2020 Line recruit test

Models

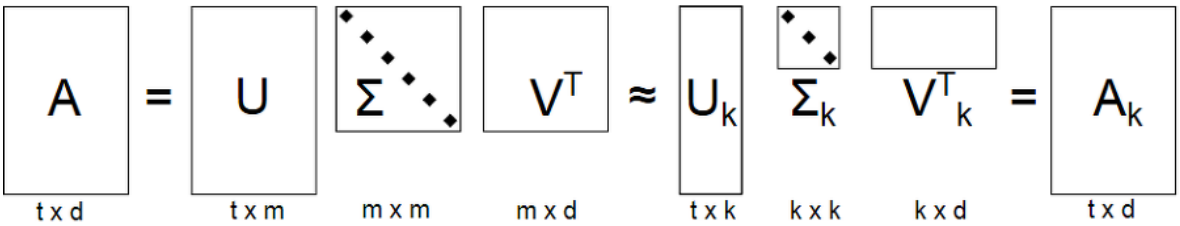
Matrix Factorization

In matrix factorization the goal is to estimate matrix $X \in R^{I \times J}$ containing the ratings given by a user i to a movie j, using a matrix decomposition method called Singular Value Decomposition(SVD).

Collaborative Filtering is a method of making automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users (collaborating). The underlying assumption of the collaborative filtering approach is that if a person *A* has the same opinion as a person *B* on an issue, A is more likely to have B's opinion on a different issue than that of a randomly chosen person.

Simply **SVD** is to decompose a matrix of $m \times n$ into three matrices(U, Σ, V) as shown below. First, Use the SVD to create a matrix of user matrix(U), property matrix(Σ) and movie matrix(V) using given movie ratings.

If you do this, we can get diagonal matrix(Σ) which can called features. Using the computed U, V, and key features of Σ, can create approximate of original matrix. So, we can predict undefined values, using created U, $Sigma$ and V.



Implementations

Python is a simple language that is easy enough to understand directly. So it's not difficult to see and understand the code right away. But here are tips for Python beginners.

`lib.recommender.Recommender`

Default recommender class. You can choose which algorithm to use for the recommender system, but only `factorization` (implement of *Matrix Factorization Techniques for Recommender Systems*) is currently implemented.

`models.factorization`

This class is basically written in both `Python` and `Cython`. This is because the matrix operation takes too long, so increase the calculation efficiency using `Cython`. *If `Cython` is not installed, run `Python` backend automatically.*

Notice By default, `.py` and `.pyx` code is supposed to do the same. This is a function for operate acceleration when `Cython` is supported, and if the library is not found, the same result is configured to run in just python. The details of the code may differ slightly due to computational efficiency or `Cython` constraints, but as a result, they perform the same.

This class accepts parameters **factors**, **epochs**, **init_mean**, **init_derivation**, **learning_rate**, **regression_rate**.

And, there are two methods. Simply, `fit` create feature matrix and `predict` return predicted value using created feature matrix.

- `fit`

  Train with train data. Create `bias` and `param` of each user, item. `unique` is indexer to compress given data. Calculate `dot` and `error` to update `bias` and `param`. `lr` and `reg` is rate of update values.

  Calculate current errors at *line 65-66*.

  ```
  dot = sum(param_item[i, f] * param_user[u, f] for f in range(self.factors))
  err = r - (mean + biase_user[u] + biase_item[i] + dot)
  ```

  Update `bias` parts at *line 69-70*.

  ```
  biase_user[u] += self.lr * (err - self.reg * biase_user[u])
  biase_item[i] += self.lr * (err - self.reg * biase_item[i])
  ```

  Update `param` parts at *line 73-74*.

  ```
  param_user[u] += self.lr * (err * param_item[i] - self.reg * param_user[u])
  param_item[i] += self.lr * (err * param_user[u] - self.reg * param_item[i])
  ```

- `predict`

  Return prediction value which create using `bias` and `param` matrix.

Requirements

- NumPy: is the fundamental package for scientific computing with Python.
- tqdm: is make loops show a smart progress meter.

Optional

- Cython: support compiled language, generates `Cython` extension modules, accelerate computing performance.

install packages using pip

```
pip install -r requirements.txt
```

Tested @ python3.7 in Ubuntu 18.04 LTS, macOS Catalina and Windows 10 (WSL2)

Run process

First of all, If you want to using `Cython` build it as follow:

```
python setup.py build_ext --inplace
```

And run main script using divided into train and test dataset. Before that, split train and test dataset using `scripts/split.py`. Below scripts generate `dataset1_train/test.csv`, `dataset2_train/test.csv` and `tiny_train/test.csv` in `./data/dataset` directory. Also you can split dataset different condition using `--axis` and `--split` parameters (See also file docstring and help message).

```
python scripts/split.py --dataset ./data/ml-20m/ratings.csv --result
./data/dataset

python main.py --train ./data/dataset/dataset1_train.csv --test
./data/dataset/dataset1_test.csv --result ./result.csv
```

Or using whole dataset directory with hard-coded condition (first, second, tiny). **First** and **second** condition corresponds to given `Dataset 1` and `Dataset 2`. **Tiny** is used for quick experimentation.

- **first** (train: *1104505203 <= timestamp <= 1230735592*, test: *1230735600 <= timestamp <= 1262271552*)
- **second** (train: *timestamp <= 1388502016*, test: *1388502017 <= timestamp*)
- **tiny** (train: *1104505203 <= timestamp <= 1104555203*, test: *1230735600 <= timestamp <= 1230755600*)

```
python main.py --dataset [dataset_directory (./data/ml20m)] --mode [first,
second, tiny]
```

Performance (supplementary)

Parameter search using `./scripts/parameter_search.py` and `./data/search.json`.

- best: *0.906* in **Dataset 1** (`./B_results_DS1.csv`).
- best: *0.945* in **Dataset 2** (`./B_results_DS2.csv`).

To reproduce results, append below parameters when run `main.py`.

- Dataset 1: `--factor 50 --epoch 20 --mean .0 --dev .05 --lr .005 --reg .02`
- Dataset 2: `--factor 100 --epoch 20 --mean .0 --dev .01 --lr .005 --reg .02`

Dataset 1

- train (timestamp condition between 1104505203 and 1230735592, 5187587 rows)
- test (timestamp condition between 1230735600 and 1262271552, 930093 rows)

Error	Factor	Epoch	Mean	Dev	Lr	Reg
0.9062965664	50	20	0	0.05	0.005	0.02
0.9064882695	1000	20	0	0.001	0.005	0.02
0.9066755623	100	10	0	0.05	0.01	0.02
0.9069686128	100	20	0	0.001	0.005	0.02
0.907114876	150	150	0	0.1	0.001	0.05
0.9074043211	150	100	0	0.05	0.001	0.05
0.9077045023	100	20	0	0.1	0.005	0.02
0.9077125512	25	100	0	0.1	0.001	0.01
0.9082157874	200	100	0	0.2	0.005	0.05
0.908252472	150	100	0	0.1	0.01	0.05
0.9090876701	100	100	0	0.1	0.005	0.1
0.909943722	25	20	0	0.2	0.005	0.01
0.9103295262	50	20	0	0.1	0.005	0.1
0.9110503496	150	10	0	0.2	0.005	0.05
0.9113505705	150	20	0	0.1	0.005	0.01
0.9131840053	150	200	0	0.1	0.0001	0.02
0.9131874063	200	10	0	0.1	0.01	0.01
0.9141151526	150	150	0	0.05	0.0001	0.02
0.9143238066	1024	256	0	0.001	0.001	0.001
0.9150647162	25	100	0	0.05	0.0001	0.05

Dataset 2

- train (timestamp condition under 1388502016, 19152913 rows)
- test (timestamp condition over 1388502017, 847350 rows)

Error	Factor	Epoch	Mean	Dev	Lr	Reg
0.9447267353	100	20	0	0.01	0.005	0.02
0.9455785902	100	20	0	0.001	0.005	0.01
0.9458027524	100	20	0	0.1	0.005	0.02
0.9459471339	100	20	0	0.001	0.005	0.02
0.947802059	100	20	0	0.005	0.005	0.05
0.9538850398	2048	32	0	0.01	0.001	0.05
0.9548304784	100	20	0	0.001	0.005	0.001
0.9577116744	100	20	0	0.005	0.001	0.001
0.9584485671	100	20	0	0.005	0.001	0.05
0.9590505826	100	20	0	0.01	0.001	0.02
0.9593056715	100	20	0	0.005	0.001	0.01
0.9607800371	100	20	0	0.001	0.001	0.02
0.9615054369	100	20	0	0.001	0.001	0.01
0.9653931637	2048	32	0	0.01	0.0001	0.01
0.9653997554	256	32	0	0.1	0.0001	0.05
0.9665724879	2048	20	0	0.001	0.0001	0.05
0.966572501	100	20	0	0.005	0.0001	0.05
0.9672215359	100	20	0	0.01	0.0001	0.02
0.9674862554	100	20	0	0.001	0.0001	0.01
0.967486467	100	20	0	0.01	0.0001	0.01