Translative Neural Team Recommendation: From Multilabel Classification to Sequence Prediction

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Abstract

Neural team recommendation has achieved state-of-the-art performance in forming teams of experts whose success in completing complex tasks is *almost surely* guaranteed. The proposed models frame the problem as a Boolean multilabel classification, mapping the dense vector representations of required skills to the sparse occurrence (multi-hot) vector representation of an optimum subset of experts using multilayer feedforward neural networks. Such approaches, however, suffer from the curse of sparsity in the high-dimensional vector of optimum experts in the output layer. In this paper, we propose to reformulate the team recommendation problem into a sequence prediction task and leverage seq-to-seq models, including transformers, to map an input sequence of the required subset of skills onto an output sequence of the optimum subset of experts. Our experiments on four large-scale datasets from various domains, with distinct distributions of skills in teams, show that the seq-to-seq approach is consistently superior overall in a host of classification and information retrieval metrics. Our codebase is available at `https://github.com/fani-lab/OpeNTF/tree/nmt`.

CCS Concepts

• Information systems → Recommender systems; **• Human-centered computing → Social recommendation**; **• Computing methodologies → Neural networks**.

Keywords

Neural Team Recommendation; Seq-to-Seq; Transformer; Social IR;

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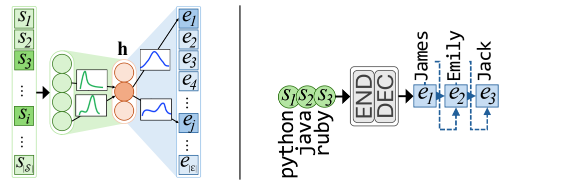

Figure 1: Multilabel[43] vs. seq-to-seq team recommendation.

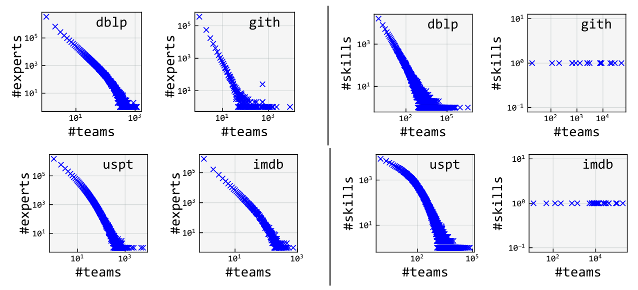

Figure 2: Distribution of teams over experts (left) and skills (right) for `dblp`, `uspt`, `imdb`, and `gith` datasets.

1 Introduction

As modern projects have been surpassing the capacity of individuals, collaborative teams of experts have become vital in today's diverse landscape across academia [25, 47, 61], industry [1, 13, 27], law [4, 24], freelancing [18], and healthcare [48, 50], and the success of projects hinges on the effectiveness of teams. Assembling an effective team can be seen as social information retrieval (Social IR), where the right group of experts, rather than relevant information, is desired to accomplish a task at hand [22, 23]; a tedious, error-prone, and suboptimal process should it be manual, as it is predisposed to hidden personal and societal biases [40], falls short for an overwhelming number of experts, and fails to consider a multitude of criteria to optimize simultaneously [2]. Therefore, a rich body of computational methods, from operations research [3, 12, 15, 28, 52, 58, 59, 64] social network analysis [19, 31, 51] and more recently, machine learning [6, 16, 42, 44], have been proposed for team recommendation, also known as team allocation, team selection, team composition, and team configuration. Among such methods, neural models have brought state-of-the-art efficacy and efficiency due to the iterative and online learning procedure, and availability of training datasets.

By and large, proposed neural models frame the team recommendation problem as a *multilabel* Boolean classification task, learning the distributions of experts and their skill sets in the context of teams in the past to draw a subset of experts whose history of collaborations is statistically more likely successful. As seen in Figure 1 (left), they map a dense low-dimensional vector representation (embedding) of a required subset of skills onto the output layer, which is an occurrence (multi-hot) vector representation of a successful (optimum) team. In the output layer, each expert is mapped

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to a label and would be recommended if their class's prediction probability is close to 1 [42, 43]. Such models, however, suffer from the curse of sparsity in the output layer. Due to the large number of labels (experts), neural classifiers, which learn their parameters based on average loss values over all labels, may underfit as the average loss becomes near `0` over a very large number of experts. While researchers have tried weighted cross-entropy [44] and negative sampling heuristics [6] to fill the gap, such models still suffer from the lack of sufficient efficacy.

In this paper, unlike existing approaches, which first learn skill embeddings and then transfer them to a neural multilabel classifier, we propose to reformulate the problem into an end-to-end sequence prediction task between pairs of ⟨sequence of required skills ⟶ sequence of optimum experts⟩ and employ recurrent and transformer-based seq-to-seq neural models, as seen in Figure 1 (right).

Seq-to-seq approaches have gained significant traction for their efficacy not only in natural language tasks, but also in recommendation systems for sequence modelling like `transformer4rec` [9], `sas-rec` [30], and `bert4rec` [53]. However, despite the similarity, applying the seq-to-seq approach for team recommendation withholds its own unique challenges: (1) training datasets have their own unique skill and expert sets, and therefore, the pretaining or finetuning approach, which is successful for tasks like product recommendation, has limited applications for team recommendations; (2) Moreover, a team recommender works with two distinct sets of skills and experts where their distributions over teams are highly domain-dependent. As seen in Figure 2 (left), the distributions of teams over experts in all datasets are long-tailed as many experts (researchers in `dblp`, developers in `gith`, inventors in `uspt`, and cast and crew in `imdb`) have participated in very few teams (papers in `dblp`, software repositories in `gith`, patents in `uspt`, and movies in `imdb`). However, with respect to the set of skills, while `dblp` and `uspt` suffer further from the long-tailed distribution of skills in teams, `gith` and `imdb` follow a more fair distribution, as shown in Figure 2 (right). Specifically, `gith` and `imdb` have a limited variety of skills (programming languages in `gith` and genres in `imdb`), which are employed by many teams. To our knowledge, no work has explored the seq-to-seq approach for the team recommendation task in the context of such challenges before our study.

2 Related Works

On the one hand, there has been extensive work on seq-to-seq models and transformers for sequential recommendation systems [30, 53, 55, 63]. Hidasi et al. [20] were among the first to apply recurrent neural networks for sequence-based recommendations, stacking `gru` units with learning-to-rank losses to leverage user-item sequences where collaborative filtering fails. Similarly, Wu et al. [60] used `lstm` with `softmax` loss to capture temporal patterns. Tang et al. [55] applied convolution layers to produce effective user embeddings while addressing efficiency and scalability [30, 55]. A breakthrough came with Kang et al. [30] introducing `sas-rec`, a transformer-based model with left-to-right self-attention and point-wise ranking loss. Later, Sun et al. [53] proposed `bert4rec`, employing bidirectional self-attention with a point-wise ranking loss on item sequences. These transformers are now optimized and released by nvidia's `transformers4rec` [8, 9, 21, 30, 53] for product recommendations at scale. Despite extensive research and industrial successes of sequence modelling for user-item recommendation, its application for team recommendation is yet to be studied, and to our knowledge, we are the first to bridge this gap.

On the other hand, team recommendation has long attracted both social and computer science researchers whose proposed approaches can be categorized as: (1) search-based methods using operation research methods [3, 12, 15, 28, 52, 58, 59, 64] or expert network analysis [19, 31, 51], (2) reinforcement-based methods [14, 38, 65], and (3) learning-based methods [16, 33, 42–44, 49]. While search- and reinforcement-based techniques are theoretically sound, they often struggle with scalability, making learning-based approaches preferable. Within the learning-based category, simple feedforward networks [44] were used initially, which were later improved with variational Bayesian networks [7, 43, 44] to address popularity bias via Gaussian uncertainty. Dashti et al. [6] further enhanced performance by using negative sampling to mitigate the dominance of popular experts. However, these methods assume independent expert selection, overlooking team dynamics. To capture collaborative relationships, graph neural network-based methods emerged. Rad et al. [42] incorporated expert collaboration graphs with `metapath2vec` [11] for *skill* embeddings, and Kaw et al. [33] used deep graph infomax [57] with graph convolution networks with attention layers to improve upon skill embeddings. Despite these advances, current neural methods treat team recommendation as a multilabel classification problem, assuming *experts* can be selected independently, and hence fail to capture real-world team dynamics. Moreover, such models rely on high-dimensional multi-hot output representations for experts, leading to computational inefficiencies for a large pool of experts.

3 Problem Definition

Given a set of skills $\mathcal{S} = \{s_i\}$ and a set of experts $\mathcal{E} = \{e_j\}$, a team is a tuple $(\mathbf{s}, \mathbf{e})$ where an ordered list of experts $\mathbf{e} \subseteq \mathcal{E}$ collectively cover an ordered list of required skills $\mathbf{s} \subseteq \mathcal{S}$ to accomplish a task at hand. Further, $\mathcal{T} = \{(\mathbf{s}, \mathbf{e})_k\}$ indexes all instances of successful teams. For a given set of skills $\mathbf{s}$, the team recommendation problem aims at identifying an optimal subset of experts $\mathbf{e}$ such that their collaboration in the predicted team is successful. More concretely, the team recommendation problem is to learn a mapping function f of parameters $\boldsymbol{\theta}$ such that $\forall(\mathbf{s}, \mathbf{e}) \in \mathcal{T}; f_{\boldsymbol{\theta}}(\mathbf{s}) = \mathbf{e}$.

4 Proposed Approach

We propose to transform the team recommendation task into a seq-to-seq modelling task, mapping a dynamic-length input sequence of required skills onto a dynamic-length output sequence of predicted experts while leveraging the autoregression and global attention mechanisms, which capture dependencies *beyond* independent expert probabilities in multilabel classification.

We estimate $f_\theta(\mathbf{s})$ on a parallel dataset whose pairs of sequences are pairs of $(\mathbf{s}, \mathbf{e}) \in \mathcal{T}$, transforming the ordered list of required skills $\mathbf{s} = [s_{i_1}, \ldots, s_{i_n}]$ into an optimum ordered list of experts $\mathbf{e} = [e_{j_1}, \ldots, e_{j_m}]$. We then employ a seq-to-seq encoder-decoder neural architecture [5, 26, 29, 41, 54] to maximize the conditional

Table 1: Statistics of the raw and preprocessed datasets.

	dblp		uspt		imdb		gith	
teams $\mathcal{T}$	publications		patents		movies		software repos	
experts $\mathcal{E}$	authors		inventors		cast & crew		developers	
skills $\mathcal{S}$	keywords		subclasses		(sub) genres		prog. lang.	
success	published		issued		produced		released	
statistics	raw	prep.	raw	prep.	raw	prep.	raw	prep.
$\|\mathcal{T}\|$	4.9M	99K	7.1M	152K	507K	32K	133K	46K
$\|\mathcal{E}\|$	5.0M	14K	3.5M	13K	877K	2.0K	453K	1.2K
$\|\mathcal{S}\|$	90K	30K	242K	67K	28	23	20	20
#teams w/ one expert	769K	**0**	2.6M	**0**	323K	**0**	**0**	**0**
avg. #experts/team	3.06	3.29	2.51	3.79	1.88	3.98	5.52	7.53
avg. #skills/team	8.57	9.71	6.29	9.97	1.54	1.76	1.37	1.57

probability $p(\mathbf{e}|\mathbf{s})$ to learn f_θ. The encoder maps the *sequence* of skills $[s_{i_1},\ldots,s_{i_n}]$ onto $\mathbf{h}_n$ and the decoder generates the sequence of experts $[e_{j_1},\ldots,e_{j_m}]$ from the $\mathbf{h}_n$, one expert at a time, decomposing the conditional probability $p(\mathbf{e}|\mathbf{s})$ as $\prod_{k=1}^{m} p(e_{j_k}|e_{j_{<k}},\mathbf{s})$ and seeking the maximum probability among subsets of experts as an optimum team for $\mathbf{s}$, i.e., $f_\theta(\mathbf{s})=\mathbf{e}$. The probability of generating an expert at the decoder can be conditioned not only on $\mathbf{h}_n$ but also on all $\mathbf{h}_{<n}$ at the encoder, enabling the decoder to *attend* to all skills in the input sequence selectively [41]. To reduce the computational complexity at the encoder and the decoder, a seq-to-seq model may have *no* recurrent connections, like in transformers [56], enabling parallel calculation of $\mathbf{h}_{<n}$ at the encoder and $\mathbf{h}_{>=n}$ at the decoder, an architecture that yielded promising performance on machine translation and led to extensive research on seq-to-seq modelling [10, 46, 62].

5 Experiment

We seek to answer the following research questions:
RQ1. Does the seq-to-seq approach yield performance improvements over existing multilabel neural team recommenders?
RQ2. Which seq-to-seq model performs the best (worst) for team recommendation?
RQ3. How well does the seq-to-seq approach generalize across different domains in team recommendation?

5.1 Setup

Datasets. Our testbed includes four benchmark datasets in team recommendation literature: dblp [16, 33, 37, 39, 42–45] and uspt [16, 34], which follow similar long-tailed distributions for *both* experts and skills over teams, and imdb [6, 16, 35] and gith [16, 31, 32], which follow long-tailed distribution of experts *but* uniform distribution of skills over teams. Each dataset was preprocessed to ensure a team consisted of more than 3 experts, and each expert participated in at least 75 teams. Table 1 shows the mapping of raw data properties to the team $\mathcal{T}$, skill $\mathcal{S}$, and expert $\mathcal{E}$ sets, along with a summary of statistics.
Baselines. We compare two categories of baselines: (1) existing neural team recommenders including variational Bayesian feedforward neural network with multi-hot (bnn) [44] and dense (bnn_emb) [43] vector representation in the input layer; (2) seq-to-seq models including recurrent recommender network (rrn) [60], vanilla recurrent neural network with attention (rnn-att) [66], convolutional seq-to-seq (convs2s) [17], and the transformer [56].

Table 2: Hyperparameters and running settings for models.

	transformer	convs2s	rnn-att	rrn,bnn bnn_emb
batch size	128	8^+, 128	128	128
learning rate	Vaswani et al. [56]			0.1
epochs	20	1^+, 20	20	20
optimizer	Adam			
hidden layer size	512	128	128, 512*	128
hidden activation	relu, softmax	glu	tanh, sigmoid	relu
output layer	128	128	128	$\|\mathcal{E}\|$
output activation	softmax			sigmoid

$^+$: convs2s model setting for uspt dataset.

The transformer recommends experts through its parallel self-attention mechanism, where each selection considers both the entire skill sequence and all previously predicted experts simultaneously, capturing dependencies regardless of their sequence position. The convs2s model, on the other hand, processes skill-expert relationships through stacked convolutional layers that create hierarchical representations. Lower layers capture local skill-expert matches, while deeper layers learn broader team composition patterns, capturing relationships between distant elements in the sequence efficiently. The rnn-att learns the expert selection sequentially, and in the hidden state, the expert choice is updated using attention to focus on which expert is relevant to which skill. The rrn model is an item-user recommender system that assumes dynamic (temporal) embeddings for users and items to capture behavioral trajectories using lstm for better prediction accuracy. We used opennmt-py [36] for implementation of seq-to-seq models except for rrn whose code has kindly been provided by its authors [60]. Table 2 summarizes the models' hyperparameters and running settings.
Evaluation. We randomly select 15% of teams for the test set and perform 3-fold cross-validation on the remaining teams for model training over 20 epochs for all the models in all datasets except for the convs2s in uspt dataset with 1 epoch due to intractable time complexity, which results in one trained model per fold. Given a team $(\mathbf{s},\mathbf{e})$ from the test set, we compare the sequence of experts $\mathbf{e}'$, predicted by the model of each fold, with the observed subset of experts $\mathbf{e}$ and report the average performance of models on all folds in terms of classification metrics including precision, recall, as well as information retrieval metrics including normalized discounted cumulative gain (ndcg) and mean average precision (map) at $k \in \{2,5,10\}$ first generated sequence of experts. The final results are obtained by averaging the performance metrics across all folds for a robust evaluation of the model's predictive capabilities while minimizing fold-specific variation in the data distribution.

5.2 Results

Foremost, we acknowledge that all models achieve low values of evaluation metrics for practical applications of team recommendation, which is primarily due to the simplicity of the neural model architectures and the small number of training epochs given the intensive computational demands for such methods coupled with our limited computational resources; metric values are reported in % for ease of readability and comparison. Our main goal is to showcase the optimum solution setting, seq-to-seq vs. multilabel classification for team recommendation.

In response to **RQ1**, i.e., whether seq-to-seq models yield better performance vs. feedforward models, the results from Table 3 demonstrate that *all* seq-to-seq models outperform the feedforward ones across metrics and datasets. This can be attributed to conditioning of expert recommendation on the previously recommended experts in the output sequence, allowing for more robust prediction compared to the inherent sparse activations in the output layer of feedforward models. Notably, seq-to-seq models' relative improvements have been as high as `82x` in some datasets, suggesting the right track for the most suitable neural architecture for team recommendation. The only exception is `rrn`, which performs on par or even poorer than the feedforward baselines and will be discussed more in **RQ2**.

In response to **RQ2**, looking into the seq-to-seq models for the best (worst) performance, from Table 3, the `transformer` consistently outperforms other models across *most* datasets and metrics. This is because the `transformer` benefits from (1) its self-attention mechanism, which allows capturing the relevance of skills independently and simultaneously, (2) the encoder-decoder structure effectively captures the input skill domain and the output expert domain regardless of position in the sequence due to (1), and (3) the parallel processing. The runner-up, however, depends on the underlying distribution of skills over teams (the input sequence) in a dataset. In `dblp` and `uspt`, `convs2s` is the runner-up, whereas in `imdb` and `gith`, `rnn-att` is the second-best. The `convs2s` model's performance is particularly strong on large datasets like `uspt` with long-tailed distributions of skills and experts over teams. The `rnn-att` model's performance is affected by the dataset's distribution shape, struggling with long-tailed distributions but performing well on uniformly distributed skills like in `imdb`. Lastly, the worst seq-to-seq model is `rrn`, as mentioned in **RQ1**, which falls short of consistently outperforming compared to feedforward baselines across datasets and metrics. Specifically, `rrn` uses `lstm` without attention mechanism, which means all relevant skills must be in a fixed-size hidden state to be used as historical information.

To answer **RQ3**, i.e., whether the outperformance of seq-to-seq models can generalize to various domains, the results from Table 3 demonstrate superior performance compared to the baselines in all four datasets across metrics. However, the extent of improvement depends on the underlying dataset, esp., the distribution of skills over teams. In `imdb` and `gith`, where the skills are distributed uniformly in the input sequence, the improvement extends to `5x` on average across metrics. In contrast, when the skills are distributed in a long-tailed fashion, the improvement increases to about `82x`. For both types of distributions of skills, the improvement is at least `2x`. This showcases how well the seq-to-seq models generalize to various domains over the baselines.

Table 3: Comparative results of multilabel vs. seq-to-seq neural team recommendation methods.

	k	transformer	convs2s	rnn-att	rrn	bnn	bnn_emb
dblp							
%precision	2	**10.4119**	2.4998	3.6176	0.0570	0.0570	0.1124
	5	**7.0113**	1.6122	2.3581	0.0391	0.0663	0.1290
	10	**3.5392**	0.8242	1.1992	0.0472	0.0710	0.1251
%recall	2	**6.3457**	1.5071	2.1698	0.0380	0.0351	0.0668
	5	**10.5477**	2.4177	3.5115	0.0630	0.0993	0.1909
	10	**10.6397**	2.4760	3.5753	0.1552	0.2118	0.3699
%ndcg	2	**10.3611**	2.4770	3.5822	0.0478	0.0538	0.1083
	5	**10.4597**	2.4276	3.5184	0.0523	0.0806	0.1555
	10	**10.4824**	2.4487	3.5391	0.0959	0.1330	0.2397
%map	2	**5.9463**	1.3554	1.9412	0.0217	0.0242	0.0474
	5	**9.2909**	2.0008	2.8791	0.0281	0.0411	0.0792
	10	**9.3210**	2.0127	2.8930	0.0446	0.0558	0.1033
uspt							
%precision	2	**41.7289**	28.5717	23.9729	0.0239	0.0657	0.3663
	5	**31.0677**	24.6530	17.7873	0.0383	0.0769	0.4123
	10	**16.5169**	15.2382	9.4717	0.0654	0.0910	0.3748
%recall	2	**23.1038**	13.9104	12.9871	0.0140	0.0353	0.1608
	5	**41.1643**	28.8167	23.0358	0.0500	0.0976	0.4509
	10	**42.6086**	33.7595	23.8896	0.1370	0.2212	0.8141
%ndcg	2	**41.6095**	28.3606	23.9146	0.0221	0.0655	0.3652
	5	**42.0309**	30.0325	23.8227	0.0408	0.0883	0.4531
	10	**42.1435**	31.4137	23.8270	0.0868	0.1481	0.6094
%map	2	**22.4053**	13.0305	12.4784	0.0096	0.0266	0.1212
	5	**38.6272**	24.4598	21.3567	0.0186	0.0433	0.2027
	10	**39.7591**	27.1994	22.0112	0.0340	0.0592	0.2583
imdb							
%precision	2	1.5454	1.6097	**1.6985**	0.0000	0.2128	0.4255
	5	1.4574	1.4552	**1.4804**	0.8511	0.5106	0.5106
	10	**0.9035**	0.8998	0.9027	0.8511	0.4255	0.6383
%recall	2	0.7669	0.7952	**0.8193**	0.0000	0.1418	0.2837
	5	**1.8093**	1.8013	1.8043	1.4184	0.8511	0.8511
	10	**2.2085**	2.1926	2.1792	2.8369	1.3050	1.9574
%ndcg	2	1.5479	1.6173	**1.7003**	0.0000	0.1646	0.3292
	5	1.7364	1.7595	**1.7883**	0.8163	0.5699	0.5923
	10	1.9039	1.9222	**1.9333**	1.4606	0.7848	1.1358
%map	2	0.6172	0.6506	**0.6650**	0.0000	0.0709	0.1418
	5	1.0327	**1.0487**	1.0450	0.3191	0.2600	0.2813
	10	1.0914	**1.1041**	1.0975	0.6265	0.3148	0.4389
gith							
%precision	2	**32.1596**	25.0590	29.7008	0.0000	3.0693	7.3267
	5	**21.6055**	16.9509	20.1806	0.1980	2.8515	4.7129
	10	**12.7104**	9.9503	12.0029	0.0990	2.6931	3.3861
%recall	2	**13.8543**	11.0787	12.8103	0.0000	1.2164	3.5441
	5	**22.2914**	18.0735	20.7963	0.0619	2.8846	5.1580
	10	**24.0868**	19.4837	22.6186	0.0619	5.1174	6.1885
%ndcg	2	**32.4291**	25.3569	29.7647	0.0000	3.1365	6.4753
	5	**28.2538**	22.3664	26.1975	0.1679	3.2893	5.8418
	10	**26.9900**	21.5849	25.1263	0.1090	4.2340	6.2665
%map	2	**12.9552**	10.5164	11.9759	0.0000	1.0104	2.3424
	5	**19.3215**	15.5615	17.9982	0.0206	1.5706	3.0822
	10	**20.7984**	16.6428	19.4844	0.0206	2.1633	3.3837

6 Concluding Remarks and Future Work

In this paper, we studied the team recommendation problem as a sequence prediction task through seq-to-seq neural architectures. The results show that these architectures yield performance improvements over existing feedforward models, with the `transformer` model consistently outperforming other models across all datasets and metrics. The findings also highlight the importance of considering the distribution of skills over teams, as different seq-to-seq models exhibit strengths in different datasets and distribution types. Our future work includes investigating seq-to-seq models that incorporate additional contextual factors, such as geolocation (for geo-aware team recommendation), and the prioritization of skills or experts based on criteria like their importance to a project.

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