Service Point Placement By Customer Geolocation Clustering

Location, Location, Location When Distance, Distance, Distance Matters

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ABSTRACT

This project has been developed for COMP592DL - Project in Data Science, for the MSc in Data Science at the University of Nicosia.

The purpose of this project is to try to identify the optimal number and placement of physical store locations, for a retailer company that depends on a physical network for the distribution of goods and services to its customers. The target variable is the minimization of the distance to the nearest service point by the retailer's customers.

For this project, we have gathered open-source data to serve as a sample population, and used the k-Means unsupervised clustering algorithm, for the model development. The results of the model are the optimal number and geographical positions of service points for a retailer company, based on the actual point geolocations of the retailer's customers. The service points proposed by the developed model minimize the distance-to-be-travelled by the customers to the nearest service point, with the least number of service points, while suggesting a reduced number of service points, resulting to better customer service with reduced operating costs.

KEYWORDS

Geolocation, Location, Address, Service Points, k-Means Clustering, Big Data

INTRODUCTION

The location of a physical store is important for any retailer company that relies on a distributed branch network for the promotion of its goods and services. The distance to the nearest service point is an important factor to consider, as it is a measure of convenience for its customers. The initial set-up costs required for the establishment of a new service point should be carefully weighed against the expected benefits [1], as future relocations or new establishments translate to additional, unnecessary costs. The insights of this model would be useful to the retailer company's management as it would facilitate data driven decision making regarding the retailer's physical service point locations by considering the geospatial distribution of its customer base.

The service point location problem is known as the **Maximal Covering Location Problem** and has been formally defined since 1974 [2]. The initial problem statement was to identify service points that would maximize population coverage over a desired service distance by locating a fixed number of facilities. The desired service distance is the farthest distance a customer would have to travel to reach a facility. The number of facilities is the cost factor to enter the decision process. For a given number of facilities, there may exist various location solutions, therefore their cost-effectiveness should be examined. The best solution is the one that maximizes population coverage within the desired service distance for a fixed level of expenditure (i.e., cost of service points).

Various improvements to this problem statement exist in the literature. In [3], the concept of Weighted Benefit Maximal Covering was introduced by supporting the assumption of "step" distances. The number of distance steps could be varied per case examined, and a different weight could be applied to each step in the distance intervals. The notion of partial coverage for the Maximal Covering Location Problem was introduced in [4]. The proposed model would classify a service point as fully covered when found within a minimum critical distance, as partially covered when found between a minimum and a maximum critical distance, and as not serviced when beyond the maximum critical distance. In [5], the notion of the service quality was introduced, by replacing the actual distance measurement in the proposed model, with a service level function of the distance to the nearest service point.

Reference [6] identifies the limitation in the previous solutions to the maximal covering location problem with respect to accurate demand representation. The demand, which in our case is the retailer's customers, was represented by a set of discrete points with weights on a grid to represent the volume, thus aggregating demand to a single point. The differentiation in [6] was to assume uniform distribution of demand within the specified grid regions to calculate the population coverage. The results showed significant differentiation in the proposed optimal service point locations.

For this project we will be dealing with the service point placement for a banking institution, which was also the case examined in [1]. A basic assumption in the study was that the distance a customer was willing to travel was influenced by the population density at the demand point. Customers in high density areas were willing to travel less distance to be serviced, whereas customers in low density areas were willing to travel greater distance to be serviced. Additional literature suggests that bank customers tend to travel to the nearest appropriate banking facility or ATM to be serviced [7].

Thus, locational convenience has always been an objective for banking institutions.

For the purposes of this project, we have managed to represent each individual demand point by its actual, accurate geolocation without aggregation. This was possible with the translation of sample text addresses to their digital equivalent through utilization of the Google Maps Geocoding API available in Google Cloud Platform. The geographical coordinates were also used for the distance calculation between individual demand points and service points.

The outcome of this project is the identification of the optimal service point number and location with the use of the k-means clustering algorithm on the actual geospatial representation of demand. The model's suggested locations have been compared against two sample companies' existing service points. The results of the model show a significant improvement in minimizing the distance to be travelled to the nearest service point, while at the same time proposing a reduced number of service points.

DATA SOURCES

The data source for the model's sample population was the Cyprus National OpenData Portal [8]. More specifically, we have used the following files from the "Μητρώο Εγγεγραμμένων Εταιρειών, Εμπορικών Επωνυμιών και Συνεταιρισμών στην Κύπρο" [9]: "Κατάλογος Οργανισμών", which contains the list of all legal entities of Cyprus that are registered with the Registrar of Companies, and "Κατάλογος Διευθύνσεων Εγγεγραμμένου Γραφείου", which is a list of all the registered office addresses of legal entities registered in Cyprus. The two files can be joined together to form one unified dataset based on the address sequence number, present as a key in both files.

The geolocations for the registered office addresses have been found by calling the Google Maps Geocoding API in Google Cloud Platform, with each text address as parameter.

We have also gathered information regarding the existing physical branch network for from a sample company's website, and a competitor company's website. The two sources have been used as baseline, and for comparison and evaluation of the model's performance. The companies selected for this project are in the banking industry, since they rely on a distributed network of physical branches for customer service, and their service point locations are publicly available. For the rest of this project, they will simply be referred to as CompA and CompB without disclosing any further details.

PREPROCESSING STEPS

The preprocessing steps that have been performed are described below per area:

1 Addresses

- For the address translation we have dropped the Address Line 2, which contained mostly information on building and/or flat number which are not useful for the address translation.
- Dropped addresses that returned 'Null' as geolocations from the Geocoding API.
- Matching of the unique text addresses with the geolocations received from the Geocoding API, was performed in Microsoft Excel. Further matching of the unique geocoded addresses with the initial addresses was also performed in Microsoft Excel.

The population of addresses through preprocessing steps has changed as follows:

Total Initial Addresses	178.916
Unique Initial Addresses	124.297
Unique Geocoded Addresses	79.894
Total Geocoded Addresses	115.191

2 Customers

- Filtered for active customers, recognized by their ORGANISATION_STATUS to be equal to 'Εγγεγραμμένη'
- Dropped unnecessary customer details
- Dropped customers without a key address sequence number
- Dropped customers with addresses outside the range of Cyprus geocoordinates. Following investigation, Cyprus lies at a latitude of 34˚33˚ - 35˚34˚ North and longitude 32˚16˚ - 34˚37˚ East approximately. Further adjustment of these coordinates was necessary, to filter out entities registered in the Turkish occupied part of Cyprus unfortunately. Also, the valid range used is a best approximation, since the interesting region cannot be exactly defined by rectangular geometry. This was necessary because distance to the service point is of high importance, therefore addresses outside of a specific range were removed as outliers.

The population of customers through preprocessing steps has changed as follows:

Total Initial Customers	509.647
Total Filtered Customers	238.725
Filtered Customers with Geocoded Addresses	218.738
Filtered Customers with Geocoded Addresses within Cyprus Geocoordinates	217.788

MODEL DEVELOPMENT

For the model development, initially we measured the Haversine distance [10] of all customers to every existing service point of CompA and CompB. The Haversine distance formula calculates distances between points on a sphere. Given that the Earth is spherical, the Haversine distance gives a more accurate distance measurement between coordinates than the Euclidean distance, which measures distances on a flat surface [11].

The service points of CompA were 60, and the service points of CompB were 42. Initially, we calculated the minimum distance of each customer to the nearest service point of CompA and CompB. We then grouped by the nearest derived service point, to calculate

the mean, median, min, max, 5th percentile and 95th percentile for comparison purposes with the model's recommendations per service point. Next, we calculated the volume of customers per service point. Additional metrics for comparison purposes regarding mean and median number of customers per service point were also calculated.

For the model development we have used the k-Means clustering method [12]. To determine the optimal number of clusters [13], we have measured the sum of squared distances (error rate) between each data point to its respective cluster center (centroid). The goal of k-means clustering is to minimize the error rate by identifying compact and well-defined clusters. The error rate has been plotted against the number of clusters, in a plot widely known as the "elbow" plot [14].

In the "elbow" plot, as the number of clusters increases, the error rate generally decreases because more clusters provide a better fit for the data points. However, the rate of improvement in the fit will decrease as more clusters are added, eventually reaching a point where adding more clusters does not lead to a significant reduction in the error rate. This is because the additional clusters only capture the noise or minor variations in the data, rather than reveal meaningful patterns. The elbow point is a good trade-off between having a small number of clusters and minimizing the within-cluster sum of squared distances.

A business explanation of the "elbow" plot in this case, is that the number of clusters represents the number of service points to be maintained by the business. The cost-effectiveness of setting up an additional service point should be examined against the benefit gained in terms of the improvement in the total distance to be travelled to the nearest company's service points [2].

The cost of each service point is made up of the initial setup cost, for example land acquisition, construction, or renovation, and the cost for its ongoing operation, for example rent (if not owned), employee payroll, utilities, and facility maintenance [7]. The benefit is the improvement in the total distance to the nearest service point as calculated for all customers in the dataset. The "elbow" point marks the point that the improvement in benefit (error rate) starts diminishing. Therefore, the cost-effectiveness of adding service points past the elbow point is also diminished.

For the sample model population, there are 2 noticeable "elbow" points – at 31 and 37 clusters, as shown in Figure 1. For our model we have decided to proceed with the more conservative approach and set the optimal number of clusters to 37.

For each of the service points we have collected their geographic coordinates, which have in turn been translated to actual Cyprus addresses, as shown in Figure 2.

RESULTS

The results of the k-Means clustering model, with regards to the number of service points, showed that the optimal number of

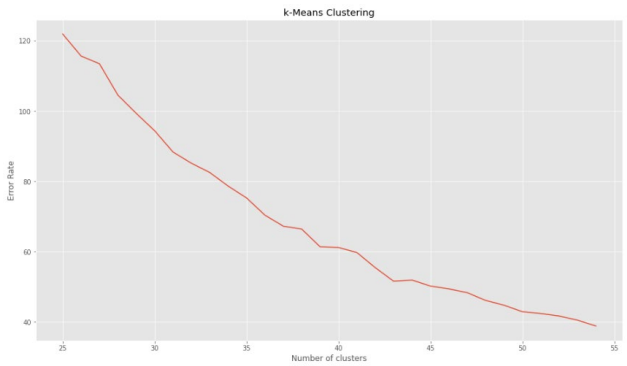

Figure 1 The "elbow" plot of the sum of squared distances (error rate) against the number of clusters for the developed k-Means clustering model

Service Point	NoOfCustomers	SP_coor	SP Address
0	40647	(35.165411, 33.357317)	5985+53P, Themistokli Dervi, Nicosia, Cyprus
1	9644	(34.695984, 33.031706)	Spyrou Kyprianou Ave 104, Limassol, Cyprus
2	6194	(34.928684, 33.601897)	Chalkidikis 14, Aradippou 7101, Cyprus
3	2032	(34.837709, 32.433364)	Miltiadi Stylianou Ave 4, Tala 8577, Cyprus
4	5200	(35.040622, 33.974079)	2XRF+6J Paralimni, Cyprus
5	1216	(35.107277, 33.211556)	4646+WJ Ayioi Trimithias, Cyprus

Figure 2 Location details and number of customers to be serviced for a sample of the service points proposed by the developed model

service points is 37, compared with 60 and 42 service points of CompA and CompB respectively. Therefore, both companies would initially benefit from decreased operational costs from the reduced number of service points they would have to maintain. The results of the k-Means clustering, with 37 clusters on our dataset, are shown on a map of Cyprus in Figure 3.

For each of the customers in the final dataset, we have calculated whether they are closer to a service point of CompA, or CompB, with most customers being closer to a service point of CompA, as shown in Figure 4.

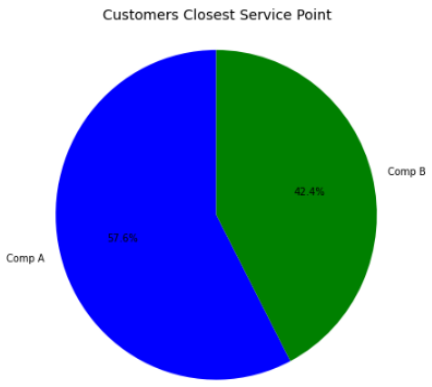

Figure 4 Percentage of customers to nearest service point by company

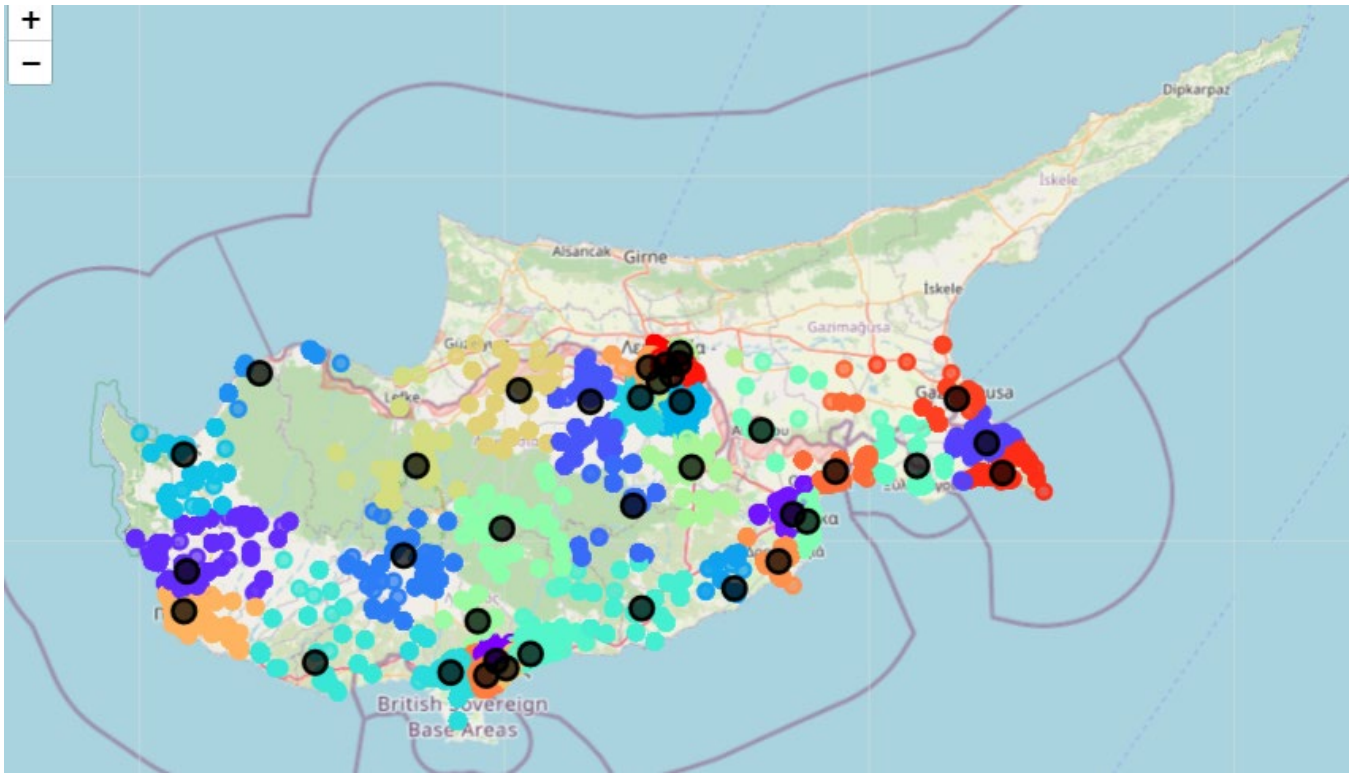

Figure 3 A colour map visualization of the 37 clusters returned as results of the proposed k-Means clustering model

Another interesting result was the boxplot of the distance distribution of the 3 instances shown in Figure 5. The plot showed that even though there are a lot of distance outliers in all 3 instances, yet the model's outliers are significantly less than CompA and CompB, and the maximum distance of the model is at 20km, compared to the max distance of CompA and CompB, being 27km and 35km respectively. This suggests that adopting the model's service point suggestions, that the farthest away customer, would have to travel 20 km to a service point, which is an improvement for both companies.

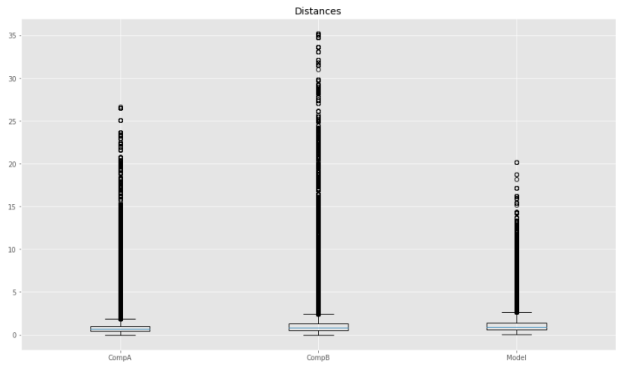

Figure 5 Boxplot of the distance to the nearest service point for each company and the model's proposal

This was even further investigated by finding the distance to the nearest service point at the 95th percentile. The 95th percentile is an important percentile in that it measures the maximum distance to be travelled to the nearest service point by 95% of the sample population of customers. The top 5% could be dismissed as outliers. The measurements are shown in Figure 6, and are significant, because it reveals that through the optimal service point placement, the distance to the nearest service point was almost halved from around 7km for both CompA and CompB, to 3,2km for the model's service point suggestions. It is also important to mention that this was achieved without significantly distorting the minimum distance to travel at the 5th percentile – the minimum distance that 95% of the population would have to travel – does not exceed the value of 0.2km.

The distance to the nearest service point was also measured by the distance range to the nearest service point for comparison purposes, shown in Figure 7. From the plot we notice that CompA's service points are placed to serve the vast majority of its customers under <1km (160k). The number of customers being serviced from service points in the 1-5km range are only 25% of the customers serviced in <1km (40k), and the number continues to decrease further for the 5-10, 10-20 and >20 km range. CompB's service points follow a more balanced pattern, closer to the model's pattern.

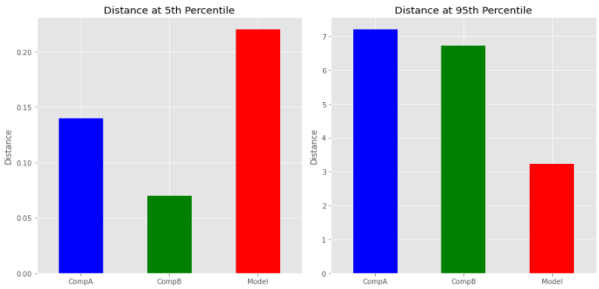

Figure 6 Distance in km to the nearest service point at 5th and 95th percentile for each company and the model's proposal

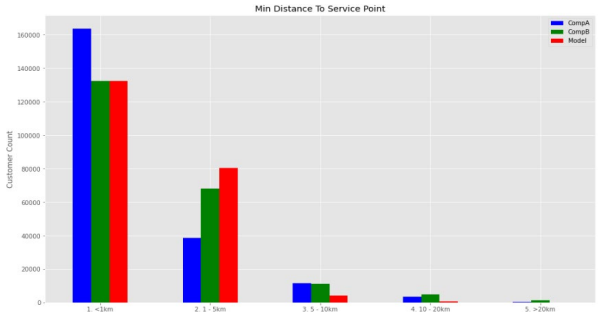

Figure 7 Distance range to the nearest service point

The proposed model's service points, suggest service point placement such that the number of customers being serviced by service points in the <1km and 1-5km range do not present great variability as CompA's service point placement. It is also noticeable that there are no customers in the >20km range.

Another interesting measurement was the count of the number of customers per service point. The customers were counted to the nearest service point in each of the 3 instances for comparison. We have then proceeded to define the branch size as a function of the number of customers in its vicinity as shown by Figure 8. The results of the service point sizes based on the definition of proposed branch size according to the number of customers to be serviced are shown in Figure 9.

From the distribution plot in Figure 9, we notice that CompA and CompB have mostly small and medium-sized branches in terms of the customers being serviced. The model proposes a wider and more balanced range of branch sizes. This is mostly noticeable in the "Medium" category of branches, where Company A and Company B have 32 and 30 branches respectively, whereas the model suggests only 16 medium-sized branches.

The size of the branch can also be interpreted in terms of the staff needed to service the branch's customers. The reduced number of branches, as well as the calculated staff needs, translate to reduced operating costs, while maintaining a high quality of service to the company's customers.

A sample differentiation of the service point placement depicted by the difference in colors, and the service point size depicted by the

	ServicePointSize	CustomersServiced	CompA	CompB	Model
0	ATM	<500	2	0	4
1	Small	500-2.000	22	8	12
2	Medium	2.000-10.000	32	30	16
3	Large	10.000-20.000	3	3	3
4	ExtraLarge	>20.000	1	1	2

Figure 8 Definition of Service Point Size as a function of the number of customers in its vicinity

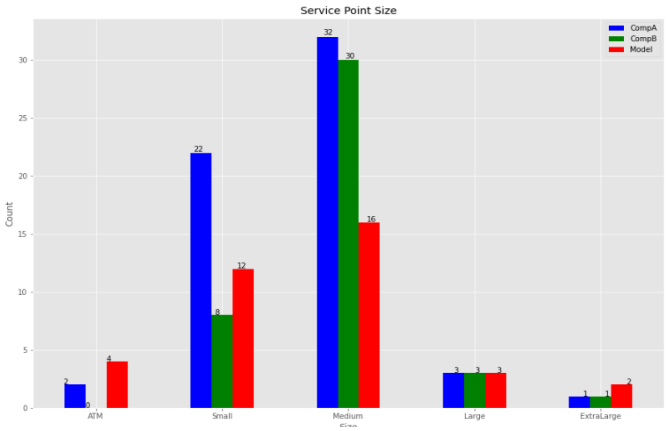

Figure 9 Number and size of branches for each company and the model's

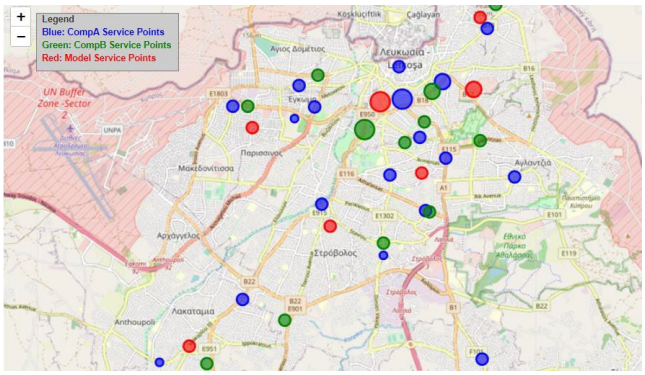

Figure 10 Sample differentiation of the distribution and size of service points for CompA, CompB and the model suggestions for an area in Nicosia

marker's radius, is shown in Figure 10, for a sample area in Nicosia city.

The project has been implemented with PySpark and Python code. The initial data processing and address translation to geolocations has been implemented with PySpark and ran on virtual machines deployed in Google Cloud Platform's DataProc with a Jupyter notebook. The rest of the project was implemented with Python 3.9 and ran on local Jupyter notebooks. All data soures and output files have been uploaded to a Google Cloud Storage Bucket, with public read access. The developed code with explanations on the

processing steps for the interested reader can be found in the public GitHub Repository https://github.com/consmalekkou/Service-Point-Placement-By-Customer-Geo-Location-Clustering[15].

CONCLUSION

For the purposes of this project, we have succeeded in proposing a near-optimal service point placement for a retailer company, by using the company's customers' geolocation as a data source. This data-driven approach, and utilization of machine learning method, can benefit a retailer company whose interest is to minimize distance to its customers. The suggested service point locations appear strategically spaced-out, and from the results on the sample population, we have managed to propose locations so that 95% of the retailer's customers will be serviced by service points placed less than 3.2km away. At the same time, we have proposed a minimal number of service points, with calculated branch sizes in terms of staff needed to serve customers in the service point's vicinity. The retailer company would therefore benefit both from reduced operating costs and calculated staffing needs per service point, while offering better customer service through minimization of the distance to its customers.

FUTURE WORK

Future work on this subject would be to identify different options to customer geolocation gathering. One such option would be through cellular phone data.

Another option would be to compare the actual service point preferences of customers, versus the proposed / nearest service points as identified in the model, to understand if any other factors affect the customer's preferred service point location, other than its proximity.

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