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Geographic Feature Engineering with Points-of-Interest from OpenStreetMap

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Abstract: Although geographic patterns have been considered in statistical modelling for many years, new volunteered geographical information is opening opportunities for estimating variables of the city using the urban characteristics of places. Studies have shown the effectiveness of using Points-of-Interest (PoI) data in various predictive applications domains involving geographic data science, e.g. crime hot spots, air quality and land usage analysis. However, it is hard to find the data sources mentioned in these studies and which are the best practices of extracting useful covariates from them. In this study, we propose the *Geohunter*, a reproducible geographic feature engineering procedure that relies on OpenStreetMap, with a software interface to commonly used tools for geographic data analysis. We also analysed two feature engineering procedures, the quadrat method and KDE in which we conduct a qualitative and quantitative evaluation to suggest which better translate geographic patterns of the city. Further, we provide some illustrative examples of *Geohunter* applications.

1 INTRODUCTION

There is a growing demand for measurement and monitoring of landscape-level patterns and processes (Gustafson, 1998), and modern sources of data are becoming useful for predictive analysis. Although geographic patterns have been considered in statistical modelling for many years, new volunteered geographical information is opening opportunities for estimating variables of the city using the urban characteristics of places. For example, when it is asked for some inference on crime concentration within the urban space, it may be reasonable to argue that street network may be an important predictor (Davies and Johnson, 2015), as well as estimating air quality levels where the presence of natural spaces within the city may be useful. In this paper we detail a methodology to extract such covariates by using an OpenStreetMap interface and compare two methods to decompose city data into layers of information. Our goal is to represent the city into densities of points-of-interest, as Figure 1 depicts.

Supported by volunteered geographical information and data from points-of-interest (PoI), researchers in many fields continue to investigate the association between geographical patterns and the studied domain. For example, spatiotemporal crime pre-

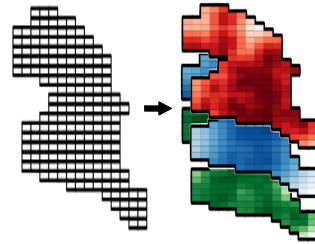


Figure 1: Geographic features as city layers.

diction (Lin et al., 2018), energy retail (Hopf, 2018), land usage (Estima and Painho, 2013) and several others. With a variety of methods for representing such patterns, researchers extract the density of PoI within city-regions. For example, Yin et al. (Yuan et al., 2012) classified functional regions in Beijing using a topic modelling based technique that helps to define a place as it was a document. Yuan et al. (Yin et al., 2011) have addressed, including mobility data on a similar topic modelling approach. Lin et al. (Lin et al., 2018) extracted geographic features by counting the number of PoI within grid cells.

Even that previous studies have examined the usage of geographic features, the validation of a more appropriate feature engineering method is rarely discussed. For spatial predictions and urban analytics, we believe that PoI **density**, instead of quantity, may

benefit predictive modelling in many applications, due to a few reasons. Tobler’s First Law of Geography (TFL), also mentioned by geographers as “spatial dependency”, suggests that characteristics of near places are contiguously correlated together. Also, it is reasonable to think that predictive models can benefit more from a diverse and balanced variable distribution, and by counting items within cells, having few samples may be a threat for this, as we show.

To calculate PoI density, we evaluate the count-based baseline method, which we refer here to as the quadrat method, against kernel density estimation (KDE) that generally produces relatively smoother distributions. We evaluate these two by measuring the spatial autocorrelation of the features provided with Moran’s I , and spatial heterogeneity with the q -index, which shall indicate how uneven features are distributed. To visually compare these methods, we conduct a qualitative assessment based on visual inspection of the spatial distribution for different sample sizes.

Also, from the best of our knowledge, we did not find that related studies show a clear and reproducible geographic feature engineering procedures, either a piece of software that would support such analysis. For this reason, we propose and demonstrate *Geohunter*, a reproducible geographic feature engineering framework that fetches OpenStreetMap data and calculates the density of points-of-interest throughout the city. We implemented it as open-source python-package, currently with the functionalities of (i) loading data from the OpenStreetMap API, (ii) parse OpenStreetMap data into commonly-used geometric-based data structures (Geopandas (Jordahl, 2014)) and (iii) to extract geographic features from points-of-interest with the methods used in this work.

This paper is divided as follows. In Section II, we describe some aspects of the data source, the two geographic feature engineering methods used, our evaluation approach, the evaluation approach, and provide some details about the *Geohunter*. In Section III, we show the results of our experiments, both in qualitative and quantitative assessments. Finally, in Section IV, we discuss some possible outcome analysis that illustrates the usefulness of such geographic features.

2 DATA AND METHODS

2.1 OpenStreetMap Data

Over the last decade, WEB-based GIS technologies were created to provide reliable representations

of the urban environment. Among them, OpenStreetMap certainly gained notoriety due to its substantial community-based contributions and because of its open data policy. It drove the growth of the Volunteered Geographic Information (VGI) culture, and many studies, e.g. (Kounadi, 2009; Camboim et al., 2015), have assessed the quality of information on the platform. Nowadays, one can quickly request its data through, for example, the Overpass¹ API. OpenStreetMap has a particular data model to represent objects or Points-of-Interest (PoI) composed of “nodes”, “ways” and “relations”, and each object can be created, tagged and verified by the community. There are a set of defined and most used tags to classify PoIs, also referred to as “map features” (a complete description of them is provided in OpenStreetMap documentation²).

The Overpass API receives requests in a specific query language (Overpass QL) and returns data containing geographical coordinates and several other attributes of the requested PoIs. For more details about the structuring of these queries, we recommend the API documentation. As mentioned, the returned elements follow the typology of (i) nodes, which defines points in space, (ii) ways, which defines linear characteristics and area boundaries, and (iii) relations, which are used to explain how other elements work together. An arbitrary PoI can be composed by a relation of several ways and nodes. This typology is not directly related to the geometric concepts of points, lines and polygons.

The physical aspects of elements are described by tags attached to them. Each tag is used to describe different aspects of an element, which can have an unlimited number of tags describing them (assigned by the community). Furthermore, tags are defined by a pair *key:value*, for instance, a church can be represented by the tag *building:church*, and also by *amenity:place_of_worship*. For this paper, we select tags with the purpose of illustrating the method discussed further in this paper which can involve a variety of PoI. Table 1 details the keys, values and amounts of data within the boundaries of Natal, Brazil.

2.2 Geographic Feature Engineering Methods

For each geographic object listed in Table 1, we extract a separate feature layer which describes density values for places in the city. These places can be defined following an administrative division of the city

¹https://wiki.openstreetmap.org/wiki/Overpass_API

²https://wiki.openstreetmap.org/wiki/Map_Features

Table 1: Points-of-interest samples from data in Natal, Brazil.

Map Features	Tags	Quantity
Amenity	restaurant	246
	school	188
	hospital	48
	place_of_worship	154
	police	39
Leisure	*	1248
Highway	primary	661
	residential	8122
	bus_stop	417
Tourism	*	190
Natural	sand	54
	wood	49
	beach	16
Shop	*	1023

or an artificial grid configuration. The latter has the advantage of resolution parametrization, i.e. one can use a finer or coarser grid depending on the application purposes. Regular geometries, such as points, rectangles and even hexagons, are often used as the spatial unit of analysis, or *grid cell*. In this paper, we use an artificial grid composed of squares of 1km by 1km to assess the aggregation methods described below. The aggregation of points within grid cells is a relevant aspect for crafting better features.

2.2.1 Quadrat Method

A naive approach is to count the amount of PoI items in regions of the city, which in this work, we refer to as the quadrat method since the areas are square cells. This method can be further generalized considering other arbitrary geometries, using the same counting method stated before. In the case of administrative regions, one should normalize these values considering the respective areal density.

2.2.2 Kernel Density Estimation

The second approach consists of sampling the underlying probability density function, given a set of samples using a kernel. KDE is a mechanism to do so in a non-parametric manner, firstly introduced by Rosenblatt (Rosenblatt, 1956) and Parzen (Parzen, 1962).

Illustrated by Figure 2, it consists of applying a kernel function to return a density estimation of a set of arbitrary points, in particular for our study a grid of points regularly spaced. Equation 1 defines it for bidimensional estimation, where h is the bandwidth parameter of the kernel function K applied, and $d_{x,y}(i)$ is the distance between all the occurrences i and the grid point described by the coordinates x, y .

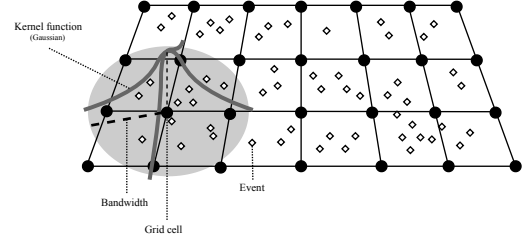


Figure 2: An illustration of Kernel Density Estimation and its parameters. Each black point (grid cell) represents an arbitrary place in which a kernel function applies a density estimation around a bandwidth. For a set of events/points, this procedure returns an array of KDE values indexed by the identifier of the cell.

$$f(x, y | h) = \frac{1}{nh^2} \sum_{i=1}^n K\left(\frac{d_{x,y}(i)}{h}\right) \quad (1)$$

In this sense, KDE practitioners have discussed rules and formulas to select internal parameters. In general, smaller bandwidths retrieve spiky distributions which may cause overfitting, and larger bandwidths generate too smooth surfaces, with low variation between places thus resulting in underfitting. Silverman (Silverman, 1986) suggests a rule of thumb of selecting bandwidth of Gaussian kernels with $h = 1.06\hat{\sigma}n^{-\frac{1}{5}}$, considering $\hat{\sigma}$, as $\hat{\sigma}$ the standard deviation and n the sample size. Still, for other kernels, the likelihood maximization proposed by Jaki et al. (Jaki and West, 2008) can be applicable. They suggest exploring a parametrized version of KDE, which they called Maximum Kernel Likelihood Estimation (MKLE), providing an approach to select the best parameter configuration by maximizing the log-likelihood, even providing a formula for Gaussian kernels. In a similar approach, Mohler et al. (Mohler et al., 2011) and Hu et al. (Hu et al., 2018) suggested to search for optimal parameters through likelihood cross-validation. For this study, we chose to work with the Silverman's method for KDE parameter selection, using the Gaussian kernel. The KDE implementation we used is from the heavily used *scipy* python-package (Virtanen et al., 2020).

As mentioned, in this paper, we are working with square grids, instead of a point-based grid. Although some related work has applied KDE with square grids

(using the centroid of the square to apply KDE), we argue that the bandwidth assumes a circular format, not square. Instead, first, we apply KDE with a point-based grid spaced by half of the square grid resolution parameter. To get the resulting density estimation on the square grid cells, we average the KDE results of the grid points within the square grid cells.

2.3 Evaluation Method

We conduct the feature engineering approaches with a grid resolution of 1km by 1km to quantify the influence of grid cell size on the quality of feature distribution. For a quantitative evaluation, we measure the Moran's I for global Spatial Autocorrelation (SA) (Anselin, 1995). We consider spatial autocorrelation an important measure following the Tobler's First Law of Geography that suggests near places are more similar among each other, and our purpose is to represent PoI underlying density better. On the other hand, we measure the q -statistic for Spatial Stratified Heterogeneity (SSH) to handle the traditional concept in the geography of spatial heterogeneity, in which Leitner et al. (Leitner et al., 2018) suggests that local uniqueness should condition generalizations and pattern extraction. Also, we conduct a qualitative analysis by visual inspection of the feature distribution generated by the baseline and by KDE, with two feature items taken from different sample sizes.

The Moran's I is expressed in equation 2, where N is the number of spatial units index by i and j , x the variable of interest, \bar{x} its mean, w_{ij} a matrix of spatial weights, and W the sum of all weights in w_{ij} . It quantifies how much neighbours cells does correlate with each other, and it ranges from -1 to 1. The metric interpretation indicates that one means perfect clustering (high spatial autocorrelation) of similar values, -1 means perfect dispersion, and 0 means perfect randomness (no spatial autocorrelation) (Anselin, 1995).

$$I = \frac{N \sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{W \sum_i (x_i - \bar{x})^2} \quad (2)$$

The q -statistic is expressed in Equation 3, where L is the number of strata, N the size of the population and σ^2 the variance of the attribute. It assesses data heterogeneity among grid stratification, and it varies from 0 to 1. The strata are sets of grid cells, for instance, cells within the administrative neighbourhoods. A value close to 0 indicates that variances within strata are similar (homogeneous). Conversely, when values are close to 1 stratus's variation are more heterogeneous among each other, thus more prone to represent different patterns among places. For further details on the importance of measuring the q -statistic,

we refer to (Wang et al., 2016) that provide seminal arguments and additional formal description on it.

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^L N_h \sigma_h^2 \quad (3)$$

2.4 The GEOHUNTER Python-package

To provide an open-source tool for other researchers to extract geographic features and to ensure experiment reproducibility, we developed the *Geohunter*³ python-package. It aims to obtain and parse data from OpenStreetMap to robust geospatial data structures, as provided by the GeoPandas package (Jordahl, 2014).

The workflow of *Geohunter* starts with a bounding area, which can be taken from an input file for the city shape (spatially encoded files, such as shapefile or GeoJSON) or we can get it from the *Geohunter*, setting a bounding box and request it with its OpenStreetMap unique tags. One can easily request any data, including PoI and city shapes, by calling our API facade, setting the tags and the values wanted. Then, *Geohunter* parse and execute the Overpass query, get the results and parse as GeoPandas' GeoDataFrame.

The grid object also uses the city shape, and *Geohunter* provides functions for generating square grid bounded by a particular area. Then, the grid and PoI are used as input for the feature engineering method, considering quadrat and KDE methods. By default, we use Silverman's method to retrieve KDE parameters used, as mentioned before. The output is a matrix, where each column represents a geographic feature, and each row indicate a tuple of feature values for a given grid cell. In the package's GitHub repository, there are a few examples on how to use *Geohunter*, including to reproduce or clarify the experiment described in this paper.

3 RESULTS

Using the dataset gathered from Natal, Brazil, we extracted geographic features using both methods, quadrat and KDE. Since there is a diverse set of sample sets, ranging from beaches with 16 samples, to residential streets with 8122, we argue that useful comparisons can be made on different scenarios.

³<https://geohunter.readthedocs.io/en/latest/>

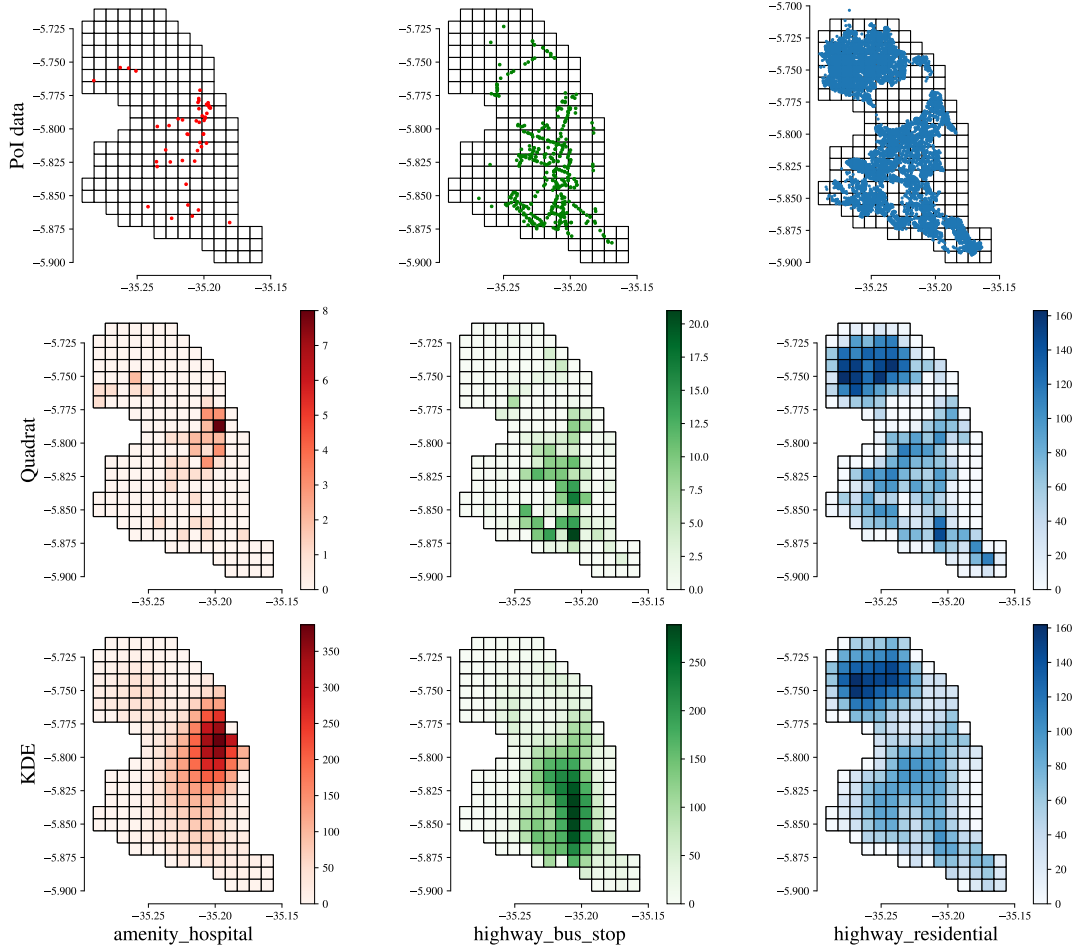


Figure 3: The density of PoI data (first row) using the quadrat method (second row) and KDE (third row) for three categories. Hospitals map with 48 points in red is representative because it shows that with a few samples, the method visually differs significantly. Bus stops map with 417 items in green also follows such difference. On the right side, residential streets map with 8122 samples in blue shows that with a massive amount of points, it is hard to detect a difference in feature distribution visually, but KDE still generated a smoother map.

3.1 Qualitative Assessment

To demonstrate the visual effect of the extracted features in a grid with 1km by 1km cells, we present the Figure 3. It has the spatial density of three PoI items (48 hospitals in red, 417 bus stops in green and 8122 residential streets in blue), as well as their feature distribution with the quadrat method (middle row) and KDE (last row). We pick these three because they represent different sample sizes and support further inspections on possible sample size-dependent behaviour. Note that with fewer samples, the quadrat method is more likely to have neighbour cells with totally different values when comparing to KDE. However, when having a massive amount of samples, the maps become more similar to each other. With this visual inspection, one can find that KDE-based features

are relatively more parsimonious than quadrat ones, in all three cases, even when more data is available. In a possible question involving what is the coverage area of hospitals, we argue that the KDE ones are more likely to represent the reality.

3.2 Quantitative Assessment

In section 2.3, we discussed that the quantitative evaluation conducted in this article is guided by two essential concepts of geography, spatial autocorrelation through Moran's I , and spatial heterogeneity, calculated through q -statistic (Wang et al., 2016). These metrics are relevant to evaluate our hypothesis that KDE is, in fact, more meaningful for PoI density representation, following the geography rules described earlier.

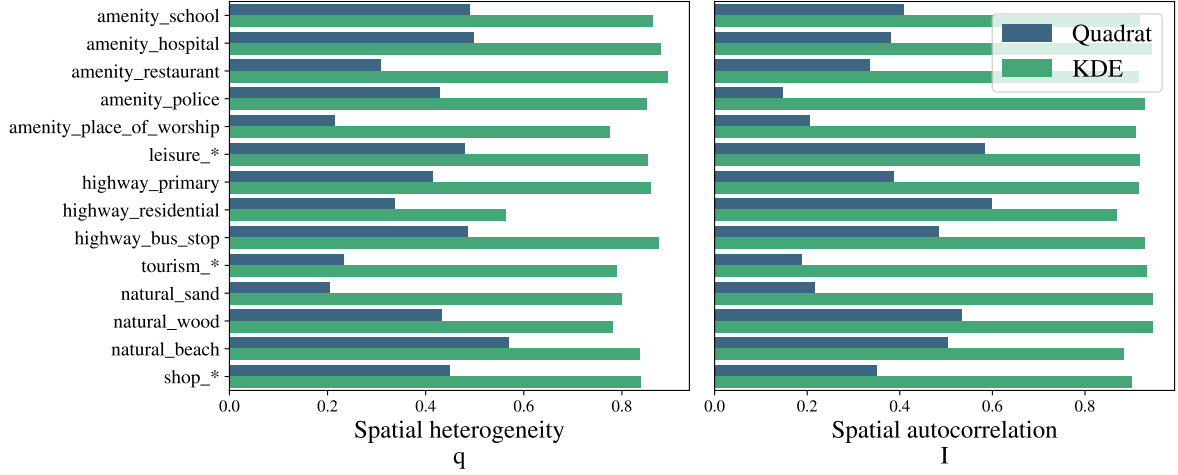


Figure 4: Comparison between the quadrat method and KDE regarding spatial heterogeneity (q) and spatial autocorrelation (I) for all features extracted. Clearly, KDE performed better than quadrat in both metrics, even in cases where more samples are available (e.g. *highway_residential*).

In this sense, we report in Figure 4 the results of these metrics for the quadrat and KDE methods, with the grid resolution of 1km by 1km. Note that KDE overcomes quadrat-based features in all scenarios, with high values of both q and I , which indicate that features extracted with KDE have higher spatial autocorrelation and heterogeneity between cells. Such a pattern was noticed even when massive amounts of samples are available, e.g. residential streets (*highway_residential*).

4 DISCUSSION

In Section II, we mentioned that results obtained using the *Geohunter* Package can be used as input for a diverse set of predictive algorithms. To illustrate some of the possible applications of using these features, here we provide some examples on spatial pattern analysis of urban spaces using geographic features.

First, we used K-means on *Geohunter*'s output for the city of Natal using Table 1 features. For comparison reasons, K-means was performed with five clusters, similar to the same number of administrative regions in Natal, which is four. Figure 5 shows the administrative regions (left) and the clustering results (right). It is possible to assess the difference between city characteristics in both images. Using the clustering results, we have some areas of resemblance in an inter-regional fashion. Bodies of water (tightly related to touristic areas), commercial zones and suburbs (represented by clusters 1, 2 and 3 respectively) are related to various administrative regions of the

city. We also argue that this output is more useful than traditional counting data obtained by cities census, at least for this type of application. Other example is illustrated in Figure 6, where we show three cluster of the city given the three features early mentioned, hospitals, bus stops and residential streets.

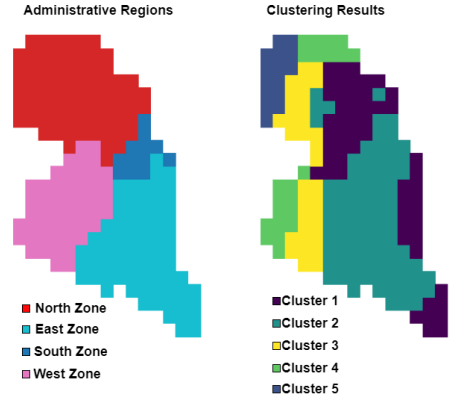


Figure 5: Comparison between Natal's administrative areas (left) and the result of clustering using geographic features acquired from *Geohunter* (right).

Also, as stated before, with *Geohunter*, it is possible to obtain the density of several features in the city. This can be used, for example, to analyse the density of police stations or hospitals in it, which is useful information to city planners to do decisions based on. Also, it is possible to make other analysis, such as, the relation between city facilities (hospitals, schools, police stations) and crime spots, air pollution density, traffic, agglomerations and several other urban phenomena.

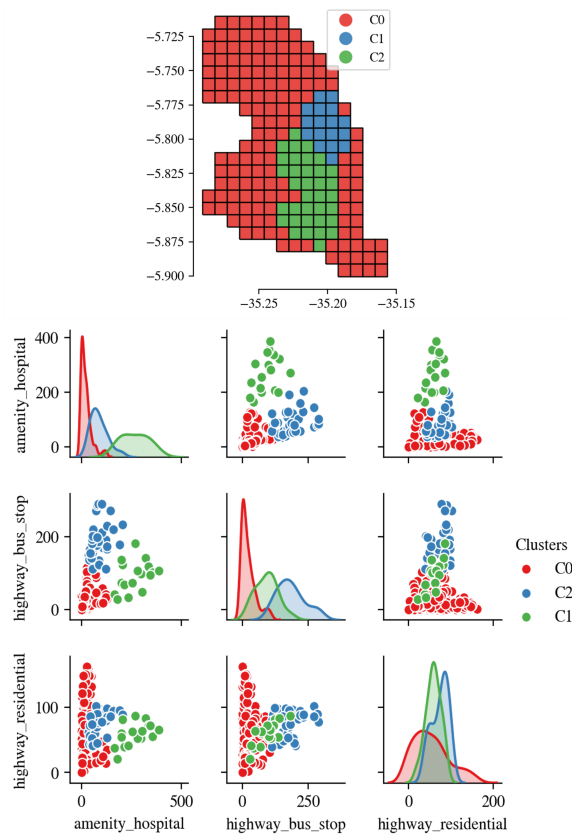


Figure 6: Clustering three zones of the city considering hospitals, bus stops and residential streets. Above, note the spatial distribution of the clusters, and below, the distribution of the features for each cluster. The area C0 is characterized as with almost no hospitals, a few bus stops and a varying amount of residential streets, while C1 and C2 are easily distinguished by the number of bus stops and hospitals.

5 CONCLUSION

In this paper, we proposed a reproducible framework for geographic feature engineering in which future work can rely on to analyse geographic patterns of urban spaces with an easy interface to OpenStreetMap. We assessed two spatial aggregation methods regarding their spatial heterogeneity and autocorrelation. In our experiments, we provided evidence that the usage of the KDE, if compared with the quadrat method, has much to contribute in terms of urban representation and feature engineering. Also, we presented the *Geohunter* python-package to create an interface with OpenStreetMap data and a heavily used geospatial tool (GeoPandas (Jordahl, 2014)). We provided a brief example using the features to illustrate its applicability. For future work, we suggest taking these features and applying for environmental and urban pre-

dictions and experimenting with different grid resolution and parameter settings. Modern data sources support uncovering more geographical patterns, and we argue that it is time to pursue ubiquitous analysis.

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