Serving Tensorflow Models with Kubernetes

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Step One: Get An Account
Go To goo.gl/sgZ2Qp to start

Google Cloud

Your Instructors

Ron
Bodkin

Brian
Foo

Cassie
Kozyrkov

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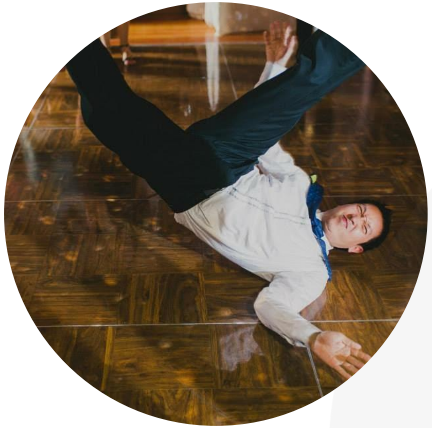

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Overview

- Tensorflow
  - Building and Running Tensorflow graphs & APIs
  - Tensorflow Serving for Online Predictions
- Docker and Kubernetes
  - A brief history of containers
  - Kubernetes: pods and services
- The Marriage of TF Serving and Kubernetes

Building and Running Tensorflow Graphs

Build a Tensorflow Graph

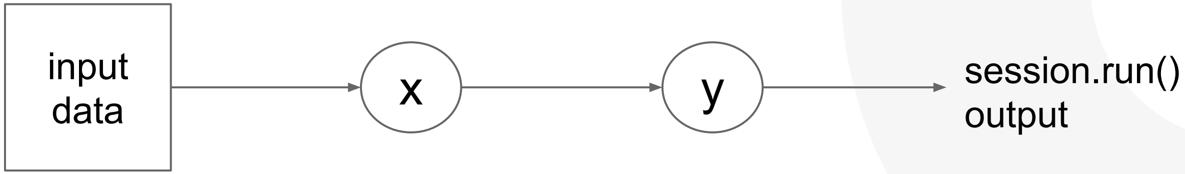
```
import tensorflow as tf

x = tf.placeholder(tf.float32, shape=(100))

# Some preloaded model weights and biases

w = tf.get_variable('weights', shape=(100))

b = tf.get_variable('bias', shape=[])

y = tf.tensordot(w, x, 1) + b
```

Run the Tensorflow Graph

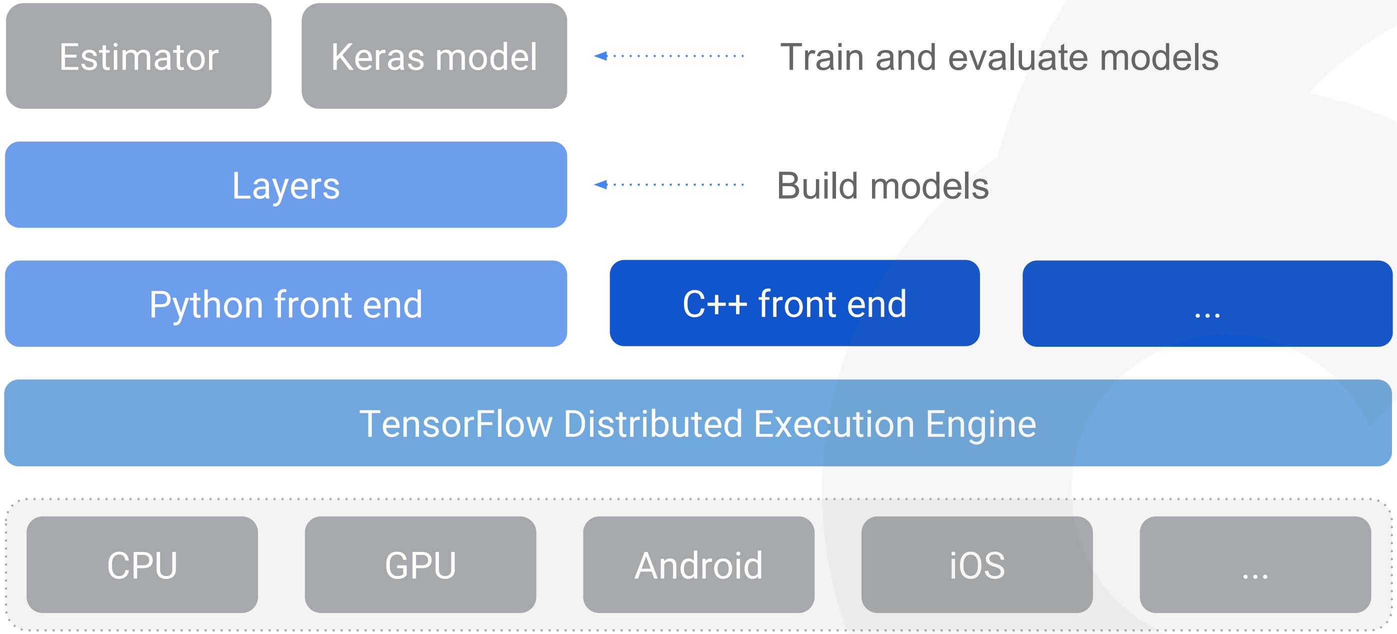
```
import tensorflow as tf
x = tf.placeholder(tf.float32, shape=(100))
# Some preloaded model weights and biases
w = tf.get_variable('weights', shape=(100))
b = tf.get_variable('bias', shape=[])
y = tf.tensordot(w, x, 1) + b
```

```
with tf.Session() as sess:
  print(sess.run(y, feed_dict={x: input_data}))
```

Data entrypoint for predictions



Different APIs for TF

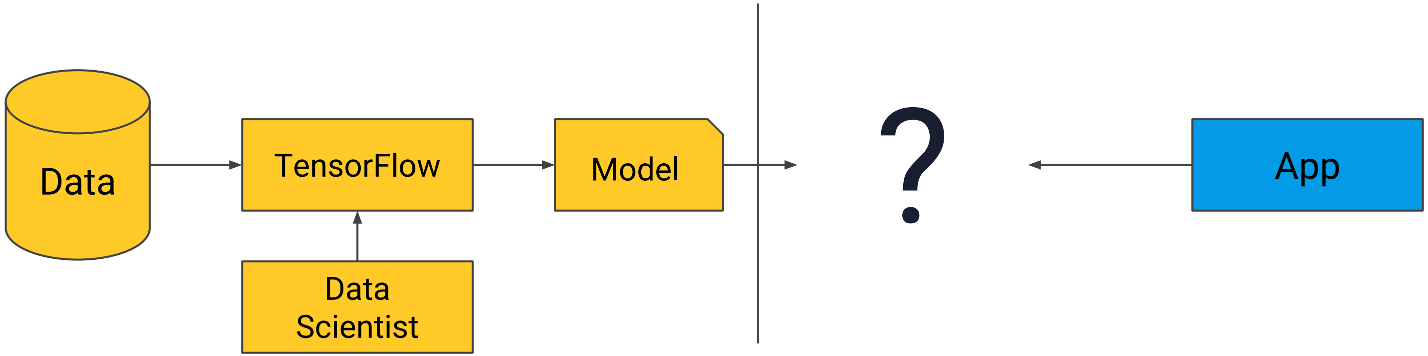


Google Cloud

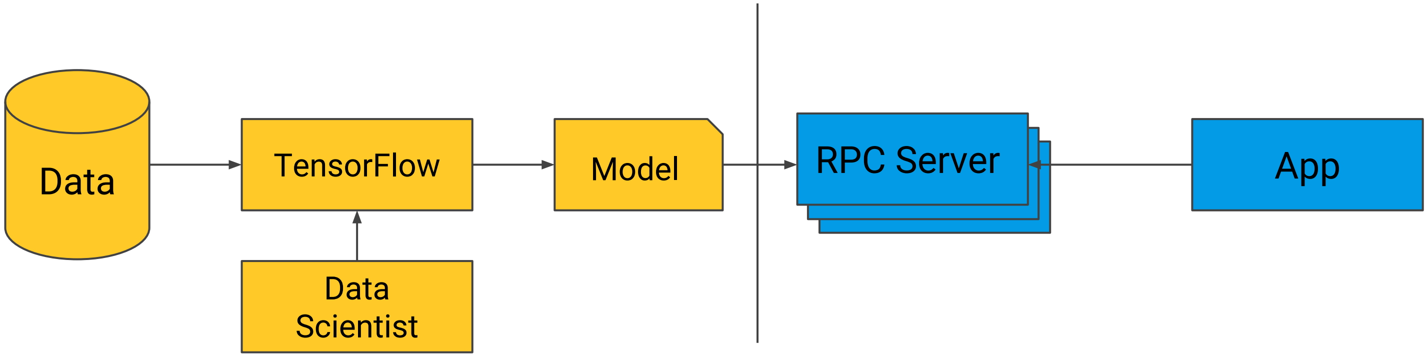
What is Serving?

Serving is how you *apply* a ML model,
after you've trained it

What is Serving?



What is Serving?



TensorFlow Serving Goals

- Online, low latency
- Multiple models in a single process
- Multiple *versions* of a model loaded over time
- Compute cost varies in real-time to meet product demand
  - auto-scale with CloudML, Docker & K8s
- Aim for the efficiency of mini-batching at training time …
  - except with requests arriving asynchronously

TFX: TensorFlow-Based ML deployment at Google

Integrated Frontend for Job Management, Monitoring, Debugging, Data/Model/Evaluation Visualization

Shared Configuration Framework and Job Orchestration

Tuner

Data Ingestion | Data Analysis | Data Transformation | Data Analysis | Trainer | Model Evaluation and Validation | Serving | **Logging**

Shared Utilities for Garbage Collection, Data Access Controls

Pipeline Storage

Docker and Kubernetes

A Brief History of Containers

2008

In 2008, Linux introduced containers.

- Isolated environment for running applications, except...
- All applications must have a common OS Kernel (e.g. Ubuntu, Debian, etc.)

Enter Docker...

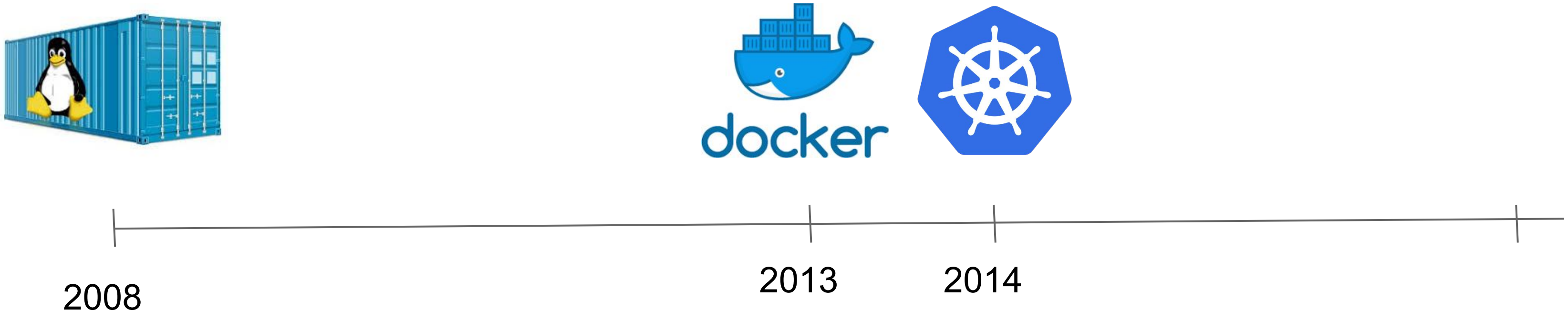
2008

2013

In 2013, Docker found a way around the shared kernel problem.

- Application containers have their own OS kernel.
- Flexible resource requirements.
- Perfect for cloud computing!

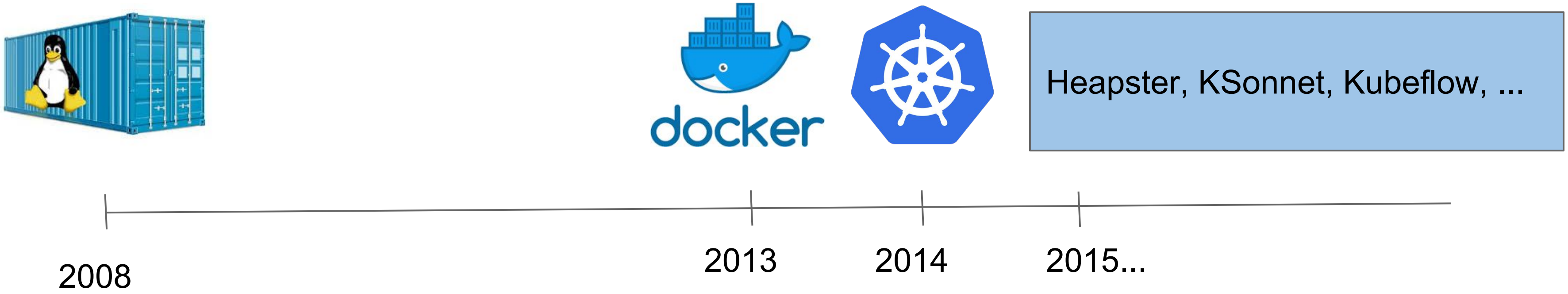
Enter Kubernetes



In 2014, Google open sourced Kubernetes.

- Deploy Docker containers to any number of machines
- Create load balancing and front-end services to handle external requests.
- Automatically restart backend containers when they fail.

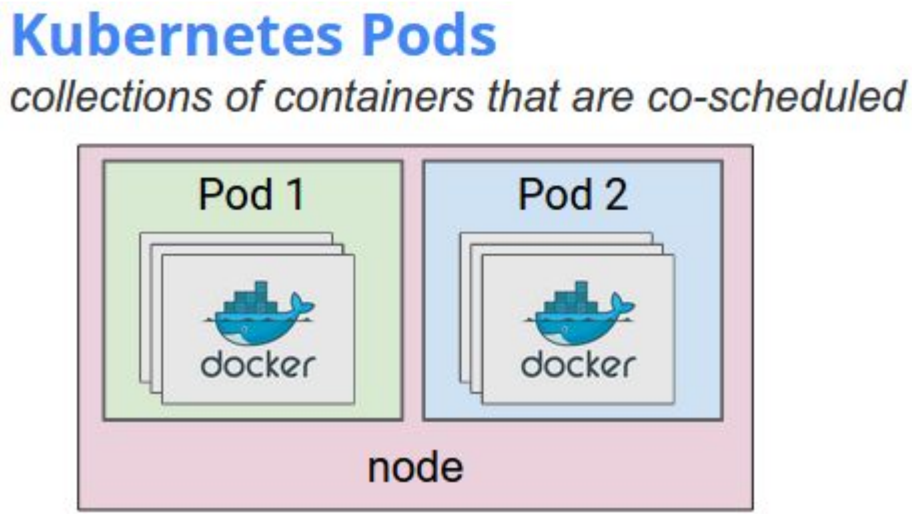
And Many More...



Example projects built on top of Kubernetes:

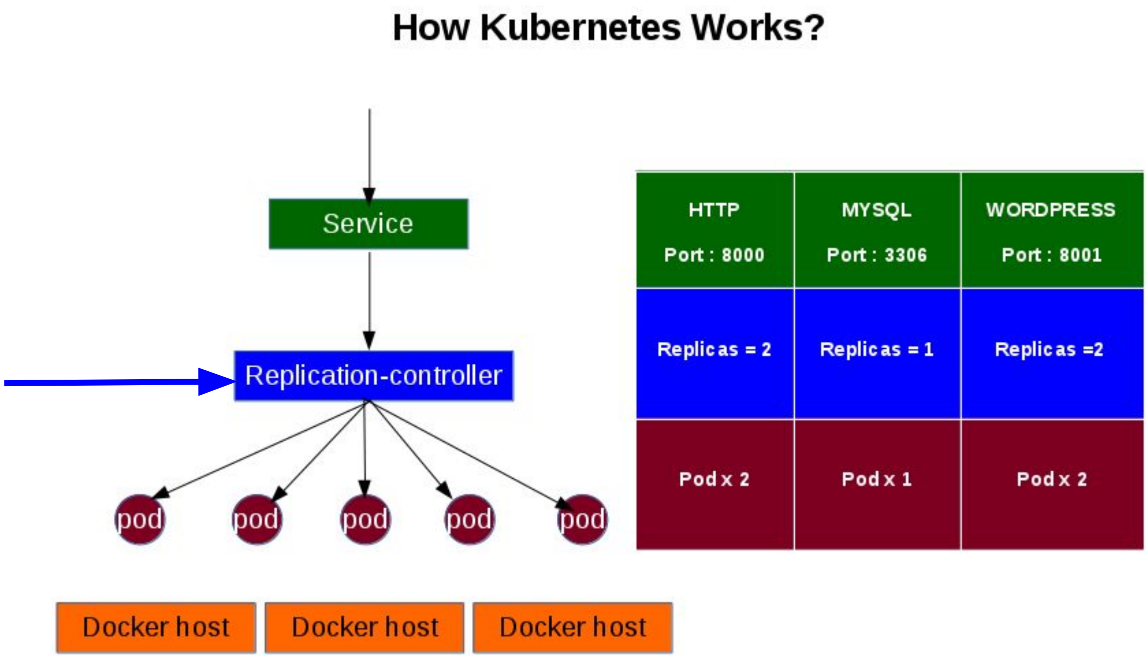
- Monitoring (Heapster)
- Deployment languages (KSonnet)
- Deployment automation (Kubeflow for ML)
- and many more!

Kubernetes in a Nutshell



Kubernetes in a Nutshell

Manual or
auto-scaling!



Tensorflow Serving using Kubernetes

TF Serving on Kubernetes Workflow

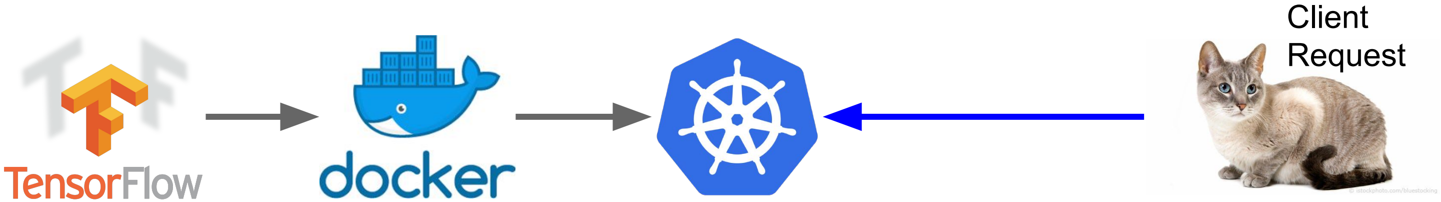
Label: cat
Prob: 97.6%

What do we want?

- A prediction service that can handle multiple client requests
- Load-balancing across TF model servers
- Ability to scale up

TF Serving on Kubernetes Workflow

Exercises



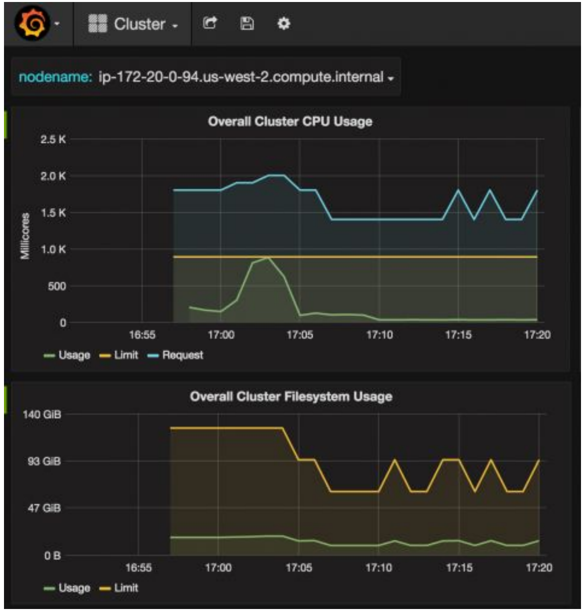
How do we get there?

- Convert TF training code to model for serving.
- Package model in Docker container and upload to a registry.
- Use **Kubernetes** to:
  - Deploy container on multiple back-end pods.
  - Deploy a front-end service to send client requests to a backend pod.
- Send protobufs (encoded JSONs) containing images to kubernetes cluster.
- Load testing.

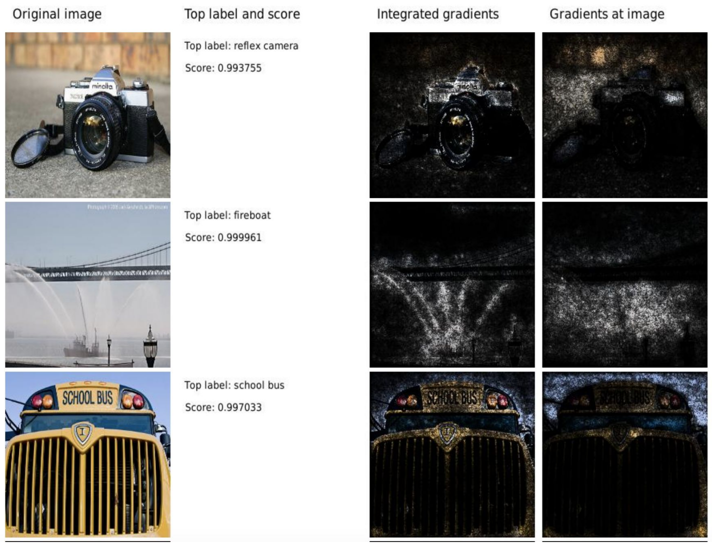
Monitoring, Interpretation, and Keras

Bonus Exercises

Heapster Grafana Dashboard (Pod and Cluster Resource Usage)



Model Understanding and Visualization using Integrated Gradients



Codelab Time!

Open a Chrome incognito window.

Log in at events.qwiklabs.com

If you don't have an account register at **goo.gl/sgZ2Qp**

Recap and Demos

Acknowledgements and Additional Resources

Special thanks to:

- Kubeflow: providing Docker images and templates for TF Serving on Kubernetes
  David Aronchick, Jeremy Lewi, Vishnu Kannan (Google); Peng Yu (Shopify)

- Google Cloud ML: GPU batch profiling work using Beam and Tensorflow

Reference - Model Visualization:

- Sundararajan, Taly, Yan. ***Axiomatic Attribution for Deep Networks.*** ICML 2017. Link: arxiv.org/pdf/1703.01365.pdf

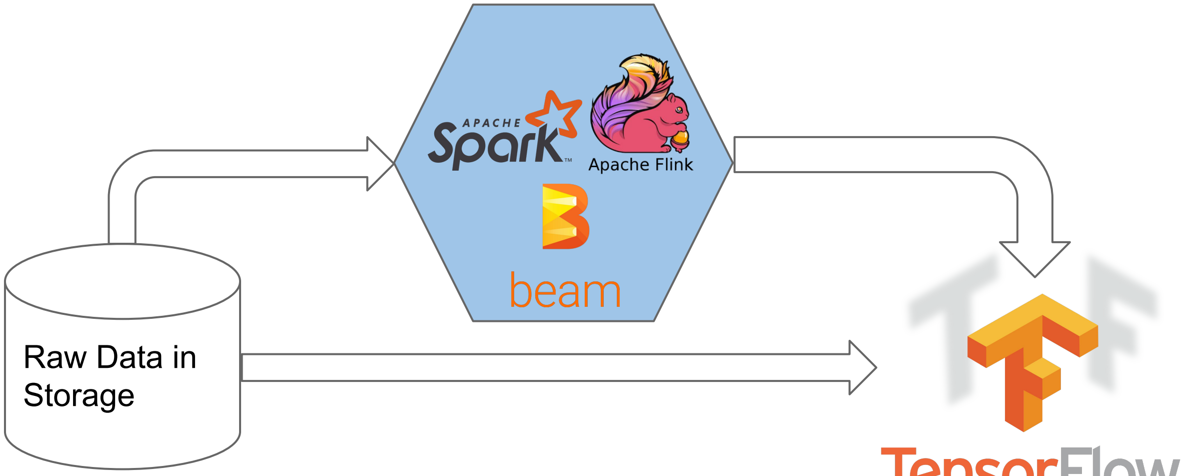
Thank you

1. Please leave feedback
2. Resources at goo.gl/Sg6ecA
3. Save any work you want to keep

Appendix: pipelines versus Client-Server Architectures

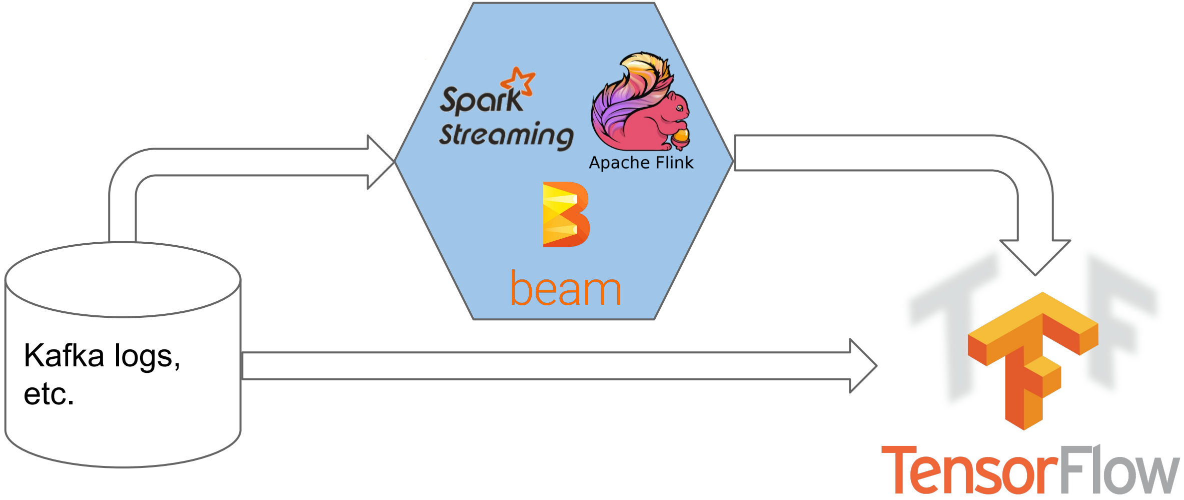
Pipeline Architecture: Batch/Online Processing

- Read offline data from local/HDFS/Google Storage/AWS
- Preprocess (clean, filter, aggregate) using Spark/Beam/Flink
- Create batches to run through a TF graph
- Update model params (training) / Collect inference results (serving)



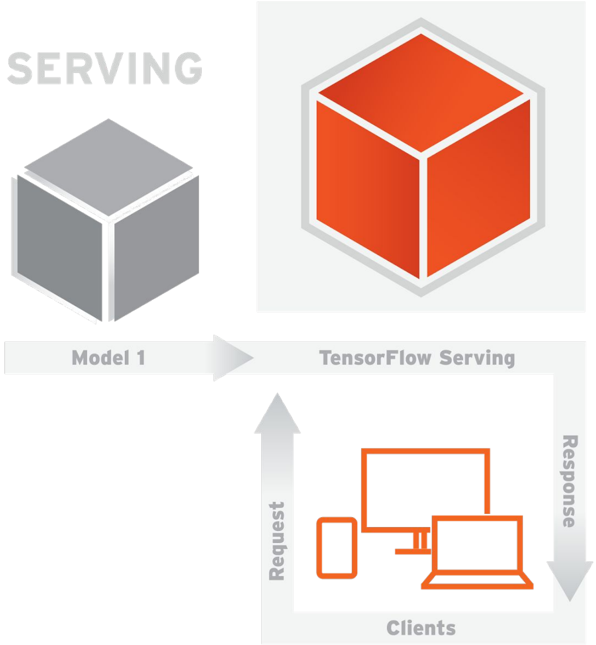
Pipeline Architecture: Batch/Online Processing

- **Benefits**:
  - Full control over pipeline application and model!
- **Limitations**:
  - **Language Dependency:** Requires Python, or Java JNI to C++
  - **No Proprietary Models:** Requires graph and model params to be exposed in code.
  - **Experience:** Months to years of expertise to build, debug, and manage pipelines effectively.



Client-Server Architecture: Tensorflow Serving

- Asynchronous and Streaming Model Serving
- Efficient implementation in c++
- Server build can be optimized for native environment
    - CPUs or GPUs
    - Just-in-time (JIT) compilation
    - etc.



Client-Server Architecture: Tensorflow Serving

- Asynchronous and Streaming Model Serving
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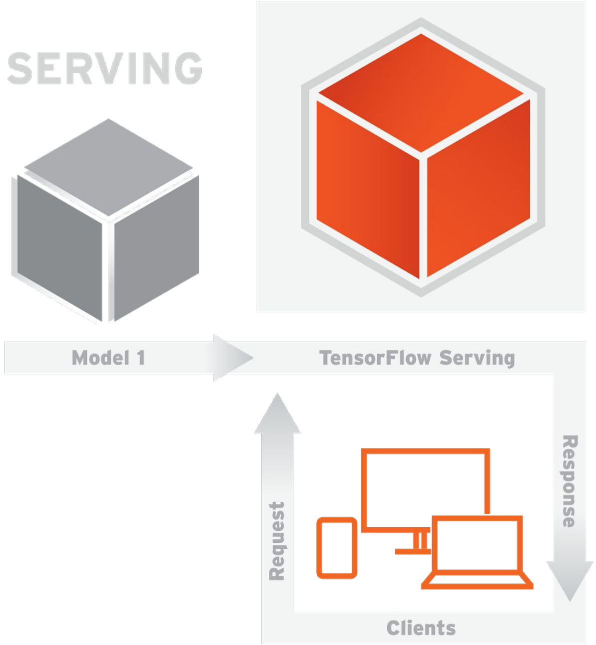
- Build can be optimized for the environment (CPUs or GPUs)
- **Language independent Protobufs!**
    - RESTful API calls using serialized dictionaries
    - Send dictionary of data
    - Receive dictionary of prediction results



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- Build can be optimized for the environment (CPUs or GPUs)
- **Language independent Protobufs!**
  - RESTful API calls using serialized dictionaries
  - Send dictionary of data
  - Receive dictionary of prediction results
- How do we guarantee identical serving environments?
- How do we scale?
- How do we handle failures gracefully?