Lab 10

January 29, 2022

Machine Learning Lab

Lab 10

0.0.1 Importing Packages

[1]:
```
import pandas as pd                                          #Importing Pandas
import numpy as np                                           #Importing Numpy
import matplotlib.pyplot as plt                              #Importing Matplotlib
from sklearn.decomposition import NMF                        #Importing SKlearn Non␣
↪Negative Matrix Factorization
from sklearn.model_selection import GridSearchCV             #Importing GridSearchCV
import warnings                                              #Importing Warnings
warnings.filterwarnings('ignore')
```

0.0.2 Exercise 1: Exploring Movie Recommendation Dataset

Reading Datasets

Reading the dataset file containing Users and Items references

[2]:
```
u_data = pd.read_csv('ml-100k/ml-100k/u.data', sep='\t', names=['user id',␣
↪'item id', 'rating', 'timestamp'], header=None)
u_data.head()
```

[2]:

	user id	item 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

Reading the Users Data

[3]:
```
u_user = pd.read_csv('ml-100k/ml-100k/u.user', sep='|', names=['user id',␣
↪'age', 'gender', 'occupation', 'zip code'])
u_user.head()
```

[3]:

	user id	age	gender	occupation	zip code
0	1	24	M	technician	85711

```
1        2  53      F       other    94043
2        3  23      M      writer    32067
3        4  24      M  technician    43537
4        5  33      F       other    15213
```

Reading the Genre Data

[4]:
```
u_genre = pd.read_csv('ml-100k/ml-100k/u.genre', sep='|', names=['genre', 'id'])
u_genre.head()
```

[4]:
```
        genre  id
0     unknown   0
1      Action   1
2   Adventure   2
3   Animation   3
4  Children's   4
```

Reading the Items/Movies Data

[5]:
```
u_item = pd.read_csv('ml-100k/ml-100k/u.item', encoding='latin-1', sep='|',␣
↪names=['movie id','movie title','release date','video release date','IMDb␣
↪URL','unknown','Action','Adventure','Animation','Children\'s','Comedy','Crime','Documentary
u_item.head()
```

[5]:
```
   movie id        movie title release date  video release date  \
0         1   Toy Story (1995)  01-Jan-1995                 NaN
1         2   GoldenEye (1995)  01-Jan-1995                 NaN
2         3  Four Rooms (1995)  01-Jan-1995                 NaN
3         4  Get Shorty (1995)  01-Jan-1995                 NaN
4         5     Copycat (1995)  01-Jan-1995                 NaN

                                            IMDb URL  unknown  Action  \
0  http://us.imdb.com/M/title-exact?Toy%20Story%2…        0       0
1  http://us.imdb.com/M/title-exact?GoldenEye%20(…        0       1
2  http://us.imdb.com/M/title-exact?Four%20Rooms%…        0       0
3  http://us.imdb.com/M/title-exact?Get%20Shorty%…        0       1
4  http://us.imdb.com/M/title-exact?Copycat%20(1995)        0       0

   Adventure  Animation  Children's  …  Fantasy  Film-Noir  Horror  Musical  \
0          0          1           1  …        0          0       0        0
1          1          0           0  …        0          0       0        0
2          0          0           0  …        0          0       0        0
3          0          0           0  …        0          0       0        0
4          0          0           0  …        0          0       0        0

   Mystery  Romance  Sci-Fi  Thriller  War  Western
0        0        0       0         0    0        0
1        0        0       0         1    0        0
2        0        0       0         1    0        0
```

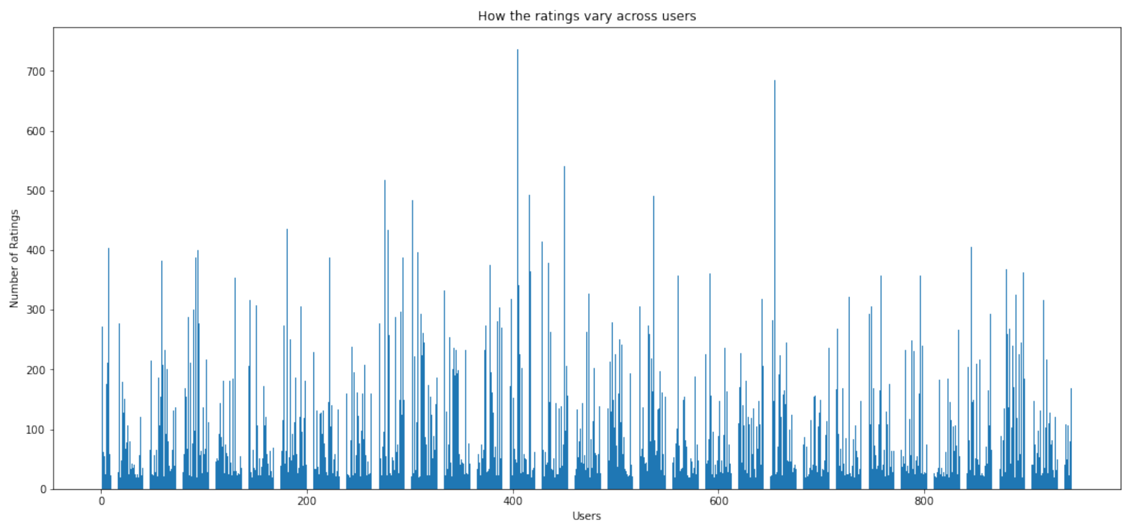
```
3          0          0         0          0     0          0
4          0          0         0          1     0          0

[5 rows x 24 columns]
```

Showcasing how the ratings vary across users

[6]:
```python
#For finding total ratings across user,
#First we group the data based on user Id and then count the total rows which␣
↪will indicate total ratings given by users
rating_across_users = u_data.groupby(by = 'user id')['rating'].count().
↪sort_values(ascending=True)

#Plotting the Graph: Users vs Number of Ratings
fig = plt.figure(figsize=(18,8))
plt.bar(rating_across_users.index, rating_across_users.values)
plt.title('How the ratings vary across users')
plt.xlabel('Users')
plt.ylabel('Number of Ratings')
plt.show()
```

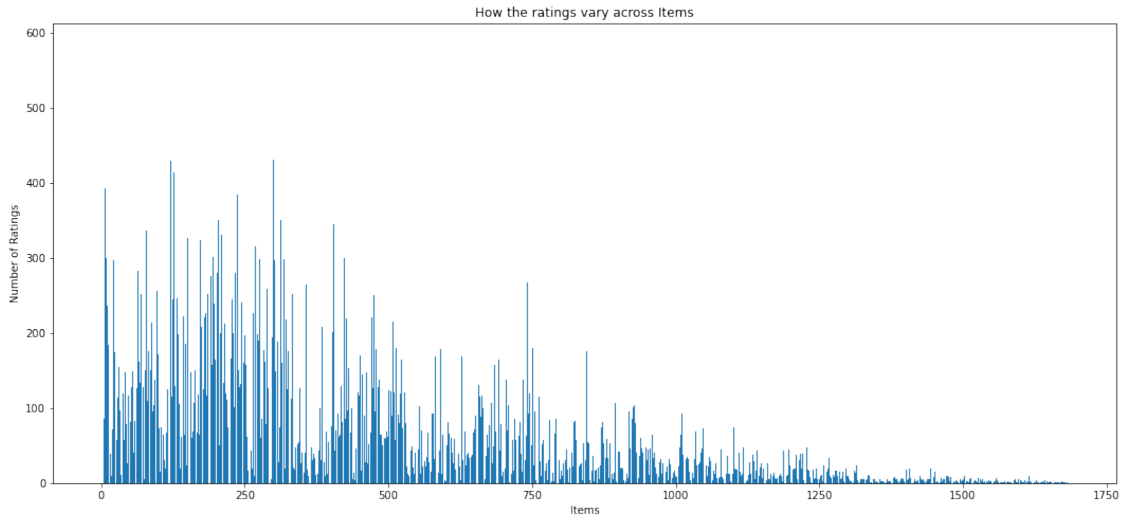


Showcase how the ratings vary across items

[7]:
```python
#For finding total ratings across Items,
#First we group the data based on item Id and then count the total rows which␣
↪will indicate total ratings given for Items
rating_across_items = u_data.groupby(by='item id')['rating'].count().
↪sort_values(ascending = True)

#Plotting the Graph: Users vs Number of Ratings
```

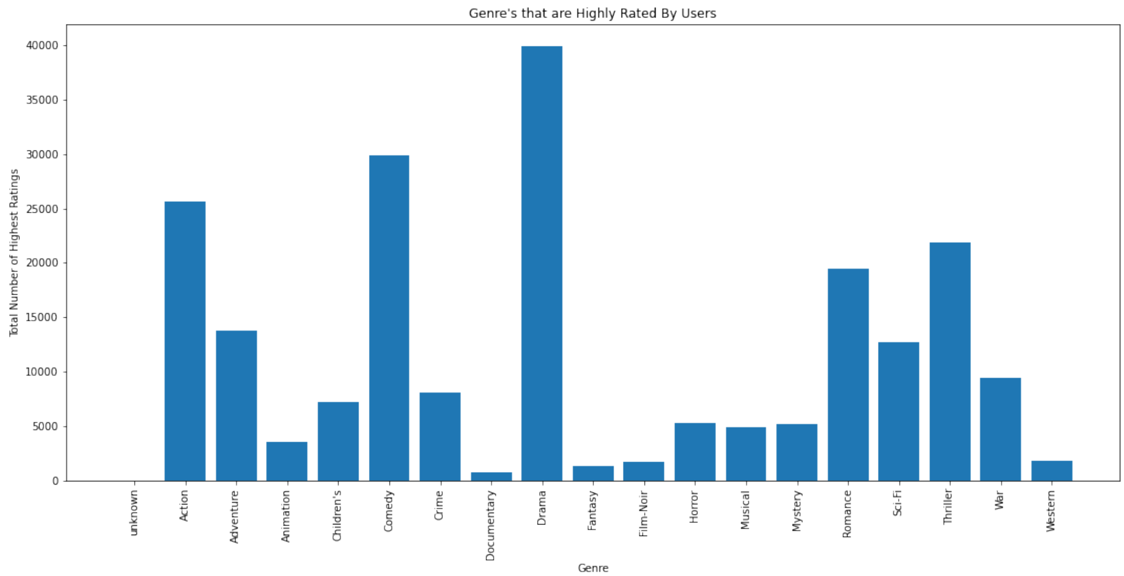
```
fig = plt.figure(figsize=(18,8))
plt.bar(rating_across_items.index, rating_across_items.values)
plt.title('How the ratings vary across Items')
plt.xlabel('Items')
plt.ylabel('Number of Ratings')
plt.show()
```



Are there genres that are more highly rated than others?

[8]:
```
#First Extracting only that rows that has the maximum ratings i.e. 5
#Then to find the genre and there count, we can simply sum up all the rows␣
↪horizontaly and the result will show there count individually
highest_rated_items = u_data[u_data['rating'] == max(u_data['rating'])]
highest_rated_items = pd.merge(u_data, u_item, left_on='item id',␣
↪right_on='movie id')
highest_rated_items = (highest_rated_items[list(u_genre['genre'])] == 1).
↪sum(axis=0)

#Plotting the graph indicating total ratings for each genre
fig = plt.figure(figsize=(18,8))
plt.bar(highest_rated_items.index, highest_rated_items.values)
plt.title('Genre\'s that are Highly Rated By Users')
plt.xlabel('Genre')
plt.ylabel('Total Number of Highest Ratings')
plt.xticks(rotation = 90)
plt.show()
```



What age groups prefer what genres based on ratings?

[9]:
```
#Defining different age brackets with a difference of 10 each
age_bracket = np.arange(0,80,10)
```

[10]:
```
#Creating a dictionary to hold best genre for each age group
aged_group_preference = {}

#Extracting rows in which the item highest Ratings i.e. 5
merged_df = u_data[u_data['rating'] == max(u_data['rating'])]

#Merging the datasets
merged_df = pd.merge(merged_df, u_item, left_on='item id', right_on='movie id')
merged_df = pd.merge(merged_df, u_user, on='user id')

#Iterating over all the age groups
for age in age_bracket:
    #Extracting ratings which are given by users in the specified age bracket
    aged_df = merged_df[merged_df['age'].between(age, age+10)]

    #Suming the Genre count and getting the genre with the maximum count and␣
↪saving it into the dictionary
    aged_group_preference['{}-{}'.format(age, age+10)] =␣
↪(aged_df[list(u_genre['genre'])] == 1).sum(axis=0).idxmax(axis = 0)

#Converting the Dictionary into a Dataframe for Displaying the results
aged_df = pd.DataFrame.from_dict(aged_group_preference, orient='index').
↪reset_index()
```

```
aged_df.columns = ['Age Group', 'Popular Genre']
aged_df
```

[10]:

	Age Group	Popular Genre
0	0-10	Comedy
1	10-20	Drama
2	20-30	Drama
3	30-40	Drama
4	40-50	Drama
5	50-60	Drama
6	60-70	Drama
7	70-80	Drama

0.0.3 Exercise 2: Implementing basic matrix factorization (MF) technique for recommender systems

[11]:
```
#Initializing the random seed value
random_seed = 3116
```

Normalizing the data

[12]:
```
def normalize_matrix(matrix):
    #Normalizing the dataset by: (X - X.mean)/X.standard_Deviation
    return (matrix - matrix.mean())/matrix.std()
```

Function to transform the dataset into a Rating Matrix of Users and Item

[13]:
```
def extract_rating_matrix(dataset):
    #Initializing the rating matrix with zeros
    rating_matrix = np.zeros(shape=(number_of_users, number_of_items))

    #Iterating over all the rows of the dataset
    for row in dataset:
        #The row represent the users and the column represent the items and the␣
↪corresponding value represent the rating for that item
        rating_matrix[row[0]-1, row[1]-1] = row[2]

    #Returning the Rating matrix
    return rating_matrix
```

Function to perform K-fold cross validation and return the training and the validation sets

[14]:
```
def k_fold_cross_validation(dataset, k, K):
    #Checking if the given k is larger than the allowed K partitions
    if k >= K:
        raise Exception('The Requested k-Fold should not be Greater than total␣
↪Folds')
```

```
    #Calculating the Validation set size based on dataset size and total␣
↪partitions given
    set_size = int(len(dataset)/K)

    #Splitting the Dataset into Training and Validation sets based on set size.
↪The size
    #set size calculated above and all the remaining data points after removing␣
↪test
    dataset_train = np.delete(dataset,[i for i in␣
↪range(k*set_size,(k*set_size)+set_size)],axis=0)
    dataset_validation = dataset[k*set_size:(k*set_size)+set_size,:]

    #Returning the created Training and Validation datasets.
    return dataset_train, dataset_validation
```

Function to calculate the RMSE between the actual rating matrix and the predicted rating matrix

[15]:
```
def rmse(rating_matrix, p , q):
    #Returning the RMSE
    return np.sqrt(np.divide(np.sum(np.square(np.subtract(rating_matrix, np.
↪dot(p, q)))),rating_matrix.shape[0] * rating_matrix.shape[1]))
```

Function which implements Stochastic Gradient Descent (SGD) for learning the matrix P and Q

[16]:
```
def learn_latent_factors(dataset_train, dataset_test, lamda, alpha, K):
    #Extracting and normalizing the Rating matrix of the Training dataset
    r = normalize_matrix(extract_rating_matrix(dataset_train))

    #Extracting and normalizing the Rating matrix of the Test dataset
    r_v = normalize_matrix(extract_rating_matrix(dataset_test))

    #Intializing the random P and Q matrix for matrix factorization, there␣
↪dimensions are as follows:
    #P -> (# of users, K latent Features)
    #Q -> (K latent Features, # of Items)
    p = np.random.normal(normal_dis_mean, normal_dis_std, size =␣
↪(number_of_users, K))
    q = np.random.normal(normal_dis_mean, normal_dis_std, size = (K,␣
↪number_of_items))

    #Intializing lists for storing the train and test RMSE in each Epochs
    train_rmse = np.array([])
    validation_rmse = np.array([])

    #Learning the matrix P and Q for specified number of Epochs
    for i in range(epochs):
```

```
        #Iterating over all the rows in the training dataset
        for row in dataset_train:
            #Extracting the User Id and Item Id from the row
            user_id, item_id = row[0] - 1, row[1] - 1

            #Calculating the difference between the actual rating and the␣
↪predicted rating
            e = r[user_id, item_id] - np.dot(p[user_id,:], q[:,item_id])

            #Iterating over all the latent feature
            for k in range(K):
                #Updating the values of Pu,k and Qi,k
                p[user_id, k] = p[user_id, k] + alpha * (e * q[k, item_id] -␣
↪lamda * p[user_id, k])
                q[k, item_id] = q[k, item_id] + alpha * (e * p[user_id, k] -␣
↪lamda * q[k, item_id])

        #Appending the Train and Validating RMSE in the list
        train_rmse = np.append(train_rmse, rmse(r, p, q))
        validation_rmse = np.append(validation_rmse, rmse(r_v, p, q))

        #Checking the Stopping Condition,Stopping the Learning process when the␣
↪difference between the last two epoch is negligible
        if i > 1 and (validation_rmse[-2] - validation_rmse[-1] < 0.001):
            break

    #Returning the calculated P, Q, Train RMSE and Validation RMSE
    return p, q, train_rmse, validation_rmse
```

Optimizing the hyper-parameters i.e. regularization constant, learning rate, k latent dimensions

Initializing variables to be used by different functions

[17]:
```
#Number of Unique Users in the Dataset
number_of_users = len(u_user)

#Number of Unique Items in the Dataset
number_of_items = len(u_item)

#Initializing the Training set Size
train_ratio = 0.9
```

Initializing variables storing the values of parameters of different algorithm

[18]:
```
#Number of Epochs
epochs = 10
```

```
#Mean for Normal Distribution samples
normal_dis_mean = 0

#Standard Deviation for Normal Distribution samples
normal_dis_std = 1

#Number of Folds for K fold cross validation
K_folds = 5
```

Initializing different Hyperparameters sets for Hyperparameter Optimization

[19]:
```
lamdas = [0.1, 0.2, 0.3]
alphas = [0.005, 0.003, 0.001]
latent_k = [10,20,30]
```

Merging and Splitting the Dataset

[20]:
```
#Merging the u.data and u.item dataset
merged_df = pd.merge(u_data, u_item, left_on='item id', right_on='movie id')

#Merging the merged dataset with u.users
merged_df = pd.merge(merged_df, u_user, on='user id')
```

[21]:
```
#Extracting the rows randomly from the merged dataset for Training set
merged_train = merged_df.sample(frac=train_ratio)

#Droping that rows which are included in training dataset
merged_test = merged_df.drop(merged_train.index)

#Converting the dataset into numpy arrays
merged_train = merged_train.to_numpy()
merged_test = merged_test.to_numpy()
```

Performing the Hyperparameter Optimization

[22]:
```
#Initializing a matrix for storing the training RMSE for each Hyperparameter␣
↪combination
hyperparameters_train_rmse = np.
↪zeros(shape=(len(lamdas),len(alphas),len(latent_k)))

#Initializing a matrix for storing the Validating RMSE for each Hyperparameter␣
↪combination
hyperparameters_validation_rmse = np.
↪zeros(shape=(len(lamdas),len(alphas),len(latent_k)))
```

[23]:
```
#Iterating for all values of Lambdas
for index_l, lamda in enumerate(lamdas):

    #Iterating for all values of Alphas
```

```
    for index_a, alpha in enumerate(alphas):

        #Iterating for all values of Latent Features
        for index_lk, l_k in enumerate(latent_k):

            #Initializing the average Training and Validating RMSE for each K␣
↪fold
            average_train_rmse, average_validation_rmse = 0 , 0

            #Iterating for all values of K fold
            for k in range(K_folds):

                #Splitting the training dataset into Train and Validation using␣
↪K fold Cross validation
                train, validation = k_fold_cross_validation(merged_train, k,␣
↪K_folds)

                #Applying the SGD for Calculating the matrix P and Q using a␣
↪hyperparameter combination
                p, q, train_rmse, validation_rmse =␣
↪learn_latent_factors(merged_train, validation, lamda, alpha, l_k)

                #Adding the Training and Validation RMSE
                average_train_rmse += train_rmse[-1]
                average_validation_rmse += validation_rmse[-1]

            #Averaging the values for Train and Validation RMSE
            average_train_rmse, average_validation_rmse = average_train_rmse/
↪K_folds, average_validation_rmse/K_folds

            #Printing the Output of RMSE for selected Hyperparameter Combination
            print('Hyperparameter Selected: ')
            print('Lambda: {}\tAlpha: {}\tLatent Features: {}'.format(lamda,␣
↪alpha, l_k))
            print('Training RMSE: {}\tValidation RMSE: {}\n'.
↪format(average_train_rmse, average_validation_rmse))

            #Saving the calculated RMSE in the list of both Training and␣
↪Validation
            hyperparameters_train_rmse[index_l,index_a,index_lk] =␣
↪average_train_rmse
            hyperparameters_validation_rmse[index_l,index_a,index_lk] =␣
↪average_validation_rmse
```

```
Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.005    Latent Features: 10
```

```
Training RMSE: 2.868509893658427        Validation RMSE: 2.9597379940278317

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.005    Latent Features: 20
Training RMSE: 3.342494949756881        Validation RMSE: 3.426598602951947

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.005    Latent Features: 30
Training RMSE: 3.6669460422303857       Validation RMSE: 3.7275822539444823

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.003    Latent Features: 10
Training RMSE: 2.6233389226393014       Validation RMSE: 2.72348065261489

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.003    Latent Features: 20
Training RMSE: 3.2864389817621222       Validation RMSE: 3.3727021002841555

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.003    Latent Features: 30
Training RMSE: 3.750172900671404        Validation RMSE: 3.817480761038103

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.001    Latent Features: 10
Training RMSE: 2.458437646820484        Validation RMSE: 2.51997618557773

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.001    Latent Features: 20
Training RMSE: 3.293304418318679        Validation RMSE: 3.366715418916641

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.001    Latent Features: 30
Training RMSE: 3.9002412563875226       Validation RMSE: 3.977953930799921

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.005    Latent Features: 10
Training RMSE: 2.736373374601422        Validation RMSE: 2.830550185541351

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.005    Latent Features: 20
Training RMSE: 3.20244993547063 Validation RMSE: 3.286403732468172

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.005    Latent Features: 30
Training RMSE: 3.3908482812611154       Validation RMSE: 3.4498445597873904

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.003    Latent Features: 10
```

```
Training RMSE: 2.4924098604959584       Validation RMSE: 2.592825962359919

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.003    Latent Features: 20
Training RMSE: 3.1436635614832955       Validation RMSE: 3.2291171435295105

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.003    Latent Features: 30
Training RMSE: 3.474573512313772        Validation RMSE: 3.542423211713325

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.001    Latent Features: 10
Training RMSE: 2.380917903078778        Validation RMSE: 2.4444837319566686

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.001    Latent Features: 20
Training RMSE: 3.1564327820813505       Validation RMSE: 3.2308621391027303

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.001    Latent Features: 30
Training RMSE: 3.6973659274472945       Validation RMSE: 3.775103542152378

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.005    Latent Features: 10
Training RMSE: 2.645282438520627        Validation RMSE: 2.7380224819409738

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.005    Latent Features: 20
Training RMSE: 3.034819788659462        Validation RMSE: 3.1202311240426512

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.005    Latent Features: 30
Training RMSE: 3.1882769363770995       Validation RMSE: 3.247268782831602

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.003    Latent Features: 10
Training RMSE: 2.363905106792751        Validation RMSE: 2.462203321638701

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.003    Latent Features: 20
Training RMSE: 3.0188006023682847       Validation RMSE: 3.1057964678622327

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.003    Latent Features: 30
Training RMSE: 3.2893276953753534       Validation RMSE: 3.355826853021143

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.001    Latent Features: 10
```

```
Training RMSE: 2.2769188343833044        Validation RMSE: 2.3355294300340343

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.001    Latent Features: 20
Training RMSE: 3.0163392379154494        Validation RMSE: 3.0984016342988783

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.001    Latent Features: 30
Training RMSE: 3.5067156353032347        Validation RMSE: 3.5857673503648924
```

Computing the Validation RMSE

Finding the Best Hyperparameter Combination

[24]:
```python
#Finding the index containing the minimum RMSE
i,j,k = np.where(hyperparameters_validation_rmse ==␣
 ↪hyperparameters_validation_rmse.min())

#Printing the Results
print('Best Hyperparameter with the Minimum Validation RMSE:')
print('Lambda: {}\tAlpha: {}\tLatent Features: {}'.format(lamdas[i.
 ↪item()],alphas[j.item()],latent_k[k.item()]))
print('Validation RMSE: {}'.format(hyperparameters_validation_rmse[i,j,k].
 ↪item()))
```

```
Best Hyperparameter with the Minimum Validation RMSE:
Lambda: 0.3     Alpha: 0.001    Latent Features: 10
Validation RMSE: 2.3355294300340343
```

Computing the Test RMSE

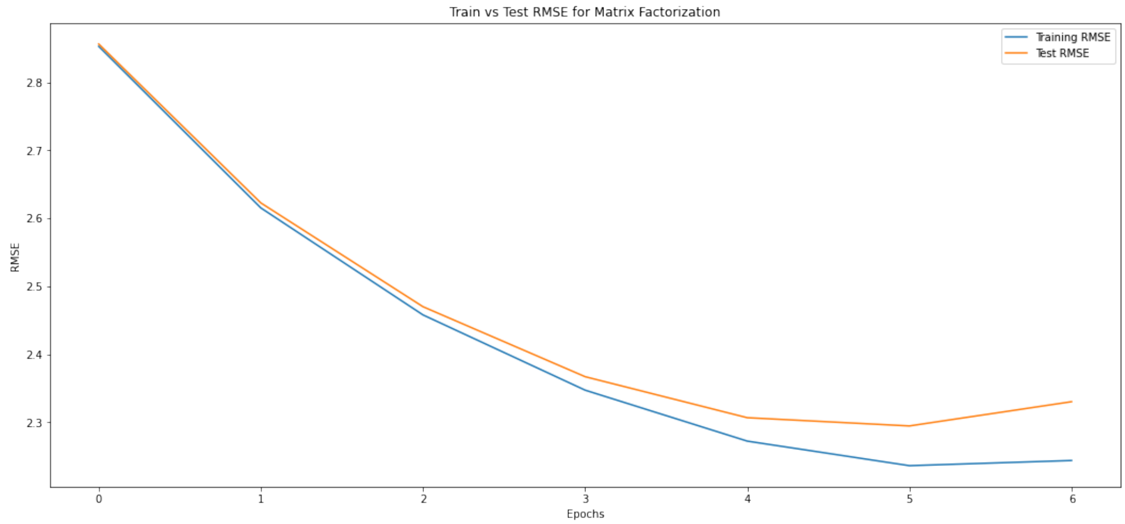
[25]:
```python
#Performing Matrix Factorization on the Test Dataset with Best Combination of␣
 ↪Hyperparameters
best_lamda, best_alpha, best_latent_k = lamdas[i.item()], alphas[j.item()],␣
 ↪latent_k[k.item()]
p, q, train_rmse, test_rmse = learn_latent_factors(merged_train, merged_test,␣
 ↪best_lamda, best_alpha, best_latent_k)
print('The Test RMSE: {}'.format(test_rmse[-1]))
```

```
The Test RMSE: 2.3302891774428147
```

Plotting the Training RMSE vs Test RMSE for each Epochs

[26]:
```python
fig = plt.figure(figsize=(18,8))
plt.plot([i for i in range(len(train_rmse))], train_rmse, label='Training RMSE')
plt.plot([i for i in range(len(test_rmse))], test_rmse, label='Test RMSE')
plt.title('Train vs Test RMSE for Matrix Factorization')
plt.xlabel('Epochs')
plt.ylabel('RMSE')
```

```
plt.legend()
plt.show()
```



0.0.4 Exercise 3: Recommender Systems using matrix factorization sckitlearn

Performing the Hyperparameter Optimization using Grid Search

[27]:
```
#Initializing a matrix for storing the training RMSE for each Hyperparameter␣
↪combination
hyperparameters_train_rmse = np.zeros(shape=(len(lamdas),len(latent_k)))

#Initializing a matrix for storing the Validating RMSE for each Hyperparameter␣
↪combination
hyperparameters_validation_rmse = np.zeros(shape=(len(lamdas),len(latent_k)))
```

[28]:
```
#Iterating for all values of Lambdas
for index_l, lamda in enumerate(lamdas):

    #Iterating for all values of Latent Features
    for index_lk, l_k in enumerate(latent_k):

        #Initializing the average Training and Validating RMSE for each K fold
        average_train_rmse, average_validation_rmse = 0 , 0

        #Iterating for all values of K fold
        for k in range(K_folds):

            #Splitting the training dataset into Train and Validation using K␣
↪fold Cross validation
```

```
            train, validation = k_fold_cross_validation(merged_train, k,␣
↪K_folds)

            #Using Sklearn NMF function to Matrix Factorization
            model = NMF(init='random',n_components = l_k, alpha=lamda,␣
↪random_state=random_seed)

            #Extracting matrix W after fitting the Training Rating Matrix
            W = model.fit_transform(extract_rating_matrix(train))

            #Extracting matrix H after fitting the Training Rating Matrix
            H = model.components_

            #Adding the Training and Validation RMSE
            average_train_rmse += rmse(extract_rating_matrix(train), W, H)
            average_validation_rmse += rmse(extract_rating_matrix(validation),␣
↪W, H)

        #Averaging the values for Train and Validation RMSE
        average_train_rmse, average_validation_rmse = average_train_rmse/
↪K_folds, average_validation_rmse/K_folds

        #Printing the Output of RMSE for selected Hyperparameter Combination
        print('Hyperparameter Selected: ')
        print('Lambda: {}\tAlpha: {}\tLatent Features: {}'.format(lamda, alpha,␣
↪l_k))
        print('Training RMSE: {}\tValidation RMSE: {}\n'.
↪format(average_train_rmse, average_validation_rmse))

        #Saving the calculated RMSE in the list of both Training and Validation
        hyperparameters_train_rmse[index_l,index_lk] = average_train_rmse
        hyperparameters_validation_rmse[index_l,index_lk] =␣
↪average_validation_rmse
```

```
Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.001    Latent Features: 10
Training RMSE: 0.6455496004386772       Validation RMSE: 0.5209734831178708

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.001    Latent Features: 20
Training RMSE: 0.6261437430899222       Validation RMSE: 0.5438638955517104

Hyperparameter Selected:
Lambda: 0.1     Alpha: 0.001    Latent Features: 30
Training RMSE: 0.6109459061417086       Validation RMSE: 0.5647186020802145

Hyperparameter Selected:
```

```
Lambda: 0.2     Alpha: 0.001    Latent Features: 10
Training RMSE: 0.6455410880933105       Validation RMSE: 0.5208110910569509

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.001    Latent Features: 20
Training RMSE: 0.6261731256168357       Validation RMSE: 0.543679951253973

Hyperparameter Selected:
Lambda: 0.2     Alpha: 0.001    Latent Features: 30
Training RMSE: 0.6110123444640454       Validation RMSE: 0.5642144169255127

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.001    Latent Features: 10
Training RMSE: 0.6455446309854551       Validation RMSE: 0.5206179302358835

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.001    Latent Features: 20
Training RMSE: 0.6261767517512596       Validation RMSE: 0.5435347118224222

Hyperparameter Selected:
Lambda: 0.3     Alpha: 0.001    Latent Features: 30
Training RMSE: 0.6109843575875654       Validation RMSE: 0.5640316855817946
```

Computing the Validation RMSE

Finding the Best Hyperparameter Combination

[29]:
```
#Finding the index containing the minimum RMSE
i,j = np.where(hyperparameters_validation_rmse ==␣
 ↪hyperparameters_validation_rmse.min())

#Printing the Results
print('Best Hyperparameter with the Minimum Validation RMSE:')
print('Lambda: {}\tLatent Features: {}'.format(lamdas[i.item()],latent_k[j.
 ↪item()]))
print('Validation RMSE: {}'.format(hyperparameters_validation_rmse[i,j].item()))
```

```
Best Hyperparameter with the Minimum Validation RMSE:
Lambda: 0.3     Latent Features: 10
Validation RMSE: 0.5206179302358835
```

Computing the Test RMSE

[30]:
```
#Performing Matrix Factorization on the Test Dataset with Best Combination of␣
 ↪Hyperparameters
test_model = NMF(init='random',n_components = 10, alpha=0.3,␣
 ↪random_state=random_seed)
```

```python
#Extracting matrix W after fitting the Training Rating Matrix
W = test_model.fit_transform(extract_rating_matrix(merged_test))

#Extracting matrix H after fitting the Training Rating Matrix
H = test_model.components_
```

[31]:
```python
print('Test RMSE: {}'.format(rmse(extract_rating_matrix(merged_test), W, H)))
```

```
Test RMSE: 0.27566461477377874
```

From the above results, we can see that the RMSE of the Test set from my implementation of SGD came out to be around 2.33 whereas the RMSE of Test set from the Sklearn implementation of NMF came out to be 0.27, which is a huge improvement.Furthermore, I also observes that the time taken to run every epoch was also very large as compared to the Sklearn implementation which makes it more interesting.