NASSCOM MINI PROJECT

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SECTION: 5COM2

Predict Fuel Efficiency

Let's import the necessary libraries to get started with this task:

In [42]:
```
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
```

In [45]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd


# Make NumPy printouts easier to read.
np.set_printoptions(precision=3, suppress=True)
```

In [2]:
```
dataset = pd.read_csv("/content/dataset.txt",sep=",")
```

In [54]:
```
dataset.head()
```
Out[54]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	car name	USA
0	18.0	8	307.0	130	3504	12.0	70	chevrolet chevelle malibu	1.0
1	15.0	8	350.0	165	3693	11.5	70	buick skylark 320	1.0
2	18.0	8	318.0	150	3436	11.0	70	plymouth satellite	1.0
3	16.0	8	304.0	150	3433	12.0	70	amc rebel sst	1.0
4	17.0	8	302.0	140	3449	10.5	70	ford torino	1.0

In [53]:
```
dataset.tail()
```
Out[53]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	car name	US
393	27.0	4	140.0	86	2790	15.6	82	ford mustang gl	1
394	44.0	4	97.0	52	2130	24.6	82	vw pickup	0
395	32.0	4	135.0	84	2295	11.6	82	dodge rampage	1
396	28.0	4	120.0	79	2625	18.6	82	ford ranger	1
397	31.0	4	119.0	82	2720	19.4	82	chevy s-10	1

In [52]:
```
print("presenceof null values:"+str(dataset.isnull().values.any()))
```
```
presenceof null values:False
```

Clean the data

In [46]:
```
dataset.isna().sum()
```

Out[46]:
```
mpg             0
cylinders       0
displacement    0
horsepower      0
weight          0
acceleration    0
model year      0
car name        0
USA             0
Europe          0
Japan           0
dtype: int64
```

Drop those rows to keep this initial tutorial simple:

In [55]:
```
dataset = dataset.dropna()
dataset
```

Out[55]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	car name	U
0	18.0	8	307.0	130	3504	12.0	70	chevrolet chevelle malibu	-
1	15.0	8	350.0	165	3693	11.5	70	buick skylark 320	-
2	18.0	8	318.0	150	3436	11.0	70	plymouth satellite	-
3	16.0	8	304.0	150	3433	12.0	70	amc rebel sst	-
4	17.0	8	302.0	140	3449	10.5	70	ford torino	-
...	...	...	...	...	...	...	...	...	
393	27.0	4	140.0	86	2790	15.6	82	ford mustang gl	-
394	44.0	4	97.0	52	2130	24.6	82	vw pickup	(
395	32.0	4	135.0	84	2295	11.6	82	dodge rampage	-
396	28.0	4	120.0	79	2625	18.6	82	ford ranger	-
397	31.0	4	119.0	82	2720	19.4	82	chevy s-10	-

398 rows × 11 columns

In [56]:
```
dataset.index
```

Out[56]:
```
Int64Index([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,
            ...
            388, 389, 390, 391, 392, 393, 394, 395, 396, 397],
           dtype='int64', length=398)
```

In [7]:
```
dataset.columns
```

Out[7]:
```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'model year', 'origin', 'car name'],
      dtype='object')
```

In [8]:
```
origin = dataset.pop('origin')
dataset['USA'] = (origin == 1)*1.0
dataset['Europe'] = (origin == 2)*1.0
dataset['Japan'] = (origin == 3)*1.0
print(origin)
```

```
0      1
1      1
2      1
3      1
4      1
      ..
393    1
394    2
395    1
396    1
397    1
Name: origin, Length: 398, dtype: int64
```

Now, let's split the data into training and test sets:

In [9]:
```
train_dataset = dataset.sample(frac=0.8,random_state=0)
test_dataset = dataset.drop(train_dataset.index)
print(train_dataset)
```

```
      mpg  cylinders  displacement  ...  USA  Europe  Japan
65   14.0          8         351.0  ...  1.0     0.0    0.0
132  25.0          4         140.0  ...  1.0     0.0    0.0
74   13.0          8         302.0  ...  1.0     0.0    0.0
78   21.0          4         120.0  ...  0.0     1.0    0.0
37   18.0          6         232.0  ...  1.0     0.0    0.0
..    ...        ...           ...  ...  ...     ...    ...
207  20.0          4         130.0  ...  0.0     1.0    0.0
279  29.5          4          98.0  ...  0.0     0.0    1.0
227  19.0          6         225.0  ...  1.0     0.0    0.0
148  26.0          4         116.0  ...  0.0     1.0    0.0
143  26.0          4          97.0  ...  0.0     1.0    0.0

[318 rows x 11 columns]
```

In [10]:
```
print(test_dataset)
```

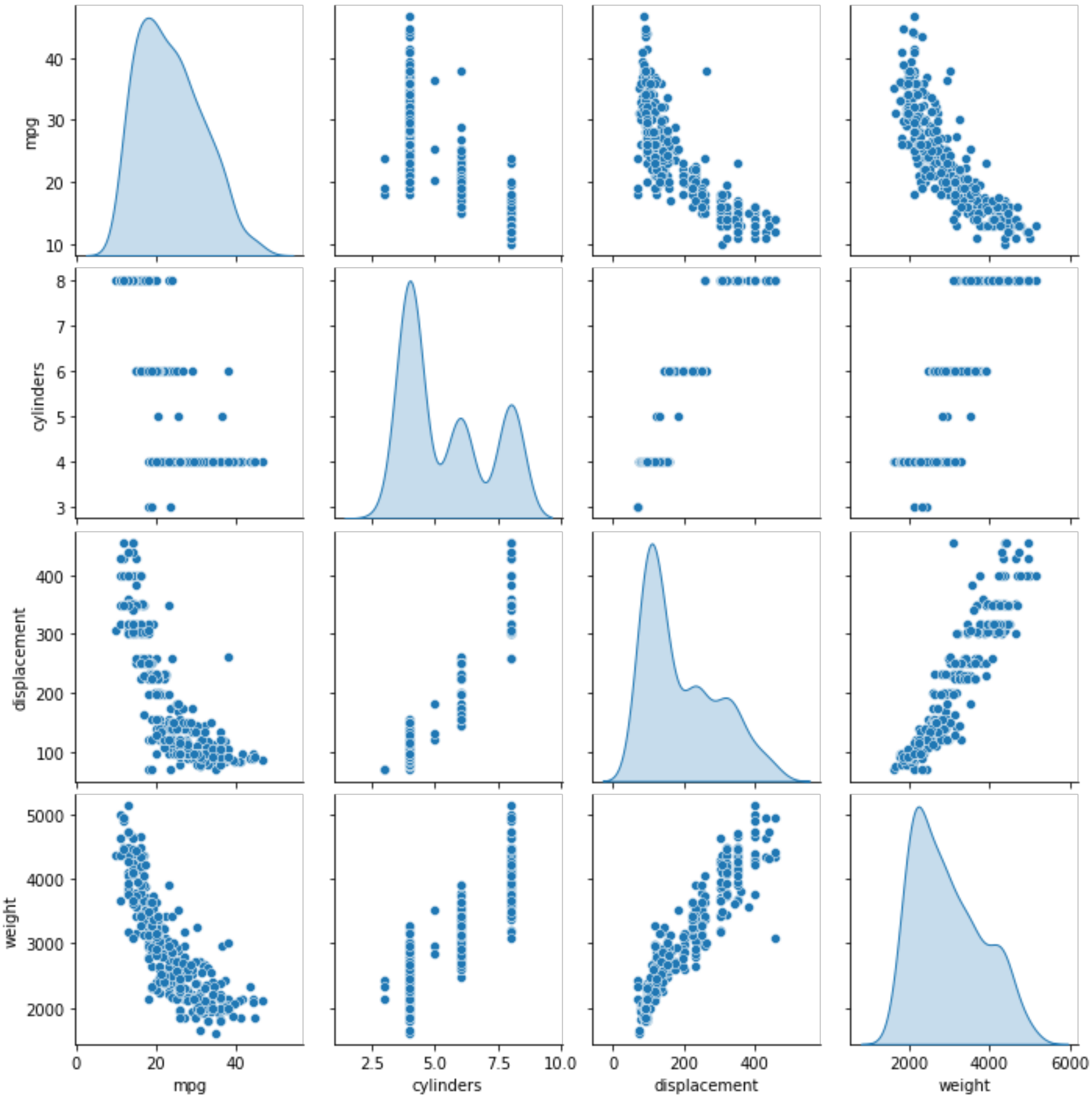
```
      mpg  cylinders  displacement  ...  USA  Europe  Japan
9    15.0          8         390.0  ...  1.0     0.0    0.0
25   10.0          8         360.0  ...  1.0     0.0    0.0
28    9.0          8         304.0  ...  1.0     0.0    0.0
31   25.0          4         113.0  ...  0.0     0.0    1.0
32   25.0          4          98.0  ...  1.0     0.0    0.0
..    ...        ...           ...  ...  ...     ...    ...
368  27.0          4         112.0  ...  1.0     0.0    0.0
370  31.0          4         112.0  ...  1.0     0.0    0.0
382  34.0          4         108.0  ...  0.0     0.0    1.0
384  32.0          4          91.0  ...  0.0     0.0    1.0
396  28.0          4         120.0  ...  1.0     0.0    0.0

[80 rows x 11 columns]
```

visualize the data by using the seaborn’s pair plot method:

In [11]:
```
import seaborn as sns
sns.pairplot(train_dataset[['mpg', 'cylinders', 'displacement', 'weight']], diag_kind='kde')
```

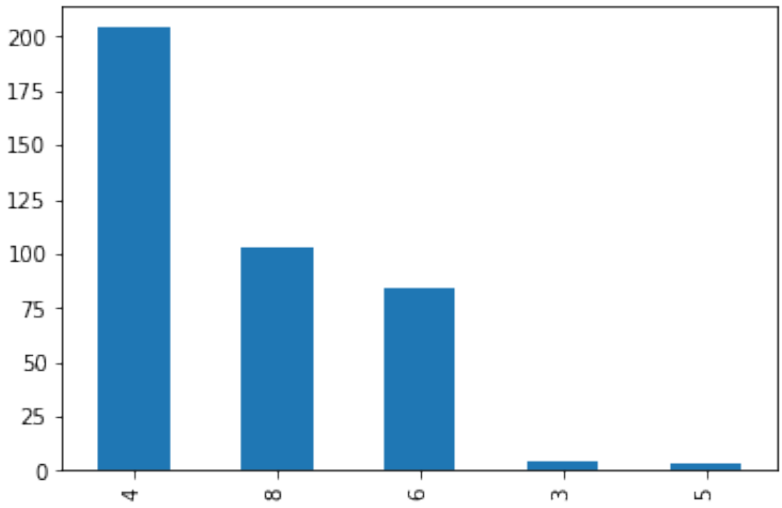
Out[11]:
```
<seaborn.axisgrid.PairGrid at 0x7f0dfcfc5750>
```



using bar plot

In [16]:
```
pd.value_counts(dataset['cylinders']).plot.bar()
```

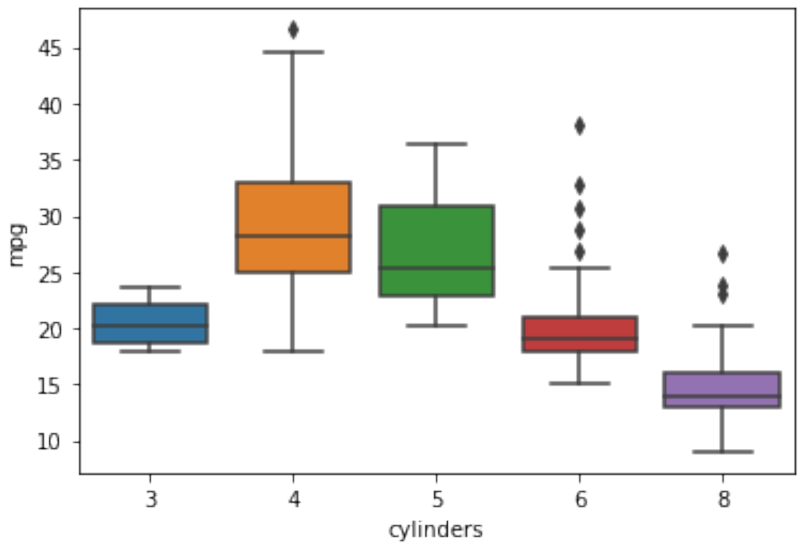
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0deb1efe90>



prediction using box plot

In [18]:
```
sns.boxplot(x='cylinders',y='mpg',data=dataset)
```

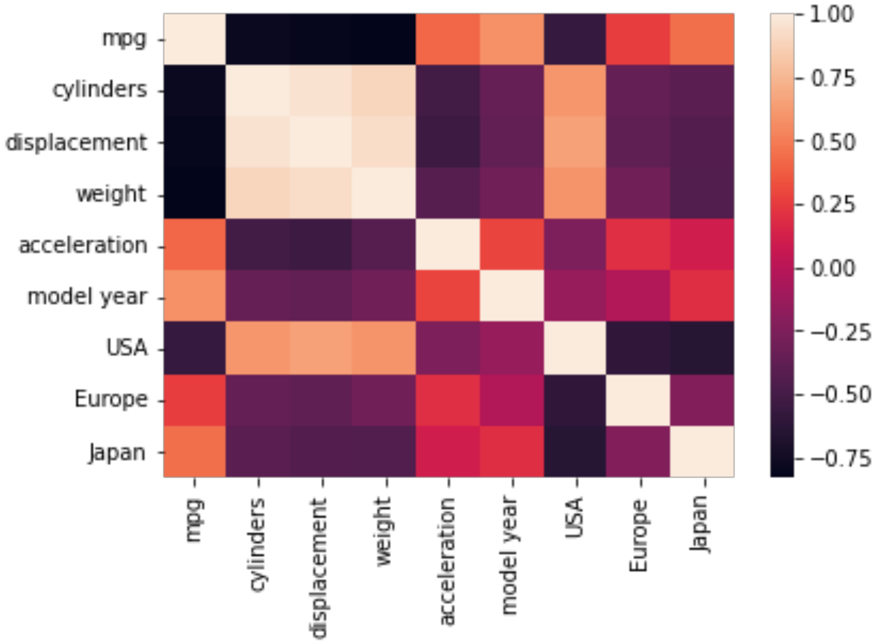
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0deb049950>



A boxplot will help us better visualize what is happening with the data. Using seaborn's builtin boxplot method, I've made the plot below, which plots car origin against the mpgs of the individual cars:

Heat map

In [71]:
```
corr = dataset.corr()
sns.heatmap(corr)
plt.show()
```



Now,separate the target values from the features in the dataset. This label is that feature that I will use to train the model to predict fuel efficiency:

In [19]:
```
train_labels = train_dataset.pop('mpg')
test_labels = test_dataset.pop('mpg')
print(train_labels)
```

```
65     14.0
132    25.0
74     13.0
78     21.0
37     18.0
       ...
207    20.0
279    29.5
227    19.0
148    26.0
143    26.0
Name: mpg, Length: 318, dtype: float64
```

In [20]:
```
print(test_labels)
```

```
9      15.0
25     10.0
28      9.0
31     25.0
32     25.0
       ...
368    27.0
370    31.0
382    34.0
384    32.0
396    28.0
Name: mpg, Length: 80, dtype: float64
```

In [62]:
```
train_features = train_dataset.copy()
test_features = test_dataset.copy()

train_labels = train_features.pop('cylinders')
test_labels = test_features.pop('cylinders')
```

overall statistics

In [21]:
```
train_stats=train_dataset.describe()
train_stats.pop("cylinders")
train_stats=train_stats.transpose()
train_stats
```

Out[21]:

	count	mean	std	min	25%	50%	75%	max
displacement	318.0	193.061321	103.812742	70.0	100.25	151.0	259.50	455.0
weight	318.0	2963.823899	844.749805	1613.0	2219.25	2792.5	3571.25	5140.0
acceleration	318.0	15.595912	2.796282	8.0	13.90	15.5	17.30	24.8
model year	318.0	75.946541	3.705266	70.0	73.00	76.0	79.00	82.0
USA	318.0	0.641509	0.480313	0.0	0.00	1.0	1.00	1.0
Europe	318.0	0.163522	0.370424	0.0	0.00	0.0	0.00	1.0
Japan	318.0	0.194969	0.396801	0.0	0.00	0.0	0.00	1.0

Normalize The Data

In [22]:
```
def norm(x):
  return (x - train_stats['mean']) / train_stats['std']
normed_train_data = norm(train_dataset)
normed_test_data = norm(test_dataset)
normed_train_data
```

Out[22]:

	Europe	Japan	USA	acceleration	car name	cylinders	displacement	horsepo
65	-0.441445	-0.491351	0.746369	-0.928344	NaN	NaN	1.521380	
132	-0.441445	-0.491351	0.746369	0.502127	NaN	NaN	-0.511125	
74	-0.441445	-0.491351	0.746369	0.144509	NaN	NaN	1.049377	
78	2.258163	-0.491351	-1.335607	1.396171	NaN	NaN	-0.703780	
37	-0.441445	-0.491351	0.746369	-0.034300	NaN	NaN	0.375086	
...	...	...	...	...	...	...	...	
207	2.258163	-0.491351	-1.335607	0.037224	NaN	NaN	-0.607453	
279	-0.441445	2.028805	-1.335607	0.359080	NaN	NaN	-0.915700	
227	-0.441445	-0.491351	0.746369	0.752459	NaN	NaN	0.307657	
148	2.258163	-0.491351	-1.335607	-0.570726	NaN	NaN	-0.742311	
143	2.258163	-0.491351	-1.335607	-0.391917	NaN	NaN	-0.925333	

318 rows × 10 columns

In [23]:
```
normed_test_data
```

Out[23]:

	Europe	Japan	USA	acceleration	car name	cylinders	displacement	horsepo
9	-0.441445	-0.491351	0.746369	-2.537624	NaN	NaN	1.897057	
25	-0.441445	-0.491351	0.746369	-0.570726	NaN	NaN	1.608075	
28	-0.441445	-0.491351	0.746369	1.038553	NaN	NaN	1.068642	
31	-0.441445	2.028805	-1.335607	-0.570726	NaN	NaN	-0.771209	
32	-0.441445	-0.491351	0.746369	1.217362	NaN	NaN	-0.915700	
...	...	...	...	...	...	...	...	
368	-0.441445	-0.491351	0.746369	1.074315	NaN	NaN	-0.780842	
370	-0.441445	-0.491351	0.746369	0.216033	NaN	NaN	-0.780842	
382	-0.441445	2.028805	-1.335607	0.466365	NaN	NaN	-0.819373	
384	-0.441445	2.028805	-1.335607	0.037224	NaN	NaN	-0.983129	
396	-0.441445	-0.491351	0.746369	1.074315	NaN	NaN	-0.703780	

80 rows × 10 columns

In [64]:
```
train_dataset.describe().transpose()[['mean', 'std']]
```

Out[64]:

	mean	std
cylinders	5.427673	1.682941
displacement	193.061321	103.812742
weight	2963.823899	844.749805
acceleration	15.595912	2.796282
model year	75.946541	3.705266
USA	0.641509	0.480313
Europe	0.163522	0.370424
Japan	0.194969	0.396801

Build The Model

In [43]:
```
def build_model():
  model = keras.Sequential([
    layers.Dense(64, activation=tf.nn.relu, input_shape=[len(train_
dataset.keys())]),
    layers.Dense(64, activation=tf.nn.relu),
    layers.Dense(1)
  ])

  optimizer = tf.keras.optimizers.RMSprop(0.001)

  model.compile(loss='mean_squared_error',
                optimizer=optimizer,
                metrics=['mean_absolute_error', 'mean_squared_error
'])
  return model
model = build_model()
model
```

Out[43]:
```
<keras.engine.sequential.Sequential at 0x7f0d955370d0>
```

In [94]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                704
_________________________________________________________________
dense_1 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 65
=================================================================
Total params: 4,929
Trainable params: 4,929
Non-trainable params: 0
_________________________________________________________________
```

During this notebook, we built a model that could reliably predict a car's mpg given some information about the car within 2.5 mpg of the actual value.

This model could be trained with newer car data and be used to predict competitor's future mpg ratings for upcoming cars, allowing companies to potentially resources currently used on R&D today on making more efficient, more popular vehicles that outshine competitors.

While our model may be inaccurate in some cases, we talked about how our dataset can contain inaccurate values for the mpg, and oftentimes, our predictions are more accurate than the values in the dataset.

For newer cars, the collected data is significantly more reliable, so our model will be able to perform better with a different, more accurate dataset.

If you want to optimize spending your resources and outshine the competition, Cocolevio's machine learning models can help you get the edge you need to succeed in your market.