데이터관리와 분석

프로젝트#2: DB mining & Automated Recommendation System

12조 2017-15751 장준혁 2017-18868 조형찬 2017-10854 최의현 2017-13918 황재훈 2017-10089 윤성진



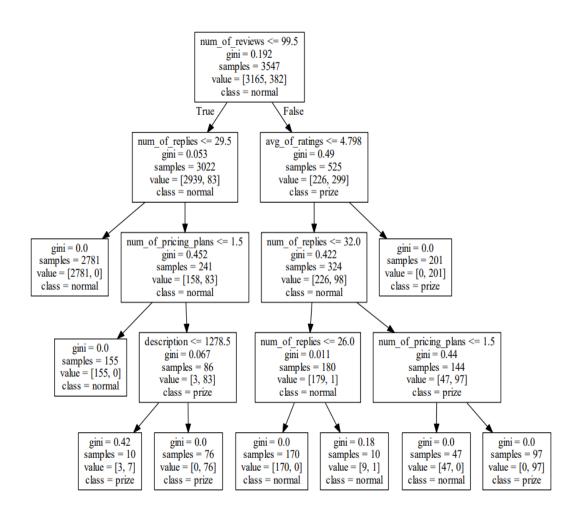
```
cursor.execute('''DROP TABLE IF EXISTS app_prize_list;''')
#cursor.execute('''ALTER Table app DROP app_prize;''') #재실행시에는 이 코드를 같이 돌릴 필요가 있음
cursor.execute('''ALTER TABLE app ADD (app_prize TINYINT(1) default 0);''')
cursor.execute('''
f_apl = open('C:/Users/User/Downloads/DMA_project2/DMA_project2/app_prize_list.txt', 'r', encoding='utf-8')
d_apl = f_apl.readlines()
for i in range(0, len(d_apl)):
    li_apl = d_apl[i].replace('\n', '')
   li_apl = li_apl.split(', ')
   cursor.execute('''
                  (li_apl))
cnx.commit()
f_apl.close()
cursor.execute('''
cursor.execute('''DROP TABLE IF EXISTS app_prize_list;''')
cnx.commit()
print('1-1 clear')
```

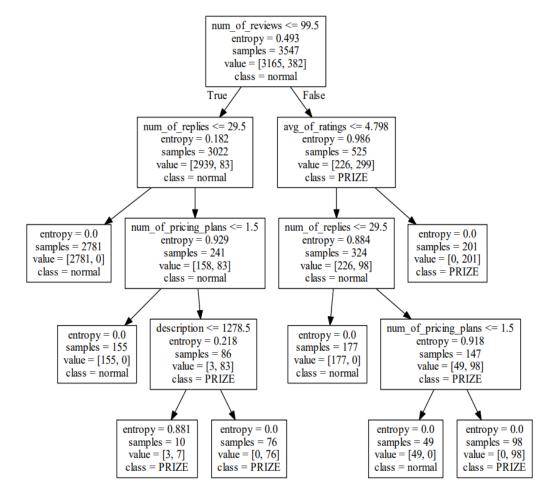


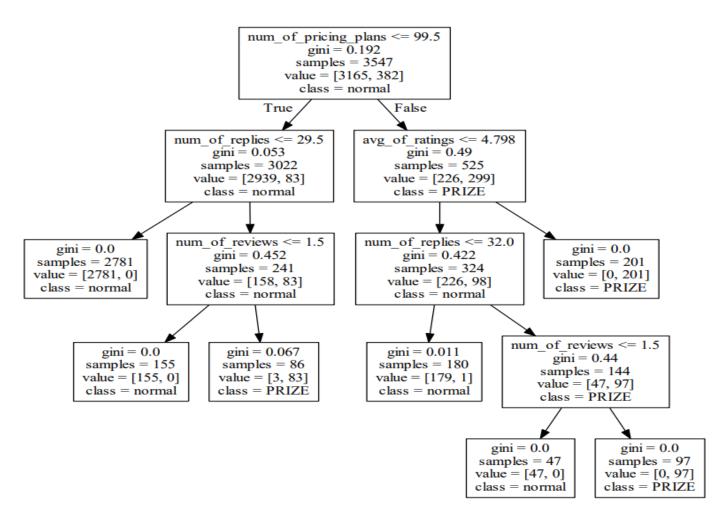
```
# TODO: Requirement 1-2. WRITE MYSQL QUERY AND EXECUTE. SAVE to .csv file
col_names = ['id', 'app_prize', 'description', 'have_pricing_hint', 'num_of_categories', 'num_of_pricing_plans',
fopen = open('DMA_project2_team%02d_part1.csv' % team, 'w', encoding='utf-8')
for col in col names:
    fopen.write(col)
        fopen.write('\n')
       fopen.write(',')
nested_query = '''
    (select count(*) from reply where app.developer_id=reply.developer_id group by developer_id)) as num_of_replies
cursor.execute(nested_query)
rows = cursor.fetchall()
for row in rows:
    for i in range(0, 9):
            fopen.write(str(row[i]))
            fopen.write('\n')
            fopen.write(str(row[i]))
            fopen.write(',')
fopen.close()
print('1-2 clear')
```

```
app_info_dt = pd.read_csv('./DMA_project2_team%02d_part1.csv' %team)
app_prize_dt = app_info_dt['app_prize']
cols_for_train = ['description', 'have_pricing_hint', 'num_of_categories', 'num_of_priding_plans', 'num_of_reviews',
app_info_dt = app_info_dt[cols_for_train]
print('preprocessing is done')
DT_gini = tree.DecisionTreeClassifier(criterion='gini', max_depth=5, min_samples_leaf=10, random_state=0)
DT_gini.fit(X=app_info_dt, y=app_prize_dt)
graph = tree.export_graphviz(DT_gini, out_file=None, feature_names=['description', 'have_pricing_hint',
                                                                    'num_of_replies'], class_names=['normal', 'PRIZE'])
graph = graphviz.Source(graph)
graph.render('DMA_project2_team12_part1_gini', view=True)
print('create DT with gini')
# entropy DT
DT_entropy = tree.DecisionTreeClassifier(criterion='entropy', max_depth=5, min_samples_leaf=10, random_state=0)
DT_entropy.fit(X=app_info_dt, y=app_prize_dt)
graph = tree.export_graphviz(DT_entropy, out_file=None, feature_names=['description', 'have_pricing_hint',
                                                                       'num_of_replies'], class_names=['normal', 'PRIZE'])
graph = graphviz.Source(graph)
graph.render('DMA_project2_team12_part1_entropy', view=True)
print('create DT with entropy')
print('1-3 clear')
```

R1-3 결과







#gini모델- 개선 여지 보여 채택

#max-depth=4로 채택(over-fitting 방지)

#Min-samples-leaf 5로 바꿈(상세하게 분류)

#Min-impurity_decrease 0.002로 (overfitting 방지)

#have_pricing_hint(중요한 기준이 아니라 삭제)

```
cursor.execute('''create or replace view category_score as
fopen = open('DMA_project2_team%02d_part2_category.csv' % team, 'w', encoding='utf-8', newline='')
col_category=['category_id','category_title','num_developer','num_user','num_app','score']
for col in col_category:
    fopen.write(col)
   if col == 'score':
        fopen.write('\n')
        fopen.write(',')
writer = csv.writer(fopen)
cursor.execute('select * from category_score')
a = cursor.fetchall()
for i in a:
    writer.writerow(i)
fopen.close()
print('2-1 clear')
```

```
cursor.execute(
cursor.execute(
col_UIR=['user','category','rating']
for col in col_UIR:
    fopen.write(col)
        fopen.write('\n')
        fopen.write(',')
writer2 = csv.writer(fopen)
cursor.execute('''SELECT * FROM partial_user_item_rating''')
b = cursor.fetchall()
for i in b:
    writer2.writerow(i)
fopen.close()
print('2-2 clear')
```

```
# TODO: Requirement 2-3. MAKE HORIZONTAL VIEW
# file name: DMA_project2_team##_part2_horizontal.pkl

df = pd.read_csv('./DMA_project2_team12_part2_UIR.csv', names=['id', 'category', 'rating'], header=0)

df1 = df.pivot_table(index='id', columns='category', values='rating')

for i in range(2, 11):
    df1 = df1.replace(i, 1)

df1 = df1.fillna(0)

df1.to_pickle('DMA_project2_team12_part2_horizontal.pkl')
```

```
# TODO: Requirement 2-4. ASSOCIATION ANALYSIS
# filename: DMA_project2_team##_part2_association.pkl (pandas dataframe)
frequent_itemsets = apriori(df1, min_support=0.05, use_colnames=True)
rules = association_rules(frequent_itemsets, metric='lift', min_threshold=2)
rules.to_pickle('DMA_project2_team12_part2_association.pkl')
cursor.close()
print('2-3 and 2-4 clear')
```

	antecedents	consequer	antecedent support	consequent support	support	confidence	lift
1368	frozenset({'Pro	frozenset({	0.107654185	0.089207048	0.052588	0.488491049	5.475924
1367	frozenset({'Fir	frozenset({	0.089207048	0.107654185	0.052588	0.589506173	5.475924
11660	frozenset({'Fin	frozenset({	0.088656388	0.107654185	0.052037	0.586956522	5.452241
11663	frozenset({'Pro	frozenset({	0.107654185	0.088656388	0.052037	0.483375959	5.452241
11656	frozenset({'Sto	frozenset({	0.107103524	0.089207048	0.052037	0.485861183	5.446444
11667	frozenset({'Fir	frozenset({	0.089207048	0.107103524	0.052037	0.583333333	5.446444
1369	frozenset({'Fin	frozenset({	0.122797357	0.080121145	0.052588	0.428251121	5.345045
1366	frozenset({'Inv	frozenset({	0.080121145	0.122797357	0.052588	0.656357388	5.345045
11664	frozenset({'Fin	frozenset({	0.122797357	0.079570485	0.052037	0.423766816	5.325678
11659	frozenset({'Sto	frozenset({	0.079570485	0.122797357	0.052037	0.653979239	5.325678



	anteceden	consequents	antecedent support	consequent support	support	confidence	lift
13066	frozenset({	frozenset({'Find	0.05589207	0.314977974	0.055892	1	3.174825
170104	frozenset({	frozenset({'Mar	0.073513216	0.308645374	0.073513	1	3.239964
169936	frozenset({	frozenset({'Find	0.063601322	0.314977974	0.063601	1	3.174825
169944	frozenset({	frozenset({'Stor	0.063601322	0.314427313	0.063601	1	3.180385
169948	frozenset({	frozenset({'Mar	0.063601322	0.309196035	0.063601	1	3.234194
169976	frozenset({	frozenset({'Mar	0.063601322	0.308645374	0.063601	1	3.239964
170064	frozenset({	frozenset({'Find	0.073513216	0.314977974	0.073513	1	3.174825
8366	frozenset({	frozenset({'Find	0.080947137	0.314977974	0.080947	1	3.174825
170072	frozenset({	frozenset({'Stor	0.073513216	0.314427313	0.073513	1	3.180385
8370	frozenset({	frozenset({'Stor	0.080947137	0.314427313	0.080947	1	3.180385



R3-1

```
lef get_top_n(algo, testset, id_list, n=10, user_based=True):
  results = defaultdict(list)
  if user_based:
      testset_id = [t for t in testset if (t[0] in id_list)]
      predictions = algo.test(testset_id)
      for uid, iid, true_r, est, _ in predictions:
          # TODO: results는 user_id를 key로, [(item_id, estimated_rating)의 tuple이 모인 list]를 value로 갖는 dictionary
          results[uid].append((iid, est))
      testset_id = [t for t in testset if (t[1] in id_list)]
      predictions = algo.test(testset_id)
      for uid, iid, true_r, est, _ in predictions:
          results[iid].append((vid, est))
  for id_, ratings in results.items():
      # TODO: rating 순서대로 정렬하고 top-n개만 유지
      temp_rating=sorted(ratings, key=lambda x:x[1], reverse=True)
      results[id_]=temp_rating[:n]
  return results
```

R3-2-1

```
# TODO: set algorithm for 3-2-1
sim_options = {'name': 'cosine', 'user_based': True}
user_knnbasic = surprise.KNNBasic(sim_options=sim_options)
user_knnbasic.fit(trainset)
results = get_top_n(user_knnbasic, testset, uid_list, n=10, user_based=True)
with open('3-2-1.txt', 'w') as f:
    for uid, ratings in sorted(results.items(), key=lambda x: x[0]):
        f.write('User ID %s top-10 results\n' % uid)
        for iid, score in ratings:
            f.write('Item ID %s\tscore %s\n' % (iid, str(score)))
        f.write('\n')
print('3-2-1.txt completed')
```

R3-2-2

```
sim_options1 = {'name': 'pearson', 'user_based': True}
user_knnwithmeans = surprise.KNNWithMeans(sim_options=sim_options1)
user_knnwithmeans.fit(trainset)
results = get_top_n(user_knnwithmeans, testset, uid_list, n=10, user_based=True)
with open('3-2-2.txt', 'w') as f:
    for uid, ratings in sorted(results.items(), key=lambda x: x[0]):
        f.write('User ID %s top-10 results\n' % uid)
        for iid, score in ratings:
            f.write('Item ID %s\tscore %s\n' % (iid, str(score)))
        f.write('\n')
print('3-2-2.txt completed')
```

R 3-2-3

```
candidate_list_ub = []
ub_sim_options_list = [{'name': 'cosine', 'user_based': True}, {'name': 'msd', 'user_based': True},
                       {'name': 'pearson', 'user_based': True}]
for i in ub_sim_options_list:
    algo_list = [surprise.KNNBasic(sim_options=i), surprise.KNNWithMeans(sim_options=i),
                 surprise.KNNWithZScore(sim_options=i), surprise.KNNBaseline(sim_options=i)]
    for algo in algo_list:
        start = time.time()
        cv = surprise.model_selection.cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=False)
        cv_time = str(datetime.timedelta(seconds=int(time.time() - start)))
        mean_rmse = '{:.3f}'.format(np.mean(cv['test_rmse']))
        mean_mae = '{:.3f}'.format(np.mean(cv['test_mae']))
        if algo == algo_list[0]:
            which_algo = 'KNNBasic'
        elif algo == algo_list[1]:
            which_algo = 'KNNWithMeans'
        elif algo == algo_list[2]:
            which_algo = 'KNNWithZScore'
            which_algo = 'KNNBaseline'
        candidate = [which_algo, i, mean_rmse, mean_mae, cv_time]
        print(candidate)
        candidate_list_ub.append(candidate)
print('minimize mean_rmse =', min(candidate_list_ub, key=lambda x: x[2]))
print('minimize mean_mae = ', min(candidate_list_ub, key=lambda x: x[3]))
print('minimize cv_time = ', min(candidate_list_ub, key=lambda x: x[4]))
```

R3-2-3 고려사항

- # RMSE / MAE / time 세가지 경우에 대해 살펴보았다.
- # k: (max)number of nearest neighbors
- # k가 너무 작으면 noise points에 민감해지고 k가 너무 크면 다른 class에 속한 points들을 포함할 가능성이 커지는 점을 고려했다. (ch.8 slide 50)
- # 실제로 k를 증가시켜 (k=150 등) cross validation을 해보면, 같은 algorithm과 name 하에서 k만 변화시켰을 때 RMSE와 MAE에 큰 영향을 주지 못함을 확인할 수 있었다.
- # 따라서, k=40 (default value) 로 특별히 변화시키지 않고 algorithm의 종류와 유사도 (name)의 종류만 변화시켜 성능을 비교 및 평가하였다.
- # 사용한 algorithm의 종류: KNNBasic, KNNWithMeans, KNNWithZScore, KNNBaseline
- # 사용한 유사도(name)의 종류: cosine, msd, pearson
- # 따라서, 총 12개 model에 대해 성능을 비교 및 평가하였다.

R3-2-3 결과

```
KNNBasic', {'name': 'cosine', 'user_based' True}, '0.907', '0.606', '0:01:47']
['KNNWithMeans', {'name': 'cosine', 'user_based': True}, '0.864', '0.628', '0:01:51']
['KNNWithZScore', {'name': 'cosine', 'user_based': True}, '0.866', '0.621', '0:01:55']
['KNNBaseline', {'name': 'cosine', 'user_based': True}, '0.848', '0.584', '0:01:54']
['KNNBasic', {'name': 'msd', 'user_based': True}, '0.846', '0.571', '0:01:10']
['KNNWithMeans', {'name': 'msd', 'user_based': True}, '0.834', '0.613', '0:01:15']
['KNNWithZScore', {'name': 'msd', 'user_based': True}, '0.852', '0.616', '0:01:16']
['KNNBaseline', {'name'; 'msd', 'user_based'; True}, '0.818', '0.563', '0:01:18']
 ['KNNBasic', {'name': 'pearson', 'user_based': True}, '0.912', '0.638', '0:02:08']
 ['KNNWithMeans', {'name': 'pearson', 'user_based': True}, '0.858', '0.610', '0:02:17']
['KNNWithZScore', {'name': 'pearson', 'user_based': True}, '0.850', '0.592', '0:02:13']
 ['KNNBaseline', {'name': 'pearson', 'user_based': True}, '0.867', '0.603', '0:02:14']
```

rmse

mae

time

R3-2-3 결과 (최종결과)

```
minimize mean_rmse = ['KNNBaseline', {'name': 'msd', 'user_based': True}, '0.818',
 '0.563', '0:01:18']
 minimize mean_mae = ['KNNBaseline', {'name': 'msd', 'user_based': True}, '0.818',
 '0.563', '0:01:18']
 minimize cv_time = ['KNNBasic', {'name': 'msd', 'user_based': True}, '0.846',
 '0.571', '0:01:10']
 따라서, 가장 좋은 성능을 보이는 모델 best model ub은 (RMSE 기준)
best_model_ub = surprise.KNNBaseline(sim_options = {'name: 'msd', 'user_based': True})
이다.
```

R3-3-1

R3-3-2

```
sim_options2 = {'name': 'cosine', 'user_based': False}
item_knnbasic = surprise.KNNBasic(sim_options=sim_options2)
item_knnbasic.fit(trainset)
results = get_top_n(item_knnbasic, testset, iid_list, n=10, user_based=False)
with open('3-3-1.txt', 'w') as f:
    for iid, ratings in sorted(results.items(), key=lambda x: x[0]):
       f.write('Item ID %s top-10 results\n' % iid)
       for uid, score in ratings:
            f.write('User ID %s\tscore %s\n' % (uid, str(score)))
       f.write('\n')
print('3-3-1.txt completed')
```

```
sim_options3 = {'name': 'pearson', 'user_based': False}
item_knnwithmeans = surprise.KNNWithMeans(sim_options=sim_options3)
item_knnwithmeans.fit(trainset)
results = get_top_n(item_knnwithmeans, testset, iid_list, n=10, user_based=False)
with open('3-3-2.txt', 'w') as f:
   for iid, ratings in sorted(results.items(), key=lambda x: x[0]):
        f.write('Item ID %s top-10 results\n' % iid)
        for uid, score in ratings:
           f.write('User ID %s\tscore %s\n' % (uid, str(score)))
        f.write('\n')
print('3-3-2.txt completed')
```

R3-3-3

```
candidate_list_ib = []
ib_sim_options_list = [{'name': 'cosine', 'user_based': False}, {'name': 'msd', 'user_based': False},
                       {'name': 'pearson', 'user_based': False}]
for i in ib_sim_options_list:
    algo_list = [surprise.KNNBasic(sim_options=i), surprise.KNNWithMeans(sim_options=i),
                 surprise.KNNWithZScore(sim_options=i), surprise.KNNBaseline(sim_options=i)]
    for algo in algo_list:
        start = time.time()
        cv = surprise.model_selection.cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=False)
        cv_time = str(datetime.timedelta(seconds=int(time.time() - start)))
        mean_rmse = '{:.3f}'.format(np.mean(cv['test_rmse']))
        mean_mae = '{:.3f}'.format(np.mean(cv['test_mae']))
        if algo == algo_list[0]:
            which_algo = 'KNNBasic'
        elif algo == algo_list[1]:
            which_algo = 'KNNWithMeans'
        elif algo == algo_list[2]:
            which_algo = 'KNNWithZScore'
            which_algo = 'KNNBaseline'
        candidate = [which_algo, i, mean_rmse, mean_mae, cv_time]
        print(candidate)
        candidate_list_ib.append(candidate)
print('minimize mean_rmse =', min(candidate_list_ib, key=lambda x: x[2]))
print('minimize mean_mae = ', min(candidate_list_ib, key=lambda x: x[3]))
print('minimize cv_time = ', min(candidate_list_ib, key=lambda x: x[4]))
```

R3-3-3 결과

```
['KNNBasic', {'name': 'cosine', 'user_based': False}, '1.183', '0.877', '0:00:01']
['KNNWithMeans', {'name': 'cosine', 'user_based': False}, '0.818', '0.581', '0:00:02']
['KNNWithZScore', {'name': 'cosine', 'user_based': False}, '0.791', '0.551', '0:00:02']
['KNNBaseline', {'name': 'cosine', 'user_based': False}, '0.817', '0.579', '0:00:02']
['KNNBasic', {'name': 'msd', 'user_based': False}, '1.039', '0.716', '0:00:01']
['KNNWithMeans', {'name': 'msd', 'user_based': False}, '0.795', '0.558', '0:00:01']
['KNNWithZScore', {'name': 'msd', 'user_based': False}, '0.782', '0.542', '0:00:02']
['KNNBaseline', {'name': 'msd', 'user_based': False}, '0.792', '0.556', '0:00:03']
['KNNBasic', {'name': 'pearson', 'user_based': False}, '1.118', '0.842', '0:00:01']
['KNNWithMeans', {'name': 'pearson', 'user_based': False}, '0.798', '0.564', '0:00:02']
['KNNWithZScore', {'name'; 'pearson', 'user_based'; False}, '0.764', '0.533', '0:00:02']
['KNNBaseline', {'name': 'pearson', 'user_based': False}, '0.796', '0.562', '0:00:03']
['KNNBasic', {'name': 'cosine', 'user_based': False}, '1.183', '0.877', '0:00:01']
['KNNWithMeans', {'name'; 'cosine', 'user_based'; False}, '0.818', '0.581', '0:00:02']
['KNNWithZScore', {'name': 'cosine', 'user_based': False}, '0.791', '0.551', '0:00:02']
['KNNBaseline', {'name': 'cosine', 'user_based': False}, '0.817', '0.579', '0:00:02']
['KNNBasic', {'name': 'msd', 'user_based': False}, '1.039', '0.716', '0:00:01']
['KNNWithMeans', {'name'; 'msd', 'user_based'; False}, '0.795', '0.558', '0:00:01']
['KNNWithZScore', {'name'; 'msd', 'user_based'; False}, '0.782', '0.542', '0:00:02']
['KNNBaseline', {'name': 'msd', 'user_based': False}, '0.792', '0.556', '0:00:03']
['KNNBasic', {'name': 'pearson', 'user_based': False}, '1.118', '0.842', '0:00:01']
['KNNWithMeans', {'name': 'pearson', 'user_based': False}, '0.798', '0.564', '0:00:02']
['KNNWithZScore', {'name'; 'pearson', 'user_based'; False}, '0.764', '0.533', '0:00:02']
['KNNBaseline', {'name': 'pearson', 'user_based': False}, '0.796', '0.562', '0:00:03']
```

time

rmse

mae

R3-3-3 결과 (최종결과)

user based 부분만 False로 변경하여 수행하였다.

cv time은 매우 작게 나오게 되는 점을 유의하여야 한다.

3-2-3에서 similarity matrix들이 이미 계산되어 있으므로 이어서 3-3-3을 수행했을 때

```
minimize mean_rmse = ['KNNWithZScore', {'name': 'pearson', 'user_based': False},
  '0.764', '0.533', '0:00:02']
  minimize mean_mae = ['KNNWithZScore', {'name': 'pearson', 'user_based': False},
  '0.764'. '0.533'. '0:00:02']
  minimize cv_time = ['KNNBasic', {'name': 'cosine', 'user_based': False}, '1.183',
  '0.877', '0:00:01']
따라서, 가장 좋은 성능을 보이는 모델 best model lb는 (RMSE 기준)
best_model_lb = surprise.KNNWithZScore(sim_options = {'name: 'pearson', 'user_based':
False}) 이다.
3-3-3에서 다양한 알고리즘 비교를 위해 고려한 사항은 다음과 같다.
                                                                                                 고려사항
# 3-2-3과 같은 방식으로 성능 비교 및 평가하였다.
```

R3-4-1

```
# TODO: set algorithm for 3-4-1
svd_50 = surprise.SVD(n_factors=100, n_epochs=50, biased=False)
svd_50.fit(trainset)
results = get_top_n(svd_50, testset, uid_list, n=10, user_based=True)

with open('3-4-1.txt', 'w') as f:
    for uid, ratings in sorted(results.items(), key=lambda x: x[0]):
        f.write('User ID %s top-10 results\n' % uid)
        for iid, score in ratings:
            f.write('Item ID %s\tscore %s\n' % (iid, str(score)))
            f.write('\n')
print('3-4-1.txt completed')
```

R3-4-3

```
# TODO: set algorithm for 3-4-3
svdpp_50 = surprise.SVDpp(n_factors=100, n_epochs=50)
svdpp_50.fit(trainset)
results = get_top_n(svdpp_50, testset, uid_list, n=10, user_based=True)

with open('3-4-3.txt', 'w') as f:
    for uid, ratings in sorted(results.items(), key=lambda x: x[0]):
        f.write('User ID %s top-10 results\n' % uid)
        for iid, score in ratings:
             f.write('Item ID %s\tscore %s\n' % (iid, str(score)))
             f.write('\n')
print('3-4-3.txt completed')
```

R3-4-2

```
# TODO: set algorithm for 3-4-2
svd_100 = surprise.SVD(n_factors=200, n_epochs=100, biased=True)
svd_100.fit(trainset)
results = get_top_n(svd_100, testset, uid_list, n=10, user_based=True)

with open('3-4-2.txt', 'w') as f:
    for uid, ratings in sorted(results.items(), key=lambda x: x[0]):
        f.write('User ID %s top-10 results\n' % uid)
        for iid, score in ratings:
            f.write('Item ID %s\tscore %s\n' % (iid, str(score)))
        f.write('\n')
print('3-4-2.txt completed')
```

R3-4-4

```
# TODO: set algorithm for 3-4-4
svdpp_100 = surprise.SVDpp(n_factors=100, n_epochs=100)
svdpp_100.fit(trainset)
results = get_top_n(svdpp_100, testset, uid_list, n=10, user_based=True)

with open('3-4-4.txt', 'w') as f:
    for uid, ratings in sorted(results.items(), key=lambda x: x[0]):
        f.write('User ID %s top-10 results\n' % uid)
        for iid, score in ratings:
            f.write('Item ID %s\tscore %s\n' % (iid, str(score)))
        f.write('\n')
print('3-4-4.txt completed')
```

R3-4-5

```
candidate_list_mf = []
for factors in range(50, 250, 50):
    for epochs in range(10, 40, 10):
        SVD_biased = surprise.SVD(n_factors=factors, n_epochs=epochs, random_state=0, biased=True)
        SVD_unbiased = surprise.SVD(n_factors=factors, n_epochs=epochs, random_state=0, biased=False)
        SVDpp = surprise.SVDpp(n_factors=factors, n_epochs=epochs, random_state=0)
        NMF_biased = surprise.NMF(n_factors=factors, n_epochs=epochs, random_state=0, biased=True)
        NMF_unbiased = surprise.NMF(n_factors=factors, n_epochs=epochs, random_state=0, biased=False)
        algo_list = [SVD_biased, SVD_unbiased, SVDpp, NMF_biased, NMF_unbiased]
        for algo in algo_list:
            start = time.time()
           cv = surprise.model_selection.cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=False)
            cv_time = str(datetime.timedelta(seconds=int(time.time() - start)))
            mean_rmse = '{:.3f}'.format(np.mean(cv['test_rmse']))
            mean_mae = '{:.3f}'.format(np.mean(cv['test_mae']))
            if algo == algo_list[0]:
               which_algo = 'SVD_biased'
            elif algo == algo_list[1]:
                which_algo = 'SVD_unbiased'
           elif algo == algo_list[2]:
               which_algo = 'SVDpp'
           elif algo == algo_list[3]:
               which_algo = 'NMF_biased'
               which_algo = 'NMF_unbiased'
            candidate = ['n_factors = %s' % factors, 'n_epochs = %s' % epochs, 'algorithm = %s' % which_algo,
                         mean_rmse, mean_mae, cv_time]
            print(candidate)
            candidate_list_mf.append(candidate)
print('minimize mean_rmse = ', min(candidate_list_mf, key=lambda x: x[3]))
print('minimize mean_mae = ', min(candidate_list_mf, key=lambda x: x[4]))
print('minimize cv_time = ', min(candidate_list_mf, key=lambda x: x[5]))
```

R3-4-5 고려사항

3-4-5에서 고려한 사항은 다음과 같다.

```
# n_factors: latent factor 수 (default=100)
```

- # default 값을 중심으로 해서 50, 100, 150, 200의 값을 가지도록 설정하였다.
- # n_epochs: SGD 수행 횟수 (default=20)
- # default 값을 중심으로 해서 10, 20, 30의 값을 가지도록 설정하였다.
- # SVD 및 <u>NMF의</u> 경우에는 biased or unbiased 고려하였다.

R3-4-5 결과

```
time
['n_fe fors = 50', 'n_spechs = 10', 'alsorithm = SVD_biased', '0.804', '0.562',
"0:00:04"1
['n_factors = 50', 'n_epochs = 10', 'algorithm = SVD_unbiased', '0.780', '0.515',
"0:00:04"]
['n_factors = 50', 'n_epochs = 10', 'elsorithm = SVDpp', '0.756', '0.513', '0:00:38']
['n_factors = 50', 'n_epochs = 10', 'algorithm = NMF_biased', '2.516', '1.801',
"0:00:05"]
I'n factors = 50'. 'n epochs = 10'. 'alsorithm = NMF_unbiased', '2.047', '1.698',
"0:00:05"]
Un_fasters = 50', in_spechs = 20', lalsorithm = SVD_biased', '0.779', '0.539',
"0:00:08"1
I'm factors 5 50', 'n spechs 5 20', 'algorithm 5 SVD_unbiased', '0.779', '0.514',
"0:00:08"]
['n_factors = 50', 'n_epochs = 20', 'algorithm = SVDpp', '0.752', '0.512', '0:01:13']
['n_factors = 50', 'n_epochs = 20', 'algorithm = NMF_biased', '0.997', '0.647',
"0:00:11"]
['n_factors = 50', 'n_epochs = 20', 'alsorithm = NMF_unbiased', '0.963', '0.737',
"0:00:10"]
['n_factors = 50', 'n_spechs = 30', 'algorithm = SVD_biased', '0.773', '0.535',
"0:00:12"]
['n_factors = 50', 'n_epochs = 30', 'algorithm = SVD_unbiased', '0.771', '0.510',
"0:00:11"]
['n_factors = 50', 'n_epochs = 30', 'algorithm = SVDpp', '0.752', '0.513', '0:01:49']
I'm factors = 50', in epochs = 30', lalgorithm = NMF_biased', '1.501', '0.852',
"0:00:16"1
['n_factors = 50', 'n_epochs = 30', 'algorithm = NMF_unbiased', '0.766', '0.553',
"0:00:15"]
```

rmse

mae

R3-4-5 결과 (최종결과)

```
minimize mean_rmse = ['n_factors = 150', 'n_epochs = 10', 'algorithm = SVDpp',
'0.747', '0.514', '0:01:26']
minimize mean_mae = ['n_factors = 50', 'n_epochs = 30', 'algorithm =
SVD_unbiased', '0.771', '0.510', '0:00:11']
minimize cy_time = ['n_factors = 50', 'n_epochs = 10', 'algorithm = SVD_biased',
'0.804', '0.562', '0:00:04']
따라서, 가장 좋은 성능을 보이는 모델 best model mf는 (RMSE 기준)
best_model_mf = surprise.<u>SVDpp(n_factors=150, n_epochs=10, random_state=0) 이다</u>.
```

감사합니다