DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

ANSWER KEY SUBMISSION

Course Code: 18CSE481T

Date of Exam & Session	31/03/2023 FN	Category of Exam	CLA2
Course Name	Applied Machine Learning	Course Code	18CSE481T
Name of the Faculty submitting	Dr. M. Mahasree	Date of submission of Answer Key	12/04/2023
Department to which the faculty belongs to	CSE	Total Marks	50

PART A(10x1= 10) ANSWER ALL THE QUESTIONS

Q.No.	MCQ Questions	Marks	CO	BL	PI
1.	The signal that is used in speech recognition is known as? (A). Acoustic signal (B). Electric signal (C). Electromagnetic signal (D). Radar	1	2	1	1.5.1
2.	Select the dominant modality for communication between humans? (A). Hear (B). Speech (C). Smell (D). None of these	1	2	1	1.5.1
3.	MFCC uses (A). Filter banks and tan transform (B). Features and sine transform (C). Filter banks and cosine transform (D). Features and cosine transform	1	2	1	1.5.1
4.	How we can describe the state of the process in HMM? (A). Literal (B). Single random variable (C). Single discrete random variable (D). None of these	1	2	1	1.5.1
5.	Which of the following algorithm is applicable for solving temporal probabilistic reasoning? (A). Hill-climbing search algorithm (B). Hidden Markov model (C). Depth-first search algorithm (D). Breadth-first search algorithm	1	2	1	1.5.1

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6.	Which function is used to load the letters data? (A). crf.load_data() (B). loaddata() (C). load() (D). data()	1	3	1	1.5.1
7.	What is the method used to train the CRF? (A). train() (B). crf() (C). crf.train() (D). crf_train()	1	3	1	1.6.1
8.	Which one is not a form of time series data? (A). int64 (B). float64 (C). bool (D). Double	1	3	1	1.5.1
9.	How to import numpy? (A). import numpy as np (B). import numpy c (C). import np (D). import numpy as num	1	3	1	1.6.1
10.	How to convert the data into a pandas data frame? (A). DataFrame() (B). pd.DataFrame() (C). pd_DataFrame() (D). pdDataFrame()	1	3	1	1.6.1

PART B (4 X 4= 16) ANSWER ANY FOUR QUESTIONS

Q. No.	Questions	Marks	co	BL	PI
	What is the method to avoid overfitting? Methods (4)				
11	Early stopping. Pruning Regularization Ensembling Data augmentation.	4	2	1	1.3.1
12	Differentiate supervised and unsupervised machine learning. Supervised (2) Unsupervised(2)	4	2	1	2.1.1

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	Supervised Learning	Unsupervised Learning				
	Supervised learning algorithms are trained using labeled data.	Unsupervised learning algorithms are trained using unlabeled data.				
	Supervised learning model takes direct feedback to check if it is predicting correct output or not.	Unsupervised learning model does not take any feedback.				
	Supervised learning model predicts the output.	Unsupervised learning model finds the hidden patterns in data.				
	In supervised learning, input data is provided to the model along with the output.	In unsupervised learning, only input data is provided to the model.				
	The goal of supervised learning is to train the model so that it can predict the output when it is given new data.	The goal of unsupervised learning is to find the hidden patterns and useful insights from the unknown dataset.				
	Supervised learning needs supervision to train the model.	Unsupervised learning does not need any supervision to train the model.				
	Supervised learning can be categorized in Classification and Regression problems.	Unsupervised Learning can be classified in Clustering and Associations problems.				
13	Why instance-based learning algas Lazy learning algorithm? In machine learning, lazy learning where induction and generalization classification is performed. Becan instance-based learning algorithm learning algorithm.	g can be described as a method on processes are delayed until use of the same property, an m is sometimes called lazy	4	2	1	1.1.2
14	Illustrate about Conditional Ran Conditional Random Fields or C graph model that take neighboring for tasks like classification. Predict model, which implements depended Graph choice depends on the appropriate of the chain CRFs are popular in natural in image-based tasks, the graph clocations in an image to enform predictions.	g sample context into account ction is modeled as a graphical encies between the predictions. oplication, for example linear language processing, whereas would connect to neighboring	4	3	2	1.1.2
15	How Hidden Markov Models per Steps (2) Markov models are a useful class of data. 1. Initializing a Markov chain 2. Modelling transitions between s 3. Equilibrium or Stationary District Code(2) import numpy as np p_init = np.array([1/3., 1/3] p_init = np.array([0.1, 0.8] p_transition = np.array([[0.90, 0.05, 0.05], [0.01, 0.90, 0.09], [0.07, 0.03, 0.9]]) p_transition	of models for sequential-type states ibution 3., 1/3.])	4	3	2	1.3.1

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	<pre>p_state_t = [p_init] for i in range(200): # 200 time steps sorta, kinda, approximates infinite time :) p_state_t.append(p_state_t[-1]@</pre>				
	p_transition_example)				
	<pre>state_distributions.plot();</pre>				
16	Write a program to display users selected year calendar on to the console. import calendar year = int(input ("Please enter the Year: ")) # Here, it will take the year month = int(input ("Please enter the month: ")) # Here, it will take the month # Now, we will display the calendar Print ("The Calendar of: ", calendar.month(year, month))	4	3	3	2.1.1

PART C (2 X 12= 24) ANSWER THE QUESTIONS

N _O	Questions	Marks	СО	BL	PI
17	A) Explain the concept of transforming audio signals into the frequency domain Sampling (6) Quantization (6) Speech is the primary form of human communication and is also a vital part of understanding behaviour and cognition. Speech Recognition in Artificial Intelligence is a technique deployed on computer programs that enables them in understanding spoken words. As images and videos, sound is also an analog signal that humans perceive through sensory organs. For machines, to consume this information, it needs to be stored as digital signals and analyzed through software. The conversion from analog to digital consists of the below two processes: Sampling: It is a procedure used to convert a time-varying (changing with time) signal s(t) to a discrete progression of real numbers x(n). Sampling period (Ts) is a term that defines the interval between two successive discrete samples. Sampling Frequency (fs = 1/Ts) is the inverse of the sampling period. Common sampling frequencies are 8 kHz, 16 kHz, and 44.1 kHz. A 1 Hz sampling rate means one sample per second and therefore high sampling rates mean better signal quality. Quantization: This is the process of replacing every real number generated by sampling with an approximation to obtain a finite precision (defined within a range of bits). In the majority of scenarios, 16 bits per sample are used for the representation of a single quantized sample. Therefore, raw audio samples generally have a signal range of -215 to 215 although, during analysis, these	Marks 12	2	BL 2	PI 2.5.2

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data analytics architecture: The capture of speech (words, sentences, phrases) given by a human. You can think of this as the Data Acquisition part of any general Machine Learning workflow. Transforming audio frequencies to make it machine-ready. This process is the data pre-processing part where we clean features of the data for the machine to process it. Application of Natural Language Processing (NLP) on the acquired data to understand the content of speech. Synthesis of the recognized words to help the machine speak a similar dialect.				
Analog to Digital Signal Conversion of Stereo Signal Time-Domain Extraction Time-Domain to Frequency-Domain Conversion Fourier Transform Frequency Distribution Frequency Distribution Frequency Distribution MFCC				
OR		•		
		i	1	1
Steps (6) Expanation (6) The first thing to do before classifying speech using HMM is to extract its feature and store it in a vector using MFCC. The MFCC process as follows: Frame the signal into short frames (20–40 ms) For each frame calculate the Discrete Fourier Transform Compute the mel-spaced filter-bank Take the logarithm of all filter-bank energies Take the Discrete Cosine Transform (DCT) of the log filter-bank energies. Keep 13 DCT coefficients and discard the rest.	12	2	2	2.6

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N: No of states in HMM

M: Total different symbol per state

 π : Initial state distribution (π = π i)

A: State transition probability distribution A=[aij]

B: Observation symbol probability distribution

 π , A and B from [1] are called HMM model and notated by $\lambda(\lambda=(A,B,\pi))$. In order to apply HMM, there are 3 things that need to be done: [5]

1) Calculate Parameter

The main purpose of this step is to compute probability of observation sequence O={O1,O2,OT} given the model. The algorithm that used in this step is forward and backward algorithm.

2) Find Optimal State Sequence

The most common solution to find optimal state sequence is viterbi algorithm. Viterbi algorithm is a dynamic programming algorithm that calculates transition state path given observation sequence of symbols [6].

3) Estimating the Model Parameters

Estimation of model parameters is needed in order to adjust the model parameter (A,B,π) , according to a certain optimally criteria. Baum-Welch algorithm is one of the techniques that used to solve this problem. It is an iterative method to estimate the new values for the model parameters.

B. Voice Activity Detection

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Another important issue in speech recognition system is to determine active speech periods and silent periods within a given speech signal [7]. Speech can be characterized as discontinue signal because information is present only if someone is speaking. The regions where information presents called active region and the pauses between talking are called inactive or silence region. An algorithm employed to detect the presence or absence of speech is referred to as a voice activity detector (VAD) [7].

In general, VAD takes the feature from an input signal, spit those signals into frames (5-40ms), and then compare those value with threshold taken from the region that only contains noise. A sound is present (VAD = 1) if the value exceeds the threshold and not present or silent if the value is lower the threshold (VAD = 0). The success of VAD algorithm in splitting the speech depends on the threshold value.

VAD algorithm that used in this system is an Energy-based VAD. A threshold value is calculated by averaging first 40 frames (10ms per frame) with the assumption that user will not speak in first 0.4 seconds after record button is clicked.

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	A				
	Assume that x(i) is ith speech sample. If frame length is N, then				
	the jth frame can be written like (1).				
	$f_{j}=\{x((j-1)N+1)x(j.N))\}(1)$				
	View SourceRight-click on figure for MathML and additional				
	features. Energy value can be calculated by using (2)				
	Ej= $1N\sum_{i=(j-1)N+1}$ i.N x2(i)(2)				
	View SourceRight-click on figure for MathML and additional				
	features.where Ej is energy at jth frame and xi is speech sample at				
	jth frame.				
	a) Describe the Time series and sequential data with				
	examples.				
	Time Series Definition (2)				
	The components of time-series data (3)				
	Diagram(1)				
	A time series is a series of data points indexed (or listed or				
	graphed) in time order. Most commonly, a time series is a sequence				
	taken at successive equally spaced points in time. In plain				
	language, time-series data is a dataset that tracks a sample over				
	time and is collected regularly. Examples are commodity price,				
	stock price, house price over time, weather records, company sales				
	data, and patient health metrics like ECG.				
	data, and patient hearth metrics like ECO.				
	Trend — The data has a long-term movement in a series, whether				
	it's upwards or downwards. It may be caused by population				
	growth, inflation, environmental change or the adoption of				
	technology. Examples could be the long-term increase in the US				
	stock market in the past ten years,				
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	Seasonality — The data is correlated with calendar-related effects,				
	whether it's weekly, monthly, or seasonally, and it's domain-				
	specific. For example, for most e-commerce platforms, their sales				
	around December rise because of Christmas.				
	<pre><matplotlib.axessubplots.axessubplot 0x7fe36fe92890="" at=""></matplotlib.axessubplots.axessubplot></pre>				
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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

1. Create a new Python file, and import the following packages:

```
import datetime
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.finance import
quotes_historical_yahoo_ochl
from hmmlearn.hmm import GaussianHMM
```

2. Get the stock quotes from Yahoo finance. There is a method available in matplotlib to load this directly:

3. There are six values in each quote. Let's extract the relevant data such as the closing value of the stock and the volume of stock that is traded along with their corresponding dates:

```
# Extract the required values
dates = np.array([quote[0] for quote in quotes],
dtype=np.int)
closing_values = np.array([quote[2] for quote in
quotes])
volume_of_shares = np.array([quote[5] for quote
in quotes])[1:]
```

4. Let's compute the percentage change in the closing value of each type of data. We will use this as one of the features:

```
# Take diff of closing values and computing rate
of change
diff_percentage = 100.0 *
np.diff(closing_values) / closing_values[:-1]
dates = dates[1:]
```

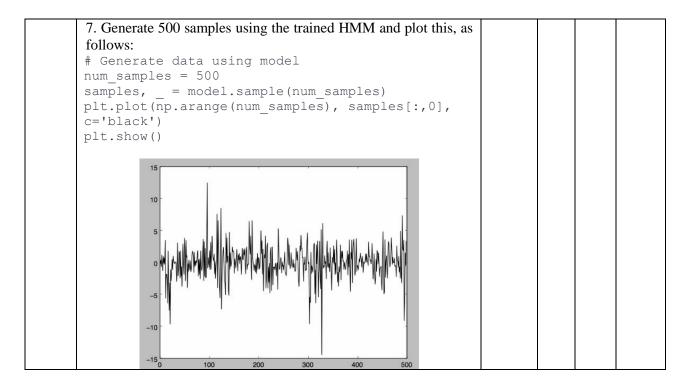
5. Stack the two arrays column-wise for training

```
# Stack the percentage diff and volume values
column-wise for training
X = np.column_stack([diff_percentage,
volume_of_shares])
```

6. Train the HMM using five components:

```
# Create and train Gaussian HMM
print "\nTraining HMM..."
model = GaussianHMM(n_components=5,
covariance_type="diag", n_iter=1000)
model.fit(X)
```

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING



COURSE COORDINATOR

Course Code: 18CSE481T

HOD/CSE

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Signature of the Faculty