Abstract

Simulation-based learning (SBL) is gaining popularity as a low-cost and convenient training technique in a vast range of applications. However, for a SBL platform to be fully utilized as an effective training tool, it is essential that feedback on performance is provided automatically in real-time during training. It is the aim of this paper to develop an efficient and effective feedback extraction method for the provision of real-time feedback in SBL. Existing methods either have low effectiveness in improving novice skills or suffer from low efficiency, resulting in their inability to be used in real-time. In this paper, we propose a neural network based method (NNFB) to extract feedback based on the adversarial technique. NNFB utilizes a bounded update to minimize a $L_1$ regularized loss via back-propagation. We empirically show that NNFB can be used to extract simple, yet effective feedback. Also, NNFB was observed to have high effectiveness and efficiency when compared to existing methods, thus making it a promising option for real-time feedback extraction in SBL.

1 Introduction

It has been found that supporting the learning process through interactive feedback is important [Billings, 2012]. Appropriate and timely feedback intervention increases learning motivation, facilitates skill acquisition/retention, and reduces the uncertainty of how a student is performing [Davis, 2005]. With the development of virtual reality techniques, simulation-based learning (SBL) has become an effective training platform in a range of applications including surgery [Wijewickrema et al., 2015], military training [Cosma and Stanic, 2011], and driver/pilot training [de Groot et al., 2011]. However, it still requires the presence of human experts so that real-time feedback can be provided during training to ensure that relevant skills are learned. This has been one of the obstacles for the spread of SBL systems [Lateef and others, 2010]. As such, it is important to automate the provision of real-time feedback in SBL.

Feedback extraction/generation is a classical problem in artificial intelligence (AI) systems. Intelligent tutoring systems are one such class of AI systems that aims to provide immediate instruction or feedback to learners [Billings, 2012]. Another are autonomous driving systems that take the images of the road/surroundings as input and output feedback to the car to adjust the steering wheel/accelerator [Chen et al., 2015]. In reinforcement learning systems such as mobile robot navigation, the hardware or software agent learns its behaviour based on reward feedback from the environment [Sutton and Barto, 1998].

When compared to the above mentioned applications, SBL is a different problem, as its aim is to instigate the acquisition of advanced skills and procedures [Frasson and Blanchard, 2012]. As such, SBL requires a higher degree of “hands-on” experiential interaction. Figure 1 shows an example of such a SBL system: a Temporal Bone Surgical Simulator [Kennedy et al., 2013]. Feedback in SBL is not just for completing the task, but also to assist the acquisition of expert-level skills throughout the task [Steadman et al., 2006]. Most existing intelligent tutoring systems work in well-established domains that follow fixed rules, such as algebra and physics. As such, their use in SBL that requires a high level of user interaction is minimal [Lateef and others, 2010]. Autonomous driving systems and reinforcement learning systems mainly focus on the outcome and mostly deal with cognitive tasks using computer vision techniques. Therefore, feedback extraction methods in these systems are not directly transferable to SBL, especially for non-cognitive SBL scenarios. The aim of this paper is to develop a feedback extraction method for the use in SBL via supervised learning.

Feedback extraction in SBL has three challenges. First, feedback should be extracted and delivered in a timely manner as delayed feedback can lead to confusion or even cause fatal consequences in reality. For example, in surgical simulation, delayed feedback can cause fatal damage to the virtual patient. The time-limit for real-time feedback extraction in SBL is 1 second after inappropriate action is detected. This is because feedback should be provided before the learner makes the next move [Rojas et al., 2014]. Second, feedback should be provided in a form of actionable instructions that can be followed by the trainee to improve skills or correct mistakes. This is because SBL tasks often consist of a series of delicate operations that require precise instructions. Third, feedback should be simple, referring to only a few aspects of the skill, as practically people cannot focus on many things at
Other works utilize artificial intelligence techniques to extract feedback that can change adaptively in response to the novice’s abilities and skills. One example is the use of Dynamic Time Warping (DTW) to classify a time series of surgical data and support feedback provision in lumbar disk herniation surgery [Forestier et al., 2012]. However, this approach is less accurate at the beginning of a procedure when not much data is available. A supervised pattern mining algorithm was used in temporal bone surgery to identify significant behavioural patterns, classified as novice or expert, based on existing examples [Zhou et al., 2013b]. Here, when a novice pattern is detected during drilling, the closest expert pattern was delivered as feedback. However, it is very difficult to identify significant expert/novice patterns as novices and experts often share a large proportion of similar patterns.

A similar attempt used a prediction model to discriminate the expertise levels using random forests, and then extract feedback directly from the prediction model itself [Zhou et al., 2013a]. Here, the extracted feedback was the optimal change that would change a novice level to an expert, based on votes of the random forest (Split Voting (SV)). Decision trees and random forests were used in other research areas as well to provide feedback. For example, a decision tree based method was used in customer relationship management to change disloyal customers to loyal ones [Yang et al., 2013]. Extracting feedback from additive tree models such as random forest, adaboost and gradient boosted trees is NP-hard, but the exact solution can be found by solving a transformed integer linear programming (ILP) problem [Cui et al., 2015].

In this paper, we propose a neural network based method to extract feedback using the adversarial technique. One intriguing property of neural networks is that the input can be changed by maximizing the prediction error so that it moves into a different class with high confidence [Szegedy et al., 2013]. This property has been used to generate adversarial examples from deep neural nets in image classification [Goodfellow et al., 2014]. An adversarial example is formed by applying small perturbations (imperceptible to human eyes) to the original image, such that the neural network misclassifies it with high confidence. Although the adversarial example has similarities to the feedback problem in that they both change the input to a different class, they are not synonymous. First, the adversarial example is formed by adding intentionally-designed noise that may result in states that do not exist or have practical meaning in a real-world dataset such as that of the feedback problem. Second, only a few changes to inputs are recommended for feedback, to make it useful to follow. These considerations lead to the formal problem definition below.

2 Related Work

The simplest way to provide feedback in SBL is the rule-based approach, for example, the “follow-me” approach (ghost drill) [Rhiemora et al., 2011] and the “step-by-step” approach [Wijewickrema et al., 2016] in surgical simulation. These approaches however have drawbacks. It may be hard for a novice who has limited experience to follow a ghost drill at his own pace, and step-by-step feedback will not respond if the trainee does not follow the suggested paths.

In this section, we discuss the real-time feedback process, and show how skill/behaviour level is defined in SBL applications. We then formally define the feedback extraction problem as applied to SBL.
3.1 Real-time Feedback Process

Figure 2 illustrates the real-time feedback process in SBL. It operates in two steps: 1) offline training and 2) real-time feedback provision. In the offline stage, a feedback extraction method is trained via supervised learning on labelled (novice/expert) skill samples. In real-time, when a trainee is practising on the simulator, his/her skill will be captured and input into the feedback extraction method to obtain feedback about where improvement is required. Technically, feedback is the suggested action that can improve novice skill to expert skill. Finally, the feedback will be delivered immediately to the trainee to improve behaviour. The focus of this paper is the feedback extraction method as highlighted in grey.

3.2 Definition of User Skill

SBL often works with multivariate time series data. This is because a SBL task often consists of a series of steps over a period of time. The skill level is usually defined over a period of time, based on the values of certain skill metrics.

In general, skill metrics are: 1) motion-based, 2) time-based, 3) position-based, or 4) system settings. Motion-based metrics are often signals captured from haptic devices or sensors, for example, the speed and engine rpm in a driving simulator. Time-based metrics measure quantities such as reaction time in military training. Position-based metrics relate to the location of the current procedure and include quantities such as position coordinates and distance to landmarks. System settings refer to measures that affect the environment such as the magnification level in surgical simulation.

**Definition 1.** In simulation-based learning, user skill is a feature vector summarizing user behaviour over an arbitrary period of time and annotated with class labels.

For example, consider a SBL environment for surgery. Here, the level of skill can be defined by the quality of a stroke, a continuous motion of the drill with no abrupt changes in direction. The period of time here, over which the user behaviour is summarised, is the time interval of the complete stroke. Metrics that define the quality of a stroke within this time interval include measures such as stroke length, speed, acceleration, duration, straightness, and force [Zhou et al., 2015]. We denote such a skill metric as a feature. A vector of feature values that defines user skill is an instance and is associated with a class label that denotes the skill level (expert or novice).

3.3 Feedback Extraction Problem

Here, we define the feedback extraction problem in an expert-novice perspective. We acknowledge that there may be more than 2 levels of expertise in some SBL applications. However, this can be easily addressed using the one-vs-rest approach.

In SBL, the feedback extraction problem is to find the optimal action that can be taken to change a novice instance to an expert instance. Suppose the dataset \( D \) consists of \( m \) features, \( n \) instances defined by the feature vector \( x = (x_1, ..., x_m) \), and associated with a class label \( y \in \{0, 1\} \) (1: expert, 0: novice). \( H(x) \) is a prediction model learnt over \( D \). The feedback extraction problem can then be defined as:

**Problem 1.** Given a prediction model \( H(x) \) and a novice instance \( x \), the problem is to find the optimal action \( A : x \rightarrow x_f \) that changes \( x \) to an instance \( x_f \) under limited cost \( C \) such that \( x_f \) has the highest probability of being in the expert class:

\[
\mathop{\text{argmax}}_{A : x \rightarrow x_f} H(x_f)
\]

subject to \( \mathcal{C}(x, x_f) \leq C \), where, feedback \( A : x \rightarrow x_f \) involves one or multiple feature changes (increase/decrease). For example, \( A : (force = 0.2, \text{duration} = 0.3) \rightarrow (force = 0.5, \text{duration} = 0.3) \) is “increase force to 0.5”. \( \mathcal{C}(x, x_f) \) is the cost function measuring the potential cost of feedback \( A \). In SBL, \( \mathcal{C}(x, x_f) = \|x - x_f\|_0 \), i.e., the number of changed features. The cost limit \( C \) is often a small integer such as 1 or 2 in SBL so as to meet the requirements discussed in Section 4.

4 Neural Network based Feedback Extraction

To tackle the feedback extraction problem, we propose the use of a neural network as the prediction model \( H(x) \) and introduce a method that directly extracts feedback from the neural network. Let \( H_{\theta}(x) \), with parameters/weights \( \theta \), be the neural network learnt with respect to the loss function \( J(\theta, x, y) \), where \( x \) is the input or feature vector, \( y \) the class value associated with \( x \), and \( y^* \) the target class we want \( x \) to be in.

Recall that during the training process, the weights \( \theta \) are updated so that the loss \( J(\theta, x, y) \) is minimized. Therefore, if we keep \( \theta \) fixed while the input \( x \) is updated so that \( J(\theta, x, y) \) is maximized, we can get a new instance that has high confidence of being in the opposite class to its original class [Szegedy et al., 2013].

To maximize \( J(\theta, x, y) \), the input can be updated in the positive direction of the gradient following Equation 1, where \( \epsilon \) is the learning rate.

\[
x = x + \epsilon \nabla_x J(\theta, x, y)
\] (1)

This is the property that has been used to generate adversarial examples in image classification. Since adversarial examples require small perturbations on the input image, Goodfellow et al., 2014 applied a sign function to linearize the loss function around the current value of \( \theta \), as shown in Equation 2. This method updates all the pixels of the input image once to get small perturbations.

\[
x = x + \epsilon \text{sign}(\nabla_x J(\theta, x, y))
\] (2)
Equation (1) works well for two-class tasks. However, for multi-class tasks, there are more than one opposite classes to \( y \). This means using Equation (1) cannot guarantee the new instance has high confidence in the target class \( y^* \). The alternative is minimizing the loss \( J(\theta, X, y^*) \) with respect to the specific target class \( y^* \) as defined in Equation (4).

\[
x = x - \epsilon \nabla_x J(\theta, x, y^*)
\] (3)

Although Equation (3) works for both two-class and multi-class tasks, it still has two potential problems that limit its use for feedback extraction in SBL. First, it may change all input features, thus violating the constraint (e.g., \( |x - x_f| \leq C \)) of Problem 1. Second, the update may explode the values of inputs to extremely small or large values, similar to the exploding gradient problem [Pascanu et al., 2012]. However, in practice, some features may have a certain value range outside of which the feature is meaningless.

To solve the first problem, we introduce a L1 regularization term to \( J(\theta, x, y^*) \) to control the sparsity of the change so as to extract simple feedback. The new loss function is defined in Equation (5), where \( \lambda \) is the regularization parameter and \( x_0 \) is the original input that needs to be changed.

\[
J(\theta, x, y^*) = J(\theta, x, y^*) + \lambda ||x - x_0||_1
\] (4)

To solve the second problem, we propose a bounded update approach (see Equations (5) and (6)) as an alternative to Equation (3). It incorporates the value range (defined by lower and upper bounds) of a feature into the update so as to ensure the updated feature value is still within range.

\[
x = x - \epsilon S_x \left( a S_x - \frac{a}{2} (1 + S_x) + \frac{b}{2} (1 - S_x) \right)
\] (5)

\[
S_x = \text{sign}(\nabla_x J'(\theta, x, y^*))
\] (6)

\( S_x \) is the sign of the partial derivative of \( J'(\theta, x, y^*) \) with respect to \( x \). The upper and lower bounds of \( x \) are \( a \) and \( b \) respectively, i.e., \( x_i \in [a_i, b_i] \).

According to Equation (5), if the gradient \( \nabla_x J'(\theta, x, y^*) \) is positive (i.e., \( S_{x_i} = 1 \)), the update will become \( x_i = x_i - \epsilon(x_i - a_i) \) which means \( x_i \) moves a small step towards its lower bound \( a_i \). Similarly, a negative gradient gives \( x_i = x_i + \epsilon(b_i - x_i) \), gives a move towards its upper bound \( b_i \). No update will be applied if the gradient is zero, as in this case, \( S_{x_i} = 0 \). This bounded update not only guarantees the correct update direction to minimize the loss, but also make sure that \( x_i \in [a_i, b_i] \) always holds true (see Lemma 1 and proof).

**Lemma 1.** If \( a_i \leq x_i \leq b_i \), \( 0 < \epsilon \ll 1 \), and \( x_i' = x_i - \epsilon S_{x_i} (x_i S_{x_i} - \frac{a_i}{2} (1 + S_{x_i}) + \frac{b_i}{2} (1 - S_{x_i})) \), then \( a_i \leq x_i' \leq b_i \).

**Proof.** The sign function \( S_{x_i} \) only has 3 outputs: 1.0 or -1.

**Case 1.** If \( S_{x_i} = 0 \), then \( x_i' = x_i \).

In this case, \( a_i \leq x_i' \leq b_i \) holds true.

**Case 2.** If \( S_{x_i} = 1 \), then \( x_i' = x_i - \epsilon (x_i - a_i) \).

In this case, \( x_i' - a_i = (1 - \epsilon)(x_i - a_i) \) and \( x_i' - b_i = \epsilon(a_i - x_i) + (x_i - b_i) \). Then, \( a_i \leq x_i \leq b_i \) and \( 0 < \epsilon \ll 1 \) gives \( x_i - a_i \geq 0 \), \( x_i - b_i \leq 0 \) and \( 1 - \epsilon > 0 \). Therefore, \( x_i' - a_i \geq 0 \) and \( x_i' - b_i \leq 0 \), that is, \( a_i \leq x_i' \leq b_i \).

**Case 3.** If \( S_{x_i} = -1 \), then \( x_i' = x_i + \epsilon(b_i - x_i) \).

In this case, \( x_i' - a_i = \epsilon(b_i - x_i) + (x_i - a_i) \) and \( x_i' - b_i = (1 - \epsilon)(x_i - b_i) \). Similarly, \( b_i - x_i \geq 0 \), \( x_i - a_i \geq 0 \) and \( 1 - \epsilon > 0 \) gives \( x_i - a_i \geq 0 \) and \( x_i - b_i \leq 0 \), that is, \( a_i \leq x_i' \leq b_i \).

To conclude, in all cases, \( a_i \leq x_i' \leq b_i \) holds true. \( \square \)

Equations (4), (5) and (6) give the definition of the proposed “neural network-based feedback (NNFB) method”. NNFB takes a novice instance \( x \) as input, iteratively updates \( x \) (different from the one-time-update in generating adversarial examples) until it converges or meets the terminating criteria. Let the extracted new instance be \( x_f \), the feedback is then the action \( A : x \to x_f \) (see the example in Problem 1).

When feedback is delivered, we need to ensure that it contains only \( C \) features. Although, the \( L1 \) regularization reduces the number of feature changes in general, in the absence of valid feedback with a low number of feature changes, it may still result in ones with higher numbers of feature changes. To overcome this issue, we suggest a post-selection process that iteratively tests all feature changes and select the ones with \( C \) or less changes that result in the best improvements.

The proposed method (NNFB) is easily generalizable to different SBL applications. The regularization term in \( J'(\theta, x, y^*) \) can be modified according to requirements (for example, \( L2 \) norm for applications that prefer small changes). Moreover, NNFB has flexible control over feature changes as the lower and upper bounds are adjustable for different features and even different input instances. For example, we can set \( a_i = b_i = x_i \) for a categorical feature that cannot be changed, such as gender. This flexibility also benefits those applications that have discrete cost functions as some explicit cost limits can be easily incorporated into the bounds.

5 Experimental Validation

In this section, we first describe the two real-world datasets that were used in the experiments. Then, we briefly introduce the existing methods that the proposed method was compared against, followed by the experimental setup. Finally, we discuss the experiment results.

5.1 Datasets

We tested our method on two real-world SBL datasets. The datasets were collected on a temporal bone surgical simulator designed to train surgeons in ear-related surgery. The datasets were obtained from 7 expert and 12 novice surgeons performing two different surgeries that require very different surgical technique (namely, cortical mastoidectomy and posterior tympanotomy). Dataset 1 (D1) includes 60K instances (28K and 32K expert and novice instances respectively) while
Dataset 2 (D2) includes 14k instances (9k expert instances and 5k novice instances). Instances in both datasets comprise 6 numeric features: stroke length, drill speed, acceleration, time elapsed, the straightness of the trajectory and drill force (see example in Section 3.2 for more details). Both datasets were normalized to the range of [0, 1] using feature scaling as follows, where \( x \) and \( x' \) are the original and scaled feature vectors respectively and \( x_{\text{min}} \) and \( x_{\text{max}} \) are the minimum and maximum feature values of \( x \) respectively.

\[
x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]

### 5.2 Compared Methods

Existing feedback extraction methods compared with NNFB are as follow.

- **Split Voting (SV):** This is the random forest based state-of-the-art extraction method for providing real-time feedback [Zhou et al., 2013a] as discussed in Section 2.
- **Integer Linear Programming (ILP):** This method solves the random forest feedback extraction problem by transforming it to an integer linear programming problem [Cui et al., 2015] as discussed in Section 2.
- **Random Iterative (RI):** This method randomly selects a feature and iteratively selects the best value among the feature’s value partitions in the random forest [Cui et al., 2015].
- **Random Random (RR):** This method randomly picks a feature from a novice instance and selects a random change to that feature as the suggested feedback.

### 5.3 Experimental Setup

For testing, we randomly chose one novice participant, then took all instances performed by this novice as the test set. The remaining instances were used for training. This simulates the real-world scenario of an unknown novice using the simulator. Parameter tuning was performed on the training data based on a 11-fold leave-one-novice-out cross-validation. In each fold, we took all instances from one randomly chosen novice as the validation set.

All methods were restricted to extract feedback with only one feature change, which is a typical requirement in SBL. This is a binary task as there are only 2 skill levels (expert and novice). All methods were then evaluated using 2 measures: 1) efficiency and 2) effectiveness. Overall, a good feedback extraction method should have high effectiveness and efficiency (low time-cost).

Efficiency was measured using the time-cost (in seconds) spent on average to extract feedback for one novice instance. The novice instance \( x \) will be changed to the target instance \( x_f \) by the feedback \( A : x \rightarrow x_f \) (see Section 3.3). Thus, we use the quality of the target instances (i.e., \( \{x_f\} \)) to measure the effectiveness of the feedback. As defined in Equation (8), effectiveness \( E \) is the percentage of expert instances in \( \{x_f\} \).

\[
E = \frac{|\{x_f | x_f \text{ is an expert instance} \}|}{|\{x_f\}|}
\]

However, how instances are classified is dependent on the classifier used. Therefore, to determine the effectiveness of the compared methods, we trained 6 independent classifiers on the training set. The 6 classifiers are: neural network (NN), random forest (RF), logistic regression (LR), SVM (RBF kernel), naive Bayes (NB) and KNN (K = 10). An extraction method that scores consistently high levels of \( E \) across classifiers is deemed effective.

Experiments were carried out on a typical PC with 2.40GHz CPU. The ILP solver used for the ILP method was CPLEX\(^1\) as suggested by the authors, and the neural network/random forest implementations we used were from scikit-learn. Default settings in scikit-learn were used for parameters not specifically mentioned here.

### 5.4 Parameter Tuning

Parameter tuning was performed on the training data with a 11-fold leave-one-novice-out cross-validation as mentioned above in Section 5.3. A two-layer neural network architecture was used for NNFB. For D1, a neural network with 250 hidden neurons was selected for NNFB while a random forest with 120 trees was selected for SV, RI and ILP. For D2, NNFB used a neural network with 120 hidden neurons while SV, RI and ILP used a random forest with 100 trees. These parameters were selected based on the turning point of the number of hidden neurons or the number of trees with respect to the mean squared error (MSE) of the neural network or random forest respectively.

In terms of the regularization parameter \( \lambda \) in NNFB, Figure 3 indicates that larger \( \lambda \) results in simple feedback with a fewer number of feature changes. When \( \lambda = 1 \), a feedback on average consists of only one feature change, but remains highly confident \( (H(x_f) > 0.7) \) to change a novice instance to an expert instance. Therefore, we chose \( \lambda = 1 \) for NNFB. Since datasets have been normalised, the upper bounds for all features are 1 and the lower bounds are 0. Other settings for

\(^1\)https://www-01.ibm.com/software/commerce/optimization/cplex-optimizer
NNFB include Rectified Linear Unit (ReLU) activation function \cite{Glorot11}, cross entropy loss and learning rate $\epsilon = 1 \times 10^{-4}$.

### 5.5 Results

We first demonstrate the overall performance considering both effectiveness and efficiency. Figure 4 illustrates the effectiveness of each method as evaluated using 6 independent different classifiers with respect to the time-cost (inverses to efficiency) for each dataset. As seen in the figure, the proposed method shows the desired performance of highest effectiveness at an acceptably low time-cost (meets the real-time time-limit) when compared to the other methods. This proves that the adversarial technique can be used to extract effective and timely feedback for SBL.

![Box Plot](image)

Figure 4: This is a box plot of the tested effectiveness vs. time-cost. Each method has two boxes w.r.t. datasets $\mathcal{D}1$ and $\mathcal{D}2$. The box shows the range of the effectiveness tested by 6 independent classifiers. Colored view is recommended.

Table 1: The effectiveness (mean±std) tested by 6 independent classifiers. The best results are highlighted in bold.

|       | NN  | RF  | LR   | SVM  | NB   | KNN  |
|-------|-----|-----|------|------|------|------|
| $\mathcal{D}1$ | RR  | 0.19±0.06 | 0.23±0.10 | 0.35±0.07 | 0.27±0.06 | 0.32±0.12 | 0.30±0.05 |
|       | RI  | 0.44±0.07 | 0.39±0.04 | 0.50±0.08 | 0.46±0.06 | 0.42±0.12 | 0.40±0.08 |
|       | SV  | 0.63±0.07 | 0.59±0.06 | 0.60±0.07 | 0.62±0.06 | 0.50±0.11 | 0.53±0.07 |
|       | ILP | 0.72±0.04 | **0.87±0.00** | 0.71±0.05 | 0.76±0.04 | **0.70±0.11** | **0.76±0.04** |
|       | NNFB | **0.86±0.01** | 0.82±0.08 | **0.78±0.05** | **0.82±0.04** | 0.68±0.14 | 0.73±0.08 |
| $\mathcal{D}2$ | RR  | 0.21±0.04 | 0.22±0.07 | 0.29±0.04 | 0.37±0.02 | 0.32±0.11 | 0.32±0.06 |
|       | RI  | 0.48±0.04 | 0.49±0.04 | 0.47±0.09 | 0.52±0.05 | 0.47±0.12 | 0.43±0.10 |
|       | SV  | 0.61±0.08 | 0.69±0.04 | 0.62±0.05 | 0.61±0.07 | 0.56±0.11 | 0.59±0.04 |
|       | ILP | 0.88±0.04 | **0.90±0.02** | 0.79±0.07 | **0.77±0.03** | 0.78±0.12 | **0.84±0.09** |
|       | NNFB | **0.92±0.02** | 0.82±0.06 | **0.81±0.07** | 0.72±0.05 | **0.79±0.11** | 0.81±0.07 |

Table 2: The time-cost (mean±std in seconds) for extracting one feedback, tested on Dataset $\mathcal{D}1$ and $\mathcal{D}2$.

|       | $\mathcal{D}1$ | $\mathcal{D}2$ |
|-------|---------------|---------------|
| RR    | 0.013±0.004   | 0.014±0.001   |
| RI    | 0.504±0.098   | 0.401±0.020   |
| SV    | 0.023±0.003   | 0.017±0.003   |
| ILP   | 31.738±2.439  | 27.760±3.107  |
| NNFB  | 0.142±0.029   | 0.121±0.016   |

### 6 Conclusion

In this paper, we introduced a novel method for real-time feedback extraction in simulation-based learning environments. The proposed method (NNFB) extracts feedback directly from a neural network based on the adversarial technique. To satisfy a specific requirement in SBL, that is to ensure that the suggested action is simple enough to practically undertake, we used a $L1$ regularization term to extract feedback/actions with a fewer number of feature changes. Furthermore, we introduced a bounded update to constraint the feature value into a reasonable range so that the feedback is of practical meaning. We explored theoretically the validity of NNFB, and showed empirically that it outperforms existing methods in providing effective real-time feedback.
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