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(54) DIFFUSION-REWARD ADVERSARIAL IMITATION LEARNING

(71) Applicant: **NVIDIA Corporation**, Santa Clara, CA (US)

(72) Inventors: **Min-Hung Chen**, Zhubei City (TW); **Yu-Chiang Wang**, Taipei City (TW); **Hsiang-Chun Wang**, Taipei City (TW); **Chun-Mao Lai**, Tainan City (TW); **Shao-Hua Sun**, Taipei City (TW)

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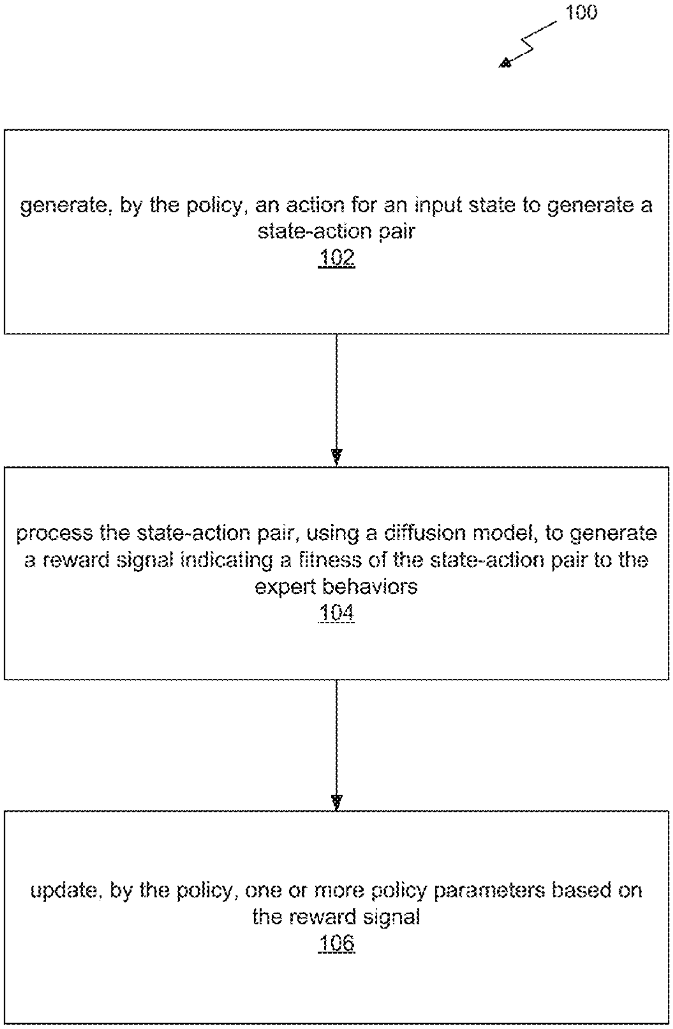
(57) ABSTRACT

Imitation learning, or artificial intelligence-based learning from demonstration, aims to acquire an agent policy by observing and mimicking the behavior demonstrated in expert demonstrations. Imitation learning can be used to generate reliable and robust learned policies in a variety of tasks involving sequential decision-making, such as autonomous driving and robotics tasks. However, current imitation learning solutions are limited in their ability to generalize states or goals unseen from the expert's demonstrations. The present disclosure integrates a diffusion model into generative adversarial imitation learning, which, in terms of prior solutions, can provide superior performance in generalizing to states or goals unseen from the expert's demonstrations, provide data efficiency for varying the amounts of available expert data, and capture more robust and smoother rewards.


100
generate, by the policy, an action for an input state to generate a state-action pair
102
process the state-action pair, using a diffusion model, to generate a reward signal indicating a fitness of the state-action pair to the expert behaviors
104
update, by the policy, one or more policy parameters based on the reward signal
106

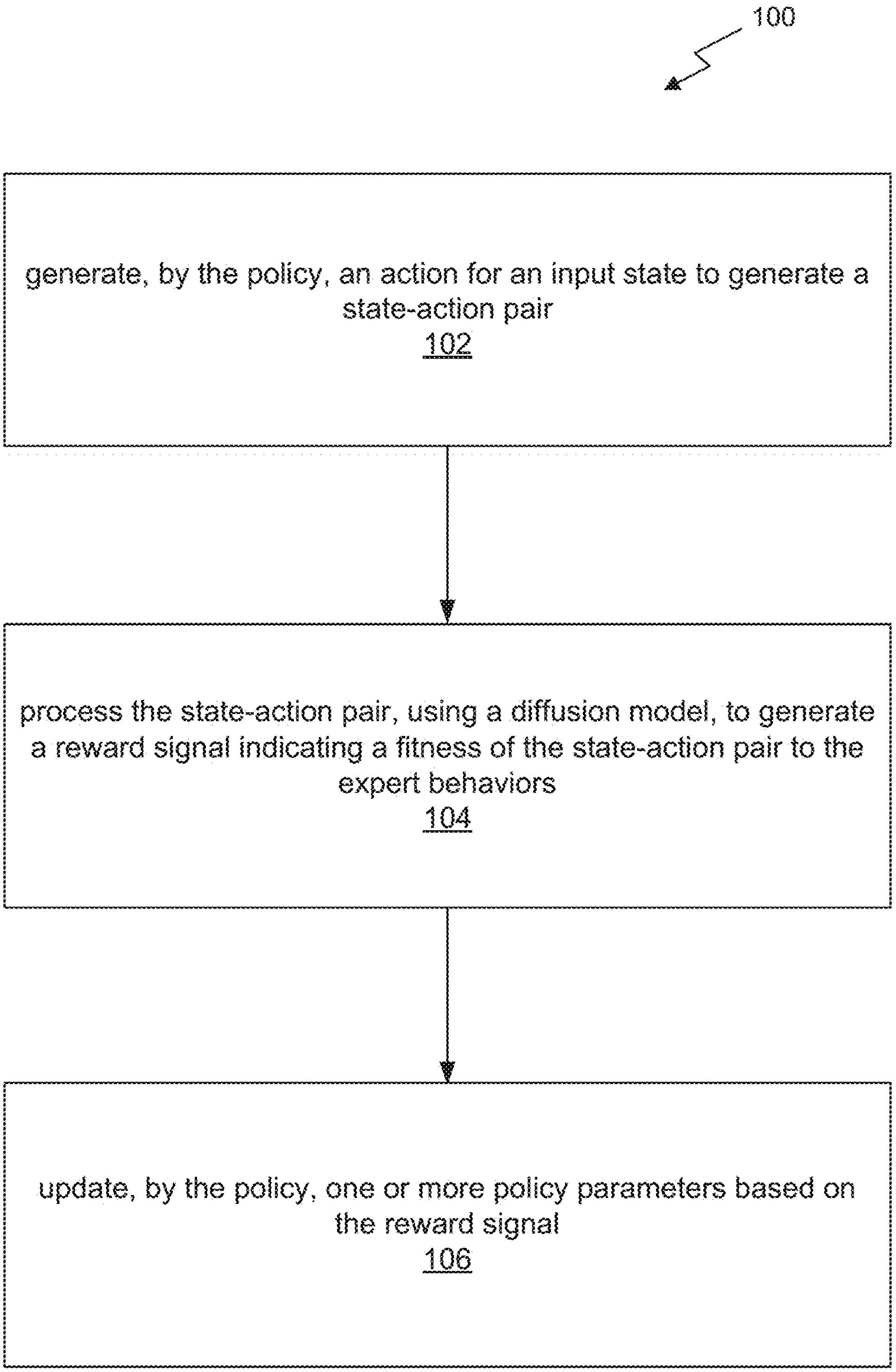

100
generate, by the policy, an action for an input state to generate a state-action pair
102
process the state-action pair, using a diffusion model, to generate a reward signal indicating a fitness of the state-action pair to the expert behaviors
104
update, by the policy, one or more policy parameters based on the reward signal
106

Fig. 1

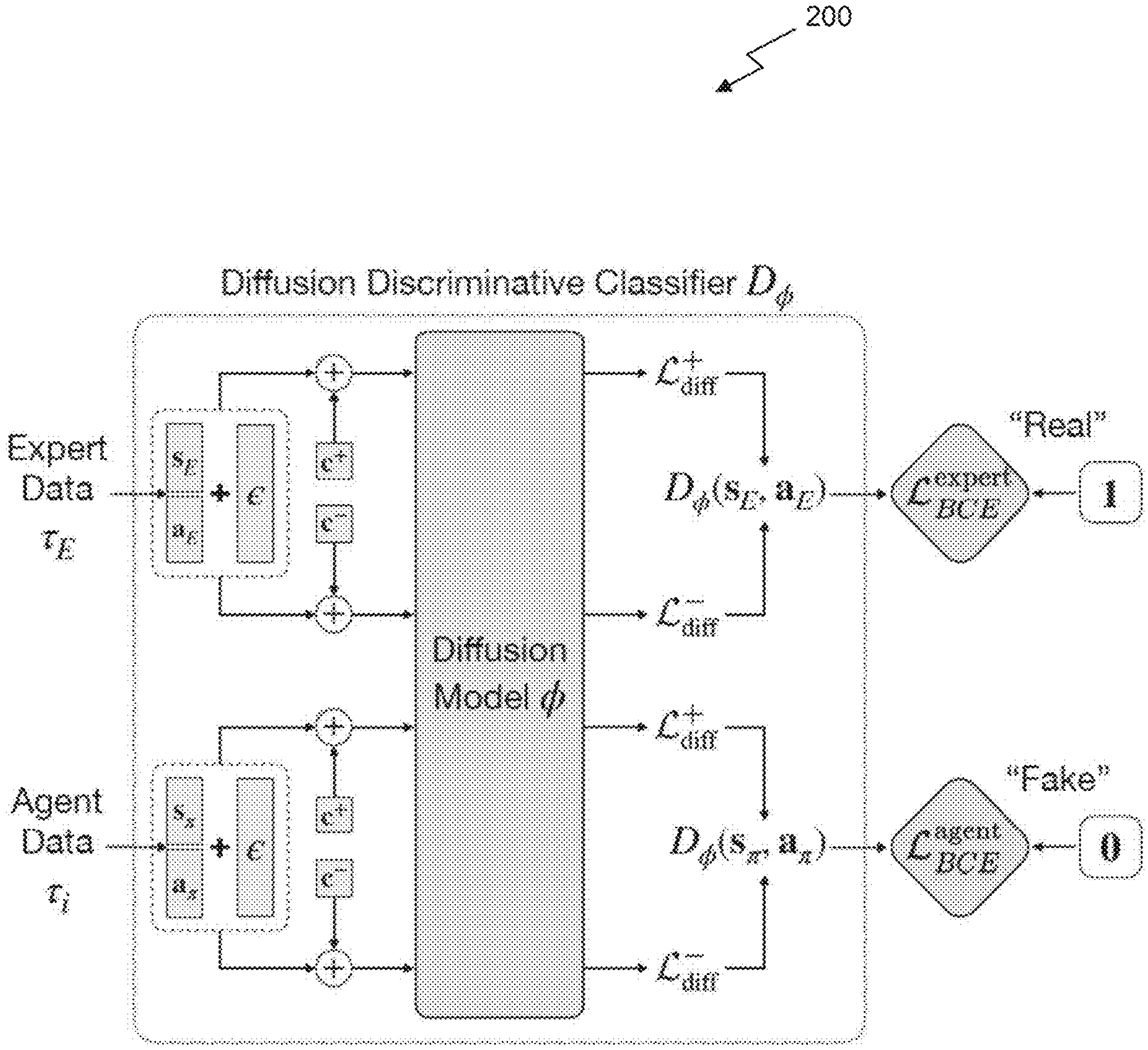

200
Diffusion Discriminative Classifier D_ϕ
Expert Data τ_E
$\mathbf{s}_E$
$\mathbf{a}_E$
+
ϵ
$\mathbf{c}^+$
$\mathbf{c}^-$
Diffusion Model ϕ
$\mathcal{L}^+_{\text{diff}}$
$\mathcal{L}^-_{\text{diff}}$
$D_\phi(\mathbf{s}_E, \mathbf{a}_E)$
"Real"
$\mathcal{L}^{\text{expert}}_{BCE}$
1
Agent Data τ_i
$\mathbf{s}_\pi$
$\mathbf{a}_\pi$
$D_\phi(\mathbf{s}_\pi, \mathbf{a}_\pi)$
"Fake"
$\mathcal{L}^{\text{agent}}_{BCE}$
0

Fig. 2

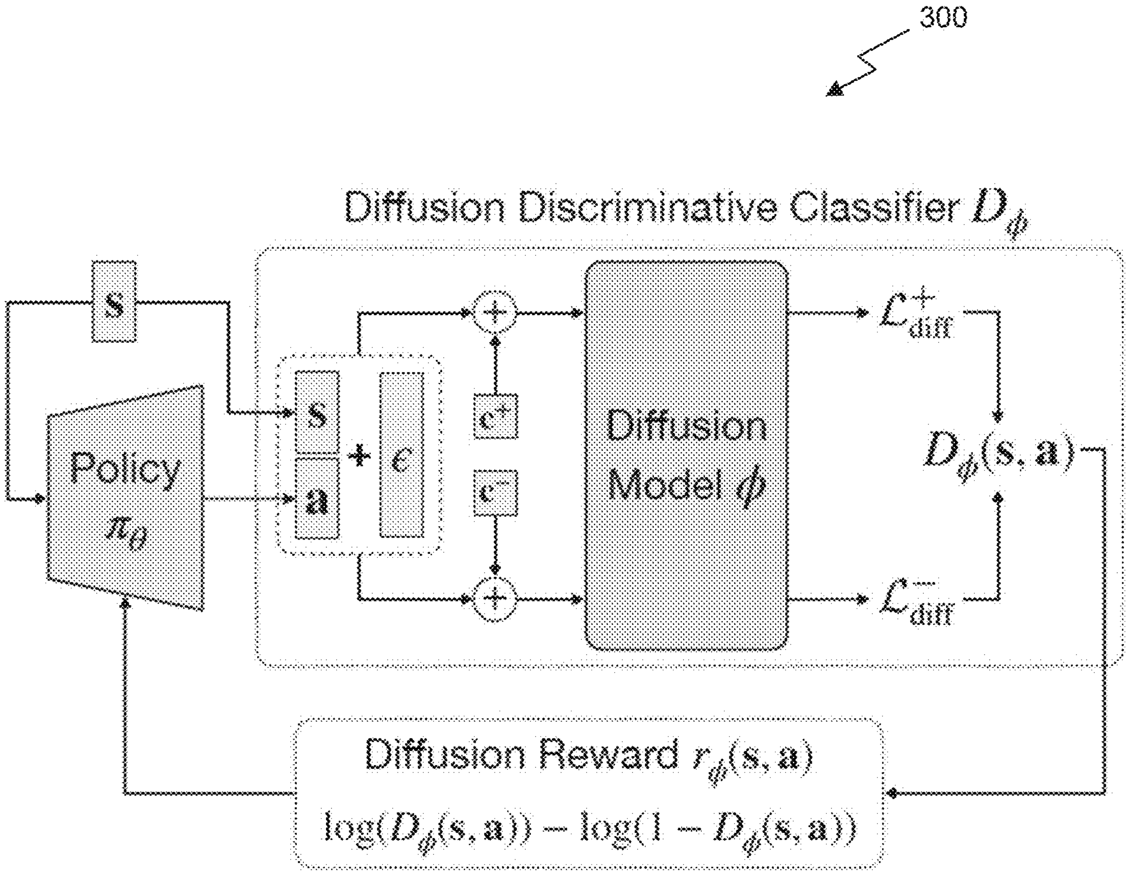

300
Diffusion Discriminative Classifier D_ϕ
$\mathbf{s}$
Policy π_θ
$\mathbf{s}$
$\mathbf{a}$
+
ϵ
$\mathbf{c}^+$
$\mathbf{c}^-$
Diffusion Model ϕ
$\mathcal{L}^+_{\text{diff}}$
$\mathcal{L}^-_{\text{diff}}$
$D_\phi(\mathbf{s}, \mathbf{a})$
Diffusion Reward $r_\phi(\mathbf{s}, \mathbf{a})$
$\log(D_\phi(\mathbf{s}, \mathbf{a})) - \log(1 - D_\phi(\mathbf{s}, \mathbf{a}))$

Fig. 3

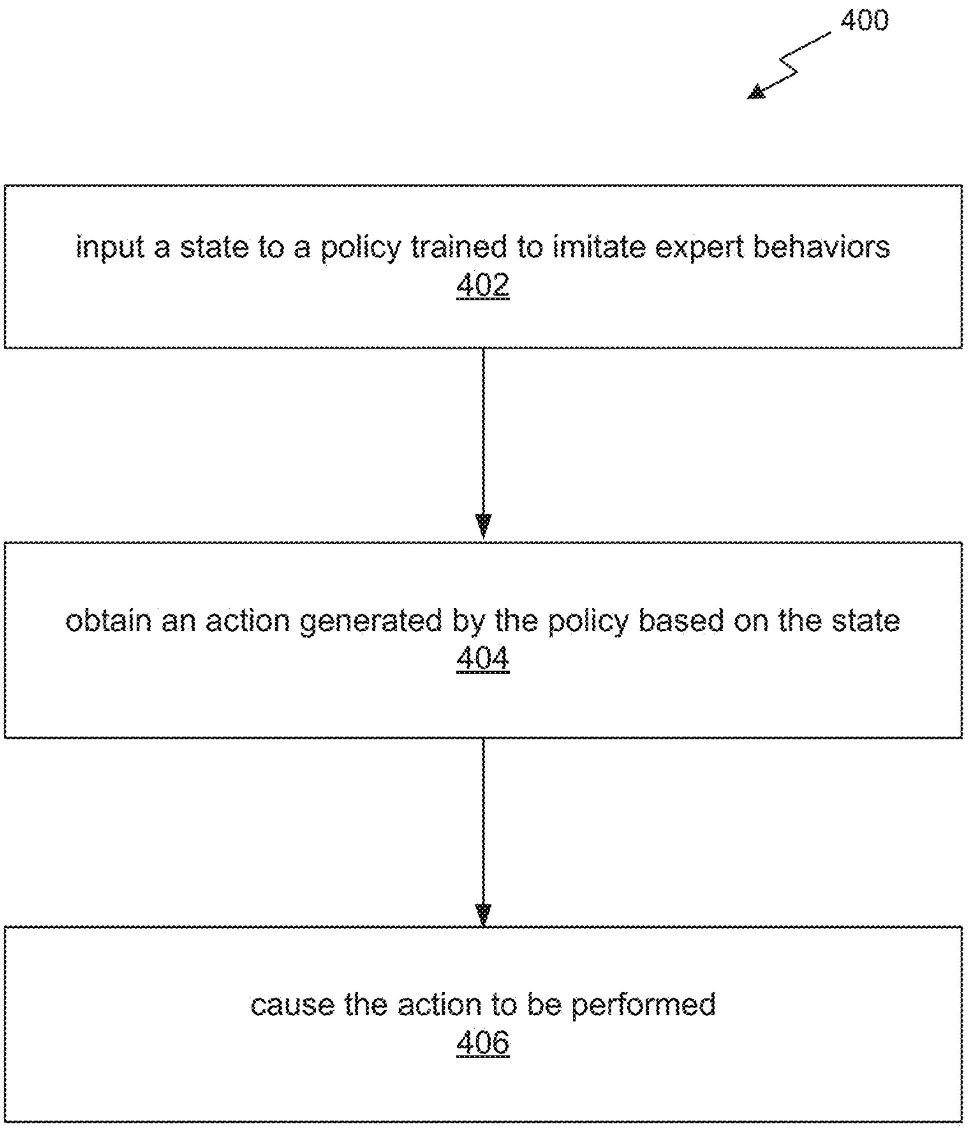

400
input a state to a policy trained to imitate expert behaviors
402
obtain an action generated by the policy based on the state
404
cause the action to be performed
406

Fig. 4

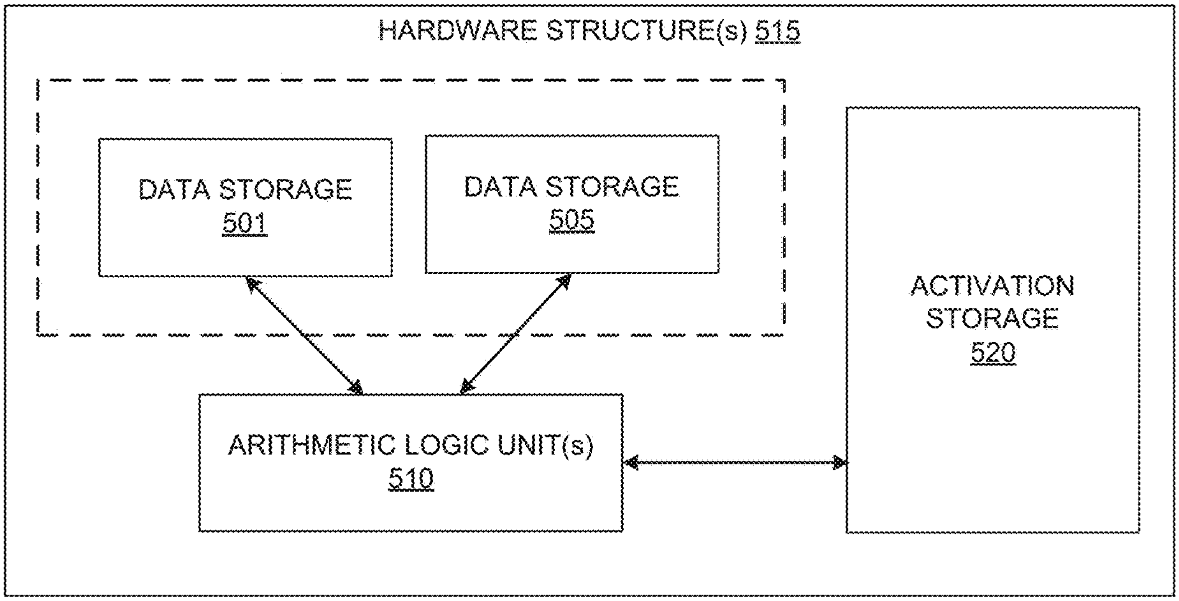

HARDWARE STRUCTURE(s) 515
DATA STORAGE
501
DATA STORAGE
505
ACTIVATION
STORAGE
520
ARITHMETIC LOGIC UNIT(s)
510

Fig. 5A

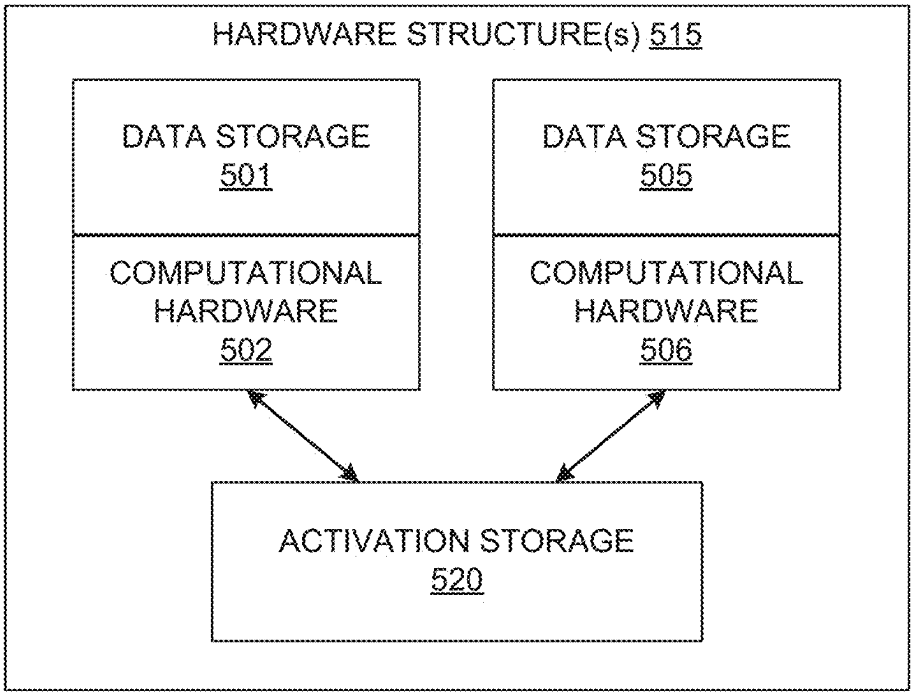

HARDWARE STRUCTURE(s) 515
DATA STORAGE 501
COMPUTATIONAL HARDWARE 502
DATA STORAGE 505
COMPUTATIONAL HARDWARE 506
ACTIVATION STORAGE 520

Fig. 5B

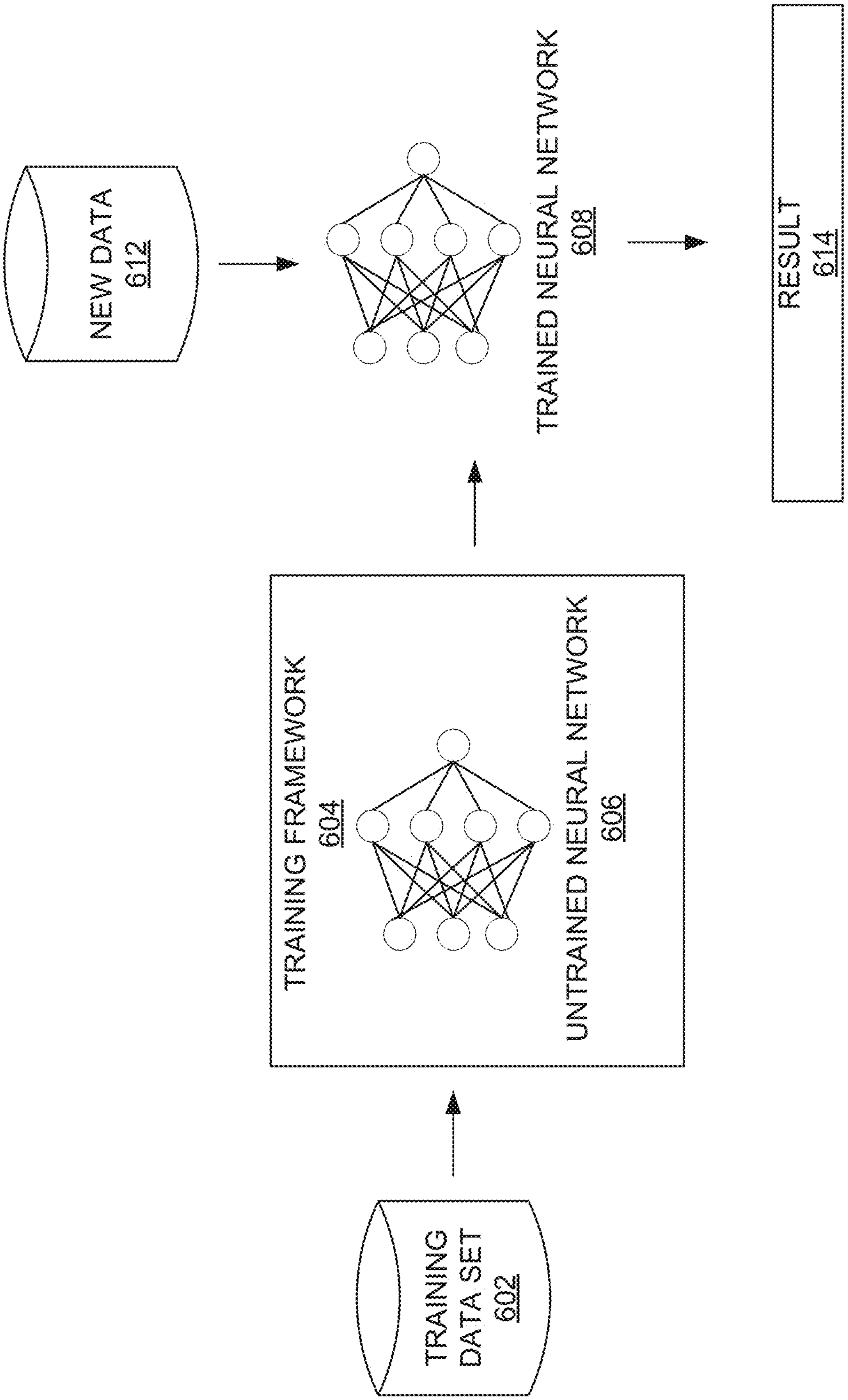

TRAINING DATA SET 602
TRAINING FRAMEWORK 604
UNTRAINED NEURAL NETWORK 606
TRAINED NEURAL NETWORK 608
NEW DATA 612
RESULT 614

Fig. 6

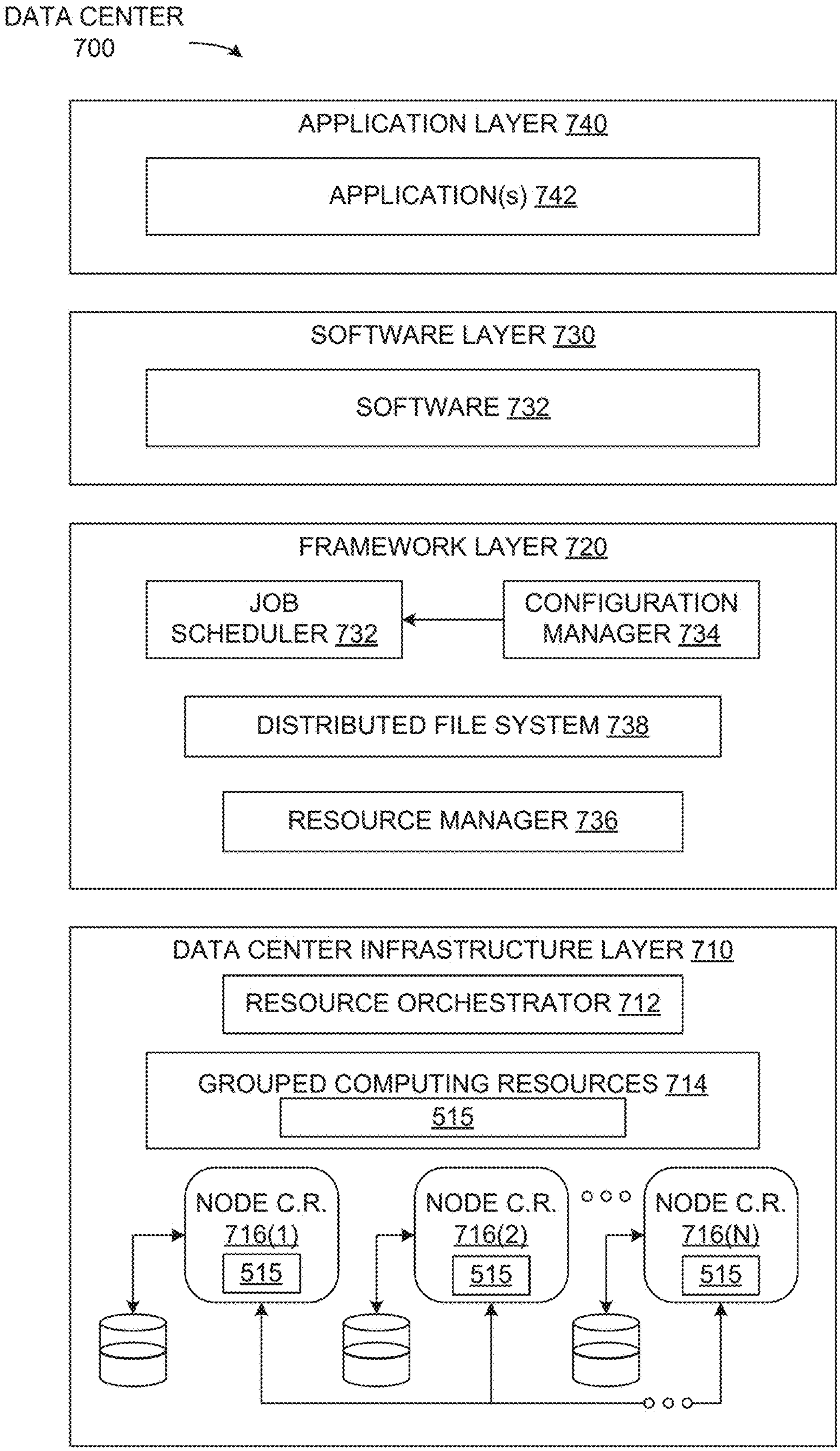

DATA CENTER
700
APPLICATION LAYER 740
APPLICATION(s) 742
SOFTWARE LAYER 730
SOFTWARE 732
FRAMEWORK LAYER 720
JOB SCHEDULER 732
CONFIGURATION MANAGER 734
DISTRIBUTED FILE SYSTEM 738
RESOURCE MANAGER 736
DATA CENTER INFRASTRUCTURE LAYER 710
RESOURCE ORCHESTRATOR 712
GROUPED COMPUTING RESOURCES 714
515
NODE C.R. 716(1)
515
NODE C.R. 716(2)
515
NODE C.R. 716(N)
515

Fig. 7

DIFFUSION-REWARD ADVERSARIAL IMITATION LEARNING

CLAIM OF PRIORITY

[0001] This application claims the benefit of U.S. Provisional Application No. 63/556,294 (Attorney Docket No. NVIDP1394+/24-TP-0201US01) titled "DIFFUSION REWARDS GUIDED ADVERSARIAL IMITATION LEARNING," filed Feb. 21, 2024, the entire contents of which is incorporated herein by reference.

TECHNICAL FIELD

[0002] The present disclosure relates to artificial intelligence-based imitation learning.

BACKGROUND

[0003] Imitation learning, or artificial intelligence-based learning from demonstration, aims to acquire an agent policy by observing and mimicking the behavior demonstrated in expert demonstrations. Various imitation learning methods have enabled deploying reliable and robust learned policies in a variety of tasks involving sequential decision-making, especially in the scenarios where devising a reward function is intricate or uncertain, or when learning in a trial-and-error manner is expensive or unsafe.

[0004] Among various methods in imitation learning, generative adversarial imitation learning (GAIL) has been widely adopted due to its effectiveness and data efficiency. GAIL learns a generator policy to imitate expert behaviors through reinforcement learning and a discriminator to differentiate between the expert and the generator's state-action pair distributions, resembling the idea of generative adversarial networks (GANs). Despite its established theoretical guarantee, GAIL training is notoriously brittle and unstable. To alleviate this issue, significant efforts have been put into improving GAIL's sample efficiency, scalability, robustness, and generalizability by modifying loss functions, developing improved policy learning algorithms, and exploring various similarity measures of distributions.

[0005] However, current solutions are still limited in their ability to generalize states or goals unseen from the expert's demonstrations. Further, these solutions are limited in their ability to provide robust and smooth rewards.

[0006] There is a need for addressing these issues and/or other issues associated with the prior art. For example, there is a need to integrate a diffusion model into generative adversarial imitation learning, which, in terms of prior solutions, can provide superior performance in generalizing to states or goals unseen from the expert's demonstrations, provide data efficiency for varying the amounts of available expert data, and capture more robust and smoother rewards.

SUMMARY

[0007] A method, computer readable medium, and system are disclosed for training a policy to imitate expert behaviors included in at least one expert demonstration. The policy generates an action for an input state to generate a state-action pair. A diffusion model is used to process the state-action pair to generate a reward signal indicating a fitness of the state-action pair to the expert behaviors. In an embodiment, a diffusion discriminative classifier, which is based on the diffusion model, generates the reward signal. The policy updates one or more policy parameters based on the reward signal.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008] FIG. **1** illustrates a flowchart of a method for training a policy to imitate expert behaviors included in at least one expert demonstration, in accordance with an embodiment.

[0009] FIG. **2** illustrates a system framework for training a diffusion discriminative classifier, in accordance with an embodiment.

[0010] FIG. **3** illustrates a system framework for learning a policy using the diffusion discriminative classifier of FIG. **2**, in accordance with an embodiment.

[0011] FIG. **4** illustrates a flowchart of a method for using a policy trained to imitate expert behaviors, in accordance with an embodiment.

[0012] FIG. **5**A illustrates inference and/or training logic, according to at least one embodiment;

[0013] FIG. **5**B illustrates inference and/or training logic, according to at least one embodiment;

[0014] FIG. **6** illustrates training and deployment of a neural network, according to at least one embodiment;

[0015] FIG. **7** illustrates an example data center system, according to at least one embodiment.

DETAILED DESCRIPTION

[0016] FIG. **1** illustrates a flowchart of a method **100** for training a policy to imitate expert behaviors included in at least one expert demonstration, in accordance with an embodiment. The method **100** may be performed by a device, which may be comprised of a processing unit, a program, custom circuitry, or a combination thereof, in an embodiment. In another embodiment, a system comprised of a non-transitory memory storage comprising instructions, and one or more processors in communication with the memory, may execute the instructions to perform the method **100**. In another embodiment, a non-transitory computer-readable media may store computer instructions which when executed by one or more processors of a device cause the device to perform the method **100**.

[0017] As mentioned above, the method **100** is performed for training a policy to imitate expert behaviors. The policy refers to a set of rules or strategies that defines the decision-making process of an agent to achieve an objective. Accordingly, the policy may be referred to as an agent policy. Given an input state, the policy is configured to generate the action to be taken by the agent. In an embodiment, the policy may be initialized prior to the training. Such initialization may allow the policy to generate actions for given states, even prior to the training disclosed herein.

[0018] The policy in particular is trained through machine learning to imitate the expert behaviors, and therefore the policy may be a machine learning model. Expert behaviors refer to the actions taken by an expert at various states, which in combination represent an optimal or targeted decision-making process to achieve the objective. In the context of the present description, the expert behaviors are included in at least one expert demonstration.

[0019] In an embodiment, the at least one expert demonstration includes a recording of an expert performing a task (i.e. to achieve the objective). In an embodiment, the at least one expert demonstration is represented by expert data that includes a set of data points. Each data point in the set of data points may consist of expert state-action pairs, with each such pair including a state and an action taken by the expert in the state.

[0020] The method **100** may be repeated over multiple iterations to train the policy. Thus, the policy may be incrementally optimized toward imitating the expert behaviors. In a first iteration of the method **100**, the initialized version of the policy may be employed. The method **100** may be repeated until an optimization objective has been met.

[0021] Returning to the method **100**, in operation **102**, the policy generates an action for an input state to generate a state-action pair. In particular, a state is input to the policy to cause the policy to generate the action for the state. The input state and the generated action represent the state-action pair. As mentioned above, in a first training iteration, an initialized version of the policy may be used to generate the state-action pair.

[0022] In operation **104**, a diffusion model is used to process the state-action pair to generate a reward signal indicating a fitness of the state-action pair to the expert behaviors. The diffusion model refers to a machine learning model that has been trained to gradually remove noise added to data points, and thus at inference time a diffusion process of the model denoises a given input over one or more steps. The noise refers to (e.g. random or pseudo-random) artifacts that are present in the data.

[0023] In an embodiment, a diffusion process of the diffusion model may be used to denoise the state-action pair. In an embodiment, the reward signal may be generated from the denoised state-action pair output by the diffusion model. In an embodiment, the diffusion model may form the denoised state-action pair via a single step of the diffusion process.

[0024] In an embodiment, the diffusion model is a component of a diffusion discriminative classifier, such that the reward signal is generated by the diffusion discriminative classifier via the diffusion model. In an embodiment, the reward signal may be generated by (1) computing a first diffusion loss that measures a fitness of the denoised state-action pair to a distribution of the expert behaviors, (2) computing a second diffusion loss that measures a fitness of the denoised state-action pair to a distribution of agent behaviors, and (3) computing the reward signal based on the first diffusion loss and the second diffusion loss. In an embodiment, the reward signal may be computed within a range bounded by a first value and a second value. In an embodiment, the first value may be indicative of a fitness to the distribution of the expert behaviors and the second value may be indicative of a fitness to the distribution of the agent behaviors.

[0025] In an embodiment, the method **100** may comprise training the diffusion model for use in generating a reward signal for a given state-action pair. In this embodiment, the diffusion model may be trained on expert data that includes a set of expert data points, wherein each expert data point in the set of expert data points consists of expert state-action pairs each including a state and an action taken by an expert in the state, and agent data that includes a set of agent data points, wherein each agent data point in the set of agent data points consists of agent state-action pairs each including a state and an action taken by an agent in the state. In an embodiment, the diffusion model may be trained to distinguish the expert data from the agent data.

[0026] In an embodiment, for each input expert state-action pair, the diffusion model may generate a denoised expert state-action pair, and further a first diffusion loss is computed that measures a fitness of the denoised expert state-action pair to a distribution of the expert data, a second diffusion loss may be computed that measures a fitness of the denoised expert state-action pair to a distribution of the agent data, and the first diffusion loss and the second diffusion loss may be integrated to compute a value of the expert state-action pair within a range bounded by a first value and a second value, where the first value is indicative of a fitness to the distribution of the expert data and the second value is indicative of a fitness to the distribution of the agent data. In an embodiment, for each input agent state-action pair, the diffusion model may generate a denoised agent state-action pair, and further a third diffusion loss may be computed that measures a fitness of the denoised agent state-action pair to a distribution of the agent data, a fourth diffusion loss may be computed that measures a fitness of the denoised agent state-action pair to a distribution of the agent data, and the third diffusion loss and the fourth diffusion loss may be integrated to compute a value of the agent state-action pair within the range bounded by the first value and the second value. In an embodiment, additionally for each input expert state-action pair, an expert binary cross-entropy loss may be computed from the value of the expert state-action pair, and parameters of the diffusion model may be updated based on the expert binary cross-entropy loss. In an embodiment, additionally for each input agent state-action pair, an agent binary cross-entropy loss may be computed from the value of the agent state-action pair, and the parameters of the diffusion model may be updated based on the agent binary cross-entropy loss.

[0027] Following the generation of the reward signal in operation **104**, the policy updates one or more policy parameters based on the reward signal in operation **106**. The policy parameters refer to one or more adjustable parameters of the policy. In an embodiment, the one or more policy parameters may be updated to maximize the reward signal.

[0028] To this end, the method **100** integrates the diffusion model into the training process for a policy aimed at imitating expert behaviors. In an embodiment, the policy may be trained for a single task. In this embodiment, the expert behaviors that the policy is trained to imitate may demonstrate the single task. In another embodiment, the policy may be trained for a plurality of different tasks. In this embodiment, the expert behaviors that the policy is trained to imitate may demonstrate the plurality of different tasks.

[0029] In one embodiment the policy may be trained for at least one robotics task. The robotic task(s) may include gripping, pushing, moving, etc. of objects, for example. In another embodiment, the policy may be trained for at least one autonomous driving task. For example, the autonomous driving task(s) may include accelerating, decelerating, stopping, turning, merging, etc.

[0030] In an embodiment, the method **100** may further comprise deploying the trained policy for use by a downstream application to generate actions for given states. In this embodiment, the application may input a detected state to the policy to generate an action which the application then cause to be taken. In an embodiment, the downstream application may include a robotics application. In another embodiment, the downstream application may include an autonomous driving application.

[0031] Further embodiments will now be provided in the description of the subsequent figures. It should be noted that the embodiments disclosed herein with reference to the method **100** of FIG. **1** may apply to and/or be used in combination with any of the embodiments of the remaining figures below.

[0032] FIG. **2** illustrates a system framework **200** for training a diffusion discriminative classifier, in accordance with an embodiment. The trained diffusion discriminative classifier may then be used with the system framework **300** of FIG. **3** to train a policy, as described in detail below.

[0033] The system framework **200** aims to generate a diffusion discriminative classifier that yields a diffusion model reward given an agent state-action pair without going through the entire diffusion generation process. In other words, once trained, the diffusion discriminative classifier operates to extract the learning signal from a portion of the diffusion denoising steps, rather than using the entire process. In an embodiment, the diffusion discriminative classifier may be configured to provide a binary classification signal using just one denoising step.

[0034] In general, a diffusion loss (i.e., the difference between the predicted noise and the injected noise) indicates how well the data fits the target distribution since the diffusion loss is the upper bound of the negative log-likelihood of data in the target distribution. The present system framework **200** is configured to calculate “realness” rewards based on the diffusion loss computed by denoising the state-action pairs from the policy, which indicates how well the state-action pairs fit the expert behavior distributions. The diffusion loss $\mathcal{L}_{diff}$ is formulated per Equation 1.

$$\mathcal{L}_{diff}(s, a, c) = \mathbb{E}_{t\sim T}\left[\|\epsilon_{\phi}(s, a, \epsilon, t|c) - \epsilon\|^2\right] \qquad \text{Equation 1}$$

[0035] where c∈{c^+, c^-}, and the real label c^+ corresponds to the condition for fitting expert data while the fake label c^- corresponds to agent data. In an embodiment, c^+ is implemented as 1 and c^- as 0.

[0036] To approximate the expectation in Equation 1, random sampling is used, which achieves the result with just a single denoising step. Subsequently, given a state-action pair (s, a), $\mathcal{L}_{diff}$ (s, a, c^+) measures how well (s, a) fits the expert distribution and $\mathcal{L}_{diff}$ (s, a, c^-) measures how well (s, a) fits the agent distribution. For simplicity, the notations $\mathcal{L}_{diff}^+$ and $\mathcal{L}_{diff}^-$ will be used hereinbelow to represent $\mathcal{L}_{diff}$ (s, a, c^+) and $\mathcal{L}_{diff}$ (s, a, c^-), respectively. Additionally, $\mathcal{L}_{diff}^{+,-}$ denotes $\mathcal{L}_{diff}^+$ and $\mathcal{L}_{diff}^-$ given a state-action pair. Given state-action pairs sampled from an expert demonstration, $\mathcal{L}_{diff}^+$ should be close to 0, and $\mathcal{L}_{diff}^-$ should be a large value; on the contrary, given agent state-action pairs, $\mathcal{L}_{diff}^+$ should be a large value and $\mathcal{L}_{diff}^-$ should be close to 0, and $\mathcal{L}_{diff}^-$.

[0037] While $\mathcal{L}_{diff}^+$ and $\mathcal{L}_{diff}^-$ can indicate the “realness” or the “fakeness” of a state-action pair to some extent, optimizing a policy (per system framework **300** of FIG. **3**) using rewards with this wide value range [0,∞) can be difficult. To address this issue, the diffusion model is transformed into a binary classifier that provides “realness” in a bounded range of [0, 1]. Specifically given the diffusion model's output $\mathcal{L}_{diff}^{+,-}$, a diffusion discriminative classifier $D_{\varnothing}$: S×A→$\mathbb{R}$ is constructed per Equation 2.

$$D_{\phi}(s, a) = \frac{e^{-\mathcal{L}_{diff}(s,a,c^+)}}{e^{-\mathcal{L}_{diff}(s,a,c^+)} + e^{-\mathcal{L}_{diff}(s,a,c^-)}} = \sigma(\mathcal{L}_{diff}(s, a, c^-) - \mathcal{L}_{diff}(s, a, c^+)) \qquad \text{Equation 2}$$

[0038] where σ(x)=1/(1+e^{-x}) denotes the sigmoid function. The classifier integrates $\mathcal{L}_{diff}^+$ and $\mathcal{L}_{diff}^-$ to compute the “realness” of a state-action pair within a bounded range of [0, 1]. Based on the design of the diffusion discriminative classifier, learning a policy with the classifier (as described with respect to the system framework **300** of FIG. **3** below) allows for optimizing this objective to bring a policy's occupancy measure closer to the expert's. Consequently, the proposed diffusion discriminative classifier $D_{\varnothing}$ can be optimized with the loss function in Equation 3.

$$\mathcal{L}_D = \mathbb{E}_{(s,a)\in\tau_E}\underbrace{[-\log(D_{\phi}(s, a))]}_{\mathcal{L}_{BCE}^{expert}} + \mathbb{E}_{(s,a)\in\tau_i}\underbrace{[-\log(D_{\phi}(s, a))]}_{\mathcal{L}_{BCE}^{agent}} \qquad \text{Equation 3}$$

[0039] where $\mathcal{L}_D$ sums the expert binary cross-entropy loss $\mathcal{L}_{BCE}^{expert}$ and the agent binary cross-entropy loss $\mathcal{L}_{BCE}^{agent}$ E, and τ_E and τ_i represent a sampled expert trajectory and a collected agent trajectory by the policy **7L** at training step i. The diffusion discriminative classifier parameters ϕ are then updated based on the gradient of $\mathcal{L}_D$ to improve its ability to distinguish expert data from agent data.

[0040] The discriminator $D_{\varnothing}$ is trained to predict a value closer to 1 when the input state-action pairs are sampled from expert demonstration (i.e., trained to minimize $\mathcal{L}_{diff}^+$ and maximize $\mathcal{L}_{diff}^-$), and 0 if the input state-action pairs are obtained from the agent online interaction (i.e., trained to minimize $\mathcal{L}_{diff}^-$ and maximize $\mathcal{L}_{diff}^+$). To this end, instead of optimizing the diffusion loss $\mathcal{L}_{diff}$, the binary cross entropy losses calculated based on the denoising results are directly optimized to train the diffusion model as a binary classifier.

[0041] FIG. **3** illustrates a system framework **300** for learning a policy using the diffusion discriminative classifier of FIG. **2**, in accordance with an embodiment.

[0042] The system framework **300** operates to update the discriminator and a policy alternately. In the discriminator step, the diffusion discriminative classifier (trained per the system framework **200** of FIG. **2**) is updated with the gradient of $\mathcal{L}_D$ per Equation 3. In the policy step, an adversarial inverse reinforcement learning objective is adopted as the diffusion reward signal to train the policy, per Equation 4.

$$r_{\phi}(s, a) = \log(D_{\phi}(s, a)) - \log(1 - D_{\phi}(s, a)) \qquad \text{Equation 4}$$

[0043] The policy parameters θ can be updated using a reinforcement learning algorithm to maximize the diffusion rewards provided by the diffusion discriminative classifier, bringing the policy closer to the expert policy. In an embodiment, proximal policy optimization may be used as the policy update algorithm. An embodiment of the algorithm is presented in Table 1, which may be implemented as illustrated in FIG. **3**.

TABLE 1

```
Input: Expert trajectories $\tau_E$ , initial policy parameters $\theta_0$, initial diffusion discriminator parameters $\phi_0$, and discriminator learning rate $\eta_\phi$
for i = 0, 1, 2, . . . do
    Sample agent transitions $\tau_i \sim \pi_{\theta_i}$
    Compute the output of diffusion discriminative classifier $D_\phi$ (Equation 2) and the loss function $\mathcal{L}_D$ (Equation 3)
    Update the diffusion model $\phi_{i+1} \leftarrow \phi_i - \eta_\phi \nabla \mathcal{L}_D$
    Compute the diffusion reward $r_\phi(s, a)$ with Equation 4
    Update the policy $\theta_{i+1} \leftarrow \theta_i$ with a reinforcement learning algorithm with respect to reward $r_\phi$
end for
```

[0044] The presently disclosed system framework **300** improves upon prior solutions that employ an unconditional diffusion model to denoise state-action pairs from both experts and agents, at least in part because those solutions only implicitly reflects the likelihood of state-action pairs belonging to the expert class through diffusion loss, making it challenging to explicitly distinguish between expert and agent behaviors. In contrast, the presently disclosed system framework **300** uses a conditional diffusion model that directly conditions real (c^+) and fake (c^-) labels, which allows the model to explicitly calculate and compare the probabilities of state-action pairs belonging to either the expert or agent class. This signal for binary classification is clearer and more robust to input noise, and further aligns more closely with the objectives of the system framework **300** as a whole, leading to more stable and efficient learning of the policy.

[0045] FIG. **4** illustrates a flowchart of a method **400** for using a policy trained to imitate expert behaviors, in accordance with an embodiment. With respect to the present embodiment, the policy has been trained per the method **100** of FIG. **1** and/or the system framework **300** of FIG. **3**. In an embodiment, the policy is deployed (e.g. to a cloud server, datacenter, etc.) for use thereof. In an embodiment, an application may perform the method **400** to use the policy for one or more application-specific tasks.

[0046] In operation **402**, a state is input to the policy trained to imitate expert behaviors. The state refers to the state of an agent. For example, the state may be a configuration, location, current behavior, etc. of the agent.

[0047] In operation **404**, an action generated by the policy based on the state is obtained. The action refers to an action to be taken by the agent. The action is predicted by the policy as one that mimics an expert behavior with respect to the input state. In some examples, the action may be for the agent to change the configuration, change the location, change the current behavior, etc.

[0048] In operation **406**, the action is caused to be performed. In an embodiment, performing the action may cause the agent to perform a task. For example, the action may be performed to cause the agent to perform an autonomous driving task or a robotics task.

[0049] In an embodiment, performing the action may cause the agent to be placed in a new state. In an embodiment, the method **100** may be repeated for the new state. In this way, actions of the agent may be controlled using the policy.

[0050] In embodiments, the policy may be trained for a single task or for a plurality of different tasks. Accordingly, in an embodiment, the method **100** may be performed (and optionally repeated) for the agent to complete the single task. In another embodiment, the method **100** may be performed and repeated for the agent to complete two or more of the plurality of different tasks.

Exemplary Use Case—Autonomous Driving Application

[0051] In an embodiment, the method **100** may be performed by an autonomous driving application that is being used to control operations of an autonomous driving vehicle. In this exemplary embodiment, the autonomous driving application inputs a state of the autonomous driving vehicle (e.g. location, speed, environment, etc.) to the policy. The policy processes the state to generate an action for the autonomous driving vehicle (e.g. stopping, accelerating, deceleration, changing lanes, etc.). The autonomous driving application causes the autonomous driving vehicle to perform the action.

Exemplary Use Case—Robotics Application

[0052] In an embodiment, the method **100** may be performed by a robotics application that is being used to control operations of a robot. In this exemplary embodiment, the robotics application inputs a state of the robot (e.g. configuration, location, environment, etc.) to the policy. The policy processes the state to generate an action for the robot (e.g. gripping, moving, pushing, etc.). The robotics application causes the robot to perform the action.

Machine Learning

[0053] Deep neural networks (DNNs), including deep learning models, developed on processors have been used for diverse use cases, from self-driving cars to faster drug development, from automatic image captioning in online image databases to smart real-time language translation in video chat applications. Deep learning is a technique that models the neural learning process of the human brain, continually learning, continually getting smarter, and delivering more accurate results more quickly over time. A child is initially taught by an adult to correctly identify and classify various shapes, eventually being able to identify shapes without any coaching. Similarly, a deep learning or neural learning system needs to be trained in object recognition and classification for it get smarter and more efficient at identifying basic objects, occluded objects, etc., while also assigning context to objects.

[0054] At the simplest level, neurons in the human brain look at various inputs that are received, importance levels are assigned to each of these inputs, and output is passed on to other neurons to act upon. An artificial neuron or perceptron is the most basic model of a neural network. In one example, a perceptron may receive one or more inputs that represent various features of an object that the perceptron is being trained to recognize and classify, and each of these features is assigned a certain weight based on the importance of that feature in defining the shape of an object.

[0055] A deep neural network (DNN) model includes multiple layers of many connected nodes (e.g., perceptrons, Boltzmann machines, radial basis functions, convolutional layers, etc.) that can be trained with enormous amounts of input data to quickly solve complex problems with high accuracy. In one example, a first layer of the DNN model breaks down an input image of an automobile into various sections and looks for basic patterns such as lines and angles. The second layer assembles the lines to look for higher level patterns such as wheels, windshields, and mirrors. The next layer identifies the type of vehicle, and the final few layers generate a label for the input image, identifying the model of a specific automobile brand.

[0056] Once the DNN is trained, the DNN can be deployed and used to identify and classify objects or patterns in a process known as inference. Examples of inference (the process through which a DNN extracts useful information from a given input) include identifying handwritten numbers on checks deposited into ATM machines, identifying images of friends in photos, delivering movie recommendations to over fifty million users, identifying and classifying different types of automobiles, pedestrians, and road hazards in driverless cars, or translating human speech in real-time.

[0057] During training, data flows through the DNN in a forward propagation phase until a prediction is produced that indicates a label corresponding to the input. If the neural network does not correctly label the input, then errors between the correct label and the predicted label are analyzed, and the weights are adjusted for each feature during a backward propagation phase until the DNN correctly labels the input and other inputs in a training dataset. Training complex neural networks requires massive amounts of parallel computing performance, including floating-point multiplications and additions. Inferencing is less compute-intensive than training, being a latency-sensitive process where a trained neural network is applied to new inputs it has not seen before to classify images, translate speech, and generally infer new information.

Inference and Training Logic

[0058] As noted above, a deep learning or neural learning system needs to be trained to generate inferences from input data. Details regarding inference and/or training logic **515** for a deep learning or neural learning system are provided below in conjunction with FIGS. **5**A and/or **5**B.

[0059] In at least one embodiment, inference and/or training logic **515** may include, without limitation, a data storage **501** to store forward and/or output weight and/or input/output data corresponding to neurons or layers of a neural network trained and/or used for inferencing in aspects of one or more embodiments. In at least one embodiment data storage **501** stores weight parameters and/or input/output data of each layer of a neural network trained or used in conjunction with one or more embodiments during forward propagation of input/output data and/or weight parameters during training and/or inferencing using aspects of one or more embodiments. In at least one embodiment, any portion of data storage **501** may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory.

[0060] In at least one embodiment, any portion of data storage **501** may be internal or external to one or more processors or other hardware logic devices or circuits. In at least one embodiment, data storage **501** may be cache memory, dynamic randomly addressable memory ("DRAM"), static randomly addressable memory ("SRAM"), non-volatile memory (e.g., Flash memory), or other storage. In at least one embodiment, choice of whether data storage **501** is internal or external to a processor, for example, or comprised of DRAM, SRAM, Flash or some other storage type may depend on available storage on-chip versus off-chip, latency requirements of training and/or inferencing functions being performed, batch size of data used in inferencing and/or training of a neural network, or some combination of these factors.

[0061] In at least one embodiment, inference and/or training logic **515** may include, without limitation, a data storage **505** to store backward and/or output weight and/or input/output data corresponding to neurons or layers of a neural network trained and/or used for inferencing in aspects of one or more embodiments. In at least one embodiment, data storage **505** stores weight parameters and/or input/output data of each layer of a neural network trained or used in conjunction with one or more embodiments during backward propagation of input/output data and/or weight parameters during training and/or inferencing using aspects of one or more embodiments. In at least one embodiment, any portion of data storage **505** may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory. In at least one embodiment, any portion of data storage **505** may be internal or external to on one or more processors or other hardware logic devices or circuits. In at least one embodiment, data storage **505** may be cache memory, DRAM, SRAM, non-volatile memory (e.g., Flash memory), or other storage. In at least one embodiment, choice of whether data storage **505** is internal or external to a processor, for example, or comprised of DRAM, SRAM, Flash or some other storage type may depend on available storage on-chip versus off-chip, latency requirements of training and/or inferencing functions being performed, batch size of data used in inferencing and/or training of a neural network, or some combination of these factors.

[0062] In at least one embodiment, data storage **501** and data storage **505** may be separate storage structures. In at least one embodiment, data storage **501** and data storage **505** may be same storage structure. In at least one embodiment, data storage **501** and data storage **505** may be partially same storage structure and partially separate storage structures. In at least one embodiment, any portion of data storage **501** and data storage **505** may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory.

[0063] In at least one embodiment, inference and/or training logic **515** may include, without limitation, one or more arithmetic logic unit(s) ("ALU(s)") **510** to perform logical and/or mathematical operations based, at least in part on, or indicated by, training and/or inference code, result of which may result in activations (e.g., output values from layers or neurons within a neural network) stored in an activation storage **520** that are functions of input/output and/or weight parameter data stored in data storage **501** and/or data storage **505**. In at least one embodiment, activations stored in activation storage **520** are generated according to linear algebraic and or matrix-based mathematics performed by ALU(s) **510** in response to performing instructions or other code, wherein weight values stored in data storage **505** and/or data **501** are used as operands along with other values, such as bias values, gradient information, momentum values, or other parameters or hyperparameters, any or all of which may be stored in data storage **505** or data storage **501** or another storage on or off-chip. In at least one embodiment, ALU(s) **510** are included within one or more processors or other hardware logic devices or circuits, whereas in another embodiment, ALU(s) **510** may be external to a processor or other hardware logic device or circuit that uses them (e.g., a co-processor). In at least one embodiment, ALUs **510** may be included within a processor's execution units or otherwise within a bank of ALUs accessible by a processor's execution units either within same processor or distributed between different processors of different types (e.g., central processing units, graphics processing units, fixed function units, etc.). In at least one embodiment, data storage **501**, data storage **505**, and activation storage **520** may be on same processor or other hardware logic device or circuit, whereas in another embodiment, they may be in different processors or other hardware logic devices or circuits, or some combination of same and different processors or other hardware logic devices or circuits. In at least one embodiment, any portion of activation storage **520** may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory. Furthermore, inferencing and/or training code may be stored with other code accessible to a processor or other hardware logic or circuit and fetched and/or processed using a processor's fetch, decode, scheduling, execution, retirement and/or other logical circuits.

[0064] In at least one embodiment, activation storage **520** may be cache memory, DRAM, SRAM, non-volatile memory (e.g., Flash memory), or other storage. In at least one embodiment, activation storage **520** may be completely or partially within or external to one or more processors or other logical circuits. In at least one embodiment, choice of whether activation storage **520** is internal or external to a processor, for example, or comprised of DRAM, SRAM, Flash or some other storage type may depend on available storage on-chip versus off-chip, latency requirements of training and/or inferencing functions being performed, batch size of data used in inferencing and/or training of a neural network, or some combination of these factors. In at least one embodiment, inference and/or training logic **515** illustrated in FIG. **5**A may be used in conjunction with an application-specific integrated circuit ("ASIC"), such as Tensorflow® Processing Unit from Google, an inference processing unit (IPU) from Graphcore™, or a Nervana® (e.g., "Lake Crest") processor from Intel Corp. In at least one embodiment, inference and/or training logic **515** illustrated in FIG. **5**A may be used in conjunction with central processing unit ("CPU") hardware, graphics processing unit ("GPU") hardware or other hardware, such as field programmable gate arrays ("FPGAs").

[0065] FIG. **5**B illustrates inference and/or training logic **515**, according to at least one embodiment. In at least one embodiment, inference and/or training logic **515** may include, without limitation, hardware logic in which computational resources are dedicated or otherwise exclusively used in conjunction with weight values or other information corresponding to one or more layers of neurons within a neural network. In at least one embodiment, inference and/or training logic **515** illustrated in FIG. **5**B may be used in conjunction with an application-specific integrated circuit (ASIC), such as Tensorflow® Processing Unit from Google, an inference processing unit (IPU) from Graphcore™, or a Nervana® (e.g., "Lake Crest") processor from Intel Corp. In at least one embodiment, inference and/or training logic **515** illustrated in FIG. **5**B may be used in conjunction with central processing unit (CPU) hardware, graphics processing unit (GPU) hardware or other hardware, such as field programmable gate arrays (FPGAs). In at least one embodiment, inference and/or training logic **515** includes, without limitation, data storage **501** and data storage **505**, which may be used to store weight values and/or other information, including bias values, gradient information, momentum values, and/or other parameter or hyperparameter information. In at least one embodiment illustrated in FIG. **5**B, each of data storage **501** and data storage **505** is associated with a dedicated computational resource, such as computational hardware **502** and computational hardware **506**, respectively. In at least one embodiment, each of computational hardware **506** comprises one or more ALUs that perform mathematical functions, such as linear algebraic functions, only on information stored in data storage **501** and data storage **505**, respectively, result of which is stored in activation storage **520**.

[0066] In at least one embodiment, each of data storage **501** and **505** and corresponding computational hardware **502** and **506**, respectively, correspond to different layers of a neural network, such that resulting activation from one "storage/computational pair **501/502**" of data storage **501** and computational hardware **502** is provided as an input to next "storage/computational pair **505/506**" of data storage **505** and computational hardware **506**, in order to mirror conceptual organization of a neural network. In at least one embodiment, each of storage/computational pairs **501/502** and **505/506** may correspond to more than one neural network layer. In at least one embodiment, additional storage/computation pairs (not shown) subsequent to or in parallel with storage computation pairs **501/502** and **505/506** may be included in inference and/or training logic **515**.

Neural Network Training and Deployment

[0067] FIG. **6** illustrates another embodiment for training and deployment of a deep neural network. In at least one embodiment, untrained neural network **606** is trained using a training dataset **602**. In at least one embodiment, training framework **604** is a PyTorch framework, whereas in other embodiments, training framework **604** is a Tensorflow, Boost, Caffe, Microsoft Cognitive Toolkit/CNTK, MXNet, Chainer, Keras, Deeplearning4j, or other training framework. In at least one embodiment training framework **604** trains an untrained neural network **606** and enables it to be trained using processing resources described herein to generate a trained neural network **608**. In at least one embodiment, weights may be chosen randomly or by pre-training using a deep belief network. In at least one embodiment, training may be performed in either a supervised, partially supervised, or unsupervised manner.

[0068] In at least one embodiment, untrained neural network **606** is trained using supervised learning, wherein training dataset **602** includes an input paired with a desired output for an input, or where training dataset **602** includes input having known output and the output of the neural network is manually graded. In at least one embodiment, untrained neural network **606** is trained in a supervised manner processes inputs from training dataset **602** and compares resulting outputs against a set of expected or desired outputs. In at least one embodiment, errors are then propagated back through untrained neural network **606**. In at least one embodiment, training framework **604** adjusts weights that control untrained neural network **606**. In at least one embodiment, training framework **604** includes tools to monitor how well untrained neural network **606** is converging towards a model, such as trained neural network **608**, suitable to generating correct answers, such as in result **614**, based on known input data, such as new data **612**. In at least one embodiment, training framework **604** trains untrained neural network **606** repeatedly while adjust weights to refine an output of untrained neural network **606** using a loss function and adjustment algorithm, such as stochastic gradient descent. In at least one embodiment, training framework **604** trains untrained neural network **606** until untrained neural network **606** achieves a desired accuracy. In at least one embodiment, trained neural network **608** can then be deployed to implement any number of machine learning operations.

[0069] In at least one embodiment, untrained neural network **606** is trained using unsupervised learning, wherein untrained neural network **606** attempts to train itself using unlabeled data. In at least one embodiment, unsupervised learning training dataset **602** will include input data without any associated output data or "ground truth" data. In at least one embodiment, untrained neural network **606** can learn groupings within training dataset **602** and can determine how individual inputs are related to untrained dataset **602**. In at least one embodiment, unsupervised training can be used to generate a self-organizing map, which is a type of trained neural network **608** capable of performing operations useful in reducing dimensionality of new data **612**. In at least one embodiment, unsupervised training can also be used to perform anomaly detection, which allows identification of data points in a new dataset **612** that deviate from normal patterns of new dataset **612**.

[0070] In at least one embodiment, semi-supervised learning may be used, which is a technique in which in training dataset **602** includes a mix of labeled and unlabeled data. In at least one embodiment, training framework **604** may be used to perform incremental learning, such as through transferred learning techniques. In at least one embodiment, incremental learning enables trained neural network **608** to adapt to new data **612** without forgetting knowledge instilled within network during initial training.

Data Center

[0071] FIG. **7** illustrates an example data center **700**, in which at least one embodiment may be used. In at least one embodiment, data center **700** includes a data center infrastructure layer **710**, a framework layer **720**, a software layer **730** and an application layer **740**.

[0072] In at least one embodiment, as shown in FIG. **7**, data center infrastructure layer **710** may include a resource orchestrator **712**, grouped computing resources **714**, and node computing resources ("node C.R.s") **716**(**1**)-**716**(N), where "N" represents any whole, positive integer. In at least one embodiment, node C.R.s **716**(**1**)-**716**(N) may include, but are not limited to, any number of central processing units ("CPUs") or other processors (including accelerators, field programmable gate arrays (FPGAs), graphics processors, etc.), memory devices (e.g., dynamic read-only memory), storage devices (e.g., solid state or disk drives), network input/output ("NW I/O") devices, network switches, virtual machines ("VMs"), power modules, and cooling modules, etc. In at least one embodiment, one or more node C.R.s from among node C.R.s **716**(**1**)-**716**(N) may be a server having one or more of above-mentioned computing resources.

[0073] In at least one embodiment, grouped computing resources **714** may include separate groupings of node C.R.s housed within one or more racks (not shown), or many racks housed in data centers at various geographical locations (also not shown). Separate groupings of node C.R.s within grouped computing resources **714** may include grouped compute, network, memory or storage resources that may be configured or allocated to support one or more workloads. In at least one embodiment, several node C.R.s including CPUs or processors may grouped within one or more racks to provide compute resources to support one or more workloads. In at least one embodiment, one or more racks may also include any number of power modules, cooling modules, and network switches, in any combination.

[0074] In at least one embodiment, resource orchestrator **722** may configure or otherwise control one or more node C.R.s **716**(**1**)-**716**(N) and/or grouped computing resources **714**. In at least one embodiment, resource orchestrator **722** may include a software design infrastructure ("SDI") management entity for data center **700**. In at least one embodiment, resource orchestrator may include hardware, software or some combination thereof.

[0075] In at least one embodiment, as shown in FIG. **7**, framework layer **720** includes a job scheduler **732**, a configuration manager **734**, a resource manager **736** and a distributed file system **738**. In at least one embodiment, framework layer **720** may include a framework to support software **732** of software layer **730** and/or one or more application(s) **742** of application layer **740**. In at least one embodiment, software **732** or application(s) **742** may respectively include web-based service software or applications, such as those provided by Amazon Web Services, Google Cloud and Microsoft Azure. In at least one embodiment, framework layer **720** may be, but is not limited to, a type of free and open-source software web application framework such as Apache Spark™ (hereinafter "Spark") that may utilize distributed file system **738** for large-scale data processing (e.g., "big data"). In at least one embodiment, job scheduler **732** may include a Spark driver to facilitate scheduling of workloads supported by various layers of data center **700**. In at least one embodiment, configuration manager **734** may be capable of configuring different layers such as software layer **730** and framework layer **720** including Spark and distributed file system **738** for supporting large-scale data processing. In at least one embodiment, resource manager **736** may be capable of managing clustered or grouped computing resources mapped to or allocated for support of distributed file system **738** and job scheduler **732**. In at least one embodiment, clustered or grouped computing resources may include grouped computing resource **714** at data center infrastructure layer **710**. In at least one embodiment, resource manager **736** may coordinate with resource orchestrator **712** to manage these mapped or allocated computing resources.

[0076] In at least one embodiment, software **732** included in software layer **730** may include software used by at least portions of node C.R.s **716(1)**-**716**(N), grouped computing resources **714**, and/or distributed file system **738** of framework layer **720**. one or more types of software may include, but are not limited to, Internet web page search software, e-mail virus scan software, database software, and streaming video content software.

[0077] In at least one embodiment, application(s) **742** included in application layer **740** may include one or more types of applications used by at least portions of node C.R.s **716(1)**-**716**(N), grouped computing resources **714**, and/or distributed file system **738** of framework layer **720**. one or more types of applications may include, but are not limited to, any number of a genomics application, a cognitive compute, and a machine learning application, including training or inferencing software, machine learning framework software (e.g., PyTorch, TensorFlow, Caffe, etc.) or other machine learning applications used in conjunction with one or more embodiments.

[0078] In at least one embodiment, any of configuration manager **734**, resource manager **736**, and resource orchestrator **712** may implement any number and type of self-modifying actions based on any amount and type of data acquired in any technically feasible fashion. In at least one embodiment, self-modifying actions may relieve a data center operator of data center **700** from making possibly bad configuration decisions and possibly avoiding underutilized and/or poor performing portions of a data center.

[0079] In at least one embodiment, data center **700** may include tools, services, software or other resources to train one or more machine learning models or predict or infer information using one or more machine learning models according to one or more embodiments described herein. For example, in at least one embodiment, a machine learning model may be trained by calculating weight parameters according to a neural network architecture using software and computing resources described above with respect to data center **700**. In at least one embodiment, trained machine learning models corresponding to one or more neural networks may be used to infer or predict information using resources described above with respect to data center **700** by using weight parameters calculated through one or more training techniques described herein.

[0080] In at least one embodiment, data center may use CPUs, application-specific integrated circuits (ASICs), GPUs, FPGAs, or other hardware to perform training and/or inferencing using above-described resources. Moreover, one or more software and/or hardware resources described above may be configured as a service to allow users to train or performing inferencing of information, such as image recognition, speech recognition, or other artificial intelligence services.

[0081] Inference and/or training logic **515** are used to perform inferencing and/or training operations associated with one or more embodiments. In at least one embodiment, inference and/or training logic **515** may be used in system FIG. **7** for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0082] As described herein, a method, computer readable medium, and system are disclosed to provide a policy that imitates expert behavior. In accordance with FIGS. **1**-**4**, embodiments may provide a diffusion model and a policy each usable for performing inferencing operations and for providing inferenced data. The diffusion model and/or policy may be stored (partially or wholly) in one or both of data storage **501** and **505** in inference and/or training logic **515** as depicted in FIGS. **5**A and **5**B. Training and deployment of the diffusion model and/or policy may be performed as depicted in FIG. **6** and described herein. Distribution of the diffusion model and/or policy may be performed using one or more servers in a data center **700** as depicted in FIG. **7** and described herein.

What is claimed is:

1. A method, comprising:

at a device, training a policy to imitate expert behaviors included in at least one expert demonstration by:

generating, by the policy, an action for an input state to generate a state-action pair;

processing the state-action pair, using a diffusion model, to generate a reward signal indicating a fitness of the state-action pair to the expert behaviors; and

updating, by the policy, one or more policy parameters based on the reward signal.

2. The method of claim **1**, wherein the policy is a machine learning model.

3. The method of claim **1**, wherein the at least one expert demonstration includes a recording of an expert performing a task.

4. The method of claim **3**, wherein the at least one expert demonstration is represented by expert data that includes a set of data points, wherein each data point in the set of data points consists of expert state-action pairs each including a state and an action taken by the expert in the state.

5. The method of claim **1**, wherein the policy is initialized prior to the training.

6. The method of claim **1**, wherein the reward signal is generated by a diffusion discriminative classifier that includes the diffusion model.

7. The method of claim **6**, wherein the reward signal is generated from a denoised state-action pair output by the diffusion model.

8. The method of claim **7**, wherein the diffusion model forms the denoised state-action pair via a single step of a diffusion process.

9. The method of claim **8**, wherein the reward signal is generated by:

computing a first diffusion loss that measures a fitness of the denoised state-action pair to a distribution of the expert behaviors,

computing a second diffusion loss that measures a fitness of the denoised state-action pair to a distribution of agent behaviors, and

computing the reward signal based on the first diffusion loss and the second diffusion loss.

10. The method of claim **9**, wherein the reward signal is computed within a range bounded by a first value and a second value.

11. The method of claim **10**, wherein the first value is indicative of a fitness to the distribution of the expert behaviors and the second value is indicative of a fitness to the distribution of the agent behaviors.

12. The method of claim **1**, wherein the one or more policy parameters are updated to maximize the reward signal.

13. The method of claim **1**, further comprising:

at the device, training the diffusion model.

14. The method of claim **13**, wherein the diffusion model is trained on:

expert data that includes a set of expert data points, wherein each expert data point in the set of expert data points consists of expert state-action pairs each including a state and an action taken by an expert in the state, and

agent data that includes a set of agent data points, wherein each agent data point in the set of agent data points consists of agent state-action pairs each including a state and an action taken by an agent in the state.

15. The method of claim **14**, wherein the diffusion model is trained to distinguish the expert data from the agent data.

16. The method of claim **15**, wherein for each input expert state-action pair, the diffusion model generates a denoised expert state-action pair and:

a first diffusion loss is computed that measures a fitness of the denoised expert state-action pair to a distribution of the expert data,

a second diffusion loss is computed that measures a fitness of the denoised expert state-action pair to a distribution of the agent data, and

the first diffusion loss and the second diffusion loss are integrated to compute a value of the expert state-action pair within a range bounded by a first value and a second value,

wherein the first value is indicative of a fitness to the distribution of the expert data and the second value is indicative of a fitness to the distribution of the agent data.

17. The method of claim **16**, wherein for each input agent state-action pair, the diffusion model generates a denoised agent state-action pair and:

a third diffusion loss is computed that measures a fitness of the denoised agent state-action pair to a distribution of the agent data,

a fourth diffusion loss is computed that measures a fitness of the denoised agent state-action pair to a distribution of the agent data, and

the third diffusion loss and the fourth diffusion loss are integrated to compute a value of the agent state-action pair within the range bounded by the first value and the second value.

18. The method of claim **17**, wherein:

additionally for each input expert state-action pair:

an expert binary cross-entropy loss is computed from the value of the expert state-action pair, and

parameters of the diffusion model are updated based on the expert binary cross-entropy loss; and

additionally for each input agent state-action pair:

an agent binary cross-entropy loss is computed from the value of the agent state-action pair, and

the parameters of the diffusion model are updated based on the agent binary cross-entropy loss.

19. The method of claim **1**, wherein the policy is trained for a single task.

20. The method of claim **1**, wherein the policy is trained for a plurality of different tasks.

21. The method of claim **1**, wherein the policy is trained for at least one robotics task.

22. The method of claim **1**, wherein the policy is trained for at least one autonomous driving task.

23. The method of claim **1**, further comprising, at the device:

deploying the trained policy for use by a downstream application to generate actions for given states.

24. The method of claim **23**, wherein the downstream application includes a robotics application.

25. The method of claim **23**, wherein the downstream application includes an autonomous driving application.

26. A system, comprising:

a non-transitory memory storage comprising instructions; and

one or more processors in communication with the memory, wherein the one or more processors execute the instructions to train a policy to imitate expert behaviors included in at least one expert demonstration by:

generating, by the policy, an action for an input state to generate a state-action pair;

processing the state-action pair, using a diffusion model, to generate a reward signal indicating a fitness of the state-action pair to the expert behaviors; and

updating, by the policy, one or more policy parameters based on the reward signal.

27. The system of claim **26**, wherein the policy is a machine learning model.

28. The system of claim **26**, wherein the at least one expert demonstration includes a recording of an expert performing a task.

29. The system of claim **26**, wherein the policy is initialized prior to the training.

30. The system of claim **26**, wherein the reward signal is generated by a diffusion discriminative classifier that includes the diffusion model.

31. The system of claim **30**, wherein the reward signal is generated from a denoised state-action pair output by the diffusion model.

32. The system of claim **31**, wherein the diffusion model forms the denoised state-action pair via a single step of a diffusion process.

33. The system of claim **26**, wherein the policy is trained for at least one of:

at least one robotics task, or

at least one autonomous driving task.

34. A non-transitory computer-readable media storing computer instructions which when executed by one or more processors of a device cause the device to train a policy to imitate expert behaviors included in at least one expert demonstration by:

generating, by the policy, an action for an input state to generate a state-action pair;

processing the state-action pair, using a diffusion model, to generate a reward signal indicating a fitness of the state-action pair to the expert behaviors; and updating, by the policy, one or more policy parameters based on the reward signal.

35. The non-transitory computer-readable media of claim **34**, wherein the reward signal is generated by a diffusion discriminative classifier that includes the diffusion model.

36. The non-transitory computer-readable media of claim **35**, wherein the reward signal is generated from a denoised state-action pair output by the diffusion model.

37. The non-transitory computer-readable media of claim **36**, wherein the diffusion model forms the denoised state-action pair via a single step of a diffusion process.

38. The non-transitory computer-readable media of claim **34**, wherein the policy is trained for at least one of:

at least one robotics task, or

at least one autonomous driving task.

* * * * *