GENERATIVE

Lab Manual

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.

Course outcomes (Course Skill Set):

At the end of the course the student will be able to:

- Develop the ability to explore and analyze word embeddings, perform vector arithmetic to investigate word relationships, visualize embeddings using dimensionality reduction techniques
- Apply prompt engineering skills to real-world scenarios, such as information retrieval, text generation.
- Utilize pre-trained Hugging Face models for real-world applications, including sentiment analysis and text summarization.
- Apply different architectures used in large language models, such as transformers, and understand their advantages and limitations.

Assessment Details (both CIE and SEE)

The weightage of Continuous Internal Evaluation (CIE) is 50% and for Semester End Exam (SEE) is 50%. The minimum passing mark for the CIE is 40% of the maximum marks (20 marks out of 50) and for the SEE minimum passing mark is 35% of the maximum marks (18 out of 50 marks). A student shall be deemed to have satisfied the academic requirements and earned the credits allotted to each subject/ course if the student secures a minimum of 40% (40 marks out of 100) in the sum total of the CIE (Continuous Internal Evaluation) and SEE (Semester End Examination) taken together

Continuous Internal Evaluation (CIE):

CIE marks for the practical course are **50 Marks**.

The split-up of CIE marks for record/ journal and test are in the ratio **60:40**.

- Each experiment is to be evaluated for conduction with an observation sheet and record write-up. Rubrics for the evaluation of the journal/write-up for hardware/software experiments are designed by the faculty who is handling the laboratory session and are made known to students at the beginning of the practical session.
- Record should contain all the specified experiments in the syllabus and each experiment write-up will be evaluated for 10 marks.
- Total marks scored by the students are scaled down to **30 marks** (60% of maximum marks).
- Weightage to be given for neatness and submission of record/write-up on time.
- Department shall conduct a test of 100 marks after the completion of all the experiments listed in the syllabus.
- In a test, test write-up, conduction of experiment, acceptable result, and procedural knowledge will carry a weightage of 60% and the rest 40% for viva-voce.
- The suitable rubrics can be designed to evaluate each student's performance and learning ability.
- The marks scored shall be scaled down to **20 marks** (40% of the maximum marks).

The Sum of scaled-down marks scored in the report write-up/journal and marks of a test is the total CIE marks scored by the student.

Semester End Evaluation (SEE):

- SEE marks for the practical course are 50 Marks.
- SEE shall be conducted jointly by the two examiners of the same institute, examiners are appointed by the Head of the Institute.

- The examination schedule and names of examiners are informed to the university before the conduction of the examination. These practical examinations are to be conducted between the schedule mentioned in the academic calendar of the University.
- All laboratory experiments are to be included for practical examination.
- (Rubrics) Breakup of marks and the instructions printed on the cover page of the answer script to be strictly adhered to by the examiners. OR based on the course requirement evaluation rubrics shall be decided jointly by examiners.
- Students can pick one question (experiment) from the questions lot prepared by the examiners jointly.
- Evaluation of test write-up/ conduction procedure and result/viva will be conducted jointly by examiners.

General rubrics suggested for SEE are mentioned here, writeup-20%, Conduction procedure and result in -60%, Viva-voce 20% of maximum marks. SEE for practical shall be evaluated for 100 marks and scored marks shall be scaled down to 50 marks (however, based on course type, rubrics shall be decided by the examiners)

Change of experiment is allowed only once and 15% of Marks allotted to the procedure part are to be made zero.

The minimum duration of SEE is 02 hours

Suggested Learning Resources:

Books:

1. Modern Generative AI with ChatGPT and OpenAI Models: Leverage the Capabilities of OpenAI's LLM for Productivity and Innovation with GPT3 and GPT4, by Valentina Alto, Packt Publishing Ltd, 2023.
2. Generative AI for Cloud Solutions: Architect modern AI LLMs in secure, scalable, and ethical cloud environments, by Paul Singh, Anurag Karuparti ,Packt Publishing Ltd, 2024.

Web links and Video Lectures (e-Resources):

- **https://www.w3schools.com/gen_ai/index.php**
- **https://youtu.be/eTPiL3DF27U**
- **https://youtu.be/je6AlVeGOV0**
- **https://youtu.be/RLVqsA8ns6k**
- **https://youtu.be/0SAKM7wiC-A**
- **https://youtu.be/28_9xMyrdjg**
- **https://youtu.be/8iuiz-c-EBw**
- **https://youtu.be/7oQ8VtEKcgE**
- **https://youtu.be/seXp0VWWZV0**

Experiment 1: Exploring Pre-trained Word Vectors and Word Relationships Using Vector Arithmetic.

Objective:

- To understand pre-trained word vectors and how they represent words as numbers in a continuous space.
- To explore word relationships using vector arithmetic.
- To perform arithmetic operations on word vectors and analyze the results using simple examples.

In this experiment, we will learn about pre-trained word vectors and how they help us represent words in a way that computers can understand. These vectors capture the meaning and context of words. For example, the word "apple" can be represented as a set of numbers that encode its meaning. Words with similar meanings will have similar vectors.

We will also explore **vector arithmetic**, which is a way to perform mathematical operations on these word vectors to discover relationships between words.

Example:
If you subtract the vector for "cat" from "kitten" and add the vector for "puppy," you get a word related to young dogs—**"dog"**.

What Are Pre-trained Word Vectors?

Pre-trained word vectors are created by training models on large text datasets. Each word is mapped to a numerical vector, typically with 100 to 300 dimensions, which captures the meaning and context of the word.

Why Use Pre-trained Word Vectors?

- **Efficient:** No need to train a model from scratch.
- **Context-Aware:** Similar words are close to each other in the vector space.
- **Useful for NLP Tasks:** Such as translation, sentiment analysis, and question-answering.

Example:
The word "banana" might be represented as a vector like this:
`[0.4, -0.7, 0.1, ..., 0.9]`

Vector Arithmetic in Word Vectors

Vector arithmetic allows us to perform mathematical operations on word vectors. By adding or subtracting vectors, we can reveal hidden relationships between words.

Example:
If we want to find out what "lion" is to "cub" as "dog" is to "puppy," we can use the following equation:

cub≈lion−adult+young\text{cub} ≈ \text{lion} - \text{adult} + \text{young}cub≈lion−adult+young

Word Relationships with Real-Time Examples

Example 1: Animal Relationships

- Vector("kitten") - Vector("cat") + Vector("dog") ≈ Vector("puppy")

Example 2: Fruit Relationships

- Vector("orange") - Vector("fruit") + Vector("tropical") ≈ Vector("mango")

Sample Program: Exploring Animal and Fruit Relationships

```
# Install Gensim if not already installed

!pip install gensim



from gensim.models import KeyedVectors



# Load pre-trained GloVe vectors (100-dimensional)

from gensim.downloader import load

word_vectors = load('glove-wiki-gigaword-100')  # Automatically downloads the model



# Example 1: Animal relationship (kitten → cat, puppy → dog)

result = word_vectors.most_similar(positive=['kitten', 'dog'], negative=['cat'], topn=1)

print("Result of 'kitten - cat + dog':", result[0][0])  # Expected output: 'puppy' or a related word



# Example 2: Fruit relationship (orange → fruit, mango → tropical fruit)

result = word_vectors.most_similar(positive=['orange', 'tropical'], negative=['fruit'], topn=1)

print("Result of 'orange - fruit + tropical':", result[0][0])  # Expected output: 'mango' or a related
word
```

Output:

```
Requirement already satisfied: gensim in /usr/local/lib/python3.11/dist-packages (4.3.3)
Requirement already satisfied: numpy<2.0,>=1.18.5 in /usr/local/lib/python3.11/dist-packages (from gensim) (1.26.4)
Requirement already satisfied: scipy<1.14.0,>=1.7.0 in /usr/local/lib/python3.11/dist-packages (from gensim) (1.13.1)
Requirement already satisfied: smart-open>=1.8.1 in /usr/local/lib/python3.11/dist-packages (from gensim) (7.1.0)
Requirement already satisfied: wrapt in /usr/local/lib/python3.11/dist-packages (from smart-open>=1.8.1->gensim) (1.1
[==================================================] 100.0% 128.1/128.1MB downloaded
Result of 'kitten - cat + dog': puppy
Result of 'orange - fruit + tropical': storm
```

Experiment 2: Visualizing Word Embedding's and Generating Semantically Similar Words.

Objective:

- To visualize word embedding's using dimensionality reduction techniques like **PCA** or **t-SNE**.
- To select 10 words from a specific domain (e.g., sports, technology) and analyze the clusters and relationships between them.
- To generate contextually rich outputs by finding semantically similar words using pre-trained word embedding's.

Dimensionality Reduction for Word Embeddings

Word embedding's like GloVe or Word2Vec represent words in high-dimensional spaces (usually 100 to 300 dimensions). **Dimensionality reduction** techniques help us visualize these high-dimensional embedding's in a 2D or 3D space. This makes it easier to observe clusters and relationships between words.

Techniques:

1. **Principal Component Analysis (PCA):** A linear method to reduce dimensions while preserving maximum variance.
2. **t-SNE (t-Distributed Stochastic Neighbour Embedding):** A non-linear method that captures local structure and forms better clusters for visualization.

Real-Time Visualization and Semantic Similarity Generation

Step 1: Visualize 10 Words from a Specific Domain

We will select 10 words from the **technology domain** and visualize their embeddings using t-SNE.

Step 2: Generate 5 Semantically Similar Words for a Given Input

Given an input word, we will use pre-trained word vectors to find the 5 most semantically similar words.

Sample Program

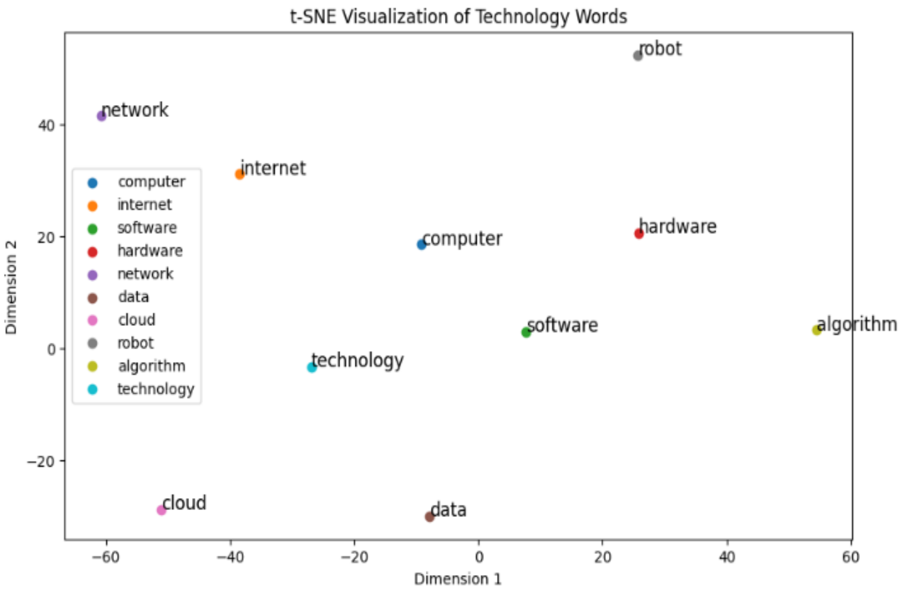
```
# Install required libraries

!pip install gensim matplotlib scikit-learn numpy



import matplotlib.pyplot as plt

from sklearn.manifold import TSNE
```

```
from gensim.downloader import load

import numpy as np  # Import NumPy for array conversion



# Load pre-trained word vectors (GloVe - 100 dimensions)

word_vectors = load('glove-wiki-gigaword-100')



# Select 10 words from the "technology" domain (ensure words exist in the model)

tech_words = ['computer', 'internet', 'software', 'hardware', 'network', 'data', 'cloud', 'robot',
'algorithm', 'technology']

tech_words = [word for word in tech_words if word in word_vectors.key_to_index]



# Extract word vectors and convert to a NumPy array

vectors = np.array([word_vectors[word] for word in tech_words])



# Reduce dimensions using t-SNE

tsne = TSNE(n_components=2, random_state=42, perplexity=5)  # Perplexity is reduced to match
the small sample size

reduced_vectors = tsne.fit_transform(vectors)



# Plot the 2D visualization

plt.figure(figsize=(10, 6))

for i, word in enumerate(tech_words):

    plt.scatter(reduced_vectors[i, 0], reduced_vectors[i, 1], label=word)

    plt.text(reduced_vectors[i, 0] + 0.02, reduced_vectors[i, 1] + 0.02, word, fontsize=12)

plt.title("t-SNE Visualization of Technology Words")

plt.xlabel("Dimension 1")
```

```
plt.ylabel("Dimension 2")

plt.legend()

plt.show()


# Generate 5 semantically similar words for a given input word

input_word = 'computer'

if input_word in word_vectors.key_to_index:

    similar_words = word_vectors.most_similar(input_word, topn=5)

    print(f"5 words similar to '{input_word}':")

    for word, similarity in similar_words:

        print(f"{word} (similarity: {similarity:.2f})")

else:

    print(f"'{input_word}' is not in the vocabulary.")
```

Output:

```
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib) (1.17.0)
Requirement already satisfied: wrapt in /usr/local/lib/python3.11/dist-packages (from smart-open>=1.8.1->gensim) (1.17.2)
```




```
5 words similar to 'computer':
computers (similarity: 0.88)
software (similarity: 0.84)
technology (similarity: 0.76)
pc (similarity: 0.74)
hardware (similarity: 0.73)
```

Experiment 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.

Objective:

1. Train a custom **Word2Vec** model on a small domain-specific dataset (medical text).
2. Analyze how the embeddings capture domain-specific word relationships.
3. Generate similar words for a given input to observe how the model learned from the domain-specific data.

```
# Install required library

!pip install gensim

from gensim.models import Word2Vec

# Step 1: Create a small dataset (list of medical-related word lists)
medical_data = [
    ["patient", "doctor", "nurse", "hospital", "treatment"],
    ["cancer", "chemotherapy", "radiation", "surgery", "recovery"],
    ["infection", "antibiotics", "diagnosis", "disease", "virus"],
    ["heart", "disease", "surgery", "cardiology", "recovery"] ]

# Step 2: Train a Word2Vec model
model = Word2Vec(sentences=medical_data, vector_size=10, window=2,
min_count=1, workers=1, epochs=50)

# Step 3: Find similar words for a given input word
input_word = "patient"
if input_word in model.wv:
    similar_words = model.wv.most_similar(input_word, topn=3)
    print(f"3 words similar to '{input_word}':")
    for word, similarity in similar_words:
        print(f"{word} (similarity: {similarity:.2f})")
else:
    print(f"'{input_word}' is not in the vocabulary.")
```

Output:

```
Requirement already satisfied: gensim in /usr/local/lib/python3.11/dist-packages (4.3.3)
Requirement already satisfied: numpy<2.0,>=1.18.5 in /usr/local/lib/python3.11/dist-packages (from gensim) (1.26.4)
Requirement already satisfied: scipy<1.14.0,>=1.7.0 in /usr/local/lib/python3.11/dist-packages (from gensim) (1.13.1)
Requirement already satisfied: smart-open>=1.8.1 in /usr/local/lib/python3.11/dist-packages (from gensim) (7.1.0)
Requirement already satisfied: wrapt in /usr/local/lib/python3.11/dist-packages (from smart-open>=1.8.1->gensim) (1.1
3 words similar to 'patient':
nurse (similarity: 0.59)
doctor (similarity: 0.34)
chemotherapy (similarity: 0.29)
```

What This Code Does:

1. **Creates a small medical dataset** using lists of related words.
2. **Trains a Word2Vec model** to learn relationships between these words.
3. **Finds 3 words similar to the input word**, showing how well the model captures relationships.

Experiment 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.

When interacting with Generative AI models (like GPT), the quality of the output often depends on how well the input prompt is framed. Enhancing prompts using **word embeddings** helps improve the model's understanding and provides more **contextually rich and detailed responses**.

Here's how we can enhance prompts using **Word2Vec embeddings**:

Use Word Embeddings:
Word embeddings represent words as vectors in a continuous vector space. Words with similar meanings have similar vector representations. For example, the word "AI" might be similar to "machine learning" or "artificial intelligence."

Retrieve Similar Words:
By training or using pre-trained word embeddings, we can find words that are semantically close to the original prompt. These similar words help make the prompt richer.

Example:
Original Prompt: "Explain the impact of AI on technology."
Enriched Prompt: "Explain the impact of AI, machine learning, deep learning, and data science on technology."

Generate Responses:
Use a Generative AI model (e.g., OpenAI GPT) to generate responses for both the original and enriched prompts.
Comparison: The enriched prompt will usually yield a more detailed and relevant response.

```
# Step 1: Pre-defined dictionary of words and their similar terms (static word embeddings)

word_embeddings = {

    "ai": ["machine learning", "deep learning", "data science"],

    "data": ["information", "dataset", "analytics"],

    "science": ["research", "experiment", "technology"],

    "learning": ["education", "training", "knowledge"],

    "robot": ["automation", "machine", "mechanism"]

}
```

```
# Step 2: Function to find similar words using the static dictionary
def find_similar_words(word):
    if word in word_embeddings:
        return word_embeddings[word]
    else:
        return []

# Step 3: Function to enrich a prompt with similar words
def enrich_prompt(prompt):
    words = prompt.lower().split()
    enriched_words = []
    for word in words:
        similar_words = find_similar_words(word)
        if similar_words:
            enriched_words.append(f"{word} ({', '.join(similar_words)})")
        else:
            enriched_words.append(word)
    return " ".join(enriched_words)

# Step 4: Original prompt
original_prompt = "Explain AI and its applications in science."

# Step 5: Enrich the prompt using similar words
enriched_prompt = enrich_prompt(original_prompt)
```

```
# Step 6: Print the original and enriched prompts

print("Original Prompt:")

print(original_prompt)

print("\nEnriched Prompt:")

print(enriched_prompt)
```

Output:

```
Original Prompt:
Explain AI and its applications in science.

Enriched Prompt:
explain ai (machine learning, deep learning, data science) and its applications in science.
```

Experiment 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.

```
# Step 1: Pre-defined dictionary of words and their similar terms
word_embeddings = {
    "adventure": ["journey", "exploration", "quest"],
    "robot": ["machine", "automation", "mechanism"],
    "forest": ["woods", "jungle", "wilderness"],
    "ocean": ["sea", "waves", "depths"],
    "magic": ["spell", "wizardry", "enchantment"]
}

# Step 2: Function to get similar words for a seed word
def get_similar_words(seed_word):
    if seed_word in word_embeddings:
        return word_embeddings[seed_word]
    else:
        return ["No similar words found"]

# Step 3: Function to create a short paragraph using the seed word and similar words
def create_paragraph(seed_word):
    similar_words = get_similar_words(seed_word)
    if "No similar words found" in similar_words:
        return f"Sorry, I couldn't find similar words for '{seed_word}'."

    # Construct a short story using the seed word and similar words
    paragraph = (
        f"Once upon a time, there was a great {seed_word}. "
        f"It was full of {', '.join(similar_words[:-1])}, and {similar_words[-1]}. "
        f"Everyone who experienced this {seed_word} always remembered it as a remarkable tale."
    )
    return paragraph

# Step 4: Input a seed word
seed_word = "adventure"  # You can change this to "robot", "forest", "ocean", "magic", etc.

# Step 5: Generate and print the paragraph
story = create_paragraph(seed_word)
print("Generated Paragraph:")
print(story)
```

Output:

```python
    return paragraph

# Step 4: Input a seed word
seed_word = "adventure"  # You can change this to "robot", "forest", "ocean", "magic", etc.

# Step 5: Generate and print the paragraph
story = create_paragraph(seed_word)
print("Generated Paragraph:")
print(story)
```

```
Generated Paragraph:
Once upon a time, there was a great adventure. It was full of journey, exploration, and quest. Everyone who experienced this adventure always remembered it as a remarkable tale.
```

What This Program Does:

1. **Uses a static dictionary** of word embeddings to find similar words for a given seed word.
2. **Constructs a short paragraph** using the seed word and its similar words.
3. **Prints the paragraph**, creating a small story based on the seed word.

Experiment 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.

Pre-trained model: A model that has already been trained on a large dataset and can perform sentiment analysis without needing additional training.
Hugging Face Pipeline: An easy way to use pre-trained models for tasks like sentiment analysis, text generation, translation, etc.
Real-world application: Analyzing customer reviews or social media comments to understand user feedback.

Sample Program:

```
# Step 1: Install and import the necessary library
# You can uncomment and run this in Google Colab
# !pip install transformers

from transformers import pipeline

# Step 2: Load the sentiment analysis pipeline
sentiment_analyzer = pipeline("sentiment-analysis")

# Step 3: Define sample sentences for analysis
sentences = [
    "I love using this product! It makes my life so much easier.",
    "The service was terrible, and I'm very disappointed.",
    "It's an average experience, nothing special but not bad either."]

# Step 4: Analyze the sentiment for each sentence
for sentence in sentences:
    result = sentiment_analyzer(sentence)[0]
    print(f"Sentence: {sentence}")
    print(f"Sentiment: {result['label']} (Score: {result['score']:.2f})\n")
```

Output:

```
config.json: 100%  629/629 [00:00<00:00, 41.3kB/s]
model.safetensors: 100%  268M/268M [00:04<00:00, 68.4MB/s]
tokenizer_config.json: 100%  48.0/48.0 [00:00<00:00, 2.55kB/s]
vocab.txt: 100%  232k/232k [00:00<00:00, 1.62MB/s]
Device set to use cpu
Sentence: I love using this product! It makes my life so much easier.
Sentiment: POSITIVE (Score: 1.00)

Sentence: The service was terrible, and I'm very disappointed.
Sentiment: NEGATIVE (Score: 1.00)

Sentence: It's an average experience, nothing special but not bad either.
Sentiment: POSITIVE (Score: 0.91)
```

What This Program Does:

1. **Loads a pre-trained Hugging Face model** for sentiment analysis.
2. **Analyzes the sentiment** of sample sentences.
3. **Prints the sentiment label** (`POSITIVE`, `NEGATIVE`, or `NEUTRAL`) along with a confidence score.

Experiment 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.

Sample Program:

```
# Step 1: Import the Hugging Face pipeline
from transformers import pipeline

# Step 2: Load the summarization pipeline
summarizer = pipeline("summarization")

# Step 3: Input a long passage for summarization
long_text = """
Artificial Intelligence (AI) is transforming various industries by automating tasks, improving efficiency,
and enabling new capabilities. In the healthcare sector, AI is used for disease diagnosis, personalized medicine,
and drug discovery. In the business world, AI-powered systems are optimizing customer service, fraud detection,
and supply chain management. AI's impact on everyday life is significant, from smart assistants to recommendation
systems in streaming platforms. As AI continues to evolve, it promises even greater advancements in fields like
education, transportation, and environmental sustainability.
"""

# Step 4: Summarize the input passage
summary = summarizer(long_text, max_length=50, min_length=20,
do_sample=False)[0]["summary_text"]

# Step 5: Print the summarized text
print("Summarized Text:")
print(summary)
```

Output:

```
config.json: 100%        1.80k/1.80k [00:00<00:00, 97.4kB/s]
pytorch_model.bin: 100%  1.22G/1.22G [00:11<00:00, 126MB/s]
model.safetensors: 69%   849M/1.22G [00:12<00:02, 128MB/s]
tokenizer_config.json: 100%  26.0/26.0 [00:00<00:00, 717B/s]
vocab.json: 100%         899k/899k [00:00<00:00, 9.76MB/s]
merges.txt: 100%         456k/456k [00:00<00:00, 10.5MB/s]
Device set to use cpu
Summarized Text:
 Artificial Intelligence (AI) is transforming various industries by automating tasks, improving efficiency, and enabling new capabilities . In the healthcare sector, AI is used for disease
```

What This Program Does:

1. **Uses Hugging Face's `pipeline("summarization")`** to load a pre-trained summarization model.
2. **Processes a long text passage** and reduces it to a concise summary.
3. **Prints the summarized version**, which highlights the key points.

Experiment 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.

Step-by-Step Explanation

- **Install necessary libraries**: We will install `langchain`, `cohere`, and `langchain-community`.
- **Set up the Cohere API**: Obtain your Cohere API key by logging into Cohere's platform.
- **Load a text document** from Google Drive.
- **Create a Langchain Prompt Template** to process the document and return the result in a particular format.

```
# Step 1: Install necessary libraries
!pip install langchain cohere langchain-community

# Step 2: Import the required modules
from langchain.llms import Cohere
from langchain.prompts import PromptTemplate
from langchain import LLMChain
from google.colab import drive

# Step 3: Mount Google Drive to access the document
drive.mount('/content/drive')

# Step 4: Load the text document from Google Drive
file_path = "/content/drive/MyDrive/sample_text.txt"  # Change this path to your file location
with open(file_path, "r") as file:
    text = file.read()

# Step 5: Set up Cohere API key
cohere_api_key = "YOUR_COHERE_API_KEY"  # Replace with your actual Cohere API key

# Step 6: Create a prompt template
prompt_template = """
Summarize the following text in three bullet points:
{text}
"""

# Step 7: Configure the Cohere model with Langchain
llm = Cohere(cohere_api_key=cohere_api_key)
prompt = PromptTemplate(input_variables=["text"], template=prompt_template)

# Step 8: Create an LLMChain with the Cohere model and prompt template
chain = LLMChain(llm=llm, prompt=prompt)

# Step 9: Run the chain on the loaded text
result = chain.run(text)

# Step 10: Display the formatted output
print("Summarized Output in Bullet Points:")
print(result)
```

What This Program Does:

1. **Mounts Google Drive** to access a text document (`sample_text.txt`).
2. **Reads the document's content** and prepares it for processing.
3. **Uses Langchain's PromptTemplate** to create a structured request for summarization.
4. **Cohere LLM processes** the text and returns the summarized output in a **bullet-point format**.

Output:

```
Summarized Output in Bullet Points:

- AI is transforming industries like healthcare, business, and education.

- Smart assistants and recommendation systems are examples of AI's impact on daily life.

- Future advancements will bring improvements in transportation and sustainability.
```

Experiment 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.**

Step-by-Step Explanation:

1. **Install necessary libraries**: Install `langchain`, `pydantic`, and `wikipedia-api`.
2. **Take institution name as input**.
3. **Use Pydantic to define a schema** for the output (structured format).
4. **Fetch institution details from Wikipedia** and format the output according to the schema.

```
# Step 1: Install necessary libraries

!pip install langchain pydantic wikipedia-api



# Step 2: Import required modules

from langchain.llms import Cohere

from langchain.prompts import PromptTemplate

from langchain import LLMChain

from pydantic import BaseModel

import wikipediaapi



# Step 3: Define a Pydantic schema for the institution's details

class InstitutionDetails(BaseModel):

    founder: str

    founded: str

    branches: str

    employees: str

    summary: str
```

```
# Step 4: Function to fetch details from Wikipedia with user-agent specified

def fetch_wikipedia_summary(institution_name):

    wiki_wiki = wikipediaapi.Wikipedia(language='en',
user_agent="InstitutionInfoBot/1.0 (contact: youremail@example.com)")

    page = wiki_wiki.page(institution_name)

    if page.exists():

        return page.text

    else:

        return "No information available on Wikipedia for this institution."

# Step 5: Prompt template for extracting relevant details

prompt_template = """

Extract the following information from the given text:

- Founder

- Founded (year)

- Current branches

- Number of employees

- 4-line brief summary

Text: {text}

Provide the information in the following format:

Founder: <founder>

Founded: <founded>

Branches: <branches>

Employees: <employees>

Summary: <summary>
```

```
"""



# Step 6: Take institution name as input

institution_name = input("Enter the name of the institution: ")



# Step 7: Fetch Wikipedia data for the institution

wiki_text = fetch_wikipedia_summary(institution_name)



# Step 8: Set up Cohere (Replace YOUR_COHERE_API_KEY with your actual key)

cohere_api_key = "YOUR_COHERE_API_KEY"

llm = Cohere(cohere_api_key=cohere_api_key)



# Step 9: Create the Langchain prompt and chain

prompt = PromptTemplate(input_variables=["text"], template=prompt_template)

chain = LLMChain(llm=llm, prompt=prompt)



# Step 10: Run the chain and parse the output

response = chain.run(wiki_text)



# Step 11: Parse the response using Pydantic

try:

    details = InstitutionDetails.parse_raw(response)

    print("Institution Details:")

    print(f"Founder: {details.founder}")
```

```
    print(f"Founded: {details.founded}")

    print(f"Branches: {details.branches}")

    print(f"Employees: {details.employees}")

    print(f"Summary: {details.summary}")

except Exception as e:

    print("Error parsing the response:", e)
```

Output:

```
Enter the name of the institution: Google

Institution Details:

Founder: Larry Page, Sergey Brin

Founded: 1998

Branches: Global offices in more than 50 countries

Employees: Over 100,000

Summary: Google is a multinational technology company specializing in internet-related services and products. It is known for its search engine, online advertising, cloud computing, and software. Google is one of the Big Five tech companies. It was founded by Larry Page and Sergey Brin in 1998.
```

Experiment 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-by-step Explanation

1. **Load the IPC text document**.
2. **Create a chatbot** using a basic question-answering chain.
3. **Users can ask questions**, and the chatbot will retrieve relevant sections from the IPC.

Sample Program:

```
# Step 1: Install necessary packages
!pip install langchain pydantic wikipedia-api openai

# Step 2: Import required modules
from langchain.chains import load_qa_chain
from langchain.docstore.document import Document
from langchain.llms import OpenAI

# Step 3: Load the Indian Penal Code text from a file
ipc_file_path = "path_to_your_ipc_file.txt"  # Replace with the actual path to your IPC text file

# Read the IPC document
with open(ipc_file_path, "r", encoding="utf-8") as file:
    ipc_text = file.read()

# Step 4: Create a Langchain Document object
ipc_document = Document(page_content=ipc_text)

# Step 5: Set up OpenAI (or any other LLM of your choice)
llm = OpenAI(openai_api_key="YOUR_OPENAI_API_KEY", temperature=0.3)  # Use
temperature=0.3 for more factual responses

# Step 6: Create a simple question-answering chain
qa_chain = load_qa_chain(llm, chain_type="stuff")

# Step 7: Chat with the chatbot
print("Chatbot for the Indian Penal Code (IPC)")
print("Ask a question about the Indian Penal Code (type 'exit' to stop):")

while True:
    user_question = input("\nYour question: ")
    if user_question.lower() == "exit":
        print("Goodbye!")
        break

    # Use the QA chain to answer the question
    response = qa_chain.run(input_documents=[ipc_document], question=user_question)
    print(f"Answer: {response}")
```

Output:

```
Chatbot for the Indian Penal Code (IPC)
Ask a question about the Indian Penal Code (type 'exit' to stop):

Your question: What is Section 302 of the IPC?
Answer: Section 302 of the Indian Penal Code refers to punishment for murder,
which is punishable with death or life imprisonment and a fine.

Your question: exit
Goodbye!
```