Logistic regression

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What is the need of non-linear regression?

LAB: Need of logisticregression?

- Dataset: Product Sales Data/Product_sales.csv
- What are the variables in the dataset?
- Build a predictive model for Bought vs Age
- What is R-Square?
- If Age is 4 then will that customer buy the product?
- If Age is 105 then will that customer buy the product?

Code: Need of logistic regression?

```
import sklearn as sk
from sklearn import linear_model

from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(sales[["Age"]], sales[["Bought"]])

age1=4
predict1=lr.predict(age1)
predict1

age2=105
predict2=lr.predict(age2)
predict2
```

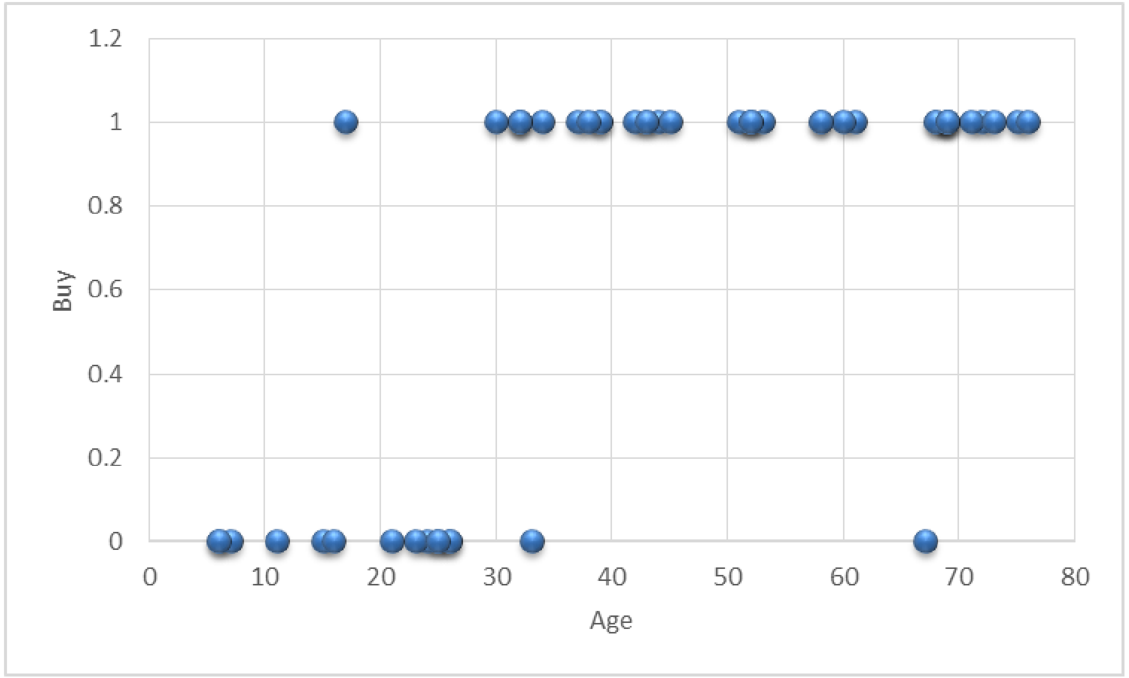
Something wrong

- The model that we built above is not right.
- There is certain issues with the type of dependent variable
- The dependent variable is not continuous it is binary
- We can’t fit a linear regression line to this data

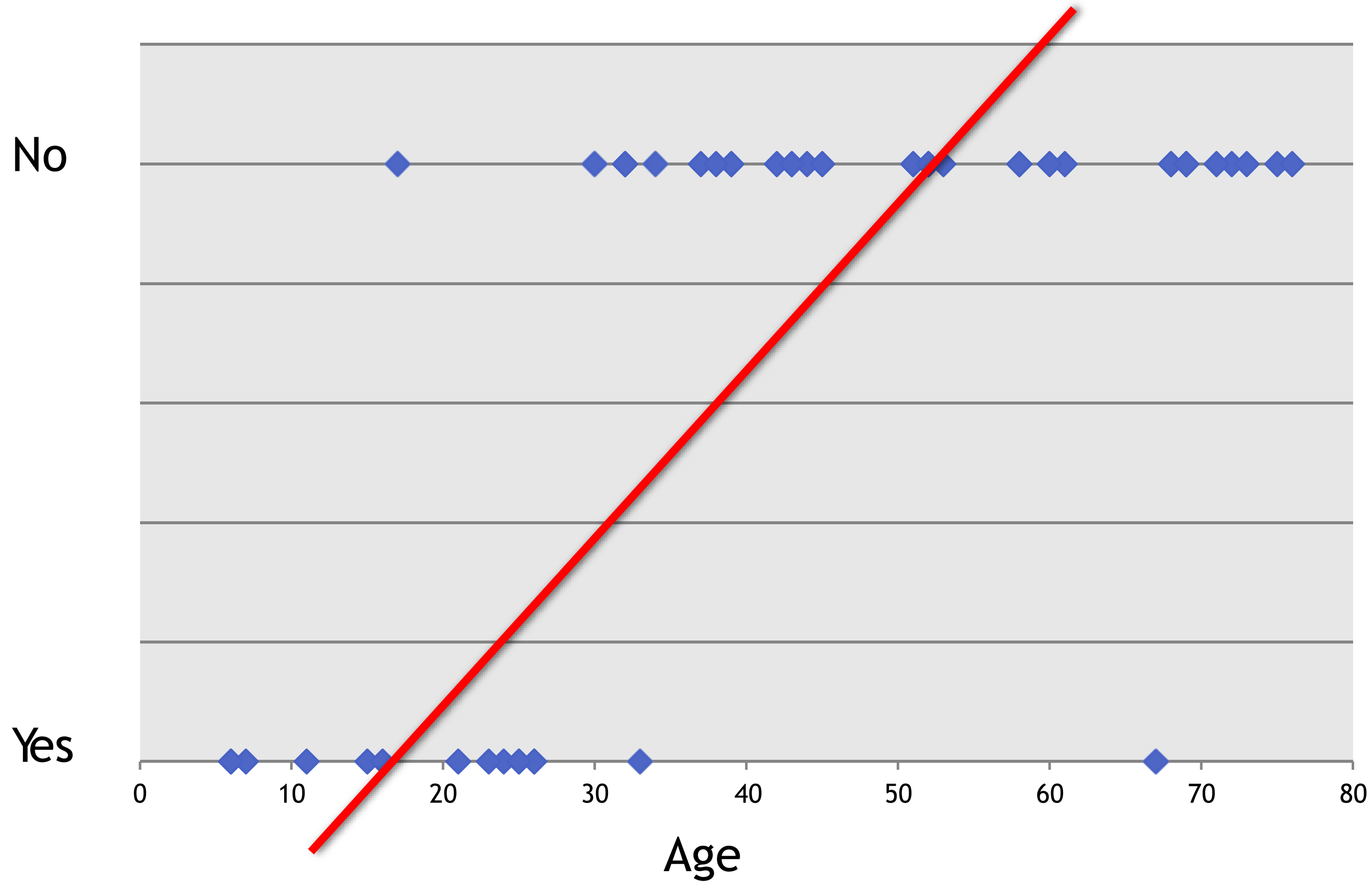
Why not linear?

Why not linear?

- Consider Product sales data. The dataset has two columns.
  - Age – continuous variable between 6-80
  - Buy(0- Yes ; 1-No)



Why not linear?

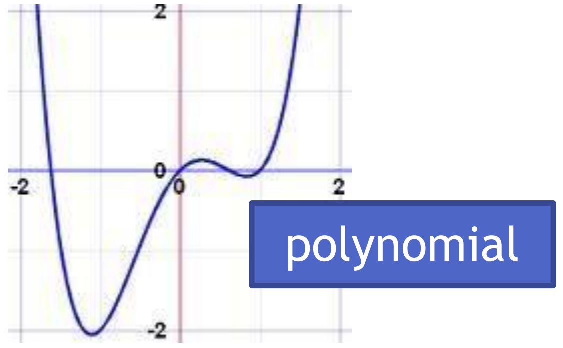


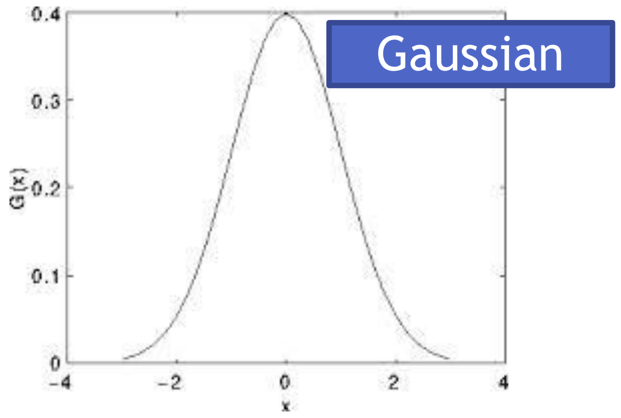
Real-life examples

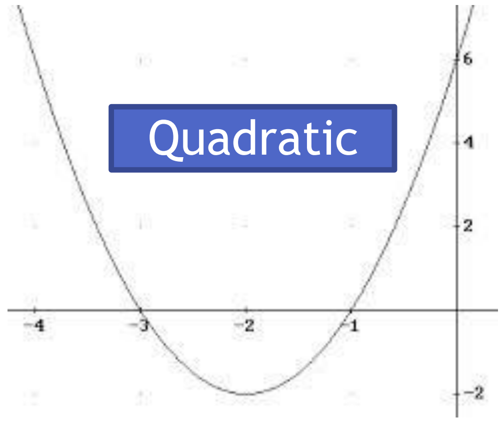
- Gaming - Win vs. Loss
- Sales - Buying vs. Not buying
- Marketing – Response vs. No Response
- Credit card & Loans – Default vs. Non Default
- Operations – Attrition vs. Retention
- Websites – Click vs. No click
- Fraud identification –Fraud vs. Non Fraud
- Healthcare –Cure vs. No Cure

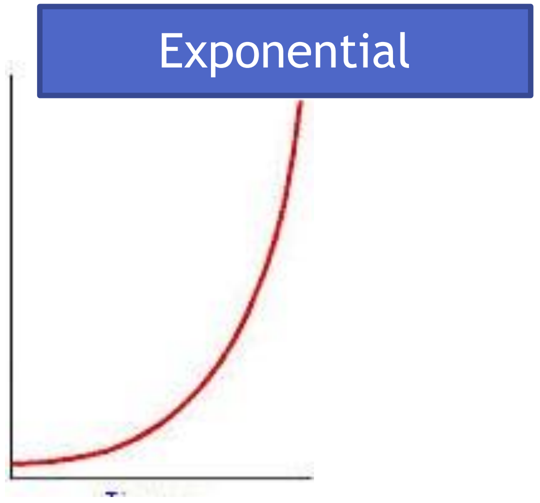
A Logistic Function

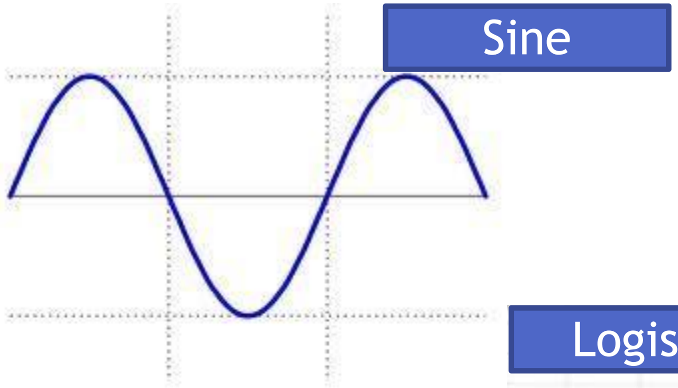
Some Nonlinear functions

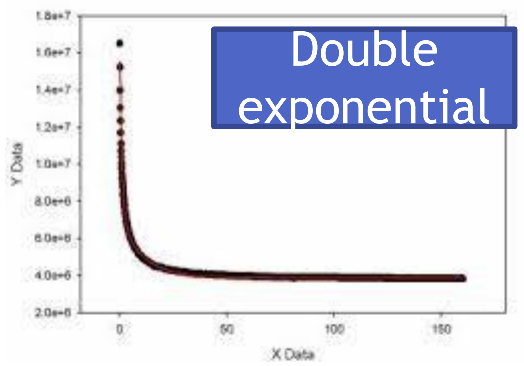


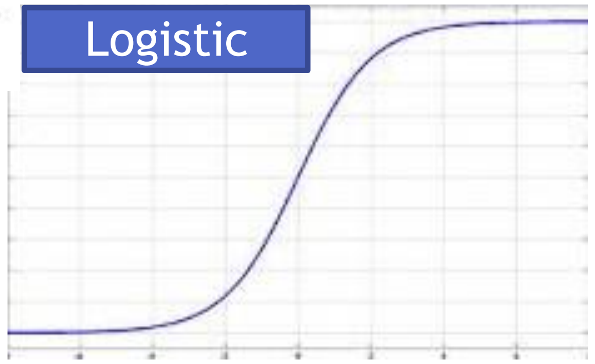




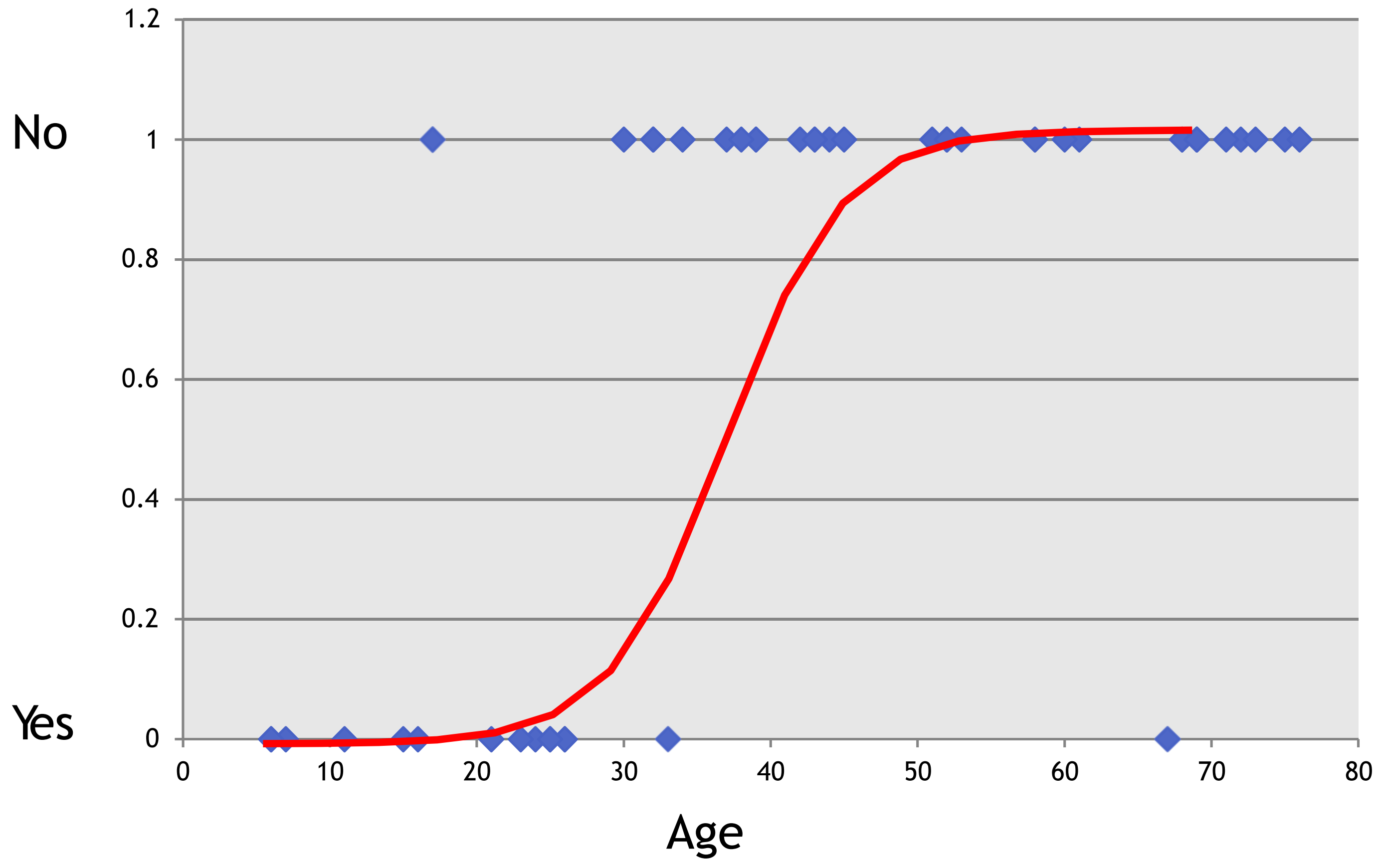






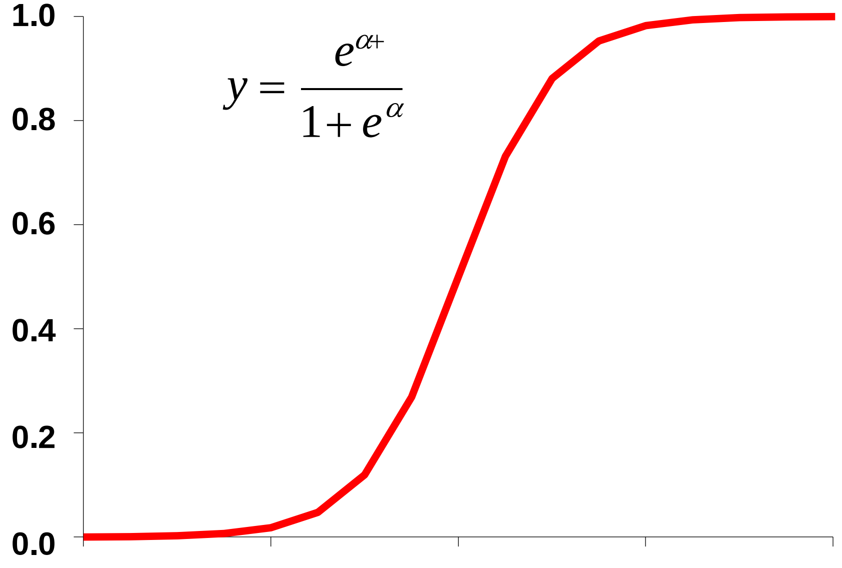


A Logistic Function



The Logistic function

- We want a model that predicts probabilities between 0 and 1, that is, S-shaped.
- There are lots of s-shaped curves. We use the logistic model:
- $y = \exp(\beta_0 + \beta_1 X) \,/ [1 + \exp(\beta_0 + \beta_1 X)\,]$



Logistic Regression Output

- In logistic regression, we try to predict the probability instead of direct values
- Y is binary, it takes only two values 1 and 0 instead of predicting 1 or 0 we predict the probability of 1 and probability of zero
- This suits aptly for the binary categorical outputs like YES vs NO; WIN vs LOSS; Fraud vs Non Fraud

Logistic Regression Line

Lab: Logistic Regression

- Dataset: Product Sales Data/Product_sales.csv
- Build a logistic Regression line between Age and buying
- A 4 years old customer, will he buy the product?
- If Age is 105 then will that customer buy the product?

Code: Logistic Regression

```
from sklearn.linear_model import LogisticRegression
logistic = LogisticRegression()
logistic.fit(sales[["Age"]],sales["Bought"])

logistic.coef_
logistic.intercept_
#A 4 years old customer, will he buy the product?
age1=4
predict_age1=logistic.predict(age1)
print(predict_age1)

#If Age is 105 then will that customer buy the product?
age2=105
predict_age2=logistic.predict(age2)
print(predict_age2)
```

Multiple Logistic Regression

Multiple Logistic Regression

- The dependent variable is binary
- Instead of single independent/predictor variable, we have multiple predictors
- Like buying / non-buying depends on customer attributes like age, gender, place, income etc.,

LAB: Multiple Logistic Regression

- Dataset: Fiberbits/Fiberbits.csv
  - Active_cust variable indicates whether the customer is active or already left the network.
- Build a model to predict the chance of attrition for a given customer using all the features.

Code: Multiple Logistic Regression

```
Fiber=pd.read_csv("D:\\Google Drive\\Training\\Datasets\\Fiberbits\\Fiberbits.csv")
list(Fiber.columns.values)    ###to get variables list

#Build a model to predict the chance of attrition for a given customer using all the features.
from sklearn.linear_model import LogisticRegression
logistic1= LogisticRegression()

###fitting logistic regression for active customer on rest of the variables#######
logistic1.fit(Fiber[["income"]+['months_on_network']+['Num_complaints']+['number_plan_changes']+['relocated']+['monthly_bill']+['technical_issues_per_month']+['Speed_test_result']],Fiber[['active_cust']])
```

Goodness of fit for a logistic regression

Goodness of fit for a logistic regression

- Classification Matrix
- AIC and BIC
- ROC & AUC

Classification Table & Accuracy

		Actual	
		0	1
Predicted	0	True positive (TP)	False Negatives(FN)
	1	False positive (FP)	True Negatives(TN)

- Also known as confusion matrix
- Accuracy=(TP+TN)/(TP+FN+FP+TN)

LAB: Confusion Matrix & Accuracy

- Create confusion matrix for Fiber bits model
- Find the accuracy value for fiber bits model
- Change try three different threshold values and note down the changes in accuracy value

Code: Confusion Matrix & Accuracy

```
from sklearn.cross_validation import train_test_split
from sklearn.metrics import confusion_matrix###for using confusion matrix###

predict1=logistic1.predict(Fiber[["income"]+['months_on_network']+['Num_complaints']+['nu
mber_plan_changes']+['relocated']+['monthly_bill']+['technical_issues_per_month']+['Speed
_test_result']])
predict1

cm1=confusion_matrix(Fiber[['active_cust']],predict1)
print(cm1)

#####from confusion matrix calculate accuracy
total1=sum(sum(cm1))
print(total1)

accuracy1=(cm1[0,0]+cm1[1,1])/total1
accuracy1
```

Multicollinearity

Multicollinearity

- The relation is between X and Y is non linear, we used logistic regression
- The multicollinearity is an issue related to predictor variables.
- Multicollinearity need to be fixed in logistic regression as well.
- Otherwise the individual coefficients of the predictors will be effected by the interdependency
- The process of identification is same as linear regression

LAB-Multicollinearity

- Is there any multicollinearity in fiber bits model?
- Identify and remove multicollinearity from the model

LAB-Multicollinearity

```
def vif_cal(input_data, dependent_col):
    x_vars=input_data.drop([dependent_col], axis=1)
    xvar_names=x_vars.columns
    for i  in range(0,xvar_names.shape[0]):
        y=x_vars[xvar_names[i]]
        x=x_vars[xvar_names.drop(xvar_names[i])]
        rsq=sm.ols(formula="y~x", data=x_vars).fit().rsquared
        vif=round(1/(1-rsq),2)
        print (xvar_names[i], " VIF = " , vif)

#Calculating VIF values using that function
vif_cal(input_data=Fiber, dependent_col="active_cust")
```

Individual Impact of Variables

Individual Impact of Variables

- Out of these predictor variables, what are the important variables?
- If we have to choose the top 5 variables what are they?
- While selecting the model, we may want to drop few less impacting variables.
- How to rank the predictor variables in the order of their importance?
- We can simply look at the z values of the each variable. Look at their absolute values
- Or calculate the Wald chi-square, which is nearly equal to square of the z-score
- Wald Chi-Square value helps in ranking the variables

LAB: Individual Impact of Variables

- Identify top impacting and least impacting variables in fiber bits models
- Find the variable importance and order them based on their impact

Code: Individual Impact of Variables

```
import statsmodels.formula.api as sm

m1=sm.Logit(Fiber['active_cust'],Fiber[["income"]+['months_on_network']+['Num_compl
aints']+['number_plan_changes']+['relocated']+['monthly_bill']+['technical_issues_p
er_month']+['Speed_test_result']])
m1
m1.fit()
m1.fit().summary()
m1.fit().summary2()
```

Conclusion: Logistic Regression

Conclusion: Logistic Regression

- Logistic Regression is the base of all classification algorithms
- A good understanding on logistic regression and goodness of fit measures will really help in understanding complex machine learning algorithms like neural networks and SVMs
- One has to be careful while selecting the model, all the goodness of fit measures are calculated on training data. We may have to do cross validation to get an idea on the test error

Thank you

Appendix

AIC and BIC

- AIC and BIC values are like adjusted R-squared values in linear regression
- Stand-alone model AIC has no real use, but if we are choosing between the models AIC really helps.
- Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models
- If we are choosing between two models, a model with less AIC is preferred
- AIC is an estimate of the information lost when a given model is used to represent the process that generates the data

AIC and BIC

- AIC= -2ln(L)+ 2k
  - L be the maximum value of the likelihood function for the model
  - k is the number of independent variables
- BIC is a substitute to AIC with a slightly different formula. We will follow either AIC or BIC throughout our analysis

- If you are choosing between two models, if both of them have same level of accuracy then you can choose a model that has low AIC value