Google Colab Setup

Only for users on Google Colab

In [1]:
```python
# Define functions to connect to Google and change directories
def connectDrive():
    from google.colab import drive
    drive.mount('/content/drive', force_remount=True)

def changeDirectory(path):
    import os
    original_path = os.getcwd()
    os.chdir(path)
    new_path = os.getcwd()
    print("Original path: ",original_path)
    print("New path: ",new_path)

# Connect to Google Drive
#connectDrive()

# Change path
#changeDirectory("/content/drive/My Drive/github/handson-unsupervised-learni
```

Setup

In [1]:
```
'''Main'''
import numpy as np
import pandas as pd
import os, time, re
import pickle, gzip, datetime
from datetime import datetime
from zipfile import ZipFile
from urllib.request import urlretrieve

'''Data Viz'''
import matplotlib.pyplot as plt
import seaborn as sns
color = sns.color_palette()
import matplotlib as mpl

%matplotlib inline

'''Data Prep and Model Evaluation'''
from sklearn import preprocessing as pp
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import log_loss
from sklearn.metrics import precision_recall_curve, average_precision_score
from sklearn.metrics import roc_curve, auc, roc_auc_score, mean_squared_erro

'''Algos'''
import lightgbm as lgb

'''TensorFlow and Keras'''
import tensorflow as tf
from tensorflow import keras
K = keras.backend

from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Activation, Dense, Dropout
from tensorflow.keras.layers import BatchNormalization, Input, Lambda
from tensorflow.keras.layers import Embedding, Flatten, dot
from tensorflow.keras import regularizers
from tensorflow.keras.losses import mse, binary_crossentropy
```

Check library versions & set seed

In [2]:
```
import sys, sklearn
print(f'sklearn    {sklearn.__version__}')
print(f'tensorflow {tf.__version__}')
print(f'keras      {keras.__version__}')
print(f'numpy      {np.__version__}')
```

```
sklearn    1.3.2
tensorflow 2.4.1
keras      2.4.0
numpy      1.20.0
```

In [3]:
```
# To make the output stable across runs
tf.random.set_seed(42)
np.random.seed(42)
```

In [4]:
```
# Check use of GPU
if tf.test.gpu_device_name():
    print('Default GPU Device: {}'.format(tf.test.gpu_device_name()))
else:
   print("Please install GPU version of TF, if GPU is available.")
```

```
Default GPU Device: /device:GPU:0
```

Data Preparation

MovieLens Dataset

MovieLens 20M Dataset	
ratings	20,000,263
movies	27,278
users	138,493

Load the Data

```
 Note: you can just read data directrly
 pd.read_pickle(current_path + "/datasets/ml-20m/ratingReducedPickl
e")
```

In [6]:
```
# Download and read into Pandas DataFrame
current_path = os.getcwd()
urlretrieve("http://files.grouplens.org/datasets/movielens/ml-20m.zip", \
            current_path+"/datasets/movielens.zip")
ZipFile(current_path+"/datasets/movielens.zip", "r").extractall(current_path
```

In [9]:
```
current_path = os.getcwd()
ratingDF = pd.read_csv(current_path+"/datasets/ml-20m/ratings.csv")
```

In [10]:
```
# Convert fields into appropriate data types
ratingDF.userId = ratingDF.userId.astype(str).astype(int)
ratingDF.movieId = ratingDF.movieId.astype(str).astype(int)
ratingDF.rating = ratingDF.rating.astype(str).astype(float)
ratingDF.timestamp = ratingDF.timestamp.apply(lambda x: \
                        datetime.utcfromtimestamp(x).strftime('%Y-%m-%d %H:%
```

In [8]:
```python
# Store DataFrame as pickle for faster loading in the future
ratingDF.to_pickle(current_path+"/datasets/ml-20m/ratingPickle")
ratingDF = pd.read_pickle(current_path+"/datasets/ml-20m/ratingPickle")
```

In [11]:
```python
# Preview data
ratingDF.head()
```

Out[11]:

	userId	movieId	rating	timestamp
0	1	2	3.5	2005-04-02 23:53:47
1	1	29	3.5	2005-04-02 23:31:16
2	1	32	3.5	2005-04-02 23:33:39
3	1	47	3.5	2005-04-02 23:32:07
4	1	50	3.5	2005-04-02 23:29:40

In [12]:
```python
ratingDF.describe()
```

Out[12]:

	userId	movieId	rating
count	2.000026e+07	2.000026e+07	2.000026e+07
mean	6.904587e+04	9.041567e+03	3.525529e+00
std	4.003863e+04	1.978948e+04	1.051989e+00
min	1.000000e+00	1.000000e+00	5.000000e-01
25%	3.439500e+04	9.020000e+02	3.000000e+00
50%	6.914100e+04	2.167000e+03	3.500000e+00
75%	1.036370e+05	4.770000e+03	4.000000e+00
max	1.384930e+05	1.312620e+05	5.000000e+00

In [10]:
```python
# Calculate summary statistics on full dataset
n_users = ratingDF.userId.unique().shape[0]
n_movies = ratingDF.movieId.unique().shape[0]
n_ratings = len(ratingDF)
avg_ratings_per_user = n_ratings/n_users

print(f'Number of unique users: {n_users}')
print(f'Number of unique movies: {n_movies}')
print(f'Number of total ratings: {n_ratings}')
print(f'Average number of ratings per user: {round(avg_ratings_per_user,1)}
```

```
Number of unique users: 138493
Number of unique movies: 26744
Number of total ratings: 20000263
Average number of ratings per user: 144.4
```

In [14]:
```
# Reduce size of dataset : 只取rating分數是屬於TOP 1000的電影的資料列,此時資料
movieIndex = ratingDF.groupby("movieId").count().sort_values(by=
                "rating",ascending=False)[0:1000].index
#有包含這top 1000 movies的資料
ratingDFX2 = ratingDF[ratingDF.movieId.isin(movieIndex)]
ratingDFX2.count() #Count non-NA cells for each column.
```

Out[14]:
```
userId       12840344
movieId      12840344
rating       12840344
timestamp    12840344
dtype: int64
```

In [16]:
```
ratingDFX2
```

Out[16]:

	userId	movieId	rating	timestamp
0	1	2	3.5	2005-04-02 23:53:47
1	1	29	3.5	2005-04-02 23:31:16
2	1	32	3.5	2005-04-02 23:33:39
3	1	47	3.5	2005-04-02 23:32:07
4	1	50	3.5	2005-04-02 23:29:40
...	...	...	...	...
20000243	138493	53996	4.5	2009-12-03 18:31:44
20000249	138493	59315	4.0	2009-10-17 22:22:18
20000252	138493	60069	4.0	2009-11-13 17:51:27
20000258	138493	68954	4.5	2009-11-13 15:42:00
20000261	138493	70286	5.0	2009-11-13 15:42:24

12840344 rows × 4 columns

In [12]:
```
# 接著在從上述表格, 隨機挑出1000 users, 故資料剩下約9萬筆
userIndex = ratingDFX2.groupby("userId").count().sort_values(by=
    "rating",ascending=False).sample(n=1000, random_state=2018).index
ratingDFX3 = ratingDFX2[ratingDFX2.userId.isin(userIndex)]
ratingDFX3.count()
```

Out[12]:
```
userId       90213
movieId      90213
rating       90213
timestamp    90213
dtype: int64
```

In [13]:
```
# Reindex movie ID
movies = ratingDFX3.movieId.unique()
moviesDF = pd.DataFrame(data=movies,columns=['originalMovieId'])
moviesDF['newMovieId'] = moviesDF.index+1
moviesDF.head()
```

Out[13]:

	originalMovieId	newMovieId
0	50	1
1	163	2
2	216	3
3	296	4
4	333	5

In [14]:
```
# Reindex user ID
users = ratingDFX3.userId.unique()
usersDF = pd.DataFrame(data=users,columns=['originalUserId'])
usersDF['newUserId'] = usersDF.index+1
usersDF.head()
```

Out[14]:

	originalUserId	newUserId
0	49	1
1	260	2
2	311	3
3	319	4
4	499	5

In [15]:
```
# Generate newly merged DataFrame
ratingDFX3 = ratingDFX3.merge(moviesDF,left_on='movieId',
                              right_on='originalMovieId')
ratingDFX3.drop(labels='originalMovieId', axis=1, inplace=True)
ratingDFX3 = ratingDFX3.merge(usersDF,left_on='userId',
                              right_on='originalUserId')
ratingDFX3.drop(labels='originalUserId', axis=1, inplace=True)
ratingDFX3.head()
```

Out[15]:

	userId	movieId	rating	timestamp	newMovieId	newUserId
0	49	50	5.0	2013-05-03 02:50:26	1	1
1	49	163	3.5	2013-05-03 02:43:37	2	1
2	49	216	3.0	2013-05-03 02:45:58	3	1
3	49	296	5.0	2013-05-03 02:50:13	4	1
4	49	333	3.0	2013-05-03 02:44:38	5	1

In [16]:
```python
# Save as pickle
pickle_file = os.path.sep.join(['', 'datasets', 'movielens_data', 'ratingRe
ratingDFX3.to_pickle(current_path + "/datasets/ml-20m/ratingReducedPickle")
ratingDFX3 = pd.read_pickle(current_path + "/datasets/ml-20m/ratingReducedP
```

Read dataset

In [7]:
```python
# Download and read into Pandas DataFrame
current_path = os.getcwd()
ratingDFX3 = pd.read_pickle(current_path + "/datasets/ml-20m/ratingReducedP
```

In [21]:
```python
ratingDFX3.head(10)
```

Out[21]:

	userId	movieId	rating	timestamp	newMovieId	newUserId
0	49	50	5.0	2013-05-03 02:50:26	1	1
1	49	163	3.5	2013-05-03 02:43:37	2	1
2	49	216	3.0	2013-05-03 02:45:58	3	1
3	49	296	5.0	2013-05-03 02:50:13	4	1
4	49	333	3.0	2013-05-03 02:44:38	5	1
5	49	475	4.5	2013-05-03 02:45:40	6	1
6	49	527	3.5	2013-05-03 02:49:22	7	1
7	49	593	4.0	2013-05-03 02:51:10	8	1
8	49	610	4.0	2013-05-03 02:46:44	9	1
9	49	785	3.5	2013-05-03 02:44:34	10	1

In [22]:
```python
np.sum(ratingDFX3.isnull(),axis=0)  # or df.isna()
```

Out[22]:
```
userId        0
movieId       0
rating        0
timestamp     0
newMovieId    0
newUserId     0
dtype: int64
```

In [23]:
```python
ratingDFX3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 90213 entries, 0 to 90212
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   userId      90213 non-null  int32
 1   movieId     90213 non-null  int32
 2   rating      90213 non-null  float64
 3   timestamp   90213 non-null  object
 4   newMovieId  90213 non-null  int64
 5   newUserId   90213 non-null  int64
dtypes: float64(1), int32(2), int64(2), object(1)
memory usage: 4.1+ MB
```

In [24]:
```python
ratingDFX3.describe()
#rating 最小值是 0.5
```

Out[24]:

	userId	movieId	rating	newMovieId	newUserId
count	90213.000000	90213.000000	90213.000000	90213.000000	90213.000000
mean	69174.188787	4344.580870	3.625896	400.148748	490.860408
std	40122.438358	11066.728397	1.025440	280.464924	283.210360
min	49.000000	1.000000	0.500000	1.000000	1.000000
25%	33512.000000	553.000000	3.000000	139.000000	249.000000
50%	67793.000000	1380.000000	4.000000	364.000000	482.000000
75%	103394.000000	3072.000000	4.000000	615.000000	725.000000
max	138172.000000	81845.000000	5.000000	1000.000000	1000.000000

In [25]:
```python
# Calculate summary statistics on reduced dataset
n_users = ratingDFX3.userId.unique().shape[0]
n_movies = ratingDFX3.movieId.unique().shape[0]
n_ratings = len(ratingDFX3)
avg_ratings_per_user = n_ratings/n_users

print(f'Number of unique users: {n_users}')
print(f'Number of unique movies: {n_movies}')
print(f'Number of total ratings: {n_ratings}')
print(f'Average number of ratings per user: {round(avg_ratings_per_user,1)}
```

```
Number of unique users: 1000
Number of unique movies: 1000
Number of total ratings: 90213
Average number of ratings per user: 90.2
```

In [26]:
```python
# Split into validation and test, such that each is 5% of the dataset
X_train, X_test = train_test_split(ratingDFX3, test_size=0.10, \
                                   shuffle=True, random_state=2018)
X_valid, X_test = train_test_split(X_test,     test_size=0.50, \
                                   shuffle=True, random_state=2018)
```

In [27]:
```python
# Confirm size of train, validation, and test datasets
for (l,x) in [('train',X_train),('validation',X_valid),('test',X_test)]:
    print(f'Size of {l} set: {len(x)}')
```

```
Size of train set: 81191
Size of validation set: 4511
Size of test set: 4511
```

```python
X_train
```

row[5] row[6]

	userId	movieId	rating	timestamp	newMovieId	newUserId
77796	118358	2918	4.0	2005-03-17 13:11:50	725	841
20109	48345	1907	3.0	2003-01-26 05:32:21	345	347
61046	25880	74458	4.0	2010-11-21 09:47:32	75	180
58074	73713	39	4.0	1999-02-07 05:07:01	465	522
77706	117584	590	4.0	1996-09-11 08:24:35	255	831
...	...	...	...	...	...	...

X.itertuples()

ratings_train[840][724]=4.0

In [28]:
```python
# Generate ratings matrix for train, validation and test
ratings_train = np.zeros((n_users, n_movies))
ratings_valid = np.zeros((n_users, n_movies))
ratings_test  = np.zeros((n_users, n_movies))
for (X,ratings) in [(X_train,ratings_train),(X_valid,ratings_valid),(X_test
    for row in X.itertuples(): #itertuples:pandas datqframe中取出列
        ratings[row[6]-1, row[5]-1] = row[3]
```

In [29]:
```python
X_train
```

Out[29]:

	userId	movieId	rating	timestamp	newMovieId	newUserId
77796	118358	2918	4.0	2005-03-17 13:11:50	725	841
20109	48345	1907	3.0	2003-01-26 05:32:21	345	347
61046	25880	74458	4.0	2010-11-21 09:47:32	75	180
58074	73713	39	4.0	1999-02-07 05:07:01	465	522
77706	117584	590	4.0	1996-09-11 08:24:35	255	831
...	...	...	...	...	...	...
10388	27131	52	5.0	2000-07-03 18:02:48	634	195
40092	108946	2028	4.0	2001-01-31 05:48:49	57	769
84745	32312	5299	4.0	2005-03-27 06:42:32	380	243
80098	93974	508	5.0	2003-01-20 07:06:12	39	654
60006	7934	1210	5.0	2011-09-21 19:02:01	138	61

In [36]:
```
ratings_train[840][724]
```
Out[36]:
```
4.0
```
In [45]:
```
ratings_train[0][:50]
```
Out[45]:
```
array([5. , 3.5, 0. , 5. , 3. , 4.5, 3.5, 4. , 4. , 3.5, 2.5, 0. , 3. ,
       4. , 4. , 4. , 3. , 4. , 4.5, 3. , 3.5, 4. , 3.5, 4. , 4. , 3.5,
       4. , 4. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
       0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ])
```
In [37]:
```
ratings_train.shape, ratings_valid.shape, ratings_test.shape
```
Out[37]:
```
((1000, 1000), (1000, 1000), (1000, 1000))
```
In [38]:
```
# Calculate the sparsity of the train, validation & test rating matrices
def calc_sparsity(label, ratings):
    sparsity = float(len(ratings.nonzero()[0]))
    sparsity /= (ratings.shape[0] * ratings.shape[1])
    sparsity *= 100
    print('{:s} Sparsity: {:4.2f}%'.format(label, sparsity))
```
In [39]:
```
for (lbl, rtg) in [('Train',ratings_train),('Validation',ratings_valid),('Te
    calc_sparsity(lbl,rtg)
```
```
Train Sparsity: 8.12%
Validation Sparsity: 0.45%
Test Sparsity: 0.45%
```
Perform Baseline Experiments

In [131]:
```
ratings_valid.shape
```
Out[131]:
```
(1000, 1000)
```

In [132]:

```
ratings_valid[0]
```

```
Out[132]: array([0., 0., 3., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.])
```

In [133]:
```
ratings_valid.nonzero()
```
Out[133]:
```
(array([  0,   1,   1, ..., 998, 998, 998], dtype=int64),
 array([  2,  35,  36, ..., 966, 968, 985], dtype=int64))
```
In [134]:
```
# Flatten the sprace matrix with the rations for the validation set. This w
#numpy.nonzero():returns two arrays,
#The first array represents the row indices where the non-zero elements are
#The second array represents the column indices where the non-zero elements
actual_valid = ratings_valid[ratings_valid.nonzero()].flatten()
```
In [135]:
```
actual_valid
```
Out[135]:
```
array([3., 1., 3., ..., 3., 3., 4.])
```
In [136]:
```
len(actual_valid)
```
Out[136]:
```
4511
```
Experiment One

Assign naive 3.5 rating and calculate baseline MSE

比較的基準是你對於電影評價的預測評價和他實際上對此電影的評價

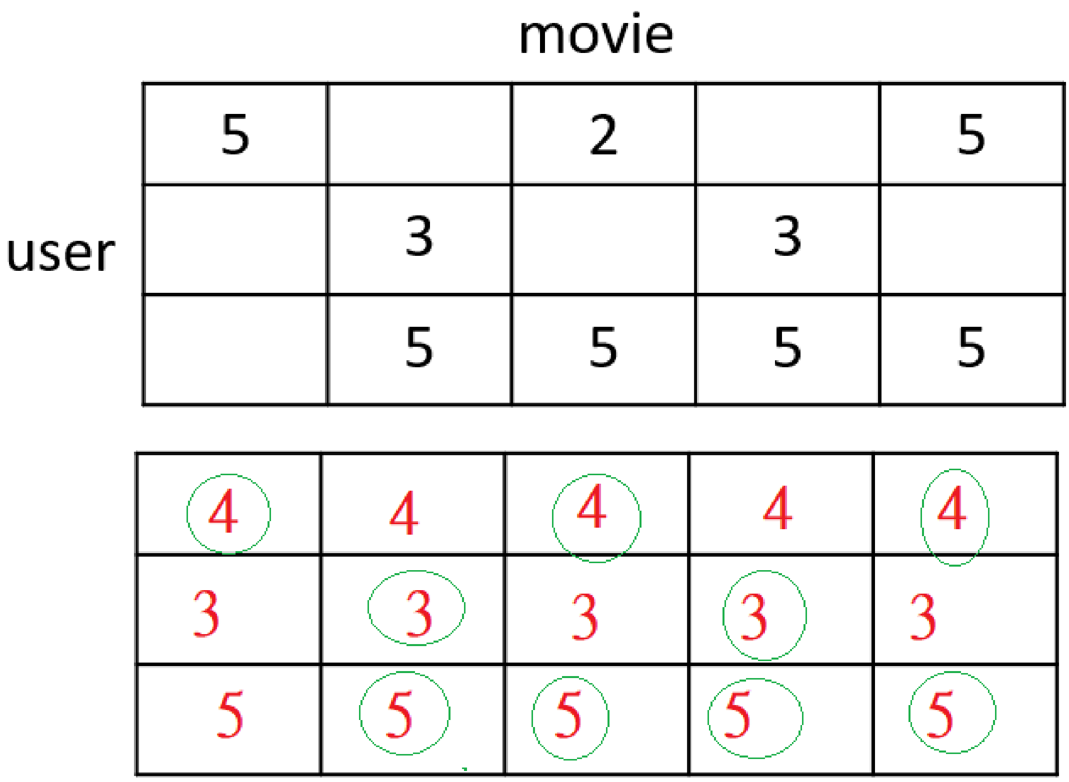
In [137]:
```
pred_valid = np.zeros((len(actual_valid),1))
```
In [138]:
```
pred_valid.shape
```
Out[138]:
```
(4511, 1)
```
In [139]:
```
pred_valid
```
Out[139]:
```
array([[0.],
       [0.],
       [0.],
       ...,
       [0.],
       [0.],
       [0.]])
```
In [140]:
```
pred_valid[pred_valid==0]=3.5
```

In [141]:
```
pred_valid
```
Out[141]:
```
array([[3.5],
       [3.5],
       [3.5],
       ...,
       [3.5],
       [3.5],
       [3.5]])
```

In [121]:
```
naive_prediction = mean_squared_error(pred_valid, actual_valid)
print(f'Mean squared error using naive prediction: {round(naive_prediction,
```
```
Mean squared error using naive prediction: 1.06
```

Experiment Two

Predict a user's rating based on user's average rating for all other movies



In [153]:
```
ratings_train.shape
```
Out[153]:
```
(1000, 1000)
```

In [154]:
```python
ratings_train
```

Out[154]:
```
array([[5. , 3.5, 0. , ..., 0. , 0. , 0. ],
       [4. , 0. , 0. , ..., 0. , 0. , 0. ],
       [5. , 3. , 0. , ..., 0. , 0. , 0. ],
       ...,
       [0. , 4. , 0. , ..., 0. , 0. , 0. ],
       [4. , 2. , 1.5, ..., 0. , 0. , 0. ],
       [0. , 0. , 0. , ..., 0. , 0. , 0. ]])
```

In [159]:
```python
ratings_valid_pred = np.zeros((n_users, n_movies))
print(ratings_valid_pred.shape)
```

```
(1000, 1000)
```

In [160]:
```python
ratings_valid_pred
```

Out[160]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

In [162]:
```python

i = 0
for row in ratings_train:  #ratings_valid_pred 每個人對其沒有看過的電影都設成
    ratings_valid_pred[i][ratings_valid_pred[i]==0] = np.mean(row[row>0])
    #ratings_valid_pred[i][ratings_valid[i]==0] = np.mean(row[row>0])
    i += 1

#比較的基準是你對於電影評價的預測評價和他實際上對此電影的評價
#故只取ratings_valid_pred中屬於ratings_valid有評價的電影出來和actual_valid做比
pred_valid = ratings_valid_pred[ratings_valid.nonzero()].flatten()



user_average = mean_squared_error(pred_valid, actual_valid)
print(f'Mean squared error using user average: {round(user_average,3)}')
```

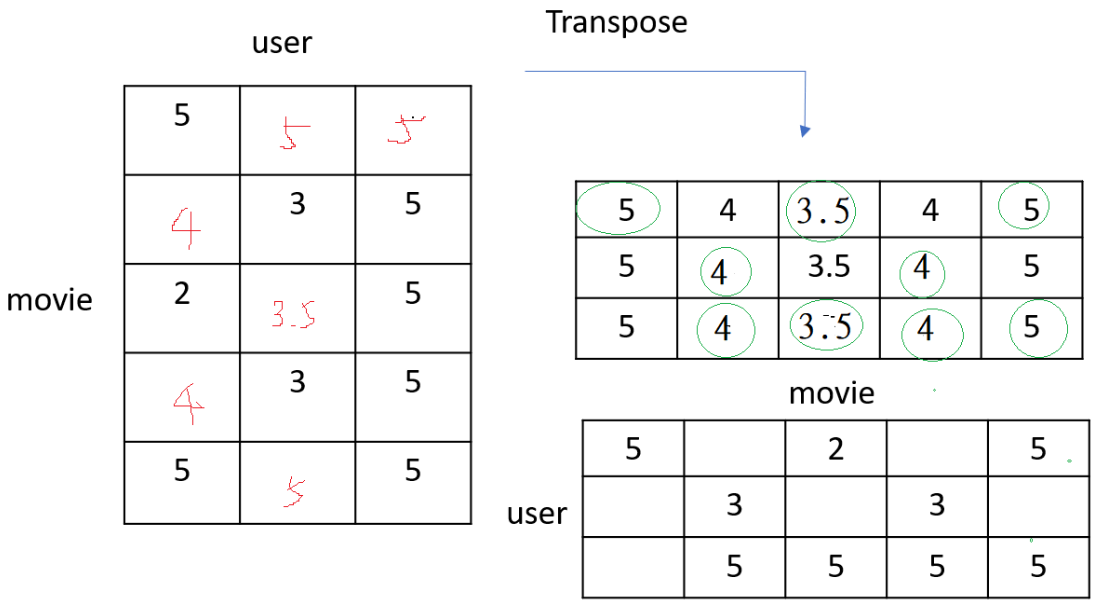
```
Mean squared error using user average: 0.909
```

In [96]:
```python
ratings_valid_pred
```

Out[96]:
```
array([[4.32291667, 3.45108696, 3.37      , ..., 0.        , 4.04166667,
        3.77777778],
       [4.32291667, 3.45108696, 3.37      , ..., 4.13235294, 4.04166667,
        3.77777778],
       [0.        , 3.45108696, 3.37      , ..., 4.13235294, 4.04166667,
        3.77777778],
       ...,
       [4.32291667, 3.45108696, 3.37      , ..., 4.13235294, 4.04166667,
        3.77777778],
       [4.32291667, 3.45108696, 3.37      , ..., 4.13235294, 4.04166667,
        3.77777778],
       [4.32291667, 3.45108696, 3.37      , ..., 4.13235294, 4.04166667,
        3.77777778]])
```

Experiment Three

Predict a user's rating for a movie based on the average rating other users have given that movie

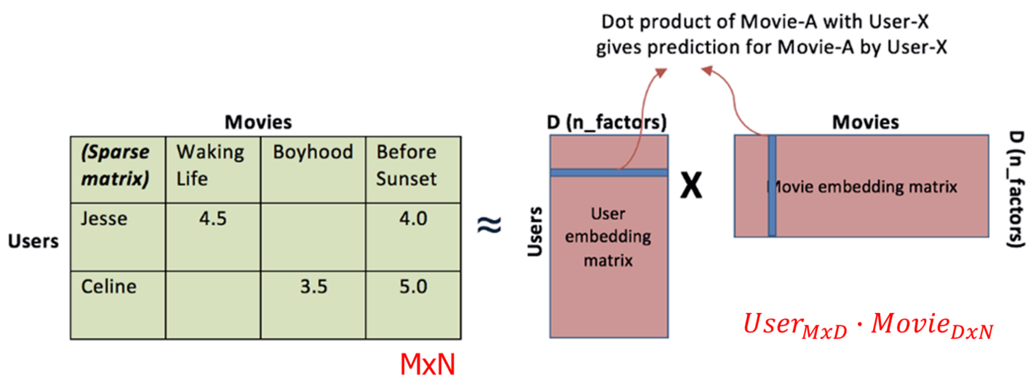



```
In [147]: ratings_valid_pred = np.zeros((n_users, n_movies)).T
i = 0
for row in ratings_train.T:
    ratings_valid_pred[i][ratings_valid_pred[i]==0] = np.mean(row[row>0])
    i += 1

ratings_valid_pred = ratings_valid_pred.T
pred_valid = ratings_valid_pred[ratings_valid.nonzero()].flatten()
movie_average = mean_squared_error(pred_valid, actual_valid)
print(f'Mean squared error using movie average: {round(movie_average,3)}')
```

```
Mean squared error using movie average: 0.914
```

Matrix Factorization

Experiment Four - Recommender System using Matrix Factorization



One Latent Factor

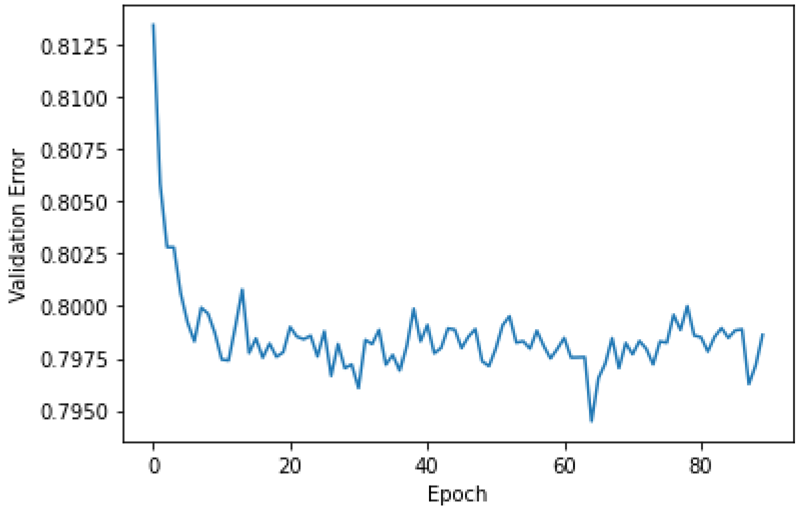
In [29]:
```
n_latent_factors = 1

user_input = Input(shape=[1], name='user')
user_embedding = Embedding(input_dim=n_users + 1,
                           output_dim=n_latent_factors,
                           name='user_embedding')(user_input)
user_vec = Flatten(name='flatten_users')(user_embedding)

movie_input = Input(shape=[1], name='movie')
movie_embedding = Embedding(input_dim=n_movies + 1,
                            output_dim=n_latent_factors,
                            name='movie_embedding')(movie_input)
movie_vec = Flatten(name='flatten_movies')(movie_embedding)

product = dot([movie_vec, user_vec], axes=1)
model = Model(inputs=[user_input, movie_input], outputs=product)
model.compile('adam', 'mean_squared_error')
```

In [30]:
```
history = model.fit(x=[X_train.newUserId, X_train.newMovieId],
                    y=X_train.rating, epochs=100,
                    validation_data=([X_valid.newUserId, X_valid.newMovieId]
                    verbose=1)
```

```
2538/2538 [==============================] - 11s 4ms/step - loss: 0.7227
- val_loss: 0.7980
Epoch 62/100
2538/2538 [==============================] - 11s 4ms/step - loss: 0.7306
- val_loss: 0.7991
Epoch 63/100
2538/2538 [==============================] - 11s 4ms/step - loss: 0.7203
- val_loss: 0.7995
Epoch 64/100
2538/2538 [==============================] - 11s 4ms/step - loss: 0.7275
- val_loss: 0.7983
Epoch 65/100
2538/2538 [==============================] - 11s 4ms/step - loss: 0.7273
- val_loss: 0.7983
Epoch 66/100
2538/2538 [==============================] - 11s 4ms/step - loss: 0.7293
- val_loss: 0.7980
Epoch 67/100
2538/2538 [==============================] - 11s 4ms/step - loss: 0.7246
- val_loss: 0.7988
```

In [31]:
```
pd.Series(history.history['val_loss'][10:]).plot(logy=False)
plt.xlabel("Epoch")
plt.ylabel("Validation Error")
print(f"Minimum MSE: {round(min(history.history['val_loss']),3)}")
```

```
Minimum MSE: 0.794
```



Experiment Five - Recommender System using Matrix Factorization

Three Latent Factor

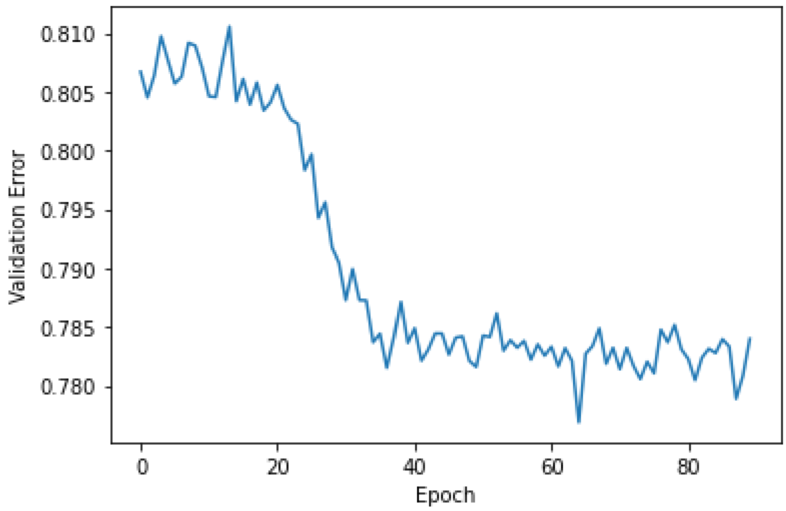
In [32]:
```
n_latent_factors = 3

user_input = Input(shape=[1], name='user')
user_embedding = Embedding(input_dim=n_users + 1,
                           output_dim=n_latent_factors,
                           embeddings_regularizer=regularizers.l1(10e-7),
                           name='user_embedding')(user_input)
user_vec = Flatten(name='flatten_users')(user_embedding)

movie_input = Input(shape=[1], name='movie')
movie_embedding = Embedding(input_dim=n_movies + 1,
                            output_dim=n_latent_factors,
                            embeddings_regularizer=regularizers.l1(10e-7),
                            name='movie_embedding')(movie_input)
movie_vec = Flatten(name='flatten_movies')(movie_embedding)

product = dot([movie_vec, user_vec], axes=1)
model = Model(inputs=[user_input, movie_input], outputs=product)
model.compile('adam', 'mean_squared_error')
```

In [33]:
```python
history = model.fit(x=[X_train.newUserId, X_train.newMovieId],
                    y=X_train.rating, epochs=100,
                    validation_data=([X_valid.newUserId, X_valid.newMovieId]
                    verbose=1)
```

```
Epoch 33/100
2538/2538 [==============================] - 13s 5ms/step - loss: 0.7270
- val_loss: 0.8026
Epoch 34/100
2538/2538 [==============================] - 13s 5ms/step - loss: 0.7224
- val_loss: 0.8023
Epoch 35/100
2538/2538 [==============================] - 13s 5ms/step - loss: 0.7146
- val_loss: 0.7983
Epoch 36/100
2538/2538 [==============================] - 13s 5ms/step - loss: 0.7226
- val_loss: 0.7997
Epoch 37/100
2538/2538 [==============================] - 14s 5ms/step - loss: 0.7157
- val_loss: 0.7942
Epoch 38/100
2538/2538 [==============================] - 13s 5ms/step - loss: 0.7065
- val_loss: 0.7956
Epoch 39/100
2538/2538 [==============================] - 13s 5ms/step - loss: 0.7091
```

In [34]:
```python
pd.Series(history.history['val_loss'][10:]).plot(logy=False)
plt.xlabel("Epoch")
plt.ylabel("Validation Error")
print(f"Minimum MSE: {round(min(history.history['val_loss']),3)}")
```

```
Minimum MSE: 0.777
```



Conclusion

In [ ]:
```python
import datetime as dt
print("Completed: ", dt.datetime.now())
```