Distributed Data Classification

Chih-Jen Lin
Department of Computer Science
National Taiwan University

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Outline

1. Introduction: why distributed classification
2. Example: a distributed Newton method for logistic regression
3. Discussion from the viewpoint of the application workflow
4. Conclusions

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2. Example: a distributed Newton method for logistic regression
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4. Conclusions

Why Distributed Data Classification?

- The usual answer is that data are too big to be stored in one computer
- However, we will show that the whole issue is more complicated

Let's Start with An Example

- 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

  ```
  $time ./train rcv1_test.binary
  ```
- Total time: 50.88 seconds

  Loading time: 43.51 seconds

- For this example

$$\text{loading time} \gg \text{running time}$$

- In fact, two seconds are enough $\Rightarrow$ test accuracy becomes stable

Loading Time Versus Running Time

- 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 $q \geq 1$.
- Running time is often larger than loading because $q > 1$ (e.g., $q = 2$ or 3)

  Example: kernel methods

Loading Time Versus Running Time (Cont'd)

- Therefore,
$$l^{q-1} > \text{ a big constant}$$
and traditionally machine learning and data mining papers consider only running time
- When l is large, we may use a linear algorithm (i.e., $q = 1$) for efficiency

Loading Time Versus Running Time (Cont'd)

- An important conclusion of this example is that computation time may not be the only concern

  - If running time dominates, then we should design algorithms to reduce number of operations

  - If loading time dominates, then we should design algorithms to reduce number of data accesses
- This example is on one machine. Situation on distributed environments is even more complicated

Possible Advantages of Distributed Data Classification

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 moving data to these 100 machines may be difficult!

Fault tolerance

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

Possible Disadvantages of Distributed Data Classification

- More complicated (of course)
- 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

Outline

Logistic Regression

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

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

where

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

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

Newton Methods

- Newton direction

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

- This is the same as solving Newton linear system

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

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

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

- But Hessian has a special form

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

Newton Methods (Cont'd)

- X: data matrix. D diagonal with

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

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

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

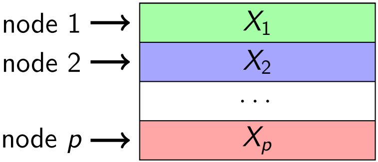
- Therefore, we have a Hessian-free approach
- Other details; see Lin et al. (2008) and the software LIBLINEAR

Parallel Hessian-vector Product

- Hessian-vector products are the computational bottleneck

$$X^T D X \mathbf{s}$$

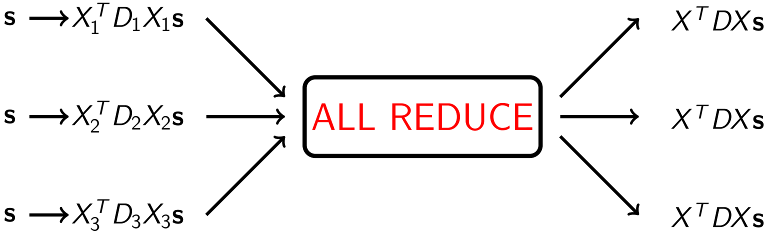
- Data matrix X is now distributedly stored



$$X^T D X \mathbf{s} = X_1^T D_1 X_1 \mathbf{s} + \cdots + X_p^T D_p X_p \mathbf{s}$$

Parallel Hessian-vector Product (Cont'd)

We use allreduce to let every node get $X^T DX\mathbf{s}$

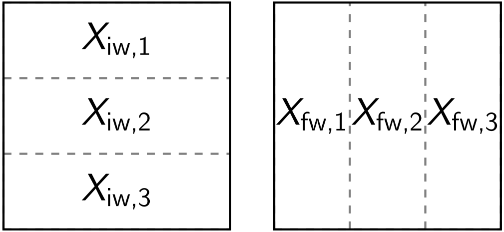


Allreduce: reducing all vectors $(X_i^T D_i X_i \mathbf{x}, \forall i)$ to a single vector $(X^T DX\mathbf{s} \in R^n)$ and then sending the result to every node

Parallel Hessian-vector Product (Cont'd)

- Then each node has all the information to finish a Newton method
- We don't use a master-slave model because implementations on master and slaves become different
- We use MPI here, but will discuss other programming frameworks later

Instance-wise and Feature-wise Data Splits



Instance-wise Feature-wise

- Feature-wise: each machine calculates part of the Hessian-vector product

$$(\nabla^2 f(\mathbf{w})\mathbf{v})_{\text{fw},1} = \mathbf{v}_1 + C X_{\text{fw},1}^T D(X_{\text{fw},1}\mathbf{v}_1 + \cdots + X_{\text{fw},p}\mathbf{v}_p)$$

Instance-wise and Feature-wise Data Splits (Cont'd)

- $X_{\text{fw},1}\mathbf{v}_1 + \cdots + X_{\text{fw},p}\mathbf{v}_p \in R^l$ must be available on all nodes (by allreduce)
- Amount of data moved per Hessian-vector product:
  Instance-wise: $O(n)$, Feature-wise: $O(l)$

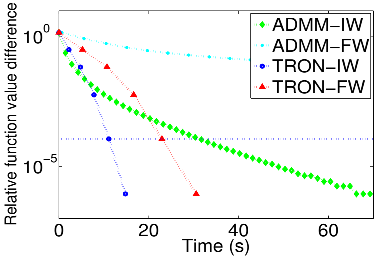
Experiments

- Two sets:

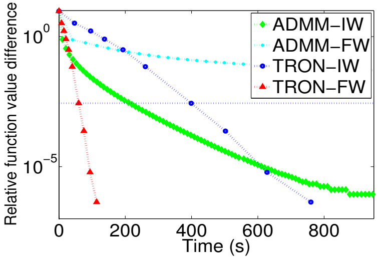
Data set	l	n	#nonzeros
epsilon	400,000	2,000	800,000,000
webspam	350,000	16,609,143	1,304,697,446

- We use Amazon AWS
- We compare
  - TRON: Newton method
  - ADMM: alternating direction method of multipliers (Boyd et al., 2011; Zhang et al., 2012)

Experiments (Cont'd)



epsilon



webspam

- 16 machines are used
- Horizontal line: test accuracy has stabilized
- TRON has faster convergence than ADMM
- Instance-wise and feature-wise splits useful for $l \gg n$ and $l \ll n$, respectively

Other Distributed Classification Methods

- We give only an example here (distributed Newton)
- There are many other methods
- For example, distributed quasi Newton, distributed random forests, etc.
- Existing software include, for example, Vowpal_Wabbit (Langford et al., 2007)

Outline

Training Is Only Part of the Workflow

- Previous experiments show that for a set with

  0.35M instances and 16M features,

  distributed training using 16 machines takes 50 seconds
- This looks good, but is not the whole story
- Copying data from Amazon S3 to 16 local disks takes more than 150 seconds
- Distributed training may not be the bottleneck in the whole workflow

Example: CTR Prediction

- CTR prediction is an important component of an advertisement system

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

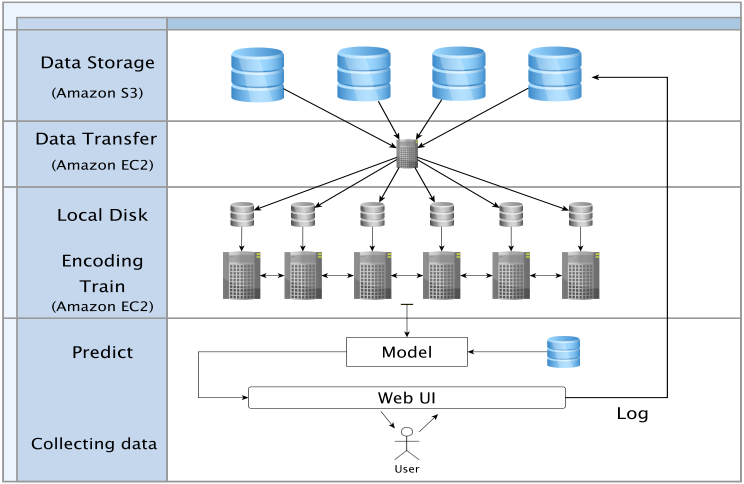
- A sequence of events

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

- A binary classification problem. We use the distributed Newton method described above

Example: CTR Prediction (Cont'd)

System Architecture



Example: CTR Prediction (Cont'd)

- We use data in a sliding window. For example, data of past week is used to train a model for today's prediction
- We keep renting local disks
- A coming instance is immediately dispatched to a local disk
- Thus data moving is completed before training
- For training, we rent machines to mount these disks
- Data are also constantly removed

Example: CTR Prediction (Cont'd)

- This design effectively alleviates the problem of moving and copying data before training
- However, if you want to use data 3 months ago for analysis, data movement becomes a issue
- This is an example showing that distributed training is just part of the workflow
- It is important to consider all steps in the whole application
- See also an essay by Jimmy Lin (2012)

What if We Don't Maintain Data at All?

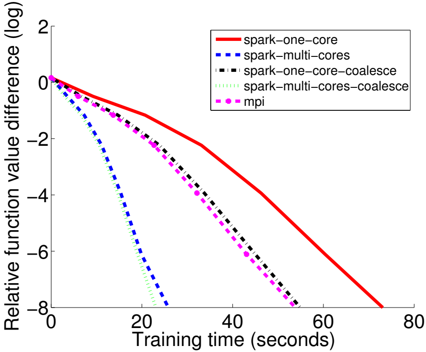
- We may use an online setting so an instance is used only once
- Advantages: the classification implementation is simpler than methods like distributed Newton
- Disadvantage: you may worry about accuracy
- The situation may be application dependent

Programming Frameworks

- We use MPI for the above experiments
- How about others like MapReduce?
- MPI is more efficient, but has no fault tolerance
- In contrast, MapReduce is slow for iterative algorithms due to heavy disk I/O
- Many new frameworks are being actively developed
  1. Spark (Zaharia et al., 2010)
  2. REEF (Chun et al., 2013)
- Selecting suitable frameworks for distributed classification isn't that easy!

A Comparison Between MPI and Spark

Data set	l	n	
epsilon	400,000	2,000	dense features
rcv1	677,399	47,236	sparse features



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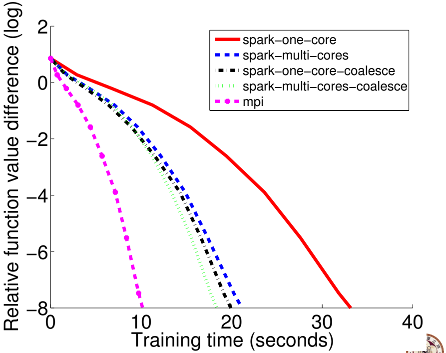

rcv1

A Comparison Between MPI and Spark (Cont'd)

8 nodes in a local cluster (not AWS) are used. Spark is slower, but in general competitive

Some issues may cause the time differences

- C versus Scala
- Allreduce versus master-slave setting

Distributed LIBLINEAR

- We recently released an extension of LIBLINEAR for distributed classification
- 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. We are working hard to improve the Spark version
- Your comments are very welcome.

Outline

Conclusions

- Designing distributed training algorithm isn't easy. You can parallelize existing algorithms or create new ones
- Issues such as communication cost must be solved
- We also need to know that distributed training is only one component of the whole workflow
- System issues are important because many programming frameworks are still being developed
- Overall, distributed classification is an active and exciting research topic