

# 2- FastAPI Practise

**By:** Saleh Alsaeed  
eng. Esraa Madhi

---

---

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.

---

---

### 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.

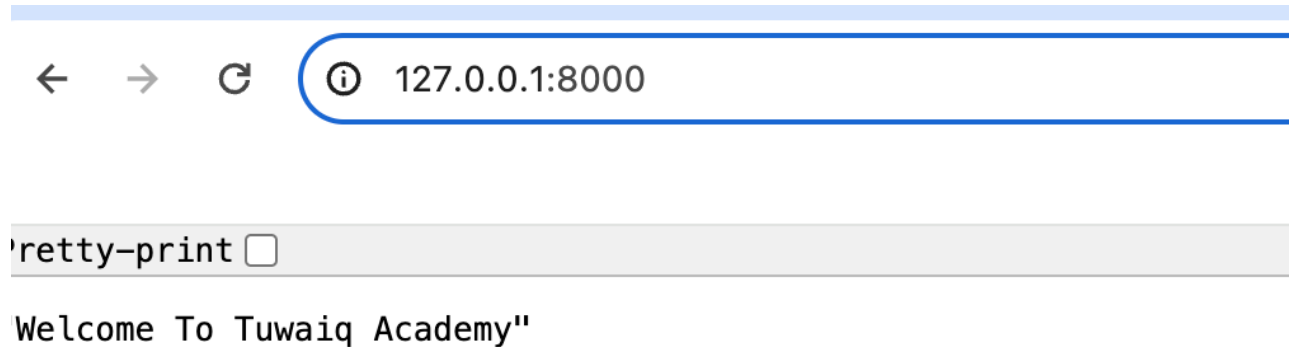
---

### 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.



### 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://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://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>