Generative AI

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.

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.

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

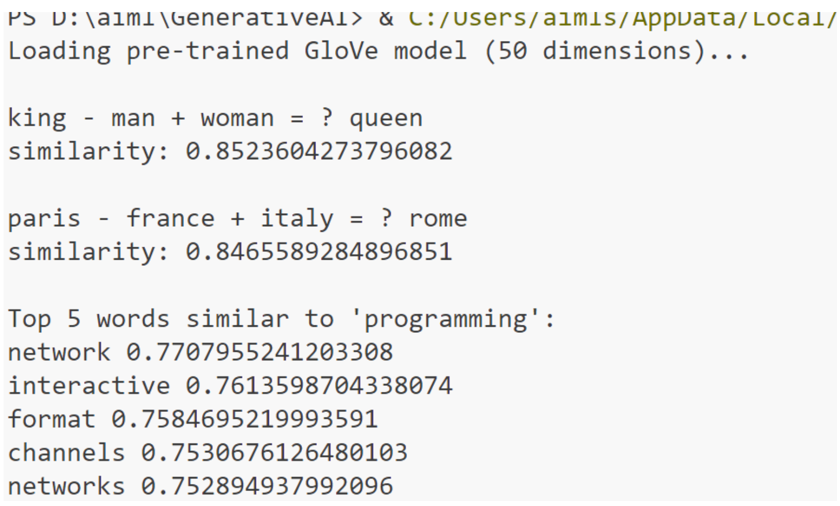
Code:

```
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 4: 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()
```

Explanation:

Gensim is used to perform vector arithmetic and analyze word relationships in a 50-dimensional semantic space. First, the GloVe model (glove-wiki-gigaword-50) is loaded, containing word vectors trained on a large corpus of text. The ewr() function showcases examples of vector arithmetic. It finds the most semantically similar word to a computed vector using the most_similar method. For instance, king - man + woman predicts a word that reflects the concept of "queen," while paris - france + italy predicts a word like "rome." The function also retrieves the top 5 words most similar to "programming." This illustrates how word embeddings capture meaningful relationships and analogies between words in the vector space.

Output:



```
PS D:\aiml\GenerativeAI> & C:/Users/aimls/AppData/Local/
Loading pre-trained GloVe model (50 dimensions)...

king - man + woman = ? queen
similarity: 0.8523604273796082

paris - france + italy = ? rome
similarity: 0.8465589284896851

Top 5 words similar to 'programming':
network 0.7707955241203308
interactive 0.7613598704338074
format 0.7584695219993591
channels 0.7530676126480103
networks 0.752894937992096
```

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.

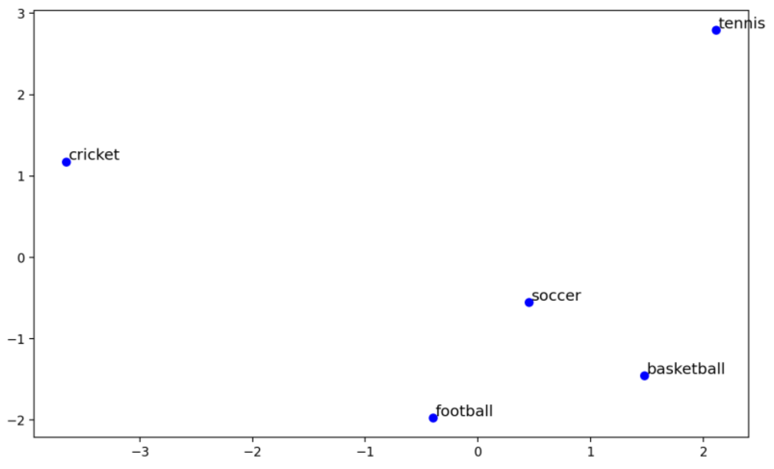
Code:

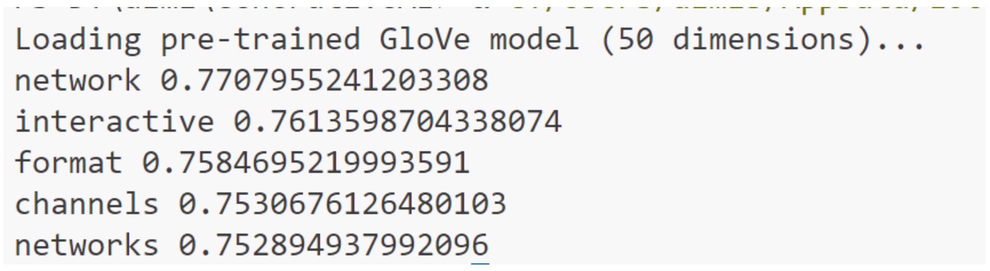
```python
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from gensim.downloader import load

# 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")
```

Explanation:
Word embeddings are input to PCA (Principal Component Analysis) for dimensionality reduction. Semantic relationships among words are analyzed using a pre-trained GloVe model. The GloVe embeddings (glove-wiki-gigaword-50) are loaded via Gensim, providing 50-dimensional

vector representations of words. The rd function reduces these embeddings to 2 dimensions using PCA, making them suitable for visualization. The visualize function plots the 2D representations of selected words (e.g., "football", "basketball", etc.), displaying their relative semantic positions in the vector space. The gsm function retrieves and prints the top 5 semantically similar words for a given word (e.g., "programming") using the GloVe model's most_similar method. This process helps illustrate both the semantic relationships between words and their visual clustering in a lower-dimensional space.

Output:





```
Loading pre-trained GloVe model (50 dimensions)...
network 0.7707955241203308
interactive 0.7613598704338074
format 0.7584695219993591
channels 0.7530676126480103
networks 0.752894937992096
```

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.

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")
```

Explanation:

The cw function trains the model on a small, tokenized dataset of sentences using the Gensim Word2Vec implementation. Key parameters include vector_size (50-dimensional embeddings), window (context window size), min_count (minimum word frequency), and epochs (number of training passes). Once trained, the anal function retrieves the top 5 semantically similar words for a given input word using the most_similar method, revealing the relationships learned from the corpus. In the example, the model is trained on a dataset with sentences about medical and legal topics. Queries like "patient" and "court" analyze the embeddings, returning words from the corpus that are contextually related, showcasing how Word2Vec captures semantic relationships in custom text corpora.

Output:

```
Analysis for word patient
the 0.2704925239086151
treat 0.2675760090351105
mellitus 0.20430020987987518
The 0.19626492261886597
Symptoms 0.19223201274871826
Analysis for word court
a 0.2577084004878998
defendant 0.23732653260231018
reviewing 0.16933836042881012
was 0.16483157873153687
contract 0.16124068200588226
```

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

Code:

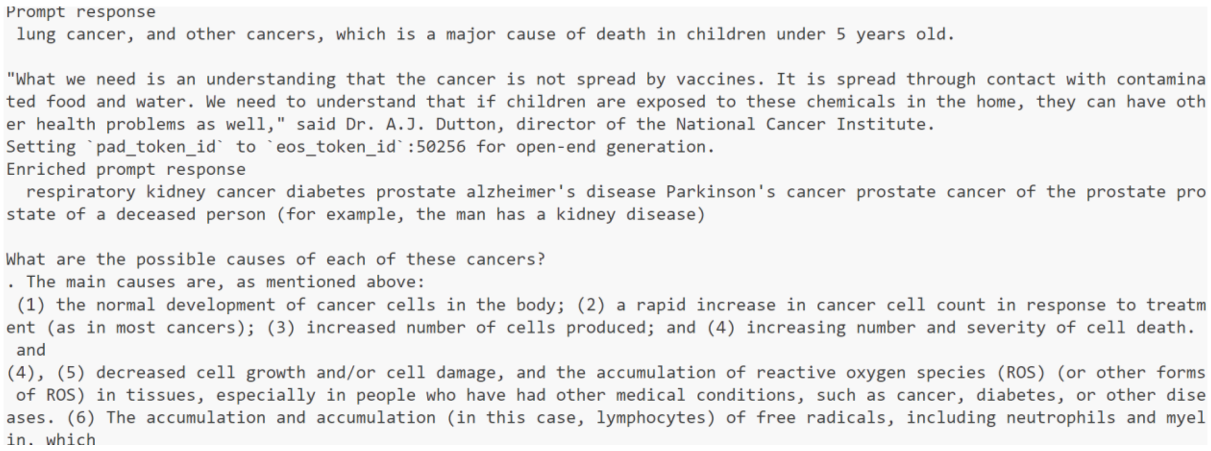
```python
from gensim.downloader import load
import torch
from transformers import pipeline

# Load pre-trained word embeddings (GloVe)
model = load("glove-wiki-gigaword-50")  # GloVe model with 50 dimensions
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)
        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)
```

```python
# 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("Prompt 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("Enriched prompt response\n",response[0]["generated_text"])
```

Explanation

Given prompt is enriched using pre-trained **GloVe word embeddings** and then generate responses using a **GPT-2 model**. The enrich() function adds contextually similar words to the original prompt by finding the most similar words for each term in the prompt using GloVe. After enriching the prompt, both the original and enriched prompts are fed into the GPT-2 model to generate responses. The model's output is controlled with parameters like max_length, top_p, and temperature to ensure diversity and coherence in the generated text. This approach allows for comparing how enriching a prompt can affect the generated response.

Output:



```
Prompt response
 lung cancer, and other cancers, which is a major cause of death in children under 5 years old.

"What we need is an understanding that the cancer is not spread by vaccines. It is spread through contact with contamina
ted food and water. We need to understand that if children are exposed to these chemicals in the home, they can have oth
er health problems as well," said Dr. A.J. Dutton, director of the National Cancer Institute.
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.
Enriched prompt response
  respiratory kidney cancer diabetes prostate alzheimer's disease Parkinson's cancer prostate cancer of the prostate pro
state of a deceased person (for example, the man has a kidney disease)

What are the possible causes of each of these cancers?
. The main causes are, as mentioned above:
 (1) the normal development of cancer cells in the body; (2) a rapid increase in cancer cell count in response to treatm
ent (as in most cancers); (3) increased number of cells produced; and (4) increasing number and severity of cell death.
 and
(4), (5) decreased cell growth and/or cell damage, and the accumulation of reactive oxygen species (ROS) (or other forms
 of ROS) in tissues, especially in people who have had other medical conditions, such as cancer, diabetes, or other dise
ases. (6) The accumulation and accumulation (in this case, lymphocytes) of free radicals, including neutrophils and myel
in, which
```

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.

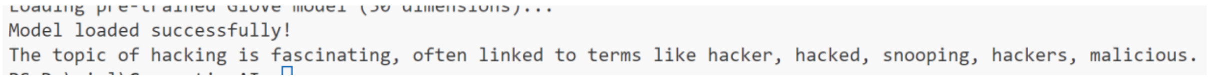
Code:

```python
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 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 
"
    random.shuffle(sws)  # Shuffle to add variety
    for word in sws:
        paragraph += str(word) + ", "

    paragraph = paragraph.rstrip(", ") + "."
    return paragraph

iw = "hacking"
sws = model.most_similar(iw, topn=5)
words = [word for word, s in sws]
paragraph = create_paragraph(iw, words)
print(paragraph)
```

Explanation:

The code starts by loading the GloVe model to find the top 5 most similar words to the input word (iw, in this case, "hacking"). These similar words are obtained using the most_similar method, which identifies words with close semantic meaning. The create_paragraph function constructs a paragraph by concatenating the input word with its similar terms in a sentence structure. The similar words are shuffled to add variation, and the paragraph is formatted to end cleanly. This creates a contextualized, short descriptive paragraph, showcasing relationships between the input word and related terms.

Output:



```
Loading pre-trained GloVe model (50 dimensions)...
Model loaded successfully!
The topic of hacking is fascinating, often linked to terms like hacker, hacked, snooping, hackers, malicious.
```

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.

Code:

```
from transformers import pipeline

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

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: {feedback}")
        print(f"Sentiment: {sentiment_label} (Confidence:
{sentiment_score:.2f})\n")
```

Explanation:

This Python code analyzes the sentiment of customer feedback using a pre-trained sentiment analysis model from the **Hugging Face Transformers library.** The pipeline("sentiment-analysis") function initializes a sentiment analysis model that categorizes text as either "POSITIVE" or "NEGATIVE" with an associated confidence score. A list of feedback comments is iterated through, and for each comment, the model predicts the sentiment label and its confidence. The results, including the original feedback, sentiment, and confidence score, are printed. This approach simplifies sentiment analysis tasks, making it easy to process and interpret text data.

Output:

```
Feedback: The product is amazing! I love it!
Sentiment: POSITIVE (Confidence: 1.00)

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

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

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

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

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.

Code:

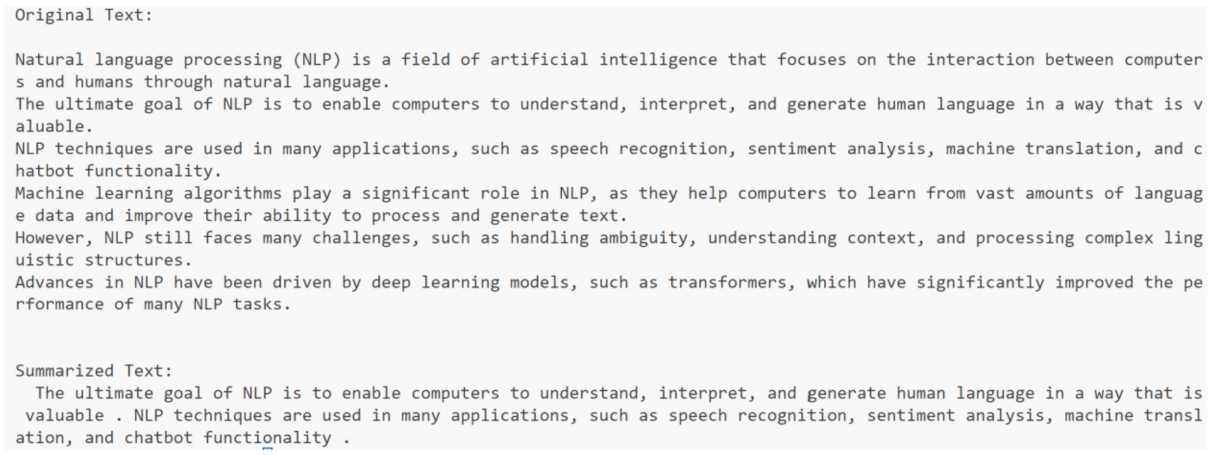
```python
from transformers import pipeline

# Load the pre-trained summarization pipeline
summarizer = pipeline("summarization")

# 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)
```

Explanation:

This Python code utilizes the **Hugging Face Transformers library** to summarize a passage using a pre-trained text summarization model. The pipeline("summarization") initializes the summarizer, and the function summarize_text processes the input text, generating a concise summary while preserving key ideas. Parameters like max_length and min_length ensure the summary stays within a specified length range. When provided with a detailed passage on natural language processing, the summarizer extracts its essence, highlighting the main points in fewer words. The original and summarized texts are then displayed for comparison.

Output:



```
Original Text:

Natural language processing (NLP) is a field of artificial intelligence that focuses on the interaction between computer
s 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 v
aluable.
NLP techniques are used in many applications, such as speech recognition, sentiment analysis, machine translation, and c
hatbot functionality.
Machine learning algorithms play a significant role in NLP, as they help computers to learn from vast amounts of languag
e 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 ling
uistic structures.
Advances in NLP have been driven by deep learning models, such as transformers, which have significantly improved the pe
rformance of many NLP tasks.


Summarized Text:
  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 transl
ation, and chatbot functionality .
```

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.

Code:

```python
from google.oauth2.service_account import Credentials
from googleapiclient.discovery import build
from langchain.prompts import PromptTemplate
from langchain.llms import Cohere
from langchain.chains import LLMChain

# Set your Cohere API Key
import cohere

# Function to load a text document from Google Drive
def ld(ds, fid):
    request = ds.files().get_media(fileId=fid)
    file_content = request.execute()
    return file_content.decode('utf-8')

# Google Drive File ID and Credentials
fid = '1do91VkEgCECFFwnb0Eamo6cOyA6DyUWE'
creds = Credentials.from_service_account_file(
    'credentials.json',
    scopes=["https://www.googleapis.com/auth/drive.readonly"]
)
ds = build('drive', 'v3', credentials=creds)
document_text = ld(ds, fid)

# Create prompt template
prompt_template = """{document_text}"""
# Format the prompt with the loaded document content
formatted_prompt = prompt_template.format(document_text=document_text)

# Load Cohere for language model generation with low temperature for
deterministic output
cohere_model =
Cohere(cohere_api_key="88t76YKbB5CMN6b0WBUgq1NUaN7KxqJu7Ci3K0W4",
temperature=0.0)

# Set up LangChain LLM with Cohere
llm_chain = LLMChain(llm=cohere_model,
prompt=PromptTemplate(template=formatted_prompt))

# Generate output using the LLMChain
output = llm_chain.run(input_document=document_text)
print(output)
```

Explanation:

The provided Python code loads a text document from Google Drive using the Google Drive API and processes it with a Cohere language model via LangChain for generating structured text output. It begins by authenticating with Google Drive using a service account and fetching the document's content using its file ID. The content is then formatted into a prompt template, which is designed to guide the Cohere language model in generating a response. The Cohere model is configured with a low temperature (temperature=0.0) to ensure deterministic and consistent output. The LangChain library connects the prompt and the Cohere model to create a language model chain (LLMChain), which processes the input document and generates a structured summary or response. Finally, the output is printed, providing a predictable and context-aware text generation based on the input document.

Output:

```
 Space exploration has captivated humans for decades, from the first space flight to recent missions to Mars. We've achi
eved milestones like the Apollo 11 mission to the Moon in 1969, and space exploration has since shifted towards scientif
ic research, such as studying Mars for potential past life. Private companies like SpaceX are crucially contributing to
the field, advancing reusable rocket technology. Space exploration will likely yield new insights about the universe, ot
her life forms, and humanity's future. International collaborations are also increasing, striving for human achievement
in space.
```

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.

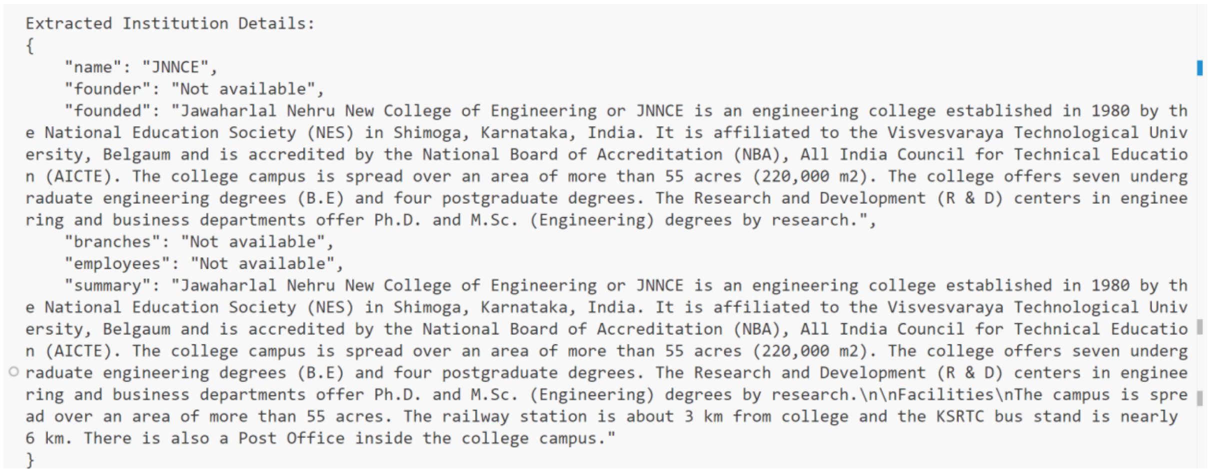
Code:

```
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

# 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)
    content = page.text

    # Basic parsing for demonstration purposes
    founder = next((line for line in content.split('\n') if "founder" in
line.lower()), "Not available")
    founded = next((line for line in content.split('\n') if "founded" in
line.lower() or "established" in line.lower()), "Not available")
    branches = next((line for line in content.split('\n') if "branch" in
line.lower()), "Not available")
    employees = next((line for line in content.split('\n') if "employee" in
line.lower()), "Not available")
    summary = "\n".join(content.split('\n')[:4])

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

details = fetch("JNNCE")
print("\nExtracted Institution Details:")
print(details.model_dump_json(indent=4))  # Use model_dump_json instead of
.json()
```

Explanation:

The code uses the wikipediaapi library to fetch information about an institution from Wikipedia and the pydantic library to structure the data. It defines a Pydantic model, InstitutionDetails, with fields such as name, founder, founded date, branches, employees, and a summary. The fetch function retrieves the Wikipedia page for a given institution name, parses its content, and extracts key details using simple string matching for terms like "founder," "founded," and "employee." A summary is generated from the first few lines of the content. Finally, the extracted data is returned as an InstitutionDetails instance and displayed in JSON format using the model_dump_json method. This approach ensures a structured representation of institution information.

Output:



```
Extracted Institution Details:
{
    "name": "JNNCE",
    "founder": "Not available",
    "founded": "Jawaharlal Nehru New College of Engineering or JNNCE is an engineering college established in 1980 by th
e National Education Society (NES) in Shimoga, Karnataka, India. It is affiliated to the Visvesvaraya Technological Univ
ersity, Belgaum and is accredited by the National Board of Accreditation (NBA), All India Council for Technical Educatio
n (AICTE). The college campus is spread over an area of more than 55 acres (220,000 m2). The college offers seven underg
raduate engineering degrees (B.E) and four postgraduate degrees. The Research and Development (R & D) centers in enginee
ring and business departments offer Ph.D. and M.Sc. (Engineering) degrees by research.",
    "branches": "Not available",
    "employees": "Not available",
    "summary": "Jawaharlal Nehru New College of Engineering or JNNCE is an engineering college established in 1980 by th
e National Education Society (NES) in Shimoga, Karnataka, India. It is affiliated to the Visvesvaraya Technological Univ
ersity, Belgaum and is accredited by the National Board of Accreditation (NBA), All India Council for Technical Educatio
n (AICTE). The college campus is spread over an area of more than 55 acres (220,000 m2). The college offers seven underg
raduate engineering degrees (B.E) and four postgraduate degrees. The Research and Development (R & D) centers in enginee
ring and business departments offer Ph.D. and M.Sc. (Engineering) degrees by research.\n\nFacilities\nThe campus is spre
ad over an area of more than 55 acres. The railway station is about 3 km from college and the KSRTC bus stand is nearly
6 km. There is also a Post Office inside the college campus."
}
```

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.

Code:

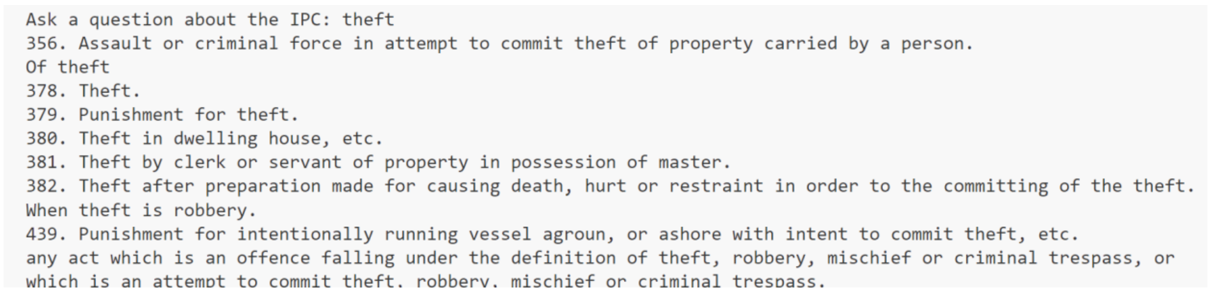
```python
import pdfplumber

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

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

```python
# 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()
```

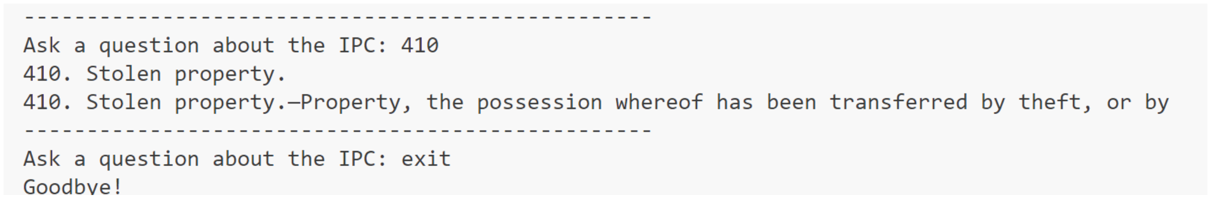
Explanation:

The code extracts text from an IPC (Indian Penal Code) PDF document using the pdfplumber library and allows users to query specific sections of the IPC. The extract function reads the text content from each page of the PDF, and the search function looks for matching lines in the document based on the user's query. It performs a case-insensitive search for relevant sections. The chatbot function provides an interactive interface where users can ask questions about the IPC, and it responds with the matching text from the document. The program continues until the user enters "exit", at which point it terminates.

Output:



```
Ask a question about the IPC: theft
356. Assault or criminal force in attempt to commit theft of property carried by a person.
Of theft
378. Theft.
379. Punishment for theft.
380. Theft in dwelling house, etc.
381. Theft by clerk or servant of property in possession of master.
382. Theft after preparation made for causing death, hurt or restraint in order to the committing of the theft.
When theft is robbery.
439. Punishment for intentionally running vessel agroun, or ashore with intent to commit theft, etc.
any act which is an offence falling under the definition of theft, robbery, mischief or criminal trespass, or
which is an attempt to commit theft, robbery, mischief or criminal trespass.
```



```
--------------------------------------------------
Ask a question about the IPC: 410
410. Stolen property.
410. Stolen property.—Property, the possession whereof has been transferred by theft, or by
--------------------------------------------------
Ask a question about the IPC: exit
Goodbye!
```