parth.pandey13103447@gmail.com_15

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1 SGD Algorithm to predict movie ratings

2 Task 1 Solutions

2.1 Imports

[1]:
```
import pandas as pd
from scipy.sparse import csr_matrix
from sklearn.utils.extmath import randomized_svd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score

%matplotlib inline
```

2.2 Reading the csv file

[2]:
```
data=pd.read_csv('ratings_train.csv')
data.head()
```

[2]:

	user_id	item_id	rating
0	772	36	3
1	471	228	5
2	641	401	4
3	312	98	4
4	58	504	5

[3]:
```
data.shape
```

[3]: (89992, 3)

2.3 Create your adjacency matrix

[4]:
```
M = data['user_id'].max() + 1
N = data['item_id'].max() + 1
adjacency_matrix = csr_matrix((data['rating'].values, (data['user_id'].values,␣
↪data['item_id'].values)), shape=(M,N))
```

Grader function - 1

[5]:
```
def grader_matrix(matrix):
    assert(matrix.shape==(943,1681))
    return True
grader_matrix(adjacency_matrix)
```

[5]:
```
True
```

2.4 SVD decompostion

Sample code for SVD decompostion

[6]:
```
matrix = np.random.random((20, 10))
U, Sigma, VT = randomized_svd(matrix, n_components=5,n_iter=5,␣
↪random_state=None)
print(U.shape)
print(Sigma.shape)
print(VT.T.shape)
```

```
(20, 5)
(5,)
(10, 5)
```

2.5 Write your code for SVD decompostion

[7]:
```
# Please use adjacency_matrix as matrix for SVD decompostion
# You can choose n_components as your choice
U, Sigma, VT = randomized_svd(adjacency_matrix, n_components=100,n_iter=5,␣
↪random_state=42)
print(U.shape)
print(Sigma.shape)
print(VT.T.shape)
```

```
(943, 100)
(100,)
(1681, 100)
```

2.6 Compute mean of ratings

[8]:
```
def m_u(ratings):
    '''In this function, we will compute mean for all the ratings'''
    # you can use mean() function to do this
    # check this (https://pandas.pydata.org/pandas-docs/stable/reference/api/
 ↪pandas.DataFrame.mean.html) link for more details.
    return np.mean(ratings)
```

[9]:
```
mu=m_u(data['rating'])
print(mu)
```

```
3.529480398257623
```

Grader function -2

[10]:
```
def grader_mean(mu):
    assert(np.round(mu,3)==3.529)
    return True
mu=m_u(data['rating'])
grader_mean(mu)
```

[10]:
```
True
```

2.7 Initialize

Initialize ${ B_{i}} $ and $ {C_{j}} $

Hint : Number of rows of adjacent matrix corresponds to user dimensions(B_i), number of columns of adjacent matrix corresponds to movie dimensions (C_j)

[11]:
```
def initialize(dim):
    '''In this function, we will initialize bias value 'B' and 'C'.'''
    # initalize the value to zeros
    # return output as a list of zeros
    return np.zeros(shape=dim)
```

[12]:
```
dim= (943,1) # give the number of dimensions for b_i (Here b_i corresponds to␣
 ↪users)
b_i=initialize(dim)
```

[13]:
```
dim= (1681,1)
# give the number of dimensions for c_j (Here c_j corresponds to movies)
c_j=initialize(dim)
```

Grader function -3

[14]:
```
def grader_dim(b_i,c_j):
    assert(len(b_i)==943 and np.sum(b_i)==0)
```

```
    assert(len(c_j)==1681 and np.sum(c_j)==0)
    return True
grader_dim(b_i,c_j)
```

[14]: True

2.8 Compute dL/db_i

[15]:
```
def derivative_db(user_id,item_id,rating,U,V,mu,alpha):
    '''In this function, we will compute dL/db_i'''
    return -2 * (rating - mu - b_i[user_id] - c_j[item_id] - np.dot(U[user_id],␣
↪V[:, item_id])) + 2 * alpha * (b_i[user_id])
```

Grader function -4

[16]:
```
def grader_db(value):
    assert(np.round(value,3)==-0.931)
    return True
U1, Sigma, V1 = randomized_svd(adjacency_matrix, n_components=2,n_iter=5,␣
↪random_state=24)
# Please don't change random state
# Here we are considering n_componets = 2 for our convinence
alpha=0.01
value=derivative_db(312,98,4,U1,V1,mu,alpha)
grader_db(value)
```

[16]: True

2.9 Compute dL/dc_j

[17]:
```
def derivative_dc(user_id,item_id,rating,U,V,mu, alpha):
    '''In this function, we will compute dL/dc_j'''
    return -2 * (rating - mu - b_i[user_id] - c_j[item_id] - np.dot(U[user_id],␣
↪V[:, item_id])) + 2 * alpha * (c_j[item_id])
```

Grader function - 5

[18]:
```
def grader_dc(value):
    assert(np.round(value,3)==-2.929)
    return True
U1, Sigma, V1 = randomized_svd(adjacency_matrix, n_components=2,n_iter=5,␣
↪random_state=24)
# Please don't change random state
# Here we are considering n_componets = 2 for our convinence
r=0.01
value=derivative_dc(58,504,5,U1,V1,mu,alpha)
```

```
grader_dc(value)
```

[18]: True

2.10 Compute MSE (mean squared error) for predicted ratings

for each epoch, print the MSE value

[19]:
```
epochs = range(1,100)
alpha=0.9
learning_rate = 0.09
loss = []
n = data.shape[0]
for epoch in epochs:
    temp_loss = 0
    if len(loss) >= 2 and (loss[-2] - loss[-1]) <= 10**-5:
        print(loss[-1], loss[-2], loss[-1] - loss[-2])
        break
    for user, movie, ratings in data.values:
        b_i[user] = b_i[user] - learning_rate * derivative_db(user, movie,␣
↪ratings, U , VT, mu, alpha)
        c_j[movie] = c_j[movie] - learning_rate * derivative_dc(user, movie,␣
↪ratings, U , VT, mu, alpha)
        y_pred = mu + b_i[user] + c_j[movie] + np.dot(U[user], VT[:, movie])
        temp_loss += (ratings - y_pred)**2

    print(temp_loss/n)
    loss.append(temp_loss/n)
```

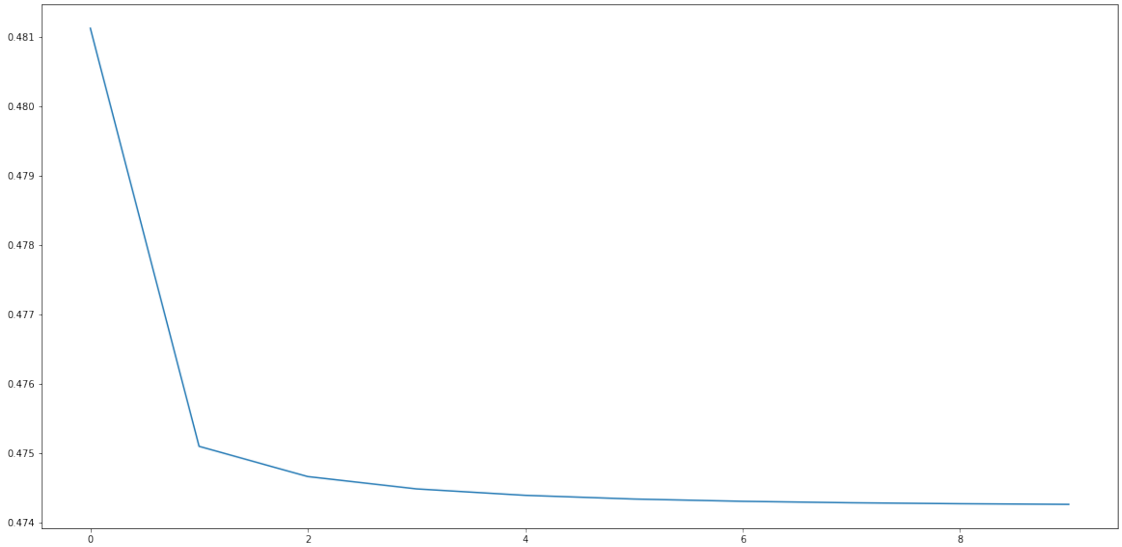
```
[0.48112105]
[0.47509623]
[0.4746602]
[0.47448255]
[0.47439018]
[0.47433664]
[0.47430369]
[0.47428264]
[0.47426885]
[0.47425968]
[0.47425968] [0.47426885] [-9.17611467e-06]
```

2.11 Plot epoch number vs MSE

- epoch number on X-axis
- MSE on Y-axis

[20]:
```
_, ax = plt.subplots(1, 1, figsize=(20,10))
ax.plot(loss)
```

```
plt.show()
```



3 Task 2

[21]:
```
df = pd.read_csv("user_info.csv.txt")
df.shape
```

[21]: (943, 4)

[22]:
```
df.head()
```

[22]:

	user_id	age	is_male	orig_user_id
0	0	24	1	1
1	1	53	0	2
2	2	23	1	3
3	3	24	1	4
4	4	33	0	5

[23]:
```
x_train = []
y_train = []
for ele,lab in zip(df['user_id'].values, df['is_male'].values):
    x_train.append(U[ele])
    y_train.append(lab)
```

[24]:
```
x_train = np.array(x_train)
y_train = np.array(y_train)
```

[25]:
```
x_train.shape
```

[25]: (943, 100)

[26]:
```
y_train.shape
```

[26]: (943,)

[30]:
```
clf = LogisticRegression(C=0.09)
clf.fit(x_train, y_train)
y_pred = clf.predict(x_train)
conf = confusion_matrix(y_train, y_pred)
acc  = accuracy_score(y_train, y_pred)
```

[31]:
```
conf
```

[31]:
```
array([[  0, 273],
       [  0, 670]])
```

[32]:
```
acc
```

[32]: 0.7104984093319194

- Conclusion : By Scaling the feature vector of U does not affect the prediction of is_male as a target feature