Big-data Machine Learning

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Outline

1. Introduction
2. Algorithms for distributed data analytics
3. Discussion and conclusions

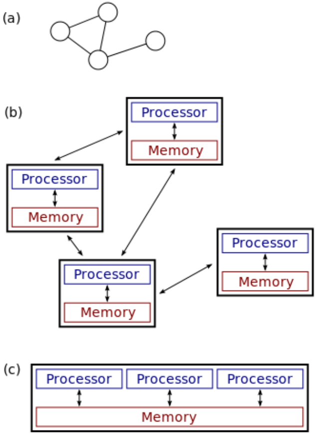
Outline

Big Data

- People talk about volume, velocity, variety, value and veracity
- All are important, but today we will focus on volume

Big-data Machine Learning

- We consider the situation that data are larger than the capacity of a computer
- So in a sense we are talking about distributed data mining or machine learning
- Today we won't talk about things such as GPU-based machine learning



(a), (b): distributed systems

Image from Wikimedia

From Small to Big Data

Two important differences:

Negative side:

- Methods for big data analytics are not quite ready, not even mentioned to integrated tools

Positive side:

- Some (Halevy et al., 2009) argue that the almost unlimited data make us easier to mine information

I will discuss the first difference

Possible Advantages of Distributed Data Analytics

Parallel data loading

- Reading several TB data from disk is slow
- Using 100 machines, each has $1/100$ data in its local disk $\Rightarrow$ $1/100$ loading time
- But having data ready in these 100 machines is another issue

Fault tolerance

- Some data replicated across machines: if one fails, others are still available

Possible Advantages of Distributed Data Analytics (Cont'd)

Workflow not interrupted

- If data are already distributedly stored, it's not convenient to reduce some to one machine for analysis

Possible Disadvantages of Distributed Data Analytics

- More complicated (of course)

  Note that you can always subsample data to one machine for deep analysis
- Communication and synchronization

  Everybody says moving computation to data, but this isn't that easy

Going Distributed or Not Isn't Easy to Decide

- Quote from Yann LeCun (KDnuggets News 14:n05)
  "I have seen people insisting on using Hadoop for datasets that could easily fit on a flash drive and could easily be processed on a laptop."
- Now disk and RAM are large. You may load several TB of data once and conveniently conduct all analysis
- The decision is application dependent

Challenges in Distributed Environments

We must consider

- Computation time
- Loading time
- Communication/synchronization time

In the past, we focus only on the computation time

Loading time

We use the following example to illustrate that computation time is not the only concern

- Using a linear classifier LIBLINEAR (Fan et al., 2008) to train the rcv1 document data sets (Lewis et al., 2004).
- # instances: 677,399, # features: 47,236
- On a typical PC: Total time: 50.88 seconds. Loading time: 43.51 seconds

In fact, 2 seconds are enough to get stable test accuracy

loading time $\gg$ running time

Loading Time (Cont'd)

- To see why this happens, let's discuss the complexity
- Assume the memory hierarchy contains only disk and number of instances is l
- Loading time: $l \times$ (a big constant)

  Running time: $l^q \times$ (some constant), where $q \geq 1$.
- Traditionally running time is larger because of using nonlinear algorithms (i.e., $q > 1$)
- But when l is large, we may use a linear algorithm (i.e., $q = 1$) for efficiency $\Rightarrow$ loading time may dominate

Small Analysis versus Big Analysis

- Big data, small analysis

  versus

  Big data, big analysis
- If you need a single record from a huge set, it's reasonably easy
- For example, accessing your high-speed rail reservation is fast
- However, if you want to analyze the whole set by accessing data several time, it can be much harder

Outline

1. Introduction
2. Algorithms for distributed data analytics
   - Example: a distributed Newton method for logistic regression
   - Other existing implementations
   - Successful applications
3. Discussion and conclusions

Existing Algorithms on One Machine

- Most existing data mining/machine learning methods were designed without considering data access and communication of intermediate results
- They iteratively use data by assuming they are readily available
- Example: doing least-square regression isn't easy in a distributed environment

Algorithms for Distributed Data Analytics

This is an on-going research topic.

Roughly there are two types of approaches

1. Parallelize existing (single-machine) algorithms
2. Design new algorithms particularly for distributed settings

Of course there are things in between

Outline

Logistic Regression

- Training data $\{y_i, \boldsymbol{x}_i\}, \boldsymbol{x}_i \in R^n, i = 1, \ldots, l, \; y_i = \pm 1$
- l: # of data, n: # of features
- Regularized logistic regression

$$\min_{\boldsymbol{w}} f(\boldsymbol{w}),$$

where

$$f(\boldsymbol{w}) = \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{l} \log\left(1 + e^{-y_i \boldsymbol{w}^T\boldsymbol{x}_i}\right).$$

- C: regularization parameter decided by users
- Twice differentiable, so we can use Newton methods

Newton Methods

- Newton direction

$$\min_{\boldsymbol{s}} \quad \nabla f(\boldsymbol{w}^k)^T \boldsymbol{s} + \frac{1}{2}\boldsymbol{s}^T \nabla^2 f(\boldsymbol{w}^k)\boldsymbol{s}$$

- This is the same as solving Newton linear system

$$\nabla^2 f(\boldsymbol{w}^k)\boldsymbol{s} = -\nabla f(\boldsymbol{w}^k)$$

- Hessian matrix $\nabla^2 f(\boldsymbol{w}^k)$ too large to be stored

$$\nabla^2 f(\boldsymbol{w}^k) : n \times n, \quad n : \text{ number of features}$$

- But Hessian has a special form

$$\nabla^2 f(\boldsymbol{w}) = \mathcal{I} + CX^T DX,$$

Newton Methods (Cont'd)

- X: data matrix. D diagonal with

$$D_{ii} = \frac{e^{-y_i \boldsymbol{w}^T \boldsymbol{x}_i}}{(1 + e^{-y_i \boldsymbol{w}^T \boldsymbol{x}_i})^2}$$

- Using Conjugate Gradient (CG) to solve the linear system. Only Hessian-vector products are needed

$$\nabla^2 f(\boldsymbol{w})\boldsymbol{s} = \boldsymbol{s} + C \cdot X^T(D(X\boldsymbol{s}))$$

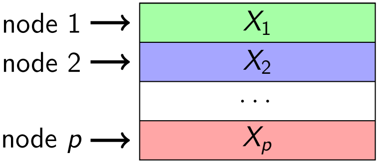
- Therefore, we have a Hessian-free approach
- Other details; see Lin et al. (2008) and the software LIBLINEAR

Parallel Hessian-vector Product

- Hessian-vector products are the computational bottleneck

$$X^TDX\boldsymbol{s}$$

- Data matrix X is now distributedly stored



$$X^TDX\boldsymbol{s} = X_1^TD_1X_1\boldsymbol{s} + \cdots + X_p^TD_pX_p\boldsymbol{s}$$

Distributed LIBLINEAR

- The above method is now available as an extension of the software LIBLINEAR
- See `http://www.csie.ntu.edu.tw/~cjlin/libsvmtools/distributed-liblinear`
- We support both MPI and Spark
- The development is still in an early stage.

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Vowpal_Wabbit (Langford et al., 2007)

- It started as a linear classification package on a single computer
- After version 6.0, Hadoop support has been provided
- A hybrid approach: parallel stochastic gradient initially and switch to LBFGS (quasi Newton)
- In Agarwal et al. (2014), they train 17B samples with 16M features on 1K nodes by 10 passes $\Rightarrow$ 70 minutes

Sibyl from Google

- Based on the algorithm in Collins et al. (2002)
- Idea:

$$f(\boldsymbol{w}) \approx A(\boldsymbol{w}) = \sum_{i=1}^{n} A_i(w_i)$$

Minimize

$$A_i(w_i), \forall i$$

in parallel

Outline

Example of Distributed Machine Learning

- Computational advertising (in particular, click-through rate prediction) is an area that heavily uses distributed linear classification

  We will explain what CTR prediction is
- See also applications mentioned in Google's Sibyl talk

Example: CTR Prediction

- Definition of CTR:

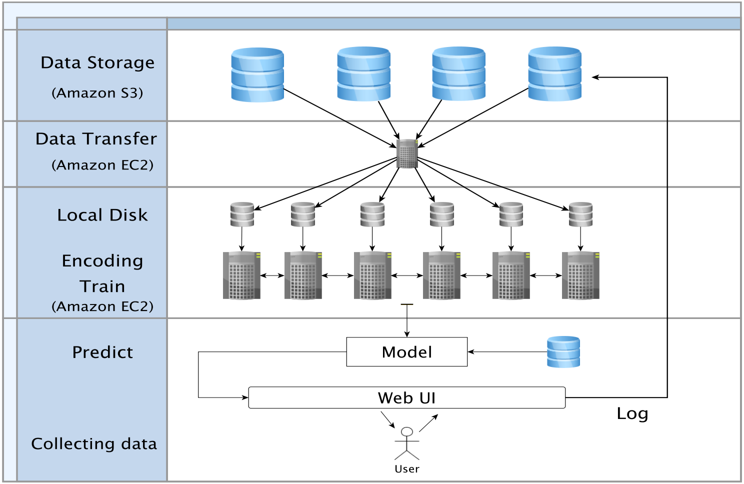
$$\text{CTR} = \frac{\#\ \text{clicks}}{\#\ \text{impressions}}.$$

- A sequence of events

Not clicked	Features of user
Clicked	Features of user
Not clicked	Features of user
...	...

- A binary classification problem.

Example: CTR Prediction (Cont'd)



Outline

Design Considerations for Distributed Training

- On one computer, often we do batch rather than online learning

  Online and streaming learning may be more useful for big-data applications
- The example (Newton method) we showed is a synchronous parallel algorithms

  Maybe asynchronous ones are better for big data?

System Issues

- Platforms are still being actively developed. We must check technical details
- Example: in developing distributed Newton methods on Spark (an in-memory cluster-computing platform), we must consider details of
  - Spark
  - Scala
- For example, you want to know
  - the difference between **mapPartitions** and **map** in Spark, and
  - the slower **for** loop than **while** loop in Scala

Workflow Issues

- Data analytics is often only part of the workflow of a big-data application
- By workflow, I mean things from raw data to final use of the results
- Other steps (e.g., feature generation or data movements) may be more complicated or more time consuming than the analytics step

Open-source Developments

- Open-source developments are very important for big data analytics
- How it works:

  The company must do an application X. They consider an open-source tool Y. But Y is not enough for X. Then their engineers improve Y and submit pull requests
- Through this process, core developers of a project are formed. They are from various companies

Conclusions

- Big-data machine learning is in its infancy
- It's challenging to development algorithms and tools in a distributed environment
- To start, we should take algorithms, systems, and applications together into consideration
- Hopefully we will get some breakthroughs in the near future