Ripe Pumpkins

An Online Movie Recommender Engine – Pumpkinmeter

Prepared by Sri Lakshmi Mallipudi

Pumpkin Meter - Online Movie Recommender Engine

Problem

- Ripe Pumpkins plans to
  - Implement Pumpkinmeter, a measurement of collaborative recommendations for millions of fans.
  - Identify the potential in the Ripe Pumpkins' new initiative, Pumpkinmeter score.

Objective

- To provide personalized movie recommendations for users based on their preferences and improve the movie-watching experience.

Goal

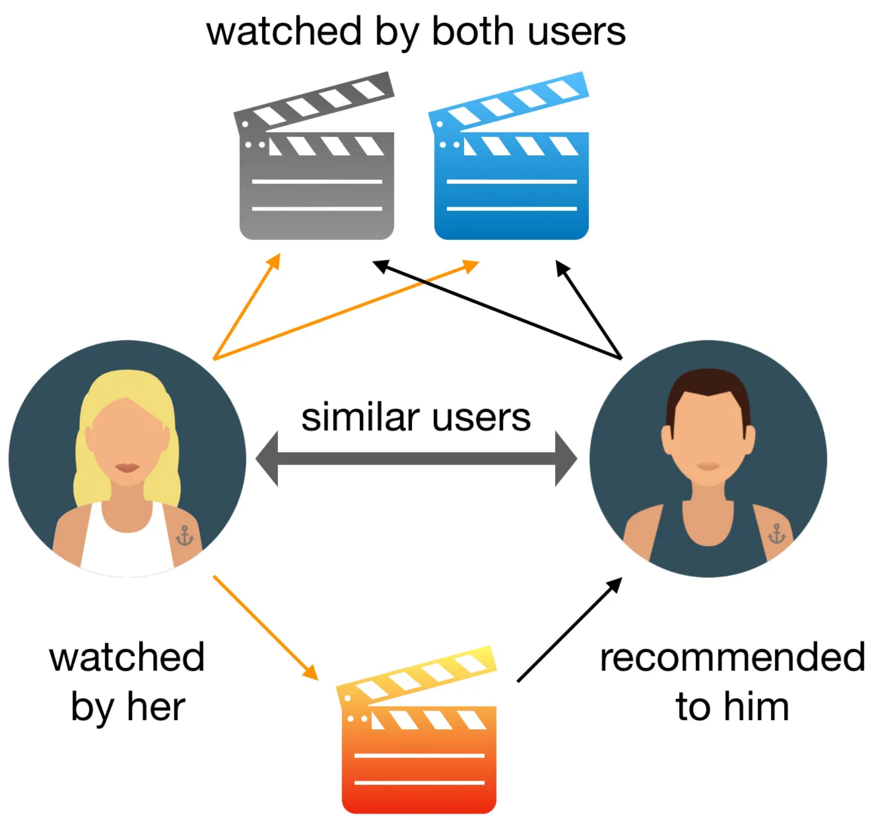
- To enhance user satisfaction by delivering tailored movie suggestions that match their tastes and interests.

Why Pumpkin Meter?

- In today's digital age, the abundance of movie choices can be overwhelming for users.
- Users desire a seamless and enjoyable movie-watching experience
- Pumpkin Meter simplifies and optimizes the movie selection process by providing accurate and personalized recommendations.
- It takes into account users' individual preferences and delivers highly relevant movie suggestions.
- By leveraging advanced algorithms and collaborative recommendation techniques, Pumpkin Meter ensures users discover the movies they are most likely to enjoy.

How Pumpkin Meter Works?

- Pumpkin Meter utilizes advanced recommendation algorithms and data aggregation techniques to generate personalized movie recommendations.
- It collects user data, including ratings, reviews, and movie preferences, to create comprehensive user profiles.
- By analyzing these profiles and comparing them to the vast database of movies, it identifies patterns and similarities to make accurate recommendations.
- The Pumpkin Meter score is calculated based on collaborative filtering, taking into account the preferences of similar users to determine the compatibility between users and movies.
- With each user interaction, Pumpkin Meter refines its recommendations, ensuring a dynamic and continuously improving user experience.



Evaluation of Pumpkinmeter

We evaluated the recommender engine using two test scenarios for two users.

Generated the top 15 recommended movies for each user in two scenarios.

Scenarios: Filtering out movies with less than 25 ratings and less than 100 ratings

from the latest datasets collected and made available through MovieLens website by GroupLens Research.

User 1 - Ratings and Recommendations

Ratings

- House of the Dead, The (2003): 2
- Forrest Gump (1994): 4
- Avatar (2009): 5
- Battle Planet (2008): 2
- Sherlock Holmes (2009): 5
- The Mummy (2017): 4
- The Jungle Book (2016): 3
- Twilight (2008): 4
- It Follows (2014): 1
- Dune (2000): 5

Recommendations

Scenario -1

- Loose Change 9/11: An American Coup (2009)
- Endless Love (2014)
- Naomi and Ely's No Kiss List (2015)
- Bad Boys 3
- Tyler Perry's Meet the Browns (2008)
- Aashiqui 2 (2013)
- Cats (1998)
- Woodlawn (2015)
- Burma Conspiracy
- My Little Pony
- Cutting Edge
- Miracles from Heaven (2016)
- 2016: Obama's America (2012)
- Now You See Me 2 (2016)

Scenario - 2

- Endless Love (2014)
- Now You See Me 2 (2016)
- Now You See Me (2013)
- Fuck You
- The Choice (2016)
- Love
- The Longest Ride (2015)
- Avengers: Infinity War - Part I (2018)
- Act of Valor (2012)
- The Best of Me (2014)
- Safe Haven (2013)
- Doctor Who: Voyage Of The Damned (2007)
- Last Song
- Lucky One
- Life as We Know It (2010)

User 2 - Ratings and Recommendations

Ratings

- Shutter Island (2010): 3
- Speed (1994): 1
- Jurassic Park (1993): 2
- Aladdin (1992): 4
- Die Hard 2 (1990): 2
- Rush Hour (1998): 3
- RoboCop (1987): 5
- Avengers, The (2012): 4
- Good Day to Die Hard, A (2013): 4
- Rush (2013): 5

Recommendations

Scenario -1

- Cosmos
- Black Mirror
- Fight Club (1999)
- Black Mirror: White Christmas (2014)
- Iqbal (2005)
- Demetri Martin. Person. (2007)
- In This Corner of the World (2016)
- Planet Earth II (2016)
- Band of Brothers (2001)
- Death Note: R2 - L o Tsugu Mono (2008)
- Pulp Fiction (1994)
- Tom Segura: Completely Normal (2014)
- Death Note Rewrite: Genshisuru Kami (2007)
- Ghost in the Shell: Stand Alone Complex - The Laughing Man (2005)
- Horace and Pete (2016)

Scenario - 2

- Cosmos
- Black Mirror
- Fight Club (1999)
- Black Mirror: White Christmas (2014)
- Planet Earth II (2016)
- Band of Brothers (2001)
- Pulp Fiction (1994)
- Ghost in the Shell: Stand Alone Complex - The Laughing Man (2005)
- Berserk: The Golden Age Arc 2 - The Battle for Doldrey (2012)
- Dark Knight
- Matrix
- Planet Earth (2006)
- Inception (2010)
- Generation Kill (2008)
- Interstellar (2014)

Interpretation of the Results

User 1:

- Scenario 1: The top recommended movies are relatively less well-known or popular films. These movies have received high ratings from a smaller number of users who have watched them. This scenario allows for more niche and lesser-known movie recommendations that align with User 1's preferences.
- Scenario 2: The top recommended movies in this scenario are still relatively less popular but have received a higher number of ratings compared to the previous scenario. These movies have a broader appeal and have been rated by a larger user base. User 1 can expect recommendations that strike a balance between popularity and personalized preferences.

User 2:

- Scenario 1: The top recommended movies include popular TV shows like "Black Mirror" and "Band of Brothers," along with movies like "Fight Club" and "Pulp Fiction." These recommendations indicate User 2's interest in critically acclaimed and thought-provoking content.
- Scenario 2: The recommendations in this scenario largely overlap with Scenario 1 since User 2's preferences align with popular and highly rated content. User 2 can expect a mix of popular TV shows, movies, and documentaries, catering to their preference for high-quality and widely recognized entertainment.

Insights and Foresights

- **Personalized recommendations:** Both scenarios demonstrate the capability of the recommender system to provide personalized movie recommendations based on the user’s individual preferences and ratings.

- **Niche vs. popular recommendations:** Scenario 1 offers recommendations that are more niche, catering to specific tastes and preferences. This can be appealing to users looking for unique and lesser-known content. In contrast, Scenario 2 strikes a balance between popular and personalized recommendations, offering a wider range of choices.

- **User engagement and satisfaction:** By understanding users' preferences and suggesting relevant movies, the recommender system enhances user satisfaction and engagement. Users are more likely to continue using the service and exploring new movies based on the system's accurate recommendations.

- **Business growth potential:** Accurate and personalized recommendations contribute to customer retention and attract new users. This can lead to increased user engagement and higher customer satisfaction and ultimately drive revenue growth for Ripe Pumpkins.

Conclusion

- Pumpkinmeter successfully generated personalized movie recommendations for the two users.
- The system considered the users' ratings and leveraged the dataset to provide tailored suggestions.
- User 1 demonstrated a preference for niche and unconventional movies.
- User 2 showed a preference for well-known and critically acclaimed films.
- The system's ability to adapt to different scenarios and provide relevant recommendations highlights its effectiveness in catering to individual preferences.
- The insights gained from these test scenarios can inform future enhancements to the recommendation engine and contribute to improving customer satisfaction and loyalty.