Aishat Abdulgafar

This research intends to focus on developing a machine learning model that can forecast the price of a car using machine learning. I plan to use this work to investigate a linear regression model for predicting market car prices. The iterative nature of machine learning is significant because models may autonomously evolve as they are exposed to fresh data. They use past computations to make consistent, repeatable judgments and results. It's not a new science, but it's gaining ground. While there are several real-world applications of machine learning, one of the most recognized is prediction problems.

Objective

- To build a supervised machine learning model for forecasting the price of a car based on multiple attributes.
- Providing graphical comparisons to provide a better view.

Machine Learning Model

I will be utilizing Jupyter python for the implementation of machine learning concepts and the reason is because of the numerous inbuilt methods in the form of package libraries present in python. This research will be a supervised learning algorithm that will utilize different models that will predict the car price given new instances. Assessing the model's input data quality enhances system performance and creates the most accurate predictions possible.

How your solution

I plan on implementing a scalable model for predicting the car price prediction using some of the regression techniques based on some of the features in the dataset.

Supervised/unsupervised learning

This is a supervised learning algorithm.

How would your performance be measured?

The major aim of this project is to predict car prices based on the features using some of the regression techniques and algorithms.

Does the performance align with the measured objectives

yes

This project aims to detect features that impact predicting the price of used cars, and experiments are performed to investigate an optimal algorithm for price prediction of used cars. The algorithms selected for experimenting are Linear Regression (LR), Light Gradient Boosted Machine (LGBM), Random Forest Regression (RFR), and Decision Tree Regression (DTR). These algorithms are further compared using performance metrics of regression models

Get the data.

The dataset suitable for this study was gotten from Kaggle and I applied the preprocessing techniques to the data.

2. Get the Data

In [2]:
```
car_data = pd.read_csv("Car_Price_datasets.csv")
car_data.head()
```

Out[2]:

	Unnamed: 0	price	brand	model	year	title_status	mileage	color	vin	lot	state	country	condition
0	0	6300	toyota	cruiser	2008	clean vehicle	274117.0	black	jtezu11f88k007763	159348797	new jersey	usa	10 days left
1	1	2899	ford	se	2011	clean vehicle	190552.0	silver	2fmdk3gc4bbb02217	166951262	tennessee	usa	6 days left
2	2	5350	dodge	mpv	2018	clean vehicle	39590.0	silver	3c4pdcgg5jt346413	167655728	georgia	usa	2 days left
3	3	25000	ford	door	2014	clean vehicle	64146.0	blue	1ftfw1et4efc23745	167753855	virginia	usa	22 hours left
4	4	27700	chevrolet	1500	2018	clean vehicle	6654.0	red	3gcpcrec2jg473991	167763266	florida	usa	22 hours left

In [3]:
```
car_data
```

Out[3]:

	Unnamed: 0	price	brand	model	year	title_status	mileage	color	vin	lot	state	country	condition
0	0	6300	toyota	cruiser	2008	clean vehicle	274117.0	black	jtezu11f88k007763	159348797	new jersey	usa	10 days left
1	1	2899	ford	se	2011	clean vehicle	190552.0	silver	2fmdk3gc4bbb02217	166951262	tennessee	usa	6 days left
2	2	5350	dodge	mpv	2018	clean vehicle	39590.0	silver	3c4pdcgg5jt346413	167655728	georgia	usa	2 days left
3	3	25000	ford	door	2014	clean vehicle	64146.0	blue	1ftfw1et4efc23745	167753855	virginia	usa	22 hours left
4	4	27700	chevrolet	1500	2018	clean vehicle	6654.0	red	3gcpcrec2jg473991	167763266	florida	usa	22 hours left
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2494	2494	7800	nissan	versa	2019	clean vehicle	23609.0	red	3n1cn7ap9kl880319	167722715	california	usa	1 days left
2495	2495	9200	nissan	versa	2018	clean vehicle	34553.0	silver	3n1cn7ap5jl884088	167762225	florida	usa	21 hours left
2496	2496	9200	nissan	versa	2018	clean vehicle	31594.0	silver	3n1cn7ap9jl884191	167762226	florida	usa	21 hours left
2497	2497	9200	nissan	versa	2018	clean vehicle	32557.0	black	3n1cn7ap3jl883263	167762227	florida	usa	2 days left
2498	2498	9200	nissan	versa	2018	clean vehicle	31371.0	silver	3n1cn7ap4jl884311	167762228	florida	usa	21 hours left

2499 rows × 13 columns

Explore the data to gain insights.

3. Exploring the Data

In [4]:
```
car_data.shape
```
Out[4]:
```
(2499, 13)
```

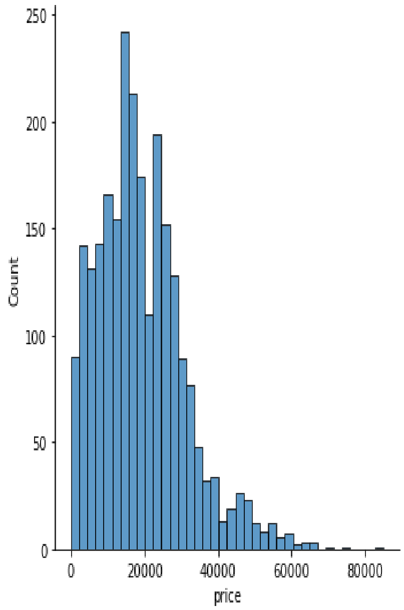
In [5]:
```
car_data.min()
```
Out[5]:
```
Unnamed: 0                      0
price                           0
brand                       acura
model                        1500
year                         1973
title_status        clean vehicle
mileage                       0.0
color                       beige
vin             19uua96529a004646
lot                     159348797
state                     alabama
country                    canada
condition             1 days left
dtype: object
```

In [6]:
```
car_data.info
```
Out[6]:
```
<bound method DataFrame.info of       Unnamed: 0  price      brand    model  year   title_status   mileage  \
0              0   6300     toyota  cruiser  2008  clean vehicle  274117.0
1              1   2899       ford       se  2011  clean vehicle  190552.0
2              2   5350      dodge      mpv  2018  clean vehicle   39590.0
3              3  25000       ford     door  2014  clean vehicle   64146.0
4              4  27700  chevrolet     1500  2018  clean vehicle    6654.0
...          ...    ...        ...      ...   ...            ...       ...
2494        2494   7800     nissan    versa  2019  clean vehicle   23609.0
2495        2495   9200     nissan    versa  2018  clean vehicle   34553.0
2496        2496   9200     nissan    versa  2018  clean vehicle   31594.0
2497        2497   9200     nissan    versa  2018  clean vehicle   32557.0
2498        2498   9200     nissan    versa  2018  clean vehicle   31371.0

       color                  vin        lot       state country  \
0      black    jtezu11f88k007763  159348797  new jersey     usa
1     silver    2fmdk3gc4bbb02217  166951262   tennessee     usa
2     silver    3c4pdcgg5jt346413  167655728     georgia     usa
3       blue    1ftfw1et4efc23745  167753855    virginia     usa
```

In [6]:
```
car_data.info
```
Out[6]:
```
<bound method DataFrame.info of       Unnamed: 0  price      brand    model  year   title_status   mileage  \
0              0   6300     toyota  cruiser  2008  clean vehicle  274117.0
1              1   2899       ford       se  2011  clean vehicle  190552.0
2              2   5350      dodge      mpv  2018  clean vehicle   39590.0
3              3  25000       ford     door  2014  clean vehicle   64146.0
4              4  27700  chevrolet     1500  2018  clean vehicle    6654.0
...          ...    ...        ...      ...   ...            ...       ...
2494        2494   7800     nissan    versa  2019  clean vehicle   23609.0
2495        2495   9200     nissan    versa  2018  clean vehicle   34553.0
2496        2496   9200     nissan    versa  2018  clean vehicle   31594.0
2497        2497   9200     nissan    versa  2018  clean vehicle   32557.0
2498        2498   9200     nissan    versa  2018  clean vehicle   31371.0

       color                  vin        lot       state country  \
0      black    jtezu11f88k007763  159348797  new jersey     usa
1     silver    2fmdk3gc4bbb02217  166951262   tennessee     usa
2     silver    3c4pdcgg5jt346413  167655728     georgia     usa
3       blue    1ftfw1et4efc23745  167753855    virginia     usa
4        red    3gcpcrec2jg473991  167763266     florida     usa
...      ...                  ...        ...         ...     ...
2494     red    3n1cn7ap9kl880319  167722715  california     usa
2495  silver    3n1cn7ap5jl884088  167762225     florida     usa
2496  silver    3n1cn7ap9jl884191  167762226     florida     usa
2497   black    3n1cn7ap3jl883263  167762227     florida     usa
2498  silver    3n1cn7ap4jl884311  167762228     florida     usa

          condition
0      10 days left
1       6 days left
2       2 days left
3     22 hours left
4     22 hours left
...             ...
2494    1 days left
2495  21 hours left
2496  21 hours left
2497    2 days left
2498  21 hours left

[2499 rows x 13 columns]>
```

In [31]:
```
sns.displot(car_data['price'])
```

Out[31]: <seaborn.axisgrid.FacetGrid at 0x2437ab66cd0>



Prepare the data to better expose the underlying data patterns to Machine Learning algorithms.

4. Prepare the Data

Data Cleaning

In [10]:
```
#Dropping the unnecessary columns and data
drop_columns = ['Unnamed: 0', 'condition', 'vin', 'lot']
```

In [11]:
```
car_data = car_data.drop(drop_columns, axis = 1)
```

In [12]:
```
car_data.head()
```

Out[12]:

	price	brand	model	year	title_status	mileage	color	state	country
0	6300	toyota	cruiser	2008	clean vehicle	274117.0	black	new jersey	usa
1	2899	ford	se	2011	clean vehicle	190552.0	silver	tennessee	usa
2	5350	dodge	mpv	2018	clean vehicle	39590.0	silver	georgia	usa
3	25000	ford	door	2014	clean vehicle	64146.0	blue	virginia	usa
4	27700	chevrolet	1500	2018	clean vehicle	6654.0	red	florida	usa

In [13]:
```
car_data.loc[car_data['price'] < 500].head()
```

Out[13]:

	price	brand	model	year	title_status	mileage	color	state	country
141	0	dodge	van	2008	salvage insurance	177948.0	orange	utah	usa
144	0	dodge	door	2014	salvage insurance	123660.0	silver	utah	usa
188	175	chrysler	door	2000	salvage insurance	231240.0	red	north carolina	usa
196	0	ford	mpv	2017	clean vehicle	76858.0	white	texas	usa
206	25	chevrolet	vehicl	2020	salvage insurance	7232.0	black	kentucky	usa

In [14]:
```
car_data = car_data.drop(car_data.loc[car_data['price'] == car_data['price'].min()].index)
```

In [15]:
```
for column in car_data.columns:
    print(ascii(car_data[column][0]))
```

6300

In [15]:
```
for column in car_data.columns:
    print(ascii(car_data[column][0]))
```

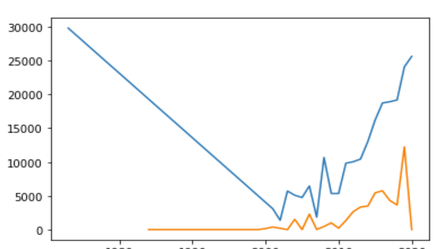

```
6300
'toyota'
'cruiser'
2008
'clean vehicle'
274117.0
'black'
'new jersey'
' usa'
```

In [16]:
```
car_data['country'] = car_data['country'].apply(lambda x:x.replace(" ", ""))
ascii(car_data['country'][1])
```

Out[16]: "'usa'"

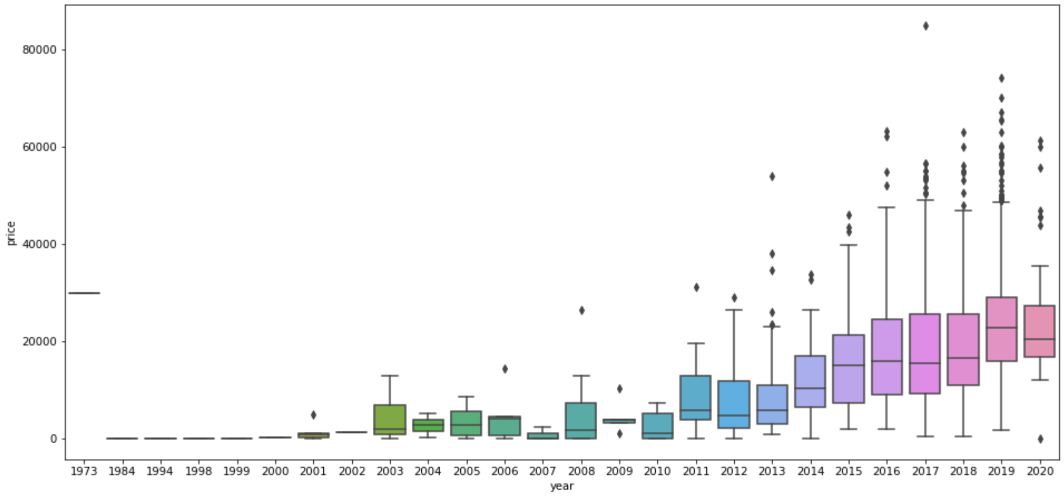
In [17]:
```
car_data_gb = deepcopy(car_data)
avg_cost = car_data_gb.groupby(by=["title_status", "year"])['price'].mean()
plt.plot(avg_cost['clean vehicle'], label = "clean")
plt.plot(avg_cost['salvage insurance'], label = "damaged")
```

Out[17]: [<matplotlib.lines.Line2D at 0x2a3d77cdc70>]



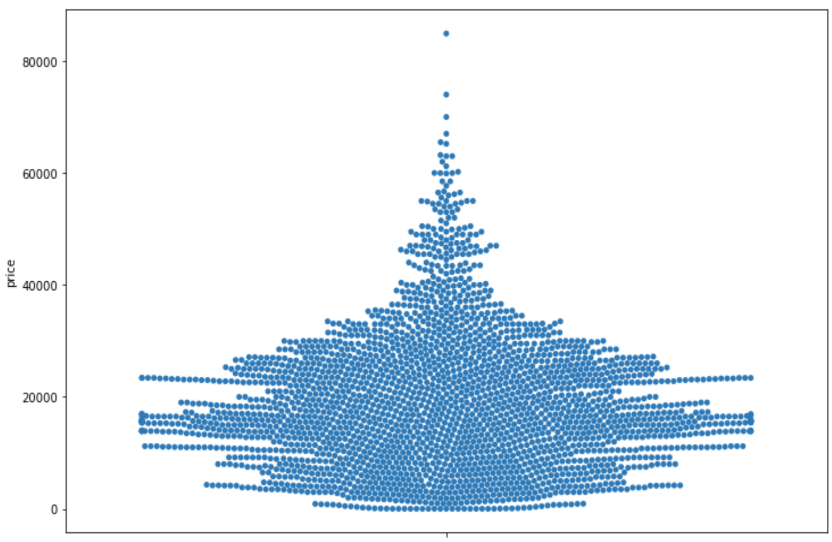
In [18]:

```
car_data_pnr = car_data[['price', 'year']]
fig, ax = plt.subplots(figsize=(16, 8))
fig = sns.boxplot(x=car_data['year'], y=car_data['price'])
```



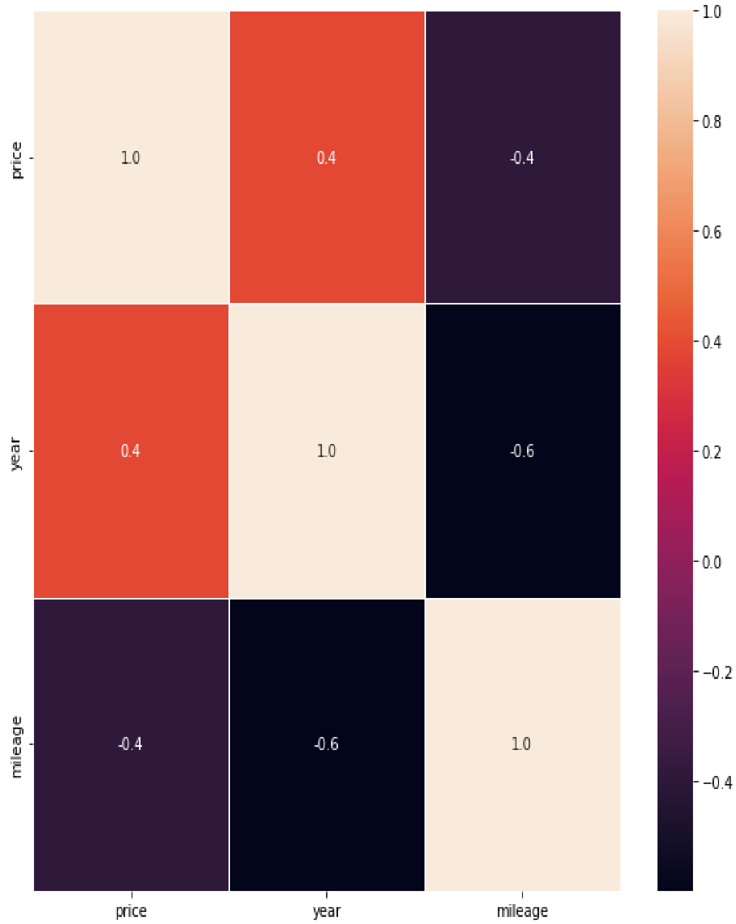
In [19]:

```
plt.rcParams['figure.figsize']=(12,8)
sns.swarmplot(y=car_data["price"]);
```



In [20]:

```
f,ax = plt.subplots(figsize=(10, 10))
sns.heatmap(car_data.corr(), annot=True, linewidths=.5, fmt= '.1f',ax=ax)
plt.show()
```



Explore many different models and shortlist the best ones and fine-tune your models and combine them into a great solution.

Machine Learning Models and Training

In [21]:
```
from copy import deepcopy
from sklearn import preprocessing
data_ml = deepcopy(car_data)

X = data_ml.drop(["title_status"], axis = 1)
y = data_ml['title_status']

color_encoder = preprocessing.OrdinalEncoder()
color_encoded = color_encoder.fit(X)
color_encoded = color_encoded.fit_transform(X)
X = color_encoded
X
```

Out[21]:
```
array([[165.,  27.,  25., ...,   2.,  24.,   1.],
       [ 57.,   8.,  92., ...,  37.,  35.,   1.],
       [138.,   7.,  75., ...,  37.,   7.,   1.],
       ...,
       [233.,  24., 119., ...,  37.,   6.,   1.],
       [233.,  24., 119., ...,   2.,   6.,   1.],
       [233.,  24., 119., ...,  37.,   6.,   1.]])
```

In [22]:
```
y = y.apply(lambda x: 0 if x == "clean vehicle" else 1)
y
```

Out[22]:
```
0       0
1       0
2       0
3       0
4       0
       ..
2494    0
2495    0
2496    0
2497    0
2498    0
Name: title_status, Length: 2456, dtype: int64
```

In [23]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
print(X_train.shape, y_train.shape)
```

```
(1964, 8) (1964,)
```

In [24]:
```
log = LogisticRegression()
log.fit(X_train, y_train)
```

```
C:\Users\Aishat\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:763: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[24]:
```
LogisticRegression()
```

In [25]:
```
print(log.score(X_test, y_test))
```

```
0.9654471544715447
```

In [26]:
```
# To view the coefficients
log.coef_
```

Out[26]:
```
array([[-1.60545256e-02,  2.54306918e-02, -1.07047510e-02,
        -9.88224188e-02,  6.09209552e-04, -6.24430067e-04,
        -1.88673662e-02,  8.43607169e-01]])
```

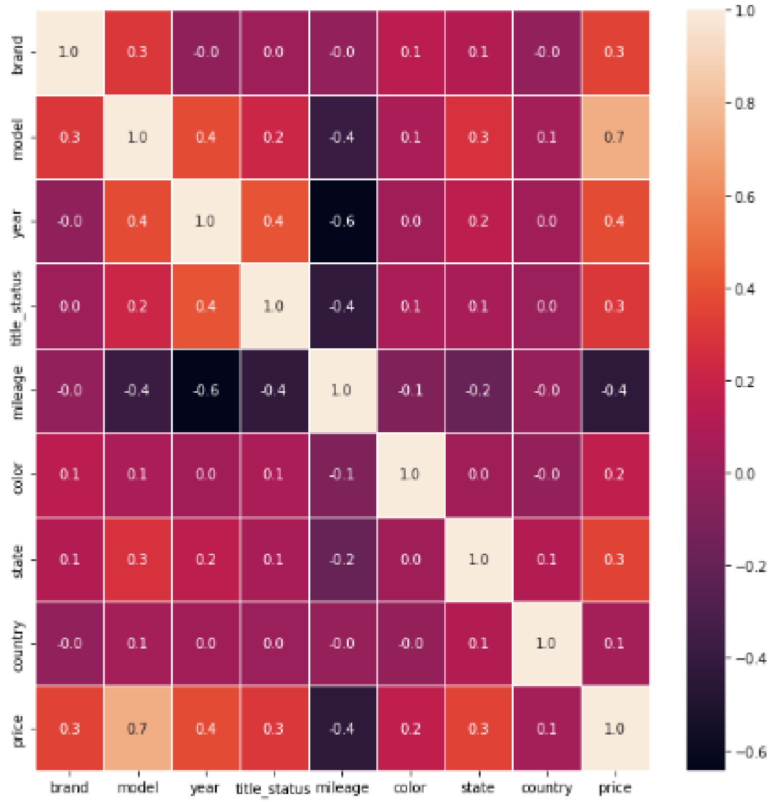
In [27]:
```
categorical_features=[feature for feature in car_data.columns if car_data[feature].dtype=='O']

numerical_features=[feature for feature in car_data.columns if car_data[feature].dtype!='O']
```

In [28]:

```
X=car_data.drop('price',axis=1)
y=car_data['price']

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_state=0)

train_set=pd.concat([X_train,y_train],axis=1)
test_set=pd.concat([X_test,y_test],axis=1)
```

In [29]:

```
for feature in categorical_features:
    feature_labels=train_set.groupby(feature)['price'].mean().sort_values().index
    feature_labels={k:i for i,k in enumerate(feature_labels,0)}
    train_set[feature]=train_set[feature].map(feature_labels)
    test_set[feature]=test_set[feature].map(feature_labels)

test_set.dropna(inplace=True)

scaler=StandardScaler()

scaled_X_train=pd.DataFrame(scaler.fit_transform(train_set.drop('price',axis=1)), columns=X_train.columns)
scaled_X_train.index=train_set.index
scaled_X_test=pd.DataFrame(scaler.transform(test_set.drop('price',axis=1)), columns=X_test.columns)
scaled_X_test.index=test_set.index
scaled_train=pd.concat([scaled_X_train,train_set['price']],axis=1)
scaled_test=pd.concat([scaled_X_test,test_set['price']],axis=1)
X_train=scaled_train.drop('price',axis=1)
y_train=scaled_train['price']
X_test=scaled_test.drop('price',axis=1)
y_test=scaled_test['price']

f,ax = plt.subplots(figsize=(10, 10))
sns.heatmap(scaled_train.corr(), annot=True, linewidths=.5, fmt= '.1f',ax=ax)
plt.show()
```



In [30]:
```
def try_model(model):
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)
    pd.DataFrame(y_pred)
    return 'Model Testing Accurancy: ', r2_score(y_test, y_pred)
```

In [31]:
```
neigh = KNeighborsRegressor(n_neighbors=6)
try_model(neigh)
```

Out[31]: ('Model Testing Accurancy: ', 0.6057170996784735)

In [32]:
```
forest = RandomForestRegressor(max_depth=50, random_state=1)
try_model(forest)
```

Out[32]: ('Model Testing Accurancy: ', 0.6379092698912274)

In [33]:
```
XGB = XGBRegressor(n_estimators=500, max_depth=20, eta=0.1, subsample=0.7, colsample_bytree=0.8)
try_model(XGB)
```

Out[33]: ('Model Testing Accurancy: ', 0.6286777276250803)

There has been a consistent increase in the used cars industry over the past decade as there is an increase in the usage of cars. Used cars are attracting more attention as they are more affordable than new ones. This situation demands high-performance algorithms that can be used to predict prices for used cars.

I was able to build a supervised machine-learning model for forecasting the price of a used car based on multiple attributes. I also provided some interesting graphs for comparisons to provide a better view.

In my research study the following:

I found out that Mercedes-Benz has the highest price.

In [7]:
```
car_data.sort_values("price")
```

Out[7]:

	Unnamed: 0	price	brand	model	year	title_status	mileage	color	vin	lot	state	country	condition
410	410	0	chevrolet	door	1995	salvage insurance	274706.0	green	2gcec19h8s1195266	167425634	arizona	usa	2 days left
330	330	0	ford	door	1996	salvage insurance	296860.0	green	1falp62w5th144314	167359712	california	usa	19 hours left
331	331	0	ford	door	2006	salvage insurance	203158.0	red	1fmzk04136ga07119	167610991	illinois	usa	17 hours left
339	339	0	ford	door	2002	salvage insurance	214800.0	black	3fafp37372r151014	167360232	south carolina	usa	2 days left
496	496	0	ford	pickup	1996	salvage insurance	252588.0	red	1ftef15n0tlc14455	167357804	oklahoma	usa	17 hours left
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1215	1215	65500	ford	srw	2019	clean vehicle	6500.0	black	1ft7w2bt0kec44818	167718954	indiana	usa	21 hours left
277	277	67000	dodge	challenger	2019	clean vehicle	10944.0	blue	2c3cdzl97kh518237	167759490	ohio	usa	21 hours left
1336	1336	70000	ford	drw	2019	clean vehicle	9643.0	no_color	1ft8w3dt3kee48276	167780680	illinois	usa	2 days left
1340	1340	74000	ford	drw	2019	clean vehicle	10536.0	no_color	1ft8w4dt6ked32656	167780682	illinois	usa	2 days left
502	502	84900	mercedes-benz	sl-class	2017	clean vehicle	25302.0	silver	wddjk7ea3hf044968	167607883	florida	usa	2 days left

2499 rows × 13 columns

Ford has a 56.68% probability of a price more than the average price for all cars

Probability that FORD car brand has a higher price than the average price for all cars?

In [8]:
```
print(round(car_data[(car_data['brand']=='ford') & (car_data['price'] > car_data['price'].mean())].shape[0] / car_data[car_d
```

```
56.68 %
```

I also found out that black, grey, and green are the most popular colors for the cheapest cars

The most popular color in the cheapest cars?

In [9]:
```
car_data[car_data['price'] == car_data['price'].min()]['color'].value_counts()
```

Out[9]:
```
black         6
gray          6
green         6
white         5
red           5
silver        4
blue          4
orange        2
gold          2
maroon        1
yellow        1
light blue    1
Name: color, dtype: int64
```

Summary

A multiple linear regression model was used which is characterized by more than 1 independent variable. After deciding upon the data preparation, we finally come to the model building part wherein the final model is built using 6 different features as shown in the figure and we get the value of r2-squared to be 0.8851 which tends the model to have an accuracy of 88.51% in the model, we must ensure to test that the error terms are always normally distributed having to mean equal to zero, with less correlation with the predictors and lastly, the variance of the error terms must be constant. We then plot the error terms. Thus, we come to know that the conclusion is the initial predictor value of correlation.