CT1 Individual Assignment (MLOps)

End to End MLOps Workflow for Bank Term Deposit Marketing

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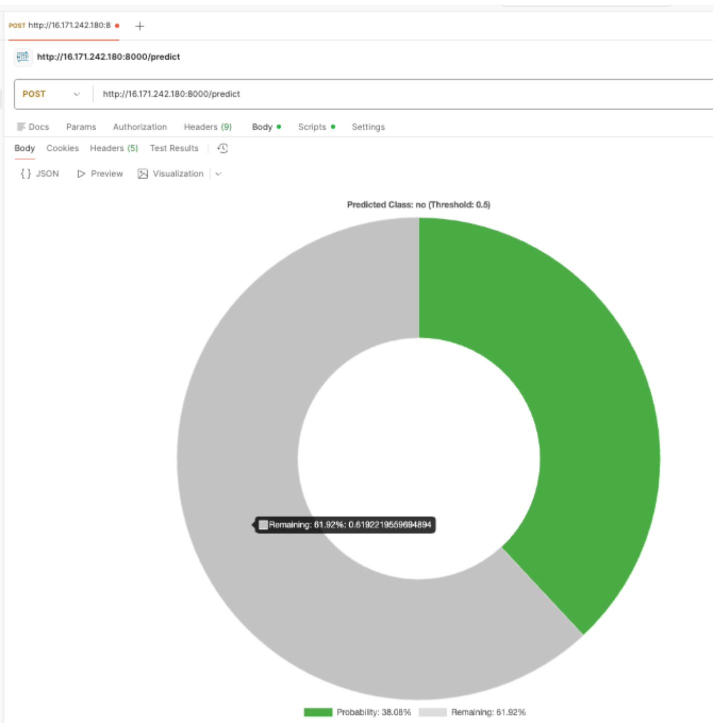
1. Business Problem and Objective

- Briefly describe the bank's marketing context
  - The bank runs outbound campaigns to sell term deposits to customers.
  - Contacting every customer is costly. Only a small fraction accepts the offer.
- State the business objective clearly
  - Build a prediction model that identifies customers who are most likely to subscribe to a term deposit.
  - Use this model to prioritize outreach and improve campaign efficiency.

Target variable:

- y = 1 if customer subscribes to term deposit
- y = 0 otherwise



2. Dataset and Modelling Approach

2.1 Dataset Overview

- Mention dataset name and size
  - 4119 observations
  - 21 columns (20 input features plus target y)
- Feature groups
  - Client and demographic attributes (age, job, marital, education, etc.)
  - Campaign interaction variables (duration, campaign, previous, contact, month, day_of_week, poutcome)
  - Macroeconomic indicators (emp.var.rate, cons.price.idx, cons.conf.idx, euribor3m, nr.employed)

2.2 Model and Preprocessing

- Algorithm
  - **Logistic Regression** for binary classification
- Preprocessing pipeline
  - Numeric features scaled using StandardScaler
  - Categorical features encoded using OneHotEncoder with handle_unknown set to ignore
- Handling class imbalance
  - Used class_weight balanced in Logistic Regression to give more weight to the minority positive class

2.3 Key Evaluation Metrics

- Report test set metrics from the notebook
  - ROC AUC
  - Precision, recall, F1 for both classes, with focus on the positive class (y = 1)
  - Confusion matrix to show trade off between true positives and false positives
- One short interpretation
  - For example, "The model achieves a ROC AUC of 0.**9423**. This indicates good ranking ability between converters and non converters and makes the model suitable for prioritising leads in marketing campaigns."

```
ROC AUC: 0.9423

Classification report:
              precision    recall  f1-score   support

           0      0.977     0.880     0.926       734
           1      0.460     0.833     0.593        90

    accuracy                          0.875       824
   macro avg      0.719     0.857     0.760       824
weighted avg      0.921     0.875     0.890       824


Confusion matrix:
[[646  88]
 [ 15  75]]
```

3. MLOps Pipeline Implementation

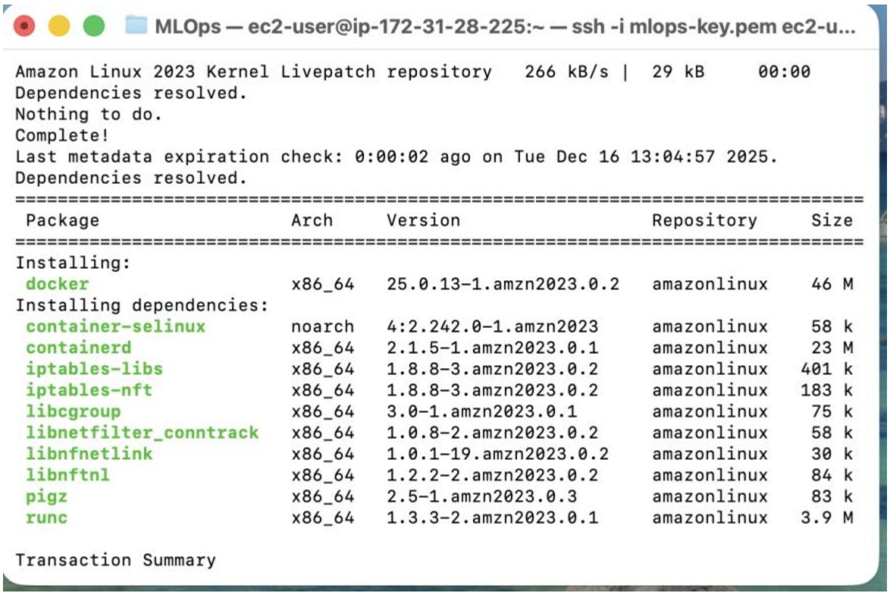
3.1 Local Model Development

- Tools
  - Python and Jupyter notebook
  - scikit learn for modeling, joblib for saving the model
- Steps
  - Loaded bank-additional.csv
  - Performed basic EDA
  - Defined numeric and categorical feature lists
  - Built preprocessing plus Logistic Regression pipeline
  - Trained and evaluated the model
  - Saved the model as bank_term_deposit_model.joblib

```python
# Train the model and evaluate

clf.fit(X_train, y_train)

y_proba = clf.predict_proba(X_test)[:, 1]
y_pred = (y_proba >= 0.5).astype(int)

print("ROC AUC: {:.4f}".format(roc_auc_score(y_test, y_proba)))

print("\nClassification report:")
print(classification_report(y_test, y_pred, digits=3))

print("\nConfusion matrix:")
print(confusion_matrix(y_test, y_pred))
```

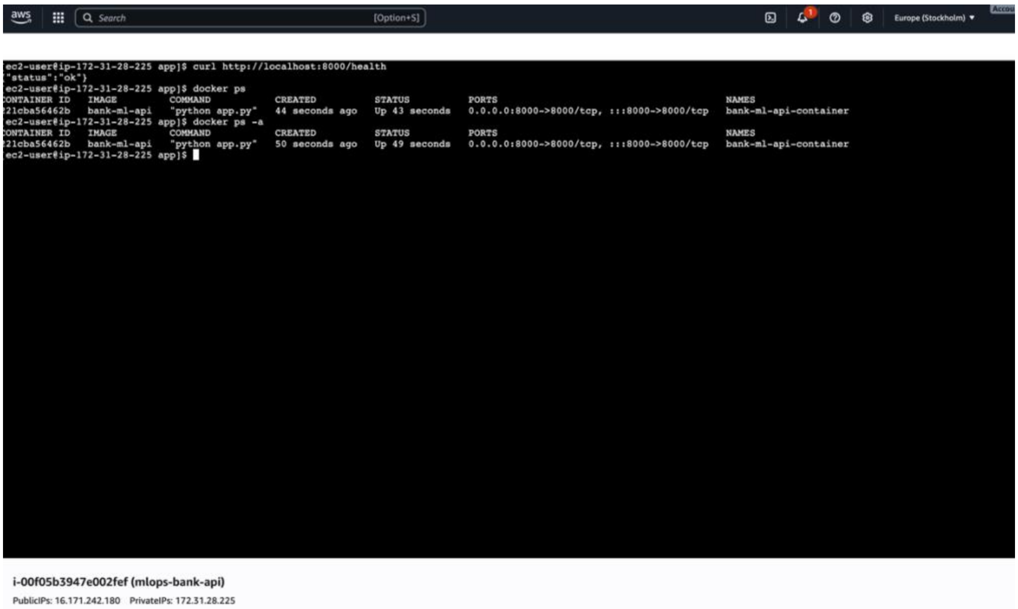
3.2 API and Containerization with Docker

- API layer
  - Implemented a Flask app in app.py with two endpoints
    - GET /health to verify service status
    - POST /predict to accept JSON input and return prediction and probability
  - The API expects all 20 original input fields and returns “yes” or “no” along with probability
- Docker container
  - Defined Dockerfile based on python:3.11 slim
  - Installed dependencies from requirements.txt
  - Copied app.py and bank_term_deposit_model.joblib into the container
  - Exposed port 8000 and used gunicorn to serve the Flask app



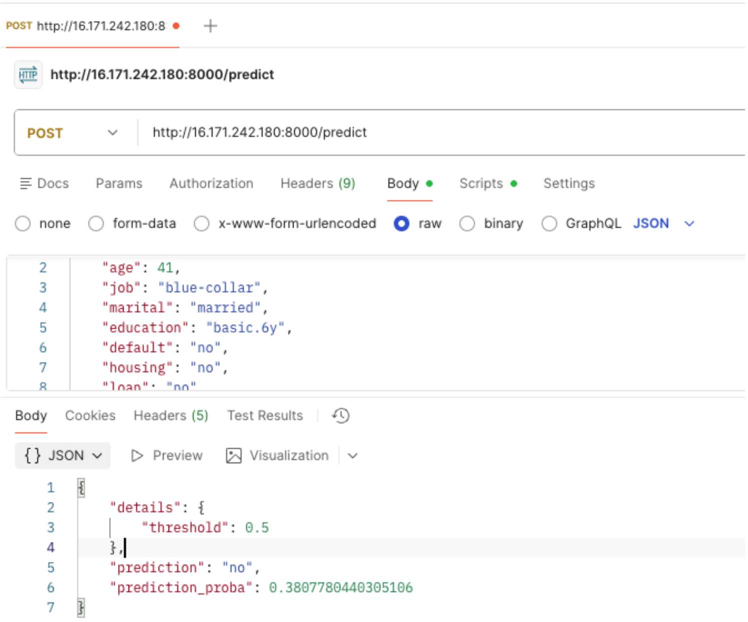
3.3 AWS Deployment and Inference

- AWS setup
  - Launched an EC2 instance
  - Installed Docker on the instance
  - Copied code and model files to the instance
  - Built the Docker image and ran the container on port 8000
- Public endpoint testing
  - Used the EC2 public IP and port 8000
  - Verified health endpoint using curl or browser
  - Sent POST requests using curl or Postman to /predict with a sample JSON request
  - Confirmed that the prediction and probability received from the deployed model matched local predictions for the same record



- EC2 instance or SSH session showing the container running

- Postman or terminal showing a successful prediction response from the public endpoint



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4. Conclusion

- **Summarised workflow**
  - Built a supervised classification model locally using the bank marketing dataset to predict term deposit subscription (y)
  - Performed preprocessing through a single reproducible pipeline (numeric scaling and categorical one hot encoding), trained a Logistic Regression model with class balancing, and evaluated performance using ROC AUC, classification report, and confusion matrix (ROC AUC = **0.9423**, accuracy = **0.875**)
  - Containerized the application using Docker (Dockerfile + requirements), validated it locally, and then deployed the same container to an AWS EC2 instance with port 8000 exposed for public access
- **Business value**
  - The deployed model enables the bank to prioritize outreach toward customers most likely to subscribe, improving campaign efficiency by reducing unnecessary calls/emails while increasing conversion rates.
  - With strong ranking capability (ROC AUC **0.9423**) and high recall for the positive class (**0.833**), the solution is well-suited for marketing use cases where capturing potential subscribers is critical, and targeting thresholds can be tuned to match budget, call capacity, and cost per contact.