Recommender Systems

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I. Introduction

A. Domain

A recommender system (RS) seeks to predict the 'rating' that a user would given to an item. They rose to prominence after the publicity of the Netflix Prize [1], which sought to improve recommendations on Netflix's platform by 10%.

There are many flavours of RS: content-based, collaborative, knowledge-based, context-aware, *e.t.c*. This coursework is concerned with context-aware recommender systems (CARS).

A context is *"any information useful to characteristize the situation of an entity (e.g. a user or an item) that can affect the way users interact with systems"* [**?**]. User preferences, and therefore ratings, may differ from one context to another. Context types include physical, social, and modal (i.e. pertaining to mood).

B. Related work review

RS are increasingly well studied. The seminal paper on context-aware recommender systems (CARS) was *Matrix F*

C. Purpose / aim

The purpose of this coursework is to develop a CARS. The focus is on the implementation and evaluation, rather than performance, of the system.

II. Methods

A. Data type, source

The dataset used is `MusicMicro` [2].

Talk about user data considered, item data considered, and context select.

As the `MusicMicro` dataset is rather limited, the only available context is *physical*. The phyiscal context comprises spatiotemporal data such as time, location, activity, and environmental conditions.

Importantly, songs are not assigned *ratings*, per se. The 'rating' is binary: whether a song was listened to or not. The problem is therefore one of classification, rather than regression.

Only the top 100 most active users - those with the most recommendations - were used in order to constrain the time taken to calculate recommendations.

This has the side-effect of negating the 'cold start' problem. As the focus of this coursework is on CARS, rather than tackling this problem, this was deemed an acceptable simplification of the problem.

[1] https://netflixprize.com/

[2] http://www.cp.jku.at/datasets/musicmicro/index.html

B. Feature extraction and selection methods

I suppose this becomes a matter of pre-processing

C. User profiling and prediction methods

Prediction uses singular value decomposition (SVD), with the number of latent factors $k = 25$. SVD seeks to decompose a ratings matrix R into two singular value matrices, V and Q, such that R

User profiling is simple. The top 10 recommendations are presented to the user.

D. Evaluation methods

III. Implementation

A. Recommendation algorithm

The recommendation algorithm used is Context-Aware Matrix Factorisation (CAMF). There are three varieties of CAMF:

- CAMF-C: a parameter for each contextual condition
- CAMF-CC: a parameter for each contextual condition and item category
- CAMF-CI: a parameter for each contextual condition and item

CAMF-CC was found to offer superior results, but there is no clear categorisations in the `MusicMicro` dataset. CAMF-CI was found to take a prohibitively long time to train, so CAMF-C was used instead.

B. Output (recommendations / predictions) presentation

Recommendations are displayed on a simple website originally developed for the Software, Systems and Applications III Web Technology submodule. This application uses Python, Flask, and Bootstrap in a much more user-friendly format than a simple CLI.

The physical context is easy to implicitly retrieve. In this instance, the user's IP address is used to calculate location, and temporal information can be similarly easily obtained. Drop-downs are provided to allow user selection of contextual conditions for testing.

User characteristics are by and large irrelevant. With no frame of reference in the original dataset, it is impossible to learn contextual parameters for fields such as age or device used.

IV. Evaluation results

Mean absolute error (MAE) was calculated as 0.219 using:

$$\frac{1}{|\tau|}\sum_{(u,i)\in\tau} |\hat{r}_{ui} - r_{ui}|$$

MAE *with* context ($\mathrm{MAE_B}$) was calculated as 0.048, a reduction of over 78%, using:

$$\frac{1}{|\tau|}\sum_{(u,i)\in\tau}|\hat{r}_{ui} - r_{ui} - \sum_{j=1}^{k} B_{jc_j}|$$

Code for these calculations may be found in `benchmark.py`.

And accuracy of usage predictions (precision, recall)

V. Conclusion

A. Limitations

Many of the limitations in this coursework are due to the simplicity of the dataset. This was a deliberate choice. The code written is robust, extensible, and could easily be adapted to another dataset. This coursework is intended to demonstrate how CAMF-C, rather than the nuances of the data itself. That said, it is worth highlighting the following:

- SVD is only performed once. WIth a limited dataset, and a constrained number of users (100), it is possible to perform SVD live, after every user rating, to update recommendations appropriately. However, without the functionality for users to rate songs, doing so is pointless.
- Contextual information is limited. A consequence of the dataset. In [**?**], the music dataset is evaluated using 8 contextual factors and 27 contextual conditions. In this coursework, the inclusion of countries increased the number of contextual conditons to approximately 35, with only 4 contextual factors: `weekend`, `season`, `month`, and `country`. Even so, results show a marked decrease in MAE.

B. Further developments

This coursework could be extended by comparing the three varieties of CAMF. The UI could also be expanded, with functionality allowing a user to rate tracks. The use of a more complex dataset - such as `#nowplaying-RS` [3] - would allow the exploration of more complex contexts such as mood.

References

[1] G. Eason, B. Noble, and I. N. Sneddon, “On certain integrals of Lipschitz-Hankel type involving products of Bessel functions,” Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955.

[2] J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[3] I. S. Jacobs and C. P. Bean, “Fine particles, thin films and exchange anisotropy,” in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[4] K. Elissa, “Title of paper if known,” unpublished.

[5] R. Nicole, “Title of paper with only first word capitalized,” J. Name Stand. Abbrev., in press.

[6] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, “Electron spectroscopy studies on magneto-optical media and plastic substrate interface,” IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].

[7] M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

[3]https://zenodo.org/record/3248543#.XlelyG52vxB