THE UNIVERSITY OF SYDNEY

Personalised Job Recommendation on Mobile Devices

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SUMMARY

- **Implemented various personalisation algorithms on a large job data set in the context of mobile devices. A hybrid approach of collaborative filtering and content based recommendation achieved twice the precision of recommending a job that would be viewed in comparison to collaborative filtering.**

BACKGROUND

- **User model** – preferences, beliefs and/or characteristics that a user exhibits which can then be used by applications to provide a more personalised experience.
- **Personalisation** - is the process of tailoring relevant information, in this case jobs, to a user based on their user model.

MOTIVATION

- **Privacy** - all user models for the majority of job websites are stored online on the server in a central location. This may cause concern as users are unaware of the what the data is being used for, or how vulnerable it is to attacks.
- **Personalisation of jobs** – jobs that are recommended are not random like they appear in a newspaper, personalisation will provide jobs that are useful to the user based on past feedback.
- **No constant network connection** - Server-side personalisation, as seen on many job listing websites, require a constant connection as the server produces the recommendations, however moving the personalisation to the client-side enables the mobile device to be not as reliant on the server (it will still require to download job lists).
- **Usability** – studies show [1] that users have short attention spans when using mobile device applications. The recommendation algorithm must be efficient in executing within the resources available by the device. Too slow and the application will be unusable.

AIM

What recommendation techniques are more precise in retrieving relevant job listings to the user whilst constrained by the limited hardware imposed by the mobile device?

CONTENT BASED

Content based (CB) filtering is used to generate job recommendations based on the attributes of the jobs the user has provided explicit feedback towards. A user model is produced by iterating though every job the user has provided feedback to and adjusting various weights assigned to features based on what jobs the user likes/dislikes. The user model is then used to compare against other unseen jobs to determine whether they exhibit the job features that they have indicated interest towards (see figure 1).

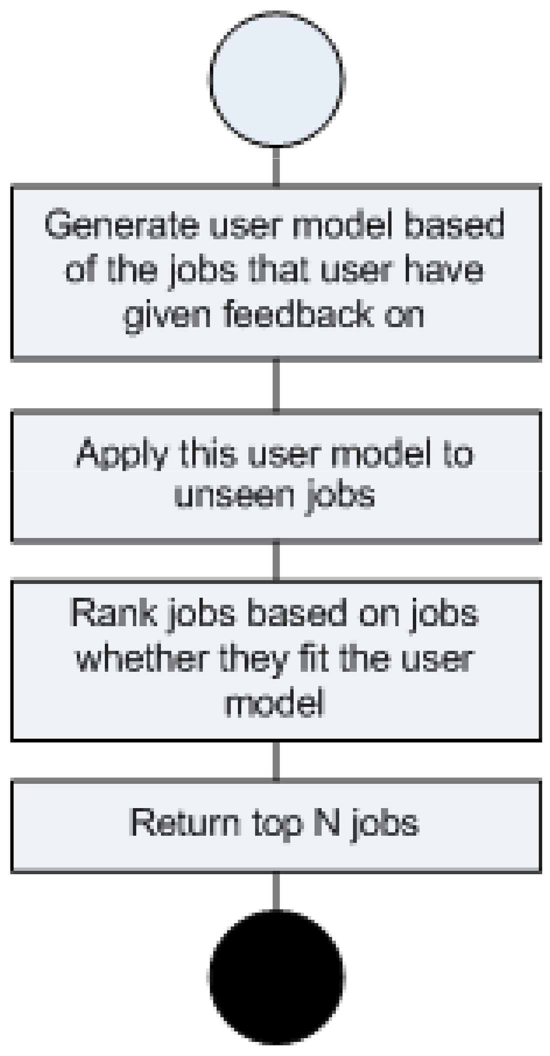

Figure 1: Content Based

This method requires no external information from other users and is ideal in terms of reducing privacy concerns among users. However, comparing the developed user model against a significant list of unseen jobs may prove problematic for the mobile device.

COLLABORATIVE FILTERING

Collaborative filtering (CF) is the process of finding patterns in user behavior by using techniques that involve multiple user data. In this algorithm we recommend jobs to a user based on a CF model that is produced over a training set to predict what job a user is likely to view (figure 2).

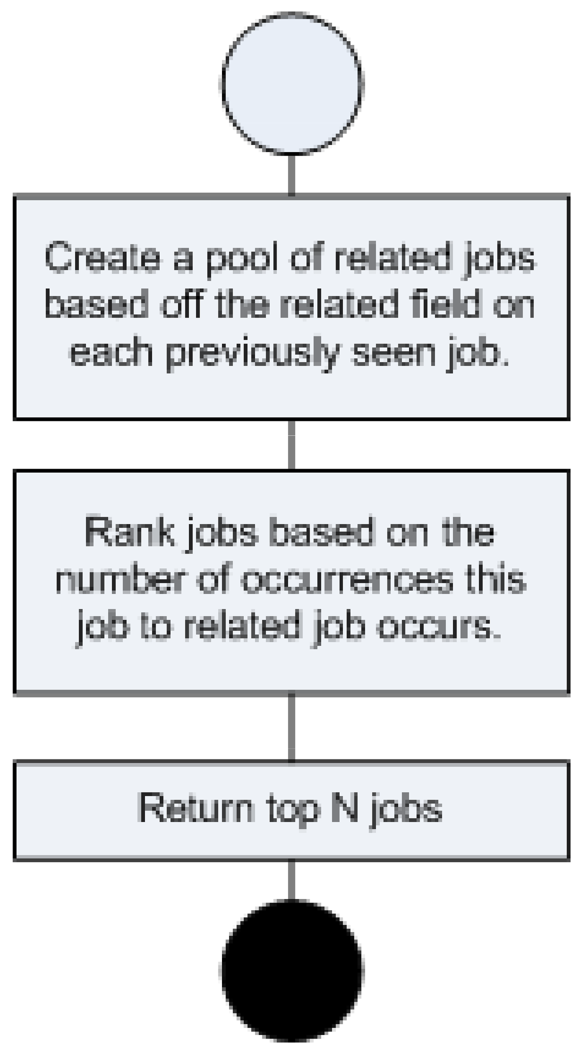

Figure 2: Collaborative Filtering

HYBRID APPROACH

This approach combines the two elements of content based and collaborative filtering. The first step is to get related jobs that the user may be interested in, this was done by using a CF (left side of figure 3). Secondly, generating a user model based of the feedback the user has given to previous jobs and then applying this model to the related jobs returned by the CF (right side of figure 3).

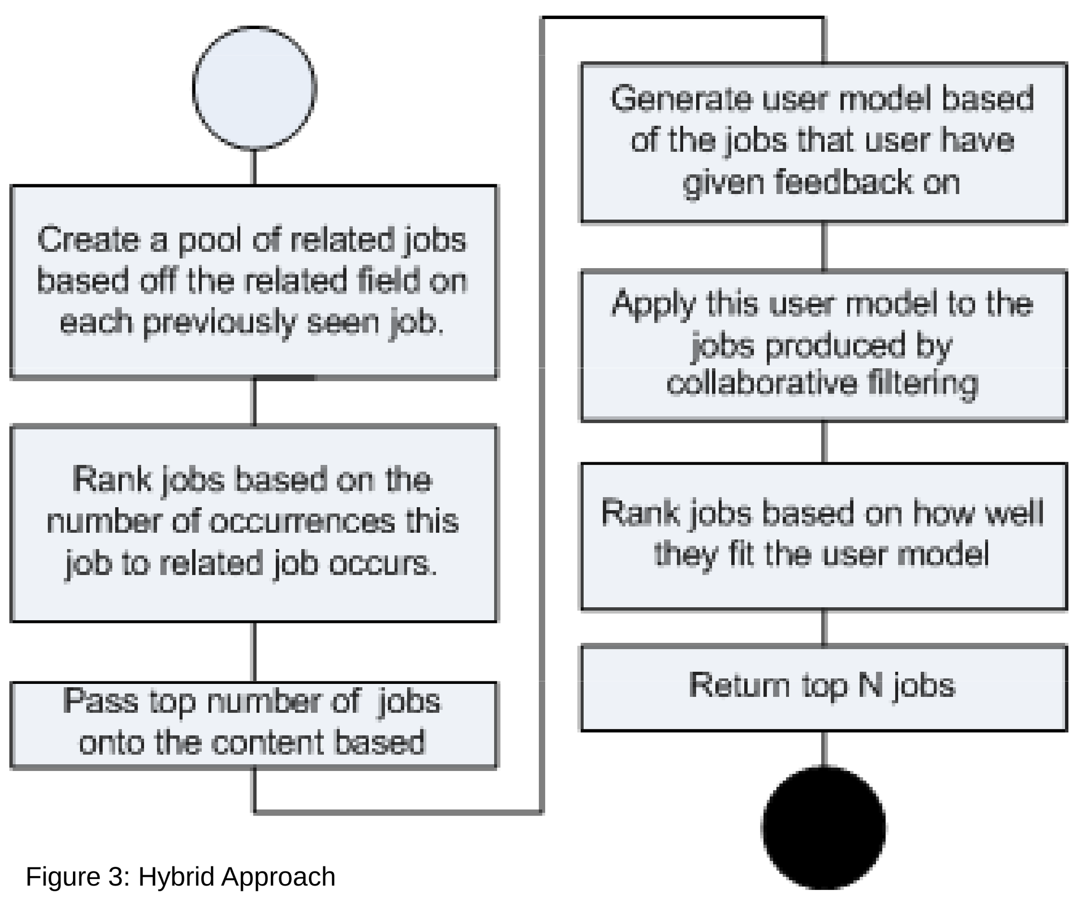

Figure 3: Hybrid Approach

METHOD

In order to test the algorithms, a real world data set containing what users viewed what job was obtained. This data was then split into a ratio of 9:1 for training and testing. This was done multiple times to form different dataset arrangements to ensure validity.

Each algorithm was then able to access the training data and use this to recommend N number of jobs to each user. These recommendations were then compared against the testing set to check whether they were actually seen by the user. If the job was seen by the user, it was deemed a true positive (TP), where on the other hand if a job did not appear it would be a false positive (FP).

This gathered information allows precision to be calculated and used to compare against the other algorithms.

RESULTS & CONCLUSION

The hybrid approach manages to achieve a better average precision than that of the collaborative filtering algorithm.

Top N Jobs	Precision (%)	Standard Dev(%)
1	9.966	0.46
2	8.526	0.33
3	7.525	0.26
4	6.828	0.25
5	6.252	0.24
10	4.747	0.12
20	3.434	0.06
30	2.784	0.03
40	2.385	0.02
50	2.101	0.02

Table 1: Results from Hybrid Approach

Top N Jobs	Precision (%)	Standard Dev(%)
1	4.751	0.03
2	3.883	0.08
3	3.422	0.09
4	3.070	0.08
5	2.775	0.08
10	2.056	0.04
20	1.452	0.02
30	1.169	0.00
40	0.996	0.01
50	0.877	0.01

Table 2: Results from Collaborative Filtering

FUTURE WORK

- Implement into the Career Organiser Android application on a mobile device
- Gather more information from areas beyond the user model to further enhance the personalised experience such as Facebook and Linkedin

REFERENCES

[1] Böhmer, M.; Hecht, B.; Schöning, J.; Krüger, A. & Bauer, G. Falling Asleep with Angry Birds, Facebook and Kindle - A Large Scale Study on Mobile Application Usage. *Proceedings of the 13th International Conference on Human-Computer Interaction with Mobile Devices and Services, ACM,* **2011**