



An End-to-End Data Science Project

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Workshop overview:

Session 1

Prep & Analytics

12.09.2021

*Start with the business problem, set the foundation up, find data source, preprocess
Start the descriptive analytics pipeline)*

Session 2

Machine learning

19.09.2021

Implemented analytics pipeline, Build and evaluate prediction model(s), use Mlflow to keep track of the various experiments

Session 3

Deployment in Prod

03.09.2021

Create prediction functions and production class, develop an API, create a dashboard that the user will access and call the API

What you will do:

- **During the sessions:** You will get tasks to be done
- **After the sessions:**
 - You will complete the whole covered phases
 - Dig deeper into the various technologies discussed

i.e.: No Spoon-feeding :-)



***& let's get started
and pick-up where we've left off***

Part 1
**Machine learning
hands-on**

Part 2
**Productionizing
the model**



Part 1

Machine learning hands-on



MLflow recap

Summary

Track with Mlflow

```
In [9]: # Initialize client and experiment
client = MlflowClient()
mlflow.set_experiment(EXPERIMENT_NAME)
exp = client.get_experiment_by_name(EXPERIMENT_NAME)

In [10]: # Start a new run and track
with mlflow.start_run(experiment_id=exp.experiment_id):
    mlflow.log_param("pca_var", PCA_VAR)      # Track model parameter
    mlflow.log_metric("MSE", mse_test)        # Track error value
    mlflow.log_artifact(EXPORT_MODEL_PATH)    # Track exported model
```

Retrieve experiment

```
In [3]: # Initialize client
client = MlflowClient()

# Get experiment
exp = client.get_experiment_by_name(EXPERIMENT_NAME)
```

```
In [4]: # Get all runs
runs = mlflow.search_runs([exp.experiment_id])
runs
```

| | run_id | experiment_id | status | artifact_uri | metrics.MSE | params.pca_var |
|---|----------------------------------|---------------|----------|---|-------------|----------------|
| 0 | 41e1628508fc4a2f83651cecede6d8a | 1 | FINISHED | file:///home/deena_gergis/mlflow_illustration/... | 57.884313 | 1 |
| 1 | d39dec7e183450d87f679fb044c6e66 | 1 | FINISHED | file:///home/deena_gergis/mlflow_illustration/... | 31.675892 | 0.95 |
| 2 | 77c97ff7b2fe46d9becba4c230dd3193 | 1 | FINISHED | file:///home/deena_gergis/mlflow_illustration/... | 31.831237 | 0.8 |
| 3 | f11b91bf1c7441c5bacc7e73adfbbe59 | 1 | FINISHED | file:///home/deena_gergis/mlflow_illustration/... | 57.884313 | 0.3 |

Tutorial:

<https://www.linkedin.com/pulse/mlflow-better-way-track-your-models-deena-gergis/>

Repo:

https://github.com/Deena-Gergis/mlflow_tracking



Part 1: Modelling Training

- 1. Clean your data*
- 2. Decide on your modelling strategy*
- 3. Decide about the evaluation metric*
- 4. Train a baseline model*
- 5. Train more sophisticated models*
- 6. Decide which model will be used*



Part 2: Production

- 1. Develop prediction functions*
- 2. Refactor your code to clean script*
- 3. Create an API on top*
- 4. Integrate the API with the product*



Assignment:

*Create a product using
Dash or Streamlit and call
the API from within*



Questions?