MovieMood
Movies from your Music, for your Mood

Will Dudek, Neil Prabhu, Josefina Ruggieri, Sumedh Shah, and Neta Tartakovsky
Problem

- Current recommendation engines use your **watching history** to make suggestions
- Multiple streaming platforms today result in **endless content** to choose from
- Average American spends **32+ hours/week listening to music**, and spend **hours curating playlists** for every mood

MovieMood uses **emotional experience** of listening to music to **recommend movies that match the mood** of your music playlist.
Impact & Market Opportunity

Music fanatics looking for entertainment

Unique emphasis on mood

Competitors don’t have this level of specificity
MVP Demo

https://moviemood.streamlit.app/
Oppenheimer (film)

FILM TITLE

PLOT SUMMARY

REPRESENTATIVE

Director: Christopher Nolan. Writer: Christopher Nolan. Actors: John Lithgow, Ciarán Hinds, and Tim Blake Nelson. Plot: In 1942, Dr. Oppenheimer is recruited to Los Alamos by President Franklin D. Roosevelt to lead the Manhattan Project. The team's goal is to create an atomic bomb, and the story follows their journey towards success.

RELEASE DATE

Scraping Wikipedia

Querying OMDb

Request:

https://www.omdbapi.com/{QUERY}

Result:

Title, Year, Rated, Released, Runtime, Genre, Director, Writer, Actors, Plot, Language, Country, Awards, Poster, Ratings, Metascore, imdbRating, imdbVotes, imdbID, Type, DVD, BoxOffice, Production, Website, Response
Modeling Approach
MovieMood Architecture

**Input**
- OMDB/Wikipedia Movie Data
- Spotify Song Features

**Content Layer**
- Music to Movie Genre Classification

**Mood Layer**
- Open AI Sentiment Scoring
- Music to Mood Classification

**Intermediate Nodes**
- Movies' Mood Vectors
- Song Mood Vectors
- Cosine Similarity

**Output**
- Top 5 Movie Recommendations

**Key**
- Datasets
- Modeling
- Model Output
Movie Sentiment Scoring (Step 1)

Prompt

Based on this movie plot “...” [and this genre “...”] rank each mood happy, sad, energetic, calm on a scale from 0 to 1

Open AI GPT 3.5

Output

To rank each mood (happy, sad, energetic, calm) on a scale from 0 to 1 based on the given movie plot, we need to analyze the emotions and atmosphere conveyed in the plot. Keep in mind that this is a subjective interpretation, and different individuals may assign different scores. Here’s one possible ranking:

- **Happy**: 0.1
  - The plot does not have a predominant happy mood. There are elements of adventure and excitement, but they are overshadowed by darker themes.
- **Sad**: 0.6
  - The plot contains sad elements, such as the death of characters and the loss of the sea people’s future. The overall mood leans towards melancholy.
- **Energetic**: 0.2
  - While there is some level of energy and action in the plot, especially during the conflicts and the search for pearls, the predominant mood is not highly energetic.
- **Calm**: 0.3
  - There are moments of calm, particularly during interactions with Syrene and the underwater scenes. However, the overall plot is not predominantly calm.

This ranking suggests that the plot has a somewhat sad and melancholic atmosphere with elements of action and adventure. The happy and calm moods are less prominent in this story. Please note that the emotional interpretation of a plot can vary from person to person, and these scores are based on one interpretation.
## Music to Mood (Step 2)

### Audio features from user’s playlist

<table>
<thead>
<tr>
<th>Song 1</th>
<th>Dance-ability</th>
<th>Acousticianess</th>
<th>Energy</th>
<th>Instrumentalness</th>
<th>Liveness</th>
<th>Valence</th>
<th>Loudness</th>
<th>Speechiness</th>
<th>Tempo</th>
</tr>
</thead>
<tbody>
<tr>
<td>HIGH</td>
<td>HIGH</td>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
<td>HIGH</td>
</tr>
<tr>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>HIGH</td>
</tr>
<tr>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
</tr>
<tr>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
</tr>
<tr>
<td>LOW</td>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
</tr>
</tbody>
</table>

### Mood Levels

- **Happy/Sad Model**
  - Happy
  - Sad

- **Energetic/Calm Model**
  - Energetic
  - Calm

---

**Input**

OMDB/Wikipedia Movie Data

**Music to Mood Classification**

**Mood Layer**

**Song Mood Vectors**
Music to Mood (Step 2)

Happy/Sad Model Results

<table>
<thead>
<tr>
<th>Model</th>
<th>F1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forest</td>
<td>0.824</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>0.803</td>
</tr>
<tr>
<td>GBM</td>
<td>0.780</td>
</tr>
<tr>
<td>SVM</td>
<td>0.780</td>
</tr>
</tbody>
</table>

Energetic/Calm Model Results

<table>
<thead>
<tr>
<th>Model</th>
<th>F1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forest</td>
<td>0.994</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>0.978</td>
</tr>
<tr>
<td>GBM</td>
<td>0.989</td>
</tr>
<tr>
<td>SVM</td>
<td>0.989</td>
</tr>
</tbody>
</table>

Example Songs’ Moods

<table>
<thead>
<tr>
<th>Song</th>
<th>happy</th>
<th>sad</th>
<th>energetic</th>
<th>calm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vampire - Olivia Rodrigo</td>
<td>MED</td>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
</tr>
<tr>
<td>Pink - Lizzo</td>
<td>HIGH</td>
<td>LOW</td>
<td>MED</td>
<td>LOW</td>
</tr>
<tr>
<td>WHAT'S POPPIN - Jack Harlow</td>
<td>MED</td>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
</tr>
<tr>
<td>Bad Blood - Taylor Swift</td>
<td>MED</td>
<td>LOW</td>
<td>MED</td>
<td>LOW</td>
</tr>
<tr>
<td>Daydreaming - Harry Styles</td>
<td>HIGH</td>
<td>LOW</td>
<td>HIGH</td>
<td>MED</td>
</tr>
</tbody>
</table>
**Bridging Music and Movies (Step 3)**

- vampire – Olivia Rodrigo
- Pink – Lizzo
- WHATS POPPIN – Jack Harlow
- Bad Blood – Taylor Swift
- Daydreaming – Harry Styles

![Diagram of music clusters and vectors](image-url)
Gathered soundtracks from Spotify for 110 high grossing movies.

Assign most prominent genre label to movie soundtrack songs.

Assigned each song within movie soundtrack same genre label.

**Examples:**
- *Star Wars Last Jedi:* Action/Sci-Fi → Sci-Fi
- *Magic Mike XXL:* Comedy/Drama → Comedy

**Training Data**

<table>
<thead>
<tr>
<th>IMDB Genre Tag</th>
<th># Songs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Action</td>
<td>606</td>
</tr>
<tr>
<td>Comedy</td>
<td>357</td>
</tr>
<tr>
<td>Drama</td>
<td>317</td>
</tr>
<tr>
<td>Horror</td>
<td>276</td>
</tr>
<tr>
<td>Romance</td>
<td>196</td>
</tr>
<tr>
<td>Sci-Fi</td>
<td>562</td>
</tr>
</tbody>
</table>
Music to Movie Genre (Step 4)

Audio features from user’s playlist

<table>
<thead>
<tr>
<th></th>
<th>Dance-ability</th>
<th>Acousticness</th>
<th>Energy</th>
<th>Instrumentalness</th>
<th>Valence</th>
<th>Loudness</th>
<th>Tempo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Song 1</td>
<td>HIGH</td>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
<td>HIGH</td>
<td>HIGH</td>
<td>HIGH</td>
</tr>
<tr>
<td>Song 2</td>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
</tr>
<tr>
<td>Song 3</td>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
<td>HIGH</td>
<td>LOW</td>
</tr>
<tr>
<td>Song 4</td>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
<td>LOW</td>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
</tr>
<tr>
<td>Song n</td>
<td>LOW</td>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
<td>HIGH</td>
<td>HIGH</td>
<td>LOW</td>
</tr>
</tbody>
</table>

Ensemble genre classification

1. Choose top probability genres

Filtered genre movies

Action
Comedy
Drama
Horror
Romance
Sci-Fi

Input
Spotify Song Features

Music to Movie Genre Classification

Content Layer
Top Movie Genres

4
### Model Results (AUC Weighted Scores)

<table>
<thead>
<tr>
<th>Model</th>
<th>Action</th>
<th>Comedy</th>
<th>Drama</th>
<th>Horror</th>
<th>Romance</th>
<th>Sci-Fi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forest</td>
<td>0.604</td>
<td>0.668</td>
<td>0.649</td>
<td>0.663</td>
<td>0.723</td>
<td>0.653</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>0.621</td>
<td>0.690</td>
<td>0.590</td>
<td>0.596</td>
<td>0.693</td>
<td>0.653</td>
</tr>
<tr>
<td>Light GBM</td>
<td>0.636</td>
<td>0.732</td>
<td>0.673</td>
<td>0.669</td>
<td>0.777</td>
<td>0.683</td>
</tr>
</tbody>
</table>

### Example Top Genre Distributions

- **Vampire (Olivia Rodrigo):**
  - Comedy (0.83)
  - Romance (0.95)
  - Drama (0.8)

- **Pink from Barbie (Lizzo):**
  - Comedy (0.99)

- **WHATS POPPING (Jack Harlow):**
  - Comedy (0.99)
  - Drama (0.66)

- **Bad Blood (Taylor Swift):**
  - Comedy (0.84)
  - Romance (0.59)

- **Daydreaming (Harry Styles):**
  - Comedy (0.98)
  - Drama (0.79)
MovieMood Architecture Recap

**Input**
- OMDB/Wikipedia Movie Data
- Spotify Song Features

**Content Layer**
- Music to Movie Genre Classification
- Top Movie Genres

**Mood Layer**
- Open AI Sentiment Scoring
- Music to Mood Classification
- Movies' Mood Vectors
- Song Mood Vectors

**Cosine Similarity**

**Output**
- Top 5 Movie Recommendations

**Key**
- Datasets
- Modeling
- Model Output
Model Validation
Model Validation (Technical)

Initial Approach:
4-class Classifier

Improved Approach:
binary classifiers + regularization + scaling
Model Validation (Qualitative)

- Validated that recommended movies matched the moods of the music accurately.

- Upbeat/Pop Music → Action, Comedy, Rom-Com Movies
- Chill Music → Horror Movies
MovieMood Beta Test

Recruited ~20 test users

User uploaded Spotify playlist to application

User received 5 movie recommendations

Provide feedback on movie recommendations and website

1. How likely are you to watch this movie (1-5)?
2. Did the recommendations line up with your mood (1-5)?
3. Provide feedback on making recs more personalized.
4. What other functionality would you like to see?

Incorporate feedback and tweak model as necessary
Beta Test Results

How likely are you to watch these movies? 3 / 5 → 4 / 5
How much did recommendations line up with mood? 3 / 5 → 4 / 5

Top User feedback:
1. Detect variance in my playlists
2. View movie details without “googling”
3. Recommend movies closer to my mood

Version 1

Version 2

Optional Filtering Drop Down:
- Movie genres
- Movie ratings
- IMDb score

More details
Based on a true story. After graduating from Emory University, Christopher McCandless abandoned his possessions, gave his entire savings account to charity, and hitchhiked to Alaska to live in the wilderness. Along the way, Christopher encounters a series of characters who shape his life.

Runtime: 148 minutes
Rated: R
IMDb Score: 8.1
Genre: Adventure, Biography, Drama
Directed by: Sean Penn
Leading Actors: Emile Hirsch, Vince Vaughn, Catherine Keener

Go to IMDb Page →
MovieMood User Testimonials

"These are all very popular movies that I have either watched or thought about watching and match my mood wheel."

"The website is SUPER easy to use, I love that you just drag and drop your file and it automatically generates the movie recs for you without you having to navigate anywhere else or even push a single button."

"Felt much more up my alley in the types of movies I would watch without looking at ratings."

"Amazing enhancements – The filters and regenerate are great additions. I’d love to use it next time I am looking for a movie!"

"My playlist is a bit diverse, so I do see the recommendations aligning with most of my playlist."
Challenges & Solutions

Challenges

- Bridging between datasets with no common features
- How to increase dimensionality for better quality recommendations?
- How to validate E2E model with no labelled dataset?

Solutions

- Mood Vectors
- Multi-layered application
- Test Cohort with Survey Data
Top Roadmap Items

Cross Music
Platform Integration:
Include platforms like Amazon Music, Apple Music, Spotify, Pandora, SoundCloud, etc.

Theme Layer:
Theme / key-phrase mapping from song lyrics to similar plot summaries

User Feedback Incorporation:
User feedback to improve future recommendations
We strive to **bridge the gap between music and movies**, and enrich users' emotional journeys, to create a uniquely **personalized** and **curated** multimedia experience.
Acknowledgements

- Capstone Instructors, Todd Holloway & Joyce Shen
- NYU Professor & Netflix Prize Winner, Chris Volinsky
- MIDS Alum, Max Eagle
Appendix

2. Moodify project