Evaluation of Mahout ItemSimilarity on AWS Elastic MapReduce

Postgraduate Diploma In Information Technology

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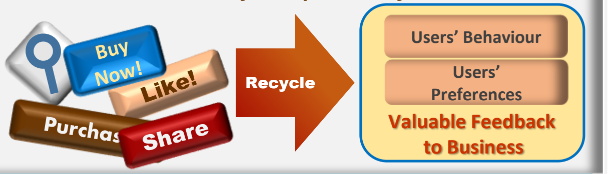
Introduction

- Recommender systems are tools to help people discover preferable items by reusing others' opinions and users' interactions with devices that were previously discarded.
- The motivation of this research is to evaluate an algorithm of the recent recommendation technique in order to provide results that are useful academically and practically.

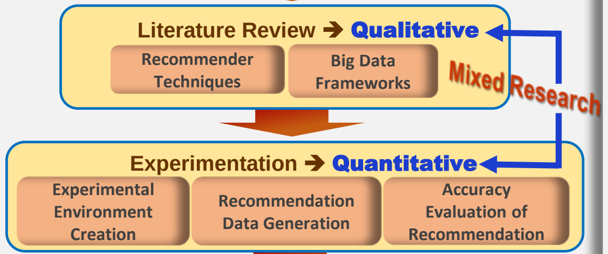


Research Objectives

1. To investigate and identify strengths and limitations of available recommender system techniques and big data frameworks.
2. To provide evaluation results of a recommender system over a big data framework.

Research Questions and Methodology

Q1. What are the strengths and limitations of available recommendation techniques and underlying big data frameworks?



Q2. How effective is the recommender system with Mahout in recommending relevant items over a big data framework?

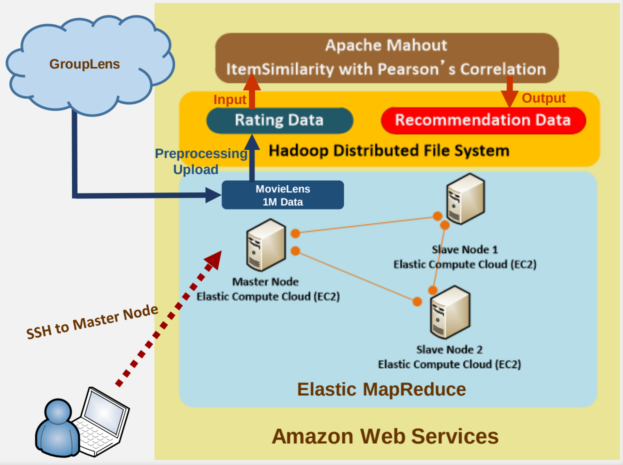
Literature Review of Recommendation Techniques

	Non-personalised	Content-based	User-based Collaborative Filtering	Item-based Collaborative Filtering
Degree of automation	Low (Schafer, Konstan, & Riedl, 1999)	High	High	High
Degree of recommendation transparency	High	High	Low	High
Degree of recommendation novelty	Low	Low (Adomavicius, & Tuzhilin, 2005)	High	High
Has cold start problem for new items	Yes	No (Bobadilla et al, 2012)	Yes (Bobadilla et al, 2012)	Yes (Bobadilla et al, 2012)
Has cold start problem for new users	No	Yes (Adomavicius, & Tuzhilin, 2005)	Yes (Lam, Vu, Le, & Duong, 2008)	No (Bobadilla et al, 2012)
Degree of quality of items recommended	High	Low (Kim et al., 2010)	High (Kim et al., 2010)	High (Kim et al., 2010)
Has matrix sparsity problem	N/A	No	Yes (Anand, & Bharadwaj, 2011)	No (Anand, & Bharadwaj, 2011)

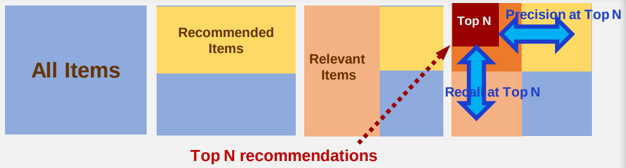
Literature Review of Big Data Frameworks

	MapReduce	Spark
Designed for	Batch processing (Condie et al. 2010)	Real time processing that involves iterative/interactive operation (Zaharia et al. 2012)
In-memory Processing support	No (Zaharia et al. 2012)	Yes (Zaharia et al. 2012)
Intermediate computation results are stored in	Hard disk (Zaharia et al. 2012)	Memory (Zaharia et al. 2012)
Fault tolerance is ensured by	Data duplication (Gu, & Li, 2013)	Backup of computation logic (Zaharia et al. 2012)
Granularity of updates	Fine-grained (Zaharia et al. 2012)	Coarse-grained (Zaharia et al. 2012)
Bottle neck	Frequent disk I/O (Gu, & Li, 2013)	Large memory consumption (Gu, & Li, 2013)
Compatible with Mahout evaluation module	Yes (Apache, n.d.)	No (Apache, n.d.)

Experimental Environment and Recommendation Data Generation



Evaluation of Recommendation Accuracy

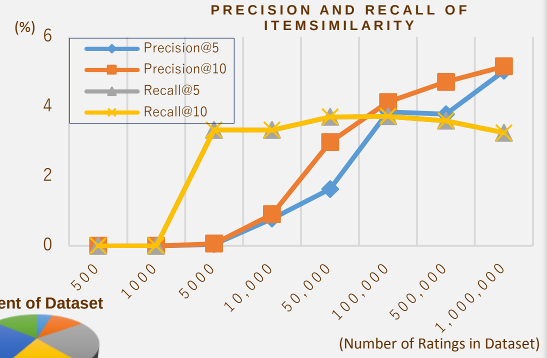


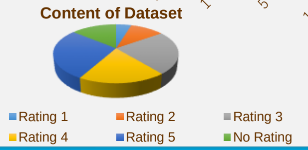
Precision of top N recommendations: The proportion of top N recommendations that are relevant recommendations

Recall of top N recommendations: The proportion of relevant recommendations that are top N recommendations

Results

- Accuracy of algorithm was evaluated by implementing the Mahout evaluation module. The results showed the low precision and recall.
- These results seemed to be caused by the selected algorithm and the content of the dataset used.





Conclusion

- The experimentation results indicated that the Mahout's item-based collaborative filtering, ItemSimilarity with Pearson's correlation similarity algorithm was not effective in recommending relevant items with the particular dataset used in this experimentation.
- Further investigation revealed that precision and recall of Pearson's correlation similarity algorithm seem to be significantly affected by content of datasets.
- The technologies used in recommender systems are still experimental and evolving rapidly to overcome their limitations.

References

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