¿Cómo montar un sistema de experimentación con mlflow?

PyConES 2023

¡GRACIAS!

¿Quien soy?

Maialen Berrondo (Mai)

Trabajo en Auth0 | Okta Machine Learning Engineer



Contacto

Linkedin: Maialen Berrondo

Twitter: @MaialenBerrondo

Github: 13Mai13/pycones23 -> Todo el material

subido

Introducción

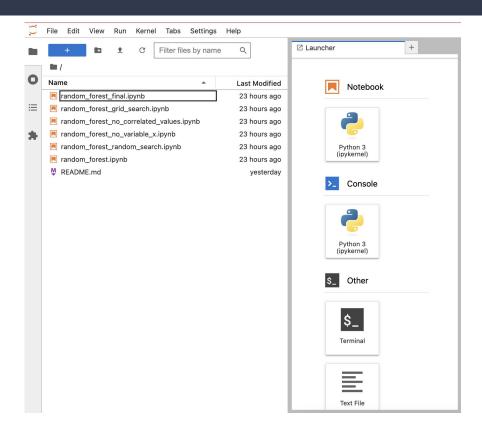
¿Qué es mlflow?

- Open Source
- Gestión de experimentos
- Reproducibilidad de resultados

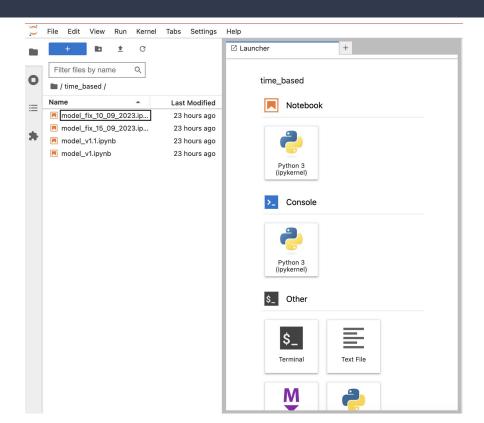


Problema de la gestión de experimentos

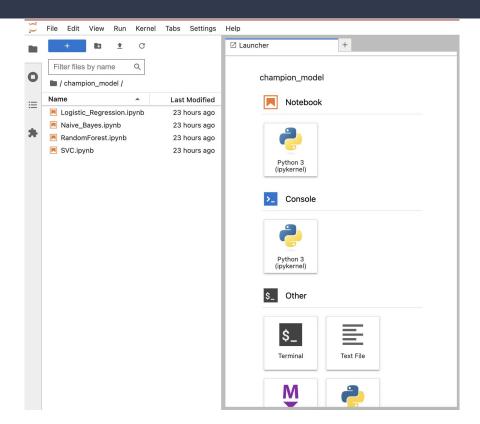
¿Cuál es el problema de la gestión de experimentos?



¿Cuál es el problema de la gestión de experimentos?



¿Cuál es el problema de la gestión de experimentos?



Problemas comunes

 Automatización del proceso de generación de modelos

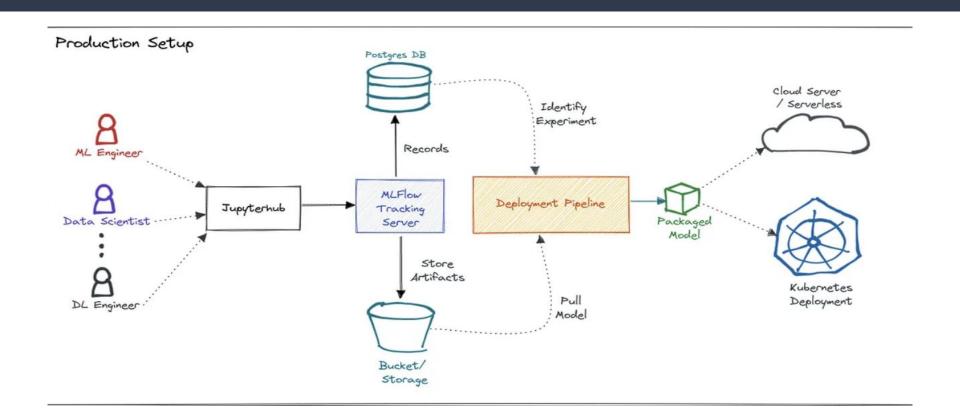
Gestión del ciclo de vida de modelos

Colaboración entre equipos

Maturity Model



Reproducibilidad y Colaboración



Reproducibilidad y Colaboración

Data scientist MLOps Engineer Tracking backend Review & Select Model Registry Deploy Monitor

MLflow

¿ Qué ofrece MLflow?

UI

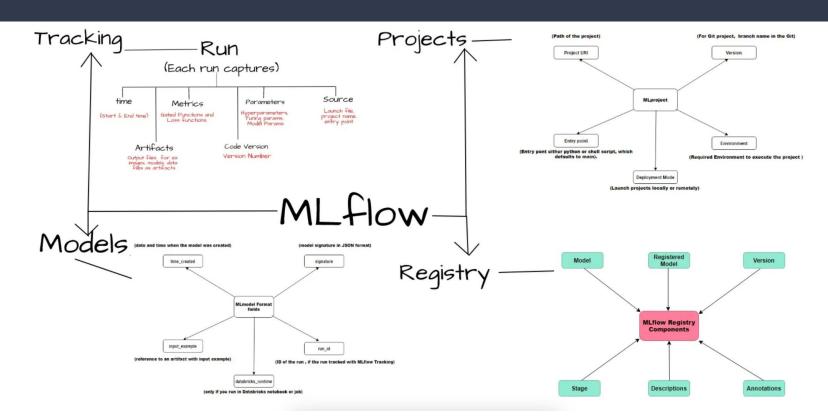
API para python

Agnóstico en cuanto a: Cloud y base de datos

Compatibilidad con notebooks



¿ Qué ofrece MLflow?



¿ Qué ofrece MLflow?



Record and query experiments: code, data, config, and results.



PROJECTS

Package data science code in a format that enables reproducible runs on many platforms



MODEL REGISTRY

Store, annotate, and manage models in a central repository



MODELS

Deploy machine learning models in diverse serving environments

Pasos para implementar MLflow

Instalación de mlflow





Mlflow en local



Mlflow docker

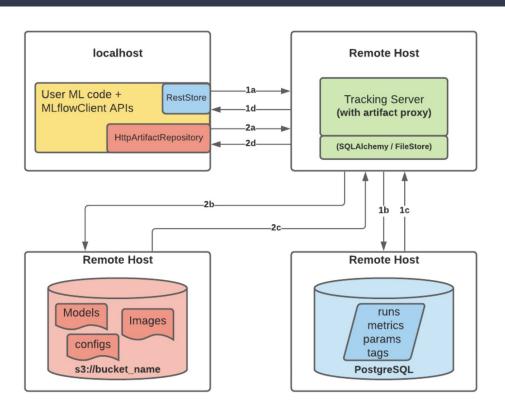
```
...
                             dockerfile
FROM python:3.11.0rc2-slim-bullseye
WORKDIR /home/mlflow
COPY entrypoint.sh .
COPY requirements.txt .
RUN apt update && apt upgrade -y
RUN apt -y install postgresql postgresql-contrib nginx
RUN pip install --upgrade pip && pip install -r requirements.txt
COPY nginx.conf /etc/nginx/nginx.conf
EXPOSE 8080
ENTRYPOINT ["/home/mlflow/entrypoint.sh"]
```

```
#!/bin/bash

service nginx start

mlflow server \|
--host localhost \
--port 5001 \
--static-prefix /mlflow \
--backend-store-uri
postgresql://${POSTGRES_USERNAME}:${POSTGRES_PASSWORD}@${POSTGRES_HOST}/mlflow \
--default-artifact-root s3://mlflow-artifacts-eu-central-1/
```

Integración con sistemas de almacenamiento



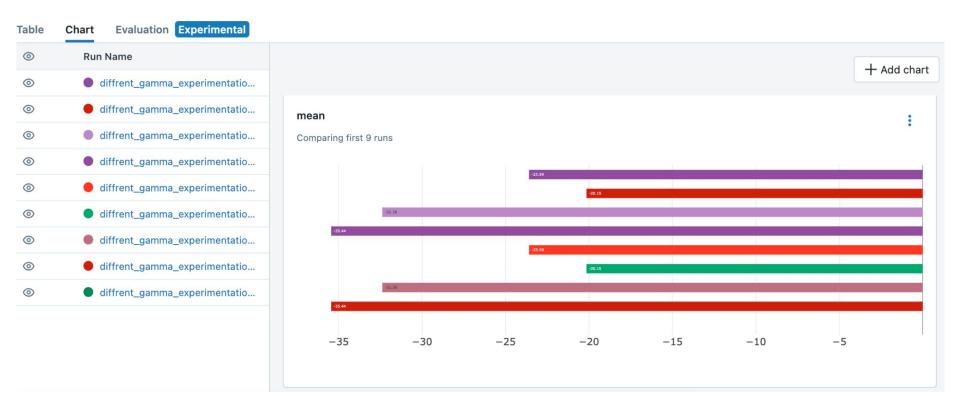
Creación de un experimento en MLflow

```
experiment
MLFLOW_TRACKING_URI = "http://localhost:5000/"
client = MlflowClient(tracking_uri=MLFLOW_TRACKING_URI)
mlflow.set_tracking_uri(MLFLOW_TRACKING_URI)
mlflow.set_experiment("v4")
```

Registro de parámetros, métricas y artefactos en un experimento

```
...
                                      experiment
for gamma in [0.001, 0.01, 0.1, 0.5]:
    with mlflow.start_run(run_name=f"diffrent_gamma_experimentation_{gamma}") as
run:
        mlflow.log_input(mlflow.data.from_pandas(data), context="training")
        params = {'kernel':'rbf', 'C': 1e3, 'gamma': gamma}
        sk_learn_svr = SVR(**params)
        scores = cross_val_score(sk_learn_svr, x_scaled, y, cv=KFold(n_splits=10),
scoring='neg_mean_squared_error')
        mlflow.log_param("parameters", params)
        mlflow.log_metrics({'mean': scores.mean(), 'std': scores.std()})
        mlflow.sklearn.log_model(
            sk_model=sk_learn_svr,
            artifact_path="sklearn-model",
            registered_model_name="sk-learn-random-forest-reg-model"
```

Seguimiento del rendimiento y comparación de experimentos



MLProjects

```
...
               mlflow_projects
my_mlflow_project/
    MLproject
    conda.yaml
    code/
        train.py
        predict.py
    data/
        dataset.csv
```

MLProjects

```
...
                                 MLproject.yaml
name: my_mlflow_project
entry_points:
  train:
    command: "python code/train.py"
    parameters:
      data_path: {type: str, description: "Path to the training data"}
      max_depth: {type: int, default: 5, description: "Maximum tree depth"}
  predict:
    command: "python code/predict.py"
    parameters:
      model_uri: {type: str, description: "URI of the trained model"}
      input_data: {type: str, description: "Input data for prediction"}
dependencies:
  conda:
    channels:
      - defaults
    dependencies:
      - scikit-learn=0.24.1
      - pandas=1.2.3
```

MLProjects



Versionado de modelos

```
...
                      mlflow.<model_flavor>.log_model()
mlflow.set_experiment("Model Registry")
m1 = 0.7
m2 = 0.8
with mlflow.start_run(run_name="first model run") as run:
    params = {"parameter1": 1, "parameter2": 2}
    sk_learn_model = """<Model of choice>(**params)"""
    # Log parameters and metrics using the MLflow APIs
    mlflow.log_params(params)
    mlflow.log_param("param_1", randint(0, 100))
    mlflow.log_metrics({"metric_1": m1, "metric_2": m2})
    # Log the sklearn model and register as version 1
    mlflow.sklearn.log_model(sk_model=sk_learn_model,
                             artifact_path="model",
                             registered_model_name="ModelOfChoice")
```

Versionado de modelos

```
mlflow.register_model()

result = mlflow.register_model("runs:/<run_id>/<path>", "model")
```

Versionado de modelos y etiquetado de versiones

```
...
                        create_registered_model()
from mlflow.tracking import MlflowClient
client = MlflowClient()
"""Creates an empty registered model with no version associated"""
client.create_registered_model("model-of-choice")
"""create a new version of the model"""
result = client.create_model_version(name="model",
                                      source="mlruns/0/<path>",
                                      run_id="<run_id>")
"""Renaming a Registered model"""
client.rename_registered_model(name="<old_model>",
                               new_name="<new_model>")
"""Promoting a model to Production stage"""
client.transition_model_version_stage(name="<model>",
                                       version=2,
                                       stage="Production")
```



```
...
import mlflow.sagemaker
mlflow.sagemaker.deploy(
    model_uri="runs:/<RUN_ID>/model",
    role="arn:aws:iam::123456789:role/service-role/MySageMakerRole",
    endpoint_name="my-endpoint"
```

```
...
import mlflow.azureml
mlflow.azureml.register(model_uri="runs:/<RUN_ID>/model",
                        model_name="my-model",
                        workspace_name="my-workspace",
                        subscription_id="your-subscription-id",
                        resource_group="your-resource-group")
```

```
...
import mlflow.gcp
mlflow.gcp.deploy(
    model_uri="runs:/<RUN_ID>/model",
    model_name="my-model",
    project_id="your-project-id",
    region="us-central1",
    runtime_version="2.3",
```

Mlflow serving of model

```
mlflow models serve -m /Users/mlflow/mlflow-
prototype/mlruns/0/7c1a0d5c42844dcdb8f5191146925174/artifacts/model -p 1234
```

```
curl -X POST -H "Content-Type:application/json; format=pandas-split" --data
'{"columns":["alcohol", "chlorides", "citric acid", "density", "fixed acidity",
"free sulfur dioxide", "pH", "residual sugar", "sulphates", "total sulfur dioxide",
"volatile acidity"], "data":[[12.8, 0.029, 0.48, 0.98, 6.2, 29, 3.33, 1.2, 0.39, 75,
0.66]]}' http://127.0.0.1:1234/invocations
```

serving models - mlflow serve

Deep Dive

Autologging

PyTorch

Metrics

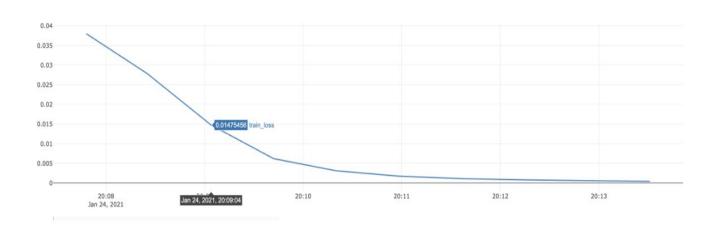
Name	Value
acc 🗠	0
acc_epoch 🗠	0.003
acc_step 🗠	0
train_loss 🗠	0.028
train_loss_epoch 🗠	0.089
train_loss_step 🗠	0.028



https://mlflow.org/docs/latest/python_api/mlflow.pytorch.html

https://bytepawn.com/automatic-mlflow-logging-for-pytorch.html

PyTorch



Sklearn & TensorFlow

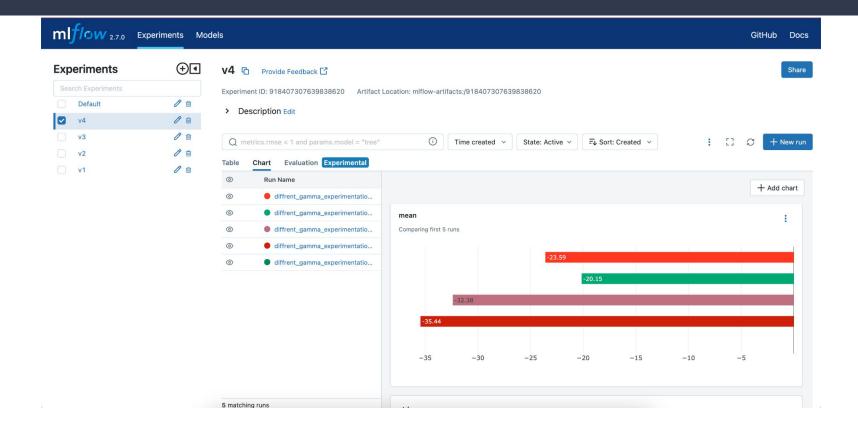




https://mlflow.org/docs/latest/python_api/mlflow.sklear n.html https://mlflow.org/docs/latest/python_api/mlflow.t ensorflow.html

Monitoreo y visualización de experimentos

Interfaz web de MLflow



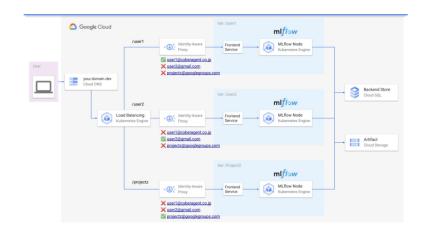
Escalabilidad y producción

Escalabilidad horizontal de mlflow

 Clusters -> Integración con multiples plataformas

Paralelismo

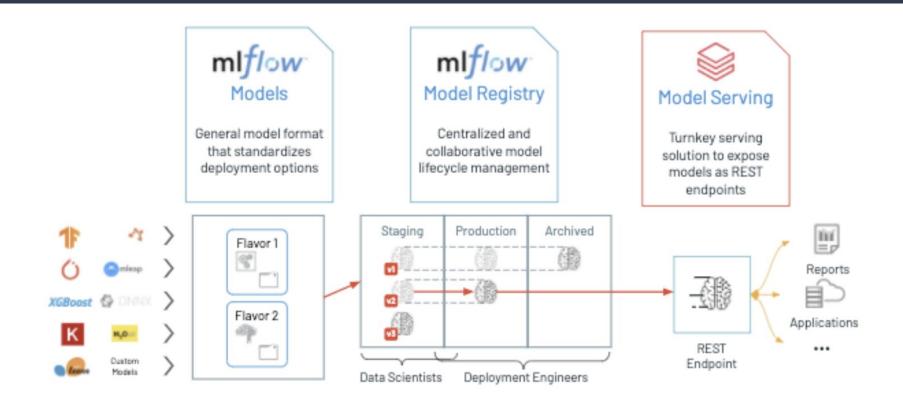
Almacenamiento y monitoreo distribuido



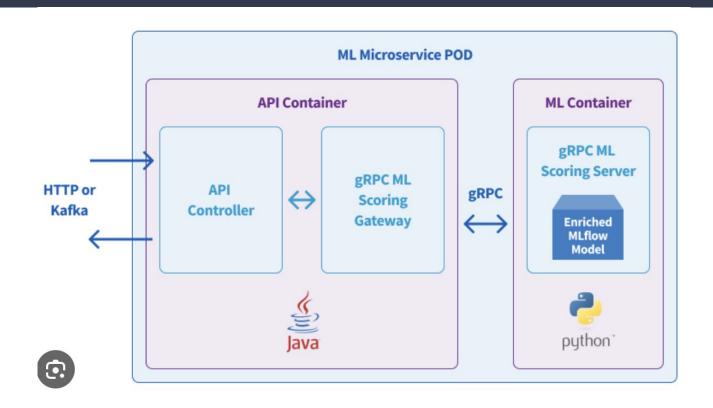
MLFlow + k8s:

https://medium.com/artefact-engineering-and-data-science/serving-ml-models-at-scale-using-mlflow-on-kubernetes-a83390718a92

Implementación en entornos de producción



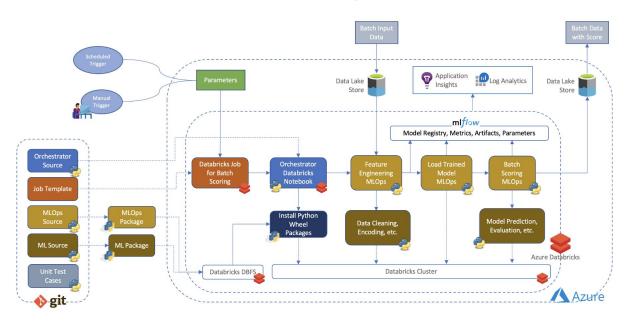
Implementación en entornos de producción



Implementación en entornos de producción

Batch Scoring

Batch Scoring



Otras soluciones

Diferentes industrias

Internal ML Platforms (Open Source)











Feature Stores











Internal ML Platforms







FBLearner Flow

ML Platform solutions (Enterprise)

Feature Stores













Kubeflow



Kubeflow vs MLflow





Kubeflow vs MLflow





Conclusiones y Recomendaciones

Recomendaciones

Separación por experimentos

Automatización de pipelines

Versionado de modelos

• Separar experimentación de producción



¿Preguntas?

Recursos de interés

Documentación oficial:
 https://mlflow.org/docs/latest/index.html

Github: https://github.com/13Mai13/pycones23/

 Registro de modelos:
 https://medium.com/walmartglobaltech/modeland-data-versioning-an-introduction-to-mlflow-a nd-dvc-260347cd0f6e

Python

¡GRACIAS DE NUEVO!

Contacto

Linkedin: Maialen Berrondo

Twitter: @MaialenBerrondo

Github: 13Mai13/pycones23 -> Todo el material

subido