영화 추천 시스템

인공지능

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Part 1

인구 통계 필터링

시작하기 전에 필요한 것

영화에 점수를 매기거나 등급을 매기기 위한 측정 기준이 필요합니다.

모든 영화의 점수를 계산해야 합니다.

점수를 정렬하고 사용자에게 가장 좋은 평가를 받은 동영상을 추천해야 합니다.

투표수:3

투표수:40

$$Weighted\,Rating\,(WR) = \left(\frac{v}{v+m} \cdot R\right) + \left(\frac{m}{v+m} \cdot C\right)$$

001

```
In [4]:
C= df2['vote_average'].mean()
C
Out[4]:
6.092171559442011
```

002

```
In [5]:
m= df2['vote_count'].quantile(0.9)
m
Out[5]:
1838.4000000000015
```

003

```
In [6]:
q_movies = df2.copy().loc[df2['vote_count'] >= m]
q_movies.shape
Out[6]:
(481, 23)
```

```python
In [7]:
def weighted_rating(x, m=m, C=C):
    v = x['vote_count']
    R = x['vote_average']
    # Calculation based on the IMDB formula
    return (v/(v+m) * R) + (m/(m+v) * C)
```

```python
In [8]:
# Define a new feature 'score' and calculate its value with `weighted_rating()`
q_movies['score'] = q_movies.apply(weighted_rating, axis=1)
```

```python
In [9]:
#Sort movies based on score calculated above
q_movies = q_movies.sort_values('score', ascending=False)

#Print the top 15 movies
q_movies[['title', 'vote_count', 'vote_average', 'score']].head(10)
```

	title	vote_count	vote_average	score
1881	The Shawshank Redemption	8205	8.5	8.059258
662	Fight Club	9413	8.3	7.939256
65	The Dark Knight	12002	8.2	7.920020
3232	Pulp Fiction	8428	8.3	7.904645
96	Inception	13752	8.1	7.863239
3337	The Godfather	5893	8.4	7.851236
95	Interstellar	10867	8.1	7.809479
809	Forrest Gump	7927	8.2	7.803188
329	The Lord of the Rings: The Return of the King	8064	8.1	7.727243
1990	The Empire Strikes Back	5879	8.2	7.697884

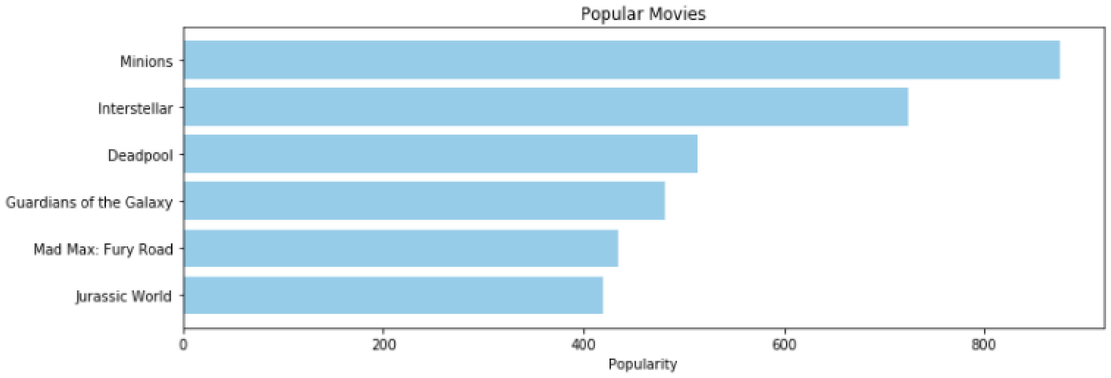
In [10]:

```
pop= df2.sort_values('popularity', ascending=False)
import matplotlib.pyplot as plt
plt.figure(figsize=(12,4))

plt.barh(pop['title'].head(6),pop['popularity'].head(6), align='center',
        color='skyblue')
plt.gca().invert_yaxis()
plt.xlabel("Popularity")
plt.title("Popular Movies")
```

Out[10]:

```
Text(0.5,1,'Popular Movies')
```



Part 2

콘텐츠 기반 필터링

줄거리 설명 기반 추천

```
In [11]: df2['overview'].head(5)
```

```
Out[11]:
0    In the 22nd century, a paraplegic Marine is di...
1    Captain Barbossa, long believed to be dead, ha...
2    A cryptic message from Bond's past sends him o...
3    Following the death of District Attorney Harve...
4    John Carter is a war-weary, former military ca...
Name: overview, dtype: object
```

In [12]:

```
#Import TfIdfVectorizer from scikit-learn
from sklearn.feature_extraction.text import TfidfVectorizer

#Define a TF-IDF Vectorizer Object. Remove all english stop words such as 'the', 'a'
tfidf = TfidfVectorizer(stop_words='english')

#Replace NaN with an empty string
df2['overview'] = df2['overview'].fillna('')

#Construct the required TF-IDF matrix by fitting and transforming the data
tfidf_matrix = tfidf.fit_transform(df2['overview'])

#Output the shape of tfidf_matrix
tfidf_matrix.shape
```

Out[12]:

```
(4803, 20978)
```

$$similarity = \cos(\theta) = \frac{A \cdot B}{\|A\| \, \|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

In [13]:

```python
# Import linear_kernel
from sklearn.metrics.pairwise import linear_kernel

# Compute the cosine similarity matrix
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
```

In [14]:

```python
#Construct a reverse map of indices and movie titles
indices = pd.Series(df2.index, index=df2['title']).drop_duplicates()
```

In [15]:

```
# Function that takes in movie title as input and outputs most similar movies
def get_recommendations(title, cosine_sim=cosine_sim):
    # Get the index of the movie that matches the title
    idx = indices[title]

    # Get the pairwsie similarity scores of all movies with that movie
    sim_scores = list(enumerate(cosine_sim[idx]))

    # Sort the movies based on the similarity scores
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)

    # Get the scores of the 10 most similar movies
    sim_scores = sim_scores[1:11]

    # Get the movie indices
    movie_indices = [i[0] for i in sim_scores]

    # Return the top 10 most similar movies
    return df2['title'].iloc[movie_indices]
```

In [16]:

```
get_recommendations('The Dark Knight Rises')
```

Out[16]:

```
65                              The Dark Knight
299                              Batman Forever
428                              Batman Returns
1359                                     Batman
3854    Batman: The Dark Knight Returns, Part 2
119                               Batman Begins
2507                                  Slow Burn
9            Batman v Superman: Dawn of Justice
1181                                        JFK
210                              Batman & Robin
Name: title, dtype: object
```

장르 및 키워드 기반 추천

In [19]:

```
# Get the director's name from the crew feature. If director is not listed, return N
aN
def get_director(x):
    for i in x:
        if i['job'] == 'Director':
            return i['name']
    return np.nan
```

In [20]:

```
# Returns the list top 3 elements or entire list; whichever is more.
def get_list(x):
    if isinstance(x, list):
        names = [i['name'] for i in x]
        #Check if more than 3 elements exist. If yes, return only first three. If n
o, return entire list.
        if len(names) > 3:
            names = names[:3]
        return names

    #Return empty list in case of missing/malformed data
    return []
```

In [25]:

```
def create_soup(x):
    return ' '.join(x['keywords']) + ' ' + ' '.join(x['cast']) + ' ' + x['director'] + ' ' + '
'.join(x['genres'])
df2['soup'] = df2.apply(create_soup, axis=1)
```

In [26]:

```
# Import CountVectorizer and create the count matrix
from sklearn.feature_extraction.text import CountVectorizer

count = CountVectorizer(stop_words='english')
count_matrix = count.fit_transform(df2['soup'])
```

In [27]:

```
# Compute the Cosine Similarity matrix based on the count_matrix
from sklearn.metrics.pairwise import cosine_similarity

cosine_sim2 = cosine_similarity(count_matrix, count_matrix)
```

In [28]:

```
# Reset index of our main DataFrame and construct reverse mapping as before
df2 = df2.reset_index()
indices = pd.Series(df2.index, index=df2['title'])
```

In [29]:

```
get_recommendations('The Dark Knight Rises', cosine_sim2)
```

Out[29]:

```
65                The Dark Knight
119                 Batman Begins
4638    Amidst the Devil's Wings
1196                 The Prestige
3073            Romeo Is Bleeding
3326               Black November
1503                       Takers
1986                       Faster
303                      Catwoman
747                Gangster Squad
Name: title, dtype: object
```

Part 3

협업 필터링

아이템 기반 협업 필터링

	The Avengers	Sherlock	Transformers	Matrix	Titanic	Me Before You
A	2		2	4	5	2.94*
B	5		4			1
C			5		2	2.48*
D		1		5		4
E			4			2
F	4	5		1		1.12*
Similarity	-1	-1	0.86	1	1	

잠재요소

사용자나 아이템이 가지고 있는 속성이나 개념을 설명하는 아이디어

In [31]:

```
from surprise import Reader, Dataset, SVD, evaluate
reader = Reader()
ratings = pd.read_csv('../input/the-movies-dataset/ratings_small.csv')
ratings.head()
```

Out[31]:

	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205

```
In [34]: trainset = data.build_full_trainset()
         svd.fit(trainset)

Out[34]: <surprise.prediction_algorithms.matrix_factorization.SVD at 0x7f87050c8748>
```

In [35]:

```
ratings[ratings['userId'] == 1]
```

Out[35]:

	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205
5	1	1263	2.0	1260759151
6	1	1287	2.0	1260759187
7	1	1293	2.0	1260759148
8	1	1339	3.5	1260759125
9	1	1343	2.0	1260759131
10	1	1371	2.5	1260759135
11	1	1405	1.0	1260759203
12	1	1953	4.0	1260759191
13	1	2105	4.0	1260759139
14	1	2150	3.0	1260759194
15	1	2193	2.0	1260759198
16	1	2294	2.0	1260759108
17	1	2455	2.5	1260759113
18	1	2968	1.0	1260759200
19	1	3671	3.0	1260759117

In [36]:

```python
svd.predict(1, 302, 3)
```

Out[36]:

```
Prediction(uid=1, iid=302, r_ui=3, est=2.756291780279027, details={'was_impossible': False})
```

결론

인구 통계 필터링은 모든 사용자에게 일반화된 추천을 제공하지만,
특정 사용자의 관심사와 취향에는 민감하지 않다.

콘텐츠 기반 필터링은 특정 아이템을 기준으로 유사한 아이템을 추천한다. 하지만
누구나 같은 추천을 받을 수 있기 때문에 사용자의 개인적인 취향을 포착하지 못한다.

협업 필터링은 사용자가 평가한 아이템과의 유사성을 기준으로 아이템을 추천한다.

원본 캐글 링크

https://www.kaggle.com/ibtesama/getting-started-with-a-movie-recommendation-system

감사합니다.