Regression Overview

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What is a regression Problem?

- A subcategory supervised learning
- A way of measuring the relationship between two or more variables
- Task: predicting a continuous variable
 - Fit a curve given a set of data points
- One feature
 - Linear Regression
- More than one features
 - Multiple linear regression
 - or Multivariate linear regression

Regression Setting

Given

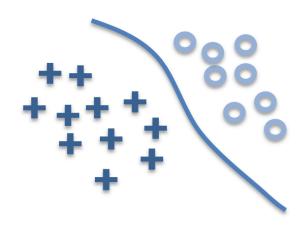
- A dataset D
 - D = {X₁,X₂,..} is a set of rows/instances/examples
 - Each instance in D is described by values for a set of features/attributes X = {x₁,x₂,...}
 - Each instance in D is associated with a real number, y = {y₁,y₂,...}; So, y is a continuous variable
- Learning
 - y = f(input instance)
- Predict
 - target value for new instances

Classification vs Regression

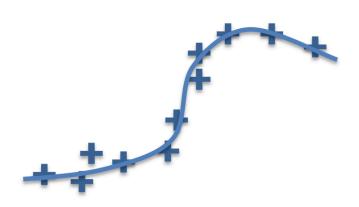
Predicting discrete vs Continuous

X ₁	X ₂	 Xn	У
			y ₁
			y2
			y2
			Y3
			y1

Difference between Classification & Regression

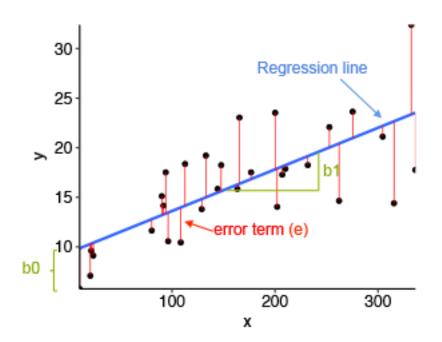


Classification



Regression

Linear Regression



LR: $y_i = b_0 + b_1 x_1^i + e$

Assumptions:

- Linearity: The relationship between X and the mean of Y is linear.
- Homoscedasticity: The variance of residual is the same for any value of X
- Independence: Observations are independent of each other
- Normality: For any fixed value of X, Y is normally distributed

How to fit the line?

$$min_b ||Xb - y||^2$$

MLR:
$$y_i = b_0 + b_1 x_1^i + b_2 x_2^i + ... + b_n x_n^i + e$$

$$e \sim N(0, \sigma^2)$$

Linear Regression

sklearn.linear_model.LinearRegression

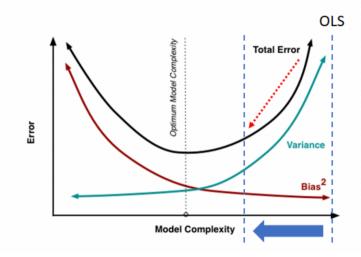
 $class\ sklearn.linear_model.LinearRegression(*, fit_intercept=True, normalize=False, copy_X=True, n_jobs=None, positive=False)$ [source]

Parameters to look at

- fit_intercept
- normalize

- A variation of linear regression
- Addresses some problems in linear regression
 - OLS doesn't consider which independent variable is more important than others
 - OLS is an unbiased estimator/model
 - We need to consider bias for better performance
 - Bias means how equally a model cares about its predictors/features

- The OLS estimation usually gives low bias, high variance
 - Why?
 - OLS treats all the variables equally; becomes more complex as new variables are added
 - bias is related with a model failing to fit the training set
 - variance is related with a model failing to fit the testing set



- A constraint is added to linear regression
 - Aka Ridge constraint

$$y_i = b_0 + b_1 x_1^i + b_2 x_2^i + ... + b_n x_n^i + +e$$
 $e \sim N(0, \sigma^2)$
subject to
 $b_0^2 + b_1^2 + b_2^2 + ... + b_n^2 \le C^2$

Optimize

$$min_b \|Xb - y\|_2^2 + \alpha \|b\|_2^2$$

sklearn.linear_model.Ridge¶

class sklearn.linear_model. Ridge(alpha=1.0, *, fit_intercept=True, normalize=False, copy_X=True, max_iter=None, tol=0.001, solver='auto', random_state=None) [source]

Parameters to look at

- alpha
- auto
 - Optimization solver

Logistic Regression

A special type of linear regression

- Target variable is categorical
- Features could be any types

Used for classification

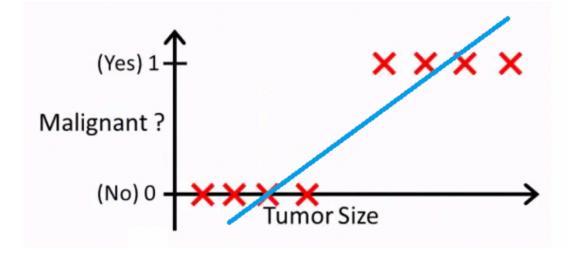
- Then, why is it called regression?
 - It's not a classifier on its own
 - Logistic regression + a decision rule = a classifier

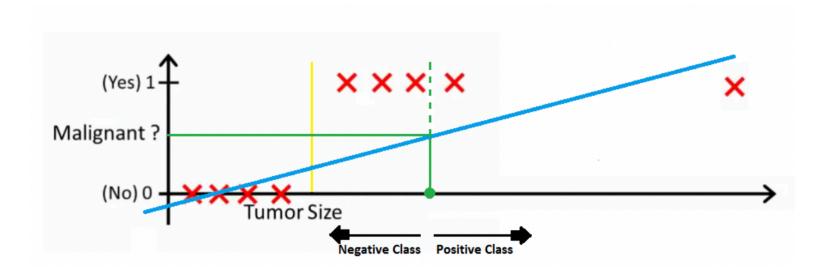
It a probabilistic classifier

Discriminative model

$$P(C \mid \mathbf{X}) \quad C = c_1, \dots, c_L, \mathbf{X} = (X_1, \dots, X_n)$$

Why not use linear regression?





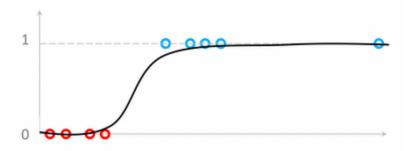
Enter Logistic Regression

Remember linear regression

$$y_i = b_0 + b_1 x_1^i + b_2 x_2^i + \dots + b_n x_n^i + e$$

In logistic regression:

$$P(C = c|X) = y_i = \frac{1}{1 + e^{-(b_0 + b_1 x_1^i + b_2 x_2^i + \dots + b_n x_n^i)}}$$



Logistic Regression

A special type of regression

- Target variable is categorical
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Used for classification

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Conclusion

Three linear models

- Linear regression
- Ridge regression
 - Linear regression with a constraint
- Logistic regression
 - Used in classification