AIED Project proposal: β-VAEpre

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1 Goal

Our goal is the identification and the analysis of at-risk students using their background and academic involvement as features. In other words, we're dealing with a classification task with 2 classes that take students' data as input and classify these latter as at-risk or not. Classifying a student as at risk enables the teacher to intervene early which has shown to be very effective[1].

The problem with this type of task in AIED resides in the training dataset, usually, the educational datasets have a low percentage of at-risk students, so we often have imbalanced datasets[2, 3]. The meaning of imbalanced in this case is that the number of target cases is a very small portion of the entire dataset.

In this work, we'll try to achieve a similar implementation of the framework described in the paper of Xu Du et al. [4] that relies on the use of a variational autoencoder (VAE) to solve the problem of unbalanced datasets and on the use of a neural network to solve the prediction task.

As we also wish to get a better understanding of the variance and the different profiles of an at risk student for which we can leverage the latent representation of the VAE. Since it is of low dimension and hopefully disentangled we aim to reconstruct and analyze the different profiles of an at risk student.

2 Datasets

To achieve this task we relied on the use of two educational datasets.

The first dataset has been taken from Kalboard 360, a learning management system(LMS) that provides access to educational resources from any device with an Internet connection, with the use of a learner activity tracker tool[5, 6]. This first dataset consists of 480 student records and 16 features, these latter can be grouped into three groups: demographic features, academic background features and behavioural features.

The second dataset has been taken from student achievement in secondary education of two Portuguese schools with the use of school reports and questionnaires[7]. It consists of 639 samples and 33 features, even in this case we have demographic features and academic background features, but, unlike the first dataset, we don't have behavioural features. A novelty, compared to the first one, is the presence of social features.

3 Methods

To tackle this problem of predicting at risk students we will use different classifiers using both advanced techniques like Neural Networks [8] and more interpretable and simple methods like Logistic Regression.

To address the imbalance of the datasets usually one would use Random Over Sampling or Random Under Sampling such that the final training data is close to being balanced. One can also use class weights [9] in the loss function to make samples from the minority class have a stronger impact on the

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loss. Those approaches will usually lead to overfitting on the minority class thus we aim to generate an augmented dataset which has small differences in between the different samples.

Based on the LVAEpre [4] approach we will use a Variational Auto Encoder (VAE) [10] to augment the dataset of at risk students. Thus it will result in an augmented dataset in which the samples are different from each other. To further increase the disentanglement and thus interpretability of the VAE we will rely on the β-VAE which can favor disentangled latent representations. We will use this method such that we can interpret the latent space of the VAE which should allow us to get a good understanding of the variance of an at risk student.

For the implementation of our approach and the analysis of the datasets we will rely on PyTorch [11] and Scikit Learn. The code will also be made publicly available through GitHub [1].

4 Evaluation

We will compare our model to several baselines: simple logistic regression and neural networks, with under- and oversampling or with class weights penalizing the dominant class.

Since we are particularly interested in the performance of our classifier on the minority class, we will use as metrics we will use the F1 score, the ROC AUC and for interpretability also balanced accuracy, which is less misleading on imbalanced datasets than accuracy.

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