

DeUmbra Moving Your Machine Learning Models to Production with Tensor Flow Extended

Jonathan Mugan

Moving From Our Hut to the Production Floor

Your model is going to live for a long time. Not just for a demo.

You must know when to update it. The world changes.

You must ensure production data matches training data. Data reflects its origins.

You may need to track multiple model versions. E.g., for different states.

You need to batch the input to serving. One-at-a-time is slow.







Interchangeable Parts and the ML Revolution

- TensorFlow Extended (TFX)
- TFX used internally by Google and recently open sourced
- Represents your pipeline to production as a sequence of components
- Building any one model is more work, but for large endeavors, TFX helps to keep you organized



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Data Ingestion: ExampleGen

- Pulls in your data and put it into binary format
- Also splits it into train and test
- Protocol Buffers
- tf.Example into a TFRecord file

https://www.tensorflow.org/tutorials/load_data/tfrecord https://www.tensorflow.org/tfx/guide/examplegen

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TensorFlow Data Validation: StatisticsGen, SchemaGen, Example Validator

Looks at your data and generates a schema, which you manually update.

It makes sure the data you pass in later during serving is still in the same format and hasn't drifted.

Also has a great way to visualize data, FACETS, we will see later.

https://www.tensorflow.org/tfx/guide/tfdv

Example Schema

	Туре	Presence	Valency	Domain
Feature name				
'race'	STRING	required	single	'race'
'gender'	STRING	required	single	'gender'
'diabetes_comp'	INT	required	single	-
'metastic_cancer'	INT	required	single	-
'perc_hs_grad'	FLOAT	required	single	-
'mh_30d_before_opioids'	INT	required	single	-
'recent_mme'	FLOAT	required	single	-
'drug_screen_gt90d_lt120mme'	INT	required	single	-
'weight_loss'	INT	required	single	-

TensorFlow Transform: Transform

Converts your data

- E.g., One-hot encoding, categorical with a vocab
- Part of TensorFlow graph, for better or worse
- Good for transformations that require looking at all values

Example: tft.scale_to_z_score subtracts mean and divides by standard deviation

Features come in many types, and TensorFlow Transform converts them into a format that can be ingested by a machine learning model.

Nice to have this explicit. <u>https://www.tensorflow.org/tfx/guide/transform</u>

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Estimator or Keras Model: Trainer

- Trains the model: Part we are all familiar with
- Except uses an Estimator
- Can use KERAS

tf.keras.estimator.model_to_estimator()

https://www.tensorflow.org/tfx/guide/trainer

TensorFlow Model Analysis: Evaluator, Model Validator

Evaluator Component

- Evaluates the model.
- Uses TensorFlow Model Analysis (TFMA), which we will see shortly.
- <u>https://www.tensorflow.org/tfx/guide/evaluator</u>

Model Validator Component

- You set a baseline (such as the current serving model) and a metric (such as AUC)
- Marks in the metadata if the model passes the baseline.
- https://www.tensorflow.org/tfx/guide/modelval

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Validation Outcomes: Pusher

- Pushes the model to Serving if it is validated
- I.e., if your new model is better than the existing model, push it to the model server.

For a deeper understanding, see Ice-T's 1988 hit song, "I'm Your Pusher"

https://www.tensorflow.org/tfx/guide/pusher

TensorFlow Serving

- Uses the model to perform inference
- Called via gRPC APIs or RESTFUL APIs
- Easy to get running with Docker
- You can call a particular version of a model
- Takes care of batching

https://www.tensorflow.org/tfx/guide/serving

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Table:

Artifact

2	8	R,	
---	---	----	--

0

	id	type_id		uri
	Filter	Filter	Filter	
1	1	1	/home/jmugan/data/otf/tfx/data_rx_od_chronic	
2	2	3	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/CsvExampleGen/examples/1/train/
3	3	3	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/CsvExampleGen/examples/1/eval/
4	4	5	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/StatisticsGen/output/2/train/
5	5	5	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/StatisticsGen/output/2/eval/
6	6	7	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/SchemaGen/output/3/
7	7	10	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/ExampleValidator/output/5/
8	8	11	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/Transform/transform_output/6/
9	9	3	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/Transform/transformed_examples/6/train/
10	10	3	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/Transform/transformed_examples/6/eval/
11	11	13	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/Trainer/output/7/
12	12	15	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/ModelValidator/blessing/8/
13	13	16	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/ModelValidator/results/8/
14	14	18	/home/jmugan/airflow/tfx/pipelines/otf_	d_chronic/Evaluator/output/9/
15	15	20	/home/jmugan/airflow/tfx/pipelines/otf_e	d_chronic/Pusher/model_push/10/

Looking at the table Artifact using the DB Browser for SQLite

Table: Type

S
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	id	name	is_artifact_type	input_type	output_type
	Filter	Filter	Filter	Filter	Filter
1	1	ExternalPath	1	NULL	NULL
2	2	CsvExampleGen	0	NULL	NULL
3	3	ExamplesPath	1	NULL	NULL
4	4	StatisticsGen	0	NULL	NULL
5	5	ExampleStatisticsPath	1	NULL	NULL
6	6	SchemaGen	0	NULL	NULL
7	7	SchemaPath	1	NULL	NULL
8	8	Transform	0	NULL	NULL
9	9	ExampleValidator	0	NULL	NULL
10	10	ExampleValidationPath	1	NULL	NULL
11	11	TransformPath	1	NULL	NULL
12	12	Trainer	0	NULL	NULL
13	13	ModelExportPath	1	NULL	NULL
14	14	ModelValidator	0	NULL	NULL
15	15	ModelBlessingPath	1	NULL	NULL
16	16	ModelValidationPath	1	NULL	NULL
17	17	Evaluator	0	NULL	NULL
18	18	ModelEvalPath	1	NULL	NULL
19	19	Pusher	0	NULL	NULL
20	20	ModelPushPath	1	NULL	NULL

The Types of Artifacts

The type_id field from the previous slide maps here Table:

	artifact_id	name	is_custom_property	int_value	double_value	string_value
	Filter	Filter	Filter	Filter	Filter	Filter
1	1	type_name	0	NULL	NULL	ExternalPath
2	1	split	0	NULL	NULL	
3	1	state	0	NULL	NULL	published
4	1	span	0	1	NULL	NULL
5	2	type_name	0	NULL	NULL	ExamplesPath
6	2	split	0	NULL	NULL	train
7	2	state	0	NULL	NULL	published
8	2	span	0	1	NULL	NULL
9	3	split	0	NULL	NULL	eval
10	3	state	0	NULL	NULL	published
11	3	span	0	1	NULL	NULL
12	3	type_name	0	NULL	NULL	ExamplesPath
12	4	colit	0	AILU I	ALL I.	train

You can see the properties of the artifacts in the ArtifactProperty table

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Pipeline Management with Apache Airflow

Allows you to trigger and keep track of pipelines.

2	Airflow	DAGs	Data Profiling 💙	Browse 💙	Admin 🗸	Docs 🗸	About 🗸				
DAGs											
										Search	:
	0	DAG						Schedule	Owner	Recent Tasks	Last Run
G	Off							None	Airflow	000000000	2019-08-20 02:27 🚯
Ø	On							None	Airflow	000000000	2019-08-20 03:33 🚯
Ø	Off	taxi						None	Airflow		
Ø	Off	taxi_solutior	ı					None	Airflow	00000000000	2019-08-14 00:36 🚯

Pipeline Management with Apache Airflow

Pipeline Management with Apache Airflow

- You can also use Kubeflow https://github.com/tensorflow/tfx/blob/master/tfx/examples/chicago_taxi_pipeline/taxi_pipeline_kubeflow_gcp.py
- And Apache Beam https://github.com/tensorflow/tfx/blob/master/tfx/examples/chicago_taxi_pipeline/taxi_pipeline_beam.py

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TensorFlow 2.0

- Don't have to define the graph separately
 - More like PyTorch
- There are two ways you can do computation:
 - Eager: like PyTorch, just compute
 - tf.function: You decorate a function and call it

TensorFlow 1.x session

import tensorflow as tf

```
x = tf.Variable(13)
y = tf.placeholder(tf.int32)
```

```
z = x + bob
init = tf.global_variables_initializer()
```

```
with tf.Session() as sess:
    sess.run(init)
    z_out = sess.run(z,{y:24})
```

print(z_out)

output 33

```
TensorFlow 2.x function
```

import tensorflow as tf

x = tf.Variable(13)

```
@tf.function
def bob(y) -> tf.Variable:
    print(tf.executing_eagerly())
    if y > 55:
        return y + 3
    else:
        return y - 4
```

```
z = x + bob(24)
print(z.numpy())
```

output False 33

Still get performance of Session https://www.tensorflow.org/guide/function

```
TensorFlow 2.x
    eager
import tensorflow as tf
x = tf.Variable(13)
def bob(y) -> tf.Variable:
    print(tf.executing_eagerly())
    if y > 55:
        return y + 3
   else:
        return y - 4
z = x + bob(24)
print(z.numpy())
```

```
True
output 33
```

Debug like a civilized person https://www.tensorflow.org/guide/eager

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Data

- tf.train.Example is tf.train.Feature protobuf message, where each value has a name and a type (tf.train.BytesList, tf.train.FloatList, tf.train.Int64List)
- TFRecord is a format for storing sequences of binary records, each record is tf.train.Example
- tf.data.Dataset can take in TFRecord and create an iterator for batching
- tf.parse_example unpacks tf.Example into standard tensors.

https://www.tensorflow.org/tutorials/load_data/tf_records

Features

 tf.feature_column, where you further specify what it is, such as one-hot, vocabulary, and embeddings and such.

tf.train.Example specifies what it is for storage, and tf.feature_column is for the input to a model.

https://www.tensorflow.org/guide/feature_columns

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To build a model you need

- format of model input
 - tf.feature_column
- model architecture and hyperparameters
 - tf.estimator
 - (or KERAS with tf.keras.estimator.model_to_estimator)
- function to deliver training data
 - tf.estimator.TrainSpec from tf.data
- function to deliver eval data
 - tf.estimator.EvalSpec from tf.data
- function to deliver serving data
 - tf.estimator.FinalExporter

TensorFlow Estimator

• Estimator is a wrapper for regular TensorFlow that automatically scales to multiple machines and automatically outputs results to TensorBoard

Shout out to model explainability using estimator using boosted trees https://www.tensorflow.org/tutorials/estimator/boosted_trees_model_understanding https://www.tensorflow.org/tutorials/estimator/boosted_trees

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TensorBoard

TensorBoard

Plotting of prescribers Red has more overdose Green has fewer

3D plots not that useful, but they look cool

You can even use TensorBoard from PyTorch https://pytorch.org/docs/stable/tensorboard.html

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TensorFlow Data Validation (TFDV)

- We need to understand our data as well as possible.
- TFDV provides tools that make that less difficult.
- Helps to identify bugs in the data by showing you pictures that don't look right.
- <u>https://www.tensorflow.org/tfx/data_validation/get_started</u>

Sor Fe	^{t by} ature order		- □ R	everse order	Feature	search (re	egex enable	ed)		
Features: V int(70) V float(12) V string(2)										
	Numeric Fea	itures (82)							Chart to show	
	count	missina	mean	std dev	zeros	min	median	max	Standard -	
r	not weaned	moomg	moun		20100		moular	THE T	log expand	
	80.5k	0%	0.95	0.22	4.88%	0	1	1	10K	
									0.1 0.3 0.5 0.7 0.9	
é	age 80.5k	0%	40.51	13.62	0%	3	39	104	4К	
									10 30 50 70 90	
r	apid_dose_e	escalation								
	80.5k	0%	0.03	0.17	96.87%	0	0	1	10K	
,	stennorosie								0.1 0.3 0.5 0.7 0.9	
	80.5k	0%	0.01	0.09	99.22%	0	0	1	20K	

Non-uniformity

Reverse order Feature search (regex enabled)

Features: V int(70) V float(12) V string(2)

-

Numeric Fea	tures (82)							Chart to show
count	missing	mean	std dev	zeros	min	median	max	
add_screen_g	gt90d_gt120m	me						3
80.5k	0%	0	0	100%	0	0	0	20К
adi_quartile								-
80.5k	0%	0	0	100%	0	0	0	20К
add_screen_c	gt90d_90mme							а
80.5k	0%	0	0	100%	0	0	0	20К
drug_screen_	_gt90d_gt120n	nme		4000/				1
80.5K	0%	0	0	100%	0	U	0	20K
maoi_overlap								· · · · · · · · · · · · · · · · · · ·
80.5k	0%	0	0.01	100%	0	0	1	20K
metastic_can	cer							0.1 0.3 0.5 0.7 0.9
80.5k	0%	0	0.02	99.98%	0	0	1	20K
drug screen	at90d lt120m	me						0.1 0.3 0.5 0.7 0.9
80.5k	0%	0	0.01	100%	0	0	1	20K
humphone								0.1 0.3 0.5 0.7 0.9
80.5k	0%	0	0	100%	0	0	1	20К
								0.1 0.3 0.5 0.7 0.9
ed recent m	ma variability							

By sorting by non-uniformity, we can debug features.

In general, we can make sure the distributions are what we would expect.

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TensorFlow Model Analysis (TFMA)

Show accuracy Visualization Sort by Sort by Slice Visualization Slice Solution Slice Solution Solution

We can see how well our model does by each slice.

We see that this model does much better for females than males.

https://www.tensorflow.org/tfx/guide/tfma

feature	accuracy	accuracy_baseline	auc	auc_precision_recall	average_loss			
gender:M	0.57293	0.53354	0.70861	0.71211	0.90811			
gender:F	0.74527	0.67612	0.80165	0.64202	0.54457			

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What-IF Tool

- The What-If Tool applies a model from TensorFlow Serving to any data you give it.
 - <u>https://pair-code.github.io/what-if-tool/index.html</u>
- Change a record and see what the model does
- Find the most similar record with a different classification
- Can be used for fairness. Adjust the model so it is equally likely to predict "yes" for each group
 - <u>https://www.coursera.org/lecture/machine-learning-business-professionals/activity-applying-fairness-concerns-with-the-what-if-tool-review-OmYda</u>

What-If Tool showing the the probability of overdose for individual features.

crimes_100k

hiv

obesity

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Alternatives (kind of)

They all do something a little different, with pieces straddling different sides of the data science/production divide

- MLflow https://mlflow.org/docs/latest/index.html
- Netflix Metaflow <u>https://github.com/Netflix/metaflow</u>
- Sacred <u>https://github.com/IDSIA/sacred</u>
- Dataiku DSS <u>https://www.dataiku.com/product/</u>
- Polyaxon <u>https://polyaxon.com/</u>
- Facebook Ax <u>https://www.ax.dev/</u>

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Streamlit Dashboard

```
# streamlit run jwm_streamlit.py
import streamlit as st
import numpy
import pandas
```

```
st.title('Not my circus, not my monkeys')
st.write('frightened cats prefer a little alcohol in their milk')
st.markdown('## Free bratwurst!')
```

Not my circus, not my monkeys

frightened cats prefer a little alcohol in their milk

Free bratwurst!

Table of Thermopylae

	chickens	misunderstandings	resolutions
0	2	6	9
1	1	-2	9
2	33	5	-1
3	4	74	3

```
st.write("Table of Thermopylae")
df = pandas.DataFrame({
    'chickens': [2, 1, 33, 4],
    'misunderstandings': [6, -2, 5, 74],
    'resolutions': [9, 9, -1, 3]
})
st.write(df)
```

```
st.write("El Hombre de la Triste Figura ")
chart_data = pandas.DataFrame(
    numpy.random.randn(15, 3),
    columns=['cats', 'dogs', 'sasquatch'])
st.line_chart(chart_data)
```


- Writes to the browser
- Works well for artifacts in the ML pipeline.

https://github.com/streamlit/streamlit/ https://streamlit.io/docs/getting_started.html

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from typing import Dict, List
import enum
from dataclasses import dataclass

class EvalCondition(enum.Enum):

BASIC='basic' SAMPLE_WEIGHT= 'sample_weight' AUGMENT_PREDICTION='augment_prediction' AUGMENT_GAN='augment_gan' AUGMENT_PREDICTION_AND_GAN= 'augment_pred_gan'

@dataclass

class Turtle: size: float name: str

@dataclass

```
class EvalArtifact:
    name: str
    eval_condition: EvalCondition
    num_chickens: Dict[str,int]
```

```
def my_function(ea: EvalArtifact) -> List[Turtle]:
    t1 = Turtle(6,ea.name)
    t2 = Turtle(2,ea.name)
    return [t1,t2]
```

```
ea = EvalArtifact('Anita',EvalCondition.BASIC,{'man':45})
print(my_function(ea))
```

Typing, Dataclasses, and Enum

You can build interchangeable parts right in Python.

Not new of course, but they make Python a little less wild west.

Output: [Turtle(size=6, name='Anita'), Turtle(size=2, name='Anita')]

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TFX Disadvantages

- Steep learning curve
- Changes constantly (but not while you are watching it)
- Somewhat inflexible, you can create your own components, but steep learning curve
- No hyperparameter search (yet, <u>https://github.com/tensorflow/tfx/issues/182</u>)

TFX Advantages

- Set up to scale
- Documents your process through artifacts
- Warm-starting: as new data comes in, you don't have to start training over. Keeps models fresh
- Tools to see data and debug problems
- Don't have to rerun what is already run

Where to Start

- Jupyter notebook tutorial <u>https://www.tensorflow.org/tfx/tutorials/tfx/components</u>
- Airflow tutorial

https://www.tensorflow.org/tfx/tutorials/tfx/airflow_workshop

Happy Hour!

6500 River Place Blvd. Bldg. 3, Suite 120 Austin, TX. 78730

Jonathan Mugan, Ph. D. Email: jmugan@deumbra.com

Appendix

- Original TFX paper <u>https://ai.google/research/pubs/pub46484</u>
- Documentation
 - <u>https://www.tensorflow.org/tfx</u>
 - <u>https://www.tensorflow.org/tfx/tutorials</u>
 - <u>https://www.tensorflow.org/tfx/guide</u>
 - <u>https://www.tensorflow.org/tfx/api_docs</u>

