ATME College of Engineering

13th KM Stone, Bannur Road, Mysore - 560 028

Department of CSE–Artificial Intelligence & Machine Learning

(Academic Year 2025-26)

LABORATORY MANUAL

SUBJECT: Generative AI Laboratory
SUB CODE: BAIL657C

SEMESTER: VI

SCHEME: 2022

Prepared By	Verified By	Approved by
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Institute Vision

- Development of academically excellent, culturally vibrant, socially responsible and globally competent human resources.

Institute Mission

- To keep pace with advancements in knowledge and make the students competitive and capable at the global level.
- To create an environment for the students to acquire the right physical, intellectual, emotional and moral foundations and shine as torch bearers of tomorrow's society.
- To strive to attain ever-higher benchmarks of educational excellence.

Department Vision

To impart technical education in the field of Artificial intelligence and machine learning of topnotch quality with a high level of professional competence, social obligation, and global cognizance among the students.

Department Mission

- To impart technical education that is up to date, relevant and makes students to compete at global level
- Fostering an ambiance where students can adopt the suitable moral, intellectual, emotional, and physical attributes to shine as the leaders of tomorrow's society.
- To strive to meet ever higher educational standard.

Program Outcomes (PO's)

1. Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. 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.

3. 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.

4. 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.

5. 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.

6. 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.

7. 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.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

10. 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.

11. 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.

12. 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 Educational Objectives (PEO's):

PEO1: Graduates will be able to hone their problem-solving abilities and capacity to offer solutions to challenges that arise in the actual world.

PEO2: Able to design and develop AI based solutions to real-world problems in a business, research, or social environment.

PEO3: Graduates shall acquire and inculcate corporate culture, core attributes, and leadership qualities as well as professional etiquette's and lifelong learning.

Program Specific Outcomes (PSO's)

PSO1: Ability to design and develop artificial intelligent based solutions by applying optimal algorithms to solve real world issues.

PSO2: Ability to apply suitable AI tools and techniques to offer solutions in the various domains of engineering.

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

CONTENTS

INTRODUCTION

- **Installation Guide**
- **First Install Python 3.11 then follow these steps**
- Download the **GloVe 6B** model used for the first four experiments from the following link: **GloVe 6B Model.**
- Once the GloVe model is downloaded, extract all the files to the directory where your Jupyter notebooks are located.
- Install the required libraries. *(Please restart the kernel after each installation.)*

a. Experiments 1, 2, 3:
  - !pip install gensim
  - !pip install --upgrade transformers

b. Experiment 4:
  - !pip install --upgrade langchain
  - !pip install langchain-core
  - !pip install langchain-community
  - !pip install -qU langchain-google-genai
  - **Note:** This part will be covered during the FDP: Obtain a Google API Key → **Google API Key.**
  - !pip install faiss-cpu

c. Experiments 5, 6, 7:
  - **Note:** This part will be covered during the FDP: Obtain a Hugging Face API Key → **Hugging Face API Key.**
  - !pip install sentence_transformers
  - !pip install langchain-huggingface
  - !pip install --user tf-keras
  - !pip install --user numpy==1.24.4
  - !pip install --upgrade --quiet huggingface_hub

d. Experiment 8:
  - **Note:** This part will be covered during the FDP: Obtain a Cohere API Key → **Cohere API Key**.
  - !pip install langchain-cohere
  - !pip install gdown

e. Experiment 9:
  - !pip install --upgrade --quiet wikipedia

f. Experiment 10: !pip install gradio

Sl.No	Course	LexLink
1	IntroductiontoArtificialIntelligence	lex_8840337130015322000
2	Introductiontoreinforcementlearning	lex_auth_01350196693139456075
3	IntroductiontoDeep learning	lex_auth_012782105116811264219
4	GenerativeEcosystem	lex_auth_01402940631726489655
5	IntroductiontoLang chain	lex_auth_013838826667655168805
6	IntroductiontoPrompt Engineering	lex_auth_013719953643773952304

Introduction to Natural Language Processing

Structured Data

- Quantitative Data
- Ex: Data base, table
- Can be indexed, processed using conventional technique like SQL

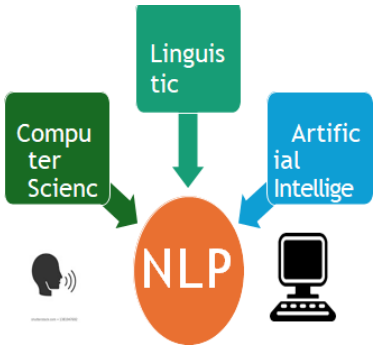
Unstructured Data

- Qualitative Data which is typically text-heavy, contain date, facts etc..
- Ex: email, multimedia files, photos etc..
- Can't indexed and processed using conventional technique like SQL

% of structured and Unstructured data

What is NLP

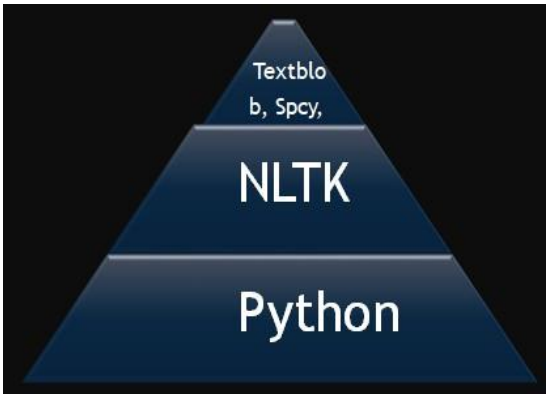
Natural language processing (NLP) is a subfield of linguistics, computer science, information engineering, and artificial intelligence concerned with the interactions between computers and human (natural) languages

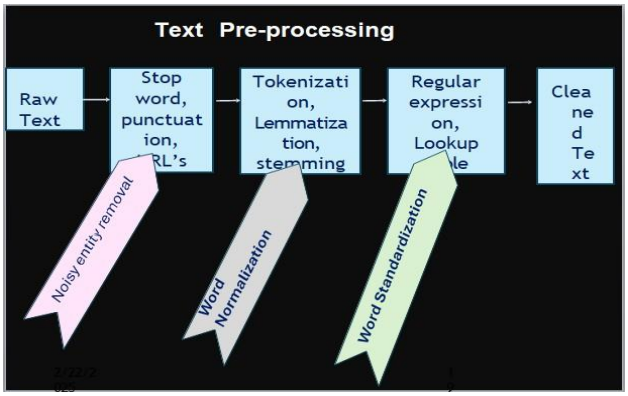


Important Libraries for NLP (python)

- **Scikit-learn**: Machine learning in Python
- **Natural Language Toolkit (NLTK):** The complete toolkit for all NLP techniques.
- **Pattern** – A web mining module for the with tools for NLP and machine learning.
- **TextBlob** – Easy to use nl p tools API, built on top of NLTK and Pattern.
- **spaCy** – Industrial strength N LP with Python and Cython.
- **Gensim** – Topic Modelling for Humans
- **Stanford Core NLP** – NLP services and packages by Stanford NLP Group.

Python library with simple API to access its methods and perform basic NLP tasks.





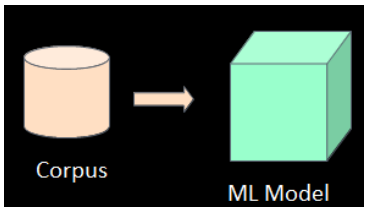
Word embeddings

Goal of Word Embeddings is to:

1. reduce dimensionality of the output vector
2. use a word to predict the words around it
3. Preserve/capture the word semantics

What's an embedding?

Machine learning algorithms can only take low-dimensional numerical data as inputs.



- Word embedding- Aims to gather the features of the natural Language Text data.
- It is called - feature engineering of natural language processing models.

Word2Vec is one most used Word embedding technique

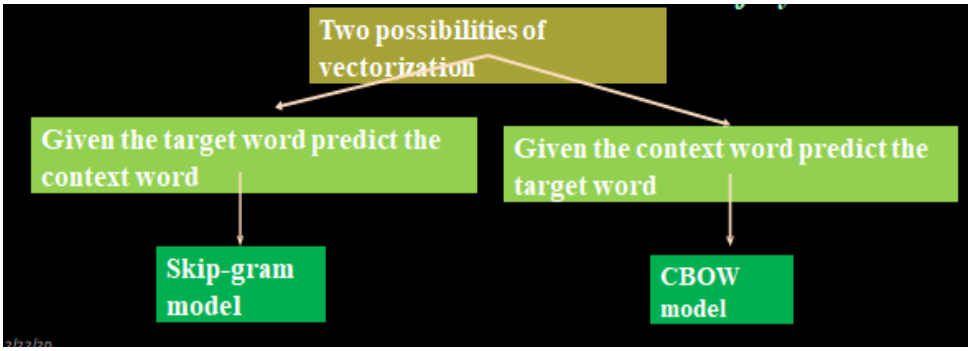
lets first state the objective Word2Vec.

1. Convert the natural language word to vector
2. Preserve the context and the relation between the words.

. Let's analyze with an example:

"Infosys is the second largest Indian IT company. It is headquartered in Bangalore."

How do we make machine to understand "It" means "Infosys".

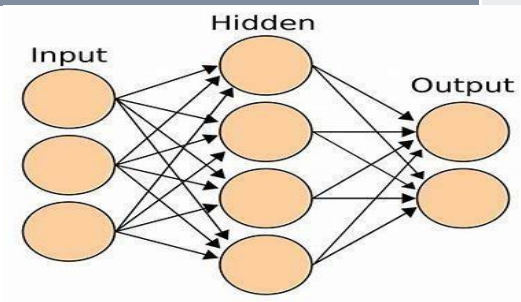


Word2Vec

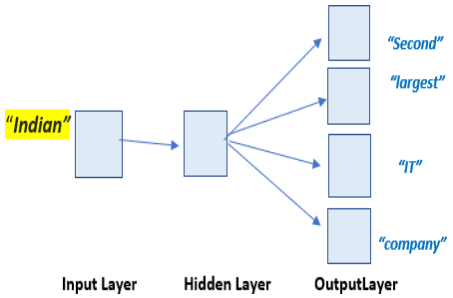
- Word2vec generates embeddings from words.
- Words are encoded into one-hot vectors.
- Fed into a hidden layer that generates hidden weights.
- Those hidden weights are then used to predict other nearby words.
- **Hidden weights** are returned as embeddings and the model is tossed out.
- Given sufficient data and the context, it can make accurate prediction of the words with context.
- Like "**King"** is a "**man**" and "**Queen**" is "**women**".

Context of a word- W_i is nothing but the words surrounding it.

CBOW model	Skipgram model
In the given window, input is the Centre word and output(predicted) is the context words	In the given window, context words are the input and output is the Centre word
Suitable for small datasets	Suitable large dataset

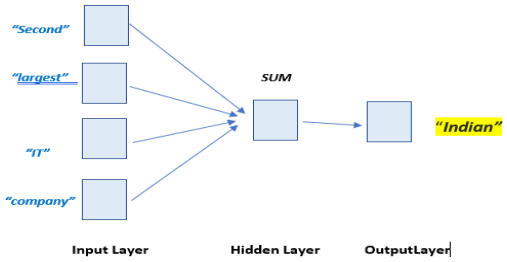


Skipgram word embedding



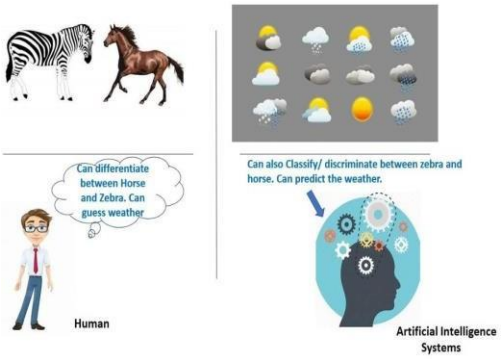
central word closer to the neighboring words.

CBOW model representation

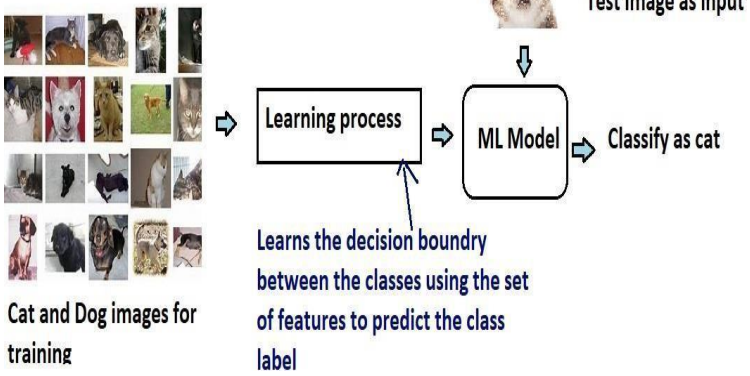


Surrounding word closer to the central word.

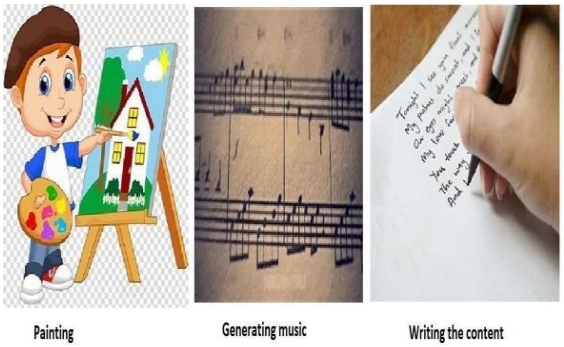
Discriminative AI

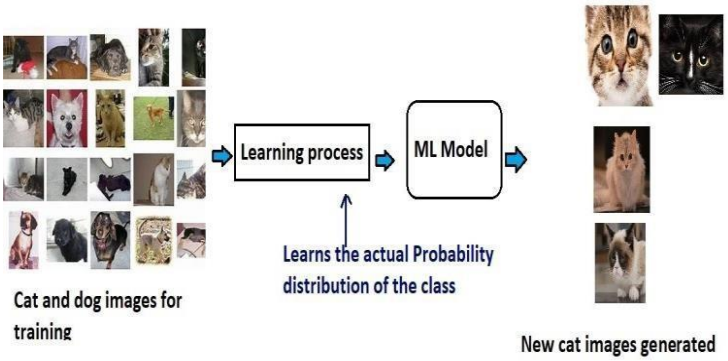


Decsriminative AI



Generative skill in Human

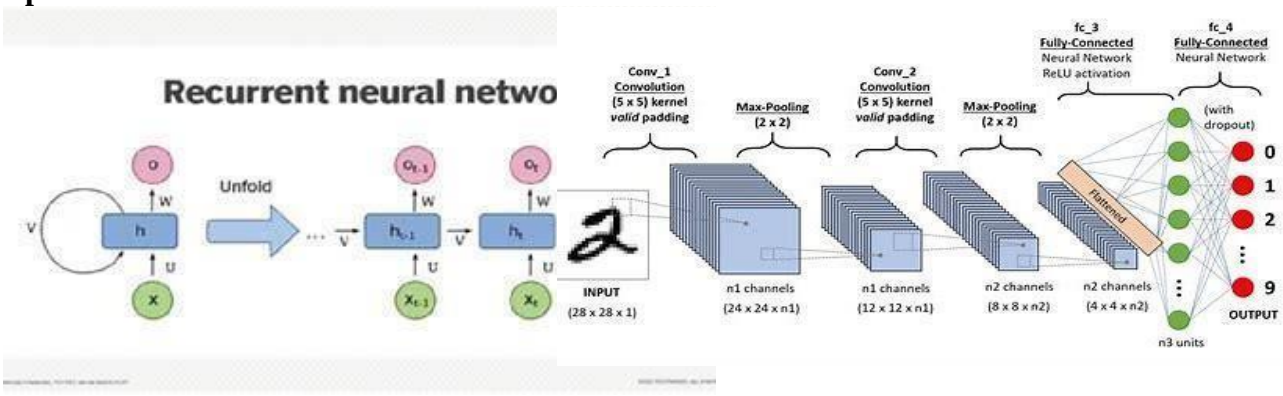




Inspired from such a generative skill, new generation of artificial intelligence techniques have evolved which are called as "Generative Models".

A significant amount of data from different domains such as **images, text or voice** have made it possible to train the generative models so that, they can generate similar data instances.

pretrained models



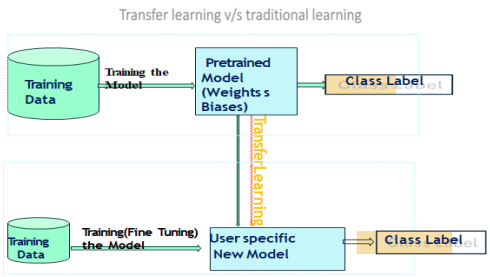
What do you think are techniques that make AI models to generates new data?

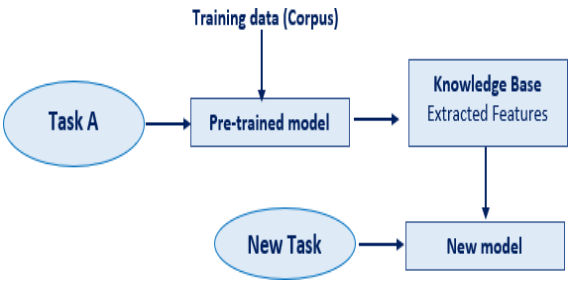
Deep Learning techniques:

- Convolutional Neural networks
- Recurrent Neural Networks and Long Short-Term Memory

Each Problem requires the model to be trained Instead of building a model from scratch to solve a similar problem, you use the model trained on other problem as a starting point.

Transfer learning v/s traditional learning





- In the context of NLP, it is a method in which deep learning model trained on a large corpus,.
- Is used to perform similar tasks on another dataset.
- Such a deep learning model is also called as pre-trained model.

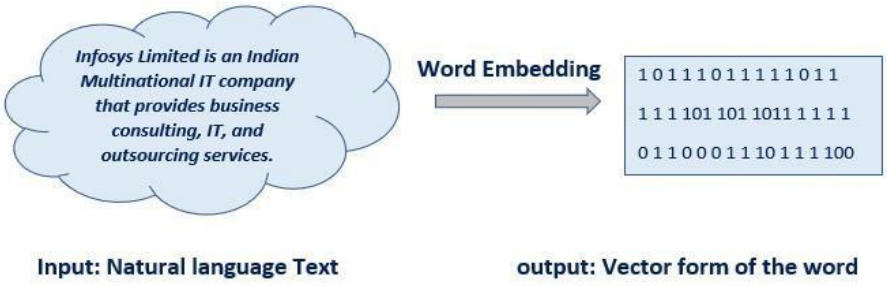
Text Generation Models (LLMs - Large Language Models)

Model	Developer	Key Features
GPT-4	OpenAI	Advanced LLM for text generation, reasoning, and multimodal tasks.
GPT-3.5	OpenAI	High-quality text generation, coding Assistance, and chatbots.
LLaMA 2	Meta AI	Open-source LLM for research and commercial use.
Claude 2	Anthropic	AI model focused on safety, reasoning, and large- context understanding.
PaLM 2	Google DeepMind	Google's LLM, optimized for reasoning and multilingual tasks.
Mistral 7B	Mistral AI	Lightweight, open-source LLM with high efficiency.
BLOOM	BigScience	Open multilingual model with 176B parameters.
T5 (Text-to-Text Transfer Transformer)	Google	Converts all NLP tasks into text-to-text format.
BERT	Google	Bi-directional transformer for understanding context in text.

Vectorization

It is the process of converting words into numbers.

It is a methodology in NLP to map words or phrases from vocabulary to a corresponding vector of real numbers which is used to find word predictions, similarities etc.



Embeddings are dense numerical representations of real-world objects and semantic relationships expressed as a Feature vector.

Word embedding technique aims to gather the features of the natural Laungage Text data. So, it is the **feature engineering** of natural language processing models. Some of the **word embedding** techniques are:

- PCA
- SVD

- TF-IDF
- **Word2Vec**

One-Hot Encoding

- unsupervised technique maps a single category to a vector and generates a binary representation
- Each unique word in vocabulary by setting a unique token with value 1 and rest 0 at other positions in the vector.
- OHE vector represents in the form of 1, and 0 where 1 stands for the position where the word exists and 0 everywhere else.

Drawbacks: Sparsity

One-Hot Encoding

Ex: "Probability and statistics is foundation for ML"

Tokens= ["Probability" ,"and", "statistics", "foundation", "ML"]

Vector for "Probability" : [1 0 0 0 0]

Vector for "statistics":[0 0 1 0 0]

Disadvantages

1. The Size of the vector = count of unique words in the vocabulary.
2. Does not capture the relationships between different words. Therefore, it does not convey information about the context.

Pre-trained word embedding model

GloVe is a pre-trained word embedding model developed by researchers at Stanford University.

It captures semantic meaning and word relationships using word co-occurrence statistics from a large text corpus

Where is GloVe Used?

NLP Applications – Sentiment analysis, machine translation, chatbots.

Search Engines – Improving query understanding.

Recommendation Systems – Enhancing personalized content.

Text Classification – Spam detection, topic modeling**.**

Pre-trained GloVe Models

Model	Vocabulary Size	Embedding Dimensions
glove.6B	400K	50, 100, 200, 300
glove.42B	1.9M	300
glove.840B	2.2M	300
glove.twitter.27B	1.2M	25, 50, 100, 200

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

Soln:

```
!pip install gensim
```

#Gensim: A Python library for NLP and word embeddings.

```
from gensim.scripts.glove2word2vec import glove2word2vec
from gensim.models import KeyedVectors

# Paths to the GloVe file and output Word2Vec file
glove_input_file = "/content/glove.6B.100d.txt"  # Path to GloVe file
word2vec_output_file = "/content/glove.6B.100d.word2vec.txt"  # Output file in Word2Vec format

# Convert GloVe format to Word2Vec format
glove2word2vec(glove_input_file, word2vec_output_file)

# Load the converted Word2Vec model
model = KeyedVectors.load_word2vec_format(word2vec_output_file, binary=False)

# Test the loaded model
print(model.most_similar("king"))
```

#GloVe embeddings are converted to Word2Vec format for compatibility with libraries like Gensim, which require the Word2Vec format for efficient vector operations and model functionality.

Output:

[('prince', 0.7682328820228577), ('queen', 0.7507690787315369), ('son', 0.7020888328552246), ('brother', 0.6985775232315063), ('monarch', 0.6977890729904175), ('throne', 0.6919989585876465), ('kingdom', 0.6811409592628479), ('father', 0.6802029013633728), ('emperor', 0.6712858080863953), ('ii', 0.6676074266433716)]

Explore Word Relationships

Example 1: Find Similar Words

```
similar_to_mysore = model.similar_by_vector(model['mysore'], topn=5)
print(f"Words similar to 'mysore': {similar_to_mysore}")
```

Output: Words similar to 'mysore': [('mysore', 1.0), ('cochin', 0.6752076148986816), ('hyderabad', 0.6592637896537781), ('jaipur', 0.6591896414756775), ('perak', 0.6516631245613098)]

Example 2: Gender Analogy (king - man + woman = queen)

```
# Perform vector arithmetic
result_vector_1 = model['actor'] - model['man'] + model['woman']

# Find the most similar word
```

```
result_1 = model.similar_by_vector(result_vector_1, topn=1)
print(f"'actor - man + woman' = {result_1}")
```

Output: 'actor - man + woman' = [('actress', 0.9160683155059814)]

Example 3: Country-City Relationship (India - Delhi + Bangalore)

```
# Perform vector arithmetic
result_vector_2 = model['india'] - model['delhi'] + model['washington']

# Find the most similar word
result_2 = model.similar_by_vector(result_vector_2, topn=3)
print(f"'India - Delhi + Washington' = {result_2}")
```

Output: 'India - Delhi + Washington' = [('states', 0.8375228643417358), ('united', 0.8281229734420776), ('washington', 0.8155243396759033)]

Perform Arithmetic Operations

```
scaled_vector = model['hotel'] * 2  # Scales the 'king' vector by a factor of 2
result_2 = model.similar_by_vector(scaled_vector, topn=3)
result_2
```

[('hotel', 1.0),
('hotels', 0.7933705449104309),
('restaurant', 0.7762866020202637)]

Example 2: Normalizing Vectors

```
import numpy as np
normalized_vector = model['fish'] / np.linalg.norm(model['fish'])
result_2 = model.similar_by_vector(normalized_vector, topn=3)
result_2
```

[('fish', 1.0), ('shrimp', 0.7793381810188293), ('salmon', 0.760814368724823)]

Example 3: Averaging Vectors

```
average_vector = (model['king'] + model['woman'] + model['man']) / 3
result_2 = model.similar_by_vector(average_vector, topn=3)
result_2
```

[('man', 0.9197071194648743),
('woman', 0.8637868165969849),
('father', 0.8270207047462463)]

Model Comparision

```
# Paths to the GloVe file and output Word2Vec file
glove_input_file = "/content/glove.6B.50d.txt"  # Path to GloVe file
word2vec_output_file = "/content/glove.6B.50d.word2vec.txt"  # Output file in Word2Vec format

# Convert GloVe format to Word2Vec format
glove2word2vec(glove_input_file, word2vec_output_file)

# Load the converted Word2Vec model
```

```
model_50d = KeyedVectors.load_word2vec_format(word2vec_output_file, binary=False)

# Paths to the GloVe file and output Word2Vec file
glove_input_file = "/content/glove.6B.100d.txt"  # Path to GloVe file
word2vec_output_file = "/content/glove.6B.100d.word2vec.txt"  # Output file in Word2Vec format

# Convert GloVe format to Word2Vec format
glove2word2vec(glove_input_file, word2vec_output_file)

# Load the converted Word2Vec model
model_100d = KeyedVectors.load_word2vec_format(word2vec_output_file, binary=False)
```

Calculate similarity between two words

```
word1 = "hospital"
word2 = "doctor"

# Similarity in 50d
similarity_50d = model_50d.similarity(word1, word2)

# Similarity in 100d
similarity_100d = model_100d.similarity(word1, word2)

# Results
print(f"Similarity (50d) between '{word1}' and '{word2}': {similarity_50d:.4f}")
print(f"Similarity (100d) between '{word1}' and '{word2}': {similarity_100d:.4f}")
```

Output : Similarity (50d) between 'hospital' and 'doctor': 0.6724

Similarity (100d) between 'hospital' and 'doctor': 0.6901

Calculate distance between two words

```
# Calculate distance between two words
distance_50d = model_50d.distance(word1, word2)
distance_100d = model_100d.distance(word1, word2)

# Results
print(f"Distance (50d) between '{word1}' and '{word2}': {distance_50d:.4f}")
print(f"Distance (100d) between '{word1}' and '{word2}': {distance_100d:.4f}")
```

Distance (50d) between 'hospital' and 'doctor': 0.3276
Distance (100d) between 'hospital' and 'doctor': 0.3099

Analysis of Results

1. **'actor - man + woman' = actress (0.916)**
    - The result confirms that the model has captured gender analogies, where subtracting "man" and adding "woman" to "actor" produces the semantically related word "actress."
2. **'India - Delhi + Washington' = ['states', 0.838], ['united', 0.828], ['washington', 0.816]**
    - The arithmetic operation shows that "India - Delhi + Washington" produces words like "states" and "united," suggesting a shift from a city to broader political entities, such as countries or states.
3. **Scaling Vectors ('hotel' * 2) = [('hotel', 1.0), ('hotels', 0.793), ('restaurant', 0.776)]**
    - The scaled vector results in "hotel" being the most similar to itself, and its plural form "hotels" is the second most similar, followed by related terms like "restaurant."
4. **Normalizing Vectors ('fish') = [('fish', 1.0), ('shrimp', 0.779), ('salmon', 0.761)]**
    - Normalizing the vector for "fish" leads to very similar words like "shrimp" and "salmon," which are semantically related types of fish.
5. **Averaging Vectors ('king' + 'woman' + 'man') / 3 = [('man', 0.920), ('woman', 0.864), ('father', 0.827)]**
    - Averaging the vectors of "king," "woman," and "man" results in "man" and "woman" being the most similar words, indicating that the averaged vector represents a central concept of human relationships.
6. **Similarity and Distance Calculation for 'hospital' and 'doctor':**
    - **Similarity**: 0.6724 (50d) vs. 0.6901 (100d)
        - The similarity between "hospital" and "doctor" is higher in the 100d model, indicating that the higher-dimensional model captures the relationship between these words more accurately.
    - **Distance**: 0.3276 (50d) vs. 0.3099 (100d)
        - The distance between "hospital" and "doctor" is smaller in the 100d model, confirming that the 100d model finds them closer in the vector space, aligning with the similarity results.

Conclusion

- Higher-dimensional models (100d) generally provide more accurate and nuanced word relationships, both in terms of **similarity** and **distance**.
- Arithmetic operations like scaling, averaging, and vector shifts (analogies) allow deeper exploration of word meanings and relationships, and these can vary slightly with model dimensions.

Program 2: Use dimensionality reduction (e.g., PCA or t-SNE) to visualize word embeddings for program 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

Soln:

```
!pip install gensim
```

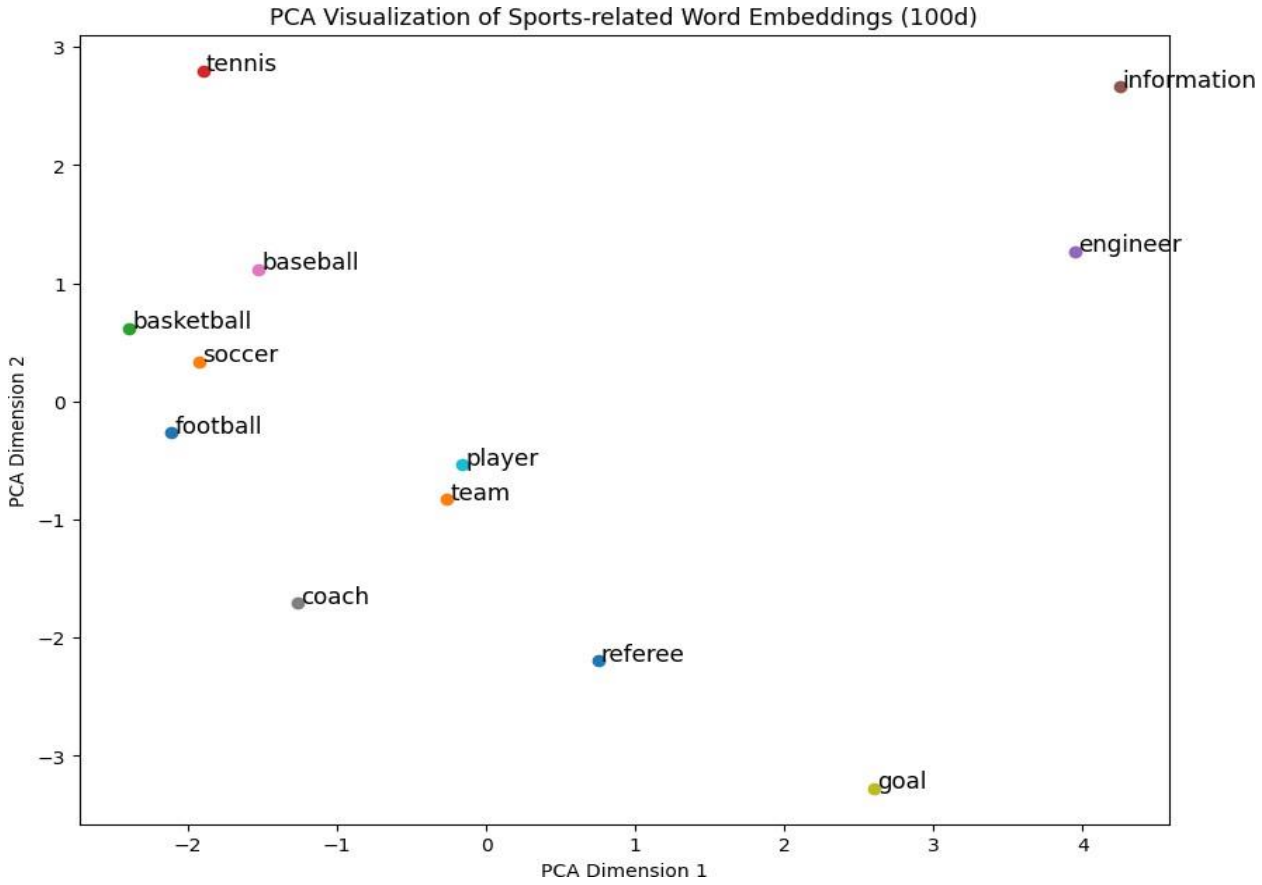
#Gensim: A Python library for NLP and word embeddings.

Use dimensionality reduction (e.g., PCA or t-
SNE) to visualize word embeddings for PG1. 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 aprogram to generate 5 semantically similar words for a given input.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from gensim.models import KeyedVectors

# Load pre-trained GloVe embeddings (100d model)
model_100d = KeyedVectors.load_word2vec_format("/content/glove.6B.100d.word2vec.txt", binary=False,limit=500000)

# Select 10 words from a specific domain (sports) # Included other words to show how embeddings are different
words = ['football', 'soccer', 'basketball', 'tennis','engineer','information', 'baseball', 'coach', 'goal', 'player', 'referee', 'team']
word_vectors = np.array([model_100d[word] for word in words])

# Dimensionality reduction using PCA
# Using PCA to reduce to 2D for visualization
pca = PCA(n_components=2)
pca_result = pca.fit_transform(word_vectors)

# Plotting the words in 2D space
plt.figure(figsize=(10, 8))
for i, word in enumerate(words):
plt.scatter(pca_result[i, 0], pca_result[i, 1])
plt.text(pca_result[i, 0] + 0.02, pca_result[i, 1], word, fontsize=12)
plt.title("PCA Visualization of Sports-related Word Embeddings (100d)")
plt.xlabel("PCA Dimension 1")
plt.ylabel("PCA Dimension 2")
plt.show()
# 5 Semantically Similar Words Generator Function
```

```
def get_similar_words(word, model, topn=5):
similar_words = model.similar_by_word(word, topn=topn)
return similar_words

# Example: Get 5 words similar to "football"
similar_words_football = get_similar_words('football', model_100d, topn=5)
print(f"Words similar to 'football': {similar_words_football}")
```

Output:



Output: Words similar to 'football': [('soccer', 0.8732221722602844), ('basketball', 0.8555637001991272), ('league', 0.815336287021637), ('rugby', 0.8007532954216003), ('hockey', 0.7833694815635681)]

```
# Select the words you want to print embeddings for
words_to_print = ['football', 'soccer']

# Print their embeddings
for word in words_to_print:
if word in model_100d:
print(f"Vector embedding for '{word}':\n{model_100d[word]}\n")
else:
print(f"Word '{word}' not found in the embeddings model.")
```

Output:

Vector embedding for 'football':
[0.43865 0.10537 0.45972 -1.0724 -1.2471 0.76351
0.47528 0.083857 -0.9127 -0.27328 -0.018591 -1.184
0.22748 0.16847 -0.52158 0.11339 1.3757 0.11892
-0.37683 0.51149 -0.8833 0.96259 0.18143 -0.407
0.036181 -0.74432 -0.0027401 -0.70068 0.53103 0.45114
-0.72884 1.0631 -0.28008 -0.63848 0.15645 -0.46927
-1.0071 1.033 -1.4354 -0.27485 0.048984 0.13951
0.43072 -0.78791 0.41097 0.58509 1.0155 -0.1839
0.27487 -0.90866 -0.30441 -0.17396 0.020941 0.62813
0.10978 -2.3885 -0.56364 -0.27193 0.98728 0.70608
-0.512 0.52636 -0.78503 -0.68714 0.38121 0.097582
-0.20237 0.43208 -0.30527 0.57925 0.62619 -0.47415
0.33834 -0.28421 -0.097465 0.19597 0.54849 0.59918
-0.41576 0.1021 0.6766 0.0042009 -0.12354 -0.76613
-0.27436 -0.68248 -1.0789 -0.16708 0.81671 0.026999
-0.38707 0.40448 -1.0995 0.64718 -0.12802 -0.26084
-0.96701 0.88078 1.012 -0.022223]

Vector embedding for 'soccer':

[8.3777e-01 5.1890e-01 6.4015e-01 -6.2606e-01 -9.7474e-01 1.0127e+00
6.2729e-02 4.4316e-01 -8.3299e-01 7.9888e-02 -1.1815e-02 -1.1265e+00
1.2554e-01 -3.4206e-01 -5.1422e-01 3.8526e-01 1.0032e+00 -1.5172e-03
-2.2684e-01 3.5658e-01 -6.2449e-01 8.7271e-01 3.6670e-01 4.6462e-01
-1.0046e-01 -4.4798e-01 -2.1813e-01 -5.6423e-01 5.6665e-01 5.1601e-01
-5.6511e-01 7.1919e-01 -6.5347e-01 -9.5952e-02 5.6028e-01 -4.9956e-01
-7.4757e-01 6.8516e-01 -1.4518e+00 -1.1207e-01 1.0241e-01 3.0537e-02
1.1326e-02 -8.6873e-01 6.3622e-01 4.9539e-01 3.0538e-01 7.7133e-02
7.4048e-02 -7.1163e-01 -1.9159e-01 -3.4168e-01 -4.7185e-01 5.6794e-01
3.7454e-01 -1.9207e+00 -8.6040e-01 5.7058e-01 1.0700e+00 9.2101e-01
-6.4825e-01 5.3516e-01 -1.5556e-01 -9.0021e-01 -1.7459e-01 3.3146e-02
-5.7512e-01 2.9963e-01 -4.0008e-01 -1.0765e-01 4.1384e-01 -7.2178e-01
1.1442e-01 -2.1291e-01 5.4949e-02 1.3213e-01 7.8766e-01 8.9291e-02
-6.6689e-01 3.3998e-01 9.7163e-01 -8.4871e-02 1.7542e-01 -4.6039e-01
-8.5885e-02 -7.5960e-01 -1.5071e+00 2.1545e-01 2.1209e-01 -4.4837e-01
-2.5882e-01 3.3814e-01 -4.7979e-01 2.1059e-01 2.3621e-01 -3.6699e-01
-8.1440e-01 5.4515e-01 9.7946e-01 2.3367e-01]

Program 3:Train a custom Word2Vec model on a small dataset. Train embeddings on a domain-specific corpus (e.g., legal, medical) and analyze how embeddings capture domain-specific semantics

Soln:

```
!pip install gensim
```

#Gensim: A Python library for NLP and word embeddings.

Important Steps

1. **Tokenization**: Converts sentences into lists of lowercase tokens for processing.
2. **Word2Vec Training**:
   - vector_size: Sets the embedding dimension to 50.
   - window: Uses a context window of 3 words.
   - sg: Skip-gram (sg=1) is used, which works better for smaller datasets.
   - epochs: The number of training iterations.
3. **Visualization**: PCA reduces the high-dimensional word vectors to 2D for visualization, helping to understand semantic relationships.
4. **Semantic Analysis**: The most_similar method identifies words that are semantically similar based on embeddings.

Example: Legal Corpus

```
from gensim.models import Word2Vec
from gensim.utils import simple_preprocess
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
```

```
legal_corpus = [
"The court ruled in favor of the plaintiff.",
"The defendant was found guilty of negligence.",
"A breach of contract case was filed.",
"The agreement between parties must be honored.",
"The lawyer presented compelling evidence.",
"Legal documents must be drafted carefully.",
"The jury deliberated for several hours.",
"A settlement was reached between the parties.",
"The plaintiff claimed damages for losses incurred.",
"The contract outlined the obligations of both parties."
]
# Example legal corpus
legal_corpus = [
"The court ruled in favor of the plaintiff.",
"The defendant was found guilty of negligence.",
"A breach of contract case was filed.",
"The agreement between parties must be honored.",
"The lawyer presented compelling evidence.",
"Legal documents must be drafted carefully.",
```

```
"The jury deliberated for several hours.",
"A settlement was reached between the parties.",
"The plaintiff claimed damages for losses incurred.",
"The contract outlined the obligations of both parties."
]

# Preprocess the corpus
tokenized_corpus = [simple_preprocess(sentence) for sentence in legal_corpus]

# Train the Word2Vec model legal_word2vec = Word2Vec(sentences=tokenized_corpus,
vector_size=50,
# Embedding dimension window=3,
# Context window size min_count=1,
# Minimum word frequency sg=1,
# Skip-gram model epochs=100
# Training epochs
)

# Save the model for later use
legal_word2vec.save("legal_word2vec.model")
```

```
# Analyze embeddings: Display vector for a specific word
word = "lawyer"
if word in legal_word2vec.wv:
print(f"Vector embedding for '{word}':\n{legal_word2vec.wv[word]}\n")
else:
print(f"Word '{word}' not found in the Word2Vec model.")
```

Output:

```
Vector embedding for 'lawyer':
[ 0.00373483  0.01353383  0.00585796 -0.01324683  0.01500349 -0.01261986
0.01892563  0.00698961 -0.0087639  -0.01023367 -0.00875896 -0.01318524
0.01972703 -0.00463062  0.01525868 -0.01837575  0.0055629  -0.00126356
0.01417167 -0.01969541  0.01564029 -0.00948072 -0.0107858  -0.01128642
-0.00610619 -0.00604345 -0.00693252 -0.01396556  0.00086967 -0.00136903
-0.00358557  0.00685404 -0.01432065 -0.00657563  0.00952303  0.01720192
-0.01858611  0.01418636  0.01038651 -0.00818817  0.01832661 -0.01858529
0.01404059  0.01154918  0.00326395 -0.01036671 -0.00841038 -0.00736812
0.00374052  0.00413726]
```

```
# Visualize embeddings using PCA
words_to_visualize = ["court", "plaintiff", "defendant", "agreement", "lawyer", "evidence", "contract",
"settlement", "jury", "damages"]
word_vectors = [legal_word2vec.wv[word] for word in words_to_visualize]
word_vectors
```

Output:

[array([-0.01018794, -0.0037532 , -0.01479373, 0.00535417, 0.00549183,
-0.00194653, -0.00904275, -0.00120178, 0.01239534, 0.005502 ,
-0.01752885, -0.00888894, 0.00678894, 0.00598825, -0.01972261,
0.01158325, -0.01438892, -0.01200779, 0.00463451, -0.01056976,
0.00906795, 0.01991566, -0.00384839, 0.01845003, 0.00452612,
0.02153785, 0.0106156 , -0.0164802 , -0.0075984 , 0.01259563,
0.01069134, 0.01610584, 0.01608272, 0.01619358, -0.02157517,
0.00898223, -0.00762749, 0.00642556, 0.01106042, 0.00757853,
0.01795846, 0.00227335, -0.00347768, 0.01356644, -0.00962057,
0.00016249, 0.01841913, -0.01246461, 0.00897428, -0.01424266], dtype=float32),
array([-0.01382369, 0.0011437 , -0.01449836, -0.00296123, 0.00624782,
0.00982854, 0.00482432, 0.00674102, -0.01035763, 0.0125059 ,
-0.01251031, 0.00691753, -0.01420641, 0.00583739, -0.01051113,
-0.00608784, -0.00284186, 0.01448168, 0.00904517, -0.01370935,
0.00321437, -0.01510567, 0.01918532, 0.01829434, -0.00426899,
0.00343321, 0.00058916, 0.01309333, -0.0183534 , 0.00069488,
0.0132396 , 0.0028656 , 0.00451153, -0.01875341, 0.01468391,
-0.01201477, -0.00313035, 0.00620906, -0.0025351 , 0.00151398,
0.0066815 , -0.01435055, -0.02045849, 0.01987134, 0.01433266,
-0.01331776, 0.00661788, -0.00128313, 0.01081608, -0.01213262],
dtype=float32),
array([-0.01735372, 0.00324048, -0.00153466, -0.01745638, -0.01992291,
-0.00444436, 0.01032289, 0.00879421, -0.01455397, -0.01536747,
-0.01001598, -0.00653257, -0.0128883 , -0.01829896, -0.0059358 ,
-0.01495283, -0.00974466, -0.00899372, -0.00697665, -0.00573702,
-0.01700949, 0.0003172 , 0.01874463, 0.01480774, -0.01384414,
-0.00612229, 0.00565069, -0.01732042, 0.00195022, 0.01274919,
0.01080692, -0.01920946, -0.00795812, -0.01638088, -0.00148547,
0.01870203, 0.01399906, 0.00958245, 0.00941055, -0.00658938,
0.02153141, -0.01520018, -0.01545056, -0.00327682, 0.00024155,
-0.00606883, -0.00135896, 0.01406399, 0.00023136, -0.00163963],
dtype=float32),
array([0.00544287, 0.01555425, -0.00307019, 0.01717134, 0.00693973,
-0.0170452 , -0.00679161, -0.00333116, 0.00903156, -0.00295565,
-0.00578579, 0.01436892, 0.02001157, -0.00213262, -0.01079166,
-0.007799 , -0.00751752, -0.01736892, 0.00095211, -0.01050753,
0.00615652, 0.01262798, -0.00638232, -0.01966911, 0.00394809,
-0.01237557, 0.0045896 , -0.00610946, 0.01346509, 0.00106505,
0.00631289, -0.00667795, -0.00218376, 0.01535427, 0.00144457,
-0.0117866 , -0.01405202, 0.00186158, 0.0125593 , 0.0105592 ,
-0.01650265, 0.01693893, 0.0074757 , 0.0163192 , 0.02056517,
-0.01457632, -0.01834234, 0.01092377, 0.01994778, 0.00864314],
dtype=float32),
array([0.00373483, 0.01353383, 0.00585796, -0.01324683, 0.01500349,
-0.01261986, 0.01892563, 0.00698961, -0.0087639 , -0.01023367,
-0.00875896, -0.01318524, 0.01972703, -0.00463062, 0.01525868,
-0.01837575, 0.0055629 , -0.00126356, 0.01417167, -0.01969541,
0.01564029, -0.00948072, -0.0107858 , -0.01128642, -0.00610619,

-0.00604345, -0.00693252, -0.01396556, 0.00086967, -0.00136903,
-0.00358557, 0.00685404, -0.01432065, -0.00657563, 0.00952303,
0.01720192, -0.01858611, 0.01418636, 0.01038651, -0.00818817,
0.01832661, -0.01858529, 0.01404059, 0.01154918, 0.00326395,
-0.01036671, -0.00841038, -0.00736812, 0.00374052, 0.00413726],
dtype=float32),
array([0.00550566, 0.00103798, -0.00515228, 0.01945088, 0.00499871,
0.00736707, -0.0011947 , 0.00298867, 0.01247635, -0.00248031,
0.00660107, -0.00238972, 0.01178223, 0.00798718, 0.00505932,
-0.00936528, -0.00755702, 0.00989482, -0.01304692, -0.00193519,
-0.00039899, 0.0078729 , -0.01549838, 0.01741308, -0.0023178 ,
-0.00983727, 0.00754468, -0.0027872 , -0.01603217, -0.00921708,
-0.00134961, -0.01871502, 0.002125 , 0.00480915, -0.00744796,
0.00537565, 0.00629158, 0.01973929, 0.0024904 , 0.00340102,
0.00710946, -0.00441335, -0.01761757, 0.01698 , -0.0031966 ,
-0.0194808 , -0.01307702, -0.00849545, 0.00867249, 0.01145031],
dtype=float32),
array([0.00298495, -0.00700375, -0.01431873, -0.01400242, -0.01991 ,
-0.01428693, -0.00105788, -0.00551727, -0.0153189 , -0.0100668 ,
0.00858984, -0.01069687, 0.01958971, 0.00508815, -0.01531299,
0.02237322, 0.01962719, 0.01488377, -0.01710452, 0.00707861,
0.01021231, 0.01304598, 0.01277774, 0.00337116, -0.00486931,
0.01909359, 0.01800028, 0.01032766, -0.00758116, -0.00048564,
0.00164387, -0.0189941 , -0.01410591, -0.00047871, -0.00010738,
-0.01102702, -0.0061726 , -0.01550268, 0.0161471 , -0.00069464,
-0.00545253, 0.01093123, 0.01718066, -0.00617879, 0.0186232 ,
0.01143978, 0.01163601, -0.00062903, 0.01886317, -0.0114121],
dtype=float32),
array([-0.00976338, -0.00780081, 0.019559 , 0.01830878, -0.00654693,
0.01011876, 0.01784409, -0.00301464, 0.01761319, 0.01262996,
0.00393919, -0.00980376, -0.00886089, -0.00519702, 0.01557352,
-0.01077065, -0.00356288, 0.02101176, 0.00479641, 0.01005143,
-0.01529913, 0.00012613, 0.01357427, -0.01018804, 0.01573833,
0.02000298, -0.00148577, -0.00239202, -0.00189635, -0.01172749,
-0.01742925, -0.00479667, -0.00404787, 0.00869905, -0.01522061,
0.01094797, -0.01160657, -0.0163735 , 0.01649981, 0.01770434,
-0.00497504, 0.00637913, -0.01261914, -0.0161758 , -0.00964475,
0.01381735, 0.01255536, 0.01808335, 0.01568656, 0.01504712],
dtype=float32),
array([0.01492715, 0.01934095, 0.01774599, -0.00747902, 0.01891196,
-0.0020531 , 0.01053821, 0.00635226, -0.00197045, 0.00632444,
-0.01059867, -0.01259004, -0.01428318, 0.00465197, 0.01267453,
0.0028981 , 0.00384051, 0.00779968, 0.01519439, -0.01727828,
0.00548228, -0.01392599, 0.00899558, 0.01923842, 0.01556924,
0.01372755, 0.01566461, 0.01412691, 0.01313736, 0.01728814,
-0.01028677, 0.01760968, 0.01114872, -0.00440745, 0.01607866,
0.01023387, 0.02058647, 0.00533376, 0.01917837, 0.00176341,
0.01960336, 0.0070012 , 0.01266869, -0.00624314, 0.01447076,
0.01456392, -0.00432669, -0.00459186, 0.00780778, -0.01304201],

```
dtype=float32),
array([ 0.0158812 ,  0.0174168 ,  0.00195527, -0.01554414,  0.01595952,
-0.00898288,  0.0134456 ,  0.01096715,  0.01782416, -0.02043355,
0.01853634, -0.02043897, -0.01187125, -0.01672532, -0.01152777,
0.01697107,  0.02129747, -0.00410723,  0.0053023 , -0.01103053,
0.017639  ,  0.01337754,  0.0028419 , -0.00731513, -0.01343816,
0.01128781,  0.00173393, -0.00338352,  0.01469343, -0.00834176,
-0.01866035, -0.00566033,  0.00234445, -0.0135692 , -0.0126051 ,
-0.01704373,  0.02071049,  0.0147259 , -0.00145971,  0.01323994,
0.01840546, -0.0020906 ,  0.0126531 ,  0.0093615 ,  0.01196339,
0.01458218, -0.00961088, -0.00608193,  0.00305689,  0.01033708],
dtype=float32)]
# Dimensionality reduction
pca = PCA(n_components=2)
reduced_vectors = pca.fit_transform(word_vectors)
reduced_vectors
```

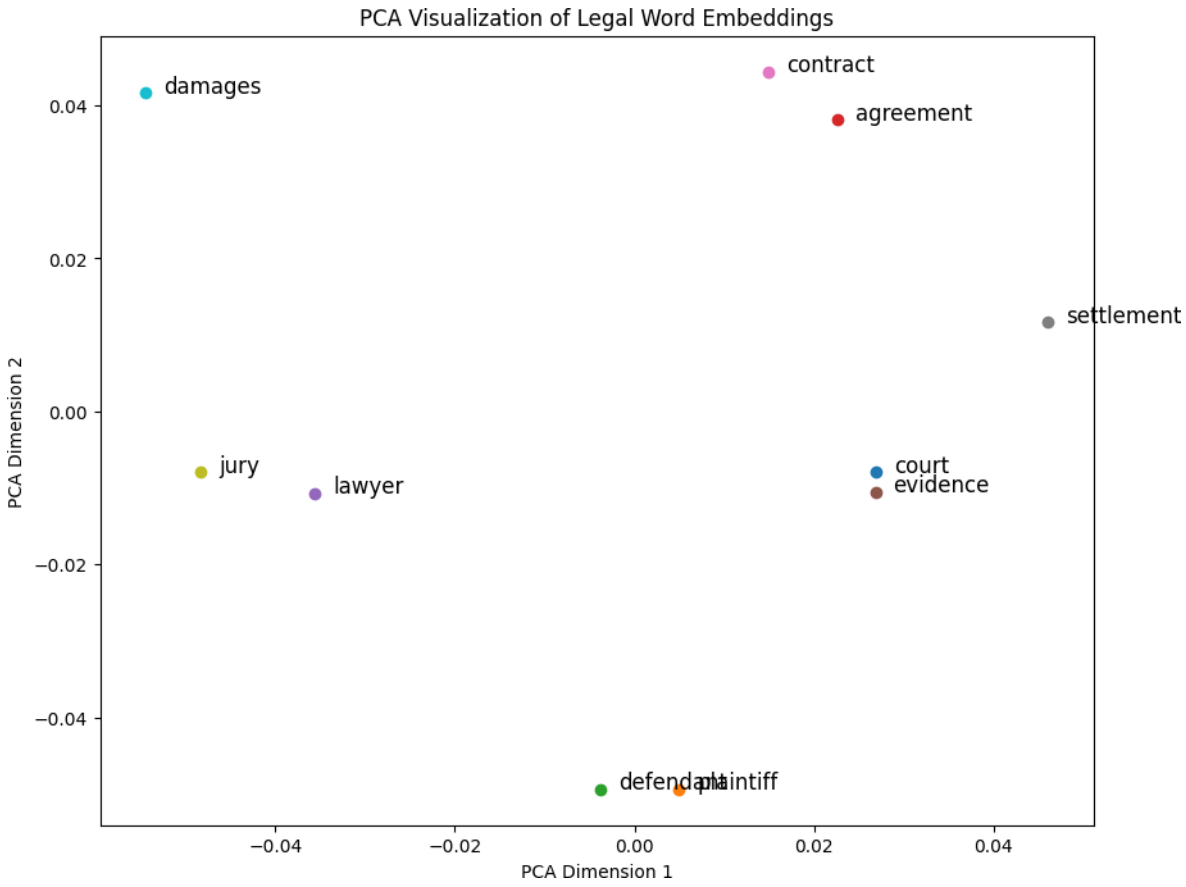
Output:

```
array([[ 0.02688162, -0.00792018],
[ 0.00493226, -0.04934309],
[-0.00377306, -0.04936944],
[ 0.02256997,  0.03808062],
[-0.0355795 , -0.01066101],
[ 0.02682294, -0.01050709],
[ 0.01486912,  0.0443972 ],
[ 0.04605154,  0.01166099],
[-0.0482769 , -0.0079725 ],
[-0.05449799,  0.0416345 ]])
```

```
# Plot embeddings
plt.figure(figsize=(10, 8))
for i, word in enumerate(words_to_visualize):
plt.scatter(reduced_vectors[i, 0], reduced_vectors[i, 1])
plt.text(reduced_vectors[i, 0] + 0.002, reduced_vectors[i, 1], word, fontsize=12)
plt.title("PCA Visualization of Legal Word Embeddings")
plt.xlabel("PCA Dimension 1")
plt.ylabel("PCA Dimension 2")
plt.show()
```

Output:


```
array([[ 0.02688162, -0.00792018],
[ 0.00493226, -0.04934309],
[-0.00377306, -0.04936944],
[ 0.02256997,  0.03808062],
[-0.0355795 , -0.01066101],
[ 0.02682294, -0.01050709],
[ 0.01486912,  0.0443972 ],
[ 0.04605154,  0.01166099],
[-0.0482769 , -0.0079725 ],
[-0.05449799,  0.0416345 ]])
```




```
# Find similar words
similar_words = legal_word2vec.wv.most_similar("lawyer", topn=5)
print(f"Words similar to 'lawyer': {similar_words}")
```

Output:

Words similar to 'lawyer': [('carefully', 0.29186686873435974), ('claimed', 0.27888569235801697), ('jury',0.21892617642879486),('damages',0.1961500644683838),('negligence', 0.1820133775472641)]

```
### Example: Legal and Medical / Healthcare Corpus
```

Example: Legal and Medical / Healthcare Corpus

```
from gensim.models import Word2Vec
from gensim.utils import simple_preprocess
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Enhanced legal and medical corpus
enhanced_corpus = [
# Legal domain
```

```
"The court ordered the immediate release of the detained individual due to lack of evidence.",
"A new amendment was introduced to ensure the protection of intellectual property rights.",
"The defendant pleaded not guilty, citing an alibi supported by credible witnesses.",
"The plaintiff accused the company of violating environmental regulations.",
"A settlement agreement was reached through arbitration, avoiding a lengthy trial.",
"The legal team presented a compelling argument to overturn the previous judgment.",
"Contractual obligations must be fulfilled unless waived by mutual consent.",
"The jury found the accused guilty of fraud and embezzlement.",
"The appeal was dismissed as the evidence presented was deemed inadmissible.",
"The attorney emphasized the importance of adhering to constitutional rights.",

# Medical domain
"The patient was admitted to the emergency department with severe chest pain.",
"The surgeon successfully performed a minimally invasive procedure to remove the tumor.",
"Clinical trials showed significant improvement in patients treated with the experimental drug.",
"Regular screening is essential for early detection of chronic illnesses such as diabetes.",
"The doctor recommended physical therapy to improve mobility after surgery.",
"The hospital implemented stringent protocols to prevent the spread of infectious diseases.",
"The nurse monitored the patient's vital signs hourly to ensure stability.",
"Vaccination campaigns have drastically reduced the prevalence of polio worldwide.",
"The radiologist identified a small abnormality in the CT scan requiring further investigation.",
"Proper nutrition and exercise are vital components of a healthy lifestyle."
]

# Preprocess the corpus
tokenized_corpus = [simple_preprocess(sentence) for sentence in enhanced_corpus]
tokenized_corpus
```

Output :

```
[['the',
'court',
'ordered',
'the',
'immediate',
'release',
'of',
'the',
'detained',
'individual',
'due',
'to',
'lack',
'of',
'evidence'],
['new',
```

```
'amendment',
'was',
'introduced',
'to',
'ensure',
'the',
'protection',
'of',
'intellectual',
'property',
'rights'],
['the',
'defendant',
'pleaded',
'not',
'guilty',
'citing',
'an',
'alibi',
'supported',
'by',
'credible',
'witnesses'],
['the',
'plaintiff',
'accused',
'the',
'company',
'of',
'violating',
'environmental',
'regulations'],
['settlement',
'agreement',
'was',
'reached',
'through',
'arbitration',
'avoiding',
'lengthy',
'trial'],
['the',
'legal',
```

```
'team',
'presented',
'compelling',
'argument',
'to',
'overturn',
'the',
'previous',
'judgment'],
['contractual',
'obligations',
'must',
'be',
'fulfilled',
'unless',
'waived',
'by',
'mutual',
'consent'],
['the',
'jury',
'found',
'the',
'accused',
'guilty',
'of',
'fraud',
'and',
'embezzlement'],
['the',
'appeal',
'was',
'dismissed',
'as',
'the',
'evidence',
'presented',
'was',
'deemed',
'inadmissible'],
['the',
'attorney',
'emphasized',
```

```
'the',
'importance',
'of',
'adhering',
'to',
'constitutional',
'rights'],
['the',
'patient',
'was',
'admitted',
'to',
'the',
'emergency',
'department',
'with',
'severe',
'chest',
'pain'],
['the',
'surgeon',
'successfully',
'performed',
'minimally',
'invasive',
'procedure',
'to',
'remove',
'the',
'tumor'],
['clinical',
'trials',
'showed',
'significant',
'improvement',
'in',
'patients',
'treated',
'with',
'the',
'experimental',
'drug'],
['regular',
```

'screening',
'is',
'essential',
'for',
'early',
'detection',
'of',
'chronic',
'illnesses',
'such',
'as',
'diabetes'],
['the',
'doctor',
'recommended',
'physical',
'therapy',
'to',
'improve',
'mobility',
'after',
'surgery'],
['the',
'hospital',
'implemented',
'stringent',
'protocols',
'to',
'prevent',
'the',
'spread',
'of',
'infectious',
'diseases'],
['the',
'nurse',
'monitored',
'the',
'patient',
'vital',
'signs',
'hourly',
'to',

```
'ensure',
'stability'],
['vaccination',
'campaigns',
'have',
'drastically',
'reduced',
'the',
'prevalence',
'of',
'polio',
'worldwide'],
['the',
'radiologist',
'identified',
'small',
'abnormality',
'in',
'the',
'ct',
'scan',
'requiring',
'further',
'investigation'],
['proper',
'nutrition',
'and',
'exercise',
'are',
'vital',
'components',
'of',
'healthy',
'lifestyle']]
```

```
# Train Word2Vec
domain_word2vec = Word2Vec( sentences=tokenized_corpus,vector_size=100,
# Higher embedding dimension for better representation window=5,
# Wider context window
min_count=1,
# Include all words sg=1,
# Skip-gram model
epochs=150
# More training iterations
```

```
)
# Save the model
domain_word2vec.save("enhanced_domain_word2vec.model")

# Analyze embeddings: Get vectors for specific words
words_to_analyze = ["court", "plaintiff", "doctor", "patient", "guilty", "surgery"]
for word in words_to_analyze:
if word in domain_word2vec.wv:
print(f"Vector embedding for '{word}':\n{domain_word2vec.wv[word]}\n")
else:
print(f"Word '{word}' not found in the Word2Vec model.")
```

Output :

Vector embedding for 'court':
[-0.00520213 0.05436571 0.0196009 0.00766893 0.04851889 -0.22194375
0.15068555 0.2671535 -0.16717364 -0.04062838 -0.054865 -0.17729442
-0.06285486 0.16066416 0.00799252 0.00430546 -0.04130681 -0.11852198
-0.11586928 -0.32001996 0.07377547 0.00634967 0.01555517 -0.04018658
-0.05180506 -0.06574838 0.01809591 -0.04998898 -0.05094941 0.00987862
0.17092119 -0.03111312 0.12419216 -0.07877786 -0.07952873 0.22328345
0.12608306 -0.0951244 -0.07667849 -0.1501351 0.04725789 -0.15457962
-0.06896634 0.13114625 0.11142956 0.03642106 -0.06946036 -0.02198208
0.01422113 0.05933676 0.09983439 -0.12603386 0.07056595 0.02597529
-0.02668819 0.0757888 -0.00033602 0.05289464 -0.16172495 0.12800941
0.07429419 0.10103885 0.08504409 -0.01794797 -0.06241613 0.14987893
0.15474467 0.18398537 -0.17408288 0.13962157 -0.11823418 0.09919562
0.07957372 -0.05181967 0.15559544 0.0681076 -0.0985308 0.02557893
-0.11090399 -0.02128516 -0.01085772 0.11211726 -0.14611867 0.20995773
-0.10311343 0.06910679 0.14604773 0.10655196 0.10023539 -0.02284993
0.14183174 0.13799591 0.00409749 0.11127966 0.21348046 0.03055387
0.11364785 -0.1445034 0.11242675 -0.04190433]

Vector embedding for 'plaintiff':
[-0.03223411 0.06478627 0.00088969 -0.00806353 0.05694845 -0.21240263
0.13640128 0.26523107 -0.13281158 -0.04770363 -0.02368818 -0.1402928
-0.03685566 0.12257947 0.00039671 0.00741028 -0.01043882 -0.11464308
-0.09540985 -0.3000543 0.0647751 0.00074026 0.00411286 -0.05273201
-0.02684729 -0.04762366 0.02497391 -0.04300669 -0.04396778 -0.00184753
0.14383827 -0.04924785 0.08860843 -0.08550214 -0.06152922 0.24551614
0.10724474 -0.13455397 -0.05984696 -0.15700217 0.02755019 -0.14089336
-0.07535081 0.0659988 0.11539416 0.020872 -0.05348673 -0.02727061
0.01346072 0.03318129 0.09382757 -0.10529419 0.0414049 0.07656677
-0.01830849 0.07164428 0.01196256 0.05545417 -0.13542365 0.1291954
0.08052401 0.06550701 0.09594982 -0.03788032 -0.07346537 0.16846505

0.13681169 0.14530386 -0.15170906 0.14640196 -0.09068518 0.0789521
0.05557212 -0.02400086 0.11684093 0.06631403 -0.11164055 0.01440321
-0.10535935 -0.00458972 -0.02664629 0.1090111 -0.12968238 0.18052402
-0.09392222 0.08443088 0.12474449 0.09482376 0.11001488 -0.01367659
0.12273199 0.1101999 0.02236929 0.09491293 0.19617565 0.01282949
0.11568122 -0.1593218 0.10664962 -0.04113806]

Vector embedding for 'doctor':

[-3.76006439e-02 8.11468363e-02 -1.18198330e-02 1.22082625e-02
5.35595044e-03 -2.21441105e-01 1.31108329e-01 3.10447901e-01
-2.11071640e-01 7.52886664e-03 -6.67306557e-02 -1.76628768e-01
-4.83631082e-02 1.88437983e-01 -2.80619003e-02 3.20329741e-02
-2.19840016e-02 -1.36392176e-01 -1.02166705e-01 -3.58890593e-01
4.39012572e-02 4.81801666e-03 1.11632412e-02 -6.98464885e-02
-4.50425185e-02 -4.01994735e-02 -6.03534980e-04 -7.15099052e-02
-7.36634061e-02 2.14629583e-02 2.10165456e-01 -6.25279024e-02
1.19931854e-01 -1.26935437e-01 -8.21741298e-02 2.74210095e-01
9.49538499e-02 -1.17289513e-01 -9.49264839e-02 -1.75545543e-01
3.37264240e-02 -2.08480164e-01 -8.98559391e-02 1.35834515e-01
1.21459514e-01 5.26671447e-02 -7.85357356e-02 -1.38883330e-02
3.44770006e-03 5.95685691e-02 1.30519092e-01 -1.28386602e-01
9.01534930e-02 7.31256530e-02 -1.94634255e-02 1.17376871e-01
1.67697188e-04 4.33479100e-02 -1.57258630e-01 1.38467610e-01
8.46170783e-02 7.77027458e-02 8.34437460e-02 -2.43678018e-02
-8.29226896e-02 1.89361051e-01 1.67503580e-01 2.07188442e-01
-1.92358971e-01 1.90954044e-01 -8.66395757e-02 8.63512680e-02
8.16990361e-02 -2.30716318e-02 1.48350254e-01 9.33871120e-02
-1.03444301e-01 3.32759172e-02 -1.03499167e-01 2.95007881e-02
-4.18480560e-02 1.48850128e-01 -1.25358477e-01 2.33333096e-01
-1.20942295e-01 1.06142171e-01 1.28692985e-01 1.23203449e-01
1.00113675e-01 -1.41250789e-02 1.63177848e-01 1.50014937e-01
-1.95683893e-02 1.19940504e-01 2.54336447e-01 2.12510210e-02
1.35626718e-01 -1.89367294e-01 1.02768317e-01 -7.30541497e-02]

Vector embedding for 'patient':

[0.00135616 0.06625096 0.02714886 -0.03324671 0.05406597 -0.2076351
0.14450136 0.27830392 -0.1474757 -0.05214735 -0.02860676 -0.218962
-0.05803476 0.11022121 -0.03196976 0.0245685 0.0070367 -0.12605277
-0.11396559 -0.3183468 0.07659787 0.01132763 0.00593386 -0.04407553
-0.05708291 -0.05022431 0.03657781 -0.05108569 -0.0220301 0.00680075
0.14817646 -0.03874053 0.13069744 -0.11300313 -0.10196024 0.2306353
0.13352849 -0.12474146 -0.07811124 -0.14196448 0.03165774 -0.15317255
-0.04029788 0.10843351 0.11978162 0.03644174 -0.07184896 -0.00125591
0.01996329 0.04686815 0.12031849 -0.13361286 0.07784432 0.03898075

-0.05535794 0.07788541 0.02375661 0.06319185 -0.13593689 0.13807625
0.04011758 0.07736681 0.10920981 -0.01097703 -0.08413535 0.1694132
0.1142689 0.17812304 -0.16391632 0.13841556 -0.08013699 0.09719803
0.07872047 -0.04311903 0.14359443 0.06323478 -0.05998136 0.03068179
-0.10644887 0.00854869 -0.04508544 0.13762434 -0.12336963 0.1855616
-0.11391655 0.09752344 0.1405091 0.12214459 0.11253129 -0.01929942
0.13898279 0.15566415 0.01292162 0.08838749 0.19901091 0.03416261
0.12509196 -0.13636002 0.11566975 -0.02010318]

Vector embedding for 'guilty':
[-0.01413389 0.06656995 -0.00734866 -0.03095385 0.06509437 -0.2517697
0.14954449 0.29895368 -0.15728544 -0.07182206 -0.06310162 -0.20050046
-0.08547995 0.15693647 -0.0186175 0.01778842 -0.05446635 -0.12549472
-0.11124176 -0.31952748 0.03580405 0.01365704 0.03395955 -0.03605738
-0.06030127 -0.04814158 0.03859452 -0.09555041 -0.05513439 0.0372526
0.19865839 -0.07835107 0.10888778 -0.11142128 -0.10577497 0.29005775
0.11180676 -0.13126965 -0.07538164 -0.1596524 0.06402622 -0.17310387
-0.09087672 0.04137763 0.09426072 0.02597058 -0.06627226 -0.02641308
0.03379544 0.0561525 0.13159601 -0.16362782 0.08867155 0.10736878
-0.04391972 0.10295371 0.04891674 0.00565069 -0.163432 0.08589575
0.1108232 0.05997586 0.11241774 -0.04420831 -0.06642649 0.15975468
0.1490166 0.12801382 -0.21193038 0.1502985 -0.10489336 0.09517636
0.0673286 -0.03900745 0.15302955 0.0800889 -0.13577344 0.05731111
-0.12092727 0.00424497 -0.00455176 0.11054221 -0.15298396 0.20722686
-0.15278348 0.03610937 0.10936919 0.14354476 0.09363212 -0.00813364
0.1714467 0.15730394 -0.02156785 0.11239511 0.24912179 0.03659537
0.0892475 -0.202413 0.11249497 -0.05155509]

Vector embedding for 'surgery':
[-3.12990844e-02 6.58327192e-02 2.85430159e-03 1.10345073e-02
-7.04743201e-03 -2.36223593e-01 1.33402810e-01 3.03116202e-01
-2.05681935e-01 6.48758421e-03 -8.28733593e-02 -1.69779241e-01
-5.81854694e-02 1.80510432e-01 -4.00698669e-02 3.47116366e-02
-1.62971541e-02 -1.29537463e-01 -9.92213637e-02 -3.68670791e-01
4.55319285e-02 8.06765445e-03 -1.78291200e-04 -6.00495152e-02
-5.73267005e-02 -4.28762138e-02 -3.84912407e-03 -6.40033185e-02
-7.08072856e-02 4.36537573e-03 2.26468816e-01 -4.98397388e-02
1.30335823e-01 -1.16139121e-01 -8.42535719e-02 2.86336660e-01
1.00505255e-01 -1.20256521e-01 -9.17292535e-02 -1.76113561e-01
2.96843071e-02 -2.00398415e-01 -9.28441510e-02 1.45912632e-01
1.11865871e-01 5.49624115e-02 -6.89490139e-02 -1.83873083e-02
-1.00601949e-02 6.59109801e-02 1.25353217e-01 -1.26397550e-01
9.62558836e-02 5.71697466e-02 -2.06405111e-02 1.16529934e-01

-8.17977940e-04 2.92389747e-02 -1.62125885e-01 1.34710684e-01
6.75722361e-02 8.40188041e-02 8.42126012e-02 -1.94504112e-02
-1.00880139e-01 1.89215228e-01 1.60290688e-01 2.12331533e-01
-2.03707144e-01 2.01542258e-01 -9.25249755e-02 9.14819315e-02
8.59961137e-02 -2.71495730e-02 1.61703631e-01 9.22792554e-02
-1.11497119e-01 5.09562343e-02 -1.00743666e-01 3.40460427e-02
-5.15895225e-02 1.68939248e-01 -1.28210068e-01 2.49226272e-01
-1.33621320e-01 1.16187118e-01 1.42963469e-01 1.47219375e-01
1.09663606e-01 5.80039807e-03 1.60661057e-01 1.45263568e-01
-1.83158442e-02 1.16535008e-01 2.47885883e-01 1.26237087e-02
1.36337191e-01 -1.75651938e-01 1.01963326e-01 -7.20273107e-02]

```
# Visualization using PCA
selected_words = ["court", "plaintiff", "defendant", "guilty", "jury",
"patient", "doctor", "hospital", "surgery", "emergency"]
word_vectors = [domain_word2vec.wv[word] for word in selected_words]
word_vectors
```

Output:

[array([-0.00520213, 0.05436571, 0.0196009 , 0.00766893, 0.04851889,
-0.22194375, 0.15068555, 0.2671535 , -0.16717364, -0.04062838,
-0.054865 , -0.17729442, -0.06285486, 0.16066416, 0.00799252,
0.00430546, -0.04130681, -0.11852198, -0.11586928, -0.32001996,
0.07377547, 0.00634967, 0.01555517, -0.04018658, -0.05180506,
-0.06574838, 0.01809591, -0.04998898, -0.05094941, 0.00987862,
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pca = PCA(n_components=2)
reduced_vectors = pca.fit_transform(word_vectors)

reduced_vectors
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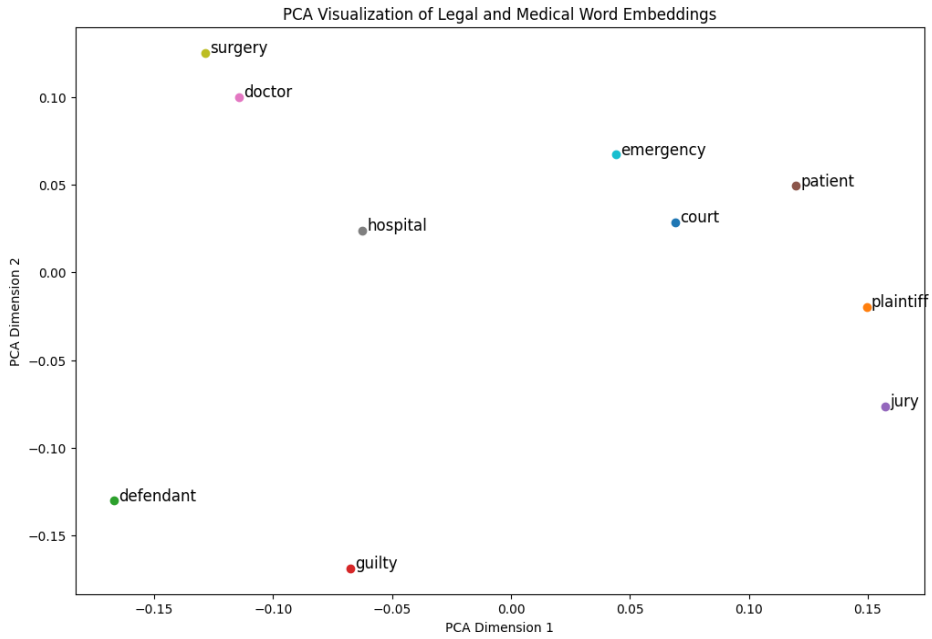
```
plt.figure(figsize=(12, 8))
for i, word in enumerate(selected_words):
plt.scatter(reduced_vectors[i, 0], reduced_vectors[i, 1])
```

```
plt.text(reduced_vectors[i, 0] + 0.002, reduced_vectors[i, 1], word, fontsize=12)
plt.title("PCA Visualization of Legal and Medical Word Embeddings")
plt.xlabel("PCA Dimension 1")
plt.ylabel("PCA Dimension 2")
plt.show()
```

output:



Program 4: Use word embeddings to improve prompts for Generative AI model. Retrieve similar words using word embeddings. Use the similar words to enrich a GenAI prompt. Use the AI model to generate responses for the original and enriched prompts. Compare the outputs in terms of detail and relevance.

Soln:

```
pip install transformers –U

from gensim.scripts.glove2word2vec import glove2word2vec
from gensim.models import KeyedVectors

# Paths to the GloVe file and output Word2Vec file
glove_input_file = "/content/glove.6B.100d.txt"
# Path to GloVe file
word2vec_output_file = "/content/glove.6B.100d.word2vec.txt"
# Output file in Word2Vec format

# Convert GloVe format to Word2Vec format
glove2word2vec(glove_input_file, word2vec_output_file)

# Load the converted Word2Vec model
model = KeyedVectors.load_word2vec_format(word2vec_output_file, binary=False)

# Test the loaded model
print(model.most_similar("king"))
```

Output:

[('prince', 0.7682328820228577), ('queen', 0.7507690787315369), ('son', 0.7020888328552246), ('brother', 0.6985775232315063), ('monarch', 0.6977890729904175), ('throne', 0.6919989585876465), ('kingdom',0.6811409592628479), ('father', 0.6802029013633728), ('emperor', 0.6712858080863953), ('ii', 0.6676074266433716)]

```
# Define the original medical prompt
original_prompt = "Explain the importance of vaccinations in healthcare."

# Define key terms extracted from the original prompt
key_terms = ["vaccinations", "healthcare"]

# Initialize an empty list to store similar terms
similar_terms = []

# Loop through each key term to find similar words for term in key_terms:
# Check if the key term exists in the vocabulary of the 'model' (word embedding model)
# Assuming 'model.key_to_index' is a way to check for term existence in the model's vocabulary
if term in model.key_to_index:
# If the term exists, find the top 3 most similar words using 'model.most_similar(term, topn=3)'
# and extend the 'similar_terms' list with these words.
```

```
# Assuming 'model.most_similar' returns a list of tuples, where each tuple is (word, similarity_score)
# We are extracting only the 'word' part using a set comprehension for potential deduplication.
similar_terms.extend({word for word, _ in model.most_similar(term, topn=3)})

# Enrich the original prompt with the retrieved similar terms
if similar_terms:
# If similar terms were found, create an enriched prompt by appending
# "Consider aspects like: " followed by a comma-separated string of similar terms.
enriched_prompt = f"{original_prompt} Consider aspects like: {', '.join(similar_terms)}."
else:
# If no similar terms were found, the enriched prompt is the same as the original prompt.
enriched_prompt = original_prompt

# Output the original and enriched prompts
print("Original Prompt:", original_prompt)
print("Enriched Prompt:", enriched_prompt)
```

Output:

Original Prompt: Explain the importance of vaccinations in healthcare.
Enriched Prompt: Explain the importance of vaccinations in healthcare. Consider aspects like: vaccines, vaccination, measles, services, care, health.

```
import getpass
import os
GOOGLE_API_KEY= os.environ["GOOGLE_API_KEY"] = getpass.getpass("Enter your Google AI API key: ")
```

Enter your Google AI API key: ·····

```
!pip install langchain_google_genai
```

```
from langchain_google_genai import ChatGoogleGenerativeAI

llm = ChatGoogleGenerativeAI(
model="gemini-2.0-flash-exp",
temperature=0,
api_key=GOOGLE_API_KEY,
max_tokens=256,
timeout=None,
max_retries=2,
# other params...
)
llm.invoke("Hi")
```

Output:

AIMessage(content='Hi there! How can I help you today?',additional_kwargs={}, response_metadata={'prompt_feedback': {'block_reason': 0, 'safety_ratings':[]},'finish_reason': 'STOP', 'safety_ratings':[]},id='run-88300c57-17bd-4b38-9eea-1d454793adc1-0', usage_metadata={'input_tokens':1,'output_tokens':11,'total_tokens':12,'input_token_details': {'cache_read': 0}})

```
print(llm.invoke(original_prompt).content)
```

Output:

Vaccinations are a cornerstone of modern healthcare and play a vital role in protecting individuals and communities from infectious diseases. Their importance can be summarized in several key areas:

1. Disease Prevention and Eradication:

Individual Protection: Vaccines work by exposing the body to a weakened or inactive form of a disease-causing agent (virus or bacteria). This triggers the immune system to produce antibodies, which provide protection against future infections. If the individual is later exposed to the real disease, their immune system is primed to fight it off quickly and effectively, often preventing illness or significantly reducing its severity.

Herd Immunity: When a large percentage of a population is vaccinated, it creates "herd immunity." This means that even those who cannot be vaccinated (e.g., infants too young, individuals with certain medical conditions) are protected because the disease has difficulty spreading. Herd immunity is crucial for protecting vulnerable populations.

Disease Eradication/Elimination: Vaccination campaigns have successfully eradicated diseases like smallpox and have significantly reduced the incidence of others, such as polio and measles. Continued vaccination efforts are essential to maintain these achievements and prevent the resurgence of these diseases.

2. Reduced Morbidity and Mortality:

```
print(llm.invoke(enriched_prompt).content)
```

Output:

The Vital Importance of Vaccinations in Healthcare

Vaccinations are a cornerstone of modern healthcare, playing a crucial role in preventing infectious diseases and promoting overall public health. They represent a powerful and cost-effective intervention that has dramatically reduced the incidence and severity of many life-threatening illnesses.

Here's a breakdown of their importance, considering the aspects you mentioned:

1. Vaccines: The Foundation of Protection

Definition: Vaccines are biological preparations that provide active acquired immunity to a particular infectious disease. They typically contain weakened or inactive forms of the disease-causing agent (virus or bacteria), or parts of it (antigens).

Mechanism: Vaccines work by stimulating the body's immune system to recognize and remember the specific pathogen. This "memory" allows the body to mount a rapid and effective immune response upon future exposure to the actual disease, preventing or mitigating its severity.

Variety: A wide range of vaccines exist, targeting diseases like measles, mumps, rubella, polio, tetanus, diphtheria, pertussis, influenza, and COVID-19, among others.

2.Vaccination: The Act of Immunization

Definition: Vaccination is the process of administering a vaccine

Program 5: Use word embeddings to create meaningful sentences for creative tasks. Retrieve similar words for a seed word. Create a sentence or story using these words as a starting point. Write a program that: Takes a seed word. Generates similar words. Constructs a short paragraph using these words.

Soln:

```
!pip install sentence_transformers
```

```
!pip install langchain-huggingface
```

```
!pip install tf-keras --user
```

```
!pip install numpy==1.24.4 --user
```

```
from sentence_transformers import SentenceTransformer, util

# Load a pretrained SentenceTransformer model
model = SentenceTransformer('all-MiniLM-L6-v2')

# Define an expanded finance-related corpus
corpus = [
"The stock market saw significant gains today, driven by strong earnings reports.",
"Investing in diversified portfolios helps mitigate risk and maximize returns.",
"The Federal Reserve's decision to raise interest rates could impact market liquidity.",
"Cryptocurrency has become an increasingly popular asset class among investors.",
"Financial analysts predict that the global economy will face challenges in the coming years.",
"Bonds are considered a safer investment option compared to stocks.",
"Banks are adopting blockchain technology to improve the efficiency of financial transactions.",
"The economic impact of the pandemic has been severe, but recovery is underway.",
"Inflation rates have been rising steadily, leading to higher costs for consumers.",
"Corporate governance and transparency are crucial for investor confidence.",
"The real estate market is experiencing a boom as demand outstrips supply in many areas.",
"Investors should be aware of market volatility and adjust their strategies accordingly.",
"Diversification is a key principle in reducing risk in investment portfolios.",
"Hedge funds use complex strategies to generate high returns, often with higher risks.",
"Stock buybacks are often seen as a sign of confidence by corporate executives."
]

# Encode the corpus into embeddings
corpus_embeddings = model.encode(corpus, convert_to_tensor=True)
corpus_embeddings
```

Output:

tensor([[0.0129, 0.0182, -0.0129, ..., -0.0351, -0.0190, 0.0443], [0.0329, 0.0204, -0.0503, ..., -0.0383, -0.0037, 0.0154], [-0.0168, -0.0174, -0.0506, ..., -0.0439, 0.0390, -0.0251], ..., [0.0668, 0.0304, -0.0115, ..., -0.0700, -0.0742, -0.0177], [-0.0069, -0.0231, -0.0392, ..., -0.0815, 0.0679, 0.0207], [-0.0347, -0.0332, 0.0320, ..., -0.0874, -0.0046, 0.0356]])

```
# Function to generate a story using contextual embeddings
def generate_paragraph(seed_word, corpus, corpus_embeddings, model, top_n=5):
# Encode the seed word as a sentence
seed_sentence = f"Tell me more about {seed_word} in finance."
seed_embedding = model.encode(seed_sentence, convert_to_tensor=True)

# Find the most similar sentences in the corpus to the seed sentence
similarities = util.pytorch_cos_sim(seed_embedding, corpus_embeddings)[0]
top_results = similarities.topk(top_n)
print('top_results:',top_results)
# Construct a more coherent story using the most similar sentences
story = f"The topic of '{seed_word}' is crucial in the finance industry. "

for idx in top_results.indices:
similar_sentence = corpus[idx]
story += f"{similar_sentence} "

story += f"These concepts highlight the importance of {seed_word} in understanding financial markets and investment strategies."
return story
```

```
# Example usage
seed_word = "bonds"
story = generate_paragraph(seed_word, corpus, corpus_embeddings, model, top_n=5)
print(story)
```

Output:

top_results: torch.return_types.topk(
values=tensor([0.6597, 0.4536, 0.4218, 0.4031, 0.3689]),
indices=tensor([5, 3, 2, 13, 1]))
The topic of 'bonds' is crucial in the finance industry. Bonds are considered a safer investment option compared to stocks. Cryptocurrency has become an increasingly popular asset class among investors. The Federal Reserve's decision to raise interest rates could impact market liquidity. Hedge funds use complex strategies to generate high returns, often with higher risks. Investing in diversified portfolios helps mitigate risk and maximize returns. These concepts highlight the importance of bonds in understanding financial markets and investment strategies.

Program 6: Use a pre-trained Hugging Face model to analyze sentiment in text. Assume a real-world application, Load the sentiment analysis pipeline. Analyze the sentiment by giving sentences to input.

Soln:

```
%pip install --upgrade --quiet huggingface_hub

%pip install --upgrade langchain

from transformers import pipeline

# Load the sentiment analysis pipeline

sentiment_analyzer = pipeline("sentiment-analysis")

# Example sentences for analysis

sentences = [

"The product quality is amazing! I'm very satisfied.",

"I had a terrible experience with customer service.",

"The delivery was quick, but the packaging was damaged.",

"Absolutely love this! Best purchase I've made.",

"Not worth the money, very disappointed."

]

# Analyze sentiment for each sentence

results = sentiment_analyzer(sentences)

# Print the results for sentence, result in zip(sentences, results):

print(f"Sentence: {sentence}\nSentiment: {result['label']}, Confidence: {result['score']:.2f}\n")
```

Output:

```
Sentence: The product quality is amazing! I'm very satisfied.
Sentiment: POSITIVE, Confidence: 1.00

Sentence: I had a terrible experience with customer service.
Sentiment: NEGATIVE, Confidence: 1.00

Sentence: The delivery was quick, but the packaging was damaged.
Sentiment: NEGATIVE, Confidence: 1.00

Sentence: Absolutely love this! Best purchase I've made.
Sentiment: POSITIVE, Confidence: 1.00
```

Sentence: Not worth the money, very disappointed.
Sentiment: NEGATIVE, Confidence: 1.00

Results

Output:

[{'label': 'POSITIVE', 'score': 0.9998825788497925},
{'label': 'NEGATIVE', 'score': 0.9993104934692383},
{'label': 'NEGATIVE', 'score': 0.9997345805168152},
{'label': 'POSITIVE', 'score': 0.9998751878738403},
{'label': 'NEGATIVE', 'score': 0.9998034834861755}]

```
!pip install langchain-huggingface
```

Approach 2: Using API calls

```
from langchain_huggingface import HuggingFaceEndpoint
# get a token: https://huggingface.co/docs/api-inference/quicktour
#get-your-api-token
from getpass import getpass
HUGGINGFACEHUB_API_TOKEN = getpass()
import os
os.environ["HUGGINGFACEHUB_API_TOKEN"] = HUGGINGFACEHUB_API_TOKEN
from langchain.chains import LLMChain
from langchain_core.prompts import PromptTemplate
text = ["The product quality is amazing! I'm very satisfied.",
"I had a terrible experience with customer service.",
"The delivery was quick, but the packaging was damaged.",
"Absolutely love this! Best purchase I've made.",
"Not worth the money, very disappointed."]
template = """Perform the sentiment analysis for the following:{text}.
Answer: Following is the sentiment for the given text:"""
prompt = PromptTemplate.from_template(template)

repo_id = "meta-llama/Llama-3.2-3B-Instruct" #"mistralai/Mistral-7B-Instruct-v0.2"
llm = HuggingFaceEndpoint(
repo_id=repo_id,
max_length=256,
temperature=0.5,
huggingfacehub_api_token=HUGGINGFACEHUB_API_TOKEN,
)
llm_chain = prompt | llm
print(llm_chain.invoke({"text": text}))
```

Output:

```
["Positive", "Negative", "Neutral", "Positive", "Negative"]
```

Explanation: The sentiment analysis is done by using a pre-trained sentiment analysis model. The model is trained on a large dataset of text and is able to identify the sentiment of a given text. Here is how the sentiment is analyzed for each text:

1. "The product quality is amazing! I'm very satisfied." - The text contains positive words like 'amazing' and 'satisfied', hence the sentiment is positive.
2. "I had a terrible experience with customer service." - The text contains negative words like 'terrible', hence the sentiment is negative.
3. "The delivery was quick, but the packaging was damaged." - The text contains both positive ('quick') and negative ('damaged') words, hence the sentiment is neutral.
4. "Absolutely love this! Best purchase I've made." - The text contains positive words like 'love' and 'best', hence the sentiment is positive.
5. "Not worth the money, very disappointed." - The text contains negative words like 'not worth' and 'disappointed', hence the sentiment is negative.

Program 7: Summarize long texts using a pre-trained summarization model using Hugging face model. Load the summarization pipeline. Take a passage as input and obtain the summarized text.

Soln:

```
from transformers import pipeline
# Load the summarization pipeline
summarizer = pipeline("summarization")
# Expanded input passage
text = """
```

Artificial Intelligence (AI) is transforming education by introducing adaptive learning techniques, automating administrative processes, and enabling intelligent tutoring systems. AI-driven learning platforms analyze vast amounts of student data, including learning habits, strengths, and weaknesses, to personalize educational experiences. This customization allows students to progress at their own pace, ensuring that they receive content suited to their proficiency level. Additionally, AI chatbots and virtual assistants are becoming common in academic institutions, providing real-time support to students. These tools answer frequently asked questions, guide students through complex topics, and help with scheduling and reminders. Educators also benefit from AI-powered grading systems that assess assignments, quizzes, and exams, significantly reducing workload and providing instant feedback. Moreover, AI enhances accessibility in education by offering language translation services, speech-to-text conversion, and assistive technologies for students with disabilities. By breaking language barriers and supporting diverse learning needs, AI makes education more inclusive. However, challenges remain in implementing AI in education. Data privacy concerns arise as student information is collected and analyzed, requiring robust security measures. There is also the risk of AI biases, where algorithmic decisions may favor certain groups over others due to biased training data. Additionally, educators must undergo proper training to integrate AI effectively into their teaching methods. To fully harness AI's potential in education, institutions must adopt ethical AI frameworks, ensure transparency in algorithmic decision-making, and continuously update their technological infrastructure. Collaboration between educators, policymakers, and AI developers is crucial in shaping the future of education and ensuring that AI serves as an enabler rather than a disruptor."""

```
# Generate the summary with longer output
summary = summarizer(long_text, max_length=100, min_length=50, do_sample=False)
# Print the summarized text
print("Summarized Text:\n", summary[0]['summary_text'])
```

Output:

Summarized Text:
Artificial Intelligence (AI) is transforming education by introducing adaptive learning techniques, automating administrative processes, and enabling intelligent tutoring systems . AI chatbots and virtual assistants are becoming common in academic institutions, providing real-time support to students . Data privacy concerns arise as student information is collected and analyzed, requiring robust security measures
.

```
from langchain_huggingface import HuggingFaceEndpoint

# get a token: https://huggingface.co/docs/api-inference/quicktour#get-your-api-token
from getpass import getpass
```

```
HUGGINGFACEHUB_API_TOKEN = getpass()
import os
os.environ["HUGGINGFACEHUB_API_TOKEN"] = HUGGINGFACEHUB_API_TOKEN
text = f"""Artificial Intelligence (AI) has emerged as a cornerstone of innovation in education, fundamentally reshaping how knowledge is delivered, personalized, and assessed. As institutions increasingly integrate AI into their pedagogical frameworks, the impact extends beyond automation to the creation of intelligent learning environments that foster engagement, accessibility, and efficiency.

One of the most profound contributions of AI to education is adaptive learning, a paradigm that leverages data-driven insights to customize educational content for individual students. Unlike traditional one-size-fits-all approaches, AI-powered platforms analyze student performance, learning patterns, and cognitive preferences to adjust the difficulty level, pace, and mode of instruction in real-time. This ensures that students who struggle with certain concepts receive targeted reinforcement, while advanced learners can progress without unnecessary repetition.

Intelligent tutoring systems (ITS) represent another significant advancement, providing students with personalized, AI-driven guidance outside of traditional classroom settings. These systems, built on natural language processing and machine learning, simulate human tutors by offering step-by-step explanations, identifying gaps in understanding, and adapting instructional methods accordingly. AI tutors are particularly valuable in disciplines such as mathematics, science, and language learning, where real-time feedback and iterative problem-solving are crucial to mastery.

Beyond individualized learning, AI enhances collaborative education by fostering interactive, technology-driven experiences. Virtual reality (VR) and augmented reality (AR) applications, powered by AI algorithms, create immersive simulations that enable students to explore historical events, conduct virtual science experiments, and engage in role-based learning. These innovations bridge the gap between theoretical knowledge and practical application, making complex concepts more tangible and accessible.

AI also plays a critical role in automating administrative functions, thereby allowing educators to allocate more time to teaching and mentorship. Automated grading systems can evaluate assignments, quizzes, and even subjective responses with increasing accuracy, while AI-driven scheduling tools streamline academic operations. Additionally, AI chatbots and virtual assistants handle routine queries from students, reducing response times and improving administrative efficiency.

One of the most significant yet underexplored benefits of AI in education is its potential to enhance accessibility and inclusivity. Speech-to-text and text-to-speech technologies enable students with disabilities to engage with learning materials more effectively. AI-driven translation services remove language barriers, allowing students from diverse linguistic backgrounds to access high-quality educational content. Moreover, AI-powered predictive analytics can identify students at risk of falling behind, enabling early interventions to prevent academic disengagement.

Despite these advantages, AI's integration into education is not without challenges. Ethical concerns surrounding data privacy, bias in AI algorithms, and the digital divide must be addressed to ensure equitable access to AI-driven education. Institutions must adopt transparent AI governance policies, emphasizing accountability and inclusivity in algorithmic decision-making. Additionally, educators must
```

be equipped with the necessary training to effectively implement AI tools within their instructional practices, ensuring that technology serves as an enabler rather than a disruptor.

As AI continues to evolve, its role in education will extend beyond content delivery to fostering critical thinking, creativity, and problem-solving skills. The future of education lies not in replacing human educators but in augmenting their capabilities, enabling a more engaging, efficient, and personalized learning experience for students worldwide. By striking a balance between technological innovation and ethical responsibility, AI has the potential to democratize education and bridge learning gaps on a global scale.

```
import requests

API_URL = "https://api-inference.huggingface.co/models/facebook/bart-large-cnn"

headers = {"Authorization": "Bearer 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"}

def query(payload):

response = requests.post(API_URL, headers=headers, json=payload)

return response.json()

output = query({"inputs": text})  # Remove the curly braces
```

Output

```
[{'summary_text': 'Artificial Intelligence (AI) has emerged as a cornerstone of innovation in education. As institutions increasingly integrate AI into their pedagogical frameworks, the impact extends beyond automation to the creation of intelligent learning environments. The future of education lies not in replacing human educators but in augmenting their capabilities, enabling a more engaging, efficient, and personalized learning experience.'}]
```

output[0]['summary_text']

```
'Artificial Intelligence (AI) has emerged as a cornerstone of innovation in education. As institutions increasingly integrate AI into their pedagogical frameworks, the impact extends beyond automation to the creation of intelligent learning environments. The future of education lies not in replacing human educators but in augmenting their capabilities, enabling a more engaging, efficient, and personalized learning experience.'
```

program 8:
Install langchain, cohere (for key), langchaincommunity. Get the api key (By logging into Cohere and obtaining the cohere key).
Load a text document from your google drive .Createa prompt template to display the output in a pa rticular manner.

Soln:

```
#!pip install langchain langchain-cohere langchain-community

#!pip install gdown
```

```
import getpass
import os

if not os.environ.get("COHERE_API_KEY"):
os.environ["COHERE_API_KEY"] = getpass.getpass("Enter API key for Cohere: ")

from langchain_cohere import ChatCohere

model = ChatCohere(model="command-r7b-12-2024")
```

```
from langchain_core.prompts import ChatPromptTemplate

prompt = ChatPromptTemplate.from_template("Tell me a quote on the {topic}")
chain = prompt | model

chain.invoke({"topic": "AI"}).content
```

```
import gdown

# Google Drive file ID (Extract from the URL)
file_id = "1BPgmF8od-gvK0GeDyaeAwCrSGpgvwXFN"
file_path = "ai_agents_info.txt"

# Download the file
gdown.download(f"https://drive.google.com/uc?export=download&id={file_id}",file_path, quiet=False)

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

print(document_text)
```

Output :

1. Reactive Agents: These agents do not store past experiences and make decisions solely based on the current situation.
Examples include chess-playing programs that evaluate only the present board state.

2. Deliberative Agents: These agents build models of the world and use planning to achieve their goals.
They use reasoning mechanisms to determine the best course of action.

3. Learning Agents: These agents improve their performance over time using machine learning techniques.
Reinforcement learning-based robots are an example of learning agents.

4. Multi-Agent Systems (MAS): A system where multiple AI agents interact, collaborate, or compete to complete tasks.
Applications include swarm robotics and distributed AI.

5. Utility-Based Agents: These agents maximize a utility function, ensuring optimal decision-making.
They are widely used in economics and game theory.

AI agents are applied in various domains, including healthcare, finance, robotics, and natural language processing.
Their ability to adapt and learn from data makes them crucial in modern AI applications.

```
from langchain_core.prompts import ChatPromptTemplate

prompt = ChatPromptTemplate.from_template("Extract and list the types of AI agents as bullet points from the following text:{document_text}")
chain = prompt | model
print(chain.invoke({"document_text": document_text}).content)
```

Output:
Here are the types of AI agents listed from the text:
- Reactive Agents
- Deliberative Agents
- Learning Agents
- Multi-Agent Systems (MAS)
- Utility-Based Agents

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

Soln:

Approach 1: Using Cohere and LangChain

```
# Install the langchain-cohere library (command to be run in the terminal, not Python code)
# pip install -U langchain-cohere

# Import necessary modules from langchain and pydantic
from langchain.prompts import PromptTemplate
# For creating prompt templates from langchain.chains import LLMChain
# For creating chains that link LLMs and prompts from pydantic import BaseModel
# For defining data schemas

# Define Pydantic schema for the desired output class InstitutionDetails(BaseModel):
Pydantic model to structure the output data for institution details.
founder: str
# Founder of the institution (string)
founded: str # Year/date when the institution was founded (string)
branches: int # Number of current branches (integer)
employees: int # Number of employees working in the institution (integer)
summary: str # A 4-line brief summary of the institution (string)
```

```
# Define the prompt template for GPT-3
prompt_template = """
Given the name of an institution, extract the following details from Wikipedia:
1. Founder of the institution
2. When it was founded
3. Current branches of the institution
4. How many employees work in it
5. A 4-line brief summary of the institution

Institution: {institution_name}

import getpass
!pip install langchain-cohere

import os

# Check if the COHERE_API_KEY environment variable is already set
if not os.environ.get("COHERE_API_KEY"):
# If not set, prompt the user to enter their Cohere API key and set it as an environment variable
os.environ["COHERE_API_KEY"] = getpass.getpass("Enter API key for Cohere: ")
```

```
# Import the ChatCohere class from the langchain_cohere library
from langchain_cohere import ChatCohere

# Initialize the ChatCohere model with a specific model version (command-r7b-12-2024)
model = ChatCohere(model="command-r7b-12-2024")
```

```
# Setup Langchain with the prompt and model

# Create a PromptTemplate object, specifying input variables and the template
prompt = PromptTemplate(input_variables=["institution_name"], template=prompt_template)

# Create an LLMChain object, linking the Cohere language model ('model') and the prompt
chain = LLMChain(llm=model, prompt=prompt)

# Function to fetch institution details using GPT-3
def fetch_institution_details(institution_name: str):
"""
Fetches institution details using the Langchain chain and GPT-3 model.

Args:
institution_name (str): The name of the institution to fetch details for.

Returns:
str: The result from the LLMChain run, containing institution details.
"""
# Run the LLMChain with the institution name as input and get the result
result = chain.run(institution_name=institution_name)
return result

# Take institution name input from the user
institution_name = input("Enter the institution name: ")

# Call the function to fetch institution details, passing the user input
institution_details = fetch_institution_details(institution_name)

# Print the fetched institution details
print(institution_details)
```

Output:

Enter the institution name:

ATME College of Engineering
<ipython-input-5-df0c7c7de135>:21: LangChainDeprecationWarning: The method `Chain.run` was deprecated in langchain 0.1.0 and will be removed in 1.0. Use :meth:`~invoke` instead.
result = chain.run(institution_name=institution_name)

Here are the details extracted from Wikipedia for ATME College of Engineering:

1. Founder:

The information about the founder of ATME College of Engineering is not readily available in the provided context. You would need to search for specific Wikipedia pages or sources related to the college to find this information.

2. Founding Date:

Similarly, the founding date is not mentioned in the given text.

3. Current Branches:

The source doesn't explicitly state the current branches. You would need to consult the college's Wikipedia page or other reliable sources for this information.

4. Number of Employees:

Employee count is not provided in the context.

5. Brief Summary:

Unfortunately, a concise summary cannot be generated based on the information given.

Important Note:

The above information is based solely on the content you provided. To obtain accurate and up-to-date details, it's crucial to consult the official Wikipedia page for ATME College of Engineering or other reliable sources.

Approach 2 Using WikiPediaAPIWrapper

```
%pip install --upgrade --quiet  wikipedia
from langchain_community.tools import WikipediaQueryRun
from langchain_community.utilities import WikipediaAPIWrapper
```

```
from pydantic import BaseModel, Field
import re

# Step 1: Define the Pydantic schema
class InstitutionDetails(BaseModel):
founder: str = Field(..., description="Founder of the institution")
founded_year: str = Field(..., description="Year the institution was founded")
branches: list[str] = Field(..., description="Current branches in the institution")
employees: str = Field(..., description="Number of employees in the institution")
summary: str = Field(..., description="A brief 4-line summary of the institution")
```

```
# Step 2: Create a custom output parser
def parse_wikipedia_content(content: str) -> InstitutionDetails:
founder_match = re.search(r"Founded by\s*([\w\s,]+)", content)
founded_year_match = re.search(r"Established in\s*(\d{4})", content)
branches_match = re.findall(r"(\b[A-Z][a-zA-Z\s]+ Campus\b)", content)
employees_match = re.search(r"(\d{3,6})\s*employees", content)

summary_sentences = content.split(". ")[:4]  # Extract first 4 sentences

return InstitutionDetails(
founder=founder_match.group(1) if founder_match else "Not Found",
founded_year=founded_year_match.group(1) if founded_year_match else "Not Found",
branches=branches_match if branches_match else ["Not Found"],
employees=employees_match.group(1) if employees_match else "Not Found",
summary=". ".join(summary_sentences)
)

# Step 3: Fetch details from Wikipedia
wiki = WikipediaQueryRun(api_wrapper=WikipediaAPIWrapper())
institution_name = "Apple Company"
wiki_content = wiki.run(institution_name)

# Step 4: Parse and display results
institution_details = parse_wikipedia_content(wiki_content)
print(institution_details.model_dump_json(indent=4))
```

Output:

{
"founder": "Not Found",
"founded_year": "Not Found",
"branches": [
"Not Found"
],
"employees": "Not Found",
"summary": "Page: Apple Inc.\nSummary: Apple Inc. is an American multinational corporation and technology company headquartered in Cupertino, California, in Silicon Valley. It is best known for its consumer electronics, software, and services. Founded in 1976 as Apple Computer Company by Steve Jobs, Steve Wozniak and Ronald Wayne, the company was incorporated by Jobs and Wozniak as Apple Computer, Inc"
}

Program 10: Build a chatbot for the Indian Penal Code. We'll start by downloading the official Indian Penal Code document, and then we'll create a chatbot that can interact with it. Users will be able to ask questions about the Indian Penal Code and have a conversation with it.

Soln:

```
!pip install gradio

!pip install faiss-cpu

!pip install pypdf
from langchain.text_splitter import RecursiveCharacterTextSplitter
, SentenceTransformersTokenTextSplitter  # Import text splitters from langchain

import numpy as np  # Import NumPy for numerical operations

from pypdf import PdfReader  # Import PdfReader to read PDF files

from tqdm import tqdm  # Import tqdm for progress bar visualization

def word_wrap(string, n_chars=72):
"""
Wraps a long string to a specified number of characters per line.

Args:
string (str): The string to wrap.
n_chars (int, optional): The maximum number of characters per line. Defaults to 72.

Returns:
str: The word-wrapped string.
"""
if len(string) < n_chars:
return string  # Return the string directly if it's shorter than the character limit
else:
# Find the last space before the character limit and insert a newline
return string[:n_chars].rsplit(' ', 1)[0] + '\n' + \
word_wrap(string[len(string[:n_chars].rsplit(' ', 1)[0]) + 1:], n_chars)

from pypdf import PdfReader # Import PdfReader from the pypdf library

reader = PdfReader("/content/20240628171056482 3BNS_IPC_Comparative.pdf") # Create a PdfReader object to read the PDF file "BNS (IPC).pdf"
pdf_texts = [p.extract_text().strip() for p in reader.pages] # Extract text from each page of the PDF, strip whitespace, and store in a list

# Filter out empty strings from the list of extracted texts
pdf_texts = [text for text in pdf_texts if text]
```

```
print(word_wrap(pdf_texts[0])) # Print the word-wrapped version of the first text element extracted from the PDF
```

Output:

Corresponding Section Table Of Bharatiya Nyaya Sanhita 2023, (BNS)
New Addition Change Deletedp
Bharatiya Nyaya Sanhita,
2023 (BNS)
Indian Penal Code,
1860 (IPC)
CHAPTER I – PRELIMINARY CHAPTER
I – INTRODUCTION
1. Short title, commencement and application.
1. Title and extent of operation of the Code.
1(2)New Sub-Section
1(3) 2. Punishment of offences committed within India.
1(4) 3Punishment of offences committed beyond, but which by law may be tried within, India.
1(5) 4. Extension of Code to extra-territorial offences.
1(6) 5. Certain laws not to be affected by this Act.
2. Definitions.
2(1) 'act'
33. "Act". "Omission"
2(2) 'animal'
47. "Animal".
2(3) 'child' New Sub-Section
2(4) 'counterfeit'
28."Counterfeit".
2(5) 'Court'
20. "Court of Justice".
2(6) 'death'
46."Death".
2(7) 'dishonestly'
24. "Dishonestly".
2(8) 'document'
29. "Document".Deleted
29A. "Electronic record".
2(9)'fraudulently'
25. "Fraudulently"
2(10) 'gender'
8. Gender.
2(11) 'good faith'
52. "Good faith"
2(12) 'Government'
17."Government".Deleted
18. "India".
2(13) 'harbour'
52A. "Harbour".
2(14) 'injury'

44. “Injury”.
2(15) ‘illegal’and “legally bound to do”.
43. “Illegal”. “Legally bound to do”.
2(16) ‘Judge’
19. “Judge”.
2(17) ‘life’
45. “Life”.
2(18) ‘local law’
42. “Local law”.
2(19)‘man’
10. “Man”. “Woman”.
2(20) ‘month’ and ‘year’
49. “Year”.“Month”.
2(21) ‘movable property’
22. “Movable property”
2(22) ‘number’
9. Number.
2(23) ‘oath’
51. “Oath”.
2(24) ‘offence’
40. “Offence”.
2(25) ‘omission’
33. “Act”. “Omission”
2(26) ‘person’
11. “Person”.
2(27) ‘public’
12. “Public”.
Deleted 14- “Servant of Government”.
2(28) ‘public servant’
21. “Public servant”.
2(29)‘reason to believe’
26. “Reason to believe”
Deleted 50. “Section”.
2(30) ‘special law’
41. “Special law”.

```
# [5]: from langchain.text_splitter import RecursiveCharacterTextSplitter,
SentenceTransformersTokenTextSplitter # Import text splitters from langchain

character_splitter = RecursiveCharacterTextSplitter( # Initialize RecursiveCharacterTextSplitter
separators=["\n\n", "\n", ". ", " ", ""], # Define separators to split text by priority (double newline, newline,
sentence end, space, character)
chunk_size=1000, # Define the maximum chunk size in characters
chunk_overlap=20 # Define the overlap between adjacent chunks in characters
)

character_split_texts = character_splitter.split_text('\n\n'.join(pdf_texts))
 # Split the PDF texts into chunks using the defined character splitter, joining the pdf texts with double
newlines first
```

```
print(word_wrap(character_split_texts[10]))
# Print the word-wrapped version of the 11th chunk (index 10)
print(f"\nTotal chunks: {len(character_split_texts)}")
# Print the total number of chunks created
```

Output :

```
other than death.
104. When such right extends to causing any harm

other than death.
43. Commencement and continuance of right of

private defence of property.
105. Commencement and continuance of the
right of
private defence of property.
44. Right of private defence
against deadly assault
when there is risk of harm to innocent person.

106. Right of private defence against deadly assault
when there is
risk of harm to innocent person.
CHAPTER IV
OF ABETMENT, CRIMINAL
CONSPIRACY AND
ATTEMPT
Of abetment
CHAPTER V
OF ABETMENT
45. Abetment of a thing.
107. Abetment of a thing.
46. Abettor.
108. Abettor.
47. Abetment in India of offences outside India.
108A. Abetment in India of offences outside India.
48. Abetment outside India for offence in India. New Section
49. Punishment of abetment if act abetted is committed in consequence and where no express
provision is made for its punishment.
109. Punishment of abetment if the act abetted is

Total chunks: 76
```

```
!pip install langchain-community
```

```
from getpass import getpass # Import getpass for secure password input

#from Langchain import HuggingFaceHub # commented out line, likely an old import statement
```

```
from langchain_community.llms import HuggingFaceHub # Import HuggingFaceHub from langchain_community for language models
import os # Import os module for environment variables

inference_api_key = getpass() # Prompt user to enter their Hugging Face API key securely
#place your huggingface API key after running this cell
os.environ["HUGGINGFACEHUB_API_TOKEN"] = inference_api_key # Set the Hugging Face API key as an environment variable

inference_api_key # Display the API key (for debugging or confirmation, but generally not recommended to print API keys)

from langchain_community.embeddings import HuggingFaceInferenceAPIEmbeddings # Import HuggingFaceInferenceAPIEmbeddings for embeddings

embedding_function = HuggingFaceInferenceAPIEmbeddings( # Initialize HuggingFaceInferenceAPIEmbeddings
api_key=inference_api_key, # Pass the API key for authentication
model_name="sentence-transformers/all-MiniLM-l6-v2" # Specify the model to use for embeddings (all-MiniLM-l6-v2)
)

from langchain_community.vectorstores import FAISS # Import FAISS for vector storage
db = FAISS.from_texts(character_split_texts, embedding_function) # Create a FAISS vector database from the split texts and embedding function

print(db.index.ntotal) # Print the total number of vectors in the FAISS index
```

```
query = "What does BNS Section 72 talks about ?" # Define the query string to search for in the vector database

retrieved_documents = db.similarity_search(query) # Perform a similarity search in the vector database 'db' using the defined query
# and store the retrieved documents in the 'retrieved_documents' variable
```

```
retrieved_documents
```

Output:

[Document(id='4a103413-5d76-4a97-962c-3acbd19420ab', metadata={}, page_content='Bharatiya Nyaya Sanhita, \n2023 (BNS) \nIndian Penal Code, \n1860 (IPC) \n341 (4) New Sub-Section \n342. Counterfeiting device or mark used for \nauthenticating documents described in section 338, \nor possessing counterfeit marked material. \n342(1) \n475. Counterfeiting device or mark used for \nauthenticating documents described in section 467, \nor possessing counterfeit marked material. \n342(2) 476. Counterfeiting device or mark used for \nauthenticating documents other than those \ndescribed in section 467, or possessing counterfeit \nmarked material. \n343. Fraudulent cancellation, destruction, etc., of \nwill, authority to adopt, or valuable security. \n477. Fraudulent cancellation, destruction, etc., of

\nwill, authority to adopt, or valuable security. \n344. Falsification of accounts. 477A. Falsification of accounts. \nOf property marks Of Property and Other Marks \n345. Property mark. \n345 (1) \n479. Property mark. \n345 (2) 481. Using a false property mark.'),
Document(id='ab84c414-3953-4acf-9836-83999e22f6d8', metadata={}, page_content='Bharatiya Nyaya Sanhita, \n2023 (BNS) \nIndian Penal Code, \n1860 (IPC) \n36. Right of private defence against act of a person \nof unsound mind, etc. \n98. Right of private defence against the act of a \nperson of unsound mind, etc. \n37. Acts against which there is no right of private \ndefence. \n99. Acts against which there is no right of private \ndefence. \n38. When right of private defence of body extends \nto causing death. \n100. When the right of private defence of the body \nextends to causing death. \n39. When such right extends to causing any harm \nother than death. \n101. When such right extends to causing any harm \nother than death. \n40. Commencement and continuance of right of \nprivate defence of body. \n102. Commencement and continuance of the right of \nprivate defence of the body. \n41. When right of private defen ce of property \nextends to causing death. \n103. When the right of private defence of property \nextends to causing death. \n42. When such right extends to causing any harm'),
Document(id='cbb8de09-9066-4811-b2cd-70d16c72ce6b', metadata={}, page_content='other than death. \n104. When such right extends to causing any harm \nother than death. \n43. Commencement and continuance of right of \nprivate defence of property. \n105. Commencement and continuance of the right of \nprivate defence of property. \n44. Right of private defence against deadly assault \nwhen there is risk of harm to innocent person. \n106. Right of private defence against deadly assault \nwhen there is risk of harm to innocent person. \nCHAPTER IV \nOF ABETMENT, CRIMINAL CONSPIRACY AND \nATTEMPT \nOf abetment \nCHAPTER V \nOF ABETMENT \n45. Abetment of a thing. 107. Abetment of a thing. \n46. Abettor. 108. Abettor. \n47. Abetment in India of offences outside India. 108A. Abetment in India of offences outside India. \n48. Abetment outside India for offence in India. New Section \n49. Punishment of abetment if act abetted is \ncommitted in consequence and where no express \nprovision is made for its punishment. \n109. Punishment of abetment if the act abetted is'),
Document(id='5efd3561-80d2-4010-babb-808f6cbee0b7', metadata={}, page_content='146. Unlawful compulsory labour. 374. Unlawful compulsory labour. \nCHAPTER VII \nOF OFFENCES AGAINST THE STATE \nCHAPTER VI \nOF OFFENCES AGAINST THE STATE \n147. Waging, or attempting to wage war, or \nabetting waging of war, against Government of \nIndia. \n121. Waging, or attempting to wage war, or abetting \nwaging of war, against the Government of India. \n148. Conspiracy to commit offences punishable by \nsection 147. \n121A. Conspiracy to commit offences punishable by \nsection 121. \n149. Collecting arms, etc., with intention of waging \nwar against Government of India. \n122. Collecting arms, etc., with intention of waging \nwar against the Government of India. \n150. Concealing with intent to facilitate design to \nwage war. \n123. Concealing with intent to facilitate design to \nwage war. \n151. Assaulting President, Govern or, etc., with \nintent to compel or restrain exercise of any lawful \npower. \n124. Assaulting President, Governor, etc., with intent')]

```
!pip install gradio
```

```
!pip install cohere
```

```
# Bharathiya Nyay Sanhita - IPC Chatbot

import cohere # Import the Cohere library for language model interaction
import gradio as gr # Import Gradio for creating a user interface

from langchain_community.vectorstores import FAISS # Import FAISS for vector storage

# Initialize the Cohere client
```

```
co = cohere.Client('eA50e27b88O7ycXim4jLv5BxMJurbufz9e1AMJNz') # Replace 'YOUR API' with your actual Cohere API key

# Initialize the FAISS vector store
db = FAISS.from_texts(character_split_texts, embedding_function) # Create a FAISS index from the text chunks and embedding function

print("Total indexed documents in FAISS:", db.index.ntotal) # Print the number of documents indexed in the FAISS vector store
```

Output:

Total indexed documents in FAISS: 76

```
def rag(query, retrieved_documents, model="command"):
"""
Performs Retrieval-Augmented Generation (RAG) to answer a query based on retrieved documents using Cohere's chat model.

Args:
query (str): The user's question or query.
retrieved_documents (list): A list of documents retrieved from a vector database that are relevant to the query.
model (str, optional): The Cohere chat model to use. Defaults to "command".

Returns:
str: The generated answer from the Cohere chat model.
"""
# Extract the page content from each retrieved document and join them into a single string with double newlines as separators.
information = "\n\n".join([docs.page_content for docs in retrieved_documents])

# Define the messages to be sent to the Cohere chat model.
# This includes a system message to set the context and a user message with the query and retrieved information.
messages = [
{
"role": "system",
"content": """You are a helpful expert in Bharatiya Nyay Sanhita (BNS).
Your users are asking questions about information contained in Bharatiya Nyay Sanhita document.
You will be shown the user's question, and the relevant information from given document.
Note that if asked for section get BNS section number.
Answer the user's question using only this information.""" # System message to guide the model's behavior as a BNS expert.
},
{
"role": "user",
```

```
"content": f"Question: {query}. \n Information: {information}" # User message containing the user's query and the retrieved information.
}
]

# Call the Cohere chat API to get a response based on the provided messages.
response = co.chat( # Using the 'co' Cohere client (assumed to be initialized elsewhere)
model=model, # Specify the model to use
message=query, # Pass the user's query as the main message
documents=messages # Pass the list of messages including system and user prompts
)

return response.text # Return the text of the generated response from the Cohere chat model.
```

```
# Define the chatbot function
def chatbot(query):

Chatbot function to answer user queries based on retrieved documents using RAG.

Args:
query (str): The user's question or query.

Returns:
tuple: A tuple containing the response from the RAG model and the source text from retrieved documents.
Returns an error message and empty source text if an exception occurs.

try:
# Query FAISS to get retrieved documents
retrieved_documents = db.similarity_search(query, k=5) # Perform similarity search in FAISS database 'db' using the query and retrieve top 5 documents

# Debug: print retrieved documents
# print("Retrieved Documents:", retrieved_documents) # Commented out debug print statement

# Call the RAG function
response = rag(query, retrieved_documents) # Call the rag function (defined previously) to generate a response using the query and retrieved documents

source_text = "\n\n".join([doc.page_content for doc in retrieved_documents]) # Combine the page content of retrieved documents into a single string separated by double newlines
return response, source_text # Return the generated response and the combined source text

except Exception as e: # Catch any exceptions that might occur during the process
# Debug: print exception details
print("Error:", e) # Print the error message to the console

return str(e), "" # Return the error message as a string and an empty string for source text in case of error
```

```
# Set up the Gradio interface
iface = gr.Interface( # Create a Gradio Interface object

fn=chatbot, # Pass the user query to the chatbot function. 'chatbot' is assumed to be a function defined elsewhere in the code.
inputs=gr.Textbox(lines=2, placeholder="Ask a Bharatiya Nyay Sanhita (BNS /IPC) question..."), # Define the input component as a textbox with 2 lines and a placeholder text.

outputs=[ # Define the output components as a list
gr.Textbox(label="Response", lines=4), # First output is a textbox labeled "Response" with 4 lines.
gr.Textbox(label="Source Text", lines=10) # Second output is a textbox labeled "Source Text" with 10 lines.
],
title="Bharatiya Nyay Sanhita", # Set the title of the Gradio interface.
description="Ask any Bharathiya Nyay Sanhita related question, and I will provide answers based on the relevant information." # Set the description of the Gradio interface.
)

# Launch the Gradio interface
iface.launch() # Launch the Gradio interface to start the chatbot application.
```

Output :

Query

Kidnapping

Response

In the Bharatiya Nyay Sanhita (BNS), kidnapping is defined as below:

- Kidnapping or abducting in order to murder or for ransom etc.
- Kidnapping or abducting in order to subject a person to grievous hurt, slavery, etc Importation of a girl or boy from a foreign country (Section 141)
- Wrongfully concealing or keeping in confinement, kidnapped or abducted person Trafficking of person
- Exploitation of a trafficked person - Habitual dealing in slaves

The BNS also outlines punishments for those found guilty of kidnapping.

363A. Kidnapping or maiming a minor for purposes of begging.
140. Kidnapping or abducting in order to murder or for ransom etc.
364. Kidnapping or abducting in order to murder.
364A. Kidnapping for ransom, etc.
365. Kidnapping or abducting with intent secretly and wrongfully to confine person.
367. Kidnapping or abducting in order to subject person to grievous hurt, slavery, etc.
141. Importation of girl or boy from foreign country.
366B. Importation of girl from foreign country.
142. Wrongfully concealing or keeping in confinement, kidnapped or abducted person.

368. Wrongfully concealing or keeping in confinement, kidnapped or abducted person.
143. Trafficking of person.
370. Trafficking of person.
144. Exploitation of a trafficked person
370A. Exploitation of a trafficked person
145. Habitual dealing in slaves.
371. Habitual dealing in slaves.

Bharatiya Nyaya Sanhita,
2023 (BNS)
Indian Penal Code,
provocation. provocation.
134. Assault or criminal force in attempt to comm it theft of property carried by a person.
356. Assault or criminal force in attempt to commit theft of property carried by a person.
135. Assault or criminal force in attempt to wrongfully to confine a person.
357. Assault or criminal force in attempt wrongfully to confine a person.
136. Assault or criminal force on grave provocation.
358. Assault or criminal force on grave provocation. Of kidnapping, abduction, slavery and forced labour
Of Kidnapping, Abduction, Slavery and Forced Labour
137. Kidnapping.
359. Kidnapping.
360. Kidnapping from India.
361. Kidnapping from lawful guardianship.
363. Punishment for kidnapping.
138. Abduction.
362. Abduction.
139. Kidnapping or maiming a child for purposes of begging.
Bharatiya Nyaya Sanhita,
2023 (BNS)
Indian Penal Code,
379. Punishment for theft.
304. Snatching. New Section
305. Theft in a dwelling house, or means of transportation or place of worship, etc.
380. Theft in dwelling house, etc.
306. Theft by clerk or servant of property in possession of master.
381. Theft by clerk or servant of property in possession of master.
307. Theft after preparation made for causing death, hurt or restraint in order to committing of theft.
382. Theft after preparation made for causing death, hurt or restraint in order to the committing of the theft.
Of extortion Of Extortion
308. Extortion.
383. Extortion.
384. Punishment for extortion.
385. Putting person in fear of injury in order to commit extortion.
387. Putting person in fear of death or of grievous hurt, in order to commit extortion.
386. Extortion by putting a person in fear of death or
398. Attempt to commit robbery o r dacoity when armed with deadly weapon.
313. Punishment for belonging to gang of robbers, dacoits, etc.
401. Punishment for belonging to gang of thieves. Of criminal misappropriation of property Of Criminal
Misappropriation of Property

314. Dishonest misappropriation of property.
403. Dishonest misappropriation of property.
315. Dishonest misappropriation of property possessed by deceased person at the time of his death.
404. Dishonest misappropriation of property possessed by deceased person at the time of his death. Of criminal breach of trust Of Criminal Breach of Trust others.
336. Act endangering life or personal safety of others.
337. Causing hurt by act endangering life or personal safety of others.
338. Causing grievous hurt by act endangering life or personal safety of others. Of wrongful restraint and wrongful confinement Of wrongful restraint and wrongful confinement
126. Wrongful restraint.
339. Wrongful restraint.
341. Punishment for wrongful restraint.
127. Wrongful confinement.
340. Wrongful confinement.
342. Punishment for wrongful confinement.
343. Wrongful confinement for three or more days.
344. Wrongful confinement for ten or more days.
345. Wrongful confinement of person for whose liberation writ has been issued.
346. Wrongful confinement in secret.
347. Wrongful confinement to extort property, or constrain to illegal act.
348. Wrongful confinement to extort confession, or compel restoration of property.

Query

Kidnapping

Response

In the Bharatiya Nyay Sanhita (BNS), kidnapping is defined as below:

- Kidnapping or abducting in order to murder or for ransom etc-
Kidnapping or abducting in order to subject a person to grievous hurt, slavery, etc. Importation of a girl or boy from a foreign country - Wrongfully concealing or keeping in confinement, kidnapped or abducted person - Trafficking of person - Exploitation of a trafficked person
- Habitual dealing in slaves
The BNS also outlines punishments for those found guilty of kidnapping.

363A. Kidnapping or maiming a minor for purposes of begging.
140. Kidnapping or abducting in order to murder or for ransom etc.
364. Kidnapping or abducting in order to murder.
364A. Kidnapping for ransom, etc.
365. Kidnapping or abducting with intent secretly and wrongfully to confine person.
367. Kidnapping or abducting in order to subject person to grievous hurt, slavery, etc.
141. Importation of girl or boy from foreign country.
366B. Importation of girl from foreign country.
142. Wrongfully concealing or keeping in confinement, kidnapped or abducted person.
368. Wrongfully concealing or keeping in confinement, kidnapped or abducted person.
143. Trafficking of person.
370. Trafficking of person.

144. Exploitation of a trafficked person.
370A. Exploitation of a trafficked person
145. Habitual dealing in slaves.
371. Habitual dealing in slaves.

Bharatiya Nyaya Sanhita,
2023 (BNS)
Indian Penal Code,
provocation. provocation.
134. Assault or criminal force in attempt to comm it theft of property carried by a person.
356. Assault or criminal force in attempt to commit theft of property carried by a person.
135. Assault or criminal force in attempt to wrongfully to confine a person. (Change)
357. Assault or criminal force in attempt wrongfully to confine a person.
136. Assault or criminal force on grave provocation. 358. Assault or criminal force on grave provocation. Of kidnapping, abduction, slavery and forced labour Of Kidnapping, Abduction, Slavery and Forced Labour
137. Kidnapping.
359. Kidnapping.
360. Kidnapping from India.
361. Kidnapping from lawful guardianship.
363. Punishment for kidnapping.
138. Abduction.
362. Abduction.
139. Kidnapping or maiming a child for purposes of begging.
Bharatiya Nyaya Sanhita,
2023 (BNS)
Indian Penal Code,
379. Punishment for theft.
304. Snatching. New Section
305. Theft in a dwelling house, or means of transportation or place of worship, etc.
380. Theft in dwelling house, etc.
306. Theft by clerk or servant of property in possession of master.
381. Theft by clerk or servant of property in possession of master.
307. Theft after preparation made for causing death, hurt or restraint in order to committing of theft.
382. Theft after preparation made for causing death, hurt or restraint in order to the committing of the theft. Of extortion Of Extortion
308. Extortion.
383. Extortion.
384. Punishment for extortion.
385. Putting person in fear of injury in order to commit extortion.
387. Putting person in fear of death or of grievous hurt, in order to commit extortion.
386. Extortion by putting a person in fear of death or
398. Attempt to commit robbery o r dacoity when armed with deadly weapon.
313. Punishment for belonging to gang of robbers, dacoits, etc.
401. Punishment for belonging to gang of thieves. Of criminal misappropriation of property Of Criminal Misappropriation of Property
314. Dishonest misappropriation of property.
403. Dishonest misappropriation of property.

315. Dishonest misappropriation of property possessed by deceased person at the time of his death.
404. Dishonest misappropriation of property possessed by deceased person at the time of his death. Of criminal breach of trust Of Criminal Breach of Trust others.
336. Act endangering life or personal safety of others.
337. Causing hurt by act endangering life or personal safety of others.
338. Causing grievous hurt by act endangering life or personal safety of others. Of wrongful restraint and wrongful confinement Of wrongful restraint and wrongful confinement
126. Wrongful restraint.
339. Wrongful restraint.
341. Punishment for wrongful restraint.
127. Wrongful confinement.
340. Wrongful confinement.
342. Punishment for wrongful confinement.
343. Wrongful confinement for three or more days.
344. Wrongful confinement for ten or more days.
345. Wrongful confinement of person for whose liberation writ has been issued.
346. Wrongful confinement in secret.
347. Wrongful confinement to extort property, or constrain to illegal act.
348. Wrongful confinement to extort confession, or compel restoration of property.

Viva Questions With Answers

1. What is Generative AI?
Generative AI refers to a type of artificial intelligence that can generate new data, such as text, images, audio, or code, based on the patterns it has learned from the training data.

2. How does Generative AI differ from traditional AI?
Traditional AI focuses on classification, prediction, and decision-making, whereas Generative AI creates new content or data similar to its training set.

3. What are some applications of Generative AI?
Applications include natural language generation (e.g., chatbots), image synthesis, code generation, music composition, and drug discovery.

4. What are GANs?
GANs (Generative Adversarial Networks) are a class of machine learning frameworks where two neural networks (generator and discriminator) compete to improve the quality of generated data.

5. What is the difference between GANs and VAEs?
GANs generate data using a generator-discriminator approach, while VAEs (Variational Autoencoders) use probabilistic methods to encode and decode data, emphasizing data distribution.

Technical Questions

6. What are the components of a GAN?
GANs consist of a Generator (creates synthetic data) and a Discriminator (evaluates the authenticity of the data).

7. What is the role of the loss function in Generative AI models?
The loss function helps optimize the model by reducing the difference between the generated output and the expected data.

8. What is prompt engineering in language models?
Prompt engineering is the process of crafting specific input prompts to guide a generative language model to produce desired outputs.

9. Explain the difference between GPT and BERT.
GPT (Generative Pre-trained Transformer) is a unidirectional model focused on text generation, while BERT (Bidirectional Encoder Representations from Transformers) is a bidirectional model designed for understanding and classification tasks.

10. What are transformers in Generative AI?
Transformers are neural network architectures that use self-attention mechanisms to process sequential data, making them efficient for language and sequence modeling.

11. How does reinforcement learning improve Generative AI models?
Reinforcement Learning with Human Feedback (RLHF) fine-tunes models to align their outputs with human preferences, improving quality and relevance.

12. What are diffusion models in Generative AI?
Diffusion models are probabilistic methods that generate high-quality images by iteratively denoising random noise.

13. What is the significance of the latent space in generative models?
The latent space represents a compressed encoding of input data, enabling models to manipulate and generate similar but novel data.

14. What are the challenges in training GANs?
Challenges include mode collapse (limited diversity in output), unstable training, and difficulty in balancing the generator and discriminator.

15. How do zero-shot and few-shot learning relate to Generative AI?
Zero-shot learning enables models to perform tasks without specific training, while few-shot learning allows them to adapt with minimal examples.

16. How are Generative AI models trained for text generation?
They are trained on large text datasets using transformer architectures, focusing on predicting the next word in a sequence.

17. What is the role of pre-training and fine-tuning in large language models?
Pre-training helps the model learn general patterns from large datasets, and fine-tuning adapts it for specific tasks or domains.

18. How do image generation models like DALL·E work?
DALL·E uses a transformer architecture to generate images from textual descriptions by learning text-image relationships.

19. What are the ethical concerns in Generative AI?
Concerns include bias, misinformation, copyright infringement, and misuse for creating deepfakes or harmful content.

20. How is Generative AI used in video synthesis?
It generates video content frame by frame using models like GANs or diffusion-based techniques, trained on motion and style patterns.

Trends and Future Prospects

21. What is fine-tuning in the context of generative models?
Fine-tuning involves adapting a pre-trained model to a specific task or domain by training it on a smaller, task-specific dataset.

22. What are ethical AI principles for Generative AI?
Principles include fairness, transparency, accountability, privacy protection, and minimizing harm.

23. What advancements are driving the growth of Generative AI?
Key advancements include improved transformer models, larger datasets, better hardware, and innovations in self-supervised learning.

24. What are token embeddings in Generative AI models?

Token embeddings are vector representations of input data (e.g., words or pixels) that models use to understand relationships and context.

25. What is the future of Generative AI?

Generative AI is expected to evolve with better efficiency, multimodal capabilities, personalized outputs, and real-world applications like healthcare and education.