GURU NANAK DEV ENGINEERING COLLEGE

(Affiliated to VTU, Belagavi & Approved By AICTE, New Delhi)
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DEPARTMENT OF CSE (DATA SCIENCE) ENGINEERING

GENERATIVE AI LAB MANUAL

SEMESTER - VITH

(BAIL657C)

Generative AI		Semester	6
Course Code	**BAIL657C**	CIE Marks	50
Teaching Hours/Week (L:T:P: S)	0:0:1:0	SEE Marks	50
Credits	01	Exam Hours	100
Examination type (SEE)	Practical		

Course objectives:

- Understand the principles and concepts behind generative AI models
- Explain the knowledge gained to implement generative models using Prompt design frameworks.
- Apply various Generative AI applications for increasing productivity.
- Develop Large Language Model-based Apps.

Sl.NO	**Experiments**
1.	Explore pre-trained word vectors. Explore word relationships using vector arithmetic. Perform arithmetic operations and analyze results.
2.	Use dimensionality reduction (e.g., PCA or t-SNE) to visualize word embeddings for Q 1. Select 10 words from a specific domain (e.g., sports, technology) and visualize their embeddings. Analyze clusters and relationships. Generate contextually rich outputs using embeddings. Write a program to generate 5 semantically similar words for a given input.
3.	Train a custom Word2Vec model on a small dataset. Train embeddings on a domain-specific corpus (e.g., legal, medical) and analyze how embeddings capture domain-specific semantics.
4.	Use word embeddings to improve prompts for Generative AI model. Retrieve similar words using word embeddings. Use the similar words to enrich a GenAI prompt. Use the AI model to generate responses for the original and enriched prompts. Compare the outputs in terms of detail and relevance.
5.	Use word embeddings to create meaningful sentences for creative tasks. Retrieve similar words for a seed word. Create a sentence or story using these words as a starting point. Write a program that: Takes a seed word. Generates similar words. Constructs a short paragraph using these words.
6.	Use a pre-trained Hugging Face model to analyze sentiment in text. Assume a real-world application, Load the sentiment analysis pipeline. Analyze the sentiment by giving sentences to input.
7.	Summarize long texts using a pre-trained summarization model using Hugging face model. Load the summarization pipeline. Take a passage as input and obtain the summarized text.
8.	Install langchain, cohere (for key), langchain-community. Get the api key(By logging into Cohere and obtaining the cohere key). Load a text document from your google drive . Create a prompt template to display the output in a particular manner.
9.	Take the Institution name as input. Use Pydantic to define the schema for the desired output and create a custom output parser. Invoke the Chain and Fetch Results. Extract the below Institution related details from Wikipedia: **The founder of the Institution. When it was founded. The current branches in the institution . How many employees are working in it. A brief 4-line summary of the institution.**
10	Build a chatbot for the Indian Penal Code. We'll start by downloading the official Indian Penal Code document, and then we'll create a chatbot that can interact with it. Users will be able to ask questions about the Indian Penal Code and have a conversation with it.

PROGRAM 1:

1. **Explore pre-trained word vectors. Explore word relationships using vector arithmetic. Perform arithmetic operations and analyze results.**

```
import gensim.downloader as api

# Load pre-trained Word2Vec model (Google News)
print("Loading model... (This may take a while)")
model = api.load("word2vec-google-news-300")
print("Model loaded!")

# Function to find similar words
def find_similar(word):
    try:
        similar_words = model.most_similar(word)
        print(f"\nWords similar to '{word}':")
        for w, score in similar_words[:5]:  # Show top 5
            print(f"{w}: {score:.4f}")
    except KeyError:
        print(f"'{word}' not found in the vocabulary.")

# Function to perform word arithmetic
def word_arithmetic(word1, word2, word3):
    try:
        result = model.most_similar(positive=[word1, word2], negative=[word3])
        print(f"\n'{word1}' - '{word3}' + '{word2}' = '{result[0][0]}' (Most similar
word)")
    except KeyError as e:
        print(f"Error: {e}")

# Function to check similarity between two words
def check_similarity(word1, word2):
    try:
        similarity = model.similarity(word1, word2)
        print(f"\nSimilarity between '{word1}' and '{word2}': {similarity:.4f}")
    except KeyError as e:
        print(f"Error: {e}")

# Function to find the odd one out
def odd_one_out(words):
    try:
        odd = model.doesnt_match(words)
        print(f"\nOdd one out from {words}: {odd}")
    except KeyError as e:
        print(f"Error: {e}")
```

```
# Run the functions
find_similar("king")
word_arithmetic("king", "woman", "man")  # Expected output: "queen"
check_similarity("king", "queen")
odd_one_out(["apple", "banana", "grape", "car"])  # "car" should be the odd one
```

OUTPUT

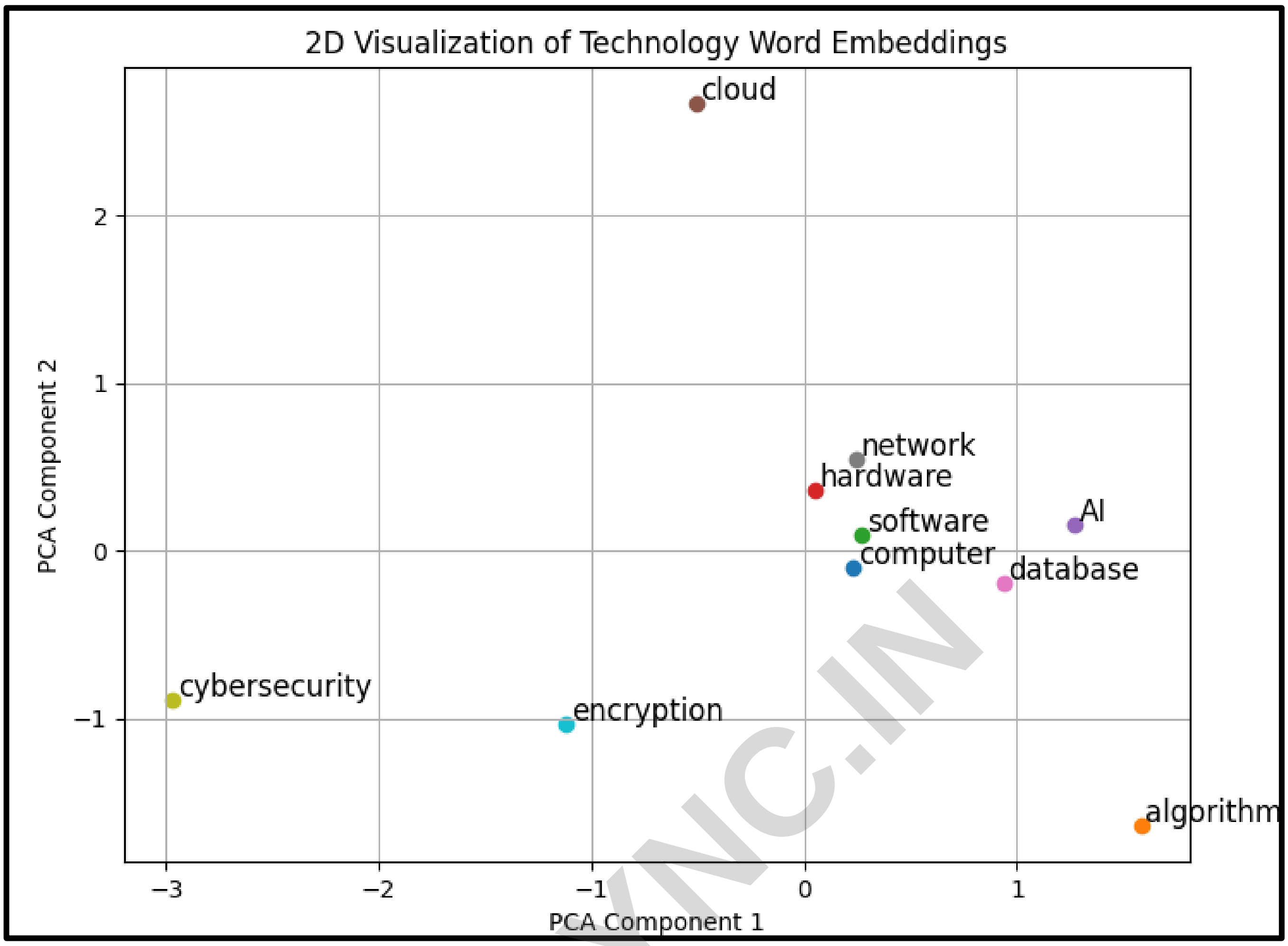
```
Loading model... (This may take a while)
Model loaded!

Words similar to 'king':
kings: 0.7138
queen: 0.6511
monarch: 0.6413
crown_prince: 0.6204
prince: 0.6160

'king' - 'man' + 'woman' = 'queen' (Most similar word)

Similarity between 'king' and 'queen': 0.6511

Odd one out from ['apple', 'banana', 'grape', 'car']: car
```

PROGRAM -2

Use dimensionality reduction (e.g., PCA or t-SNE) to visualize word embeddings for Q 1. Select 10 words from a specific domain (e.g., sports, technology) and visualize their embeddings. Analyze clusters and relationships. Generate contextually rich outputs using embeddings. Write a program to generate 5 semantically similar words for a given input.

```
import gensim.downloader as api
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# Load pre-trained Word2Vec model (Google News)
print("Loading model... (This may take a while)")
model = api.load("word2vec-google-news-300")
print("Model loaded!")

# Select 10 words from the Technology domain
tech_words = ["computer", "algorithm", "software", "hardware", "AI",
        "cloud", "database", "network", "cybersecurity", "encryption"]

# Get their word vectors
word_vectors = np.array([model[word] for word in tech_words])

# Perform PCA to reduce to 2D
pca = PCA(n_components=2)
reduced_vectors = pca.fit_transform(word_vectors)

# Plot the words in 2D
plt.figure(figsize=(8,6))
for word, (x, y) in zip(tech_words, reduced_vectors):
    plt.scatter(x, y)
    plt.text(x+0.02, y+0.02, word, fontsize=12)

plt.title("2D Visualization of Technology Word Embeddings")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.grid()
plt.show()

# Function to find 5 similar words
def find_similar_words(word):
    try:
        similar_words = model.most_similar(word, topn=5)
        print(f"\n5 words similar to '{word}':")
        for w, score in similar_words:
            print(f"{w}: {score:.4f}")
    except KeyError:
        print(f"'{word}' not found in the vocabulary.")

# Test with an input word
find_similar_words("AI")
```

OUTPUT



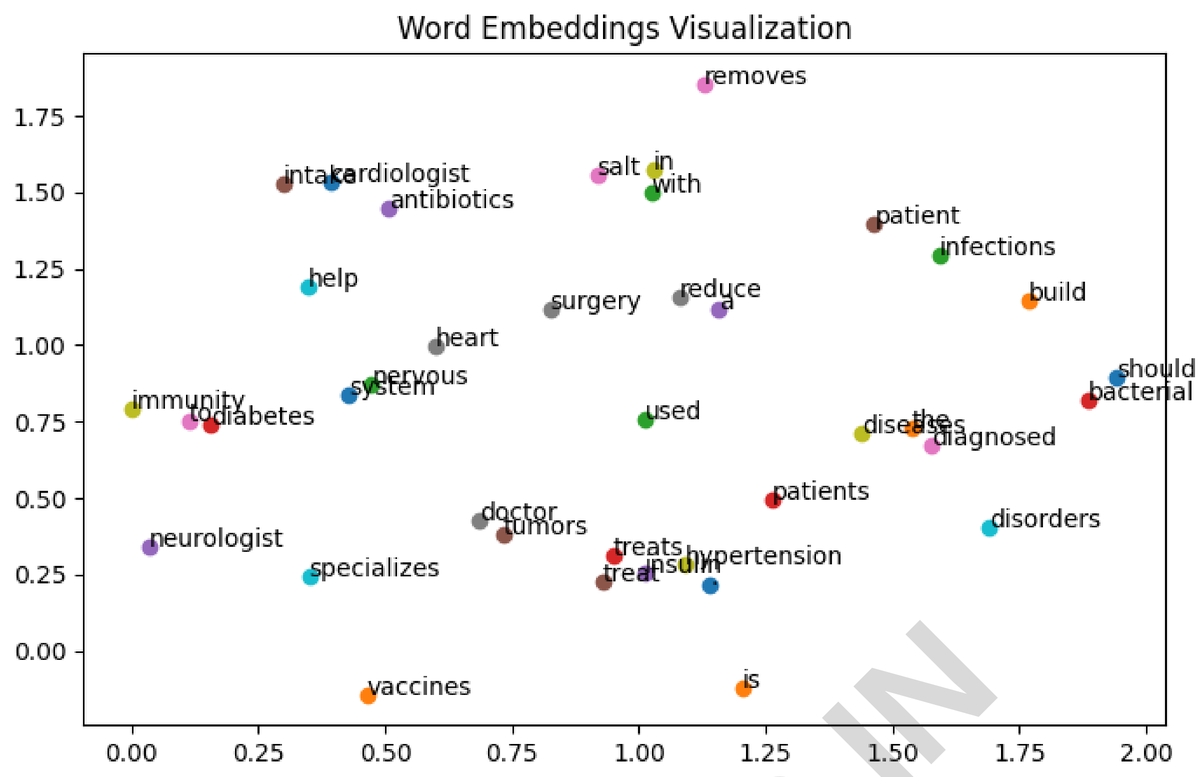
```
Loading model... (This may take a while)
Model loaded!

5 words similar to 'AI':
Steven_Spielberg_Artificial_Intelligence: 0.5576
Index_MDE_##/###/####: 0.5415
Enemy_AI: 0.5256
Ace_Combat_Zero: 0.5227
DOA4: 0.5183
```

PROGRAM -3

Train a custom Word2Vec model on a small dataset. Train embeddings on a domain-specific corpus (e.g., legal, medical) and analyze how embeddings capture domain-specific semantics.

```
import gensim
from gensim.models import Word2Vec
import nltk
from nltk.tokenize import word_tokenize
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE

# Medical corpus
medical_corpus = [
    "The doctor diagnosed the patient with diabetes.",
    "Insulin is used to treat diabetes.",
    "A cardiologist specializes in heart diseases.",
    "Patients with hypertension should reduce salt intake.",
    "Antibiotics treat bacterial infections.",
    "Vaccines help build immunity.",
    "Surgery removes tumors.",
    "A neurologist treats nervous system disorders.",
]

# Tokenization
nltk.download('punkt')
tokenized_corpus = [word_tokenize(sentence.lower()) for sentence in
medical_corpus]

# Train Word2Vec model
model = Word2Vec(sentences=tokenized_corpus, vector_size=50, window=5,
min_count=1, workers=4)

# Save model
model.save('medical_word2vec.model')

def plot_embeddings(model):
    words = list(model.wv.index_to_key)
    word_vectors = model.wv[words]

    # Reduce dimensions using t-SNE
    tsne = TSNE(n_components=2, random_state=42)
    reduced_vectors = tsne.fit_transform(word_vectors)

    plt.figure(figsize=(8, 5))
    for i, word in enumerate(words):
        x, y = reduced_vectors[i]
        plt.scatter(x, y)
        plt.annotate(word, (x, y), fontsize=10)

    plt.title("Word Embeddings Visualization")
    plt.show()

# Plot word embeddings
plot_embeddings(model)

# Find similar words
def find_similar_words(word):
    if word in model.wv:
        similar_words = model.wv.most_similar(word, topn=5)
        print(f"Words similar to '{word}':")
        for similar, score in similar_words:
            print(f"{similar} (Similarity: {score:.2f})")
    else:
        print(f"'{word}' not found in vocabulary")

# Example usage
find_similar_words("diabetes")
```

OUTPUT



```
Words similar to 'diabetes':
neurologist (Similarity: 0.23)
help (Similarity: 0.20)
used (Similarity: 0.19)
vaccines (Similarity: 0.17)
surgery (Similarity: 0.13)
```

PROGRAM -4

Use word embeddings to improve prompts for Generative AI model. Retrieve similar words using word embeddings. Use the similar words to enrich a GenAI prompt. Use the AI model to generate responses for the original and enriched prompts. Compare the outputs in terms of detail and relevance.

Follow the steps to run the program if error occurs

step1 : - Update the opt tree
python -m pip install --upgrade "optree>=0.13.0"

step 2: install tf keras library
pip install tf-keras

step3:- Fix TensorFlow one DNN Warnings run the program in VSCODE termninal

set TF_ENABLE_ONEDNN_OPTS=0 # Windows Command Prompt

Step 4 :- check the required libraries
pip install --upgrade transformers gensim torch tensorflow optree

Now run the program

```
import gensim.downloader as api
from transformers import pipeline

# Load embedding model
embedding_model = api.load("glove-wiki-gigaword-100")

original_prompt = "Describe the beautiful landscapes during sunset."

def enrich_prompt(prompt, embedding_model, n=5):
    words = prompt.split()
    enriched_prompt = []

    for word in words:
        word_lower = word.lower()

        if word_lower in embedding_model:
            similar_words = embedding_model.most_similar(word_lower, topn=n)
            similar_word_list = [w[0] for w in similar_words]
            enriched_prompt.append(" ".join(similar_word_list))  # Join similar words as a phrase
        else:
            enriched_prompt.append(word)  # Keep the word as is if not found
    return " ".join(enriched_prompt)

enriched_prompt = enrich_prompt(original_prompt, embedding_model)

# Load text generation model
generator = pipeline("text-generation", model="gpt2")

# Generate responses
original_response = generator(original_prompt, max_length=50, num_return_sequences=1)
enriched_response = generator(enriched_prompt, max_length=50,
num_return_sequences=1)

# Print results
print("Original prompt response")
print(original_response[0]['generated_text'])

print("\nEnriched prompt response")
print(enriched_response[0]['generated_text'])
```

OUTPUT

```
Original prompt response
Describe the beautiful landscapes during sunset. View the entire project »

View more photos View slideshow

View gallery

Enriched prompt response
explain describing distinguish understand define this part one of same lovely
gorgeous wonderful charming magnificent landscape seascapes cityscapes scenery
paintings after early since following days sunset. cityscape paintings after all great of
beautiful seascapes and also a vast beautiful
```

PROGRAM -5

Use word embeddings to create meaningful sentences for creative tasks. Retrieve similar words for a seed word. Create a sentence or story using these words as a starting point. Write a program that: Takes a seed word. Generates similar words. Constructs a short paragraph using these words

```
import random
import gensim.downloader as api

# Load a pre-trained word embedding model
model = api.load("glove-wiki-gigaword-50")  # 50D GloVe embeddings

def get_similar_words(seed_word, top_n=5):
    """Retrieve similar words for the given seed word."""
    try:
        similar_words = [word for word, _ in model.most_similar(seed_word,
topn=top_n)]
        return similar_words
    except KeyError:
        return []

def create_paragraph(seed_word):
    """Generate a short paragraph using the seed word and its similar words."""
    similar_words = get_similar_words(seed_word)

    if not similar_words:
        return f"Could not find similar words for '{seed_word}'. Try another word!"

    # Create a simple paragraph
    paragraph = (
        f"Once upon a time, a {seed_word} embarked on a journey. Along the way, it
encountered "
        f"a {random.choice(similar_words)}, which led it to a hidden
{random.choice(similar_words)}. "
        f"Despite the challenges, it found {random.choice(similar_words)} and
embraced the "
        f"adventure with {random.choice(similar_words)}. In the end, the journey
was a tale of "
        f"{random.choice(similar_words)} and discovery."
    )

    return paragraph
```

```
# Example usage
seed_word = input("Enter a seed word: ").strip().lower()
print("\nGenerated Story:\n")
print(create_paragraph(seed_word))
```

OUTPUT

```
Enter a seed word: adventure

Generated Story:

Once upon a time, a adventure embarked on a journey. Along the way, it
encountered a adventures, which led it to a hidden adventures. Despite the
challenges, it found romance and embraced the adventure with mystery. In the end,
the journey was a tale of mystery and discovery.
```

PROGRAM -6

Use a pre-trained Hugging Face model to analyze sentiment in text. Assume a real-world application, Load the sentiment analysis pipeline. Analyze the sentiment by giving sentences to input.

```
from transformers import pipeline

# Load the sentiment analysis pipeline
sentiment_analyzer = pipeline("sentiment-analysis")

def analyze_sentiment(text):
   """Analyze sentiment of the input text using Hugging Face pipeline."""
   result = sentiment_analyzer(text)
   label = result[0]['label']
   score = result[0]['score']

   return f"Sentiment: {label} (Confidence: {score:.2f})"

# Example usage
while True:
   user_input = input("Enter a sentence for sentiment analysis (or 'exit' to quit):
").strip()
   if user_input.lower() == 'exit':
      break
   print(analyze_sentiment(user_input))
```

OUTPUT

```
Device set to use CPU
Enter a sentence for sentiment analysis (or 'exit' to quit): I love this product! It's
amazing
Sentiment: POSITIVE (Confidence: 1.00)
Enter a sentence for sentiment analysis (or 'exit' to quit): This is the worst
experience ever
Sentiment: NEGATIVE (Confidence: 1.00)
Enter a sentence for sentiment analysis (or 'exit' to quit): The service was okay,
nothing special
Sentiment: NEGATIVE (Confidence: 0.99)
```

PROGRAM -7

Summarize long texts using a pre-trained summarization model using Hugging face model. Load the summarization pipeline. Take a passage as input and obtain the summarized text.

```
from transformers import pipeline

# Load the summarization model
summarizer = pipeline("summarization", model="facebook/bart-large-cnn")

# Take user input for the text passage
text = input("Enter the text you want to summarize:\n")

# Summarize the text
summary = summarizer(text, max_length=100, min_length=30, do_sample=False)

# Print the summarized text
print("\nSummarized Text:")
print(summary[0]['summary_text'])
```

OUTPUT

Enter the text you want to summarize: The Indian Penal Code (IPC) is the official criminal code of India. It was drafted in 1860 by the first law commission of India, under the chairmanship of Thomas Babington Macaulay. The IPC covers a wide range of offenses, including crimes against the state, public tranquillity, human body, property, and morality. It provides detailed provisions for punishment, ranging from fines to imprisonment and even the death penalty for severe crimes. Over the years, various amendments have been made to the IPC to accommodate evolving legal and social requirements. The code serves as the foundation for criminal law in India, ensuring justice and order in society.

Summarized Text:
The Indian Penal Code (IPC) is the official criminal code of India. It was drafted in 1860 by the first law commission of India, under the chairmanship of Thomas Babington Macaulay. The code covers a wide range of offenses, including crimes against the state, public tranquillity, human body, property, and morality.

PROGRAM -8

Install langchain, cohere (for key), langchain-community. Get the api key(By logging into Cohere and obtaining the cohere key). Load a text document from your google drive . Create a prompt template to display the output in a particular manner

```
from langchain.prompts import PromptTemplate
from langchain_community.llms import Cohere

# Set your Cohere API key
COHERE_API_KEY = "YOUR_COHERE_API"  # Replace with your actual API key

# Read the text file
file_path = "Artificial_Intelligence.txt"  # Replace with your file name

with open(file_path, "r", encoding="utf-8") as file:
    document_text = file.read()

print("File loaded successfully!")
```

Output 1:- File loaded successfully!

```
# Create a simple prompt template
prompt_template = PromptTemplate(
    input_variables=["text"],
    template="Summarize the following text in a simple way:\n\n{text}"
)

# Initialize the Cohere model
llm = Cohere(cohere_api_key=COHERE_API_KEY)

# Run the text through Cohere
output = llm.invoke(prompt_template.format(text=document_text))

# Display the result
print("Summary:\n", output)
```

OUTPUT 2:-

```
Summary:
 Here's a simplified summary of the text:

Artificial Intelligence (AI) is a technology that makes machines smart. It enables them to perform tasks like humans by learning, solving problems, and making decisions. AI is used in many areas to help improve performance. Some examples of AI include machine learning, deep learning, and robotics. However, there are some concerns about AI, like ensuring privacy and fairness, and how it could impact jobs. Overall, AI can be very helpful, but it's important to use it responsibly.
```

PROGRAM -9

Take the Institution name as input. Use Pydantic to define the schema for the desired output and create a custom output parser. Invoke the Chain and Fetch Results. Extract the below Institution related details from Wikipedia: The founder of the Institution. When it was founded. The current branches in the institution . How many employees are working in it. A brief 4-line summary of the institution.

```
from pydantic import BaseModel
import wikipediaapi

# Define the Pydantic schema
class InstitutionDetails(BaseModel):
    name: str
    founder: str
    founded_year: str
    branches: str
    employees: str
    summary: str

# Wikipedia extraction function
def fetch_institution_details(institution_name: str) -> InstitutionDetails:
    wiki_wiki = wikipediaapi.Wikipedia(user_agent="MyWikipediaScraper/1.0
(contact: myemail@example.com)", language="en")
    page = wiki_wiki.page(institution_name)

    if not page.exists():
        raise ValueError("Institution page does not exist on Wikipedia")

    # Extract information (this part needs actual content parsing)
    summary = " ".join(page.summary.split(".")[:4]) + "."
    # Placeholder extraction logic
    founder = "Not Available"
    founded_year = "Not Available"
    branches = "Not Available"
    employees = "Not Available"

    for section in page.sections:
        if "founder" in section.title.lower():
            founder = section.text.split(". ")[0]
        if "founded" in section.title.lower():
            founded_year = section.text.split(". ")[0]
        if "branches" in section.title.lower():
            branches = section.text.split(". ")[0]
        if "employees" in section.title.lower():
            employees = section.text.split(". ")[0]

    return InstitutionDetails(
        name=institution_name,
        founder=founder,
        founded_year=founded_year,
        branches=branches,
        employees=employees,
        summary=summary
    )

# Example invocation
institution_name = input("Enter Institution Name: ")
try:
    details = fetch_institution_details(institution_name)
    print(details.model_dump_json(indent=4))

except ValueError as e:
    print(str(e))
```

OUTPUT

```
Enter Institution Name:  Harvard University
{
   "name": "Harvard University",
   "founder": "Not Available",
   "founded_year": "Not Available",
   "branches": "Not Available",
   "employees": "Not Available",
   "summary": "Harvard University is a private Ivy League research university in Cambridge, Massachusetts, United States  Founded October 28, 1636, and named for its first benefactor, the Puritan clergyman John Harvard, it is the oldest institution of higher learning in the United States  Its influence, wealth, and rankings have made it one of the most prestigious universities in the world \nHarvard was founded and authorized by the Massachusetts General Court, the governing legislature of colonial-era Massachusetts Bay Colony."
}
```

PROGRAM 10

Build a chatbot for the Indian Penal Code. We'll start by downloading the official Indian Penal Code document, and then we'll create a chatbot that can interact with it. Users will be able to ask questions about the Indian Penal Code and have a conversation with it.

Step 1: Download the IPC PDF File
Before running the chatbot, you must download the Indian Penal Code (IPC) PDF. Use the following Python script to download it:

```python
import requests

def download_ipc_pdf(url, save_path="ipc.pdf"):
   try:
      response = requests.get(url)
      response.raise_for_status()
      with open(save_path, 'wb') as f:
         f.write(response.content)
      print(f"Downloaded IPC PDF to: {save_path}")
   except requests.exceptions.RequestException as e:
      print(f"Request error: {e}")
   except Exception as e:
      print(f"Unexpected error: {e}")

if __name__ == "__main__":
   ipc_pdf_url ="https://www.indiacode.nic.in/bitstream/123456789/4219/1/THE-INDIAN-PENAL-CODE-1860.pdf"
   download_ipc_pdf(ipc_pdf_url)
```

Instructions:

1. **Save this script** as a .py file (e.g., download_ipc.py).
2. **Run the script** to download the IPC PDF to your local system. By default, the file will be saved as ipc.pdf.
3. **Ensure the file** is saved in the directory where you intend to run the chatbot application, or provide the appropriate path.

Step 2: Run the Chatbot

Once the IPC PDF is downloaded, you can proceed with running the chatbot. The chatbot will read from the ipc.pdf file to provide responses based on the Indian Penal Code.

```
import PyPDF2
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import string
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

def extract_text_from_pdf(pdf_path):
    text = ""
    try:
        with open(pdf_path, 'rb') as file:
            reader = PyPDF2.PdfReader(file)
            for page in reader.pages:
                text += page.extract_text() or ""
        return text
    except FileNotFoundError:
        print(f"Error: File not found at {pdf_path}")
        return ""
    except Exception as e:
        print(f"Error extracting text from PDF: {e}")
        return ""

def preprocess_text(text):
    if not text:
        return []
    text = text.lower()
    text = text.translate(str.maketrans('', '', string.punctuation))
    tokens = word_tokenize(text)
    stop_words = set(stopwords.words('english'))
    tokens = [word for word in tokens if word not in stop_words]
    return tokens

def create_index(text):
    index = {}
    try:
        section_pattern =
r"((?:CHAPTER|SECTION)\s+\w+\.?\s+.*?)(?:(?:CHAPTER|SECTION)\s+\w+\.?\s+|$
)"
        matches = re.findall(section_pattern, text, re.DOTALL | re.IGNORECASE)
        for match in matches:
            title_match = re.search(r"^(?:CHAPTER|SECTION)\s+\w+\.?\s+(.*?)(?=\n)",
match, re.DOTALL | re.IGNORECASE)
            if title_match:
                title = title_match.group(1).strip()
                content = match[title_match.end():].strip()
                index[title] = content
        return index
    except Exception as e:
        print(f"Error creating index: {e}")
        return {}

def get_most_relevant_section(query, index):
    try:
        if not index:
            return None
        sections = list(index.values())
        section_titles = list(index.keys())
        vectorizer = TfidfVectorizer()
        tfidf_matrix = vectorizer.fit_transform(sections + [query])
        query_vector = tfidf_matrix[-1]
        similarities = cosine_similarity(query_vector, tfidf_matrix[:-1]).flatten()
        if not similarities.any():
            return None
        most_relevant_index = similarities.argmax()
        return section_titles[most_relevant_index]
    except Exception as e:
        print(f"Error finding relevant section: {e}")
        return None
```

```
def get_section_text(section_title, index):
   try:
      return index.get(section_title)
   except Exception as e:
      print(f"Error getting section text: {e}")
      return None

def generate_response(query, index):
   if not index:
      return "I'm sorry, I cannot process the IPC without the index. Please ensure the
IPC content is loaded."
   relevant_section_title = get_most_relevant_section(query, index)
   if not relevant_section_title:
      return "I'm sorry, I couldn't find relevant information in the IPC for your query."
   section_text = get_section_text(relevant_section_title, index)
   if not section_text:
      return "I found the relevant section, but I'm unable to retrieve the details."
   cleaned_text = re.sub(r'\n\s*\n+', '\n\n', section_text.strip())
   cleaned_text = re.sub(r'[ \t]+\n', '\n', cleaned_text)
   cleaned_text = re.sub(r'\n+', '\n', cleaned_text)
   response = f"Here's what I found in the Indian Penal Code,
**{relevant_section_title}**:\n\n{cleaned_text}"
   return response

def chatbot(index):
   print("Welcome to the Indian Penal Code Chatbot! Ask me anything about the IPC.
Type 'exit' to quit.")
   while True:
      query = input("You: ")
      if query.lower() == "exit":
         break
      response = generate_response(query, index)
      print(f"Chatbot: {response}\n")

if __name__ == "__main__":
   pdf_path = "ipc.pdf"  # Path to your local IPC PDF
   ipc_text = extract_text_from_pdf(pdf_path)
   if ipc_text:
      ipc_index = create_index(ipc_text)
      if ipc_index:
         chatbot(ipc_index)
      else:
         print("Failed to create index. Chatbot cannot start.")
```

```
    else:
        print("Failed to extract text from PDF. Chatbot cannot start.")
```

OUTPUT

```
Welcome to the Indian Penal Code Chatbot! Ask me anything about the IPC. Type 'exit' to quit.
You: Murder
Chatbot: Here's what I found in the Indian Penal Code, **word "offence" includes every**:

act committed outside 1*[India] which, if committed in 1*[India] would
be punishable under this Code.
2*[Illustration]
3***A, 4*[who is 5*[a citizen of India]], commits a murder in
Uganda. He can be tried and convicted of murder in any place in
1*[India] in which he may be found.
6* * * * *
5.
Certain laws not to be affected by this Act.
7*[5. Certain laws not to be affected by this Act.--Nothing in
this Act shall affect the provisions of any Act for punishing mutiny
and desertion of officers, soldiers, sailors or airmen in the service
of the Government of India or the provision of any special or local
law.]

You: exit
```