CUSTOMIZED MOVIE RECOMMENDATION SYSTEM USING MULTIMODAL EMOTION ANALYSIS

by

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CONTENTS

ABSTRACT

Traditional movie recommendation systems such as Douban and IMDb generate suggestions by analyzing user preferences—such as movie genres, ratings, and favorite actors—derived from past viewing experiences. However, these approaches are often biased and incomplete, sometimes failing to recommend movies that truly align with users' interests. Notably, two crucial factors—movie reviews from previous viewers and users' real-time emotions—are frequently overlooked in conventional systems. This paper introduces a customized multimodal movie recommendation system that incorporates both the implicit emotions embedded in movie reviews and users' current moods to enhance recommendation accuracy. Our system leverages sentiment analysis on movie reviews and integrates a user-friendly web platform that employs sentiment analysis, speech emotion recognition, and facial emotion recognition. By analyzing textual input, voice input, and facial expression, the system accurately assesses users' emotions before generating personalized recommendations. We explore the relationship between users' moods and recommended movie genres through a questionnaire-based study. Additionally, we evaluated sentiment analysis models, including SnowNLP, Hugging Face Transformer, and TextBlob, using Weibo datasets. The results demonstrated that SnowNLP outperformed the other models, making it the most suitable choice for our system. Ultimately, our system generates a personalized movie recommendation list by integrating users' real-time emotions with scientific movie ratings, which combine Douban scores and sentiment analysis of movie reviews. This approach provides a more refined, emotionally aware, and user-centric recommendation experience.

Keywords: Sentiment analysis, Web crawler, Movie recommendation, Multimodal emotion detection, Data cleaning

ACKNOWLEDGEMENTS

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Chapter 1

INTRODUCTION

With the rapid development of modern society, people are constantly bombarded with vast amounts of data. However, individuals have diverse backgrounds and preferences, and they only need a fraction of this information to meet their specific requirements. In this context, recommendation systems—information filtering tools designed to suggest items, products, or services based on users' preferences, behavior, or contextual data—have become increasingly popular among internet users[4]. A movie recommendation system is a prime example of this, providing users with tailored movie suggestions. Major platforms like Netflix already employ such systems, offering recommendations based on users' past viewing habits, often selecting movies of similar genres or from the same directors[9]. However, since users' moods and interests frequently change, relying solely on past viewing behavior may not always yield the most relevant recommendations.

Given such limitations, Multimodal Emotion Analysis is preferred for our research. This technology refers to the process of identifying a person's emotional state using multiple types of data (modalities), such as text, speech, and facial expressions, rather than relying on a single data type. The idea is that emotions can be better understood and more accurately classified when information from various modalities is combined[16]. Multimodal emotion Analysis mainly includes four parts: Sentiment Analysis, Facial Emotion Recognition, Speech Emotion Recognition, and Body Gesture Recognition. In this research, we mainly focus on the first three of them and pay more attention to Sentiment Analysis. Sentiment Analysis (also known as opinion mining) is a natural language processing (NLP) technique used to determine the emotional tone, opinion, or attitude expressed in a piece of text[3]. It involves classifying text into categories such as positive, negative, or neutral, and can also assess the intensity or polarity of sentiments[10]. There are currently many sentiment analysis tools available like

SnowNLP, Hugging Face Transformers, TextBlob, and so on. We will conduct an experiment on these tools using the Weibo dataset and choose the one that is most appropriate for our Douban movie dataset.

A web crawler (also known as a web spider or web robot) is an automated program or script that systematically browses the web and collects information from websites. It imitates the way people visit the website by making requests, but are able to gain much more information in a shorter period of time[1]. We will use this technology to gain the movie information.

Our research proposes a multimodal movie recommendation system that considers both the implicit emotions embedded in movie reviews and users' current moods. To recommend appropriate movie genre, we developed a user-friendly website that collects text, voice, and facial expression data in an engaging manner. Using multimodal emotion analysis, the system will determine the user's current mood along with a confidence score. Based on the correlation between mood and movie preferences—established through questionnaire data—we will recommend suitable movie genres. To recommend appropraite movie scores, we will first extract relevant information, including movie titles, URLs, ratings, and genres, from Douban, a popular Chinese movie platform. Then, we will conduct sentiment analysis experiments using the Weibo dataset to identify the most effective sentiment analysis model for Chinese text. Finally, we will analyze the sentiment of movie reviews and generate an overall movie score by integrating both sentiment analysis results and existing movie ratings.The key contribution of this research lies in incorporating both the emotional context of movie reviews and users' real-time moods into the recommendation process. Additionally, we introduce an intuitive interface powered by multimodal emotion analysis to assess users' current moods, enhancing the interactivity and personalization of the recommendation system[15].

Chapter 2

RELATED WORK

In recent years, content-based recommendation systems and collaborative filtering techniques have been widely used in personalized recommendation fields. Traditional recommendation systems primarily rely on users'historical preferences, movie ratings, and similarities between users. However, with advancements in natural language processing and multimodal emotion analysis, emotion-driven recommendation systems have emerged as a new research direction.

The application of multimodal emotion analysis especially sentiment analysis in recommendation systems has gained significant attention, as numerous studies demonstrate the direct impact of users' emotional states on their consumption choices. For example, Poria et al. (2016) proposed a movie recommendation system based on sentiment classification, using users' social media emotions as a key input[8]. Tripathi and Singh (2021) further explored the integration of sentiment analysis with recommendation systems, employing deep learning models to classify the sentiment in user reviews, thereby improving recommendation accuracy[7]. Zhao and Zhang (2020) explored the integration of sentiment analysis with topic modeling (LDA) to enhance movie recommendation systems. By analyzing the sentiment in user reviews and applying LDA to uncover hidden topics, they improved the recommendation process, enabling more personalized and emotion-aware movie suggestions. The combination of sentiment scores and LDA topics allowed for greater accuracy in matching movies with user preferences[13].

Platforms like Douban, which provide both user reviews and ratings, also play a crucial role in enhancing personalized recommendation systems. Elahi et al. (2023) investigated how combining sentiment analysis with rating data can offer more precise movie recommendations[2]. Unlike traditional rating-based recommendation systems, this approach takes into account both users' ratings and the implicit emotional information embedded in their reviews, creating a multi-dimensional movie recommendation experience. Kumar and Sharma (2021) introduced E-MRS, an emotion-based movie recommender system that utilizes emotion recognition to enhance recommendations. They used the questionnaire to check which movie people wanted to watch based on which emotions(joy, love, sadness, anger). What's more, they emphasize using color to check people's current emotions, the researchers let people choose three colors and test their emotions based on the colors they chose[15]. Patel and Gupta (2021) also considered the importance of mood, they let the audience choose their current mood to avoid data privacy and use the conventional handwritten rules for features in machine learning to give recommendations based on the mood users choose[14].

Based on this foundation, our project also pays attention to the importance of movie comments on movie recommendations and does sentiment analysis of movie comments like Elahi et al.(2023). In addition, our project also considers the importance of the user's current mood and will use the questionnaire to check the relationship between mood and movie. But instead of using color to check users' moods, we innovatively test users' typed words, speech, and facial expressions, then do a multimodal emotional analysis on them to test their moods. We believe that this way will be more accurate and more convenient for users to test their current moods and recommend appropriate movies.

Chapter 3

MATERIAL AND METHODS

3.1 Project flowchart

Our project flowchart is presented in the image below. Our system initiates by recommending suitable movie genres (such as comedy, animation, adventure, etc.) based on users' current emotional states. We will detect users' current moods through text, audio, and video inputs on our emotion-detection website. Subsequently, we will examine the correlation between users' current moods and movie genres via a questionnaire[15]. This process will enable us to determine the appropriate movie genres for users according to their present moods. After identifying the suitable movie genres, we will endeavor to obtain appropriate ratings for each movie. First, we will select an appropriate sentiment-analysis model. After evaluating the performance of Hugging Face Transformer, TextBlob, and SnowNLP on one thousand Weibo comments, the SnowNLP model is chosen because of its high accuracy. Then, the SnowNLP model will be employed to conduct sentiment analysis on movie reviews from Douban for each movie, and an overall sentiment analysis score will be assigned. Subsequently, we will integrate the sentiment analysis score with the original movie rating to calculate an overall score for each movie. We will also use two user cases to illustrate the necessity of this combination. Finally, a movie list featuring suitable movie genres and ratings will be provided to users.

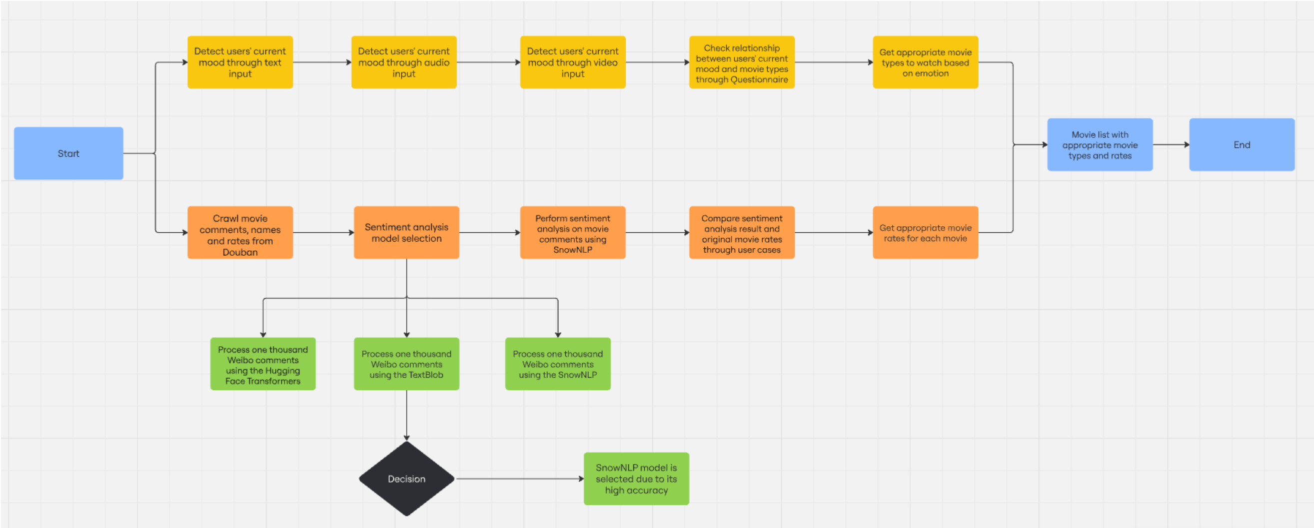

Figure 3.1: Project Flowchart

3.2 Multimodal emotion detection

Our system will consider using both text-based models, audio-based models, and video-based models during the emotion detection part[16]. For the text-based model, our system will develop a chat robot using the Flask framework and a pre-trained transformer model to do emotional analysis. For the audio-based model, we developed a website with technologies including machine learning, audio processing, audio visualization, and random image generation. For the video-based model, we combine MTCNN for face detection, OpenCV for image capture, and DeepFace for emotional analysis of the detected face from a camera feed. Each model will generate an emotional state together with its confidence rate after the test finishes.

3.3 Questionnaire

In this step, we are inspired by Kumar and Sharma (2021) and consider using the questionnaire to test the relationship between users' current mood and movie types. We will invite a certain number of participants and let them choose the movie types they prefer when their emotional states are happy, anger, disgust, fear, neutral, sadness, and surprise. The final result will be used by our recommendation system after detecting users' current mood.

The image below is one of the questions in the questionnaire. Participants will be asked to select at least one movie genre they prefer based on their current mood, which can be happy, angry, disgust, fear, neutral, sad, or surprise. There are a total of seven questions in the questionnaire.

* 1.当您的当前情绪是开心时，您希望看哪些类型的电影？(When your current mood is happy, which movie types do you prefer?) [至少选1项]

- 喜剧(Comedy)
- 爱情(Love)
- 剧情(Plot)
- 战争(War)
- 动作(Action)
- 犯罪(Crime)
- 科幻(Science fiction)
- 冒险(Adventure)
- 动画(Animation)
- 历史(History)
- 灾难(Disaster)
- 悬疑(Suspense)

Figure 3.2: Questionnaire Design

3.4 Sentiment Analysis Model Choosing

In our sentiment analysis experiment, we evaluated three models: TextBlob, Hugging Face Transformers, and SnowNLP, all implemented using Python. We selected the Weibo dataset from Kaggle for testing, as the majority of Weibo' s text is in Chinese, which aligns with the data from the Douban movie platform. Furthermore, the Weibo dataset contains thousands of comments, providing a robust sample size for our analysis. Prior to conducting the experiment, we preprocessed the data using the panda' s library and regular expressions to clean the dataset by removing URLs and special characters from the original file. After data cleaning, we selected one thousand Weibo comments for which we had predefined sentiment labels—positive, negative, or neutral. We then ran all three sentiment analysis models on this subset of comments and evaluated their performance based on accuracy and efficiency. The model that demonstrates the highest proficiency in classifying the sentiments will be chosen for integration into our movie recommendation system. The cleaned Weibo dataset is shown in the picture above.

	review
0	更博了爆照了帅的呀就是越来越爱你生快傻缺
1	土耳其的事要认真对待否则直接开除很是细心酒店都全部OK啦
2	姑娘都羡慕你呢还有招财猫高兴
3	美
4	梦想有多大舞台就有多大
...	...
995	回复和爱美食懂美食的人分享体验感觉真好
996	一定要看啊请大家多多指教看起
997	这些啊转发微博
998	想起的片花对着喊快跑后面的巧克力要爆浆啦感谢大家晚安
999	好玩这个真的超叼的这个cool哦哦

Figure 3.3: Weibo dataset

3.5 Data Extraction

In this step, we employed web scraping techniques to extract movie data from Douban, a prominent Chinese movie review platform. The extraction process was implemented using Python' s requests library to send HTTP requests [6]. We identified the relevant URLs from Douban' s movie section, including lists of top- rated movies, popular movies, and movies by genre. For each movie, we aimed to extract movie names, original movie rates, and movie comments. These fields provide essential information for recommendation and sentiment analysis. What' s more, as movie lists span multiple pages, we dynamically navigated through the pagination by identifying URL patterns for each subsequent page. After collecting the raw HTML content, we filtered and cleaned the data, removing any irrelevant tags and structures using the panda' s library. Data was then stored in structured formats such as CSV or JSON for subsequent analysis.

3.6 Sentiment Analysis based on viewing comments

After selecting the appropriate sentiment analysis model, we will analyze one hundred comments for each movie to determine the number of positive comments. The system will then combine the original movie' s rating with the sentiment analysis results to calculate an overall score for each film. This scoring method is more comprehensive and scientific than relying solely on movie ratings, as it also incorporates the sentiment expressed in user reviews.

3.6.1 Case Study 1

When explaining why we consider integrating the sentiment analysis results with the original movie ratings on Douban to generate an overall score for each movie, rather than relying solely on the original Douban ratings, we conducted two case studies. In the first case study, we employed SnowNLP to perform sentiment analysis on 34 movie reviews of the renowned film Titanic. The outcome revealed that the average sentiment score was 8.8, significantly lower than the original Douban movie rating of 9.5. This case study clearly demonstrates a substantial disparity between the original movie rating and the sentiment analysis results derived from movie reviews. Thus, it is essential to combine these two elements to obtain an overall score. The sentiment analysis result and original movie rating are shown in the picture below.

```
20  不管是片中的爱情、亲情和友情，全片中的情感都是为了透视人性而设置。然而对于人性的解读和判断，...   1.000000
21  看过影片，很多经典影像和片段仍在脑海中反复回荡，像两位恋人在航船桅杆上的浪漫一幕。能跟自己相...   1.000000
22  一部电影 一场爱情的诠释 让我们懂得了爱情的真挚与美好 杰克--穷画家一枚 罗斯--贵族小姐...   1.000000
23  虽然泰坦尼克号沉没了，可是杰克和罗丝爱情却是永恒的。 坐着头等舱的罗丝，她有一颗善良，纯真，...   1.000000
24  1912年4月15日，号称永不沉没的泰坦尼克号永远沉没了；2012年4月14日，我一个人在电...   0.912194
25  泰坦尼克号建造于北爱尔兰的最大城市贝尔法斯特的哈南德·沃尔夫造船厂。船体于1911年5月31...   0.002833
26  1、1998年上映的时候我读初中二年级。我家那里影院在4月的某个周二只上映一天，票倒是有，不...   0.028903
27  97年的时候，当时我还上高一，住宿生；当时，满街的都是录像厅，用个黑板子，往街上一放，最新好...   0.075270
28  沉没之船上永不沉没的爱情绝唱 一部人类应时时审视自己劣根性的警世箴言 一则包融信念、勇气、牺...   1.000000
29  再次回味这部距今已近20年的电影仿佛还能感受到两人不妥协而肆意的爱。 那是几年前，3D电影如...   1.000000
30  前几天又看了一遍泰坦尼克号，补充之前忘记说的感受 这次看的时候没有把注意力放在男女主身上，而...   0.999998
31  He saved me,in every way that a person can be ...   1.000000
32  卡尔爱露丝吗？答案是爱。但就像爱他的钱一样爱。 爱一个人和爱钱应该是不一样的吧。 钱无关于...   0.996845
33  杰克为什么会爱上露丝？因为她美貌、性感、压抑又大胆！露丝为什么喜欢杰克？因为他有才华、善良、...   1.000000
34  2023.3.27 盆友们！内陆真的重映了！终于可以把欠下的票补上♡˙︶˙♡ 偶然发现 三年...   0.998110
Average Sentiment Score: 0.8835150603413482
```

Figure 3.4: Sentiment analysis result for Titanic

Figure 3.5: Original Douban rating for Titanic

3.6.2 Case Study 2

In the second case study, we conducted sentiment analysis with the SnowNLP model on 39 movie reviews of the film The Martian. The outcome of the sentiment analysis indicated that the average sentiment score was 9.5, significantly surpassing the movie's original rating of 8.5 on Douban. This case study further revealed a substantial discrepancy between the sentiment analysis score and the original Douban rating. Such a disparity underscores the necessity of integrating these two scores to derive a more comprehensive and accurate overall movie score.

```
25  影片结尾，当被成功救援的马特达蒙，开始现身说法，给航天局的学生们讲授他的太空历险遭遇时，我会...   1.000000
26  典型的好莱坞式科幻电影， 马克不是那种无所不能的英雄，时势造英雄用在电影里再合适不过了，他被...  1.000000
27  先刷了书再去电影院刷了剧，被自己剧透地不要不要的。总体来说电影改编地很不错，不过由于篇幅限制...   0.999974
28  电影很好看。大帅哥演技在线，电影特效很震撼，外太空的生活很传奇，同伴间的情谊也很温暖。 这就...  1.000000
29  有一个人类的植物学家，他天性乐观，外加身体健康，而且多才多艺，会开车，会电脑，会做饭，会机械...   0.999901
30  很无聊的电影。全片转折不多，高潮不多，该煽情的地方没催泪点，该搞笑的地方just so so...   0.110104
31  《火星救援》是由美国二十世纪福斯电影公司出品的科幻冒险片，由雷德利·斯科特执导，马特·达蒙、 ...  1.000000
32  火星救援是最近最期待的电影，然而看过有些失望，不幸流为最好的都剪在预告片里了的一类电影。觉得...   1.000000
33  有上当的感觉。 上映前听说这是一个关于一个人被困火星然后坚持等待救援的故事，我立刻就被强烈的...  0.999883
34  二战末期，美军千辛万苦从前线将他救回，并耗费数十年时间训练成价值三千万美金的杀人利器。然而二...   1.000000
35  太空片里最让我害怕的场景，就是在宇航服里喘不过来气的样子了。再多看几次这样的场景，相信我就会...   0.917055
36  文/故城 《火星救援》没有接过《银翼杀手》的衣钵，也不是《异形》或《普罗米修斯》的延续，这恐...  0.999983
37  文/梦见乌鸦 他是宇航员里最会种土豆的农民，农民里最会拆解飞船的修理工，修理工里数理化最好的...  0.998971
38  看完后还是心潮澎湃有木有！ 最喜欢理科男了，天啦噜居然还是个植物学家，在火星上种土豆，编剧真...  0.999999
39  没看电影之前我想像中的应该是前面做些铺垫后面有很激烈很刺激的那种救援场面，那种山崩地裂排山倒...   0.999992
Average Sentiment Score: 0.9480392120396826
```

Figure 3.6: Sentiment analysis result for The Martian

Figure 3.7: Original Douban rating for The Martian

Chapter 4

RESULTS

4.1 Multimodal emotional analysis webpage

4.1.1 Text-based emotional analysis model

We have developed an emotional chatbot that will have a conversation with users by asking them five questions. Then the pre-trained transformer model will do an emotional analysis based on the users' answers and detect the users' final emotion with the confidence rate shown. The final emotion will be either one of the seven emotions listed (happy, anger, disgust, fear, neutral, sadness, and surprise).

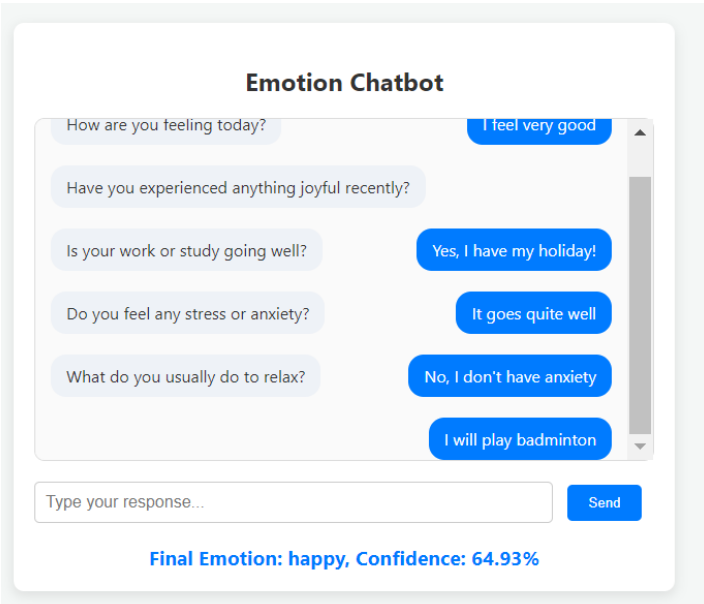

Figure 4.1: Text-based emotional analysis webpage

4.1.2 Audio-based emotional analysis model

We have also developed an audio-based emotional detection website. Once users click the start recording button, a random picture will appear and users will have ten seconds to describe what happens in the picture. Users can check whether their voices are being recorded by seeing the voice visualization on the website. After ten seconds finish, the predicted emotion with the confidence rate will be shown. The final emotion will be either one of the seven emotions listed (happy, anger, disgust, fear, neutral, sadness, and surprise).

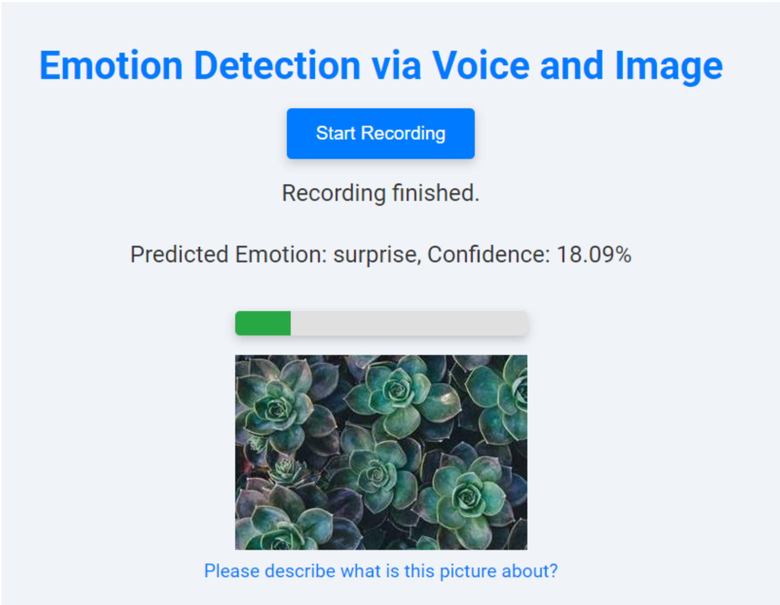

Figure 4.2: Audio-based emotional analysis webpage

4.1.3 Video-based emotional analysis model

We successfully developed a video-based emotion detection website. When users click the Capture and Start Analysis button, the system initiates active scanning, highlighted by a red bounding box around the user' s face and a blue scanning line moving vertically to indicate the scanning process. During the scan, the detected emotion and its confidence rate are displayed in real-time on the right side of the video feed. Once the blue timeline visualization completes its pass, the final detected emotion, along with its overall confidence rate, is displayed at the bottom of the video. The final result corresponds to one of seven possible emotions: happy, anger, disgust, fear, neutrality, sadness, or surprise.

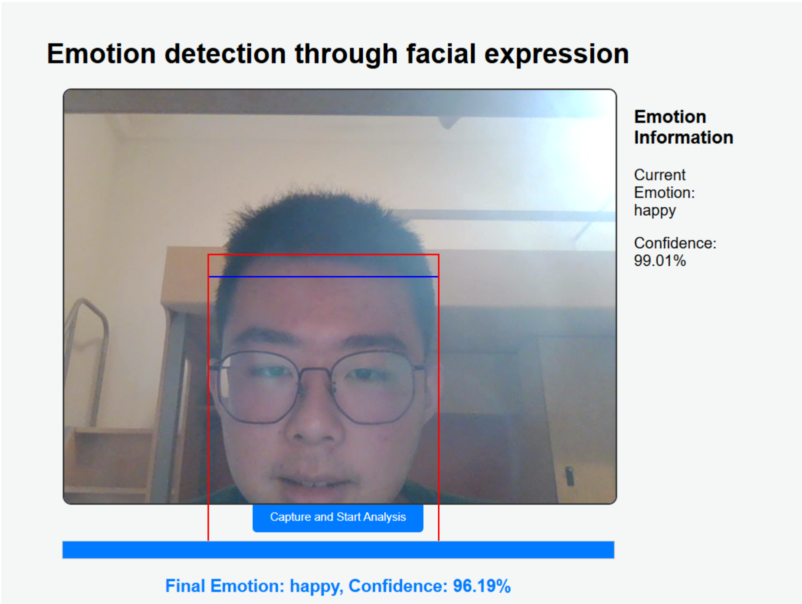

Figure 4.3: Video-based emotional analysis webpage

4.2 Relationship between users' current mood and movie types recommendation

So far, twelve participants have completed our questionnaire. We have created several ways of data visualization for each mood category to analyze which movie genres are most suitable for recommendation based on users' current moods—happy, anger, disgust, fear, neutrality, sadness, or surprise. The bar charts and corresponding analysis results are presented below.

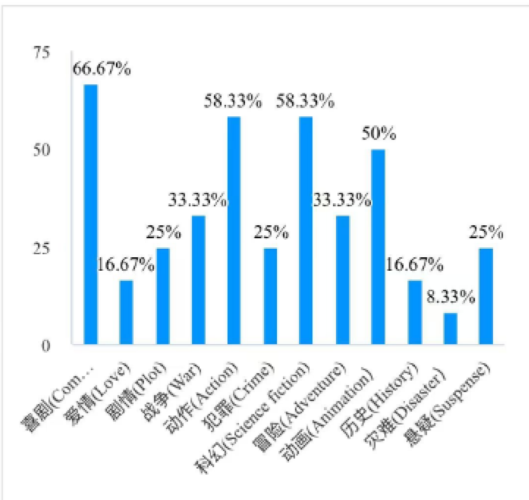

Figure 4.4: Data analysis result for Happy mood

According to the data analysis results shown above, Comedy is the most preferred genre when participants feel happy, with a preference rate of 66.67 percent. Action and Science Fiction are also popular choices, with preference rates of 58.33 percent. Therefore, our recommendation system will prioritize suggesting Comedy, Action, and Science Fiction movies when a user's current mood is detected as happy.

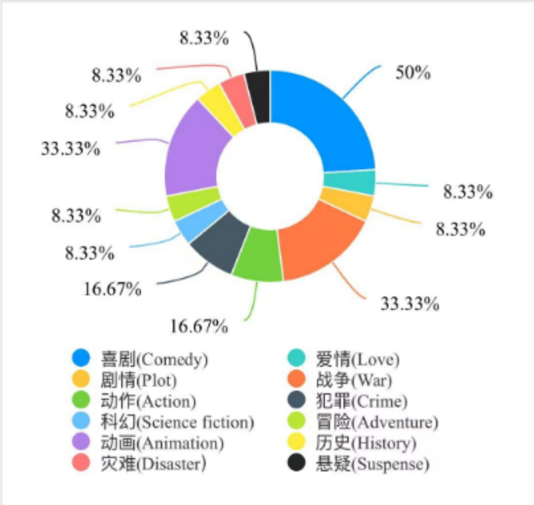

Figure 4.5: Data analysis result for Angry mood

According to the data analysis results shown above, Comedy is the most preferred genre when participants feel angry, with a preference rate of 50 percent. War and Animation are also popular choices, with preference rates of 33.33 percent. Therefore, our recommendation system will prioritize suggesting Comedy, War, and Animation movies when a user's current mood is detected as angry.

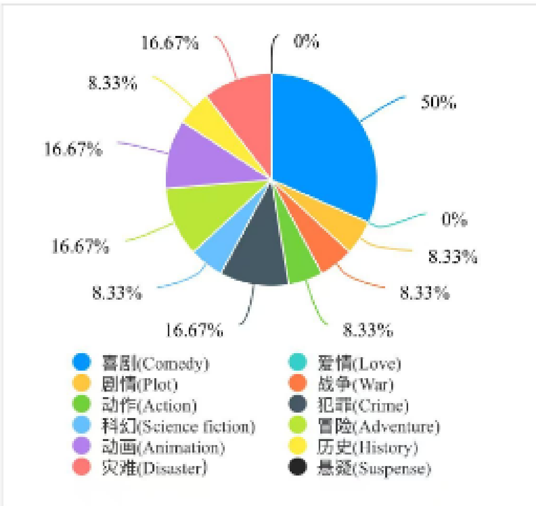

Figure 4.6: Data analysis result for Disgust mood

Based on the data analysis results shown above, Comedy emerges as the most preferred genre when participants experience disgust, with a preference rate of 50 percent. In contrast, the preference rates for all other movie genres under the same emotional state are below 20 percent, indicating that participants largely avoid these genres when feeling disgust. Consequently, our recommendation system will suggest only Comedy movies when a user's current mood is detected as disgust.

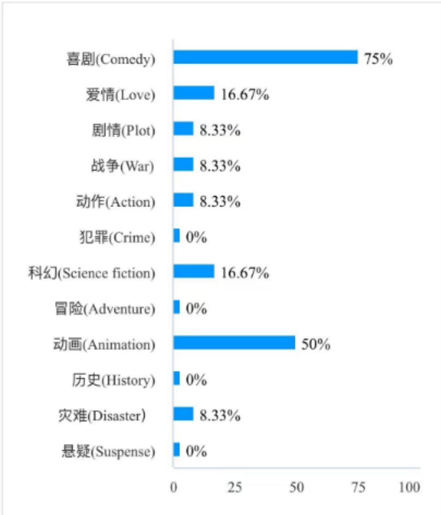

Figure 4.7: Data analysis result for Fear mood

According to the data analysis results shown above, Comedy is the most preferred genre when participants feel fear, with a high preference rate of 75 percent. Animation is also a popular choice, with preference rates of 50 percent. Therefore, our recommendation system will prioritize suggesting Comedy and Animation movies when a user's current mood is detected as fear.

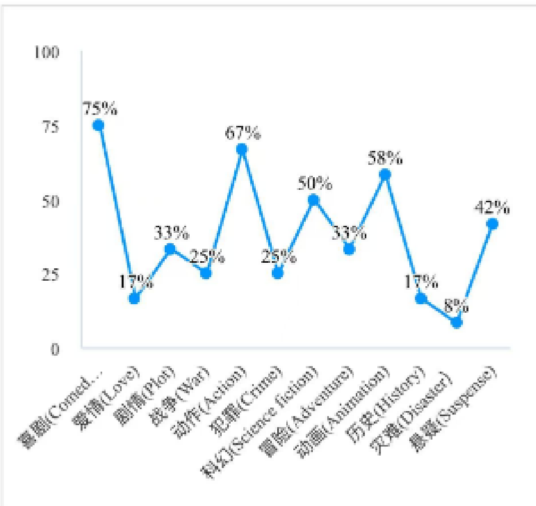

Figure 4.8: Data analysis result for Neutral mood

According to the data analysis results shown above, Comedy is the most preferred genre when participants feel neutral, with a high preference rate of 75 percent. Additionally, Action, Animation, and Science Fiction are also popular genres, each with preference rates exceeding 50 percent. Therefore, our recommendation system will prioritize suggesting Comedy, Action, Animation, and Science Fiction movies when a user's current mood is detected as neutral.

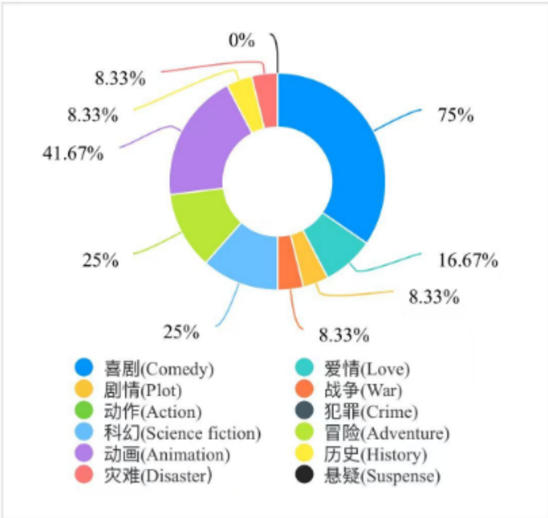

Figure 4.9: Data analysis result for Sadness mood

According to the data analysis results shown above, Comedy is the most preferred genre when participants feel sad, with a preference rate of 75 percent. Animation is also a popular choice, with a preference rate of 41.67 percent. Therefore, our recommendation system will prioritize suggesting Comedy, and Animation movies when a user's current mood is detected as sad.

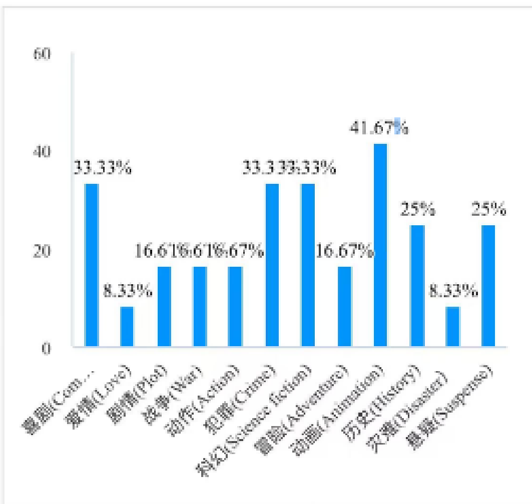

Figure 4.10: Data analysis result for Surprise mood

According to the data analysis results shown above, Animation is the most preferred genre when participants feel surprised, with a preference rate of 41.67 percent. Additionally, Comedy, Crime, and Science Fiction are also popular choices, each with a preference rate of 33.33 percent. As a result, our recommendation system will prioritize suggesting Animation, Comedy, Crime, and Science Fiction movies when a user's current mood is detected as surprised.

4.3 Sentiment Analysis Model choosing result

4.3.1 TextBlob sentiment analysis model

In our sentiment analysis model experiment, we initially applied the TextBlob sentiment analysis model to process one thousand cleaned Weibo comments. The results indicated that all comments were classified as Neutral with a confidence score of zero. This outcome suggests that the TextBlob model is not well-suited for analyzing Chinese text, demonstrating that it is not an ideal choice for our Movie Recommendation System. The following figure shows our testing result.

	review	sentiment	confidence
0	更博了爆照了帅的呀就是越来越爱你生快傻缺	Neutral	0.0
1	土耳其的事要认真对待否则直接开除很是细心酒店都全部OK啦	Neutral	0.0
2	姑娘都羡慕你呢还有招财猫高兴	Neutral	0.0
3	美	Neutral	0.0
4	梦想有多大舞台就有多大	Neutral	0.0
...	...	...	...
995	回复和爱美食懂美食的人分享体验感觉真好	Neutral	0.0
996	一定要看啊请大家多多指教看起	Neutral	0.0
997	这些啊转发微博	Neutral	0.0
998	想起的片花对着喊快跑后面的巧克力要爆浆啦感谢大家晚安	Neutral	0.0
999	好玩这个真的超叼的这个cool哦哦	Neutral	0.0

1000 rows × 3 columns

Figure 4.11: TextBlob model testing result

4.3.2 Transformers sentiment analysis model

Next, we tested our one thousand cleaned Weibo comments using the Hugging Face Transformers model. The results showed that 90.9 percent of the comments were classified as negative, while only 9.1 percent were classified as positive. Although the performance is an improvement over the previous TextBlob model, it is still far from accurate, indicating that the Transformer model may not be the ideal choice for our Movie Recommendation System. The pie chart below illustrates our test results.

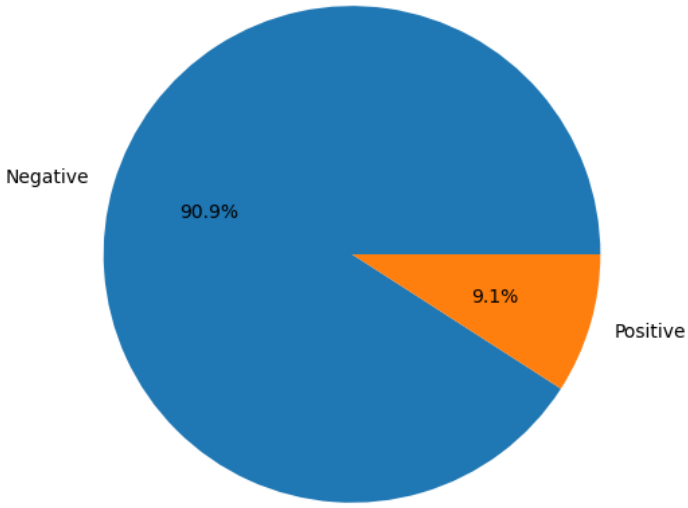

Figure 4.12: Transformer model testing result

4.3.3 SnowNLP sentiment analysis model

Finally, we tested one thousand Weibo comments using the SnowNLP sentiment analysis model. The results indicate that 55.9 percent of the comments are positive, 26.5 percent are negative, and the remaining comments are neutral. This outcome closely matches our expected classification, demonstrating that the SnowNLP sentiment analysis model is the most suitable option among the three models for processing Douban comments and Chinese text. The pie chart below illustrates our test results.

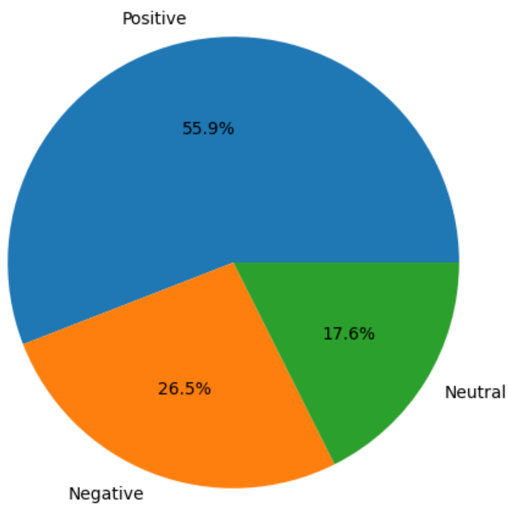

Figure 4.13: SnowNLP model testing result

4.4 Movie comments sentiment analysis result

Figure 4.14: Douban website with movie comments

We extracted movie comments from the Douban website. The image above depicts one of the movies we analyzed, which has a total of 13,301 comments. For this project, we will focus on collecting 100 comments and conducting sentiment analysis on them. The sentiment analysis results for this movie are displayed in the image below. We collected approximately 100 comments for each movie and performed sentiment analysis using the SnowNLP model. The sentiment analysis scores for individual comments are listed on the right. The overall sentiment score for the movie is determined by calculating the mean of all 95 sentiment analysis scores.

```
                                                        comment  sentiment
0   距离斯蒂芬·金（Stephen King）和德拉邦特（Frank Darabont）们缔造这...   1.000000
1   周末看了一部美国影片《肖申克的救赎》（《The Shawshank Redemption》）...   1.000000
2   原文转自： 我们都是肖申克里等待救赎的灵魂 01 “你来对地方了，这里人人都无罪。” Red...   0.999972
3   时间会证明经典的价值，虽然在某些时刻会被误判和忽视。 用上面这句话来描述电影《肖申克的救赎》...   0.999999
4   一、缘起 从来没想过给《肖申克的救赎》写一篇影评，也许是生怕暴露自己只是个不谙世事的初级影迷...   0.998812
..                                                          ...        ...
91  上周末电影频道重播肖申克的救赎（以下简称肖）又在豆瓣引起了一次不小的轰动，把人们的视线又一次...   1.000000
92  《肖申克的救赎》是一场关于笼中鸟如何飞往自由的梦，看了它，甚至会让人觉得重生。 之前有很多精...   1.000000
93  对于生命的意义，很多人还没有弄清，我就是这样。 如果你和我一样，那可以看看“肖申克的救赎”。 ...   1.000000
94  很难有一部电影能比《肖申克的救赎》能更好的诠释梦想与救赎这两个词的关联和真谛，电影予人带来心...   1.000000
95  一个年轻有为有着大好前途的银行家，妻子背叛了他，他也被冤枉而锒铛入狱。本以为他这样的身份，又...   0.999946

[96 rows x 2 columns]
Average Sentiment Score: 0.9697958878231508
```

Figure 4.15: Sentiment analysis result

4.5 Final Result

The final movie list presented to users is shown in the image below. Our system has the capability to recommend the most suitable movie genre according to the users' current emotional state. For the recommended movie genre, we will suggest the top three movies for users' reference. These movies are selected based on the combined average score of the Original Movie Rating and the Sentiment Analysis Score. Subsequently, users are able to select their preferred movie to watch from the movie recommendation list provided by our system.

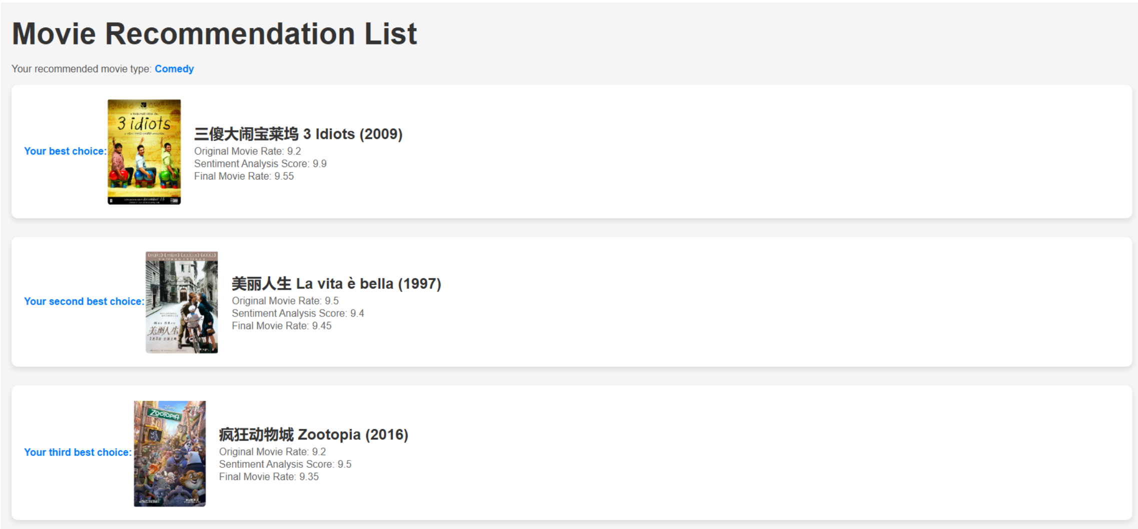

Figure 4.16: The final movie list shown to users

Chapter 5

DISCUSSION

The Customized Movie Recommendation System using Multimodal Emotion Analysis highlights the transformative potential of integrating emotional context into the recommendation system. By enabling users to assess their current mood and combining sentiment analysis with Douban ratings, the system delivers highly personalized and emotionally resonant movie suggestions. This approach surpasses traditional recommendation systems that rely solely on user preferences and ratings, offering a deeper connection between users' emotional states and their viewing choices.

The system excels in aligning recommendations with users' psychological needs, particularly for individuals seeking content that matches or improves their mood. For example, it can provide uplifting movies for users experiencing sadness or light-hearted content for those feeling neutral. By bridging the gap between emotions and media preferences, the system fosters a more immersive and satisfying user experience.

However, the system's effectiveness is inherently tied to the accuracy of its Multimodal Emotion Analysis. Challenges such as ambiguous user inputs or varying cultural interpretations of emotions can reduce the precision of the sentiment analysis model [11]. Furthermore, reliance on external data sources like Douban, which predominantly caters to Chinese audiences, limits the system's applicability across diverse linguistic and cultural groups, potentially alienating a broader international audience.

To address these limitations, future advancements should focus on several key areas. First, the accuracy of sentiment detection can be enhanced by leveraging cutting-edge natural language processing (NLP) techniques, such as fine-tuning large language models (LLMs) or incorporating domain-specific training data. Second, the inclusion of additional data sources, such as IMDb or globally diverse datasets, could increase the system's adaptability and ensure broader cultural relevance. Lastly, improving the multimodal integration of text, audio, and visual emotion recognition could further refine the system' s emotional context modeling, delivering even more nuanced recommendations [12].

Despite these challenges, this project underscores the immense potential of emotion-driven recommendation systems. By intertwining emotional intelligence with advanced recommendation algorithms, such systems pave the way for a new era of deeply personalized and engaging user experiences. This approach not only enhances entertainment platforms but could also inspire broader applications in areas like mental health, education, and customer service, where understanding user emotions is critical.

Chapter 6

CONCLUSIONS

In conclusion, the Customized Movie Recommendation System using Multimodal Emotional Analysis introduces an innovative and transformative approach to enhance the movie selection experience. By seamlessly combining user-generated mood descriptions with Multimodal Emotional Analysis and integrating Douban user ratings, the system delivers highly personalized movie recommendations that account for both users' current emotional states and the collective sentiment from movie reviews. This dual-layered recommendation methodology not only caters to users' specific movie preferences but also ensures that the suggested content resonates emotionally, creating a more engaging and satisfying experience.

The primary advantage of this movie recommendation system lies in its high level of personalization and its strong integration of user feedback. By analyzing users' current moods through text, voice, and facial expression inputs, the system achieves an accuracy exceeding 50%, recommending movie genres based on the scientifically established correlation between moods and movie preferences derived from questionnaires. Moreover, the system considers implicit emotions embedded in movie reviews. Leveraging SnowNLP, which achieves an accuracy rate exceeding 90%, the system refines movie ratings to ensure they are more precise and reflective of users' sentiments. This user-centric and feedback-driven movie recommendation system enhances the movie-watching experience by tailoring recommendations to users' moods and providing more accurate movie ratings.

Looking ahead, future developments will prioritize several key enhancements. Refining the accuracy of sentiment analysis is critical, and this can be achieved by adopting state-of-the-art natural language processing models, enhancing multimodal integration, and incorporating additional emotion datasets to better understand subtle emotional nuances. Expanding the system’ s applicability is another priority. This involves scaling it to support larger and more diverse datasets, integrating global platforms like IMDb and Rotten Tomatoes, and adapting the system to accommodate multilingual and multicultural audiences.

Beyond entertainment, this system holds promise for broader applications, including mental health support, educational content curation, and personalized customer experiences. By tailoring recommendations to users’ emotional needs, it could serve as a valuable tool for fostering emotional well-being and enhancing overall satisfaction in various domains. As it evolves, the platform has the potential to redefine how emotion-driven technologies are leveraged to create more meaningful, human-centric experiences.

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Appendix A

REFLECTION

My signature work, "Customized Movie Recommendation System Using Multimodal Emotional Analysis," takes an innovative approach by considering both the implicit emotions embedded in movie comments and users' current moods when recommending movies. This marks a significant improvement over traditional recommendation systems, which primarily rely on past viewing experiences, often leading to bias and incomplete recommendations. Throughout the process of developing my signature work, three thematic courses—Data Acquisition and Visualization, Introduction to Databases, and Introduction to Computer Science—have played a crucial role in inspiring me and equipping me with the fundamental skills and knowledge necessary for my project. Additionally, the patience and continuous guidance of my mentors during my capstone courses have helped me refine my project and improve my academic writing. Without the courses I took at Duke Kunshan University, I would not have been able to successfully complete my signature work.

Data Acquisition and Visualization

This course has been the most inspiring and influential in motivating me to complete my signature work. Throughout the course, several meaningful and engaging labs provided hands-on practice and essential skills in Data Acquisition and Visualization. In the first part, Data Acquisition, I learned how to use Web Crawler APIs to extract information from websites, which laid a solid technical foundation for crawling movie data from Douban for my signature work. I also gained experience using pandas for data cleaning and discovered Kaggle, a valuable platform for finding datasets. This knowledge was crucial in helping me locate and preprocess the Weibo dataset for sentiment analysis experiments. Additionally, the professor introduced us to Transformer models for sentiment analysis, sparking my interest and leading me to explore other models, such as SnowNLP, which turned out to be an ideal sentiment analysis tool for my project. In the second part, Data Visualization, I learned to use Tableau and D3.js for data visualization, giving me multiple options to illustrate the relationship between users' emotions and movie genres in my signature work. More importantly, the course provided foundational knowledge of HTML, CSS, and JavaScript, equipping me with the necessary skills to develop a multimodal emotion detection website. In conclusion, the practical and valuable knowledge gained from this course has been instrumental in preparing me to successfully complete my signature work.

Introduction to Databases

In this course, the professor introduced us to semi-structured data formats such as XML and JSON, which are commonly used for storing and exchanging structured data between different systems and applications. I learned that JSON, with its key-value pair structure, is simpler and more compact, making it ideal for data transmission. This knowledge proved valuable during the web crawling process in my signature work. Since some websites use JSON to transmit data, understanding its structure allowed me to efficiently extract information from JSON-based websites. Additionally, I learned that one of JSON' s key advantages is its fast parsing speed, which makes it well-suited for frontend-backend communication. Leveraging this, I used JSON in combination with the Flask framework to establish communication between the frontend and backend of my multimodal emotion detection website. Moreover, the foundational knowledge of Relational Databases and Structured Query Language (SQL) provided me with an alternative to storing movie data beyond just CSV and Excel files in my project.

Introduction to Computer Science

This course provided fundamental Python knowledge, covering topics such as writing functions, recursion, and loops. It also introduced essential data structures, including binary trees, heaps, and linked lists. This foundational knowledge has been crucial for my signature work project, as most of the code—including web scraping, sentiment analysis, and the backend of my multimodal emotion detection website—is written in Python. Without this solid foundation, I would not have been able to successfully complete my project. Additionally, I learned to use essential tools like Jupyter Notebook, which allowed me to present my project results more effectively by keeping outputs organized within the notebook. This tool was particularly useful during my sentiment analysis model testing experiments. I would like to express my deepest gratitude to the professor of this course for his exceptional teaching, which has provided me with a strong Python foundation.

Capstone Courses

The two Capstone Courses: Capstone 495 and 496 - provided me with a valuable opportunity to have frequent one-on-one meetings with my mentor. I deeply appreciate my mentor’s guidance throughout these courses, which allowed me to continuously improve my signature work project and experience the joy of conducting research. In Capstone 495, I had weekly meetings with my professor to discuss ways to enhance my multimodal emotion detection website. Initially, inspired by the Data Acquisition and Visualization course, I only considered using sentiment analysis to detect users’ emotions. However, after sharing my ideas, my professor encouraged me to adopt a multimodal approach, incorporating text, audio, and video inputs to achieve a more scientific and comprehensive emotion detection system. I found this idea highly valuable and devoted significant effort to implementing it. My mentor also provided practical feedback on my website design. For instance, for text input, he suggested making emotion detection more interactive by using a conversational approach, where the system asks a series of connected questions to analyze emotions—making the experience more engaging. For video input, he recommended adding a visualized scanning function that highlights the user’s face and displays real-time detection results near the scanned area. These ideas significantly improved the interactivity and user experience of my website. In Capstone 496, the focus shifted towards academic writing. After reviewing my initial draft, my mentor suggested redesigning the project flowchart into a linear format to improve clarity and conciseness. He also advised adding user case studies to illustrate why sentiment analysis for movie comments is necessary compared to traditional rating methods. Additionally, he recommended restructuring my paper by introducing user emotion detection first before discussing sentiment-based movie rating, as this sequence aligns better with the reader’s understanding. These practical suggestions greatly enhanced the quality of my signature work paper. In conclusion, these two courses provided me with frequent discussions with my mentor, helping me refine my signature work project step by step. Without my mentor’s valuable guidance, I would not have been able to complete my project as effectively as I did.