Streaming Machine Learning Algorithms with Big Data Systems

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Motivation

- Data volume generated per day is increasing in a very high rate.
- Low latency is a must for increasing consumer demand on various services.
- Existing batch algorithms need to be optimized for online learning.
- Machine learning algorithms have become very important when formulating most of the supervised learning problems with less computing power.
How to design Streaming Machine Learning algorithms?

- Simply need to do train a machine learning algorithm in real-time without storing a large batches of data.
- Some algorithms can be trained by just observing a datapoint only once.
  - **Initialization stage**: Observe a number of data points (K elements at least if it is a clustering problem, depending on the algorithm this must be well-defined).
  - **Model Evaluation**: Calculate a gradient or model value for the observed elements.
  - **Model Synchronization**: Synchronize the model value across all the processes when using distributed training.
  - Re-do the whole process per element after the initialization stage.
- Some algorithms need an iterative streaming algorithm to ensure the accuracy to be in an expected level.
  - **Model evaluation**: Here we observe \( w \) number of elements by formulating a window in a stream and do an iterative computation on it for \( t \) iterations. Here \( t \ll T \), \( T \) refers to the number of iterations required in batch mode to compute the optimum model.
Convergence of HPC and Big Data

Objective

- Design low-latency training on big data systems and identifying effective systems for online training
- Provide API solutions to design streaming applications on both HPC and dataflow programming models.
- Evaluate the importance of HPC frameworks for strengthening the big data stack for intensive computations.
Streaming Machine Learning Algorithms

- **Non-Iterative Setting**
  - KMeans Clustering

- **Iterative Setting**
  - Support Vector Machine (Linear Kernel for Binary classification)
Streaming SVM

Algorithm 1 Iterative SGD SVM
1: \textbf{INPUT:} \([x, y] \in S, w \in R^d, t \in R^+\)
2: \textbf{OUTPUT:} \(w \in R^d\)
3: \textbf{procedure} ISGDSVM\((S, w, t)\)
4: \hspace{1em} \textbf{for} \(i = 0\) to \(n\) \textbf{do}
5: \hspace{2em} \textbf{if} \((g(w; (x_i, y_i)) == 0)\) \textbf{then}
6: \hspace{3em} \(\nabla J^t = w\)
7: \hspace{2em} \textbf{else}
8: \hspace{3em} \(\nabla J^t = w - C x_i y_i\)
9: \hspace{1em} \(w = w - \alpha \nabla J^t\)
10: \textbf{return} \(w\)

Algorithm 2 Iterative Streaming SVM
1: \textbf{INPUT:} \(X_\infty, Y_\infty \in S_\infty, w \in R^d, l \in R^+, s \in R^+, m < K, m \in R^+\)
2: \textbf{OUTPUT:} \(w \in R^d\)
3: \textbf{procedure} ISSVM\((\tilde{S}_i, w, T, l, s)\)
4: \hspace{1em} \textbf{In Parallel K Machines} \([\tilde{S}_1, \ldots, \tilde{S}_b] \subset S_\infty\)
5: \hspace{1em} \textbf{procedure} \textsc{Window}\((\tilde{S}_m, w, l, s)\)
6: \hspace{2em} \textbf{for} \(t = 0\) to \(T\) \textbf{do}
7: \hspace{3em} \textbf{procedure} ISGDSVM\((\tilde{S}_m, w, t)\)
8: \hspace{1em} \textbf{All Reduce}(w)
9: \textbf{return} \(w\)
Streaming KMeans

Algorithm 3 Online KMeans

1: INPUT: $X = \{x_1, ..., x_m\}; x_i \in \mathbb{R}^m$
2: $V = \{v_1, ..., v_k\} v_i \in \mathbb{R}^m, k \leq n$
3: OUTPUT: $V$
4: procedure STREAMING-KMEANS($X, V$)
5:     procedure WINDOW($\bar{X}, \bar{V}$)
6:         for $x_j$ in $\bar{X}$ do
7:             if $j \leq k$ then
8:                 $v_i = x_j$
9:                 $k_i = 1$
10:                $i = i + 1$
11:            else
12:                $v_i = \arg\min_i ||x_j - v_i||$
13:                $v_i = v_i + \frac{1}{n_i + 1}[x_j - v_i]$
14:                $n_i = n_i + 1$
15:         All_Reduce(V)
return $V$
Discretization of a Stream
Tumbling Windows
Sliding Windows
Workflow of a Streaming ML Algorithm

1. **Data Source**
2. **Source Task**
   - Pre-Process Data
   - Do Stream Data
3. **Window Compute Task**
   - Generate Mini-Batches
   - Do Iterative Computation
4. **Sink Task**
   - Receive Computed Data
   - Do Evaluation on Models

**Hyperparameters**
- Window Length
- Sliding Length
- Window Type
- Iterations
# Streaming Platforms

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Apache Storm v1.2.8
Apache Flink v1.9.0
Twister2 v0.3.0
Experiment Configuration

- Intel(R) Xeon(R) Platinum 8160 CPU @ 2.10 GHz (250 GB RAM)
- Streaming SVM: Binary Classification on 49K long stream for training and 90K sample for model testing.
- Streaming KMeans: Clustering 1000 centroids, 49K long stream for training.
- 8 Physical nodes each with 16 processes (128 parallelism).
- Use count-based window setting to do a stress test on each big data framework used.
Streaming SVM

Tumbling Windowing

Sliding Windowing

*5,10 refers to sliding length, window length.
Obtained after experimenting with different configs towards optimum results obtained in batch mode.
Streaming KMeans

*5,10 refers to sliding length, window length. Obtained after experimenting with different configs towards optimum results obtained in batch mode.
Conclusions and Future Work

● Windowing APIs are vital for designing iterative streaming applications.
● High performance computing model can be adopted in Big Data frameworks to provide better performance for streaming applications.
● Experimenting with a larger data stream (minimum of 1 Million of more data points per a job)
● Structured data streaming with stream discretization.
● Expanding experiment configurations for testing window config sensitivity on algorithm convergence.
● Scaling for a bigger experiment setting (1024+ cores)
● Extending experiments for more machine learning algorithms.
Thank you

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