Regression

June 16, 2019

1 Regression

Prediction of the output of a continuos value (like price or probability)

[2]:
```
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

print(tf.__version__)
```

```
1.13.1
```

1.1 Fecthing data

[3]:
```
dataset_path = keras.utils.get_file("auto-mpg.data", "https://archive.ics.uci.
↪edu/ml/machine-learning-databases/auto-mpg/auto-mpg.data")
```

[3]:
```
column_names = ['MPG','Cylinders','Displacement','Horsepower','Weight',
                'Acceleration', 'Model Year', 'Origin']
raw_dataset = pd.read_csv(dataset_path, names=column_names,
                      na_values = "?", comment='\t',
                      sep=" ", skipinitialspace=True)

dataset = raw_dataset.copy()
dataset.tail()
```

[3]:

	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	\
393	27.0	4	140.0	86.0	2790.0	15.6	
394	44.0	4	97.0	52.0	2130.0	24.6	
395	32.0	4	135.0	84.0	2295.0	11.6	

```
396  28.0          4         120.0        79.0  2625.0          18.6
397  31.0          4         119.0        82.0  2720.0          19.4

     Model Year  Origin
393          82       1
394          82       2
395          82       1
396          82       1
397          82       1
```

1.2 Cleaning data

These is the count of unknown values for each feature.

[4]:
```
dataset.isna().sum()
```

[4]:
```
MPG             0
Cylinders       0
Displacement    0
Horsepower      6
Weight          0
Acceleration    0
Model Year      0
Origin          0
dtype: int64
```

The simplest solution is to drop these rows.

[5]:
```
dataset = dataset.dropna()
```

The Origin feature is categorical not numerical, so we convert it to one-hot.

[6]:
```
origin = dataset.pop('Origin')
dataset['USA'] = (origin == 1)*1.0
dataset['Europe'] = (origin == 2)*1.0
dataset['Japan'] = (origin == 3)*1.0
dataset.tail()
origin.tail()
```

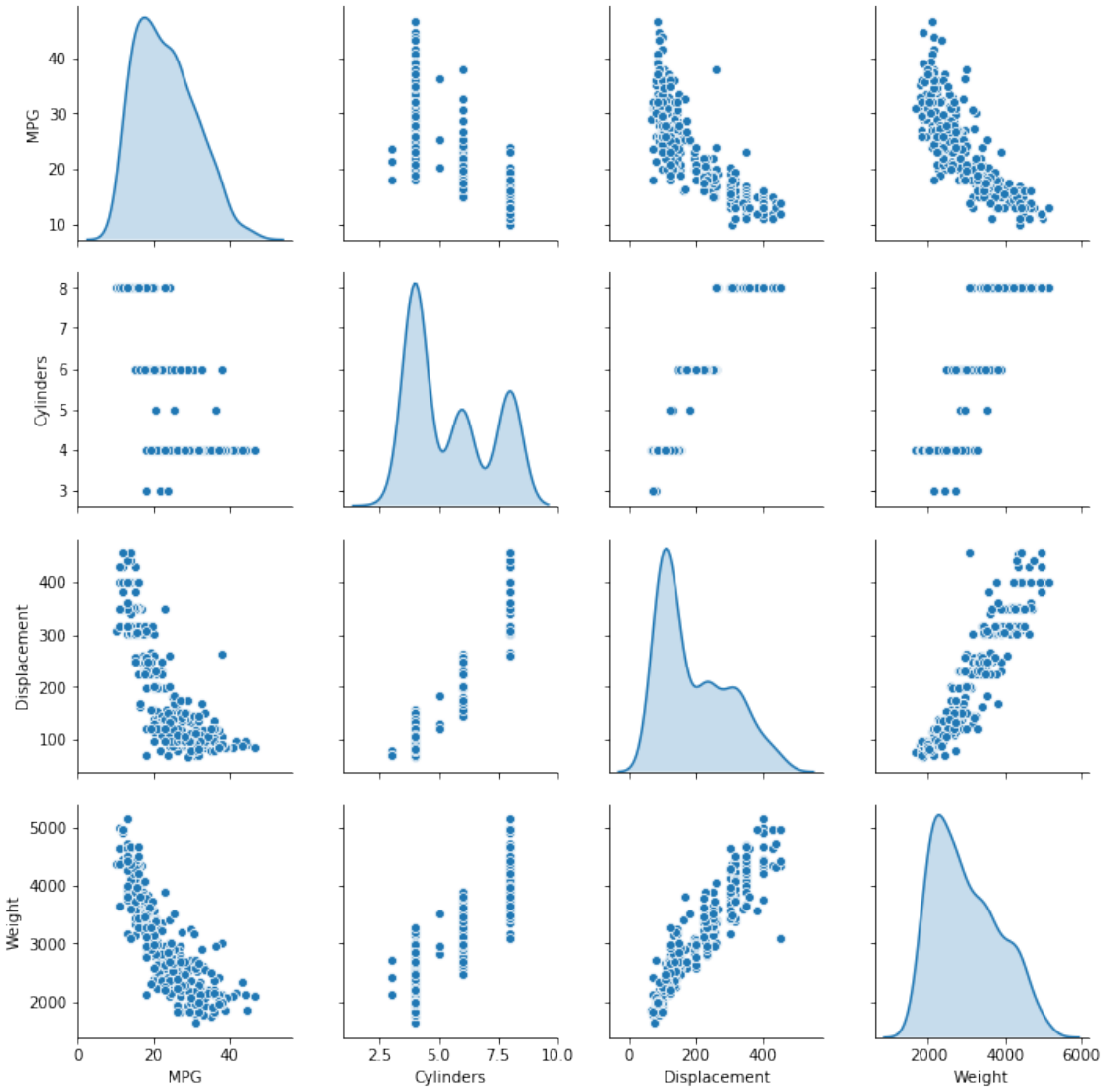
[6]:
```
393    1
394    2
395    1
396    1
397    1
Name: Origin, dtype: int64
```

1.3 Preparing train and test set

[7]:
```
train_dataset = dataset.sample(frac=0.8,random_state=0)
test_dataset = dataset.drop(train_dataset.index)
```

[8]:
```
sns.pairplot(train_dataset[["MPG", "Cylinders", "Displacement", "Weight"]],␣
↪diag_kind="kde")
```

[8]:
```
<seaborn.axisgrid.PairGrid at 0x22a4fee52b0>
```



Overall statistics

[9]:
```
train_stats = train_dataset.describe()
train_stats.pop("MPG")
train_stats = train_stats.transpose()
```

```
train_stats
```

[9]:

	count	mean	std	min	25%	50%	\
Cylinders	314.0	5.477707	1.699788	3.0	4.00	4.0	
Displacement	314.0	195.318471	104.331589	68.0	105.50	151.0	
Horsepower	314.0	104.869427	38.096214	46.0	76.25	94.5	
Weight	314.0	2990.251592	843.898596	1649.0	2256.50	2822.5	
Acceleration	314.0	15.559236	2.789230	8.0	13.80	15.5	
Model Year	314.0	75.898089	3.675642	70.0	73.00	76.0	
USA	314.0	0.624204	0.485101	0.0	0.00	1.0	
Europe	314.0	0.178344	0.383413	0.0	0.00	0.0	
Japan	314.0	0.197452	0.398712	0.0	0.00	0.0	

	75%	max
Cylinders	8.00	8.0
Displacement	265.75	455.0
Horsepower	128.00	225.0
Weight	3608.00	5140.0
Acceleration	17.20	24.8
Model Year	79.00	82.0
USA	1.00	1.0
Europe	0.00	1.0
Japan	0.00	1.0

Split features from labels

[10]:
```
train_labels = train_dataset.pop('MPG')
test_labels = test_dataset.pop('MPG')
```

Standarization of the data Features have very different ranges. It is good practice to standarize them, both training and test set. Afterwards this standarization should be applied to any data supplied to the model.

[4]:
```
def std(x):
  return (x - train_stats['mean']) / train_stats['std'] # std = standard␣
 ↪deviation

std_train_data = std(train_dataset)
std_test_data = std(test_dataset)
```

```
     ␣
↪---------------------------------------------------------------------------

      NameError                                 Traceback (most recent call␣
↪last)

      <ipython-input-4-24784954a5c0> in <module>
```

```
      2   return (x - train_stats['mean']) / train_stats['std'] # std =␣
↪standard deviation
      3
----> 4 std_train_data = std(train_dataset)
      5 std_test_data = std(test_dataset)


NameError: name 'train_dataset' is not defined
```

1.4 Building model

[12]:
```
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
```

[13]:
```
model = build_model()
model.summary()
```

```
WARNING:tensorflow:From C:\Users\Pedro\AppData\Roaming\Python\Python37\site-
packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate_with (from
tensorflow.python.framework.ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From C:\Users\Pedro\AppData\Roaming\Python\Python37\site-
packages\tensorflow\python\keras\utils\losses_utils.py:170: to_float (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Use tf.cast instead.
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                640
_________________________________________________________________
dense_1 (Dense)              (None, 64)                4160
```

```
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 65
=================================================================
Total params: 4,865
Trainable params: 4,865
Non-trainable params: 0
_________________________________________________________________
```

Using a batch of 10 examples, we get a result of expected shape and type

[14]:
```
example_batch = std_train_data[:10]
example_result = model.predict(example_batch)
example_result
```

[14]:
```
array([[ 0.07452573],
       [ 0.14103524],
       [ 0.5635772 ],
       [-0.01620242],
       [ 0.00851503],
       [ 0.17594233],
       [-0.00834686],
       [ 0.02530932],
       [ 0.09892672],
       [-0.05652761]], dtype=float32)
```

1.5 Training the model

[15]:
```
# Display training progress by printing a single dot for each completed epoch
class PrintDot(keras.callbacks.Callback):
  def on_epoch_end(self, epoch, logs):
    if epoch % 100 == 0: print('')
    print('.', end='')

EPOCHS = 1000

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

```
WARNING:tensorflow:From C:\Users\Pedro\AppData\Roaming\Python\Python37\site-
packages\tensorflow\python\ops\math_ops.py:3066: to_int32 (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Use tf.cast instead.

...
```

```
...
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```
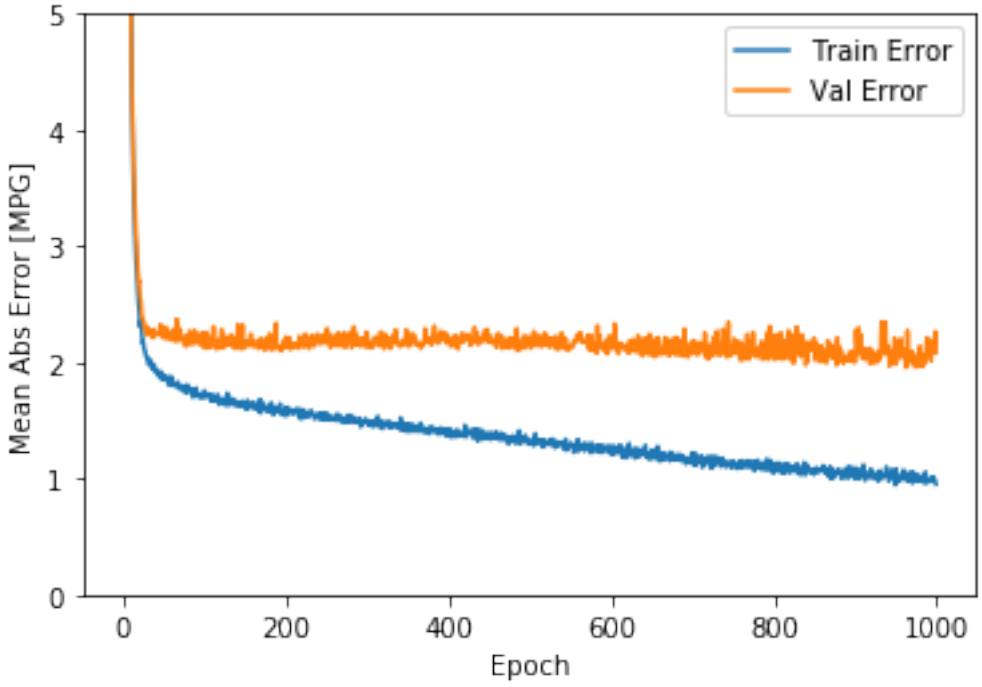
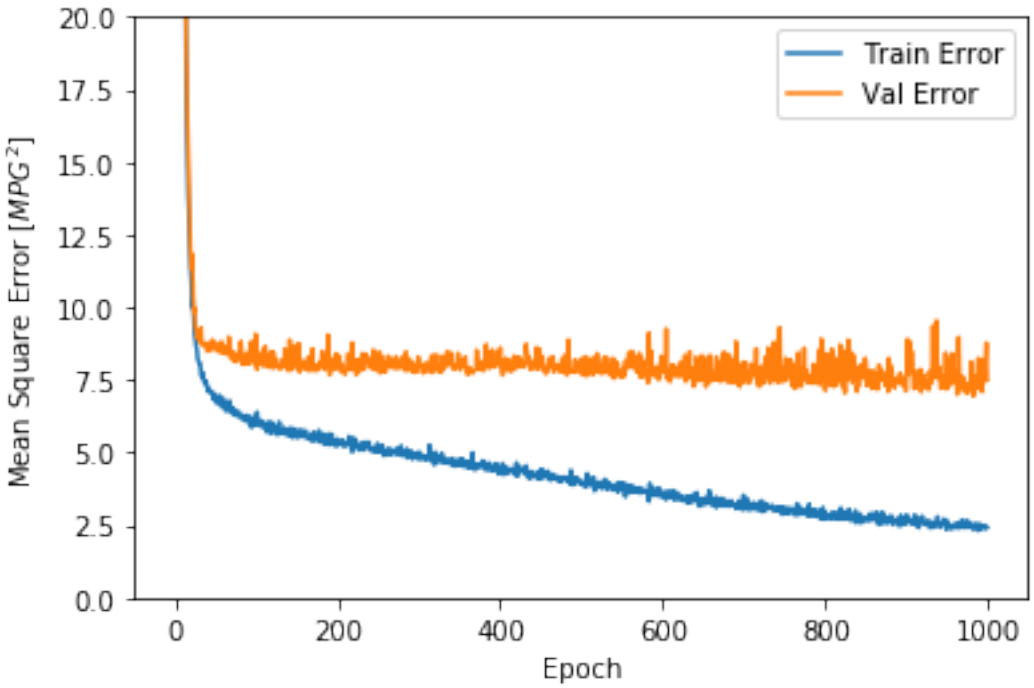

[16]:
```
hist = pd.DataFrame(history.history)
hist['epoch'] = history.epoch
hist.tail()
```

[16]:
```
         loss  mean_absolute_error  mean_squared_error  val_loss  \
995  2.419831             1.001674            2.419831  7.761292
996  2.492154             1.014695            2.492154  7.445597
997  2.375593             0.980913            2.375593  8.305652
998  2.407437             0.981926            2.407437  8.774310
999  2.419821             0.952775            2.419821  7.496795

     val_mean_absolute_error  val_mean_squared_error  epoch
995                 2.100382                7.761292    995
996                 2.082788                7.445597    996
997                 2.197683                8.305653    997
998                 2.265940                8.774309    998
999                 2.084954                7.496795    999
```

[17]:
```
def plot_history(history):
  hist = pd.DataFrame(history.history)
  hist['epoch'] = history.epoch

  plt.figure()
  plt.xlabel('Epoch')
  plt.ylabel('Mean Abs Error [MPG]')
  plt.plot(hist['epoch'], hist['mean_absolute_error'],
           label='Train Error')
  plt.plot(hist['epoch'], hist['val_mean_absolute_error'],
           label = 'Val Error')
```

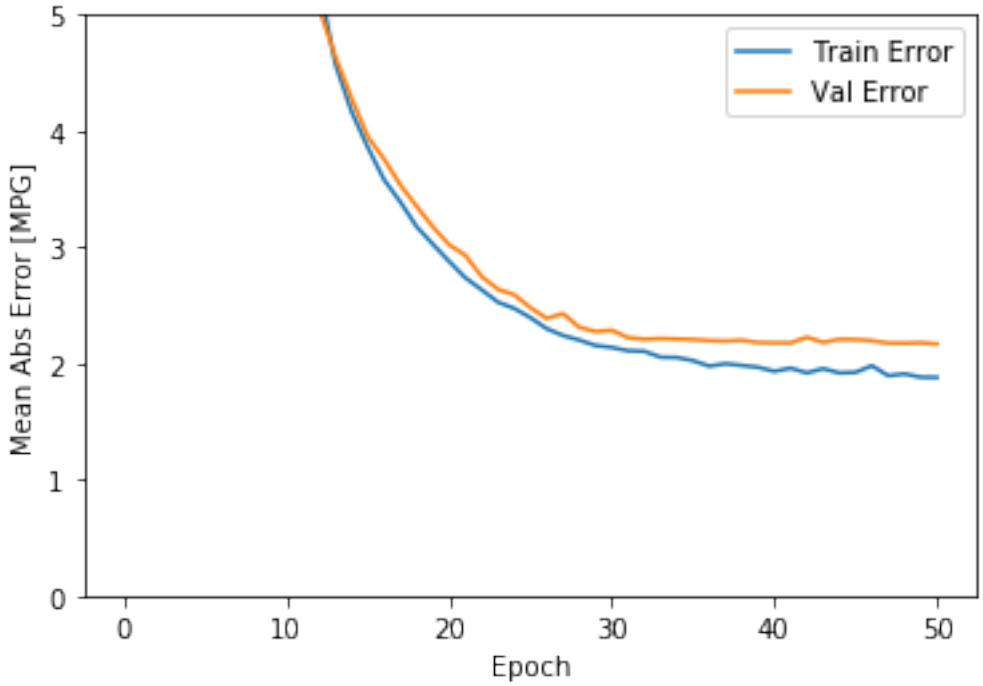
```
  plt.ylim([0,5])
  plt.legend()

  plt.figure()
  plt.xlabel('Epoch')
  plt.ylabel('Mean Square Error [$MPG^2$]')
  plt.plot(hist['epoch'], hist['mean_squared_error'],
           label='Train Error')
  plt.plot(hist['epoch'], hist['val_mean_squared_error'],
           label = 'Val Error')
  plt.ylim([0,20])
  plt.legend()
  plt.show()


plot_history(history)
```

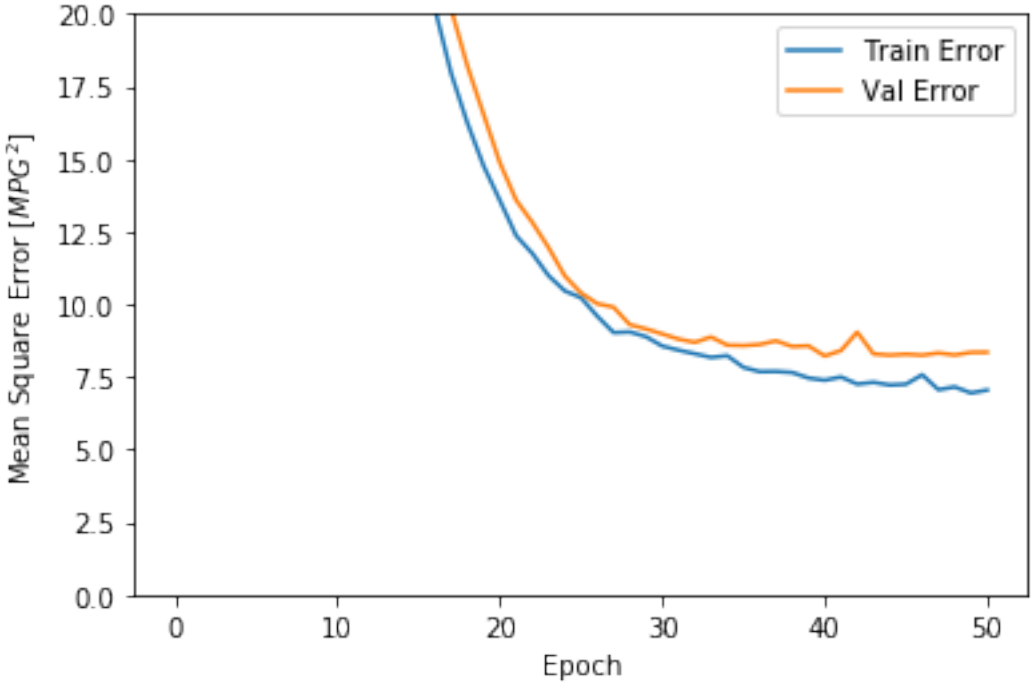




This model show degradation of the validation error after around 100 epochs. So we will add an EarlyStopping callback that is checked at end of every epoch and then stop when validation score doesn't improve.

[18]:
```
model = build_model()

# The patience parameter is the amount of epochs without improvement before␣
 ↪training should stop
early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=10)

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

plot_history(history)
```


Train Error
Val Error
Mean Abs Error [MPG]
Epoch
0
1
2
3
4
5
0
10
20
30
40
50


Train Error
Val Error
Mean Square Error [MPG^2]
Epoch
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
0
10
20
30
40
50

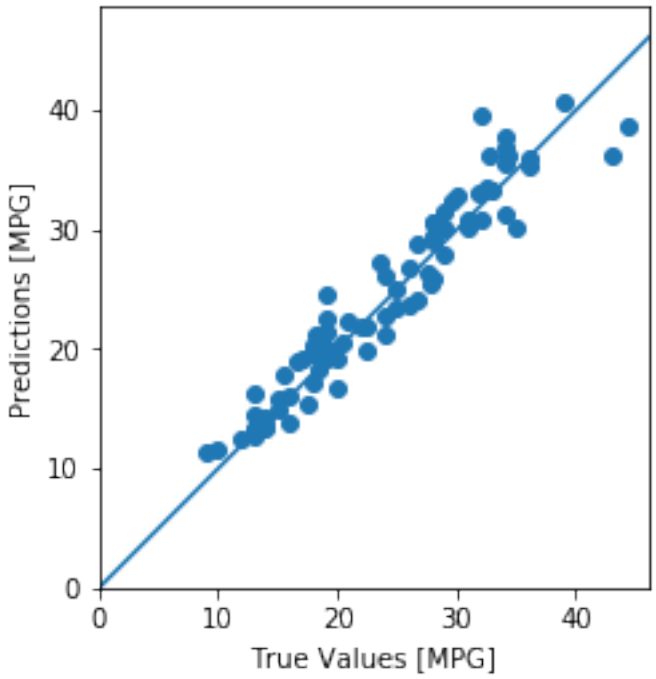
1.6 Evaluation

[19]:
```
loss, mae, mse = model.evaluate(std_test_data, test_labels, verbose=0)

print("Testing set Mean Abs Error: {:5.2f} MPG".format(mae))
```

```
Testing set Mean Abs Error:  1.88 MPG
```

Predictions The model predicts reasonably well.

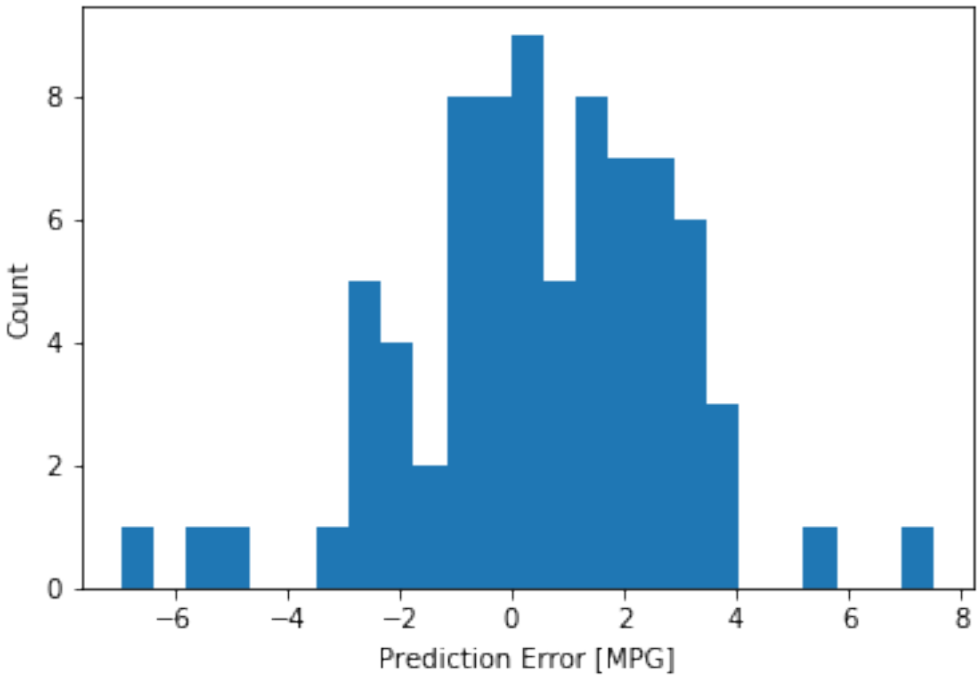
[20]:
```
test_predictions = model.predict(std_test_data).flatten()

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])
```



Error distribution

[21]:
```
error = test_predictions - test_labels
plt.hist(error, bins = 25)
```

```
plt.xlabel("Prediction Error [MPG]")
_ = plt.ylabel("Count")
```



1.7 Conclusion

- Mean Squared Error (MSE) is a common loss function used for regression problems (different loss functions are used for classification problems).
- Similarly, evaluation metrics used for regression differ from classification. A common regression metric is Mean Absolute Error (MAE).
- When numeric input data features have values with different ranges, each feature should be scaled independently to the same range.
- If there is not much training data, one technique is to prefer a small network with few hidden layers to avoid overfitting.
- Early stopping is a useful technique to prevent overfitting.