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Predictive Big Data Analytics for Service Requests: A Framework

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Abstract

Nowadays, valuable big data are generated and collected rapidly from numerous rich data sources. Following the initiatives of open data, many organizations including municipal governments are willing to share their data such as open big data regarding non-emergency city service requests from their residents. Big data analytics on these open big data can be for social good. Hence, in this article, we present a framework for predictive big data analytics for service requests. The framework mines historical open big data to discover patterns about service requests, and predicts the demands for these services in the future. The discovered knowledge and predictions may provide policy makers deeper understanding of their data and requested services so that appropriate actions could take place. Evaluation on open big data from the City of Winnipeg demonstrates the usefulness of our framework for conducting predictive big data analytics for service requests.

Keywords: Big Data; Open Data; Data Management; Data Mining; Non-Emergency Municipal Services; Service Requests; Location-Based Recommender System (LBRS)

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1. Introduction

In the current era of big data [1, 2], huge volumes of valuable data can be easily generated and collected at a rapid velocity from a wide variety of rich data sources. In recent years, the initiates of open data also led to the willingness of many government, researchers, and organizations to share their data and make them publicly accessible. Examples of open big data include biodiversity data [3], census data [4], financial time series [5-7], healthcare and disease reports (e.g., COVID-19 data) [8-10], patent register [11], social networks [12-14], transportation data [15-17], weather data [18], data related to social and economic situations [19], and data related to requests for non-emergency services provided by cities to their residents.

Embedded in these big data are useful information and valuable knowledge that can be discovered by *data science* [20-22]—which make good uses of data mining algorithms [23-30], data analytics methods [31-34,61], machine learning tools [35-38], data retrieval [39], and/or mathematical and statistical modeling [40]. Analyzing these big data can be for social good.

In many cities in the Americas (e.g., Canada, Costa Rica, Panama, USA), a special single telephone number—namely, 311—has been set up to support non-emergency municipal service requests. Residents in a municipality or city can dial 311 to request for *non-emergency services* (cf. 911 to request for *emergency services* like serious crime, fire, medical emergency, etc.). Similar single non-emergency numbers are also available in other parts of the world (e.g., 115 in Germany for public administration's customer service).

When a call is made to the 311 Contact Centre, it can a request for information (e.g., permit processing, animal control, building inspections, traffic/parking issues, hours of operation of civic offices and facilities, assessment and taxation, transit schedules) or non-emergency services (e.g., sewer back-up, water main break, bulky garbage collection). Hence, analyzing and mining the data collected at the 311 Contact Centre for these big non-emergency services helps the city to get an insight on its residents' requests, which in turn support effective management and allocation of the available resources to appropriate municipal departments. Consequently, proper actions (e.g., providing better services) can be taken place to meet the city residents' demand and thus enhance their living condition. Furthermore, mining these non-emergency city service requests also helps other users to get an insight on many other aspects. For example, it helps discover implicit, previously unknown and potential useful information and knowledge like socioeconomic and demographic features for predicting of political engagement [41], real estate values [42], geo-correlation among service types [43], as well as public health and urban decay [44].

In this paper, we present a big data mining system to analyze and mine big data on non-emergency city service requests. Our *key contributions* of this paper is the resulting big data mining system. It makes good use of frequent pattern mining to determine the popularity of service requests. Based on the discovered patterns, it makes good location-based predictive recommendations.

The remainder of this paper is organized as follows. The next section discusses related work. Section 3 describes our big data mining system on non-emergency service requests. Section 4 shows evaluation results on real-life 311 service request data. Finally, Section 5 draws the conclusions.

2. Related Work

There have been some related works on analyzing 311 data. For instance, Wang et al. [42], as well as Zha and Veloso [43], used random forest to classify 311 data. Athens et al. [44] applied natural language processing (NLP) to audio calls for identification of urban blight to improve public health. Eshleman and Yang [45] conducted sentiment analysis on Twitter tweets to study 311 civil complaints. With an aim to build a smart city, Tariq et al. [46] applied convolutional neural networks (CNN) to both 311 and urban noise data for noise detection. Yusuf et al. [47] applied Bayesian networks to make causal inference to 311 administrative data. Pamukçu and Zobel [48] examined 311 reactions to the global health emergency—namely, COVID-19 pandemic.

Besides adding new functionalities for the aforementioned purposes and applications, there have also been some related works on measuring the 311 performance in various cities. For instance, Chatfield and Reddick [49] studied

311 data from Houston[†]. Hagen et al. [50] analyzed 311 data from Miami[‡]. Wu [51] examined the 311 system in San Francisco[§]. Choi et al. [52] compared 311 calls from various cities with an aim find commonalities and disparities.

In contrast, our current paper aims to find frequent characteristics associated with popular 311 service requests. The discovered knowledge supports predictive recommendation [53] such as location-based recommendation [54]. Moreover, we evaluated our data mining system with real-life 311 data from a Canadian city of Winnipeg.

3. Our Data Mining System

In this section, we describe our data mining system. It analyzes and mines the 311-service request history from the neighborhood to support the prediction of what kind of services are most likely to be in demand in the future. It can be considered as a non-trivial combination of frequent pattern mining, stream mining, and location-based recommender system (LBRS).

3.1. Data Preprocessing

The system first examines the 311 call history, which may consist both information requests and service requests. In this paper, we handle the latter. Typically, each record in the history log of *311-service requests* contains features like service request date and time, request category area (e.g., by-law enforcement), request type (e.g., neighborhood livability compliant), district, neighborhood, and GPS location. With these features, our system preprocesses and derives generalized information related to date and time. For example, service request date can be generalized into the day of the week, month, quarter (or season), and year. Similarly, service request timestamp can be generalized into the hour of the day, short time interval (e.g., morning, afternoon, evening, night) of the day, and 12-hour time interval (i.e., AM or PM). In addition to the temporal hierarchy that can be formed by these derived features, two hierarchies can be formed by the features existed in the 311 call history log:

- Service request type can be generalized into category area.
- Service GPS location can be generalized into a neighborhood, which in turn can be further generalized into a district (or electoral ward)

See Fig. 1 for temporal, categorical and spatial hierarchy.

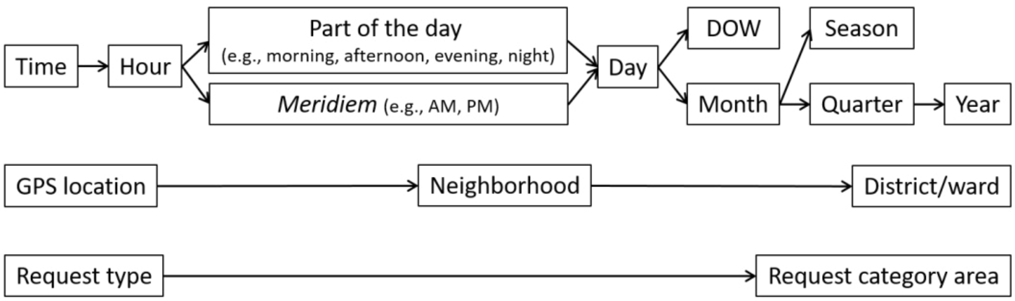

Fig. 1. Temporal, categorical and spatial hierarchy.

3.2. Data Mining

Once the data are preprocessed, our system then analyzes and mines the preprocessed data. To speed up the mining process and aim for location-based recommendation, we assign a LBRS for each neighborhood and assigned LBRS

[†] https://www.houstontx.gov/311/
[‡] https://gis-mdc.opendata.arcgis.com/
[§] https://data.sfgov.org/City-Infrastructure/311-Cases/vw6y-z8j6

focuses on the data for the neighborhood. This makes logical sense that the demand for each neighborhood may vary. As a side-benefit, mining can be carried out in parallel. Each LBRS focuses the mining only on a subset (e.g., neighborhood) instead of the entire data. Hence, the mining process is sped up. Moreover, if any of the parallel processor is not operating, the main processor could reassign the task to another processor for location-based recommendation so that the interruptions are unnoticeable to users. Furthermore, having location-based recommendation enables users to express their local preferences and makes it easy for the LBRS to incorporate these local preferences.

Each LBRS mines the data specific for a neighbourhood and discovers frequent patterns (or more specifically, maximal patterns). A *maximal pattern* is a frequent pattern such that none of its superset is frequent.

Note that, although we mentioned earlier that each LBRS is assigned to a neighborhood, the concept can be generalized. Depending on the available resources (LBRS) and the number of locations, we could assign LBRS based on the hierarchical structure—in which several neighborhoods can be generalized into a district (or electoral ward). Several districts can be generalized into a city, which can then be generalized into a province and a country. With this hierarchy, we could assign a LBRS to a country, a province, a city, a distinct, or a neighborhood.

3.3. Location-Based Recommendation

Once maximal frequent patterns are discovered from each dataset corresponding a neighborhood, our system makes different types of recommendations. Season-based recommendation is one of them. To elaborate, residents in a city may request different services depending on the seasons. For example, there are more service requests on snow removal on roads (which is an instance of the category area of street maintenance) in the winter than the summer. Conversely, there are more service requests on boulevard mowing (which is an instance of the category area of parks and urban forestry) in the summer than the winter. Moreover, partially due to advancements in technology or progressive improvements of city services throughout the years, the service requests from recent winters may be a more accurate reflection of the *recent* demand than the *historical* demand from the city residents. Consequently, our system uses a time-decay or time-fading data processing model so that recent demands are weighted heavier than historical demands when incorporating the information. The mined maximal frequent patterns discovered from mining service request log provides decision makers in the city with some insights about its residents' demands in different seasons. They help make predictive recommendations based on the season so that decision makers in the city could take appropriate actions (e.g., putting resources on certain service areas according to the season) in attempt to meet its residents' demands.

Similarly, time-based recommendation is another type predicted by our system. The mined maximal frequent patterns discovered from mining service request log provides decision makers in the city with some insights about its residents' demands in different days of the week or at different time in a day. They help make predictive recommendations based on the time so that decision makers in the city could take appropriate actions (e.g., putting resources responding to requestors) in attempt to meet its residents' demands.

4. Evaluation

To evaluate our data mining system, we used real-life open data collected from the 311 Contact Centre[**] in a Canadian city of Winnipeg. In this city, the 311 Contact Centre was established as early as January 16, 2009. Since then, it has served as an easy-to-remember phone number to connect to the city, and as a single point-of-access to all non-emergency city services. Residents can access the center 24/7 by various channels—including phone, email, self-service, social media, etc. For example, as of May 2021[††], phone has been the most popular channel (accounting for 73% of interactions), followed by email (which accounted for 20% of interaction). The center handles request for a

[**] https://data.winnipeg.ca/browse?category=Contact+Centre+-+311

[††] https://data.winnipeg.ca/Contact-Centre-311/311-Performance-Metric-Interaction-By-Channel-2021/gejk-42v3

service or information, concerns, and registration for city programs. Among them[‡‡], service requests accounted for 65% of business, and information requests accounted for 34%.

The city has been collecting request logs from 2014 to present. As recent data would be a more realistic reflection of the current trends in residents' demand, we focus on those data collected from 2018. In the dataset, service request date, time, category area, ward, neighborhood, and GPS location are captured. Here, the dataset captures eight service request category areas: animal services, by-law enforcement, garbage & recycling, insect control, parks & urban forestry, sewer & drainage, street maintenance, as well as water. For the GPS location, it is accurate up to 500m in both latitude and longitude. It is partially due to the inherited measurement inaccuracy and privacy-preserving mechanism to blur the location of the request services for protecting the individual identity.

4.1. Analytical Evaluation

Let us consider a dataset D that contains n records and takes $time(D)$ to run. When D is distributed into k disjoint partitions $\{D_1, D_2, D_3, ..., D_k\}$ where $1 \leq k \leq n$. When conducting frequent pattern mining on each partition in serial, the total execution time would be the sum of the execution time for each partition, i.e., $time(D_1) + time(D_2) + time(D_3) + ... + time(D_k)$. This would result in $time(D)$, or plus extra communication costs.

The good news is that mining of each partition does not need to be performed in serial. As each partition is disjoint, the mining process can be performed in parallel. Consequently, the total execution time would be the maximum among the execution time for all partitions, i.e., $max\{time(D_i) \mid 1 \leq i \leq k\}$. An adversary may argue that, as D is distributed into k disjoint partitions by neighborhood, D may not be evenly distributed. The resulting distribution can be skewed. Without loss of generality, if $D_j \approx D$ for some $j \in [1, k]$, then $max\{time(D_i) \mid 1 \leq i \leq k\} = time(D_j) \approx time(D)$. Fortunately, such a total time for parallel mining would be bound above by the total time for serial mining of k partitions. Moreover, in the unlikely event that $D_j \approx D$, we could redistribute D_j into multiple small partitions $D_{j,m}$ (such that $D_j = \cup D_{j,m}$) to be executed by parallel mining.

4.2. Empirical Evaluation

Regarding the potential problem associated with extremely skewed data (e.g., $D_j \approx D$), we observed that most the real-life datasets would not be that extreme. For example, in the Winnipeg service request dataset D used for evaluation, size of the maximum partition D_j is approximately 7% of D, i.e., D_j accounts for 10,862 of the 147,014 service requests in D among all 237 neighborhoods (which can be generalized into 15 electoral wards) in the Canadian city of Winnipeg. Hence, $max\{time(D_i) \mid 1 \leq i \leq k\} = time(D_j) \approx time(0.07\ D)$. This leads to significant saving in execution time. Fig. 2 shows the top-20 neighborhoods in terms of their numbers of service requests.

To support predictive recommendation, our data mining system first preprocesses the historical service request log, builds (temporal, categorical and spatial) hierarchy as shown in Fig. 2, and distributes the data into disjoint partitions based on their neighborhoods from where the service requests were made. Then, it analyzes and mines the preprocessed data to discover maximal frequent patterns, which reveals popular service requests from each neighborhood in every season. Here, as the system uses time-decay model, heavier weights are put on recent data than historical data to reflect recent trends in residents' demand in city services.

In the winter, after gathering maximal frequent patterns from all contributing neighborhoods, we observed that the most frequently requested service was street maintenance (e.g., snow removal - roads). This accounted for closely to a half (more precisely, 0.49) of all requested services in recent winters. The distribution of this service request was quite evenly distributed. Among all contributing neighborhoods, top-3 contributors were Jefferson, Munroe East and Rossmere-A (with each of them contributing less than 2% of the street maintenance requests in the winter).

[‡‡] https://data.winnipeg.ca/Contact-Centre-311/311-Performance-Metric-Service-Request-vs-Informat/qq8g-8hgg

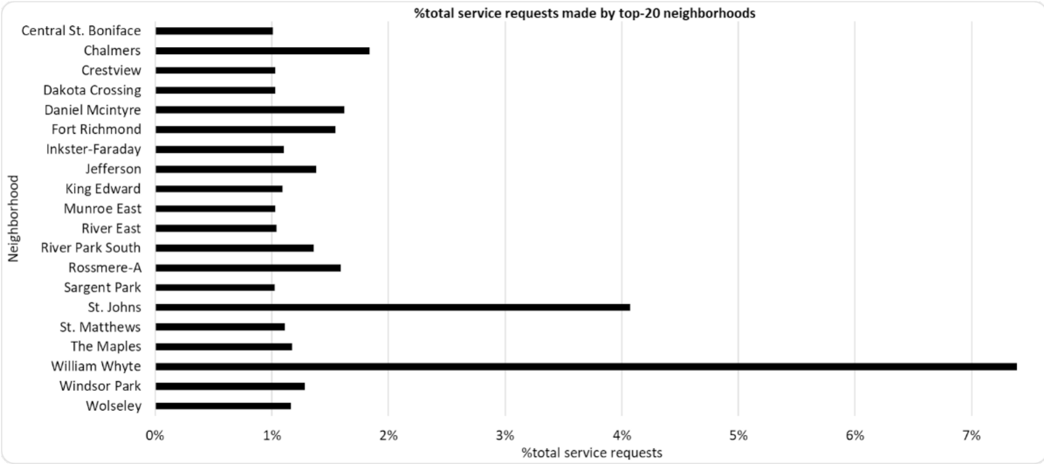

Fig. 2. Percentage of service requests made from top-20 neighborhoods.

The next most frequently requested service was garbage & recycling (e.g., missed garbage and/or recycling collection), accounting for 0.25 of all requested services in recent winters. Again, the requests were quite evenly distributed, with Rossmere-A being the top contributor (which contributing to 2.46% of the garbage & recycling requests in the winter).

The third most frequently requested service was by-law enforcement (e.g., neighborhood liveability complaints), accounting for 0.15 of all winter requests. Unlike the top-2 requested services, its distribution was not evenly distributed—with 24.55% and 14.24% of by-law enforcement requests (i.e., 0.04 and 0.02 of all winter requests over all category areas) made from William Whyte and St. Johns, respectively.

In contrast to these frequently requested services, both insect control and parks & urban forestry are areas that rarely requested in the winter. Hence, based on the aforementioned discovered frequent patterns, our system predicts high demand on the top-3 service areas in the coming winter. In terms of season-based recommendation, our system recommends devoting more resources from the two rarely requested areas to the three frequently requested areas.

Our mining and season-based recommendation is not confined to just winter. We also evaluated our big data mining system for the remaining three seasons. The results are consistent with our observation for the winter. To elaborate, as shown in Fig. 3, the top-3 service requests were street maintenance, by-law enforcement, and garbage & recycling. Note that their rankings with the top-3 may vary from season to season. More precisely:

- In the spring, by-law enforcement (e.g., neighborhood liveability complaints) became the most frequently requested service, putting street maintenance (e.g., potholes) to be the second most popular service.
- In the summer, by-law enforcement (e.g., neighborhood liveability complaints) once again became the most frequently requested service. However, the second most popular service was garbage & recycling (e.g., missed garbage and/or recycling collection), which pushed street maintenance (e.g., graffiti) to be the third most frequently requested service in recent summers.
- In the fall, garbage & recycling became the most frequently requested service. With by-law enforcement stayed at the second place, street maintenance (e.g., graffiti) was pushed to be the third most frequently requested service in recent falls.
- In the winter, as observed above, street maintenance (e.g., snow removal - roads) was the main concern. Hence, it was the most frequently requested service. The next two frequently requested services were garbage & recycling and by-law enforcement.

Despite minor differences in ranking within the top-3 service requests, they were consistently appeared in the annual ranking of top-3 service requests shown in Fig. 3.

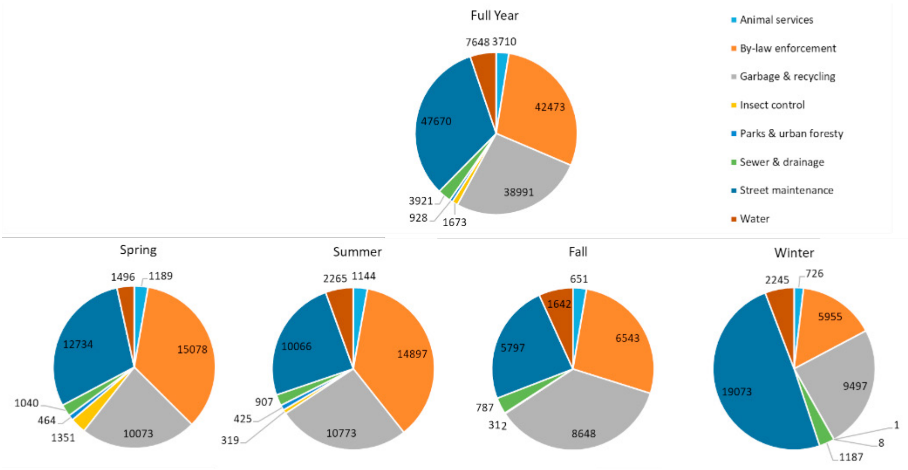

Fig. 3. The annual and seasonal numbers of service requests by their service category areas.

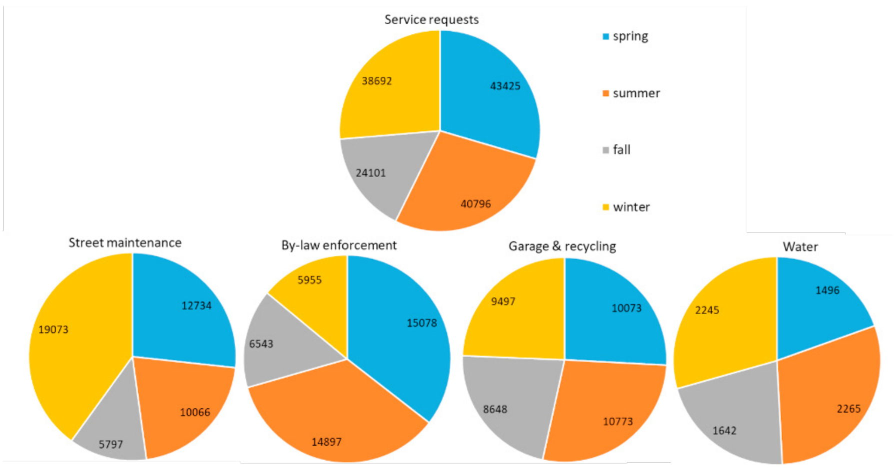

Fig. 4. The numbers of service requests by seasons.

While Fig. 3 shows the relative ranking (and absolute frequencies) of eight popular service request category areas and their seasonal compositions, Fig. 4 shows the absolute frequencies of service requests for each season. In addition, the figure also reveals how the composition of the eight category areas changed from a season to another. Among the four seasons, residents made the highest number of service requests in the spring and dropped to the second in the summer. They requested the least in the fall, but the number raised to the third highest in the winter. Moreover, in both spring and summer, due to nice weather, residents tend to have more outdoor gatherings than in the fall or winter. This may explain why by-law enforcement (e.g., neighborhood liveability complaints) was observed to dominate the numbers of service requests in these two seasons. In the winter, due to cold weather and snowfall, residents tend to focus more on street maintenance (e.g., snow removal).

5. Conclusions

Nowadays, valuable big data are generated and collected rapidly from numerous rich data sources. Following the initiatives of open data, many organizations including municipal governments are willing to share their data such as open big data regarding 311 non-emergency city service requests from their residents. Big data analytics on these open big data can be for social good. Hence, in this article, we present a framework for predictive big data analytics for service requests. The framework non-trivially integrates frequent pattern mining and location-based recommendation. It analyzes and mines the open big data to discover frequently occurring patterns like popular city service requests. To reveal recent trends in demand for city services, our framework conducts mining with a time-decay model in a way that heavier weights are put on recent data rather than historical data. The patterns discovered from recent data help predict (e.g., season-based predictions) future service requests. They also help obtain an insight about demand for services, and enable decision makers to take appropriate actions to enhance the living condition of city residents. Evaluation on real-life open big data from the City of Winnipeg, Canada, demonstrates the usefulness of our framework for conducting predictive big data analytics for service requests.

As *ongoing and future work*, we exploit and transfer the learned knowledge from the predictive big data analytics of *service requests* to discover useful knowledge from the predictive big data analytics of *information requests*. Moreover, we incorporate relevant techniques (e.g., OLAP) [55-60] into the framework to further enhance results of our predictive big data analytics. Finally, another ongoing line of research considers security aspects of the investigated problem (e.g., [62]).

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