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Batch Code: LISUM21  
Submission Date: July 19, 2023  
Submitted to: GitHub

### Step 1: Selected EV data

```
In [5]: print(clean_ev_data)
```

	Brand	Model	AccelSec	TopSpeed_KmH	\
0	Tesla	Model 3 Long Range Dual Motor	4.6	233	
1	Volkswagen	ID.3 Pure	10.0	160	
2	Polestar	2	4.7	210	
3	BMW	iX3	6.8	180	
4	Honda	e	9.5	145	
..	...	...	...	...	...
98	Nissan	Ariya 63kWh	7.5	160	
99	Audi	e-tron S Sportback 55 quattro	4.5	210	
100	Nissan	Ariya e-4ORCE 63kWh	5.9	200	
101	Nissan	Ariya e-4ORCE 87kWh Performance	5.1	200	
102	Byton	M-Byte 95 kWh 2WD	7.5	190	

	Range_Km	Efficiency_WhKm	FastCharge_KmH	RapidCharge	PowerTrain	\
0	450	161	940	Yes	AWD	
1	270	167	250	Yes	RWD	
2	400	181	620	Yes	AWD	
3	360	206	560	Yes	RWD	
4	170	168	190	Yes	RWD	

```
In [6]: print(norm_ev_data)
```

	Brand	Model	Accel	TopSpeed	Range	\
0	Tesla	Model 3 Long Range Dual Motor	4.6 sec	233 km/h	450 km	
1	Volkswagen	ID.3 Pure	10.0 sec	160 km/h	270 km	
2	Polestar	2	4.7 sec	210 km/h	400 km	
3	BMW	iX3	6.8 sec	180 km/h	360 km	
4	Honda	e	9.5 sec	145 km/h	170 km	
..	...	...	...	...	...	...
98	Nissan	Ariya 63kWh	7.5 sec	160 km/h	330 km	
99	Audi	e-tron S Sportback 55 quattro	4.5 sec	210 km/h	335 km	
100	Nissan	Ariya e-4ORCE 63kWh	5.9 sec	200 km/h	325 km	
101	Nissan	Ariya e-4ORCE 87kWh Performance	5.1 sec	200 km/h	375 km	
102	Byton	M-Byte 95 kWh 2WD	7.5 sec	190 km/h	400 km	

	Efficiency	FastCharge	RapidCharge	PowerTrain	\
0	161 Wh/km	940 km/h	Rapid charging possible	All Wheel Drive	
1	167 Wh/km	250 km/h	Rapid charging possible	Rear Wheel Drive	
2	181 Wh/km	620 km/h	Rapid charging possible	All Wheel Drive	
3	206 Wh/km	560 km/h	Rapid charging possible	Rear Wheel Drive	
4	168 Wh/km	190 km/h	Rapid charging possible	Rear Wheel Drive	
..	...	...	...	...	...
98	191 Wh/km	440 km/h	Rapid charging possible	Front Wheel Drive	
99	258 Wh/km	540 km/h	Rapid charging possible	All Wheel Drive	
100	194 Wh/km	440 km/h	Rapid charging possible	All Wheel Drive	
101	232 Wh/km	450 km/h	Rapid charging possible	All Wheel Drive	
102	238 Wh/km	480 km/h	Rapid charging possible	All Wheel Drive	

	PlugType	BodyStyle	Segment	Seats	PriceEuro
0	Type 2 CCS	Sedan	D	5	55480
1	Type 2 CCS	Hatchback	C	5	30000
2	Type 2 CCS	Liftback	D	5	56440
3	Type 2 CCS	SUV	D	5	68040
4	Type 2 CCS	Hatchback	B	4	32997
..	...	...	...	...	...
98	Type 2 CCS	Hatchback	C	5	45000
99	Type 2 CCS	SUV	E	5	96050
100	Type 2 CCS	Hatchback	C	5	50000
101	Type 2 CCS	Hatchback	C	5	65000
102	Type 2 CCS	SUV	E	5	62000

[103 rows x 14 columns]

## Step 2: Saved the Gradient Boosting Regression Model

### Gradient Boosting Regression Model

```
In [11]: # Selected features and target variables to build model around
X = norm_ev_data[['TopSpeed', 'Range']]
y = norm_ev_data['PriceEuro']

In [12]: # Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.5, random_state = 42)

In [13]: # Created and trained the Gradient Boosting Regression model
gbr_model = GradientBoostingRegressor()

# Trained the model using the training data
gbr_model.fit(X_train, y_train)

Out[13]: ▼ GradientBoostingRegressor
GradientBoostingRegressor()

In [14]: # Saved the trained model to a file for Flask deployment
with open('gbr_model.pkl', 'wb') as file:
    pickle.dump(gbr_model, file)

In [15]: # Made predictions on the test set
y_pred = gbr_model.predict(X_test)

# Calculated the mean squared error and R-squared score
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print the evaluation metrics
print('Mean Squared Error:', mse)
print('R-squared Score:', r2)

Mean Squared Error: 998166209.4394575
R-squared Score: 0.09532714133017783

In [16]: plt.figure(figsize=(12, 5))

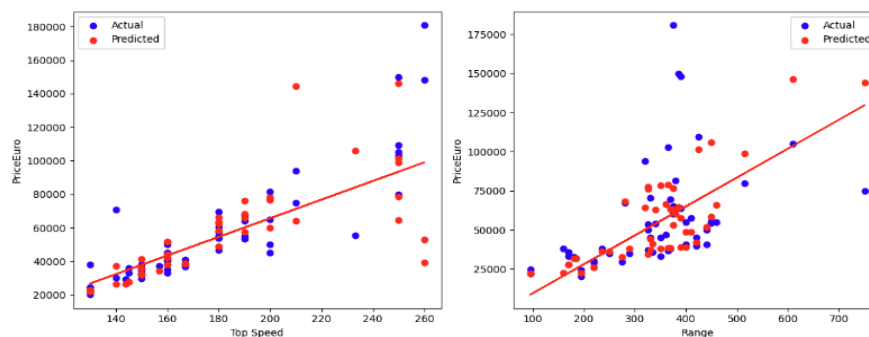
# Scatter plot for TopSpeed vs PriceEuro
plt.subplot(1, 2, 1)
plt.scatter(X_test['TopSpeed'], y_test, color='blue', label='Actual')
plt.scatter(X_test['TopSpeed'], y_pred, color='red', label='Predicted')
plt.xlabel('Top Speed')
plt.ylabel('PriceEuro')
plt.legend()

# Added the trend line for TopSpeed vs PriceEuro
trend_line_top_speed = np.polyfit(X_test['TopSpeed'], y_pred, 1)
plt.plot(X_test['TopSpeed'], np.polyval(trend_line_top_speed, X_test['TopSpeed']), color='red')

# Scatter plot for Range vs PriceEuro
plt.subplot(1, 2, 2)
plt.scatter(X_test['Range'], y_test, color='blue', label='Actual')
plt.scatter(X_test['Range'], y_pred, color='red', label='Predicted')
plt.xlabel('Range')
plt.ylabel('PriceEuro')
plt.legend()

# Added the trend line for Range vs PriceEuro
trend_line_range = np.polyfit(X_test['Range'], y_pred, 1)
plt.plot(X_test['Range'], np.polyval(trend_line_range, X_test['Range']), color='red')

plt.tight_layout()
plt.show()
```



Deployed the model on to Flask app called “Par\_App”

```
from flask import Flask, request, jsonify

app = Flask('Par_App')

# Load the trained model
with open('gbr_model.pkl', 'rb') as file:
    gbr_model = pickle.load(file)

# Define an API endpoint for predictions
@app.route('/predict', methods=['POST'])
def predict():
    data = request.get_json()
    top_speed = data['TopSpeed']
    range_km = data['Range']
    prediction = gbr_model.predict([[top_speed, range_km]])
    return jsonify({'prediction': float(prediction[0])})

if __name__ == '__main__':
    app.run(debug = True, port = 9000)
```

```
* Serving Flask app 'Par_App'
* Debug mode: on
```

```
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
```

```
* Running on http://127.0.0.1:9000
```