```
import os
from tqdm import tqdm
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import warnings
warnings.filterwarnings('ignore')
```

MovieLens 데이터셋 불러오기

```
root_path = os.getcwd()
          path = os.path.join(root_path, 'data/ml-latest-small/')
          ratings_df = pd.read_csv(os.path.join(path, 'ratings.csv'), encoding='utf-8')
          tags_df = pd.read_csv(os.path.join(path, 'tags.csv'), encoding='utf-8')
          movies_df = pd.read_csv(os.path.join(path, 'movies.csv'), index_col='movield', encodi
          tags_df.head()
            userld movield
                                       tag
                                             timestamp
         0
                 2
                      60756
                                            1445714994
                                     funny
                 2
         1
                      60756
                             Highly quotable
                                            1445714996
         2
                 2
                      60756
                                  will ferrell 1445714992
         3
                 2
                      89774
                                Boxing story
                                            1445715207
                 2
                      89774
                                     MMA 1445715200
In [7]:
          movies_df.head()
Out[7]:
                                         title
                                                                                genres
         movield
               1
                               Toy Story (1995) Adventure|Animation|Children|Comedy|Fantasy
               2
                                 Jumanji (1995)
                                                               Adventure|Children|Fantasy
               3
                       Grumpier Old Men (1995)
                                                                       Comedy|Romance
               4
                         Waiting to Exhale (1995)
                                                                 Comedy|Drama|Romance
```

Genres 를 이용한 movie representation

Father of the Bride Part II (1995)

```
total_count = len(movies_df.index)
total_genres = list(set([genre for sublist in list(map(lambda x: x.split('|'), movie
total_genres
```

Comedy

```
Out[35]: ['Mystery',
           'Documentary',
           '(no genres listed)',
           'Fantasy'
           'Thriller',
           'Sci-Fi'
           'Children',
           'War',
           'Romance',
           'Western',
           'IMAX',
           'Crime',
           'Adventure',
           'Drama',
           'Musical',
           'Action',
           'Horror',
           'Comedy'
           'Film-Noir'
           'Animation']
In [40]:
           genre_count = dict.fromkeys(total_genres)
           for each_genre_list in movies_df['genres']:
               for genre in each_genre_list.split('|'):
                   if genre_count[genre] == None:
                       genre_count[genre] = 1
                   else:
                        genre_count[genre] = genre_count[genre] + 1
In [41]:
           genre_count
          {'Mystery': 573,
Out[41]:
            'Documentary': 440,
           '(no genres listed)': 34,
           'Fantasy': 779,
'Thriller': 1894,
           'Sci-Fi': 980.
           'Children': 664.
           'War': 382,
           'Romance': 1596,
           'Western': 167,
           'IMAX': 158,
           'Crime': 1199,
           'Adventure': 1263,
           'Drama': 4361,
           'Musical': 334,
           'Action': 1828,
           'Horror': 978,
           'Comedy': 3756,
           'Film-Noir': 87,
           'Animation': 611}
In [42]:
           for each_genre in genre_count:
               genre_count[each_genre] = np.log10(total_count/genre_count[each_genre])
           genre_count
Out[42]: {'Mystery': 1.2304935032683613,
            'Documentary': 1.3451954487495636,
           '(no genres listed)': 2.457169208193496,
           'Fantasy': 1.0971106675631865,
           'Thriller': 0.7112681505684965,
           'Sci-Fi': 0.9974220495432563,
```

```
'Children': 1.1664800458677336,
'War': 1.4065847623240424,
'Romance': 0.7856152382210405,
'Western': 1.7659316540881678,
'IMAX': 1.7899910382813284,
'Crime': 0.9098289421369025,
'Adventure': 0.8872447746804204,
'Drama': 0.3490620385623247,
'Musical': 1.4649016584241867,
'Action': 0.7266719338379385,
'Horror': 0.9983092704481497,
'Comedy': 0.4139225416416778,
'Film-Noir': 2.0491288726171324,
'Animation': 1.2026069149931968}
```

genre 를 이용한 Movie representation 생성

```
In [43]:
          genre_representation = pd.DataFrame(columns=sorted(total_genres), index=movies_df.ind
           for index, each_row in tqdm(movies_df.iterrows()):
               dict_temp = {i: genre_count[i] for i in each_row['genres'].split('|')}
               row_to_add = pd.DataFrame(dict_temp, index=[index])
               genre_representation.update(row_to_add)
          9742it [00:31, 312.03it/s]
In [44]:
          genre representation
Out[44]:
                     (no
                   genres
                            Action Adventure Animation Children Comedy Crime Documentary
                                                                                                 Dram
                   listed)
          movield
                1
                     NaN
                             NaN
                                     0.887245
                                                1.202607
                                                         1.16648 0.413923
                                                                            NaN
                                                                                         NaN
                                                                                                  Na
                2
                    NaN
                             NaN
                                     0.887245
                                                   NaN
                                                         1.16648
                                                                     NaN
                                                                            NaN
                                                                                         NaN
                                                                                                  Na
                                                            NaN 0.413923
                3
                     NaN
                             NaN
                                        NaN
                                                   NaN
                                                                            NaN
                                                                                         NaN
                                                                                                  Na
                                                                 0.413923
                                                                                         NaN 0.34906
                4
                    NaN
                             NaN
                                        NaN
                                                   NaN
                                                            NaN
                                                                            NaN
                5
                     NaN
                                        NaN
                                                            NaN 0.413923
                             NaN
                                                   NaN
                                                                            NaN
                                                                                         NaN
                                                                                                  Na
           193581
                    NaN 0.726672
                                        NaN
                                                1.202607
                                                            NaN 0.413923
                                                                            NaN
                                                                                         NaN
                                                                                                  Na
           193583
                    NaN
                              NaN
                                        NaN
                                                1.202607
                                                            NaN 0.413923
                                                                            NaN
                                                                                         NaN
                                                                                                  Na
           193585
                    NaN
                              NaN
                                        NaN
                                                                                         NaN 0.34906
                                                   NaN
                                                            NaN
                                                                     NaN
                                                                            NaN
           193587
                    NaN
                         0.726672
                                        NaN
                                                1.202607
                                                            NaN
                                                                     NaN
                                                                            NaN
                                                                                         NaN
                                                                                                  Na
           193609
                    NaN
                             NaN
                                        NaN
                                                   NaN
                                                            NaN 0.413923
                                                                            NaN
                                                                                         NaN
                                                                                                  Na
         9742 rows × 20 columns
```

Tag를 이용한 Movie representation 생성

```
tags_df.head()
```

```
Out [46]:
             userld movield
                                           timestamp
          0
                 2
                      60756
                                           1445714994
                                    funny
          1
                 2
                      60756 Highly quotable
                                          1445714996
          2
                 2
                      60756
                                 will ferrell 1445714992
          3
                 2
                      89774
                               Boxing story 1445715207
          4
                 2
                      89774
                                    MMA 1445715200
In [49]:
          movies_df.loc[60756] # Comedy -> funny : Reasonable !
                    Step Brothers (2008)
         title
Out[49]:
                                  Comedy
          Name: 60756, dtype: object
          # get unique tag
          tag_column = list(map(lambda x: x.split(','), tags_df['tag']))
          unique_tags = list(set(list(map(lambda x:x.strip(), list([tag for sublist in tag_col
          print(len(unique_tags))
          1589
          ### Compute IDF for tag
          total_movie_count = len(set(tags_df['movield']))
          # key: tag, value: number of movies with such tag
          tag_count_dict = dict.fromkeys(unique_tags)
          for each_movie_tag_list in tags_df['tag']:
               for tag in each_movie_tag_list.split(','):
                   if tag_count_dict[tag.strip()] == None:
                       tag_count_dict[tag.strip()] = 1
                   else:
                       tag_count_dict[tag.strip()] += 1
          tag_idf = dict()
           for each_tag in tag_count_dict:
               tag_idf[each_tag] = np.log10(total_movie_count / tag_count_dict[each_tag])
          tag_idf
Out[62]: {'Sean Connery': 3.196452541703389,
            Tarantino': 2.7193312869837265,
           'Stoner Movie': 3.196452541703389,
           'Jude Law': 2.895422546039408,
           'stupid': 3.196452541703389,
           'unusual': 3.196452541703389,
           'Hungary': 3.196452541703389,
           'Boxing story': 3.196452541703389,
           'black-and-white': 3.196452541703389,
           'lawn mower': 3.196452541703389,
           'masculinity': 3.196452541703389,
           'terminal illness': 2.7193312869837265,
           'insomnia': 3.196452541703389,
           'wonderwoman': 3.196452541703389,
           'missing children': 3.196452541703389,
           'Everything you want is here': 3.196452541703389,
           'dumpster diving': 3.196452541703389,
           'family': 2.351354501689132,
           'wapendrama': 3.196452541703389,
           'iconic': 3.196452541703389,
```

```
'celebrity fetishism': 3.196452541703389,
'sentimental': 2.895422546039408,
'intense': 2.5943925503754266,
'homosexuality': 3.196452541703389,
'stupid but funny': 3.196452541703389,
'King Arthur': 2.5943925503754266,
'scenic': 3.196452541703389,
'wizards': 3.196452541703389,
'Tolstoy': 3.196452541703389,
'Arthur C. Clarke': 3.196452541703389,
'jack nicholson': 2.895422546039408,
'Visually appealing': 3.196452541703389,
'nerds': 3.196452541703389,
'Hugh Jackman': 2.895422546039408,
'Bill Murray': 3.196452541703389,
'adventure': 2.2933625547114453,
'free speech': 3.196452541703389,
'based on a TV show': 2.5943925503754266,
'Police': 3.196452541703389,
'fighting': 3.196452541703389,
'depressing': 2.5943925503754266,
'innovative': 3.196452541703389,
'marijuana': 3.196452541703389,
'imagination': 2.895422546039408,
'cult': 2.895422546039408,
"artsy": 3.196452541703389,
'relaxing': 3.196452541703389,
'Dogs': 3.196452541703389,
'virtual reality': 3.196452541703389,
'Indonesia': 3.196452541703389,
'space': 2.050324506025151,
'Henry Darger': 3.196452541703389,
'Simon Pegg': 3.196452541703389,
'money': 3.196452541703389,
'Al Pacino': 2.4974825373673704,
'unpredictable': 3.196452541703389,
'Sci-Fi': 3.196452541703389,
sports': 2.4974825373673704,
'start of a beautiful friendship': 3.196452541703389,
'big wave': 3.196452541703389,
'Poor plot development': 3.196452541703389,
'surfing': 2.895422546039408,
show business': 2.5943925503754266,
'Rachel Weisz': 2.7193312869837265,
'mathematics': 2.7193312869837265,
'Medieval': 3.196452541703389,
'characters': 2.895422546039408,
'Recap': 3.196452541703389,
'boksdrama': 3.196452541703389.
'irony': 3.196452541703389,
'fast paced': 3.196452541703389.
'deafness': 3.196452541703389.
'moody': 2.895422546039408,
'basketball': 2.5943925503754266.
'Istanbul': 3.196452541703389.
'Maggie Gyllenhaal': 3.196452541703389.
'loneliness': 2.5943925503754266,
'spiders': 3.196452541703389.
'TERRORISM': 3.196452541703389,
'Conan': 3.196452541703389,
'fantasy world': 2.7193312869837265,
'jungle': 3.196452541703389,
'Rita Hayworth can dance!': 3.196452541703389.
'KIDNAPPING': 3.196452541703389.
'challenging': 3.196452541703389,
'claymation': 2.895422546039408,
'Amtrak': 3.196452541703389,
'rebellion': 3.196452541703389,
'cerebral': 2.4183012913197452,
```

```
'financial crisis': 3.196452541703389,
'CGI': 3.196452541703389,
'Bette Davis': 3.196452541703389,
'dreams': 3.196452541703389,
'daniel radcliffe': 3.196452541703389,
'1980s': 2.895422546039408,
'heroin': 2.895422546039408.
'FIGHTING THE SYSTEM': 3.196452541703389,
'World War II': 2.2422100322640643,
'Rachel McAdams': 3.196452541703389,
'unlikely hero': 3.196452541703389,
'r:some violence': 3.196452541703389,
'tricky': 3.196452541703389,
'pixar': 2.895422546039408,
'Star Trek': 2.895422546039408,
'science fiction': 3.196452541703389,
'Captain Kirk': 3.196452541703389,
'Dickens': 2.4974825373673704,
'bromantic': 3.196452541703389,
'wine': 3.196452541703389,
'wistful': 3.196452541703389,
'schizophrenia': 2.895422546039408,
'new society': 3.196452541703389,
'opera': 3.196452541703389,
'England': 2.196452541703389,
'harry potter': 3.196452541703389,
'Dark': 3.196452541703389,
'Lou Gehrig': 3.196452541703389,
'adorable': 3.196452541703389,
'freedom': 3.196452541703389,
'con artists': 3.196452541703389,
'intimate': 3.196452541703389,
'Chile': 3.196452541703389,
'new york': 2.895422546039408,
'Judaism': 2.4974825373673704,
'Huey Long': 3.196452541703389,
'colorful': 3.196452541703389,
'intelligent sci-fi': 3.196452541703389,
'hallucinatory': 2.2422100322640643,
'Charlotte Bronte': 3.196452541703389,
'needed more autobots': 3.196452541703389,
confrontational': 2.895422546039408,
monologue': 3.196452541703389,
courtroom drama': 2.895422546039408,
predictable': 2.351354501689132,
DEPRESSING': 3.196452541703389,
'Mindfuck': 3.196452541703389,
'Olympics': 2.895422546039408,
'Studio Ghibli': 2.895422546039408,
'Teen movie': 3.196452541703389.
'bad writing': 3.196452541703389,
'emma thompson': 3.196452541703389,
'tension building': 3.196452541703389.
'heroic bloodshed': 3.196452541703389,
'psychological': 2.155059856545164,
'Turkey': 3.196452541703389,
'E. M. Forster': 3.196452541703389.
'Vulgar': 3.196452541703389,
'Bad story': 3.196452541703389,
'imdb top 250': 2.155059856545164,
'big top': 3.196452541703389.
'Holy Grail': 3.196452541703389.
'coma': 2.895422546039408,
'Hepburn and Tracy': 2.4974825373673704.
'indiana jones': 2.895422546039408.
'quirky romantic': 3.196452541703389,
'seen more than once': 2.895422546039408,
'Dull': 3.196452541703389,
'humor': 2.895422546039408,
```

```
'POW': 2.895422546039408,
'Rogue': 3.196452541703389,
'David Fincher': 3.196452541703389,
'star wars': 3.196452541703389,
'Amish': 2.895422546039408,
'Katzanzakis': 3.196452541703389,
'fast-paced': 3.196452541703389,
'unintelligent': 3.196452541703389,
'pigs': 3.196452541703389,
'diabetes': 3.196452541703389,
'r:sustained strong stylized violence': 3.196452541703389,
'first was much better': 3.196452541703389,
'awesome': 2.895422546039408,
'Brittany Murphy': 3.196452541703389,
'Christopher Lloyd': 2.895422546039408,
'Well Done': 3.196452541703389,
'drugs & music': 3.196452541703389,
'symbolism': 2.895422546039408,
'weather forecaster': 3.196452541703389,
'Bad writing': 3.196452541703389,
'deadpan': 3.196452541703389,
'Justin Timberlake': 3.196452541703389,
'android(s)/cyborg(s)': 3.196452541703389,
great screenplay': 3.196452541703389,
'twins': 2.4183012913197452,
'hilarious': 2.7193312869837265,
procedural': 3.196452541703389,
cult classic': 3.196452541703389,
gun tactics': 3.196452541703389,
'Enterprise': 3.196452541703389,
'alter ego': 3.196452541703389,
'beautifully filmed': 3.196452541703389,
'jazz': 2.895422546039408,
'classic': 2.155059856545164,
'Quirky': 3.196452541703389,
'Roger Avary': 3.196452541703389,
'travolta': 3.196452541703389,
'real estate': 3.196452541703389,
goofy': 2.895422546039408,
'lies': 3.196452541703389,
great cinematography': 3.196452541703389,
anger': 3.196452541703389,
'Mystery': 2.7193312869837265,
abortion': 3.196452541703389,
alternate universe': 2.895422546039408,
drugs': 2.196452541703389,
cate blanchett': 3.196452541703389,
creepy': 2.2422100322640643,
good dialogue': 2.4974825373673704,
martial arts': 2.2933625547114453,
Ghosts': 3.196452541703389,
gintama': 3.196452541703389.
mafia': 2.7193312869837265,
diner': 3.196452541703389,
'British': 3.196452541703389,
political right versus left': 3.196452541703389.
shark': 3.196452541703389,
'Epic': 3.196452541703389,
'Francis Ford Coppola': 3.196452541703389,
'submarine': 2.895422546039408,
'mythology': 3.196452541703389,
'Afghanistan': 3.196452541703389.
'costume drama': 3.196452541703389,
'r:strong language': 3.196452541703389,
'AIDs': 2.895422546039408,
'tragedy': 3.196452541703389.
'vertriloguism': 3.196452541703389.
'butler': 3.196452541703389,
'scandal': 2.895422546039408.
```

```
'reciprocal spectator': 2.895422546039408,
'classic sci-fi': 2.7193312869837265,
'nonlinear storyline': 3.196452541703389,
'trippy': 2.895422546039408,
'Harper Lee': 3.196452541703389,
gruesome': 3.196452541703389,
matchmaker': 3.196452541703389,
sofia coppola': 3.196452541703389,
prostitution': 2.351354501689132,
'Great villain': 3.196452541703389,
'disappointing': 3.196452541703389,
'undercover cop': 3.196452541703389,
'nonlinear': 2.7193312869837265,
'Christmas': 2.2933625547114453,
'futuristic': 2.895422546039408,
'military': 2.2422100322640643,
'Jaime Pressly': 3.196452541703389,
'setting:space/space ship': 3.196452541703389,
'Neil Patrick Harris': 3.196452541703389,
'blindness': 2.5943925503754266,
'ransom': 3.196452541703389,
'2D animation': 3.196452541703389,
'milkshake': 3.196452541703389,
'ryan reynolds': 3.196452541703389,
'SNL': 3.196452541703389,
'HORRIBLE ACTING': 3.196452541703389,
'Nick Hornby': 2.895422546039408,
'alternate endings': 2.895422546039408,
'Guns': 3.196452541703389,
'lion': 3.196452541703389,
'brothers': 3.196452541703389,
'meditative': 2.895422546039408,
'stylish': 2.4974825373673704,
'violence in america': 2.895422546039408,
'black humor': 3.196452541703389,
'satirical': 2.895422546039408,
'organized crime': 2.4974825373673704,
'Chuck Palahniuk': 3.196452541703389,
cameo:Whoopi Goldberg': 3.196452541703389,
'unexplained': 3.196452541703389,
'haunting': 3.196452541703389,
'terrorism': 2.4974825373673704,
'silly': 2.7193312869837265,
'humour': 3.196452541703389,
'Dwayne Johnson': 3.196452541703389,
'DC Comics': 3.196452541703389,
'Peta Wilson': 3.196452541703389,
gold': 3.196452541703389,
'irreverent': 2.7193312869837265,
great ending': 2.895422546039408.
'bad language': 3.196452541703389.
'carnival': 3.196452541703389,
'No DVD at Netflix': 3.196452541703389.
'horror': 2.5943925503754266,
'original': 2.895422546039408,
psychology': 1.8742332469694698,
character development : 3.196452541703389,
'Thor': 3.196452541703389,
great humor': 3.196452541703389,
'General Motors': 3.196452541703389,
'biography': 3.196452541703389.
camp': 3.196452541703389,
gentle': 3.196452541703389,
'notable soundtrack': 2.895422546039408,
'Gangs': 3.196452541703389,
'Morrow': 3.196452541703389,
'photography': 2.7193312869837265,
'Alfred Hitchcock': 2.5943925503754266,
'last man on earth': 2.895422546039408,
```

```
'Seann William Scott': 2.895422546039408,
'longing': 3.196452541703389,
'men in drag': 2.4183012913197452,
Beautiful': 2.7193312869837265,
'remaster': 3.196452541703389,
'Mark Wahlberg': 3.196452541703389,
'It was melodramatic and kind of dumb': 3.196452541703389,
'mindfuck': 2.050324506025151,
'Nerd': 3.196452541703389,
'e-mail': 3.196452541703389,
'father-son relationship': 3.196452541703389,
'dating': 2.895422546039408,
'justice': 3.196452541703389,
'John Grisham': 2.5943925503754266,
'fucked up': 3.196452541703389,
'Disaster': 3.196452541703389,
'ships': 3.196452541703389,
'McDonalds': 3.196452541703389,
'out of order': 3.196452541703389,
'weddings': 2.895422546039408,
amazing artwork': 3.196452541703389,
'stiller': 3.196452541703389,
'bad ass': 3.196452541703389,
'audience intelligence underestimated': 2.895422546039408,
'tense': 2.2422100322640643,
'test tag': 3.196452541703389,
'Suspense': 3.196452541703389,
'music': 1.9923325590474643,
'bromance': 2.895422546039408,
'stone age': 3.196452541703389,
'dance marathon': 3.196452541703389,
'Henry James': 2.895422546039408,
'dinosaurs': 2.895422546039408,
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'parody': 2.5943925503754266,
'Notable Nudity': 3.196452541703389.
'marvel': 2.895422546039408,
'oil': 3.196452541703389,
'multiple stories': 3.196452541703389.
'cheeky': 3.196452541703389,
'Rogers and Hammerstein': 2.895422546039408.
```

```
'downbeat': 2.895422546039408,
symbolic': 3.196452541703389,
'invisibility': 3.196452541703389,
'roald dahl': 3.196452541703389,
'ben stiller': 3.196452541703389,
'mel gibson': 3.196452541703389,
'incest': 3.196452541703389,
'surprise ending': 3.196452541703389,
'touching': 2.4183012913197452,
painter': 3.196452541703389,
post-college': 3.196452541703389,
'far fetched': 3.196452541703389,
'Sci-fi': 3.196452541703389,
'understated': 2.895422546039408,
edward norton': 2.895422546039408,
'Death': 3.196452541703389,
'Music': 3.196452541703389,
'Steven Spielberg': 2.895422546039408,
'dogs': 2.5943925503754266,
'samurai': 2.4974825373673704,
'bad-ass': 3.196452541703389,
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space station': 3.196452541703389,
slow action': 3.196452541703389,
'Captain America': 3.196452541703389,
James Fennimore Cooper': 3.196452541703389,
small towns': 3.196452541703389,
ben affleck': 3.196452541703389,
gunfight': 3.196452541703389,
adolescence: 2.155059856545164,
the catholic church is the most corrupt organization in history': 3.196452541703389,
paranoid': 2.5943925503754266,
purity of essence': 3.196452541703389,
Colin Farrell': 3.196452541703389,
'mental hospital': 3.196452541703389,
'Siam': 3.196452541703389,
'illusions': 3.196452541703389,
'Sad': 3.196452541703389,
'immigrants': 2.5943925503754266,
'Union': 3.196452541703389,
'sniper': 2.895422546039408,
'Ryan Reynolds': 2.5943925503754266,
'muppets': 3.196452541703389,
'Thrilling': 3.196452541703389,
'class': 2.7193312869837265,
'superman': 3.196452541703389,
'heist': 2.082509189396552,
'singers': 3.196452541703389,
'Bugs Bunny': 3.196452541703389.
'free to download': 3.196452541703389.
'tom hardy': 3.196452541703389,
'Thanksgiving': 3.196452541703389,
'passion': 3.196452541703389,
great soundtrack': 2.4183012913197452,
'twists & turns': 2.895422546039408.
'love': 2.895422546039408,
'not funny': 3.196452541703389,
'Marvel': 2.895422546039408,
'bank': 3.196452541703389,
'John Malkovich': 3.196452541703389,
'Trey Parker': 3.196452541703389,
'satire': 2.1172712956557644,
'different': 3.196452541703389.
'independent': 3.196452541703389,
'Saturday Night Live': 3.196452541703389,
'Pixar': 2.5943925503754266,
'Oscar (Best Effects - Visual Effects)': 3.196452541703389.
'French': 3.196452541703389,
```

```
'road trip': 3.196452541703389,
 'comedy': 2.0203612826477078,
 accident': 3.196452541703389,
 'based on a play': 3.196452541703389,
 'Star Wars': 2.895422546039408,
 'theater': 2.895422546039408,
 'M. Night Shyamalan': 2.895422546039408,
 'Seth Rogen': 2.5943925503754266,
 'inspirational': 2.351354501689132,
 'comic book': 2.155059856545164,
 'Matrix': 3.196452541703389,
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 'fantasy': 2.4183012913197452,
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 'Coen Bros': 3.196452541703389,
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s!': 3.196452541703389.
 dark comedy': 1.8742332469694698,
 'Comedy': 2.5943925503754266,
 'r:violence': 3.196452541703389,
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 'bible': 3.196452541703389,
 'Gulf War': 3.196452541703389,
 'narrated': 2.895422546039408,
 'film history': 3.196452541703389,
 'Hemingway': 2.895422546039408,
 'Not Seen': 3.196452541703389,
 'Amy Adams': 3.196452541703389,
 'friendship': 2.4974825373673704,
 'Day and Hudson': 3.196452541703389,
 'vampire': 2.895422546039408,
 'Agatha Christie': 2.895422546039408,
 'food': 2.7193312869837265,
 'long takes': 3.196452541703389,
 'philosophy': 2.4183012913197452,
 'Wizards': 2.5943925503754266,
 'Visually stunning': 2.895422546039408,
 'Halloween': 3.196452541703389,
 'stop looking at me swan': 3.196452541703389,
 'witty': 2.4183012913197452,
 'Mafia': 2.196452541703389,
 'film-noir': 3.196452541703389,
 'teachers': 3.196452541703389,
 'werewolf': 3.196452541703389,
 'space craft': 3.196452541703389,
 'dystopia': 2.4974825373673704,
 'arthouse': 3.196452541703389,
 'Natalie Portman': 3.196452541703389.
 'DC': 3.196452541703389,
 'art house': 3.196452541703389,
 'luke skywalker': 2.895422546039408,
 'sex': 3.196452541703389,
 'blind': 2.7193312869837265,
 'pop culture references': 3.196452541703389.
 'California': 3.196452541703389.
 'Housekeeper': 3.196452541703389,
 'entirely dialogue': 3.196452541703389.
 'racism': 2.2422100322640643,
 'Moses': 3.196452541703389,
 'Howard Hughes': 3.196452541703389,
 'Depressing': 3.196452541703389.
 'Seth MacFarlane': 3.196452541703389.
 'mecha': 3.196452541703389,
 'killer': 3.196452541703389,
 'Dodie Smith': 3.196452541703389,
```

In []:

```
'Academy award (Best Supporting Actress)': 3.196452541703389,
  'meaningless violence': 3.196452541703389,
  'Emma Stone': 3.196452541703389,
  'Creature Feature': 3.196452541703389,
  spacecraft': 3.196452541703389,
  '2001-like': 3.196452541703389,
  'fairy tale': 3.196452541703389,
  'subway': 3.196452541703389,
 'China': 3.196452541703389,
  'FBI': 2.895422546039408,
  'Peter Pan': 2.895422546039408,
  'magic board game': 3.196452541703389,
 'Ray Bradbury': 2.895422546039408,
 'fast-paced dialogue': 3.196452541703389,
 'Jim Morrison': 3.196452541703389,
 . . . }
 # create tag representation
 tag_representation = pd.DataFrame(columns=sorted(unique_tags), index=list(set(tags_df
 for name, group in tqdm(tags_df.groupby(by='movield')):
     temp_list = list(map(lambda x:x.split(','), list(group['tag'])))
     temp_tag_list = list(set(list(map(lambda x:x.strip(), list([tag for sublist in t
     dict_temp = {i: tag_idf[i.strip()] for i in temp_tag_list}
     row_to_add = pd.DataFrame(dict_temp, index=[group['movield'].values[0]])
     tag_representation.update(row_to_add)
 tag_representation = tag_representation.sort_index(0)
 tag_representation
1572/1572 [02:55<00:00, 8.96it/s]
                  06 Oscar
                Nominated
                                                                         2001-
        "artsy"
                           1900s 1920s 1950s 1960s 1970s 1980s 1990s
                Best Movie
                                                                                   women
                                                                           like
                Animation
     1
          NaN
                     NaN
                            NaN
                                   NaN
                                         NaN
                                                NaN
                                                      NaN
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     2
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     3
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 184471
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187593
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187595
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193565
          NaN
                     NaN
                            NaN
                                   NaN
                                         NaN
                                                NaN
                                                      NaN
                                                             NaN
                                                                    NaN
                                                                          NaN
                                                                                     NaN
1572 rows × 1589 columns
```

```
# tag representation 확인
movies_df.head()
```

title genres

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

```
tag_representation.loc[1].dropna()
```

2.497483 fun 2.895423 pixar Name: 1, dtype: object

tag_representation.loc[2].dropna()

Robin Williams 2.719331 fantasy 2.418301 game 3.196453 3.196453 magic board game Name: 2, dtype: object

Fianl Movie Representation 생성

movie_representation = pd.concat([genre_representation, tag_representation], axis=1). print(movie_representation.shape) movie_representation.describe()

(9742, 1609)

	(no genres listed)	Action	Adventure	Animation	Children	Comedy	Crime
count	9742.000000	9742.000000	9742.000000	9742.000000	9742.000000	9742.000000	9742.000000
mean	0.008576	0.136354	0.115027	0.075425	0.079506	0.159587	0.111978
std	0.144915	0.283726	0.298052	0.291593	0.293989	0.201476	0.298916
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000	0.413923	0.000000
max	2.457169	0.726672	0.887245	1.202607	1.166480	0.413923	0.909829

8 rows × 1609 columns

콘텐츠 유사도 평가 (cosine similarity)

```
In [71]:
          from sklearn.metrics.pairwise import cosine_similarity
          def cos_sim_matrix(a, b):
              \cos_{\sin} = \cos_{\sin} \arcsin_{arity(a, b)}
              result_df = pd.DataFrame(data=cos_sim, index=[a.index])
              return result_df
          cs_df = cos_sim_matrix(movie_representation, movie_representation)
          cs df.head()
                  0
                          1
                                   2
                                           3
                                                    4
                                                        5
                                                                 6
                                                                         7
                                                                             8
                                                                                               9
                                                                                      9 ...
            1.000000 0.124438 0.008403 0.040571 0.011755
                                                      0.0 0.016339 0.331122 0.0 0.131794
                                                                                            0.064
         0.000
           0.008403 0.000000
                             1.000000
                                     0.179391 0.011294
                                                      0.0 0.072246
                                                                   0.000000
                                                                            0.0
                                                                                0.000000
                                                                                           0.006
           0.040571 0.000000 0.179391
                                     1.000000 0.054530 0.0 0.348828
                                                                  0.000000
                                                                            0.0
                                                                                0.000000
                                                                                         ... 0.031
            0.011755 0.000000 0.011294 0.054530 1.000000 0.0 0.640342 0.000000 0.0 0.000000
                                                                                         ... 0.009
        5 rows × 9742 columns
          cs_df[1].sort_values(ascending=False)
                   1.000000
         46972
                   0.322201
         158813
                   0.300850
         119655
                   0.300850
         80748
                   0.300850
         4921
                   0.000000
         4920
                   0.000000
         4919
                   0.000000
         4917
                   0.000000
         193609
                   0.000000
         Name: 1, Length: 9742, dtype: float64
        유사도 평가 결과
          print(movies_df.loc[2])
          print(movies_df.loc[46972])
          print(movies_df.loc[158813])
          print(movies_df.loc[80748])
         title
                               Jumanji (1995)
                   Adventure | Children | Fantasy
         genres
         Name: 2, dtype: object
                   Night at the Museum (2006)
         title
                   Action|Comedy|Fantasy|IMAX
         genres
         Name: 46972, dtype: object
                   Alice Through the Looking Glass (2016)
         title
                               Adventure | Children | Fantasy
         genres
         Name: 158813, dtype: object
                   Alice in Wonderland (1933)
         title
                   Adventure | Children | Fantasy
         genres
         Name: 80748, dtype: object
```

성능평기

```
train_df, test_df = train_test_split(ratings_df, test_size=0.2, random_state=1234)
          print(train_df.shape)
          print(test_df.shape)
         (80668, 4)
         (20168, 4)
          test userids = list(set(test df.userld.values))
          result_df = pd.DataFrame()
          for user_id in tqdm(test_userids):
              user_record_df = train_df.loc[train_df.userId == int(user_id), :]
              user_sim_df = cs_df.loc[user_record_df['movield']] # (n, 9742) 차원 : n은 유저가
              user_ratings_df = user_record_df[['rating']] # (n, 1) 차원
              sim_sum = np.sum(user_sim_df.T.to_numpy(), -1) # (9742, 1) # 유저가 매긴 영화유사
              prediction = np.matmul(user_sim_df.T.to_numpy(), user_ratings_df.to_numpy()).flat
              prediction_df = pd.DataFrame(prediction, index=cs_df.index).reset_index()
              prediction_df.columns = ['movield', 'pred_rating']
              prediction_df = prediction_df[['movield', 'pred_rating']][prediction_df.movield.i
              temp_df = prediction_df.merge(test_df[test_df.userId == user_id], on='movieId')
              result_df = pd.concat([result_df, temp_df], axis=0)
         610/610 [00:06<00:00. 92.27it/s]
In [96]:
          result_df.head(10)
Out[96]:
            movield pred_rating userId rating
                                             timestamp
         0
                  1
                       4.145652
                                    1
                                          4.0
                                              964982703
         1
                 50
                       3.650755
                                    1
                                          5.0
                                              964982931
         2
                216
                       2.670124
                                          5.0
                                              964981208
         3
                223
                       2.612844
                                          3.0
                                              964980985
         4
                231
                       4.215284
                                    1
                                          5.0
                                              964981179
         5
                235
                       3.619820
                                    1
                                          4.0
                                              964980908
         6
                316
                       4.136756
                                              964982310
                                    1
                                          3.0
         7
                457
                       3.218743
                                    1
                                          5.0
                                              964981909
         8
                543
                       3.729524
                                    1
                                          4.0 964981179
         9
                592
                       4.024728
                                    1
                                          4.0 964982271
          mse = mean_squared_error(y_true=result_df['rating'].values, y_pred=result_df['pred_ra
          rmse = np.sgrt(mse)
          print(mse, rmse)
```

		1.40000040700041 1.1637707337301076					
)	[]	:					