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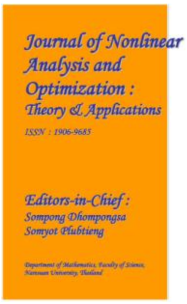

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IMITATING DRIVING BEHAVIOR SYSTEM THROUGH ARTIFICIAL INTELLIGENCE (AI) TECHNOLOGIES

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ABSTRACT: Modeling predicting and analyzing driver behaviors are essential to advanced driver assistance systems (ADAS) and the comprehensive understanding of complex driving scenario. With the rapid development and massive usage of internet over the past decade, the vulnerabilities of network security have become an important issue. Our approach is to use three learning techniques in parallel gated recurrent unit (GRU), convolution neural network as deep techniques and Random Forest as an ensemble technique.The continuous application of artificial intelligence (AI) technologies in online education has led to significant progress, especially in the field of Intelligent Tutoring Systems (ITS), online courses and learning management systems (LMS). An important research direction of the field is to provide with customized learning trajectories modeling.First, we adapt the concept of semi-supervised generative adversarial networks to the imitation learning context. Second, we employ a learnable latent distribution to align the generated and expert data distributions. In this paper policy framework is shaped by combining the human knowledge with GAIL (HKGAIL).HKGAIL embeds human decision models into the learning process to infer the under-lying structure of expert demonstrations. The proposed CDBL framework is demonstrated to outperform existing methods in behavior prediction through a case study. Finally, future works, potential challenges and emerging trends in this area are highlighted. We apply our method to a domain plagued by the cold-start problem, knowledge tracing (KT), and the results show that our novel method could effectively improve the KT model's prediction accuracy in a cold-start scenario

INDEX TERMS: Driver behaviorsConnected vehicles Continual learning Machine learning Intelligent transportation systems,Generative adversarial imitation learning Intelligent tutoring systems

1. INTRODUCTION

In conjunction with the evolution of intelligent transportation systems, developing novel technologies, such as autonomous driving and vehicle-to-everything (V2X) communication, is increasingly regarded as a crucial solution for enhancing traffic efficiency and reducing accident rates [1,2]. Meanwhile, we have witnessed the rapid advancement of autonomous driving perception, planning, and control algorithms in recent years [1]. The first intrusion detection system was proposed in 1980 [2]. Since then, many mature IDS products have arisen many IDSs still suffer from a high false alarm rate, generating many alerts for low nonthreatening situations, which raises the burden for security analysts and can cause seriously harmful attack to be ignored [3]. Real-world demonstrations are typically coupled by multi-modal behaviors. To disentangle interpretable and meaningful behavior representations, InfoGAIL [13] utilizes the concept of maximizing mutual information between discrete or continuous latent variables to generate corresponding samples in an unsupervised manner [4]. Thee proposes an approach to incorporate human knowledge into GAIL policy updates to extend GAIL HKGAIL, a novel adversarial mimicry framework for bottleneck discrepancies caused by the stochastic decisionsof GAIL’s generators. HKGAIL consists of a generator and a human decision-maker. The discriminate or learns a reward function to explain the behavior and generator learns the policy directly from thedemonstration under the guidance of the discriminator and thehuman decision-make [5]. A recurrent neural network (RNN) with gated recurrent unit (GRU) base, a convolution neural network (CNN) and a non-parametric method named Random Forest, are used for detecting the type of connection which classifies them as normal or attack [6]. The pattern matching has traditionally been simple, looking for exploitive activity such as connections from certain IP addresses with histories of intrusive behavior an intrusion into a computer network can be more complex, with the complexity being both spatial and temporal [7].

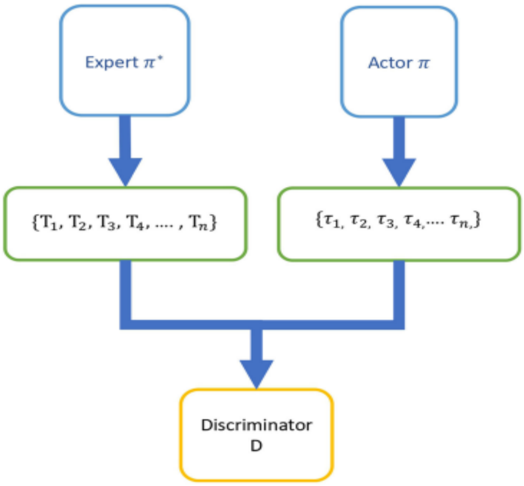
Expert π^*
Actor π
$\{T_1, T_2, T_3, T_4, ..., T_n\}$
$\{\tau_1, \tau_2, \tau_3, \tau_4, ... \tau_n,\}$
Discriminator
D

Fig. 1: Mechanism of generative adversarial imitation learning.

2. RELATED WORKS

The statistical learning-based driver model is a data-driven approach that aims to model and predict driver behaviour by leveraging statistical and machine learning techniques. [9].AGaussian mixture model (GMM) is employedintomodel the driver pedal operation pattern in the car scenario, where two GMM models are separately built to learn the gas and brake pedal [10]. Misuse detection is also called signature-based detection. The detection process matches the signatures of samples using a signature database. The main problem in constructing misuse detection systems is to design efficient signatures [11]. On the other hand, anomaly detection is used to detect unknown attacks. There are different ways to find out the anomalies. Different machine learning techniques are introduced in order to identify the anomalies [12].The paper presently enhances SVM categorization accurateness and faster training and testing times. We propose Sim-GAIL, a student modeling approach, to generate simulation data for ITS training. It is the first method, to the best of our knowledge, that uses Generative Adversarial Imitation Learning (GAIL) to implement student modeling to address the challenge of lacking training data and the cold-start problem[8] analyses several ML-based approaches for intrusion detection for identifying various issues. Issues related to the detection of low-frequency attacks are discussed with a possible solution to improve the performance further [14].They also apply a modified long short-term memory (LSTM) which is simple recurrent unit (SRU) that allows the system to learn the important features of intrusions. With this system, they achieve 99.73% accuracy on the ”KDD99” dataset and 99.62% on manually divided ”NSL-KDD” dataset [15].

3. SYSTEM ARCHITECTURE

A Gaussian mixture model (GMM) is model the driver pedal operation pattern in the car-following scenario, where two GMM models are separately built to learn the gas and brake pedal [16]. It is important to note that this entire process requires no supervised information. Many famous auto encoder variants exist such as de noising auto encoders and sparse auto encoders [17]. Info GAIL is learned in an unsupervised manner, obtaining the desired disentangled behavior representations can prove to be challenging. The difficulty is compounded when the expert demonstrations are imbalanced, We propose Elastic semi-supervised InfoGAIL (Ess-InfoGAIL) with three improvements to InfoGAIL: i) A semi-supervised learning architecture, ii) a learnable latent skill distribution and iii)

RIM with an approximate label prior. The network architecture of Ess-InfoGAIL[18].To obtain contextual information each unit in an RNN receives not only the current state but also previous states this characteristic causes RNNs to often suffer from vanishing or exploding gradients [19].

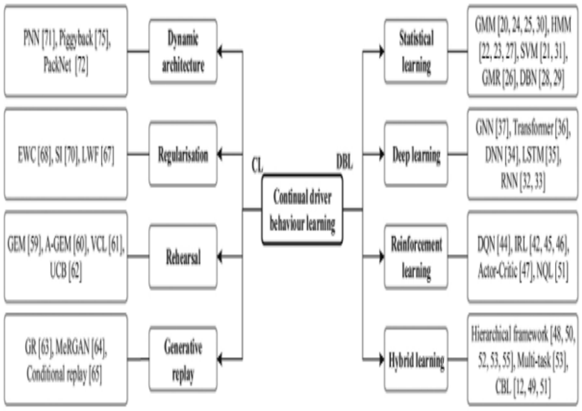
PNN [71], Piggyback [75], PackNet [72]
Dynamic architecture
EWC [68], SI [70], LWF [67]
Regularisation
GEM [59], A-GEM [60], VCL [61], UCB [62]
Rehearsal
GR [63], MeRGAN [64], Conditional replay [65]
Generative replay
CL
Continual driver behaviour learning
DBL
Statistical learning
GMM [20, 24, 25, 30], HMM [22, 23, 27], SVM [21, 31], GMR [26], DBN [28, 29]
Deep learning
GNN [37], Transformer [36], DNN [34], LSTM [35], RNN [32, 33]
Reinforcement learning
DQN [44], IRL [42, 45, 46], Actor-Critic [47], NQL [51]
Hybrid learning
Hierarchical framework [48, 50, 52, 53, 55], Multi-task [53], CBL [12, 49, 51]

Fig. 2: The structure of an auto encoder

4. PROPOSED SYSTEM

DBLemerges advanced deep neural networks based on deep learning such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks. Capitalizing on the ability of deep learning algorithms to process large-scale, high-dimensional data and automatically extract complex features, patterns and relationships governing driving behaviour, including vehicle dynamics, traffic context, and environmental factors [20]. A driver intention prediction method is proposed in Ref. [32] for predicting driver target destinations at unsignalized intersections using RNN. By considering a time sequence data of the vehicle's previous observation as input, the model can predict the driver's crossing strategy with good accuracy and prediction window before conflicts. [21]. After many efforts by using several learning techniques even implementing unsupervised methods, he HKGAIL framework, through the pre-trained humandecisionmaker, we can acquire human knowledge policies HKGAIL policy-shaping is to transform human knowledge in to policy and combine them with agent policy to affect the learning process of the agent.

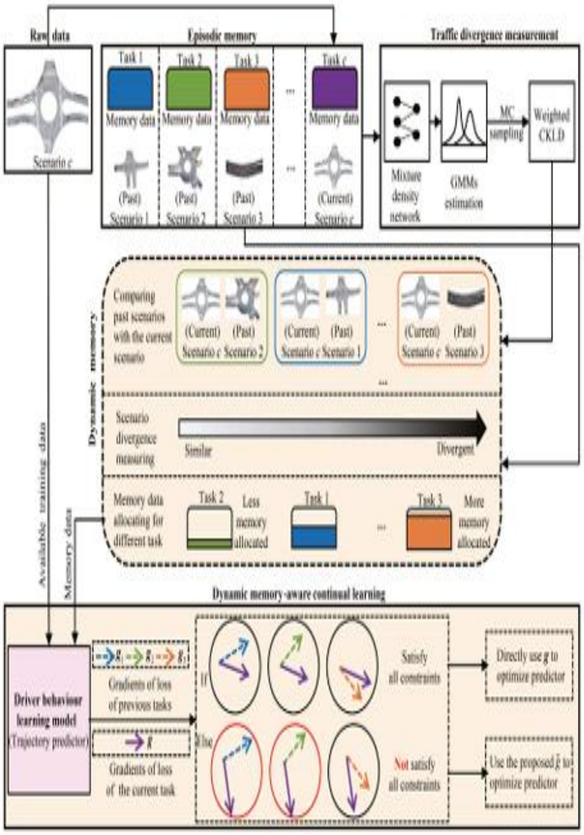
Raw data
Scenario c
Episodic memory
Task 1
Task 2
Task 3
Task c
Memory data
(Past) Scenario 1
(Past) Scenario 2
(Past) Scenario 3
(Current) Scenario c
Traffic divergence measurement
Mixture density network
GMMs estimation
MC sampling
Weighted CKLD
Dynamic memory
Comparing past scenarios with the current scenario
(Current) Scenario c
(Past) Scenario 2
(Past) Scenario 1
(Past) Scenario 3
Scenario divergence measuring
Similar
Divergent
Memory data allocating for different task
Less memory allocated
More memory allocated
Available training data
Memory data
Dynamic memory-aware continual learning
Driver behaviour learning model (Trajectory predictor)
g_1 g_2 g_3
Gradients of loss of previous tasks
g
Gradients of loss of the current task
If
Else
Satisfy all constraints
Not satisfy all constraints
Directly use g to optimize predictor
Use the proposed $\tilde{g}$ to optimize predictor

Fig. 3: Proposed Dynamic Gradient Scenario Memory (D-GSM)

5. METHODOLOGYS

Our Sim-GAIL model is built upon generative adversarial imitation learning (GAIL) [20], which aims to solve the problem of Imitation Learning of having difficulty in dealing with constant regularization and not being able to match occupancy measures in large environments [22]. One machine learning algorithm or technique for developing an intrusion detection system can be used as a standalone classifier or single classifier. A scene-aware driver behavior model based on a dynamic Bayesian network(DBN)is introduced [23], which models the driver states as a discrete hidden variable. Facilitated with a stimulus-response model (SRM) behavior representation, the combined model can provide more accurate acceleration prediction in car-following scenarios

Decision Tree Creating a classifier for predicting the value of a target class for an unseen test instance, based on several already known instances is the task of Decision tree (DT). Through a sequence of decisions, an unseen test instance is being classified by a Decision tree.

Naive Bayes: On the basis of the class label given Naive Bayes assumes that the attributes are conditionally independent and thus tries to estimate the class-conditional probability [15]. Naive Bayes often produces good results in the classification where there exist simpler relations

K-nearest neighbor: Various distance measure techniques are being used in K-nearest neighbor. K-nearest neighbor finds out k number of samples in training data that are nearest to the test sample and then it assigns the most frequent class label among the considered training samples to the test sample.

Artificial Neural Network: (ANN) is a processing unit for information which was inspired by the functionality of human brains [23]. Typically neural networks are organized in layers which are made up of a number of interconnected nodes which contain a function of activation.

Support Vector Machines: (SVM) was introduced in mid1990’s [5]. The concept behind SVM for intrusion detection basically is to use the training data as a description of only the normal class of objects or which is known as non-attack in intrusion detection system and thus assuming the rest as anomalies [11].

Fuzzy Logic: For reasoning purpose, dual logic's truth values can be either absolutely false (0) or absolutely true (1), but in Fuzzy logic these kinds of restrictions are being relaxed [60]. That means in Fuzzy logic the range of the degree of truth of a statement can hold the value between 0 and 1 along with '0' and '1'[13].

6. GENETIC ALGORITHMS

Genetic algorithms are a family of problem-solving techniques goal of genetic algorithms is to create optimal solutions to problems. Potential solutions to the problem to be solved are encoded as sequences of bits, characters or numbers [23].

An Auto-Encoder (AE) is a type of neural networks with the same number of neurons in both input and output layer [24]. It is mainly used for dimensionality reduction for better representation of data. Auto-Encoder is an unsupervised learning model and applies back propagation. The input and output layer consist of N nodes and hidden layer consist of K nodes. Hidden layer of AE is known as abstract layer. For a given training data set X with m samples, the encoder performs the mapping of input vector to hidden vector using mapping function.

```
Input: Dataset D= {x1, x2, ..…..xm} with m samples, number of hidden layers L
Output: Output of each hidden unit
Step 1: for l ∈[1, L] do
    Step 2: initialize Wl= 0, Wl ’= 0, bl= 0, bl ’= 0
    Step 3: define the l-th hidden layer representation vector hl= f(Wl hl-1+ bl)
    Step 4: define the l-th hidden layer output xl’= f(Wl’hl+bl)
    Step 5: while not stopping criterion do
        Step 6: calculate hl from hl-1
        Step 7: calculate yl
        Step 8: calculate the loss function
        Step 9: update layer parameters θl= (Wl, bl) and θl’= (Wl ’ , bl ’ )
    Step 10: end while
Step 11: end for
Step 12: Initialize (Wl+1, bl+1) at the supervised layer
Step 13: calculate the labels for each sample xi of the training dataset D
Step 14: perform BP in a supervised way to tune parameter of all layers;
```

7. EXPERIMENT RESULTS

The proposed research for implementing deep learning algorithms are implemented using machine learning library. The performance of Deep auto encoder is compared with classical machine learning algorithms. Support vector machine and artificial neural network are the most popular approaches for single learning algorithm classifiers and number of comparative samples is less but the comparison result implies that Support Vector machine is by far the most common and considered single classification technique. We quantitatively analyze Ess-InfoGAIL’s behavior disentanglement performance, complex tasks with numerous behavior modes, both GAIL and InfoGAIL often encounter mode collapse, where their policies manifest behavior corresponding to only a subset of the behavior modes due to a lack of prior behavior representation knowledge

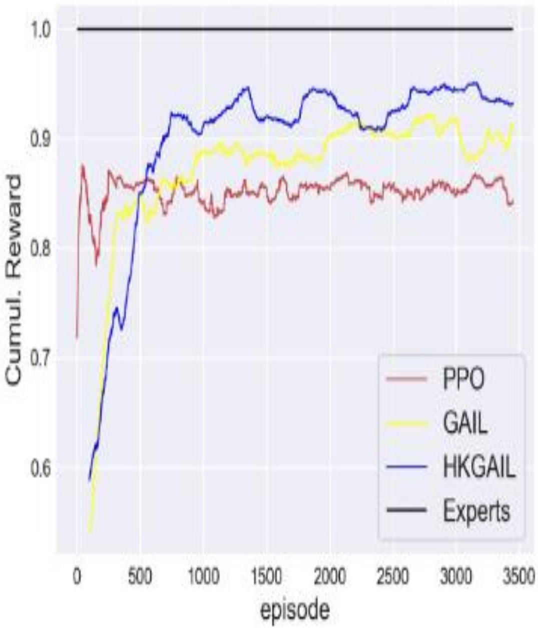

Fig. 4: Distribution of Single classifiers

8. CONCLUSION AND FUTURE WORK

We propose a new approach to incorporate human knowledge into GAIL policy updates, HKGAIL, anovel adversarial imitation framework for addressing the bottle-neck discrepancies caused by the stochastic decision making ofGAIL's generators. To verify the effectiveness of CDBL, a case study in interactive driving behaviour prediction is presented, which develops a dynamic memory mechanism by utilising the divergence measurement of driving scenarios.Our proposed IDS is able to update the dataset and learn to deal with new misclassified records.The policy generated by the RL-based method places more emphasis on high-difficulty and high-reward actions. Such a policy works well for obtaining higher cumulative rewards, but it does not match the action distribution of real students' trajectories. Besides, the distribution of 'lecture' actions whose default rewardsvalue is very small and unstable. There are multiple new intrusions were seen within each broader category. When the model was trained and evaluated on the train-validation split, the model performance was quite high, compared to test set accuracy where new intrusions are seen. Removal of redundant and irrelevant features for the training phase is a key factor for system performance. Consideration of feature selection will play a vital role in the classification techniques in future work.further enhance Sim-GAIL's capabilities and contribute to the advancement of humanmodeling techniques in the field of Intelligent Tutoring System.Further verified its controllability and scalability in scenarios with higher imbalance degrees and more behavior modes imitation tasks in the real world. Although there are some limitations, such as the need to provide a small amount of labeled data for each category and preset the number of modal categories

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