# Unlocking Urban Sentiments about 15-Min City through Hashtags

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## ABSTRACT

The 15-min city concept promotes active transportation and sustainable lifestyles by ensuring essential amenities within a 15-min radius from residences. While attracting significant interest, concerns about potential limitations on freedom of movement have been raised. This study aimed to gain broad insights into public perceptions and understanding of the 15-min city concept. Text mining and sentiment analysis techniques were applied to extract prevailing sentiments. The findings indicated that positive and negative sentiments were evenly distributed among the collected tweets, suggesting a balanced and diverse range of opinions. These opinions are what helps shape the policy and legislation, especially when prominent individuals with a large online presence endorse or reject a specific idea or theory. To further enhance the analysis, three different machine learning classifiers, namely naïve Bayes, logistic regression, and support vector machine, were employed to classify the sentiments expressed in the tweets. The framework developed in this study and the insights derived from the sentiment analysis offer valuable resources for policymakers and urban planners seeking to comprehend and embrace emerging urban concepts like the 15-min city.

## INTRODUCTION

The 15-minute city concept, developed by Carlos Moreno, aims to create localized, healthy, equitable, and sustainable lifestyles by ensuring essential amenities within a 15-minute radius of residences. These amenities include access to groceries, healthcare, schools, parks, cultural institutions, and public transportation options, focusing on promoting active transportation through bike lanes and pedestrian pathways. Due to its potential benefits, the concept has gained immense interest from local authorities, urban planners, property professionals, and companies worldwide. However, as with any transformative idea, the 15-minute city has yet to be without its share of criticisms. Some campaigners have expressed concerns about potential limitations on freedom of movement and the challenges associated with implementing such a radical shift in urban planning. Despite these reservations, the 15-minute city holds immense promise in promoting equity, fostering stronger neighborhoods and communities, and bridging the gap between urban and suburban areas.

Sentiment analysis, also known as opinion mining, is a natural language processing (NLP) technique that involves determining and extracting the emotional tone, attitude or opinion expressed in a piece of text. The goal of sentiment analysis employed in this study is to understand the subjective information conveyed by the text and classify it as positive or negative. Applications of sentiment analysis are diverse and include social media monitoring, customer feedback analysis, product reviews, and many others. It enables businesses and organizations to gain insights into public opinion, make data driven decisions, and respond effectively to customer feedback.

As the internet has evolved from traditional passive platforms to interactive spaces with user-generated content, social networks have become valuable data generation sources. Among these platforms, Twitter (now known as X; however, we used the previous name 'Twitter' in this paper) stands out as a prominent social media platform where millions of registered users actively share their opinions and perceptions. Leveraging knowledge discovery and data mining techniques on social networks, especially on Twitter, can prove instrumental in understanding public sentiment and reception towards emerging concepts such as the 15-minute city. Sentiment analysis and text mining on Twitter play a crucial role in gaining a comprehensive understanding of how the public responds to the 15-minute city concept. By tapping into social media data, researchers can uncover valuable insights into the level of acceptance, potential impact, and anticipated challenges associated with this innovative urban planning approach. Such knowledge can prove indispensable in informing decision-makers and policymakers, enabling them to create and implement more effective and inclusive policies for the future of urban development.

This paper's analysis of sentiment towards the 15-minute city concept as expressed on Twitter is conducted using different machine learning models. In this study, sentiment analysis was conducted on Twitter data using the hashtag '#15minutescities' to gauge public perceptions, opinions, and emotions related to this concept. This study aims to shed light on the overall sentiment landscape surrounding the 15-minute city idea by examining and interpreting the sentiments in a vast pool of user-generated content. This research contributes to understanding how the public perceives and engages with this innovative urban planning model and the potential implications it may have for the future of urban development. This study aims to examine the following two research questions:

- **Research Question 1:** How do Twitter users perceive the 15-minute city concept? What sentiments and opinions are expressed with the hashtag '#15minutescities,' and can machine learning models predict the sentiments accurately?
- **Research Question 2:** What are the potential implications of Twitter sentiment towards the 15-minute city concept for future urban development policies and decision-making?

The rest of this paper is organized as follows: the literature review section reviews of the relevant literature on the 15-minute city concept, sentiment analysis on social media platforms, and how public opinion shapes policy. The methodology section outlines the methodology employed in data collection and sentiment analysis. The results and discussion section presents our findings, offering insights into the sentiments expressed on Twitter regarding the 15-minute city. Finally, in the conclusion section, the paper summarizes the research and suggests avenues for future exploration in this dynamic and rapidly evolving field.

## LITERATURE REVIEW

Several studies have assessed the 15-minute city concept. Stanley et al. (2015) examined the concept of a '20-minute city' proposed in Plan Melbourne to achieve sustainable Australian cities. It emphasized the importance of density, supportive public transport, and walking in creating a metropolitan area composed of smaller 20-minute cities. The paper encouraged stakeholders to contribute ideas for further development and progress in implementing the 20-minute city concept in Australia. Abdullah et al. (2022) assessed the knowledge and awareness of both planning and engineering students and practitioners regarding the concept of the 15-

minute city through a questionnaire survey in Lahore, Pakistan. Results revealed low awareness of the 15-minute city concept, with planning degree holders and attendees of more urban and transport planning seminars demonstrating higher awareness. Civil and Transportation Engineers exhibited lower awareness. Findings suggest the need to enhance awareness among professionals to promote sustainable solutions like the 15-minute city concept. Staricco (2022) developed a methodology to implement the 15-minute city concept, testing it in Turin, Italy. Results indicated that in dense European cities, the 15-minute target may not always be necessary as many services are already within walking distance, and service locations influence accessibility. The study suggests incorporating accessibility measures from regional sciences to enhance the operationalization of the 15-minute city concept. Papas et al. (2023) conducted a literature review on studies implementing the 15-minute city model in various large cities worldwide, focusing on Paris as an example. They found that this model facilitates socio-economic growth in neighborhoods and encourages citizens' participation in neighborhood redesign, emphasizing the need for a cultural change instead of just urban planning.

Much work has been done on the topic of sentiment analysis. Reddy et al. (2021) conducted sentiment analysis using methodologies such as logistic regression, evaluates web content from various sources, including social media, product reviews, and events, to classify sentiments and provide actionable insights for businesses seeking to enhance products and customer experiences in response to the growing volume of feedback data. They found that the Logistic Regression with grid search model proves to be the most effective in analyzing product reviews for polarity, showcasing the potential of natural language processing techniques to enhance business decision-making and marketing strategies. Shaziya et al. (2015) preformed sentiment analysis within the context of opinion mining, utilizing the Weka platform to classify 2000 movie reviews from the Cornell University dataset. Employing information gain for feature selection, the study demonstrates the enhanced performance of classifiers, specifically naïve bayes and SVM, through the reduction of the feature set. The research emphasizes the importance of feature selection, proposing an initial model with potential for further enhancement and exploration, particularly in preprocessing, tokenization, and the use of hybrid techniques in sentiment analysis.

How public opinion influence policy has been evaluated by several researchers. Mikael Persson (2021) evaluated the intricate a correlation between policy changes and the preferences of high socio-economic status citizens, yet the underlying mechanisms are not well-explored. This research investigates the role of political representatives in connecting public opinions and policy changes. The study confirms biases in policy responsiveness in Sweden, revealing that political representatives better represent the opinions of socioeconomically advantaged groups, raising questions about whether the underrepresentation of the less advantaged in policy changes is due to misperception, preferences, or information gaps, necessitating further research. Pacheco and Maltby (2017) examined how public opinion influenced the diffusion of Affordable Care Act (ACA) policy choices from 2010 to 2014, finding that gubernatorial ACA announcements and grant activity increased support for the ACA in nearby states, with gubernatorial announcements responding more significantly to shifts in ACA support. The results highlight the importance of considering both policy feedback and opinion learning mechanisms in understanding influence that public opinion has on policy implementation.

The literature review highlights the growing interest in the 15-minute city concept as a pathway to sustainable and connected urban environments. Studies have explored various aspects, including walkability, accessibility to essential services, and potential implementation in different cities worldwide. Several studies have also explored sentiment analysis of digital platforms and the level of influence that they have on policy decisions. Despite challenges and varying public opinion, the concept offers valuable insights for creating more liveable, resilient, and environmentally friendly cities in the future.

## METHODOLOGY

After data collection, the data must be cleaned and translated to reduce noise and establish a consistent language across all samples. The cleaned text is then translated using the Google Translate API for non-English tweets (now known as posts), ensuring accuracy through a validation mechanism. Lastly, sentiment analysis and classification are carried out using machine-learning algorithms trained on a dataset of movie reviews. The algorithms, including naive Bayes, logistic regression, and support vector machine, are applied to the Twitter data to gain insights across diverse domains. The document term matrix is refined using the TF-IDF algorithm to optimize model performance and improve the accuracy of sentiment analysis.

### Data Collection

This study used an opensource R package, ‘academicTwitter’ to collect the tweets associated with the hashtag ‘#15minutecities’. The data collection spanned from January 1, 2016, to May 30, 2023, and resulted in 20,773 tweets associated with the mentioned hashtag. Each of these tweets contained 31 columns providing various information, including 'tweet id,' 'text,' 'timestamp,' and 'sourcetweet_id.'

### Data Preprocessing

This study showcased advanced data preprocessing techniques applied to the collected data. The dataset is strategically divided into quarters to expedite processing, ensuring efficient execution. Within these subsets, a new column with 'clean text' is processed by subsequent transformations. The following major steps are taken for the ‘clean text’ generation:

- By utilizing the regular expression pattern r'@(\w+)\s', which matches words preceded by the '@' symbol, mentions are identified. If the extracted mentions result in a list, they are joined into a single string using the 'join' method; otherwise, an empty string is assigned.
- Hashtags are extracted from the 'clean text' column and stored in a new column named 'hashtag'. The regular expression pattern r'#(\w+)\s' is employed to identify words preceded by the '#' symbol, indicating hashtags.
- In the subsequent step, regular expressions search for links within the 'text1' column. URLs beginning with 'http://' or 'https://' are captured and stored in a new column named 'links.' This process facilitates the organization and separation of links found within the text data. The researchers install and import the 'emoji' package to effectively handle emojis.
- The emoji library provides access to many emojis through Unicode standards. A function called 'extract_emojis' is defined to isolate English emojis from a given string. This function uses the emoji library to remove and store emojis from the text. This function is then applied to the 'text1' column, and the resulting emojis are stored in a new column named 'emoji.' This enables the identification and isolation of emojis within the text data.

- Other data cleaning includes removing mentions (words beginning with '@'), hashtags (words beginning with '#'), links, emojis, punctuation, and a specific prefix ('RT :').
- After cleaning the 'text_clean' column, it is further processed by replacing multiple consecutive whitespaces with a single whitespace, effectively condensing excessive whitespace within the text data. Finally, all the texts in the tweets are converted to lowercase for consistency.

## Term Frequency – Inverse Document Frequency (TF-IDF)

TF-IDF is a numerical statistic that assesses the relevance of keywords to specific documents, enabling automatic identification and categorization Silge and Robinson (2017). Term frequency (TF) denotes the frequency with which a term, typically a word, appears within a document. The underlying principle assumes that terms appearing more frequently within a document are more important or relevant to that document. It is commonly calculated utilizing the following formula:

$$\mathrm{TF} = \mathrm{t} / \mathrm{d} \tag{1}$$

Where:

- $t$ represents the number of occurrences of the term in the document.
- $d$ represents the total number of terms in the document.

Inverse document frequency (IDF) evaluates the significance of a term across the entire collection of documents. The IDF value increases when a term is found in fewer documents throughout the collection, implying that the term offers greater informational value or distinctiveness. It is calculated as follows:

$$\mathrm{IDF} = \log\,(\mathrm{t} / \mathrm{D}) \tag{2}$$

Where:

- $t$ represents the total occurrences of the term across the entire collection of documents.
- $D$ represents the entire collection of documents. $D$ is a set that contains all the documents being analyzed or considered.

Upon computation of both the TF and the IDF, the TF-IDF score for a given term in a document can be derived by multiplying the TF and IDF values. Higher TF-IDF scores for terms within a document indicate a heightened level of relevance or importance. In summary, TF-IDF is utilized in the models employed throughout the following sections to transform the text data into numerical features that capture the importance or relevance of terms within the documents. These TF-IDF features are then used for training the models and making predictions or classifications on new data. TF-IDF can be calculated using the equation below.

$$\mathrm{TF} - \mathrm{IDF} = \mathrm{TF} * \mathrm{IDF} \tag{3}$$

## Classification Algorithms

### Naïve Bayes (NB)

The Multinomial NB Classifier is a text classification method that uses probability and multinomial distribution. It converts text data into a nominal form to compute with integer values. This classifier is effective in analyzing and categorizing text by leveraging probabilities. It is a valuable tool for text classification tasks due to its probabilistic approach and efficient handling of text data. The formula used for NB models is based on Bayes' theorem, a fundamental theorem in probability theory Farisi et al. (2019). NB models are probabilistic classifiers that assume independence between the features given the class label. The formula for NB can be expressed as:

$$\mathrm{P}(\mathrm{y} \mid \mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{p}) = (\mathrm{P}(\mathrm{y}) * \mathrm{P}(\mathrm{x}_1 \mid \mathrm{y}) * \mathrm{P}(\mathrm{x}_2 \mid \mathrm{y}) * \ldots * \mathrm{P}(\mathrm{x}_\mathrm{p} \mid \mathrm{y})) / \mathrm{P}(\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{p}) \quad (4)$$

Where:

- $P(y \mid x_1, x_2, \ldots, x_\mathrm{p})$ is the posterior probability of the class label y given the input features $x_1, x_2, \ldots, x_\mathrm{p}$.
- $P(y)$ is the prior probability of the class label y.
- $P(x_\mathrm{i} \mid y)$ is the conditional probability of feature $\mathrm{x_i}$ given the class label y.
- $P(x_1, x_2, \ldots, x_\mathrm{p})$ is the probability of the input features $x_1, x_2, \ldots, x_\mathrm{p}$ occurring together.

## Logistic Regression (LR)

This experiment uses LR for classification due to its sigmoid activation and improved accuracy compared to NB algorithms Reddy et al. (2021). It is applied to binary logistic models with a dependent variable having two alternative values, represented as "0" and "1". The log-odds for the "1" value in the model are a linear combination of independent variables, which can be either binary or continuous. The corresponding likelihood for the "1" value ranges between 0 and 1, and the logistic function is used to transform log-odds into probabilities. The formula for LR can be expressed as:

$$P(y = 1 \mid X) = 1 / (1 + e \wedge -(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_\mathrm{p} X_\mathrm{p})) \quad (5)$$

Where:

- $P(y = 1 \mid X)$ represents the probability of the outcome variable $(y)$ being 1 given the input features (X).
- e is the base of the natural logarithm (approximately 2.71828).
- $\beta_0, \beta_1, \beta_2, \ldots, \beta_\mathrm{p}$ are the coefficients or weights assigned to each input feature $X_1, X_2, \ldots, X_\mathrm{p}$, respectively.
- $X_1, X_2, \ldots, X_\mathrm{p}$ are the input features.

## Support Vector Machine (SVM)

The SVM algorithm is employed for sentiment analysis of two pre-classified sets of tweets. SVM is a well-known supervised machine learning approach widely used for classification purposes. It has proven highly effective in various aspects of text categorization and has shown better performance than NB classifiers in many instances. The equation used for SVM is based on the concept of finding an optimal hyperplane that separates different classes in a dataset. SVM is a supervised learning algorithm for classification and regression tasks Feng et al. (2022). In the case of linearly separable classes, the formula for SVM is shown in Equation 6. The decision rule for SVM is given in Equation 7.

$$w^T * x + b = 0 \quad (6)$$

$$f(x) = sign(w^T * x + b) \quad (7)$$

Where:

- $w$ is the weight vector perpendicular to the separating hyperplane.
- $x$ is the input feature vector.
- $b$ is the bias term, which determines the offset of the hyperplane from the origin.

If $f(x)$ is positive, the input sample x is classified as one class, and if f(x) is negative, it is classified as the other class. To determine the optimal hyperplane, SVM maximizes the margin (the distance between the hyperplane and the closest data points of each class). The support vectors are the data points on the margin or inside it.

## Text Network Analysis

Text network analysis (TNA) is a powerful tool within text mining as it uncovers hidden trends in unstructured text data (Hunter, 2014; Kwayu et al. 2021). TNA uses nodes and edges to establish relationships between keywords within a corpus (a large, structured body of text). The nodes in this network correspond to individual keywords, while the edges represent their relationships or connections. The keywords' frequency and co-occurrence within the network are indicated by the sizes of the nodes and the edges, respectively.

# RESULTS AND DISCUSSIONS

The training dataset comprises 40,000 movie reviews obtained from a modified dataset by Phadnis (2021) on IMDB reviews from Lakshmipathni (2019), each paired with a sentiment label indicating positive or negative sentiment. The dataset has intentionally been balanced, containing an equal number of positive and negative sentiment samples, with 20,000 reviews in each category. This balance ensures that sentiment analysis models trained on this data can effectively generalize both positive and negative sentiments.

Movie reviews hold considerable value for sentiment analysis tasks, particularly in analyzing sentiments in Twitter data, due to shared language patterns and sentiment expressions. Training models on movie reviews improve understanding of short texts and informal language, enhancing performance on Twitter data. Utilizing transfer learning with pre-trained models enables the adaptation of knowledge from movie reviews to Twitter data, fostering improved sentiment analysis capabilities. The movie review dataset has two columns: 'text' and 'sentiment.' The 'text' column captures the raw textual form of movie reviews, which can vary significantly in length and content. These texts authentically express diverse opinions and experiences various individuals share about the movies they have watched. The 'sentiment' column corresponds to sentiment labels, with 'pos' denoting positive sentiment and 'neg' denoting negative sentiment.

This movie review data is used to train and test models for application on the 15-minute cities dataset. The '15-minute data' is split into a 75% training and 25% test sets. This split ratio allows a significant portion of the data to be used for training sentiment analysis models. In contrast, a separate portion is utilized to evaluate their performance on unseen data. This approach aids in assessing the models' generalization capabilities and ensures reliable sentiment analysis results, even when applied to new, real-world data, such as Twitter posts. By leveraging appropriate models, such as SVM, NB, and LR, sentiment analysis models can effectively interpret sentiments expressed in textual data, including Twitter posts. Leveraging the well-balanced nature of the dataset and the chosen models, sentiment analysis provides meaningful insights into sentiments conveyed across diverse domains.

For this binary classification, this study used the following performance metrics to evaluate the model performance. Table 1 shows a breakdown of these performance metrics across the three models used in this study.

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{8}$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \tag{9}$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN} \tag{10}$$

$$\text{F1} - \text{score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \tag{11}$$

Where,

- True Positive (TP) refers to the instances correctly predicted as positive by the classifier.
- True Negative (TN) represents the instances correctly predicted as negative by the classifier.
- False Positive (FP) refers to the instances predicted as positive but are negative.
- False Negative (FN) refers to the instances predicted as negative but are positive.

**Table 1. Performance Metrics.**

| **Performance Metrics** | **Naïve Bayes** | **Logistic Regression** | **Support Vector Machine** |
|---|---|---|---|
| Accuracy | .8424 | .8741 | .8755 |
| Precision | .8427 | .8743 | .8758 |
| Recall | .8424 | .8741 | .8755 |
| F1-score | .8424 | .8741 | .8755 |

Across all three classifiers, this study observed relatively high accuracy values (see Table 1), indicating that the models make correct predictions for a significant portion of instances in the evaluation set.

- The SVM classifier achieves the highest accuracy at 0.8755, followed closely by LR at 0.8741 and NB at 0.8424.
- In terms of precision, all three classifiers perform well. The SVM classifier achieves the highest precision of 0.8758, followed by LR at 0.8743 and NB at 0.8427. These precision scores indicate that the models have a high level of correctness when identifying positive instances.
- The recall values are also quite high for all three classifiers. The SVM classifier exhibits a recall of 0.8755, LR and NB have a recall of 0.8741. These scores indicate that the models can accurately capture a significant portion of the positive instances in the evaluation set.

- When considering the F1-score, this study observes similar values for all three classifiers. The SVM classifier, LR, and NB all have an F1-score of 0.8755. These scores suggest that the models balance minimizing FPs and capturing TPs.

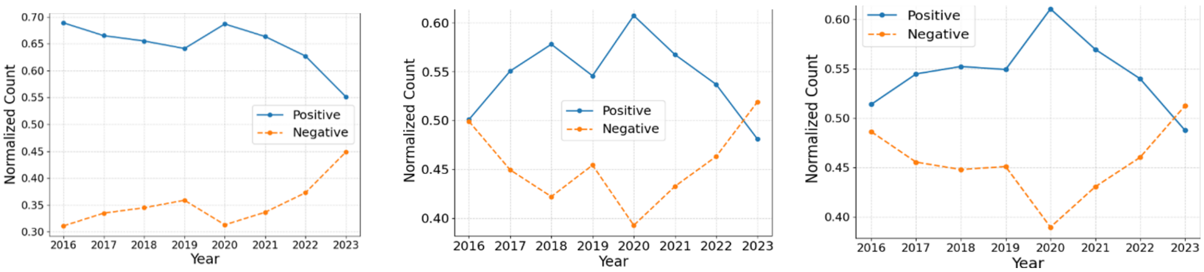
Overall, the performance of the SVM classifier is consistently strong across all metrics, followed closely by LR and then NB. The SVM classifier's robust performance can be attributed to its ability to find an optimal hyperplane that maximizes the margin between classes in the feature space. LR, which uses a linear decision boundary, performs well and is particularly suitable for problems with linearly separable classes. It effectively learns the relationship between features and class labels. Although slightly lower in performance, NB relies on the assumption of independence between features. It performs well in scenarios where this assumption holds, such as text classification. The results indicate that SVM and LR classifiers tend to outperform NB in accuracy, precision, recall, and F1 score. The superior performance of SVM can be attributed to its ability to handle complex decision boundaries, while LR benefits from its simplicity and linear decision boundary assumption. Despite its simplicity and assumption of feature independence, NB still delivers reasonable performance but lags slightly behind the other two classifiers.

## Training Data Influence

The performance of machine learning models heavily relies on the training data, influencing their results. Similar accuracy, recall, and F1 scores across different classifiers can occur due to various factors related to the distribution of classifications within the training set. Factors like balanced data distribution can lead to similar performance, while severe class imbalance or data representation issues can impact accurate classification. Proper preprocessing, addressing class imbalances, feature selection, and handling missing or noisy data are essential for optimal performance. Hyperparameter tuning and model selection further improve performance and enable differentiation between classifiers' capabilities.

Figure 1 shows the results of sentiment polarity analysis using SVM and LR models. It reveals a consistent shift in sentiment around 2022-2023, boosting the credibility of this observation. The convergence of results from both models strengthens the reliability of the identified sentiment shift during that period. Various factors like socio-political events, cultural changes, economic fluctuations, or technological advancements might contribute to this shift. These shifts indicate changes in the overall sentiment, reflecting how people perceive and feel about certain issues, topics, or entities. While these results don't explain why the shift occurred, they can be used to document and understand when shifts in sentiment occurred. Future research within this subject could further identify causal relationships between these shifts and outside factors that could have contributed to the shift.

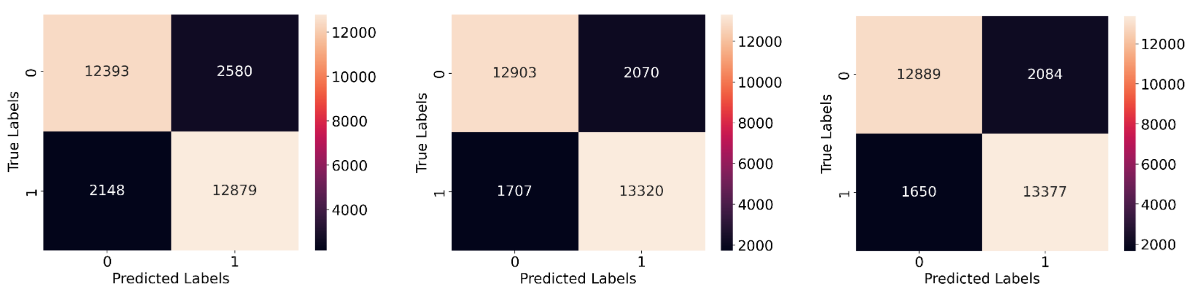
On the other hand, the NB model doesn't show a similar sentiment shift as observed in SVM and LR models from 2022-2023. This difference is likely due to inherent factors in the NB algorithm, such as its simplistic assumptions and limitations in capturing complex sentiment patterns. The NB algorithm assumes feature independence, which might not accurately reflect real-world situations, limiting its ability to capture nuanced shifts in sentiment over time. While the NB model performs slightly worse than SVM and LR models, this alone doesn't explain its failure to capture the sentiment shift. It's essential to consider the NB algorithm's predictive power and generalization limitations compared to more advanced models.




NB LR SVM

**Figure 1. Normalized score by the algorithms used.**

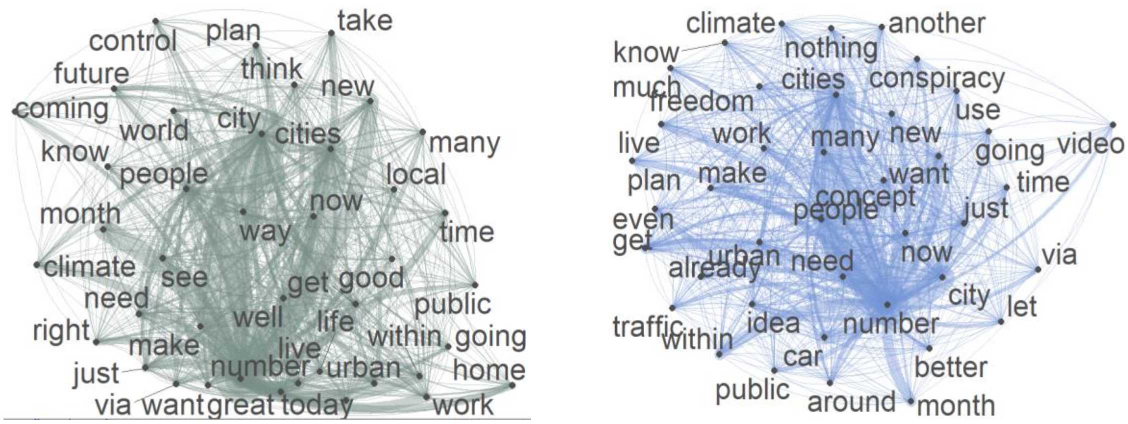
Figure 2 shows the confusion metrices for sentiment analysis across the three machine learning models, with 0 representing negative sentiment and 1 representing positive sentiment. The SVM model demonstrates a well-balanced performance with high TP and TN values, indicating its ability to classify both positive and negative sentiment instances accurately. However, it does have some misclassifications, with a moderate number of FP and FN predictions. The LR model also shows a balanced performance with high TP and TN values and exhibits slightly fewer FP and FN predictions than the SVM model, further demonstrating its effectiveness in sentiment classification. In contrast, the NB model achieves lower TP and TN values, indicating a slightly lower ability to classify both positive and negative sentiment instances accurately. It also has a higher rate of misclassifications, with a relatively higher number of FP and FN predictions. Based on the confusion matrices analysis, it can be concluded that the SVM and LR models perform better in sentiment classification than the NB model. Both models consistently demonstrate higher TP and TN values and produce fewer misclassifications (FP and FN) than the NB model.




NB LR SVM

**Figure 2. Confusion matrices by the used algorithms.**

Figure 3 shows text networks of both positive and negative sentiments in 15-minute cities. In the positive sentiments, some significant keywords include *great*, *people*, *want*, *work*, *home*, *future*, and *plan*. Great is heavily connected with other keywords, suggesting those who view 15-minute cities in a positive light consider them to be a great concept. They also think that 15-minute cities will offer a good life with better access to both work and home, although they may require some planning for the future. For the negative sentiments, some of the main keywords include conspiracy, freedom, car, and concept, suggesting that those who view 15-minute cities in a negative light may consider the concept to be a conspiracy aiming to reduce their freedom and take away their cars.



**Positive** **Negative**

**Figure 3. Text network of positive and negative sentiments.**

## CONCLUSIONS

This paper conducts a comprehensive sentiment analysis using three classifiers—SVM, LR, and NB—revealing notable sentiment shifts from 2022 to 2023. The consistent findings from SVM and LR enhance the credibility of observed patterns, emphasizing the potential applications of sentiment analysis beyond social media. Policymakers can leverage this approach to swiftly gauge public opinions on various subjects, facilitating a nuanced understanding of societal views and reactions to new ideas or theories. Understanding shifts in sentiment can allow for contextual understanding of the factors that lead consumers and members of society to hold views in any given direction. The study underscores the importance of selecting appropriate classifiers and considering factors like training data, preprocessing, and model selection for optimal sentiment analysis outcomes.

While using SVM, LR, and NB classifiers in this study demonstrates their strong performance and capabilities, it also has some limitations that should be considered. Firstly, the study's findings may lack generalizability, as the evaluation set might not fully represent all possible sentiment variations in different contexts. Given that our dataset was not labeled, we had to rely on transfer learning from movie reviews. A potential limitation with these reviews is that they tend to be longer in length than tweets. To address this, future research should focus on cross-domain evaluation, testing the classifiers on diverse datasets from various domains to ensure their applicability across different contexts. In addition, while SVM and LR models exhibit high performance, they may lack interpretability on their own, making it challenging to understand the reasons behind their predictions. Future research could focus on developing high accuracy and interpretability models to gain better insights into sentiment analysis results. Finally, investigating methods to handle noisy and mislabeled data can enhance the classifiers' performance and real-world applicability. Addressing these limitations and pursuing these future research directions will advance the field of sentiment analysis and enable its broader application in various domains.

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