## Problem Set 1 for lecture Mining Massive Datasets

Due October 28, 2024, 23:59 CET

In this problem set you should use as computational libraries only NumPy, SciPy, Pandas, or Polars (whatever is necessary). Do not use JAX, PyTorch, TensorFlow etc. (except for Exercise #4, details are provided below). Of course, you should implement the main code yourself, i.e. calling a function from a library for recommendation systems to 'solve' an exercise is not allowed. Submit the complete source code including run setups and logs of the output from unit tests/test runs. It is recommended to use a git repository for the development (but submit only the final source files, not the repository).

Exercise 1 (1 point)

Complete the blanks in the file cf\_algorithms\_to\_complete.py located on the GitHub repository. These blanks are indicated by the function named complete\_code. Check the correctness of your code by executing the provided Colab script.

Exercise 2 (3 points)

Implement centered cosine distance for sparse matrices and sparse vectors.

- a) Implement functions to calculate centered cosine similarity of vector-vector pairs and matrix-vector pairs which accept sparse data as inputs. The functions should be named centered\_cosine\_sim and fast\_centered\_cosine\_sim (latter for a sparse matrix and vector). You might use the library scipy.sparse or other.
- b) Write unit tests (one or more) for each function. In particular, test the function centered\_cosine\_sim using the following input data
  - vector  $\mathbf{x} = [x_0, x_1, ..., x_i, ..., x_{k-1}]$
  - vector\_y =  $[y_0, y_1, ..., y_i, ..., y_{k-1}]$
  - $y_j = x_i$  with i + j = k 1

Test the function with

- **b.1)**  $k = 100, x_i = i + 1$
- **b.2)** k = 100

If  $i \in [c, c+10, c+20, c+30, ..., c+90]$  with c = [2, 3, 4, 5, 6], then  $x_i$  is NaN; otherwise,  $x_i = i+1$ .

Exercise 3 (3 points)

Rewrite the code in the file cf\_algorithms\_to\_complete.py (after filling blanks) to support sparse utility matrices (UMs), using the functions implemented in Exercise #2. This means that the function rate\_all\_items in the file cf\_algorithms\_to\_complete.py should accept a sparse UM after rewriting. Consider that you need to preprocess data differently, in particular you should keep only a sparse version of the UM um\_movielens in memory. Let your code report the size of this matrix (similarly as in the provided routine read\_movielens\_file\_and\_convert\_to\_um). Implement a unit test which compares the results against the dense original version.

Exercise 4 (5 points)

Write code which processes the MovieLens 25M data set and creates data structures (e.g. Python shelves) rated\_by[] and user\_col[] described in Lecture 2. Your implementation should keep the usage of RAM reasonably low (in particular, do not load all input data at once). Note that the contents of the data structure user\_col[] should be sparse vectors (use data structures compatible with those in Exercise #2).

In this exercise, you can use the routine load\_movielens\_tf provided in data\_util.py in the GitHub repository to load the dataset (and so as an exception, you may use the library TensorFlow Datasets).

Exercise 5 (4 points)

Perform the following tasks:

- a) Implement a function for estimating rating of user x on item i via collaborative filtering, using functions implemented in Exercises #3 and #4.
- b) Run the function on the following user-item pairs and report the results:

Pair no.	1	2	3	4	5	6	7	8	9	10
userID	828	2400	3765	4299	5526	6063	7045	8160	9682	10277
movieID	11	4725	1270	4020	2432	4525	4100	6300	1212	7355

c) Compute and report the maximum memory usage of your rating function (to simplify, you might use the size of the whole Python process) for each of the 6 first user-item pairs from the above table (restart your script each time).