Movie Recommender Case Study

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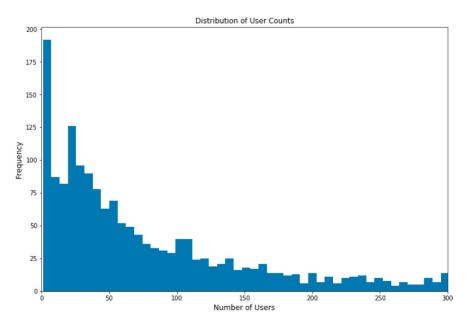
Members: Hamilton, Nabor, Sonia, Match

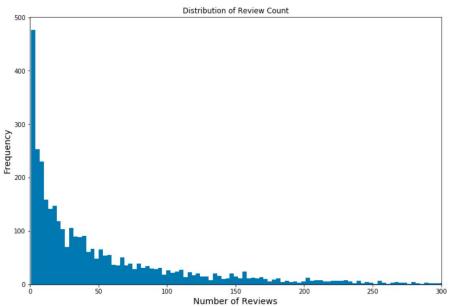
Initial Observations

- Most movies are reviewed by less than ~50 people.
- Most users review less than ~10 movies
- Data is very sparse
- ALS will generate a lot of NaNs

(insert photoshopped movie poster here)

Initial Observations





Model Implementation

- Train/test split on time series
- UVD + ALS
- Tested various hyperparams
 - Rank
 - Max iterations
 - Regularization
- Imputed NaNs with movie average
 - Popular movies have higher mean ranking
 - Better than just global mean ranking

(insert photoshopped movie poster here)

Results

Best evaluation metric:

Moses score = 3.54

		user	rating
movie	title		
2858	American Beauty (1999)	2901	4.328852
1196	Star Wars: Episode V - The Empire Strikes Back (1980)	2516	4.290143
260	Star Wars: Episode IV - A New Hope (1977)	2515	4.452087
1210	Star Wars: Episode VI - Return of the Jedi (1983)	2456	4.019544
589	Terminator 2: Judgment Day (1991)	2284	4.067863
2028	Saving Private Ryan (1998)	2245	4.326503
480	Jurassic Park (1993)	2232	3.755376
1270	Back to the Future (1985)	2183	3.983509
2571	Matrix, The (1999)	2172	4.316298
1580	Men in Black (1997)	2156	3.730519

Conclusions

- Very large number of NaNs
- Scoring metric heavily dependent on imputed NaN values
- Need better imputation method or build model to reduce NaN count
- Alternatively, gather A LOT more data
- ALS would not work efficiently if new data was introduced
 - SDG is better

Next Steps

- Improve impute NaN strategy to include mean user score using weighted mean
 - Weighted Mean = alpha x movie mean ranking + (1-alpha) x user mean ranking
- Adjust model based on reviews per user/reviews per movie
- Implement SVD model
- Combine content-based filtering
- Apply clustering methods

(insert photoshopped movie poster here)

Thank you

Questions?

(...and here)