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Addressing Temporal Dependence, Concept Drifts, and Forgetting in Data Streams

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1) Challenges of Learning from Data Streams

	SML	CL	TSA
1) Managing changes in data distribution (**concept drifts**).	X	X	
2) Learning continuously from single data points or mini-batches.	X		
3) Remembering all the acquired knowledge (avoid **catastrophic forgetting**).		X	
4) Handling **temporal dependence**.			X

- **SML**: Streaming Machine Learning
- **CL**: Continual Learning
- **TSA**: Time Series Analytics

Ziffer, G. et al. **Towards Time-Evolving Analytics: Online Learning for Time-dependent Evolving Data Streams.** Data Science (Preprint), 1–16

2) Research Goal

How do streaming models behave in the case of elaborated temporal dependence?

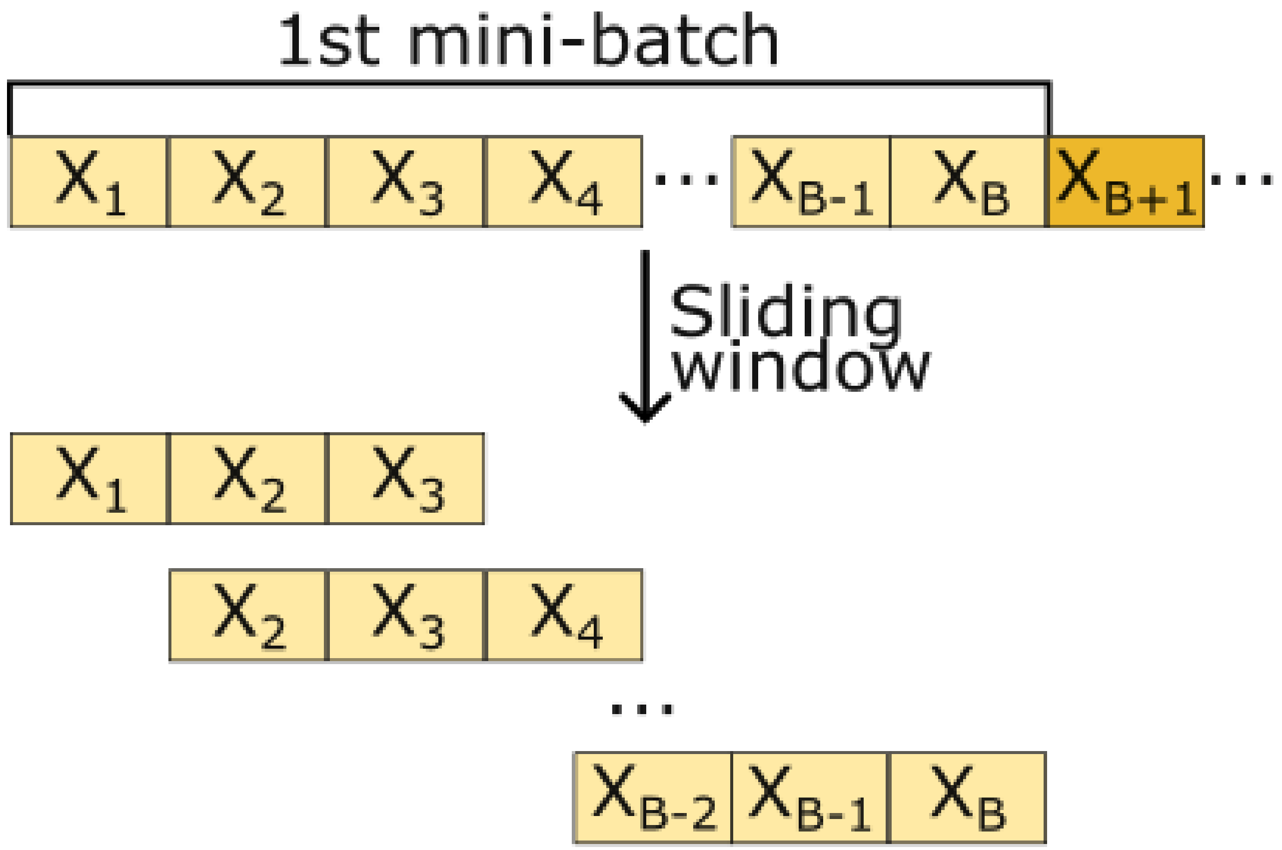
Comparison between:

- SML models
- SML models with **temporal augmentation**

$$X_t^{TA} = X_t \cup \{y_{t-1}, \dots, y_{t-k}\}$$

- Our previous solution **cPNN**

3a) cPNN: Taming Temporal Dependence when Learning Continuously



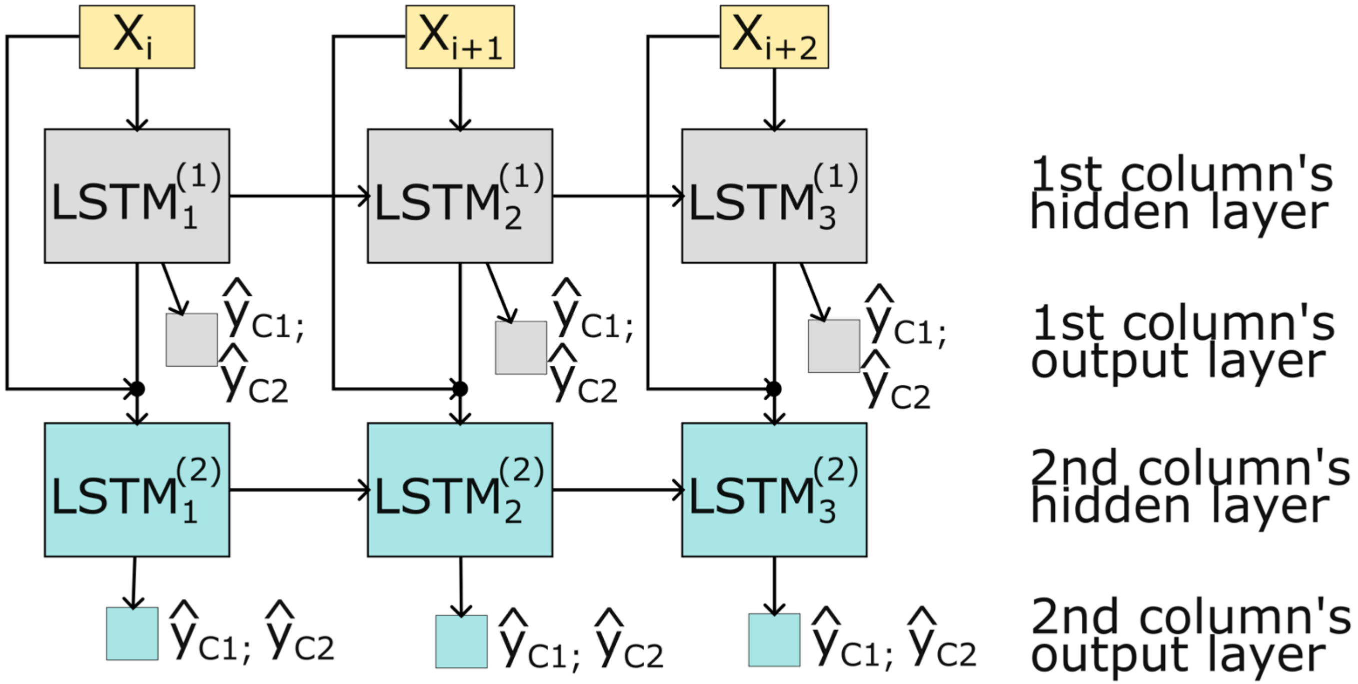
- Accumulate data points in **mini-batches.**
- Apply **windowing** on the mini-batch to build the **sequences.**
- Input the sequences to LSTM (**cLSTM**).

Giannini, F., Ziffer, G., & Della Valle, E. (2023). **cPNN: Continuous Progressive Neural Networks for Evolving Streaming Time Series**. In Pacific-Asia Conference on Knowledge Discovery and Data Mining (pp. 328-340).

Lemos Neto, Á. C., Coelho, R. A., & Castro, C. L. D. (2022). **An Incremental Learning Approach Using Long Short-term Memory Neural Networks**. *Journal of Control, Automation and Electrical Systems*, *33*(5), 1457-1465.

3b) cPNN: Addressing Concept Drifts and Forgetting

- **Transfer learning** to adapt to new concepts quickly.
- **Freezing the weights** to avoid catastrophic forgetting.



https://github.com/federicogiannini13/cPNN_extended

Rusu, A.A et al. **Progressive Neural Networks**. CoRR abs/1606.04671 (2016)

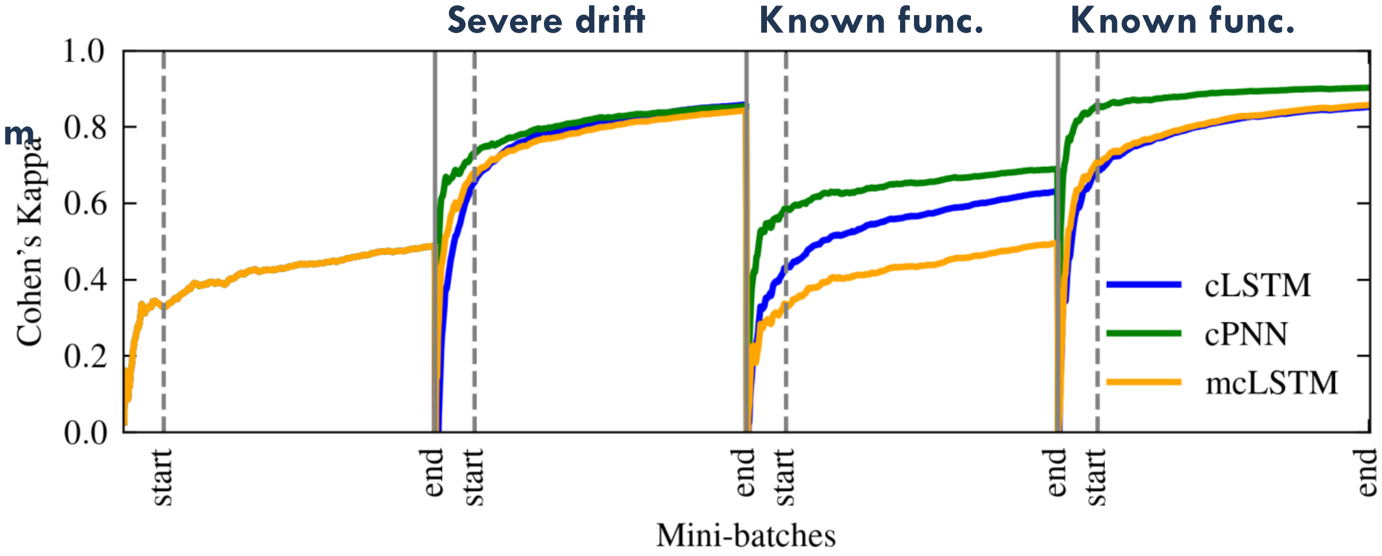
Cossu, A. et al. **Continual Learning with Gated Incremental Memories for Sequential Data Processing**. In: IJCNN. pp. 1–8. IEEE (2020)

4a) Experiments: Setting

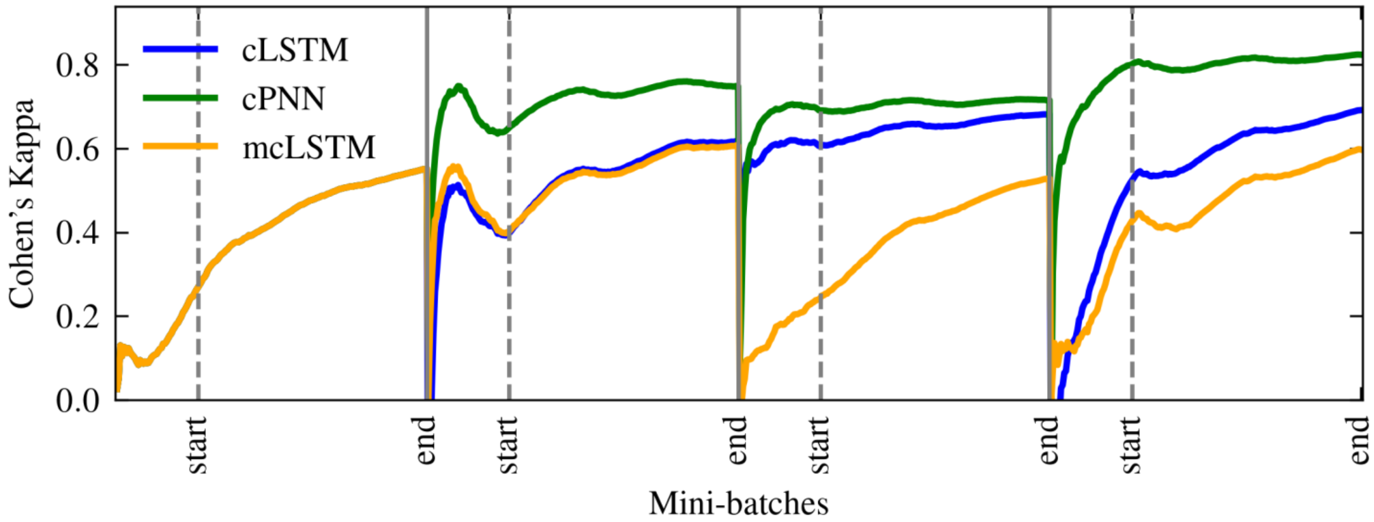
- Both **synthetic** and **real** data streams.
- Three **abrupt concept drifts**.
- Some drifts are **severe** (they change more than 50% labels).
- The remaining drifts are called **mild**.
- Some boundary functions are reproposed.

4b) Experiments: Ablation Study

Synthetic data stream



Weather data stream



Ablated versions:

- cLSTM: no drift management
- mcLSTM: no transfer learning

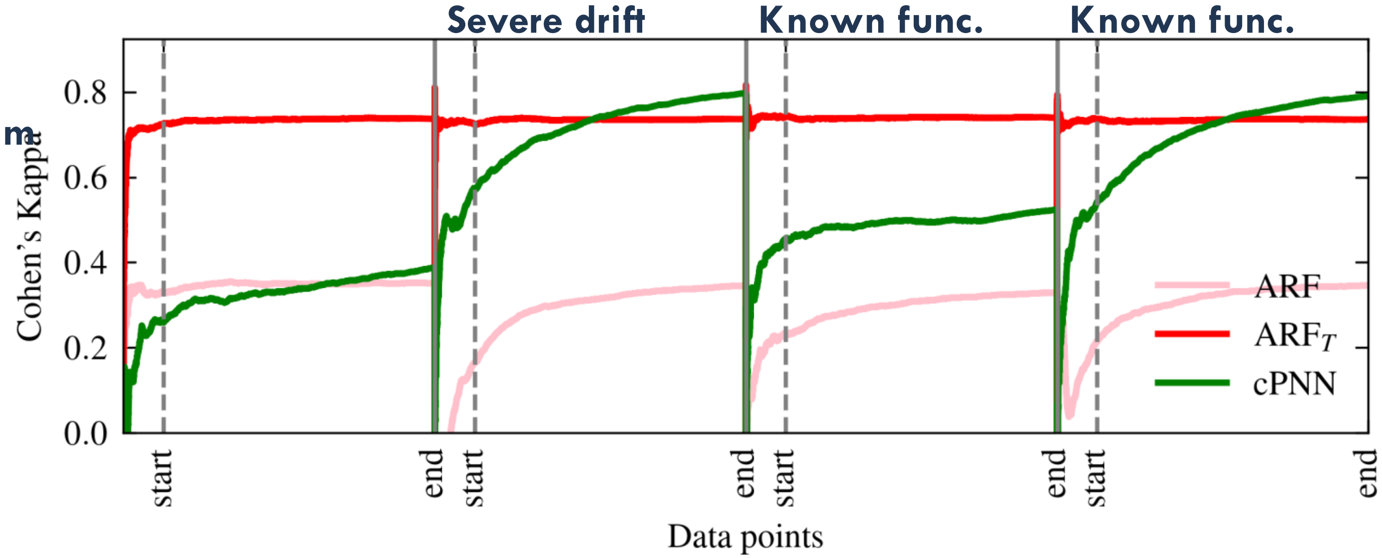
cPNN adapts quicker.

When the drift is severe cLSTM struggles.

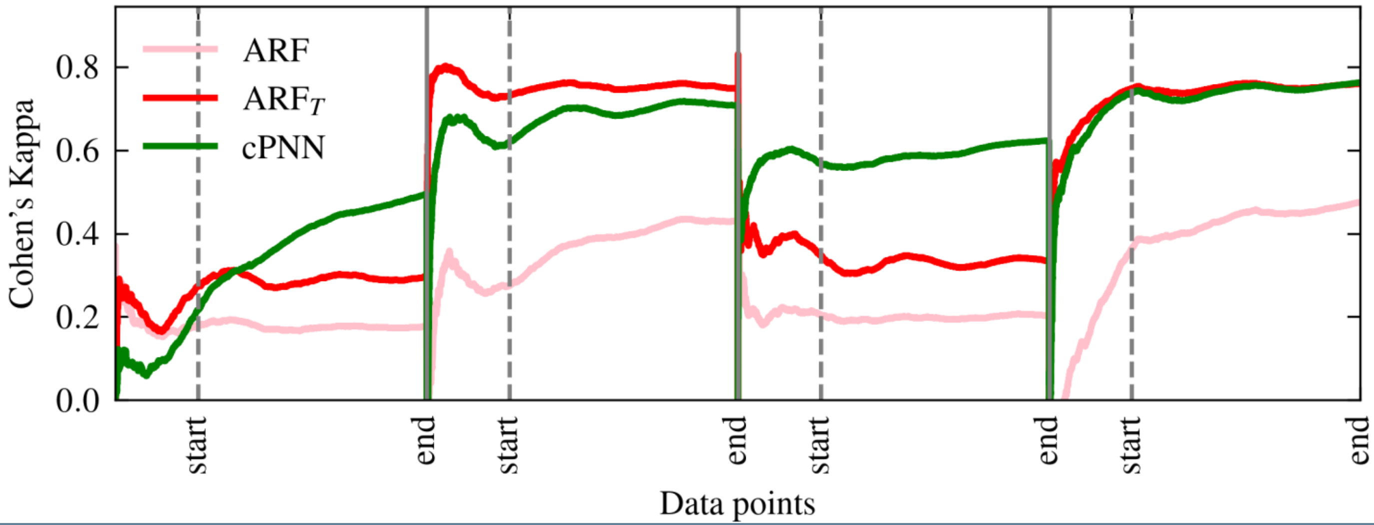
mcLSTM is quite always the worst.

4c) Experiments: Comparison with SML Models

Synthetic data stream



Weather data stream



ARF model cannot learn.

Temporal augmentation has a bias on the previous label.

cPNN can learn properly all the functions.

5) Conclusions and Future Works

Conclusions

- cPNN pioneers a solution to deal jointly with all the challenges of data streams.
- cPNN adapts quickly to concept drifts thanks to transfer learning.
- SML models cannot learn with temporal dependence.
- Temporal augmentation is biased on the previous label.

Future works

- Quantisation to reduce the memory footprint.
- Study of forgetting.
- Federated Learning.

Thank you!

Any questions?

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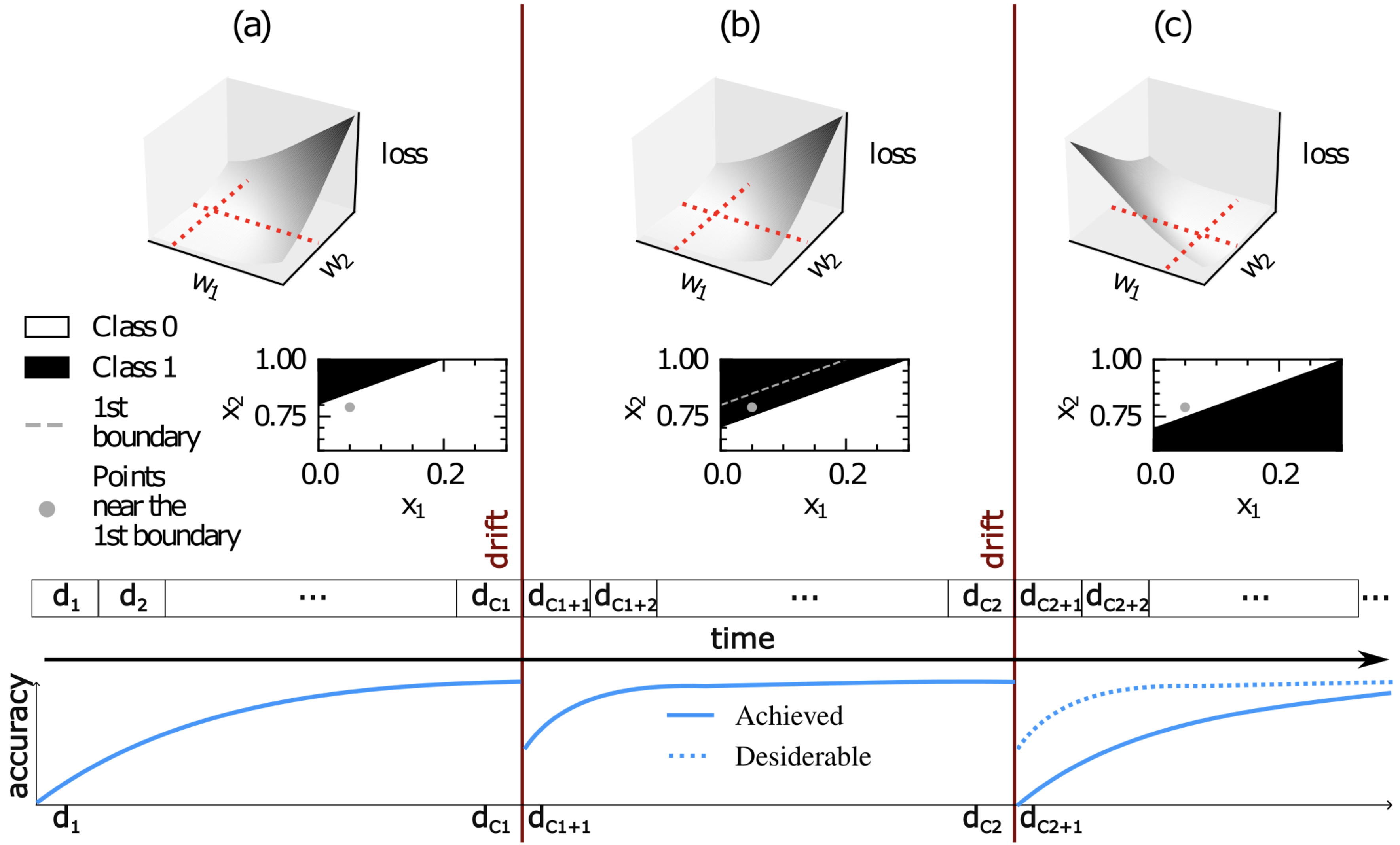
https://github.com/federicogiannini13/cPNN_extended

Extra Slides

Outline

1. Challenges of learning in dynamic environments
2. Research goal
3. cPNN: Continuous Progressive Neural Networks
4. Experiments
5. Conclusions and Future Works

Problems of SGD for Evolving Data Streams



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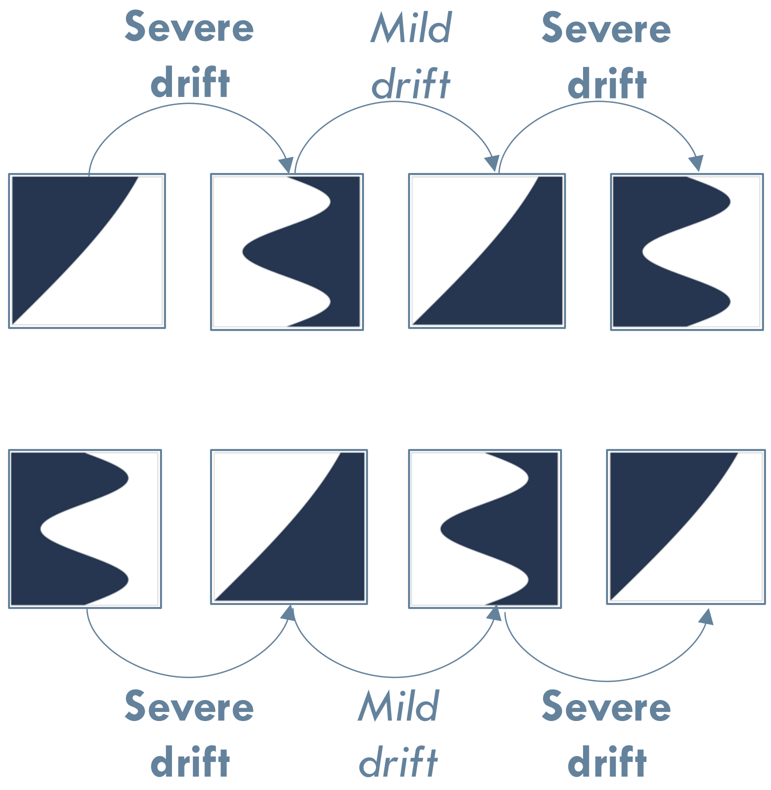
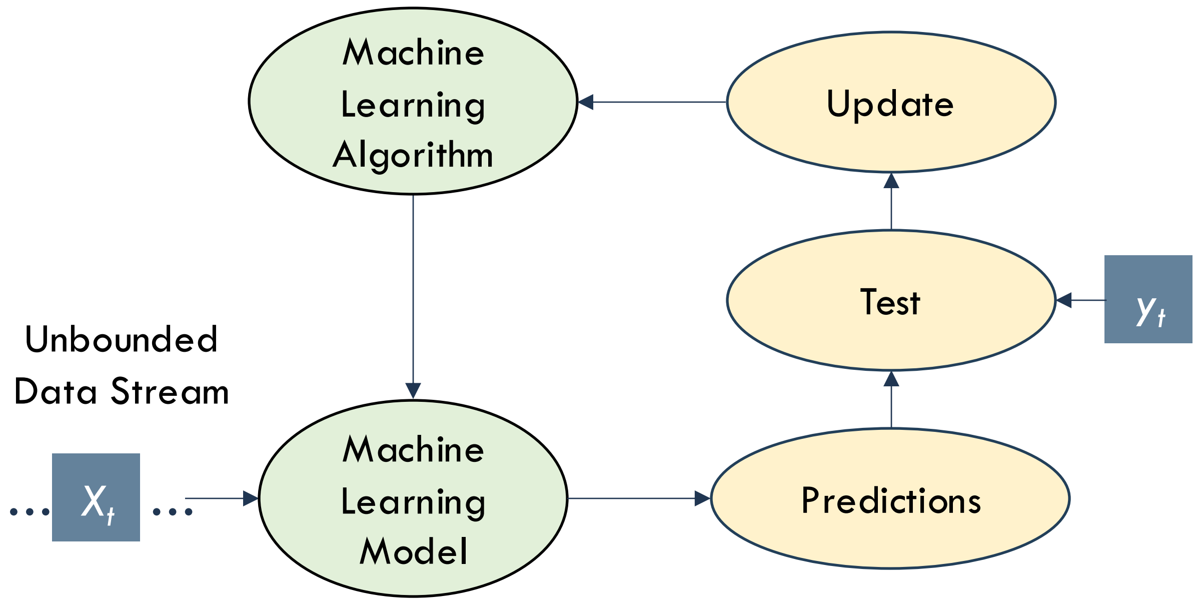
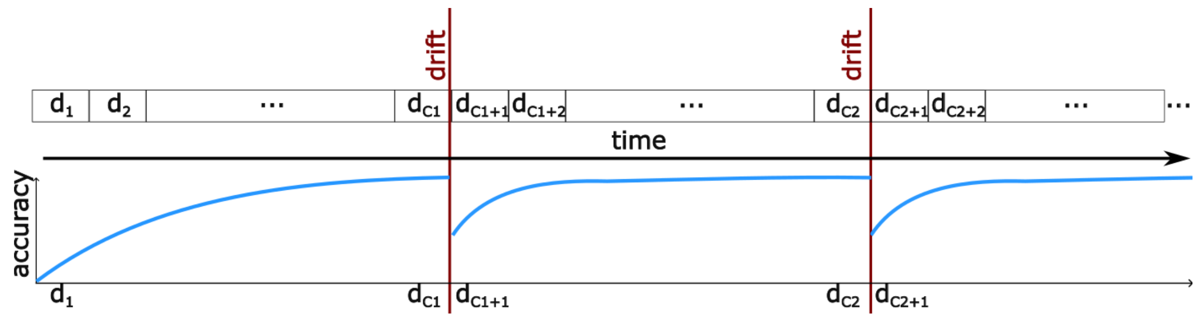
Experimental Setting

- Both synthetic and real weather data streams.
- Two boundary functions alternated (four classification functions).
- Three **abrupt concept drifts.**
- Some drifts are **severe** (more than 50% label changes), and others are **mild.**
- Two studies:
    - cPNN ablation study
    - Comparison between cPNN, SML models (ARF and HAT) and SML models with temporal augmentation.



Evaluation





- Cohen's Kappa Score computed continuously in a prequential evaluation way.
- Score reset after concept drifts.
- Ablation study accumulates data points in mini-batches also for inference.