



KIET Group of Institutions, Ghaziabad

Department of Computer Applications

(An ISO – 9001: 2015 Certified & 'A' Grade accredited Institution by NAAC)

Artificial Intelligence Lab

KCA 351: Session 2021-22

Experiment – No-8

1.Problem Statement : Write a program to demonstrate the working of Bayesian network using heart disease dataset "<https://archive.ics.uci.edu/ml/machine-learning-databases/heart-disease/processed.cleveland.data>". Calculate the probability of model =

BayesianModel([("A","B"),("B","C"),("C","RESULT")]) while considering the following 14 attributes

- A. #3 (age)
- B. #4 (sex)
- C. #9 (cp)
- D. #10 (trestbps)
- E. #12 (chol)
- F. #16 (fbs)
- G. #19 (restecg)
- H. #32 (thalach)
- I. #38 (exang)
- J. #40 (oldpeak)
- K. #41 (slope)
- L. #44 (ca)
- M. #51 (thal)
- N. #58 (num) (the predicted attribute)



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Program:

```
import numpy as np
import pandas as pd
import csv
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.models import BayesianModel
from pgmpy.inference import VariableElimination

heartDisease = pd.read_csv('heart.csv')
heartDisease = heartDisease.replace('?', np.nan)

print('Sample instances from the dataset are given below')
print(heartDisease.head())

print('\n Attributes and datatypes')
print(heartDisease.dtypes)

model= BayesianModel([('age', 'heartdisease'), ('sex', 'heartdisease'), ('exan
g', 'heartdisease'), ('cp', 'heartdisease'), ('heartdisease', 'restecg'), ('hear
tdisease', 'chol')])
print('\n Learning CPD using Maximum likelihood estimators')
model.fit(heartDisease, estimator=MaximumLikelihoodEstimator)

print('\n Inferencing with Bayesian Network:')
HeartDiseasetest_infer = VariableElimination(model)

print('\n 1. Probability of HeartDisease given evidence= restecg')
q1=HeartDiseasetest_infer.query(variables=['heartdisease'], evidence={'rest
ecg':1})
print(q1)

print('\n 2. Probability of HeartDisease given evidence= cp ')
q2=HeartDiseasetest_infer.query(variables=['heartdisease'], evidence={'cp':
2})
print(q2)
```



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Output :

Learning CPD using Maximum likelihood estimators

Inferencing with Bayesian Network:

1. Probability of HeartDisease given evidence= restecg

heartdisease	phi(heartdisease)
heartdisease(0)	0.1012
heartdisease(1)	0.0000
heartdisease(2)	0.2392
heartdisease(3)	0.2015
heartdisease(4)	0.4581

2. Probability of HeartDisease given evidence= cp

heartdisease	phi(heartdisease)
heartdisease(0)	0.3610
heartdisease(1)	0.2159
heartdisease(2)	0.1373
heartdisease(3)	0.1537
heartdisease(4)	0.1321



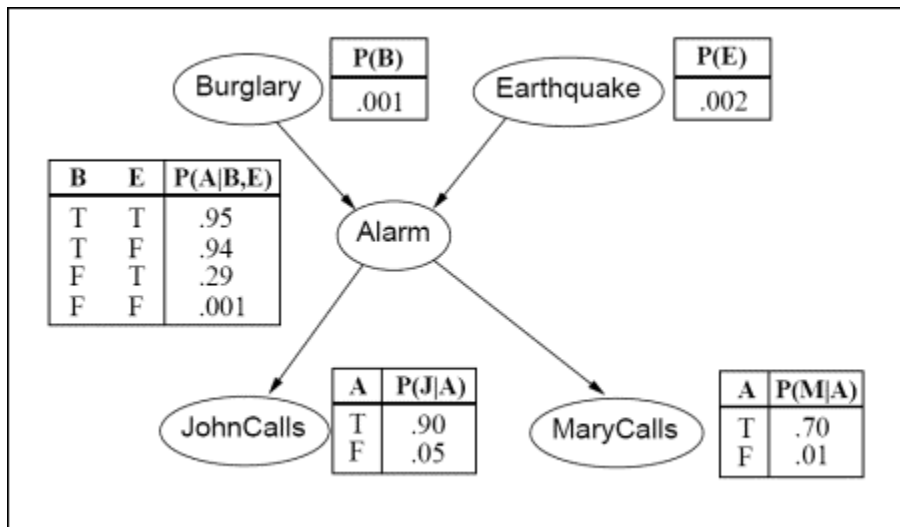
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2.Problem Statement : Write a program to demonstrate the working of Bayesian network for the following graph:



- Calculate the probability of a burglary if John and Mary calls (0: True, 1: False)
- Calculate the probability of alarm starting if there is a burglary and an earthquake (0: True, 1: False)

Calculate the probability of alarm starting if there is a burglary and an earthquake (0: True, 1: False)



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Program:

```
pip install pgmpy
import pgmpy. inference
import pgmpy. models
import networkx as nx
import pylab as plt
model = pgmpy. models . BayesianNetwork ((( ' Burglary ' , 'Alarm ' ) , ( '
    Earthquake ' , 'Alarm ' ) ,
                                           ( 'Alarm ' , ' JohnCalls ' ) , (
'Alarm ' , 'MaryCalls ' ) ] )
# Define conditional probability distributions (CPD)
# Probability of burglary (True , False )
cpd burglary = pgmpy. factors . discrete .TabularCPD(" Burglary " , 2 , [[
0.001] , [0.999]])
# Probability of earthquake (True , False )
cpd earthquake = pgmpy. factors . discrete .TabularCPD("Earthquake" , 2 ,
[[0.002] , [0.998]])
# Probability of alarm going of (True , False ) given a burglary and/or ea
rthquake
cpd alarm = pgmpy. factors . discrete .TabularCPD( 'Alarm ' , 2 , [[0.95 ,
    0.94 , 0.29 , 0.001] , [0.05 , 0.06 , 0.71 , 0.999]] ,
                                           evidence =['Burglary ' ,
'Earthquake '] , evidence card =[2, 2])
# Probability that John calls (True , False ) given that the alarm has sou
nded
cpd john = pgmpy. factors . discrete .TabularCPD( ' JohnCalls ' , 2 , [[0.
90 , 0.05] , [0.10 , 0.95]] , evidence =['Alarm '] , evidence card =[2])
# Probability that Mary calls (True , False ) given that the alarm has sou
nded
cpd mary = pgmpy. factors . discrete .TabularCPD( ' MaryCalls ' , 2 , [[0.
70 , 0.01] , [0.30 , 0.99]] , evidence =['Alarm '] , evidence card =[2])
# Add CPDs to the network structure
model . add cpds ( cpd burglary , cpd earthquake , cpd alarm , cpd john ,
cpd mary)
# Check i f the model is valid , throw an exception otherwise
model . check model ()
# Print probability distributions
print ( ' Probability distribution , P( Burglary ) ')
print ( cpd burglary )
print ()
```



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```
print ( ' Probability distribution , P(Earthquake ) ' )
print ( cpd earthquake )
print ( )
print ( ' Joint probability distribution , P(Alarm | Burglary , Earthquake
) ' )
print ( cpd alarm )
print ( )
print ( ' Joint probability distribution , P( JohnCalls | Alarm) ' )
print ( cpd john )
print ( )
print ( ' Joint probability distribution , P(MaryCalls | Alarm) ' )
print (cpd mary) print ( ) # Plot the model
nx. draw(model , with labels=True) plt . savefig ( ' alarm1 .png ' ) plt .
close ( )
# Perform variable elimination for inference
# Variable elimination (VE) is a an exact inference algorithm in bayesian
networks
infer = pgmpy. inference . VariableElimination (model)
# Calculate the probability of a burglary i f John and Mary calls (0: True
, 1: False )
posterior probability = infer . query ([ ' Burglary ' ] , evidence={'JohnCa
lls ' : 0 , 'MaryCalls ' : 0})
# Print posterior probability
print ( ' Posterior probability of Burglary i f JohnCalls (True) and MaryC
alls(True) ' )
print ( posterior probability )
print ( )
# Calculate the probability of alarm starting i f there is a burglary and
an earthquake (0: True , 1: False )
posterior probability = infer . query ([ ' Alarm ' ] , evidence= { ' Burglar
y ' : 0 , 'Earthquake ' : 0})
# Print posterior probability
print ( ' Posterior probability of Alarm sounding i f Burglary (True) and
Earthquake(True) ' )
print ( posterior probability )
print ( )
```



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Output :

Probability distribution, P(Burglary)

Burglary(0)	0.001
Burglary(1)	0.999

Probability distribution, P(Earthquake)

Earthquake(0)	0.002
Earthquake(1)	0.998

Joint probability distribution, P(Alarm | Burglary, Earthquake)

Burglary	Burglary(0)	Burglary(0)	Burglary(1)	Burglary(1)
Earthquake	Earthquake(0)	Earthquake(1)	Earthquake(0)	Earthquake(1)
Alarm(0)	0.95	0.94	0.29	0.001
Alarm(1)	0.05	0.06	0.71	0.999

Joint probability distribution, P(JohnCalls | Alarm)

Alarm	Alarm(0)	Alarm(1)
JohnCalls(0)	0.9	0.05
JohnCalls(1)	0.1	0.95

Joint probability distribution, P(MaryCalls | Alarm)

Alarm	Alarm(0)	Alarm(1)
MaryCalls(0)	0.7	0.01
MaryCalls(1)	0.3	0.99

Posterior probability of Burglary if JohnCalls(True) and MaryCalls(True)

Burglary	phi(Burglary)
Burglary(0)	0.2842
Burglary(1)	0.7158

Finding Elimination Order: : 0/0 [00:00<?, ?it/s]

0/0 [00:00<?, ?it/s]

Posterior probability of Alarm sounding if Burglary(True) and Earthquake(True)

Alarm	phi(Alarm)
Alarm(0)	0.9500
Alarm(1)	0.0500