What are the types of Regressions?

* Linear Regression

Linear Regression establishes a relationship between **dependent variable (Y)** and one or more **independent variables (X)** using a **best fit straight line** (also known as regression line).

It is represented by an equation **Y=a+b\*X + e**, where a is intercept, b is slope of the line and e is error term. This equation can be used to predict the value of target variable based on given predictor variable(s).

* **Logistic Regression**

Logistic regression is used to find the probability of event=Success and event=Failure. We should use logistic regression when the dependent variable is binary (0/ 1, True/ False, Yes/ No) in nature. Here the value of Y ranges from 0 to 1 and it can represented by following equation.

#### Important Points:

* Logistic regression is widely used for **classification problems**
* Logistic regression doesn’t require linear relationship between dependent and independent variables.  It can handle various types of relationships because it applies a non-linear log transformation to the predicted odds ratio
* To avoid over fitting and under fitting, we should include all significant variables. A good approach to ensure this practice is to use a step wise method to estimate the logistic regression
* It requires **large sample sizes** because maximum likelihood estimates are less powerful at low sample sizes than ordinary least square
* The independent variables should not be correlated with each other i.e. **no multi collinearity**.  However, we have the options to include interaction effects of categorical variables in the analysis and in the model.
* If the values of dependent variable is ordinal, then it is called as **Ordinal logistic regression**
* If dependent variable is multi class then it is known as **Multinomial Logistic regression**.
* **Polynomial Regression**

A regression equation is a polynomial regression equation if the power of independent variable is more than 1. The equation below represents a polynomial equation:

y=a+b\*x^2

#### Important Points:

While there might be a temptation to fit a higher degree polynomial to get lower error, this can result in over-fitting. Always plot the relationships to see the fit and focus on making sure that the curve fits the nature of the problem. Here is an example of how plotting can help:

* **Stepwise Regression**

This form of regression is used when we deal with multiple independent variables. In this technique, the selection of independent variables is done with the help of an automatic process, which involves *no* human intervention.

This feat is achieved by observing statistical values like R-square, t-stats and AIC metric to discern significant variables. Stepwise regression basically fits the regression model by adding/dropping co-variates one at a time based on a specified criterion. Some of the most commonly used Stepwise regression methods are listed below:

* Standard stepwise regression does two things. It adds and removes predictors as needed for each step.
* Forward selection starts with most significant predictor in the model and adds variable for each step.
* Backward elimination starts with all predictors in the model and removes the least significant variable for each step.
* **Ridge Regression**

Ridge Regression is a technique used when the data suffers from multicollinearity (independent variables are highly correlated). In multicollinearity, even though the least squares estimates (OLS) are unbiased, their variances are large which deviates the observed value far from the true value. By adding a degree of bias to the regression estimates, ridge regression reduces the standard errors.

**Important Points:**

* The assumptions of this regression is same as least squared regression except normality is not to be assumed
* Ridge regression shrinks the value of coefficients but doesn’t reaches zero, which suggests no feature selection feature
* This is a regularization method and uses [l2 regularization](https://en.wikipedia.org/wiki/Regularization_(mathematics)).
* **Lasso Regression**

Similar to Ridge Regression, Lasso (Least Absolute Shrinkage and Selection Operator) also penalizes the absolute size of the regression coefficients. In addition, it is capable of reducing the variability and improving the accuracy of linear regression models.  Look at the equation below: Lasso regression differs from ridge regression in a way that it uses absolute values in the penalty function, instead of squares. This leads to penalizing (or equivalently constraining the sum of the absolute values of the estimates) values which causes some of the parameter estimates to turn out exactly zero. Larger the penalty applied, further the estimates get shrunk towards absolute zero. This results to variable selection out of given n variables.

#### Important Points:

* The assumptions of lasso regression is same as least squared regression except normality is not to be assumed
* Lasso Regression shrinks coefficients to zero (exactly zero), which certainly helps in feature selection
* Lasso is a regularization method and uses [l1 regularization](https://en.wikipedia.org/wiki/Regularization_(mathematics))
* If group of predictors are highly correlated, lasso picks only one of them and shrinks the others to zero

* **ElasticNet Regression**

ElasticNet is hybrid of Lasso and Ridge Regression techniques. It is trained with L1 and L2 prior as regularizer. Elastic-net is useful when there are multiple features which are correlated. Lasso is likely to pick one of these at random, while elastic-net is likely to pick both.

[elastic net regression](https://www.analyticsvidhya.com/wp-content/uploads/2015/08/Elastic_Net.png)

A practical advantage of trading-off between Lasso and Ridge is that, it allows Elastic-Net to inherit some of Ridge’s stability under rotation.

#### Important Points:

* It encourages group effect in case of highly correlated variables
* There are no limitations on the number of selected variables
* It can suffer with double shrinkage

