Reading the data

```
!git clone https://github.com/alexeygrigorev/mlbookcamp-code
```

```
fatal: destination path 'mlbookcamp-code' already exists and is not an empty directory.
```

```
import pandas as pd
import numpy as np
import seaborn as sns
sns.set()
from matplotlib import pyplot as plt
%matplotlib inline
```

```
df = pd.read_csv('/content/mlbookcamp-code/chapter-02-car-price/data.csv')
```

```
#Length of the data
len(df)
```

```
11914
```

```
#Seeing the first '3' rows of the data
df.head(3)
```

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors	Market Category	Vehicle Size	Vehicle Style	highwa MF
0	BMW	1 Series M	2011	premium unleaded (required)	335.00	6.00	MANUAL	rear wheel drive	2.00	Factory Tuner,Luxury,High-Performance	Compact	Coupe	2
1	BMW	1 Series	2011	premium unleaded (required)	300.00	6.00	MANUAL	rear wheel drive	2.00	Luxury,Performance	Compact	Convertible	2
2	BMW	1	2011	premium unleaded	300.00	6.00	MANUAL	rear wheel drive	2.00	Luxury,High-	Compact	Coupe	2

Étapes suivantes : Générer du code avec df Afficher les graphiques recommandés New interactive sheet

```
#Seeing the last '3' rows of the data
df.tail(3)
```

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors	Market Category	Vehicle Size
11911	Acura	ZDX	2012	premium unleaded (required)	300.00	6.00	AUTOMATIC	all wheel drive	4.00	Crossover,Hatchback,Luxury	Midsize
11912	Acura	ZDX	2013	premium unleaded (recommended)	300.00	6.00	AUTOMATIC	all wheel drive	4.00	Crossover,Hatchback,Luxury	Midsize
11913	Lincoln	Zephyr	2006	regular unleaded	221.00	6.00	AUTOMATIC	front wheel drive	4.00	Luxury	Midsize

```
#Observing th columns of our dataset
df.columns
```

```
Index(['Make', 'Model', 'Year', 'Engine Fuel Type', 'Engine HP',
       'Engine Cylinders', 'Transmission Type', 'Driven_Wheels',
       'Number of Doors', 'Market Category', 'Vehicle Size', 'Vehicle Style',
       'highway MPG', 'city mpg', 'Popularity', 'MSRP'],
      dtype='object')
```

```
#Checking the number of columns without the need to count them one by one
len(df.columns)
```

```
16
```

As we see this dataset contains multiple columns: **make**: brand of the car (BMW,Toyota..)

model:model of a car.

year:year when the car was manifactured.

engine_fuel-type:type of the fuel the engine needs (diesel,electric..)

engine_hp:horsepower of the engine.

engine_cylindre:number of cylindres in the egine.

transmission_type:type of transmission (automatic or manual)

driven_wheels:front,rear,all.

number_of_doors:number of doors a car has.

market_category:luxury,crossover,..

vehicule_size:compact,midsize or large.

vehicule_style:sedan or convertible.

highway_mpg:miles per gallon (mpg) on the highway.

city_mpg:miles per gallon in the city.

popularity:number of times the car was mentioned in a Twitter stream.

msrp:manufacturer's suggested retail price.

```
#Getting a general info about the dataset such as types and null values for each column
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11914 entries, 0 to 11913
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Make               11914 non-null  object 
 1   Model              11914 non-null  object 
 2   Year               11914 non-null  int64  
 3   Engine Fuel Type   11911 non-null  object 
 4   Engine HP          11845 non-null  float64
 5   Engine Cylinders   11884 non-null  float64
 6   Transmission Type  11914 non-null  object 
 7   Driven_Wheels      11914 non-null  object 
 8   Number of Doors    11908 non-null  float64
 9   Market Category    8172 non-null   object 
 10  Vehicle Size       11914 non-null  object 
 11  Vehicle Style      11914 non-null  object 
 12  highway MPG        11914 non-null  int64  
 13  city mpg           11914 non-null  int64  
 14  Popularity         11914 non-null  int64  
 15  MSRP               11914 non-null  int64  
dtypes: float64(3), int64(5), object(8)
memory usage: 1.5+ MB
```

```
for col in df.columns:
  print(col , "has: ", df[col].nunique() , " values")
  print(df[col].value_counts().nlargest())
  print("\n","*"*20,"\n")
```

```
 ********************

Vehicle Style has:  16  values
Vehicle Style
Sedan            3048
4dr SUV          2488
Coupe            1211
Convertible       793
4dr Hatchback     702
Name: count, dtype: int64

 ********************

highway MPG has:  59  values
highway MPG
24    876
23    801
26    778
22    753
25    731
Name: count, dtype: int64

 ********************

city mpg has:  69  values
city mpg
17    1230
16    1106
```

Some Cleaning

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11914 entries, 0 to 11913
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Make               11914 non-null  object 
 1   Model              11914 non-null  object 
 2   Year               11914 non-null  int64  
 3   Engine Fuel Type   11911 non-null  object 
 4   Engine HP          11845 non-null  float64
 5   Engine Cylinders   11884 non-null  float64
 6   Transmission Type  11914 non-null  object 
 7   Driven_Wheels      11914 non-null  object 
 8   Number of Doors    11908 non-null  float64
 9   Market Category    8172 non-null   object 
 10  Vehicle Size       11914 non-null  object 
 11  Vehicle Style      11914 non-null  object 
 12  highway MPG        11914 non-null  int64  
 13  city mpg           11914 non-null  int64  
 14  Popularity         11914 non-null  int64  
 15  MSRP               11914 non-null  int64  
dtypes: float64(3), int64(5), object(8)
memory usage: 1.5+ MB
```

```
#We're gonna change all columns to lowercase and replace the space between words with '_'
df.columns=df.columns.str.lower().str.replace(' ','_')
```

```
#making a list of the columns with data type 'object'
string_columns=list(df.dtypes[df.dtypes=='object'].index)
print(string_columns)
for col in string_columns:
  df[col]=df[col].str.lower().str.replace(' ','_')
```

```
['make', 'model', 'engine_fuel_type', 'transmission_type', 'driven_wheels', 'market_category', 'vehicle_size', 'vehicle_style']
```

```
#Chaning the 'make' column's name to 'brand'
df.rename(columns={'make':'brand'},inplace=True)
#Changing the 'msrp' column's name to 'price'
df.rename(columns={'msrp':'price'},inplace=True)
```

```
df.head()
```

	brand	model	year	engine_fuel_type	engine_hp	engine_cylinders	transmission_type	driven_wheels	number_of_doors
0	bmw	1_series_m	2011	premium_unleaded_(required)	335.00	6.00	manual	rear_wheel_drive	2.00
1	bmw	1_series	2011	premium_unleaded_(required)	300.00	6.00	manual	rear_wheel_drive	2.00
2	bmw	1_series	2011	premium_unleaded_(required)	300.00	6.00	manual	rear_wheel_drive	2.00
3	bmw	1_series	2011	premium_unleaded_(required)	230.00	6.00	manual	rear_wheel_drive	2.00
4	bmw	1_series	2011	premium_unleaded_(required)	230.00	6.00	manual	rear_wheel_drive	2.00

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```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11914 entries, 0 to 11913
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   brand              11914 non-null  object
 1   model              11914 non-null  object
 2   year               11914 non-null  int64
 3   engine_fuel_type   11911 non-null  object
 4   engine_hp          11845 non-null  float64
 5   engine_cylinders   11884 non-null  float64
 6   transmission_type  11914 non-null  object
 7   driven_wheels      11914 non-null  object
 8   number_of_doors    11908 non-null  float64
 9   market_category    8172 non-null   object
 10  vehicle_size       11914 non-null  object
 11  vehicle_style      11914 non-null  object
 12  highway_mpg        11914 non-null  int64
 13  city_mpg           11914 non-null  int64
 14  popularity         11914 non-null  int64
 15  price              11914 non-null  int64
dtypes: float64(3), int64(5), object(8)
memory usage: 1.5+ MB
```

Exploratory Data Analysis

```
pd.options.display.float_format='{:.2f}'.format
df.describe()
#This following code will allow us to see some observations of our numeric dataset
```

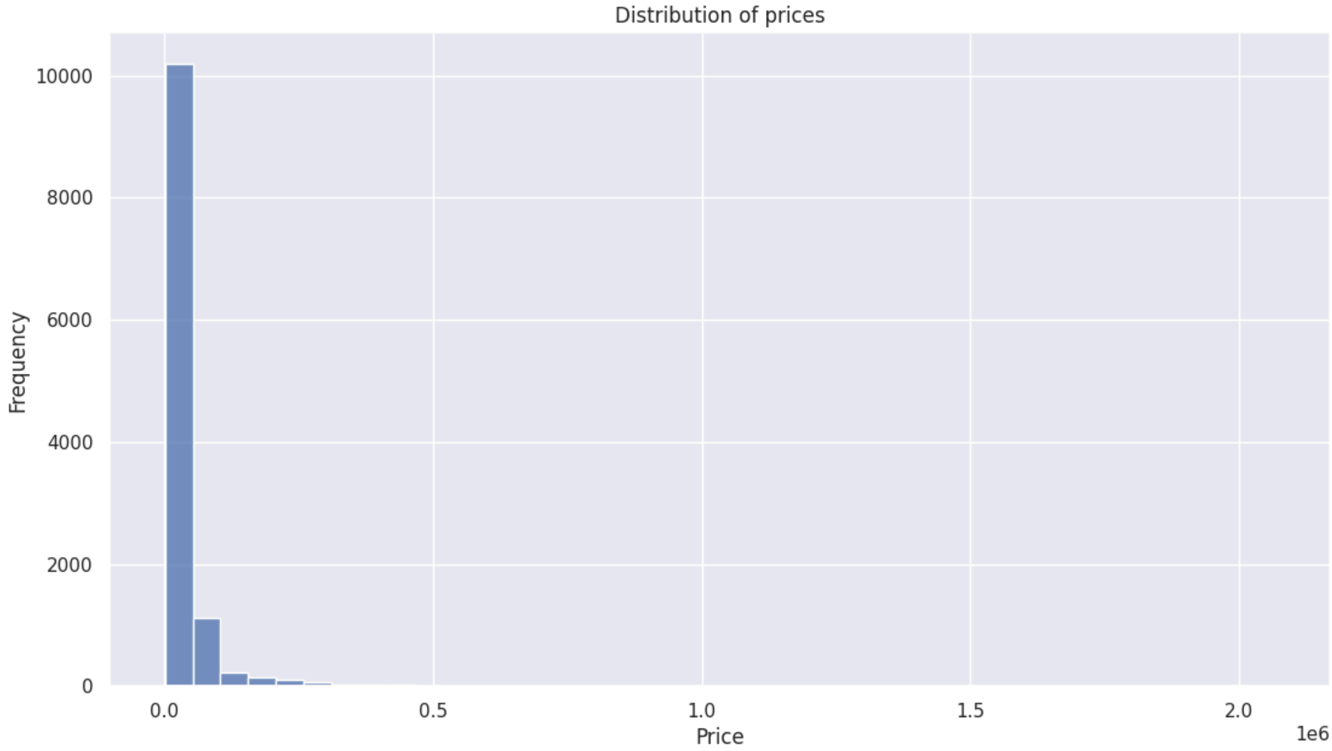
	year	engine_hp	engine_cylinders	number_of_doors	highway_mpg	city_mpg	popularity	price
count	11914.00	11845.00	11884.00	11908.00	11914.00	11914.00	11914.00	11914.00
mean	2010.38	249.39	5.63	3.44	26.64	19.73	1554.91	40594.74
std	7.58	109.19	1.78	0.88	8.86	8.99	1441.86	60109.10
min	1990.00	55.00	0.00	2.00	12.00	7.00	2.00	2000.00
25%	2007.00	170.00	4.00	2.00	22.00	16.00	549.00	21000.00
50%	2015.00	227.00	6.00	4.00	26.00	18.00	1385.00	29995.00
75%	2016.00	300.00	6.00	4.00	30.00	22.00	2009.00	42231.25
max	2017.00	1001.00	16.00	4.00	354.00	137.00	5657.00	2065902.00

```
df.describe(include=['O'])
#This way we can see object's observation in addition to the numeric ones seeing in the above code
```

	brand	model	engine_fuel_type	transmission_type	driven_wheels	market_category	vehicle_size	vehicle_style
count	11914	11914	11911	11914	11914	8172	11914	11914
unique	48	914	10	5	4	71	3	16
top	chevrolet	silverado_1500	regular_unleaded	automatic	front_wheel_drive	crossover	compact	sedan
freq	1123	156	7172	8266	4787	1110	4764	3048

Target variable analysis (price)

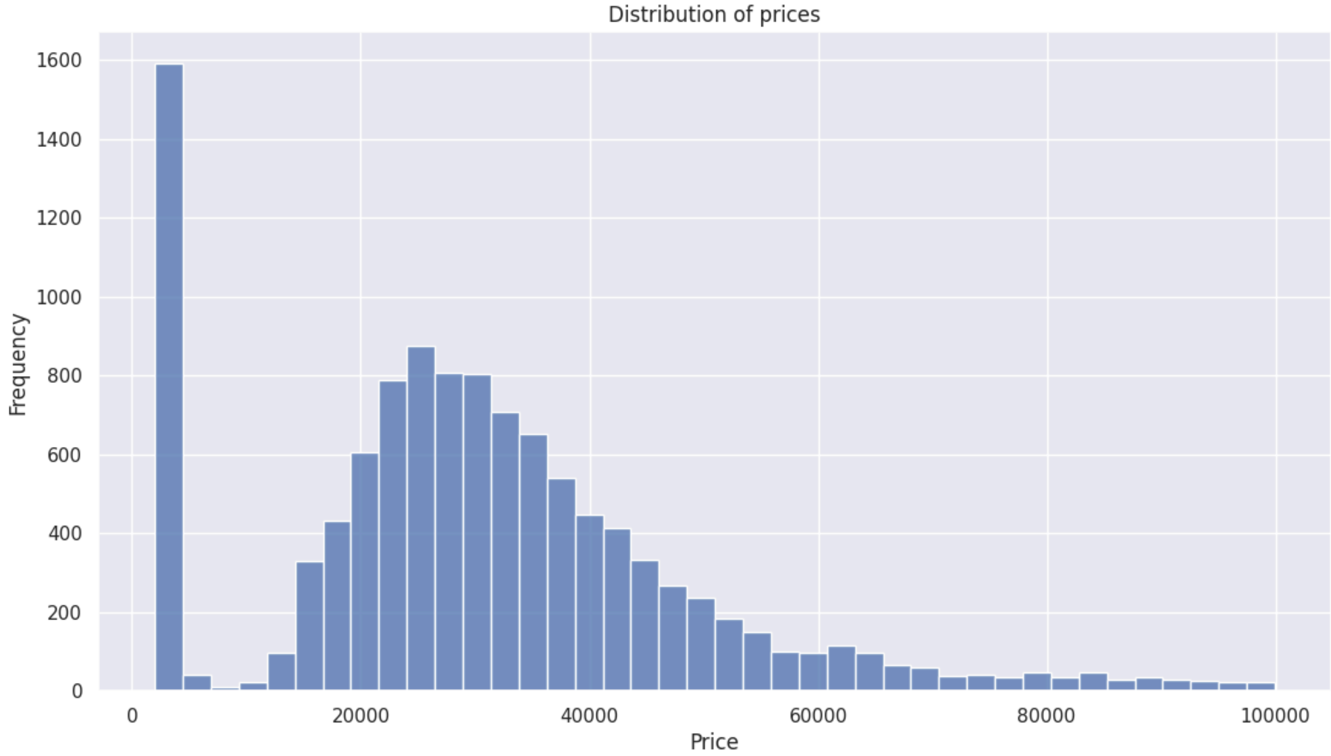
```
plt.figure(figsize=(13,7))
sns.histplot(df.price,bins=40) #bins specifies the number of interval we to divide our data into
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.title('Distribution of prices')
plt.show()
```



This is a **long tail** distribution, which is a typical situation for many items with low prices and very few expensive ones.

We can have a clearer look by zooming in a bit and looking at values below $100,000

```
plt.figure(figsize=(13,7))
sns.histplot(df.price[df.price<100000],bins=40)
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.title('Distribution of prices')
plt.show()
```

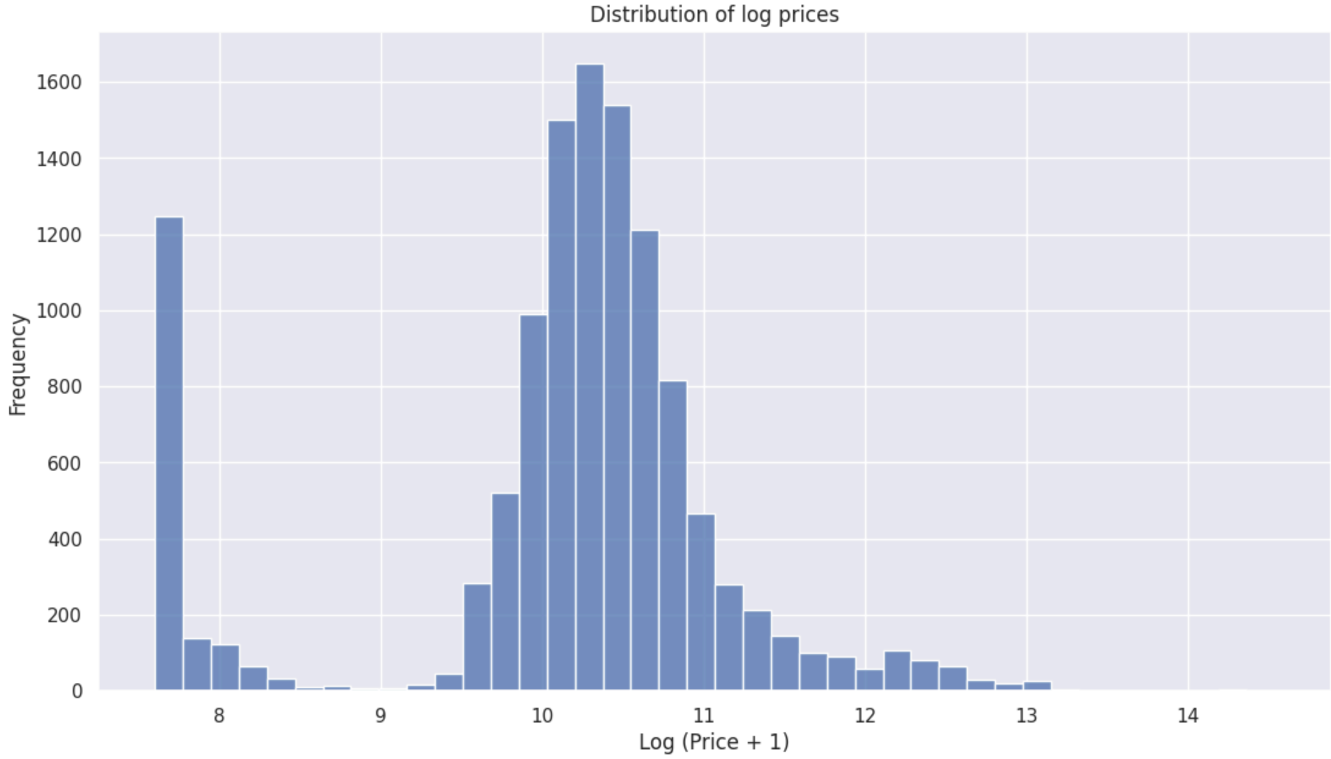


The long tail makes it quite difficult for us to see the distribution, but it has an even stronger effect on a model: such distribution can greatly confuse the model, so it won't learn well enough.

One way to solve this problem is **log** transformation.

Log Transformation

```
df['log_price']=np.log1p(df.price)
plt.figure(figsize=(13,7))
sns.histplot(df.log_price,bins=40)
plt.xlabel('Log (Price + 1)')
plt.ylabel('Frequency')
plt.title('Distribution of log prices')
plt.show()
```



The efect of the long tail is removed; and we can see the entire distribution in one plot.

The +1 part is important in cases that have zeros. The logarithm of zero is minus infinity, but the logarithm of one is zero.

For our specefic case, Zero values aren't an issue-all the prices we have start at $2,000 -but it's still a convention that we follow.

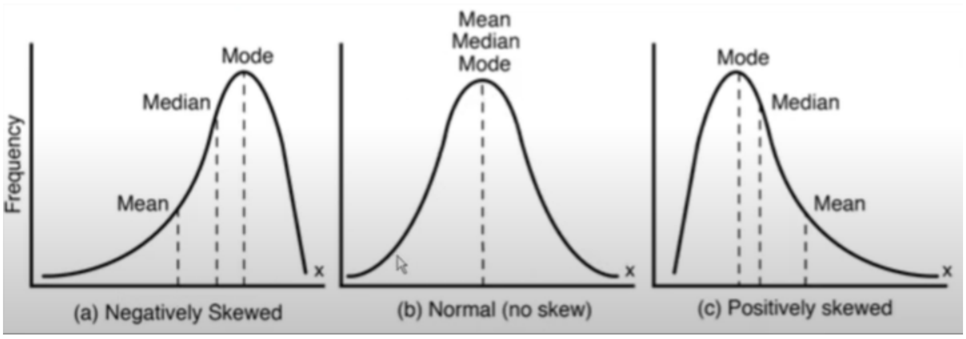
```
df.price.skew()
```

```
11.771987129334972
```

```
df.log_price.skew()
```

```
-0.9178678067039072
```

Positive Skewness vs Negative Skewness



Check missing values

```
df.isnull().sum()
```

	0
brand	0
model	0
year	0
engine_fuel_type	3
engine_hp	69
engine_cylinders	30
transmission_type	0
driven_wheels	0
number_of_doors	6
market_category	3742
vehicle_size	0
vehicle_style	0
highway_mpg	0
city_mpg	0
popularity	0
price	0
log_price	0

We should keep in mind that we need to handle missing values in order to correctly train our machine

In our case, luckily our target which is the price has no missing values

Check categorical columns

```
string_columns
```

```
['make',
 'model',
 'engine_fuel_type',
 'transmission_type',
 'driven_wheels',
 'market_category',
 'vehicle_size',
 'vehicle_style']
```

Some of the categorical columns might need to be trasformed to numerical form

Some Observations

```
#Average price of BMW cars in the datset
df.price[df['brand']=='bmw'].mean()
#it's the same as df.groupby('brand').mean()['price']['bmw']
```

```
61546.76347305389
```

```
df.groupby('brand')
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7ca200c5dde0>
```

```
#Comparing the average price for cars before 2015
df.price[df['year']<2015].mean()
```

```
35457.18770062511
```

```
#Comparing the average price for cars after 2015
df.price[df['year']>=2015].mean()
```

```
45667.156463719766
```

Validation framework

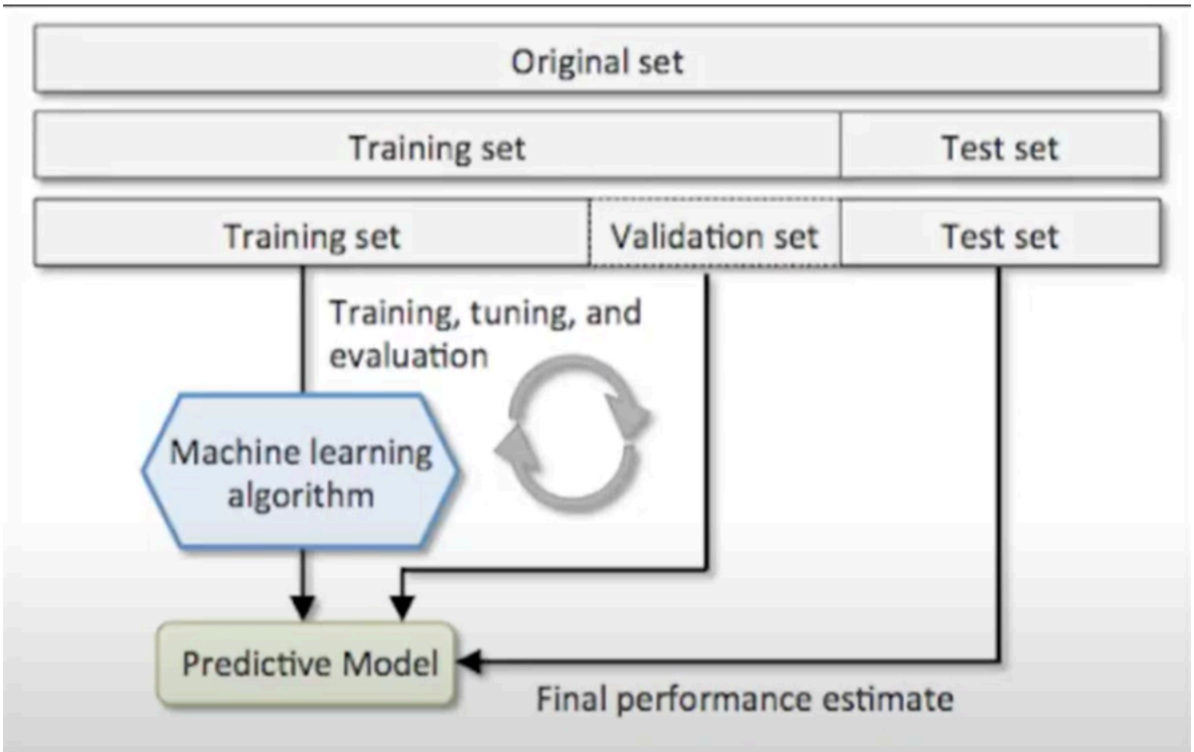


Image credit: https://vitalflux.com/hold-out-method-for-training-machine-learning-model/

```
np.random.seed(2) #Fixes the random seed to make sure that the results are reproducible
n=len(df)
n_test=int(0.2*n)
n_val=int(0.2*n)
n_train=n-(n_test+n_val)
print('No of rows for training : ',n_train)
print('No of rows for validation : ',n_val)
print('No of rows for testing : ',n_test)
```

```
No of rows for training :  7150
No of rows for validation :  2382
No of rows for testing :  2382
```

```
idx=np.arange(n)
print(idx)
np.random.shuffle(idx)
print(idx)
```

```
[    0     1     2 ... 11911 11912 11913]
[2735 6720 5878 ... 6637 2575 7336]
```

```
df_shuffled=df.iloc[idx]
print(df.index)
print(df_shuffled.index)
```

```
RangeIndex(start=0, stop=11914, step=1)
Index([ 2735,  6720,  5878, 11190,  4554,  8001,  2882,   649,   616,  4459,
       ...
        6751,   433,  4770, 11527,  1099,  2514, 11798,  6637,  2575,  7336],
      dtype='int64', length=11914)
```

```
df_shuffled
```

	brand	model	year	engine_fuel_type	engine_hp	engine_cylinders	transmission_type	driven_wheels	number_of_doo
2735	chevrolet	cobalt	2008	regular_unleaded	148.00	4.00	manual	front_wheel_drive	2
6720	toyota	matrix	2012	regular_unleaded	132.00	4.00	automatic	front_wheel_drive	4
5878	subaru	impreza	2016	regular_unleaded	148.00	4.00	automatic	all_wheel_drive	4
11190	volkswagen	vanagon	1991	regular_unleaded	90.00	4.00	manual	rear_wheel_drive	3
4554	ford	f-150	2017	flex-fuel_(unleaded/e85)	385.00	8.00	automatic	four_wheel_drive	4
...	...	...	...	...	...	...	...	...	
2514	chevrolet	chevy_van	1998	regular_unleaded	200.00	6.00	automatic	rear_wheel_drive	3
11798	subaru	xv_crosstrek	2014	regular_unleaded	160.00	4.00	automatic	all_wheel_drive	4
6637	dodge	magnum	2006	regular_unleaded	250.00	6.00	automatic	all_wheel_drive	4
2575	honda	civic	2016	regular_unleaded	174.00	4.00	automatic	front_wheel_drive	4
7336	subaru	outback	2015	regular_unleaded	256.00	6.00	automatic	all_wheel_drive	4

11914 rows × 17 columns

Étapes suivantes : Générer du code avec df_shuffled | Afficher les graphiques recommandés | New interactive sheet

```
df
```

	brand	model	year	engine_fuel_type	engine_hp	engine_cylinders	transmission_type	driven_wheels	numbe
0	bmw	1_series_m	2011	premium_unleaded_(required)	335.00	6.00	manual	rear_wheel_drive	
1	bmw	1_series	2011	premium_unleaded_(required)	300.00	6.00	manual	rear_wheel_drive	
2	bmw	1_series	2011	premium_unleaded_(required)	300.00	6.00	manual	rear_wheel_drive	
3	bmw	1_series	2011	premium_unleaded_(required)	230.00	6.00	manual	rear_wheel_drive	
4	bmw	1_series	2011	premium_unleaded_(required)	230.00	6.00	manual	rear_wheel_drive	
...	...	...	...	...	...	...	...	...	
11909	acura	zdx	2012	premium_unleaded_(required)	300.00	6.00	automatic	all_wheel_drive	
11910	acura	zdx	2012	premium_unleaded_(required)	300.00	6.00	automatic	all_wheel_drive	
11911	acura	zdx	2012	premium_unleaded_(required)	300.00	6.00	automatic	all_wheel_drive	
11912	acura	zdx	2013	premium_unleaded_(recommended)	300.00	6.00	automatic	all_wheel_drive	
11913	lincoln	zephyr	2006	regular_unleaded	221.00	6.00	automatic	front_wheel_drive	

11914 rows × 17 columns

Étapes suivantes : Générer du code avec df | Afficher les graphiques recommandés | New interactive sheet

```
df_train=df_shuffled.iloc[:n_train].copy()
df_val=df_shuffled.iloc[n_train:n_train+n_val].copy()
df_test=df_shuffled.iloc[n_val+n_train:].copy()
```

```
df_train.shape
```

```
(7150, 17)
```

```
df_val.shape
```

```
(2382, 17)
```

```
df_test.shape
```

```
(2382, 17)
```

```
y_train=df_train.log_price.values
y_val=df_val.log_price.values
y_test=df_test.log_price.values
```

Baseline solution

```
base = ['engine_hp','engine_cylinders','highway_mpg','city_mpg','popularity'] #Numerical data only
#base = ['engine_hp','engine_cylinders']
```

```
df[base]
```

	engine_hp	engine_cylinders	highway_mpg	city_mpg	popularity
0	335.00	6.00	26	19	3916
1	300.00	6.00	28	19	3916
2	300.00	6.00	28	20	3916
3	230.00	6.00	28	18	3916
4	230.00	6.00	28	18	3916
...	...	...	...	...	...
11909	300.00	6.00	23	16	204
11910	300.00	6.00	23	16	204
11911	300.00	6.00	23	16	204
11912	300.00	6.00	23	16	204
11913	221.00	6.00	26	17	61

11914 rows × 5 columns

```
df[base].isnull().sum()
```

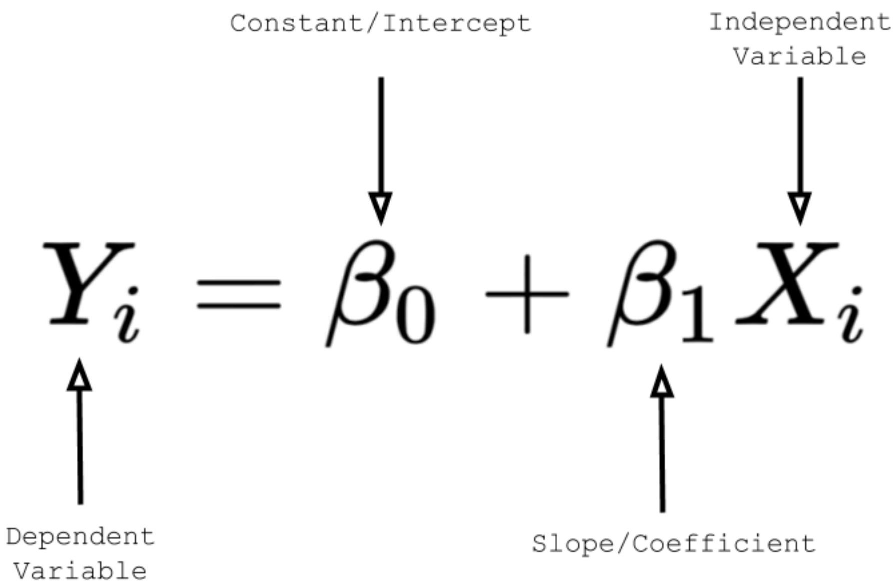
	0
engine_hp	69
engine_cylinders	30
highway_mpg	0
city_mpg	0
popularity	0

There are still missing values, We will fill them with the **mean** value

Handling Missing Values

```
def prepare_X(df):
  df_num=df[base]
  df_num=df_num.fillna(df_num.mean())
  X=df_num.values
  return X
```

Linear Regression



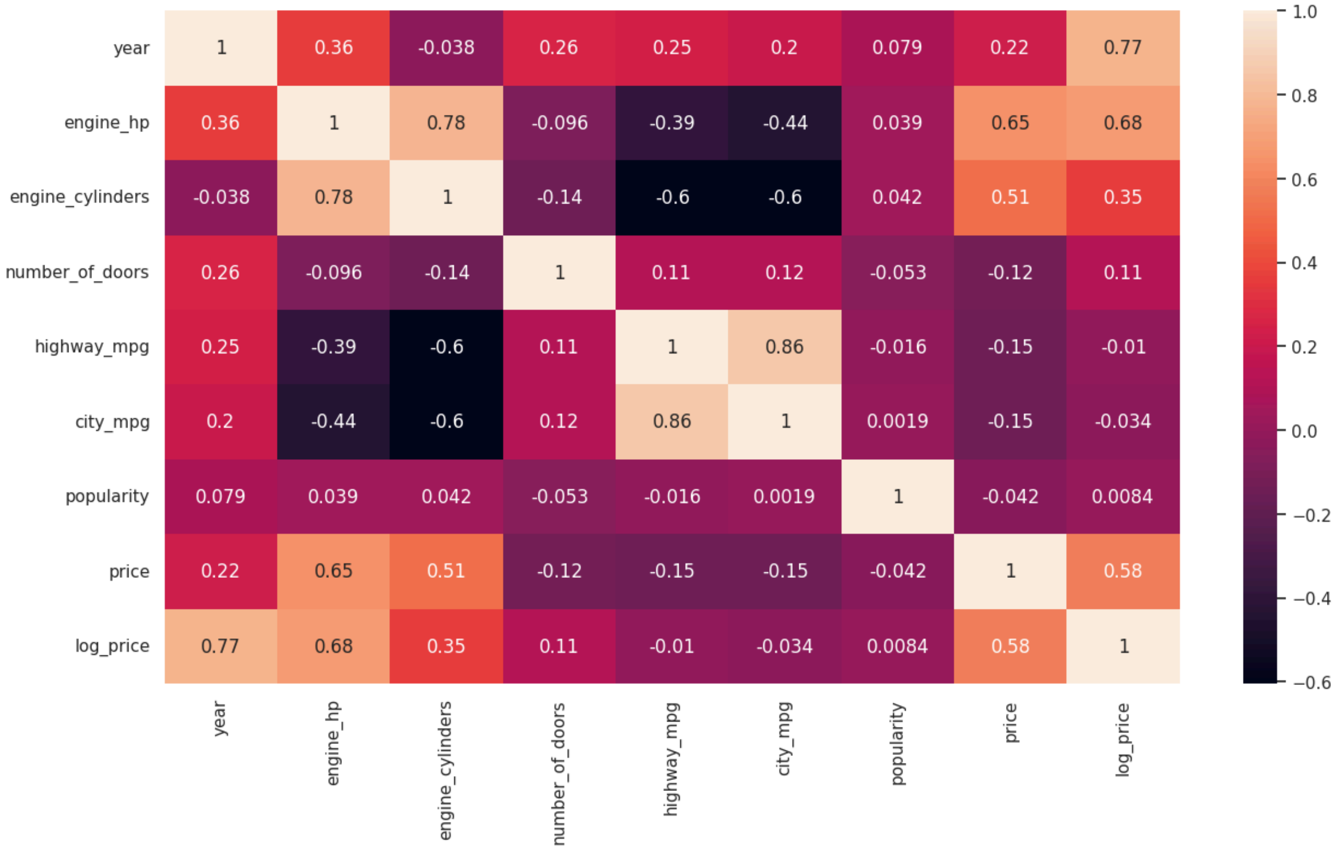
$$w_0 + \sum_{j=1}^{n} x_{ij} w_j$$

$$g(x_i) = g(x_{i1}, x_{i2}, x_{i3}) = w_0 + \sum_{j=1}^{3} x_{ij} w_j = w_0 + x_{i1} w_1 + x_{i2} w_2 + x_{i3} w_3$$

```
df_train.select_dtypes(include=np.number).corr()
```

	year	engine_hp	engine_cylinders	number_of_doors	highway_mpg	city_mpg	popularity	price	log_price
year	1.00	0.36	-0.04	0.26	0.25	0.20	0.08	0.22	0.77
engine_hp	0.36	1.00	0.78	-0.10	-0.39	-0.44	0.04	0.65	0.68
engine_cylinders	-0.04	0.78	1.00	-0.14	-0.60	-0.60	0.04	0.51	0.35
number_of_doors	0.26	-0.10	-0.14	1.00	0.11	0.12	-0.05	-0.12	0.11
highway_mpg	0.25	-0.39	-0.60	0.11	1.00	0.86	-0.02	-0.15	-0.01
city_mpg	0.20	-0.44	-0.60	0.12	0.86	1.00	0.00	-0.15	-0.03
popularity	0.08	0.04	0.04	-0.05	-0.02	0.00	1.00	-0.04	0.01
price	0.22	0.65	0.51	-0.12	-0.15	-0.15	-0.04	1.00	0.58
log_price	0.77	0.68	0.35	0.11	-0.01	-0.03	0.01	0.58	1.00

```
plt.figure(figsize=(15,8))
_=sns.heatmap(df_train.select_dtypes(include=np.number).corr(),annot=True)
```




```
def linear_regression(xi):
  n=len(xi)     #Number of features used
  pred=w0       #Initial / Base prediction
  for j in range(n):
    pred+=w[j]*xi[j]    #Formula = w0+ sigma[0:n-1]{w[j]*xi[j]}
  return pred
```

Using Normal Equation

Normal equation

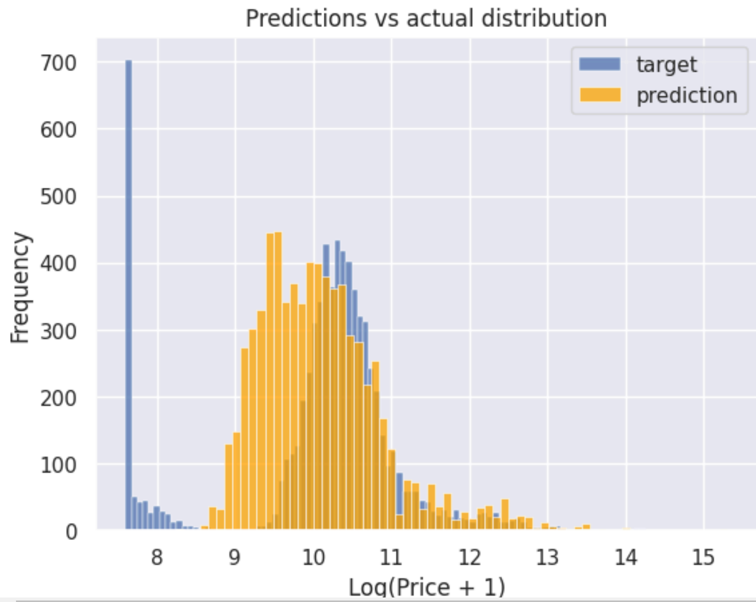
$$\Theta = (X^T X)^{-1} X^T y$$

```
def train_linear_regression(X,y):
  ones = np.ones(X.shape[0])
  X = np.column_stack((ones,X))
  w = np.linalg.inv(X.T.dot(X)).dot(X.T).dot(y)
  return w[0],w[1:]
```

```
X_train=prepare_X(df_train)
w_0,w=train_linear_regression(X_train,y_train) #y_train is the actual price
y_pred=w_0+X_train.dot(w) #y_pred is the predicted price
```

```
sns.histplot(y_train,label='target')
sns.histplot(y_pred,label='prediction',color='orange')
#Comparing the actual price vs the predicted one
plt.legend()
plt.xlabel('Log(Price + 1)')
plt.ylabel('Frequency')
```

```
plt.title('Predictions vs actual distribution')
plt.show()
```



Model Evaluation

$$RMSE=\sqrt{\frac{\sum_{i=1}^{N}(Predicted_i-Actual_i)^2}{N}}$$

```
def rmse(y,y_pred):
  error=y_pred-y
  mse=(error**2).mean()
  return np.sqrt(mse)
```

```
rmse(y_train,y_pred)
```

```
0.7574439819012008
```

```
#We gonna do the same thing for the validation
X_val=prepare_X(df_val)
y_pred=w_0+ X_val.dot(w)
```

```
rmse(y_val,y_pred)
```

```
0.7502502346381938
```

Simple Feature Engineering

To improve our model, we can ceate other features and add them to the existing features. This process is called **feature engineering**

```
base
```

```
['engine_hp', 'engine_cylinders', 'highway_mpg', 'city_mpg', 'popularity']
```

```
sorted(df.year.unique())
```

```
[1990,
 1991,
 1992,
 1993,
 1994,
 1995,
 1996,
```

```
       1997,
       1998,
       1999,
       2000,
       2001,
       2002,
       2003,
       2004,
       2005,
       2006,
       2007,
       2008,
       2009,
       2010,
       2011,
       2012,
       2013,
       2014,
       2015,
       2016,
       2017]
```

```
def prepare_X(df):
  df=df.copy()
  features=base.copy()
  df['age']=2017-df.year #Because the dataset was created in 2017 (which we can verify by checking df_train.year.max())
  features.append('age')
  df_num=df[features]
  df_num=df_num.fillna(df_num.mean())
  X=df_num.values
  return X
```

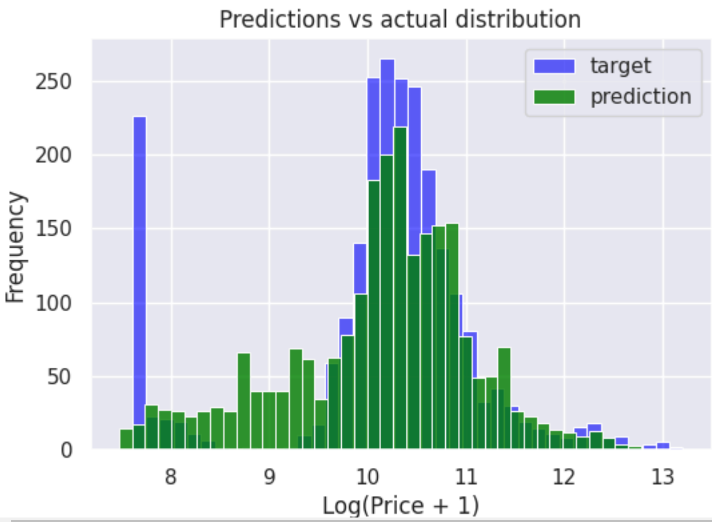
```
X_train=prepare_X(df_train)
w_0,w=train_linear_regression(X_train,y_train)
y_pred=w_0+X_train.dot(w)
print('Train RMSE: ',rmse(y_train,y_pred))

X_val=prepare_X(df_val)
y_pred=w_0+X_val.dot(w)
print('Validation RMSE: ',rmse(y_val,y_pred))
```

```
Train RMSE:  0.5117454503079418
Validation RMSE:  0.5070033906013028
```

Adding **age** was quite helpful for the model

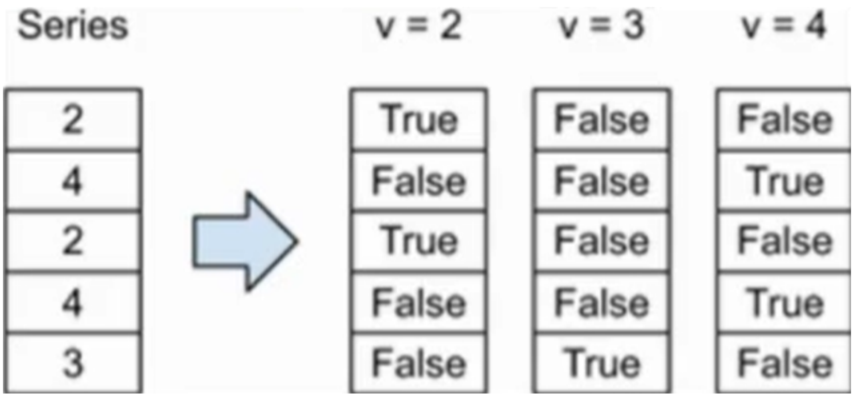
```
plt.figure(figsize=(6,4))
sns.histplot(y_val,label='target',color='blue',alpha=0.6,bins=40) #alpha controls the transparency of the bar
sns.histplot(y_pred,label='prediction',color='green',alpha=0.8,bins=40)
plt.legend()
plt.xlabel('Log(Price + 1)')
plt.ylabel('Frequency')
plt.title('Predictions vs actual distribution')
plt.show()
```



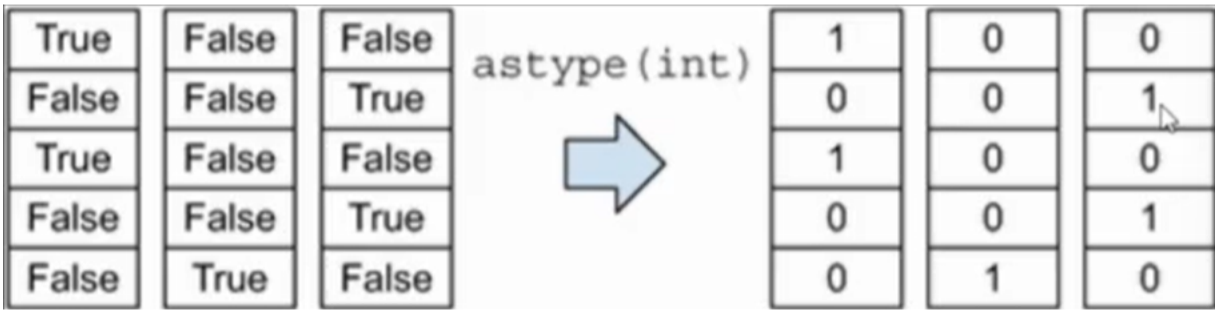
Handling Categorical Variables

```
df.number_of_doors.value_counts()
```

number_of_doors	count
4.00	8353
2.00	3160
3.00	395



Handling No. of doors (One Hot Encoding)




```
df['brand'].value_counts().head(10)
```

brand	count
chevrolet	1123
ford	881
volkswagen	809
toyota	746
dodge	626
nissan	558
gmc	515
honda	449
mazda	423
cadillac	397

```
def prepare_X(df):
  df=df.copy()
  features=base.copy()
  df['age']=2017-df.year
  features.append('age')
  for v in [2,3,4]:
    feature='num_doors_%s'%v
    df[feature]=(df['number_of_doors']==v).astype(int)
    features.append(feature)
  for v in ['chevrolet','ford','volkswagen','toyota','dodge']:
    feature='is_brand_%s'%v
    df[feature]=(df['brand']==v).astype(int)
```

```
    features.append(feature)
  df_num=df[features]
  df_num=df_num.fillna(df_num.mean())
  X=df_num.values
  return X


X_train=prepare_X(df_train)
w_0, w=train_linear_regression(X_train,y_train)
y_pred=w_0+X_train.dot(w)
print('train: ',rmse(y_train,y_pred))
X_val=prepare_X(df_val)
y_pred=w_0+X_val.dot(w)
print('validation: ',rmse(y_val,y_pred))
```

```
train:  0.5010764007201611
validation:  0.4982643557277196
```

```
df['engine_fuel_type'].value_counts()
```

engine_fuel_type	count
regular_unleaded	7172
premium_unleaded_(required)	2009
premium_unleaded_(recommended)	1523
flex-fuel_(unleaded/e85)	899
diesel	154
electric	66
flex-fuel_(premium_unleaded_required/e85)	54
flex-fuel_(premium_unleaded_recommended/e85)	26
flex-fuel_(unleaded/natural_gas)	6
natural_gas	2

```
#We gonna repeat the same thing but this time we're gonna ad the 'engine_fuel_type' to the preperation function
def prepare_X(df):
  df=df.copy()
  features=base.copy()
  df['age']=2017-df.year
  features.append('age')
  for v in [2,3,4]:
    feature='num_doors_%s'%v
    df[feature]=(df['number_of_doors']==v).astype(int)
    features.append(feature)
  for v in ['chevrolet','ford','volkswagen','toyota','dodge']:
    feature='brand_%s'%v
    df[feature]=(df['brand']==v).astype(int)
    features.append(feature)
  for v in ['regular_unleaded', 'premium_unleaded_(required)','premium_unleaded_(recommended)', 'flex-fuel_(unleaded/e85)']:
    feature='is_type_%s' % v
    df[feature]=(df['engine_fuel_type']==v).astype(int)
  df_num=df[features]
  df_num=df_num.fillna(df_num.mean())
  X=df_num.values
  return X


X_train=prepare_X(df_train)
w_0,w=train_linear_regression(X_train,y_train)
y_pred=w_0+X_train.dot(w)
print('train: ',rmse(y_train,y_pred))
X_val=prepare_X(df_val)
y_pred=w_0+X_val.dot(w)
print('validation: ',rmse(y_val,y_pred))
```

```
train:  0.5010764007201611
validation:  0.4982643557277196
```

```
df['transmission_type'].value_counts()
```

transmission_type	count
automatic	8266
manual	2935
automated_manual	626
direct_drive	68
unknown	19

```
df['driven_wheels'].value_counts()
```

driven_wheels	count
front_wheel_drive	4787
rear_wheel_drive	3371
all_wheel_drive	2353
four_wheel_drive	1403

```
df['market_category'].value_counts().head(5)
```

market_category	count
crossover	1110
flex_fuel	872
luxury	855
luxury,performance	673
hatchback	641

```
df['vehicle_style'].value_counts().head(5)
```

vehicle_style	count
sedan	3048
4dr_suv	2488
coupe	1211
convertible	793
4dr_hatchback	702

```
#We gonna repeat the same thing but this time we're gonna add new columns to the preperation function
def prepare_X(df):
  df=df.copy()
  features=base.copy()
  df['age']=2017-df.year
  features.append('age')
  for v in [2,3,4]:
    feature='num_doors_%s'%v
    df[feature]=(df['number_of_doors']==v).astype(int)
    features.append(feature)
  for v in ['chevrolet','ford','volkswagen','toyota','dodge']:
    feature='brand_%s'%v
    df[feature]=(df['brand']==v).astype(int)
    features.append(feature)
  for v in ['regular_unleaded','premium_unleaded_(required)','premium_unleaded_(recommended)','flex-fuel_(unleaded/e85)']:
    feature='is_type_%s'%v
    df[feature]=(df['engine_fuel_type']==v).astype(int)
```

```
      features.append(feature)
    for v in ['automatic','manual','automated_manual']:
      feature='is_transmission_%s'%v
      df[feature]=(df['transmission_type']==v).astype(int)
      features.append(feature)
    df_num=df[features]
    df_num=df_num.fillna(df_num.mean())
    X=df_num.values
    return X


X_train=prepare_X(df_train)
w_0,w=train_linear_regression(X_train,y_train)
y_pred=w_0+X_train.dot(w)
print('train: ',rmse(y_train,y_pred))
X_val=prepare_X(df_val)
y_pred=w_0+X_val.dot(w)
print('validation: ',rmse(y_val,y_pred))
```

```
train:  0.47227213583716005
validation:  0.4653694386689132
```

We gonna keep trying to add columns to the preperation seeking better train and validation scores

```
def prepare_X(df):
    df = df.copy()
    features = base.copy()

    df['age'] = 2017 - df.year
    features.append('age')

    for v in [2, 3, 4]:
        feature = 'num_doors_%s' % v
        df[feature] = (df['number_of_doors'] == v).astype(int)
        features.append(feature)

    for v in ['chevrolet', 'ford', 'volkswagen', 'toyota', 'dodge']:
        feature = 'brand_%s' % v
        df[feature] = (df['brand'] == v).astype(int)
        features.append(feature)

    for v in ['regular_unleaded', 'premium_unleaded_(required)', 'premium_unleaded_(recommended)', 'flex-fuel_(unleaded/e85)']:
        feature = 'is_type_%s' % v
        df[feature] = (df['engine_fuel_type'] == v).astype(int)
        features.append(feature)

    for v in ['automatic', 'manual', 'automated_manual']:
        feature = 'is_transmission_%s' % v
        df[feature] = (df['transmission_type'] == v).astype(int)
        features.append(feature)

    for v in ['front_wheel_drive', 'rear_wheel_drive', 'all_wheel_drive', 'four_wheel_drive']:
        feature = 'is_driven_wheels_%s' % v
        df[feature] = (df['driven_wheels'] == v).astype(int)
        features.append(feature)

    for v in ['crossover', 'flex_fuel', 'luxury', 'luxury,performance', 'hatchback']:
        feature = 'is_style_%s' % v
        df[feature] = (df['market_category'] == v).astype(int)
        features.append(feature)

    for v in ['compact', 'midsize', 'large']:
        feature = 'is_size_%s' % v
        df[feature] = (df['vehicle_size'] == v).astype(int)
        features.append(feature)

    for v in ['sedan', '4dr_suv', 'coupe', 'convertible', '4dr_hatchback']:
        feature = 'is_style_%s' % v
        df[feature] = (df['vehicle_style'] == v).astype(int)
        features.append(feature)

    df_num = df[features]
    df_num = df_num.fillna(df_num.mean())
    X = df_num.values
    return X


X_train=prepare_X(df_train)
w_0,w=train_linear_regression(X_train,y_trair
y_pred=w_0+X_train.dot(w)
```

```
print('train: ',rmse(y_train,y_pred))
X_val=prepare_X(df_val)
y_pred=w_0+X_val.dot(w)
```

```
train:  2219.4977297377545
validation:  795.8906366825912
```

```
w_0.astype(int)
```

```
77440924946976912
```

```
w.astype(int)
```

```
array([                4,               133,                83,
                      87,                 0,                65,
                   76152,             76653,             76029,
                     -75,               -87,               296,
                    -181,                64,              1753,
                    1499,              1645,              1882,
                    4513,              4348,              4323,
       -77440924947065216, -77440924947064944, -77440924947064576,
       -77440924947064240,                55,                79,
                     -71,              -204,              -280,
                    -455,              -243,              -329,
                       0,                 0,                 0,
                       0,                 0])
```

Regularization

$$w = (X^T X + \alpha I)^{-1} X^T y$$

```
def train_linear_regression_reg(X,y,r=0.0):
  ones=np.ones(X.shape[0])
  X=np.column_stack([ones,X])
  XTX=X.T.dot(X)
  reg=r*np.eye(XTX.shape[0])
  XTX=XTX+reg
  XTX_inv=np.linalg.inv(XTX)
  w=XTX_inv.dot(X.T).dot(y)
  return w[0],w[1:]
```

```
X_train=prepare_X(df_train)
```

```
for r in [0 , 0.001 , 0.01 , 1 , 10]:
  w_0,w=train_linear_regression_reg(X_train,y_train,r=r)
  print('%5s, %.2f, %.2f, %.2f' %(r,w_0,w[13],w[21]))
```

```
    0, 77440924946976912.00, 64.03, -77440924947065216.00
0.001, 6.96, -0.10, 1.76
 0.01, 6.95, -0.10, 1.76
    1, 6.04, -0.10, 1.52
   10, 4.32, -0.09, 1.07
```

```
X_train=prepare_X(df_train)
w_0,w=train_linear_regression_reg(X_train,y_train,r=0)
y_pred=w_0+X_train.dot(w)
print('train: ',rmse(y_train,y_pred))
X_val=prepare_X(df_val)
y_pred=w_0+X_val.dot(w)
print('val: ',rmse(y_val,y_pred))
```

```
train:  2219.4977297377545
val:  795.8906366825912
```

```
X_train=prepare_X(df_train)
w_0,w=train_linear_regression_reg(X_train,y_train,r=0.01)
y_pred=w_0+X_train.dot(w)
print('train: ',rmse(y_train,y_pred))
X_val=prepare_X(df_val)
```