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Research Internship Report

Project Title:

Derivation of K-Means Algorithm for Dynamic Data Clustering using TDA and ML

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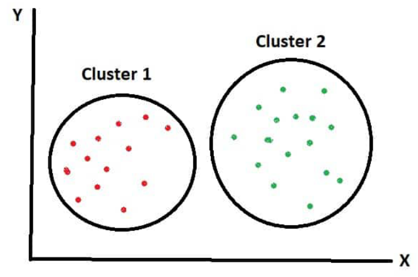
INTRODUCTION

What is Clustering?
Clustering is the process of dividing datasets into clusters(groups) with similar data points(features) and each cluster is represented by its unique cluster id.



Applications of Clustering:

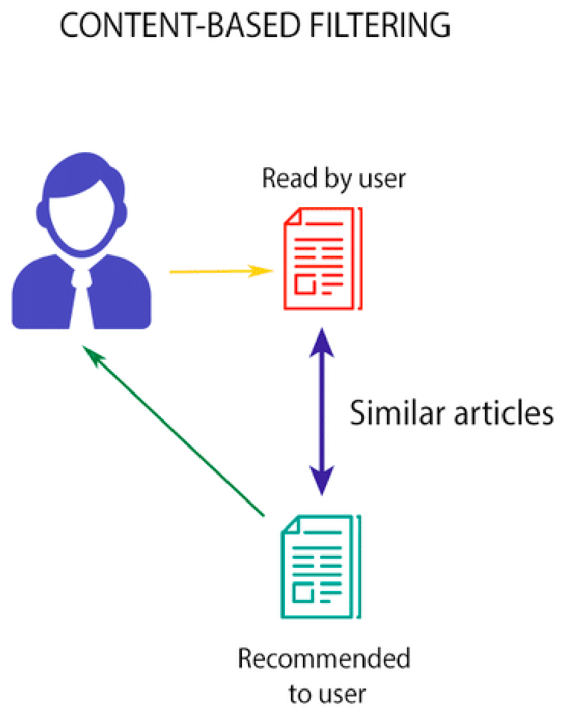
- Market monitoring
- Social media analysis
- E-Commerce/OTT App Recommendation Algorithm
- Image Recognition in Traffic Control System

Difference between K-Means and Dynamic K-Means Algorithms:

- In K-Means, K (no. of clusters) is defined by the user whereas Dynamic K-Means automatically determines the number of clusters.
- Also, K-Means operates over a fixed dataset while the Dynamic K-Means operates over a changing dataset.
- K-Means has no convergence criteria whereas Dynamic K-Means operates over a convergence criterion to ensure the stability of dataset.

Real Life Applications of Dynamic K-Means Algorithms

- Amazon Product Recommendation Algo



- Netflix Movie/TV Show Recommendation Algo

Raitings
Watch history
Devise
NETFLIX
Search
Credit calculation
Re-watching program

Dynamic K-Means Clustering Analysis

Three major steps involved in the process are as follows –

- Initialization: Initialize k centroids randomly.
- Update Phase: For each incoming data point, assign it to the nearest centroid(cluster) based on the Euclidean distance.

$$d((x,y),(a,b)) = \sqrt{(x-a)^2 + (y-b)^2}$$

Euclidean distance formula

- Centroid Update: After each data point assignment, update the centroid of the corresponding cluster by considering the new data point. The update can be incremental, reducing the computational cost of recalculating centroids manually.

Topological Data Analysis (TDA)

What is TDA?

Topological Data Analysis (TDA) is a branch of data analysis that aims to extract topological and geometric features from complex data sets. It provides a way to study the shape, structure, and connectivity of data points and uncover hidden patterns and relationships that might not be evident through traditional statistical methods.

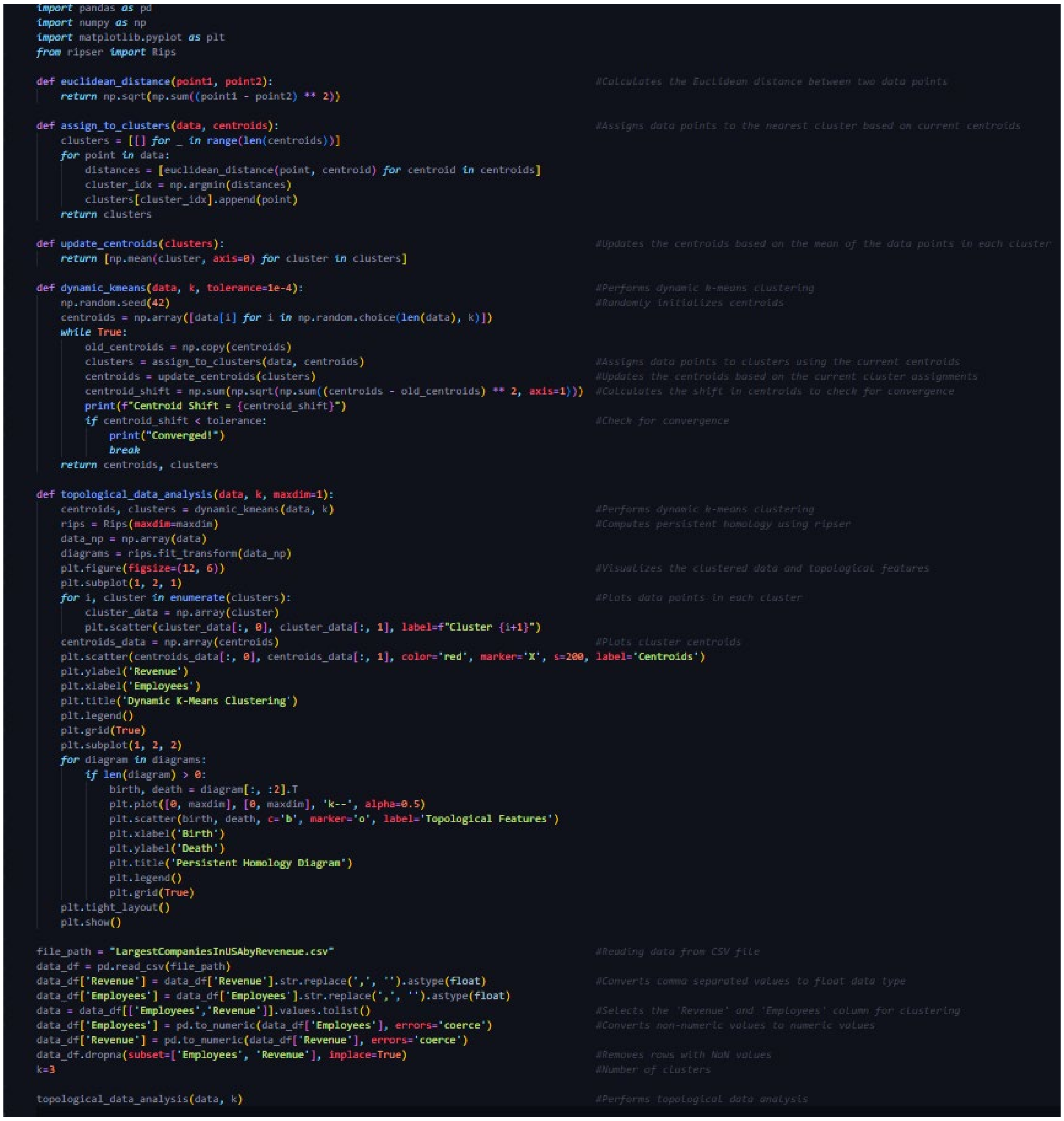
Applications of TDA:

- Image and Signal Processing
- Machine Learning and Data Mining
- IoT
- Robotics
- Social Network Analysis
- Natural Language Processing
- And many more….

To perform TDA in the project, following python library has been considered:

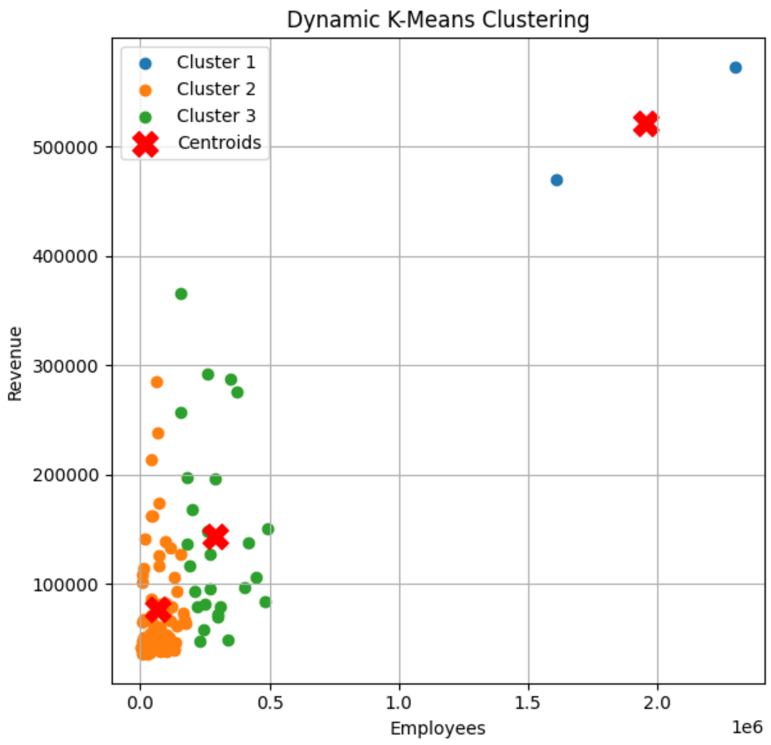
Ripser, which works on the principle of Vietoris Rips Complex that is used to study the relationships between the set of points in a metric space.

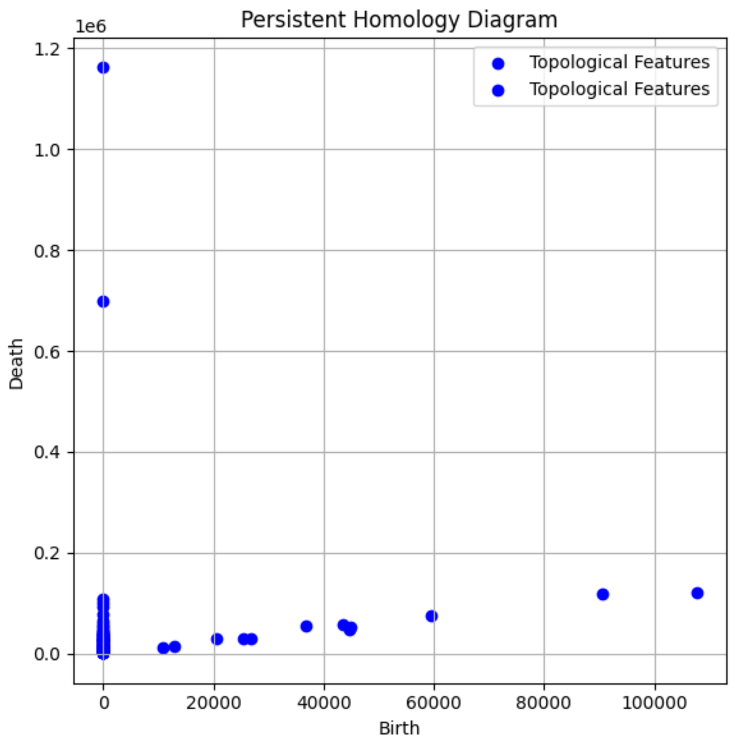
CODE



```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from ripser import Rips

def euclidean_distance(point1, point2):                                                     #Calculates the Euclidean distance between two data points
    return np.sqrt(np.sum((point1 - point2) ** 2))

def assign_to_clusters(data, centroids):                                                    #Assigns data points to the nearest cluster based on current centroids
    clusters = [[] for _ in range(len(centroids))]
    for point in data:
        distances = [euclidean_distance(point, centroid) for centroid in centroids]
        cluster_idx = np.argmin(distances)
        clusters[cluster_idx].append(point)
    return clusters

def update_centroids(clusters):                                                             #Updates the centroids based on the mean of the data points in each cluster
    return [np.mean(cluster, axis=0) for cluster in clusters]

def dynamic_kmeans(data, k, tolerance=1e-4):                                                #Performs dynamic k-means clustering
    np.random.seed(42)                                                                      #Randomly initializes centroids
    centroids = np.array([data[i] for i in np.random.choice(len(data), k)])
    while True:
        old_centroids = np.copy(centroids)
        clusters = assign_to_clusters(data, centroids)                                      #Assigns data points to clusters using the current centroids
        centroids = update_centroids(clusters)                                              #Updates the centroids based on the current cluster assignments
        centroid_shift = np.sum(np.sqrt(np.sum((centroids - old_centroids) ** 2, axis=1)))  #Calculates the shift in centroids to check for convergence
        print(f"Centroid Shift = {centroid_shift}")
        if centroid_shift < tolerance:                                                      #Check for convergence
            print("Converged!")
            break
    return centroids, clusters

def topological_data_analysis(data, k, maxdim=1):
    centroids, clusters = dynamic_kmeans(data, k)                                           #Performs dynamic k-means clustering
    rips = Rips(maxdim=maxdim)                                                              #Computes persistent homology using ripser
    data_np = np.array(data)
    diagrams = rips.fit_transform(data_np)
    plt.figure(figsize=(12, 6))                                                             #Visualizes the clustered data and topological features
    plt.subplot(1, 2, 1)
    for i, cluster in enumerate(clusters):                                                  #Plots data points in each cluster
        cluster_data = np.array(cluster)
        plt.scatter(cluster_data[:, 0], cluster_data[:, 1], label=f"Cluster {i+1}")
    centroids_data = np.array(centroids)                                                    #Plots cluster centroids
    plt.scatter(centroids_data[:, 0], centroids_data[:, 1], color='red', marker='X', s=200, label='Centroids')
    plt.ylabel('Revenue')
    plt.xlabel('Employees')
    plt.title('Dynamic K-Means Clustering')
    plt.legend()
    plt.grid(True)
    plt.subplot(1, 2, 2)
    for diagram in diagrams:
        if len(diagram) > 0:
            birth, death = diagram[:, :2].T
            plt.plot([0, maxdim], [0, maxdim], 'k--', alpha=0.5)
            plt.scatter(birth, death, c='b', marker='o', label='Topological Features')
            plt.xlabel('Birth')
            plt.ylabel('Death')
            plt.title('Persistent Homology Diagram')
            plt.legend()
            plt.grid(True)
    plt.tight_layout()
    plt.show()

file_path = "LargestCompaniesInUSAbyReveneue.csv"                                           #Reading data from CSV file
data_df = pd.read_csv(file_path)
data_df['Revenue'] = data_df['Revenue'].str.replace(',', '').astype(float)                  #Converts comma separated values to float data type
data_df['Employees'] = data_df['Employees'].str.replace(',', '').astype(float)
data = data_df[['Employees','Revenue']].values.tolist()                                     #Selects the 'Revenue' and 'Employees' column for clustering
data_df['Employees'] = pd.to_numeric(data_df['Employees'], errors='coerce')                 #Converts non-numeric values to numeric values
data_df['Revenue'] = pd.to_numeric(data_df['Revenue'], errors='coerce')
data_df.dropna(subset=['Employees', 'Revenue'], inplace=True)                               #Removes rows with NaN values
k=3                                                                                         #Number of clusters

topological_data_analysis(data, k)                                                          #Performs topological data analysis
```

OUTPUT





Graphical view of the dataset using Dynamic K-Means (left) and Persistent Homology portraying TDA

CONCLUSION

Therefore, from the above graph it is clear that –

- Cluster 1 having more employees is having a higher revenue as compared to the rest of the companies.
- Cluster 2 having lesser employees is having a lower revenue due to lack of productivity in those companies.
- Similarly, Cluster 3 having lesser employees than Cluster 1 but more than Cluster 2 is having a better revenue growth over time.

Hence, the following operation implies that having more employees leads to a higher revenue over a certain period.

REFERENCES

- https://www.analyticsvidhya.com/blog/2016/11/an-introduction-to-clustering-and-different-methods-of-clustering/
- https://www.kaggle.com/code/ryanholbrook/clustering-with-k-means
- https://developers.google.com/machine-learning/clustering/overview

Dataset of "Largest Companies in USA" is downloaded from –

- https://www.kaggle.com/datasets