

## Different models, recommend top 10 movies

```
In [1]: import math
import copy
import pickle
from pathlib import Path
from itertools import zip_longest
from collections import defaultdict
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, KFold
import torch
from torch import nn
from torch import optim
from torch.nn import functional as F
from torch.optim.lr_scheduler import _LRScheduler
from time import time
from collections import defaultdict
```

```
In [2]: from model_archs import EmbeddingNet, EmbeddingNetGender, EmbeddingNetAge, EmbeddingNetGenderAge
```

```
In [26]: def set_random_seed(state=1):
gens = (np.random.seed, torch.manual_seed, torch.cuda.manual_seed)
for set_state in gens:
    set_state(state)

RANDOM_STATE = 1
set_random_seed(RANDOM_STATE)
n_users = 6040
n_movies = 3706
dataset_sizes = {'train': 800167, 'val': 200042}
```

```
In [27]: # batch-wise data iterator
class ReviewsIterator:
    def __init__(self, X, y, batch_size=32, shuffle=True):
        X, y = np.asarray(X), np.asarray(y)

        if shuffle:
            index = np.random.permutation(X.shape[0])
            X, y = X[index], y[index]

        self.X = X
        self.y = y
        self.batch_size = batch_size
        self.shuffle = shuffle
        self.n_batches = int(math.ceil(X.shape[0] // batch_size))
        self._current = 0

    def __iter__(self):
        return self

    def __next__(self):
        return self.next()

    def next(self):
        if self._current >= self.n_batches:
            raise StopIteration()
        k = self._current
        self._current += 1
        bs = self.batch_size
        return self.X[k*bs:(k + 1)*bs], self.y[k*bs:(k + 1)*bs]

def batches(X, y, bs=32, shuffle=True):
    for xb, yb in ReviewsIterator(X, y, bs, shuffle):
        xb = torch.LongTensor(xb)
        yb = torch.FloatTensor(yb)
        yield xb, yb.view(-1, 1)
```

```

In [38]: def get_precision_recall(df_final, k=10, threshold=3.5):
    # map prediction to each user --> similar to top n
    # {id:(pred, truth)}
    user_pred_truth = defaultdict(list)
    for row in df_final.itertuples():
        _, user_id, movie_id, truth, pred = row
        user_pred_truth[user_id].append((pred, truth))

    precisions = dict()
    recalls = dict()

    for user_id, user_ratings in user_pred_truth.items():
        # Sort user ratings by estimated value
        user_ratings.sort(key=lambda x: x[0], reverse=True)

        # Number of relevant items
        n_rel = sum((true_r >= threshold) for (_, true_r) in user_ratings)

        # Number of recommended items in top k
        n_rec_k = sum((est >= threshold) for (est, _) in user_ratings[:k])

        # Number of relevant and recommended items in top k
        n_rel_and_rec_k = sum(((true_r >= threshold) and (est >= threshold))
                               for (est, true_r) in user_ratings[:k])

        # Precision@K: Proportion of recommended items that are relevant
        precisions[user_id] = n_rel_and_rec_k / n_rec_k if n_rec_k != 0 else 1

        # Recall@K: Proportion of relevant items that are recommended
        recalls[user_id] = n_rel_and_rec_k / n_rel if n_rel != 0 else 1

    # mean precision and recall
    mean_precision = sum(prec for prec in precisions.values()) / len(precisions)
    mean_recall = sum(rec for rec in recalls.values()) / len(recalls)
    print("Prec10 {:.4f}|Rec10 {:.4f}".format(mean_precision, mean_recall))

# get topn
def get_top_n(df_final, n=10):
    """
    key: user_id
    value: his top 10 highest movies as well as ratings
    """
    # map predictions to each user
    top_n = defaultdict(list)
    for row in df_final.itertuples():
        _, user_id, movie_id, truth, pred = row
        top_n[user_id].append((movie_id, pred))

    # sort the pred for each user
    for user_id, pred_ratings in top_n.items():
        pred_ratings.sort(key=lambda x: x[1], reverse=True)
        top_n[user_id] = pred_ratings[:n]
    return top_n

def get_train_pred_top10(df, df_final, datasets, user_id=1635, n=10):
    """
    df: the original df --> contain movie name
    df_final: the final df with predicted ratings
    datasets: the datasets with training and testing datasets
    user_id: the user id to be queried
    n: top_n
    """
    # step 1, get top n from df_final
    top_n = get_top_n(df_final, n)
    assert(user_id in top_n), "user_id {} is not in testing data, try another user such as 1635".format(user_id)
    pred_ratings = top_n[user_id]

    # step 2: user information
    user = df[df['user_id'] == user_id]
    age = list(set(user['age']))[0]
    sex = list(set(user['sex']))[0]
    info = "User {}, age {}, {}, ".format(user_id, age, sex)

    # step 2, build df_train
    df_train = pd.DataFrame(datasets['train'][0])
    df_train['rating'] = datasets['train'][1]

    # step 3, find all movies user_id has been rated 5
    # df_refined = df_train[(df_train['user_id'] == user_id) & (df_train['rating'] == 5)]
    df_refined = df_train[df_train['user_id'] == user_id]
    movie_id_sets_train = set(df_refined['movie_id'])
    info = "{} has rated {} movies in training set\n".format(info, len(movie_id_sets_train))
    print(info)

    # step 4: get the top n
    # print("===== ")
    # print("\nTop {} recommendations\n".format(n))

```

```
for (movie_id, rating) in pred_ratings:
    movie_name = list(set(df[df['movie_id'] == movie_id]['movie_title']))[0]
    info = "ID {:<4d}|Rating {:<2f}|{}".format(movie_id, rating, movie_name)
    if movie_id in movie_id_sets_train:
        info = "{} , but this movie has been rated during training!!!".format(info)
    print(info)
```

```
In [29]: # load preprocessed df
df = pd.read_csv("ml-1m_dl.csv")
print(df.shape)
df.head()
```

(1000209, 9)

Out[29]:

	movie_id	movie_title	user_id	age	sex	occupation	rating	sex_index	age_index
0	1	Toy Story (1995)	1	1	F	10	5	0	0
1	48	Pocahontas (1995)	1	1	F	10	5	0	0
2	150	Apollo 13 (1995)	1	1	F	10	5	0	0
3	260	Star Wars: Episode IV - A New Hope (1977)	1	1	F	10	4	0	0
4	527	Schindler's List (1993)	1	1	F	10	5	0	0

```
In [30]: # load dataset
datasets = pickle.load(open('ml-1m_dl.pkl','rb'))
datasets['val'][1]
```

Out[30]:

6301204.0
2293985.0
7583773.0
1592405.0
2542524.0
...
8751994.0
7439214.0
5271634.0
6233633.0
1200983.0
Name: rating, Length: 200042, dtype: float32

Compare following models

	Arch	Index	n_factor	n_hidden	g_factor	a_factor	RMSE	Recall
	EmbeddingNet	6	200	1000	-	-	0.8787	0.5528
	EmbeddingNetGender	8	200	1000	25	-	0.8721	0.5637
	EmbeddingNetAge	12	150	1000	-	15	0.8724	0.5647
	EmbeddingNetGenderAge	5	200	1000	10	10	0.8688	0.5698

Compare following users

	user_id	gender	age
	1	F	1
	19	M	1
	176	F	18
	181	M	18
	253	F	25
	261	M	25
	704	F	35
	749	M	35
	1428	F	45
	1565	M	45
	1961	F	50
	2088	M	50
	5020	F	56
	5583	M	56

```
In [54]: user_id_list = [1, 19, 176, 181, 253, 261, 704, 749, 1428, 1565, 1961, 2088, 5020, 5583]
```

```
In [53]: # set(df[(df['sex'] == 'M') & (df['age'] == 56)][ 'user_id'])
```

## Now let's begin

### 1. No gender, no age

```
In [39]: def get_result_df(datasets, model, best_weights, bs, save_path=None):
    '''
    model_parameter1_best.weights
    '''
    minmax = (1.0, 5.0)
    device = torch.device('cpu')
    model.load_state_dict(best_weights)
    groud_truth, predictions = [], []

    val_size = len(datasets['val'][0])
    # print("Total val size: {}".format(val_size))

    with torch.no_grad():
        for batch in batches(*datasets['val'], shuffle=False, bs=bs):
            x_batch, y_batch = [b.to(device) for b in batch]
            outputs = model(x_batch[:, 0], x_batch[:, 1], minmax)
            groud_truth.extend(y_batch.tolist())
            predictions.extend(outputs.tolist())

        last_num = val_size % bs
        # print("Last num: {}".format(last_num))
        dataset_last = (datasets['val'][0][-last_num:], datasets['val'][1][-last_num:])
        # print("Last dataset: {}".format(len(dataset_last[0])))
        for batch in batches(*dataset_last, shuffle=False, bs=1):
            x_batch, y_batch = [b.to(device) for b in batch]
            outputs = model(x_batch[:, 0], x_batch[:, 1], minmax)
            groud_truth.extend(y_batch.tolist())
            predictions.extend(outputs.tolist())

    groud_truth = np.asarray(groud_truth).ravel()
    predictions = np.asarray(predictions).ravel()

    assert(predictions.shape[0] == val_size)

    final_loss = np.sqrt(np.mean((predictions - groud_truth)**2))
    # print("RMSE: {:.4f}".format(final_loss))

    df_final = pd.DataFrame(datasets['val'][0][['user_id', 'movie_id']])
    df_final['truth'] = datasets['val'][1]
    df_final['pred'] = predictions

    if save_path is not None:
        print("Save weight to:{}".format(save_path))
        with open(save_path, 'wb') as file:
            pickle.dump(best_weights, file)

    return df_final # note that here the sex and age is not included
```

```
In [32]: # load model
n_factors = 200
hidden = [1000,1000,1000]
embedding_dropout = 0.05
dropouts = [0.5,0.5,0.25]
# training
lr = 1e-3
wd = 1e-5
bs =2000
n_epochs = 100
patience = 10

model = EmbeddingNet(n_users, n_movies,
                    n_factors=n_factors,
                    hidden=hidden,
                    embedding_dropout=embedding_dropout,
                    dropouts=dropouts)
best_weights = pickle.load(open("saved_models/noSex_noAge_para6.weights", 'rb'))
```

```
In [55]: df_final = get_result_df(datasets, model, best_weights, bs, save_path=None)
         for user_id in user_id_list:
             get_train_pred_top10(df, df_final, datasets, user_id=user_id, n=10)
         print("==== =====\n")
```

User 1, age 1, F, has rated 41 movies in training set

ID 260	Rating 4.290243	Star Wars: Episode IV - A New Hope (1977)
ID 1	Rating 4.190775	Toy Story (1995)
ID 1961	Rating 4.174579	Rain Man (1988)
ID 595	Rating 4.166494	Beauty and the Beast (1991)
ID 2804	Rating 4.131517	Christmas Story, A (1983)
ID 1022	Rating 4.043647	Cinderella (1950)
ID 2791	Rating 3.990579	Airplane! (1980)
ID 1207	Rating 3.976852	To Kill a Mockingbird (1962)
ID 2687	Rating 3.972957	Tarzan (1999)
ID 608	Rating 3.905061	Fargo (1996)

=====

User 19, age 1, M, has rated 189 movies in training set

ID 2858	Rating 4.309461	American Beauty (1999)
ID 2571	Rating 4.237044	Matrix, The (1999)
ID 2028	Rating 4.189097	Saving Private Ryan (1998)
ID 1198	Rating 4.167509	Raiders of the Lost Ark (1981)
ID 457	Rating 4.154977	Fugitive, The (1993)
ID 1	Rating 4.143876	Toy Story (1995)
ID 1321	Rating 4.122013	American Werewolf in London, An (1981)
ID 1148	Rating 4.068268	Wrong Trousers, The (1993)
ID 1270	Rating 4.031488	Back to the Future (1985)
ID 2064	Rating 4.014668	Roger & Me (1989)

=====

User 176, age 18, F, has rated 58 movies in training set

ID 1196	Rating 4.510611	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 3552	Rating 4.434868	Caddyshack (1980)
ID 1197	Rating 4.257071	Princess Bride, The (1987)
ID 2378	Rating 4.249933	Police Academy (1984)
ID 1307	Rating 4.216447	When Harry Met Sally... (1989)
ID 2011	Rating 4.208655	Back to the Future Part II (1989)
ID 2795	Rating 4.164939	Vacation (1983)
ID 1544	Rating 4.015627	Lost World: Jurassic Park, The (1997)
ID 3715	Rating 3.991545	Burglar (1987)
ID 1968	Rating 3.975549	Breakfast Club, The (1985)

=====

User 181, age 18, M, has rated 242 movies in training set

ID 1136	Rating 4.839367	Monty Python and the Holy Grail (1974)
ID 1240	Rating 4.525747	Terminator, The (1984)
ID 1732	Rating 4.508242	Big Lebowski, The (1998)
ID 1213	Rating 4.504430	GoodFellas (1990)
ID 1704	Rating 4.382651	Good Will Hunting (1997)
ID 2000	Rating 4.331407	Lethal Weapon (1987)
ID 2683	Rating 4.302487	Austin Powers: The Spy Who Shagged Me (1999)
ID 1291	Rating 4.288813	Indiana Jones and the Last Crusade (1989)
ID 2028	Rating 4.288600	Saving Private Ryan (1998)
ID 2706	Rating 4.264375	American Pie (1999)

=====

User 253, age 25, F, has rated 41 movies in training set

ID 246	Rating 4.240369	Hoop Dreams (1994)
ID 3083	Rating 4.081717	All About My Mother (Todo Sobre Mi Madre) (1999)
ID 3408	Rating 4.023458	Erin Brockovich (2000)
ID 3751	Rating 3.976006	Chicken Run (2000)
ID 1089	Rating 3.943969	Reservoir Dogs (1992)
ID 2599	Rating 3.909781	Election (1999)
ID 446	Rating 3.868521	Farewell My Concubine (1993)
ID 296	Rating 3.858854	Pulp Fiction (1994)
ID 1127	Rating 3.835043	Abyss, The (1989)
ID 1533	Rating 3.750873	Promise, The (La Promesse) (1996)

=====

User 261, age 25, M, has rated 297 movies in training set

ID 1221	Rating 4.675239	Godfather: Part II, The (1974)
ID 2692	Rating 4.622235	Run Lola Run (Lola rennt) (1998)
ID 3741	Rating 4.455191	Badlands (1973)
ID 1283	Rating 4.388023	High Noon (1952)
ID 1225	Rating 4.374327	Amadeus (1984)
ID 1307	Rating 4.212987	When Harry Met Sally... (1989)
ID 3424	Rating 4.159008	Do the Right Thing (1989)
ID 1265	Rating 4.144706	Groundhog Day (1993)
ID 2542	Rating 4.104301	Lock, Stock & Two Smoking Barrels (1998)
ID 3706	Rating 4.069049	Angel Heart (1987)

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User 704, age 35, F, has rated 61 movies in training set

ID 2959	Rating 3.921731	Fight Club (1999)
ID 2761	Rating 3.888439	Iron Giant, The (1999)

ID 2490	Rating 3.747899	Payback (1999)
ID 3911	Rating 3.701699	Best in Show (2000)
ID 3384	Rating 3.686259	Taking of Pelham One Two Three, The (1974)
ID 2390	Rating 3.568743	Little Voice (1998)
ID 3893	Rating 3.484054	Nurse Betty (2000)
ID 3896	Rating 3.462925	Way of the Gun, The (2000)
ID 3298	Rating 3.428260	Boiler Room (2000)
ID 3185	Rating 2.903764	Snow Falling on Cedars (1999)

=====

User 749, age 35, M, has rated 375 movies in training set

ID 2762	Rating 4.272712	Sixth Sense, The (1999)
ID 1276	Rating 4.179347	Cool Hand Luke (1967)
ID 1954	Rating 4.135741	Rocky (1976)
ID 912	Rating 3.999698	Casablanca (1942)
ID 908	Rating 3.956526	North by Northwest (1959)
ID 1196	Rating 3.902882	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 1090	Rating 3.894553	Platoon (1986)
ID 1204	Rating 3.869633	Lawrence of Arabia (1962)
ID 2423	Rating 3.821836	Christmas Vacation (1989)
ID 3072	Rating 3.791842	Moonstruck (1987)

=====

User 1428, age 45, F, has rated 41 movies in training set

ID 1206	Rating 5.187326	Clockwork Orange, A (1971)
ID 908	Rating 5.048565	North by Northwest (1959)
ID 2227	Rating 4.868504	Lodger, The (1926)
ID 1282	Rating 4.369121	Fantasia (1940)
ID 175	Rating 4.292841	Kids (1995)
ID 3930	Rating 3.958838	Creature From the Black Lagoon, The (1954)
ID 2291	Rating 3.911605	Edward Scissorhands (1990)
ID 3927	Rating 3.810028	Fantastic Voyage (1966)
ID 3926	Rating 3.601877	Voyage to the Bottom of the Sea (1961)
ID 3450	Rating 3.579489	Grumpy Old Men (1993)

=====

User 1565, age 45, M, has rated 37 movies in training set

ID 2997	Rating 3.997089	Being John Malkovich (1999)
ID 348	Rating 3.948089	Bullets Over Broadway (1994)
ID 224	Rating 3.928763	Don Juan DeMarco (1995)
ID 2396	Rating 3.893962	Shakespeare in Love (1998)
ID 34	Rating 3.818663	Babe (1995)
ID 2599	Rating 3.816698	Election (1999)
ID 1732	Rating 3.598989	Big Lebowski, The (1998)
ID 357	Rating 3.582452	Four Weddings and a Funeral (1994)
ID 3129	Rating 3.297520	Sweet and Lowdown (1999)
ID 619	Rating 3.196335	Ed (1996)

=====

User 1961, age 50, F, has rated 71 movies in training set

ID 318	Rating 4.328104	Shawshank Redemption, The (1994)
ID 1198	Rating 4.283365	Raiders of the Lost Ark (1981)
ID 1196	Rating 4.243160	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 858	Rating 4.169449	Godfather, The (1972)
ID 457	Rating 3.843350	Fugitive, The (1993)
ID 2951	Rating 3.820276	Fistful of Dollars, A (1964)
ID 2501	Rating 3.709575	October Sky (1999)
ID 1036	Rating 3.688698	Die Hard (1988)
ID 296	Rating 3.680509	Pulp Fiction (1994)
ID 2966	Rating 3.662994	Straight Story, The (1999)

=====

User 2088, age 50, M, has rated 355 movies in training set

ID 589	Rating 4.872320	Terminator 2: Judgment Day (1991)
ID 3469	Rating 4.719260	Inherit the Wind (1960)
ID 1304	Rating 4.704005	Butch Cassidy and the Sundance Kid (1969)
ID 480	Rating 4.703722	Jurassic Park (1993)
ID 2396	Rating 4.701219	Shakespeare in Love (1998)
ID 1207	Rating 4.612859	To Kill a Mockingbird (1962)
ID 1222	Rating 4.605288	Full Metal Jacket (1987)
ID 2951	Rating 4.601109	Fistful of Dollars, A (1964)
ID 3737	Rating 4.582014	Lonely Are the Brave (1962)
ID 541	Rating 4.555644	Blade Runner (1982)

=====

User 5020, age 56, F, has rated 84 movies in training set

ID 938	Rating 4.152769	Gigi (1958)
ID 3792	Rating 4.143832	Duel in the Sun (1946)
ID 3171	Rating 3.939328	Room at the Top (1959)
ID 1210	Rating 3.882236	Star Wars: Episode VI - Return of the Jedi (1983)
ID 3723	Rating 3.874931	Hamlet (1990)
ID 592	Rating 3.862677	Batman (1989)
ID 3712	Rating 3.822860	Soapdish (1991)

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ID 3751|Rating 3.787452|Chicken Run (2000)
ID 2021|Rating 3.735971|Dune (1984)
ID 2784|Rating 3.683913|Masque of the Red Death, The (1964)
=====
```

User 5583, age 56, M, has rated 95 movies in training set

```
ID 2858|Rating 4.600380|American Beauty (1999)
ID 260 |Rating 4.597151|Star Wars: Episode IV - A New Hope (1977)
ID 2396|Rating 4.411871|Shakespeare in Love (1998)
ID 1198|Rating 4.354239|Raiders of the Lost Ark (1981)
ID 2571|Rating 4.199419|Matrix, The (1999)
ID 920 |Rating 4.155070|Gone with the Wind (1939)
ID 457 |Rating 4.062383|Fugitive, The (1993)
ID 714 |Rating 3.989401|Dead Man (1995)
ID 3176|Rating 3.921952|Talented Mr. Ripley, The (1999)
ID 2951|Rating 3.907883|Fistful of Dollars, A (1964)
=====
```

## 2. With gender, no age

```
In [57]: def get_result_df(datasets, model, best_weights, bs, save_path=None):
        """
        model_parameter1_best.weights
        """
        minmax = (1.0, 5.0)
        device = torch.device('cpu')
        model.load_state_dict(best_weights)
        groud_truth, predictions = [], []

        val_size = len(datasets['val'][0])
        # print("Total val size: {}".format(val_size))

        with torch.no_grad():
            for batch in batches(*datasets['val'], shuffle=False, bs=bs):
                x_batch, y_batch = [b.to(device) for b in batch]
                outputs = model(x_batch[:, 0], x_batch[:, 1], x_batch[:, 2], minmax)
                groud_truth.extend(y_batch.tolist())
                predictions.extend(outputs.tolist())

            last_num = val_size % bs
            # print("Last num: {}".format(last_num))
            dataset_last = (datasets['val'][0][-last_num:], datasets['val'][1][-last_num:])
            # print("Last dataset: {}".format(len(dataset_last[0])))
            for batch in batches(*dataset_last, shuffle=False, bs=1):
                x_batch, y_batch = [b.to(device) for b in batch]
                outputs = model(x_batch[:, 0], x_batch[:, 1], x_batch[:, 2], minmax)
                groud_truth.extend(y_batch.tolist())
                predictions.extend(outputs.tolist())

        groud_truth = np.asarray(groud_truth).ravel()
        predictions = np.asarray(predictions).ravel()

        assert(predictions.shape[0] == val_size)

        final_loss = np.sqrt(np.mean((predictions - groud_truth)**2))
        # print("RMSE: {:.4f}".format(final_loss))

        df_final = pd.DataFrame(datasets['val'][0][['user_id', 'movie_id']]
        df_final['truth'] = datasets['val'][1]
        df_final['pred'] = predictions

        if save_path is not None:
            print("Save weight to:{}".format(save_path))
            with open(save_path, 'wb') as file:
                pickle.dump(best_weights, file)

        return df_final # note that here the sex and age is not included
```



```
In [56]: n_factors = 200
hidden = [1000] * 3
g_factor = 25

embedding_dropout = 0.05
dropouts = [0.5, 0.5, 0.25]
# training
lr = 1e-3
wd = 1e-5
bs = 2000
n_epochs = 100
patience = 10

model = EmbeddingNetGender(n_users, n_movies, n_factors=n_factors, hidden=hidden, dropouts=dropouts, g_factor=g_factor)
best_weights = pickle.load(open("saved_models/withSex_noAge_para8.weights", 'rb'))
```

```
In [58]: df_final = get_result_df(datasets, model, best_weights, bs, save_path=None)
         for user_id in user_id_list:
             get_train_pred_top10(df, df_final, datasets, user_id=user_id, n=10)
         print("==== =====\n")
```

User 1, age 1, F, has rated 41 movies in training set

ID 1207	Rating 4.472710	To Kill a Mockingbird (1962)
ID 595	Rating 4.381732	Beauty and the Beast (1991)
ID 260	Rating 4.348394	Star Wars: Episode IV - A New Hope (1977)
ID 1022	Rating 4.278702	Cinderella (1950)
ID 1	Rating 4.227912	Toy Story (1995)
ID 1961	Rating 4.132434	Rain Man (1988)
ID 2804	Rating 4.101287	Christmas Story, A (1983)
ID 1287	Rating 4.100507	Ben-Hur (1959)
ID 608	Rating 4.038425	Fargo (1996)
ID 2687	Rating 3.977126	Tarzan (1999)

=====

User 19, age 1, M, has rated 189 movies in training set

ID 1198	Rating 4.499864	Raiders of the Lost Ark (1981)
ID 2571	Rating 4.402059	Matrix, The (1999)
ID 110	Rating 4.342436	Braveheart (1995)
ID 2028	Rating 4.332126	Saving Private Ryan (1998)
ID 2858	Rating 4.234061	American Beauty (1999)
ID 356	Rating 4.213253	Forrest Gump (1994)
ID 1210	Rating 4.158370	Star Wars: Episode VI - Return of the Jedi (1983)
ID 1148	Rating 4.136994	Wrong Trousers, The (1993)
ID 1278	Rating 4.099858	Young Frankenstein (1974)
ID 1610	Rating 4.097485	Hunt for Red October, The (1990)

=====

User 176, age 18, F, has rated 58 movies in training set

ID 1307	Rating 4.286402	When Harry Met Sally... (1989)
ID 1197	Rating 4.262366	Princess Bride, The (1987)
ID 1196	Rating 4.262207	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 1544	Rating 4.239976	Lost World: Jurassic Park, The (1997)
ID 3715	Rating 4.155063	Burglar (1987)
ID 2011	Rating 4.072795	Back to the Future Part II (1989)
ID 2795	Rating 4.042375	Vacation (1983)
ID 3039	Rating 4.029671	Trading Places (1983)
ID 2378	Rating 3.985162	Police Academy (1984)
ID 1968	Rating 3.961801	Breakfast Club, The (1985)

=====

User 181, age 18, M, has rated 242 movies in training set

ID 1213	Rating 5.055884	GoodFellas (1990)
ID 1136	Rating 4.980361	Monty Python and the Holy Grail (1974)
ID 2028	Rating 4.515006	Saving Private Ryan (1998)
ID 1240	Rating 4.469388	Terminator, The (1984)
ID 1704	Rating 4.294208	Good Will Hunting (1997)
ID 1291	Rating 4.257468	Indiana Jones and the Last Crusade (1989)
ID 1732	Rating 4.150012	Big Lebowski, The (1998)
ID 1610	Rating 4.117481	Hunt for Red October, The (1990)
ID 3543	Rating 4.112954	Diner (1982)
ID 3360	Rating 4.094992	Hoosiers (1986)

=====

User 253, age 25, F, has rated 41 movies in training set

ID 3083	Rating 4.408238	All About My Mother (Todo Sobre Mi Madre) (1999)
ID 446	Rating 4.388174	Farewell My Concubine (1993)
ID 246	Rating 4.357580	Hoop Dreams (1994)
ID 3408	Rating 4.151003	Erin Brockovich (2000)
ID 2599	Rating 4.136911	Election (1999)
ID 3751	Rating 4.130851	Chicken Run (2000)
ID 1533	Rating 4.004681	Promise, The (La Promesse) (1996)
ID 296	Rating 3.898038	Pulp Fiction (1994)
ID 2704	Rating 3.749000	Lovers on the Bridge, The (Les Amants du Pont-Neuf) (1991)
ID 1127	Rating 3.587751	Abyss, The (1989)

=====

User 261, age 25, M, has rated 297 movies in training set

ID 1221	Rating 4.586732	Godfather: Part II, The (1974)
ID 1283	Rating 4.574106	High Noon (1952)
ID 1225	Rating 4.431887	Amadeus (1984)
ID 2692	Rating 4.392269	Run Lola Run (Lola rennt) (1998)
ID 3741	Rating 4.255603	Badlands (1973)
ID 2542	Rating 4.240274	Lock, Stock & Two Smoking Barrels (1998)
ID 551	Rating 4.138992	Nightmare Before Christmas, The (1993)
ID 1732	Rating 4.135163	Big Lebowski, The (1998)
ID 1265	Rating 4.116796	Groundhog Day (1993)
ID 3361	Rating 4.113025	Bull Durham (1988)

=====

User 704, age 35, F, has rated 61 movies in training set

ID 3911	Rating 4.095551	Best in Show (2000)
ID 2959	Rating 4.082156	Fight Club (1999)

ID 2761	Rating 3.953966	Iron Giant, The (1999)
ID 3384	Rating 3.823550	Taking of Pelham One Two Three, The (1974)
ID 2390	Rating 3.747732	Little Voice (1998)
ID 3298	Rating 3.505182	Boiler Room (2000)
ID 3185	Rating 3.443740	Snow Falling on Cedars (1999)
ID 3893	Rating 3.435017	Nurse Betty (2000)
ID 2490	Rating 3.340688	Payback (1999)
ID 3896	Rating 3.281293	Way of the Gun, The (2000)

=====

User 749, age 35, M, has rated 375 movies in training set

ID 2762	Rating 4.250895	Sixth Sense, The (1999)
ID 1196	Rating 4.077009	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 3114	Rating 3.852480	Toy Story 2 (1999)
ID 1204	Rating 3.821676	Lawrence of Arabia (1962)
ID 1210	Rating 3.818435	Star Wars: Episode VI - Return of the Jedi (1983)
ID 2791	Rating 3.815598	Airplane! (1980)
ID 1610	Rating 3.803171	Hunt for Red October, The (1990)
ID 969	Rating 3.782071	African Queen, The (1951)
ID 1276	Rating 3.781012	Cool Hand Luke (1967)
ID 3897	Rating 3.757148	Almost Famous (2000)

=====

User 1428, age 45, F, has rated 41 movies in training set

ID 908	Rating 4.991136	North by Northwest (1959)
ID 1282	Rating 4.807029	Fantasia (1940)
ID 1206	Rating 4.801775	Clockwork Orange, A (1971)
ID 2227	Rating 4.693388	Lodger, The (1926)
ID 175	Rating 4.290076	Kids (1995)
ID 2291	Rating 4.252073	Edward Scissorhands (1990)
ID 3930	Rating 4.174327	Creature From the Black Lagoon, The (1954)
ID 3927	Rating 4.008096	Fantastic Voyage (1966)
ID 1580	Rating 3.940378	Men in Black (1997)
ID 3926	Rating 3.710525	Voyage to the Bottom of the Sea (1961)

=====

User 1565, age 45, M, has rated 37 movies in training set

ID 2396	Rating 4.019731	Shakespeare in Love (1998)
ID 2997	Rating 3.972599	Being John Malkovich (1999)
ID 34	Rating 3.844083	Babe (1995)
ID 2599	Rating 3.788674	Election (1999)
ID 357	Rating 3.756473	Four Weddings and a Funeral (1994)
ID 1732	Rating 3.732164	Big Lebowski, The (1998)
ID 348	Rating 3.689384	Bullets Over Broadway (1994)
ID 3129	Rating 3.605549	Sweet and Lowdown (1999)
ID 224	Rating 3.497573	Don Juan DeMarco (1995)
ID 619	Rating 2.260920	Ed (1996)

=====

User 1961, age 50, F, has rated 71 movies in training set

ID 318	Rating 4.274407	Shawshank Redemption, The (1994)
ID 1198	Rating 4.134890	Raiders of the Lost Ark (1981)
ID 858	Rating 4.117238	Godfather, The (1972)
ID 2501	Rating 4.052022	October Sky (1999)
ID 1196	Rating 3.969681	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 457	Rating 3.879099	Fugitive, The (1993)
ID 3578	Rating 3.860467	Gladiator (2000)
ID 1036	Rating 3.832394	Die Hard (1988)
ID 2951	Rating 3.640119	Fistful of Dollars, A (1964)
ID 296	Rating 3.620668	Pulp Fiction (1994)

=====

User 2088, age 50, M, has rated 355 movies in training set

ID 1304	Rating 4.821420	Butch Cassidy and the Sundance Kid (1969)
ID 1222	Rating 4.818082	Full Metal Jacket (1987)
ID 589	Rating 4.795949	Terminator 2: Judgment Day (1991)
ID 480	Rating 4.750465	Jurassic Park (1993)
ID 541	Rating 4.738379	Blade Runner (1982)
ID 3737	Rating 4.733196	Lonely Are the Brave (1962)
ID 702	Rating 4.729947	Faces (1968)
ID 3469	Rating 4.723322	Inherit the Wind (1960)
ID 599	Rating 4.681270	Wild Bunch, The (1969)
ID 1301	Rating 4.678211	Forbidden Planet (1956)

=====

User 5020, age 56, F, has rated 84 movies in training set

ID 938	Rating 4.417951	Gigi (1958)
ID 3751	Rating 4.282625	Chicken Run (2000)
ID 3792	Rating 4.174982	Duel in the Sun (1946)
ID 3723	Rating 4.134624	Hamlet (1990)
ID 2872	Rating 4.092530	Excalibur (1981)
ID 1210	Rating 4.057086	Star Wars: Episode VI - Return of the Jedi (1983)
ID 3171	Rating 4.043768	Room at the Top (1959)

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ID 2143|Rating 4.015172|Legend (1985)

ID 329 |Rating 3.970602|Star Trek: Generations (1994)

ID 592 |Rating 3.850215|Batman (1989)

=====

User 5583, age 56, M, has rated 95 movies in training set

ID 260 |Rating 4.686344|Star Wars: Episode IV - A New Hope (1977)

ID 2396|Rating 4.616703|Shakespeare in Love (1998)

ID 1198|Rating 4.601224|Raiders of the Lost Ark (1981)

ID 920 |Rating 4.486513|Gone with the Wind (1939)

ID 1291|Rating 4.467784|Indiana Jones and the Last Crusade (1989)

ID 2858|Rating 4.353408|American Beauty (1999)

ID 3406|Rating 4.259543|Captain Horatio Hornblower (1951)

ID 2571|Rating 4.236502|Matrix, The (1999)

ID 457 |Rating 4.211889|Fugitive, The (1993)

ID 1266|Rating 4.115752|Unforgiven (1992)

=====

In [ ]:

In [ ]:

### 3. No gender, with age

In [59]:

```
def get_result_df(datasets, model, best_weights, bs, save_path=None):
    """
    model_parameter1_best.weights
    """
    minmax = (1.0, 5.0)
    device = torch.device('cpu')
    model.load_state_dict(best_weights)
    groud_truth, predictions = [], []

    val_size = len(datasets['val'][0])
    # print("Total val size: {}".format(val_size))

    with torch.no_grad():
        for batch in batches(*datasets['val'], shuffle=False, bs=bs):
            x_batch, y_batch = [b.to(device) for b in batch]
            outputs = model(x_batch[:, 0], x_batch[:, 1], x_batch[:, 3], minmax)
            groud_truth.extend(y_batch.tolist())
            predictions.extend(outputs.tolist())

        last_num = val_size % bs
        # print("Last num: {}".format(last_num))
        dataset_last = (datasets['val'][0][-last_num:], datasets['val'][1][-last_num:])
        # print("Last dataset: {}".format(len(dataset_last[0])))
        for batch in batches(*dataset_last, shuffle=False, bs=1):
            x_batch, y_batch = [b.to(device) for b in batch]
            outputs = model(x_batch[:, 0], x_batch[:, 1], x_batch[:, 3], minmax)
            groud_truth.extend(y_batch.tolist())
            predictions.extend(outputs.tolist())

    groud_truth = np.asarray(groud_truth).ravel()
    predictions = np.asarray(predictions).ravel()

    assert(predictions.shape[0] == val_size)

    final_loss = np.sqrt(np.mean((predictions - groud_truth)**2))
    # print("RMSE: {:.4f}".format(final_loss))

    df_final = pd.DataFrame(datasets['val'][0][['user_id', 'movie_id']]
    df_final['truth'] = datasets['val'][1]
    df_final['pred'] = predictions

    if save_path is not None:
        print("Save weight to:{}".format(save_path))
        with open(save_path, 'wb') as file:
            pickle.dump(best_weights, file)

    return df_final # note that here the sex and age is not included
```

```
In [60]: n_factors = 150
hidden = [1000] * 3
a_factor = 15

embedding_dropout = 0.05
dropouts = [0.5, 0.5, 0.25]
# training
lr = 1e-3
wd = 1e-5
bs = 2000
n_epochs = 100
patience = 10

model = EmbeddingNetAge(n_users, n_movies, n_factors=n_factors, hidden=hidden, dropouts=dropouts, a_factor=a_factor)
best_weights = pickle.load(open("saved_models/noSex_withAge_parallel2.weights", 'rb'))
```

```
In [61]: df_final = get_result_df(datasets, model, best_weights, bs, save_path=None)
         for user_id in user_id_list:
             get_train_pred_top10(df, df_final, datasets, user_id=user_id, n=10)
         print("==== =====\n")
```

User 1, age 1, F, has rated 41 movies in training set

ID 1207	Rating 4.489090	To Kill a Mockingbird (1962)
ID 1961	Rating 4.385052	Rain Man (1988)
ID 595	Rating 4.291056	Beauty and the Beast (1991)
ID 1287	Rating 4.273516	Ben-Hur (1959)
ID 260	Rating 4.243756	Star Wars: Episode IV - A New Hope (1977)
ID 1	Rating 4.169435	Toy Story (1995)
ID 2804	Rating 4.160616	Christmas Story, A (1983)
ID 608	Rating 4.145622	Fargo (1996)
ID 1022	Rating 4.098650	Cinderella (1950)
ID 2791	Rating 4.021626	Airplane! (1980)

=====

User 19, age 1, M, has rated 189 movies in training set

ID 2571	Rating 4.618315	Matrix, The (1999)
ID 2858	Rating 4.527251	American Beauty (1999)
ID 2028	Rating 4.471524	Saving Private Ryan (1998)
ID 110	Rating 4.467456	Braveheart (1995)
ID 1210	Rating 4.332788	Star Wars: Episode VI - Return of the Jedi (1983)
ID 1148	Rating 4.304241	Wrong Trousers, The (1993)
ID 1198	Rating 4.231340	Raiders of the Lost Ark (1981)
ID 356	Rating 4.198155	Forrest Gump (1994)
ID 2502	Rating 4.141893	Office Space (1999)
ID 919	Rating 4.115625	Wizard of Oz, The (1939)

=====

User 176, age 18, F, has rated 58 movies in training set

ID 2795	Rating 4.319016	Vacation (1983)
ID 3039	Rating 4.305584	Trading Places (1983)
ID 1196	Rating 4.250363	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 1197	Rating 4.174350	Princess Bride, The (1987)
ID 3552	Rating 4.136608	Caddyshack (1980)
ID 1544	Rating 4.105245	Lost World: Jurassic Park, The (1997)
ID 1307	Rating 3.962842	When Harry Met Sally... (1989)
ID 1968	Rating 3.958197	Breakfast Club, The (1985)
ID 2011	Rating 3.934531	Back to the Future Part II (1989)
ID 2378	Rating 3.920125	Police Academy (1984)

=====

User 181, age 18, M, has rated 242 movies in training set

ID 1213	Rating 4.887247	GoodFellas (1990)
ID 1136	Rating 4.665027	Monty Python and the Holy Grail (1974)
ID 1732	Rating 4.521598	Big Lebowski, The (1998)
ID 778	Rating 4.462507	Trainspotting (1996)
ID 1291	Rating 4.346444	Indiana Jones and the Last Crusade (1989)
ID 3424	Rating 4.343379	Do the Right Thing (1989)
ID 2028	Rating 4.336349	Saving Private Ryan (1998)
ID 1704	Rating 4.287665	Good Will Hunting (1997)
ID 36	Rating 4.188827	Dead Man Walking (1995)
ID 353	Rating 4.113652	Crow, The (1994)

=====

User 253, age 25, F, has rated 41 movies in training set

ID 246	Rating 4.271537	Hoop Dreams (1994)
ID 3083	Rating 4.237897	All About My Mother (Todo Sobre Mi Madre) (1999)
ID 3408	Rating 4.178385	Erin Brockovich (2000)
ID 2599	Rating 4.157721	Election (1999)
ID 3751	Rating 4.137932	Chicken Run (2000)
ID 446	Rating 4.059258	Farewell My Concubine (1993)
ID 296	Rating 3.992813	Pulp Fiction (1994)
ID 1089	Rating 3.963421	Reservoir Dogs (1992)
ID 1533	Rating 3.776638	Promise, The (La Promesse) (1996)
ID 1127	Rating 3.741367	Abyss, The (1989)

=====

User 261, age 25, M, has rated 297 movies in training set

ID 1221	Rating 4.741171	Godfather: Part II, The (1974)
ID 2692	Rating 4.545064	Run Lola Run (Lola rennt) (1998)
ID 3741	Rating 4.393841	Badlands (1973)
ID 1732	Rating 4.355713	Big Lebowski, The (1998)
ID 1283	Rating 4.322998	High Noon (1952)
ID 3424	Rating 4.259820	Do the Right Thing (1989)
ID 1225	Rating 4.243003	Amadeus (1984)
ID 1307	Rating 4.227256	When Harry Met Sally... (1989)
ID 2542	Rating 4.175666	Lock, Stock & Two Smoking Barrels (1998)
ID 1265	Rating 4.101122	Groundhog Day (1993)

=====

User 704, age 35, F, has rated 61 movies in training set

ID 2959	Rating 3.980768	Fight Club (1999)
ID 3384	Rating 3.857615	Taking of Pelham One Two Three, The (1974)



```
ID 2761|Rating 3.845630|Iron Giant, The (1999)
ID 3911|Rating 3.842279|Best in Show (2000)
ID 2390|Rating 3.429466|Little Voice (1998)
ID 2490|Rating 3.384069|Payback (1999)
ID 3298|Rating 3.332826|Boiler Room (2000)
ID 3893|Rating 3.308586|Nurse Betty (2000)
ID 3185|Rating 3.174899|Snow Falling on Cedars (1999)
ID 3896|Rating 2.829831|Way of the Gun, The (2000)
=====
```

User 749, age 35, M, has rated 375 movies in training set

```
ID 2762|Rating 4.453091|Sixth Sense, The (1999)
ID 1196|Rating 4.043712|Star Wars: Episode V - The Empire Strikes Back (1980)
ID 1210|Rating 3.932474|Star Wars: Episode VI - Return of the Jedi (1983)
ID 1610|Rating 3.897503|Hunt for Red October, The (1990)
ID 912 |Rating 3.849423|Casablanca (1942)
ID 293 |Rating 3.824950|Professional, The (a.k.a. Leon: The Professional) (1994)
ID 1090|Rating 3.820425|Platoon (1986)
ID 1954|Rating 3.820174|Rocky (1976)
ID 3098|Rating 3.787492|Natural, The (1984)
ID 3114|Rating 3.786118|Toy Story 2 (1999)
=====
```

User 1428, age 45, F, has rated 41 movies in training set

```
ID 908 |Rating 5.156441|North by Northwest (1959)
ID 1206|Rating 5.059811|Clockwork Orange, A (1971)
ID 1282|Rating 4.960043|Fantasia (1940)
ID 2227|Rating 4.823973|Lodger, The (1926)
ID 175 |Rating 4.449563|Kids (1995)
ID 2291|Rating 4.441682|Edward Scissorhands (1990)
ID 1580|Rating 4.028945|Men in Black (1997)
ID 3930|Rating 4.006862|Creature From the Black Lagoon, The (1954)
ID 3926|Rating 4.002057|Voyage to the Bottom of the Sea (1961)
ID 3927|Rating 3.862918|Fantastic Voyage (1966)
=====
```

User 1565, age 45, M, has rated 37 movies in training set

```
ID 2396|Rating 4.527424|Shakespeare in Love (1998)
ID 34 |Rating 4.309412|Babe (1995)
ID 2997|Rating 4.110594|Being John Malkovich (1999)
ID 2599|Rating 4.068440|Election (1999)
ID 357 |Rating 4.006423|Four Weddings and a Funeral (1994)
ID 224 |Rating 3.816521|Don Juan DeMarco (1995)
ID 348 |Rating 3.769893|Bullets Over Broadway (1994)
ID 3129|Rating 3.648651|Sweet and Lowdown (1999)
ID 1732|Rating 3.618274|Big Lebowski, The (1998)
ID 619 |Rating 2.897219|Ed (1996)
=====
```

User 1961, age 50, F, has rated 71 movies in training set

```
ID 1198|Rating 4.401946|Raiders of the Lost Ark (1981)
ID 318 |Rating 4.127230|Shawshank Redemption, The (1994)
ID 2501|Rating 4.069268|October Sky (1999)
ID 858 |Rating 4.011808|Godfather, The (1972)
ID 457 |Rating 3.899220|Fugitive, The (1993)
ID 1036|Rating 3.809142|Die Hard (1988)
ID 1196|Rating 3.797349|Star Wars: Episode V - The Empire Strikes Back (1980)
ID 296 |Rating 3.667643|Pulp Fiction (1994)
ID 608 |Rating 3.621137| Fargo (1996)
ID 3578|Rating 3.554532|Gladiator (2000)
=====
```

User 2088, age 50, M, has rated 355 movies in training set

```
ID 1207|Rating 4.869573|To Kill a Mockingbird (1962)
ID 1304|Rating 4.786379|Butch Cassidy and the Sundance Kid (1969)
ID 1303|Rating 4.725040|Man Who Would Be King, The (1975)
ID 2396|Rating 4.690739|Shakespeare in Love (1998)
ID 3469|Rating 4.678252|Inherit the Wind (1960)
ID 1197|Rating 4.664592|Princess Bride, The (1987)
ID 909 |Rating 4.644711|Apartment, The (1960)
ID 1028|Rating 4.613358|Mary Poppins (1964)
ID 599 |Rating 4.559749|Wild Bunch, The (1969)
ID 3062|Rating 4.546902|Longest Day, The (1962)
=====
```

User 5020, age 56, F, has rated 84 movies in training set

```
ID 3751|Rating 4.254084|Chicken Run (2000)
ID 3171|Rating 4.187455|Room at the Top (1959)
ID 3723|Rating 4.175472|Hamlet (1990)
ID 2872|Rating 4.106682|Excalibur (1981)
ID 592 |Rating 3.972631|Batman (1989)
ID 1210|Rating 3.960043|Star Wars: Episode VI - Return of the Jedi (1983)
ID 3792|Rating 3.937494|Duel in the Sun (1946)
```

```
ID 329 |Rating 3.890255|Star Trek: Generations (1994)
ID 938 |Rating 3.861818|Gigi (1958)
ID 2470|Rating 3.749801|Crocodile Dundee (1986)
=====
```

User 5583, age 56, M, has rated 95 movies in training set

```
ID 2396|Rating 4.670719|Shakespeare in Love (1998)
ID 920 |Rating 4.581555|Gone with the Wind (1939)
ID 1198|Rating 4.536726|Raiders of the Lost Ark (1981)
ID 1266|Rating 4.425125|Unforgiven (1992)
ID 457 |Rating 4.403832|Fugitive, The (1993)
ID 2858|Rating 4.361459|American Beauty (1999)
ID 260 |Rating 4.331812|Star Wars: Episode IV - A New Hope (1977)
ID 1291|Rating 4.310675|Indiana Jones and the Last Crusade (1989)
ID 3406|Rating 4.271886|Captain Horatio Hornblower (1951)
ID 3203|Rating 4.100273|Dead Calm (1989)
=====
```

## 4. With gender, with age

```
In [62]: def get_result_df(datasets, model, best_weights, bs, save_path=None):
        """
        model_parameter1_best.weights
        """
        minmax = (1.0, 5.0)
        device = torch.device('cpu')
        model.load_state_dict(best_weights)
        groud_truth, predictions = [], []

        val_size = len(datasets['val'][0])
        # print("Total val size: {}".format(val_size))

        with torch.no_grad():
            for batch in batches(*datasets['val'], shuffle=False, bs=bs):
                x_batch, y_batch = [b.to(device) for b in batch]
                outputs = model(x_batch[:, 0], x_batch[:, 1], x_batch[:, 2], x_batch[:, 3],minmax)
                groud_truth.extend(y_batch.tolist())
                predictions.extend(outputs.tolist())

            last_num = val_size % bs
            # print("Last num: {}".format(last_num))
            dataset_last = (datasets['val'][0][-last_num:], datasets['val'][1][-last_num:])
            # print("Last dataset: {}".format(len(dataset_last[0])))
            for batch in batches(*dataset_last, shuffle=False, bs=1):
                x_batch, y_batch = [b.to(device) for b in batch]
                outputs = model(x_batch[:, 0], x_batch[:, 1], x_batch[:, 2], x_batch[:, 3],minmax)
                groud_truth.extend(y_batch.tolist())
                predictions.extend(outputs.tolist())

        groud_truth = np.asarray(groud_truth).ravel()
        predictions = np.asarray(predictions).ravel()

        assert(predictions.shape[0] == val_size)

        final_loss = np.sqrt(np.mean((predictions - groud_truth)**2))
        # print("RMSE: {:.4f}".format(final_loss))

        df_final = pd.DataFrame(datasets['val'][0][['user_id','movie_id']]
        df_final['truth'] = datasets['val'][1]
        df_final['pred'] = predictions

        if save_path is not None:
            print("Save weight to:{}".format(save_path))
            with open(save_path, 'wb') as file:
                pickle.dump(best_weights, file)

        return df_final # note that here the sex and age is not included
```

```
In [63]: n_factors = 200
hidden = [1000] * 3
embedding_dropout = 0.05
dropouts = [0.5, 0.5, 0.25]
g_factor = 10
a_factor = 10

# training
lr = 1e-3
wd = 1e-5
bs = 2000
n_epochs = 100
patience = 10

model = EmbeddingNetGenderAge(n_users, n_movies,
                              n_factors=n_factors, hidden=hidden, dropouts=dropouts, g_factor=g_factor, a_factor=a_factor)
best_weights = pickle.load(open("saved_models/both_para5.weights", 'rb'))
```

```
In [64]: df_final = get_result_df(datasets, model, best_weights, bs, save_path=None)
         for user_id in user_id_list:
             get_train_pred_top10(df, df_final, datasets, user_id=user_id, n=10)
         print("==== =====\n")
```

User 1, age 1, F, has rated 41 movies in training set

ID 1207	Rating 4.742472	To Kill a Mockingbird (1962)
ID 608	Rating 4.574499	Fargo (1996)
ID 260	Rating 4.477774	Star Wars: Episode IV - A New Hope (1977)
ID 2804	Rating 4.427573	Christmas Story, A (1983)
ID 1	Rating 4.336008	Toy Story (1995)
ID 595	Rating 4.332149	Beauty and the Beast (1991)
ID 1287	Rating 4.243710	Ben-Hur (1959)
ID 1961	Rating 4.211578	Rain Man (1988)
ID 2791	Rating 4.161878	Airplane! (1980)
ID 2687	Rating 4.089414	Tarzan (1999)

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User 19, age 1, M, has rated 189 movies in training set

ID 2858	Rating 4.862138	American Beauty (1999)
ID 2571	Rating 4.595146	Matrix, The (1999)
ID 1198	Rating 4.542353	Raiders of the Lost Ark (1981)
ID 2028	Rating 4.518578	Saving Private Ryan (1998)
ID 1148	Rating 4.458857	Wrong Trousers, The (1993)
ID 1210	Rating 4.328912	Star Wars: Episode VI - Return of the Jedi (1983)
ID 356	Rating 4.303192	Forrest Gump (1994)
ID 110	Rating 4.270610	Braveheart (1995)
ID 2949	Rating 4.199471	Dr. No (1962)
ID 1278	Rating 4.189931	Young Frankenstein (1974)

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User 176, age 18, F, has rated 58 movies in training set

ID 1196	Rating 4.566271	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 1307	Rating 4.487173	When Harry Met Sally... (1989)
ID 1197	Rating 4.370369	Princess Bride, The (1987)
ID 2795	Rating 4.265700	Vacation (1983)
ID 3039	Rating 4.134203	Trading Places (1983)
ID 3552	Rating 4.088376	Caddyshack (1980)
ID 1968	Rating 4.066108	Breakfast Club, The (1985)
ID 3715	Rating 3.939243	Burglar (1987)
ID 1544	Rating 3.935678	Lost World: Jurassic Park, The (1997)
ID 2378	Rating 3.927120	Police Academy (1984)

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User 181, age 18, M, has rated 242 movies in training set

ID 1213	Rating 5.075797	GoodFellas (1990)
ID 1136	Rating 4.939441	Monty Python and the Holy Grail (1974)
ID 2028	Rating 4.829145	Saving Private Ryan (1998)
ID 3424	Rating 4.555366	Do the Right Thing (1989)
ID 1291	Rating 4.510047	Indiana Jones and the Last Crusade (1989)
ID 1732	Rating 4.479739	Big Lebowski, The (1998)
ID 1704	Rating 4.405294	Good Will Hunting (1997)
ID 1240	Rating 4.388027	Terminator, The (1984)
ID 778	Rating 4.248252	Trainspotting (1996)
ID 2706	Rating 4.207235	American Pie (1999)

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User 253, age 25, F, has rated 41 movies in training set

ID 446	Rating 4.609703	Farewell My Concubine (1993)
ID 3083	Rating 4.484456	All About My Mother (Todo Sobre Mi Madre) (1999)
ID 246	Rating 4.368542	Hoop Dreams (1994)
ID 3408	Rating 4.078164	Erin Brockovich (2000)
ID 3751	Rating 3.972930	Chicken Run (2000)
ID 2599	Rating 3.938196	Election (1999)
ID 1533	Rating 3.908612	Promise, The (La Promesse) (1996)
ID 1127	Rating 3.715311	Abyss, The (1989)
ID 296	Rating 3.711310	Pulp Fiction (1994)
ID 1089	Rating 3.585794	Reservoir Dogs (1992)

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User 261, age 25, M, has rated 297 movies in training set

ID 1221	Rating 4.728684	Godfather: Part II, The (1974)
ID 1225	Rating 4.486713	Amadeus (1984)
ID 1283	Rating 4.431026	High Noon (1952)
ID 3424	Rating 4.383136	Do the Right Thing (1989)
ID 3741	Rating 4.287354	Badlands (1973)
ID 2692	Rating 4.268642	Run Lola Run (Lola rennt) (1998)
ID 1732	Rating 4.256298	Big Lebowski, The (1998)
ID 1307	Rating 4.192164	When Harry Met Sally... (1989)
ID 3738	Rating 4.117684	Sugarland Express, The (1974)
ID 2542	Rating 4.092818	Lock, Stock & Two Smoking Barrels (1998)

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User 704, age 35, F, has rated 61 movies in training set

ID 3911	Rating 4.029378	Best in Show (2000)
ID 2959	Rating 4.018937	Fight Club (1999)

ID 3384	Rating 3.996497	Taking of Pelham One Two Three, The (1974)
ID 2761	Rating 3.957870	Iron Giant, The (1999)
ID 2390	Rating 3.736249	Little Voice (1998)
ID 3298	Rating 3.426171	Boiler Room (2000)
ID 2490	Rating 3.385803	Payback (1999)
ID 3896	Rating 3.247116	Way of the Gun, The (2000)
ID 3893	Rating 3.208550	Nurse Betty (2000)
ID 3185	Rating 2.915368	Snow Falling on Cedars (1999)

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User 749, age 35, M, has rated 375 movies in training set

ID 912	Rating 4.309187	Casablanca (1942)
ID 2762	Rating 4.179867	Sixth Sense, The (1999)
ID 1196	Rating 4.139338	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 908	Rating 4.019060	North by Northwest (1959)
ID 3114	Rating 3.976644	Toy Story 2 (1999)
ID 1204	Rating 3.945578	Lawrence of Arabia (1962)
ID 1090	Rating 3.912392	Platoon (1986)
ID 2791	Rating 3.910148	Airplane! (1980)
ID 1210	Rating 3.895487	Star Wars: Episode VI - Return of the Jedi (1983)
ID 1276	Rating 3.884572	Cool Hand Luke (1967)

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User 1428, age 45, F, has rated 41 movies in training set

ID 1206	Rating 5.144929	Clockwork Orange, A (1971)
ID 908	Rating 4.884665	North by Northwest (1959)
ID 1282	Rating 4.669325	Fantasia (1940)
ID 2291	Rating 4.464828	Edward Scissorhands (1990)
ID 2227	Rating 4.437533	Lodger, The (1926)
ID 175	Rating 4.327851	Kids (1995)
ID 3927	Rating 3.956764	Fantastic Voyage (1966)
ID 1580	Rating 3.852091	Men in Black (1997)
ID 3450	Rating 3.774438	Grumpy Old Men (1993)
ID 3930	Rating 3.772157	Creature From the Black Lagoon, The (1954)

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User 1565, age 45, M, has rated 37 movies in training set

ID 2997	Rating 4.326965	Being John Malkovich (1999)
ID 2396	Rating 4.082603	Shakespeare in Love (1998)
ID 2599	Rating 4.032507	Election (1999)
ID 34	Rating 3.887970	Babe (1995)
ID 1732	Rating 3.823928	Big Lebowski, The (1998)
ID 357	Rating 3.812804	Four Weddings and a Funeral (1994)
ID 348	Rating 3.777414	Bullets Over Broadway (1994)
ID 3129	Rating 3.565782	Sweet and Lowdown (1999)
ID 224	Rating 3.546489	Don Juan DeMarco (1995)
ID 619	Rating 3.473640	Ed (1996)

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User 1961, age 50, F, has rated 71 movies in training set

ID 858	Rating 4.472063	Godfather, The (1972)
ID 1198	Rating 4.229097	Raiders of the Lost Ark (1981)
ID 2501	Rating 3.993985	October Sky (1999)
ID 318	Rating 3.988014	Shawshank Redemption, The (1994)
ID 1196	Rating 3.975174	Star Wars: Episode V - The Empire Strikes Back (1980)
ID 457	Rating 3.907841	Fugitive, The (1993)
ID 1036	Rating 3.817840	Die Hard (1988)
ID 608	Rating 3.781312	Fargo (1996)
ID 2966	Rating 3.621969	Straight Story, The (1999)
ID 2951	Rating 3.599778	Fistful of Dollars, A (1964)

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User 2088, age 50, M, has rated 355 movies in training set

ID 1222	Rating 4.947099	Full Metal Jacket (1987)
ID 589	Rating 4.920642	Terminator 2: Judgment Day (1991)
ID 1303	Rating 4.879650	Man Who Would Be King, The (1975)
ID 1207	Rating 4.868109	To Kill a Mockingbird (1962)
ID 2947	Rating 4.852085	Goldfinger (1964)
ID 3737	Rating 4.842061	Lonely Are the Brave (1962)
ID 1304	Rating 4.811199	Butch Cassidy and the Sundance Kid (1969)
ID 541	Rating 4.784345	Blade Runner (1982)
ID 702	Rating 4.783013	Faces (1968)
ID 3469	Rating 4.738050	Inherit the Wind (1960)

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User 5020, age 56, F, has rated 84 movies in training set

ID 3792	Rating 4.405981	Duel in the Sun (1946)
ID 938	Rating 4.348991	Gigi (1958)
ID 3723	Rating 4.287194	Hamlet (1990)
ID 3171	Rating 4.264806	Room at the Top (1959)
ID 2872	Rating 4.224791	Excalibur (1981)
ID 3712	Rating 4.182477	Soapdish (1991)
ID 3751	Rating 4.051610	Chicken Run (2000)

ID 2143	Rating 3.944847	Legend (1985)
ID 1210	Rating 3.910752	Star Wars: Episode VI - Return of the Jedi (1983)
ID 2405	Rating 3.904504	Jewel of the Nile, The (1985)

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User 5583, age 56, M, has rated 95 movies in training set

ID 920	Rating 4.687065	Gone with the Wind (1939)
ID 2396	Rating 4.656053	Shakespeare in Love (1998)
ID 1198	Rating 4.611466	Raiders of the Lost Ark (1981)
ID 1266	Rating 4.485502	Unforgiven (1992)
ID 2571	Rating 4.403478	Matrix, The (1999)
ID 260	Rating 4.379815	Star Wars: Episode IV - A New Hope (1977)
ID 2858	Rating 4.375957	American Beauty (1999)
ID 1291	Rating 4.359865	Indiana Jones and the Last Crusade (1989)
ID 553	Rating 4.277444	Tombstone (1993)
ID 3176	Rating 4.163035	Talented Mr. Ripley, The (1999)

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