Recommended System

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Examples

Content-Based Recommendation Systems

Example: Dataset Description

The ml-latest Dataset describes 5-star rating and free-text tagging activity from MovieLens, a movie recommendation service. It contains 27,000,000 ratings and 1,100,000 tag applications applied to 58,000 movies by 280,000 users. Includes tag genome data with 14 million relevance scores across 1,100 tags. The data are contained in the files *genome-scores.csv*, *genome-tags.csv*, *links.csv*, *movies.csv*, *ratings.csv* and *tags.csv*.

ratings.csv

User Id	movie Id	Rating	Time stamp
1	307	3.5	1256677221
…	…	…	…

tags.csv

User Id	movie Id	tag	Time stamp
14	110	philosophy	1442615158
…	…	…	…

movies.csv

movieId title genres

links.csv

movieId imdbId tmdbId

Genome-scores.csv

movieId tagId relevance

Genome-tags.csv

tagId tag

Load the MovieLens Data

Download the file ml_latest.zip here and then unzip into the data/ directory.

```
In [7]: !ls data/

README.txt          genome-tags.csv   ml-latest.zip   ratings.csv
genome-scores.csv   links.csv         movies.csv      tags.csv
```

```
In [8]: # Read dataframes
df_movies = pd.read_csv('data/movies.csv')
df_links = pd.read_csv('data/links.csv')
df_ratings = pd.read_csv('data/ratings.csv')
df_genome_tags = pd.read_csv('data/genome-tags.csv')
df_genome_scores = pd.read_csv('data/genome-scores.csv')

# Merge scores and tags
df_movie_tags_in_text = pd.merge(df_genome_scores, df_genome_tags, on='tagId')[['movieId', 'tag', 'relevance']]

# Only keep tags with relevance higher than 0.3
df_movie_tags = df_genome_scores[df_genome_scores.relevance > 0.3][['movieId', 'tagId']]
```

Merge score and tags

Show the movie with Id 1:

```
In [9]: df_movies[df_movies.movieId == 1]
Out[9]:
```

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy

Encode Features

Convert the above tags into a vector representation:

```
In [53]: tf_idf = TfidfVectorizer()
```

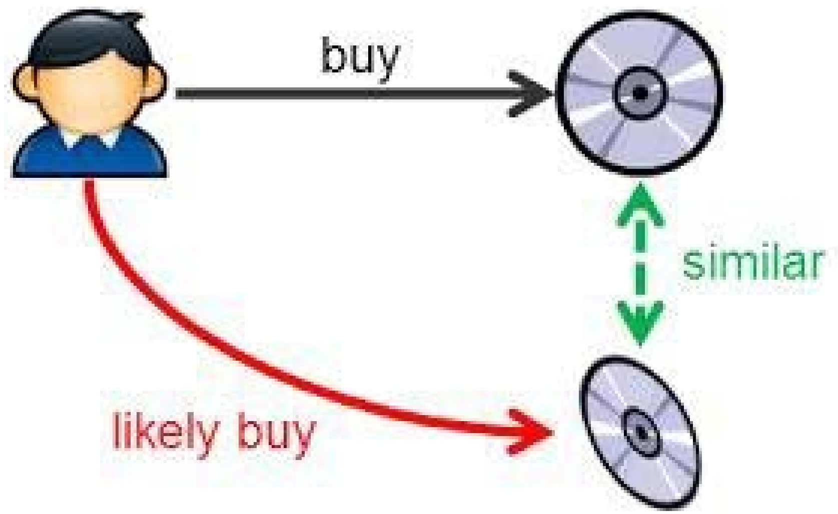
```
In [54]: df_movies_tf_idf_described = tf_idf.fit_transform(df_data_with_tags.movie_tags)
```

The TF*IDF algorithm is used to weigh a keyword in any document and assign the importance to that keyword based on the number of times it appears in the document.

	movieId	title	genres	rating_mean	rating_median	num_ratingsdf_tags_per_movie	movie_tags
1	2	Jumanji (1995)	Adventure|Children|Fantasy	3.246583	3.0	27143.0	193 345 1076 1074 389 1090 61 439 454 29 717 4...
2	3	Grumpier Old Men (1995)	Comedy|Romance	3.173981	3.0	15585.0	302 387 417 742 1057 810 299 445 465 1102 264 ...
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance	2.874540	3.0	2989.0	302 545 387 613 497 179 396 742 299 445 412 80...
4	5	Father of the Bride Part II (1995)	Comedy	3.077291	3.0	15474.0	376 387 1004 497 417 348 742 299 445 1102 264 ...
5	6	Heat (1995)	Action|Crime|Thriller	3.844211	4.0	28683.0	297 423 622 467 303 465 162 758 300 1051 269 3...

df_data_with_tags (13176 rows x 7 columns)

How can we find the similarity between items?



- In model-building stage, the system first find the similarity between all pairs of items;
- Then, it uses the most similar items to a user's already-rated items to generate a list of recommendations in recommendation stage.

Cosine Similarity $sim(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$

Calculating Cosine Similarity

$$sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$$

Calculate cosine similarity

```
In [*]: m2m = cosine_similarity(df_movies_tf_idf_described)

In [*]: df_tfidf_m2m = pd.DataFrame(cosine_similarity(df_movies_tf_idf_described))

In [*]: index_to_movie_id = df_data_with_tags['movieId']

In [*]: df_tfidf_m2m.columns = [str(index_to_movie_id[int(col)]) for col in df_tfidf_m2m.columns]

In [*]: df_tfidf_m2m.index = [index_to_movie_id[idx] for idx in df_tfidf_m2m.index]
```

```
In [104]: df_tfidf_m2m.head()
```

Out[104]:

	1	2	3	4	5	6	7	8	9	10	...	184987	184997	185029	185135	185425
1	1.000000	0.359995	0.140584	0.163904	0.197146	0.267026	0.240104	0.233925	0.075557	0.223134	...	0.231415	0.323718	0.449159	0.415062	0.115754
2	0.359995	1.000000	0.116658	0.123059	0.119013	0.090835	0.215883	0.221415	0.167558	0.221940	...	0.309822	0.231912	0.207119	0.253158	0.151519
3	0.140584	0.116658	1.000000	0.192486	0.407801	0.090215	0.246536	0.151995	0.077091	0.142224	...	0.118169	0.198064	0.173156	0.146563	0.090056
4	0.163904	0.123059	0.192486	1.000000	0.278716	0.075740	0.334642	0.200485	0.049504	0.079378	...	0.151011	0.195374	0.211978	0.181477	0.214305
5	0.197146	0.119013	0.407801	0.278716	1.000000	0.085531	0.309019	0.151632	0.067623	0.109039	...	0.147010	0.264331	0.182410	0.163857	0.117392

5 rows × 13176 columns

Most similar movies to “Toy Story”

```
In [23]: df_tfidf_m2m.iloc[0].sort_values(ascending=False)[:10]
Out[23]: 1        1.000000
         3114     0.737982
         4886     0.736047
         2355     0.721830
         78499    0.708378
         76093    0.685637
         5218     0.653424
         4306     0.642794
         6377     0.639971
         68954    0.635059
         Name: 1, dtype: float64
```

Sort the result in descending order

cosine similarity

movieId

```
In [132]: df_data_with_tags[df_data_with_tags.movieId == 3114]
Out[132]:
```

	movieId	title	genres	rating_mean	rating_median	num_ratingsdf_tags_per_movie	movie_tags
2809	3114	Toy Story 2 (1999)	Adventure|Animation|Children|Comedy|Fantasy	3.809977	4.0	29820.0	193 30 1051 215 452 840 61 897 1035 1090 454 2...

```
In [25]: df_data_with_tags[df_data_with_tags.movieId == 4886]
Out[25]:
```

	movieId	title	genres	rating_mean	rating_median	num_ratingsdf_tags_per_movie	movie_tags
4331	4886	Monsters, Inc. (2001)	Adventure|Animation|Children|Comedy|Fantasy	3.861679	4.0	8708.0	216 215 669 664 663 765 136 497 490 493 690 10...

Examples

Collaborative Filtering based Recommendation Systems

Example: Dataset Description

The last.fm Dataset contains social networking, tagging, and music artist listening information from a set of 2K users from Last.fm online music system. We'll focus on two files: **user_artists.dat** — plays counts of artist by user; artists.dat — id, name as they contain all data required to make recommendations for new music artists to a user.

user_artists.dat

userID	artistID	weight
2	51	13883
2	52	11690
…	…	…

artists.dat

id	name
1	MALICE MIZER
2	Diary of Dream
…	…

Loading the Data

Loading the data

```
In [17]: plays = pd.read_csv('data/user_artists.dat', sep='\t')
         artists = pd.read_csv('data/artists.dat', sep='\t', usecols=['id','name'])
         ap = pd.merge(artists, plays,left_on="id",right_on="artistID")
         ap = ap.rename(columns={"weight": "playCount"})
         ap.head()
```

Merge articles and plays

Out[17]:

	id	name	userID	artistID	playCount
0	1	MALICE MIZER	34	1	212
1	1	MALICE MIZER	274	1	483
2	1	MALICE MIZER	785	1	76
3	2	Diary of Dreams	135	2	1021
4	2	Diary of Dreams	257	2	152

Rank the artists based on how much they were played by the users

```
In [18]: artist_rank = ap.groupby(['name']).agg({'userID' : 'count', 'playCount' : 'sum'}) \
           .rename(columns={"userID" : 'totalUniqueUsers', "playCount" : "totalArtistPlays"}) \
           .sort_values(['totalArtistPlays'], ascending=False)

         artist_rank['avgUserPlays'] = artist_rank['totalArtistPlays'] / artist_rank['totalUniqueUsers']
         ap = ap.join(artist_rank, on="name", how="inner").sort_values(['playCount'], ascending=False)
         ap.head()
```

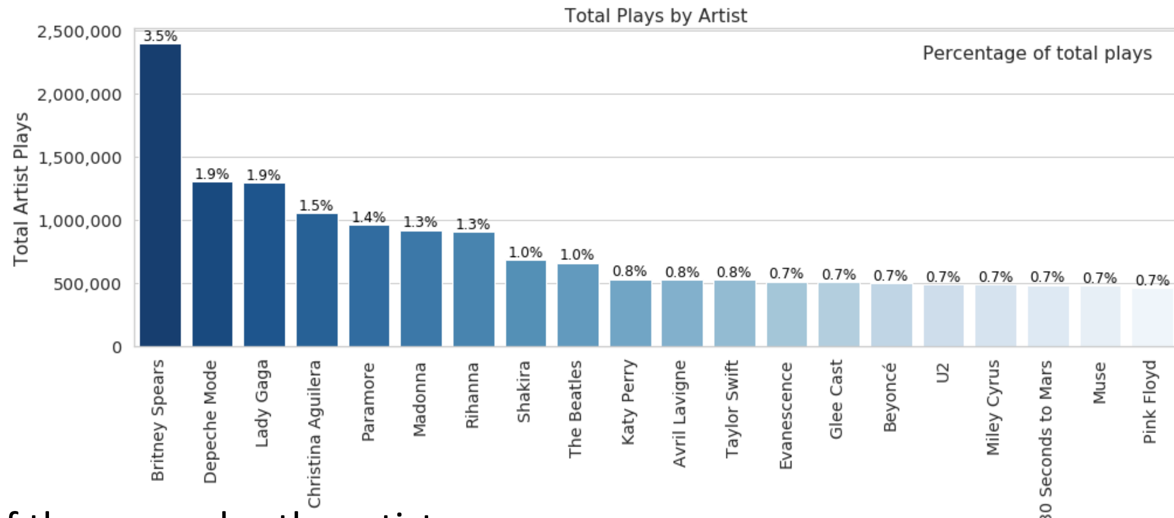
Merge the results with the previous data frame

Out[18]:

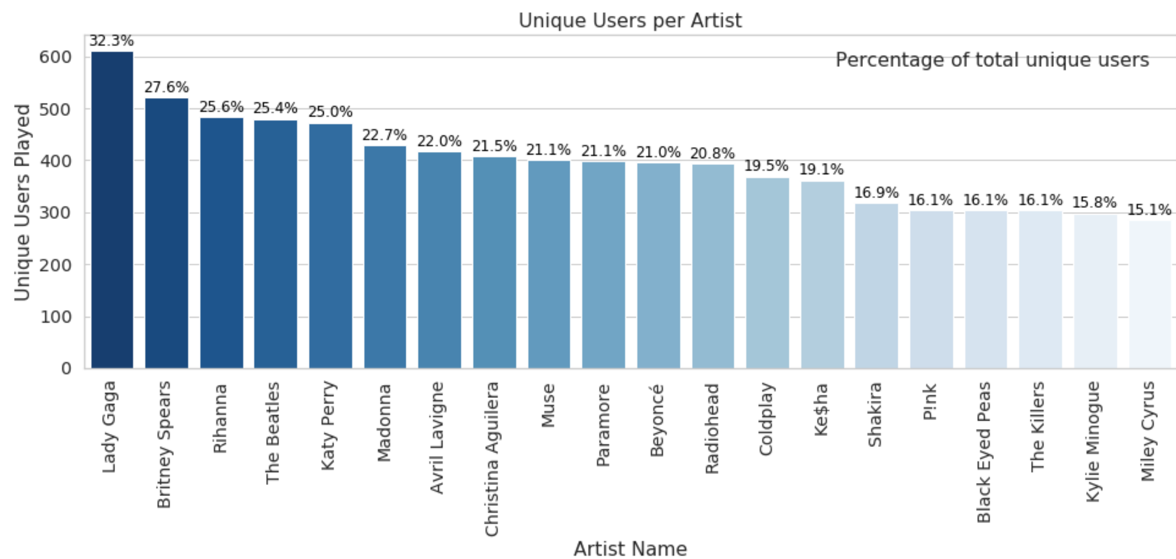
	id	name	userID	artistID	playCount	totalUniqueUsers	totalArtistPlays	avgUserPlays
2800	72	Depeche Mode	1642	72	352698	282	1301308	4614.567376
35843	792	Thalía	2071	792	324663	26	350035	13462.884615
27302	511	U2	1094	511	320725	185	493024	2664.994595
8152	203	Blur	1905	203	257978	114	318221	2791.412281
26670	498	Paramore	1664	498	227829	399	963449	2414.659148

Exploration

The names of the artists that were played most:



How much of the users play the artist:



Preprocessing

Data scaling

```
In [78]: pc = ap.playCount
         play_count_scaled = (pc - pc.min()) / (pc.max() - pc.min())

         ap = ap.assign(playCountScaled=play_count_scaled)

         ratings_df = ap.pivot(index='userID', columns='artistID', values='playCountScaled')
         ratings = ratings_df.fillna(0).values

         sparsity = float(len(ratings.nonzero()[0]))
         sparsity /= (ratings.shape[0] * ratings.shape[1])
         sparsity *= 100
         print('{:.2f}%'.format(sparsity))

         0.28%
```

Squish the play counts in the [0,1] range and add a new column

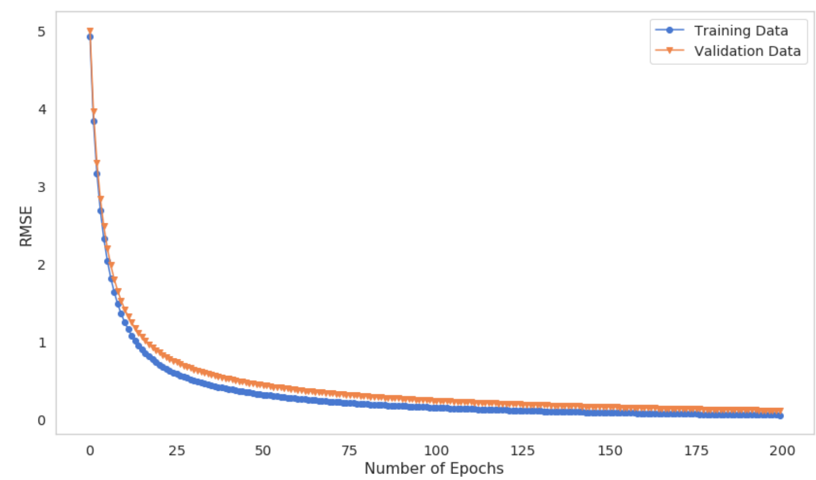
```
In [77]: train, val = train_test_split(ratings)
         train.shape

Out[77]: (1892, 17632)
```

Training by SGD

```python
def fit(self, X_train, X_val):
    m, n = X_train.shape

    self.P = 3 * np.random.rand(self.n_latent_features, m)
    self.Q = 3 * np.random.rand(self.n_latent_features, n)

    self.train_error = []
    self.val_error = []

    users, items = X_train.nonzero()

    for epoch in range(self.n_epochs):
        for u, i in zip(users, items):
            error = X_train[u, i] - self.predictions(self.P[:,u], self.Q[:,i])
            self.P[:, u] += self.learning_rate * (error * self.Q[:, i] - self.lmbda * self.P[:, u])
            self.Q[:, i] += self.learning_rate * (error * self.P[:, u] - self.lmbda * self.Q[:, i])

        train_rmse = rmse(self.predictions(self.P, self.Q), X_train)
        val_rmse = rmse(self.predictions(self.P, self.Q), X_val)
        self.train_error.append(train_rmse)
        self.val_error.append(val_rmse)

    return self
```

CF Gradient Decent Update

```python
def predict(self, X_train, user_index):
    y_hat = self.predictions(self.P, self.Q)
    predictions_index = np.where(X_train[user_index, :] == 0)[0]
    return y_hat[user_index, predictions_index].flatten()
```



Making Recommendations

```
In [91]: user_id = 1236
         user_index = ratings_df.index.get_loc(user_id)
         predictions_index = np.where(train[user_index, :] == 0)[0]

         rating_predictions = recommender.predict(train, user_index)
```

Make recommendations for user 1236

```
In [94]: create_artist_ratings(artists, predictions_index, rating_predictions)
Out[94]:
```

	id	name	rating
0	5014	Towers of London	0.506186
1	11792	Burn Down Rome	0.499209
2	12380	Symphony X - "V" The New Mitology Suite	0.495009
3	12815	auncia	0.493578
4	13827	Thavius Beck	0.491191
5	13843	Rock Kills Kid	0.482907
6	15312	Aphex Twin, Drukqs	0.475207
7	16136	Jason Anderson	0.474715
8	17010	Neil Patrick Harris	0.472820
9	17737	Chá de Abu	0.472218

Recommendation list

Further Practice

Further tasks:

- Implement Content based recommended system using project dataset
- Implement Collaborative Filtering based recommended system using project dataset

Further readings:

- https://realpython.com/build-recommendation-engine-collaborative-filtering/
- https://en.wikipedia.org/wiki/Tf%E2%80%93idf#:~:text=which%20it%20occurs.-,Definition,document%20or%20a%20web%20page.
- https://www.kdnuggets.com/2019/09/machine-learning-recommender-systems.html
- https://github.com/grahamjenson/list_of_recommender_systems
- An academic Survey

Thank you !

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