



Machine Learning Lifecycle with Kubeflow on Azure Kubernetes Service (AKS)

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Agenda

- What is the typical ML workflow and some of their shortcomings
- Why DevOps?
- Why Containers, Kubernetes, and Helm?
- Intro to Kubeflow, Helm, Argo
- Demos
 - Image classification with Inception v3 and transfer learning
 - Automate repeatable ML experiments with containers
 - Deploy ML components to Kubernetes with Kubeflow
 - Scale and test ML experiments with Helm
 - Manage training jobs and pipelines with Argo
 - Serve trained models for inference with TF Serving
 - Rapid prototyping with self-service Jupyter notebook from JupyterHub

Simplified ML Workflow/Pipeline

- Keeping track of datasets is hard
- How to do automatic retraining when data changes?
- Storage and network bottlenecks

Data Preparation

- Slow sequential training
- Hard to explore hyperparameter space
- Distributed training is difficult to setup

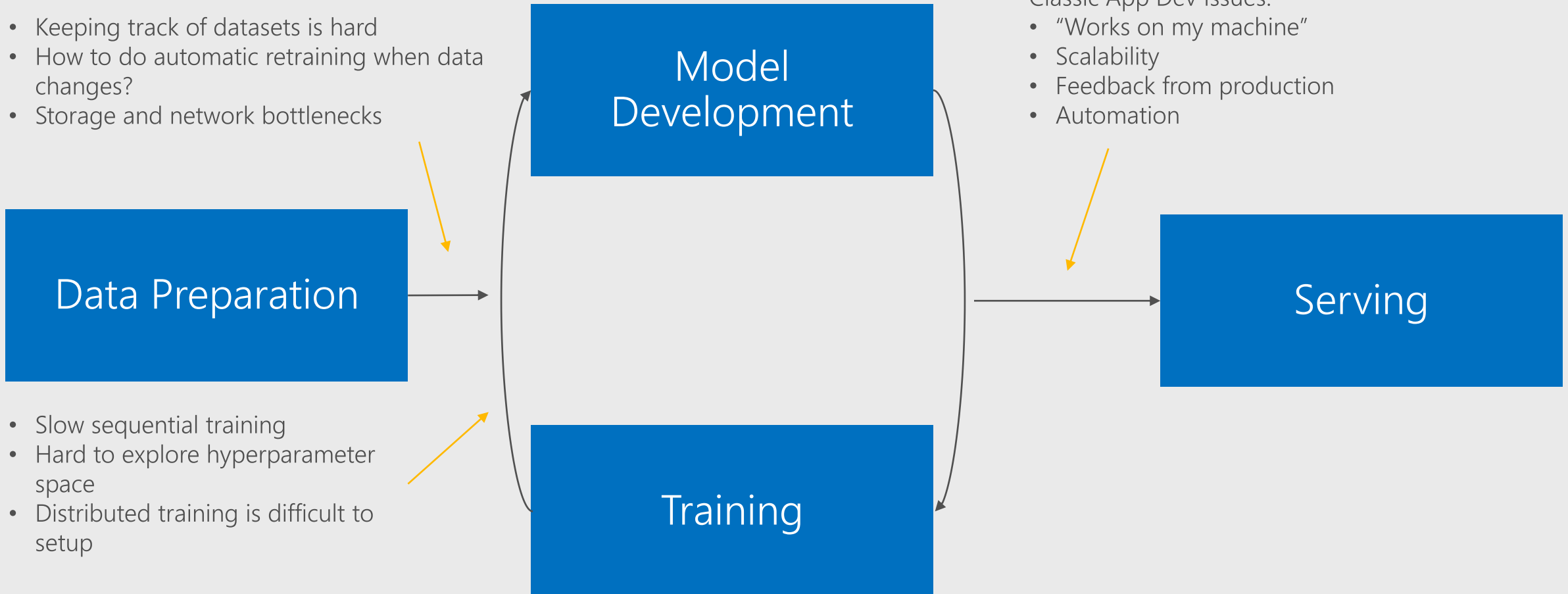
Model Development

Training

Classic App Dev Issues:

- "Works on my machine"
- Scalability
- Feedback from production
- Automation

Serving



What is DevOps?

- “A cross-disciplinary community of practice dedicated to the study of building, evolving and operating rapidly-changing resilient systems at scale” (Jez Humble)
- Applying Agile practices to operations
 - Infrastructure as code
 - Ops teams embracing source control (git)
 - Automated testing
 - Repeatable/consistent
 - CI/CD
- This has worked well for App Dev. Now time for AI/ML
 - But, must ensure data scientist are not hindered by structure

Why Containers, Kubernetes & Helm?

- Container
 - Contains everything needed to run your application
 - Build once run anywhere
 - Starts in seconds: Great for scalability
 - Images are stored in a centralized place (Docker Hub, Azure Container Registry, gcr, ECR etc.)
- Container orchestration
 - Automating deployment, scaling, and management of containerized applications
 - Declarative
 - Can be a mix of GPU or CPU nodes
- Massive Scale
 - OpenAI dedicates up to 10k cores for a single experiment
- Autoscaling capabilities: Pay for what you use, scale down when idle
- Parallel training instead of sequential: huge time saver for large trainings

Kubeflow

- Machine Learning Toolkit for Kubernetes
 - To make ML workflows on Kubernetes simple, portable, and scalable
- Training controllers – simplify and manage the deployment of training jobs
 - TFJob – custom resource to handle drivers and config
 - Tensorflow, PyTorch, MXNet, Chainer, and more
- JupyterHub to create and manage interactive Jupyter notebooks
- Model serving – serve exported models with TF Serving or Seldon
- Additional components for storage, workflow, etc.

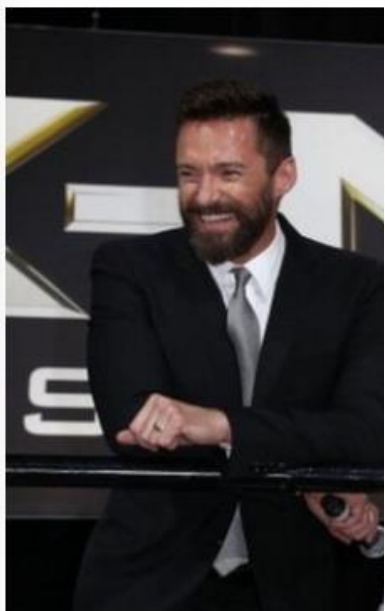
Artificial Intelligence solves critical life problems



NEWS

[Home](#) [Video](#) [World](#) [US & Canada](#)[Asia](#) [China](#) [India](#)'Disappearance' of
Fan BingbingBy Kerry Allen
BBC Monitoring

🕒 1 August 2018



Fan Bingbing recently received global

Chinese star Fan Bingbing seen in
disappearance

By Ben Westcott, CNN

🕒 Updated 6:28 AM ET, Wed October 17, 2018



Fan Bingbing seen after lengthy disappearance 00:35

ENTERTAINMENT



Fan Bingbing outside the airport in Beijing.

[Home](#) / [Entertainment](#) / [Movies](#)Fan Bingbing spotted for first time in months, outside
Beijing airport

📅 OCTOBER 17, 2018

📁 ENTERTAINMENT, MOVIES, PEOPLE

BY AGENCY

Demo: Find 范冰冰

Image classification with Inception v3 and transfer learning

- Generate dataset and labels for Fan Bingbing and not Fan Bingbing
- Using transfer learning, take a trained model Inception v3, retrain a new top layer for new classes of images

Data Preparation

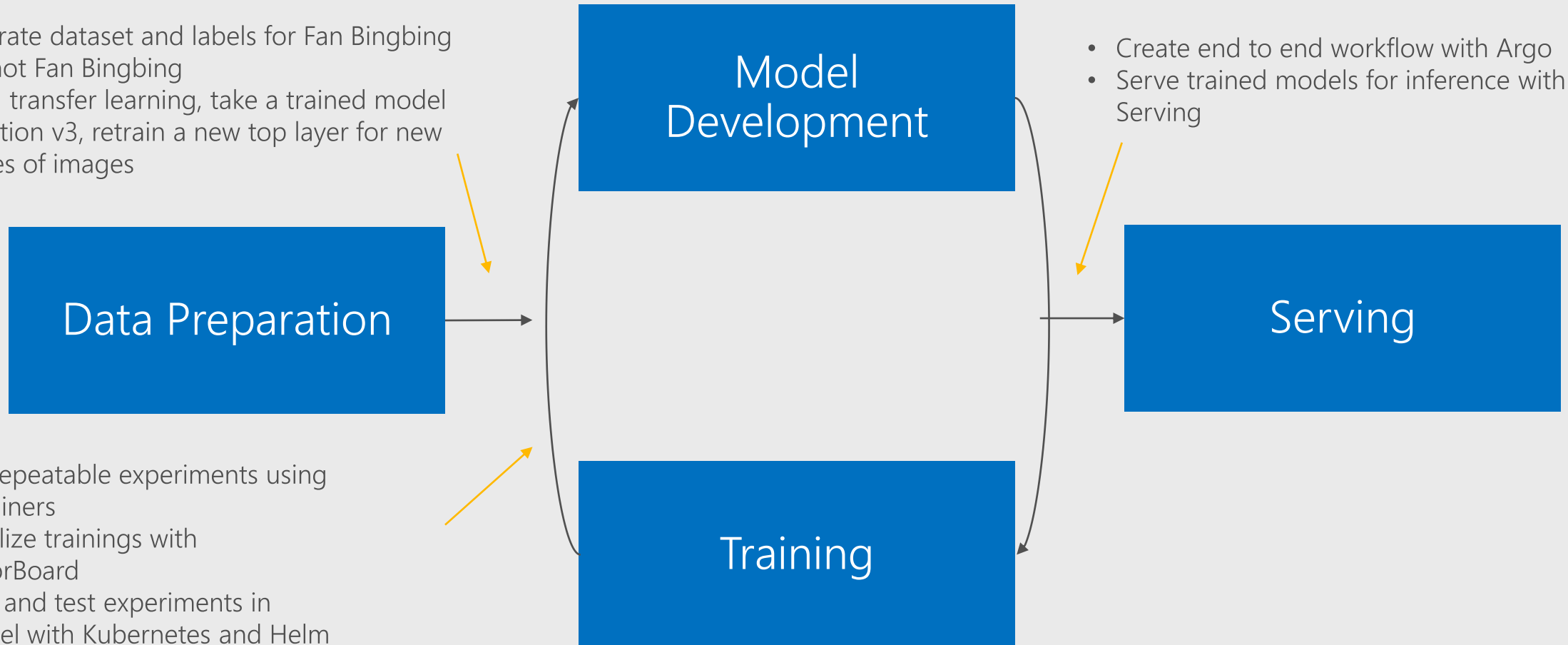
Model Development

Training

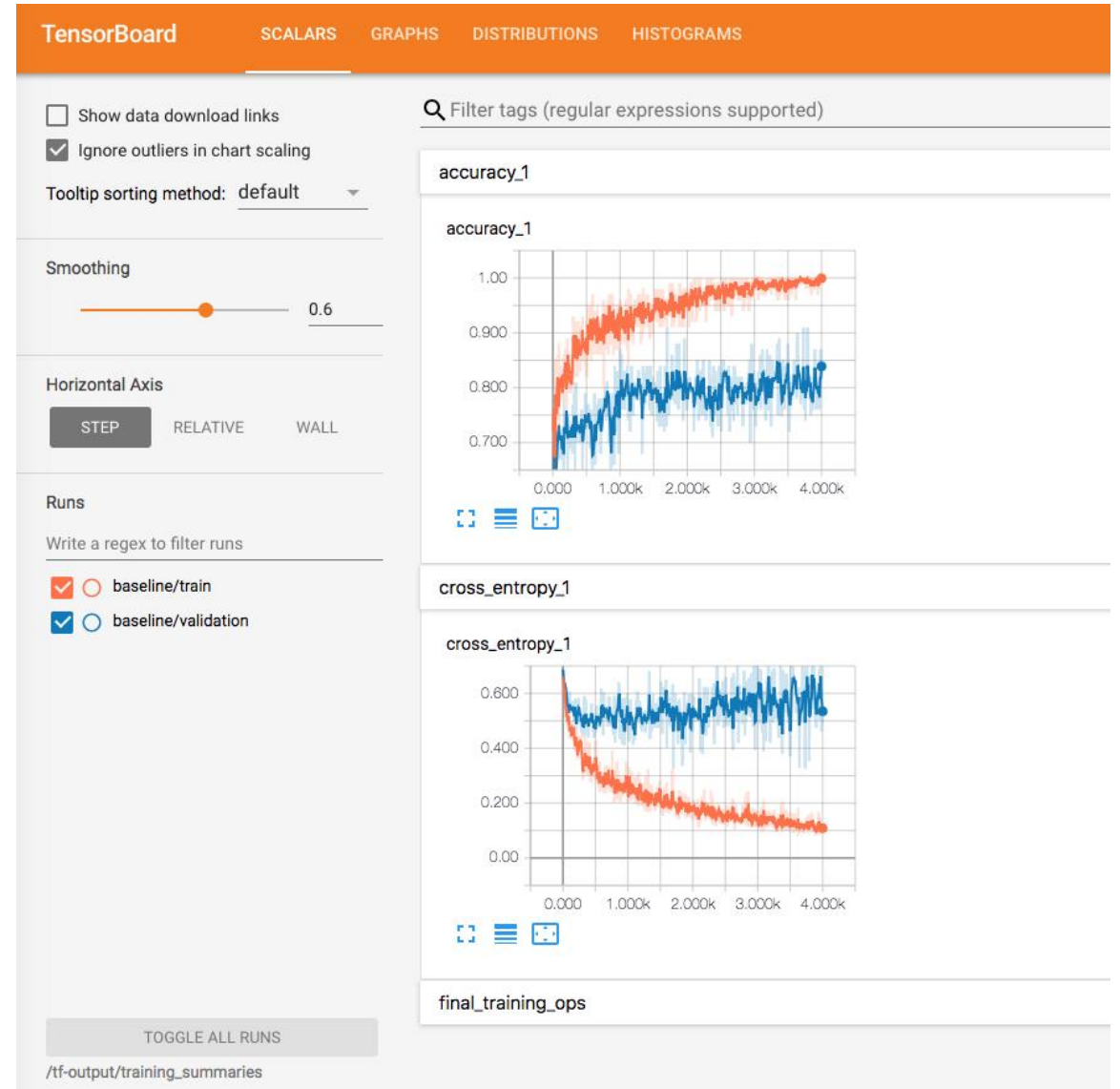
Serving

- Run repeatable experiments using containers
- Visualize trainings with TensorBoard
- Scale and test experiments in parallel with Kubernetes and Helm

- Create end to end workflow with Argo
- Serve trained models for inference with TF Serving



Demo: Run TensorFlow Training with Containers



- <https://www.youtube.com/watch?v=7Ndx3HKaS5s>

Demo: Serving the Model with TF Serving

- Options for serving
 - Wrap model in a web framework (eg – Flask)
 - Tensorflow Serving
 - Seldon



- <https://www.youtube.com/watch?v=t13F33I27TI>

A large, irregular blue ink splash or blotch serves as the background for the text. The splash is centered and has a textured, painterly appearance with various shades of blue and white. The text is white and centered within the splash.

Demo: Run TensorFlow Training with Kubeflow

- <https://www.youtube.com/watch?v=lvH3ivDrocw>
- <https://www.youtube.com/watch?v=OQvO0pFaeEc>

Demo: Scale and Test Experiments in Parallel using Kubernetes, TFJob, Helm, Virtual Kubelet, & ACI

- Spin up pods for each variation of hyperparameters
- One centralized TensorBoard instance
- Autoscaling will create / remove container instances as needed to save cost



- <https://www.youtube.com/watch?v=EtOuo1dj56c>
- <https://www.youtube.com/watch?v=E1p9bTN-fYc>



Demo: Create End to End ML Pipelines with Argo

- <https://www.youtube.com/watch?v=5zJrvWY9srs>
- <https://www.youtube.com/watch?v=2P50c-srIkA>

Kubeflow Pipelines

...

```
create_cluster_op =  
CreateClusterOp('create-cluster',  
project, region, output)
```

```
analyze_op = AnalyzeOp('analyze',  
project, region,  
create_cluster_op.output, schema,  
train_data,  
'%s/{{workflow.name}}/analysis' % output)
```

```
transform_op = TransformOp('transform',  
project, region,  
create_cluster_op.output, train_data,  
eval_data, target, analyze_op.output,  
'%s/{{workflow.name}}/transform' %  
output)
```

...

Pipelines

Experiments

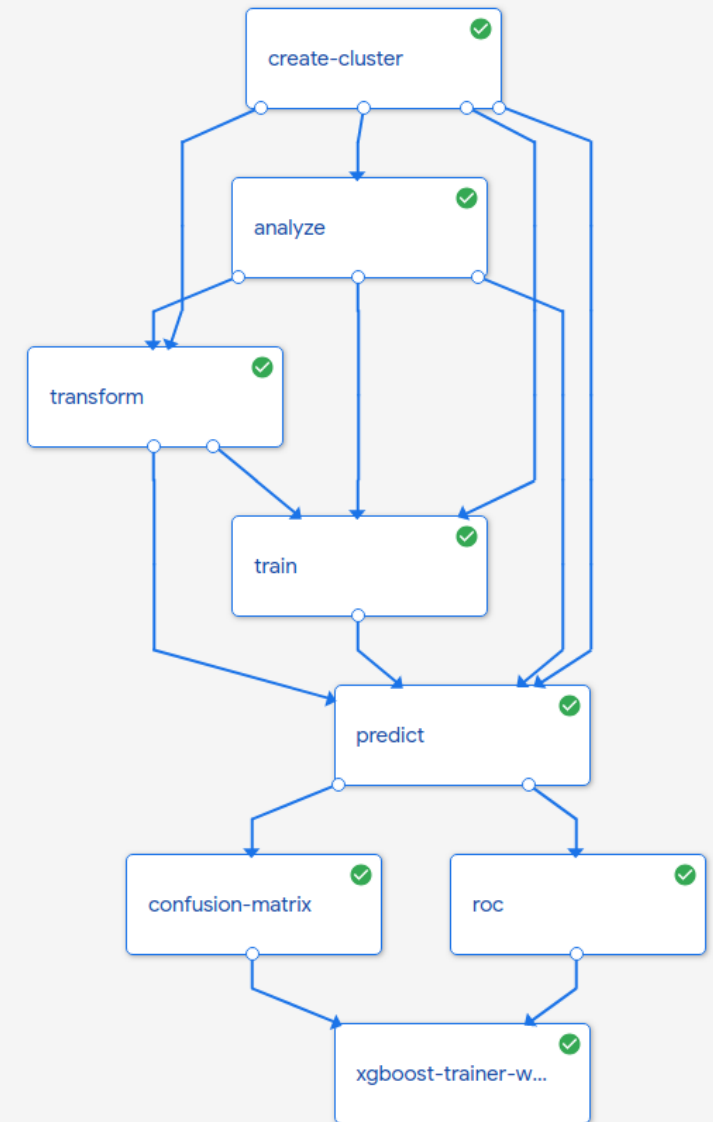
Notebooks

Experiments > XGB

← SFPD Case Resolution Pipeline with XGBoost

Graph

Config

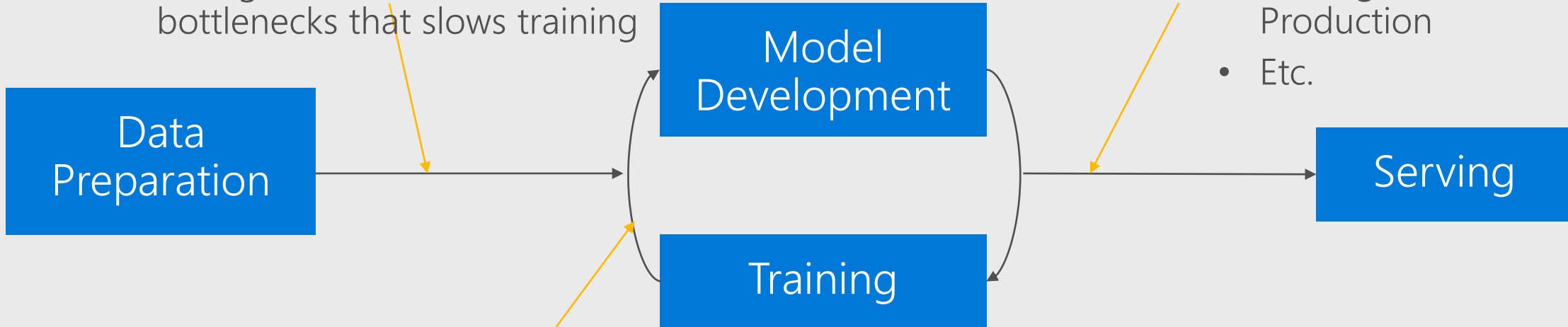


Demo: Rapid prototyping with self-service Jupyter notebook from JupyterHub

- <https://www.youtube.com/watch?v=kGr6mTUEBhs>
- <https://www.youtube.com/watch?v=8MTGAT6qsXo>

What's Next?

- Keeping track of datasets
- How to do automatic retraining when data changes ?
- Storage and Network bottlenecks that slows training



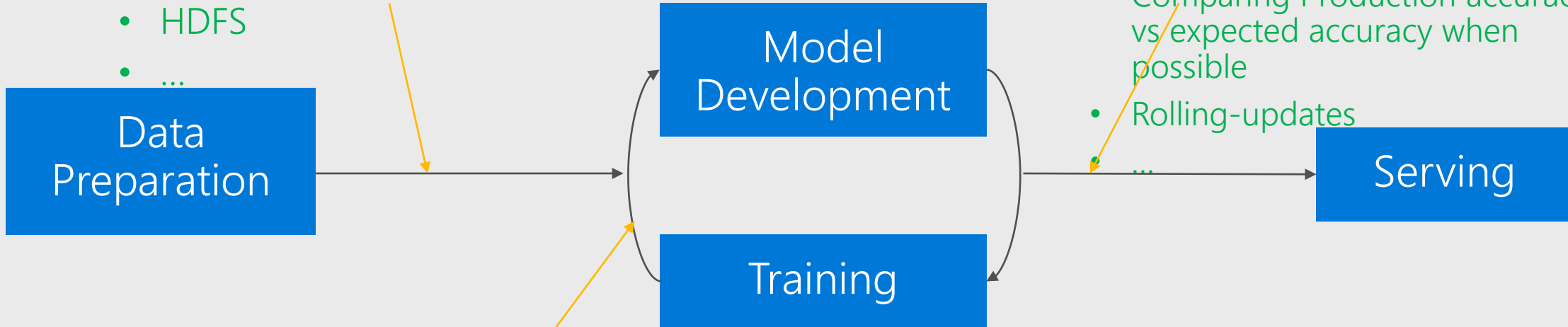
Classic App dev. issues:

- Reproducibility ("it works on my machine")
- Scalability
- Getting feedback from Production
- Etc.

- Slow Sequential Training
- Hard to explore hyper-parameters space
- Distributed training is hard to set up

What's Next?

- Pachyderm can version datasets and trigger new trainings when changes occur
- Distributed File Systems
 - NFS
 - HDFS
 - ...



Classic DevOps solutions:

- Containers
- CI/CD
- Autoscaling
- A/B testing and canary release of Models
- Comparing Production accuracy vs expected accuracy when possible
- Rolling-updates

(one) Solution is Kubernetes:

- Highly Scalable
- Easy to explore hyper-parameters space
- Easy to do distributed training

But really, Data Scientists shouldn't have to care about containers, kubernetes and all that stuff

Blog / Announcements

Announcing general availability of Azure Machine Learning service: A look under the hood

Posted on December 4, 2018

 **Venky Veeraraghavan**, Group Program Manager, Microsoft Azure

Today, we are announcing the general availability of [Azure Machine Learning service](#).

Azure Machine Learning service contains many advanced building, training, and deploying machine learning model skill levels to identify suitable algorithms and hyperparameters such as PyTorch, TensorFlow, and scikit-learn allow data scientists for machine learning further improve productivity by enabling models deployed in the cloud and on the edge. All these capabilities are available anywhere, including data scientists' workstations.

We built Azure Machine Learning service working closely with our customers to improve customer service, build better products and create new examples.

TAL, a 150-year-old leading life insurance company in Australia, is improving customer experience. Traditionally, TAL's quality assurance team reviewed 100 percent of cases. Using Azure Machine Learning service, it is now able to review 100 percent of cases.

"Azure Machine Learning regularly lets TAL's data scientists build models with less effort, faster, and more accurately, delivering faster outcomes and the opportunity to roll out many more models than was previously possible. There is

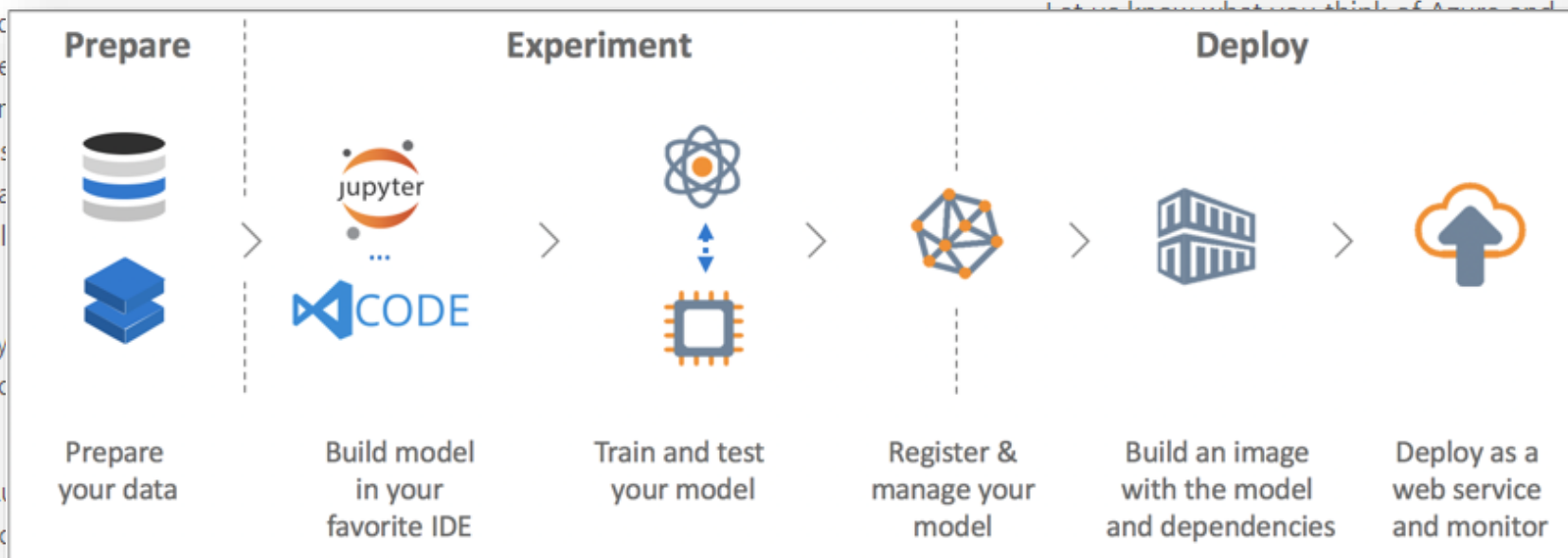


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<https://azure.microsoft.com/blog/azure-machine-learning-service-a-look-under-the-hood/>

Resources

- Source code for this talk:
<https://github.com/ritazh/kubecon-ml>
- Kubeflow labs for AKS:
<https://github.com/Azure/kubeflow-labs>
- Provision a Kubernetes cluster on Azure:
<https://github.com/Azure/kubeflow-labs/tree/master/2-kubernetes#provisioning-a-kubernetes-cluster-on-azure>

