2- FastAPI Practise

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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
```

It's important to note that the number of libraries you install depends on the specific requirements of your project, and there may be additional dependencies beyond these two.

Getting Started!

1. **Setting Up Your Project**

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.

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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.

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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.

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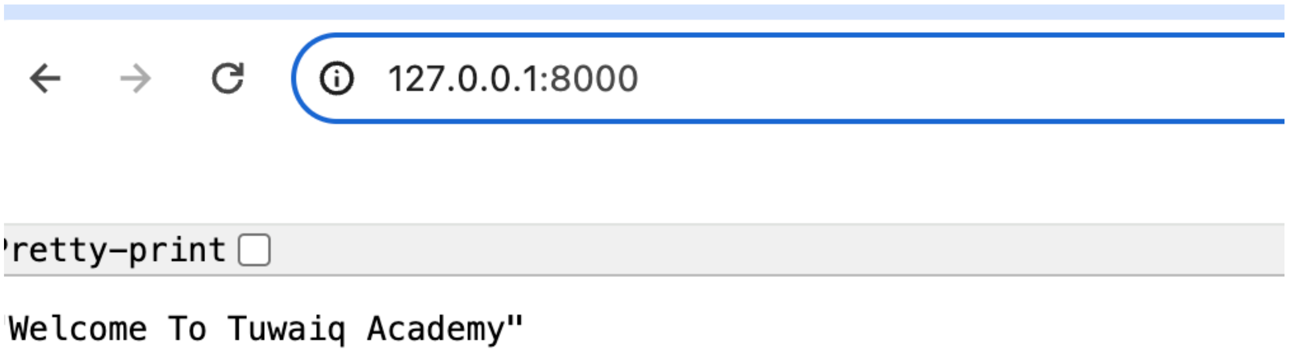
4. Accessing Your FastAPI Application

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.

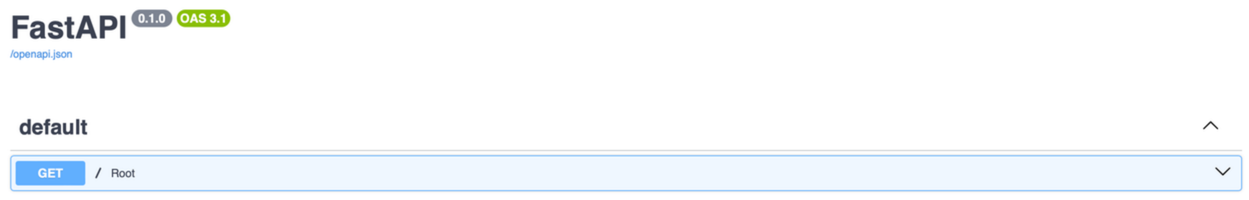

127.0.0.1:8000

'retty-print

```
Welcome To Tuwaiq Academy"
```

Interactive Documentation:
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.



Defining Different HTTP Methods:

```
from fastapi import FastAPI, HTTPException

app = FastAPI()

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

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

FastAPI makes it simple to create API endpoints with various HTTP methods. Let's extend the example by adding a POST endpoint for creating a new item and a PUT endpoint for updating an existing item.

In this example:

- The `create_item` endpoint accepts a POST request with a JSON payload representing an item.

- The `update_item` endpoint accepts a PUT request with a path parameter (`item_id`) and a JSON payload representing the updated item.

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.

- Try to receive input first (add the next 3 blocks code in `main.py` file.

```
from pydantic import BaseModel


# Define a Pydantic model for input data validation
class InputFeatures(BaseModel):
    Year: int
    Engine_Size: float
    Mileage: float
    Type: str
    Make: str
    Options: str
```

```
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 == 'Sta
ndard'
        }
    return dict_f
```

```
@app.get("/predict")
def predict(input_features: InputFeatures):
    return preprocessing(input_features)
```

- In your terminal, run the following request:

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

- Modify **preprocessing** function to do scaling for 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 == 'Sta
ndard'
        }

    # 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. **Create Prediction Endpoint:** Define an API endpoint that receives input data, processes it, and returns predictions made 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 **"Host your ML application.pdf"**

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

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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-using-fastapi-6ab6aef7e777