

Sommaire

Using Machine Learning for Water Potability Classification



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Introduction & Environnement

MLOps: A set of practices to deploy and maintain machine learning models in production reliably and efficiently.

Importance of MLOps

- Streamlining Workflows: Automates and manages the end-to-end machine learning lifecycle, improving productivity and model performance.

Key Components

- Version Control: Tracks changes to data, code and models.
- Automation: Automates repetitive tasks such as model training and deployment.
- Monitoring: Continuously monitors model performance and data quality.
- Testing: Ensures model reliability through rigorous testing.

Environnement



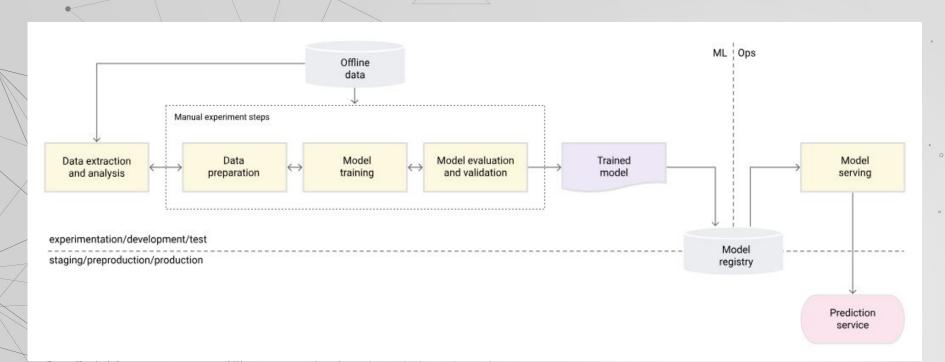








ML OPS Niveau 0 : rappel

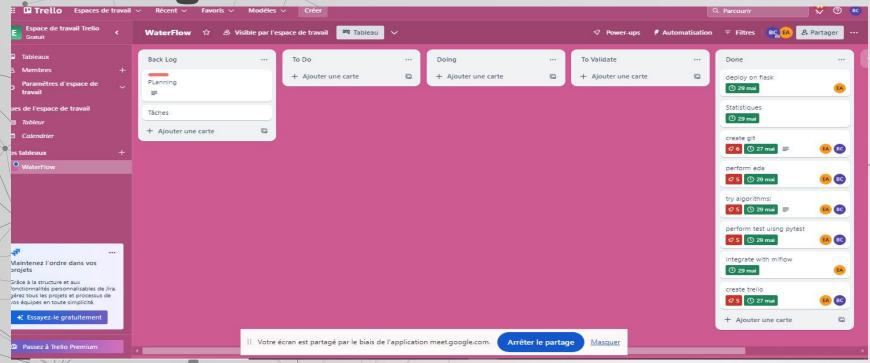


Managed the machine learning lifecycle using MLflow
Components: Tracking, Projects, Models, Registry
Benefits: Experiment tracking, reproducibility, model management







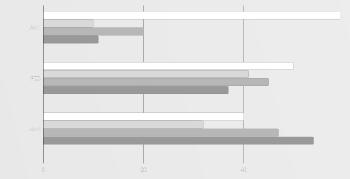


- Used Trello for project management
- Organized tasks and milestones
- Monitored progress and collaborated effectively





VALEURS MANQUANTES



PH 14.99

SULFATE 23.84

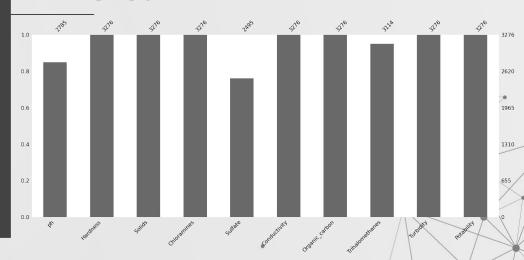
TRIHALOMETHANES 4.95

DÉTECTION DES VALEURS MANQUANTES

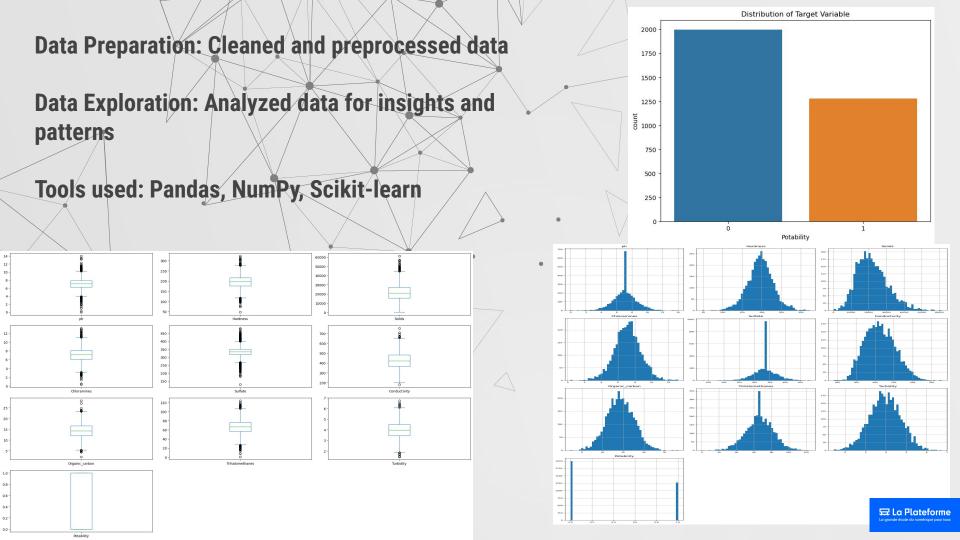
AIDE A LA PRISE DE DÉCISION SUR LES COLONNE.

	Total	Manquants	
ph	3276	491	14.99
Hardness	3276	0	0.00
Solids	3276	0	0.00
Chloramines	3276	0	0.00
Sulfate	3276	781	23.84
Conductivity	3276	0	0.00
Organic_carbon	3276	0	0.00
Trihalomethanes	3276	162	4.95
Turbidity	3276	0	0.00
Potability	3276	0	0.00

HISTOGRAMME



Stratégie choisie pour les valeurs manquantes : les moyennes.



Data Version Control (DVC)



What is DVC?

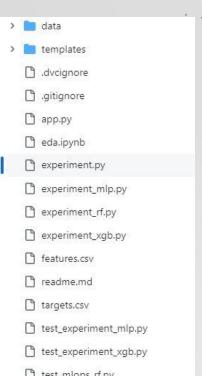
DVC: A tool for versioning data and machine learning models, enabling reproducibility and collaborated data science projects.

Importance of DVC

- Data Versioning: Keeps track of changes to datasets and models.
- Reproducibility: Ensures experiments can be reliably reproduced.
- Collaboration: Facilitates collaboration among data scientists by managing data dependencies.

Key Features

- Data Management: Efficiently manages large datasets.
- Pipeline Management: Automates and tracks machine learning pipelines.
- Integration: Integrates seamlessly with Git for version control

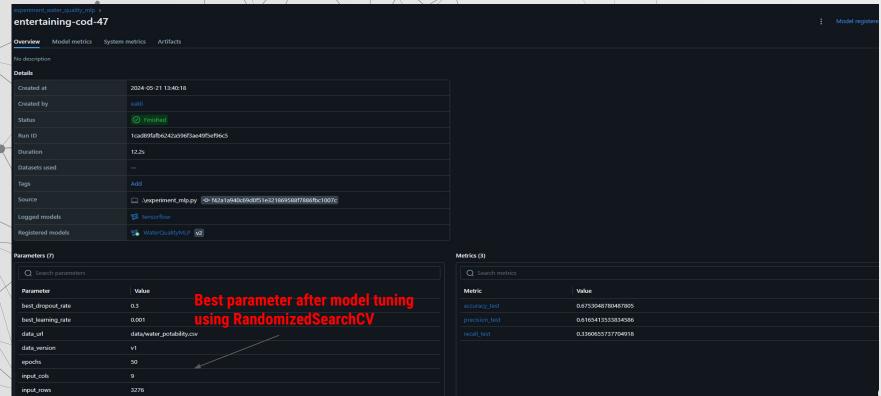


Model Training

Split data into training and validation and test sets

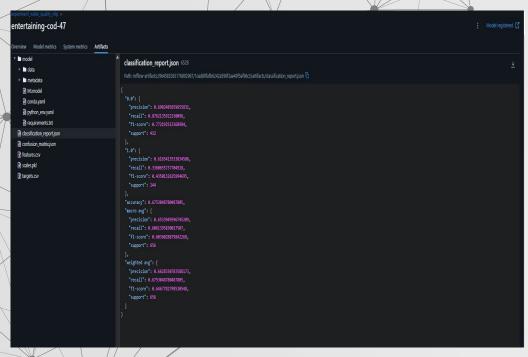
Trained a binary classification model using MLP, Random Forest XBoost

Hyperparameter tuning with RandomizedSearchCV with more focus on MLP



Prediction & Evaluation

Made predictions on the validation set
Evaluation metrics: Accuracy, Precision, Recall
Confusion Matrix and Classification Report



```
entertaining-cod-47
Overview Model metrics System metrics Artifacts
   model
                                                        confusion_matrix.json 107B
    ► data
                                                        Path: mlflow-artifacts:/964585265176892967/1cad89fafb6242a596f3ae49f5ef96c5/artifacts/confusion matrix.json
    ► metadata
      MLmodel
     onda.yaml
     python_env.yaml
     d classification_report.json
   d confusion_matrix.json
   r features.csv
   a scaler.pkl

    targets.csv
```



MLflow Configuration

Configured MLflow server on port 5000
Initialized MLflow experiment:
"experiment_water_quality_mlp"
Logged model and metadata during training

```
v def main():
      mlflow.set tracking uri("http://localhost:5000")
      experiment name = "experiment water quality mlp"
      experiment id = mlflow.create experiment(experiment name)
      client = mlflow.tracking.MlflowClient()
      experiment = client.get_experiment(experiment id)
      data path = 'data/water potability.csv'
      repo = r'C:\Users\eakli\Downloads\task\ecole\mlops-mlflow'
      version = 'v1'
      data = load data(data path, repo, version)
      X train, X val, X test, y train, y val, y test, feature names, scaler = preprocess data(data)
      best params = tune hyperparameters(X train, y train)
      final model = train final model(X train, y train, X val, y val, best params)
      evaluate and log model (final model, X test, y test, feature names, experiment id, data path, version, y train, y val, best params, scaler)

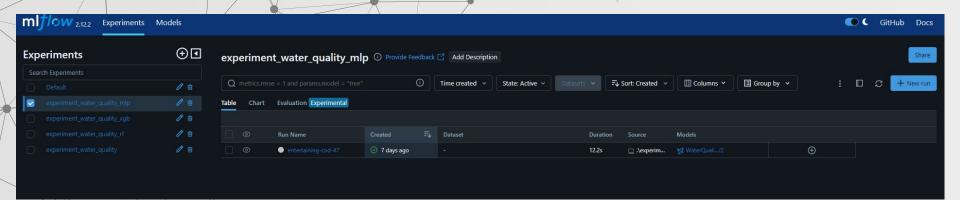
√ if name == " main ":
      main()
```

Model Transition

Explored different model versions in MLflow

Transitioned the best model which is MLP to the Model Registry

Ensured model meets quality criteria before transition





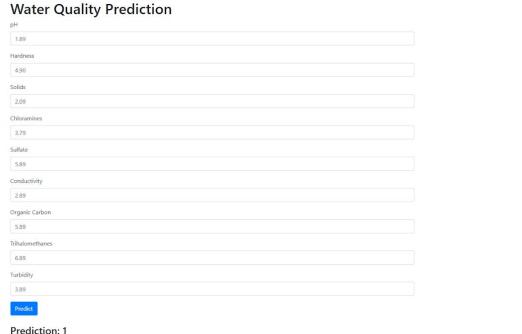
Model Deployment

Deployed the registered model using Flask Created an API for real-time predictions Integrated with a web interface for user input



```
app = Flask( name )
# Set the MLflow tracking URI
mlflow.set tracking uri("http://localhost:5000")
# Load model from the MLflow Model Registry
model name = "WaterQualityMLP"
model version = 2
model = mlflow.keras.load model(f"models:/{model name}/{model version}")
# Load scaler used during training
scaler = joblib.load("artifacts/scaler.pkl")
@app.route('/')
def home():
   return render template('index.html')
@app.route('/predict', methods=['POST'])
def predict():
   # Get form data
   data = request.form.to dict()
   # Convert form data to DataFrame
   input df = pd.DataFrame([data])
   # Ensure the input data contains all necessary features
   required features = [
        "ph", "Hardness", "Solids", "Chloramines", "Sulfate",
        "Conductivity", "Organic_carbon", "Trihalomethanes", "Turbidity"
```

Flask Application Demo





- Live demonstration of the web application
- How to use the web interface to input data
- Real-time prediction results displayed on the UI



Using Pytest for Unit Testing

- Ensured code reliability and correctness with pytest
- Created unit tests for data processing and model functions
- Integrated tests into the CI/CD pipeline
- Benefits: Early bug detection, improved code quality

```
rootdir: C:\Users\eakli\Downloads\task\ecole\mlops-mlflow
plugins: hydra-core-1.3.2, mock-3.14.0

collected 2 items

test_experiment_mlp.py::test_load_data PASSED [50%]
test_experiment_mlp.py::test_main PASSED [100%]
```

C:\Users\eakli\anaconda3\envs\env_mlops\Lib\site-packages\mlfl

```
import pytest
from experiment mlp import load data, preprocess data, create model, train final model
   data = load_data('data/water_potability.csv', 'repo', 'v1')
    assert not data.empty
def test preprocess data():
   data = load_data('data/water potability.csv', 'repo', 'v1')
   X_train, X_val, X_test, y_train, y_val, y_test, feature_names, scaler = preprocess_da
    assert X train.shape[0] > 0
   assert y train.shape[0] > 0
   model = create_model(input_shape=9, learning_rate=0.001, dropout_rate=0.5)
    assert model is not None
def test train final model():
   data = load_data('data/water_potability.csv', 'repo', 'v1')
   X_train, X_val, X_test, y_train, y_val, y_test, feature_names, scaler = preprocess_da
   best_params = {'learning_rate': 0.001, 'dropout_rate': 0.5, 'epochs': 50}
   model = train final model(X train, y train, X val, y val, best params)
    assert model is not None

☐ La Plateforme
```





□ La Plateforme

References

MLflow: A Tool for Managing the Machine Learning Lifecycle — MLflow 2.13.0 documentation

Home | Data Version Control · DVC

Home - MLOps Community



THANK YOU

