Movie Recommendation Engine and Feedback Analysis

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Lab 4: Movie Recommendation

Lab Goal:

Use past movie ratings to predict how users will rate unwatched movies and generate recommendations for these users.

Recommendation Systems:

Movie recommendation systems feeds new user ratings into an engine to generate future recommendations, so recommendations are constantly updated.

Our Extensions:

1) Check if the initial preferences of the group of users change as more movies are seen
2) Check if group is recommended with a varying set of movies over time
3) Check is recommendations will converge to highly rated genre as more movies are seen

Methods: Overview

Part 1: Recommendation Engine Development

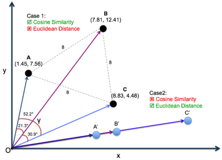
- Collaborative Filtering Techniques
- Machine Learning Algorithms Employed:
  - K-Nearest Neighbors
  - Matrix Factorization

Part 2: Simulation

- Simulate user ratings to answer the following questions:
  - Do movie recommendations change over time?
  - If so, how do they change over time?
  - Do global recommendations converge to one or more popular movies?

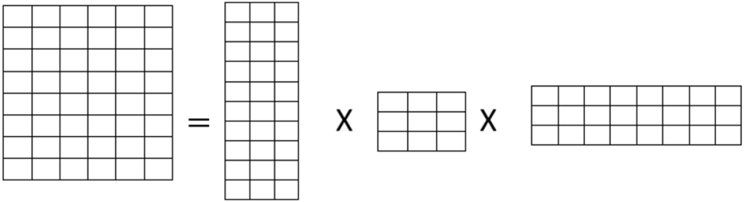
Model 1: K-Nearest Neighbors (KNN)

- KNN is a non-parametric machine learning algorithm that is used in classification and regression
- New data points are classified based on proximity to its number of nearest neighbors, where k represents the number of neighbors
- Using euclidean distance to measure distances suffers from the curse of dimensionality (use cosine similarity instead)



- This method has a few drawbacks, so we ended up generating a model using matrix factorization

Model 2: Matrix Factorization



$$M = U \times D \times I^T$$

where,
M := (n x n) utility matrix.

U := (n x r) represents the relationship between users and latent factors.

D := (r x r) diagonal matrix, which describes the strength of each latent factor.

I^T := (r x n) matrix, which indicates the similarity between items and latent factors.

Simulation Design

1. Begins each simulation with user movie ratings data
2. Runs base data through the recommendation engine to recommend a movie to 'watch'
   - 2.1 One movie generated for every user
   - 2.2 Intentional randomness. User randomly pics 1 from their 5 highest recommended movies
3. Updates the user movie ratings database
4. Runs modified database through the rec engine again, for 2nd generation movie rec
   - 4.1 Up through 20 generations of movies
   - 4.2 Data, and thus recommendations, change over time
5. Simulation: repeat steps 1-4 multiple times
   - 5.1 'Alternate Universes' of Netflix binges
   - 5.2 Intentional randomness becomes important here
6. Simulation allows us to see trends in how recommendations tend to change

Methods: Simulation Pseudo-code

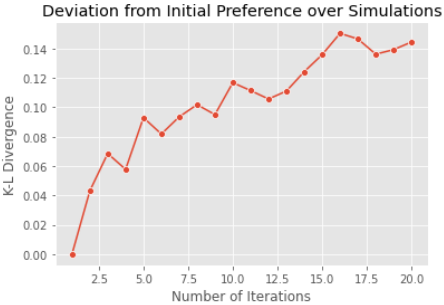
```
class Simulation():

  #INITIALIZE: use raw df of users's movie ratings
  def __init__(self, user_movie_df):
    self.user_movie_df = user_movie_df
    self.sim_results = []

  def simulate(self, n_sim, n_movie):

    for i in range(n_sim):
      #start each sim with the original data
      temp_user_movie_df = self.user_movie_df.copy(deep=True)

      for j in range(n_movie):

        #REC ENGINE: recommend and rate 1 movie for every user
        movie_recs = rec_engine(temp_user_movie_df)

        #UPDATE data for next run
        temp_user_movie_df.update(movie_recs)

      #STORE the result of this sim iteration
      self.sim_results.append(temp_user_movie_df)


# Execute ---------------------------------------------------
sim = Simulation(user_movie_df)
sim.simulate(n_sim=100)
sim.user_movie_df
```

Note the use of a simulation class

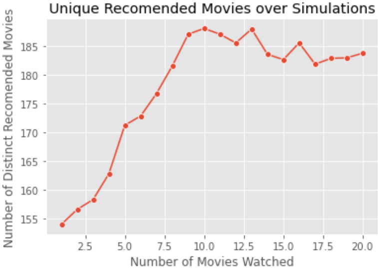
Results: Change in Group Preferences Over Time

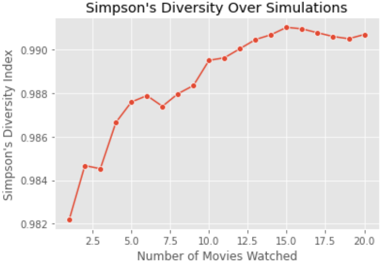
- Calculate the initial genre distribution and the genre distribution of the ith iteration
- Calculate the Kullback-Leibler divergence (KLD) between initial genre distribution and the genre distribution of the ith iteration

$$KL(P||Q) = \sum p_i(x) log(\frac{p_i(x)}{q_i(x)})$$



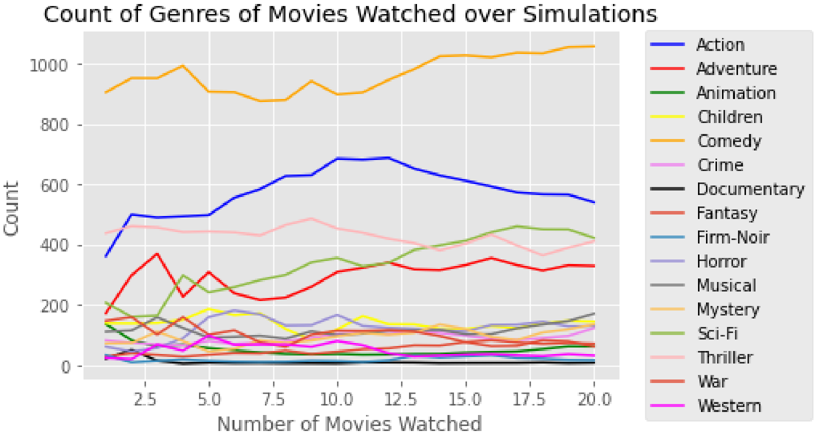
Homogenization of the User Experience





$$D = 1 - \left(\frac{\sum n(n-1)}{N(N-1)} \right)$$

Popularity Bias



Summary

- There was a higher deviation from the initial preference over time. This suggest that the taste of the users shift over time as more movies are watched by users
- More unique set of movies are recommended over time as more movies are watched by users
- More popular genres are more recommended over time as more movies are watched by users

References

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