UTM
UNIVERSITI TEKNOLOGI MALAYSIA

Sentiment Analysis of Global Reception Differences of the Film Ne Zha

PRESENTATION SLIDE

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MCS241010

Innovating Solutions

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Background Study

In recent years, sentiment analysis, a part of NLP, has been used in opinion tracking, brand study, and market research. In movies, audience comments show personal feelings and can also affect future viewers. Studying reviews of *Ne Zha* from different countries helps us see cultural differences and improve how Chinese films are shared with the world.

Problem Statement

Ne Zha is a popular Chinese animated film that got a lot of attention both in China and overseas. Many people from other countries shared their reviews online. These comments show both praise and cultural differences in how people understand the film.

This study looks at reviews from China, the U.S., and Malaysia. Using a multilingual sentiment model, we find how emotions are expressed differently across regions.

The goal is to understand global audience feelings and help improve how Chinese films are shared worldwide.

Research Question

What are the similarities and differences in the emotions expressed by viewers in the three countries after watching the show?

Which emotional keywords or themes are most representative in the audience's comments?

Is there a relationship between the audience's emotional tendencies and their rating performance?

SCOPE OF STUDY

Data Collection:From the community, more in-depth

Model Category:Using a semi-supervised model is more conducive to subsequent data regression

Analysis Content:In addition to positive and negative evaluations, extract the top words at both ends

Research Limitation: Only the text itself is analyzed. In addition, the review sampling will be limited to user reviews published within one year of the movie's release.

Literature Review

Author	Research Title	Year	Research Focus	Technology scope
Paneru	Sentiment analysis of movie reviews: A flask application using CNN with RoBERTa embeddings	2025	Traditional methods fall short in capturing the deep contextual relationships within text.	CNN; Deep learning; Flask application; Movie reviews; Natural language processing (NLP); RoBERTa; Sentiment analysis
Wankhade	A survey on sentiment analysis methods, applications, and challenges	2022	These challenges create impediments to accurately interpreting sentiments and determining the appropriate sentiment polarity.	Machine learning; Sentiment analysis; Social media; Text analysis; Word embedding
Aloysius	A Novel Method to Reduce False Positives and Negatives in Sentiment Analysis	2022	In this work rule-based and machine-learning algorithms are experimented to create a suitable model that gives equal importance to the reduction of positive and negative false values and accuracy.	Machine Learning; Natural Language Processing; Sentiment Analysis

Literature Review

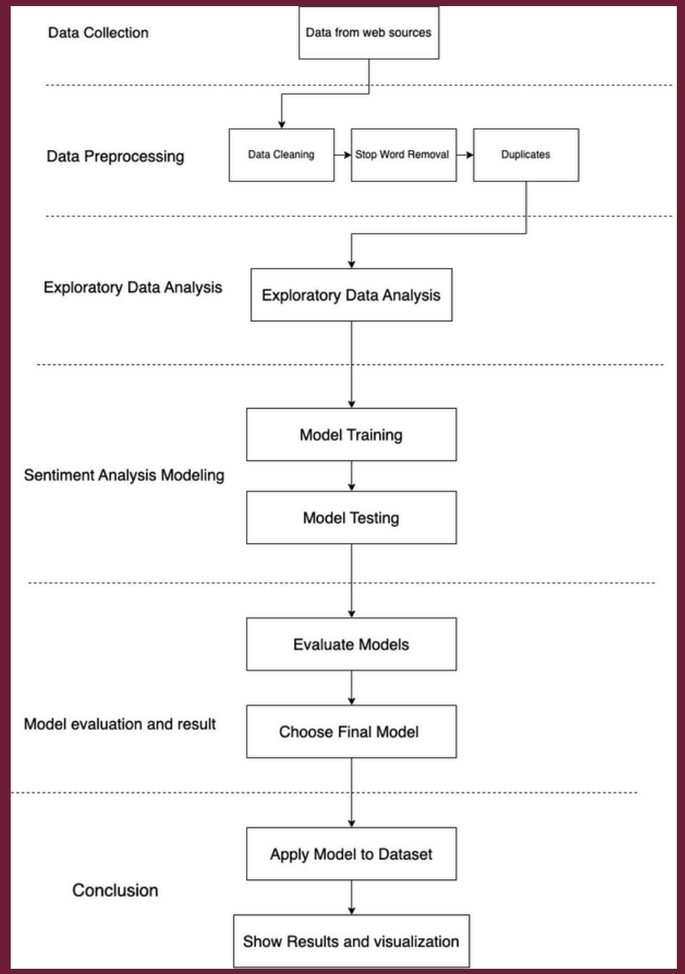
Research Gap

1. Lack of cross-cultural emotional comparison analysis
2. Few analyses of the international acceptance of domestic films
3. Insufficient in-depth research on the emotional intensity and structural characteristics of user reviews

Proposed Solutions

1. Introducing cross-cultural comparative analysis methods
2. Combining traditional statistics with deep learning methods for multi-level analysis
3. Using "Nezha" as a case study to promote the systematization of public opinion research on domestic films

Research Methodology Flow



In order to fully complete the multi-country sentiment analysis, this study is divided into the following five stages:

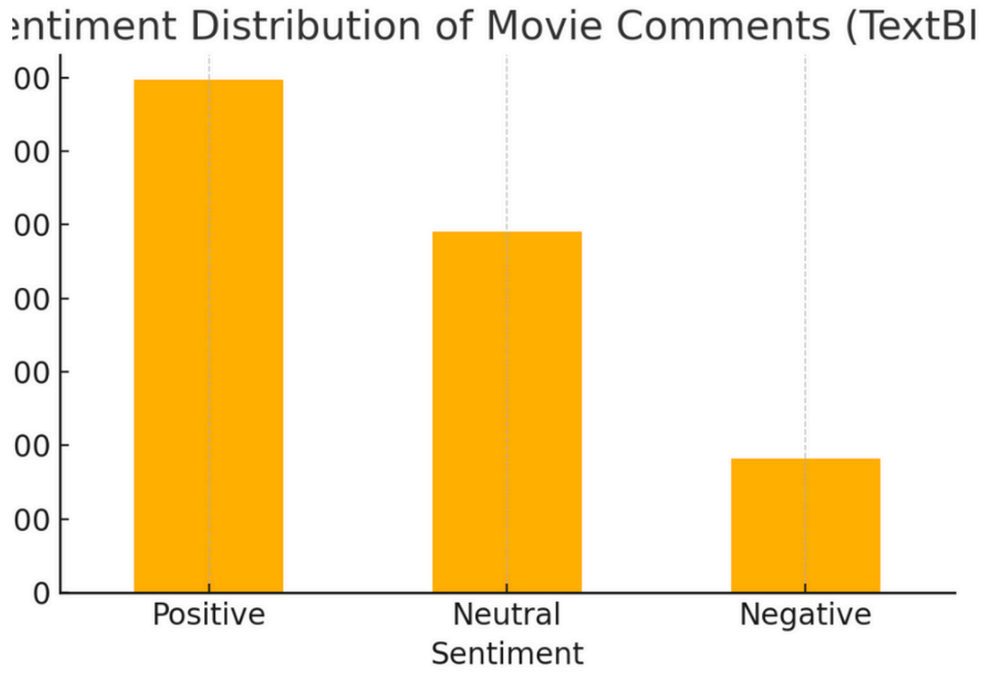
- Phase 1： Data Collection
- Phase 2： Data preprocessing
- Phase 3： Exploratory Data Analysis
- Phase 4： Sentiment Analysis Modeling
- Phase 5： Model evaluation and result comparison

Exploratory Data Analysis

	timestamp	score	upvotes	downvotes	golds	comment	c
1	1740129612	73	73	0	0	At that tim	
1	1740137130	27	27	0	0	in 1980s, Ch	1
1	1740136234	22	22	0	0	80s record k	
1	1740151423	3	3	0	0	Lion king d	3
1	1740146467	2	2	0	0	Titanic nun	3
1	1740138437	3	3	0	0	TFA to TLJ	
1	1740147840	5	5	0	0	Really? TFA	4
1	1740129812	4	4	0	0	Video renta	
1	1740131958	21	21	0	0	That's the U	5

Key columns include the comment text (comment), user region (region), sentiment category (sentiment_), number of upvotes (upvotes), overall score (score), and timestamp information (date, timestamp). Each comment is associated with a unique identifier (comment_id), along with the author's username (author) and the source URL (url).

Exploratory Data Analysis



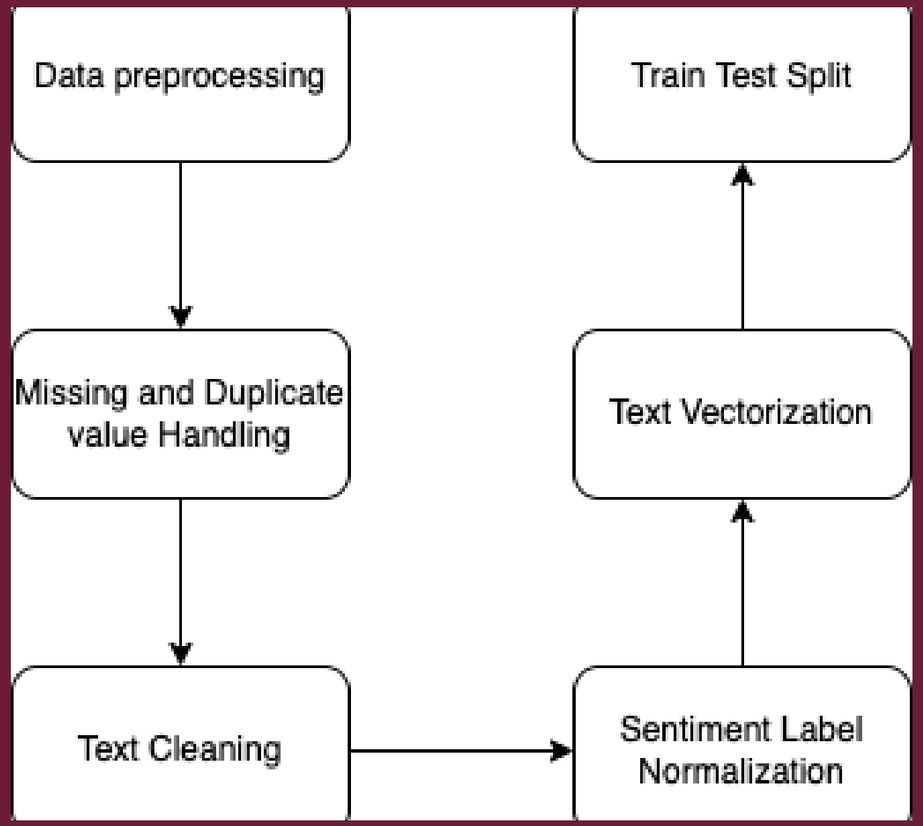
A dataset of 10,000 comments was used, among which positive comments dominated, the proportion of Sentiment Distribution neutral comments was also high, and the proportion of negative comments was the lowest.

Exploratory Data Analysis

Region	Positive	Neutral	Negative
China	3440	569	222
Malaysia	2828	636	192
US	701	3702	1404

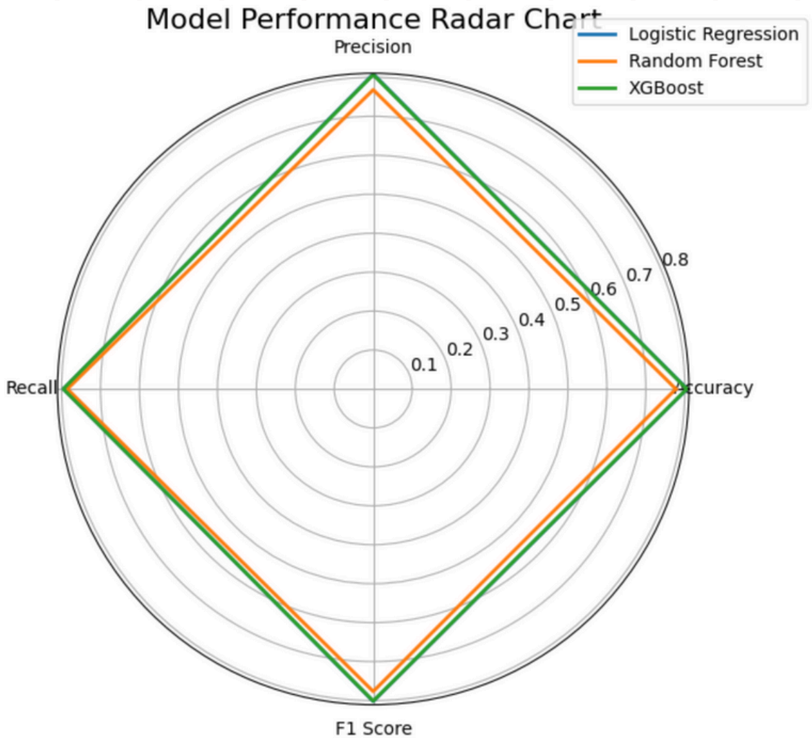
Positive emotions dominated the reviews in China and Malaysia, with most viewers approving and sympathizing with the film. In contrast, the number of neutral and negative reviews from American audiences was significantly higher, showing a more critical or distant attitude towards the film.

Data PreProcessing



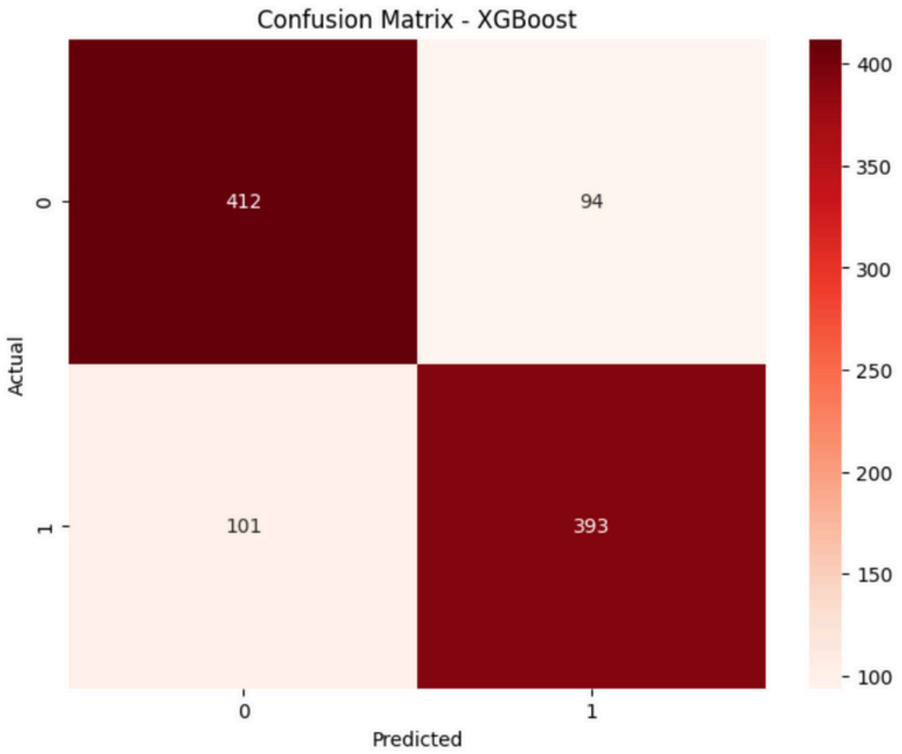
First, the original comment data is processed for missing values and duplicate values, and invalid comments and duplicate records are deleted. On this basis, text cleaning operations are performed, including removing HTML tags, punctuation marks, special characters, and stop words. Subsequently, the sentiment labels are unified and standardized, and the original annotations are integrated into three categories: positive, negative, and neutral. After the text preprocessing is completed, the text is vectorized using methods such as TF-IDF or BERT to convert natural language into numerical representations that can be used for model training. Finally, the data is divided into a training set and a test set (80%:20%) in a certain ratio to prepare for model building.

Model comparison



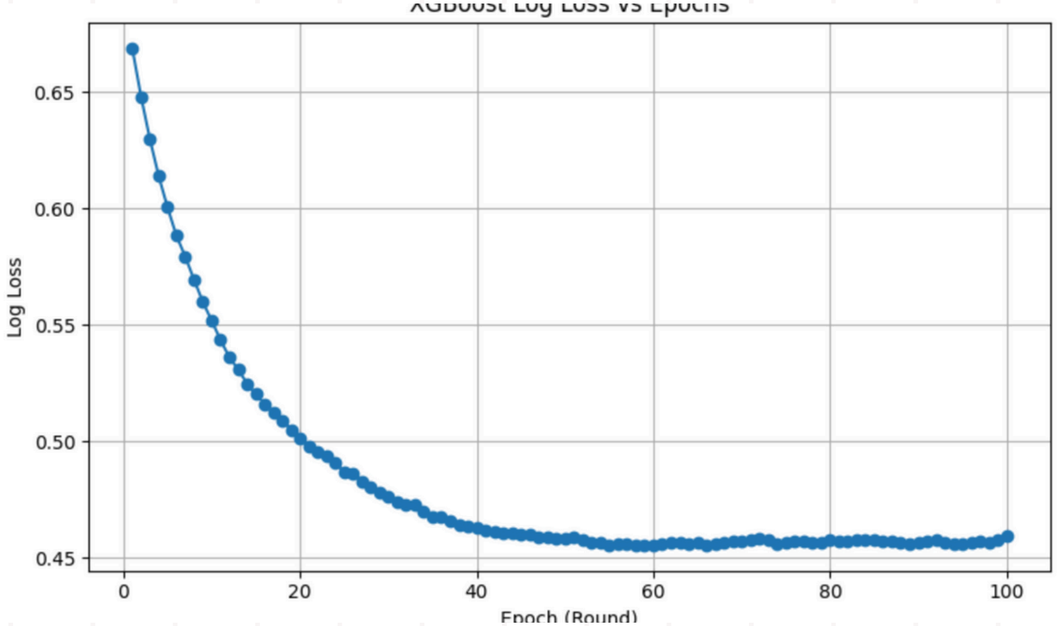
LogisticRegression, RandomForest, and XGBoost were introduced to assist in classification. XGBoost performed best and was used to explain differences in audience responses between countries, rather than emphasizing model performance.

Model Matrix



confusion matrix illustrates how well XGBoost handles timent classification, particularly in distinguishing between itive, neutral, and negative reviews. Values along the gonal represent correct predictions, while the off-diagonal s indicate misclassified instances. A clearer diagonal gests the model is making reliable distinctions between timent categories.

Model Log Loss

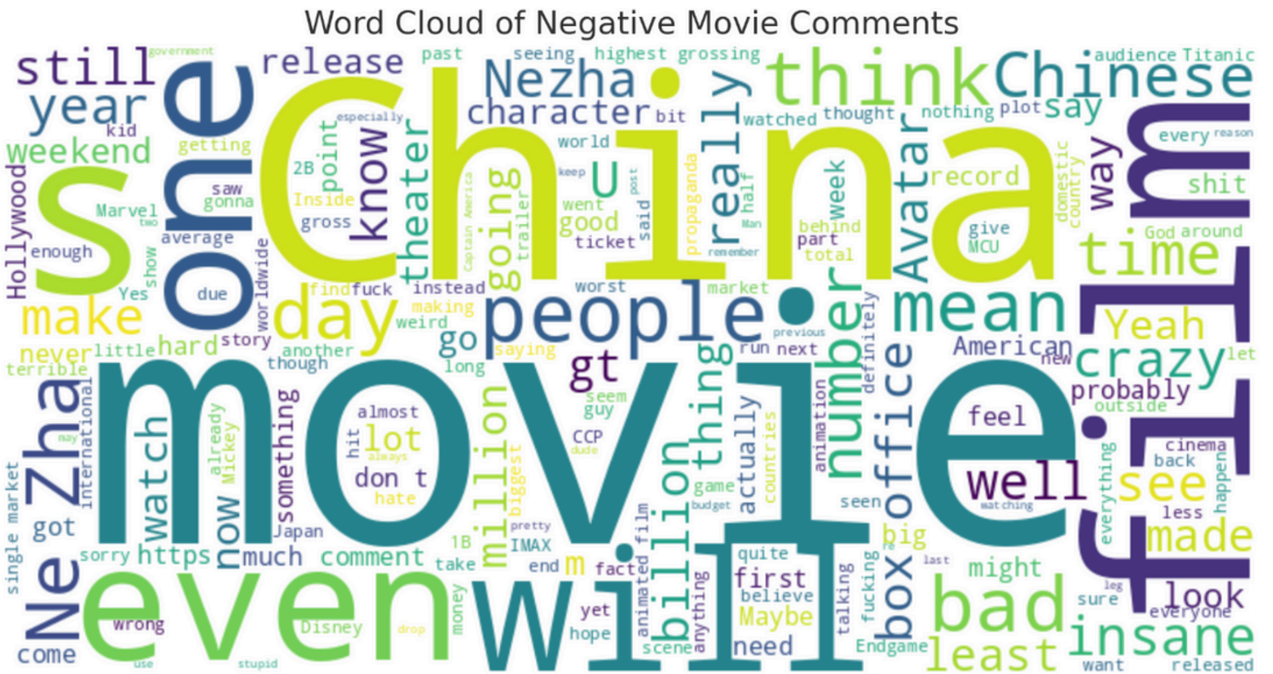


As can be seen from the figure, the loss value of the model drops rapidly in the first 60 rounds of training, indicating that the model is effectively learning emotional features. Then the curve gradually stabilizes, indicating that the model has converged and there is no obvious overfitting phenomenon. Overall, the model performs stably during the training process and has good generalization potential.

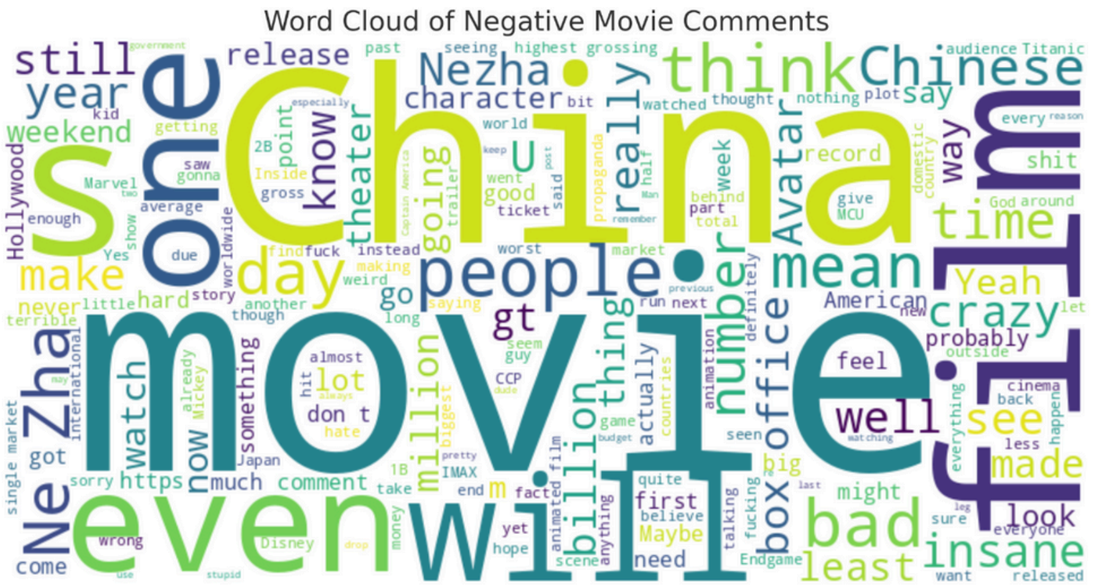
Initial Finding and Result

- Visual Effects and Animation Quality

The words "animation", "visuals" and "quality" appear frequently in the reviews, indicating that the production level of the film, especially the visual and technical presentation, has won recognition from the audience.



Initial Finding and Result



- Plot and emotion

In the word cloud, words such as "story", "emotional", and "touching" have a high frequency, indicating that the film has a strong appeal in plot design and emotional expression, which resonates with the audience.

Initial Finding and Result

- Differences in culture or values

Keywords such as "propaganda", "CCP", and "China" appearing in a negative context may mean that some foreign audiences associate the film content with politics and ideology, triggering negative emotions.

Initial Finding and Result

- Character image or emotional expression

Words including "Ne Zha", "character" and "emotion" appeared in negative reviews, indicating that some viewers felt that the characterization of the protagonist and the emotional expression of the character were insufficient.

Summary

Presents the differences in emotional reactions of audiences in different countries to Nezha 2, and explains them by combining keyword analysis and comment samples. The sentiment analysis model （XGboost） is used as an auxiliary tool in this study to help us reveal cross-national differences in cultural acceptance, narrative style preferences, etc., and provides data support for the subsequent overseas strategies of Chinese films.

Future Work

Future research can be expanded in the following directions:

1.Introduce real geographic location information: obtain real user regions through platform region tags or IP information to improve the accuracy of regional analysis;

2.Introduction of multilingual and local language models: Adopt regional pre-trained models such as Chinese-BERT and MalayBERT to avoid translation bias;

3.Emotional evolution analysis in the time dimension: Track the emotional changes before and after the movie is released and analyze the emotional trends;

THANK YOU

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