In [8]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy import stats
```

In [9]:

```
# Read data
names = ['userid', 'itemid', 'rating', 'timestamp']
raw_data = pd.read_csv('./ml-100k/u.data', sep='\t', names=names)

# save data in a numpy array where each user ratings have their own rows
userids = sorted(list(raw_data['userid'].unique()))
itemids = sorted(list(raw_data['itemid'].unique()))

# first save in list of lists, use None values if user has not rated item
data = [[None] * len(itemids) for x in range(len(userids))]

# find ratings made by each user
for i in range(len(userids)):
    # dict of ratings for user i+1 (key = itemid, value = rating)
    user_ratings = dict(zip(raw_data.loc[raw_data['userid'] == (i+1)].itemid, raw_data.
    for j in range(len(itemids)):
        # check if user has rated item with id j+1
        if j+1 in user_ratings:
            data[i][j] = user_ratings[j+1]

data = np.array(data)
```

User-based colloborative filtering approach from Assignment 1

In [10]:

```
# a, b = userids, data = whole data set
def similarity(a,b, data):
    data_a = data[a-1] # remember that indexing starts from 0, but userids from 1
    data_b = data[b-1]

    # dicts with itemids and ratings
    dict_a = {i: r for i, r in enumerate(data_a, start=1) if r is not None}
    dict_b = {i: r for i, r in enumerate(data_b, start=1) if r is not None}

    # intersections of common itemids
    P = list(set(dict_a).intersection(set(dict_b)))

    if len(P) < 2:
        return 0

    # keep only common itemids
    dict_a = {id: dict_a[id] for id in P}
    dict_b = {id: dict_b[id] for id in P}

    # Create constants
    const_a = list(dict_a.values())
    const_b = list(dict_b.values())

    sim, p = stats.pearsonr(const_a, const_b)

    # Check for NaN
    if sim != sim:
```

```
        return 0
    return sim

# Similarity matrix
N = 0
sim_matrix = [[1] * len(userids) for x in range(len(userids))]
for i in range(len(userids)):
    for j in range(i+1, len(userids)):
        sim_matrix[i][j] = sim_matrix[j][i] = similarity(i+1, j+1, data)

sim_matrix = np.array(sim_matrix)

# a = userid, p = itemid, data = whole data set,
# sim = similarity matrix t = similarity threshold
def predict(a, p, data, sim_matrix, t):
    sim = sim_matrix[a-1]
    # mean of ratings given by user a
    mean_a = np.mean([r for r in data[a-1] if r is not None])

    # transform similarities to dict (key = userid, value = similarity) and filter out
    sim = {i: s for i, s in enumerate(sim, start=1) if s >= t}

    n = 0
    d = 0

    for b in sim:
        # chekc if user b has not rated the item
        if data[b-1][p-1] == None:
            continue

        mean_b = np.mean([r for r in data[b-1] if r is not None])
        n += sim[b] * (data[b-1][p-1] - mean_b)
        d += sim[b]

    if n == 0:
        return mean_a

    return mean_a + n/d
```

```
B:\Anaconda\envs\recommender\lib\site-packages\scipy\stats\stats.py:4023: PearsonRConsta
ntInputWarning: An input array is constant; the correlation coefficient is not defined.
  warnings.warn(PearsonRConstantInputWarning())
```

Average aggregation method from Assignment 2

In [12]:

```
# g = groud of users (list of usedids), i = itemid, data = whole dataset
def average_aggregation(g, i, data):
    # ratings for item i, given by users in the group
    ratings = []

    # obtaing ratings, either from data or predict it
    for user in g:
        rating = data[user-1][i-1]
        if rating == None:
            rating = predict(user, i, data, sim_matrix, 10)
        ratings.append(rating)

    return np.average(ratings)
```

Assignment 3

GroupListSat and UserListSat functions

In [14]:

```
def groupListSat(data, grouplist, user):
        sat = 0

        for item in grouplist:
            score = data[user-1][item-1]
            if score == None:
                score = predict(user, item, data, sim_matrix, 10)
            sat += score

        return sat
```

In [15]:

```
def userListSat(data, user, n):
    predictions = {}

    for item in itemids:
        score = data[user-1][item-1]
        if score == None:
            score = predict(user, item, data, sim_matrix, 0.0)
        predictions[item] = score

    # sort predictions and take 20 highest
    most_relevant = dict(sorted(predictions.items(), key=lambda x: x[1], reverse=True))
    most_relevant = dict(list(most_relevant.items())[:n])

    return sum(most_relevant.values())
```

Method for producing sequential group reccomendations

In [21]:

```
# data = whole dataset, g = group, mu = number of iterations, n = number of reccommenda
def sequential_recommendations(data, g, mu, n):
    # keep track of satisfactions over all iterations, used for plotting bar graph
    satisfactions_mu = []

    # define alpha and least satisfied user, for first iteration least satisfied user d
    alpha = 0
    least_satisfied = 0

    for m in range(mu):
        # user satisfactions during each iteration
        satisfactions = []

        # group recommendation scores for all items
        scores = {}

        for i in itemids:
            avg_score = average_aggregation(g, i, data)

            leastScore = data[least_satisfied-1][i-1]
```

```
            if leastScore == None:
                leastScore = predict(least_satisfied, i, data, sim_matrix, 10)

            scores[i] = (1-alpha)*avg_score + alpha*leastScore

        # sort scores and take top n recommendations
        scores = dict(sorted(scores.items(), key=lambda x: x[1], reverse=True))
        recommendations = dict(list(scores.items())[:n])

        # calculate GroupListSat values
        for user in g:
            satisfactions.append(groupListSat(data, recommendations, user) / userListSa
        satisfactions_mu.append(satisfactions)

        # Least satisfied user during this iteration
        least_satisfied = g[satisfactions.index(min(satisfactions))]

        # original alpha calculation
        #alpha = max(satisfactions) - min(satisfactions)

        # improved alpha calculation with modified mean squared error
        alpha = 0
        for s in satisfactions:
            alpha += (max(satisfactions)-s) ** (2/3)
        alpha = alpha / len(satisfactions)

        # print recommendations
        df = pd.DataFrame(list(zip(list(recommendations.keys()), list(recommendations.v
        print('Iteration:', m+1)
        print(df)

    # plot satisfactions
    fig = plt.figure()
    X = np.arange(1,mu+1)
    satisfactions_mu = np.transpose(np.array(satisfactions_mu))

    ax = fig.add_axes([0,0,1,1])
    shift = 0
    for sat in satisfactions_mu:
        bar = ax.bar(X + shift, sat, width = 0.1)
        shift += 0.1
```

Produce top-20 recommendations for a group of 3 users in 5 different sequences

Calculate UserListSat values for predifiend group of users

In [17]:

```
g = [1, 2, 3]
userListSatCache = {}
for user in g:
    userListSatCache[user] = userListSat(data, user, 20)
```

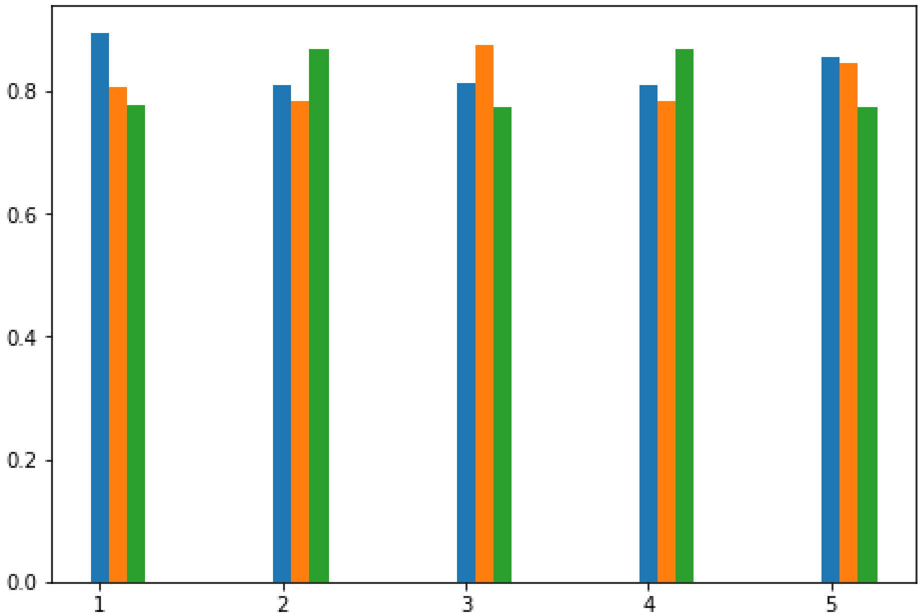
Produce and show sequential recommendations

In [22]:

```
sequential_recommendations(data, g, 5, 20)
```

```
Iteration: 1
    itemid    rating
0       50  4.265432
1      100  4.265432
2      127  4.265432
3      242  4.265432
4      181  4.236559
5      320  4.106657
6      321  4.106657
7      328  4.106657
8      340  4.106657
9      346  4.106657
10     347  4.106657
11       1  3.932099
12      13  3.932099
13      14  3.932099
14     111  3.932099
15     251  3.932099
16     269  3.932099
17     268  3.903226
18       6  3.835325
19       9  3.835325
Iteration: 2
    itemid    rating
0      320  4.238591
1      321  4.238591
2      328  4.238591
3      340  4.238591
4      346  4.238591
5      347  4.238591
6      181  4.201623
7       50  4.048461
8      100  4.048461
9      127  4.048461
10     242  4.048461
11     318  3.806801
12     327  3.806801
13     329  3.806801
14     331  3.806801
15     342  3.806801
16     344  3.806801
17     348  3.806801
18     268  3.769832
19       1  3.764357
Iteration: 3
    itemid    rating
0       50  4.351076
1      100  4.351076
2      127  4.351076
3      242  4.351076
4      181  4.175129
5      320  4.060373
6      321  4.060373
7      328  4.060373
8      340  4.060373
9      346  4.060373
10     347  4.060373
11     251  4.056607
12     275  3.941850
13     283  3.941850
```

```
14     285  3.941850
15     311  3.941850
16     313  3.941850
17     316  3.941850
18       1  3.940015
19      13  3.940015
Iteration: 4
    itemid    rating
0      320  4.216076
1      321  4.216076
2      328  4.216076
3      340  4.216076
4      346  4.216076
5      347  4.216076
6      181  4.207585
7       50  4.085489
8      100  4.085489
9      127  4.085489
10     242  4.085489
11     318  3.801088
12     327  3.801088
13     329  3.801088
14     331  3.801088
15     342  3.801088
16     344  3.801088
17     348  3.801088
18       1  3.792983
19      13  3.792983
Iteration: 5
    itemid    rating
0       50  4.348241
1      100  4.348241
2      127  4.348241
3      242  4.348241
4      181  4.177163
5      320  4.061905
6      321  4.061905
7      328  4.061905
8      340  4.061905
9      346  4.061905
10     347  4.061905
11     251  4.052485
12       1  3.939753
13      13  3.939753
14      14  3.939753
15     111  3.939753
16     269  3.939753
17     275  3.937228
18     283  3.937228
19     285  3.937228
```



In [ ]: