Part 6 - Stream Mining

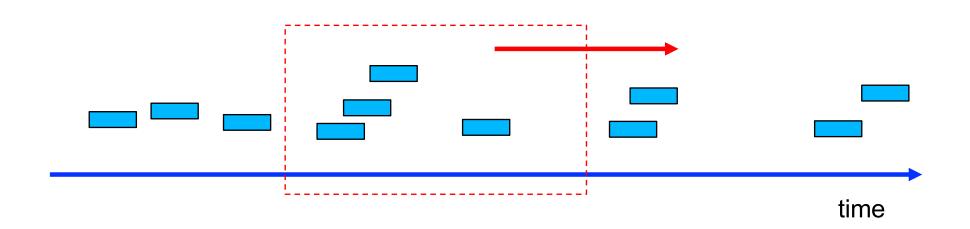
Adapted from:

DATA STREAM MINING: A Practical Approach. By Albert Bifet and Richard Kirkby, 2009.

Agenda

- Introduction
- Data Stream Mining Basics
 - Requirements
 - Cycle
 - Challenges

Data streams



Introduction

- Data mining allows larger data sets to be handled;
- Data doesn't fit memory?
 - Sample, temporary storage, subsets...
- New data is available?
 - Retrain the model with the addition of new data;

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Introduction

- Solution: Data Stream Mining
 - Naturally copes with data sizes many times greater than memory;
 - Works with challenging real-time applications (difficult for ML or DM);
 - Training examples arrive in a high speed, potentially endless, stream;
 - Updates its model incrementally as each example is inspected;
 - Capable of giving a prediction at any time;

Agenda

- Introduction
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- Data Stream Requirements:
 - 1) Inspect each example only once;
 - 2) Use limited amount of memory;
 - 3) Work in a limited amount of time;
 - 4) Be ready to predict at any point.

Classification cycle:

- 1) Receives example;
- 2) Updates data structures;
- 3) Ready for the next example or prediction.

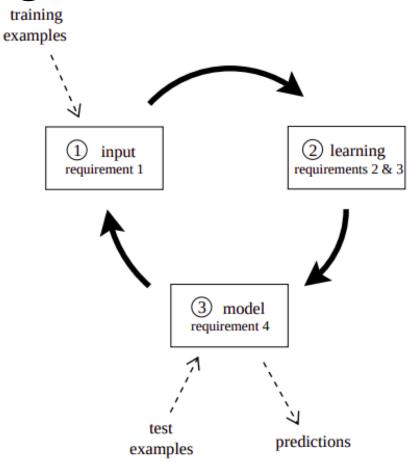


Figure 1.1: The data stream classification cycle.

- Possible approaches:
 - Wrapper creates batches of examples to be applied using traditional batch learner to induce a model. Challenges:
 - Determining appropriate batch sizes (size VS response time VS quality);
 - Training times not controlable by a wrapper algorithm;
 - Memory management.
 - 2) Adaptation adapted algorithms designed specifically for data stream problems. Advantages:
 - Greater control over processing time per example;
 - Better memory management at a finer-grained level.

- Challenges
 - 1) Streams are not static and can change over time;
 - 2) Harder to evaluate performance;

- Change detection
 - 1) Concept Change
 - Concept drift
 - Concept shift
 - 2) Distribution or sampling change

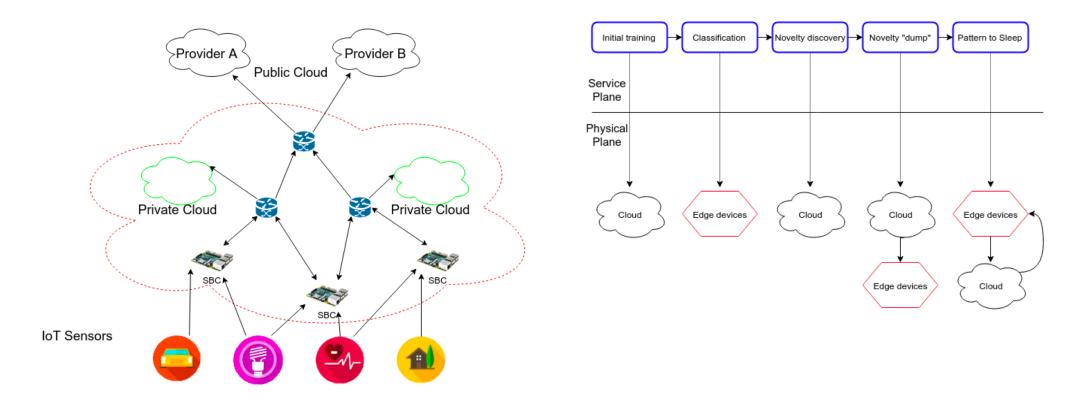
- Concept is the class being predicted.
 - Concept change is change of underlying concept over time;
 - Drift describes a gradual change.
 - Shift describes an abrupt change.
 - Distribution change refers to data distribution change. It can happen while the concept stays the same. Increases the error rate of the model.
- The design of a change detector is a tradeoff between detecting true changes and avoiding false alarms.

- Example of strategies for detecting changes
 - CUSUM Test
 - Geometric Moving Average (GMA)
 - Statistical Test
 - Drift Detection Method (DDM)
 - Exponential Weighted Moving Average (EWMA)

- Challenges
 - 1) Streams are not static and can change over time;
 - 2) Harder to evaluate performance;

- Performance Evaluation
 - Holdout: alternative to CV, creates a train subset and a test subset;
 - Interleaved Test-Then-Train: does both for each example arriving;

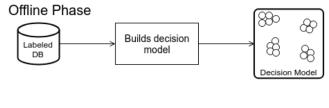
Example: IDSA-IoT



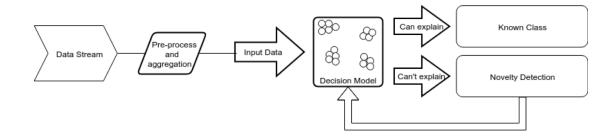
Cassales, G. W., Senger, H., de Faria, E. R., & Bifet, A. (2019, June). *IDSA-IoT: An Intrusion Detection System Architecture for IoT Networks*. In 2019 IEEE Symposium on Computers and Communications (ISCC) (pp. 1-7). IEEE.

Evaluation

- Three algorithms
 - MINAS
 - ECSMiner
 - AnyNovel
- Dataset
 - Kyoto



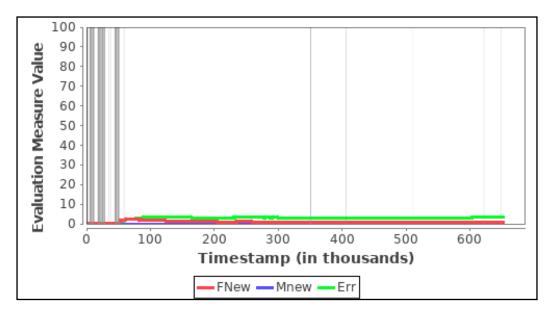
Online Phase



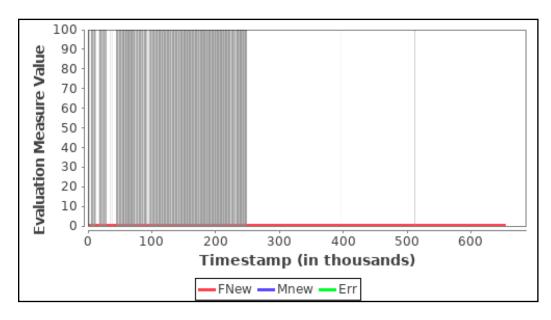
Metrics

- Fnew: the % of normal class examples incorrectly identified as novelty
- Mnew: the % of novelty examples erroneously classified as normal class
- Error: (FN + FP) / number of examples classified

Results



Binary classification with a label delivery delay of 50,000 examples and total feedback (ECSMiner).



Binary classification with label delivery delay of 50,000 examples and partial feedback of 1% (ECSMiner)

Exercise

- Install MOA
 - https://moa.cms.waikato.ac.nz/getti ng-started/
 - Unzip the file
- Windows systems:
 - Execute moa-release-2019.05.0/bin/moa.bat
- Linux/MacOS:
 - Execute moa-release-2019.05.0/bin/moa.sh

- •Go to directory: part-6-Stream-Mining/Lab
- Open file1.LAB-MOA-Intro