networks defined on the three sets: users, tags and resources. Recall that a multiplex network is a multi-layer network defined over the same set of nodes but each layer contains a different set of edges. We apply a community detection algorithm to each multiplex in order to compute clusters of users, resources and tags. Different approaches for community detection in multiplex networks can be applied[4], including a) *Layer aggregation* (denoted LA) approaches where we first combine all layers and then apply community detection algorithm to the resulting unipartite network, b) *Ensemble clustering* (denoted EC) approaches where we apply a community detection algorithm to each layer then we combine the obtained clusterings, and c) *Multi-layer approaches* that consist in adapting existing algorithms to the multi-layer nature of multiplex networks [4, 7]. The abstract hypergraph is then constructed by replacing each community of each type by a single abstract node.

3. EXPERIMENTS

We have applied the proposed approach to a real dataset extracted from the *Bibsonomy* folksonomy taken from *HetRec 2011* [2]. We experimented the approach using *FolkRank* as a *base-line* graph-based tag recommender [5]. Two community detection algorithms are selected, the well known *Louvain* approach [1] and a seed-centric approach developed in our team, the *Licod* algorithm [10]. Both algorithms are used in combination with layer aggregation and ensemble clustering and in their respective generalized versions to multi-layer networks : *GenLouvain*[7] and *MuxLicod* [4]. Another two parameters of the approach are the number of abstract tags to recommend and the number of final tags to recommend. We evaluate the results in terms of both precision and execution time. We have varied the number of abstract tags (denoted $k_{clutser}$) (resp. tags (denoted k_{tag})) to recommend from 1 to 4 (most of resources in the dataset have up to 4 tags). Figure 1 shows the obtained results for $k_{tag} = 3$. The proposed approach yields better results than raw FolkRank with different graph-coarsening approaches but the improvement in terms of precision is rather limited. However, obtained execution times show clearly the advantage of the approach (see table 1), where the execution time drops from 1115 s. to 93 s. when using the Muxlicod algorithm. These executions times are computed for the set of 510 queries composing the test set.

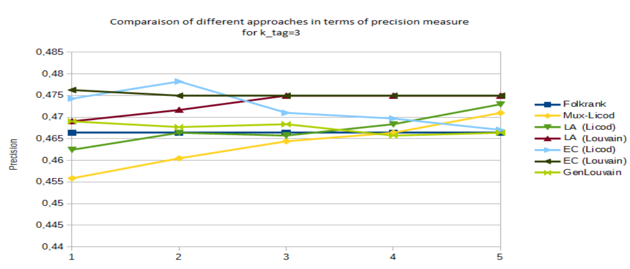

Figure 1: Results in terms of precision for $k_{tag} = 3$

4. CONCLUSION

A graph-coarsening based approach for tag recommendation computation is proposed. The approach yields slightly improved results than raw FolkRank but at much less execution cost. This is a promising result that needs to be confirmed on other datasets and for other basic approaches other than FolkRank. The approach can also be used as a framework for benchamarking and comparing different multiplex community detection algorithms.

Table 1: Global execution time for all testing queries

Approach	Execution Time (second)
Folkrank	1115
MuxLicod	93
GenLouvain	348
EC(Licod)	154
EC(Louvain)	152
LA(Licod)	850
LA(Louvain)	690

5. REFERENCES

[1] V. D. Blondel, J.-l. Guillaume, and E. Lefebvre. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008:P10008, 2008.

[2] I. Cantador, P. Brusilovsky, and T. Kuflik., editors. *2nd workshop on information heterogeneity and fusion in recommender systems (hetrec 2011).*, York, NY, USA, 2011. ACM.

[3] M. Gueye, T. Abdessalem, and H. Naacke:. Strec: An improved graph-based tag recommender. In *RSWeb workshop, RecSys*, 2013.

[4] M. Hmimida and R. Kanawati. Community detection in multiplex networks: A seed-centric approach. *Networks and Heterogeneous Media*, 10(1):71–85, March 2015.

[5] R. Jäschke, L. B. Marinho, A. Hotho, L. Schmidt-Thieme, and G. Stumme. Tag recommendations in folksonomies. In *Knowledge Discovery in Databases: PKDD 2007*, pages 506–514, Warsaw, Poland, 2007.

[6] H.-N. Kim and A. El-Saddik. Personalized pagerank vectors for tag recommendations: inside folkrank. In *ACM conference on Recommender systems*, pages 45–52, 2011.

[7] P. J. Mucha, T. Richardson, K. Macon, M. A. Porter, and J.-P. Onnela. Community structure in time-dependent, multiscale, and multiplex networks. *Science*, 328(5980):876–878, 2010.

[8] S. Papadopoulos, Y. Kompatsiaris, and A. Vakali. A graph-based clustering scheme for identifying related tags in folksonomies. In T. B. Pedersen, M. K. Mohania, and A. M. Tjoa, editors, *DaWak*, volume 6263 of *Lecture Notes in Computer Science*, pages 65–76. Springer, 2010.

[9] M. Pujari and R. Kanawati. Tag recommendation by link prediction based on supervised machine learning. In *Sixth International AAAI Conference on Weblogs and Social Media (ICWSM'2012)*, pages 547–550, Dublin, June 2012.

[10] Z. Yakoubi and R. Kanawati. Licod: Leader-driven approaches for community detection. *Vietnam Journal of Computer Science*, 1(4):241–256, 2014.