metarecommendr

Predicting your next Game, Movie, TV Show

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Presentation Outline

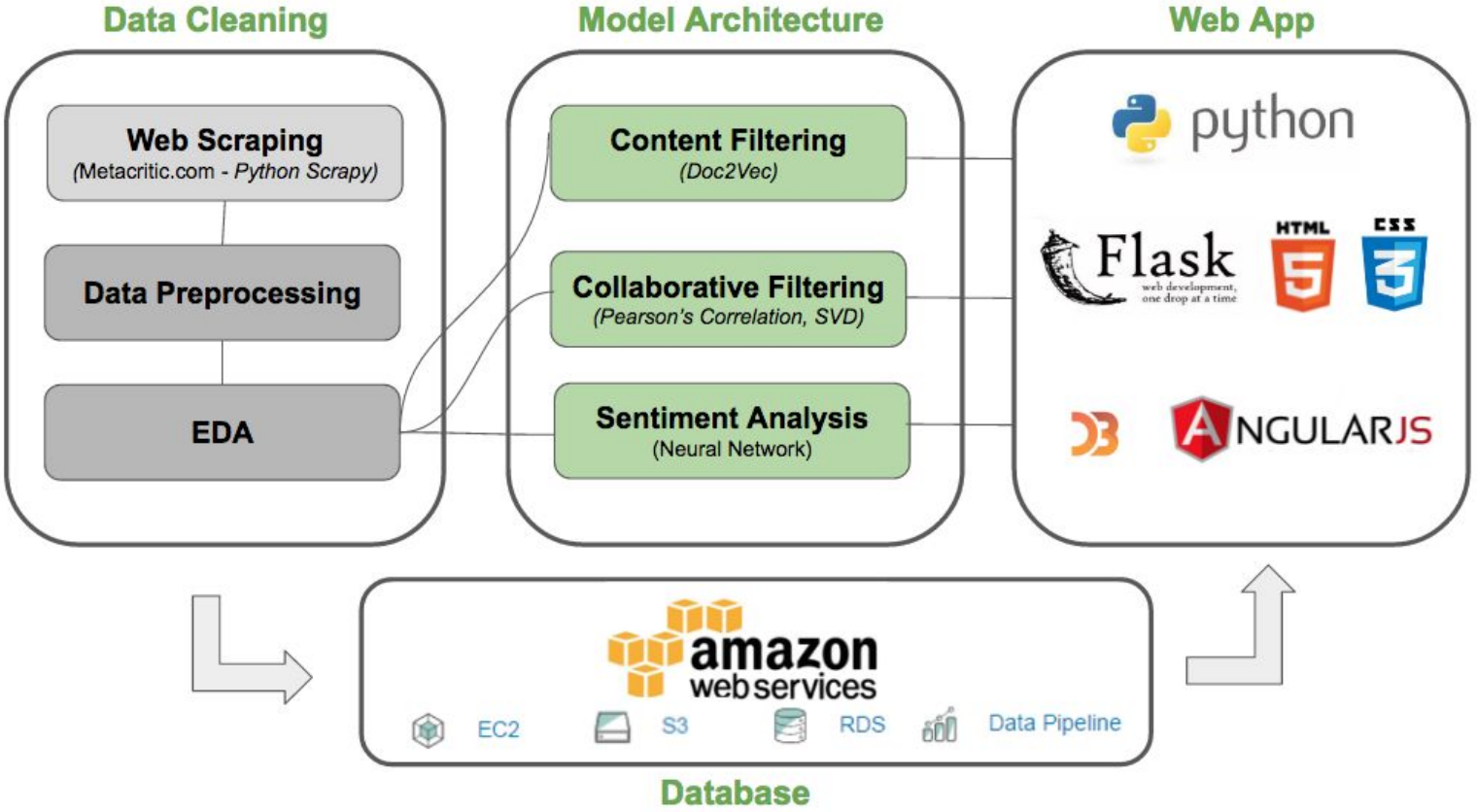
1. Introduction
2. Web Scraping
3. EDA
4. Model Architecture
    a. Content Filtering
    b. Collaborative Filtering
    c. Sentiment Analysis
5. App Demo

metarecommendr

1. Introduction: *Metacritic*

- Metacritic offers a centralized platform aggregating reviews for different media products *(Video games, Movies, Music, TV Shows)*
  - Aggregated Critic reviews from 1-100, all in English
  - User reviews from 1-10, not restricted to English
- Problem:
  - Product suggestions is usually within the same category
    - Need to sift through lots of text to find non-obvious recommendations
  - User Interface can be too crowded with information
  - Review Sentiment sometimes does not correspond to score
- Solution:
  - Metarecommendr
    - Optimized recommendations using collaborative and content filtering
    - Clean Interface to find products
    - Review Grader to check sentiment of user reviews

1. metarecommendr - *Project Workflow*



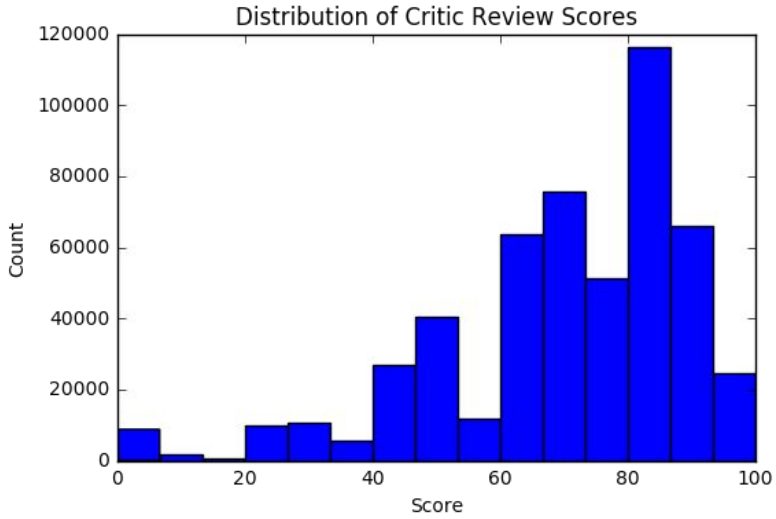
2. Web scraping: *Python Scrapy*

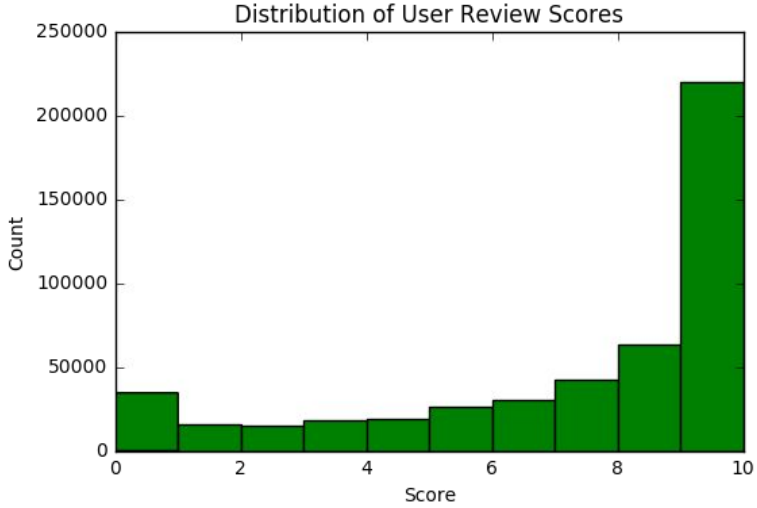
- Website: www.metacritic.com
- ~1 Million reviews scraped in 10 days via Python Scrapy
  - Data scope:
    - Movies: Last 10 years
    - TV Shows: All TV shows
    - Games: All games
- Since metacritic is more popular among gamers, there are more game reviews

Games, TV, Movies	**Reviews Field**
Name	Publication
Link	Author
Image Link	Date
Developer	ReviewType *(Critic or User)*
Rating	Review Content
Release Date	Score
Summary	
System	

3. EDA: *Overall Statistics*

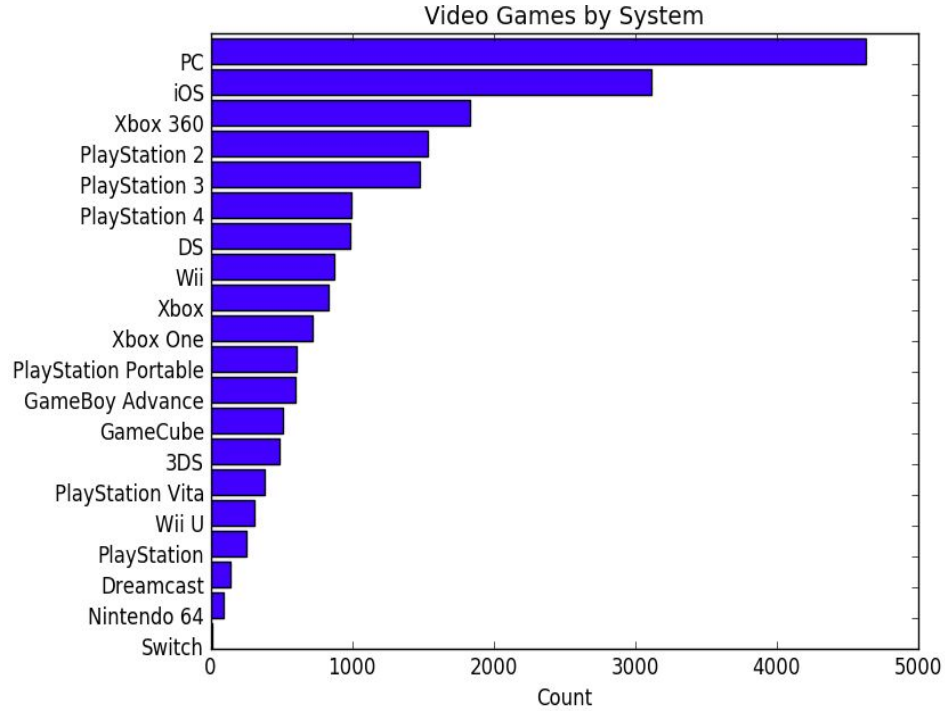
- # Items
  - Games: 20416
  - Movies: 5470
  - TV Shows: 1978
- Critic Reviews:
  - 514,304 Critic Reviews
    - Mean: 68.96
    - Median: 74.0
    - Standard Deviation: 19.98
- User Reviews:
  - 484,278 User Reviews
    - Mean: 7.03
    - Median: 8.0
    - Standard Deviation: 3.16

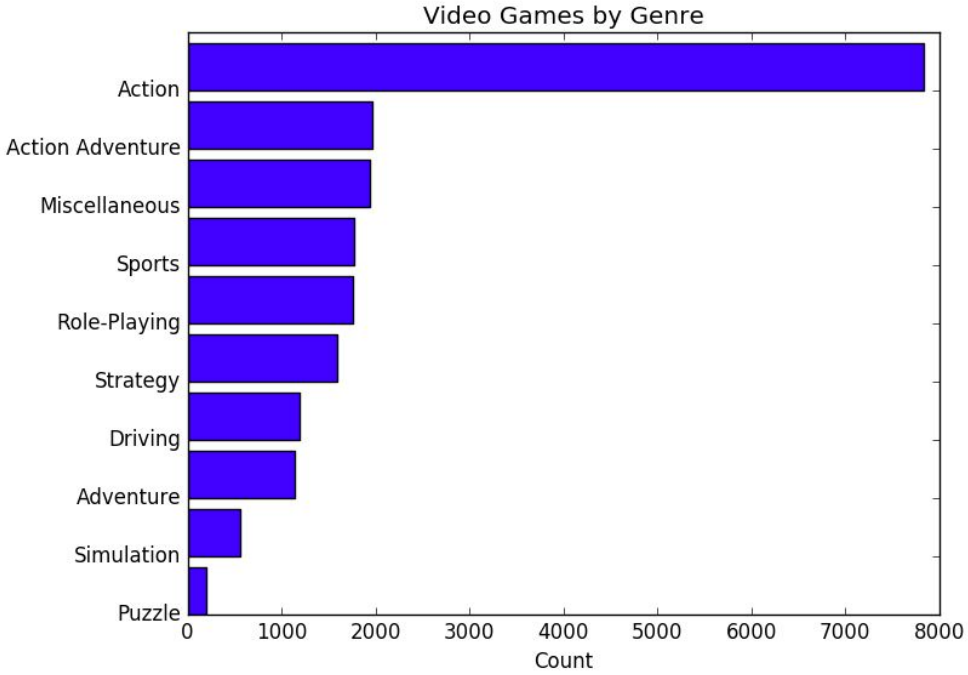




3. EDA: Video *Games*

- Action games and PC games are the most common video games



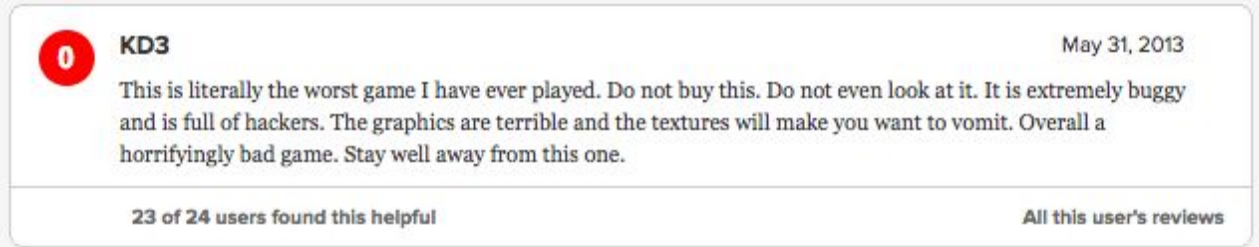


3. EDA: *Games - Interesting findings*

- A bad video game may cause people to leave more reviews

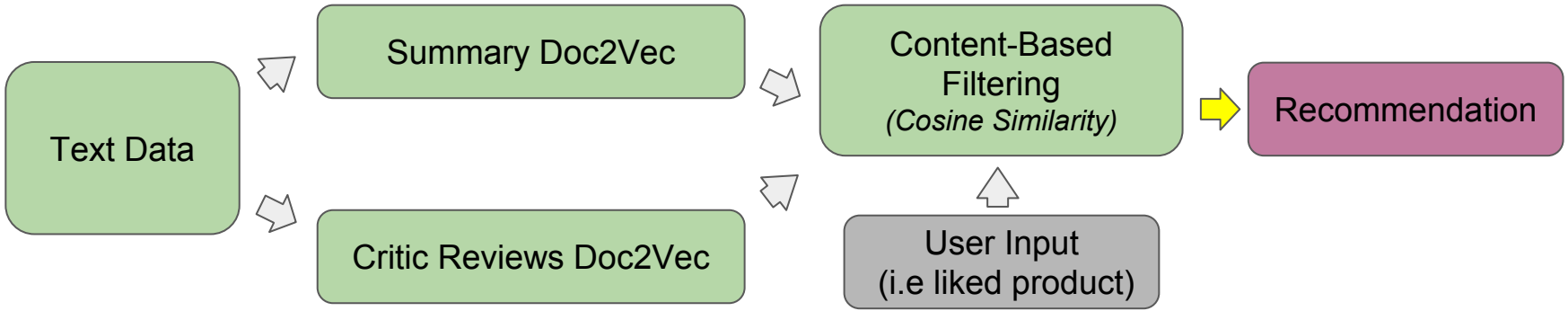
Top 5 Most Reviewed Games*(Count on Critics+Users)*

	uniqueID	count	name	AvgCritRat	AvgUserRat
0	7638	2266	Call of Duty: Modern Warfare 3	88.33	3.60
1	13089	2227	Diablo III	87.71	3.87
2	1389	1847	The Last of Us	94.83	9.24
3	13210	1761	The Elder Scrolls V: Skyrim	93.78	7.81
4	253	1619	Infestation: Survivor Stories (The War Z)	21.31	1.85



4. Content-Based Filtering: *unstructured text data is powerful!*

- Content-based filtering uses the item's metadata to make a recommendation
- Transformed text reviews into a vector representation using *Doc2Vec* algorithm in Python's Gensim library
  - Doc2Vec for item summaries and critic reviews
    - Over 500,000 reviews of 30,000 items aggregated into one corpus
- Computed cosine similarity to compare user input with database of items, returning items with the highest cosine similarity



4.b) Collaborative Filtering: *Pearson's Correlation*

Pearson Similarity Using Critic and User Ratings

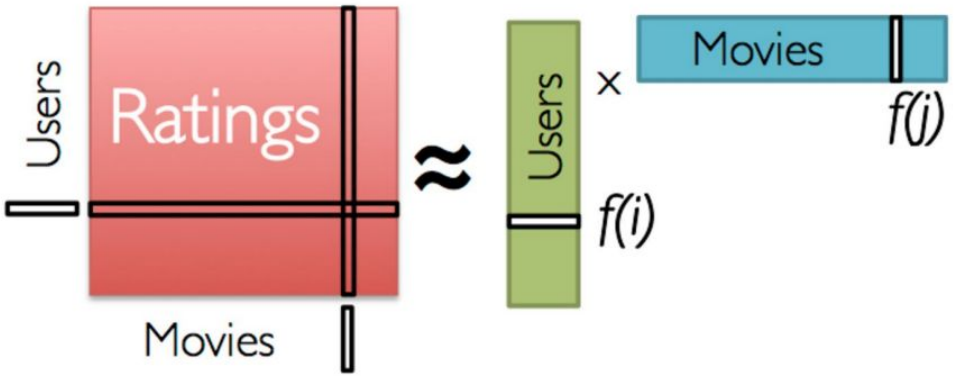
- Item to Item Matrix

- Restricted to items with more than 100 reviews to reduce the size of the matrix

	3	25	51	73	95	171	182
3	1	0.443913	0.308666	0.0381164	0.365199	0.184312	0.078321
25	0.443913	1	-0.00955871	-0.235418	-0.036264	-0.206055	0.187101
51	0.308666	-0.00955871	1	0.340238	0.262468	0.257613	-0.0237654
73	0.0381164	-0.235418	0.340238	1	0.326446	0.369903	0.366808
95	0.365199	-0.036264	0.262468	0.326446	1	0.305	0.152899
171	0.184312	-0.206055	0.257613	0.369903	0.305	1	0.282427
182	0.078321	0.187101	-0.0237654	0.366808	0.152899	0.282427	1
253	0.717126	0.862439	0.609682	0.204226	0.593271	-0.30922	0.35344
313	0.847922	0	0.255282	0.467417	0.929063	0.627763	0.403403
337	0	0.00663741	0	0	0	0.526075	0.221095

4.b) Collaborative Filtering: *SVD*

- Recommendation based on:
  - User's past ratings (explicit information)
  - History of like-minded users
- Problem: User-item matrix is very sparse!
  - Solution: SVD - latent matrix factorization of user-item matrix to find latent features
  - Used SVD's implementation in Scipy's library



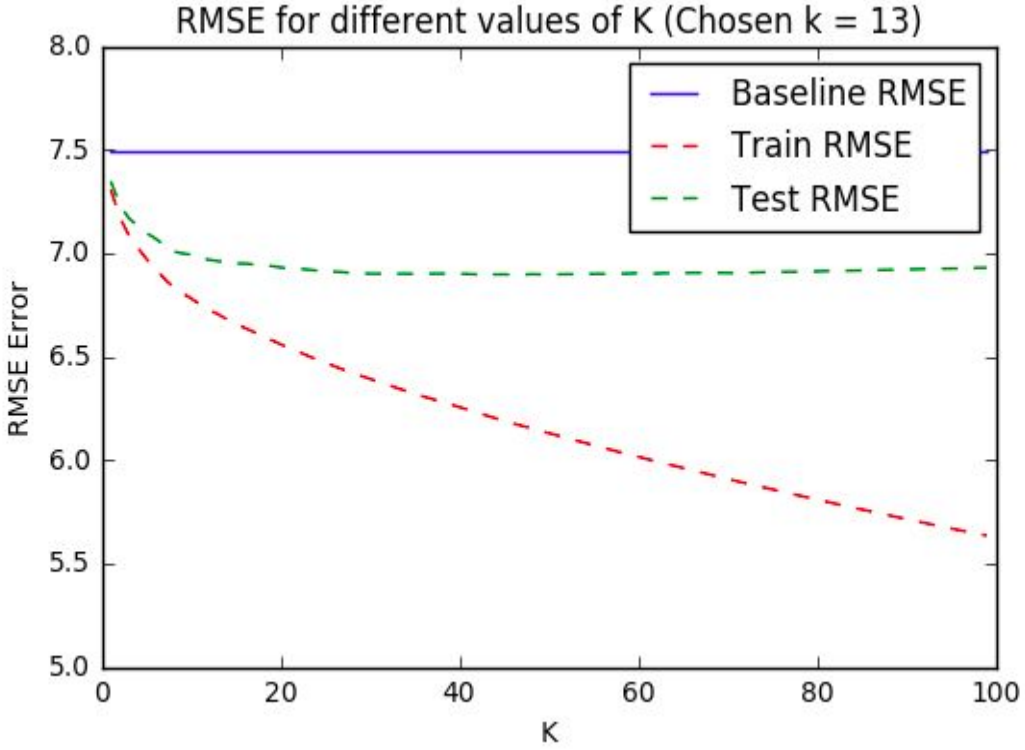
4.b) Collaborative Filtering: *SVD - Predicting User Rating*

- Predicted User Rating (formula)

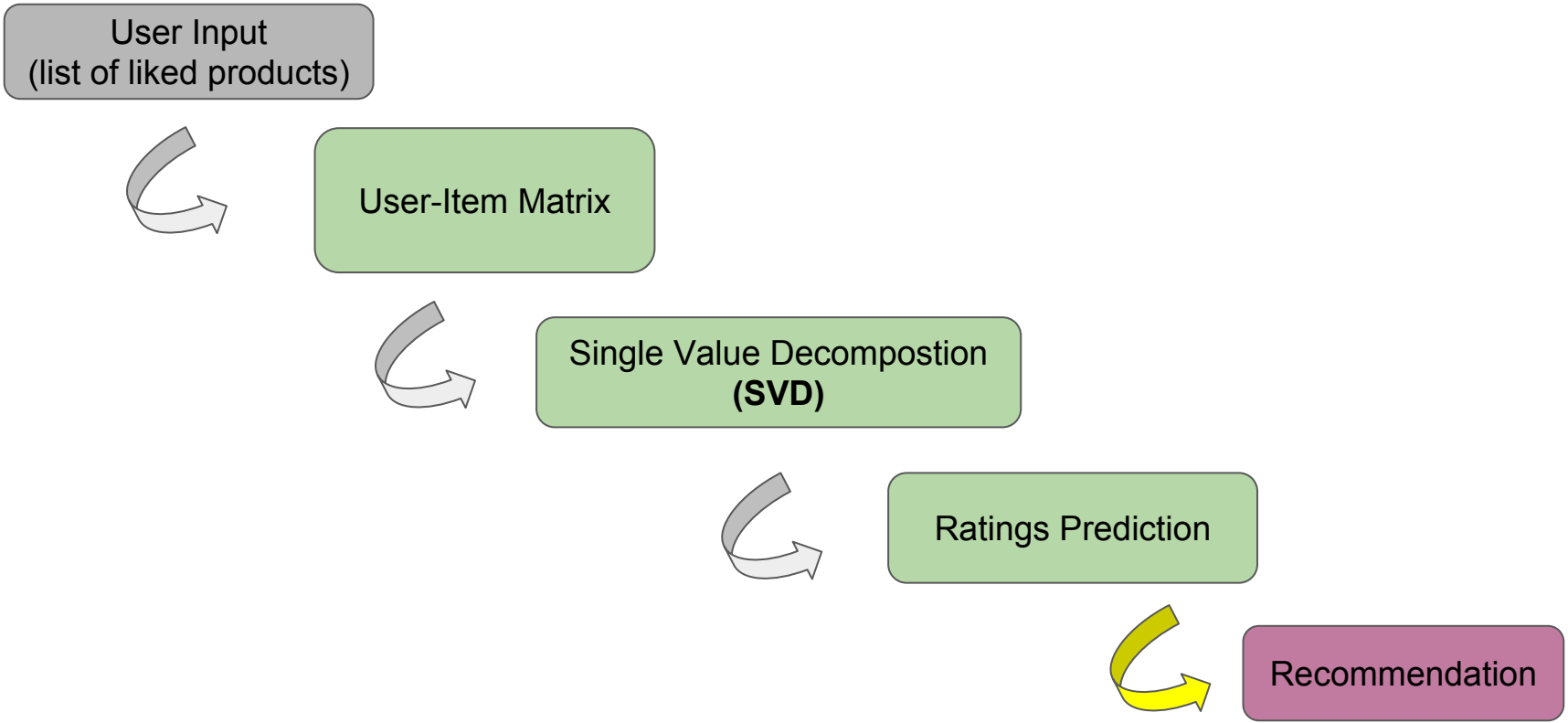
$$\mathbf{A}_{nxp} = \mathbf{U}_{nxn}\,\mathbf{S}_{nxp}\,\mathbf{V}^{\mathbf{T}}_{pxp}$$

- Best Model
  - K =13 (from scree plot)
  - Entire dataset RMSE: 6.07
  - Baseline RMSE: 7.5
  - Improvement: ~ 19%

$$\mathrm{RMSE} = \left[\left(\sum_{i=1}^{n}(y_i - \hat{y}_i)\right)\Big/ n\right]^{1/2}$$



4.b) Collaborative Filtering: *SVD - Recommendations*

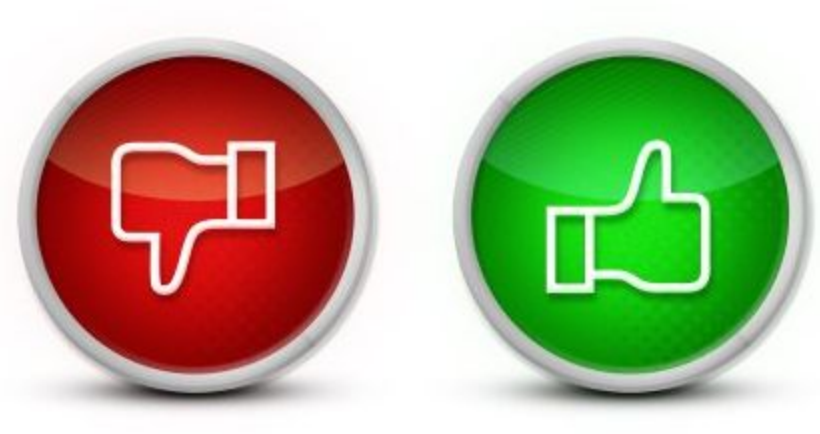


Note: Current version of app restricts user-item matrix to users with > 50 reviews

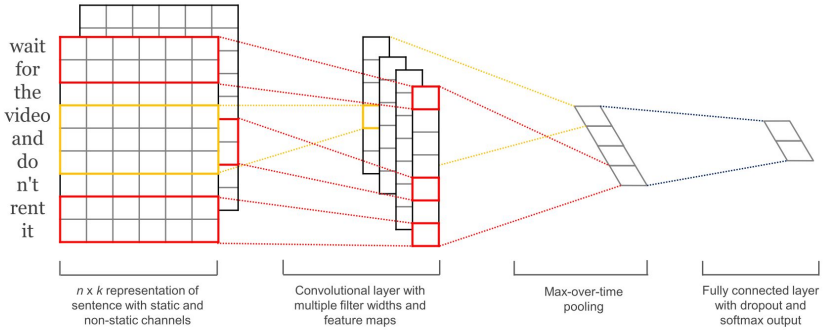
4.c) Sentiment Analysis: *Tested Machine Learning Models*

- Logistic Regression and SVM
  - Around 75% test accuracy
  - Doc2Vec to create features

- Neural Network
  - 90% validation accuracy
  - Tokenized corpus
  - 10,000 word dictionary



4.c) Sentiment Analysis: *Neural Network Architecture*



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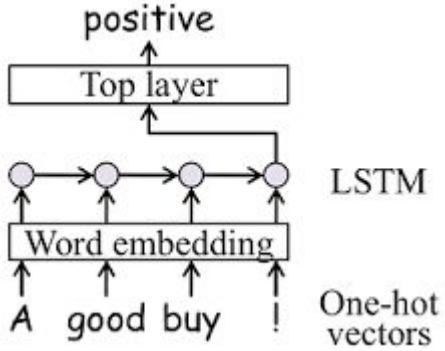

- Tried Recurrent NN alone - poor results
- Tried Convolution NN alone - better results
- Found best results when combined
  - 2 Convolution and pool layers
  - 2 recurrent layers - LSTM (Long Short Term Memory)
  - 3 dense, fully connected layers
  - 3 epochs

4.c) Sentiment Analysis: *Best NN Results*

```
Train on 121233 samples, validate on 80822 samples
Epoch 1/3
121233/121233 [==============================] - 677s - loss: 0.3316 - acc: 0.8579 - val_loss
: 0.2735 - val_acc: 0.8834
Epoch 2/3
121233/121233 [==============================] - 685s - loss: 0.2412 - acc: 0.9041 - val_loss
: 0.2583 - val_acc: 0.8961
Epoch 3/3
121233/121233 [==============================] - 682s - loss: 0.2036 - acc: 0.9215 - val_loss
: 0.2423 - val_acc: 0.9010
Accuracy: 90.10%
```

5) Flask Web Application

- Web application built using Flask in Python
  - AngularJS: great framework for building dynamic web apps
  - Database: MySQL on AWS RDS
- Live demo

[Extra Slide] Future Improvements

- Hybrid Recommendation system
- Neural network to summarize text
- Improve score prediction
- Improve scaling efficiency
- A/B testing
  - Content vs collaborative
  - User onboarding
  - Click through rate