Quick to production with the best of Spark and Tensorflow

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Rue Gilt Groupe

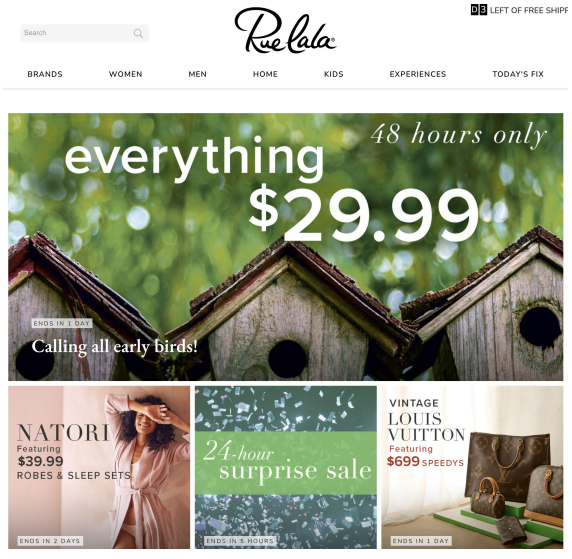
Who are we

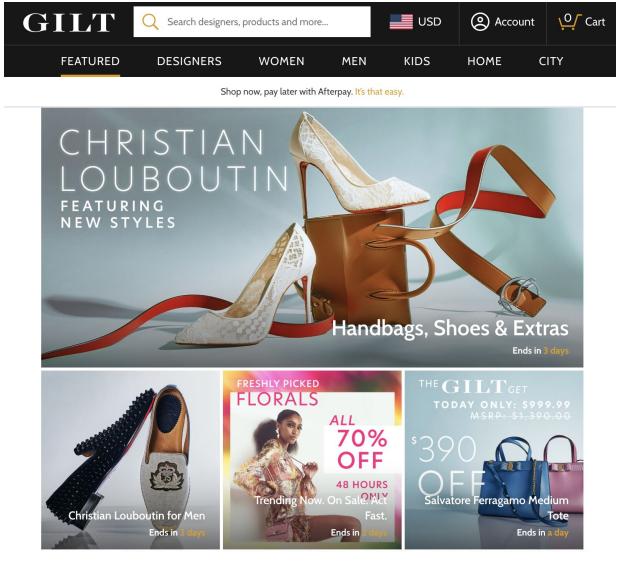
RUE GILT GROUPE

Rue Gilt Groupe is a fashion technology company based in Boston.

Our **50M+ members** get exclusive access to **private sales** on **must have brands** from an ever changing catalog of **3M+ products**

ruelala.com





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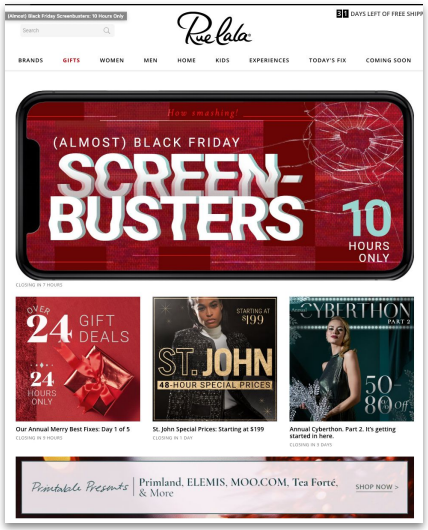
Data Science at Rue Gilt Groupe (RGG)

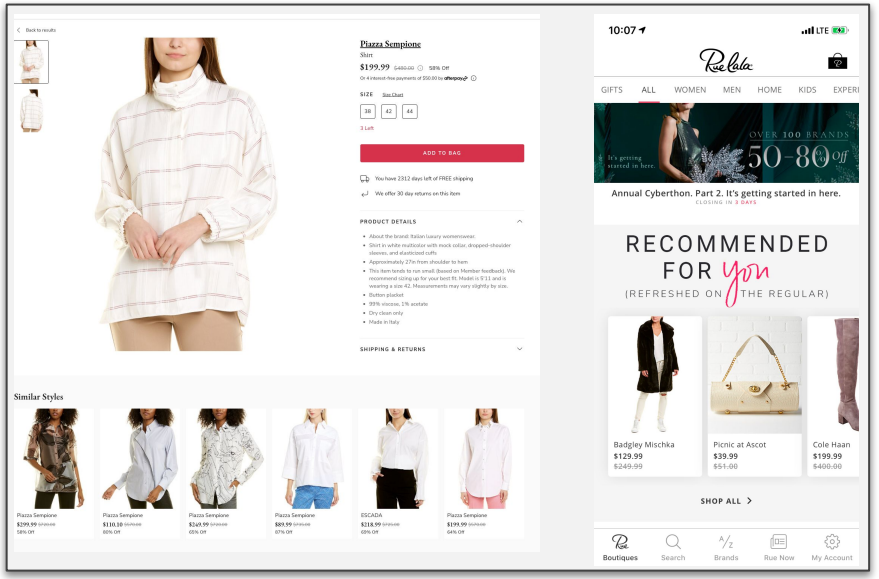
We are a close-knit group of passionate data scientists who thrive on collaboration and innovation

We work on various projects including **NLP, CV, time-series Forecasting, Recommenders**

We use ML to **personalize** the site and email experiences of our members among others projects

Sorting main pages





Product recs

Our 2020 ML stack

We leverage Spark and container based ML pipelines extensively

In addition to this, we use common ML packages like sklearn, xgBoost, openCV, prophet, ...

Developing next-gen Models

*Developing the next generation of products pushed us to expand **beyond Spark ML** and leverage state-of-the-art deep learning models in **Tensorflow***

- ➢ Solution to **quickly** move from a working prototype to a production model
- ➢ Did not want added complexity with more MLOps code
- ➢ **Minimal** approach perfect for a **small-medium** full stack Data science team
- ➢ Enable **rapid prototyping and experimentations**
- ➢ Lets Data Scientists and ML Engineers **focus more on research** and **actual ML tasks**

What we will cover

- This talk will focus on how we were able to achieve all of the above using some recent advancements in Tensorflow 2 and extension libraries for Spark by merging the **best of both Spark and Tensorflow worlds**
- **Enable Quick Distributed training** in tensorflow on GPU and CPU clusters
- MLFlow model registry as a **central model storage** ensuring consistency for all downstream batch and realtime inference jobs

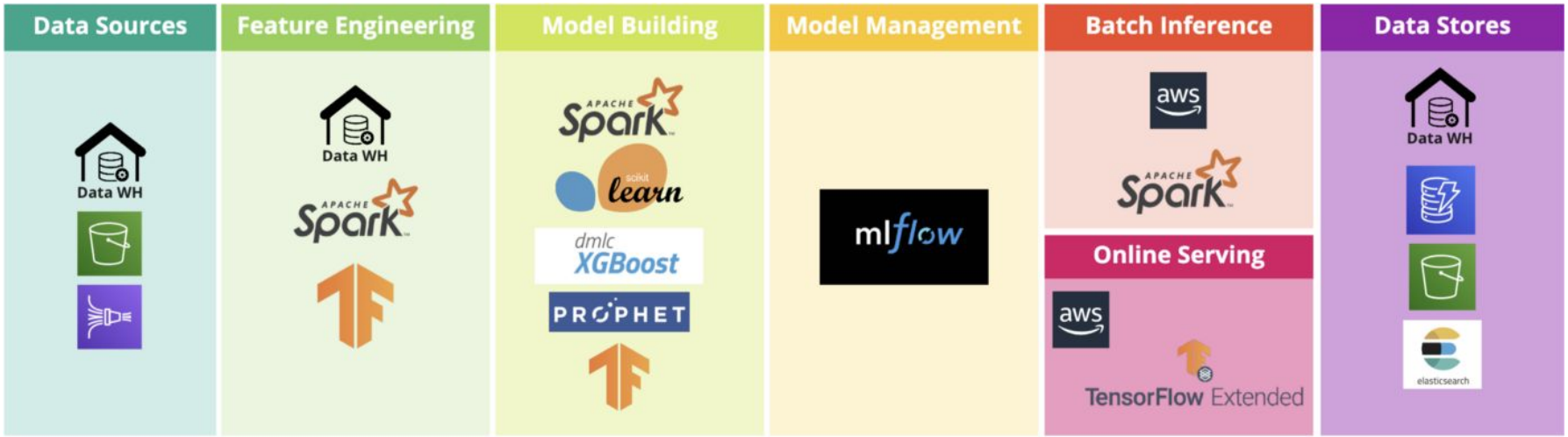
How this helped us at RGG

- Models using huge clickstream datasets are difficult to train on a single instance
- Developed a prototype for a **GRU based personalization model for new members**
- Converted our prototype to a production model quickly in **less than 2 weeks**
- A/B Test proved our new members loved their deep learning recs with **>25% lift in CTR**!

Our 2021 next-gen ML stack

Using these tools we successfully integrated Tensorflow into our spark ML pipelines

Flexibility to choose from Spark or Tensorflow ecosystem at any ML stage



Next up for us

Some of the next projects that we are planning with these tools,

- Develop deep learning models for all of our personalization and recommenders
- Online session based recommendations
- Better text representation with cutting edge language models (BERT and more)
- Product Tagging and Catalog Management with NER, text and image models
- Leverage image resources better with Autoencoders and vision models
- Online recommendations using Reinforcement Learning
- Realtime intent detection for a user session

Let’s get started with some Spark features

Apache Spark

- Popular open source big data processing platform
- Write code in multiple programming languages
- Run pipelines on a single-node or clusters
- Work on structured and unstructured data
- Batch and streaming pipelines
- Distributed Machine learning with Spark ML

Data Pipelines in multiple languages

- Easy-to-use APIs in SQL, Python, Java, R, and/or Scala
- User-defined functions extend spark SQL functionalities

Data engineers

```
# in python
import pyspark.sql.functions as f
@f.udf("string")
def say_hello(name: str) -> str:
      return f"Hello {name}"
sqlContext.udf.register("say_hello",
say_hello)
```

Data Analysts/Data Scientists

```
-- uses the udf in sql
SELECT say_hello('Bob')
```

Pandas UDFs

Allows using a pandas UDF to manipulate spark dataframes

Manipulate spark dataframe as pandas DataFrames instead of a per row transformation

```
@f.pandas_udf("string")
def simple_udf(iterator: Iterator[pd.Series]) -> Iterator[pd.Series]:
    for x in iterator:
        yield pd.Series(list(map(lambda r: r + "1", x)))
```

Spark ML

- Scalable implementations of many common ML algorithms, including
  - Traditional ML models like Regression, Trees, Multilayer Perceptron, Naive Bayes
  - Text models like Bag of words, Word2Vec, TF-IDF, LDA
  - ALS-based Collaborative Filtering and FP-Growth mining
  - Locality Sensitive Hashing and Random Projection for ANN and approx joins
- Libraries are available to integrate sklearn, XGBoost, tensorflow, pytorch and others

Let’s look at some Tensorflow features

Tensorflow

- Machine learning framework maintained and used within Google
- V2 has adopted the core principle of **progressive disclosure of complexity** from Keras

  You should always be able to get into lower-level workflows in a gradual way. You shouldn't fall off a cliff if the high-level functionality doesn't exactly match your use case. You should be able to gain more control over the small details while retaining a commensurate amount of high-level convenience. source
- TFx extends tensorflow beyond model building and to end to end ML pipelines
- A lot of extension libraries that extends Tensorflow capabilities
- Great tutorials and guides on the official website for anyone to get started quickly
  - https://www.tensorflow.org/tutorials
  - https://www.tensorflow.org/guide

TF Data

TensorFlow

- TF APIs for data loading and manipulation using Tensorflow datasets
- Recommended way to load data into a tensorflow 2.x model
- **TFRecordDataset** is a tf dataset that can load data directly from **tfRecord** files
- Does a lot of great optimizations behind the scenes including prefetching and caching
    - While training on GPU, prefetch uses the CPU to load the next n batches
    - **tf.data.AUTOTUNE** can automatically adapt prefetching (and others) to your cluster

```
dataset = (tf.data.TFRecordDataset(filenames=[list of tfrecord files]))
                .batch(1000)
                .shuffle(10000)
                .prefetch(tf.data.AUTOTUNE))
```

TF Distribute

TensorFlow

- Provides distributed training strategies in synchronous/asynchronous mode, on GPU/TPU, etc
- Automatically assigns **default strategy** to every training loop
- **A single-node development code can be converted to a distributed code by adding a few lines initially when we start development**

```
# we can also add more conditions here, eg check for num workers
# add more strategies as needed
if tf.config.list_physical_devices('GPU'):
    my_strategy = tf.distribute.MirroredStrategy()
else:  # Use the Default Strategy
    my_strategy = tf.distribute.get_strategy()

with my_strategy:
    # wrap all the training code within this scope
    ...
```

Distributing Datasets

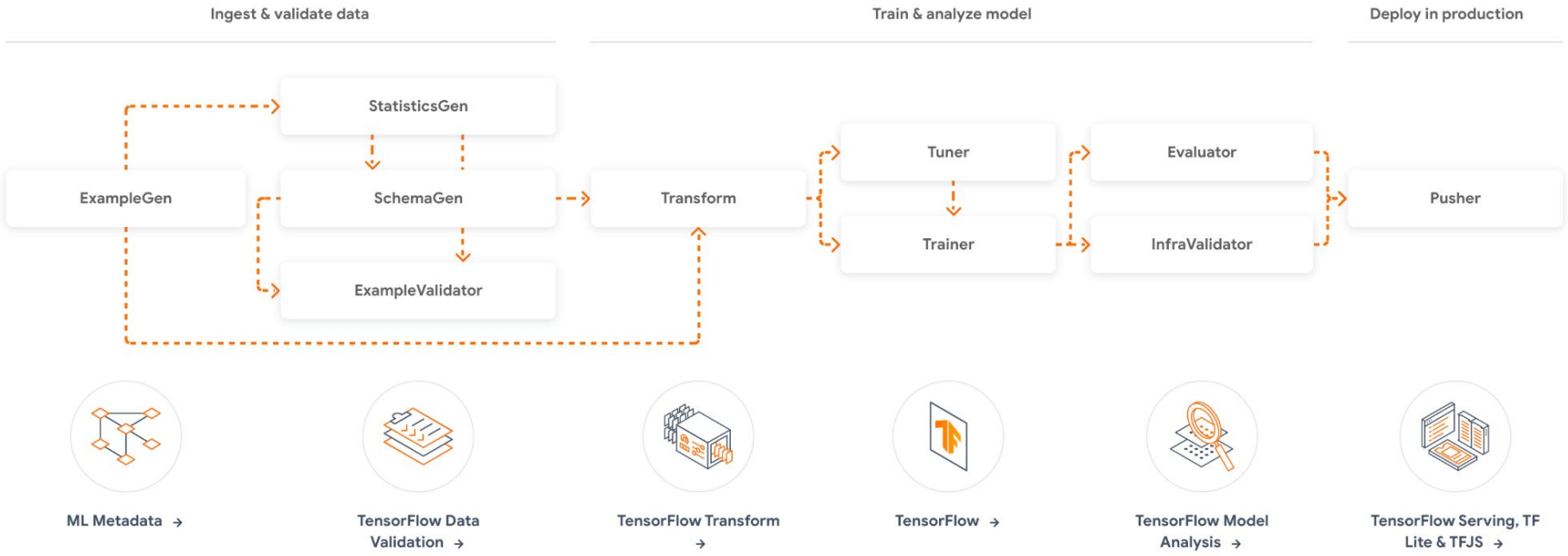
TensorFlow

Convert a tf dataset to a distributed dataset in a few lines of code

```
# There are two shard policies, DATA and FILE
options = tf.data.Options()
options.experimental_distribute.auto_shard_policy =
tf.data.experimental.AutoShardPolicy.DATA
dataset.with_options(options)
```

TF Extended (TFx)

- End-to-end machine learning platform for tensorflow
- Everything from data ingestion to model serving and monitoring



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Some cool TFx components

TensorFlow

- **Tensorflow Serving**
  - Core Tensorflow component responsible for deploying and online serving
  - Loads and serves a model at a high performant REST endpoint
  - Docker containers provided by google with different flavors of tensorflow
  - Can be scaled as needed using dockerized containers for online recommendations
- **Tensorflow Transform**:
  - Performs feature engineering and transforms
  - Alternative to using Spark (as in our case)
- **Tensorflow Model Analysis (TFMA)**
  - Model validations
  - Monitoring issues and drifts in models

TF Recommenders

TensorFlow

- Extension library for building Deep learning Recommenders
- Provides easy to use wrappers for models, custom metrics and losses
- Exposes google's *scann* approximate nearest neighbor engine as a Layer
- Simplifies building models for
  - Retrieval (narrow down entire corpus to a few thousand candidates)
  - Ranking (rank top candidates to a handful with more complex architecture)
  - Multitask recommenders (learn from multiple objectives)
  - Deep Cross Networks (capture explicit feature interactions between items)
  - and more

More Extension Libraries and tools

TensorFlow

- **TF Ranking**
  - Build Learning-to-Rank (LTR) models
  - commonly used loss functions like pointwise, pairwise, and listwise
  - ranking metrics like Mean Reciprocal Rank and NDCG
- **TF Agents**
  - Enables building contextual bandit and RL agents
- **TF Hub**
  - Collection of the latest pre-trained models for text, image, video, audio, and more
  - Easily pull to any existing model as a layer with simple code,

```
# sometimes we also need to load preprocessing layers
bert_path="https://tfhub.dev/tensorflow/bert_en_uncased_L-12_H-768_A-12/4"
bert_embeddings = hub.KerasLayer(bert_path, trainable=False)
```

MLFlow

- Great for experiment tracking, reproducibility and model management
- **Compare metrics** from different runs and **pick** the best model
- **Manage models** using MLFlow models and Model Registry
- Single source of truth for all models and its versions ensuring **consistency**
- **Autologging** capabilities for common frameworks

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Linking them all

TF records with Spark

- TFRecord is a tf native file format that stores sequences of binary records as **Examples**
- Reading and writing tfrecords from Spark ensures that Spark and TFx uses same format
- Enables the flexibility of using Spark or TFx at any point of our ML lifecycle
- Other approaches like Petastorm achieves similar goals but loses the interoperability with TFx

```
# Write tfRecords as Example from a Spark Dataframe
some_df.write.format("tfrecords")
       .option("recordType", "Example")
       .mode("overwrite")
       .save(save_path))
```

Spark Tensorflow Distributor

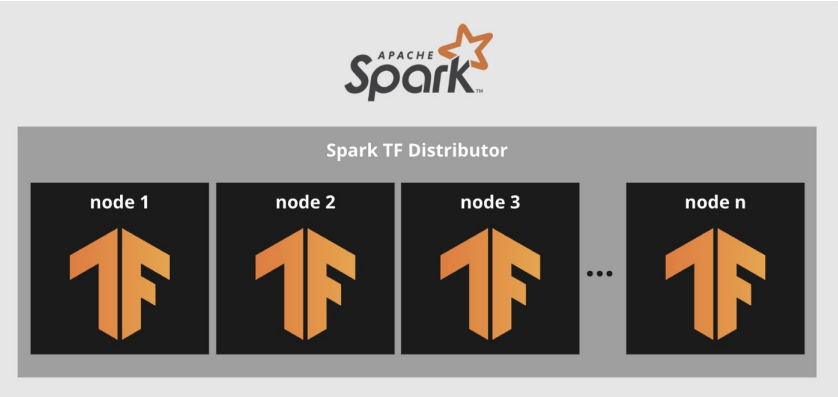
- Part of the TensorFlow ecosystem
- Enables running **tf.distribute strategies** inside Spark jobs
- **Delegate** cluster management and communication to **Spark**
- Also runs on CPU clusters
- Straightforward usage,
    - Define both dataset loading and TF model building code in a **train** method
    - Pass the number of workers in the cluster and train method to the distributed runner

```
num_workers = 10
# add local_mode=True for local testing
# you can also specify another strategy in the train method and turn on
custom_strategy=True
MirroredStrategyRunner(num_slots=num_workers).run(train)
```

Spark Tensorflow Distributor

Under the hood this library automates a lot of infrastructure code

- Communication between nodes
- designation of chief and worker nodes
- Supports custom_strategy to use other tf.distribute strategies (TPUs, GPUs, etc)
    - Update train method with new strategy, add custom_strategy=True to the runner



Who is the chief here

- At times we need to know what the role of a node is especially which one is chief
- Treat callbacks and other operations differently on chief
    - Don’t need all the workers (over)writing the model checkpoints to the same path!
- tf.distribute works by specifying a tf_config environment variable on each node
    - config also includes a node index where *node 0 is the chief node*
- We can find the role of a node using this code,

```
if 'TF_CONFIG' in os.environ:
    tf_config = json.loads(os.environ['TF_CONFIG'])
    node_index = tf_config['task']['index']
    is_chief = node_index == 0
```

Dont forget to save your models!

Since the training happens on a cluster and not just a single instance,

we don’t have access to the final trained model unless we handle it explicitly!

That means you might be running training for days *but there would be no way to retrieve your final model (yikes!)*.

We can use ModelCheckpoint or BackupAndRestore callbacks to handle this

```
save_best_callback = ModelCheckpoint(
                        filepath=s3://persist_path, # Somewhere on persistent
                        storage
                        monitor=monitor_metric,
                        save_best_only=True)
```

Batch Inference in Spark

- Use pandas UDFs to run model inference with the latest model from registry
- Pandas UDF needs an output schema
- Use a column (like batch) to group your spark dataframe and then use

  `.groupBy(grouping_col).applyInPandas(your_pandas_udf, schema)`
- If your models are pure tensorflow, we can load MLFlow models directly in spark with

  `mlflow.pyfunc.spark_udf`

Recap

ML Stage	*How*
Data Ingestion	**Use Spark to read from data sources**
Feature Engineering	**Create data pipelines in Spark** **Write data to persistent store as TFRecords**
Model Building	**Read TFRecords in distributed code** **Train distributed tensorflow model on Spark** **Save trained model to MLFlow**
Model Selection and Management	**Pick the best model from MLFlow and add to model registry** **Use production model in all downstream applications**
Batch Inference	**Load model from MLFlow registry in a pandas UDF** **Add the UDF into the inference Spark pipeline**

Unlocking Realtime Inference

- Realtime inference enables exciting use cases involving direct feedback from our members
- Leverage Spark Streaming to process the realtime data
- Build an online inference service using TF serving and the model from model registry
- Some use cases are,
    - In-session Recommendations
    - Intent and shopping pattern detection
    - Location based trending products
    - Advanced recommendations using Reinforcement Learning

Pros of this Approach

- Great for smaller teams who want to focus on ML and less infrastructure
- Quickly transition from prototype to production models
- Flexibility to choose right framework for the use case at any stage of the ML lifecycle
- Scalable deep learning pipelines with minimal MLOps code
- Run distributed deep learning loads on Spark GPU/CPU clusters with fault tolerance
- Use all of tensorflow ecosystem and extension libraries
- Central storage, versioning, and management of models using MLflow

Open Challenges

- Distributed training does not gracefully handle fault recovery (in the case of a dead worker)
  - Parameter server strategy could be a better fit for this case
- Tuning and finding the right amount of nodes for the cluster still requires some manual effort
- Cryptic and messy Tensorflow error messages
- APIs between Keras and Tensorflow are in a state of flux

Q&A

Thank you!