This report contains all parts, please just read this report

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Part 1, Q1

Q1: 1. In order to compute the table of the joint distribution $P(X, Y, Z)$, we need to expand and simplify it first, then substitute corresponding value into it, so following is the step:

$P(X, Y, Z)$

Step 1: Use Product Rule: treat X, Y as the whole:

$\cancel{= P(X,Y) * P(Z|X,Y)}$

$= P(Z) \times P(X, Y|Z)$

Step 2: Use Bayes Rule:

$= \cancel{P(Z)} \times \frac{P(X,Y) \cdot P(Z|X,Y)}{\cancel{P(Z)}}$

Step 3: Since Z is $\boxed{\text{independent}}$ from X given Y, which is $\boxed{Z \perp X|Y}$, so, we can get: $\boxed{P(Z|X,Y) = P(Z|Y)}$ and $P(Z, X|Y) = P(Z|Y) \cdot P(X|Y)$, thus, by using ~~Indep~~ these, we can get:

$= P(X,Y) \cdot P(Z|X,Y)$ simplified from Step 2

$\cancel{= P(X,Y) = P(}$

$= P(X,Y) \cdot P(Z|Y)$: Use this formular

Step 4: Use Product Rule again:

$= P(X) \cdot P(Y|X) \cdot P(Z|Y)$

Finally, we got that $\boxed{P(X,Y,Z) = P(X) \cdot P(Y|X) \cdot P(Z|Y)}$

Next, subsitute corresponding values and ~~draw~~ get result and draw table.

By using the provided two conditional distribution, we get:

e.g. ~~P(X,Y,Z) = P(~~ $P(X=0, Y=0, Z=0)$

$= P(X=0) \times P(Y=0 \mid X=0) \times P(Z=0 \mid Y=0)$

$= 0.35 \times 0.10 \times 0.70$

$= 0.0245$

The above example shows how it's computed, in order for saving the space, I just draw the table below.

X	Y	Z	P(X,Y,Z) which is $P(X)\cdot P(Y \mid X)\cdot P(Z \mid Y)$
0	0	0	$0.0245 = 0.35 \times 0.1 \times 0.7$
0	0	1	$0.0105 = 0.35 \times 0.1 \times 0.3$
0	1	0	$0.063 = 0.35 \times 0.9 \times 0.2$
0	1	1	$0.252 = 0.35 \times 0.9 \times 0.8$
1	0	0	$0.273 = 0.65 \times 0.6 \times 0.7$
1	0	1	$0.117 = 0.65 \times 0.6 \times 0.3$
1	1	0	$0.052 = 0.65 \times 0.4 \times 0.2$
1	1	1	$0.208 = 0.65 \times 0.4 \times 0.8$

Q1, 2. $\boxed{P(X,Y) = P(X)\cdot P(Y \mid X) \text{ [Product Rule]}}$

$\therefore P(X=0, Y=0) = P(X=0)\cdot P(Y=0 \mid X=0)$

$= 0.35 \times 0.1$

$= 0.035$

$P(X=0, Y=1) = P(X=0)\cdot P(Y=1 \mid X=0)$

$= 0.35 \times 0.9$

$= 0.315$

$$P(X=1, Y=0) = P(X=1) \cdot P(Y=0 \mid X=1)$$
$$= 0.65 \times 0.6$$
$$= 0.39$$
$$P(X=1, Y=1) = P(X=1) \cdot P(Y=1 \mid X=1)$$
$$= 0.65 \times 0.40$$
$$= 0.26$$

The full joint probability table of X and Y $P(X, Y)$ is shown below:

X	Y	P(X, Y)
0	0	0.035
0	1	0.315
1	0	0.39
1	1	0.26

Q1 3a) $P(Z=0) = P(X=0, Y=0, Z=0) + P(X=0, Y=1, Z=0)$

Sum Rule $\cancel{[\text{Sum Rule}]} + P(X=1, Y=0, Z=0) + P(X=1, Y=1, Z=0)$

$= P(X=0) \times P(Y=0|X=0) \times P(Z=0|Y=0) +$

Formular from previous Question

$P(X=0) \times P(Y=1|X=0) \times P(Z=0|Y=1) +$

$P(X=1) \times P(Y=0|X=1) \times P(Z=0|Y=0) +$

$P(X=1) \times P(Y=1|X=1) \times P(Z=0|Y=1)$

$= 0.0245 + 0.063 + 0.273 + 0.052$

$P(Z=0) = 0.4125$

Q1, 3b) $P(X=0, Z=0)$

$= P(X=0, Y=0, Z=0) + P(X=0, Y=1, Z=0)$ Sum Rule

$= 0.0245 + 0.063$

$= 0.0875$

Q1 3c) $P(X=1, Y=0 | Z=1)$

$= \dfrac{P(X=1, Y=0) \cdot P(Z=1 | X=1, Y=0)}{P(Z=1)}$ Bayes Rule

$= \dfrac{P(X=1, Y=0) \cdot P(Z=1 | Y=0)}{1 - P(Z=0)}$ $\dfrac{\text{InDepedence}}{\text{Normalisation Rule}}$

$= \dfrac{P(X=1) \cdot P(Y=0 | X=1) \cdot 0.3}{1 - 0.4125}$ Product Rule

$= \dfrac{0.65 \times 0.6 \times 0.3}{0.5875}$ $\boxed{= \frac{234}{1175} \approx 0.1991}$

Q1,3 d) $P(X=0 \mid Y=0, Z=0)$

$$= \frac{P(X=0)\cdot P(Y=0, Z=0 \mid X=0)}{P(Y=0, Z=0)}$$ Bayes Rule

$$= \frac{P(X=0, Y=0, Z=0)}{P(Y=0)\cdot P(Z=0 \mid Y=0)}$$ Inverse use Product Rule

Product Rule

$$= \frac{P(X)\cdot P(Y \mid X)\cdot \cancel{P(Z \mid Y)}}{P(Y=0)\cdot \cancel{P(Z=0 \mid Y=0)}}$$ expand it

$$= \frac{P(X=0)\cdot P(Y=0 \mid X=0)}{P(X=0, Y=0, Z=0) + P(X=1, Y=0, Z=0) + P(X=1, Y=0, Z=1) + P(X=0, Y=0, Z=1)}$$ Sum Rule

$$= \frac{0.35 \times 0.1}{0.0245 + 0.273 + 0.117 + 0.0105}$$

$$\boxed{= \frac{0.035}{0.425} \approx 0.08235 = \frac{7}{85}}$$

Q2 i) $P(B,C) = P(B|C) \times P(C)$ Product Rule

$= 0.2 \times 0.4$

$= 0.08$

ii) $P(\neg A|B) = 1 - P(A|B)$ Normalisation Rule

$= 1 - 0.3$

$= 0.7$

~~iv) $P(A,B,C) =$~~

iii) $P(A,B|C) = P(A|C) \cdot P(B|C)$

$= 0.5 \times 0.2$

$= 0.1$

$\boxed{\text{Indepedence } A \perp B | C \quad P(A,B|C) \cancel{= P(A|C)} = P(A|C) \cdot P(B|C) \cancel{P(A|B)}}$

iv) $P(A|B,C) = P(A|C)$

$= 0.5$

$\boxed{\text{Independence } A \perp B | C \quad P(A|B,C) = P(A|C)}$

Q2 V) $P(A,B,C) = P(A) \cdot P(B,C|A)$ Product Rule

$= P(A) \cdot \frac{P(B,C) \times P(A|B,C)}{P(A)}$ Bayes Rule

$= P(B,C) \times P(A|C)$ Indepedence

$= P(C) \times P(B|C) \times P(A|C)$ Product

$= 0.4 \times 0.2 \times 0.5$

$= 0.04$

Q3 DragonflyDomain : { Common, Rare }, D=DragonFly

Step 1: ∵ 0.3% belongs to Rare Species, $\boxed{\therefore P(D=Rare)=0.003}$

And $\boxed{P(D=Common)=0.997}$, which is $1-P(D=Rare)=0.997$

Step 2: Then, 0.1% is mutation with extra wing, so, from this we can get : $\boxed{P(exWing \mid D=common)=0.001}$, which means the posterior/conditional probability that the dragonfly has extra set of wing given that the dragonfly belongs to the Common species is 0.001.

Step 3: Also, since All rare species DragonFly got extra Wing, which means the posterior probability that the dragonfly has extra set of wings given that it belongs to rare ~~is~~ specices is 1. it can be written as $\boxed{P(exWing \mid D=Rare)=1}$

Step 4: ~~This Question require us to calculate~~

This Question given us that the DragonFly:D has extra wings and require us to calculate the probability of this Dragonfly D belongs to Rare species, which is ~~R~~

$\boxed{P(D=Rare \mid exWing) = ?}$

Step 5: Bayes Rule

$$P(D=Rare \mid exWing) = \frac{P(D=Rare) \times P(exWing \mid D=Rare)}{P(exWing)}$$

~~Normalisation Rule~~ $\boxed{\text{Sum Rule}}$

$$= \frac{P(D=Rare) \times P(exWing \mid D=Rare)}{P(exWing, D=Rare) + P(exWing, \cancel{Comm} D=Common)}$$

Product Rule

$$= \frac{P(D=Rare) \times P(exWing \mid D=Rare)}{P(D=Rare) \times P(exWing \mid D=Rare) + P(D=Common) \times P(exWing \mid D=Common)}$$

$$= \frac{0.003 \times 1}{0.003 \times 1 + 0.997 \times 0.001}$$

Q3Ans $\boxed{= \frac{3000}{3997} \approx 0.7506}$

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PART 2:

1. The conditional probabilities P(Fi | C) for each feature i and each class label.

```
Printing the conditional_prob P(Fi|C)......
                P(F=1True | C=Spam)     P(F=0False | C=Spam)    P(F=1True | C=notSpam)  P(F=0False | C=notSpam)
Feature0        0.6730769230769231      0.3269230769230769      0.35333333333333333     0.6466666666666666
Feature1        0.5961538461538461      0.40384615384615385     0.5733333333333334      0.4266666666666667
Feature2        0.46153846153846156     0.5384615384615384      0.34    0.66
Feature3        0.6153846153846154      0.38461538461538464     0.3933333333333333      0.6066666666666667
Feature4        0.5     0.5     0.3333333333333333      0.6666666666666666
Feature5        0.36538461538461536     0.6346153846153846      0.4666666666666667      0.5333333333333333
Feature6        0.7884615384615384      0.21153846153846154     0.5     0.5
Feature7        0.7692307692307693      0.23076923076923078     0.3466666666666667      0.6533333333333333
Feature8        0.34615384615384615     0.6538461538461539      0.24    0.76
Feature9        0.6730769230769231      0.3269230769230769      0.2866666666666667      0.7133333333333334
Feature10       0.6730769230769231      0.3269230769230769      0.58    0.42
Feature11       0.7884615384615384      0.21153846153846154     0.3333333333333333      0.6666666666666666
Finish
```

The above screenshot shows the full table of the probability P(Fi | C), which is the likelihood.
It's the probability value of seeing the specified evidence(i.e. feature) if the hypothesis/proposition (classLabel C) is met. It limits the view to only focus on instances with the corresponding classLabel(e.g. C=Spam), it is the degree of belief that the feature evidence Fi with the given classLabel.

2. For each instance in the unlabelled set, given the input vector F = (f1, f2, . . . , f12), the probability P(C = 1, F) (enumerator of P(C = 1|F), score of spam), the probability P(C = 0, F) (enumerator of P(C = 0|F), score of non-spam), and the predicted class of the input vector.

Below screenshots shows each unlabelled instances and its corresponding P(Class=Spam, F) P(Class=notSpam, F), the score of spam, the score of notSpam.
By comparing the score of spam and the score of not spam, classify and predict the instance as the class with the higher score.
The result of my algorithm predict and classify Email{ 2 3 6 9 } as spam emails And Email{ 1 4 5 7 8 10 } as Not spam emails.

The content from below screenshots can also be seen via sampleout_part2.txt, also if you run my java program in the terminal with the java -jar command, you can also see it from there.

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```
Unlabelled emails:
        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        2.8203300896645487E-6
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        4.6460111808235214E-4
By comparing, we can get:
        NotSpam is higher
So, 1th email is classify as notSpam email.

        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        5.419093286372265E-5
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        4.047343858358765E-5
By comparing, we can get:
        Spam is higher
So, 2th email is classify as spam email.

        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        1.9214758874882057E-4
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        1.2245217568518894E-4
By comparing, we can get:
        Spam is higher
So, 3th email is classify as spam email.
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        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        4.694895352268654E-6
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        6.137559386555346E-4
By comparing, we can get:
        NotSpam is higher
So, 4th email is classify as notSpam email.

        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        6.183611426537248E-5
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        8.76882105542243E-5
By comparing, we can get:
        NotSpam is higher
So, 5th email is classify as notSpam email.

        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        6.11086305681328E-5
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        4.305853373976855E-5
By comparing, we can get:
        Spam is higher
So, 6th email is classify as spam email.
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        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        3.0932652596320864E-6
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        3.357645998846445 7E-4
By comparing, we can get:
        NotSpam is higher
So, 7th email is classify as notSpam email.

        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        6.269057693522123E-5
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        3.8065842127886084E-4
By comparing, we can get:
        NotSpam is higher
So, 8th email is classify as notSpam email.

        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        1.9214758874882057E-4
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        3.5634648612222245E-5
By comparing, we can get:
        Spam is higher
So, 9th email is classify as spam email.
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        The posterior prob with P(C=spam | allFeatures), which is only the numerator value:
                P(C=Spam, allFeatures) (aka P(C=Spam) * P(C=Spam | allFeatures)) is:
                        1.9355206497697885E-5
        The posterior prob with P(C=noSpam | allFeatures), which is only the numerator value:
                P(C=noSpam, allFeatures): (aka P(C=noSpam) * P(C=noSpam | allFeatures) ) is:
                        6.808731643033888E-4
By comparing, we can get:
        NotSpam is higher
So, 10th email is classify as notSpam email.

Totally, we have 4 spam emails:which are Email{ 2  3  6  9 }
        And 6 notSpam emails:which are Email{ 1  4  5  7  8  10 }
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3. The derivation of the Naive Bayes algorithm assumes that the attributes are conditionally independent. Why is this like to be an invalid assumption for the spam data? Discuss the possible effect of two attributes not being conditionally independent

It is likely to be an invalid assumption for the spam data because the zero probability may occur. Due to the assumption, the numerator of the posterior can be computed as P(Class) * all the likelihood (i.e. P(feature1 | Class) *P(feat2 | Class) *...*P(feat12 | Class)), so if one of the feature's likelihood is 0, the posterior will be 0 and will lead the prediction of the new instance to be not-spam email. ***However****, that particular feature has never occurred for the spam data during the training on labelled email set doesn't mean it will never* *occur forever in the future or other unseen instances, so the probability should be highly very low rather than purely 0(i.e. impossible), therefore, the assumption of the naive Bayes is like to be an invalid for the spam data.*

Discuss the possible effect of two attributes not being conditionally independent.

Not conditionally independent means we have to compute the posterior based on P(Class) * P(att1,...,att12 | Class) not the simple P(Class) * P(att1 |Class) *... * P(att11 | Class)* P(att12 | Class).
Therefore, the possible effect can be the posterior probability is hard to be measured since the training samples are not big enough, which will cause the classification prediction to be incorrect, which means this algorithm can not be very useful and be applied in many areas.

Part 3: Building Bayesian Network

This part is to build a Bayesian Network for the problem described below.

Problem Description

Dr. Rachel Nicholson is a Professor, who lives far away from her university. So, she prefer to work at home and she only comes to her office if she has research meetings with her postgraduate students, or teaching lectures for undergraduate students, or she has both meetings and teaching:

- The probability for Rachel to have meetings is 70%, the probability of Rachel has lectures is 60%.
- If Rachel has both meetings and lectures, the probability of Rachel comes to her office is 95%.
- If Rachel only has meetings (without lectures), the probability of Rachel comes to her office is 75% because she can Skype with her students.

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- If Rachel only has lectures (without meetings), the probability of Rachel comes to her office is 80%.
- If Rachel has neither meetings nor lectures, there is a only 6% chance that she comes to the office.
- When Rachel is in her office, half the time her light is off (when she is trying to hide from others to get work done quickly).
- When she is not in her office, she leaves her light on only 2% of the time since the cleaners come for cleaning.
- When Rachel is in her office, 80% of the time she logged onto the computer.
- Because she sometimes work from home, 20% of the time she is not in her office, she is still logged onto the computer.

Note regarding the calculation, you should show your *working process* of the calculation to demonstrate that you *know how to calculate* them.

1. Construct a Bayesian network to represent the above scenario. (Hint: First decide what your domain variables are; these will be your network nodes. Then decide what the causal relationships are between the domain variables and add directed arcs in the network from cause to effect. Finally, you have to add the prior probabilities for nodes without parents, and the conditional probabilities for nodes that have parents.)

Domain Variables: {Meetings, Lectures, Office, Light, Computer}
By looking at the problem description, the causal relation ship should be:
{ P(Office | meeting,lecture), P(Light | Office) , P(Computer | Office) }

Within use the normalisation Rule based on the description bullet point above, we can get the full table of the conditional probability and the prior of P(Lecture) and P(Meeting), which are all attached on my graph.
The graph is shown below:

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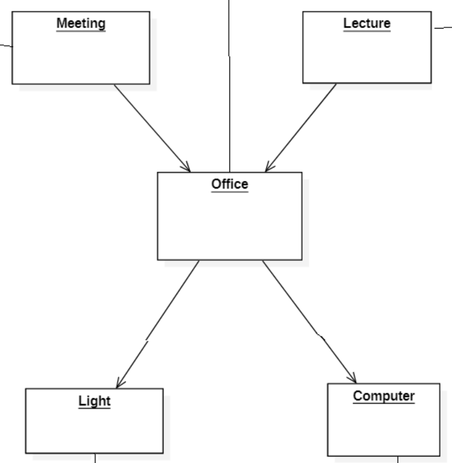
Office	Meeting	Lecture	P(Office | meeting,lecture)
true	true	true	0.95
false	true	true	0.05
true	true	false	0.75
false	true	false	0.25
true	false	true	0.8
false	false	true	0.2
true	false	false	0.06
false	false	false	0.94

Meeting	P(Meeting)
true	0.7
false	0.3

Lecture	P(Lecture)
true	0.6
false	0.4



Light	Office	P(Light | Office)
off	true	0.5
on	true	0.5
on	false	0.02
off	false	0.98

Computer	Office	P(Computer | Office)
logon	true	0.8
logoff	true	0.2
logon	false	0.2
logoff	false	0.8

2. Calculate how many free parameters in your Bayesian network ?

Using M to represent Meetings, Le to Lectures, O to Office, Li to Light, And C to Computer

My free parameters are shown in the graph below:

2. $$\left(|M|-1+|Le|-1+|M|\times|Le|\times(|O|-1)\right)+\left(|O|-1+|O|\times(|Li|-1)+|O|\times(|C|-1)\right)$$
$$=(2-1+2-1+2\times2\times(2-1))+(2-1+2\times(2-1)+2\times(2-1))$$
$$=(1+1+4)+(1+2+2)$$
$$=11$$

The number is 11

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3. What is the joint probability that Rachel has lectures, has no meetings, she is in her office and logged on her computer but with lights off

3. P(lec=True, Meet=False, Office=True, Computer=logOn, Light=off)

With in use the formular on lec1b slide, I know that for BN structure's joint prob (factorisation) can be factorize as: $P(X_1, \dots X_m) = \prod_i P(X_i \mid Parents(X_i))$

So, for our formular, it's equals to:

$= P(Le=True) \cdot P(M=False) \cdot \cancel{P(O)}\ P(O=True \mid M=False, Le=True) \times P(Li=Off \mid Office=True) \cdot P(C=logOn \mid O=True)$

$= 0.6 \times 0.3 \times \cancel{0.25}\ 0.8 \times 0.5 \times 0.8$

$= 0.0576$

We can see that the probability is 0.0576

4. Calculate the probability that Rachel is in the office.

4 P(Office = True) T: True, F: False

Normalisation Rule, on Parents

1 $= P(O=True, M=T, Le=T) + P(O=T, M=T, Le=F) + P(O=T, M=F, Le=T) + P(O=T, M=F, Le=F)$

Product Rule

2 $= P(O=T \mid M=T, Le=T) \cdot P(M=T, Le=T) + P(M=T, Le=F) \times P(O=T \mid M=T, Le=F) + P(O=T \mid M=F, Le=T) \cdot P(M=F, Le=T) + P(M=F, Le=F) \cdot P(O=T \mid M=F, Le=F)$

3 $= P(O=T \mid M=T, Le=T) \cdot P(M=T) \cdot P(Le=T) + P(M=T) \cdot P(Le=F) \cdot P(O=T \mid M=T, Le=F) + P(O=T \mid M=F, Le=T) \cdot P(M=F) \cdot P(Le=T) + P(M=F) \cdot P(Le=F) \cdot P(O=T \mid M=F, Le=F)$

Meeting and Lecture are independent, so P(M)P(Le) = P(M, Le)

4 $= (0.95 \times 0.7 \times 0.6) + (0.7 \times 0.4 \times 0.75) + (0.8 \times 0.3 \times 0.6) + \cancel{(0.06 \times 0.3 \times 0.6)} + (0.3 \times 0.4 \times 0.06)$

5 $= \cancel{0.399 + 0.21 + 0.144 + 0.0072}$

$\boxed{= 0.7602}$

By using the normalisation rule on the office' parents, and then apply the product rule, and then use independence

P(Meeting) * P(Lecture) = P(Meeting, Lecture)since Meeting and Lecture are independent.

We can get: the probability of P(Office = true) = 0.7602

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5. If Rachel is in the office, what is the probability that she is logged on, but her light is off.

Since Rachel is already in the office, which is the effect is given. Therefore, we need to calculate:

P(Computer=logOn, Light=off|Office = True)

= P(Computer=logOn|Office = True)*P(Light=off | Office=True)

Computer is independent from Light given Office

= 0.8 * 0.5

= 0.4

The probability is 0.4

6. Suppose a student checks Rachel's login status and sees that she is logged on. What effect does this have on the student's belief that Rachel's light is on ?

From this question description, we can see that 2 variables are Computer and the light, but from my graph, we can see that Computer and the Light are independent, which means the login status of Computer does not affect the light status, so I think there will be no effect.