MLops

Make life easy

Common problems with scaling ML

Getting started

Mundane steps with lots of boilerplate

Iterating quickly

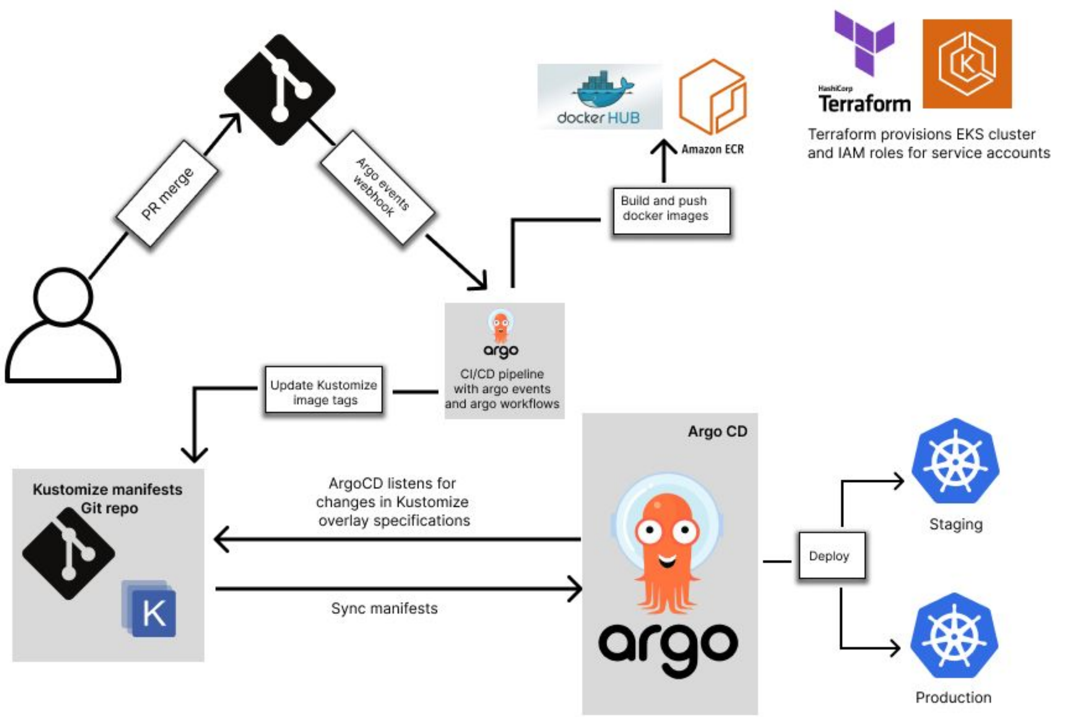
Slow redundant iterative development

Hard to experiment and compare different models/algorithms

Productionizing

Incorporating ML models into production backend and handing off to engineers is very manual and bottlenecked

Gitops CI/CD for any software product



PR merge

Argo events webhook

docker HUB

Amazon ECR

Build and push docker images

HashiCorp Terraform

Terraform provisions EKS cluster and IAM roles for service accounts

argo

CI/CD pipeline with argo events and argo workflows

Update Kustomize image tags

Kustomize manifests Git repo

ArgoCD listens for changes in Kustomize overlay specifications

Sync manifests

Argo CD

argo

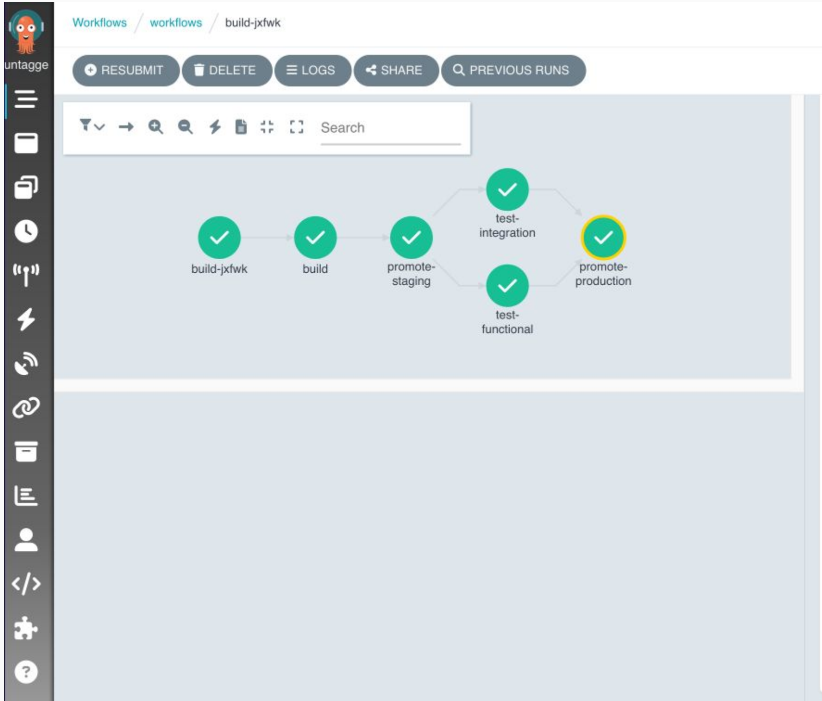
Deploy

Staging

Production

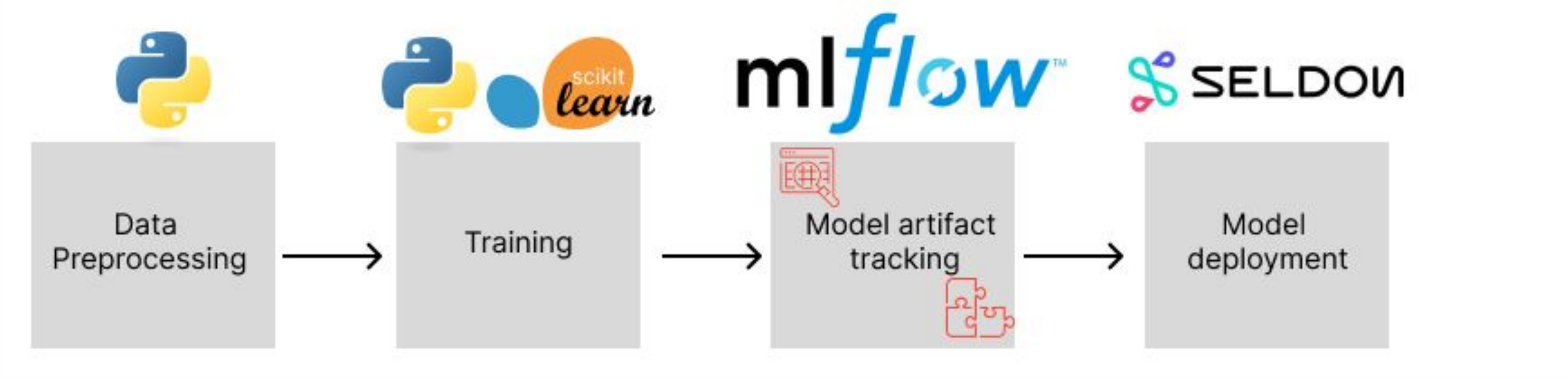
Argo workflows for CI/CD

1. Team makes change to MERN stack application and makes a Github PR
2. Github sends a webhook POST request to Argo event source
3. The CICD workflow trigger source is started
4. Docker image is built for frontend and backend and pushed to docker registry
5. New image tags are updated in Kustomization.yaml file
6. ArgoCD picks this up and updates the deployment
7. Integration tests can be carried out in the staging environment to test that APIs endpoints can be reached and they return the expected results.
8. If all goes well, then we can update manifests in the production cluster



CI/CD for ML pipelines

Machine learning as composable units



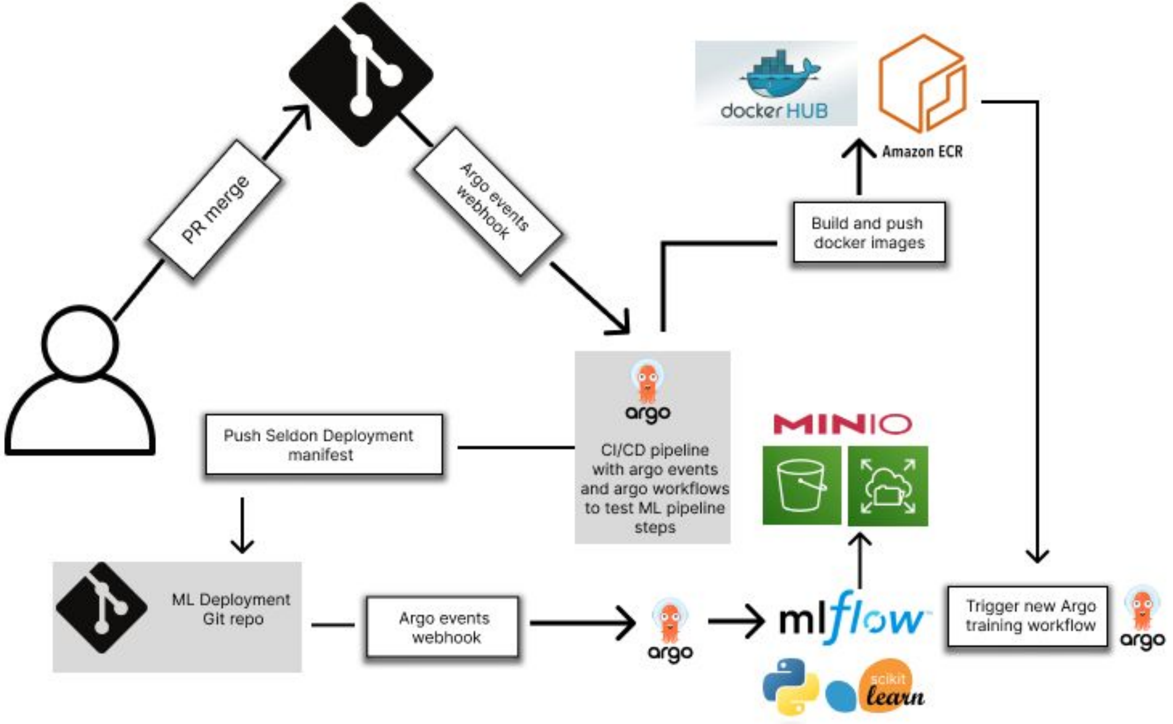
Data Preprocessing → Training → Model artifact tracking → Model deployment

CI/CD for ML training pipeline

Training pipeline will store serialized model (.pkl file) to persistent NFS volume. It will also register the model with MLflow so we always know the properties of the model being used in production.

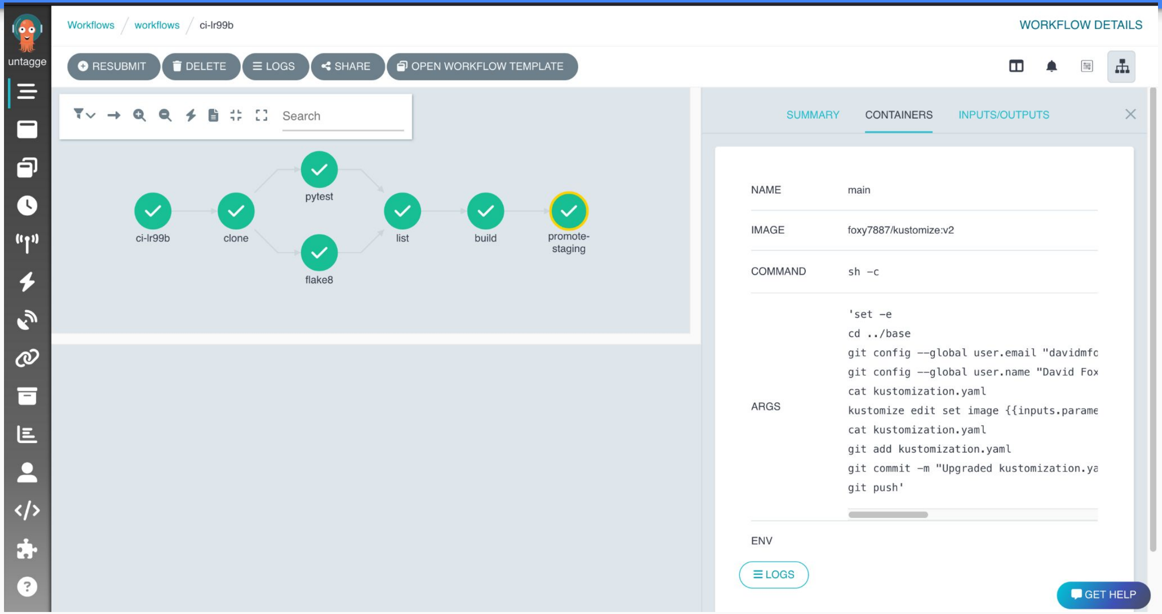
MLflow artifact storage will use minio locally and s3 in the cloud.

The training pipeline will be an Argo CronWorkflow, which can be run on some prespecified schedule.


PR merge
Argo events webhook
docker HUB
Amazon ECR
Build and push docker images
argo
CI/CD pipeline with argo events and argo workflows to test ML pipeline steps
Push Seldon Deployment manifest
MINIO
ML Deployment Git repo
Argo events webhook
argo
mlflow
Trigger new Argo training workflow
argo
scikit learn

CI/CD for Machine Learning

1. Once a model has been experimented and it has found to outperform the model in production, it is then modularized into ML pipeline steps, which are later containerized. Each pipeline step should be unit tested.
2. The next steps would be:
    a. Build docker image with build-kit
    b. Update image tags in staging Kustomize files for argo training workflow
3. This ensures that the argo training workflow will use the most up-to-date image for the training pipeline steps



NAME main

IMAGE foxy7887/kustomize:v2

COMMAND sh -c

ARGS

```
'set -e
cd ../base
git config --global user.email "davidmfc
git config --global user.name "David Fox
cat kustomization.yaml
kustomize edit set image {{inputs.parame
cat kustomization.yaml
git add kustomization.yaml
git commit -m "Upgraded kustomization.ya
git push'
```

ENV

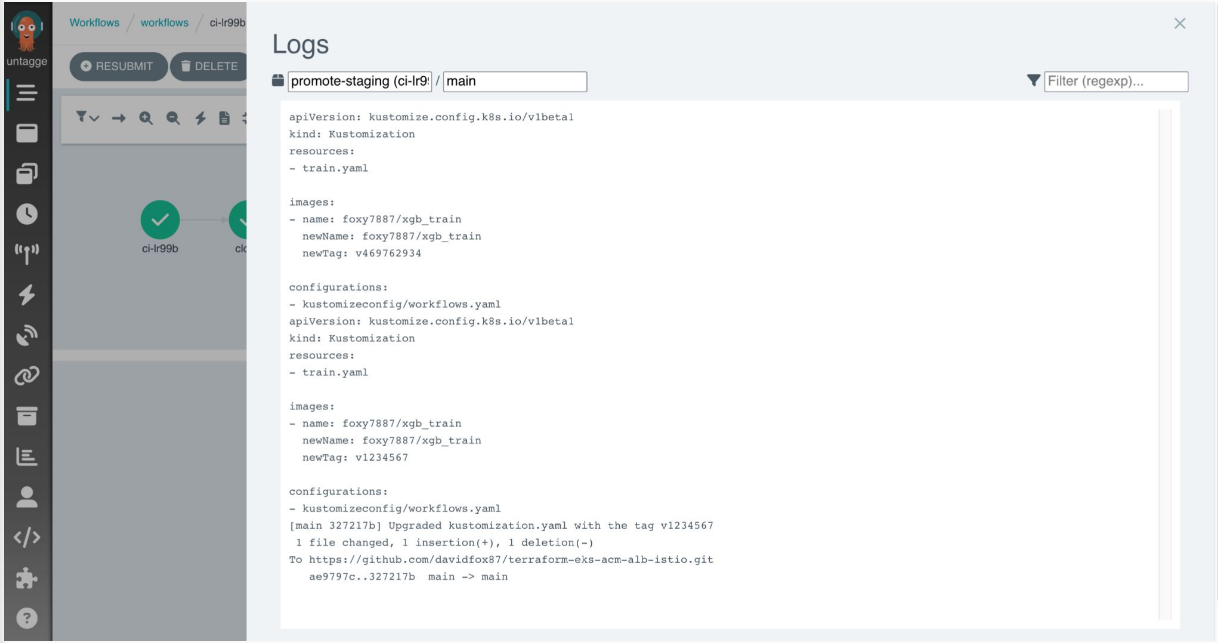
CI/CD for Machine Learning

We can observe the docker logs from the promote to staging step of the DAG.

This shows what the image tag read in the kustomization.yaml before and after the following command was run:

```
kustomize edit set image
{{inputs.parameters.image}}=
{{inputs.parameters.image}}:
{{inputs.parameters.tag}}
```

Argo CD will see that the kustomize file has changed and apply our updated CronWorkflow training pipeline to the cluster.

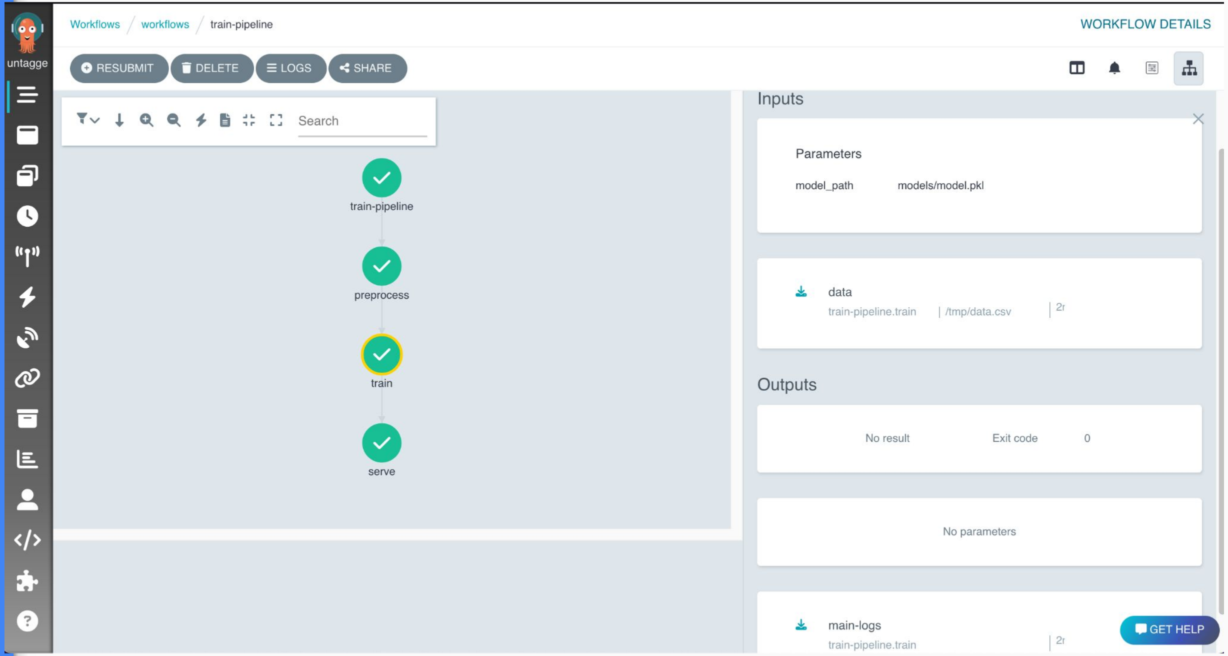

untagge
Workflows / workflows / ci-lr99b
RESUBMIT
DELETE
ci-lr99b
clc
Logs
promote-staging (ci-lr9! / main
Filter (regexp)...

```
apiVersion: kustomize.config.k8s.io/v1beta1
kind: Kustomization
resources:
- train.yaml

images:
- name: foxy7887/xgb_train
  newName: foxy7887/xgb_train
  newTag: v469762934

configurations:
- kustomizeconfig/workflows.yaml
apiVersion: kustomize.config.k8s.io/v1beta1
kind: Kustomization
resources:
- train.yaml

images:
- name: foxy7887/xgb_train
  newName: foxy7887/xgb_train
  newTag: v1234567

configurations:
- kustomizeconfig/workflows.yaml
[main 327217b] Upgraded kustomization.yaml with the tag v1234567
 1 file changed, 1 insertion(+), 1 deletion(-)
To https://github.com/davidfox87/terraform-eks-acm-alb-istio.git
   ae9797c..327217b  main -> main
```

Training and serving pipeline

1. Loads the data from Blob storage (minio, s3) but can also fetch from SQL tables
2. Preprocess can relabel columns, engineer features, impute missing data, scale features
3. Train will train an ML model
   a. Logs and registers the model with MLflow
   b. Save serialized pickle to NFS persistent storage
4. Serve will use seldon-core library to deploy the model in the NFS persistent storage as a prediction RESTful microservice.

Requests to the prediction microservice are routed through the istio- gateway and service mesh (next slide).



Inputs

Parameters

model_path models/model.pkl

data
train-pipeline.train | /tmp/data.csv | 2r

Outputs

No result Exit code 0

No parameters

main-logs
train-pipeline.train | 2r

Making predictions

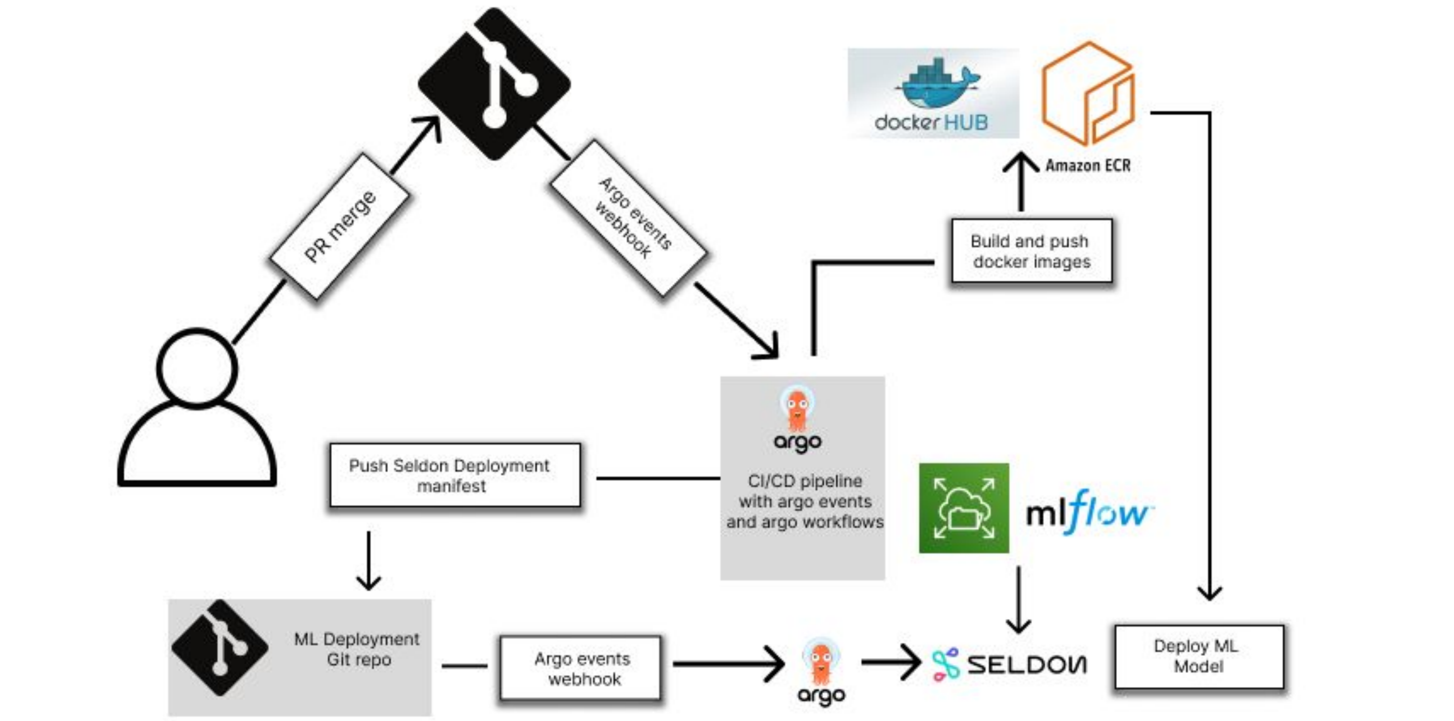
From “outside” the cluster (Note, that in the cloud, we will reach istio-ingressgateway through an ingress)

```
port-forward to istio-ingressgateway service:
kubectl port-forward $(kubectl get pods -l istio=ingressgateway -n istio-system -o jsonpath='{.items[0].metadata.name}') -n istio-system
8004:8080

curl -X POST      -H 'Content-Type: application/json'  \
   -d '{"data": { "ndarray": [[1,2,3,4,5]]}}'   \
http://localhost:8080/seldon/<NAMESPACE>/<SELDON-DEPLOYMENT-NAME>/api/v1.0/predictions
```

Internal to the cluster from any other kubernetes deployment (Deployment, Job, Pod):

```
curl -X POST \
         -H 'Content-Type: application/json' \
         -d '{"data": { "ndarray": [[1,2,3,4,5]]}}' \
http://<SELDON-DEPLOYMENT-NAME>.<NAMESPACE>.svc.cluster.local:8000/api/v1.0/predictions
```

CICD of the inference pipeline



Making this work in the cloud

Crossplane and Argo CD

Deploy infrastructure using the Kubernetes API. No need to switch to completely different environment (Terraform/Pulumi).

If infrastructure is defined declaratively with K8s manifests, then we can use Kustomize and Argo CD to sync any changes to the cluster and crossplane will make sure that the state as defined in the manifests is reflected in our AWS environment.