Predicting Interview's attendance by implementing Naive Bayes Technique using Big Data Programming with Hadoop

Report Of Industrial Training Submitted For Partial Fulfillment Of The Requirement For The Degree Of
BACHELOR OF TECHNOLOGY
In
COMPUTER SCIENCE AND ENGINEERING
By

Aniruddha Sadhukhan

REGISTRATION NO – ***151170110009 of 2015-16***

UNIVERSITY ROLL NO - ***11700115009***

UNDER THE SUPERVISION OF
Mr. Titas Roy Chowdhury
Course Coordinator, Globsyn Finishing School

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
RCC INSTITUTE OF INFORMATION TECHNOLOGY
[Affiliated to Maulana Abul Kalam Azad University of Technology]
CANAL SOUTH ROAD, BELIAGHATA, KOLKATA – 700 015

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CERTIFICATE of ACCEPTANCE

The report of the Industrial Training titled ***Predicting Interview's attendance by implementing Naive Bayes Technique using Big Data Programming with Hadoop*** submitted by ***Aniruddha Sadhukhan*** (REGISTRATION NO – ***151170110009 of 2015-16*** , UNIVERSITY ROLL NO – ***11700115009*** of B. Tech. (CSE) 7th Semester of 2018) is hereby recommended to be accepted for the partial fulfillment of the requirements for B.Tech (CSE) degree in Maulana Abul Kalam Azad University of Technology.

Name of the Examiner	Signature with Date
1.	.....
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Provisional Certificate

This is to certify that **Aniruddha Sadhukhan** of **RCC Institute Of Information Technology** has successfully completed the program in **Big Data Programming with Hadoop** at Globsyn Finishing School's Summer School 2018

Place : Kolkata

Authorized Signatory

Date : August 25,2018

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Gradesheet

Name : **Aniruddha Sadhukhan**
College : **RCC Institute Of Information Technology**
Technology: **Big Data Programming with Hadoop**
Project : Predicting interviews attendance using Naive Bayes
Duration : **June 2018 - July 2018**
Grade : **A+**

Place : Kolkata

Course Coordinator

Date : August 25,2018

Globsyn Finishing School

LEGEND			
Marks (%)	Grade	Points	Remarks
>84	A+	8	Outstanding
80-84	A	7	Excellent
70-79	B+	6	Very Good
60-69	B	5	Good
54-59	C+	4	Satisfactory
47-53	C	3	Fair
40-46	D	2	Pass
<40	F	0	Fail

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I are obliged to my fellow project team members, for the valuable informations provided by them in their respective fields. I am grateful to them for their cooperation during the period of the assignment.

Date: 4th December,2018

Aniruddha Sadhukhan

Regd. No. : 151170110009 of 2015-16

University Roll No. : 11700115009

B. Tech (CSE) – 7th Semester, 2018, RCCIIT

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PROJECT OBJECTIVE

We were given a dataset including various fields like client name, gender, location, answers to various questions asked over phone etc.

Based on this we have to predict the real appearance of candidates in the interview. This is used by the recruiting agencies to predict if any possible candidates would really be present for the interview after talking over the phone.

SOURCE AND DESCRIPTION OF DATA

- The data has been provided by the institute.
- The data set consists of ***22 discrete specification columns and 1234 number of records.***

Sl. No.	Specification Criteria	Description & Remarks	Examples
1	DATE OF INTERVIEW	The date on which the interview has been scheduled.As per the given data set the date of interview does not have any effect on the observed attendance.Hence, we are not taking into consideration the date of interview for predicting the outcome.	
2	CLIENT NAME	The name of the company where the interview is scheduled.	'Hospira', 'Aon Hewitt', 'UST',etc
3	INDUSTRY	The type of industry where the interview has been fixed.	'Pharmaceuticals', 'IT Services','Electronics',etc
4	LOCATION	Location of the company.	'Chennai', 'Gurgaon',etc
5	POSITION TO BE CLOSED	The position that has been offered to the candidate.	'Production-Sterile' 'Selenium testing',etc
6	NATURE OF SKILLSET	The type of skill required for the job.	'Routine ', 'Oracle ',etc
7	INTERVIEW TYPE	Type of interview to be conducted.	'Scheduled ', 'Walkin ',etc
8	NAME (CAND ID)	The name of the candidate.As per the given data set the candidate name and ID does not have any effect on the observed attendance. Hence, we are not taking this into consideration for predicting the outcome.	

9	GENDER	The gender of the candidate.	'Male', 'Female',
10	CANDIDATE CURRENT LOCATION	Current location of the candidate.If the current location of the candidate is same as that of the job location the candidate is likely to take up the interview.	'Delhi ', 'chennai ',etc
11	CANDIDATE JOB LOCATION	Location of where the job is to be carried out.If the native location is same as the job location the candidate is likely to take up the job.	'Hosur ', 'Bangalore ', 'Chennai ',etc
12	INTERVIEW VENUE	Venue where the interview is scheduled.If the interview venue is same as job location the candidate is likely to appear for the interview.	'Hosur ', 'Gurgaon ', etc
13	CANDIDATE NATIVE LOCATION	Native location of candidate.If the native location is same as the job location the candidate is likely to take up the job.	'Hosur ', 'Trichy', etc
14	HAVE YOU OBTAINED NECESSARY PERMISSION TO START AT THE REQUIRED TIME	Set of questions that affect the appearance of interview.	'Yes ', 'No ', 'Not yet'
15	HOPE THERE WILL BE NO UNSCHEDULED MEETINGS TIME		'Yes ', 'Na ', 'No ', etc
16	CAN I CALL YOU THREE HOURS BEFORE THE INTERVIEW AND FOLLOW AND FOLLOW UP ON YOUR ATTENDANCE FOR THE INTERVIEW	Specifies the time when to make a call.	'Yes ', 'No ', 'No Dont ', etc
17	CAN I HAVE AN ALTERNATIVE NUMBER/ DESK NUMBER		'Yes ', 'No ', etc
18	ARE YOU CLEAR WITH THE VENUE DETAILS AND THE LANDMARK		'Yes ', 'No ', etc
19	HAS THE CALL LETTER BEEN SHARED		'Yes ', 'Havent Checked ', etc
20	EXPECTED ATTENDANCE		'Yes ', 'Uncertain ', 'No ', etc
21	OBSERVED ATTENDANCE		'No ', 'Yes ', etc
22	MARITAL STATUS		'Single', 'Married'

METHODOLOGY

➢ *Supervised Machine Learning*

The majority of practical machine learning uses supervised learning.

Supervised learning is where we have input variables (x) and an output variable (Y) and we use an algorithm to learn the mapping function from the input to the output.

$$Y = f(X)$$

The goal is to approximate the mapping function so well that when you have new input data (x) that you can predict the output variables (Y) for that data.

It is called supervised learning because the process of an algorithm learning from the training dataset can be thought of as a teacher supervising the learning process. We know the correct answers, the algorithm iteratively makes predictions on the training data and is corrected by the teacher. Learning stops when the algorithm achieves an acceptable level of performance.

➢ *Binary classification*

Binary or binomial classification is the task of classifying the elements of a given set into two groups (predicting which group each one belongs to) on the basis of a classification rule.

The actual output of many binary classification algorithms is a prediction score. The score indicates the system's certainty that the given observation belongs to the positive class.

Binary Classification would generally fall into the domain of **Supervised Learning** since the training dataset is labelled. And as the name suggests it is simply a special case in which there are only two classes.

➢ *Naive Bayes classifiers*

Naive Bayes classifiers are a collection of classification algorithms based on **Bayes' Theorem**. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

To start with, let us consider a dataset.

Consider a fictional dataset that describes the weather conditions for playing a game of golf. Given the weather conditions, each tuple classifies the conditions as fit("Yes") or unfit("No") for playing golf.

Here is a tabular representation of our dataset.

	Outlook	Temperature	Humidity	Windy	Play Golf
0	Rainy	Hot	High	False	No
1	Rainy	Hot	High	True	No
2	Overcast	Hot	High	False	Yes
3	Sunny	Mild	High	False	Yes
4	Sunny	Cool	Normal	False	Yes
5	Sunny	Cool	Normal	True	No
6	Overcast	Cool	Normal	True	Yes
7	Rainy	Mild	High	False	No
8	Rainy	Cool	Normal	False	Yes
9	Sunny	Mild	Normal	False	Yes
10	Rainy	Mild	Normal	True	Yes
11	Overcast	Mild	High	True	Yes
12	Overcast	Hot	Normal	False	Yes
13	Sunny	Mild	High	True	No

The dataset is divided into two parts, namely, **feature matrix and the response vector.**

- Feature matrix contains all the vectors(rows) of dataset in which each vector consists of the value of dependent features. In above dataset, features are ‘Outlook’, ‘Temperature’, ‘Humidity’ and ‘Windy’.
- Response vector contains the value of class variable(prediction or output) for each row of feature matrix. In above dataset, the class variable name is ‘Play golf’.

Assumption

The fundamental Naive Bayes assumption is that each feature makes an:

- independent
- equal

contribution to the outcome.

With relation to our dataset, this concept can be understood as:

- We assume that no pair of features are dependent. For example, the temperature being ‘Hot’ has nothing to do with the humidity or the outlook being ‘Rainy’ has no effect on the winds. Hence, the features are assumed to be independent.
- Secondly, each feature is given the same weight(or importance). For example, knowing only temperature and humidity alone can’t predict the outcome accurately. None of the attributes is irrelevant and assumed to be contributing equally to the outcome.

Note: The assumptions made by Naive Bayes are not generally correct in real- world situations. In-fact, the independence assumption is never correct but often works well in practice.
Now, before moving to the formula for Naive Bayes, it is important to know about Bayes’ theorem.

Bayes' Theorem

Bayes' Theorem finds the probability of an event occurring given the probability of another event that has already occurred. Bayes' theorem is stated mathematically as the following equation:

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

where A and B are events and P(B) ≠ 0.

- Basically, we are trying to find probability of event A, given the event B is true. Event B is also termed as **evidence**.
- P(A) is the **priori** of A (the prior probability, i.e. Probability of event before evidence is seen). The evidence is an attribute value of an unknown instance(here, it is event B).
- P(A|B) is a posteriori probability of B, i.e. probability of event after evidence is seen.

Now, with regards to our dataset, we can apply Bayes' theorem in following way:

$$P(y|X) = \frac{P(X|y)P(y)}{P(X)}$$

where, y is class variable and X is a dependent feature vector (of size n) where:

$$X = (x_1, x_2, x_3, ..., x_n)$$

Just to clear, an example of a feature vector and corresponding class variable can be: (refer 1st row of dataset)

X = (Rainy, Hot, High, False)
y = No

So basically, P(X|y) here means, the probability of "Not playing golf" given that the weather conditions are "Rainy outlook", "Temperature is hot", "high humidity" and "no wind".

Naive assumption

Now, it's time to put a naive assumption to the Bayes' theorem, which is, **independence** among the features. So now, we split **evidence** into the independent parts.

Now, if any two events A and B are independent, then,

P(A,B) = P(A)P(B)

Hence, we reach to the result:

$$P(y|x_1, ..., x_n) = \frac{P(x_1|y)P(x_2|y)...P(x_n|y)P(y)}{P(x_1)P(x_2)...P(x_n)}$$

which can be expressed as:

$$P(y|x_1, ..., x_n) = \frac{P(y)\prod_{i=1}^{n} P(x_i|y)}{P(x_1)P(x_2)...P(x_n)}$$

Now, as the denominator remains constant for a given input, we can remove that term:

$$P(y|x_1, ..., x_n) \propto P(y) \prod_{i=1}^{n} P(x_i|y)$$

Now, we need to create a classifier model. For this, we find the probability of given set of inputs for all possible values of the class variable y and pick up the output with maximum probability. This can be expressed mathematically as:

$$y = argmax_y P(y) \prod_{i=1}^{n} P(x_i|y)$$

So, finally, we are left with the task of calculating P(y) and P(x_i | y).

Please note that P(y) is also called **class probability** and P(x_i | y) is called **conditional probability.**

The different naive Bayes classifiers differ mainly by the assumptions they make regarding the distribution of P(x_i | y).Let us try to apply the above formula manually on our weather dataset. For this, we need to do some precomputations on our dataset.

We need to find P(x_i | y_j) for each x i in X and y_j in y. All these calculations have been demonstrated in the tables below:

Outlook

	Yes	No	P(yes)	P(no)
Sunny	2	3	2/9	3/5
Overcast	4	0	4/9	0/5
Rainy	3	2	3/9	2/5
Total	9	5	100%	100%

Temperature

	Yes	No	P(yes)	P(no)
Hot	2	2	2/9	2/5
Mild	4	2	4/9	2/5
Cool	3	1	3/9	1/5
Total	9	5	100%	100%

Humidity

	Yes	No	P(yes)	P(no)
High	3	4	3/9	4/5
Normal	6	1	6/9	1/5
Total	9	5	100%	100%

Wind

	Yes	No	P(yes)	P(no)
False	6	2	6/9	2/5
True	3	3	3/9	3/5
Total	9	5	100%	100%

Play		P(Yes)/P(No)
Yes	9	9/14
No	5	5/14
Total	14	100%

So, in the figure above, we have calculated P(x_i | y_j) for each x_i in X and y_j in y manually in the tables 1-4. For example, probability of playing golf given that the temperature is cool, i.e P(temp. = cool | play golf = Yes) = 3/9.

Also, we need to find class probabilities (P(y)) which has been calculated in the table 5. For example, P(play golf = Yes) = 9/14.

So now, we are done with our pre-computations and the classifier is ready!

Let us test it on a new set of features (let us call it today):

today = (Sunny, Hot, Normal, False)

So, probability of playing golf is given by:

$$P(Yes|today) = \frac{P(SunnyOutlook|Yes)P(HotTemperature|Yes)P(NormalHumidity|Yes)P(NoWind|Yes)P(Yes)}{P(today)}$$

and probability to not play golf is given by:

$$P(No|today) = \frac{P(SunnyOutlook|No)P(HotTemperature|No)P(NormalHumidity|No)P(NoWind|No)P(No)}{P(today)}$$

Since, P(today) is common in both probabilities, we can ignore P(today) and find proportional probabilities as:

$$P(Yes|today) \propto \frac{2}{9}.\frac{2}{9}.\frac{6}{9}.\frac{6}{9}.\frac{9}{14} \approx 0.0141$$

and

$$P(No|today) \propto \frac{3}{5}.\frac{2}{5}.\frac{1}{5}.\frac{2}{5}.\frac{5}{14} \approx 0.0068$$

Now, since

$$P(Yes|today) + P(No|today) = 1$$

These numbers can be converted into a probability by making the sum equal to 1 (normalization):

$$P(Yes|today) = \frac{0.0141}{0.0141+0.0068} = 0.67$$

and

$$P(No|today) = \frac{0.0068}{0.0141+0.0068} = 0.33$$

Since

$$P(Yes|today) > P(No|today)$$

So, prediction that golf would be played is ‘Yes’.

The method that we discussed above is applicable for discrete data. In case of continuous data, we need to make some assumptions regarding the distribution of values of each feature. The different naive Bayes classifiers differ mainly by the assumptions they make regarding the distribution of P(x_i | y).

HARDWARE AND SOFTWARE REQUIREMENTS

Hadoop cluster is used which is made of commodity hardware

- ***MASTER'S RECOMMENDATION***
  - ***4–6 1TB hard disks*** (1 for OS [RAID 1], 2 for the FS image [RAID 5/6], 1 for JournalNode)
  - 2 CPUs(8-12 cores per CPU), running at least 2-2.5GHz
  - ***128-512GB of RAM***
  - Bonded Gigabit Ethernet or 10Gigabit Ethernet

- ***SLAVE'S RECOMMENDATION***
  - ***12-24 1-4TB hard disks*** in a JBOD (Just a Bunch Of Disks) configuration
  - 2 CPUs(8-12 cores per CPU), running at least 2-2.5GHz
  - ***64-128GB of RAM***
  - Bonded Gigabit Ethernet or 10Gigabit Ethernet

- ***SOFTWARE***
  - Hadoop 2.2.0 or above runs well on Linux operating systems like: RedHat Enterprise Linux (RHEL), CentOS, Ubuntu
  - Hadoop is written in Java. The recommended Java version is Oracle JDK 1.6.31

DATA CLEANSING

- Rows in which some data were missing or all the 23 data weren't present are ignored
- Some data included incorrect punctuation marks or non-word characters and are rectified
- Some values were nearly similar(e.g: liaison and liabilities, liaison & liabilities, liaison liabilities) and were changed to a single value
- Rows where some discrepancy in data was there were rectified

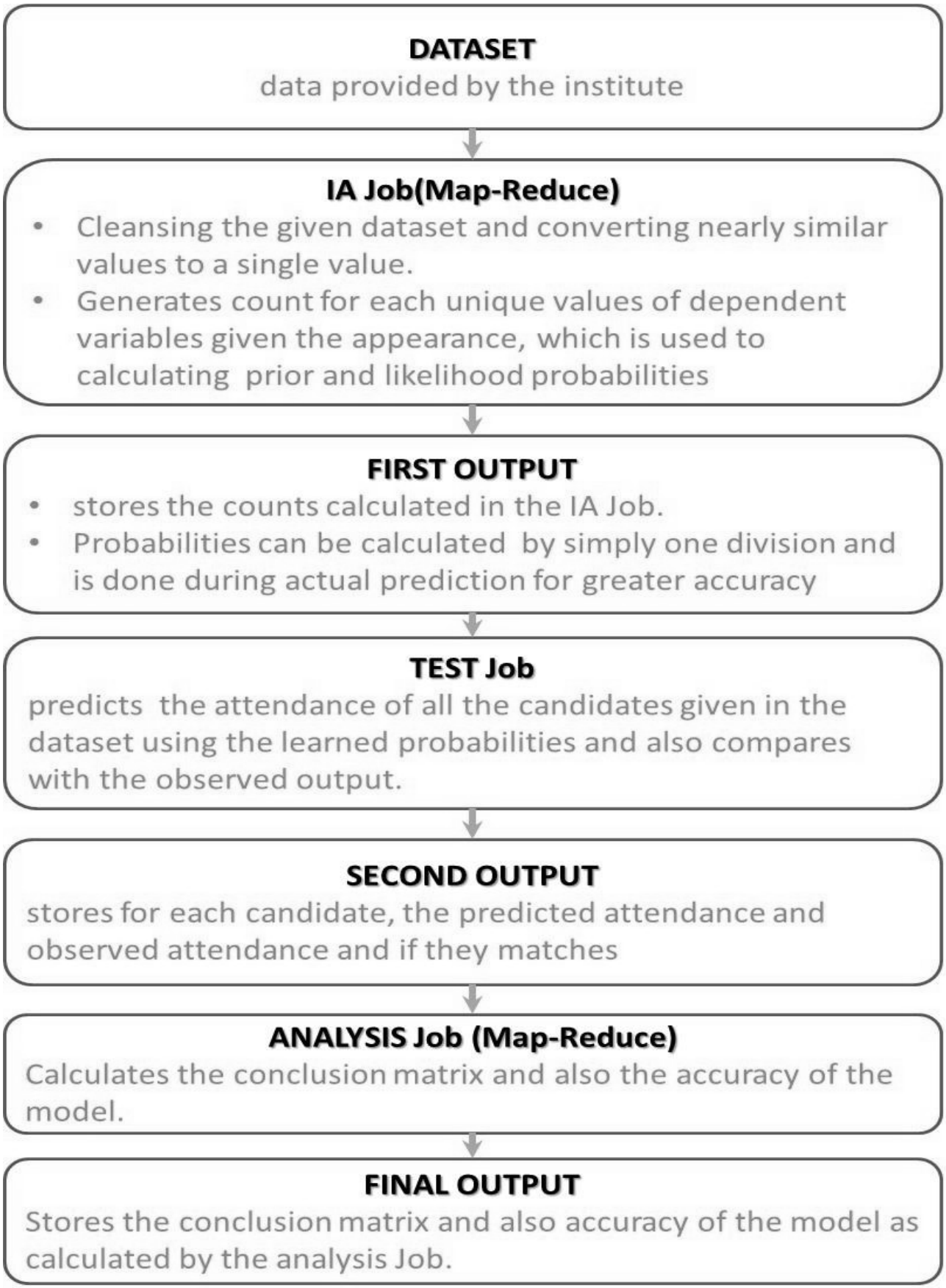
DATA PROCESSING

Concept of Map-Reduce has been used to process the data.

Three jobs have been used namely:-

- **IA Job :** MAPPER with multiple REDUCERS (depending on size of dataset)
- **TEST Job:** Only MAPPER and no REDUCER
- **ANALYSIS Job:** MAPPER with 1 REDUCER

WORK FLOW DIAGRAM



SOURCE CODE

➔ Code for package ani

➢ IAMapper.java

```
package ani;
import java.io.IOException;
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.commons.lang.StringUtils;
public class IAMapper extends Mapper<LongWritable,Text,Text,TupleWritable>
{
	private Text outkey = new Text();
	private TupleWritable outval = new TupleWritable();
	private int i;
	@Override
	protected void map(LongWritable key, Text value,Context context)
	throws IOException, InterruptedException
	{
		if(key.get()!=0)
		{
			String line = value.toString().trim();
			String word[] = line.split(",");
			if(word!=null && word.length >22 && word[7]!=null)
			{
				try
				{
					for(i=1;i<20;i++)
					{
						if(i>0 && i<5)
						{
			outkey.set("x"+i+"_"+word[i].toLowerCase().replaceAll("[^A-Za-z]+", ""));
						}
						else if(i==5)
						{
							if(Character.isDigit(word[5].charAt(0)))
								outkey.set("x5_unknown");
							else{
			word[5] = word[5].toLowerCase().replaceAll("[^A-Za-z]+","");
			if(StringUtils.getLevenshteinDistance(word[5] ,"biosimilars")<4)
						outkey.set("x5_biosimilars");
			else if(StringUtils.getLevenshteinDistance(word[5] ,"lendingliablities")<11)
						outkey.set("x5_lendingliablities");
			else outkey.set("x5_"+word[5]);
						}
					}
					else if(i==6)
					{
				word[6] = word[6].toLowerCase().replaceAll("[^A-Za-z]+","");
			if(StringUtils.getLevenshteinDistance(word[6] ,"scheduledwalkin")<3)
```

```
                    outkey.set("x6_scheduledwalkin");
else outkey.set("x6_"+word[6]);
                }
                else if(i==7)
                {
                    if(word[8].equalsIgnoreCase("male"))
                            outkey.set("x7_male");
                    else outkey.set("x7_female");
                }
                else if(i==8)
                {
                    if(word[9].equalsIgnoreCase(word[10]))
                            outkey.set("x8_yes");
                    else outkey.set("x8_no");
                }
                else if(i==9)
                {
                    if(word[9].equalsIgnoreCase(word[11]))
                            outkey.set("x9_yes");
                        else outkey.set("x9_no");
                    }
                    else if(i==10)
                    {
                        if(word[12].equalsIgnoreCase(word[10]))
                            outkey.set("x10_yes");
                        else outkey.set("x10_no");
                    }
                    else if(i>10 && i<14)
                    {
                        if(word[i+2].equalsIgnoreCase("yes"))
                            outkey.set("x"+i+"_"+"yes");
                        else if(word[i+2].equalsIgnoreCase("no"))
                            outkey.set("x"+i+"_"+"no");
                        else if(word[i+2].equalsIgnoreCase("NA"))
                            outkey.set("x"+i+"_"+"na");
                        else
                            outkey.set("x"+i+"_"+"uncertain");
                    }
                    else if(i>13 && i<17)
                    {
                        if(word[i+3].equalsIgnoreCase("yes"))
                            outkey.set("x"+i+"_"+"yes");
                        else if(word[i+3].equalsIgnoreCase("no"))
                            outkey.set("x"+i+"_"+"no");
                        else if(word[i+3].equalsIgnoreCase("NA"))
                            outkey.set("x"+i+"_"+"na");
                        else
                            outkey.set("x"+i+"_"+"uncertain");
                    }
                    else if(i==17)
```

```
                                        {
                                                if(word[20].equalsIgnoreCase("no"))
                                                        outkey.set("x17_"+"no");
                                                else if(word[20].equalsIgnoreCase("UNCERTAIN"))
                                                        outkey.set("x17_"+"uncertain");
                                                else if(word[20].equalsIgnoreCase("NA"))
                                                        outkey.set("x17_"+"na");
                                                else
                                                        outkey.set("x17_"+"yes");
                                        }
                                        else if(i==18)
                                        {
                                                if(word[22].equalsIgnoreCase("Single"))
                                                        outkey.set("x18_s");
                                                else outkey.set("x18_m");
                                        }
                                        else if(i==19)
                                        {
                                                outkey.set("y");
                                        }
                                        if(word[21].equalsIgnoreCase("yes"))
                                                outval.set(1, 0);
                                        else outval.set(0, 1);
                                        context.write(outkey, outval);
                                }
                        }catch(Exception e){}
                }
        }
    }
}
```

➢ IAReducer.java

```
package ani;
import java.io.IOException;
import java.util.Iterator;
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapreduce.Reducer;
public class IAReducer extends Reducer<Text, TupleWritable, Text, TupleWritable>
{
        private TupleWritable outval = new TupleWritable();
        @Override
        protected void reduce(Text key, Iterable<TupleWritable> values,Context context)
                        throws IOException, InterruptedException
        {
          int sumy = 0,sumn = 0;
          for(TupleWritable t : values)
          {
                        sumy = sumy + t.getYes();
                        sumn = sumn + t.getNo();
          }
          outval.set(sumy,sumn);
```

```
        context.write(key, outval);
      }
}
```

- **TupleWritable.java**

```
package ani;
import java.io.DataInput;
import java.io.DataOutput;
import java.io.IOException;
import org.apache.hadoop.io.*;
public class TupleWritable implements Writable
{
      private IntWritable yes = new IntWritable();
      private IntWritable no= new IntWritable();
      public void set(int y,int n)
      {
        yes.set(y);
        no.set(n);
      }
      public int getNo()
      {
        return no.get();
      }
      public int getYes()
      {
        return yes.get();
      }
      @Override
      public void readFields(DataInput inpstream) throws IOException
      {
                yes.readFields(inpstream);
                no.readFields(inpstream);
      }
      @Override
      public void write(DataOutput outstream) throws IOException
      {
                yes.write(outstream);//read write order to be maintained
                no.write(outstream);
      }
      @Override
      public String toString() {
        return String.valueOf(yes.get())+"\t"+String.valueOf(no.get());
      }
}
```

- **IADriver.java**

```
package ani;
import java.io.IOException;
import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapreduce.Job;
```

```
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
public class IADriver
{
	public static void main(String[] args) throws IOException, ClassNotFoundException,
InterruptedException
	{
	  Configuration config = new Configuration();
	  Job job = Job.getInstance(config);
	  job.setJarByClass(IADriver.class);
	  job.setMapperClass(IAMapper.class);
	  job.setReducerClass(IAReducer.class);
	  job.setCombinerClass(IAReducer.class);
	  job.setOutputKeyClass(Text.class);
	  job.setOutputValueClass(TupleWritable.class);
	  job.setNumReduceTasks(3);
	  FileInputFormat.addInputPath(job, new Path("datasets"));//can be called multiple times
	  FileOutputFormat.setOutputPath(job, new Path("ProbabilitiesLists"));
	  job.waitForCompletion(true);//starts processing
	}
}
```

➔ **Code for package test**

➢ **TestMapper.java**

```
package test;
import java.io.BufferedReader;
import java.io.FileReader;
import java.io.IOException;
import java.util.HashMap;
import org.apache.commons.lang.StringUtils;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapreduce.Mapper;
public class TestMapper extends Mapper<LongWritable, Text, Text, Text>
{
	HashMap<String,String> map = new HashMap<String,String>();
	private Text outkey = new Text(),outval = new Text();
	@Override
	protected void setup(Context context)
	throws IOException, InterruptedException
	{
	  Path path[] = context.getLocalCacheFiles();
	  if (path != null && path.length > 0)
	  {
		for(Path p : path)
		{
			String strpath = p.toString();
			FileReader file = new FileReader(strpath);
			BufferedReader breader = new BufferedReader(file);
			while(true)
			{
```

```
                        String line = breader.readLine();
                        if (line == null) break;
                        String words[] = line.split("\t");
                        map.put(words[0],words[1]+" "+words[2]);
                    }
                    breader.close();
                    file.close();
                }
            }
        }
        @Override
        protected void map(LongWritable key, Text value,Context context)
        throws IOException, InterruptedException
        {
            if(key.get()!=0)
            {
                String line = value.toString().trim();
                String word[] = line.split(","),attr ="",appear;
                int i;
                double Py,Pn, x[] = new double[2] ,ny[]= new double[2] ;
                if(word!=null && word.length >22 && word[7]!=null &&
word[7].startsWith("Candidate"))
                {
                    ny[0] = Double.valueOf(map.get("y").split(" ")[0]);
                    ny[1] = Double.valueOf(map.get("y").split(" ")[1]);
                    //Initialise Py with P(y=yes) & Pn with P(y=no)
                    Py = ny[0]/(ny[0]+ny[1]);
                    Pn = ny[1]/(ny[0]+ny[1]);
                    for(i=2;i<19;i++)
                    {
                        if(i>0 && i<5)
                        {
                            attr="x"+i+"_"+word[i].toLowerCase().replaceAll("[^A-Za-
z]+", "");
                        }
                        else if(i==5)
                        {
                            attr = word[5].toLowerCase().replaceAll("[^A-Za-z]+", "");
                            if(StringUtils.getLevenshteinDistance(attr ,"biosimilars")<4)
                                attr="x5_biosimilars";
                    else if(StringUtils.getLevenshteinDistance(attr,"lendingliablities")<11)
                                attr="x5_lendingliablities";
                            else attr="x5_"+attr;
                        }
                        else if(i==6)
                        {
                            attr = word[6].toLowerCase().replaceAll("[^A-Za-z]+", "");
                        if(StringUtils.getLevenshteinDistance(attr ,"scheduledwalkin")<3)
                                attr = "x6_scheduledwalkin";
                            else attr = "x6_"+attr;
```

```
}
else if(i==7)
{
	if(word[8].equalsIgnoreCase("male"))
		attr = "x7_male";
	else attr = "x7_female";
}
else if(i==8)
{
	if(word[9].equalsIgnoreCase(word[10]))
		attr = "x8_yes";
	else attr = "x8_no";
}
else if(i==9)
{
	if(word[9].equalsIgnoreCase(word[11]))
		attr = "x9_yes";
	else attr = "x9_no";
}
else if(i==10)
{
	if(word[12].equalsIgnoreCase(word[10]))
		attr = "x10_yes";
	else attr = "x10_no";
}
else if(i>10 && i<14)
{
	if(word[i+2].equalsIgnoreCase("yes"))
		attr = "x"+i+"_"+"yes";
	else if(word[i+2].equalsIgnoreCase("no"))
		attr = "x"+i+"_"+"no";
	else if(word[i+2].equalsIgnoreCase("NA"))
		attr = "x"+i+"_"+"na";
	else
		attr = "x"+i+"_"+"uncertain";
}
else if(i>13 && i<17)
{
	if(word[i+3].equalsIgnoreCase("yes"))
		attr = "x"+i+"_"+"yes";
	else if(word[i+3].equalsIgnoreCase("no"))
		attr = "x"+i+"_"+"no";
	else if(word[i+3].equalsIgnoreCase("NA"))
		attr = "x"+i+"_"+"na";
	else
		attr = "x"+i+"_"+"uncertain";
}
else if(i==17)
{
	if(word[20].equalsIgnoreCase("no"))
```

```
                                        attr = "x17_"+"no";
                                else if(word[20].equalsIgnoreCase("UNCERTAIN"))
                                        attr = "x17_"+"uncertain";
                                else if(word[20].equalsIgnoreCase("NA"))
                                        attr = "x17_"+"na";
                                else
                                        attr = "x17_"+"yes";
                        }
                        else if(i==18)
                        {
                                if(word[22].equalsIgnoreCase("Single"))
                                        attr = "x18_s";
                                else attr = "x18_m";
                        }
                        if (map.containsKey(attr))
                        {
                                x[0] = Double.valueOf(map.get(attr).split(" ")[0]);
                                x[1] = Double.valueOf(map.get(attr).split(" ")[1]);
                                //Updating Py = Py * P(x=attr | y = yes)
                                //Updating Pn = Pn * P(x=attr | y = yes)
                                Py = Py * x[0] / ny[0];
                                Pn = Pn * x[1] / ny[1];
                        }
                }
                //"yes = "+Py*100+"% \t no = "+Pn*100+"%"
                if (Py>=Pn)
                        appear = "yes";
                else appear = "no ";
                if(appear.trim().equalsIgnoreCase(word[21].trim()))
                        outkey.set("Output Matched    ");
                else outkey.set("Output Not Matched");
    outval.set("Observed : "+word[21].trim()+"\tPredicted : "+appear+" <--"+word[7].trim());
                context.write(outkey, outval);
            }
        }
    }
}
```

- **TestDriver.java**

```
package test;
import java.io.IOException;
import java.net.URI;
import java.net.URISyntaxException;
import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
import ani.IADriver;
```

```
import ani.IAMapper;
import ani.IAReducer;
import ani.TupleWritable;
public class TestDriver
{
	public static void main(String[] args) throws IOException, ClassNotFoundException,
InterruptedException, URISyntaxException
	{
	  Configuration config = new Configuration();
	  Job job = Job.getInstance(config);
	  /*Path cwpath = new Path("ProbabilitiesLists/");
	  URI uri = cwpath.toUri(); //URI : any kind of locator*/
	  job.addCacheFile(new URI("/user/edureka/ProbabilitiesLists/part-r-00000")); //Distributed
Cache is in action
	  job.addCacheFile(new URI("/user/edureka/ProbabilitiesLists/part-r-00001"));
	  job.addCacheFile(new URI("/user/edureka/ProbabilitiesLists/part-r-00002"));
	  job.setJarByClass(TestDriver.class);
	  job.setMapperClass(TestMapper.class);
	  job.setOutputKeyClass(Text.class);
	  job.setOutputValueClass(Text.class);
	  job.setNumReduceTasks(1);
	  FileInputFormat.addInputPath(job, new Path("datasets"));//can be called multiple times
	  FileOutputFormat.setOutputPath(job, new Path("OutputMatches"));
	  job.waitForCompletion(true);
	}
}
```

➔ **Code for package analysis**

➢ **AnalysisMapper.java**

```
package analysis;
import java.io.IOException;
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapreduce.Mapper;
public class AnalysisMapper extends Mapper<LongWritable, Text, NullWritable, Text>
{
	private Text outval = new Text();
	private NullWritable outkey = NullWritable.get();
	@Override
	protected void map(LongWritable key, Text value,Context context)
	throws IOException, InterruptedException
	{
		String line = value.toString().trim();
		String word[] = line.split("\t");
		String observed  = word[1].split(" ")[2].toLowerCase().trim();
		String predicted = word[2].split(" ")[2].toLowerCase().trim();
		outval.set(observed+" "+predicted);
		context.write(outkey, outval);
	}
}
```

➢ **AnalysisReducer.java**

```
package analysis;
```

```
import java.io.IOException;
import java.util.Iterator;
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapreduce.Reducer;
public class AnalysisReducer extends Reducer<NullWritable, Text, NullWritable, Text>
{
	private Text outval = new Text();
	@Override
	protected void reduce(NullWritable key, Iterable<Text> values,Context context)
			throws IOException, InterruptedException
	{
	  Iterator<Text> itr = values.iterator();
	  int yy= 0,yn = 0, ny = 0,nn = 0;
	  float accuracy;
	  while(itr.hasNext())
	  {
			outval = itr.next();
			String observed  = outval.toString().split(" ")[0].trim();
			String predicted = outval.toString().split(" ")[1].trim();
			if(observed.equals("yes") && predicted.equals("yes"))	yy=yy+1;
			else if (observed.equals("yes") && predicted.equals("no"))	yn=yn+1;
			else if (observed.equals("no") && predicted.equals("yes"))	ny=ny+1;
			else if (observed.equals("no") && predicted.equals("no")) nn=nn+1;
	  }
	  accuracy = ((float)(yy+nn)/(yy+yn+ny+nn)*100);
	  String out =    "Observed yes , Predicted yes : "+yy+
					"\nObserved yes , Predicted no  : "+yn+
					"\nObserved no  , Predicted yes : "+ny+
					"\nObserved no  , Predicted no  : "+nn+
					"\n\nAccuracy : "+accuracy+"%";
	  outval.set(out);
	  context.write(key, outval);
	}
}
```

- **AnalysisDriver.java**

```
package analysis;
import java.io.IOException;
import java.net.URI;
import java.net.URISyntaxException;
import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.NullWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
import ani.IADriver;
import ani.IAMapper;
import ani.IAReducer;
```

```
import ani.TupleWritable;
public class AnalysisDriver
{
      public static void main(String[] args) throws IOException, ClassNotFoundException,
InterruptedException, URISyntaxException {
         Configuration config = new Configuration();
         Job job = Job.getInstance(config);
         job.setJarByClass(AnalysisDriver.class);
         job.setMapperClass(AnalysisMapper.class);
         job.setReducerClass(AnalysisReducer.class);
         job.setOutputKeyClass(NullWritable.class);
         job.setOutputValueClass(Text.class);
         job.setNumReduceTasks(1);
         FileInputFormat.addInputPath(job, new Path("OutputMatches"));
         FileOutputFormat.setOutputPath(job, new Path("Analysis"));
      job.waitForCompletion(true);
      }
}
```

OUTPUT

➢ ***Output of IA job:***

A small portion of the output of IA job is given below:

```
x11_no      6     73
x11_yes     651   240
x13_na      103   164
x14_no      2     14
x14_yes     682   260
x15_uncertain   1     1
x16_na      103   162
x17_no      1     92
x17_yes     666   219
x1_aonhewitt    24    4
x1_barclays     5     0
x1_pfizer   51    24
x1_prodapt  6     11
x1_ust      10    8
x2_itproductsandservices    34    11
x2_pharmaceuticals    96    69
x3_bangalore    193   99
x3_gurgaon  22    11
x4_dotnet   10    8
x4_productionsterile  0     5
x4_seleniumtesting    4     1
```

*The first column states each unique values of the **dependent variables** and next two columns indicates the count of those unique values in the dataset given Observed Attendance = Yes and No respectively.*

➢ ***Output of Test Job:***

A small portion of the output of Test job is given below:

```
Output Matched      Observed : No       Predicted : no  <--Candidate 1
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1232
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1231
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1230
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1229
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1228
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1227
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1226
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1225
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1224
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1223
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1222
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1221
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1220
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1219
Output Matched      Observed : Yes      Predicted : yes <--Candidate 1218
                               ⋮
Output Not Matched      Observed : No     Predicted : yes <--Candidate 730
Output Not Matched      Observed : No     Predicted : yes <--Candidate 729
Output Not Matched      Observed : No     Predicted : yes <--Candidate 1025
Output Not Matched      Observed : No     Predicted : yes <--Candidate 728
Output Not Matched      Observed : No     Predicted : yes <--Candidate 204
Output Not Matched      Observed : No     Predicted : yes <--Candidate 525
Output Not Matched      Observed : No     Predicted : yes <--Candidate 279
Output Not Matched      Observed : No     Predicted : yes <--Candidate 1020
Output Not Matched      Observed : No     Predicted : yes <--Candidate 724
Output Not Matched      Observed : No     Predicted : yes <--Candidate 1018
Output Not Matched      Observed : No     Predicted : yes <--Candidate 1017
Output Not Matched      Observed : Yes    Predicted : no  <--Candidate 523
Output Not Matched      Observed : Yes    Predicted : no  <--Candidate 124
Output Not Matched      Observed : Yes    Predicted : no  <--Candidate 521
Output Not Matched      Observed : Yes    Predicted : no  <--Candidate 379
Output Not Matched      Observed : No     Predicted : yes <--Candidate 202
```

➢ ***Output of Analysis Job (Final Output):***

```
Observed yes , Predicted yes : 650
Observed yes , Predicted no  : 111
Observed no  , Predicted yes : 214
Observed no  , Predicted no  : 216

Accuracy : 72.712006%
```

This final output gives the ***Conclusion Matrix*** *and also the* ***accuracy*** *of all the predictions made.*

It is to be noted that the most important part of the Conclusion Matrix is when the algorithm <u>Predicts No but it is Observed Yes</u>. Because if the prediction matches, it's great but if it is predicted Yes and Observed No, then no big problem can arise. Problem occurs when it is predicted No and so no preparations are made for those candidates but the candidates comes to attend the interview. So we should keep this as low as possible.

FUTURE IMPROVEMENT

The prediction analysis has been done based on a batch processing system instead of a real time system. For further improvement this has to be transformed into real time system using Apache Spark.

OTHER DOMAINS WHERE THIS CONCEPTS CAN BE USED

This Naive Bayes approach using MapReduce can be used similarly in many other applications:

- Churn Detection
- Vote Prediction
- Email Spam Detection
- News article categorization
- Sentiment Analysis
- Facial recognition
- Handwriting Recognition
- Weather Prediction

CONCLUSION

From a given data set, we have calculated the conditional probability for each value of the dependent attributes given the appearance of the candidates using Naive Bayes supervised machine learning.

After that we have predicted the candidate appearance and cross checked with the observed appearance and we have got a satisfactory **73% accuracy.** So we can say that this application is working as expected.