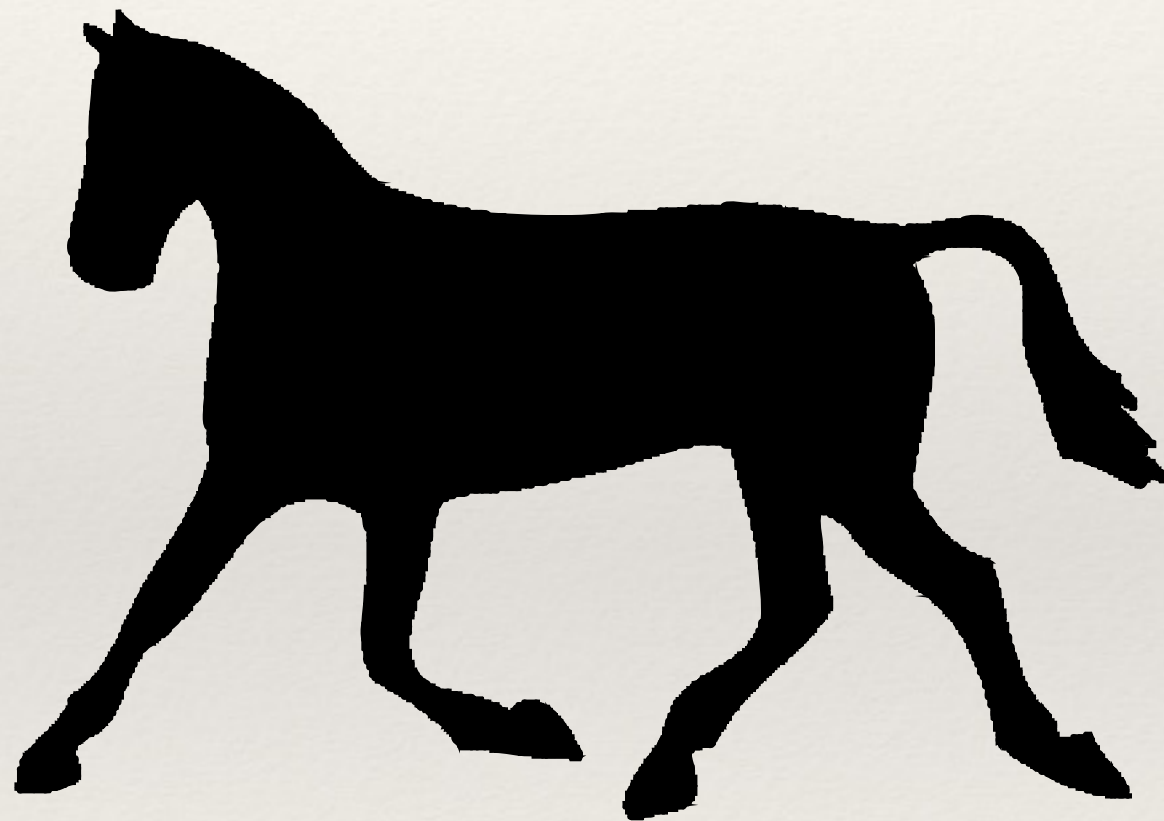
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- ❖ Consider:
  - ❖ Spaces  
 $X, Y$
  - ❖ Continuous map  
 $f: X \rightarrow Y$
  - ❖ Cover  
 $Y = \cup Y_i$
- ❖ The cover pulls back to a cover  
 $X = \cup f^{-1}Y_i$
- ❖ Refine cover to connected components  
 $X = \cup X_j; X_j \in \pi_0 f^{-1}Y_i$
- ❖ If each  $X_j$  is contractible,  
Nerve lemma  $\rightarrow$  nerve complex  $\simeq X$ .

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# Topological background

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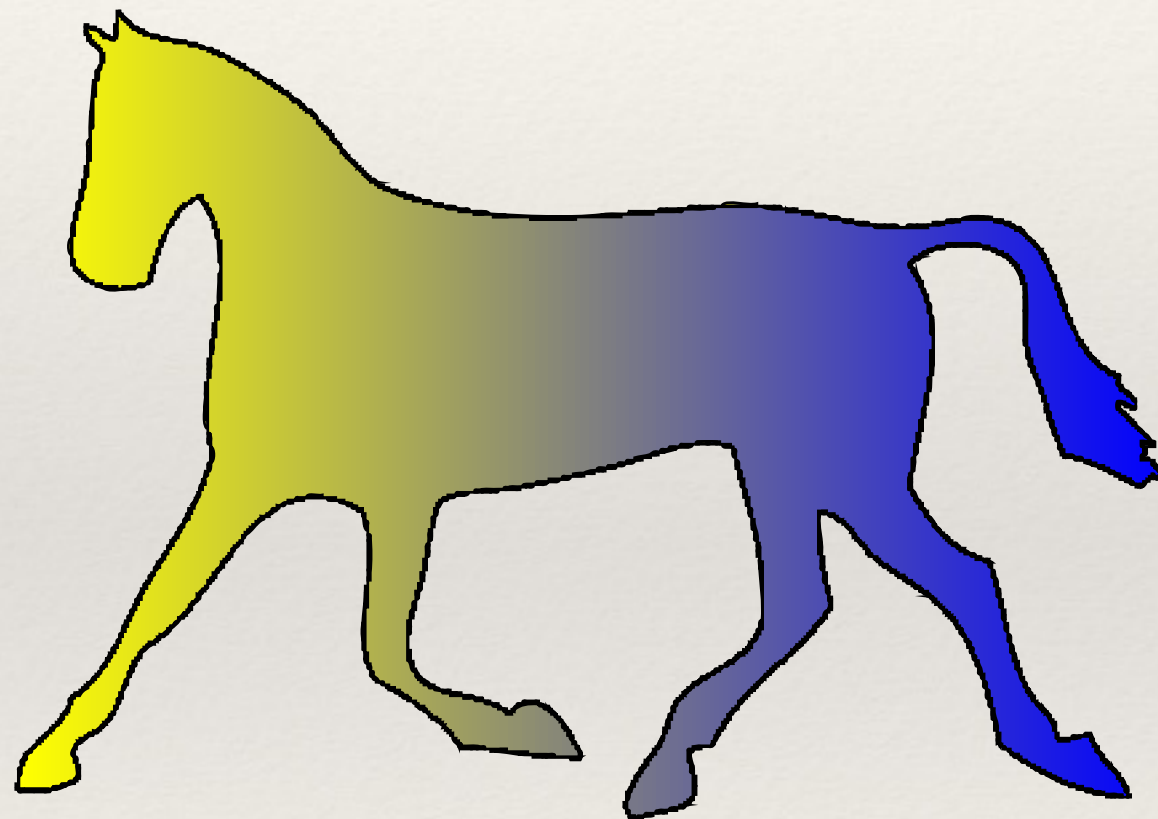




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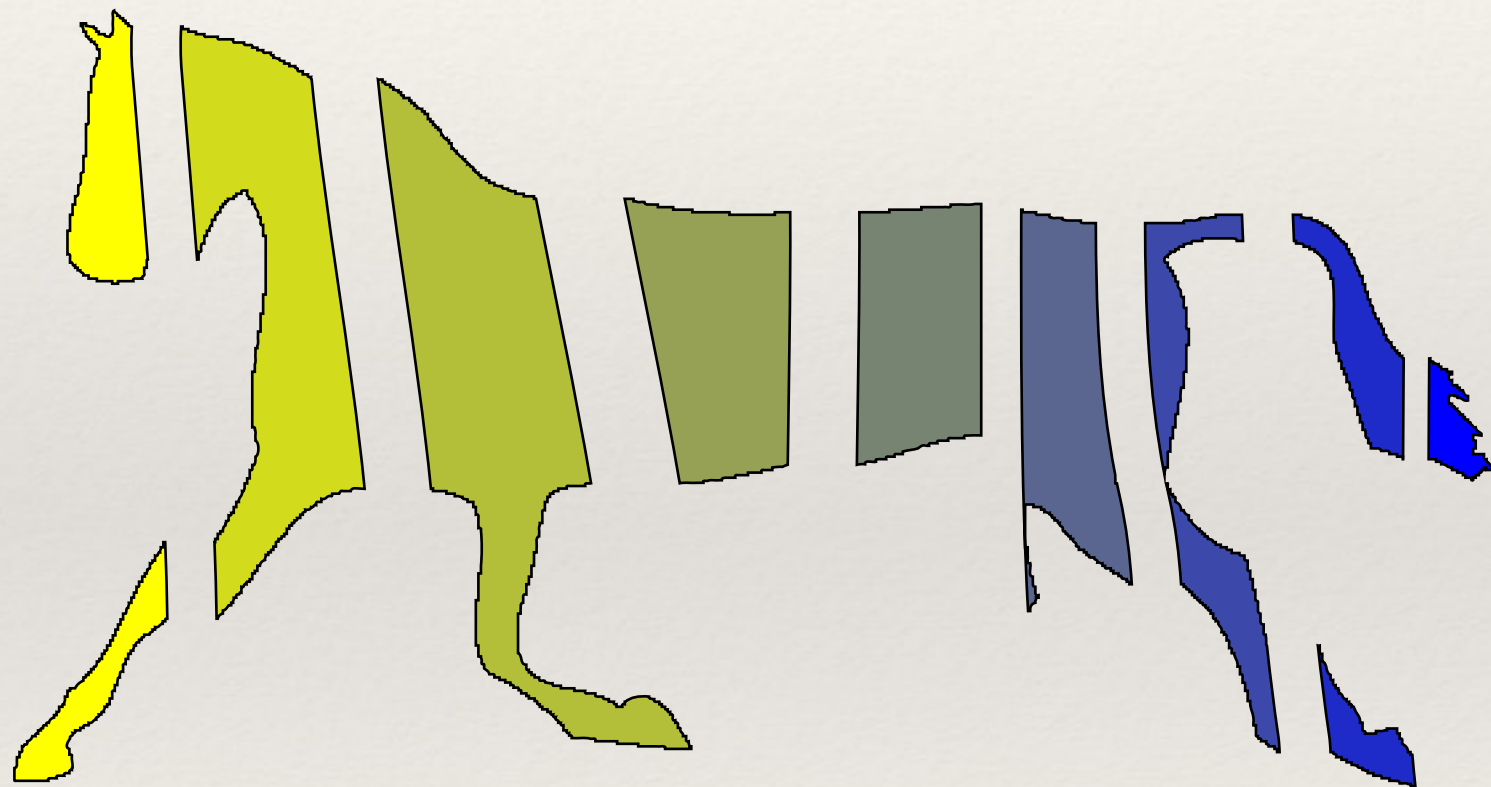
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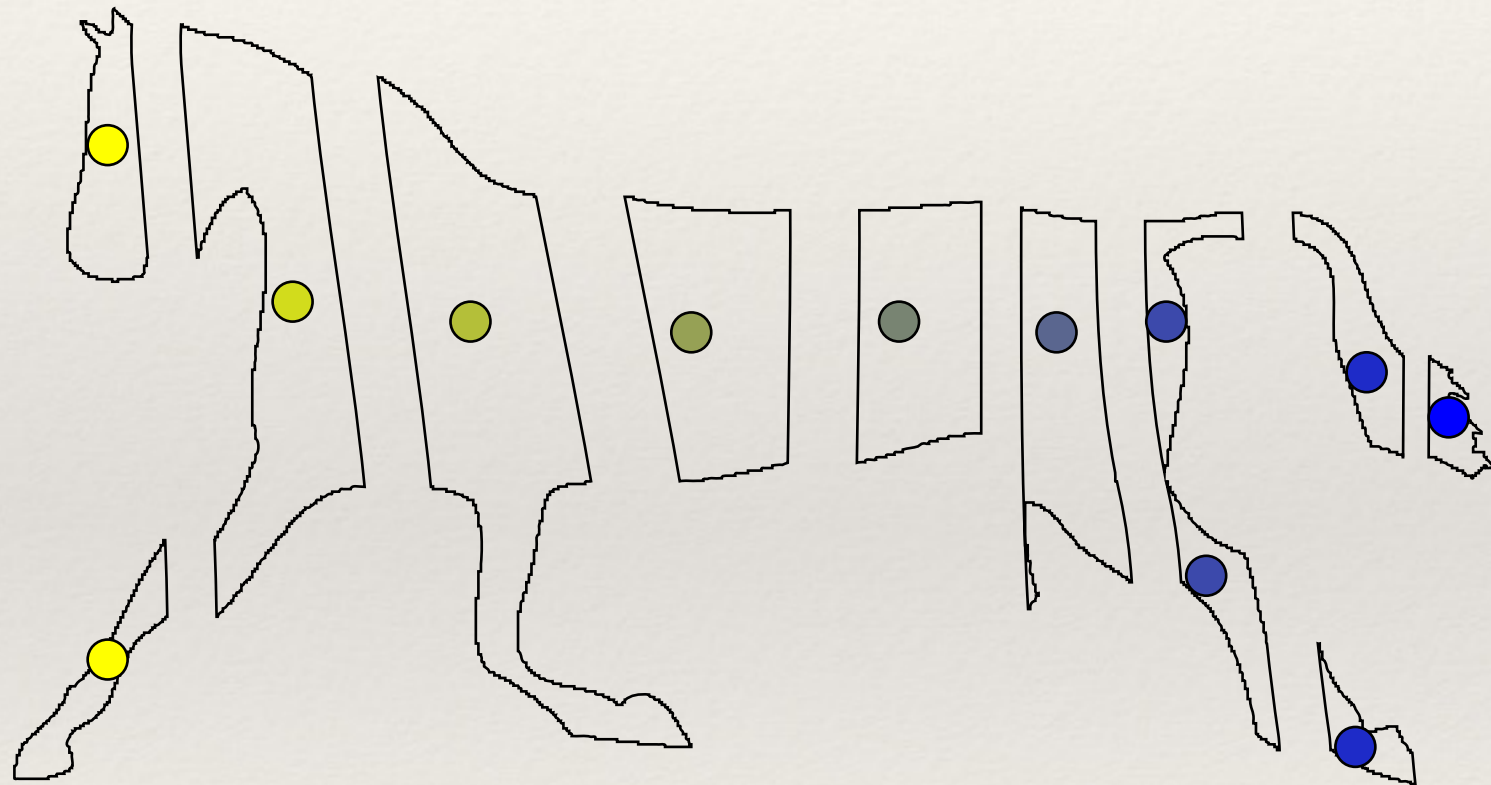




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# Topological background

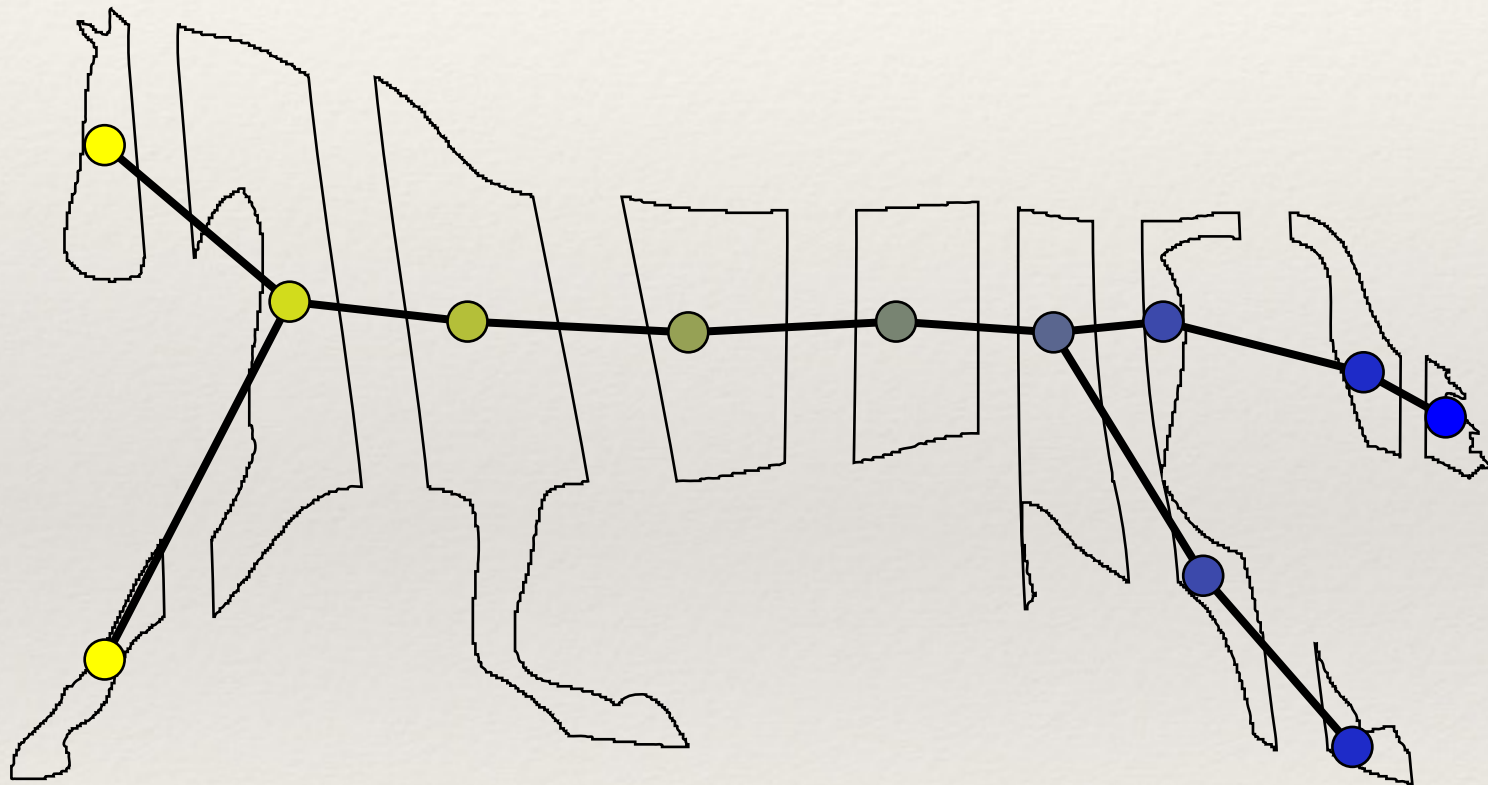
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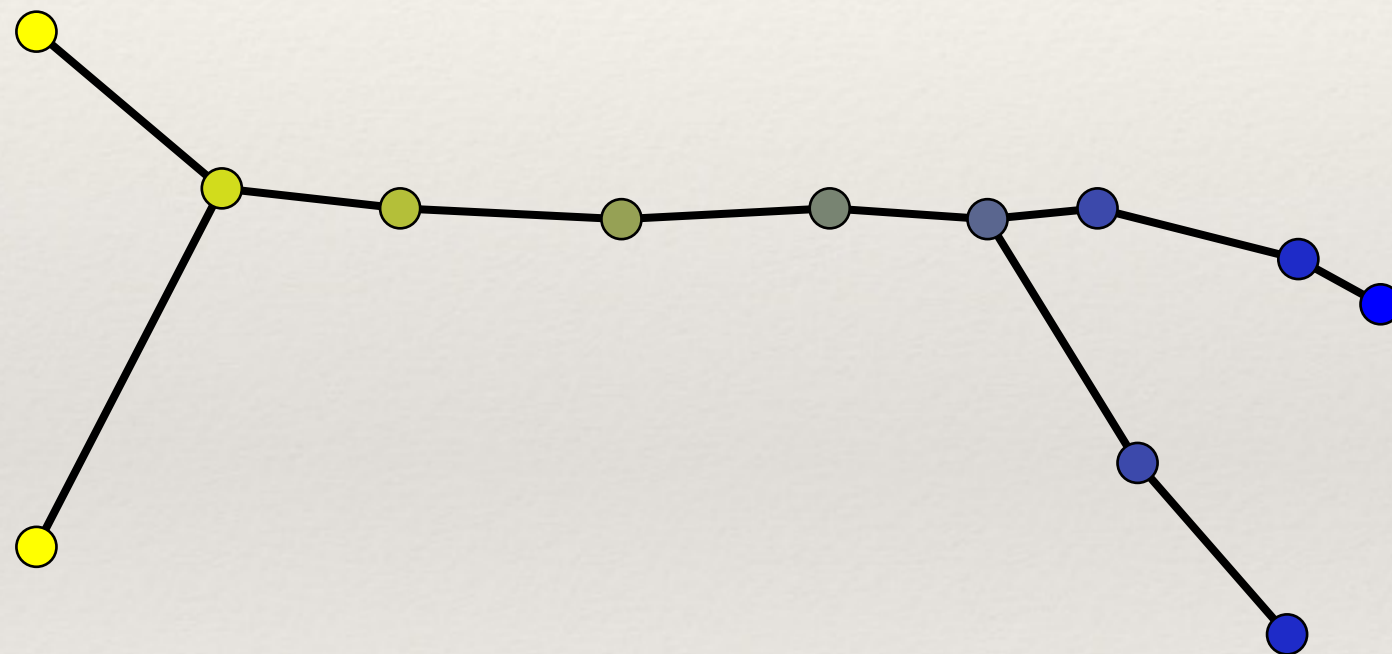




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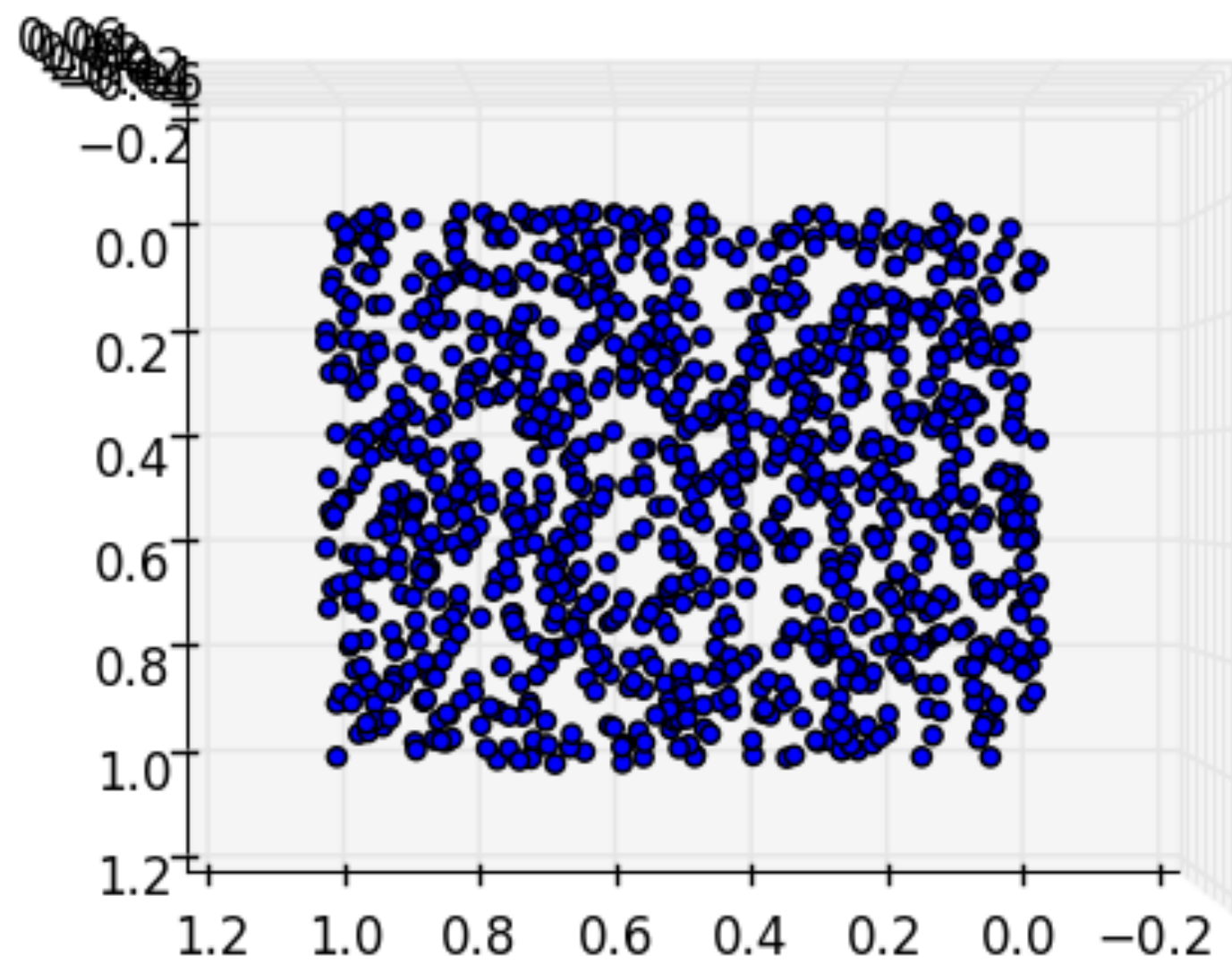


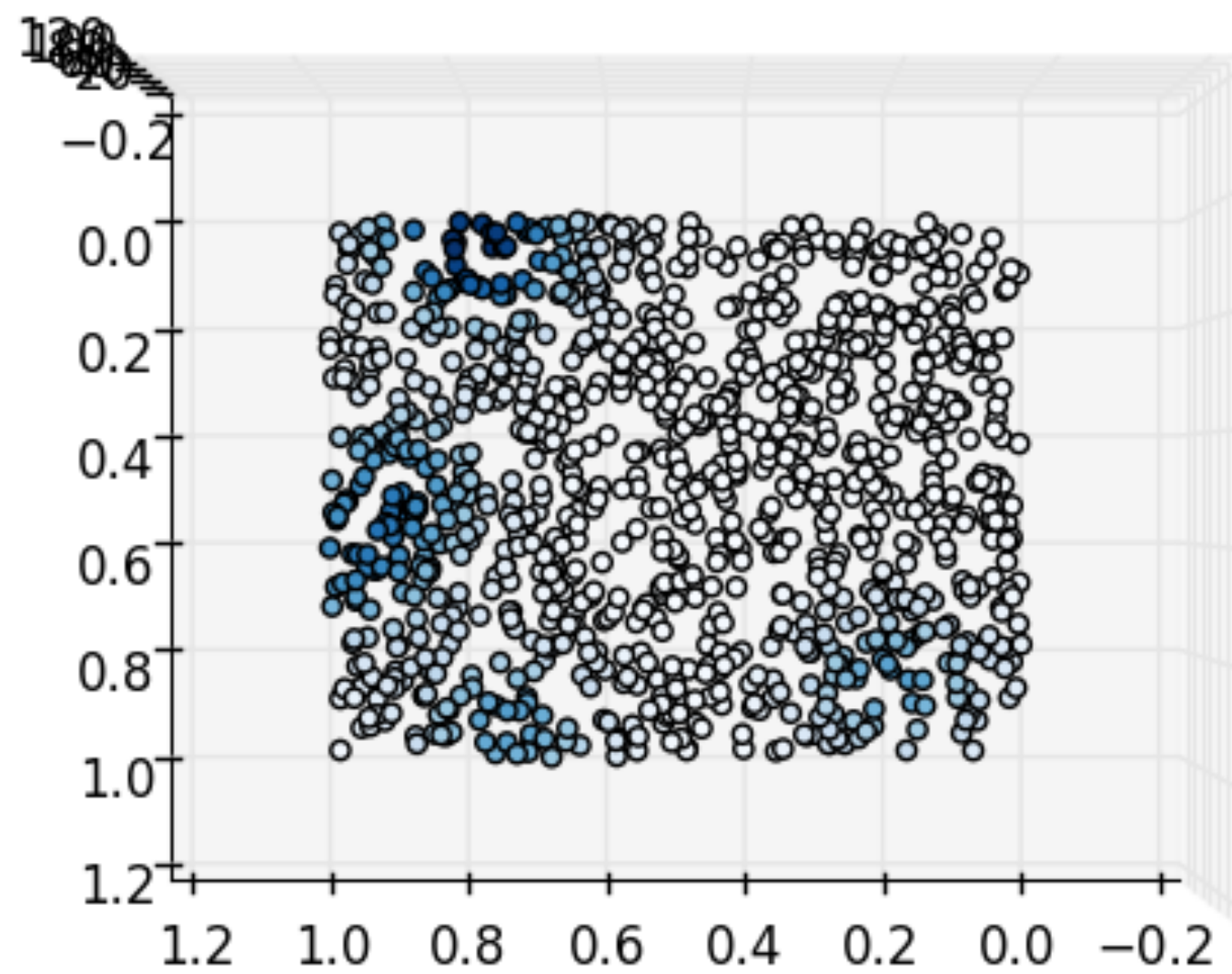
# From topology to data: a dictionary

- ❖ Topological space
- ❖ Continuous map  
 $X \rightarrow Y$
- ❖ Cover
- ❖  $\pi_0$
- ❖ Nerve complex
- ❖ Point cloud
- ❖ *Filter* function or *lens*  
 $X \rightarrow \mathbb{R}^d$
- ❖ Partition with overlap
- ❖ Clustering wrt *metric*.
- ❖ Nerve complex

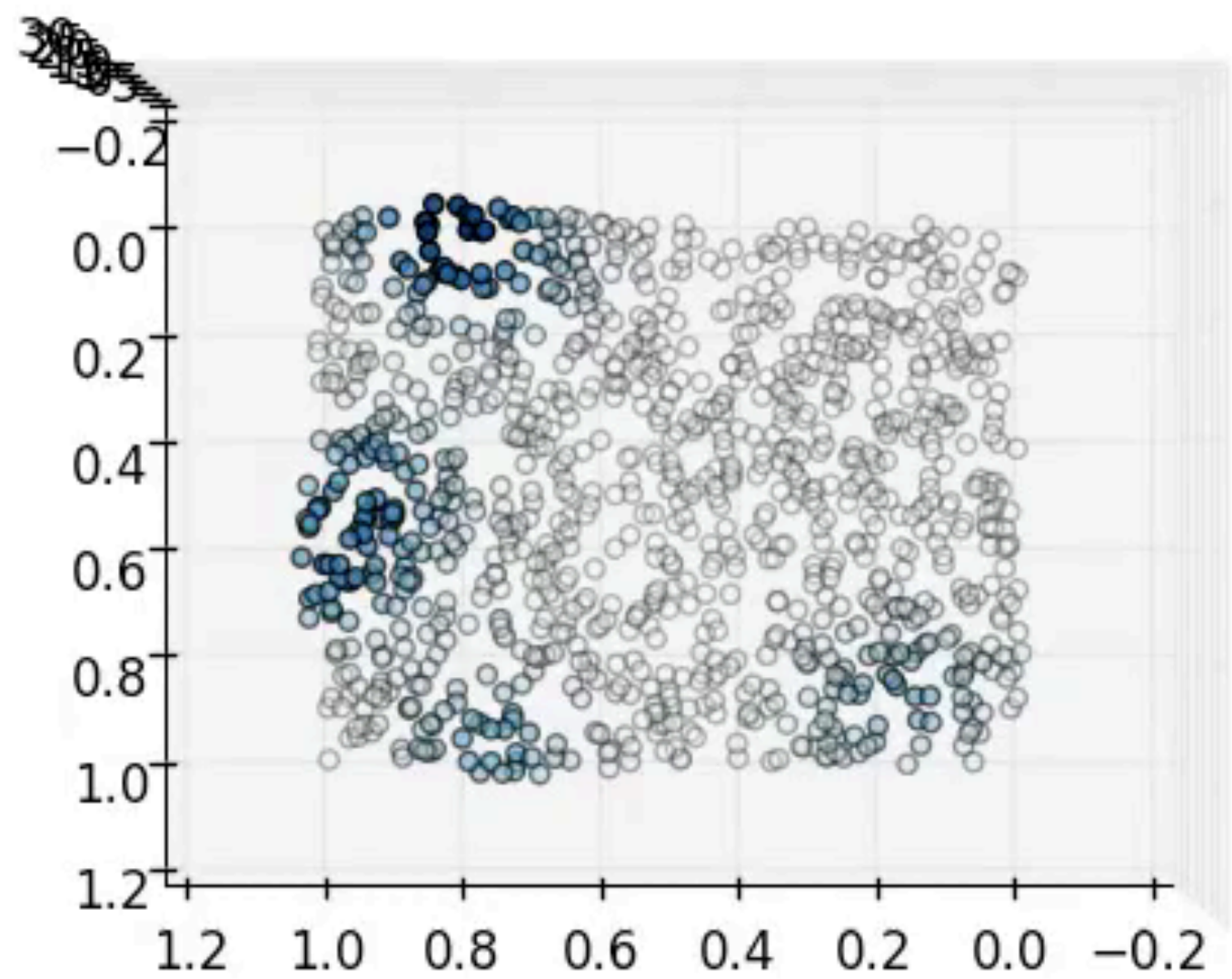
Mapper is parametrized by a choice of **lens(es)**, of **metric**, of (parameters for) **partition** and of **clustering** method.

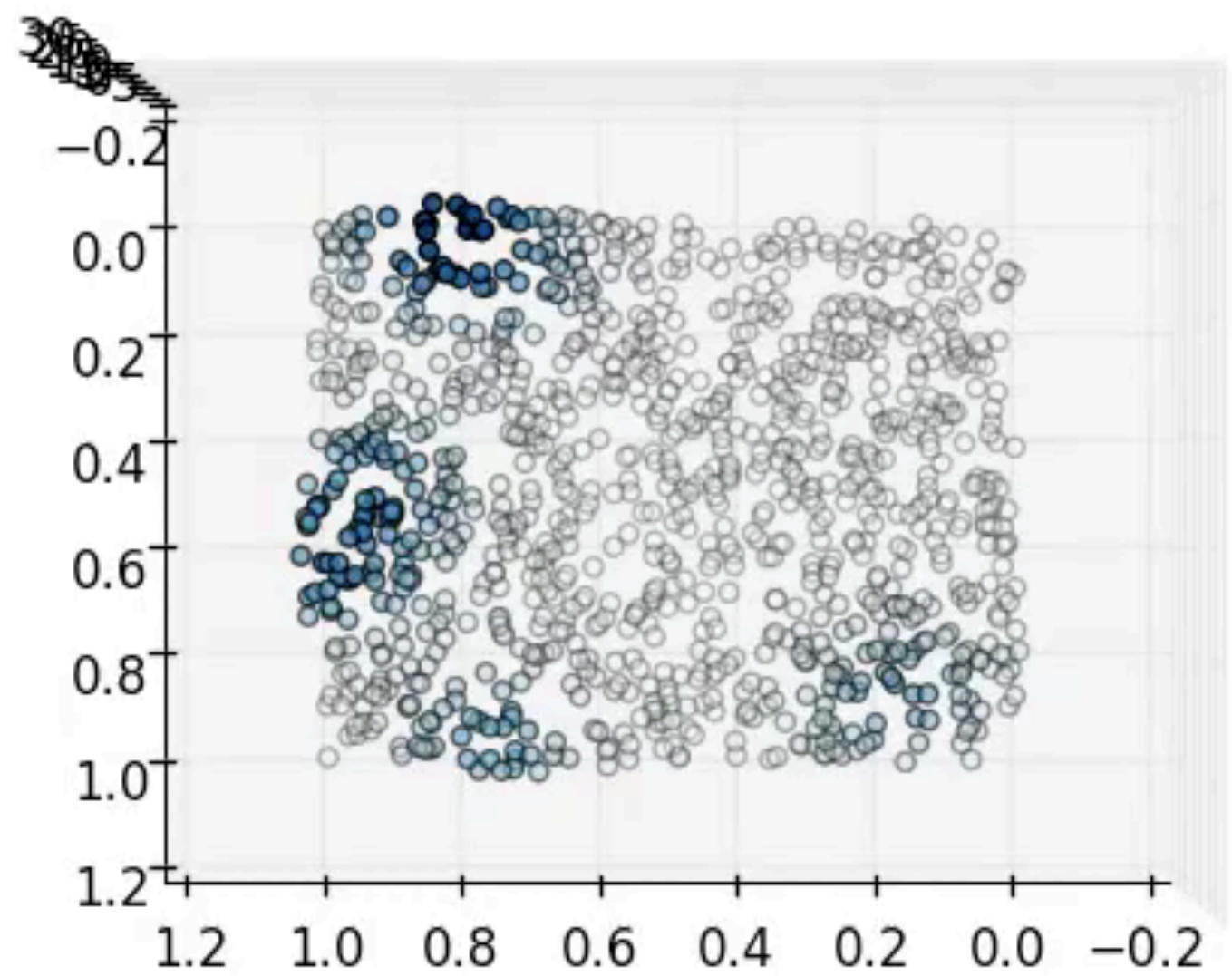




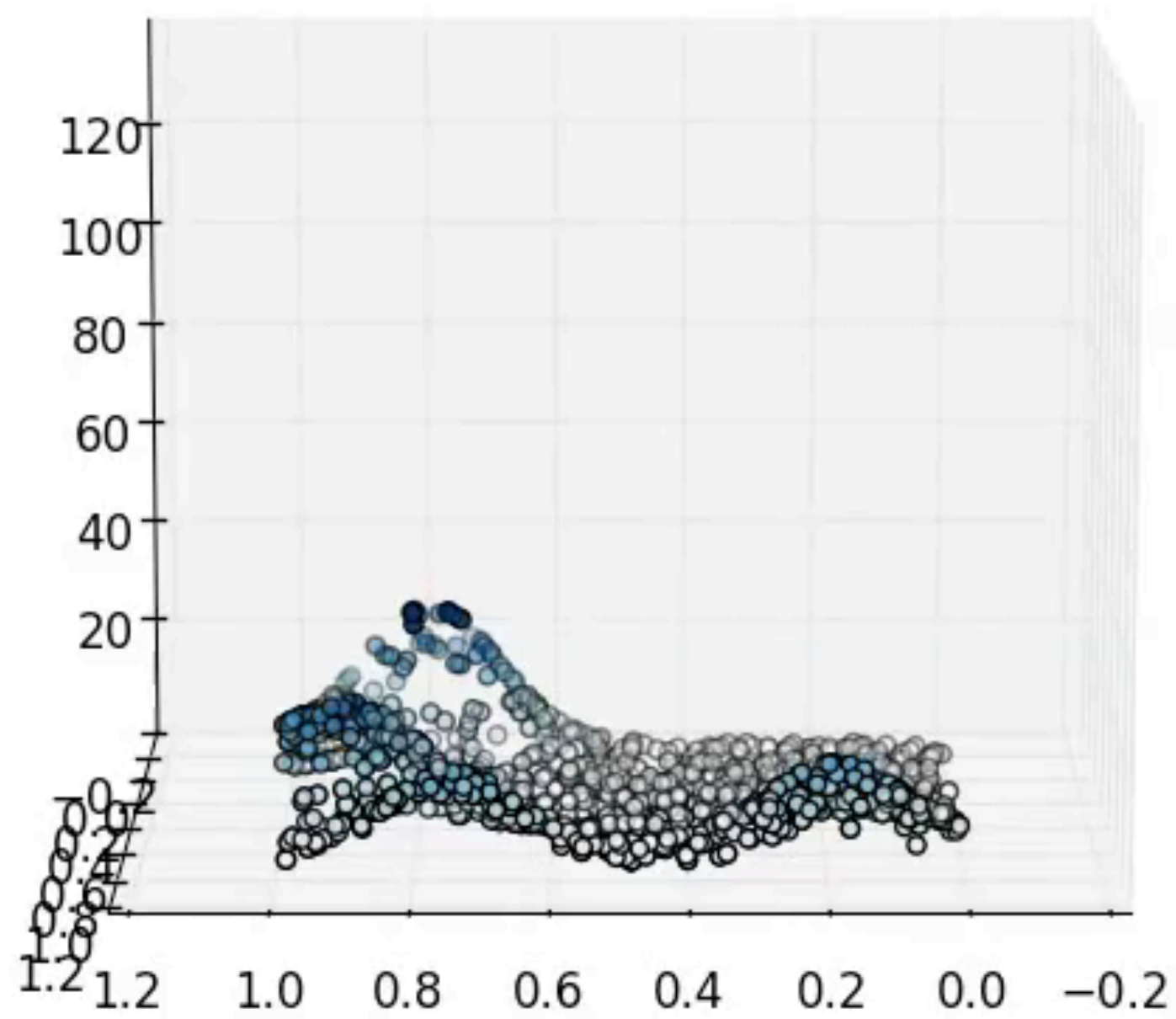


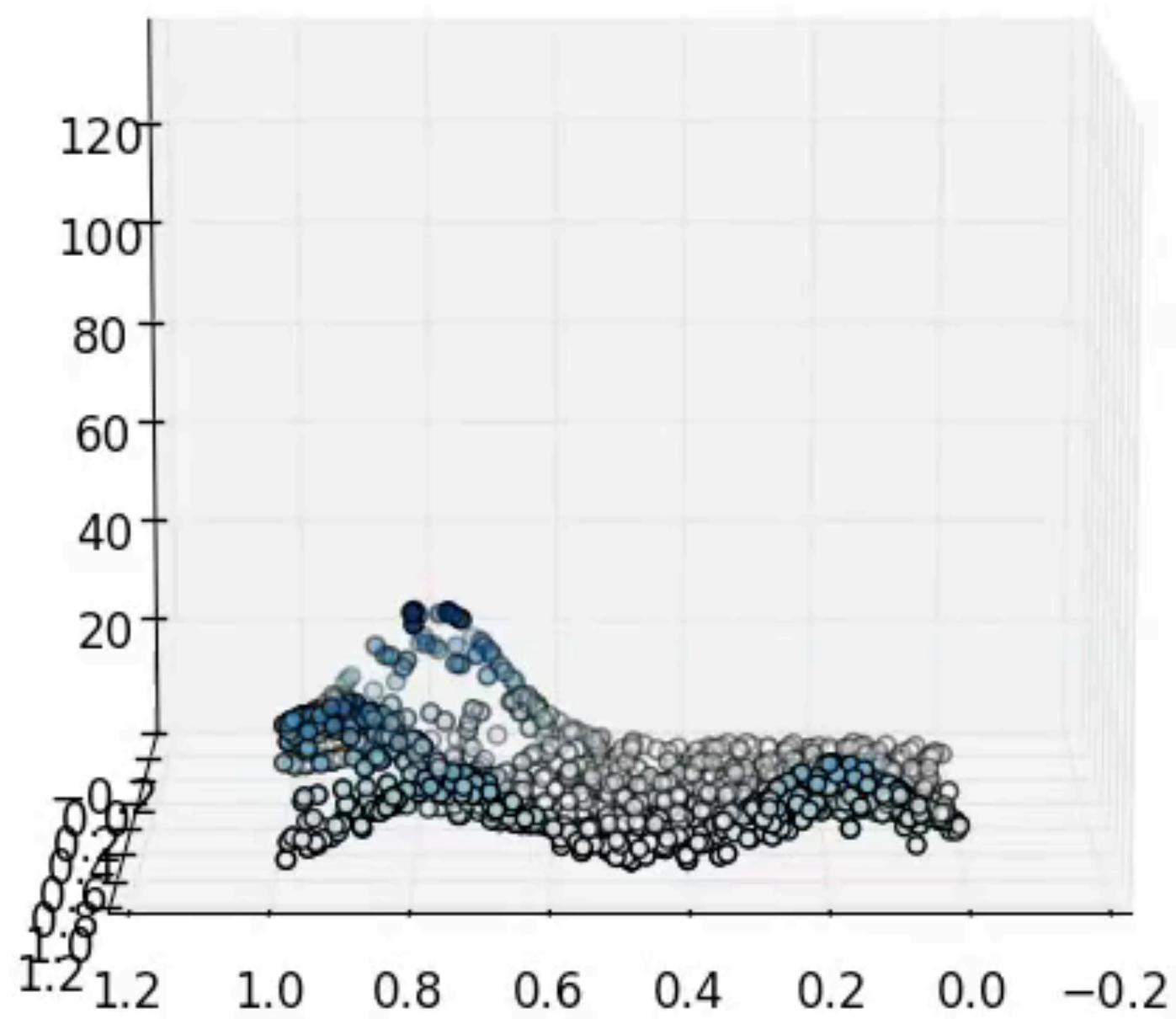


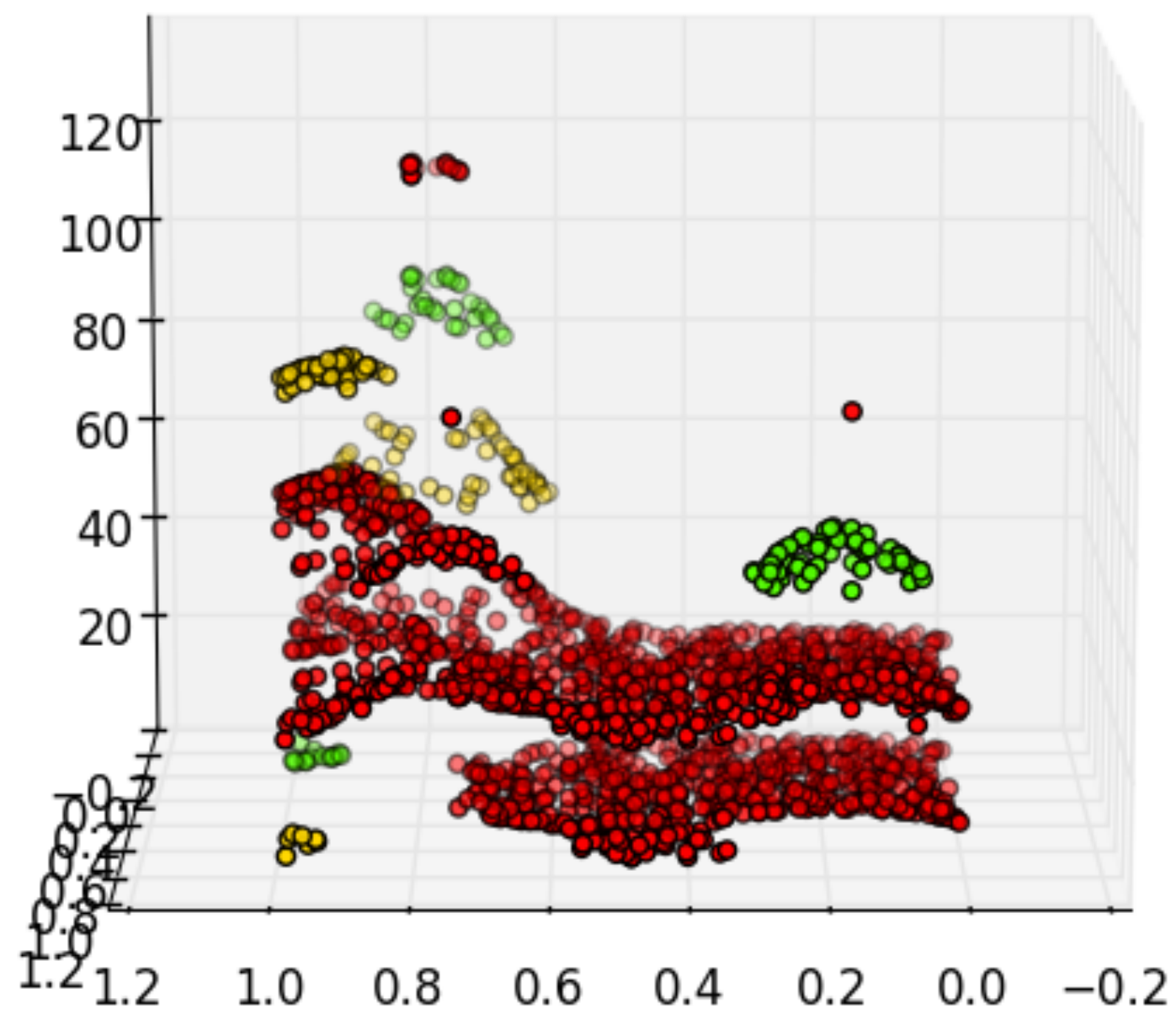




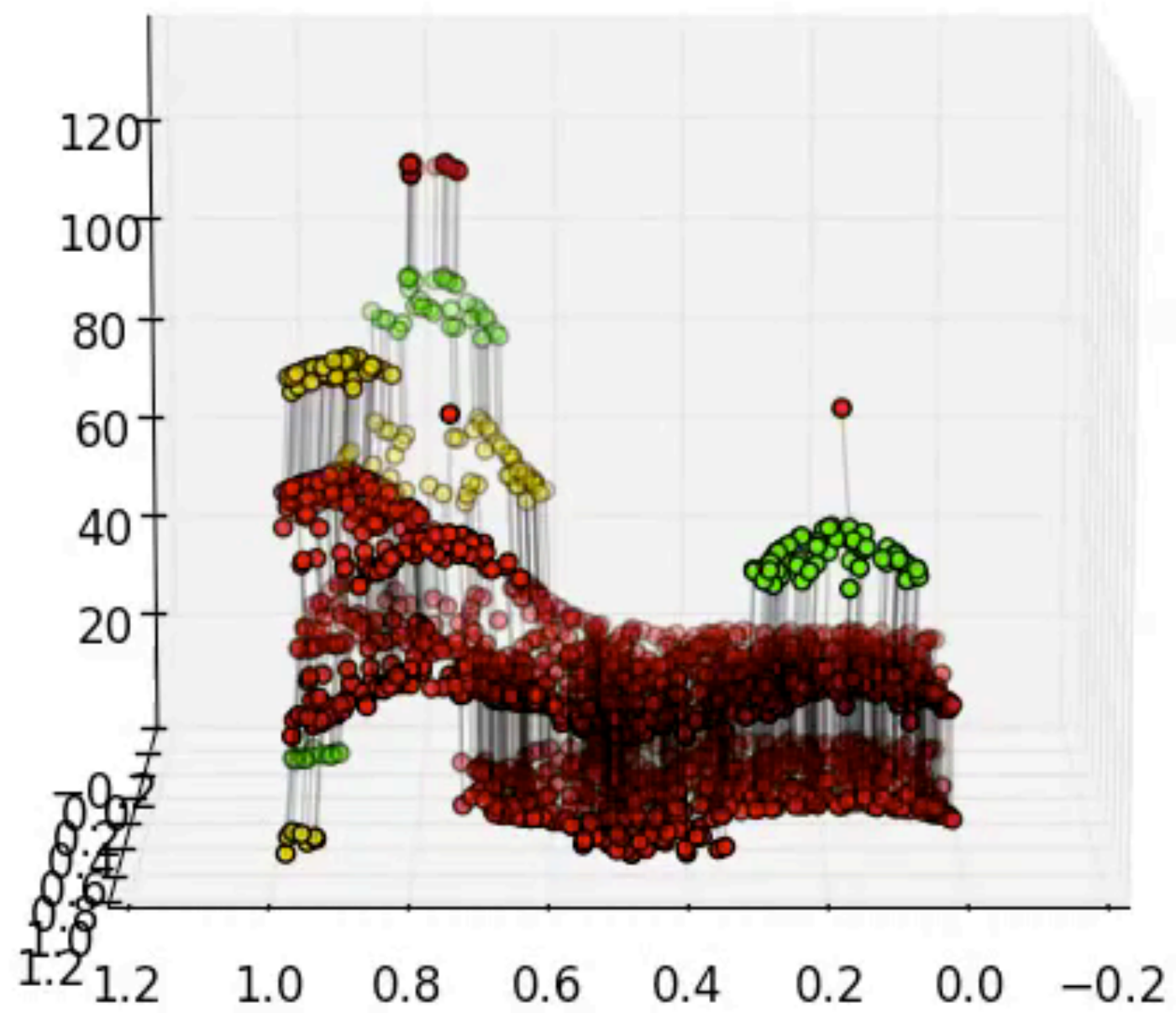


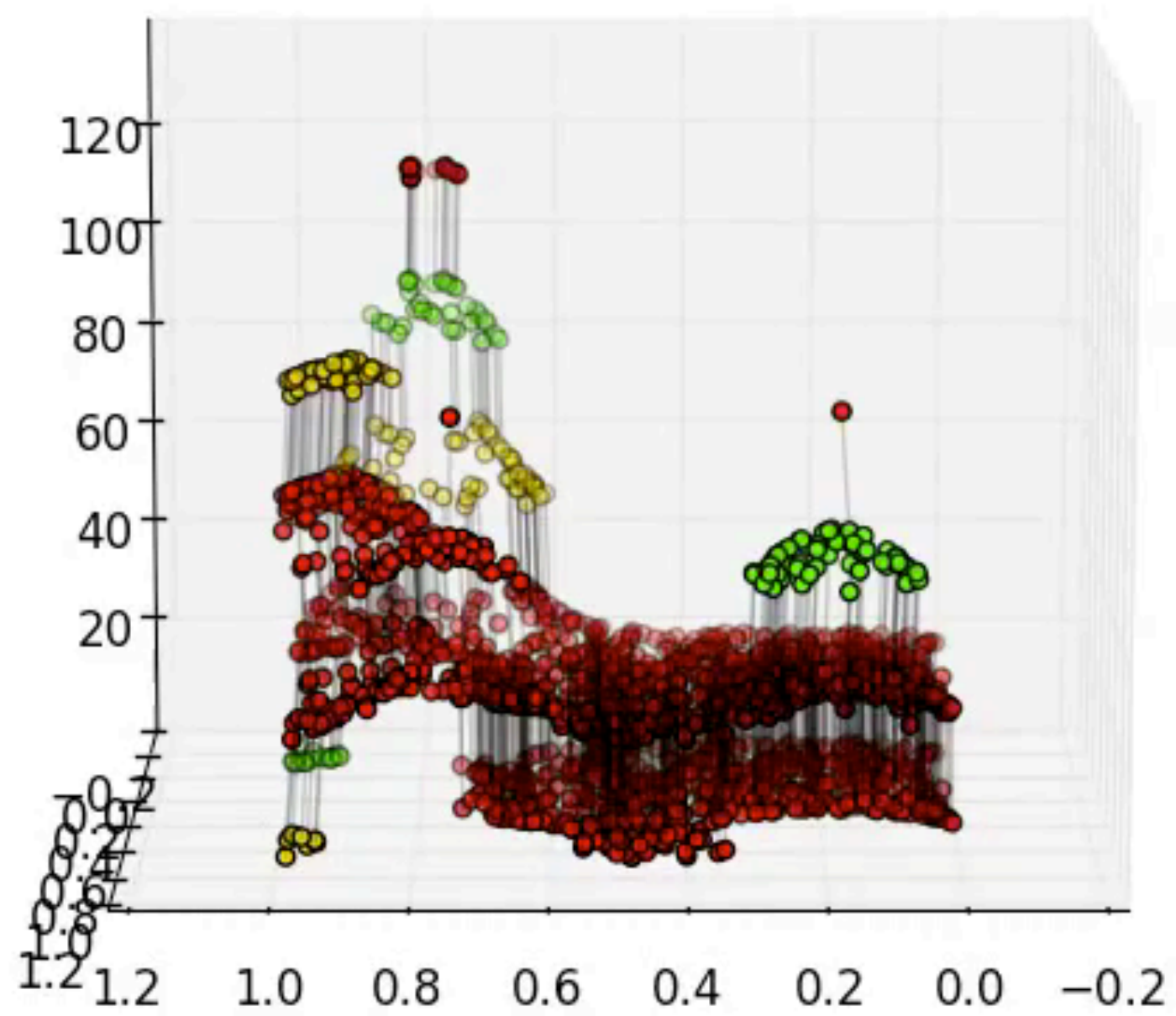












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# Implementations

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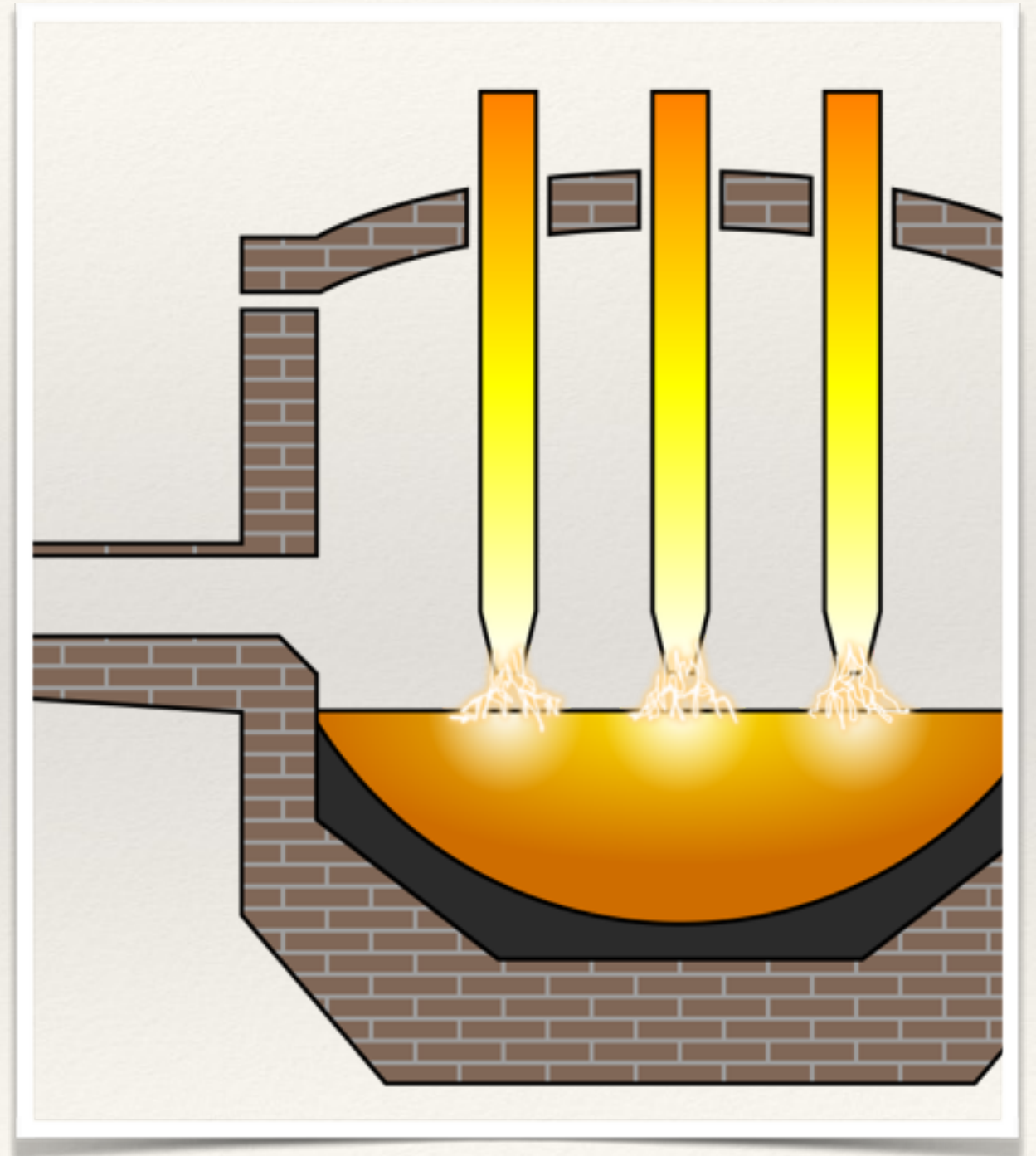
- ❖ mapper.m
- ❖ Ayasdi Core
- ❖ PyMapper
- ❖ TDAMapper (R)
- ❖ mirkoklukas / tda-mapper-py
- ❖ MLWave / kepler-mapper



# Electric Arc Furnaces

# Electric Arc Furnace

- ❖ Works by producing electric arcs from electrodes to scrap metal, producing heat that melts the metal.
- ❖ Standard 3-phase 220V 50Hz electricity.
- ❖ Consumes  $\sim 0.4$  kWh/kg; theoretical minimum is  $\sim 300$  kWh.





# Electric Arc Furnace

- ❖ Furnace in Avesta run by Outokumpu Stainless.
- ❖ Stainless: expensive scrap, high price output.
- ❖ Single charge produces 100 tonnes stainless steel.
- ❖ Approximately 5000 charges per year — 15-20 per day.





# Temperature constraints

- ❖ Optimal temperature  $\sim 1600^{\circ}$
- ❖ Too low: not fully smelted
- ❖ Too high: entire batch spoiled
- ❖ Reference measurement possible: single use probe expensive and leaks heat.
- ❖ Metallurgical models available.  
Error spans  $\pm 400^{\circ}$ .  
IQR  $-120^{\circ} \text{ — } +18^{\circ}$





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# Model parameters

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- ❖ Known factors at any time point in production:

Element composition of the scrap

Energy used

Temperature of added scrap

Injected additives: amount & temperature

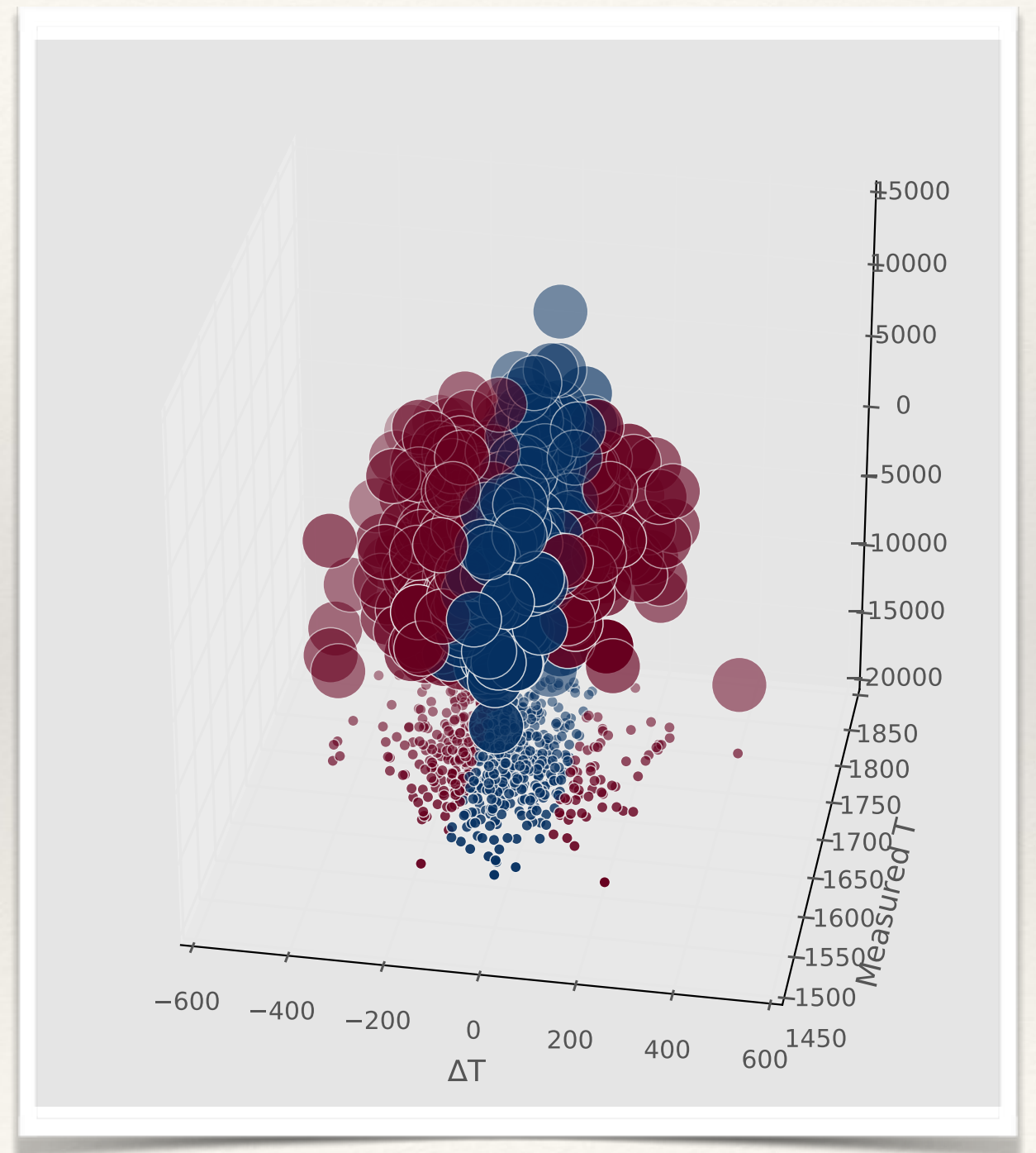
Metallurgical model prediction

- ❖ **Question:** Can we classify model failure modes, and dynamically recognize them?  
Can we dynamically compensate?

# Process diagnostics

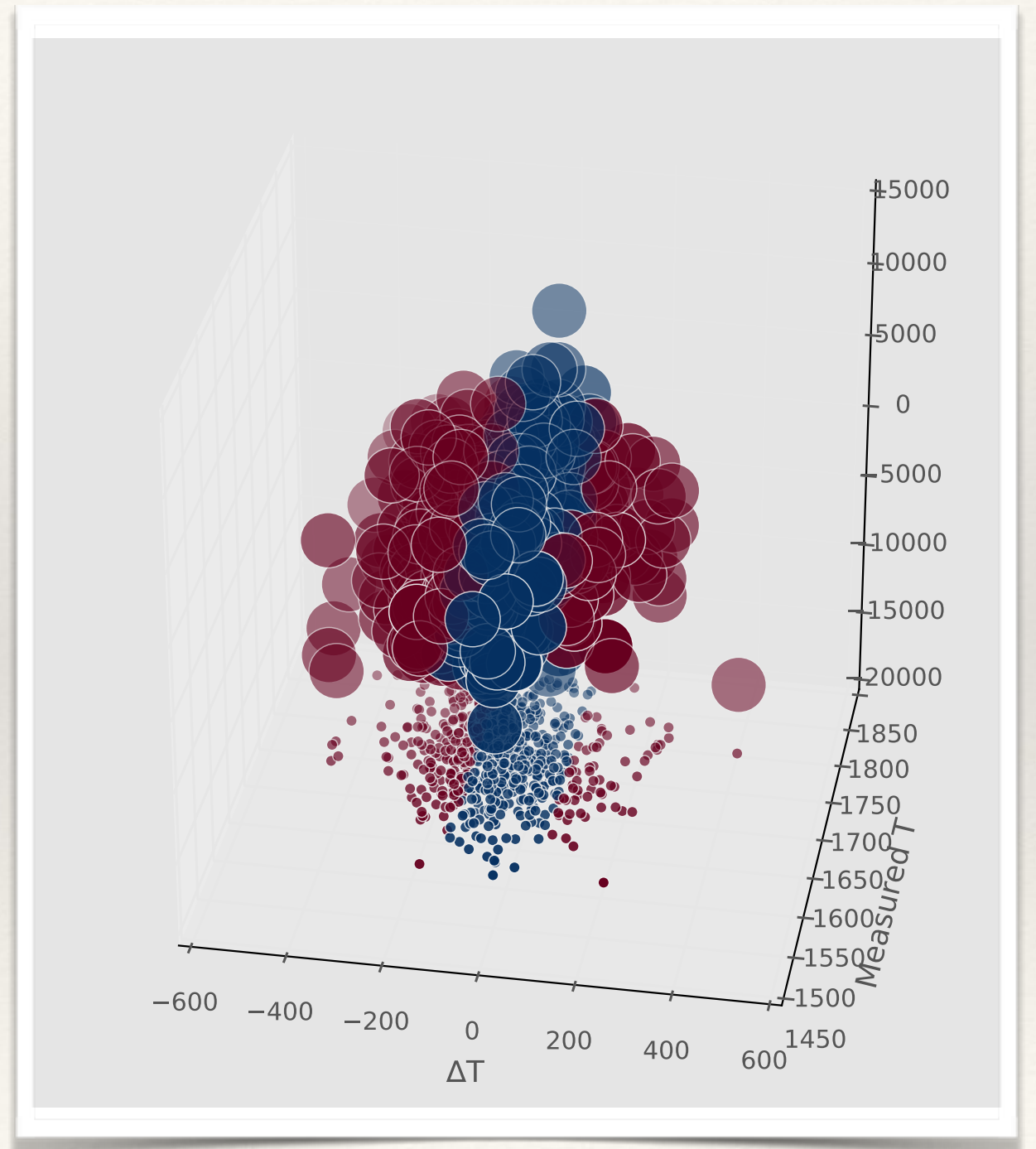


# Basic idea: Mapper on fibres



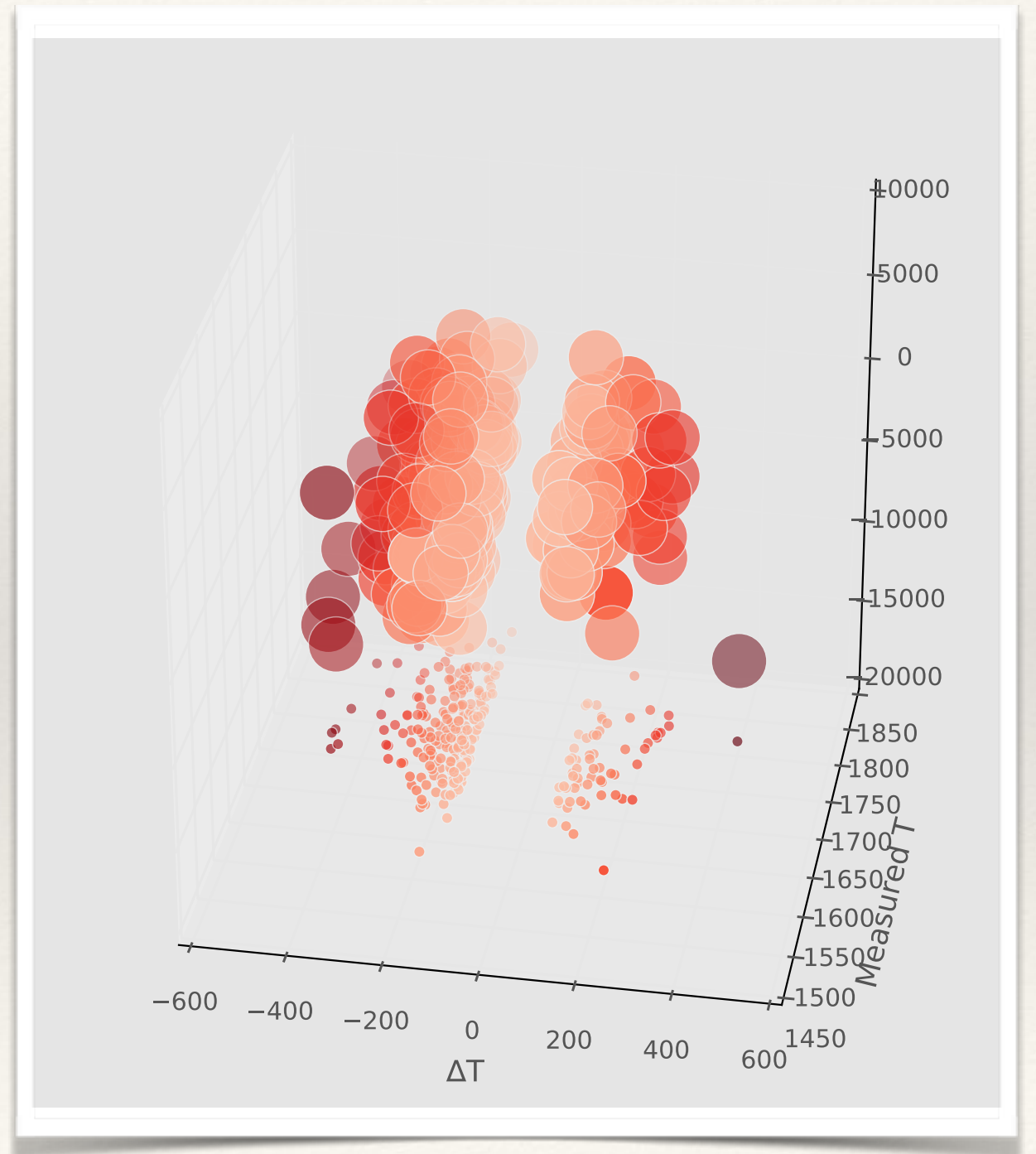
# Basic idea: Mapper on fibres

- ❖ Process model is a function  
[input data]  $\rightarrow$  [model output]
- ❖ Given input data, we can find  
both measurement  $[T]$ ,  
prediction  $[T+\Delta T]$  and  
prediction error  $[\Delta T]$ .
- ❖ Idea: study fibres of the map  
[input data]  $\rightarrow \Delta T \times T$



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- ❖ Idea: study fibres of the map  
[input data]  $\rightarrow \Delta T \times T$
- ❖ Esp.: large values of  $|\Delta T|$ .





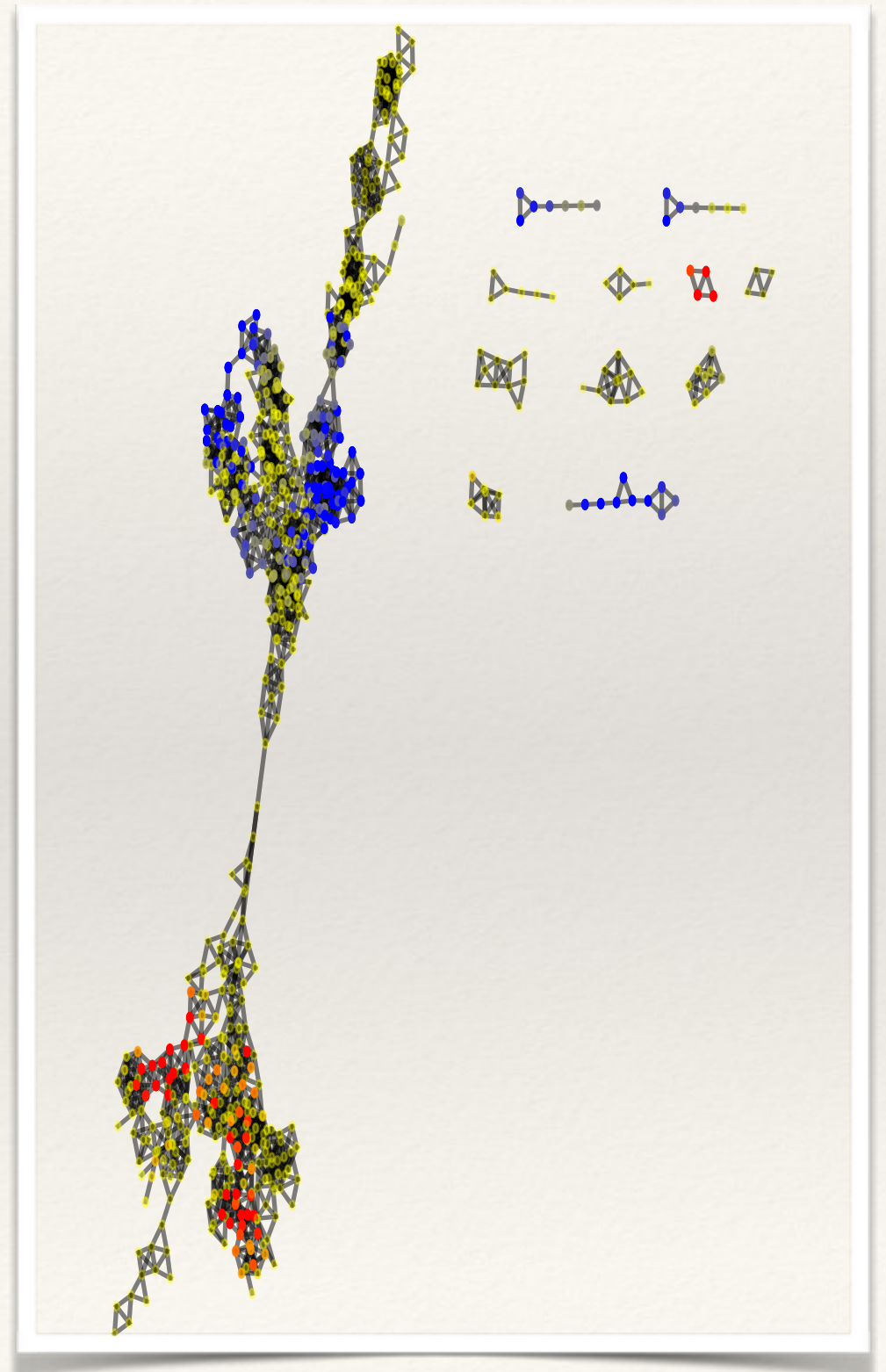
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# Master plan

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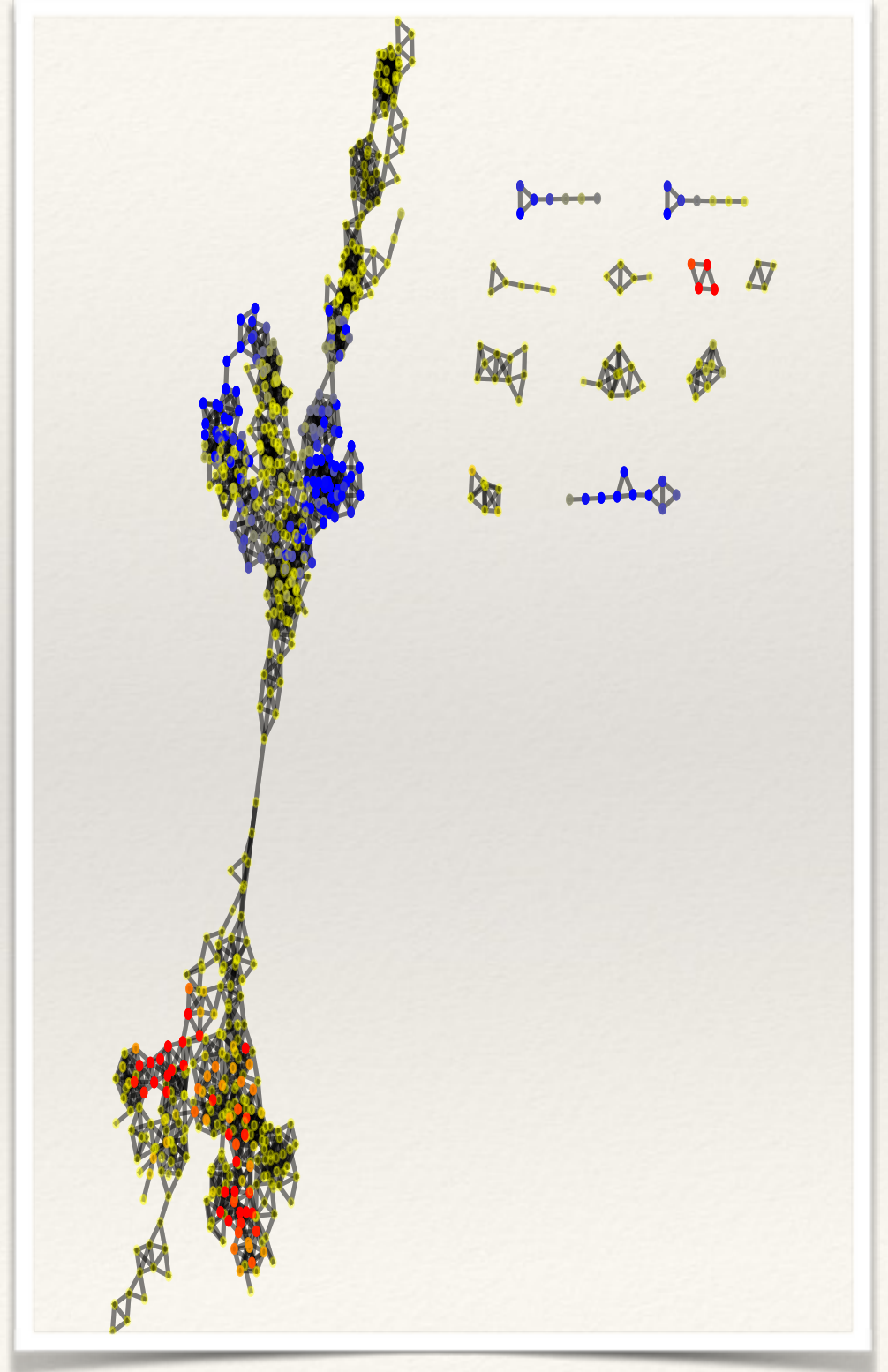
- ❖ Flares and features in Mapper  
→ classification of fibre shape
- ❖ Look for shape of input data over extreme values
- ❖ Find failure modes that can be recognized in production
- ❖ Test on future data!

# The shape of steel



# The shape of steel

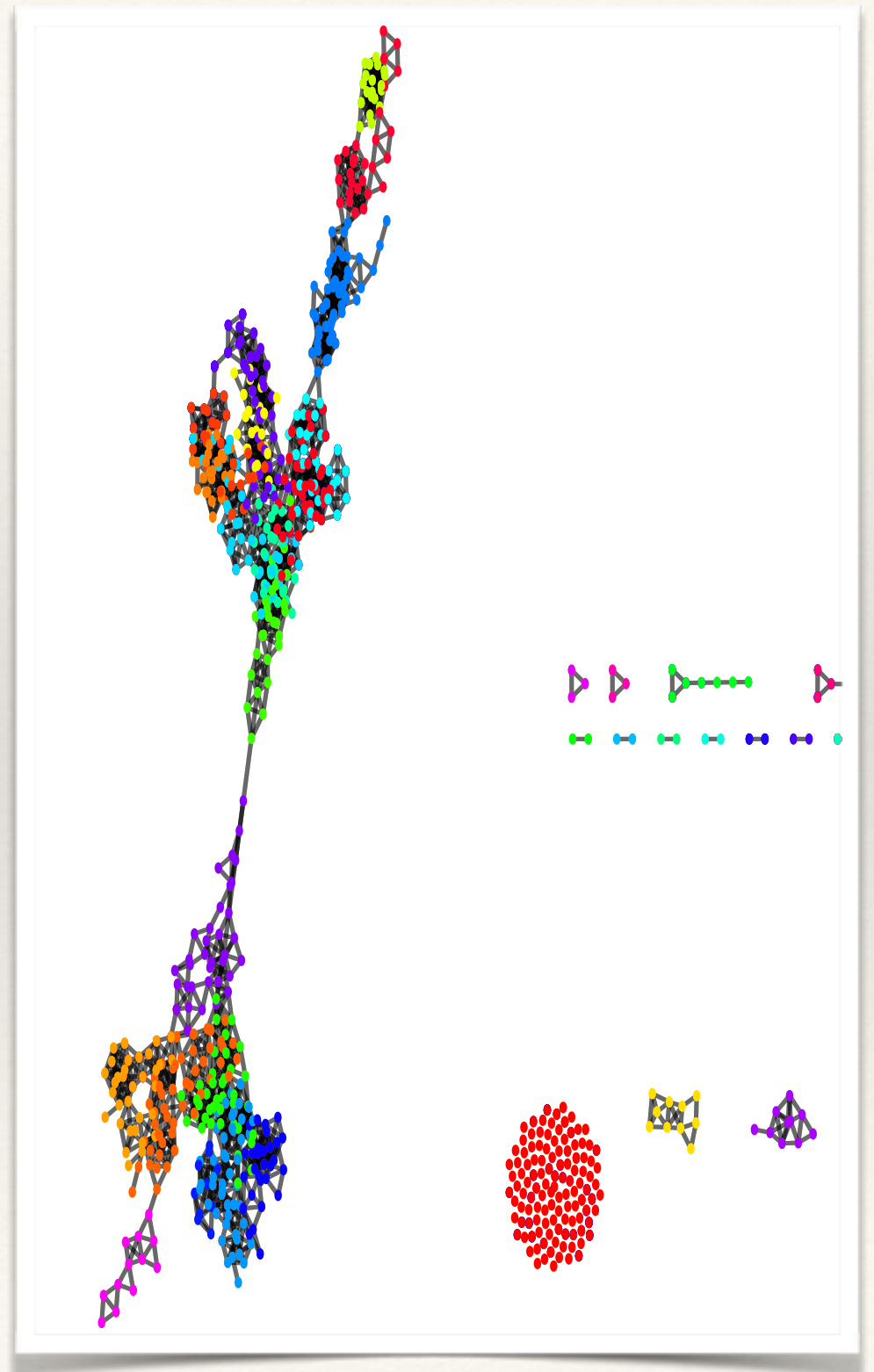
- ❖ Mapper shape from  
Ayasdi Core  
Metric: Variance Normalized  
Euclidean  
Lenses:  
PCA1, PCA2,  $\Delta T$ , T





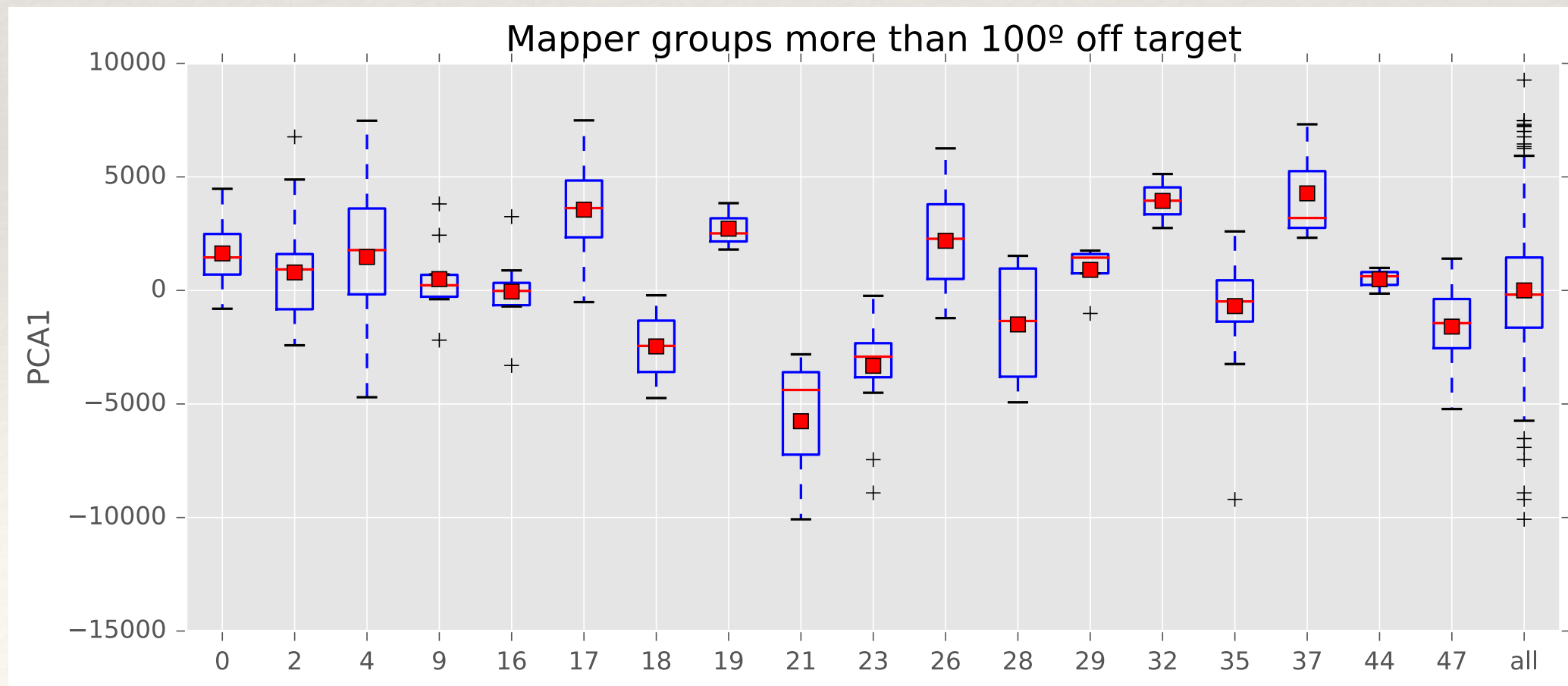
# The shape of steel

- ❖ Mapper shape from Ayasdi Core  
Metric: Variance Normalized Euclidean  
Lenses:  
PCA1, PCA2,  $\Delta T$ , T
- ❖ Core-generated auto-groups.



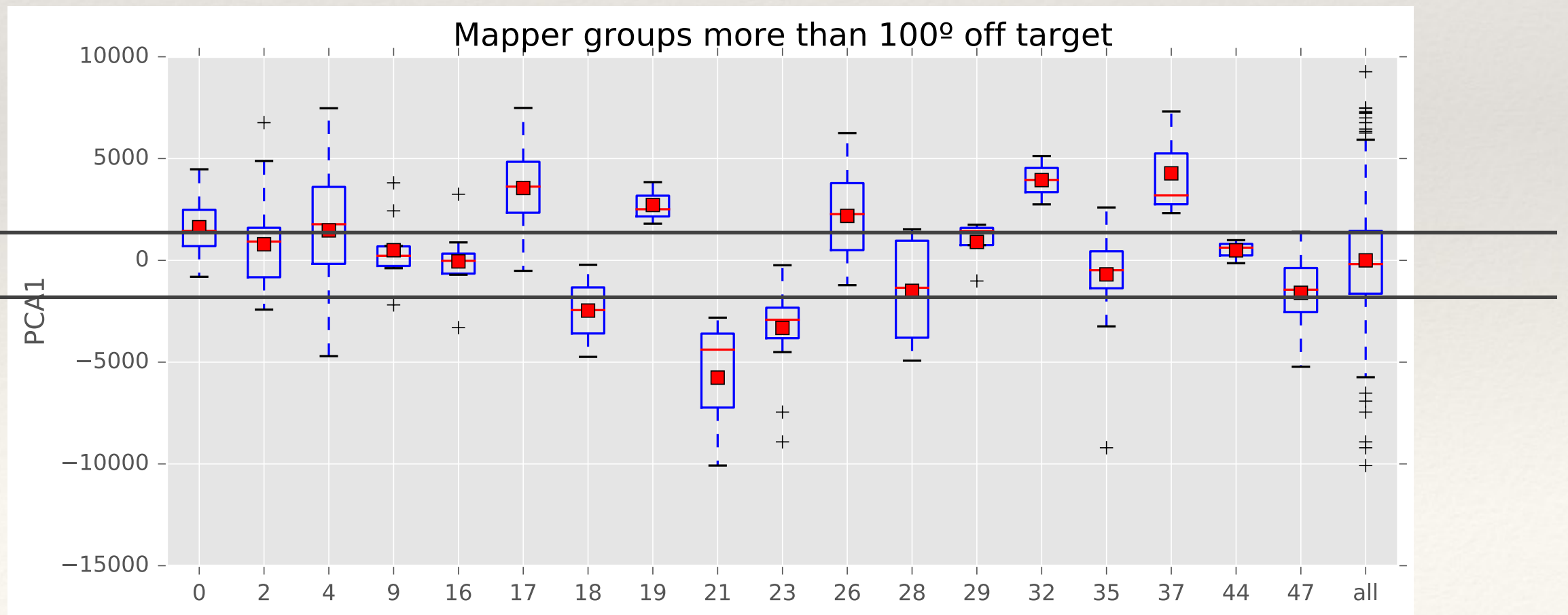
# Find recognizable extremes

- ❖ Drop singleton auto groups
- ❖ Drop auto groups with any error less than  $100^\circ$
- ❖ Compute global PCA, eyeball distribution of PCA1 among remaining auto groups



# Find recognizable extremes

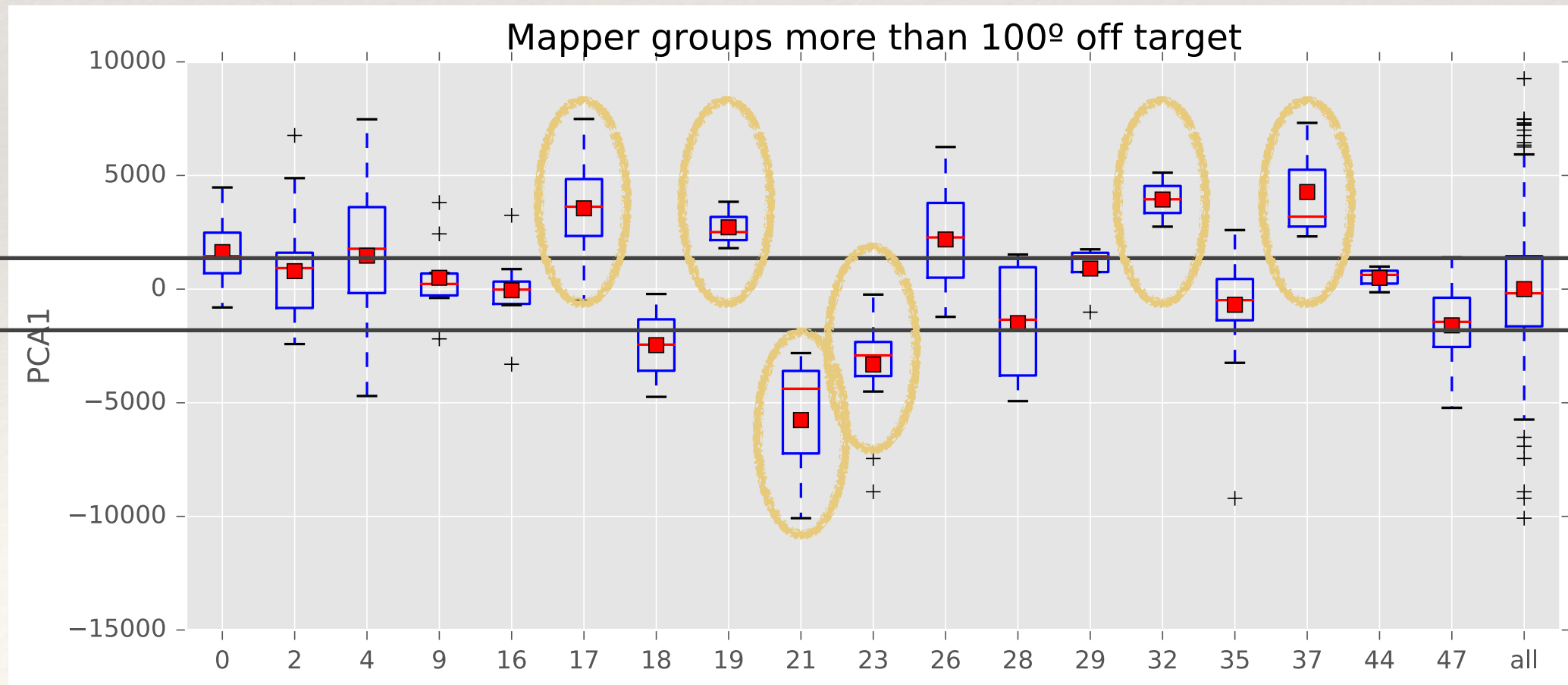
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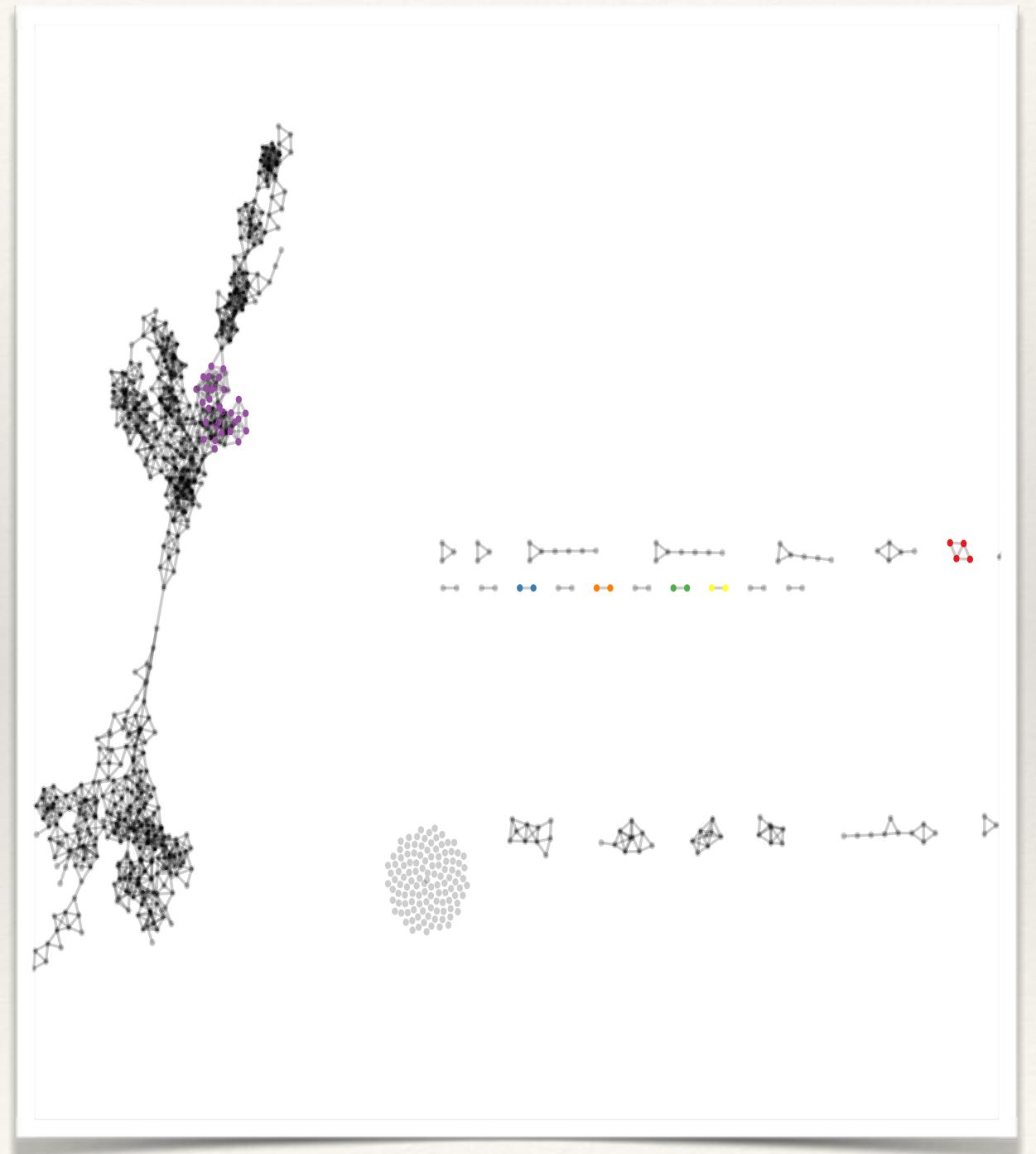
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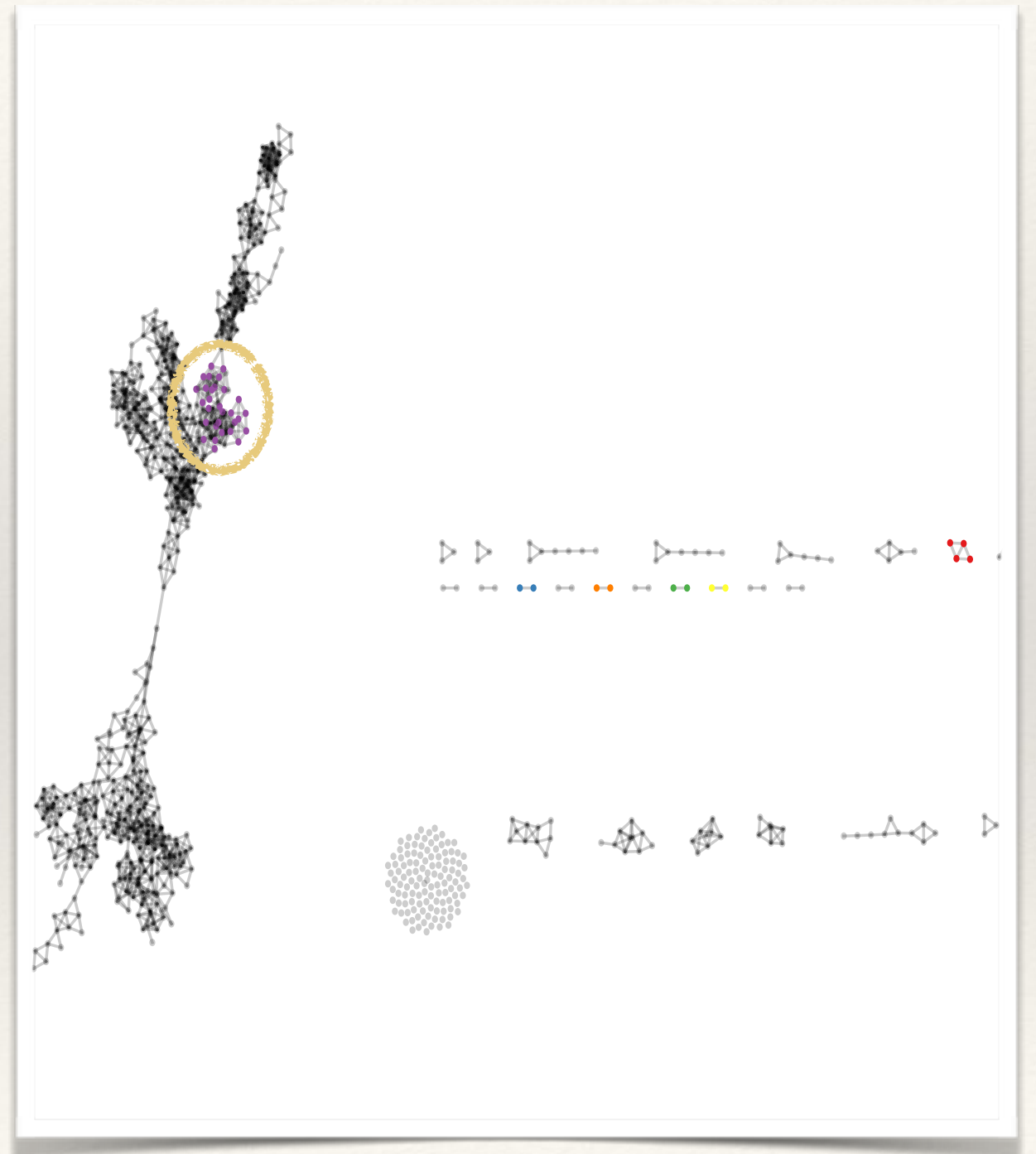
# Candidate failure modes

- ❖ Auto-generated groups 17, 19, 21, 23, 32, 37.
- ❖ Most are very small. Group 23 bigger.
- ❖ **Question:** Can we detect membership in Group 23?



# Candidate failure modes

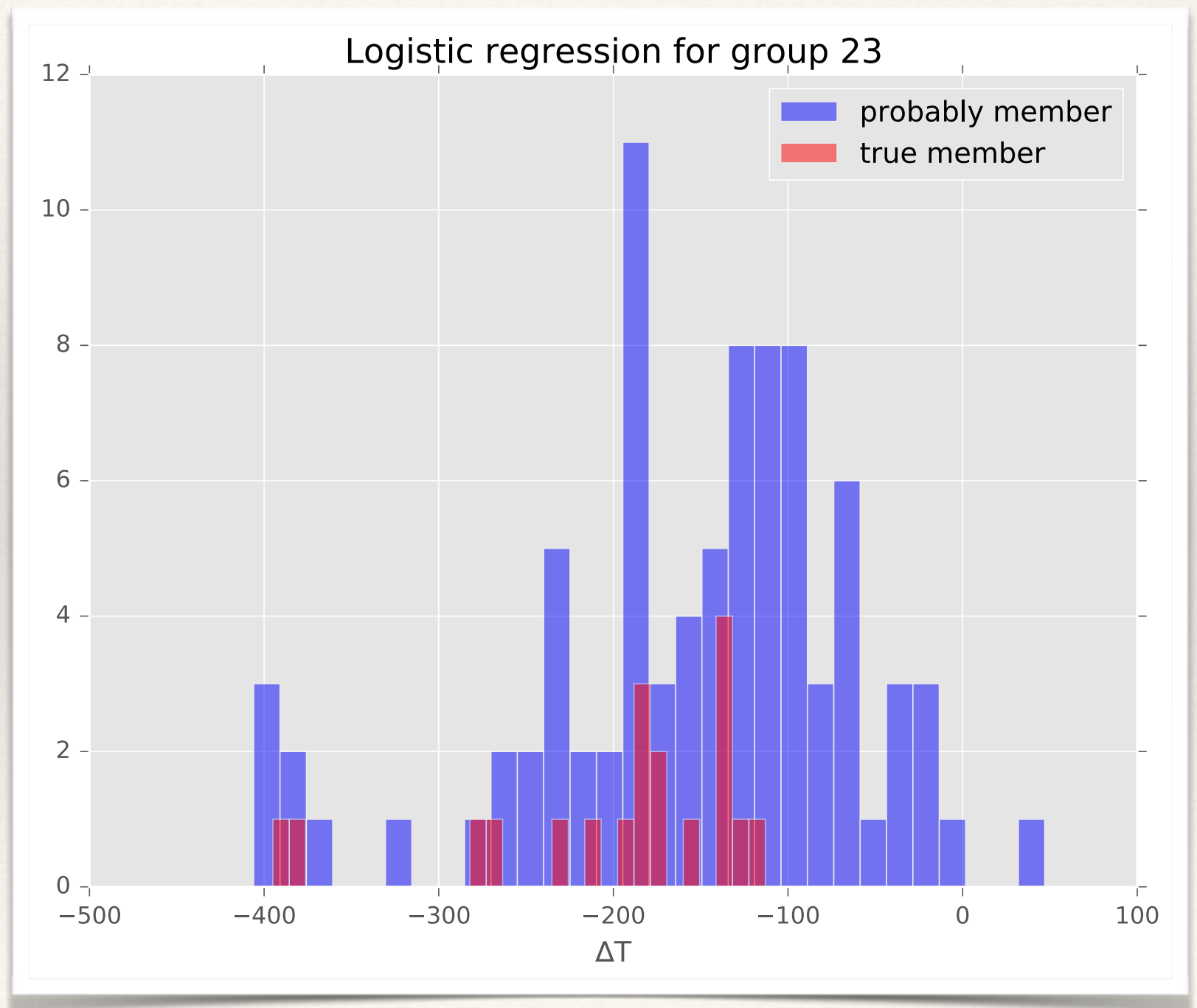
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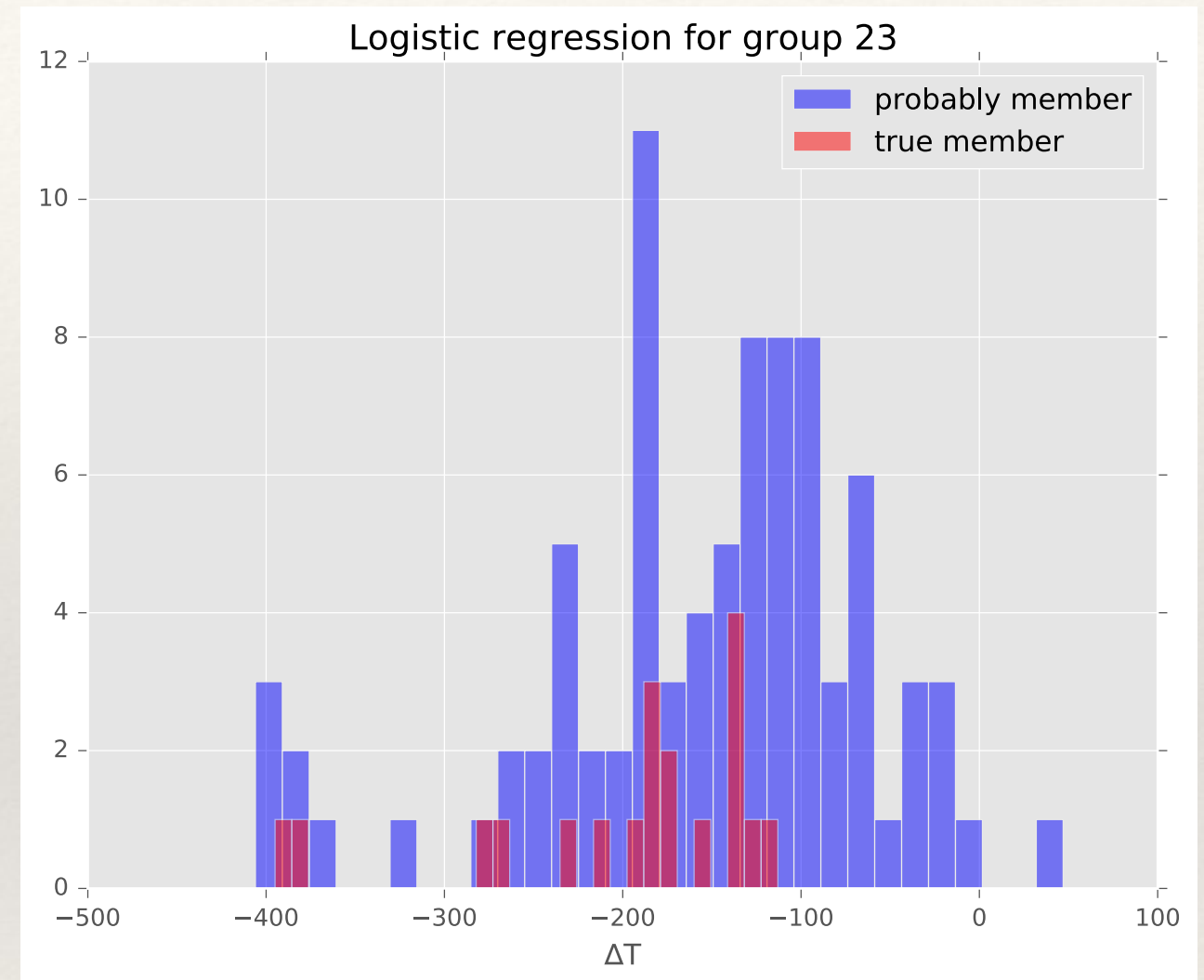
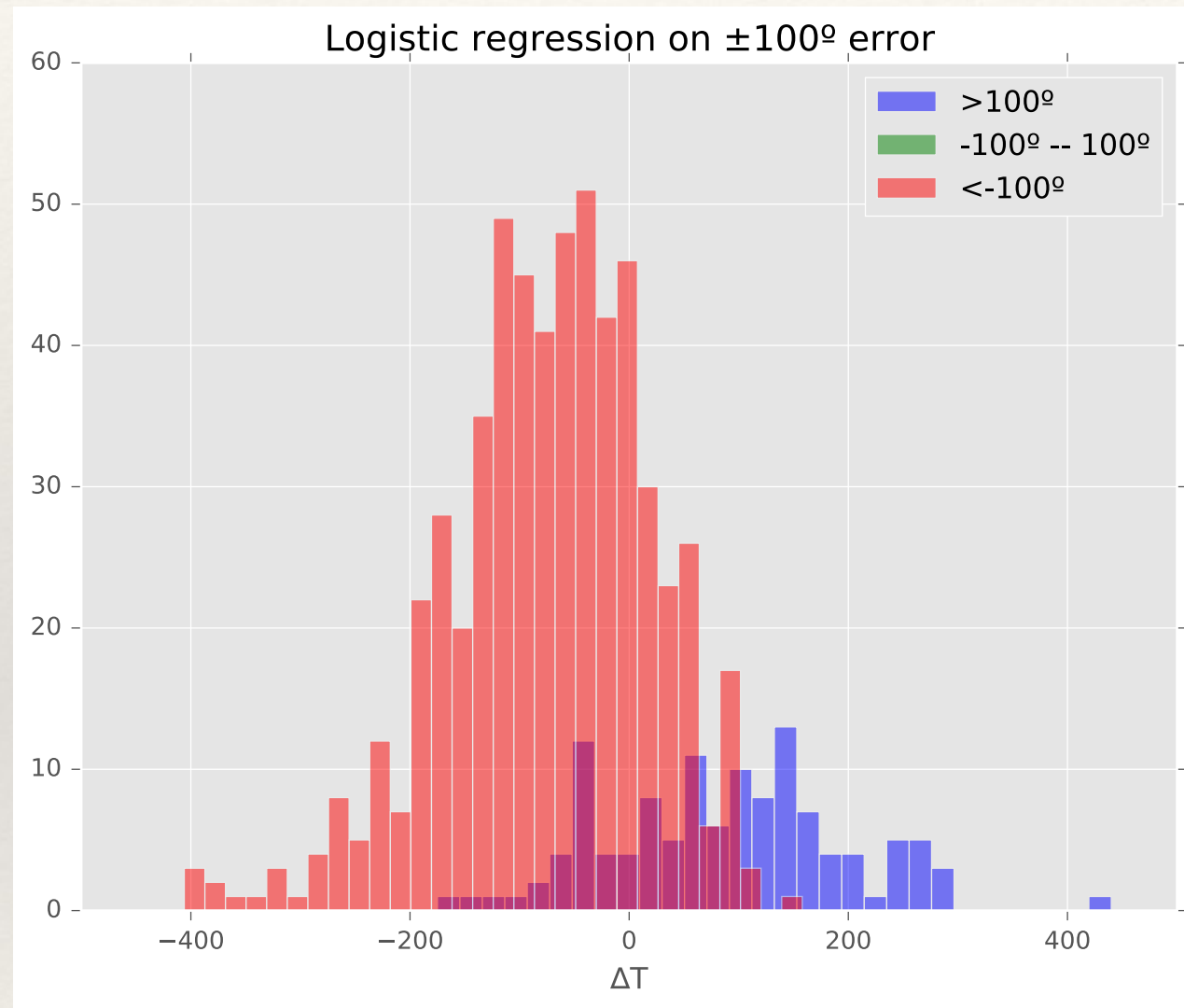


# Membership detection, 23

- ❖ Logistic regression, class-balanced sampling
- ❖ A **lot** of false positives.
- ❖ Probably improves with better classifiers.
- ❖ Certainly improves with more data.
- ❖ Already somewhat useful results.



# Why not just do naive regression?



❖ Far fewer false positives

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# Where do we go from here?

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- ❖ Collect more data
- ❖ Validate these classifiers
- ❖ Test other possibly better classifiers
- ❖ Analyze the sound of the furnace:
  - frequency spectra correspond to smelting stages
  - use Mapper to find recognizable smelting modes?



Thank you for listening

