

Emosical: An Emotion-Annotated Musical Theatre Dataset

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Abstract

This paper presents Emosical, a multi-modal open-source dataset of musical films. Emosical comprises video, vocal audio, text, and character identity paired samples with annotated emotion tags. Emosical provides rich emotion annotations for each sample by inferring the background story of the characters. To achieve this, we leverage the musical theatre script, which contains the characters’ complete background stories and narrative contexts. The annotation pipeline includes feeding the speaking character, text, global persona, and context of the dialogue and song track into a large language model. To verify the effectiveness of our tagging scheme, we perform an ablation study by bypassing each step of the pipeline. The ablation results show the usefulness of each component in generating accurate emotion tags. A subjective test is conducted to compare the generated tags of each ablation result. We also perform a statistical analysis to find out the global characteristics of the collected emotion tags. Emosical would enable expressive synthesis and tagging of the speech and singing voice in the musical theatre domain in future research. Emosical is publicly available at <https://github.com/gillosae/emosical>.

1 Introduction

As a fundamental aspect of human experience, recognizing emotion requires a depth of understanding in the multi-domains. With the advances in deep learning techniques, various approaches delve into detecting emotion through expressed emotion from different modalities (Poria et al., 2017). Studies aim to detect emotion through the domain of text (Pang et al., 2008; Socher et al., 2013), speech (Satt et al., 2017; Akçay and Oğuz, 2020), and facial expressions (Zafeiriou et al., 2015; Li and Deng, 2020). Furthermore, approaches to integrate multiple modalities (Zadeh et al., 2017; Lian et al., 2023) have been introduced.

While those techniques have advanced the understanding of human emotions in different domains, emotion recognition still remains a challenge. First, it is hard to capture ground-truth emotion, which is expressed through both linguistic and non-linguistic elements. This complexity requires multi-modal data to capture the emotional context fully, but integrating and synchronizing such diverse inputs presents technical difficulties (Baltrušaitis et al., 2018). Although some models are trained using recorded multi-modal datasets (Busso et al., 2008), creating these datasets is resource-intensive and lacks the scalability and diversity needed to fully capture the complexity of human emotions.

Additionally, human emotions are complex and subtle, with the inherent ambiguity of expressed emotional cues and variations in cultural expressions (Russell, 2003). Thus, existing models struggle to recognize emotions from expressed features at a fine-grained level, mostly clustering emotions into coarse categories (Ververidis and Kotropoulos, 2006). We suspect that knowledge of the underlying personality or situation makes it easier to infer one’s emotion more accurately and finely, which is a capability missing in most datasets.

We propose that *theatre* is a particularly effective medium for addressing these challenges. Theatre naturally encompasses multi-modal emotional expressions since actors and directors use various techniques such as dialogue, music, lighting, and stage design to communicate a wide range of emotions to the audience (Artaud, 1938). These emotions are typically expressed with an emphasis for greater impact (Stanislavski, 1948), making it easier to capture and analyze them effectively. Also, the theatre has the unique property of containing a ‘script’ for the play, which enables the inference of each character’s storyline and personality. In this view, theatre contains a diverse range of expressed emotions conveyed through multiple modalities

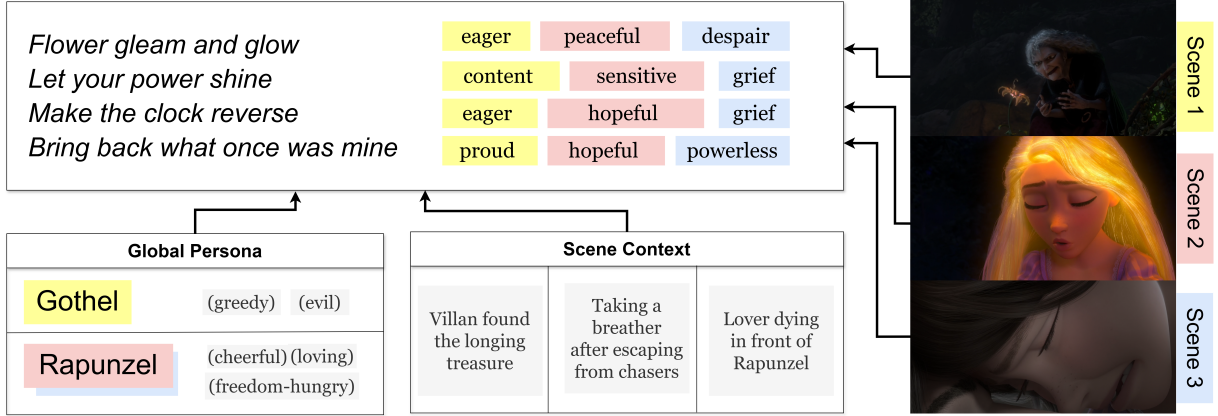


Figure 1: Emotion inferring process of ‘Healing Incantation’ in ‘Tangled.’

that are deeply rooted in each character’s narrative context, making it a suitable medium for emotion research.

In response, we build Emosical, an emotion-annotated theatre dataset. Specifically, we select *musical theatre* for our dataset in order to contain singing samples. There is no theatre dataset specifically curated for machine learning purposes. It might be due to theatre’s inherent complexity, which combines spoken natural language, audio, and visual elements, making it hard to create complex recordings manually. Therefore, we design an annotation pipeline that infers emotion from the narrative by leveraging the script from each theatre.

Our annotation pipeline aims to analyze and annotate the narrative’s emotions as automatically as possible. Thus, we crawl musical theatre films and apply them as pipeline input. We require theatre film video with the timestamp and speaker identity aligned SRT file as the inputs. In the pipeline, we feed the character, text, global persona, and context of the dialogue and song track into an LLM to obtain the corresponding emotion tag per sample.

Our annotation pipeline captures emotion effectively by capturing the narrative context through fed inputs. In musical theatre, some prominent songs tend to be reprised and presented multiple times throughout the act, conveying different emotional nuances. Figure 1 shows an example; the number ‘Healing Incantation’ of ‘Tangled’ is the case, which emerges once at an introductory moment, once at a highly-elated scene, and lastly at the ending part of the movie. In the figure, the three reprised songs have distinctly different emotions, clearly indicating diverse emotional expressions. ‘Healing Incantation’ is reprised triple times in the movie. Even though they all have the same lyrics

our tagging pipeline tags corresponding singing emotions well by inferring emotions from the context and character’s persona. Through our pipeline, even though the song consists of the same lyrics, the resulting tags are different due to different scene contexts fed to obtain the tags.

This pipeline has another advantage that it applies to building some types of emotion-paired datasets, which are hard to develop. For instance, there is no public singing data annotated with emotions aside from Livingstone and Russo (2018). Unlike speech, singing demands attention to nuances like pitch, tone, and emotional delivery (Sundberg, 1987). Even though singing is a powerful medium that conveys expressive emotional expression, it is hard to record a singing voice sample with specific emotions manually. However, our approach enables emotional inference on any kind of data, including singing - under the condition that the identity’s background context is given.

Through text, video, and vocal-aligned samples with rich emotion annotations, we aim for Emosical to be primarily used to understand the relationship between theatre’s multi-modal characteristics and emotions. Additionally, we hope the dataset could also be used for tasks such as emotion tagging and emotional synthesis for each modality; a baseline system for the former is developed and evaluated as an example. To this end, Emosical provides detailed and fine-grained emotion annotation for every short segment. Unlike emotion-annotated datasets (McKeown et al., 2012; Nojavanasghari et al., 2016), which tend to annotate emotions in broad groups over long segments, our dataset with dense emotion tags annotated to short data samples allows for more precise and temporal studies of emotional changes.

Dataset	Modality				Annotation		Dataset Size			
	Text	Speech	Singing	Video	Identity	Emotion	#Movies	#Samples	#Speakers	#Tags
ESD (Zhou et al., 2022)	✓	✓				✓	-	350	20	5
EmoDB (Burkhardt et al., 2005b)	✓	✓			✓	✓	-	535	10	7
RAVDESS (Livingstone and Russo, 2018)	✓	✓	✓	✓	✓	✓	-	2452	24	8
IEMOCAP (Busso et al., 2008)	✓	✓		✓		✓	-	10039	10	9
CMU-MOSEI (Zadeh et al., 2018)	✓	✓		✓	✓	✓	-	23453	1000	
MELD (Poria et al., 2019)	✓	✓		✓	✓	✓	-	13000	260	7
SEMAINE (McKeown et al., 2012)		✓		✓	✓	✓	✓	80	4	5
OMG-Emotion (Barros et al., 2018)	✓	✓		✓		✓	✓	7371		7
EmotiW (Dhall et al., 2023)		✓		✓		✓	✓	1809		7
VocalSet (Wilkins et al., 2018)	✓			✓			-	3560	20	-
OpenSinger (Huang et al., 2021)	✓			✓			-	43075	93	-
M4Singer (Zhang et al., 2022)	✓			✓			-	20942	20	-
MPII-MD (Rohrbach et al., 2015a)	✓			✓			94	68337	-	-
MovieQA (Tapaswi et al., 2016)	✓			✓			140	6771	-	-
V2C-Animation (Chen et al., 2022)	✓	✓		✓	✓	✓	26	10217	153	8
Cognimuse (Zlatintsi et al., 2017)	✓	✓		✓	✓	✓	13	11109		-
Emosical (ours)	✓	✓	✓	✓	✓	✓	20	27294	261	128

Table 1: Comparison of various open-source datasets with Emosical.

We summarize our contributions as follows:

- We present Emosical, the first open-source musical film dataset with emotion annotations.
- Our dataset contains singing voice samples with identity and emotion annotation, which most existing singing voice dataset lacks.
- We build an automatic emotion tagging pipeline that utilizes the musical film script to infer the background story of the singer.
- We provide a baseline tagging model trained on our dataset, which predicts emotion labels from the speech and singing voice signals.

2 Related Works

Table 1 summarizes several key characteristics of the related datasets and compares them with ours.

Multimodal Emotion Recognition Datasets. A multitude of datasets have been developed for multimodal emotion recognition by integrating various modalities such as video, audio, and text. The IEMOCAP (Interactive Emotional Dyadic Motion Capture) dataset (Busso et al., 2008) includes audiovisual data from actors performing scripted and improvised scenarios designed to elicit specific emotions. Similarly, the CMU Multimodal Opinion Sentiment and Emotion Intensity (CMU-MOSEI) dataset (Bagher Zadeh et al., 2018) offers emotion-annotated video segments from YouTube videos. The Multimodal EmotionLines Dataset (MELD) (Poria et al., 2019) consists of dialogue sequences

from the TV series annotated with emotion labels, including synchronized video, audio, and textual data, appropriate for emotion recognition in conversational contexts.

The SEMAINE database (McKeown et al., 2012) contains audiovisual recordings of interactions between humans and an avatar designed to elicit emotional responses, including high-quality audio and video data with continuous annotations for emotion dimensions such as arousal and valence. The RÉCital Corpus for Multimodal Emotion Analysis (RECOLA) dataset (Ringeval et al., 2013) includes audio, video, and physiological data recorded from participants during team working tasks, annotated for continuous emotion dimensions, making it a comprehensive resource for studying dynamic emotional expressions. The OMG-Emotion dataset (Barros et al., 2018) contains video recordings of people reacting to predefined stimuli, with annotations for continuous emotion dimensions, providing continuous perspectives on emotional responses.

The Audio-Visual Emotion Challenge (AVEC) (Ringeval et al., 2019) provides datasets, including synchronized video and audio recordings annotated with emotional states. The Emotion Recognition in the Wild (EmotiW) challenge (Dhall et al., 2023) similarly features datasets capturing spontaneous expressions of emotions in real-world environments, including video, audio, and textual data, suitable for developing emotion recognition systems that work in naturalistic settings.

Speech Emotion Recognition Datasets. The Emotional Speech Database (EmoDB) (Burkhardt et al., 2005a) includes recordings of professional actors who simulated seven different emotions. The Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) (Livingstone and Russo, 2018) contains actors vocalizing two lexically matched statements. Each expression is labeled for one of eight emotional states, offering a rich dataset for both speech and song emotion recognition. The Speech Emotion Recognition (ESD) dataset (Zhou et al., 2022) is a multilingual dataset containing emotional speech data, which provides a diverse set of emotional speech samples for cross-lingual emotion recognition studies.

Film Datasets. Film-specific datasets offer extensive resources for analyzing the complex interplay of visual, auditory, and narrative elements in movies. The V2C-Animation dataset (Chen et al., 2021) focuses on animated videos and includes video clips with corresponding textual descriptions. The MPII Movie Description Dataset (Rohrbach et al., 2015b) is a large-scale collection of movie clips annotated with natural language descriptions. MovieQA (Tapaswi et al., 2016) is a dataset designed to test story comprehension through question-answering tasks based on movie plots, integrating visual, textual, and auditory information to evaluate narrative understanding. Cognimuse (Zlatintsi et al., 2017) is a comprehensive dataset that includes multimodal annotations (audio, visual, and textual) of Hollywood movies, with detailed annotations for scene boundaries, character interactions, and emotion.

3 Dataset

Overview. Table 2 shows the overall statistics of Emosical. It comprises 27294 samples, totaling 20 hours, from 20 distinct musical films, including animation musicals, musical movies, and theatre recordings. Each sample is a tuple of {vocal audio, video, text, character} accompanied by annotated emotion tags. Vocal audio samples include 21040 speech and 6254 singing samples. The overall structure of the dataset is shown in Figure 2. The dataset collection and the annotation process are shown in Figure 3.

Dataset Structure. Given that the movies are not freely available, we offer automated scripts to process the data and links for downloading each film.

Statistics	Count
Total # of films	20
Total # of video/audio segments	27294
The average length of segments	2.66s
Total # of distinct speakers	479
Total # of speech samples	21040
Total # of singing samples	6254
Total # of words in scripts	162277
Total # of unique words in scripts	15610
Total # of emotion tags	128

Table 2: Summary of Emosical dataset statistics.

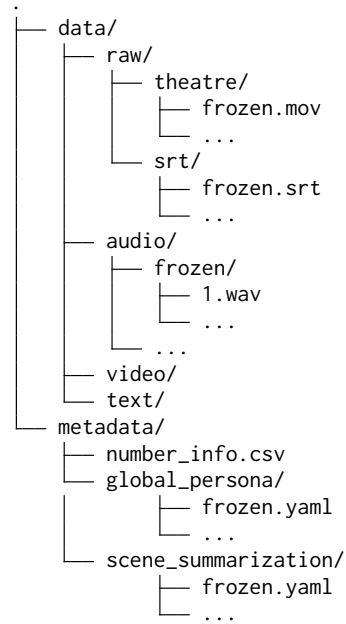


Figure 2: Structure of Emosical.

We provide subtitle files (in SRT extension; throughout the paper, we will denote them as SRT files) that contain characters and text aligned to the movie. These SRT files are different from the publicly available ones and have more precise timestamps. We also provide metadata that contains emotion and vocal type per sample, as well as noisy audio recordings, which will be cleaned with an enhancement model. To use the dataset, users will first place movie video files in the `data/raw/theatre` directory and place them along with corresponding subtitle files in the `data/raw/srt` directory. Then, users can run the provided code, which transforms the dataset into the compiled form with additional directories, including `data/audio/`, `data/video`, and `data/text`. We also provide metadata that shows which clip corresponds to which scene so users can access individual video/audio clips from specific scenes of each movie.

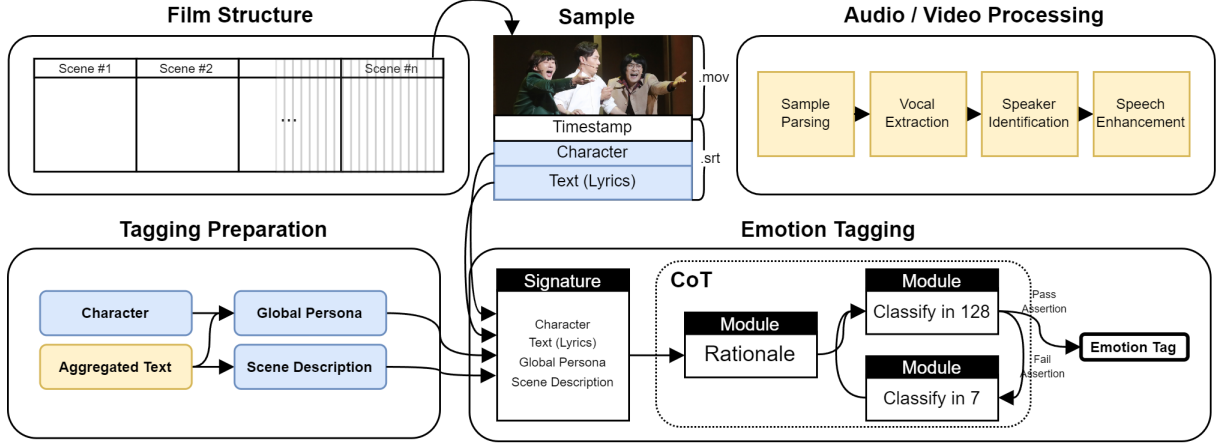


Figure 3: Dataset collection pipeline of Emosical.

3.1 Dataset Creation

We aim to develop a dataset suitable for multimodal emotion analysis of musical theatre. Additionally, we aim for our dataset to be applicable for multiple purposes, including voice synthesis and tagging tasks utilizing our audio dataset. To suit these purposes, we construct a data generation pipeline that is especially focused on audio processing. The pipeline can be automatically run when raw video files, prepared SRT files, and metadata are given.

Timestamp Correction. Our dataset leverages the publicly available original SRT files. SRT files contain the sequential number of current utterances, starting and ending points in the video timeline, and corresponding text. However, as they are for subtitles, their timestamps are not sufficiently precise for our purposes, e.g., splitting the video and audio with timestamps. Therefore, we need to precisely tune the timestamp and text of each SRT segment to contain the starting and ending point of each utterance properly. To achieve this, we first utilized a transcription alignment tool Gentle (Hawkins et al., 2024) to create the rough timestamps. Then, we manually post-processed those to ensure accuracy and to set each sample’s length to be within 10 seconds. The provided SRT files are post-processed ones.

Video/Audio Segmentation. For each video, we utilize the MoviePy library (Zulko et al., 2024) to parse samples according to the starting and ending timestamps in its corresponding SRT file. We also extract the corresponding audio data and convert the stereo audio into mono by summing the left and right channels. These processings are done with

the ffmpeg toolkit (Tomar, 2006).

Vocal Isolation and Enhancement. Considering the potential audio applications such as voice synthesis and tagging tasks, it is desirable to have clean voice signals without any background noise. Therefore, before segmenting the audio, we separate all the voice signals from the remaining using the open-source Demucs model (Rouard et al., 2023). After the segmentation, we perform the following two extra steps. First, we manually check for noisy audio files. For noisy audio, we further remove the background noise by employing the background noise reduction model, SGMSE (Richter et al., 2023). Second, we filter out audio clips that do not satisfy the following requirements: (i) no overlapping speech and singing voices, (ii) no residual noise, and (iii) negligible processing artifacts. We manually exclude these segments since we aim to curate an automatically processable dataset.

Speaker Identification. After collecting video clips, audio segments, and their corresponding text, each is annotated with the corresponding speaker’s identity and matched against the SRT file. This is useful not only as an additional feature of the dataset but also for the emotion annotation pipeline; it helps large language models (LLMs) effectively distinguish each character and recognize the emotional nuances conveyed through the storyline; refer to Section 3.2 for the details. To identify speakers, we first select representative audio samples for each main character. Then, we use a pre-trained speaker diarization model and assign a speaker with the highest similarity to each speech/singing segment. Note that our audio samples include both speech and singing from the same speakers. This

is called a *cross-genre* setup, which is known to be challenging, especially when singing voices are involved (Li et al., 2022). We used WeSpeaker (Wang et al., 2023), the only publicly available pre-trained cross-genre model. However, it should be noted that the model was trained on a dataset in the Chinese language (Li et al., 2022), potentially leading to inaccurate estimations for the English films. Therefore, to ensure the accuracy of the speaker annotation, we manually checked each annotation and fixed it if necessary. Through this data collection pipeline, we finally gather a triplet of {vocal, text, speaker} for audio data. In the metadata, each voice segment is annotated with binary data that distinguishes singing voice segments from speech.

3.2 Emotion Annotation

As we collected the {video, audio (vocal), character, text} data through the aforementioned pipeline, we now aim to annotate the emotion for each sample. To achieve this, we focus on the storyline of the theatre to further infer the emotion of the character line by line. Note that this approach is similar to Bhattacharya et al. (2023), which generated story descriptions to handle downstream tasks. We leverage full text from the SRT file and feed it to a LLM. Specifically, the annotation process integrates four key components for each character: (i) global persona, (ii) scene summarization, (iii) visual description, and (iv) the text of each sample.

Global Persona. For each character, we define a global persona that encapsulates their overarching traits and narrative role. We obtain the global persona by feeding the whole script into the large language model and prompting it to summarize the character’s overall storyline and personality. As the latter ablation study shows, this is crucial for understanding the emotional context of their actions and expressions throughout the movie.

Scene Separation and Summarization. We separate the entire text into multiple scenes to effectively summarize the context of each section of the film. Then, we feed the aggregated text of the scene into LLM to obtain a summarized story. Summarizing the scene helps infer the characters’ emotional state when they commence certain utterances, thereby guiding the LLM in generating accurate emotion tags afterward. Overall, feeding global persona and context summarization helps LLM follow the storyline and understand the character’s personality throughout the musical theatre.

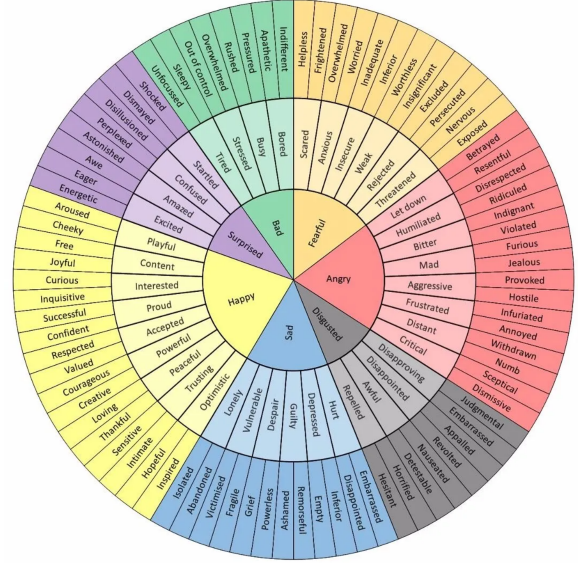


Figure 4: 128 emotion wheels with 7 primary, 40 secondary, and 81 tertiary emotions.

As a result, it aids LLM in successfully guessing the character’s emotional state when saying specific text or singing specific lyrics.

The Emotion Wheel. Most emotion-annotated datasets categorize emotions into 4 to 8 groups (Zhou et al., 2022; Burkhardt et al., 2005a; Livingstone and Russo, 2018). However, it is desirable to use a more sophisticated taxonomy of emotion labels to capture the nuanced emotions conveyed in the musical film. This motivates us to leverage the emotion wheel. The Plutchik emotion wheel (Plutchik and Kellerman, 2013) is developed to categorize human emotions based on the idea that distinct emotions can be mixed to create other emotions. We use the expanded version of Plutchik’s original emotion wheel. The “128 Emotion Wheel” is gradually structured with primary, secondary, and tertiary emotions to provide a more granular understanding of human emotional experiences (Roberts, 2024). These 128 emotions are sub-classes of the primary 7 emotions (‘angry,’ ‘disgusted,’ ‘sad,’ ‘happy,’ ‘surprised,’ ‘bad,’ and ‘fearful’), making each label suitable for primary emotion clustering, enabling easy comparison with other datasets. Also, diverse tags can enrich the input language when training the model for prompting purposes.

LLM Prompting with DSPy. With the character’s global persona, scene summarization, sample description, and text with the character ready at hand, we feed them with prompts into the LLM

(Chat-GPT 3.5 Turbo (Brown et al., 2020)) to generate emotion annotations for each line of the dataset.

We utilize DSPy (Khatab et al., 2023), a framework to optimize LLM prompts and weights with small training data. In the DSPy framework, we define the Signature, which outlines what information we provide to the LLM. Our Signature is defined as {character, text, visual description, scene context, global persona} to include all necessary details on a full picture of the scene and characters. We manually created 50 training samples consisting of Signature elements and the ground-truth emotion tag with its rationale.

Then, we proceed to fine-tune our LLM. The fine-tuning process involves the chain-of-thought (CoT) (Wei et al., 2022) method. Specifically, our CoT uses 3 DSPy modules. The first module asks LLM to generate a rationale about the situation that the speaker encountered based on the input Signature. This guides the LLM in following a concrete reasoning process. Next, the second module makes LLM classify the emotion based on the former output rationale, which leads to more accurate and contextually relevant tags.

However, our LLM sometimes predicts an emotion tag outside the 128 emotion wheel due to the unconstrained nature of the LLM. To mitigate this, we apply DSPy Assertion (Singhvi et al., 2024), which poses constraints to guide the LLM’s output. If the emotion tag doesn’t meet the assertions, DSPy.Suggest triggers the backtracking process. This LLM re-evaluates the input context to generate a new emotion tag. However, when the backtracking exceeds the pre-defined maximum number, the third module is introduced, prompting the LLM to classify the emotion into seven primary emotions. Lastly, we prompt the LLM to classify the emotion from the sub-emotions of the primary emotion. This fine-tuned LLM significantly exceeds the accuracy of the untrained baseline LLM.

3.3 Data Split

We provide additional metadata for the dataset split for development and test purposes. We split the 20 films into 16 and 4; the latter is used only for tests. The 16 movies are further split, where random 80% of each movie is used for the development while the remaining are used for the test. This split allows us to evaluate the models both in *seen* (in-distribution) and *unseen* (possibly out-of-distribution) film.

	AUC	Precision	Recall	F-score
Ours	0.690	0.739	0.690	0.710
Speech-based	0.173	0.355	0.173	0.184
Text-based	0.286	0.635	0.286	0.338

Table 3: Emotion-tagging pipeline vs. other models.

	Base		Fine-tuned	
	Train	Test	Train	Test
BootstrapFewShot	43.86	58.82	31.58	82.35
+ RandomSearch (ours)	43.86	58.82	45.61	85.29

Table 4: Baseline LLM vs. Fine-tuned LLM.

4 Evaluation and Analysis

4.1 Emotion Tagging Pipeline

We evaluate the effectiveness of our emotion-tagging pipeline versus other baseline models. For comparison with other emotion-tagging baselines, we change our pipeline to classify each sample into seven emotions (anger, disgust, fear, joy, neutral, sadness, surprise). The evaluation is performed on a human-annotated dataset we created from a short musical theatre film. We perform evaluation on the handcrafted dataset because our pipeline requires global persona and context input, which is only available from the full theatre script. We compare our pipeline with publicly available speech-based (Hartmann, 2022) and text-based (R-F, 2022) pre-trained models in Table 3.

4.2 LLM Finetuning

In the emotion-tagging pipeline, we fine-tune LLM (GPT-turbo 3.5), leveraging DSPy with human-annotated training data consisting of 50 training and 200 test samples. The final pipeline leverages chain-of-thought and BootstrapFewshotWithRandomSearch as a teleprompter. Fine-tuned LLM leveraging our pipeline significantly exceeds the baseline LLM, as shown in Table 4.

4.3 Ablation Study

To validate the usefulness of each component fed to an LLM in the pipeline, we conduct an ablation study by bypassing each component. Our proposed model feeds global persona, previous context, singer, and lyrics to LLM to bring out the final emotion tag. We bypass each step to compare the usefulness. Ablations are of four groups: Ablation1 (Text), Ablation2 (Text + Character), Ablation3 (Text + Character + Scene Summarization),

	AUC	F-score	Precision	Recall
Singing	0.598	0.219	0.146	0.178
Speech	0.573	0.153	0.225	0.221
Both	0.611	0.129	0.120	0.167

Table 7: Voice emotion tagging results with different dataset configurations.

2017) with a OneCycleLR learning rate scheduler (Smith and Topin, 2019). The performance of the baseline tagging model is reported in Table 7.

5 Conclusion

We presented a novel dataset, Emosical, the first open-source multimodal dataset specifically curated for musical films with comprehensive emotion annotations. By integrating video, audio, text, and character identity with emotion tags derived from a detailed narrative context, Emosical provides a rich resource for advancing research in emotion recognition, synthesis, and tagging in the musical theatre domain.

Our dataset leveraged a novel annotation pipeline, incorporating global persona, scene context, visual description, and dialogue or lyrics to generate nuanced emotion tags using a large language model (LLM). Through statistical analysis and a series of ablation studies, we demonstrated the effectiveness of our tagging scheme. Our subjective evaluations further validated the precision and reliability of our annotations.

Additionally, we proposed a baseline tagging model for emotion recognition in singing voices, setting a foundation for future research in this area. Emosical opens up new avenues for exploring the interplay between various modalities in conveying emotions and can serve as a valuable resource for developing more emotionally resonant systems.

Future work may include expanding the dataset to encompass more diverse genres and languages, refining the emotion tagging pipeline, and exploring its applications in various multimodal emotion recognition and synthesis tasks. We believe Emosical can contribute to further research in multimodal understanding of emotion expressions in musical theatre.

6 Limitations

Several limitations should be noted for future work and improvements in Emosical.

- *Diversity of Source Material.* The dataset is currently limited to 20 distinct musical films, which may not fully capture the wide range of emotional expressions and styles present across different musical theatre productions. So, we plan to expand the dataset to include more films, as well as musical recordings from live theatre performances to enhance the generalizability of models trained on this data.
- *Manual Intervention During Data Processing.* While we automated much of the data processing pipeline, certain steps, such as verifying SRT timestamp accuracy and checking speaker diarization results, still require human intervention. Further refinement and automation of these processes would improve the efficiency and scalability of dataset creation.
- *Emotion Tagging Granularity.* Although we employ an extensive set of 128 emotion tags based on the emotion wheel, this granularity can lead to challenges in ensuring consistent and accurate tagging across samples. In some cases, the subtleties between closely related emotions might be difficult to distinguish, leading to potential ambiguities.
- *Dependency to LLMs.* Our emotion tagging relies on LLMs’ capabilities. While these models offer sophisticated natural language understanding, they are not infallible and can sometimes generate inaccurate or inconsistent tags, especially when faced with highly nuanced emotional expressions.
- *Bias and Representation.* The selected musical films may reflect certain cultural biases and predominantly represent Western musical theatre traditions. This limits the applicability of the dataset for studying emotions in a more global and culturally diverse context. Future efforts should include a more diverse range of films from various cultures and languages.
- *Temporal Context and Dynamics.* While the dataset includes scene summarization and global persona information, capturing the full temporal dynamics and evolution of emotions over longer periods within the films remains a challenge. Future work could focus on better integrating temporal context to understand how emotions develop and change over time.
- *Quality of Vocal Isolation.* We observed that the quality of isolated vocals varies, particu-

larly when background music or noise is complex. Improving vocal isolation methods or exploring alternative approaches could enhance the clarity and usability of the audio samples.

- *Evaluation Metrics and Human Subjectivity.* Emotions' subjective nature indicates that human evaluations can vary, impacting the consistency of our MOS tests and other evaluation metrics. Developing more objective and standardized evaluation methods would be beneficial for assessing the quality of annotations.

Addressing these limitations in future iterations of Emosical will help create a more robust and comprehensive dataset, ultimately contributing to the advancement of multimodal emotion recognition and synthesis research in the domain of musical theatre.

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