

# Linear Regression Theory

## Regression Model Assumptions

### Assumption 1

Linear Regression Model is linear in the parameters though it may not be linear in the variables i.e. the slope coefficients are always raised to power 1. The variables may be raised to any power. The regression model thus, takes the form  $y_i = \beta_1 + \beta_2 X_i + u_i$  ( $\beta_1$  is intercept,  $\beta_2$  is coefficient,  $X_i$  is variable,  $u_i$  is disturbance

The conditional expectation of  $y$ ,  $E(y | X_i)$  is a linear function of the parameters i.e. the  $\beta$ s.  $y$  is linearly related to  $X$  when the rate of change of  $y$  with respect to  $X$  (i.e. slope or derivative of  $y$  with respect to  $X$ ,  $dy/dx$ ) is independent of the value of  $X$ . For e.g.

1. if  $y = 10x$  then  $dy/dx = 10$ , which is independent of  $x$  i.e. for all values of  $x$ ,  $dy/dx$  is constant.
2. If  $y = 10x^2$  then  $dy/dx = 20x$  i.e. the rate of change of  $y$  depends on the current value of  $x$ . It is dependent on  $X$ . Hence the function is not linear in  $X$

The deviation  $u_i$  in each  $X_i$  prediction can be positive or negative. Technically  $u_i$  is known as stochastic disturbance or stochastic error term

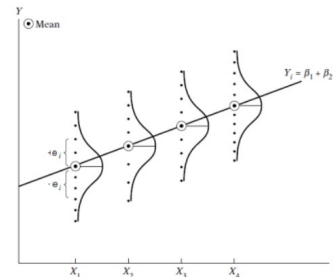
## Regression Model Assumptions

### Assumption 2

1. X values are independent of the error term. Values taken by the regressor X may be considered fixed in repeated trials / sample. The error in prediction of each trial is independent of the value of X.
2. Error term  $u_i$ , represents the impact of the variables not considered for the model. Since the assumption that X predictors are independent of one another, it applies to even those variables not considered

### Assumption 3

1. The mean value of disturbance  $u_i$  is zero. Given the value of  $X_i$ , the means or expected value of the random disturbance  $E(u_i | X_i) = 0$  i.e.  $E(u_i) = 0$
2. Population of y corresponding to a given  $X_i$  is distributed around its mean value, implies no specification bias / error in the model indicating that the model is correctly specified.



3. Specification error results from leaving out important variables or choosing wrong functional form to express relationship between y and X.

## Regression Model Assumptions

### Assumption 4

1. Homoscedasticity or Constant Variance of  $u_i$ , the variance of the error / disturbance is the same regardless of the value of  $X$
2.  $\text{Var}(u_i) = E[ u_i - E(u_i | X_i)]^2 = E(u_i^2 | X_i)$  because of assumption 3 ( $E(u_i) = 0$ ).
3.  $= E(u_i^2)$  for a given  $X_i$  = constant variance (representation for homoscedasticity)

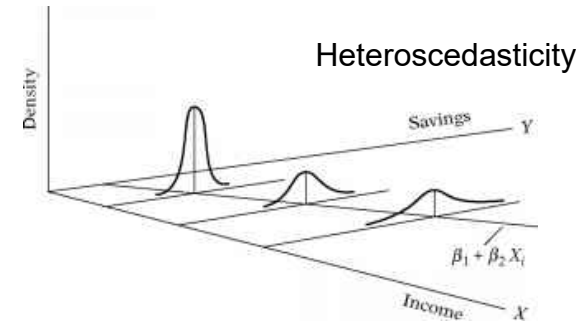
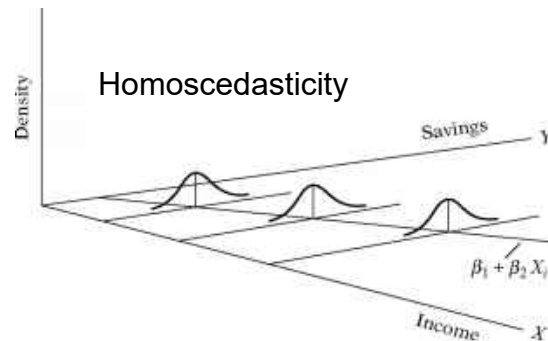


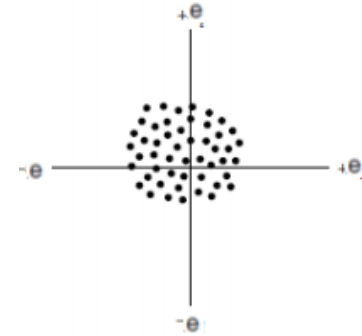
Image source: <https://www.rhayden.us/regression-models/the-nature-of-heteroscedasticity.html>

4. The likelihood that the  $y$  observations coming from the population with  $X = X_i$  would be closer to the population regression function than those coming from the populations corresponding to  $X = X_2$ ,  $X = X_3$  and so on. The reliability of predicted  $Y$  will fall
5. By invoking Assumption 4, we stress equal importance to all  $y$  values corresponding to different values of  $X$

## Regression Model Assumptions

### Assumption 5

1. No autocorrelation between disturbances  $u_i$ . Given any two X values,  $X_i$  and  $X_j$  ( $i \neq j$ ), the correlation between any two  $u_i$  and  $u_j$  is zero i.e. no serial or autocorrelation
2. This assumption is justified when time is not an attribute i.e. the trials / records are not generated in any time-series fashion



### Assumption 6

1. The number of observations  $n$  must be greater than the number of parameters to be estimated. In data science parlance, the depth should be much greater than breadth i.e. number of records much larger than the number of columns to avoid curse of dimensionality situation.

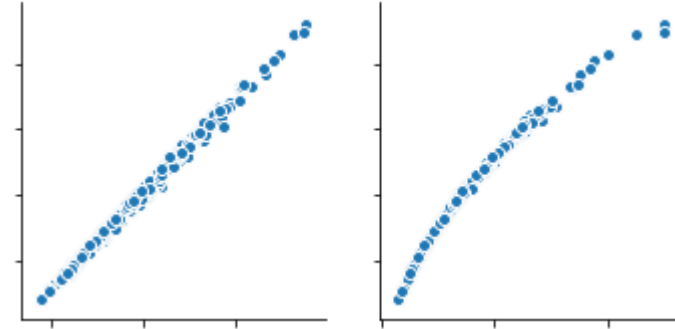
### Assumption 7

1. The X should have variance. The values should not be constant. In Data Science parlance, X should have variance. Further the outliers should not exist

## Regression Model Assumptions

### Assumption 8

1. There no perfect collinearity between the predictor variables X
2. In case of perfect collinearity, the scatter plot will be line
3. Most often we come across less than perfect collinearity



### Assumption 9

1. The model is correctly specified i.e. neither overfit or underfit

### Assumption 10

The stochastic term  $u_i$  is normally distributed. The error term 'e' follows the normal distribution with zero mean and (constant) variance

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

where the symbol  $\sim$  means distributed as and N stands for the normal distribution, the terms in the parentheses representing the two parameters of the normal distribution, namely, the mean and the variance. If this assumption is violated, the statistical tests such as t, and F in regression may not be valid.

Note: All the assumptions pertain to population regression function only.

## Significance of stochastic disturbance term

1. The disturbance term  $u_i$  is a surrogate for the variables that are left out of the model but have a collective impact on the output  $y$ .
2. The reason why those variables were left out could be many
3. We may not fully understand how those variables impact the output (theoretically weak)
4. Lack of data for those variables. Some variables are not quantitative by nature and we may not have a way to capture such data for e.g. personality of an individual that impacts his/her monthly expenses
5. Peripheral variables – Some variables have a weak influence on the target and their joint influence may be very weak. Such variables can be represented by the  $u_i$
6. Intrinsic randomness in the process. For e.g. personality of individuals may vary significantly even when the most of the measurable attributes are same
7. Principle of parsimony requires that we keep our models as simple as possible (Occam's razor). If significant part of  $y$ 's behavior can be captured by a few variables, then why not keep it simple. Let the other variables collective effort be represented by the  $u_i$

## Disturbance term expected value

**Assumptions 3** (The mean value of disturbance  $u_i$  is zero) ..... Why?

1. Let linear regression model be  $y_i = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \beta_k X_{ki} + u_i$  (a data point in K dimensions)
2. Assume  $E(U_i | X_{2i}, X_{3i}, \dots, X_{ki}) = W$  (W is a constant , in standard model  $W = 0$ )
3. Conditional expectations of the equation for  $y_i$  can be expressed as
  - a.  $E(y_i | X_{2i}, X_{3i}, \dots, X_{ki}) = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \beta_k X_{ki} + W$
  - b.  $\Rightarrow (\beta_1 + W) + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \beta_k X_{ki}$
  - c.  $\Rightarrow \alpha + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \beta_k X_{ki}$  where  $\alpha = (\beta_1 + W)$
4. Given the training data, the Xs are treated as constant while the  $\beta$ s are the variables
5. **If the assumption 3 is not fulfilled, we cannot solve the equation for  $\beta_1$ !**



## Heteroscedasticity of disturbance

Homoscedasticity or Constant Variance of  $u_i$ , the variance of the error / disturbance is the same regardless of the value of  $X$ .

Violation of this assumption leads to Heteroscedasticity. There are several reasons for this –

1. As the processes mature and stabilize over a number of operations, the variability in the output falls.  
For e.g. a new coder may show more variance in coding productivity and an experienced one
2. As one input variable grows, the process outputs vary more for e.g. as monthly household income grows, there is more choice to spend on and hence the savings may fluctuate depending on the household preferences
3. Data collection techniques improve, the data collected first may show more variations than the data collected last
4. Outliers can lead to heteroscedasticity
5. Skewness in data can lead to heteroscedasticity. For e.g. few individuals with extremely high incomes will contribute most to the variations
6. The model specified may not be the correct one. We chose a simple linear model while the model should be relatively more complex

## **Heteroscedasticity of disturbance (Contd...)**

Variance of  $u_i$ , homoscedastic or heteroscedastic plays no part in the determination of the coefficients.

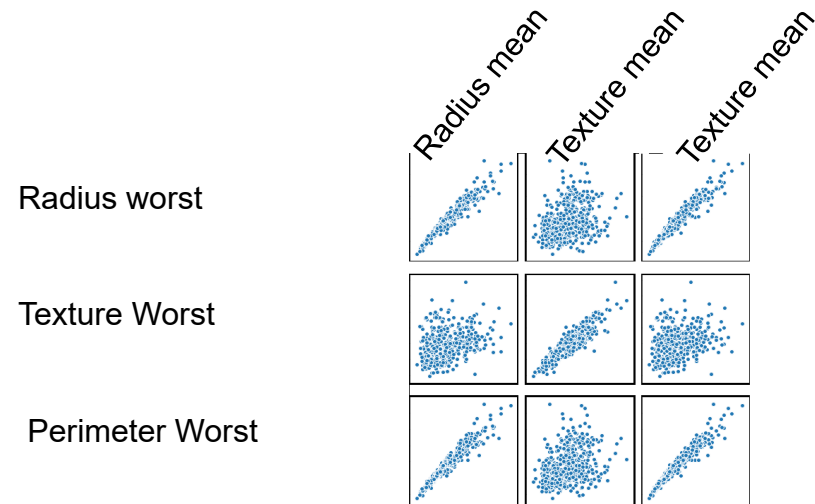
Even with heteroscedasticity the coefficients will converge to the population value of the coefficients. Infact the distribution of the coefficients remains asymptotically normally distributed.

The problems is, the coefficients will have lot of variance and make the overall model less accurate. The OLS method does not take into account the heteroscedastic nature of certain attributes relative to others. It gives same weightage to all attributes. On the other hand GLS (Generalized Least Square) method takes into account such difference and gives lesser weight to attributes with more heteroscedasticity and in the process result in better models

## **Multi-Collinearity**

## Multi Collinearity – What is it?

Multicollinearity is that situation where the independent variables in the linear model are not truly independent i.e. they are correlated. For e.g. in the Wisconsin Breast Cancer dataset the first three attributes “radius mean”, “perimeter mean” and “texture mean” is shown below. The first two are strongly correlated



## Multi Collinearity – Types of multicollinearity

1. **Structural multicollinearity:** This type occurs when we create features from existing features and build a model using all of the features. For example, using “Radius” and “Area” as two variables. When features are generated, ensure the generated feature and the original features do not strongly correlate, if they do, you may want to drop the original feature as long as the generated feature contains all the information from the original
2. **Data multicollinearity:** This type of multicollinearity is an artifact of the data itself. The nature of the variables is such that they correlate. For e.g. in auto-mpg.csv, the columns “weight” and “horsepower” of a car will correlate positively. In case there are such correlating variables in the data, they may be combined into a composite variable using techniques such as PCA

## Multi Collinearity

1. Assumptions 8 (There no perfect collinearity between the predictor variables  $X$ ) – is technically known as the assumption of no collinearity or no multicollinearity when more than one variables is involved
2. Formally, no collinearity means there exists no two numbers  $\lambda_2$  and  $\lambda_3$  such that  $\lambda_2 X_2 + \lambda_3 X_3 = 0$ . If such a relationship exists, then  $X_2$  and  $X_3$  are said to be collinear or linearly dependent
3. On the other hand if the equation holds only when  $\lambda_2$  and  $\lambda_3 = 0$  , then the variables are non-collinear
4. In simple terms, multicollinearity is the situation when two or more variables used in a model, are related to each other i.e. change in values of one leads to change in values of other
5. The problem with having multicollinearity is in the inability to understand how one variable influences the target. There is no way to estimate separate influence of each variable on target. Thus no way to estimate the partial regression coefficients

## Multi Collinearity (Contd...)

6. If multicollinearity is perfect, the regression coefficients of X variables are indeterminate and their standard errors are infinite
7. If multicollinearity is less than perfect, the regression coefficients, although determinate, possess large standard errors, which means the coefficients cannot be estimated with confidence
8. High degree of multicollinearity will not take away the property of being best unbiased linear estimators. It violates none of the regression assumptions. The only problem is that it will result in hard to determine coefficients with small standard errors
9. But the same problem occurs when we have too few observations or the independent variables have small variances

## Multi Collinearity – What is the problem?

1. Independent variables should be *independent* of one another. Instead, if they correlate strongly, it can lead to sub-optimal model and mislead in terms of statistical results such as P values
2. The main objective of regression analysis is to express the relationship between each predictor variable and the dependent variable independently.
3. The regression coefficient is a measure of mean change in the dependent variable for each 1 unit change in an independent variable keeping all other independent variables constant. However, with collinear independent variables, it will not be possible to change one variable keeping others constant!
4. The coefficient estimates for an independent variable Vs the target variable can swing wildly based on inclusion or exclusion of other correlated independent variables are in the model. The coefficients become very sensitive to changes in the model structure
5. Multicollinearity reduces the precision of the estimate coefficients, which weakens the statistical power of your regression model. You might not be able to trust the p-values to identify independent variables that are statistically significant

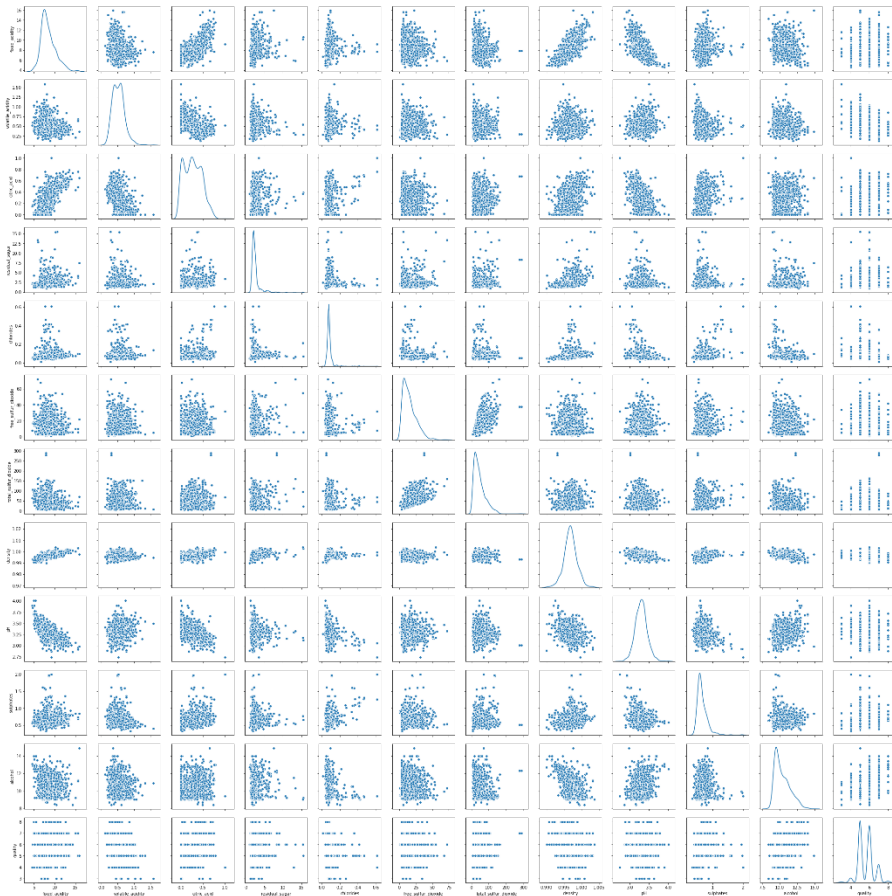


## Multi Collinearity – Testing for multicollinearity with Variation Inflation Factor (VIF)

1. The variance inflation factor (VIF) identifies correlation between independent variables and the strength of that correlation.
2. Statsmodel based linear models provide a VIF for each independent variable
3. VIFs start at 1 and have no upper limit.
  - a. A value of 1 indicates that there is no correlation between this independent variable and any others
  - b. VIFs between 1 and 5 suggest that there is a moderate correlation, but it is not severe enough to warrant corrective measures
  - c. VIFs greater than 5 represent critical levels of multicollinearity where the coefficients are poorly estimated, and the p-values are questionable.

## Testing for multicollinearity with Variation Inflation Factor (VIF)

Red wines dataset, correlation between features and VIF values  
Most attributes have very high value of VIF



fixed\_acidity ---> 80.0219390812402  
volatile\_acidity ---> 16.57719262878206  
citric\_acid ---> 9.774864397481704  
residual\_sugar ---> 4.906541592370461  
chlorides ---> 6.529251770198401  
free\_sulfur\_dioxide ---> 6.448644902127925  
total\_sulfur\_dioxide ---> 6.877056111151861  
density ---> 1445.240488945372  
pH ---> 1037.4662099590764  
sulphates ---> 20.65264657492166  
alcohol ---> 121.46712238121306



StatsModel+Linea  
+Model+Wine+VI