Improving Multi-Interest Network with Stable Learning

Zhaocheng Liu
Kuaishou Technology
China

Yingtao Luo
University of Washington
United States

Di Zeng
Kuaishou Technology
China

Qiang Liu
Institute of Automation, Chinese Academy of Sciences
China

Daqing Chang
Kuaishou Technology
China

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1 INTRODUCTION
Sequential recommender systems aim to predict the next item(s) that a user might be interested in based on historical interactions. In the background of information explosion, they have become vital to alleviate the information overload problem and enhance user experiences. Given historical behaviors, accurately characterizing and representing users’ dynamic preferences is the core concern of research in sequential recommendation. Traditional methods [15, 38] assume that the next action is conditioned on only the previous action (or previous few). They adopt Markov chain and matrix factorization to capture short-range item transitions. Due to the rapid development of deep learning, various deep neural networks are exploited to model the complex high-order sequential dependencies, including recurrent neural networks [14, 50], convolutional neural networks [44] and attention mechanism-based networks [20, 30, 32, 42, 46]. With a user’s historical behaviors, these deep learning-based approaches usually generate an overall embedding as user representation. More recent advances [2, 25] argue that a unified user embedding is hard to encode the different aspects of the user’s interests. Therefore, they propose the multi-interest networks which represent one user with multiple vectors to capture the user’s multiple interests and significantly outperform previous models.

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Despite the effectiveness of multi-interest networks, there are some challenges demanding further explorations. A vital challenge is, multi-interest networks may concentrate more and more on the subtle dependencies among captured interests, which harms the generalization ability. In this paper, we introduce the widely used Hilbert-Schmidt Independence Criterion (HSIC) \cite{9, 10} to measure the degree of independence among captured interests. Then, we trace the change of HSIC on the training set and recall on the validation set when training the state-of-the-art multi-interest networks, i.e., ComiRec \cite{2}. Taking Figure 1 for example, due to the random initialization of model parameters, the value of HSIC and recall are nearly zero at first step, and they rapidly rise along with the increase of training steps. For ComiRec, after 20000 steps, the value of HSIC (i.e., the red curve) begins to increase slowly while the value of recall (i.e., the blue curve) stops rising and even begins to decline. To some extent, for ComiRec, this example reveals that excessive interests shifts from training phase to test phase, which breaks the marginal distribution of captured interests. Therefore, there exists dependencies among interests may harm the model performance during inference stage, and limit the model’s generalization ability.

In real scenarios, as illustrated in Figure 2, we dissect above problem in recommender systems as follows. Due to the existence of diverse interests of users and the noisy nature of implicit feedback \cite{37, 47, 52}, multi-interest networks can capture various interests, even including irrelevant interests (i.e., the interests that are irrelevant to a given target item). As prior work \cite{4, 34, 51} points out the sample selection bias problem, the corresponding items of captured interests are usually retrieved together to get exposure and collected into training data. Therefore, there exists dependencies among captured interests. Multi-interest models are misled by these subtle dependencies, resulting in the spurious correlations between irrelevant interests and target items are captured. However, due to the rapid changing of recommender systems and the temporal evolution of user interest, the marginal distribution of captured interests shifts from training phase to test phase, which breaks the subtle dependencies among multiple interests. In such cases, the captured spurious correlations may be invalid in test phase, results in the drop of models’ performance, known as Out-Of-Distribution (OOD) generalization problem \cite{41}.

To alleviate such OOD generalization problem, we aim to find a way to avoid multi-interest networks capturing the spurious correlations between irrelevant interests and targets at all possible. As it’s hard to distinguish irrelevant interests from captured interests, we turn to directly eliminating the dependencies among captured interests. We propose a novel multi-interest network, named DEep Stable Multi-Interest Learning (DESMIL). Inspired by sample reweighting techniques \cite{23, 53}, the interest decorrelation regularizer in DESMIL aims to estimate a weight for each sample such that captured interests are decorrelated on the weighted training data. Specifically, in training phase, given a specified sample, DESMIL mixes every captured interest’s representation with sample weight, and adopts HSIC as independence testing statistics to measure any pair of such mixed representation. DESMIL minimizes such statistics via finding optimal training sample weights while keeping the trainable parameters of multi-interest networks fixed. Our design can ensure that the sample weight is reduced when the dependencies among captured interests’ representation is strong. Meanwhile, same sample weights are exploited to weight the classic sampled softmax loss and when optimizing such weighted loss, the sample weights are all fixed. Therefore, the proposed DESMIL can make multi-interest networks concentrate more on the training samples whose dependencies between multiple interests are weak.

We conduct extensive experiments to verify the effectiveness of the proposed DESMIL on both public recommendation datasets and large-scale industrial dataset. In particular, to validate the OOD performance of different models, we changes the splitting method of datasets to simulate different covariate shifts. Experimental results demonstrate that our proposed DESMIL outperforms state-of-the-art models by a significant margin. In order to reveal the reason why DESMIL works to a certain extent, we also conduct comprehensive model analysis including visualizing the probability distribution of

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**Figure 1:** The curves of HSIC on the training set and Recall@50 on the validation set when training ComiRec on the Book dataset. In the early stage, both HSIC and recall increase rapidly. With the convergence of recall, HSIC further increases, which may harm the model performance.

**Figure 2:** In training phase, due to interests of users and exposure in recommender systems during data collection, the user interactions may always contain dog and cat together. Misled by the subtle dependency, multi-interest networks may partially attribute to spurious correlation instead of focusing on true causation. However, in test phase, the subtle dependency between dog and cat is broken due to the rapid changing of recommender systems and the temporal evolution of user interests. Therefore, model fails to make trustworthy predictions.
the training sample weights learned by DESMIL and the change of recall and HSIC of DESMIL through training steps.

To summarize, the main contributions of this paper are:

- We empirically show that excessive dependencies among interests may harm the model performance, and point out a promising way to solve the OOD generalization problem for multi-interest networks is to eliminate subtle dependencies among captured interests.
- We propose a novel multi-interest network which eliminates dependencies between captured interests via learning weights for training samples.
- Extensive experiments have been conducted and the effectiveness and OOD performance of the proposed DESMIL is fully verified.

2 RELATED WORK

In this section, we review some works on sequential recommendation, deep multi-interest models and stable learning.

2.1 Sequential Recommendation

How to effectively extract user interests from users’ historical behaviors is a critical problem in sequential recommendation [7], which is a major task in recommender systems. In some traditional models [11, 12, 15, 38], Markov chain and matrix factorization are widely used to model users’ historical behaviors. Among them, the most representative model is FPMC [38], which proposes to use a personalized Markov chain for capturing each user’s behaviors, and train the model with a factorization model for capturing collaborative information.

With the rapid development of deep learning in past years, various deep neural networks such as recurrent neural network [14, 29, 50], convolutional neural networks [44, 46] and attention-based networks [20, 26, 30, 32, 42] have been successfully exploited in the design of deep sequential recommendation model. Generally, the user historical information is represented by the output of deep neural networks. Thanks to the strong capacity of deep models, the recommendation accuracy has been greatly improved by these models [7]. Recently, contrastive learning has been applied in sequential recommendation [31, 48, 55], for dealing with sparsity and noise in data. Moreover, CauseRec [52] proposes to generate out-of-distribution counterfactual samples, and both model original samples and counterfactual samples with contrastive loss.

2.2 Deep Multi-interest Models

In real recommendation scenario, a user may have multiple interests in most time. Intuitively, the recommendation diversity is also a helpful property for user experience. However, an overall user preference representation as in most works above can hardly grasp the diversity essence of user interests [28]. Starting from this, there are works [2, 3, 25, 33, 43, 54] studying how to effectively extract user’s multiple interests in sequential recommendation with multiple user representations.

MIND [25] proposes a multi-interest extractor layer based on the dynamic routing mechanism [16, 17, 39]. As the procedure of dynamic routing can be seen as soft-clustering, the user’s historical behaviors can be grouped into different clusters. Meanwhile, a label-aware attention mechanism is proposed to effectively aggregate the multiple user preference representations in training. Besides, Cen et al. [2] proposes a controllable multi-interest Framework called ComiRec. In ComiRec, both dynamic routing and self-attentive models can be adopted to extract multiple user interests. Furthermore, ComiRec shows that a controllable aggregation module balancing the accuracy and diversity is beneficial. Lately, instead of implicitly generating user’s multiple interests by clustering the user behaviors, SINE [43] directly maintains a pool of conceptual prototypes to represent the all set of user’s potential interests. Then a self-attention mechanism is used to decide which prototypes are activated as the user’s multiple interests.

2.3 Stable Learning

The out-of-distribution problem [41] is a common challenge in real-world scenarios, and stable learning has become a successful way to deal with this recently. Stable learning aims to learn a stable predictive model that achieves uniformly good performance on any unknown test data [22]. To achieve this goal, the framework of most stable learning works can be divided into two steps: sample weight learning and weighted training. Specifically, samples weights are learned to decorrelate features in training data, and then weighted training is conducted to train models on weighted feature distribution, which is approach to independent identically feature distribution. Along this strand, various decorrelation methods [22–24, 40] have been proposed to learn sample weights and train linear stable models. Moreover, StableNet [53] proposes to adopt random Fourier features to eliminate non-linear dependencies among features in convolutional neural networks. And StableGNN [6] proposes to decorrelate features in graph neural networks. Lately, Xu et al. [49] theoretically proves that the stability of least square regression and binary classification can be guaranteed with mutually independence of feature variables under mild conditions.

3 METHODOLOGY

In this section, we formulate the problem and introduce the proposed DESMIL in detail, and the overview of DESMIL is illustrated in Figure 3. To be noted, in Section 3.4, we introduce HSIC as independence testing statistics and empirically show the relationship between HSIC and model performance in training phase.

3.1 Problem Formulation

In the setting of sequential recommendation, assume we have a set of users \( U = \{u_1, u_2, \ldots, u_m\} \) and a universe of items \( I = \{i_1, i_2, \ldots, i_J\} \). For each user \( u \), we have a sequence of historical behaviors \( S^u = (S_1^u, \ldots, S_{\tau_u}^u) \), where \( S_i^u \in I \) and the index \( t \) of \( S_i^u \) denotes the order of a specified behavior occurs in \( S^u \). In training phase, for user \( u \) at step \( t \), the model’s input and the expected output can be thought as \((S_1^u, \ldots, S_t^u)\) and \( S_{t+1}^u \), respectively. Given all users’ sequences \( S \), the goal of sequential recommendation is to recommend each user a list of items that maximize her/his future needs. Besides, as each item is relevant to interests of user, the proposed DESMIL aims to capture the representation vectors of user interest. We use \( c \) to denote the number of such representation vectors.
3.2 Embedding Layer
We adopt the widely-used embedding technique to embed id features into low-dimensional dense vectors. Specifically, given the input sequence \((S^0_u, \ldots, S^t_u)\), we create an embedding matrix \(V \in \mathbb{R}^{|I| \times d}\) where \(d\) is the number of latent dimensions, and retrieve the input embedding matrix by applying the embedding look-up operation. Besides, to make the proposed DESMIL be aware of the positions of historical items, we inject the corresponding trainable position embedding matrix \(P \in \mathbb{R}^{t \times d}\) into the input embedding matrix. The final input embedding matrix \(E \in \mathbb{R}^{t \times d}\) can be formulated as

\[
E = \begin{bmatrix}
V S^0_u + P_1 \\
\vdots \\
V S^t_u + P_t
\end{bmatrix}.
\]

3.3 Multi-Interest Extractor
The multi-interest extractor is exploited to generate multiple representation vectors to capture diverse interests of users. Prior multi-interest networks [2, 25] implements the multi-interest extractor via the dynamic routing mechanism [39] or the attention mechanism [27]. Empirically, as shown in prior work [2, 52], self-attention based multi-interest networks show the strong ability to capture user interests and get comparable results with the dynamic routing based methods. Therefore, we adopt the self-attention mechanism to obtain an attention matrix \(A \in \mathbb{R}^{c \times t}\) as

\[
A = \text{softmax}(W_2 \tanh(W_1 E^T)),
\]

where \(W_1 \in \mathbb{R}^{d \times d}\) and \(W_2 \in \mathbb{R}^{c \times k}\) are trainable transformation matrices. Then, we obtain the multi-interest representation matrix \(M \in \mathbb{R}^{c \times d}\) as

\[
M = AE.
\]

Thus, for every user, we adopt \(c\) representation vectors to capture her/his diverse interests.

3.4 Dependencies Among Captured Interests
Prior multi-interest networks capture \(c\) representations for user’s multiple interests through the multi-interest extractor. When they have been deployed to serve online traffic, the corresponding items of \(c\) captured correlated interests are usually retrieved together to get exposure and collected into training data, known as the sample selection bias problem [4, 34, 51]. Model may incorrectly concentrate on the dependencies among \(c\) interests instead of the true causation between relevant interests and target items. Unfortunately, in real scenarios, due to the rapid changing of recommender systems and the temporal evolution of user interest, the test distribution shifts from the training distribution. To achieve stable performance under such distribution shift, we have to make model focus on the true causation.
To alleviate above problem, we first need to measure the degree of independence between any pair of captured interests $M_i$ and $M_j$, in the high-dimensional representation space, which is infeasible to resort to histogram-based measures. In this paper, we introduce the widely used HSIC [9, 10] to be such independence testing statistics, which is the Hilbert-Schmidt norm of the cross-covariance operator between the distributions in Reproducing Kernel Hilbert Space (RKHS). For two random variables $U$ and $V$, the formulation of HSIC is:

$$
HSIC(U, V) = \mathbb{E}_{u,v} [k_u(u, v')k_v(v, v')] + \mathbb{E}_{u'}[k_u(u, u')]\mathbb{E}_{v'}[k_v(v, v')] - 2\mathbb{E}_{u,v}[k_u(u, u')\mathbb{E}_{v'}[k_v(v, v')]],
$$

where $\mathbb{E}_{u,v}$ denotes the expectation over independent pairs $(u, v)$ and $(u', v')$ drawn from $P(U, V)$, and $k_u$ and $k_v$ are kernel functions. We use the Radial Basis Function (RBF) kernel which is formulated as:

$$
k(u, v) = \exp(-\frac{|u - v|^2}{\sigma^2}).
$$

Given $m$ samples drawn from $P(U, V)$, the empirical HSIC [9] is defined as

$$
\widehat{HSIC}(U, V) = \frac{1}{(m-1)^2} \text{tr}(K_U K_V P),
$$

where $K_U \in \mathbb{R}^{m \times m}$ and $K_V \in \mathbb{R}^{m \times m}$ have entries $K_{ij} = k(U_i, U_j)$ and $K_{ij} = k(V_i, V_j)$, and $P = I - \frac{1}{m}11 \in \mathbb{R}^{m \times m}$ is the centering matrix. To be noted, $\text{tr}(K_U K_V P) = 0$ if and only if $U \perp V$.

As shown in Figure 1, taking ComiRec-SA [2] as an example, in training phase, we record the averaged HSIC value among captured interests’ representations and the recall on validation set. Due to the random initialization of model parameters, the value of HSIC and recall are nearly zero at first step, and they rapidly rise along with the increase of training steps. Around 10000 steps, HSIC slightly declines, but recall keeps rising. After 20000 steps, the value of HSIC begins to increase slowly while the value of recall stops rising and even begins to decline. To some extent, for multi-interest networks, this example reveals the trade-offs between the dependencies among interests and model performance on validation set.

As the HSIC is differentiable for back-propagation, to eliminate the influence of dependencies among captured interests, some prior work [1] directly adds it to the original task loss and solve the weighted overall loss by alternative updates. However, as shown in Figure 1, the value of HSIC and recall rise together in the early stage of training. Directly alternating minimizing HSIC and original task loss may increase the instability of training and slow down the convergence speed. Thus, we need to find more “soft” way to eliminate the dependencies among captured interests and make model concentrate more on underlying true causation between interests and targets.

### 3.5 Training & Serving

Inspired by sample reweighting techniques [23, 53], we propose a interest decorrelation regularizer which aims to estimate a weight for each sample such that interests are decorrelated on the weighted training data. Specifically, let $w \in \mathbb{R}_n^q$ be the set of sample weight for training data where $n$ is the number of training samples. We use $w^{(q)}$ to denote sample weights after the calculation in training epoch $q$, and initialize samples weights as ones, i.e., $w \in \mathbb{R}^q$.

Given the $h$-th training sample with user $u$, let $V_{S_{h,i}}$ denotes the embedding of the target item and $M_i \in \mathbb{R}^{k \times d}$ be the corresponding captured interests’ representations for the input sequence $S_h$. Specifically, we adopt the same interest selection in [2] to choose a interest representation from captured interests to represent user embedding $M_u$, which can be formulated as

$$
M_u = M[\text{argmax} (MV_{S_{h,i}} \cdot \cdot \cdot)].
$$

Then, the original objective function for the $h$-th training sample can be formulated as

$$
\mathcal{L}_h = -\log \left( \frac{\exp(M_u V_{S_{h,i}})}{\sum_{i \in I} \exp(M_u V_i)} \right),
$$

which can be implemented by the sampled softmax technique [5, 18] considering computational efficiency. At training epoch $q$, applying sample weights for weighted training, the objective function $\mathcal{L}_{h}$ of the proposed DESMIL can be formulated as

$$
\mathcal{L}^{(q)}_{h} = w^{(q)} \mathcal{L}_{h}.
$$

Then, we need to calculate sample weight $w^{(q)}_h$ for decorrelating interests in above model. The previous sample weight $w^{(q-1)}_h$ of the $h$-th training sample is exploited to reweight $M$ as

$$
\tilde{M}_h = w^{(q-1)}_h M.
$$

Then, we can find the new optimal sample weight $w^{(q)}_h$ that minimizes dependency among captured interests of $h$-th training sample as

$$
\hat{w}^{(q)}_h = \text{argmin}_w \sum \lambda \text{HSIC}(\tilde{M}_i, M_j),
$$

where $\lambda$ is the decorrelation importance which controls the convergence rate of $w$. To be noted, Eq (11) can be easily implemented via tensorflow\(^1\) to support batch training efficiently.

To be noted, we alternatively update the sample weights via Eq (11) and the model parameters via optimizing $\mathcal{L}^{(q)}_{h}$ with respect to model parameters $\theta$. The detailed procedure of our model is shown in Algorithm 1.

At serving time, sample weights are not involved and only the backbone model that generates the user representation is needed, producing multiple representation vectors for each user. Each interest embedding can independently retrieve top-N items based on an approximate nearest neighbor approach [19]. These items constitute the final set of candidate items for the matching stage of recommender systems.

### 4 EXPERIMENTS

In this section, we perform extensive experiments to evaluate the performance of our model. Firstly, we introduce datasets, comparison models and metrics used for evaluation. Then, quantitative results and visualization are discussed to empirically analyze the proposed DESMIL.

\(^1\)https://www.tensorflow.org/
Algorithm 1 Training process of DESMIL.

Input: Training dataset $D_{tr}$, maximum training epoch $Epoch$ and batch size $B$.

Output: Model parameters $\theta$.

1. Initialize the iteration variable $q \leftarrow 0$.
2. Initialize the best iteration variable $q_{best} \leftarrow 0$.
3. Initialize sample weights $w^{(0)} \leftarrow 1^n$.
4. Initialize model parameters $\theta^{(0)}$ via glorot uniform initializer [8].
5. repeat
6. Extract next batch from $D_{tr}$.
7. $q \leftarrow q + 1$.
8. Keeping $w^{(q-1)}$ fixed and optimizing $\sum_h \mathcal{L}_h^{(q)}$ via updating $\theta^{(q)}$, where $\mathcal{L}_h^{(q)}$ is defined in Eq. (9).
9. Keeping $\theta^{(q)}$ fixed and updating the corresponding batch sample weights $w^{(q)}_B$ via Eq. (11) on samples in the batch.
10. Update $q_{best} \leftarrow q$, if better validation result achieved.
11. until early stopped or maximum training epoch is reached.
12. return $\theta^{(q_{best})}$.

### 4.1 Experimental Setup

**Datasets.** We evaluate our proposed model on three public datasets and a large-scale commercial datasets as described in the following.

- **Book Dataset.** The book dataset is part of the Amazon product data in the "book" category. This dataset is introduced in [13, 35], which consists of product reviews spanning May 1996 to July 2014 from Amazon.com. There are 603668 users, 367982 items and 8898041 user behaviors in total.

- **Movies and TV Dataset.** The Movies and TV dataset is part of the updated Amazon Review Data [36]. This dataset contains product reviews in the "Movies and TV" category from May 1996 to Oct 2018. There are 304763 users, 89590 items, and 3506470 user behaviors in total.

- **CDs and Vinyl Dataset.** The CDs and Vinyl dataset is also part of the updated Amazon Review Data [36]. This dataset contains product reviews in the "CDs and Vinyl" category from May 1996 to Oct 2018. There are 129237 users, 145522 items, and 1682049 user behaviors in total.

- **Industrial Dataset.** The Industrial dataset is sampled from real-world mobile application logs, and all records have been anonymized and sanitized. This dataset has 5886272 users, 1195809 items and 103579419 user behaviors in total.

### Table 1: Results on Public and industrial Datasets. Best performances are indicated by bold fonts and the strongest baselines are underlined. The improvement (Improv.) indicates the relative increase of our model over baselines on metrics.

| Datasets          | Metric   | POP  | GRU4Rec | Y-DNN   | SASRec | MIND  | ComiRec | CauseRec | DESMIL | Improv. |
|-------------------|----------|------|---------|---------|---------|-------|---------|----------|--------|---------|
| **Book**          | Recall@20| 1.37 | 3.47    | 4.40    | 4.76    | 5.10  | 5.92    | 5.75     | 7.52   | 27.03%  |
|                   | Recall@50| 2.40 | 6.50    | 7.31    | 7.78    | 7.64  | 9.33    | 9.36     | 11.06  | 18.16%  |
|                   | NDCG@20  | 2.26 | 3.55    | 4.59    | 4.84    | 5.09  | 4.17    | 4.66     | 5.46   | 7.27%   |
|                   | NDCG@50  | 3.94 | 4.42    | 5.54    | 5.74    | 5.97  | 5.47    | 6.28     | 7.24   | 15.28%  |
|                   | HR@20    | 3.02 | 7.84    | 9.89    | 8.82    | 10.59| 11.70   | 12.45    | 14.86  | 19.36%  |
|                   | HR@50    | 5.23 | 12.38   | 14.94   | 13.79   | 15.56| 18.04   | 20.23    | 21.53  | 6.43%   |
| **Movies and TV** | Recall@20| 3.59 | 13.20   | 12.38   | 14.43   | 14.87| 15.46   | 15.30    | 15.76  | 1.94%   |
|                   | Recall@50| 6.62 | 17.66   | 17.31   | 18.27   | 19.55| 18.87   | 19.24    | 20.90  | 6.91%   |
|                   | NDCG@20  | 5.30 | 15.07   | 12.64   | 14.49   | 15.80| 14.73   | 15.10    | 15.31  | \      |
|                   | NDCG@50  | 9.66 | 16.21   | 14.11   | 16.72   | 17.23| 16.17   | 16.83    | 17.36  | 0.75%   |
|                   | HR@20    | 6.51 | 22.67   | 21.32   | 23.25   | 25.34| 25.87   | 25.94    | 26.42  | 1.85%   |
|                   | HR@50    | 11.73| 29.54   | 29.46   | 30.43   | 32.93| 33.68   | 33.90    | 34.80  | 2.65%   |
| **CDs and Vinyl** | Recall@20| 0.993| 4.39    | 5.24    | 6.92    | 7.55 | 7.96    | 7.77     | 8.75   | 9.92%   |
|                   | Recall@50| 1.89 | 6.07    | 7.72    | 8.52    | 10.32| 11.23   | 11.12    | 12.09  | 7.66%   |
|                   | NDCG@20  | 1.58 | 4.81    | 5.42    | 6.44    | 7.93 | 6.84    | 7.51     | 7.79   | \      |
|                   | NDCG@50  | 3.12 | 5.42    | 6.36    | 7.10    | 8.88 | 8.01    | 8.57     | 8.86   | \      |
|                   | HR@20    | 2.11 | 8.47    | 10.40   | 12.86   | 14.28| 14.35   | 14.49    | 15.73  | 8.56%   |
|                   | HR@50    | 4.08 | 11.79   | 15.46   | 16.29   | 19.38| 20.26   | 20.66    | 21.89  | 5.95%   |
| **Industrial**    | Recall@20| 1.01 | 6.31    | 6.28    | 6.81    | 6.96 | 7.23    | 7.02     | 8.41   | 16.32%  |
|                   | Recall@50| 1.75 | 9.88    | 10.76   | 11.02   | 11.29| 11.51   | 11.76    | 12.87  | 9.44%   |
|                   | NDCG@20  | 1.92 | 9.15    | 7.25    | 8.27    | 8.91 | 8.58    | 8.60     | 9.19   | 3.14%   |
|                   | NDCG@50  | 3.28 | 10.60   | 9.20    | 9.78    | 10.75| 10.35   | 10.54    | 11.28  | 4.93%   |
|                   | HR@20    | 2.55 | 17.04   | 16.73   | 17.05   | 17.52| 17.89   | 18.33    | 20.50  | 11.84%  |
|                   | HR@50    | 4.38 | 24.97   | 23.94   | 25.11   | 26.21| 26.56   | 26.77    | 29.45  | 10.01%  |
For the classic dataset splitting, the Book dataset follows the official repository of ComiRec. For the OOD splitting, for each user \( u \), if the length of the sequence of historical behaviors \( S_u \) is less than 10, \( S_u \) will be partitioned to training set only.

**Competitors.** We compare our proposed model to the following baselines for evaluation.
- **POP**: a simplest baseline that ranks items according to their popularity (i.e., the number of interactions).
- **GRU4Rec** [14]: an early sequential recommendation model based on recurrent neural network.
- **Y-DNN** [5]: one of the most successful deep learning models for industrial recommender systems.
- **SASRec** [20]: a state-of-the-art model that uses self-attention network for the sequential recommendation.
- **MIND** [25]: a state-of-the-art multi-interest sequential recommendation model with dynamic routing for modeling user’s diverse interests in the matching stage.
- **ComiRec** [2]: a state-of-the-art sequential recommendation model with multi-interest extraction module to generate multiple user interests and aggregation module to obtain top-N items. We use the SA setting of ComiRec which is described as ComiRec-SA in the original paper.
- **CauseRec** [52]: a state-of-the-art sequential recommendation model that performs contrastive user representation learning to model the counterfactual data distribution to confront the sparsity and noise nature of observed user interactions.

Meanwhile, we implement our proposed DESMIL model with TensorFlow 1.14 and Faiss in Python 3.7. Experiments on public datasets are conduct using a single Linux server with 4 Intel(R) Xeon(R) CPU E5-2680 v4@ 2.40GHz, 256G RAM, and 8 NVIDIA GeForce RTX 2080 Ti.

**Parameter Configuration.** The dimension of item embedding is set to 64. The batch size for Book dataset and Industrial Dataset is set to 1024, while the batch size for the Movies and TV dataset and the CDs and Vinyl dataset is set to 128, according to the best performances of ComiRec. The number of negative samples for sampled softmax loss is set to 10. All models use early stopping based on the Recall@50 on the validation set. The decorrelation importance and the number of interests are tuned in the range of \( \{0.01, 0.1, 1.0, 10.0, 100.0\} \) and the range of \( \{2, 4, 6, 8\} \), respectively. We use the Adam optimizer [21] with learning rate \( \text{lr} = 0.001 \) for optimization.

**Evaluation Metrics.** We use the top \( p \) Recall Rate, Normalized Discounted Cumulative Gain (NDCG), and Hit Rate (HR) to evaluate the sequential recommendation model performance. We select \( p = 20, 50 \) in the experiments. The three metrics measure the model performance with different criteria. Recall@\( p \) is often considered
the most important factor for a model to be used in the industry. Recall@p is defined as the fraction of relevant items found in the top p recommended items. NDCG@p further considers the normalization of gains and the ranking of correctly recommended items, where items with higher relevance affect the final score more. HR@p is defined as the proportion of top p recommended samples found in the test set.

4.2 Results and Analysis

Firstly, we conduct experiments on dataset splitting following previous work [2]. Specifically, we split samples into training, validation and test set according to the corresponding users (namely classic splitting). Considering interaction time of samples in training, validation and test set may overlap, in such kind of data splitting, samples in different sets share relative similar data distribution. In Table 1, we show the performance comparison on the four datasets. All the presented results are averaged by five independent results with different seeds. From the table, we can tell that DESMIL, CauseRec, ComiRec and MIND outperform earlier deep learning models such as SASRec, Y-DNN and GRU4Rec. And POP performs poorly. Among the three state-of-the-art models, MIND performs relatively better on NDCG, ComiRec performs relatively better on recall rates, CauseRec performs relatively better on hit rates. To be noted, as we follow the correct calculation of NDCG which is corrected by the authors in the official repository of ComsiRec [2] to evaluate each model, the NDCG results of ComsiRec and CauseRec are lower than what are reported in the original papers. Moreover, according to results in Table 1, our model relatively outperforms previous state-of-the-art models by 1.94% to 27.03% in Recall and by 1.85% to 19.36% in Hit Rate. These improvements are significant. When evaluated by the metric of NDCG, our proposed model outperforms other models on the Book dataset and the Industrial dataset by large margins from 3.14% to 15.28%. But on the Movies and the TV dataset and the CDs and Vinyl dataset, DESMIL achieves very slightly lower but acceptable NDCG results, compared with MIND. In real applications, Recall is often considered as the most important metric as it can best reflect the performance of real-world recommender systems facing enormous candidate set of items and almost equally important but limited exposure positions. Comprehensively considering the importance of Recall and the significant improvements measured by Recall and Hit Rate, DESMIL still greatly outperforms other compared models, and achieves promising performances on all the four datasets.

Secondly, we conduct performance comparison on OOD data, for investigating whether recommendation models can provide stable predictions. Considering data distribution and dependencies among captured interests may change in different time periods, we conduct the following data splitting (namely OOD splitting). We use the first 50% and the following 10% samples in sequences as training set and validation set respectively. After training on above data is completed, we adopt the first z of samples and the left 1 − z of samples in sequences as input historical behaviors and the test samples, respectively. To simulate different ratio of covariate shift [41, 49], z takes value in the range of {0.5, 0.6, 0.7, 0.8, 0.9}. In Figure 4, we illustrate performance comparison on such OOD datasets with different ratio of simulated covariate shift. For simplicity, we only show results evaluated by Recall@50. To be noted, compared with [2], such data splitting is more applicable and reasonable considering real-world recommender systems, for we usually train models based data collected before a time point, and use the models online for predicting samples after the time point.
observe from the figure that, DESMIL stably outperforms the state-of-the-art models ComiRec and CauseRec by large margins. These results further show the effectiveness and stability of DESMIL under distribution shifts.

Thirdly, we need to investigate the impact of some key hyper-parameters. We conduct experiments on datasets under the classic splitting, which stays the same as in Table 1. We illustrate hyper-parameter study measured by Recall@50, NDCG@50 and HR@50 in Figure 5, 6 and 7 respectively. Similar phenomenons are shared across figures measured by different evaluation metrics. As shown in the figures, the selection of the decorrelation importance coefficient $\lambda$ to control the convergence rate of training sample weight does not affect the model performances very much. So we can simply set $\lambda = 1.0$ for most datasets. Meanwhile, the optimal number $c$ of interests may vary among different datasets. The optimal number of interests for the Book dataset, the CDs and Vinyl dataset and the Movies and TV dataset is $c = 2$, and for Industrial dataset is $c = 6$. Overall speaking, the performance of DESMIL with varying hyperparameters is relatively stable, especially in some ranges of the hyperparameters. This does not leave us too much burden for hyperparameter tuning in practice.

4.3 Visualization

In Figure 8, we visualize the change of HSIC on the training set and Recall on validation set when training DESMIL and ComiRec on the Book dataset. Both DESMIL and ComiRec use early stopping and the training of them terminates at different step, which results in the different length of curves shown in Figure 8. It should be noted that DESMIL performs optimization of HSIC by sample weighting in the training phase, while the calculation of HSIC, which is shown in Figure 8, is not weighted. Different from DESMIL, ComiRec does not control the optimization of HSIC (i.e., dependencies among interests) at all. At the first 10000 steps, the HSIC and Recall of both models increase. Then, the HSIC of ComiRec continues to rise while the HSIC of DESMIL is well under control, which makes it possible for DESMIL to update more steps and obtain better performance. Similar as the Book dataset, we further illustrate the curves of HSIC on the training set and Recall on validation set when training DESMIL and ComiRec on the CDs and Vinyl dataset and the Movies and TV dataset. As shown in Figure 9, for the CDs and Vinyl dataset, after the first 40000 steps, the HSIC of DESMIL is well under control while the HSIC of ComiRec continues to rise. As shown in Figure 10, for the Movies and TV dataset, the HSIC of DESMIL continues to rise while more slower than the HSIC of ComiRec. From these curves, we can observe a clear correlation between the controlled HSIC and the space for optimization of Recall.

In Figure 11, we visualize the probability distribution of sample weights for the Book dataset in a histogram. This shows that the sample weights of user interests are mostly around the values from 0.8 to 1.0, with some located near the value of 0.0. The value near 1.0 means no change of sample weight while the value near 0.0 means a sharp change of sample weight in the loss function. This shows that most data in the Book dataset does not require specific decorrelation techniques while some data points are indeed marginalized. These marginalized data points may decrease the influence of some popular but unfitted user interests and interacted items on the overall model training, and allowing the model to focus on data points that actually possesses causal effect on the prediction even when the environment changes.
In this paper, for multi-interest networks, we introduce HSIC as independence testing statistics to measure the degree of independence among captured interests. We trace the HSIC and model performance in training phase, and observe that the continuous increase of HSIC may affect model performance in the middle and late stage of training. Thus, we point out that eliminating the influence of dependencies among captured interests is a promising way to alleviate OOD generalization problem in recommender systems. Based on this, we propose a novel deep stable multi-interest learning for sequential recommendation. The interest decorrelation regularizer in DESMIL tries to eliminate the influence of subtle dependencies between captured interests via learning weights for training samples, which is a soft way to make model concentrate more on underlying true causation. Extensive experiments have been conducted to demonstrate that DESMIL achieves superior performance on public benchmarks, large-scale industrial dataset and the synthetic dataset which simulates the OOD data. Besides, the comprehensive model analysis uncovers the reason why DESMIL works to a certain extent.

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Figure 11: The histogram of sample weight on the Book dataset.

5 CONCLUSION

In this paper, for multi-interest networks, we introduce HSIC as independence testing statistics to measure the degree of independence among captured interests. We trace the HSIC and model performance in training phase, and observe that the continuous increase of HSIC may affect model performance in the middle and late stage of training. Thus, we point out that eliminating the influence of dependencies among captured interests is a promising way to alleviate OOD generalization problem in recommender systems. Based on this, we propose a novel deep stable multi-interest learning for sequential recommendation. The interest decorrelation regularizer in DESMIL tries to eliminate the influence of subtle dependencies between captured interests via learning weights for training samples, which is a soft way to make model concentrate more on underlying true causation. Extensive experiments have been conducted to demonstrate that DESMIL achieves superior performance on public benchmarks, large-scale industrial dataset and the synthetic dataset which simulates the OOD data. Besides, the comprehensive model analysis uncovers the reason why DESMIL works to a certain extent.
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