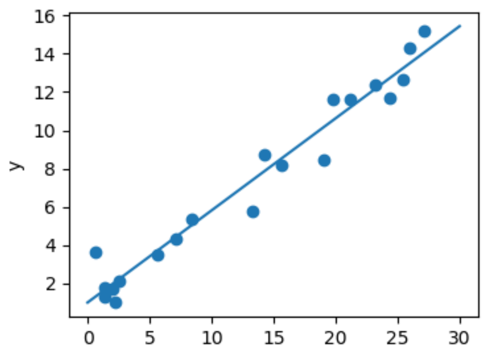
SIMPLE LINEAR REGRESSION WITH JUPYTER NOTEBOOK

DR. ALVIN ANG



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CONTENTS

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INTRODUCTION

- Simple Linear Regression has already been described here (using Excel)
  - https://www.alvinang.sg/s/How-to-Perform-Simple-Linear-Regression-using-Excel-Dr-Alvin-Ang-watermarked.pdf
- In this manuscript, we will make use of a dataset containing 202 car models (and their attributes) and see how Linear Regression can be applied to it (using Jupyter Notebook / Python).
- The dataset is here:
  - https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/DA0101EN/automobileEDA.csv
- Specifically, we will
  - Load and Glance at the Dataset.
  - Visualize / Plot the regression model.
  - Generate a Linear Regression Equation.
  - Use a Residual Plot to visually inspect if Linear Regression fits the model
  - Use R2 and MSE as indicators to determine the accuracy of the Linear Regression fit.

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PART I: LOAD AND GLANCE AT THE DATASET

STEP 1: ENSURE ACCESS TO JUPYTER NOTEBOOK

- There are many ways to access Jupyter Notebook.
- Refer here: https://www.alvinang.sg/s/How-to-Access-CSV-Files-using-PyCharm-Anaconda-or-Skills-Network-Lab-by-Dr-Alvin-Ang.pdf

STEP 2: IMPORT LIBRARIES AND HAVE A GLANCE AT THE DATASET

- Import Libraries Code:
    - import pandas as pd
    - import numpy as np
    - import matplotlib.pyplot as plt
- Load Data and Store in Dataframe df Code:
    - path = 'https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/DA0101EN/automobileEDA.csv'
    - df = pd.read_csv(path)
    - df.head()
- Output:

ymboling	normalized-losses	make	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...	compression-ratio	horsepower	peak-rpm	city-mpg	highway-mpg	price
3	122	alfa-romero	std	two	convertible	rwd	front	88.6	0.811148	...	9.0	111.0	5000.0	21	27	13495.0
3	122	alfa-romero	std	two	convertible	rwd	front	88.6	0.811148	...	9.0	111.0	5000.0	21	27	16500.0
1	122	alfa-romero	std	two	hatchback	rwd	front	94.5	0.822681	...	9.0	154.0	5000.0	19	26	16500.0
2	164	audi	std	four	sedan	fwd	front	99.8	0.848630	...	10.0	102.0	5500.0	24	30	13950.0
2	164	audi	std	four	sedan	4wd	front	99.4	0.848630	...	8.0	115.0	5500.0	18	22	17450.0

vs × 29 columns

- Or you could just click on https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/DA0101EN/automobileEDA.csv to view the dataset.

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PART II: VISUALIZE / PLOT THE REGRESSION MODEL

STEP 1: LOAD THE LR MODULES AND CREATE THE LR OBJECT

- Load the LR Module Code:
    - from sklearn.linear_model import LinearRegression
- Create the LR Object Code:
    - lm = LinearRegression()
    - lm
- Output:
    - LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

STEP 2: DEFINE OUR X AND Y

- We create
    - X → "highway-mpg"
    - Y → "price"
- Code:
    - X = df[['highway-mpg']]
    - Y = df['price']

STEP 3: FIT / TRAIN THE LINEAR MODEL

- Code:
    - lm.fit(X,Y)
- Output:
    - LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

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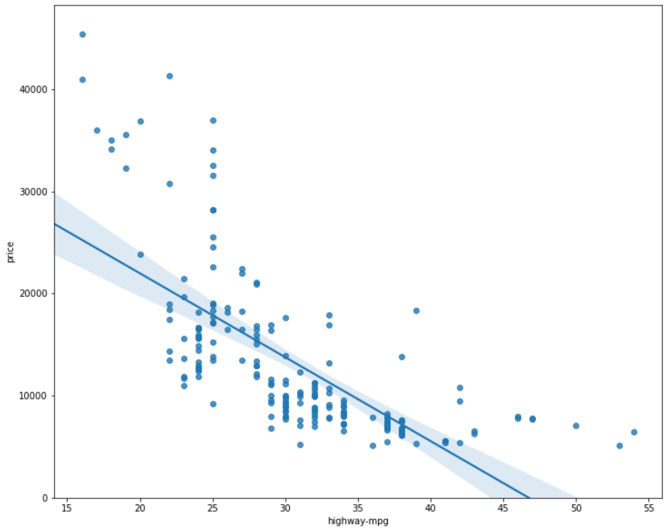
STEP 4: IMPORT THE VISUALIZATION PACKAGE SEABORN

- Code:
  - import seaborn as sns
  - %matplotlib inline

STEP 5: VISUALIZE PRICE VS HIGHWAY-MPG

- Code:
  - width = 12
  - height = 10
  - plt.figure(figsize=(width, height))
  - sns.regplot(x="highway-mpg", y="price", data=df)
  - plt.ylim(0,)
- Output:
  - (0.0, 48250.106831059355)
  - 

- Comments:

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- Price is negatively correlated to highway-mpg.
- The data points are scattered badly around the regression line.
- A linear model is NOT the best fit.

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PART III: GENERATE A LINEAR REGRESSION EQUATION

STEP 1: FIND THE Y-INTERCEPT

- Y-Intercept refers to the C of the Y = mX + C.
- Code:
    - lm.intercept_
- Output:
    - 38423.3058581574

STEP 2: FIND THE GRADIENT

- Gradient refers to the m of the Y = mX +C
- Code:
    - lm.coef_
- Output:
    - array([-821.73337832])
- This means that the Linear Equation is
    - price = 38423.31 - 821.73 x highway-mpg → Y = C + mX

STEP 3: TEST SOME PREDICTIONS

- Since we already have the LR Equation Y = mX +C, we test it using the first 5 rows of values of the Dataset.
- Code:
    - Yhat=lm.predict(X)
    - Yhat[0:5]
- Output:

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- array([16236.50464347, 16236.50464347, 17058.23802179, 13771.3045085 , 20345.17153508])

- Note that the first 5 rows of the "highway-mpg" are as follows:

highway-mpg	price
27	13495
27	16500
26	16500
30	13950
22	17450

- In other words, the "forecasted" values in the prediction array were using the values
    - 27 / 27 / 26 / 30 / 22
- This differs quite a bit from the real pricings!

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PART IV: USE A RESIDUAL PLOT TO VISUALLY INSPECT IF LINEAR REGRESSION FITS THE MODEL

- Residual plot has been described and defined here:
  - https://www.alvinang.sg/s/Multiple-Regression-MR-by-Dr-Alvin-Ang.pdf
  - A residual plot is a graph that shows the residuals on the vertical y-axis and the independent variable on the horizontal x-axis.
- What is a Residual? The difference between the observed value (y) and the predicted value (Yhat).
- If the points in a Residual Plot are randomly spread out around the x-axis, then a linear model is appropriate for the data.
- Because randomly spread out residuals means that the variance is constant, and thus the linear model is a good fit for this data.
- Code:
  - width = 12
  - height = 10
  - plt.figure(figsize=(width, height))
  - sns.residplot(df['highway-mpg'], df['price'])
  - plt.show()
- Output:

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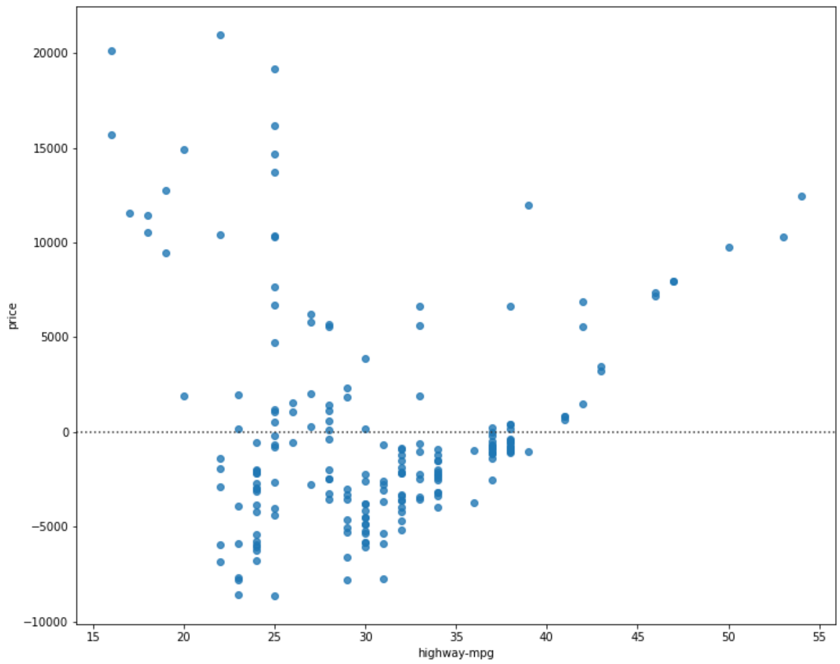

- Comments:
    - This residual plot shows that the residuals are not randomly spread around the x-axis.
    - Maybe a non-linear model is more appropriate for this data.

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PART V: USE R2 AND MSE AS INDICATORS TO DETERMINE THE ACCURACY OF THE LINEAR REGRESSION FIT

- R2 has been explained here:
  - https://www.alvinang.sg/s/How-to-Perform-Simple-Linear-Regression-using-Excel-Dr-Alvin-Ang-watermarked.pdf
  - R squared, also known as the coefficient of determination, is a measure to indicate how close the data is to the fitted regression line.
- Mean Squared Error (MSE) has been explained here:
  - https://www.alvinang.sg/s/Forecasting-by-Dr-Alvin-Ang-watermarked-hjr9.pdf
  - The Mean Squared Error measures the average of the squares of errors, that is, the difference between actual value (y) and the estimated value (ŷ).

STEP 1: CALCULATE THE R2 FOR "HIGHWAY_MPG" VS "PRICE"

- Code:
  - #highway_mpg_fit
  - lm.fit(X, Y)
  - # Find the R^2
  - print('The R-square is: ', lm.score(X, Y))
- Output:
  - The R-square is: 0.4965911884339176
- Comment:
  - We can say that ~ 49.659% of the variation of the "price" is explained by this simple linear model "highway_mpg".
  - Below 50% means that actually a linear model is not a good fit…which means that the actual data is far from the fitted line…

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STEP 2: CALCULATE THE MSE

FIRSTLY, PREDICT THE OUTPUT "YHAT"

- Code:
  - Yhat=lm.predict(X)
  - print('The output of the first four predicted value is: ', Yhat[0:4])
- Output:
  - The output of the first four predicted value is: [16236.50464347 16236.50464347 17058.23802179 13771.3045085]

SECONDLY, IMPORT THE FUNCTION "MEAN_SQUARED_ERROR"

- Code:
  - from sklearn.metrics import mean_squared_error

THIRDLY, OBTAIN THE MSE

- Code:
  - mse = mean_squared_error(df['price'], Yhat)
  - print('The mean square error of price and predicted value is: ', mse)
- Output:
  - The mean square error of price and predicted value is: 31635042.944639888
- Comment:
  - At this point, we are unable to say if MSE is high or low.
  - MSE is used to measure against another method of fitting i.e. it cannot be used as a standlone measure.
  - That is, currently we are doing Linear Regression (LR) for model fitting and we have this MSE.

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- We can only compare this MSE with another MSE of another model fit… E.g. Multiple Regression (MR)… in which we will showcase this in another article.

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CONCLUSION

- In this article, we used Linear Regression (LR) on a dataset containing 200 car models.
- We used Python / Jupyter Notebook to run the codes.
- Specifically, we wanted to find out whether LR was a good fit or not.
- These we presented in this article:
    - Visualize / Plot the regression model.
    - Generate a Linear Regression Equation.
    - Use a Residual Plot to visually inspect if Linear Regression fits the model
    - Use R2 and MSE as indicators to determine the accuracy of the Linear Regression fit.

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Dr. Alvin Ang earned his Ph.D., Masters and Bachelor degrees from NTU, Singapore. He is a scientist, entrepreneur, as well as a personal/business advisor. More about him at www.AlvinAng.sg.

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