

Article

Studying and Clustering Cities Based on Their Non-Emergency Service Requests

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Abstract: This study offers a new perspective in analyzing 311 service requests (SRs) across the country by representing cities based on the types of their SRs. This not only uncovers temporal patterns of SRs in each city over the years but also detects cities with the most or least similarity to other cities based on their SR types. The first challenge is to gather 311 SRs for different cities and standardize their types since they differ in various cities. Implementing our analyses on close to 42 million SR records in 20 cities from 2006 to 2019 is the second challenge. Representing clusters of cities and outliers effectively, and providing justifications for them, is the last challenge. Our attempt resulted in 79 standardized SR types. We applied the principal component analysis to depict cities on a two-dimensional canvas based on their standardized SR types. Among our main findings are the following: many cities are observing a fall in requests regarding the condition of roads and sidewalks but a rise in requests concerning transportation and traffic; requests regarding garbage, cleaning, rodents, and complaints have also been rising in some cities; new types of requests have emerged and soared in recent years, such as requests for information and regarding shared mobility devices; requests about parking meters, information, sidewalks, curbs, graffities, and missed garbage pick up have the highest variance in their rates across different cities, i.e., they have a large rate in some cities while a low rate in others; the most consistent outliers, in terms of SR types, are Washington DC, Baltimore, Las Vegas, Philadelphia, Chicago, and Baton Rouge.



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1. Introduction

The 311 services offer a centralized platform for residents to report non-emergency problems, request municipal services, and obtain information about the city services. Examples of non-emergency issues include tree debris, graffities, potholes, and sanitation complaints. The 311 number was reserved in the United States in February 1997 for reporting non-emergency problems by the U.S. Federal Communication Commission [1]. Its pilot program was initiated in Baltimore in October 1996 [2,3] and then expanded to other American, Canadian, and West European countries, such as Germany, Finland, Sweden, and the United Kingdom. In addition to phone calls, requests can be submitted by text message, email, walk-ins, mobile applications, web forms, and social media [4].

It was originally intended to allow citizens to voluntarily police their community for non-emergency municipal problems and identify areas of needed service. It was created in response to the 911 number being overwhelmed by both emergency and non-emergency calls. With many cities keeping track of 311 SRs and accumulating them over the years, a valuable and large set of these reports, with spatial and temporal tags, is created. Opening this dataset to the public has incentivized researchers to mine different patterns and relationships among SRs, some of which are reviewed in Section 2.

Unfortunately, cities across the United States apply different coding conventions in recording their 311 SRs and are inconsistent in their SR types. This lack of data standardization is a major hurdle in performing machine-learning analyses on cities collectively and

has limited the spatial extent of many studies in the literature to one city. Section 3 provides further details about these inconsistencies and how they are overcome in this study.

Our collection and standardization of 42 million geocoded SR events has the potential to reveal important information about the distribution of government-provided services and physical conditions across the country. This study provides visualizations of these distributions, their temporal development over the years, and their variations across cities. This would potentially provide insight into the underlying causes and pave the way to more coordinated, comprehensive, and informed responses to municipal problems. This work is distinguished from its predecessors not only in its purpose but also in the data size, the novelty of the analysis, and findings. Section 4 explains our methodology for clustering cities and Section 5 presents and discusses the results. Section 6 concludes this study with some future research venues.

2. Related Work

Chatfield and Reddick [5] highlighted the lack of 311 data analytics usage in critical processes by municipalities to enable them in sensing and responding to citizens' needs in an agile, adaptive, and coordinated way and to create public values. For instance, 311 data analytics could be used in monitoring emerging trends, budget allocations [6], to gain a better understanding of citizens' satisfaction with government services performance [7], and to move towards the ultimate goal of smarter cities [8].

Kernel density estimation (KDE) in spatial analysis converts a set of points or events into a cell-based density surface. In other words, a grid is laid over the points and the density of points in each cell is estimated and smoothed using a kernel, such as the Gaussian kernel. This density reflects the likelihood of an event happening in that cell. The spatial-temporal KDE, proposed by Brunsdon et al. [9], estimates the likelihood of an event occurring at location s and time t through the following equation, where (s_i, t_i) is the i -th observed event, n is the total number of observed events, K_s and K_t are spatial and temporal kernels (an example of which is the Gaussian kernel), and h_s and h_t are those kernels' bandwidths.

$$p(s, t) = \frac{1}{nh_s^2 h_t} \sum_{i=1}^n K_s\left(\frac{s - s_i}{h_s}\right) K_t\left(\frac{t - t_i}{h_t}\right) \quad (1)$$

Arguing that the above KDE approach models space and time independently, Xu et al. [3] proposed the following equation to estimate the likelihood of an event occurring at location s and time t :

$$p(s, t) = \sum_{(s_i, t_i) \in (S, T)} K_s(s - s_i) w(S, t - t_i) / \sum_{(s_i, t_i) \in (S, T)} w(S, t - t_i) \quad (2)$$

In this equation, the temporal kernel (K_t) is replaced with a temporal weight (w). The temporal weight is multiplied by the output of the spatial kernel. The temporal weight is determined based on a temporal autocorrelation model that considers the trend and weekly seasonality. Based on the time difference between t and t_i , the temporal autocorrelation model assigns a weight to the i -th event that will be multiplied by $K_s(s - s_i)$. The temporal autocorrelation model is separately developed for each spatial-temporal window (S, T) . Only events falling in (S, T) would participate in developing the autocorrelation model for this window. Additionally, only events falling in the (S, T) window that contain s would participate in calculating $p(s, t)$ in Equation (2). The subscript in $\sum_{(s_i, t_i) \in (S, T)}$ indicates this condition. Xu et al. used this model to forecast the daily number of sanitation SRs (e.g., garbage cart problems and general cleaning) in Chicago from 2011 to 2016. They considered four weeks as their temporal window (T) and community areas or neighborhoods as their spatial window (S), of which there are 77 in Chicago. Their model resulted in almost the same root mean square error (RMSE) as the Brunsdon et al. [9] model in Equation (1).

Wang et al. [10] applied k-means clustering to census tracts in Chicago, Boston, and New York City (NYC), from 2012 to 2015, based on their relative frequency of SR types. They showed that these clusters are homogeneous in terms of income, racial decomposition, employment, and education. They also showed a correlation between house prices and SR types at the zip code level. Minkoff [11] showed that, in NYC from 2007 to 2012, government-sponsored services, such as repairing streets and sidewalks and general cleaning, are over reported in census tracts with higher rates of income, children under 18, and homeownership, and lower rates of minorities, and older houses. Noise and graffiti related problems are under reported in the same census tracts. Clark et al. [12] showed that the Hispanic population in Boston underuses the 311 service. Kontokosta et al. [13] showed that neighborhoods with higher educational attainment, higher proportions of female, elderly, non-Hispanic White, and Asian residents, along with neighborhoods with higher incomes and rents in NYC, over report no heat or no hot water in the building via the 311 service. They further showed that neighborhoods with non-English speakers, higher unemployment rates, and higher proportions of minority populations, male residents, and unmarried adults under report these problems. O'Brien [14] showed that most 311 services in Boston are requested by people who live within two blocks of the location where the service is requested and three quarters of the 311 services are requested by homeowners.

White and Trump [15] showed that lower voter turnout and higher campaign donations are observed in NYC neighborhoods with higher volumes of 311 SRs. Wheeler [16] used linear regression to show that the number of non-emergency reports regarding detritus and infrastructure problems has only a small correlation with the rate of serious crimes, such as robbery and homicide, in Washington DC. Lu and Johnson [17] showed that in Edmonton, Canada from 2013 to 2015, there has been a shift from phone calls to internet-based channels for requesting 311 services. They also showed that younger people with a college degree and non-citizens prefer internet-based channels, while older people without a college degree and citizens prefer phone calls for requesting 311 services.

Our work is not only different from previous works in its purpose but it also takes a large step forward in terms of the data size and the novelty of the analysis. We have collected 311 SR records for 20 cities across the United States for their available history. We standardized the attribute names and SR types across the cities and years. This allowed us to compare SR type distributions over the years and among the cities and to find cities with similar or dissimilar types of SRs in each year. This study's findings provide insight into the temporal and spatial patterns of SR types, providing municipalities and local governments with a picture of where their city used to stand, where it stands right now, where it is headed in the future, and how it compares with other cities.

3. Data Description

A comprehensive effort has been made to collect the 311 SR records for all cities in the United States, as long as they are open to the public. One of the largest centers providing municipal data about cities in the United States is the US City Open Data Census (USCODC). This center provides the link to 311 SR records in any US city, if it is open to the public. The first issue was that not all links were operational at the time. After careful sweeping of those links on 29 June 2020, the 311 SRs were downloaded for 20 cities, for all the years that the data were available. For each city, only years for which the SRs are available for the entire year (i.e., from 1 January to 31 December) are preserved in our collection. This prevents underestimating the number of SRs for that year in that city. Our collection contains a total of 42 million SRs for 20 cities from 2006 to 2019, although not all cities have their data available for all these years. Table 1 lists the number of SRs per city and year in our dataset.

Table 1. Number of SRs per year and in each city.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	
Santa Monica	97	190	251	703	877	728	647	466	814	4162	4486	5641	14,681	19,830	
Kansas City		83,075	137,894	119,269	110,276	96,113	90,199	90,462	89,329	96,941	103,955	109,811	124,280	166,018	
San Francisco			172,912	185,920	194,907	205,750	258,801	307,204	345,177	450,233	510,244	599,330	660,522		
NYC				2,031,815	1,961,600	1,796,175	1,839,975	2,114,002	2,300,763	2,391,428	2,491,971	2,747,952	2,456,827		
Baltimore					772	1060	1363	2033	611,908	672,096	700,337	671,087	780,424	768,429	
D.C.						601	56,149	197,873	145,001	145,707	102,416	65,277	76,059	98,180	103,840
Oakland						33,647	37,995	47,294	56,888	61,826	66,889	75,932	80,740	77,851	110,928
Louisville						106,380	106,296	105,503	96,335	94,605	104,145	102,039	102,135	124,741	
Cincinnati							54,987	91,390	97,314	107,931	111,857	106,897	115,872	107,406	
Las Vegas							18,818	3443	2281	2830	6449				
New Orleans								41,316	41,230	42,151	47,976	50,134	52,881		
Austin									127,761	136,875	129,874	132,409	151,025	178,172	
Philadelphia										406,650	453,055	154,402	9662	1471	
Baton Rouge											78,690	80,102	98,083	112,100	
Gainesville											1396	2413	2288	2392	
Pittsburgh											78,047	79,852	100,459	94,955	
Minneapolis											51,764				
San Diego												144,404	182,781	309,202	
Los Angeles												1,131,781			
Chicago													1,826,465		

SR records published by different cities across the United States do not follow the same standard, if any. This has resulted in inconsistencies in the number, title, content, style, separator, and order of attributes in different datasets. Additionally, and more importantly to this study, SR types have inconsistent names in different cities. We manually standardized the aforementioned items in our dataset. More details about this standardization are provided in Section 4.1.

4. Methodology for Clustering Cities

We intend to find US cities that receive similar types of SRs with similar proportions. In other words, we want to find out what US cities face mostly similar or significantly different types of municipal problems. To this aim, we need to standardize SR types and create a feature vector for each city. Each standardized SR type is a feature. A feature vector refers to a vector containing the frequency of each standardized SR type. Section 4.1 discusses how the feature vector for each city is constructed and Section 4.2 explains our clustering method.

4.1. Feature Vectors

As mentioned before, the names of SR types are not standardized across different cities. Therefore, features do not overlap in different cities, which results in long and sparse feature vectors, which in turn results in every city having a zero similarity to any other city. This undermines the clustering results. We need cities to have standard names for their SR types. In other words, if two features represent the same concept in two different cities, they should have the same name in both cities. We used the description of each SR, metadata, and manuals describing the SR types for each city to understand and unify the names of SR types. Before standardizing SR types, there were a total of 6227 different SR types in the entire dataset. After standardization, this number reduced to 79. These 79 standardized SR types cover 95% of SR records in the entire dataset. Table 2 lists the standardized SR types, grouped in 12 general categories.

SR types with instances only in one city, as well as unspecific SR types, such as “Other”, “Request for service”, or “General” are omitted. Those omitted records represent 5% of the entire dataset, their type is referred to as “Other” in the rest of this paper, and their SR types are not reported in Table 2 because of their large number. Not only is the SR type “Other” ineffective in clustering, but also this consideration remarkably reduces the number of standardized SR types. In other words, clustering the cities will happen only based on the 79 standardized SR types, because the SR type “Other” does not represent the same SR type in different cities. However, SRs with the type “Other” will be considered when the relative frequency of each standardized SR type is calculated, in order to assure that the relative frequencies reflect each city’s dataset in its entirety.

The data are available for multiple years at each city. To fairly cluster the cities, we do not mix SRs from different years into one set. Rather, we offer a different clustering of cities for each single year. Therefore, each city will have a different feature vector for each year. Each year, only cities which have data available for that year will participate in the clustering.

Larger cities naturally receive more SRs than smaller cities. If the absolute numbers of SRs are used for clustering, large cities will form one cluster and small cities another, solely because of the large gap between their number of SRs. The solution is to use the relative frequency of each SR type rather than its absolute number. If two cities have similar proportions of the same SR types they will be considered similar, regardless of how large or small their absolute numbers of SRs are. Using the relative frequency instead of the absolute frequency has another advantage as well. It standardizes the values of all features to range between 0 and 1. Therefore, no further standardization is required for the feature values before clustering.

4.2. Clusters and Outliers in a Two-Dimensional Visualization of Cities

Presenting only the results of clustering is not as effective as providing visualizations of clusters; visualization not only makes it easier to observe the clusters and outliers, but also reveals details about the compactness or spread of clusters and how far each outlier is from the cluster.

The 79 SR types mean there are 79 features or dimensions. While cities can be represented in a 79-dimensional space, they cannot be visualized in that space. A simple visualization is restricted to two dimensions. Therefore, we need to reduce the dimensionality from 79 to 2, in order to depict the distribution of cities and clusters therein. Samples cannot be as spread in a lower dimensional space after projection as they were in a higher dimensional space before projection. In other words, when data are projected from a higher dimensional space to a lower dimensional space, the distribution of samples will be more restricted; more restriction in the lower dimensional space means that samples cannot be spread with the same variance as in the higher dimensional space. Therefore, dimensionality reduction, in order to solve real-world problems, is always associated with variance loss. An ideal dimensionality-reduction method would minimize this variance loss. One of the most effective methods in doing so is principal component analysis (PCA) [18]. This method first looks for the direction of the highest variance in the original space that is the direction along which samples are stretched most. This direction does not necessarily need to align with any of the original features. This direction is called the first principal direction. Then, this method finds the direction with the second highest variance in the original space, with the only constraint that the second direction must be orthogonal to the first. This direction is called the second principal direction. The next principal directions could be found the same way. If samples are to be projected on a two-dimensional space, this method stops after finding the second principal direction and projects the samples on the first and second principal directions. The result of this projection is the transformation we had in mind to visualize the cities.

Since principal directions after the second principal direction are dismissed in the projection, the variance associated with those principal directions is also lost. The higher the percentage of variance preserved by the first two principal directions, the more reliable the two-dimensional visualization. We will report what percentage of the variance is preserved, after the dimensionality is reduced to two, for each of our visualizations in the next section.

In addition to PCA, we apply factor analysis (FA) to reduce dimensionality too, and compare their results. FA is a linear model that performs a maximum likelihood estimate of the so-called loading matrix, which is the transformation of the latent variables to the observed ones, using an SVD based approach. It assumes that observations are caused by a linear transformation of lower dimensional latent variables and added Gaussian noise. Factors are distributed according to a Gaussian distribution with zero mean and unit covariance, and noise is distributed with a zero mean and an arbitrary diagonal covariance matrix. While the PCA component is a linear combination of the observed variable, in FA, the observed variables are linear combinations of the generated variables. While the PCA components are fully orthogonal to each other, FA components are not required to be orthogonal. While the PCA components explain the maximum amount of variance, FA explains the covariance in the data.

5. Results and Discussion

5.1. Changes in SR Types over the Years

Figure 1 portrays the rate of different SR categories in different cities and years. These categories are explained in Table 2.

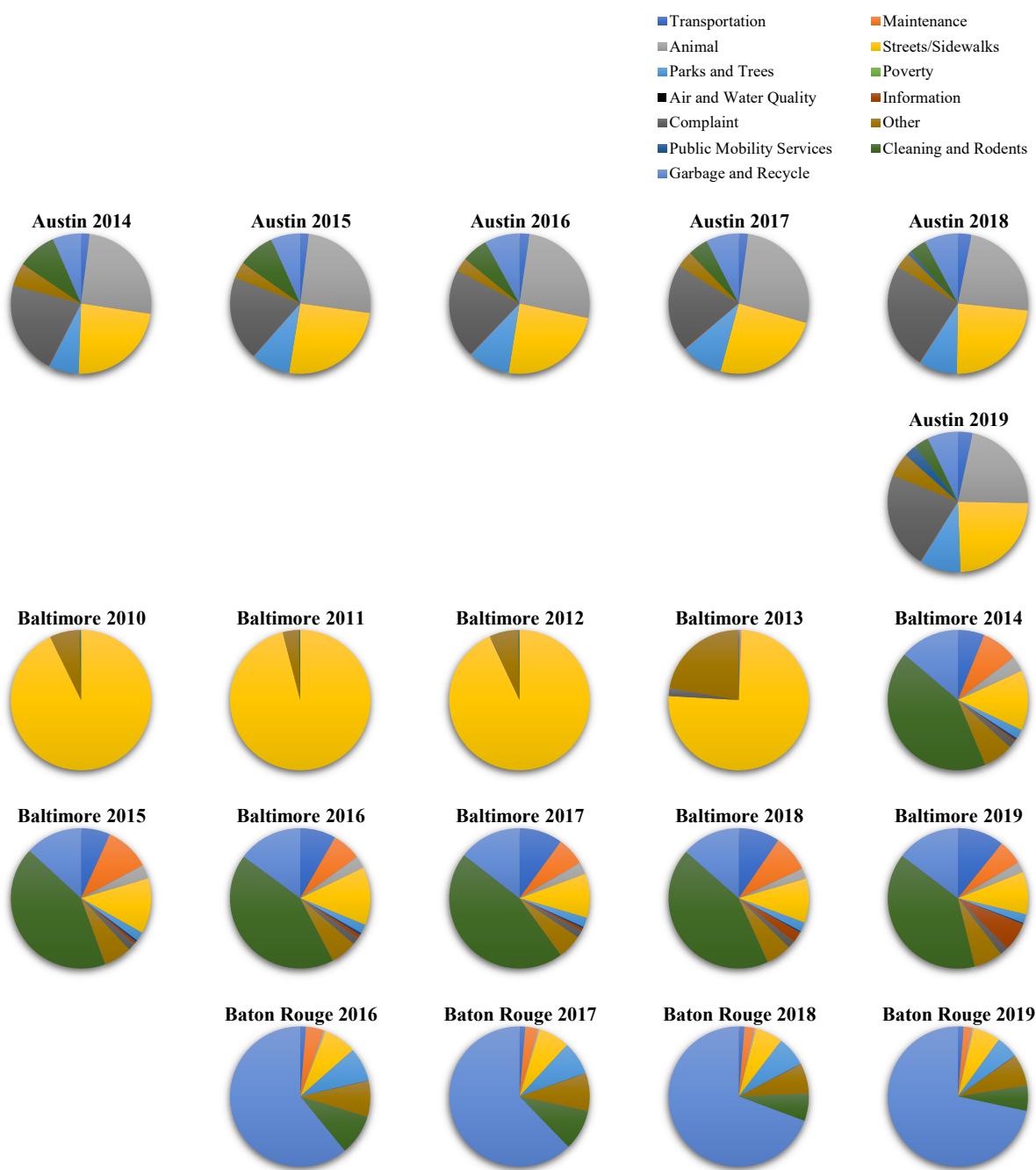


Figure 1. Cont.

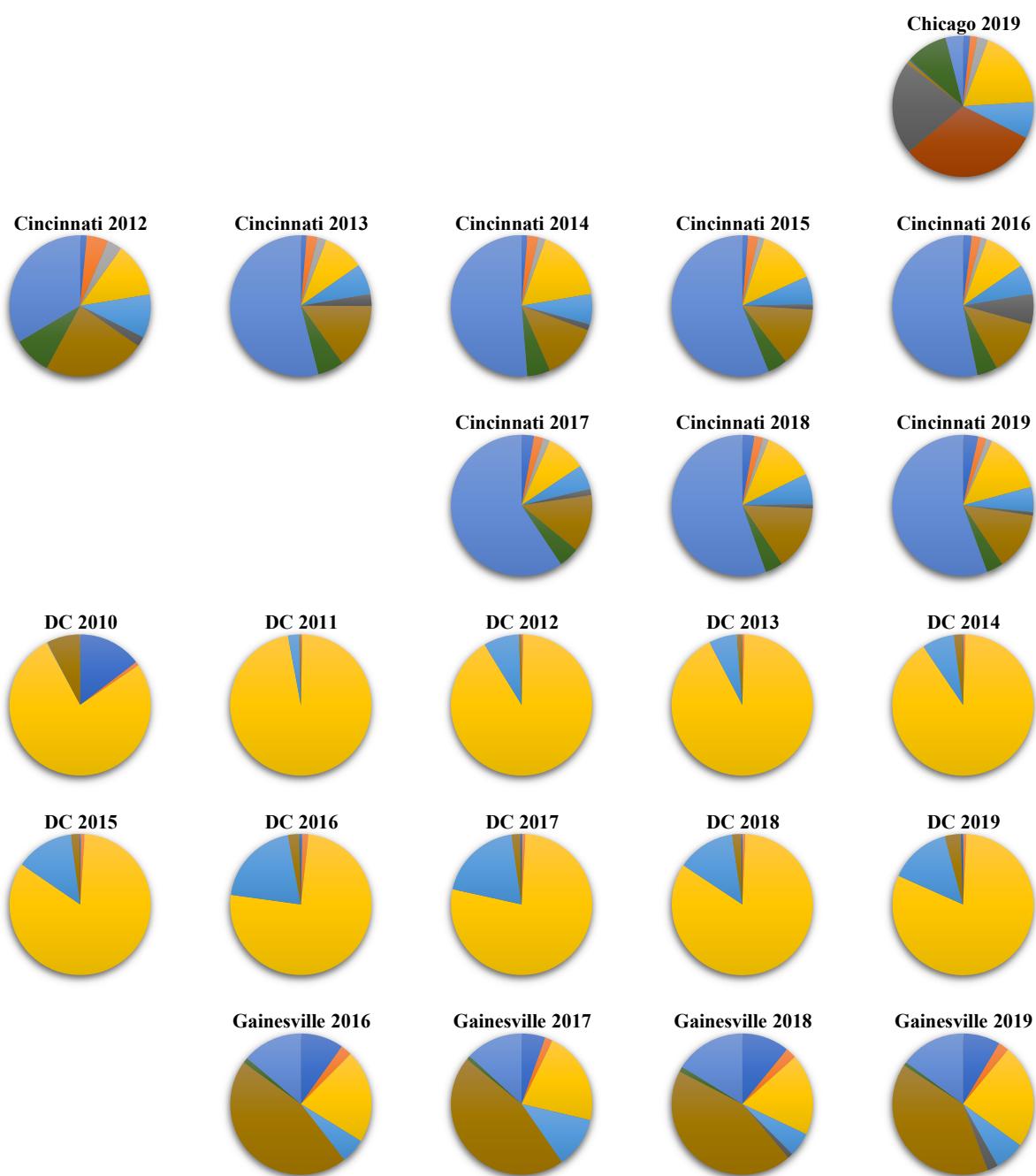


Figure 1. Cont.

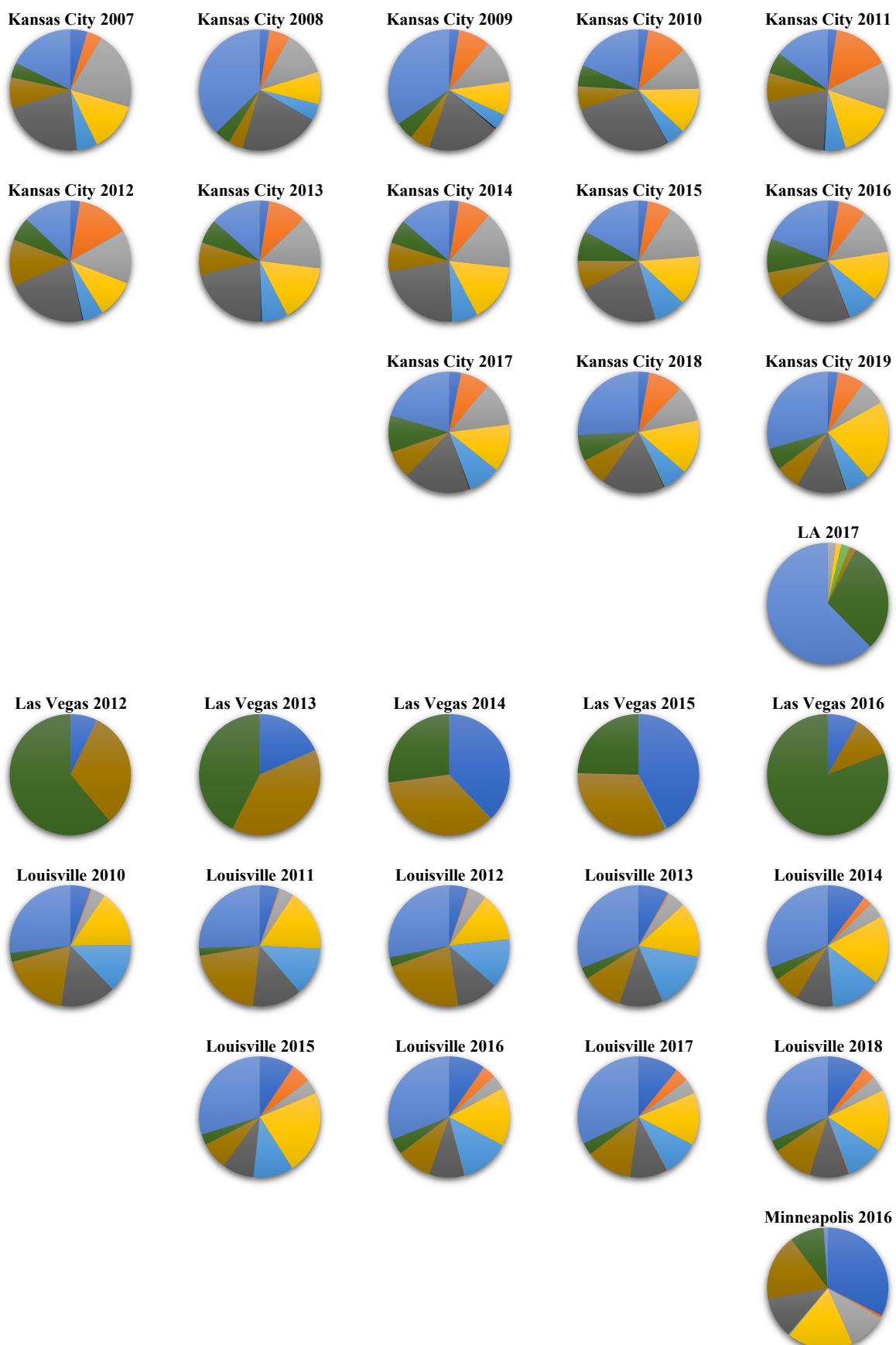


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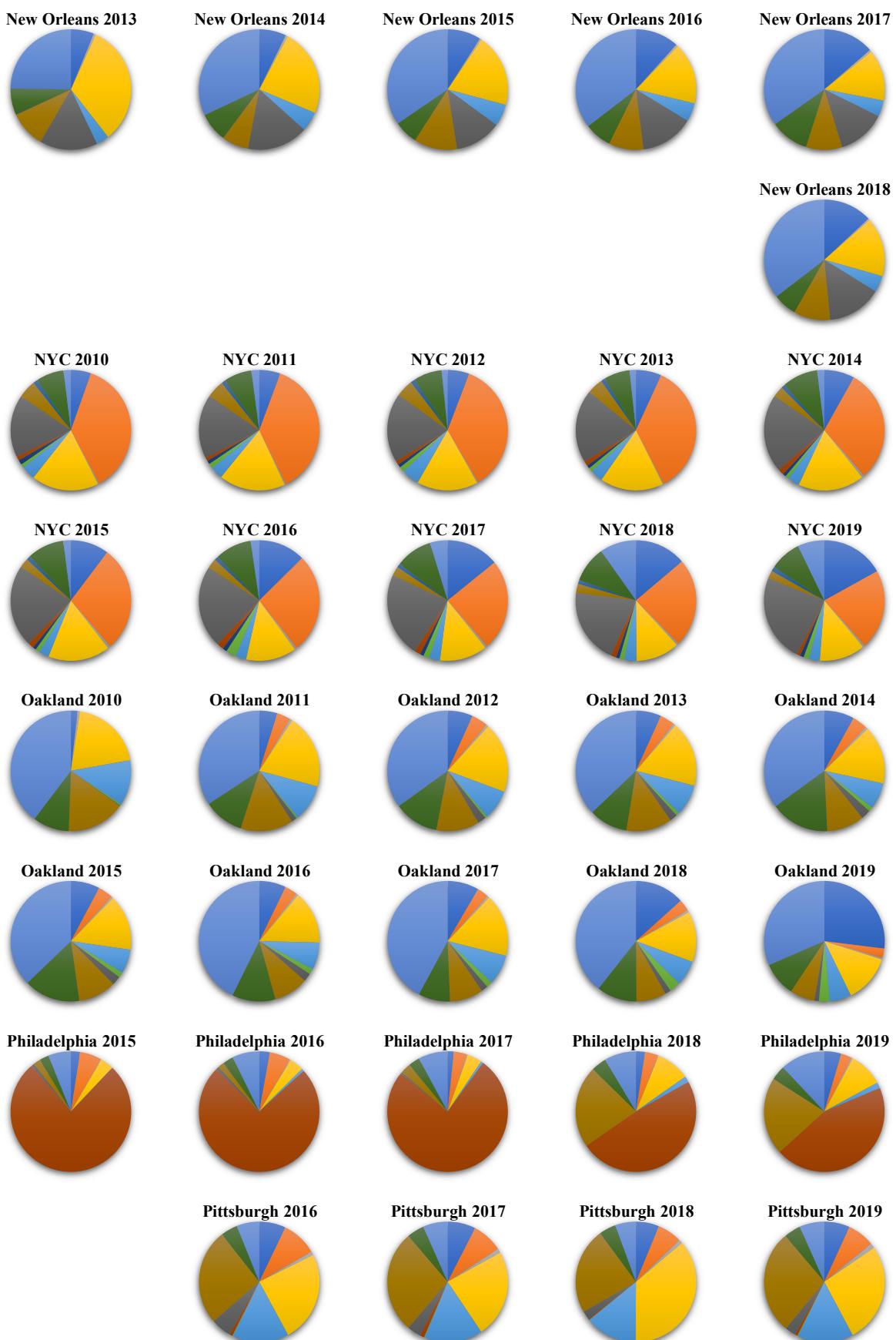


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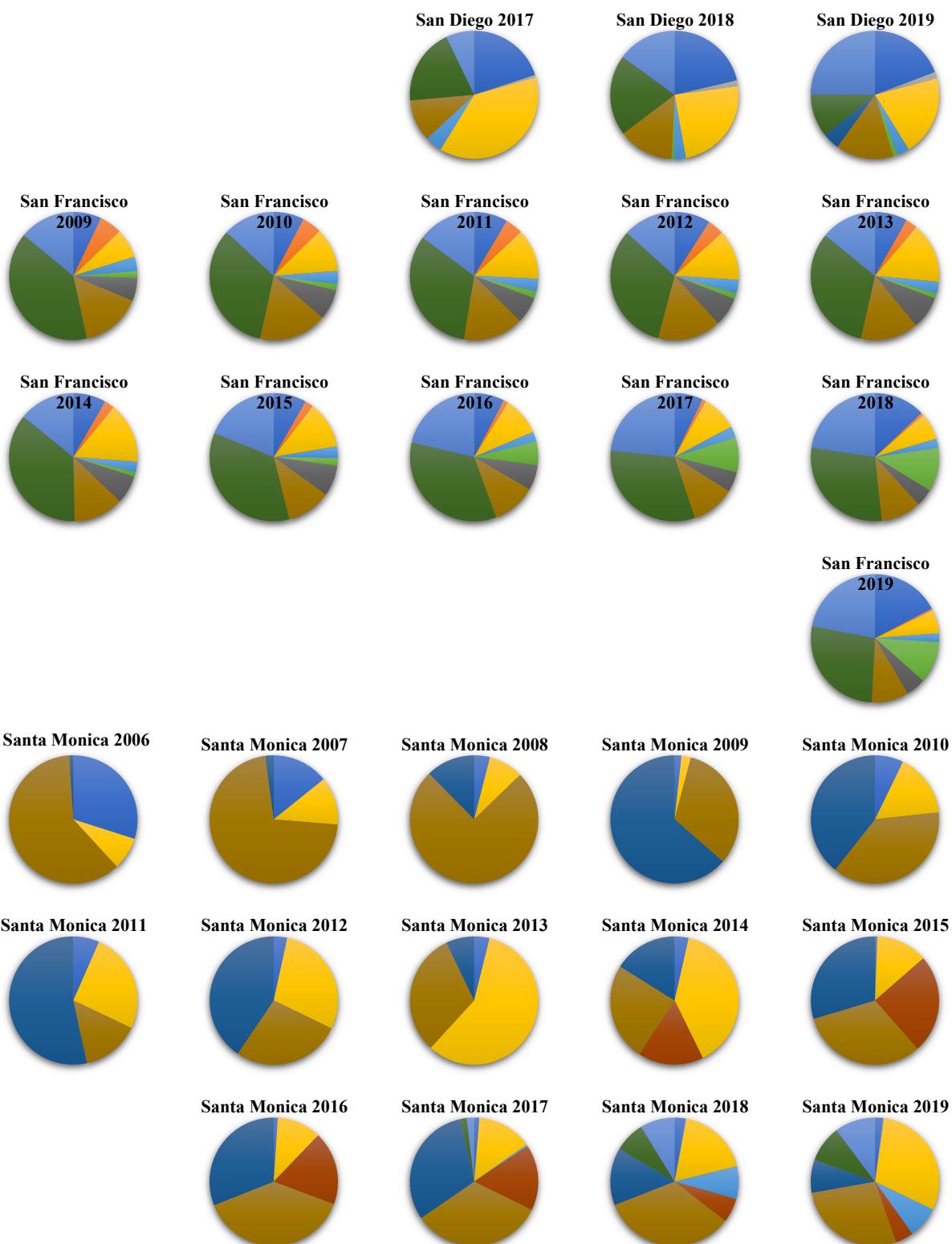


Figure 1. SR type frequencies per city and per year.

According to Figure 1, the patterns of general request categories have not changed much in Austin, over the years. Throughout the years, requests regarding streets and sidewalks and animals have formed almost half of all the requests, with complaints being the third major category.

In Baltimore, almost all the requests were concerning streets and sidewalks in 2010. This category's rate suddenly dropped to 14% in 2014 and decreased to 10% gradually by 2019. In 2014, requests regarding cleaning and rodents not only appeared as a new major category but also became the most frequent category, forming almost half of all the requests. This remained the most frequent category in the following years. Requests concerning streets and sidewalks became the second most frequent category in 2014. However, it gradually shrank in rate, giving their second place to the growing category of requests regarding transportation. In 2019, requests for information rose to become a major category as well.

In Baton Rouge and Cincinnati, requests regarding garbage and recycling have consistently formed more than half of all the requests, with their rates rising gradually every year in Baton Rouge.

In Chicago, almost one third of requests were for information in 2019, the only year for which data are available for Chicago. Complaints and requests regarding streets and sidewalks form the second and third most frequent categories in this city.

In DC, almost all the requests have consistently been about streets and sidewalks. Transportation was the second most frequent category, only in 2010. Since 2011, parks and trees have been the second major category, which gradually rose in rate every year.

Gainesville has a diverse set of request categories, none of which significantly dominate the others. Requests concerning streets and sidewalks, garbage and recycling, parks and trees, and transportation have consistently been more frequent throughout the years.

In Kansas City, complaints were the most frequent category up until 2016, when they started to gradually shrink in rate and give their first place to garbage and recycling as the most frequent category. Requests regarding animals, streets and sidewalks, maintenance, and parks and trees have also been major categories over the years.

In LA, requests regarding garbage and recycling formed almost two thirds of all the requests in 2017, with the remaining requests being mostly about cleaning and rodents. Data for LA are only available in 2017.

In Las Vegas, almost two third of all the requests were concerning cleaning and rodents in 2012. This rate gradually fell, reaching only a quarter of all the requests in 2015. In 2016, however, this category's rate soared to 80%. The second major category in Las Vegas has consistently been transportation.

Louisville has had a diverse set of request categories throughout the years. Garbage and recycling has consistently been the most frequent category, taking almost one third of all the requests every year. The other major categories have consistently been streets and sidewalks, parks and trees, and complaints. Requests about transportation have been gradually growing in this city, becoming one of the major categories in 2018.

Data for Minneapolis are only available in 2016, when the transportation category formed one third of all the requests. Other major categories were streets and sidewalks, animals, and cleaning and rodents.

In New Orleans, requests concerning garbage and recycling have consistently formed about one third of all the requests. Requests regarding streets and sidewalks have been the second major category with their share gradually falling over the years and giving their place to requests about transportation. Complaints and requests concerning cleaning and rodents have been other major categories in New Orleans.

In NYC, the vast majority of requests have always been about maintenance and streets and sidewalks. Despite consistently being major categories over the years, these two categories have been gradually shrinking in rate, giving their place to the rising categories of complaints, transportation, garbage and recycling, and cleaning and rodents.

In Oakland, requests concerning garbage and recycling have consistently formed at least one third of all the requests. The second major category was streets and sidewalks in 2010, but its rate gradually decreased until it gave its second place to the rising category of transportation in 2019.

In Philadelphia, more than three quarters of requests were for information in 2015. However, this category's rate gradually fell over the years, reaching less than half of all the requests in 2019. On the other hand, requests concerning streets and sidewalks and garbage and recycling have been gradually increasing in rate over the years.

In Pittsburgh, a growing number of requests are about streets and sidewalks, transportation, and cleaning and rodents. On the other hand, requests regarding parks and trees and maintenance have been falling in rate over the years.

San Diego's most frequent category up until 2018 was streets and sidewalks, but it gave its place to garbage and recycling in 2019. Requests regarding transportation and cleaning and rodents have been the next major categories.

In San Francisco, almost 40% of requests were regarding cleaning and rodents in 2009, but this category's share gradually fell to 27% by 2019. The fastest growing categories in this city have been garbage and recycling and transportation. Requests regarding streets and sidewalks had a rising rate from 2009 to 2013, but a falling rate afterwards. Requests regarding maintenance also had a shrinking rate, falling from 6% in 2009 to less than 1% in 2019.

In Santa Monica, requests regarding transportation had the highest rate in 2006, but their rate gradually dropped to close to 0 in 2015 and gradually rose to 2% in 2019. Requests regarding streets and sidewalks, forming only 8% of all the requests in 2006, grew to 58% by 2013, fell to 11% by 2016, and rose again to 30% by 2019. Public mobility services appeared as a new category of requests with a 12% rate in 2008. Their rate soared to 64% in 2009. It remained a major category until 2017, but its rate dropped to 15% in 2018 and 8% in 2019. Requests for information appeared as a major category, with a 16% share, in 2014. This share reached 25% in the following year but started to fall afterwards, reaching only 5% by 2019. Requests concerning garbage and recycling, cleaning and rodents, and parks and trees started to rise and become major categories in Santa Monica since 2018.

5.2. Visual Clustering of Cities Based on SR Type Rates

Table 3 shows features with more than 1% contribution in the PCA transformation. These features played a bigger role in creating the two-dimensional visualizations. These contributions are calculated based on the coefficients of features in the PCA linear transformation. Features with higher contributions are those whose values have higher variances across cities.

Table 3. Features with more than 1% contribution in the PCA transformation.

Feature	Contribution	Feature	Contribution
Parking Meter Repair/Request	9.88%	Street/Road Sign Repair/Replacement/New	2.72%
Information Request	9.36%	Tree Care/Removal/Debris and Tall Grass/Weed	2.71%
Sidewalk/Curb Repair	8.03%	Cleaning and Sanitation	2.44%
Graffiti Removal	7.48%	Animal Control/Care	2.38%
Missed Garbage/Recycling Pick-up	6.05%	Street/Road Repair	2.38%
Bus Operator/Late/Safety Complaint	5.58%	Nuisance Complaint	2.00%
Bulky Items	5.31%	Illegal Dumping	1.95%
Street Light Repair/Add	4.19%	Garbage/Recycling Collection	1.75%
Garbage/Recycling Cart Repair/Replacement/New Service	3.86%	Construction and Plumbing	1.67%
Parking Violation	3.68%	Sewage/Storm Water	1.52%
Property Violations	3.66%	Abandoned Vehicle	1.40%

Figure 2 displays cities as points on a two-dimensional canvas based on the similarity among their SR types. In other words, cities closer to each other on this canvas have similar rates of the same SR types. These visualizations were developed based on the methodology in Section 4, separately for each year. As mentioned in Section 4.2, reducing the dimensionality (number of SR types) from 79 to 2, using the PCA transformation, comes with a cost in the form of lost variance. At the top of each visualization, the percentage of the variance preserved after dimensionality reduction is mentioned inside the parentheses; the higher the percentage, the more reliable the visualization. At the bottom of this figure the results of dimensionality reduction, using the FA approach, for 2018 and 2019 are depicted, which are similar to that of the PCA.

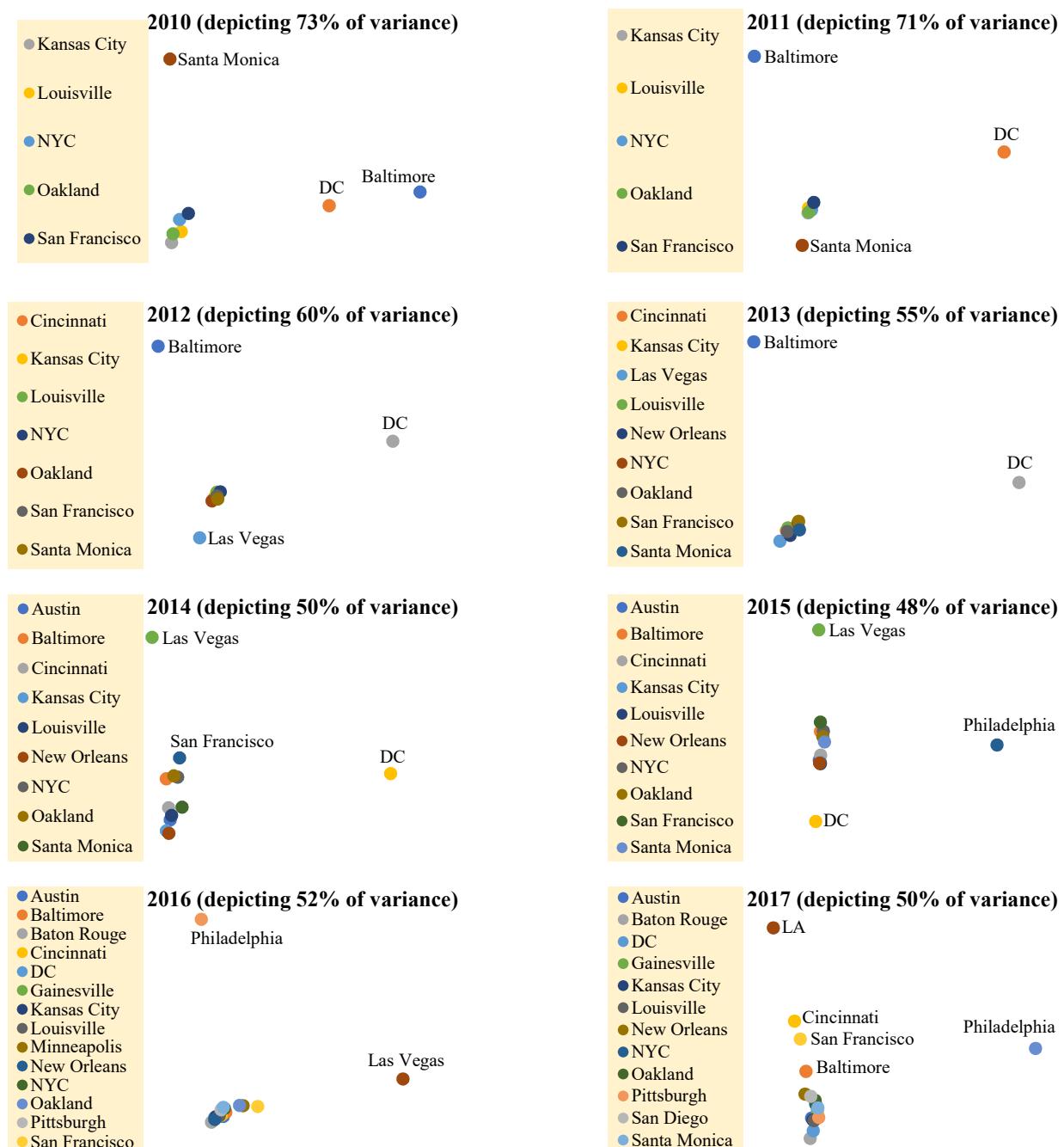


Figure 2. Cont.

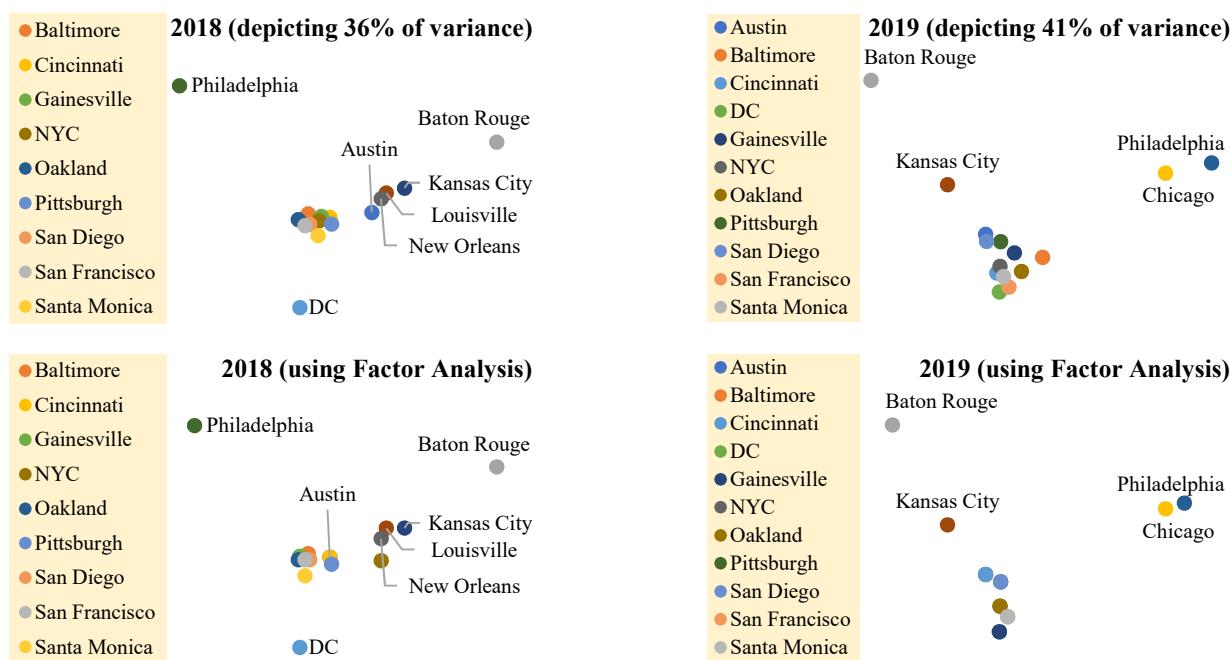


Figure 2. Visual clustering of cities based on non-emergency SR type rates in different years.

PCA takes advantage of all the original features and linearly combines them to best preserve the distance between the samples after projection to the two-dimensional space. This comes with the disadvantage that it is not possible to explain the distribution of samples in the two-dimensional space based on the original features. However, we attempt to provide such explanations heuristically. Due to the large number of features (79), offering even heuristic justifications of clusters and outliers could be complex, difficult, and inaccurate. In the following, we attempt to provide such explanations based on the 12 main categories of requests in Table 2, rather than the original 79 features.

In 2010, among cities whose data are available for this year, Santa Monica was farthest from other cities. The main reason is that almost 40% of SRs in Santa Monica were from the public mobility services category, which was not a common category in other cities. Baltimore and DC were two other outliers because of their large category of streets and sidewalks, which has much lower rates in other cities.

In 2011, Baltimore and DC were outliers for the same reason; more than 96% of their requests were concerning streets and sidewalks while this percentage was between 13% and 25% in other cities. These two cities were also not next to each other because the type of their remaining 4% of requests was different. Santa Monica was closer to the dense cluster of most cities in 2011 than the previous year because as its rate of cleaning and rodents category slightly shrank, that of other cities slightly rose, moving them closer to each other.

In 2012 and 2013, Baltimore and DC remained outliers for the same reason. In 2012, Las Vegas was slightly outside of the dense cluster of most cities because 61% of its requests fell in the cleaning and rodents category. This percentage was much smaller in other cities. Additionally, Las Vegas did not have as large a rate as other cities in categories such as streets and sidewalks, parks and trees, and complaints.

In 2014, DC remained an outlier for the same reason. However, Baltimore was no longer an outlier, because its rate of requests regarding streets and sidewalks sharply dropped to a rate closer to that of other cities. Las Vegas remained an outlier this year as well, because majority of its requests were about cleaning and rodents and transportation, with not many requests from other categories.

In 2015, DC and Las Vegas remained outliers for the same reason. This year, Philadelphia was an outlier too, because 77% of its requests were for information, which was much higher than other cities.

In 2016, Las Vegas and Philadelphia remained outliers for the same reason. However, DC got much closer to other cities, because of two reasons: first, its share of requests from the streets and sidewalks category slightly decreased while other cities had a slight growth in this category; second, other cities received a higher rate of requests regarding parks and trees, which was a major category in DC.

In 2017, Philadelphia remained an outlier for the same reason. LA was an outlier because 62% of its requests were from the garbage and recycling category, which was much higher than other cities.

In 2018, data were available for 16 cities, the highest of all years. Philadelphia remained an outlier for the same reason. DC became an outlier once again because the rate of its requests regarding streets and sidewalks soared to 84%, while other cities observed a decrease in this category's rate. Baton Rouge was an outlier this year because of its 69% share of requests regarding garbage and recycling, which was much higher than other cities.

In 2019, Philadelphia and Baton Rouge remained outliers for the same reason. Chicago was an outlier as well. Chicago formed a couple with Philadelphia because they both had a large category of requests for information. Other categories also shared similar rates in these two cities, except for the category of complaints, with a 21% rate in Chicago and less than 1% in Philadelphia. Kansas City also stepped slightly outside of the dense cluster of most cities, towards Baton Rouge, because of the increase in its requests regarding garbage and recycling.

6. Conclusions and Future Directions

An interesting pattern in many cities, such as Baltimore, Louisville, New Orleans, NYC, Oakland, and San Francisco, is the decrease in SRs regarding streets and sidewalks and the increase in requests about transportation, in the past decade. This pattern is the result of the dramatic rise in the number of vehicles on the streets. It shows that the slow boost in quality and capacity of roads does not meet the dramatic rise in transportation demand, resulting in a shift in request types from streets and sidewalks to transportation. Requests regarding garbage, cleaning, rodents, and complaints have also been rising in some cities, reflecting the insufficiency of those cities' infrastructure to keep up with the population growth. New types of requests have emerged and soared in recent years, such as requests for information and regarding shared mobility devices, reflecting the popularity of shared mobility devices, despite being a new service, and their unexpected problems and complaints.

The most consistent outliers, in terms of SR types are: Washington DC and Baltimore because of their much higher rate of requests concerning the condition of streets and sidewalks; Las Vegas because of its much higher rate of requests regarding graffiti, cleaning, and rodents; Philadelphia and Chicago because of their much higher rate of requests for information; and Baton Rouge because of its much higher rate of requests regarding garbage collection.

One future direction is to expand this study to other countries, where the 311 service is available, and to compare cities worldwide. This will allow us to find cities with similar problems across the world and compare their policies, outcomes, and experiences. Another future direction is to fuse the knowledge obtained from 311 SRs in this study with knowledge about road and pedestrian networks and online social media, to gain a deeper understanding and wider picture of problems, circumstances, causes, and possibly solutions.

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