DS114- FastAPI Practise



By: Saleh Alsaeed eng. Esraa Madhi

Getting Started!

1. Setting Up Your Project

• To begin using FastAPI, the first step is to install the required libraries, namely FastAPI itself and Unicorn. You can achieve this by using the following pip command:

pip install fastapi uvicorn pydantic

• Start by creating a new folder for your project. Within this folder, create a file named main.py. This file will contain the initial FastAPI code.

2. Writing Your First FastAPI Code

In the main.py file, add the following code:

```
from fastapi import FastAPI

app = FastAPI()

@app.get("/")
def root():
    return "Welcome To Tuwaiq Academy"
```

This simple FastAPI application creates an instance of the FastAPI class and defines a single route ("/") that returns a welcome message.

3. Running Your FastAPI Server Locally

To run your FastAPI server locally, open your command line in the same path of the file main.py and enter the following command:

```
uvicorn main:app --reload
```

The main refers to the name of your Python file (main.py), and app is the name of the FastAPI instance in your code. The --reload flag enables automatic reloading of the server when changes are made to the code.

- Optional: --host and --port:
 - Specify the host and port on which your FastAPI server will run. For example:

```
uvicorn main:app --reload --host 0.0.0.0 --port 8000
```

- This command runs the server on all available network interfaces (0.0.0.0) and sets the port to 8000.
- Optional: --workers`:
 - Configure the number of worker processes to handle incoming requests. For example:

```
uvicorn main:app --reload --workers 4
```

 This command starts the server with 4 worker processes. The number can be adjusted based on your server's requirements and available resources.

- Optional: --log-level:
 - Set the log level for the server. Options include critical, error, warning, info, and debug. For example:

```
uvicorn main:app --reload --log-level debug
```

 This command sets the log level to debug, providing more detailed logs for debugging purposes.

4. Accessing Your FastAPI Application

Open your web browser and navigate to the following URL:

http://127.0.0.1:8000 or http://localhost:8000

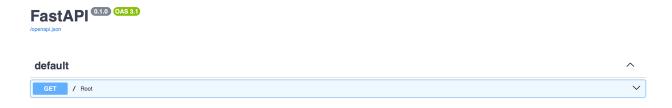
You should see your FastAPI application's welcome message displayed in the browser. This confirms that your FastAPI server is up and running locally.



Welcome To Tuwaiq Academy"

FastAPI generates interactive documentation automatically, which can be accessed at /docs and /redoc:

- Swagger UI (/docs):
 - Visit http://127.0.0.1:8000/docs or http://localhost:8000/docs in your browser.
 - You'll see an interactive UI where you can explore your API, send requests, and view responses.
 - The interactive documentation is generated based on the types and comments in your code.



6. Defining Different HTTP Methods to pass input:

```
from fastapi import FastAPI, HTTPException

app = FastAPI()

# GET request
@app.get("/")
def read_root():
    return {"message": "Welcome to Tuwaiq Academy"}

# post request
@app.post("/items/{item_id}")
def create_item(item_id: item_id):
    return {"item": item_id}
```

Accessing Your FastAPI Application

Open your web browser and navigate to the following URL:

• http://127.0.0.1:8000/items/3 or http://localhost:8000/items/3

FastAPI for Machine Learning Deployment

1. Save your model and any scaler:

```
import joblib
joblib.dump(model, 'knn_model.joblib')
joblib.dump(scaler, 'Models/scaler.joblib')
```

Go to the notebook of knn model or any model you built it before and run those 2 lines at the end of the notebook

2. Load Your Model in the API script:

Start by loading your trained machine learning model into your application in main.py file.

```
import joblib
model = joblib.load('knn_model.joblib')
scaler = joblib.load('Models/scaler.joblib')
```

3. Preprocessing input data:

Implement functions to preprocess the incoming data into a format your model expects.

• **Step 1:** First, let's create an input for the API that matches the features used in the model. Add the following three blocks of code to the main.py file.

```
from pydantic import BaseModel

# Define a Pydantic model for input data validation

# Note: Feel free to change the paramters in this class accord
ing to your model input
```

```
class InputFeatures(BaseModel):
    Year: int
    Engine_Size: float
    Mileage: float
    Type: str
    Make: str
    Options: str
```

```
def preprocessing(input_features: InputFeatures):
    """function that applies the same preprocessing steps (use
d on the training data) to a new test row, ensuring consistence
y with the training data preprocessing pipeline."""
    dict f = {
            'Year': input_features.Year,
            'Engine_Size': input_features.Engine_Size,
            'Mileage': input_features.Mileage,
            'Type Accent': input features.Type == 'Accent',
            'Type_Land Cruiser': input_features.Type == 'Land
Cruiser',
            'Make_Hyundai': input_features.Make == 'Hyundai',
            'Make_Mercedes': input_features.Make == 'Mercede
s',
            'Options_Full': input_features.Options == 'Full',
            'Options Standard': input features.Options == 'Sta
ndard'
        }
    return dict_f
```

```
@app.post("/predict")
def predict(input_features: InputFeatures):
```

```
return preprocessing(input_features)
```

In your terminal, run the following request:

```
curl -X POST "http://localhost:8000/predict" \
    -H "Content-Type: application/json" \
    -d '{
        "Year": 2020,
        "Engine_Size": 2.5,
        "Mileage": 15000,
        "Type": "Accent",
        "Make": "Hyundai",
        "Options": "Full"
    }'
```

• Step 2: Update the preprocessing function to include scaling and complete all necessary preparation steps for the input data:

```
def preprocessing(input_features: InputFeatures):
    dict_f = {
        'Year': input_features.Year,
        'Engine_Size': input_features.Engine_Size,
        'Mileage': input_features.Mileage,
        'Type_Accent': input_features.Type == 'Accent',
        'Type_Land Cruiser': input_features.Type == 'Land Cruiser',

        'Make_Hyundai': input_features.Make == 'Hyundai',
        'Make_Mercedes': input_features.Make == 'Mercede
s',

        'Options_Full': input_features.Options == 'Full',
        'Options_Standard': input_features.Options == 'Standard'
```

```
# Convert dictionary values to a list in the correct order
features_list = [dict_f[key] for key in sorted(dict_f)]

# Scale the input features
scaled_features = scaler.transform([list(dict_f.values
())])
return scaled_features
```

4. Update Prediction Endpoint:

Modify the API endpoint to accept input data, process it, and return the predictions generated by your model.

```
@app.post("/predict")
async def predict(input_features: InputFeatures):
   data = preprocessing(input_features)
   y_pred = model.predict(data)
   return {"pred": y_pred.tolist()[0]}
```

In your terminal, run the following request:

```
curl -X POST "http://localhost:8000/predict" \
    -H "Content-Type: application/json" \
    -d '{
        "Year": 2020,
        "Engine_Size": 2.5,
        "Mileage": 15000,
        "Type": "Accent",
        "Make": "Hyundai",
        "Options": "Full"
    }'
```

5. Follow steps in "DS114- Host Your ML Application"

Extra Resources for Deployment into Docker Container:

- https://towardsdatascience.com/step-by-step-approach-to-build-your-machine-learning-api-using-fast-api-21bd32f2bbdb
- https://dev.to/code_jedi/machine-learning-model-deployment-with-fastapi-and-docker-llo
- https://engineering.rappi.com/using-fastapi-to-deploy-machine-learning-models-cd5ed7219ea

Resources:

- https://fastapi.tiangolo.com/tutorial/path-params/
- https://www.tutorialspoint.com/fastapi/fastapi_rest_architecture.htm
- https://medium.com/@reza.shokrzad/fastapi-the-modern-toolkit-for-machine-learning-deployment-af31d72b6589
- https://www.datacamp.com/tutorial/introduction-fastapi-tutorial
- https://dorian599.medium.com/ml-deploy-machine-learning-models-usingfastapi-6ab6aef7e777