SECLEDS: Sequence Clustering in Evolving Data Streams via Multiple Medoids and Medoid Voting

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Cyber Analytics Lab

Sequence clustering in streaming environments

- Stream clustering
  - Cluster infinitely many data items

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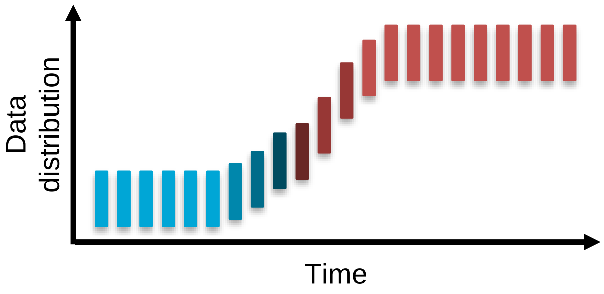

Sequence clustering in streaming environments

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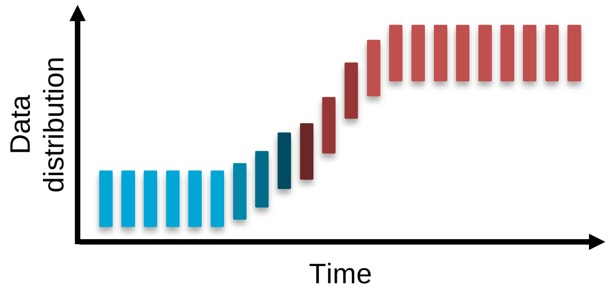

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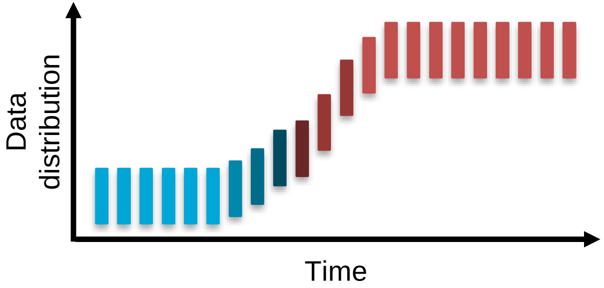

- Sequence clustering while streaming

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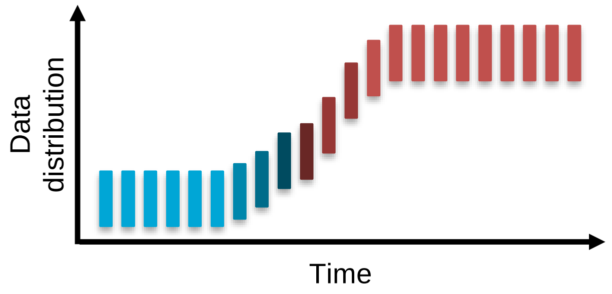
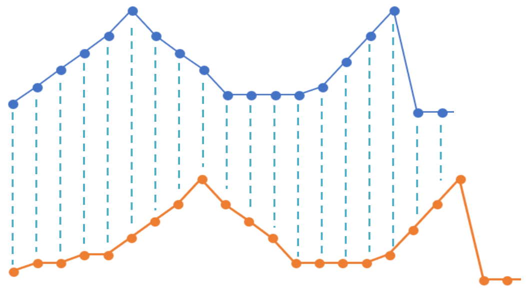


- Sequence clustering while streaming

Out-of-sync sequences
  - Alignment-based distances, e.g., DTW
  - Expensive and limited support



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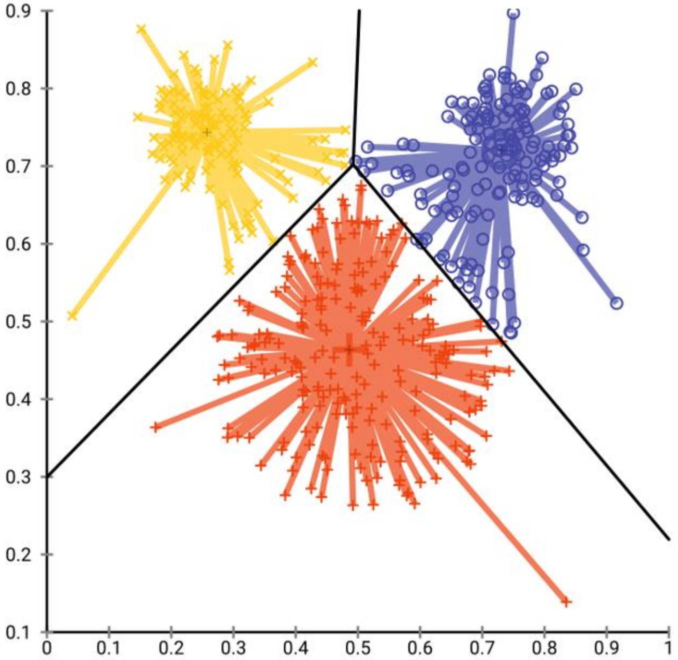
K-medoids or Partitioning Around Medoids (PAM)

- K-centroids → actual data items
- Supports non-metric distances



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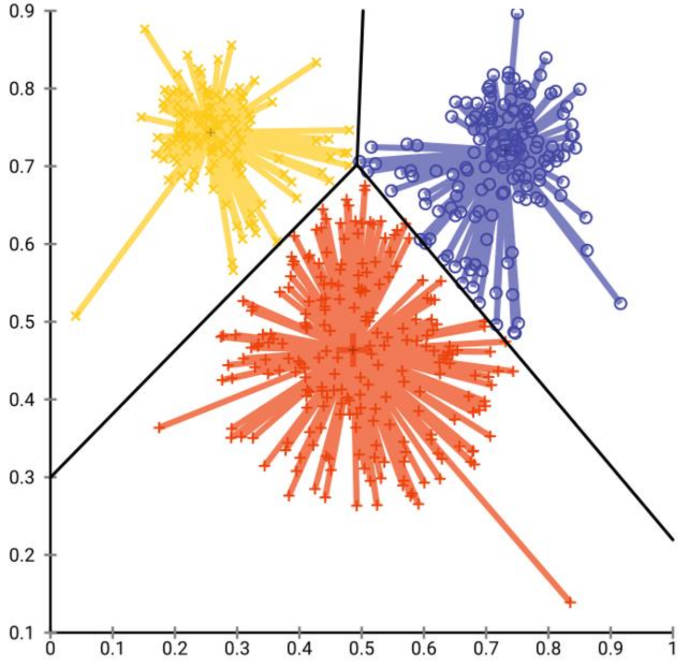
Computationally expensive for streaming



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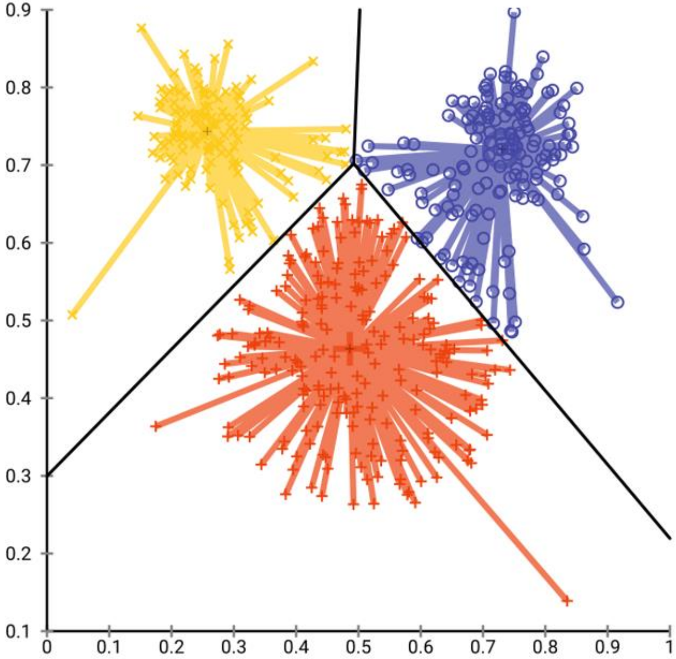
❌ Computationally expensive for streaming

❌ No support for concept drift



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SECLEDS: SEquence CLustering in Evolving Data Streams

- Lightweight streaming variant of k-medoids with p-medoids

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- Lightweight streaming variant of k-medoids with p-medoids

- Important properties
  1. Constant memory footprint
  2. Multiple medoids
  3. Medoid voting scheme

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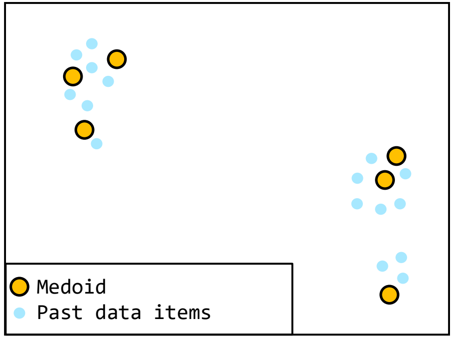
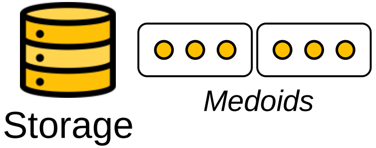
Constant memory footprint

- Only stores the medoids $\rightarrow \mathcal{O}(kp)$

$t = t_{x-1}$





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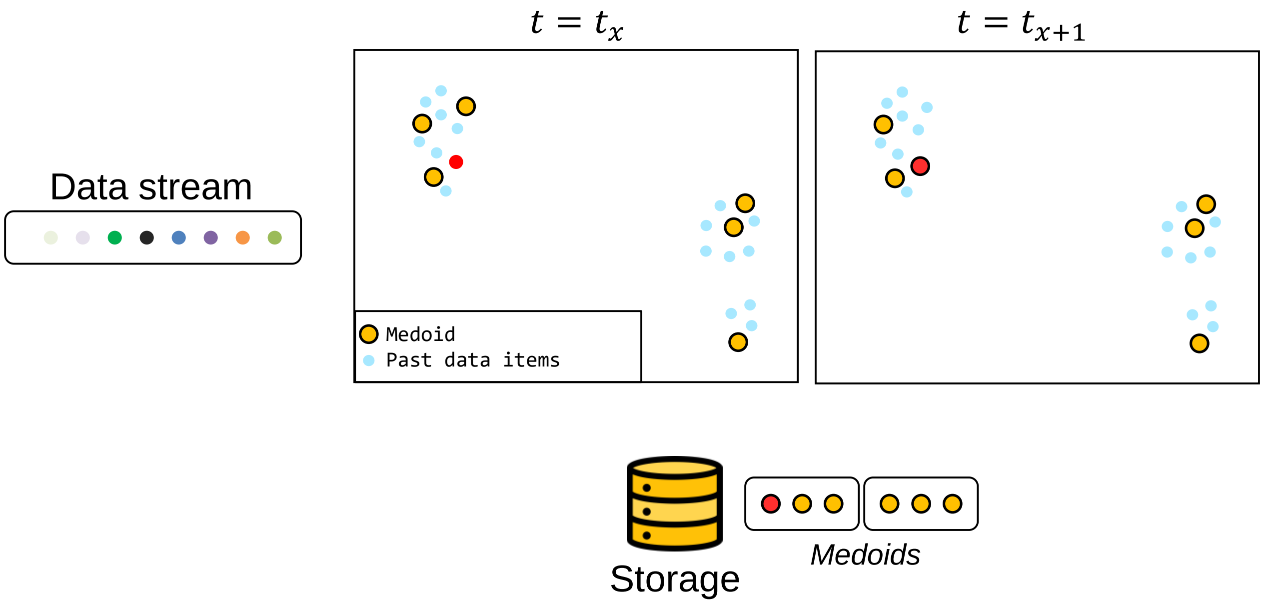
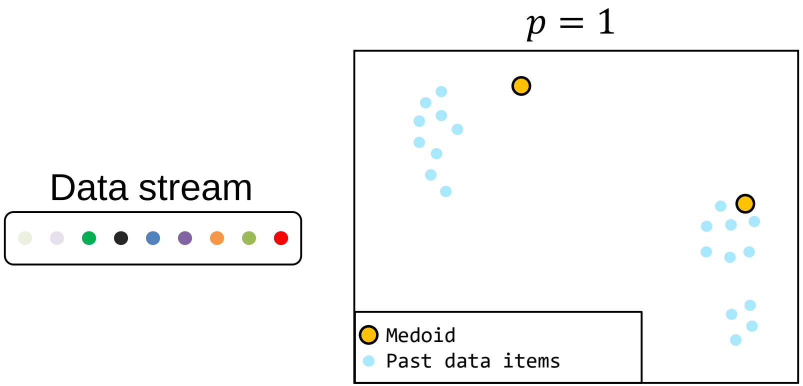


Multiple medoids

- p-medoids represent each cluster
  - *p = configurable parameter*



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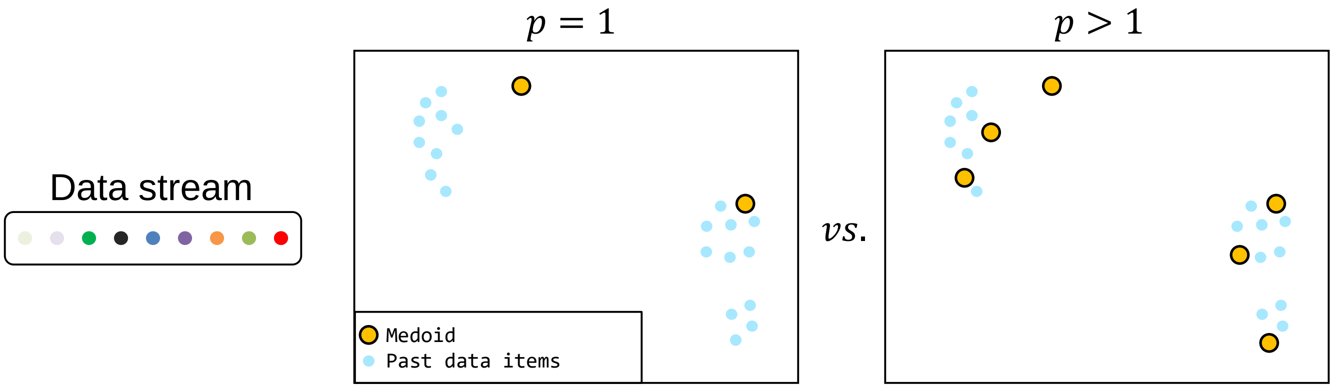

Multiple medoids

- p-medoids represent each cluster
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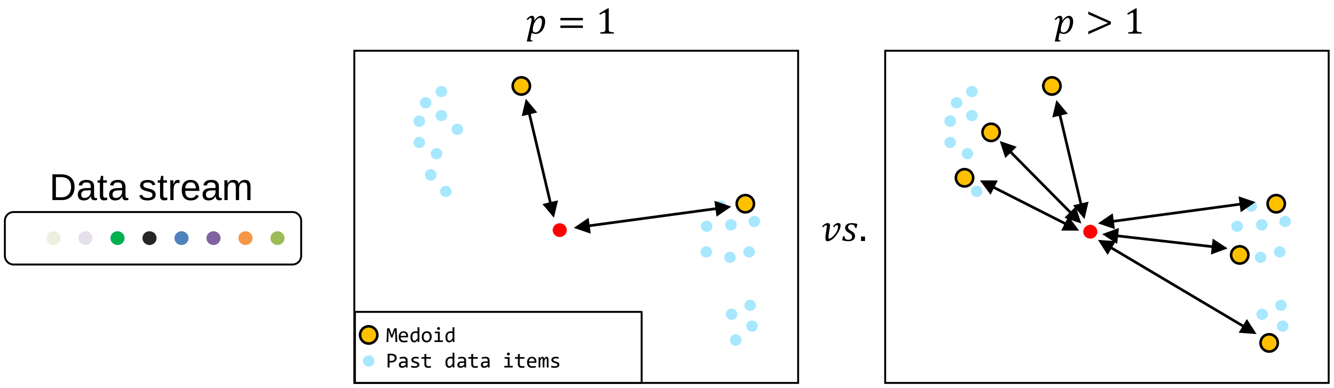
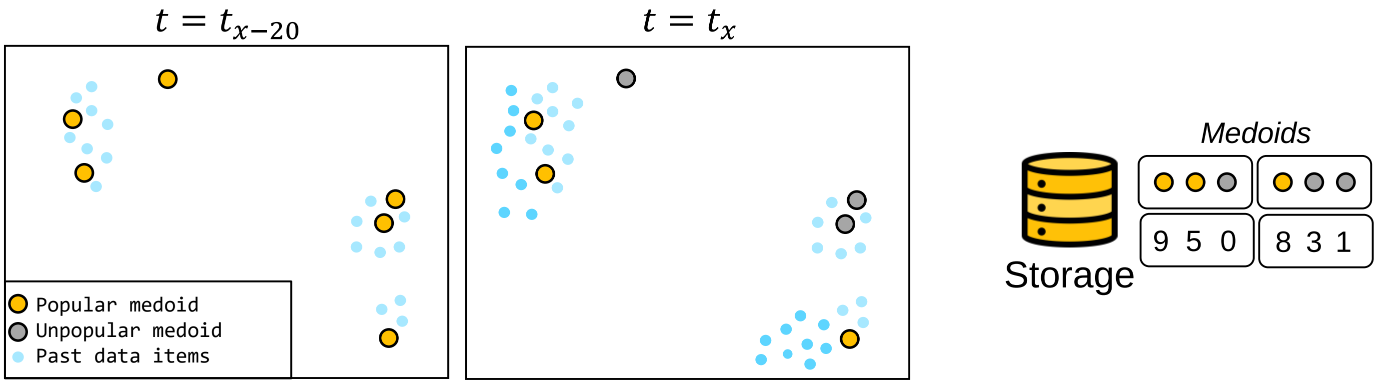
- Assignment based on minimum average distance
  - Reduces influence of irrelevant medoids



Medoid voting scheme

- Votes maintained for each medoid
  - Captures the fraction of close recent data
  - Exponential decay to forget past votes



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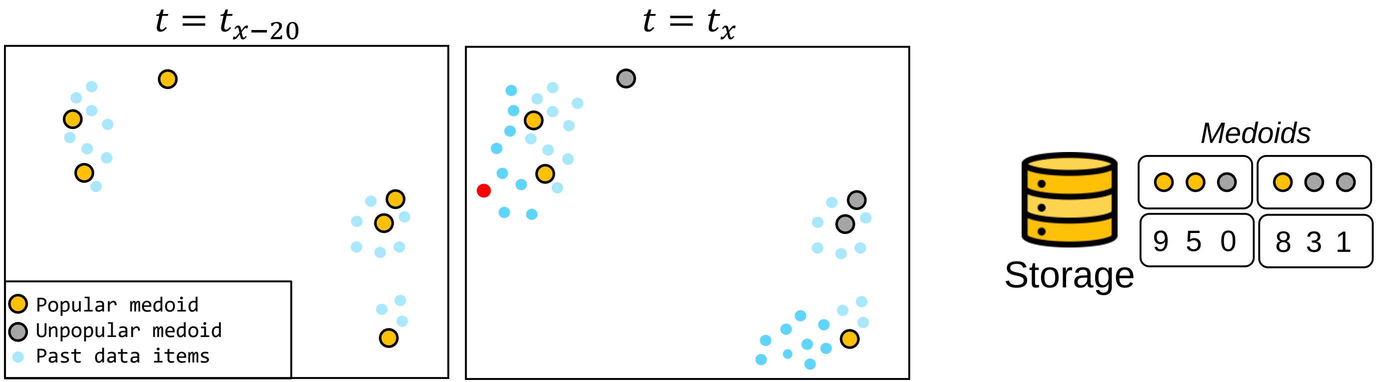
- Which medoids to replace?
  - The one with the least votes → irrelevant medoid



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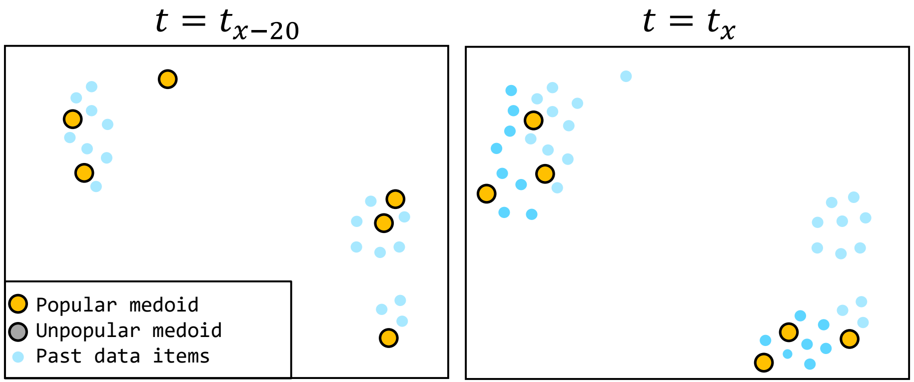
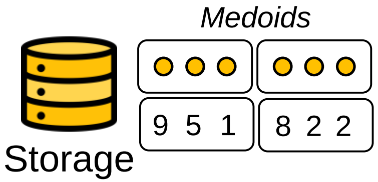
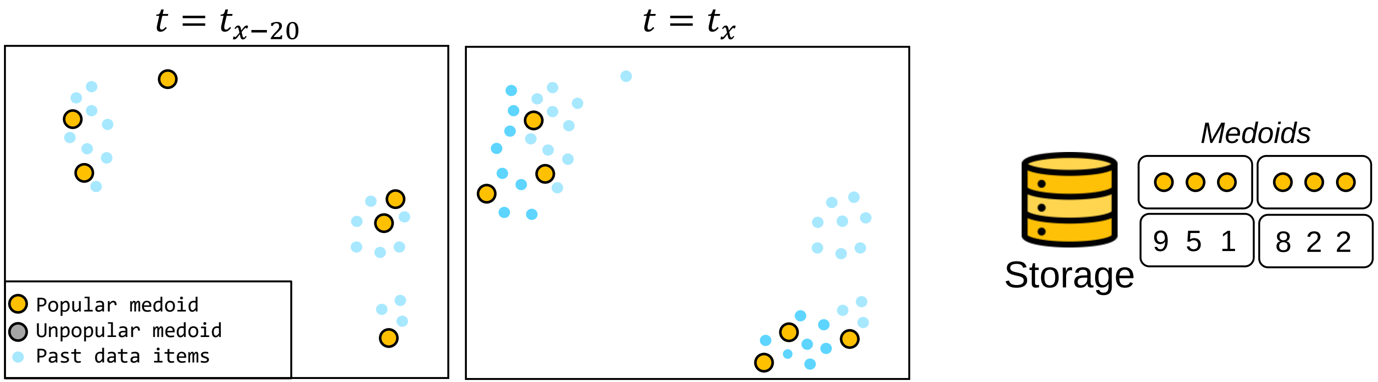




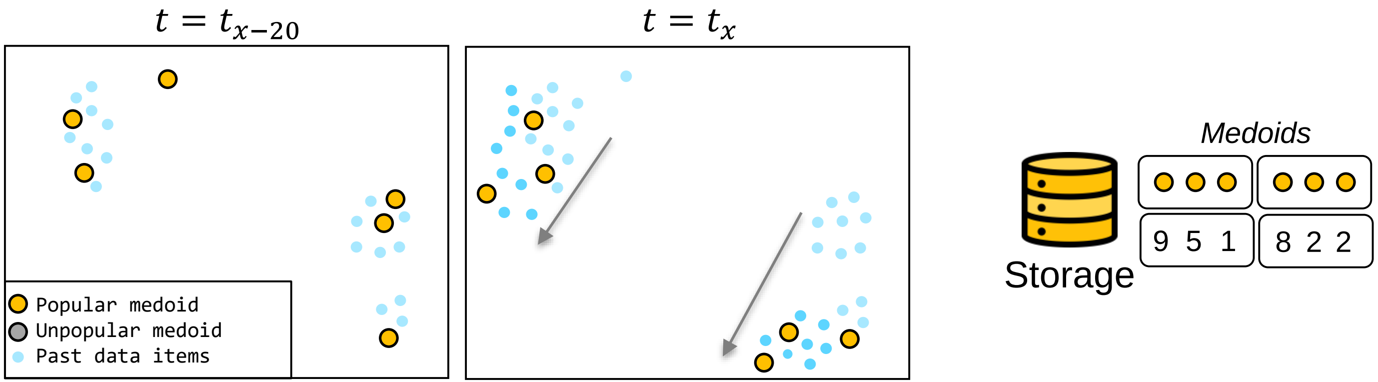
Medoid voting scheme

- Estimates center of mass without distance computations
  - Enables the use of expensive distance measures



Medoid voting scheme

- Estimates center of mass without distance computations
  - Enables the use of expensive distance measures
- Concept drift with k-evolving clusters
  - Keep relevant medoids | Replace irrelevant medoids



SECLEDS

Algorithm 1: SECLEDS for clustering sequences in evolving streams

Input: Data stream, nclusters, nprototypes: $S,\ k,\ p$

function SECLEDS(S, k, p)
  $b \leftarrow 1.5 \cdot k \cdot p$
  $\mathbb{B} \leftarrow$ Collect b items from S
  $\mathcal{C} \leftarrow$ INIT($\mathbb{B},\ k,\ p$) // INIT
  forall s *in* $S[b:]$ **do**
    $cid \leftarrow \arg\min_{1 \leq cid \leq k} \frac{1}{p} \cdot \sum_{j=1}^{p} d(s, m_{cid,j})$ // ASSIGN
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- From a batch, initialize clusters using a non-uniform sampling strategy

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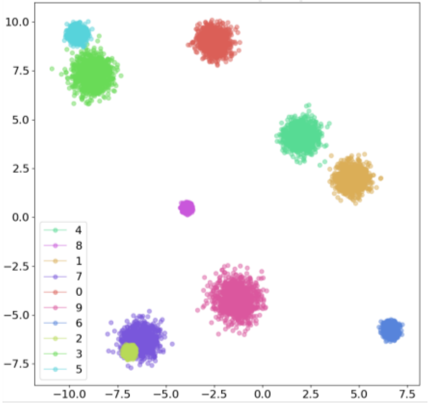
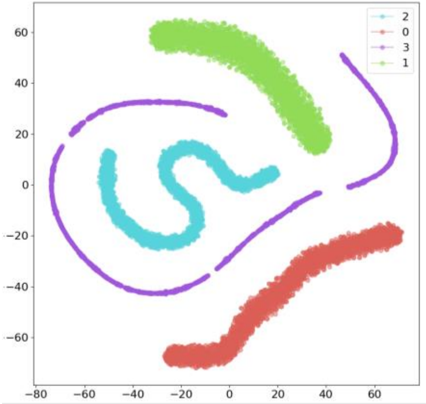
Datasets

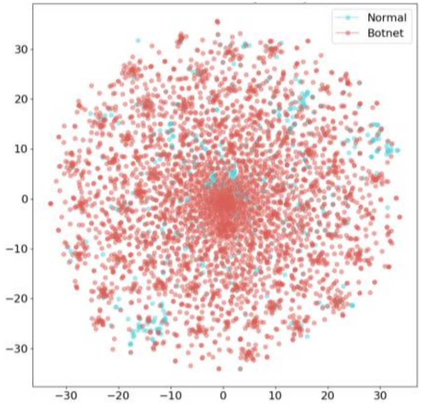
2D: Blobs *(k=10)*



Seq: Sine curves *(k=4)*



Seq: Network traffic *(k=2)*



Datasets

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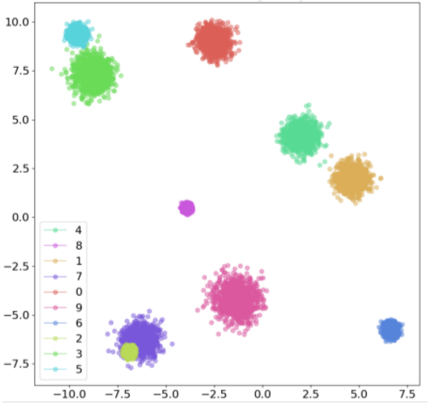

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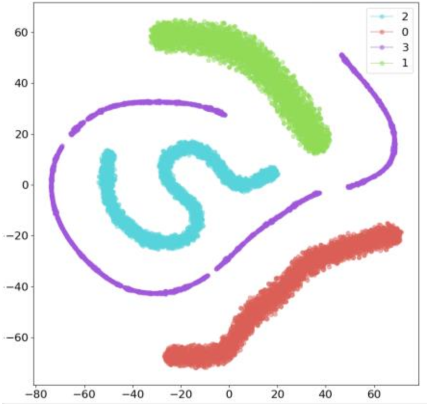

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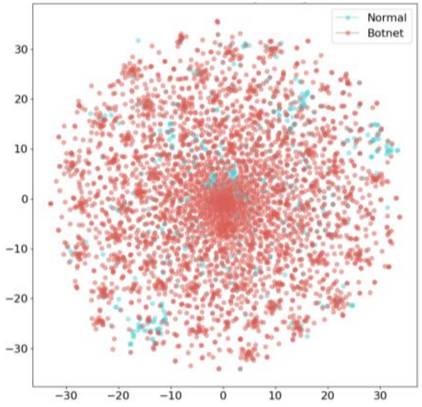

Baselines

Streaming: CluStream[1], StreamKM++

Batch: Minibatch k-means

Offline: BanditPAM[2]

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1. Aggarwal, Charu C., et al. "A framework for clustering evolving data streams." Proceedings 2003 VLDB conference. Morgan Kaufmann, 2003.
2. Tiwari, Mo, et al. "Banditpam: Almost linear time k-medoids clustering via multi-armed bandits." Advances in Neural Information Processing Systems 33 (2020): 10211-10222.

Results [1/4]: Distance computations

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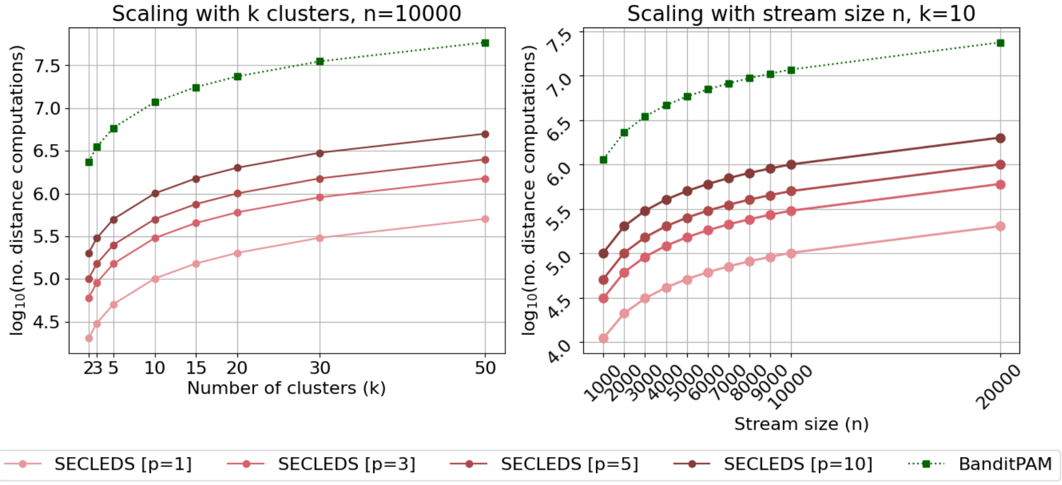
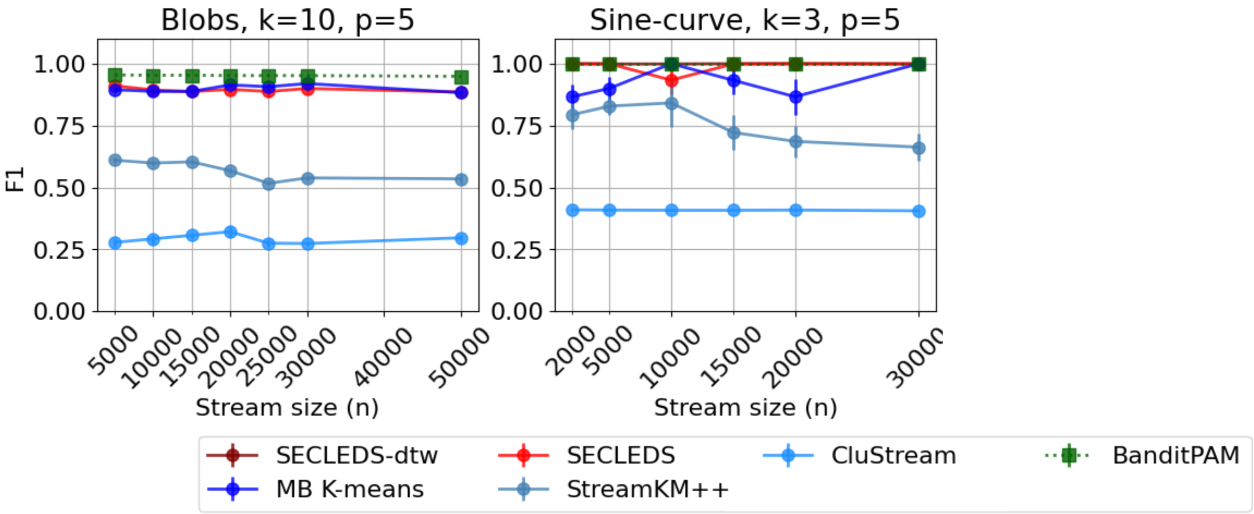
- Reduces required distance computations by **83.7%**



Results [2/4]: Performance

- Outperforms all streaming baselines without concept drift
  - Competitive performance with BanditPAM



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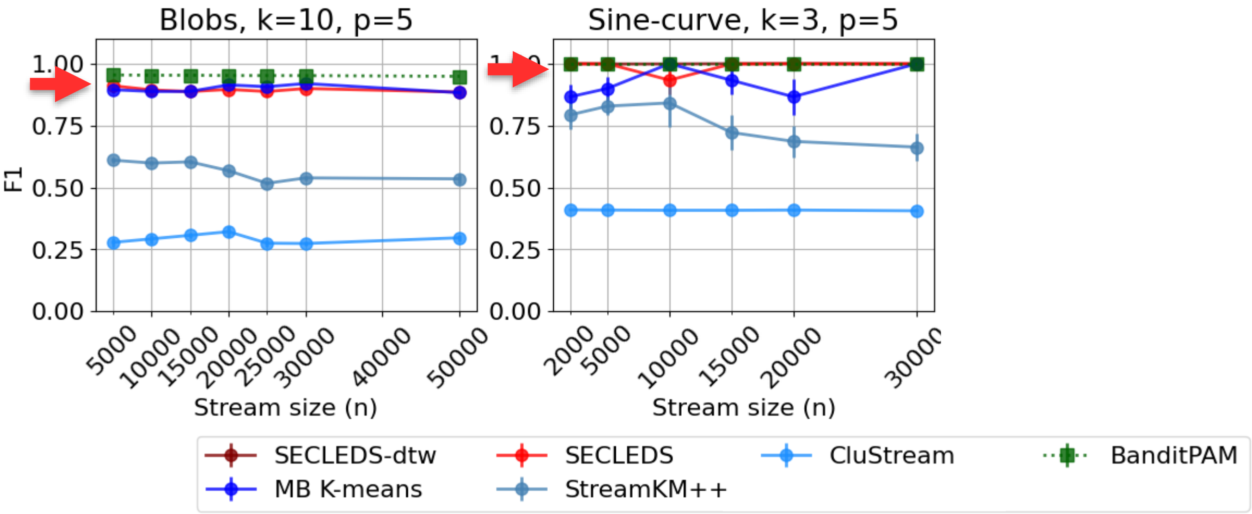
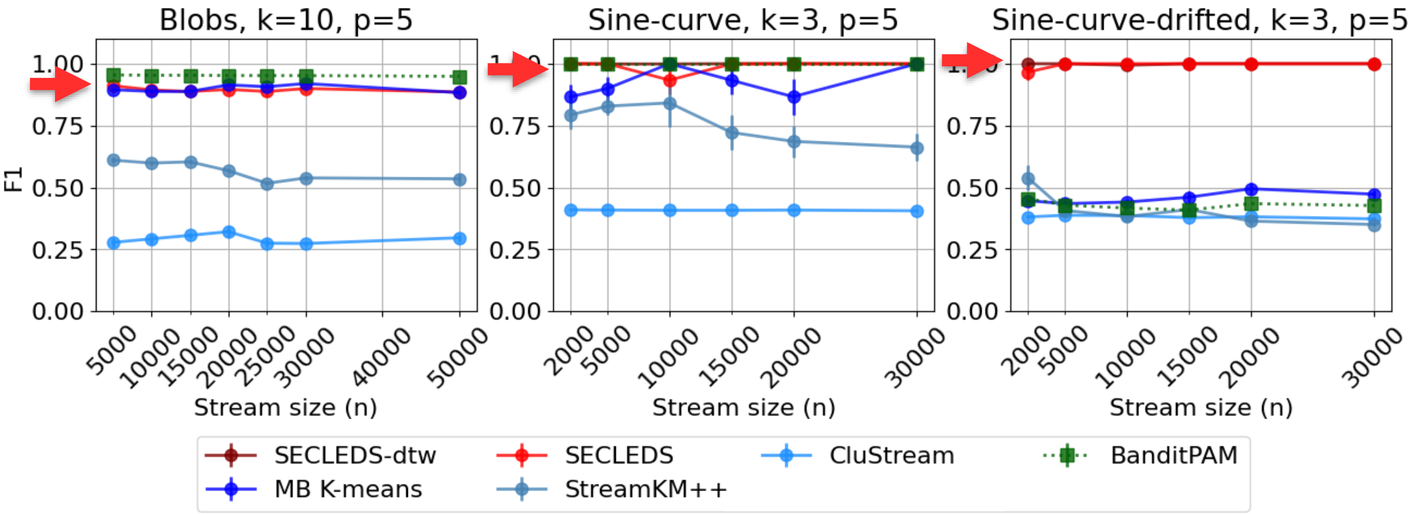


Results [2/4]: Performance

- Outperforms all streaming baselines without concept drift
  - Competitive performance with BanditPAM
- Outperforms all baselines by **138.7%** with concept drift



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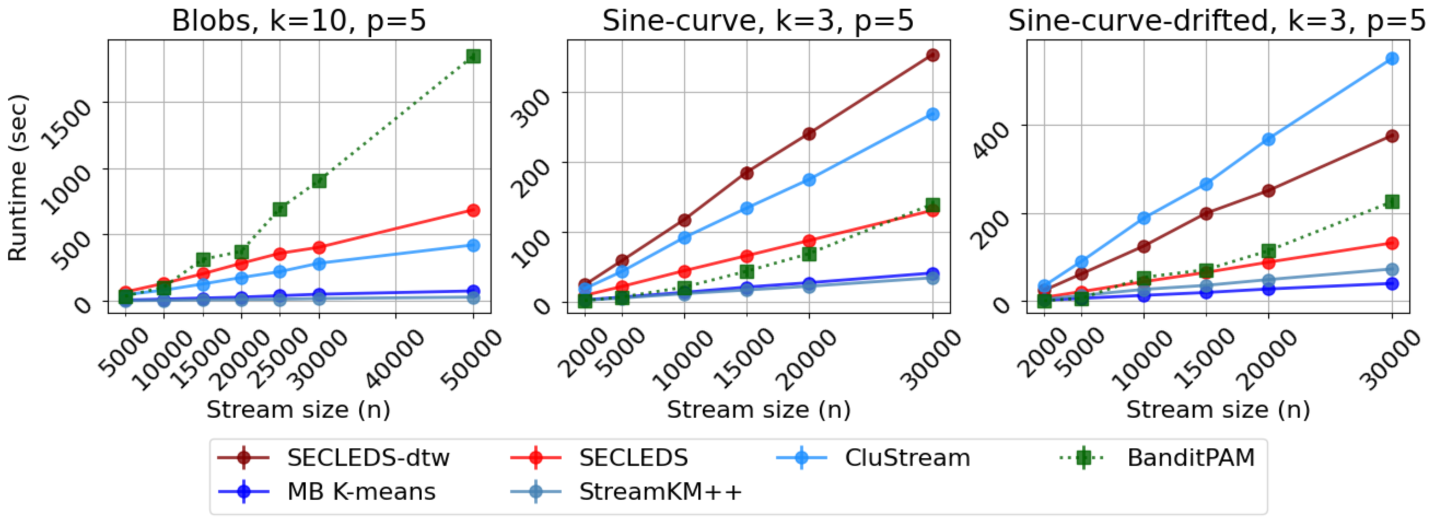
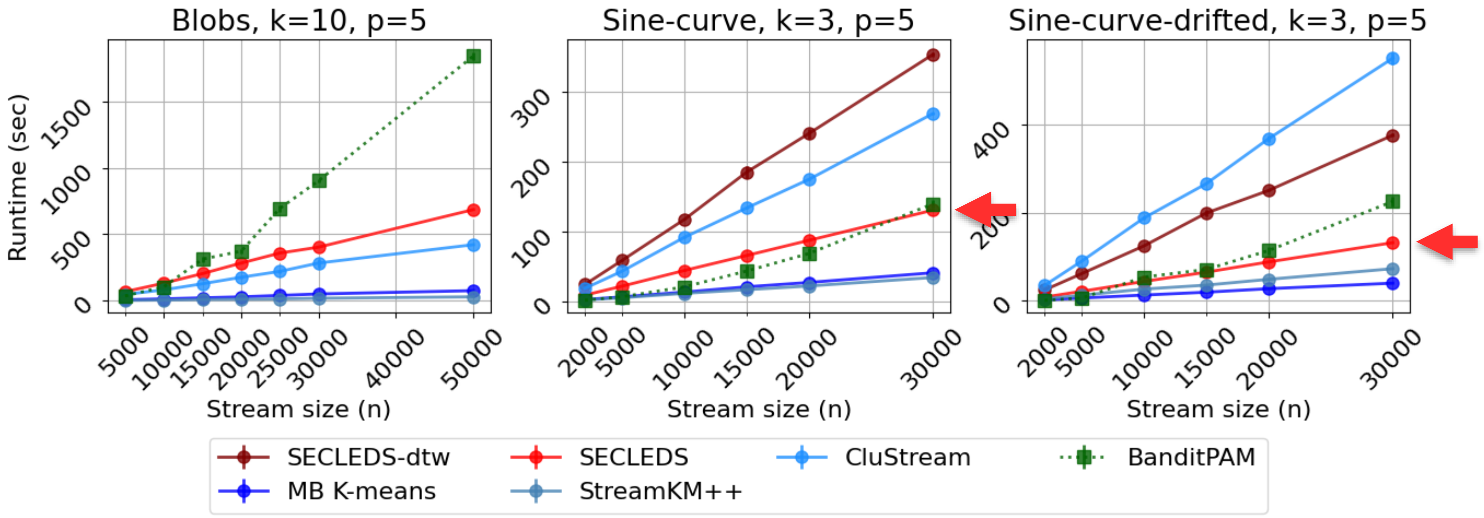
Results [3/4]: Runtime

- Runtime scales almost linearly *w.r.t.* stream size → $\mathcal{O}(nkp)$



Results [3/4]: Runtime

- Runtime scales almost linearly *w.r.t.* stream size → $\mathcal{O}(nkp)$
- Faster than banditPAM and CluStream for sequence clustering



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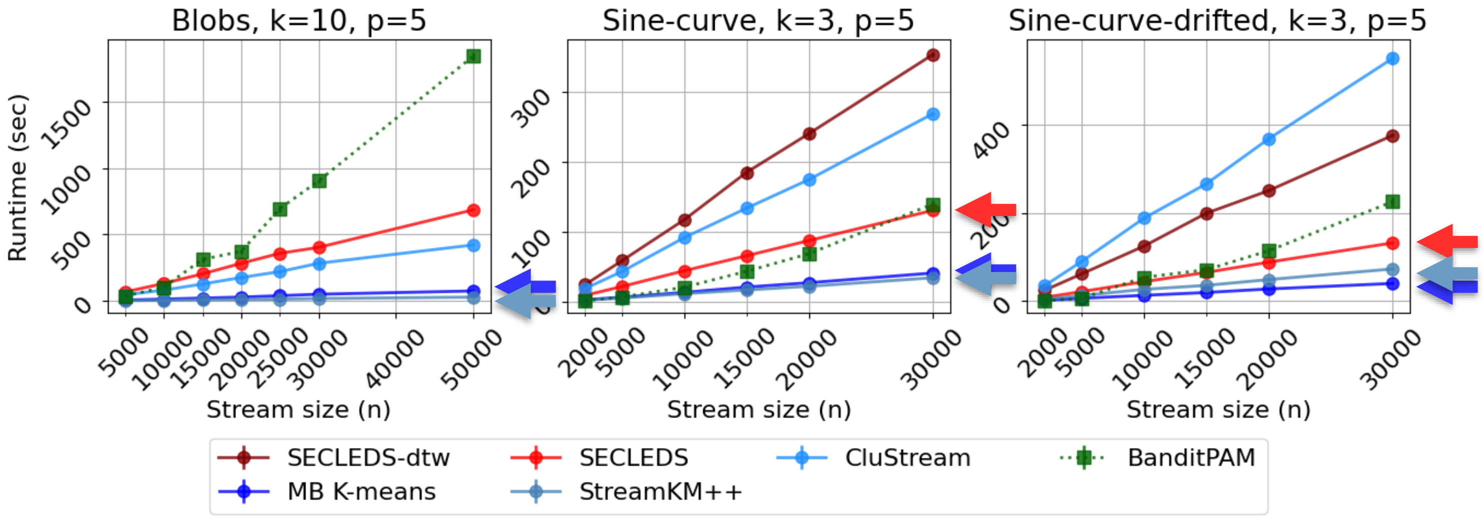
Results [3/4]: Runtime

- Runtime scales almost linearly *w.r.t.* stream size → $\mathcal{O}(nkp)$
- Faster than banditPAM and CluStream for sequence clustering



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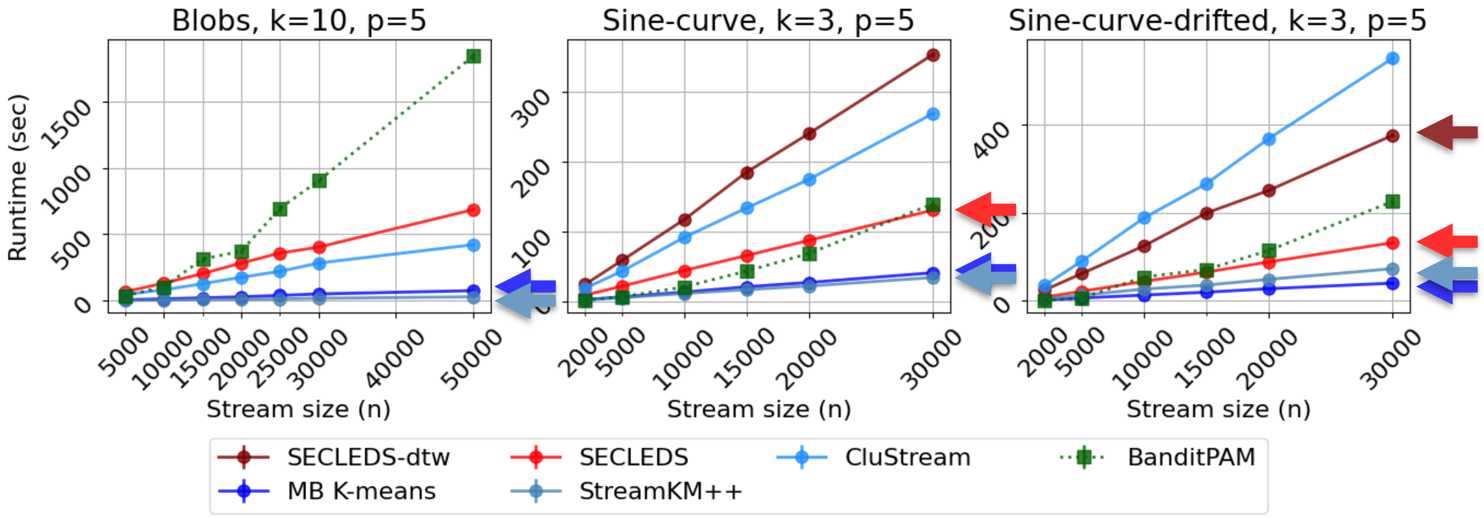

Results [4/4]: Network traffic use case

- Temporal pattern preserving network traffic sampling
  - Periodically store medoids

	# distances (10^6)	Runtime (sec)	F1 (k=2)	F1 (k=5)
BanditPAM	10.3	984.8	0.64	0.38
SECLEDS-eu	**2.1**	**631.8**	0.79	0.76
SECLEDS-dtw	**2.1**	1626.89	**0.81**	**0.80**

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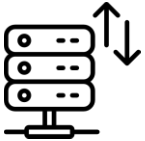
Results [4/4]: Network traffic use case

- Temporal pattern preserving network traffic sampling
  - Periodically store medoids
- Clusters 5.5h network traffic in **< 30 minutes**
  - Supporting network bandwidth of up to **1.08 Gb/s** with DTW



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Future work

- Medoid-aware clustering
  - Better coverage, but additional distance computations required
- Theoretical properties of SECLEDS
  - Empirically works but limited theoretical understanding
- Optimized implementation
  - Runtime efficient C implementation

Takeways

- SECLEDS → lightweight streaming k-medoids with multiple medoids
  - Medoid voting → concept drift using k-evolving clusters
- Cluster sequences in high-bandwidth data streams
  - Reduces required distance computations
- Exceptional clustering performance with concept drift
  - Outperforms all streaming baselines regardless of concept drift
- SECLEDS can be used to intelligently sample network traffic

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Thank you! Questions?

- SECLEDS is a lightweight streaming variant of k-medoids.
- Efficiently clusters sequences in high-bandwidth data streams with concept drift.
- Can be used for temporal pattern-preserving network traffic sampling.

SECLEDS is open-source!

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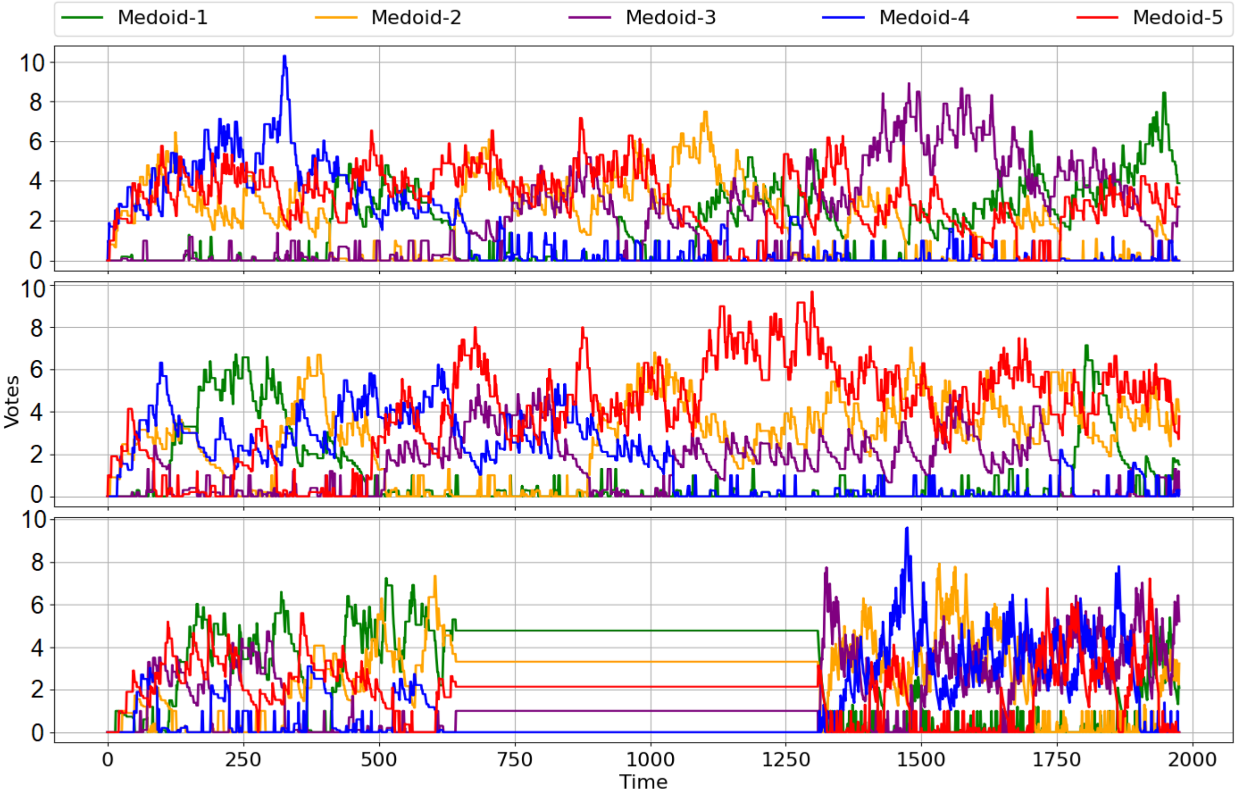
*Icons courtesy Smashicons, Pixel perfect, Freepik, Roundicons from www.flaticons.com

Extras

Uniformly distributed stream

Incrementally drifted stream

Class-ordered stream



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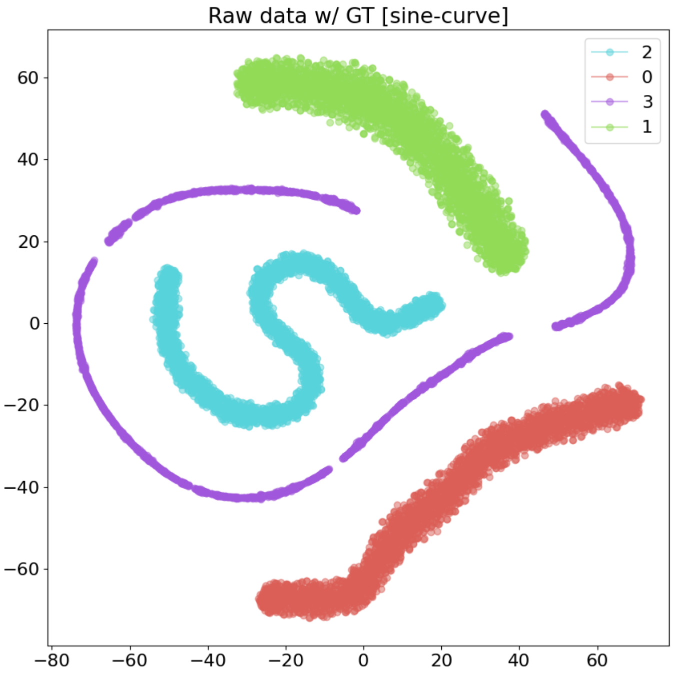
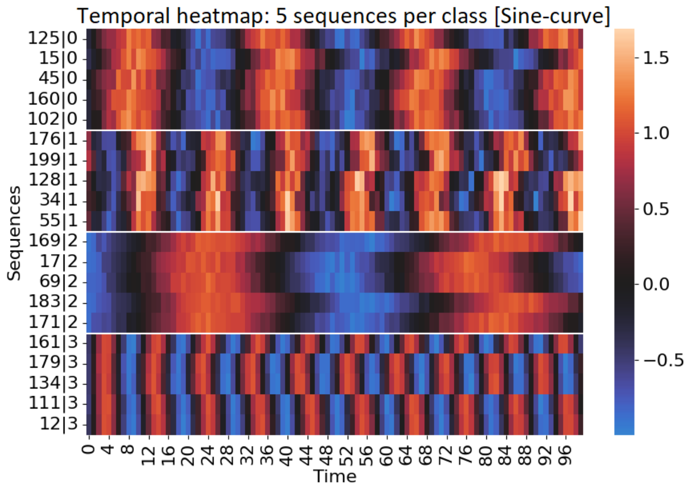
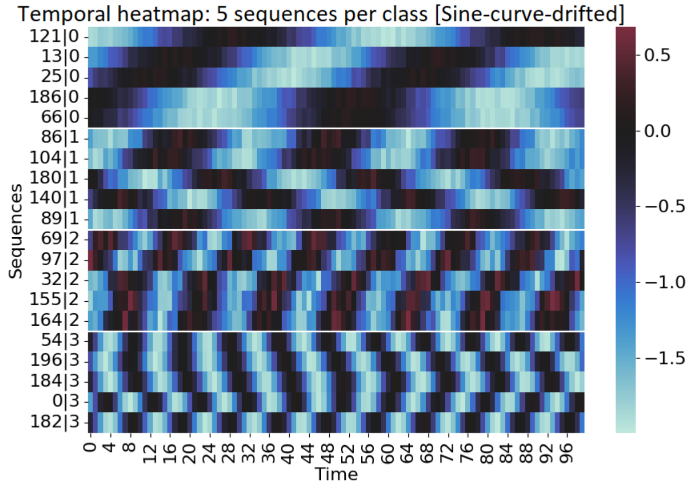
Extras







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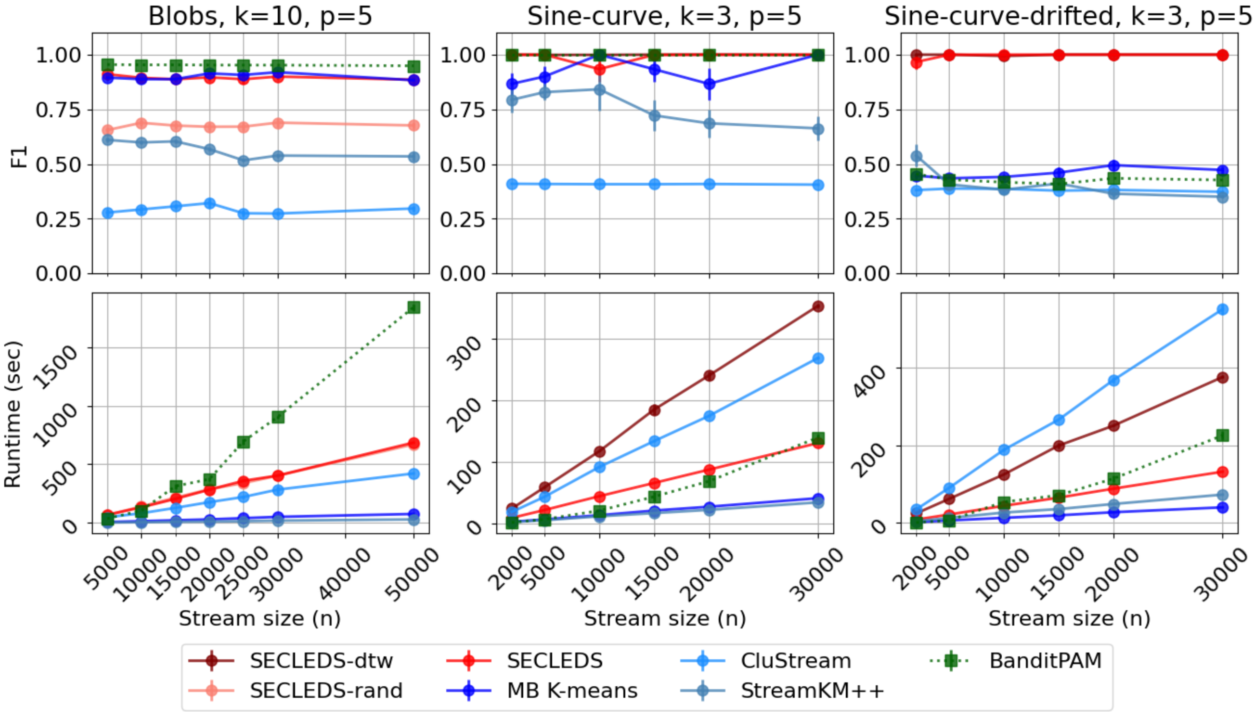
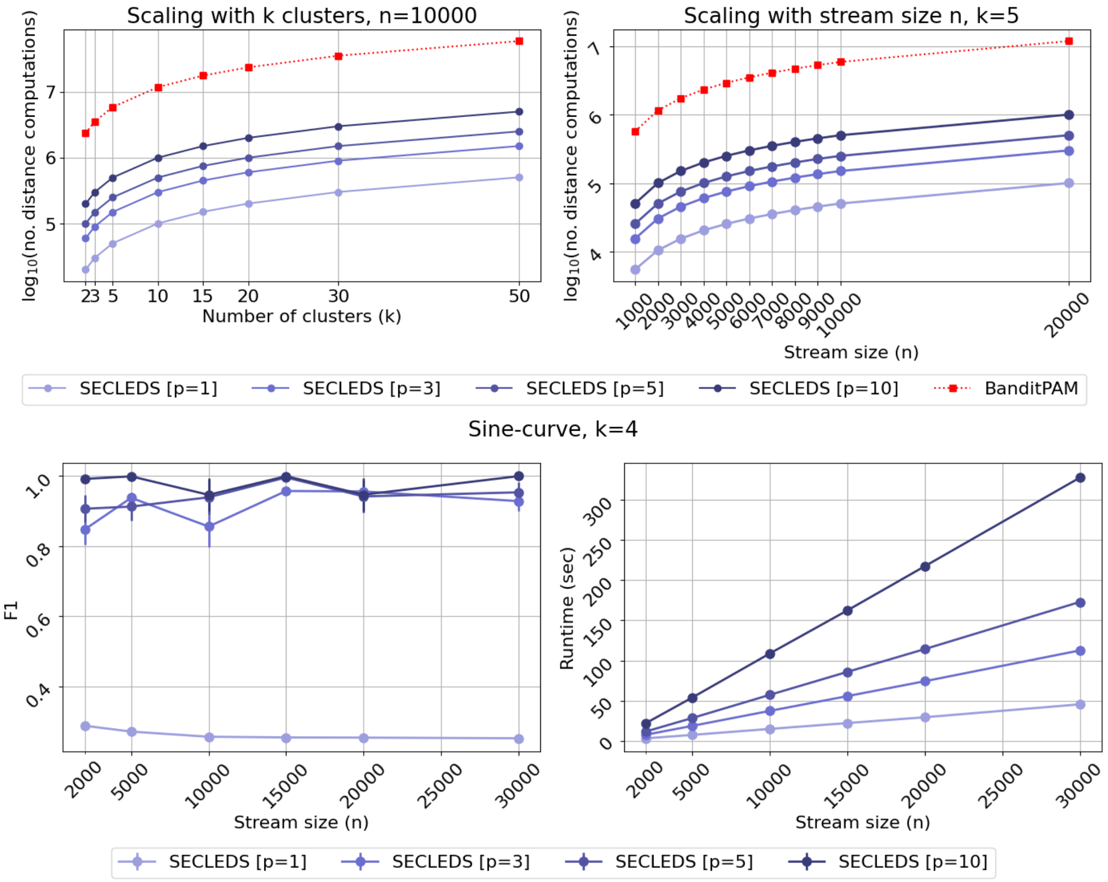
Extras



Blobs, k=10, p=5
Sine-curve, k=3, p=5
Sine-curve-drifted, k=3, p=5
F1
Runtime (sec)
Stream size (n)
SECLEDS-dtw
SECLEDS-rand
SECLEDS
MB K-means
CluStream
StreamKM++
BanditPAM

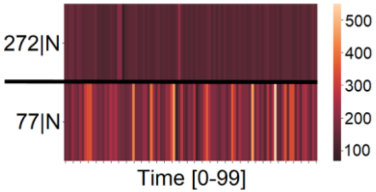
Extras



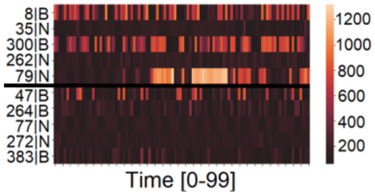
Scaling with k clusters, n=10000
log10(no. distance computations)
Number of clusters (k)
Scaling with stream size n, k=5
log10(no. distance computations)
Stream size (n)
SECLEDS [p=1]
SECLEDS [p=3]
SECLEDS [p=5]
SECLEDS [p=10]
BanditPAM
Sine-curve, k=4
F1
Stream size (n)
Runtime (sec)
Stream size (n)
SECLEDS [p=1]
SECLEDS [p=3]
SECLEDS [p=5]
SECLEDS [p=10]

Extras

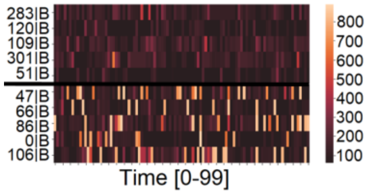
k=2



BanditPAM

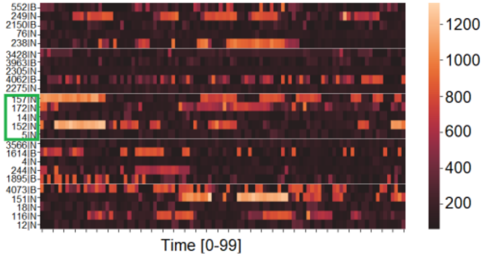


SECLEDS-eu

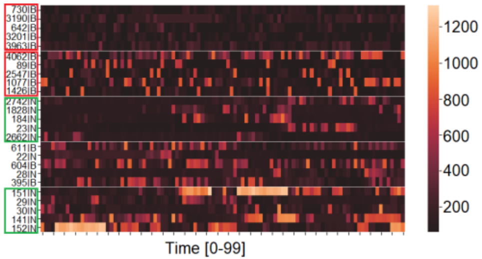


SECLEDS-dtw

k=5



SECLEDS-eu



SECLEDS-dtw

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