Double Robust Joint Learning for Factorization Machine on Data Missing Not at Random

Xing Hong
Group 3
Recommendation System
City, Country
line 5:email address or ORCID

Mingyu Li
Group 3
Recommendation System
City, Country
line 5:email address or ORCID

Dongming Li
Group 3
Recommendation System
City, Country
line 5:email address or ORCID

Ziyu Liu
Group 3
Recommendation System
City, Country
line 5:email address or ORCID

Hantian Zhang
Group 3
Recommendation System
City, Country
line 5:email address or ORCID

Abstract

While using a recommendation system to predict the ratings, it is common that many users-to-items ratings are missing. And what makes prediction even trickier is that these missing ratings are missing not at random (MNAR), meaning that there are other factors contributing to why some ratings are missing. The common approaches to reduce the prediction errors for those missing ratings are using imputed errors, or weight observed ratings with the propensities of being observed. But Each of them is not perfect since they still show severely biased performance or heavily influenced by the variance of propensities when estimating. To generate a better recommendation system algorithm that could generate a satisfactory outcome, a new estimator combining the imputed errors and propensities in a double-robust way is designed to take unbiased performance estimation and meanwhile reduce the effect of the propensity variance. In addition, we perform joint learning of error imputation and rating prediction based on the estimator to acquire a more reliable performance, which shows a better result than the dataset without double-robust joint learning.

Keywords

EIB (error-imputation-based), IPS (inverse-propensity-score), Double Robust (DR), Logistic Regression, Joint Learning

1 Introduction

A recommendation system is an algorithm predicting users' behaviors. The recommendation list includes the features of users, the features of items, and the user-item past interactions (Zhang, et al.2017). The goal of the recommendation system is to induce the relationship between these features and the behavior of the users.

However, there are some critical issues that need to be considered.

A recommendation system often suffers from a high proportion of missing data. For those data, they are missing not at random (MNAR). In specific, when a person does not vote for a particular item, his view on that item will not be recorded. There could be all kinds of reasons that he does not make his rating, such as his mood, his accessibility to rating, or his inclination to be a part of any rating. Thus, data missing at random (MAR) approach does not give us an unbiased result. We have an example demonstrating why that is the case below based on the idea that people tend to vote for their favorite items. The big number in the middle stands for the rating of a particular group of people. Those with greens/red square stand for those who have rated (not necessarily their true ratings), and the rest is merely prediction. In the first column: Horror (movies). We have 11 horror movie lovers voted five and 3 romance movie lovers voted one. Clearly, the outcome is severely biased by simply taking the mean.

Observed losses are misleading due to selection bias

Those MNAR data make the prediction of rating much more complicated, and it is difficult to make sure the estimate performance is good enough (Steck, 2011). The performance of a prediction model is shown in its prediction inaccuracy, which means the average prediction errors like mean square error (MSE) for all ratings (Salakhutdinov et al., 2007). When estimate the prediction rating with MNAR ratings, only consider the observed ratings, like the one just shown in graph, is severely biased, then the prediction model can greatly overestimate or underestimate the prediction inaccuracy, which also called as the bias (Little & Rubin, 2014).

There are two approaches to deal with the MNAR problem recently: (1) The error-imputation-based (EIB) approach calculates the imputed error like prediction error estimated by each MNAR rating, but it often has a great bias due to the imputation inaccuracy, i.e., deviations of the imputed errors from the prediction errors (Duďık et al., 2011), which can also influence the training session and enlarge the prediction inaccuracy (Steck, 2013). (2) The inverse-propensity-scoring (IPS) approach inversely weights the prediction error for each observed rating with its propensity (Schnabel et al., 2016), but it is often influenced by the high variance of the propensities (Thomas & Brunskill, 2016), and once the propensities are inversed, the training losses will be unstable, and the generalization will be poor.

Rather than those recent approaches, we proposed a double-robust estimator that combines those recent approaches. It calculates the imputed errors and inversely weights each prediction error with its propensity to reduce the bias of prediction inaccuracy. To minimize bias, the joint learning of a prediction model and an imputation model is proposed. The imputation model trains to obtain two hyper-parameter values that minimizes imputation error after the prediction model makes its prediction, while the prediction model learns to decrease the prediction errors according to the imputation model using the imputation error that was just generated. In this way, the prediction model and imputation model gradually regularize each other to decrease prediction inaccuracy and imputation inaccuracy (Wang et al., 2019).

This paper aims to discuss three methods to deal with MNAR, which includes error-imputation-based model, inverse-propensity-score model, and Double Robust Method. After comparing experiments using these methods, it will be clear that the Double Robust method produces outcome with less bias compared to other recent approaches.

2 Preliminaries

2.1 Imputation

The error-imputation-based (EIB) approach computes an imputed error, i.e., an estimated value of the prediction error, for each missing rating (Steck, 2013). This estimator predicts the rating inaccuracy by the following equation:

$$\varepsilon_{EIB}\left(\hat{R}, R^{O}\right) = \frac{1}{|D|}\sum_{u,i\in D}(o_{u,i}e_{u,i} + (1 - o_{u,i})\hat{e}_{u,i})$$

We are going to build an imputation model and compute imputed error based on MSE (mean square error) formula:

$$\hat{e}_{u,i} = \omega(\hat{r}_{u,i} - \gamma)^2$$

where $\hat{r}_{u,i}$ are predicted ratings for user(u) item(i) pairs and ω and γ are hyper-parameters (Steck, 2010).

2.2 IPS-Propensity Model

An alternative for EIB is Inverse-Propensity-Scoring. In this method, the first thing to do is computing the propensity that is the probability of observing the true rating $r_{u,i}$. The mathematical expression of the propensity term is:

$$P_{u,i} = P\left(O_{u,i} = 1 \middle| X, X_{hid}, Y\right)$$

The propensity can be calculated by naive bayes or logistic regression method.

2.2.1 Naïve bayes:

By using Naïve Bayes, it is assumed that the dependency between covariates X, X_{hid} and other ratings. Thus, the equation could be simplified to:

$$P_{u,i} = P\left(O_{u,i} = 1 \middle| Y\right)$$

Here, we only need observed ratings to compute the IPS estimator.

Thus, the equation to obtain the propensity is:

$$P\left(O_{u,i} = 1 \middle| Y_{u,i} = r\right) = \frac{P(Y = r|O = 1)P(O = 1)}{P(Y = r)}$$

2.2.2 Logistic regression:

Then, the learned propensity $\hat{p}_{u,i}$ will be used to inversely weight each prediction error for observed ratings and define an inverse-propensity-scoring (IPS) estimator that estimates the prediction inaccuracy with formula:

$$\varepsilon_{IPS}(\hat{R}, R^O) = \frac{1}{|D|} \sum_{u,i \in D} \frac{o_{u,i} e_{u,i}}{\hat{p}_{u,i}}$$

In the later experiment, we decide to use the logistic regression method as it is more intuitive and convenient to compute the propensities.

3. Joint learning

One of the problems encountered in the training of the recommendation system model using the double robust predictor is that the imputation model often forms a large error deviation, which deteriorates the training of the prediction model. To prevent this problem, a method called joint learning is used to train the imputation model and the prediction model.

The main algorithm of this method is to train the imputation model and the prediction model respectively in the same loop. First, the prediction model needs to formulate an initial hyperparameter θ to predict an initial prediction rating $\hat{r}_{u,i}$ and use it to get the initial predict error $e_{u,i}$ as a constant. Then use initial $\hat{r}_{u,i}$ and $e_{u,i}$ in imputation model and training the model with loss function:

$$L_e(\theta, \varphi) = \sum_{u,i \in O} \frac{(\hat{e}_{u,i} - e_{u,i})^2}{\hat{p}_{u,i}} + v||\varphi||^2{}_F$$

to update hyperparameter φ by taking the derivative. So that the imputed error $\hat{e}_{u,i}$ will be updated as well. Then use the updated imputed error $\hat{e}_{u,i}$ in prediction model as a constant and training the model with loss function:

$$L_r(\theta, \varphi) = \sum_{u,i \in D} \hat{e}_{u,i} + \frac{o_{u,i}(e_{u,i} - \hat{e}_{u,i})}{\hat{p}_{u,i}} + v||\theta||^2{}_F$$

to update the hyperparameter θ, so that the predict rating $\hat{r}_{u,i}$ and predict error $e_{u,i}$ will be updated as well. Then put this updated information into $L_e(\theta, \varphi)$ and repeat the above steps until optimal loss is achieved.

The double robust method ensures the unbiased prediction mathematically. The formula of double robust loss function is:

$$L_{DR}(\theta, \varphi) = \frac{1}{D} \sum_{u,i \in D} [\hat{e}_{u,i} + \frac{o_{u,i}(L_r(\theta) - \hat{e}_{u,i})}{\hat{p}_{u,i}}]$$

$$E[L_{DR}(\theta, \varphi)] = E[L_r(\theta) + \frac{(o_{u,i} - \hat{p}_{u,i})(L_r - \hat{e}_{u,i})}{\hat{p}_{u,i}}$$

$$= E[L_r(\theta) + \frac{(p_{u,i} - \hat{p}_{u,i})(e_{u,i} - \hat{e}_{u,i})}{\hat{p}_{u,i}}]$$

If true propensity equals predicted propensity or true predicted error equal imputed error:

$$\frac{(p_{u,i} - \hat{p}_{u,i})(e_{u,i} - \hat{e}_{u,i})}{\hat{p}_{u,i}} = 0$$

In short, the expected value of this doubly robust method will be equal to the expected value of the prediction model when either ($p_{u,i}$ = $\hat{p}_{u,i}$ or $e_{u,i}$ = $\hat{e}_{u,i}$). In other words, this doubly robust method will be unbiased if either the imputation model or the propensity model is unbiased.

4 Experiment

Data Introduction

Unbiased estimation of our prediction inaccuracy needs MAR ratings, as we decided to adapt real world dataset as follows.

*Coat Shopping Dataset. (*Schnabel et al., 2016*)*

The dataset simulating MNAR data of customers shopping for a coat in an online store including 6,960 MNAR and 4,640 MAR ratings of 290 users to 300 coats, therefore, 87,000 possible user-items pair. We use MNAR ratings for training and MAR ratings for testing.

Experiment Setup

For feature engineering, we use Auto-Encoder to reduce dimensions in order to improve the generalization ability of our model. (Hinton & Salakhutdinov, 2006) Given that the feature for coats contains gender (2), type (16), color (13), promotes (2), 33 columns in one-hot encoded form, while features for user contains 14 columns of features. In this case, we use Auto-encoder as an approach to avoid the problem of having a sparse feature matrix. As a result, reducing coat features of type to 10 and coat features of colors to 7 is possible, and concatenated to form a feature matrix for user item pairs with 30 features.

Logistic Regression on Propensities

A standard regularized logistic regression (Pedregosa et al., 2011) was trained using all pairs of user and item covariates as features and cross-validated to optimize log-likelihood of the self-selected observations. As a result, a matrix of propensities for all user item pairs with a score of 0.92 can be constructed.

Prediction model

Factorization Machines (FM) is a flexible and powerful modeling framework for collaborative filtering recommendation. (S. Rendle, 2010) To be more specific, Factorization Machines (FM) is a generic supervised learning model that map arbitrary real-valued features into a low-dimensional latent factor space and can be applied naturally to a wide variety of prediction tasks including regression, classification, and ranking. In our case, we will use this FM as a parametric model using combined features of user item pairs to predict ratings.

Imputation model

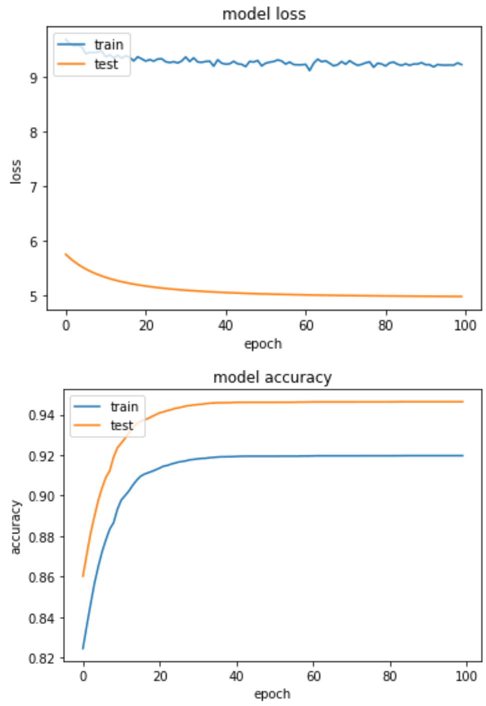
We alternate between training the prediction and imputation models via stochastic gradient descent (Bottou, 1998). Given the property of Doubly Robust Estimator, we compute the prediction error by the difference (instead of the absolute or squared difference), so the imputation model can learn to distinguish whether a predicted rating is larger or smaller than the true rating. As mentioned in the joint learning section, the loss function for stochastic gradient descent is given by prediction error, observed error and learned propensities.

Joint Learning

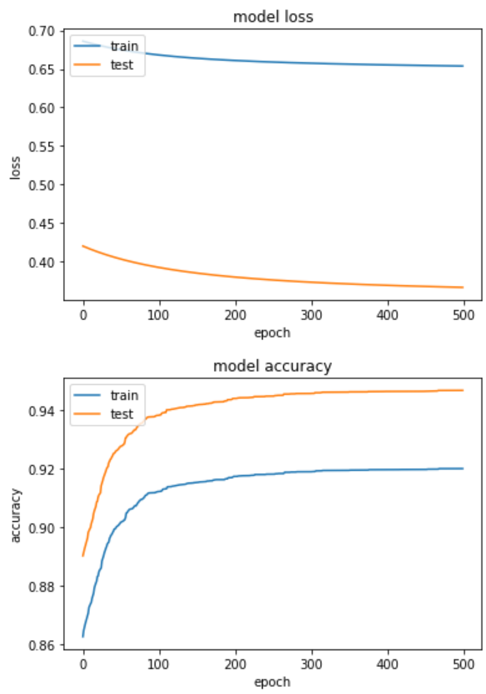
In our dataset, we use MNAR ratings for training and MAR for testing on COAT.

	MSE	MAE
MNAR Naïve FM	3.645	1.513
MNAR DR	3.183	1.432
Test Naïve FM	1.547	1.191
Test DR	**1.244**	**1.038**

Double Robust Factorization Machine



Naïve Factorization Machine



T

The Testing set has higher accuracy and lower loss than the Training set because the Testing set is MAR

Conclusion

We found an effective approach to figure out the rating of missing not at random data for recommendation system. First, we proposed a double-robust estimator, in which way to estimate the prediction inaccuracy by using imputed errors and propensities. Then, we proposed a joint learning approach based on the double-robust estimator, it learns rating prediction and error imputation in a joint learning way to make sure a low prediction inaccuracy. We also completed a compared experiment according to the real-world dataset, and the result shows that our approach performs better than those commonly used ones since the estimator just designed significantly reduces the bias of estimating the prediction inaccuracy.

References

Bottou, Léon (1998). "Online Algorithms and Stochastic Approximations". Online Learning and Neural Networks. Cambridge University Press. ISBN 978-0-521-65263-6.

Dudı́k, M., Langford, J., and Li, L. Doubly robust policy evaluation and learning. In ICML, 2011.

Hinton, G., & Salakhutdinov, R. (2006). Reducing the Dimensionality of Data with Neural Networks. Science, 313(5786), 504-507. doi: 10.1126/science.1127647

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cour- napeau, D., Brucher, M., Perrot, M., and Duchesnay, E. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12:2825–2830, 2011.

Salakhutdinov, R., Mnih, A., and Hinton, G. Restricted boltzmann machines for collaborative filtering. In *ICML*, 2007.

Schnabel, T., Swaminathan, A., Singh, A., Chandak, N., and Joachims, T. Recommendations as treatments: Debiasing learning and evaluation. In ICML, 2016.

Steck, H. Item popularity and recommendation accuracy. In RecSys, 2011.

Steck, H. Evaluation of recommendations: rating-prediction and ranking. In RecSys, 2013.

S. Rendle, "Factorization Machines," 2010 IEEE International Conference on Data Mining, 2010, pp. 995-1000, doi: 10.1109/ICDM.2010.127.

Thomas, P. and Brunskill, E. Data-efficient off-policy policy evaluation for reinforcement learning. In ICML, 2016.

Wang, X., Zhang, R., Sun, Y., & Qi, J. (2019, May). Doubly robust joint learning for recommendation on data missing not at random. In International Conference on Machine Learning (pp. 6638-6647). PMLR.

Wang, X., Zhang, R., Sun, Y., and Qi, J. Kdgan: Knowledge distillation with generative adversarial networks. In NeurIPS, 2018.

Zhang, S., Yao, L., and Sun, A. Deep learning based recommender system: A survey and new perspectives. arXiv preprint arXiv:1707.07435, 2017.