Northeastern University
College of Professional Studies

A Comprehensive Report on Election Bridge: Pioneering Data-Driven Civic Engagement and Intelligence

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Executive Summary

Election Bridge, co-created by the visionary entrepreneurs Ackeem Evans and Jermaine Hartsfield, heralds a significant shift in civic engagement, tackling the communication gap between citizens and their government with a data-centric model. This report explores Election Bridge's transformative use of technology, which has redefined civic participation by harnessing advanced data analytics to offer deeper insights into public opinion and policy-making, thus fostering a more informed and responsive democratic process.

The comprehensive dataset presented captures a detailed record of Portland, Maine's city council orders, enriched with demographic data from users of a civic application. It provides an in-depth view of the legislative measures and a transparent look at the political influence behind them.

The data was refined using advanced tools such as pandas and spaCy to extract and organize information from PDFs, which streamlined the dataset for analysis. Review of the 'Issue Category' showed a focus on education, infrastructure, safety, and the environment. User engagement data revealed diverse interests across demographics, guiding targeted policy development.

Methodologically, the report details the use of unsupervised learning algorithms for policy categorization, with Word Net outperforming other techniques in effectiveness. Geographical classification of policies was achieved using the Google API, which enabled a thorough understanding of policy distribution across Portland's neighborhoods.

The modeling phase initially deployed Naive Bayes, SVM, and Random Forest Classifier algorithms, which unfortunately yielded poor results. This led to a strategic shift towards K-means Clustering, which successfully categorized the data into five distinct clusters and provided a structured approach to data understanding. This adaptation in modeling strategy highlighted the importance of matching analysis techniques to the dataset's inherent structure.

In conclusion, despite the initial challenges with machine learning models, K-means Clustering has proven to be an effective alternative. Election Bridge's progression highlights the critical role of data analytics in advancing civic engagement. The report recommends enhancing data quality, filling information gaps, and re-evaluating predictive models to improve outcomes.

Looking ahead, it is suggested that further refinement of predictive models, a deeper understanding of user engagement patterns, and the development of an impact assessment framework for Election Bridge are key areas for future research. These efforts will likely contribute to the platform's success in promoting effective communication and informed decision-making within the civic landscape.

Keywords: Civic Engagement, Data Analytics, Predictive Modeling, User Demographics, Policy Categorization, Machine Learning, K-means Clustering, Data Quality, Feature Engineering, Civic Application.

1. Introduction

Election Bridge, co-founded by visionary entrepreneurs Ackeem Evans and Jermaine Hartsfield, marks a transformative moment in the realm of civic engagement. Originally conceived to address the communication disconnect between citizens and their government, Election Bridge has undergone a significant evolution. This shift is characterized by its adoption of a data-centric model, signaling a move towards fostering civic intelligence. In this report, we delve into the journey of Election Bridge, placing a spotlight on the crucial influence of technology in reshaping the dynamics of civic participation.

At its core, Election Bridge harnesses the power of advanced data analytics. This strategic choice is not merely a technological upgrade; it represents a profound commitment to enhancing democratic involvement. By analyzing vast amounts of data, Election Bridge offers insightful perspectives on public opinion and governmental policies, thereby enriching the dialogue between the populace and governmental entities. This approach sets a new standard in the synergy between technology and civic engagement, aiming to create more informed, responsive, and interactive governance structures.

The implications of Election Bridge's innovations are far-reaching. As we explore their strategies and achievements, it becomes evident that the company is not just changing the way citizens interact with their government; it is redefining the very nature of civic participation in the digital age. This report seeks to understand how Election Bridge's pioneering use of data analytics is bridging the gap between citizens and government, thus ushering in a new era of empowered and engaged citizenship.

2. Dataset

2.1. Overview

This dataset provides a comprehensive portrayal of Portland, Maine's city council orders, supplemented by demographic information from the users of a civic application. It thoroughly records each council order, detailing the intent and scope of the legislative measures, as well as the chronological milestones from their inception to their implementation. The dataset illuminates the backgrounds and political clout of the individuals sponsoring these orders, thus contributing to a transparent view of the legislative process.

A key feature of the dataset is its chronological tracking, which charts the progression of the council orders and is vital for assessing the council's efficiency in legislative action. Distinctive to this dataset is the demographic detail it contains regarding the civic app's users, covering aspects such as age, residence, and personal interests. This data enables a detailed exploration of civic involvement, showcasing how the city council's efforts align with the varied needs and responses of its constituency.

2.2. Acknowledgement

The data was furnished by the sponsor, Election Bridge.

2.3. Dataset Description

2.3.1. Policy Data

Number of columns: 8
Number of Rows: 390

Variable	Class Type
Classification Number	String
Type	String
Description	String
Link	String
Passage Date	String
Effective Date	String
Issue Category	String
Category Types	String

Figure 1. Table of Variable Types for Policy Data

2.3.2. User Data

Number of columns: 9
Number of Rows: 500

Variable	Class Type
Person	Integer
Address	String
Age	Integer
Interest	String
Environmental	Integer
Infrastructure	Float
Education	Float
Zoning	Float
Safety	Float

Figure 2. Table of Variable Types for User Data

2.4. Data Preparation

Utilizing libraries such as pandas, spaCy, PyPDF2, and re, we have managed to extract information from PDF documents and placed it into a designated 'PDF Content' column within our dataset. This extracted data has been instrumental in categorizing policies and

sorting addresses into their respective neighborhoods, with the results being compiled in a newly created 'Address' column. We've streamlined the dataset by removing columns that were deemed non-essential, such as 'Classification Number', 'Type', 'Passage Date', 'Effective Date', and 'Category Types'. Following a meticulous process to address any missing or null values, we have ensured that the dataset is now complete and ready for subsequent analysis or applications.

3. Analysis

The 'Issue Category' field within the policy data presents a wide array of classified entries, with 'Education' leading at 114 entries and a notable number, 84, listed as 'Uncategorized', showing a substantial portion not confined to specific categories. There's a significant count within combined 'Education', 'Infrastructure', and 'Safety' categories, while instances of 'Safety' and 'Infrastructure' alone are fewer. 'Environment' related entries are occasionally linked with 'Education' and 'Infrastructure', but are less frequent, similar to 'Zoning' related categories. This suggests a prioritization of education, infrastructure, safety, and environmental issues. Conversely, the user data exhibits an equitable spread across categories, with 'Safety' slightly ahead at 105 entries, and 'Education' and 'Infrastructure' not far behind. 'Zoning' surprisingly matches 'Infrastructure' in frequency, while 'Environment' trails slightly. This indicates a broad user interest in these principal civic areas.

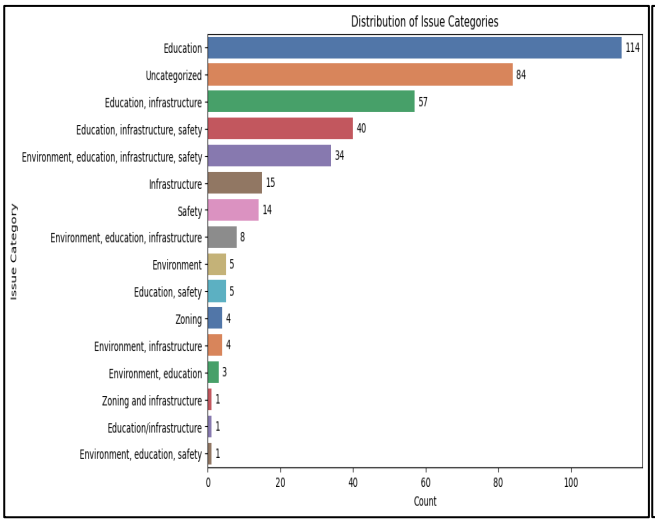

Figure 3. Distribution of Issue Categories

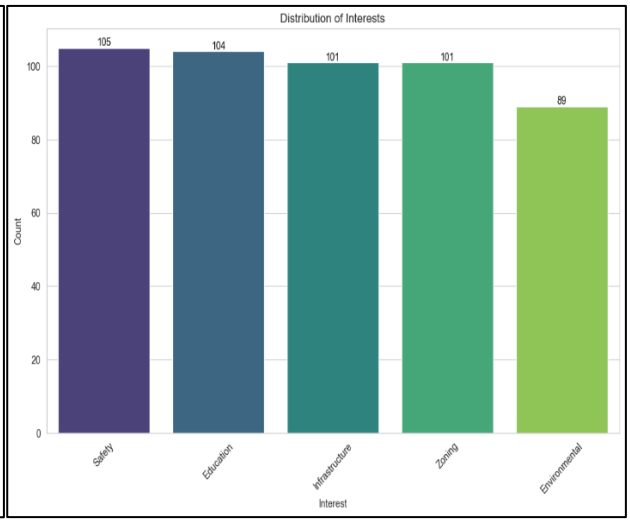

Figure 4. Distribution of User Interest

The user demographics of the dataset predominantly span from young adults to middle-aged individuals, covering the age range of 18 to 54 years. Within these age groups, there is a noticeable divergence in policy interests: the younger segment of users tends to show a preference for Education and Environmental policies, while the older demographics exhibit a stronger interest in topics related to Infrastructure, Zoning, and Safety. This distribution indicates varying priorities across different age groups, reflecting the distinct concerns and perspectives that come with different stages of life.

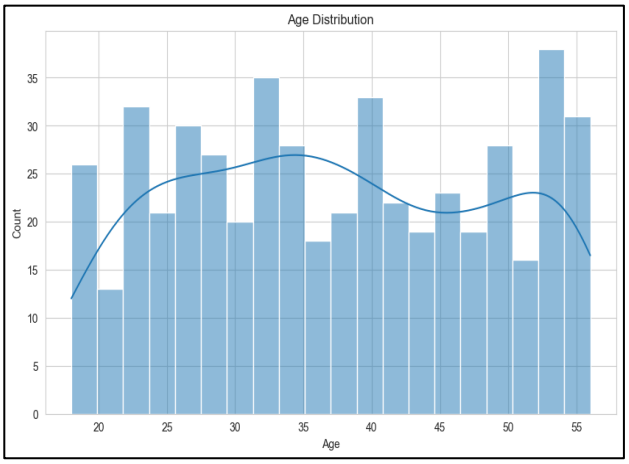

Figure 5. Age Distribution

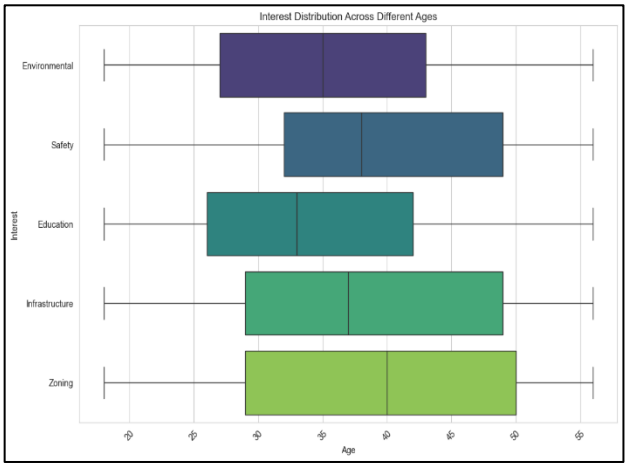

Figure 6. Interest Distribution Across Ages

The dataset reveals distinct interests in policy areas that vary by neighborhood. Users from Bayside and Deering exhibit a heightened interest in Education-related issues. In contrast, those residing in Munjoy Hill and Back Cove show a preference for Infrastructure policies. Meanwhile, Zoning concerns are more prominent among residents of East Bayside, East End, and Parkside. Safety is the priority for individuals in the West End and Old Port areas.

Demographic patterns also emerge from the dataset, indicating that Highland is home to a younger population when compared to Bayside, where the user base trends older. This geographical distribution of age and interests provides valuable insights for tailored community planning and policy development.

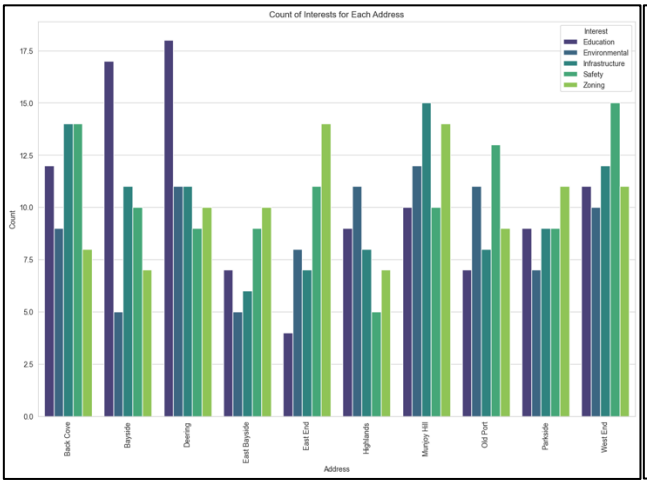

Figure 7. Distribution of Interest Across Address

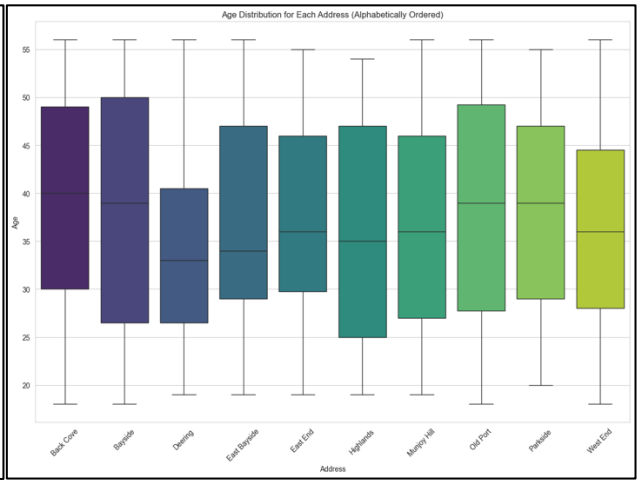

Figure 8. Age Distribution Across Address

4. Methodology

4.1. Policy Categorization

In the process of automating policy categorization from PDF documents, a series of steps were taken to analyze the content effectively using unsupervised learning algorithms. These algorithms employed keyword-matching techniques to systematically classify policies based on their textual content, enabling the automated grouping of policies into predefined categories by identifying key terms. To facilitate this process, we first defined basic keywords for each category.

The first technique utilized word vectors for keyword matching, which resulted in 200 policies remaining uncategorized. The second method involved the use of a BERT model for keyword matching, leaving 352 policies unclassified. The third strategy applied Lbl2Vec, an embedding-based method for document retrieval, which narrowed the uncategorized policies down to 167. The final approach adopted Word Net for keyword matching, significantly reducing the number of uncategorized policies to 89.

Upon evaluation, Word Net demonstrated a 77% success rate, surpassing Lbl2Vec, which had a 57% accuracy rate in categorizing policies. Although Lbl2Vec offers the convenience of quick category checks through manual labels, Word Net's superior precision indicates its greater efficacy for the task at hand. Consequently, the decision was made to implement Word Net as the primary tool for policy categorization going forward.

	Description	Link	Issue Category
1	AMENDMENT TO PORTLAND CITY CODE CHAPTER 8\nRe:...	https://content.civicplus.com/api/assets/b2e87...	Zoning and infrastructure
2	ORDER APPROVING THE APPLICATION FOR, ACCEPTANC...	https://content.civicplus.com/api/assets/ea087...	Environment
3	ORDER APPROVING MODIFICATION TO TWO-PARTY AGRE...	https://content.civicplus.com/api/assets/299d3...	Infrastructure
4	ORDER ACCEPTING AND ADOPTING THE 2020 HOUSING ...	https://content.civicplus.com/api/assets/e1184...	Infrastructure
5	ORDER APPROPRIATING $36,000 FROM THE HOUSING T...	https://content.civicplus.com/api/assets/1768f...	Infrastructure
...	...	...	...
386	ORDER ACCEPTING AND APPROPRIATING $9,428.57 IN...	https://content.civicplus.com/api/assets/89003...	Education
387	PROPOSING AN AMENDMENT TO PORTLAND CITY CHARTE...	https://content.civicplus.com/api/assets/a147d...	Education, infrastructure, Safety
388	ORDER APPOINTING AND SETTING SALARY OF MARK W....	https://content.civicplus.com/api/assets/a258d...	Education
389	CONTINUING RESOLUTION IN LIEU OF FISCAL YEAR 2...	https://content.civicplus.com/api/assets/19ab9...	Uncategorized
390	AMENDMENT TO DOWNTOWN HEIGHT OVERLAY AND BAYSI...	https://content.civicplus.com/api/assets/175b1...	Uncategorized

Figure 9. Results of WordNet Categorization

4.2. Geographical Categorization

To categorize policies geographically, we employed the Google API. This phase encompassed the extraction of street addresses from the PDF documents, followed by their categorization into different neighborhoods located within the City of Portland. This geographical classification was instrumental in gaining insights into how policies were

distributed across different areas. In cases where precise street addresses were unavailable or not explicitly mentioned, a broader classification was applied, grouping them under 'City of Portland'. This systematic approach ensured the categorization of all policies, ensuring a comprehensive overview that encompassed both policy types and their geographical relevance to various segments of Portland.

	Description	Link	Issue Category	PDF Content	Extracted Addresses	Address
1	AMENDMENT TO PORTLAND CITY CODE CHAPTER 8\nRe:...	https://content.civicplus.com/api/assets/b2e87...	Zoning and infrastructure	Order 12 -19/20 \nPassage: 7-0 (Batson and Co...	[3 is hereby amended as follows, 5 is hereby a...	City of Portland
2	ORDER APPROVING THE APPLICATION FOR, ACCEPTANC...	https://content.civicplus.com/api/assets/ea087...	Environment	Order 84 -19/20 \nPassage: 8 -0 (Cook absent)...	[000 Brownfields assessment grant from the, 00...	City of Portland
3	ORDER APPROVING MODIFICATION TO TWO-PARTY AGRE...	https://content.civicplus.com/api/assets/299d3...	Infrastructure	Order 83 -19/20 \nPassage: 8 -0 (Cook absent) ...	[00 is hereby approved in substantially the fo...	City of Portland
4	ORDER ACCEPTING AND ADOPTING THE 2020 HOUSING ...	https://content.civicplus.com/api/assets/e1184...	Infrastructure	\nOrder 146 -19/20 \nPassage: 9 -0 on 3/ 2/20...	[2020 HOUSING TRUST FUND ANNUAL PLAN, 2020 Hou...	City of Portland
5	ORDER APPROPRIATING $36,000 FROM THE HOUSING T...	https://content.civicplus.com/api/assets/1768f...	Infrastructure	Order 54 -19/20 \nPassage: 8 -0 (Ali absent) o...	[000 FROM THE HOUSING TRUST FUND, 18 LUTHER ST...	City of Portland
...	...	...	...	...	...	...
386	ORDER ACCEPTING AND APPROPRIATING $9,428.57 IN...	https://content.civicplus.com/api/assets/89003...	Education	Order 2 55-22/23 \nPassage as an emergency : 7...	[57 IN ASSISTANCE TO, 57 from the United State...	City of Portland
387	PROPOSING AN AMENDMENT TO PORTLAND CITY CHARTE...	https://content.civicplus.com/api/assets/a147d...	Education, infrastructure, Safety	Order 260 -22/23 \nMotion to amend to set eff...	[30 days after approval at the election, 0 on ...	City of Portland
388	ORDER APPOINTING AND SETTING SALARY OF MARK W....	https://content.civicplus.com/api/assets/a258d...	Education	Orders \Appointments \Police Chief Sauschuck ...	[]	City of Portland
389	CONTINUING RESOLUTION IN LIEU OF FISCAL YEAR 2...	https://content.civicplus.com/api/assets/19ab9...	Uncategorized	Order 263- 22/23 \nPassage as an emergency : 7...	[7 of the City Charter, 428 per month is hereb...	City of Portland
390	AMENDMENT TO DOWNTOWN HEIGHT OVERLAY AND BAYSI...	https://content.civicplus.com/api/assets/175b1...	Uncategorized	Order 173- 22/23 \nPassage: 9 -0 on 4/24/2023 ...	[211 CUMBERLAND AVENUE, 211 Cumberland Avenue,...	Westcott

Figure 10. Results of Geographical Categorization

5. Modeling

The model's objective is to forecast the policy category, relying on two primary predictor variables: the 'Issue Category' and the 'Address'. Within this framework, the 'Policy Category' serves as the target variable. The relationship can be concisely expressed through the equation:

$$P = F\,(I, A)$$

In this equation, '*F'* denotes the mathematical function that integrates the Issue Category (I) and Geographical Address (A) to anticipate the Policy Description Category (P). This equation encapsulates the core concept of our predictive framework, emphasizing the interplay between the nature of the issue and its geographical context in shaping policy categorizations.

5.1. Naive Bayes, SVM (Support Vector Machine), and Random Forest Classifier

In the initial phase of our approach, we employed the first three techniques, which consisted of the utilization of three distinct machine learning algorithms: Naive Bayes, SVM (Support Vector Machine), and Random Forest Classifier.

Our approach involved training the dataset using a partition of 80-20, effectively dividing it into two subsets: a training set and a testing set. This division allowed us to validate the performance of the machine learning algorithms on an independent dataset, ensuring the robustness and accuracy of our predictive model. The performance of each model is shown in the table below, illustrating their respective effectiveness in categorizing policies based on the 'Issue Category' and 'Address'.

	Accuracy	Precision	Recall	F1 Score
Naïve Bayes	0.012821	0.000217	0.012821	0.000427
SVM	0.012821	0.000229	0.012821	0.000450
Random Forest Classifier	0.000000	0.000000	0.000000	0.000000

Figure 11. Results of Naïve Bayes, SVM (Support Vector Machine) and Random Forest Classifier Model

5.2. K-Means Clustering

Considering the less-than-ideal performance observed with our initial three models, we made the strategic decision to adopt a different methodology, opting for K-means Clustering as our revised approach.

Our approach involved several steps. First, we applied one-hot encoding to the 'Address' and 'Issue Category' variables and employed TF-IDF vectorization for the 'Description' field. These processed components were then merged into a unified dataset. Subsequently, we set the number of clusters (k) to 5 within the K-Means algorithm. This choice was in alignment with our objective of analyzing and categorizing policies into five distinct categories.

The outcomes of K-means Clustering revealed:

- **Cluster 0:** Contains 114 data points, making it the largest cluster. This suggests that a significant portion of our dataset shares similar characteristics that distinguish them from other clusters.
- **Cluster 1:** Consists of 84 data points, representing the second-largest cluster and another substantial grouping within the dataset.
- **Cluster 2:** Comprises 40 data points, indicating a smaller cluster, which implies a more unique or less frequent grouping in the dataset.
- **Cluster 3:** Encompasses 95 data points, making it the third-largest cluster and a notable grouping.
- **Cluster 4:** Includes 57 data points, positioning it as a moderate-sized cluster, larger than the smallest but smaller than the largest clusters.

These results suggest that your data can be divided into groups that share certain commonalities, with some groups being more common (larger clusters) and others being less common (smaller clusters).

This transition to K-means Clustering allowed for a more effective categorization of policies, addressing the limitations of our initial models.

6. Key Findings and Discussion

6.1. Naive Bayes, SVM (Support Vector Machine), and Random Forest Classifier

It is quite concerning to see that both the Naive Bayes and SVM models are performing so poorly, with their accuracy barely above the 1% mark. Not to mention, their precision and F1 scores are extremely low. It doesn't stop there, unfortunately. The Random Forest model seems to be completely ineffective, as it's showing absolutely no predictive accuracy — all of its performance metrics are at zero.

This paints a rather bleak picture and strongly implies there are fundamental problems that need to be addressed. It could be a matter of the models not fitting the data properly, or perhaps there are deeper issues with the quality of the data itself or the features that have been chosen for the modeling process.
Given these dire performance figures, we had to consider alternative approaches. As a result, K-means clustering was adopted in the hopes of improving the performance by identifying more homogenous groups within the data. The idea was that by creating these clusters, the models might have a better chance of discerning patterns and yielding more accurate predictions.

6.2. K-Means Clustering

Following the unsatisfactory performance of the initial models we applied, namely Naive Bayes, SVM, and Random Forest, we opted for a strategic pivot towards K-means Clustering to better approach our data analysis.

As illustrated in the diagram below, the application of the K-means clustering technique effectively segregated the dataset into five distinct groups. These divisions correspond with the analytical categories we previously identified, highlighting the capability of the K-means algorithm to organize the data into clearly delineated segments. The clustering results support the notion that the data can be partitioned into distinct groups that share particular characteristics, with some groups being more prominent, as suggested by the larger clusters. This was a strategic move in light of the inadequate performance of our initial selection of models, and it provided a more structured approach to understanding our data

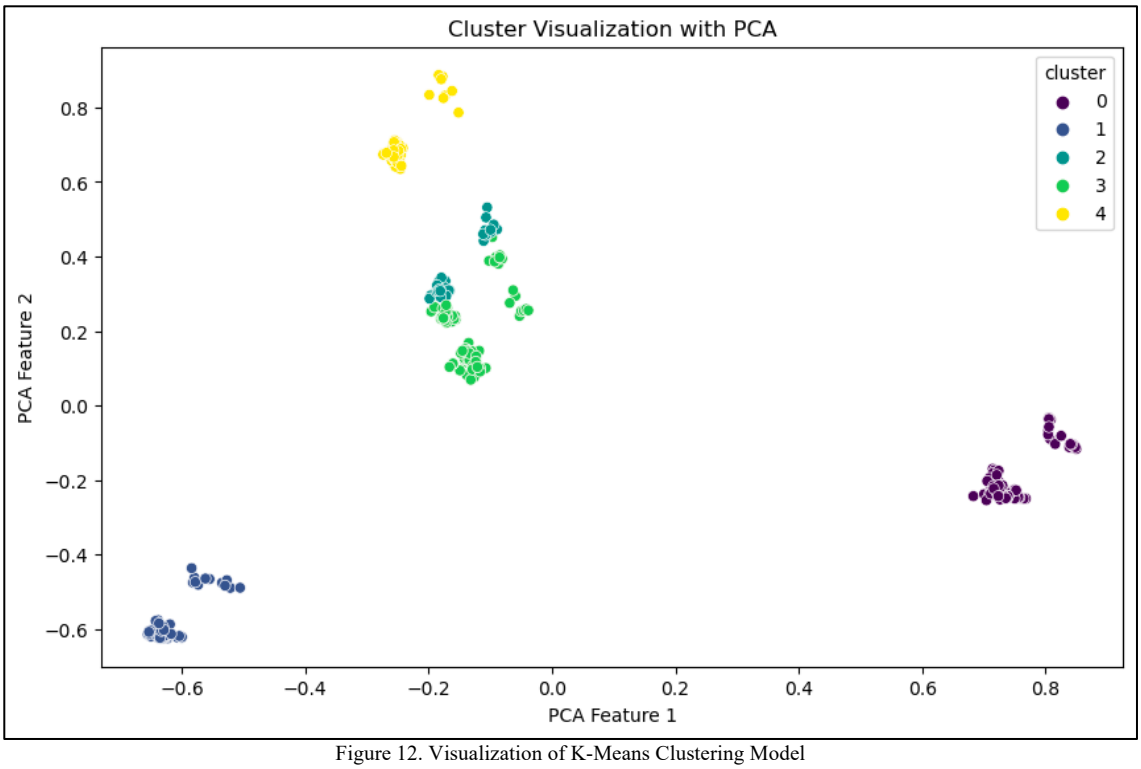

Figure 12. Visualization of K-Means Clustering Model

In summary, the performance analysis of the Naive Bayes, SVM, and Random Forest Classifier models revealed critically low accuracy and poor precision and F1 scores, indicating a severe misalignment between the models and the data. This necessitated a shift in strategy, leading to the adoption of K-means clustering. The successful application of K-means managed to categorize the data into five distinct and meaningful clusters, aligning with our analytical objectives. This reorientation towards a clustering approach not only highlights the adaptability of the analysis process but also underscores the importance of matching the right data analysis techniques to the inherent structure of the dataset.

7. Summary and Conclusion

Election Bridge's initiative, represents a significant stride in enhancing civic engagement through technology. This report has examined their journey from addressing communication barriers to embracing a data-driven approach that strengthens civic intelligence. Election Bridge's leverage of advanced data analytics signifies a deep commitment to fostering informed democratic participation. Their work is carving out new avenues for citizens to engage with government, providing a nuanced understanding of public sentiment and policy impact.

The dataset, rich with Portland's legislative actions and user demographics, provides a transparent view of civic interactions and legislative effectiveness. The thoughtful preparation and analysis of this data underscore the importance of meticulous data handling to derive actionable insights.

Our analysis revealed variances in civic interests across age groups and neighborhoods, reflecting the diverse fabric of community priorities. This diversity underscores the potential of tailored policies to meet specific community needs.

However, traditional modeling techniques initially employed—Naive Bayes, SVM, and Random Forest—showed dismal performance, prompting a strategic pivot to K-means clustering. This move proved beneficial, as K-means effectively segmented the dataset into meaningful clusters that mirrored our analytic categories, enhancing our understanding of the data.

In conclusion, while the initial models faltered, K-means clustering emerged as a robust alternative, demonstrating the importance of adaptive strategies in data analysis. Election Bridge's evolution signifies a transformative chapter in civic engagement, ushering in a new era where data analytics serve as a bridge between citizens and their government. The success of this endeavor lies not only in the adoption of advanced technologies but also in the willingness to iterate and adapt in the face of challenges. This bodes well for the future of civic participation, indicating a bright horizon for data-empowered democracy.

8. Recommendation

After thorough analysis, the ensuing recommendations are proposed:

1. **Data Quality Enhancement:** It is recommended to thoroughly assess and bolster the quality of the dataset to ensure completeness, accuracy, and pertinence. Particular emphasis should be placed on enhancing address details to facilitate more effective categorization.
2. **Address Detail Completion:** It is advised to address the gaps in address information. Recommendations include considering data enrichment strategies, potentially through external data sources, to augment areas where street address details are lacking or incomplete.
3. **Policy Classification Improvement:** A recommendation is put forth to clarify and standardize the criteria used for policy classification. Developing a more rigorous framework for categorization could diminish ambiguity and enhance the interpretability of the machine learning outcomes.
4. **Feature Engineering Optimization:** A re-evaluation of the feature selection and engineering process is recommended. Identifying features that more accurately reflect policy nuances could significantly improve the results of clustering or classification.
5. **Model Selection Reassessment:** It is recommended to reassess the current machine learning models in use and to consider alternative models that may be more apt for the specific characteristics of the dataset, such as its high dimensionality and the sparse nature of text data.

By adhering to these recommendations, an improvement in the machine learning models' performance and the clarity of policy categorization should be attainable.

9. Future Research Direction

As directions for future research, the following areas could be explored:

1. **Predictive Model Enhancement:** Future efforts should concentrate on advancing the refinement of predictive models. The goal would be to significantly improve the precision of category forecasts, thereby increasing the ratio of accurate predictions.
2. **Analysis of User Engagement Trends:** Investigate the behavioral patterns of users engaging with the platform. This research should aim to glean insights into user interactions that could inform and optimize user experience design and functionality.
3. **Civic Engagement Impact Evaluation:** It is advisable to construct an evaluation framework dedicated to assessing the influence of Election Bridge on civic participation. This framework would measure the platform's success in fostering effective communication between citizens and their government and its role in shaping policy decisions.

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