Mining massive Datasets WS 2017/18

Problem Set 4

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Exercise 04

a) Load the data into Spark (RDD), converting each row into Ratings3 data structure. Split your dataset through random sample, 50% into training and the remaining 50% into test data.

   `siehe U5_Ex4.py`

b) Use the Spark Mlib implementation of the Alternating Least Squares (ALS)4to train the ratings. Train your model using 10 latent factors and 5 iterations. Save the model to disk after training and submit the serialized model as part of the solution.

   `look into folder "./serialized/"`

c) Predict the ratings of the test data and estimate the prediction quality through Mean Squared Error (MSE). Submit the obtained MSE as part of the solution.

   ```
   siehe U5_Ex4.py
   Mean Squared Error = 1.4089626800206299
   ```

Exercise 05

Study the code of Albert Au Yeung for matrix factorization by GD (see slide ?References? on lecture 06).

a) Apply it to the utility matrix used in lecture 06 (slide "Recall: Utility Matrix"). Do you obtain the same matrices Q and P as shown in the lecture (slide "Latent Factor Models")? Submit as solutions your matrices Q, P and the full matrix R.

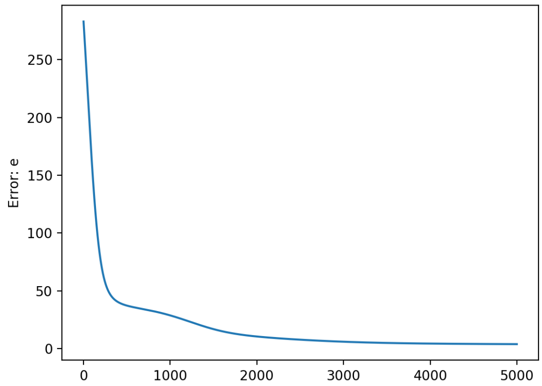
   ```
   Utility Matrix:
   [[1 0 3 0 0 5 0 0 5 0 4 0]
    [0 0 5 4 0 0 4 0 0 2 1 3]
    [2 4 0 1 2 0 3 0 4 3 5 0]
    [0 2 4 0 5 0 0 4 0 0 2 0]
    [0 0 4 3 4 2 0 0 0 0 2 5]]
   ```

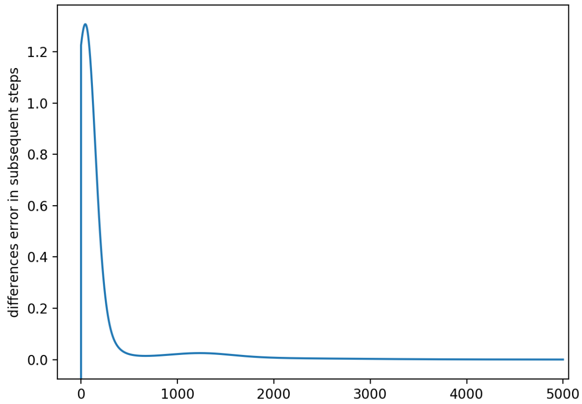
```
 [1 0 3 0 3 0 0 2 0 0 4 0]]

P_Items_x_Features:
[[ 1.16482079  2.10927657  0.33377973]
 [-0.36529105  1.82670981  1.7490211 ]
 [ 2.23435165  0.99895337  0.16300664]
 [ 0.26892799  1.78827864  1.44666862]
 [ 0.98234642  0.65571352  1.81046416]
 [ 1.47180934  1.33842574  0.58534001]]
Q_Users_x_Features:
[[ 0.85874813  1.50577869  0.27737099 -0.06739603  0.20751181  0.61557246
   0.63068878 -0.12666912  0.97616569  0.93279814  1.78547743  1.98452877]
 [-0.15083256  0.59195287  1.04037346  0.96010801  1.2641353   1.97523311
   1.4244988   1.34004677  1.7287707   0.8344548   0.97725507  0.95529413]
 [ 0.4779314   0.34549956  1.67081246  1.29957806  1.71812591  0.07752532
   0.93788975  1.00716243  0.55460263  0.46795842 -0.1407221   1.22489854]]
New_Utility_Matrix:
[[ 0.84166392  3.1178754   3.07520619  2.38040184  3.48160063  4.9092209
   4.05234994  3.01515283  4.96862874  3.00283366  4.09409229  4.7354462 ]
 [ 0.24669178  1.13556468  4.72142554  4.05144734  5.23844462  3.51890801
   4.01214994  4.25569602  3.77138951  2.0020331   0.88681659  3.16248796]
 [ 1.84597661  4.01209113  1.93138243  1.02035656  2.00653249  3.36120825
   2.98507066  1.21979504  3.99846265  2.99406083  4.94267806  5.58809602]
 [ 0.65261913  1.9633461   4.35218243  3.57887476  4.80199072  3.80996529
   4.07382633  3.81934242  4.15636822  2.42007398  2.024191    4.01404971]
 [ 1.60996287  2.49286238  3.97960742  2.91618905  4.14336446  2.04024927
   3.25163377  2.5776853   3.09659938  2.31071615  2.13998442  4.79352892]
 [ 1.34178771  3.21073882  2.77869321  1.9465342   3.00305687  3.5950868
   3.3838239   2.19665276  4.07519209  2.76367158  3.85349543  4.91642036]]

  No we don't get the same results as in the lecture.
```

b) Modify the code so that the error e is stored (or printed after each iteration), and plot the error over iterations (for matrix in a)), as well as the differences of the error in subsequent steps. Plot:





Note: More information in file: Error_Values.txt

c) Bonus, 3 points: In this code the learning rate "alpha" is a constant (alpha = 0.0002). How could you change the code to speed up the convergence? Explain your idea and implement your solution. There are several aproaches to this problem:

- 1. One is to set alpha to a value and divide it by the number of data (alpha/N)
- 2. Another one is the "Bold Driver" method where the alpha is changed in every iteration. If the error decreases you have to increase the alpha learning rate. If the error value increases (because we jumped over a minima) then you go 1 iteration back and decrease the learning-rate alpha.
- 3. Another: where you start with a "big" alpha and decrease it in every iteration with a appropriate value

  My Idea is Option (2) implementation code:
  look into: U5_Ex5_mod.py