Natural Language Code Search With Kubeflow

2018/12/14

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http://bit.ly/2SjbLRS

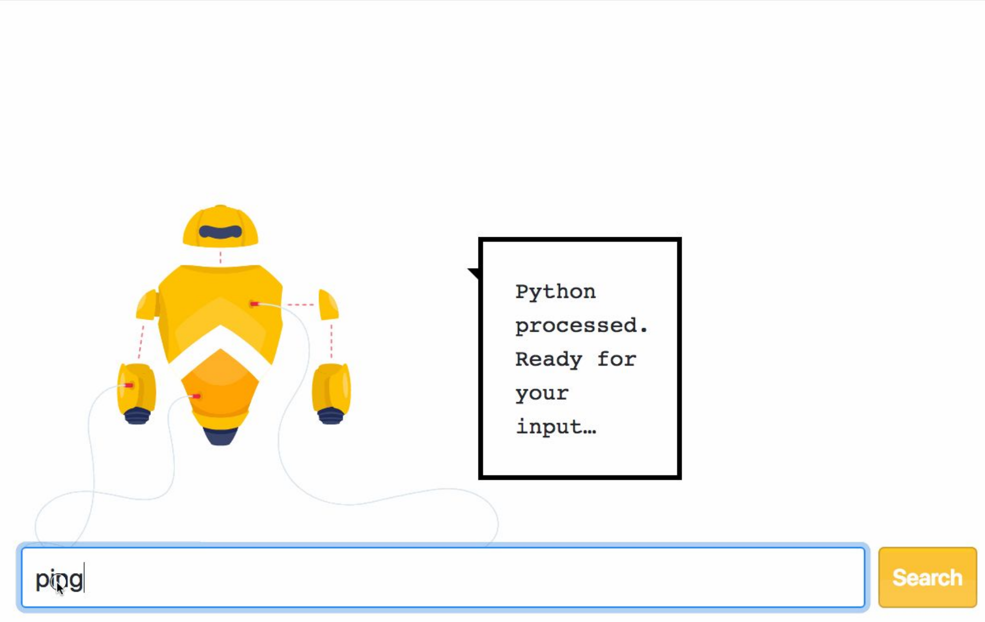
Agenda

Summary: Kubeflow makes it easy to build and deploy ML products.

- Intro: Building Natural Language Code Search At GitHub
- Why Kubeflow?
  - Productionizing ML takes too long
- What is Kubeflow?
  - A Kurnetes native platform for ML
- Walk through how Kubeflow can accelerate turning experiments into production
- Demo
- Summary

Idea: Semantic Code Search

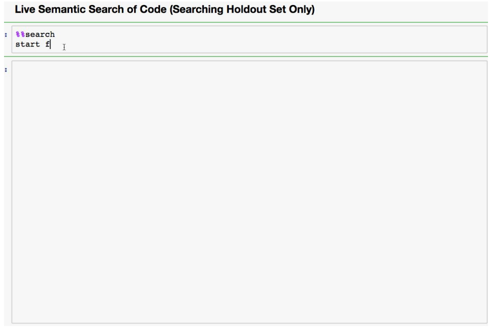
- Build a way to search code using natural language.
- Query: Natural language describing what code does
- Result: relevant code matching the query
- Code (kubeflow/examples)
- Blog Post by Hamel Husain



- https://experiments.github.com/semantic-code-search

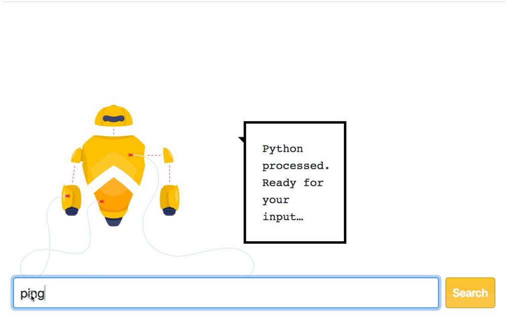
Going from an idea to a product

Prototype MVP With Demo In Jupyter Notebook: **2 Weeks**



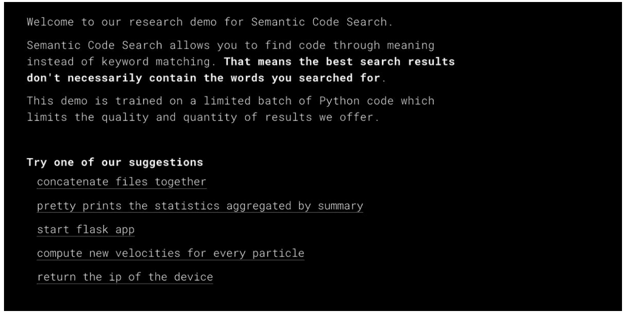
https://github.com/hamelsmu/code_search

Demo with front-end mockup with blog post: **+3 Days**



https://towardsdatascience.com/semantic-code-search-3cd6d244a39c

Experiments.Github.Com: **+3 Months**

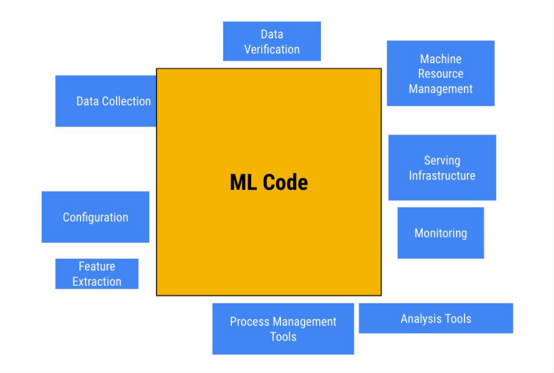


https://experiments.github.com/

Perception: ML Products are mostly about ML

- "Someone else" will take care of production
- Most time & effort is spent building the model
- Data Science teams often given headcount and resourced that reflect this understanding of the world
- There isn't as big of a data scientist shortage as you think!.

Team structure reflects perception



GitHub Circa August 2018:

- **10 Data Scientists**
- **1 Front End, 1 Data Engineer**
- No ML Infra. DIY

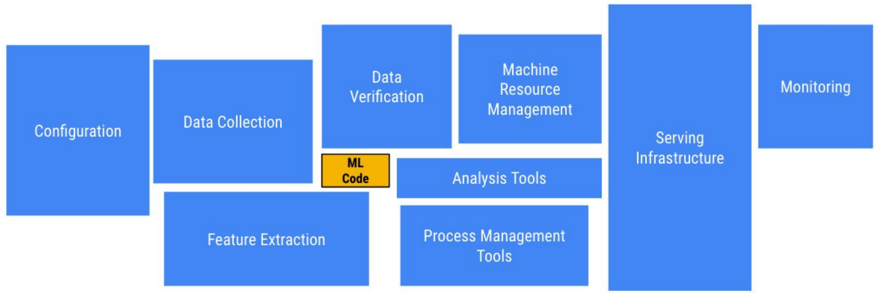
Datascientists

Devops

Reality:

- Infrastructure/DevOps team want to know a model is useful before investing in productinization
- Datascientists often don't know if a model is really useful without launching it
- Building the model is often the least costly step of productionization
    - 2 weeks to build model in notebook
    - 3 months to launch on experiments.com

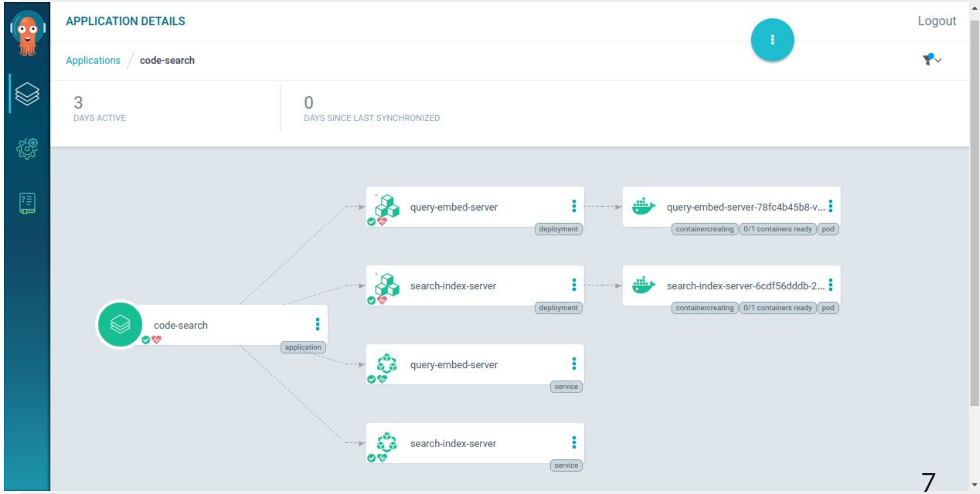
ML Requires DevOps; lots of it



Source: [Sculley et al.: Hidden Technical Debt in Machine Learning Systems]

Argo CD

- Declarative Continuous Delivery for Kubernetes
- Keeps resources in a cluster in sync with manifests in a git repository



Kubeflow: A platform for building ML products

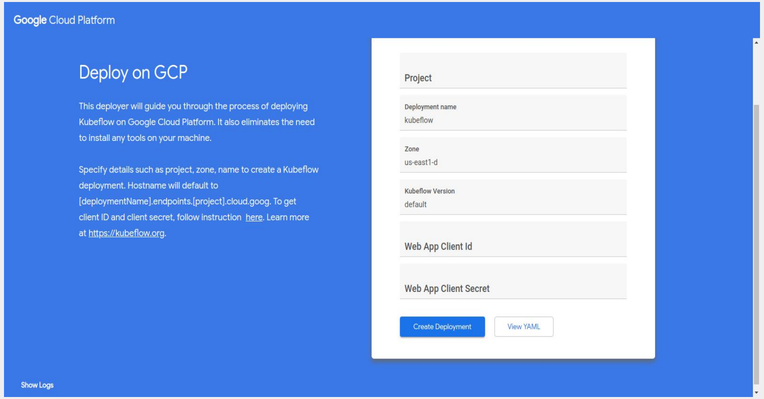
- **Leverage containers and Kubernetes to solve the challenges of building ML products**
  - Reduce the time and effort to get models launched
- **Why Kubernetes**
  - Kubernetes has won
  - Kubernetes runs everywhere
  - Enterprises can adopt shared infrastructure and patterns for ML and non ML services
  - Knowledge transfer across the organization
- Kubeflow is open
  - No lock in
  - 120+ Members
  - 20+ Organizations
  - Stats available @ http://devstats.kubeflow.org

ML Components

- Goal: components for every stage of ML
- Examples:
  - Experimentation / Data Exploration
    - Jupyter/JupyterHub
  - Training
    - K8s CRDs for distributed training for PyTorch & TFJob
    - Katib - For HP Tuning
  - Inference
    - Beam transforms for batch inference
  - Workflows:
    - Pipelines
  - Feature Store
    - Feast (from GOJEK)

Deployment

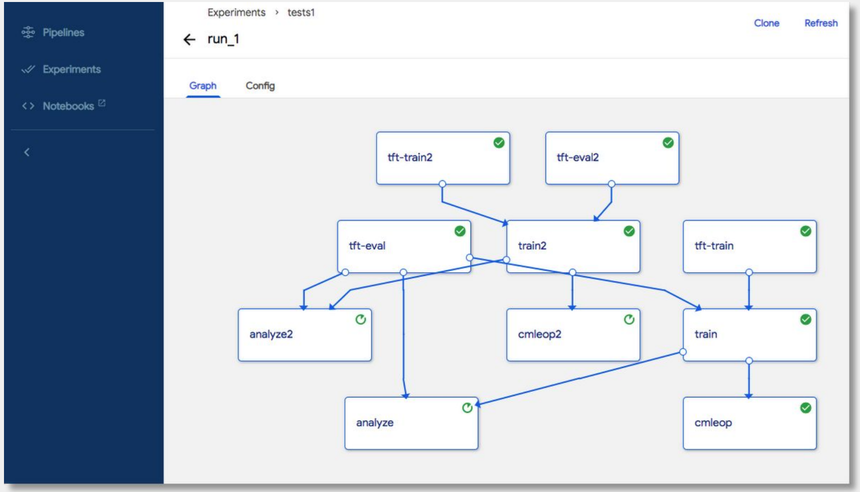
- Make it easy to deploy components as a cohesive platform
  - CLI kfctl
  - Web UI
- Web UI currently GCP only
  - Ask your vendor to add support
  - See current members at
  - https://github.com/kubeflow/community/blob/master/member_organizations.yaml



https://deploy.kubeflow.cloud

Pipelines

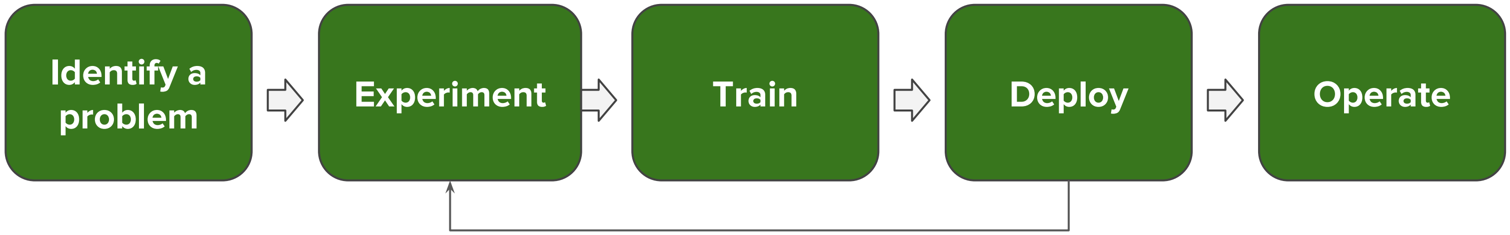
- Define complex ML workflows
  - in Python
- Run pipelines regularly
- Visualize all runs and track all the results
- [Example]
- Powered by Argo




```
tfteval = dsl.ContainerOp(
     name = 'tft-eval',
     image = 'gcr.io/google-samples/taxi',
     arguments = [ "--input_handle", ...]
     )
tfttrain = dsl.ContainerOp(...)
tftrain.after(tfteval)
```

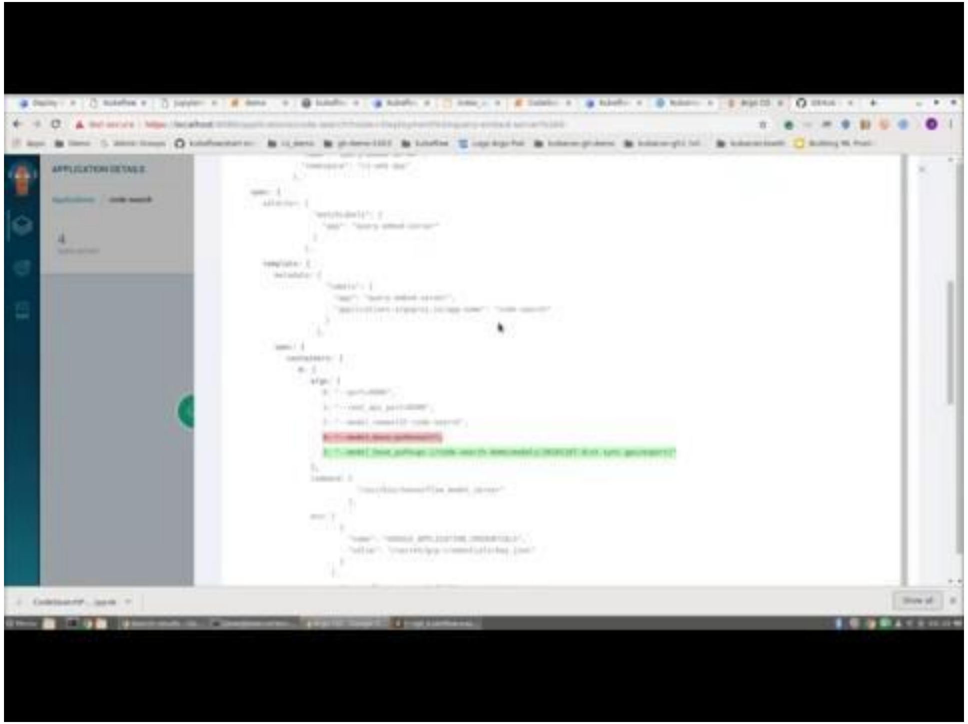
Going from an idea to production

- Multiple steps involved in building the model
- Each step has different resource requirements
    - Resource management is a big problem
- Application consists of multiple microservices



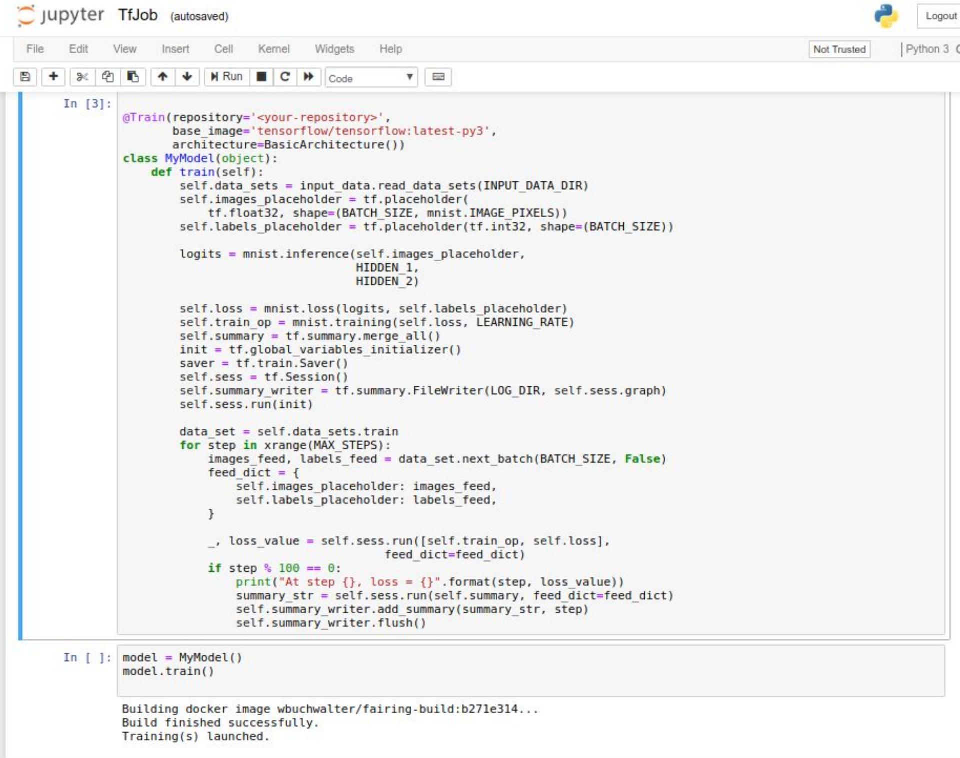
Demo

Demo Video



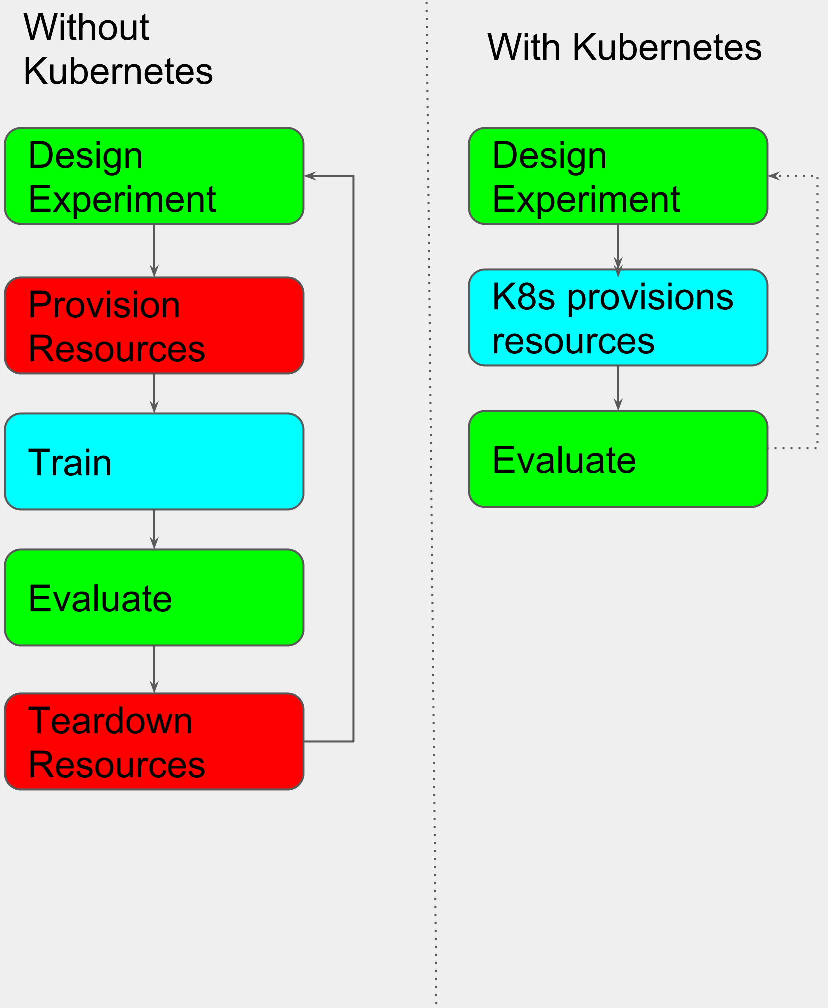
Notebooks & Kubeflow

- Easily launch notebooks via UI
- Fairing is a library that makes it easy to use K8s from a notebook
  - Notebook -> container -> TFJob
- **Datascientists can leverage K8s without knowing K8s**
- Started by Microsoft
- Inspired by Lyft Learn
- Kudos Arrikto for the new JupyterHub spawner UI



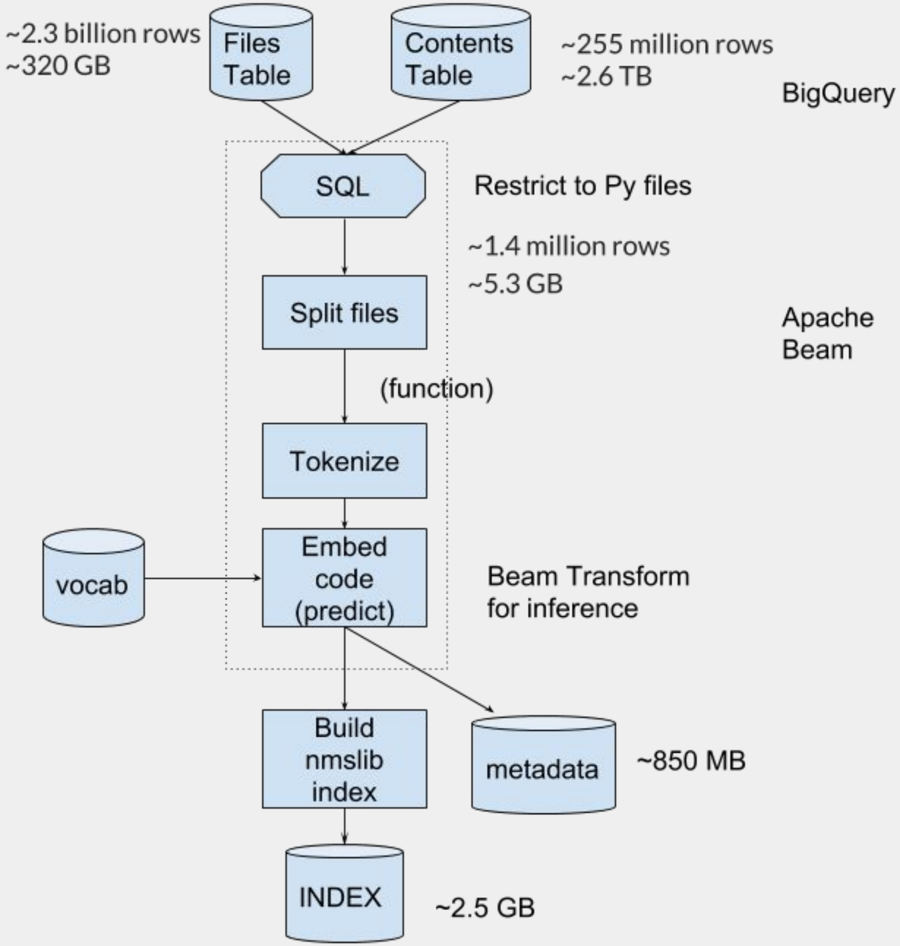
Training

- Scale horizontally
    - Multiple experiments
        - Different vocab sizes, loss functions
    - TFJob for Distributed Training
- Scale vertically
    - Multiple GPUs (K80, P100, V100, T4)
- Multiple users
- **Kubernetes takes care of resource management so datascientists can focus on experiment design & analysis**



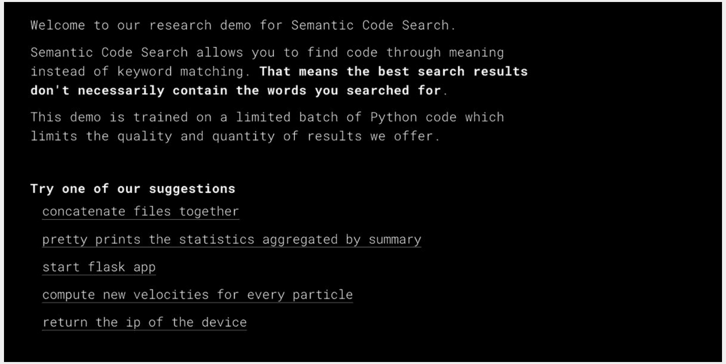
Offline Inference

- Embeddings for all python functions (possible search results) are precomputed
- Embeddings are indexed using nmslib to enable fast lookup in response to a query
- Scale out & up
    - Beam Job = 347 vCPU hr
    - Build nmslib index ~28 GB Ram



Online Inference

- TFServing to compute query embeddings
- Index server provides fast lookup
- Launching a public experiment is costly
  - ~ 3 months
  - No devops support
  - Security concerns
- So much room for improvement!
  - GitHub building our Kubeflow infra.



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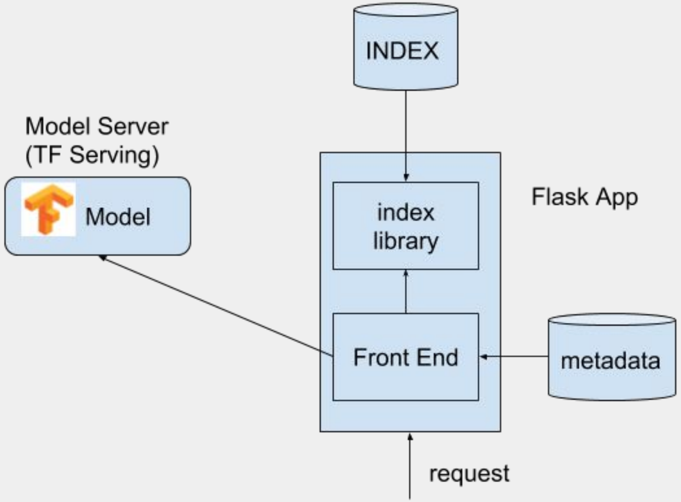
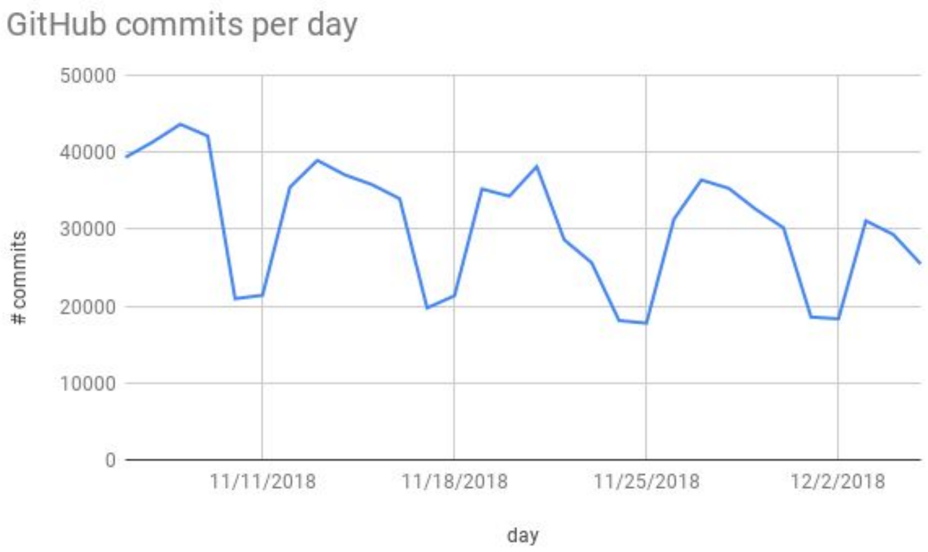


Keeping the index fresh

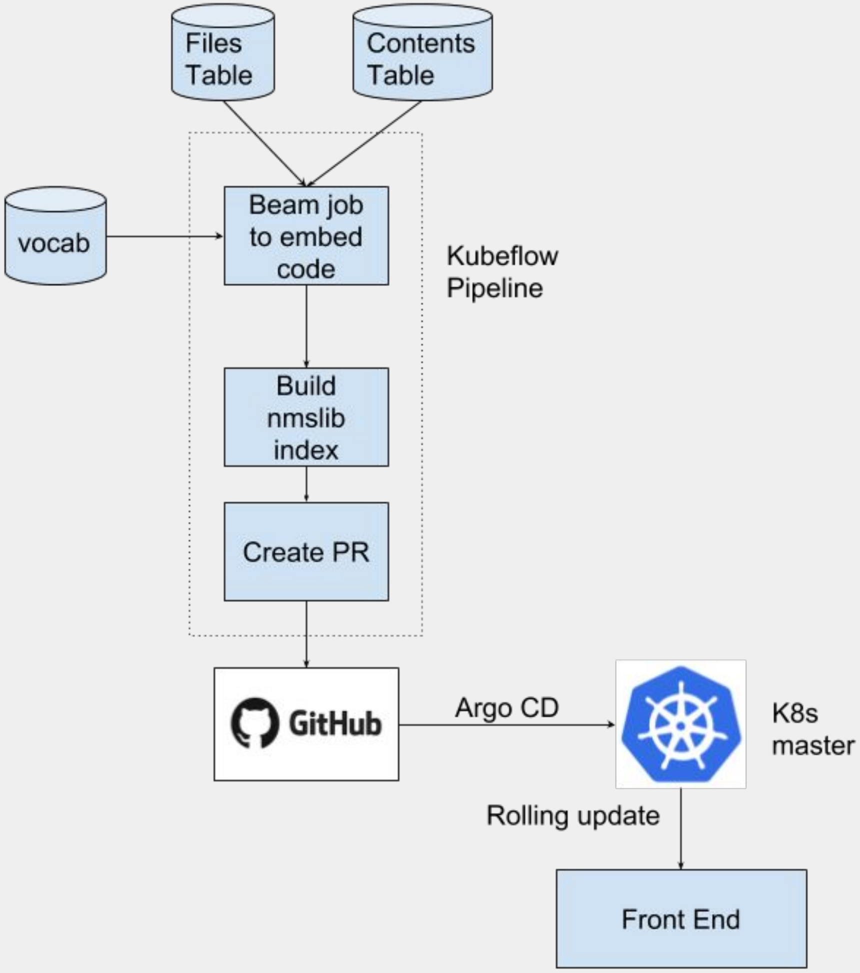
- Code is constantly changing in GitHub
- If we don't update the index frequently quality of the results will deteriorate
- Common problem in ML products



From BigQuery table
bigquery-public-data.github_repos.commits

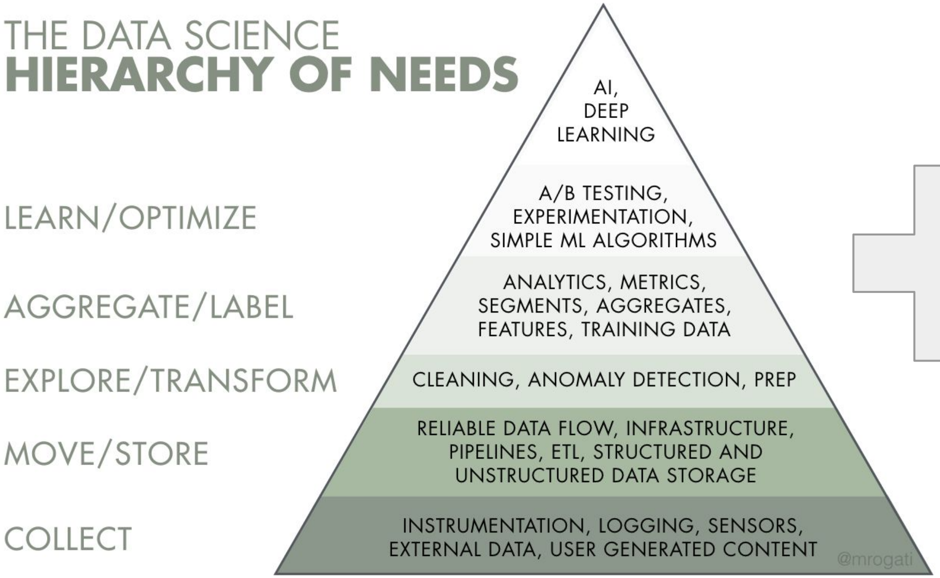
Updating the Index

- Use Kubeflow pipelines to periodically run the steps to compute the index
- Pipeline creates a PR updating the index served by the front end
- Argo CD synchronizes the deployed infrastructure
- Pipeline code: https://github.com/kubeflow/examples/tree/master/code_search/pipeline

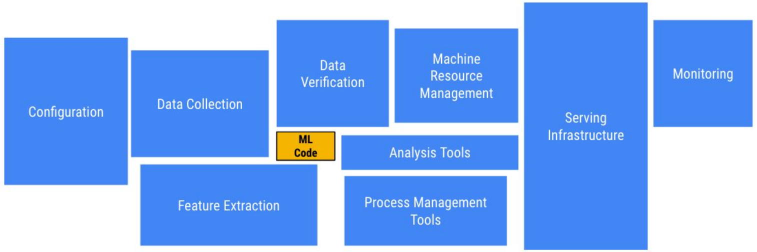


State of ML in Industry

You Probably Don’t Need To Hire Another ML-Data Scientist



Source: [Monica Rogatti’s Hierarchy of Needs]



Source: [Sculley et al.: Hidden Technical Debt in Machine Learning Systems]

Special Thanks

Sanyam Kapoor - Google Intern Ported model to Kubeflow

Yang Pan - Googler who build the pipeline

Chris Beitel - Director ML Research UCSF - Helped with training training the model

Lukasz Kaiser and Ryan Sepassi - Googlers behind Tensor2Tensor; helped with model design with T2T

Jesse Suen and Danny Thomson - Intuit engineers working on Argo CD and integration with Kubeflow

ML and Kubeflow Related Talks

12/11 11:40 - 12:15 Using Kubernetes to Offer Scalable Deep Learning on Alibaba Cloud Kai Zhang & Yang Che
12/11 13:45 - 15:10 Tutorial: Kubeflow End-to-End: GitHub Issue Summarization chasm@ amyruh@
12/11 15:40 - 16:15 Machine Learning as Code: and Kubernetes with Kubeflow jaysmith@ aronchick@
12/11 16:30 - 17:05 Why Data Scientists Love Kubernetes Sophie Watson & William Benton
12/12 10:50 - 11:25 Natural Language Code Search for GitHub Using Kubeflow jlewi@ & Hamel Husein
12/12 11:40 - 12:15 Nezha: A Kubernetes Native Big Data Accelerator For Machine Learning Huamin Chen & Yuan Zhou
12/12 14:35 - 15:10 Eco-Friendly ML: How the Kubeflow Ecosystem Bootstrapped Itself Peter MacKinnon
12/12 15:40 - 16:15 Deep Dive: Kubeflow BoF

Kubeflow Related Booths

- Agile Stacks (Booth S/E 22)
    - See a demo of automated deployment of Kubeflow and ML pipelines on AWS and on-prem bare metal, tightly integrated with infrastructure services for scheduling, monitoring, logging, data management, storage, and security.
- Arrikto (Booth S/E 43)
    - Come see a multi-cloud ML workflow (ingress of multi-GB data, pre-processing, distributed training, and inference in distinct locations) with Kubeflow + Arrikto!
- One Convergence (Booth S/E49)
    - OnPrem Deep Learning as a Service

More Info

- Kubeflow Docs - https://www.kubeflow.org/
- Code - https://github.com/kubeflow/examples/tree/master/code_search
- GitHub Experiments - https://experiments.github.com/
- Argo CD- https://github.com/argoproj/argo-cd
- Tensor2Tensor - https://github.com/tensorflow/tensor2tensor

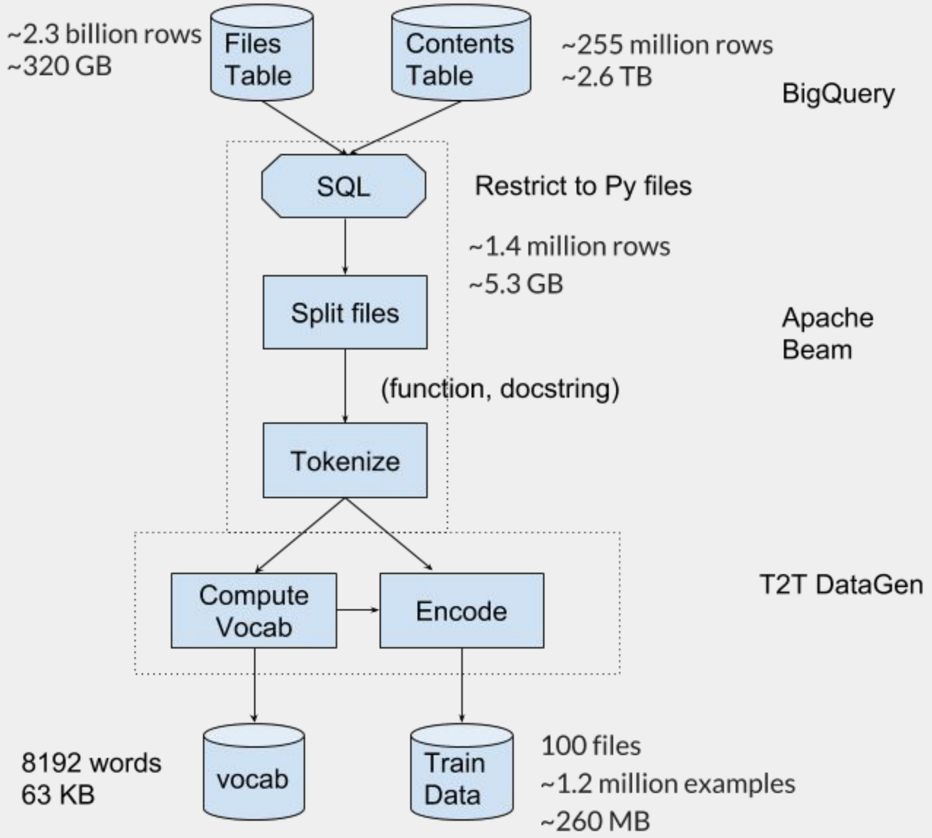
Kubeflow

Thank You

Appendix: Extra Slides

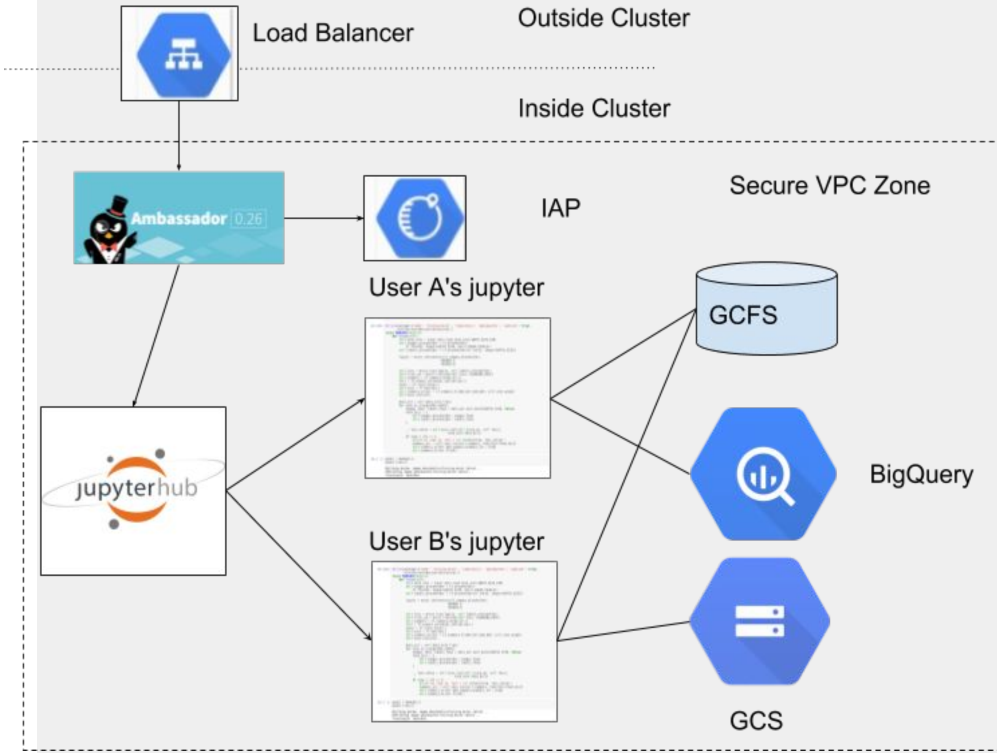
Data Preparation

- 3 Different compute engines involved
  - SQL(BigQuery)
  - Beam(Dataflow)
  - T2T Binary (K8s Job)
- **Beam Job ~108 vCPU hours**
  - Need to scale vertically and/or horizontally
  - Kubernetes enables both



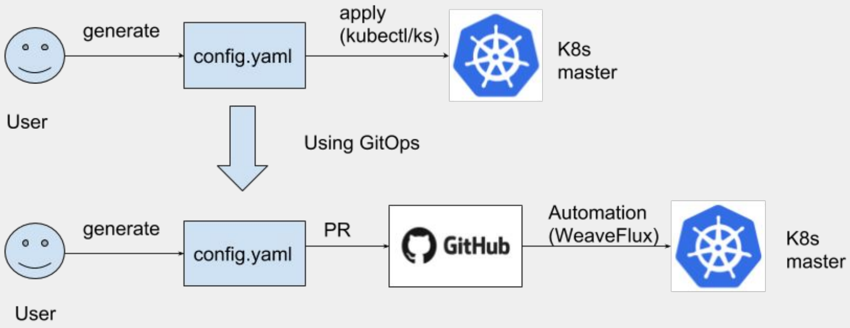
Deploying notebooks

- Easily launch notebooks
- Access notebooks securely: https://kubeflow.acme.com/jupyter
- Shared storage (NFS) for collaboration
- Connect to data warehouse
- Enforce enterprise security policies



Enable GitOps for ML

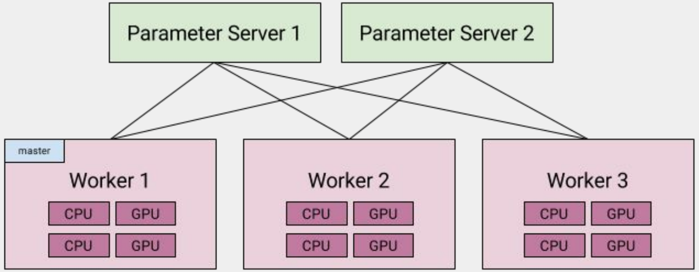
- Fully declarative
- kfctl is a two step process
  - Create configs
  - Apply configs
- GitOps reduces the toil of managing infrastructure
  - Automation (e.g. WeaveFlux) keeps infrastructure up to date
  - Allows for automatic policy enforcement



TFJob

- Integrates TF distributed training and estimator API with K8s
- Use K8s to scale out training and leverage accelerators
- TF specific controller takes care of managing all the K8s resources
    - K8s services
    - Pods
- Users benefit from K8s toolchain
    - kubectl for CLI
    - K8s dashboard for monitoring

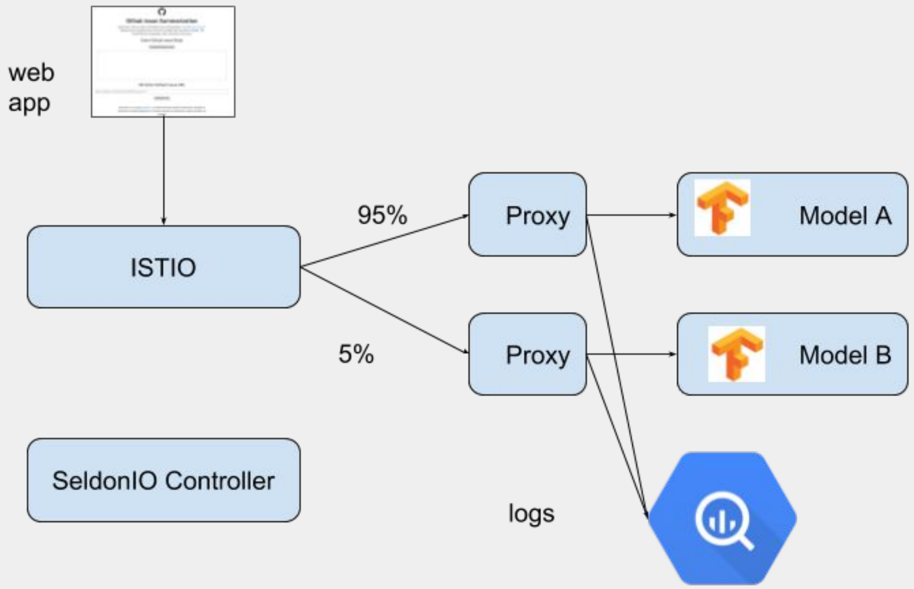
```
apiVersion: kubeflow.org/v1alpha2
kind: TFJob
metadata:
  name: tf-job-simple
  namespace: kubeflow
spec:
 tfReplicaSpecs:
   Workers:
     replicas: 3
     template:
       spec:
         containers:
         - image: acme/myjob
```



TFServing

- Collaborating with TF to create a K8s native story for TFServing
- Adding prometheus exporter for metrics
- ISTIO for telemetry and traffic splitting
- **Opportunity to leverage K8s to simplify pushing models**
    - Need to measure model quality
    - Global rollout needed to uniformly sample traffic across

model push ≠ binary push

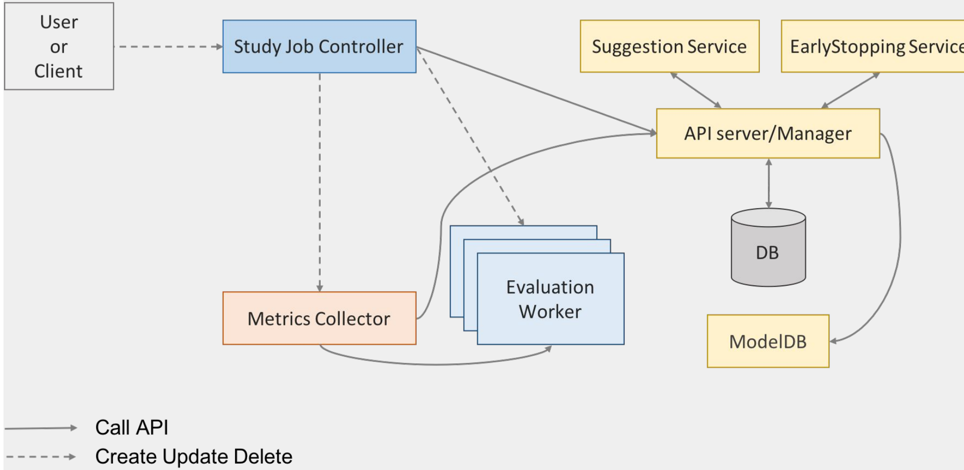


GPU Serving

- NVIDIA Inference Server - Optimized for GPUs
- Using TF Serving

Katib(HP Tuner)

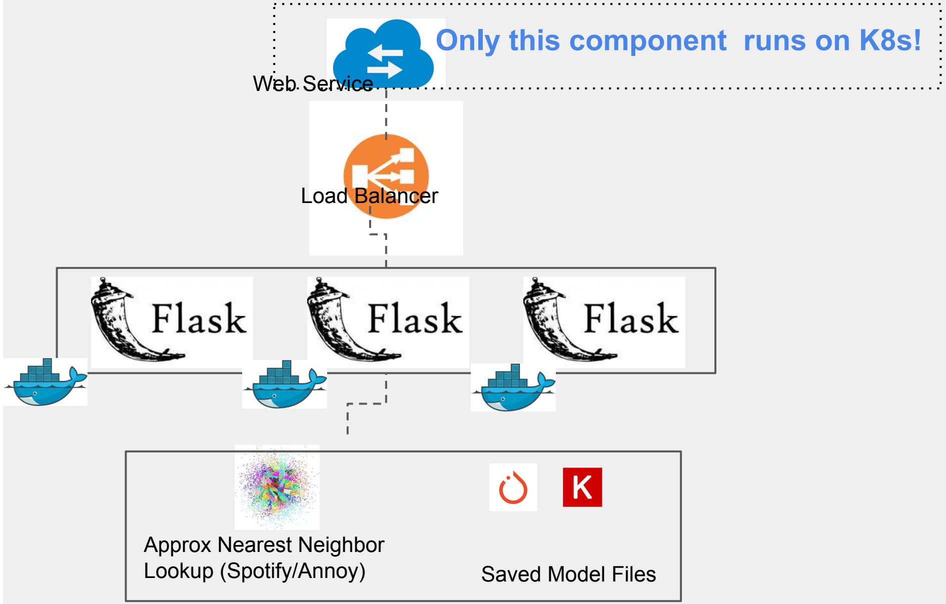
- Pluggable microservice architecture for HP tuning
  - Different optimization algorithms
  - Different frameworks
- StudyJob (K8s CR) (example)
  - Hides complexity from user
  - No code needed to do HP tuning

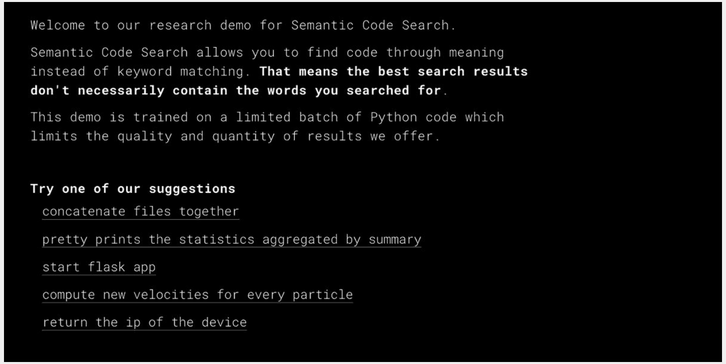


Design Doc

Experiments.GitHub.com

- Launching a public experiment is costly
  - No devops support
  - Security concerns
- So much room for improvement!
  - Currently building our Kubeflow infra.
- ~ 3 months

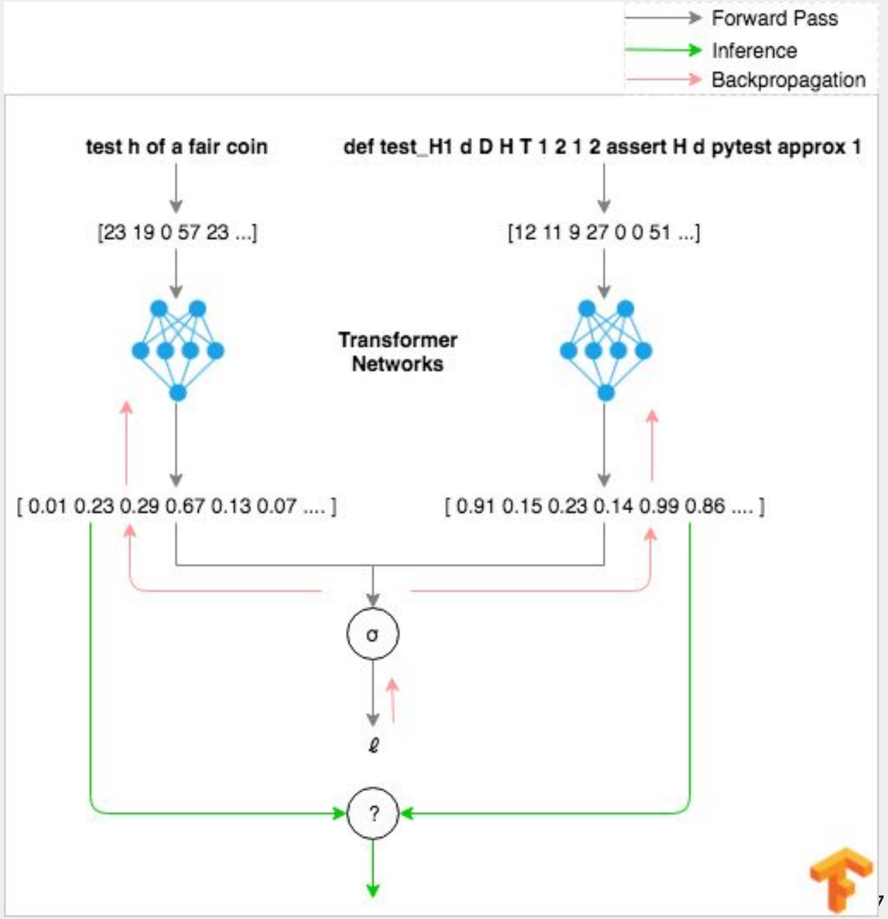




https://experiments.github.com/semantic-code-search

The model

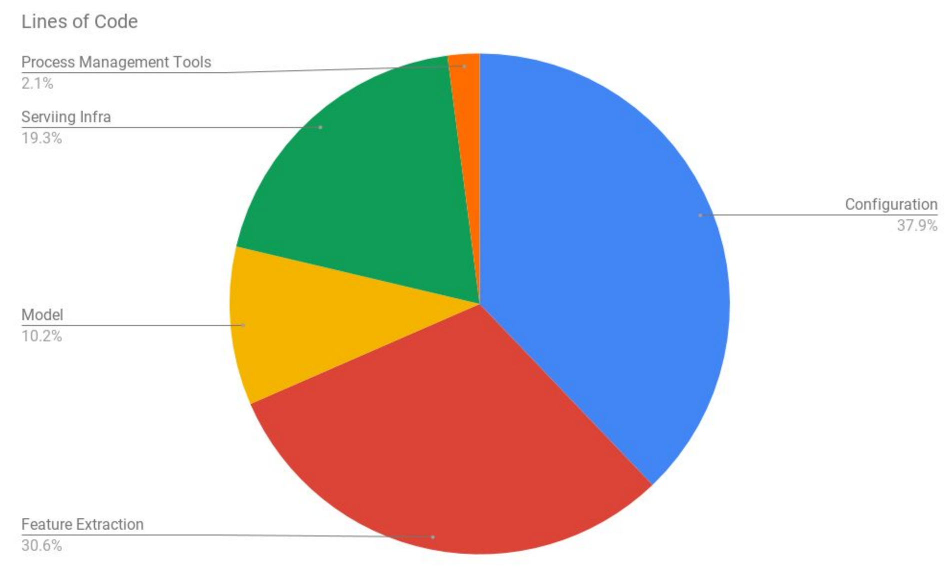
- Model embeds search query and code in the same space
  - predicts how well the code matches the query
- Built on Tensor2Tensor library of models



Code Breakdown

1. Building ML productions requires lots of devops
2. Kubeflow makes it easy to build ML products using Kubernetes

Most code & config is not related to the model



Big industry challenge

ginablaber
@ginablaber

Follow

The story of enterprise Machine Learning: “It took me 3 weeks to develop the model. It’s been >11 months, and it’s still not deployed.” @DineshNirmalIBM #StrataData #strataconf

10:19 AM - 7 Mar 2018