Evaluating the Accuracy and Coverage performance of Collaborative Filtering, Content-based, and Hybrid Recommender Systems

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Introduction

- Recommender systems harness data to provide personalized recommendations for users.
- These recommendations ease the burden on the user of sifting through all of their options while simultaneously increasing the platform's likelihood of providing accurate recommendations to the user.
- There are three overarching types of recommender systems: collaborative filtering, content-based, and hybrid methods.
    - Collaborative filtering can be performed using a user-based method, an item-based method, through matrix factorization, or even through a neural network.
    - Content-based methods utilize item descriptions and a profile of user interests.
    - Hybrid methods combine components of collaborative filtering and content-based methods to limit the disadvantages of either method individually [1].
- We developed and evaluated 10 recommender systems.

Thesis

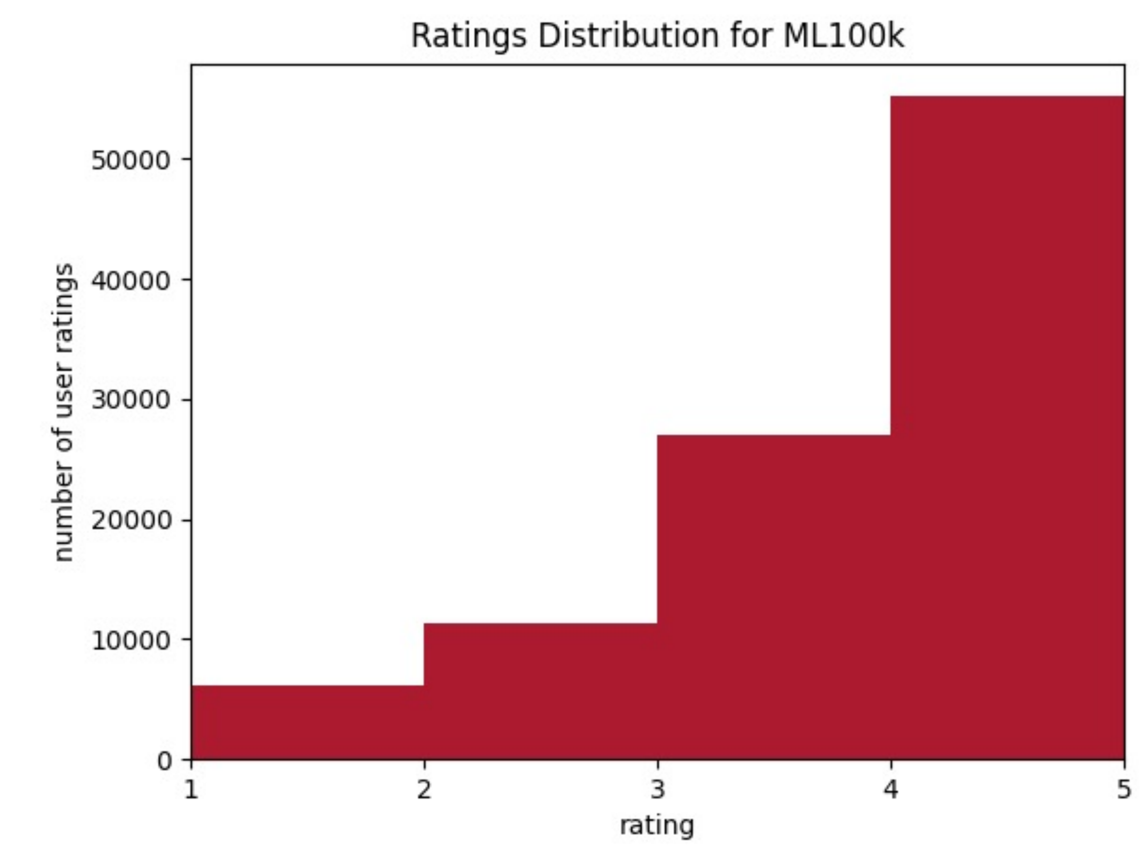
- Recommender systems to be evaluated:
    - (4) Neighborhood-based user- and item-based collaborative filtering (CF) using Euclidean and Pearson distance for neighborhood determination [4,5].

$$\text{Euclidean distance} = \sqrt{\sum_{i \in S_{uv}} (r_{ui} - r_{vi})^2}$$

$$\text{Pearson distance} = \frac{\sum_{i \in S_{uv}} (r_{ui} - \bar{r_u})(r_{vi} - \bar{r_v})}{\sqrt{\sum_{i \in S_{uv}} (r_{ui} - \bar{r_u})^2 \sum_{i \in S_{uv}} (r_{vi} - \bar{r_v})^2}}$$

        - Explore different values of similarity threshold and similarity significance weighting.
    - (2) Matrix factorization CF using stochastic gradient descent and alternating least squares [6].
        - Explore different values of regularization, number of factors, and learning rate (for gradient descent).
    - (1) Neural collaborative filtering (NCF) [3].
    - (1) Term frequency-inverse document frequency content filtering (TFIDF-CB).
    - (2) Hybrid model using a) item-based CF with each of Euclidean and Pearson and b) TFIDF-CB.
- We hypothesize that the hybrid models will outperform all individual recommender systems based on [1].

Experimental Design



- Figure 1 shows the statistics for the ML100k dataset.
- We implemented 10 different recommender systems ranging from user-based collaborative filtering nearest neighbor models to neural networks.
- In order to evaluate the 10 models, we used mean-squared error (MSE) and the accuracy-coverage metric [2].
- These models were tuned using a grid-search approach, with the accuracy-coverage metric determining the "best" set of hyperparameters. The hyperparameter sets were only considered if they yielded a coverage of at least 80%.

Related Work

- [1] Robin Burke. 2002. Hybrid Recommender Systems: Survey and Experiments.
- [2] Carlos Seminario and David Wilson. 2012. Case study evaluation of Mahout as a recommender platform.
- [3] Xiangnan He et al. 2017. Neural Collaborative Filtering.
- [4] Desrosiers and Karypis. 2011. A comprehensive survey of neighborhood-based recommendation methods.
- [5] Herlocker et al. 1999. An algorithmic framework for performing collaborative filtering.
- [6] Koren et al. 2009. Matrix factorization techniques for recommender systems.

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