Quantifying the Effects of Recommendation Systems

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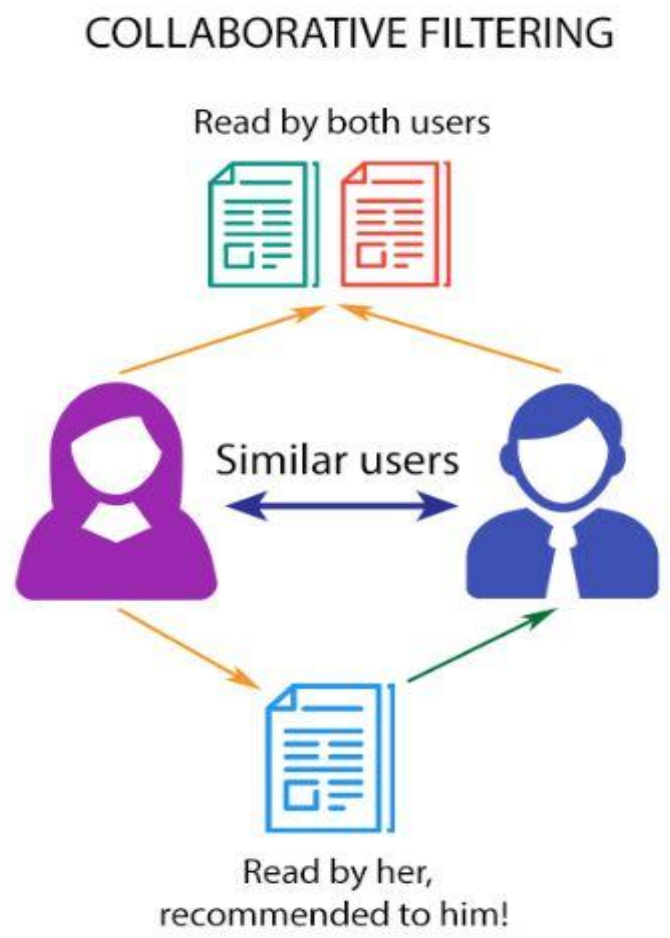
Problem Statement

- Recommendation systems using collaborative filtering (CF) models could cause homogeneity because of the popularity bias and its continuous feedback loop.
  - Popularity bias is when online platforms optimize recommendations based on what is considered popular with the majority group, which can homogenize users' interests and perceptions.
- Goal: create a simple CF model to quantify the effects of the possible inequalities in recommendation systems.
- A challenge we faced was that some of the users did not provide ratings, which made it harder to make accurate recommendations.

Background

- We are using UC Berkeley's joke dataset from Jester 5.0 for analysis.
- Our recommendation model makes recommendations using CF.
  - In other words, the ratings that users have made will influence the recommendations being made.
- In each experiment, test users were given a set # of jokes to rate on a scale from -10 to +10 before receiving a recommendation.
  - -10 – not funny
  - +10 – very funny



Recommendation Score Calculation

$$\rho X, Y = \frac{cov(X, Y)}{\sigma_X \sigma_Y}$$

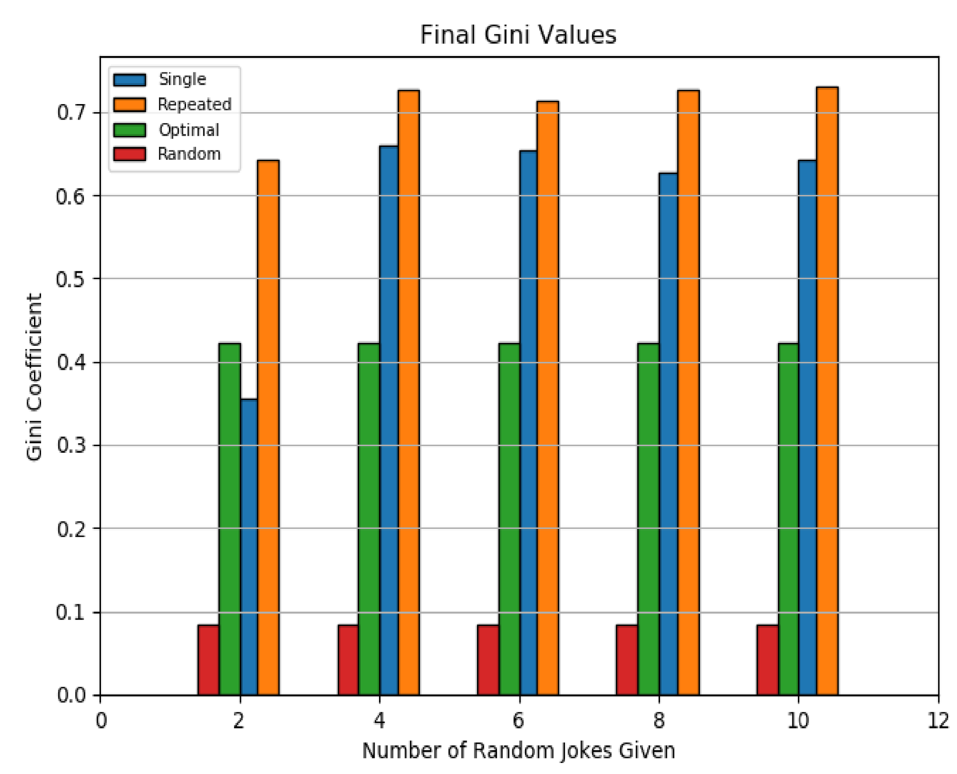
Pearson Formula:
- X = a user in training set
- Y = a test user
- cov = covariance
- $\sigma_X \sigma_Y$ = standard deviations of X, Y

- We compare user similarities with Pearson correlation.
  - 0 – different preferences
  - 1 – similar preferences
- A recommendation score is calculated using the similarity score and the rating for a particular item.
- The item with the highest recommendation score gets recommended.

Gini Comparison

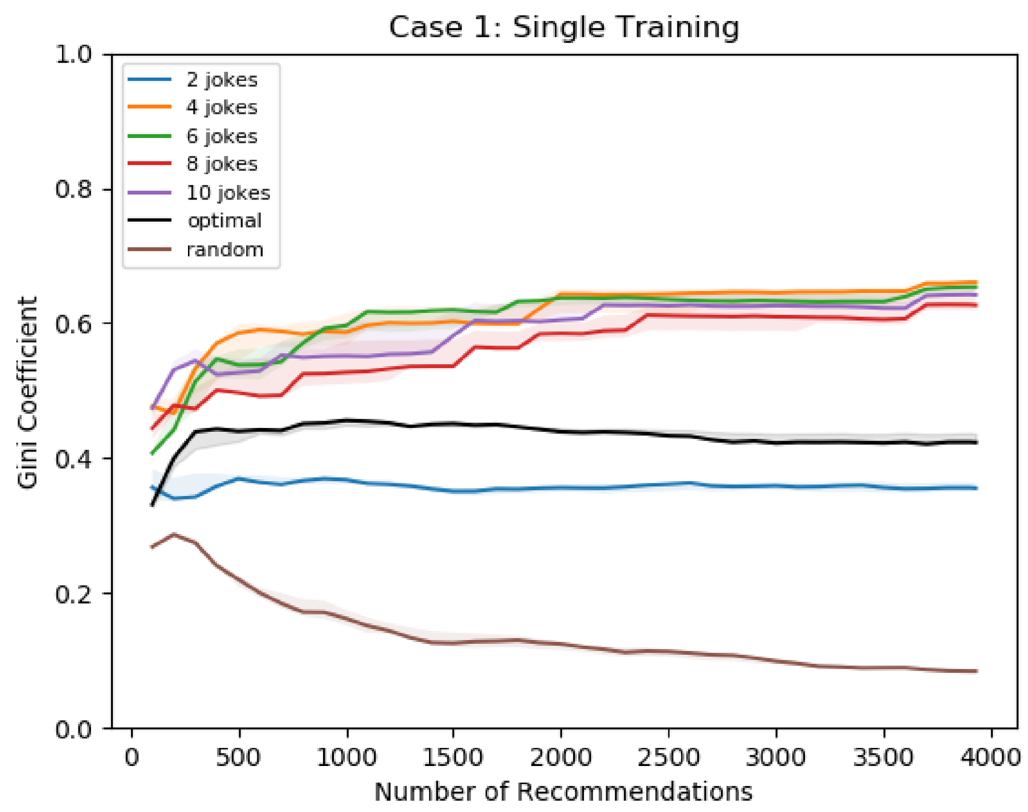
$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} |x_i - x_j|}{2\sum_{i=1}^{n}\sum_{j=1}^{n} x_j}$$

Gini Formula:
- n = total # of recommended jokes
- x_i = # of times for joke *i*
- x_j = # of times for joke *j*

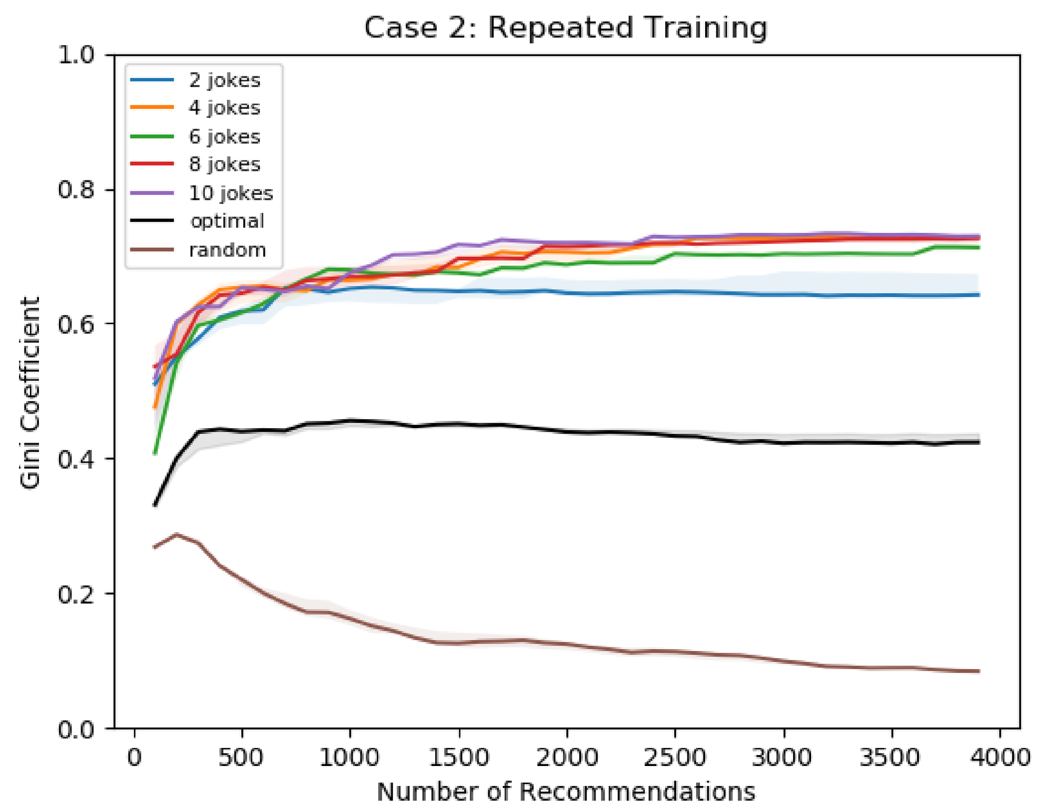


- Repeated training has the highest Gini so it has the highest inequality.

Evaluation Using Gini Coefficient



Case 1: Single training
- training set stays static and does not get updated



Case 2 : Repeated training
- training set is updated with new test users every 100 recommendations

Question:
- Does repeated training increase inequality?

Experiment:
- At every 100 recommendations we record the current gini for both trainings.
- We compare both cases to the optimal and random ginis for set # of jokes.

Results:
- A set of 2 jokes has the most significant increase in inequality.
- Slope comparisons near the start emphasize the inequalities in case 2.
- Final gini values for case 2 are higher than those for case 1.
  - This shows that repeated training increases inequalities.

If interested contact Sunshine Chong (schong@mail.ccsf.edu)
Work performed under REU Site program
supported by NSF grant #1659886