Learning spatial inequalities: a clustering approach

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Abstract. *The rationality of transport as a distributive instrument of people and opportunities is recently discussed in transportation planning field. The measures of spatial inequalities could inform about transport provision and land use, featuring the opportunities to be accessed by specific groups. To meet the challenge of applying complementary methodological approaches to integrate information, this work aims at analysing spatial inequalities by using clustering analysis. Using such approach, it was possible to identify patterns of accessibility and income in São Paulo municipality through the years of 2000 and 2010. In 2010, a new group is formed in the inner-city border. In both years, there are distinguished conditions of accessibility on the city outskirts.*

1. Introduction

The role played by transportation planning in reinforcing poverty and social disadvantages evidence the need to incorporate analysis of social exclusion, equity and inequalities into the policymakers practice (Lucas, 2012). Recent research point out the importance of specifying objectives and measures regarding multiple dimensions of social equity and the different effects on distinguished individuals, groups, communities and regions (Manaugh et al., 2015). To point out some techniques to assess inequalities, current studies refer to, for instance, the Gini Index to evaluate the cumulative percentage of access of a specific group (Delbosc & Currie, 2011). In addition to this, new developments in the computational literature field present data mining techniques, which focus on knowledge extraction from large and complex datasets. This field encompasses a specific class of techniques, which deal with ideas of knowledge acquisition, namely Machine Learning (ML) techniques. They are useful to explore high dimensional data in order to: (i) identify and describe hidden patterns in the dataset with unsupervised learning and (ii) predict values of continuous and categorical variables with supervised learning.

In the transportation area, ML techniques are applied mainly to: (i) explore big data on traffic and transit (Fusco et al., 2016; Mahrsi et al., 2017); (ii) make prediction of travel model choice (Hagenauer & Helbich, 2017; Zhu et al., 2017) and travel time (Gal et al., 2014); (iii) quantify interdependence between land use and transport delivery (Hu et al., 2016). Therefore, most applications deal with high complexity data in order to better understand the object of study and extract knowledge from it.

Especially, unsupervised learning aims at identifying and describing groups, given the instances proximity in their features' space. Dimensionality reduction techniques are useful to identify relevant features before the application of ML algorithms. This procedure can reduce computational costs, remove noise and make the dataset easier to use (Harrington, 2016). For clustering techniques, no class should be predicted and the instances should be divided into groups similar features (Joseph et al., 2016). For some algorithms, the desired number of groups should be informed in advance.

Regarding the measures and indicators, some concepts are already used in the transportation literature. An important measure is accessibility to opportunities and infrastructure elements. They are developed to inform, above all, the decision makers, about the number and availability of spatially distributed potential opportunities to be reached, given a cost of travel. Also, in the transportation literature, the monthly income of the householders is used to feature deprived groups in order to describe the socioeconomic level of the residents and transportation users (Delbosc & Currie, 2011; Pereira et al., 2017).

Based on the motivation of proposing innovative approaches to inform the decision making (Lucas, 2012), this study aims at identifying income and opportunity inequalities through the years 2000 and 2010 in the Sao Paulo municipality, and their change due to enhancing and improving the traffic infrastructure. In this time, new metro lines were built. Dimensionality reduction and clustering techniques were applied to analyze groups in two frames: The entire São Paulo municipality and the surroundings of two new metro lines, which started to operate after 2000. These two analyses allow us to understand the city as a whole and especially regions with transportation improvements. The goal of this work is not to explain the consequences of the new metro structure, but to identify differences before and after the line operation. Thus, the analysis is to infer changes in the socio-economic situation and accessibility at the census tract level.

The next section describes the data and techniques applied, as well as the preprocessing steps in order to determine relevant features. Section 3 shows the results and further discussions. Finally, the conclusion is stated.

2. Materials and Methods

This investigation, first, built a representative dataset to characterize inequalities of transportation and a deprived group. A two-step approach with dimensionality reduction and clustering analysis, already presented in literature (Ibes, 2015), was applied. Then, the spatial pattern of the entire city and the neighborhood of two new metro lines was analyzed for the two years investigated in this study (Figure 1).

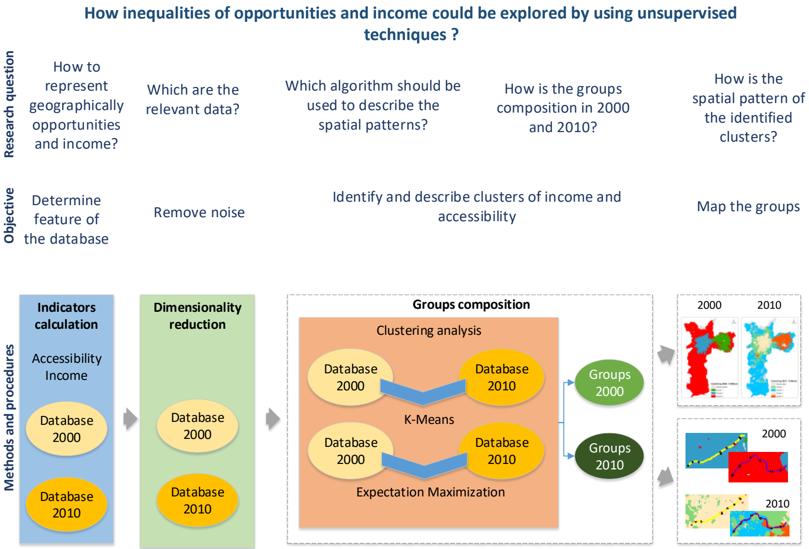

How inequalities of opportunities and income could be explored by using unsupervised techniques ?
Research question
How to represent geographically opportunities and income?
Which are the relevant data?
Which algorithm should be used to describe the spatial patterns?
How is the groups composition in 2000 and 2010?
How is the spatial pattern of the identified clusters?
Objective
Determine feature of the database
Remove noise
Identify and describe clusters of income and accessibility
Map the groups
Methods and procedures
Indicators calculation
Accessibility
Income
Database 2000
Database 2010
Dimensionality reduction
Database 2000
Database 2010
Groups composition
Clustering analysis
Database 2000
Database 2010
K-Means
Database 2000
Database 2010
Expectation Maximization
Groups 2000
Groups 2010
2000
2010
2000
2010

Figure 1 – Main research question, steps and methodology

2.1. Database

Accessibility measures

Based on configuration of the São Paulo municipality metro network (Logiodice, 2016; Tomasiello, 2016), in the two-time periods, 2000 and 2010, the inference of transit travel time was used to estimate the travel cost for the accessibility indicators. The network was built firstly for 2010 and regressed to 2000 with the increased impedance of the travel time in the new parts of metro lines. The network changes, depicted in Figure 2, comprise the new metro and train stations constructed after 2000, mainly yellow and lilac lines as well as stations of green line. For the accessibility indicators, the same urban equipment (e.g. hospitals and others) was used, therefore, the changes in accessibility levels reflect the changes in the transportation network.

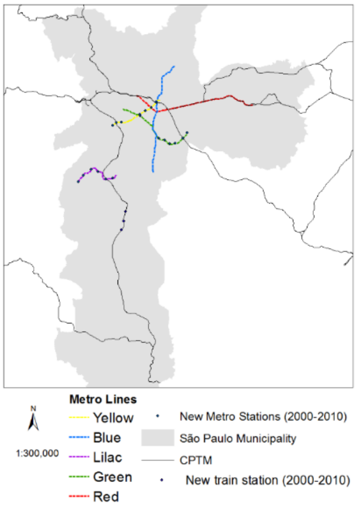


Figure 2 - - Transit lines of metro and train in São Paulo municipality: yellow and lilac lines were built after 2000

The accessibility metric used was the cumulative opportunities to evaluate the potential number of urban equipment to be reached, given a travel time (Neutens, Schwanen, Witlox, & de Maeyer, 2010; Páez, Scott, & Morency, 2012; Siqueira-Gay, Giannotti, & Tomasiello, 2016). The travel time threshold was calculated based on Department for Transport Business Plan (2012) from UK and represents the median of the all travel with public transportation with specific purpose. The accessibility indicators used are shown in Table 1 and the main steps for calculation are shown in Figure 3. This leads to six accessibility features for each census tract.

Table 1 – Accessibility measures

Type of accessibility measure	Urban facilities	Indicator
Cumulative opportunities	Hospitals	Number of hospitals to be reached within 60 minutes of travel time by transit
	Health centers	Number of health centers to be reached within 60 minutes of travel time by transit
	Public schools	Number of public schools to be reached within 45 minutes of travel time by transit
	Private schools	Number of private schools to be reached within 45 minutes of travel time by transit
	Sports centers	Number of sports centers to be reached within 50 minutes of travel time by transit
	Museums and public libraries	Number of museums and libraries to be reached within 50 minutes of travel time by transit

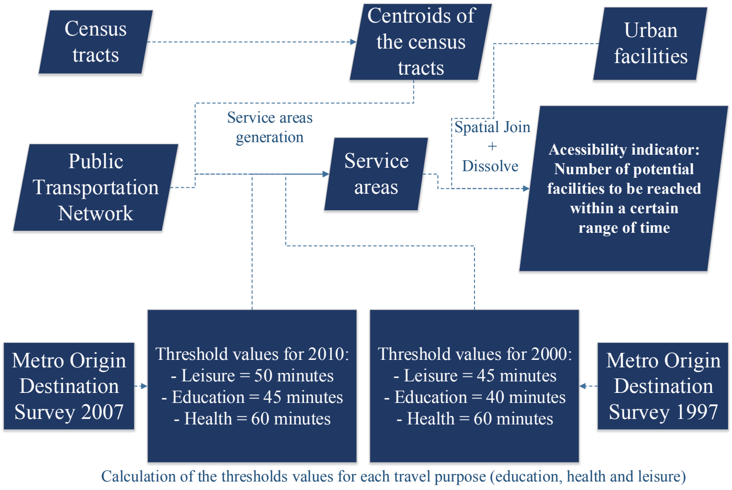

Census tracts
Centroids of the census tracts
Urban facilities
Service areas generation
Spatial Join + Dissolve
Public Transportation Network
Service areas
Acessibility indicator: Number of potential facilities to be reached within a certain range of time
Metro Origin Destination Survey 2007
Threshold values for 2010: - Leisure = 50 minutes - Education = 45 minutes - Health = 60 minutes
Threshold values for 2000: - Leisure = 45 minutes - Education = 40 minutes - Health = 60 minutes
Metro Origin Destination Survey 1997
Calculation of the thresholds values for each travel purpose (education, health and leisure)

Figure 3 – Main steps of accessibility measures calculation

Census

The census variable selected was the average monthly income of the householder (Figure 4. In order to exclude economic inflation from the analysis, the value was divided by the minimum salaries (in 2000 it was R$ 151,00 and in 2010, R$510,00). Then, categorical values were set to help to better identify the groups of interest (low, intermediate and high income) in the clusters composition. Table 2 show the income indicators used in the dataset. Even after normalizing the income by minimum salaries, the purchasing power of the minimum wage may have changed along years. In this context, we decided to keep this approach, rather simplistic, and leave for future works the adoption of a more enhanced normalization for income, which may achieve a complex discussion.

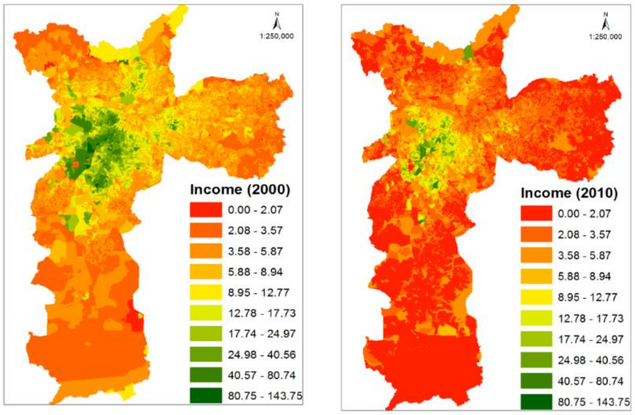


Figure 4 – Spatial patterns and values of income in 2000 and 2010

Table 2 – Variable of 2000 and 2010 Census used in the analysis

Census Variables		Indicators	
Income	Average monthly income of householder	Families that earn up to 3 minimum salaries	1 (Low)
		Families that earn from 3 to 10 minimum salaries	2 (Medium)
		Families that earn more than 10 minimum salaries	3 (High)

The income adds one additional feature to the data instances, leading to a total number of seven features for each data set. In the database of 2000, 13278 instances were analyzed and in 2010, 18953. The difference in the number of census tracts is due to the changes in the urban area and population growth during the years. The missing values of census data were removed from the database - they represent less than 1% of all data in 2000 and 3% in 2010. The software for Machine Learning used was Weka (Witten et al., 2011); ArcMap 10.5 was used for spatial analysis and visualization.

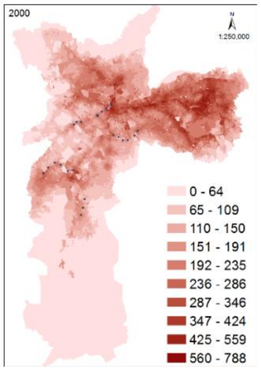
2.2 Analysis

The Principal Component Analysis (PCA) is a well-known technique for dimensionality reduction (Joseph et al., 2016). After this, for the clusters composition, two algorithms were tested: K-Means and Expectation Maximization (EM). The objective was to test the response of spatial pattern of each algorithm. K-Means is a popular algorithm due to its intuitive character and low computational cost (Joseph et al., 2016; Zaki & Meira, 2013). It involves two main steps: the cluster assignment and the centroid update. Firstly, the number of clusters "k" are set and each point of the sample is assigned according to its proximity of the mean. The group of points closes to the mean value constitute one cluster. In the next step, the centroids of each cluster are updated. The convergence occurs if the cluster centroid does not change between the iterations. The EM algorithm assumes that each cluster is featured by a multivariate normal distribution. In the first step, the parameters of the probability distribution, median and covariance matrix are estimated. In the sequence, the log likelihood expected value, i.e. the conditional probability, is maximized. The algorithm is also simplified to analyze spatial data (Griffith, 2012). In this study, the classical approach implemented in Weka was used and no information about the spatial relation of the instances was considered.

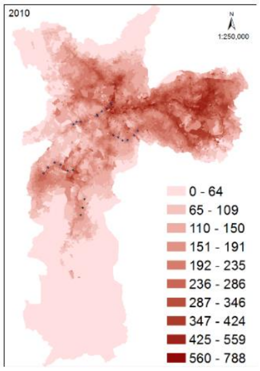
3. Results and discussion

3.1 Accessibility indicators

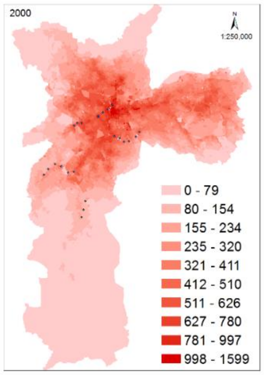
The accessibility indicators are visualized and analyzed. The main changes between 2000 and 2010 occur close to metro station areas, especially in the lilac line. As this region has fewer transit alternatives, the travel time changed considerably with the construction of the fast transit system. In the central area, however, this effect is not visible, as it disposes of a greater supply of bus lines. A similar effect refers to the accessibility to some culture facilities the city center, where there is no relevant difference between the years, as there the main part of the facilities is concentrated. Figure 5 depicts the number of respective urban facilities to be reached given a travel time. The dots are the new metro and train stations implemented between 2000 and 2010. The division scale was natural breaks. The quality of the service is not assessed in this analysis, only the existence of facility. The travel time inference changed but the offer of urban facilities is the same on both years of analysis.



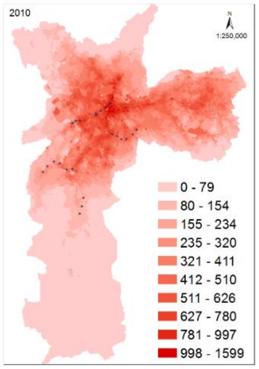
Number of public schools to be reached in 45 minutes (2000)



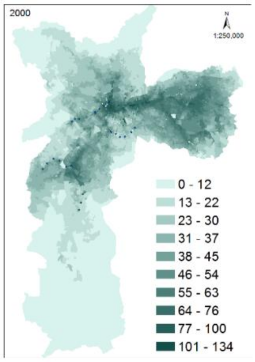
Number of public schools to be reached in 45 minutes (2010)



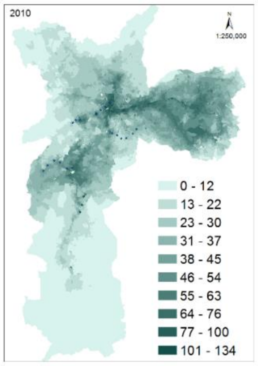
Number of private schools t be reached in 45 minute (2000)



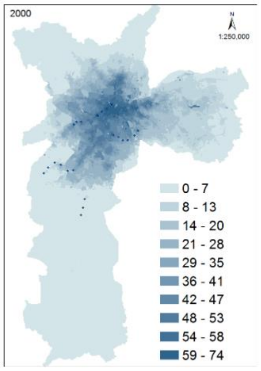
Number of private schools to be reached in 45 minutes (2010)



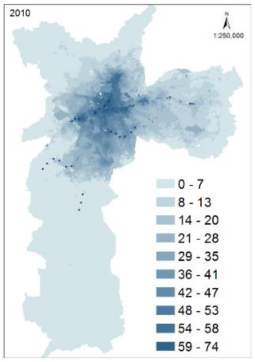
Number of health centers to be reached in 60 minutes (2000)



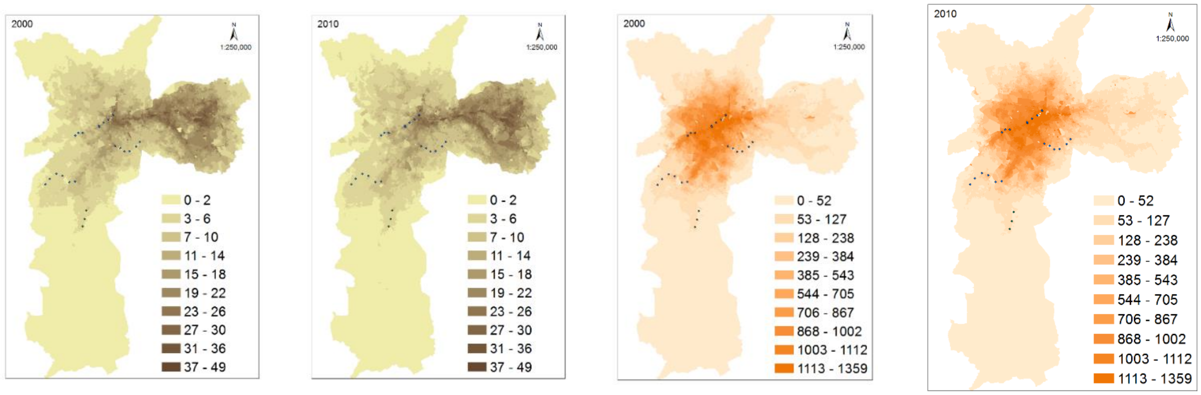
Number of health centers to be reached in 60 minutes (2010)



Number of hospitals to be reached in 60 minutes (2000)



Number of hospitals to be reached in 60 minutes (2010)



Number of sports facilities to be reached in 50 minutes (2000)

Number of sports facilities to be reached in 50 minutes (2010)

Number of culture facilities to be reached in 50 minutes (2000)

Number of culture facilities to be reached in 50 minutes (2010)

Figure 5 – Accessibility measures of 2000 and 2010

3.2 Clustering

The PCA transformation was applied to generate a new dataset that represents about 95% of the original variance. The results show four components in 2000 and 2010 instead of seven variables of accessibility and income, as the original dimension. In 2000, the first two main components explain about 87% of the sample variance and are related to income and public schools, respectively (See in Table 3, line "cumulative variance"). In 2010, the first two also explain about 86% but both are mainly related to income[1] (Table 3).

Table 3 – Results of PCA analysis in the 2000 (left) and 2010 (right)

	Eigenvectors				Variables
	V1	V2	V3	V4	
Cumulative variance	**0.62**	**0.87**	**0.94**	**0.97**	
Loads of each variable in eigenvector composition	-0.40	-0.36	-0.28	-0.09	Hospitals
	-0.46	-0.07	-0.18	0.34	PrivSchools
	-0.38	0.39	0.14	-0.72	SportCenters
	-0.41	0.33	0.06	-0.07	HealthCenters
	-0.36	-0.43	-0.35	-0.09	Culture
	-0.36	0.45	0.15	0.59	PublicSchools
	-0.23	-0.48	0.85	0.02	Income

	Eigenvectors				Variables
	V1	V2	V3	V4	
Cumulative variance	**0.62**	**0.86**	**0.93**	**0.96**	
Loads of each variable in eigenvector composition	-0.38	-0.38	0.22	0.06	Hospitals
	-0.40	0.33	-0.35	-0.23	PrivSchools
	-0.38	0.41	-0.34	0.11	SportCenters
	-0.46	0.04	-0.18	0.39	HealthCenters
	-0.40	-0.31	0.05	-0.77	Culture
	-0.36	-0.45	0.14	0.44	PublicSchools
	-0.24	0.52	0.82	-0.01	Income

For the clustering analysis using K-Means, the first step is to determine the number of clusters k. For that, the elbow curve (Figure 6) displays the sum of squared error, that represent the distance between the clusters and the "best" number of clusters is the inflexion of the curve. The figure depicts the number of three clusters in 2000 and four in 2010.

[1] Table 3 depicts the values of each variable load in the eigen vector composition. The higher the value of variable load, more correlated that indicator is with the respective component.

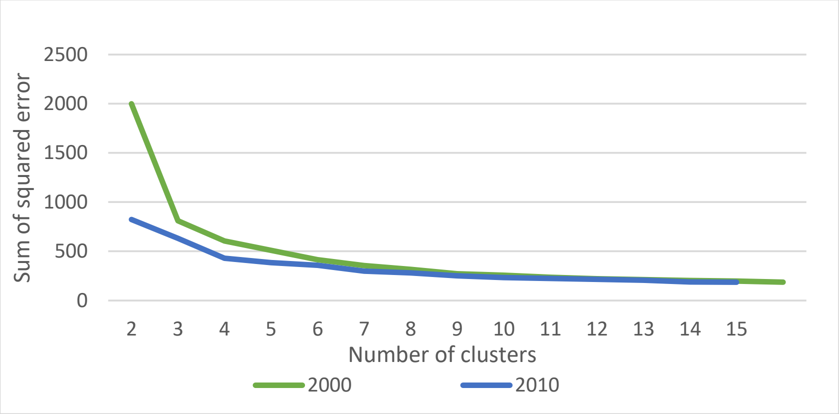


Figure 6 – Elbow curve to determine the best number of clusters

Based on the number of clusters, both algorithms were tested in Weka. The EM algorithm estimates the parameters to maximize the log probability of the observed data. On the other hand, K-Means calculates the distances between the instances and assigns the observed data into similar groups. The model's parameters exported from Weka are depict in Table 4.

Table 4 – Model's parameters

K-Means	2000	2010
Distance Function	Eucledian	Eucledian
Number of seeds	10	10
Initialization method	Random	Random
Number of clusters	3	4
Number of iterations	16	11
Within cluster sum of squared errors	604.15	428.95
EM	**2000**	**2010**
Number of clusters	3	4
Number of iterations	55	100
Log likehood	-4.73	-4.48

The maps show (Figure 7) that the K-Means algorithms performs better considering the spatial pattern of income (Figure 4) and general tendency of the accessibility levels (Figure 5). As shown by other related works, it also provide similar patterns to other exploratory analysis of accessibility in São Paulo (Arbex et al., 2016). In Table 5 the percentage of assignments and percentage of population show on both years, differences between the population in each cluster.

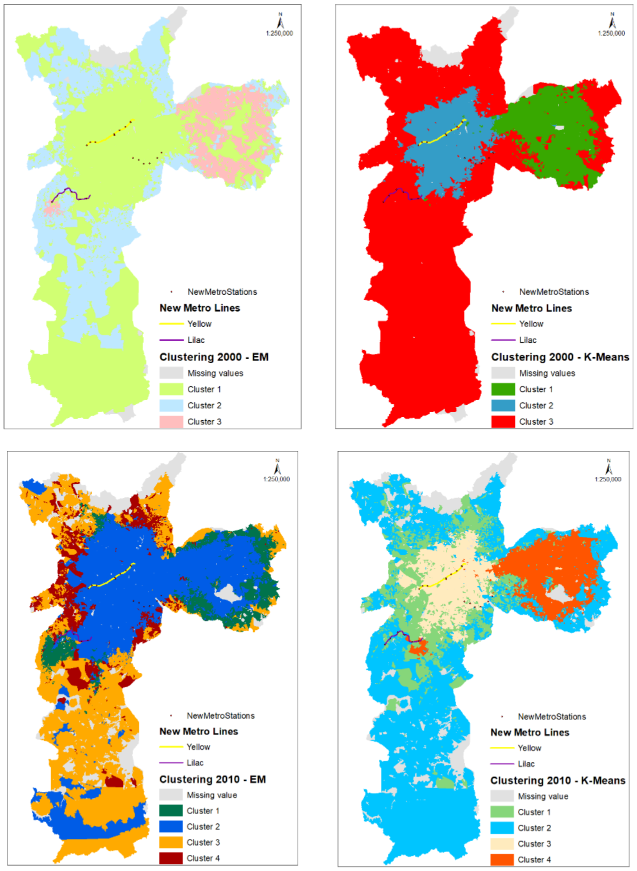


Figure 7 – Spatial patterns of the 2000 and 2010 groups formed by using EM and K-Means algorithms

Table 5 – The percentage of instances and population assigned in each cluster

	2000			
	EM		K-Means	
Cluster	Percentage of instances	Percentage of population	Percentage of instances	Percentage of population
1	52%	46%	23%	22%
2	30%	35%	22%	17%
3	18%	19%	55%	61%
	2010			
	EM		K-Means	
Cluster	Percentage of instances	Percentage of population	Percentage of instances	Percentage of population
1	16%	18%	19%	17%
2	50%	47%	45%	48%
3	25%	27%	18%	15%
4	9%	8%	18%	20%

The groups composition generated by K-Means can be seen in Figure 8. Clustering only determines groups, but it does not provide a classification. Therefore, the clusters have to be interpreted. In 2000, the group with high income (2) (See Figure 4) is in the inner city and present high level of all types of accessibility. In 2010, the group with high income (3) located in the city center present high accessibility level to all facilities but not to sport centers. It is important to highlight the good offer of hospitals to this group face the others, especially those with low income in both years. Also, the heterogeneity in the peripherical region of the city is stressed. In both years, the east zone present distinguished group from the south and north of the city. In 2000, the cluster in this region (1) presents the lowest income level but good offer of public schools, sports facilities and health centers. In 2010, this pattern remains in the group 4. In 2000, the group that encompasses the urban fringe of the city (3) presents the lowest level of accessibility to all facilities. Since the spatial extension of this group is big, it aggregates distinct income groups as in the deep south are the extremely poor and in the city center border, there are some residents with intermediate income. Therefore, the average value of income in this group is not the lowest one. in 2010, there is a new group in the border of the inner city (1). It represents an intermediate income cluster with good level of accessibility to all facilities.

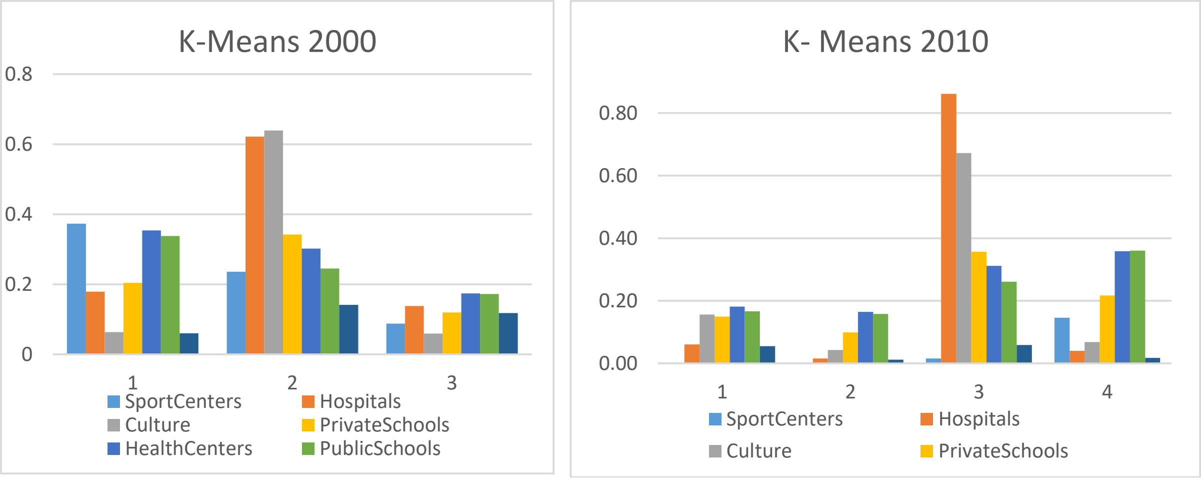


Figure 8 – The mean value of the indicators in each cluster[2]

The new yellow line is located in the city center connecting "Luz" central station to "Butantã" in the west zone of São Paulo municipality (Figure 7). In the surroundings of the stations, there is a cluster with high income and high accessibility in both years. Given that in this central area there is a considerable offer of public transportation, the new measures do not capture the increment of accessibility. Therefore, looking in the surroundings, on both years, the group is the same: high income and high accessibility.

On the other hand, the lilac line, in the south, connects "Capão Redondo" to "Largo Treze" stations. In 2000, the region is marked by the low-income group, however, in 2010, the region presents three distinguished groups (1, 2, 4). The metro stations in this region represents a relevant transportation improvement since there is no other fast transit alternative in this area.

[2] The income is the average of minimum salaries normalized and accessibility is the average of the value assigned for each group

The methodological steps and analysis could be adapted to other cities and context, for instance, in the case of new transportation infrastructure built for World Cup and Olympic games as in the study of Pereira et al. (2017). For this, the requirement is the availability of transportation data with travel times and opportunities, which could be acquired with the government survey as Origin-Destination, GTFS and GPS-based big data. The socioeconomic data is easier to get in the Brazilian context due to the existence of Census in every 10 years.

4. Conclusion and future work

The clustering analysis showed interesting results in learning about inequalities of opportunities and income in São Paulo municipality. The proximity of instances reveals relevant groups in 2000 and 2010, mainly: (i) new group in the inner-city border in 2010; (ii) heterogeneous conditions in the city outskirts in both years and; (iii) the surroundings of the new metro line located in the south region has more heterogeneous groups than the central one. Further developments could be made exploring other features of deprived groups, improving the accessibility measures with competition and quality of services and exploring other techniques to analyze the impact of transportation infrastructure on the citizens' life.

5. Acknowledgements

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