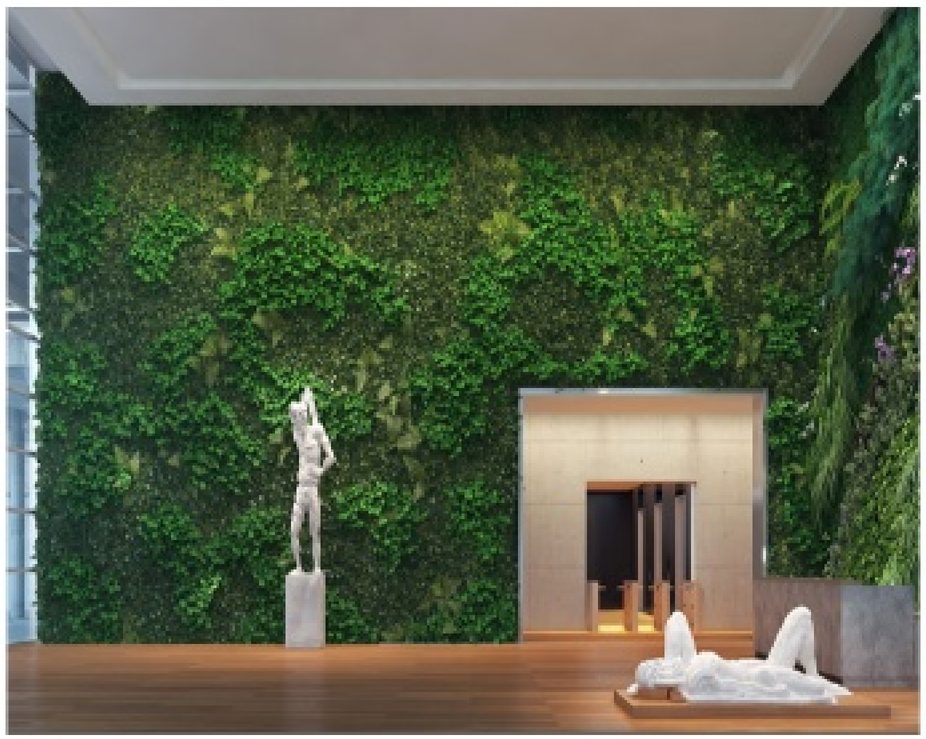
SPARK SUMMIT 2017

An Online Spark Pipeline: Semi-Supervised Learning and Online Retraining with Spark Streaming.

Presented: J. White Bear

IBM
Spark Technology Center



- Founded in 2015.
- Location:
  - Physical: 505 Howard St., San Francisco CA
  - Web: http://spark.tc Twitter: @apachespark_tc
- Mission:
  - Contribute intellectual and technical capital to the Apache Spark community.
  - Make the core technology enterprise- and cloud-ready.
  - Build data science skills to drive intelligence into business applications — http://bigdatauniversity.com
- Key statistics:
  - About 50 developers, co-located with 25 IBM designers.
  - Major contributions to Apache Spark http://jiras.spark.tc
  - Apache SystemML is now a top level Apache project !
  - Founding member of UC Berkeley AMPLab and RISE Lab
  - Member of R Consortium and Scala Center

About Me

Education

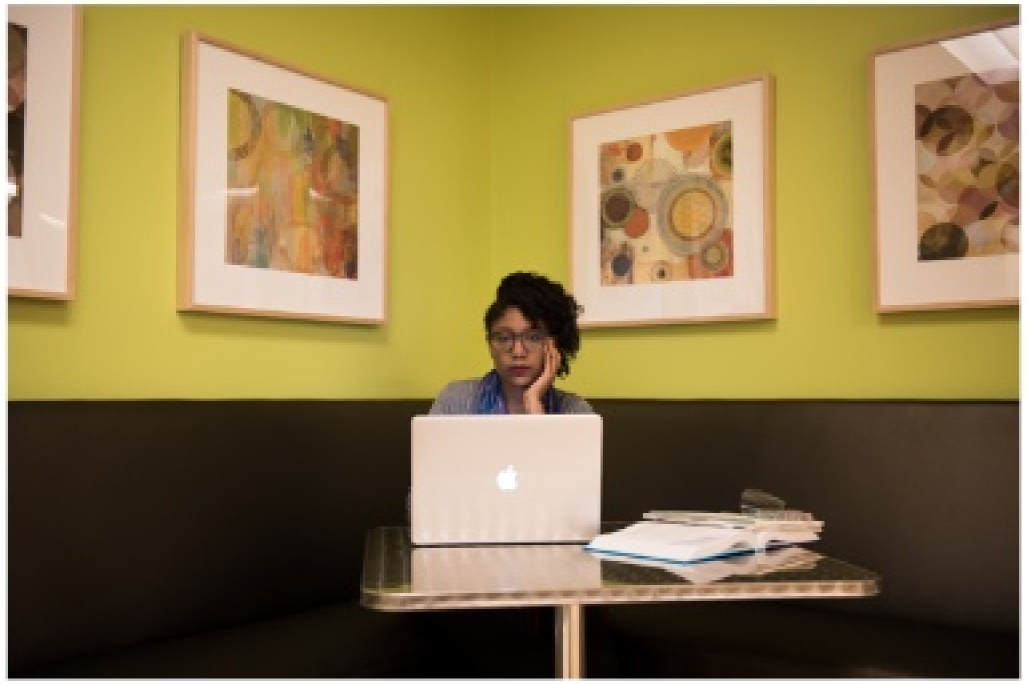
- University of Michigan- Computer Science
    - Databases, Machine Learning/ Computational Biology, Cryptography
- University of California San Francisco, University of California Berkeley-
    - Multi-objective Optimization/Computational Biology/Bioinformatics
- McGill University
    - Machine Learning/ Multi-objective Optimization for Path Planning/ Cryptography

Industry

- IBM
- Amazon
- TeraGrid
- Pfizer
- Research at UC Berkeley, Purdue University, and every university I ever attended. ☺

Fun Facts (?)

I love research for its own sake. I like robots, helping to cure diseases, advocating for social change and reform, and breaking encryptions. Also, most activities involving the Ocean and I usually hate taking pictures. ☺



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Why do we need online semisupervised learning?

Why online learning?

- Incremental/Sequential learning for real-time use cases
- Predicts/learns from the newest data
- Optimized for low latency in real-time cases
- Often used in conjunction with streaming data

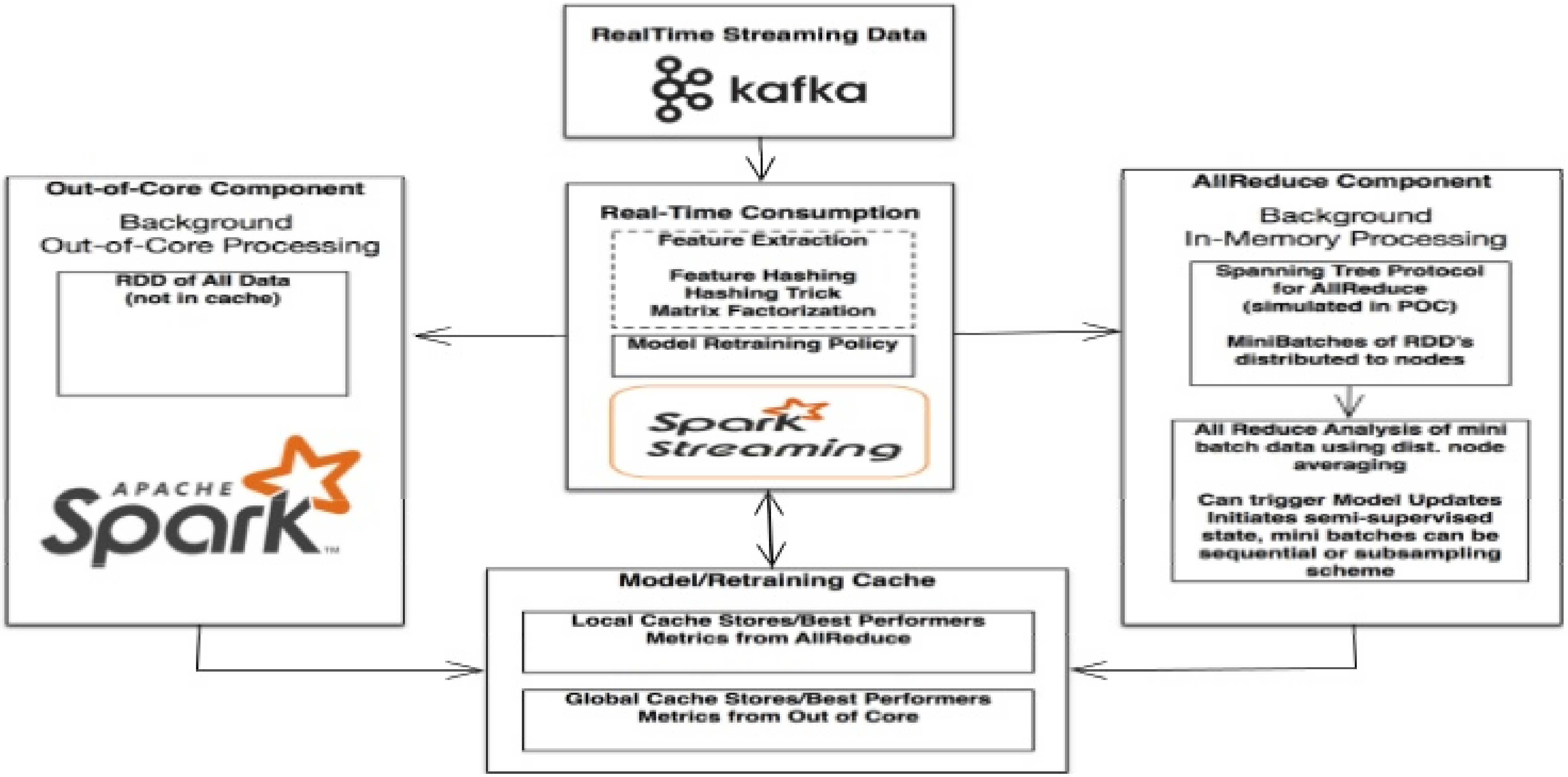
Semi-supervised learning

- Smaller training sets, less labeled data
- Classifying or predicting unlabeled data
- The underlying distribution P(x,y) may or may not be known/ stable (PAC learning)
- How/Why do we bring these ideas together?

Key Challenges

- Acquiring a sufficient ratio training data
  - Batch learning is much slower and more difficult to update a model
- Maintaining accuracy
  - Concept drift
  - Catastrophic events
- Meeting latency requirements particularly in real-time scenarios, like autonomous vehicles
- What about unlabeled data?....

The Framework: Hybrid Online and Semi-Supervised learning



A Reliable Effective Terascale Linear Learning System
Alekh Agarwal, Olivier Chapelle, Miroslav Dudik, John Langford

Why this framework?

- Abundance of unlabeled data requires semi-supervised learning
  - Real-time learning in the IoT setting
- Semi-Supervised learning can improve predictions
  - Empirically studied for online use case with Big Data
- We need to address the challenges of incremental sequential learning without losing valuable historical data
- We need to optimize for low latency without overly sacrificing accuracy
- You may have an online case but you are not guaranteed labeled data and definitely not in a timely fashion
- Hybrid frameworks address these challenges and allow for future data mining to understand and correct for how your data changes over time

Online and Semi-supervised Learning: Online Constraint

$$\min_{\mathbf{w}\in\mathcal{R}^d} \sum_{i=1}^{n} l(\mathbf{w}^\top \mathbf{x}_i; y_i) + \lambda \mathcal{R}(\mathbf{w})$$

Supervised learning over a batch

$$\frac{1}{n}\sum_{i=1}^{n} l(\mathbf{w}^\top \mathbf{x}_i; y_i) + \frac{\lambda}{n}\mathcal{R}(\mathbf{w})$$

Online learning over a mini-batch from a streaming data set

$$\frac{m}{n}\sum_{i=\mathbb{S}_k}^{n} l(\mathbf{w}^\top \mathbf{x}_i; y_i) + \frac{\lambda}{n}\mathcal{R}(\mathbf{w})$$

Distributed learning over a mini-batch from a streaming data set

Online and Semi-supervised Learning: Semi-supervised Constraint

Let x_p be an example where $x_p = (x_{p1}, x_{p2}, x_{p2}, ..., x_{pD}, \omega)$ where x_p belongs to class ω and a $\mathcal{D}$ dimensional space. x_{pi} is the value of the ith feature of the pth sample.

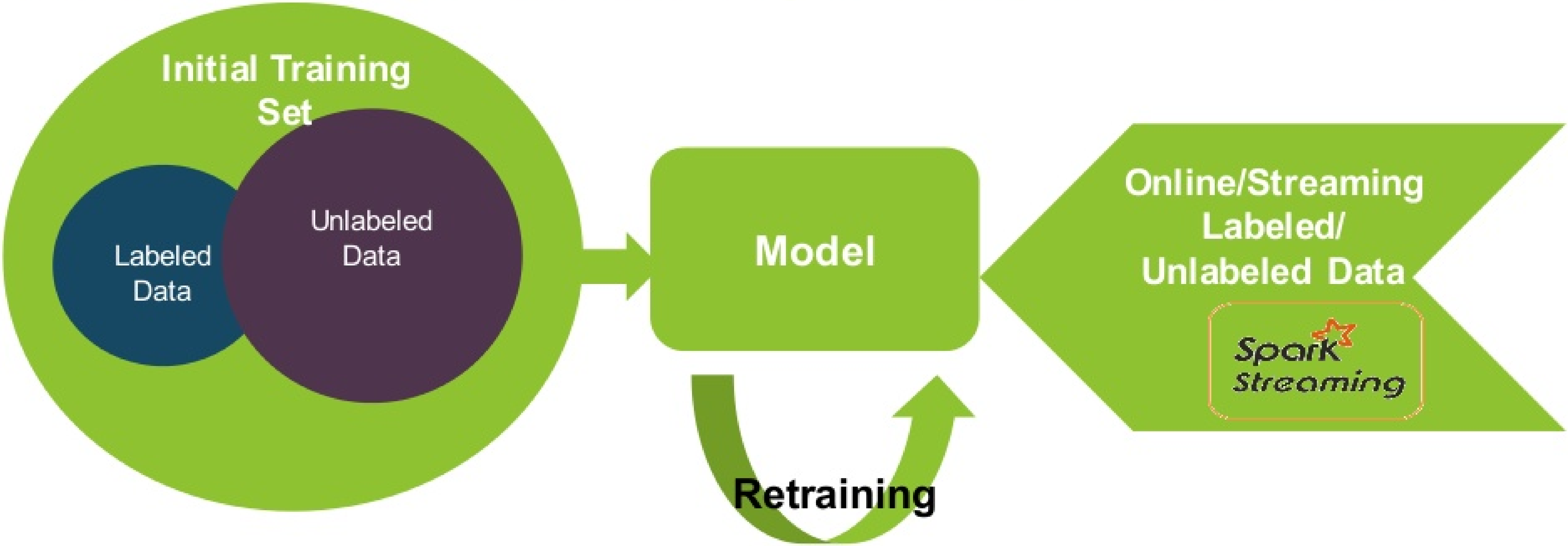
Assume a labeled set. $\mathcal{L}$ with n instances of x, with ω known. Assume a labeled set. $\mathcal{U}$ with m instances of x, with ω unknown. Assume that the number of labeled instances $\mathcal{L}$, is less than the number of unlabeled instances, $\mathcal{U}$.

$\mathcal{L} \cup \mathcal{U}$ represents the training set, $\mathcal{T}$.

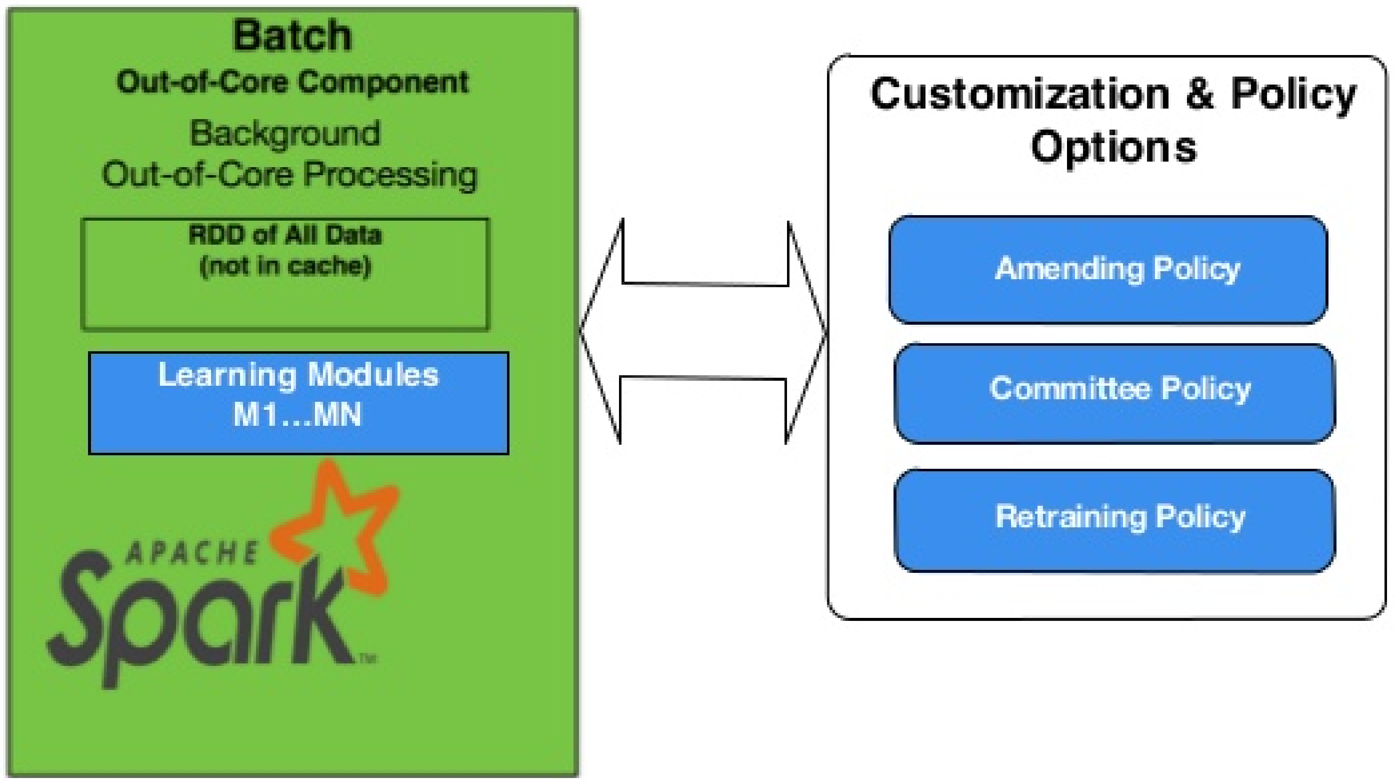
We want to infer a hypothesis using $\mathcal{T}$ and use this hypothesis to predict labels we have not yet seen.

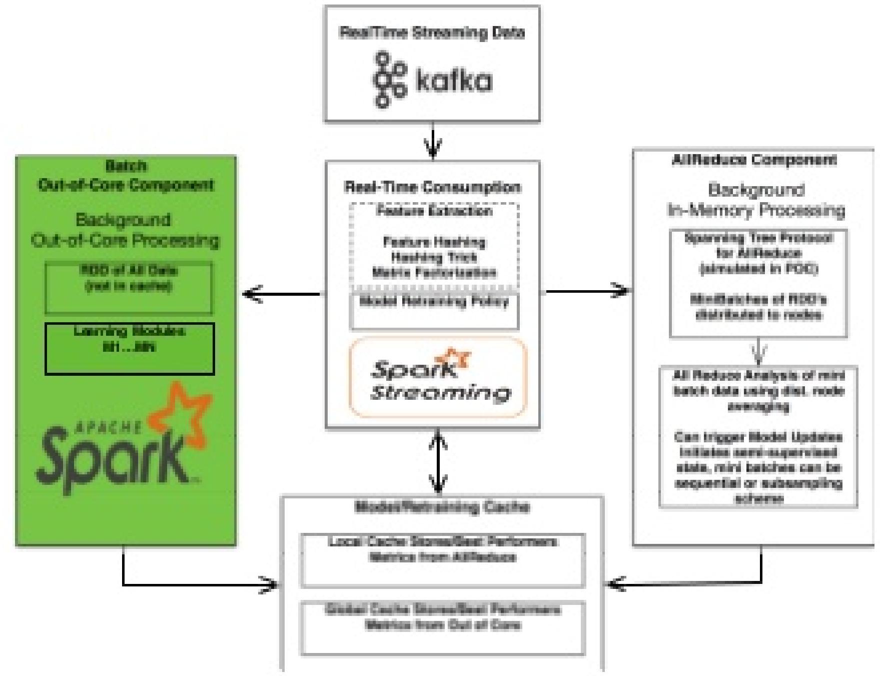
The semi-supervised learning case.

Online and Semi-supervised Learning: Semi-supervised Constraint



The Framework: Batch Component





The Framework: Batch Component

- Features
  - Out-of-Core, can run as a background process
  - Ensemble Learning: Multiple model/ Co-training learning algorithms
  - Amending Policy
  - Retrain Policy
  - Active Learning Policy
  - Custom Parameters

The Framework: Batch Component

CoTraining Algorithm #1

[Blum&Mitchell, 1998]

Given: labeled data L,

unlabeled data U

Loop:

Train g1 (hyperlink classifier) using L

Train g2 (page classifier) using L

Allow g1 to label *p* positive, *n* negative examps from U

Allow g2 to label *p* positive, *n* negative examps from U

Add these self-labeled examples to L

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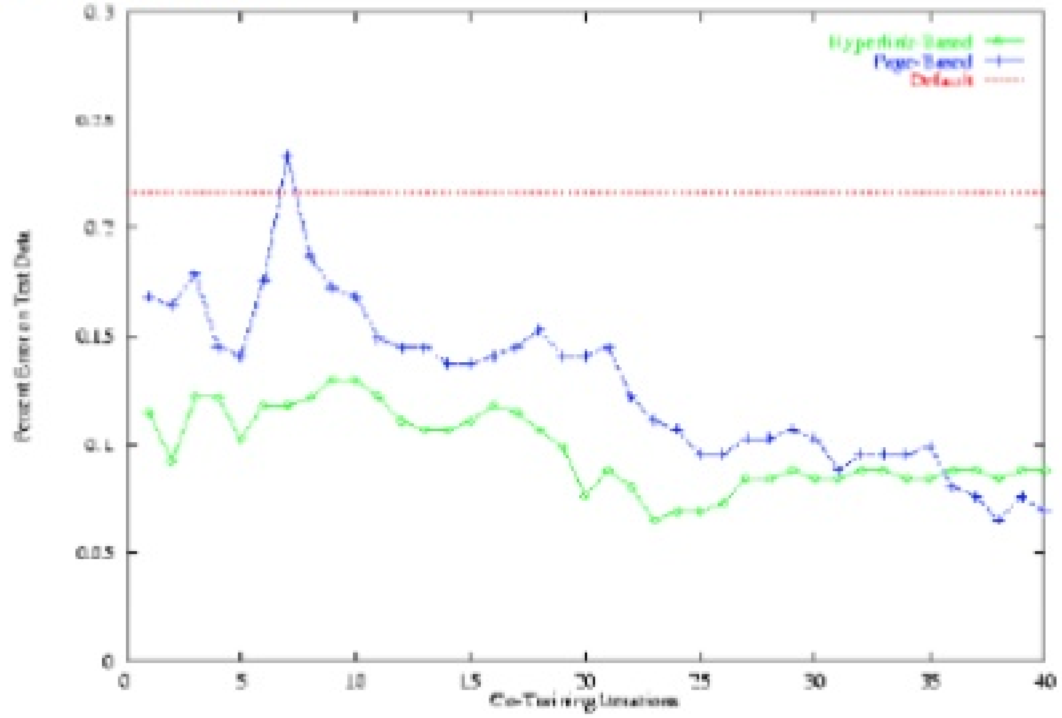
The Framework: Batch Component

CoTraining: Experimental Results

- begin with 12 labeled web pages (academic course)
- provide 1,000 additional unlabeled web pages
- average error: learning from labeled data 11.1%;
- average error: cotraining 5.0%

Typical run:



Semi-Supervised Learning
Edited by Olivier Chapelle, Bernhard Schölkopf and Alexander Zien
Learning from labeled and unlabeled data
Tom Mitchell, CMU

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The Framework: Batch Component

- Multiple Model Learning/ Co-training
  - Expandable learning modules: multiple learning algorithms
  - Co-training for high-dimensionality, improved confidence
  - Accounts for different biases across learning techniques to strengthen the hypothesis
  - Improves confidence estimates in practice
  - Yields better results when there is a significant diversity among the models.
  - Reduces variance and helps to avoid overfitting

The Framework: Batch Component

Given a model, m $\in \mathcal{M}$

$$y_m(x) = h(x) + \epsilon_m(x) \tag{4}$$

We can get the average error over all models, $E_{average}$

$$E_{average} = \frac{1}{\mathcal{M}} \sum_{m=1}^{\mathcal{M}} \mathbb{E}_x[\epsilon_m(x)^2] \tag{5}$$

Regression: Modal averaging sum of squares/ Prediction confidence

Multiple Model-Based Reinforcement Learning
Kenji Doya, Kazuyuki Samejima,Ken-ichi Katagiri and Mitsuo Kawato

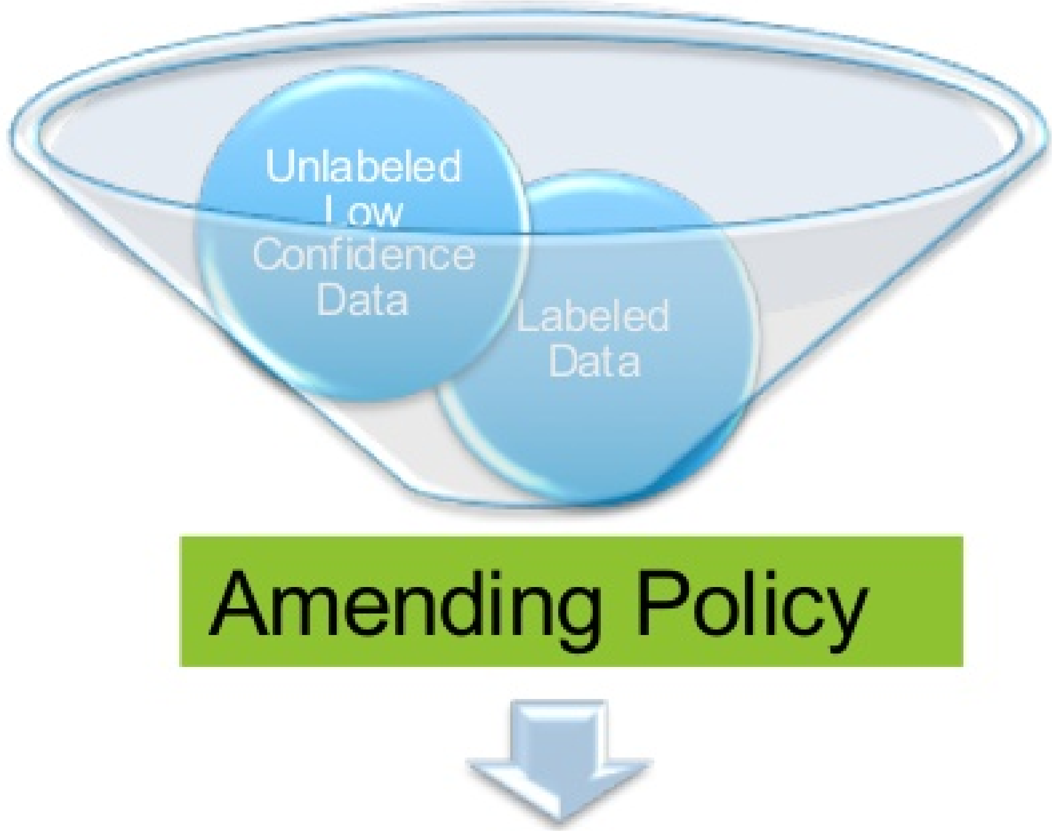
Vainsencher, Daniel, Shie Mannor, and Huan Xu. "Learning multiple models via regularized weighting." Advances in Neural Information Processing Systems. 2013.

The Framework: Batch Component

- Amending Policy
  - Instances are added sequentially and maintain order
  - Only the most 'confident' predictions are added
  - If validation is received, inaccurate predictions are removed and retrained (w/n a threshold)
  - Low confidence, unlabeled data are stored for future validation or rescoring

Avrim Blum and Tom Mitchell. 1998. Combining labeled and unlabeled data with co-training. In *Proceedings of the eleventh annual conference on Computational learning theory* (COLT' 98). ACM, New York, NY, USA, 92-100. DOI=http://dx.doi.org/10.1145/279943.279962

The Framework: Batch Component



Training Batch

Avrim Blum and Tom Mitchell. 1998. Combining labeled and unlabeled data with co-training. In *Proceedings of the eleventh annual conference on Computational learning theory* (COLT' 98). ACM, New York, NY, USA, 92-100. DOI=http://dx.doi.org/10.1145/279943.279962

The Framework: Batch Component

- Retrain Policy
  - Loss Minimization
    - Increases in expected loss above threshold
  - Accuracy
    - Ratio/Number of incorrect predictions
  - Schedule
    - Regular retraining schedule
  - Optimizations
    - Limited to a window over the given data set
      - Train over a specific time period to optimize for catastrophic events and concept shifts
    - Subsampling
      - Very large datasets can set a subsampling methodology to improve batch processing speed

The Framework: Batch Component

- What happens to low confidence predictions?
- Active Learning Policy
  - Separate dataset holds these instances
  - Human labeling and/or an oracle is queried for accurate labels

- Google has over 10,000 contractors performing this function
  - https://arstechnica.com/features/2017/04/the-secret-lives-of-google-raters/
- Facebook is hiring 3000 new content monitors for a job AI cannot do
  - http://www.popsci.com/Facebook-hiring-3000-content-monitors
- Netflix/Amazon are bringing in humans to improve the CTR recommendations
  - http://blog.echen.me/2014/10/07/moving-beyond-ctr-better-recommendations-through-human-evaluation/

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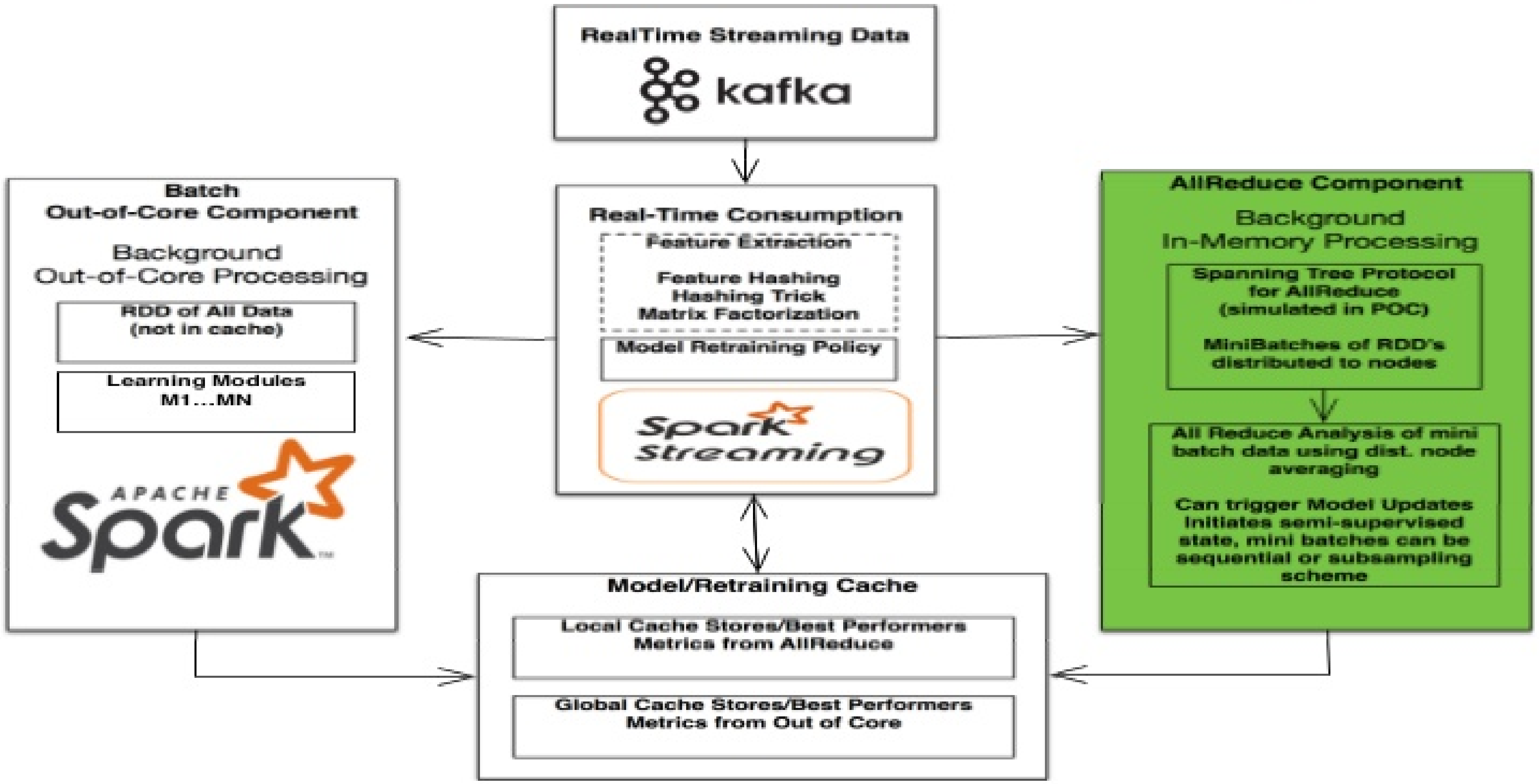
The Framework: Batch Component

- Custom Parameters:
  - Window Size
    - Specify a time or range
  - Amending times
    - Schedule when amending policy runs
    - Default is automated at accuracy rates
  - Loss threshold
    - Specify maximum loss for a given loss function
  - Accuracy threshold
    - Specify the precision/recall rates before retraining is called on batch
  - Subsampling
    - Run a random subsample to train

The Framework: All-Reduce Component



A Reliable Effective Terascale Linear Learning System
Alekh Agarwal, Olivier Chapelle, Miroslav Dudik, John Langford

The Framework: All-Reduce Component

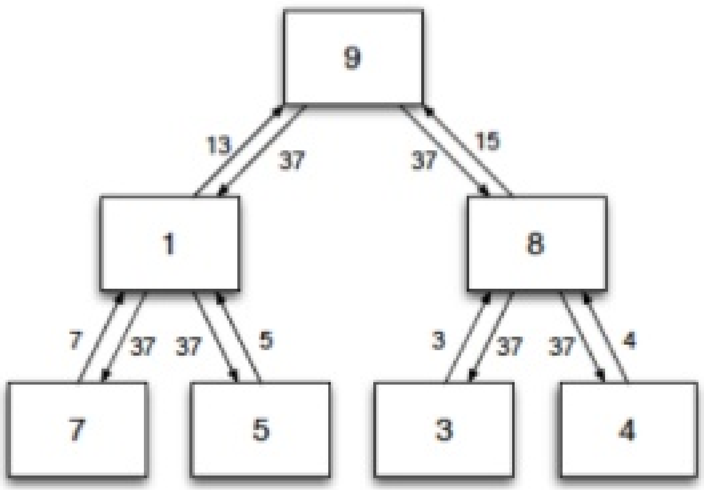


Figure 1: AllReduce operation. Initially, each node holds its own value. Values are passed up the tree and summed, until the global sum is obtained in the root node (reduce phase). The global sum is then passed back down to all other nodes (broadcast phase). At the end, each node contains the global sum.

- SGD/ LBFGS/Regression
- In-memory
- Minimal network latency
- Mini-batches of n/m for each nodes
- Head nodes holds an average of the weight parameters
- Can be added to existing implementations to optimize for online training

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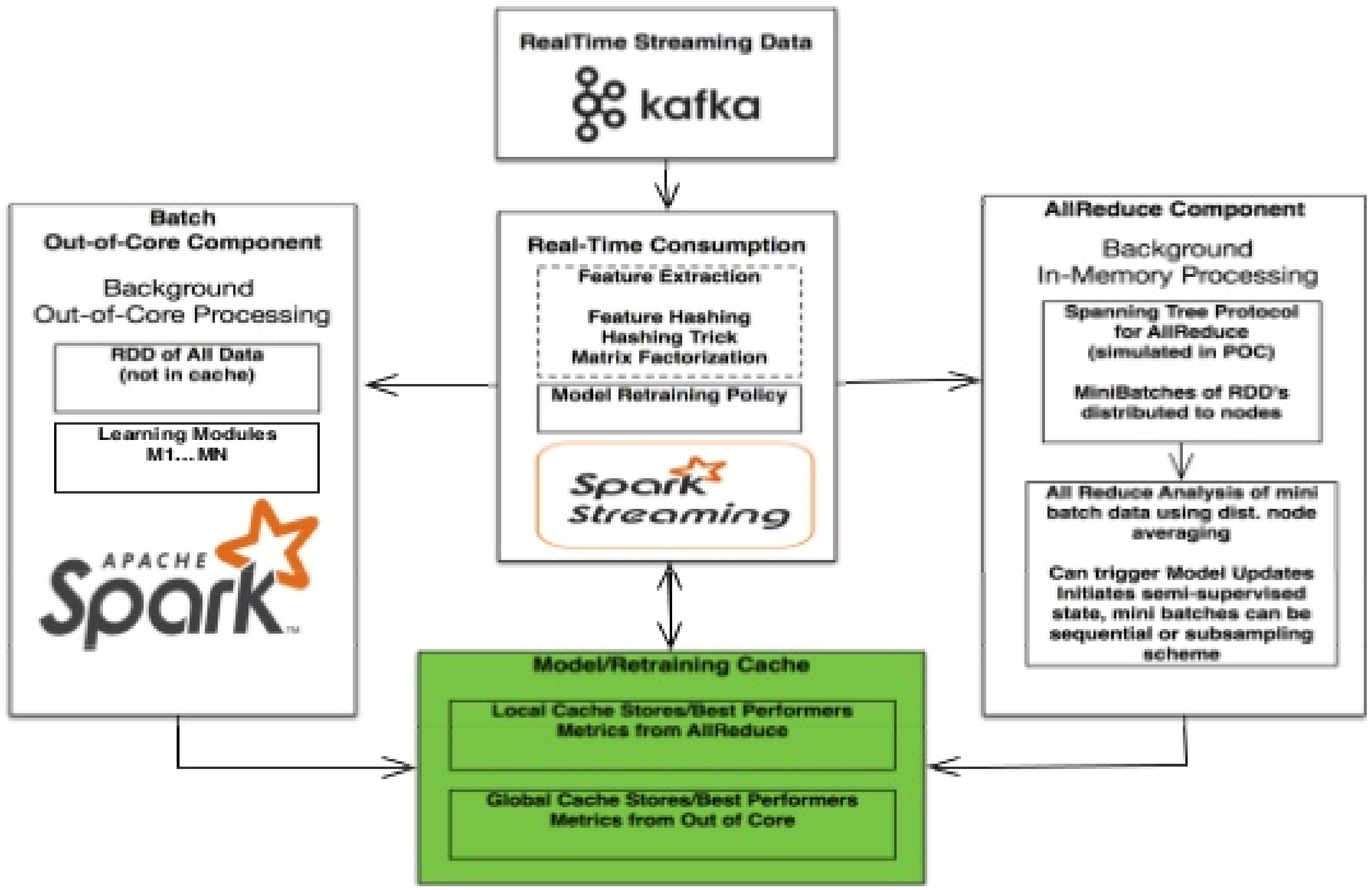
The Framework: Cache Component

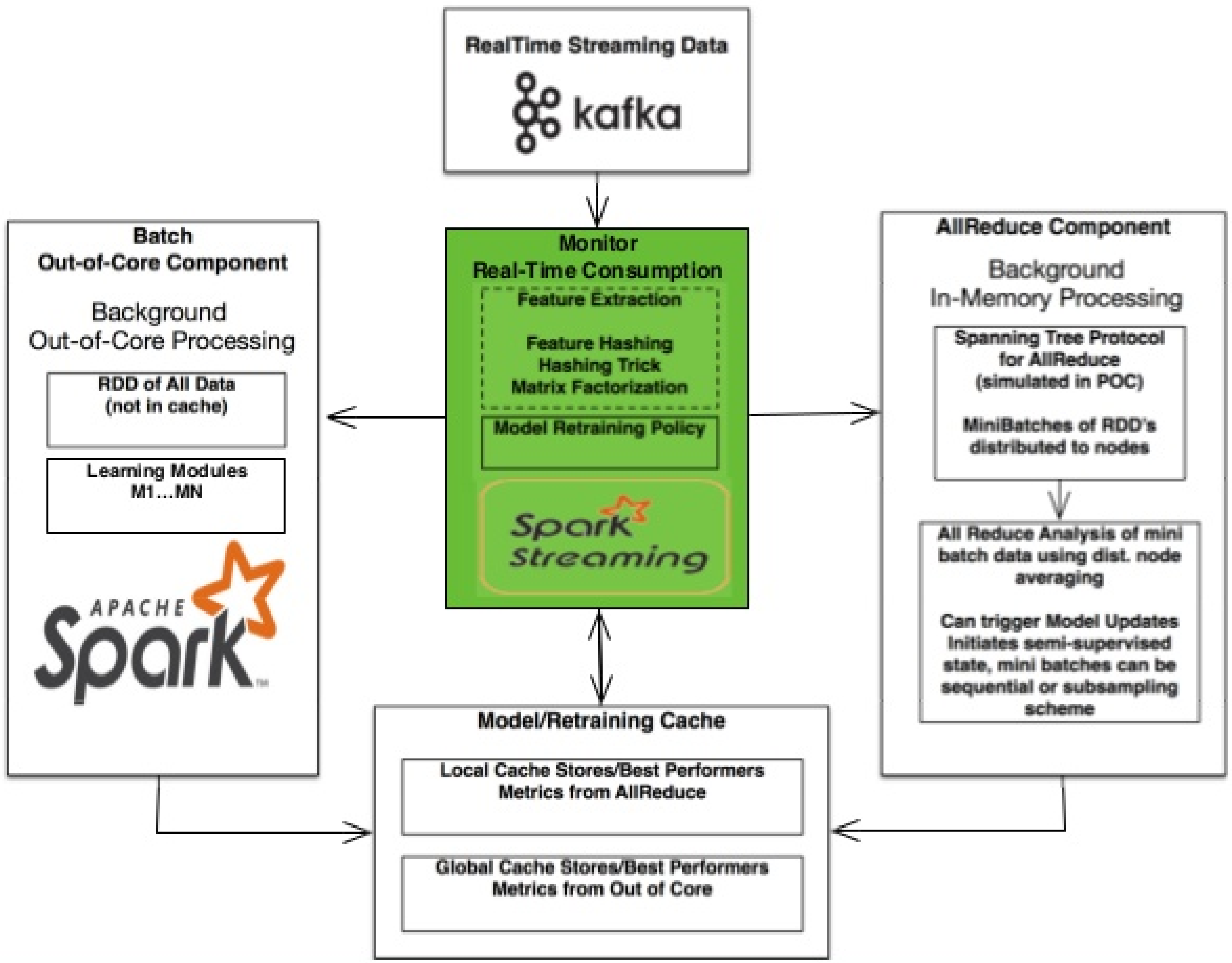


Bringing it all together…

The Framework: Cache Component

- Model Weights & Loss
- Custom Parameters
- When a the retraining policy is triggered in the monitor
  - A new best performing weight vector is selected from the cache
  - The running model weights are updated and used in real-time predictions

The Framework: Monitor Component



The Framework: Monitor Component

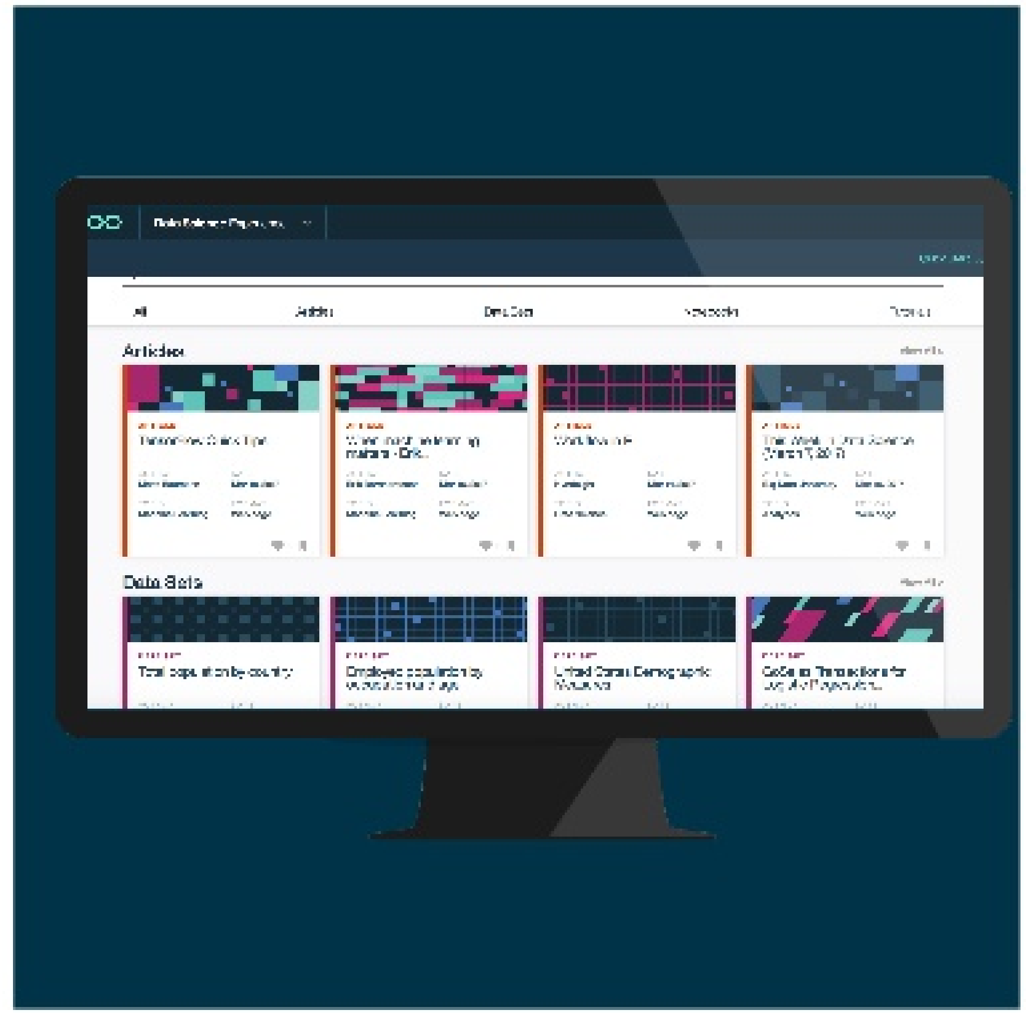
- Retraining in All-Reduce happens after each online pass
- Option 1: Makes real-time prediction with only local latency when initiated (Model Retrain Policy)
  - very low latency
  - stable predictions
  - Significant change in weights since last pass
  - Loss Minimization
    - Increases in expected loss above threshold
  - Accuracy

- Option 2: Can opt to use All-Reduce weights after the online pass
  - Low Latency
  - Greater sensitivy
  - Periodic queries to cache fro best weights (Model Retrain Policy)

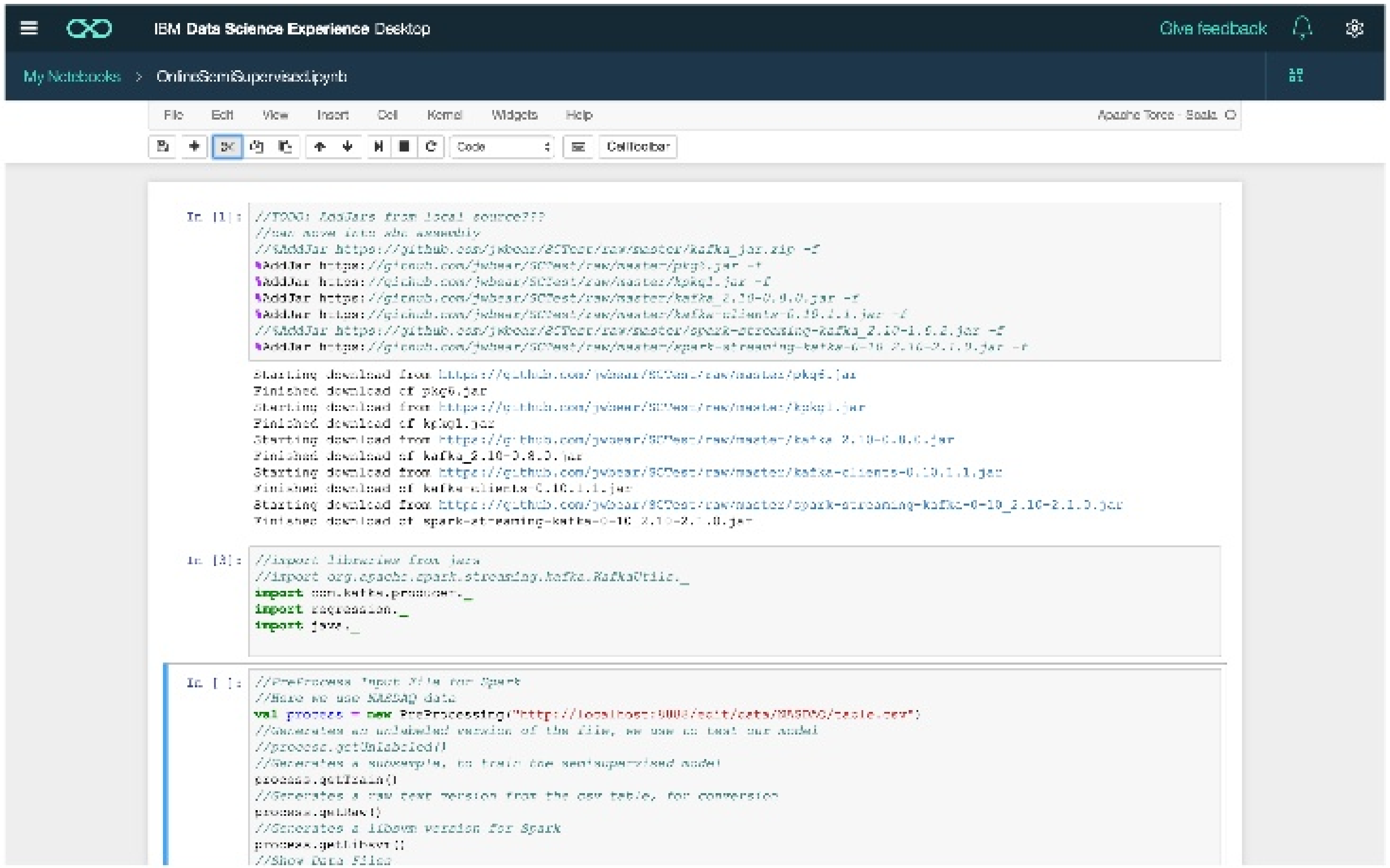
Performance: IBM's Data Science Experience

IBM Data Science Experience is an environment that brings together everything that a Data Scientist needs.

It includes the most popular **Open Source tools** such as Code in Scala/Python/R/SQL, Jupyter Notebooks, RStudio IDE and Shiny apps, Apache Spark and IBM unique value-add functionalities with community and social features, integrated as a first class citizen to make Data Scientists more successful.



Performance: IBM's Data Science Experience



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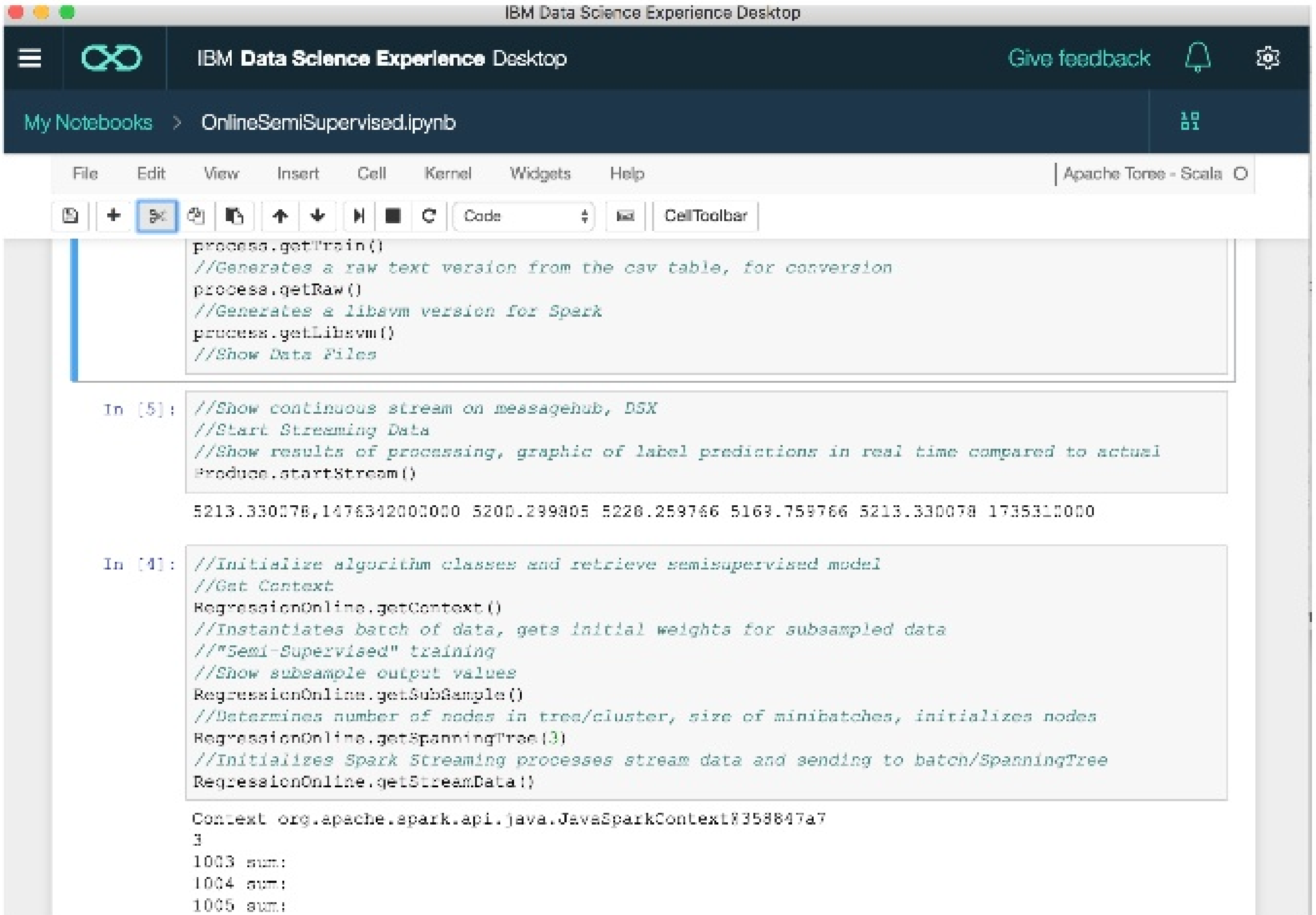
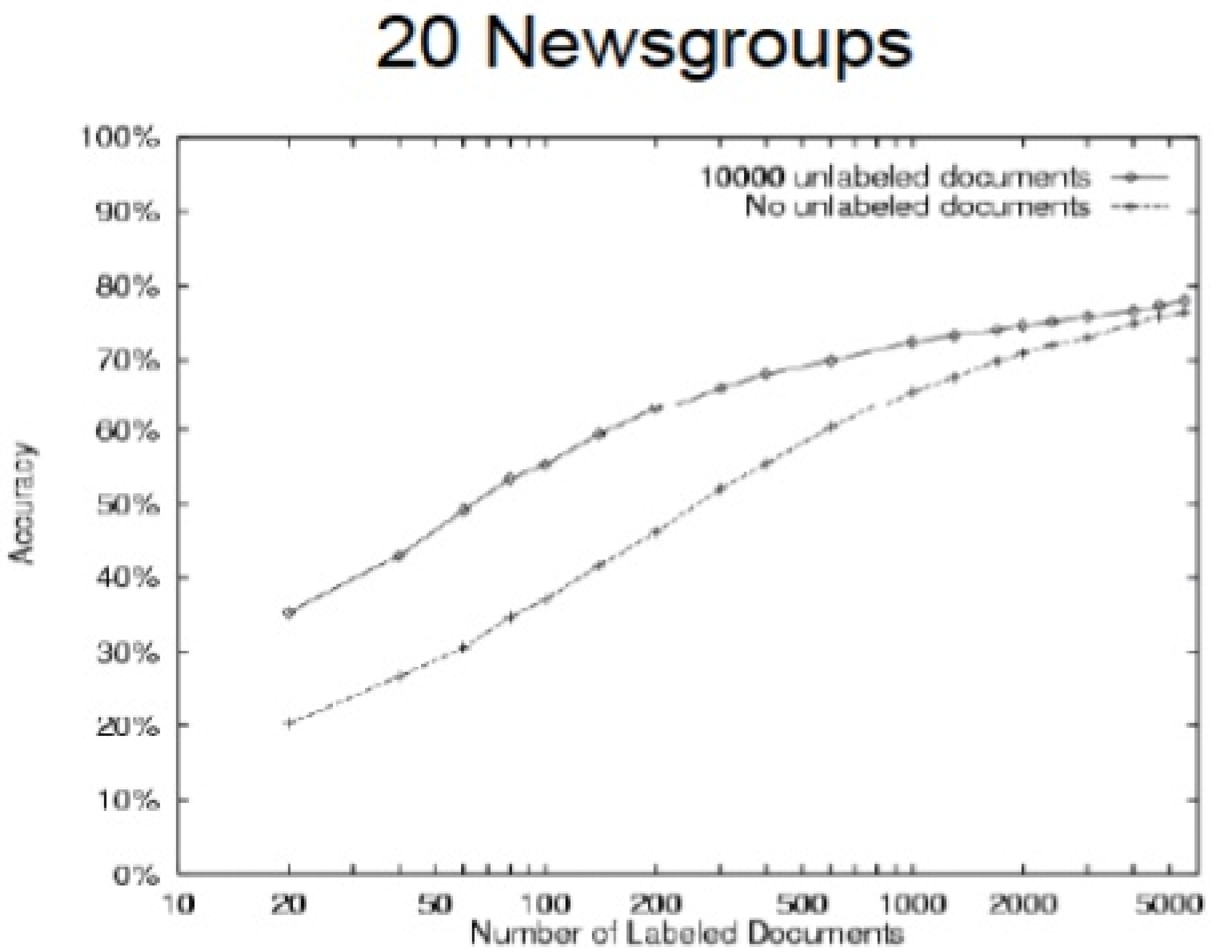
Performance: IBM's Data Science Experience



Performance: Accuracy Gains



Important question! In many cases, unlabeled data is plentiful, labeled data expensive

- Medical outcomes (x=<symptoms,treatment>, y=outcome)
- Text classification (x=document, y=relevance)
- Customer modeling (x=user actions, y=user intent)
- Sensor interpretation (x=<video,audio>, y=who's there)

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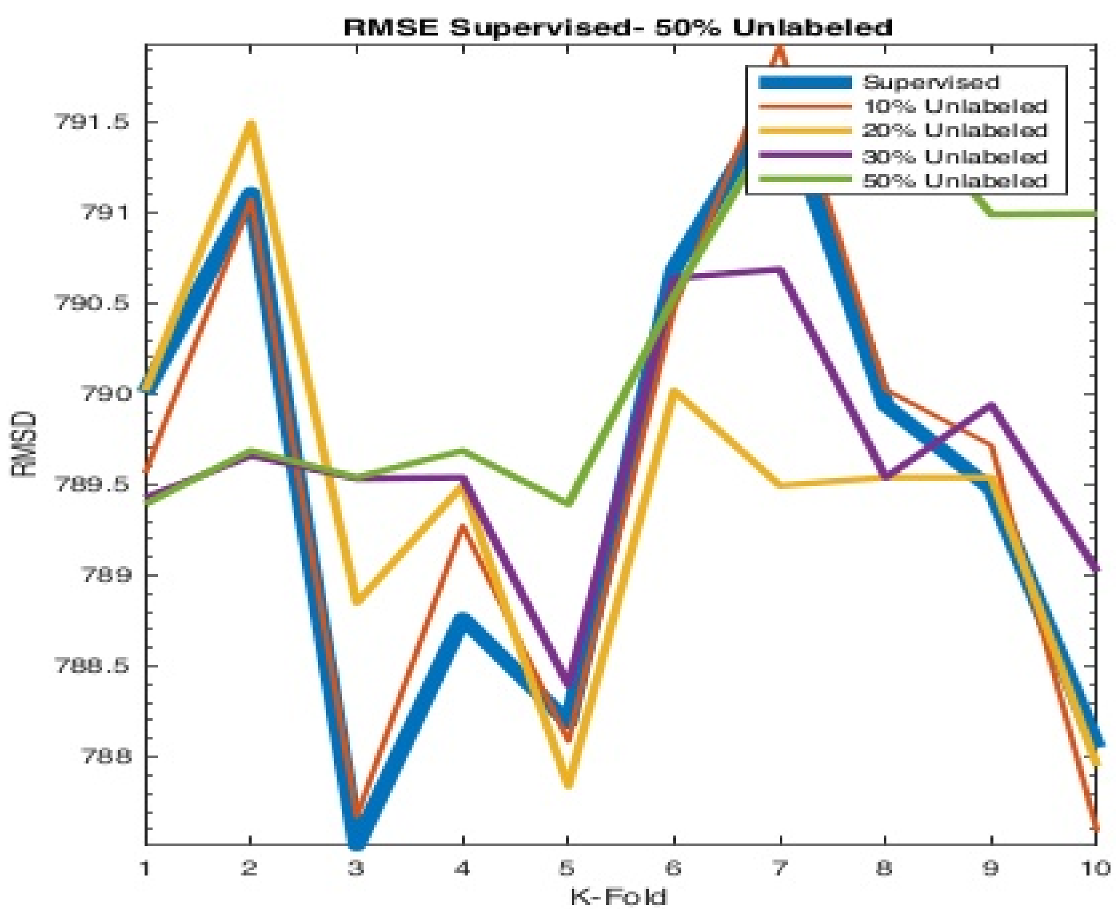
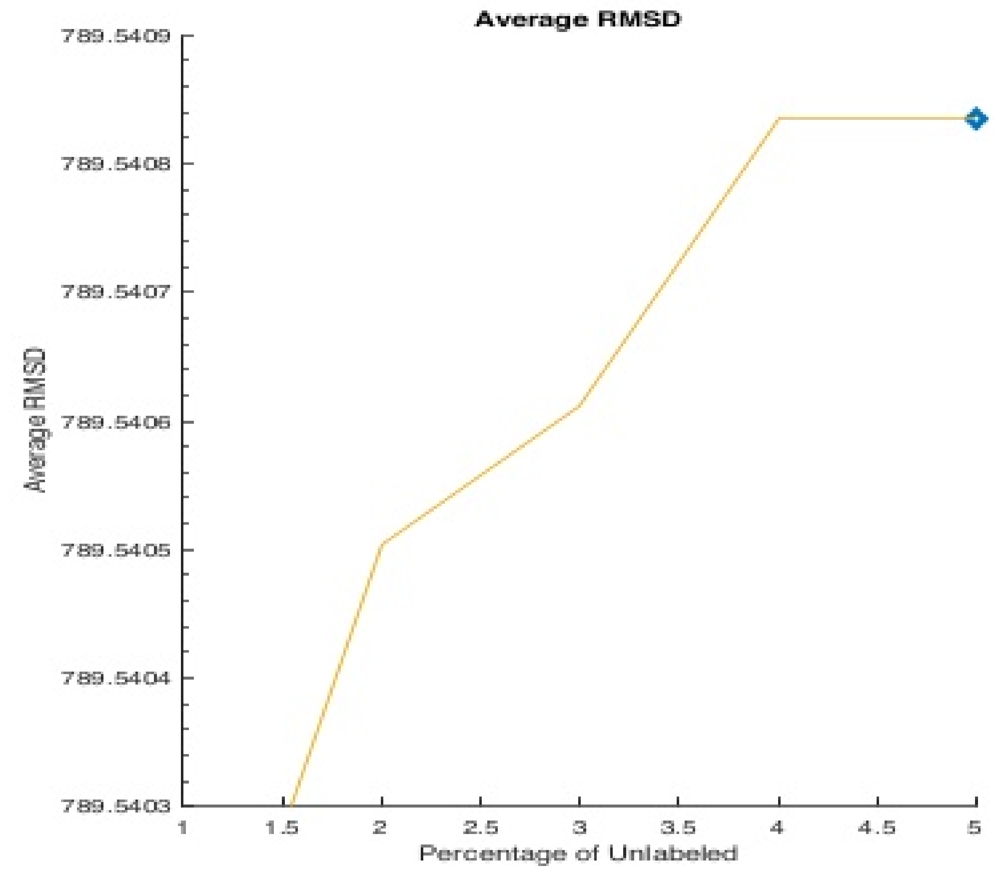
Performance: NASDAQ

- NASDAQ Data
  - Daily stock market values since 1971; ~50K instances
  - Features (excerpt)
    - Date, Open, High, Low, Close ,Volume, Adj Close
  - Fully Labeled, y = close
  - k fold cross validation
  - Regression

Performance (1): Linear Regression





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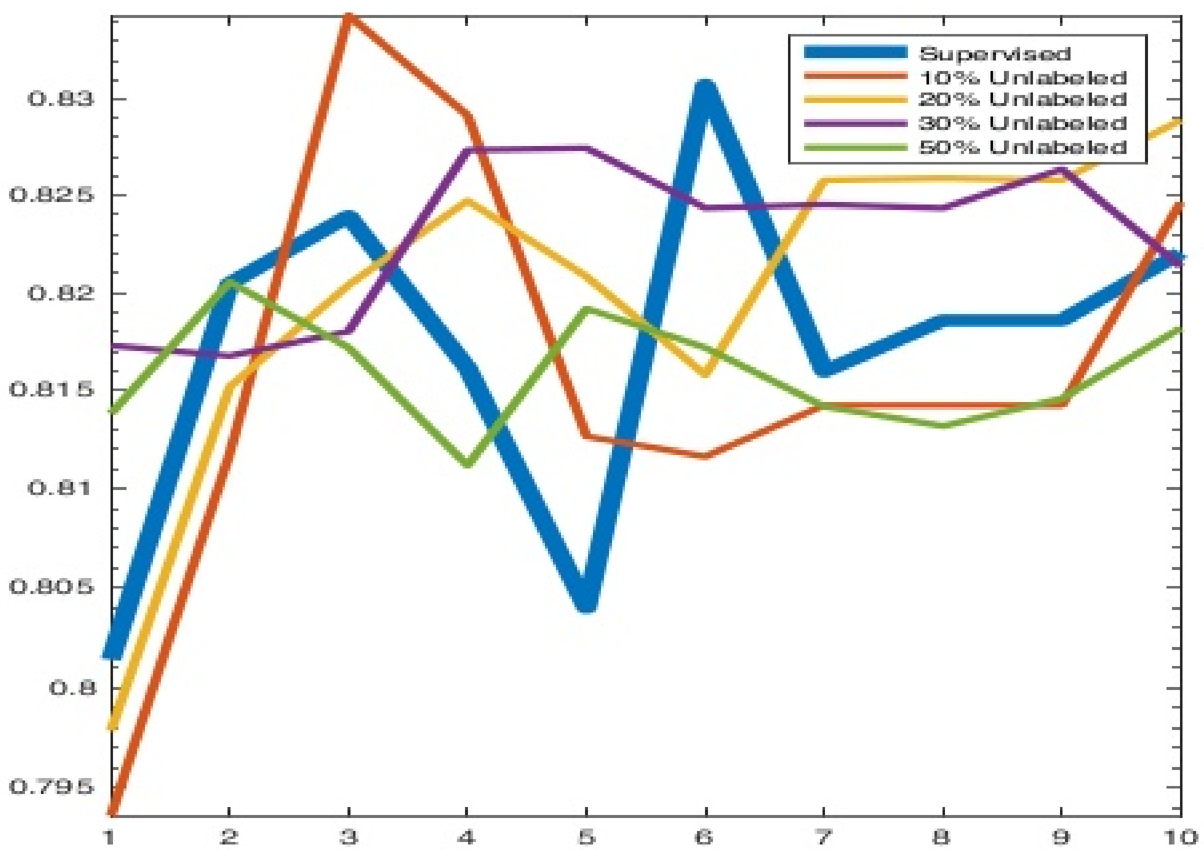
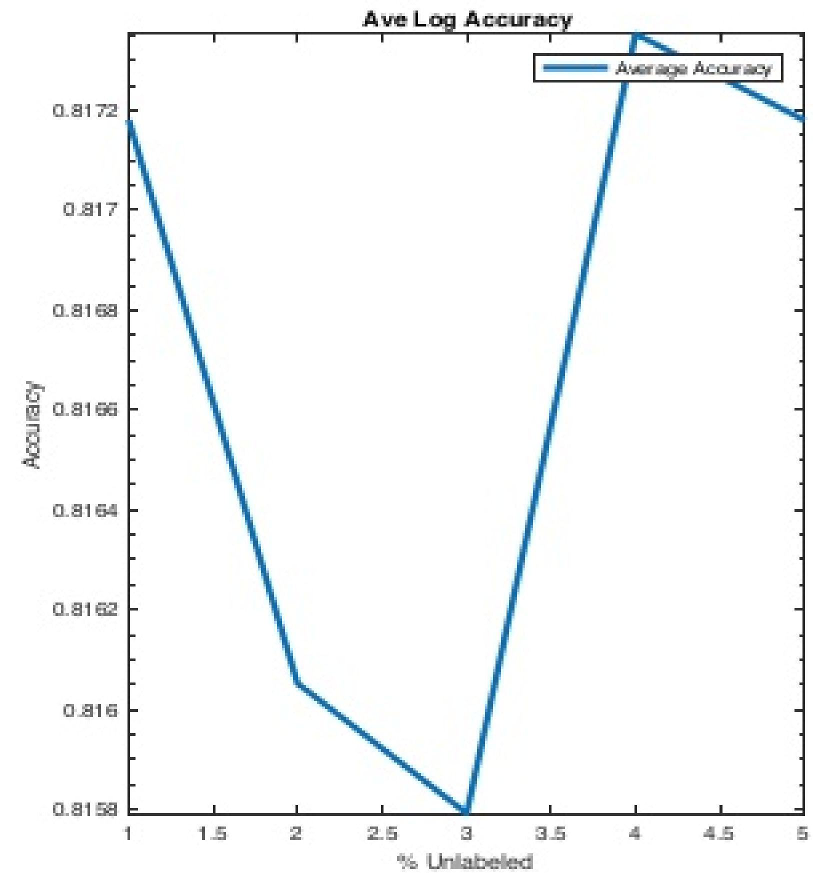
Performance (1A): Classification





Performance (2): Online & Semi-Supervised

- HealthStats provides key health, nutrition and population statistics gathered from a variety of international sources
- Global Health Data since1960; ~100K instances
  - Features (excerpt)
    - This dataset includes 345 indicators, such as immunization rates, malnutrition prevalence, and vitamin A supplementation rates across 263 countries around the world. Data was collected on a yearly basis from 1960-2016.Fully Labeled, y = close
  - k fold cross validation
  - Classification

Performance (3): Online Semi-Supervised Learning

- IBM Employee Attrition and Performance
  - Uncover the factors that lead to employee attrition
  - Features (excerpt)
    - Education 1 'Below College' 2 'College' 3 'Bachelor' 4 'Master' 5 'Doctor'EnvironmentSatisfaction 1 'Low' 2 'Medium' 3 'High' 4 'Very High'JobInvolvement 1 'Low' 2 'Medium' 3 'High' 4 'Very High'JobSatisfaction 1 'Low' 2 'Medium' 3 'High' 4 'Very High'PerformanceRating 1 'Low' 2 'Good' 3 'Excellent' 4 'Outstanding'RelationshipSatisfaction 1 'Low' 2 'Medium' 3 'High' 4 'Very High'WorkLifeBalance 1 'Bad' 2 'Good' 3 'Better' 4 'Best'Fully Labeled
  - k fold cross validation
  - Classification

Future Work

- More complex real-time data sets
- Real-Time Streaming and Semi-Supervised Learning for Autonomous Vehicles
- IoT and the Autonomous Vehicle in the Clouds: Simultaneous Localization and Mapping (SLAM) with Kafka and Spark Streaming (Spark Summit East 2017)
- Full Framework!!!

Future Work

- Improving Batch retraining policy to incorporate more information about the distributions of data
- Investigating model switching vs retraining
- Adding boosting mechanisms in batch
- Adding feature extraction for high dimensionality
- Expansion of Spark Streaming ML algorithms

Further Reading

A Reliable Effective Terascale Linear Learning System
Alekh Agarwal, Olivier Chapelle, Miroslav Dudik, John Langford

The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition (Springer Series in Statistics) 2nd Editionby Trevor Hastie (Author), Robert Tibshirani (Author), Jerome Friedman

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Thank You.

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