VAE-IPS: A Deep Generative Recommendation Method for Unbiased Learning from Implicit Feedback

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Abstract

In this paper, in order to mitigate the influence of bias in the recommendation system on the recommendation effect, the author proposed an IPS-based deep generation recommendation model, VAE-IPS. In this reproduction work, I have implemented the recommendation model VAE-IPS proposed in this paper, and further used a more accurate performance score estimation method to improve VAE-IPS. Finally, the validity of the model is proved by comparing with the baseline method.

Keywords: Variational autoencoder, Implicit feedback.

1 Introduction

In the recommendation system, the items displayed to each user are usually different. For example, the system will recommend items in their own directions to a science fiction fan and a martial arts fan respectively; Each user's feedback may be reserved, for example, only when they are particularly satisfied or dissatisfied will they give feedback to the item. These problems will lead to biased user feedback data in the recommendation system. If these biases are ignored, the recommendation model will not be optimal.

In order to weaken the negative effects of bias, the existing work proposes to use a counterfactual estimation technique, namely, Inverse Propensity Scoring (IPS). IPS-based debias methods are widely used in matrix factorization recommendation model, but not be used in deep generative recommendation model. The existing deep generative recommendation model, VAE, has a good recommendation effect, but it ignores the bias problem in the generative process. Therefore, this paper proposes a deep generative recommendation model based on IPS, VAE-IPS, which optimizes the ideal generative objective of VAE through IPS debias method, corrects the bias in implicit feedback data, and thus improves the performance of the recommendation system.

2 Notations

In this section, I will introduce some basic notations and their explanations which are used in the after sections.

Let u denote a user and U denote a set of m users. Let i denote an item and I denote a set of n items. Let $D = U \times I$ denote a set of all user-item pairs. $C \in \{0,1\}^{m \times n}$ is a click matrix, where $c_{u,i}$ is a Bernoulli random variable representing a click between the user u and item i. If the user u click the item i, $c_{u,i} = 1$; otherwise, $c_{u,i} = 0$. $R \in \{0,1\}^{m \times n}$ is a relevance matrix, where $r_{u,i}$ is a Bernoulli random variable representing the true relevance between the user u and item i. If the user u is relevant with the item i, $r_{u,i} = 1$; otherwise, $r_{u,i} = 0$. $O \in \{0,1\}^{m \times n}$ is a observation matrix, where $o_{u,i}$ is a random variable representing whether the user u has observed the item i. If the user u has observed the item i, $o_{u,i} = 1$; otherwise, $o_{u,i} = 0$.

3 Related Works

In this section, I will introduce some existing works related with recommendation models.

3.1 Variational AutoEncoder for Collaborative Filtering

Mult-VAE applies Variational autoencoder (VAE) to collaborative filtering for implicit feedback[1]. VAE is a non-linear probabilistic model, which can transcend the linear factor model. Mult-VAE introduce a generative model with multinomial likelihood and use Bayesian inference for parameter estimation. The objective function to be maximized in Mult-VAE can be described as follows:

$$L_{u,i}^{vae} = E_{q_\phi}[c_{u,i}\log(\pi_\theta(z_{u,i})) + (1 - c_{u,i})\log(1 - \pi_\theta(z_{u,i}))] - D(q_\phi(z_{u,i})||p(z_{u,i})) \tag{1}$$

where $z_{u,i}$ is the user-item latent variable, $\pi_\theta(z_{u,i})$ is the relevance score for the pair (u,i), $q_\phi(z_{u,i})$ is the posterior distribution over $z_{u,i}$, $p(z_{u,i})$ is the standard Gaussian distribution over $z_{u,i}$.

According to the proof in the Reference[2], it can be known that the estimator of Mul-VAE is biased.

3.2 Relevance Matrix Factorization

RelMF is implicit feedback recommendation model based on the latent factor model as the MF[3]. This model makes the following assumption for all user−item pairs.

$$P(c_{u,i} = 1) = P(o_{u,i} = 1) \cdot P(r_{u,i} = 1) = \rho_{u,i} \cdot \gamma_{u,i} \tag{2}$$

where $\rho_{u,i} = P(o_{u,i} = 1)$ is the observation probability of the item i by the user u and $\gamma_{u,i} = P(r_{u,i} = 1)$ is the relevance probability. This assumption means that if the user u has observed the item i and u is relevant with i, u will click i.

Given this assumption, the estimator is defined as follows:

$$L_{RelMF}(\widehat{R}) = \frac{1}{|D|}\sum_{(u,i)\in D}\left[\frac{c_{u,i}}{\rho_{u,i}}\delta_{u,i}^{(1)} + \left(1 - \frac{c_{u,i}}{\rho_{u,i}}\right)\delta_{u,i}^{(0)}\right] \tag{3}$$

where $\widehat{R}$ is a prediction matrix, $\delta_{u,i}^{(R)}$ $(R \in \{0,1\})$ denotes the local loss for the user−item pair. The local loss function can be the cross-entropy function or the sum-of-squared function.

This estimator of RelMF model is biased through the analysis in the Reference[4].

4 Method

This paper proposes a deep generative recommendation model based on IPS, VAE-IPS, which optimizes the ideal generative objective of VAE through IPS debias method. The unbiased estimator of VAE-IPS is defined as follows:

$$L_{u,i}^{ips} = E_{q_\phi}\left[\frac{c_{u,i}}{\rho_{u,i}}\log(\pi_\theta(z_{u,i})) + \left(1 - \frac{c_{u,i}}{\rho_{u,i}}\right)\log(1 - \pi_\theta(z_{u,i}))\right] - D(q_\phi(z_{u,i})||p(z_{u,i})) \tag{4}$$

This estimator is proved as an unbiased estimate of the true generative objective. The detailed proof process is given in this paper.

For estimating the propensity score, the author used the following relative popularity of items.

$$\rho_{*,i} = (\frac{|U_i|}{\max_{i' \in I} |U_{i'}|})^{\eta} \tag{5}$$

where $|U_i|$ denote the number of users that prefers item i, $\eta \leqslant 1$ and I set $\eta = 0.5$ in this experiment. However, I believe that it is very one-sided to only consider the information from the item perspective, and it is impossible to estimate an accurate propensity score. In this regard, I use a more accurate propensity score estimation method proposed in the Reference[5] to improve VAE-IPS.The estimation of propensity score as follows:

$$\rho_{u,i} = (\frac{|I_u| \cdot |U_i|}{\max_{u' \in U} |I_{u'}| \cdot \max_{i' \in I} |U_{i'}|})^{\eta} \tag{6}$$

where $|I_u|$ denote the number of items interacted by user u. This method not only considers the relative popularity of items, but also considers the user activity, taking into account the user perspective and item perspective information.

5 Implementation Details and Improvement

5.1 Comparing with Released Source Codes

No related source codes are available.

5.2 Experimental Setup

5.2.1 Dataset

I used the Yohoo!R3 dataset, an explicit feedback dataset which contains ratings for songs collected in the music recommendation scenario. In this dataset, the training set includes 15400 users who freely choose to score 1000 songs, with a total of 311704 rating data. The test set contains the rating data of the first 5400 users, who are required to rate 10 randomly selected songs.

In this expriment, I regard all ratings($\geqslant 4$) as positive implicit feedback and the rest of rating($\leqslant 4$) as unlabeled implicit feedback. Then I randomly split the training set into two part, 90% for training and 10% for validation. For test, I directly used the original test set in the Yohoo!R3 dataset.

5.2.2 Baselines

I used the VAE and RelMF model as baselines, which are described in Section 3.1 and Section 3.2, respectively. For the implementation of the RelMF, I used the available code provided at https://github.com/usaito/unbiased-implicit-rec-real.

5.2.3 Evaluation Metrics

I used DCG@K, Recall@K, MAP@K as the evaluation metrics ($K \in \{1, 3, 5\}$). These evaluation metrics are defined as follows:

$$DCG@K = \frac{1}{|U|} \sum_{u \in U} \sum_{i \in I_u^{test}: r_{u,i}=1} \frac{\mathbb{I}\{\widehat{Z_{u,i}} \leqslant K\}}{\log(\widehat{Z_{u,i}} + 1)} \tag{7}$$

$$Recall@K = \frac{1}{|U|}\sum_{u \in U}\sum_{i \in I_u^{test}: r_{u,i}=1} \frac{\mathbb{I}\{\widehat{Z_{u,i}} \leqslant K\}}{\sum_{i \in I_u^{test}} r_{u,i}} \tag{8}$$

$$MAP@K = \frac{1}{|U|}\sum_{u \in U}\sum_{i \in I_u^{test}: r_{u,i}=1} \sum_{k=1}^{K} \frac{\mathbb{I}\{\widehat{Z_{u,i}} \leqslant k\}}{k} \tag{9}$$

where $\widehat{Z_{u,i}}$ is the predicted ranking of item i for user u , I_u^{test} is a set of items rated by user u in the test set.

5.2.4 Hyper-parameter Tuning Criteria

To tune Hyper-parameter, I used the validation set and DCG@5 as the metric. For Mul-VAE, VAE-IPS and VAE-IPS-Imp, the range of the dimensions of the latent factors is {5, 10, 15, ..., 50}, and the range of the L2-regularization hyper-parameter is $[10^{-6}, 1]$. In addition, I set the batch size as 2^{10} and the number of iterations as 100, and I adopt the Adam optimizer with the initial learning rate of 0.01.

5.3 Improvement

In the whole reproduction process, I completed the dataset preprocessing, completed the calculation of propensity score, built the recommendation model using the tensorflow framework, and completed the model training and parameter tuning process successfully.

In particular, I used a estimation method of propensity score to improve VAE-IPS, which considered user activity and relative popularity of items to estimate more accurate propensity score.

6 Results and Analysis

As shown in the Table 1, this paper proposed model VAE-IPS is empirically shown to be both effective and efficient, and it outperforms other two baselines. For example, it improving the DCG@5 by 12.65%, Recall@5 by 5.53%, and MAP@5 by 16.47% over the RelMF. This result presents that VAE-IPS can effectively mitigate the negative effect of biases in deep generation model. Especially, our improved model VAE-IPS-Imp outperforms all other methods. This result proves that applying a more accurate propensity score estimation method to the VAE-IPS can improve the recommendation performance.

表 1: Performance of different methods on Yahoo! R3 dataset.

	DCG			Recall			MAP		
Method	@1	@3	@5	@1	@3	@5	@1	@3	@5
RelMF	0.1821	0.3771	0.4593	0.1625	0.3941	0.5892	0.1813	0.3265	0.4075
Mul-VAE	0.2149	0.4250	0.5058	0.1850	0.4266	0.6182	0.2141	0.3749	0.4594
VAE-IPS	0.2228	0.4396	0.5174	0.1915	0.4358	0.6218	0.2220	0.3921	0.4746
VAE-IPS-Imp	0.2295	0.4469	0.5259	0.1961	0.4384	0.6276	0.2287	0.4004	0.4833

7 Conclusion and Future Work

In this paper reproduction work, I implemented an unbiased VAE generation estimator using IPS based debias method in the deep generation model, and proved that the recommendation performance of VAE-IPS is better than other baseline methods through experiments. I further improved VAE-IPS and used a more accurate method to estimate propensity score. Experiments show that this improved method has better effect than other methods.

In the future, one direction that can be further studied is to design a more general debias model or a more accurate method for estimating the propensity score.

References

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