

How to Manage Your ML Models?

Hannes Hansen

8.11.2024

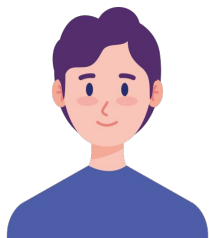
Goal

Lifecycle of a ML model

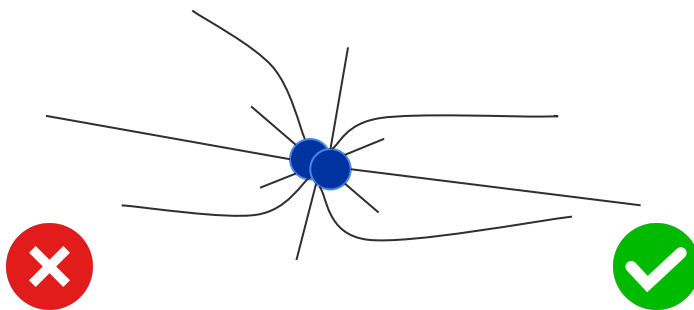
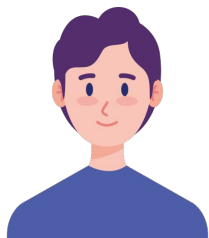
Challenges you might face

How a Model Registry can help

A brief ML Journey

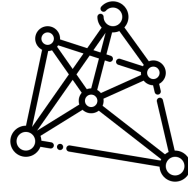


A brief ML Journey

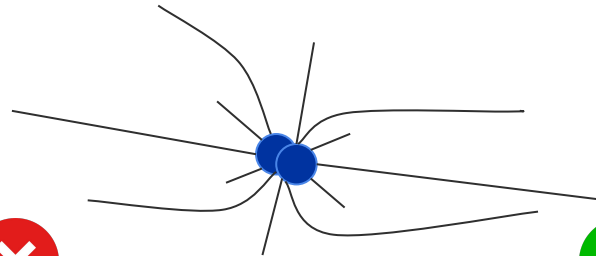
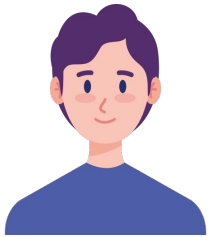
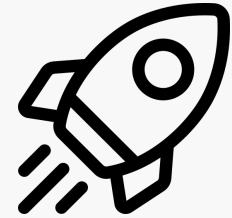


A brief ML Journey

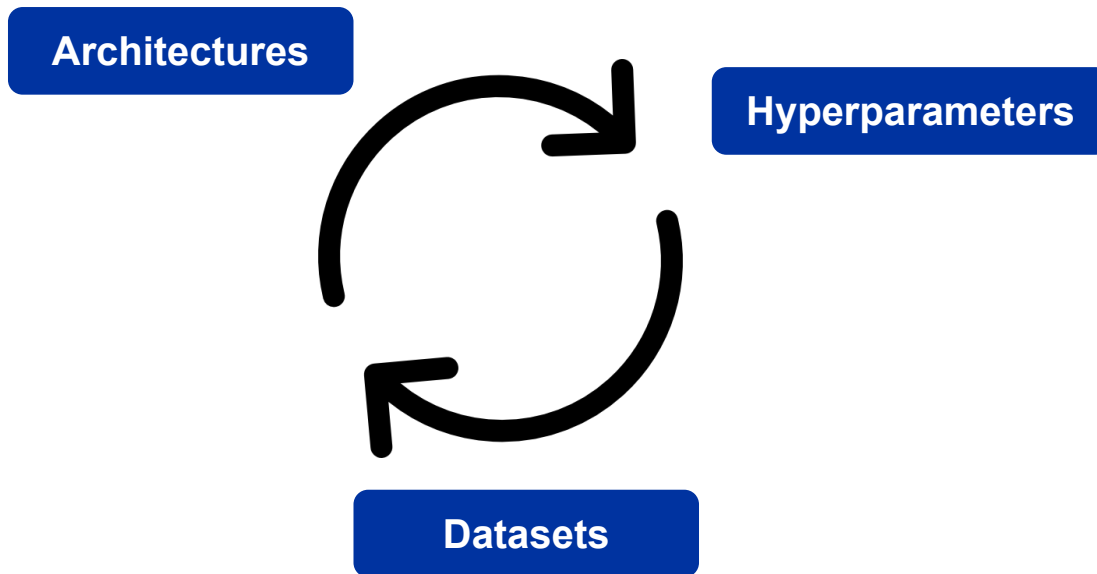
Prototyping



Production



Prototyping



Prototyping

```
1 n_estimators = 10
2 model = RandomForestClassifier(n_estimators=n_estimators).fit(train_data_v1)
3 score = accuracy(truth, model.predict(test_data))
4 model.save("model_10_trees.pkl")
```

Prototyping



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1 n_estimators = 10
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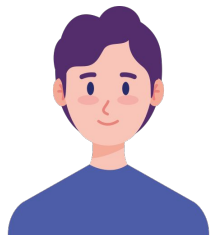


```
1 n_estimators = 20
2 ...
3 model.save("model_20_trees.pkl")
```


Model Registry



- Central storage for your models and metadata
- Access via API
- <https://mlflow.org/>



- Models
- Plots
- Configuration

Model
Registry

Prototyping

```
1 mlflow.log_metric("accuracy", 0.8)
```

Prototyping

```
mlflow.log_metric("accuracy", 0.8)
```

```
mlflow.log_param("n_estimators", 10)
```

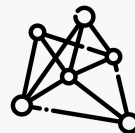
Prototyping

```
1 mlflow.log_metric("accuracy", 0.8)
```


```
1 mlflow.log_param("n_estimators", 10)
```

```
1 mlflow.sklearn.log_model(  
2     model,  
3     artifact_path="model",  
4     registered_model_name="model.dev"  
5 )
```

Unique Model Identifier









model.dev

Description 

No description

Details


Created at	2024-11-01 17:53:40
Created by	hannes
Experiment ID	0 
Status	 Running
Run ID	0e906ec3c8ad4a1a8c490391d89ed832 
Duration	
Datasets used	—
Tags	Add
Source	 lineage.py  92063d1
Logged models	—
Registered models	 model.dev v1

Parameters (1)

Parameter	Value
n_estimators	10







Metrics (1)

Metric	Value
accuracy	0.8

Description 

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Parameters (1)

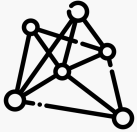
Parameter	Value
n_estimators	10

Metrics (1)

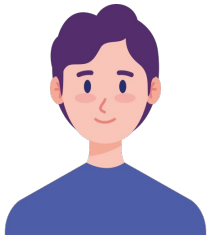
Metric	Value
accuracy	0.8

Going to Production

Prototyp

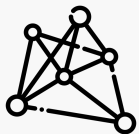


model.dev



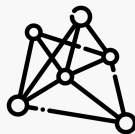
Going to Production

Prototyp



model.dev

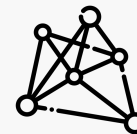
Staging



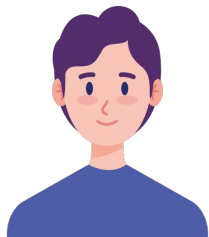
model.staging



Production



model.prod



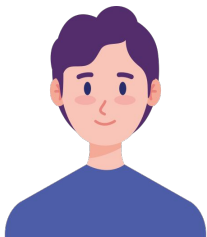
Going to Production

```
1 client.copy_model_version("models:/model.dev/1", "model.staging")
2 client.copy_model_version("models:/model.staging/1", "model.prod")
```

Name 	Latest version
model.dev	Version 1
model.prod	Version 1
model.staging	Version 1

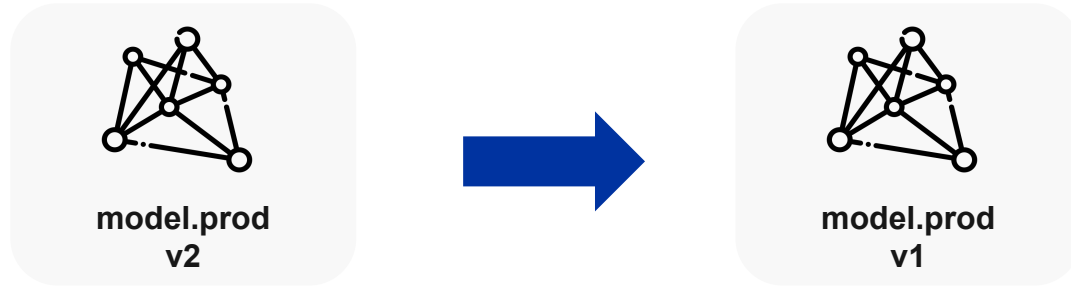
Updates

```
1 model = RandomForestClassifier(n_estimators=30).fit(train_data_v2)
2 ...
3 mlflow.sklearn.log_model(
4     model,
5     artifact_path="model",
6     registered_model_name="model.dev"
7 )
```



Name 	Latest version
model.dev	Version 2
model.prod	Version 2
model.staging	Version 2

Rollback



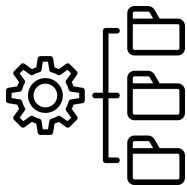
Model Registry



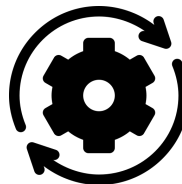
Model Storage



Model Versioning



Model Lineage



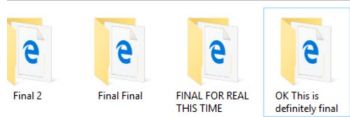
Stage Transitioning



I prefer the real version control



I said the *real* version control



Perfection

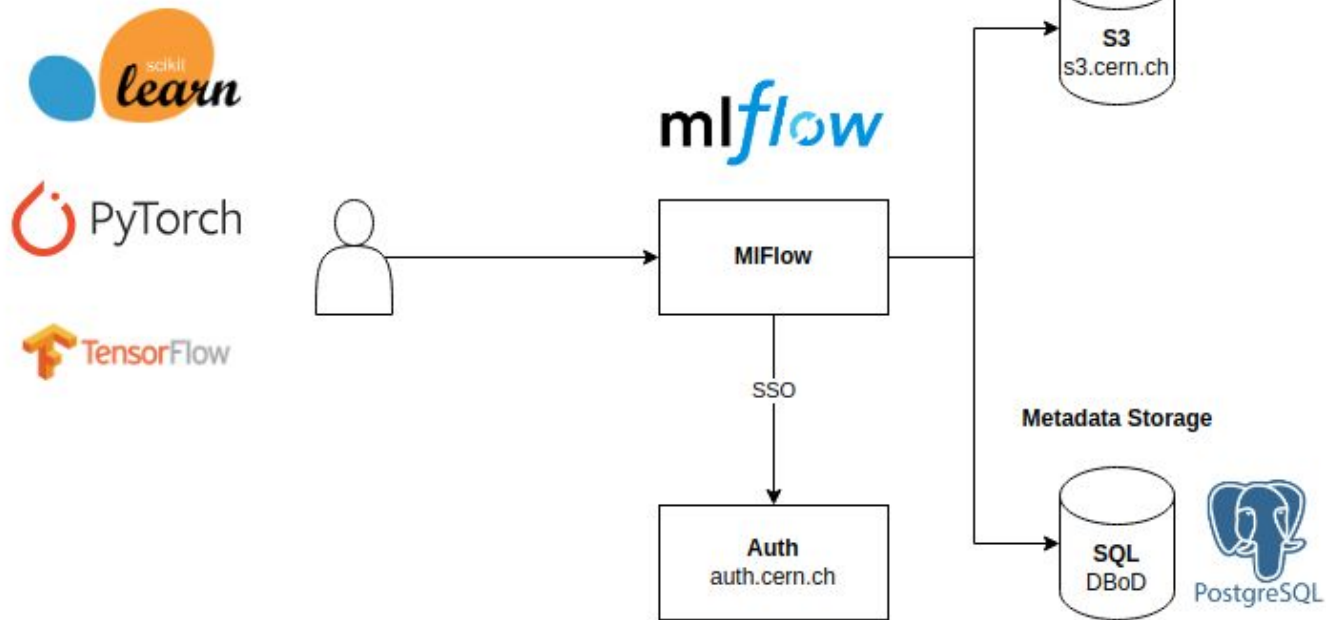


home.cern

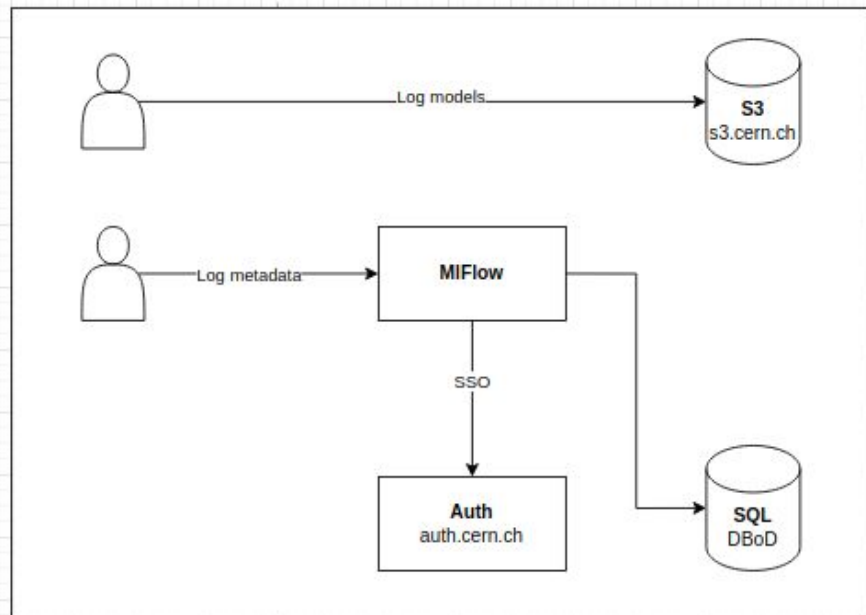
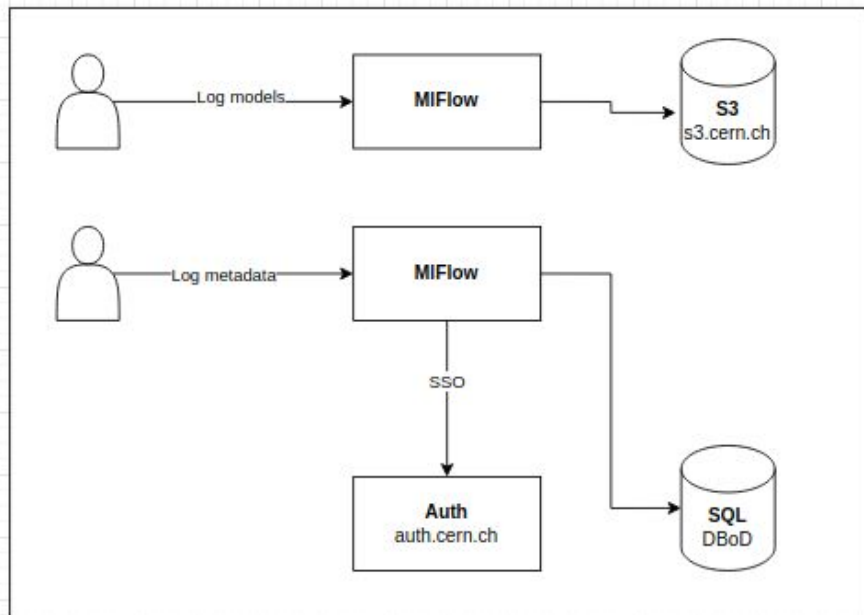
Custom Models

```
1 import mlflow
2 import torch
3
4 class CustomModel(mlflow.pyfunc.PythonModel):
5     def __init__(self):
6         self.model = torch.Linear()
7
8     def predict(self, context, model_input, params=None):
9         prediction = self.model(torch.tensor(model_input))
10        return prediction
11
12 with mlflow.start_run():
13     mlflow.pyfunc.log_model(
14         "custom_model",
15         python_model=CustomModel(),
16         pip_requirements=["torch==2.0.0"]
17     )
```

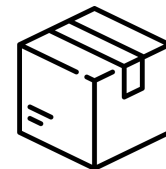
Architecture



Architecture

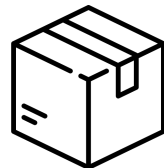


Packaging



- **Model is the output of a training process**
- **Needs to be serialized for storage**
 - Weight matrix of a linear layer in a **weights.npy**
 - Pickle file of an sklearn model or PyTorch mode **model.pkl**
 - ONNX **model.onnx**
- **Depending on the format, you might need more information**
 - Dependencies e.g. `scikit-learn==1.5.2`

```
1 import mlflow
2
3 model = RandomForestClassifier()
4 mlflow.sklearn.log_model(
5     model,
6     artifact_path="model",
7     registered_model_name="model.dev",
8     pip_requirements=["scikit-learn=1.5.2"]
9 )
```



▼ model

- MLmodel
- conda.yaml
- model.pkl
- python_env.yaml**
- requirements.txt

model/python_env.yaml 120B

Path: mlflow-artifacts:/0/058580faa54c43eea8155b9b8b283c69/artifacts/model/python_env.yaml

```
python: 3.12.4
build_dependencies:
- pip==24.2
- setuptools==72.1.0
- wheel==0.43.0
dependencies:
- -r requirements.txt
```

▼ model

- MLmodel
- conda.yaml
- model.pkl
- python_env.yaml
- requirements.txt**

model/requirements.txt 94B

Path: mlflow-artifacts:/0/058580faa54c43eea8155b9b8b283c69/artifacts/model/requirements.txt

```
mlflow==2.16.2
cloudpickle==3.0.0
numpy==2.1.1
pandas==2.2.3
scikit-learn==1.5.2
scipy==1.14.1
```