Goals for future from last year

1. Finish Scaling up. I want a kilonode program.
2. Native learning reductions. Just like more complicated losses.
3. Other learning algorithms, as interest dictates.
4. Persistent Demonization

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1. Finish Scaling up. I want a kilonode program.

Some design considerations

- Hadoop compatibility: Widely available, scheduling and robustness
- Iteration-firendly: Lots of iterative learning algorithms exist
- Minimum code overhead: Don't want to rewrite learning algorithms from scratch
- Balance communication/computation: Imbalance on either side hurts the system

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- Balance communication/computation: Imbalance on either side hurts the system
- Scalable: John has nodes aplenty

Current system provisions

- Hadoop-compatible AllReduce
- Various parameter averaging routines
- Parallel implementation of Adaptive GD, CG, L-BFGS
- Robustness and scalability tested up to 1K nodes and thousands of node hours

Basic invocation on single machine

```
./spanning_tree
../vw --total 2 --node 0 --unique_id 0 -d $1
--span_server localhost > node_0 2>&1 &
../vw --total 2 --node 1 --unique_id 0 -d $1
--span_server localhost
killall spanning_tree
```

Command-line options

- `--span_server <arg>`: Location of server for setting up spanning tree
- `--unique_id <arg> (=0)`: Unique id for cluster parallel job
- `--total <arg> (=1)`: Total number of nodes used in cluster parallel job
- `--node <arg> (=0)`: Node id in cluster parallel job

Basic invocation on a non-Hadoop cluster

- Spanning-tree server: Runs on cluster gateway, organizes communication

  ```
  ./spanning_tree
  ```

- Worker nodes: Each worker node runs VW

  ```
  ./vw --span_server <location> --total <t> --node
  <n> --unique_id <u> -d <file>
  ```

Basic invocation in a Hadoop cluster

- Spanning-tree server: Runs on cluster gateway, organizes communication

  ```
  ./spanning_tree
  ```

- Map-only jobs: Map-only job launched on each node using Hadoop streaming

  ```
  hadoop jar $HADOOP_HOME/hadoop-streaming.jar
  -Dmapred.job.map.memory.mb=2500 -input <input>
  -output <output> -file vw -file runvw.sh -mapper
  ´runvw.sh <output> <span_server>´ -reducer NONE
  ```

  - Each mapper runs VW
  - Model stored in <output>/model on HDFS
  - runvw.sh calls VW, used to modify VW arguments

mapscript.sh example

//Hadoop-streaming has no specification for number of mappers, we calculate it indirectly

```
total=<total data size>
mapsize=`expr $total / $nmappers`
maprem=`expr $total % $nmappers`
mapsize=`expr $mapsize + $maprem`
```

`./spanning_tree` //Starting span-tree server on the gateway
//Note the argument min.split.size to specify number of mappers

```
hadoop jar $HADOOP_HOME/hadoop-streaming.jar
-Dmapred.min.split.size=$mapsize
-Dmapred.map.tasks.speculative.execution=true -input
$in_directory -output $out_directory -file ../vw -file
runvw.sh -mapper runvw.sh -reducer NONE
```

Communication and computation

- Two main additions in cluster-parallel code:
    - Hadoop-compatible AllReduce communication
    - New and old optimization algorithms modified for AllReduce

Communication protocol

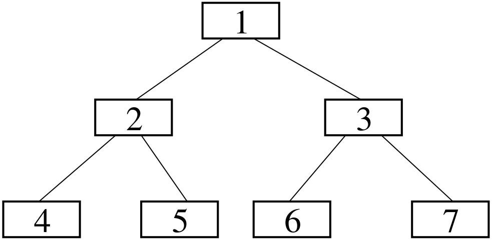
- Spanning-tree server runs as daemon and listens for connections
- Workers via TCP with a node-id and job-id
- Two workers with same job-id and node-id are duplicates, faster one kept (speculative execution)
- Available as mapper environment variables in Hadoop
  - `mapper=`printenv mapred_task_id | cut -d "_" -f 5``
  - `mapred_job_id=`echo $mapred_job_id | tr -d ´job_´``

Communication protocol contd.

- Each worker connects to spanning-tree sever
- Server creates a spanning tree on the n nodes, communicates parent and children to each node
- Node connects to parent and children via TCP
- AllReduce run on the spanning tree

AllReduce

- Every node begins with a number (vector)



- Extends to other functions: max, average, gather, . . .

AllReduce

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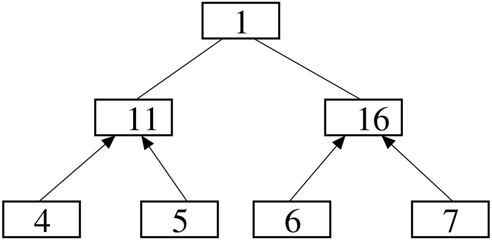

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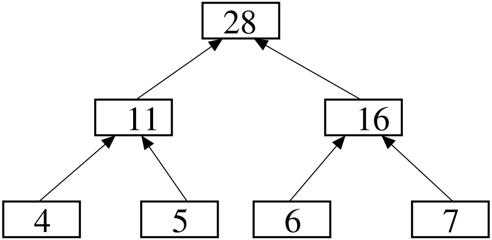
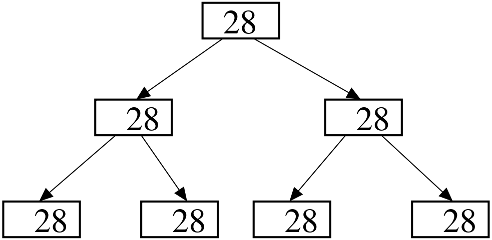


- Extends to other functions: max, average, gather, ...

AllReduce

- Every node begins with a number (vector)
- Every node ends up with the sum



- Extends to other functions: max, average, gather, ...

AllReduce Examples

- Counting: $n =$ `allreduce(1)`
- Average: `avg = allreduce(`n_i`)/allreduce(1)`
- Non-uniform averaging: `weighted_avg = allreduce(`$n_i w_i$`)/allreduce(`w_i`)`
- Gather: `node_array = allreduce(`$\{0, 0, \ldots, \underbrace{1}_{i}, \ldots, 0\}$`)`

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- Current code provides 3 routines:
  - `accumulate(<params>)`: Computes vector sums
  - `accumulate_scalar(<params>)`: Computes scalar sums
  - `accumulate_avg(<params>)`: Computes weighted and unweighted averages

Machine learning with AllReduce

- Previously: Single node SGD, multiple passes over data
- Parallel: Each node runs SGD, averages parameters after every pass (or more often!)
- Code change:

```
 if(global.span_server != "") {
     if(global.adaptive)

accumulate_weighted_avg(global.span_server,
params->reg);
     else
          accumulate_avg(global.span_server,
params->reg, 0);
}
```

- Weighted averages computed for adaptive updates, weight features differently

Machine learning with AllReduce contd.

- L-BFGS requires gradients and loss values
- One call to AllReduce for each
- Parallel synchronized L-BFGS updates
- Same with CG, another AllReduce operation for Hessian
- Extends to many other common algorithms

Communication and computation

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Hybrid optimization for rapid convergence

- SGD converges fast initially, but slow to squeeze the final bit of precision
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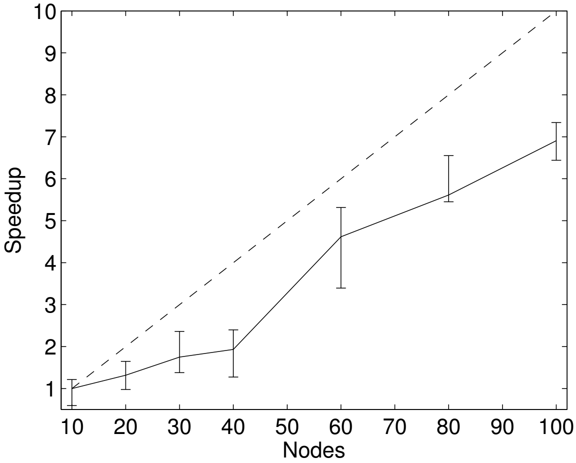
- Each node performs few local SGD iterations, averaging after every pass
- Switch to L-BFGS with synchronized iterations using AllReduce
- Two calls to VW

Speedup

- Near linear speedup



Hadoop helps

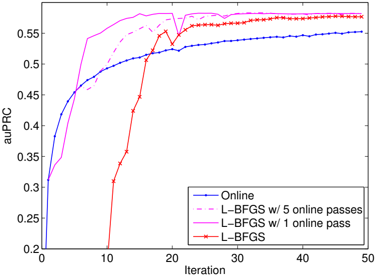
- Naïve implementation driven by slow node
- Speculative execution ameliorates the problem

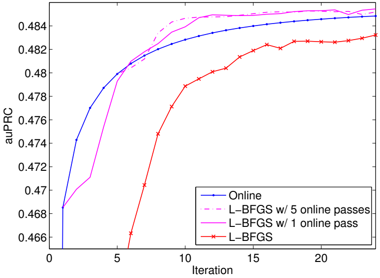
Table: Distribution of computing time (in seconds) over 1000 nodes. First three columns are quantiles. The first row is without speculative execution while the second row is with speculative execution.

	5%	50%	95%	Max	Comm. time
Without spec. exec.	29	34	60	758	26
With spec. exec.	29	33	49	63	10

Fast convergence

- auPRC curves for two tasks, higher is better





Conclusions

- AllReduce quite general yet easy for machine learning
- Marriage with Hadoop great for robustness
- Hybrid optimization strategies effective for rapid convergence
- John gets his kilonode program