Case Study

A SIMPLIFIED RESTAURANT LOCATION ANALYSIS USING MACHINE LEARNING

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AUTHOR NOTE

Introduction

With a population of about 1.54 million, Munich is the third-largest city in Germany, with one of the highest proportions of foreign nationals in the country – 27.6 percent. It is expected that the resident population will exceed the 1.7 million mark in 2030 with an increasing portion of young, well-educated adults (City of Munich, 2019). It is the capital of Bavaria, the second state by Gross Domestic Product (GDP) in Germany (Statistik BW, 2019), and accounts for 19% of the state GDP (City of Munich, 2019).

As any other metropole, Munich offers a large demand for restaurants, which business is part of the second-largest sector per number of employees in the city (MUC.RAW, 2019). The local portal Mux.de counts 2.771 restaurants in the urban area (MUX.DE, 2019). New entrants are attracted by the high profitability, with an EBITDA up to 35% (Macrotrends, 2019). The Munich restaurants market is highly fragmented and dominated by small businesses with less than 10 employees (Gruner et al., 2016). The degree of rivalry is high.

New entrants need to take into account a number of factors to succeed, including an accurate selection of the location. In the following an analysis will be conducted drawing on location data to elaborate recommendations for the selection of an appropriate district for a premium Italian restaurant. The project is intended to assist the decision of investors interested in entering the Munich market with a fine dining restaurant business, as the food market in Germany continues to see a trend towards premiumization, according to the Agricolture and Agri-Food Canada Market Access Secretariat (2015).

This paper is written as part of the IBM Data Science Professional Certificate program (Coursera, 2019). The primary objective of this educational exercise is to demonstrate how to apply analytics techniques and machine learning on location data to gain insights that can be used to support recommendations. Assumptions will be taken about the target customer base, leaving the market positioning of the above-mentioned business outside of the scope of this study. Only open data will be used to conduct the analysis.

Problem definition

There are a number of factors to be considered to identify a suitable location for restaurants that depend from their market positioning. Those include the following ones, each of which triggers one or multiple strategic questions:

Culinary Trends. Is the offer in line with the consumer trends?

Demographic. Is there a customer base that is willing to buy the service and pay a premium for it? Is there a chance for recurring clients?

Neighborhood. Which venues are available nearby?

Infrastructure. Is the restaurant reachable? Is there any public transportation connection? Are there parking areas?

Competition. How many restaurants/dining services are nearby? Are they premium ones?

The research will analyze the above-mentioned success factors to identify evidences that will support recommendations for the selection of an appropriate location.

Research approach

The study will use a pragmatist approach to answer the research questions. The fieldwork will be conducted using a mixed method consisted in integrating quantitative secondary data with qualitative evaluations to assist the interpretation of the results.

Data collection

Geographical data

The list of the districts in Munich can be retrieved from (Statistisches Amt München, 2019). The data includes the number of habitants and the surface of the districts. The data has been republished on Wikipedia (Wikipedia, 2018) in a semi-structured format. Therefore, the latter source will be preferred.

The list of the postal codes of Munich is available in (Landeshauptstadt München, 2019), while the polygons of the corresponding to the ZIP codes are available in GeoJSON at (SUCHE-POSTLEITZAHL.ORG, 2019).

Culinary Trends

The main purpose of the analysis of this factor is to verify if a potential customer base exists. To analyze this aspect, the results of the survey about the culinary trends in Germany provided by Civey (2018) will be used.

Demographic

The demographic and lifestyle characteristics of the population can support the identification of geographical areas that are more suitable than others for a fine dining restaurant. Characteristics like population density, age distribution, per capita income, and number of households can be used to identify the customer profiles available in a geographical area.

The following metrics will be considered (Gaille, 2016):

1. Pre-capita income, as household with a higher household income spend more;
2. Residents age, (a) considering that individuals aged 35 to 44 spent the most per capita on food away from home; (b) young, urban professionals with no kids – dine at higher-priced restaurants; (c) Older adults and empty nesters (down-scale) – eat on-premise at inexpensive sit-down restaurants, buffets and fast food eateries. (d) individuals aged 45-54 with children older than 18 years and those aged 55-64 have consistent food expenditure at restaurants;
3. Number of households, (a) as one-person households have the highest per-capita spending; (b) households with only a husband and wife have the highest per-capita spending; (c) Busy parents of children use drive-thru and carry-out restaurants;

For the purpose of this research only residents will be considered, as resident population usually represents a sizable market whose dining behavior and preferences can be fairly accurately assessed (University of Wisconsin-MadisonExtension, 2011).

(Statistisches Amt München, 2019) offers detailed information about the demographic of the municipal districts that include number of people, resident age, and number of households.

The average pre-capita income in the districts is available in (TZ, 2011). Although the data is relatively hold, it can be normalized to provide an indicator of the average buying power in the districts.

Neighborhood

The availability and frequency of venue categories within the districts can support the neighborhood classification. The venues will be retrieved using the Foursquare API (Foursquare, 2019).

Infrastructure

The availability of infrastructures such as public transportation and parking areas within the districts can support the neighborhood classification. The data will be retrieved using the Foursquare API (Foursquare, 2019).

Competition

The degree of competition within the district can be estimated using the number existing restaurants classified by served food (Italian, Asian, Greek, etc.) and ideally cost indicator. The data will be primarily retrieved using the Foursquare API (Foursquare, 2019).

Research method and data preparation

The research was designed to gather evidences about the preferences of the residents in the city and the appetite for an Italian fine dining service. Each of the six factors that define the problem subject of this paper were analyzed. The study aimed at evaluating common patterns to segment the neighborhoods based on their environmental and demographic characteristics. The evaluation of patterns requires a consistent number of observations to be reliable. To gain access to large amount of good quality data, the secondary data described in the previous sections was considered.

First of all, boroughs data was collected merging the following sources:

1. (Wikipedia, 2018): containing the list of the boroughs, the number of residents, and the surface;
2. (Statistisches Amt München, 2019): containing the number of residents in the boroughs, their age group (<6, 6-14, 15-44, 45-64, >=65), and the number of households per number of households (1 to 5);
3. (TZ, 2011): containing the pre-capita income in the boroughs.

Following a pragmatic approach, the demographic data of 2019 was combined with the available average pre-capita income information, assuming that the geographical distribution of the pre-capita income did not changed significantly over the last years.

There were few issues in the data set that required a cleaning process to allow the match. The naming of the borough – used in some cases as key to merge the data sets – was slightly different in the sources or it adopted a different notation. 'Sendling' missed the per-capita income. For that the average was used. The demographic data was complete; therefore, no further correction was needed.

The demographic factors identified in the above section consider specific age buckets, namely 35-44 years, 45-54 years, and 55-64 years. Only households with adult children are considered potential customers. As (Statistisches Amt München, 2019) uses different age buckets and the number of households are not differentiated, the needed figures were inferred considering the average age distribution in Munich shown in Figure 1. The demographic statistics where normalized over the surface of the boroughs, assuming a uniform distribution of the population. The bucket 35-44 years was approximated to the nearest bucket 28-44 years.

The data was further transformed considering the following factors:

1. one-person households have the highest per-capita spending in restaurants;
2. households with only a husband and wife have the highest per-capita spending;
3. busy parents of children use drive-thru and carry-out restaurants;

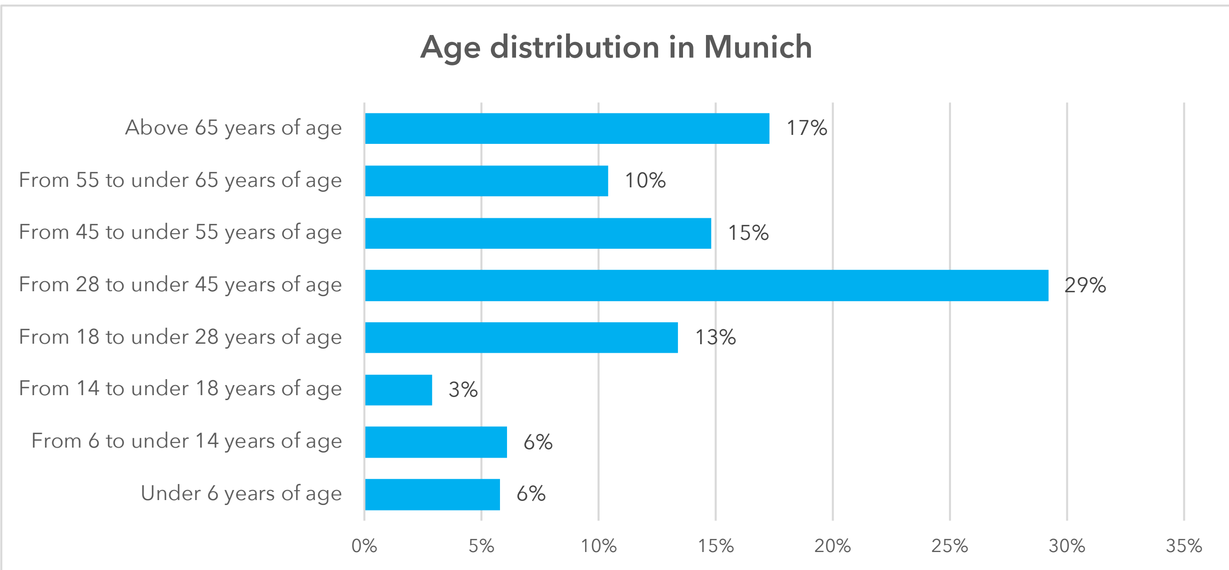

Figure 1 Age distribution in Munich. Source: (Statistisches Amt München, 2018, S. 4)

It was assumed that households with one household are adults only. The households composed by adults only were calculated considering the age distribution. Finally, the values have been normalized over the surface.

The resulting dataset listed the data for the 25 boroughs in Munich.

The list of neighborhoods in Munich and the corresponding geographical information were obtained merging:

1. (Landeshauptstadt München, 2019): containing the list of the postcode of the neighborhoods belonging to the boroughs in Munich;
2. (SUCHE-POSTLEITZAHL.ORG, 2019): containing the centroids of the neighborhoods in Germany and their surface. The dataset downloaded contained also the number of residents within the neighborhoods. Anyway, no source was mentioned in the website and the data could not be reconciled with the one available in (Statistisches Amt München, 2019), which was an authoritative source. For this reason, that information was disregarded.

44 neighborhoods belong to multiple boroughs. (Statistisches Amt München, 2019) does not provide information about the geographical composition of the boroughs in terms of neighborhoods. The composition could not be inferred using the surface data available in (SUCHE-POSTLEITZAHL.ORG, 2019), as there were 44 neighborhoods belonging to multiple boroughs against 26 equations that can be defined starting from the aggregated surface of the boroughs (25 boroughs + 1 total surface). In this case, the system of linear equations has infinitely many solutions. Solving the problem with linear programming techniques, will add additional noise to the data, as it cannot be ensured that the optimal solution identified is actually reflecting the one used for the study.

It was therefore assumed that residents are uniformly distributed in the borough areas.

The borough data was decomposed at neighborhoods level, considering the mean values for postcodes belonging to multiple boroughs.

Finally, the data was enriched with the list of the venues available in the neighborhoods retrieved from Foursquare (Foursquare Labs Inc., 2019). The top ten categories by frequency in the neighborhood were considered.

The feature matrix included 20 features for each of the 74 neighborhoods.

The list of all restaurants was used to build a second dataset to estimate the degree of rivalry within the neighborhoods.

The selected features are summarized in Figure 2. Data was processed using 'Python' programming language and displayed graphically in order to develop understanding and draw conclusions.

Category	Feature	Reason for selection
Venues	1_MFV, 2_MFV, 3_MFV, 4_MFV, 5_MFV, 6_MFV, 7_MFV, 8_MFV, 9_MFV, 10_MFV	The top 10 most frequent venues (MFV) provide intrinsic information about resident preferences
Demographics	Density, Foreigners, Income, Age_28_44, Age_45_64, 1HH, 2HH_Adults, 3HH_Adults, 4HH_Adults, 5HH_Adults	The features support the selection of the neighborhoods considering the target customer base.
Pre-Capita Income	Income	The feature is an indicator of the buying power of the residents in the area
Venues	Count of restaurants, bar, and similar services in the neighborhoods by category	The list of all the restaurants and similar services in the area can be used to estimate the degree of rivalry in the neighborhoods.

Figure 2 Features selected for the analysis

Research results analysis

Demographic and income data analysis

The boroughs data resulted normally distributed, except for surface and presence of foreigners that were skewed, as shown in Figure 3. A small number of peripherical neighborhoods have a surface much larger than the old and central ones. According to (Landeshauptstadt München, 2019b) those are developing areas for which high growth is expected by 2040.

The Pearson's cross-correlation analysis showed a moderate inverse correlation ($\rho = -0.675$) between '*average pre-capita income*' and '*percentage of foreigners*' in the area, with moderate statistical significance, having a p-value of 0.0002.

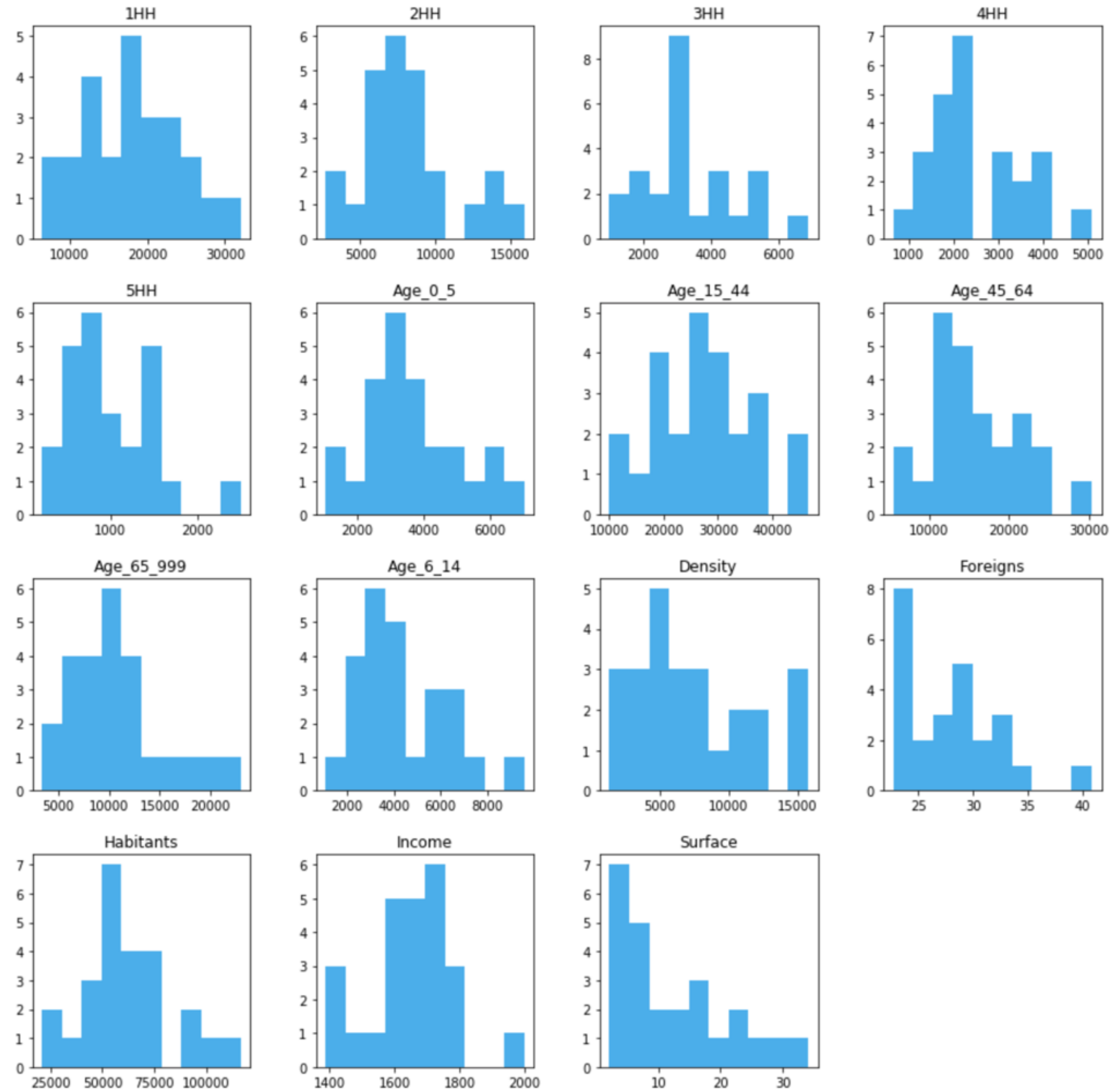

Figure 3 Borough data exploratory analysis

The distribution of the residents density has a standard deviation of 4093.98, indicating values spread out over a wide range. The choropleth in Figure 4 shows that neighborhoods in the center and south of the city have a higher density of residents compared to the peripheral ones. According to (Landeshauptstadt München, 2019b), in those areas the population is expected to grow between 30% and 90% by 2040.

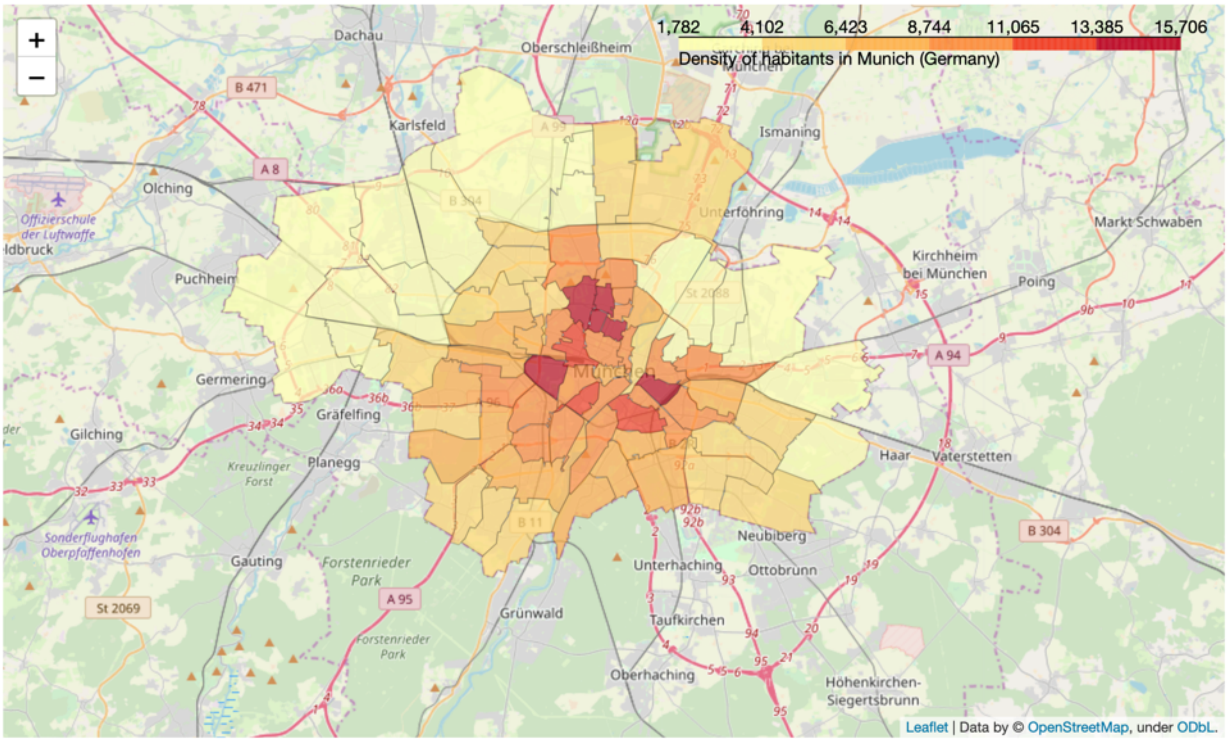

Figure 4 Density of habitants per km² in Munich

The per-capita income presented in Figure 5 has a standard deviation of 132.82, indicating values concentrated around the mean. Also developing areas show income in the mean range. Only Feldmoching-Hasenbergl (80933), Schwanthalerhöhe (80339), Milbertshofen-Am Hart (80937) have pre-capita income within the 25th quantile.

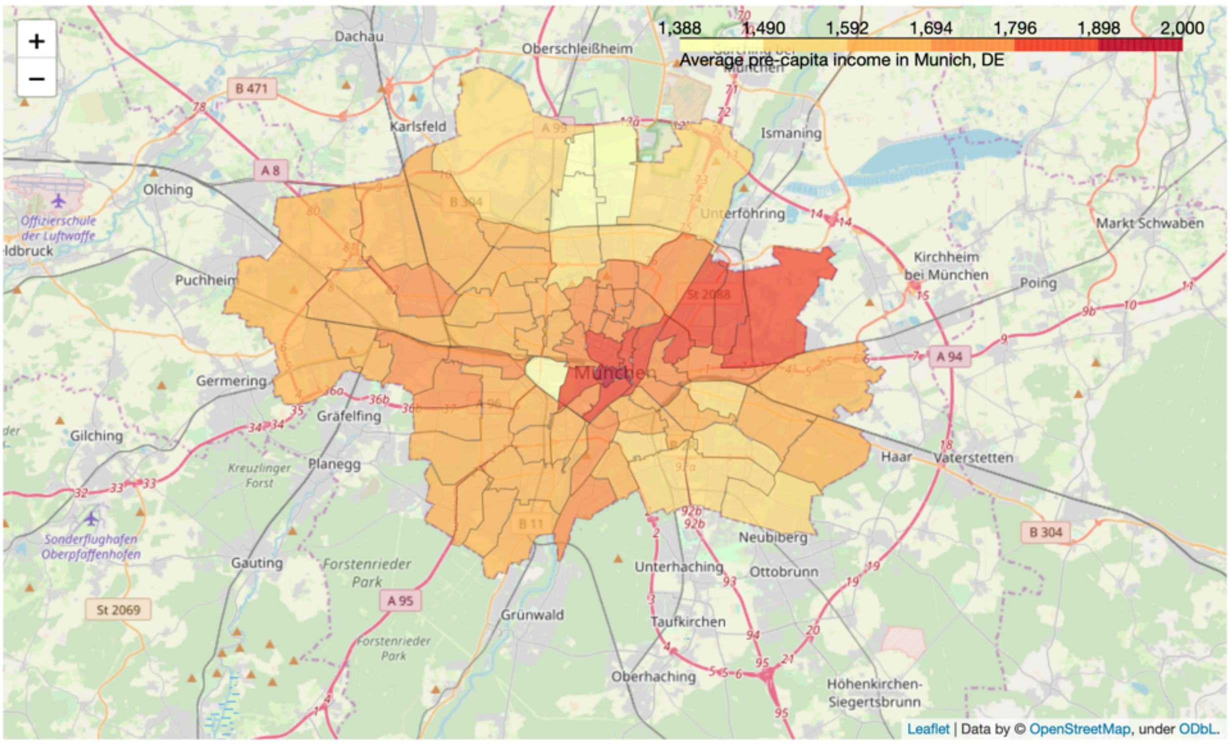

Figure 5 Average pre-capita income in Munich by neighboroughs

Foursquare APIs were used to find venues in the neighborhoods. The top 100 venues within a radius of 4 km from the neighborhood centroid were considered. The resulting venues were filtered using the returned address, to ensure accuracy of the selection also in the smallest neighborhoods in the city center.

1457 venues were retrieved from the Foursquare database and the top 10 most frequent venues (MFV) for each neighborhood were identified. In addition, the list of all the available restaurants was extracted. The resulting data set presented in Figure 6 shows that '*Italian Restaurant*' is the second most frequent venue category in Munich.

From Figure 7 it can be observed that the there are few areas with very high concentration of restaurants. The distribution does not follow specific patterns. It can be observed that the concentration of restaurants does not correlate with the resident density. Indeed, Trudering-Riem (81829) and Bogenhausen (81925) report a density within the lowest 25th percentile but are within the upper percentile for number of Italian restaurants. Normalizing the values by the number of habitants in the age of interest (adults from 28 to 64 years old), only Altstadt-Lehel (80331) remains in the upper 75^{th} percentile, confirming the market saturation in the area.

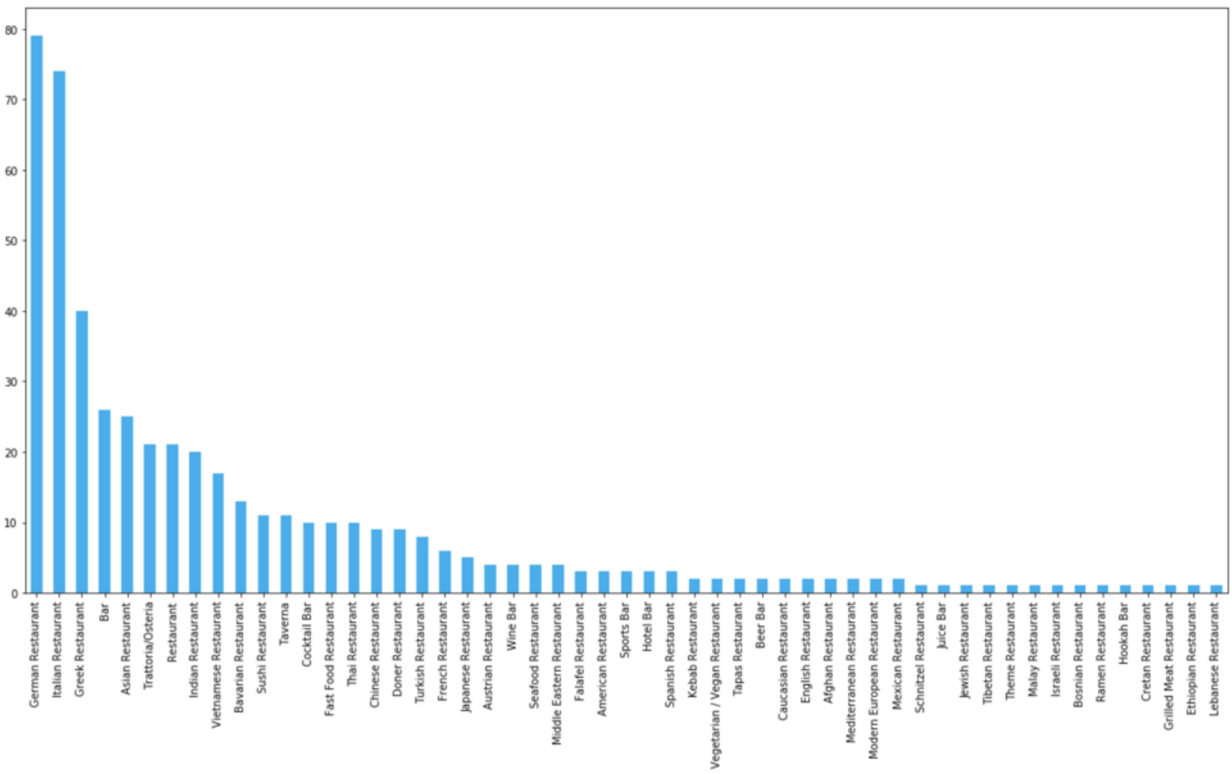

Figure 6 Number of restaurants per category in Munich. Source: Foursquare

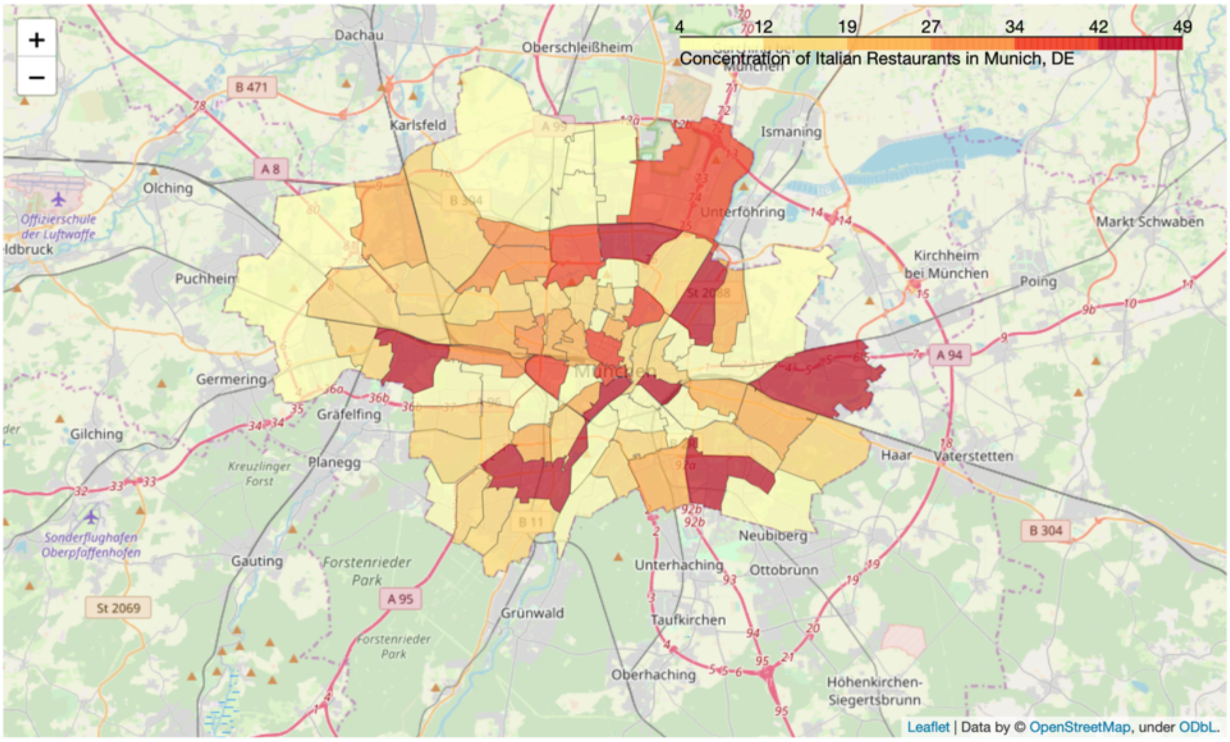

Figure 7 Italian restaurants in Munich

Clustering

To identify patterns that support a classification of the neighborhoods, a multivariate statistical technique (Sekaran & Bougie, 2013, p. 305) was used to consider relationships among the 20 features selected. The k-means clustering algorithm (MacQueen, 1967, p. 281-297) was selected to partition observations into *k* clusters, with an unsupervised algorithm.

The optimal number of clusters was selected with the '*elbow*' method (Ketchen & Shook, 1996), considering the within-cluster sum of squares. The result, presented in Figure 8, shows that the optimal number of clusters is 4.

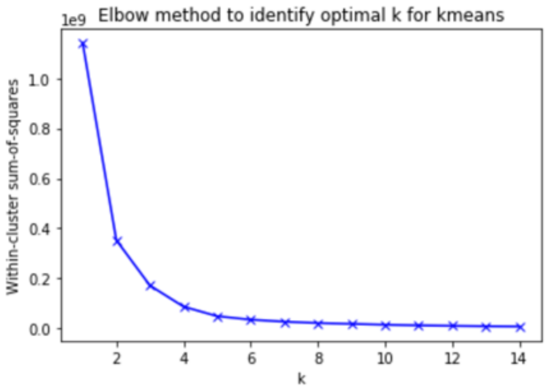

Figure 8 Elbow method to identify optimal number of clusters using K-Means algorithm

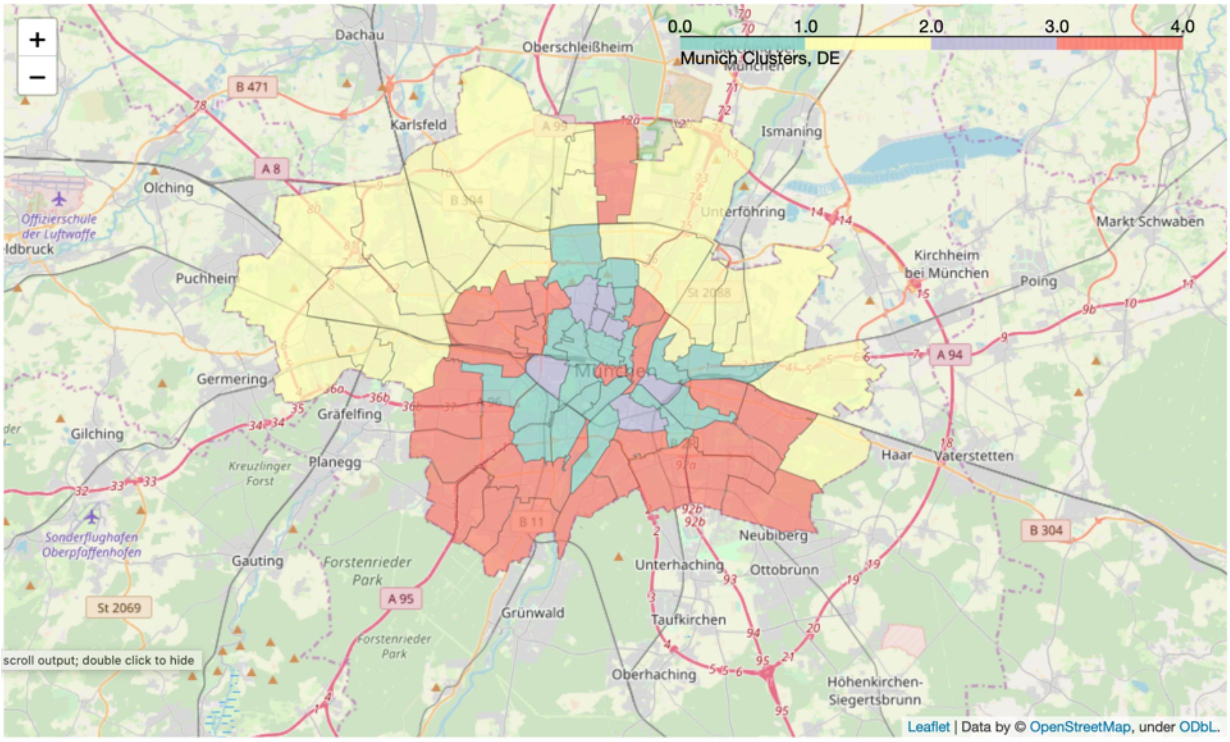

Figure 9 Result of the k-means clustering of neighborhoods in Munich

The result is displayed in Figure 9. The clusters identified can be described as follow:

Cluster 0: High income. Number of 1 household larger than any other cluster. Very high resident density.

This cluster is characterized by high income and high concentration of 1 household. The density of residents is also very high.

Cluster 1: Mid income. High concentration of families and foreigners. Fast food and dining services exceed restaurants.

Fast foods and dining services exceed restaurants. That suggests the presence of a customer base that prefers drive-thru and carry-out restaurants. The data suggests also high presence of families. The density of the population for km^2 is in mid-lower range (25-50 quantile). The average income is in a low-mid range (25 to 50 quantile). High concentration of bus stops suggests a population that need quick access to cheap transportation.

Cluster 2: Very high density. Mid Income. Very high concentration of restaurants.

The cluster is characterized by very high residents' density. Income are in the mid-range. The concentration of restaurants is very high.

Cluster 3: Highest concentration of foreigners. Mid-high income. Mid density. Large offer for restaurants also foreign ones.

The cluster is characterized by the highest concentration of foreigners. Income are in the mid-high range. Residents density is in the mid-range. There is a large offer for restaurants also of foreign cuisines.

Recommendations

To select locations that guarantee competitive advantage, the neighborhoods were scored considering the following criteria:

- Alignment between business idea and neighborhood environment;
- Alignment of internal differentiating business capabilities with right market position;
- Degree of rivalry in the neighborhood.

It resulted that the clusters labeled with 0, 2, and 3 were the most suitable for the service subject of this study. Neighborhoods in such clusters host residents with high-end income and consistent adult population in the age of interest.

Cluster 1 groups neighborhoods in which fast foods and dining services exceed restaurants. That suggests the presence of a customer base that prefers drive-thru and carry-out services. The density of the population per km^2 is in mid-lower range (25^{th} -50^{th} percentile). The average pre-capita income is also in a low-mid range (25^{th} -50^{th} percentile), confirmed by high presence of bus stops. Indeed, public bus routes attract low-income residents because they offer an affordable means of transportation, according to (Miller, 2018). The characteristic of the cluster suggests low potential for fine dining services. Due to the low match with the business subject of this study, neighborhoods in that cluster were excluded.

Score	Feature	Weight	Reason
Demographic Score	Age_28_44	5	People in that age range, have the highest pre-capita spending in restaurants
	Age_45_64	5	
	1HH	5	One and two households have the highest pre-capita spending in restaurants
	2HH_Adults	5	
	3HH_Adults	4	Families with adult children have a moderate spending in restaurants.
	4HH_Adults	3	
	5HH_Adults	2	
Income Score	Income	5	People with high income tend to spend more in restaurants than those with a lower one

Figure 10 Neighborhood score and feature selected with corresponding weight

The remaining neighborhoods were scored in a range 1 (low) to 5 (high), along the dimensions of demographics and pre-capita income, weighting features – normalized using a min-max scaler – as shown Figure 10. The weights express the relative importance of the feature for the business under analysis.

It should be considered that the degree of rivalry in the cluster 2 is the greatest one, as different categories of restaurants appear as top 3 most frequent venues. The population density is also 50% higher than the one in the other clusters, while the pre-capita income is in the mid-range.

The degree of rivalry was scored considering the culinary trends. According to a study of Civey (2018) presented in Figure 11, the Italian cuisine is the most favorite one in Germany, preferred by the 33,8% of the population, followed by German (30.10%), Thai/Vietnamese (8.3%), Greek (6.9%), Chinese (4.7%), and Japanese (2.8%) ones. The study also shows that the trend is quite stable across different age groups.

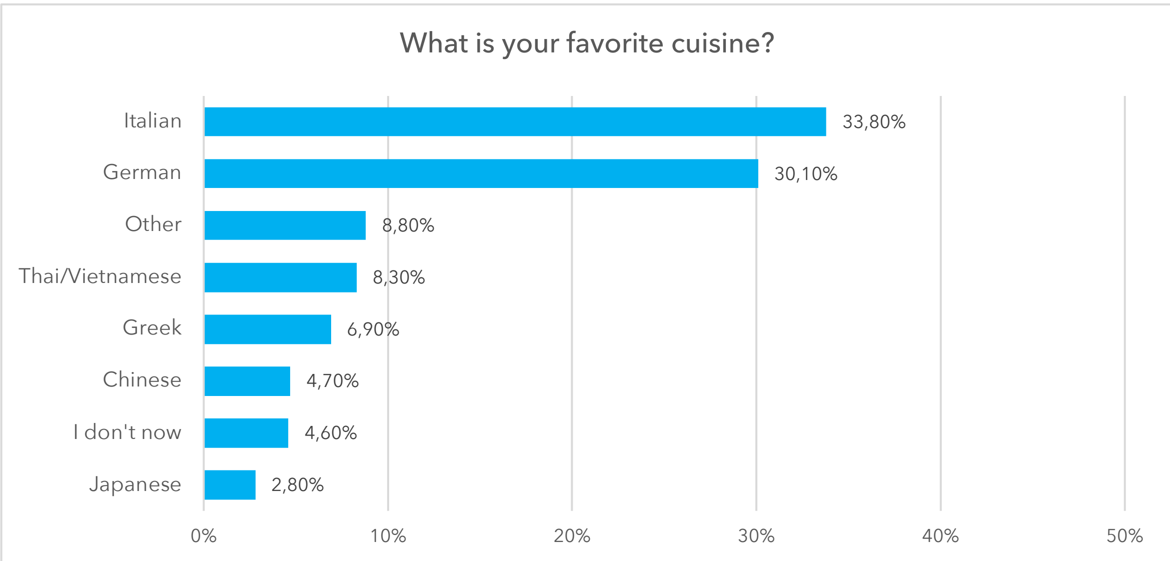

Figure 11 Preferred cuisine in Germany. Source: (Civey, 2018)

Group	Venues Category	Weight
Italian Restaurants	Italian Restaurant, Trattoria/Osteria	5
German Restaurants	Austrian Restaurant, Bavarian Restaurant, Beer Bar, German Restaurant, Schnitzel Restaurant	4
Asian Restaurants	Asian Restaurant, Chinese Restaurant, Japanese Restaurant, Sushi Restaurant, Thai Restaurant, Vietnamese Restaurant	4
Greek Restaurants	Cretan Restaurant, Greek Restaurant, Taverna	3
Others		3

Figure 12 Restaurants groups and related weight for the calculation of the rivalry score

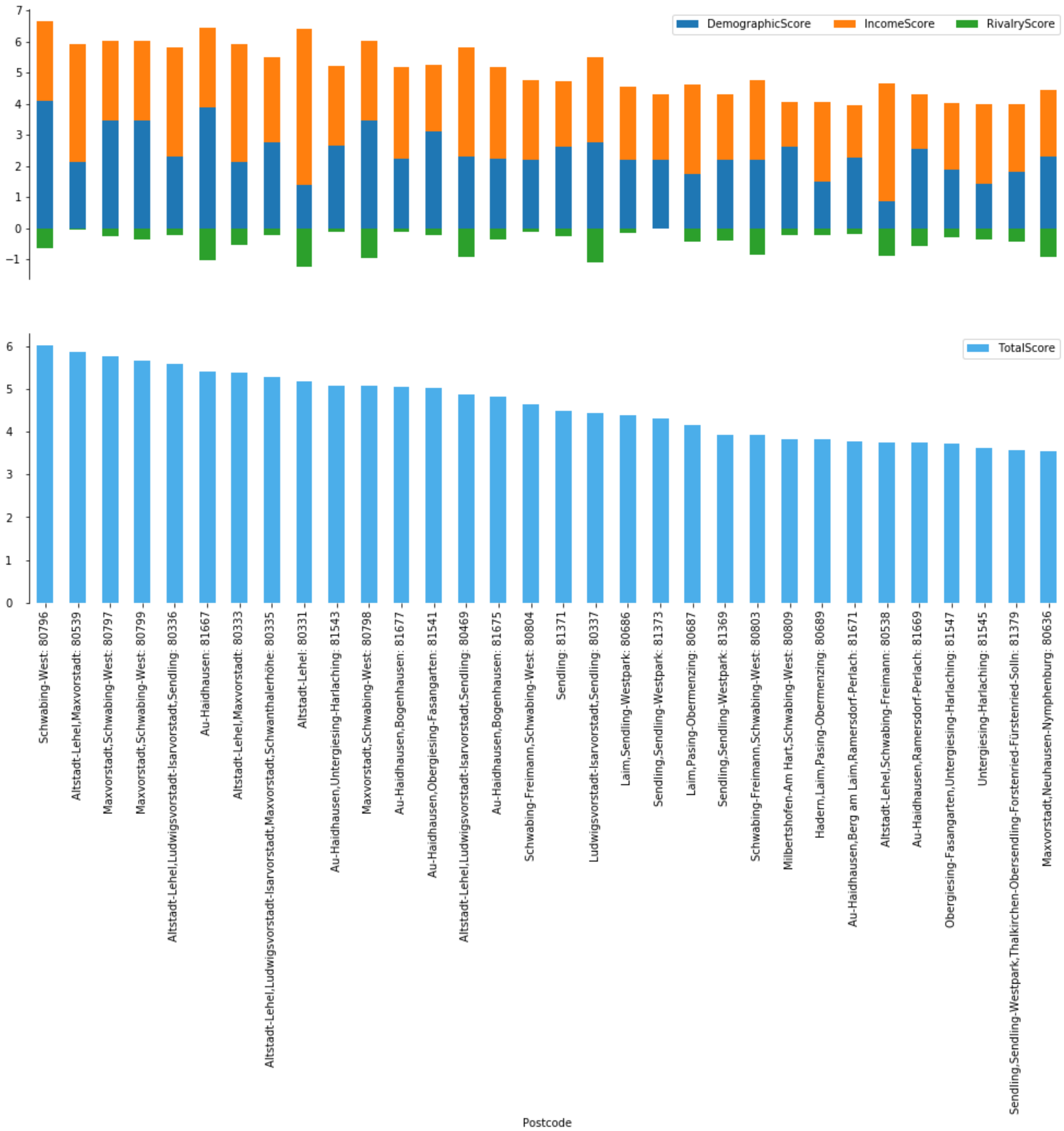

Figure 13 Score of the neighborhoods with total score greater than 3.5

The venues were classified in five groups considering the top four most preferred cuisine, as presented in Figure 12. Culinary trends are weighted using their position in Figure 11. Thai/Vietnamese, Chinese, and Japanese cuisines are aggregated in a single category, as sometime venues returned by Foursquare cannot be uniquely assigned. The score resulted in the weighted average of the frequency of the restaurants per category normalized with a min-max scaler.

Figure 13 presents the final score of the neighborhoods, computed as sum of the above-mentioned scores. Given the above evidences, it is recommended to select locations scoring 5.0 or more, as shown in

Postcode	Cluster	Borough	Demog.	Income	Rivalry	Total
80796	2	Schwabing-West	4.09	2.55	-0.62	6.02
80539	0	Altstadt-Lehel,Maxvorstadt	2.13	3.77	-0.04	5.87
80797	2	Maxvorstadt,Schwabing-West	3.47	2.55	-0.25	5.77
80799	2	Maxvorstadt,Schwabing-West	3.47	2.55	-0.35	5.67
80336	0	Altstadt-Lehel,Ludwigsvorstadt-Isarvorstadt,Sendling	2.32	3.49	-0.21	5.60
81667	2	Au-Haidhausen	3.88	2.55	-1.02	5.41
80333	0	Altstadt-Lehel,Maxvorstadt	2.13	3.77	-0.52	5.38
80335	0	Altstadt-Lehel,Ludwigsvorstadt-Isarvorstadt,Maxvorstadt,Schwanthalerhoehe	2.76	2.75	-0.22	5.29
80331	3	Altstadt-Lehel	1.40	5.00	-1.23	5.17
81543	0	Au-Haidhausen,Untergiesing-Harlaching	2.66	2.55	-0.12	5.09
80798	2	Maxvorstadt,Schwabing-West	3.47	2.55	-0.94	5.08
81677	0	Au-Haidhausen,Bogenhausen	2.23	2.96	-0.12	5.07
81541	2	Au-Haidhausen,Obergiesing-Fasangarten	3.10	2.14	-0.21	5.02

Figure 14, in order to have a strong match with the market positioning of the service in scope of this paper. A minimum score of 5.2 should be preferred.

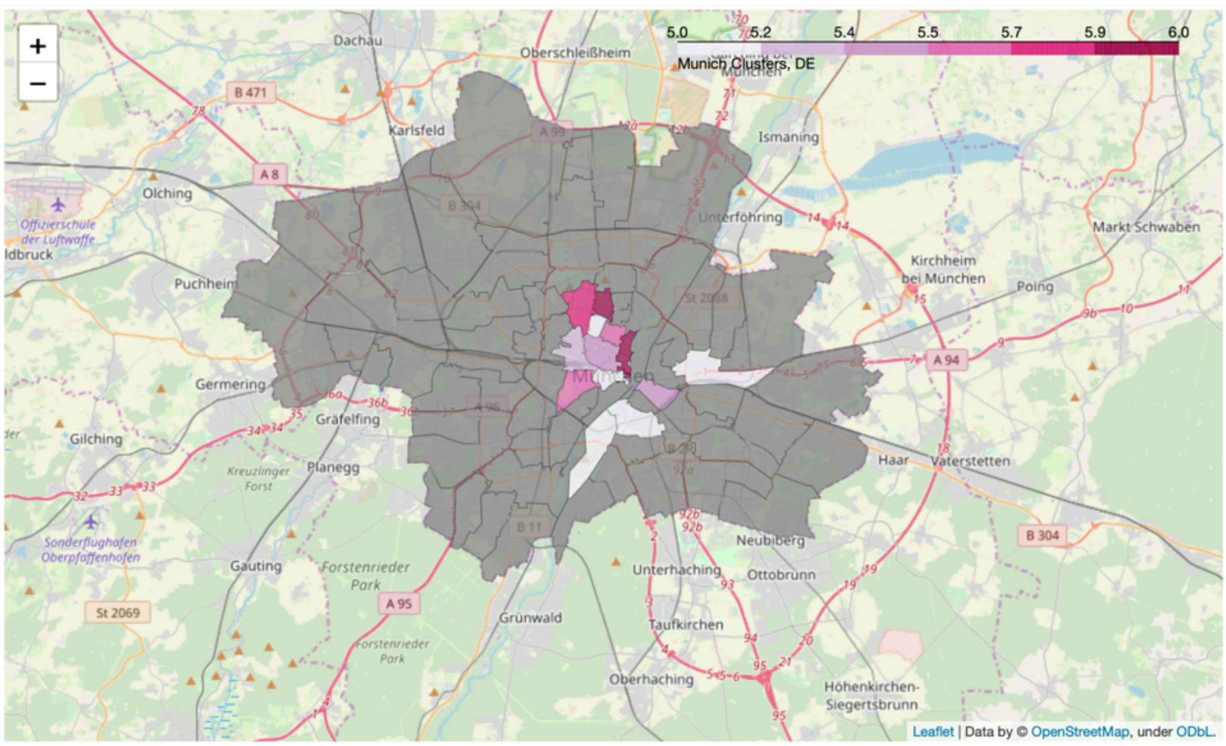

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Figure 14 Recommended neighborhoods and related scores

Conclusion

This study analyzed the neighborhoods in Munich and provided a scoring model for the selection of a location for an Italian fine dining service. The initial screening was performed using an unsupervised machine learning algorithm to identify residents' behavioral pattern. The model can be used by managers to take informed decisions about restaurant locations. The model developed for an Italian fine dining service, can be generalized, modifying the weighting scores according to the business marketing positioning strategy.

The analysis could also be refined using multiple location data providers to broaden the set of venues. The scoring model can be refined including commercial real estate parameters, like rental costs. Finally, the analysis can be repeated considering demographic growth predictions, as the ones provided in (Landeshauptstadt München, 2019b).

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