PRESENTATION CONTENTS

Sentiment Analysis of Public Opinion on Trump’s 2025 China Tariff Policy Based on "X"

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Course Name:Research Design and Analysis in Data Science
Video link： https://youtu.be/2tlyUj43A4k

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INTRODUCTION

Background & Problem Statement

Why should we stop **tariffs** when EVERYONE charges us **tariffs** ????

3

Trump increased **tariffs** because china already had them. **Trum** jus balanced them. Btw china is having the exact trade war with canada and EU but media won't cover because it does not involve the US

1 1 63

Trump's 2025 tariff policy on China drew broad global attention, sparking heated discussions on the "X" (Twitter) platform.

Social media plays a crucial role in policy discourse; studies show Trump's tweets can sway public sentiment and even financial markets.

Trump increased **tariffs** because china already had them. **Trum** jus balanced them. Btw china is having the exact trade war with canada and EU but media won't cover because it does not involve the US

1 1 63

The fact that **Trum** made clear that he didn't understand **tariffs**, the global economy or global trade before he was elected doesn't give him an excuse for what he's doing.

1 2 49

Research Gap: Few studies have analyzed public sentiment surrounding the 2025 China tariff policy, and it remains unclear how emotions shift before and after the announcement due to limited quantitative analysis. Moreover, existing sentiment research largely depends on costly manual labeling. Limited work has explored using lexicon-based tools like VADER to generate pseudo-labels and build semi-supervised classification models.

The biggest losers in the USA is the Stock industries and those who invest in them. They are getting a whipping from **Trum**, I even think that's where most of his opps invested. Smart him though, he has seen china's infrastructure which I think the **Tariffs** will ....

1 24

Research Questions & Objectives

Research Questions	Research Objectives
1.What are the dominant public sentiments toward Trump's 2025 China tariff policy on social media? 2.How do public sentiments shift before, during, and after the policy announcement? 3.Can pseudo-labels generated via VADER be effectively used to train machine learning models for sentiment classification?	1. To analyze public sentiment trends regarding Trump's 2025 China tariff policy based on posts from "X". 2. To identify emotional shifts across key policy stages (before, during, after). 3. To construct a balanced dataset using VADER-generated pseudo-labels. 4. To evaluate the performance of supervised and ensemble machine learning models on sentiment classification.

Research Scope

SCOPE

Data Scope

Twitter data related to Trump's 2025 China tariff policy, collected via API from January to May 2025, focusing on English-language tweets.

Methodological Scope

- Perform sentiment analysis using VADER and NLP techniques.
- Generate pseudo-labels from VADER scores to construct a balanced dataset.
- Train and evaluate supervised machine learning models (e.g., SVM, Logistic Regression).

Temporal Scope

The data were collected from January to May 2025

Research Depth & Phases

- Current phase: Analysis of static tweet data and sentiment classification using VADER.
- Extended phase (future work): Expand to prediction models and cross-platform comparison (e.g., Reddit vs X).

LITERATURE REVIEW

Sentiment Analysis Studies

Sentiment analysis is an NLP technique for automatically identifying the subjective emotional tendency of text (positive, negative, or neutral). Common approaches include lexicon-based methods, machine learning models, and deep learning models.

Numerous studies have applied sentiment analysis to social media opinion data (e.g. elections, public health), using models such as VADER, Naïve Bayes, SVM, LSTM, and BERT.

Existing model framework

key finding	Methodology	Refrence
Among the three classification algorithms of decision tree, KNN and naive Bayes, **Naive Bayes performs better** in "X" data analysis, and the performance accuracy **reaches 60.69%**	**1.Vader** is used as the model 2.Supervised classification techniques **(decision tree, KNN, Naive Bayes)** were used to test the correctness of the model	Zangmo, D., Dar, A. I., Kumar, R., & Mishra, V. N. (2024). Sentimental analysison U.S. election. AIP Conference Proceedings, 3005(1),020024.https://doi.org/10.1063/5.0210583
BERT model performed best, with accuracy of 86%, accuracy of 85%, recall of 87% and F1 score of 86%.	**SVM, LSTM, and Bert models** are trained, and model performance is evaluated by accuracy, precision, recall, and F1 score.	Elmassry et al. (2024) presented sentiment analysis using ML on both balanced and unbalanced datasets (ICCSCE 2024).
In the imbalanced dataset, LIWC-22 is suitable for estimating the proportion of negative sentiment, **VADER classifies negative reviews best (better for long reviews**), NLP tools are broadly consistent with human coding, and ChatGPT 4.0 performs worse.	VADER (NLP dictionary method) TEXT2DATA (T2D) LIWC-22 (Psychological Dictionary of Language) ChatGPT 4.0 (LLM)	Gandy, L. M., Ivanitskaya, L. V., Bacon, L. L., & Bizri-Baryak, R. (2025). Public health discussions on social media: Evaluating automated sentiment analysis methods. *JMIR Formative Research, 9*, e57395. https://doi.org/10.2196/57395

LITERATURE REVIEW

Existing model framework

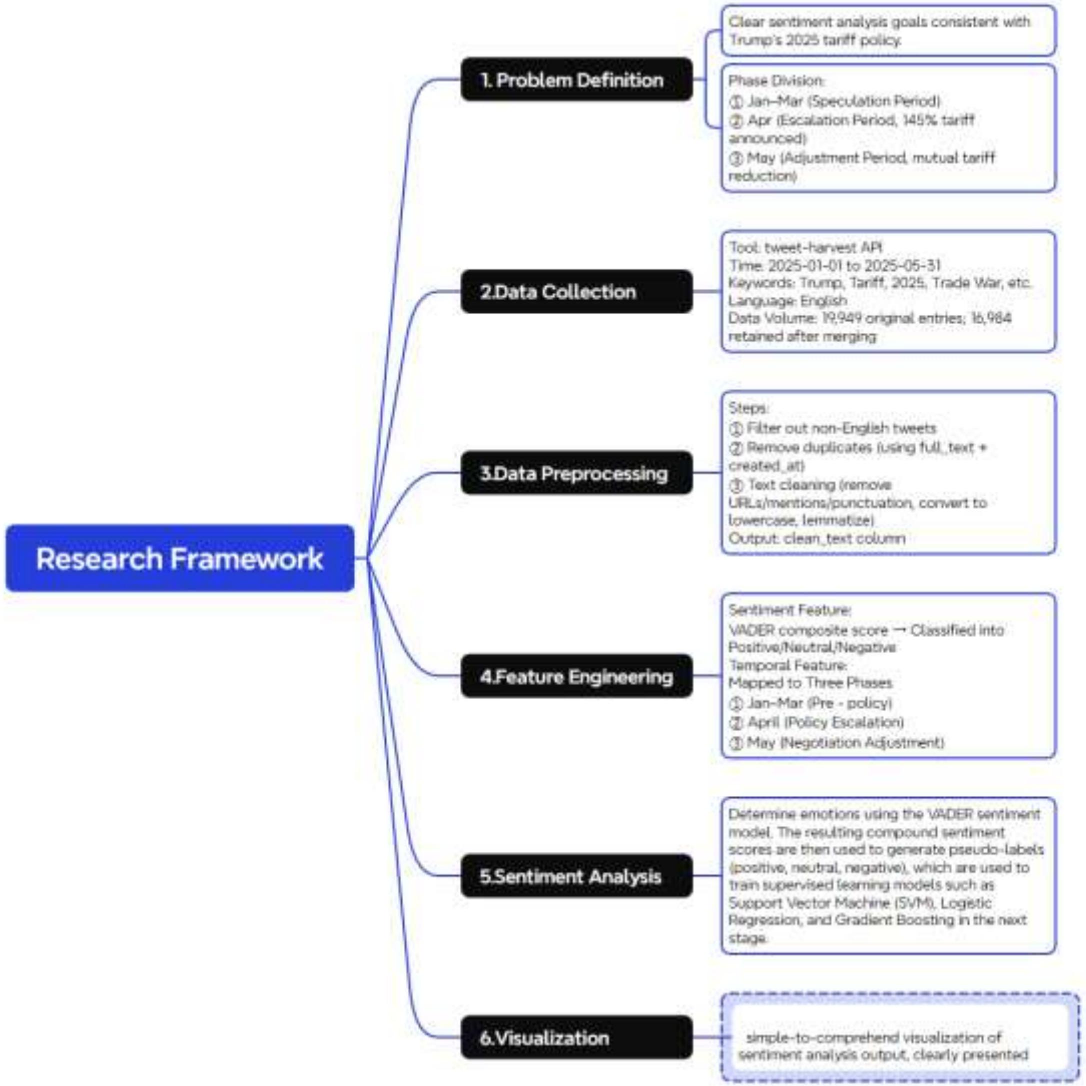
key finding	Methodology	Refrence
The SAVSA model significantly improves the accuracy of sentiment classification in COVID-19 vaccine related tweets, which is better than a single sentiment analysis method, and is suitable for the situation of unbalanced social media data.	**SentiWordNet** and **VADER** Two-stage Sentiment Analysis Model **(SAVSA)**	Perumal Chockalingam, S., & Thambusamy, V. (2024). Enhancing sentiment analysis of user response for COVID-19 vaccinations tweets using SentiWordNet-adjusted VADER sentiment analysis (SAVSA): A hybrid approach. In K. Iyakutti, P. Balasubramaniam, & K. R. Subramanian (Eds.), *Lecture Notes in Networks and Systems: Vol. 1046. Proceedings of the International Conference on Recent Advances in Computational Techniques (IC-RACT 2024)* (pp. 437–451). Springer. https://doi.org/10.1007/978-3-031-64813-7_43
The integrated approach of VADER and word **cloud enhances the accuracy and interpretability of sentiment analysis**, helping users gain more intuitive insights from text data	**VADER** sentiment analysis tool and **word cloud visualization technology**	Chavan, R., Latthe, S., Dhorepati, M., Suryawanshi, A., Sharma, N., & Salge, A. (2024). Sentiment analysis using VADER & word cloud techniques. In *AIP Conference Proceedings* (Vol. 3217, No. 1, Article 020012). AIP Publishing. https://doi.org/10.1063/5.0234543

The **VADER** lexicon-based tool performs well on short texts like tweets and remains robust on imbalanced data, making it the primary method chosen for this study. VADER also integrates readily with visualizations (e.g. word clouds), facilitating intuitive presentation of sentiment insights.

RESEARCH METHODOLOGY

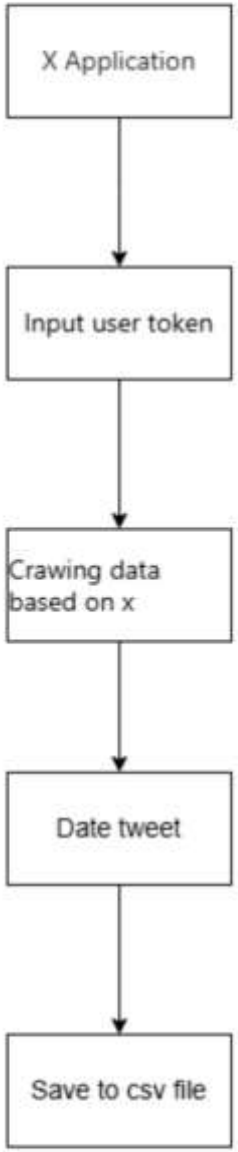
RESEARCH METHODOLOGY

Research Methodology Overview



The research framework follows a standard data science project life cycle and is divided into the following stages:

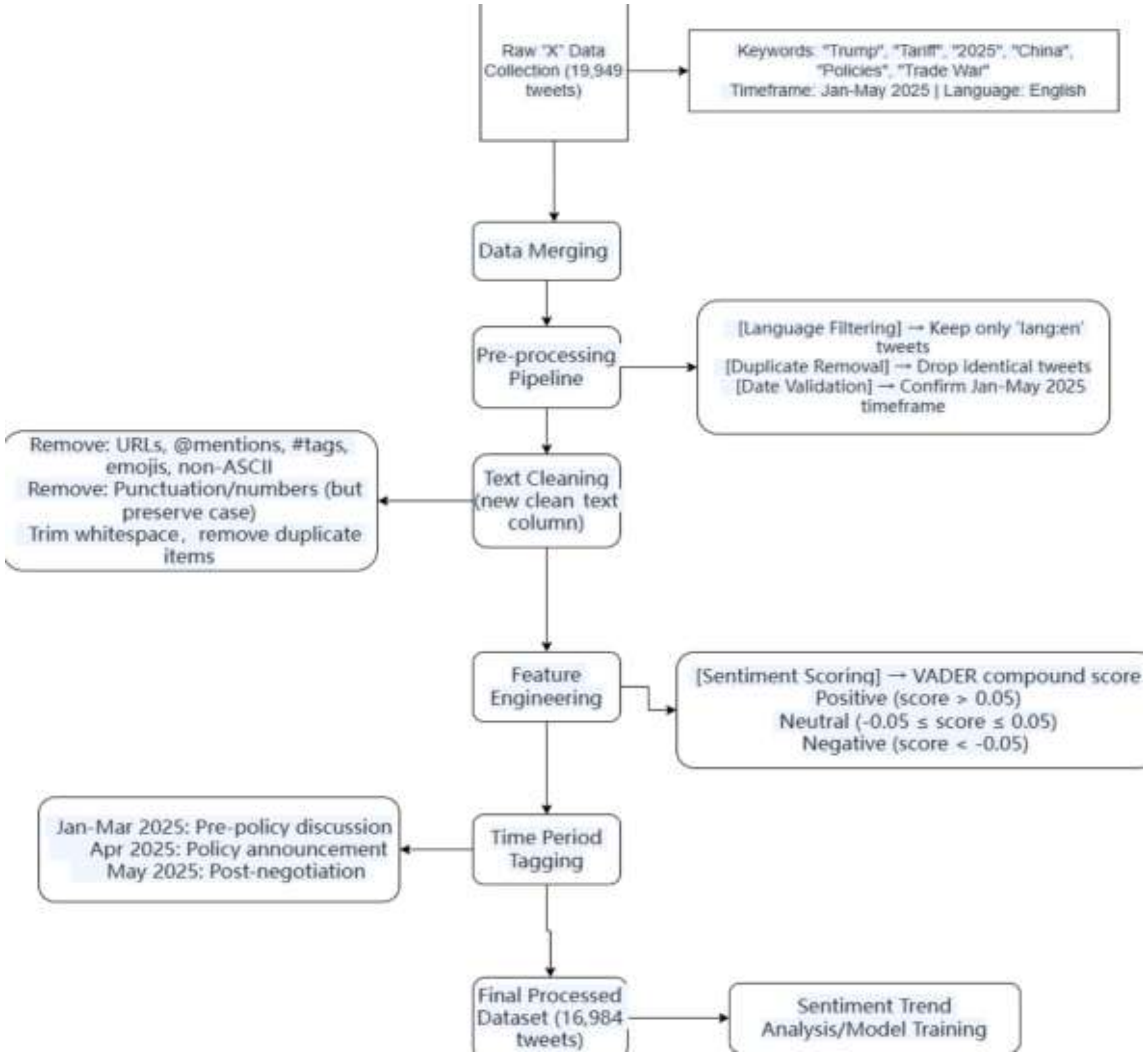
1. Question definition:Clear sentiment analysis goals consistent with Trump's 2025 tariff policy.
2. Data collection: Collect the significant "X" data with the appropriate keywords and in a particular time span.
3. Data preparation: Prepare the data and clean it thoroughly in order to make it more credible.
4. Feature construction: Develop features from emotions and time in a correct analysis.
5. Sentiment analysis:Emotions are identified using the VADER model. The compound scores generate pseudo-labels (positive, neutral, negative), which are then used to train supervised models including SVM, Logistic Regression, Gradient Boosting, and Random Forest..
6. Visualization; simple-to-comprehend visualization of sentiment analysis output, clearly presented



X Application Tweet Data Collection Flowchart

This flowchart describes the data collection process starting from the X Application (formerly Twitter), involving user token input, data crawling based on X, tweet information extraction, and finally saving as a CSV file.

Tweet Data Processing



Raw Data Collection

Starts with gathering 19,949 tweets from X (Jan-May 2025, English language, using keywords like “Trump,” “Tariff,” etc.).

Core Processing Stages

Merges raw data.

Preprocesses via:

- Language filtering (keep only English).
- Deduplication (remove duplicate tweets).
- Date validation (ensure Jan-May 2025 timeframe).

Cleans text: Removes URLs, @mentions, emojis, punctuation, etc.

Engineers features: Applies VADER for sentiment scoring (positive/neutral/negative).

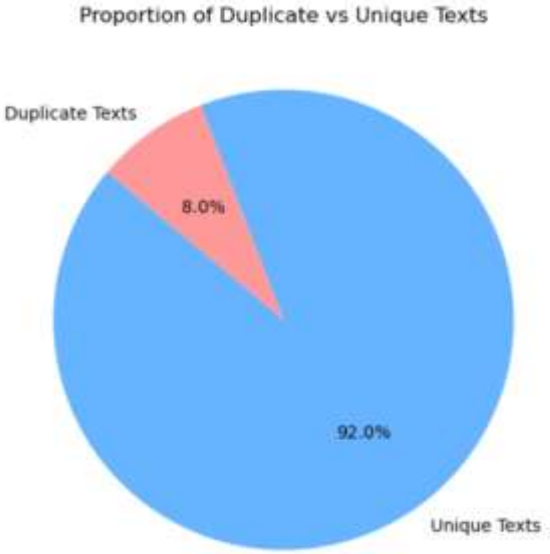
Tags time periods: Classifies tweets into “pre-policy discussion,” “policy announcement,” “post-negotiation” stages.

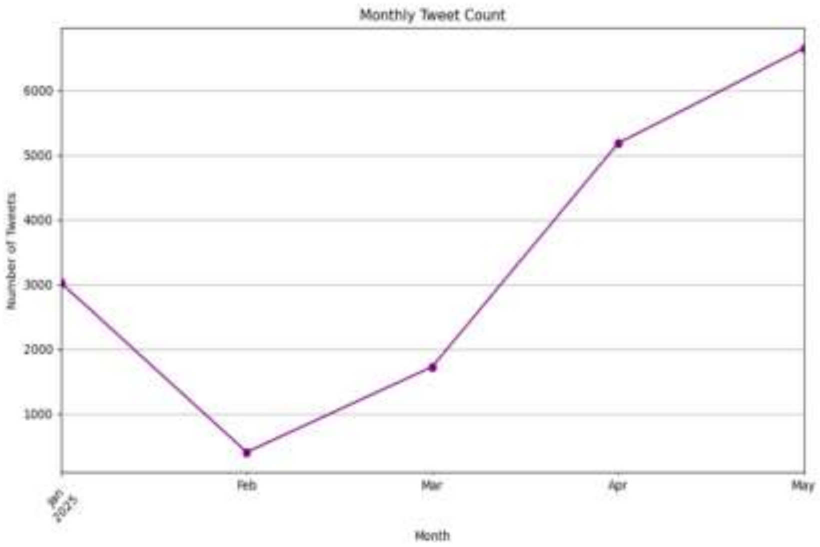
Output & Purpose

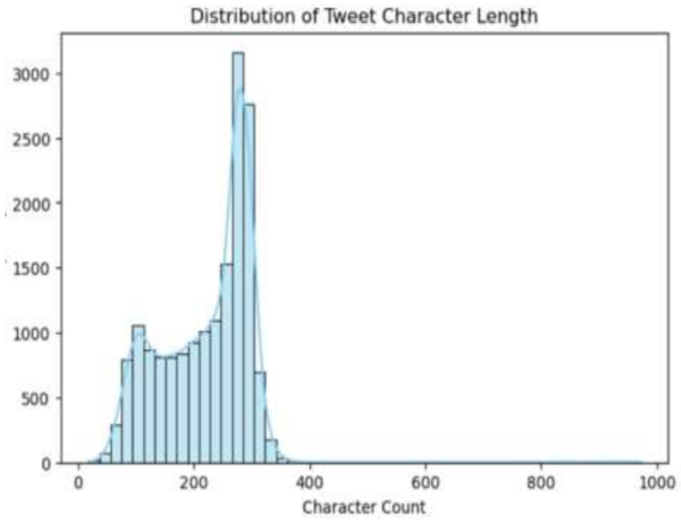
Generates a final dataset of 16,984 cleaned tweets, used for sentiment trend analysis and model training.

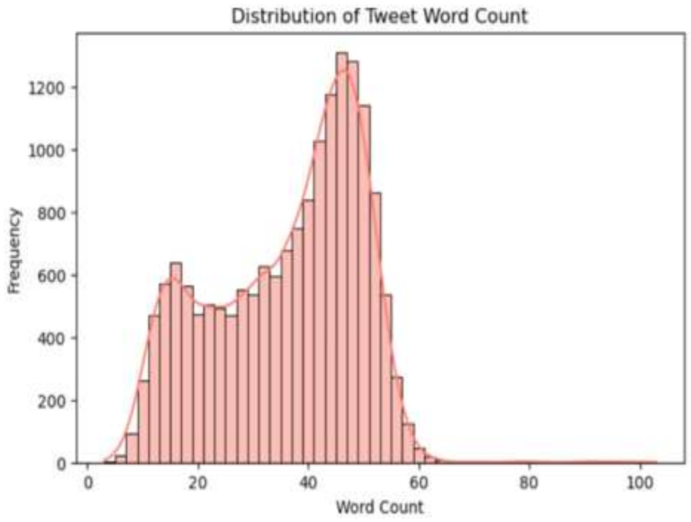
RESEARCH METHODOLOGY

Descriptive Data Analysis









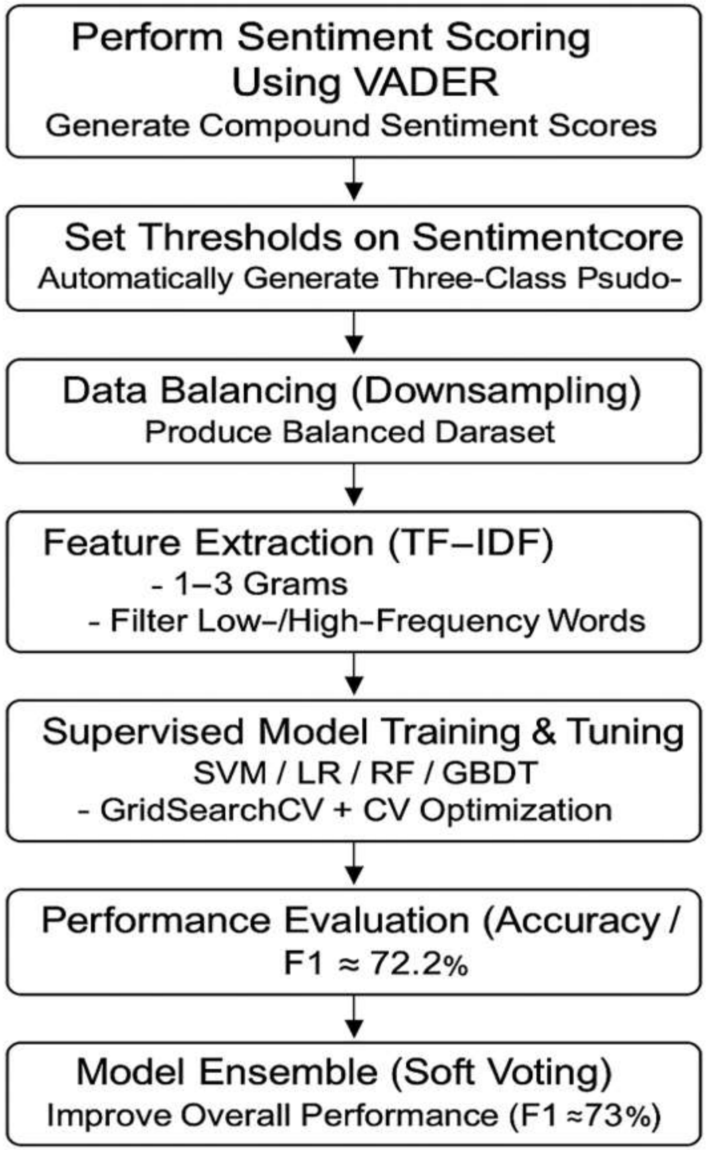
- After text cleaning, a total of about 16,984 tweets were collected (from January to May 2025). The number of tweets published during February to May increased significantly, indicating that public discussion increased significantly at key time points.

- The text of tweets is generally short, and the distribution of word count shows a long-tail feature.

- A preliminary check confirmed that the data covered the intended time range and that the language filter was correct..

RESEARCH METHODOLOGY

Extended analysis of emotion classification model based on VADER pseudo-label



In addition, we plan to use VADER's output sentiments as pseudo-labels to train a supervised classifier, building a semi-supervised sentiment classification model to improve analysis accuracy. (including SVM, Logistic Regression, Gradient Boosting, and Random Forest.)

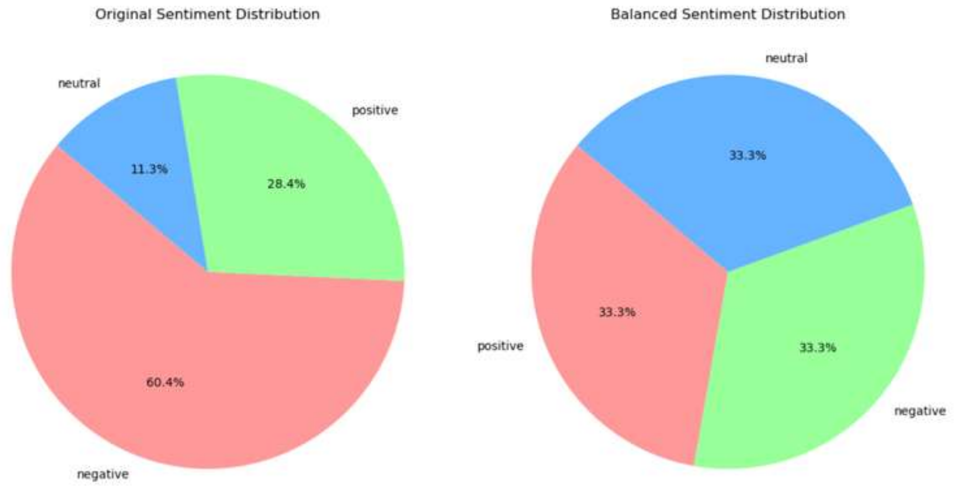
RESEARCH METHODOLOGY

Extended analysis of emotion classification model based on VADER pseudo-label

Pseudo-label Generation

	clean_text	month	policy_period	char_count	word_count	vader_compound	vader_sentiment
1	oogle tamil learn the definition of word tariff	2025-01	Jan-Mar	300	50	-0.7845	negative
2	and rupiah for now usd and gold are bullish	2025-01	Jan-Mar	121	24	0.0	neutral
3	ary with china to follow setting up trade war	2025-01	Jan-Mar	138	30	-0.6486	negative
4	ary with china to follow setting up trade war	2025-01	Jan-Mar	128	20	-0.6486	negative
5	china total trade billion trade deficit billion	2025-01	Jan-Mar	269	44	-0.6705	negative
6	he would already taking democracy to china	2025-01	Jan-Mar	284	46	0.7003	positive
7	ka was going to end up paying a tariff as well	2025-01	Jan-Mar	189	28	0.2732	positive
8	talk again when trump puts a tariff on china	2025-01	Jan-Mar	86	13	0.2732	positive
9	hina and increase our ties to europe i am not	2025-01	Jan-Mar	295	52	-0.4767	negative
10	chinas going to end up paying a tariff as well	2025-01	Jan-Mar	209	39	-0.0258	neutral
11	ymore then has been as hell blame fentanyl	2025-01	Jan-Mar	225	39	-0.8734	negative
12	t tariff on china please free tibet from china	2025-01	Jan-Mar	99	13	0.6808	positive
13	the demand mitigating much of the problem	2025-01	Jan-Mar	301	43	0.3744	positive
14	have laws tariff monday on mexico can china	2025-01	Jan-Mar	265	49	-0.765	negative
15	on the weak walking back his tariffs on china	2025-01	Jan-Mar	287	49	-0.7351	negative
16	ryone but the us this could tank the us stock	2025-01	Jan-Mar	302	48	0.4118	positive
17	able to afford a decent gpu for my crypto art	2025-01	Jan-Mar	235	44	-0.3612	negative
18	cause biden was too afraid to confront china	2025-01	Jan-Mar	284	47	-0.8442	negative
19	acrosstheboard tariffs on china and or tariffs	2025-01	Jan-Mar	281	45	0.0	neutral
20	n the process of doing china tariff bloomberg	2025-01	Jan-Mar	61	11	0.0	neutral
21	p paying a tariff as well anomalies para todos	2025-01	Jan-Mar	79	15	0.2732	positive
22	sa says china to end up paying a tariff as well	2025-01	Jan-Mar	53	12	0.2731	positive
23	ump were in the process of doing china tariff	2025-01	Jan-Mar	77	11	0.0	neutral
24	trump busy with tariffs into the close today	2025-01	Jan-Mar	175	33	0.2732	positive

Data balance processing。



4.14 Balanced dataset pie chart

Extended analysis of emotion classification model based on VADER pseudo-label

Feature Extraction

```python
tfidf = TfidfVectorizer(
    max_features=8000,    # 增加特征数量
    ngram_range=(1, 3),   # 包含一元、二元和三元语法
    min_df=3,             # 忽略低频词
    max_df=0.7,           # 忽略高频词
    sublinear_tf=True,    # 使用对数TF
    stop_words='english'
)

# 特征降维（可选）
svd = TruncatedSVD(n_components=1000, random_state=42)
```

The core goal is to transform tweets into numerical features for short-text sentiment analysis by: extracting 1-3-gram phrases (focusing on policy semantics/emotional differentiation), optimizing the feature space to retain 8,000 informative terms, filtering words with min_df=3/max_df=0.7 (to control noise), logarithmically scaling frequencies, and preserving emotional punctuation via TF-IDF.

Supervised model training and hyperparameter optimization

```python
# 5. 模型选择与优化
print("\n模型训练与优化...")

# 定义更优的模型和参数网格
models = {
    'Logistic Regression': {
        'model': LogisticRegression(max_iter=2000, random_state=42, class_weight='balanced'),
        'params': {
            'clf__C': [0.01, 0.1, 1, 10],
            'clf__solver': ['saga', 'liblinear'],
            'clf__penalty': ['l1', 'l2']
        }
    },
    'SVM': {
        'model': SVC(probability=True, random_state=42, class_weight='balanced'),
        'params': {
            'clf__C': [0.1, 1, 10],
            'clf__kernel': ['linear', 'rbf'],
            'clf__gamma': ['scale', 'auto']
        }
    },
    'Random Forest': {
        'model': RandomForestClassifier(n_estimators=200, random_state=42, class_weight='balanced_subsample'),
        'params': {
            'clf__max_depth': [None, 30, 50],
            'clf__min_samples_split': [2, 5, 10],
            'clf__min_samples_leaf': [1, 2, 4]
        }
    },
    'Gradient Boosting': {
        'model': GradientBoostingClassifier(n_estimators=200, random_state=42),
        'params': {
            'clf__learning_rate': [0.01, 0.1],
            'clf__max_depth': [3, 5],
            'clf__subsample': [0.8, 1.0]
        }
    }
}

# 存储评估结果
results = {}
best_models = {}
```

```python
# 使用分层K折交叉验证
cv = StratifiedKFold(n_splits=3, shuffle=True, random_state=42)

for name, model_info in models.items():
    print(f"\n=== 优化 {name} ===")

    # 创建管道
    pipeline = Pipeline([
        ('tfidf', tfidf),
        # ('svd', svd),  # 如果需要降维可以启用
        ('clf', model_info['model'])
    ])

    # 网格搜索
    grid_search = GridSearchCV(
        pipeline,
        model_info['params'],
        cv=cv,
        scoring='accuracy',
        n_jobs=-1,  # 使用所有核心
        verbose=1
    )

    grid_search.fit(X_train, y_train)

    # 获取最佳模型
    best_model = grid_search.best_estimator_
    best_params = grid_search.best_params_

    # 评估测试集
    y_pred = best_model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred, average='weighted')

    print(f"{name} 最佳参数: {best_params}")
    print(f"{name} 测试集准确率: {acc:.4f}")
    print(f"{name} 测试集F1值: {f1:.4f}")
    print(classification_report(y_test, y_pred))

    # 保存结果
    results[name] = {
        'model': best_model,
        'accuracy': acc,
        'f1': f1,
        'params': best_params,
        'report': classification_report(y_test, y_pred, output_dict=True)
    }
    best_models[name] = best_model
```

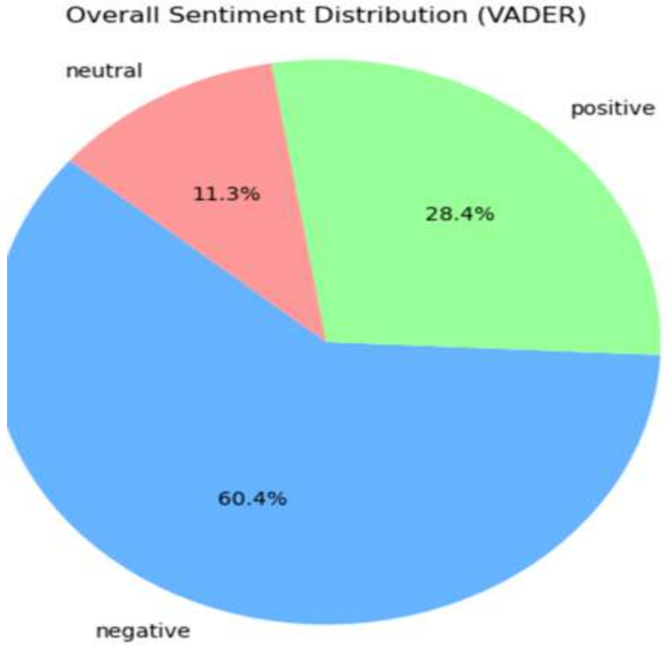
4.19 K-fold cross validation

Then, several classification models such as logistic regression, support vector machine (SVM), random forest and Gradient Boosting are trained and evaluated. This model uses GridSearchCV and 3 fold cross validation for hyperparameter tuning.

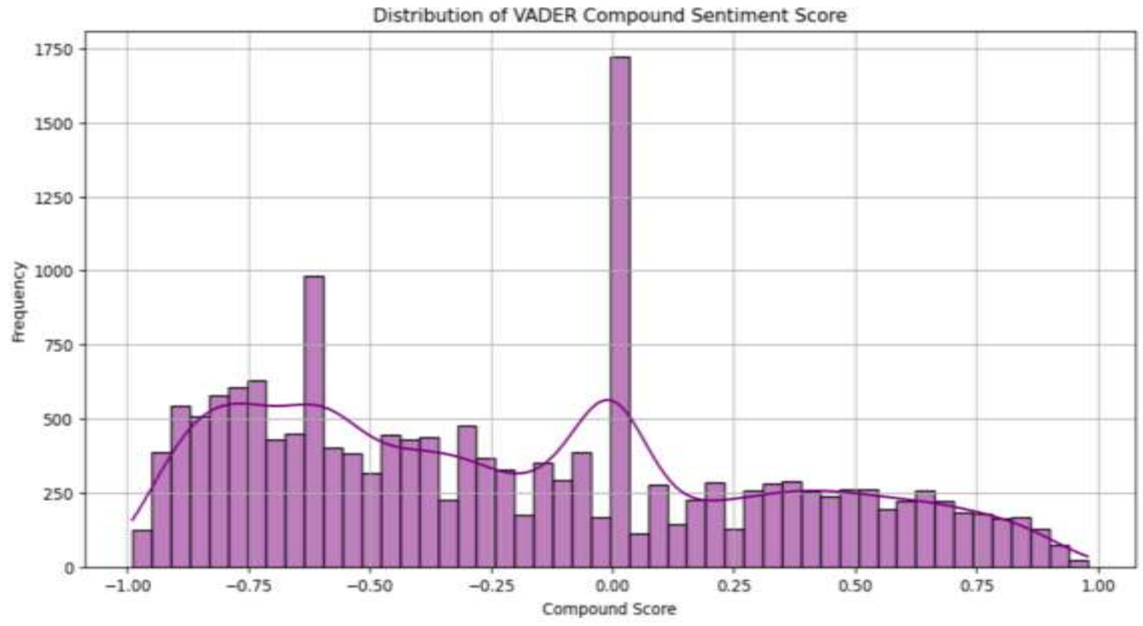
INITIAL FINDINGS & RESULTS

INITIAL FINDINGS & RESULTS

Overall Sentiment Distribution



4.10 Overall Sentiment Distribution



4.6 Distribution of VADER Compound Sentiment Score

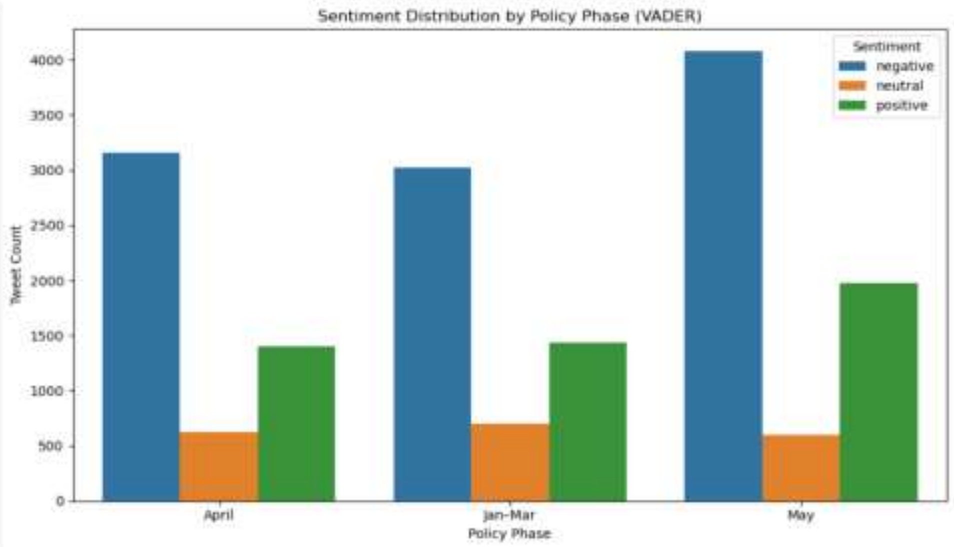
Overall Public Sentiment: Approximately **60%** of tweets expressed negative sentiment, versus about 28% positive and 12% neutral – indicating that public sentiment was mainly negative.

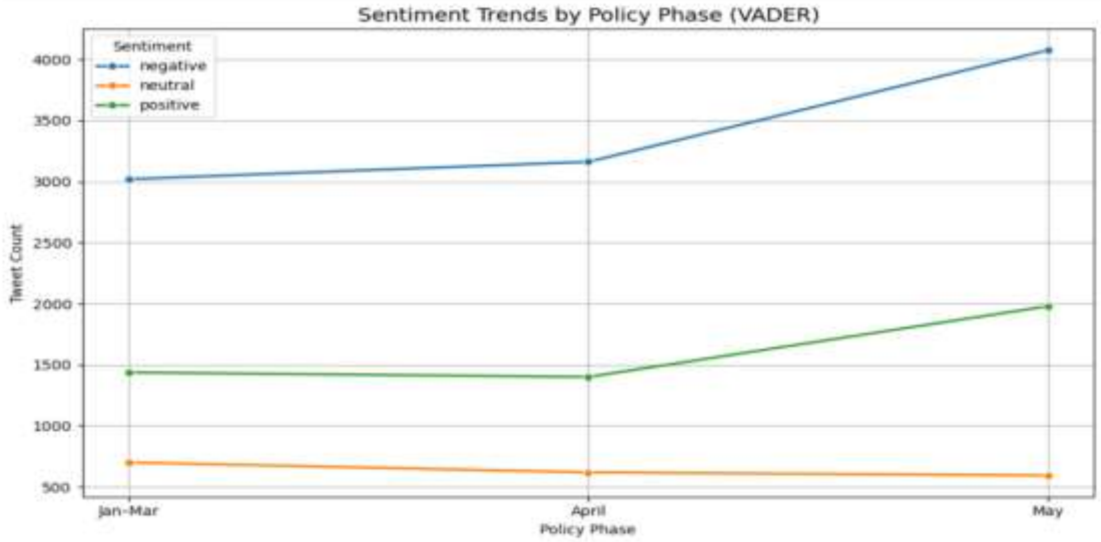
Neutral scores were the most frequent in the sentiment score distribution (many tweets had compound scores near 0), but in terms of classified tweets, **negative tweets greatly outnumbered positive tweets (roughly 2:1)**.

INITIAL FINDINGS & RESULTS

Sentiment Trends by Policy Phase

4.3.2 Count emotions in stages



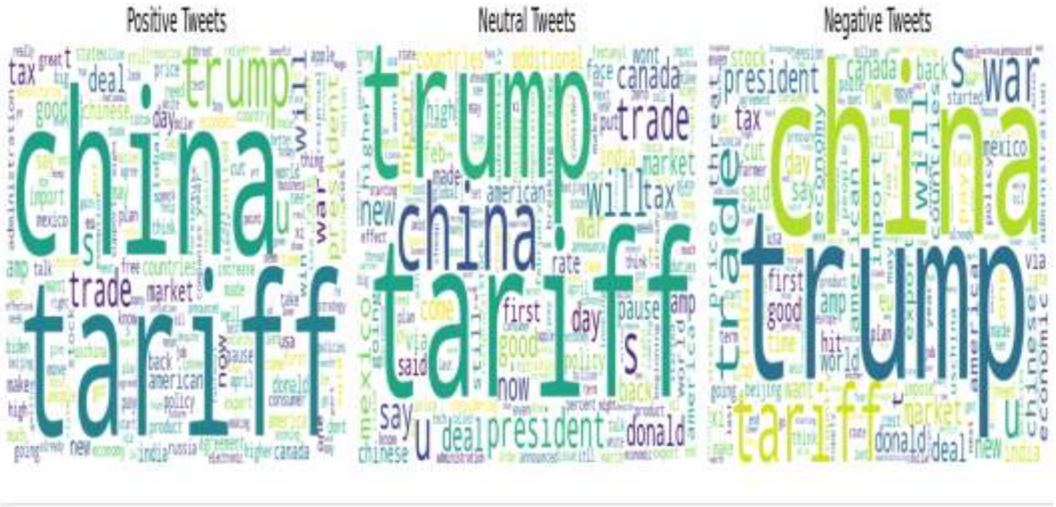


4.8 Sentiment Trends

1. **Jan-Mar (Policy Fermentation Period) Sentiment Dominance**:
   Negative-dominated (≈3,100 tweets). Neutral (≈700) and positive (≈1,400) have low proportions
   Trend: Negative stable; neutral/positive show no significant fluctuations
2. **April (Extreme Confrontation Period) Sentiment Dominance**:
   Negative still dominant (slightly increased to ≈3,200 tweets), positive rebounds sharply (≈1,450), neutral remains flat (≈700)
   Trend: Negative accelerates; positive rebounds from a low level; neutral continues to decline
3. **May (Temporary Tariff Cuts + Negotiation Period) Sentiment Dominance:**
   Dual peaks of negative (≈4,100) and positive (≈2,000); neutral hits bottom (≈600)
   Trend: Negative surges rapidly; positive continues to rise; neutral drops to the lowest

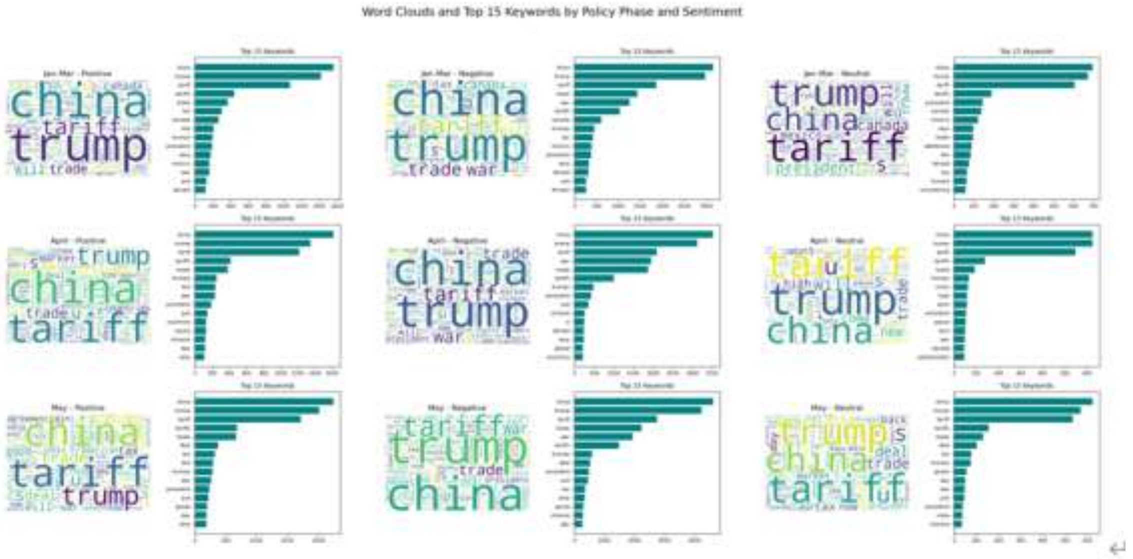
INITIAL FINDINGS & RESULTS

Word cloud map



The overall positive tweets are accompanied by words such as "deal", "support" and "benefit", implying policy approval. Negative tweets often include words such as "war", "fear" and "lost", reflecting public concern and criticism.

sentiment dimension	Jan-Mar (fermentation)	April (confrontation)	May (relaxation)
positive	Look forward to the policy "will"	Looking forward to the "deal"	Recognize the "agreement"
negative	Worried about the "trade war"	Worried about "market"	Query the "deal"
Neutral	Record "president"	Record "Policy Landing" (will/come)	Record the "deal"



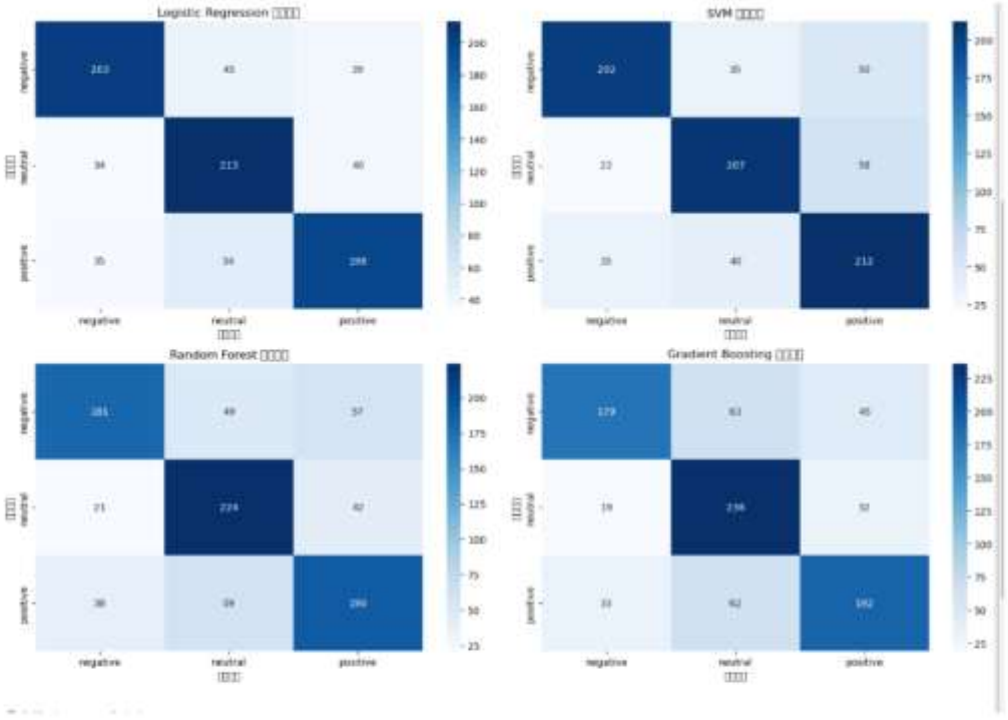
4.9 High-frequency words of emotions at different stages

- Common high-frequency words in positive sentiment tweets include "will", "deal", etc., reflecting supporters' optimism and expectations about the effect of the policy
- Negative sentiment tweets often include phrases such as "trade war," suggesting opponents are concerned about escalating conflict and its economic consequences
- Negative sentiment posts tended to have more conflict and worry language (e.g., more words like "war" and "against"), while positive posts tended to use words related to policy benefits and victories

INITIAL FINDINGS & RESULTS

Model Performance Comparison

Model name	Accuracy	F1 Score	Optimal superparameter configuration
SVM	0.721254	0.722012	clf_C: 10, clf_gamma: 'scale', clf_kernel: 'rbf'
Logistic Regression	0.713124	0.713203	clf_C: 10, clf_penalty: 'l1', clf_solver: 'liblinear'
Gradient Boosting	0.704994	0.703387	clf_learning_rate: 0.1, clf_max_depth: 5, clf_subsample: 1.0
Random Forest	0.691057	0.690126	clf_max_depth: None, clf_min_samples_leaf: 1, clf_min_samples_split: 10



4.21 Confusion matrix

Among supervised classifiers trained on VADER pseudo-labeled data, the best individual models were **Support Vector Machine (SVM)** and Logistic Regression, with accuracies around **71–72%** (SVM ~72.1%, Logistic ~71.3%).

In a single model, SVM and logistic regression performed best, and SVM was slightly better than logistic regression. The accuracy and F1 value of decision tree-based models (random forest and gradient boosting model) are relatively low, which may be related to the limited data set size or the noise of false labels.

INITIAL FINDINGS & RESULTS

integration model

```
最佳模型: SVM (准确率: 0.7213)
最佳模型已保存为 'best_sentiment_model.pkl'

尝试集成模型...
集成模型准确率: 0.7305
              precision    recall  f1-score   support

    negative       0.76      0.71      0.74       287
     neutral       0.71      0.76      0.74       287
    positive       0.72      0.72      0.72       287

    accuracy                           0.73       861
   macro avg       0.73      0.73      0.73       861
weighted avg       0.73      0.73      0.73       861

集成模型表现更佳, 已保存为 'best_ensemble_model.pkl'

优化完成!
```

4.23 Model integration complete

- A **soft-voting ensemble model** (combining the top-performing SVM, Logistic, and Gradient Boosting classifiers) achieved the highest overall performance, with accuracy and F1 around **73.0%**, exceeding any single model.
- The strong result of the ensemble indicates that **combining classifiers can leverage complementary strengths, thus improving sentiment classification on pseudo-labeled data**.

Summary of Initial Findings

Predominantly Negative Sentiment: Public opinion toward the 2025 tariff policy was largely negative, indicating a baseline of dissatisfaction or concern regarding the policy.

Notable Polarization: As the policy unfolded, public sentiment evolved into a pattern of “negative dominance – bipolar opposition – loss of neutrality” – negative and positive camps grew further apart, and neutral, rational voices faded.

Methodology Validation: Using VADER for unsupervised sentiment analysis provided quick insights, and the pseudo-label + ensemble supervised model improved sentiment classification accuracy to about **73%**, demonstrating the feasibility of this semi-supervised approach.

These findings highlight the volatile nature of public opinion under policy shocks, and showcase the value of combining lexicon-based analysis with machine learning models to quantify social media sentiment.

SUMMARY & FUTURE WORK

SUMMARY & FUTURE WORK

Summary & Future Work

Summary

- This study systematically analyzed social media sentiment changes triggered by Trump’s 2025 China tariff policy, finding that public opinion evolved with policy intensity in a dynamic pattern characterized by **“negative dominance – bipolar opposition – diminishing neutrality”**.

- The results confirmed the applicability of **VADER sentiment analysis** for political public opinion, and by using a **pseudo-label + ensemble learning** approach we improved sentiment classification performance (accuracy up to ~73%), demonstrating the feasibility of low-cost semi-supervised opinion modeling.

- The findings of this research tentatively contribute to a quantitative framework for interpreting public emotional responses to policy shifts. The developed analytical workflow could potentially serve as a basis for future assessments of policy communication efficacy and public sentiment monitoring, holding potential theoretical and practical relevance that warrants further scholarly inquiry.

Future Work

- **Pseudo-label Quality:** VADER’s auto-generated labels can misjudge complex semantics (irony, ambiguity), affecting model performance. Future work could incorporate active learning or limited manual labeling to improve pseudo-label accuracy and model generalization.
- **Leverage Advanced Models:** We relied on TF–IDF and other shallow features, which don’t capture contextual semantics. Future studies can integrate pretrained Transformer-based models (e.g. BERT, RoBERTa) to better recognize subtle sentiments, sarcasm, and complex context.
- **Expand Data Coverage:** This study focused only on English tweets from one platform, which limits generalizability. Future work can analyze multiple social media platforms (e.g. Reddit, Facebook) and other languages, to compare public responses across different cultural contexts and enhance the breadth of the research.

THANK YOU