Climate Change Sentiment Analysis Based On Gender

Alexander Nyström
Linköping University
IDA
Linköping, Sweden
aleny301@student.liu.se

Abstract

This paper presents a comprehensive text mining framework for analyzing public discourse on climate change from social media. Using over 88 million tweets, this research implemented one key tasks: sentiment analysis. Sentiment analysis captured nuanced sentiment trends by gender over time. Results highlight gender differences in climate change sentiment and temporal variations in public opinion, providing insights into societal perceptions.

1 Introduction

Understanding public opinion on climate change is essential for capturing societal perspectives and informing policy decisions. Social media platforms like X (formerly known as Twitter) provide a valuable resource for analyzing real-time discourse on this global issue. However, extracting meaningful insights from noisy, large-scale social media data requires robust preprocessing and analytical techniques.

This work builds on prior research, including a similar approach detailed in an ACL paper that successfully employed BERT for stance detection in climate change discourse. Inspired by their methodology, I developed a comprehensive pipeline to analyze over 88 million tweets. The pipeline includes:

- **Climate filtering**: Extracting climate-related tweets using a curated list of keywords (e.g., #climatechange, global warming).
- **Gender prediction**: Inferring the gender of tweet authors based on user names.
- **Preprocessing**: Removing noise (e.g., URLs, hashtags, empty tweets).

After preprocessing, the goal of this research was addressed: Sentiment analysis focused on exploring attitudes across genders and temporal dimensions, revealing significant trends in public discourse on climate change.

1.1 Research Hypothesis

This study hypothesizes that:

1. In wealthier countries, sentiment values related to climate change will be stronger among women compared to men.

2. Women will express positive sentiment values more frequently than men, reflecting their higher engagement with climate advocacy and mitigation.

These hypotheses build on existing research, which highlights gender as a critical factor in shaping public attitudes and emotional responses to global challenges like climate change (Bush and Clayton, 2023).

2 Related Work

Sentiment analysis has been widely explored in the context of climate change. Early studies utilized classical machine learning models such as Naive Bayes and SVMs to analyze opinions from Twitter feeds (Cody et al., 2015). However, these approaches often struggled with nuanced language and noisy data, prompting a shift towards deep learning methods. For instance, deep neural networks achieved 88.1% accuracy in binary classification of believers and deniers on climate change tweets (Chen et al., 2019).

Lexicon-based methods, such as VADER and TextBlob, remain popular for sentiment analysis due to their simplicity and speed. They have been applied to assess public sentiment during events like Hurricane Sandy (Kryvasheyeu et al., 2016). However, these methods often lack the contextual understanding required for more complex analyses. To address this, hybrid approaches combining lexicon-based and deep learning models have emerged as a robust solution (Giachanou and

Crestani, 2016). My work builds on this by leveraging both types of models and optimizing their weights to improve sentiment scoring.

The methodology and dataset provided by Effrosynidis et al. (Effrosynidis et al., 2022) served as a significant inspiration for this study. Their work employed a BERT-based model for stance detection on climate change tweets, demonstrating pre-trained transformers' effectiveness in handling noisy social media data. Although their data set included gender as an enriched column, they did not explicitly analyze the stance or sentiment of both genders on a temporal axis. Building upon their framework, I extended the analysis to fill this gap by incorporating gender-based sentiment trends and examining stances across time.

Gendered patterns in climate change attitudes have been widely explored in prior research. Bush et al. (Bush and Clayton, 2023) found that individuals in wealthier nations generally perceive climate change as less urgent, with a sharper decline in concern among men. In contrast, women are more likely to view climate change as a significant issue and advocate for mitigation measures. This study draws upon these findings to hypothesize that women exhibit stronger sentiment values toward climate change, even in affluent contexts where general concern diminishes.

While spatio-temporal analysis of Twitter activity has provided valuable insights in past studies (Kryvasheyeu et al., 2016), geolocation analysis was not feasible in this study due to API limitations. Instead, I focused on gender-based sentiment analysis, drawing inspiration from previous work that examined gender-specific sentiment trends in UK and Spanish tweets (Loureiro and Alló, 2020).

3 Data

3.1 Datasets Used

This study utilized four datasets:

- **Original Dataset**: 88 million tweets collected via X's API, filtered to 104,545 tweets related to climate change, sourced from the Twitter100M dataset (Enryu43, 2024).

- **Twitter Climate Change Sentiment Dataset**: Used for evaluating sentiment models (Qian, 2020).

- **Climate Change Twitter Dataset (Expert Dataset)**: Employed for comparative analysis (Effrosynidis et al., 2022).

3.2 Data Creation

The original dataset was collected using X's API and included tweets from a broad timeline. The other datasets were sourced from publicly available repositories like Kaggle, which were created by prior researchers and contained labeled tweets for sentiment or climate change relevance.

3.3 Preprocessing

Preprocessing was applied to the original dataset to ensure relevance and cleanliness. The data was filtered to retain only English-language tweets and keyword-based filtering was applied to focus on climate change topics. Additionally, noise such as URLs, mentions, and empty tweets was removed. These steps ensured the data was suitable for sentiment analysis.

4 Methodology

4.1 Dataset and Preprocessing

The primary dataset, comprising over 88 million tweets collected via X's API from 2009 to 2023, was preprocessed as described in Section 3.3.

4.2 Gender Prediction

To enrich the dataset with gender information, I utilized the Python package 'chicksexer', a character-level LSTM-based gender classifier trained on over 160,000 names. A 95% probability threshold was initially applied for classification, and adjustments were explored to optimize coverage.

4.3 Sentiment Analysis

To perform sentiment analysis, I adopted a hybrid approach that combined the outputs from multiple models:

- **Models Used**: VADER, TextBlob, Flair (LSTM and BERT), and SenticNet. Each model produced a sentiment score ranging from -1 to 1.

- **Weight Optimization**: The weights for the models were optimized using a grid search algorithm applied to the Sentiment140 dataset. The optimization process explored all possible weight combinations within a specified range (0.2 to 0.8) with a step size of 0.2. Each weight combination was evaluated based on the F1 score of the combined sentiment predictions, and the set of weights yielding the highest F1 score was selected.

- **Weighted Scoring**: The final sentiment score for each tweet was computed as a weighted average of the individual model scores, with the optimized weights reflecting the varying reliability and context-sensitivity of the models.

4.4 Geolocation Analysis

Geolocation analysis was initially planned to explore regional differences in sentiment, but this was infeasible due to X's API limitations. Specifically, the API restricted user information to one GET request per day, making it impractical to gather data for 19,000 users.

4.5 Implementation Details

The implementation utilized a combination of libraries and frameworks tailored to the specific requirements of each model. For instance, VADER and TextBlob, as lexicon-based models, relied on their respective Python libraries, while Flair (LSTM and BERT) and SenticNet were implemented using deep learning frameworks. Training and evaluation of the BERT-based stance detection model were conducted in PyTorch with the Hugging Face Transformers library. All computations were performed on a T4 GPU in Google Colab, with preprocessing and weight optimization completed within the computational constraints of the free-tier resources.

5 Results

5.1 Dataset Overview

After preprocessing, the dataset was reduced to 104,545 tweets. The dataset represented 19,136 unique users, with the following gender distribution. To maximize the number of classified users, the classification threshold was lowered from 95% to 87%, reducing the percentage of "unknown" users from 42% to 29%.

Gender	Count	Percentage
Male	9,424	49.2%
Female	5,503	28.7%
Unknown	4,209	22.1%

Table 1: Distribution of Users by Gender

5.2 Sentiment Analysis

The optimized weights for the sentiment models were as follows: VADER: 0.20, TextBlob: 0.20, Flair LSTM: 0.20, Flair BERT: 0.80, SenticNet: 0.20.

This weighting scheme heavily prioritized Flair BERT, a context-sensitive model, due to its superior performance in capturing nuanced sentiments, while assigning equal but lower weights to the remaining models. Flair LSTM, SenticNet, VADER, and TextBlob contributed less to the final sentiment scores, as their context-sensitivity or reliability was comparatively lower. The reduced reliance on lexicon-based models like VADER and TextBlob addressed their tendency to misinterpret complex or context-dependent language, thereby improving the overall robustness of the sentiment analysis.

5.2.1 Temporal Sentiment Analysis Results

To examine how sentiment toward climate change varied over time, I analyzed the sentiment values on a temporal axis, focusing on quarterly mean sentiment scores from 2009 to 2023. To improve the readability of the trends and reduce the appearance of volatility due to insufficient data in specific quarters, a rolling average was applied to smooth the plotted values. The results are presented in Figure 1, which compares two datasets. The data from this work is labeled as *Original*.

The analysis revealed notable trends:

- Female sentiment values were consistently higher than male sentiment values, indicating greater positivity or urgency in their attitudes toward climate change.
- Sentiment fluctuations were observed across both genders, with significant dips and peaks corresponding to major climate-related events or global discussions.
- Toward the later years (after second quarter for 2021), the gap between male and female sentiment values appeared to narrow slightly, although females still exhibited stronger sentiment overall.

These findings reinforce existing research suggesting that women are generally more engaged with climate change issues and demonstrate greater emotional investment in advocating for environmental mitigation.

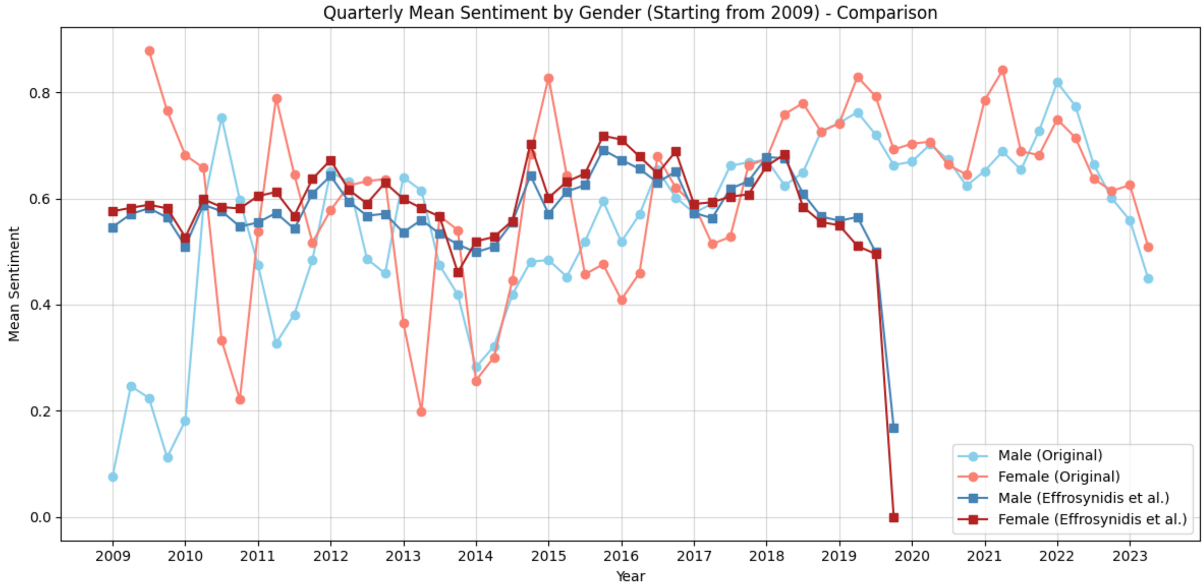

Figure 1: Comparison of Sentiment Trends between the Expert Dataset and My Dataset.

5.3 Comparison with Expert Dataset

To visualize the differences between the sentiment trends observed in my dataset and the Climate Change Twitter Dataset by Effrosynidis et al. (Effrosynidis et al., 2022), a comparative plot was created (Figure 1). The plot highlights the greater stability in sentiment trends in the expert dataset compared to the more volatile patterns in my dataset. These differences may be attributed to the smaller size of my dataset and the methodological choice to optimize weights for individual models.

5.4 Hypothesis Validation

The hypothesis that women exhibit stronger and more positive sentiment values toward climate change compared to men was confirmed. Despite geolocation limitations, women consistently showed higher mean sentiment scores across most years, with minor exceptions.

The magnitude of the difference varied over time, likely influenced by major climate events or policy changes. These findings support prior research indicating that women are generally more engaged and concerned about climate change than men.

6 Discussion

6.1 Key Insights

The results aligned with the initial hypothesis, demonstrating that women generally exhibit higher sentiment values toward global warming compared to men. This trend was particularly evident between 2009 and the beginning of 2015. However, after 2015, the sentiment values between genders became more similar, with fewer noticeable differences. This temporal shift suggests that external factors, such as global events or increased awareness campaigns, may have influenced both genders to converge in their sentiment toward climate change.

6.2 Comparison with Prior Work

By comparing my findings with those from the Climate Change Twitter Dataset by Effrosynidis et al. (Effrosynidis et al., 2022), key differences emerged. Their model displayed greater robustness and stability, while my sentiment trends appeared more volatile. This discrepancy could stem from methodological differences, such as my use of weight optimization with the Sentiment140 dataset versus their equally weighted approach. Additionally, their dataset was significantly larger, containing 15.8 million tweets related to climate change after preprocessing, compared to the approximately 104,000 tweets in my dataset.

Despite these differences, my work had access to more recently created tweets, allowing for an updated analysis of gendered sentiment trends. This highlights the potential value of using newer datasets to capture evolving discourse on climate change.

6.3 Limitations

One major limitation was the inability to incorporate geolocation data due to X's API restrictions. This led to a redirection of focus toward analyzing gender differences rather than regional sentiment variations. Additionally, the smaller number of tweets available for certain years may have impacted the validity of the observed temporal trends.

Another limitation concerns the automatic prediction of gender from names. Although this approach allowed for the enrichment of the dataset, it raises concerns about both the validity and ethics of inferring gender solely based on names. Such methods may misrepresent individuals whose names do not meet traditional gender norms, and the inherent biases in the available name databases may affect the results. Although this method is acceptable for this project, it remains a limitation that could influence the interpretation of gender-based sentiment analysis.

The weight optimization for the hybrid sentiment model was performed using a grid search algorithm. However, due to computational constraints, the search space was limited to a fixed range of values (0.2 to 0.8 with a step size of 0.2), resulting in 4^5 possible combinations. Although this approach aimed to balance efficiency and accuracy, it may have led to convergence at a local optimum rather than identifying the global optimum. This limitation, along with the relatively small size of the data set, may have contributed to the observed volatility in sentiment trends compared to more robust models in prior research.

6.4 Future Work

Future research could explore other social media platforms, such as Reddit or Meta's Threads, which provide access to geolocation data. This would allow for a more comprehensive analysis of how regional factors influence sentiment toward climate change. Additionally, expanding the dataset to include a broader range of languages could help validate the hypothesis that women in wealthier countries exhibit higher sentiment values than men. Exploring these avenues could provide deeper insights into the intersection of gender, sentiment, and regional context in the discourse on climate change.

7 Conclusion

This study explored gendered sentiment toward climate change using a hybrid sentiment analysis model on a dataset of over 104,000 tweets. The findings confirmed that women generally exhibit stronger and more positive sentiment values compared to men, aligning with prior research. Despite limitations such as the absence of geolocation data and smaller dataset size, the study highlights the value of incorporating gendered perspectives in climate discourse analysis. Future research could expand this work by analyzing multilingual datasets and leveraging other social media platforms with geolocation capabilities.

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