Machine Learning for Data Streams

Albert Bifet (@abifet)

TU Berlin
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IoT and INDUSTRY 4.0

- Interoperability: IoT
- Information transparency: virtual copy of the physical world
- Technical assistance: support human decisions
- Decentralized decisions: make decisions on their own
IoT versus Big Data
AI/Machine Learning is the new Electricity

- **Machine learning** is a type of artificial intelligence (AI) that provides computers with the ability to learn without being explicitly programmed.

- **Machine learning** focuses on the development of computer programs that can teach themselves to grow and change when exposed to new data.
Imperative Programming

The programmer specifies an explicit sequences of steps to follow to produce a result.

Decision: +, -
Computer Science

Data

Imperative Programming

while {
  for {
    do {..}
  }
}

Decision: +, -

Software 1.0
Machine Learning

Machine Learning Algorithm

Decision: +, -

Data

Software 2.0
Scale drives machine learning progress

Many of the ideas of deep learning (neural networks) have been around for decades. Why are these ideas taking off now?

Two of the biggest drivers of recent progress have been:

- **Data availability.** People are now spending more time on digital devices (laptops, mobile devices). Their digital activities generate huge amounts of data that we can feed to our learning algorithms.

- **Computational scale.** We started just a few years ago to be able to train neural networks that are big enough to take advantage of the huge datasets we now have.
AI Systems

• According to Nikola Kasabov, AI systems should exhibit the following characteristics:
  • Accommodate new problem solving rules incrementally
  • Adapt online and in real time
  • Are able to analyze itself in terms of behavior, error and success.
  • Learn and improve through interaction with the environment (embodiment)
  • Learn quickly from large amounts of data (Big Data)
  • Have memory-based exemplar storage and retrieval capacities
  • Have parameters to represent short and long term memory, age, forgetting, etc.
Data Streams

- Maintain models online
- Incorporate data on the fly
- Unbounded training sets
- Resource efficient
- Detect changes and adapts
- Dynamic models
Data Set

Classifier Algorithm builds Model

Model

Analytic Standard Approach

Finite training sets
Static models
Data Stream Approach

Infinite training sets
Dynamic models
Adversarial Learning

- Need to **retrain!**
  - Things change over time
  - How often?
  - Data unused until next update!
    - Value of data wasted
AI Challenges
CÉDRIC VILLANI
Mathematician and
Member of the French Parliament

FOR A MEANINGFUL ARTIFICIAL INTELLIGENCE

TOWARDS A FRENCH AND EUROPEAN STRATEGY
1. Open AI
MOA

• Massive Online Analysis is a framework for online learning from data streams.

• It is closely related to WEKA

• It includes a collection of offline and online as well as tools for evaluation:
  • classification, regression
  • clustering, frequent pattern mining

• Easy to extend, design and run experiments
MOA

Richard Kirkby

Software Developer at 11Ants Analytics Ltd

Geoff Holmes

Dean of Computing & Mathematical Sciences University of Waikato

Bernhard Pfahringer

Computer Science Department University of Waikato
Main Contributors

- **Weka ML Group**: Peter Reutemann, Eibe Frank, Mike Mayo

- Jesse Read, Indrė Žliobaitė, Philipp Kranen, Hardy Kremer, Timm Jansen, Marwan Hassani, Thomas Seidl, Dimitris Georgiadis, Anastasios Gounaris, Apostolos N. Papadopoulos, Kostas Tsichlas, Yannis Manolopoulos, Dariusz Brzeziński, Ricard Gavaldà, Alex Catarineu, Joao Gama, Ricardo Sousa, Joao Duarte, Aljaž Osojnik, ...
WEKA: the bird
MOA: the bird

The Moa (another native NZ bird) is not only flightless, like the Weka, but also extinct.
MOA: the bird

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Stream Setting

- Process an example at a time, and inspect it only once (at most)
- Use a limited amount of memory
- Work in a limited amount of time
- Be ready to predict at any point
Stream Evaluation

- Holdout Evaluation
- Interleaved Test-Then-Train or Prequential
Stream Evaluation

Holdout an independent test set

- Apply the current decision model to the test set, at regular time intervals
- The loss estimated in the holdout is an unbiased estimator
Stream Evaluation

Prequential Evaluation

• The error of a model is computed from the sequence of examples.

• For each example in the stream, the actual model makes a prediction based only on the example attribute-values.

\[ S = \sum_{i=1}^{n} L(y_i, \hat{y}_i). \]
Clustering
MOA Algorithms

- Multi-label/ Multi-target
- Outlier Detection
- Concept Drift Detection
- Active Learning
- Frequent Itemset Mining
- Frequent Graph Mining
- Recommendation Systems
Command Line


- This command creates a comma separated values file:
  - training the DecisionStump classifier on the WaveformGenerator data,
  - using the first 100 thousand examples for testing,
  - training on a total of 100 million examples,
  - and testing every one million examples
ADAMS
Advanced Data Mining And Machine Learning System
scikit-multiflow

A multi-output/multi-label and stream data framework. Inspired by MOA and MEKA, following scikit-learn philosophy.

Github Repository
from skmultiflow.data.generators.waveform_generator import WaveformGenerator
from skmultiflow.classification.trees.hoeffding_tree import HoeffdingTree
from skmultiflow.evaluation.evaluate_prequential import EvaluatePrequential

# 1. Create a stream
stream = WaveformGenerator()
stream.prepare_for_use()

# 2. Instantiate the HoeffdingTree classifier
ht = HoeffdingTree()

# 3. Setup the evaluator
eval = EvaluatePrequential(show_plot=True, pretrain_size=1000,
                           batch_size=50, random_state=42)

# 4. Run evaluation
eval.eval(stream=stream, classifier=ht)
Waveform Generator - 1 target, 3 classes

Accuracy

Kappa

Samples

Model 0 (sliding 200 samples)

Model 0 (global)
scikit-multiflow

Jesse Read
Ecole Polytechnique
France

Jacob Montiel
Telecom ParisTech
France
Learning Fast and Slow
**THE 2 SYSTEMS**

**System 1 (Fast Thinking)**
- Continuously scans our environment.
- Fast but error-prone
- Works automatically & effortlessly via shortcuts, impulses and intuition.

**System 2 (Slow Thinking)**
- Used for specific problems, only if necessary
- Takes effort to analyze, reason, solve complex problems, exercise self-control.
- Slow but reliable
Learning Fast and Slow

Table 1: The Fast and Slow systems for Machine Learning.

<table>
<thead>
<tr>
<th>FAST SYSTEM</th>
<th>SLOW SYSTEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cheap (mem., time)</td>
<td>Expensive (mem., time)</td>
</tr>
<tr>
<td>Always ready</td>
<td>Trains on large batches</td>
</tr>
<tr>
<td>Robust to drifts, adapts</td>
<td>Complex and robust models</td>
</tr>
<tr>
<td>Focus on the present</td>
<td>Generalize the larger scheme</td>
</tr>
</tbody>
</table>
Learning Fast and Slow
Learning Fast and Slow

Figure 2: FSC operation modes.
Learning Fast and Slow

Figure 2: FSC operation modes.
Learning Fast and Slow
2. Green AI
Part 4 — Using Artificial Intelligence to Help Create a More Ecological Economy

More than ever before, the revolution triggered by the development of digital technologies and their widespread adoption tends to obscure its impact on the environment\(^1\). Nevertheless, there is an urgent need to take this on board. Two years ago, the American Association of Semi-Conductor Manufacturers predicted that by 2040, the global demand for data storage capacity, which grows at the pace of the progress of AI, will exceed the available world production of silicon\(^2\).

By 2040 the energy required for computation will equally have exceeded world energy production. Furthermore, by 2040 the energy required for computation will equally have exceeded world energy production; the progress of the blockchain may also cause our energy requirements to rocket. It is vital to educate as many people as possible about these issues and to act promptly to avoid shortages. At a time when global warming is a scientific certainty, it is no longer possible to pursue technological and societal developments if those are completely detached from the need to preserve our environment.
AlexNet to AlphaGo Zero: A 300,000x Increase in Compute

![Graph showing the increase in compute power from AlexNet to AlphaGo Zero](image-url)
Deep neural networks are energy hungry and growing fast.

AI is being powered by the explosive growth of deep neural networks.

AI algorithms will be measured by the amount of intelligence they provide per joule.
Green AI

• One pass over the data

• Approximation algorithms: small error $\varepsilon$ with high probability $1-\delta$
  
  • True hypothesis $H$, and learned hypothesis $\hat{H}$

  • $\Pr[|H - \hat{H}| < \varepsilon|H|] > 1-\delta$
Approximation Algorithms

- What is the largest number that we can store in 8 bits?

1 0 1 0 1 0 1 0
Approximation Algorithms

- What is the largest number that we can store in 8 bits?

---

It is possible to use a small counter to keep approximate counts of large numbers. The resulting expected error can be rather precisely controlled. An example is given in which 8-bit counters (bytes) are used to keep track of as many as 130,000 events with a relative error which is substantially independent of the number $n$ of events. This relative error can be expected to be 24 percent or less 95 percent of the time (i.e. $\sigma = n/8$). The techniques could be used to advantage in multichannel counting hardware or software used for the monitoring of experiments or processes.
Approximation Algorithms

- What is the largest number that we can store in 8 bits?

\[ f(x) = \frac{\log(1 + x/30)}{\log(1 + 1/30)} \]

\[ f(0) = 0, f(1) = 1 \]
What is the largest number that we can store in 8 bits?
Green AI

- Transform Big Data into Small Data
  - Vertical: reducing features
  - Horizontal: reducing instances
- Make data stream methods more energy efficient
  - Use Energy as a measure, not time and memory
Compressed Sensing

Definition 1 (Restricted Isometry Property) A $m \times n$ sensing matrix $A$ satisfies the restricted isometry property, $(k, \epsilon)$-RIP, if it acts as a near-isometry with distortion factor $\epsilon$, over all $k$-sparse vectors. In other words, for any $k$-sparse vector $\mathbf{x} \in \mathbb{R}^n$ the following near-isometry property holds:

$$(1 - \epsilon) \| \mathbf{x} \|_2 \leq \| A \mathbf{x} \|_2 \leq (1 + \epsilon) \| \mathbf{x} \|_2.$$
Coresets

Coreset of a set $P$ with respect to some problem
Small subset that approximates the original set $P$.

- Solving the problem for the coreset provides an approximate solution for the problem on $P$.

$(k, \varepsilon)$-coreset

A $(k, \varepsilon)$-coreset $S$ of $P$ is a subset of $P$ that for each $C$ of size $k$

$$(1 - \varepsilon) \text{cost}(P, C) \leq \text{cost}_w(S, C) \leq (1 + \varepsilon) \text{cost}(P, C)$$
3. Explainable AI
relations and reinforce solidarity. Diversity should also figure within these priorities. In this respect, the situation in the digital sector is alarming, with women very poorly represented. Their under-representation may lead to the spread of nurture gender-biased algorithms.

Finally, our digital society could not be governed by black box algorithms: artificial intelligence is going to play a decisive role in critical domains for human flourishing (health, banking, housing, etc) and there is currently a high risk of embedding existing discrimination into AI algorithms or creating new areas where it might occur. Further, we also run the risk that normalization may spread attitudes that could lead to the general development of algorithms within artificial intelligence. It should be possible to open these black boxes, but equally to think ahead about the ethical issues that may be raised by algorithms within artificial intelligence.

A meaningful AI finally implies that AI should be explainable: explaining this technology to the public so as to demystify it—and the role of the media is vital from this point of view—but also explaining artificial intelligence by extending research into explicability itself. AI specialists themselves frequently maintain that significant advances could be made on this subject.
Starting May 25, the European Union will require algorithms to explain their output, making deep learning illegal.

12:59 AM - Jan 29, 2018

❤️ 343  📣 248 people are talking about this
The EU General Data Protection Regulation (GDPR) is the most important change in data privacy regulation in 20 years - we're here to make sure you're prepared.

Art. 22 GDPR
Automated individual decision-making, including profiling

(1) The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her.
Lime: Explaining the predictions of any machine learning classifier

"Why Should I Trust You?": Explaining the Predictions of Any Classifier

Marco Tulio Ribeiro, Sameer Singh, Carlos Guestrin, KDD 2016
Decision Tree

- Each node tests a feature.
- Each branch represents a value.
- Each leaf assigns a class.
- Greedy recursive induction:
  - Sort all examples through the tree.
  - $x_i$ = most discriminative attribute.
  - New node for $x_i$, new branch for each value, leaf assigns majority class.
  - Stop if no error | limit on #instances.

Car deal?

Road Tested?

- Yes
- No

Mileage?

- High
- Low

Age?

- Recent
- Old

- ✓
- ✗
HOEFFDING TREE

- Sample of stream enough for near optimal decision
- Estimate merit of alternatives from prefix of stream
- Choose sample size based on statistical principles
- When to expand a leaf?
  - Let $x_1$ be the most informative attribute, $x_2$ the second most informative one
  - Hoeffding bound: split if $G(x_1) - G(x_2) > \varepsilon = \sqrt{\frac{R^2 \ln(1/\delta)}{2n}}$
TensorForest: Scalable Random Forests on TensorFlow

Thomas Colthurst, Gilbert Hendry, Zachary Nado, D. Sculley
Google Inc.
{thomaswc, gilberth, znado, dsculley}@google.com

Abstract

We present TensorForest, a highly scalable open-sourced system built on top of TensorFlow for the training and evaluation of random forests. TensorForest achieves scalability by combining a variant of the online Hoeffding Tree algorithm with the extremely randomized approach, and by using TensorFlow’s native support for distributed computation. This paper describes TensorForest’s architecture, analyzes several alternatives to the Hoeffding bound for per-node split determination, reports performance on a selection of large and small public datasets, and demonstrates the benefit of tight integration with the larger TensorFlow platform.
Rules

• Problem: very large decision trees have context that is complex and hard to understand

• Rules: self-contained, modular, easier to interpret, no need to cover universe

• $\mathcal{L}$ keeps sufficient statistics to:
  
  • make predictions
  
  • expand the rule
  
  • detect changes and anomalies
Adaptive Model Rules


- Ruleset: ensemble of rules
- Rule prediction: mean, linear model
- Ruleset prediction
  - Weighted avg. of predictions of rules covering instance $x$
  - Weights inversely proportional to error
  - Default rule covers uncovered instances

E.g: $x = [4, -1, 1, 2]$

$$\hat{f}(x) = \sum_{R_l \in S(x_i)} \theta_l \hat{y}_l,$$
Adaptive Random Forest

Adaptive random forests for evolving data stream classification.

Gomes, H M; Bifet, A; Read, J; Barddal, J P; Enembreck, F; Pfahringer, B; Holmes, G; Abdessalem, T.


- Based on the original Random Forest by Breiman
ADWIN

An adaptive sliding window whose size is recomputed online according to the rate of change observed.

Figure 1: Iterations of the cut check procedure in ADWIN
ADWIN

- Classification
  - Adaptive Naive Bayes (Bifet et al. 2007)
  - Decision Trees: Hoeffding Adaptive Trees (Bifet et al. 2009)
  - ADWIN Bagging (Bifet et al. 2009)
  - Leveraging Bagging (Bifet et al. 2010)
  - Stacking of Restricted Hoeffding Trees (Bifet et al. 2012)
  - Multilabel Classification (Read et al. 2012)
  - Adaptive kNN (Bifet et al. 2013)
  - Random Forests (Marron et al. 2014)

- Frequent Pattern Mining
  - Frequent Closed Tree Mining (Bifet et al. 2008)
  - Frequent Closed Graph Mining (Bifet et al. 2011)
Parallel ADWIN

Scalable Detection of Concept Drifts on Data Streams with Parallel Adaptive Windowing

Philipp M. Grulich\textsuperscript{1} \quad René Saitenmacher\textsuperscript{1} \quad Jonas Traub\textsuperscript{1}  
Sebastian Breß\textsuperscript{1,2} \quad Tilmann Rabl\textsuperscript{1,2} \quad Volker Markl\textsuperscript{1,2}

\textsuperscript{1}Technische Universität Berlin \quad \textsuperscript{2}DFKI GmbH

\textbf{ABSTRACT}

Machine learning techniques for data stream analysis suffer from concept drifts such as changed user preferences, varying weather conditions, or economic changes. These concept drifts cause wrong predictions and lead to incorrect business decisions. Concept drift detection methods such as adaptive windowing (ADWIN) allow for adapting to concept drifts on the fly.

In this paper, we examine ADWIN in detail and point out its throughput bottlenecks. We then introduce several parallelization alternatives to address these bottlenecks. Our optimizations lead to a speedup of two orders of magnitude over the original ADWIN implementation. Thus, we explore parallel adaptive windowing to provide scalable concept detection for high-velocity data streams with millions of tuples per second.

We chose ADWIN because it has proven its capabilities in a wide range of real-world applications: ADWIN was combined with Kalman Filters and demonstrated with Naïve Bayes and k-means clustering [1]. Furthermore, ADWIN is used for an online version of the Bagging method by Oza and Rusell [5] and in a parameter-free variant of the Space Saving algorithm [4]. Moreover, ADWIN is available in the open source MOA framework [3].

In this paper, we present the following contributions:

1. We analyze the original ADWIN approach, point out its scalability limitations, and identify its bottlenecks.
2. We parallelize ADWIN to overcome its bottlenecks and to provide scalable concept drift adaptation in real-time.
3. We evaluate the latency and throughput of our solution. It achieves two orders of magnitude speedup over the original ADWIN implementation and 54 times speedup in...
4. Ethical Issues
The use of deep learning algorithms, which feed off data for the purposes of personalization and assistance with decision-making, has given rise to the fear that social inequalities are being embedded in decision algorithms. In fact, much of the recent controversy surrounding this issue concerns discrimination towards certain minorities or based on gender (particularly black people, women and people living in deprived areas). American experience has also brought us several similar examples of the effects of discrimination in the field of crime prevention.

Because systems that incorporate AI technology are invading our daily lives, we legitimately expect them to act in accordance with our laws and social standards. It is therefore essential that legislation and ethics control the performance of AI systems. Since we are currently unable to guarantee a \textit{priori} the performance of a machine learning system (the formal certification of machine learning is still currently a subject of research), compliance with this requirement necessitates the development of procedures, tools and methods which will allow us to audit these systems in order to evaluate their conformity to our legal and ethical frameworks. This is also vital in case of litigation between different parties who are objecting to decisions taken by AI systems.
The EU General Data Protection Regulation (GDPR) is the most important change in data privacy regulation in 20 years - we're here to make sure you're prepared.

Art. 17 GDPR

Right to erasure (‘right to be forgotten’)

(1) The data subject shall have the right to obtain from the controller the erasure of personal data concerning him or her without undue delay and the controller shall have the obligation to erase personal data without undue delay where one of the following grounds applies:
Should data have an expiration date?
5. Distributed Machine Learning for Data Streams
Vision

Streaming

Distributed

IoT Big Data Stream Mining
APACHE SAMOA

G. De Francisci Morales, A. Bifet: “SAMOA: Scalable Advanced Massive Online Analysis”. JMLR (2014)
Creating a Flink Adapter on Apache SAMOA

Apache Scalable Advanced Massive Online Analysis (SAMOA) is a platform for mining data streams with the use of distributed streaming Machine Learning algorithms, which can run on top of different Data Stream Processing Engines (DSPEs).

As depicted in Figure 20, Apache SAMOA offers the abstractions and APIs for developing new distributed ML algorithms to enrich the existing library of state-of-the-art algorithms [27, 28]. Moreover, SAMOA provides the possibility of integrating new DSPEs, allowing in that way the ML programmers to implement an algorithm once and run it in different DSPEs [28].

An adapter for integrating Apache Flink into Apache SAMOA was implemented in scope of this master thesis, with the main parts of its implementation being addressed in this section. With the use of our adapter, ML algorithms can be executed on top of Apache Flink. The implemented adapter will be used for the evaluation of the ML pipelines and HT algorithm variations.

Figure 20: Apache SAMOA’s high level architecture.
Vertical Partitioning

N. Kourtellis, G. De Francisci Morales, A. Bifet, A. Murdopo: “VHT: Vertical Hoeffding Tree”, 2016

Single attribute tracked in single node
Apache SAMOA Team

Gianmarco De Francisci Morales, Nicolas Kourtellis, Matthieu Morel, Arindo Murdopo, Antonio Severien, and Olivier Van Laere
http://huawei-noah/github.io/streamDM

StreamDM

streamDM: Data Mining for Spark Streaming
Summary

- Machine Learning for Data Streams useful for finding approximate solutions with reasonable amount of time & limited resources

- Challenges:
  - Open AI
  - Green AI
  - Explainable AI
  - Ethical Issues
  - Distributed Data Stream Mining
Green Data Mining

International Workshop on Energy Efficient Data Mining and Knowledge Discovery

1st International Workshop on Energy Efficient Data Mining and Knowledge Discovery

Co-located with ECML PKDD 2018
Thanks!

@abifet
MACHINE LEARNING FOR DATA STREAMS
Albert Bifet
Ricard Gavaldà
Geoffrey Holmes
Bernhard Pfahringer
with Practical Examples in MOA