DEEP LEARNING TO BIG DATA ANALYTICS ON APACHE SPARK* USING BIGDL

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Outline

BigDL

- Apache Spark* + High Performance + Deep Learning

Speech recognition:

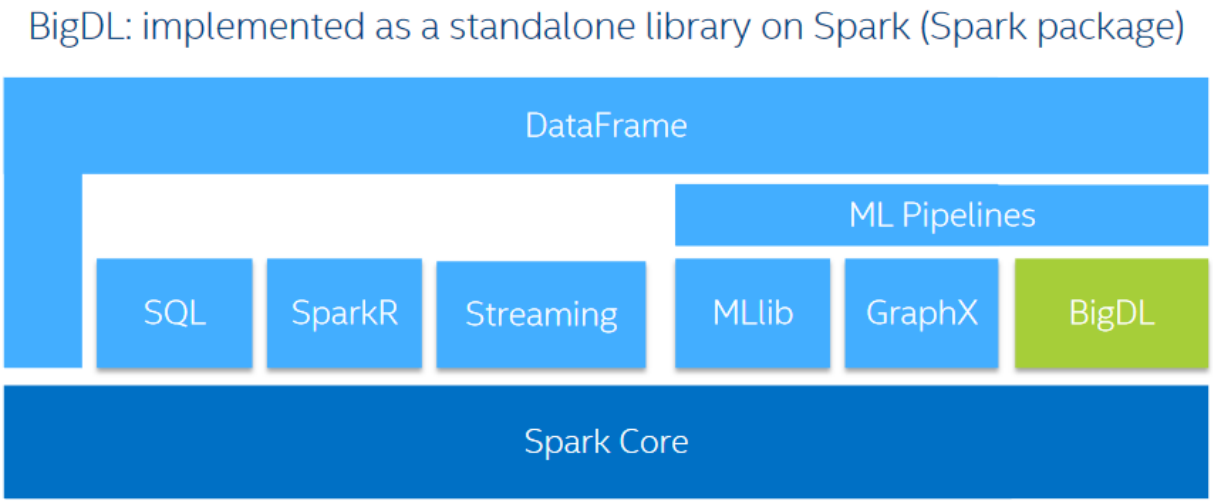
- Deep Speech 2 on BigDL: ML Pipeline + BigDL

Object detection:

- Faster RCNN and SSD on BigDL

What is BigDL?

BigDL is a distributed deep learning library for Apache Spark*



BigDL: Deep learning on Apache Spark*

BigDL open sourced on Dec 30, 2016

https://github.com/intel-analytics/BigDL

- Apache Spark*, MKL Acceleration, High performance

Rich function

- AlexNet, GoogleNet, VGG, Faster R-CNN, SSD, Deep Speech, Recommendation...
- Scala/Java + Python
- AWS EC2, TensorBoard, Notebook, caffe/torch load/export...

Popularity

- Support from Cloud: Microsoft, Amazon, Cloudera, Databricks...
- Community. 1700+ stars

Basic Component

Tensor:

- ND-array data structure
- Generic data type
- Rich and fast math operations (powered by Intel MKL)

Layers

- 113+ layers (Conv, 3D Conv, Pooling, 3D Pooling, FC ...)

Criterion

- 23+ criterions (DiceCoefficient, ClassNLL, CrossEntropy ...)

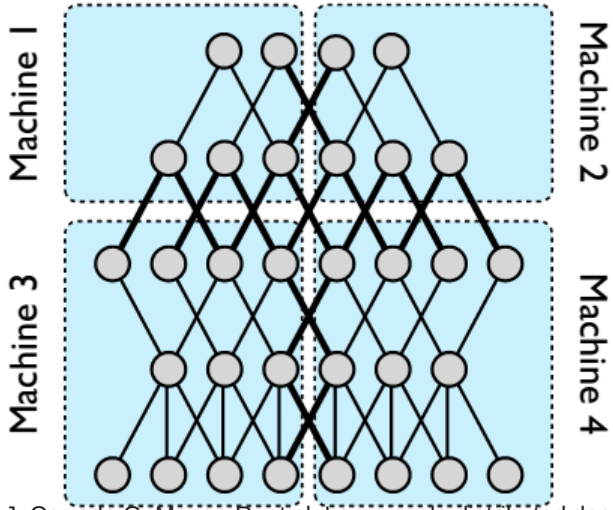
Optimization

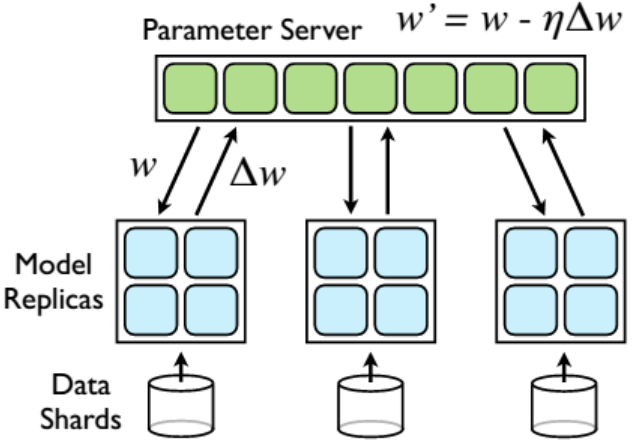
- SGD, Adagrad, LBFGS
- **Community contribution**: Adam, Adadelta, RMSprop, Adamx

Pattern

Model Parallelism

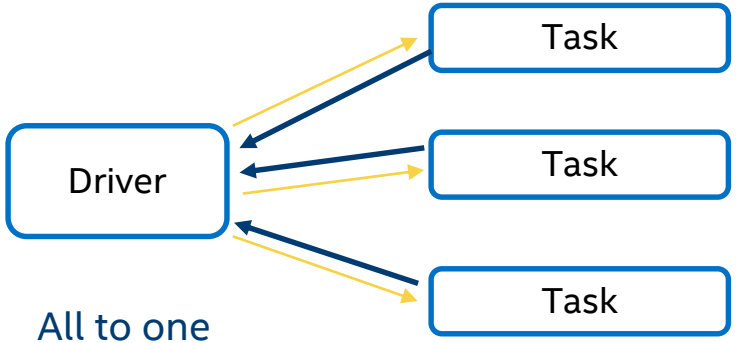
Data Parallelism



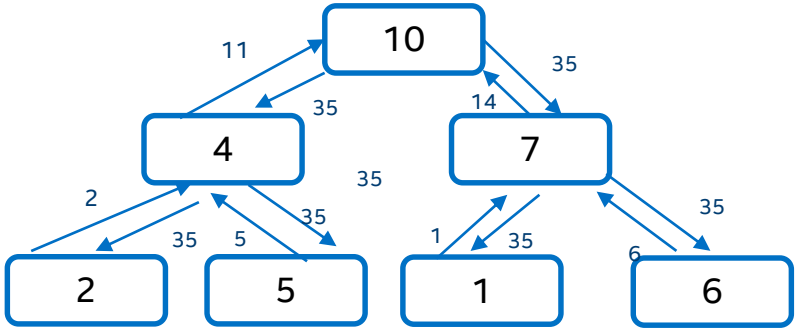


Source: Dean J, Corrado G, Monga R, et al. Large scale distributed deep networks[C]//Advances in neural information processing systems. 2012: 1223-1231.

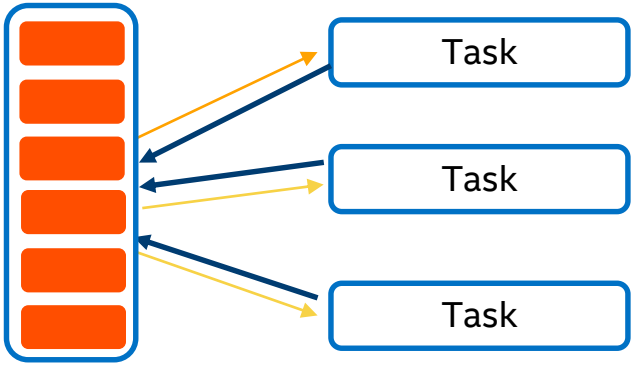
Communication Model



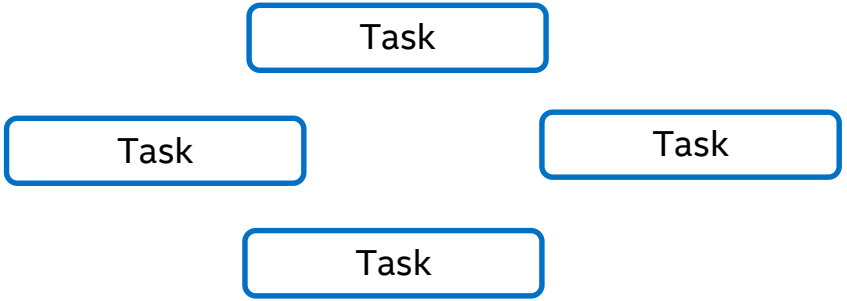
All to one



All reduce (tree aggregation)

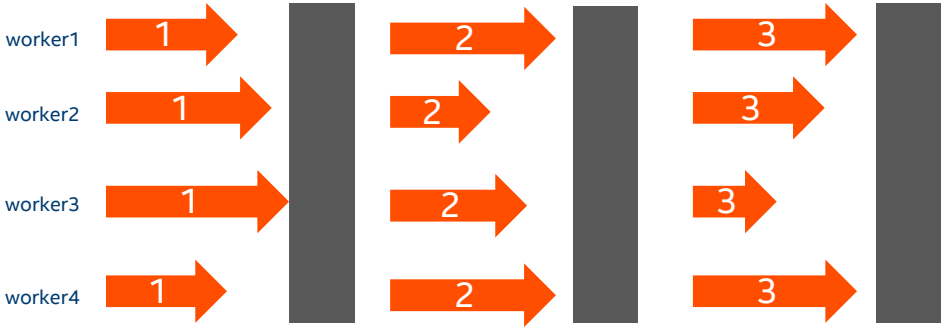


Parameter Server

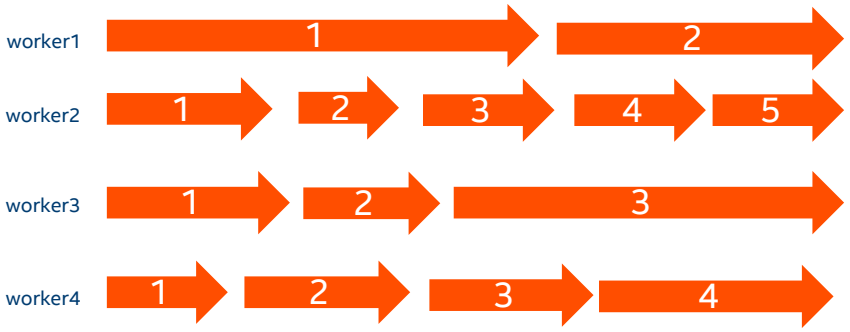


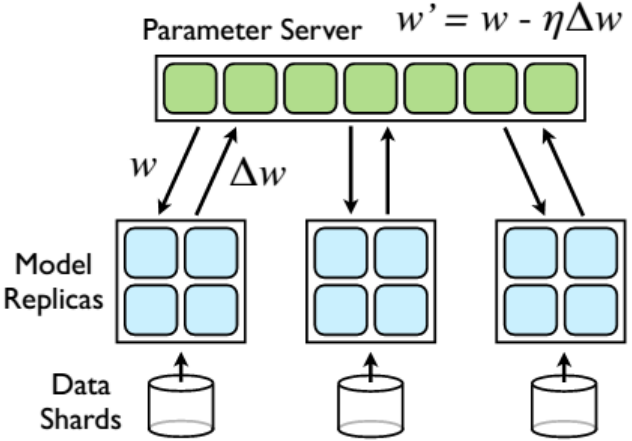
All reduce

Bulk Synchronous Parallel (BSP)



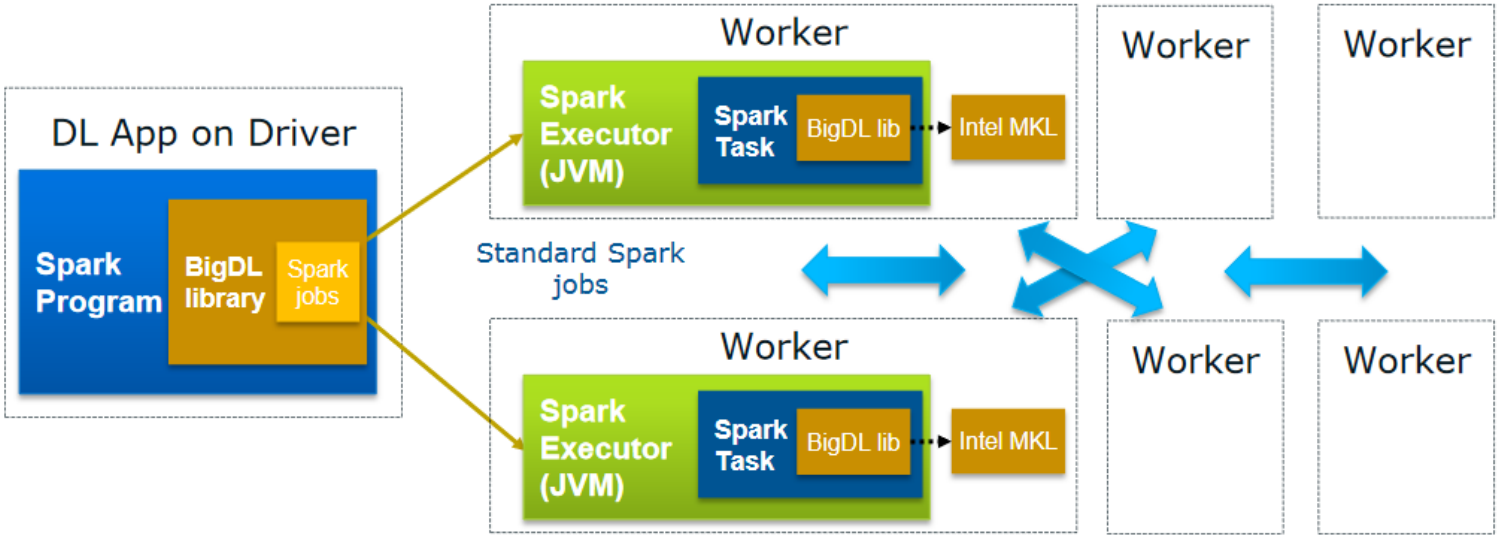
Asynchronous Synchronous Parallel (ASP)





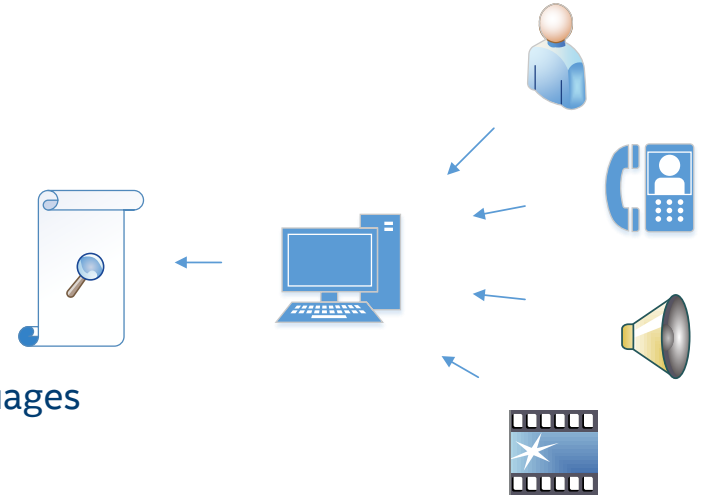
Source: Dean J, Corrado G, Monga R, et al. Large scale distributed deep networks[C]//Advances in neural information processing systems. 2012: 1223-1231.

Run as standard Apache Spark* jobs



DEEP SPEECH 2 WITH BIGDL

Speech Recognition



Challenges

- Audio → text
- Speaker variability, Channel variability, Different languages

Solutions:

- Hybrid system:
  - DNNs, Hidden Markov Models (HMMs), context-dependent phone models, Lexicon models, GMM.
  - Domain expertise and multi-stage
- ✓ DNN end to end:
  - DNN. Much easier
  - More data, better model

Deep Speech 2 for Speech Recognition

- "The Deep Speech 2 ASR pipeline approaches or **exceeds the accuracy of Amazon Mechanical Turk human workers** on several benchmarks, works in **multiple languages** with little modification, and is deployable in a production setting."
- "Table 13 shows that the DS2 system **outperforms humans in 3 out of the 4 test sets and is competitive on the fourth**. Given this result, we suspect that there is little room for a generic speech system to further improve on clean read speech without further domain adaptation."

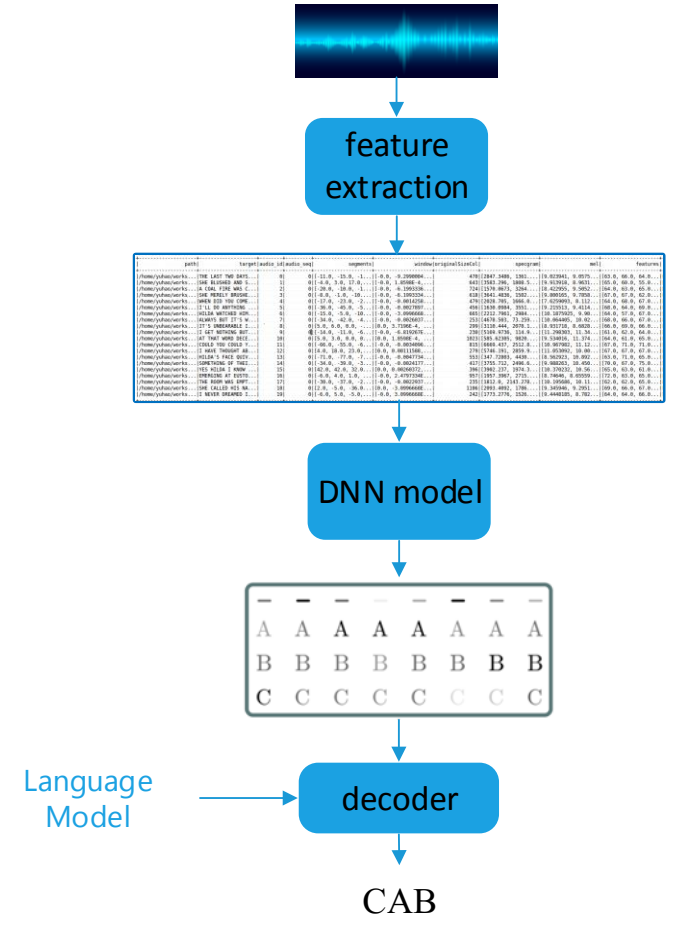
Read Speech			
Test set	DS1	DS2	Human
WSJ eval'92	4.94	3.60	5.03
WSJ eval'93	6.94	4.98	8.08
LibriSpeech test-clean	7.89	5.33	5.83
LibriSpeech test-other	21.74	13.25	12.69

Table 13: Comparison of WER for two speech systems and human level performance on read speech.

Deep Speech 2 on BigDL

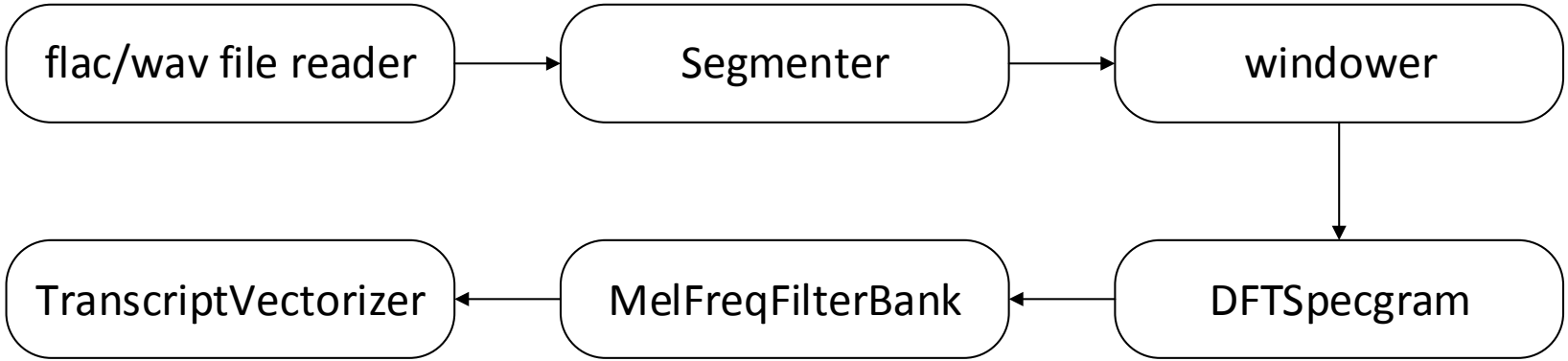
Deep Speech 2: End-to-End Speech Recognition in English and Mandarin

Baidu Research – Silicon Valley AI Lab*
Dario Amodei, Rishita Anubhai, Eric Battenberg, Carl Case, Jared Casper, Bryan Catanzaro, Jingdong Chen, Mike Chrzanowski, Adam Coates, Greg Diamos, Erich Elsen, Jesse Engel, Linxi Fan, Christopher Fougner, Tony Han, Awni Hannun, Billy Jun, Patrick LeGresley, Libby Lin, Sharan Narang, Andrew Ng, Sherjil Ozair, Ryan Prenger, Jonathan Raiman, Sanjeev Satheesh, David Seetapun, Shubho Sengupta, Yi Wang, Zhiqian Wang, Chong Wang, Bo Xiao, Dani Yogatama, Jun Zhan, Zhenyao Zhu



Deep Speech 2 on BigDL: Feature transformers

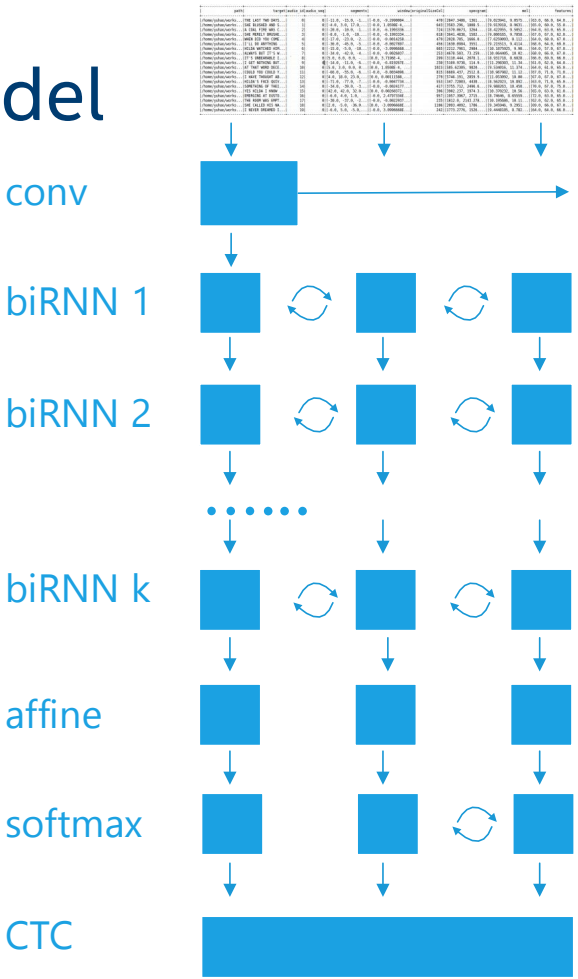
Apache Spark* ML Pipeline



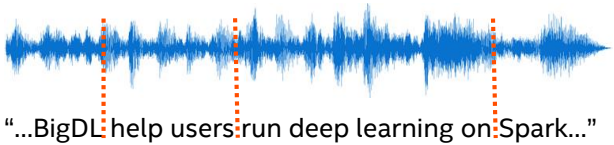
Deep Speech 2 on BigDL: Model

```
val model = Sequential[T]()
  .add(conv)
  .add(ReLU[T]())
  .add(Squeeze(4))
  .add(brnn)
  .add(linear1)
  .add(HardTanhDS[T](0, 20, true))
  .add(linear2)
```

9 layers biRNN: >50 Million parameters



Deep Speech 2 on BigDL: CTC Loss



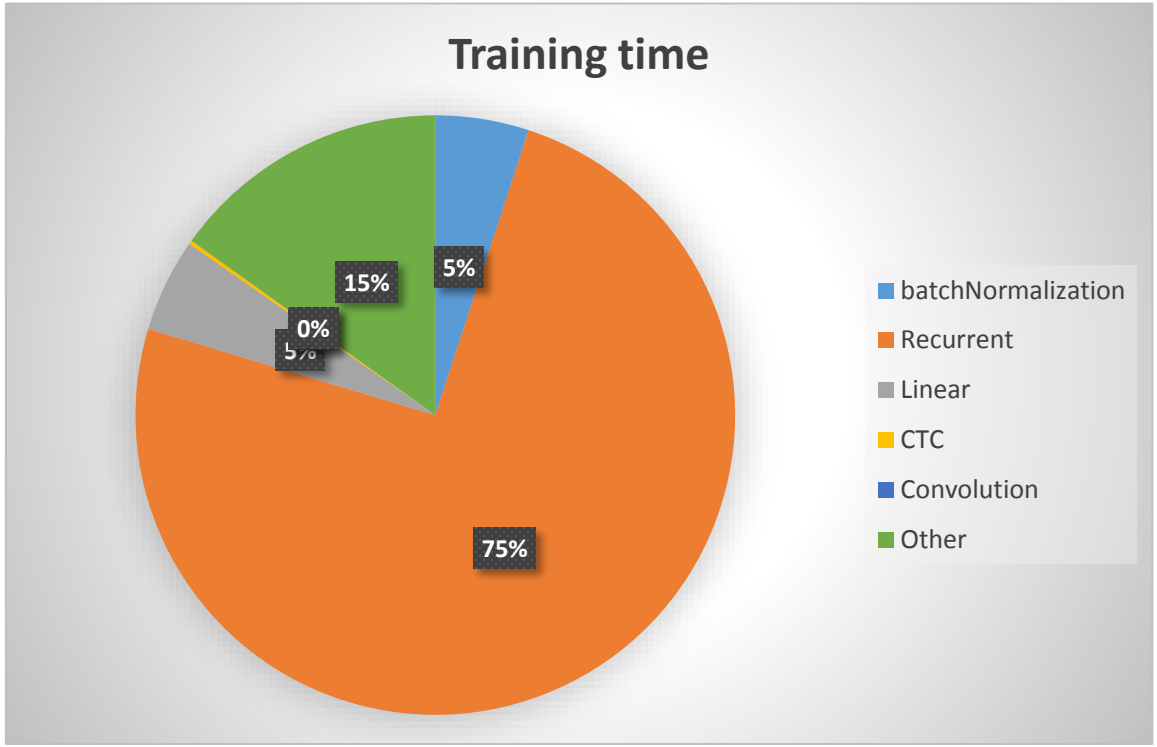
Connectionist Temporal Classification

- a loss function useful for performing supervised learning on sequence data, without needing an alignment between input data and labels. (Alex Graves etc. 2006)
- Raw waveforms and text transcription

BigDL developed first open source CTC on Java/Scala

- Loss/Gradient in consistency with baidu/warp-ctc
- JNI version about 3X faster than Scala version, but CTC only takes 0.2% of the training time.

Deep Speech 2 on BigDL: Model training



With libriSpeech, 5 RNN layer, 30 seconds uttLength, 30 epoches.

Deep Speech 2 on BigDL: Decoder

Existing decoder:

- BestPathDecoder (argmax) wer = 27%
- VocabDecoder wer = 22%

	t1	t2	t3	t4	...
A	0.01	0.1	0.7	0.03	
B	0.05	0.01	0.2	0.5	
C	0.01	0.1	0.09	0.01	
D	0.8	0.05	0.01	0.01	
...	...	...	...	...	
Blank	0.1	0.6	0.01	0.4	
	D	-	A	B	

Contribution welcome

- decoder with Language Model, expect wer < 10%

Deep Speech 2 with AN4 data

- Deep Speech 2 (8 layer, 5 RNN), uttLength 8 seconds
  - Word Error Rate with hold-out validation dataset

	wer(without LM)
Deep Speech on Tensorflow	12.4%
BigDL	< 5%

Deep Speech 2 with LibriSpeech

- Deep Speech 2 (12 layers, 9 RNN), uttLength 30 seconds
  - Word Error Rate with hold-out validation dataset

	cer	wer(without LM)
Hannun, et al. (2014)	10.7	35.8
Graves-Jaitly (ICML 2014)	9.2	30.1
Hwang-Sung (ICML 2016)	10.6	38.4
BigDL	8.7	32.4

- Still under further tuning and optimization.
  - More training data
  - Optimizer (Adam, SGD, nesterov)

Deep Speech 2 on BigDL: Summary

Feature transformers:

- Flac/wav Reader, Windower, TimeSegmenter, TranscriptVectorizer, DFTSpecgram, MelFrequencyFilterBank

Model training and inference

- Big DL container, optimizer, Convolution, BatchNormalization, Bi-RNN

CTC (Connectionist Temporal Classification) loss

- Scala or JNI (warp-ctc)

Decoder

- ArgmaxDecoder, VocabDecoder

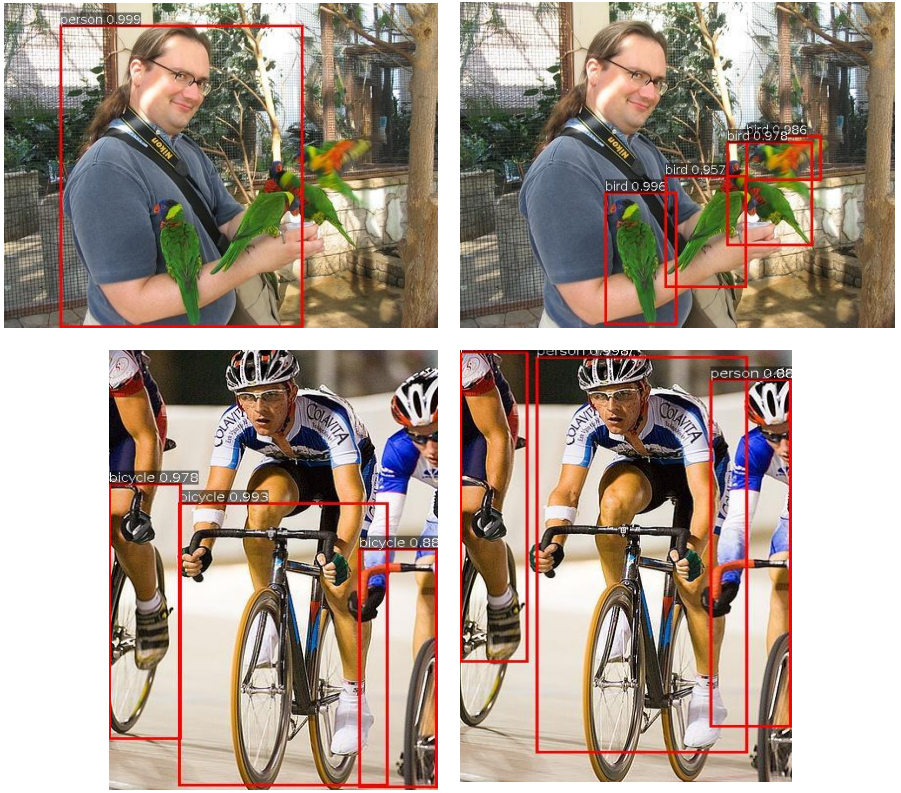
Evaluation

- wer, cer

OBJECT DETECTION WITH BIGDL

SSD: Single Shot Multibox Detector

- State-of-the-art object detection pipeline
- Single shot

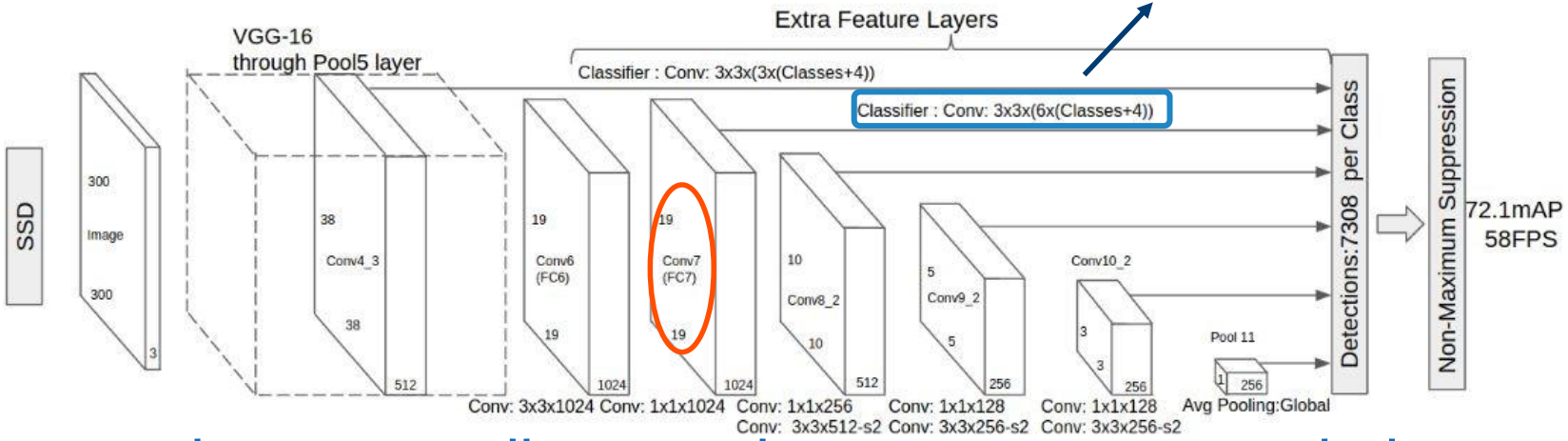


Images from PASCAL(http://host.robots.ox.ac.uk/pascal/VOC/)

Liu, Wei, et al. "SSD: Single shot multibox detector." European Conference on Computer Vision. Springer International Publishing, 2016.

The Single Shot Detector (SSD)

Convolutional predictors for detection



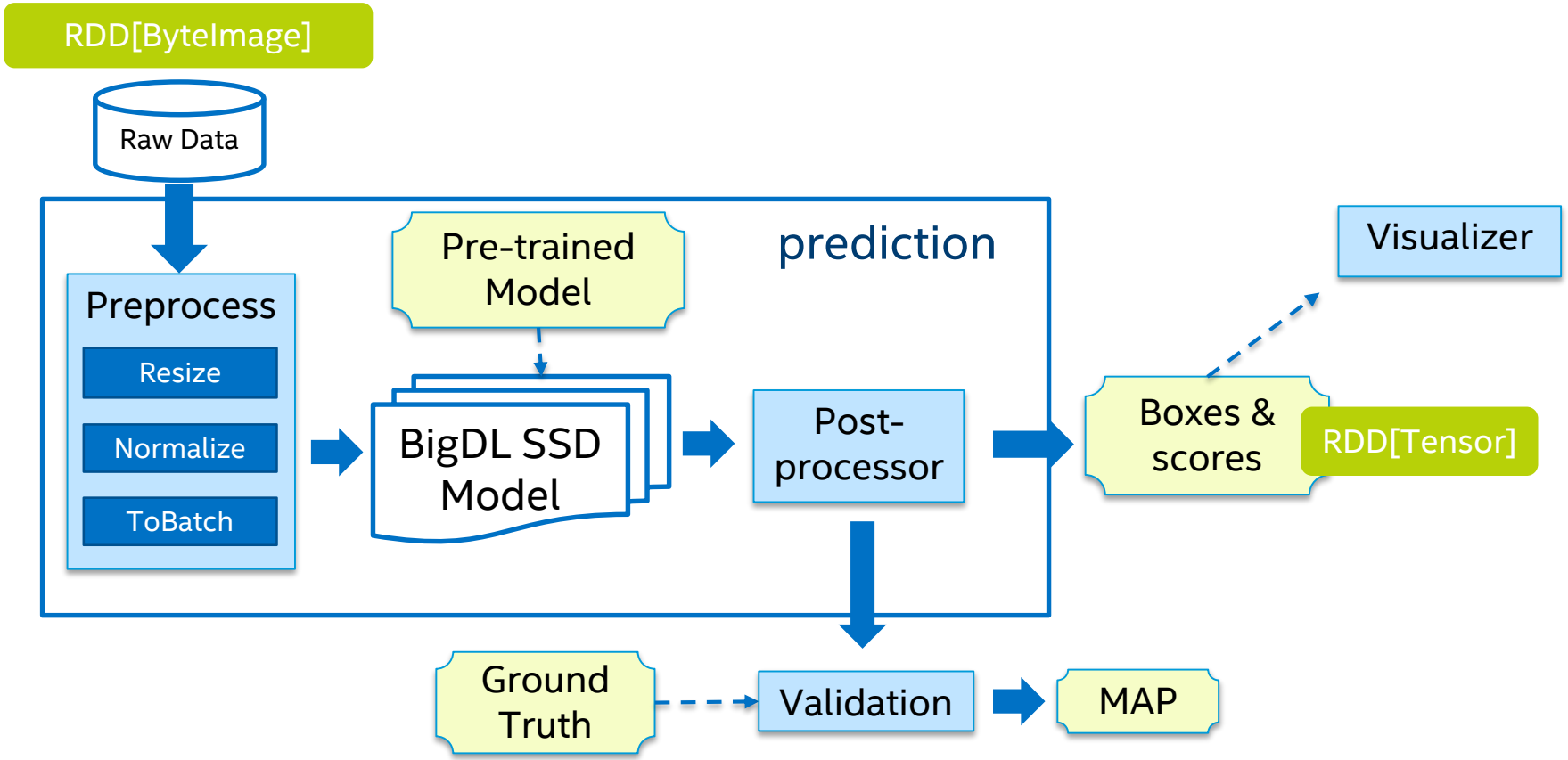
base network

fc6 and fc7 converted to convolutional

collection of bounding boxes and scores for each category

Multi-scale feature maps for detection: observe how conv feature maps decrease in size and allow predictions at multiple scales

SSD Pipeline



SSD + VGG 300x300 test over Pascal VOC 2007

- SSD + VGG 300x300 with pretrained model over voc07+12
  - Mean Average Precision

	Caffe Model	BigDL
MAP	77.2	77.3

SSD + VGG 512x512 test over Pascal VOC 2007

- SSD + VGG 512x512 with pretrained model over voc07+12
  - Mean Average Precision

	Caffe Model	BigDL
MAP	79.6	79.6

BigDL Community

analytics-zoo

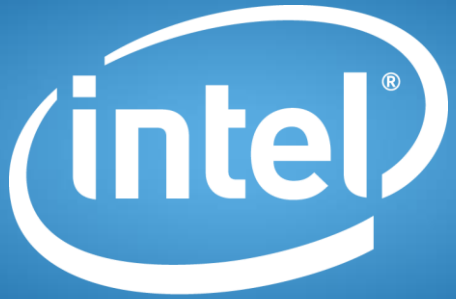
https://github.com/intel-analytics/analytics-zoo

Join Our Mail List

bigdl-user-group+subscribe@googlegroups.com

Report Bugs And Create Feature Request

https://github.com/intel-analytics/BigDL/issues



Software

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