**Goal**

The goal of this project is to use a recommender system to predict which teacher would maximize which student’s test score(s) in order to help the school put students with teachers who are best for them. This will be achieved by looking at some purposefully masked test score data from the school and checking if the recommender system is able to “fill in” similar predicted scores. If the scores are close enough, we know that the program works with the school’s data.

**Intro**

**Recommender Systems** are software tools that give predictions of user preferences. Netflix, for one, uses recommender systems used to predict movies that each user might like based on ratings of previous movies.

**Method**

We use a recommender system based on the one used for the Netflix Prize, a competition that Netflix started in 2006 in order to find a more effective way to recommend movies to users. It includes collaborative filtering, which allows users who like similar movies to be matched and then be recommended new movies based on that match, and matrix factorization, which allows one to incorporate more information than nearest-neighbor techniques like implicit feedback and confidence levels of ratings. Specifically, we use pycsrd, a regularized singular value decomposition solver for collaborative filtering written in python, and modify it in order to take in Campus School test score data instead of Netflix’s movie ratings data. This graph is a fictional example of the first two vectors from a matrix decomposition of movie ratings data. The movies are placed based on their two factor vectors. Increasing the factor’s model’s dimensionality increases the accuracy of the predictions.

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**Campus School**

The **Smith College Campus School** is a coeducational day school enrolling students from Northampton and the surrounding communities in grades K through 6. There are 2 classrooms at each grade level and 18-21 students per class.

**Campus School Data Set**

We looked at anonymized test scores for 313 students over 3 grade levels, covering 5 consecutive years. The students’ scores are in 10 categories: Reading, Vocabulary, Reading Composite, Language, Language Mechanics, Language Composite, Mathematics, Math Computation, Math Composite, and Total Score. We analyzed the students’ total scores.

**Graph of the error outputs (with Campus School data as input):**

**Train err** is the error of the training data, where the program already knows the desired output. The error calculated is the RMSE (Root Mean Square Error), which is the difference between the predicted and actual results. **Probe err** is the error of the masked data, where the program does not already know the desired output. The colored cells of the empty graph on the right represent the masked data. The program first predicts those masked scores and then “gets” the actual scores from the original unmasked data set, represented by the gridded graph. It then produces the RMSE by comparing the predicted and actual scores.

**Future Work**

Future work would be to see if there is an improvement in the RMSEs when looking at the individual reading, writing, and mathematics categories, not just the students’ total test scores. In addition, pycsrd currently removes 10% of one large connected portion of our data. Future work would be to remove more controlled areas of our data instead, in order to hopefully enable the program to provide more accurate predictions.

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