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9th International Scientific Symposium REGION ENTREPRENEURSHIP DEVELOPMENT





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A scientific paper

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USING LOCATION-BASED SOCIAL NETWORKS FOR OPTIMAL PLACEMENT OF TOURIST FACILITIES: ZAGREB CASE STUDY

ABSTRACT

In the last decade, the advance of services and social networks that can store location coordinates and ratings by visitors has had a significant impact on how potential visitors choose their visit destination. The destination can be a landmark, a city, a restaurant, a hotel, etc., and people visiting the destination can be tourists or locals. Also, the data from these services can be used to analyse the location before potential investment in the tourist facility by an investor. Clustering unsupervised machine learning algorithms can be used for that analysis, combining individual municipalities of a city into clusters that have similar properties, making potential investors informed about municipality's properties.

In this paper, the main goal is to propose an optimal placement model based on the available information. A prerequisite for this is the analysis of location-based service that can be used to make decisions about the location of a restaurant or bar, and the amount of information available at these service for the city of Zagreb. The proposed model is based on a k-means algorithm that belongs to unsupervised machine learning algorithms.

The result of the analysis is the list of municipalities in the city of Zagreb divided into clusters with similar properties. The municipalities are divided into six clusters and that division brings objective knowledge to the potential investor. These results can be used as a basis for decision-making or as a test of expert recommendation. The proposed model can be used for other purposes, depending on the area of interest and the amount of data available on the service.

Key words: big data, tourist facility, LBSN, foursquare.

1. Introduction

In 2010, about 300 million smartphones were sold. Since 2015, sales have stopped growing, amounting to about one billion and a half smartphones a year (Holst, 2019). One of the essential components of smartphones is the satellite navigation module. This module uses satellites to provide geospatial positioning and make this information available to a smartphone (longitude, latitude, and altitude). Precision can be from a few centimetres to meters. The most popular and the oldest navigation satellite system is the Global Positioning System (GPS) made and

operated by the United States of America. Its development started in the 1970s and the system was fully operational in 1990s. The Global'naya Navigatsionnaya Sputnikova Sistema (GLONASS) is developed by Russian Federation and it can be used today, as well as the European global navigation satellite system Galileo (Teunissen & Montenbruck, 2017, VII). Chinese global navigation system BeiDou is still in the development phase (Yang, et al., 2019, 7).

Smartphones use one or more satellite navigation systems, which gives them a whole new set of functionality. With the use of data communication with the Internet, satellite navigation can serve to accurately locate users at any time. This capability has enabled the development of a range of services, and among other things have emerged social networks that use users locations. The first ideas about this service came out at the beginning of the century, and the authors recognized the huge potential of social networking and satellite navigation. Goel proposed in 2001 that real-time interactivity between wireless networks and Global Position System have big potential. The author proposed the tool with three-layer structure and these layers are: Personal Filtering, Information Layering and Social Networking (Goel, 2001). Three years later Melinger et al. proposed the first mobile social network called Socialight. It was in the development stage and included the location-based messaging system and other social network features (Melinger, et al., 2004, 1). By the end of the first decade of this century, location-based social networks became widespread. Long et al. published a paper about a first globally popular location-based social network called *Foursquare* and they analysed the reasons for its popularity (Long, et al., 2013, 3362).

In this paper data from location-based social networks will be used for Zagreb municipalities clustering for selection optimal placement of tourist facility. Zagreb is the capital city of Croatia, an European Union country. In the second section of the paper, location-based social networks will be explained. In the third section, unsupervised machine learning algorithms that will be used for clustering will be explained. The fourth section includes data, methodology and results. Finally, discussion and conclusion are in the fifth and sixth section.

2. Location-based social networks

Gordon and Silva defined Location-Based Social Networks (LBSN) as social network sites that include location information into shared contents (Gordon & Silva, 2011, 11). The first Location-Based Social Network was Dodgeball that allows members to send their location with SMS but it has been acquired and discontinued by Google (Krishnamurthy & Pelechrinis, 2013, 132). Location-Based Social Networks usually have two types of location information:

- a) continuous trajectory,
- b) discrete locations.

When LBSN records user continuous trajectory then members of a social network who are allowed can access the location of a user any time. The approach that uses discrete locations is usually controlled by users. When a user decides, he or she can check-in on some interesting location and share this location with other members. Both types of location recording approach have advantages and disadvantages. Discrete location approach has more contextual information but continuous trajectories have more information about the movement. Generally, the check-in concept is used more often than continuous trajectory concept and the check-in concept produces more valuable information (Krishnamurthy & Pelechrinis, 2013, 130).

As mentioned in the Introduction, growth in Location-Based Social Networks usage has been fuelled by the growth of smartphone with a satellite navigation module purchases. LBSN service is most commonly used by users as an app on a smartphone.

Krishnamurthy & Pelechrinis proposed four categories of Location-Based Social Networks:

- a) Location Sharing Services
- b) Location Guides
- c) Business-Oriented LBSNs
- d) Gaming-Oriented LBSNs (Krishnamurthy & Pelechrinis, 2013, 132).

Location Sharing Services category is the simplest and these services came first because of their simplicity. The primary objective of these services is to allow other users to know the real-time location of an active user who shares his/her location. The earliest LBSN belonged to that category.

Location guides category services are more advanced than Location Sharing Services and its primary purpose is to store and share interesting locations. An example from that category is Gowalla, LBSN that was able to provide interest places based on the opinions of other members. Gowalla was acquired by Facebook in 2011 after four years of existence but it has been shut down.

We can say that Business-Oriented LBSNs category is different because their founders had a viable business model from the beginning. LBSNs from that category used the opportunity to exploit collected information about venues to enhancing commerce at such venues. There are lots of such LBSNs and some of them are Foursquare, Yelp and Shopkick. Research in this paper is based on Foursquare LBSN so it will be described in detail. In China there are different LBSNs from Business-Oriented category and of them is Jiepang that is called "Chinese Foursquare" (Chiang, 2012).

The last category that was proposed by Krishnamurthy & Pelechrinis was Gaming-Oriented LBSNs. The authors state that services from that category usually provide smartphone application that is a platform for gaming, location sharing and advertising. Frith analysed games implemented in the Foursquare platform and concluded that some users render locations as digital objects that have to be collected (Krishnamurthy & Pelechrinis, 2013, 133) (Frith, 2013, 249).

2.1. Foursquare

Foursquare Labs Inc. is an American company with headquarter in New York City. It was launched in 2009 but it takes almost a decade for them to start making a profit (Miller, 2017). Co-founders are Dennis Crowley and Naveen Selvadurai. Crowley built the experience on a similar LBSN called Dodgeball that has been sold to Google in 2005 (Gonsalves, 2005).

Their LBSN services can be accessed with different applications and tools. They started with the concept of real-time location sharing and primary store discrete locations with data that users collected on these locations. Their first application for a smartphone was named simply *Foursquare* and it enabled users to share their locations complemented with comments and pictures, with friends. Users could do this on the web or SMS service but the main idea is to do it with a smartphone.

In 2014 Foursquare Labs Inc. launched another application called *Swarm* that included location sharing and social networking. The same year they upgraded main application *Foursquare*, changed its name to *Foursquare City Guide* and removed location sharing and social networking from it. The screens of both can be seen in figure 1 (Summers, 2014).

One of the main features that are available from Foursquare services is the *Places API*. It is a service primarily intended for developers and analysts that can be queried about any place using an HTTP request. It can be used for free but for larger query volumes users have to pay this service. Key features are:

- a) "real-time access to over 105 million places available across 190 countries,
- b) use custom API endpoints to power geo-tagging, venue search and recommendations,
- c) leverage 70+ venue attributes and 900+ categories and
- d) create location experiences with access to user-generated tips, tastes & photos."

It has been used for research in this paper (Foursquare Labs Inc., n.d.).

Coffee & Tea

Near me

E FILTERS

PRICE O OPEN NOW

Zagrebat-a katodrole

prelointuth veza

Zagrebat-a katodrole

Windowski Search this area

Antwolasia

Ifficure in Zagrebat

Antwolasia

Ifficure in Zagrebat

Nothing to See Here

Looks like you don't have any places here. Try a different perspective in another part of the map.

Saved

Saved

Saved

Saved

Figure 1: Foursquare City Guide and Swarm screens on the Android platform

Source: authors

3. Unsupervised machine learning algorithms

Unsupervised machine learning deals with problems where the data is not labelled. Algorithms from that machine learning category simply find similar data points in multi-dimensional space and put them in clusters. Mohammed et al. consider that most important unsupervised machine learning algorithms are:

- a) K-means
- b) Hidden Markov model
- c) Principal component analysis

d) Gaussian mixture model (Mohammed, et al., 2016, 140)

In this paper, the K-means algorithm is used.

K-means algorithm is a well known unsupervised machine learning algorithm proposed by Steinhaus in 1956. (Steinhaus, 1956). The main principle of that algorithm is the principle of least squares. It can be simply explained as grouping data on a finite number of groups with the goal that the sum of the squared deviation of group members from the centre of the group is minimized. It can be defined as:

$$WCSS = \sum_{c_i \in C} \sum_{j=1...d} \sum_{x,y \in c_i} (x_{ij} - y_{ij})^2$$

where WCSS is the abbreviation for a within-cluster sum of squares and the main goal is to minimize it (Kriegel, et al., 2017, 12). This method is an iterative method and it starts with random positions of cluster centres. In each iteration, the central point is updated and it depends on cluster members. Because of a random selection of initial k-means, after every optimisation, we can get different clusters (Mohammed, et al., 2016, 129).

K-means algorithm is often used in scientific papers that deal with data from Location-Based Social Networks. Yang et al. used the k-means algorithm to cluster LBSN users and they propose a cultural mapping approach based on the data from LBSNs (Yang, et al., 2016). Modsching et al. used k-means algorithm to discover tourists activity areas and they found that twenty clusters are the optimal number in their research in the city of Gorlitz in Germany (Modsching, et al., 2008). Claypo and Jaiyen used k-means algorithm for clustering of customer opinions for Thain restaurants into positive and negative groups. They used about one thousand text reviews from website th.tripadvisor.com (Claypo & Jaiyen, 2015). Isanan used k-means algorithm to retrieve restaurant category data on the Philippines and he used data from Foursquare and Google services (Isanan, 2019). In this paper, k-means algorithm implementation from the scikit-learn library is used (Scikit-Learn community, 2020).

4. Zagreb case study

4.1. Data and methodology

Zagreb is the capital city of Republic Croatia and official 2011 census counted almost 800000 residents. In 2011, the city of Zagreb has about 600 000 tourist arrivals but only six years later this number was more than doubled. In 2017 tourist arrivals number was more than 1,3 million (Kesar, et al., 2018, 192). This is recognised by global and regional restaurant and fast food corporations, like Subway and Lars&Sven, and they have opened or announced the opening of their restaurants and fast food outlets (teen385.com, 2019) (Punkufer.hr, 2019).

Table 1: Zagreb municipalities with the area and population data

	Municipalities	Area (km²)	Population (2011)	Population (2001)	Population density (2001)
1.	Donji Grad	3.01	37,123	45,108	14,956.2
2.	Gornji Grad – Medveščak	10.12	31,279	36,384	3,593.5
3.	Trnje	7.37	42,126	45,267	6,146.2

	Municipalities	Area (km²)	Population (2011)	Population (2001)	Population density (2001)
4.	Maksimir	14.35	49,448	49,750	3,467.1
5.	Peščenica – Žitnjak	35.30	56,446	58,283	1,651.3
6.	Novi Zagreb – istok	16.54	59,227	65,301	3,947.1
7.	Novi Zagreb – zapad	62.59	58,025	48,981	782.5
8.	Trešnjevka – sjever	5.83	55,342	55,358	9,498.6
9.	Trešnjevka – jug	9.84	66,595	67,162	6,828.1
10.	Črnomerec	24.33	39,040	38,762	1,593.4
11.	Gornja Dubrava	40.28	62,221	61,388	1,524.1
12.	Donja Dubrava	10.82	36,461	35,944	3,321.1
13.	Stenjevec	12.18	51,849	41,257	3,387.3
14.	Podsused – Vrapče	36.05	45,771	42,360	1,175.1
15.	Podsljeme	60.11	19,249	17,744	295.2
16.	Sesvete	165.26	70,633	59,212	358.3
17.	Brezovica	127.45	12,040	10,884	85.4
	TOTAL	641.43	792,875	779,145	1,214.9

Source: Croatian Bureau of Statistics, 2011; Croatian Bureau of Statistics, 2001

One of the most important factors for the success of fast food outlets or restaurant is its location. The main goal of this paper is to provide a method for municipalities clustering in Zagreb that is based on available data on Foursquare LBSN and k-means algorithm. This method is well-known before tourist facility location selection but Zagreb's special feature is the low availability of quantitative data on which decision can be made. Some cities have much more quantitative data available on the government web sites and the good example is Hong Kong with their annually Population and Household Statistics Analysed by District (The Government of the Hong Kong Special Administrative Region, 2019).

The city of Zagreb is divided into seventeen municipalities and they are listed in the table number one. On figure 2, there is a satellite picture with municipalities borders and it can be seen that there are many differences between municipalities in size, position etc.



Figure 2: Zagreb satellite picture with municipalities borders

Source: authors

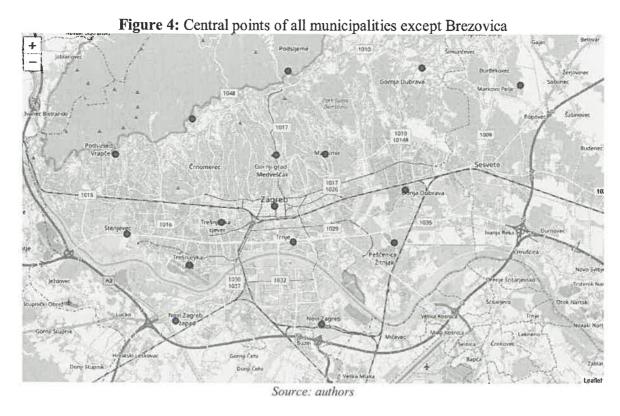
To analyse municipalities in Zagreb, Foursquare API is used (Foursquare Inc., n.d.). Their API enables search for locations based on longitude, latitude, and radius. Due to incomplete information entered into the Foursquare database, the municipality of a particular location is not known. This problem is solved in such a way that each municipality is defined as a polynomial and the polynomial points are stored in files. After that central point of every municipality has been found and this information was used for Foursquare queries. On figure 3, an example of one municipality polygon definition can be seen.

Figure 3: Municipality polygon example

1-	it Switch View Encoding Language
• =	86 196 196 PC
105.ca	·a
1	LAT, LONG
2	15.999311,45.811528
3	16.017087,45.796825
4	16.000323,45.795839
5	16.002607,45.783964
5	16.053774,45.757968
7	16.104917,45.790154
8	16.124535,45.787782
9	16.124879,45.801496
10	16.046467,45.799993
11	16.046321,45.817971
12	

Source: authors

Central points of all municipalities except Brezovica can be seen in figure 4. Brezovica is a big municipality on southwest that cannot be seen without zoom out. This municipality can be seen along the bottom edge of figure 2.



1084 venues were obtained after the data was withdrawn for all 17 municipalities. After withdrawing, the data were prepared for the k-means algorithm but one of the common questions when using the k-means algorithm is how many clusters we want. There are many methods for that decision available in the literature but we tried with all values between 2 and 10 clusters. Results can be seen in table number 2.

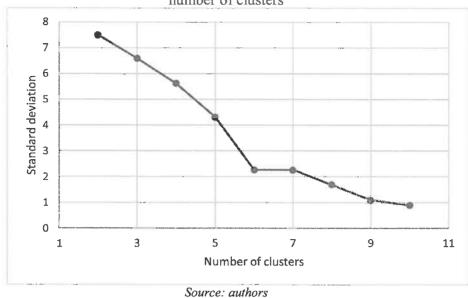
Table 2: Number of municipalities in one cluster

Number of clusters			Nu	mber of	municip	alities in	one clus	ter		
1	17									
2	16	1								
3	15]	1							
4	14	1	1	1						
5	12	2	1	1	1					
6	6	6	2	1	1	1				
7	6	6	1	1	1	1	1			
8	5	5	2	1	1	1	1	1		
9	4	3	3	2	1	1	1	1	1	
10	4	2	2	2	2	1	1	1	r	1

Source: authors

When this data is presented graphically in a way to calculate the standard deviation of the municipality number, we get the graph in figure 5.

Figure 5: The standard deviation of the number of municipalities in a cluster depends on the number of clusters



It is interesting that with six clusters there is a sharp drop in standard deviation so six clusters have been chosen. The whole program in Python can be seen on the Github: https://github.com/kristian1971/RED2020 Zagrebstory.

4.2. Results

On figure 6, sixteen central points of six clusters can be seen but in different colours depends on cluster affiliation of the municipality.

Figure 6: Central points of all municipalities (except Brezovica) divided into six clusters



Source: authors

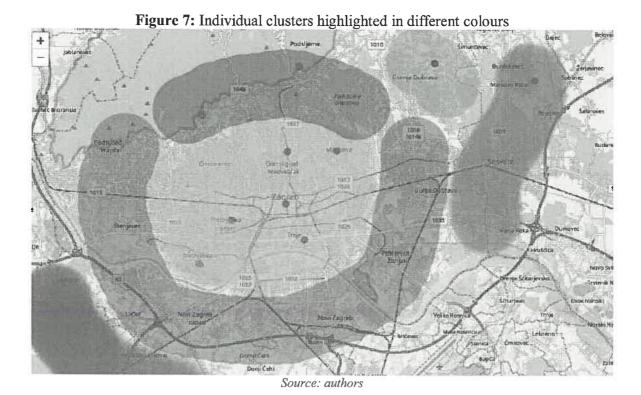
In table number 3 cluster affiliation of all municipalities can be seen, as well as ten the most common venues in a particular municipality.

Table 3: Ten most common venues for all municipalities

	N. 6	Class		2-4	2.4	444	Eth.	6th	7th	941.	9th	10th
	Municipali ty	Clus	1st MCV	2nd MCV	3rd MCV	4th MCV	5th MCV	MCV	MCV	8th MCV	MCV	MCV
10	Gornja Dubrava	0	Pizza Place	Grocer y Store	Forest	Park	Middle Eastern Rest	Diner	Dessert Shop	Dog Run	Drugst øre	Food
0	Donji grad	1	Café	Plaza	Restaur ant	Bar	Dessert Shop	Hostel	Theatre	Histori c Site	Coffee Shop	Burger Joint
1	Gornji grad	1	Café	Dessert Shop	Ваг	Plaza	Medite rranean Rest	Park	Pub	Theatre	Hostel	Bistro
2	Trnje	i	Café	Bar	Restaur ant	Plaza	Hotel	Pizza Place	BBQ Joint	Coffee Shop	Eastern Europe an Rest	Dessert Shop
3	Maksimir	1	Café	Bar	Dessert Shop	BBQ Joint	Pizza Place	Theatre	Park	Restaur ant	Wine Bar	Bakery
7	Tresnjevka - sjever	1	Café	Bar	BBQ Joint	Plaza	Restaur ant	Mediter ranean Rest	Dessert Shop	Burger Joint	Gym	Park
8	Tresnjevka - jug	1	Bar	Café	BBQ Joint	Pizza Place	Gym	Dessert Shop	Eastern Europe an Rest	Superm arket	Pub	Restaur ant
15	Sesvete	2	Restaur	Café	Wine Bar	Farm	Flea Market	Fish Market	Field	Fast Food Rest	Farmer S Market	Electro nies Store
_												
	Note:			Esc. 181		l and	C Mine			Market N		
4	Pescenica	4	Superm arket	Furnitu re/ Home	Restaur	Café	Bar	Bakery			Plaza	Chines
4 5		4	THE RESERVE OF THE PARTY OF THE	Furnitu re/			THE ST	Bakery Pizza Place	Grocer	Bus		Chines e Restaur ant
	Pescenica Novi Zagreb- Istok Novi Zagreb-		arket	Furnitu re/ Home Store	ant	Café	Bar	Pizza	Grocer y Store Restaur	Bus Station Wine	Plaza	Chines e Restaur ant Coffee Shop
5	Pescenica Novi Zagreb- Istok Novi	4	arket Café	Furnitu re/ Home Store Superm arket	Bar	Café Grocer y Store Pizza	Bar Pet Store Restaur	Pizza Place Nightel	Grocer y Store Restaur ant Shoppi	Bus Station Wine Bar	Plaza Shoppi ng Mall BBQ	Chines e Restaur ant Coffee Shop Dessert Shop
5	Pescenica Novi Zagreb- Istok Novi Zagreb- Zapad Donja	4	Café Café	Furnitu re/ Home Store Superm arket Superm arket	Bar Bar	Café Grecer y Store Pizza Place	Bar Pet Store Restaur ant Grocer	Pizza Place Nightel ub	Grocer y Store Restaur ant Shoppi ng Mall	Bus Station Wine Bar Beach Restaur ant Superm arket	Plaza Shoppi ng Mall BBQ Joint Shoppi	Chines e Restaur ant Coffee Shop Desserr Shop Furniture/ Home
5 6	Pescenica Novi Zagreb- Istok Novi Zagreb- Zapad Donja Dubrava	4 4	Café Café Café	Furnitu re/ Home Store Superm arket Superm arket Superm arket BBQ	Bar Bar	Café Grecer y Store Pizza Place Pizza Place	Bar Pet Store Restaur ant Grocer y Store Grocer	Pizza Place Nightel ub Clothin g Store Fast Food	Grocer y Store Restaur ant Shoppi ng Mall BBQ Joint Eastern Europe	Bus Station Wine Bar Beach Restaur ant	Plaza Shoppi ng Mall BBQ Joint Shoppi ng Mall Electro	Chines e Restaur ant Coffee Shop Dessert Shop Furnitu re/ Home Store Pub
5 6 111	Pescenica Novi Zagreb- Istok Novi Zagreb- Zapad Donja Dubrava Stenjevec	4 4	Café Café Café Café	Furnitu re/ Home Store Superm arket Superm arket Superm arket BBQ Joint	Bar Bar Bar Grocer	Cafe Grecer y Store Pizza Place Pizza Place Pizza Place Superm	Pet Store Restaur ant Grocer y Store Grocer y Store	Pizza Place Nightel ub Clothin g Store Fast Food Rest	Grocer y Store Restaur ant Shoppi ng Mall BBQ Joint Eastern Europe an Rest Restaur	Bus Station Wine Bar Beach Restaur ant Superm arket Mediter ranean Restaur	Plaza Shoppi ng Mall BBQ Joint Shoppi ng Mall Electro nics Store Pizza	Chines e Restaur ant Coffee Shop Dessert Shop Furnitu re/ Home Store Pub

Source: authors

On figure 7 individual clusters highlighted in different colours can be seen.



5. Discussion

Many authors used k-means or another clustering algorithm for urban municipalities analyse. Assem et al. used it to discover spatiotemporal functional regions in one Ney York City district (Assem, et al., 2016). Sun et al. proposed method for the city centres detection with the LGOG cluster method using LBNS data (Sun, et al., 2016). Hong and Jung proposed analytical method of cluster analysis for Foursquare data. They conclude that a qualitative approach for fully interpreting and analysing is important. Objects of their analyse were coffee shops in Seattle (Hong & Jung, 2017).

Our approach was a little bit different because we have started with municipalities and defined central points of every municipality. After that Foursquare service was queried and k-means cluster analyse has been performed on that data. Similar municipalities have been put in the same clusters and we have performed analyse with a different number of clusters.

In the literature three main methods for determining the optimal number of clusters have been suggested: silhouette, elbow and gap statistic methods (Krishna, et al., 2018, 301) (Kassambara, 2018). In this paper, we used the simplified method based on standard deviation values of cluster size and propose this method for such simple examples but this method has to be thoroughly compared with other methods.

Final results with six clusters can be seen in figure 7 and table number 3. The information in the table complements the figure and helps with interpretation. Figure 7 points the municipalities that are primarily intended for residential use and they belong to cluster number 4. Cluster number 1 shows that this is a downtown area dominated by café's, bars and restaurants. There are no supermarkets in that cluster between ten the most common venues in the municipality (only in one case). Other clusters are specific and are mostly municipalities on the outskirts of the city.

Finally, these results can be used by the potential investor because cluster division brings objective knowledge to a potential investor. These results can be used as a basis for decision-making or as a test of expert recommendation. The suggested approach is not new but the main contribution of the paper is in the proposed method that can be used on the occasions when we have low availability of quantitative data.

The proposed model can be compared with other models but it is not easy to compare our results with other papers because we couldn't find any published analyse that deals with Zagreb municipalities and clustering. Some organisations like Croatian Bureau of Statistics have quantitative data and they combined data from different sources but they do did not make these data publicly available. Before two years they merged administratively with spatial data from the Register of Business Entities with the Spatial Statistical Register (Croatian Bureau of Statistics, 2018). Posloncec-Petric et al. also published a paper in which they presented the project "GIS database of census districts according to the 2001 population census". This project includes a database with Registry of business units and spatial information. That database is primarily made for the Zagreb City Office for Strategic Planning and Development and it is not publicly available (Poslončec-Petrić, et al., 2011).

6. Conclusion

The paper indicates that it is possible to use just location-based social network data for basic clustering of city municipalities. The city of Zagreb is not as digitized as it could be by the city government but using the available data from the Foursquare service we can obtain usable objective knowledge. With such basic information, potential investors have a more accurate view of the characteristics and similarities of individual municipalities of the Zagreb city. It is very important for foreign investors that are not familiar with the specifics and structure of individual municipalities.

The presented approach can be improved in several aspects. More information from different sources can be included before clustering, like population density or average population income by municipalities. Another possibility of improvement is to include data from other location-aware services like Google Maps, Yelp or Instagram. Croatian Bureau of Statistics has much more accurate data divided by one square kilometre areas so that data can be also used to improve the model.

Finally, our government must recognize that it is in the general interest to make information about business entities and their density available on public services. The availability of this information may make our country more interesting to potential investors and enable our entrepreneurs to develop business based on new technologies.

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