Practical No: 1

Aim: Document Indexing and Retrieval

- **Implement an inverted index construction algorithm.**
- **Build a simple document retrieval system using the constructed index.**

Theory :

- An Inverted Index is a data structure used in information retrieval systems to efficiently retrieve documents or web pages containing a specific term or set of terms.
- In an inverted index, the index is organised by terms (words), and each term points to a list of documents or web pages that contain that term.
- Inverted indexes are widely used in search engines, database systems, and other applications where efficient text search is required.
- They are especially useful for large collections of documents, where searching through all the documents would be prohibitively slow. An inverted index is an index data structure storing a mapping from content, such as words or numbers, to its locations in a document or a set of documents.

Rules to create an inverted index -

1) The text of each document is first preprocessed by removing stop words : Stop words are the most occurring and useless words in documents like “I”, “the”, “we”, “is”, and “an”.
2) The text is tokenized, meaning that it is split into individual terms.
3) The terms are then added to the index, with each term pointing to the documents in which it appears.

Practical:

Input:

```
import nltk # Import NLTK to download stopwords
from nltk.corpus import stopwords  # Import stopwords from NLTK

# Define the documents
document1 = "The quick brown fox jumped over the lazy dog"
document2 = "The lazy dog slept in the sun"
```

```
# Get the stopwords for English language from NLTK
nltk.download('stopwords')
stopWords = stopwords.words('english')

# Step 1: Tokenize the documents
# Convert each document to lowercase and split it into words
tokens1 = document1.lower().split()
tokens2 = document2.lower().split()

# Combine the tokens into a list of unique terms
terms = list(set(tokens1 + tokens2))

# Step 2: Build the inverted index
# Create an empty dictionary to store the inverted index as well as a dictionary
to store number of occurrences
inverted_index = {}
occ_num_doc1 = {}
occ_num_doc2 = {}

# For each term, find the documents that contain it
for term in terms:
    if term in stopWords:
        continue
    documents = []
    if term in tokens1:
        documents.append("Document 1")
        occ_num_doc1[term] = tokens1.count(term)
    if term in tokens2:
        documents.append("Document 2")
        occ_num_doc2[term] = tokens2.count(term)
```

```
inverted_index[term] = documents

# Step 3: Print the inverted index
for term, documents in inverted_index.items():
    print(term, "->", end=" ")
    for doc in documents:
        if doc == "Document 1":
            print(f"{doc} ({occ_num_doc1.get(term, 0)}),", end=" ")
        else:
            print(f"{doc} ({occ_num_doc2.get(term, 0)}),", end=" ")
    print()
print("Performed by 740_Pallavi & 743_Deepak")
```

Output:

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\deepa\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
quick -> Document 1 (1),
lazy -> Document 1 (1), Document 2 (1),
sun -> Document 2 (1),
jumped -> Document 1 (1),
fox -> Document 1 (1),
slept -> Document 2 (1),
dog -> Document 1 (1), Document 2 (1),
brown -> Document 1 (1),
Performed by 740_Pallavi & 743_Deepak
```

Practical No: 2

Aim: Retrieval Models

- **Implement the Boolean retrieval model and process queries.**
- **Implement the vector space model with TF-IDF weighting and cosine similarity.**

Theory :

A) Boolean Retrieval Model -

- A Boolean model is a fundamental concept in Information Retrieval (IR) that is used to represent and retrieve documents or information based on Boolean logic.

- In this model, a document is typically represented as a set of terms (words or phrases), and queries are also represented using Boolean operators (AND, OR, NOT) to specify the desired information.

Here's how the Boolean model works in IR:

1. **Document Representation:** Each document in the collection is represented as a set of terms. These terms can be extracted from the document's content and can be single words, phrases, or other units of information.

2. **Query Representation:** Queries are also represented as sets of terms, and Boolean operators (AND, OR, NOT) are used to combine these terms to express the user's information needs. For example, a query might be "cats AND dogs," meaning the user wants documents that contain both "cats" and "dogs."

3. **Boolean Operators:**

- AND: "cats AND dogs,"
  both "cats" and "dogs" will be retrieved.
- OR: "cats OR dogs,"
  "cats" or "dogs" or both will be retrieved.
- NOT: "cats NOT dogs"
  "cats" but not "dogs."

B) TF-IDF

- Term Frequency - Inverse Document Frequency (TF-IDF) is a widely used statistical method in information retrieval.
- It measures how important a term is within a document relative to a collection of documents.

Term Frequency (TF): TF of a term or word is the number of times the term appears in a document compared to the total number of words in the document.

$$TF = \frac{\text{number of times the term appears in the document}}{\text{total number of terms in the document}}$$

Inverse Document Frequency(IDF):

- IDF of a term reflects the proportion of documents in the corpus that contain the term.

  IDF = log(N / df) where,

  N= total no. of documents

  df = no. of documents containing a term

- The TF-IDF of a term is calculated by multiplying TF and IDF scores. **TF-IDF = TF*IDE**

C) Cosine Similarity -

- **Cosine similarity** is a measure of similarity between two non-zero vectors defined in an inner product space.
- Cosine similarity is the cosine of the angle between the vectors. ● The cosine similarity always belongs to the interval [−1,1].
- In cosine similarity, data objects in a dataset are treated as a vector. ● The formula to find the cosine similarity between two vectors is -

$$\text{cosine similarity} = S_C(A,B) := \cos(\theta) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\cdot\sqrt{\sum_{i=1}^{n} B_i^2}},$$

Here A . B is the product of the vector.

Practical:

A) Implement the Boolean retrieval model and process queries:

Input:

```
documents = {
    1: "apple banana orange",
    2: "apple banana",
    3: "banana orange",
    4: "apple"
}

# Function to build an inverted index using dictionaries
def build_index(docs):
    index = {}  # Initialize an empty dictionary to store the inverted index
    for doc_id, text in docs.items():  # Iterate through each document and its text
        terms = set(text.split())  # Split the text into individual terms
        for term in terms:  # Iterate through each term in the document
            if term not in index:
                index[term] = {doc_id}  # If the term is not in the index, create a new set with document ID
            else:
                index[term].add(doc_id)  # If the term exists, add the document ID to its set
    return index  # Return the built inverted index
```

```
# Building the inverted index
inverted_index = build_index(documents)

# Function for Boolean AND operation using inverted index
def boolean_and(operands, index):
    if not operands:  # If there are no operands, return all document IDs
        return list(range(1, len(documents) + 1))

    result = index.get(operands[0], set())  # Get the set of document IDs for the first operand
    for term in operands[1:]:  # Iterate through the rest of the operands
        result = result.intersection(index.get(term, set()))  # Compute intersection with sets of document IDs
    return list(result)  # Return the resulting list of document IDs

# Function for Boolean OR operation using inverted index
def boolean_or(operands, index):
    result = set()  # Initialize an empty set to store the resulting document IDs
    for term in operands:  # Iterate through each term in the query
        result = result.union(index.get(term, set()))  # Union of sets of document IDs for each term
    return list(result)  # Return the resulting list of document IDs

# Function for Boolean NOT operation using inverted index
def boolean_not(operand, index, total_docs):
    operand_set = set(index.get(operand, set()))  # Get the set of document IDs for the operand
    all_docs_set = set(range(1, total_docs + 1))  # Create a set of all document IDs
```

```
    return list(all_docs_set.difference(operand_set))  # Return documents not in the operand set

# Example queries
query1 = ["apple", "banana"]  # Query for documents containing both "apple" and "banana"
query2 = ["apple", "orange"]  # Query for documents containing "apple" or "orange"

# Performing Boolean Model queries using inverted index
result1 = boolean_and(query1, inverted_index)  # Get documents containing both terms
result2 = boolean_or(query2, inverted_index)  # Get documents containing either of the terms
result3 = boolean_not("orange", inverted_index, len(documents))  # Get documents not containing "orange"

# Printing results
print("Documents containing 'apple' and 'banana':", result1)
print("Documents containing 'apple' or 'orange':", result2)
print("Documents not containing 'orange':", result3)
print("Performed by 740_Pallavi & 743_Deepak")
```

Output:

```
Documents containing 'apple' and 'banana': [1, 2]
Documents containing 'apple' or 'orange': [1, 2, 3, 4]
Documents not containing 'orange': [2, 4]
Performed by 740_Pallavi & 743_Deepak
```

B) Implement the vector space model with TF-IDF weighting and cosine similarity:

Input:

```
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
# Import necessary libraries
import nltk # Import NLTK to download stopwords
from nltk.corpus import stopwords  # Import stopwords from NLTK
import numpy as np  # Import NumPy library
from numpy.linalg import norm  # Import norm function from NumPy's linear algebra module

# Define the training and test sets of text documents
train_set = ["The sky is blue.", "The sun is bright."]  # Documents
test_set = ["The sun in the sky is bright."]  # Query

# Get the stopwords for English language from NLTK
nltk.download('stopwords')
stopWords = stopwords.words('english')

# Initialize CountVectorizer and TfidfTransformer objects
vectorizer = CountVectorizer(stop_words=stopWords)  # CountVectorizer to convert text to matrix of token counts
transformer = TfidfTransformer()  # TfidfTransformer to convert matrix of token counts to TF-IDF representation

# Convert the training and test sets to arrays of TF-IDF features
trainVectorizerArray = vectorizer.fit_transform(train_set).toarray()  # Fit-transform training set
testVectorizerArray = vectorizer.transform(test_set).toarray()  # Transform test set

# Display the TF-IDF arrays for training and test sets
```

```
print('Fit Vectorizer to train set', trainVectorizerArray)
print('Transform Vectorizer to test set', testVectorizerArray)

# Define a lambda function to calculate cosine similarity between vectors
cx = lambda a, b: round(np.inner(a, b) / (norm(a) * norm(b)), 3)

# Iterate through each vector in the training set
for vector in trainVectorizerArray:
    print(vector)  # Display each vector in the training set
    # Iterate through each vector in the test set
    for testV in testVectorizerArray:
        print(testV)  # Display each vector in the test set
        cosine = cx(vector, testV)  # Calculate cosine similarity between vectors
        print(cosine)  # Display the cosine similarity

# Fit the transformer to the training set and transform it to TF-IDF
representation
transformer.fit(trainVectorizerArray)
print()
print(transformer.transform(trainVectorizerArray).toarray())

# Fit the transformer to the test set and transform it to TF-IDF representation
transformer.fit(testVectorizerArray)
print()
tfidf = transformer.transform(testVectorizerArray)
print(tfidf.todense())
```

Output:

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\deepa\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
Fit Vectorizer to train set [[1 0 1 0]
 [0 1 0 1]]
Transform Vectorizer to test set [[0 1 1 1]]
[1 0 1 0]
[0 1 1 1]
0.408
[0 1 0 1]
[0 1 1 1]
0.816

[[0.70710678 0.         0.70710678 0.        ]
 [0.         0.70710678 0.         0.70710678]]

[[0.         0.57735027 0.57735027 0.57735027]]
Performed by 740_Pallavi & 743_Deepak
```

Practical No: 3

Aim: Spelling Correction in IR Systems

- **Develop a spelling correction module using edit distance algorithms.**
- **Integrate the spelling correction module into an information retrieval system.**

Theory:

Edit Distance :

- Edit distance is a measure of the similarity between two strings by calculating the minimum number of single-character edits (insertions, deletions, or substitutions) required to change one string into the other.
- The smaller the edit distance, the more similar the strings are.

Consider two strings str1 and str2 of length M and N respectively.

For finding edit distance there are performed below operations -

1. Operation 1 (INSERT): Insert any character before or after any index value
2. Operation 2 (REMOVE): Remove a character
3. Operation 3 (Replace): Replace a character at any index value with some other character

Practical:

Input:

```
# A Naive recursive python program to find minimum number
# operations to convert str1 to str2
def editDistance(str1, str2, m, n):
    # If first string is empty, the only option is to insert all characters of second
string into first
    if m == 0:
        return n
    # If second string is empty, the only option is to remove all characters of first
string
    if n == 0:
```

```
        return m
    # If last characters of two strings are same, nothing much to do. Ignore last characters and get count for remaining strings.
    if str1[m-1] == str2[n-1]:
        return editDistance(str1, str2, m-1, n-1)
    # If last characters are not same, consider all three operations on last character of first string, recursively compute minimum cost for all three operations and take minimum of three values.
    return 1 + min(editDistance(str1, str2, m, n-1), # Insert
                   editDistance(str1, str2, m-1, n), # Remove
                   editDistance(str1, str2, m-1, n-1) # Replace
                   )
# Driver code
str1 = "sunday"
str2 = "saturday"
print('Edit Distance is: ', editDistance(str1, str2, len(str1), len(str2)))
```

Output:

```
PS C:\Users\Administrator\Documents\Sem 6\IR>
Edit Distance is:  3
Performed by 740 Pallavi & 743 Deepak
```

Practical No: 4

Aim: Evaluation Metrics for IR Systems

A) Calculate precision, recall, and F-measure for a given set of retrieval results.

B) Use an evaluation toolkit to measure average precision and other evaluation metrics.

Theory:

1. Precision:

- Precision is the ratio of correctly predicted positive observations to the total predicted positives.
- It is also called Positive Predictive Value (PPV).
- Precision is calculated using the following formula:

Precision = TP / TP+FP

Where:

• TP (True Positives) is the number of instances correctly predicted as positive. • FP (False Positives) is the number of instances incorrectly predicted as positive.

High precision indicates that the model has a low rate of false positives. In other words, when the model predicts a positive result, it is likely to be correct.

2. Recall:

- Recall is the ratio of correctly predicted positive observations to all observations in actual class.
- Recall is calculated using the following formula:

Recall= TP /TP+FN

Where:

• TP (True Positives) is the number of instances correctly predicted as positive. • FN (False Negatives) is the number of instances incorrectly predicted as negative.

High recall indicates that the model has a low rate of false negatives. In

other words, the model is effective at capturing all the positive instances.

Confusion Matrix :

	Predicted No	Predicted Yes
Actual No	True Negative	False Positive
Actual Yes	False Negative	True Positive

3. F-measure:

- The F-measure is a metric commonly used in performance evaluation.
- It combines precision and recall into a single value, providing a balanced measure of a model's performance.

- The formula for F-measure is:

$$F - measure = 2 * \frac{Precision * Recall}{Precesion + Recall}$$

- The F-measure ranges from 0 to 1, where 1 indicates perfect precision and recall.

4. Average Precision:

Average Precision is used to find the Average of the model precision based on relevancy of result. • Algorithm:

In order to find Average Precision:

1) Take 2 variables X and Y as 0
2) We will then go through the prediction from left to right:
3) In case the prediction is 0, we will only increment Y by 1 and not find prediction score
4) In case the prediction is 1, we will increment both X and Y by 1
5) After incrementing, we use the formula X/Y to get the current position prediction score.
6) Lastly we will find summation of all prediction scores and divide them by total number of positive predictions.

A) Calculate precision, recall, and F-measure for a given set of retrieval results.

Input:

```
def calculate_metrics(retrieved_set, relevant_set):
    true_positive = len(retrieved_set.intersection(relevant_set))
    false_positive = len(retrieved_set.difference(relevant_set))
    false_negative = len(relevant_set.difference(retrieved_set))

    '''
    (Optional)
    PPT values:
    true_positive = 20
    false_positive = 10
    false_negative = 30
    '''

    print("True Positive: ", true_positive
          ,"\nFalse Positive: ", false_positive
          ,"\nFalse Negative: ", false_negative ,"\n")

    precision = true_positive / (true_positive + false_positive)
    recall = true_positive / (true_positive + false_negative)
    f_measure = 2 * precision * recall / (precision + recall)

    return precision, recall, f_measure

retrieved_set = set(["doc1", "doc2", "doc3"]) #Predicted set
relevant_set = set(["doc1", "doc4"]) #Actually Needed set (Relevant)

precision, recall, f_measure = calculate_metrics(retrieved_set, relevant_set)
```

```
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F-measure: {f_measure}")
```

Output:

```
PS C:\Users\Administrator\Documents\Se
cuments/Sem 6/IR/prac4_1.py"
True Positive:  1
False Positive:  2
False Negative:  1

Precision: 0.3333333333333333
Recall: 0.5
F-measure: 0.4
Performed by 740 Pallavi & 743 Deepak
```

B) Use an evaluation toolkit to measure average precision and other evaluation metrics.

Input:

```
from sklearn.metrics import average_precision_score

y_true = [0, 1, 1, 0, 1, 1] #Binary Prediction
y_scores = [0.1, 0.4, 0.35, 0.8, 0.65, 0.9] #Model's estimation score

average_precision = average_precision_score(y_true, y_scores)

print(f'Average precision-recall score: {average_precision}'
```

Output:

```
PS C:\Users\Administrator\Documents\Sem 6\IR> & C:/
cuments/Sem 6/IR/prac4_2.py"
Average precision-recall score: 0.8041666666666667
Performed by 740 Pallavi & 743 Deepak
```

Practical No: 5

Aim: Text Categorization

A) Implement a text classification algorithm (e.g., Naive Bayes or Support Vector Machines).

B) Train the classifier on a labelled dataset and evaluate its performance.

Theory:

Naive Bayes

- The Naïve Bayes algorithm is a supervised learning algorithm, which is based on **Bayes theorem** and used for solving classification problems.
- It is mainly used in *text classification* that includes a high-dimensional training dataset.
- Naive Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions.
- It is a probabilistic classifier, which means it predicts on the basis of the probability of an object.
- Some popular examples of Naive Bayes Algorithm are **spam filtration, Sentimental analysis, and classifying articles**.

Bayes' Theorem:

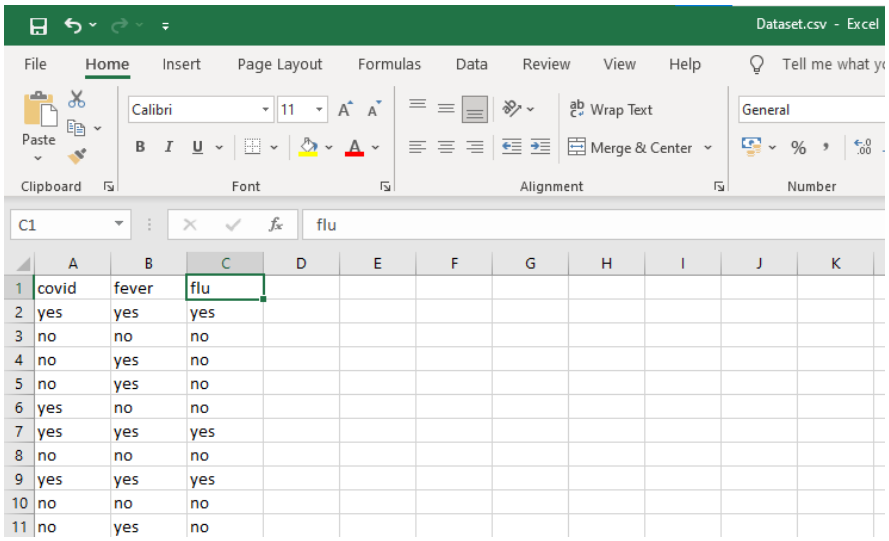
- Bayes' theorem is also known as **Bayes' Rule** or **Bayes' law**, which is used to determine the probability of a hypothesis with prior knowledge. It depends on the conditional probability.

- The formula for Bayes' theorem is given as:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

Create two CSV file:

Dataset.csv file:



Dataset.csv - Excel

File Home Insert Page Layout Formulas Data Review View Help Tell me what y

Paste Clipboard Calibri 11 Font Wrap Text Merge & Center Alignment General Number

C1 flu

	A	B	C	D	E	F	G	H	I	J	K
1	covid	fever	flu								
2	yes	yes	yes								
3	no	no	no								
4	no	yes	no								
5	no	yes	no								
6	yes	no	no								
7	yes	yes	yes								
8	no	no	no								
9	yes	yes	yes								
10	no	no	no								
11	no	yes	no								

Practical:

Input:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, classification_report

# Load the CSV file
df = pd.read_csv(r"C:\Users\Administrator\Documents\Sem 6\IR\Dataset.csv")
data = df["covid"] + "" + df["fever"]
X = data.astype(str)      # Test data
y = df['flu']             # Labels

# Splitting the data into training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
random_state = 42)

# Converting data into bag-of-data format to train the model
vectorizer = CountVectorizer()
```

```
# initializing the converter
X_train_counts = vectorizer.fit_transform(X_train)
# converting the training data
X_test_counts = vectorizer.transform(X_test)
# converting the test data
# using and training the multinomial model of naive bayes algorithm
classifier = MultinomialNB()            # initializing the classifier
classifier.fit(X_train_counts, y_train) # training the classifier

# loading another dataset to test if the model is working properly
data1 = pd.read_csv(r"C:\Users\Administrator\Documents\Sem 6\IR\Test.csv")
new_data = data1["covid"] + "" + data1["fever"]
new_data_counts = vectorizer.transform(new_data.astype(str))     # converting
the new data

# making the model to predict the results for new dataset
predictions = classifier.predict(new_data_counts)

# Output the results
new_data = predictions
print(new_data)

# retrieving the accuracy and classification report
accuracy = accuracy_score(y_test, classifier.predict(X_test_counts))
print(f"\nAccuracy: {accuracy:.2f}")

print("Classification Report: ")
print(classification_report(y_test, classifier.predict(X_test_counts)))

# Convert the predictions to a DataFrame
predictions_df = pd.DataFrame(predictions, columns = ['flu_prediction'])
```

```
# concatenate the original DataFrame with the predictions DataFrame
data1 = pd.concat([data1, predictions_df], axis = 1)

# write the DataFrame back to CSV
data1.to_csv(r"C:\Users\Administrator\Documents\Sem 6\IR\Test1.csv", index = False)
```

Output:

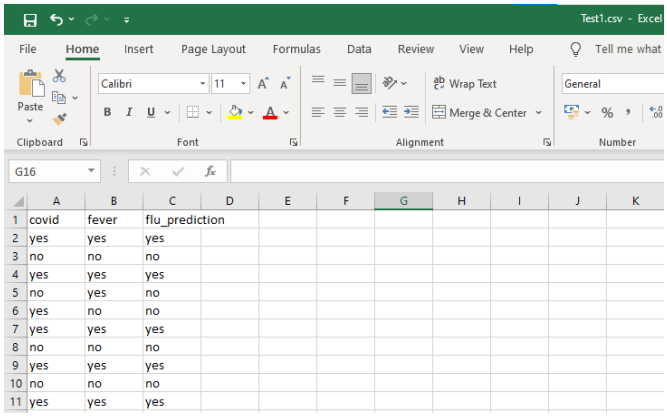
```
Documents/Sem 6/IR/prac_5.py"
['yes' 'no' 'yes' 'no' 'no' 'yes' 'no' 'yes' 'no' 'yes']

Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

          no       1.00      1.00      1.00         2

    accuracy                           1.00         2
   macro avg       1.00      1.00      1.00         2
weighted avg       1.00      1.00      1.00         2

Performed by 740_Pallavi & 743_Deepak
```



	A	B	C
1	covid	fever	flu_prediction
2	yes	yes	yes
3	no	no	no
4	yes	yes	yes
5	no	yes	no
6	yes	no	no
7	yes	yes	yes
8	no	no	no
9	yes	yes	yes
10	no	no	no
11	yes	yes	yes

Practical No: 6

Aim: Clustering for Information Retrieval
Implement a clustering algorithm (e.g., K-means or hierarchical clustering).
Apply the clustering algorithm to a set of documents and evaluate the clustering results.

Theory:
K-Means Clustering:

- K-Means Clustering is an Unsupervised Learning algorithm, which groups the unlabeled dataset into different clusters.
- Here K defines the number of predefined clusters that need to be created in the process, as if K=2, there will be two clusters, and for K=3, there will be three clusters, and so on.
- It allows us to cluster the data into different groups and a convenient way to discover the categories of groups in the unlabeled dataset on its own without the need for any training.
- The main aim of this algorithm is to minimise the sum of distances between the data point and their corresponding clusters.
- The algorithm takes the unlabeled dataset as input, divides the dataset into k-number of clusters, and repeats the process until it does not find the best clusters. The value of k should be predetermined in this algorithm.

- The k-means clustering algorithm mainly performs two tasks:
    1. Determines the best value for K centre points or centroids by an iterative process.
    2. Assigns each data point to its closest k-centre. Those data points which are near to the particular k-centre, create a cluster.

Working of K-means Algorithm -
Step-1: Select the number K to decide the number of clusters.
Step-2: Select random K points or centroids. (It can be different from the input dataset).
Step-3: Assign each data point to their closest centroid, which will form the predefined K clusters.
Step-4: Calculate the variance and place a new centroid of each cluster.

Step-5: Repeat the third steps, which means assign each datapoint to the new closest centroid of each cluster.
Step-6: If any reassignment occurs, then go to step-4 else go to FINISH.
Step-7: The model is ready.

Practical

Input:

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans

documents = ["Cats are known for their agility and grace", #cat doc1
        "Dogs are often called ‘man’s best friend’.", #dog doc1
        "Some dogs are trained to assist people with disabilities.", #dog doc2
        "The sun rises in the east and sets in the west.", #sun doc1
        "Many cats enjoy climbing trees and chasing toys.", #cat doc2
        ]

# Create a TfidfVectorizer object
vectorizer = TfidfVectorizer(stop_words='english')

# Learn vocabulary and idf from training set.
X = vectorizer.fit_transform(documents)

# Perform k-means clustering
kmeans = KMeans(n_clusters=3, random_state=0).fit(X)

# Print cluster labels for each document
print(kmeans.labels_)
```

Output:

```
[0 1 1 2 0]
Performed by 740_Pallavi & 743_Deepak
```

Practical No: 7

Aim: Web Crawling and Indexing

A) Develop a web crawler to fetch and index web pages.

B) Handle challenges such as robots.txt, dynamic content, and crawling delays.

Theory

Crawling: Google downloads text, images, and videos from pages it found on the internet with automated programs called crawlers.

Indexing: Google analyses the text, images, and video files on the page, and stores the information in the Google index, which is a large database.

Crawling Process -

1) **Starting Point:** The crawling process usually begins with a set of seed URLs, which can be provided manually or generated through algorithms. These URLs serve as the starting points for the web crawlers.

2) **Queue of URLs:** Web crawlers maintain a queue of URLs, often referred to as the URL frontier. This queue represents the set of URLs that the crawler is yet to visit. New URLs are continuously added to this queue during the crawling process.

3) **Parsing Content:** When a web crawler visits a webpage, it parses the HTML content to extract links (URLs) embedded within the page. This process involves examining HTML tags and, in some cases, executing JavaScript to discover additional links.

4) **Respecting Directives:** Crawlers adhere to rules specified in the robots.txt file, which indicates areas of a website that should not be crawled. Additionally, crawlers may implement policies to filter out certain types of content or URLs.

5) **Avoiding Redundancy:** To prevent redundancy and ensure efficient crawling, duplicate URLs are often identified and removed from the crawling queue.

6) **Traversal Strategy**: Crawlers can follow various traversal strategies, such as depth-first or breadth-first, as they explore the web. The chosen strategy determines the order in which pages are crawled.

7) **Politeness:** To avoid overloading web servers with too many requests, crawlers may introduce a crawl delay between successive requests.

8) **Retrieving Web Pages:** Crawlers download the content of web pages, including HTML, text, images, and other resources. The downloaded content is then processed for indexing.

Indexing Process -

1) **HTML Parsing:** The content retrieved by the crawler is parsed to extract relevant information. This involves analysing the HTML structure to identify text, metadata, and other elements on the page.

2) **Isolating Textual Content:** From the parsed content, the crawler isolates the textual information, such as the body of the page, headings, and other relevant textual data.

3) **Breaking into Tokens**: The textual content is tokenized, breaking it down into smaller units, typically words or phrases. Tokenization facilitates efficient indexing and retrieval based on keywords.

4) **Data Organization:** The extracted information is organized into an index, which is a structured database allowing for fast and efficient retrieval. The index includes details about keywords, their locations, and other relevant metadata.

5) **Optimising for Retrieval:** The index is often organised as an inverted index, mapping each term to the documents or web pages where it

appears. This structure enables quick retrieval of documents containing specific terms.

6) **Additional Information:** In addition to textual content, metadata such as page title, URL, and other relevant details may be included in the index to enhance the search experience.
7) **Real-time Changes:** Search engines continuously update their indexes to reflect changes on the web. This ensures that the search results remain current and accurate.

Practical

Input:

```
import requests
from bs4 import BeautifulSoup
import time
from urllib.parse import urljoin, urlparse
from urllib.robotparser import RobotFileParser

def get_html(url):
    headers = {'User-Agent': 'Mozilla/5.0 (Windows NT 10.0; Win64; x64)
AppleWebKit/537.36 (KHTML, like Gecko) Chrome/58.0.3029.110
Safari/537.3'}
    try:
        response = requests.get(url, headers=headers)
        response.raise_for_status()
        return response.text
    except requests.exceptions.HTTPError as errh:
        print(f"HTTP Error: {errh}")
    except requests.exceptions.RequestException as err:
        print(f"Request Error: {err}")
    return None
```

```
def save_robots_txt(url):
    try:
        robots_url = urljoin(url, '/robots.txt')
        robots_content = get_html(robots_url)
        if robots_content:
            with open('robots.txt', 'wb') as file:
                file.write(robots_content.encode('utf-8-sig'))
    except Exception as e:
        print(f"Error saving robots.txt: {e}")

def load_robots_txt():
    try:
        with open('robots.txt', 'rb') as file:
            return file.read().decode('utf-8-sig')
    except FileNotFoundError:
        return None

def extract_links(html, base_url):
    soup = BeautifulSoup(html, 'html.parser')
    links = []
    for link in soup.find_all('a', href=True):
        absolute_url = urljoin(base_url, link['href'])
        links.append(absolute_url)
    return links

def is_allowed_by_robots(url, robots_content):
    parser = RobotFileParser()
    parser.parse(robots_content.split('\n'))
    return parser.can_fetch('*', url)

def crawl(start_url, max_depth=3, delay=1):
```

```
    visited_urls = set()

    def recursive_crawl(url, depth, robots_content):
        if depth > max_depth or url in visited_urls or not
is_allowed_by_robots(url, robots_content):
            return
        visited_urls.add(url)
        time.sleep(delay)

        html = get_html(url)
        if html:
            print(f"Crawling {url}")
            links = extract_links(html, url)

            for link in links:
                recursive_crawl(link, depth + 1, robots_content)

    save_robots_txt(start_url)
    robots_content = load_robots_txt()
    if not robots_content:
        print("Unable to retrieve robots.txt. Crawling without restrictions.")

    recursive_crawl(start_url, 1, robots_content)

# Example usage:
print("Performed by 740_Pallavi & 743_Deepak")
crawl('https://wikipedia.com', max_depth=2, delay=2)
```

Output:

```
Performed by 740_Pallavi & 743_Deepak
Crawling https://wikipedia.com
Crawling https://en.wikipedia.org/
Crawling https://ja.wikipedia.org/
Crawling https://ru.wikipedia.org/
Crawling https://de.wikipedia.org/
Crawling https://es.wikipedia.org/
Crawling https://fr.wikipedia.org/
Crawling https://it.wikipedia.org/
Crawling https://zh.wikipedia.org/
Crawling https://fa.wikipedia.org/
Crawling https://pl.wikipedia.org/
Crawling https://ar.wikipedia.org/
```

robot.txt file:

robots.txt

```
# robots.txt for http://www.wikipedia.org/ and friends
#
# Please note: There are a lot of pages on this site, and there are
# some misbehaved spiders out there that go _way_ too fast. If you're
# irresponsible, your access to the site may be blocked.
#

# Observed spamming large amounts of https://en.wikipedia.org/?curid=NNNNNN
# and ignoring 429 ratelimit responses, claims to respect robots:
# http://mj12bot.com/
User-agent: MJ12bot
Disallow: /

# advertising-related bots:
User-agent: Mediapartners-Google*
Disallow: /

# Wikipedia work bots:
User-agent: IsraBot
Disallow:

User-agent: Orthogaffe
Disallow:

# Crawlers that are kind enough to obey, but which we'd rather not have
# unless they're feeding search engines.
User-agent: UbiCrawler
Disallow: /

User-agent: DOC
Disallow: /
```

Practical No: 8

Aim: Link Analysis and PageRank

A) Implement the PageRank algorithm to rank web pages based on link analysis.

B) Apply the PageRank algorithm to a small web graph and analyse the results.

Theory

Link Analysis:

- Link analysis is a method used to examine relationships and connections between entities in a network.
- It involves studying the links or connections between different elements to uncover patterns, structures, and insights.
- Link analysis is commonly applied in various fields, including information retrieval, social network analysis, fraud detection, and recommendation systems.

PageRank Algorithm -

- The PageRank algorithm is an algorithm used by the Google search engine to rank web pages in its search results.
- It was developed by Larry Page and Sergey Brin, the co-founders of Google, and is named after Larry Page.
- PageRank is based on the idea that the importance of a webpage is determined by the number and quality of other pages that link to it.

Working -

1) **Initialize PageRank Values:**
   Set an initial PageRank value for each node. Commonly, this is initialised to 1 divided by the total number of nodes, making the sum of all PageRank values equal to 1.

2) **Define Damping Factor and Iterations:**
   Choose a damping factor (typically 0.85) to model the probability that a user will continue navigating through the web by following links.
   Decide on the maximum number of iterations for the algorithm.

3. Iterative PageRank Calculation:

- For each iteration, update the PageRank values for each node based on the PageRanks of the nodes linking to it.
- Use the PageRank formula:
  $$PR(i) = (1 - d) + d\left(\frac{PR(1)}{L(1)} + \frac{PR(2)}{L(2)} + \ldots + \frac{PR(n)}{L(n)}\right)$$
  where:
  - $PR(i)$ is the PageRank of node i,
  - d is the damping factor,
  - $PR(j)$ is the PageRank of node j linking to node i,
  - $L(j)$ is the number of outgoing links from node j, and
  - n is the total number of nodes.

4) Convergence Check:
After each iteration, check for convergence. If the difference between the new and previous PageRank values falls below a certain threshold, the algorithm has converged, and you can stop iterating.

5) Repeat Iterations:
Continue iterating until the maximum number of iterations is reached or until convergence is achieved.

6) Final PageRank Values:
The final PageRank values represent the importance of each node in the graph based on the link structure.

Practical

Input:

```
import numpy as np

def page_rank(graph, damping_factor=0.85, max_iterations=100, tolerance=1e-6):
    # Get the number of nodes
    num_nodes = len(graph)

    # Initialize PageRank values
    page_ranks = np.ones(num_nodes) / num_nodes

    # Iterative PageRank calculation
    for _ in range(max_iterations):
        prev_page_ranks = np.copy(page_ranks)

        for node in range(num_nodes):
            # Calculate the contribution from incoming links
            incoming_links = [i for i, v in enumerate(graph) if node in v]
            if not incoming_links:
```

```
            continue

        page_ranks[node] = (1 - damping_factor) / num_nodes + \
                           damping_factor * sum(prev_page_ranks[link] /
len(graph[link]) for link in incoming_links)

        # Check for convergence
        if np.linalg.norm(page_ranks - prev_page_ranks, 2) < tolerance:
            break

    return page_ranks

# Example usage
if __name__ == "__main__":
    # Define a simple directed graph as an adjacency list
    # Each index represents a node, and the list at that index contains nodes to
which it has outgoing links
    web_graph = [
        [1, 2],     # Node 0 has links to Node 1 and Node 2
        [0, 2],     # Node 1 has links to Node 0 and Node 2
        [0, 1] , # Node 2 has links to Node 0 and Node 1
        [1,2],  # Node 3 has links to Node 1 and Node 2
    ]

    # Calculate PageRank
    result = page_rank(web_graph)

    # Display PageRank values
    for i, pr in enumerate(result):
        print(f"Page {i}: {pr}")
```

Output:

```
Page 0: 0.6725117940472367
Page 1: 0.7470731975560085
Page 2: 0.7470731975560085
Page 3: 0.25
Performed by 740_Pallavi & 743_Deepak
```