

# Data Science Intern at Data Glacier

Week 5: Cloud and API Deployment

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## 1. Introduction

In this project, we are going to deploy a machine learning model (SVM) using the Flask Framework. As a demonstration, our model help to recommend a minimum value for a soccer player based on their age and potential. After careful examination, this model is more accurate for players aged 18-28.

We will be building a machine learning model to determine recommended player value, then create an API for the model, using Flask, the Python micro-framework for building web applications. This API requests information (age + potential) from users and gives out the recommended value.

#### 2. Data Information

This data, obtained from Kaggle.com contains the details of 52 professional soccer player and their attributes.

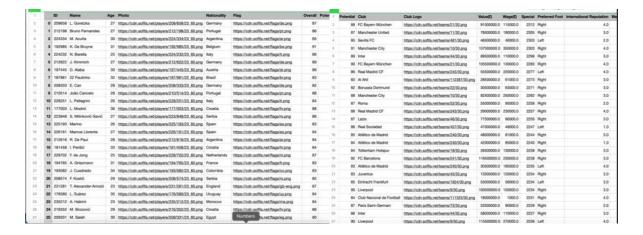


Figure 2.1: Dataset Information

# 3. Building a Model

# 3.1.1 Importing Required Libraries and Dataset

In this part, we import libraires and dataset which contains information of the players

```
In [39]: import numpy as np
import pandas as pd
import packle
from scipy.optimize import curve_fit
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

In []: # Load the FIFA23 dataset
df = pd.read_csv('FIFA23.csv')
```

Figure 3.1.1

# 3.1.2 Data Manipulating

To ensure more accuracy for our model, we filter out players ranging from age 17 (the least age in the data) -28. We also filtered out players with values < 0. These measures ensure a more accurate recommendation from the model.

```
In [130]: # Calculate the sum of Age and Potential to create a new feature
filtered_df['Age_potential'] = filtered_df['Age'] + filtered_df['Potential']

# Prepare the data for exponential curve fit

X = filtered_df['Age_potential'].values.reshape(-1,1)  # x, the addition of both age and potential
y = filtered_df['Value(f)'].values  # y, the result, the calue of the corresponding x
```

Figure 3.1.2

## 3.1.3 Building the Model

After data manipulation, we implemented linear regression on the new dataset from Scikit-learn. After this step, we generated the predicted values

```
In []: # Perform linear regression on the adjusted data
    regressor = LinearRegression()
    regressor.fit(X, y)

# Generate the predicted values
y_pred = regressor.predict(X)
```

Figure 3.1.3

## 3.1.4 Visualizing the Model

After successfully building the model, we formulated a graph to better understand this data and check for any visual trends.

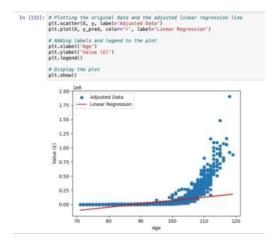


Figure 3.1.4

Figure 3.1.1

# 3.1.5 Saving the Model

After that we save our model using pickle

```
In []: # Save the model to a file
pickle.dump(regressor, open('model.pkl', 'wb'))
model = pickle.load(open('model.pkl', 'rb'))
```

Figure 3.1.5

# 4. Turning Model into Flask Framework

To properly deploy this model, we've created a framework on pycharm which request users age + potential and recommends a value. The files are as follows;

# **4.1 App.py**

The app.py file contains the main code that will be executed by the Python interpreter to run the Flask web application, it included the ML code for classifying SD.

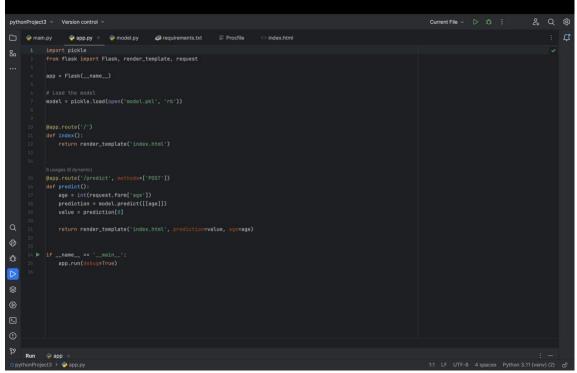


Figure 4.1: App.py

- We ran our application as a single module; thus we initialized a new Flask instance with the argument \_\_name\_\_ to let Flask know that it can find the index.html template folder (templates) in the same directory where it is located.
- Next, we used the route decorator (@app.route('/')) to specify the URL that should trigger the execution of the home function.

- Our *home* function simply rendered the *index.html* HTML file, which is in the *templates* folder.
- Inside the *predict* function, we request users age + potential the deploy the model to execute the collected data.
- Lastly, we used the *run* function to only run the application on the server when this script is directly executed by the Python interpreter, which we ensured using the *if* statement with \*name == ' main '.

#### 4.2 Index.html

The following are the contents of the index.html file that will render a text form where a user can enter a message.

```
| Second | S
```

Figure 3.2: Home.html

• Background Image, pontential.jpg located in static/images contains an image that serves as the background instead of a plain color.

## **5 Running Procedure**

Once we have done all the above, we can start running the API by either double clicking run.

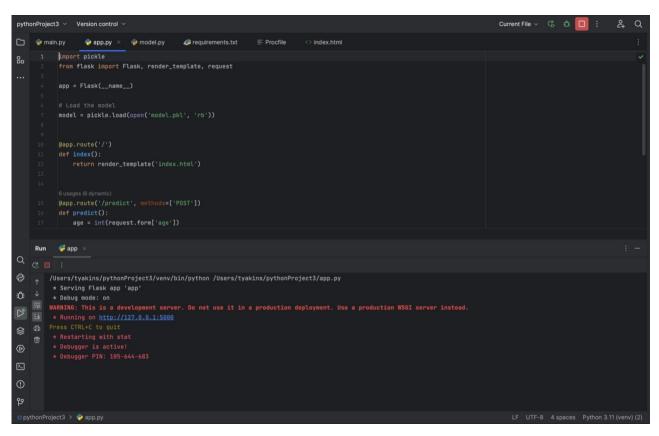


Figure 5.1 Command Execution

Next, we head over to the link provided.

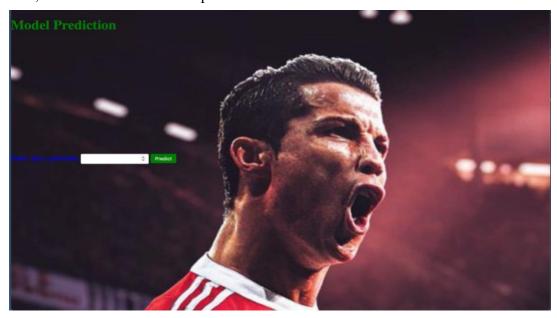


Figure 5.2: Homepage

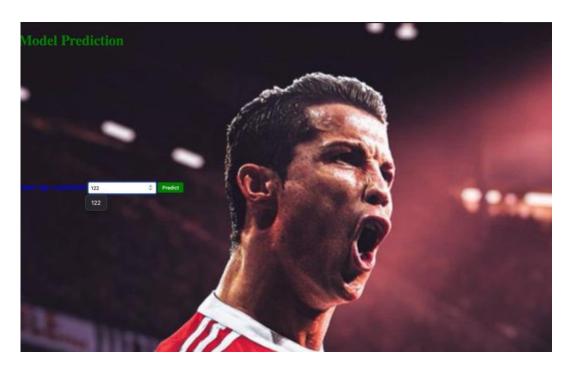


Figure 5.3: Input in The Comments Form

After entering the input click the predict button now, we can the result of our input.

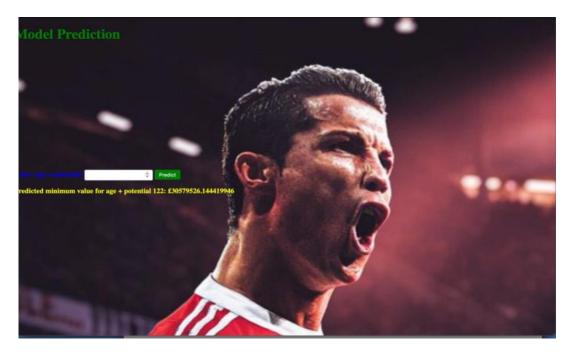


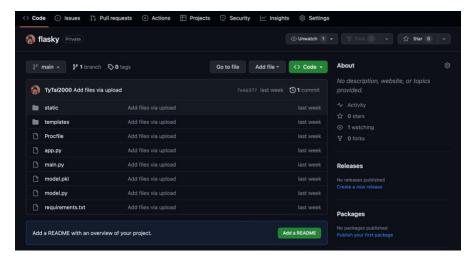
Figure 3.7: Result of Input

# 6. Deploying model using Heroku

Now that our model has been successfully deployed on flask, we are going to deploy it on a Cloud API called Heroku. We are going to upload the required file into a new GitHub repository and connect Heroku to that repo. The steps are below.

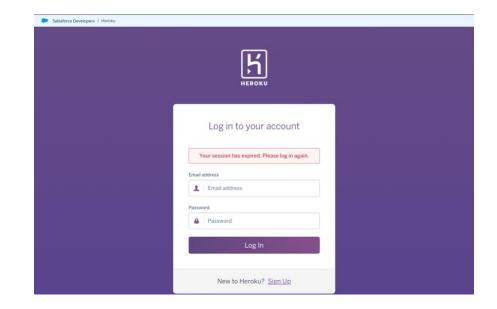
#### 6.1 Uploading file on GitHub

First, we create a GitHub repository and upload the necessary files.

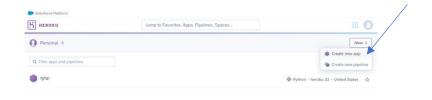


## 6.2 Setting up Heroku.

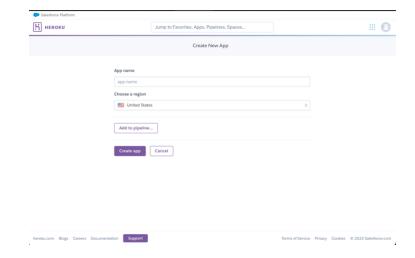
Then we create/login on Heroku.com.



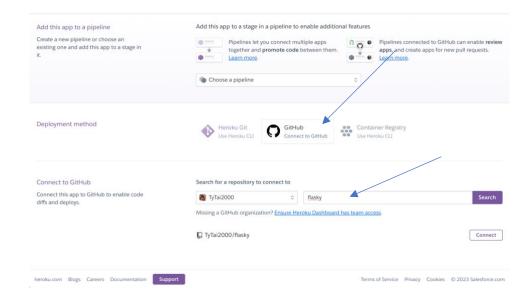
- Then we select create a new app



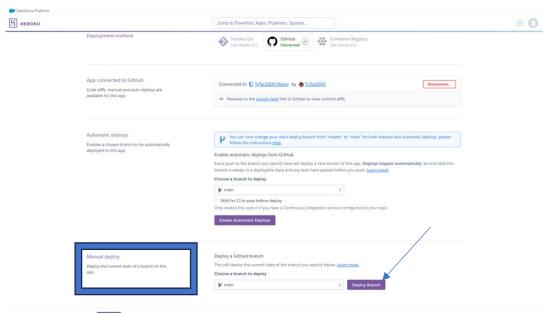
- Add a desired app name



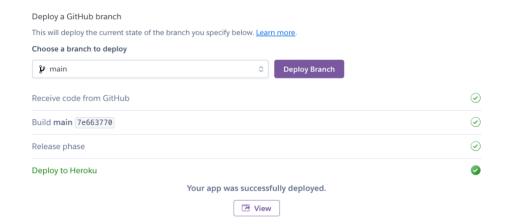
- The we connect GitHub and input the name of the repository from step 1.



- One check to ensure Heroku is ready to be deployed, then we use manual deploy and deploy the branch



- Voila!



- Web app was successfully deployed and can be accessed at <a href="https://tytai-c3bff7d0b412.herokuapp.com">https://tytai-c3bff7d0b412.herokuapp.com</a>