# MOVIE RECOMMENDATIONS

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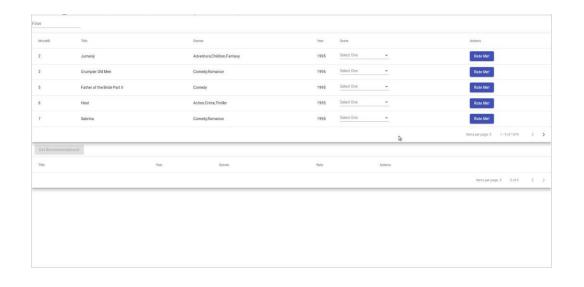
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### OUR DATASET:



- Movie Lens Latest Dataset
- 58,000 movies
- 27 million ratings
- 280,000 users
- Last updated on 09/2018
- <a href="http://grouplens.org/datasets/movielens/latest/">http://grouplens.org/datasets/movielens/latest/</a>

#### TECHNOLOGIES USED

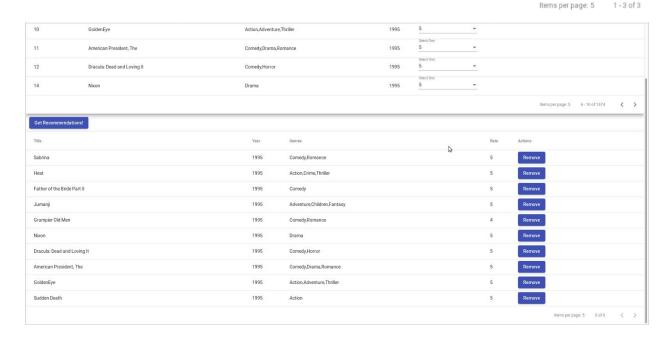


- Angular 2 for GUI
- Node and Express for Back-end
- CSV Database converted to MongoDB to make retrieval faster
- Python for running the actual recommendation algorithm

#### HOW TO USE IT:



- Select 10 or more movies or TV shows
- Rate them on a scale of 5
- Click on get recommendations
- Bazinga!



# **TECHNIQUE**

- Pre-processing
- Collaborative Filtering
  - Main method SVD (Non-Probabilistic)
  - Also tested with KNN Item-Item, and User-User

#### USER-USER AND ITEM-ITEM SIMILARITY

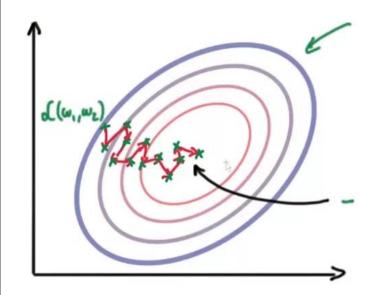
$$\hat{r}_{ui} = \mu_u + \frac{\sum_{v \in N_i^k(u)} \sin(u, v) \cdot (r_{vi} - \mu_v)}{\sum_{v \in N_i^k(u)} \sin(u, v)}$$

KNNs with means
 For user-user similarity,
 Take k nearest neighbors of the user. Use their ratings to estimate yours. Add user bias.

Similarly, the test is performed for item-item matrix

 KNNs with z scores(normalizing) is performed for user-user and itemitem.

# SINGULAR VALUE DECOMPOSITION



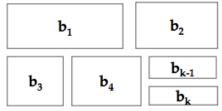
The prediction  $\hat{r}_{ui}$  is set as:

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T p_u$$

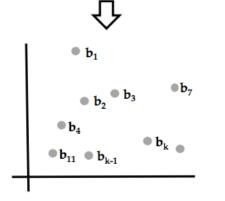
$$\sum_{r_{ui} \in R_{train}} (r_{ui} - \hat{r}_{ui})^2 + \lambda (b_i^2 + b_u^2 + ||q_i||^2 + ||p_u||^2)$$

$$\mathbf{R} pprox \mathbf{P} imes \mathbf{Q}^T = \hat{\mathbf{R}}$$

#### REINFORCEMENT LEARNING WITH BI-CLUSTERING

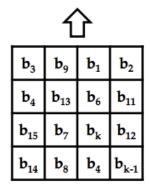


Biclusters from user-item matrix



Bicluster mapped to 2-D space

 $arg max Q_{\pi}$ 



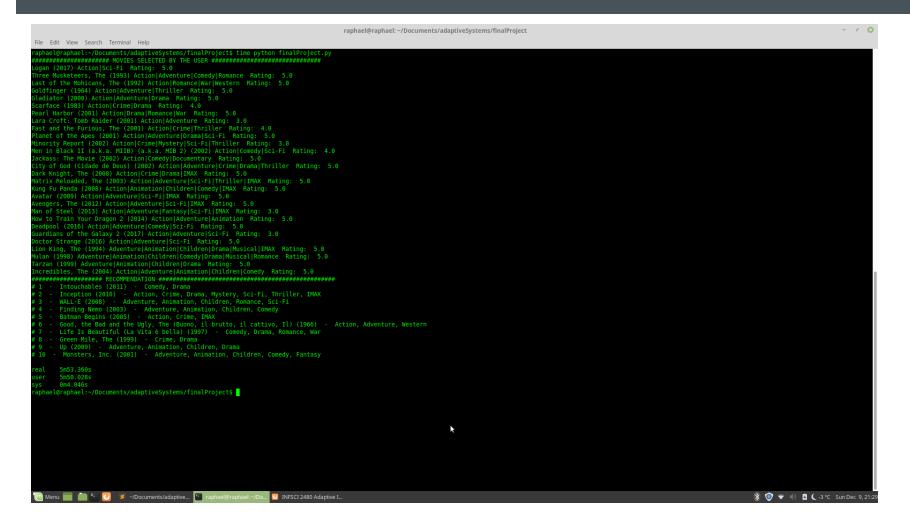
Bicluster remapped n x n grid states

$$\begin{split} \mathbf{R}(s_t, a_t, s_{t+1}) &= \mathbf{Jaccard\_Distance}(U_{s_t}, U_{s_{t+1}}) \\ &= \frac{|U_{s_t} \cap U_{s_{t+1}}|}{|U_{s_t} \cup U_{s_{t+1}}|}. \end{split}$$

## **EXPERIMENTS**

Results	KNN means User-Based	KNN means Item-Based	KNN Z-scores User-Based	KNN Z-scores Item-Based	SVD
RMSE	0.895	0.880	0.887	0.892	0.873
MAE	0.678	0.669	0.674	0.671	0.672
Fit Time	0.59	9.97	10.30	0.59	4.75
Test Time	1.37	6.65	11.56	1.40	0.17

#### TESTING WITH DIFFERENT GENRES OF MOVIE



#### TESTING WITH SUPER-HERO MOVIES

Items per page: 5

#### Get Recommendations!

- 1 Avengers, The (2012) Action, Adventure, Sci-Fi, IMAX
- 2 Batman Begins (2005) Action, Crime, IMAX
- 3 Star Trek (2009) Action, Adventure, Sci-Fi, IMAX
- 4 X-Men: Days of Future Past (2014) Action, Adventure, Sci-Fi
- 5 Toy Story 3 (2010) Adventure, Animation, Children, Comedy, Fantasy, IMAX
- 6 Guardians of the Galaxy (2014) Action, Adventure, Sci-Fi
- 7 X2: X-Men United (2003) Action, Adventure, Sci-Fi, Thriller
- 8 X-Men: First Class (2011) Action, Adventure, Sci-Fi, Thriller, War
- 9 Dark Knight Rises, The (2012) Action, Adventure, Crime, IMAX
- 10 Captain America: The Winter Soldier (2014) Action, Adventure, Sci-Fi, IMAX

Title	Year	Genres	Rate	Actions
Deadpool	2016	Action,Adventure,Comedy,Sci-Fi	5	Remove
Incredibles, The	2004	Action,Adventure,Animation,Children,Comedy	5	Remove
X-Men	2000	Action,Adventure,Sci-Fi	5	Remove
Dark Knight, The	2008	Action,Crime,Drama,IMAX	5	Remove
Avengers: Age of Ultron	2015	Action,Adventure,Sci-Fi	5	Remove
Iron Man	2008	Action,Adventure,Sci-Fi	5	Remove
Superman Returns	2006	Action,Adventure,Sci-Fi,IMAX	4	Remove
Amazing Spider-Man, The	2012	Action,Adventure,Sci-Fi,IMAX	5	Remove
Captain America: Civil War	2016	Action,Sci-Fi,Thriller	5	Remove
Despicable Me 2	2013	Animation, Children, Comedy, IMAX	5	Remove

# FUTURE IMPROVEMENTS

Implement Content Based recommendation

Make the system Hybrid

Filtering genre and popularity

Save the user preferences based on genre

Complete the Reinforcement Learning approach