BAYESIAN CLASSIFICATION

CSE 634 DATA MINING | PROF. ANITA WASILEWSKA

References

- Bayes Theorem : https://www.investopedia.com/terms/b/bayes-theorem.asp
- Bayes Classfication: https://www.tutorialspoint.com/data_mining/dm_bayesian_classification.html
- http://users.sussex.ac.uk/~christ/crs/ml/lec02b.html
- The-Morgan-Kaufmann-Series-in-Data-Management-Systems-Jiawei-Han-Micheline-Kamber-Jian-Pei-Data-Mining.-Concepts-and-Techniques-3rd-Edition-Morgan-Kaufmann-2011.pdf
- Example of Bayes Classification: https://mlcorner.wordpress.com/2013/04/28/bayesian-classifier/
- Data Mining Concepts and Techniques 2nd Edition by Jiawei Han and Micheline Kamber
- Classify mail as spam or ham using Bayes: https://github.com/varunon9/naive-bayes-classifier
- Applications of Bayes Classification: https://www.quora.com/In-what-real-world-applications-is-Naive-Bayes-classifier-used
- Sentiment Analysis using Bayes: http://suruchifialoke.com/2017-06-10-sentiment-analysis-movie/
- Classify mail using Bayes: https://medium.com/swlh/classify-emails-into-ham-and-spam-using-naive-bayes-classifier-ffddd7faa1ef

Topics

1) Introduction and Bayes Theorem
2) Naive Bayes Classification
3) Bayesian Belief Networks
4) Applications of Naive Bayes
5) Research Paper - Comparing Bayes

Introduction

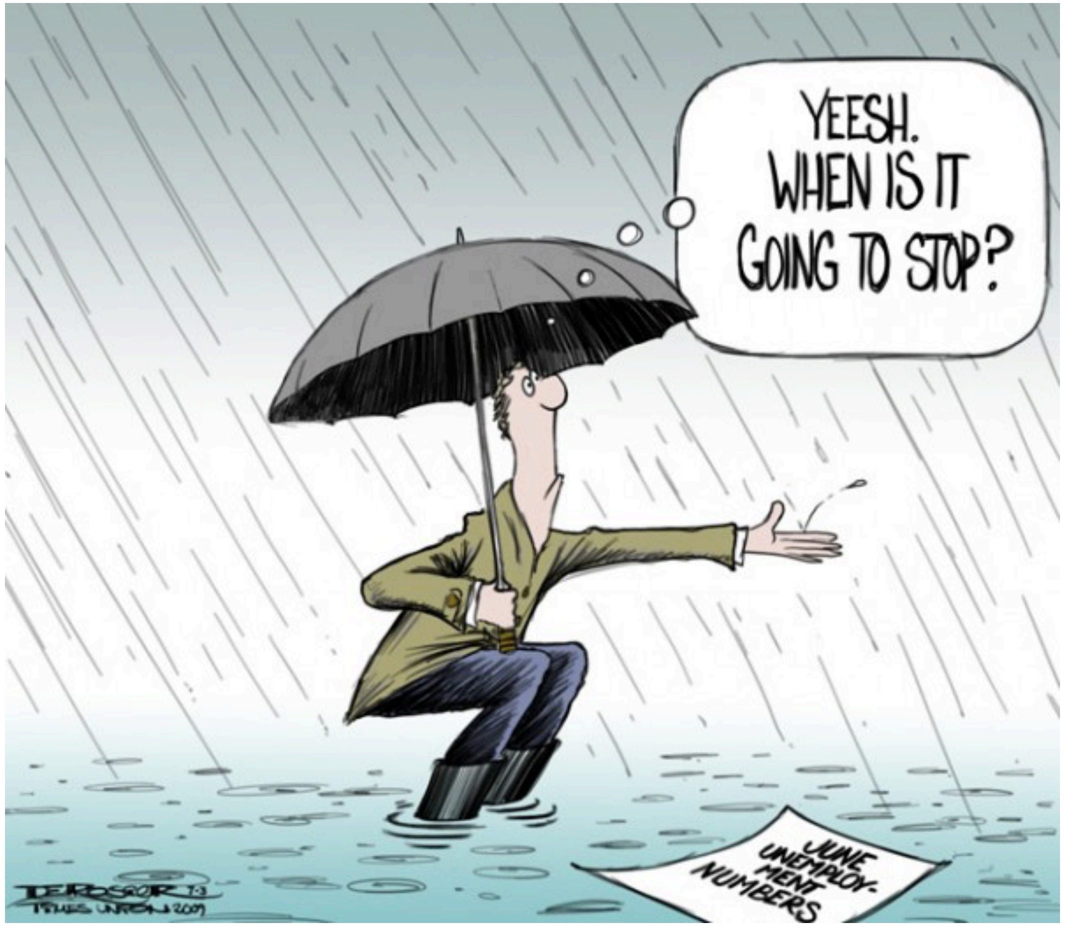
- Bayesian classifiers are the statistical classifiers based on Bayes' Theorem

- Bayesian classifiers can predict class membership probabilities i.e. the probability that a given tuple belongs to a particular class.

- It uses the given values to train a model and then it uses this model to classify new data

Source : https://www.tutorialspoint.com/data_mining/dm_bayesian_classification.htm

Where is it used?



Source : https://mlcorner.wordpress.com/2013/04/28/bayesian-classifier/

Trying to find the answer

There are only two possible events possible for the given question:

A: It is going to rain tomorrow

B: It will not rain tomorrow.

If you think intuitively

- It's either going to be raining today or it is NOt going to be raining today
- So technically there is **50% CHANCE OF RAIN** tomorrow. Correct?

Source : https://mlcorner.wordpress.com/2013/04/28/bayesian-classifier/

That's too *Naive* even for Bayes !

Bayesian theorem argues that the probability of an event taking place changes if there is information available about a related event

- This means that if you recall the previous weather conditions for the last week, and you remember that it has actually rained every single day, your answer will no longer be 50%
- The Bayesian approach provides a way of explaining how you should change your existing beliefs in the light of new evidence.
- Bayesian rule’s emphasis on prior probability makes it better suited to be applied in a wide range of scenarios

Source : https://mlcorner.wordpress.com/2013/04/28/bayesian-classifier/

What is Bayes Theorem?

- Bayes' theorem, named after 18th-century British mathematician Thomas Bayes, is a mathematical formula for determining conditional probability

- The theorem provides a way to revise existing predictions or theories given new or additional evidence.

- In finance, Bayes' theorem can be used to rate the risk of lending money to potential borrowers.

Source : https://www.investopedia.com/terms/b/bayes-theorem.asp

Bayes Formula

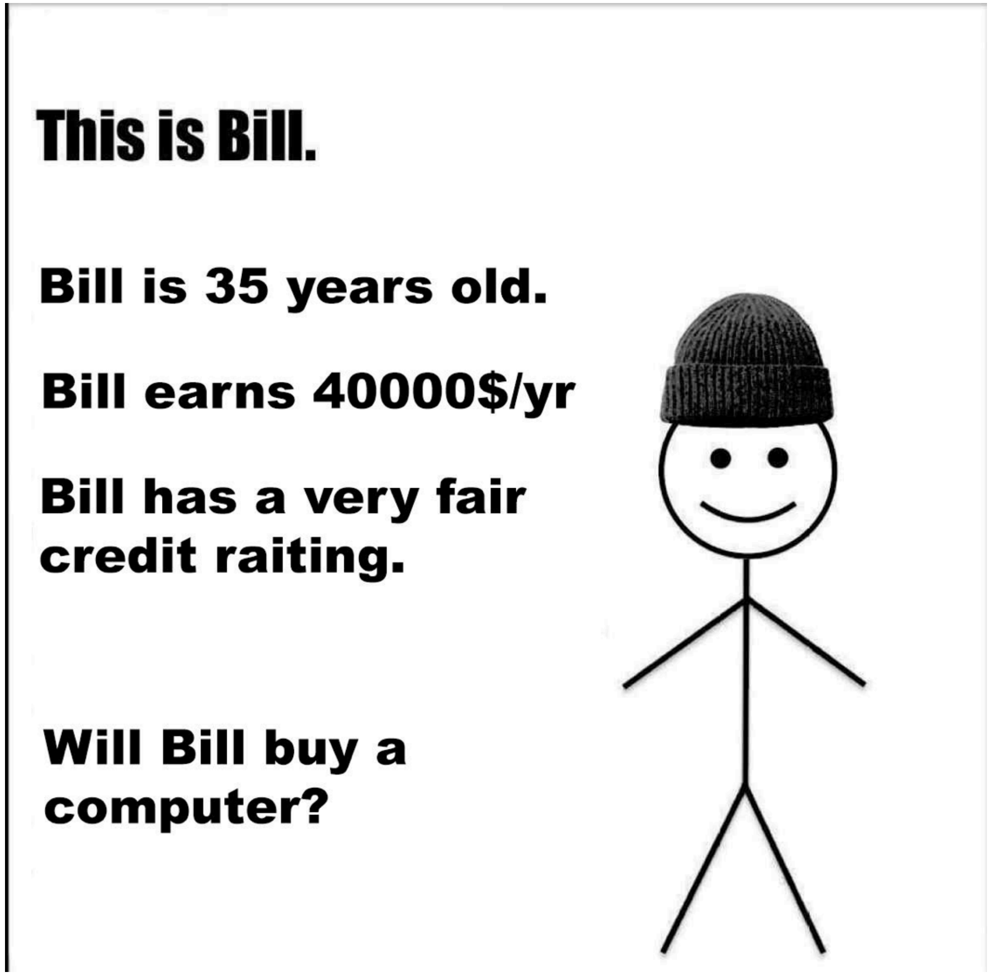
- The formula for the Bayes theorem is given as follows:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(A) \times P(B|A)}{P(B)}$$

- Bayes' theorem is also called Bayes' Rule or Bayes' Law.

Source : https://www.investopedia.com/terms/b/bayes-theorem.asp

Small Example



This is Bill.

Bill is 35 years old.

Bill earns 40000$/yr

Bill has a very fair credit raiting.

Will Bill buy a computer?

Bayes theorem to the rescue!

$$P(H|X) = P(X|H) * P(H) / P(X)$$

H: Hypothesis that Bill will buy the computer X : Bill is 35 years old with fair credit rating and income of 40000$/year

P(H|X) : The probability that Bill will buy the computer **GIVEN** that we know his age,income and credit rating [Posterior]

P(H) : Probability that Bill will buy computer (**REGARDLESS** of knowing age,income and credit rating) [Prior]

P(X|H) : Probability that someone is 35 years old, has fair credit rating, earns 40000$/yr AND has **BOUGHT** the computer. [Likelihood]

P(X) : Probability that Bill is 35 years old, has fair credit rating, earns 40000$/yr [Evidence]

Big Example

Bill now wants to play football!

(Because he is tired of using his computer)

Hi! I just cannot seem to figure out which are the best days to play football with my friends. Can you help me out?

Source : http://qr.ae/TUTR3L

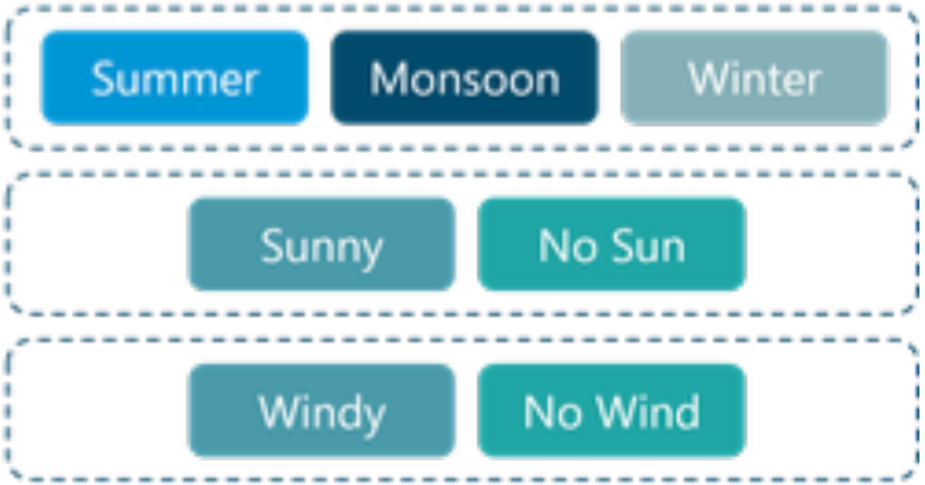
The Naive Bayes ***nerd*** is here!

I have noted down all the days it was good/bad to play football and the combination of weather metrics on that particular day.
That is perfect. We will be using Naive Bayes algorithm to predict if you should play on a particular day or not.

Source : http://qr.ae/TUTR3L

Lets identify all the factors!

All possible weather combinations



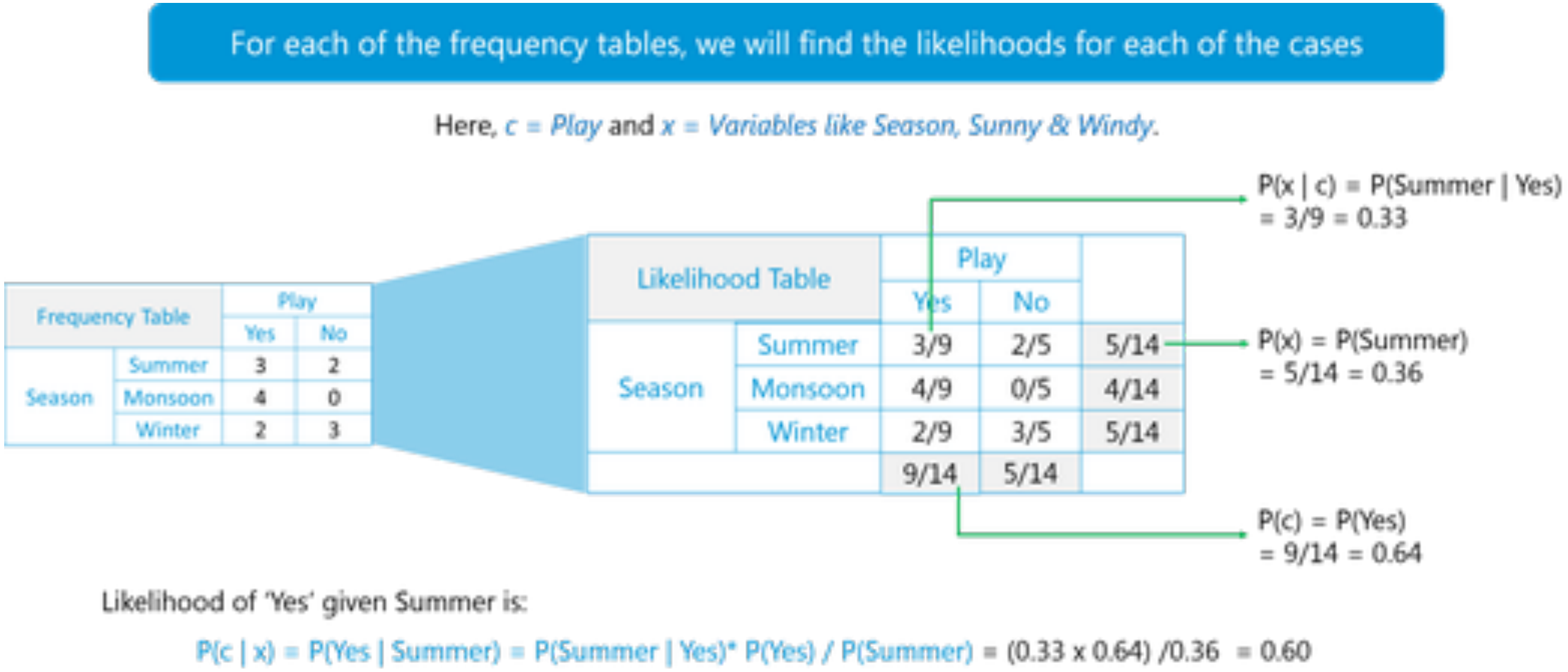
Summer Monsoon Winter

Sunny No Sun

Windy No Wind

Source : http://qr.ae/TUTR3L

Draw frequency tables for each factor



For each of the frequency tables, we will find the likelihoods for each of the cases

Here, *c* = *Play* and *x* = *Variables like Season, Sunny & Windy*.

Frequency Table		Play	
		Yes	No
Season	Summer	3	2
	Monsoon	4	0
	Winter	2	3

Likelihood Table		Play		
		Yes	No	
Season	Summer	3/9	2/5	5/14
	Monsoon	4/9	0/5	4/14
	Winter	2/9	3/5	5/14
		9/14	5/14	

P(x | c) = P(Summer | Yes)
= 3/9 = 0.33

P(x) = P(Summer)
= 5/14 = 0.36

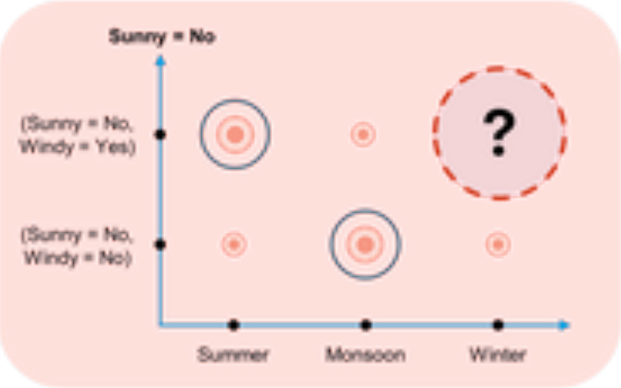
P(c) = P(Yes)
= 9/14 = 0.64

Likelihood of 'Yes' given Summer is:

P(c | x) = P(Yes | Summer) = P(Summer | Yes)* P(Yes) / P(Summer) = (0.33 x 0.64) /0.36 = 0.60

Source : http://qr.ae/TUTR3L

Find the probability



Let us use the likelihood table to predict whether to play football on (Season = Winter, Sunny = No , Windy = Yes)
Since the probability is greater than 0.5, we should play football on that day.
Yayiee!!

$$P(c \mid x) = P(\text{Play} = \text{Yes} \mid \text{Winter}, \text{Sunny} = \text{No}, \text{Windy} = \text{Yes})$$

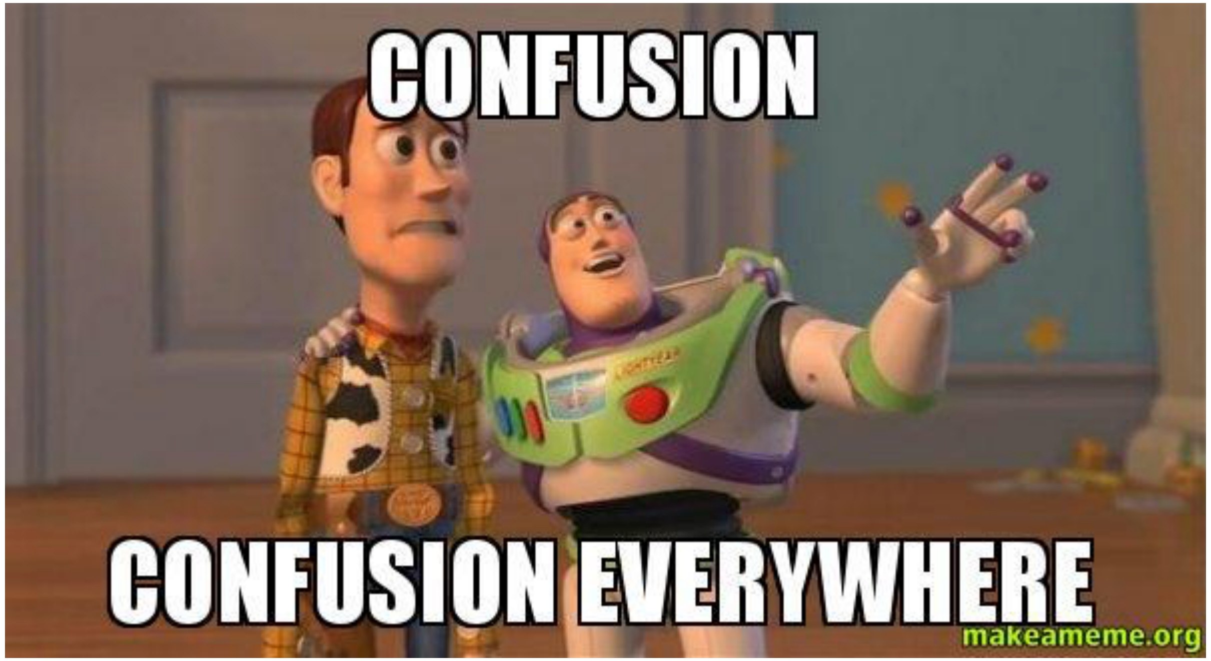
$$= \frac{P(\text{Winter} \mid \text{Yes}) * P(\text{Sunny} = \text{No} \mid \text{Yes}) * P(\text{Windy} = \text{Yes} \mid \text{Yes}) * P(\text{Yes})}{P(\text{Winter}) * P(\text{Sunny} = \text{No}) * P(\text{Windy} = \text{Yes})}$$

$$= (2/9) * (6/9) * (6/9) * (9/14) \;/\; (5/14) * (7/14) * (8/14) = 0.6223$$

Source : http://qr.ae/TUTR3L

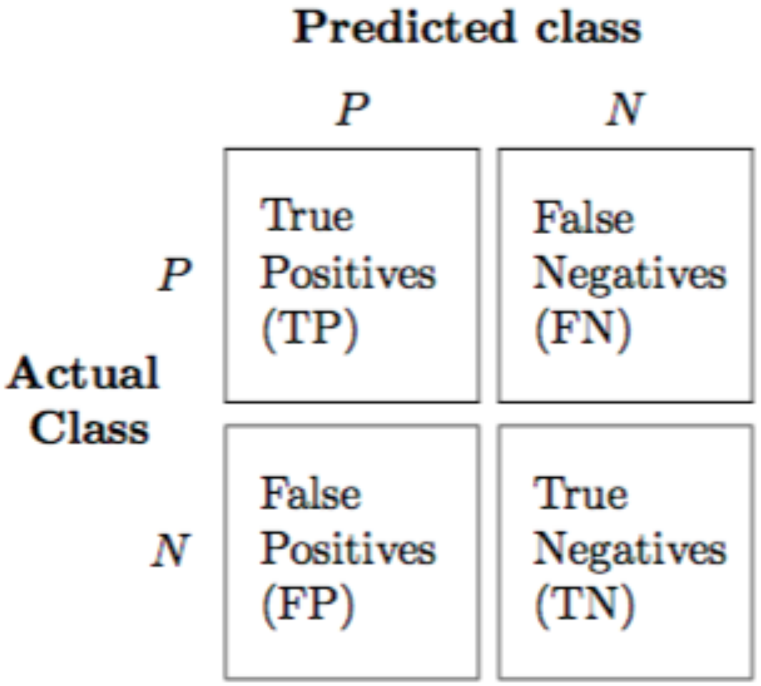
How to know if results are correct?

The Accuracy of Classification can be found out using a Confusion Matrix



Confusion Matrix

- **True Positives (TP):** number of positive examples, labeled as such.
- **False Positives (FP):** number of negative examples, labeled as positive.
- **True Negatives (TN):** number of negative examples, labeled as such.
- **False Negatives (FN):** number of positive examples, labeled as negative.



		Predicted class	
		P	*N*
Actual Class	*P*	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

Source :https://rasbt.github.io/mlxtend/user_guide/evaluate/confusion_matrix/

Finding accuracy of classification

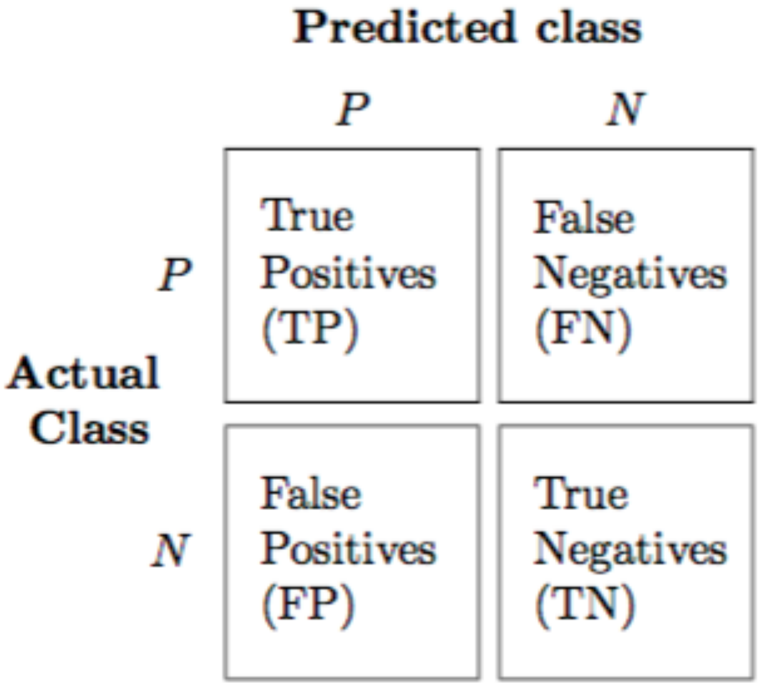
Accuracy = (TP + TN)/(TP + TN + FP + FN)

Accuracy gives us the result of total correct predictions out of all the predictions

Precision: TP/(TP + FP)
Precision answers the following question: Out of all the examples the classifier labeled as positive, what fraction were correct?

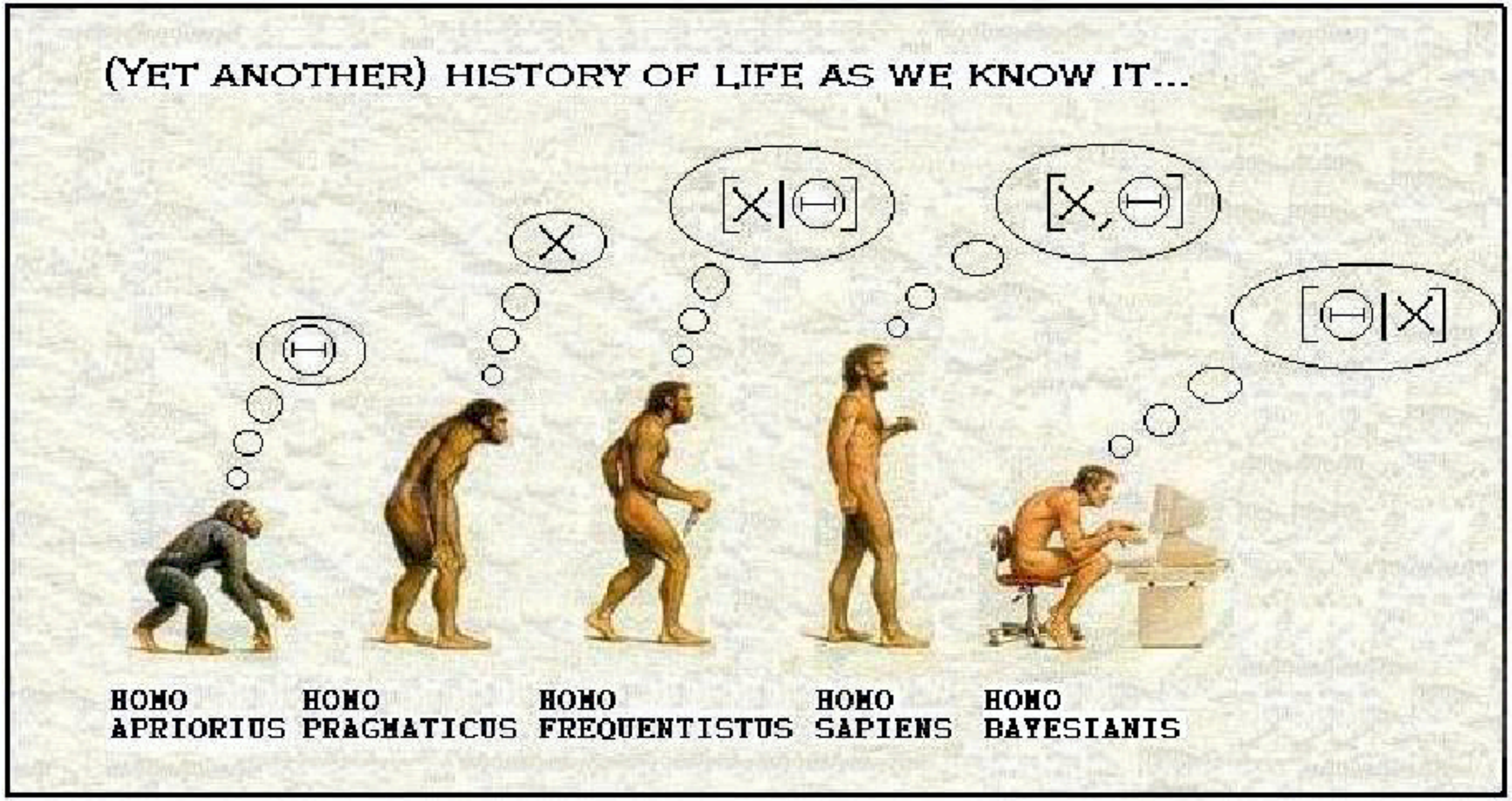
Recall : TP/(TP + FN)

Recall answers: out of all the positive examples there were, what fraction did the classifier pick up?



		Predicted class	
		P	*N*
Actual Class	*P*	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

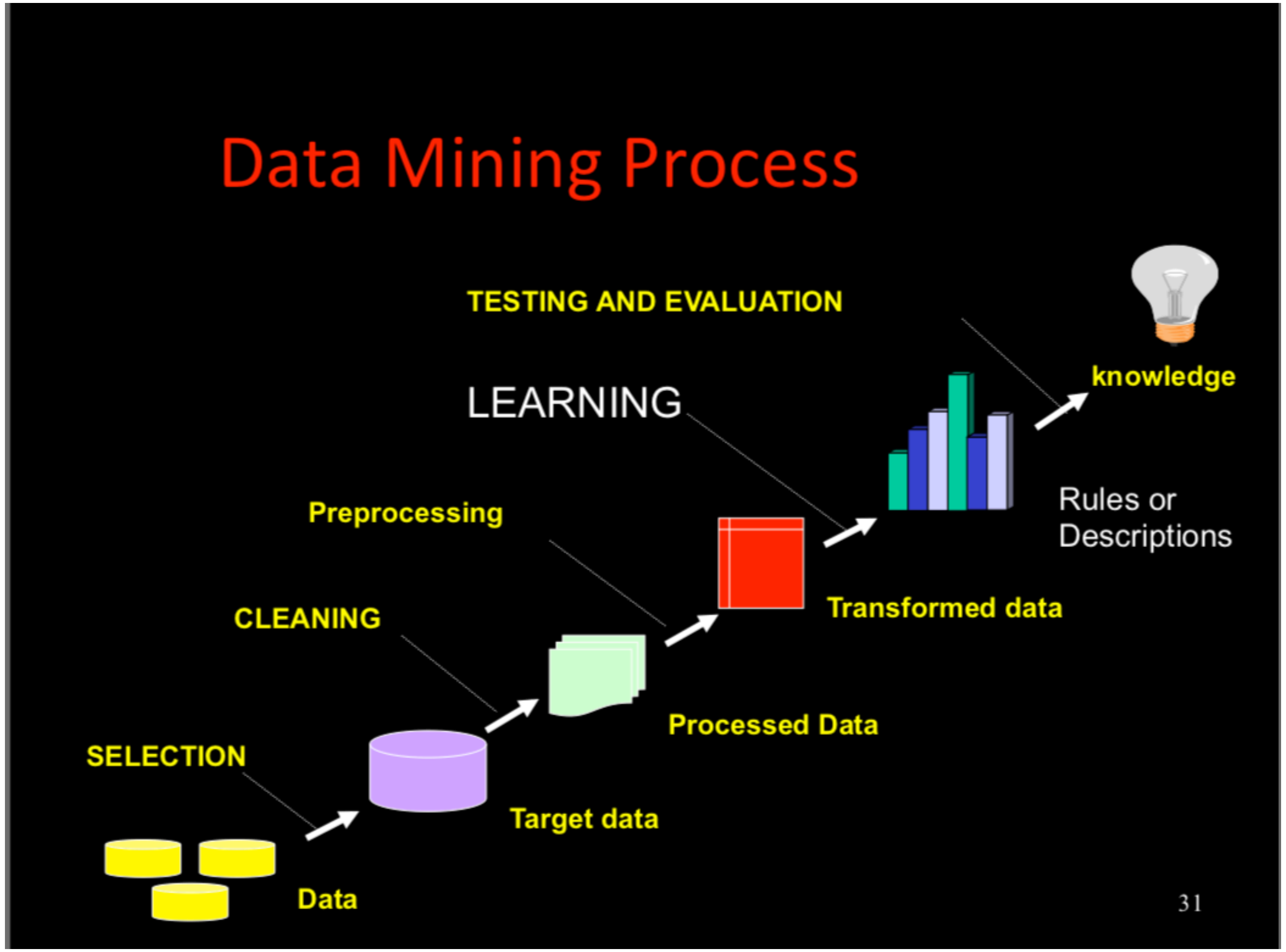
Source :https://tryolabs.com/blog/2013/03/25/why-accuracy-alone-bad-measure-classification-tasks-and-what-we-can-do-about-it/



- The Homo apriorius establishes the probability of an hypothesis, no matter what data tell.
- The Homo pragamiticus establishes that it is interested by the data only.
- The Homo frequentistus measures the probability of the data given the hypothesis.
- The Homo sapients measures the probability of the data and of the hypothesis.
- The Homo bayesianis measures the probability of the hypothesis, given the data.

Source : http://www.brera.mi.astro.it/~andreon/inference/Inference.html

Just because...



Data Mining Process

http://www3.cs.stonybrook.edu/~cse634/L3ch6classification.pdf

What are Bayesian Classifiers?

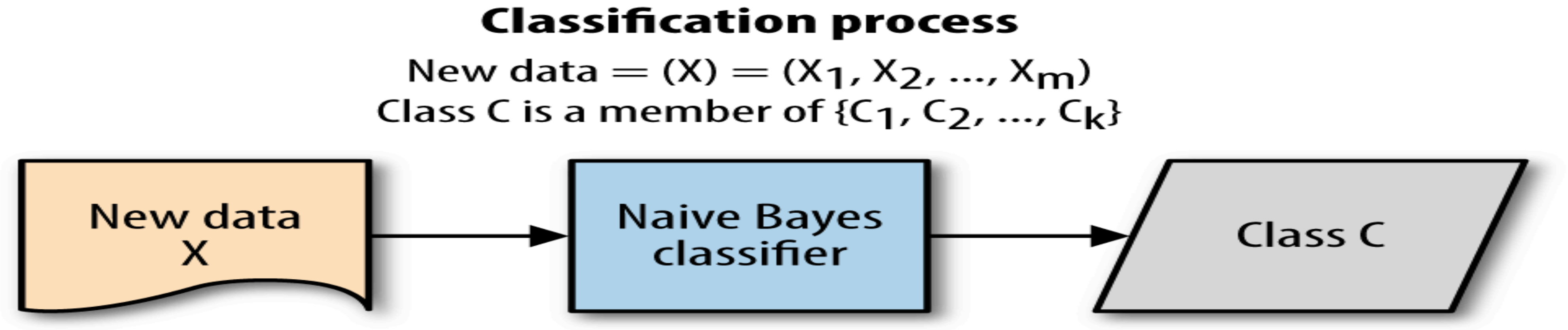
- Statistical classifiers.
- Predict class membership probabilities, such as the probability that a given tuple belongs to a particular class.
- Based on Bayes’ theorem
- Exhibits high accuracy and speed when applied to large databases.

Naive Bayes Classification

Before explaining the mathematical representations, let us see the basic principle of Bayesian classification :

Predict the most probable class for each instance. How ?

Find out the probability of the **previously unseen instance** belonging to each class, and then select the most probable class.


Classification process
New data = (X) = $(X_1, X_2, ..., X_m)$
Class C is a member of $\{C_1, C_2, ..., C_k\}$
New data X
Naive Bayes classifier
Class C

Reference : https://medium.com/@gp_pulipaka/applying-gaussian-naïve-bayes-classifier-in-python-part-one-9f82aa8d9ec4

Naive Bayes Classification

A Naive Bayes Classifier is a program which predicts a class value given a set of set of attributes.

For each known class value,

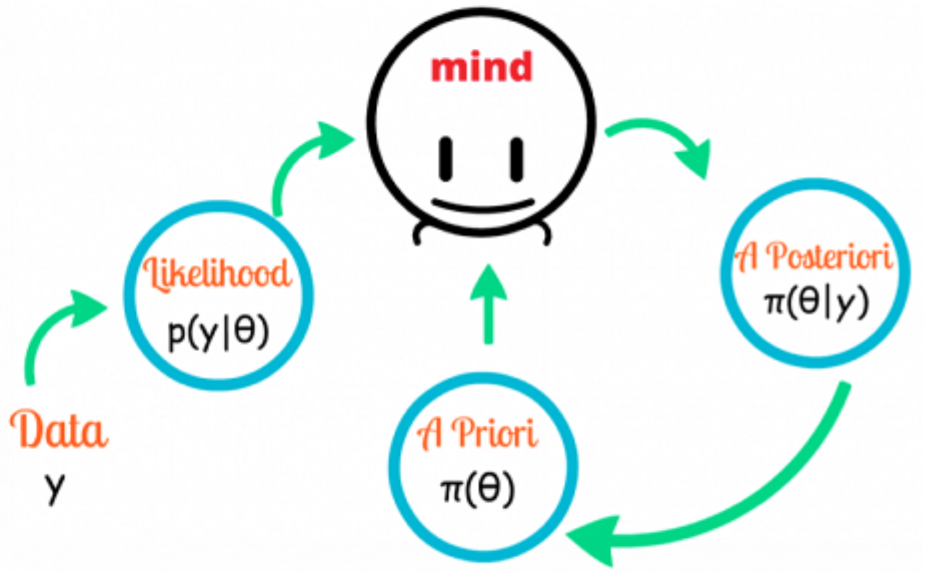
- Calculate probabilities for each attribute, conditional on the class value.
- Use the product rule to obtain a joint conditional probability for the attributes.
- Use Bayes rule to derive conditional probabilities for the class variable.

Once this has been done for all class values, output the class with the highest probability.

Model Parameters

For the Bayes classifier, we need to “learn” two functions, the likelihood and the prior.

Prior	$P(Y = y)$
Likelihood	$P(X = x \| Y = y)$



Reference :http://blog.datumbox.com/machine-learning-tutorial-the-naive-bayes-text-classifier/

Model Parameters

- **Instance Attributes** :

Instances are represented as a vector of attributes.

$$X = (X_1, \ldots, X_k)$$

- Let there are ‘m’ classes : $C_1, C_2, \ldots, C_m$.
- Classification is to derive the maximum posteriori, ie maximal **P(Ci|X)**
- The likelihood now becomes

$$P(X_1 = x_1, \ldots, X_k = x_k | Y = y)$$

This affects the number of model parameters.

Model Parameters

The problem with explicitly modeling $P(X_1,\ldots,X_n|Y)$ is that there are usually way too many parameters:

- We'll run out of space
- We'll run out of time
- And we'll need tons of training data (which is usually not available)
- It is computationally expensive to evaluate $\mathbf{P(X|C_i)}$

Conditional Independence

- A Naive Bayes Classifier assumes that attributes are **conditionally independent** given the class.

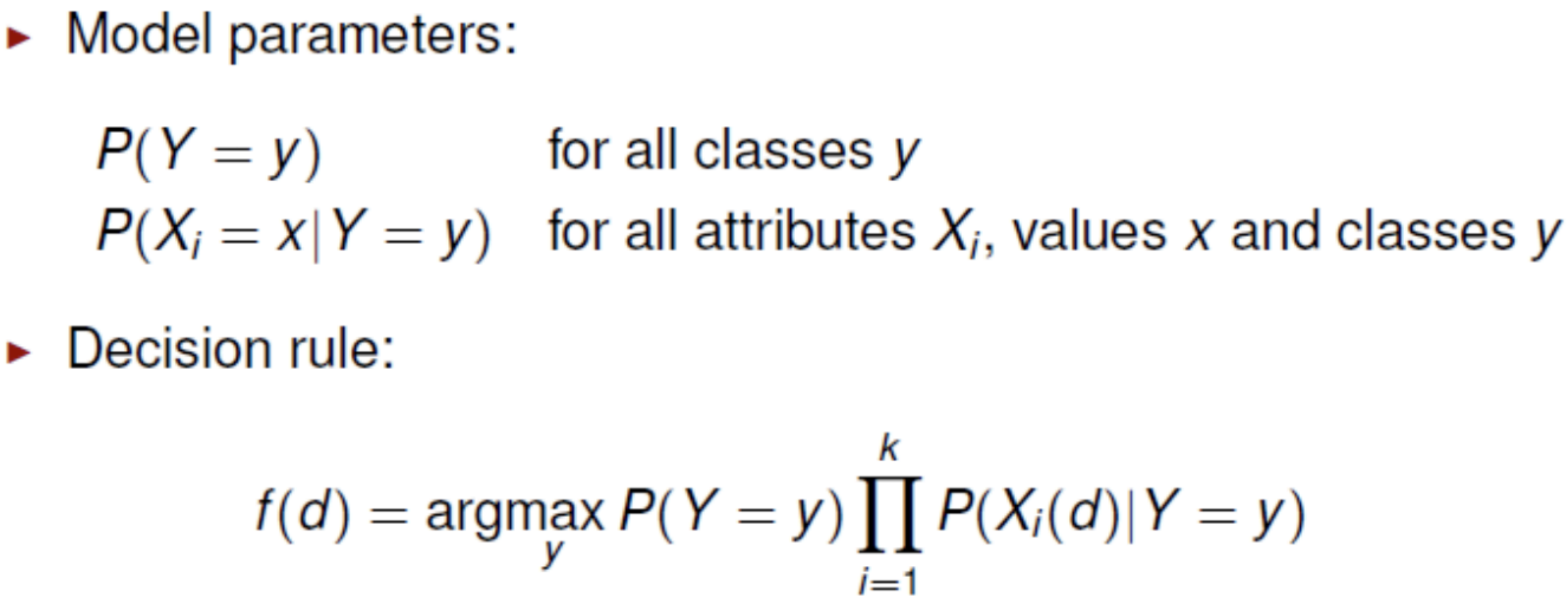
$$P(X_1, \ldots, X_k | Y) = \prod_{i=1}^{k} P(X_i | Y)$$

ie, each feature is conditionally independent of every other feature for a particular class label.

This reduces the number of model parameters.

Bayes Classification

Naive Bayes works equally well for multi valued attributes also.



- Model parameters:

$P(Y = y)$	for all classes y
$P(X_i = x \mid Y = y)$	for all attributes X_i, values x and classes y

- Decision rule:

$$f(d) = \operatorname*{argmax}_y P(Y = y) \prod_{i=1}^{k} P(X_i(d) \mid Y = y)$$

“Zero” Problem

What if there is a class, $\mathbf{C_i}$ and X has an attribute $\mathbf{X_k}$ such that none of the samples in C_i has that attribute value?

In that case $\mathbf{P(x_k|C_i) = 0}$, which results in $\mathbf{P(X|C_i) = 0}$

even though $P(x_k|C_i)$ for all the other attributes in X may be large.

“Zero” Problem - Remedy

- The class conditional probability can be re-estimated with the **‘m-estimate’** : m is the number of virtual samples ~ upto 1% of training example

- Using the **Laplacian correction** to avoid computing probability values of zero. Here we have 1 more tuple for each attribute-class pair. The “corrected” probability estimates are close to their “uncorrected” counterparts, yet the zero probability value is avoided.

Numeric Underflow Problem

- What’s nice about Naïve Bayes is that it returns probabilities.

  These probabilities can tell us how **confident the algorithm is**.

- Since we are multiplying these probabilities, it could lead to a

  floating -point underflow.

- So it is better to sum logs of probabilities rather than multiplying probabilities

Bayesian Belief Networks

- Naive Bayesian classifier assumes class conditional independence
- This assumption simplifies computation
- When this assumption is true, Naive Bayesian classifier is the most accurate in comparison with all other classifiers
- However, dependencies can exist between variables
- Bayesian Belief Networks makes no class conditional independence assumption – improvement over Naive Bayesian classifier

Bayesian Belief Networks

- Specifies joint conditional probability distributions
- Allows class conditional independencies to be defined between subsets of variables
- Provides graphical model of causal relationships
- Trained Bayesian Belief Networks can be used for classification
- Also known as Belief Networks, Bayesian Networks and Probabilistic Networks

Bayesian Belief Networks

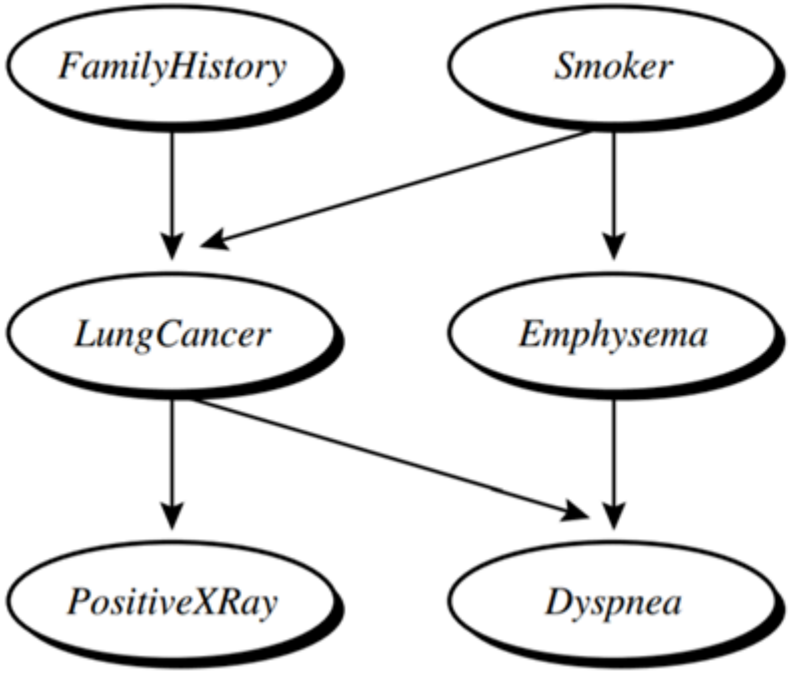
- Defined by two components
    1. A Directed Acyclic Graph
    2. Set of conditional probability tables
- Each node in the DAG represents a random variable (Discrete or Continuous valued)
- Each node may correspond to actual attributes given in the data or to “hidden variables” believed to form a relationship
- Each edge represents a probabilistic dependence

Bayesian Belief Networks

- If there is an edge from node Y to a node Z, then Y is a parent or immediate predecessor of Z, and Z is a descendant of Y

- *Each variable is conditionally independent of its non-descendants in the graph, given its parents*

Bayesian Belief Networks



	FH, S	FH, ~S	~FH, S	~FH, ~S
LC	0.8	0.5	0.7	0.1
~LC	0.2	0.5	0.3	0.9

- A simple Bayesian Belief Network

Reference: Data Mining Concepts and Techniques 2nd Edition by Jiawei Han and Micheline Kamber, Page 316

Bayesian Belief Networks

- Has Conditional Probability Table (CPT) for each variable
- CPT for a variable Y specifies the conditional distribution P(Y | Parents(Y)), where Parents(Y) are the parents of Y
- From previous example:

P(LungCancer = yes | FamilyHistory = yes, Smoker = yes) = 0.8

P(LungCancer = no | FamilyHistory = no, Smoker = no) = 0.9

Bayesian Belief Networks

- Let X = (x1,..., xn) be a data tuple described by the variables or attributes Y1,..., Yn respectively

$$P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P(x_i | Parents(Y_i))$$

- P(x1,..., xn ombination of values of X, and the values for P(xi | Parents(Yi)) correspond to the entries in the CPT for Y

Bayesian Belief Networks

- A node within the network can be selected as an **output** node, representing a **class label** attribute
- There may be more than one output node
- Various algorithms for learning can be applied to the network
- Rather than returning a single class label, the classification process can return a probability distribution that gives the probability of each class

Bayesian Belief Networks - Training

Case 1

- Network topology is given in advance
- Human experts have knowledge of the conditional dependencies which helps in designing the network
- Experts specifies conditional probabilities for the nodes that participate in direct dependencies
- There are various methods for training the belief network
- Example: Gradient Descent

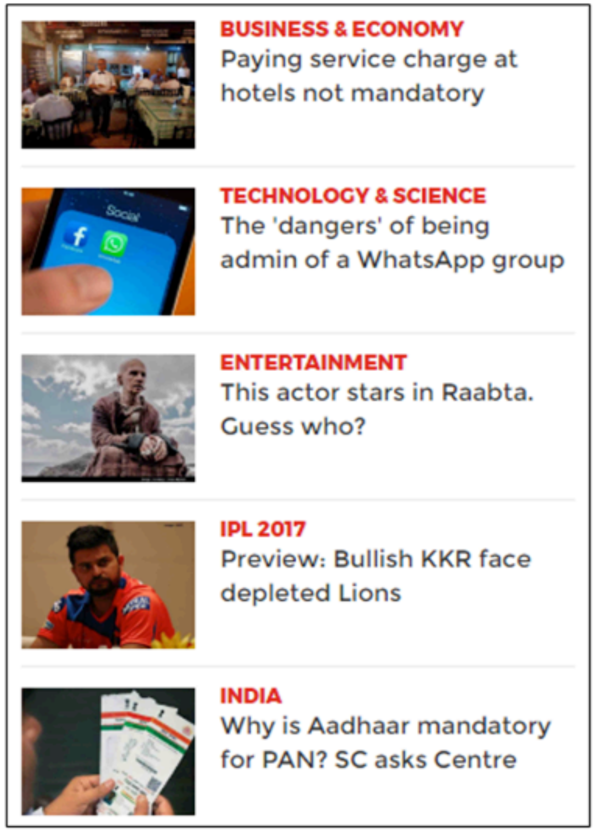
Bayesian Belief Networks - Training

Case 2

- Network topology is inferred from data
- There are several algorithms for learning the topology from the training data given observable variables
- The problem is one of Discrete Optimization

Naive Bayes in Real Life

Categorizing News



BUSINESS & ECONOMY
Paying service charge at hotels not mandatory

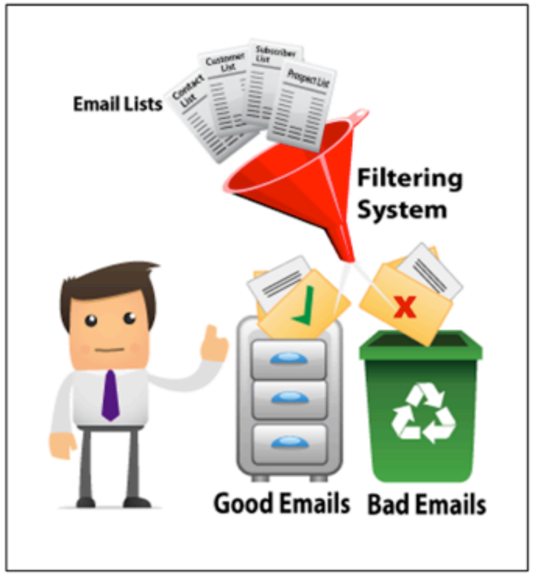
TECHNOLOGY & SCIENCE
The 'dangers' of being admin of a WhatsApp group

ENTERTAINMENT
This actor stars in Raabta. Guess who?

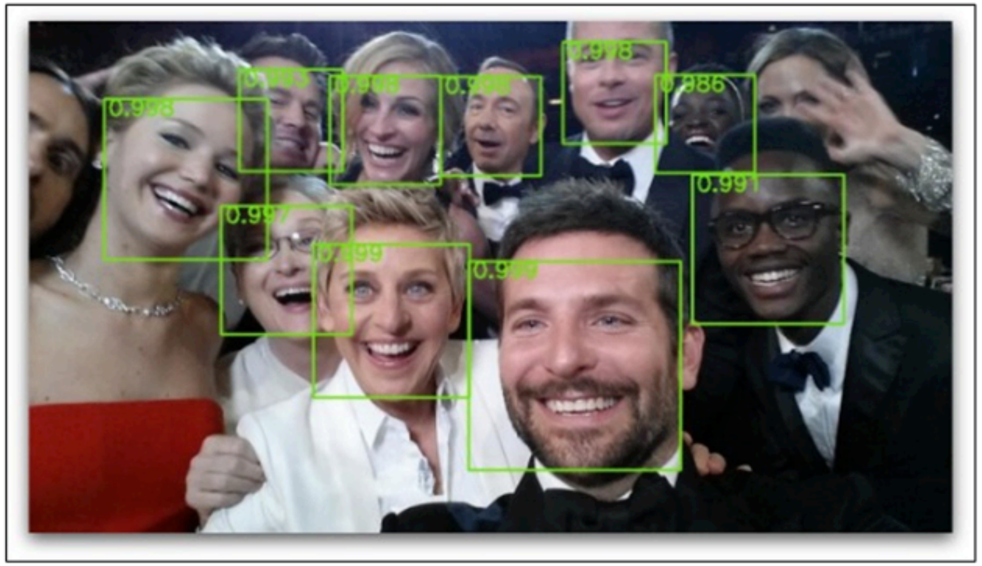
IPL 2017
Preview: Bullish KKR face depleted Lions

INDIA
Why is Aadhaar mandatory for PAN? SC asks Centre

Email Spam Detection



Face Recognition



Sentiment Analysis

https://www.quora.com/In-what-real-world-applications-is-Naive-Bayes-classifier-used

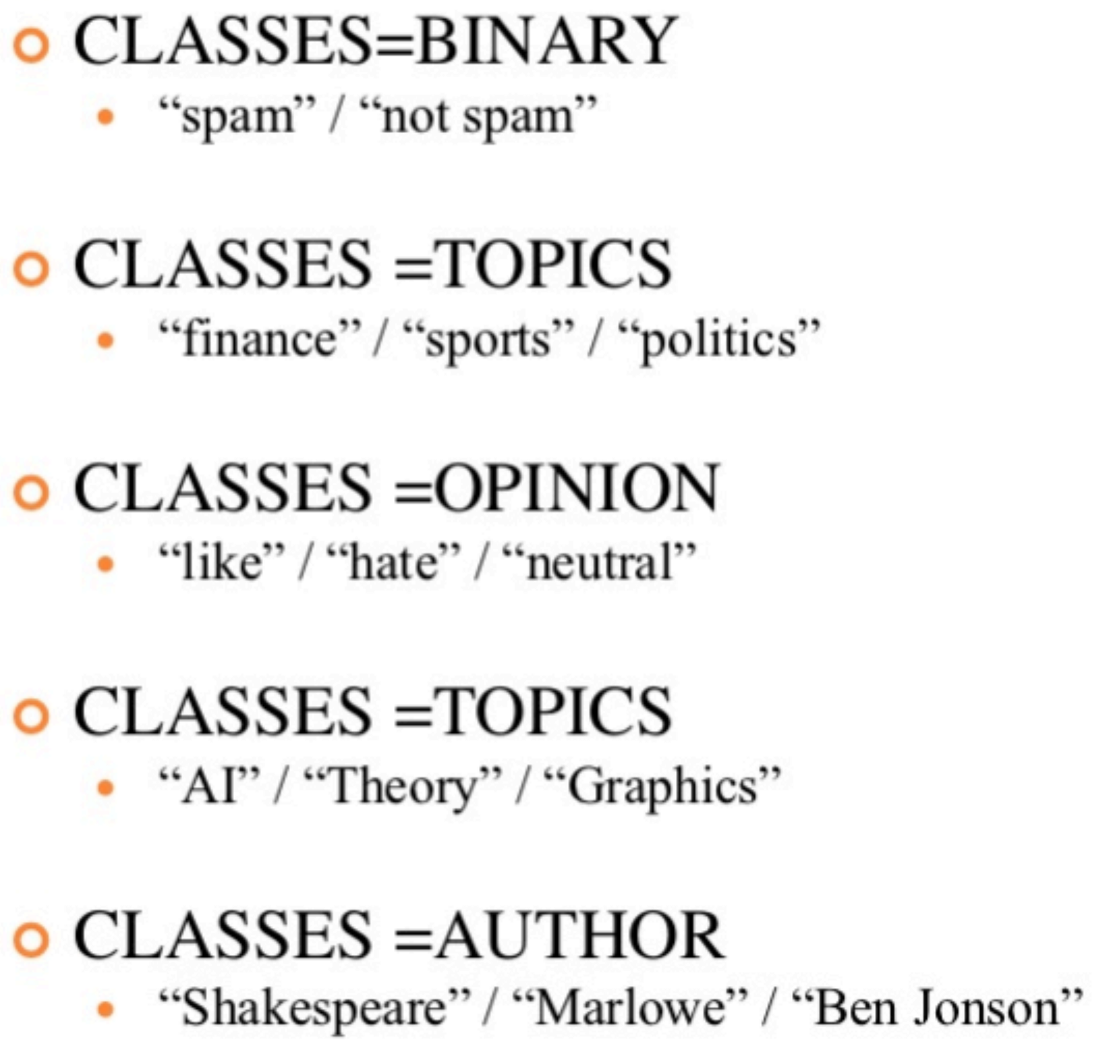
Text classification:

- Naive Bayes Classifier application.

- Why Text Classification?
    - Classify web pages by topic
    - Learning which articles are of interest
    - Information extraction
    - Internet filters.

https://www.slideshare.net/ashrafmath/naive-bayes-15644818

Examples of Text classification:



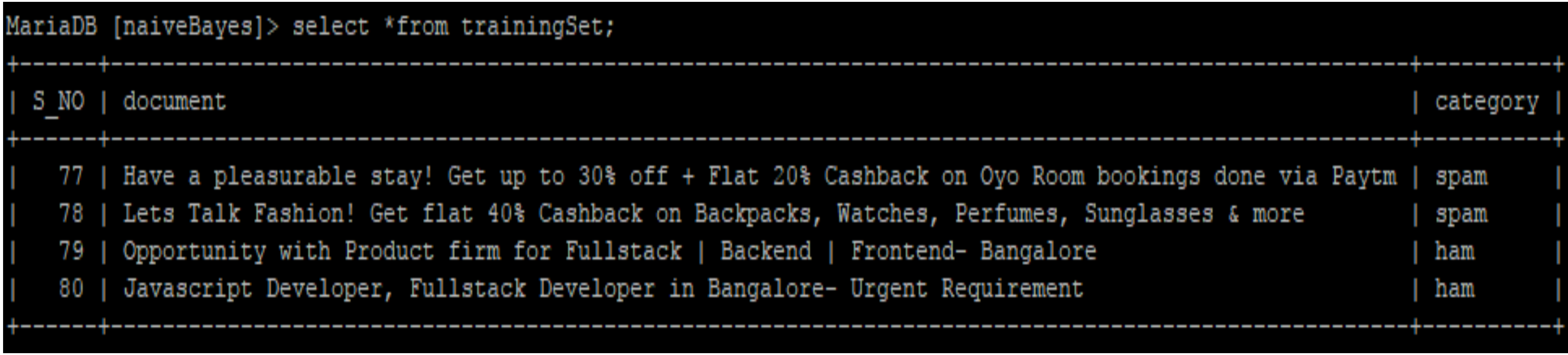
- CLASSES=BINARY
  - “spam” / “not spam”
- CLASSES =TOPICS
  - “finance” / “sports” / “politics”
- CLASSES =OPINION
  - “like” / “hate” / “neutral”
- CLASSES =TOPICS
  - “AI” / “Theory” / “Graphics”
- CLASSES =AUTHOR
  - “Shakespeare” / “Marlowe” / “Ben Jonson”

https://www.slideshare.net/ashrafmath/naive-bayes-15644818

Naive Bayes Approach

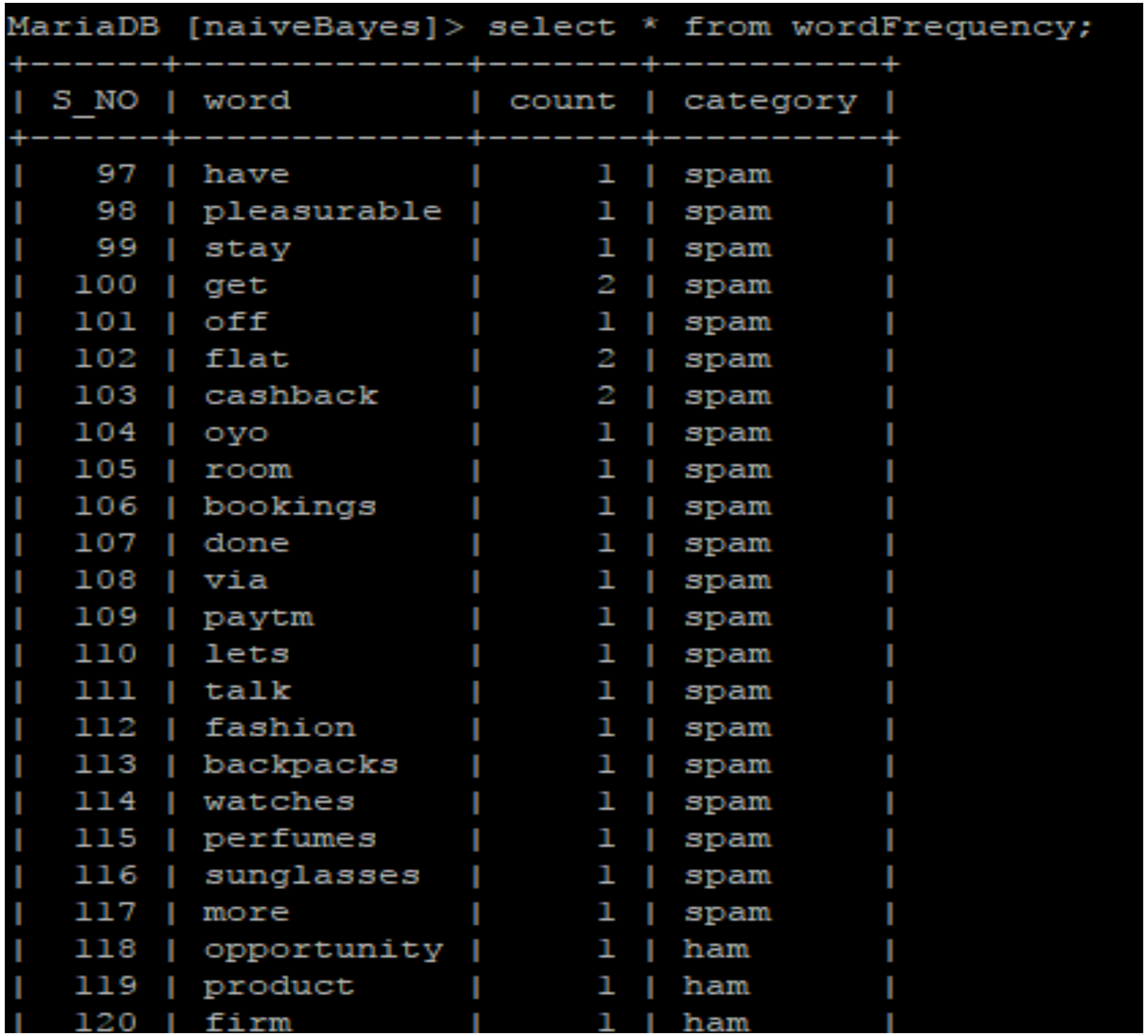
- Build the vocabulary as the list of all distinct words that appear in all the documents in the training set.
- Remove stop words and markings
- Words in the vocabulary becomes the attributes, classification is independent of position of words
- Train the classifier based on the training data set
- Evaluate the results on Test data.

Simple text classifier.

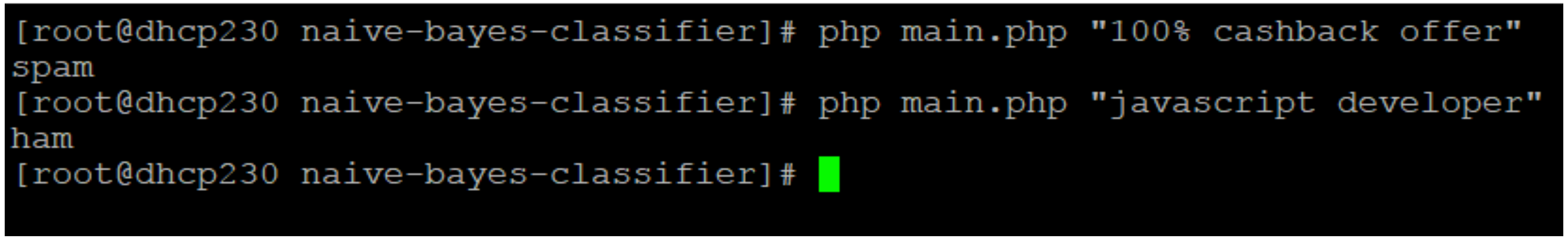


```
MariaDB [naiveBayes]> select *from trainingSet;
+------+----------------------------------------------------------------------------------------------------+----------+
| S_NO | document                                                                                           | category |
+------+----------------------------------------------------------------------------------------------------+----------+
|   77 | Have a pleasurable stay! Get up to 30% off + Flat 20% Cashback on Oyo Room bookings done via Paytm | spam     |
|   78 | Lets Talk Fashion! Get flat 40% Cashback on Backpacks, Watches, Perfumes, Sunglasses & more        | spam     |
|   79 | Opportunity with Product firm for Fullstack | Backend | Frontend- Bangalore                        | ham      |
|   80 | Javascript Developer, Fullstack Developer in Bangalore- Urgent Requirement                         | ham      |
+------+----------------------------------------------------------------------------------------------------+----------+
```

ssh root@dhcp230.fsl.cs.sunysb.edu



```
MariaDB [naiveBayes]> select * from wordFrequency;
+------+-------------+-------+----------+
| S_NO | word        | count | category |
+------+-------------+-------+----------+
|   97 | have        |     1 | spam     |
|   98 | pleasurable |     1 | spam     |
|   99 | stay        |     1 | spam     |
|  100 | get         |     2 | spam     |
|  101 | off         |     1 | spam     |
|  102 | flat        |     2 | spam     |
|  103 | cashback    |     2 | spam     |
|  104 | oyo         |     1 | spam     |
|  105 | room        |     1 | spam     |
|  106 | bookings    |     1 | spam     |
|  107 | done        |     1 | spam     |
|  108 | via         |     1 | spam     |
|  109 | paytm       |     1 | spam     |
|  110 | lets        |     1 | spam     |
|  111 | talk        |     1 | spam     |
|  112 | fashion     |     1 | spam     |
|  113 | backpacks   |     1 | spam     |
|  114 | watches     |     1 | spam     |
|  115 | perfumes    |     1 | spam     |
|  116 | sunglasses  |     1 | spam     |
|  117 | more        |     1 | spam     |
|  118 | opportunity |     1 | ham      |
|  119 | product     |     1 | ham      |
|  120 | firm        |     1 | ham      |
```



```
[root@dhcp230 naive-bayes-classifier]# php main.php "100% cashback offer"
spam
[root@dhcp230 naive-bayes-classifier]# php main.php "javascript developer"
ham
[root@dhcp230 naive-bayes-classifier]#
```

Advantages:

- Requires a small amount of training data to estimate the parameters.
- Good results obtained in most cases
- Easy to implement

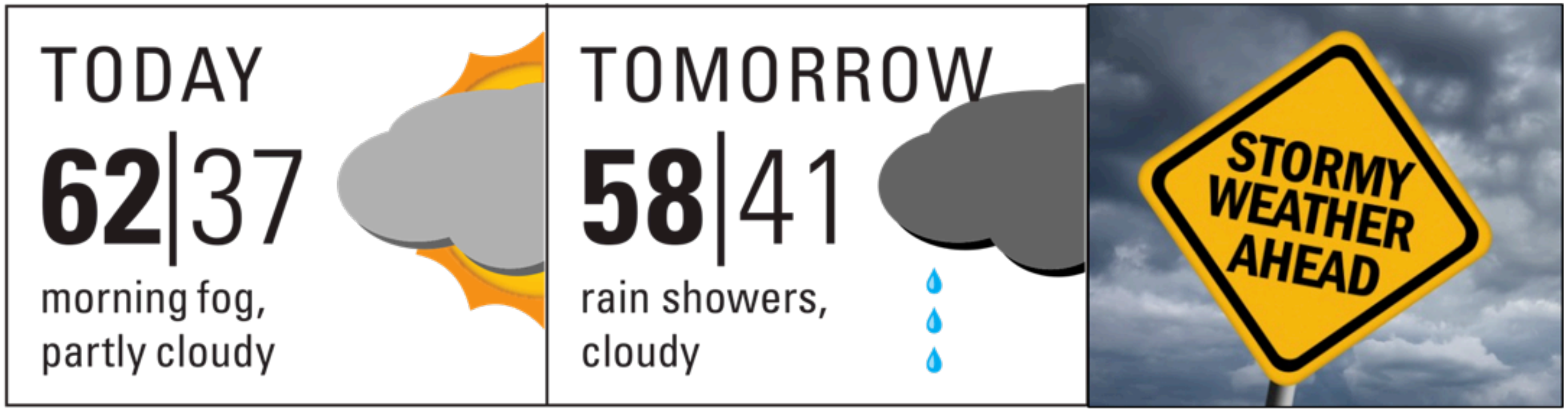
Disadvantages:

- Practically, dependencies exist among variables.

  eg: hospitals : patients: Profile: age, family history etc.

  Symptoms: fever, cough etc., Disease: lung cancer, diabetes, etc.
- Dependencies among these cannot be modelled by Naive bayesian classifier.

Weather prediction:

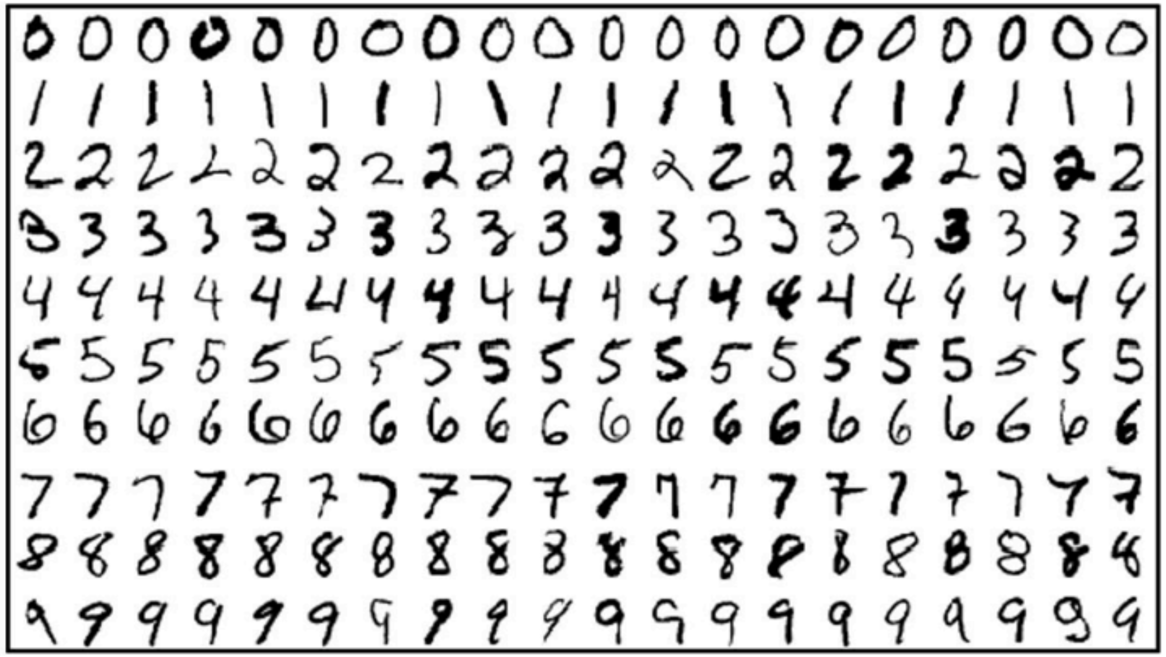


Recommendation System:

https://www.quora.com/In-what-real-world-applications-is-Naive-Bayes-classifier-used
http://suruchifialoke.com/2017-06-10-sentiment-analysis-movie

Medical Diagnosis

Digit Recognition



https://www.quora.com/In-what-real-world-applications-is-Naive-Bayes-classifier-used

PART 2

Research Paper

Research Paper

Title : Improved Study of Heart Disease Prediction System using Data Mining Classification Techniques

Authors : Chaitrali S. Dangare & Sulabha S. Apte, PhD

Journal : International Journal of Computer Applications (0975 – 888) Volume 47– No.10

Publishing Period : June 2012

Abstract

- Bayes Network has been present since time immemorial. For years, it proved to be a simple yet powerful classifier that could be used for prediction.
- The computation power required to run a bayesian classifier is considerately simpler when compared to most of the modern day classification algorithms.
- This paper debates the use of bayesian classifier along with IDT and NN and their usage in a Heart Disease Prediction System in the medical field.

We have used a cutting edge classifier to look into your medical report and analyse you. It is our new innovation.

So,What Does it Say ?

Source: bigstock-healthcare-technology-and-med-83203256.jpg

Classifiers are Important !!!

Source: bigstock-healthcare-technology-and-med-83203256.jpg

Data Set Used

- The publicly available heart disease database is used.
- The Cleveland Heart Disease database consists of 303 records & Statlog Heart Disease database consists of 270 records .
- The data set consists of 3 types of attributes: Input, Key & Predictable attribute
- The analysis was performed on 13 attributes initially followed by 2 more attributes separately.

Attribute	Description	Value
age	age	1 = male 0 = female
sex	male or female	1 = typical type 1 2 = typical type agina 3 = non-agina pain 4 = asymptomatic
cp	chest pain	Continuous value in mm hg
thestbps	resting blood pressure	Continuous value in mm/dl
chol	serum cholestrol	Continuous value in mm/dl
restecg	rest ecg results	0 = normal 1 = having_ST_T wave abnormal 2 = left ventricular hypertrophy
fbs	fasting blood sugar	1 ≥ 120 mg/dl 0 ≤ 120 mg/dl
thalach	max heart rate	Continuous value
exang	exercise induced agina	0= no 1 = yes
oldpeak	ST depression induced by exercise relative to rest	Continuous value
solpe	Slope of the peak exercise	1 = unsloping 2 = flat 3 = ownsloping
ca	Number of major vessels colored by floursopy	0-3 value
thal	Defect type	3 = normal 6 = fixed 7 = reversible defect

Table 2.1 Primary Attributes

Attribute	Description	Value
obes	obesity	1 = yes 0 = no
smoke	smoking	1= past 2 = current 3 = never

Table 2.1 Additional Attributes

Performing Naive Bayes :

- Naive Bayes classifier is based on Bayes theorem.
- This classifier algorithm uses **conditional independence.** **(NAIVE !)**
- Let X={x1 , x2 , ..., xn} be a set of n attributes.
- In Bayesian, X is considered as evidence and H be some hypothesis means, the data of X belongs to specific class C.
- We have to determine P (H|X), the probability that the hypothesis H holds given evidence i.e. data sample X.
- According to Bayes theorem the P (H|X) is expressed as

$$\boxed{P(H|X) = P\ (X|\ H)\ P\ (H)\ /\ P\ (X)}$$

Performance

⇩ Actual Output/Prediction ⇨	a (has heart disease)	b (no heart disease)
a (has heart disease)	TP	TN
b (no heart disease)	FP	FN

Confusion Matrix

	a	b
a	110	5
b	10	145

	a	b
a	100	7
b	18	145

bayes classifier

	a	b
a	123	4
b	5	138

	a	b
a	85	0
b	1	185

Decision Trees

	a	b
a	117	0
b	2	151

	a	b
a	106	0
b	0	164

Neural Networks

13 Attributes

15 Attributes

source : http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.258.8158&rep=rep1&type=pdf | Figure 3-6

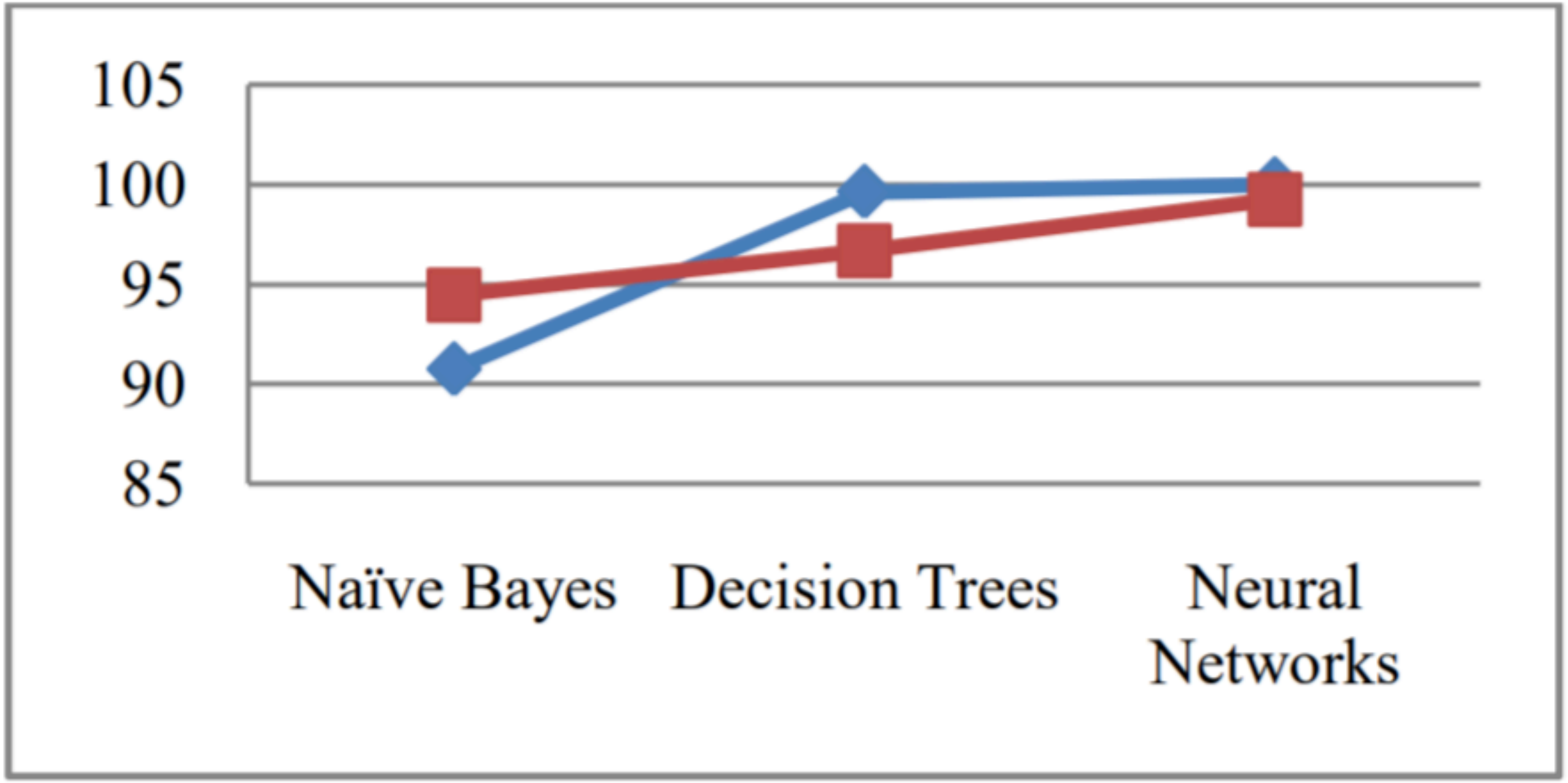
Comparison with IDT & NN

ID3 and NN classifiers are also implemented.

Classification Techniques	13 attributes	15 attributes
Naive Bayes	94.44	90.74
Decision Trees	96.66	99.62
Neural Networks	99.25	100

source : http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.258.8158&rep=rep1&type=pdf | Table 6

Prediction Accuracy



🟥 - 13 attributes

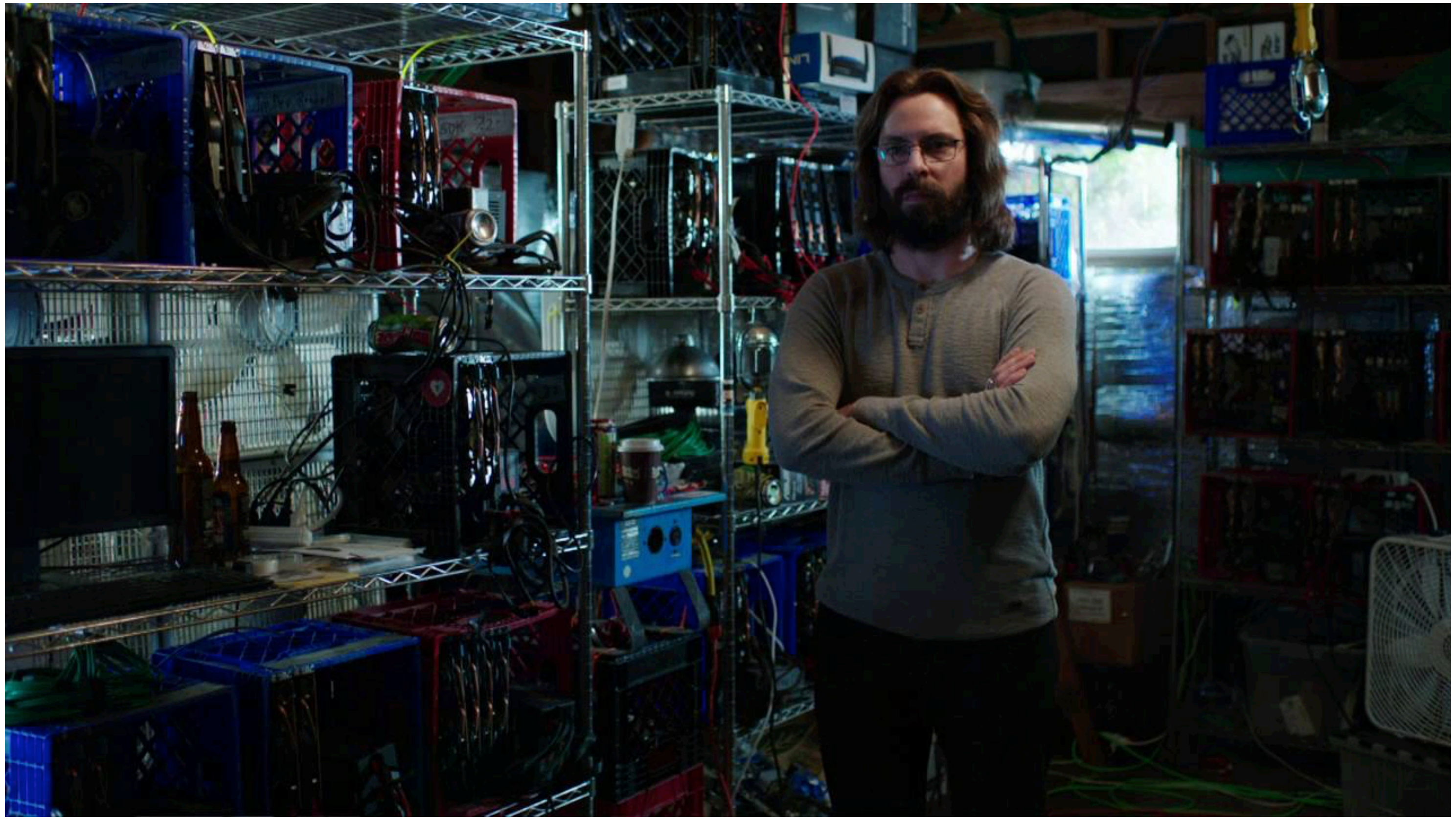
🟦 - 15 attributes

source : http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.258.8158&rep=rep1&type=pdf | Figure 2

Conclusion

- The overall objective of the work is to predict more accurately the presence of heart disease.
- It has been seen that Neural Networks provides accurate results as compared to Decision trees & Naive Bayes.
- Naive Bayes has a serious drawback where the events are considered mutually independent of each other.
- In Real life, it is very much difficult for events to be exclusively unrelated and naive bayes fails to make use of the correlation.
- However given the compute power required ,it is a reasonably efficient classifier.

FREE COMPUTE POWER !!!



Source : https://i.ytimg.com/vi/E7myDAKBgRs/maxresdefault.jpg

Want Medical Records Accessed?

YES

NO

Thank You

Questions?

Source: bigstock-healthcare-technology-and-med-83203256.jpg