Use Analytics Zoo to build an intelligent recommendation system on Office Depot

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Mar 26th, 2020

OUTLINE

- Background and use case overview
- Introduction to Analytic Zoo
- Recommenders on Analytics Zoo
- Performance and deployment by Office Depot
- Conclusion

Why Recommendation Systems?

- Help customers choose from a variety of products.
- Maintain user satisfaction and royalty.
- Turn ordinary users into potential customers.
- Increase revenue per user visit.
- ……

Big Data Journey for Recommendation

Stage I :

Office Depot tried to build intelligent models for product recommendation using Python/SAS/R.

Challenges:

They can not process this amount of data on a single machine:

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

Big Data Journey for Recommendation

Stage II :

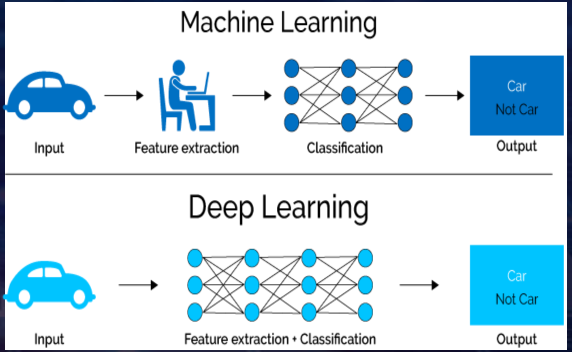
Office Depot incorporated Spark and AWS cloud into their workflow.

Challenge:

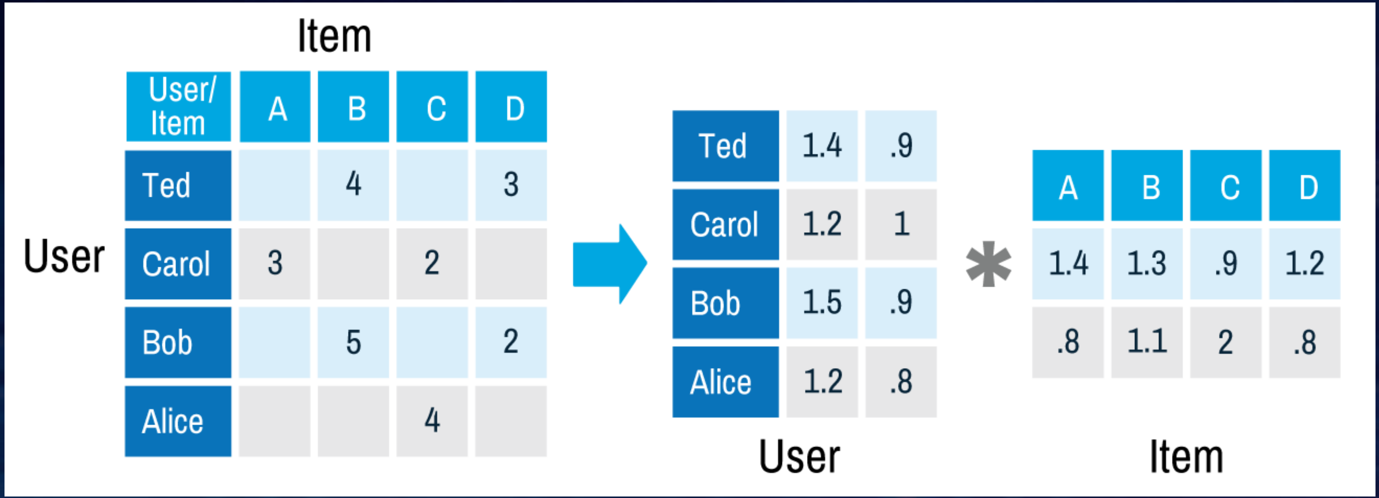
Deep learning libraries such as TensorFlow/Keras/PyTorch cannot run directly on Spark clusters.

Why deep learning?

- Better performance on larger data.
- Less manual feature engineering needed.
- Easier to involve complex functions and combine different architectures.

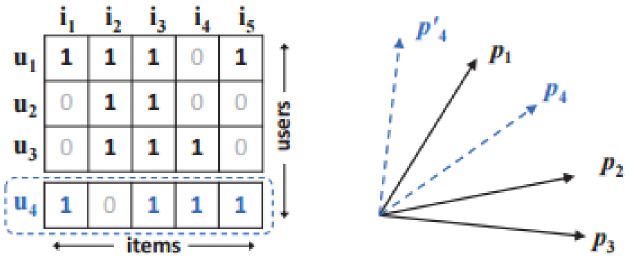


Collaborative Filtering (ALS)



- The Collaborative filtering approach works by decomposing the user-item interaction matrix into the product of two lower dimensionality rectangular matrices.
- Spark ALS (Alternating Least Squares) implementation runs matrix factorization in a parallel fashion and therefore has a pretty good scalability and performance.

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 of matrix factorization:

- Simple choice of the interaction function will hinder the performance.
- Data sparse problement.
- Not able to do incremental training.
- Cold start problem.
- Not able to capture the latest purchase intent.

...

AI ON APACHE Spark™

BigDL

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

ANALYTICS ZOO

A unified analytics and AI platform
for distributed Tensorflow, Keras, PyTorch and Ray
on Apache Spark
https://github.com/intel-analytics/analytics-zoo

Accelerating Data Analytics + AI Solutions At Scale

Analytics Zoo

Unified Big Data Analytics and AI Platform

Models & Algorithms
- Recommendation
- Time Series
- Computer Vision
- NLP

ML Workflow
- AutoML for Time Series
- Automatic Cluster Serving

Integrated Analytics & AI Pipelines
- Distributed TensorFlow & PyTorch on Spark
- RayOnSpark
- Spark Dataframes & ML Pipelines for DL
- Model Serving

Library & Framework
- Distributions (Cloudera/Databricks/....)
- Distributed Analytics (Spark/Flink/Ray/...)
- DL Frameworks (TF/PyTorch/...)
- Python Libraries (Numpy/Pandas/...)

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

Unified Big Data Analytics and AI Platform

Seamless Scaling from Laptop to Production

- Easily prototype the **integrated data analytics & AI solution**
- **"Zero" code change** from laptop to distributed cluster
- **Directly access production data** (Hadoop/Hive/HBase) without data copy
- Seamlessly deployed on **production big data clusters**

Real-World Applications

NLP Based Customer Service Chatbot for Microsoft Azure*

https://software.intel.com/en-us/articles/use-analytics-zoo-to-inject-ai-into-customer-service-platforms-on-microsoft-azure-part-1
https://www.infoq.com/articles/analytics-zoo-qa-module/

Industrial Product Defect Detection in Midea*

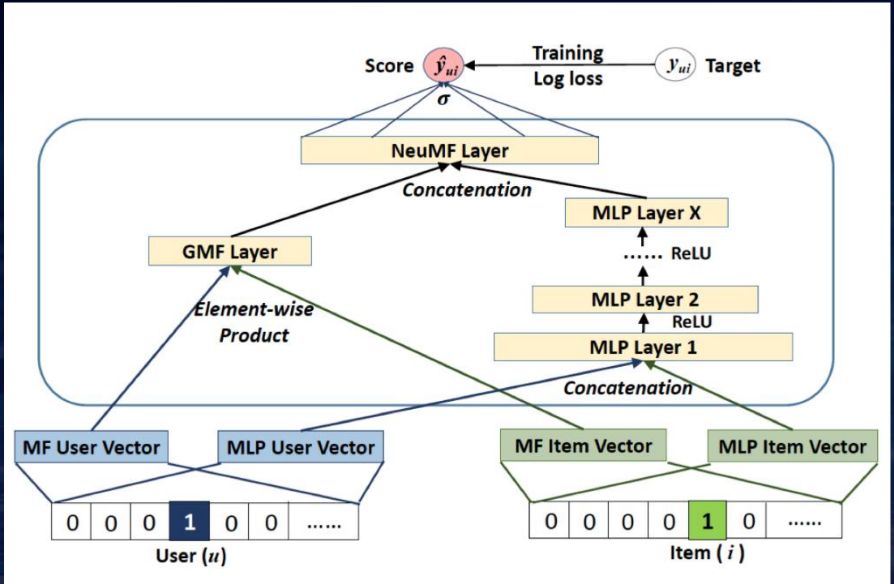
https://software.intel.com/en-us/articles/industrial-inspection-platform-in-midea-and-kuka-using-distributed-tensorflow-on-analytics

Unsupervised Time Series Anomaly Detection for Baosight*

https://software.intel.com/en-us/articles/lstm-based-time-series-anomaly-detection-using-analytics-zoo-for-apache-spark-and-bigdl

Any many more…

Neural Collaborative Filtering (NCF)

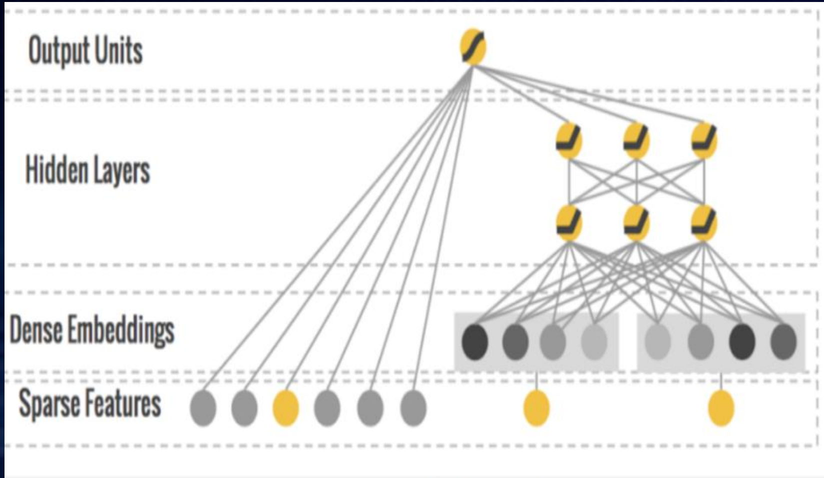


- NCF stimulates matrix factorization using DNN approach and is severed as a guideline for deep learning methods for recommendation services.
- It combines GMF with MLP to model user-item interactions.

```
from zoo.models.recommendation import NeuralCF

ncf = NeuralCF(user_count, item_count, class_num, user_embed=20,
               item_embed=20, hidden_layers=[40, 20, 10],
               include_mf=True, mf_embed=20)
ncf.compile(optimizer= "adam",
            loss= "sparse_categorical_crossentropy",
            metrics=['accuracy'])
ncf.fit(train_rdd,
        nb_epoch,
        batch_size,
        validation_data=val_rdd)
```

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

Wide & Deep Learning



Wide & Deep Models

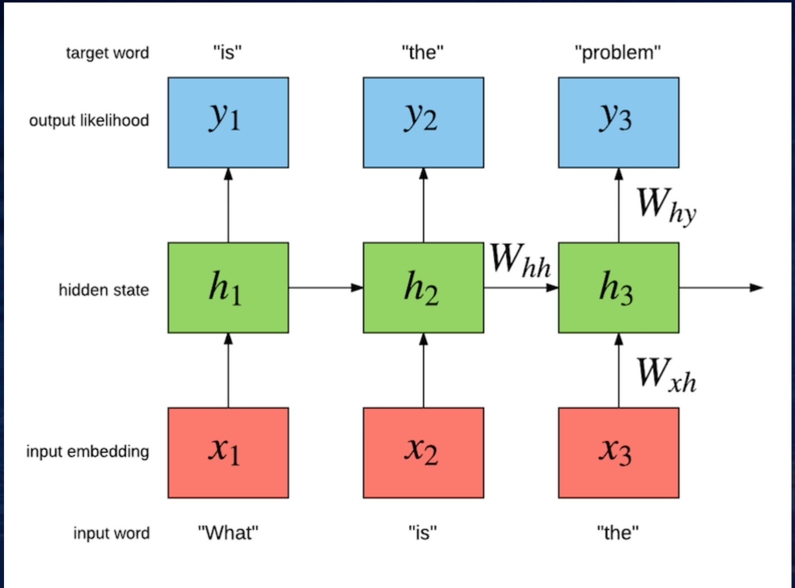
- Wide and Deep learning model can take rich data as input.
- The wide part can effectively memorize sparse feature interactions using cross-product feature transformations.
- The deep part can generalize to previously unseen feature interactions through low dimensional user and item embeddings similar to NCF.

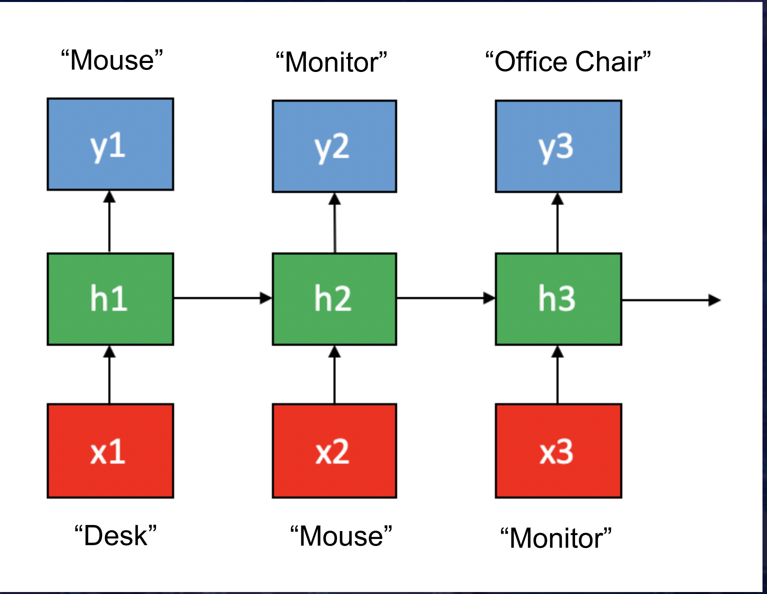
```python
from zoo.models.recommendation import WideAndDeep

# column_info can be shared by feature generation and model, where you can specify
# columns and their dimensions for each part of the model.
wnd = WideAndDeep(user_count, class_num, column_info,
                  model_type="wide_n_deep", hidden_layers=[40, 20, 10])
```

https://github.com/intel-analytics/analytics-zoo/tree/master/apps/recommendation-wide-n-deep

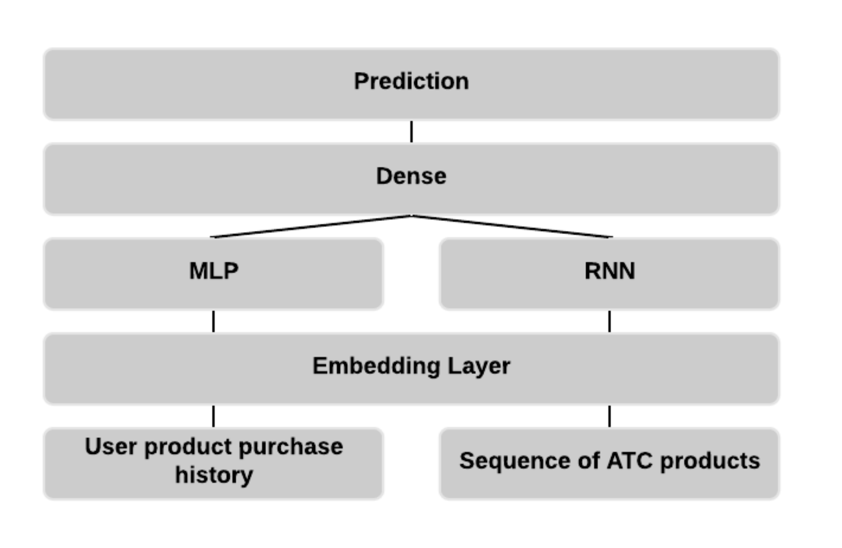
Session Recommender

- Each user session in an e-commerce system could be modeled as a sequence of web pages.
- A deep RNN could track how users browse the website using multiple hidden layers.





Session Recommender



The Good:

- Can catch the latest purchase intent from current session behavior and adjust its product recommendation in real time.
- Can 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.

```
from zoo.models.recommendation import SessionRecommender

model = SessionRecommender(item_count, item_embed=100, rnn_hidden_layers=[40, 20],
                           session_length=5, include_history=True,
                           mlp_hidden_layers=[40, 20], history_length=10)
```

Performance Comparison

Offline measurement:

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

Online measurement:

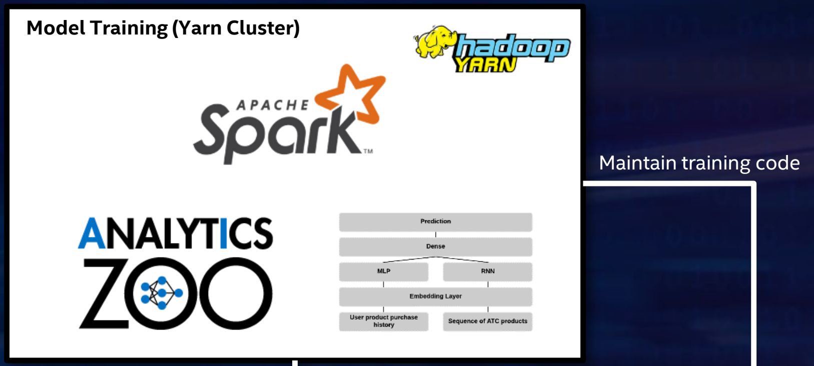
Online A/B testing shows the test group using Session Recommender lifted sales by 1% and average order value by 1.6% compared to control group.

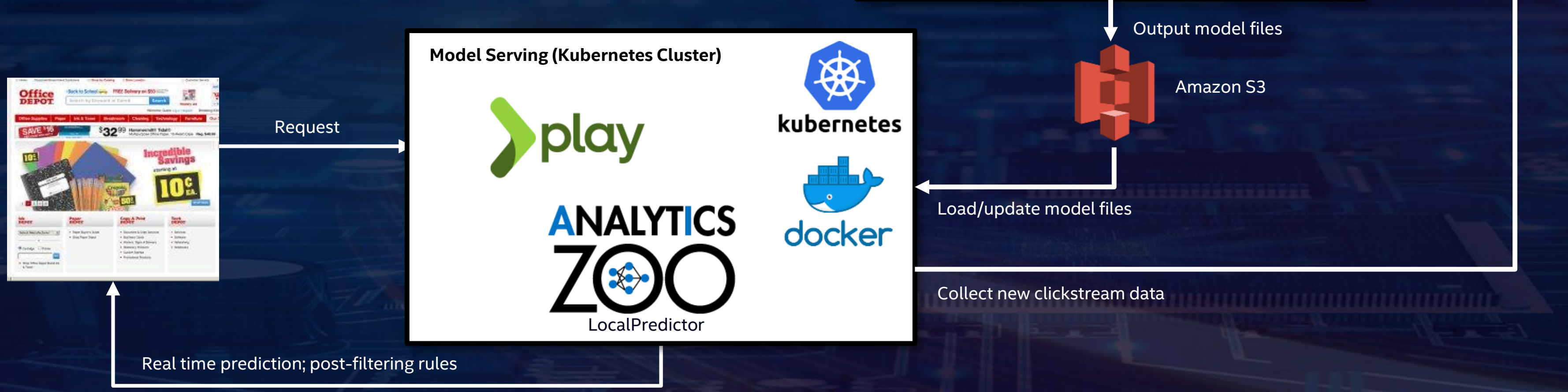
*Tested by Office Depot

Note: test data provided by Office Depot

Recommendation System In Production

- Automated model deployment pipeline.
- No down time when update model in production.
- Ability to scale up / down according to the current workload using Kubernetes.





Conclusion and Takeaways

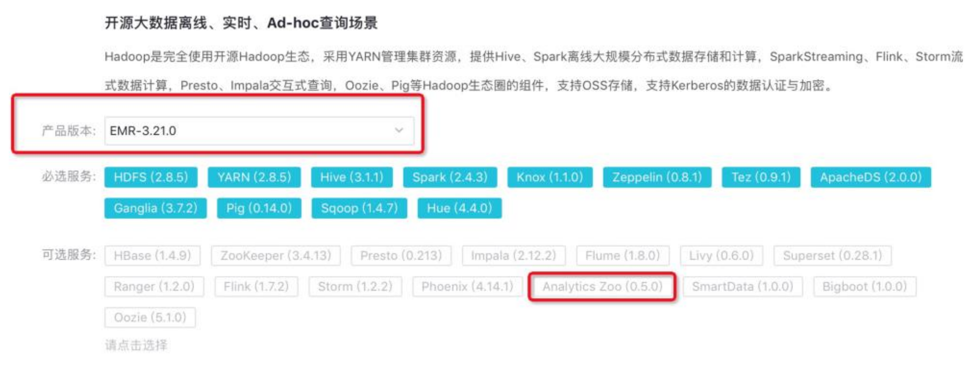
- Analytics Zoo integrates well into existing big data pipelines.
- Analytics Zoo provides model serving API for high performance real-time inference.
- Deep learning based recommendation provides more flexibility to combine different model architectures for different use cases.
- Lots of NLP algorithms (for example, transformers) can be utilized for recommendation.
- Check out the joint blog for more information:

https://software.intel.com/en-us/articles/real-time-product-recommendations-for-office-depot-using-apache-spark-and-analytics-zoo-on

Analytics Zoo on Ali E-MR

ANALYTICS ZOO + Alibaba Cloud aliyun.com

Analytics Zoo is already out-of-box on Ali EMR：



* Version upgrade for Analytics Zoo is on-going.

For more information and support, contact Wesley：

Email: wesley.du@intel.com
DingTalk:

More Information on Analytics Zoo

- Project websites
  - https://analytics-zoo.github.io/master/
  - https://github.com/intel-analytics/analytics-zoo
  - https://github.com/intel-analytics/bigdl
- Tutorials
  - CVPR 2018: https://jason-dai.github.io/cvpr2018/
  - AAAI 2019: https://jason-dai.github.io/aaai2019/
- "BigDL: A Distributed Deep Learning Framework for Big Data"
  - *In proceedings of ACM Symposium on Cloud Computing 2019 (SOCC'19)*
  - https://dl.acm.org/doi/10.1145/3357223.3362707
- Use cases
  - *Microsoft Azure, CERN, MasterCard, Baosight, Tencent, Midea, etc.*
  - https://analytics-zoo.github.io/master/#powered-by/

ANALYTICS ZOO

Unified Analytics + AI Platform

Distributed TensorFlow, Keras and BigDL on Apache Spark

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

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