

## ▼ INITIAL INFORMATION - 참조 함수

```
# !pip install scikit-surprise

import pandas as pd
import numpy as np

def load_movies_dataset() -> pd.DataFrame:
    """영화에 대한 정보 불러오기"""
    movie_data_columns = [
        'movie_id', 'title', 'release_date', 'video_release_date', 'url',
        'unknown', 'Action', 'Adventure', 'Animation', "Children's",
        'Comedy', 'Crime', 'Documentary', 'Drama', 'Fantasy', 'Film-Noir',
        'Horror', 'Musical', 'Mystery', 'Romance', 'Sci-Fi', 'Thriller',
        'War', 'Western'
    ]

    movie_data = pd.read_csv(
        'datasets/ml-100k/u.item',
        sep = '|',
        encoding = "ISO-8859-1",
        header = None,
        names = movie_data_columns,
        index_col = 'movie_id'
    )
    movie_data['release_date'] = pd.to_datetime(movie_data['release_date'])
    return movie_data

def load_ratings() -> pd.DataFrame:
    ratings_data = pd.read_csv(
        'datasets/ml-100k/u.data',
        sep = '\t',
        names=['user_id', 'movie_id', 'rating', 'timestamp']
    )
    return ratings_data

movie_data = load_movies_dataset()
ratings_data = load_ratings()

movie_data.head()

ratings_data.head(10)
```

|   | user_id | movie_id | rating | timestamp |
|---|---------|----------|--------|-----------|
| 0 | 196     | 242      | 3      | 881250949 |
| 1 | 186     | 302      | 3      | 891717742 |
| 2 | 22      | 377      | 1      | 878887116 |
| 3 | 244     | 51       | 2      | 880606923 |
| 4 | 166     | 346      | 1      | 886397596 |
| 5 | 298     | 474      | 4      | 884182806 |
| 6 | 115     | 265      | 2      | 881171488 |
| 7 | 253     | 465      | 5      | 891628467 |
| 8 | 305     | 451      | 3      | 886324817 |
| 9 | 6       | 86       | 3      | 883603013 |

```
ratings_data['user_id'].max()

943
```

## ▼ Ratings dataset

Contains the **interactions** between users and movies

- User **196** rated movie **242** with a score of **3**
- User **186** rated movie **302** with a score of **3**
- User **22** rated movie **377** with a score of **3**

```
ratings_data[ratings_data['movie_id'] == 1]['rating'].describe()

count    452.000000
mean      3.878319
std       0.927897
min       1.000000
25%       3.000000
50%       4.000000
75%       5.000000
max       5.000000
Name: rating, dtype: float64
```

Double-click (or enter) to edit

NOW SOLVE!!!!

## ▼ 해답) 문제 풀이

```
from surprise import SVD, NMF, accuracy
from surprise import Dataset, Reader
from surprise.model_selection import cross_validate, train_test_split

# Surprise has some preset datasets, including ml-100k!
# data = Dataset.load_builtin('ml-100k')

reader = Reader(rating_scale=(1, 5))
data = Dataset.load_from_df(ratings_data[['user_id', 'movie_id', 'rating']], reader)

trainset, testset = train_test_split(data, test_size=.25)

# Let's train a new Nonnegative SVD
model = SVD(n_factors=100, biased=False)
model.fit(trainset)

# In reality, we should perform a train/test split and check RMSE to see if our model is trained
# but today, for simplicity, I'm skipping this step
predictions = model.test(testset)
accuracy.rmse(predictions)

RMSE: 0.9580
0.957965924295794
```

To undo cell deletion use ⌘/Ctrl+M Z or the Undo option in the Edit menu ✕

Surprise SVD stores the product matrix under the `model.qi` attribute.

```
pd.DataFrame(model.qi).head(10)
```

|   | 0         | 1        | 2        | 3         | 4         | 5         | 6         | 7         | 8         | 9         | ... | 90        | 91        | 92        | 93        | 94       |
|---|-----------|----------|----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----|-----------|-----------|-----------|-----------|----------|
| 0 | -0.028085 | 0.007326 | 0.267067 | -0.236421 | -0.077943 | -0.019932 | -0.133990 | 0.285557  | 0.273829  | 0.001874  | ... | 0.081802  | 0.219284  | 0.120746  | -0.097746 | 0.467054 |
| 1 | 0.106267  | 0.063955 | 0.362999 | -0.038772 | 0.106562  | 0.193185  | -0.174445 | 0.112519  | 0.027699  | 0.314792  | ... | 0.093350  | 0.138825  | -0.055726 | 0.119043  | 0.368421 |
| 2 | 0.113641  | 0.480834 | 0.050770 | 0.140915  | 0.299281  | 0.073561  | -0.192111 | 0.067109  | -0.019272 | -0.087939 | ... | -0.072078 | 0.024927  | 0.147691  | -0.174189 | 0.169043 |
| 3 | -0.018501 | 0.081170 | 0.315538 | -0.381532 | 0.158467  | 0.059910  | 0.114721  | 0.254688  | 0.157660  | 0.057107  | ... | 0.014172  | 0.148316  | -0.035810 | 0.017940  | 0.218948 |
| 4 | -0.039118 | 0.117172 | 0.251221 | -0.165814 | -0.054695 | 0.022311  | -0.138875 | -0.018530 | 0.164057  | 0.120751  | ... | 0.206625  | 0.013239  | 0.039077  | -0.148116 | 0.366774 |
| 5 | 0.447446  | 0.185904 | 0.451171 | -0.394825 | 0.145879  | 0.090853  | 0.073207  | 0.055838  | 0.254270  | 0.092589  | ... | 0.093432  | -0.112373 | -0.182172 | 0.098663  | 0.085598 |
| 6 | 0.196233  | 0.145739 | 0.209179 | 0.148519  | -0.231206 | -0.062533 | -0.255633 | 0.002110  | 0.241216  | -0.068118 | ... | 0.134930  | 0.015341  | 0.026284  | -0.107322 | 0.265486 |
| 7 | -0.082921 | 0.187218 | 0.253966 | 0.043173  | 0.140965  | -0.159558 | 0.208955  | 0.067746  | 0.060982  | -0.199792 | ... | 0.205104  | 0.241081  | 0.068046  | -0.044265 | 0.355204 |
| 8 | -0.079435 | 0.260487 | 0.054842 | -0.438233 | 0.070607  | 0.118612  | 0.002515  | -0.067611 | 0.497394  | -0.344685 | ... | -0.086256 | -0.230251 | -0.221332 | -0.062740 | 0.067165 |
| 9 | 0.079875  | 0.086168 | 0.118833 | 0.002549  | -0.237364 | 0.157296  | -0.248504 | 0.123689  | 0.259569  | 0.154115  | ... | 0.465869  | 0.121347  | 0.015153  | -0.090638 | 0.393071 |

10 rows × 100 columns



## ▼ Exploring the product matrix

The matrix has `n_factors` columns (we chose 10). Every row represents a movie

```
print(f"The shape of our product matrix is {model.qi.shape}.")
print(f"There are {ratings_data['movie_id'].unique().shape[0]} unique movies movies")

The shape of our product matrix is (1638, 100).
There are 1682 unique movies movies
```

## ▼ Generating predictions with simplicity

Before looking into the latent features of our movies, let's use the API provided by Surprise. More specifically, Surprise provides us 1 API

- `model.predict` computes the rating prediction for given user and movie

Let's look at how we can use this API to generate movies that a given user may like

```
>>> model.predict('302', '1')
Prediction(uid=302, iid=1, r_ui=None, est=3.5327866666666665, details={'was_impossible': False})
```

NOTE: User ID and Movie ID are **strings**

```
# The prediction for user 196 to like movie#1 (Toy Story)
print(movie_data.loc[1])
print()
```

```

user_score_prediction = model.predict(196, 1)
print(user_score_prediction)
print(f"\n\nUSER 196 gives Toy Story: {user_score_prediction.est}")

```

```

title Toy Story (1995)
release_date 1995-01-01 00:00:00
video_release_date NaN
url http://us.imdb.com/M/title-exact?Toy%20Story%2...
unknown 0
Action 0
Adventure 0
Animation 1
Children's 1
Comedy 1
Crime 0
Documentary 0
Drama 0
Fantasy 0
Film-Noir 0
Horror 0
Musical 0
Mystery 0
Romance 0
Sci-Fi 0
Thriller 0
War 0
Western 0
Name: 1, dtype: object

user: 196      item: 1      r_ui = None      est = 3.66      {'was_impossible': False}

```

USER 196 gives Toy Story: 3.657722819161514

## Recommend 출력 함수 만들기

To undo cell deletion use ⌘/Ctrl+M Z or the Undo option in the Edit menu

```

def generate_recommended_movies_for_user(model, user_id):
    """Return a DataFrame containing recommendations for the user, and the
    associated score
    """
    results = []
    for movie_id, movie_title in movie_id_to_title_map.items():

        # For each movie, calculate score prediction
        prediction = model.predict(user_id, movie_id)
        results.append((movie_id, prediction.est, movie_title))

    return pd.DataFrame(results, columns=['movie_id', 'Estimated Prediction', 'Movie Title']).set_index('movie_id')

def display_best_and_worse_recommendations(recommendations: pd.DataFrame):
    recommendations.sort_values('Estimated Prediction', ascending=False, inplace=True)

    top_recommendations = recommendations.iloc[:10]
    top_recommendations.columns = ['Prediction (sorted by best)', 'Movie Title']
    # worse_recommendations = recommendations.iloc[-10:]
    # worse_recommendations.columns = ['Prediction (sorted by worst)', 'Movie Title']

    return top_recommendations

# Let's generate some recommendations for a user 302
recommendations = generate_recommended_movies_for_user(model, 302)
display_best_and_worse_recommendations(recommendations)

```

|          | Prediction (sorted by best) | Movie Title                                       |
|----------|-----------------------------|---|
| movie_id |                             |   |
| 1570     | 3.529347                    | Quartier Mozart (1992)                            |
| 1505     | 3.529347                    | Killer: A Journal of Murder (1995)                |
| 1533     | 3.529347                    | I Don't Want to Talk About It (De eso no se ha... |
| 1619     | 3.529347                    | All Things Fair (1996)                            |
| 1520     | 3.529347                    | Fear, The (1995)                                  |
| 1515     | 3.529347                    | Wings of Courage (1995)                           |
| 1507     | 3.529347                    | Three Lives and Only One Death (1996)             |
| 1631     | 3.529347                    | Slingshot, The (1993)                             |
| 1343     | 3.529347                    | Lotto Land (1995)                                 |
| 1659     | 3.529347                    | Getting Away With Murder (1996)                   |

## 내가 좋아하는 영화 고르고, 데이터에 추가해서 추천 영화 뽑기

```

# 나는 최근 영화만 알기 때문에 최근 영화만 살펴보기
movie_data.sort_values('release_date', ascending=False).iloc[:100]

movie_data.sort_values('release_date', ascending=False).iloc[:200].to_clipboard(sep='\t')
# 엑셀에서 내가 좋아하는 영화 선택

```

```
#선택한 내가 좋아하는 영화
my_movie_lst = pd.Series([916, 355,350,258,298,252,987,250], name='movie_id')
movie_data.loc[my_movie_lst, ['title', 'release_date']]
```

|          | title                                 | release_date |
|----------|---------------------------------------|--------------|
| movie_id |                                       |              |
| 916      | Lost in Space (1998)                  | 1998-03-27   |
| 355      | Sphere (1998)                         | 1998-02-13   |
| 350      | Fallen (1998)                         | 1998-01-16   |
| 258      | Contact (1997)                        | 1997-07-11   |
| 298      | Face/Off (1997)                       | 1997-06-27   |
| 252      | Lost World: Jurassic Park, The (1997) | 1997-05-23   |
| 987      | Underworld (1997)                     | 1997-05-09   |
| 250      | Fifth Element, The (1997)             | 1997-05-09   |

```
ratings_attach = my_movie_lst.to_frame().assign(rating=5)
ratings_attach.insert(0, 'user_id', 1000)

ratings_data_ = pd.concat([ratings_data, ratings_attach], axis=0).reset_index(drop=True)

reader = Reader(rating_scale=(1, 5))
data = Dataset.load_from_df(ratings_data[['user_id', 'movie_id', 'rating']], reader)

trainset, testset = train_test_split(data, test_size=.25)

# Let's train a new Nonnegative SVD
model = SVD(n_factors=100, biased=False)

predictions = model.test(testset)
accuracy.rmse(predictions)

RMSE: 0.9524
0.9523943284708634
```

```
# Let's generate some recommendations for a myself - user_id(1000)
recommendations = generate_recommended_movies_for_user(model, 1000)
display_best_and_worse_recommendations(recommendations)
```

|          | Prediction (sorted by best) | Movie Title                            |
|----------|-----------------------------|--|
| movie_id |                             |  |
| 64       | 5.0                         | Shawshank Redemption, The (1994)       |
| 12       | 5.0                         | Usual Suspects, The (1995)             |
| 258      | 5.0                         | Contact (1997)                         |
| 251      | 5.0                         | Shall We Dance? (1996)                 |
| 285      | 5.0                         | Secrets & Lies (1996)                  |
| 515      | 5.0                         | Boot, Das (1981)                       |
| 169      | 5.0                         | Wrong Trousers, The (1993)             |
| 357      | 5.0                         | One Flew Over the Cuckoo's Nest (1975) |
| 408      | 5.0                         | Close Shave, A (1995)                  |
| 272      | 5.0                         | Good Will Hunting (1997)               |