User-based real-time product recommendations leveraging deep learning using Analytics Zoo on Apache Spark and BigDL

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Strata
DATA CONFERENCE

Agenda

- Office Depot Overview
- What is BigDL & Analytic Zoo?
- Recommendation Use Case
- Takeaways

Office DEPOT

Office Depot, Inc. (NASDAQ:ODP) is a leading B2B integrated distribution company providing business services and supplies, products and technology solutions through its fully integrated omni-channel platform of approximately 1,350 stores, online presence, and dedicated sales professionals and technicians to small, medium and enterprise businesses. Through its banner brands Office Depot®, OfficeMax®, CompuCom® and Grand&Toy®, the company offers its customers the tools and resources they need to focus on their passion of starting, growing and running their business.

Big Data Journey for Recommendation

Stage I :

We tried to build machine learning models to do product recommendation using Python/SAS/R

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Challenge:

We can not process this amount of data on a single machine

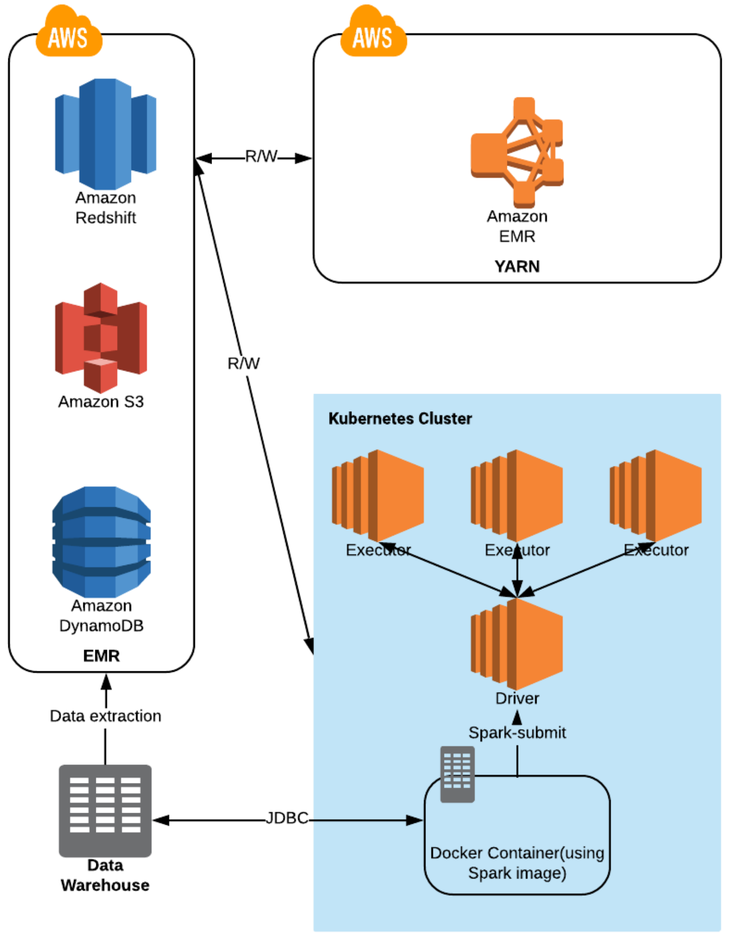
- Over 100,000,000 distinct sessions
- More than 300,000 active products selling online
- Training data often exceed 10G

Big Data Journey for Recommendation

Stage II :

We incorporated Spark and AWS cloud into our workflow

Challenge:
Deep learning libraries such as Tensorflow/Keras/PyTorch cannot run directly on Spark cluster

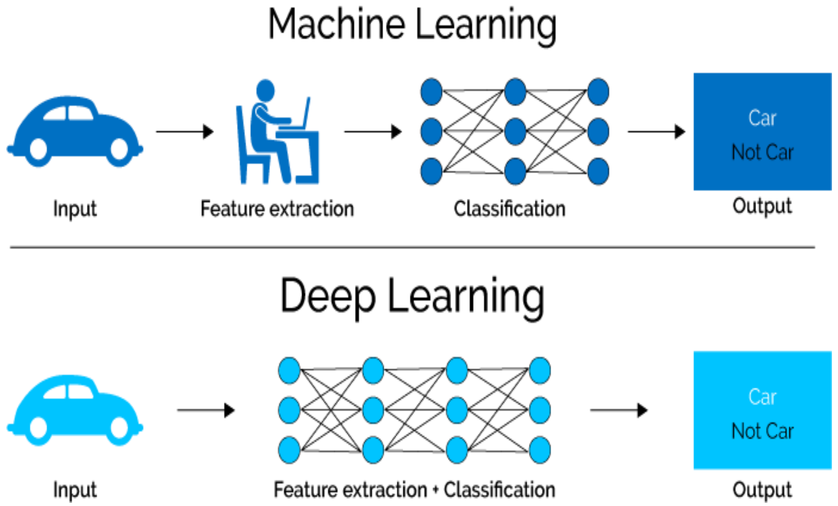


Big Data Journey for Recommendation

Stage III :

Why do we need deep learning ?

- Better performance with larger data
- Less manual feature engineering needed, feature generation and classification are tied within one system
- Easier to compute complex functions
- Flexibility to combine different architectures and output formats



AI on Apache Spark

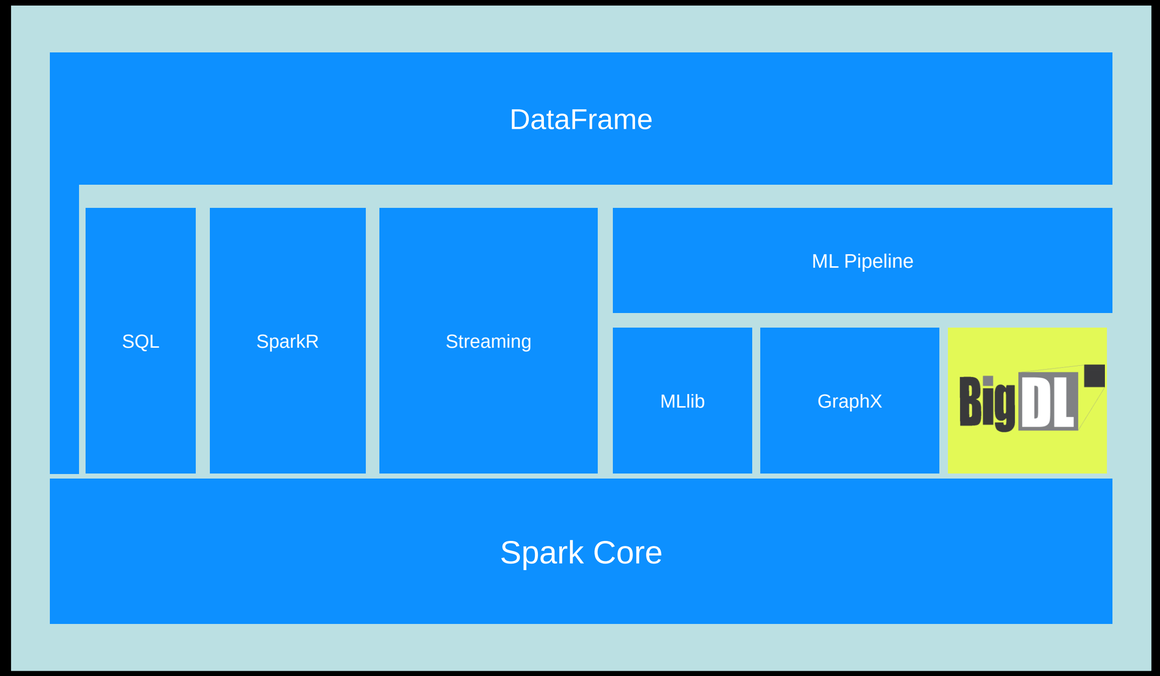
Distributed, High-Performance
Deep Learning Framework
for Apache Spark
https://github.com/intel-analytics/bigdl

Distributed TensoRflow, Keras and BigDL on Spark
Reference Use Cases, AI Models,
High-level APIs, Feature Engineering, etc.
https://github.com/intel-analytics/analytics-zoo

Unifying Analytics + AI on Apache Spark

BigDL: Bringing Deep Learning To Big Data Platform

- Distributed deep learning framework for Apache Spark*
- Make deep learning more accessible to big data users and data scientists
  - Write deep learning applications as standard Spark programs
  - Run on existing Spark/Hadoop clusters (no changes needed)
- Feature parity with popular deep learning frameworks
  - E.g., Caffe, Torch, Tensorflow, etc.
- High performance (on CPU)
  - Powered by Intel MKL and multi-threaded programming
- Efficient scale-out
  - Leveraging Spark for distributed training & inference



*Other names and brands may be claimed as the property of others

Analytics Zoo

Unified Analytics + AI Platform for Big Data

Distributed TensorFlow, Keras and BigDL on Spark

Reference Use Cases	• Anomaly detection, sentiment analysis, fraud detection, image generation, chatbot, etc.
Built-In Deep Learning Models	• Image classification, object detection, text classification, text matching, recommendations, sequence-to-sequence, anomaly detection, etc.
Feature Engineering	Feature transformations for • Image, text, 3D imaging, time series, speech, etc.
High-Level Pipeline APIs	• Distributed TensorFlow and Keras on Spark • Native support for transfer learning, Spark DataFrame and ML Pipelines • Model serving API for model serving/inference pipelines
Backbends	Spark, TensorFlow, Keras, BigDL, OpenVINO, MKL-DNN, etc.

Analytics Zoo

Build end-to-end deep learning applications for big data

- Distributed TensorFlow on Spark
- Keras-style APIs (with autograd & transfer learning support)
- nnframes: native DL support for Spark DataFrames and ML Pipelines
- Built-in feature engineering operations for data preprocessing

Productionize deep learning applications for big data at scale

- POJO model serving APIs (w/ OpenVINO support)
- Support Web Services, Spark, Storm, Flink, Kafka, etc.

Out-of-the-box solutions

- Built-in deep learning models and reference use cases

What Can you do with Analytic Zoo?

Anomaly Detection

- Using LSTM network to detect anomalies in time series data

Fraud Detection

- Using feed-forward neural network to detect frauds in credit card transaction data

Recommendation

- Use Analytics Zoo Recommendation API (i.e., Neural Collaborative Filtering, Wide and Deep Learning) for recommendations on data with explicit feedback.

Sentiment Analysis

- Sentiment analysis using neural network models (e.g. CNN, LSTM, GRU, Bi-LSTM)

Variational Autoencoder (VAE)

- Use VAE to generate faces and digital numbers

https://github.com/intel-analytics/analytics-zoo/tree/master/apps

Building and Deploying with BigDL/Analytics Zoo

http://software.intel.com/bigdl/build

Not a Full List

*Other names and brands may be claimed as the property of others

End to End Deep Learning Examples

Consumer

[Sentiment Analysis]

[Image Similarity And Search]

[Image Transfer Learning]

[Image Generation]

Health

[3D Image Support]

Finance

[Fraud Detection]

[Anomaly Detection]

Retail

Recommendation NCF

[Wide n Deep]

Manufacturing

[Object Detection]

Infrastructure

[Tensorflow support]

[Low latency serving]

Follow links above to sample code for various Deep Learning use cases

Online Real-time Recommendation

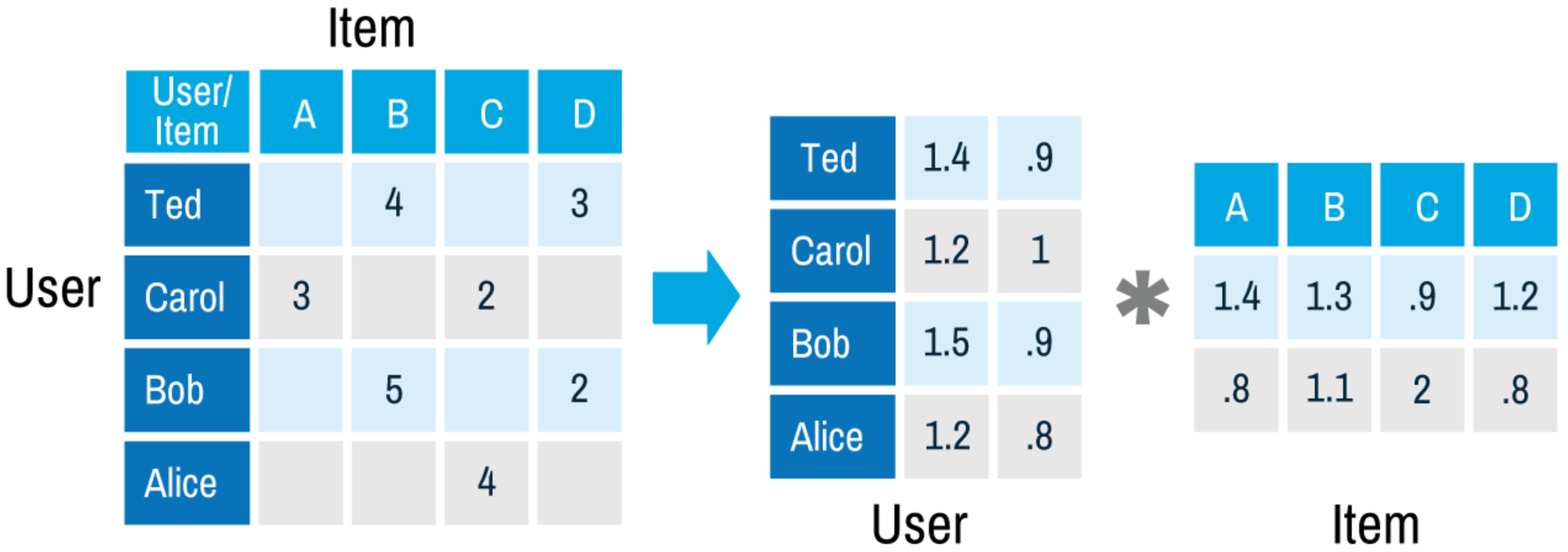
Goal:

A system able to recommend products to online customer from an active product backlog of more than 300,000 products

Challenge:

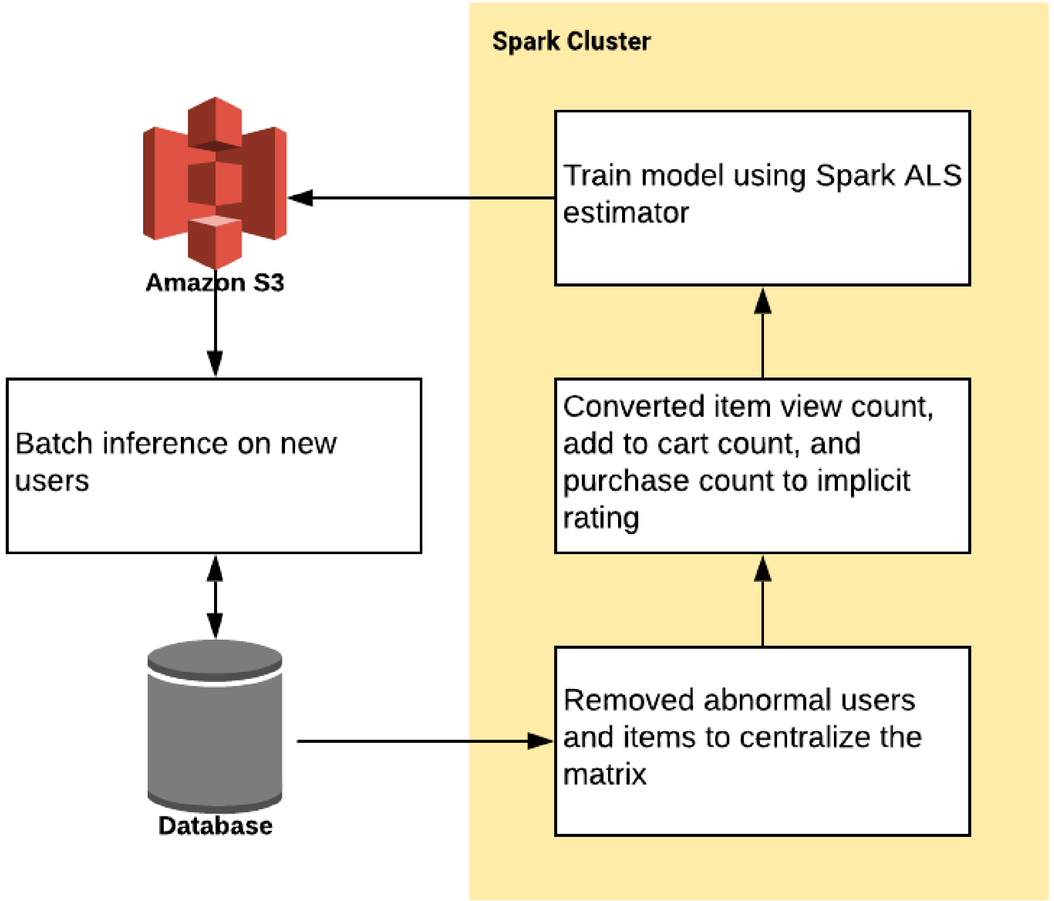
- Large amount of user and item data to process
- User's purchase intent can change frequently
- Deploy model to production with high throughput and low latency

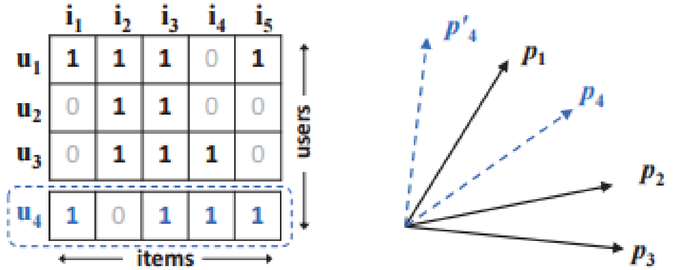
Collaborative Filtering (ALS)



The Collaborative filtering approach work by decomposing the user-item interaction matrix into the product of two lower dimensionality rectangular matrices. Spark ALS implementation runs matrix factorization in a parallel fashion and therefore has a pretty good scalability and sparseness dealing with large datasets

Collaborative Filtering (ALS)





(a) user–item matrix (b) user latent space

Figure 1: An example illustrates MF's limitation. From data matrix (a), u_4 is most similar to u_1, followed by u_3, and lastly u_2. However in the latent space (b), placing p_4 closest to p_1 makes p_4 closer to p_2 than p_3, incurring a large ranking loss.

Limitations:

- Not able to do incremental training
- Not able to capture the latest purchase intent
- Data sparse problem

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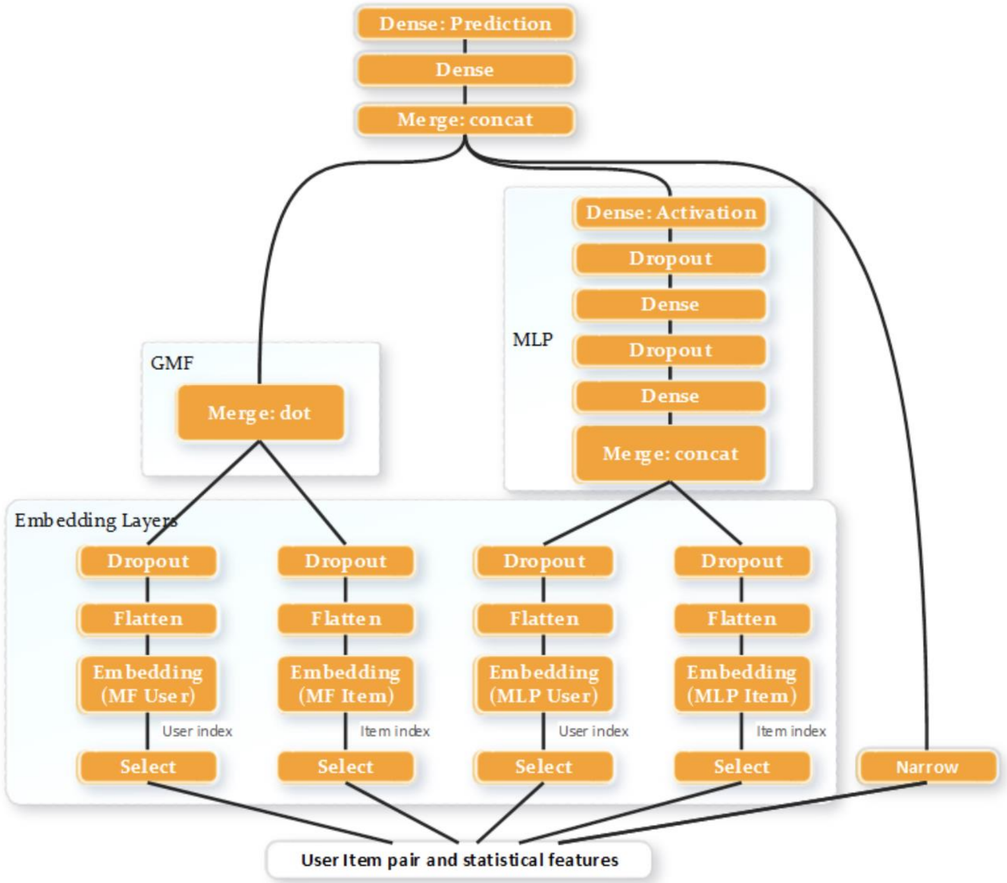
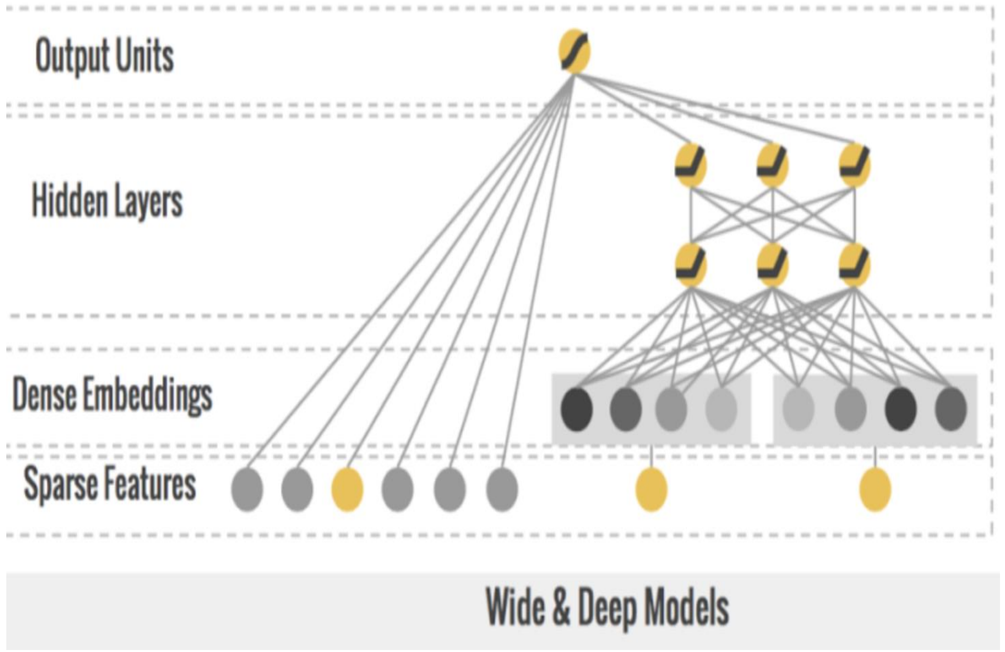
Neural Collaborative Filtering



NCF stimulates matrix factorization using DNN approach and is severed as a guideline for deep learning methods for recommendation services. It combines MF with MLP to model user-item interactions. With the same user item input, NCF outperforms traditional shallow collaborative filtering models on our dataset.

```
val ncf = NeuralCF[Float] (userCount, itemCount, numClasses,
userEmbed, itemEmbed, mfEmbed)

val optimizer = Optimizer(model = ncf, sampleRDD = trainRdds,
  criterion = ClassNLLCriterion[Float](), batchSize = batchSize)

val ncf_model = optimizer
  .setOptimMethod(new Adam[Float](learningRate = 1e-2,
learningRateDecay = 1e-5))
  .setEndWhen(Trigger.maxEpoch(maxEpoch))
  .optimize()
```

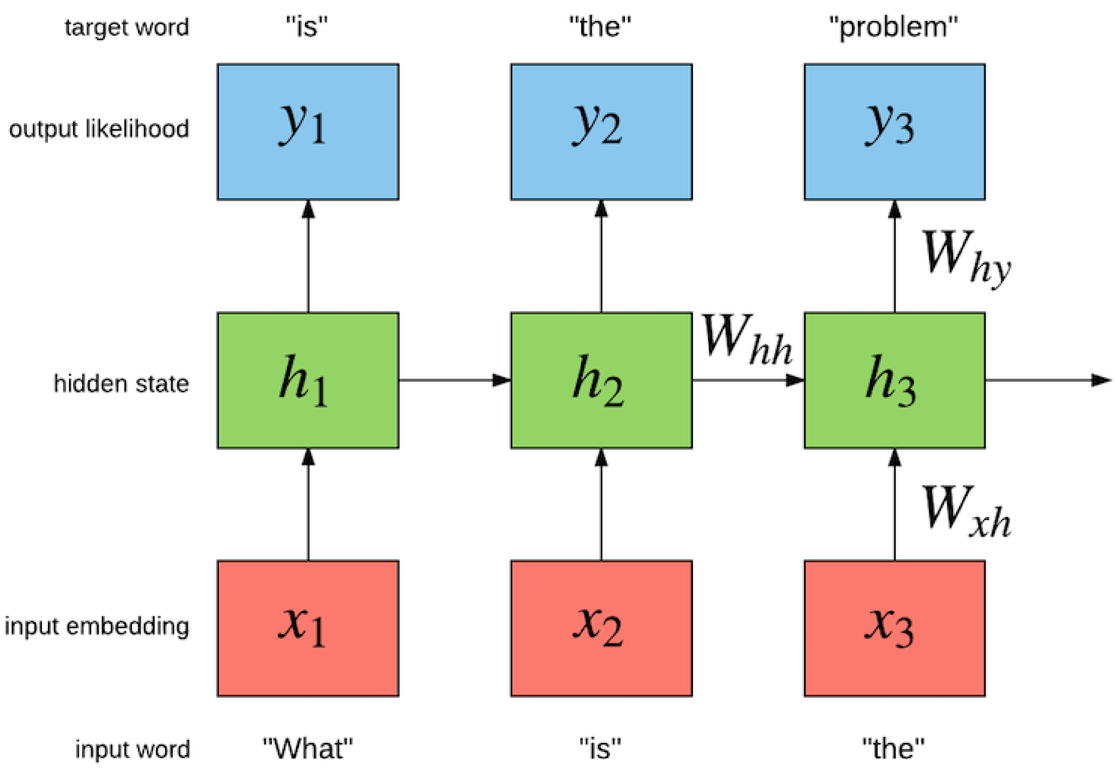
Wide and Deep Recommender

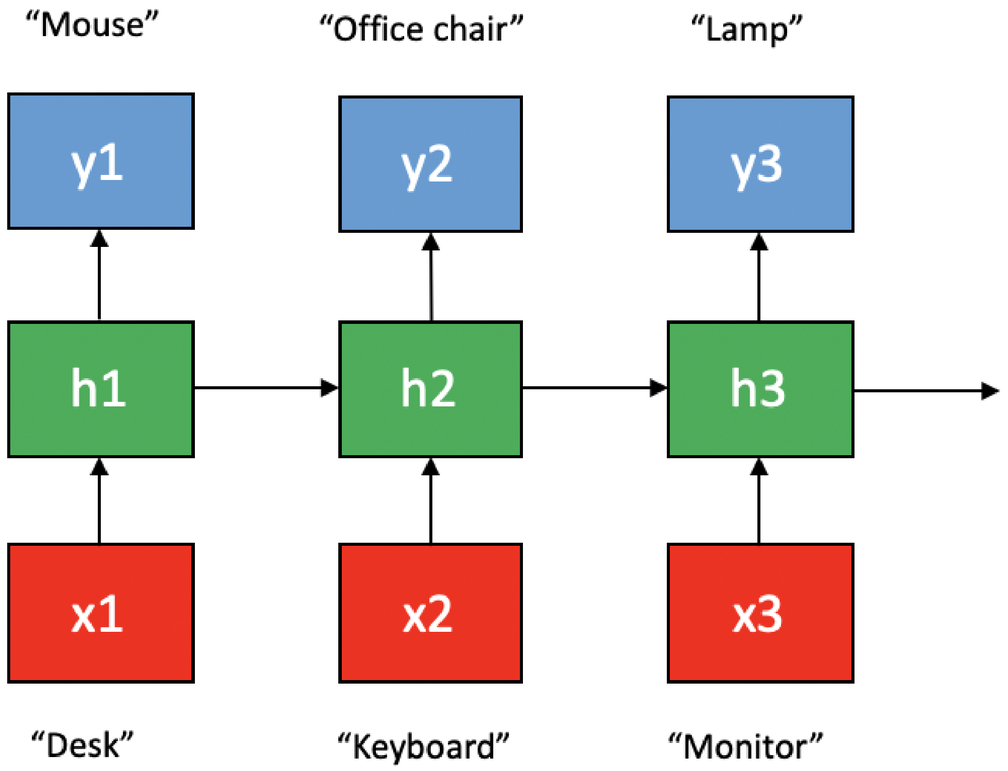


Wide and Deep Model can take rich data as input. The wide part can effectively memorize sparse feature interactions using cross-product feature transformations such as smb_flg – paper_flg, while deep part can generalize to previously unseen feature interactions through low dimensional user / item embeddings similar to NCF.

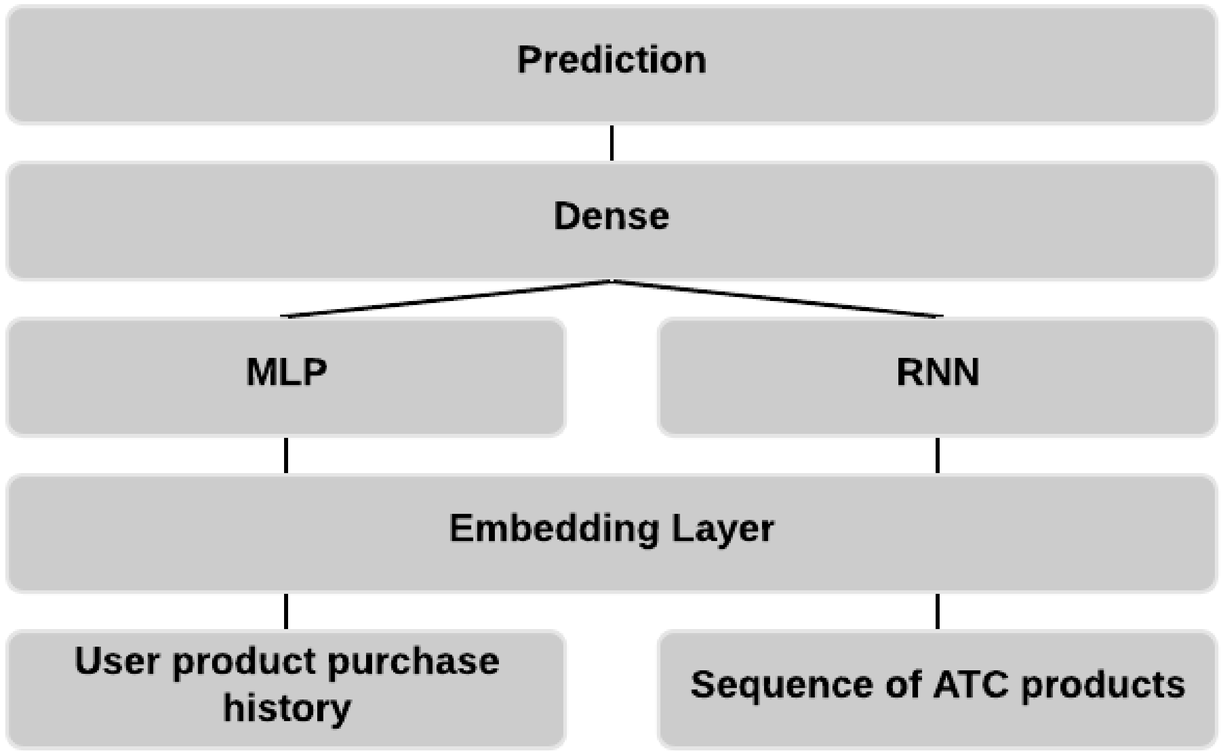
```
val wideAndDeep: = WideAndDeep[Float](modelType, numClasses, columnInfo)

val optimizer = Optimizer(model = wideAndDeep, sampleRDD = trainRdds, criterion = ClassNLLCriterion[Float](), batchSize = batchSize)

val wnd_model = optimizer
  .setOptimMethod(new Adam[Float](learningRate = 1e-2, learningRateDecay = 1e-5))
  .setEndWhen(Trigger.maxEpoch(maxEpoch)).optimize()
```

Sequence Recommender





Sequence Recommender



The Good:
Can catch the latest purchase intent from current session behavior and adjust its product recommendation in real time
Work with both anonymous / identified customers
No pre-filtering mechanism required, simpler serving architect

The Bad:
Sequence window size is hard to set
Online inference requires lots of resources

Performance Comparison

Offline measurement:

Method	Top 5 Accuracy
Sequence	52.3%
Wide & Deep	45.2%
NCF	46.7%
ALS	16.2%

Online measurement:

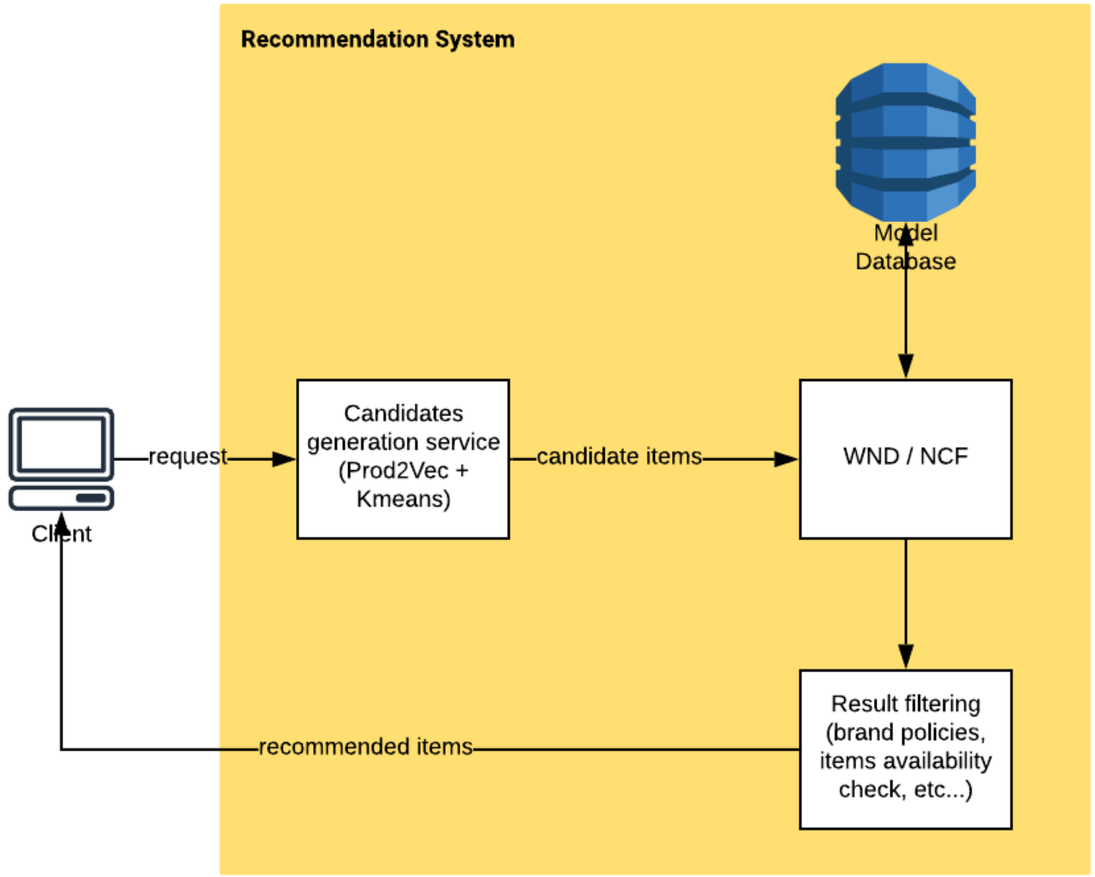
Online A/B testing shows the test group using sequence model lifted sales by 1% and average order value by 1.6% compared to control group

*Testing by Office Depot

Note: test data provided by Office Depot

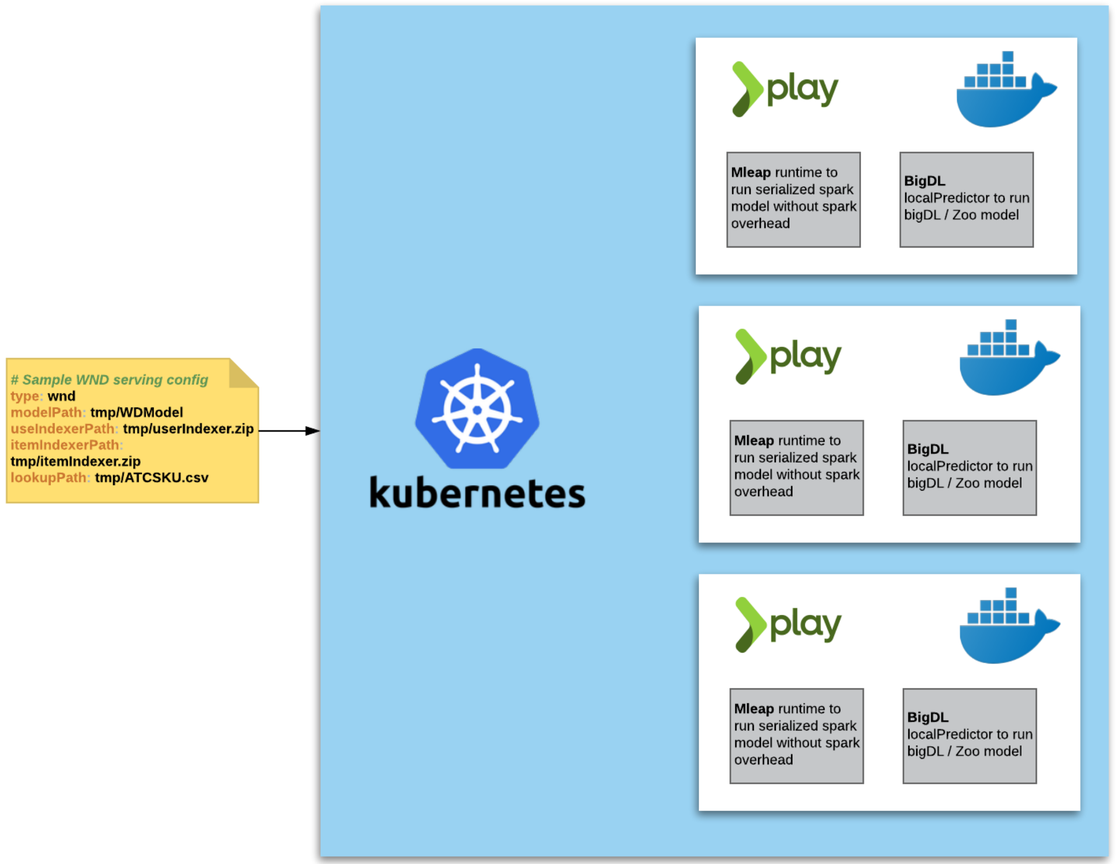
Recommendation System Deployment

- Neural embedding to generate candidate items
- Recommendation service ranking candidate items by probabilities
- Apply post filtering rules according to business needs



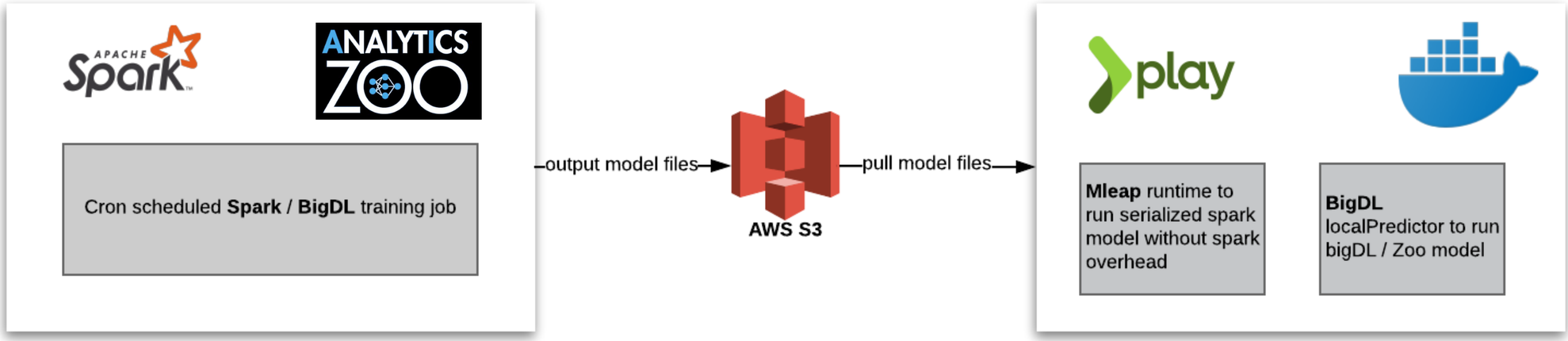
Recommendation System Deployment

- Use model configuration file to deploy different models to production
- Ability to scale up / down according to the current workload using Kubernetes

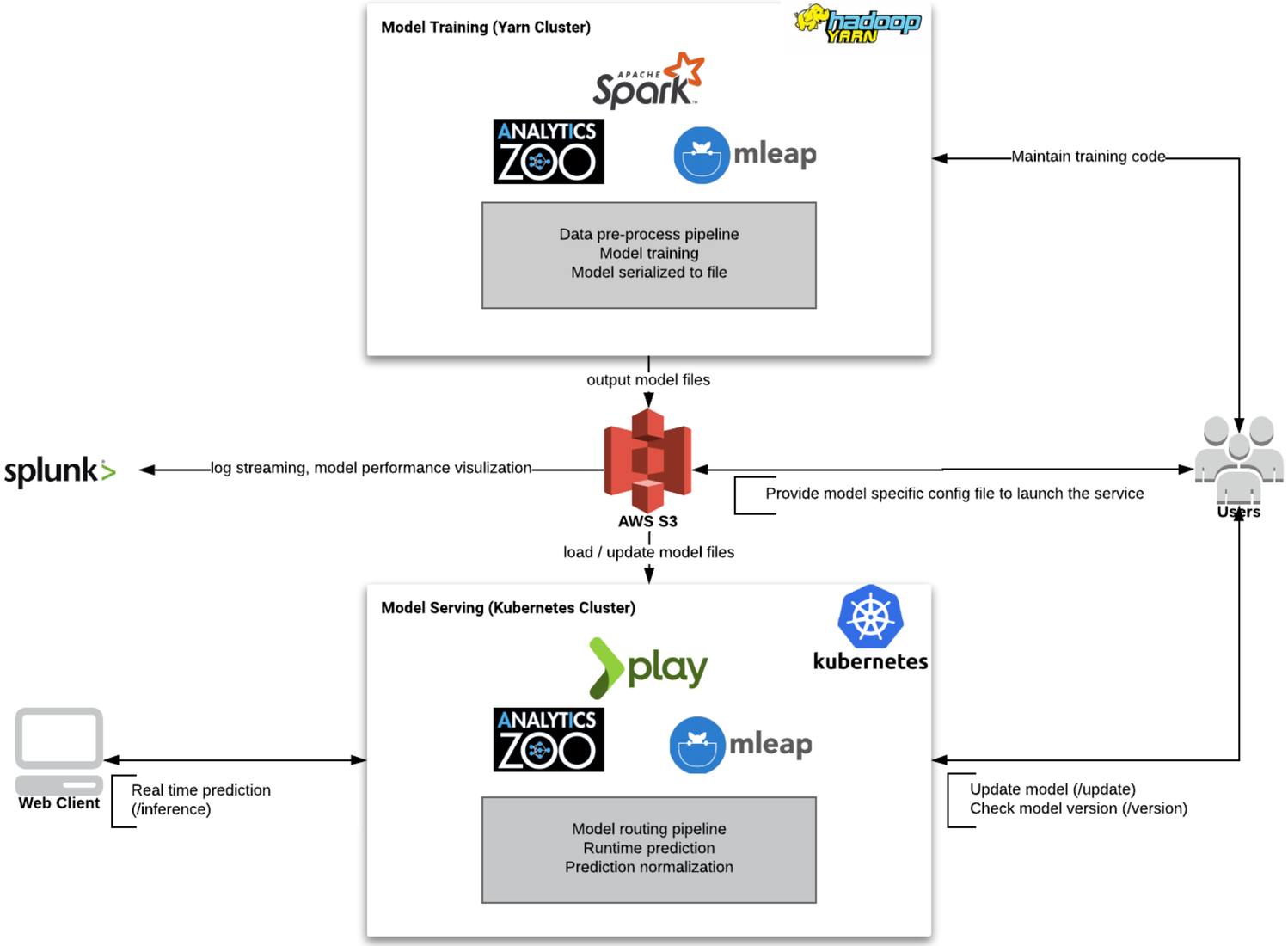


Recommendation System Deployment

- Self-updated / automated model deployment pipeline
- No down time when update model in production



Deploy Zoo Models to Production



Takeaways

- Analytics Zoo/BigDL integrates well into existing AWS Spark ETL and machine learning platform
- Analytics Zoo/BigDL provides inference/local predictor for high performance real-time inference
- Deep learning can drastically reduce manual feature engineer workload compare to traditional machine learning approach
- Deep learning based recommendation provides more flexibility to combine different model architectures for different use cases
- By mapping item to word and session to document, lots of NLP algorithms can be utilized for recommendation
- More information available at https://analytics-zoo.github.io

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Questions?