Chapter 2 ML - Simple Linear Regression

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1 Chapter 2 Linear Regression

1.1 Import Dataset

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[2]:
```
dataset = pd.read_csv('ds/Salary_Data.csv')
dataset.head()
```

[2]:

	YearsExperience	Salary
0	1.1	39343.0
1	1.3	46205.0
2	1.5	37731.0
3	2.0	43525.0
4	2.2	39891.0

dataset size

[3]:
```
dataset.shape
```

[3]: (30, 2)

1.2 Linear Regression

- a simple linear regression is defined by the equation $y = b_0 + b_1 x$
- x is the independed variable and y is a dependent variable
- b_0, b_1 are constant coefficient
- in our case x be the years of experience and y be the salary, b_0, b_1 defines the relation
- in Linear regression the goal is to best fit a straight line on the scattered plot of dataset

1.3 How Linear Regression works ?

- the fitted curve gives $y' = b_0 + b_1 x$ where the actual curve is $y = f(x)$

- thus the error $\epsilon = (y' - y)|x$
- the LR model tries to minimise ϵ iteratively to find best value for $ b_0 , b_1$

1.4 Implement Simple Linear Regression

1.4.1 Perform Data preprocessing

[4]:
```
#separate dependent and independent variables

X = dataset.iloc[:,:-1].values
Y = dataset.iloc[:,-1].values

# perform train-test-split

from sklearn.cross_validation import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.33,␣
↪random_state=10)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in favor of the
model_selection module into which all the refactored classes and functions are
moved. Also note that the interface of the new CV iterators are different from
that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

[5]:
```
X_train.shape
```

[5]:
```
(20, 1)
```

1.4.2 Verify the Split

[6]:
```
print(f'x_train size \t = {X_train.shape}')
print(f'x_test size \t = {X_test.shape}')
print(f'y_train size \t = {Y_train.shape}')
print(f'y_test size \t = {Y_test.shape}')
```

```
x_train size     = (20, 1)
x_test size      = (10, 1)
y_train size     = (20,)
y_test size      = (10,)
```

1.4.3 Feature Scalling

feature scalling is taken care by the models itself thus no explicit feature scelling is needed

1.4.4 Perform Regression

this section fits the traing set and the regression object learns the correlation between the X & Y

[7]:
```
# import the LR class
from sklearn.linear_model import LinearRegression

regressor = LinearRegression()   # create an LR object
regressor.fit(X_train, Y_train)  # fit the training data and build model
```

[7]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

1.4.5 Predict Test Set observation

- we'll create a vector of predicted salaries
- compare with actual

[8]:
```
Y_pred = regressor.predict(X_test) # perform prediction

print(Y_pred) # observe prediction
```

```
[ 90329.26994588  56076.98533315  53222.62828209  39902.29537714
  44659.55712891  93183.62699694  64640.05648633 116969.93575577
  63688.60413598  37999.39067643]
```

- Now compare the Y_pred (predicted salaries) and Y_test (real salaries).
- here the relative error of individial data sample is tested

[9]:
```
import math
error_pct=[]
for i in range(len(Y_test)):
    error_pct.append(round(math.sqrt((Y_test[i] - Y_pred[i])**2)/Y_test[i] *␣
 ↪100, 3))
error_pct
```

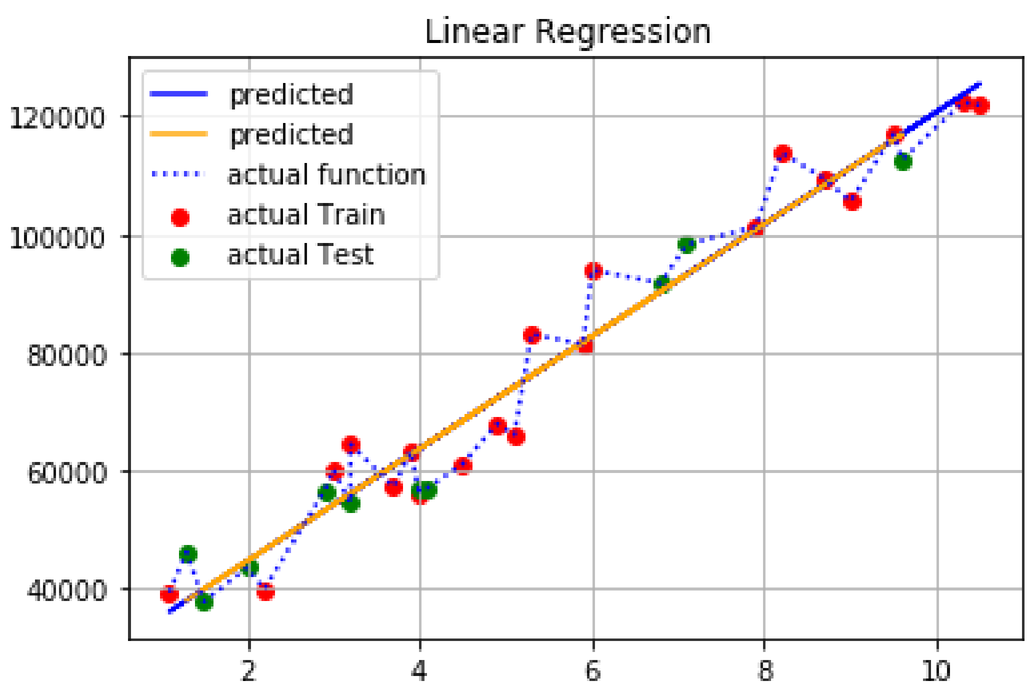
[9]:
```
[1.536, 2.997, 6.037, 5.755, 2.607, 5.179, 13.243, 3.849, 11.819, 17.759]
```

1.4.6 Visualising Test and Predict sets

[10]:
```
%matplotlib inline

plt.grid(True)
plt.title('Linear Regression ')
plt.xlabel='years of Experience'
plt.ylabel='Salary'
```

```
plt.scatter(X_train, Y_train, color = 'red' , label='actual Train') # plotting␣
 ↪the train set
plt.scatter(X_test, Y_test, color = 'green' , label='actual Test') # plotting␣
 ↪the train set
plt.plot(X_train, regressor.predict(X_train), color = 'blue' ,␣
 ↪label='predicted')
plt.plot(X_test, regressor.predict(X_test), color = 'Orange' ,␣
 ↪label='predicted')

plt.plot(X,Y, ':', color = 'blue', label='actual function')

plt.legend()
```

[10]: <matplotlib.legend.Legend at 0x17276d2e6a0>



[ ]: