Dishing Up AI: Personalized Food Recommendations Using Customer Sentiment

Team:

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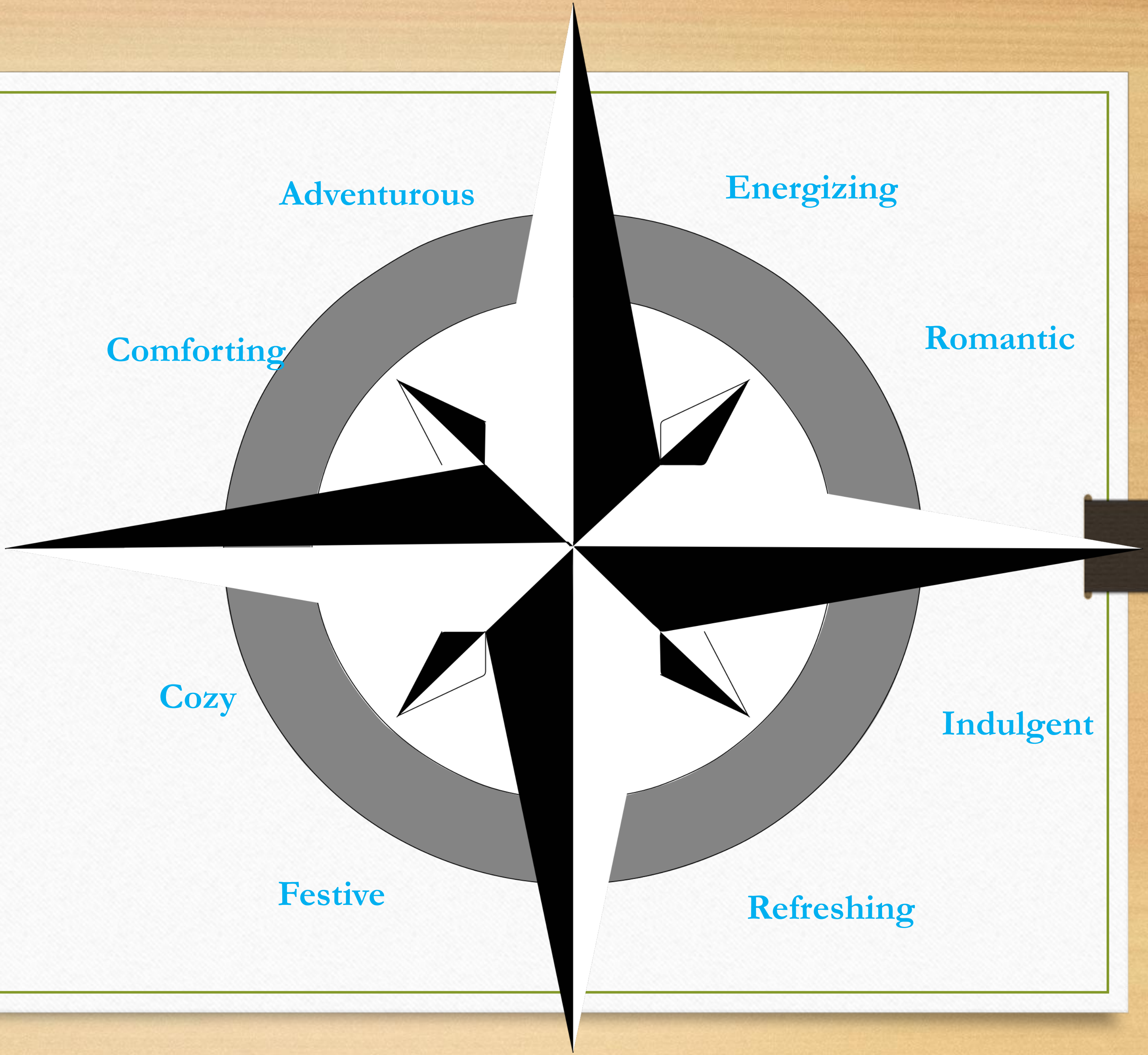


Executive Summary

Our solution uses a LLM, Sentence Transformer, and Zero-Shot Classifier Model along with an intuitive Gradio interface to deliver personalized restaurant recommendations based on users' moods for a unique dining experience.

Key Points

- Mood-based restaurant classifications
- Support for multiple models
- Interactive Gradio UI for seamless mood selection

This system redefines how users navigate dining options, providing unique, sentiment-driven suggestions for a memorable culinary experience.

Problem: The Challenge of Choosing Where to Eat

- Overwhelming options in unfamiliar places
- Diverse individual preferences
- Review overload making decisions tougher

Data Collection

- **Source:** Yelp Open Dataset
- **Join Tables:** Review, User, and Business
- **Fields:** Restaurant reviews, ratings, business attributes (e.g. cuisine, location)

Basic Data Preprocessing

- Remove missing values to ensure data integrity
- Encode data for model comparison compatibility
- Classify review using sentiment analysis

LLM Recommendation

Goal: Get a base a restaurant recommendation for our mood

Two Steps

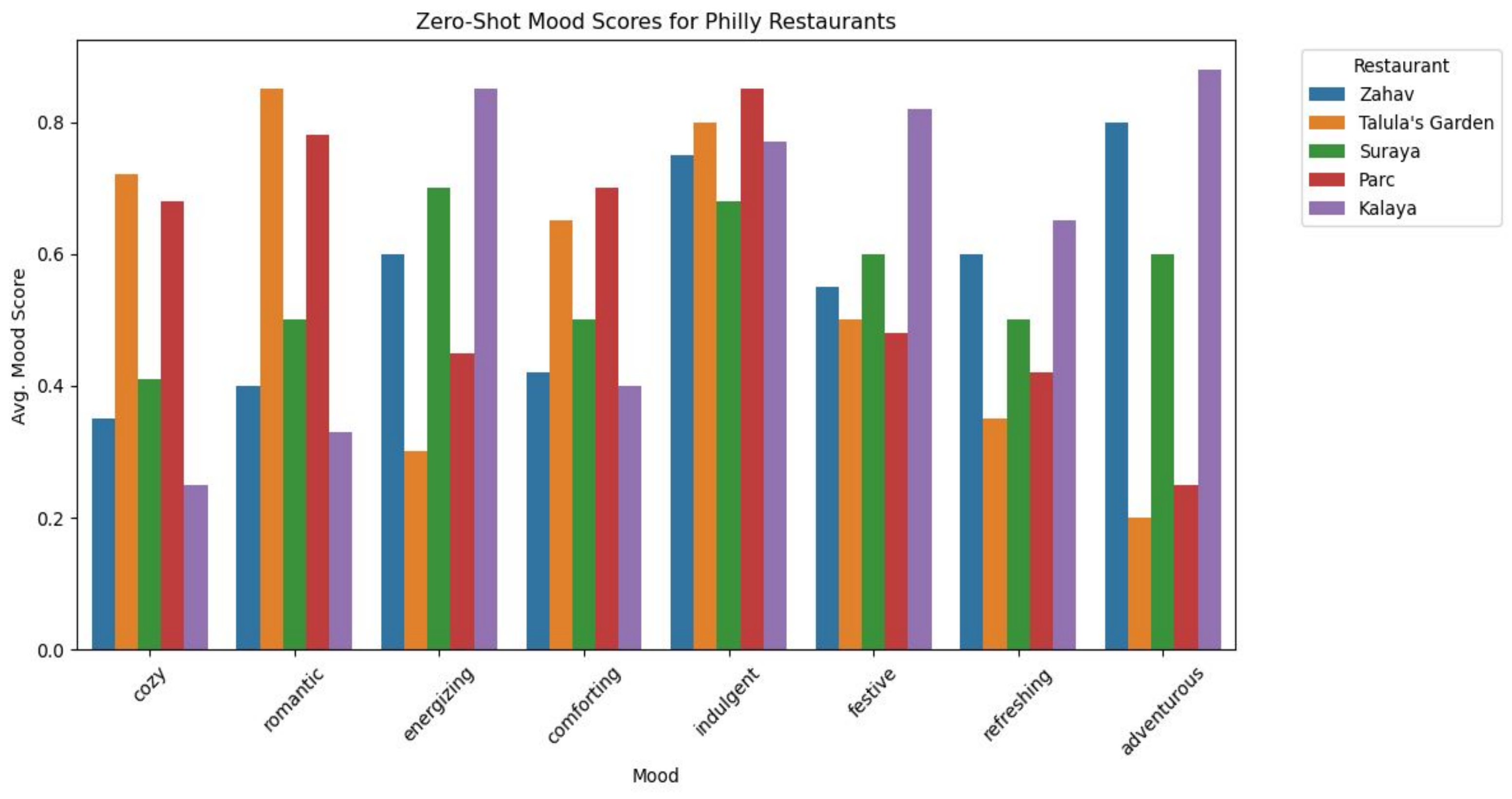
- Ask Gemini to recommend one unique, real restaurant in Philadelphia
- Ask Gemini to summarize the details of the restaurant
  - Phone, Address, Summary, Moods and Highlight

LLM Snapshot

- Platform: LangChain
- Library: langchain-google-genai
- Model: gemini-1.5-pro-latest
- Prompting: template formatted with role assignment and examples
- Parser: structured JSON output parser

Hugging Face Zero Shot Classifier

- Scores reviews across 8 moods using **multi-label classification**
- Aggregates review mood scores at the **business level**
- Ranks restaurants using mood match × rating × popularity
- Delivers top picks where the **dominant mood matches** the user's input



Optimization

- Started with **Gemini** for creative, fast recommendations
- Added **Zero-Shot** for explainability and mood scoring
- Switched to **Embeddings** for better accuracy (+10%)
- Each step improved **control, performance, and precision**

	Review	True Mood	Zero Shot	Sent Trans	Zero Shot Correct	Sent Trans Correct
0	The dim lighting and soft music made it perfec...	romantic	cozy	romantic	False	True
1	After a long day, this place just felt like a ...	comforting	cozy	comforting	False	True
2	Every dish had a spicy kick—totally fired me up!	energizing	energizing	festive	True	False
3	We wore sweaters, had hot chocolate, and watch...	cozy	cozy	cozy	True	True
4	Twinkling lights and Christmas songs everywher...	festive	festive	festive	True	True
5	The desserts were over-the-top and totally wor...	indulgent	indulgent	indulgent	True	True
6	We hiked first, then found this open-air cafe ...	refreshing	adventurous	refreshing	False	True
7	Live jazz, old-school cocktails, and candlelig...	romantic	romantic	romantic	True	True
8	The staff gave warm blankets and tea on a rain...	comforting	cozy	comforting	False	True
9	We danced under the stars after margaritas—tot...	energizing	romantic	energizing	False	True

Semantic Classification using Sentence Transformer

Hugging Face all-MiniLM-L6-v2 model to predict restaurant review moods

Pretrained Model:

1. all-MiniLM-L6-v2

Library:

1. Sentence Transformer

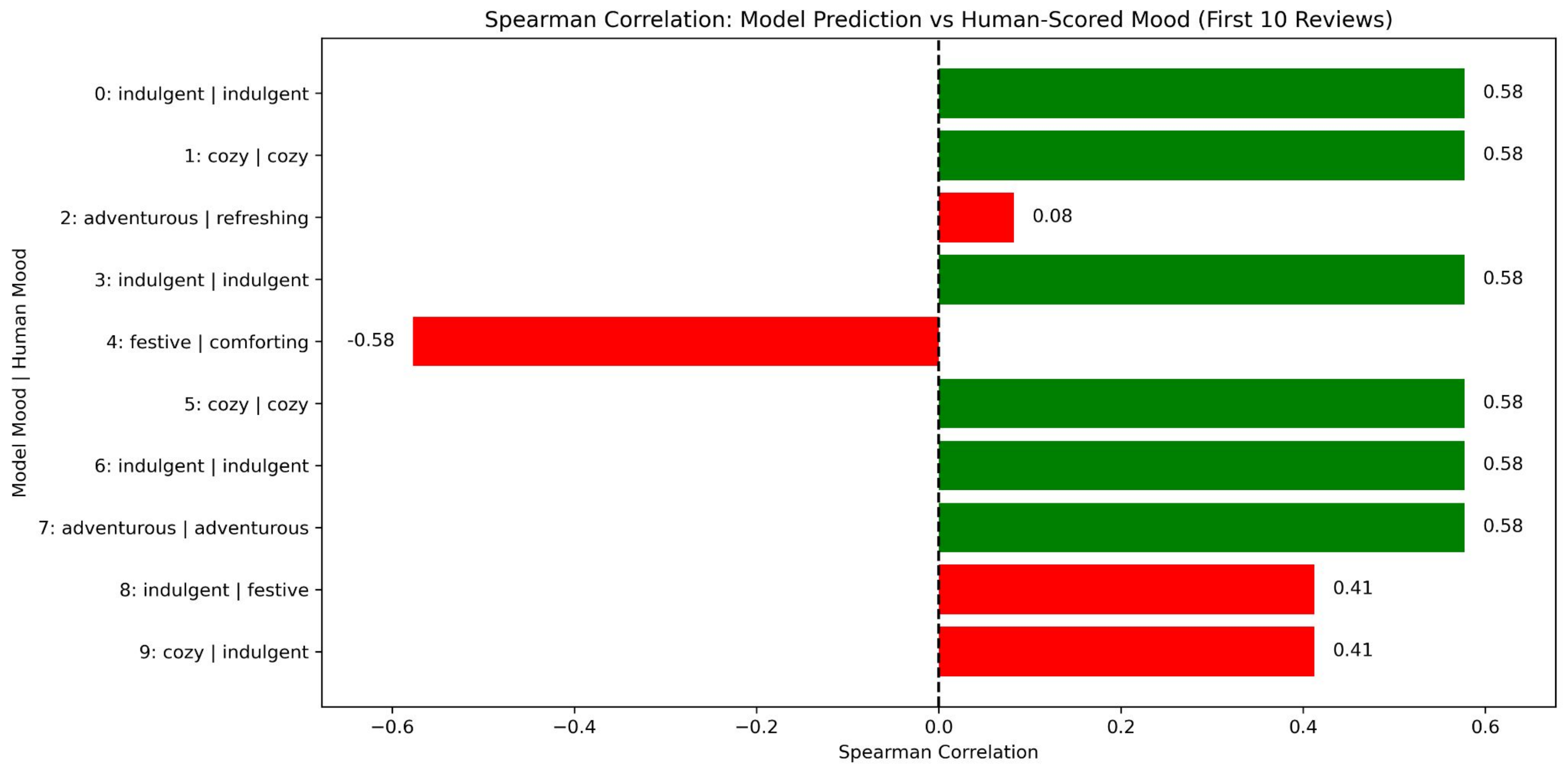
Data Processing Steps:

1. Remove Missing values
2. Encode Reviews and Mood
3. Perform Semantic Analysis
4. Classify the Reviews mood
5. Add Mood to the dataset
6. Apply Content filtering

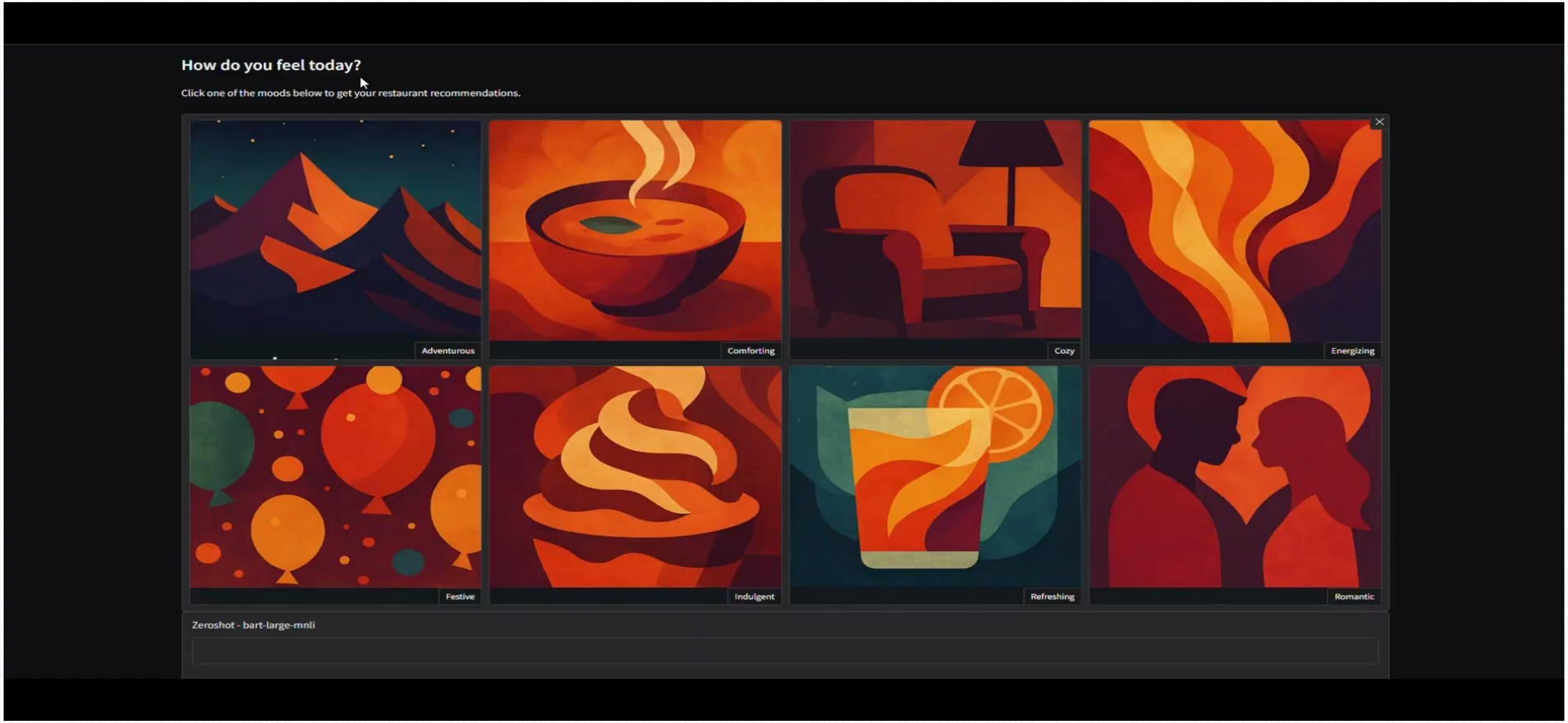
Moods:

1. Adventurous
2. Comforting
3. Energizing
4. Romantic
5. Cozy
6. Festive
7. Indulgent
8. Refreshing

all_MiniLM_L6-v2 Model Accuracy



Demo


How do you feel today?
Click one of the moods below to get your restaurant recommendations.
Adventurous
Comforting
Cozy
Energizing
Festive
Indulgent
Refreshing
Romantic
Zeroshot - bart-large-mnli

Challenges Faced

- Data Imbalance: Certain cuisines had fewer reviews
- Computer Power: Training large models on large datasets
- User Preferences: Capturing complex preferences like dietary restrictions.
- Challenges: Dataset Size exceeded 1 GB, even when limited to Philadelphia. Data was stored as a Parquet file and uploaded to HuggingFace's dataset repository.

Future Development

- Expand dataset to include global restaurants
- Enhance personalization by integrating user location data
- Add additional options in the UI
- Deploy model on a web app or platform

Q&A

"Ask us about our journey building the recommendation system!"

https://github.com/tlockhart/project-3.git