



R V College of Engineering
Department of Computer Science and Engineering
CIE 1: Scheme

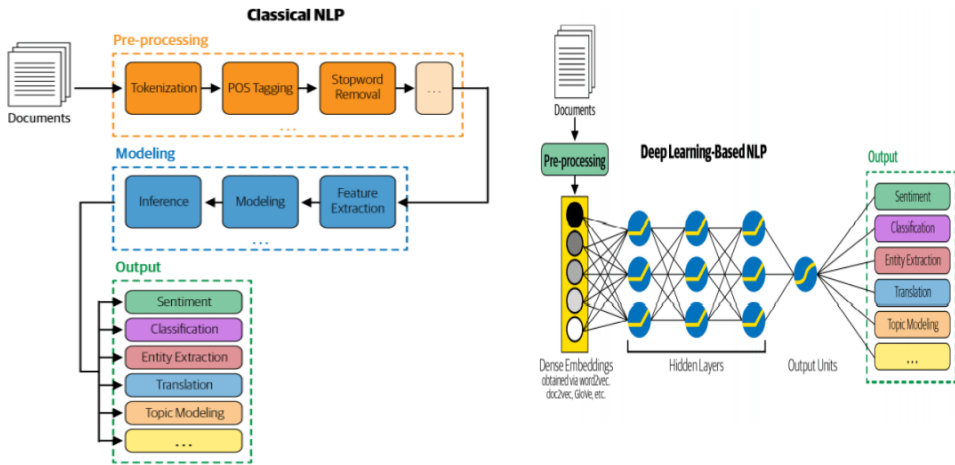
Subject : (Code)	Natural Language Processing (Group B) (IS355TBC)	Semester: 5th BE
Date :	Duration: 120 minutes	Staff: Dr.Sindhu D V
Name :	USN :	Section : A

512

Q. No	Part-A	Marks	Level	CO
1	True	1	2	2
2	Transformers model the textual context but not in a sequential manner. Given a word in the input, it prefers to look at all the words around it and represent each word with respect to its context.	1	1	1
3	NLTK	2	3	2
4	Because of aspects like ambiguity, the need for contextual information, and idioms	1	1	1
5	The number of times a word appears in a document	2	3	1
6	[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+\.[A-Za-z]{2,}	2	2	1
7	<input type="checkbox"/> Tokenization: <ul style="list-style-type: none"> Tokenization is the process of splitting text into smaller units called tokens. These tokens could be words, characters, or subwords, depending on the level of tokenization. The main goal is to break down a sentence or a piece of text into manageable chunks for further analysis. Example: <ul style="list-style-type: none"> Input text: "I love NLP." Tokens: ['I', 'love', 'NLP', '.'] <input type="checkbox"/> Lemmatization: <ul style="list-style-type: none"> Lemmatization is the process of reducing words to their base or root form, known as a lemma. Unlike stemming (which simply removes suffixes), lemmatization considers the context of the word and applies proper linguistic rules to transform words to their base form. Example: <ul style="list-style-type: none"> Input word: "running" Lemmatized form: "run" Input word: "better" Lemmatized form: "good" 	2	1	1

Q. No	Answer all questions	Marks	Level	CO
1a	<p>Despite such tremendous success, DL is still not the silver bullet for all NLP tasks when it comes to the industrial applications. Some of the key reasons for this are as follows:</p> <p>Overfitting on small datasets</p> <p>Few-shot learning and synthetic data generation</p> <p>Domain adaption</p> <p>Interpretable models</p> <p>Common sense and world knowledge.</p>	5	2	3
1b	<pre> graph LR User((User)) --> SR[Speech Recognition] SR --> NLU[Natural Language Understanding] NLU --> DM[Dialog Management] DM --> RG[Response Generation] RG --> SS[Speech Synthesis] SS --> User </pre> <ol style="list-style-type: none"> 1. Speech recognition 2. Natural Language Understanding 3. Dialog management 4. Response generation 5. Speech synthesis 	5	2	1
2	<p>Data is a heart of any ML system. In most of the industrial projects, it is often the data becomes the bottleneck.</p> <ul style="list-style-type: none"> ▪ Use public dataset ▪ Scrape data ▪ Product intervention ▪ Data augmentation <ol style="list-style-type: none"> 1. Synonym replacement 2. Back translation 3. Bigram flipping 4. Replacing entities 5. Adding noise to data 	10	4	2
3	1. Machine Translation	2m×	2	1

	2. Sentimental analysis	5=1 0		
4a	<pre> import nltk from nltk.corpus import stopwords from nltk.tokenize import word_tokenize import string # Ensure necessary resources are downloaded nltk.download('punkt') nltk.download('stopwords') # Define the function def load_and_clean_corpus(file_path): # Load the corpus from a file with open(file_path, 'r') as file: text = file.read() # Tokenize the text into words tokens = word_tokenize(text) # Convert to lowercase tokens = [word.lower() for word in tokens] # Remove punctuation tokens = [word for word in tokens if word.isalnum()] # Remove stopwords stop_words = set(stopwords.words('english')) cleaned_tokens = [word for word in tokens if word not in stop_words] return cleaned_tokens # Test the function file_path = "sample_corpus.txt" # Replace with your file's path cleaned_corpus = load_and_clean_corpus(file_path) print("Cleaned Tokens:", cleaned_corpus) </pre>	6	1,2	1
4b	<p>There are two approaches</p> <ol style="list-style-type: none"> 1. A classical NLP 2. DL pipeline 	4	3	3

	 <p>The diagram illustrates two NLP workflows. Classical NLP starts with 'Documents' leading to 'Pre-processing' (Tokenization, POS Tagging, Stopword Removal, ...). This is followed by 'Modeling' (Inference, Modeling, Feature Extraction, ...) and finally 'Output' (Sentiment, Classification, Entity Extraction, Translation, Topic Modeling, ...). Deep Learning-Based NLP starts with 'Documents' leading to 'Pre-processing'. This is followed by a neural network structure with 'Dense Embeddings obtained via wordvec, glove, etc.', 'Hidden Layers', and 'Output Units'. The 'Output Units' lead to 'Output' (Sentiment, Classification, Entity Extraction, Translation, Topic Modeling, ...).</p>			
5a.	<pre> import re import nltk from nltk.corpus import stopwords from nltk.stem import WordNetLemmatizer # Preprocessing function def preprocess_review(review): # Remove non-alphanumeric characters review = re.sub(r'\W', ' ', review) # Convert to lowercase review = review.lower() # Tokenization tokens = nltk.word_tokenize(review) # Remove stopwords stop_words = set(stopwords.words('english')) tokens = [word for word in tokens if word not in stop_words] # Lemmatization lemmatizer = WordNetLemmatizer() tokens = [lemmatizer.lemmatize(word) for word in tokens] return ' '.join(tokens) # Preprocess all reviews processed_reviews = [preprocess_review(review) for review in reviews]</pre>	10	3	2

<pre> from sklearn.feature_extraction.text import CountVectorizer # Initialize CountVectorizer vectorizer = CountVectorizer() # Transform reviews into a Bag of Words representation X = vectorizer.fit_transform(processed_reviews) from sklearn.model_selection import train_test_split from sklearn.naive_bayes import MultinomialNB from sklearn.metrics import classification_report # Sample labels (1 for positive, 0 for negative) # In a real-world scenario, these would be obtained through manual labeling or pre-labeled data. labels = [1 if 'good' in review or 'excellent' in review else 0 for review in processed_reviews] # Split the data into train and test sets X_train, X_test, y_train, y_test = train_test_split(X, labels, test_size=0.2, random_state=42) # Train Naive Bayes classifier classifier = MultinomialNB() classifier.fit(X_train, y_train) # Test the classifier y_pred = classifier.predict(X_test) # Evaluate the model print(classification_report(y_test, y_pred)) </pre>			
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Marks Distribution	Particulars		CO1	CO2	CO3	CO4	L1	L2	L3	L4	L5	L6
	Test	Max Marks	28	19	13		6	26	18	10		

BT-Blooms Taxonomy, CO-Course Outcomes, M-Marks