Zero-shot generalization using cascaded system-representations

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Abstract

This paper proposes a new framework named CASNET to learn control policies that generalize over similar robot types with different morphologies. The proposed framework leverages the structural similarities in robots to learn general-purpose system-representations. These representations can then be used with the choice of learning algorithms to learn policies that generalize over different robots. The learned policies can be used to design general-purpose robot-controllers that are applicable to a wide variety of robots. We demonstrate the effectiveness of the proposed framework by learning control policies for two separate domains: planer manipulation and legged locomotion. The policy learned for planer manipulation is capable of controlling planer manipulators with varying degrees of freedom and link-lengths. For legged locomotion, the learned policy generalizes over different morphologies of the crawling robots. These policies perform on-par with the expert policies trained for individual robot models and achieves zero-shot generalization on models unseen during training, establishing that the final performance of the general policy is bottlenecked by the learning algorithm rather than the proposed framework.

1 Introduction

Deep neural networks (DNNs) provide a convenient way for an abstract representation of data for gradient-based learning. Deep reinforcement learning (DRL) combines DNNs with reinforcement learning (RL) algorithms to solve complex tasks in a variety of domains. It has gained unprecedented success in areas of robotics, finance, video-games, health-care, etc. in recent years. These advances are made possible by hardware advances, specifically in GPU technology and the development of better learning algorithms. However, widespread adaptation of DRL in the real-world still presents a few challenges. First, DRL is well-known for its sample inefficiency. Off-policy learning algorithms mitigate this problem by reusing the past experience. But even the current state of the art algorithms of this kind frequently needs millions of interaction steps to learn viable policies in rich and complex environments. Second, DRL methods are brittle with respect to their hyperparameters. Exploration constants, learning rates, number of gradient steps, algorithm-specific constants, etc., have a profound effect on the convergence and final performance of the learned policy. Optimal values of hyperparameters vary from task to task and often require manual-tuning via trials and experiments. Finally, as hyperparameters are task-dependent, systems developed using DRL have very narrow applicability. Agents trained for one task cannot be successfully applied to other similar tasks. For example, locomotion controllers trained for one robot cannot be utilized for others with analogous morphologies without additional tuning. The narrow nature of the current DRL is a result of several factors. Very large state and action spaces, a huge number of policy parameters, and extensive hyperparameter tuning required make it difficult to train generalizable policies. The recent trend of end-to-end training of policies also inhibits
the training algorithm to learn a generalizable representation of environment or system model which can be reused for other similar tasks. Moreover, to achieve zero-shot generalization to similar tasks, the agent needs to be trained and tested on several tasks either simultaneously or sequentially, which further increases the already huge computation overhead of learning tasks in rich and complex environments.

Like biological organisms, a truly intelligent agent needs to be able to take advantage of its past experience to perform and/or learn new tasks. For that, the agent needs to organize the learned skill and information in an easy to retrieve and generalizable form. In this work, we address the narrow applicability of DRL by introducing a framework named CASNET, capable of training intelligent agents such that they easily generalize and scale to new situations. The framework leverages the similarities of robot morphologies to learn abstract representation of robot models using a conglomerate of recurrent neural networks. These representations can then be used with the choice of "off-the-shelf" learning algorithms to learn task specific policies. We evaluate the framework by using it to learn generalizable control policies for planer manipulation and legged locomotion of crawling robots. This work shows that for state of the art on and off-policy learning algorithms, the learned policies achieves the same performance level as that of the expert policies trained for individual robot models, establishing that their performance is bottlenecked by the learning algorithms instead of the proposed framework. They also achieves zero-shot generalization to robot morphologies unseen during the training.

Key contributions of this paper are summarized below:

1. We propose a new framework using which generalizable control policies can be learned. These policies can also be scaled to new variation using minimal retraining, thereby paving the path towards general purpose robot controllers.

2. The proposed framework is evaluated by learning general control policy for planer manipulation and legged locomotion using 15+ and 50+ morphologically different robot models respectively.

3. By evaluating the general policy performance against expert policies trained for specific robot model using off and on-policy learning algorithms, we establish that its performance is bound by the learning algorithm rather than the framework itself.

The rest of the paper is structured as follows: In section 2 we present a brief literature review of the current methods challenging the narrow applicability of DRL. Section 3 presents our proposed framework. In section 4 and section 5 we use the proposed framework for planer manipulation and legged locomotion of crawling robots respectively. Afterwards, in section 6 we compare our framework to another possible naive approach and present potential future directions of research. We conclude in section 7.

2 Related Works

Skill learning in robotics via reinforcement learning has been a major focus of the robotics community [1], [2], [3], [4], [5]. New off-policy learning methods, [6], [7], [8], policy transfer and distillation [9], [10], [11] have been explored to reduce the burden of collecting huge amounts of training data. More recent efforts deals with learning multiple-tasks using a single agent by taking advantage of the task structure, neural architecture or learning method. In this direction, [14] tackles multi-task reinforcement learning by using sketches to annotate the tasks with sequence of sub-tasks. These sub-tasks are solved using modular sub-policies. They jointly trained these sub-policies to concurrently maximize performance of all the task related sub-policies. Their modular method achieves high success rate in new zero-shot and adaptation tasks where the agent learns to form a suitable sketch itself. Another approach to multi-task learning [15] in which the multiple-agents coordinates to maximize their performance in related tasks without explicit task knowledge, i.e., partial observability. Other notable approaches include [16] in which agents learns to execute a sequence of instructions to solve tasks and [20] which is a combination of an off-policy correction method named V-trace and a scalable architecture for solve a large collection of tasks.
A considerable number of other prior works have also tackled zero-shot generalization using their own methods [17], [18], [19]. However, our work takes a different direction from previous approaches by learning a single task in different settings (i.e. for different robot models) instead of learning separate tasks using a single “actor”. Zero-shot generalization achieved by previous methods constitutes the actor immediately working-out new tasks but in our approach, the agent can perform the same task but with new robot models. This work primarily focus towards development of general purpose controllers. Our prior work [12] also works towards the same goal but instead focuses on selection and execution sequence of gaits rather than control. This work is most closely related to [13] which decomposes the policies into task and robot-specific modules. These modules are trained in a mix and match fashion for both visual and non-visual tasks. This method achieves zero-shot generalization to novel task and robot modules combinations not encountered during training. Our work can be approximated as an extension of [13] with all the robot modules merged into a single high-capacity function approximator.

3 Casnet

In this section, we present the proposed framework shown in Fig 1 and name it Cascaded model network (CASNET). The main idea behind the framework is that closely related systems are composed of similar elementary units assembled in specific spatial configurations. This spatial configuration of elementary units determine the systems individuality and thus its behavior. For example, manipulators are made up of varying number of actuator-link pairs attached in a particular sequence. Similarly, crawling robots are composed of various number of legs attached at specific locations on the main body. These legs in-turn are made of actuators-link pairs which forms the elementary units of crawling robots (for unactuated main body/torso of the robot). Behavior of such composite systems is determined by the spacial assemblage of their elementary units.

![Figure 1: The CASNET Framework](image)

Figure 1: The CASNET Framework: The input is received by first encoder and passed through a cascade of $N$ encoders, each of which receives encoder specific information apart from the first. The system representation learned by the $N^{th}$ encoder is passed through a multi-layered perceptron and decoded using another cascade of decoders to generate action values. Each decoder also takes as input the hidden embeddings produced by the corresponding encoders to receive spatial information about the encoded sub-systems or elementary units.

Starting from the most elementary units, CASNET uses recurrent neural networks (RNNs) to encode spatial assemblage of elementary units to form fixed-sized abstract representations of higher level sub-system. Input to the first encoder is the sequences of observations for the elementary units forming the next higher sub-system. The produced representations are then used by another RNN encoder to form representation of even higher-level, and the process is continued until a representation of the complete system is achieved.
The resulting final representation is then used to learn the required policy by passing through a suitably sized feed-forward network. Output of this network is decoded in reverse order of that of the encoders using the corresponding encoder “memory” to generate sub-system’s specific decodings. This process is continued to finally obtain action values corresponding to the elementary units. Use of recurrent neural networks to encode information makes the agent trained using the framework easily re-scalable to new robot models with greater number of sub-systems or elementary units. It can be reasonably retrained using new robot-models without losing performance for older robot models. The working of CASNET is explained using Algorithm 1. The hidden embeddings fed to decoders not only provide the required spatial information for sub-system specific decodings but also help in producing the required number of sub-system decodings. For example, consider a 4 legged robot with 2 degrees of freedom (DOFs) per leg. The number of hidden-embedding produced by first encoder per leg will be equal to the DOFs per leg. Similarly the number of embeddings produced by the second encoder will be equal to the number of legs, i.e., 4. By combining the output of the perceptron with these 4 embeddings, the first decoder will produce 4 embeddings or outputs. These in-turn will be combined with corresponding hidden embeddings of the first encoder and fed to the second decoder, which will then produce 8 single-dimension outputs, corresponding to the total DOFs of the robot.

Algorithm 1 CASNET

```plaintext
function Merge(a,b)
    merged ← Combine a and b along singleton dimensions
    return merged
end function

function Concatenate(a,b)
    concatenated ← Merge sequences in a and b
    return concatenated
end function

Input[1] ← Sequences of elementary units observations
for i in range[1, Number of encoders N] do
    Output[i] , hiddenStates[i] ← encoder_i(input[i])
    Input[i+1] ← concatenate(output[i] , specificInput[i+1])
end for

MLP_input ← merge(Output_N , Task information)
MLP_output ← MLP(MLP_input)

for i in range[1, N] do
    if i = 1 then
        Input[1] ← concatenate(hiddenStates[1] , MLP_output)
    else
        Input[i] ← concatenate(hiddenStates[i] , Output[i-1])
    end if
    Output[i] ← decoder_i(Input[i])
end for

Final output ← Output_N
```

To ensure that the learning process is not dominated by a single robot model, it is imperative to regularize the rewards or loss function of every robot model. The loss function used to train the CASNET agent is:

\[ L_{casnet} = \sum_{i=1}^{n} L_i \] (1)

Where \( L_i \) is the loss function for the \( i^{th} \) robot model. Summation of loss functions of different models ensures that the agent does not overfit to a single robot model.


4 Planer Manipulation

In this section, we use CASNET to learn a general control policy capable of controlling a number of different planer manipulators.

4.1 Training environments

To train a general policy capable of handling several model variations, it needs to be exposed to these variations during training. For planer manipulators, we fixed these variation to different number of actuator-link pairs and link lengths. OpenAI’s gym [21] with Mujoco physics engine [22] was used to create the training environments. 18 unique environments were created which are described in Table 1 and some of them are shown in Fig. 2. The objective for each environment is to reach a goal position randomly located within the manipulator’s reach. The episode starts with the manipulator at a fixed starting position and goal position randomly selected. An episode lasts for 100 time-steps.

![Select examples of custom Reacher environments. The pink dot shows the current location of the randomly places goal position and the green dot is the manipulator finger.](image)

At every time-step, the reward is the negative sum of distance between manipulator finger and average torque per actuator. Average torque regularizes torque penalty for manipulators with different number of actuator-link pairs. Every actuator has same torque limits with the control range of of -1 to +1 inclusive. The observation space for an actuator-link pair consist of joint position, joint velocity and link length. Action space consist of the control values for actuator. The input to the CASNET agent is the sequence of actuator-link observations starting from the first pair which is fixed on one side.

We segregate these environments into two sets, training and testing. As their name suggests, the training set is used to train the general control policy using CASNET while the testing set is used to evaluate the generalization capability of the learned policy. Environment which are part of the training set are marked with * in Table 1.
4.2 On-policy learning using Proximal Policy Optimization

To learn generalizable policies for planer manipulation using CASNET, we use an on-policy learning method called Proximal policy optimization (PPO) [23] with generalized advantage estimation [24]. On-policy learning algorithms result in more stable learning compared to off-policy methods as the policy being optimized is also used to collect the training data. However, this results in poor sample efficiency as past data cannot be reused to improve the policy. PPO is a policy gradient method which alternates between sampling policy and performing optimization using the sample data. To limit drastic policy change per optimization step, it uses a clipped objective function of the form:

\[
L(\theta) = \hat{E}_t(\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}_t))
\]

(2)

where,

\[
r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}
\]

(3)

Here, \(\pi_\theta\) is the stochastic policy parameterized by \(\theta\) and \(\epsilon\) is a hyperparameter whose value is usually set as 0.2. \(\hat{E}_t\), \(\hat{A}_t\) are expectation and advantage estimate respectively.

Table 1: Reacher environments

| Sr. No. | Name     | Number of links (DOFs) | Link Lengths       |
|---------|----------|------------------------|--------------------|
| 1       | Reacher_10* | 1                      | 0.1                |
| 2       | Reacher_11  | 1                      | 0.15               |
| 3       | Reacher_12  | 2                      | 0.09               |
| 4       | Reacher_20* | 2                      | 0.12, 0.12         |
| 5       | Reacher_21  | 3                      | 0.09, 0.14         |
| 6       | Reacher_22  | 3                      | 0.13, 0.15         |
| 7       | Reacher_30* | 3                      | 0.15, 0.17, 0.09   |
| 8       | Reacher_31  | 3                      | 0.08, 0.11, 0.12   |
| 9       | Reacher_32  | 4                      | 0.1, 0.1, 0.15     |
| 10      | Reacher_40* | 4                      | 0.1, 0.16, 0.13, 0.09 |
| 11      | Reacher_41  | 4                      | 0.13, 0.14, 0.07, 0.07 |
| 12      | Reacher_42  | 4                      | 0.8, 0.15, 0.09, 0.11 |
| 13      | Reacher_50* | 5                      | 0.1, 0.1, 0.1, 0.1, 0.1 |
| 14      | Reacher_51  | 5                      | 0.15, 0.08, 0.09, 0.11, 0.13 |
| 15      | Reacher_52  | 6                      | 0.1, 0.09, 0.12, 0.1, 0.14 |
| 16      | Reacher_60  | 6                      | 0.1, 0.08, 0.15, 0.15, 0.1, 0.09 |
| 17      | Reacher_61  | 6                      | 0.08, 0.09, 0.07, 0.13, 0.14, 0.07 |
| 18      | Reacher_62  | 6                      | 0.1, 0.12, 0.08, 0.13, 0.07, 0.14 |

PPO is much simpler to implement when compared to other popular on-policy learning methods such as ACER [7] and TRPO [25]. Performance wise, PPO performs better than TRPO and on par with the performance of ACER in continuous control domains.

The CASNET agent is created using vanilla RNN encoders and decoders. The encoders output 32 dimensional embeddings. The perceptron has 2 layers with second layer having 64 neurons. The decoder produce single dimensional output corresponding to the control value of the actuators. The learning curves for general policy trained for these manipulator models using CASNET and PPO are shown in Fig. 3a. For comparison, expert policies for each of these robot models are also trained individually using fully-connected neural networks and PPO with same hyperparameters values.(Fig. 3b).

The performance of the general policy on testing environments is summarized in Fig. 4. The baseline for comparison is obtained by evaluating a couple of randomly initialized policies which represents 0 percent.
100 percent represents the performance of the corresponding expert policy. As can be seen from the figure, the general policy can achieve or even surpass the performance of expert policies on robot models which are unseen during the training phase.

(a) General policy using CASNET and PPO

(b) Expert policies using PPO

Figure 3: General and expert policies learned for Reacher environments. Please note, all expert policies are learned separately but are shown together in Fig. 3b for facilitating comparison with the general policy shown in Fig. 3a.

Figure 4: Performance of the general policy on test environment for planer manipulation task

5 Legged locomotion

From Fig. 3 and 4, it can be inferred that CASNET can be used to learn policies which perform at the same level as expert policies in planer manipulation. However, Reacher environments are relatively simple with very small number of possible variations. In this section, we use the CASNET framework to learn general control policy for common types of crawling robots, which can have considerably more degrees of freedom (DOF) and variations.

5.1 Training environments

As possible variations in legged robots can be unreasonably large, we fix these alterations to robots morphology along a few discrete degrees of variations (DOVs). These include the number of legs (4/6), DOFs per leg (2/3), leg link lengths, operational joint ranges, and arbitrary leg attach locations with respect to the center of mass (COM) of the robot. These DOVs are selected as they represent the most common variations in real-world practice. Similar to planer manipulation, 56 new environments are created to train and test the general control policy and are summarized in Table 2. Each environment has the same task objective but different robot model. These robot models either have a morphology of a standard and popular crawling
robot type (Hexapod / Quadrupled) or have one or more design altercations along the chosen DOVs. Some of these robot models are shown in Fig. 5. In each environment, the tasks for the robot is to walk in a random goal direction selected at the start of each new episode. This task is chosen because of its general applicability, as it can be combined with higher level controllers to achieve higher order goals. For example, go to a target location or navigation in cluttered environments.

![Image of robot models](a) Quadrupled_10  (b) Quadrupled_20  (c) Quadrupled_23  (d) Quadrupled_42  (e) Quadrupled_53  

![Image of robot models](f) Hexapod_10  (g) Hexapod_13  (h) Hexapod_20  (i) Hexapod_42  (j) Hexapod_54

Figure 5: Select examples of custom robot models used in their initial state

In the real-world, data available to the robot controller is data from robot encoders and robot’s morphology. So, observation space of each custom robot model is engineered to only have this data to train the general policy. The observation space consists of leg attachment location with respect to COM of the robot, link lengths, joint ranges, actuator’s axis of rotation and current joint angles. All actuators have a standard control range of $-1$ to $+1$ inclusive. The action space contains the actuator’s control values.

To achieve generalization over unseen robot models, it is imperative to standardize each robot model. For all actuators, a positive actuation causes the corresponding link movement in either forward (y-axis of the robot) or downward (-z-axis of the robot) direction depending upon the axis of rotation of the actuator. Legs are numbered clockwise with respect to the robot’s z-axis. In a leg, the links and actuators are numbered starting outwards from the robot’s main body. Leg or link numbers determine the sequence in which their observations and representations are fed in encoders and decoders. The reward is the sum of movement reward, survival reward and negative torque per actuator. Movement reward is the velocity in the goal direction, i.e. advancement in the goal direction is rewarded and movements in the opposite direction are penalized. Survival reward is $+1$ for each time-step it survives and $0$ otherwise. Survival mask is false if the robot’s COM is either too close or too far from the surface. If the survival mask is false, the environment is reset. Each episode is of the fixed length of 1024 time-steps.

### 5.2 On-policy learning using PPO

To train a policy that generalizes over the created training environments, we use the CASNET framework with 2 pairs of encoders and decoders as shown in Fig. 6. First, the leg-encoder forms a representation of legs from joint positions, joint velocities and link-lengths. Second, robot-encoder forms the complete representation of the robot using leg-representations formed by leg-encoder and respective leg-attach-locations with respect to COM. The hidden embeddings produced by leg-encoder and robot-encoder captures the information about actuator-link pairs and legs respectively. The robot representation and goal information are fed to a 2 layer fully connected network (FCN). The output of this network is decoded sequentially using leg-decoder and action-decoder. Leg-decoder combines FCN’s output and hidden embeddings produced by robot-encoder to form leg-specific decodings. These decoding, combined with hidden representations from
The leg-encoder are used as input for action-decoder. Action-decoder outputs control values for actuators. The output of the FCN is also fed into a single layer value network which outputs single-dimensional state value.

Figure 6: CASNET based neural network architecture for training with PPO. Network shares parameters between actor and critic.

The learning performance for the training environments using PPO and CASNET is shown in Fig. 7 and expert policies learned using PPO on the same environments are shown in Fig. 8. From these figures, it is clear that the general policy achieves the same level of performance as that of expert policies of corresponding training environments. The performance of the general policy on test environments is shown in Fig. 9. The baseline for comparison is obtained from evaluating a couple of randomly initialized policies representing 0 percent. The performance of corresponding expert policies represents 100 percent. The general policy provides performance competitive to corresponding expert policies on all test environments. Often, the performance of the general policy is better than that of expert policies.

The environments trained and tested using CASNET have one or more alterations along a single selected DOV. However, it is possible to have a robot which simultaneously has multiple alterations along multiple DOVs. To test the performance of the general policy on such robots, we have created environments named Hexapod_5Xs and Quadrupled_5Xs. These environments are summarized in Table 3. Even for these environments, the general policy trained only using the selected training environments performs either competitively or better than expert policies as shown in Fig. 10.

5.3 Off-policy learning using Soft Actor Critic

In this section, we test CASNET’s performance for learning general control policy for legged locomotion using the current state of the art off-policy learning algorithm, Soft Actor-Critic (SAC) [8]. Being an off-policy method, SAC can utilize the data collected in past environment interactions to improve the current policy and is thus more sample efficient than PPO. SAC trains a policy that maximizes a trade-off between expected rewards and entropy (exploitation vs exploration). The objective function for SAC is as:

$$j(\pi) = \sum_{t=0}^{T} E_{(s_t,a_t) \sim p_d}[r(s_t,a_t) + \alpha H(\pi(\cdot|s_t))]$$

(4)

Here, \(H\) stands for entropy and \(\alpha\) is the trade-off coefficient. \(\alpha > 0\) and for infinite horizon settings \(T = \infty\). \(E, s, a, t, p\) and \(r\) have their usual meanings. SAC uses 5 function approximates, a policy network \(\pi\), a state value network \(V\), a target value network \(V_t\) and 2 Q-functions \(Q_1, Q_2\).

The Q functions are learned by using \(V_t\) to form Bellman backups. The loss function used is:

$$L = E_{(s,a,r,s',d) \sim D} \left[ (Q(s,a) - (r + \gamma V_t(s'))) \right]$$

(5)
Table 2: Details of custom robot model. * marked models are part of train set.

| Sr. No. | Robot type | Prefix | Leg symmetry | DOF / leg | Design Altercation |
|---------|------------|--------|--------------|-----------|--------------------|
| 1.      | Quadrupled | 10*    | Radial       | 2         | None               |
| 2.      | Quadrupled | 11*    | Radial       | 3         | 3 DOF (and 3 links) in leg 1 & 2 |
| 3.      | Quadrupled | 12     | Radial       | 2         | 2 DOF (and 2 links) in leg 4 |
| 4.      | Quadrupled | 13*    | Radial       | 3         | None               |
| 5.      | Quadrupled | 14*    | Radial       | 2         | None               |
| 6.      | Quadrupled | 20*    | Line         | 3         | 2 DOF (and 2 links) in leg 2 & 4 |
| 7.      | Hexapods   | 21     | Radial       | 3         | None               |
| 8.      | Hexapods   | 22     | Radial       | 2         | 3 DOF (and 3 links) in leg 1 |
| 9.      | Hexapods   | 23*    | Radial       | 3         | 3 DOF (and 3 links) in leg 2 |
| 10.     | Hexapods   | 24     | Radial       | 3         | 3 DOF (and 3 links) in leg 3 |
| 11.     | Hexapods   | 25*    | Radial       | 2         | 3 DOF (and 3 links) in leg 4 |
| 12.     | Hexapods   | 26*    | Radial       | 3         | None               |
| 13.     | Hexapods   | 31*    | Line         | 2         | Altered Hip1, Ankle1, Ankle4 angular limits |
| 14.     | Hexapods   | 32*    | Line         | 3         | Altered Hip3, Hip4, Ankle2, angular limits |
| 15.     | Hexapods   | 33     | Line         | 2         | Altered Hip1, Hip2, Hip3 angular limits |
| 16.     | Hexapods   | 34*    | Line         | 2         | Altered Hip3, Hip4, Ankle4 angular limits |
| 17.     | Hexapods   | 35     | Line         | 2         | Altered Hip2, Ankle1, Ankle2 angular limits |
| 18.     | Hexapods   | 41*    | Line         | 2         | Altered Hip1, Ankle3, Ankle4 lengths |
| 19.     | Hexapods   | 42     | Line         | 3         | Altered Hip2, Hip3, Ankle3 lengths |
| 20.     | Hexapods   | 43     | Line         | 2         | Altered Hip1, Hip4, Ankle2 lengths |
| 21.     | Hexapods   | 44*    | Line         | 3         | Altered Hip4, Ankle1, Ankle4 lengths |
| 22.     | Hexapods   | 45*    | Line         | 2         | Altered Hip2, Hip3, Ankle1 lengths |
| 23.     | Hexapods   | 10*    | Radial       | 3         | None               |
| 24.     | Hexapods   | 11     | Radial       | 2         | 3 DOF (and 3 links) in leg 2 |
| 25.     | Hexapods   | 12*    | Radial       | 3         | 3 DOF (and 3 links) in leg 1 & 3 |
| 26.     | Hexapods   | 13     | Radial       | 2         | 2 DOF (and 2 links) in leg 2, 4 & 6 |
| 27.     | Hexapods   | 14*    | Radial       | 3         | 2 DOF (and 2 links) in leg 3 & 5 |
| 28.     | Hexapods   | 15     | Radial       | 2         | 2 DOF (and 2 links) in leg 5 |
| 29.     | Hexapods   | 16*    | Radial       | 3         | None               |
| 30.     | Hexapods   | 20*    | Line         | 2         | Altered Hip1, Hip6, Ankle2 angular limits |
| 31.     | Hexapods   | 21*    | Line         | 3         | Altered Hip3, Hip6, Ankle4, angular limits |
| 32.     | Hexapods   | 22     | Line         | 2         | Altered Hip3, Hip4, Ankle5, angular limits |
| 33.     | Hexapods   | 23     | Line         | 3         | Altered Hip2, Hip5, Ankle6 angular limits |
| 34.     | Hexapods   | 24     | Line         | 2         | Altered Hip3, Ankle2, Ankle4 angular limits |
| 35.     | Hexapods   | 25*    | Line         | 2         | Altered Hip1, Hip2, Hip6 lengths |
| 36.     | Hexapods   | 26     | Line         | 3         | Altered Hip6, Ankle3, Ankle5, lengths |
| 37.     | Hexapods   | 31     | Radial       | 2         | Altered Hip5, Ankle2, Ankle5 lengths |
| 38.     | Hexapods   | 32*    | Radial       | 3         | Altered Hip3, Hip4, Ankle4 lengths |
| 39.     | Hexapods   | 33*    | Radial       | 3         | Altered Hip5, Ankle1, Ankle6 lengths |
| 40.     | Hexapods   | 34*    | Radial       | 2         | Altered Hip1, Ankle2, Ankle5 lengths |
Figure 7: Environments trained together using PPO and CASNET

Figure 8: Environments trained independently using PPO. Note that environments in the same plot are not trained together but are shown together for better comparison with Fig. 7.

Figure 9: Performance of the general policy trained using PPO on test environment for legged robot controller task
Table 3: Details of custom robot model. * marked models are part of train set.

| Sr. No. | Robot type | Prefix | Leg symmetry | DOF / leg | Design Altercation |
|---------|------------|--------|--------------|-----------|--------------------|
| 1.      | Quadrupled | 51     | Radial       | 2         | Leg 1 attach location |
|         |            |        |              |           | Length of Ankle1 |
|         |            |        |              |           | Range of Hip3 and Ankle4 |
| 2.      | Line       | 52     |              | 2         | 3DOF in Leg3 |
|         |            |        |              |           | Length of extra link in Leg3 |
|         |            |        |              |           | Range of Ankle1 and Hip2 |
| 3.      | Quadrupled | 53     |              | 3         | Length of extra link of Leg3 |
|         |            |        |              |           | Leg3, Leg4 attach locations |
|         |            |        |              |           | Range of extra joint in Leg2 |
| 4.      |            | 54     |              | 3         | Leg3 attach location |
|         |            |        |              |           | Length of extra link in Leg1 |
|         |            |        |              |           | Range of ankle 2 joint |
| 5.      | Radial     | 55     |              | 3         | 2 DOF in Leg1 and Leg3 |
|         |            |        |              |           | Length of extra link in Leg4 |
|         |            |        |              |           | Range of Ankle1, Hip2 and extra joint of Leg4 |
| 6.      |            | 51     |              | 2         | 3DOF in Leg2 and Leg6 |
|         |            |        |              |           | Length of Ankle2 Hip4 |
|         |            |        |              |           | Range of Hip1 extra link of Leg6 |
| 7.      | Hexapod    | 52     |              | 2         | 3DOF in Leg2 |
|         |            |        |              |           | Length of extra link in Leg2 |
|         |            |        |              |           | Range of Ankle5 |
| 8.      |            | 53     |              | 3         | Length of extra link in Leg2 |
|         |            |        |              |           | Leg 5 attach location |
|         |            |        |              |           | Range of Hip1, Ankle1 |
| 9.      |            | 54     | Line         | 3         | 2DOF in Leg2, Leg4, Leg6 |
|         |            |        |              |           | Length of extra link in Leg3 |
|         |            |        |              |           | Leg4 attach location |
| 10.     |            | 55     |              | 3         | 2 DOF in Leg6 |
|         |            |        |              |           | Leg6 attach location |
|         |            |        |              |           | Range of extra joint in Leg2 |

Figure 10: Performance of the general policy on environments with altercations along multiple DOVs. Note that the general policy is only trained on environment with altercations along a single DOV.
In equation 5, $D$ represents the buffer from which experience is sampled. $V_t$ is the target value network whose parameters are the moving average of the value network $V$. Loss for value function uses clipped $Q$ functions, i.e., minimum $Q$ value from $Q_1$ and $Q_2$ for defining the loss function as:

$$L = E_{(s \sim D, (a \sim \pi))} \left[ \left( V(s) - \min_{i=1, 2} Q_i(s, a) - \alpha \log [\pi(a|s)] \right)^2 \right] \tag{6}$$

Here, it should be noted that actions are sample from the current policy and states are sampled from the buffer. Finally, the policy parameters are learned by minimizing the expected KL-divergence of policy and exponential of $Q$ function. But first the policy is reparameterized as:

$$a_t = f(\epsilon_t, s_t) \tag{7}$$

where $\epsilon$ is the noise sampled from a distribution. This reparameterization makes sampling from the policy differentiable for gradient based learning. The objective for learning the policy parameters then becomes:

$$J(\pi) = E_{s_t \sim D, \epsilon_t \sim \mathcal{N}} \left[ \log \pi(f(\epsilon_t, s_t)|s_t) - Q(s_t, f(\epsilon_t, s_t)) \right] \tag{8}$$

Though SAC has a more complex implementation compared to PPO, it also has a much higher sample efficiency and thus faster convergence. But in our experiments, unlike PPO, SAC was unable to learn viable policies even with expert policies and extensive hyperparameter tuning for the training environments with new goal-direction in each new episode. So instead, we tested CASNET’s performance using only a fixed goal direction for each environment and episode. The learning performance using CASNET and expert policies is given in Fig. 11 and Fig. 12 respectively. The structure of the policy network used is identical to that used in PPO. The value and $Q$ networks use similar encoders and FCNs. For $Q$-networks, FCN is also fed with current actions. The output of the FCNs is fed to a single layer which outputs the $Q$ or state value.

Unlike PPO, SAC shows considerable variations in performance across environments and trials. The performance of CASNET for testing environments is compared to expert policies in Fig. 13. For all the testing environments, CASNET achieves a performance of least at 75% of the expert policies and also outperforms them often. Performance of general policy trained using SAC on robot models with alterations along multiple DOVs is shown in Fig. 14.

6 Discussion

For all the experiments presented, we have used vanilla RNNs for encoders and decoders. It has been established that vanilla RNNs are often prone to vanishing and exploding gradients [26] which make GRU and LSTM popular choices for recurrent networks. However, our tests showed no difference in final performance and convergence rate between vanilla RNN and GRU based encoders and decoders. It is, however, possible that when the number of elementary units or the number of sub-systems is especially large, for example in a centipede type robot, then LSTM or GRU based encoders and decoders might provide better performance. But for the types of robot models used in this research, they provided no advantage over vanilla RNNs.

The presented research tackled the problem of learning general-purpose control policies for a plethora of similar robot types using CASNET. Another possible but naive approach to tackle this problem could be to use an ordinary fully connected network. The fully connected network could be sized such its input dimension is equal to the largest observation space possible for the type of robots it being trained for. For robots with smaller observation space, the input to the network can be zero-padded such that it matches the size of
Figure 11: Environments trained together using SAC and CASNET

Figure 12: Environments trained independently using SAC

Figure 13: Performance of the general policy trained using SAC on test environment for legged robot controller task
the largest observation space. Similarly, output dimensions can be decided using the largest action space possible and trimming the output of the network suitably to match the action space of the corresponding robot. However, this naive approach presents a few problems:

1. **Scaling and extending**: To use a fully connected network with input padding and output trimming, it is imperative to train each part of the network. To do so, the training-set used must contain every possible combination of alterations along selected DOVs. For example, considering the case of legged locomotion presented in section [5] to learn generalizable and viable control policy using a fully-connected network, the training set must contain radially symmetrical hexapods. On the other hand, CASNET policy can leverage its experience with radially symmetrical quadrupleds to still perform competitively with expert policies. Also, extending the trained fully connected network to include other types of robot models is not possible without retraining the entire network from scratch. However, CASNET’s policies can be easily extended by selectively retraining the agent with only a few environments as RNNs form a memory to store the previously learned information. This alleviates the need to store all the training robot models if in case retraining for new model types is required. For the planer manipulation task, extending the policy to include 6 DOF manipulators only required 7.5% of the training data required to train the policy from scratch. The performance of the CASNET policy on 6 DOF manipulators is shown in fig. 15a and performance of retrained CASNET policy is shown in fig 15b.

2. **Task modularity**: Fully connected networks do not learn generalizable system representations for reuse. For different tasks that involve the same robot models, different fully-connected models need to be trained from scratch. For intelligent robots to be applicable in the real-world, they need to be able to excel at multiple tasks. Training completely separate networks for separate tasks is inefficient. However, as task and encoder-decoder modules of the CASNET policies are separate, only a new task module needs to be learned. CASNET can thus be seen as a natural extension of the previous work [13] which can not only work for different tasks but also for a variety of different robot models too.

7 Conclusion

We have introduced a new framework named CASNET, using which control policies which generalizes over a variety of similar robots can be learned. The proposed framework is tested on planer manipulation and legged locomotion tasks using state of the art on and off-policy learning algorithms. The on-par performance of the general policy learned using CASNET with expert policies demonstrate that the final performance of the general policy is bound by the learning algorithm instead of the proposed framework. We also compared CASNET with a naive approach of using a fully connected network with zero-padded inputs and output trimming and established why CASNET is superior.
Figure 15: Performance of CASNET policy on 6 DOF manipulators with or without retraining with 6 DOF manipulator

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