EDA and Preprocessing

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Examine csv files

In [2]:
```
links = pd.read_csv('data/links.csv')
display(links.head())
print(links.shape)
```

	movieId	imdbId	tmdbId
0	1	114709	862.0
1	2	113497	8844.0
2	3	113228	15602.0
3	4	114885	31357.0
4	5	113041	11862.0

```
(9742, 3)
```

In [3]:
```
links.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9742 entries, 0 to 9741
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   movieId  9742 non-null   int64  
 1   imdbId   9742 non-null   int64  
 2   tmdbId   9734 non-null   float64
dtypes: float64(1), int64(2)
memory usage: 228.5 KB
```

In [4]:
```
movies = pd.read_csv('data/movies.csv')
display(movies.head())
print(movies.shape)
```

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

```
(9742, 3)
```

In [5]:
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9742 entries, 0 to 9741
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   movieId  9742 non-null   int64 
 1   title    9742 non-null   object
 2   genres   9742 non-null   object
dtypes: int64(1), object(2)
memory usage: 228.5+ KB
```

In [6]:
```
movies.nunique()
```

Out[6]:
```
movieId    9742
title      9737
genres      951
dtype: int64
```

In [7]:
```
ratings = pd.read_csv('data/ratings.csv')
display(ratings.head())
print(ratings.shape)
```

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931

```
(100836, 4)
```

In [8]:
```
ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100836 entries, 0 to 100835
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   userId     100836 non-null  int64  
 1   movieId    100836 non-null  int64  
 2   rating     100836 non-null  float64
 3   timestamp  100836 non-null  int64  
dtypes: float64(1), int64(3)
memory usage: 3.1 MB
```

In [9]:
```
ratings.nunique()
```

Out[9]:
```
userId         610
movieId       9724
rating          10
timestamp    85043
dtype: int64
```

In [10]:
```
tags = pd.read_csv('data/tags.csv')
display(tags.head())
print(tags.shape)
```

	userId	movieId	tag	timestamp

	userId	movieId	tag	timestamp
0	2	60756	funny	1445714994
1	2	60756	Highly quotable	1445714996
2	2	60756	will ferrell	1445714992
3	2	89774	Boxing story	1445715207
4	2	89774	MMA	1445715200

```
(3683, 4)
```

In [11]:
```
tags.nunique()
```

Out[11]:
```
userId         58
movieId      1572
tag          1589
timestamp    3411
dtype: int64
```

In [12]:
```
tags.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3683 entries, 0 to 3682
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   userId     3683 non-null   int64 
 1   movieId    3683 non-null   int64 
 2   tag        3683 non-null   object
 3   timestamp  3683 non-null   int64 
dtypes: int64(3), object(1)
memory usage: 115.2+ KB
```

Address duplicates

In [13]:
```
movies[movies.duplicated(subset='title', keep=False)]
```

Out[13]:

	movieId	title	genres
650	838	Emma (1996)	Comedy|Drama|Romance
2141	2851	Saturn 3 (1980)	Adventure|Sci-Fi|Thriller
4169	6003	Confessions of a Dangerous Mind (2002)	Comedy|Crime|Drama|Thriller
5601	26958	Emma (1996)	Romance
5854	32600	Eros (2004)	Drama
5931	34048	War of the Worlds (2005)	Action|Adventure|Sci-Fi|Thriller
6932	64997	War of the Worlds (2005)	Action|Sci-Fi
9106	144606	Confessions of a Dangerous Mind (2002)	Comedy|Crime|Drama|Romance|Thriller
9135	147002	Eros (2004)	Drama|Romance
9468	168358	Saturn 3 (1980)	Sci-Fi|Thriller

Checking the MovieLens website confirms that there were two unique "Emma" movies made in 1996 and two unique "War of the Worlds" movies in 2005. The other duplicates are true duplicates.

In [14]:
```
# drop least informative movie entry for true duplicates. keep entries with the

unwanted = [168358, 6003, 32600]
indices = []
for idx, row in movies.iterrows():
    if row['movieId'] in unwanted:
        indices.append(idx)

movies.drop(index=indices, inplace=True)

movies[movies.duplicated(subset='title', keep=False)]
```

Out[14]:

	movieId	title	genres
650	838	Emma (1996)	Comedy|Drama|Romance
5601	26958	Emma (1996)	Romance
5931	34048	War of the Worlds (2005)	Action|Adventure|Sci-Fi|Thriller
6932	64997	War of the Worlds (2005)	Action|Sci-Fi

In [15]:
```
# replace movie ids in tags and ratings data

new = [2851, 144606, 147002]

tags['movieId'] = tags['movieId'].replace(unwanted, new)
ratings['movieId'] = ratings['movieId'].replace(unwanted, new)
```

In [16]:
```
movies.to_csv('data/movies_cleaned.csv')
tags.to_csv('data/tags_cleaned.csv')
ratings.to_csv('data/ratings_cleaned.csv')
```

EDA

Ratings distribution

In [17]:
```
ratings.rating.value_counts()
```

Out[17]:
```
4.0    26818
3.0    20047
5.0    13211
3.5    13136
4.5     8551
2.0     7551
2.5     5550
1.0     2811
1.5     1791
0.5     1370
Name: rating, dtype: int64
```

In [18]:
```
ratings.describe()
```

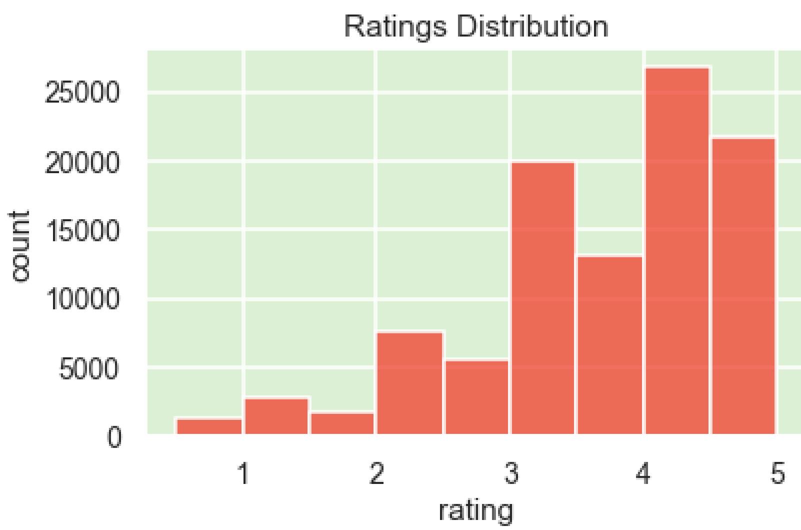
Out[18]:

	userId	movieId	rating	timestamp
count	100836.000000	100836.000000	100836.000000	1.008360e+05
mean	326.127564	19455.406988	3.501557	1.205946e+09

	userId	movieId	rating	timestamp
std	182.618491	35562.577975	1.042529	2.162610e+08
min	1.000000	1.000000	0.500000	8.281246e+08
25%	177.000000	1199.000000	3.000000	1.019124e+09
50%	325.000000	2991.000000	3.500000	1.186087e+09
75%	477.000000	8132.000000	4.000000	1.435994e+09
max	610.000000	193609.000000	5.000000	1.537799e+09

In [19]:
```
sns.set(rc={'axes.facecolor':'#dcf0d6'})
sns.set_context('talk', font_scale=0.85)
```

In [20]:
```
sns.histplot(x=ratings['rating'], data=ratings, binwidth=0.5, bins=10, color='#f
plt.title('Ratings Distribution')
plt.ylabel('count')
plt.tight_layout()
plt.savefig('images/rating-hist.png');
```



Rating count distribution

In [21]:
```
rating_counts = ratings.groupby('userId').count().reset_index()
```

In [22]:
```
rating_counts.describe()
```

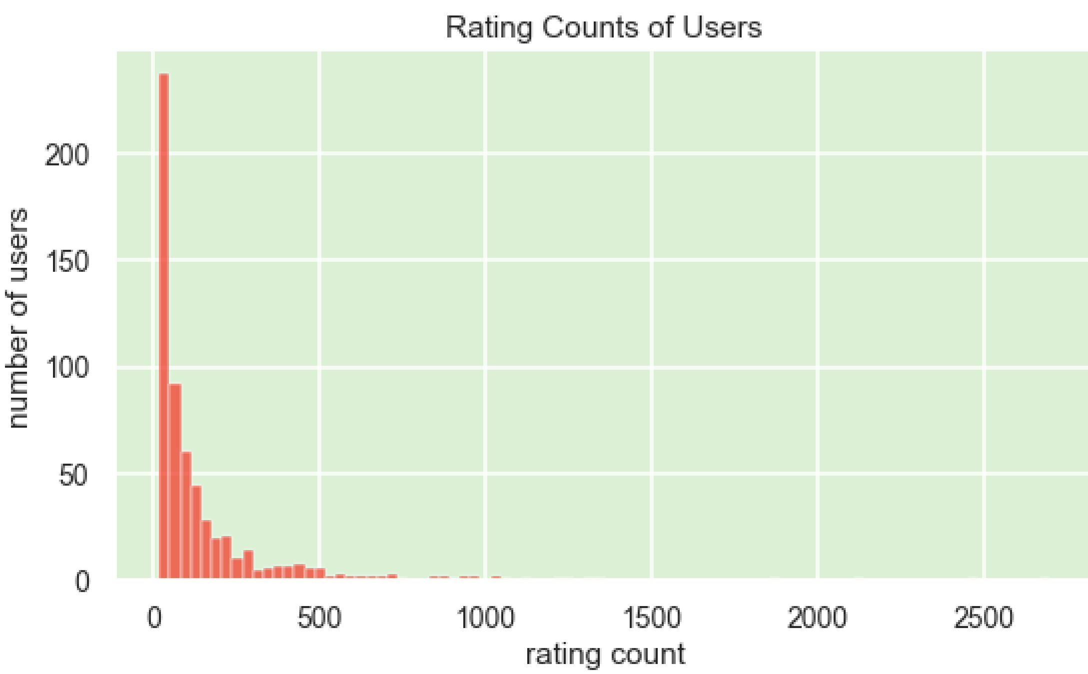
Out[22]:

	userId	movieId	rating	timestamp
count	610.000000	610.000000	610.000000	610.000000
mean	305.500000	165.304918	165.304918	165.304918
std	176.236111	269.480584	269.480584	269.480584
min	1.000000	20.000000	20.000000	20.000000
25%	153.250000	35.000000	35.000000	35.000000
50%	305.500000	70.500000	70.500000	70.500000
75%	457.750000	168.000000	168.000000	168.000000

	userId	movieId	rating	timestamp
max	610.000000	2698.000000	2698.000000	2698.000000

The userIds on file start at 1 and go up to 610. There are 610 unique users in the dataset. New users added to the database should have IDs 611 and higher. The least number of films rated for a single user is 20, while the most ratings per user is 2898. High rating counts could be do to more engagement or age of the user's account.

In [23]:
```
fig = plt.figure(figsize=(8,5))
sns.histplot(x='rating', data=rating_counts, color='#f13f2c')
plt.title('Rating Counts of Users')
plt.ylabel('number of users')
plt.xlabel('rating count')
plt.tight_layout()
plt.savefig('images/rating-count-hist.png');
```



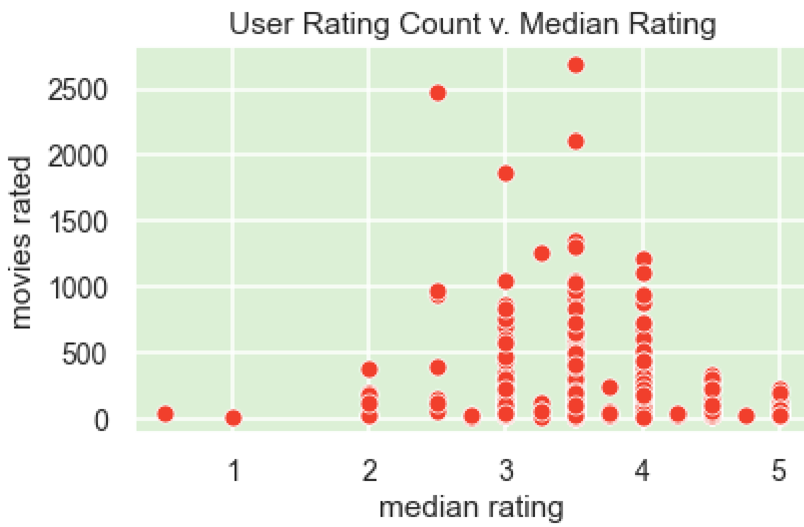
In [24]:
```
ratings_med = ratings.groupby('userId').median().reset_index()
ratingcount_rating = pd.merge(ratings_med, rating_counts, on='userId')
ratingcount_rating.head()
```

Out[24]:

	userId	movieId_x	rating_x	timestamp_x	movieId_y	rating_y	timestamp_y
0	1	1960.5	5.0	9.649824e+08	232	232	232
1	2	79132.0	4.0	1.445715e+09	29	29	29
2	3	2288.0	0.5	1.306464e+09	39	39	39
3	4	1733.5	4.0	9.645395e+08	216	216	216
4	5	346.5	4.0	8.474351e+08	44	44	44

In [25]:
```
sns.scatterplot(x='rating_x', y='rating_y', data=ratingcount_rating, color='#f13
plt.title('User Rating Count v. Median Rating')
plt.xlabel('median rating')
plt.ylabel('movies rated')
```

```
plt.tight_layout()
plt.savefig('images/ratingcount-medrating.png');
```



Genre distribution of films

In [26]:
```
movies['genres'] = movies['genres'].apply(lambda x: x.replace('|', ',').lower()
movies['genres'] = movies['genres'].replace('(no genres listed)', 'no genres lis
movies['genres_list'] = movies['genres'].apply(lambda x: x.split(','))
movies.head()
```

Out[26]:

	movieId	title	genres	genres_list
0	1	Toy Story (1995)	adventure,animation,children,comedy,fantasy	[adventure, animation, children, comedy, fantasy]
1	2	Jumanji (1995)	adventure,children,fantasy	[adventure, children, fantasy]
2	3	Grumpier Old Men (1995)	comedy,romance	[comedy, romance]
3	4	Waiting to Exhale (1995)	comedy,drama,romance	[comedy, drama, romance]
4	5	Father of the Bride Part II (1995)	comedy	[comedy]

In [27]:
```
# Get counts of genres in dataset, in descending order

all_genres = set()
for genres in movies['genres_list']:
    if genres:
        all_genres.update(genres)
all_genres
```

Out[27]:
```
{'action',
 'adventure',
 'animation',
 'children',
 'comedy',
 'crime',
 'documentary',
 'drama',
```

```
 'fantasy',
 'film-noir',
 'horror',
 'imax',
 'musical',
 'mystery',
 'no genres listed',
 'romance',
 'sci-fi',
 'thriller',
 'war',
 'western'}
```

In [28]:

```
genre_counts = {}
for i in list(all_genres):
    genre_counts[i] = 0

for _, row in movies.iterrows():
    if row['genres_list']:
        for genre in row['genres_list']:
            genre_counts[genre] +=1

genre_counts_sorted = dict(sorted(genre_counts.items(), key = lambda x: x[1], re
genre_counts_sorted
```

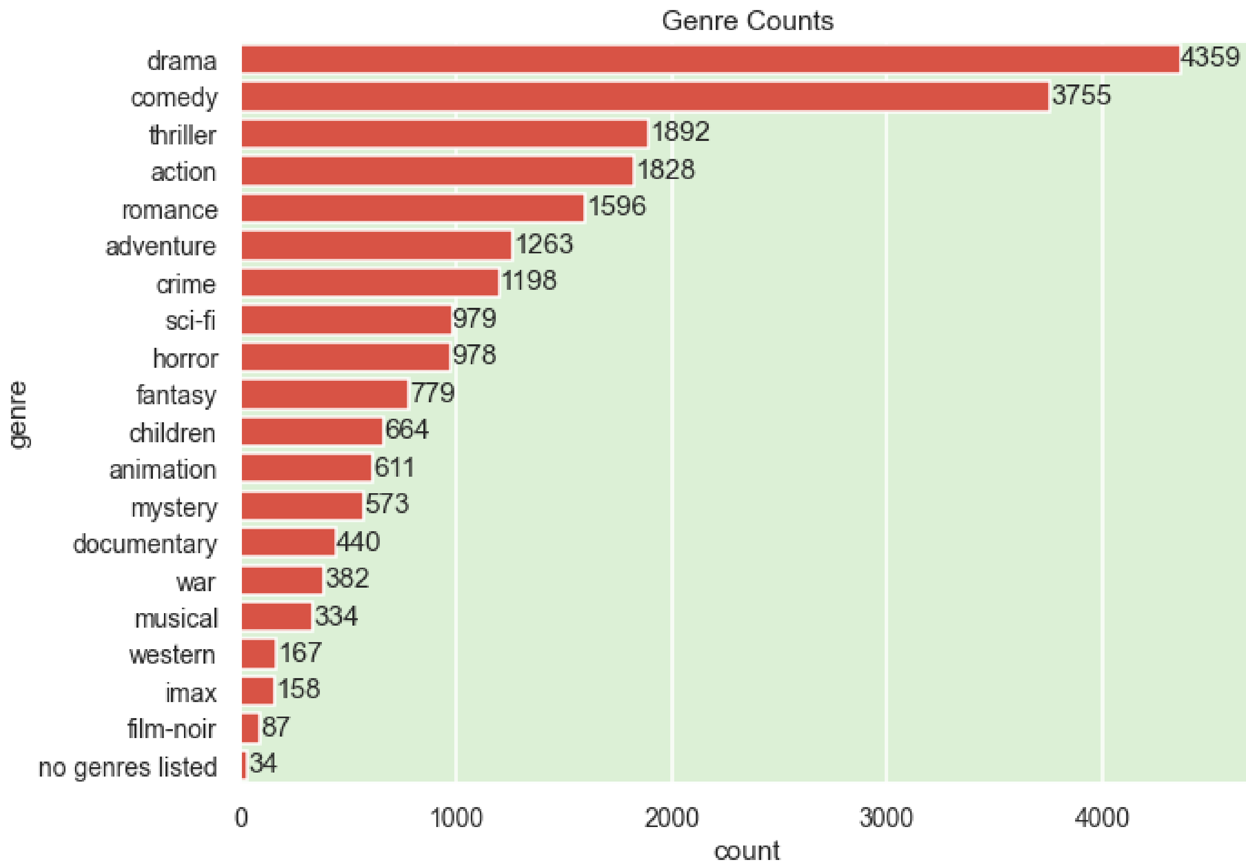
Out[28]:

```
{'drama': 4359,
 'comedy': 3755,
 'thriller': 1892,
 'action': 1828,
 'romance': 1596,
 'adventure': 1263,
 'crime': 1198,
 'sci-fi': 979,
 'horror': 978,
 'fantasy': 779,
 'children': 664,
 'animation': 611,
 'mystery': 573,
 'documentary': 440,
 'war': 382,
 'musical': 334,
 'western': 167,
 'imax': 158,
 'film-noir': 87,
 'no genres listed': 34}
```

In [29]:

```
# What is the distribution of film genres in this database?

fig = plt.figure(figsize=(10,7))
ax = sns.barplot(x=list(genre_counts_sorted.values()), y=list(genre_counts_sorte
plt.title('Genre Counts')
plt.ylabel('genre')
plt.xlabel('count')
for p in ax.patches:
    width = p.get_width()    # get bar length
    ax.text(width + 1,       # set the text at 1 unit right of the bar
            p.get_y() + p.get_height() / 2, # get Y coordinate + X coordinate /
            '{:1.0f}'.format(width), # set variable to display, 2 decimals
            ha = 'left',   # horizontal alignment
            va = 'center')  # vertical alignment
plt.xlim(0,4700)
plt.tight_layout()
plt.savefig('images/genrecounts.png');
```



Most common tags

In [30]:
```
tags_sorted = tags.tag.value_counts().reset_index()
tags_sorted.rename(columns={'index':'tag', 'tag':'count'}, inplace=True)
tags_sorted
```

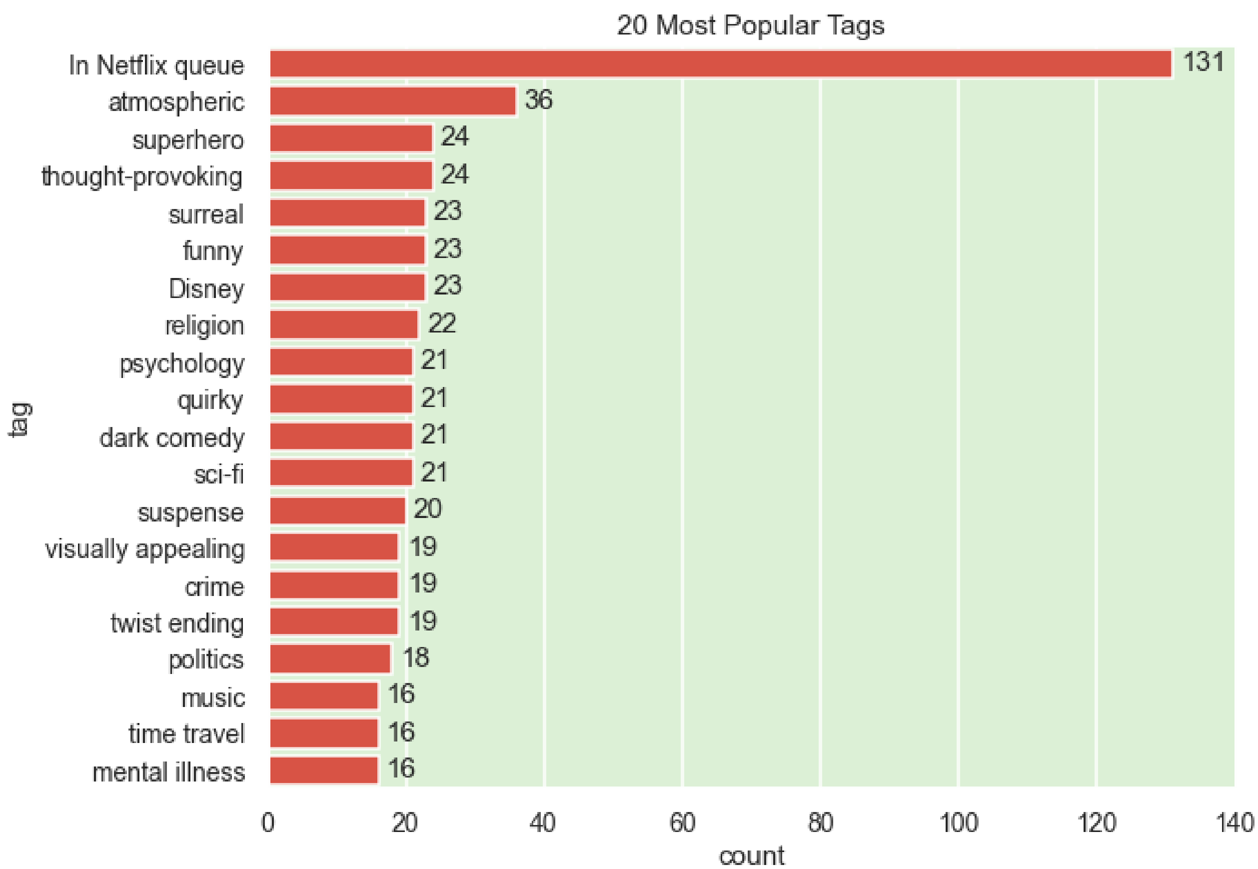
Out[30]:

	tag	count
0	In Netflix queue	131
1	atmospheric	36
2	superhero	24
3	thought-provoking	24
4	surreal	23
...	...	...
1584	Jennifer Lawrence	1
1585	asylum	1
1586	Journalism	1
1587	action choreography	1
1588	insomnia	1

1589 rows × 2 columns

In [31]:
```
fig = plt.figure(figsize=(10,7))
ax = sns.barplot(y='tag', x='count', data=tags_sorted[:20], color='#f13f2c')
```

```
#plt.xticks(rotation=90)
plt.title('20 Most Popular Tags')
for p in ax.patches:
    width = p.get_width()    # get bar length
    ax.text(width + 1,       # set the text at 1 unit right of the bar
            p.get_y() + p.get_height() / 2, # get Y coordinate + X coordinate /
            '{:1.0f}'.format(width), # set variable to display, 2 decimals
            ha = 'left',   # horizontal alignment
            va = 'center')  # vertical alignment
plt.xlim(0,140)
plt.tight_layout()
plt.savefig('images/populartags.png');
```



Percent of users who tag films

In [32]:

```
print('Num users who tag')
print(tags.userId.nunique())
print('\nValue Counts')
print(tags.userId.value_counts().head(20))
print('\nNum users who rate')
print(ratings.userId.nunique())
```

```
Num users who tag
58

Value Counts
474    1507
567     432
62      370
599     323
477     280
424     273
537     100
```

```
125      48
357      45
318      41
184      35
573      31
193      20
18       16
119      14
336      10
2         9
305       8
606       7
327       7
Name: userId, dtype: int64

Num users who rate
610
```

In [33]:
```
# any users who have tagged who have not rated?

np.setdiff1d(list(set(tags.userId)), list(set(ratings.userId)))
```

Out[33]:
```
array([], dtype=int64)
```

In [34]:
```
print('Percent of users who tag films: {}%'.format(round((58/610)*100, 2)))
```

```
Percent of users who tag films: 9.51%
```

All users who have tagged films have also rated films. The percentage of users (out of total users) who tag films is ~9.51%

In [35]:
```
ratings_tags = pd.merge(ratings, tags, how='left', on='userId')
```

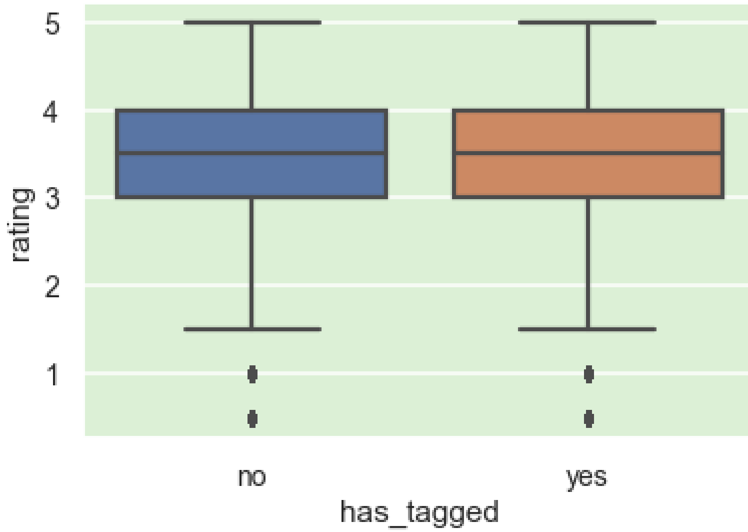
In [36]:
```
ratings_tags['has_tagged'] = ratings_tags.apply(lambda row: 'no' if pd.isnull(ro
ratings_tags.head()
```

Out[36]:

	userId	movieId_x	rating	timestamp_x	movieId_y	tag	timestamp_y	has_tagged
0	1	1	4.0	964982703	NaN	NaN	NaN	no
1	1	3	4.0	964981247	NaN	NaN	NaN	no
2	1	6	4.0	964982224	NaN	NaN	NaN	no
3	1	47	5.0	964983815	NaN	NaN	NaN	no
4	1	50	5.0	964982931	NaN	NaN	NaN	no

In [37]:
```
sns.boxplot(y='rating', x='has_tagged', data=ratings_tags)
```

Out[37]:
```
<AxesSubplot:xlabel='has_tagged', ylabel='rating'>
```



Users who have tagged films have the same rating distributions as those who have not tagged films. One group does not seem to rate more highly/generously than the other.

NLP Pre-processing

Get word vectors

In [38]:
```
tags.head()
```

Out[38]:

	userId	movieId	tag	timestamp
0	2	60756	funny	1445714994
1	2	60756	Highly quotable	1445714996
2	2	60756	will ferrell	1445714992
3	2	89774	Boxing story	1445715207
4	2	89774	MMA	1445715200

In [39]:
```
tags_combined = tags.groupby(['movieId'])['tag'].apply(lambda x: ' '.join(x)).re
tags_combined.head()
```

Out[39]:

	movieId	tag
0	1	pixar pixar fun
1	2	fantasy magic board game Robin Williams game
2	3	moldy old
3	5	pregnancy remake
4	7	remake

In [40]:
```
movies_tags = pd.merge(movies, tags_combined, how='left', on='movieId')
movies_tags = movies_tags.drop('genres_list', axis=1)
movies_tags['genres'] = movies_tags['genres'].apply(lambda x: x.replace(',', ' '
movies_tags.head()
```

Out[40]:

	movieId	title	genres	tag

	movieId	title	genres	tag
0	1	Toy Story (1995)	adventure animation children comedy fantasy	pixar pixar fun
1	2	Jumanji (1995)	adventure children fantasy	fantasy magic board game Robin Williams game
2	3	Grumpier Old Men (1995)	comedy romance	moldy old
3	4	Waiting to Exhale (1995)	comedy drama romance	NaN
4	5	Father of the Bride Part II (1995)	comedy	pregnancy remake

In [41]:
```
movies_tags['bow'] = movies_tags['genres'] + ' ' + movies_tags['tag'].fillna('')
movies_tags.head()
```

Out[41]:

	movieId	title	genres	tag	bow
0	1	Toy Story (1995)	adventure animation children comedy fantasy	pixar pixar fun	adventure animation children comedy fantasy pi...
1	2	Jumanji (1995)	adventure children fantasy	fantasy magic board game Robin Williams game	adventure children fantasy fantasy magic board...
2	3	Grumpier Old Men (1995)	comedy romance	moldy old	comedy romance moldy old
3	4	Waiting to Exhale (1995)	comedy drama romance	NaN	comedy drama romance
4	5	Father of the Bride Part II (1995)	comedy	pregnancy remake	comedy pregnancy remake

In [42]:
```
item_content = movies_tags.drop(['title', 'genres', 'tag'], axis=1)
item_content['bow'] = item_content['bow'].str.lower()
item_content.set_index('movieId', inplace=True)
item_content.head()
```

Out[42]:

	bow
movieId	
1	adventure animation children comedy fantasy pi...
2	adventure children fantasy fantasy magic board...
3	comedy romance moldy old
4	comedy drama romance
5	comedy pregnancy remake

Content-based recommender test run

In [43]:
```
item_content.to_csv('data/item_content.csv')
```

In [44]:
```
import nltk
from nltk.tokenize import word_tokenize
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics.pairwise import cosine_similarity, linear_kernel
```

In [45]:
```
tfidf = TfidfVectorizer()
tfidf_matrix = tfidf.fit_transform(item_content['bow'])

cosine_sim = cosine_similarity(tfidf_matrix)
print(cosine_sim)
```

```
[[1.         0.08806834 0.01349231 ... 0.         0.15083694 0.09576975]
 [0.08806834 1.         0.         ... 0.         0.         0.        ]
 [0.01349231 0.         1.         ... 0.         0.         0.14088282]
 ...
 [0.         0.         0.         ... 1.         0.         0.        ]
 [0.15083694 0.         0.         ... 0.         1.         0.        ]
 [0.09576975 0.         0.14088282 ... 0.         0.         1.        ]]
```

In [46]:
```
# Series containing titles
indices = pd.Series(movies_tags['title'])

def recommendations(title, cosine_sim=cosine_sim):
    recommended_movies = []
    idx = indices[indices == title].index[0]
    scores = pd.Series(cosine_sim[idx]).sort_values(ascending=False)
    top_10_indexes = list(scores.iloc[0:11].index)
    for i in top_10_indexes:
        recommended_movies.append(indices[i])
    return recommended_movies
```

In [47]:
```
indices.head()
```

Out[47]:
```
0                       Toy Story (1995)
1                         Jumanji (1995)
2                Grumpier Old Men (1995)
3               Waiting to Exhale (1995)
4     Father of the Bride Part II (1995)
Name: title, dtype: object
```

In [48]:
```
recommendations('Toy Story (1995)')
```

Out[48]:
```
['Toy Story (1995)',
 "Bug's Life, A (1998)",
 'Toy Story 2 (1999)',
 'Guardians of the Galaxy 2 (2017)',
 'Monsters, Inc. (2001)',
 'Turbo (2013)',
 "Emperor's New Groove, The (2000)",
 'The Good Dinosaur (2015)',
 'Adventures of Rocky and Bullwinkle, The (2000)',
 'Wild, The (2006)',
 'Shrek the Third (2007)']
```

In [49]:
```
recommendations('Powder (1995)')
```

Out[49]:
```
['Into the Forest (2015)',
 'SORI: Voice from the Heart (2016)',
 'Metropolis (1927)',
 'Electroma (2006)',
```

```
 'Charly (1968)',
 'Midnight Special (2015)',
 'Harrison Bergeron (1995)',
 'Man from Earth, The (2007)',
 'Giver, The (2014)',
 'Last Night (1998)',
 'I Origins (2014)']
```

In [50]:
```
recommendations('American Psycho (2000)')
```

Out[50]:
```
['Saw VI (2009)',
 "Bird with the Crystal Plumage, The (Uccello dalle piume di cristallo, L') (197
0)",
 'American Psycho (2000)',
 'Book of Shadows: Blair Witch 2 (2000)',
 'Testament of Dr. Mabuse, The (Das Testament des Dr. Mabuse) (1933)',
 'From Hell (2001)',
 'House of Wax (1953)',
 'American Psycho II: All American Girl (2002)',
 'Mindhunters (2004)',
 'Opera (1987)',
 'I Still Know What You Did Last Summer (1998)']
```

"American Psycho" is third on the list when one would expect it to be first (American Psycho should be most similar to itself). "Powder (1995)" does not even appear in the returned list. Time to investigate why this could be.

In [58]:
```
movies_tags[movies_tags['title']== 'Toy Story (1995)']
```

Out[58]:

	movieId	title	genres	tag	bow
0	1	Toy Story (1995)	adventure animation children comedy fantasy	pixar pixar fun	adventure animation children comedy fantasy pi...

Toy Story had descriptive tags

In [52]:
```
# Examine bow for American Psycho and related

movies_tags[movies_tags['title'] == 'American Psycho (2000)']
```

Out[52]:

	movieId	title	genres	tag	bow
2641	3535	American Psycho (2000)	crime horror mystery thriller	NaN	crime horror mystery thriller

In [53]:
```
movies_tags[movies_tags['title'] == 'Saw VI (2009)']
```

Out[53]:

	movieId	title	genres	tag	bow
7171	72129	Saw VI (2009)	crime horror mystery thriller	NaN	crime horror mystery thriller

In [54]:
```
movies_tags[movies_tags['title'] == "Bird with the Crystal Plumage, The (Uccello
```

Out[54]:

	movieId	title	genres	tag	bow
6070	41014	Bird with the Crystal Plumage, The (Uccello da...	crime horror mystery thriller	NaN	crime horror mystery thriller

In [55]:
```
movies_tags[movies_tags['title'] == 'Book of Shadows: Blair Witch 2 (2000)']
```

Out[55]:

	movieId	title	genres	tag	bow
2964	3973	Book of Shadows: Blair Witch 2 (2000)	crime horror mystery thriller	NaN	crime horror mystery thriller

In [56]:
```
# examine bow for Powder and related

movies_tags[movies_tags['title']== 'Powder (1995)']
```

Out[56]:

	movieId	title	genres	tag	bow
23	24	Powder (1995)	drama sci-fi	NaN	drama sci-fi

In [57]:
```
movies_tags[movies_tags['title'] == 'SORI: Voice from the Heart (2016)']
```

Out[57]:

	movieId	title	genres	tag	bow
9282	158027	SORI: Voice from the Heart (2016)	drama sci-fi	NaN	drama sci-fi

"American Psycho" and the films that come before it in the sorted list have identical bags of words and therefore have the same similarity score. Films with identical bags of words will have cosine_sim = 1 and there will be no real order amongst them. The films related to "Powder" have bags of words that contain only "drama sci-fi." This content-based recommender will do best on films with more descriptive text information (more tags from users). Otherwise, it is only finding similarities based on genre information. Adding plot synopses should also greatly improve the specificity of these recommendations.