



# Lecture 14: Recommender Systems / Matrix Factorization

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## Matrix Factorization

- user rates a very small amount of movies
- you can create a matrix, where rows are users and columns are ratings for each movie
- most of the matrix will be very sparse
- We have to assume that all movies fit into  $k$  categories (such as movie genres)
  - We can create a  $R_v$  feature vector with the degree to which each movie fits a particular category
  - Then we can create a user  $u$  vector with how much they like each category
  - Then you can put the 2 vectors into a rating function to predict how much a user might like a certain movie
    - dot product of the feature and user vectors
- our goal is to argmin  $L$  and  $R$
- some recommender systems
  - popularity
  - nearest neighbor
  - item-item

- plot a co-occurrence matrix that tells you what percent of people who bought this particular item also bought...
- you have to normalize first because there might be varying amounts in each category
- take the top k items in the row that had the highest correlation weights and then recommend that to the user
- for multiple items:
  - take the average of the scores/ratings of each item for all of those categories
  - could weight recent purchases more than older ones
- feature-based
  - store information for each feature of each movie AND also the user (age, gender, etc)
- Matrix factorization
  - actual data points will be the original sparse matrix
  - predict data points by learning the movie and user weights (ratings for each genre, author, date published, time of day, etc) and then dot producting the 2 vectors for the particular user or movie that you want to test
  - suffers from cold start problem
  - You can use ridge regularization to fix the problem of having infinite solutions that minimize the MSE on the quality metric
  - can be used for both supervised and unsupervised learning
- hybrid model