S+t-SNE

Bringing dimensionality reduction to data streams

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Motivation

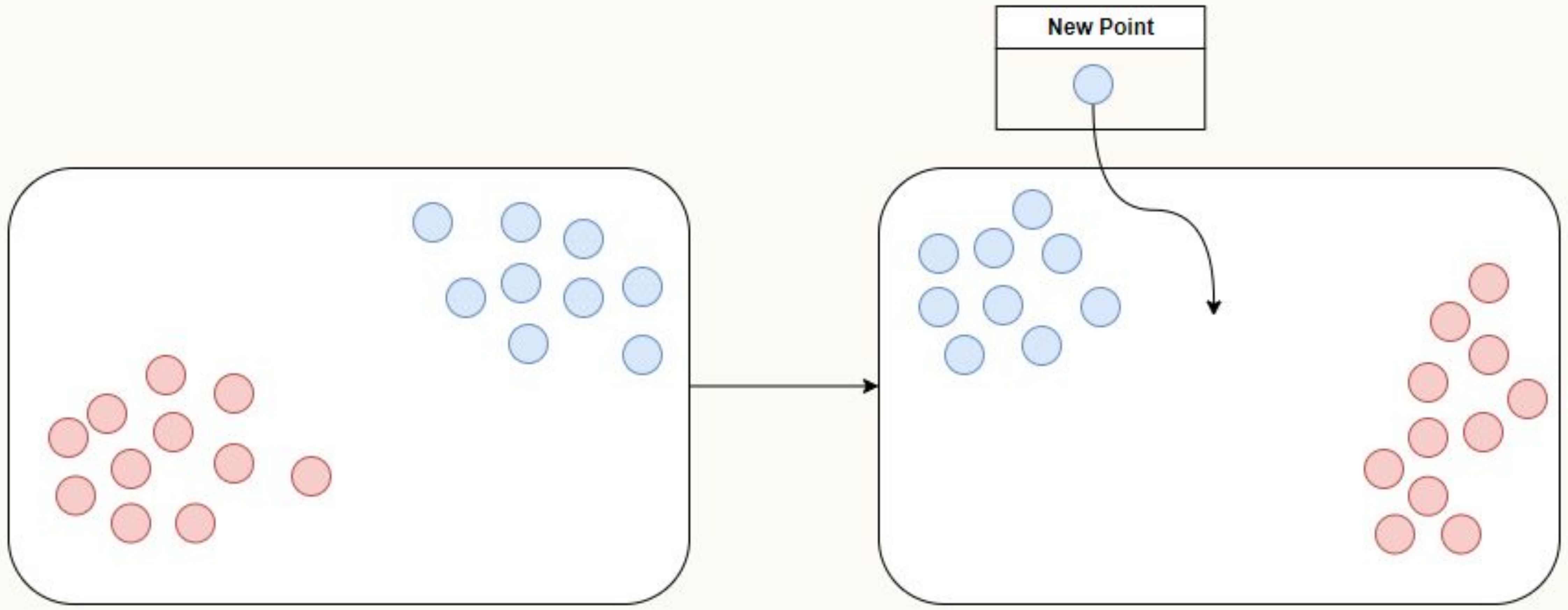
Bring all the benefits of dimensionality reduction to streams of data.

Related Work

In-Sample & Out-of-Sample

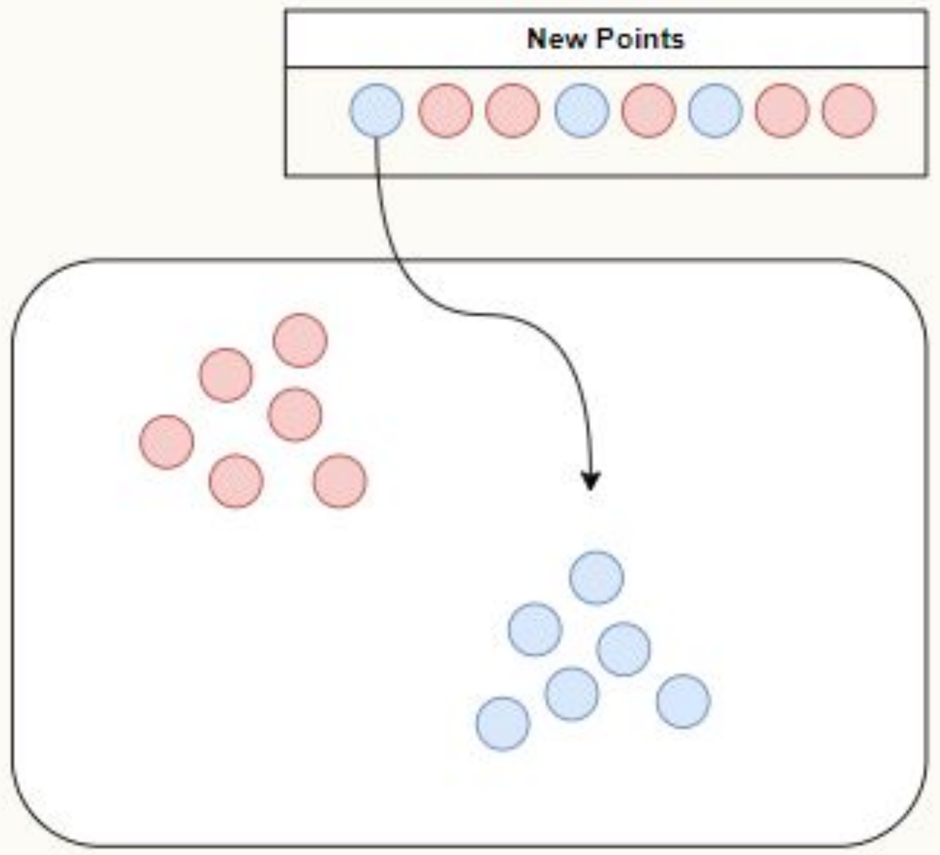
In-Sample

- ➔ t-SNE;
- ➔ UMAP;
- ➔ Classical Multidimensional Scaling (MDS);



Out-of-Sample

- ➔ Piecewise-Laplacian Projection (PLP) ;
- ➔ Least Squares Projection (LSP);
- ➔ Local Affine Multidimensional Projection (LAMP)



Problem Setup

Known approaches fail to deal with a large, possibly infinite, amount of data.

This can be attributed to either a failure to deal with the data due to a **lack of memory management** or their architectures **failing to extract meaningful information from ever increasing** amounts of data.

To hope to obtain a method to handle streamed data we must answer:

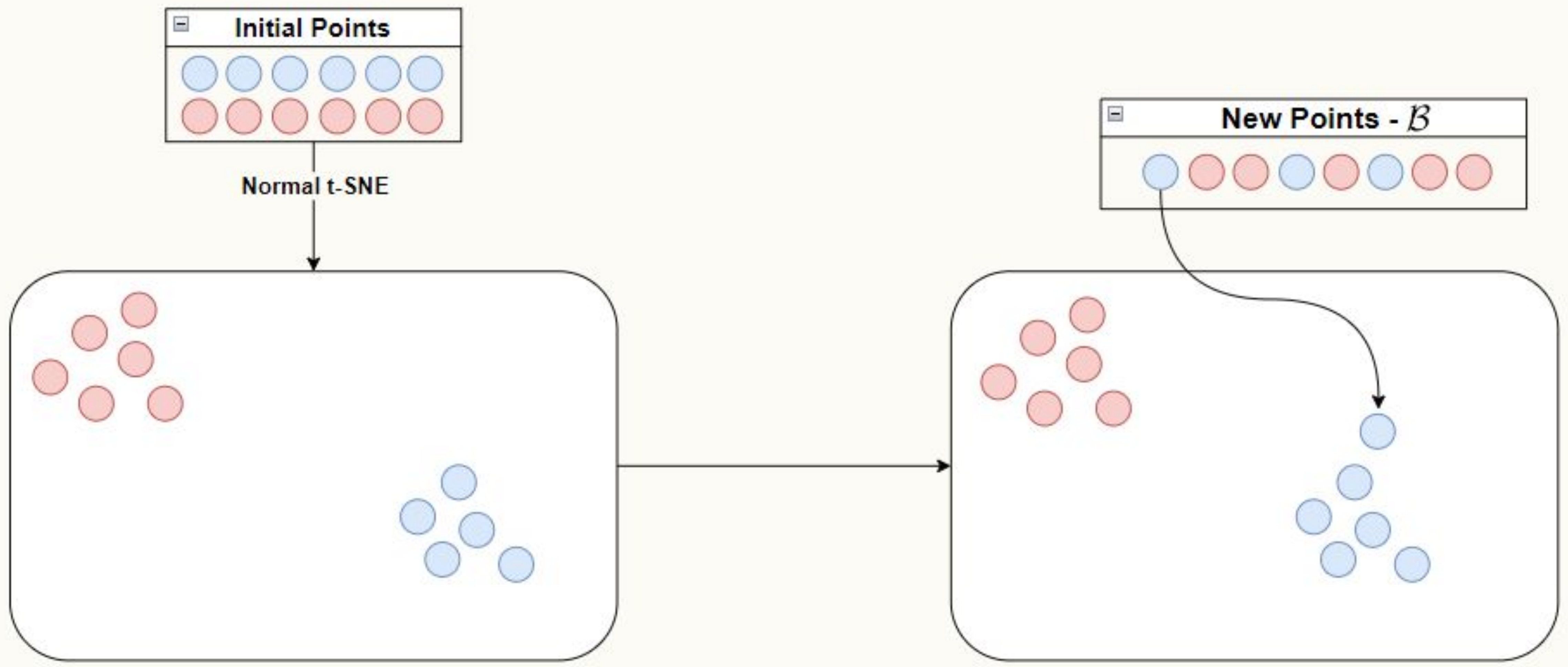
- When should we start operating on a dataset D if such dataset can be infinite?
- How can we reduce the space fingerprint of the algorithm while assuring the extracted data is meaningful?
- If D suffers concept drift, how can the existing projections be updated?

When should we start operating on a dataset D if such dataset can be infinite?

- ➔ Fixed batch-wise approach to mitigate challenges of infinite data-streams:
  - ◆ Points are accumulated until a predetermined batch size, $\mathcal{B}$, is attained;

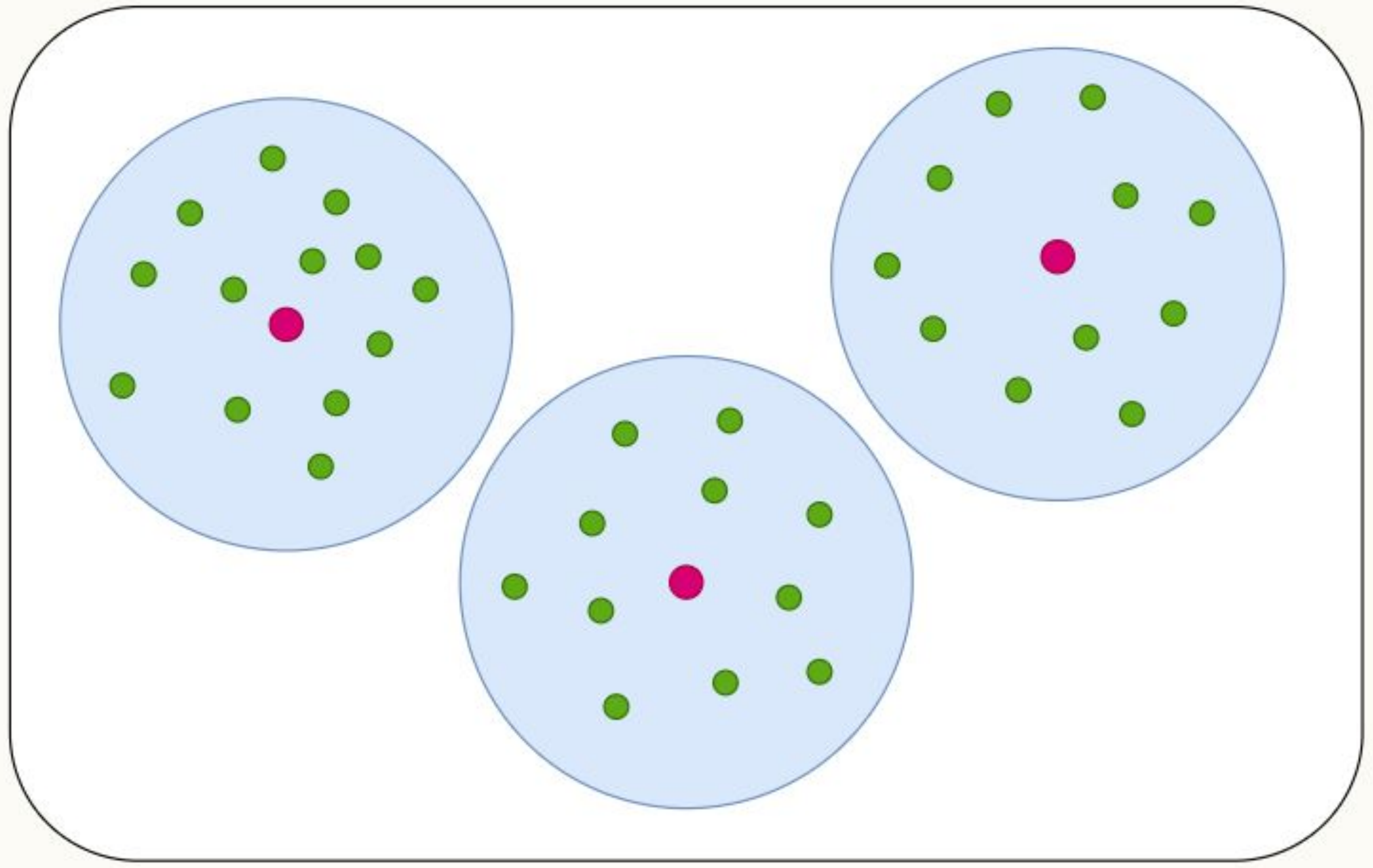
- ➔ Normal t-SNE will be applied in the first projection;

- ➔ However, after the first iteration of S+t-SNE, subsequent iterations will project in a space where points already exist;



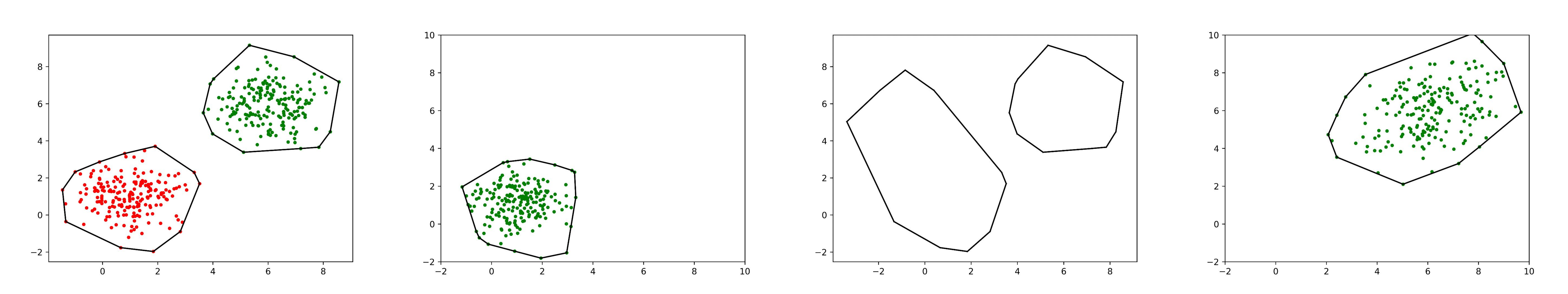
How can we reduce the space fingerprint of the algorithm while assuring the extracted data is meaningful?

- ➔ Select points based on their importance to describe the data (PEDRUL):
  - ◆ Have <u>Higher density in the original D-dimensional space</u> given a search radius **R**;
  - ◆ The neighborhood defined by **R** does not contain a subset of points from already chosen dense points;



➔ Define Regions of interest:

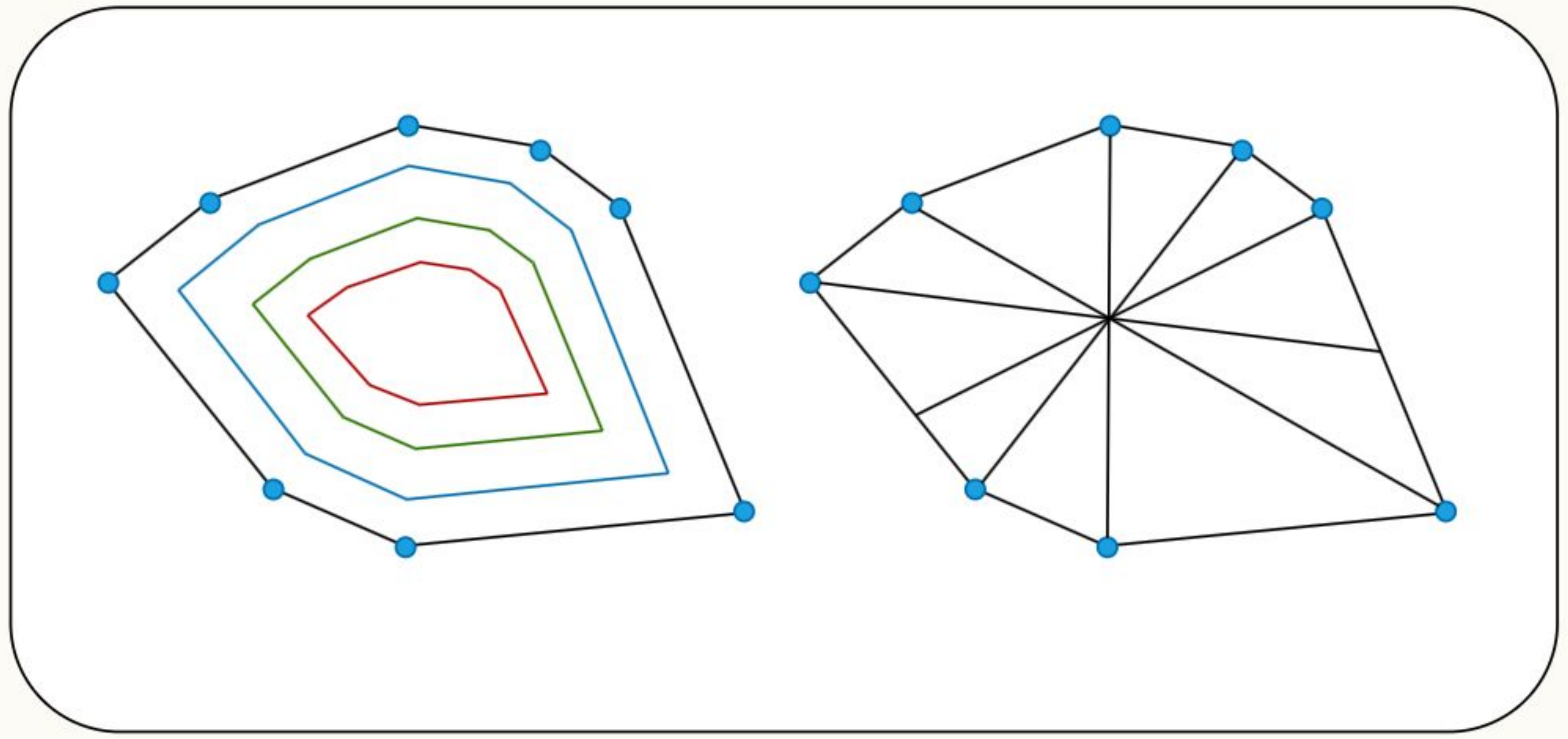
- Retaining the shape of groups of points by using a clustering algorithm applied to t-SNE projections;
- Construct a convex region around each cluster to retain the general shape of the clusters found;

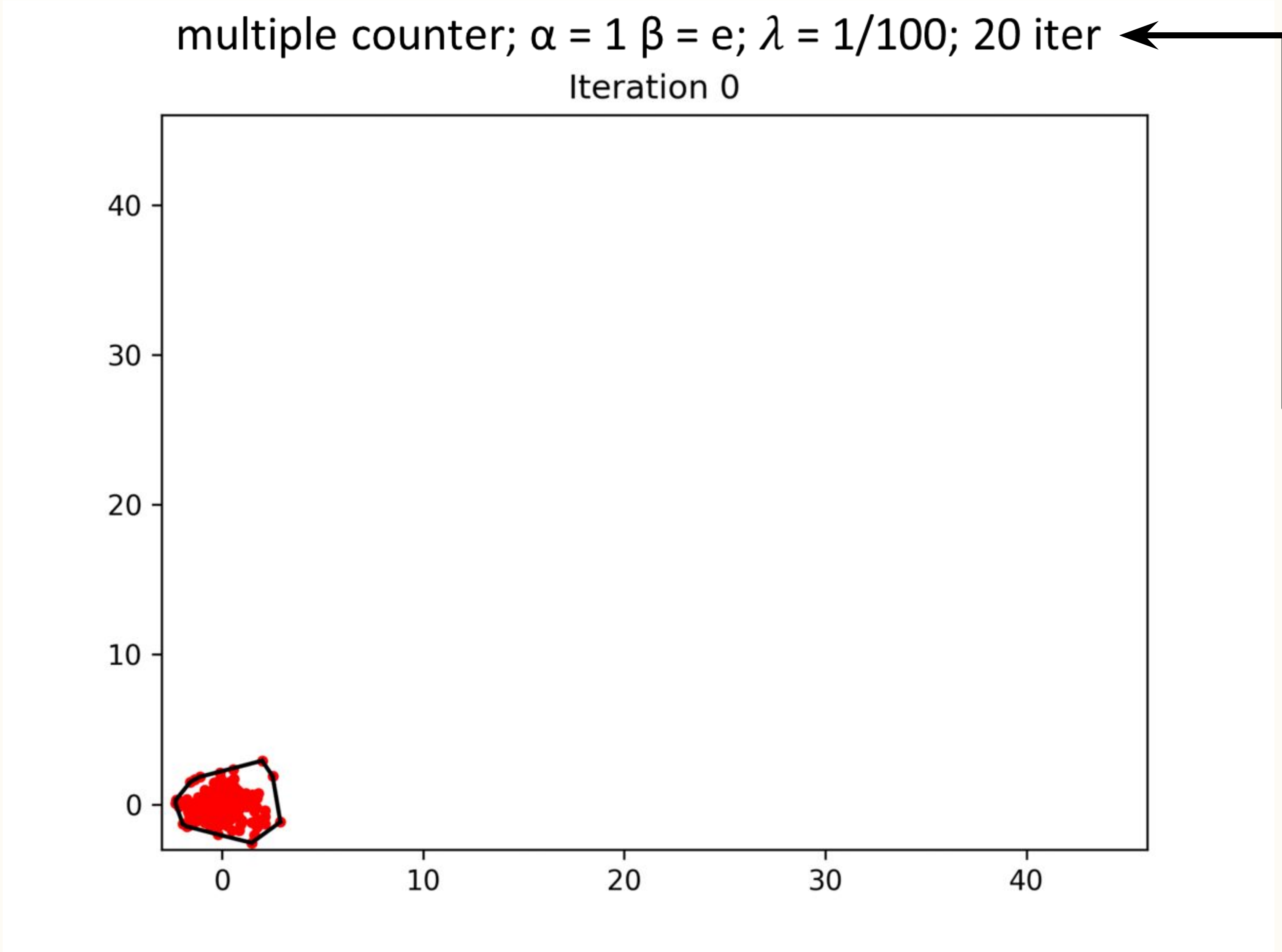


If D suffers concept drift, how can the existing projections be updated?

- ➔ Must be compatible with the approach described so far.
  - Convex polygons in, digest (look for drift), modified convex polygons out.
- ➔ Must cover the whole polygon while being efficient.
  - Divide each polygon in areas that, if removed, always result in a convex polygon.
- ➔ Must be able to evaluate the relevance of points to the projection in the current iteration
  - Blind drift detection using exponential decay for each of the spanned regions.

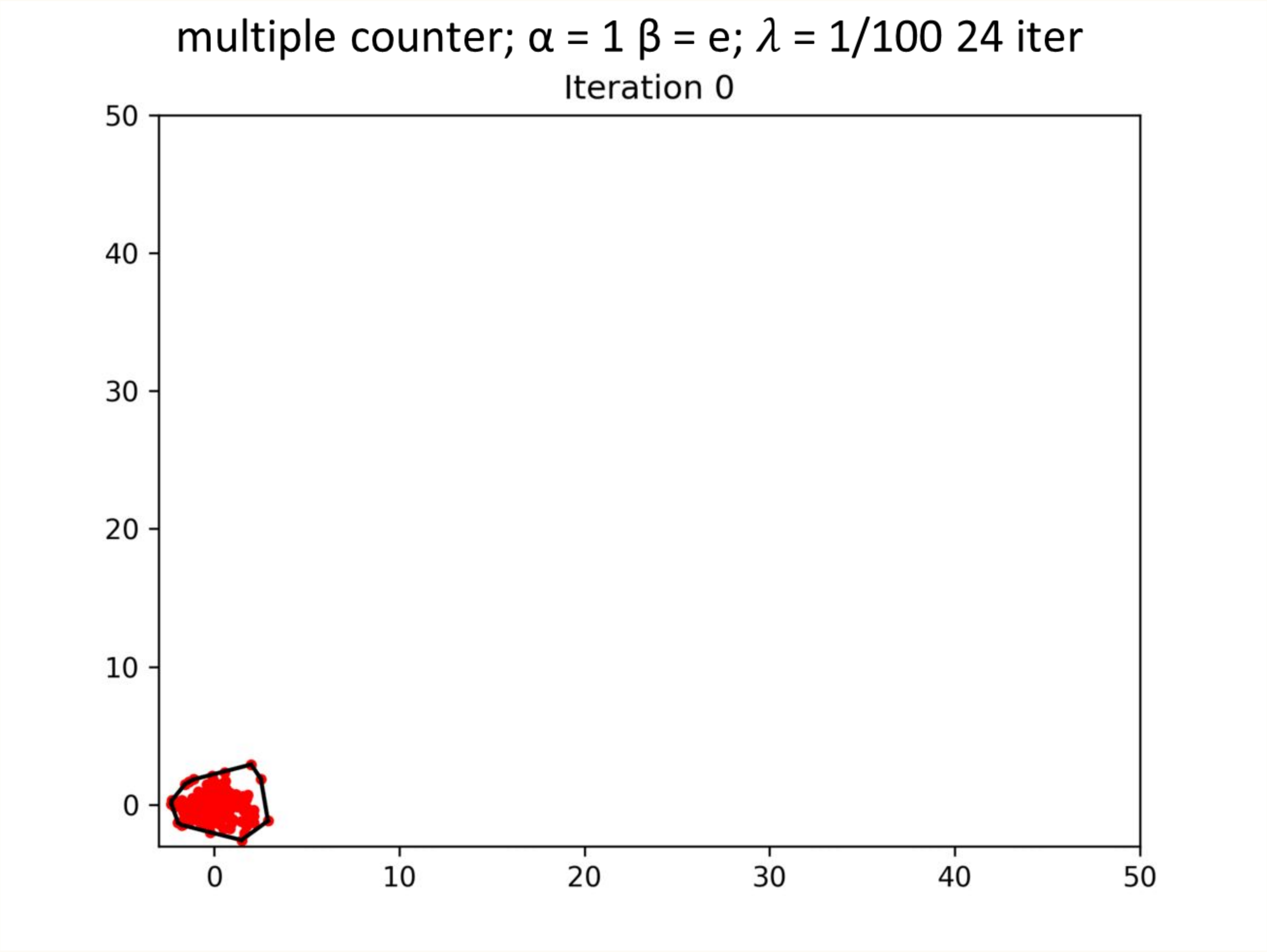
This is efficient! $O(mkp \cdot log\, n) + O(mkn \cdot log\, n)$, and, if parallel, $O(p \cdot log\, n) + O(n\, log\, n)$ where k is the maximum number of vertices in a polygon, p the number of polygons, n the maximum number of PEDRUL points in a polygon and m the number of concentric regions.

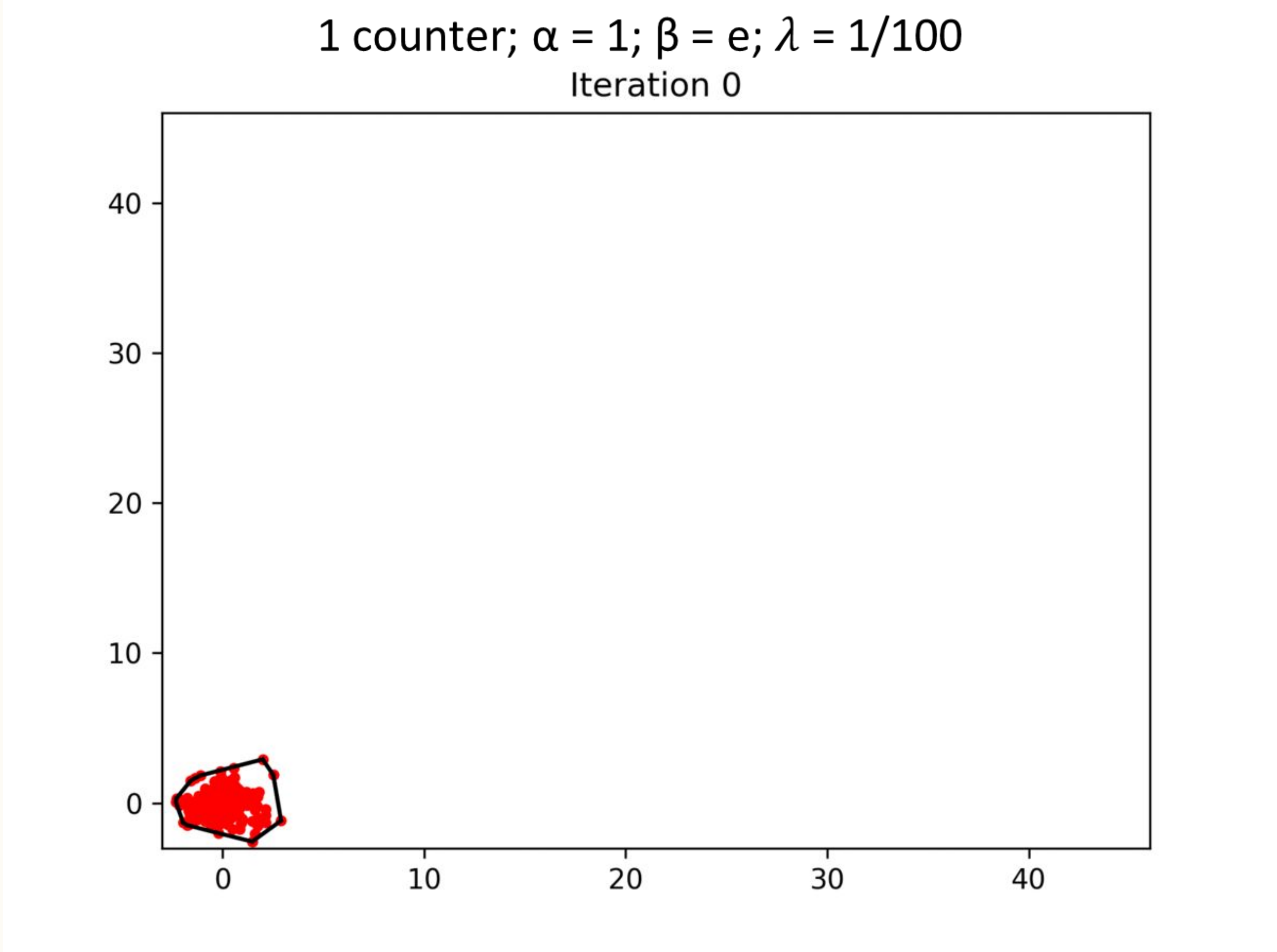




Updates of region using median cuts

$$\alpha\beta^{-\lambda t}$$

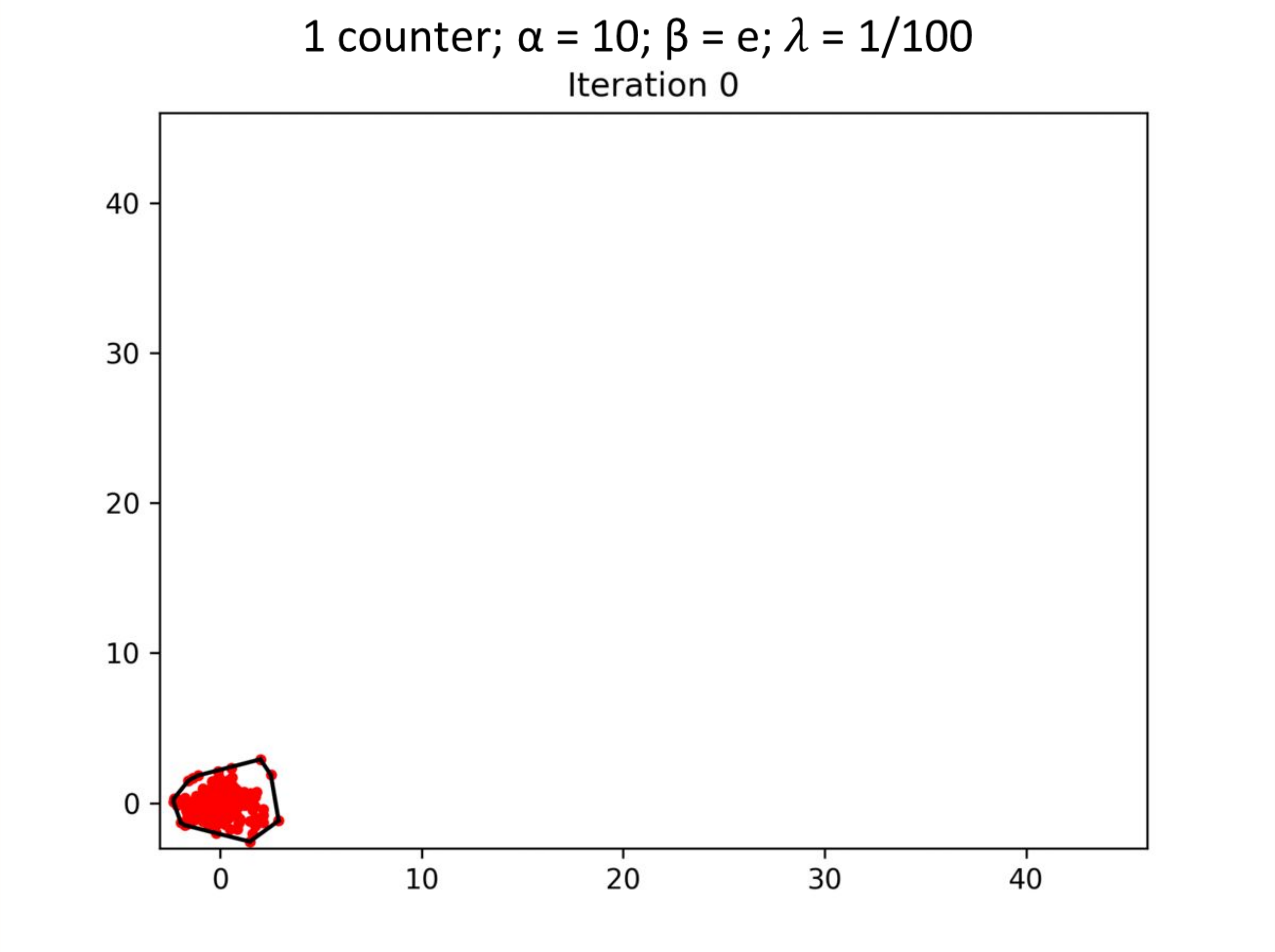




Different strategies

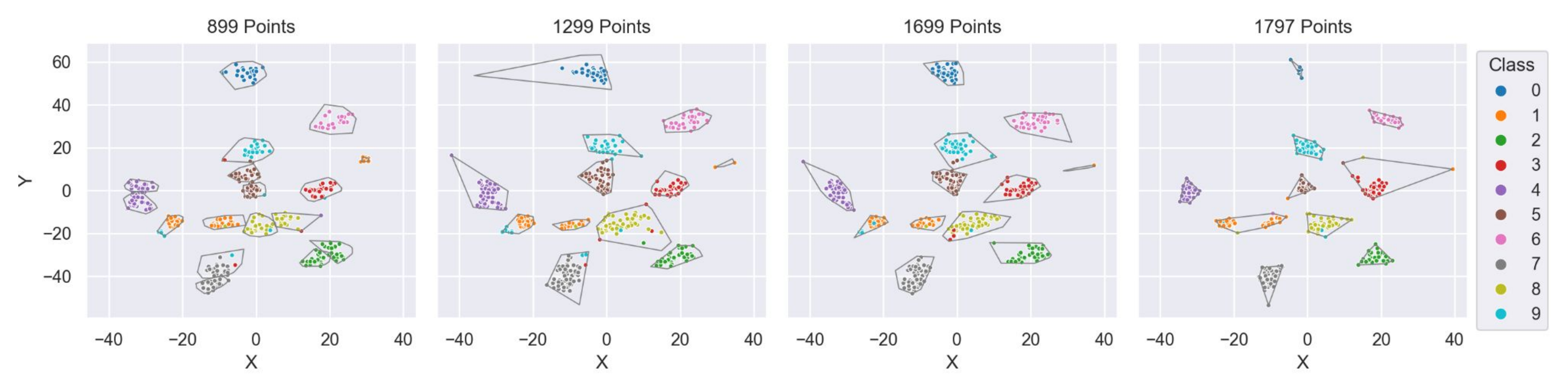
- In the single counter strategy, every region shares a counter. After a cut is made, the counter is zeroed.

- Other approach is to implement a counter per region and reset only the counter of the region it suffered an alteration.

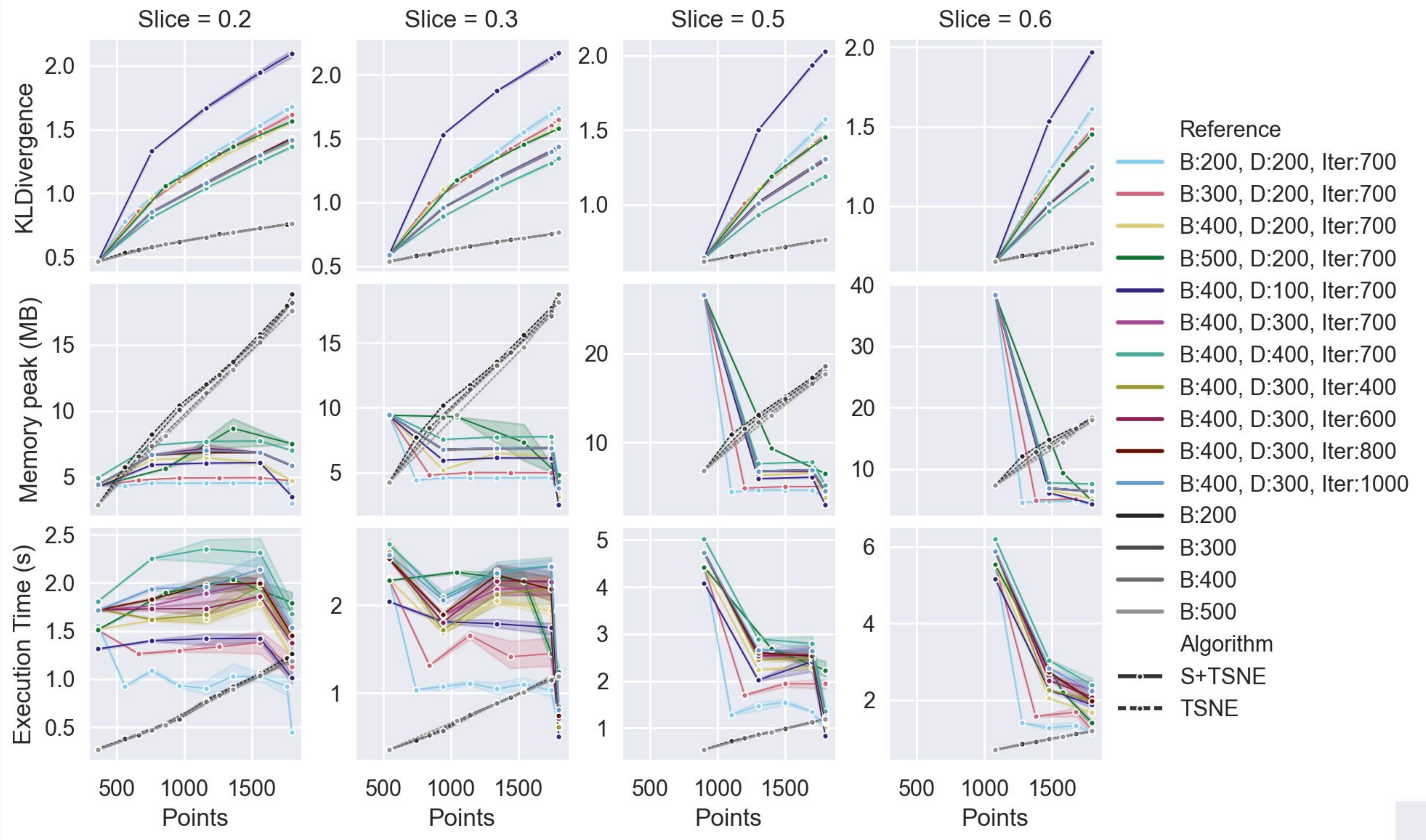


Experiments

➔ MNIST - Handwritten digits

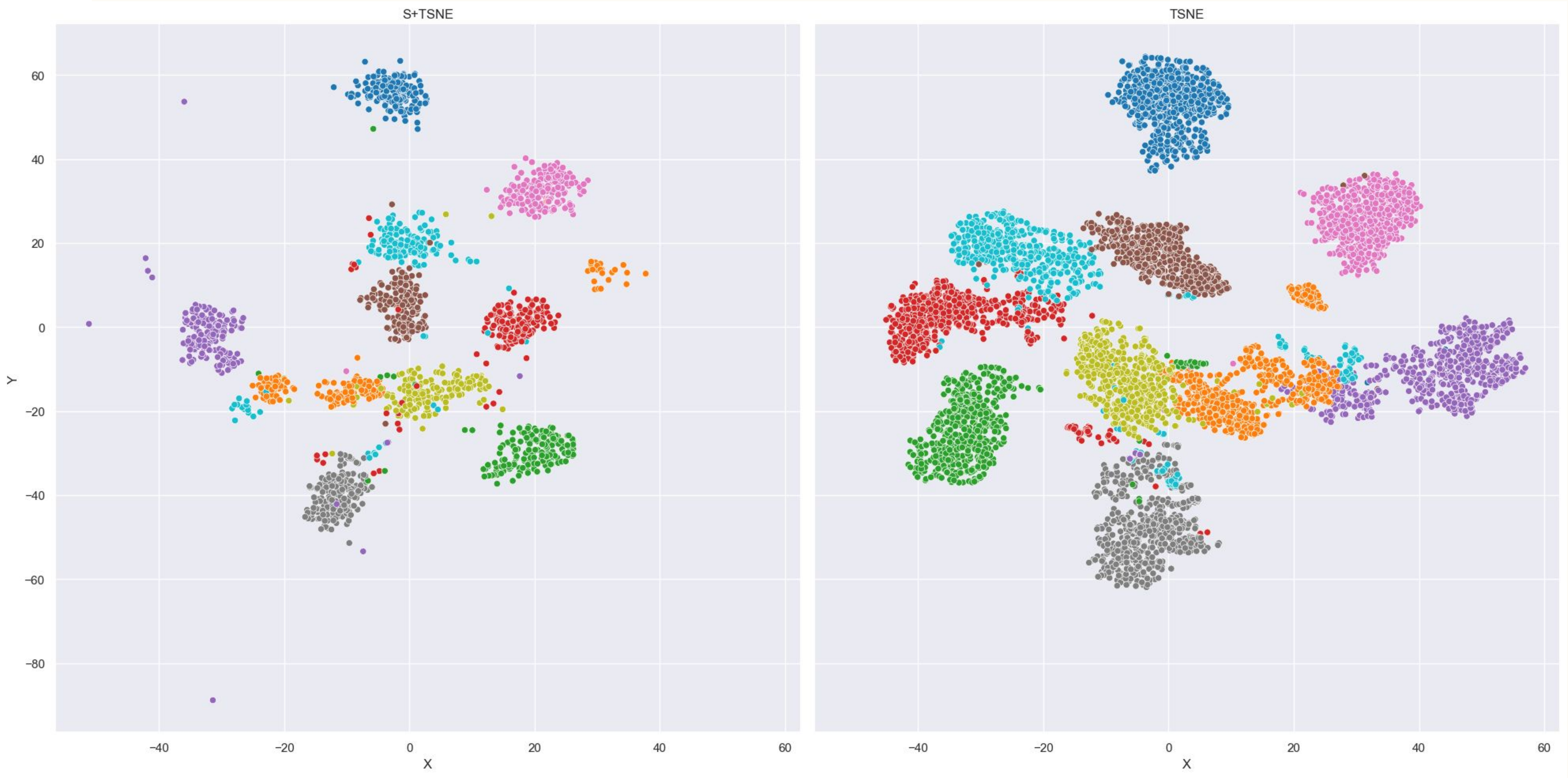


MNIST projections at different iterations of the streamed data.



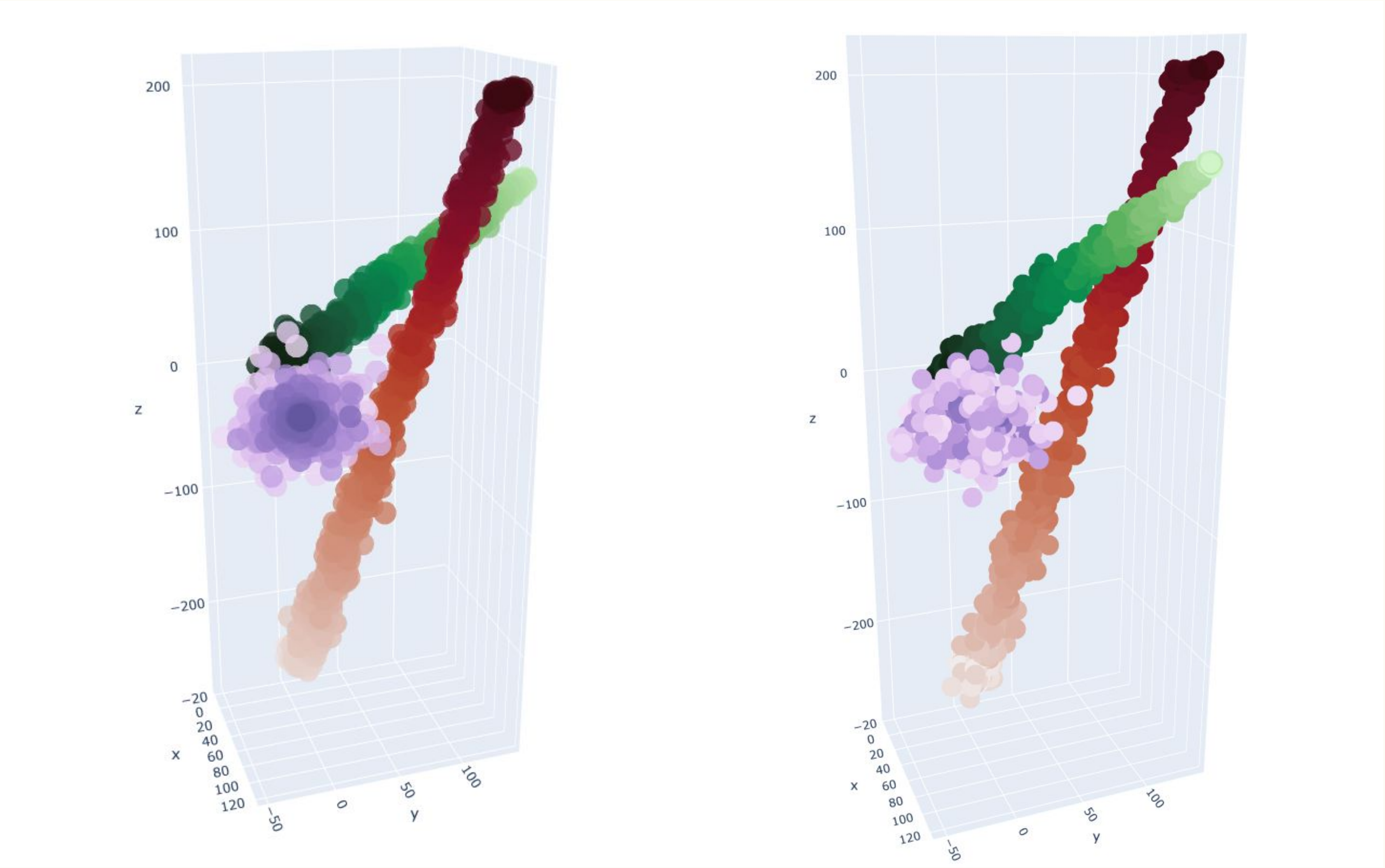
Evaluation of different set of hyperparameters on MNIST

Visual Comparison of S+t-SNE and t-SNE

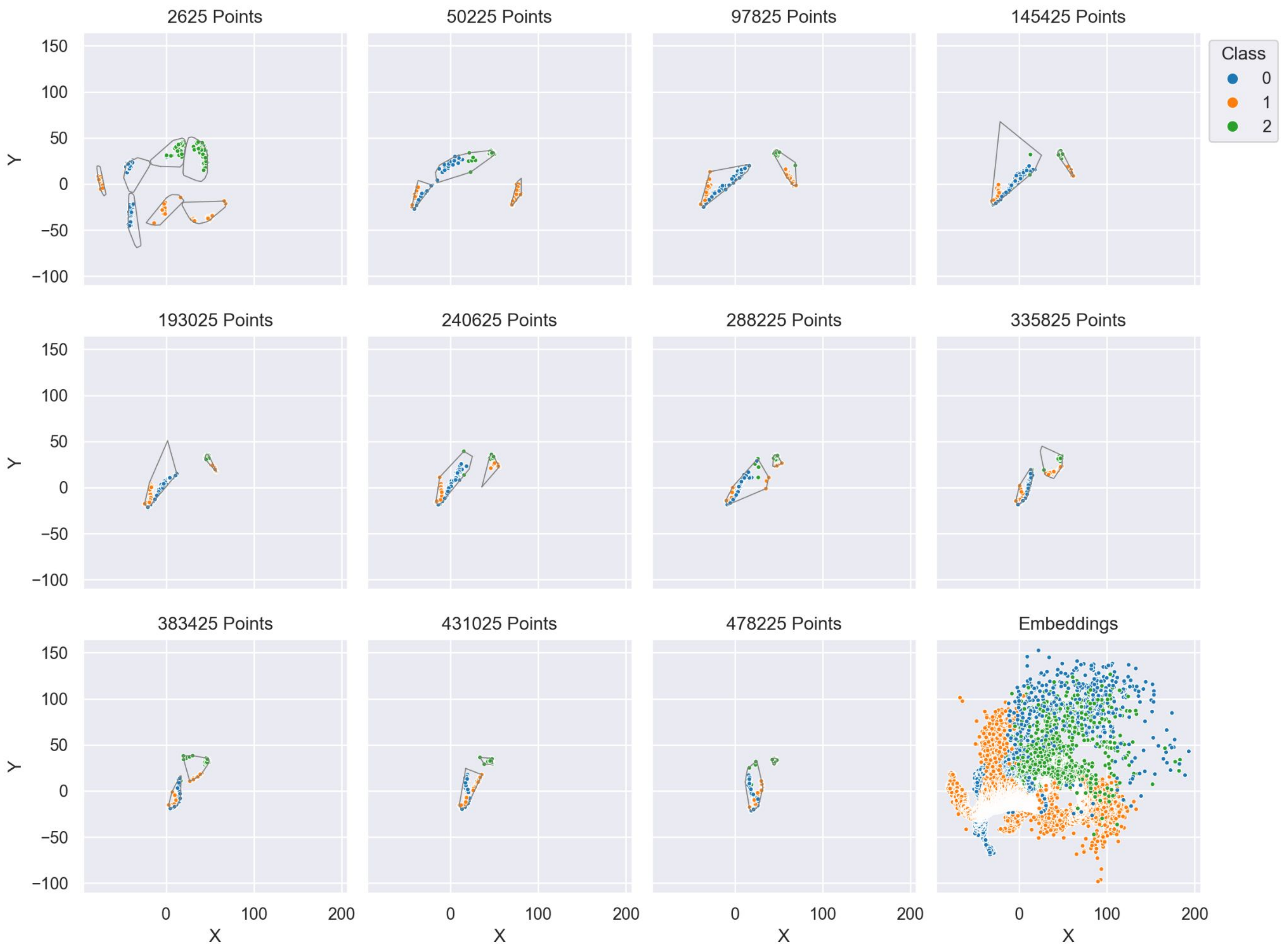


➔ Artificial 3D DataStream

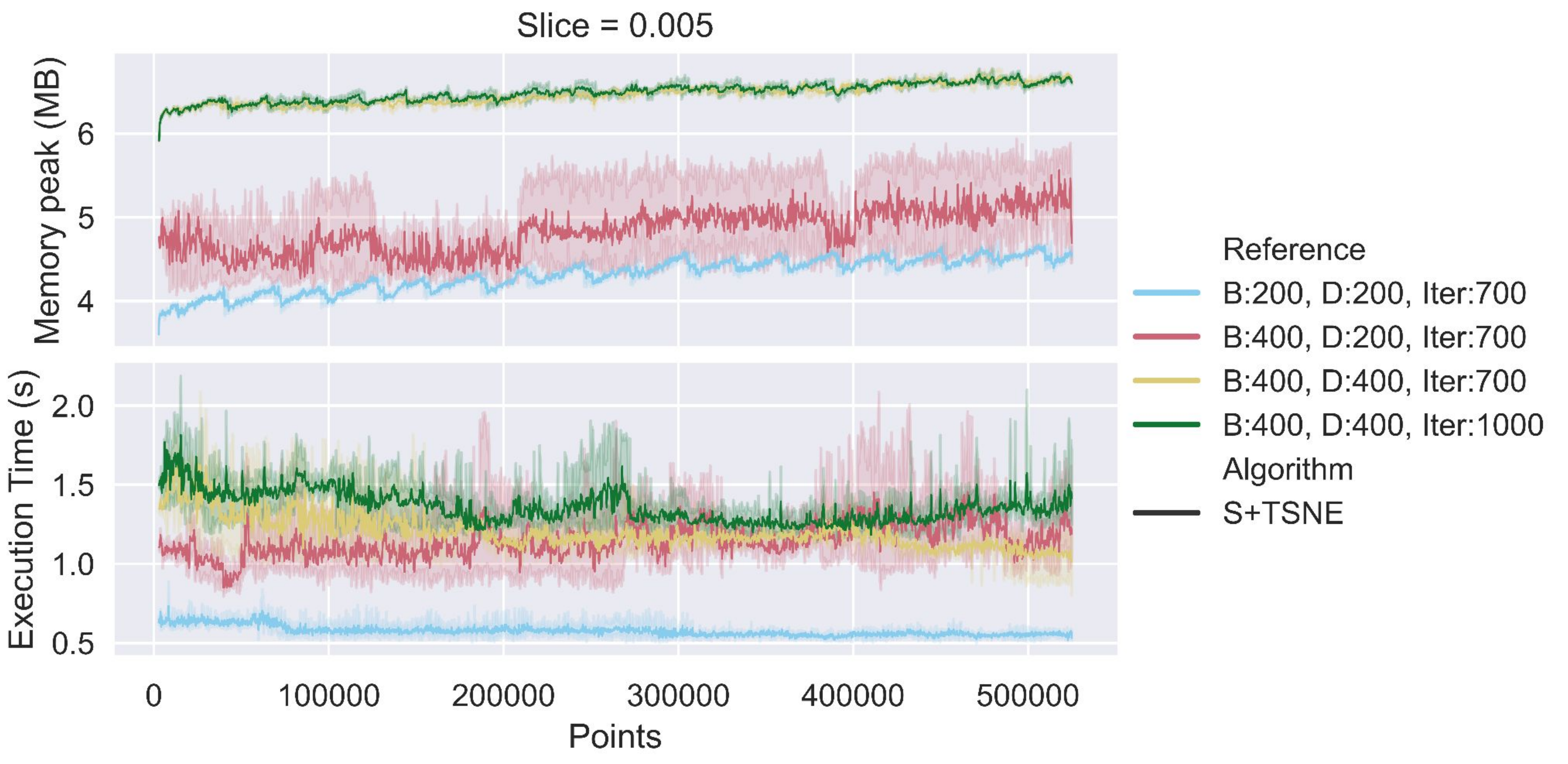
- ➔ Three 3D distributions with variability over time;
- ➔ Nearly 500.000 points to be embedded;



3D visualization of the DataStream simulated through time



Projections of S+t-SNE at different iterations of the streamed data.

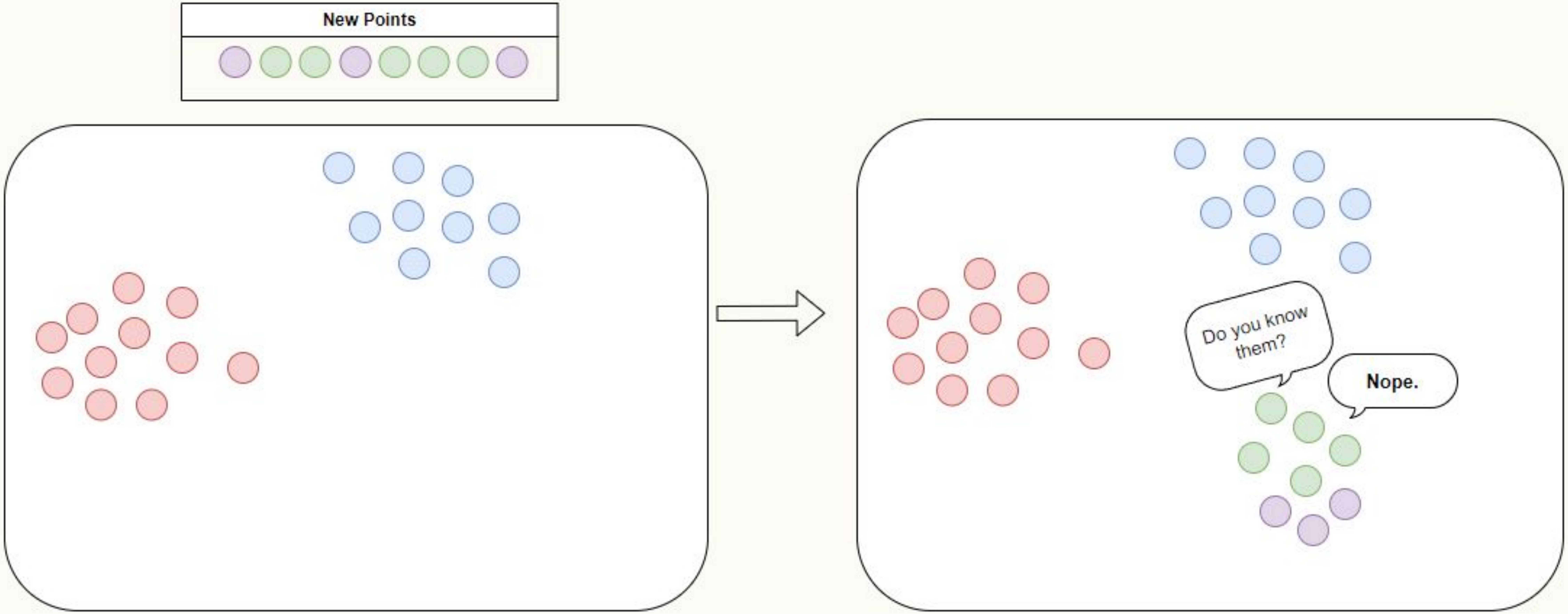


Evaluation of different set of hyperparameters the Artificial Data set

Known Limitations

➔ **"Lonely guy at a party"**

- If new points don't consider their intra-similarity but only their inter-similarity (with already projected data) points with low intra-similarity can end up close together.



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End.