Dynamic Scholarly Collaborator Recommendation via Competitive Multi-Agent Reinforcement Learning

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ABSTRACT

In an interdisciplinary environment, scientific collaboration is becoming increasingly important. Helping scholars make a right choice of potential collaborators is essential in achieving scientific success. Intuitively, the generation of collaboration relationship is a dynamic process. For instance, one scholar may first choose to work with Scholar A, and then work with Scholar B after accumulating additional academic credits. To address this property, we propose a novel dynamic collaboration recommendation method by adapting the multi-agent reinforcement learning technique to the coauthor network analysis. The collaborator selection is optimized from several different scholar similarity measurements. Unlike prior studies, the proposed method characterizes scholarly competition, a.k.a. different scholars will compete for potential collaborator at each iteration. An evaluation with the ACM data shows that multi-agent reinforcement learning plus scholarly competition modeling can be significant for collaboration recommendation.

KEYWORDS

Collaborator recommendation; dynamic; competition; reinforcement learning; multi-agent

1 INTRODUCTION

While interdisciplinary studies across multiple domains are experiencing a rapid growth in the past few decades, scientific collaboration among scholars becomes increasingly important and necessary [8]. For instance, prior studies showed that scientific collaboration can be essential for enhancing researchers' productivity [13] as well as for triggering innovation [6]. Scholar collaboration recommendation has traditionally centered on generating a ranking of potential collaborators for an author. The recommendation heavily relies on the relatedness/similarity between the source and candidate scholars. It can be estimated in different context, such as the research interest closeness [3], and the social structural proximity [4]. However, to the best of our knowledge, most existing methods only produce a static candidate collaborator list given a textual or graphical author profile. Intuitively, the generation of collaboration relationship in a scholar network should be a dynamic process. For instance, one scholar may first choose to work with Scholar A, and then work with Scholar B after accumulating additional academic credits. So, the recommendation should evolve dynamically.

In addition, recommending candidate scholars is not sufficient to guarantee the achievement of real collaboration. For most current methods, the recommendations are locally optimized—they focuses on providing a ranking list for each scholar based on their own relatedness with others. Such algorithms could recommend the same candidate to multiple scholars. Nevertheless, this candidate could not accept numerous collaborators due to the limitation of his/her time. So, scholars may need to compete for the potential candidate, even though they may not know each other. To the best of our knowledge, few existing collaboration recommendation algorithm can characterize the competition as a latent factor. In this study, we propose a novel dynamic collaboration recommendation method by adopting a multi-agent reinforcement learning technique. In this new framework, multiple authors (agents) learn the optimized chronological collaboration recommendation trajectories in a network, and they will need to compete with each other at each step. Moreover, the collaboration capacity of a candidate scholar is addressed by a function which characterizes the competition between authors, e.g., when a candidate is recommended to multiple authors, the competition function can optimize the collaboration outcome for the next iteration.

The rest of this paper is organized as follows. In Section 2 we review related work on collaboration recommendation. Section 3 explains our proposed method to address the dynamic competitive collaboration recommendation. Section 4 describes the experiments. Conclusion and future work are presented in Section 5.

2 LITERATURE REVIEW

In the literature, much attentions have been paid to collaboration recommendations. The link-based similarity and the content-based similarity are frequently used to calculate the relatedness between scholars. The former one uses the content information from the authors' publications to measure the similarity between authors (such as [3]; [7]); the latter one adopts the structure of collaboration network to measure the closeness between authors (such as [9]; [14]). Most studies combine both content-based and link-based methods and provide a ranking list of potential collaborators according to the relatedness.

For example, Chen et al. [3] designed a system that makes recommendations of collaborators based on an integration of the network structure similarity and the scholar's research interests between the source and the target authors. Similarly, Tang et al. [17] proposed

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a Cross-domain Topic Learning method (CTL) to help scholars find potential collaborators from other domains. They included the "collaboration" topics detected by CTL into the collaboration graph and applied the random walk with restart algorithm to calculate the relatedness between authors from the source and the target domains. Han et al. [9] designed a regularization based method to incorporate the local network structure, the global network structure, and the content feature to provide collaboration recommendation for junior researchers, who have less collaboration information and need more collaborator recommendation. Kong et al. [12] first utilized the topic clustering model to divide scholars into different research domains and then used the random walk model to calculate the structural similarity between authors from the same domain.

However, most of the recommendation methods proposed did not reflect the evolution of collaboration–one scholar's previous collaborations can influence his/her further collaborations. The recommendation is usually a static process and only one fixed group of collaborators is finally provided. There exists some research considering the dynamic collaboration. For example, Chaiwanarom and Lursinsap [2] used the up-to-date publication data together with other factors including social proximity, friendship, complementarity skill, research interest, and seniority of researcher to measure the research trend of potential collaborators. But still only one ranked list of potential collaborators is provided. Moreover, in these methods, each scholar is provided with a list of coauthors and a same potential collaborator could be recommended to multiple scholars, in which case not all the recommendations could be achieved. Many current research only provide locally optimized recommendation results.

In this study, we use a multi-agent reinforcement learning model with a competition function to tackle these drawbacks. Multi-agent reinforcement learning has been applied in many simulation tasks [1]. It has also been successful in a few real-life domains, such as controlling traffic signals [18], robot soccer [19], automated trading [10], and recourse management [5]. As far as we know, reinforcement learning has not been used for scholar collaboration recommendation. Reinforcement learning is designed to resolve the dynamic problem. Reinforcement learning agent learns knowledge by communicating with the environment, finding out how to correspond situations to actions, and maximizing a reward in numerical representation [16]. Multi-agent reinforcement learning integrates the results of each single agent [1]. There are various types of reinforcement learning algorithms including model-free learning methods and model-based learning methods [11]. One of the well-known algorithms is Value-Iteration [16], which tries to find the optimal action selection policy based on an iteratively updated state value. These characteristics make it appropriate to address the proposed problem.

3 METHODOLOGY

In this research, we model the evolution of collaboration among scholars. One author (hereinafter referred to source author) is looking for potential collaborators (hereinafter referred to target authors). In this study, we propose two influencing factors for the match between the source author and the target author. First, the similarity/distance between the source and target authors can play a direct role. We call this a *'personal factor'*.

The second factor focuses on the target author's status in the network. To seek for collaborators, preferential attachment can be important. People would like to connect with those popular nodes in the network. The more popular one scholar is, the higher probability that others would like to collaborate with him/her. Moreover, since forming collaboration is an evolved process, if a scholar's collaborators are also popular, there exists higher chance for others to gain more collaboration after collaborating with him/her. We call it *'environmental factor'*, which guides collaborator seeking. It requires a holistic understanding of the whole collaboration network.

3.1 Network Generation

To recommend collaborators to an author A_i, his/her research interest $topic_i$ is first considered. By comparing $topic_i$ with the keywords of existing publications for all scholars in a scholarly database G, all related researchers and their articles are extracted. So a collaboration network G' is created, where the nodes represent the authors and the edges stand for the coauthorship between the authors. The total number of authors is represented by k. The network is an unweighted one (see Figure 1.1). t different relationships between authors, which are based on their personal features, such as publications are used to measure their similarities. An author A_i will have t different similarity measures with another author A_j, as shown in Figure 1.2. The overall similarity, s_{ij} between two authors, A_i and A_j can be quantified by the weighted sum of these measures, $\sum_{m=1}^{t} \theta_m \cdot s_{ij}^m$, where s_{ij}^m is the similarity measure by the m^{th} relationship; θ_m is the weight reflecting the importance of that relationship in the overall similarity. The t weights form the vector $\vec{\theta}$. An author, A_i 's popularity, pop_i is defined by the sum of his/her overall similarities with all other authors, $\sum_{n=1,n\neq i}^{k} \sum_{m=1}^{t} (\theta_m \cdot s_{in}^m)$. It can be transformed to $\sum_{m=1}^{t} \theta_m \cdot (\sum_{n=1}^{k} s_{in}^m)$. We denote it as $\vec{\theta}^T \cdot \vec{q}_i$.

3.2 Dynamic Recommendation via Reinforcement Learning and Gradient Descent

Each author in the collaboration network is treated as a state. To guide the recommendation, the environmental factor should be learnt, i.e., the true status value of each state need to be learnt. Based on the Value Iteration algorithm [16], we propose **Gradient Value Iteration algorithm** (see Algorithm 1) to achieve this goal. Initially, the popularity of each author is assigned as his/her status value as a state. In the learning process, the status value of each state is kept updated until it reaches a stabilized value. For each iteration, $\vec{\theta}$ are updated by the gradient descent method, where the algorithm tries to minimize the Mean Squared Value Error between the current estimation of all the states' status values and their true status values. The status value of a state is updated by its original value and the discounted value of the maximum of its neighbors' status values from the collaboration network.

As Algorithm 1 shows, the proposed algorithm optimizes the composition of multiple relationships in the similarity measurement

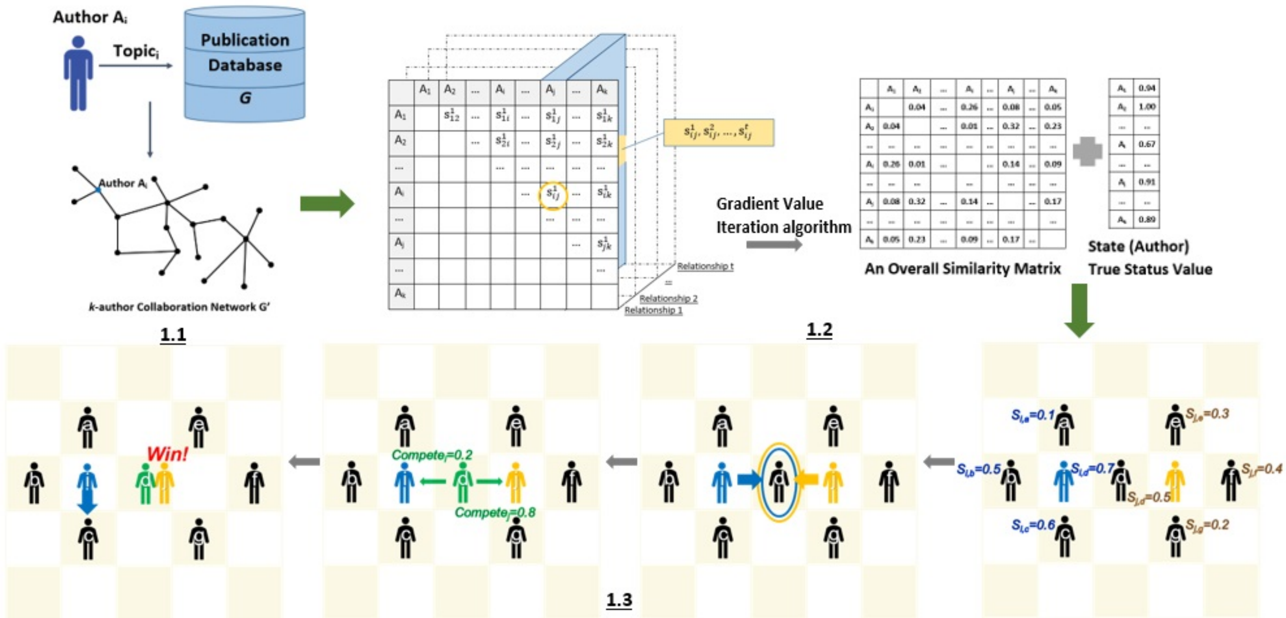

Figure 1: Toy example of the whole process

Algorithm 1 Gradient Value Iteration Algorithm for True Status Value Learning

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Input: $\vec{q}_1, \vec{q}_2, ..., \vec{q}_k$
Output: $\vec{\theta}^{final}, \vec{status}^{final}$

Begin:
$\vec{\theta} \leftarrow (1, 1, ..., 1)^T$
$\vec{status}^{new} \leftarrow ((\vec{\theta}^T \cdot \vec{q}_1), (\vec{\theta}^T \cdot \vec{q}_2), ..., (\vec{\theta}^T \cdot \vec{q}_k))^T$
$\vec{status}^{old} \leftarrow (0, 0, ..., 0)^T$
while $|\vec{status}^{new} - \vec{status}^{old}| >= threshold$ **do**
  $\vec{status}^{old} \leftarrow \vec{status}^{new}$
  $\vec{\theta} \leftarrow \vec{\theta} - \alpha \cdot \vec{status}^{old} \cdot \frac{\partial \vec{status}^{old}}{\partial \vec{\theta}}$
  $\vec{status}^{old} \leftarrow ((\vec{\theta}^T \cdot \vec{q}_1), (\vec{\theta}^T \cdot \vec{q}_2), ..., (\vec{\theta}^T \cdot \vec{q}_k))^T$
  for $i = 1$ to k **do**
    $\vec{status}^{new}[i] \leftarrow \vec{status}^{old}[i] + \lambda \cdot max(\vec{status}^{old}[sub])$
    /**sub* refers to the set of *i*'s neighbors*/
  end for
end while
$\vec{\theta}^{final} \leftarrow \vec{\theta}$
$\vec{status}^{final} \leftarrow \vec{status}^{new}$

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between two authors. Thus the true status value of each state in the collaboration network is available. Each of the source authors who seeks for potential collaborators is treated as an agent. A search function is constructed for him/her to make a decision to whom he/she would like to collaborate from all the authors in the graph. In other words, this function determines which state one agent will reach. As mentioned before, the search function, $Search(A_j|A_i)$ combines the personal factor, represented by the overall similarity, s_{ij} between the source author A_i and the target author A_j, and the environmental factor, represented by the true status value, $status_j$ of the target author. As illustrated by a toy example in Figure 1.3, authors A_i and A_j are looking for potential collaborators, so they 'look for' potential collaborators via search functions.

3.3 Agent Communication and Competition

Different from previous studies, multiple agents (in one model) are allowed to seek for collaborators simultaneously, which characterizes authors' competition as well as enhances recommendation performance. Based on search function, each author will have a ranking of potential collaborators—the higher value the search function provides to collaborate with a certain author, the higher this author will rank in the list. It is very likely that multiple authors, $A_1, A_2 ... A_h$ will reach the same candidate (state) A_e. In Figure 1.3, the author A_d is returned to A_i and A_j at the same time. In this case, A_e should choose a collaborator from this group.

To implement competition (among $A_1, A_2 ... A_h$), a competition function is proposed to compare the social proximity between the competing authors:

$$\begin{aligned} Compete(A_e|A_1, ..., A_h) = A_i, if\ prox_{ei} \\ = max\{prox_{e1}, ..., prox_{eh}\} \end{aligned} \quad (1)$$

where $prox_{ei}$ stands for the social proximity between the authors A_e and A_i in the collaboration network.

Those authors, who lose the competition, will iteratively choose and compete the next candidates on the ranking list. If a candidate is recommended to multiple authors again, new competition will be conducted recursively. This process will repeat until different candidates are assigned to all the authors. The proposed method enables global recommendation optimization, and multiple source authors need to compete in each iteration. In another word, a target author is able to choose the best collaborator from the source authors who request collaborations. In the Figure 1.3, A_d selects A_j since A_j returns a higher value of competition function than A_i. So A_i needs to seek alternative candidates.

4 EXPERIMENT

4.1 Data Sets

An ACM data set including 776,295 authors and corresponding publications from 1951 to 2015 is used in this preliminary experiment. The topic *machine learning* is selected as an example and 4,420 authors and related publications are extracted. The collaboration data before 2014 are used as the training data, which includes 7,546 unweighted edges. The data from 2014 to 2015 are used for testing. Four relationships between authors are calculated: the Jaccard similarity based on the authors' publication venues and keywords, and the Cosine similarity based on the titles and abstracts.

4.2 Experimental Setup

Experimental runs are conducted on two different setting: single-agent RL (Reinforcement Learning), and multi-agent RL with competition.

(1) Single-agent RL: One agent (author) is randomly selected as the input of the reinforcement learning model. The experiment repeats twenty times.
(2) Multi-agent RL with competition: Twenty agents (authors), that are located closely to each other, are randomly selected as the input of the reinforcement learning model; each agent needs to compete with the rest agents for collaborators.

The proposed methods are compared with five baseline models, four of which adopt the content similarity method to recommend the most related scholars. The similarity measures are provided in Subsection 4.1. The other method makes recommendation according to the authors' social proximity on the collaboration network. It adopts a random-walk-based structural similarity, which has been successfully used in link prediction research[15].

4.3 Results Analysis

The significance of each relationship in the overall similarity between two authors are learned. We find that the publication venue greatly affects the similarity measure between two authors. The next important one is the research topic, reflected by the keyword adoption and it is followed by the publication title and abstract.

For each experimental setting, we run the learning for ten steps and after each step one scholar will be recommended as a collaboration candidate. The candidates from each step form a temporal sequence of recommendation. In the last step, the final ranking list of collaborations for each agent is collected. Each learning is repeated for one hundred rounds. For evaluation, if any recommended collaboration is found in the testing period, it is labeled as a correct one; otherwise it is a wrong one. For the final ranking list, the performance is evaluated in terms of MRR (Mean Reciprocal Rank), P@3 (Precision for the top 3 recommended results), P@5, P@10, NDCG@3 (Normalized Discounted Cumulative Gain for the top 3 recommended results), NDCG@5, and NDCG@10.

Table 1: Results Comparison

	MRR	P@3	P@5	P@10	NDCG@3	NDCG@5	NDCG@10
Classic Methods							
Abstract Sim.	0.246	0.246	0.122	0.075	0.166	0.195	0.214
Keyword Sim.	0.381	0.270	0.262	0.200	0.303	0.341	0.392
Title Sim.	0.339	0.200	0.174	0.112	0.269	0.297	0.330
Venue Sim.	0.485	0.333	0.290	**0.205**	0.434	0.472	0.553
Network Prox.	0.448	0.327	0.270	0.165	0.477	0.510	0.534
RL-based Methods							
Single	0.573	0.377	0.274	0.157	0.541	0.544	0.550
Multi_With	**0.601**	**0.437**	**0.321**	0.178	**0.561**	**0.560**	**0.565**

The evaluation results are listed in Table 1. It is clear that the multi-agent reinforcement learning method outperforms other methods in most of the evaluation metrics. The final ranking list obtained from the multi-agent reinforcement learning gains the highest MRR and NDCG, which demonstrates the usefulness of competition modeling in collaboration recommendation (compared with single-agent reinforcement learning and other baseline models). The multi-agent reinforcement learning also beats the other methods regarding P@3 and P@5. Thought the venue similarity and keyword similarity baseline models are superior for P@10, it reflects the precise recommendations rank higher in the multi-agent reinforcement learning method than other methods. It is also noteworthy that among the four similarity-based baseline models, the one adopting the authors' venue similarity beats the one with the keyword similarity, followed by the title similarity and the abstract similarity in most evaluation metrics. We also witness the same trend in the trained gradient descent model, which also proofs the validity of the proposed method.

Overall, evaluation shows the usefulness of the multi-agent reinforcement learning and agent competition for a scholar collaboration recommendation task, and characterizing the evolutionary nature of collaboration can be promising to enhance the recommendation performance.

5 CONCLUSION & FUTURE WORK

In this study, we propose a novel approach–Dynamic Competitive Collaborator Recommendation. Unlike the earlier studies, a multi-agent reinforcement learning is employed to predict the chronological authors collaboration. The proposed method captures the dynamic evolution of collaboration. It can be used to characterize the scholarly competition as a latent factor for optimizing the recommendation result. Preliminary experiment shows that the proposed method is promising.

Due to the computation limitation, we only include ten authors in the final ranking list. This will be addressed in the next stage. Meanwhile, currently we only consider social similarity in the competition function. In the future work, we will set different competition criteria thus measure the competition from various perspectives. For example, the match of authors' personal features, and the potential impact of collaboration. The collaboration is dynamically evolved in nature. Scholars will either repeat collaboration with their existing collaborators, or create new collaborations. Though we capture the dynamic evolution in this research, we have not yet separated the collaboration maintaining and creation. We will improve this in our next study.

REFERENCES

[1] Lucian Busoniu, Robert Babuska, and Bart De Schutter. 2008. A comprehensive survey of multiagent reinforcement learning. *IEEE Transactions on Systems Man and Cybernetics Part C Applications and Reviews* 38, 2 (March 2008), 156–172. https://doi.org/10.1109/TSMCC.2007.913919

[2] Paweena Chaiwanarom and Chidchanok Lursinsap. 2015. Collaborator recommendation in interdisciplinary computer science using degrees of collaborative forces, temporal evolution of research interest, and comparative seniority status. *Knowledge-Based Systems* 75 (Feb. 2015), 161–172. https://doi.org/10.1016/j.knosys.2014.11.029

[3] Hung-Hsuan Chen, Liang Gou, Xiaolong Zhang, and Clyde Lee Giles. 2011. CollabSeer: a search engine for collaboration discovery. In *Proceedings of the 11th Annual International ACM/IEEE Joint Conference on Digital Libraries*. ACM, Ottawa, Canada, 231–240. https://doi.org/10.1145/1998076.1998121

[4] Sara Cohen and Lior Ebel. 2013. Recommending collaborators using keywords. In *Proceedings of the 22nd International Conference on World Wide Web*. ACM, Rio de Janeiro, Brazil, 959–962. https://doi.org/10.1145/2487788.2488091

[5] Robert H Crites and Andrew G Barto. 1998. Elevator group control using multiple reinforcement learning agents. *Machine Learning* 33, 2-3 (Nov. 1998), 235–262. https://doi.org/10.1023/A:1007518724497

[6] Jonathon N Cummings and Sara Kiesler. 2005. Collaborative research across disciplinary and organizational boundaries. *Social Studies of Science* 35, 5 (Oct. 2005), 703–722. https://doi.org/10.1177/0306312705055535

[7] Sujatha Das Gollapalli, Prasenjit Mitra, and C. Lee Giles. 2012. Similar researcher search in academic environments. In *Proceedings of the 12th ACM/IEEE-CS Joint Conference on Digital Libraries*. ACM, Washington, DC, 167–170. https://doi.org/10.1145/2232817.2232849

[8] Roger Guimera, Brian Uzzi, Jarrett Spiro, and Luis A. Nunes Amaral. 2005. Team assembly mechanisms determine collaboration network structure and team performance. *Science* 308, 5722 (April 2005), 697–702. https://doi.org/10.1126/science.1106340

[9] Shuguang Han, Daqing He, Jiepu Jiang, and Zhen Yue. 2013. Supporting exploratory people search: a study of factor transparency and user control. In *Proceedings of the 22nd ACM International Conference on Information Knowledge Management*. ACM, San Francisco, CA, 449–458. https://doi.org/10.1145/2505515.2505684

[10] Wei-Tek Hsu and Von-Wun Soo. 2001. Market performance of adaptive trading agents in synchronous double auctions. In *Pacific Rim International Workshop on Multi-Agents*. Springer, 108–121.

[11] Leslie Pack Kaelbling, Michael L. Littman, and Andrew W. Moore. 1996. Reinforcement learning: a survey. *Journal of Artificial Intelligence Research* 4 (1996), 237–285. https://doi.org/10.1613/jair.301

[12] Xiangjie Kong, Huizhen Jiang, Zhuo Yang, Zhenzhen Xu, Feng Xia, and Amr Tolba. 2016. Exploiting publication contents and collaboration networks for collaborator recommendation. *PloS One* 11, 2 (Feb. 2016), e0148492. https://doi.org/10.1371/journal.pone.0148492

[13] Sooho Lee and Barry Bozeman. 2005. The impact of research collaboration on scientific productivity. *Social Studies of Science* 35, 5 (Oct. 2005), 673–702. https://doi.org/10.1177/0306312705052359

[14] Jing Li, Feng Xia, Wei Wang, Zhen Chen, Nana Yaw Asabere, and Huizhen Jiang. 2014. ACRec: a co-authorship based random walk model for academic collaboration recommendation. In *Proceedings of the 23rd International Conference on World Wide Web*. ACM, Seoul, Korea, 1209–1214. https://doi.org/10.1145/2567948.2579034

[15] Linyuan Lü and Tao Zhou. 2011. Link prediction in complex networks: A survey. *Physica A: Statistical Mechanics and its Applications* 390, 6 (March 2011), 1150–1170. https://doi.org/10.1016/j.physa.2010.11.027

[16] Richard S Sutton and Andrew G Barto. 1998. *Reinforcement learning: An introduction*. Vol. 1. MIT press, Cambridge.

[17] Jie Tang, Sen Wu, Jimeng Sun, and Hang Su. 2012. Cross-domain collaboration recommendation. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, Beijing, China, 1285–1293. https://doi.org/10.1145/2339530.2339730

[18] Marco Wiering. 2000. Multi-agent reinforcement learning for traffic light control. In *ICML*. 1151–1158.

[19] Marco Wiering, Rafa l Sa lustowicz, and Jürgen Schmidhuber. 1999. Reinforcement learning soccer teams with incomplete world models. *Autonomous Robots* 7, 1 (1999), 77–88. https://doi.org/10.1023/A:1008921914343