Project Proposal: Enhancing Financial Fraud Detection through Reinforcement Learning-based Oversampling

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Background and Motivation

Due to the prevalence of digital payment and e-commerce, the rise in financial fraud has become a concerning issue. Hence, studies adopted numerous machine learning algorithms, including Random Forest, XGBoost, LightGBM, Feed-forward Neural Networks, and Convolutional Neural Networks, to detect finance frauds automatically [1]. A recent study [2] employed Reinforcement Learning (RL), an algorithm with an agent that tries to maximize its cumulative reward when making sequences of decisions [3], to identify finance fraud records, which outperformed most machine learning models.

The extreme class imbalance issue is a significant challenge faced by traditional machine learning classifiers due to the skewed distribution of finance fraud datasets. Usually, the number of fraud, or minority, samples is significantly lower than the legitimate ones. As a result, the diagnosis models tend to favor the majority class, or the nonfraud class, causing high false-positive rates [4].

Numerous oversampling methods were proposed to increase the minority class representation by duplicating the minority samples or generating new ones. The Synthetic Minority Oversampling Technique (SMOTE) [5] and its variations are the standard approaches for class imbalance handling at the data level [6]. Generative Adversarial Networks (GAN) [7] has also shown promising performance in generating minority samples in finance fraud datasets [8]. To overcome the weak points of individual SMOTE and GAN, the SMOTified-GAN [9], a hybrid method, was proposed.

However, traditional oversampling techniques, which purely focus on the dataset distribution, can sometimes overfit the classifiers. Hence, studies have proposed methods considering the classifiers' performance when generating minority samples. A study [10] adopted RL to synthesize minority samples directly based on the classifier's performance. AESMOTE [11] employs RL to select training samples to train an RL diagnosis model from an augmented dataset that contains original and SMOTE-generated minority samples. The reward obtained by the RL agent depends on the diagnosis model's classification performance. Similarly, the DiagSelect [12] framework adopts RL to pick a suitable subset of training samples to train machine learning classifiers.

While the RL oversampling methods demonstrated improvements from the traditional methods, either through generating minority samples or selecting training samples, their resulting F1-scores usually did not exceed 0.9 [10, 11, 12]. Therefore, it is worth redesigning the RL oversampling algorithm to optimize the generated minority samples to improve the classifiers' final performances.

Aims and Objectives

This project aims to tackle the class imbalance problem in the finance fraud dataset using a RL-based oversampling technique to improve the classification performance of machine learning models. The technique can optimize the generated samples by maximizing a reward which is defined based on the classifier's performance when trained on the augmented dataset. To achieve this aim, the objectives are:

1. To review the oversampling methods for class imbalance handling, including the utilization of RL in tackling this issue.
2. To investigate the performances of existing machine learning classifiers on finance fraud or anomaly detection.
3. To design an oversampling method using RL to generate high-quality samples or select suitable samples to improve the performance of the classifiers.
4. To evaluate the proposed RL-based oversampling method on different machine learning classifiers.

Project Plan

To accomplish the objectives of this project, milestones have been identified with appropriate time-frames, showing in Table 3.1. The first month will be spent on preliminary work and literature review. During this period, state-of-the-art fraud detection methods and oversampling techniques will be reviewed. Since this project adopts RL and machine learning, these two techniques will also be studied.

After conducting background studies, an RL-based oversampling method will be designed, implemented, and tested. The remainder of the autumn semester will focus on completing the interim report.

The first half of the spring semester primarily focuses on modifying and improving the initial design. The ultimate findings will be written either in a journal or a conference paper. Since writings take time, a three-month time-frame is allotted to complete the writing tasks.

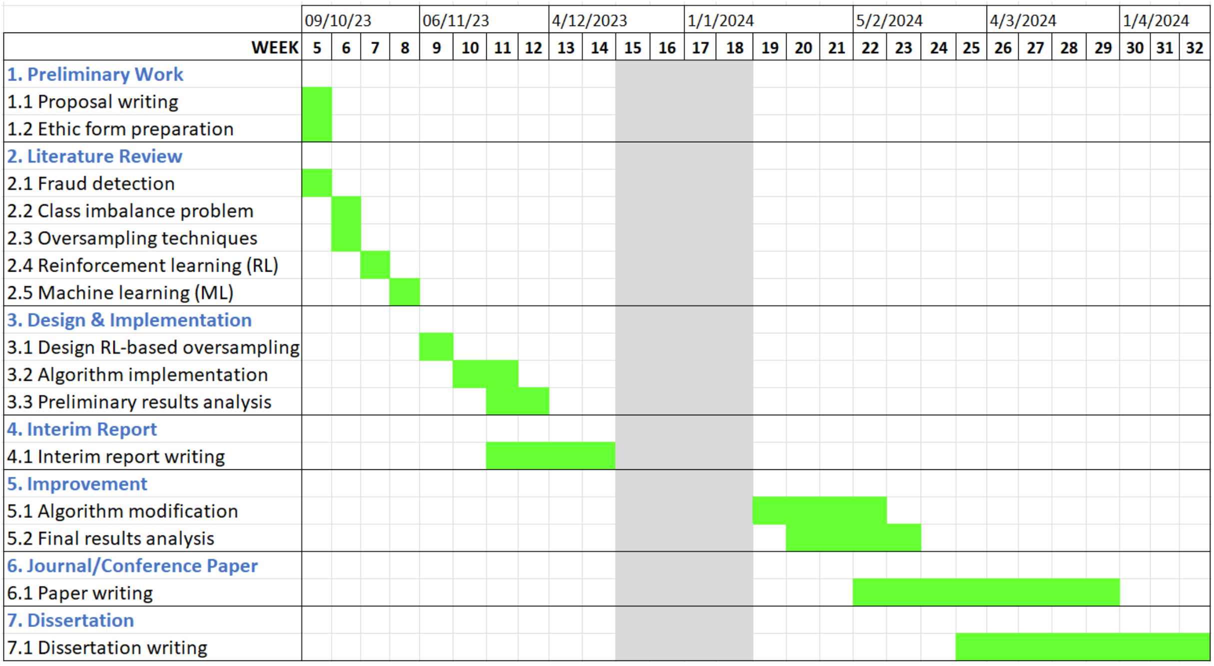

Figure 3.1: Project Milestones and Time Plan

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