```
from __future__ import absolute_import, division, print_function, unicode_literals

import pathlib

import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns


try:
  # %tensorflow_version only exists in Colab.
  %tensorflow_version 2.x
except Exception:
  pass
import tensorflow as tf

from tensorflow import keras
from tensorflow.keras import layers

print(tf.__version__)
```

```
Colab only includes TensorFlow 2.x; %tensorflow_version has no effect.
2.11.0
```

```
import pandas as pd
from sklearn.datasets import load_boston
boston = load_boston()
print(boston.data.shape) #get (numer of rows, number of columns or 'features')
print(boston.DESCR) #get a description of the dataset
```

```
(506, 13)
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value (attribute 14) is usually the target.

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of black people by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/


This dataset was taken from the StatLib library which is maintained at Carnegie Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers that address regression
problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of Collinearity', Wiley, 1980. 244-
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the Tenth International Conference o

/usr/local/lib/python3.8/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function load_boston is deprecated; `load_

    The Boston housing prices dataset has an ethical problem. You can refer to
```

```
the documentation of this function for further details
```

```
# Next, we load the data into a 'dataframe' object for easier manipulation, and also print the first few rows in order to examine it
data = pd.DataFrame(boston.data, columns=boston.feature_names)
data.head() #notice that the target variable (MEDV) is not included
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

```
#For some reason, the loaded data does not include the target variable (MEDV), we add it here
data['MEDV'] = pd.Series(data=boston.target, index=data.index)
data.describe() #get some basic stats on the dataset
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000

```
data.tail() #check out the end of the data (last 5 rows)
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99	9.67
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90	9.08
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90	5.64
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45	6.48
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90	7.88

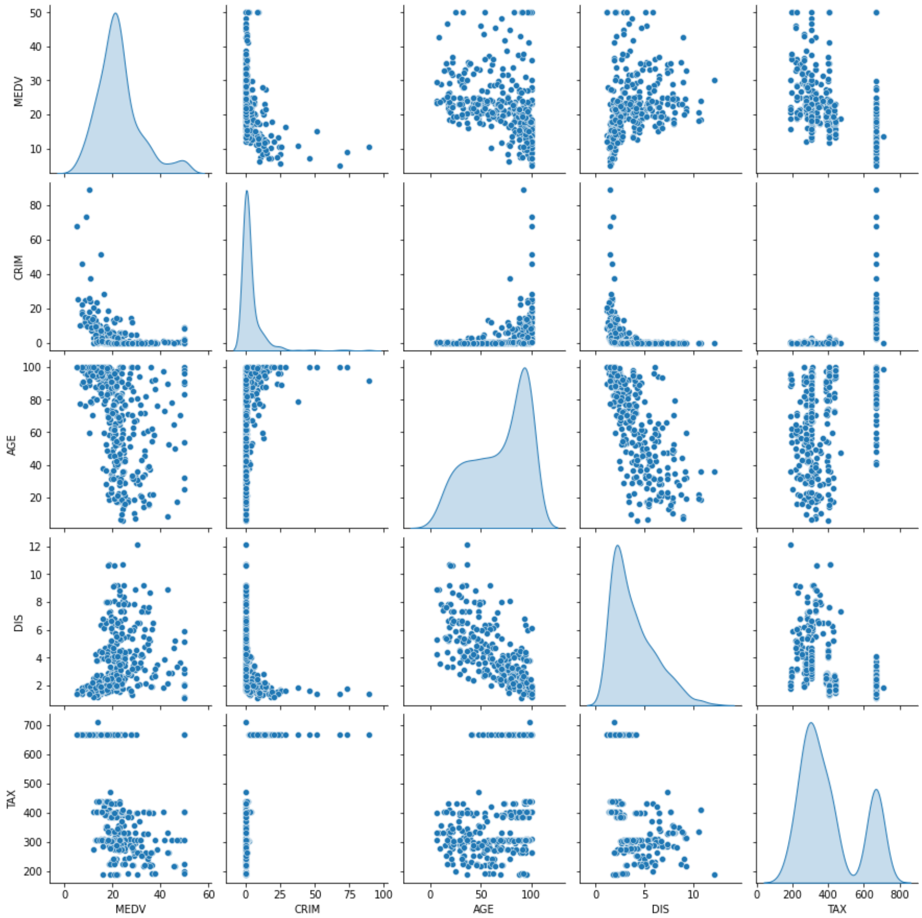
```
data.isna().sum()
```

```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
dtype: int64
```

```
train_dataset = data.sample(frac=0.7,random_state=0)
test_dataset = data.drop(train_dataset.index)
```

```
sns.pairplot(train_dataset[["MEDV", "CRIM","AGE","DIS","TAX"]], diag_kind="kde")
```

```
<seaborn.axisgrid.PairGrid at 0x7f3f1bc7e880>
```




```
train_stats = train_dataset.describe()
train_stats.pop("MEDV")
train_stats = train_stats.transpose()
train_stats
```

	count	mean	std	min	25%	50%	75%	m
CRIM	354.0	3.767375	9.418497	0.00906	0.082757	0.274475	3.077295	88.9
ZN	354.0	11.079096	23.070178	0.00000	0.000000	0.000000	12.500000	95.0
INDUS	354.0	11.185254	6.646944	0.74000	5.860000	9.795000	18.100000	27.7
CHAS	354.0	0.070621	0.256554	0.00000	0.000000	0.000000	0.000000	1.0
NOX	354.0	0.554098	0.115748	0.38500	0.453000	0.538000	0.624000	0.8
RM	354.0	6.265791	0.699380	3.56100	5.878250	6.175000	6.605500	8.7
AGE	354.0	68.057627	27.953167	6.00000	45.100000	76.500000	93.750000	100.0
DIS	354.0	3.844439	2.187514	1.12960	2.073700	3.207450	5.214600	12.1
RAD	354.0	9.440678	8.569207	1.00000	4.000000	5.000000	20.000000	24.0
TAX	354.0	407.500000	162.296676	187.00000	287.000000	337.000000	666.000000	711.0
PTRATIO	354.0	18.461299	2.149735	12.60000	17.325000	18.850000	20.200000	22.0
B	354.0	352.720650	95.764288	2.60000	373.852500	390.945000	396.225000	396.9
LSTAT	354.0	12.614011	7.020224	1.73000	7.347500	11.185000	16.635000	37.9

```
train_labels = train_dataset.pop('MEDV')
test_labels = test_dataset.pop('MEDV')
```

```
def norm(x):
  return (x - train_stats['mean']) / train_stats['std']
```

```
normed_train_data = norm(train_dataset)
normed_test_data = norm(test_dataset)
```

```
def build_model():
  model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=[len(train_dataset.keys())]),
    layers.Dense(64, activation='relu'),
    layers.Dense(1)
  ])

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

  model.compile(loss='mse',
                optimizer=optimizer,
                metrics=['mae', 'mse'])
  return model
```

```
model = build_model();
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                896

 dense_1 (Dense)             (None, 64)                4160

 dense_2 (Dense)             (None, 1)                 65

=================================================================
Total params: 5,121
Trainable params: 5,121
Non-trainable params: 0
_________________________________________________________________
```

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

```
1/1 [==============================] - 0s 347ms/step
array([[ 0.09018825],
       [-0.0524627 ],
       [ 0.30674988],
       [ 0.10789406],
       [ 0.21827169],
       [ 0.0014355 ],
       [ 0.17999958],
       [-0.08920994],
       [ 0.33306706],
       [ 0.6581632 ]], dtype=float32)
```

```
# 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(
  normed_train_data, train_labels,
  epochs=EPOCHS, validation_split = 0.2, verbose=0,
  callbacks=[PrintDot()])
```

```

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```
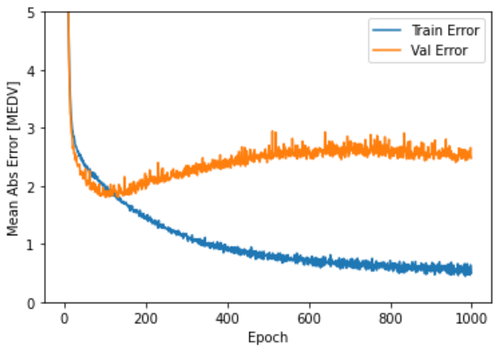
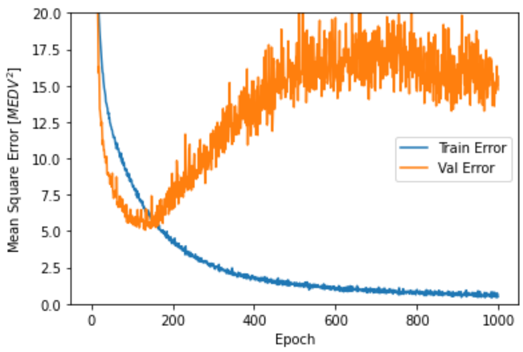

```
hist = pd.DataFrame(history.history)
hist['epoch'] = history.epoch
hist.tail()
```

	loss	mae	mse	val_loss	val_mae	val_mse	epoch
995	0.693003	0.567716	0.693003	15.031659	2.488642	15.031659	995
996	0.437564	0.464099	0.437564	16.344011	2.586914	16.344011	996
997	0.727947	0.640294	0.727947	14.969596	2.659240	14.969596	997
998	0.680283	0.568104	0.680283	15.679944	2.519410	15.679944	998
999	0.494136	0.496397	0.494136	14.722670	2.480395	14.722670	999

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

  plt.figure()
  plt.xlabel('Epoch')
  plt.ylabel('Mean Abs Error [MEDV]')
  plt.plot(hist['epoch'], hist['mae'],
           label='Train Error')
  plt.plot(hist['epoch'], hist['val_mae'],
           label = 'Val Error')
  plt.ylim([0,5])
  plt.legend()

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

```
plot_history(history)
```

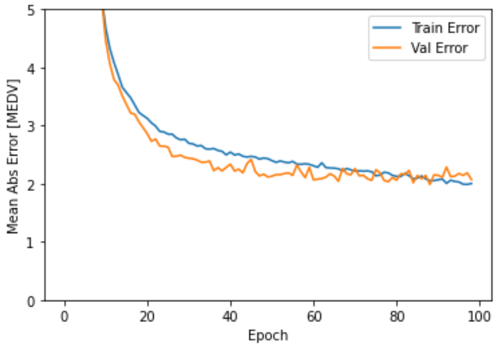


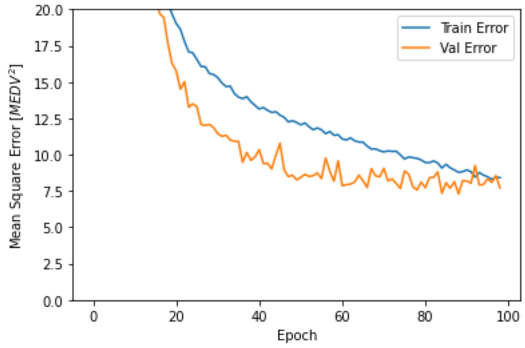



```
model = build_model()

# The patience parameter is the amount of epochs to check for improvement
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)
```



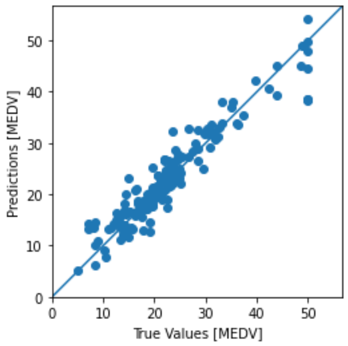



```
loss, mae, mse = model.evaluate(normed_test_data, test_labels, verbose=2)

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

```
5/5 - 0s - loss: 10.2339 - mae: 2.3418 - mse: 10.2339 - 30ms/epoch - 6ms/step
Testing set Mean Abs Error:  2.34 MEDV
```

```
test_predictions = model.predict(normed_test_data).flatten()
train_predictions = model.predict(normed_train_data).flatten()

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

```
5/5 [==============================] - 0s 3ms/step
12/12 [==============================] - 0s 2ms/step
```




```
error = test_predictions - test_labels
plt.hist(error, bins = 25)
plt.xlabel("Prediction Error [MEDV]")
_ = plt.ylabel("Count")
```

```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
mse = mean_squared_error(test_labels, test_predictions)
print('Mean Squared Error: ',mse)
mae = mean_absolute_error(test_labels, test_predictions)
print('Mean Absolute Error: ',mae)
rsq = r2_score(train_labels,train_predictions) #R-Squared on the training data
print('R-square, Training: ',rsq)
rsq = r2_score(test_labels,test_predictions) #R-Squared on the testing data
print('R-square, Testing: ',rsq)
```

```
Mean Squared Error:  11.526060494195113
Mean Absolute Error:  2.3802721861161684
R-square, Training:  0.8939664748792459
R-square, Testing:  0.8835458931882735
```