Recommender Forest for Efficient Retrieval

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Abstract

Recommender systems (RS) have to select the top-n items from a massive item set. For the sake of efficient recommendation, RS usually represents users and items as latent embeddings and relies on approximate nearest neighbor search (ANNs) to retrieve the recommendation result. Despite the reduction of running time, the representation learning is independent of ANNs index construction; thus, the two operations can be incompatible, which results in a potential loss of recommendation accuracy. To overcome the above problem, we propose the Recommender Forest (a.k.a., RecForest), which jointly learns latent embedding and index for an efficient and high-fidelity recommendation. RecForest consists of multiple K-ary trees, each of which is a partition of the item set via hierarchical balanced clustering such that each item is uniquely represented by a path from the root to a leaf. Given such a data structure, an encoder-decoder-based routing network is developed: it first encodes the context, i.e., user information, into hidden states; then, leveraging a transformer-based decoder, it identifies the top-n items via beam search. Compared with the existing methods, RecForest brings in the following advantages: 1) the false partition of the near-boundary items can be effectively alleviated by the use of multiple trees; 2) the routing operation becomes much more accurate thanks to the powerful transformer decoder; 3) the tree parameters are shared across different tree levels, making the index to be extremely memory-efficient. The experimental studies are performed on six popular recommendation datasets: with a significantly simplified training cost, RecForest outperforms competitive baseline approaches in terms of both recommendation accuracy and efficiency. The code is available at `https://anonymous.4open.science/r/RecForest-CE76/`.

1 Introduction

Recommender system (RS) is an important way to address the information overload problem. A typical recommender system needs to select the top-n items for users from a massive-scale item set. For the sake of efficient recommendation, RS usually calls for the collaboration of representation learning and Approximate Nearest Neighbour search (ANNs). In the first place, users and items are represented by embeddings in the same latent space; in the second place, the item embeddings are organized with a specific ANNs index, like SCANN and HNSW, such that the top-n recommendation to the user can be efficiently accomplished. Despite that the recommendation process is greatly accelerated from the above workflow, the recommendation quality will probably be restricted, given that the representation model is independently learned and can be incompatible with the ANN index.

In recent years, many efforts have been devoted to alleviating the incompatibility between the representation model and the ANNs index, especially the effort on joint optimization of both components. One representative class of works is the tree-based deep model (TDM) [21] and the joint optimized tree-based model (JTM) [20] from Alibaba. In both works, the item set is organized with a binary tree structure: each internal node acts like a cluster center, and each leaf node corresponds to a

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unique item. On top of the tree structure, a preference model is learned to route from the root to the leaf nodes for the top-n recommendation result. These works achieve empirical gains over the conventional two-stage methods; besides, they preserve competitive retrieval efficiency as the time cost is logarithmic to the size of the item set.

However, the existing tree-based recommenders are still restricted in many aspects. First of all, the item set is hierarchically partitioned; as a result, it is challenging to route to items located around the partition boundaries. Secondly, the routing decision is made without consideration of the previous trajectory (i.e., from the root to the direct ancestor of the current node), so the accuracy of the beam search can be limited. Thirdly, the tree-based index can be memory-consuming, given that the number of internal nodes is at the same magnitude as the leaf nodes (i.e., the number of the total items). Last but not least, the existing methods call for the joint adaptation of the representation model and tree index, so that the tree structure needs to be repetitively updated, resulting in a significant cost for the training stage.

To overcome the above limitations, we propose a novel framework, Recommender Forest (a.k.a., RecForest), for an efficient and high-fidelity recommendation. The proposed framework is highlighted for the following features.

- RecForest consists of multiple K-ary trees, each of which is a partition of the item set based on balanced hierarchical clustering. With the construction, the retrieval of the near-boundary items can be effectively improved, since a near-boundary item missed in one tree can be retrieved back on another tree.
- RecForest leverages a transformer decoder for beam search. On top of such a decoder, the routing trajectory, i.e., from the root node to the current node, can be jointly considered when the next routing decision is made. Compared with the previous methods which merely take account of the current node, the beam search becomes much more accurate since the historical routing is fully utilized.
- The tree parameters are shared across different tree levels; in other words, there are mere k vectors (corresponding to the k different branches) in each K-ary tree. Thanks to parameter sharing, RecForest becomes much more memory-efficient compared with the existing tree-based recommenders.
- Given the above settings, RecForest becomes much less sensitive to the partition of the item set. As a result, it can avoid the repetitive adaption of the tree structure, saving a considerable portion of the training cost.

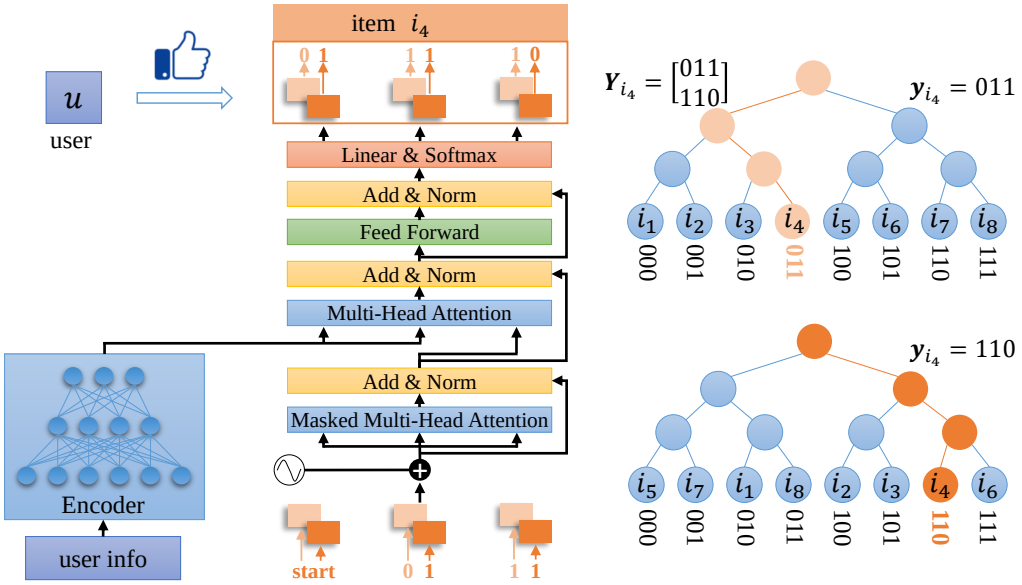
We perform comprehensive evaluations on six popular recommendation datasets. According to our experiment results, RecForest notably outperforms the existing tree-based recommenders in terms of recommendation quality and efficiency. Besides, we empirically verify that RecForest can be effectively trained with much less time cost, indicating its strong usability in real-world scenarios.

2 Recommender Forest

2.1 Preliminary

As mentioned above, RS usually represents user and item as latent embeddings, where the user's preferences for the items are measured by the inner product of the embeddings [11, 1, 7]. As a result, the top-n recommendation is boiled down to the maximum inner product search (MIPS) problem. For the sake of efficient recommendation, various ANN indexes are leveraged in practice, such as the tree-based index [10, 6]; the hash-based index [13, 14, 4, 9], the quantization-based index [2, 17, 3] and the graph-based index [8, 15, 19], etc. These indexes have been well implemented by toolkits, like FAISS, which greatly facilitates the deployment of recommendation systems in practice. However, one limitation of the current ANN-based methods is that the index construction and the representation learning are decoupled, which will probably introduce incompatibility between both modules.

To mitigate the above problem, recent works propose to jointly optimize the representation model and index, where two representative works are TDM [21] and JTM [20]. Both methods are based on the tree structures, where the top-n recommendation can be efficiently accomplished by performing a layer-wise beam search. For example, as shown in Figure 1, when the beam size is 2, these models



(a) Encoder-Decoder Framework of RecForest (b) Forest of 2 Balanced Binary Trees

Figure 2: Illustration of RecForest framework.

will score the four children of previously retrieved 2 nodes, from which the two largest children will be selected. Such a process is iteratively performed until the final top-2 leaf nodes are retrieved.

2.2 Overview

The framework of RecForest is overviewed as follows. First of all, the item set is partitioned based on hierarchical balanced Kmeans, where a tree structure is generated. The tree structure will enable an item to be efficiently retrieved with $O(\log N)$ time complexity (N is the scale of the item set). Knowing that the items located close to the partition boundary may get falsely assigned to a branch missing from the retrieval process, we propose to leverage multiple trees, where the missing probably can be largely reduced. One item is corresponding to a leaf node in the tree, which can be represented by a path stretching from the route. Suppose that the K-ary tree is utilized, each item can be represented by a sequence of branch ID $(0, ..., K-1)$. For example, in Figure 2(b), the item i_4 is represented by "011" and "110" in the corresponding binary trees, respectively. Given the hierarchical numbering of the items, the recommendation turns out to be a sequence-to-sequence problem: based on the encoded user information, paths to the most preferable items are progressively decoded via beam search, from which the top-n recommendation is made. The overall framework of RecForest is shown in Figure 2(a).

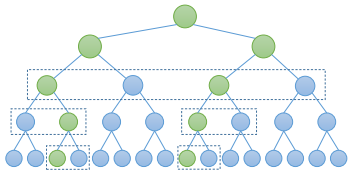


Figure 1: Beam search over a binary tree. The beam size is set 2. The nodes in the dotted box of each layer are candidates for scoring, where green nodes are selected.

For ease of understanding, we summarize the notations used in this paper. Let $\boldsymbol{x}_u$ denote the user information of u, which can be either an item sequence or user profiles. Let $\boldsymbol{y}_i \in \{0, K-1\}^H$ be the item i's branch sequence of length H and $\boldsymbol{Y}_i \in \{0, K-1\}^{T \times H}$ be a concatenation of item i's branch sequences of T trees. Formally, RecForst models the conditional probability $P(\boldsymbol{Y}_i|\boldsymbol{x}_u)$ with the seq2seq architecture.

2.3 Construction of Tree and Forest

As mentioned, the item set is organized by a tree structure, where semantically close items may fall into the same branch. We will also construct multiple trees so as to alleviate the false assignment of boundary items. Detailed workflows are illustrated as follows.

2.3.1 Tree Construction

The tree is expected to be balanced for the sake of retrieval efficiency. Thus, we leverage hierarchical balanced clustering, where each cluster is evenly divided into K children until the child note merely contains one single item. Besides, we propose to randomly sample $K^H - 1$ items (H is the height of the tree) from the entire item set, such that the constructed tree will be a complete K-ary tree. The height of the tree is up-bounded by $\lceil \log_K N \rceil$, assuming that N is the number of unique items.

We suggest the following two methods for the balanced partition of the item set. **Random**. For each cluster, the included items are randomly partitioned into K equally sized subsets. Such a method is extremely simple; yet, the semantic relationship between the items is ignored. **Balanced Kmeans** (short for Kmeans). Particularly, we first pre-train item embeddings based on an arbitrary off-the-shelf recommendation model. In our experiment, we use the Deep Interest Network (DIN) [18] for sequential recommendation and the Bayesian Personalized Ranking (BPR) [11] for non-sequential recommendation, given their effectiveness and popularity in corresponding scenarios. With such a recommendation model, the items' semantic closeness can be measured by their embedding similarity, as relevant items will be close to each other in the latent space. Then, for each cluster, the included items are evenly partitioned via Kmeans w.r.t. their embedding similarity. (Due to the space limitation, details about balanced Kmeans clustering are given in the supplemental material.)

2.3.2 Forest Construction

Different trees are desirable of being diversified such that the boundary items can be better covered from beam search. To this end, we propose a simple but effective approach, which combines the random and Kmeans tree construction. Particularly, for each cluster, a subset of the included items are randomly sampled and evenly assigned to the K children clusters; then, the remaining items are further partitioned into the K equal-sized groups via balanced Kmeans. By doing so, different trees are naturally diversified due to the inherent randomness.

2.4 RecForest Enocoder

As shown in Figure 2(a), the encoder is utilized to encode users' information and output hidden states of the users. Any NN encoder is compatible with our framework. We mainly consider sequential scenarios and non-sequential scenarios, where a sequence encoder and a feature encoder are used, respectively.

Feature Encoder In the non-sequential scenarios, user information is denoted by a feature vector, i.e. $\boldsymbol{x}_u$. We simply use a MLP for the feature encoder. $\boldsymbol{z}_u = \text{MLP}(\boldsymbol{x}_u)$. When only user id is available, we can take its embedding as hidden state, without any non-linear transformation.

Sequence Encoder In the sequential scenarios, user information is an item sequence. Concretely, $\boldsymbol{x}_u = [i_{t_1}, i_{t_2}, \ldots, i_{t_m}]$, where the item $i_{t_j} (1 \leq j \leq m)$ is the j-th interacted item of user u. It is straightforward to take item features into account. In view of Transformer's [16] state-of-the-art performance in seq2seq tasks like machine translation and speech recognition, we utilize the Transformer encoder for the sequence encoder. In particular, $\boldsymbol{z}_u =$ transformer-encoder$(\boldsymbol{x}_u)$, where the length of $\boldsymbol{z}_u$ is the same as $\boldsymbol{x}_u$. Due to space limitation, more details about the Transformer encoder are provided in the appendix.

2.5 RecForest Decoder

The decoder is to predict the next branch given the historical branches and the encoder's outputs of hidden states. As shown in Figure 2(a), we apply the Transformer [16] decoder for this task due to its powerful capacity. From down to up, following the branch embedding and positional embedding, Masked Multi-Head Attention [16] is utilized to model the complex dependence among branches at different layers. Taking the output from Masked Multi-Head Attention, Multi-Head Attention [16] is followed to encode the complex interactions between users' hidden states and historical branch representation. The Feed Forward layer then enhances the non-linearity of context-aware historical branch representation. A linear layer with the softmax activation is applied for predicting the next branch. Note that this decoder can also handle the non-sequence scenarios since a user's feature can be considered as a sequence only with one vector element.

2.6 Training

As depicted in Figure 2(b), the branch sequence of item i_4 is [0,1,1] and [1,1,0] on the two trees, respectively. The framework uses [start,0,1] to predict [0,1,1] and uses [start,1,1] to predict [1,1,0]. 'start' is a special symbol for initializing the sequence, which actually corresponds to the tree root. The transformer decoder is not shared among trees since it is observed to work better. In this case, all trees share the same training procedure, so we illustrate the training with one tree. At each layer, the training task is to predict the next branch given historical branches, which corresponds to a multi-class classification problem. Given a user u and its interacted item i, the loss for optimizing encoder and decoder is formulated as follows:

$$\mathcal{L}(u,i) = -\sum_{h=0}^{H-1} \log \text{Prob}(y_i^h | \text{cat}(\text{start}, \boldsymbol{y}_i^{[0:h]}), \boldsymbol{z}_u) \tag{1}$$

where y_i^h and $\boldsymbol{y}_i^{[0:h]}$ indicate the branch at the h-th layer and historical branches until the h-th layer respectively, and 'cat' means concatenation.

2.7 Inference

Since each leaf in the tree corresponds to an item, RecForest transforms top-n recommendation into the sequence prediction problem. In particular, we first apply the encoder for deriving the hidden state from user information and leverage the decoder to generate the top-n branch sequences, i.e., paths from the root node to leaf nodes on each tree, based on beam search. Note that each item can correspond to multiple leaf nodes (i.e. branch sequences) in each tree since some items are sampled for building a complete K-ary tree. Therefore, the generated items should be duplicated. Let C denote the union of generated candidate items from the forest. For $c \in C$, we first compute the logarithmic probability $\sum_{h=0}^{H-1} \log \text{Prob}(y_i^h | \text{cat}(\text{start}, \boldsymbol{y}_i^{[0:h]}), \boldsymbol{z}_u)$ in each tree and then sum logarithmic probabilities over all trees as the score of the item c. We then select the top-n-scored items from C for recommendation.

2.8 Complexity Analysis

Notation Let D the dimensionality of item embedding, by B the beam size of beam search, and by K the number of branches. Let T the number of trees In RecForest and the number of times to update the tree in JTM and TDM. I denotes the size of the training set. Regarding notations in SCANN, let K_{vq} the number of centroids in VQ stage, K_{pq} the number of centroids of one subspace in the PQ stage, M the number of subspaces and W the number of probed VQ cells.

Time Complexity In inference, the beam search can be finished within $O(TKB \log_K N)$ since the probabilities of KB branches at each level of all the T trees need to be calculated. Hierarchical Kmeans clustering can be done within $O(NK \log_K N)$ to build a tree index so that it takes $O(TNK \log_K N)$ to build the forest index.

Space Complexity The memory consumption of the recommendation model can be regarded as the constant consumption as it is inevitable in any recommender system so we mainly focus on the size of the index structure. For our model, we only need to keep the tree structure and a matrix with size $T \times K \times D$ which denotes the branches' embedding representations of the forests. In TDM and JTM, they not only keep the tree structure but also keep the embedding representation of all nodes, of which the size is at the same magnitude as the number of items.

We also summarize the complexity analysis of the other baselines in Table 1. Note that the indexing time of SCANN only counts the time complexity of the encoding period.

Table 1: Complexity analysis

Complexity	RecForest	JTM	TDM	IPNSW	SCANN
Inference Time	$O(TKB \log_K N)$	$O(B \log N)$	$O(B \log N)$	$O(\log N)$	$O(K_{vq} + K_{pq} + \frac{W}{K_{vq}} \cdot N)$
Indexing Time	$O(TNK \log_K N)$	$O(TI \log N)$	$O(TN \log N)$	$O(N \log N)$	$O(NMK_{pq})$
Index Size	$O(TKD)$	$O(ND)$	$O(ND)$	$O(ND)$	$O(K_{vq}D + K_{pq}D)$

3 Experiments

We conduct the experiments to answer the following research questions: **RQ-1**: Does RecForest outperform the SOTA efficient recommenders in the tradeoff between efficiency and accuracy? **RQ-2**: How does the forest-based index improve the retrieval accuracy compared to the single tree? **RQ-3**: How much effect positional embedding can take? The experiments are carried out in both sequential scenarios and non-sequential scenarios, where sequence encoder and feature encoder are utilized, respectively. Due to space limitations, we only report the results of the sequential scenario in the paper. Other results can be referred to in the appendix. These experiments are done on a Linux server with Tesla V100 GPUs.

3.1 Dataset

We evaluate the RecForest with six real-world recommendation datasets, which can be downloaded from the url[1]. The datasets are **MovieLens 10M** (abbreviated as **Movie**), **Amazon Books** (abbreviated as **Amazon**), **Tmall Click** (abbreviated as **Tmall**), **Gowalla Check-in Dataset** (abbreviated as **Gowalla**), Microsoft News Dataset (abbreviated as **MIND**). Since some datasets only include rating-based explicit feedback, they should be converted into implicit feedback for RecForest's inputs. These datasets are pre-processed by filtering the users who interact with no more than 15 items. The overall information of datasets is summarized in Table 2.

Table 2: Statistics of Datasets

Dataset	#User	#Item	#Interaction	Density
Movie	69,878	10,677	10,000,054	1.34%
Amazon	29,980	67,402	2,218,926	0.11%
Tmall	139,234	135,293	10,487,585	0.05%
Gowalla	13,583	71,436	977,425	0.10%
MIND	36,281	7,129	5,610,960	2.16%
Yelp	26,031	35,294	1,713,759	0.19%

3.2 Baselines

In the paper, we report the results of the sequential recommendation scenario, so we compare the proposed RecForest with two-stage indexes, IPNSW [8] and SCANN [3], with learnable indexes, TDM [21] and JTM [20] as well as YoutubeDNN [1] and DIN [18] based on the brute-force retrieval. Note that brute-force-based YoutubeDNN and DIN are time-prohibitive in online services, but they can be considered as two strong baselines. IPNSW and SCANN are built over item embedding of a recommender. The recommender shares the same encoder as RecForest but replaces the decoder with flat item embedding. Moreover, it is trained with the same loss as DIN. More details about baselines can be referred to the appendix.

3.3 Experimental Settings

In each dataset, we randomly choose 10% users as validation users, 10% users as test users, and all the left users as training users. Following TDM and JTM, we use a slide window to split user-item interaction histories into splices of length 70 at most. For training users' data, the first 69 interactions are used for input context and the 70-th item is regarded as the ground truth of prediction. For data of both validation users and test users, we regard the first half as context and others as ground truth.

The latent dimensionality is set to 96 in all methods. Here, for a fair comparison of running time, we implement SCANN and IPNSW with PyTorch. To construct the quantization-based index, we follow SCANN's default settings. To construct the graph index of IPNSW, the maximum degree of each node is set to 16. The beam size for any beam search is set to 100 unless specified. To learn NN models, the learning rate is all set to 1e-3 with exponential decay. The items' representations for constructing trees are obtained from item embedding of the pre-trained DIN on each dataset.

3.4 Comparison with Baselines

Settings We compare RecForest with the baselines on all datasets. RecForest uses 2 trees on the Movie and MIND, and 4 trees on other datasets. Other settings can be referred to in Section 3.3.

[1] https://drive.google.com/drive/folders/1ahiLmzU7cGRPXf5qGMqtAChte2eYp9gI

Table 3: Comparison with Baselines w.r.t NDCG@20 and NDCG@40, index memory space (MB), and inference time (second). The bold fonts indicate the best performance.

	NDCG@20	NDCG@40	Memory	Time	NDCG@20	NDCG@40	Memory	Time
Method	**Movie**				**Amazon**			
DIN	**0.5440**	0.5473	-	193.87	**0.2766**	**0.3039**	-	492.64
YoutubeDNN	0.5329	**0.5484**	-	**29.38**	0.2195	0.2491	-	**120.91**
JTM	0.5149	0.5075	10.80	12.05	0.1533	0.1683	75.99	6.64
TDM	0.4684	0.4651	10.80	9.33	0.0856	0.0949	75.99	6.61
SCANN	0.4665	0.4695	3.64	18.64	0.1529	0.1780	14.66	4.48
IPNSW	0.5330	0.5486	10.08	15.52	0.2255	0.2548	66.46	10.28
RecForest	**0.5580**	**0.5682**	**3.21**	**8.33**	**0.2339**	**0.2576**	**7.32**	**3.79**
Method	**Gowalla**				**Tmall**			
DIN	**0.2798**	**0.3095**	-	186.41	**0.2275**	**0.2491**	-	4057.69
YoutubeDNN	0.2312	0.2637	-	**53.55**	0.1736	0.1975	-	**1086.75**
JTM	0.2595	0.2484	77.56	2.64	0.0749	0.0849	151.19	30.11
TDM	0.1723	0.1775	77.56	2.55	0.0257	0.0272	151.19	29.42
SCANN	0.1839	0.2083	15.48	1.86	0.1105	0.1226	28.10	20.88
IPNSW	0.2464	0.2805	70.39	4.73	0.1696	0.1902	132.72	52.90
RecForest	**0.3783**	**0.3963**	**7.39**	**1.82**	**0.2059**	**0.2261**	**9.29**	**18.88**
Method	**MIND**				**Yelp**			
DIN	**0.7399**	**0.7399**	-	62.98	**0.2825**	**0.3117**	-	170.25
YoutubeDNN	0.7349	0.7336	-	**52.14**	0.2518	0.2850	-	**48.51**
JTM	0.5956	0.5505	6.62	5.48	0.1014	0.1300	39.47	4.21
TDM	0.5615	0.5198	6.62	5.51	0.1547	0.1515	39.47	4.34
SCANN	0.5987	0.5713	3.20	19.51	0.1729	0.2012	8.44	3.58
IPNSW	0.7346	0.7331	6.95	8.99	0.2562	0.2906	34.74	8.92
RecForest	**0.7583**	**0.7579**	**3.18**	**4.61**	**0.2766**	**0.3031**	**6.81**	**3.57**

Results All the results are shown in Table 3, where the index memory cost of RecForest indicates the decoder's memory consumption. From the table, we have the following observations.

- **RecForest significantly outperforms all efficient recommenders with indexes on all datasets w.r.t NDCG@20 and NDCG@40**. The improvements over the best baselines w.r.t NDCG@20 are 4.69%, 3.72%, 45.78%, 21.40%, 3.23%, 7.96% on the Movie, Amazon, Gowalla, Tmall, MIND, and Yelp dataset, respectively. Its superiority over two-stage baselines demonstrates the effectiveness of joint representation learning, although the graph-based index shows a strong performance. The higher accuracy than TDM and JTM indicates the benefit of learning an indexing model with fewer parameters and the power of the transformer decoder.
- **RecForest performs better than brute-force-based YoutubeDNN on all datasets and even than brute-force-based DIN on the Movie, Gowalla, and MIND datasets.** Note that we do not apply DIN for post-reranking, otherwise the retrieval accuracy can be further improved. This again confirms the superpower of the transformer decoder. Note that after fine-tuning the hyper-parameters, YoutubeDNN performs well compared to TDM and JTM, which may not be consistent with the results in TDM and JTM.
- **In addition to superior accuracy, RecForest has the advantage in index memory cost**, which is evidenced by the smallest index memory cost compared to other methods. This is because we only embed the branches and positions instead of all tree nodes in TDM and JTM. RecForest even costs fewer memories for index than the most lightweight PQ-based index – SCANN, which only stores the codes of data points and codebooks. In spite of good retrieval accuracy, the graph-based index IPNSW is memory-heavy due to the storage of graphs and data points. Note that both DIN and YoutubeDNN are based on exhaustive search so they don't consume memory for indexes.
- **RecForest is almost as fast as and sometimes even faster than SCANN for the top-n item retrieval**, which is considered as the SOTA index for MIPS in retrieval efficiency and accuracy.

This benefits from transforming the top-n recommendation into sequence prediction, which can be efficiently accomplished by beam search on GPU. More analysis is provided next.

3.5 Extensive Study between Efficiency and Accuracy

Settings The efficiency-accuracy curve is a commonly-used standard for evaluating the ANN index, so we also provide this result for better illustrating the superiority of RecForest. The study is mainly investigated on the Amazon, MIND, Gowalla, and Yelp dataset, since the other two datasets show a similar trend. To vary the retrieval time of RecForest, we adjust the beam size of beam search from 10 to 100 with step 10, where the forest consists of at most 5 trees. For TDM, JTM, and IPNSW, we adjust the beam size from 10 to 200 with step 10. For SCANN, we adjust the number of probe cells from 50 to 2,000 with step 100.

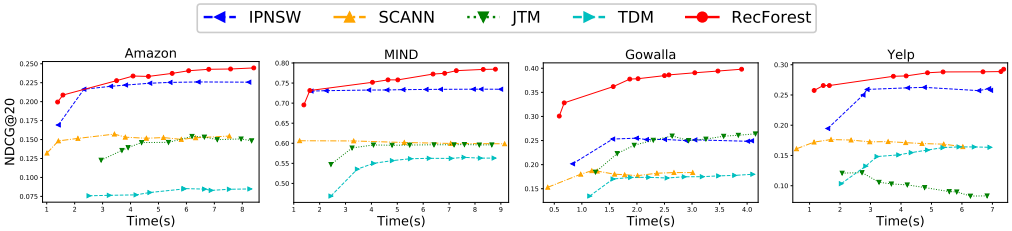


Figure 3: Tradeoff between Efficiency and Accuracy

Results The curves of different algorithms between NDCG@20 and query time are shown in Figure 3. From the figure, we have the following observations.

- **RecForest strikes the best balance between query time and retrieval accuracy on all the four datasets**, since the curve stands on top of the others. This confirms the superiority of RecForest to these competing baselines. The advantage is the most significant on the Gowalla dataset, evidenced by the biggest gap between RecForest and IPNSW.
- **With the increase of beam size, the accuracy of RecForest can improve more significantly than baselines.** This benefits from the powerful transformer decoder and the novel training paradigm as well as the forest-based index, such that the representation model and tree indexes are jointly learned better.

3.6 Ablation Study

3.6.1 Effect of Forest Construction

Settings We investigate three aforementioned ways of constructing a forest with at most 10 trees, where the branch number of each tree is set to 4. The details about forest construction can be referred to Section 2.3.2.

Results The results on the Amazon, Gowalla, MIND, and Yelp datasets are reported in Figure 4. We can observe that **Kmeans with randomness (i.e. Random+Kmeans) always performs best and improves with the increasing number of trees while the Random performs worst and does not improve as much as Random+Kmeans when the tree number increases.** The reason why the Random does not work well is that the semantic requirement is not satisfied. Since Kmeans utilizes the semantic information, it performs better than the Random, but is not affected a lot by growing the number of trees. This can be explained by the lack of diversity between trees. This answers the **RQ-2**: the use of forest-based index can lead to significant improvement of retrieval accuracy, particularly when tree construction takes semantics into account.

3.6.2 Effect of Branch Number K

Settings We conduct evaluations on a single Kmeans-constructed tree on the Movie, MIND, Gowalla and Tmall dataset, where the branch number varies in {2,4,8,10,16,18}.

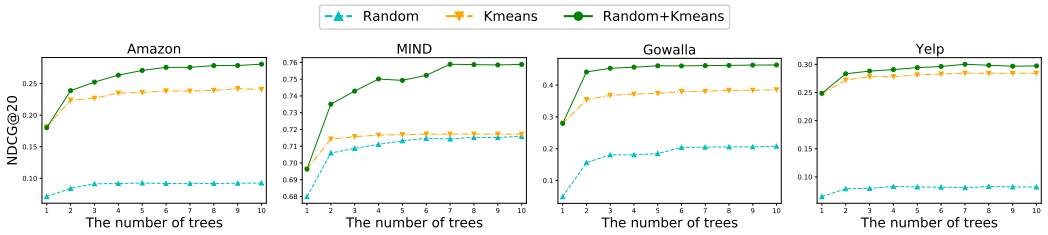


Figure 4: Ablation study: Different construction ways for forests.

Table 4: Effect of branch number

#Branch	NDCG@20			
	Amazon	MIND	Gowalla	Yelp
2	0.1624	0.6900	0.2353	0.1951
4	0.1912	0.6935	0.2795	0.2269
8	0.1864	0.6966	0.2938	0.2483
10	0.2022	0.6954	0.2843	0.2577
16	0.2031	0.6977	0.2957	0.2437
18	**0.2088**	**0.7154**	**0.3337**	**0.2581**

Results The results are shown in Table 4. We can observe that **the retrieval accuracy of RecForest improves with the growing number of branches, particularly from 2 branches to 4.** The improvement on the Gowalla and Tmall datasets is the most significant. This observation can be explained as follows: First, the vocabulary size grows, so that the decoder can be supervised by more challenging discriminative signals and the decoders' parameters grow. Secondly, the branch sequence would be shorted, reducing the error accumulation of sequence prediction to some extent.

3.6.3 Effect of Positional Embedding

Settings Since the branch sequence is used for representing an item, the branch order should be important. To this end, we compare four cases of position embedding: (1) **None** indicates that there is no position embedding; (2) Absolute position embedding (**Abs** for short) encodes the absolute positions which range from 1 to maximum length of sequence by learnable representation; (3) Relative Key [12] (**RelK** for short) focuses on attention and relative distance between tokens; (4) Relative Key Query [5] (**RelKQ** for short) is a refined version of Relative Key. Please refer to [5] for more details.

Table 5: Effect of positional embedding

Pos. Emb.	NDCG@20			
	Amazon	MIND	Gowalla	Yelp
None	0.1704	0.6476	0.1697	0.1988
Abs	0.1805	**0.6986**	**0.2632**	**0.2505**
RelK	0.1824	0.6942	0.2617	0.2402
RelKQ	**0.1840**	0.6917	0.2588	0.2492

Results The results based on from single Kmeans-constructed tree on the Amazon, MIND, Gowalla, and Yelp datasets are summarized in Table 5. We can observe that **positional embedding takes a remarkable effect on improving the retrieval capacity while different positional embedding methods do not have a significant difference in retrieval accuracy**, which answers the **RQ-3**. The effects of positional embedding are more significant on the Gowalla and Yelp datasets.

4 Conclusion and Future Work

In this paper, we propose the Recommender Forest for an efficient recommendation, which can be simply trained within the sequence-to-sequence framework. Even without updating the tree structure, RecForest enjoys a small index memory cost, low inference time, and highly-accurate recommendation. The extensive study on six real-world recommendation datasets shows that RecForest becomes a state-of-the-art efficient recommender. In the future, we explore multi-task learning, non-autoregressive prediction, and index structure learning as well as a more general framework.

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Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default **[TODO]** to [Yes] , [No] , or [N/A] . You are strongly encouraged to include a **justification to your answer**, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

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   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] Please see the future work in section 4.
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