



INTRODUCTION TO MOVIE RECOMMENDATION SYSTEM

PROBLEM

- Everyone's preference of movie is different
- Movies are hit driven – a handful of movie can drive financial success

THE CHALLENGE

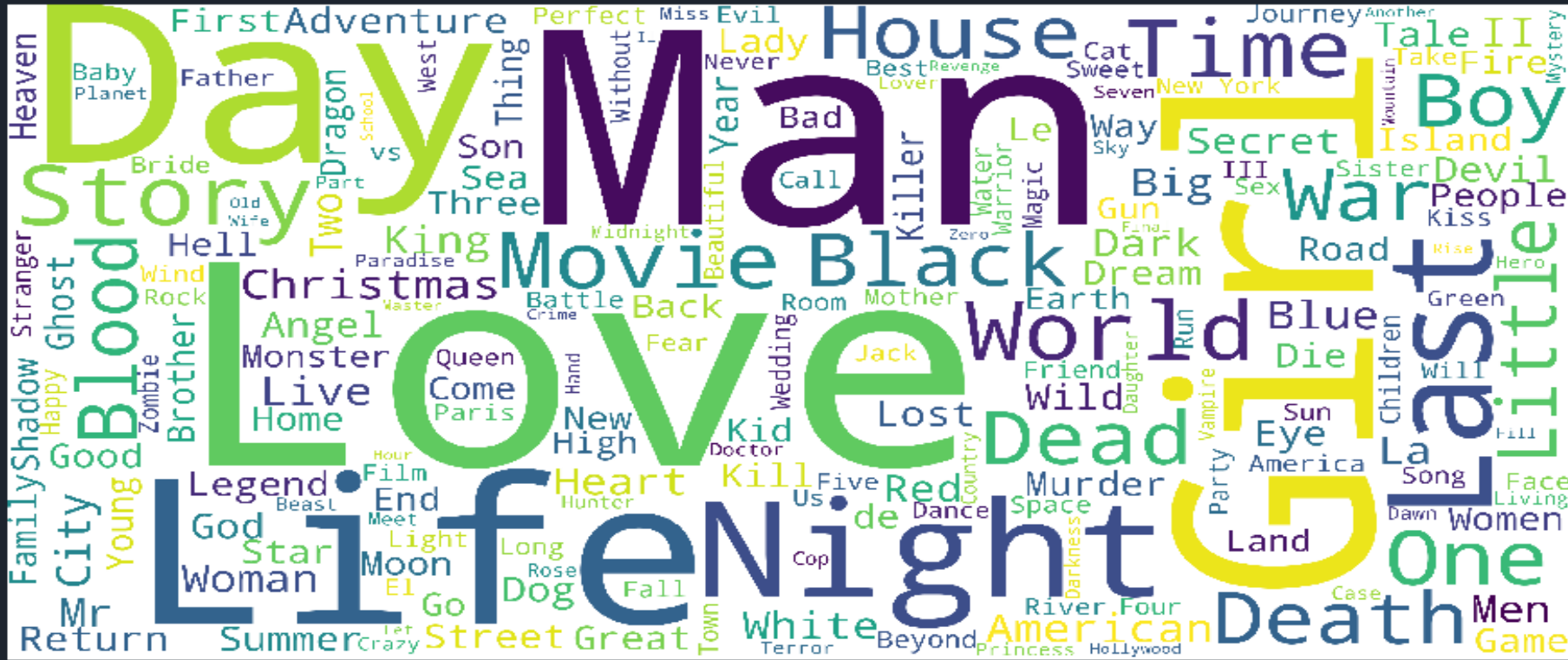
- Apply a recommendation system to market the right movie to the right audience
- Improve Effectiveness of advertisements
- Sometimes improve visibility for less popular movies

DATA

- I used the Movielens Data hosted on Kaggle.
- Containing 26 million ratings from 270,000 users for all 45,000 movies.
- Ratings are on a scale of 1-5 and have been obtained from the official GroupLens website.
- Source: <https://www.kaggle.com/rounakbanik/the-movies-dataset>

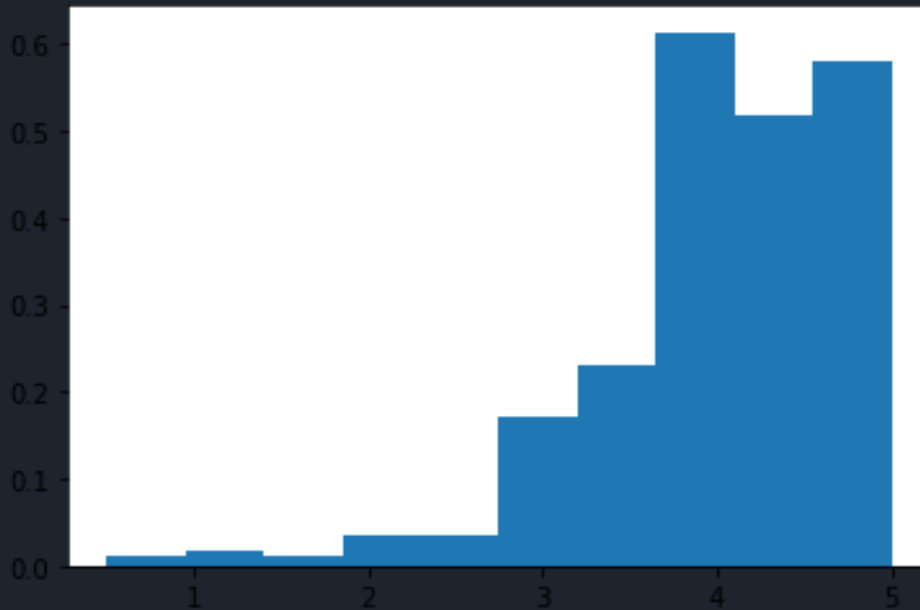
EXPLORATORY ANALYSIS

- Sample Word Cloud- Title



EXPLORATORY ANALYSIS

- Ratings



TYPES OF RECOMMENDATION SYSTEM

- Content Base

Finding and ranking similarity score

- Collaborative

Using Surprise package to predict a single user's rating

- Hybrid

CONTENT BASE FILTERING

- 1st attempt using Taglines and Overview and applying TF-IDF Vectorizer

```
In [40]: j = get_recommendations('Toy Story').head(10).index
         metadata_df_sub.loc[j,['title','tagline','overview']]
```

Out[40]:

	title	tagline	overview
3024	Toy Story 2	The toys are back!	Andy heads off to Cowboy Camp, leaving his toy...
10389	The 40 Year Old Virgin	The longer you wait, the harder it gets	Andy Stitzer has a pleasant life with a nice a...
8410	The Champ	NaN	Dink Purcell loves his alcoholic father, ex-he...
3084	Man on the Moon	Hello, my name is Andy and this is my movie.	A film about the life and career of the eccent...
11715	Factory Girl	When Andy met Edie, life imitated art.	In the mid-1960s, wealthy debutant Edie Sedgwi...
6504	What's Up, Tiger Lily?	WOODY ALLEN STRIKES BACK!	In comic Woody Allen's film debut, he took the...
1092	Rebel Without a Cause	The bad boy from a good family.	After moving to a new town, troublemaking teen...
11508	For Your Consideration	NaN	Three actors learn that their respective perfo...
5859	Class of 1984	Class of 1984. Is this the future?	Andy is a new teacher at a inner city high sch...
1952	Condorman	An action adventure romantic comedy spy story.	Comic artist and writer Woody performs a simpl...

CONTENT BASE FILTERING

- 2nd Attempt using Meta Data (Cast, Genre, Keywords, etc)

```
get_recommendations('The Godfather', cosine_sim=cosine_sim2)
3]: 1199          The Godfather: Part II
     1934          The Godfather: Part III
     10261          The Outfit
     11733          The Consequences of Love
     5309          The Gambler
     3327          ...And Justice for All
     4602          The Cotton Club
     9517          The Black Lapp
     1614          The Rainmaker
     12221          10th & Wolf
     1648          Ill Gotten Gains
     3487          Jails, Hospitals & Hip-Hop
     6744          Ruby
     7772          Mitchell
     8001          The Night of the Following Day
     5793          True Confessions
     1430          Donnie Brasco
     549          Trial by Jury
     2112          The Paradine Case
     10729          House of Strangers
     13361          Manhattan Melodrama
     276          Murder in the First
     9874          Amongst Friends
     1186          Apocalypse Now
     3640          Serpico
     4080          Pixote
     7052          Shoot the Piano Player
     8698          Branded to Kill
     11287          G-Men
     13597          Il Divo
```

COLLABORATIVE FILTERING

- Using Surprise Package
- Using other users rating to predict the rating of target user

HYBRID RECOMMENDER

- Content-base filtering first then apply collaborative filtering

```
▶ hybrid(1, "The Godfather", cosine_sim2)
```

```
2]:
```

	title	vote_count	vote_average	id	est
1186	Apocalypse Now	2112.0	8.0	28	4.613409
7052	Shoot the Piano Player	69.0	7.2	1818	4.352920
3640	Serpico	429.0	7.5	9040	4.330476
1199	The Godfather: Part II	3418.0	8.3	240	4.316102
4012	Gardens of Stone	25.0	5.5	28368	4.285536
1430	Donnie Brasco	1175.0	7.4	9366	4.125541
11733	The Consequences of Love	125.0	7.6	24653	4.119607
1614	The Rainmaker	239.0	6.7	11975	4.048667
3327	...And Justice for All	118.0	7.1	17443	4.004266
4080	Pixote	24.0	8.4	42148	3.994565

MODEL COMPARISON

- Precision at K

A method to see at threshold rating K , arbitrarily set, that how many items the system rated at least K or higher for a user

SVD

```
86]: ▶ for trainset, testset in kf.split(data):
      algo.fit(trainset)
      predictions = algo.test(testset)
      precisions, recalls = precision_recall_at_k(predictions, k=15, threshold=3.5)

      # Precision and recall can then be averaged over all users
      print(sum(prec for prec in precisions.values()) / len(precisions))
      print(sum(rec for rec in recalls.values()) / len(recalls))

0.6773641924688965
0.5724082177629027
0.6781626724448315
0.5809743942524471
0.6856334618028078
0.5842087998220512
0.6876841223307756
0.5858252813718233
0.6831897090921978
0.5819061289397528
```

MODEL COMPARISON

- Precision At K for Baseline

```
In [88]: ▶ for trainset, testset in kf.split(data):
          algo_norm.fit(trainset)
          predictions = algo_norm.test(testset)
          precisions, recalls = precision_recall_at_k(predictions, k=15, threshold=3.5)

          # Precision and recall can then be averaged over all users
          print(sum(prec for prec in precisions.values()) / len(precisions))
          print(sum(rec for rec in recalls.values()) / len(recalls))

0.5821217419887966
0.4348215174573881
0.5853237597005768
0.4336387928090972
0.5765403600913539
0.4320687982419843
0.583347459044794
0.42839280690906817
0.5825129631943087
0.43548330660210877
```

FUTURE CONSIDERATION

- Pre-grouping users with similar rating patterns for Collaborative filtering
- Better computer hardware to use more of the data
- Tree based model?