2.1 PROBABILITY DISTRIBUTION TABLE - [5 MARKS]

In this section we are expected to create a probability distibution table with following variables we are need asked to implement probability distribution table to answer a certain questions.

Before we begin let's visualize the question itself what are we actaully looking for

we are given a certain number of tips and a distribution containing wether the students follow a certain tip or not and if the follow how frequently they follow.

The distribution somehow looks like this-

	Never	Rarely	Sometimes	Often	Always
Tip 1	1	4	6	12	23
Tip 2	12	4	12	4	2
Tip 3	24	2	5	4	4

Let's try to visualize this on the code and see if we can create a probability distributation table to answer some of our questions

In [1]:
```
#necessary imports
from probability import *
from utils import print_table
from notebook import psource, pseudocode, heatmap
```

In [2]:
```
#since there is a dependence of the tip with following it hence we
class ProbDist:
    """A discrete probability distribution. You name the random var
    in the constructor, then assign and query probability of values
    >>> P = ProbDist('Flip'); P['H'], P['T'] = 0.25, 0.75; P['H']
    0.25
    >>> P = ProbDist('X', {'lo': 125, 'med': 375, 'hi': 500})
    >>> P['lo'], P['med'], P['hi']
    (0.125, 0.375, 0.5)
    """

    def __init__(self, varname='?', freqs=None):
        """If freqs is given, it is a dictionary of values - freque
        then ProbDist is normalized."""
        self.prob = {}
        self.varname = varname
        self.values = []
        if freqs:
            for (v, p) in freqs.items():
```

```
            for (v, p) in freqs.items():
                self[v] = p
            self.normalize()

    def __getitem__(self, val):
        """Given a value, return P(value)."""
        try:
            return self.prob[val]
        except KeyError:
            return 0

    def __setitem__(self, val, p):
        """Set P(val) = p."""
        if val not in self.values:
            self.values.append(val)
        self.prob[val] = p

    def normalize(self):
        """Make sure the probabilities of all values sum to 1.
        Returns the normalized distribution.
        Raises a ZeroDivisionError if the sum of the values is 0."""
        total = sum(self.prob.values())
        if not isclose(total, 1.0):
            for val in self.prob:
                self.prob[val] /= total
        return self

    def show_approx(self, numfmt='{:.3g}'):
        """Show the probabilities rounded and sorted by key, for th
        sake of portable doctests."""
        return ', '.join([('{}: ' + numfmt).format(v, p)
                          for (v, p) in sorted(self.prob.items())])

    def __repr__(self):
        return "P({})".format(self.varname)
```

In [3]:
```
#simple probability distribution table

tip_1 = ProbDist(freqs={'Never': 1, 'Rarely': 4, 'Sometimes': 6,"Of
tip_2 = ProbDist(freqs={'Never': 12, 'Rarely': 4, 'Sometimes': 12,"
tip_3 = ProbDist(freqs={'Never': 24, 'Rarely': 2, 'Sometimes': 5,"O
```

asking questions to the probabilty table ??

1- what is the probablity that a student always follows the tip 2

2- what is the probabilty that a student never follows tip 3

3- what is the probablity that a student follows tip2 sometimes only

In [4]:
```
#answering the questions based on the probability queries
print(tip_2['Always'])
print(tip_3['Never'])
print(tip_2['Sometimes'])
```

```
0.058823529411764705
0.6153846153846154
0.35294117647058826
```

lets answer more complex questions

1- what is the probabilty that a student rarely follows tip2 but always follow tip 1 and tip 3

2- what is the probability that a student never follows each of the tips

In [5]:
```
#in order to answer such questions we need a joint probability tabl
```

In [6]:
```
full_joint = JointProbDist(['Never', 'Rarely', 'Sometimes',"Often",
#for tip 1
full_joint[dict(tip_1=True, tip_2=False, tip_3=False,Never=True, Ra
full_joint[dict(tip_1=True, tip_2=False, tip_3=False,Never=False, R
full_joint[dict(tip_1=True, tip_2=False, tip_3=False,Never=False, R
full_joint[dict(tip_1=True, tip_2=False, tip_3=False,Never=False, R
full_joint[dict(tip_1=True, tip_2=False, tip_3=False,Never=False, R
#for tip_2

full_joint[dict(tip_1=False, tip_2=True, tip_3=False,Never=True, Ra
full_joint[dict(tip_1=False, tip_2=True, tip_3=False,Never=False, R
full_joint[dict(tip_1=False, tip_2=True, tip_3=False,Never=False, R
full_joint[dict(tip_1=False, tip_2=True, tip_3=False,Never=False, R
full_joint[dict(tip_1=False, tip_2=True, tip_3=False,Never=False, R

#for tip_3
full_joint[dict(tip_1=False, tip_2=False, tip_3=True,Never=True, Ra
full_joint[dict(tip_1=False, tip_2=False, tip_3=True,Never=False, R
full_joint[dict(tip_1=False, tip_2=False, tip_3=True,Never=False, R
full_joint[dict(tip_1=False, tip_2=False, tip_3=True,Never=False, R
full_joint[dict(tip_1=False, tip_2=False, tip_3=True,Never=False, R
```

Student follows tip_2=True given that he Always following tip student ?

the question is different from what is the the probability that a student follows tip2 always ?

In the above question we already know that the student Always follows the tips(Coluld be any of the tips(1,2,3) but we need to find what is his chances that he follows tip_2)

In [7]:
```
#how many students in total follow tip_2 meaning tip_2 is set to Tr
full_joint.normalize()
#what is the probability that tip_2 will be true irrespective of ot
#basically the total occurance of tip_2
evidence = dict(tip_2=True)
variables = ['tip_1', 'tip_3',"Rarely","Sometimes","Often","Always"
ans1 = enumerate_joint(variables, evidence, full_joint)
ans1
```

Out[7]: 0.2857142857142857

In [8]:
```
#here tip_2 will be true and Always will be also true

#another way to interpret the question is tip_2=True and Always=Tru

evidence = dict(tip_2=True,Always=True)
variables = ['tip_1', 'tip_3',"Rarely","Sometimes","Often","Never"]
ans2 = enumerate_joint(variables, evidence, full_joint)
ans2
```

Out[8]: 0.01680672268907563

Being able to find sum of probabilities satisfying given evidence allows us to compute conditional probabilities like **P(tip_2=True | Always=True)** as we can rewrite this as

$$P(tip_2 = True|Always = True) = \frac{P(tip_2 = True\ and\ Always = True)}{P(tip_2 = True)}$$

We have already calculated both the numerator and denominator.

In [9]:
```
#now lets see can we answer the above question given the fact that
ans2/ans1
```

Out[9]: 0.058823529411764705

In [10]:
```
#or we could directly ask the given questions with enumerate joint 
#the result may vary a little because of the internal implementatio
query_variable = 'tip_2'
evidence = dict(Always=True)
ans = enumerate_joint_ask(query_variable, evidence, full_joint)
(ans[True], ans[False])
```

Out[10]: (0.06896551724137931, 0.9310344827586207)

now let's begin to answer the complex questions asked in the begginning that we couldn't using simple probability distribution table

what is the probabilty that a student rarely follows tip2 but always follow tip 1 and tip 3?

lets break the following question into sub parts

$$P((tip_2 = True\ and\ Rarely = True)\ and\ (tip_1 = True\ and\ Always = True)\ and\ (t$$
$$= P(tip_2 = True\ and\ Rarely = True) \times P(tip_1 = True\ and\ Always = True) \times P($$

In [11]:
```
#person tip_2=True and rarely=True
evidence = dict(tip_2=True,Rarely=True)
variables = ['tip_1', 'tip_3',"Always","Sometimes","Often","Never"]
ans1 = enumerate_joint(variables, evidence, full_joint)
ans1

#tip_1=True , Always= True
evidence = dict(tip_1=True,Always=True)
variables = ['tip_2',"tip_3","Rarely","Sometimes","Often","Never"]
ans2 = enumerate_joint(variables, evidence, full_joint)
ans2

#tip_3=True and ALways=True
evidence = dict(tip_3=True,Always=True)
variables = ['tip_2',"tip_1","Rarely","Sometimes","Often","Never"]
ans3 = enumerate_joint(variables, evidence, full_joint)
ans3

#finally question 1= (tip_2 and Rarely=True)*(tip_1 and Always =tru
final=ans1*ans2*ans3 #remeber to normalize them here because it is 
final
```

Out[11]: 0.00021837701961654655

as we have seen that more complex questions can be solved while breaking the expression into chunks and similarly by breaking the expression we can solve for the second question setting each tip to true and Never =True

Conclusions-

1- we can solve for many complex questions involving givens and ands using the joint probability table which we had trouble facing with original distribution table in the very first example

as we created 3 tables for for each of the tips

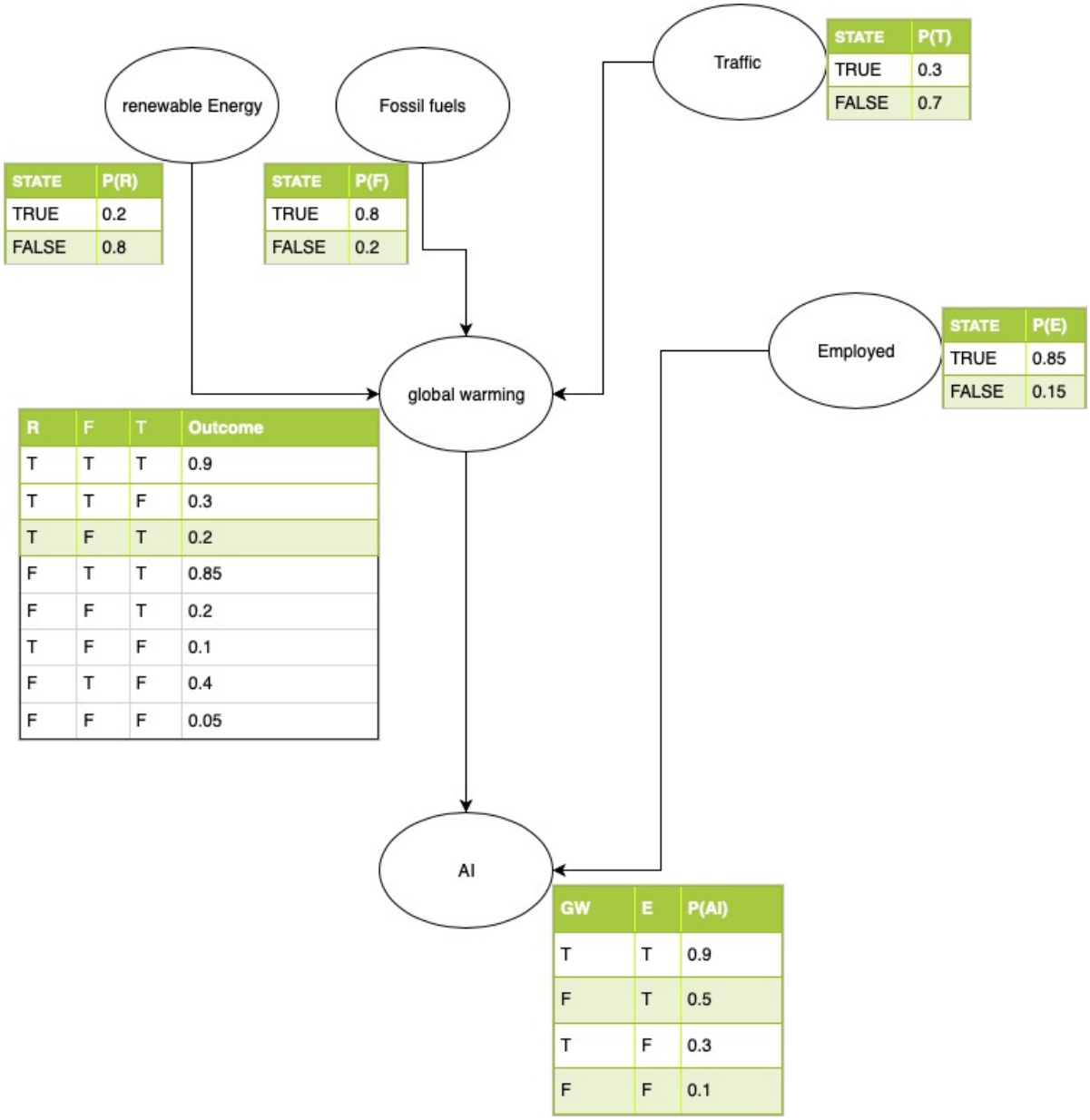
2- In the successful demo we with two examples :

First involving the given statement

Second involving ands of multiple statement

we answered the questions that were quite difficult for an individual table

Bayesian Networks [20 marks]



STATE	P(R)
TRUE	0.2
FALSE	0.8

STATE	P(F)
TRUE	0.8
FALSE	0.2

STATE	P(T)
TRUE	0.3
FALSE	0.7

STATE	P(E)
TRUE	0.85
FALSE	0.15

R	F	T	Outcome
T	T	T	0.9
T	T	F	0.3
T	F	T	0.2
F	T	T	0.85
F	F	T	0.2
T	F	F	0.1
F	T	F	0.4
F	F	F	0.05

GW	E	P(AI)
T	T	0.9
F	T	0.5
T	F	0.3
F	F	0.1

In the above task we notice that global warming is dependent on many individual nodes such as use of renewable energy, fossil fuel and cars stucking in traffic

when the global warming occurs and people are employed only then we see ai solutions being built to control the problem

or in other case when people are not employed they country can't look for ai based solutions.

let's try to reconstruct the problem using the bayes net class

In [12]:
```
class BayesNet:
    """Bayesian network containing only boolean-variable nodes."""

    def __init__(self, node_specs=None):
        """Nodes must be ordered with parents before children."""
        self.nodes = []
        self.variables = []
        node_specs = node_specs or []
        for node_spec in node_specs:
            self.add(node_spec)

    def add(self, node_spec):
        """Add a node to the net. Its parents must already be in th
        net, and its variable must not."""
        node = BayesNode(*node_spec)
        assert node.variable not in self.variables
        assert all((parent in self.variables) for parent in node.pa
        self.nodes.append(node)
        self.variables.append(node.variable)
        for parent in node.parents:
            self.variable_node(parent).children.append(node)

    def variable_node(self, var):
        """Return the node for the variable named var.
        >>> burglary.variable_node('Burglary').variable
        'Burglary'"""
        for n in self.nodes:
            if n.variable == var:
                return n
        raise Exception("No such variable: {}".format(var))

    def variable_values(self, var):
        """Return the domain of var."""
        return [True, False]

    def __repr__(self):
        return 'BayesNet({0!r})'.format(self.nodes)
```

In [13]:
```
#how to consider it as a node based problem

#independent nodes
Renewable_Energy_node = BayesNode('Renewable_Energy', '', 0.2)
Fossil_Fuels_node = BayesNode('Fossil_Fuels', '', 0.8)
Traffic_node = BayesNode('Traffic', '', 0.3)
Employed_node = BayesNode('Employed', '', 0.85)
```

In [14]:
```
# dependent nodes
Global_Warming_node = BayesNode('Global_Warming', ['Renewable_Energ
                         {(True,True,True):0.9,
                          (True,True,False):0.3,
                          (True,False,True):0.2,
                          (False,True,True):0.85,
                          (False,False,True):0.2,
                          (True,False,False):0.1,
                          (False,True,False):0.4,
                          (False,False,False):0.05,
                         })

AI_node=BayesNode('AI', ['Global_Warming', 'Employed'],
                         {(True, True): 0.9,(True, False): 0.3, (Fals
```

In [15]:
```
T,F = True,False
my_model = BayesNet([
                      ("Fossil_Fuels","",0.8),
                      ("Traffic","",0.3),
                      ("Employed","",0.85),
                      ("Renewable_Energy","",0.2),
                     ("Global_Warming",["Renewable_Energy","Fossil_F
                     ("AI",["Employed","Global_Warming"],{(T,T):0.9,
])
```

In [16]:
```
my_model
```

Out[16]:
```
BayesNet([('Fossil_Fuels', ''), ('Traffic', ''), ('Employed', ''),
('Renewable_Energy', ''), ('Global_Warming', 'Renewable_Energy Fos
sil_Fuels Traffic'), ('AI', 'Employed Global_Warming')])
```

In [17]:
```
type(my_model.variable_node("Traffic"))
```

Out[17]:
```
probability.BayesNode
```

In [18]:
```
my_model.variable_node("Traffic").cpt
```

Out[18]:
```
{(): 0.3}
```

In [19]:
```
my_model.variable_node("Global_Warming").cpt
```

Out[19]:
```
{(True, True, True): 0.9,
 (True, True, False): 0.3,
 (True, False, True): 0.2,
 (False, True, True): 0.85,
 (False, False, True): 0.2,
 (True, False, False): 0.1,
 (False, True, False): 0.4,
 (False, False, False): 0.05}
```

In [20]:
```
def enumerate_all(variables, e, bn):
    """Return the sum of those entries in P(variables | e{others})
    consistent with e, where P is the joint distribution represente
    by bn, and e{others} means e restricted to bn's other variables
    (the ones other than variables). Parents must precede children
    if not variables:
        return 1.0
    Y, rest = variables[0], variables[1:]
    Ynode = bn.variable_node(Y)
    if Y in e:
        return Ynode.p(e[Y], e) * enumerate_all(rest, e, bn)
    else:
        return sum(Ynode.p(y, e) * enumerate_all(rest, extend(e, Y,
                   for y in bn.variable_values(Y))
```

In [21]:
```
def enumeration_ask(X, e, bn):
    """Return the conditional probability distribution of variable
    given evidence e, from BayesNet bn. [Figure 14.9]
    >>> enumeration_ask('Burglary', dict(JohnCalls=T, MaryCalls=T),
    ...  ).show_approx()
    'False: 0.716, True: 0.284'"""
    assert X not in e, "Query variable must be distinct from eviden
    Q = ProbDist(X)
    for xi in bn.variable_values(X):
        Q[xi] = enumerate_all(bn.variables, extend(e, X, xi), bn)
    return Q.normalize()
```

Let us solve the problem of finding out **P(AI=True | Global_Warming=True, Empployed=True)** using the **my_model** network. **enumeration_ask** takes three arguments **X** = variable name, **e** = Evidence (in form a dict like previously explained), **bn** = The Bayes Net to do inference on.

In [22]:
```
#verify the AI from the table given that global warming and employe
ans_dist = enumeration_ask("AI",{"Global_Warming":True, "Employed":
ans_dist[True]
```

Out[22]: 0.9

Variable Elimination

The enumeration algorithm can be improved substantially by eliminating repeated calculations. In enumeration we join the joint of all hidden variables. This is of exponential size for the number of hidden variables. Variable elimination employes interleaving join and marginalization.

Before we look into the implementation of Variable Elimination we must first familiarize ourselves with Factors.

In general we call a multidimensional array of type P(Y1 ... Yn | X1 ... Xm) a factor where some of Xs and Ys maybe assigned values. Factors are implemented in the probability module as the class **Factor**. They take as input **variables** and **cpt**.

Helper Functions

There are certain helper functions that help creating the **cpt** for the Factor given the evidence. Let us explore them one by one.

make_factor is used to create the **cpt** and **variables** that will be passed to the constructor of **Factor**. We use **make_factor** for each variable. It takes in the arguments **var** the particular variable, **e** the evidence we want to do inference on, **bn** the bayes network.

Here **variables** for each node refers to a list consisting of the variable itself and the parents minus any variables that are part of the evidence. This is created by finding the **node.parents** and filtering out those that are not part of the evidence.

The **cpt** created is the one similar to the original **cpt** of the node with only rows that agree with the evidence.

In [23]:
```
def make_factor(var, e, bn):
    """Return the factor for var in bn's joint distribution given e
    That is, bn's full joint distribution, projected to accord with
    is the pointwise product of these factors for bn's variables."""
    node = bn.variable_node(var)
    variables = [X for X in [var] + node.parents if X not in e]
    cpt = {event_values(e1, variables): node.p(e1[var], e1)
           for e1 in all_events(variables, bn, e)}
    return Factor(variables, cpt)

def all_events(variables, bn, e):
    """Yield every way of extending e with values for all variables
    if not variables:
        yield e
    else:
        X, rest = variables[0], variables[1:]
        for e1 in all_events(rest, bn, e):
            for x in bn.variable_values(X):
                yield extend(e1, X, x)
```

The **all_events** function is a recursive generator function which yields a key for the orignal **cpt** which is part of the node. This works by extending evidence related to the node, thus all the output from **all_events** only includes events that support the evidence. Given **all_events** is a generator function one such event is returned on every call.

We can try this out using the example on **Page 524** of the book. We will make $\mathbf{f}_5(A) = P(m \mid A)$

answering the queries based on the table (where the direct relationship does not exist)

for example- in this section we will fetch a few queries that do not have a direct relation as in case with global warming it is directly related with occurance of fossil fuels, Renewable energy and Traffic but what if we want to predict global warming with only two variables.

Example 2- the relation of AI with respect to Fossil fuels and Employement ?

In [24]:
```
f5 = make_factor("Global_Warming",{"Fossil_Fuels":True,"Traffic":Tr
```

In [25]:
```
f5
```

Out[25]:
```
<probability.Factor at 0xa1fcf8310>
```

In [26]:
```
f5.cpt
```

Out[26]:
```
{(True, True): 0.9,
 (False, True): 0.09999999999999998,
 (True, False): 0.85,
 (False, False): 0.15000000000000002}
```

In [27]:
```
f5.variables
```

Out[27]:
```
['Global_Warming', 'Renewable_Energy']
```

In [28]:
```
f5 = make_factor("AI",{"Fossil_Fuels":False,"Employed":True},my_mod
```

In [29]:
```
f5.cpt
```

Out[29]:
```
{(True, True): 0.9,
 (False, True): 0.09999999999999998,
 (True, False): 0.5,
 (False, False): 0.5}
```

In [30]:
```
f5.variables
```

Out[30]:
```
['AI', 'Global_Warming']
```

How does Naive bayes actually work ?

before I begin explaining the Naive Bayes algorithm

I would like to source the blog that I am reffering for this demonstation of the concept

source- http://shatterline.com/blog/2013/09/12/not-so-naive-classification-with-the-naive-bayes-classifier/ (http://shatterline.com/blog/2013/09/12/not-so-naive-classification-with-the-naive-bayes-classifier/)

What is Bayes theoram ?

there are three bags that contain 2 types of balls(RED & BLUE)

BAG1- 2 Red and 5 Blue BAG2- 5 Red and 2 Blue BAG3- 2 Red and 3 Blue

Ques- given that red ball was selected what is the probability that it came from BAG3 ?

let's numerically change the question to solve our problem

let each of the bags be denoted as E1, E2 and E3

then, Probability of selecting any bag can be written as,

P(E1)=P(E2)=P(E3)=1/3

now we denote the event (A) as drawing the red ball.

then probability of drawing red balls from each of the bag can be written as

P(A|E1)=2/7 P(A|E2)=5/7 P(A|E3)=2/5

We can represent the question in a mathematical symbol as

P(E3|A)=?

which we are aiming to solve using the Bayes theoram

According to Bayes theoram,

P(E3|A)=P(A|E3) * P(E3) / (P(A|E1)P(E1)+P(A|E2)P(E2)+P(A|E3)P(E3))

or in general we can write the formula as,

$$P(E3|A) = \frac{P(A|E3) \times P(E3)}{P(A|E1) \times P(E1) + P(A|E2) \times P(E2) + P(A|E3) \times P(E3)}$$

Computing the values already calculated in the expression , we will get,

$$P(E3|A) = \frac{2/5 \times 1/3}{2/7 \times 1/3 + 5/7 \times 1/3 + 2/5 \times 1/3}$$

thus P(E3|A) was found out to be **0.2857142857**

We could also simply rewrite the entire bayes formula in a much clear representation such as,

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

or more generally as,

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

if P(B) not equals to 0

The above generalized result is very important, we will later use it for deriving Naive Bayes

coming over to the naive Bayes and linking it to the Bayes theoram

we are given a set of variables which actually define a parameter say y

so in the data we have certain x1,x2,x3,x4 that define the outcome Y

for example consider the below given example

In [31]:
```
from IPython.display import Image
from IPython.core.display import HTML
Image(url= "http://shatterline.com/blog/wp-content/uploads/2013/09/
```

Out[31]:

	Predictors				Response
	Outlook	**Temperature**	**Humidity**	**Wind**	**Class Play=Yes Play=No**
Day1	Sunny	Hot	High	Weak	No
Day2	Sunny	Hot	High	Strong	No
Day3	Overcast	Hot	High	Weak	Yes
Day4	Rain	Mild	High	Weak	Yes
Day5	Rain	Cool	Normal	Weak	Yes
Day6	Rain	Cool	Normal	Strong	No
Day7	Overcast	Cool	Normal	Strong	Yes
Day8	Sunny	Mild	High	Weak	No
Day9	Sunny	Cool	Normal	Weak	Yes
Day10	Rain	Mild	Normal	Weak	Yes
Day11	Sunny	Mild	Normal	Strong	Yes
Day12	Overcast	Mild	High	Strong	Yes
Day13	Overcast	Hot	Normal	Weak	Yes
Day14	Rain	Mild	High	Strong	No

The data contains all the information for several days and we are trying to predict wether at any given random day we should go out to play or not based on the readings from the 4 given features **(Outlook, Temperature, Humidity, Wind)**

Mathematically can be written as,using the generalized formula of Bayes Theoram

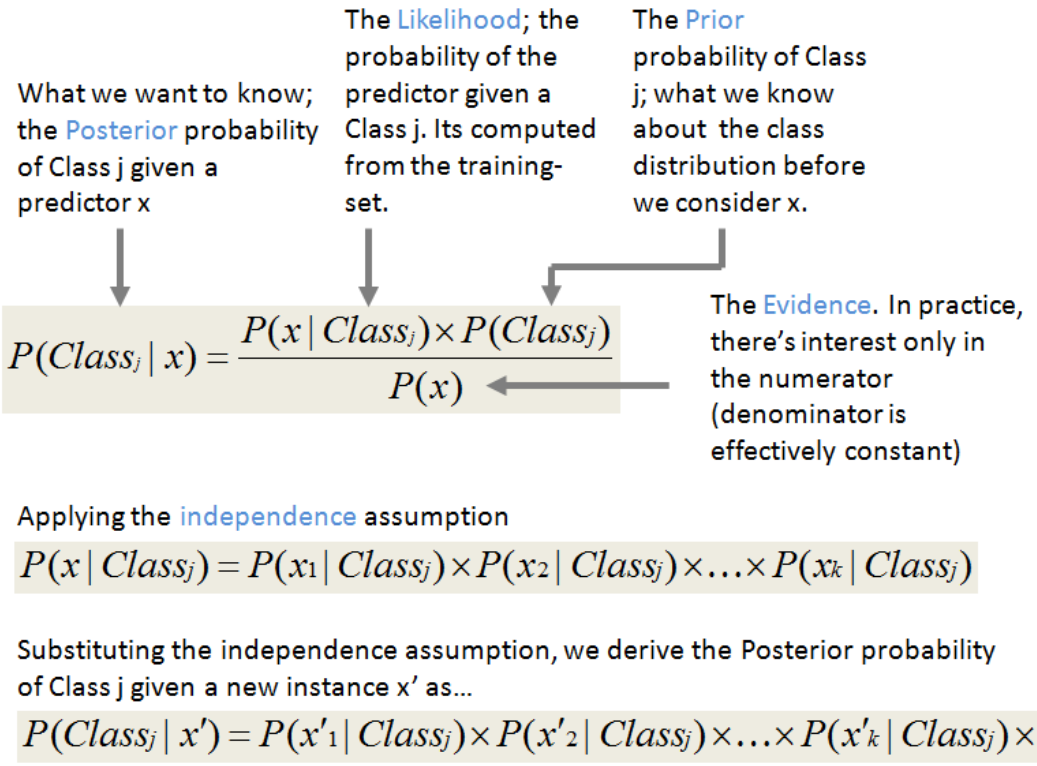
$$P(C_k|X) = \frac{P(X|C_k) \times P(C_k)}{P(X)}$$

where C_k denotes the class label and X denotes the row sample of a Day

The expression has 4 different terms and each of them has their own significance and a name associated, Below highlighted image showcases what each of those terms are called and how they can be interpreted for predicting the class labels

In [32]:
```
Image(url= "http://shatterline.com/blog/wp-content/uploads/2013/09/
```

Out[32]:



In the above image we splitted the entire Dependence of class label on each row to the dependence of the class with individual feature this can only be incorporated if the data has conditional independence meaning we can only apply the principle on conditionally independent features which in real life are rarely to be honest.

Hence the algorithm is called Naive (As it assumes that features have no correlation with each other.)

After assuming the conditional independence the expression can be split into multiple expressions with different feature in each as,

P(x1, x2 …, xk | Classj) = ∏i P(xi, | Classj), or

P(x1, x2 …, xk | Classj) = P(x1 | Classj) × P(x2 | Classj) ×…× P(xk | Classj)

Since the denominator P(x) will be same in the denominator for both of the classes i.e when play= Yes and when play= No

so it does not really impact alot on the label outcomes so for the moment let's just focus on the Numerator of the expression calculated.

hence the expression really boils down to calculating posterior for each of the feature

**P(class_play=Yes)=P(x1|class_play=Yes) * P(x2|class_play=Yes) *.....
P(xn|class_play=Yes) * P(class_play=Yes)**

we can very easily visualize the posteriors with the help of the table given below

In [33]:
```
Image(url= "http://shatterline.com/blog/wp-content/uploads/2013/09/
Image(url= "http://shatterline.com/blog/wp-content/uploads/2013/09/
```

Out[33]:

P(Outlook=o|Class $_{Play=Yes\|No}$)	Frequency		Probability in Class	
Outlook =	Play=Yes	Play=No	Play=Yes	Play=No
Sunny	2	3	2/9	3/5
Overcast	4	0	4/9	0/5
Rain	3	2	3/9	2/5
	total= 9	total=5		

P(Temperature=t|Class $_{Play=Yes\|No}$)	Frequency		Probability in Class	
Temperature =	Play=Yes	Play=No	Play=Yes	Play=No
Hot	2	2	2/9	2/5
Mild	4	2	4/9	2/5
Cool	3	1	3/9	1/5
	total= 9	total=5		

P(Humidity=h|Class $_{Play=Yes\|No}$)	Frequency		Probability in Class	
Humidity =	Play=Yes	Play=No	Play=Yes	Play=No
High	3	4	3/9	4/5
Normal	6	1	6/9	1/5
	total= 9	total=5		

P(Wind=w|Class $_{Play=Yes\|No}$)	Frequency		Probability in Class	
Wind =	Play=Yes	Play=No	Play=Yes	Play=No
strong	3	3	3/9	3/5
weak	6	2	6/9	2/5
	total= 9	total=5		

Let's say, we get a new instance of the weather condition,

x'=(Outlook=Sunny, Temperature=Cool, Humidity=High, Wind=Strong) that will have to be classified (i.e., are we going to play tennis under the conditions specified by x').

With the MAP rule, we compute the posterior probabilities. This is easily done by looking up the tables we built above.

$$P(ClassPlay = Yes|x') = P(Sunny|ClassPlay = Yes) \times P(Cool|ClassPlay = \\ \times P(Strong|ClassPlay = Yes)) \times P(ClassPlay = \\$$

= 2/9 × 3/9 × 3/9 × 3/9 × 9/14 = 0.0053

$$P(ClassPlay = No|x') = P(Sunny|ClassPlay = No) \times P(Cool|ClassPlay = N \\ \times P(Strong|ClassPlay = No) \times P(Class_Play = N$$

= 3/5 × 1/5 × 4/5 × 3/5 × 5/14 = 0.0205

Since P(ClassPlay=Yes|x') less than P(ClassPlay=No|x'), we classify the new instance x' to be "No".

what is the time complexity of the Algorithm

in order to evaluate time complexity we will say there are n rows in the data C categorical labels and d dimensions or features

then the time complexity is the number of operations required to make the look uptable is in the order of O(n*dC*)

however the space time complexity is very low as we only need to save O(d*c) such look up values in a look up table

hence many of the low latency systems prefer to use Naive Bayes instead of any other algorithm becuase it takes very low time.

fun fact - despite of the fact that there is a condional independence assumption it still works like a charm for many of the applications, One such example is the spam filter classification, It was one of the first models initially proposed for spam detection and today used as benchmark to compare all other recently developed algorithms

however it would be incomplete if I finish the topic without addressing two of the issues with Naive Bayes, That we will fix using the multinomial Naive Bayes approach

1-problem if one of the feature has 0 occurance 2-It is called the issue of numerical stability

In the first problem if say P(Sunny|classPlay=No) =0 meaning that for every occurance of Sunny there was no play condition equal to No then it could impact all the other values calculated and will turn everything to 0

To encounter that we use Laplace additive smoothing parameter called alpha

The smoothing parameter ensures that if the occurance of the word is 0 even then the output would not go to zero, it will become a small value but not 0 thus preventing the entire expression to go down

In [34]:
```
Image(url= "https://qph.fs.quoracdn.net/main-qimg-82af0a002409ddb2b
```

Out[34]:

$$p_{i,\text{ empirical}} = \frac{x_i}{N}$$

but the posterior probability when additively smoothed is

$$p_{i,\ \alpha\text{-smootbed}} = \frac{x_i + \alpha}{N + \alpha d},$$

for example,

say alpha =1(smoothing parameter) here d is the distinct values that a class can have in our weather example it will be 2 and samples will be say 10

then the expression or probability of each word becomes

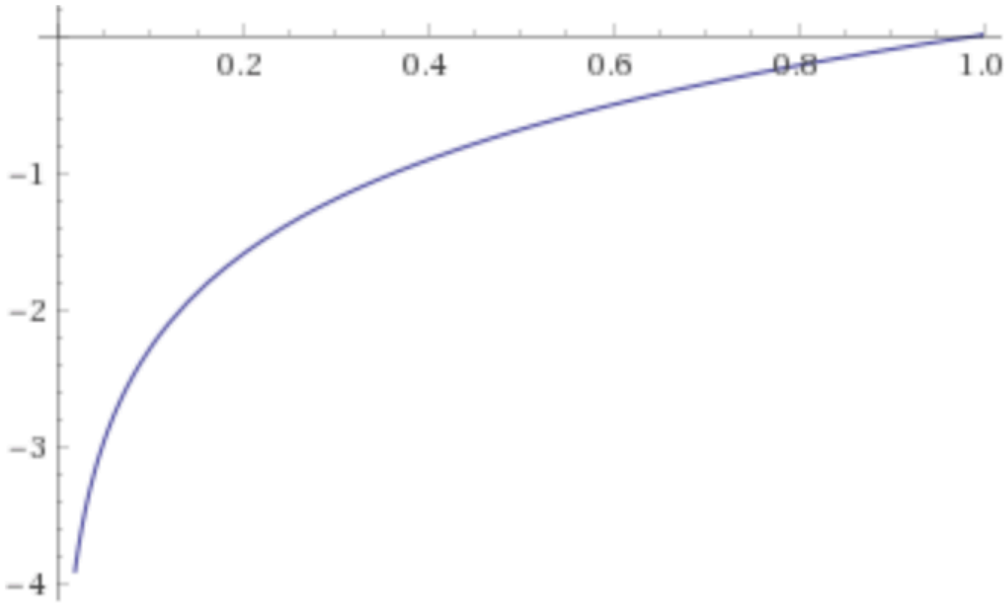
$$P(alpha_s moothed) = \frac{0 + 10}{100 + 1 \times 2}$$

hence the values turns out to be 1/102 which is not equal to 0 as it would have been if we had followed emperical formula

2- in the second problem multiplication of many such small entities could lead to a value rounded to 0 this problem is called numerical stability issue in python 16 significant digits after the decimal place are considered and with large number of features we can get into a problem where the multiplication of the probabilities could result into a value rounded up to zero

In order to deal with this problem we use log probabilities

for each probablity calculated



Since log is monotonic function means strictly increasing given any value between 0 and 1 we will get a negative value of a much bigger number associated with each liklihood, We could simply ignore the -ve sign and do the sum of each of the probabilities

P(C|x) = P(C|x1)* P(C|x2) * P(C|x3).....P(C|xn)

will now become, using the properties of log

log(P(C|X))= log(P(C|X1)) + log(P(C|X2)) + log(P(C|X3)) ..... + log(P(C|Xn))

we calculate each of these probabilities and whichever is greater for each class type will say that the result is that class

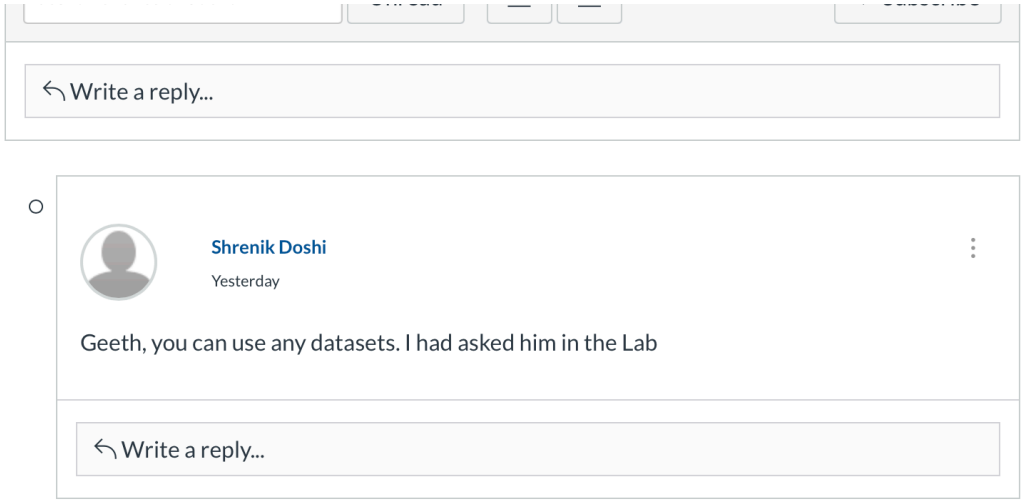
In the above example we have explained all three aspects in calculation of posterior probabilities i.e.

- Compute the “Prior” probabilities for each of the classes.
- Compute the probability of evidence.
- Compute the probability of likelihood of evidences (numerator).

According to grading rubric provided

Visualizing the selected datasets

1- loan dataset



As discussed in the lab with the profesor and on the discussion forum we are allowed to pick any dataset and not just the ones available on the uci Machine learning repository

In [35]:
```
import pandas as pd
from tqdm import tqdm
import numpy as np
import warnings
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import scipy.io as sio
warnings.filterwarnings("ignore")
name=["rate","installment","log.annual.inc","dti","fico","days.with
df = pd.read_csv("aima-data/loan_data.csv",names=name)
df.head()
```

Out[35]:

	rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.l
0	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	
1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	
2	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	
3	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	
4	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	

In [36]:
```
df.shape
```

Out[36]: (9578, 13)

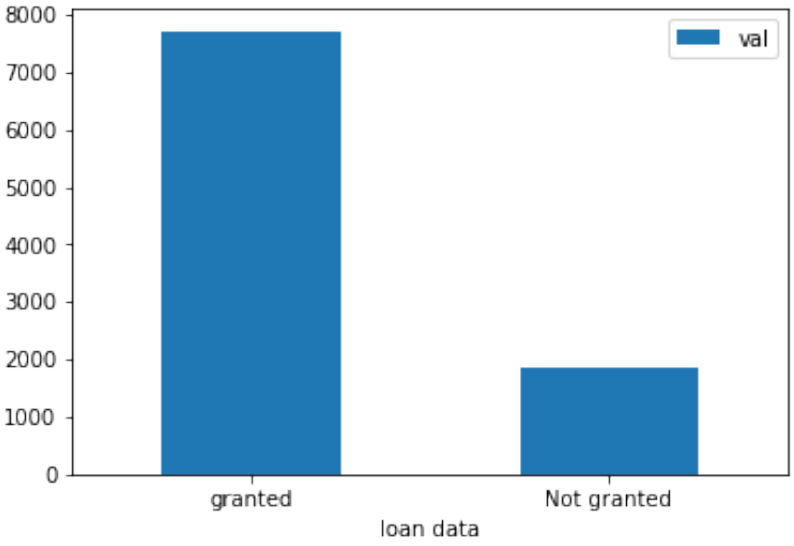
explaining each of the dataset features(There are 13 features)

the last column of the dataset explains if we the loan will be granted (1) or not (0)

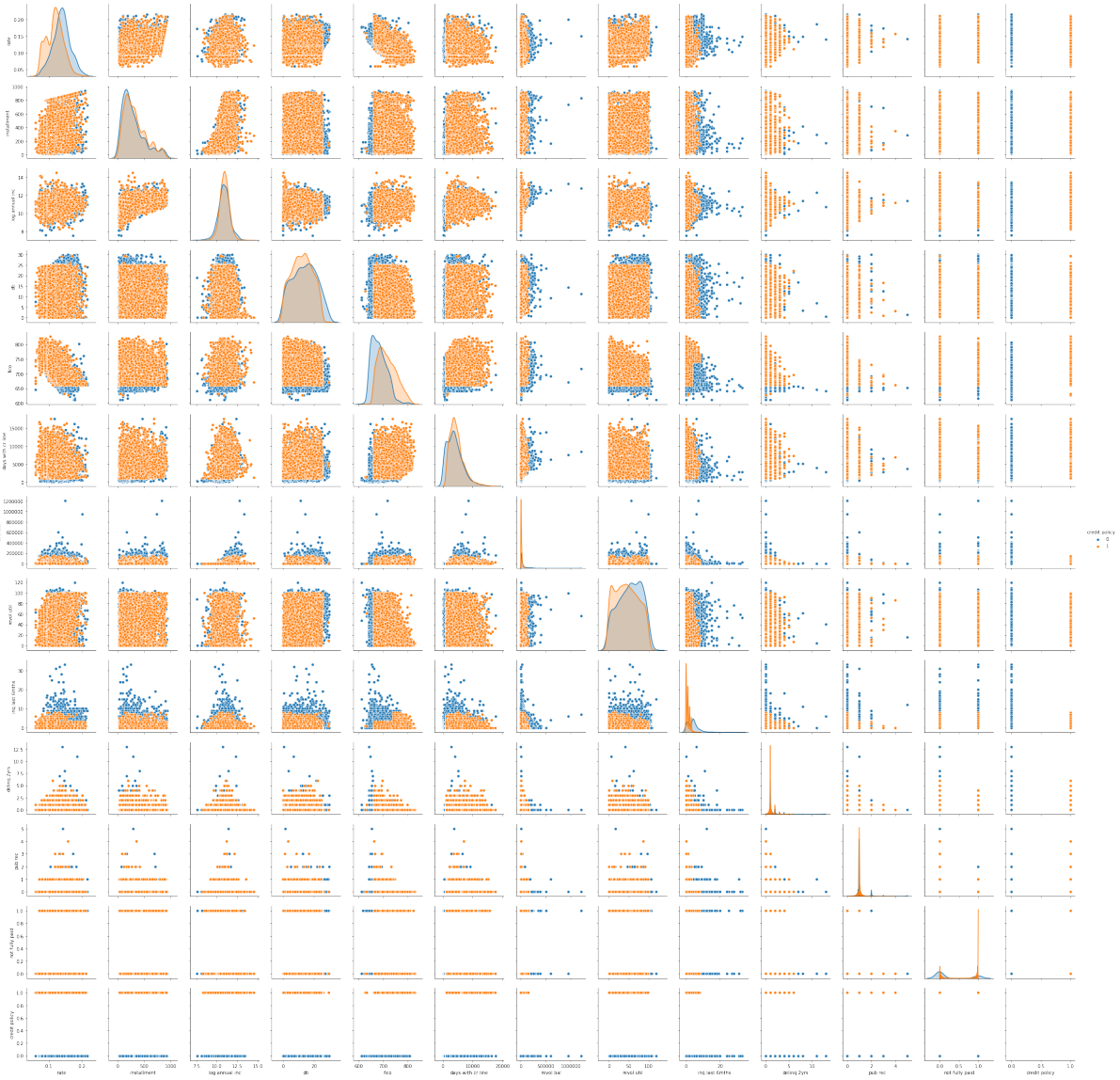
In [37]:
```
minority=df['credit.policy'].value_counts()[0]
majority=df['credit.policy'].value_counts()[1]
```

so we have 7709 samples that were granted loan and 1868 samples that were not granted

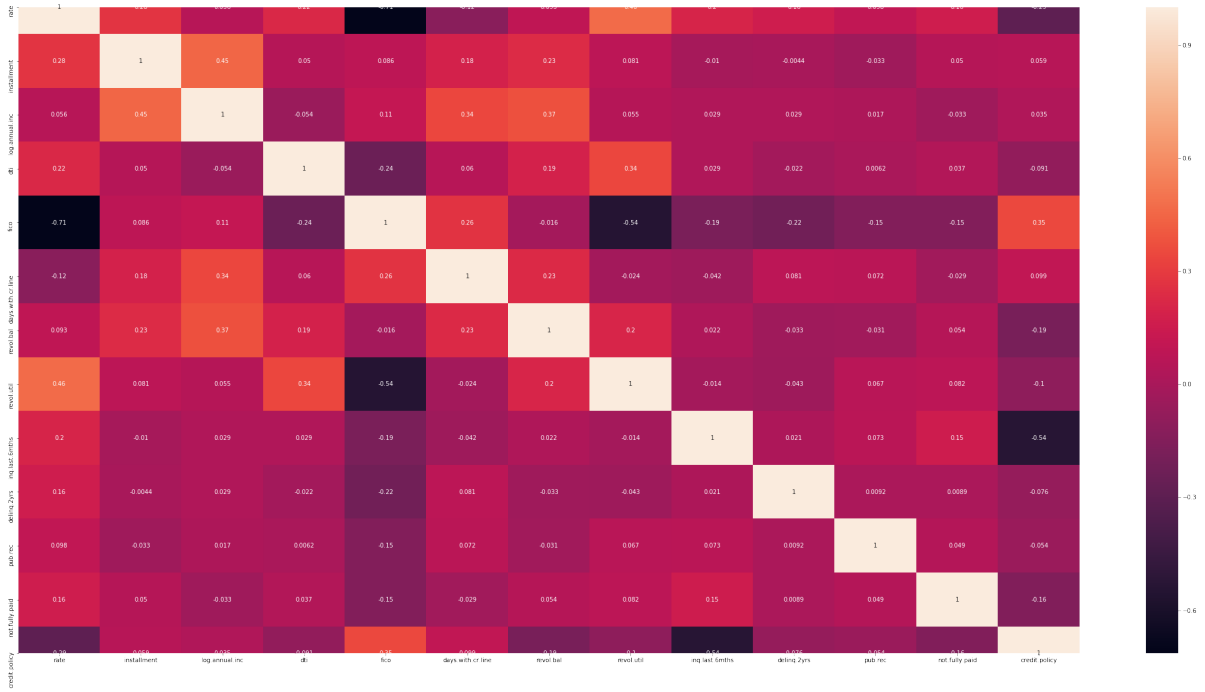
In [38]:
```
df_bar = pd.DataFrame({'loan data':['granted', 'Not granted'], 'val
ax = df_bar.plot.bar(x='loan data', y='val', rot=0)
```



In [39]:
```
# drawing the pairplot of each feature
#denotes the relation of credit policy with all the other features
g = sns.pairplot(df, hue='credit.policy')
```



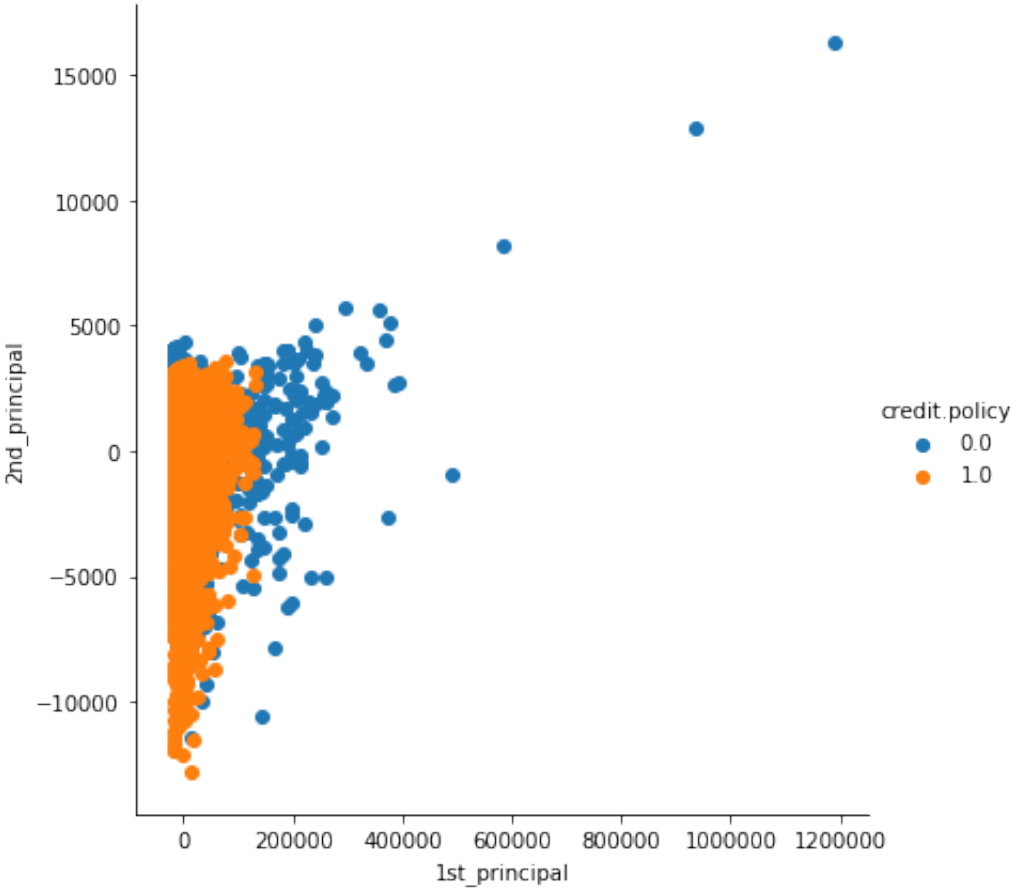
In [40]:
```
#visualizing the heat map and seeing any correlation among the feat
fig=plt.figure(figsize=(40,20))
p1 = sns.heatmap(df.corr(),annot=True)
```



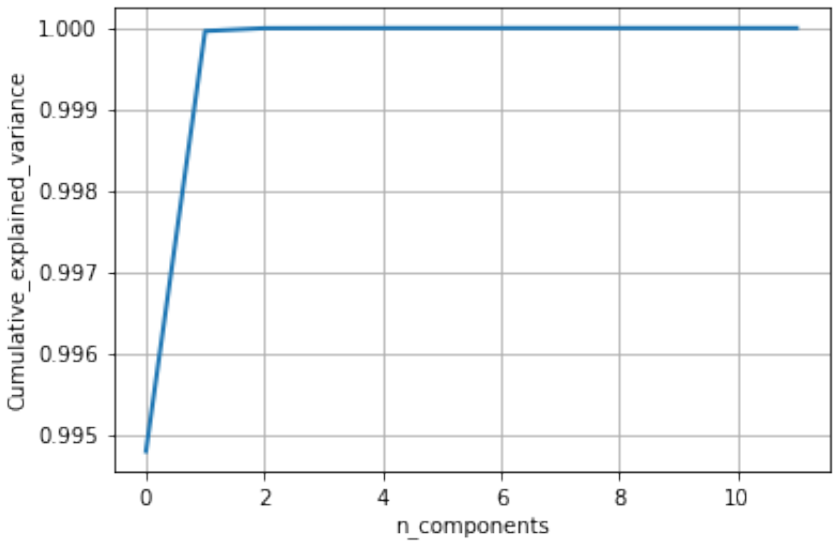
In [41]:
```
#since the data has too many features let's visualize them using so
#and TSNE
x=df.iloc[:,:-1]
y=df.iloc[:,-1]


# initializing the pca for visualization
from sklearn import decomposition
pca = decomposition.PCA()
labels=y.copy(deep=True).to_numpy()
# configuring the parameteres
# the number of components = 2
pca.n_components = 3
pca_data = pca.fit_transform(x)

# pca_reduced will contain the 2-d projects of simple data
print("shape of pca_reduced.shape = ", pca_data.shape)
print(type(pca_data),type(labels))
print(pca_data.shape,labels.shape)
pca_data = np.vstack((pca_data.T, labels)).T
# creating a new data fram which help us in ploting the result data
pca_df = pd.DataFrame(data=pca_data, columns=("1st_principal", "2nd
sns.FacetGrid(pca_df, hue="credit.policy", size=6).map(plt.scatter,
plt.show()

#3d plot on pca
import plotly.express as px
```

```
fig = px.scatter_3d(pca_df, x="1st_principal", y="2nd_principal", z
                    color="credit.policy")
fig.show()
```

```
shape of pca_reduced.shape =  (9578, 3)
<class 'numpy.ndarray'> <class 'numpy.ndarray'>
(9578, 3) (9578,)
```

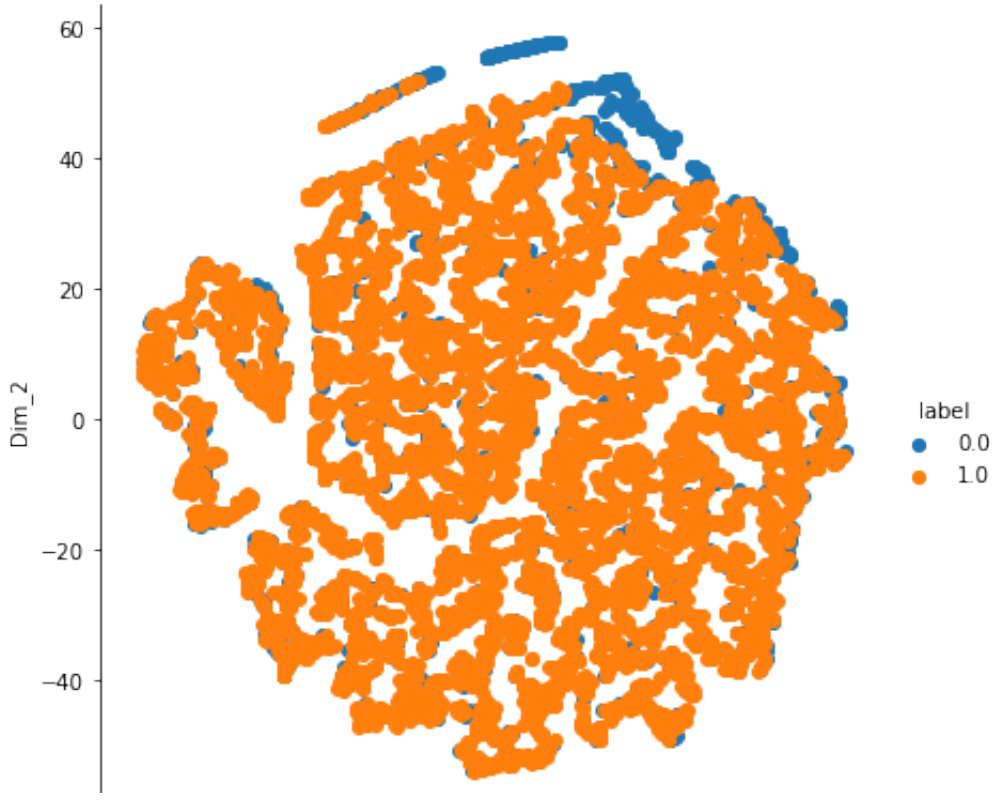


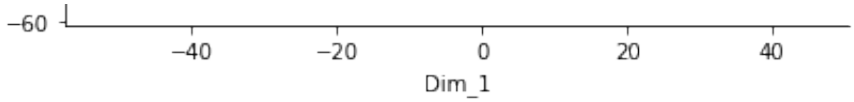
In [42]:
```
# PCA for dimensionality redcution (non-visualization)
pca.n_components = x.shape[1]
pca_data = pca.fit_transform(x)
percentage_var_explained = pca.explained_variance_ / np.sum(pca.exp
cum_var_explained = np.cumsum(percentage_var_explained)
#do a cumlative sum
# Plot the PCA spectrum
plt.figure(1, figsize=(6, 4))
plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()
```



In [43]:
```
# https://github.com/pavlin-policar/fastTSNE you can try this also,
from sklearn.manifold import TSNE
model = TSNE(n_components=2, random_state=0 ,n_iter=500,perplexity=
# configuring the parameteres
# the number of components = 2
```

```
# default perplexity = 30
# default learning rate = 200
# default Maximum number of iterations for the optimization = 1000(
tsne_data = model.fit_transform(x)
# creating a new data frame which help us in ploting the result dat
tsne_data = np.vstack((tsne_data.T, labels)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1
plt.show()

from sklearn.manifold import TSNE
model = TSNE(n_components=3, random_state=0 ,n_iter=500,perplexity=
# configuring the parameteres
# the number of components = 2
# default perplexity = 30
# default learning rate = 200
# default Maximum number of iterations for the optimization = 1000(
tsne_data = model.fit_transform(x)
tsne_data = np.vstack((tsne_data.T, labels)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "
tsne_df.describe()

import plotly.express as px

fig = px.scatter_3d(tsne_df, x='Dim_1', y='Dim_2', z='Dim_3',
                    color='label')
fig.show()

#clearly three Tsne axis are not enough to vizualize the data as th
```




−60
−40
−20
0
20
40
Dim_1

lets try to run the visualization aspect on the second dataset

in this section we will try to visualize the data from a famous cartoon show called pokemon

1- we will import the data from a csv file and do some preprocessing

2- the classification is based on anomalies where are trying to classsify the Legendary type of pokemons which are very few

here the anomaly class is the Legendary type pokemon while the inlier class is the non legendary type pokemon

Loading the dataset -2 this is the pokemon dataset

In [44]:
```
#load data to a data frame
df = pd.read_csv("aima-data/Pokemon.csv")
df.head()
```

Out[44]:

	#	Name	Type 1	Type 2	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generati
0	1	Bulbasaur	Grass	Poison	318	45	49	49	65	65	45	
1	2	Ivysaur	Grass	Poison	405	60	62	63	80	80	60	
2	3	Venusaur	Grass	Poison	525	80	82	83	100	100	80	
3	3	VenusaurMega Venusaur	Grass	Poison	625	80	100	123	122	120	80	
4	4	Charmander	Fire	NaN	309	39	52	43	60	50	65	

In [45]:
```
df.shape
```

Out[45]: (800, 13)

The data has 683 rows and 9 columns

In [46]:
```
#replacing the true false labels with 0 and 1
df.Legendary.replace({True:1,False:0},inplace=True)
df.head()
#look for both the labels
unique_labels_t1=list(df["Type 1"].unique())
unique_labels_t2=list(df["Type 2"].unique())
print(unique_labels_t1==unique_labels_t2)#false becasue of the nan

#true becasue the number of each unique elements pers list is the s
for elements in unique_labels_t1:
    if(type(elements)!=type(str())):
        unique_labels_t1.remove(elements)
for elements in unique_labels_t2:
    if(type(elements)!=type(str())):
        unique_labels_t2.remove(elements)
print(unique_labels_t1.sort()==unique_labels_t2.sort())
print(unique_labels_t1)
```

```
False
True
['Bug', 'Dark', 'Dragon', 'Electric', 'Fairy', 'Fighting', 'Fire',
'Flying', 'Ghost', 'Grass', 'Ground', 'Ice', 'Normal', 'Poison', '
Psychic', 'Rock', 'Steel', 'Water']
```

In [47]:
```
#converting thm back to the one hot encoding format
one_hot_form_1 = pd.get_dummies(df['Type 1'])
one_hot_form_2 = pd.get_dummies(df['Type 2'])
display(one_hot_form_1.shape)
#display(one_hot_form_2.describe())

#as we can see now the values of the one hot form are pretty good
```

```
(800, 18)
```

In [48]:
```
#since both col have the same 18 columns we can make combined form
final=pd.DataFrame(index=one_hot_form_1.index)
for column_name in unique_labels_t1:
    final[column_name] = one_hot_form_1[column_name] + one_hot_form
final.head()
```

Out[48]:

	Bug	Dark	Dragon	Electric	Fairy	Fighting	Fire	Flying	Ghost	Grass	Ground	Ice	N
0	0	0	0	0	0	0	0	0	0	1	0	0	
1	0	0	0	0	0	0	0	0	0	1	0	0	
2	0	0	0	0	0	0	0	0	0	1	0	0	
3	0	0	0	0	0	0	0	0	0	1	0	0	
4	0	0	0	0	0	0	1	0	0	0	0	0	

In [49]:
```
final.describe()
```

Out[49]:

	Bug	Dark	Dragon	Electric	Fairy	Fighting	Fire
count	800.000000	800.00000	800.000000	800.000000	800.000000	800.000000	800.000000
mean	0.090000	0.06375	0.062500	0.062500	0.050000	0.066250	0.080000
std	0.286361	0.24446	0.242213	0.242213	0.218081	0.248874	0.271463
min	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.00000	1.000000	1.000000	1.000000	1.000000	1.000000

In [50]:
```
df= pd.concat([df,final],sort=False,axis=1)
df.head()
df=df.drop(['Type 1','Type 2'], axis=1)
df.head()
```

Out[50]:

	#	Name	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	...	Ghost
0	1	Bulbasaur	318	45	49	49	65	65	45	1	...	0
1	2	Ivysaur	405	60	62	63	80	80	60	1	...	0
2	3	Venusaur	525	80	82	83	100	100	80	1	...	0
3	3	VenusaurMega Venusaur	625	80	100	123	122	120	80	1	...	0
4	4	Charmander	309	39	52	43	60	50	65	1	...	0

5 rows × 29 columns

In [51]:
```
#now we will extract the numerical row features
numerical_features=["Total","HP","Attack","Defense","Sp. Atk","Sp.
numerical_df=df[numerical_features]
numerical_df.head()
```

Out[51]:

	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed
0	318	45	49	49	65	65	45
1	405	60	62	63	80	80	60
2	525	80	82	83	100	100	80
3	625	80	100	123	122	120	80
4	309	39	52	43	60	50	65

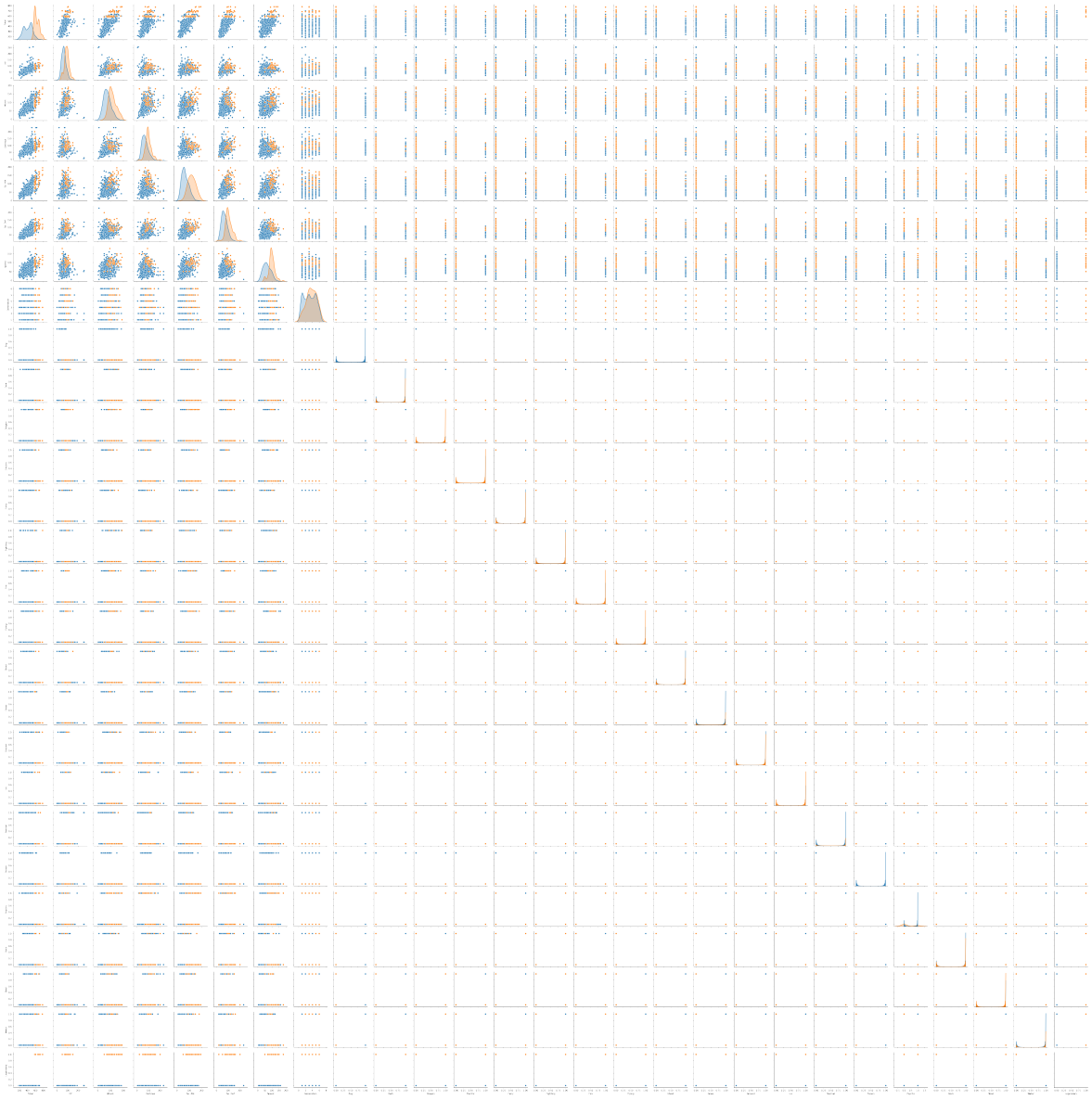
In [52]:
```
#these are the categorical features
categorical_df=df.iloc[:,9:]
```

In [53]:
```
#concatenating numerical and categorical features
final= pd.concat([numerical_df,categorical_df],sort=False,axis=1) #
final.describe()

#add a shuffling parameter

y=final["Legendary"]
x=final.drop(["Legendary"],axis=1)
print(x.shape,y.shape)
```

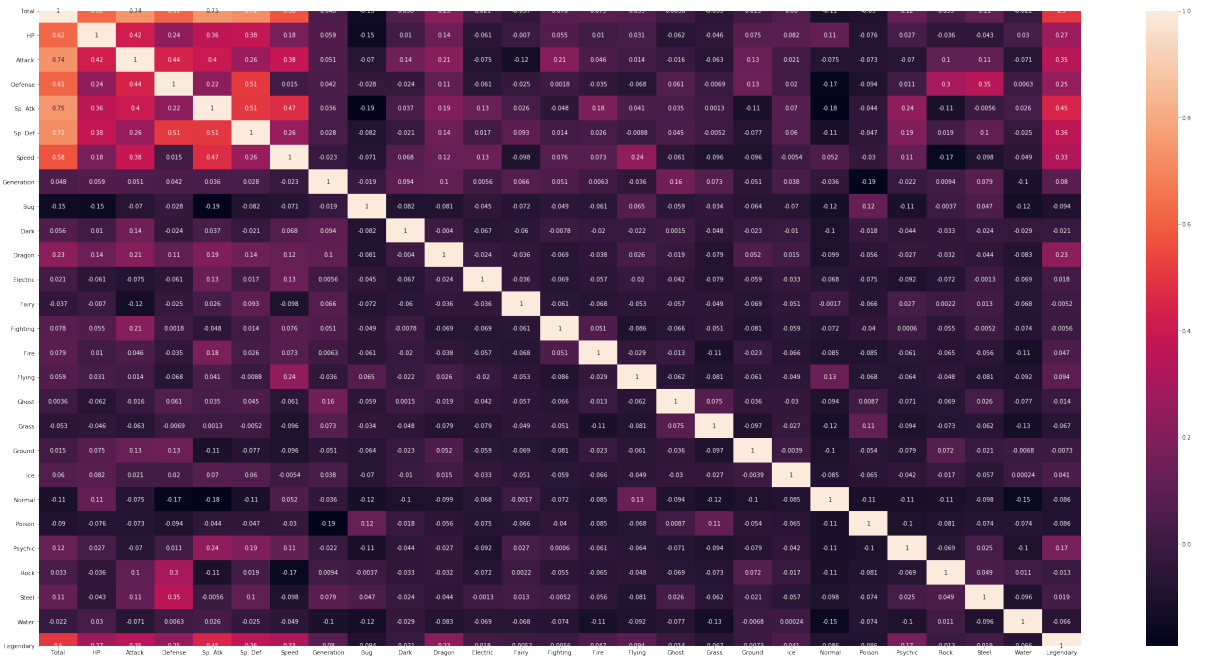
```
(800, 26) (800,)
```

In [54]:
```
df=pd.concat([x, y], axis = 1).T.drop_duplicates().T
df.head()
import copy
poke_data=copy.deepcopy(df)
minority=df['Legendary'].value_counts()[0]
majority=df['Legendary'].value_counts()[1]
```

In [55]:
```
# drawing the pairplot of each feature
#denotes the relation of credit policy with all the other features
g = sns.pairplot(df, hue='Legendary')
```



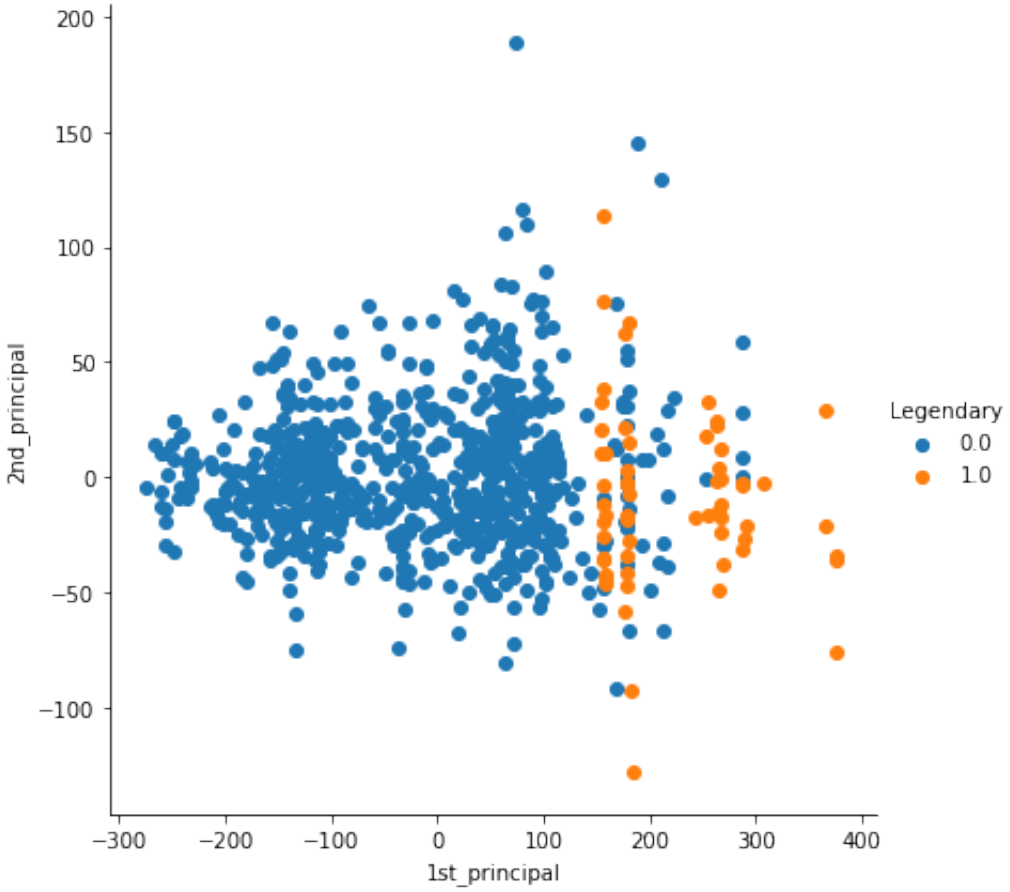
In [56]:
```
#visualizing the heat map and seeing any correlation among the feat
fig=plt.figure(figsize=(40,20))
p1 = sns.heatmap(df.corr(),annot=True)
```



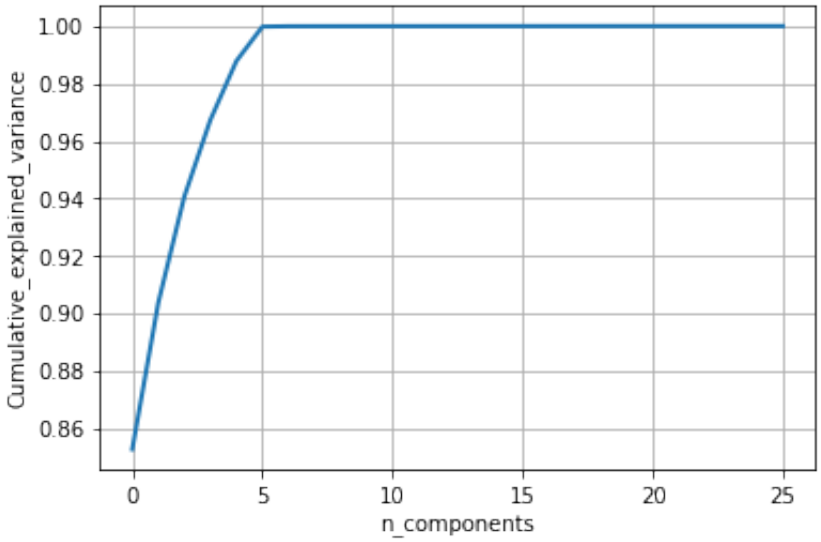
In [57]:
```
#since the data has too many features let's visualize them using so
#and TSNE
x=df.iloc[:,:-1]
y=df.iloc[:,-1]

# initializing the pca for visualization
from sklearn import decomposition
pca = decomposition.PCA()
labels=y.copy(deep=True).to_numpy()
# configuring the parameteres
# the number of components = 2
pca.n_components = 3
pca_data = pca.fit_transform(x)

# pca_reduced will contain the 2-d projects of simple data
print("shape of pca_reduced.shape = ", pca_data.shape)
print(type(pca_data),type(labels))
print(pca_data.shape,labels.shape)
pca_data = np.vstack((pca_data.T, labels)).T
# creating a new data fram which help us in ploting the result data
pca_df = pd.DataFrame(data=pca_data, columns=("1st_principal", "2nd
sns.FacetGrid(pca_df, hue="Legendary", size=6).map(plt.scatter, '1s
plt.show()

#3d plot on pca
import plotly.express as px

fig = px.scatter_3d(pca_df, x="1st_principal", y="2nd_principal", z
```

```
                    color="Legendary")
fig.show()
```

```
shape of pca_reduced.shape =  (800, 3)
<class 'numpy.ndarray'> <class 'numpy.ndarray'>
(800, 3) (800,)
```

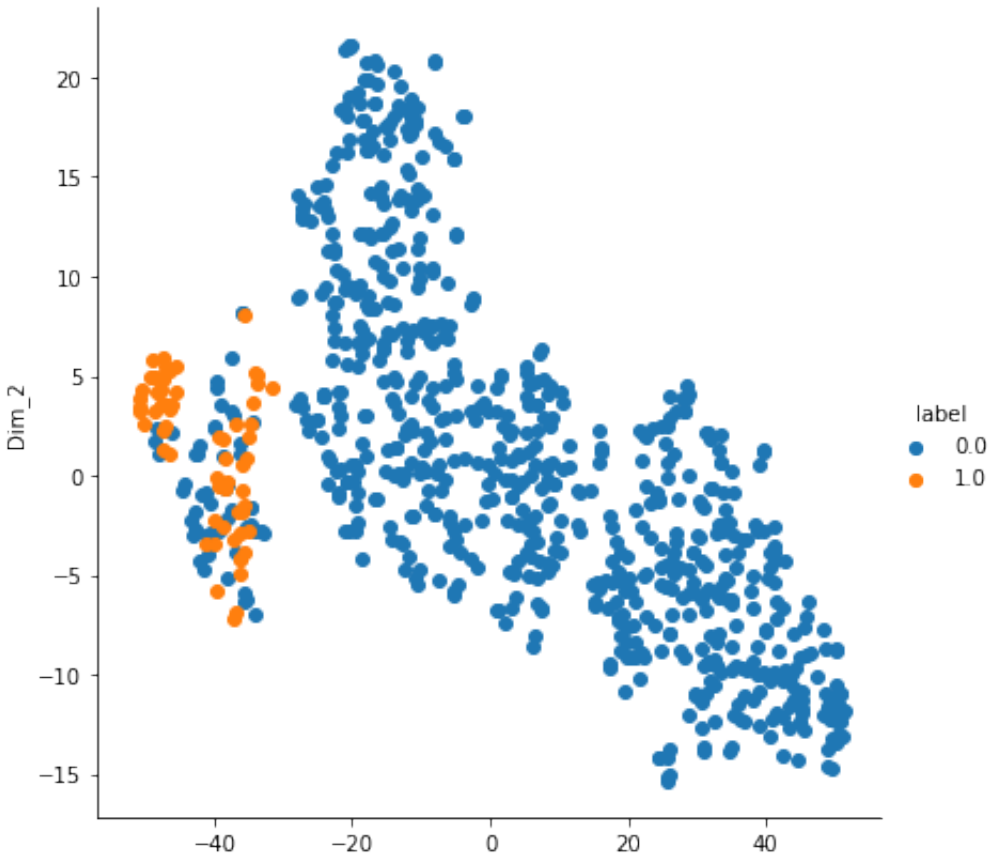


In [58]:
```
# PCA for dimensionality redcution (non-visualization)
pca.n_components = x.shape[1]
pca_data = pca.fit_transform(x)
percentage_var_explained = pca.explained_variance_ / np.sum(pca.exp
cum_var_explained = np.cumsum(percentage_var_explained)
#do a cumlative sum
# Plot the PCA spectrum
plt.figure(1, figsize=(6, 4))
plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()
```



In [59]:
```
# https://github.com/pavlin-policar/fastTSNE you can try this also,
from sklearn.manifold import TSNE
model = TSNE(n_components=2, random_state=0 ,n_iter=500,perplexity=
# configuring the parameteres
# the number of components = 2
# default perplexity = 30
# default learning rate = 200
```

```
# default learning rate = 200
# default Maximum number of iterations for the optimization = 1000(
tsne_data = model.fit_transform(x)
# creating a new data frame which help us in ploting the result dat
tsne_data = np.vstack((tsne_data.T, labels)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "

# Ploting the result of tsne
sns.FacetGrid(tsne_df, hue="label", size=6).map(plt.scatter, 'Dim_1
plt.show()

from sklearn.manifold import TSNE
model = TSNE(n_components=3, random_state=0 ,n_iter=500,perplexity=
# configuring the parameteres
# the number of components = 2
# default perplexity = 30
# default learning rate = 200
# default Maximum number of iterations for the optimization = 1000(
tsne_data = model.fit_transform(x)
tsne_data = np.vstack((tsne_data.T, labels)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=("Dim_1", "Dim_2", "
tsne_df.describe()

import plotly.express as px

fig = px.scatter_3d(tsne_df, x='Dim_1', y='Dim_2', z='Dim_3',
                    color='label')
fig.show()

#clearly three Tsne axis are not enough to vizualize the data as th
```



Dim_1

Running the python code for naive bayes(execution phase)

on data 1-(loan data)

calculating prior probabilities

In [60]:
```
from learning import *
from notebook import *
loan = DataSet(name="loan_data")
print(loan.examples[0])
print(loan.inputs)

dataset = loan

target_vals = dataset.values[dataset.target]
target_dist = CountingProbDist(target_vals)
attr_dists = {(gv, attr): CountingProbDist(dataset.values[attr])
              for gv in target_vals
              for attr in dataset.inputs}
for example in dataset.examples:
        targetval = example[dataset.target]
        target_dist.add(targetval)
        for attr in dataset.inputs:
            attr_dists[targetval, attr].add(example[attr])

#calculate the prior probability
print(target_dist[0]) #this is the probability of not getting loan
print(target_dist[1]) #this is the probability of getting loan
#print(attr_dists['setosa', 0][5.0])
```

```
[0.1189, 829.1, 11.35040654, 19.48, 737, 5639.958333, 28854, 52.1,
0, 0, 0, 0, 1]
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
0.19509394572025052
0.8049060542797495
```

calculating the evidence and liklihood

In [61]:
```
check = pd.read_csv('./aima-data/loan_data.csv',names=["rate","inst

def calculate_liklihood(target,col_name):
    return sum(check[check["credit.policy"] == target][col_name] /

cols = ["rate","installment","log.annual.inc","dti","fico","days.wi
target = [1, 0]


for i in target:
    for j in cols:
        print("\nThe column name : {} \ntarget : {} \nlikelihood pr

# sum(check[check["credit.policy"] == 1]['rate'] / check[check["cre
```

```
The column name : rate
target : 1
likelihood probablity of: 7710.000000000274
```

```
The column name : installment
target : 1
likelihood probablity of: 7710.000000000003

The column name : log.annual.inc
target : 1
likelihood probablity of: 7710.0000000000455

The column name : dti
target : 1
likelihood probablity of: 7710.000000000008

The column name : fico
target : 1

likelihood probablity of: 7710.0000000000455

The column name : days.with.cr.line
target : 1
likelihood probablity of: 7709.999999999998

The column name : revol.bal
target : 1
likelihood probablity of: 7709.999999999992

The column name : revol.util
target : 1
likelihood probablity of: 7709.9999999999645

The column name : inq.last.6mths
target : 1
likelihood probablity of: 7709.99999999977

The column name : delinq.2yrs
target : 1
likelihood probablity of: 7710.000000000062

The column name : pub.rec
target : 1
likelihood probablity of: 7709.999999999967

The column name : not.fully.paid
target : 1
likelihood probablity of: 7710.000000000214

The column name : rate
target : 0
likelihood probablity of: 1868.0000000000002

The column name : installment
target : 0
likelihood probablity of: 1867.9999999999964

The column name : log.annual.inc
```

```
target : 0
likelihood probablity of: 1868.0000000000136

The column name : dti
target : 0
likelihood probablity of: 1867.9999999999945

The column name : fico
target : 0
likelihood probablity of: 1868.000000000015

The column name : days.with.cr.line
target : 0
likelihood probablity of: 1867.999999999998


The column name : revol.bal
target : 0
likelihood probablity of: 1868.000000000001

The column name : revol.util
target : 0
likelihood probablity of: 1867.9999999999961

The column name : inq.last.6mths
target : 0
likelihood probablity of: 1868.0000000000155

The column name : delinq.2yrs
target : 0
likelihood probablity of: 1868.0000000000011

The column name : pub.rec
target : 0
likelihood probablity of: 1868.0000000000016

The column name : not.fully.paid
target : 0
likelihood probablity of: 1868.0000000000034
```

let's try to predict the label given some input features (Posterior probabilities)

In [62]:
```
def predict(example):
    def class_probability(targetval):
        return (target_dist[targetval] *
                product(attr_dists[targetval, attr][example[attr]]
                        for attr in dataset.inputs))
    return argmax(target_vals, key=class_probability)

#let's take the first row of the data and see if we can find the va
sample1=[0.1189,829.1,11.35040654,19.48,737,5639.958333,28854,52.1,
sample2=[0.1357,366.86,10.37349118,11.63,682,4710,3511,25.6,1,0,0,0
sample3=[0.1008,162.34,11.35040654,8.1,712,2699.958333,33667,73.2,1
print(predict(sample1))
```

```
1
```

Continuous

In the implementation we use the Gaussian/Normal distribution function. To make it work, we need to find the means and standard deviations of features for each class. We make use of the `find_means_and_deviations` Dataset function. On top of that, we will also calculate the class probabilities as we did with the Discrete approach.

In [63]:
```
psource(NaiveBayesDiscrete)
```

```
def NaiveBayesDiscrete(dataset):
    """Just count how many times each value of each input attribut
e
    occurs, conditional on the target value. Count the different
    target values too."""

    target_vals = dataset.values[dataset.target]
    target_dist = CountingProbDist(target_vals)
    attr_dists = {(gv, attr): CountingProbDist(dataset.values[attr
])
                  for gv in target_vals
                  for attr in dataset.inputs}
    for example in dataset.examples:
        targetval = example[dataset.target]
        target_dist.add(targetval)
        for attr in dataset.inputs:
            attr_dists[targetval, attr].add(example[attr])

    def predict(example):
        """Predict the target value for example. Consider each pos
sible value,
        and pick the most likely by looking at each attribute inde
pendently."""
        def class_probability(targetval):
            return (target_dist[targetval] *
                    product(attr_dists[targetval, attr][example[at
tr]]
                            for attr in dataset.inputs))
        return argmax(target_vals, key=class_probability)

    return predict
```

In [66]:
```
#in the last section we will explain the working of the multinomial

#multinomial Naive bayes
nBD = NaiveBayesLearner(loan, continuous=False)
print("Discrete Classifier")
print(nBD(sample1))
print(nBD(sample2))
print(nBD(sample3))

#gaussian naive bayes
#nBC = NaiveBayesLearner(loan, continuous=True)
print("\nContinuous Classifier")
#print(nBC(sample1))
#print(nBC(sample2))
#print(nBC(sample3))
```

```
Discrete Classifier
1
1
1

Continuous Classifier
```

Running the python code for naive bayes(execution phase)

on data 2-(Pokemon data)

using the same code we can generate prior, liklihood and evidence probabilities as seen in the above section for dataset 1(loan)

to make the code more compact and prevent the pdf from overshooting I will not calculate these probabilities for second dataset

In [67]:
```
from learning import *
from notebook import *
pokemon = DataSet(name="Pokemon")
print(loan.examples[0])
print(loan.inputs)

dataset = pokemon

target_vals = dataset.values[dataset.target]
target_dist = CountingProbDist(target_vals)
attr_dists = {(gv, attr): CountingProbDist(dataset.values[attr])
              for gv in target_vals
              for attr in dataset.inputs}
for example in dataset.examples:
        targetval = example[dataset.target]
        target_dist.add(targetval)
        for attr in dataset.inputs:
            attr_dists[targetval, attr].add(example[attr])

#calculate the prior probability
print(target_dist["True"]) #this is the probability of not getting
print(target_dist["False"]) #this is the probability of getting loa
#print(attr_dists['setosa', 0][5.0])
```

```
[0.1189, 829.1, 11.35040654, 19.48, 737, 5639.958333, 28854, 52.1,
0, 0, 0, 0, 1]
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
0.08208955223880597
0.9154228855721394
```

In [68]:
```
def predict(example):
    def class_probability(targetval):
        return (target_dist[targetval] *
                product(attr_dists[targetval, attr][example[attr]]
                        for attr in dataset.inputs))
    return argmax(target_vals, key=class_probability)

#let's take the first row of the data and see if we can find the va
sample1=[2,"Ivysaur","Grass","Poison",405,60,62,63,80,80,60,1] #act
sample2=[144,"Articuno","Ice","Flying",580,90,85,100,95,125,85,1] #
sample3=[146,"Moltres","Fire","Flying",580,90,100,90,125,85,90,1] #
print(predict(sample1))
```

```
False
```

In [70]:
```
#multinomial Naive bayes
nBD = NaiveBayesLearner(pokemon, continuous=False)
print("Discrete Classifier")
print(nBD(sample1))
print(nBD(sample2))
print(nBD(sample3))

#gaussian naive bayes
#nBC = NaiveBayesLearner(pokemon, continuous=True)
print("\nContinuous Classifier")
#print(nBC(sample1))
#print(nBC(sample2))
#print(nBC(sample3))
```

```
Discrete Classifier
False
True
True

Continuous Classifier
```

How to measure the performance of the model

As seen above that both the datasets are imbalnced meaning the positive number of samples are not equal to the negative number of samples

Hence the predicted label cannot be used with accuracy as the accuracy of a model always predicting no will also be high.

Thus in addition we include some extra measure such as the Confusion matrix and F1 score,

F1 score is a metric used when the dataset is heavily imbalanced as it is the harmonic mean between the precision and recall.

usually we split the data into 70/30 ratio before evaluating the score so that the training data does not participate in the testing phase, However when using the datasets with class imbalance we will not do that as the sample size of the minority class is very low

$$
\begin{aligned}
precision &= \frac{TP}{TP + FP} \\
recall &= \frac{TP}{TP + FN} \\
F1 &= \frac{2 \times precision \times recall}{precision + recall} \\
accuracy &= \frac{TP + TN}{TP + FN + TN + FP} \\
specificity &= \frac{TN}{TN + FP}
\end{aligned}
$$

how to infer Gaussian Naive bayes

we have already discussed the Multinomial Naive bayes in the explaination section

now I will explain the gaussian naive bayes

A gaussian naive bayes is used when we assume that our features roughly follow a gaussian distribution

The gaussian curve is a bell shaped function which occurs in many of the naturally occuring distributions such as height, weight etc

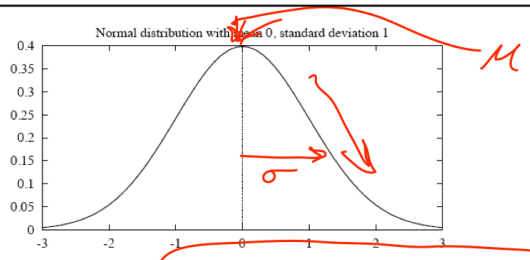
By this assumption we can scale the accuracy and see if the algorithm fits well to the given data

The gaussian function and the role of the function is provided below by using the lecture notes provided by Tom Mitchell a professor teaching concepts of machine learning in CMU in states

source=https://www.cs.cmu.edu/~epxing/Class/10701-10s/Lecture/lecture5.pdf (https://www.cs.cmu.edu/~epxing/Class/10701-10s/Lecture/lecture5.pdf)

Gaussian Distribution

(also known as "Normal" distribution)



$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$$

The probability that X will fall into the interval (a, b) is given by

$$\int_a^b p(x)dx$$

- Expected, or mean value of X, $E[X]$, is

$$E[X] = \mu$$

- Variance of X is

$$Var(X) = \sigma^2$$

- Standard deviation of X, σ_X, is

$$\sigma_X = \sigma$$

p(x) is a *probability density function*, whose integral (not sum) is 1

What if we have continuous X_i ?

Gaussian Naïve Bayes (GNB): assume

$$p(X_i = x | Y = y_k) = \frac{1}{\sqrt{2\pi\sigma_{ik}^2}} e^{-\frac{1}{2}(\frac{x-\mu_{ik}}{\sigma_{ik}})^2}$$

e.g. pixel intensity; discrete

Sometimes assume variance

- is independent of Y (i.e., σ_i),
- or independent of X_i (i.e., σ_k)
- or both (i.e., σ)

given $X_1 \cdots X_n$

how many params must we learn for Gaus. NBayes?

$2n \times 2 + 1$

prior on Y

!

Gaussian Naïve Bayes Algorithm – continuous X_i (but still discrete Y)

- Train Naïve Bayes (examples)
  for each value y_k
    estimate* $\pi_k \equiv P(Y = y_k)$
    for each attribute X_i estimate
    class conditional mean μ_{ik} , variance σ_{ik}

- Classify (X^{new})

$$Y^{new} \leftarrow \arg\max_{y_k} \; P(Y = y_k) \prod_i P(X_i^{new} | Y = y_k)$$ ✓ NB

$$Y^{new} \leftarrow \arg\max_{y_k} \; \pi_k \prod_i \mathcal{N}(X_i^{new}; \mu_{ik}, \sigma_{ik})$$ ← Normal = Gaussian ← GNB

* probabilities must sum to 1, so need estimate only n-1 parameters...

!

Type *Markdown* and LaTeX: α^2