# **Data Glacier Virtual Internship: Week 4-Flask Deployment**

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#### Abstract

Living in an Information Technology age all sectors of economy are thriving on data. The power of data analytics has enabled us to predict outcomes, with insights drawn from powerful data modeling.

This document constitutes the analysis and prediction, projected based on a file that constitutes Car details obtained from an open public source (Kaggle).

The first section of the analysis involves a summary of the Cars data (car data.csv file). The data file comprises of various data elements in its original state that requires the data to be in a clean state to make the data ready for consumption, processing and modelling the data.

Part A of the process is Data Cleansing. This is achieved by removing data not required for analysis, checking for duplicate records, or deleting any erroneous record.

Part B explains the Linear regression model in Jupyter Notebook.

Part C of the process involves creating a web page using HTML that bridges the information to allow you to easily project onto webpages using Python and Flask. Part D summarizes the deployment of the model in Flask app.

### Part A - Data Cleaning and Summarization:

• The downloaded file is a small and simple data set that comprises 8 features (columns) and around 301 observations(rows) of data. The data in the file gives us information about the Car names, year of purchase, the price of purchase, the distance the car has travelled (in kms), fuel type of the car(ex-Petrol/Diesel), the type of seller and Transmission type. This data is made presentable.

```
# Importing the Libraries:
import numpy as np
import pandas as pd
from pandas import Series, DataFrame
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import pylab
import statsmodels.api as sm
import statistics
from scipy import stats
import sklearn
import datetime
from sklearn.model_selection import train_test_split
from sklearn.ensemble.forest import RandomForestRegressor
from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
import warnings
warnings.filterwarnings("ignore", message=r"Passing", category=FutureWarning)
Cardata=pd.read csv("D:\DataGlacier\Week4 Flask\Flask-Deployment\car data.csv",low memory=False)
Cardata
```

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual
296	city	2016	9.50	11.60	33988	Diesel	Dealer	Manual
297	brio	2015	4.00	5.90	60000	Petrol	Dealer	Manual
298	city	2009	3.35	11.00	87934	Petrol	Dealer	Manual
299	city	2017	11.50	12.50	9000	Diesel	Dealer	Manual
300	hrio	2016	5 30	5 90	5/16/	Petrol	Dealer	Manual

- The average Selling and Present price values are 4.6 and 7.6 lakhs respectively. Average distance travelled is 36947.2 kms
- There are no null values but there are 2 records that are duplicates hence we drop the 2 duplicate observations.

```
M Cardata.describe()
:[4]:
                          Selling_Price Present_Price
                                                      Kms_Driven
                                                       301.000000
       count
               301.000000
                            301.000000
                                         301.000000
        mean 2013.627907
                              4.661296
                                           7.628472
                                                     36947.205980
                                                     38886.883882
         std
                 2.891554
                              5.082812
                                           8.644115
         min 2003.000000
                              0.100000
                                           0.320000
                                                       500.000000
         25% 2012.000000
                              0.900000
                                           1.200000
                                                     15000.000000
         50% 2014.000000
                              3.600000
                                           6.400000
                                                     32000.000000
                              6.000000
                                                     48767.000000
         75% 2016.000000
                                           9.900000
         max 2018.000000
                                          92.600000 500000.000000
                             35.000000
   M Cardata.isnull().sum()
[3]: Car_Name
      Year
                         0
      Selling_Price
                         0
      Present_Price
                         0
      Kms Driven
                         0
      Fuel Type
                         0
      Seller_Type
                         0
      Transmission
      dtype: int64
   ▶ Cardata.duplicated().sum()
[5]: 2
   duplicaterows = Cardata[Cardata.duplicated()]
```

[6]:

duplicaterows

93

fortuner 2015

23.00

Car\_NameYearSelling\_PricePresent\_PriceKms\_DrivenFuel\_TypeSeller\_TypeTransmission17ertiga20167.7510.7943000DieselDealerManual

30.61

```
cardata=(Cardata.drop_duplicates())
```

40000

Diesel

Dealer

Automatic

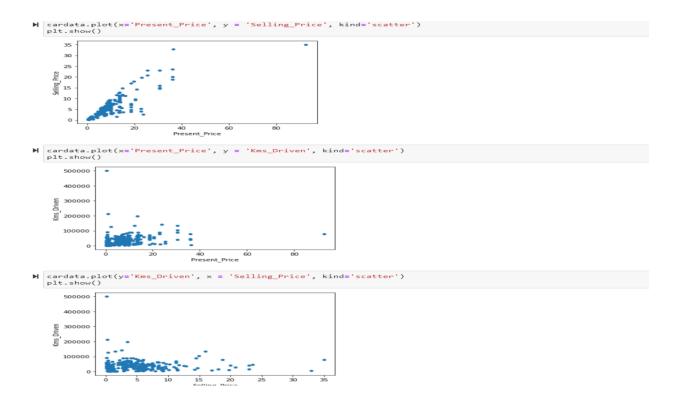
cardata

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual
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3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual
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297	brio	2015	4.00	5.90	60000	Petrol	Dealer	Manual
298	city	2009	3.35	11.00	87934	Petrol	Dealer	Manual
299	city	2017	11.50	12.50	9000	Diesel	Dealer	Manual
300	brio	2016	5.30	5.90	5464	Petrol	Dealer	Manual

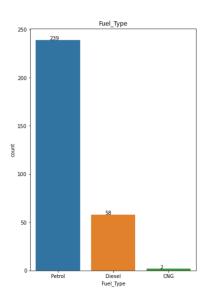
299 rows × 8 columns

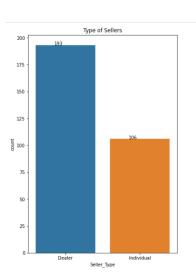
• Features Selling\_price and Present\_price are likely correlated with each other and are skewed to the right.



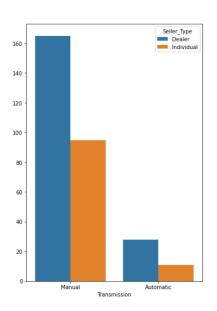


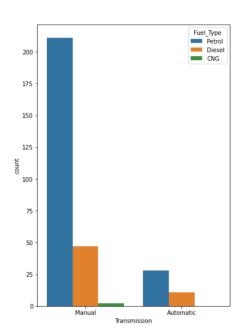
- There are 3 types of fuel (Petrol/Diesel/CNG) and Petrol is highly popular in the fuel used by these used cars.
- Two types of sellers (Dealers and Individuals) and higher number of used cars are mostly sold by Dealers.





• Among the Transmission types of the car Manual cars are highest and popular than automatic cars.





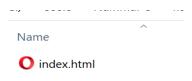
# Part B - Create a model using Linear Regression:

- We identify the numerical independent features to project the predicted values using linear regression.
- Divide the data in training and testing sets and check the shapes of train and test sets.
- Fit a linear regression.
- The r-squared value is 0.88077 Meaning that 88.07% of the variance in 'Selling\_Price' is explained by the independent features(Kms\_Driven, Present\_Price, Transmission etc)
- Saving the regression model using Pickle with file name 'Usedcarpriceprediction2.pkl'.

```
cardata1['Transmission']=[1 if v == 'Manual' else 0 for v in cardata1['Transmission']]
#cardata1 = pd.get_dummies(cardata1 , drop_first=True)
   cardata1.head()
1:
             Selling_Price
                         Present_Price Kms_Driven Fuel_Type
                                                               Seller_Type Transmission
       Year
                                                                                       Age of car
    0 2014
                    3.35
                                  5.59
                                             27000
                                                        Petrol
    1 2013
                     4.75
                                  9.54
                                             43000
                                                        Diesel
                                                                                               10
    2 2017
                     7.25
                                  9.85
                                                                                               6
                                              6900
                                                        Petrol
                                                                                               12
    3 2011
                     2.85
                                              5200
                                  4.15
                                                        Petrol
      2014
                     4.60
                                  6.87
                                             42450
                                                        Diesel
M dataset = cardata1.drop(columns=['Selling_Price', 'Fuel_Type', 'Seller_Type'])
  response = cardata1['Selling_Price']
M X_train, X_test, y_train, y_test = train_test_split(dataset, response, test_size = 0.33,random_state=80)
  print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
  print("Number transactions X_test dataset: ", X_test.shape)
  print("Number transactions y_test dataset: ", y_test.shape)
  Number transactions X_train dataset: (200, 5)
  Number transactions y_train dataset: (200,)
  Number transactions X_test dataset: (99, 5)
  Number transactions y_test dataset: (99,)
  reg=LinearRegression()
  reg.fit(X_test,y_test)
  LinearRegression()
  predict1=reg.predict(X_test)
  r2_score(predict1 , y_test)
  0.8807722889196092
    import pickle
   newfile = open('Usedcarpriceprediction2.pkl','wb')
    pickle.dump(rf,newfile)
   newfile
   <_io.BufferedWriter name='Usedcarpriceprediction2.pkl'>
```

#### Part C -HTML:

- Now, there are 5 features that HTML will have to extract feature values and save it in a list.
- We create a Templates folder and create a page (user form) to bridge the information from the flask app and the user inputs.
- One of the important criteria while creating inputs is to bear in mind that the number attributes passed from the flask and number of input attributes created in the html should **match**, else there will be an error.



- The HTML code starts with creating a form, creating headers like 'User Car price prediction' and sub headers for input fields.
- There are 5 input fields to the form: Year, Present\_Price, Kms\_Driven, Age of the car and Transmission. Each input field has an id associated to make style changes to the fields like font size, styles, padding, color, alignment etc.
- One 'submit' button to calculate the Car price.
- A prediction text to display the final output received from flask app to the user.

```
body {
     background-color: ■rgba(255,255,128,.5);
     text-align: center;
     padding: 0px;
     border-spacing: 0;
     row-gap: 0;
     column-gap: 0;
     gap:0;
 input::placeholder {
      font-size:15px;
      opacity: 0.5;
      color: ■ gray;
      font-style: italic;
#first {
     width: 200px;
     height:30px;
     font-size: +1;
     text-align: center;
     padding: 0%;
     border-spacing: 0;
 #second {
     height:30px;
     width:200px;
     font-size: +1;
     text-align: center;
     padding: 0%;
     border-spacing: 0;
     row-gap: 5;
     column-gap: 5;
```

```
#third {
    height: 30px;
    width:200px;
    font-size: +1;
    text-align: center;
    padding: 0%;
    border-spacing: 0;
    column-gap: 5;
    row-gap: 5;
 #fourth {
    height: 30px;
    width:200px;
    font-size: +1;
    text-align: center;
    padding: 0%;
    border-spacing: 0;
#fifth {
   width: 260px;
    height: 50px;
    text-align: center;
    font-size: +2;
   margin-top:30px;
    font:bolder;
    font-weight: 500px;
    padding: 0%;
    border-spacing: 5px;
#fifth:hover {
    background-color: ■white
#sixth {
    height: 30px;
   width:200px;
   font-size: +1;
    text-align: center;
    padding: 0%;
    border-spacing: 0;
```

# Part D summarizes the deployment of the model in Flask app:

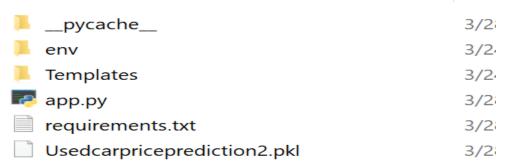
# Steps:

• The first step is to ensure that Flask is installed on the system.

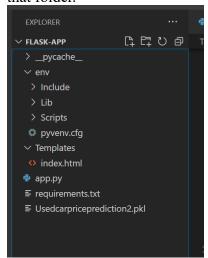
```
\flask-app> pip install flask
```

```
Requirement already satisfied: flask in c:\programdata\anaconda3\lib\site-packages (1.1.2)
Requirement already satisfied: itsdangerous>=0.24 in c:\programdata\anaconda3\lib\site-packages (from flask) (1.1.0)
Requirement already satisfied: Werkzeug>=0.15 in c:\programdata\anaconda3\lib\site-packages (from flask) (1.0.1)
Requirement already satisfied: Jinja2>=2.10.1 in c:\programdata\anaconda3\lib\site-packages (from flask) (2.11.2)
Requirement already satisfied: click>=5.1 in c:\programdata\anaconda3\lib\site-packages (from flask) (7.1.2)
Requirement already satisfied: MarkupSafe>=0.23 in c:\programdata\anaconda3\lib\site-packages (from Jinja2>=2.10.1->flask) (1.1.1
```

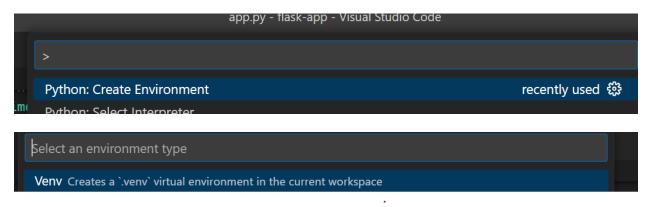
- To work with flask in VSC, I created a folder on the files system where flask is installed by the name "flask-app".
- Now when we run a flask code in the VS it will throw errors because there is no connection between the files on the system and the app.
- This prompts to create a virtual environment for the flask project on the system.



• Launch VSC, open the folder "flask-app", this will load all the files present in that folder.



- A requirements.txt file in Python lets you keep track of the modules and packages used in the projects Simply put, a requirements.txt file is simply a .txt file that This makes it easier to install the required packages.
- However, this caused me a huge issue when numpy was upgraded to 1.24. and faced errors, hence I had to downgrade the numpy version to 1.23.1 to resolve the issues. So, it's important to install and import the right versions.
- Next, I opened the Command Palette (from the View tab) and selected Python: Create Environment and then selected the Venv to create a virtual environment.
- The next step after creating the virtual environment is to start a new Terminal window that activates the virtual environment
- Ensure flask is installed in the virtual environment (python -m pip install flask).



- Checked the working of the flask app through a simple program
  - Import Flask
  - Create the 'app.py' file
- The app.py returns content like a simple string in the below code it is Hello, World!, and the Flask's app.route decorator is used to map the URL route / to the function (at the given port of the server).

```
app.py > ...
1  from flask import Flask
2  app = Flask(__name__)
3
4
5  @app.route("/")
6  def home():
7   return "Hello, World!"
8
9  if __name__=="__main__":
10  app.run(port=5000,debug=True)
11
```

```
Environment: production

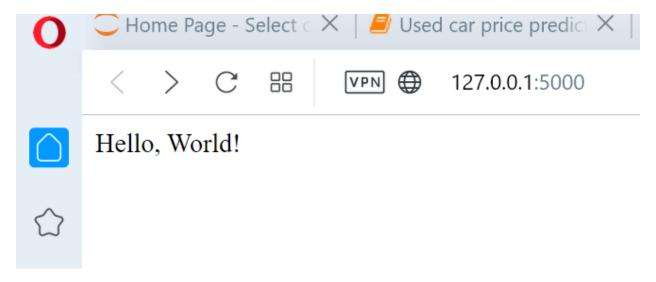
WARNING: This is a development server. Do not use it in a production deployment.

Use a production WSGI server instead.

Debug mode: off

Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
```

#### The output:



• Now that flask is up and running, the used car price prediction model is deployed on the flask app.

# Part D -Used Car price prediction: Deployment on Flask: Steps:

- Import libraries
- Load the flask instance class app.py and the python model through pickle.load method, passing the file object to be read from.
- request- contains all the data sent from the Client to Server. The data is retrieved from the Usedcarpriceprediction2.pkl file loaded earlier.
- Render\_template- The index function renders a template index.html and hence we see the result in the browser.

```
from flask import Flask, render_template, request
import requests
import pickle
import numpy as np
import sklearn
import datetime
from sklearn.preprocessing import StandardScaler

app = Flask(__name__)
model = pickle.load(open('Usedcarpriceprediction2.pkl', 'rb'))
```

- Then created two app.route methods:
- home() -which when run, establishes a connection to the server which displays the index.html webpage to the user.
- predict()-is called when input is fed to the index.html from the user and the final predict button is pressed to display the car prices.

```
@app.route('/')
def home():
    return render_template('index.html')
```

```
@app.route("/predict", methods=['POST'])
def predict():
   if request.method == 'POST':
       Year = int(request.form['Year'])
       Present_Price=float(request.form['Present_Price'])
       Kms_Driven=int(request.form['Kms_Driven'])
       Kms_Driven2=np.log(Kms_Driven)
       Age_of_car=int(request.form['Age of car'])
       Transmission=request.form['Transmission']
       if(Transmission=='Manual'):
           Transmission=1
           Transmission=0
       prediction=model.predict([[Year,Present_Price,Kms_Driven2,Age_of_car,Transmission]])
       output=round(prediction[0],2)
   return render_template('index.html',prediction_text="The price of the car is {} lakhs".format(output))
if __name__=="__main__":
   app.run(port=5000,debug=True)
```

- The data from request can be recovered using the POST methods. POST is used when the application expects the users input to be received by HTTP request.
- The predict() method (/predict) extracts features of the car data those are 5 features-Year, Present\_Price, Kms\_Driven, Age of car and Transmission and using these we will predict the used car price.
- Using these values rendering the template is in use to predict the car values.
- Save the app.py and run the code.

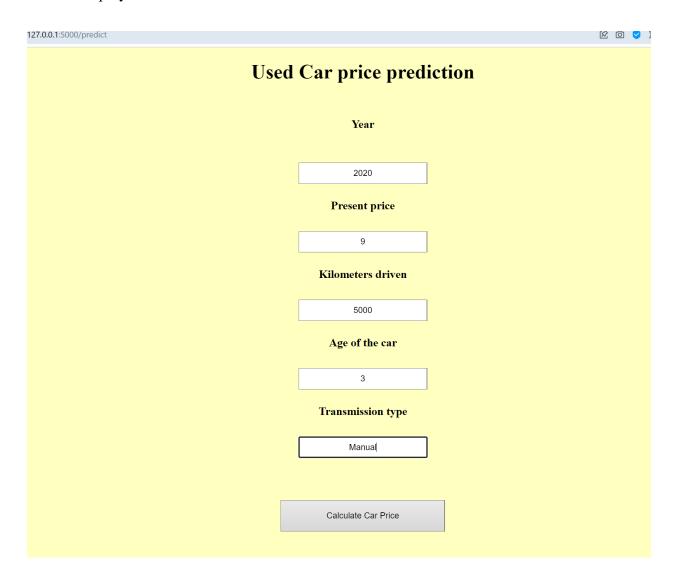
```
* Debug mode: on

* Restarting with windowsapi reloader

* Debugger is

* Debugger PI

* Running on <a href="http://127.0.0.1:5000/">http://127.0.0.1:5000/</a> (Press CTRL+C to quit)
```



127.0.0.1:5000/predict		<u></u> 经			
Used	Car price pred	iction			
	Year				
	уууу				
	Present price				
	in lakhs				
	Kilometers driven				
	Kms travelled				
	Age of the car				
	Car age in years				
	Transmission type				
	Manual/Automatic				
	Calculate Car Price				
The price of the car is 6.52 lakhs					

