STT Assignment-9

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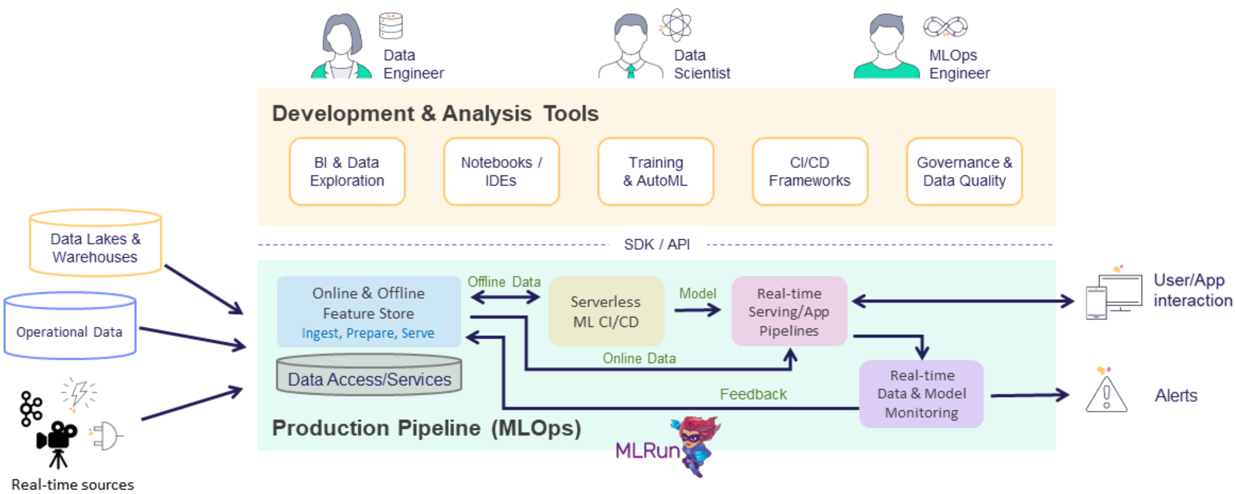
Github: https://github.com/tanishy7777/MLRun-CI-CD-Workflow

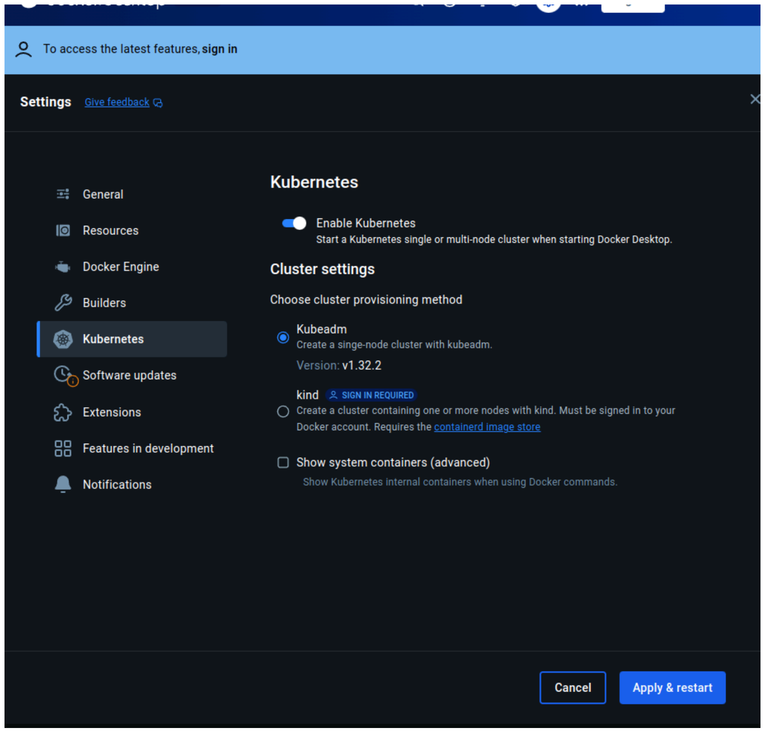
Architecture of MLRun

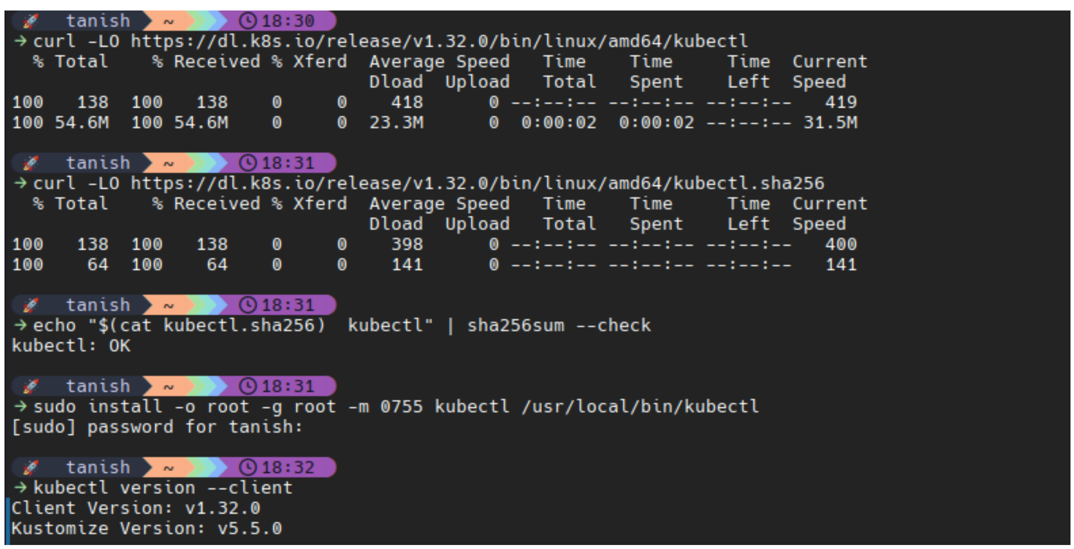
Source: https://docs.mlrun.org/en/v1.1.1/



1. Installation

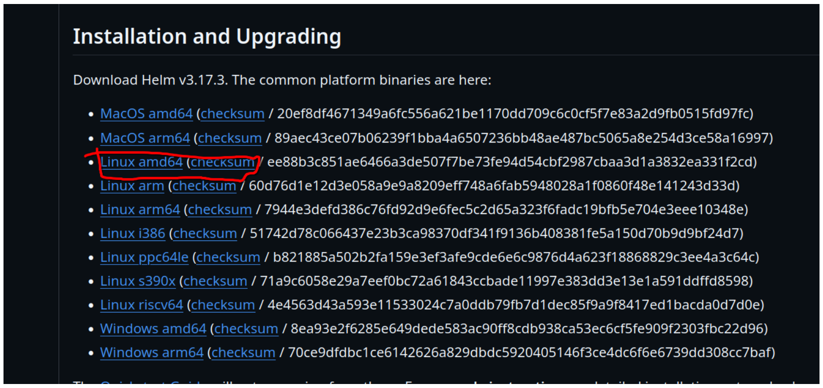
a. Docker Desktop: Installed from previous assignment.
b. Enabling Kubernetes from Docker Desktop



c. 

Installing kubectl and verifying using sha256

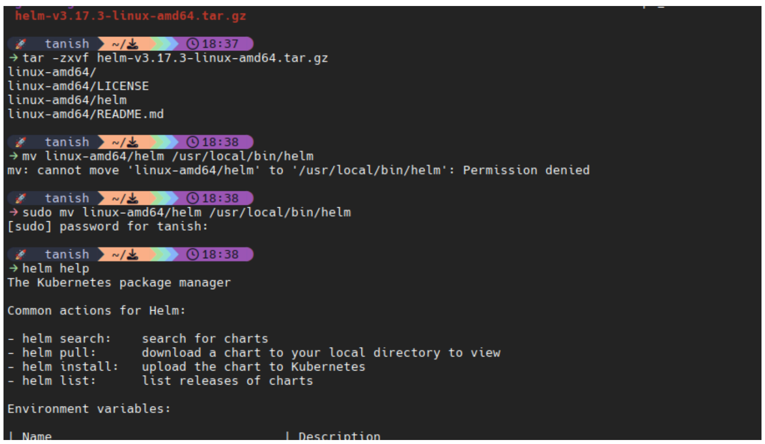
d. Installing helm from binary releases



Installation and Upgrading

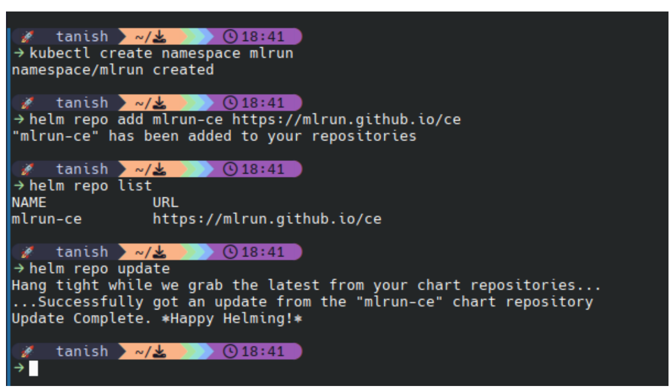
Download Helm v3.17.3. The common platform binaries are here:

- MacOS amd64 (checksum / 20ef8df4671349a6fc556a621be1170dd709c6c0cf5f7e83a2d9fb0515fd97fc)
- MacOS arm64 (checksum / 89aec43ce07b06239f1bba4a6507236bb48ae487bc5065a8e254d3ce58a16997)
- Linux amd64 (checksum / ee88b3c851ae6466a3de507f7be73fe94d54cbf2987cbaa3d1a3832ea331f2cd)
- Linux arm (checksum / 60d76d1e12d3e058a9e9a8209eff748a6fab5948028a1f0860f48e141243d33d)
- Linux arm64 (checksum / 7944e3defd386c76fd92d9e6fec5c2d65a323f6fadc19bfb5e704e3eee10348e)
- Linux i386 (checksum / 51742d78c066437e23b3ca98370df341f9136b408381fe5a150d70b9d9bf24d7)
- Linux ppc64le (checksum / b821885a502b2fa159e3ef3afe9cde6e6c9876d4a623f18868829c3ee4a3c64c)
- Linux s390x (checksum / 71a9c6058e29a7eef0bc72a61843ccbade11997e383dd3e13e1a591ddffd8598)
- Linux riscv64 (checksum / 4e4563d43a593e11533024c7a0ddb79fb7d1dec85f9a9f8417ed1bacda0d7d0e)
- Windows amd64 (checksum / 8ea93e2f6285e649dede583ac90ff8cdb938ca53ec6cf5fe909f2303fbc22d96)
- Windows arm64 (checksum / 70ce9dfdbc1ce6142626a829dbdc5920405146f3ce4dc6f6e6739dd308cc7baf)

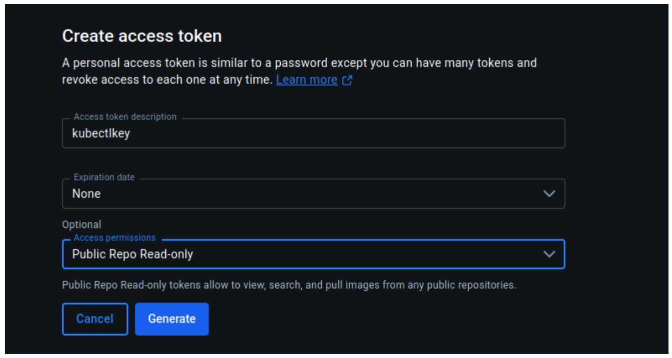


```
helm-v3.17.3-linux-amd64.tar.gz

 tanish  ~/  18:37
→ tar -zxvf helm-v3.17.3-linux-amd64.tar.gz
linux-amd64/
linux-amd64/LICENSE
linux-amd64/helm
linux-amd64/README.md

 tanish  ~/  18:38
→ mv linux-amd64/helm /usr/local/bin/helm
mv: cannot move 'linux-amd64/helm' to '/usr/local/bin/helm': Permission denied

 tanish  ~/  18:38
→ sudo mv linux-amd64/helm /usr/local/bin/helm
[sudo] password for tanish:

 tanish  ~/  18:38
→ helm help
The Kubernetes package manager

Common actions for Helm:

- helm search:    search for charts
- helm pull:      download a chart to your local directory to view
- helm install:   upload the chart to Kubernetes
- helm list:      list releases of charts

Environment variables:

| Name                                | Description
```

e. MLRun installation



```
 tanish  ~/  18:41
→ kubectl create namespace mlrun
namespace/mlrun created

 tanish  ~/  18:41
→ helm repo add mlrun-ce https://mlrun.github.io/ce
"mlrun-ce" has been added to your repositories

 tanish  ~/  18:41
→ helm repo list
NAME            URL
mlrun-ce        https://mlrun.github.io/ce

 tanish  ~/  18:41
→ helm repo update
Hang tight while we grab the latest from your chart repositories...
...Successfully got an update from the "mlrun-ce" chart repository
Update Complete. *Happy Helming!*

 tanish  ~/  18:41
→
```



Type this

kubectl --namespace mlrun create secret docker-registry registry-credentials --docker-server https://index.docker.io/v1/ --docker-username your_docker_username --docker-password your_docker_password --docker-email your_email_id

or

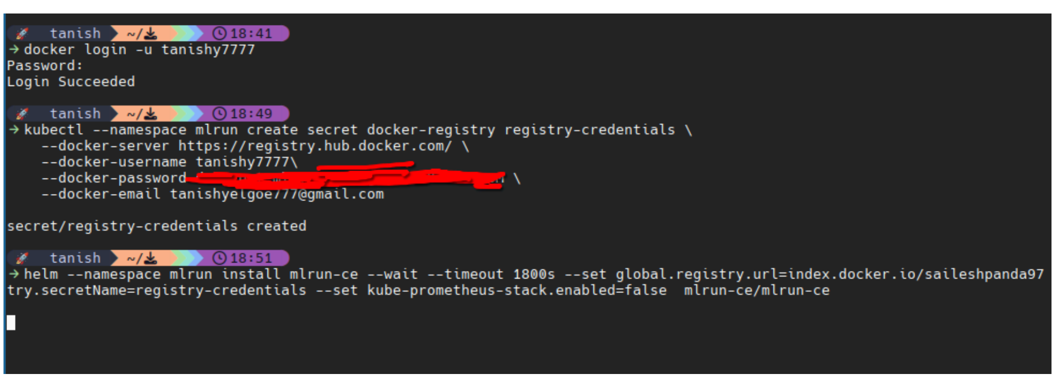
kubectl --namespace mlrun create secret docker-registry registry-credentials \

--docker-server https://registry.hub.docker.com/ \

--docker-username tanishy7777\

--docker-password <password> \

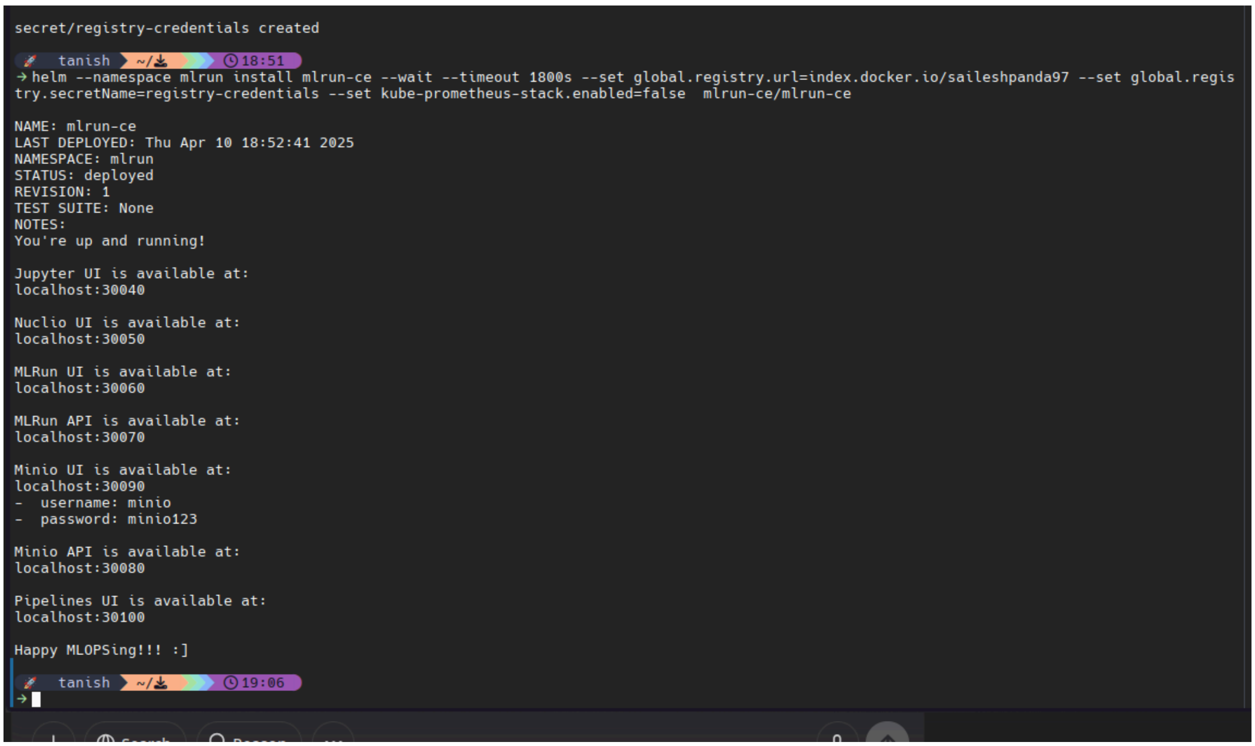
--docker-email tanishyelgoe777@gmail.com



To see the progress bar run:

watch -n 2 '
TOTAL=$(kubectl get pods -n mlrun --no-headers 2>/dev/null | grep -v Completed | wc -l)
READY=$(kubectl get pods -n mlrun --no-headers 2>/dev/null | grep "Running" | wc -l)
PERCENT=$((100 * READY / (TOTAL == 0 ? 1 : TOTAL)))
echo -ne "🚀 MLRun Setup Progress: $READY/$TOTAL pods running ($PERCENT%)\n"
'

This refreshed every 2 seconds



Installed successfully

Can check the status of pods with

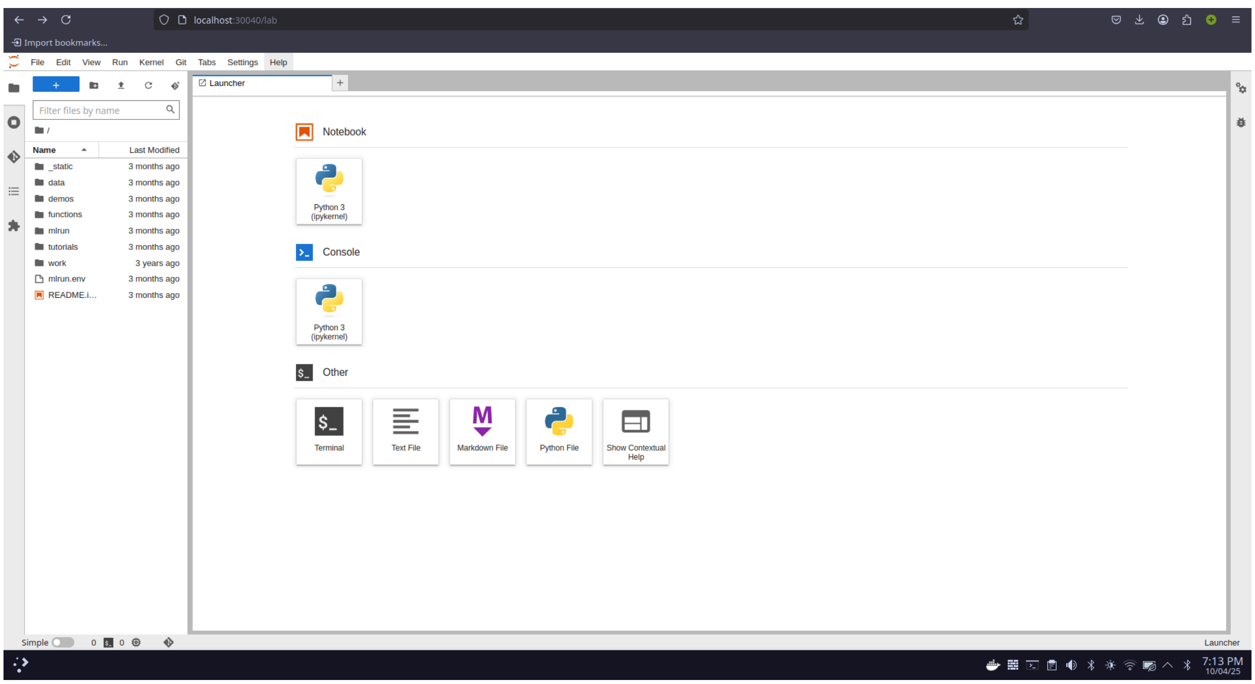
```
→ kubectl -n mlrun get pods
NAME                                               READY   STATUS    RESTARTS        AGE
metadata-envoy-deployment-86b9c85656-kc49d         1/1     Running   0               16m
metadata-grpc-deployment-5dfd66bb8d-fpvfn          1/1     Running   7 (9m42s ago)   16m
metadata-writer-7b7fc9f477-bc6dh                   1/1     Running   3 (5m30s ago)   16m
minio-65c9b8dc44-xbqpq                             1/1     Running   0               16m
ml-pipeline-5d7998ffc5-qv2xp                       1/1     Running   7 (5m53s ago)   16m
ml-pipeline-persistenceagent-69446f4bdd-pmbx6      1/1     Running   4 (5m56s ago)   16m
ml-pipeline-scheduledworkflow-8564b98f5b-zn2qw     1/1     Running   0               16m
ml-pipeline-ui-5d9ff6dc69-r42s5                    1/1     Running   0               16m
ml-pipeline-viewer-crd-6668f68cd7-8kv5m            1/1     Running   0               16m
ml-pipeline-visualizationserver-6878c5b646-9m94p   1/1     Running   0               16m
mlrun-api-chief-6d6868867f-w5h9x                   2/2     Running   1 (6m8s ago)    16m
mlrun-db-6c85956db5-zzqpb                          1/1     Running   0               16m
mlrun-jupyter-85768bb958-q6g9v                     1/1     Running   0               16m
mlrun-ui-744bcb7f44-trpdk                          1/1     Running   0               16m
mpi-operator-97dd956c5-7q5j4                       1/1     Running   0               16m
mysql-9dc78bdd7-7v9j7                              1/1     Running   0               16m
nuclio-controller-94fff55d7-f6gc4                  1/1     Running   0               16m
nuclio-dashboard-b6cfbc88d-djljk                   1/1     Running   0               16m
spark-operator-controller-855dc75b69-hhg6s         1/1     Running   0               16m
spark-operator-webhook-587b54f56-7n6jc             1/1     Running   0               16m
workflow-controller-789b47d74-cnwnv                1/1     Running   0               16m
```

All are running so,

http://localhost:30040

or

(for linux, ip addr show)



Jupyter UI

```
%pip install mlrun scikit-learn~=1.5.1 numpy~=1.26.4
```

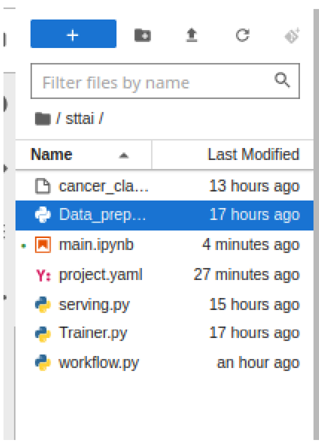
1. **Create a mlrun project(10%):**

```
[10]: import numpy
```

```
[11]: import mlrun

project = mlrun.new_project("stt9", "./", user_project=True, description="STT AI assignment 9", overwrite=True)

> 2025-04-11 09:43:05,905 [info] Overwriting project (by deleting and then creating): {"name":"stt9-jovyan"}
> 2025-04-11 09:43:05,931 [info] Waiting for project to be deleted: {"project_name":"stt9-jovyan"}
> 2025-04-11 09:43:08,972 [info] Project deleted: {"project_name":"stt9-jovyan"}
> 2025-04-11 09:43:09,023 [info] Created and saved project: {"context":"./","from_template":null,"name":"stt9-jovyan","overwrite":true,"save":true}
```

```
[12]: !python --version

Python 3.9.13
```

2. **Create the following Python script:**
   a. Data_prep.py: This fetches data using sklearn.datasets import load_breast_cancer. (Add screenshot of the code)**[10 %]**

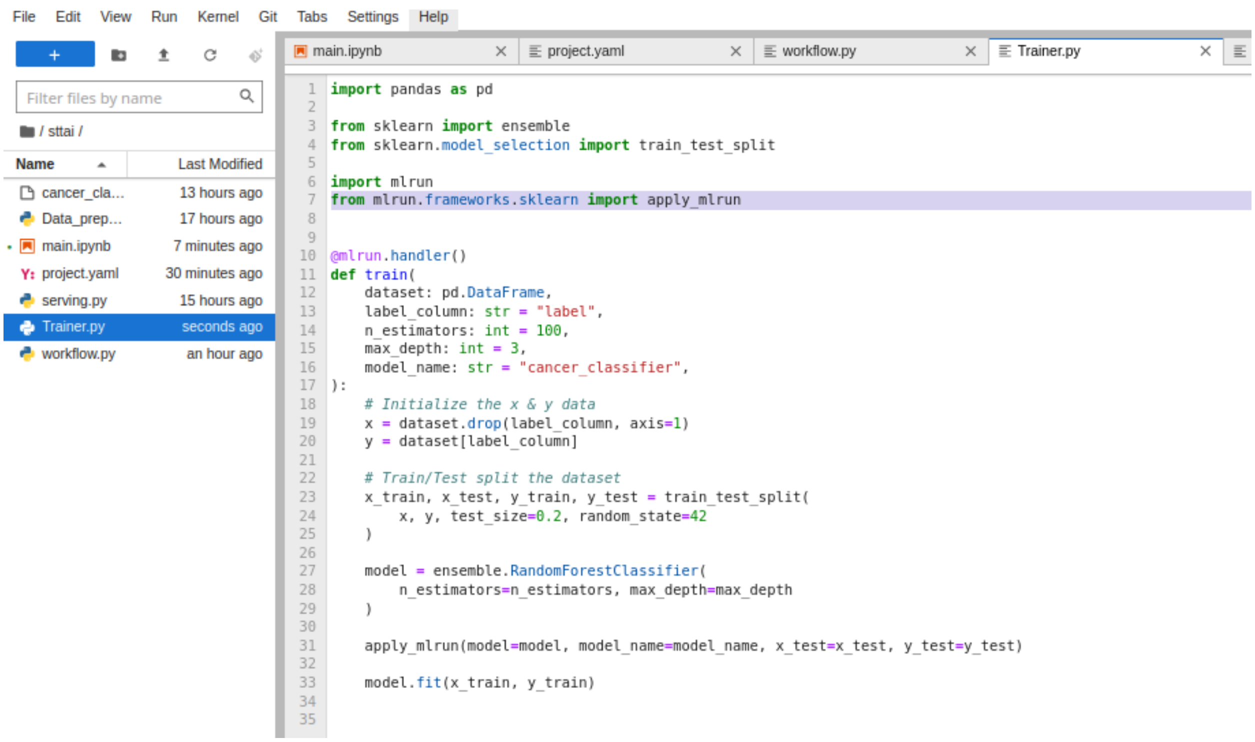



```python
import pandas as pd
from sklearn.datasets import load_breast_cancer
import mlrun


@mlrun.handler(outputs=["dataset", "label_column"])
def breast_cancer_generator():
    breast_cancer = load_breast_cancer()
    breast_cancer_dataset = pd.DataFrame(
        data=breast_cancer.data, columns=breast_cancer.feature_names
    )
    breast_cancer_labels = pd.DataFrame(data=breast_cancer.target, columns=["label"])
    breast_cancer_dataset = pd.concat(
        [breast_cancer_dataset, breast_cancer_labels], axis=1
    )

    return breast_cancer_dataset, "label"
```

Registering the function from Data_prep script in main.ipynb

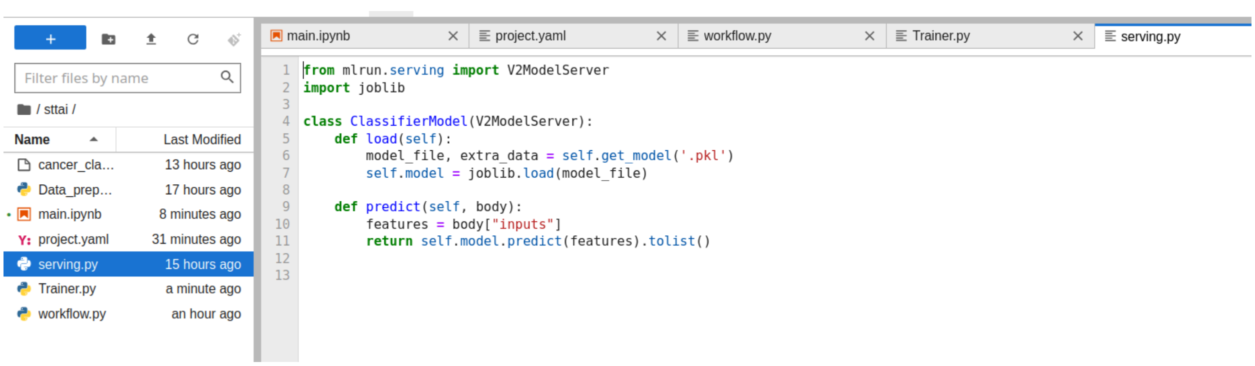
```
[8]: data_gen_fn = project.set_function(
         "Data_prep.py",
         name="Data-prep",
         kind="job",
         image="mlrun/mlrun",
         handler="breast_cancer_generator",
     )
```

   b. Trainer.py: Split the data into train test (10% test data). Train a model using the training data. Use Random forest classifier. Wrap the model with apply_mlrun from mlrun.frameworks.sklearn. (Add screenshot of the code)**[10 %]**



Registering function from Trainer.py in main.ipynb

c. serving.py: Create a model class that will inherit from mlrun.serving.V2ModelServer, enabling automatic support for model lifecycle methods like load() and predict(). (Add screenshot of the code)**[10 %]**



Registering function from serving.py in main.ipynb

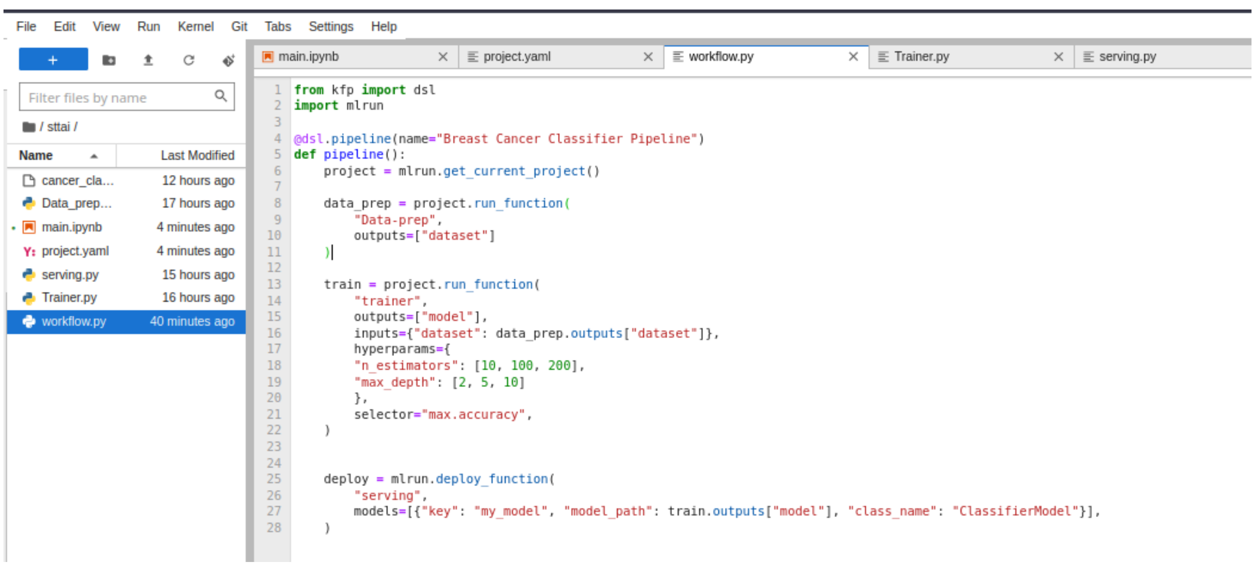
```
[15]: project.set_function(
        "serving.py",
        name="serving",
        kind="serving",
        image="mlrun/mlrun"
      )
```

```
[15]: <mlrun.runtimes.nuclio.serving.ServingRuntime at 0x7f5ca21d8e20>
```

```
[16]: project.set_workflow("main", "workflow.py")
```

d. workflow.py: Create a Python script that defines an MLRun pipeline using the @dsl.pipeline decorator. It should include the following steps:
   i. Data Ingestion(Add screenshot of the code) **[3 %]**
   ii. Model Training: Experiment with different hyperparamters(n_estimators: [10, 100, 200], max_depth=[2, 5, 10]). Keep max accuracy as selector. (Add screenshot of the code)**[4 %]**
   iii. Model Deployment: Deploy the model into the base kubernetes image(mlrun/mlrun) using mlrun.deploy_function (Add screenshot of the code)**[3 %]**

Data ingestion, model training with different hyperparameters and max accuracy as selector. Also model deployment into base kubernetes.




```python
from kfp import dsl
import mlrun

@dsl.pipeline(name="Breast Cancer Classifier Pipeline")
def pipeline():
    project = mlrun.get_current_project()

    data_prep = project.run_function(
        "Data-prep",
        outputs=["dataset"]
    )

    train = project.run_function(
        "trainer",
        outputs=["model"],
        inputs={"dataset": data_prep.outputs["dataset"]},
        hyperparams={
        "n_estimators": [10, 100, 200],
        "max_depth": [2, 5, 10]
        },
        selector="max.accuracy",
    )


    deploy = mlrun.deploy_function(
        "serving",
        models=[{"key": "my_model", "model_path": train.outputs["model"], "class_name": "ClassifierModel"}],
    )
```

Expanded screenshots from workflow.py:

Data ingestion:

```python
data_prep = project.run_function(
    "Data-prep",
    outputs=["dataset"]
)
```

Model training with different hyperparameters

```python
train = project.run_function(
    "trainer",
    outputs=["model"],
    inputs={"dataset": data_prep.outputs["dataset"]},
    hyperparams={
    "n_estimators": [10, 100, 200],
    "max_depth": [2, 5, 10]
    },
    selector="max.accuracy",
)
```

Model deployment using mlrun.deploy_function

```python
deploy = mlrun.deploy_function(
    "serving",
    models=[{"key": "my_model", "model_path": train.outputs["model"], "class_name": "ClassifierModel"}],
)
```

Registering function from workflow.py in main.ipynb

```
[30]: project.set_workflow("main", "workflow.py")

[32]: project.run("main", watch=True)

> 2025-04-10 22:31:12,621 [warning] it is recommended to use k8s secret (specify secret_name),
_secret_key directly is unsafe
> 2025-04-10 22:31:12,630 [warning] it is recommended to use k8s secret (specify secret_name),
_secret_key directly is unsafe
> 2025-04-10 22:31:12,633 [warning] it is recommended to use k8s secret (specify secret_name),
_secret_key directly is unsafe
> 2025-04-10 22:31:13,075 [info] Pipeline submitted successfully: {"id":"6e1675be-1052-4281-b15
e":"stt9-jovyan-main 2025-04-10 22-31-12"}
> 2025-04-10 22:31:13,075 [info] Pipeline run id=6e1675be-1052-4281-b154-35c19cf1987d, check UI
```

Workflow started in project stt9-jovyan id=6e1675be-1052-4281-b154-35c19cf1987d

click here to view progress

Pipeline running (id=6e1675be-1052-4281-b154-35c19cf1987d), **click here** to view the details in MLRun UI

3. Run the workflow using project.run:

1. Add the screenshot of the workflow graph **[10 %]**

```
[16]: project.set_workflow("main", "workflow.py")
```

```
[17]: project.run("main", watch=True)
```

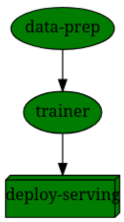
```
> 2025-04-11 09:43:10,443 [warning] it is recommended to use k8s secret (specify secret_name), specifying the aws_access_key/aws_secret_key directly is unsafe
> 2025-04-11 09:43:10,447 [warning] it is recommended to use k8s secret (specify secret_name), specifying the aws_access_key/aws_secret_key directly is unsafe
> 2025-04-11 09:43:10,449 [warning] it is recommended to use k8s secret (specify secret_name), specifying the aws_access_key/aws_secret_key directly is unsafe
> 2025-04-11 09:43:10,884 [info] Pipeline submitted successfully: {"id":"440b8e8c-7ba2-4eb8-94aa-7097f7315b82","pipeline_name":"stt9-jovyan-main 2025-04-11 09-43-10"}
> 2025-04-11 09:43:10,885 [info] Pipeline run id=440b8e8c-7ba2-4eb8-94aa-7097f7315b82, check UI for progress
```

Workflow started in project stt9-jovyan id=440b8e8c-7ba2-4eb8-94aa-7097f7315b82

click here to view progress

Pipeline running (id=440b8e8c-7ba2-4eb8-94aa-7097f7315b82), **click here** to view the details in MLRun UI

```
> 2025-04-11 09:43:11,037 [info] Started run workflow stt9-jovyan-main with run id = '440b8e8c-7ba2-4eb8-94aa-7097f7315b82' by kfp engine
> 2025-04-11 09:43:11,038 [info] Waiting for pipeline run completion: {"project":"stt9-jovyan","run_id":"440b8e8c-7ba2-4eb8-94aa-7097f7315b82"}
```



Run Results

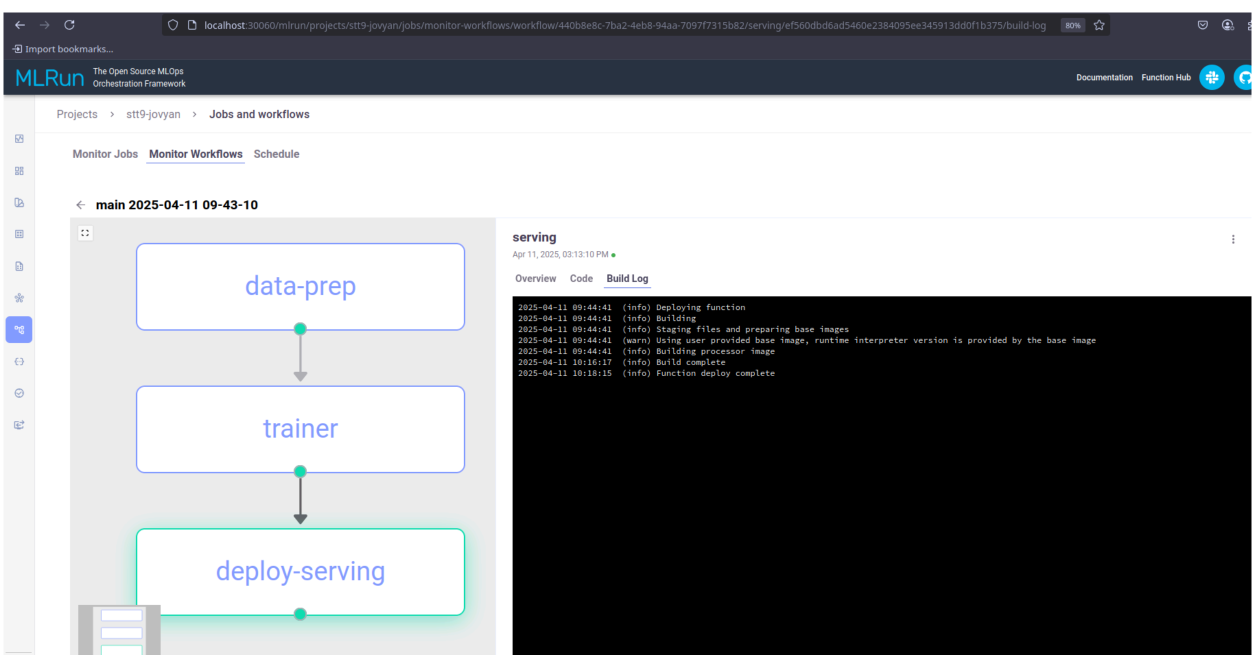
[info] Workflow 440b8e8c-7ba2-4eb8-94aa-7097f7315b82 finished, state=Succeeded

click the hyper links below to see detailed results

uid	start	state	kind	name	parameters	results
...15cac7e3	Apr 11 09:43:48	completed	run	trainer		best_iteration=7 accuracy=0.9736842105263158 f1_score=0.9790209790209791 precision_score=0.9722222222222222 recall_score=0.9859154929577465
...d683ee76	Apr 11 09:43:21	completed	run	data-prep		label_column=label

```
[17]: 440b8e8c-7ba2-4eb8-94aa-7097f7315b82
```

```
[19]: project.save()
```

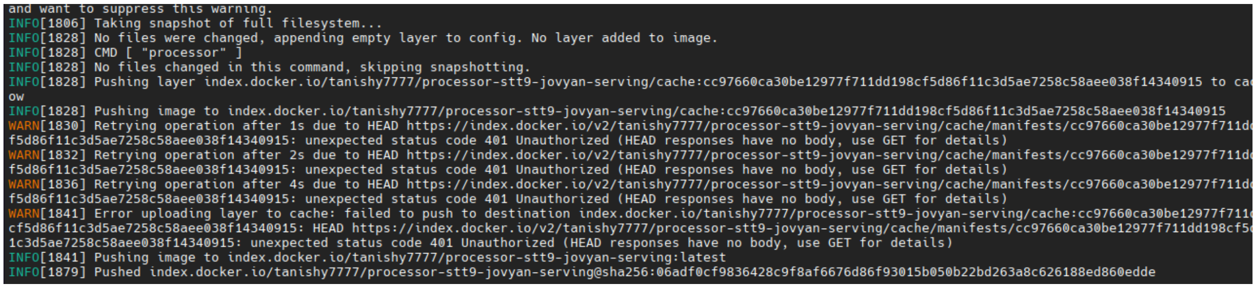


Logs:

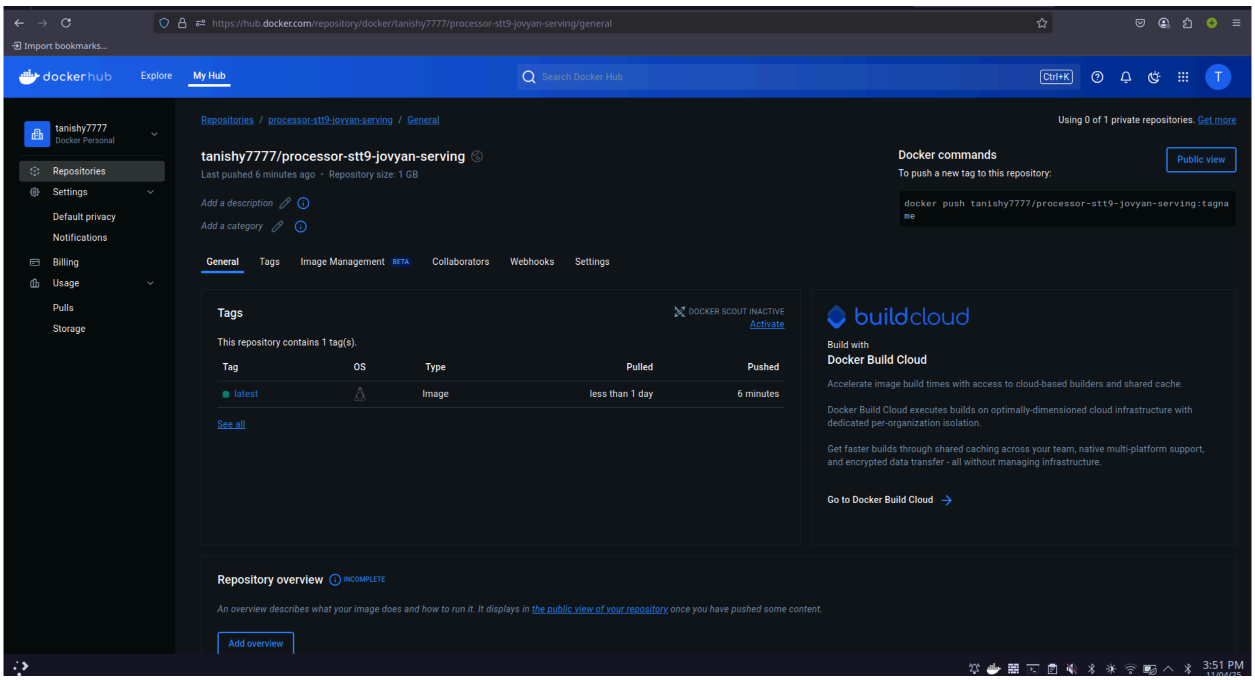
`Running the following command shows:`

```
kubectl logs
nuclio-kanikojob.processorstt9jovyanservinglatest.aunpjz
vbvg6nd -n mlrun -f
```

This shows image was pushed to dockerhub



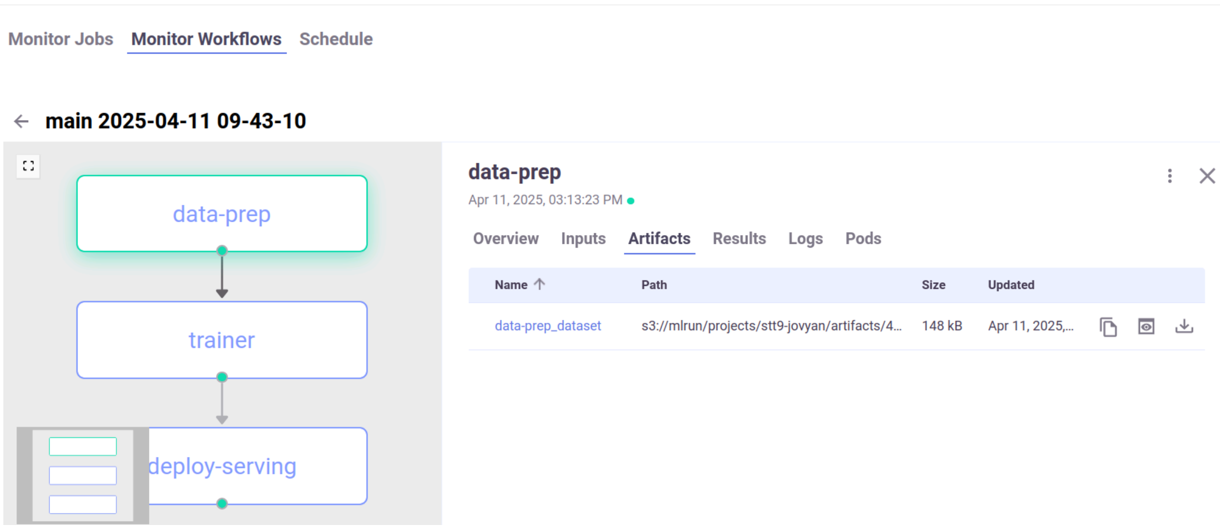
```
and want to suppress this warning.
INFO[1806] Taking snapshot of full filesystem...
INFO[1828] No files were changed, appending empty layer to config. No layer added to image.
INFO[1828] CMD [ "processor" ]
INFO[1828] No files changed in this command, skipping snapshotting.
INFO[1828] Pushing layer index.docker.io/tanishy7777/processor-stt9-jovyan-serving/cache:cc97660ca30be12977f711dd198cf5d86f11c3d5ae7258c58aee038f14340915 to ca
ow
INFO[1828] Pushing image to index.docker.io/tanishy7777/processor-stt9-jovyan-serving/cache:cc97660ca30be12977f711dd198cf5d86f11c3d5ae7258c58aee038f14340915
WARN[1830] Retrying operation after 1s due to HEAD https://index.docker.io/v2/tanishy7777/processor-stt9-jovyan-serving/cache/manifests/cc97660ca30be12977f711d
f5d86f11c3d5ae7258c58aee038f14340915: unexpected status code 401 Unauthorized (HEAD responses have no body, use GET for details)
WARN[1832] Retrying operation after 2s due to HEAD https://index.docker.io/v2/tanishy7777/processor-stt9-jovyan-serving/cache/manifests/cc97660ca30be12977f711d
f5d86f11c3d5ae7258c58aee038f14340915: unexpected status code 401 Unauthorized (HEAD responses have no body, use GET for details)
WARN[1836] Retrying operation after 4s due to HEAD https://index.docker.io/v2/tanishy7777/processor-stt9-jovyan-serving/cache/manifests/cc97660ca30be12977f711d
f5d86f11c3d5ae7258c58aee038f14340915: unexpected status code 401 Unauthorized (HEAD responses have no body, use GET for details)
WARN[1841] Error uploading layer to cache: failed to push to destination index.docker.io/tanishy7777/processor-stt9-jovyan-serving/cache:cc97660ca30be12977f711
cf5d86f11c3d5ae7258c58aee038f14340915: HEAD https://index.docker.io/v2/tanishy7777/processor-stt9-jovyan-serving/cache/manifests/cc97660ca30be12977f711dd198cf5
1c3d5ae7258c58aee038f14340915: unexpected status code 401 Unauthorized (HEAD responses have no body, use GET for details)
INFO[1841] Pushing image to index.docker.io/tanishy7777/processor-stt9-jovyan-serving:latest
INFO[1879] Pushed index.docker.io/tanishy7777/processor-stt9-jovyan-serving@sha256:06adf0cf9836428c9f8af6676d86f93015b050b22bd263a8c626188ed860edde
```



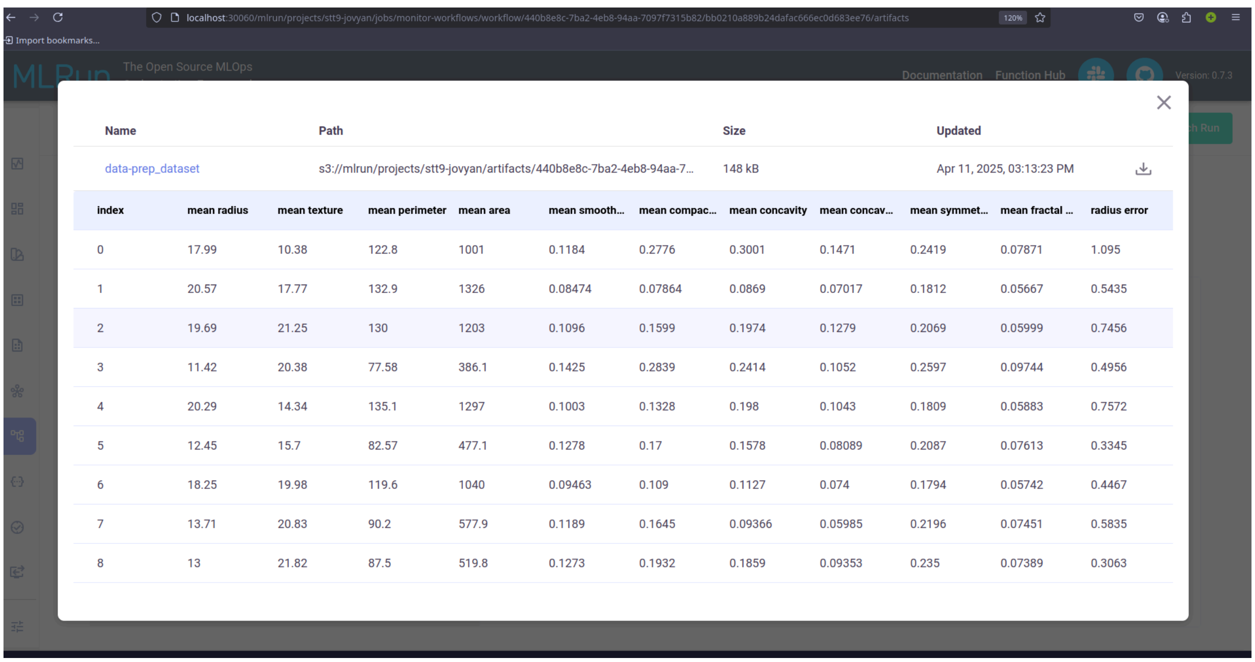
https://hub.docker.com/repository/docker/tanishy7777/processor-stt9-jovyan-serving/general

2. Add the screenshot of the Data_prep artifact and take the screenshot of the dataframe. **[10 %]**

Data_Prep artifact screenshot



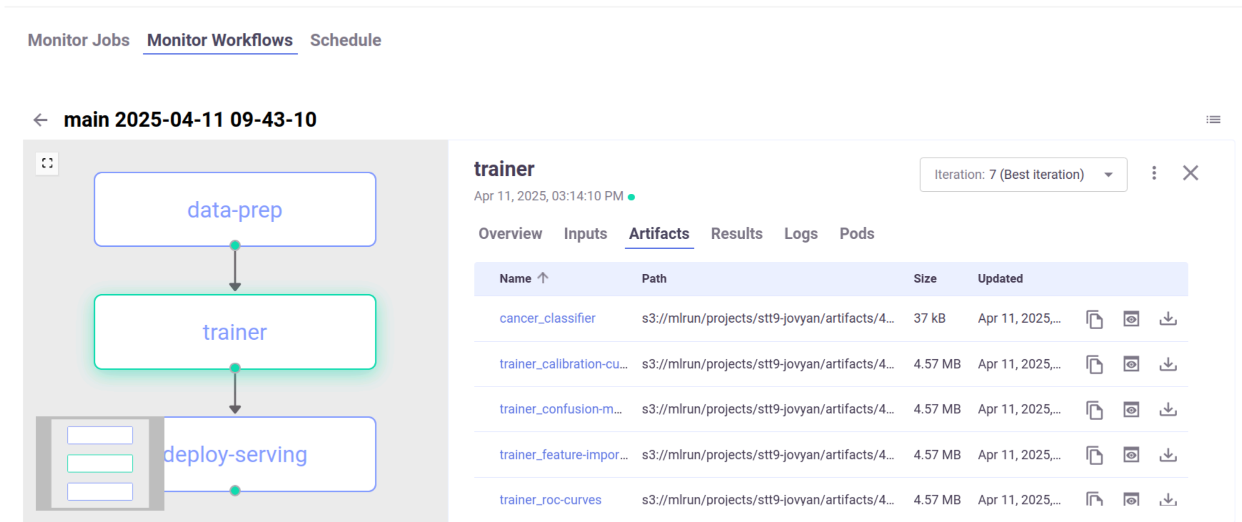
Dataframe screenshot



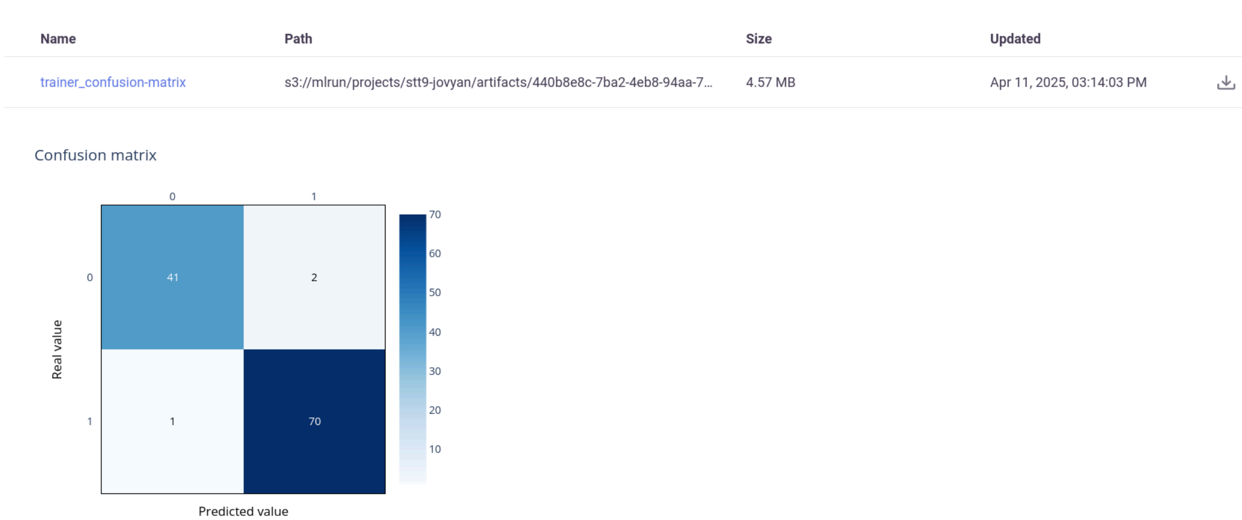
index	mean radius	mean texture	mean perimeter	mean area	mean smooth...	mean compac...	mean concavity	mean concav...	mean symmet...	mean fractal ...	radius error
0	17.99	10.38	122.8	1001	0.1184	0.2776	0.3001	0.1471	0.2419	0.07871	1.095
1	20.57	17.77	132.9	1326	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	0.5435
2	19.69	21.25	130	1203	0.1096	0.1599	0.1974	0.1279	0.2069	0.05999	0.7456
3	11.42	20.38	77.58	386.1	0.1425	0.2839	0.2414	0.1052	0.2597	0.09744	0.4956
4	20.29	14.34	135.1	1297	0.1003	0.1328	0.198	0.1043	0.1809	0.05883	0.7572
5	12.45	15.7	82.57	477.1	0.1278	0.17	0.1578	0.08089	0.2087	0.07613	0.3345
6	18.25	19.98	119.6	1040	0.09463	0.109	0.1127	0.074	0.1794	0.05742	0.4467
7	13.71	20.83	90.2	577.9	0.1189	0.1645	0.09366	0.05985	0.2196	0.07451	0.5835
8	13	21.82	87.5	519.8	0.1273	0.1932	0.1859	0.09353	0.235	0.07389	0.3063

3. Add the screenshot of the confusion-matrix artifact of train.py **[10 %]**

Trainer artifacts



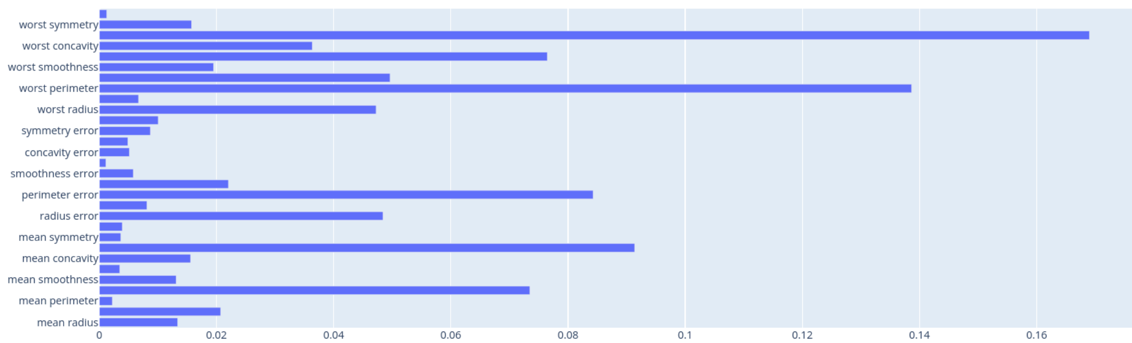
Screenshot of the confusion matrix artifact



4. Add the screenshot of feature selection artifact. **[10 %]**

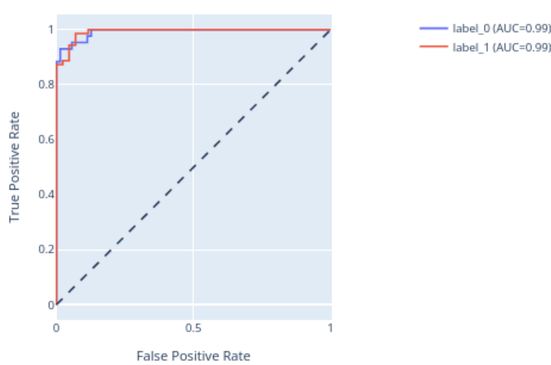
Feature selection/importance artifact

Name	Path	Size	Updated
trainer_feature-importance	s3://mlrun/projects/stt9-jovyan/artifacts/440b8e8c-7ba2-4eb8-94aa-7...	4.57 MB	Apr 11, 2025, 03:14:02 PM

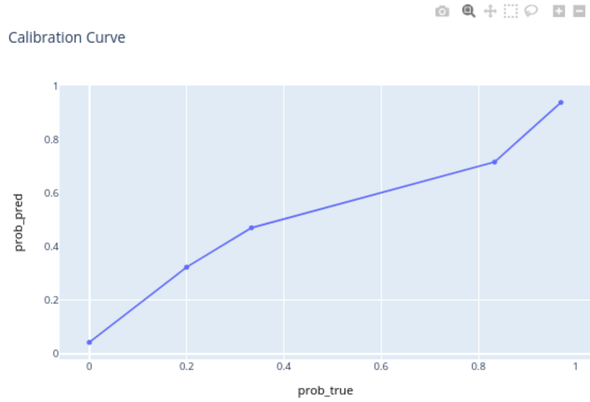


ROC curve

Name	Path	Size
trainer_roc-curves	s3://mlrun/projects/stt9-jovyan/artifacts/6e1675be-1052-4281-b154-35c19cf1987d/trainer/2/roc-curves.html	4.57 MB



trainer_calibration-curve s3://mlrun/projects/stt9-jovyan/artifacts/6e1675be-1052-4281-b154-35c19cf1987d/trainer/2/calibration-curve.h...



trainer_test_set s3://mlrun/projects/stt9-jovyan/artifacts/6e1675be-1052-4281-b154-35c19cf1987... 50.2 kB Apr 11, 2025, 04:01:52 AM

index	mean radius	mean texture	mean perimeter	mean area	mean smooth...	mean compac...	mean concavity	mean concav...	mean symmet...	mean fractal ...	r
0	12.47	18.6	81.09	481.9	0.09965	0.1058	0.08005	0.03821	0.1925	0.06373	C
1	18.94	21.31	123.6	1130	0.09009	0.1029	0.108	0.07951	0.1582	0.05461	C
2	15.46	19.48	101.7	748.9	0.1092	0.1223	0.1466	0.08087	0.1931	0.05796	C
3	12.4	17.68	81.47	467.8	0.1054	0.1316	0.07741	0.02799	0.1811	0.07102	C
4	11.54	14.44	74.65	402.9	0.09984	0.112	0.06737	0.02594	0.1818	0.06782	C

Initializing git repo and pushing

Commands:

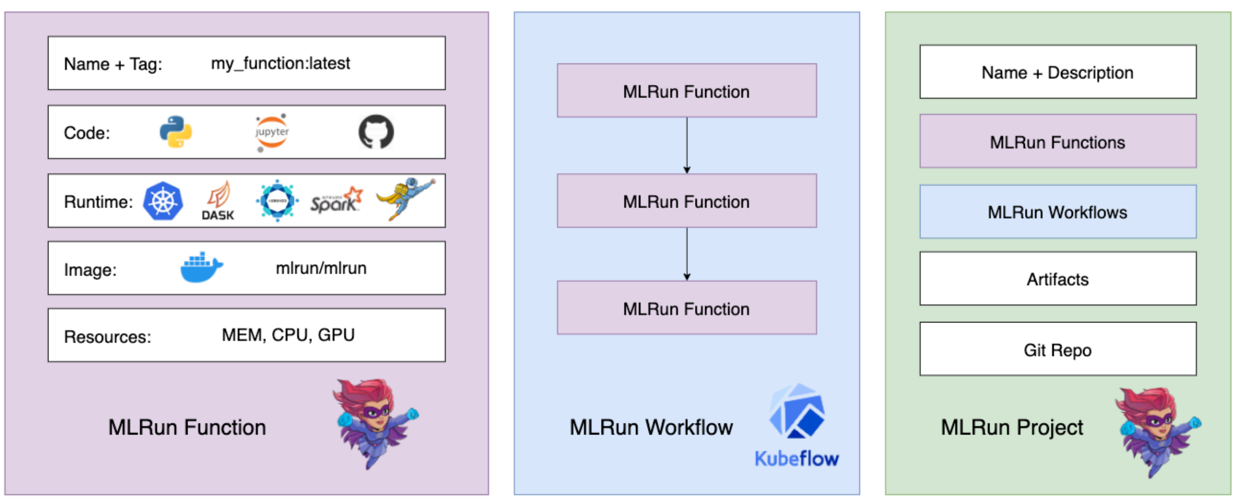
!git init
!git status
!git add .
!git config --global user.email "tanishyelgoe777@gmail.com"
!git config --global user.name "Tanish Yelgoe"
!git commit -m "MLRun project"
!git status
!git remote add origin
https://tanishy7777:<token>@github.com/tanishy7777/MLOps-Assignment.git
!git push origin master

Github repo: https://github.com/tanishy7777/MLOps-Assignment

Some important commands for reference:

1. **kubectl get pods -n mlrun**
2. `kubectl get pods -n mlrun --sort-by=.metadata.creationTimestamp`
3. `kubectl delete pod <podname>-n mlrun`
4. `kubectl port-forward -n mlrun svc/nuclio-dashboard 8070:8070 &`
   `export NUCLIO_DASHBOARD_URL=http://localhost:8070`
5. `kubectl delete pods --field-selector status.phase=Failed -n mlrun`
6. `kubectl delete pod --field-selector=status.phase=Succeeded -n mlrun`
7. `mlrun logs <pod> -n mlrun`

Note: (Not to be graded, added for self reference and learning)
MLRun Functions



Advantages of MLRun

1. Serverless Functions: You write the code, MLRun handles running it anywhere
2. Auto-logging: It tracks everything (metrics, artifacts) automatically
3. Kubernetes Integration: You can scale effortlessly on cloud clusters
4. Versioning: You can go back to old function versions if needed
5. Reusability via Function Hub: Use and share functions with others
6. CI/CD Friendly: Works great with Git and automation pipelines
7. Can also be used for hyper parameter tuning

MLRun Function Comprises of
Code: Your Python script
Required packages: pandas, scikit-learn, etc.
Resources: "I need 2 CPUs and 4GB RAM"
Metadata: Name, labels, version hash
Storage: "Save results to this location"
Deployment config: "Run on spot instance" or not

Why Use Functions?
Let's say you wrote some code to train a model. Instead of just running it like a normal Python script, MLRun lets you wrap it as a function, and now:

1. You can run it on bigger machines with more memory or GPUs (using Kubernetes)

2. You can track everything it does (using MLRun's logging)
3. You can share it with others using a function hub
4. You can version it (MLRun keeps track of changes so you can go back to old versions)

Function Lifecycle
1. You write some code
2. Wrap it as a function in MLRun
3. Register the function in a project (projects keep things organized)
4. Run the function — either in Jupyter, or on a cloud cluster