Netflix's Recommendation ML Pipeline using Apache Spark

DB Tsai

Spark Summit East - Feb 8, 2017

NETFLIX

At Netflix, we use ML everywhere

Everything is a Recommendation

Over 80% of what members watch comes from our recommendations

Recommendations are driven by Machine Learning Algorithms

NETFLIX

Jan 6th, 2016

#NetflixEverywhere

- 93+ Million Members
- 190+ Countries
- 125+ Million streaming hours / day
- 1000 hours of Original content in 2017
- ⅓ of US internet traffic during evenings

Constantly Innovating through A/B tests

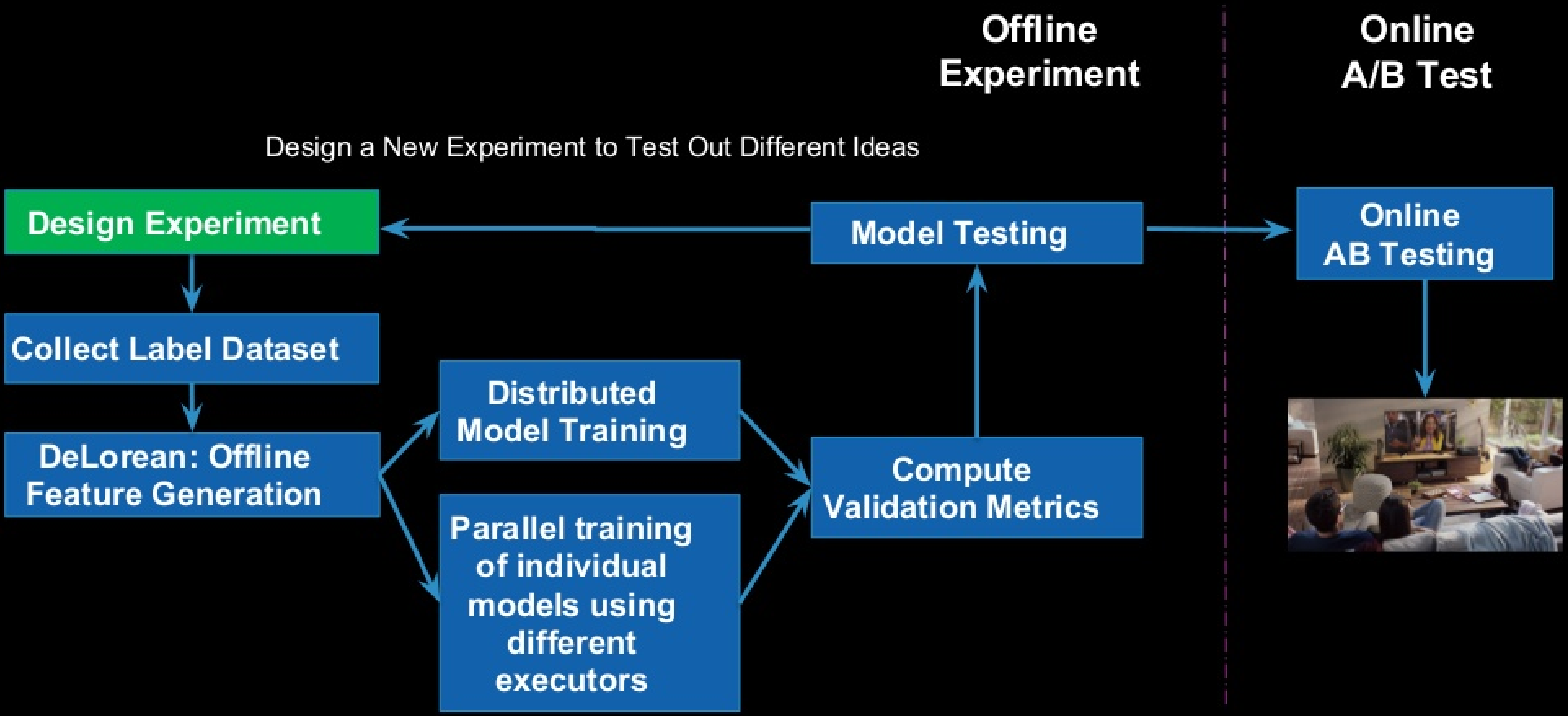
Data Driven

Try an idea offline using historical data to see if they would have made better recommendations

If it does, deploy a live A/B test to see if it performs well in Production

NETFLIX

Running an Experiment



We use a standardized data format across multiple ranking pipelines

This standardized data format is used by common tooling, libraries, and algorithms

NETFLIX

Ranking problems

Contexts: The setting for evaluating a set of items (e.g. tuples of member profiles, country, time, device, etc.)

Items: The elements to be trained on, scored, and/or ranked (e.g. videos, rows, search entities)

Labels: For supervised learning, this will be the label (target) for each item

NETFLIX

DeLorean Data Format a.k.a DMC-12

```
root
|-- profile_id: long (nullable = false)
|-- country_iso_code: string (nullable = false)
|-- items: array (nullable = true)
|    |-- element: struct (containsNull = false)
|    |    |-- show_title_id: long (nullable = false)
|    |    |-- label: double (nullable = false)
|    |    |-- weight: double (nullable = false)
|    |    |-- features: struct (nullable = false)
|    |    |    |-- feature1: double (nullable = false)
|    |    |    |-- feature2: double (nullable = false)
|    |    |    |-- feature3: double (nullable = false)
```

NETFLIX

The nested data structure avoids an expensive shuffle when ranking

The features are derived from Netflix data or the output of other trained models

The features are persisted in HIVE using Parquet

Ensemble methods are used to build rankers

NETFLIX

Transformer

https://en.wikipedia.org/wiki/Spark_(Transformers)

Transformer takes an input DataFrame and "lazily" returns an output DataFrame

Item Transformer

- Extends Spark ML's Transformer
- Accepts DMC-12 DataFrame with contextual information
- Transforms DataFrame at the item level

NETFLIX

Why DataFrame?

Catalyst Optimizations

Up-front Schema Verification

We found a 4x speedup during feature generation by migrating from RDD-based implementation to DataFrame implementation

NETFLIX

Negative Generator

Creating negatives from what member plays for supervised learning

Facts

```
root
|-- profile_id: long (nullable = false)
|-- country_iso_code: string (nullable = false)
|-- items: array (nullable = true)
|    |-- element: struct (containsNull = false)
|    |    |-- show_title_id: long (nullable = false)
|    |    |-- label: double (nullable = false)
|    |    |-- weight: double (nullable = false)
```

Facts with synthetic negatives

```
root
|-- profile_id: long (nullable = false)
|-- country_iso_code: string (nullable = false)
|-- items: array (nullable = true)
|    |-- element: struct (containsNull = false)
|    |    |-- show_title_id: long (nullable = false)
|    |    |-- label: double (nullable = false)
|    |    |-- weight: double (nullable = false)
```

NETFLIX

DeLorean Feature Generator

Creating features based on common code base in offline and online system

```
root
|-- profile_id: long (nullable = false)
|-- country_iso_code: string (nullable = false)
|-- items: array (nullable = true)
|    |-- element: struct (containsNull = false)
|    |    |-- show_title_id: long (nullable = false)
|    |    |-- label: double (nullable = false)
|    |    |-- weight: double (nullable = false)
```

```
root
|-- profile_id: long (nullable = false)
|-- country_iso_code: string (nullable = false)
|-- items: array (nullable = true)
|    |-- element: struct (containsNull = false)
|    |    |-- show_title_id: long (nullable = false)
|    |    |-- label: double (nullable = false)
|    |    |-- weight: double (nullable = false)
|    |    |-- features: struct (nullable = false)
|    |    |    |-- feature1: double (nullable = false)
|    |    |    |-- feature2: double (nullable = false)
|    |    |    |-- feature3: double (nullable = false)
```

http://techblog.netflix.com/2016/02/distributed-time-travel-for-feature.html

Creating the Dataset for Algorithms

```scala
import org.apache.spark.ml.PipelineModel
val featurePipeline = new PipelineModel(Array(
  taggerTransformer,
  countryTenureStratifiedSampler,
  negativeGenTransformer,
  featureGenTransformer
))
val featureDF = featurePipeline.transform(playFeedDF)
```

Multithreading Model Training

For single machine multi-threading algorithms, we allocate one task to one machine. Multiple tasks are running in Spark for different parameters

Broadcast in Spark has datasize limitation, we write data into HDFS, and stream the data into the trainers in executors which run single-machine multi-threading algorithms

Distributed Model Training

We use both Spark ML's algorithms and in-house ML implementations

We keep the interface similar for both multi-threading and distributed algorithms, so experimenters can try different ideas easily

Scoring and Ranking

Scorer is also a Transformer returned from the Trainer

Multiple models can be scored at the same time in parallel

The ranks are derived from sorted scores

Together with labels, we can compute metrics, NMRR, NDCG, and Recall, etc

```
root
|-- profile_id: long (nullable = false)
|-- country_iso_code: string (nullable = false)
|-- items: array (nullable = true)
|     |-- element: struct (containsNull = false)
|     |     |-- show_title_id: long (nullable = false)
|     |     |-- label: double (nullable = false)
|     |     |-- weight: double (nullable = false)
|     |     |-- features: struct (nullable = false)
|     |     |     |-- feature1: double (nullable = false)
|     |     |     |-- feature2: double (nullable = false)
|     |     |     |-- feature3: double (nullable = false)
|     |     |-- scores: struct (nullable = false)
|     |     |     |-- model1: double false
|     |     |     |-- model2: double false
```

Lessons Learned - Pipeline Abstraction

Pros

- Modularity + Tests
- Plug-N-Play
- Notebook Prototyping
- Customizability
- Schema Verification
- Serializability (AC)

Cons

- Dependent on Spark platform
- Not easy to bring to production
- Default Metric Evaluator doesn’t support ranking multiple models and type of metrics in one pass


ANY
QUESTIONS