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# CHAPTER 1: INTRODUCTION

# Background

Determining the optimal internal grouping based on unlabeled points is a huge challenge due to the ambiguity of the absolute ‘best’ criterion independent of the final goal. These types of problems are commonly known as an NP-Hard problem which involves a tradeoff of computation time versus accuracy to approximate. The goal here is to find an optimum point to achieve a sufficient accuracy in a reasonable amount of time. A classic example of an NP-Hard problem would be k-means clustering [1]. Given a finite number of points, the k-means algorithm is tasked to find k number of centers to minimize the distance of each point to each of those centers. Logically, we would like the distance between the different centers to be as far away from each other as possible. This would uncover underlying patterns that form these clusters based on their distance. Being an unsupervised algorithm, there are no labels associated to the and therefore learn only from its features.

There are various assumptions that are required to be made when operationalizing the k-means algorithm namely, the clusters are assumed to be spherical in nature. A spherical dataset is a dataset that is roughly round in a sample space. This means that the algorithm always try to construct a nice spherical shape around the centroid. Besides that, another assumption is that the data points are almost equally distributed among the clusters. The k-means algorithm also requires that the k which is the number of clusters to be approximated apriori.

The k-means algorithm is evaluated based on a metric called the Dunn Index [2]. The Dunn index measures two things which are the intra-cluster distance which is the sum of distances between all the points to the centroid as well as the inter-cluster distance of the centroids. Ideally, intra-cluster distance should be low as possible creating compact clusters whereas the inter-cluster distance should be higher to show better separation between clusters. Therefore the Dunn index is defined as the ratio of the minimum of inter-cluster distances and maximum of intra-cluster distances. So we need to maximize the Dunn index and this may be contributed by centroid which maximizes the inter-cluster distance or minimizes the intra-cluster distance

The process k-means undergoes is relatively simple that is to assign a centroid in the sample space of the data and compute the distance between every single data point to the centroid. It then assigns the data to the centroid with the lower distance. Since all the data points belong to a cluster, the mean of each cluster is computed and the centroid is shifted to the new mean. The entire process is repeated until the new mean of the centroid doesn’t change. For data with a clear separation boundary, the k-means will converge very quickly. However, for data with high dimensionality the boundaries are usually very unclear and the k-means algorithm goes on to attempt to find better centroids indefinitely

Due to advantages of the k-means algorithm, it is applied to many use cases predominantly for clustering and anomaly detection. This study tries to use K-means clustering to assign moving points to clusters and then predict the direction and speed of the various clusters. This framework can be extended to predict a possible bottleneck scenarios as well as identifying safety hazards of having a large group of people in a confined space. The ability to correctly predict changes in direction of clusters with moving points as well as the speed at which it moves brings a huge amount of benefits as it is able to be applied to predict movements of crowd in a large area and possible safety issues that it might bring.

This study tries to use K-means clustering to assign moving points to clusters and then predict the direction and speed of the various clusters. This framework can be extended to predict a possible bottleneck scenarios which could be disastrous.

# Problem statement

In this study we focus on a couple of areas namely to cluster points that are moving using the k-means algorithm. The challenge here is due to the fact that the points are constantly moving which makes presents a challenge in the realm of clustering. In order to be able to do this, an optimal strategy for applying k-means is used in order to reduce computation time while still maintaining accuracy.

Next, the direction and velocity of which the clusters are moving is also an interesting problem to solve. With the ability to get the direction of the crowd cluster movements

—The ability to accurately predict traffic speed in a large and heterogeneous road network has many useful applications, such as route guidance and congestion avoidance. In principle, data driven methods such as Support Vector Regression (SVR) can predict traffic with high accuracy, because traffic tends to exhibit regular patterns over time. However, in practice, the prediction performance can vary significantly across the network and during different time periods. Insight into those spatial and temporal trends can improve the performance of Intelligent Transportation Systems (ITS). Traditional prediction error measures such as Mean Absolute Percentage Error (MAPE) provide information about individual links in the network, but do not capture global trends. We propose unsupervised learning methods, such as k-means clustering, Principal Component Analysis (PCA), and Self Organizing Maps (SOM) to mine spatial and temporal performance trends at both network level and for individual links. We perform prediction for a large, interconnected road network, for multiple prediction horizons, with SVR based algorithm. We show the effectiveness of the proposed performance analysis methods by applying them to the prediction data of SVR.

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we look at a couple of distance

At this point we have identified the best cluster we have identified a good cluster but we’ll not know if there is a better clustering possible, so kmeans continues

So what tangible value does being able to cluster points bring?

Diving deeper into how k-means determines the cluster, a distance formula is generally used to calculate distance between data points in the sample space based on the multitude of features used. Euclidean distance is the most frequently used algorithm for this task.

For the stability validation, we selected the average proportion of non-overlap (APN), the average distance (AD) and the average distance between means (ADM) [43]

Next :methods

Assumptions

Pros and cons

Hook, what, why, how

Questions : intra and inter cluster distance. Better clustering can be obtained by trading off only?

# Problem statement

# Research Question

# Research Objective

# References

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