Cognitive Interaction Technology
Center of Excellence
Bielefeld University

Honda Research Institute Europe

Memory Models for Incremental Learning Architectures

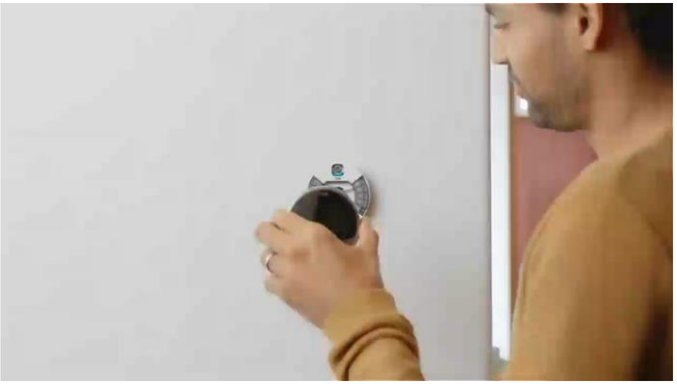
Viktor Losing, Heiko Wersing and Barbara Hammer

Outline

- Motivation
- ~~Case study: Personalized Maneuver Prediction at Intersections~~
- Handling of Heterogeneous Concept Drift

Motivation

- Personalization
  – adaptation to user habits / environments
- Lifelong-learning

Challenges - Personalized online learning

- Learning from few data

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- Sequential data with predefined order

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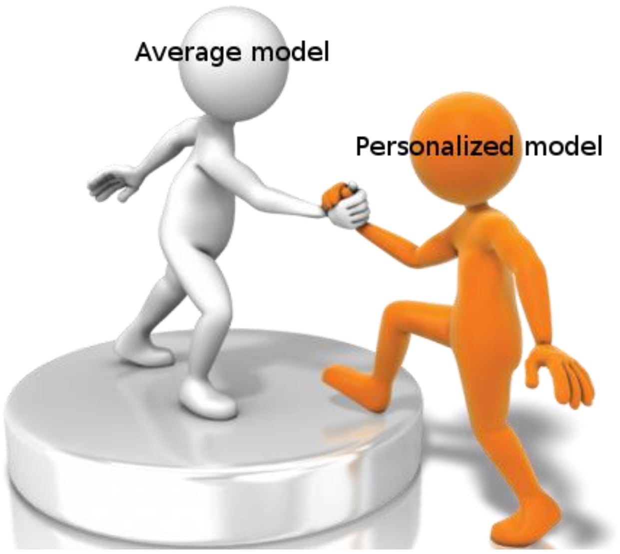
- Concept drift

Challenges - Personalized online learning

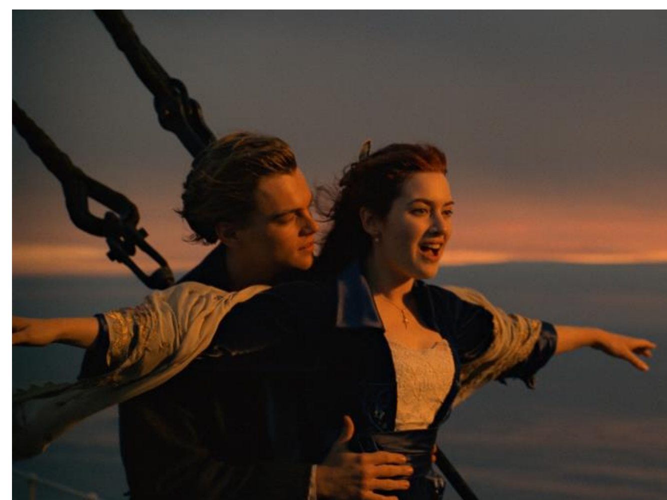
- Learning from few data
- Sequential data with predefined order
- Concept drift
- Cooperation between average and personalized model



Change is everywhere

- Coping with „arbitrary“ changes

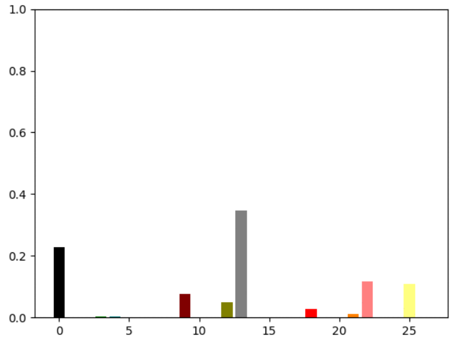
Change of taste / interest



Seasonal changes

Change of context

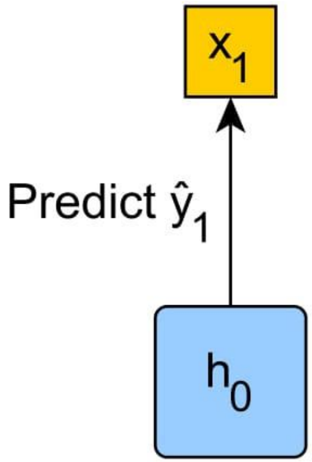
Rialto task: Change of lighting conditions



Setting

- Supervised stream classification
  - Predict for an incoming stream of features $x_1, \ldots, x_j, x_i \; \mathbb{R}^n$ the corresponding labels $y_1, \ldots y_j, y_i \in \{1, \ldots, c\}$

- On-line learning scheme
  - After each touple (x_i, y_i)generate a new model h_i to predict the next incoming example



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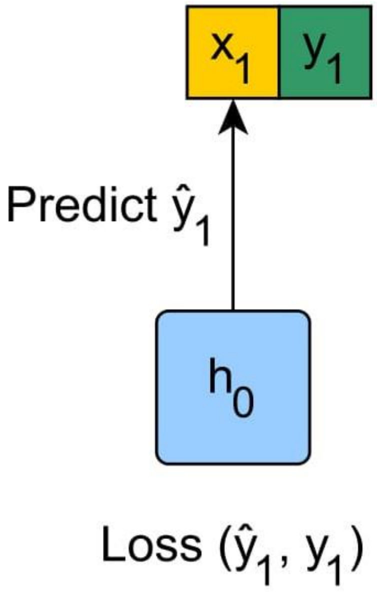

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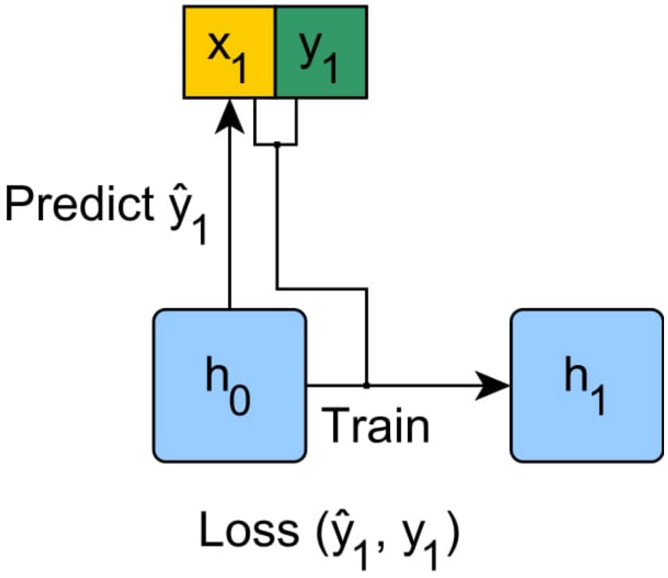

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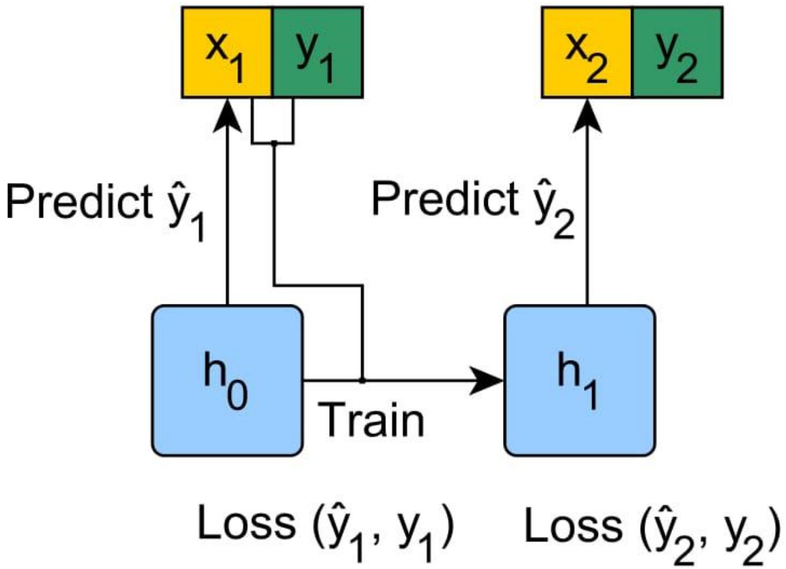

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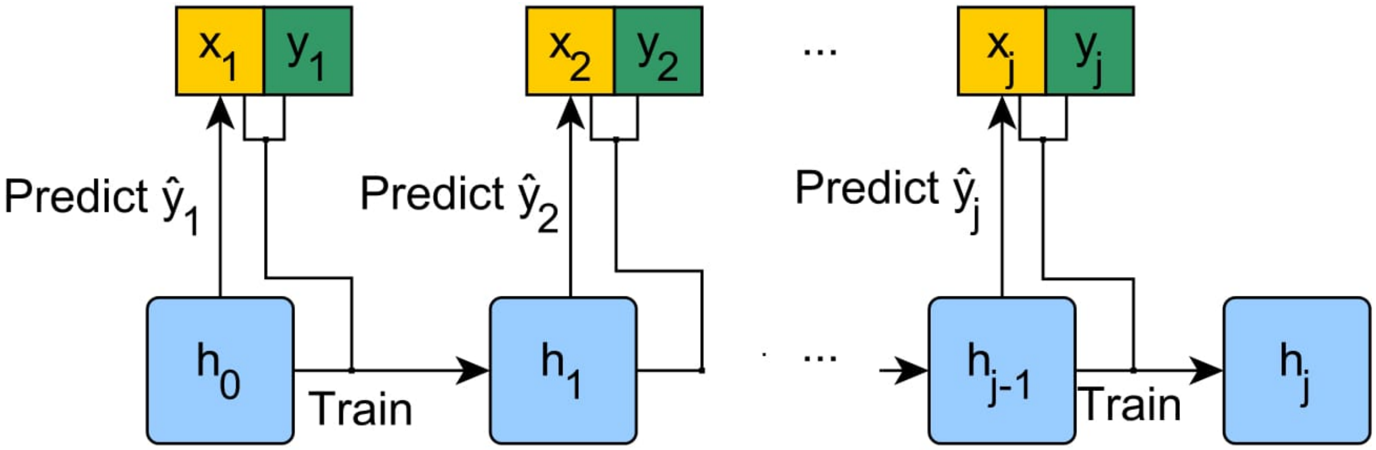

$$\text{Error} = \frac{1}{j}\ \text{Loss}(\hat{y}_1, y_1) + \text{Loss}(\hat{y}_2, y_2) \ldots + \text{Loss}(\hat{y}_j, y_j)$$

Setting

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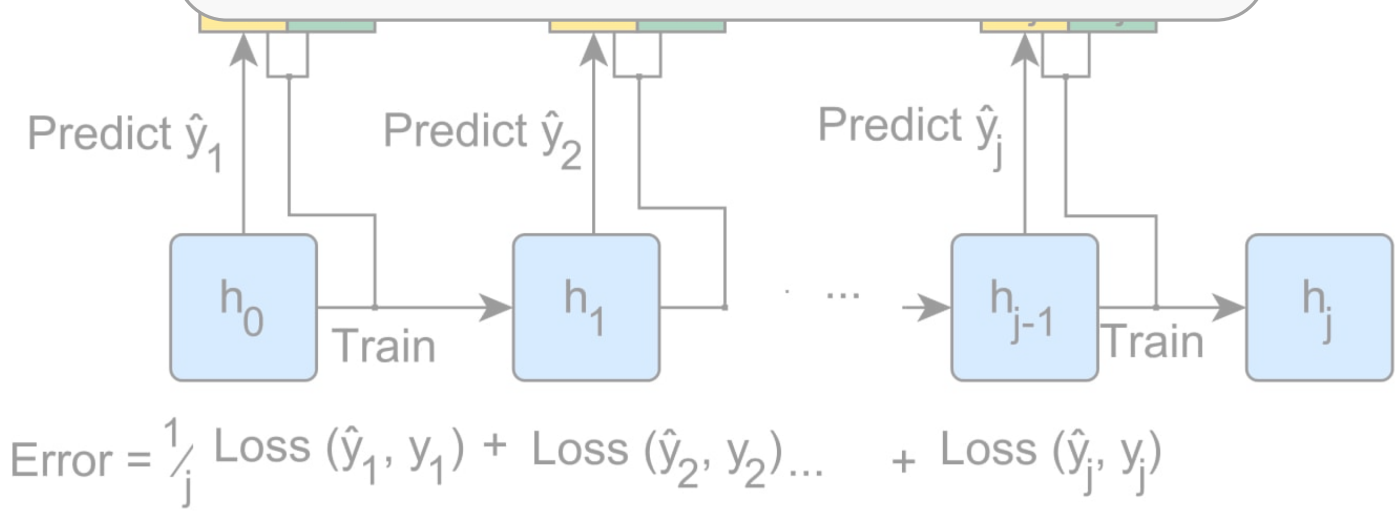
- On-line lea
  - After each the next i

Preconditions for application:
- Obtainable labels in retrospective



Definition

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$$\exists t_0, t_1 \colon P_{t_0}(X, Y) \neq P_{t_1}(X, Y)$$

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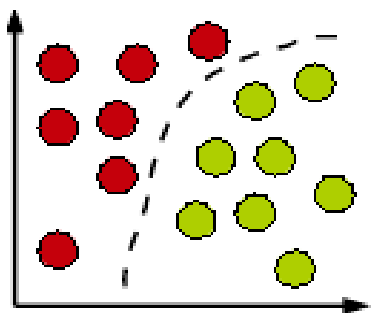

Image source : Gama et al. “A survey on concept drift adaptation”, ACM Computing Surveys 2014

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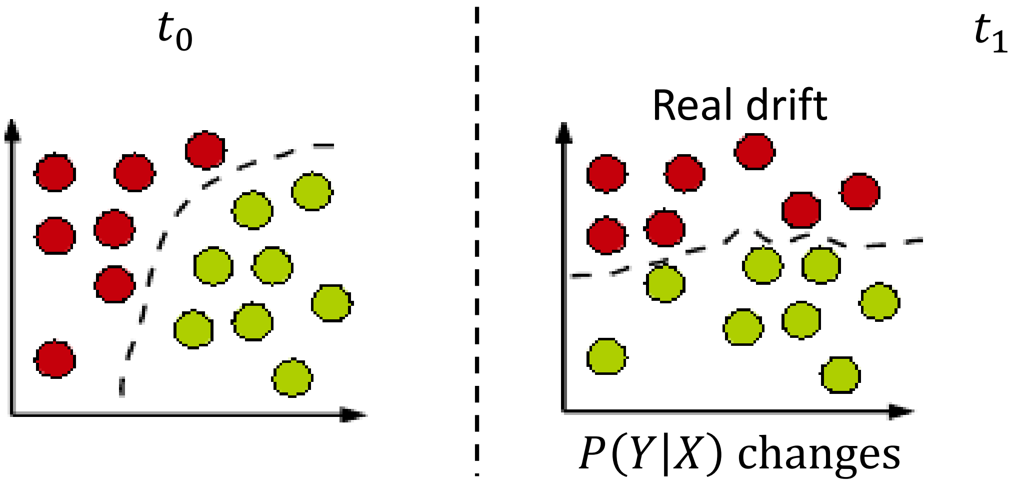

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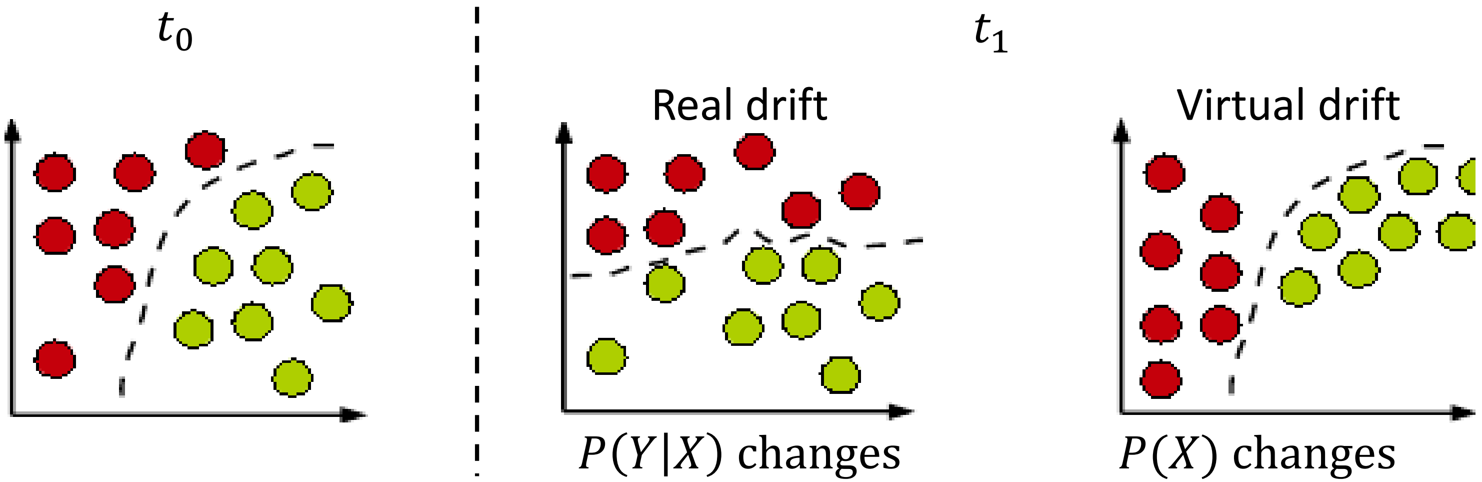

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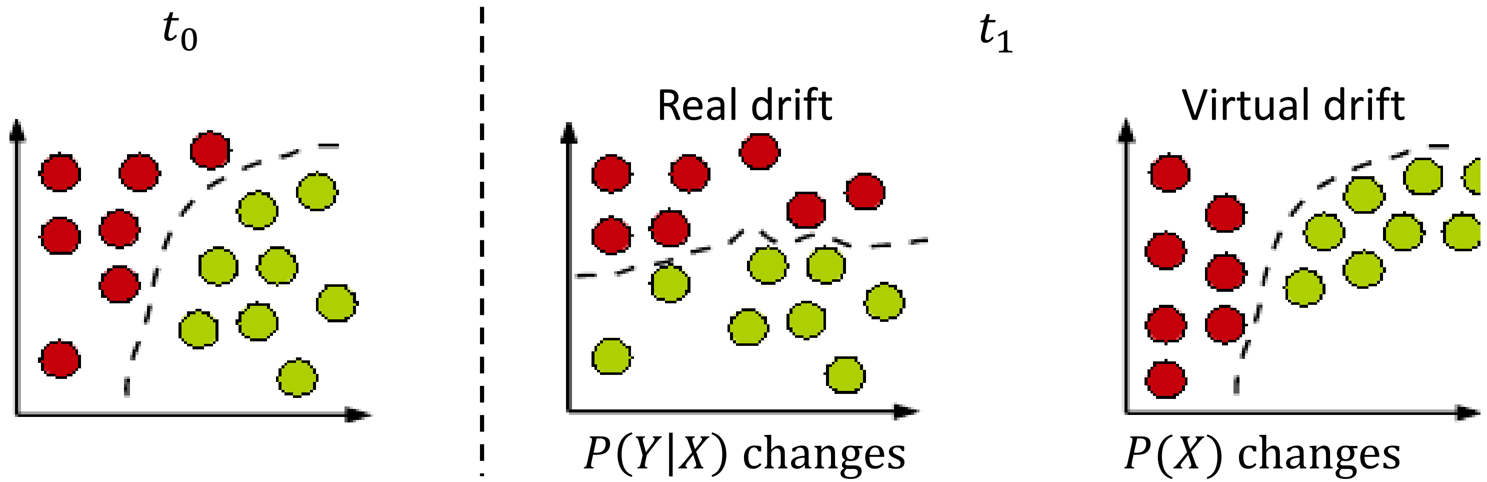

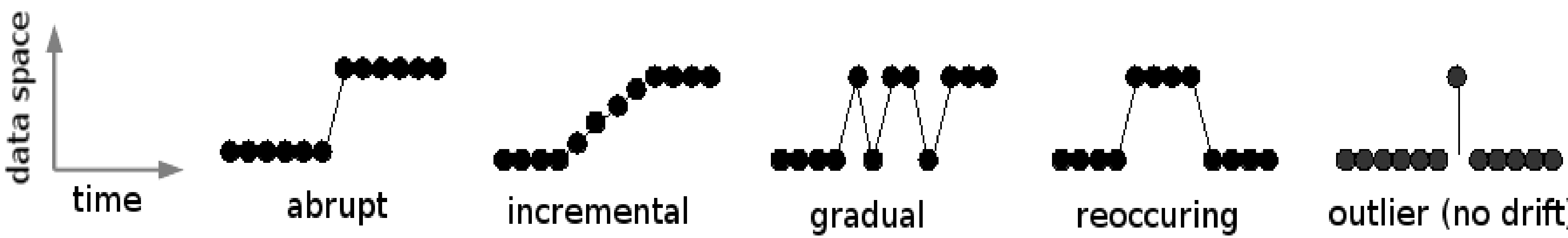

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Related work

- Dynamic sliding windows techniques
  - PAW Bifet et al. “Efficient Data Stream Classification Via Probabilistic Adaptive Windows“, ACM 2013
- Ensemble methods with various weighting schemes
  - LVGB Bifet et al. “Leveraging Bagging for Evolving Data Streams“, ECML-PKDD 2010
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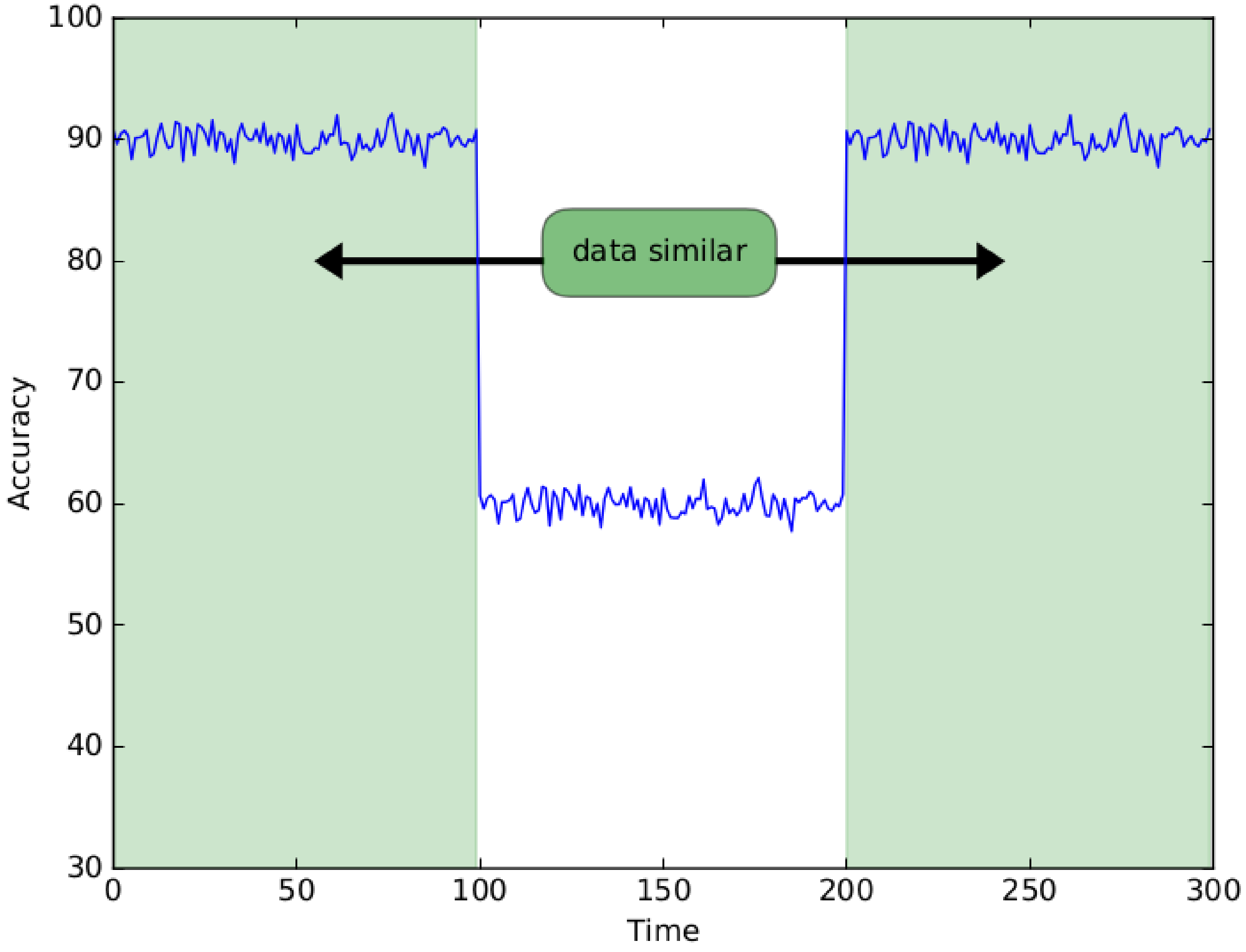
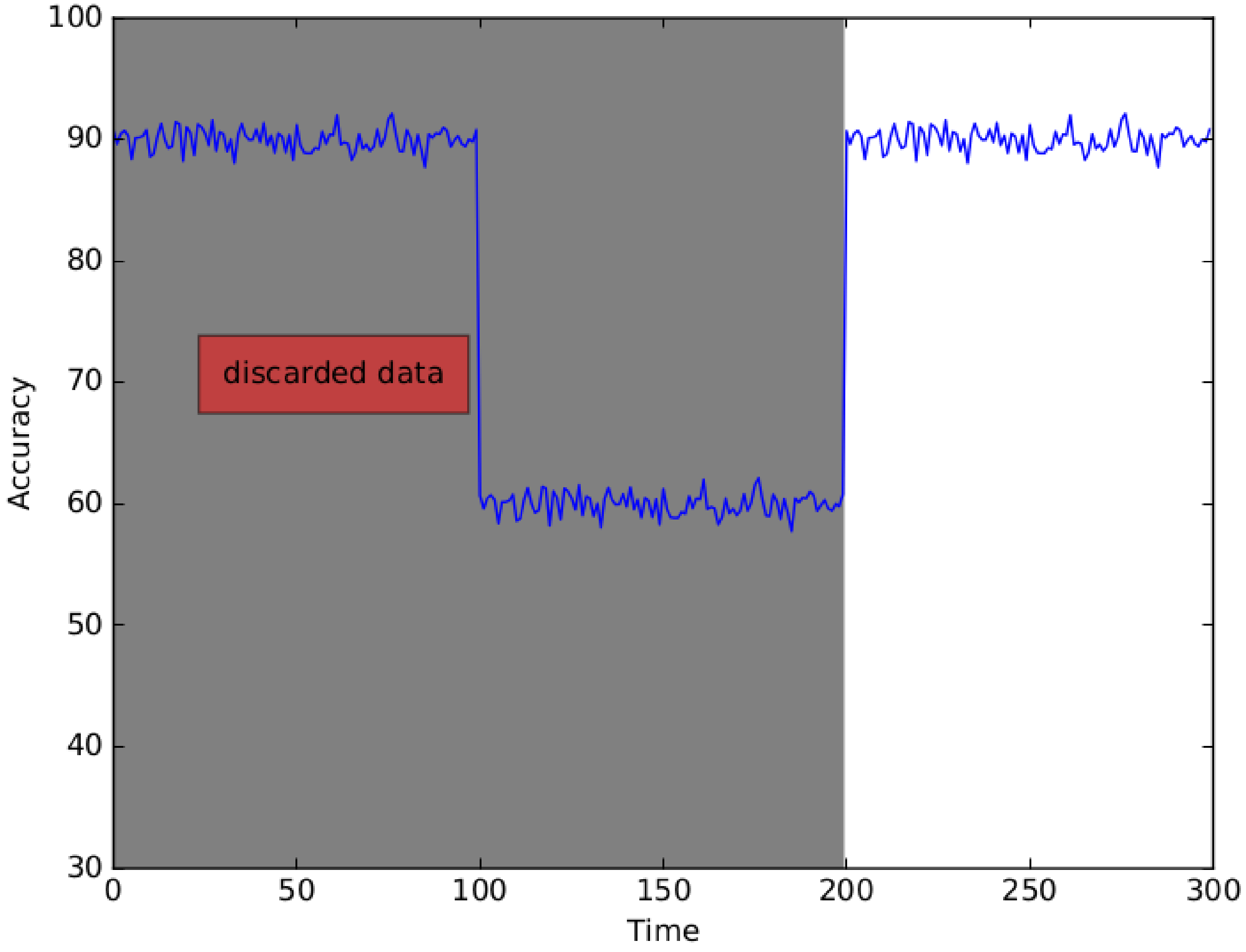
- Drawbacks:
  - Target specific drift types
  - Require hyperparameter setting according to the expected drift
  - Discard former knowledge that still may be valuable

Drawbacks

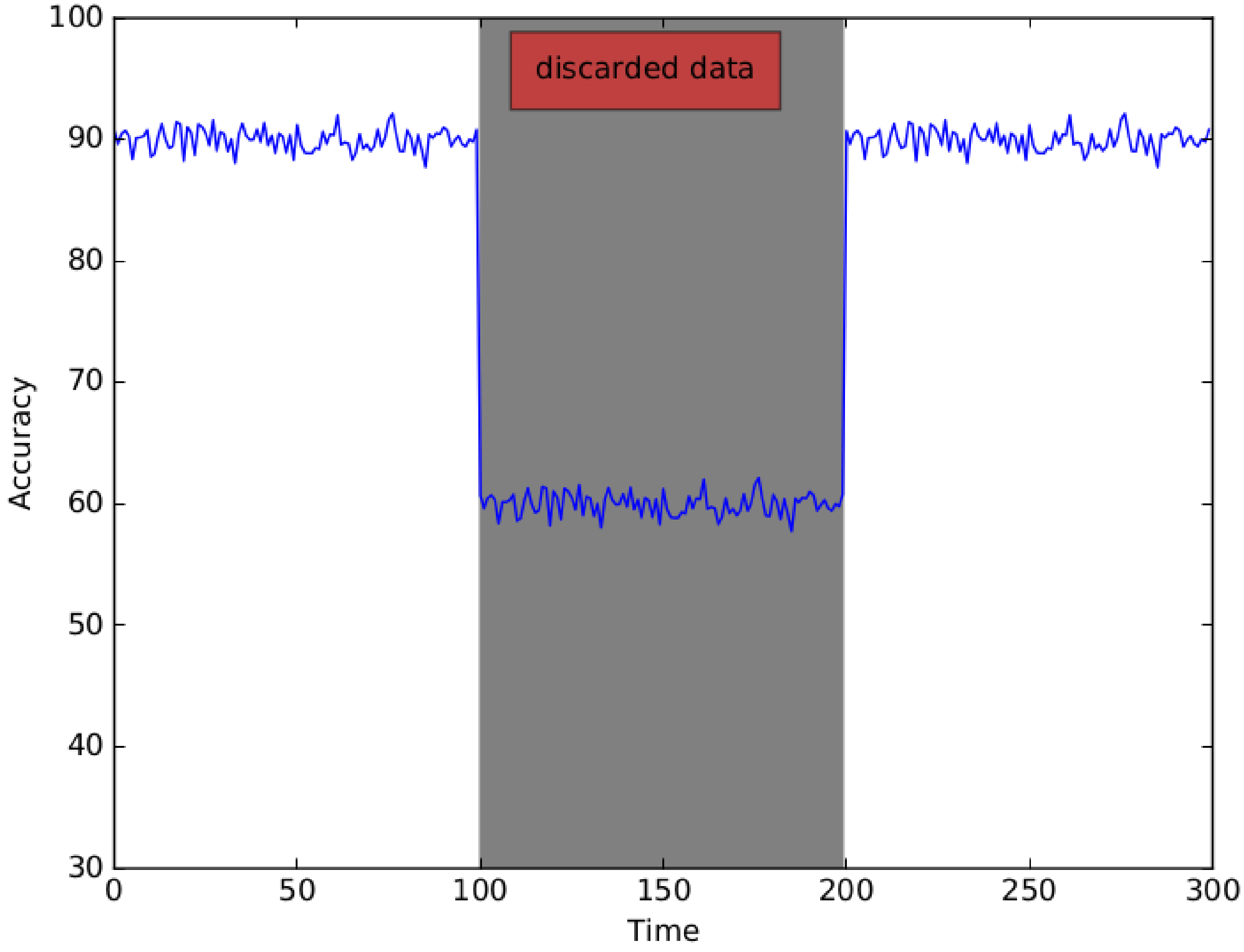


data similar
Accuracy
Time
100
90
80
70
60
50
40
30
0
50
100
150
200
250
300

Drawbacks – Usual result



Drawbacks – Desired behavior



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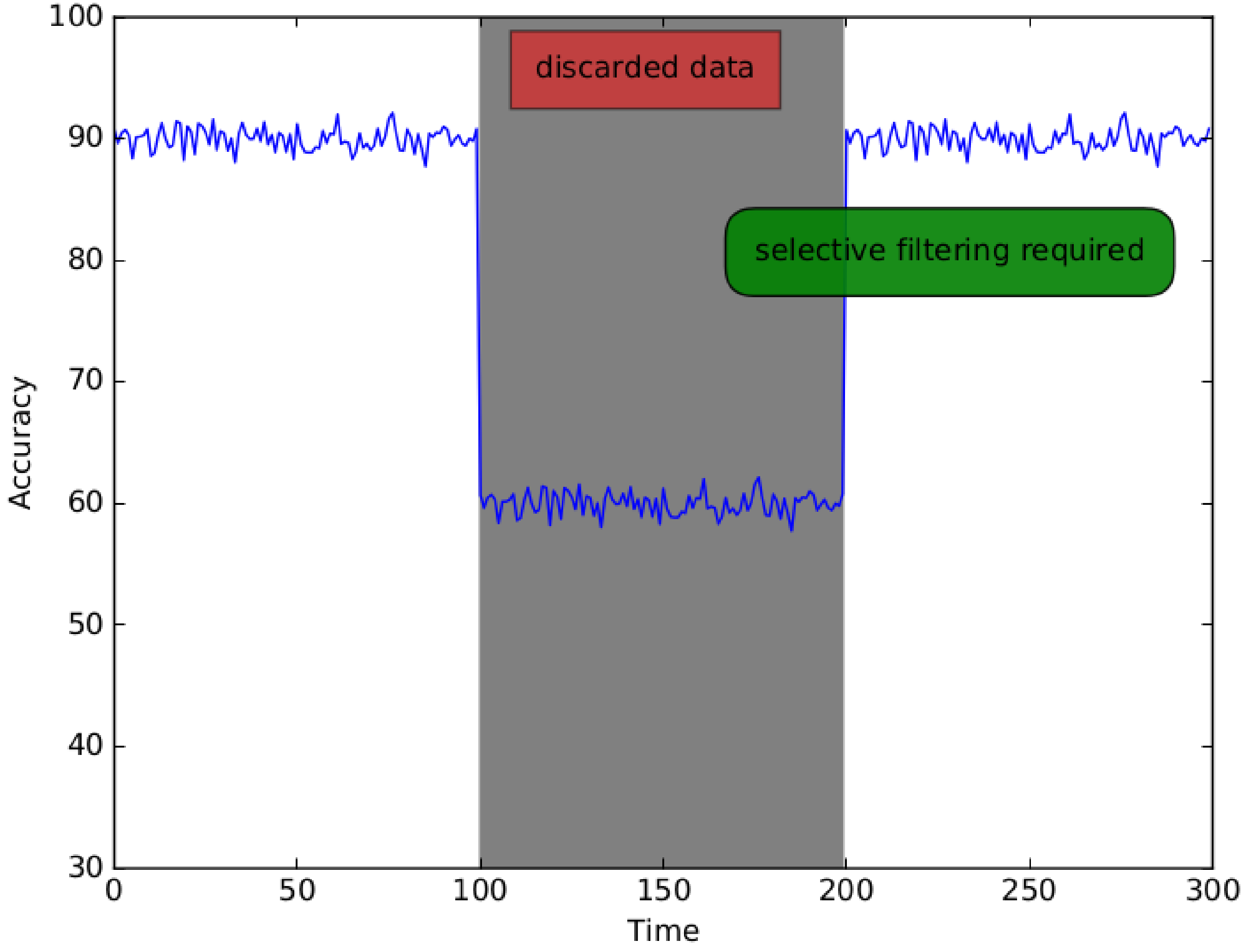

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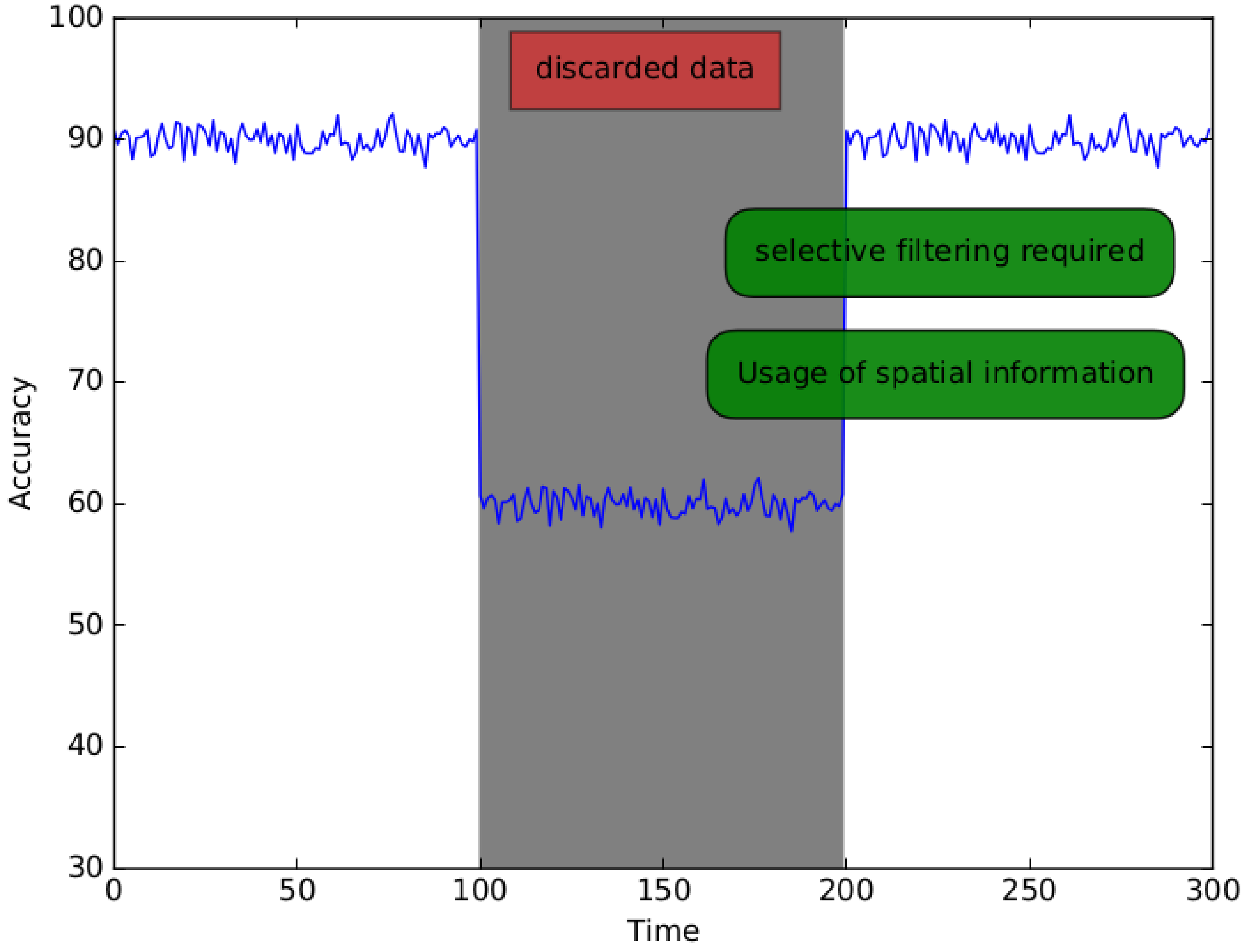
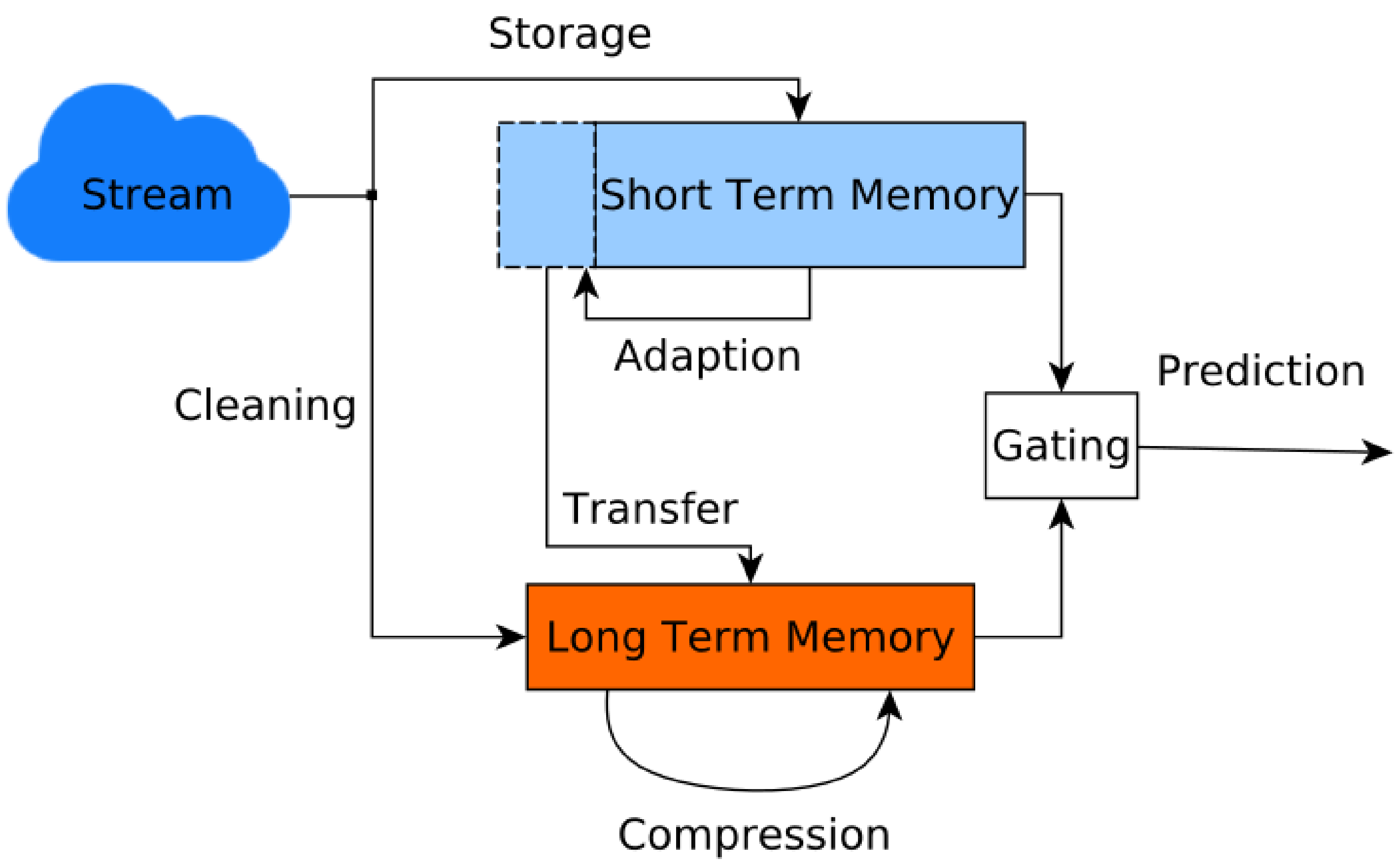


Self Adaptive Memory (SAM)



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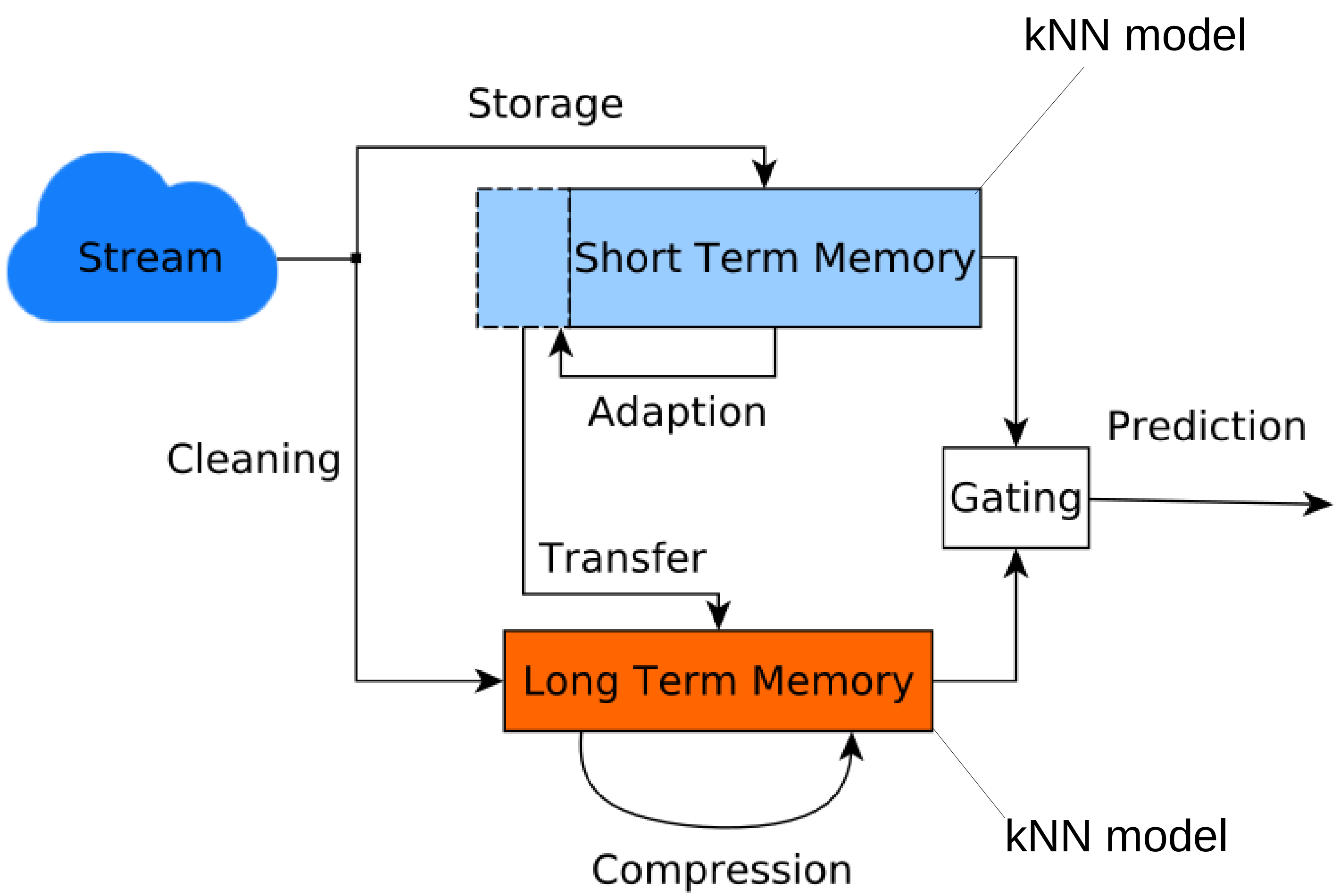

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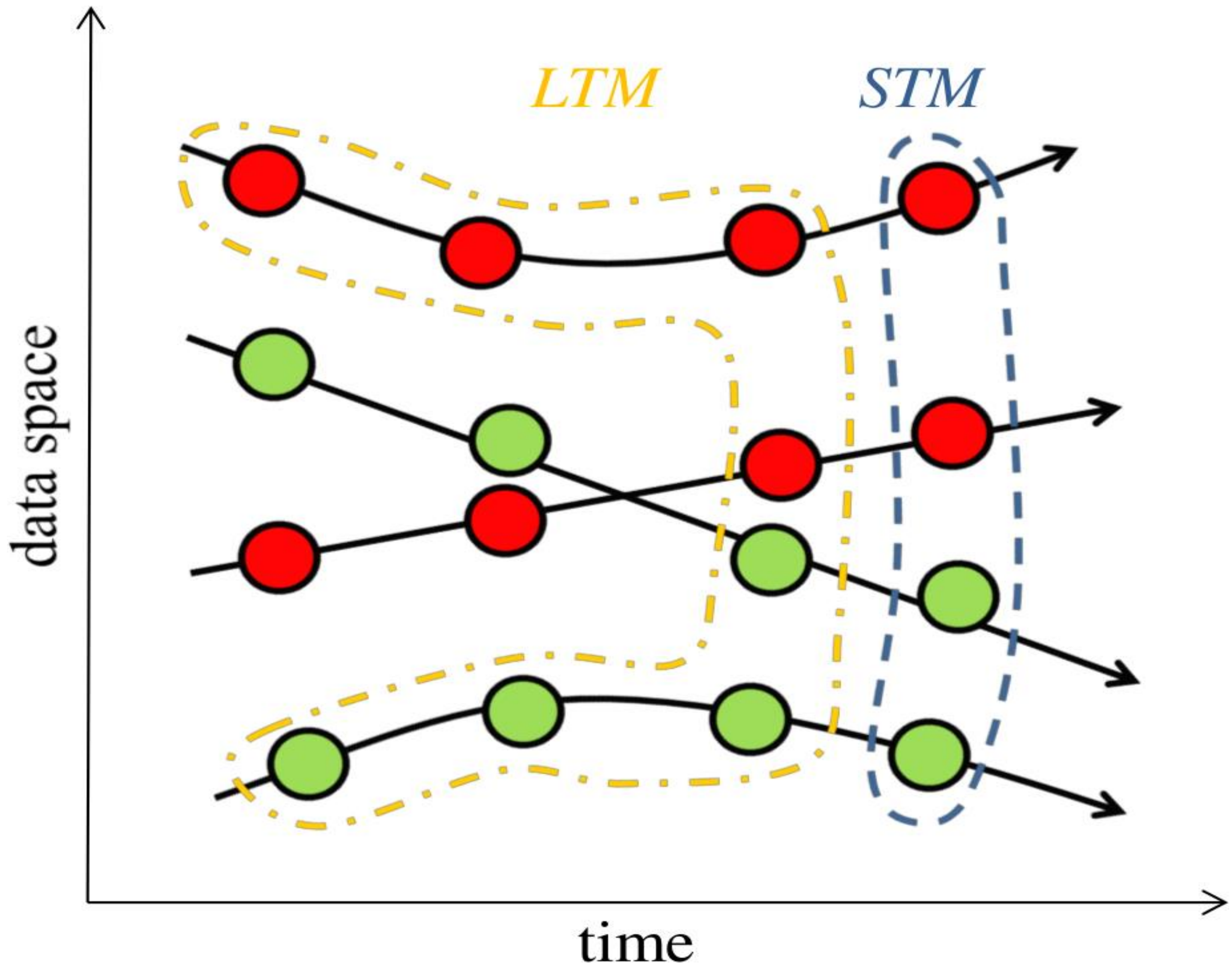
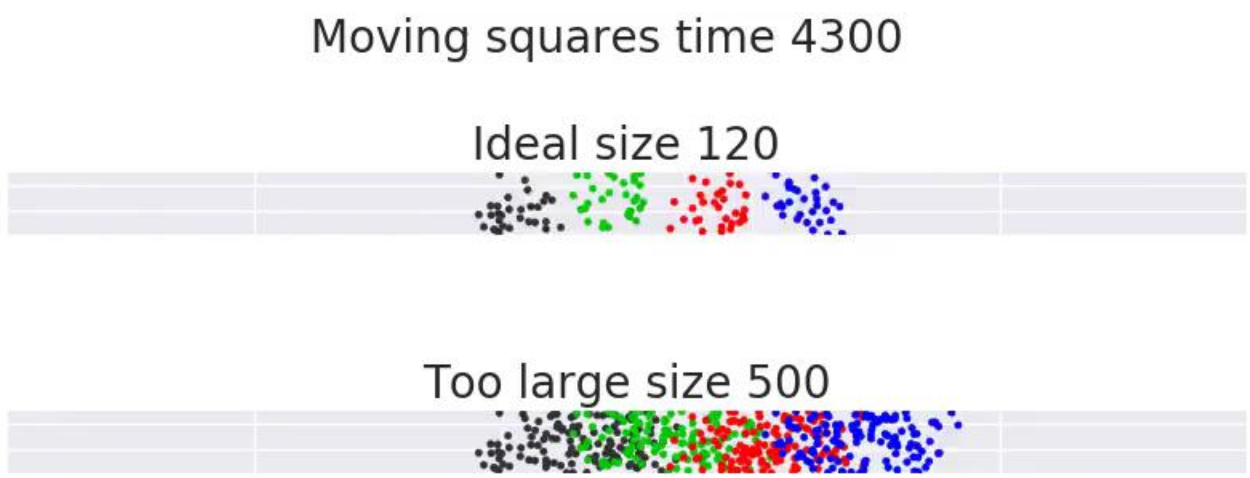


Moving squares dataset



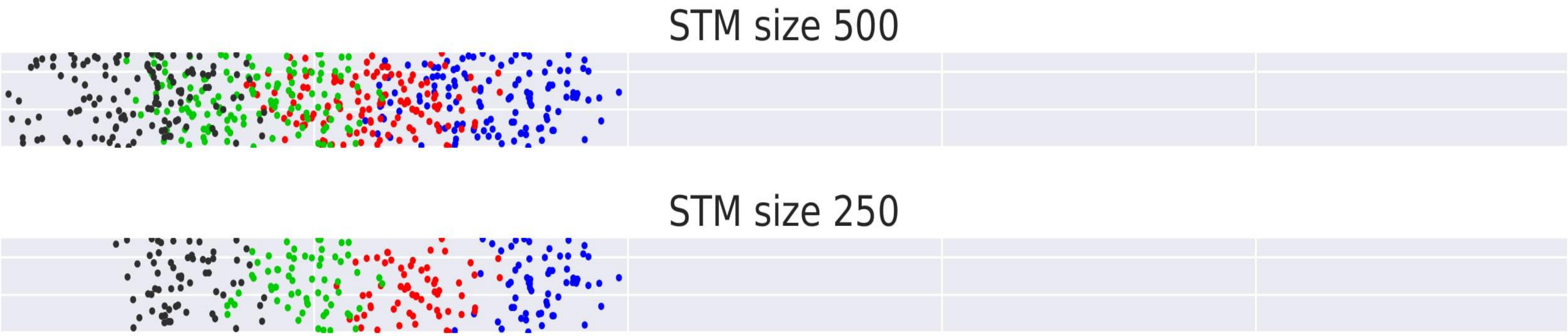
STM size adaptation

STM size adaptation

Error

27.12 %

STM size adaptation



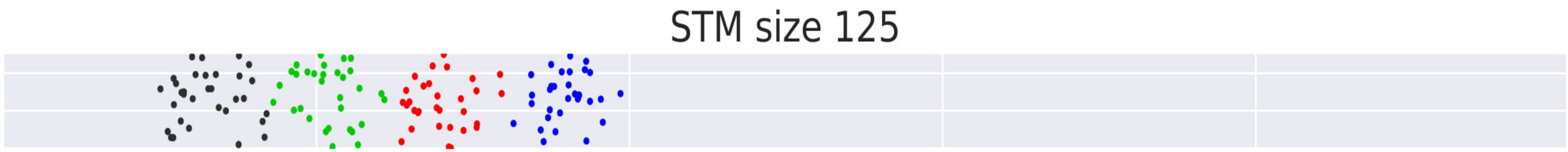
	Error
STM size 500	27.12 %
STM size 250	13.12 %

STM size adaptation

Error

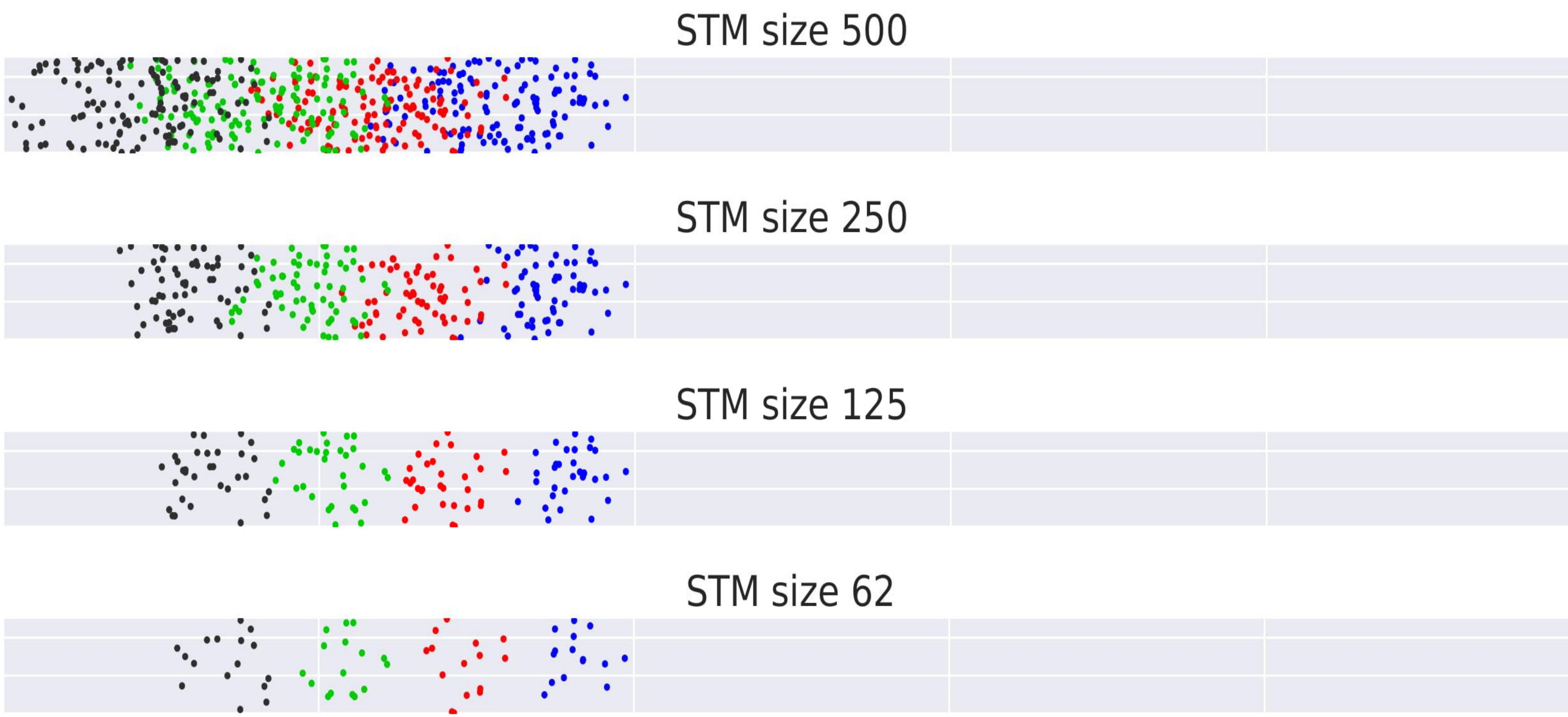
27.12 %

13.12 %



7.12 %

STM size adaptation



STM size	Error
500	27.12 %
250	13.12 %
125	7.12 %
62	0.0 %

STM size adaptation

Error

27.12 %

13.12 %

7.12 %

0.0 %

Distance-based cleaning

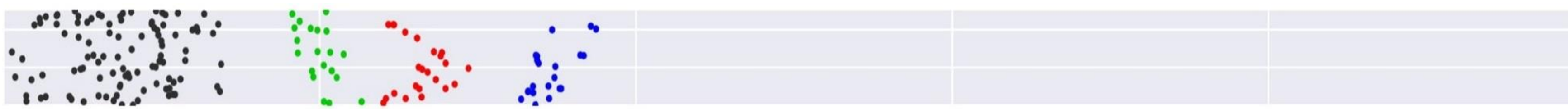
Distance-based cleaning

STM size 62

Dropped out data

cleaning

STM-consistent data



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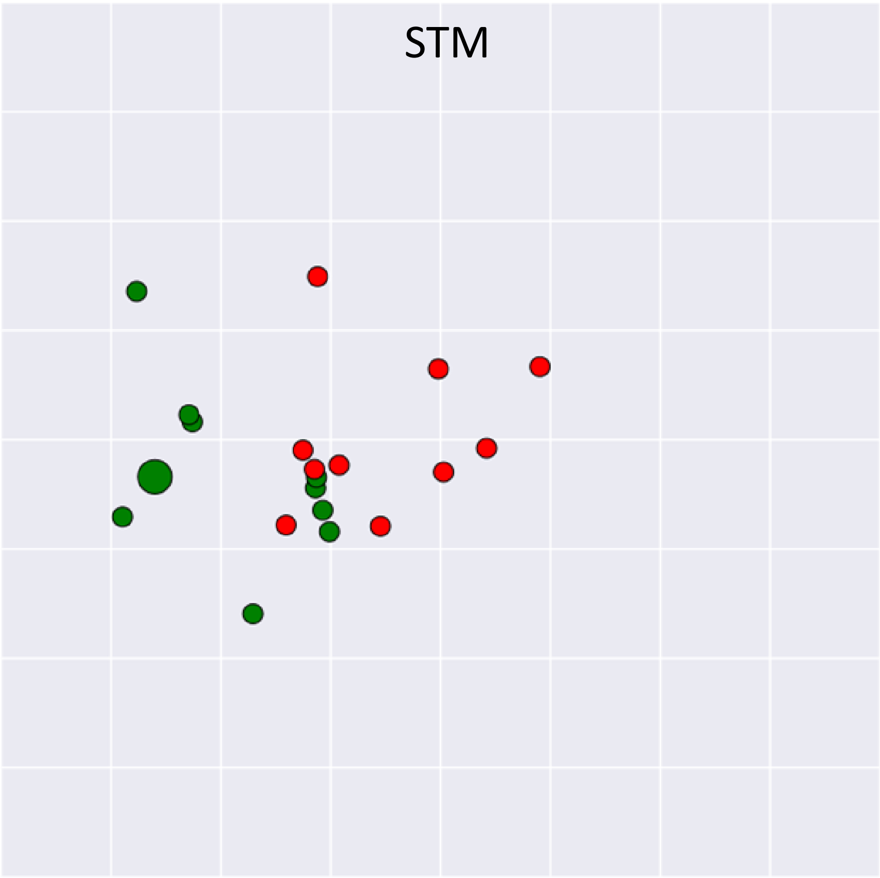

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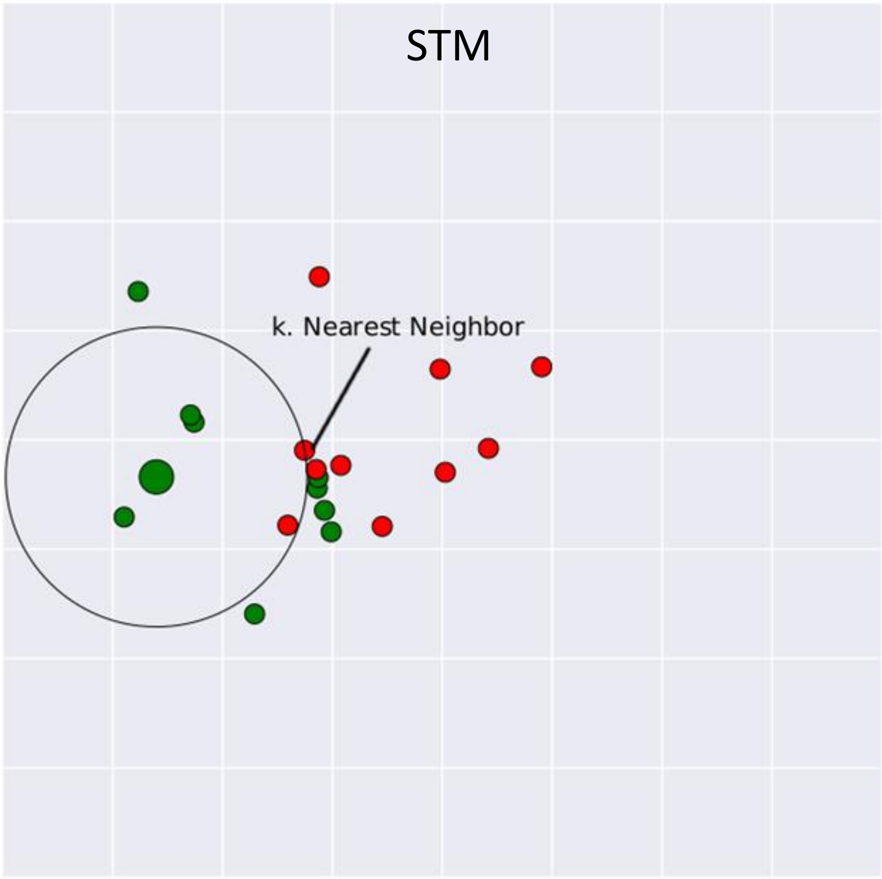

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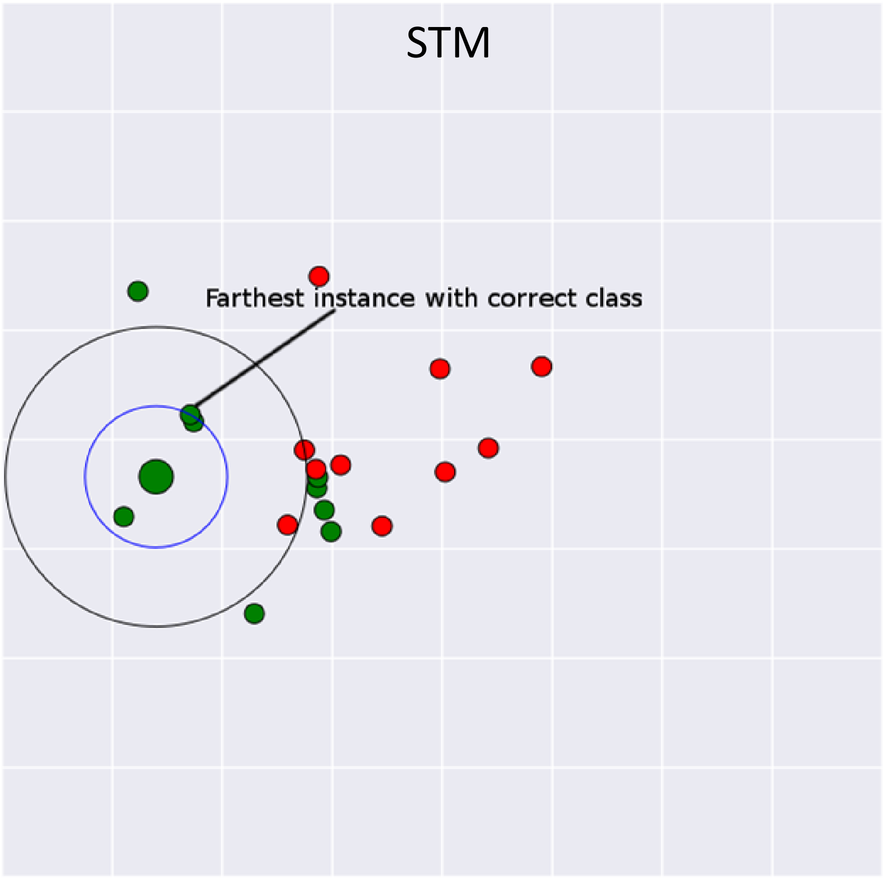

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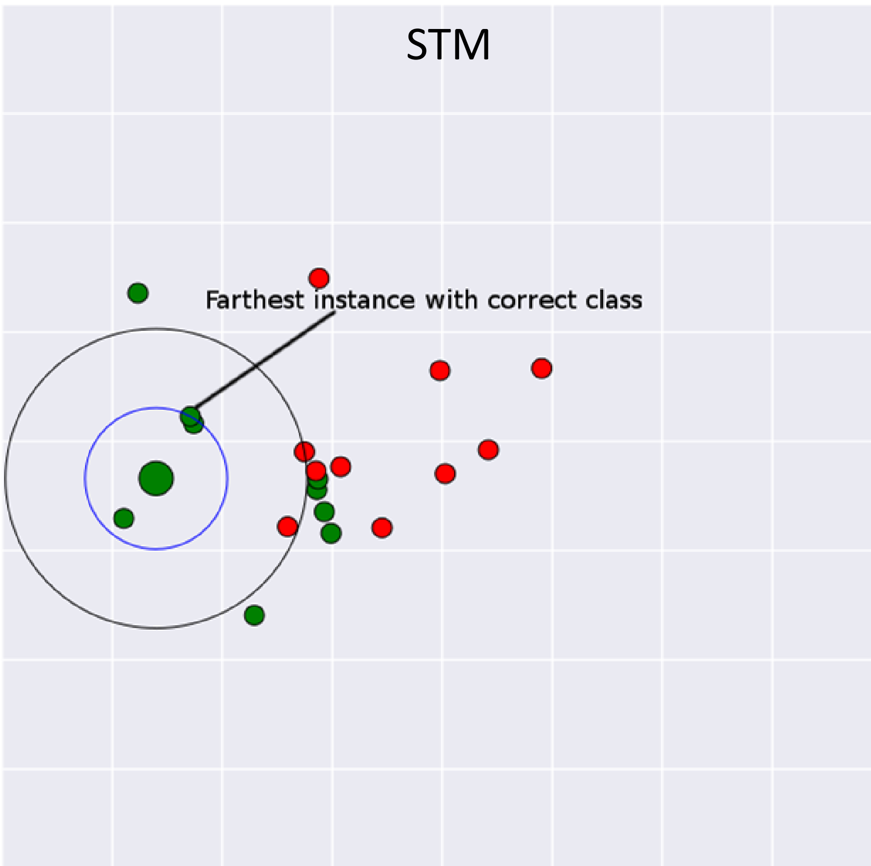

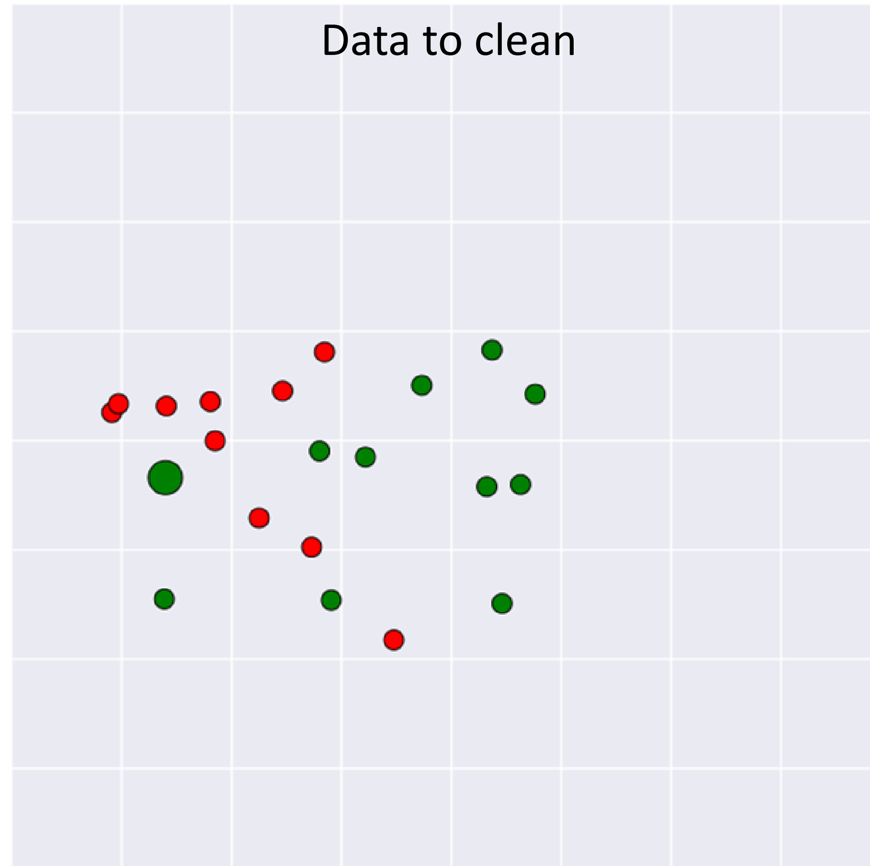

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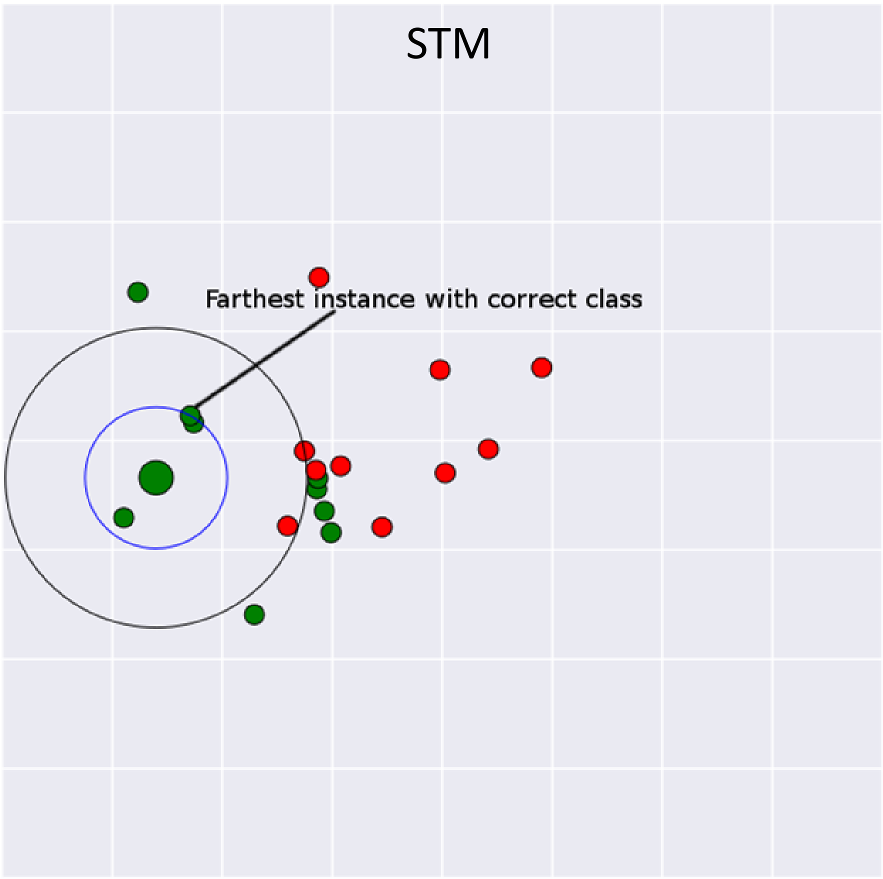

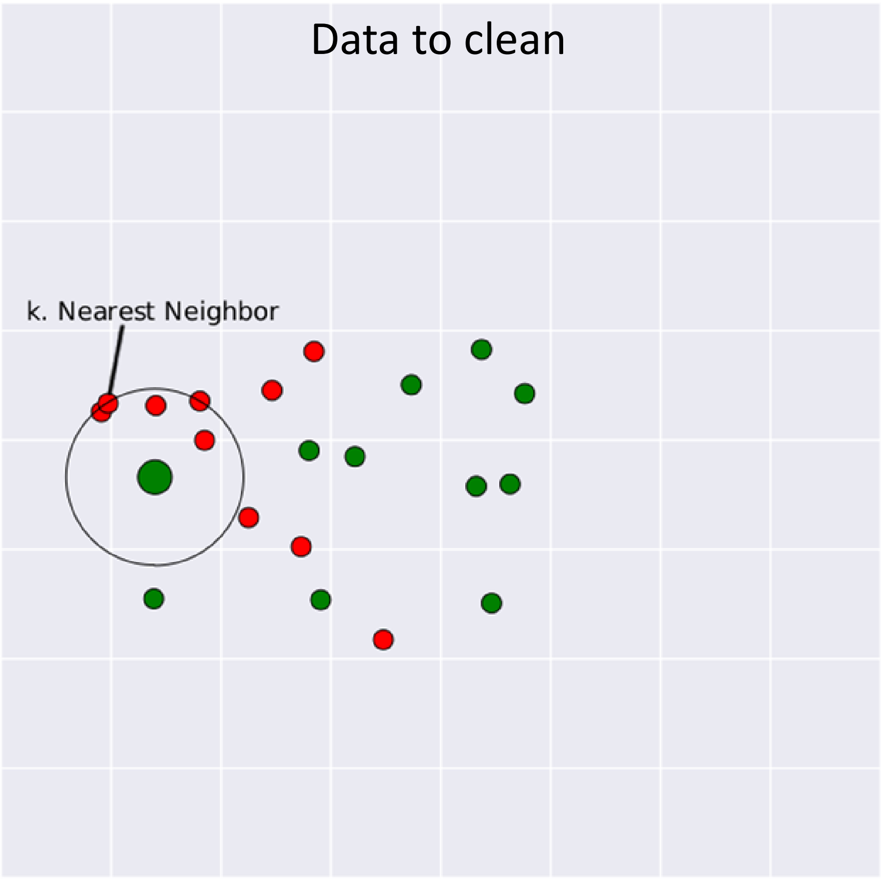

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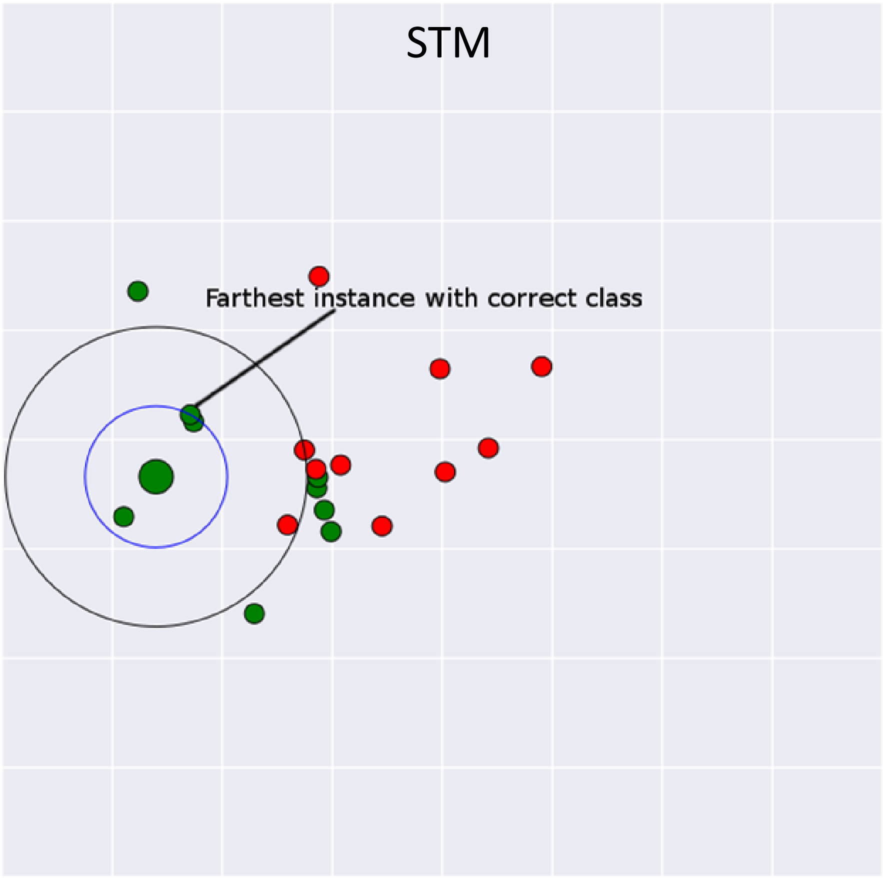
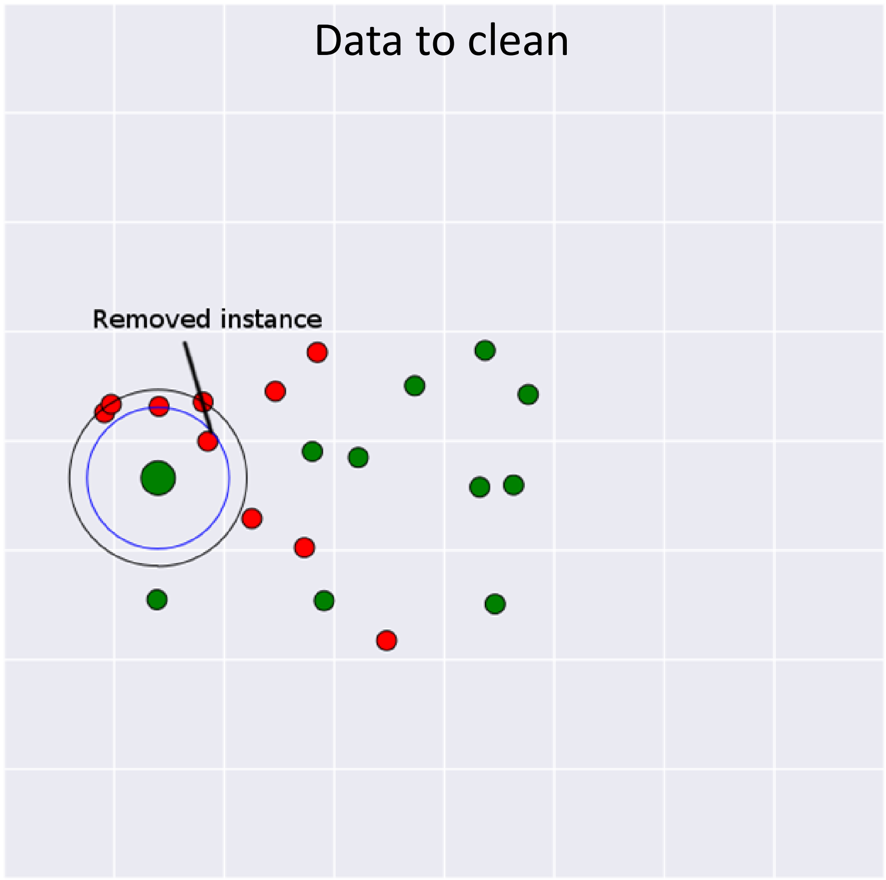
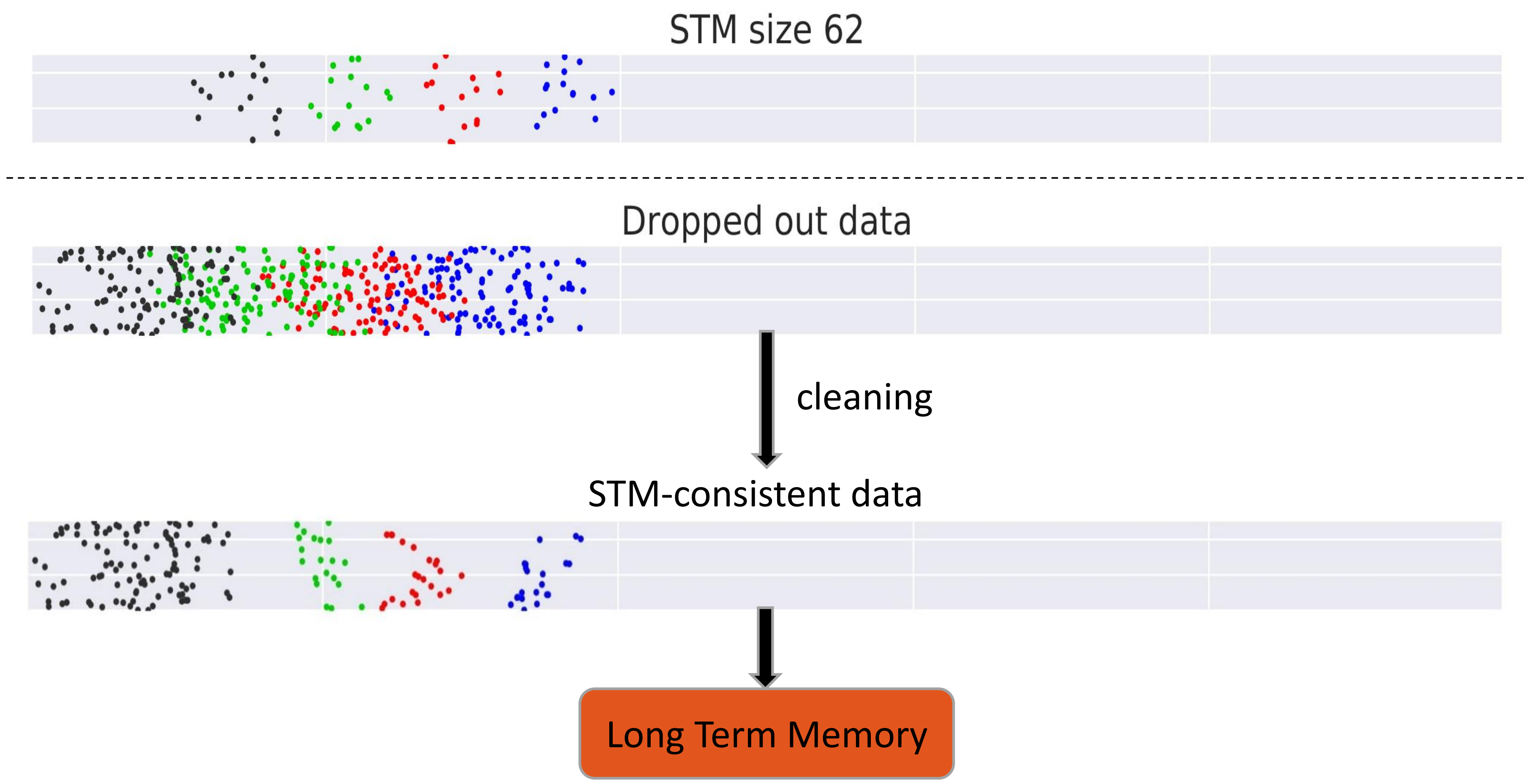




Adaptive compression



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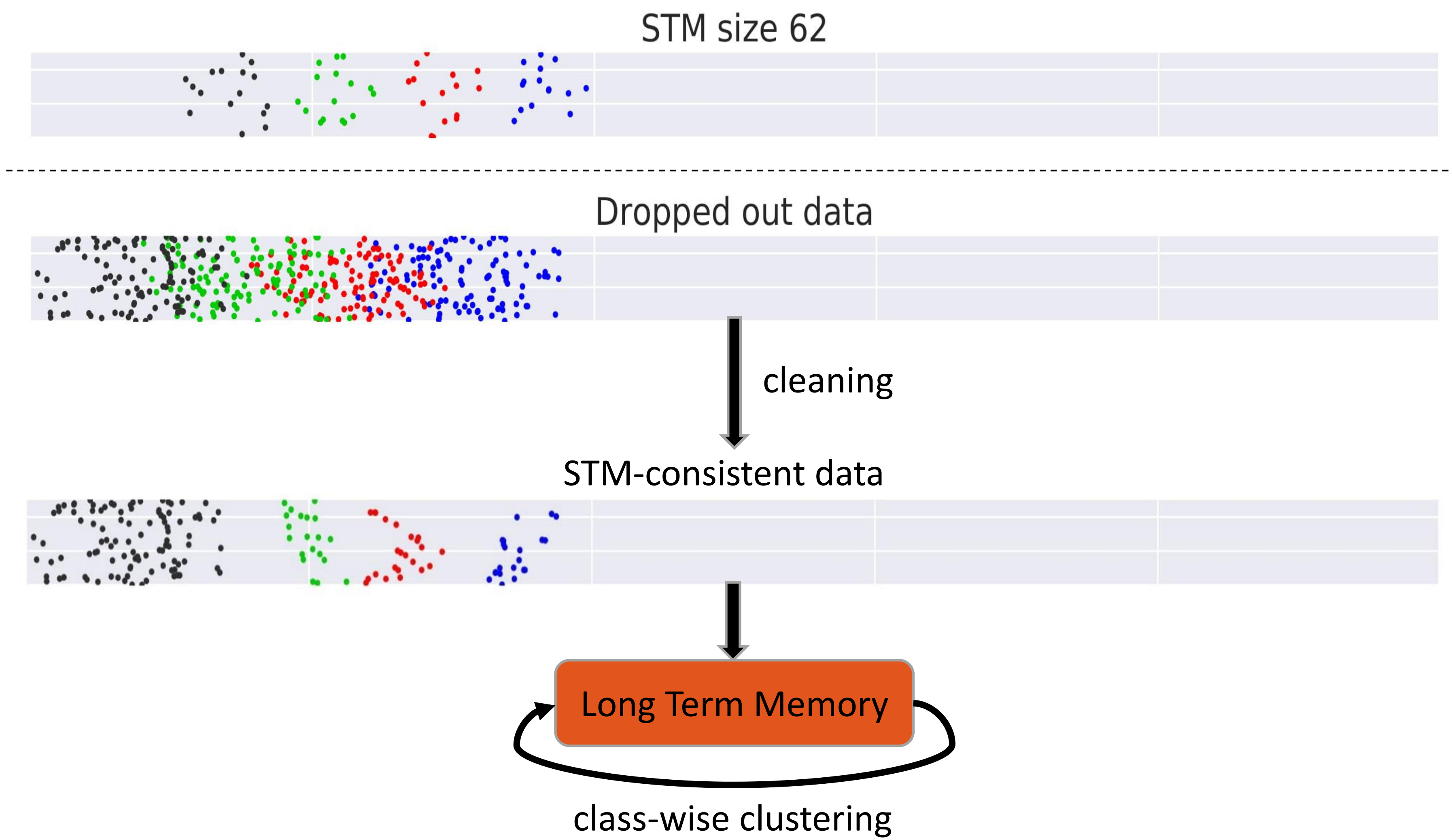
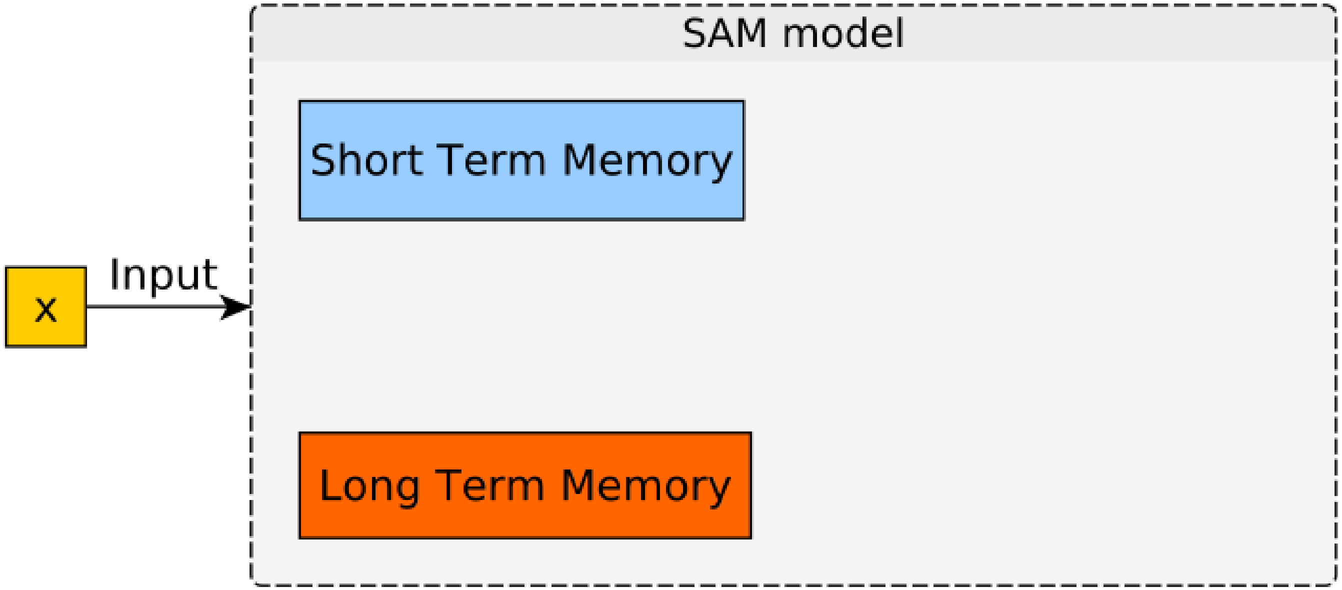


Prediction



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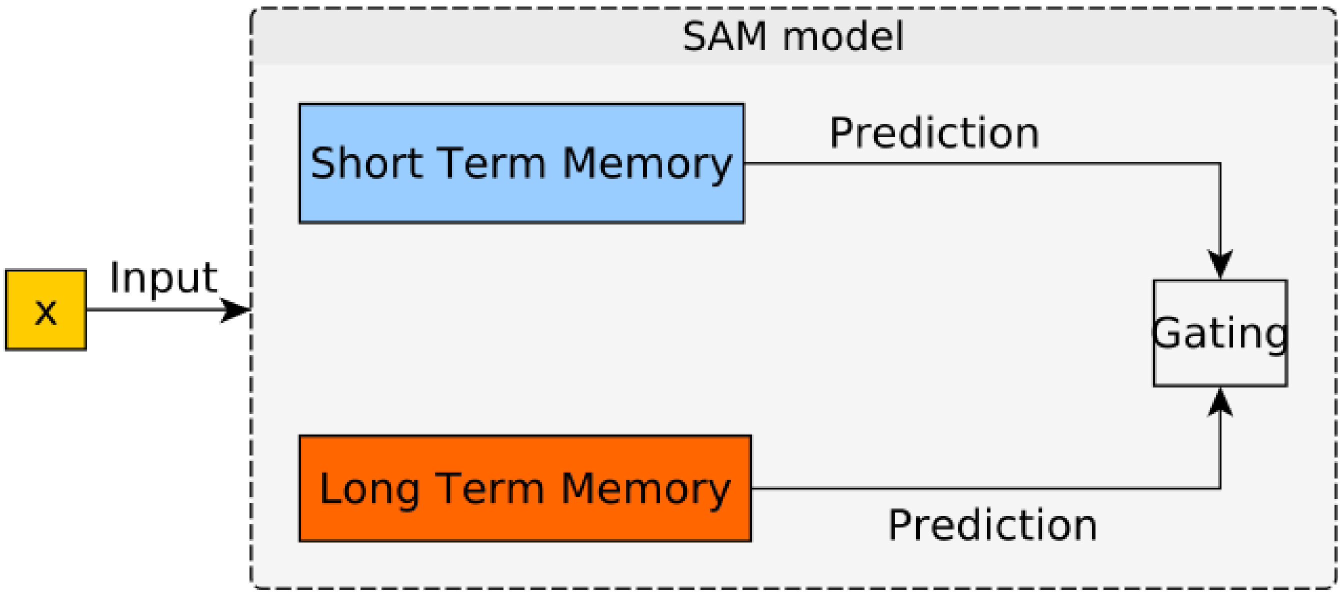
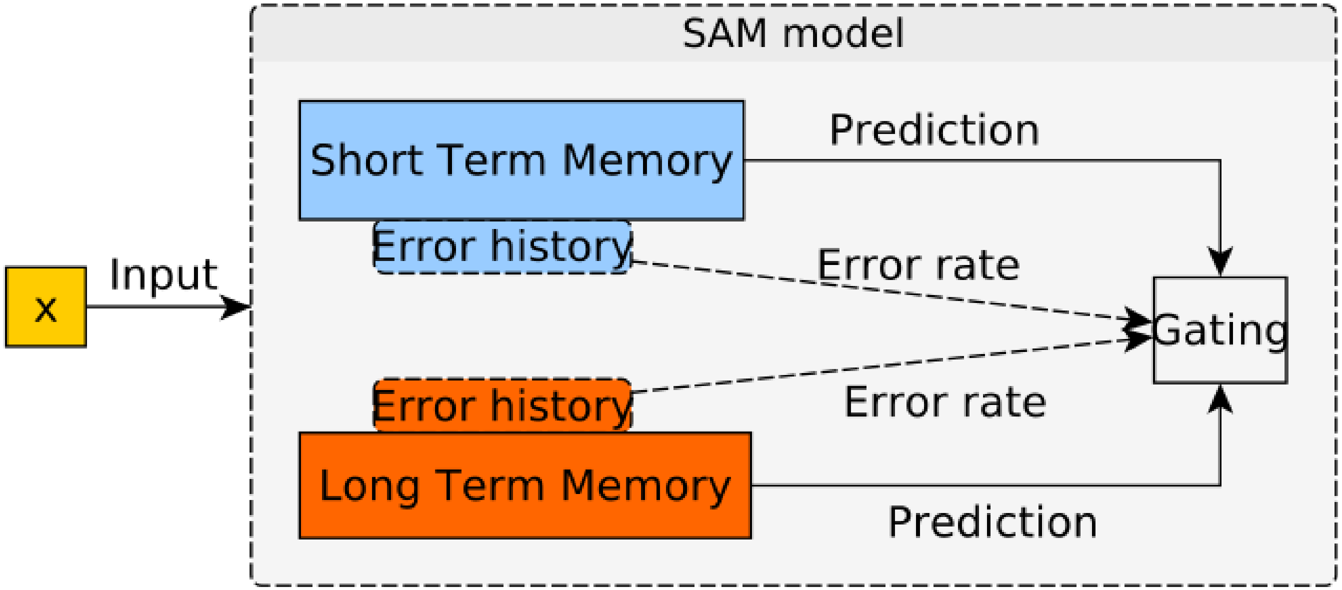
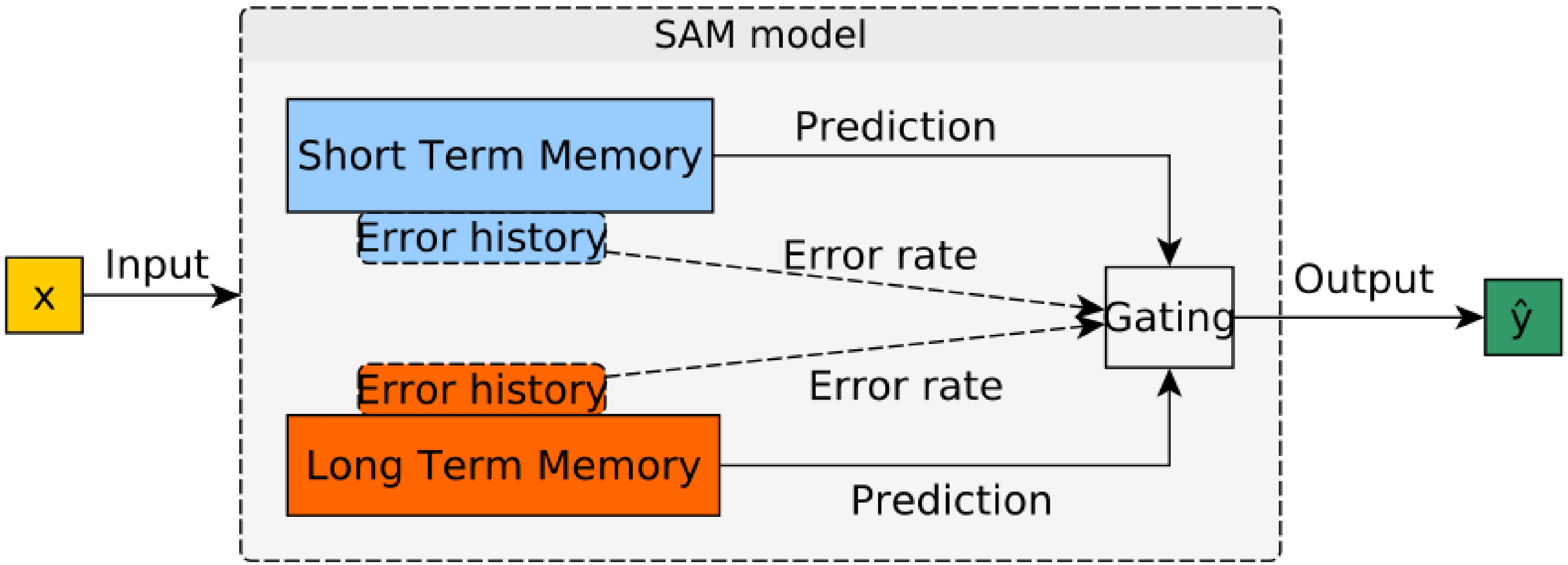

SAM model
Short Term Memory
Prediction
x
Input
Gating
Long Term Memory
Prediction

Prediction


x
Input
SAM model
Short Term Memory
Prediction
Error history
Error rate
Gating
Error history
Error rate
Long Term Memory
Prediction

Prediction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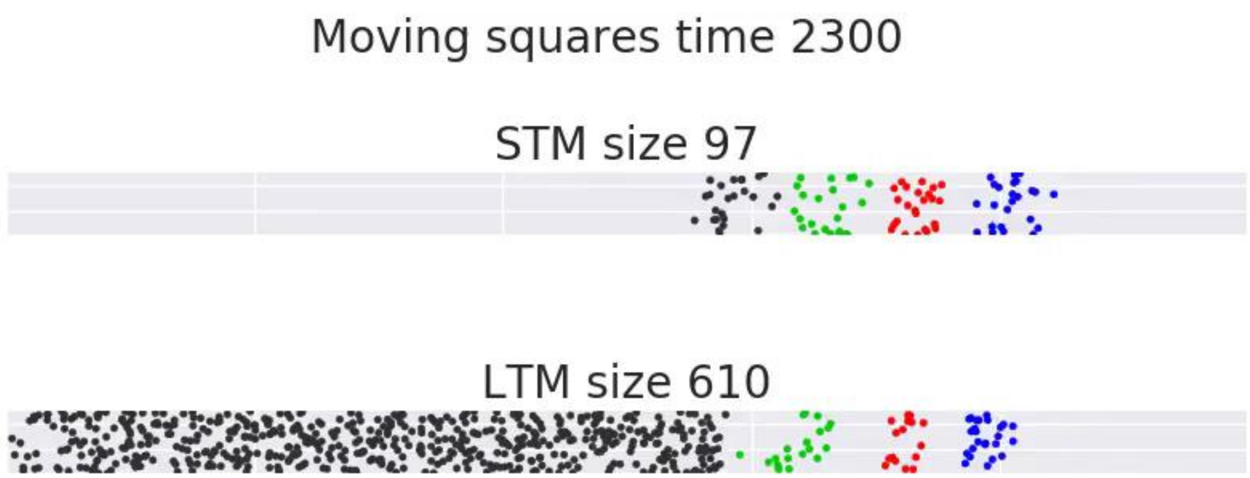
Moving squares by SAM



Results: Error rates / ranks

Dataset	LVGB	kNN_S	PAW	DACC	L++.NSE	**SAM**
SEA Concepts	**11.69**	13.83	13.39	15.68	14.48	12.50
Rotating Hyperplane	**12.53**	16.00	16.16	18.20	15.58	13.31
Moving RBF	44.84	20.36	24.04	54.34	44.50	**15.30**
Interchanging RBF	6.11	45.92	8.56	**1.40**	27.52	5.70
Moving Squares	12.17	68.87	61.01	**1.17**	65.90	2.30
Transient Chessb.	17.95	7.36	14.44	43.21	**1.98**	6.25
Mixed Drift	26.29	31.00	26.75	61.06	40.37	**13.33**
Artificial ∅	18.80	29.05	23.48	27.87	30.05	**9.81**
Artificial ∅ Rank	2.86	4.29	3.57	4.57	4.00	**1.71**
Weather	21.89	**21.53**	23.11	26.78	22.88	21.74
Electricity	**16.78**	28.61	26.13	16.87	27.24	17.52
Cover Type	9.07	**4.21**	6.76	10.05	15.00	4.8
Poker Hand	**13.65**	17.08	27.94	20.97	22.14	18.45
Outdoor	39.97	13.98	16.30	35.65	57.80	**11.25**
Rialto	39.64	22.74	24.96	28.93	40.36	**18.58**
Real world ∅	23.50	18.03	20.87	23.21	30.90	**15.40**
Real word ∅ Rank	3.17	2.33	4.00	4.17	5.33	**2.00**
Overall ∅	20.97	23.96	22.27	25.72	30.44	**12.39**
Overall ∅ Rank	3.00	3.38	3.77	4.38	4.62	**1.85**

SAM achieves best results

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SAM is robust

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Rotating Hyperplane	**12.53**	16.00	16.16	18.20	15.58	13.31
Moving RBF	44.84	20.36	24.04	54.34	44.50	**15.30**
Interchanging RBF	6.11	45.92	8.56	**1.40**	27.52	5.70
Moving Squares	12.17	68.87	61.01	**1.17**	65.90	2.30
Transient Chessb.	17.95	7.36	14.44	43.21	**1.98**	6.25
Mixed Drift	26.29	31.00	26.75	61.06	40.37	**13.33**
Artificial ∅	18.80	29.05	23.48	27.87	30.05	**9.81**
Artificial ∅ Rank	2.86	4.29	3.57	4.57	4.00	**1.71**
Weather	21.89	**21.53**	23.11	26.78	22.88	21.74
Electricity	**16.78**	28.61	26.13	16.87	27.24	17.52
Cover Type	9.07	**4.21**	6.76	10.05	15.00	4.8
Poker Hand	**13.65**	17.08	27.94	20.97	22.14	18.45
Outdoor	39.97	13.98	16.30	35.65	57.80	**11.25**
Rialto	39.64	22.74	24.96	28.93	40.36	**18.58**
Real world ∅	23.50	18.03	20.87	23.21	30.90	**15.40**
Real word ∅ Rank	3.17	2.33	4.00	4.17	5.33	**2.00**
Overall ∅	20.97	23.96	22.27	25.72	30.44	**12.39**
Overall ∅ Rank	3.00	3.38	3.77	4.38	4.62	**1.85**

Reasons for robustness

- Adaptation guided through error minimization
  - Dynamic size of the STM
  - Model selection for prediction
  - Reduction of hyperparameters
- Consistency between STM and LTM
- LTM acts as safety net

Q & A


Doubts
yes
Confused
Maybe
Accept
Unclear
No
Perplexed
Unsure
Reject