PES Institute of Technology and Management

Department of Computer Science & Design

Laboratory Manual

Semester: VI

Subject: Generative AI

Subject Code: BAIL657C

Compiled By:

Dr. Pramod

Head Of the Department

NH-206, Sagar Road, Shivamogga-577204

Ph: 08182-640733/640734 Fax: 08182-233797

www.pestrust.edu.in/pesitm

PROGRAM OUTCOMES

PO's	PO Description
PO1	**Engineering knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
PO2	**Problem analysis:** Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
PO3	**Design/development of solutions**: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
PO4	**Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
PO5	**Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
PO6	**The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
PO7	**Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
PO8	**Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
PO9	**Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
PO10	**Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
PO11	**Project management and finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
PO12	**Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOMES

PSO's	PSO Description
PSO1	An ability to design and analyze algorithms by applying theoretical concepts to build complex and computer- based systems in the domain of System Software, Computer Networks & Security, Web technologies, Data Science and Analytics.
PSO2	Be able to develop various software solutions by applying the techniques of Data Base Management, Complex Mathematical Models, Software Engineering practices and Machine Learning with Artificial Intelligence.

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):

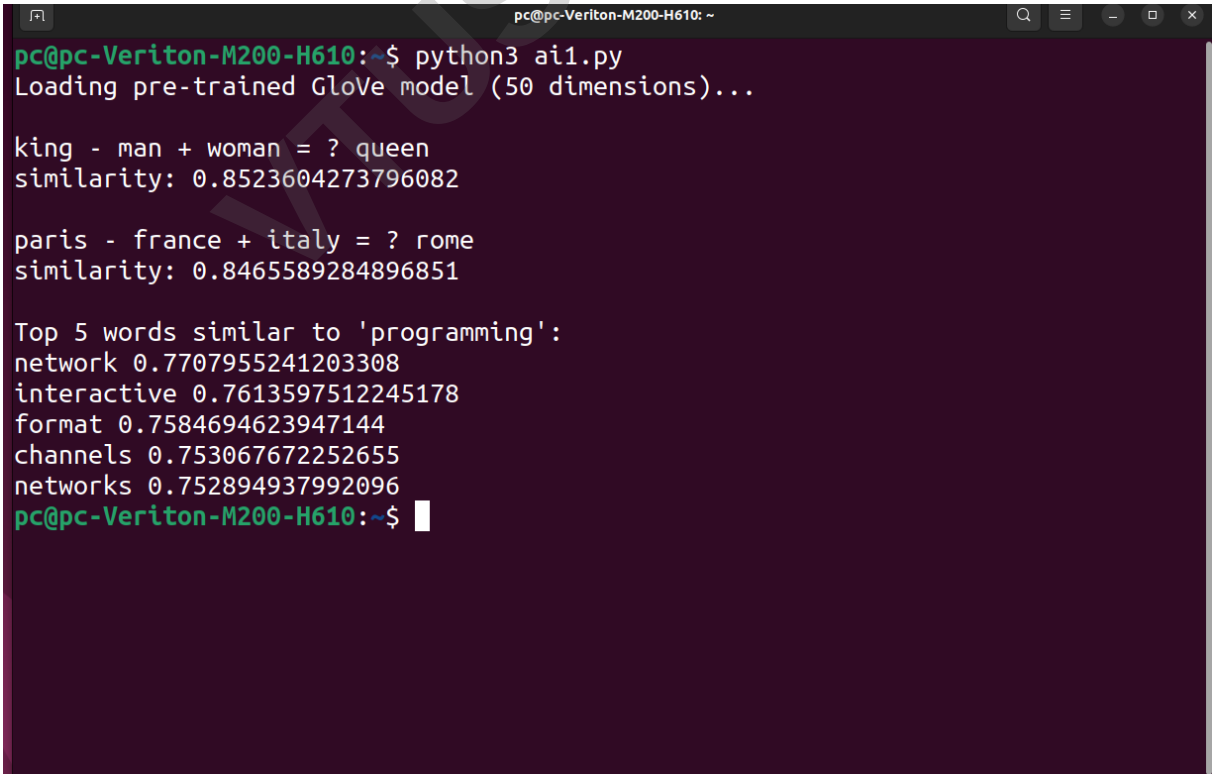
- https://www.w3schools.com/gen_ai/index.php
- https://youtu.be/eTPiL3DF27U
- https://youtu.be/je6AlVeGOV0
- https://youtu.be/RLVqsA8ns6k
- https://youtu.be/0SAKM7wiC-A
- https://youtu.be/28_9xMyrdjg
- https://youtu.be/8iuiz-c-EBw
- https://youtu.be/7oQ8VtEKcgE
- https://youtu.be/seXp0VWWZV0

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

Python Code:

```
from gensim.downloader import load

# Load the pre-trained GloVe model (50 dimensions)
print("Loading pre-trained GloVe model (50 dimensions)...")
model = load("glove-wiki-gigaword-50")

# Function to perform vector arithmetic and analyze relationships
def ewr():
    result = model.most_similar(positive=['king', 'woman'], negative=['man'], topn=1)
    print("\nking - man + woman = ?", result[0][0])
    print("similarity:", result[0][1])

    result = model.most_similar(positive=['paris', 'italy'], negative=['france'], topn=1)
    print("\nparis - france + italy = ?", result[0][0])
    print("similarity:", result[0][1])

    # Example 3: Find analogies for programming
    result = model.most_similar(positive=['programming'], topn=5)
    print("\nTop 5 words similar to 'programming':")
    for word, similarity in result:
        print(word, similarity)

ewr()
```

Output :

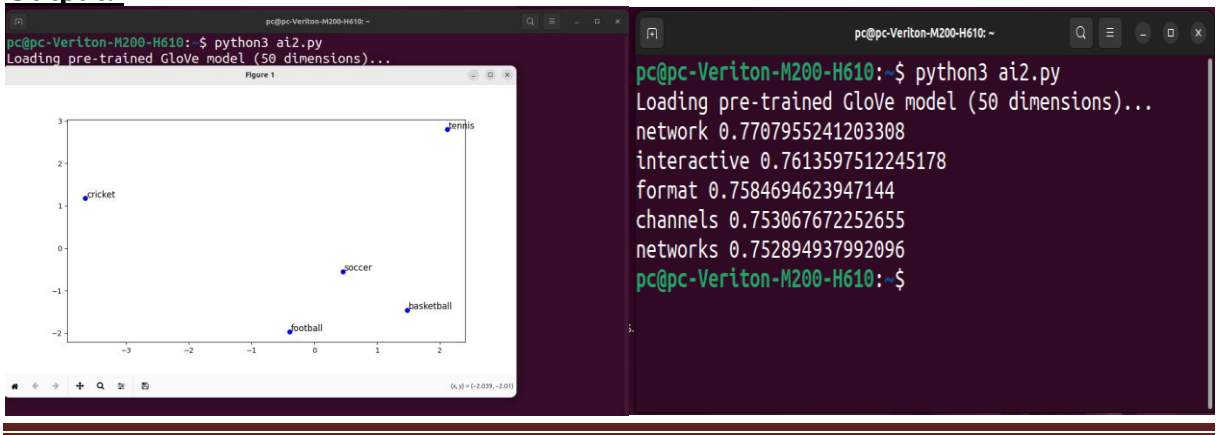


2. Use dimensionality reduction (e.g., PCA or t-SNE) to visualize word embeddings for Q 1. Select 10 words from a specific domain (e.g., sports, technology) and visualize their embeddings. Analyze clusters and relationships. Generate contextually rich outputs using embeddings. Write a program to generate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

Python Code:

```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from gensim.downloader import load

# Dimensionality reduction using PCA
def rd(ems):
    pca = PCA(n_components=2)
    r = pca.fit_transform(ems)
    return r

# Visualize word embeddings
def visualize(words, ems):
    plt.figure(figsize=(10, 6))
    for i, word in enumerate(words):
        x, y = ems[i]
        plt.scatter(x, y, marker='o', color='blue')
        plt.text(x + 0.02, y + 0.02, word, fontsize=12)
    plt.show()

# Generate semantically similar words
def gsm(word):
    sw = model.most_similar(word, topn=5)
    for word, s in sw:
        print(word, s)

# Load pre-trained GloVe model from Gensim API
print("Loading pre-trained GloVe model (50 dimensions)...")
model = load("glove-wiki-gigaword-50")

words = ['football', 'basketball', 'soccer', 'tennis', 'cricket']
ems = [model[word] for word in words]
e = rd(ems)
visualize(words, e)
gsm("programming")
```

Output:



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.

Python Code:

```
from gensim.models import Word2Vec

# Custom Word2Vec model
def cw(corpus):
    model = Word2Vec(
        sentences=corpus,
        vector_size=50,  # Dimensionality of word vectors
        window=5,        # Context window size
        min_count=1,     # Minimum frequency for a word to be considered
        workers=4,       # Number of worker threads
        epochs=10,       # Number of training epochs
    )
    return model

# Analyze trained embeddings
def anal(model, word):
    sw = model.wv.most_similar(word, topn=5)
    for w, s in sw:
        print(w, s)

# Example domain-specific dataset (medical/legal/etc.)
corpus = [
    "The patient was prescribed antibiotics to treat the infection.".split(),
    "The court ruled in favor of the defendant after reviewing the evidence.".split(),
    "Diagnosis of diabetes mellitus requires specific blood tests.".split(),
    "The legal contract must be signed in the presence of a witness.".split(),
    "Symptoms of the disease include fever, cough, and fatigue.".split(),
]

model = cw(corpus)
print("Analysis for word patient")
anal(model, "patient")
print("Analysis for word court")
anal(model, "court")
```

Output:

```
pc@pc-Veriton-M200-H610: ~
pc@pc-Veriton-M200-H610:~$ python3 ai3.py
Analysis for word patient
the 0.2704925239086151
treat 0.2675759792327881
mellitus 0.20430023968219757
The 0.19626495242118835
Symptoms 0.19223204255104065
Analysis for word court
a 0.2577084004878998
defendant 0.23732653260231018
reviewing 0.16933836042881012
was 0.16483156383037567
contract 0.16124068200588226
pc@pc-Veriton-M200-H610:~$
```

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.

Python Code:

```
from gensim.downloader import load
import torch
from transformers import pipeline

# Load pre-trained word embeddings (GloVe)
model = load("glove-wiki-gigaword-50")
torch.manual_seed(42)

# Define contextually relevant word enrichment
def enrich(prompt):
    ep = ""# Start with the original prompt
    words = prompt.split() # Split the prompt into words
    for word in words:
        sw = model.most_similar(word, topn=3)
        print("Test Data\n",sw)
        enw=[]
        for s,w in sw:
            enw.append(s)
        ep+=" " + " ".join(enw)
    return ep
# Example prompt to be enriched
op = "lung cancer"
ep = enrich(op)
# Display the results
print("Original Prompt:", op)
print("Enriched Prompt:", ep)
generator = pipeline("text-generation", model="gpt2")#, tokenizer="gpt2")
response = generator(op, max_length=200, num_return_sequences=1,
no_repeat_ngram_size=2)#top_p=0.95, temperature=0.7)
print("\n\nPrompt response\n",response[0]["generated_text"])
response = generator(ep, max_length=200, num_return_sequences=1, no_repeat_ngram_size=2)
#top_p=0.95, temperature=0.7)
print("\n\nEnriched prompt response\n",response[0]["generated_text"])
```

Output :

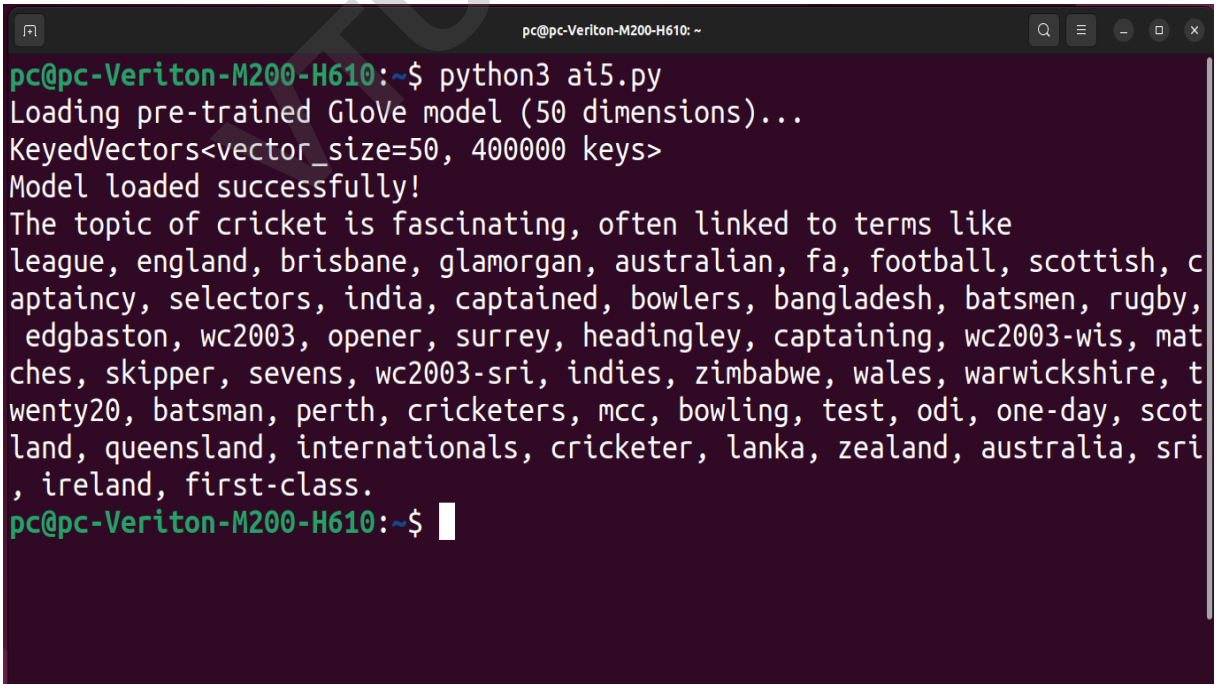
```
pc@pc-Veriton-M200-H610: ~
pc@pc-Veriton-M200-H610:~$ python3 al4.py
Test Data
 [('respiratory', 0.7848058938980103), ('kidney', 0.7656568288803101), ('cancer', 0.7609831094741821)]
Test Data
 [('diabetes', 0.863990068435669), ('prostate', 0.8504137992858887), ('alzheimer', 0.848117172718048 1)]
Original Prompt: lung cancer
Enriched Prompt:  respiratory kidney cancer diabetes prostate alzheimer
Device set to use cpu
Truncation was not explicitly activated but `max_length` is provided a specific value, please use `truncation=True` to explicitly truncate examples
to max length. Defaulting to 'longest_first' truncation strategy. If you encode pairs of sequences (GLUE-style) with the tokenizer you can select th
is strategy more precisely by providing a specific strategy to `truncation`.
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.


Prompt response
 lung cancer: what to do.

Diana Zangetsu, MSU-D
, PhD The disease was spread by the bacterium M. tuberculosis in the intestines of cats and humans. Most of the cases are attributed to the disease
spreading from people with common cats. It was the only class of bacteria in cats to cause the death of up to 50% of cancer cases. The epidemiology
of tuberculosis is still poorly understood. Epidemics of various types often occur and can be caused by small intestinal bacterial infections in ktt
tens, rats and dogs, and small numbers of parasites. Many people have been cured by cat-resistant tuberculosis. In humans, the pathogen is a human-i
nduced illness that has spread over time with a genetic basis. One way of treating it is to kill some animals and allow them to live as healthy and
healthy as possible as kittens or humans for food, but the effect can have disastrous consequences. People with early onset of chronic disease may e
ven use antl
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.


Enriched prompt response
  respiratory kidney cancer diabetes prostate alzheimer's disease asthma cardiovascular disease diabetes endometrial disease infertility heart disea
se heart failure cardiovascular diseases cardiovascular syndromes heart condition diabetes heart attacks heart diseases heart attack heart rate dysl
ipidemics chronic illnesses chronic diseases depression heart-rate disorder heart defect heart disorder cardiovascular deaths heart defects heart ri
sk heart surgery heart prevention heart medications heart procedure heart disorders heart medicine heart and heart conditions heart health heart car
e heart treatments heart transplants heart transplantation heart implantation (chromosome transplanted heart valves) heart tumor (cancerous heart) d
ouble valve angioplasty heart valve replacement surgery Heart transplant for coronary angiography Heart surgery (transplantation of heart arteries);
 double surgery of coronary artery arteries Heart transplation treatment heart surgeries (conventional cardiac surgery) coronary hypertension (unspe
cified heart problems or cardiac diseases) circulatory diseases(nervous tissue disease, non-cardiovascular conditions such as stroke, congestive hea
rt events, and congestional heart event(s)) circ
pc@pc-Veriton-M200-H610:~$
```

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.

Python Code:

```
from gensim.downloader import load
import random

# Load the pre-trained GloVe model
print("Loading pre-trained GloVe model (50 dimensions)...")
model = load("glove-wiki-gigaword-50")
print(model)
print("Model loaded successfully!")

# Function to construct a meaningful paragraph
def create_paragraph(iw, sws):
    paragraph = f"The topic of {iw} is fascinating, often linked to terms like\n"
    random.shuffle(sws)  # Shuffle to add variety
    for word in sws:
        paragraph += str(word) + ", "
    paragraph = paragraph.rstrip(", ") + "."
    return paragraph

iw = "cricket"
sws = model.most_similar(iw, topn=50)
words = [word for word, s in sws]
paragraph = create_paragraph(iw, words)
print(paragraph)
```

Output:



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.

Python Code:

```
from transformers import pipeline

# Specify the model explicitly
sentiment_analyzer = pipeline(
    "sentiment-analysis",
    model="distilbert/distilbert-base-uncased-finetuned-sst-2-english"
)

customer_feedback = [
    "The product is amazing! I love it!",
    "Terrible service, I am very disappointed.",
    "This is a great experience, I will buy again.",
    "Worst purchase I've ever made. Completely dissatisfied.",
    "I'm happy with the quality, but the delivery was delayed."
]

for feedback in customer_feedback:
    sentiment_result = sentiment_analyzer(feedback)
    sentiment_label = sentiment_result[0]['label']
    sentiment_score = sentiment_result[0]['score']

    # Display sentiment results
    print(f"Feedback is: {feedback}")
    print(f"Sentiment is: {sentiment_label} (Confidence: {sentiment_score:.2f})\n")
```

Output:

```
pc@pc-Veriton-M200-H610: ~
pc@pc-Veriton-M200-H610:~$ python3 ai6.py
Device set to use cpu
Feedback is: The product is amazing! I love it!
Sentiment is: POSITIVE (Confidence: 1.00)

Feedback is: Terrible service, I am very disappointed.
Sentiment is: NEGATIVE (Confidence: 1.00)

Feedback is: This is a great experience, I will buy again.
Sentiment is: POSITIVE (Confidence: 1.00)

Feedback is: Worst purchase I've ever made. Completely dissatisfied.
Sentiment is: NEGATIVE (Confidence: 1.00)

Feedback is: I'm happy with the quality, but the delivery was delayed.
Sentiment is: NEGATIVE (Confidence: 1.00)

pc@pc-Veriton-M200-H610:~$
```

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.

Python Code:

```
from transformers import pipeline

# Specify the model explicitly
summarizer = pipeline(
    "summarization",
    model="facebook/bart-large-cnn") # You can replace this with any other summarization model if needed
# Function to summarize a given passage
def summarize_text(text):
    # Summarizing the text using the pipeline
    summary = summarizer(text, max_length=150, min_length=50, do_sample=False)
    return summary[0]['summary_text']

text = """
Natural language processing (NLP) is a field of artificial intelligence that focuses on the interaction between computers and humans through natural language.
The ultimate goal of NLP is to enable computers to understand, interpret, and generate human language in a way that is valuable.
NLP techniques are used in many applications, such as speech recognition, sentiment analysis, machine translation, and chatbot functionality.
Machine learning algorithms play a significant role in NLP, as they help computers to learn from vast amounts of language data and improve their ability to process and generate text.
However, NLP still faces many challenges, such as handling ambiguity, understanding context, and processing complex linguistic structures.
Advances in NLP have been driven by deep learning models, such as transformers, which have significantly improved the performance of many NLP tasks.
"""
# Get the summarized text
summarized_text = summarize_text(text)
# Display the summarized text
print("Original Text:\n", text)
print("\nSummarized Text:\n", summarized_text)
```

Output:

```
pc@pc-Veriton-M200-H610: ~
pc@pc-Veriton-M200-H610:~$ python3 ai7.py
Device set to use cpu
Original Text:

Natural language processing (NLP) is a field of artificial intelligence that focuses o
n the interaction between computers and humans through natural language.
The ultimate goal of NLP is to enable computers to understand, interpret, and generate
 human language in a way that is valuable.
NLP techniques are used in many applications, such as speech recognition, sentiment an
alysis, machine translation, and chatbot functionality.
Machine learning algorithms play a significant role in NLP, as they help computers to
learn from vast amounts of language data and improve their ability to process and gene
rate text.
However, NLP still faces many challenges, such as handling ambiguity, understanding co
ntext, and processing complex linguistic structures.
Advances in NLP have been driven by deep learning models, such as transformers, which
have significantly improved the performance of many NLP tasks.


Summarized Text:
 Natural language processing (NLP) is a field of artificial intelligence that focuses
on the interaction between computers and humans through natural language. NLP techniqu
es are used in many applications, such as speech recognition, sentiment analysis, mach
ine translation, and chatbot functionality.
pc@pc-Veriton-M200-H610:~$
```

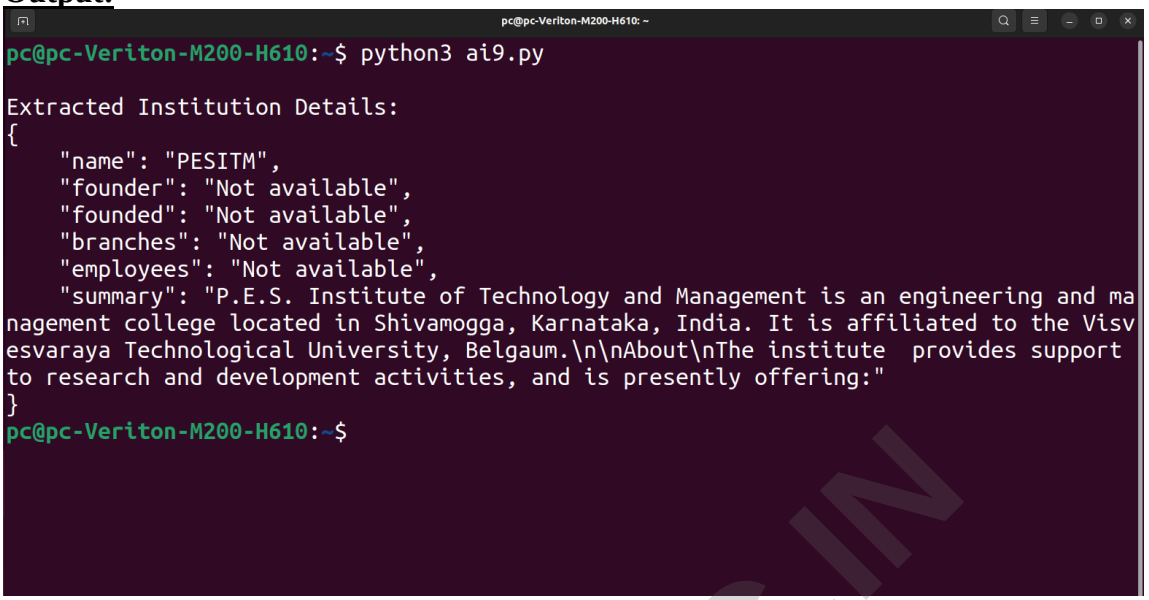
9. Take the Institution name as input. Use Pydantic to define the schema for the desired output and create a custom output parser. Invoke the Chain and Fetch Results. Extract the below Institution related details from Wikipedia: The founder of the Institution. When it was founded. The current branches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

Python Code:

```
from pydantic import BaseModel
import wikipediaapi

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

# Helper function to extract info based on keyword
def extract_info(content, keyword):
    for line in content.split('\n'):
        if keyword in line.lower():
            return line.strip()
    return "Not available"

# Function to Fetch and Extract Details from Wikipedia
def fetch(institution_name):
    user_agent = "InstitutionInfoFetcher/1.0 (https://example.com; contact@example.com)"
    wiki = wikipediaapi.Wikipedia('en', headers={"User-Agent": user_agent})
    page = wiki.page(institution_name)

    if not page.exists():
        raise ValueError(f"No Wikipedia page found for '{institution_name}'")

    content = page.text

    founder = extract_info(content, "founder")
    founded = extract_info(content, "founded") or extract_info(content, "established")
    branches = extract_info(content, "branch")
    employees = extract_info(content, "employee")
    summary = "\n".join(content.split('\n')[:4])

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

```
# Run the program
details = fetch("PESITM")
print("\nExtracted Institution Details:")
print(details.model_dump_json(indent=4))
```

Output:



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.

Python Code:

```
import fitz  # PyMuPDF

# Step 1: Extract Text from IPC PDF
def extract(file):
    text = ""
    with fitz.open(file) as pdf:
        for page in pdf:
            text += page.get_text()
    return text

# Step 2: Search for Relevant Sections in IPC
def search(query, ipc):
    query = query.lower()
    lines = ipc.split("\n")
    results=[]
    for line in lines:
        if query in line.lower():
            results.append(line)
    #results = [line for line in lines if query in line.lower()]
    if results:
        return results
    else:
        return ["No relevant section found."]
    #return results if results else ["No relevant section found."]
```

```
# Step 3: Main Chatbot Function
def chatbot():
    print("Loading IPC document...")
    ipc = extract("IPC.pdf")
    while True:
        query = input("Ask a question about the IPC: ")
        if query.lower() == "exit":
            print("Goodbye!")
            break

        results = search(query, ipc)
        print("\n".join(results))
        print("-" * 50)

chatbot()
```

Output: