Analyzing the influence of homophily on minority ranking in a network using reinforcement learning for recommendations

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Abstract. Homophily is a common effect experienced in many real-world social networks today. Minority group ranking with the effect of homophily has been extensively studied by several researchers over the past years. In today's world most of the social networks connections are formed through recommendation systems. These systems learn global and specific patterns in user behavior to recommend potential network growth opportunities. In recent years, the field of Reinforcement Learning has become very popular for different use-cases, along with recommendation algorithms. In this work we try to analyze how the learning agent which learns to provide recommendations aiding the growth of network is affected by the homophilic behavior of users and how this in turn affects minority ranking in the network. This would help in better understanding network growth and group disparities by showing the effect of a reinforcement learning agent. Our analyses will compare and contrast with popular models used currently for network growth, and try to come up with ways if minority ranking can be improved from an algorithmic point of view.

Keywords: Social Recommender · Homophily · Reinforcement learning

1 Introduction

Recommender systems are a common utility found in all social platforms today. It has become the dominant mechanism through which an individual can get connected to new people, products or events; can expand his/her own knowledge-base, or simply find new avenues for exploration within the given social space. As internet has grown the amount of information content flowing through the space is enormous, and finding relevant information has become a big challenge. Even with information being organized based on content, relevance ranking based on user preference is a big challenge which has been taken up by these recommendation systems [23].Of course this has enhanced the user experience in the platforms considerably and user engagement has been much higher [21, 13].

Research in this field was widely popularized by the Netflix Prize competition [1] in 2006. Much of the research in literature has focused on content recommendation since the business aspect of it is quiet evident. However, another kind of recommendation engines are for recommending users which play a crucial role in the growth of social networks [28, 7, 27]. Today the most popular social network platforms like Facebook, Twitter, Instagram have recommendation agents as "People you may know", "Who to Follow", "Suggested people". Recommender systems in social networks, when suggesting links uses link prediction strategies derived from the network structure. It is unknown how most of the recommender systems work in these social networks, other than that of Twitter as given in their paper [10]. Most social network growth algorithms use friend-of-friend algorithms, or random walk models to predict links. These approaches have been quite common in research and has been extensively studied in [3, 6, 10]. At the heart of these systems lie the traidic closure concept from social sciences theories which was proposed by the German sociologist Georg Simmel [26]. The way the network grows under such recommendation algorithms has been analyzed in [28]. The power-law construct with 'rich-getting-richer' is an effect which can be seen with such recommender systems.

The crucial role recommender systems play in networks, have also borne ill effects. Mostly creating highly polarized networks, with the glass ceiling and echo chamber effects being prominent [27]. The ill effects of content recommendation can be often seen in multiple news sources [5, 20, 4]. The recommender systems are modeled to maximize user engagement, but the companies are trying to tweak their AI models to have better judgement and not be overtly biased to reaffirm biases from hyper-engaged users.

With respect to social networks, homophily as a parameter has been found to be relevant in shaping how network structures evolve [8, 19]. The term homophily was introduced by Lazarsfeld et al. in their essay "Friendship as a social process" [15]. The essence of homophily can be well understood through the famous proverb *"Birds of a feather flock together"*. This parameter tries to capture and quantify the human instinct to bond with people who share common attributes with them. These attributes could be as varied as common race, age-group, gender along with common goals, ideologies or personalities. Humans being communal by nature tend to form communities and these aforementioned attributes are a way of building associations. Homophily in social structures, specially how these associations affect a given minority and majority group have been widely researched. It has been established through studies that these have varying effects on the evolving structure of a society, distribution of information and visibility of a certain group [27, 2, 19, 12].

As machine learning systems learn from user behavior, it can be expected that the intrinsic homophilic patters in humans behavior becomes a part of the algorithmic behavior too. Networks growing with the help of these biased systems would therefore imbibe this bias on the network structure itself. When a supposedly objective system would need to take some decision based on the parameters of these kind of evolved networks, it will fail to maintain it's objectivity due to the inherent bias the network possesses. Ranking systems are prevalent today to make decisions for 'employability', 'credit-score' or other services. These systems are supposed to objectively rank people based on certain parameters.

These kind of systems would be affected by a biased model of the network. This forms the crux of our work, trying to understand how the agent aided growth (termed here as algorithmic growth) of a network is influenced by homophily of the users interacting with it.

Our usage of reinforcement learning methods is stemmed from the fact that this branch of learning algorithms is widely gaining popularity due to the promising results it shows. Although there are multiple challenges currently in having a reinforcement learning agent function effectively in the real-world as studied in [9], we can expect to see these kind of systems more in the picture, much like the Alibaba using RL agent in their platform Taobao. The results from their research shows good performance in the online community over other popular ML approaches [11, 25]. Russell and Norvig in their book [24] comments *"reinforcement Learning might be considered to encompass all of AI: an agent is placed in an environment and must learn to behave successfully therein and reinforcement learning can be viewed as a microcosm for the entire AI problem"*. Reinforcement learning is the very basis by which us humans, the most effective learning agents learn to tackle novel situations in our environment. Advances in Deep RL has paved the path further, invoking the hypothesis by David Silver that AI = RL + DL. This makes a strong case to study the effects of reinforcement learning agents on network structure, specially with the combination of homophily.

2 Related Work

In this section we discuss some of the existing research in the area of ranking in social structure, with respect to minorities. Minority ranking in networks has been studied by many researchers owing to the fact that these rankings help understand a minority group effect in a network. In [12], Karimi et. al. shows how different rates of homophilic behavior and group sizes affects degree ranking of nodes in a network. The minority groups are at a disadvantage in case of an extremely homophilic network. Perception biases have been studied with respect to group size and homophily in [16]. It has also been seen in [27] where recommendations are studied to see how the algorithmic growth of a network brings out the glass ceiling effect for minorities.

Learning-To-Rank with respect to Reinforcement Learning has been studied for document retrieval, search-query rankings. These algorithms learn from click-behavior models to rank documents for queries. Click-models are stochastic models which approximate from click logs user interaction with list of items. The Multi-Armed Bandits sub-field of reinforcement learning is used to describe this problem, where there is a single state and given certain actions (or arms), which action selection would lead to the best outcome. Some of the state-of-the-art algorithms to learn ranking of online documents are - BatchRank [30] by Zoghi et al., TopRank [14] by Lattimore et. al, BubbleRank [18] by Li et al. BubbleRank is currently superior to TopRank, which is shown to be superior to BatchRank, which itself is superior to RankedExp3 [22] by Radlinski et al. which was one of the first papers to start exploring the problem of ranking documents for a query with reinforcement learning. BubbleRank however only helps in the re-ranking process, along with helping in other problems like the warm-start problem.

The existing literature focuses on document retrieval for queries, and we do not find any research which focuses on link prediction or recommendation of social ties in a online social network setting. Thus we derive our work mostly from these document retrieval algorithms, trying to fit them in our social links recommendation scenario.

3 Research Questions

We wish to explore the following research questions in this thesis -

RQ1 For a given network, how the different group of nodes in the network rank among themselves when trained using a agent learning to rank, using state-of-the-art reinforcement learning algorithms.

RQ2 Perform case studies for the existing real-world network data to see the ranking effects in them
  (a) The Facebook100 dataset [29] contains a large collection of students from 100 colleges in Facebook which was collected in 2005.
  (b) The Google+ dataset from [17] containing information for 107,614 users.

RQ3 How the structural characteristics of a network like degree distribution, growth and minority ranking are affected for a network generated with respect to varying homophily and minority sizes, by using recommender algorithms for network growth. This is studied in 2 different aspects -
  (a) The network grows using algorithms like Random-Walk and Adamic-Adar index whose customized variants are used currently in real-world social recommender systems.
  (b) The network grows using recommender systems which use Reinforcement Learning for ranking nodes for recommendation.

RQ4 How to train or reinforce learning agents to mitigate bias in ranking of minorities.

4 Methods

We consider a generative synthetic network for our study similar to [12], where the growth is based on the preferential-attachment model and homophily. The network has nodes from 2 groups, marked using the red (minority) and blue (majority) colors. An instance of this network graph G can be considered as a tuple (N, m, f, h) where N is the total number of nodes in the network, m is the number of edges each incoming node makes with existing nodes in the network, f is the fraction of minority nodes in the network and h is the symmetric homophily parameter. By tuning these values, we can generate and study different networks.

For RQ1, we intend to train our RL Learn-to-rank model with a specific clicking (or in this case, choosing) behavior and wish to see how this model finally ranks network nodes. At each iteration of the recommender model training phase, a list of nodes are provided as node connection options, and the model observes the choices made by the clicking model.

Our clicking model C works according to the following rules -

1. The model is provided with an observer node $v \in V$ and a list of options $R_v^t = (u_1^t, ..., u_k^t | u_i^t \in V - \{v\}, i \in \{1, ..., k\})$ at iteration t, where u_1^t is the 1-st ranked option and u_k^t is the k-th ranked option at time t, V being the set of all nodes in the network. On every training iteration this k sized list is provided to the clicking model for each node v.
2. The clicking model chooses a maximum of m nodes from the list according to probability α as given in equation-1

$$\alpha_v(u_i^t) = \frac{\delta(u_i^t) \times h(u_i^t, v) \times e^{-(i-1)}}{\sum_{j=1}^{k} (\delta(u_j^t) \times h(u_j^t, v) \times e^{-(j-1)})} \tag{1}$$

where $h(x, y) \in [0, 1]$ denotes the homophily between the nodes x and y, and $\delta(x)$ denotes the degree of the node x.

After running this for multiple iterations we see how the nodes rank against each other. In the next section we see some results from this.

For RQ2, we take the network data from the given sources and find out the homophily parameter. We use a similar clicking model and try to find minority ranking at different positions of the recommended nodes.

For RQ3, we grow a model with a combination of organic and algorithmic as in [27]. Our approach is as following -

1. We set the network parameters for $G(N, m, f, h)$ as has been defined previously. We want our network to finally grow to resemble G as per the given parameters.
2. We start building out network with m initial nodes, and at each iteration t we choose add phase with probability β, and growth phase with probability $1 - \beta$.
   (a) Add phase : In this phase we add a new node v to the network which chooses maximum of m nodes to connect to from $u^t \in V^t$, V^t being the set of nodes existing in the network G^t at iteration t according to the probability α in equation 2.

$$\alpha(u^t) = \frac{\delta(u^t) \times h(u^t, v)}{\sum_{w \in V^t} (\delta(w^t) \times h(w^t, v))} \tag{2}$$

(b) Growth phase : In this phase, we choose to grow the network by connecting existing nodes to each other. A fraction of nodes γ is chosen from the existing nodes V^t and selected as growing nodes. For each of the growing nodes, we choose either organic growth according to the probability η, and algorithmic growth according to the probability $1-\eta$. The algorithmic growth is aided by the recommender agent and node choices happen according to equation 1, for organic growth is done according to equation 2.

3. The reinforcement learning agent needs to be re-trained to accommodate new nodes at an interval of r iterations.

For RQ4, Existing literature suggests some methods for mitigating biases in link formation, for a better minority visibility, such as tweaking the ranking method for differing thresholds as suggested in [12] or also introducing choice probability according to node parameters in random-walk as suggested in [27]. In the reinforcement learning model, we could introduce varying reward mechanisms for choosing minority or majority group nodes, but this needs further thought and exploration.

5 Initial Experiments

We start with finding the ranking for nodes recommended in an existing network. We consider a synthetic network $G(N, m, f, h)$ with parameters $N = 1000, m = 2, f = 0.2$ as fixed parameters, and h being varied from [0.0, 1.0], step-size=0.1.

We show in figure 1 the initial structure of the network along with degree distribution and degree growth for the network, which is grown considering only preferential-attachment and homophily as in equation 2. We find our results similar to [12], showing similar network characteristics.

For the network, with varying homophily, we run our Multi-Armed Bandits approach of ranking for all the nodes as devised in [22]. We take the number of slots to be 5, thus training for 5 ranking spots per node in the network. The underlying MAB algorithm being used is ϵ-Greedy (with $\epsilon = 0.1$). We use the sample-average method for estimating the best action values, where actions are basically the choice of nodes among the network to recommend. The reward function returns 1, when the node recommended is chosen by our clicking model, and a reward value of 0 if the node recommended is not chosen. Details about the node choice model is provided in the Methods section. We train our recommender system for 10^5 iterations. We then see at which position nodes are ranked, based on the node group asking for recommendation. We also run the TopRank algorithm [14] and the Adamic-Adar Index to compare our results. Figure 2 - Figure 7 shows our results for different minority groups.

For the complete hetrophilic case, a sharp difference can be seen in the Adamic-Adar ranking and the Ranked-Bandits ranking. This is evident since the Adamic-Adar Index does not consider the homophily value for making link

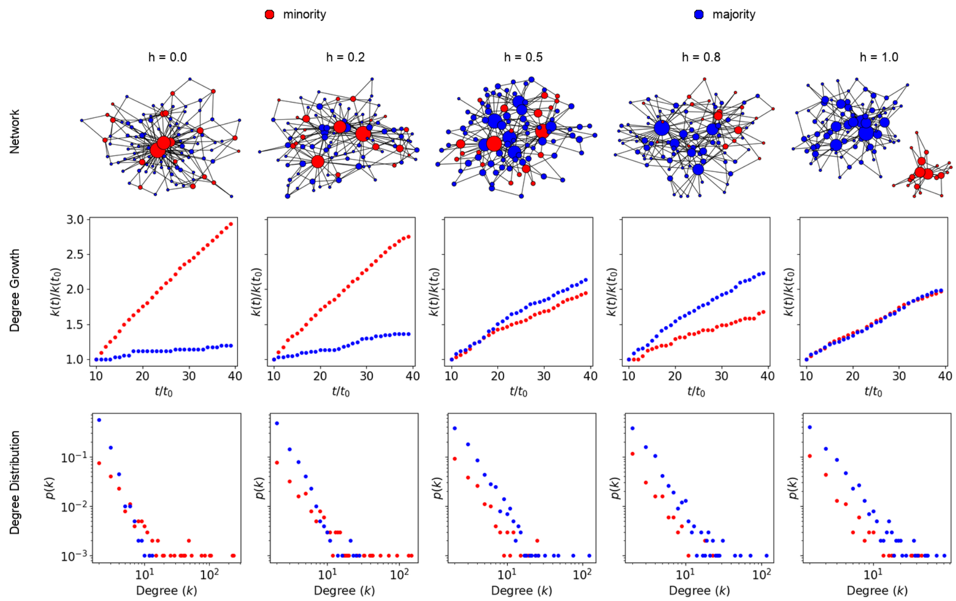

Fig. 1: Network grown using preferential-attachment and homophily. The minority fraction has been set fixed to 0.2, number of edges added per iteration is 2. The homophily parameter ranges from 0.0(complete heterophily) to 1.0(complete homophily). Tile A shows a visualization of the network with 100 nodes, for different homophily parameters. For Tile B and C, the network contains 1000 nodes, averaged over 5 iterations.

predictions, since the minority nodes have majority nodes as their neighbours always and they in turn have only minority neighbours, other minority nodes are recommended minority nodes. The Ranked-Bandit however considers the homophily parameter and hence the recommendations are more aligned to the idea of homophily.

6 Work Plan

Table 1 gives a broad overview of the tasks that will be undertaken in the scope of this thesis and the approximate time required for their completion. Both the tasks and their times are broad approximations and are subject to change or overlap amongst each other.

Implementation software requirements -

1. Computational code : written using Cython.
2. Helper Code : written using Python.

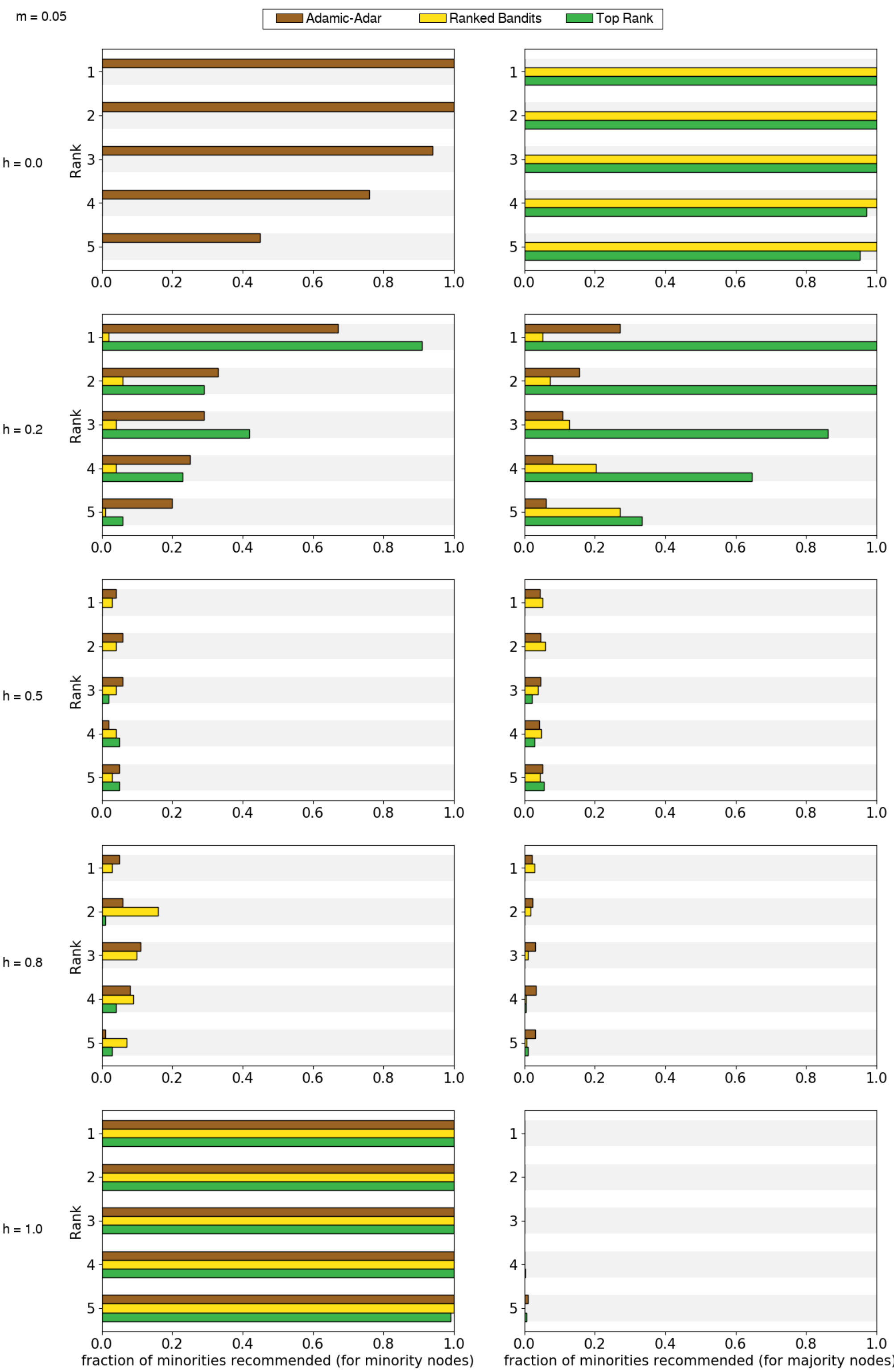

Fig. 2: Fraction of minorities recommended in the top 5 ranks for the two node groups. On the left hand side is the recommendation provided to minority nodes, while on the right-hand side are the recommendations provided to majority nodes. The 3 different ranking schemes are shown with three colors. The network considered has 1000 nodes, with a minority fraction of 0.05.

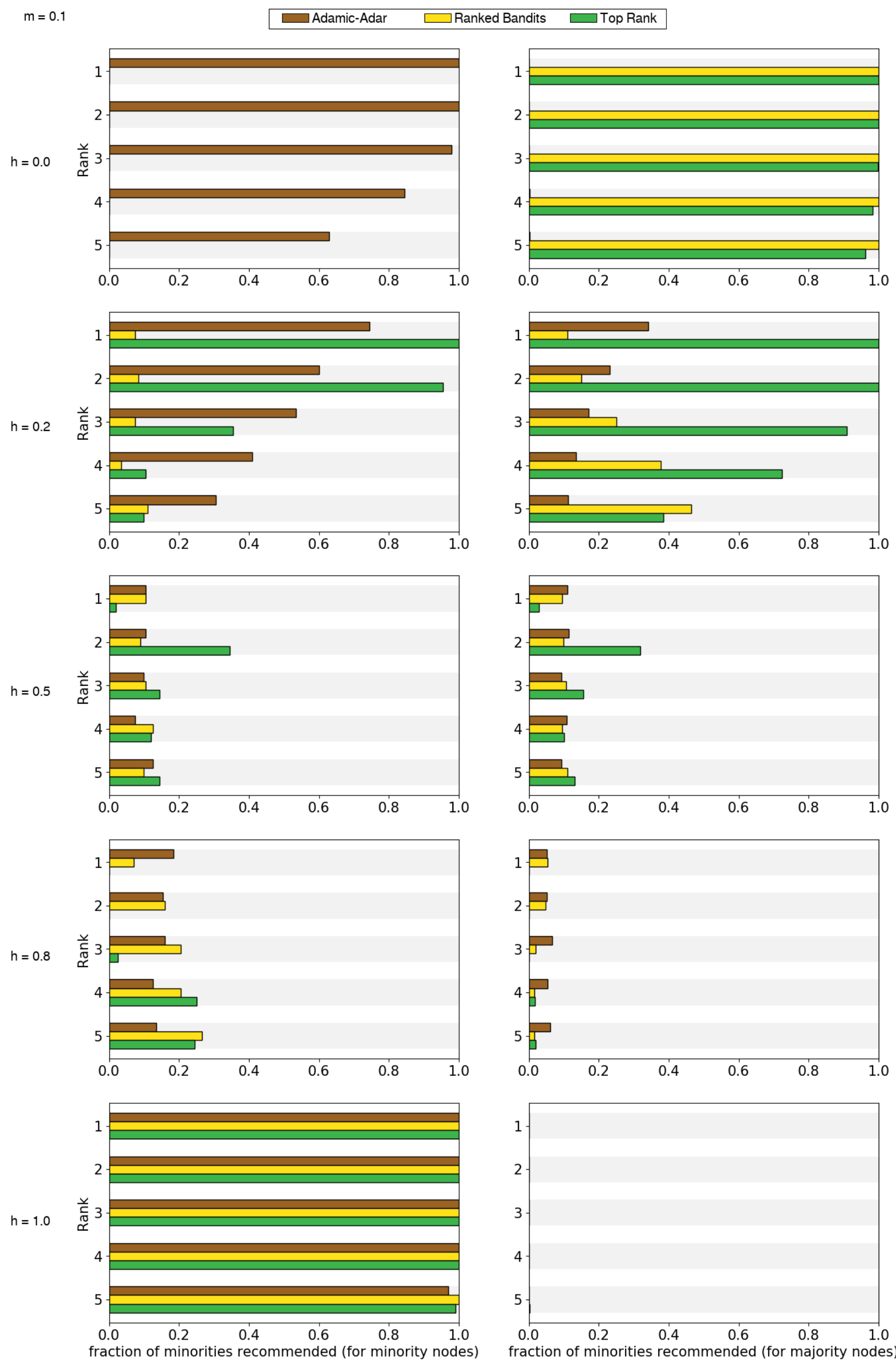

Fig. 3: Fraction of minorities recommended in the top 5 ranks for the two node groups. On the left hand side is the recommendation provided to minority nodes, while on the right-hand side are the recommendations provided to majority nodes. The 3 different ranking schemes are shown with three colors. The network considered has 1000 nodes, with a minority fraction of 0.1.

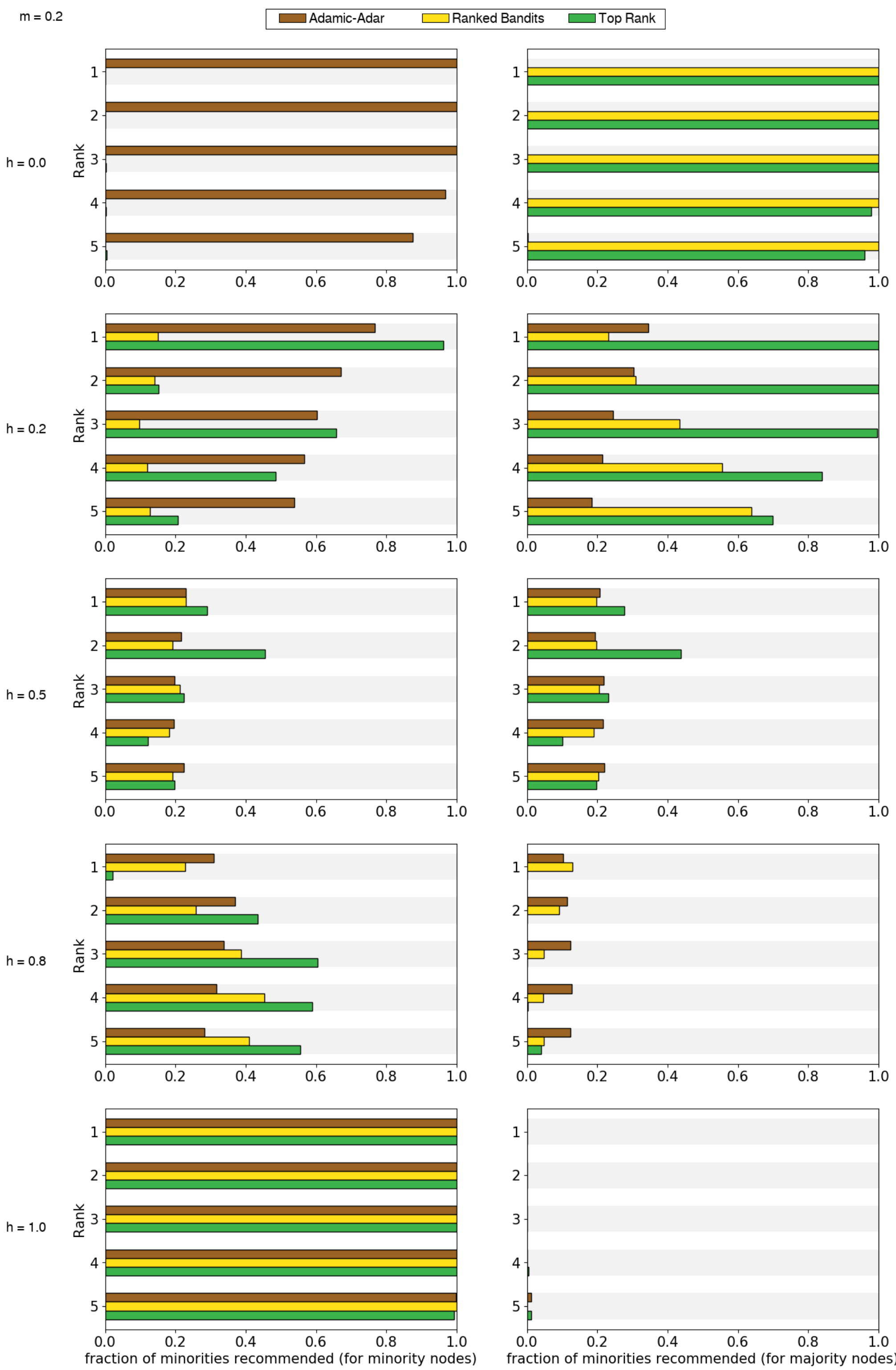

Fig. 4: Fraction of minorities recommended in the top 5 ranks for the two node groups. On the left hand side is the recommendation provided to minority nodes, while on the right-hand side are the recommendations provided to majority nodes. The 3 different ranking schemes are shown with three colors. The network considered has 1000 nodes, with a minority fraction of 0.2.

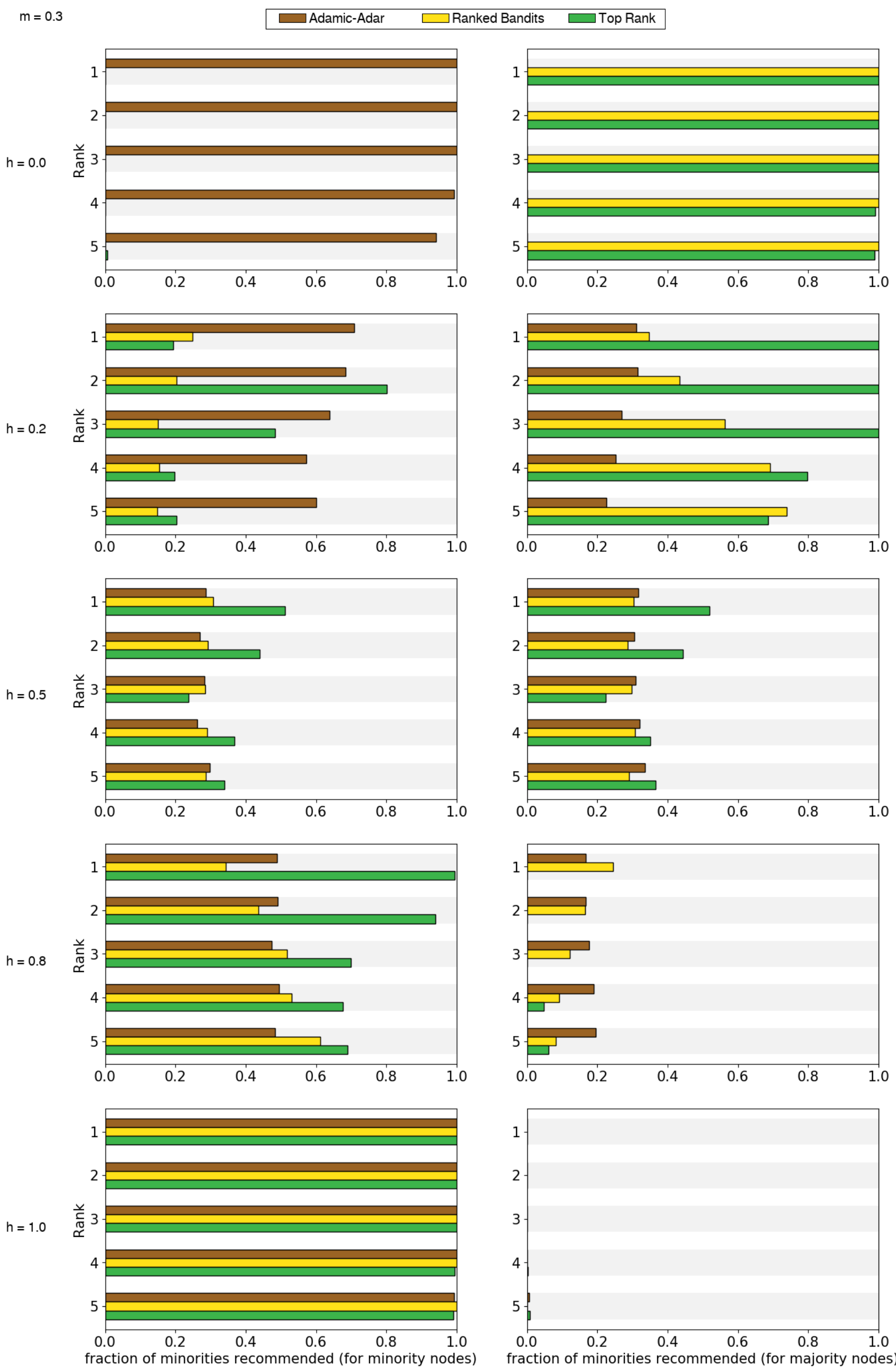

Fig. 5: Fraction of minorities recommended in the top 5 ranks for the two node groups. On the left hand side is the recommendation provided to minority nodes, while on the right-hand side are the recommendations provided to majority nodes. The 3 different ranking schemes are shown with three colors. The network considered has 1000 nodes, with a minority fraction of 0.3.

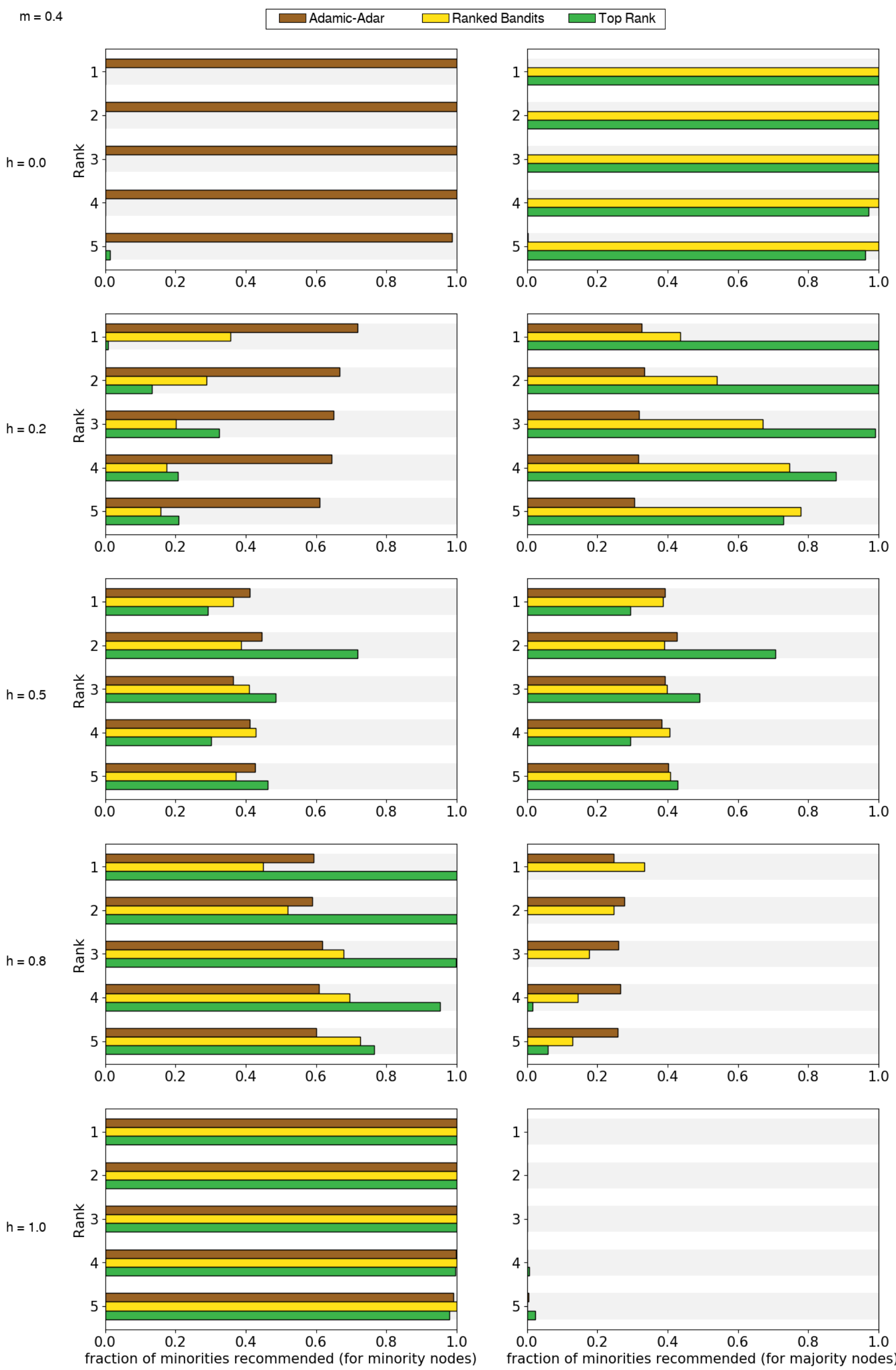

Fig. 6: Fraction of minorities recommended in the top 5 ranks for the two node groups. On the left hand side is the recommendation provided to minority nodes, while on the right-hand side are the recommendations provided to majority nodes. The 3 different ranking schemes are shown with three colors. The network considered has 1000 nodes, with a minority fraction of 0.4.

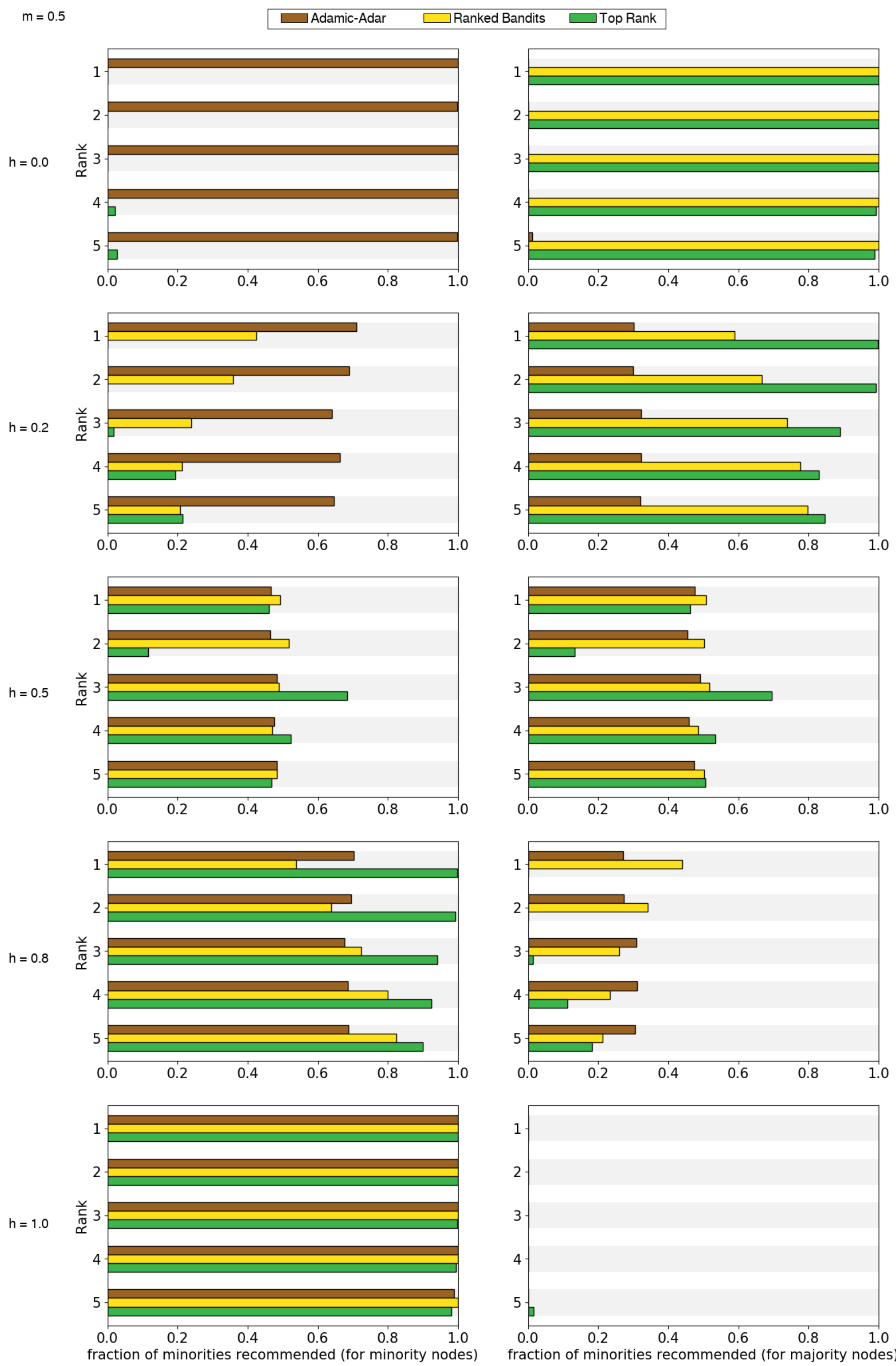

Fig. 7: Fraction of minorities recommended in the top 5 ranks for the two node groups. On the left hand side is the recommendation provided to minority nodes, while on the right-hand side are the recommendations provided to majority nodes. The 3 different ranking schemes are shown with three colors. The network considered has 1000 nodes, with a minority fraction of 0.5.

Table 1: work-plan

#	**Task**	**Time**
RQ1		2 weeks
1.1.	Implementing Ranked-Bandits algorithm [22] to rank nodes in a synthetic network	1 week
1.2.	Implementing TopRank algorithm [14] to rank nodes in a synthetic network	2 week
RQ2		3 weeks
2.1.	Implementing code to rank Instagram nodes [27] using TopRank, Ranked-Bandits, Adamic Adar and Random-Walk	1 week
2.2.	Implementing code to rank Facebook nodes [29] using TopRank, Ranked-Bandits, Adamic Adar and Random-Walk	1 week
2.3.	Implementing code to rank Google+ nodes [17] using TopRank, Ranked-Bandits, Adamic Adar and Random-Walk	1 week
RQ3		3 weeks
3.1.	Implementing code to grow a network using a recommender system	2 week
3.2.	Adapting code in 3.1 to use Ranked-Bandits, TopRank, Adamic-Adar, Random Walk and grow synthetic networks	1 week
RQ4		6 weeks
4.1.	Figuring out how to reinforce no-bias policy in reinforcement learning agent for recommender system	2 week
4.2	Implementing code for our reinforcement learning recommender as in 4.1	2 week
4.3	Testing our implemented model 4.2 with synthetic networks and seeing the network properties of the growing network	2 week
Misc.		10 weeks
5.1.	Implementing matplotlib code for different plots required	2 weeks
5.2.	Writing Thesis Draft	5 weeks
5.3.	Revision and Final submission of Thesis	3 weeks

3. Plotting of data : Python (packages - Matplotlib).
4. Handling Network Data : Python (packages - NetworkX).
5. Additional Python Packages : NumPy, SciPy.
6. Documentation : LaTeX

References

1. Netflix prize. https://www.netflixprize.com/index.html, accessed: 2020-01-08
2. Avin, C., Keller, B., Lotker, Z., Mathieu, C., Peleg, D., Pignolet, Y.A.: Homophily and the glass ceiling effect in social networks. In: Proceedings of the 2015 conference on innovations in theoretical computer science. pp. 41–50. ACM (2015)
3. Backstrom, L., Leskovec, J.: Supervised random walks: predicting and recommending links in social networks. In: Proceedings of the fourth ACM international conference on Web search and data mining. pp. 635–644. ACM (2011)
4. Captain, S.: From self-harm to terrorism, online recommendations cast a deadly shadow (2019), https://www.fastcompany.com/90416541/read-real-stories-of-how-youtube-pushed-people-down-shocking-rabbit-holes
5. Chaslot, G.: The toxic potential of youtubes feedback loop (2019), https://www.wired.com/story/the-toxic-potential-of-youtubes-feedback-loop/
6. Chen, J., Geyer, W., Dugan, C., Muller, M., Guy, I.: Make new friends, but keep the old: recommending people on social networking sites. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. pp. 201–210. ACM (2009)
7. Daly, E.M., Geyer, W., Millen, D.R.: The network effects of recommending social connections. In: Proceedings of the fourth ACM conference on Recommender systems. pp. 301–304. ACM (2010)
8. Dong, Y., Johnson, R.A., Xu, J., Chawla, N.V.: Structural diversity and homophily: A study across more than one hundred big networks. In: Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 807–816. ACM (2017)
9. Dulac-Arnold, G., Mankowitz, D., Hester, T.: Challenges of real-world reinforcement learning. arXiv preprint arXiv:1904.12901 (2019)
10. Gupta, P., Goel, A., Lin, J., Sharma, A., Wang, D., Zadeh, R.: Wtf: The who to follow service at twitter. In: Proceedings of the 22nd international conference on World Wide Web. pp. 505–514. ACM (2013)
11. Jin, J., Song, C., Li, H., Gai, K., Wang, J., Zhang, W.: Real-time bidding with multi-agent reinforcement learning in display advertising. In: Proceedings of the 27th ACM International Conference on Information and Knowledge Management. pp. 2193–2201. ACM (2018)
12. Karimi, F., Génois, M., Wagner, C., Singer, P., Strohmaier, M.: Homophily influences ranking of minorities in social networks. Scientific reports **8**(1), 11077 (2018)
13. Konstan, J.A., Riedl, J.: Recommender systems: from algorithms to user experience. User modeling and user-adapted interaction **22**(1-2), 101–123 (2012)
14. Lattimore, T., Kveton, B., Li, S., Szepesvari, C.: Toprank: A practical algorithm for online stochastic ranking. In: Advances in Neural Information Processing Systems. pp. 3945–3954 (2018)
15. Lazarsfeld, P.F., Merton, R.K., et al.: Friendship as a social process: A substantive and methodological analysis. Freedom and control in modern society **18**(1), 18–66 (1954)

16. Lee, E., Karimi, F., Jo, H.H., Strohmaier, M., Wagner, C.: Homophily explains perception biases in social networks. arXiv preprint arXiv:1710.08601 (2017)
17. Leskovec, J., Mcauley, J.J.: Learning to discover social circles in ego networks. In: Advances in neural information processing systems. pp. 539–547 (2012)
18. Li, C., Kveton, B., Lattimore, T., Markov, I., de Rijke, M., Szepesvári, C., Zoghi, M.: Bubblerank: Safe online learning to re-rank via implicit click feedback (2019)
19. McPherson, M., Smith-Lovin, L., Cook, J.M.: Birds of a feather: Homophily in social networks. Annual review of sociology **27**(1), 415–444 (2001)
20. Naughton, J.: From self-harm to terrorism, online recommendations cast a deadly shadow (2019), https://www.theguardian.com/commentisfree/2019/mar/03/self-harm-to-terrorism-online-recommendations-cast-a-deadly-shadow
21. Pu, P., Chen, L., Hu, R.: A user-centric evaluation framework for recommender systems. In: Proceedings of the fifth ACM conference on Recommender systems. pp. 157–164. ACM (2011)
22. Radlinski, F., Kleinberg, R., Joachims, T.: Learning diverse rankings with multi-armed bandits. In: Proceedings of the 25th international conference on Machine learning. pp. 784–791. ACM (2008)
23. Rashid, A.M., Albert, I., Cosley, D., Lam, S.K., McNee, S.M., Konstan, J.A., Riedl, J.: Getting to know you: learning new user preferences in recommender systems. In: Proceedings of the 7th international conference on Intelligent user interfaces. pp. 127–134. ACM (2002)
24. Russell, S.J., Norvig, P.: Artificial intelligence: a modern approach. Malaysia; Pearson Education Limited, (2016)
25. Shi, J.C., Yu, Y., Da, Q., Chen, S.Y., Zeng, A.X.: Virtual-taobao: Virtualizing real-world online retail environment for reinforcement learning. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 33, pp. 4902–4909 (2019)
26. Simmel, G.: The sociology of georg simmel, vol. 92892. Simon and Schuster (1950)
27. Stoica, A.A., Riederer, C., Chaintreau, A.: Algorithmic glass ceiling in social networks: The effects of social recommendations on network diversity. In: Proceedings of the 2018 World Wide Web Conference. pp. 923–932. International World Wide Web Conferences Steering Committee (2018)
28. Su, J., Sharma, A., Goel, S.: The effect of recommendations on network structure. In: Proceedings of the 25th international conference on World Wide Web. pp. 1157–1167. International World Wide Web Conferences Steering Committee (2016)
29. Traud, A.L., Mucha, P.J., Porter, M.A.: Social structure of facebook networks. Physica A: Statistical Mechanics and its Applications **391**(16), 4165–4180 (2012)
30. Zoghi, M., Tunys, T., Ghavamzadeh, M., Kveton, B., Szepesvari, C., Wen, Z.: Online learning to rank in stochastic click models. In: Proceedings of the 34th International Conference on Machine Learning-Volume 70. pp. 4199–4208. JMLR.org (2017)