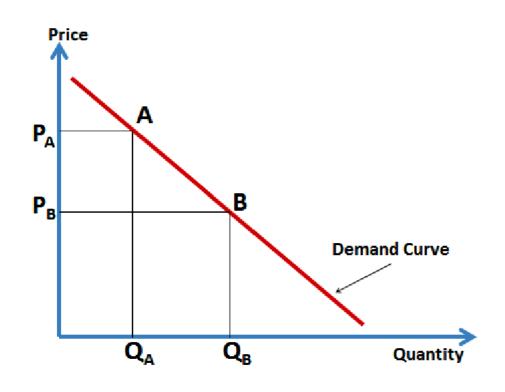
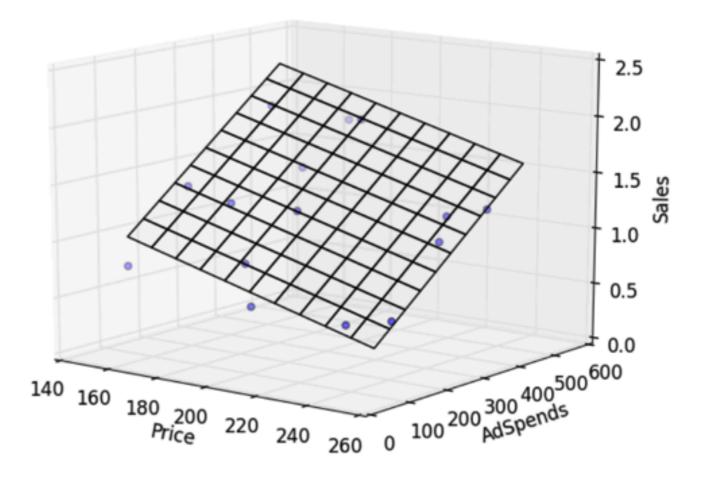
Week 5: Data Science Part-Time Course

Linear Regression

Dami Lasisi

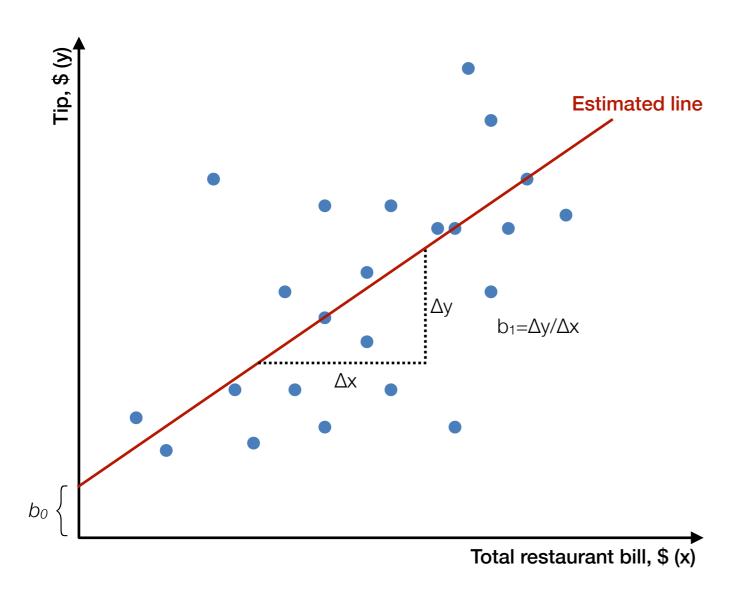




Source: https://www.researchgate.net/figure/The-Conventional-Demand-Curve_fig1_262309137

Source: https://medium.com/@dhwajraj/python-regression-analysis-part-4-multiple-linear-regression-ed09a0c31c74

We use linear regression to find statistical linear relationships between a target (dependent variable) and one or more features (predictors or independent variables).



Equation of a straight line:

$$y = mx + b$$

Linear Regression Equation:

$$y = b_0 + b_1 X_1$$

 $Tip = b_0 + b_1 Total restaurant bill$

Multiple Linear Regression Equation:

$$y = b_0 + b_1 X_1 + b_2 X_2 + ... + b_n X_n$$

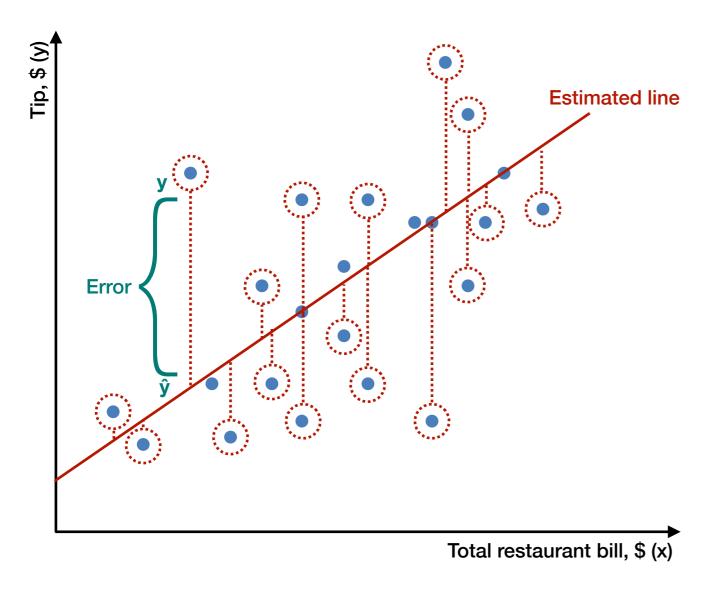
$$Tip = b_0 + b_1 Total restaurant bill + b_2 Waiter's attitude + ... + b_n Party Size$$

b₀: Intercept

b₁, ...,**b**_n: Coefficients

 $X_1,...,X_n$: Independent variables (features)

v: Dependent variable (target)



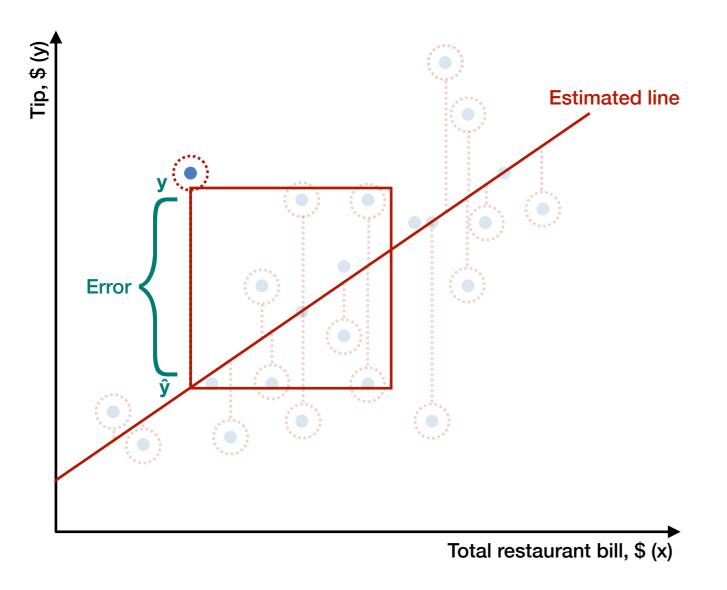
Find the best fit line that has the overall minimum error (i.e the distance between the predicted output and the actual output)

$$\hat{y} = b_0 + b_1 X_1$$

 $y = \hat{y} + Error$
 $Error = y - \hat{y}$

Objective: find that best b_0 and b_1 that minimizes $\sum (y - \hat{y})^2$





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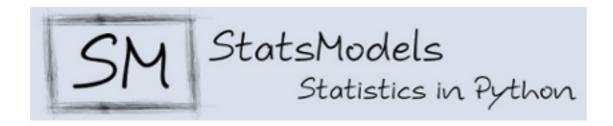


Assumptions of Linear Regression

- ► Linear and additive relationship between dependent and independent variables
- ▶ No autocorrelation
- ▶ No multicollinearity
- ▶ No heteroskedasticity
- ▶ Error terms are normally distributed

Building a Linear Regression Model in Python





Building a Linear Regression Model in Python: Scikit Learn

```
In [ ]: from sklearn.linear_model import LinearRegression

In [ ]: linreg = LinearRegression()
    linreg.fit(X, y)

In [ ]: print(linreg.intercept_)
    print(linreg.coef_)

In [ ]: linreg.predict(77)
```

Building a Linear Regression Model in Python: Statsmodel

```
In []: import statsmodels.regression.linear_model as sm
In []: lr = sm.OLS(y, X)
    results = lr.fit()
    print(results.params)
In []: result.summary()
```

Interpreting Simple Linear Regression Models

Assume that for our restaurant tips example, the model is:

Tip = 0.12 + 0.67Total restaurant bill

This means that for every dollar increase in total restaurant bill, a waiter's tip will increase on average by 67 cents. When the restaurant bill is \$0, tip will be 12 cents on average.

Interpreting Multiple Linear Regression Models

Assume that for our restaurant tips example, the model is:

Tip = 0.08 + 0.54Total restaurant bill + 0.98Waiter's attitude - 0.07Party Size

Holding all other variables constant, for every dollar increase in total restaurant bill, a waiter's tip will increase on average by 54 cents.

Holding all other variables constant, for every value increase in a waiter's attitude, the waiter's tip will increase on average by 98 cents.

Holding all other variables constant, for every additional person in party size, a waiter's tip will decrease on average by 7 cents.

When the restaurant bill is \$0, tip will be 8 cents on average.

Evaluation Metrics for Regression

- ▶ Mean absolute error (MAE): mean of the absolute values of the errors
- ▶ Mean squared error (MSE): mean of the squared errors
- ▶ Root mean squared error (RMSE): square root of the mean of the squared errors

Train/Test Split in Python

All observations

Training Set

Test Set

```
In [ ]: from sklearn import metrics
    from sklearn.model_selection import train_test_split

In [ ]: X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_state=123)
    linreg = LinearRegression()
    linreg.fit(X_train, y_train)
    y_pred = linreg.predict(X_test)
    print("MSE:", np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```