

Лекция 12 Large scale machine learning

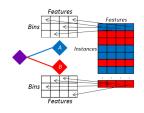
Владимир Гулин

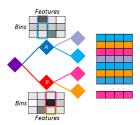
8 мая 2020 г.

## План лекции

Large scale decision trees ensembles

Large scale neural networks



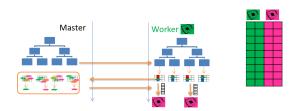


- ▶ Наблюдение 1: Одного прохода по данным достаточно на каждый уровень дерева
- ▶ Наблюдение 2: Итерироваться можно либо по точкам, либо по фичам





### Feature Distributed



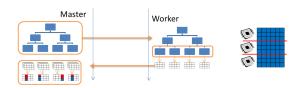
### Master

- Request workers to expand a set of nodes
- ▶ Wait to receive best per-feature splits from workers
- Select best feature-split for every node
- Request best splits' workers to broadcast per-instance assignments and residuals

### Worker

► Pass through all instances for local features, aggregating split histograms for each node

### Data Distributed



#### Master

- ► Send workers current model and set of nodes to expand
- ▶ Wait to receive local split histograms from workers
- Aggregate local split histograms, select best split for every node

#### Worker

- ▶ Pass through local data, aggregating split histograms
- Send completed local historograms to master

## Data Distributed for sparse features

| lgorithm 2 FindBestSplit                     | Algorithm 3 PV-Tree_FindBestSplit             |
|--|---|
| Input: DataSet D                             | Input: Dataset D                              |
| for all X in D.Attribute do                  | localHistograms = ConstructHistograms(D)      |
| ▷ Construct Histogram                        | Description Description   ▶ Local Voting      |
| H = new Histogram()                          | splits = []                                   |
| for all x in X do                            | for all H in localHistograms do               |
| H.binAt(x.bin).Put(x.label)                  | splits.Push(H.FindBestSplit())                |
| end for                                      | end for                                       |
| ⊳ Find Best Split                            | localTop = splits.TopKByGain(K)               |
| leftSum = new HistogramSum()                 | Gather all candidates                         |
| for all bin in H do                          | allCandidates = AllGather(localTop)           |
| leftSum = leftSum + H.binAt(bin)             | ⊳ Global Voting                               |
| rightSum = H.AllSum - leftSum                | globalTop = allCandidates.TopKByMajority(2*K) |
| split.gain = CalSplitGain(leftSum, rightSum) | ▶ Merge global histograms                     |
| bestSplit = ChoiceBetterOne(split,bestSplit) | globalHistograms = Gather(globalTop, localHis |
| end for                                      | tograms)                                      |
| end for                                      | bestSplit = globalHistograms.FindBestSplit()  |
| return bestSplit                             | return bestSplit                              |

### Results

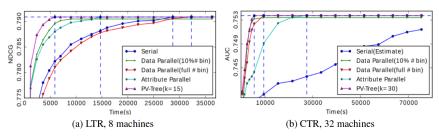
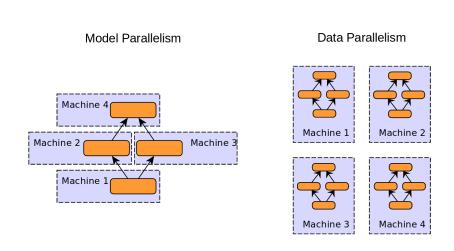


Figure 1: Performances of different algorithms

# GBM ON HADOOP

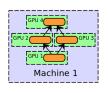
# Large scale neural networks

## **Paradigms**



# Model and data parallelism

Model and Data Parallelism





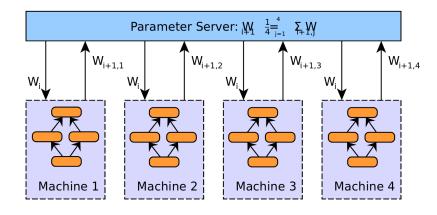




## Parameter averaging

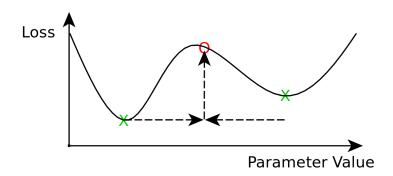
- 1. Initialize the network parameters randomly based on the model configuration
- 2. Distribute a copy of the current parameters to each worker
- 3. Train each worker on a subset of the data
- 4. Set the global parameters to the average the parameters from each worker
- 5. While there is more data to process, go to step 2

## Parameter averaging

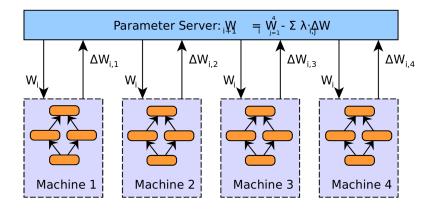


## Parameter averaging problem

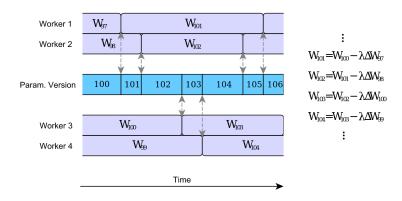
Сумма N локальных минимумов не является глобальным минимумом



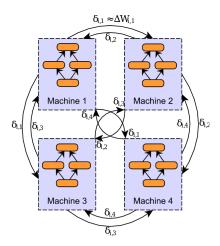
# Asynchronous Stochastic Gradient Descent



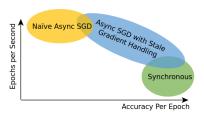
## Stale Gradient Problem



# Decentralized Asychronous Stochastic Gradient Descent



# Which Approach is Best?



# Вопросы

