Frequent Pattern Mining and Anomaly Detection in Service Requests: Model for Identifying Community Concerns and Service Inefficiencies

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***Abstract*— This study explores the use of service request data as a vital resource for identifying urban issues within Winnipeg, while developing a model applicable to other cities. The 311 system, which enables residents to report non-emergency issues, serves as a crucial tool for municipalities to enhance service delivery and optimize resource allocation. By employing frequent pattern mining, seasonal decomposition, and the Median Absolute Deviation (MAD) method, this research aims to create a model that identifies patterns and anomalies indicative of service disruptions or inefficiencies. This approach allows cities to better target their resources to meet residents' needs effectively.**

Keywords—data mining, 311, frequent pattern, seasonal decomposition, median absolute deviation (MAD)

I. Introduction

As technology advances in human society, different types of data about a specific city's conditions are collected through many means. Service requests are one important type of data that could reveal potential problems that citizens are facing in their everyday life. For example, mining service requests can help identify which neighborhoods face higher levels of service disruptions or delays. In addition, detecting unusual patterns in service requests such as sudden increase in water leaks or pest controls, can enable municipalities to quickly address unexpected infrastructure problems or environmental hazards. By analyzing frequent patterns and anomalies in service requests, the government can use the retrieved information to identify major community concerns and allocate resources efficiently to resolve the concerns.

II. Background & Related Works

In many cities across the Americas, such as Canada, Latin America, and the USA, a dedicated telephone number—311—has been established to handle non-emergency municipal service requests. This system allows residents to request non-emergency services, distinguishing it from the 911 service used for emergencies like serious crimes or medical issues.

When residents call the 311 Contact Centre, they can request information on topics like the bus schedule or recycling collection pickup, and services such as snow removal or make a complaint such as a parking violation.

Recent studies have explored various aspects of 311 service requests. For instance, the STFTiS model was developed to analyze citizens' satisfaction with municipal services by examining the spatio-temporal patterns of 311 reports [1]. This model integrates spatial analysis into traditional frequency and time interval models, offering a nuanced understanding of service demand and satisfaction. Another study focused on clustering cities based on their non-emergency service requests [2]. By standardizing request types across different cities, researchers uncovered temporal patterns and identified cities with similar or divergent service needs.

This study aims to create a model that finds frequent patterns and anomalies in a service request database using Winnipeg's 311 request database [3]. In comparison to the 2021 paper "Distributed Big Data Computing for Supporting Predictive Analytics of Service Requests" by Tianlei Wang et al. [4] that also applied frequent pattern mining on Winnipeg's 311 service request data, this project not only focuses on mining frequent patterns but also applies anomaly detection. The goal of our anomaly detection is to uncover inefficiencies, such as bottlenecks in city services that take longer than expected, thereby highlighting areas requiring immediate attention or further investigation.

The dataset analyzed in this study consists of Winnipeg 311 service request data spanning from June 2008 to October 2024. To focus on enhancing city infrastructure and optimizing the allocation of municipal resources, the analysis is limited to service requests, excluding information requests. In this paper, the term "requests" will specifically refer to service requests and will be used interchangeably.

III. Dataset Overview

The dataset utilized in this study comprises several key fields that provide comprehensive information about each service request recorded through Winnipeg's 311 system. Below is a detailed explanation of the relevant fields:

- Subject: This field categorizes the request, indicating whether it is a "Service Request", or an "Information Request".
- Reason: This field specifies the department or service area responsible for addressing the request, such as "Community Services" or "Water and Waste."
- Type: This field describes the specific nature of the request, for instance, "Housing Complaint - Yard and Accessory Buildings" or "Missed Yard Waste Collection Deficiency."
- Open Date: This timestamp records when the service request was initially made, providing a temporal context for the request.
- Closed Date: This timestamp indicates when the service request was completed. If both an Open Date and a Closed Date are present, the case is considered closed.
- Neighbourhood: This field identifies the specific neighborhood where the service is requested, offering a more precise location within a broader ward.
- Ward: This field designates the larger administrative area that encompasses several neighborhoods.
- Geometry: This field contains geolocation data, expressed in coordinates, indicating the specific location of the request. Geolocation is included when a physical location is necessary for servicing the request, such as in cases of snow removal or waste collection.

IV. Analysis of Service Request Density

This section presents an analysis of the service request density across various neighborhoods in Winnipeg, utilizing data from the 2021 Census [5] to contextualize the frequency of service requests relative to population size. The goal is to identify neighborhoods with disproportionately high service request activity, which may indicate areas with greater service needs or more active community engagement in reporting issues.

A. *Service Request Frequency and Population*

The table below lists the top 10 neighborhoods by the number of service requests, alongside their populations from the 2021 Census. These neighborhoods were the top 10 neighbourhood singletons identified through the FP-growth, for which the process is explained in Section IV.

Table 1. Top 10 Neighbourhoods by Service Requests

Neighbourhood	**Number of service requests**	**Population**
William Whyte	75,202	6,475
St. John's	64,703	82,45
Rossmere-A	57,518	13,935
Chalmers	54,096	9,965
Wolseley	53,976	7,735
River Park South	51,234	13,530
Daniel Mcintyre	48,943	9,400
The Maples	46,907	14,430
Fort Richmond	46,558	12,290
Jefferson	45,032	9,255

A heat map of all the service requests in the dataset which have a geolocation value associated with them was generated and shown in Figure 1.

The heat map showcases the distribution of requests originating from the various neighborhoods in Winnipeg. Areas of the heatmap with the highest frequency of requests appear to be in William Whyte, St. John's and Daniel McIntyre. Daniel McIntyre may appear to have a higher request frequency than the neighborhoods such as Rossemere-A or Chalmers on the heat map, in contrast to the service request count shown in Table 1, because of its closer proximity to William Whyte and St John's. However, the heat map still provides a good general representation of how the requests are distributed across the city.

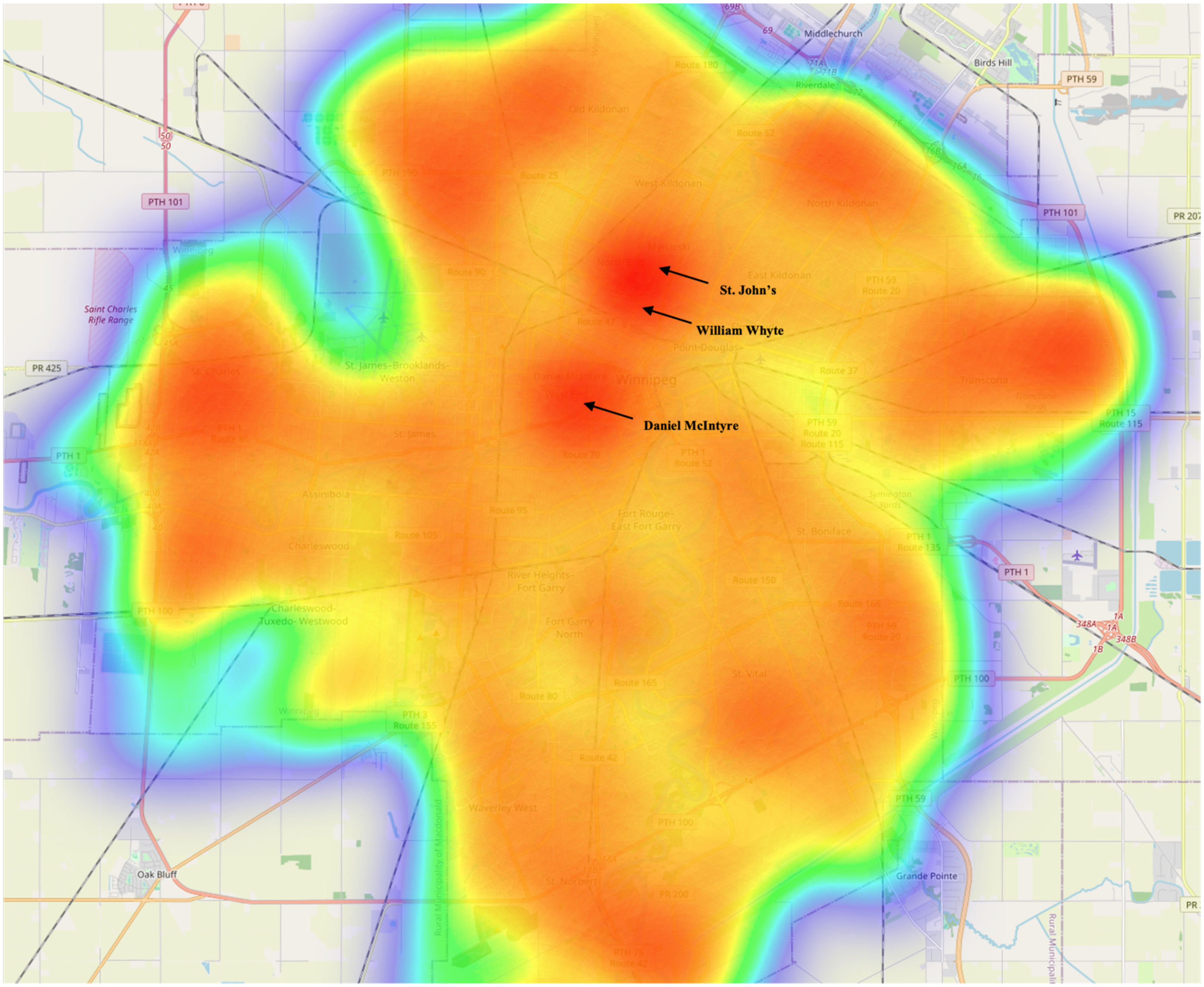

Figure 1. Heat map of service requests across Winnipeg

B. Service Request Density

To better understand the proportion of service requests relative to neighborhood size, we calculated the service request density by dividing the number of requests by the population for each neighborhood:

Table 2. Top 10 Neighbourhoods by Service Request Density

Neighbourhood	Service Request Density
William Whyte	11.61
St. John's	7.85
Wolseley	6.98
Chalmers	5.43
Daniel Mcintyre	5.21
Jefferson	4.87
Rossmere-A	4.13
Fort Richmond	3.79
River Park South	3.79
The Maples	3.25

C. Key Findings

William Whyte exhibits a notably high service request density of 11.61, nearly double that of the next highest neighborhood (St. John's at 7.85). This suggests a significant concentration of service needs in that neighbourhood.

The analysis reveals substantial variation in service request density across neighborhoods, indicating differing levels of service demand or community engagement. Neighborhoods with high service request densities may require targeted interventions and resource allocation to address underlying issues effectively.

V. Finding Frequent Patterns in 311 Service Request Data

Finding frequent patterns in service request data is beneficial for municipalities in identify recurring issues and allocate resources effectively, especially when patterns that include location data are found.

The FP-Growth algorithm is particularly well-suited for this task due to its efficiency in processing large datasets without generating candidate sets, unlike the Apriori algorithm [6]. By constructing a compact data structure called an FP-tree, FP-Growth enables faster discovery of frequent patterns, making it ideal for analyzing extensive service request databases like Winnipeg's 311 data. This study employs the use of the SPMF library, specifically its implementation of the FP-Growth algorithm [7], to mine frequent patterns within the 311 dataset.

A. Cleaning and Formatting the Data Set

To prepare the 311 Service Request data for frequent pattern mining using the FP-Growth algorithm, the dataset was first cleaned to focus on meaningful and frequent patterns. Only Service Requests associated with a neighborhood were retained, as the analysis aimed to identify recurring patterns in service request types or reasons paired with neighborhoods. Additionally, only the "Reason," "Type," "Neighborhood," and "Ward" columns were used, as other columns—such as IDs, timestamps, and geolocation—contained unique values that were not relevant to the frequent pattern analysis. This preprocessing ensured the data was both concise and relevant for the mining process.

The cleaned data was then transformed into the format required by the SPMF library to run FP-growth on it. Each unique cell value was replaced with an item ID. In addition, values are suffixed with an underscore followed by a single-letter code that signifies what category that value belongs to ("_R" for "Reason", "_T" for "Type", "_N" for "Neighbourhood", "_W" for "Ward". This will be useful for distinguishing between items in itemsets that contain both a "Reason" and "Type" item or both a "Neighbourhood" or "Ward" item.

An example of the data after cleaning is shown in the following:

Table 3. Example of cleaned request data

Reason	Type	Neighbourhood	Ward
Water and Waste_R	Breached Damage, Theft, Operator Standards_T	Mcmillan_N	Fort Rouge – East Fort Garry_W
Public Works_R	Snow Removal Street Priority 1 Reg_T	Saskatchewan North_N	St. James_W
Water and Waste_R	Missed Yard Waste Collection Deficiency_T	Springfield North_N	North Kildonan_W
Parking Authority_R	Broken Meter Report_T	South Portage_N	Fort Rouge – East Fort Garry_W

1 2 3 4
5 6 7 8
1 9 10 11
4 12 13 14

Figure 2. Example formatted request data

B. Choosing Minimum Support

Selecting a meaningful minimum support is vital in the process of running the FP-growth algorithm, as we want to avoid generating trivial patterns, without losing patterns that offer valuable insights at the same time [13]. Considering the large data size of the Winnipeg 311 request database, the following methodology is used while selecting the minimum support, through trial and error.

A relatively low minimum support of 0.02 was Initially selected to study the outcome of frequent patterns. Although frequent service request Reasons and Wards were found, this did not yield any frequent neighbourhoods, the minimum support value was lowered to 0.01. At this support value, neighbourhood singleton patterns were found, but not patterns that included both a neighbourhood and a request type or reason. The minimum support was lowered further to 0.007 to address this.

VI. Analysis of Frequent Patterns

This section presents the analysis of frequent patterns identified using the FP-growth algorithm on service request data. The analysis is organized by cardinality of the itemset, highlighting significant insights and implications for municipal service management. Within each cardinality, the top ten frequent patterns were studies.

A. Cardinality 1: Single Items

Table 4. Top 10 Singleton Frequent Patterns

Itemset	Support
Water and Waste_R	1626680
Public Works_R	1057550
Mynarski_W	358857
Point Douglas_W	269779
Fort Rouge – East Fort Garry_W	263308
Daniel McIntyre_W	261389
Community Services_R	256230
St. James_W	253692
River Heights – Fort Garry_W	241244
St. Vital_W	236529

The most frequent service request categories were identified, with Water and Waste leading significantly (1,626,680 occurrences), followed by Public Works (1,057,550 occurrences). This indicates a predominant concern for water and waste management across Winnipeg. Additionally, several wards such as Mynarski and Point Douglas showed high frequencies, suggesting localized service needs.

B. Cardinality 2: Pairs of Items

Table 5. Top 10 Frequent Pairs

Itemset		Support
Water and Waste_R	Mynarski_W	165532
Water and Waste_R	Missed Garbage Collection Deficiency_T	149526
Water and Waste_R	Request for Bulky Pick Up – 10 Items_T	147883
Water and Waste_R	Carts Damaged By Collection Crews_T	126850
Water and Waste_R	Daniel McIntyre_W	124809
Water and Waste_R	Missed Recycling Collection Deficiency_T	119890
Community Services_R	Housing Complaint – Yard and Accessory Buildings_T	119859
Water and Waste_R	Point Douglas_W	118180
Water and Waste_R	River Heights – Fort Garry_W	113639
Water and Waste_R	Transcona_W	112049

Water and Waste appears in 9 out of 10 top pairs, reinforcing its significance across various wards and specific issues. Garbage and recycling collection issues (missed collections and damaged carts) are prominent concerns within the Water and Waste category.

Mynarski Ward has the highest co-occurrence with Water and Waste, suggesting this ward may have more water and waste-related issues than others. Several other wards (Daniel McIntyre, Point Douglas, River Heights – Fort Garry, and Transcona) appear frequently in combination with Water and Waste, potentially highlighting that these areas require more attention in terms of water and waste management.

The combination of Community Services and Housing Complaints about yards and accessory buildings is the only non-Water and Waste related pair in the top 10, indicating a high level of property maintenance concerns within Winnipeg.

C. *Cardinality 3: Triples of Items*

Table 6. Top 10 Frequent Triplets

Itemset			Support
Water and Waste_R	William Whyte_N	Mynarski_W	32518
Water and Waste_R	St. John's_N	Mynarski_W	32131
Community Services_R	Housing Complaint – Yard and Accessory Buildings_T	Mynarski_W	31945
Water and Waste_R	River Park South_N	St. Norbert – Seine River_W	27724
Water and Waste_R	Rossmere-A_N	North Kildonan_W	27301
Water and Waste_R	Daniel Mcintyre_N	Daniel McIntyre_W	26428
Water and Waste_R	Wolseley_N	Daniel McIntyre_W	25551
Water and Waste_R	Chalmers_N	Elmwood – East Kildonan_W	25215

Triplets such as Water and Waste with William Whyte Neighborhood and Mynarski Ward (32,518 occurrences) were prevalent. This pattern suggests a concentrated area of concern within the Mynarski Ward, potentially indicating infrastructure challenges or higher reporting activity in this region.

It appears that the largest proportion of housing complaints regarding property maintenance is concentrated in Mynarski Ward.

D. *Key Findings*

The analysis indicates that water and waste management is a significant concern across multiple neighborhoods and wards in Winnipeg, with particular emphasis on the Mynarski Ward. Additionally, there is a notable prevalence of yard and housing complaints throughout the city. This trend may reflect either a widespread issue of property maintenance or a higher level of community engagement in reporting such matters.

VII. Detecting Anomalies in Service Request Case Duration

The motivation for analyzing anomalies in case durations of service requests stems from the need to identify and address inefficiencies in municipal service delivery. By detecting unusually long case durations, the city can uncover hidden issues impacting service efficiency. These anomalies may indicate underlying problems, such as resource shortages, process bottlenecks, or unexpected events affecting service delivery. Identifying these outliers allows city officials to investigate and address specific causes, leading to improved response times and resource allocation.

The following sections outline the methodology used for detecting anomalies in case durations of service requests.

A. *Data Preparation*

The dataset is first cleaned by removing any entries that lack either an "Open Date" or "Closed Date", since missing either one of these would not allow us to calculate the case duration. The case duration for each service request was then calculated by finding the difference between the "Closed Date" and "Open Date", and converting this difference into hours. The requests were then grouped together by their "Type".

Within each type, the case duration for requests in each unique day were aggregated by their "Open Date" to get the total case durations for each day. An example is shown below.

Table 7. Example request data before aggregation

Open Date	Case Duration (hours)
2024-12-01	4.0
2024-12-01	2.5
2024-12-03	3.0
2024-12-01	1.5

Table 8.Example request data after aggregation

Open Date	Case Duration (hours)
2024-12-01	8.0
2024-12-03	3.0

Using zero imputation [8], any missing days between the earliest and latest Open Date were filled with a case duration of zero hours, as this is necessary for applying seasonal-trend decomposition to the time series data in the next step.

Table 9. Example request data after zero imputation

Open Date	Case Duration (hours)
2024-12-01	8.0
2024-12-02	0.0
2024-12-03	3.0

B. *Seasonal-Trend Decomposition*

Seasonal-trend decomposition is employed in this analysis to examine daily total case durations for each request type by isolating trend, seasonal, and residual components [9]. This separation is essential for detecting anomalies as distinguishing between true trends and cyclical variations will improve the accuracy of the anomaly detection in the next step.

The time series of case durations, $x(t)$, is decomposed into three primary components:

$$x(t) = T(t) + S(t) + R(t)$$

Where:

- $T(t)$ represents the trend component
- $S(t)$ represents the seasonal component
- $R(t)$ represents the residual component

$$R(t) = x(t) - T(t) - S(t)$$

The residuals, often referred to as the noise or error component, represent the random variability that remains after removing the trend and seasonal effects from the data. By comparing the residuals, we can identify days with unusually long case durations.

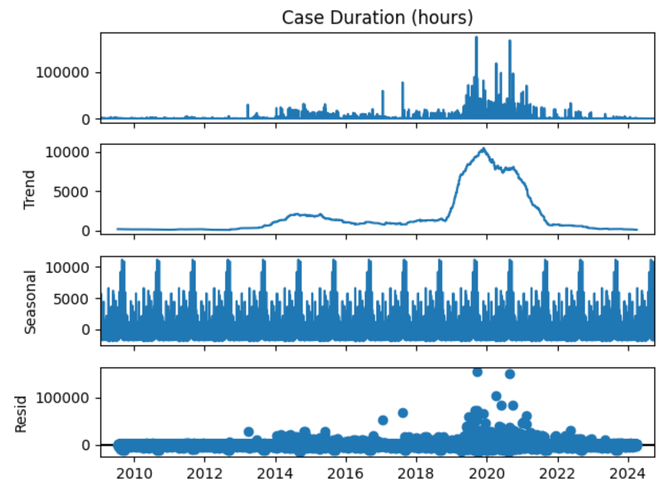

Figure 3. Seasonal decomposition of daily total case durations for request type "Turn Off Water - Repairs Emergency"

To apply seasonal-trend decomposition effectively to case duration time series data, at least 730 data points (equivalent to two years of data) are required. Sufficient data points ensure seasonal trends are accurately identified [9]. Any request type with insufficient data is excluded from the analysis.

For each eligible group, seasonal-trend decomposition is applied to the case duration data using an additive model with a period of 365 days. This annual period was selected to capture the influence of yearly weather cycles, which are likely the primary source of seasonal trends in the data. This process separates the time series into trend, seasonal, and residual components. The residuals, representing deviations from expected patterns, are then extracted for anomaly detection.

C. *Anomaly Detection*

Anomalies are identified within the residuals using the Median Absolute Deviation (MAD) method. This method is more robust to outliers compared to using the mean and standard deviation. Unlike the mean and standard deviation, the MAD is unaffected by extreme outliers, making it a better choice when detecting anomalies in data with non-normal distributions [10].

The steps to determine whether a given day's total case duration's residual is anomalous is given in the following:

1) Calculate the Median (M) *of the residuals* $R(t)$*:*

$$M = median(R(t))$$

2) Calculate the Median Absolute Deviation (MAD):

$$MAD = median(| R(t) - M |)$$

3) Calculate the Modified Z-Score for each residual:

$$Z = \frac{R(t) - M}{MAD}$$

4) Determine whether anomalous:

$$Z > 3$$

The total case duration for a given day is considered anomalous if its residual's Modified Z-Score exceeds three. The threshold of 3 was chosen as it aligns with the robust equivalent of the 68-95-99.7 rule [11], capturing the most extreme 0.3% of data points under normal-like conditions. This balance minimizes false positives while effectively detecting significant anomalies.

A chart showing the results of this method being applied to detect days in which the total case duration of all requests of a given Type "Turn Off Water – Repairs Emergency" is abnormally high is shown in Figure 4.

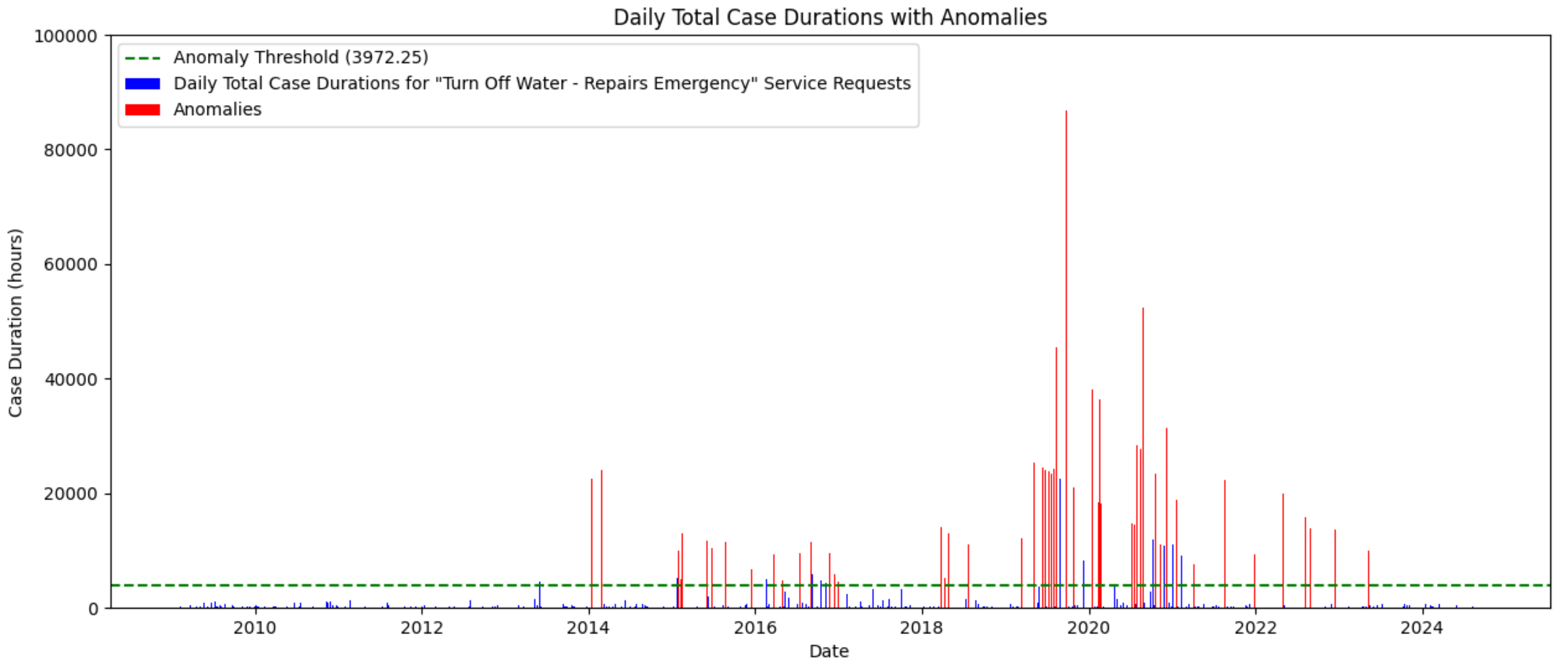

Figure 4. Time Series of Daily Total Case Durations of Type "Turn Off Water - Repairs Emergency" with Anomalies Identified

Note: Certain days exhibit total case durations that exceed the anomaly threshold but are not classified as anomalous. This occurs because the residual for those days is not deemed anomalous; the trend and seasonal components account for the majority of the total case duration.

D. *Results Compilation*

For each request type, the number of anomalous days with abnormally high total case duration was recorded, alongside the total number of requests, the total number of days within the period studied (earliest to latest Open Date of requests in that type) and the anomaly rate (number of anomalous days as a proportion of total number of days). These results provide insights into which service types exhibit unusually long case durations.

VIII. Analysis of Service Request Case Duration Anomalies

This section presents an analysis of service request types based on anomaly rate.

The anomaly rate is defined as the proportion of days that exhibit significantly higher case durations than expected patterns, as identified through seasonal decomposition and the MAD method. Understanding these anomalies provides insights into potential inefficiencies or unexpected challenges in municipal service delivery.

We focus on request types with higher anomaly rates rather than anomaly counts, as this offers a clearer picture of how inefficient or delayed requests are being addressed within a given type. The following table lists the top 10 request types with the highest anomaly rates in case duration:

Table 10. Top 10 Request Types by Anomaly Rate

Request Type	Anomalous Day Count	Total Requests	Total Number of Days	Anomaly Rate
Dutch Elm Disease Tree Inspection Request	2399	1129	5570	0.431
Ditch Overflowing Priority 3 After	2403	381	5595	0.429
Present, Partner a Program - English	1124	6	2659	0.423
Park Maint - Boat Dock/Launch Hazardous After	1592	13	3784	0.421
Request for Sealed Ballot Application	1807	178	4395	0.411
Watermain Cleaning Inquiries and Concerns	2110	2900	5185	0.407
Get Name on Voter List	1895	629	4704	0.403
Program Inquiry - English	1925	39	4788	0.402
Application to Adjust Sewer Charges	833	9	2119	0.393

The analysis of anomaly rates across various request types reveals that the highest anomaly rate is approximately 43%. Notably, the anomaly rates for the top request types are closely clustered, each around 40%. These elevated rates suggest a significant likelihood of delays or inefficiencies in processing these requests, indicating potential bottlenecks within the system.

Of particular concern is the request type "Park Maint - Boat Dock/Launch Hazardous After." Given its classification as hazardous, it is important that such requests receive expedited attention to mitigate potential risks to public safety. It is advisable for the city to investigate strategies for improving response times for requests of this nature.

Conclusion

This study has effectively demonstrated the utility of frequent pattern mining and anomaly detection in analyzing service requests to uncover significant community concerns. By examining Winnipeg's 311 request database, we identified key patterns and anomalies that highlight areas requiring immediate attention, particularly in water and waste management and property maintenance. Utilizing seasonal decomposition and the Median Absolute Deviation (MAD) method, we identified service request types that experience abnormally high rates of delay and inefficiencies. Together, these methods provide an effective model for cities to more precisely allocate resources both geographically and categorically, enhancing their ability to address community needs efficiently.

LIMITATIONS & FUTURE WORK

A key limitation of the current study is the lack of a time decay model, which would help identify issues that are more relevant to the present. Currently, both frequent pattern mining and anomaly detection methods utilize the entire dataset, giving equal weight to requests from the distant past. This approach does not account for recent changes or improvements that may have addressed inefficiencies in specific service request types or locations. Incorporating a time decay model could enhance accuracy by providing more timely and relevant insights [12].

Another concern is the reliability of the 311 request data. For example, Winnipeg's dataset includes numerous requests that are resolved immediately (with the same Open Date and Close Date) as well as others that take years to resolve. It can be hard to verify the accuracy of the data.

Additionally, interpreting results can be challenging without sufficient context and documentation regarding the various service request types and reasons. Understanding these details is crucial for assessing the significance of issues and determining whether they require additional attention.

Future work should focus on addressing these limitations by integrating a time decay model, improving data verification processes, and obtaining documentation to provide clearer context for interpreting results.

REFERENCES

[1] R. Mohammadi, M. Taleai, S. Alizadeh, and O. R. Abbasi, "STFTiS: Introducing a spatio-temporal FTiS model to investigate the level of citizens' satisfaction of 311 non-emergency services," *Transactions in GIS*, vol. 26, no. 2, pp. 980–1016, Jan. 2022, doi: https://doi.org/10.1111/tgis.12890.

[2] M. Hashemi, "Studying and Clustering Cities Based on Their Non-Emergency Service Requests," Information, vol. 12, no. 8, p. 332, Aug. 2021, doi: https://doi.org/10.3390/info12080332.

[3] "311 requests: Open data: City of winnipeg," 311 Requests | Open Data | City of Winnipeg, https://data.winnipeg.ca/Contact-Centre-311/311-Requests/u7f6-5326/about_data (accessed Nov. 12, 2024).

[4] T. Wang *et al.*, "Distributed Big Data Computing for supporting predictive analytics of service requests," *2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC)*, pp. 1723–1728, Jul. 2021. doi:10.1109/compsac51774.2021.00257

[5] City of Winnipeg and City of Winnipeg, "2021 Census - Census - City of Winnipeg," *Winnipeg.ca*, 2021. https://legacy.winnipeg.ca/census/2021/

[6] M. S.Mythili and A. R. Mohamed Shanavas, "Performance Evaluation of Apriori and FP-Growth Algorithms," International Journal of Computer Applications, vol. 79, no. 10, pp. 34–37, Oct. 2013, doi: https://doi.org/10.5120/13779-1650.

[7] "Example: Mining Frequent Itemsets using the FP-Growth Algorithm (SPMF - Java)," *Philippe-fournier-viger.com*, 2024. https://www.philippe-fournier-viger.com/spmf/FPGrowth.php (accessed Dec. 08, 2024).

[8] S. Kim, H. Kim, E. Yun, H. Lee, J. Lee, and J. Lee, "Probabilistic Imputation for Time-series Classification with Missing Data," *arXiv (Cornell University)*, Jan. 2023, doi: https://doi.org/10.48550/arxiv.2308.06738.

[9] R. B. Cleveland, W. S. Cleveland, J. E. McRae, and I. J. Terpenning, "STL: A seasonal-trend decomposition procedure based on loess," Journal of Official Statistics, vol. 6, no. 1, pp. 3–33, 1990.

[10] C. Leys, C. Ley, O. Klein, P. Bernard, and L. Licata, "Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median," Journal of Experimental Social Psychology, vol. 49, no. 4, pp. 764–766, Jul. 2013, doi: https://doi.org/10.1016/j.jesp.2013.03.013.

[11] A. Bluman, Bluman, Elementary Statistics 2015 A Step by Step Approach. Macmillan/Mcgraw-Hill School Div, 2013.

[12] Y. Gim and K. Min, "Evaluation Strategy of Time-series Anomaly Detection with Decay Function," *arXiv (Cornell University)*, Jan. 2023, doi: https://doi.org/10.48550/arxiv.2305.09691.

[13] Pang-Ning Tan, M. Steinbach, and Vipin Kumar, Pearson new international edition : introduction to data mining. Boston: Pearson Addison Wesley, 2014, p. 387.