FAIRNESS IN TabNet MODEL BY DISENTANGLED REPRESENTATION FOR THE PREDICTION OF HOSPITAL NO-SHOW

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ABSTRACT

Patient no-shows is a major burden for health centers leading to loss of revenue, increased waiting time and deteriorated health outcome. Developing machine learning (ML) models for the prediction of no-shows could help addressing this important issue. It is crucial to consider fair ML models for no-show prediction in order to ensure equality of opportunity in accessing healthcare services. In this work, we are interested in developing deep learning models for no-show prediction based on tabular data while ensuring fairness properties. Our baseline model, TabNet, uses on attentive feature transformers and has shown promising results for tabular data. We propose Fair-TabNet based on representation learning that disentangles predictive from sensitive components. The model is trained to jointly minimize loss functions on no-shows and sensitive variables while ensuring that the sensitive and prediction representations are orthogonal. In the experimental analysis, we used a hospital dataset of 210,000 appointments collected in 2019. Our preliminary results show that the proposed Fair-TabNet improves the predictive, fairness performance and convergence speed over TabNet for the task of appointment no-show prediction. The comparison with the state-of-the art models for tabular data shows promising results and could be further improved by a better tuning of hyper-parameters.

Keywords  
Patient No-Show, Tabular Data, Attentive Transformers, Fairness, Disentanglement, Representation Learning, Deep Learning.

1 Introduction

Patients who do not attend scheduled clinic appointments are referred to as no-shows. The latter is a common problem in clinics with a major impact on the economics, operation and health outcome of health centers. For example average rate of patient no-show the U.S. is estimated to be 18.8 % with a cost of 150 Billion in revenue loss [Gier, 2017][Kheirkhah et al., 2015]. No-shows affect the recruitment of additional medical staff, disrupt appointment scheduling and extend patient waiting. These missed appointments are also causing health problems due to the interrupted or delayed follow-ups on patient conditions. Several approaches have been considered to tackle patient no-shows such as sending reminder, imposing sanctions or overbooking. Personalized reminders and intelligent overbooking are promising directions that are cost effective. These approaches require developing machine learning models that can perform individualized no-show prediction based on operational and health data. Several work have been

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We used an appointment scheduling dataset from our hospital. The dataset, collected in 2019, gathered 211,028 appointments. We limit this section to references to previous work on fairness by representation learning via disentanglement. [AlMuhaideb et al., 2019]. The most commonly data features for no-show prediction can be categorized into: patient demographic, medical history, appointment details and patient behaviour [Carreras-Garcia et al., 2020]. Such data is typically available in tabular format. Therefore traditional machine learning models such as decision trees are most commonly applied. It is attractive to develop deep learning models for tabular data.

2 Related work

We limit this section to references to previous work on fairness by representation learning via disentanglement. [Louizos et al., 2015] proposed the Variational Fair Autoencoder (FVAE) where the Independence between the target and sensitive variables was controlled by the Maximum Mean Discrepancy (MMD). The invariance was also controlled through generative adversarial network where one component maximizes the accuracy of the model and the other component minimizes the dependency between sensitive and target variables [Madras et al., 2018] [Zhang et al., 2018]. Creager et al. [Creager et al., 2019] proposed a fair disentangled representation where a set of sensitive variables and target variable is given at training but the true sensitive variable is only known at test time. Recently [Sarhan et al., 2020] proposed an orthogonal disentangled representation that enforces the meaningful representation to be independent of the sensitive information. [Locatello et al., 2019] showed that fairness can be improved through disentanglement representation.

3 The Proposed Model: Fair-TabNet

Our goal is to develop a fair deep learning model for no-show classification suited for tabular data. Our baseline model is TabNet which has shown good predictive performance compared with the state-of-the-art models for tabular data [Arik and Pfister, 2019]. The main building blocks in TabNet are: 1) Feature transformers, 2) Attentive transformers and 3) Masking. We propose Fair-TabNet by introducing an additional component (\(r_s\)) in TabNet representation. \(r_s\) learns to correctly classify the sensitive variables on the training set. As depicted in Figure 1, the loss \(L_{sens}\) ensures that \(r_s\) is a good representation of sensitive variables. A second loss term, \(L_{diff} = ||r_p^T r_s||_F^2\), where \(\cdot\) is the squared Frobenius norm, encourages orthogonality between sensitive \(r_s\) and the predictive representation \(r_p\). Hence this helps the disentanglement of both representations. The loss term \(L_{diff}\) is inspired by Deep Separation Networks [Bousmalis et al., 2016].

Fair-TabNet is trained to minimize the weighted loss function \(L = L_{pred} + \lambda_d L_{sens} + \lambda_s L_{diff}\) where \(L_{pred}\) is the binary cross-entropy loss on prediction targets (no-show), \(L_{sens}\) is a categorical cross entropy loss on the sensitive variables (gender and nationality). \(\lambda_d\) and \(\lambda_s\) are hyper-parameters that control the contribution of the introduced loss functions to the overall loss.

4 Experiments

We used an appointment scheduling dataset from our hospital. The dataset, collected in 2019, gathered 211,028 appointments. The features are 1) patient information such as age, gender and nationality, 2) appointment information such as date, time, appointment duration, clinics, physician specialities, time from booking to appointment, new or follow-up appointment. In total the dataset included 42 features, in a tabular format, with numerical and categorical columns. The considered sensitive variables are Gender and Nationality. We are interested in group fairness. For Nationality variable we binarized the samples into local vs. foreigner. For the baseline TabNet, there are several hyper-parameters to choose for the experiments. We chose \(n_p=16\) for the size of \(r_p\), \(n_a = 16\), for the size of \(r_a\), \(n_{steps} = 5\) for the number of steps, \(\gamma = 1.5\). A better tuning of the hyper-parameters could lead to improvement in the predictive performance. For the proposed Fair-TabNet we chose the same parameters as in TabNet. The additional parameter in Fair-TabNet is \(n_s = 16\) for the size of the sensitive representation. The dataset is randomly split into training (70%), validation (15%) and test (15 %) such that appointments of each day will be all in one of the three subsets.

| Metric     | AU-ROC  | AU-PRC  |
|------------|---------|---------|
| LightGBM   | 77.88±0.19 | 46.3±0.46 |
| CatBoost   | 78.26±0.46 | 47.84±0.82 |
| XGBoost    | 78.74±0.42 | 47.8±0.77  |
| TabNet     | 75.93±1.78 | 43.83±3.83 |
| Fair-TabNet| 76.38±1.42 | 44.2±3.12  |

Table 1: Summary of Prediction performance.
Figure 1: Architecture of the proposed Fair-TabNet Model. The red lines, $L_{diff}$ and $L_{sens}$ are the proposed extension. TabNet architecture is depicted in Figure A.4.

| Metric | LightGBM     | CatBoost    | XGBoost     | TabNet     | Fair-TabNet |
|--------|--------------|-------------|-------------|------------|-------------|
| AOE    | 10.16±1.1    | 1.22±1.2    | 0.75±0.3    | 0.8±0.4    | 1.35±1.2    |
| DG-FPR | 12±0.9       | 1.02±1.4    | 0.43±0.1    | 0.57±0.5   | 0.71±0.6    |
| DIR    | 67.7±1.9     | 72.74±7.1   | 74.34±5.4   | 74.7±10.8  | 79.92±16.5  |
| EOD    | 8.3±1.3      | 1.4±1.2     | 1.1±0.7     | 1.1±0.8    | 1.99±2.2    |
| SPD    | 13.0±0.9     | 1.5±1.7     | 0.9±0.2     | 0.9±0.6    | 1.2±0.8     |

Table 2: Fairness performance of the compared models. The sensitive variable is Nationality (local vs. foreigner).
5 Conclusion

We proposed Fair-TabNet a deep learning model suited for tabular data as an extension of TabNet model to incorporate fairness properties for the prediction appointment no-show from tabular data. Fair-TabNet learns a disentangled representation which lead to gain in predictive and fairness performance. The predictive performance of TabNet is close to the state-of-art approach and could be improved by a better tuning of hyper-parameters.

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Table A.3: List of fairness metrics. $Y$ and $\hat{Y}$ are the predicted and the true classes respectively. The sensitive variable $S = 1$ and $S = 0$ for the deprived and privileged classes respectively. Note that generalized FPR=FPR for binary classification.

Table A.4: Fairness metrics of the different compared models. The sensitive variable is gender.
Figure A.5: Loss functions during Fair-TabNet training.
Figure A.6: Prediction performance comparison in terms of AU-ROC (Area Under ROC) and AU-PRC (Area Under Precision Recall). The values indicate the difference of in performance average between rows and columns. Positive values indicate that the model in row has a higher performance than model in column. The color indicates \(-\log_{10}(p_{value})\) of the t-test between performance on model in row and model in column.

Figure A.7: t-test results on performance difference for the compared models. The color indicates the significance level and value show the difference of average performance of the models in rows minus the model in columns. Positive values indicate that the model in row has a higher performance than model in column. The sensitive variable is gender (female vs. male).
Figure A.8: t-test results on performance difference for the compared models. The color indicates the significance level and value show the difference of average performance of the models in rows minus the model in columns. Positive values indicate that the model in row has a higher performance than model in column. The sensitive variable is nationality (local vs. foreigner).

Figure A.9: Interpretability by Variable importance in XGBoost. The sensitive variables are highly contributing to the prediction.

Figure A.10: Interpretability in Fair-TabNet from the masks and aggregated mask.