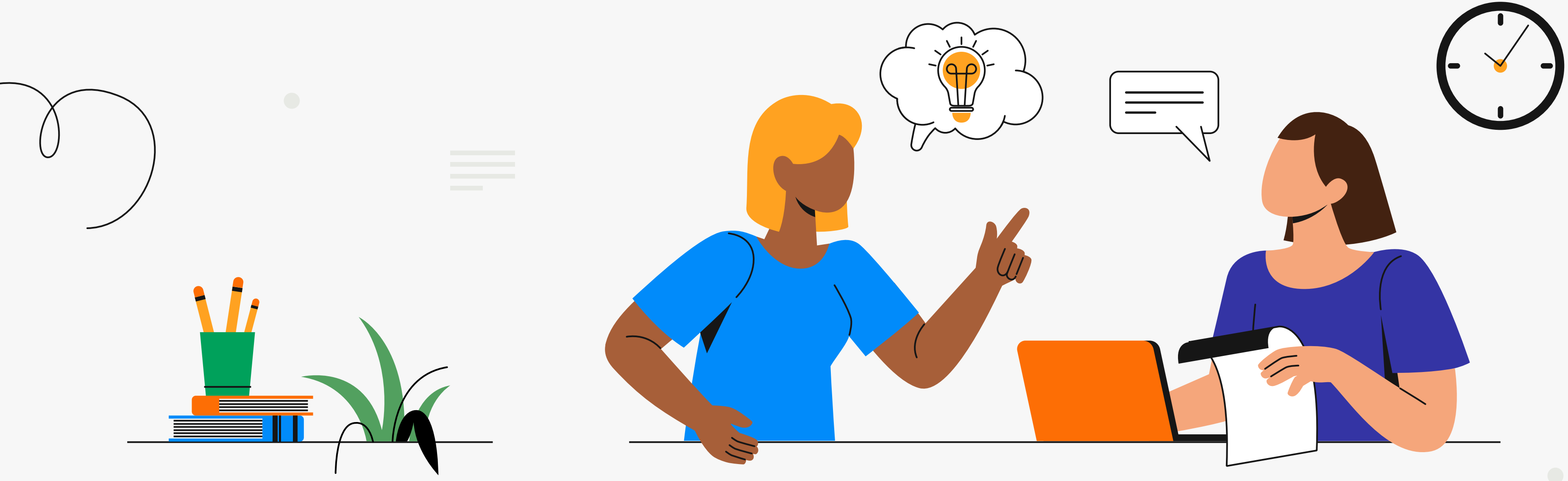
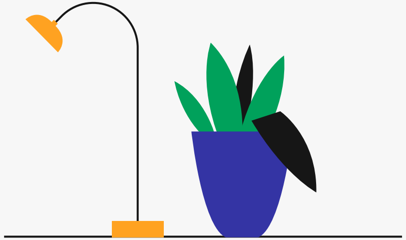
NightScape Recommender

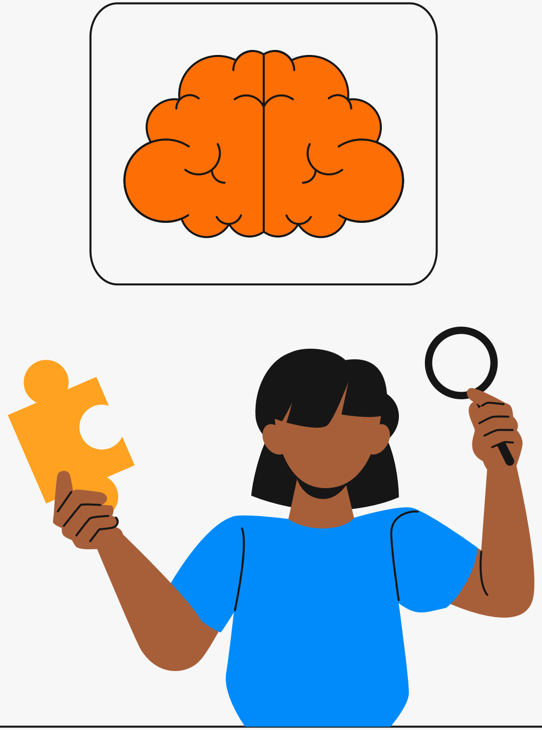


Content



01

Enhancing your Late-Night Dining Experience



Addressing the Midnight Hunger Challenge

Late-night dining *and exploration can be a challenge, especially when you're hangry and struggling to find a restaurant that fits your preferences.*

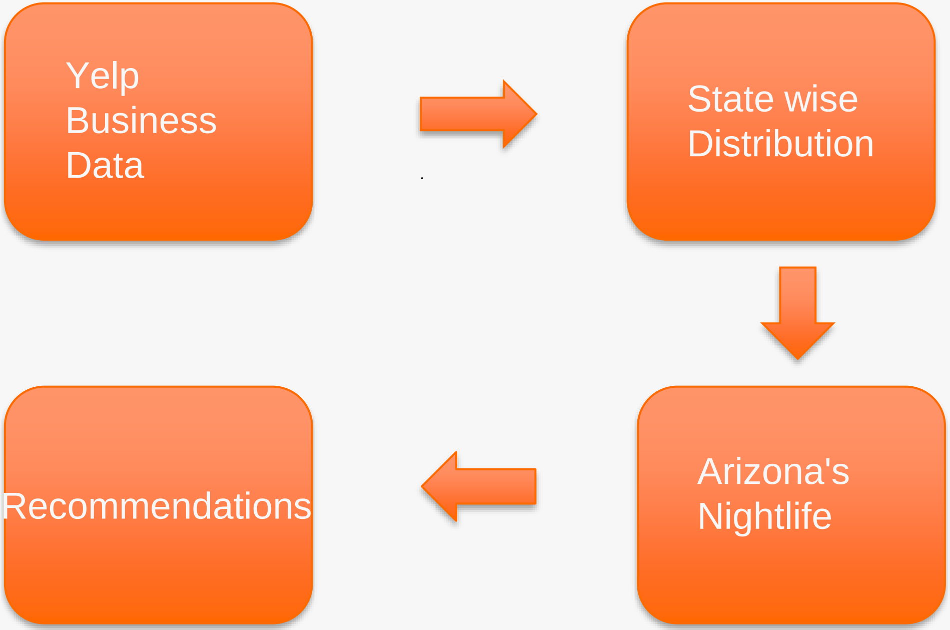
Nightscape Recommender *is our response to this common dilemma. By leveraging advanced* ***recommendation techniques****, we're here to guide you to restaurants that not only stay open late but also match your* ***culinary preferences.*** *No more wandering around hungry—let Nightscape Recommender be your guide to a delightful night out.*

"Make **late-night dining** as seamless as ordering pizza, but with more sophisticated algorithms and fewer pineapple debates."

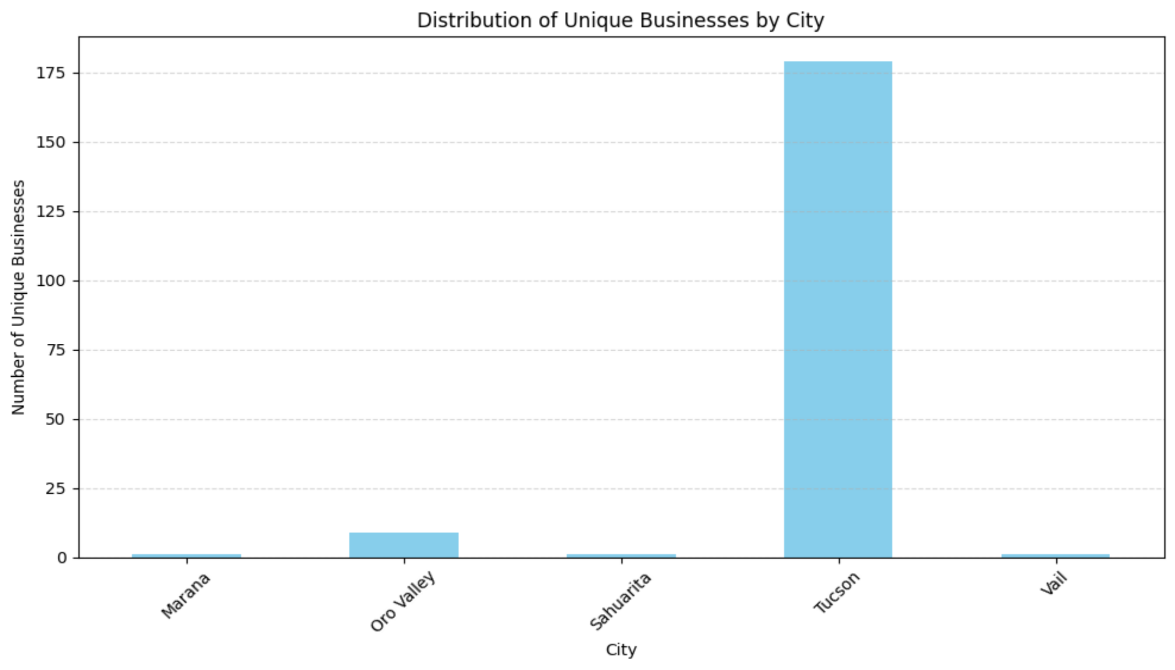
02

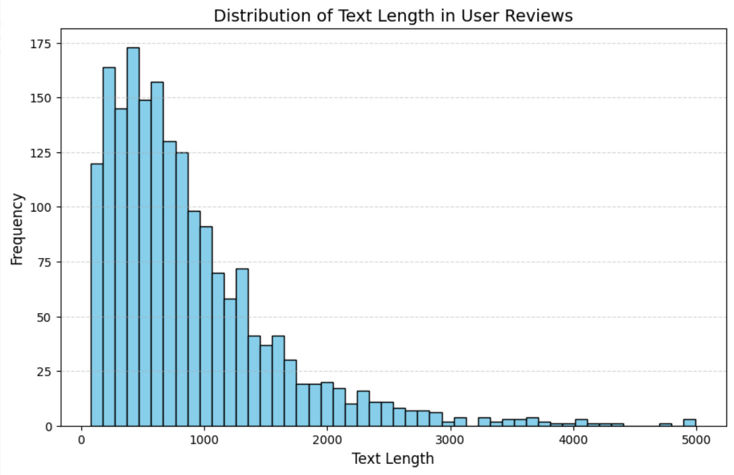
Data at the Heart of Recommendations

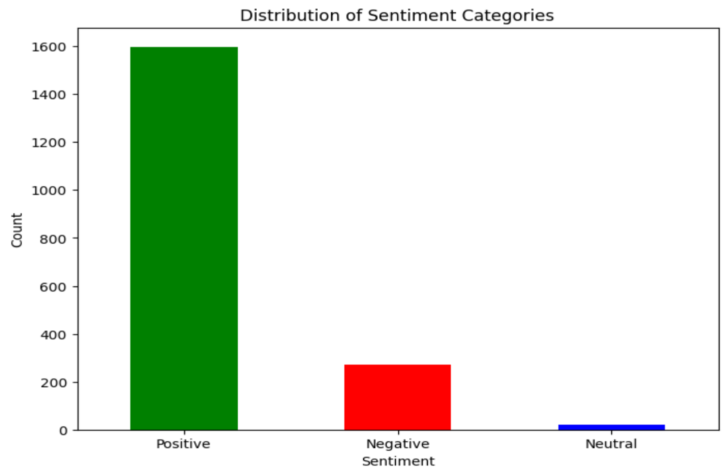
Data Prep

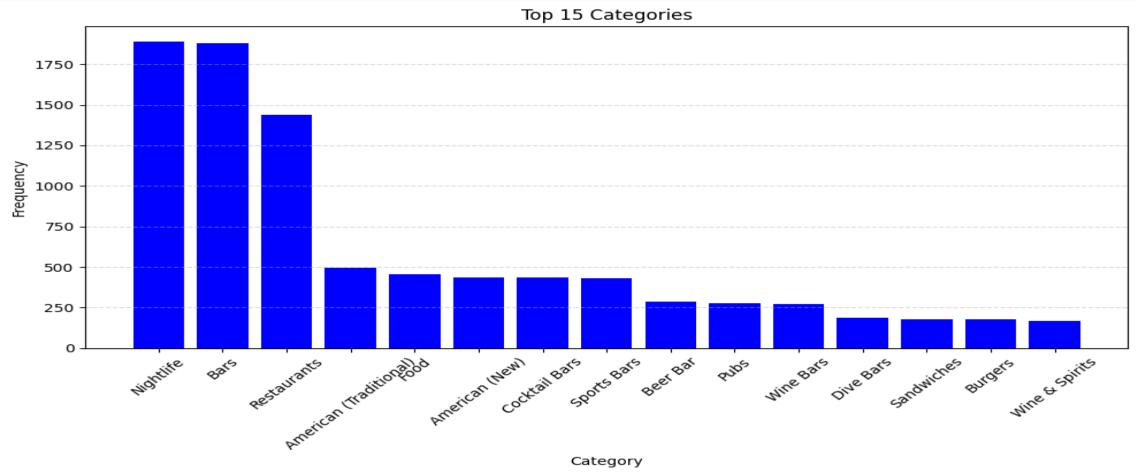

Yelp Business Data
State wise Distribution
Arizona's Nightlife
Recommendations

Exploratory Data Analysis




Distribution of Text Length in User Reviews
Frequency
Text Length
0
25
50
75
100
125
150
175
1000
2000
3000
4000
5000


Distribution of Sentiment Categories
Count
Sentiment
Positive
Negative
Neutral
0
200
400
600
800
1000
1200
1400
1600


Top 15 Categories
Frequency
Category
0
250
500
750
1000
1250
1500
1750
Nightlife
Bars
Restaurants
American (Traditional)
Food
American (New)
Cocktail Bars
Sports Bars
Beer Bar
Pubs
Wine Bars
Dive Bars
Sandwiches
Burgers
Wine & Spirits

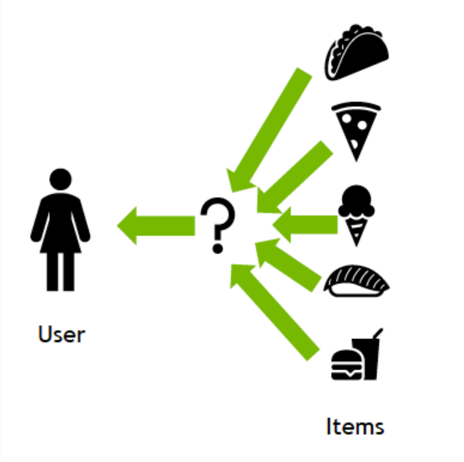
Data Preparation

Request:

- We want to find the **best night time restaurant** in Arizona.
- Build a recommendation system with content based modeling.

Data Pre-process:

- Find out the night time restaurants.
- Do the feature selection for the model building.



Data Filtering Process

yelp_academic_dataset_business

1. Selection of Arizona-based businesses.
2. Identifying operational businesses.
3. Categorizing nighttime enterprises.
4. Determining businesses operational post 10 pm.
5. Preprocessed list of 190 restaurants.

yelp_academic_dataset_review

6. Compilation of 40,000 reviews across these restaurants.
7. Extraction of top 10 valuable reviews per restaurant.
8. Final dataset comprises 1,880 reviews.

"hours"

↓

8 pm
9 pm
10 pm
11 pm
.
.

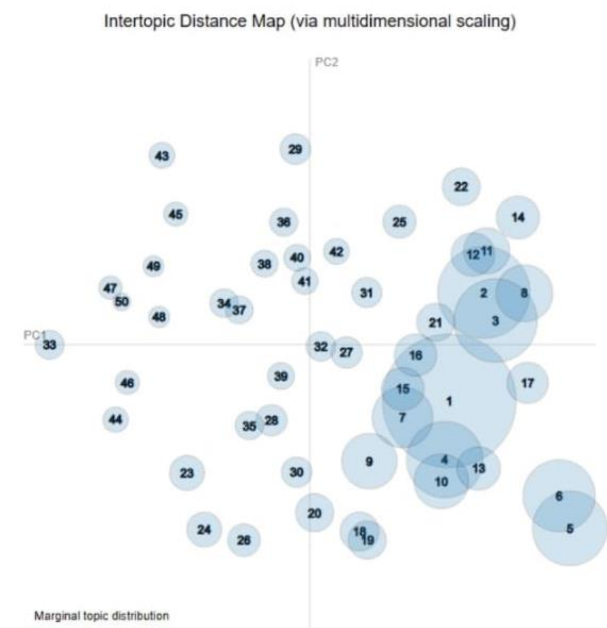
Categories Chosen (word cloud)

01 Nightlife Categories

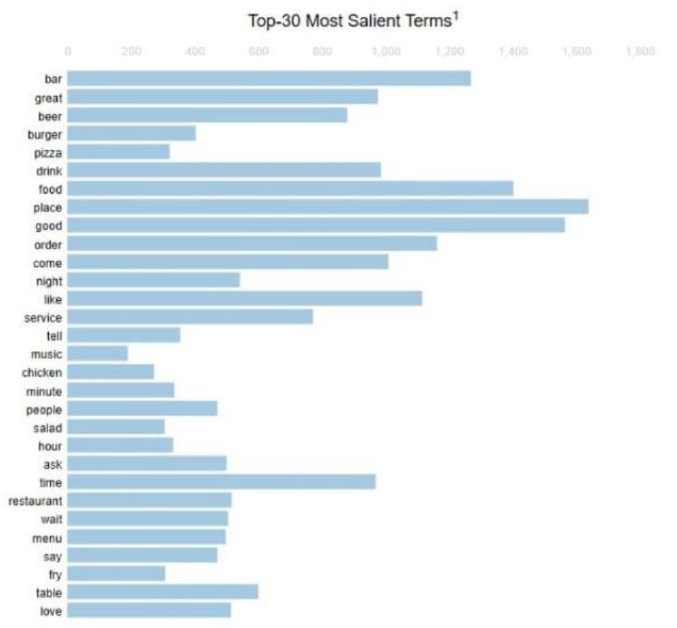
02 Non Nightlife Categories

Topic Modeling (50 Topics)

Intertopic Distance Map



Top-30 Most Salient Terms



Feature Selection

01 Categories

Ex. Restaurants, Sports , Nightlife, Bars

02 Attributes

Ex. Alcohol, HappyHour, WiFi, OutdoorSeating

03 Review

Ex. Great place to meet friends for a meal, and maybe some darts...

04 Topic Modeling - LDA

Ex. 'place', 'whiskey', 'cheese', 'want', 'high', 'check', 'favorite', 'cowpony', 'apple', 'review'

03

Recommendation Algorithm

Content Based Recommendation

Imagine this: It's late at night, and your stomach grumbles with hunger. You find yourself craving the perfect slice of pizza to satisfy your nocturnal cravings. Suddenly, a recommendation pops up, suggesting pizzas that not only match your taste but also understand your late-night pizza preferences. How did they know?

Enter the content-based recommendation algorithm, the Midnight Maestro of pizza cravings. based modeling

Why Content Based Recommenation

Independence from User-Item Interactions:

- Unlike nosy neighbors who peek into your personal preferences, content-based methods respect your privacy.
- They focus on understanding the inherent characteristics of each item.

Flexibility and Adaptability:

- These algorithms are incredibly versatile, capable of adapting to various types of items or content.

Why Content Based Recommendation

Reduced Information Overload:

- By analyzing the key features or attributes of each item, they streamline the recommendation process, even in complex and diverse datasets.

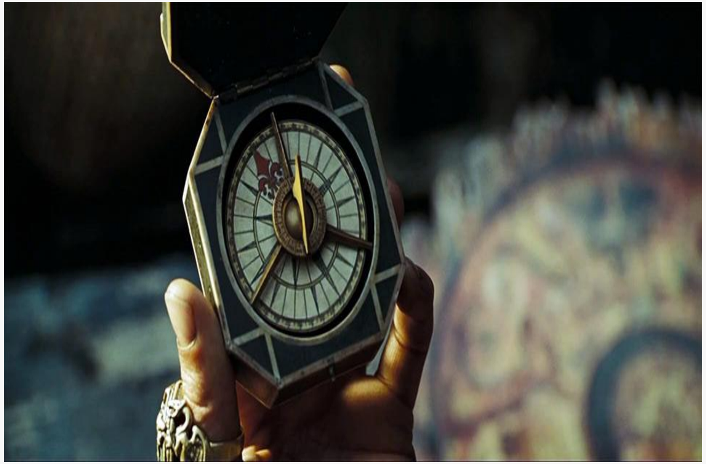
Transparency and Explainability:

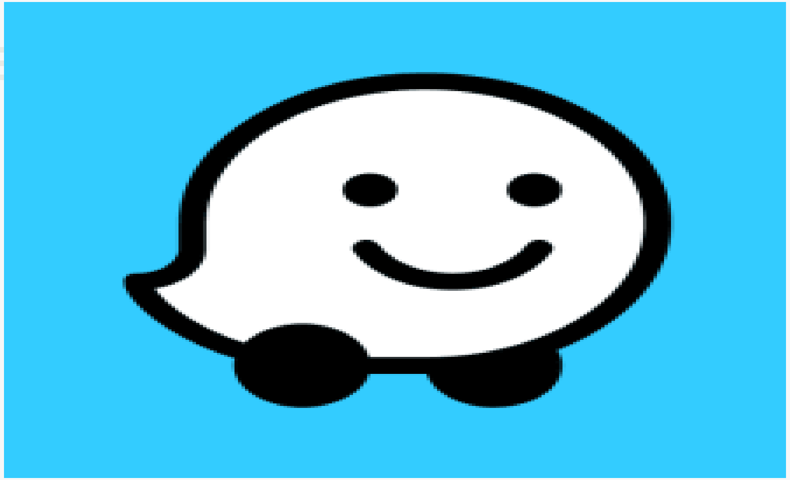
- Content-based systems offer clear insights into why a particular item is recommended to you.

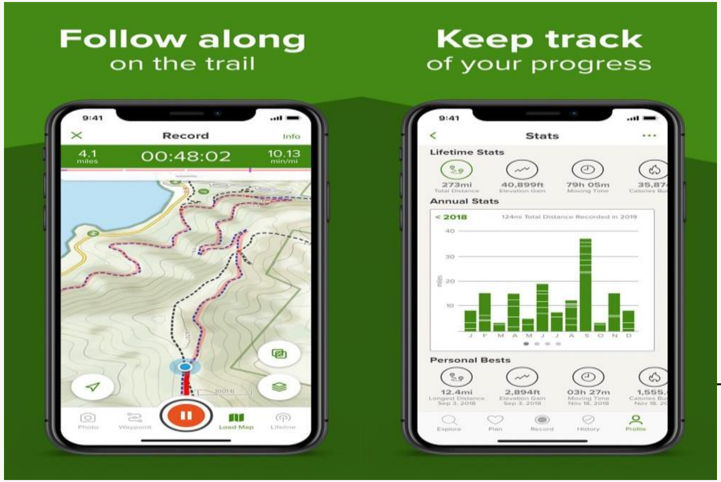
Mitigation of Data Sparsity:

- They rely on the intrinsic properties of items, rather than extensive user-item interaction data, making them well-suited for scenarios where traditional collaborative filtering approaches may struggle.

Who/What are they?







Code Snippet

```
import numpy as np
from sentence_transformers import SentenceTransformer
from sklearn.decomposition import PCA
from sklearn.metrics.pairwise import cosine_similarity

# Encode text using SentenceTransformer
X = np.array(data.text)
text_data = X
model = SentenceTransformer('distilbert-base-nli-mean-tokens')
embeddings = model.encode(text_data, show_progress_bar=True)
embed_data = embeddings
X = np.array(embed_data)

# Perform PCA
n_comp = 5
pca = PCA(n_components=n_comp)
pca.fit(X)
pca_data = pd. DataFrame(pca.transform(X))

# Compute cosine similarity matrix
cos_sim_data = pd. DataFrame(cosine_similarity(pca_data))
```

Explanation

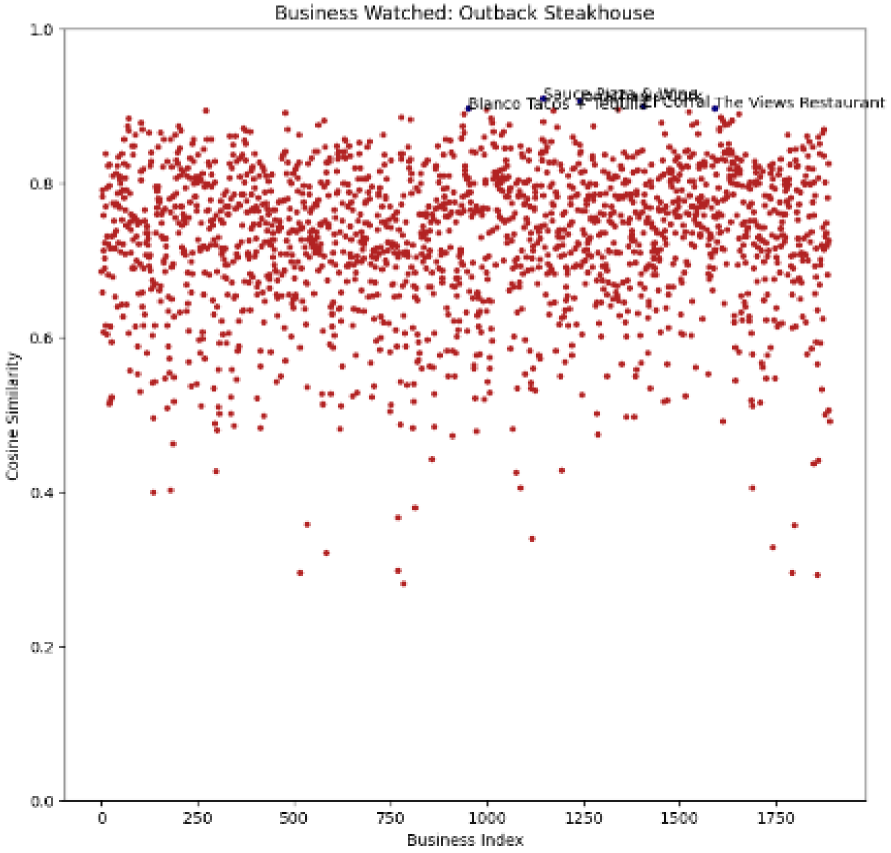
Text Encoding: Prepare for your night out with ease! Our encoding model acts as your guide, translating reviews into personalized maps to your ideal destination. It's your nightlife GPS!

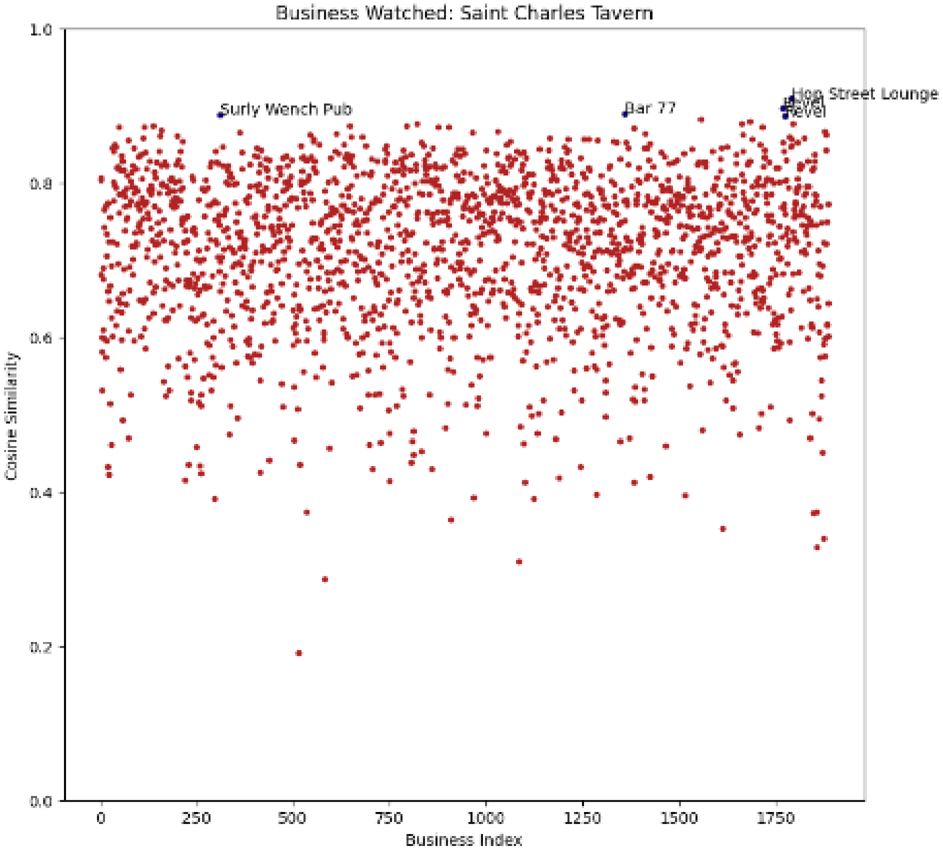
Dimensionality Reduction: In the midst of nightlife's chaos, PCA acts as your guide, sifting through the noise to spotlight the main attractions. It's like zooming in on the city's excitement, capturing its vibrant essence without the overwhelm

Cosine Similarity: As you explore various recommendations, cosine similarity serves as your compass, pointing out the similarities between options. The closer they align, the better they match your nightlife preferences. It's like finding your tribe in the bustling crowd!

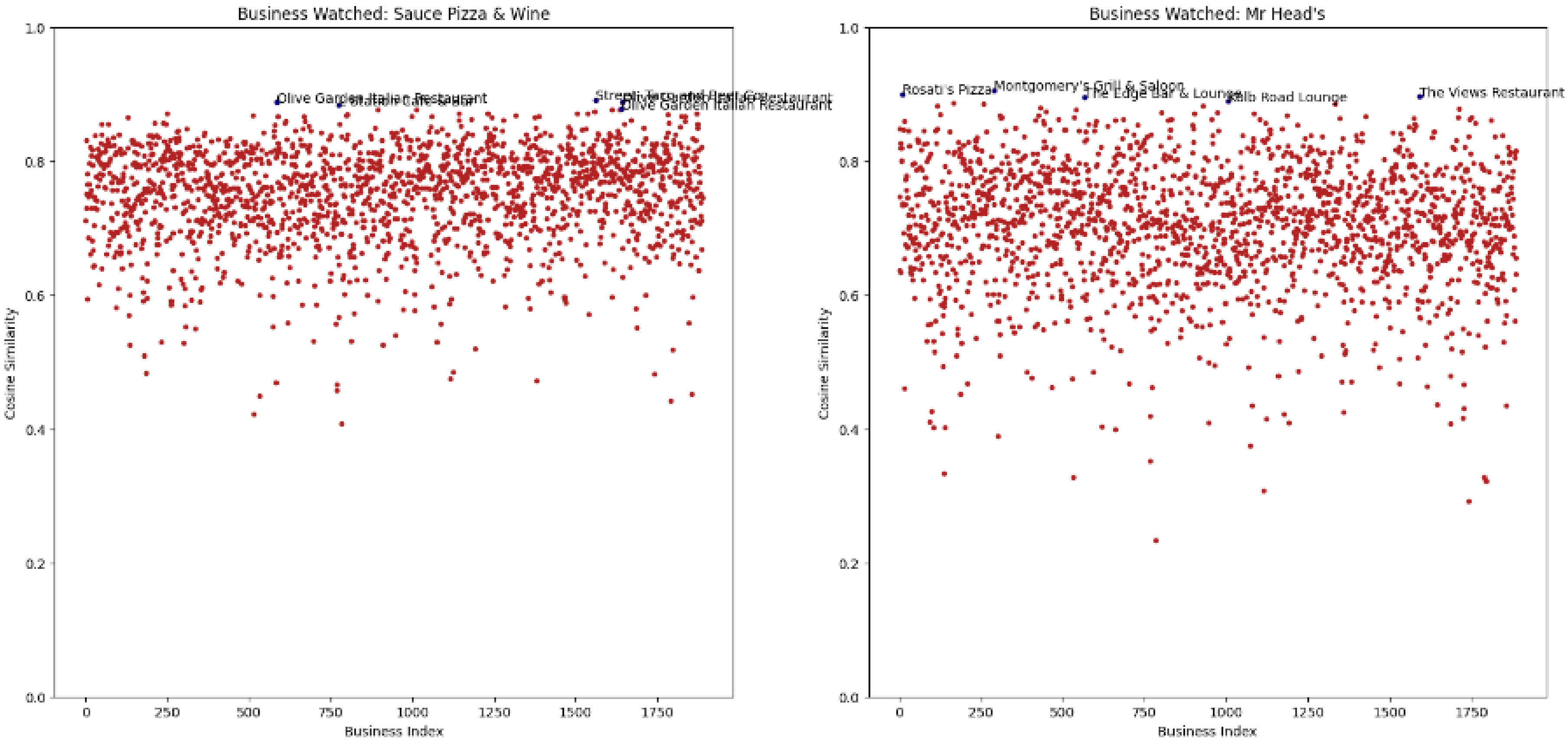
Building Similarity Matrix: Imagine navigating the streets, connecting glowing storefronts and lively venues. Each review pair forms a link, illuminating potential paths. The similarity matrix becomes your roadmap, guiding you through choices and uncovering hidden gems.

Cosine Similiarity Matrix





Cosine Similiarity Matrix



Results

Recommendations for watched business: IBT's

	Watched Business	Recommendation 1	Recommendation 2	Recommendation 3	Recommendation 4	Recommendation 5
0	IBT's	The Mint	Frog & Firkin	Kon Tiki Restaurant & Lounge	Club Congress	Danny's Baboquivari Restaurant & Lounge

Recommendations for watched business: Thunder Canyon Brewery

	Watched Business	Recommendation 1	Recommendation 2	Recommendation 3	Recommendation 4	Recommendation 5
0	Thunder Canyon Brewery	Beer Garden At Reilly Craft Pizza	Dillinger Brewing Company	Arizona Beer House	Crooked Tooth Brewing	Casa Marana Craft Beer + Wine

Recommendations for watched business: El Berraco

	Watched Business	Recommendation 1	Recommendation 2	Recommendation 3	Recommendation 4	Recommendation 5
0	El Berraco	Bob Dobbs	Perche’ No Italian Bistro	Bar Passé	Primo with Patio Dining	Trident Grill II

Recommendations for watched business: Button Brew House

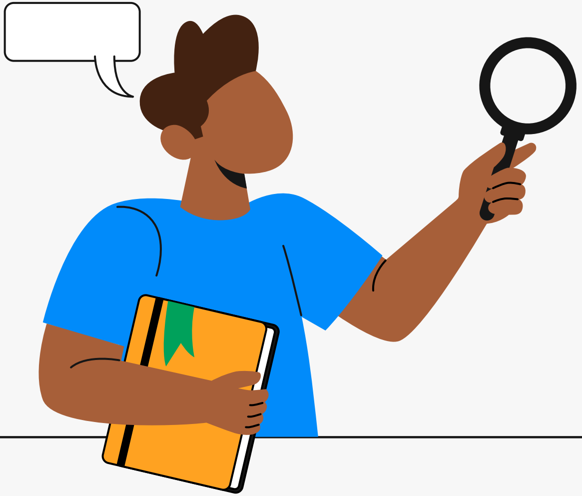
	Watched Business	Recommendation 1	Recommendation 2	Recommendation 3	Recommendation 4	Recommendation 5
0	Button Brew House	Barrio Brewing	Noble Hops Gastropub	Gentle Ben’s Brewery	Bar 77	Crooked Tooth Brewing

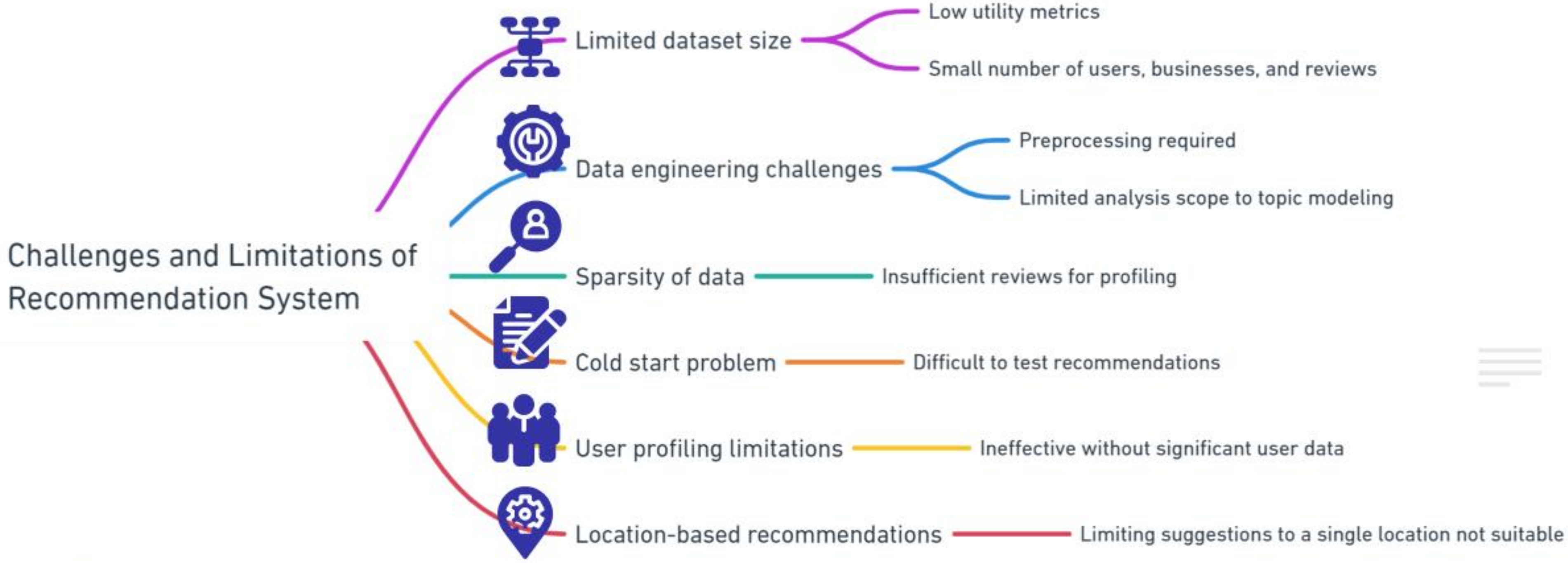
Recommendations for watched business: Empire Pizza & Pub

	Watched Business	Recommendation 1	Recommendation 2	Recommendation 3	Recommendation 4	Recommendation 5
0	Empire Pizza & Pub	Casa Marana Craft Beer + Wine	Sauce Pizza & Wine	Sauce Pizza & Wine	Magpies Gourmet Pizza	Sauce Pizza & Wine

04

Future Outlook and Conclusion




Challenges and Limitations of Recommendation System
Limited dataset size
Low utility metrics
Small number of users, businesses, and reviews
Data engineering challenges
Preprocessing required
Limited analysis scope to topic modeling
Sparsity of data
Insufficient reviews for profiling
Cold start problem
Difficult to test recommendations
User profiling limitations
Ineffective without significant user data
Location-based recommendations
Limiting suggestions to a single location not suitable

Future Enhancements of the Recommendation System

01	Expanding the dataset- To include more businesses and address Sparsity/Cold Start issues	05	Integrating with business listing/review APIs- Keep recommendations fresh with new user-generated content
02	Improve profiling and collaborative filtering- by collecting actual user feedback data	06	Weighting different features- Text, categories and attributes to refine recommendations
03	Experimenting with deep learning models- RNNs on review texts for topic modeling	07	Adding explanations to recommendations- Improve transparency and trust
04	Developing a hybrid content-collaborative approach- Leverage both business profiles and user patterns	08	A/B testing- different algorithms and parameter settings on live user traffic to further optimize the system

Posted by u/p_syche 10 months ago

23

c'mon Netflix recommendation algorithm, what did I do to you???

To Summarize, estimates of Datasets

~40,000 Total Reviews

~1,900 Reviews Analyzed

Top 10 most useful of the 190 Businesses

~190 Businesses

That remains Open post 10 PM

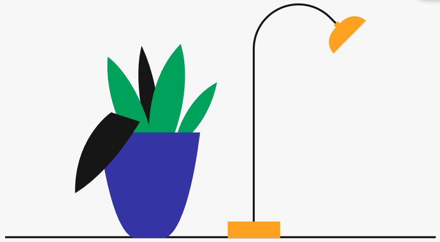
20 Defining Categories

To Summarize,

We started with a large dataset of restaurants and reviews, which we carefully filtered and processed and combined multiple sources

We built a content-based recommendation engine that suggests similar businesses to users based on these topic profiles modeled on the common themes and keywords in user reviews

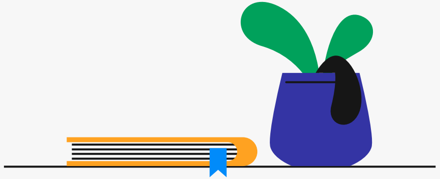
We demonstrated how our system works and addressed challenges like cold starts through randomization and explored the limitations, challenges and enhancements



In Conclusion...

- *Moving forward, the system can be improved through additional data, user feedback, and more sophisticated algorithms. With continued refinement, it has strong potential to meaningfully impact how residents and visitors explore Arizona's vibrant nightlife scene.*

- *By surfacing new and interesting dining and entertainment options tailored to individual tastes, the recommendation system aims to reinforce Arizona's reputation as a top destination for a fun and engaging night out on the town.*



Thanks!

Do you have any questions?