## Q1. Implement the given three questions of hidden markov model, on the basis of given information in the table and figure.

	Tomorrow's weather									
Today's weather	樂	<del>@</del>								
秦	0.8	0.05	0.15							
<del>@</del>	0.2	0.6	0.2							
•	0.2	0.3	0.5							

Table 1: Probabilities  $p(q_{n+1}|q_n)$  of tomorrow's weather based on today's weather

- 1. Given that today the weather is ♣, what's the probability that tomorrow is ♣ and the day after is ♠?
- 2. Assume, the weather yesterday was  $q_1 = \Re$ , and today it is  $q_2 = \Re$ , what is the probability that tomorrow it will be  $q_3 = \Re$ ?
- 3. Given that the weather today is  $q_1 = \bigcirc$ , what is the probability that it will be  $\bigcirc$  two days from now:  $q_3 = \bigcirc$ . (Hint: There are several ways to get from  $\bigcirc$  today to  $\bigcirc$  two days from now. You have to sum over these paths.)

## In [ ]:

```
import numpy as np
import pandas as pd
hidden states = ['Sunny', 'Rainy', 'Foggy']
a df = pd.DataFrame(columns=hidden states, index=hidden states)
a df.loc[hidden states[0]] = [0.8, 0.05, 0.15]
a df.loc[hidden states[1]] = [0.2, 0.6, 0.2]
a_df.loc[hidden_states[2]] = [0.2, 0.3, 0.5]
print("\n HMM matrix:\n", a df)
a_df_val = a_df.values
a df index=a df.index;
index=[0,1,2]
index dict={}
for key in a df index:
   for value in index:
        index dict[key]=value
        index.remove(value)
       break
# print(a df val)
# print(a df ind)
# print(index_dict)
seq = input('Enter the sequence: ').split()
prob till now = 1
for i in range(1,len(seq)):
   prob_till_now *= a_df_val[index_dict[seq[i-1]]][index_dict[seq[i]]]
   if i%10==1:
        print("prob of having ",seq[i]," on ", i , "st day is ",prob_till_now)
    elif i%10==2:
        print("prob of having ",seq[i]," on ", i , "nd day is ",prob till now)
```

```
elif i%10==3:
       print("prob of having ",seq[i]," on ", i , "rd day is ",prob_till_now)
        print("prob of having ",seq[i]," on ", i , "th day is ",prob till now)
print("final prob :",prob till now)
print("Yesterday was cloudy, today is foggy, the probability that tomorrow is sunny = {0}
".format(a df val[index dict['Foggy']][index dict['Sunny']]))
p1 = a df val[index dict['Rainy']][index dict['Sunny']]*a df val[index dict['Sunny']][in
dex dict['Foggy']]
p2 = a df val[index dict['Rainy']][index dict['Rainy']]*a df val[index dict['Rainy']][in
dex dict['Foggy']]
p3 = a df val[index dict['Rainy']][index dict['Foggy']]*a df val[index dict['Foggy']][in
dex dict['Foggy']]
print("Today = Rainy, Probabilty that day after tomorrow it rains = {0}".format(p1+p2+p3
) )
 HMM matrix:
       Sunny Rainy Foggy
       0.8 0.05 0.15
Sunny
Rainy
       0.2
             0.6
                   0.2
       0.2
            0.3
                    0.5
Foggy
Enter the sequence: Sunny Sunny Rainy
prob of having Sunny on 1 st day is
                                       0.8
prob of having Rainy on 2 nd day is 0.0400000000000001
final prob : 0.04000000000000001
Yesterday was cloudy, today is foggy, the probability that tomorrow is sunny = 0.2
Today = Rainy, Probabilty that day after tomorrow it rains = 0.25
```

## Q3. Write a program to construct a Bayesian network

```
considering medical data. Use this model to demonstrate the
diagnosis of heart patients using standard Heart Disease Data
Set.
In [ ]:
pip install pgmpy
Collecting pgmpy
 Downloading https://files.pythonhosted.org/packages/06/19/d508949e8ac7b32e639f15e854a5f
5ed710a4118e4f6692bddaccc390d88/pgmpy-0.1.13-py3-none-any.whl (324kB)
                                     | 327kB 6.8MB/s
Requirement already satisfied: pyparsing in /usr/local/lib/python3.7/dist-packages (from
pgmpy) (2.4.7)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-packages (fr
om pgmpy) (0.22.2.post1)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from pgmp
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages (from pgm
py) (1.1.5)
Requirement already satisfied: statsmodels in /usr/local/lib/python3.7/dist-packages (fro
m pgmpy) (0.10.2)
Requirement already satisfied: joblib in /usr/local/lib/python3.7/dist-packages (from pgm
py) (1.0.1)
Requirement already satisfied: networkx in /usr/local/lib/python3.7/dist-packages (from p
gmpy) (2.5)
Requirement already satisfied: torch in /usr/local/lib/python3.7/dist-packages (from pgmp
y) (1.7.1+cu101)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from pgmp
y) (1.19.5)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from pgmpy
(4.41.1)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-pa
ckages (from pandas->pgmpy) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (fr
om pandas->pgmpy) (2018.9)
Requirement already satisfied: patsy>=0.4.0 in /usr/local/lib/python3.7/dist-packages (fr
```

```
om statsmodels->pgmpy) (0.5.1)
Requirement already satisfied: decorator>=4.3.0 in /usr/local/lib/python3.7/dist-packages
(from networkx->pgmpy) (4.4.2)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-package
s (from torch->pgmpy) (3.7.4.3)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from p
ython-dateutil>=2.7.3->pandas->pgmpy) (1.15.0)
Installing collected packages: pgmpy
Successfully installed pgmpy-0.1.13
In [ ]:
import numpy as np
import csv
import pandas as pd
from pgmpy.models import BayesianModel
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.inference import VariableElimination
heartDisease = pd.read csv('heart.csv')
heartDisease = heartDisease.replace('?',np.nan)
model = BayesianModel([('age', 'trestbps'),
                       ('age','fbs'),
                       ('sex', 'trestbps'),
                       ('exang', 'trestbps'),
                       ('trestbps', 'target'),
                       ('fbs','target'),
                       ('target', 'restecg'),
                       ('target','thalach'),
                       ('target', 'chol')])
print('Learning CPD using Maximum Likelihood Estimators....')
model.fit(heartDisease, estimator=MaximumLikelihoodEstimator)
print('\n Inferencing with Bayesian Network....')
HeartDisease infer = VariableElimination(model)
print("\nModel is ready...\n")
model.local independencies(['age','sex','trestbps','chol','fbs','restecg','thalach','exan
g','target'])
Learning CPD using Maximum Likelihood Estimators....
 Inferencing with Bayesian Network....
Model is ready...
Out[]:
(age _|_ exang, sex)
(sex _|_ exang, fbs, age)
(trestbps _|_ fbs | exang, age, sex)
(chol | exang, age, trestbps, fbs, sex, restecg, thalach | target)
(fbs _|_ exang, sex, trestbps | age)
(restecg | exang, age, chol, trestbps, fbs, sex, thalach | target)
(thalach _{-}|_ exang, age, chol, trestbps, fbs, sex, restecg | target)
(exang _|_ fbs, age, sex)
(target | exang, age, sex | fbs, trestbps)
In [ ]:
print('\n 1. Probability of Heart Disease given Age=28')
q=HeartDisease infer.query(variables=['target'],evidence={'age':28})
print(q)
print('\n 2. Probability of Heart Disease given cholesterol = 350 and trestbps = 120')
q=HeartDisease infer.query(variables=['target'],evidence={'chol':300,'trestbps':120})
print(q)
print('\n 3. Probability of Heart Disease given age = 35 and sex = male and restecg = 1')
q=HeartDisease infer.query(variables=['target'],evidence={'age':35,'sex':0,'restecg':1})
print(q)
```

```
print('\n 3. Probabilities of Heart Disease and restecg, given age = 35 and sex = female'
q=HeartDisease infer.query(variables=['target','restecg'],evidence={'age':35,'sex':1})
/usr/local/lib/python3.7/dist-packages/pgmpy/factors/discrete/DiscreteFactor.py:519: User
Warning: Found unknown state name. Trying to switch to using all state names as state num
bers
 "Found unknown state name. Trying to switch to using all state names as state numbers"
Finding Elimination Order: : 100%| 7/7 [00:00<00:00, 1518.81it/s]
Eliminating: thalach: 100%| 7/7 [00:00<00:00, 214.44it/s]
Finding Elimination Order: : 100%| | 6/6 [00:00<00:00, 1438.29it/s]
                  | 0/6 [00:00<?, ?it/s]
Eliminating: age: 0%|
1. Probability of Heart Disease given Age=28
+----+
| target | phi(target) |
+=====+
| target(0) | 0.4058 |
+----+
| target(1) | 0.5942 |
+----+
2. Probability of Heart Disease given cholesterol = 350 and trestbps = 120
Eliminating: thalach: 100%| 6/6 [00:00<00:00, 205.80it/s]
Finding Elimination Order: : 100\%| : 5/5 [00:00<00:00, 1620 Eliminating: thalach: 100\%| | 5/5 [00:00<00:00, 225.12it/s]
                           | 5/5 [00:00<00:00, 1620.55it/s]
                           | 5/5 [00:00<00:00, 1218.85it/s]
Finding Elimination Order: : 100%|
Eliminating: thalach: 100%| 5/5 [00:00<00:00, 252.39it/s]
+----+
| target | phi(target) |
+======+====++
| target(0) | 1.0000 |
+----+
| target(1) | 0.0000 |
3. Probability of Heart Disease given age = 35 and sex = male and restecg = 1
| target | phi(target) |
+=====++=====++
| target(0) | 0.1580 |
+----+
| target(1) | 0.8420 |
+----+
3. Probabilities of Heart Disease and restecg, given age = 35 and sex = female
+----+
| target | restecg | phi(target, restecg) |
| target(0) | restecg(0) | 0.1805 |
+----+
| target(0) | restecg(1) |
+----+
| target(0) | restecg(2) |
                              0.0069 |
+----+
| target(1) | restecg(0) |
                              0.2822 |
+----+
| target(1) | restecg(1) |
                              0.3983 |
+----+
| target(1) | restecg(2) |
                              0.0041 |
+----+
```

Q2. Write a program to construct a Bayesian network for Tumor Type Classification for the attached leukemia samples dataset, and You need to classify leukemia samples into two classes based on gene expression patterns using Bayesian networks.

```
In [ ]:
import numpy
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
from sklearn.naive bayes import GaussianNB
from sklearn.metrics import confusion matrix, accuracy score, classification report
In [ ]:
train df=pd.read csv('/content/data set ALL AML train.csv')
test df=pd.read csv('/content/data set ALL AML independent.csv')
y=pd.read csv('/content/actual.csv')
In [ ]:
print(train df.shape)
print(test df.shape)
print(y.shape)
(7129, 78)
(7129, 70)
(72, 2)
In [ ]:
test df.head(3)
Out[]:
                 Gene
        Gene
              Accession
                               40 call.1 42 call.2 47 call.3 48 call.4 49 call.5 41 call.6 43 call.7 44 call.6
   Description
               Number
   AFFX-BioB-
         5 at
                 AFFX-
                            A -87
                                         22
   (endogenous BioB-5 at 342
      control)
   AFFX-BioB-
                 AFFX-
        M_at
                 BioB-
                                                                                            A -74
                               248
  (endogenous
                      200
                 M at
      control)
   AFFX-BioB-
         3_at
                 AFFX-
                                                                                            A 170
                            A 262
                                        17
                                               A 163
                                                        A -28
  (endogenous BioB-3_at
      control)
In [ ]:
train df.head(3)
Out[]:
```

Gene

Gene .

	Description	Accession Number	1	call	2	call.1	1 3	s cai	1.2	4 (	call.3	5	call.4		p C	ali.5	1	call.6	8	call.	./	y
	Gene Description AFFX-BioB-	Accession Number	_1	call	2	call.1	<del>3</del>	3 cal	1.2	4 (	all.3	5_	call.4		6_c	all.5	7	call.6	8	call.	7	9
0	5_at (endogenous control)	AFFX- BioB-5_at	214	Α	139	Α	A -76	3	Α .	- 135	Α	106	Δ	13	8	A	-72	Α	413	,	A	5
	AFFX-BioB-	A = = \( \tau \)																				
1	M_at (endogenous control)	AFFX- BioB- M_at		A	-73	A	A -49	•	Α .	- 114	A	- 125	A	<b>8</b>	<b>3</b> 5	A	- 144	Α	- 260	4	A 1	- 127
	AFFX-BioB-																					
2	3_at (endogenous control)	AFFX- BioB-3_at	-58	Α	-1	A	307	- 7	Α 2	265	Α	-76	A	21	5	A	238	Α	7	4	A 1	06
4																						<u> </u>
In	[]:																					
у.	head(3)																					
Ou	t[]:																					
	patient cance	er																				
0	1 AL	L																				
1	2 AL	.L																				
2	3 AL	.L																				
In	[]:																					
у[	'cancer'].	value_co	unts	3 ()																		
Ou	t[]:																					
	L 47 L 25 me: cancer	, dtype:	int	:64																		
rer	move cols wi	th 'call'																				
In	[]:																					
	ls = [col	for col	in t	test	df.	colı	ımns	if	' Cā	all'	in	coll										
te	st_df = te ls = [col	st_df.dr	op (d	cols	_ , 1)	)																
	ain_df = t						_ umm	S II	C	all	. TU	COI	- ]									
Ιn	[]:																					
	ain df.hea	d(3)																				
	t[]:	· - /																				
	Gene Description	Gene Accession Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	2
	AFFX-BioB-	, ==:																				
0	5_at (endogenous control)	AFFX- BioB-5_at	214	139	-76	135	106	138	-72	413	5	-88	- 165	- 67	-92	113	107	- 117	476	-81	-44	. 1
1	AFFX-BioB- M_at (endogenous	AFFX- BioB- M_at	- 153	-73	-49	- 114	- 125	-85	- 144	- 260	- 127	- 105	- 155	- 93	- 119	- 147	-72	- 219	- 213	- 150	-51	22
	control)																					
	AFFX-BioB- 3_at	AFFX-				265																

```
Gene
         Gene
merge train test data into a single df for easier preprocessing
In [ ]:
patients = [str(i) for i in range(1, 73, 1)]
X = pd.concat([train df, test df], axis = 1)[patients]
In [ ]:
X=X.T
convert 'ALL' to 0 and 'AML' to 1 and merge entire dataset into 1 df 'data'
In [ ]:
X["patient"] = pd.to numeric(patients)
y["cancer"] = pd.get_dummies(y.cancer, drop_first=True)
# add the cancer column to train data
data = pd.merge(X, y, on="patient")
In [ ]:
data.head()
Out[]:
        1
             2
                                 7
                                      8
                                             10
                                                  11
                                                      12
                                                          13
                                                               14
                                                                   15
                                                                       16
                                                                                 18
                                                                                     19
                                                                                          20
                                                                                             21 22
                   295 558 199 176 252 206
           -58
                                            -41 -831
                                                               75 381
                                                                              15091
                                                                                      7 311
                                                      653 462
                                                                      118 565
                                             19 -743 -83 182 164 141 423 11038
            -1 283 <sub>264</sub> 400 330 168
                                                                                     37 134
                                    101
                                         74
                                                1135 962 232 208 432 84 501 16692 183 378 221 67
                                        215
                   376 650
   135 114 <sup>265</sup>
                                         31 363 -934
                                     49
                                                                              15763
                                                                                     45 268 -27 43 -52
                12
                            158
                                                     577 214 <sup>142</sup> 271 107 101
                   419 585
                                253
   106 125 -76 168
                             4 122
                                     70 252 155 -471
                                                               32 213
                                                                        1 260 18128 -28 118
                   230 284
                                                     490 184
5 rows × 7131 columns
In [ ]:
X, y = data.drop(columns=["cancer"]), data["cancer"]
In [ ]:
X.shape, y.shape
Out[]:
((72, 7130), (72,))
apply standard scaler preprocessing to X cols
In [ ]:
ss=StandardScaler()
X=ss.fit_transform(X)
split data into train test data
```

control)

```
In []:
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.40, random_state= 0)

Apply Gaussian Naive Bayes
In []:
gnb=GaussianNB()
gnb.fit(X_train,y_train)
Out[]:
GaussianNB(priors=None, var_smoothing=1e-09)
In []:
y_pred=gnb.predict(X_test)
In []:
accuracy_score(y_test,y_pred)
Out[]:
0.9655172413793104
```