National Defense Education Resource Recommender of High Education Institutions Based on Knowledge-Aware Generative Adversarial Network

Lin Tang[1,2] and Lin Liu[3](✉)

[1] Key Laboratory of Educational Informatization for Nationalities Ministry of Education, Yunnan Normal University, Kunming 650500, China
[2] Yunnan Key Laboratory of Smart Education, Kunming 650500, China
[3] School of Information, Yunnan Normal University, Kunming 650500, China
maitanweng2@163.com

Abstract. As there are issues of cold start and data sparsity in existing recommendation algorithms, this paper integrates the representation learning of knowledge graph into the recommendation process of generative adversarial model, and proposes a national defense education resource recommender of high education institutions based on knowledge-aware generative adversarial (KA-IRGAN). This model extracts the related entities and relations from the comment information of resource, and constructs the feature related knowledge sub graph of national defense education resource. Then the knowledge graph embedding method is utilized to transfer the entities in the knowledge sub graph as low-dimensional vectors, so as to obtain the low-dimensional feature vector of items and students for constructing the scoring function of item preference. The generative and discriminative modules are designed in the generative adversarial framework based on knowledge-aware. The generator and discriminator achieve Nash equilibrium in the process of iterative calculation, so that the final distribution of generative model is close to the real distribution of recommended resources. The experimental results on two benchmark datasets show that KA-IRGAN is superior to the existing IGRAN model in terms of recommendation accuracy and ranking quality, and is able to provide more efficient recommendation for national defense education system of high education institutions.

Keywords: National defense education · Recommendation system · Knowledge graph · Generative adversarial network

1 Introduction

Strengthening national defense education building, especially the national defense education for reserve talents in high education institutions, which has important significance to ensure the security of ethnic minority areas, promote national unity and consolidate national defense [1]. Many research institutions have made in-depth discussion about national defense education ideas in view of the "Internet +" in recent years

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[2]. Although current national defense education website integrates a large number of high quality resources of national defense education courses, experts and media, and so on, there are few studies and applications on personalized recommendation of national defense education resources.

At present, there are two difficulties in the research of national defense education resources recommendation for high education institutions. First of all, the resources of national defense education in high education institutions cover a wide range, not only including the curriculum resources of military theory formulated by the ministry of education, but also the resources of military technological trends, national policies, current affairs and news of border, which will contain a wealth of knowledge from national defense education fields. Secondly, the problems of cold start and data sparsity exist in the defense education resources recommendation. The consciousness of students' independent learning for defense education is still weak, so it is difficult to obtain the feedback data of students' rating on resources. A few of labeled feedback data can be obtained only by means of manual annotation, which cause the problem of data sparsity and "cold start" between new users and recommended resources.

With the introduction of generative adversarial networks (GAN) and knowledge graph (KG) into recommendation system, the above key problems of current studies have been solved in a certain degree in recent years. On the one hand, the application of GAN on the recommendation algorithm provides a new researching idea to the problem of data sparsity and cold start. The generator and discriminator can work collaboratively, so that the recommendation model is trained based on labeled and unlabeled data. This way of semi-supervised learning can not only make full use of the labeled data to learn the sample distribution, but also utilize the generator to generate supplementary samples for the discriminator. On the other hand, the rise of knowledge graph also provides a new idea for the improvement of personalized recommendation system. Knowledge graph represents the information in a structured form as a semantic network, which is understandable to people, and is easier to be organized, managed and utilized. Therefore, this paper propose an knowledge-aware information retrieval network (KA-IRGAN), which combine the knowledge graph and the theory of generative adversarial. This model makes full use of knowledge entity associations in the field of national defense education to obtain more accurate and efficient recommendation with the lack of labeled data.

2 Related Studies

Current researches of recommendation system based on deep learning can be roughly divided into three categories according to the idea of traditional recommendation algorithm: content-based recommendation algorithm, collaborative filtering and hybrid recommendation algorithm [3, 4].

For content-based recommendation, deep learning is mainly used to extract hidden features of items and users from item content, user preference and feedback information (such as users' browsing records), and generate recommendations by calculating the matching degree of hidden features of users and items. When there are rich auxiliary information for users and items, deep learning model is an effective tool of feature extraction. Researchers have carried out several researches of this field since 2013, which include multi-layer perceptron [5], convolutional neural network (CNN) [6, 7], recurrent neural network (RNN) [8] and deep belief network [9].

For the collaborative filtering algorithm based on deep learning, the feedback data between users and items is regarded as the training data of deep learning model. Through the model training, the hidden representation of users or items can be obtained, so as to provide the recommendation results. Researchers have successively applied multi-layer perceptron [10], restricted Boltzmann machine [11], autoencoder [12] and RNN [13] to collaborative filter since 2007. However, the insufficient feedback data will cause the problem of data sparsity in this kind of model. Especially, generative adversarial network has been introduced into the field of recommendation algorithm in 2017 [14]. This study integrated the classical generative retrieval model and the modern discriminative retrieval model into a unified "minimax game" framework. Hereafter, further studies have been carried out by integrating matrix factorization and RNN into the generative adversarial framework [15]. Nonetheless, these studies are still based on collaborative filtering algorithm, where a large amount of user-item feedback data is required.

3 The Problem Description and Model Framework

3.1 The Vector Representation of Resource Items and Students Based on Knowledge Graph

Step1: The "relevant entities" are extracted from the user's comments on the resource items, and the "feature related knowledge sub graph" of the defense education resource is constructed. Students' comments on national defense education resources are mainly based on text, pictures, videos and so on. There are not only a large number of attribute information related to these resources, but also student preferences for these resources. The entity in the comment is the basic language unit that carries the feature information. Among them, the most intuitive and convenient feedback information is the high-quality explicit feedback called "rating" (such as the user rating of a military video); when there is no explicit feedback, the student's online behavior (including browsing history, collection history, purchase history, etc.) can be used as the implicit feedback indirectly that reflect students' opinions.

Through named entity recognition (NER) and entity linking (EL) technology, this paper analyzes and extracts the related entities and their link relations corresponding to the knowledge map from the comment information of national defense education resources. In this paper, we extract the related entity set from the comment information by NER based on conditional random fields (CRF), to make a traversal for entity name in named entity database of KG. Then, the entities are linked to the corresponding entity in KG by EL, and the ambiguity problem between the entities is solved.

Given the students set $U = \{u_n\}_{n=1}^{N}$ and the defense education resource set $I = \{i_m\}_{m=1}^{M}$, the total number of students and resources are denoted as N and M respectively. Each item of I has its related description information and students' comment information (such as name, type, function and so on). Then the resource items set selected by a specific student u is $I_u = \{i_m^u\}_{m=1}^{P}$, and P is the total number of resource items selected by student u. In the comment information of p th ($p = 1, 2, \ldots, P$) choosed by student u, we can extract k_p related entities e_p^u from KG G, the related entity set of item i_p^u was denoted as $R_p^u = \{e_{p,j}^u\}_{j=1}^{k_p}$. Therefore, according to the analysis of all items in I^u, we obtain the related entities set $R^u = \{R_p^u\}_{p=1}^{P^u}$ of student u (based on history behaviors). Each entity of R^u is connected by different correlation, so as to construct a "feature related knowledge sub graph".

Step2: Through the link relationship of KG, the feature related knowledge subgraph of student-item is expanded. In the process of extracting related entity in step 1, the number of entities is limited by the number of comments on the resource. If there is less comment information, there will be less related entities extracted from resource, that causes the problem of sparse data and single feature. In order to enrich the related entity set R^u of student u, R^u is regarded as the seed entities set in KG G, and is expanded to k order related entity set of through the link relationship of KG. Given the KG G and the set of n seed entities $E(n < |E|)$, in the KG entity-relation-entity triple $(h, r, t) \in G$, if the head h is the set of $k-1$ order related entities $h \in E^{k-1}$, then the tail t is the k order related entities set: $E^k = \left\{t|(h, r, t) \in G, \ \ \& \ \ h \in E^{k-1}\right\}$, $k = 1, 2, \ldots, H$, where H is the maximum order, so as to expand the related knowledge sub graph of defense education resource.

Step3: Using KG embedding method, the low-dimensional vector representation of entities in knowledge sub graph is obtained, and the low-dimensional vector representation of items and students in defense education resource is further obtained.

In this paper, TransR is used to represent head and tail entities in the KG entity-relation-entity triple (h, r, t) as k dimension vector $\mathbf{v}_h^k$ and $\mathbf{v}_t^k$, and the relationship r is represented as d dimension vector $\mathbf{v}_r^d$. Based on the $k \times d$ dimension transformation matrix $\mathbf{M}_r^{k \times d}$, the k dimension head and tail entity vector is mapped to the d dimension relation space: $\mathbf{v}_h^d = \mathbf{v}_h^k \mathbf{M}_r^{k \times d}$ and $\mathbf{v}_t^d = \mathbf{v}_t^k \mathbf{M}_r^{k \times d}$. The corresponding score function is defined as L2 norm $f = \left\|\mathbf{v}_h^d + \mathbf{v}_r^d - \mathbf{v}_t^d\right\|$.

The set of related entities extracted from the feedback information of item i selected by student u is expressed as $R_i^u = \{e_{i,j}^u\}_{j \in J}$, then each entity $e_{i,j}^u$ in R_i^u represents the feature of items i in different degree. Therefore, we give weight to different entitiy $e_{i,j}^u$ as ω_j on the basis of low-dimensional vector representation. The greater the weight ω_j, the stronger the entity's $e_{i,j}^u$ ability to express the characteristics of item i; if the entity $e_{i,j}^u$ is not able to reflect the feature of item i, or only represent a few portion of feature, then $\omega_j \approx 0$. At this time, the vector of the items selected by student u is expressed as $\mathbf{v}_i^u = \sum_{j \in J} \omega_j \mathbf{v}_{e_{i,j}^u}$. If the total number of items selected by student u is P, then the vector of student u is expressed as $\mathbf{u}^u = \mathbf{B}^u + \sum_{i=1}^{P} \mathbf{v}_i^u$, where $\mathbf{B}^u$ is the deviation of student u.

Step4: The implicit feedback matrix of student-item is constructed, and the scoring function of student-item pair is calculated based on knowledge-aware.

The implicit feedback is collected through students' online operation records, which is a useful complement to item feature information when there is little or no students' comments (explicit feedback). Given the set of students $U = \{u_n\}_{n=1}^{N}$ and the set of defense education resource items $I = \{i_m\}_{m=1}^{M}$, the implicit feedback of student u to item i is denoted by Q_i^u, then $Q_i^u = 1$ means that student u has given feedback to item i, otherwise $Q_i^u = 0$. By this way, an implicit feedback matrix $\mathbf{Q}$ with $N \times M$ dimension can be constructed. The score of student u to item i is expressed as:

$$p(u, \ i) = \sigma\left(\mathbf{u}^u \odot \mathbf{v}_i^u\right), \quad p(u, \ i) > 0 \tag{1}$$

Among the above equation, $\mathbf{u}^u$ and $\mathbf{v}_i^u$ are vector representations of student u and item i obtained by step 1 to step 3. $\odot$ denotes the inner product of vectors, and σ is sigmoid function used to calculate score of (u, i).

3.2 Recommendation Process of IRGAN Framework

In IRGAN framework, the student's information set $Q = \{q_u\}_{u \in U}$ (either preference information or students' historical behavior data), the items set $I = \{i_m\}_{m=1}^{M}$, and an item recommendation rating matrix $\mathbf{R} = \{r_{ui}\}_{u \in U, i \in I}$ with $N \times M$ dimension are given. r_{ui} represents the rating of student u to item i, then the recommendation process can be described as obtaining a list of items I^u related with q_u based on student's information q_u. Assuming that there is a real distribution $p_{true}(i|q_u, r)$ of items related to user information q_u, and the relevance degree of q_u and item i is r. The generator try to fit the real distribution p_{true} as much as possible according to the input user information q_u, and generates "pseudo items" i' with a probability of $G_\theta\left(i'|q_u, r\right)$. Meanwhile, the discriminator D attempts to distinguish whether the current item i is real or "pseudo items" i' from the generator G, and provides the relevance degree r of current item i and q_u, so as to make the generator G approaching to the real distribution. Iterative learning is carried out by maximizing and minimizing the objective function shown in Eq. (2) respectively. Finally, the generator G and the discriminator D are optimized together in the strategic game, and the Top-N items are recommended by the optimized rating r for student u.

$$
\begin{aligned}
J^{\theta^*,\ \phi^*} = \min_\theta \max_\phi \sum\nolimits_{u \in U} \big(&\mathbb{E}_{p_{true}(i|q_u, r)}\left[\log D_\phi(i|q_u, r)\right] \\
&+ \mathbb{E}_{G_\theta(i'|q_u, r)}\left[\log\left(1 - D_\phi\left(G_\theta\left(i'|q_u, r\right)\right)\right)\right]\big)
\end{aligned} \tag{2}
$$

Among the above Eq. (2), $f_\phi(q_u, i)$ is a discriminative recommendation model (or discriminative scoring function). f_ϕ is used to estimate the probability D_ϕ of student information q_u associated item i by the sigmoid function σ of discriminative scoring.

$$
D_\phi(i|q_u, r) = \sigma\left(f_\phi(q_u, i)\right) = \frac{\exp\left(f_\phi(q_u, i)\right)}{1 + \exp\left(f_\phi(q_u, i)\right)} \tag{3}
$$

The parameter ϕ of D_ϕ is solved by Eq. (4) using the stochastic gradient descent method (f_ϕ is differentiable for ϕ):

$$
\begin{aligned}
\phi^* = \arg\max_\phi \sum\nolimits_{u \in U} \big(&\mathbb{E}_{p_{true}(i|q_u, r)}\left[\log \sigma\left(f_\phi(q_u, i)\right)\right] \\
&+ \mathbb{E}_{G_{\theta^*}(i'|q_u, r)}\left[\log\left(1 - \sigma\left(f_\phi\left(q_u, i'\right)\right)\right)\right]\big)
\end{aligned} \tag{4}
$$

If the generative recommendation model is $g_\theta\left(q_u, i'\right)$, then the probability G_θ of selecting a specific item i' from $I = \{i_m\}_{m=1}^{M}$ can be provided by the softmax function δ:

$$
G_\theta\left(i'|q_u, r\right) = \delta\left(g_\theta\left(q_u, i'\right)\right) = \frac{\exp\left(g_\theta\left(q_u, i'\right)\right)}{\sum_{i \in I} \exp\left(g_\theta(q_u, i)\right)} \tag{5}
$$

The parameter θ of G_θ is updating by Eq. (6)

$$\begin{aligned}\theta^* &= \arg\min_\theta \sum\nolimits_{u\in U} \mathbb{E}_{G_\theta(i'|q_u,r)}\left[\log\left(1-\sigma\left(f_{\phi^*}\left(q_u,i'\right)\right)\right)\right] \\ &= \arg\max_\theta \sum\nolimits_{u\in U} \mathbb{E}_{G_\theta(i'|q_u,r)}\left[\log\left(1+\exp\left(f_{\phi^*}\left(q_u,i'\right)\right)\right)\right]\end{aligned} \tag{6}$$

In the field of recommender, the generator $G_\theta\left(i'|q_u,r\right)$ is a discrete distribution of item $i' \in I$, which is updated by the strategic gradient descent method of reinforcement learning. It can be seen from Eq. (6) that the generative process can be regarded as a simple single step Markov decision process (MDP). G_θ is the probability of current state (q_u, i) to the next state $\left(q_u, i'\right)$, and r is the reward of environmental feedback. $\log\left(1+\exp\left(f_\phi\left(q_u,i'\right)\right)\right)$ severs as a strategy and an item is selected from candidate, that is the feedback reward to the next state. In order to reduce the variance caused by the strategic gradient, we can take the strategic gradient as the baseline by setting it to 1, which is replaced by Eq. (7):

$$V(q_u, i) = 2\sigma f_\phi(q_u, i) - 1 \tag{7}$$

3.3 IRGAN Recommendation Algorithm Based on Knowledge-Aware

To integrate the KG embedding learning process into the recommendation process of IRGAN, this paper proposes a knowledge-aware IRGAN (KA-IRGAN) framework.

In IRGAN, the hidden feature vectors $\left(\mathbf{u}^u, \mathbf{v}_i^u\right)$ are obtained by matrix factorization of the item recommendation score matrix $\mathbf{R} = \{r_{ui}\}_{u\in U, i\in I}$, and then define the preference score function $s(u,i) = \mathbf{u}^u \odot \mathbf{v}_i^u + b_i$. The difference of our approach with IRGAN is that, we first represent users and resource items as low-dimensional vector $\mathbf{u}^u$ and $\mathbf{v}_i^u$ based on KG through steps 1–3 in Sect. 3.1. Then, the generative recommendation model is defined as follows:

$$g_\theta(q_u, i) = \mathbf{u}^u \odot \mathbf{v}_i^u + b_i \tag{8}$$

The probability of selecting a specific item i' is $G_\theta\left(i'|q_u,r\right)$ that the probability of state-transition is obtained from Eq. (5). Then generated (selected) "pseudo" student-item pair that $(u,i) \xrightarrow{G} \left(u,\ i'\right)$ is input to the discriminator D_ϕ. D_ϕ identifies student-item sample pair that input, and take the student-item preference score as the discriminative score or feedback reward:

$$f_\phi(q_u, i) = p(u,\ i) = \sigma\left(\mathbf{u}^u \odot \mathbf{v}_i^u\right) \tag{9}$$

It is passed to the generator G_θ. As the influence of global bias and user bias will be gradually eliminated in top-N recommendation, so they are ignored in Eqs. (8) and (9). The model parameter ϕ and θ are updated by Eq. (4) and (6). With the continuous iteration, an optimal distribution is finally obtained, that is the recommended items list of student.

4 Experimental Result

4.1 Experiment Environment

For the hardware environment, the Intel Core i7-4720HQ@2.60 GHz of quad-core processors and the internal storage with 8.00 GB are deployed, which also supports GTX960 graphics card of CUDA7.5 framework. For software environment, there are Windows 10 x64, pcharm compiling environment, Anaconda 5.1 with Python 3.5 interpreter and CPU version of tensorflow1.12.1.

4.2 Datasets and Experimental Setting

First of all, we have carried out a wide range of data collection and organization various defense education websites, and obtained a certain amount of data. There are 1047 of text resource data and 2304 of military theory course text data obtained from websites. The statistics of datasets is shown in Table 1:

Table 1. Statistics of national defense education resources.

Resource Website	Military theory	Defense mobilization	Patriotism education	Military technology	Defense news	Policies & regulations	Others
http://www.gfjyzx.com/	19	13	18	31	38	0	15
http://www.guofangjiaoyu.net/	33	3	4	0	74	38	21
http://www.mod.gov.cn/edu	10	7	412	12	21	15	13
https://military.china.com/gfjy/	15	12	60	18	22	0	14
http://www.gf81.com.cn/	20	15	15	12	24	0	23

Secondly, to compare with other collaborative filtering recommendation algorithms, especially IRGAN model, two datasets that Movielens (100k) and FilmTrust are adopted in our experiment. To do experiments. These two datasets are randomly divided into training and testing datasets based on the ratio of 4:1. MovieLens dataset is about movie scoring proposed by GroupLens team of the University of Minnesota, which was divided into many sub datasets by size, such as 100k, 1M, 10M, 20M and the latest dataset. FilmTrust is a small dataset crawled from movie website in 2011. The Movielens (100k) and FilmTrust dataset are used to compare KA-IRGAN with the original IRGAN model. The evaluation criteria used in experiment includes: the "accuracy" that reflect the proportion of students' interested items in all items (Precision@k), the normalized discounted cumulative gain(NDCG@k) usually used to measure ranking quality, and mean average precision (MAP).

4.3 Experimental Results and Analysis

The comparison results of KA-IRGAN and original IRGAN on Movielens (100k) and FilmTrust datasets are shown in Table 2 and Table 3. The experimental results are illustrated in Fig. 1, which shows the change of Precision@k with the number of recommended items k on Movielens (100k) dataset.

Table 2. Item recommendation results and performance (Movielens-100 k).

	Pre@5	Pre@10	NDCG@5	NDCG@10	MAP
IRGAN	0.3750	0.3140	0.4009	0.3723	0.2418
KA-IRGAN	0.4789	0.4465	0.4734	0.4115	0.2632

Table 3. Item recommendation results and performance (FilmTrust).

	Pre@5	Pre@10	NDCG@5	NDCG@10	MAP
IRGAN	0.2928	0.2671	0.3155	0.2913	0.2120
KA-IRGAN	0.3854	0.3247	0.3334	0.3480	0.2632

As we can see from the experimental results, KA-IRGAN has obtained significant improvement on Precision@k and NDCG@k, when the number of recommended items $k = 5$ and $k = 10$, and get better results than IGRAN on three evaluation criteria. Meanwhile, the values of Precision@k gradually decreases with the increase of the recommended items number k, which tends to be stable when $k = 15$. These experimental results indicate that KA-IRGAN has a reliable training process compared with IRGAN, and has the distinct advantage to complete resource recommendation owing to the knowledge representing abilities of KG.

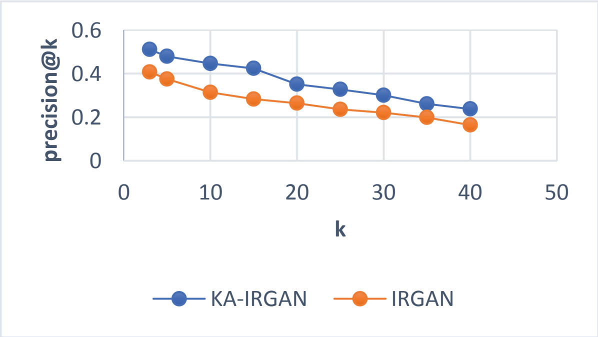

Fig. 1. The comparison of accuracy between KA-IRGAN and IRGAN with different k

5 Conclusion

For the personalized recommendation of national defense education resource of high education institutions, there are issues of cold start and data sparsity due to insufficient analysis of resource and student feature in existing recommender studies. This paper proposes a national defense education resource recommender of high education institutions based on knowledge-aware generative adversarial named KA-IRGAN. Based on the comment information of student on resource items and historical behavior in the network, this model introduces knowledge graph embedding method to learn the low dimension feature of national defense education resources and students, and integrate these features into generative adversarial model of information retrieval. The parameters of the generator and discriminator are optimized through minimax game iteration, where the distribution of generator is approaching to the real item distribution, so as to achieve more accurate recommendation.

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References

1. Yu, M.: Thoughts on strengthening national defense education in border areas under the new situation. Nat. Defence **04**, 48–50 (2016)
2. Cong, D., Li, J., Bo, S., et al.: Research on the main problems and countermeasures of the development of national defense education in colleges and universities. Beijing Educ. **12**, 30–32 (2018)
3. Huang, L., Jiang, B., Lu, S., et al.: A survey of recommendation system based on deep learning. J. Comput. Sci. **41**(07), 1619–1647 (2018)

4. Zhang, S., Yao, L., Sun, A., et al.: Deep learning based recommender system: a survey and new perspectives. ACM Comput. Surv. (CSUR) **52**(1), 5 (2019)
5. Yu, W., Zhang, H., He, X., et al.: Aesthetic-based clothing recommendation. In: Proceedings of the 2018 World Wide Web Conference, Lyon, France, pp. 649–658 (2018)
6. Gong, Y., Zhang, Q.: Hashtag recommendation using attention-based convolutional neural network. In: International Joint Conference on Artificial Intelligence (IJCAI), New York, USA, pp. 2782–2788 (2016)
7. Zhou, J.X., Liu, X.D., Gan, J.H.: Exploiting best practice of deep convolutional features for national costume image retrieval. Int. J. Performability Eng. **14**(4), 621–630 (2018)
8. Cui, Q., Wu, S., Liu, Q., et al.: MV-RNN: a multi-view recurrent neural network for sequential recommendation. IEEE Trans. Knowl. Data Eng. **14**(8), 317–331 (2018)
9. Wang, D., Liang, Y., Xu, D., et al.: A content-based recommender system for computer science publications. Knowl. Based Syst. **157**, 1–9 (2018)
10. Deldjoo, Y., Elahi, M., Quadrana, M., et al.: Using visual features based on MPEG-7 and deep learning for movie recommendation. Int. J. Multimedia Inf. Retrieval **7**(4), 207–219 (2018)
11. Wu, X., Yuan, X., Duan, C., Wu, J.: A novel collaborative filtering algorithm of machine learning by integrating restricted Boltzmann machine and trust information. Neural Comput. Appl. **31**(9), 1–8 (2018). https://doi.org/10.1007/s00521-018-3509-y
12. Zhuang, F., Luo, D., Yuan, N. J., et al. Representation learning with pair-wise constraints for collaborative ranking. In: Proceedings of the 10th ACM International Conference on Web Search and Data Mining, Cambridge, UK, pp. 567–575 (2017)
13. Liu, Q., Wu, S., Wang, L.: Multi-behavioral sequential prediction with recurrent log-bilinear model. IEEE Trans. Knowl. Data Eng. **29**(6), 1254–1267 (2017)
14. Wang, J., Yu, L., Zhang, W., et al.: IRGAN: a minimax game for unifying generative and discriminative information retrieval models. In: Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval, pp. 515–524. ACM (2017)
15. Zhao, W., Chai, H., Wang, B., et al.: Leveraging long and short-term information in content-aware movie recommendation. arXiv preprint arXiv:1712.09059 (2017)