Streaming Machine Learning
Taming Data Streams

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Me

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- **5 years** of experience in **research** in the **Streaming Machine Learning** field with **evolving** data **streams**, **concept drifts**, and **class imbalance;**
- Focus on applying **Streaming Machine Learning** techniques in **constrained** environments at the network's **edge.**

https://alessiobernardo.github.io/
https://motusml.com/

It is a Streaming World …

It is a Streaming World …

Off-shore oil operations

Smart Cities

Power turbine

Social networks

Generate data streams!

E. Della Valle, S. Ceri, F. van Harmelen, D. Fensel **It's a Streaming World! Reasoning upon Rapidly Changing Information**. IEEE Intelligent Systems 2009

… looking for reactive answers …

When a sensor on a drill indicates that it is about to get stuck, how long can I keep drilling?

Where am I likely going to run into a traffic jam during my commute tonight?

Which electrical turbine has sensor readings like any turbine that had a critical failure?

Who is driving the discussion about the top 10 emerging topics ?

Require continuous processing and reactive answer

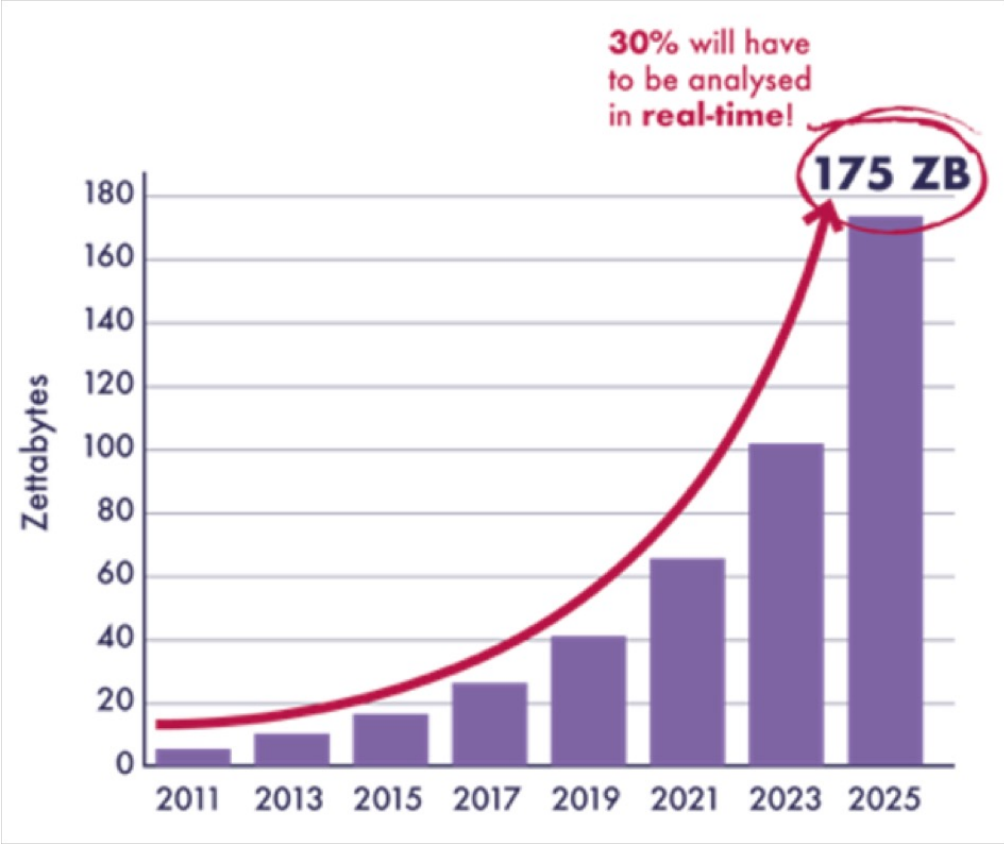
E. Della Valle, S. Ceri, F. van Harmelen, D. Fensel **It's a Streaming World! Reasoning upon Rapidly Changing Information**. IEEE Intelligent Systems 2009

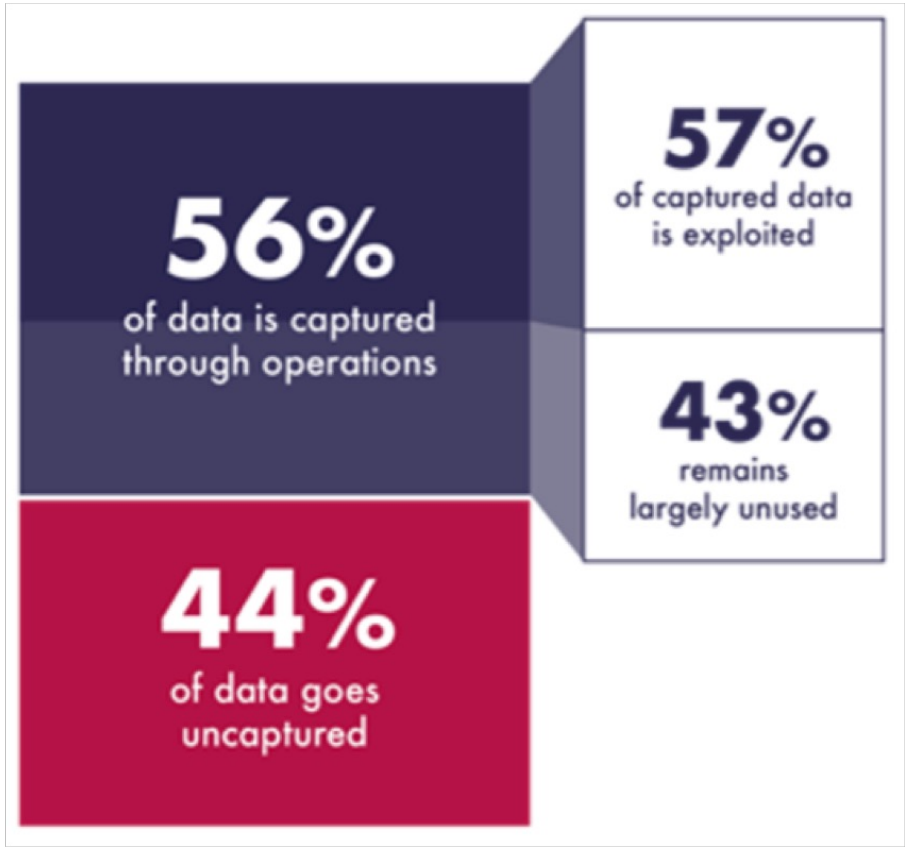
… but with conflicting requirements …

A system able to answer those queries must be able to

- handle volume
- handle velocity
- handle variety
- cope with incompleteness
- cope with noise
- provide reactive answers
- support fine-grained access
- integrate complex domain models
- offer high-level languages

… and 68% of data are not used



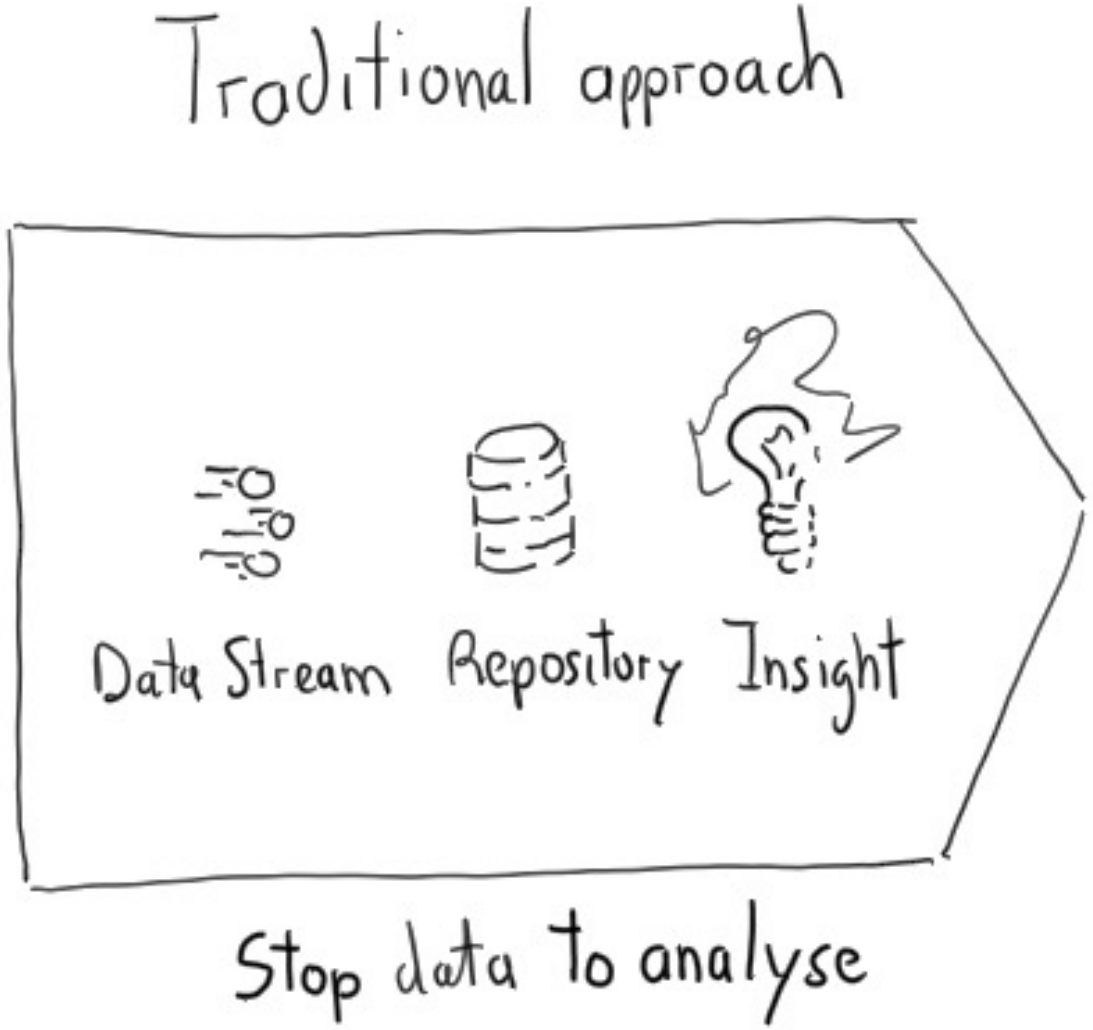


Src: Seagate

Internet minute in 2023

Src: eDiscovery Today & LTMG

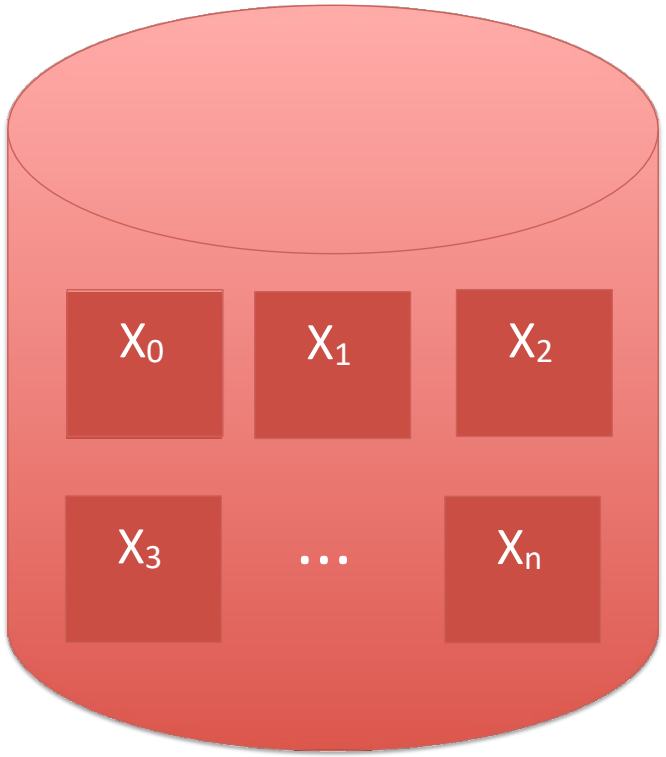
Traditional approach vs …



Batch of data

Random access to data

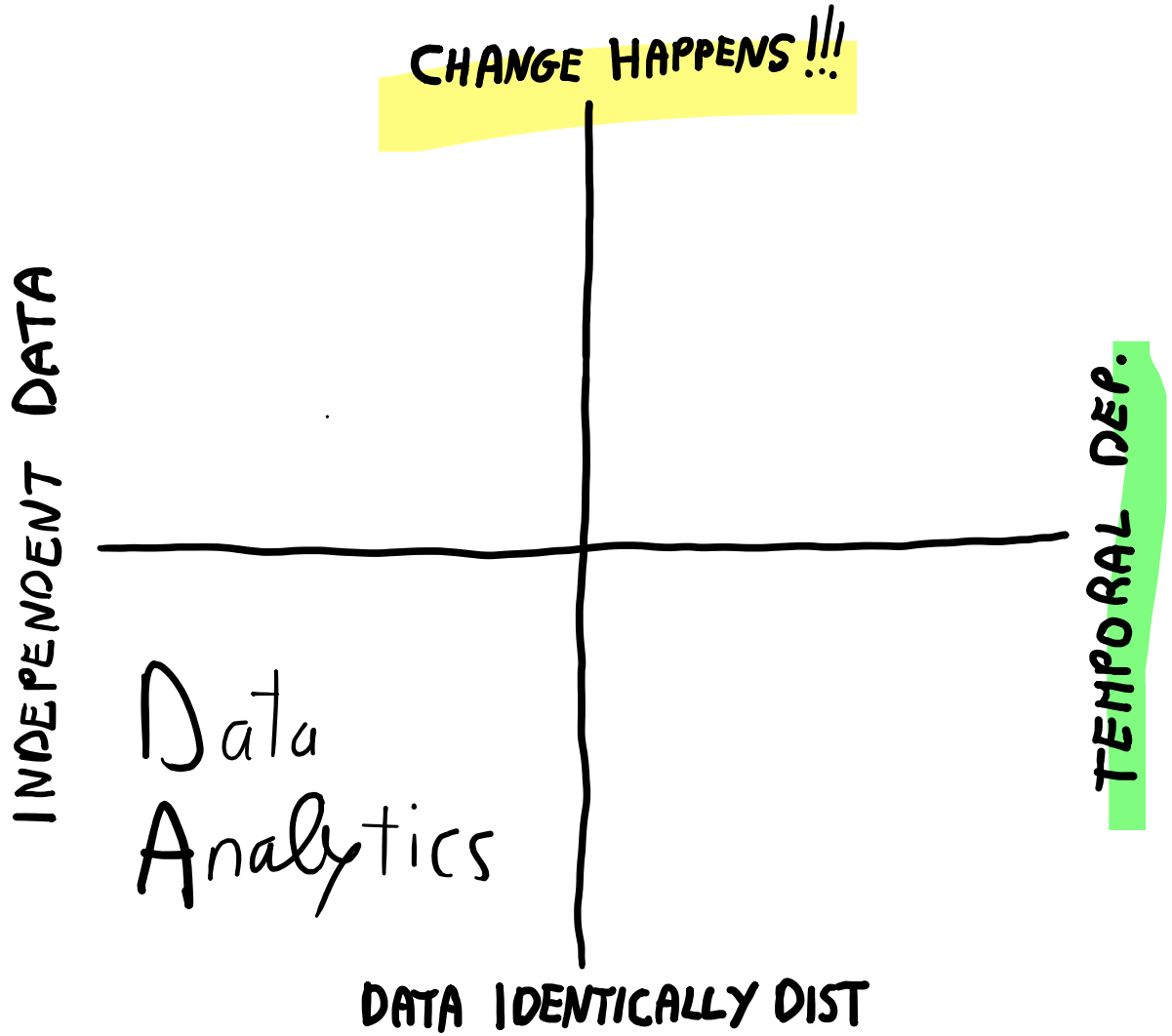
No restrictions on memory/time for training



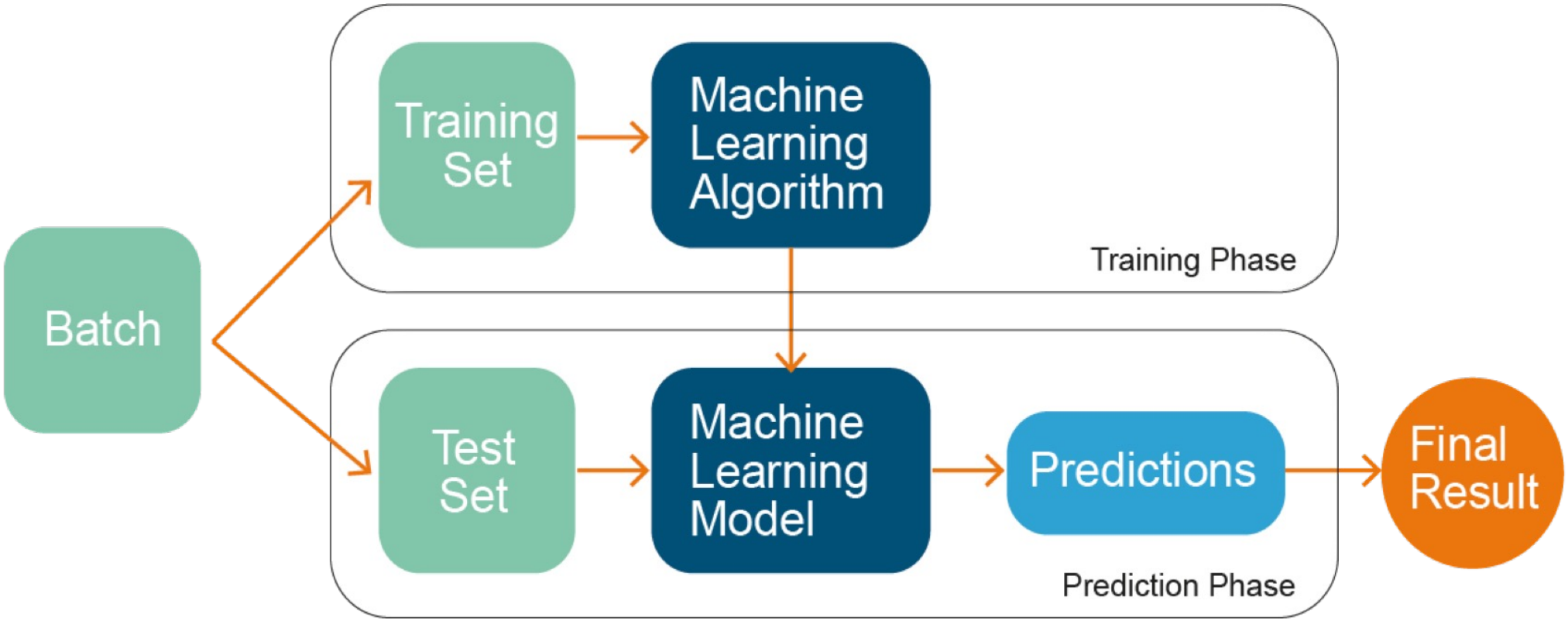
Well defined training phase

Access to all labelled data used for training

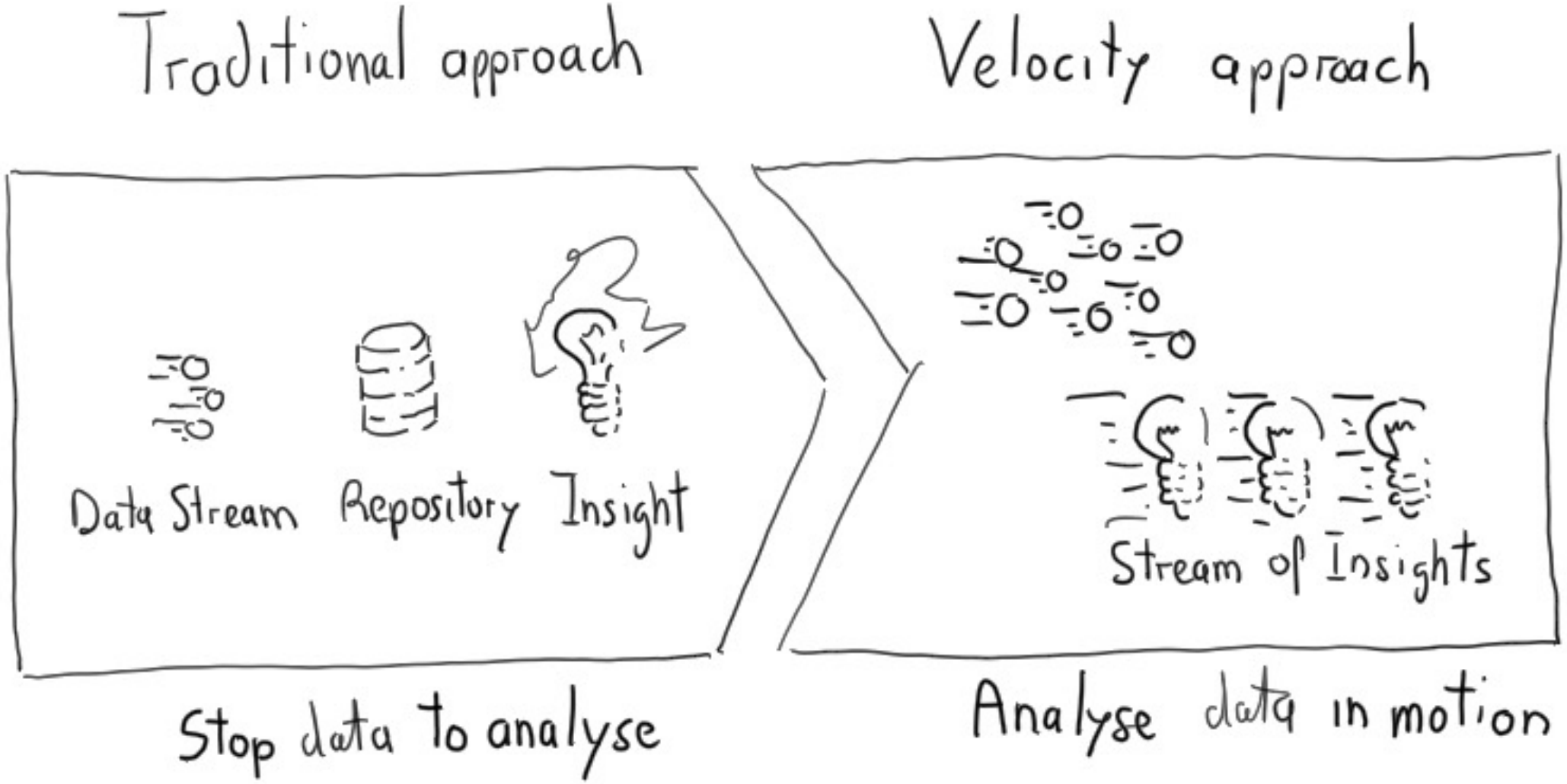
State-of-the-art



ML models


Batch
Training Set
Machine Learning Algorithm
Training Phase
Test Set
Machine Learning Model
Predictions
Final Result
Prediction Phase

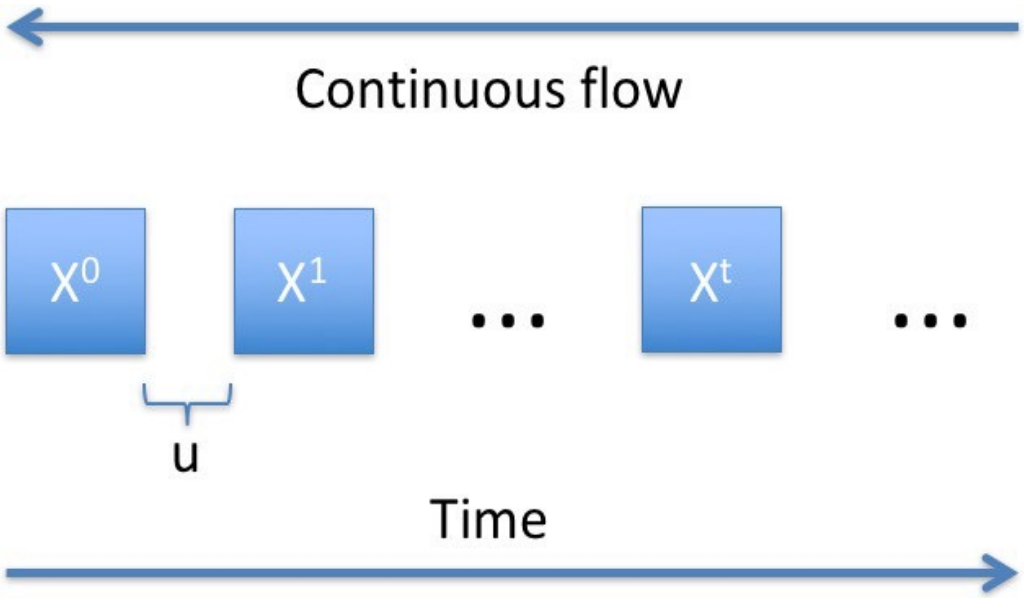
Traditional vs. Velocity-oriented approach



Data Stream

Data in a **continuous stream**, potentially in **real-time**, assuming **data** points are **independent**, **but** data stream can evolve over time (i.e., the data are **not identically distributed**)

Sequential access only

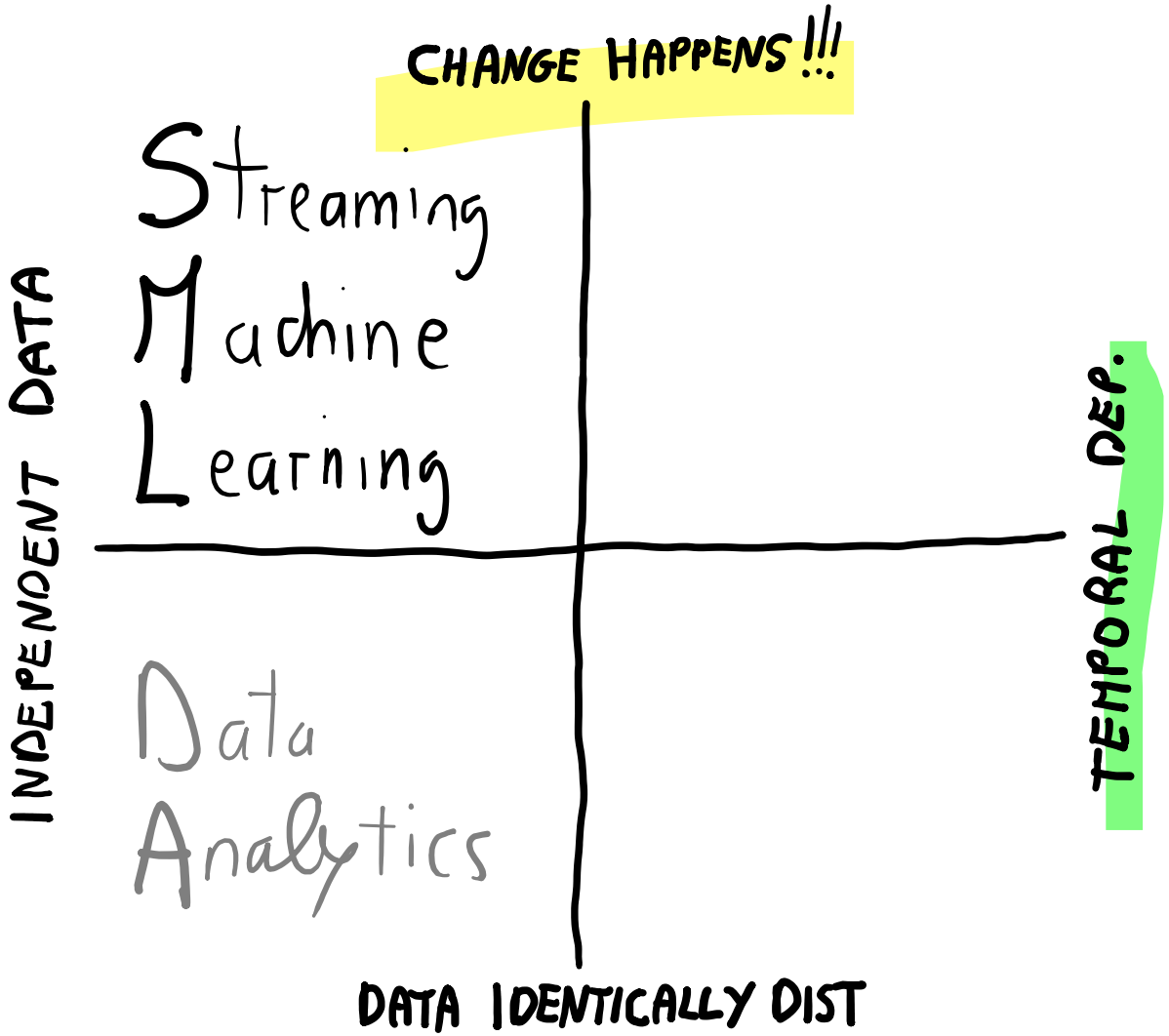


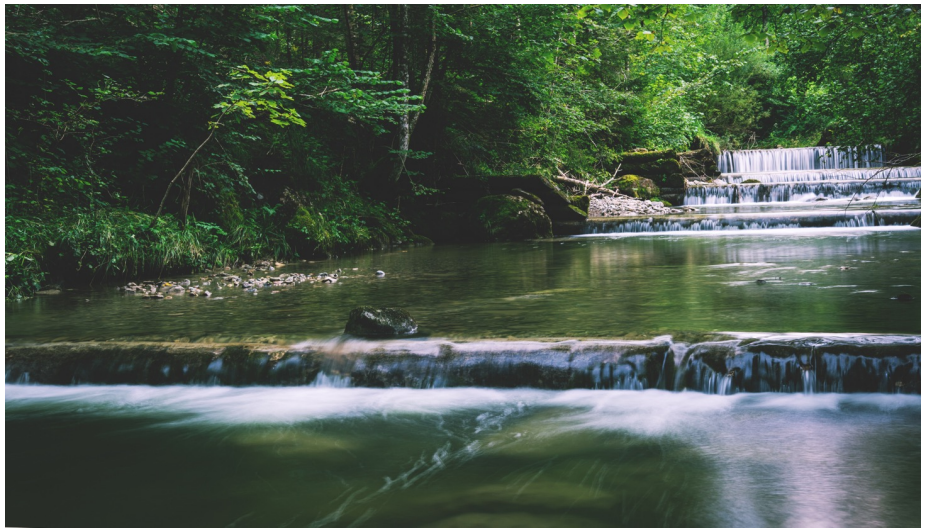
Evolving data

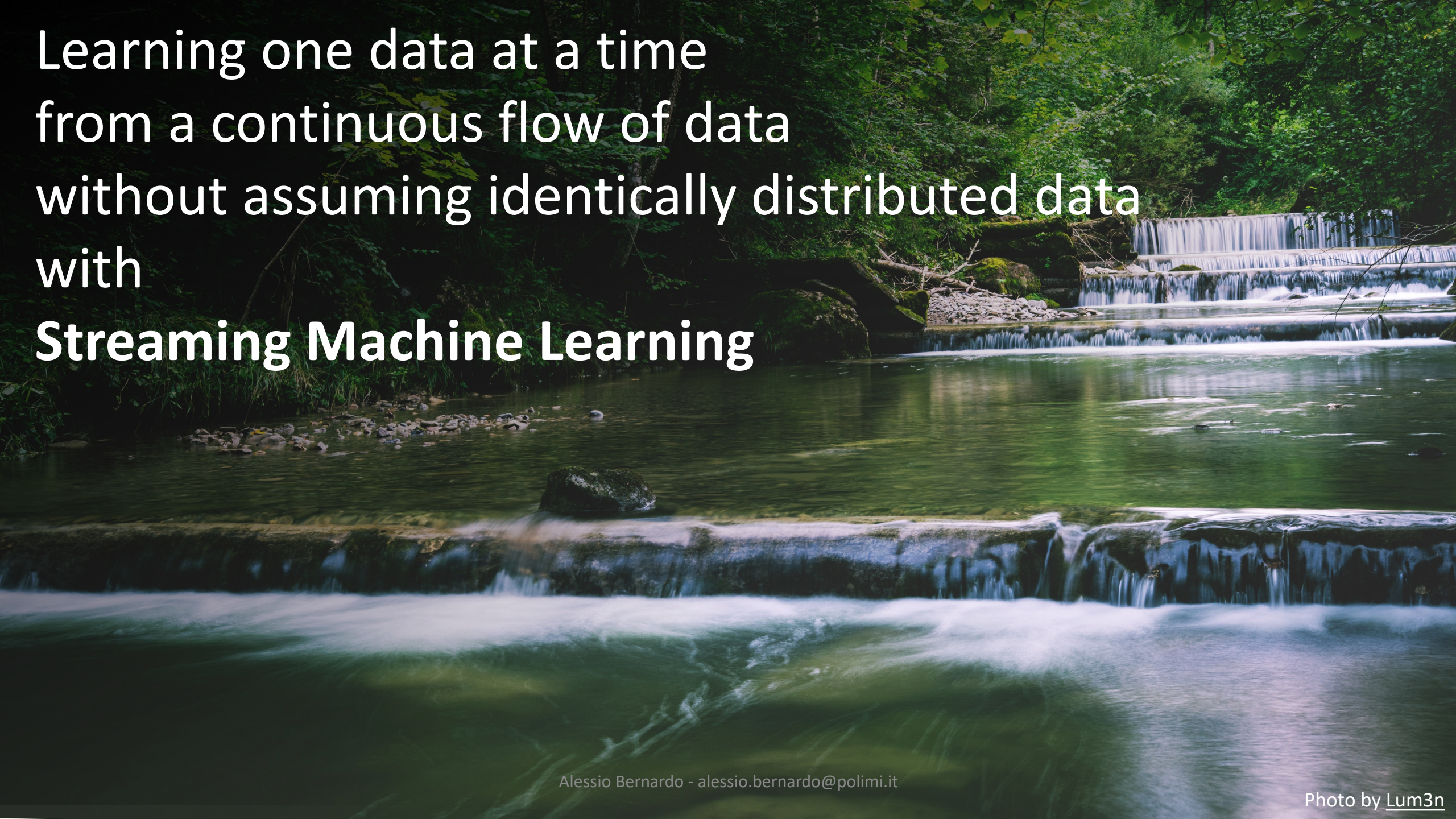
Strict time/memory requirements

Characteristics of data seen so far

State-of-the-art







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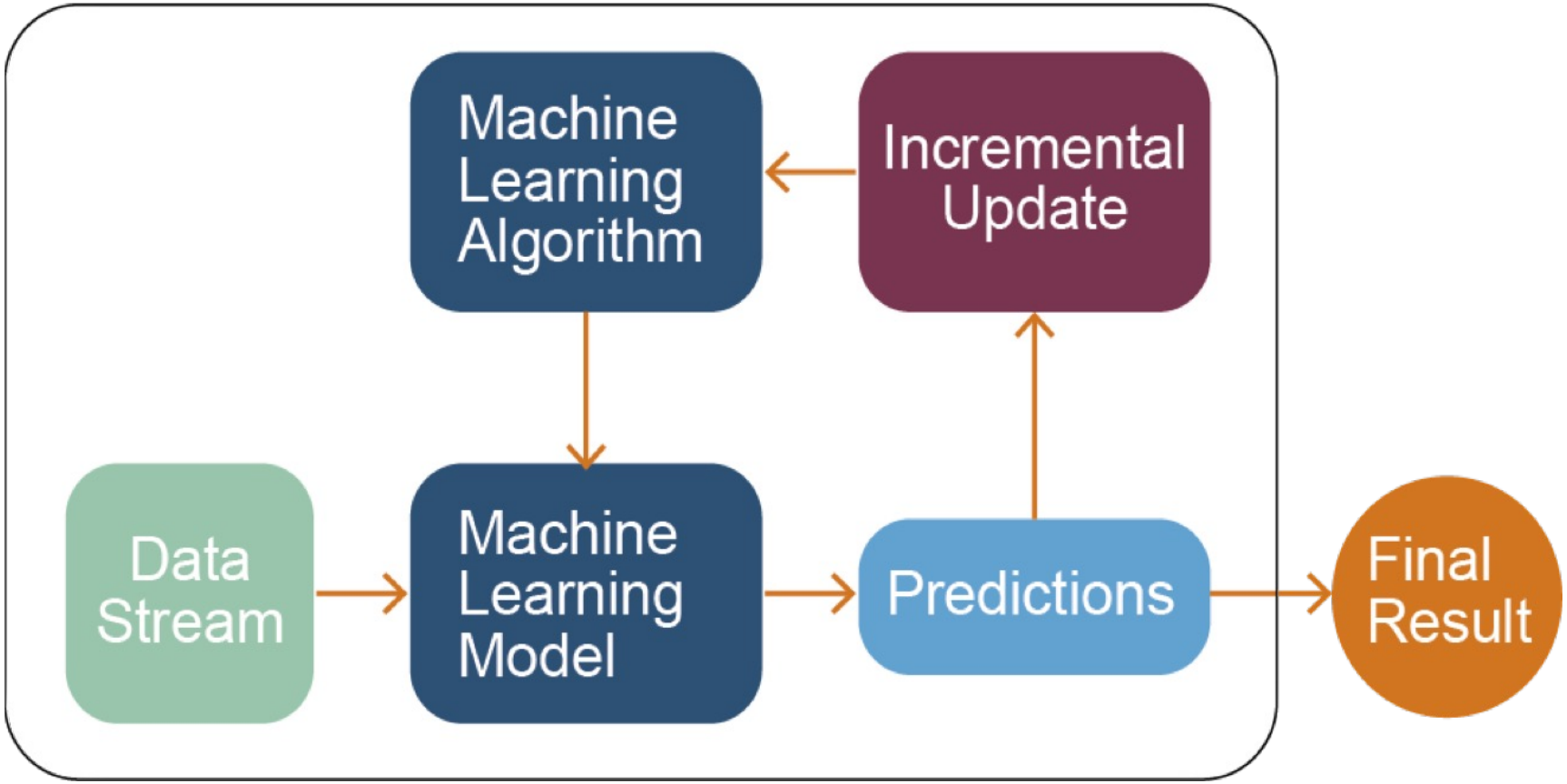
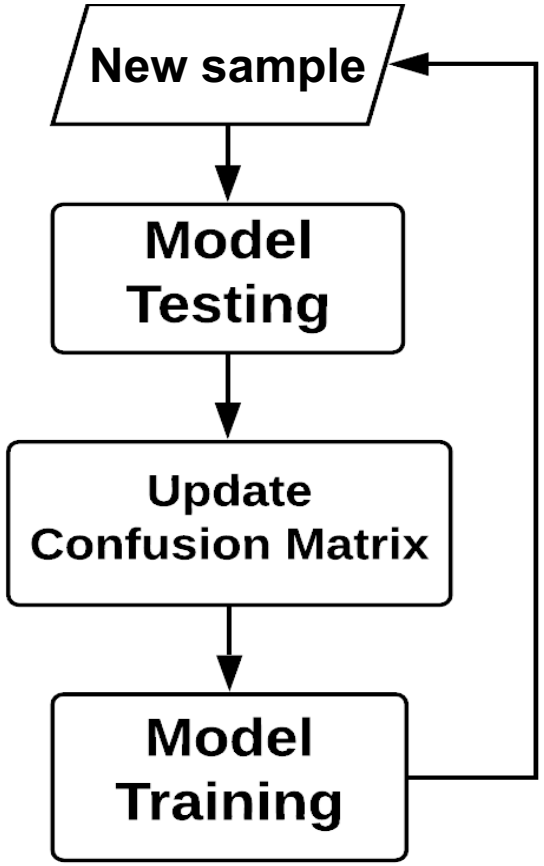
SML models



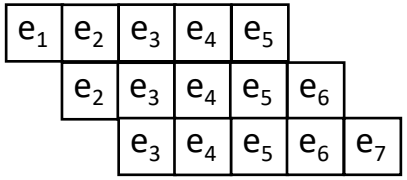
A. Bifet, G. de Francisci Morales, J. Read, G. Holmes, and B. Pfahringer **Efficient online evaluation of big data stream classifiers**. ACM SIGKDD 2015

Prequential evaluation



Estimate prequential error (PE):

- **Sliding window of size *w***



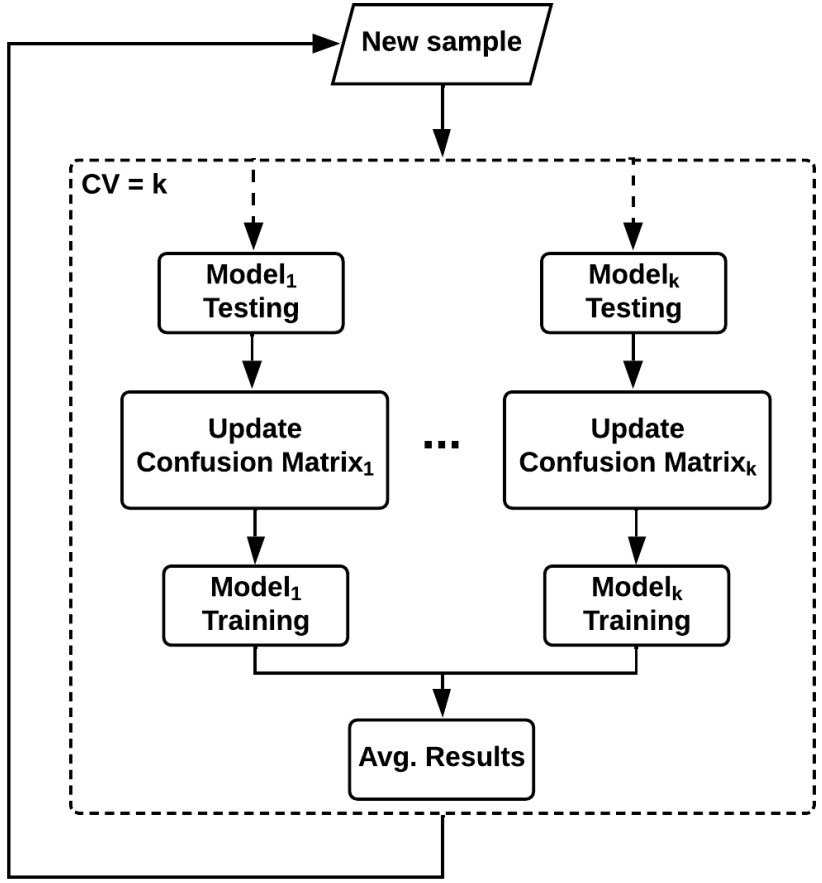
$$PE_i = \frac{1}{w} \sum_{k=i-w+1}^{w} e_k$$

- **Fading factor**

$$PE_i = \frac{\sum_{k=1}^{i} a^{i-k} * e_k}{\sum_{k=1}^{i} a^{i-k}} \quad \text{with } 0 \ll \alpha \leq 1$$

Gama, J., Sebastião, R. and Rodrigues, P.P.: **Issues in evaluation of stream learning algorithms.** In ACM KDD, 2009.

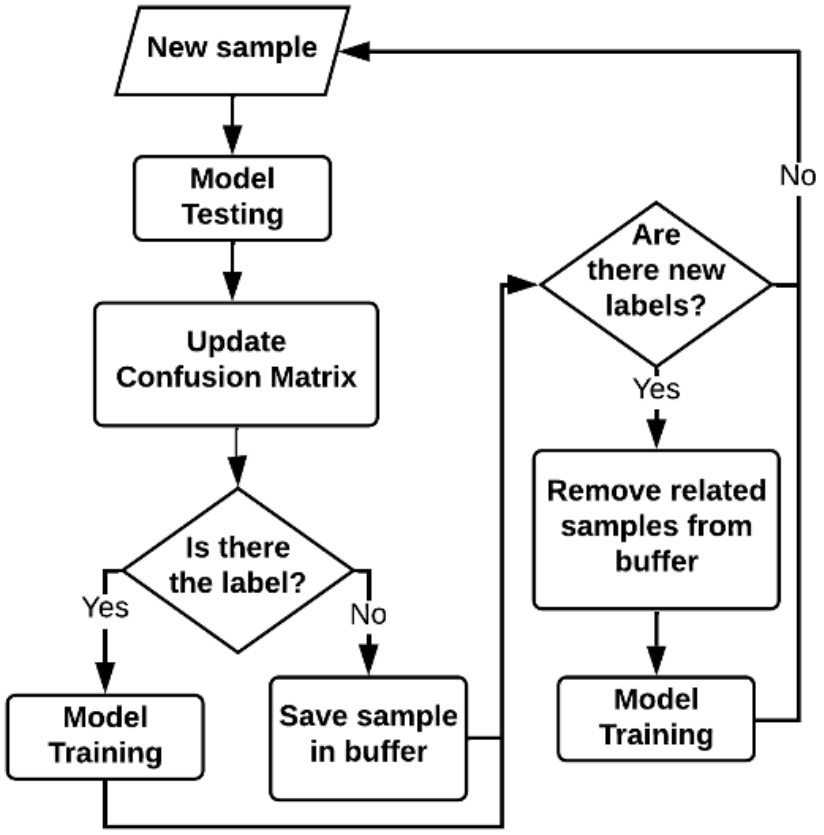
Prequential evaluation - Cross Validation



- **K-fold distributed cross-validation:**
  each sample is used for testing in one classifier selected randomly, and used for training and testing all the others
- **K-fold distributed split-validation:**
  each sample is used for training in one classifier selected randomly, and for testing in all the classifiers
- **K-fold distributed bootstrap-validation:**
  each sample is used for training in approximately 2⁄3 of the classifiers, with a separate weight in each classifier, and for testing in all the classifiers

Bifet, A., et al: **Efficient Online Evaluation of Big Data Stream Classifiers**. In ACM SIGKDD, 2015.

Prequential evaluation - Delayed



- In real environments, can happen that the label arrives **delayed** w.r.t. the features
- Test the model with the features and wait for the label to train it

Gomes, HM., et al: **Adaptive random forests for evolving data stream classification**. In Machine Learning, 2017.

Evaluation metric - Kappa statistic

$$k = \frac{p - p_{rand}}{1 - p_{rand}}$$

where p is the accuracy of the classifier under consideration and p_{rand} is the accuracy of the Random classifier.

- If the classifier is perfectly correct, then $k = 1$.
- If the classifier achieves the same accuracy as the Random classifier, then $k = 0$.

I. Žliobaitè et al. **Evaluation methods and decision theory for classification of streaming data with temporal dependence.** In Machine Learning, 2015.

Evaluation metric - Kappa-Temporal statistic

$$k = \frac{p - p_{per}}{1 - p_{per}}$$

where p is the accuracy of the classifier under consideration and p_{per} is the accuracy of the Persistent classifier.

- If the classifier is perfectly correct, then $k = 1$.
- If the classifier achieves the same accuracy as the Persistent classifier, then $k = 0$.
- If the classifier performs worse than the Persistent classifier, then $k < 0$.

I. Žliobaitè et al. **Evaluation methods and decision theory for classification of streaming data with temporal dependence.** In Machine Learning, 2015.

SML models

- Incrementally incorporate data on the fly
- Unbounded real-time data
- Resource efficient
- Dynamic models

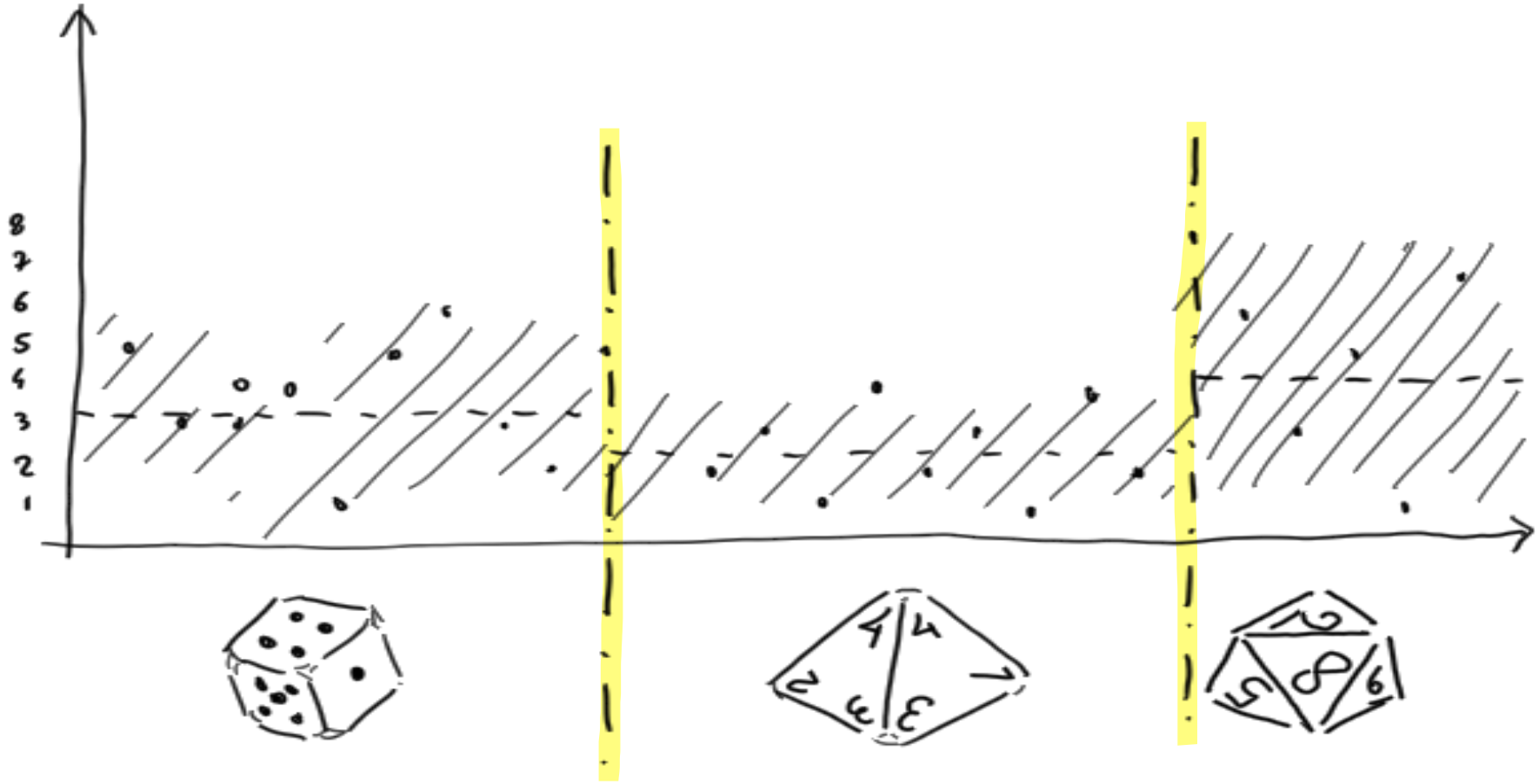
SML models

Benefits

- One sample at a time
- Incremental models
- Time & Memory management

SML models

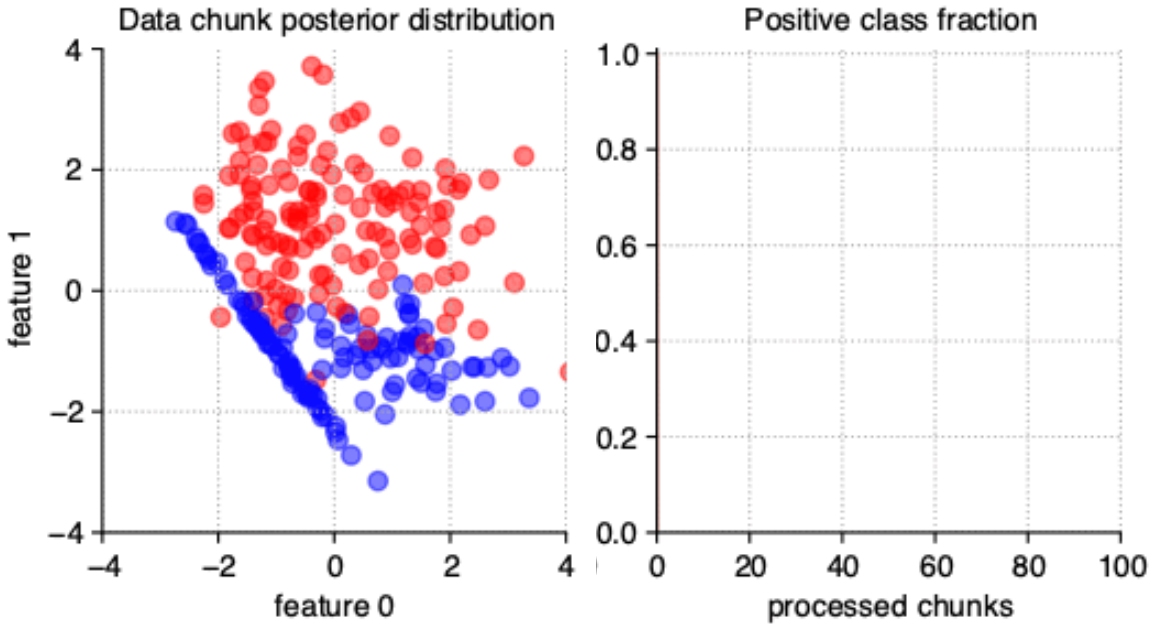
Challenges - Non identically distributed data (drifts)



SML models

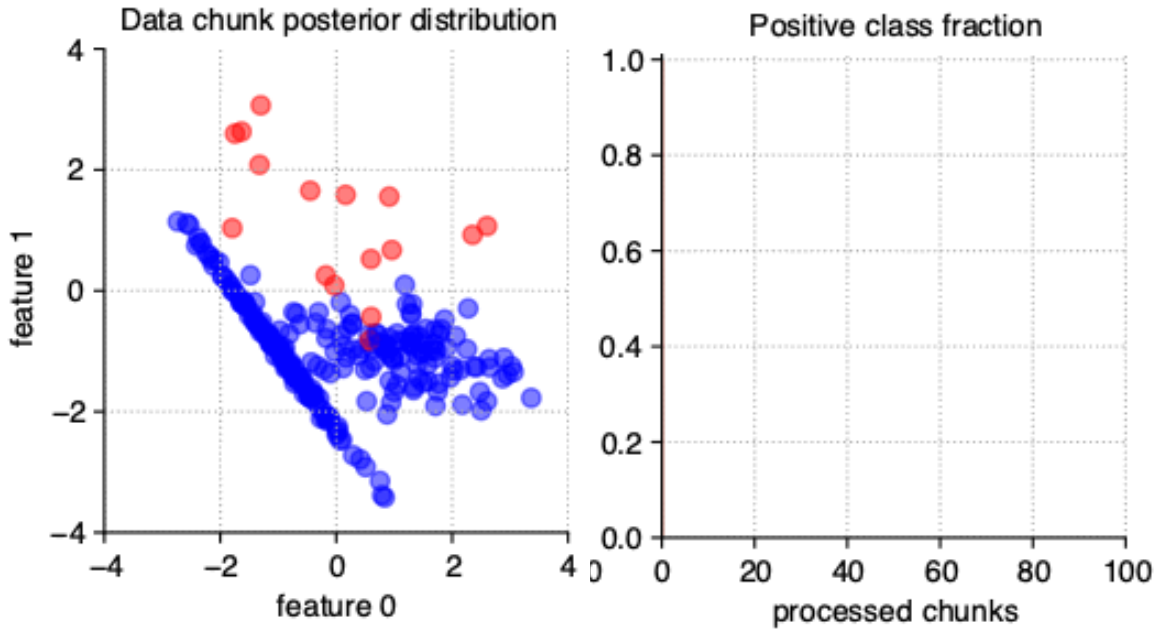
Challenges - Class imbalance

Balanced stream



src: https://stream-learn.readthedocs.io/en/latest/_images/stationary.gif

Imbalanced stream **over time**



src: https://stream-learn.readthedocs.io/en/latest/_images/dynamic-imbalanced.gif

SML models

Challenges - Hyper-parameters tuning

src: https://www.pexels.com/it-it/foto/radio-a-transistor-grigia-e-nera-157557/

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Exercise 1: From batch to stream learning

Credits

- Albert Bifet DATA STREAM MINING 2020-2021 course at Telecom Paris
- Alessio Bernardo & Emanuele Della Valle

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