fuel_efficiency

November 9, 2020

1 Fuel Efficiency Predictor

This model does an exploratory analysis of the auto-mpg dataset, and uses it to predict the fuel efficiency of different cars based on several input parameters.

[320]:
```
# imports and boilerplate
from __future__ import absolute_import, division, print_function

import pathlib

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

import sklearn
from sklearn import preprocessing

# suppressing warnings
import warnings
warnings.filterwarnings('ignore')
```

[321]:
```
# file path and reading in csv into dataframe
dataset_path = "sample_data/auto-mpg.csv"
```

[322]:
```
# creating dataframe from csv
df = pd.read_csv(dataset_path)
df['carName'] = df['carName'].str.replace('((\\t)|(\"))', '')
df.head()
```

[322]:
```
    mpg  cylinders  displacement  ... modelYear  origin
carName
0  18.0          8         307.0  ...        70       1  chevrolet chevelle
malibu
1  15.0          8         350.0  ...        70       1          buick skylark
320
```

```
2  18.0          8         318.0  ...        70        1         plymouth
satellite
3  16.0          8         304.0  ...        70        1              amc rebel
sst
4  17.0          8         302.0  ...        70        1                ford
torino

[5 rows x 9 columns]
```

[323]:
```
# quick summary of data statistics
df.describe()
```

[323]:
```
              mpg   cylinders  ...   modelYear      origin
count  398.000000  398.000000  ...  398.000000  398.000000
mean    23.514573    5.454774  ...   76.010050    1.572864
std      7.815984    1.701004  ...    3.697627    0.802055
min      9.000000    3.000000  ...   70.000000    1.000000
25%     17.500000    4.000000  ...   73.000000    1.000000
50%     23.000000    4.000000  ...   76.000000    1.000000
75%     29.000000    8.000000  ...   79.000000    2.000000
max     46.600000    8.000000  ...   82.000000    3.000000

[8 rows x 7 columns]
```

[324]:
```
# getting rid of missing data
df = df.dropna()
df = df[df.horsepower != '?']
```

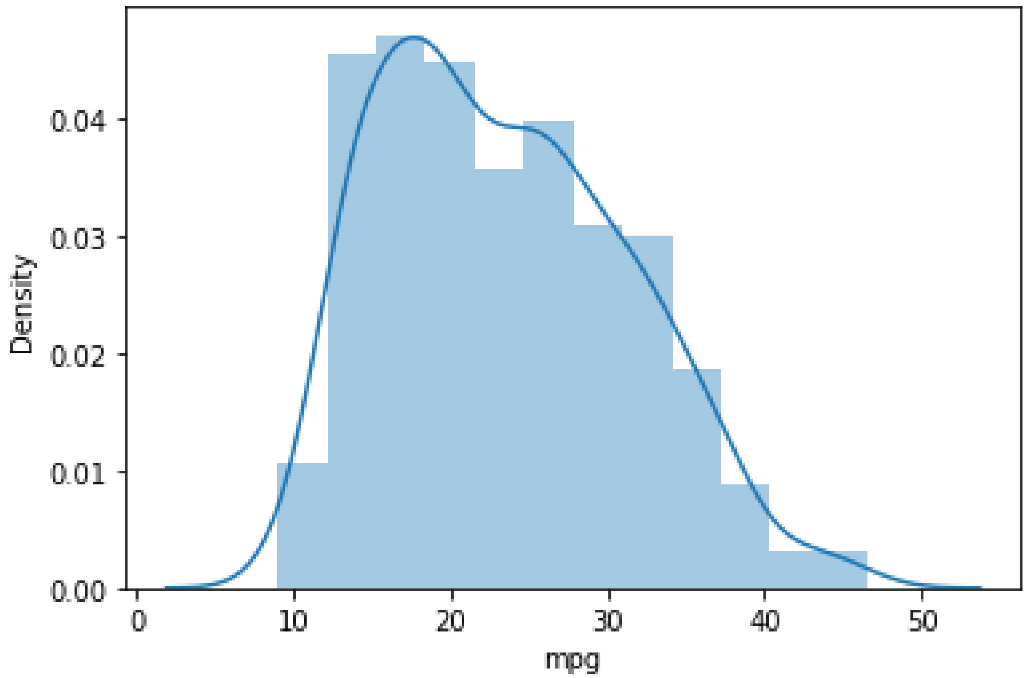
[325]:
```
# I noticed that the origin column corresponded to the location that car was␣
↪made, so I
# moved it to its own discrete column, since this data is categorical
df['countryCode'] = df.origin.replace([1, 2, 3], ['USA', 'Europe', 'Japan'])
df.head()
```

[325]:
```
    mpg  cylinders  displacement  ... origin                    carName
countryCode
0  18.0          8         307.0  ...      1  chevrolet chevelle malibu
USA
1  15.0          8         350.0  ...      1          buick skylark 320
USA
2  18.0          8         318.0  ...      1         plymouth satellite
USA
3  16.0          8         304.0  ...      1              amc rebel sst
USA
4  17.0          8         302.0  ...      1                ford torino
USA

[5 rows x 10 columns]
```

[326]:

```python
# visualizations of mpg
sns.distplot(df['mpg'])
print("Skewness: %f" % df['mpg'].skew())
print("Kurtosis: %f" % df['mpg'].kurt())
```

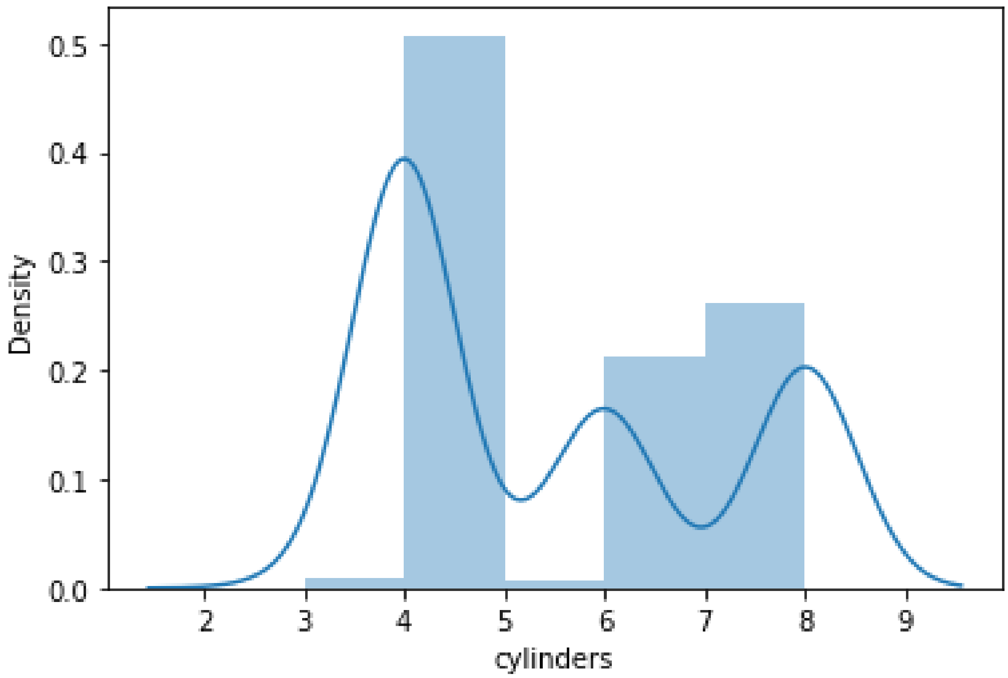
```
Skewness: 0.457092
Kurtosis: -0.515993
```



[327]:

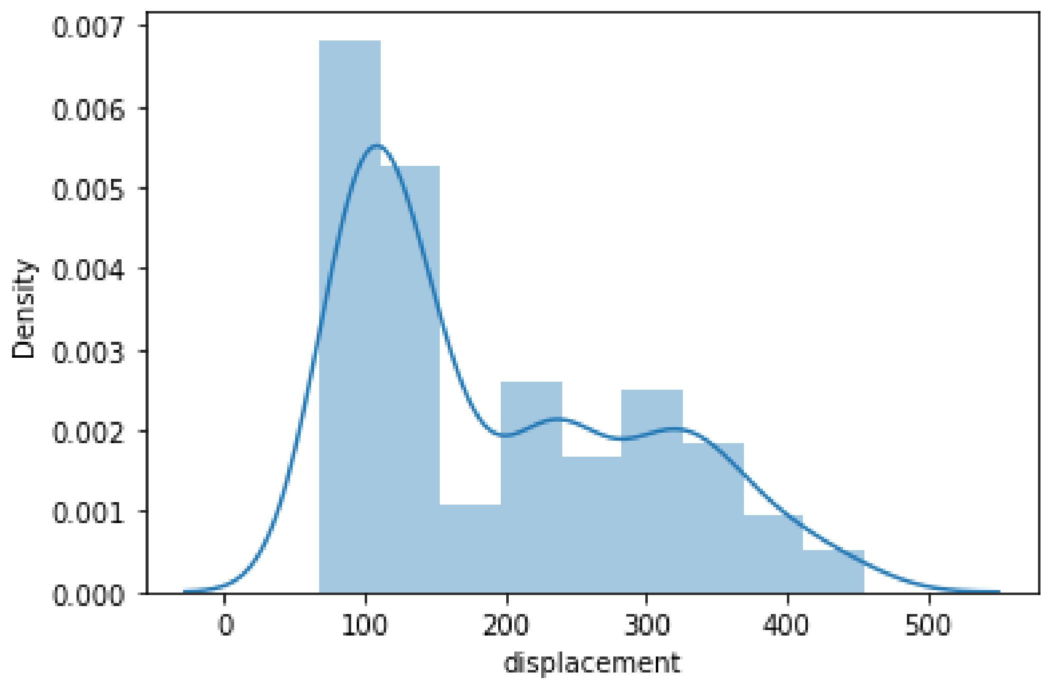
```python
# visualizations of cylinders
sns.distplot(df['cylinders'])
print("Skewness: %f" % df['cylinders'].skew())
print("Kurtosis: %f" % df['cylinders'].kurt())
```

```
Skewness: 0.508109
Kurtosis: -1.398199
```



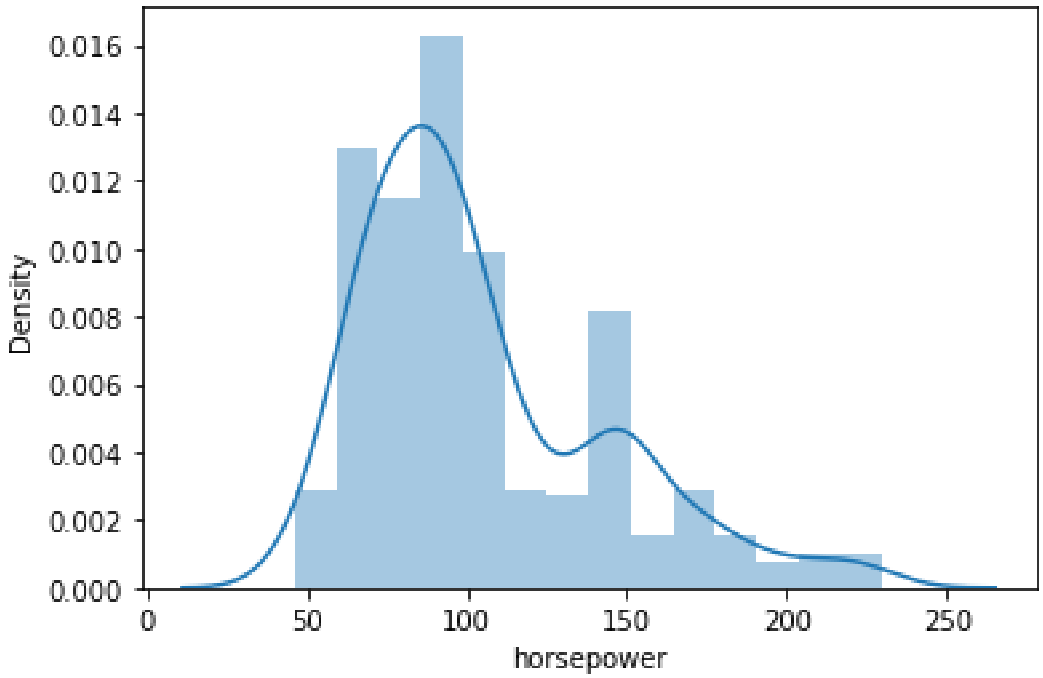
[328]:
```
# visualizations of displacement
sns.distplot(df['displacement'])
print("Skewness: %f" % df['displacement'].skew())
print("Kurtosis: %f" % df['displacement'].kurt())
```

```
Skewness: 0.701669
Kurtosis: -0.778317
```



[329]:
```
# visualizations of horsepower
sns.distplot(df['horsepower'])
print("Skewness: %f" % df['horsepower'].skew())
print("Kurtosis: %f" % df['horsepower'].kurt())
```

```
Skewness: 1.087326
Kurtosis: 0.696947
```



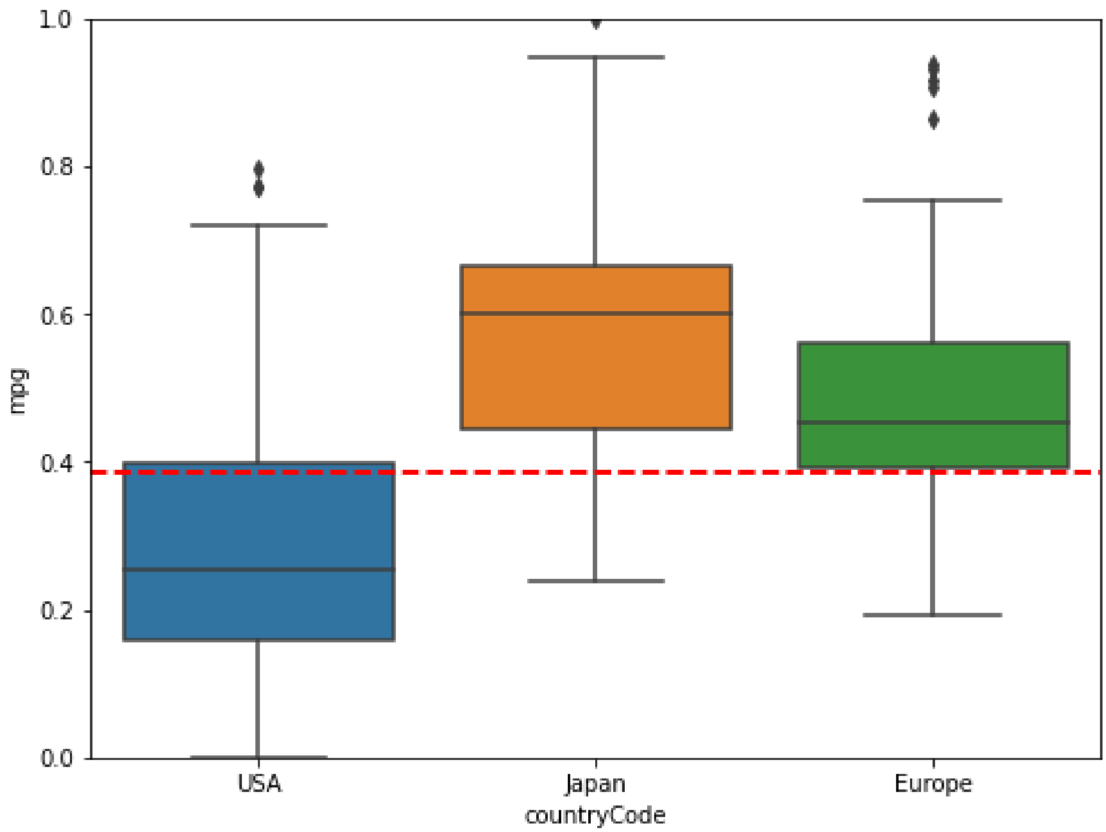
[330]:
```
# i wanted to explore some correlation relationships between different␣
 ↪features, so i decided to normalize the data first
# using minimax normalization
column_names_to_normalize = ['mpg', 'cylinders', 'displacement', 'horsepower',␣
 ↪'weight', 'acceleration', 'modelYear']
x = df[column_names_to_normalize].values
x_scaled = min_max_scaler.fit_transform(x)
df_scale = pd.DataFrame(x_scaled, columns=column_names_to_normalize, index = df.
 ↪index)
df_scale.head()
```

[330]:
```
        mpg  cylinders  displacement  ...    weight  acceleration  modelYear
0  0.239362        1.0      0.617571  ...  0.536150      0.238095        0.0
1  0.159574        1.0      0.728682  ...  0.589736      0.208333        0.0
2  0.239362        1.0      0.645995  ...  0.516870      0.178571        0.0
3  0.186170        1.0      0.609819  ...  0.516019      0.238095        0.0
4  0.212766        1.0      0.604651  ...  0.520556      0.148810        0.0

[5 rows x 7 columns]
```

[331]:
```
# visualizes the mpg relationships across the three manufacturing regions
# as we can see, cars manufactured in the united states are typically much␣
 ↪lower
# than the average mpg
```

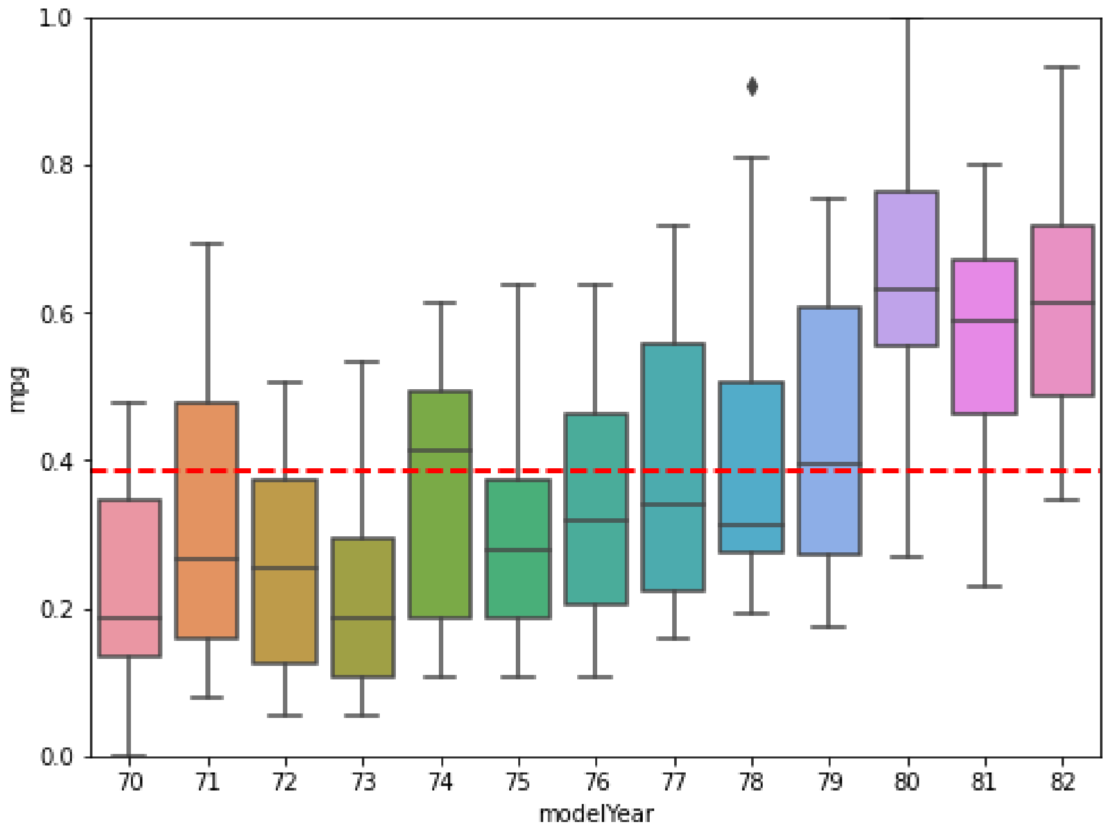
```
# japanese and european mpg are typically higher than average, indicating␣
↪differences
# in environmental standards for vehicle manufacturing

data_plt = pd.concat([df_scale['mpg'], df['countryCode']], axis = 1)
f, ax = plt.subplots(figsize=(8, 6))
fig = sns.boxplot(x='countryCode', y="mpg", data=data_plt)
fig.axis(ymin=0, ymax=1)
plt.axhline(df_scale.mpg.mean(),color='r',linestyle='dashed',linewidth=2)
```

[331]: <matplotlib.lines.Line2D at 0x7f275df82be0>



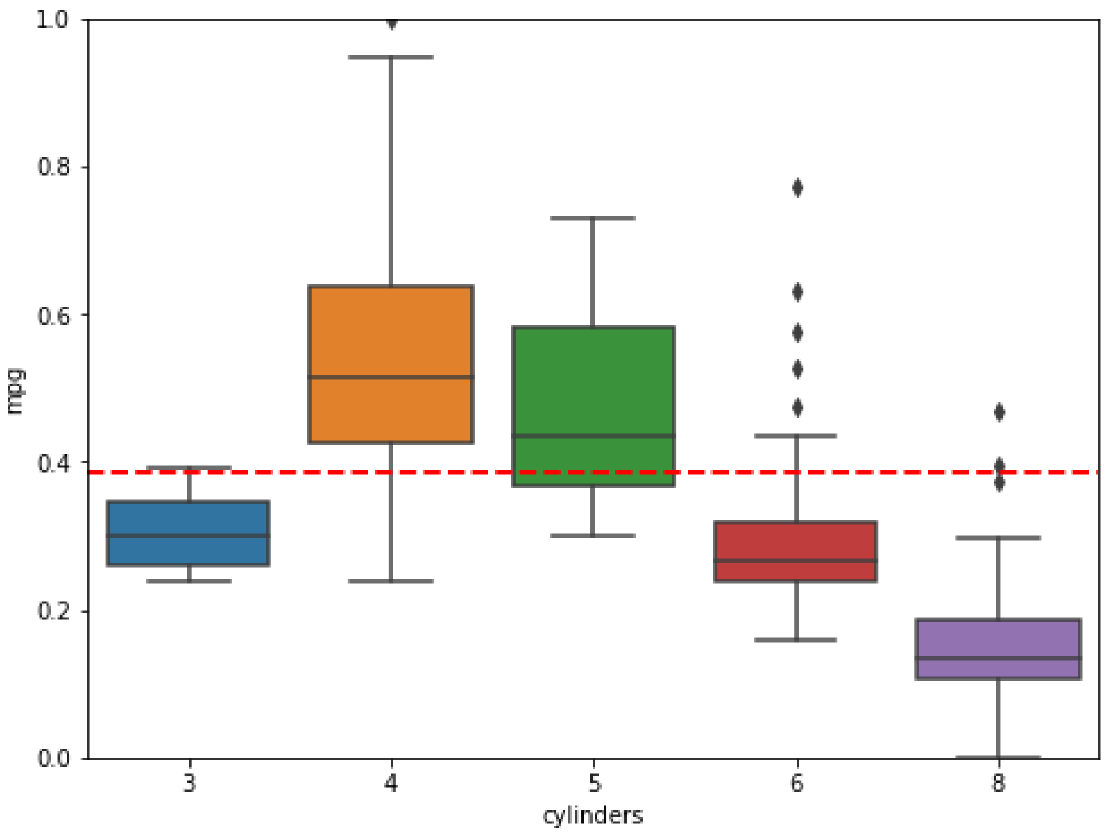
[332]:
```
# now, let's look at the trends of fuel efficiency over time
# we can see a clear uptick in fuel efficiency over time
# indicating better technology and rising fuel efficiency standards

data_plt = pd.concat([df_scale['mpg'], df['modelYear']], axis=1)
f, ax = plt.subplots(figsize=(8, 6))
fig = sns.boxplot(x='modelYear', y="mpg", data=data_plt)
fig.axis(ymin=0, ymax=1)
plt.axhline(df_scale.mpg.mean(),color='r',linestyle='dashed',linewidth=2)
```

[332]: <matplotlib.lines.Line2D at 0x7f275e0c7470>

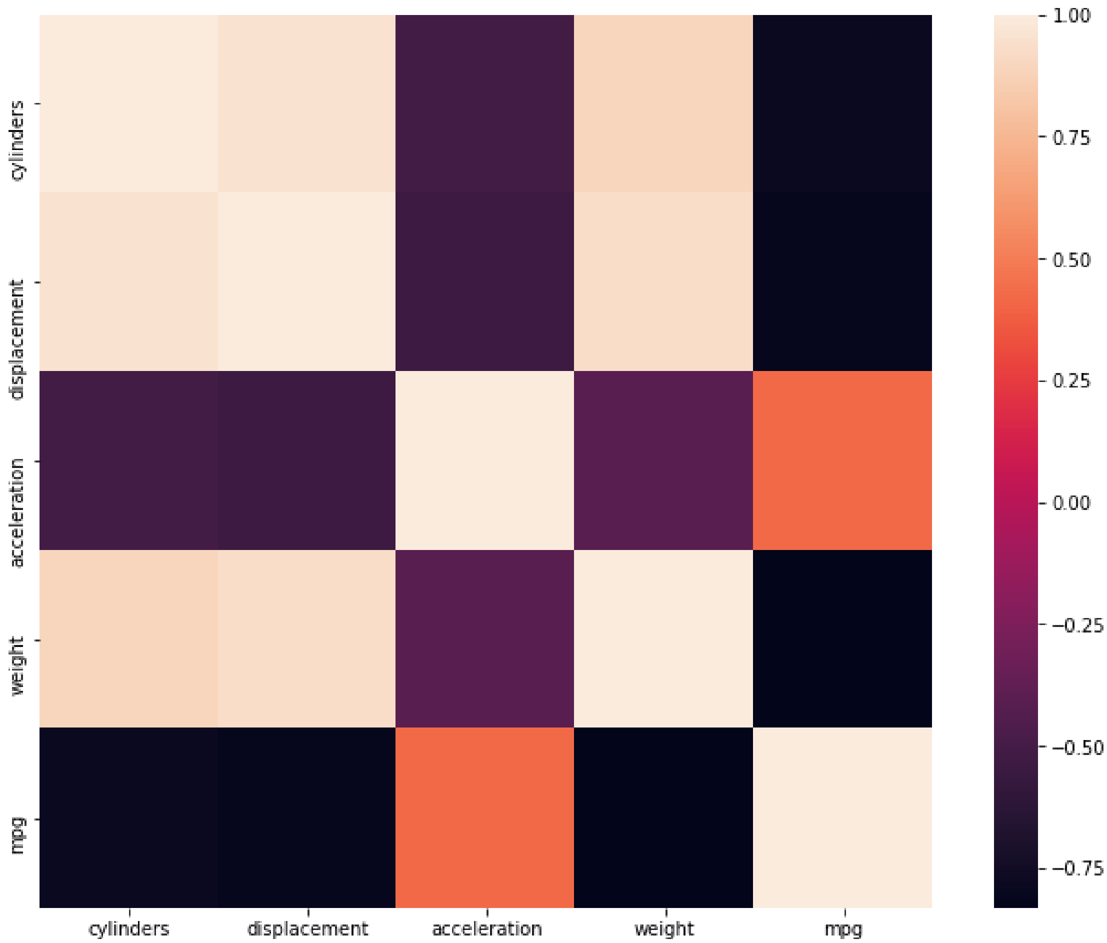


[333]:
```
# now, let's try and understand the changes in mpg with respect to the number␣
 ↪of cylinders
# that a car has. we can see that optimality is reached closer to 4 cylinders
# with lower numbers decreasing efficiency and higher numbers experiencing␣
 ↪decreasing efficiency
data_plt = pd.concat([df_scale['mpg'], df['cylinders']], axis=1)
f, ax = plt.subplots(figsize=(8, 6))
fig = sns.boxplot(x='cylinders', y="mpg", data=data_plt)
fig.axis(ymin=0, ymax=1)
plt.axhline(df_scale.mpg.mean(),color='r',linestyle='dashed',linewidth=2)
```

[333]: <matplotlib.lines.Line2D at 0x7f275db7c2e8>



[334]:
```
# let's now explore the correlations between different variables
# this might give us a sense of what features are interrelated within are model
# and whether certain features are likely to influence each other when it comes␣
↪to mpg
# this mainly focuses on quantitative features

factors =␣
↪['cylinders','displacement','horsepower','acceleration','weight','mpg']
corrmat = df[factors].corr()
f, ax = plt.subplots(figsize=(12, 9))
sns.heatmap(corrmat, square=True);
```

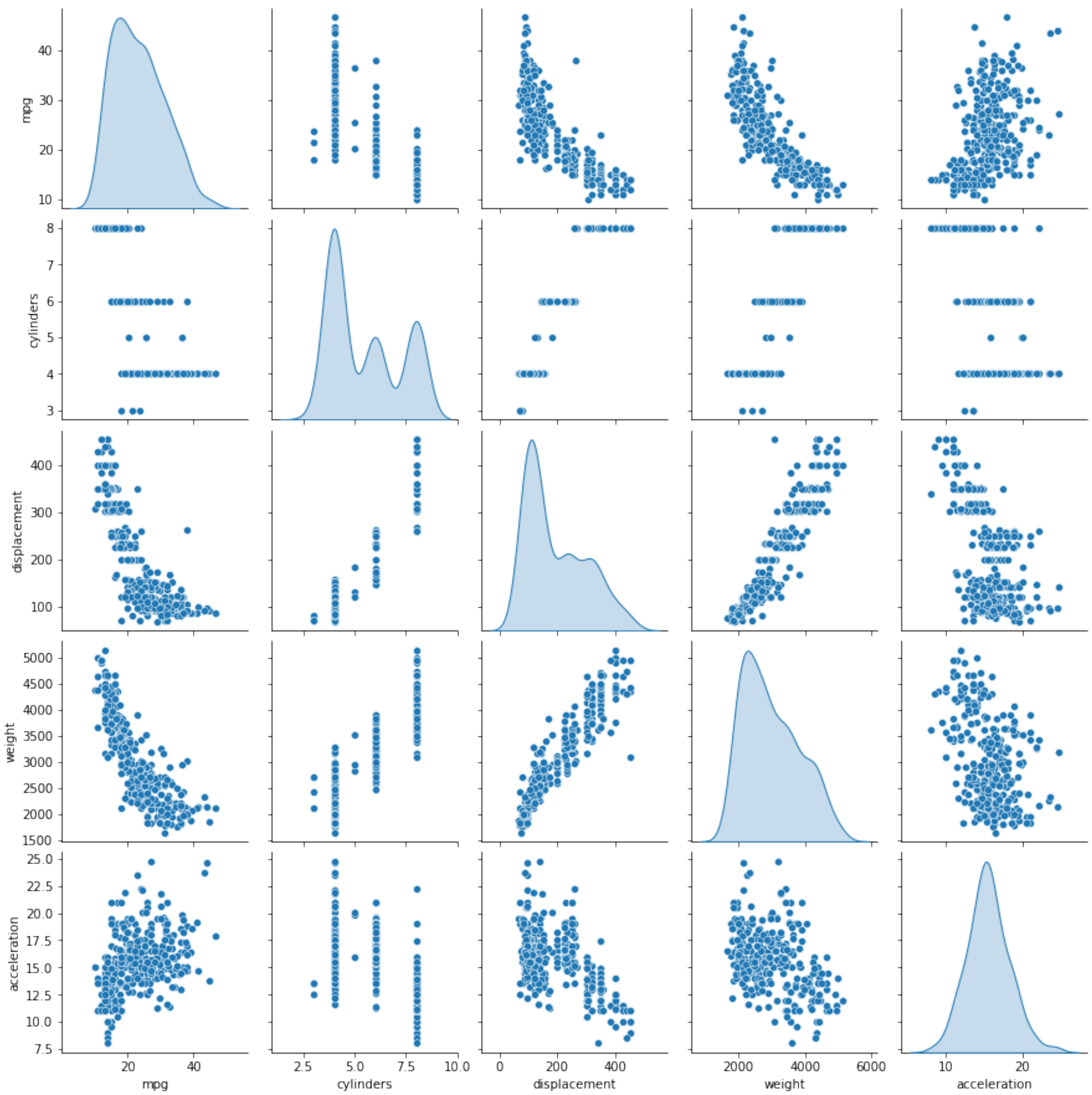


[366]:
```
# Creating training and testing datasets for the creation of our model
# We want to use these to "predict" the fuel efficiency of a given car
dataset = pd.read_csv(dataset_path)
dataset['carName'] = dataset['carName'].str.replace('((\\t)|(\"))', '')
dataset = dataset.dropna()
dataset = dataset[dataset.horsepower != '?']

# importing in new clean version of the data
origin = dataset.pop('origin')
dataset['USA'] = (origin == 1) * 1.0
dataset['Europe'] = (origin == 2) * 1.0
dataset['Japan'] = (origin == 3) * 1.0
traindf = dataset.sample(frac=0.8,random_state=0)
testdf = dataset.drop(train.index)

# this provides a quick visualization of our training dataset based on 5 key␣
↪params
```

```
sns.pairplot(traindf[["mpg", "cylinders", "displacement", "weight",␣
↪"acceleration"]], diag_kind="kde")
traindf = traindf.drop(columns=["carName"])
traindf.head()
```

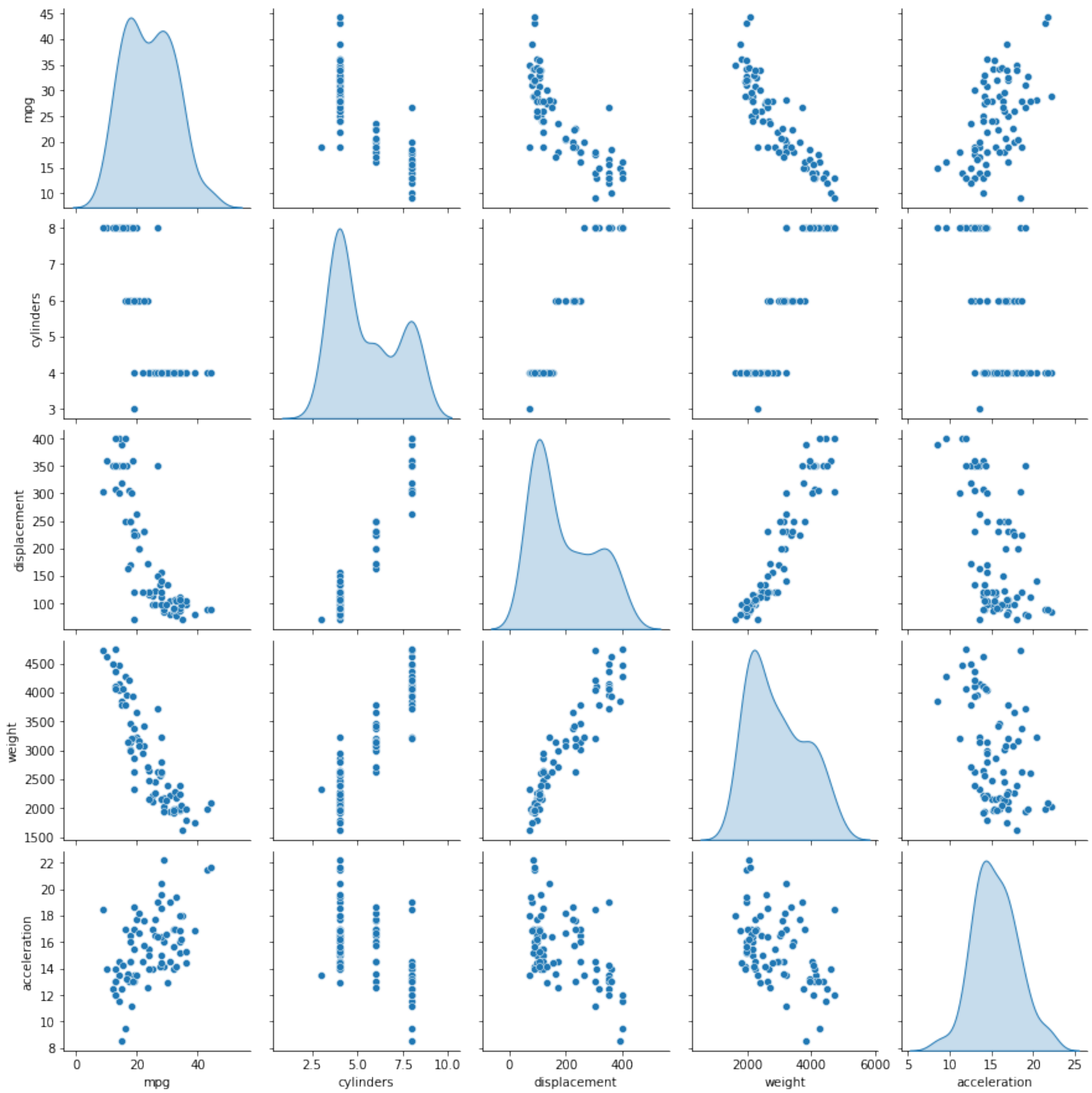
[366]:

```
      mpg  cylinders  displacement horsepower  ...  modelYear  USA  Europe
Japan
146  28.0          4          90.0         75  ...         74  1.0     0.0
0.0
282  22.3          4         140.0         88  ...         79  1.0     0.0
0.0
69   12.0          8         350.0        160  ...         72  1.0     0.0
0.0
378  38.0          4         105.0         63  ...         82  1.0     0.0
0.0
331  33.8          4          97.0         67  ...         80  0.0     0.0
1.0

[5 rows x 10 columns]
```



[367]:
```
# we want these plots to look similar between training and testing
sns.pairplot(testdf[["mpg", "cylinders", "displacement", "weight",␣
 ↪"acceleration"]], diag_kind="kde")
testdf = testdf.drop(columns=["carName"])
testdf.head()
```

[367]:
```
     mpg  cylinders  displacement horsepower  ...  modelYear  USA  Europe  Japan
9   15.0          8         390.0        190  ...         70  1.0     0.0    0.0
25  10.0          8         360.0        215  ...         70  1.0     0.0    0.0
28   9.0          8         304.0        193  ...         70  1.0     0.0    0.0
31  25.0          4         113.0         95  ...         71  0.0     0.0    1.0
33  19.0          6         232.0        100  ...         71  1.0     0.0    0.0

[5 rows x 10 columns]
```



[368]:
```
# some useful statistics about out training dataset
train_stats = traindf.describe()
train_stats.pop("mpg")
train_stats = train_stats.transpose()
train_stats


# these are the actual labels for our data, which will be used to determine how
# we train the data and compare our error to true mpg values
train_labels = traindf.pop('mpg')
test_labels = testdf.pop('mpg')
```

[372]:
```
# this essentially normalizes the data and puts each data point on the same␣
↪scale
```

```
# between 0 and 1, essentially ensuring that we are training our data on the␣
↪same scale

def norm(x):
  return (x - train_stats['mean']) / train_stats['std']
normed_train_data = norm(traindf)
normed_test_data = norm(testdf)

# the data was having issues normalizing horsepower, so for the purposes of␣
↪analysis, i dropped this column
# however, in future iterations, it would definitely make sense to include this␣
↪feature
normed_train_data = normed_train_data.drop(columns=['horsepower'])
normed_train_data
```

[372]:

```
       Europe     Japan       USA  ...  displacement  modelYear    weight
146 -0.465148 -0.495225  0.774676  ...     -1.009459  -0.516397 -1.025303
282 -0.465148 -0.495225  0.774676  ...     -0.530218   0.843910 -0.118796
69  -0.465148 -0.495225  0.774676  ...      1.482595  -1.060519  1.736877
378 -0.465148 -0.495225  0.774676  ...     -0.865687   1.660094 -1.025303
331 -0.465148  2.012852 -1.286751  ...     -0.942365   1.115971 -1.001603
..        ...       ...       ...  ...           ...        ...       ...
281 -0.465148 -0.495225  0.774676  ...      0.044872   0.843910 -0.000298
229 -0.465148 -0.495225  0.774676  ...      1.961837   0.299787  1.457223
150 -0.465148  2.012852 -1.286751  ...     -0.836932  -0.516397 -0.710099
145 -0.465148  2.012852 -1.286751  ...     -1.076553  -0.516397 -1.169870
182  2.143005 -0.495225 -1.286751  ...     -0.846517   0.027726 -0.623596

[314 rows x 8 columns]
```

[384]:

```
# this creates a multi-layer neural network based on the training dataset which␣
↪we have cleaned and provided
# since we are ignoring the horsepower column, we had to lower the number of␣
↪keys that we are considering
def build_model():
  model = keras.Sequential([
    layers.Dense(64, activation=tf.nn.relu, input_shape=[len(traindf.keys()) -␣
↪1]),
    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()
```

[376]:
```
# this highlights the model training process, and prints a dot after every
↪epoch (training period)

class PrintDot(keras.callbacks.Callback):
  def on_epoch_end(self, epoch, logs):
    if epoch % 100 == 0: print('')
    print('.', end='')

EPOCHS = 1000

history = model.fit(
  normed_train_data, train_labels,
  epochs=EPOCHS, validation_split = 0.2, verbose=0,
  callbacks=[PrintDot()])
```

```
...
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```
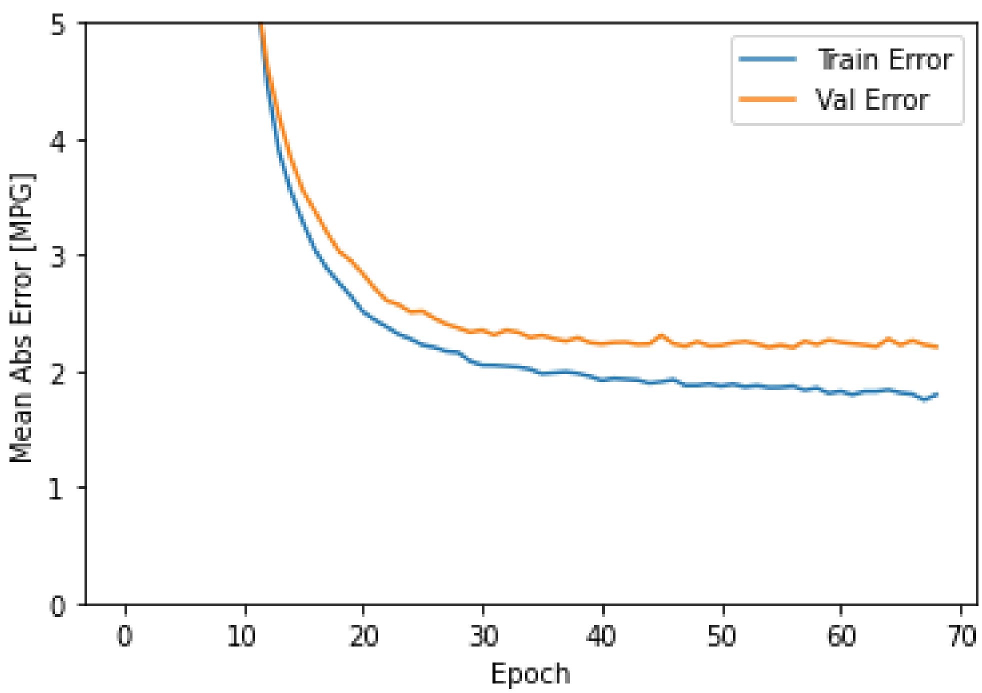
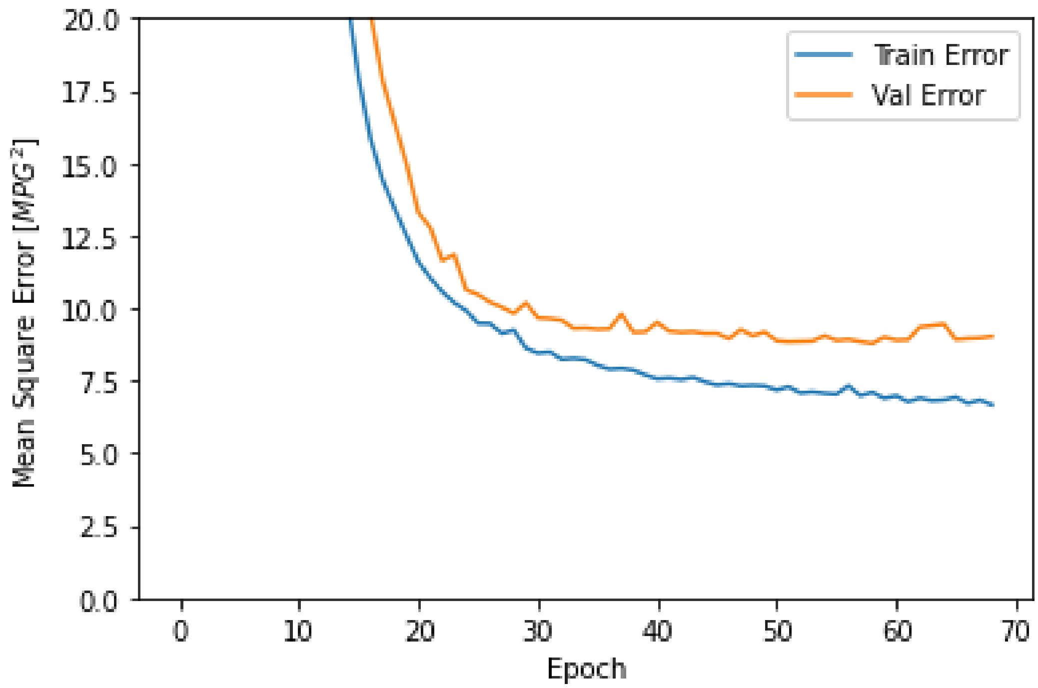

[383]:
```
# this is the training history of the model, and shows its progression towards
↪accurate predictions
hist = pd.DataFrame(history.history)
hist['epoch'] = history.epoch
hist.tail()
```

[383]:
```
        loss  mean_absolute_error  ...  val_mean_squared_error  epoch
64  6.831895             1.837125  ...                9.453544     64
```

```
65  6.930665          1.810498  ...          8.919894     65
66  6.714414          1.799366  ...          8.955868     66
67  6.829274          1.749298  ...          8.973021     67
68  6.667157          1.794449  ...          9.026224     68

[5 rows x 7 columns]
```

[381]:
```python
model = build_model()

# our model experienced a dropoff in performance earlier on, since the rate of
 ↪improvement was not really improving after a certain point
# so we use this parameter stop early
early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=10)

history = model.fit(normed_train_data, train_labels, epochs=EPOCHS,
                    validation_split = 0.2, verbose=0, callbacks=[early_stop,
 ↪PrintDot()])

plot_history(history)
```

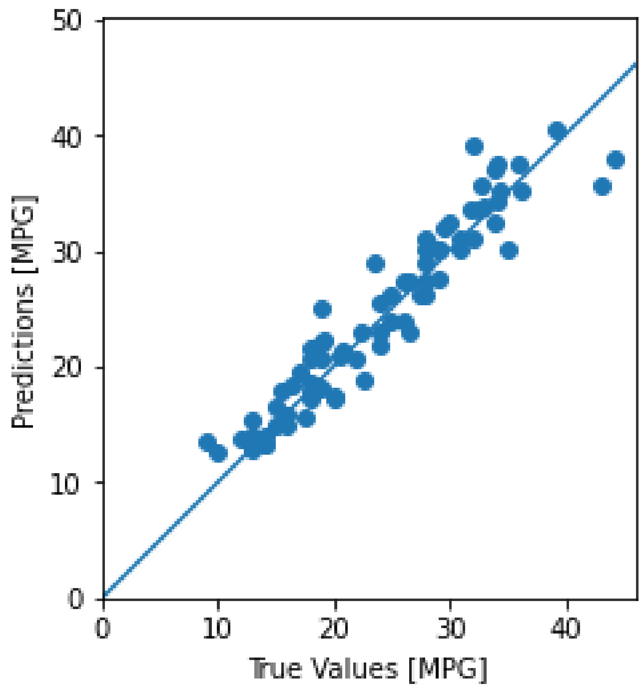




[382]:

```
# these are some final statistics about the accuracy of our model
# from this, we were able to predict the miles per gallon of a car accurately␣
↪based
# on the intaked parameters to within 2 miles per gallon

loss, mae, mse = model.evaluate(normed_test_data, test_labels, verbose=0)

print("Testing set Mean Abs Error: {:5.2f} MPG".format(mae))
test_predictions = model.predict(normed_test_data).flatten()

plt.scatter(test_labels, test_predictions)
plt.xlabel('True Values [MPG]')
plt.ylabel('Predictions [MPG]')
plt.axis('equal')
plt.axis('square')
plt.xlim([0,plt.xlim()[1]])
plt.ylim([0,plt.ylim()[1]])
_ = plt.plot([-100, 100], [-100, 100])
```

```
Testing set Mean Abs Error:  1.92 MPG
```


Predictions [MPG]
True Values [MPG]
0
10
20
30
40
50