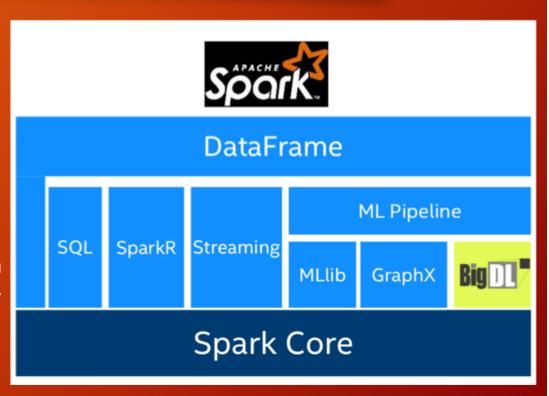
Spark BigDL

© Intel

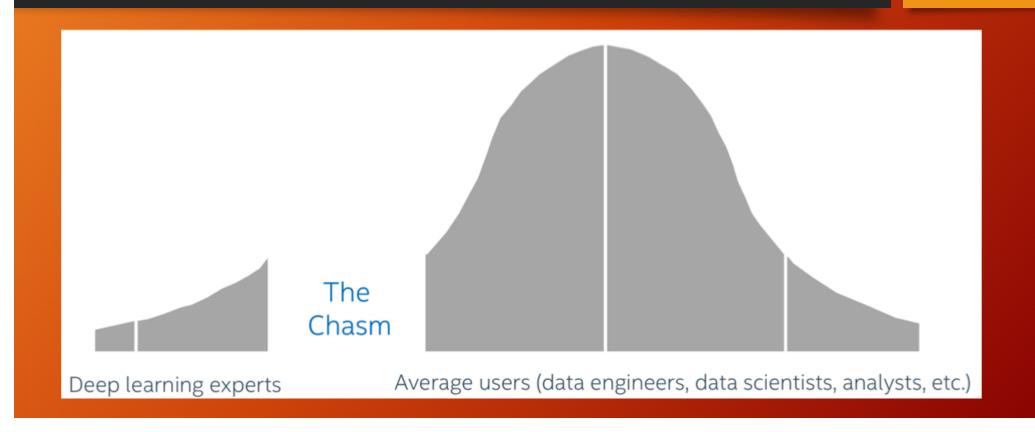
Slides based heavily on those by Jason Dai and Ding Ding, taken from Al Conference 2017 San Francisco

What is BigDL?

- BigDL is a deep learning library built for Apache Spark
- Make deep learning more accessible
 - Write deep learning applications as standard Spark programs
 - Run on existing Spark/Hadoop clusters (no changes needed)
- Feature parity with Caffe, Torch, TensorFlow
- High-performance Intel MKL library in tasks, efficient all-reduce and SGD at scale
- Works with pre-trained Keras, Caffe, or Torch models



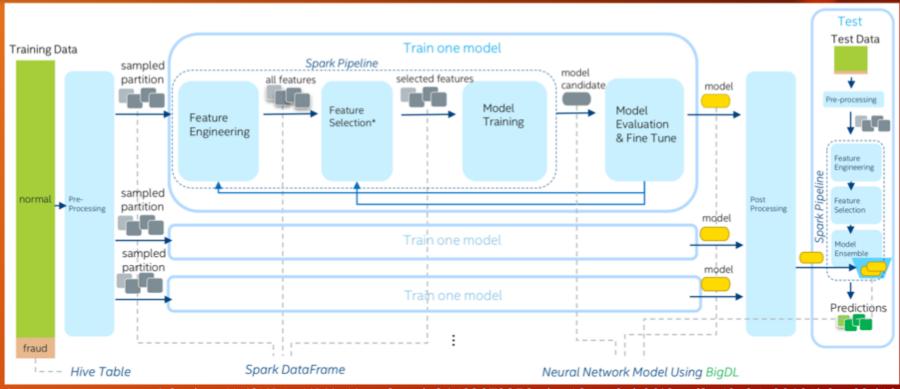
Making deep learning accessible



BigDL's Goals

- Make deep learning more accessible to big data and data science communities
- Continue the use of familiar software tools (Spark) and hardware infrastructure (Hadoop clusters) to build deep learning applications
- Analyze "big data" using deep learning on the same Hadoop/Spark cluster where the data are stored
- Add deep learning functionalities to the Big Data (Spark) programs and/or workflow
- Leverage existing Hadoop/Spark clusters to run deep learning applications
 - Shared with other workloads (e.g., ETL, data warehouse, feature engineering, statistic machine learning, graph analytics, etc.) in a dynamic and elastic fashion

Case Study: Fraud Detection for UnionPay



https://mp.weixin.qq.com/s?__biz=MzI3NDAwNDUwNg==&mid=2648307335&idx=1&sn=8eb9f63eaf2e40e24a90601b9cc03d1f

Distributed Training in BigDL

```
for (i <- 1 to N) {

batch = next_batch()
output = model.forward(batch.input)
loss = criterion.forward(output, batch.target)
error = criterion.backward(output, batch.target)
model.backward(input, error)
optimMethod.optimize(model.weight, model.gradient)
}

Synchronous SGD
```

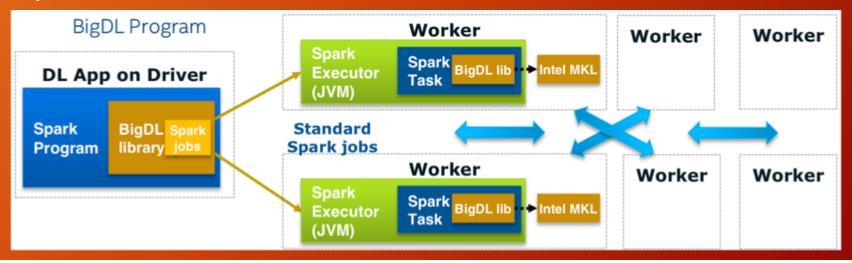
"Data parallel" vs "Model parallel"

Runtime complexity

Run as a standard Spark program

- Standard Spark jobs
 - No changes to the Spark or Hadoop clusters needed
- Iterative
 - Each iteration of the training runs as a Spark job

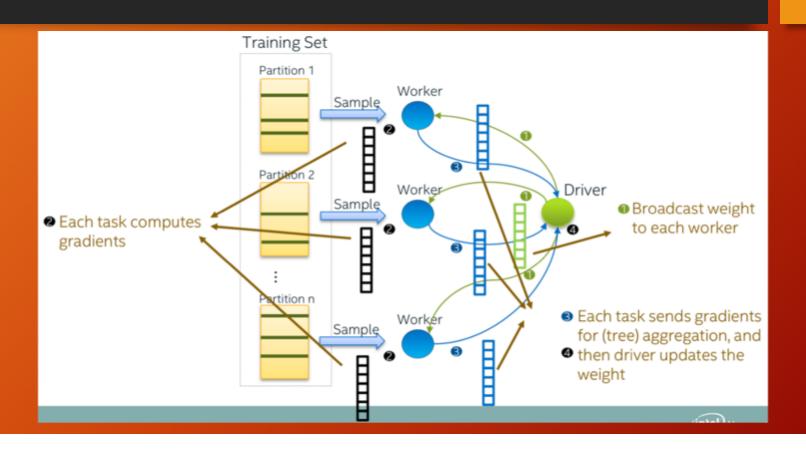
- · Data parallel
 - Each Spark task runs the same model on a subset of the data (batch)



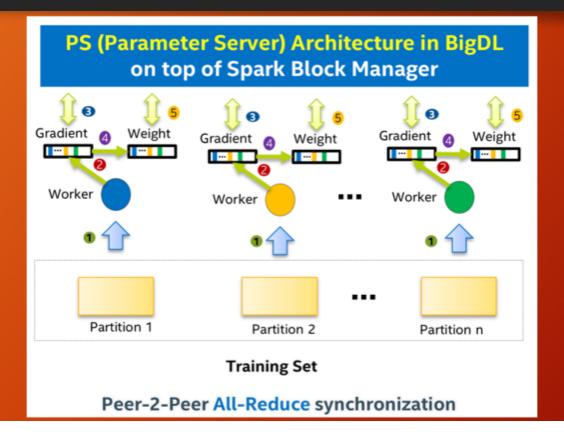
Considerations in large-scale distributed training

- Optimizing parameter synchronization and aggregation
- Optimizing task scheduling
- Scaling batch size

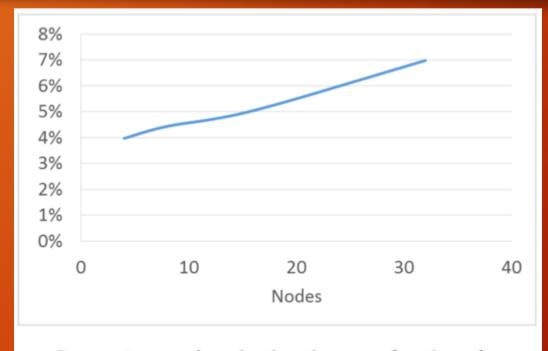
Parameter Synchronization in Spark MLlib



Parameter Synchronization in BigDL

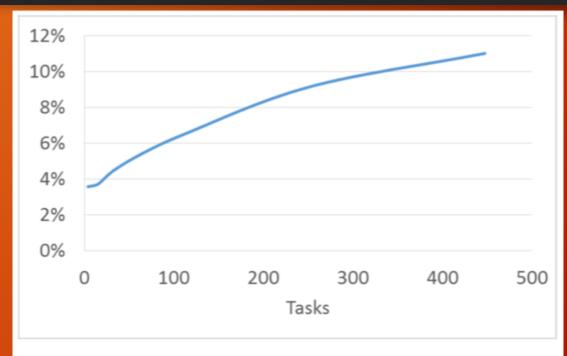


Performance of BigDL Parameter Synchronization



Parameter synchronization time as a fraction of average compute time for Inception v1 training

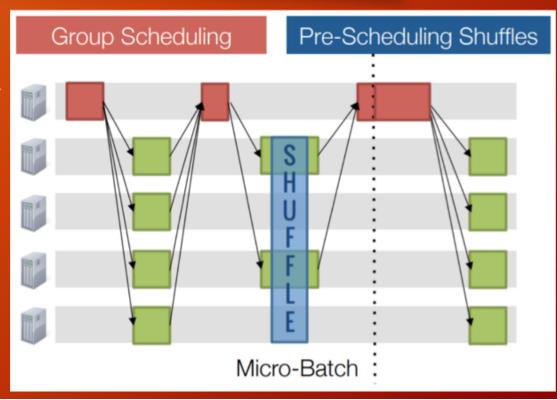
Spark Task Scheduling Overheads



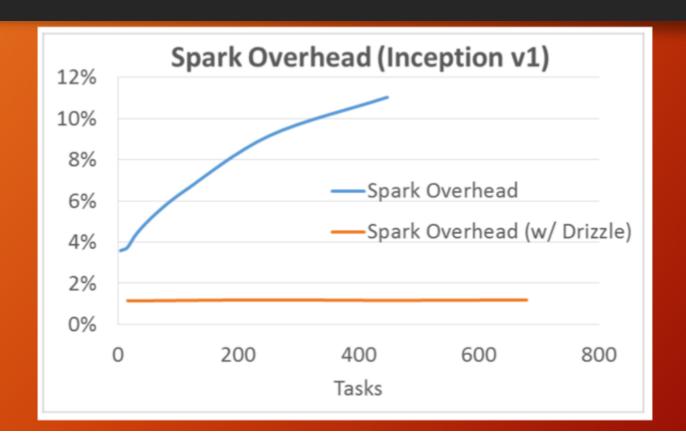
Spark overheads (task scheduling, task serde, task fetch) as a fraction of average compute time for Inception v1 training

BigDL + "Drizzle"

- A low-latency execution engine for Apache Spark, packaged in BigDL
- Fine-grained execution with coarsegrained scheduling
- Group scheduling
 - Scheduling a group of iterations at once
 - Fault tolerance, scheduling at group boundaries
- Coordinating shuffles: prescheduling
 - Pre-schedule tasks on executors
 - Trigger tasks once dependencies are met



Spark Task Scheduling Overheads, Redux



Drizzle increases mini-batch size

- Distributed synchronous mini-batch SGD
 - Increased mini-batch size
 - Can lead to loss in test accuracy

total_batch_size = batch_size_per_worker *
num_of_workers

- State-of-art method for scaling mini-batch size
 - Linear scaling rule
 - Warm-up
 - · Layer-wise adaptive rate scaling
 - Adding batch normalization

"Accurate, Large Minibatch SGD: Training ImageNet in 1Hour"

"Scaling SGD Batch Size to 32K for ImageNet Training"

Want to get started?

- As easy as pip install
 - https://bigdl-project.github.io/master/#PythonUserGuide/install-from-pip/
 - (add to custom Python startup script for Dataproc)
- · A few configuration changes to make on Dataproc, but not too bad
 - https://github.com/intel-analytics/BigDL/blob/master/docs/docs/ProgrammingGuide/run-on-dataproc.md

Questions?



References

- https://bigdl-project.github.io/master/#
- https://github.com/intel-analytics/BigDL/

Project Notes

- P1 is due *Thursday*, *February 1 at 11:59:59pm*.
 - AutoLab shuts down, and I stop considering changes on GitHub
- P2 will be released on Thursday!
 - AutoLab assignment will show up
 - Teams will be announced on Slack
 - Due Thursday, February 15 (2 weeks) at 11:59:59pm.
- P1 Lightning Talks next Wednesday!
 - Each team gives a 5-minute overview of their work (slides please)
 - Highlight the approach you took (theory, engineering, teamwork) and how it paid off (or not)—what worked, what didn't, what you'd keep, what you'd change
 - Teams will be called up randomly, so be ready to go!