
Sentiment-based Music Recommendation

By: Team 10

Table of Contents

- I. Project Introduction
 - II. About the Team
 - III. Goals & Novelty
 - IV. Architecture
 - V. Dataset
 - VI. Model
 - VII. Music Recommendation
 - VIII. Accomplishments
 - IX. Limitations
 - X. Future Direction
-

Project Introduction

- Topic
 - Music Recommendation based on KakaoTalk Status Message
- Motivation
 - Prevalence of Social Media & Messaging Application Communities
- Methods
 - Sentiment Analysis
 - Cosine Similarity on Softmax Probabilities

About the Team

오세훈

Role(s):
Project
Architecture &
Model Dev

김동락

Role(s):
Dataset
Acquisition &
Augmentation

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Role(s):
Team Presenter

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Role(s):
Model Dev

윤재식

Role(s):
Model Dev

Goals & Novelty

- Develop a system to accurately recognize emotion and recommend songs to the appropriate emotion
 - Provide the system to users through a web interface
- Novelty
 - Recommends songs based on the distribution of probability factors for each emotion label
 - Through the labeling of songs and system fine-tuning based on user feedback, song recommendations were made standardized

Architecture: Model

- KoELECTRA
- Fine-tuned on our Dataset

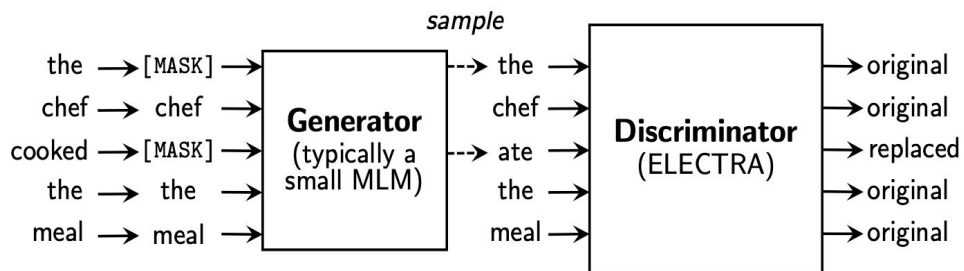


Figure 1. Overview of Replaced Token Detection

Architecture: Web Application

- Flask-based EC2 Server
- Runs a trained model to perform sentiment analysis

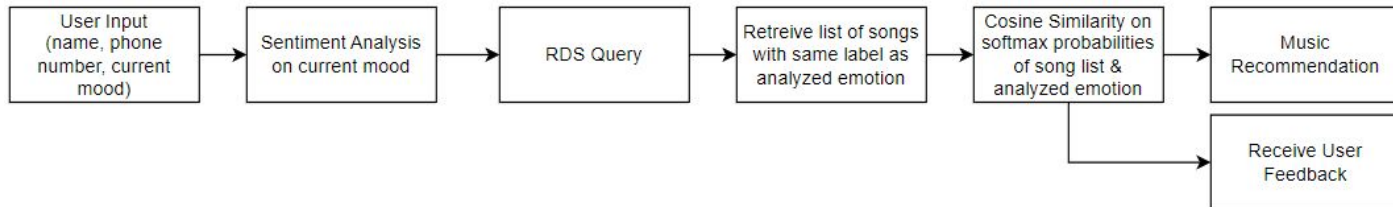


Figure 2. High level Overview of Application Workflow

Architecture: Web Application

- Frontend
 1. User inputs personal information and current mood
- Backend
 1. Fine-tuned trained model performs sentiment analysis on inputted text
 2. Predicts user's emotion probability distribution
 - i. 7 predefined emotions
 3. RDS-based DB stores predicted emotion distribution based on lyrics of ~7,500 songs
 4. Retrieve songs from DB based on user's predominant emotion distribution
 5. Recommend most similar song to user
 6. Receive feedback from user

Dataset

- AI-Hub (*training dataset*)
 - Emotions in Continuous Korean Conversations Dataset
(한국어 감정 정보가 포함된 연속적 대화 데이터셋)
 - Emotions in Discrete Korean Conversations Dataset
(한국어 감정 정보가 포함된 단발성 대화 데이터셋)
 - Audio of Korean Conversations for Sentiment Analysis Dataset
(감정 분류를 위한 대화 음성 데이터셋)
- Melon (*music dataset*)
 - Collection of playlists from Melon's 5/15~5/21 "인기" chart
 - Acquisition method: Web Crawler

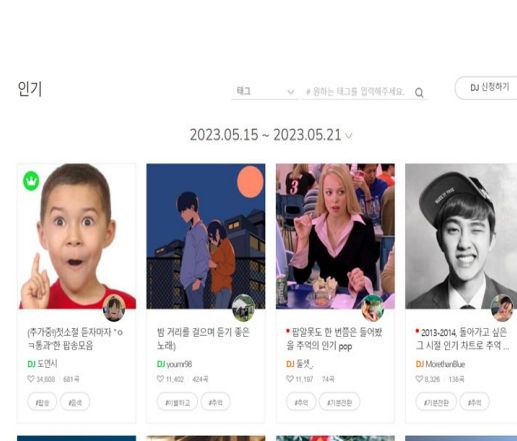


Figure 3: Melon 5.15~5.21 Playlist Screenshot

Dataset: Preprocessing

Training Dataset

1. Compiling the three dataset files into one file
2. Language Normalization
 - a. English → Korean
3. Typo Correction
 - a. ex) ㅈ립 → 중립
4. Label Normalization
 - a. Prevent data skewing
 - b. Least occurring label: 9,697 entries
→ 9,000 random entries for all labels

대화문	상황
개를 예쁘	disgust
지금도 그	disgust
맞아. 무기	sad
오늘이 발	sad

dialog #	말파	감정
5	예. 전화! 사무실에서 뭐지 일러나! 감정을 연이 얼마나 안좋은데!	분노
	그럼 직접출연하는 난 얼마나 안좋은지? 안그래? 보면 꼭... 저 생각만 하고.	혐오
	손님 왔어요.	중립
	손님? 누구?	중립
	올라요. 팀장님 친구래요.	중립
	내 친구? 친구 누구?	중립
	그걸 내가 어떻게 알아요!	분노

Sentence	Emotion
언니 동생으로 부르는게 맞는 일인가요..??	공포
그냥 내 느낌일뿐겠지?	공포
아직너무초기라서 그런거죠?	공포

Figure 4. Dataset Before Preprocessing

행복	슬픔	공포	중립	분노	혐오	놀람
9000개	9000개	9000개	9000개	9000개	9000개	9000개

Figure 5. Number of Entries per Label

Dataset: Preprocessing

Music Dataset

1. Exclude lyrics that contain English words not present in trained data
2. Treat 4 lines of lyrics as 1 sentence
 - a. ex) 아침에 일어나 너에게 / 짧은 인사를 보낸다 / 아무리 멀리 떨어져 있어도 / 나는 널 생각하고 있어 = 1 sentence
3. Emotion Probability for ALL sentences in a song calculated then averaged

lyric label
아침에 일어나 너에게 / 짧은 인사를 보낸다 / 아무
도 / 너를 떠올린다면 씩씩한 / 표정 할수있어 / 알
want to be with you / 우 우 우 / My number 1 ,
도 / 나는 환하게 웃을거야 / 혹시 오늘 너에게 / 서러
게 해 / My number 1 My only one / 때로는 지쳐 올

	A	B	C	D	E	F	G	H	I	J
1	title	lyric	label	행복	슬픔	공포	중립	분노	혐오	놀람
2	고맙소	이 나이 먹 행복		0.537855	0.454241	0.000305	0.00054	0.004025	0.002825	0.000209
3	편지	달이 뜰 때 슬픔		0.49822	0.501137	0.000152	0.000174	0.000157	7.79E-05	8.20E-05
4	나의 모든	우울해도 슬픔		0.02432	0.794013	0.000463	0.000548	0.175434	0.005101	0.000121
5	사랑이 사	여쨌면 우 슬픔		0.090752	0.856995	0.005034	0.006738	0.01828	0.017018	0.005183
6	널 바라다	우연히 너 슬픔		0.114598	0.796604	0.00037	0.000285	0.002509	0.085415	0.000219
7	술	난 저기 술 슬픔		0.079557	0.604295	0.01724	0.007027	0.25132	0.035905	0.004656
8	이 마음이	침대에 누 슬픔		0.002843	0.893716	0.006244	0.000244	0.014482	0.002565	0.079907
9	진심이었	단관한 생각 슬픔		0.006884	0.866232	0.000253	0.000178	0.121975	0.004401	7.60E-05
10	가을밤에	머나먼 별 슬픔		0.378756	0.609598	0.000545	0.000596	0.00576	0.004514	0.00023

Figure 6. Preprocessing Steps Visualized

Model

- Utilized pretrained KoELECTRA model

Model Type	Pretrained Model	Training Dataset Size	Test Accuracy	Notes
Base Model	KoELECTRA-Base	13,500	57%	Bad performance & Overfitting
Fine-Tuned Model	KoELECTRA-Small	45,000	74%	Dropout & Regularization Applied

Figure 7. Table of Models Compared

Model: Performance

- Various means explored to improve performance of Base Model
 - Changed pretrained model size
 - Cross Validation
 - K-Fold ($k = 5$)
 - Overfitting Alleviation
 - Dropout
 - L2 Regularization

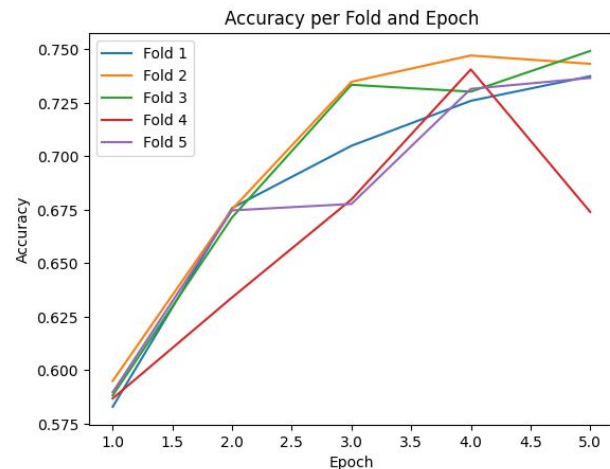


Figure 7. K-Fold Cross Validation Results of Fine-tuned Model

Model: Evaluation

- Base Model: Overfitting contributed heavily to its low performance
- Smaller pretrained model & Cross Validation
 - Dataset diversity
 - Improved generalization performance
- Dropout & L2 Regularization
 - Helped alleviate overfitting to the training data
 - Improved generalization performance

Model: Observations

- Large-scale pretrained models (KoELECTRA-Base) do not scale well with a small training dataset size
- Cross Validation, Dropout, L2 Regulation are useful methods to improve model performance
- Further improvement requires more data or different model architecture

Music Recommendation

- Utilizes Melon Dataset
 1. Sentiment Analysis is performed beforehand
- Recommendation produced by...
 1. Retrieve songs that have matching labels with the user input
 2. Cosine Similarity performed on the Emotion Probability values of songs & user text
 3. Recommend the most similar song

Music Rec: Performance

- Fundamental problem
 - Providing an objective (deterministic) result on a subjective topic
 - How can we tell if the recommendation was *actually* good?
- Solution: Gather user feedback
 - Received feedback from 100 users regarding the satisfaction of the recommendation
 - 1st model (30% of dataset): 34/100
 - 2nd model (Full dataset): 51/100
 - 3rd model (Fine-tuning w/ song data): 67/100

System in Action



Accomplishments

- Successfully utilized Sentiment Analysis to ultimately provide accurate music recommendations
- Our system provides music recommendations are correct >50% of the time
- Successfully created a Minimum Viable Product

Limitations

- Similarity in Emotion Probability values from user input & song does not guarantee that the user will like the song
- Nuances in emotions cannot be objectively analyzed
- Re-evaluation of current method of measuring similarity required
- Limited dataset → limited range of recommendable songs

Future Directions

- Usage of dedicated hardware
- Different means of measuring similarity
- Adjust the model architecture to better fit our use-case

Thank You

please feel free to ask any questions regarding our project