Towards Lifelong Self-Supervision: A Deep Learning Direction for Robotics

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Abstract
Despite outstanding success in vision amongst other domains, many of the recent deep learning approaches have evident drawbacks for robots. This manuscript surveys recent work in the literature that pertain to applying deep learning systems to the robotics domain, either as means of estimation or as a tool to resolve motor commands directly from raw percepts. These recent advances are only a piece to the puzzle. We suggest that deep learning as a tool alone is insufficient in building a unified framework to acquire general intelligence. For this reason, we complement our survey with insights from cognitive development and refer to ideas from classical control theory, producing an integrated direction for a lifelong learning architecture.

Keywords
Robotics, Deep Learning, Cognition, Autonomy, Lifelong Learning

1 Introduction
As roboticists and scientists, is our goal to engineer a solution to work for a particular task in a specified domain or is it to build a system that has the capacity to acquire general intelligence (a notion characterized by Legg and Hutter (2007))? An historic example is that success in aviation, with autonomous aerial navigation does not immediately imply success in a task like autonomous driving, which shares some similarities. Or assume that we solve autonomous driving tomorrow—likely an engineering effort like changing our highways, roads, and infrastructure with increased sensory Ng and Lin (2016) will not generalize especially well to robotic tasks in mobile manipulation. Should we then add additional sensors to all possible environments (e.g. residential homes) where autonomous systems are likely to operating in? How is it then to operate in novel, unknown, or disastrous environments? Or in space? In fact, it is under inspirations from these disastrous and unstructured domains, that have given rise to recent technological advances with the DARPA Robotics Challenge (e.g. Johnson et al. (2015); Feng et al. (2015a,b); Kohlbrecher et al. (2015); Yi et al. (2015); Kuindersma et al. (2016); Dellin et al. (2016)). This manuscript presents rather a different direction in thinking, where instead of engineering and redesigning systems to perform competently in novel tasks and domains, perhaps a system that can bootstrap its lifetime of experiences can quickly learn useful solutions in these new areas—we refer to the process by which this long-term knowledge repertoire is acquired as lifelong learning.

Lifelong learning should not address only novel domains, but also should consider optimizing behavior at existing tasks. Let’s consider the following hypothetical scenario. An autonomous system (e.g. robot, mobile manipulator, unmanned aerial vehicle (UAV), etc.) returns from a mission or accomplishes some task. We are now out of things to provide it. Likely in many cases, the robot is left somewhere in corner of a laboratory until there are subsequent tasks to accomplish. But what if instead, it uses this downtime as an emergent possibility for continuous progress?—and continue to operate, either refining its inherent representations of the world (which have generally, to this date, been hand-defined by human operators) or optimizing its inherent motion primitives (e.g. tuning internal control parameters that perhaps due to wear and tear are now highly suboptimal). What if it can learn to build complex motor behaviors, that may prove useful in future missions from exploiting existing structure in its primitives?

A misconception is that what we are referring to as lifelong learning does not necessarily imply that the system learns from scratch. It is not an end-to-end approach for motor development or task solving. In other words, it does not necessarily imply learning motor torques directly from raw sensory input. Instead, its underlying purpose is generalization and structural bootstrapping, a term coined by Worgotter et al. (2015), where existing knowledge is exploited for generalization to novel activities. We draw insight from cognitive development to learn complex motor behavior and structural representations by an account of intrinsic and extrinsic properties (e.g. environmental uncertainties) influencing the system in ways beyond engineering analyses. Lifelong learning implies that systems learn over a lifetime of complex tasks and domains, achieving generalized solutions. This form of generalizability for both domain and task is extremely important for designing robust, high-performance systems. Interestingly, a study by Pinto and Gupta (2016) found...
that convolutional networks achieved higher performance grasping when trained on both grasping and pushing tasks when compared to grasping alone, suggesting that inter-task representation sharing helps build a better understanding of the environment overall.

This manuscript provides an initial survey on recent advances in deep learning pertaining to the robotics domain and complements this review with inspirations in cognitive development and control theory outlining that the coalescence of these ideas may pave way for lifelong learning robots. We indicate that deep learning alone is likely incapable of solving all problems in a unified framework. Instead, we discuss a connectionist approach in lifelong self-supervision, drawing ideas from these other areas to tackle the acquisition of general motor intelligence. We formulate a direction by discussing how systems can intrinsically motivate themselves to attack the problem of building accurate representations of structures in the world and the development of complex motor behavior simultaneously. This particular direction incorporates the use of hierarchies of neural networks under the popularized notion of deep learning. We suggest that the use of deep learning as an approximation tool allows robots to encode complex functions that describe physical phenomena concerning interactions with the world and sensory-driven control.

### 1.1 From Computer Vision to Robotics

Deep learning has exhibited major success stories in the computer vision domain. This particular tool, popularized by Krizhevsky et al. (2012) in the ImageNet competition, showed significant promise when learned latent feature representations by a neural network that incorporated a series of convolution, pooling, and densely connected neurons outperformed existing hand crafted feature representations that have otherwise been the standard. The support from computational machinery (GPUs) allowed for efficient parallelization necessary for training neural network structures with massive datasets. Since then, the computer vision community has produced a plethora of deep learning research and have plateaued close to human level capabilities in recognition by building deeper and deeper networks Szegedy et al. (2015), fine tuning, and introducing extra features (e.g. surface normals) Madai-Tahy et al. (2016). However, that is not to say that these powerful, state of the art, demonstrations and their solutions are immediately applicable to mobile perceptual systems. There exists a number of fundamental differences in these two domains that hinder trivial compatibilities. First, the deep learning solutions in computer vision are generally supervised. Supervised learning is very constrained. And in many computer vision tasks, a particular input is associated with a single, correct output.

Yet quite evidently, this is not the case in robotics—robots do more than classification. They must perform actions in the world. They must build representations of things they sense and act on these sensory signals whereas computer vision systems do not necessarily act. Classification helps in identifying the entities in the world, but to accomplish tasks, robots must perform actions and manipulate such entities. The connection between perception and action is essential in building perceptual systems in the real world.

### 1.2 On Overgeneralization

An immediate drawback for these computer vision architectures is that studies have found that image classification has an unfortunate overgeneralization (“fooling”) phenomenon. These classification tasks take as input generally a single sensor modality, in many cases, RGB. Where deep learning tools fail is when adversarial RGB examples are construed in attempts to fool these networks into very incorrect predictions presented in studies by Szegedy et al. (2013); Nguyen et al. (2015); Carlini and Wagner (2016). In these works, hill climbing and gradient ascent methods were used to evolve images to match very incorrect classes with high probability predicted by the network. Although there is work to make these networks robust to such malicious attacks (e.g. Bendale and Boult (2015); Wang et al. (2016a)), we theorize that the addition of multiple modalities (with more than vision alone) may alleviate such intriguing and devastating phenomena, as the real world obeys certain structures that are locally constraining Kurakin et al. (2016). For instance, it is increasingly difficult to fool a predictor that reasons with depth and tactile information with physical adversarial entities. Furthermore, by the universal approximator theorem Hornik et al. (1989), multilayer feedforward networks are capable of representing arbitrarily complex functions, even those that are robust to such adversarial anomalies. It becomes then a formulation problem where models must be trained with an adversarial objective Goodfellow et al. (2014b). Other work elaborates that networks should be also realized with proper regularization Tanay and Griffin (2016). In fact, a particular variant of neural networks that implicitly enforces regularization may be beneficial. For instance, DivNet is an approach that attempts to model neuronal diversity allowing for efficient auto-pruning, in turn reducing network size and providing inherent regularization Mari et al. (2015). Another remedy realized a particular network layer called competitive overcomplete output layer to mitigate this overgeneralization problem of neural networks Kordan and Stanley (2016). Such a layer forces outputs to explicitly compete with each other, resulting in tight-fitting regions around the training data.

### 1.3 On Deep Reinforcement Learning

Impressive success stories has been shown in game domains that integrate perception and action. Namely work by Google DeepMind has pushed this particular frontier and have revolutionized the intersection between deep learning and its connection to reinforcement learning. Mnih et al. (2013, 2015) built a single learning framework that could learn to play a large number of Atari games beyond human level competence through a trial and error approach, where the only information given to the system were several game frames, the game score, and a discrete control set. A neural network was used to approximate the Q values of a discrete set of actions from several game play frames and executed the highest valued action resulting in a competent gameplay policy. The idea of using a neural network as

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1. This particular phenomenon is categorized under open set recognition. Bendale and Boult (2015) proposed a new model layer, OpenMax, that estimates the probability of input from unknown classes and rejects fooling adversarial examples.
an approximation to a value function is not something profound and novel. Dating back two and a half decades ago, Tesauro attempted to tackle the game Backgammon—a board game that had approximately $10^{20}$ states, making traditional table-based reinforcement learning infeasible. Instead, a backpropagation layered neural network was used to approximate the value function describing board positions and probabilities of victory. It was shown in various incarnations of his algorithm where both raw encodings and hand-crafted features derived from human task knowledge were used to learn competent gameplay policies Tesauro (1992, 1995a,b). Furthermore, other researchers in the past have leveraged recurrent neural networks to learn $Q$ values using a history of features to form policies Schmidhuber (1991); Lin and Mitchell (1992); Meeden et al. (1993).

Recently, the defeat of 18-time Go world champion, Lee Sedol, by DeepMind’s AlphaGo system established a major milestone for deep learning frameworks. Their success was not simply attributed to deep reinforcement learning but also clever integration with Monte Carlo tree search Silver et al. (2016)—it is to show that deep learning alone may not be the solution to all problems, but as a tool, deep learning may be used in complement with other algorithms to produce very powerful results.

### 1.4 On Domain Transfer

Unfortunately, a reason why many of these game domains are successful is that the domain is fully observable. Despite there being some studies that inject partial observability and attempt to tackle this problem with augmented memory structure Heess et al. (2015a), the algorithms developed through gameplay should not be considered as game-changing success stories in physical dynamical systems. The real world obies physics and uncertainties that can not be perfectly modeled in simulation, and as a result policies learned in simulation have difficulty generalizing to real robot systems. For instance, despite millions of training steps in over hundreds of hours of simulations, visuomotor policies learned on a Baxter simulator fails when given real world observations on the physical platform Zhang et al. (2015). Interestingly, James and Johns (2016) were able to transfer visuomotor policies learned in simulations to a real system, however, their approach required massaging the scene by occluding complex areas with a physical black box, hiding wires, and mimicking the simulation setting. The introduction of *progressive neural networks* show promise by exploiting deep composition of features amongst columns of domain-specific networks. However, immediate drawbacks are that it assumes known task boundaries and exhibits quadratic parameter growth when a new column is necessary for each novel domain. Despite alleviation to the cause, these networks still need to be trained in the new domain to achieve competence Rusu et al. (2016a). In later works, Rusu et al. (2016b), demonstrated domain transfer using features learning in MuJoCo simulation with a Kinova arm to the physical system—the reaching task they showed, however, was highly constrained in a small region of static space and still require several hours of training in the real world. A generalized method for domain alignment has recently been presented to mitigate performance loss when adapting robot visuomotor representations from synthetic to real environments Tzeng et al. (2015). The technique, however, requires paired synthetic and real views of the same scene to adapt the deep visual representations.

### 1.5 On Self-Supervision

As a result, there is no escaping the fact that robots must collect their own training data in the real world—to tackle this, various approaches by Pinto and Gupta (2015); Levine et al. (2016); Wong et al. (2016) have been proposed for self-supervision. These studies hint at methods in which robots can label their own experiences and collect potentially massive datasets pertaining to a single task. However, they provide no notion of learning beyond the task at hand—conceptually they are incapable of exhibiting lifelong learning. To address this, we suggest a direction in which robots acquire completely unsupervised visuomotor skills derived from a basis of inherent primitives that are reinforced by the world to generate behaviors that adhere to physical properties of the environment. This hierarchical set of motor behaviors should then be coupled with an intrinsically motivated structure learning module to allow continuous affordance and interaction outcome prediction regarding entities in the world—as a result, this produces permanent artifacts that can be reused for future tasks. Furthermore, the intrinsic motivator must both promise the acquisition of continuously refined forward models and the capacity for the development of arbitrarily complex motor behaviors.

This paper is in agreement with Silver et al. (2013) in which they address the machine learning community that we need to seriously consider the nature of systems that have capacity to learn over a lifetime of experiences rather than for some specified task or domain. Conceptually, this direction of thinking is relatable to the notion of *deep developmental learning* primarily proposed by Sigaud and Droniou (2016) in which first sensory motor control must transform raw sensations to a predictive process—we refer to this as a forward affordance model. They also outlined the challenges of integrating behavioral optimization and a curiosity mechanism for deep developmental systems. We suggest to attack these simultaneously through the continuous refinement of motion primitives and the exploitation of their combinatoric sequences and compositions to achieve motor development. To address the latter, we suggest intrinsic motivators driven by information theoretic measures in regards to the forward affordance model’s predictions of world state. Lastly, we quickly address a *certainty debate* dating back two decades between planning and reflexive architectures for the design of robot behavior Brooks (1987a,b). While we agree that hierarchical behavioral responses eliminates the need for planning, we take a stand that is much similar to our ideologies with deep learning—that is, to reiterate, a grandiloquent singular architecture is likely infeasible in many senses. Behavioral responses need not be learned when set rules and instructions are provided (e.g. autonomous missions and manuals where there are precise trajectories through the task)—perhaps this is where we should consider planning for task solving. As such, we firmly believe that there is no single individual or rather, what Rodney Brooks calls *theists*, that is truly correct. Instead, we find that excitement is in building a system that marries
the many 
theisms and relates technologies that are both classical and of recent “hype.” As such, this leads us to a unifying, perhaps even holistic, direction in thinking. To our knowledge, this paper is the first attempt at outlining a lifelong learning direction by integrating deep learning, cognitive development, and classical control theory.

2 Implications for Robotics

In the most simplifying sense, deep learning is an algorithmic tool that leverages neural networks as nonlinear function approximators in which weighted connections between input and output neurons are trained via error back propagation. Doing so, encodes a function that minimizes the disparity between prediction and truth by building latent representations in the hidden layers. The deep learning domain has been quickly exploding since its large success in vision popularized by the outstanding results in the ImageNet competition Krizhevsky et al. (2012), producing a plethora of general reviews on deep neural networks. As a result, we omit the basics of neural networks, convolutions, autoencoding, regularization, recurrency, and related concepts in this manuscript. The reader is referred to the following general reviews Bengio (2009); LeCun et al. (2015); Goodfellow et al. (2016) for a thorough overview. Instead, we will critique a number of deep learning frameworks most applicable to the robotics domains and outline the drawbacks and skepticism that arise with these recent works.

2.1 Detection, Estimation, and Tracking

Tools that have been popularized by the computer vision community has generally been leveraged to tackle individual components in the robotics domain. A number of these individual triumphs used neural networks as a means of approximating otherwise very complex and highly nonlinear functions pertaining to estimation and scene understanding.

For instance, tasks relating to rule-based navigation like autonomous driving in particular may require understanding the identities of objects in the world. Labeling and scene understanding can be regarded as a segmentation problem given visual input. As such, SegNet, a semantic pixel-wise segmentation encoder-decoder network, was presented to achieve competitive predictive capability Badrinarayanan et al. (2015). Other methods also attempted to solve a similar task but were either generating object proposals Noh et al. (2015); Hariparan et al. (2015) or required multi-stage training Socher et al. (2011); Zheng et al. (2015). Still, these segmentation results were shown to be especially robust for detection problems. In particular, Pinheiro et al. (2015) built a system to predict segmentation masks given input patches by using DeepMask, a neural network that generated such proposals. These proposals were then passed to an object classifier, producing state of the art segmentation results. Extensions to this work gave way to a bottom-up/top-down segmentation refinement network that was capable of generating high fidelity object masks with a 50% speedup. The network, SharpMask leveraged features from all layers of the network by first generating a course mask prediction and refining this mask in a top-down fashion Pinheiro et al. (2016).

Studies have shown that pre-trained convolutional neural network features were useful for RGB-D object recognition and pose estimation Schwarz et al. (2015). A consequence of this became a flurry of research regarding using deep architectures for detection and pose estimation. An approach for the detection of pedestrians was shown using an unsupervised multi-stage feature learning approach by Sermanet et al. (2013). Meanwhile, results indicated high accuracy in human pose estimation with DeepPose—likely this is due to deep neural networks capturing context and reasoning in a holistic manner Toshev and Szegedy (2014).

PoseNet, a convolutional neural network camera pose regressor, was presented with impressive robustness to difficult lighting, motion blur, and different camera intrinsics Kendall et al. (2015). This was later extended to a Bayesian model able to provide localization uncertainty Kendall and Cipolla (2015), establishing a critical step forward for mobile robots, especially connecting close ties to algorithms that operate under uncertainty. In work by Wilkinson and Takahashi (2015), a pretrained convolutional network was used to predict object descriptions and aspect definitions pertaining to sensory geometries in relation to objects. Unfortunately, class and object descriptors were selected as arbitrary pretrained AlexNet layers and the overall framework relied on a number of thresholds that are difficult to define.

Others continue to investigate the use of these tools to learn useful features for contexts like laser based odometry estimation Nicolai et al. (2016). In research by Byravan and Fox (2016), deep networks were used to segment rigid bodies in the scene and predict motions of these entities in SE3.

As hyperparametric approximators, these networks have been found success in the tracking regime in which recurrent neural networks were used to filter raw laser measurements and shown to infer object location and identify in both visible and occluded scenes Ondruska and Posner (2016). This technique is described as a neural network analogous to Bayesian filtering. In addition, by learning to track with a large set of unsupervised data, a new task like semantic classification could be learned by exploiting rich internal structure through inductive transfer Ondruska et al. (2016). An approach was presented by Song and Xiao (2015) where 3D bounding boxes of objects were generated through a methodology they call Deep Sliding Shapes. Given Kinect images, they learned a multiscale 3D region proposal network that is fully convolutional and identifies interesting regions in the scene. Then, an object recognition network was learned to perform 3D box regressions.

A sensory-fusion architecture that incorporated the use of LSTMs to capture temporal dependencies has been presented to anticipate and fuse information from multiple sensory modalities. This Fusion RNN was demonstrated as part of a maneuver anticipation pipeline that outperformed state of the art on a benchmark consisting of a dataset of 1180 miles of natural driving Jain et al. (2016). Similarly, Krishnan et al. (2015) developed a deep network capable of approximating a broad class of Kalman filters, enhancing them to arbitrarily complex transition dynamics and emission distributions.

Yet, despite outstanding results in classification, identification and pose estimation, and semantic segmentation, systems that perform actions in the world still require a
connection from detected entities in space to motor commands. In part, these research solutions only attempt to develop robust perceptual interfaces to autonomous systems, but however, a key, perhaps, paramount module is one that reasons over sensations and executes useful motor control. As such, perception alone may not be the answer, but somewhere in the intersection of perception, cognition, and action.

2.2 From Perception to Motor Control

A number of studies looked into introducing the predictive power of neural networks in place of traditional feature extracting perceptual pipelines to solve detection and control problems with physical robot experiments. In particular, in place of hand-designed features like those of Kragic and Christensen (2003); Maitin-Shepard et al. (2010) for grasping, Lenz et al. (2015) presented a deep architecture to learn useful feature representations for grasp detection. A two-step cascaded network system was shown where top detections were re-evaluated by the second network, allowing for quick pruning of unlikely candidate grasps. The network operated on RGB-D input and successfully generalized to execute grasps on both a Baxter and PR2 robot. Likewise, a grasp detection system was demonstrated by Wang et al. (2016b), that mapped RGB-D images to gripper grasping pose by first segmenting the graspable objects from the scene using geometric features (for both objects and gripper). They then applied a convolutional network to the graspable objects which used a structure penalty term to optimize the connections between modalities. Similarly, in work presented by van Hoof et al. (2016), deep autoencoders were used to learn compact latent representations for reinforcement learning to form policies describing tactile skills. These feedback policies were learned directly from high-dimensional space under iterative on-policy exploration and vastly outperformed a baseline policy learned directly from the raw sensor data.

Contrary to these works, instead of predicting the single best grasp pose from a given image, Johns et al. (2016) demonstrated a convolutional network that predicted a score for every possible grasp pose, such a value function described what they denote as a grasp function. They discussed that such a method can attribute to robust grasping by smoothing this grasp function with a function describing pose uncertainty. Although in their demonstrations, it appears this particular approach achieved some-80% grasp success rate, fundamental assumptions are that the object is isolated in the scene and the grasping device is a parallel jaw gripper.

In a different approach, Varley et al. (2016) showed that convolutional networks can be used for shape completion given an observed point cloud. In their method, the network learned to predict a complete mesh model of objects (filling in the occluded regions of the scene), which was then smoothed and used to support grasp planning.

The use of convolutional neural networks as a means for automatic feature extraction has been employed in imitation learning paradigms where actions are learned for an autonomous navigation task directly from raw visual data. The network is encoded with no initial knowledge of the task, targets, or environment in which it is acting in. In a simulated study Hussein et al. (2016) showed that using deep active learning can significantly improved the imitated policy through a small number of samples—this is accomplished by the network querying a teacher for the correct action to take in situations of low confidence. Unfortunately, this framework relies on the fact that there is a teacher present with competent knowledge of the domain and appropriate actions. A framework using time-delay deep neural network was shown by Noda et al. (2013) that both fused multimodal sensory information and learned sensorimotor behaviors simultaneously. They demonstrated that a single network was able to encode six object manipulation behaviors dependent on temporal sequence changes with the environment and displayed object.

Since robots operate in dynamic and partially observable environments, selecting the best action is nontrivial since it is dependent on the time history of interactions (or sequences of actions in the past). As such, ways to learn these optimal policies generally rely on a trial and error paradigm via reinforcement learning. For example, this is especially present in the recent successful demonstrations of Atari gameplay Mnih et al. (2013, 2015). Despite its demonstration through an artificial agent, the Deep Q Networks presented has immediate implications in robot control, however, may not be effective on physical domains especially when rewards are sparse making efficient exploration essential. A method proposed by Lipton et al. (2016) demonstrated exploration by Thompson sampling where using Monte Carlo samples from a Bayes-by-Backprop neural network provided improvement over the standard DQN approach that relied either on c-greedy or Boltzmann exploration.

In a particular study, Finn et al. (2016b) proposed to use neural networks as a tool to learn arbitrarily complex and nonlinear cost functions for inverse optimal control problems allowing systems to learn from demonstration using efficient sample-based approximations. Their methods were demonstrated on simulated tasks as well as on a mobile manipulator. Another study presented a belief-driven active object recognition system that used a pretrained AlexNet first to derive belief state. A Deep Q Network was then incorporated to actively examine objects by selecting actions (in hand manipulations) that minimized overall classification errors, resulting in an efficient policy for recognizing objects with high levels of accuracy Malmir et al. (2016). Instead of training the action selection network over the pretrained convolutional network, this system was later extended to be trainable end-to-end Malmir et al. (2015).

In contrast to the large population of work that uses convolution to extract useful feature representations at the output layer of a neural network and use these features to associate control, Ku et al. (2016) demonstrated a different approach. They showed that using intermediate features of a convolutional network was sufficient for gross and finer grain manipulation supporting palm and finger grasps. The technique localized features corresponding to high activations given point clouds of simple household objects through targeted backpropagation. Using this, they presented a hierarchical controller composing of finger and palm pre-posture positions on the R2 robot, however, alike work by Wilkinson and Takahashi (2015), the specific layer to obtain information from is still human defined.
From Pixel to Motion – Recently, an end-to-end strategy for visuomotor control popularized by Levine et al. (2015) has shown promise for deep learning in robotics. Using optimal control policies as supervised signal for neural networks, they demonstrated task learning relevant to local spatial features obtained through convolution. More importantly, this showed promise for an end-to-end training approach to obtain visuomotor policies producing a network that commanded motor torques directly from the raw visual input. Finn et al. (2015) proposed the use of deep spatial autoencoders to acquire informative feature points that correspond to task-relevant positions. The method learns to associate motions with these points using an efficient locally-linear reinforcement learning method—because the resulting policies are based off of these learned feature points, the robot is capable of dynamically manipulation in a closed-loop manner. Similar approaches to visuomotor control has been demonstrated by Tai and Liu (2016) the learned end-to-end exploration policies on a mobile robot and folks from nVidia for self-driving cars, where an autonomous vehicle was driven by vision alone through an end-to-end system Bojarski et al. (2016). It appears that learning motor control directly from raw sensory signals induces robustness and produces a control solution that is otherwise too complex to hand design. Likely, action outcomes are not deterministic and pose estimation future establishes uncertainties, whereas, these convolutional learning strategies aims to resolve motor commands straight from raw percepts—learning both useful feature representations and control policies simultaneously.

An issue with end-to-end methods and deep reinforcement learning in general is that it demands extremely large sets of data. For such reasons, Guided Policy Search (GPS) Levine et al. (2015) attempts to bias training for the reduction of the number of instances needed and looked to acquire visuomotor policies by the means of a supervised learning problem. A reset-free GPS algorithm was introduced by Montgomery et al. (2016) to address the issue with its requirement for a consistent set of initial states. Meanwhile, Chebotar et al. (2016) later extended GPS to account for highly discontinuous contact dynamics through an path integral optimizer and on-policy sampling to increase the diversity of instances which they argued was crucial for high generalizability.

In the original formulation of GPS, the learning problem is decomposed into a number of stages. First full-state information is used to create locally-linear approximations to the dynamics around nominal trajectories, then optimal control is used to find locally-linear policies along those trajectories. Lastly, it uses supervised learning with an Euclidean loss objective to create complex nonlinear versions of these policies that reproduce similar optimized trajectories. In other words, GPS iteratively optimizes local policies (concerning specific task instances) which are then used to train a global policy that is general across instances. However, to do this, it requires data on the physical system—robots must collect data for training to refine the network originally trained by guided policies in the form of optimal trajectories.

To collect massive sets of data, one may consider having the robot obtain its own experiences without the need of meticulous human labeling or supervision. Addressing the problem of self-supervision, work by Pinto and Gupta (2015) showed that robots can self-supervise themselves to learn visuomotor skills without manual labels. In their experiments, they demonstrated remarkable robustness where a Baxter robot self-labeled 50,000 grasp examples in over 700 hours of manipulation. Under similar inspirations, Levine et al. (2016) used a distributed system consisting of 14 robot manipulators to collect a massive dataset (800,000 grasps) over the course of two months for grasping and eye-hand coordination. However, both of these self-supervised methods considered specifying a heuristic to classify grasp examples. Unfortunately, these heuristics are human-specific and somewhat arbitrary. Wong et al. (2016) developed a comparable self-supervision approach with a key distinction being the use of feedback from closed-loop motion primitives as a supervisory signal rather than these human-specific parameters. Still, a fundamental problem for all of these studies is that they are demonstrated and tailored for a single specific, predefined task. A study by Pinto and Gupta (2016) found that learning over a number of tasks helps discover richer representations of the environment, thus outperforming models that have otherwise been trained on a single task alone. But an open research problem is to consider methods by which robots can motivate themselves to select useful tasks to learn from.

In a study with ideas analogous to adversarial training, Pinto et al. (2016) demonstrated that having a protagonist-antagonist paradigm resulted in more effective learning of visuomotor policies. They discovered that having an antagonist robot that aimed to prevent the protagonist from grasping, resulted in learning higher performance grasping, due to the necessity to learn a robust policy to overcome this adversary. In summary, they emphasize that not all data is the same. Contrary to the massive 800,000 grasping dataset presented by Levine et al. (2016), they found systems that attack harder examples tend to achieve faster convergence and higher performance.

On Abstract Parametrized Skills – End-to-end methods produce amazing results by learning visuomotor torque-level control policies straight from raw pixel information. However, two immediate drawbacks are critical for autonomous systems. Firstly, the robot can only learn very task specific motions rather than abstract notions of skills and representations reusable throughout its lifetime. In particular, GPS allows the robot to quickly encode visuomotor policies by guided trajectories acquired through optimization, but since they operate over joint torques it is difficult to decipher abstract skill boundaries\(^2\). Secondly, by operating over joint torques, the network loses control

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\(^2\)In fact, a coalition of researchers during a Robotics: Science and Systems (RSS) workshop entitled Are the Sceptics Right? Limits and Potentials of Deep Learning in Robotics (June 2016) in Michigan, USA have argued that it may not be ideal to learn end-to-end. They indicate that in the same way that we would never want to learn sort when we have quicksort, it makes little sense to learn low-level torque activations when we understand kinematics.
guarantees and parametrization insight that abstract skills derived from control-theoretic approaches may provide.

By learning at the lowest level of motor units (e.g. in configuration space over joint torques), systems need a massive set of examples and training steps to cover this space. For instance, even for a simple 2D spatial reaching task in a confined 40cm × 30cm area using a 6 DOF Kinova arm with three fingers was said to require over 50 million steps via an end-to-end (raw pixel to joint space mapping) paradigm Rusu et al. (2016b). For such reasons, learning over a parameterized space abstracts away these basic motor units and we theorize will accelerate learning.

The notion of control guarantees is of chief importance through an industrial and product-delivering perspective. Especially in scenarios where human factors are involved or other high fidelity situations, systems that acquired expertise through learning over a history of experience must exhibit certified guarantees. Indeed, the maximum activation visualization approach, “deep dream” can be used to identify convolution features to attempt to make sense of the network’s latent representations Mahendran and Vedaldi (2016), but, we are concerned with a stronger sense of guarantee, especially, in the sense of control derived from the output of these networks. In autonomous driving, for example, the system must be analyzed that one can establish certified guarantees, up to sensor noise, that regardless of input, the vehicles will never attempt to give commands that result in collision with entities in the world. Such analytics is extremely difficult to reason over if the commands are over low-level specifics like wheel torques. Rather, analysts can reason easily in Cartesian space—perhaps then, the robot should learn sets of abstract skills that operate with goals that are easily interpretable for validation and certifications. As such, the direction in which we should look into may live closer to the realm of acquiring such parametrized skills.

While there exists a plethora of work for learning these skills, (e.g. Konidaris and Barto (2009); Da Silva et al. (2012); Masson and Konidaris (2015)), we believe that to better investigate a principled formulation for lifelong learning cognitive systems, we should investigate the perspective of learning through the lens of cognitive psychologists—such allows us to better understand the development of cognition and action in living organisms. Insight from this becomes fundamental in drawing computational analogs originating from developmental processes to better design artificial, learning systems.

3 Complex Sensorimotor Hierarchies

The artificial neural networks architecture as an explanatory means to a connectionist model of cognition and action is not a concept that resides solely in computation. In fact, a number of cognitive psychologists showed intrigue when these networks were at its infancy, dating back two decades Rumelhart (1998). Most prominently, Thelen and Smith (1996) describes that such models are exciting in the sense that there exists only process. They indicate that the essence of behavior is distributed among numerous individual units, that together, in the strengths of their connections, describe behavior. They are plastic and modify themselves through dynamical processes with the world. In particular, Thelen and Smith (1996) argue against the notion that these “neural networks contain some privileged icon of behavior, abstracted from complex motivation and environmental contexts in which it is performs.” In other words, the theory that networks encode a particular context-independent behavior—something like a Central Pattern Generator (CPG) is entirely incorrect. They emphasize that behavior is context-specific, even in the case of CPGs—many studies that elicit such behavior and draw such conclusions are based off an impoverished form of induced behavior. To this regard, it may be true that behavior exists in some innate form that when given appropriate stimuli will generate seemingly high level actions—resulting in the misclassification of there being such generators. Thelen and Smith conclude that the development of these into complex behavior is entangled in motivation and context-specificity.

Following this notion, the work that has been discussed to this point fail to tackle this intertwined cobweb of action, environment, and motivation. Although reinforcement learning paradigms do describe the acquisition of action through the system’s interaction with entities in the world in context-specific situations, many of these studies fail to indicate principled motivators. Rewards are generally task-specific and user defined—not an inherent property derived by the system itself in its interpretation of situational contexts. Admittedly, even promising developmental frameworks like the ones outlined by Mungan and Kuipers (2012); Grupen and Huber (2005), are culprit to ad hoc reward structures. Most importantly, however, through Grupen and Huber (2005)’s outline of figurative schemata that organize into the development of robot behavior, they emphasize the need for control knowledge to be represented in a manner that supports generalization. Similar aspirations are found in the action schema framework Platt et al. (2006). The ability to construct and reused learned behaviors in a general manner is of fundamental importance—thus, we share a similar view on the acquisition of motor behavior. These views were originally derived from the proposal under Piaget and Cook (1952)’s account, where human infants exhibit a sensorimotor stage that lasts approximately 24 months while producing control knowledge that support generalization and reuse. Such reuse and organization implies underlying hierarchies of motor behavior.

In comparable work, Heess et al. (2016) emphasized the importance of hierarchical controllers that operate at different time scales in support of modularity and generalizability. Their work showed a promising step forward in locomotive skill transfer between a number of simulated bodies with many degrees of freedom, wherein high-level controllers modulated low-level motor skills which emerged from pretraining. Other work has looked into building implicit plans or macro-actions by interaction alone using a recurrent neural network structure Mnih et al. (2016). However, these works do not necessarily
discuss how these temporal hierarchies of options, skills or macro-actions play with intrinsic motivators, where systems derive their own reward paradigms and build continuously extended motor hierarchies. Kulkarni et al. (2016) presented a hierarchical-DQN framework which integrated hierarchical value functions and intrinsic motivation by having a top-level function learn policies over intrinsic goals and a lower-level learning policies to achieve these goals. They suggested that intrinsic motivation be derived from the space of entities and relations which is sufficiently bounded and finite in Atari games, however, may exhibit explosive growth in the physical world. Future work indicated a connection to deep generative models—wherein, in this paper, we derive intrinsic motivation from a deep generative dynamics model.

In the following subsections, we summarize work that provides systems with the ability to learn complex sensorimotor hierarchies resulting from experience and interaction with the world. Complex action-related behavior are expressed as motor hierarchies emerging through the combinatoric sequencing and composition of actions, that at the lowest level, are learned by associating sensory input to resolve motor primitives. As such, we begin at the lowest level of motor development, on how a robot can associate sensor input to activate closed-loop motor primitives. Next, we investigate learning to bootstrap these primitives to develop more complex behaviors. And lastly, we incorporate techniques present in the literature to suggest the learning of control goals that evolve primitive reflexes to intentional goal-oriented behaviors. In Section 4, we describe an intrinsically motivating paradigms that leverages the system’s ability in its understanding of the world and of its own inherent actions and representations through control contexts—such motivators are to drive the processes that govern the development of these sensorimotor behaviors and cognitive representations. A plausible unifying framework is illustrated in Figure 1 by piecing together various selected studies currently in the literature.

We now quickly elaborate on each of these pieces and on their respective subsections in this manuscript.

Section 3.1 describes how to activate motor primitives given sensory input, deriving a control context—it discusses an approximation to the function $f^T_{s, \rho}: s \mapsto \gamma^T_{\phi_i|\gamma}$. Section 3.2 investigates how to build hierarchies of complex behaviors by combining existing controllers to construct new ones under the current state description $\Gamma^T (s) = \gamma_1^T \cup \gamma_2^T \cup \ldots \cup \gamma_n^T$. This is described by learning the policy $\pi^T_{n+1}: \Gamma^T (s) \rightarrow \{\phi_1|\gamma, \phi_2|\gamma, \ldots, \phi_n|\gamma\}$. The networks proposed here approximates the value function $f^T_{n+1}: \Gamma^T (s) \rightarrow V^{n+1}_\pi (\Gamma^T (s))$, where $\Gamma^T$ is the deep control context at time $T$ encompassing all control state descriptions $\gamma^T$.

Section 3.3 describes methods to learn continuous control parameters for controllers $\phi_1|\gamma, \phi_2|\gamma, \ldots, \phi_n|\gamma$, thus approximating the function $f^T_{\rho_i}: s \mapsto \rho_{\phi_i|\gamma}$. Since both the learning of $f^T_{\pi_{n+1}}$ and $f^T_{\rho_{\phi_i|\gamma}}$ is by trial and error, it requires that environmental reward is defined. We refer to the system’s level of understanding regarding entities in the world and of its own actions to establish reward. As such, Section 4.1 discusses learning to predict the transition dynamics of the world by approximating $f^T_W: s, \rho_{\phi_i|\gamma} \mapsto s'$. Section 4.2 outlines a plausible reward structure derived from affordance predictions.

And finally, Section 5 describes how a system can exploit these learned behaviors and representations to solve useful tasks and mission in the world.

3.1 Activating Motion Primitives

In their revolutionary book, Thelen and Smith (1996) outlines the misinformations of contemporary theories in cognitive development, suggesting that it is not the case that cognitive and motor skills emerge linearly through development but these primitive forms of behaviors are inherently ingrained. They are reinforced by interaction with the environment to seek dynamically stable solutions. As a result, skills emerge from context-specific situations that are afforded by the world. It appears that local circuitry within the spinal cord mediates a number of closed-loop sensory motor reflexes—for instance, the spinal stretch reflex Purves et al. (2001). In fact, it has been observed that all humans developing infants exhibit similar chronicles of reflexive motor behaviors.

The Central Nervous System is organized according to movement patterns Aronson (1981)—with its most basic form being the reflex$^4$ Under the notion of epigenetic

$^4$Grupen and Huber (2005) expresses that packaged movement patterns “reside in the central and peripheral nervous system and range from involuntary responses to cortically mediated visual reflexes [and] contribute to the organization of behavior at the most basic level by constituting a sensorimotor instruction set for the developing organism.”
where $\omega_n$ is the natural frequency. It is assumed here that $K, B,$ and $I$ are all constants representing the proportional and derivative gains, and the scalar moment of inertia around the rotation axis respectively under a canonical spring-mass-damper model (1992). This property is established for systems formulated as harmonic oscillators similar to the above second order differential equation in the canonical form,

$$\ddot{\theta} + 2\zeta\omega_n\dot{\theta} + \omega_n^2\theta = 0$$

where $\zeta = B/(2\sqrt{KI})$ is the damping ratio and $\omega_n = \sqrt{KI}$ is the natural frequency. It is assumed here that $K, B,$ and $I$ are all constants representing the proportional and derivative gains, and the scalar moment of inertia around the rotation axis respectively under a canonical spring-mass-damper model Hebert et al. (2015). Closed-loop feedback controllers such as these have well understood proofs of stability. For instance, the proportional derivative (PD) controller such as the one we described here is provably stable Lyapunov (1992). This property is established for systems formulated as harmonic oscillators similar to the above second order differential equation. Convergence results have been proven for closed-loop controllers by Coelho and Grupen (1997) for regular convex prismatic objects when two closed-loop controllers were executed in a particular sequence. Experiments were later shown on a robot manipulator agreeing with such convergence guarantees Coelho (2001)$^5$. Likewise, optimal controllers described by regulators like linear quadratic regulators (LQRs) and its variants fall into this categorization as well. In fact, dynamically balancing robots like the uRobot platforms Kuindersma et al. (2009); Ruiken et al. (2013), implement a variant of LQR. To reiterate the notion of learning abstractions, we suggest strongly that rather than learning a balancing policy from scratch, perhaps a better direction is to consider this closed-loop controller as a skill and employing learning architectures at the skill level of abstraction.

Namely, in spirit of the flurry of work on autonomous vehicles, we emphasize that motion planners and path tracking procedures generally fall under this umbrella notion as well. In particular, path tracking in navigation at the most primitive sense, leverage a heading and longitudinal controller like those described by Hebert et al. (2015). Potential field methods for path planning Ge and Cui (2002); Wang and Chirikjian (2000); Khatib (1985) like Harmonic function path planning Connolly and Grupen (1993) have shown success dating back over two decades of research. Especially with recent advances in GPU parallelization for efficient relaxation and the logarithmic transformations to prevent diminishing gradients Wray et al. (2016), these classical methods still remain powerful path generators. An elegant control theoretic relaxation-based method to velocity planning presented by Hebert et al. (2015) is shown to be done in linear time of the path, resulting in minimal path deviations and maximal performance envelope. Many of these navigation solutions are fast and robust—so instead of replacing them completely with a learned approximation, we suggest treating resulting plans like motion primitives or inherent behaviors in the context of forming complex visuomotor hierarchies. Likewise, solutions to other motion planners like RRTs or A* variants can interpreted as motion primitives given that their trajectory can be used to describe some transient, converged, or goal completion evaluation.

Under this broad encompass, even dynamic motion primitives (DMPs) Ijspeert et al. (2003) and other powerful optimization based methods for locomotion, like those developed during the DARPA Robotics Challenge (e.g. Feng et al. (2015b); Kuindersma et al. (2016)), fall into this categorization of plausible motor primitives.

Motion primitives like these can be formalized under the Control Basis framework in which the interaction between the embodied system and the environment is modeled as a dynamical system, allowing the robot to evaluate the status of its actions as a state describing a time varying control system. These controllers $\phi_{\tau, \sigma}^\phi$, consist of a combination of potential functions $(\phi \in \Phi)$, sensory inputs $(\sigma \in \Sigma)$, and motor resources $(\tau \subseteq \mathcal{T})$ Huber et al. (1996b). Controllers achieve their objective by descending along gradients in the potential function $\nabla \phi(\sigma)$ with respect to changes in the value of the motor variables $\partial \alpha_{\tau, \sigma}$, described by the error Jacobian $J = \partial \phi(\sigma)/\partial \alpha_{\tau, \sigma}$. References to low-level motor units are computed as $\Delta \alpha_{\tau, \sigma} = \kappa J^\# \Delta \phi(\sigma)$, where $\kappa$ is a control gain, $J^\#$ is the pseudoinverse of $J$ Nakamura (1990), $\Delta \phi(\sigma)$ describes the difference between the reference and actual potential Sen and Grupen (2014).

The time history or trajectory of dynamics $(\phi, \dot{\phi})$ as a result of interactions with the environment by executing controllers have been shown to have predictive capability regarding the state of the environment. It was originally shown by Coelho and Grupen (1998) that dynamics elicited by abstract actions in the form of controllers serve as important identifiers for the current control context—one of many finite sets of dynamic models that capture system behavior. The state description $\gamma_t$ for a particular control action $\phi_{\tau, \sigma}^\phi$ at time $t$ is derived directly from the dynamics $(\phi, \dot{\phi})$ of the controller.

$^5$In the next subsection, we will discuss composite controllers which have similar convergence guarantees as outlined and proven by Platt et al. (2010).
Communication between human-robot systems is essential for their success in a shared environment. In the context of robotics, one approach is to design robots that can learn from humans, or vice versa, to enhance their capabilities. One way to achieve this is through learning-based control methods, which can be either supervised or reinforcement learning. In the former, the robot is trained to perform a specific task based on examples provided by a human teacher. In the latter, the robot learns to optimize a reward function, which can be designed to reflect the goals of the human or the system as a whole.

Reinforcement learning is a particularly interesting and widely used approach in robotics. It involves training an agent to make decisions in an environment to maximize a cumulative reward. The key components of a reinforcement learning system are the agent, the environment, the state space, the action space, and the reward function. The agent interacts with the environment, receives rewards or penalties, and updates its policy based on the received feedback. This process is repeated until the agent learns an optimal policy that maximizes the expected cumulative reward.

In the context of human-robot interaction, reinforcement learning can be used to learn control policies that are adaptable and responsive to the environment. For example, in a scenario where a humanoid robot is required to interact with a human in a shared workspace, the robot may learn to adjust its movements based on the human's actions, preferences, or needs. This can be achieved by designing a reward function that takes into account the robot's performance, the human's satisfaction, and other relevant factors. The robot can then learn to optimize this reward function, resulting in more intuitive and effective human-robot interaction.

The authors of the paper discuss the importance of learning-based control methods in robotics and their potential applications in human-robot interaction. They highlight the challenges and opportunities in this area, such as the need for robust learning algorithms that can handle noisy and uncertain environments, the requirement for efficient and safe interaction protocols, and the importance of ethical considerations in the design and deployment of human-robot systems. The paper concludes with a discussion of future directions and potential research avenues in this field.
subject to $f$ and using the null-space operator between multiple feedforward networks to generate real-valued outputs as an instance, work by Gullapalli et al. (1992) used multilayered context as a state representation. Yet, the use of neural networks to generate control actions has been demonstrated with DQNs that express a trajectory through control contexts producing a variant of $\gamma^T$-network shown in Wong et al. (2016) makes an unfortunate assumption that the motion primitive described by closed-loop controller $\phi_{gT}$ inherently defines a static control goal $g$. This particular form of goal is derived from cognitive development insight, allowing networks to learn when to execute particular abstract skills represented as reflexive actions. However, the question that remains is the encoding of how should these skills be performed. Infants readily bootstrap their innate reflexive repertoire to quickly learn the functionality of their end effectors as entities conform to their hands via palmar grasp reflex. Static parametrized goals allows for quick association-based learning, but do not generalized well to future tasks that require goals outside of innate reflex descriptions. As a result, both infants and robots must learn useful parameters to their inherent motor behaviors in response to stimuli in the world. The $\gamma^T$-networks can be extended to predict varying parameterizations of control goals by a concatenation of state and action parameters after the convolutional layers, a technique that is used in many predictive networks like those presented in Levine et al. (2015); Finn et al. (2016a). In fact, work by Takahashi et al. (2017) implemented this extension producing a variant of $\gamma^T$-networks that account for varying control goal parameters.

3.3 Continuous Control Parameterization

Each controller $\phi_{gT}$ requires a control reference that implies an error to minimize. In many cases, these goals are generally human-defined. For instance, Hart (2009a) uses hue saturation to select interesting areas in the scene. However, recently deep learning architectures were shown to be powerful tools of extracting candidate features in the world. Leveraging the predictive $\gamma^T$-networks provides these indicates stimuli in the world that derives useful control goals, or in other words, control references, that feed into these controllers $\phi_{gT}$. In fact, the null-space composition in this case, is mostly unchanged and operate almost identically. A forward propagation over each $\gamma^T$-network predicts control context or state description that indicate activations for each primitive.

In the following section, we investigate the literature in reinforcement learning, both deep and classical, for methods that learn these control references or goal parameters that take on continuous values.
Heess et al. (2015b) introduced the stochastic value gradients to learn stochastic policies through a $Q$-critic. They found that stochastic control can be supported by treating the stochasticity in the Bellman equation as a deterministic function consisting of external, Gaussian noise. From this, they revealed a “reparametrization” trick, similar to that of Kingma and Welling (2013). Meanwhile, Wawrzyński and Tanwani (2013) trained stochastic policies using a replay experience buffer with the actor-critic framework. The use of the replay buffer has been essential to ensure that data samples are independent and identically distributed. This particular technique was popularized by Mnih et al. (2015) with original insight dating back twenty years in work by Lin (1993). A trusted policy optimization approach proposed by Schulman et al. (2015), directly builds a stochastic neural network policy without this decomposition and does not require the learning of an action-value network. It appears to produce near monotonically improvements but require careful selection of updates to the policy parameters to prevent large divergences to the existing policy. Furthermore, it has been theorized that this technique appears to be less data efficient. Work by Hausknecht and Stone (2015) has demonstrated a solution to reinforcement learning in continuous parameterized action spaces, where they successfully trained a RoboCup soccer agent that scored more reliably than the 2012 champion.

Using value function estimation like these approaches for continuous domains generally uses two networks to represent the policy and value function individually Schulman et al. (2015); Lillicrap et al. (2015). There has been work however, to reformulate the original $Q$-learning scheme that results in an elegant effort that can be ported to the continuous setting—namely work by Gu et al. (2016b) has attempted to show this by learning a single network that outputs both policy and value function. Their work was based off dueling networks shown by Wang et al. (2015) where they decomposed learning into two streams corresponding to the action selection and action evaluation, not corresponding to action selection and action evaluation, not $Q$-learning. The motivation behind double $Q$ networks is that $Q$-learning, even in the tabular setting, exhibits overoptimism due to estimation errors, however, Van Hasselt et al. (2015) found that by decomposing the max operation in the target into two value functions corresponding to action selection and action evaluation, not only reduced this particular overoptimism, but also lead to performance increase.

However, approaches that rely on a model-free reinforcement learning method like traditional $Q$-learning has yet another major drawback. They are tragically inefficient with experience. For example, the learned Atari policies required millions of gameplay examples to converge to competence. Consequently, in the past a number of model-based methods like Dyna Sutton (1990, 1991), Prioritized Sweeping Moore and Atkeson (1993), and Queue-Dyna Peng and Williams (1993) have been suggested to make more efficient use of training examples while increasing computation. Many of these select $k$ samples to use for update as opposed to a single update with traditional $Q$-learning. To do this, these methods use experience to not only learn an optimal policy, but also construct a transition $\hat{T}$ and reward $\hat{R}$ model, meanwhile updating the values of $k$ additional state-action pairs. And as summarized by Kaelbling et al. (1996), Dyna does this by selecting $k$ randomly while the latter two methods prioritize the selection of the pairs to “regions of interest.” Dyna is shown to converge ten times faster than traditional $Q$-learning and the prioritized methods being two-fold faster then Dyna—thus, making much better use of experiences for learning. Quite recently, these ideas stemming back two decades of research has reincarnated into a deep learning framework that incorporates model-based acceleration for deep reinforcement learning with continuous control parameters. First, Gu et al. (2016b) reformulated $Q$-learning in the continuous setting into normalized advantage functions, an alternative to policy gradient and actor-critic methods, which decomposes the quality term $Q$ into a state value term $V$ and an advantage term $A$. This particular insight have been explored by others in the past Baird III (1993); Harmon and Baird III (1996); Wang et al. (2015). Next, they showed that policy learning can be achieved by taking a learned model of the dynamics and simulating synthetic plausible outcomes via imagination rollout and appending the experiences to the replay buffer. Doing so, increases the efficiency of data usage and is a likely candidate to learn the control parameters needed for $\gamma^T$ networks. Interestingly, these imagination rollouts according to learned dynamics models corresponds to a form of $\lambda$-return, where given this model, we can simulate a number of $n$ step trajectories by traversing this aspect transition network. We then weigh these $n$ step backups yielding a compound backup—such an update has been shown to make more efficient use of experiences Sutton and Barto (1998).

In a distributed approach, Gu et al. (2016a) introduced a parallelizable learning algorithm leveraging the normalized advantage functions, to be used across multiple robots which can pool their policy updates asynchronously resulting in accelerated learning. With almost all frameworks to date, experience updates from the replay buffer were uniformly selected from this replay buffer. In fact, it this may not be ideal since individual samples may have varying degrees of significance. As a result, Schaul et al. (2015) proposed the prioritized experience replay which samples at the same frequency they were originally experienced—this result was shown to improve state of the art, and perhaps could be a potential candidate for model-based acceleration sampling. Similar works by Zhai et al. (2016) used prioritized sampling to bias experience selections.

Model referred updates accelerates learning by simulating synthetic on-policy futures. In essence, this describes a forward dynamics model of the interactions, perhaps even over a lifetime of interaction experiences. Evidently, the use of Guided Policy Search tries to fit the dynamics in a locally-linear fashion and using the model as a reference to apply imagination rollouts by placing these cumulatively constructed synthetic experiences into the replay buffer for updates. There is in fact, a connection between these dynamics models that attribute to the increased efficiency of deep reinforcement learning methods and algorithms to provide artificial curiosity. Quite fortunately, these representations that concern the transition dynamics and
reward have immediate ties and are analogous to an interaction-based knowledge repertoire that adheres to a series of task planning and intrinsic motivation frameworks.

4 Unsupervised Affordances

The development of an interaction-based knowledge repertoire is an important structure that can be incorporated into a number of algorithms that necessitates forward models or predictions of future state. Fortunately, the learning of this action centric knowledge is a close analog of the transition dynamics that is already a component of these model-based acceleration techniques presented to make efficient use of experiences in reinforcement learning paradigms. As such, this structural acquisition has immediate ties to intrinsic motivators that seek to provide artificial curiosity to autonomous systems. Intrinsic motivators allows systems to build their own representations that reflect the inherent uncertainties of the system.

Curiosity is important for learning systems—as without a sense of curiosity, learning becomes very task specific and one dimensional—the robot can not choose to learn novel skills, only a task-specific motion for a human-defined task. For such reasons, one might consider introducing some form of curiosity Frank et al. (2015) into the approaches previously discussed. We believe that the development of motor behavior should be driven by intrinsic motivators in order to learn task-generalizable skills that can be reused in the future. While a thorough survey of intrinsic motivators is outside the scope of this paper (for further readings, see Barto (2013)), we acknowledge that a number of researchers who have applied schemes to autonomously learn new skills Utgoff and Stracuzzi (2002); Barto et al. (2004) and representations Oudeyer et al. (2007); Hart (2009b). Instead, we envision a system that accomplishes this simultaneously.

As for this, we look into insight from cognitive development. In fact, a number of studies have shown that motor development in biological systems greatly influences the development of perception and cognition. For instance, Piaget (1953, 1954) described motor skills as a mechanism that drives development in other domains by generating new sensorimotor experiences and further studies have described cognition and perception as embodied phenomena—grounded to the body and its actions Gibson (1988). Other studies have shown that infants are highly sensitive to action-outcome relations and are capable of learning contingencies between their own behavior and outcomes in the world. In particular, Libertus and Needham (2010) showed that sensory-motor experiences motivates infants to reproduce manipulation outcomes and foster reaching and grasping skills. Evidently, infants learn models through manipulation and interaction forming a sense of behavioral organization6. Such organization is an interplay between representation and motor development, driven by curiosity—which we regard, should adhere to model-referenced objectives that aim to explain the complex dynamic phenomena in the world. A common, perhaps, ubiquitous representation describes action-related contexts regarding entities in the world. Such a representation is of chief importance to cognitive systems. In fact, Hemon (2016b) argues that instead of having contemporary computational reinforcement learning agents learn each individual skill entirely from scratch, the development of a world model can be used to support adaptive behavior and learning for cognitive systems.

4.1 Predicting the Dynamics of the World

Originating from ecological approaches to visual perception, the central concept to the Gibsonian perceptual framework is the notion of an affordance, an observable environmental context that invokes a variety of latent interactions. Affordances emphasize an agent-world relationship and constitutes an interactionist account of perception as it reflects environmental signals in relation to an agent’s ability to act on those signals Chemero (2003). In the strongest sense, Gibson’s theory of direct perception holds that the transformation from signal to behavior is expressed directly by neural projections that evolve to recognize opportunities for context-specific actions actions Frank (1996); Turvey (1992). Such theories emphasize that percepts themselves provide a direct index into all the “action possibilities latent in the environment” Gibson (1977), thus, applicable actions and related outcomes are immediately recognized without necessarily identifying the object itself.

The Gibsonian notion of affordances describes action possibilities and can be seen as a surrogate of world state, induced by sensory input and interaction. Gibson’s theory of affordance advocates for modeling the environment directly in terms of the actions it affords. These representations are idiosyncratic and reflect only those actions that can be generated by the agent. Research has been done to investigate the autonomous acquisition of such affordance representations with intrinsic motivators. For instance, an example of multiple intrinsic reward functions have been proposed to learn the transition dynamics of a particular task Hester and Stone (2015). Others have looked into domain-independent intrinsic rewards, like novelty or certainty, for learning adaptive, non-stationary policies based on data gathered from experience Hart (2009b); Sequeira et al. (2014). In particular, model exploration programs have been presented by Hart (2009b), but the methods reported lacked multimodal sensor integration and do not produce knowledge structures that are easily transferable to other tasks. A multimodal structure learning paradigm was proposed by Wong and Grupen (2016) extending the ideas initially presented by Hart—in their studies, they leveraged a promising representation describing affordances

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6The developmental process from neonate to approximately a year in age consists of a precisely-timed chronicle of emergence and inhabitation of primitive, postural, or bridge reflexes that contribute to the organized development of complex behavior and skill acquisition Law et al. (2011). With age, myelination occurs in the infant, resulting in increased controllable degrees of freedom and resolution in motor activity Oudeyer et al. (2013). This form of maturation is especially prominent when fine motor control start to emerge in cases such as pincer grasp reflexes. When the infant develops appropriate skills, it begins to play and interact with the environment and objects in it by exploratory activity Oudeyer et al. (2007). Increased motor acuity and refined motor skills are important for development in general and affect what kinds of information can be extracted from the environment. As motor skills develop, complicated representations of the world can too be constructed through addition information provided through these actions Libertus and Needham (2010).
in terms of **aspect nodes**. The graphical structure called an **aspect transition graph** encodes Markovian state as nodes and actions as edges in a multi-graph Ku et al. (2014). Such a model is generally used in object identification tasks by planning in belief space (rolling out a population of these forward models) to select informative actions Sen and Grupen (2014); Ruiken et al. (2016b). Methods for robots to autonomously acquire these models has been described in work by Wong and Grupen (2016); Ruiken et al. (2016b), where systems are intrinsically motivated by a variant of the differential variance function originally proposed by Hart (2009b) to acquire complete graphical representations of objects—associating actions and futures derived from all possible interactions under controlled settings.

Evidently though, the aspect transition graph model has two major disadvantages. One being that in studies regarding learning these graphs by Hart (2009b); Wong and Grupen (2016); Ruiken et al. (2016b), it is assumed that a sample mean and variance approximates the true underlying transition distribution. Unfortunately, it is not the case that this distribute is necessarily Gaussian $\mathcal{N}(\mu, \Sigma)$, for instance, it may be arbitrarily complex and multimodal. The next large criticism is that these models assume some discretization granularity of sensory input space into aspect models. The definition of what constitutes an **aspect** is task-dependent and difficult to manage in a task-generic way. Both of these issues can be addressed by approximating this arbitrary complex representation in high dimensionality—this approximation over the Markovian state describing what constitutes an aspect and potential outcomes derived from interactions attributes to a new model, a deep aspect transition network. This network is otherwise an extension of the original aspect transition model graphical structure with the key distinction being that it captures interactions over many possible granularities, deriving a continuous form of aspect state. A fundamental extension to the graphical structure is that the deep variants makes no assumptions of aspect boundaries, rather, aspect nodes take on continuous state description.

The acquisition of a model that explains the dynamics of entities in the world and their evolution through interaction (the representation we referred to as an aspect transition network) is closely related to work that attempts to predict physics, structure, and futures given current state. Despite applicable research in deep filtering and sensor fusion approaches Krishnan et al. (2015); Jain et al. (2016), likely making predictions in the original sensory-space holds promise in robustness for planning algorithms, since actions are directly derived from future scenes. Many encoder-decoder networks hope to achieve this by upsampling to generate predictions in visual (more specifically, sensory) space. Unfortunately, the prediction in visual space may be nonsense. For instance, recall many of these hill-climbing algorithms to fool the network into predicting visually inplausible images. As such, a particular line of work have looked into guarantees that the prediction has physical properties that are relevant and meaningful in real life. Goodfellow et al. (2014a) proposed the use of generative adversarial networks (GANs) that have been widely accepted as a tool to generate visually plausible predictions that fall into the realm of reality, rather than blurred or meaningless output. This is accomplished by simulating two models: a discriminative model $D$ and a generative model $G$ who is trained to maximize the probability of $D$ making a mistake—this framework is analogous to a minimax two-player game. Building off this work, Mathieu et al. (2015) incorporated the adversarial training techniques into their convolutional network architectures to deal with blur resulting from standard mean squared error loss. They showed that their network was capable of predicting vivid future scenes under an image gradient difference loss function given a set of input sequences.

Learning the transition dynamics of entities in the world has immediate correlation with an understanding of intuitive physics. Work by Lerer et al. (2016) incorporated a variant of the DeepMask network Pinheiro et al. (2016) that was altered to support multi-class predictions and replicated a number of times to predict the segmentation trajectory of multiple time steps in the future for a falling block prediction task. A ResNet-34 was trained as the trunk of the convolutional network and their approach, PhysNet, was shown to outperform all other methods for predicting the future locations of the falling blocks. To insert spatial invariance to neural networks, work by Jaderberg et al. (2015), introduced a differentiable Deep Spatial Transformer module that can be applied to convolutional networks allowing it to be able to explicitly actively transform inherent feature maps.

Jain et al. (2015) presented a generic framework to model time-space interactions using statio-temporal graphs with a recurrent neural network architecture. The use of spatio-temporal structures impose high-level intuitions allow for improvements in modeling human motion and predicting object interactions. Prediction work by Oh et al. (2015) has made several interesting discoveries in predicting futures in the gameplay domain (namely in the game Space Invaders). They showed that a feedforward network was better at predicting precise movements of objects when recurrent structures consistently made a few pixels of translation error. Their hypothesis is due to the failure of precise statio-temporal encodings in the recurrent setting, however, they found that recurrent structures were better at predicting events that have long-term dependencies. Long-term sequential movements of objects as a result of an applied force vector at a particular location in the image were learned by a deep neural network while taking into account the geometry and appearance of the scene by using convolutions and recurrent layers in the network Mottaghi et al. (2016). Others looked into building models for action-conditioned video prediction that explicitly models the motion of pixels rather than predicting the future as a whole. This is achieved by predicting distributions over pixel motion from previous frames and as a result, the model is partially invariant to occlusions. Their model was trained on a dataset of 50,000 robot interaction videos and resulted in the learning of a “visual imagination”—a concept of predicting different futures based on the robot’s
courses of actions Finn et al. (2016a). Similarly, Santana and Hotz (2016) trained a realistic, action-conditioned vehicle simulator using generative adversarial networks. These video prediction mechanisms share a similar action-conditioned form of function approximation as aspect transition networks given by \( f_W : s, \rho_{|s|} \mapsto s' \).

Further work presented by Agrawal et al. (2016) allowed a robot to gather over 400 hours of experience by poking different objects over 50,000 times. They learned both an inverse and forward model of the dynamics—the inverse model provided supervision to build informative visual features, which then was used by the forward model to predict the interaction outcomes. They refer to these accurate models for multi-step decision making.

### 4.2 Deriving Environmental Reward

A likely candidate for environmental reward is one that is computed through an information theoretic interpretation of the affordance prediction networks corresponding to the system’s understanding of interaction and dynamics of the world. Assume the robot interacts with the world by executing some set of control programs and obtains interaction tuples \((s, \Phi, P, S)\) describing the initial state \(s\), the control programs that were executed \(\phi_i\) in \(\Phi\) with parameters \(\rho_i \in P\) resulting in future states \(s'\) in \(S\)—in this now outlines some experience dataset described by \(D_t = \{e_1, e_2, \cdots, e_n\}\) where each experience tuple consisting of \(e_i = (s, \phi_i, \rho_i, s')\).

Now consider the class of reward structures that adhere to using uncertainty and degree of understanding to penalize or promote the selection of new actions and behaviors to emerge. A prominent example of structures of this nature is the differential variance intrinsically motivated function originally proposed by Hart (2009b). Such a function motivates systems to perform actions that it is most uncertain about, allow it to exploit this reward to build new behaviors.

Wong and Grupen (2016) proposed to use this function to learn complete affordance models by showing that the system consumes rewards as representations become more accurate. Unfortunately, these metrics imply a Gaussian distribution assumption that likely fails when adapting to high dimensional sensory-spaces, as such candidate surrogates are information theoretic functions that prescribe distance metrics on predictions and truths. As such consider,

\[
I_{f_W} = H(f_W(s, \rho_{|s|})) + H(s') - H(f_W(s, \rho_{|s|}), s')
\]

where, \(I_{f_W} = I(f_W(s, \rho_{|s|}; s'))\) expresses the mutual information between the prediction of what the outcome should be according to the network \(f_W\) given state \(s\) and control parameters \(\rho_{|s|}\) and the actual outcome \(s'\)—in essence, a measure of the similarity between prediction \(f_W(s, \rho_{|s|})\) and result \(s'\).

We consider this a candidate reward scheme and express its mechanics under two plausible scenarios.

**Scenario 1, Low Mutual Information:** In the case that there is low mutual information between the output of the affordance network \(f_W\) and the true outcome \(s'\), this is attributed to two likely culprits, either the network approximating \(f_W\) is not converged, in which case, the system does not have a good understanding of the underlying dynamics of the world, or the action networks corresponding to \(f_Q, f_P, f_{\pi^*_j}\) do not approximate the appropriate control parameters or falsely predicts activations of primitives in the world. Either way, these networks are continuously trained with current dataset \(D_t\).

**Scenario 2, High Mutual Information:** In the case that there is high mutual information between these quantities, the system has acquired good approximations to interaction outcomes via \(f_W\) given its current set of controllers expressed as both primitives \(\phi_i\) in \(\Phi\) and complex encodings \(\pi_j^* \in \Pi^*\). And those behaviors have likely found useful control goals describe by the approximator \(f_{\rho_i}\). As such, this becomes a state of either habituation or emergent behavior—when high mutual information is observed, a likely course of action to continue the development of complex behaviors and interaction-based data collection is to spawn a new network \(f_{\pi^*_j+1}\) with the sole purpose of attempting to learn new behavioral control sequences and compositions that result in unexpected transition dynamics in the world. Simply, the control policy is rewarded when it learns sequences of actions that fool the dynamics prediction network \(f_W\) into new states, while the \(f_W\) networks uses these novel interactions to refine its inherent representation.

This direction of thinking is adapted from a form of adversarial training where the affordance network tries to best predict the outcome of futures under interactions while the behavioral networks attempts to learn new control parameters that the affordance network fails to predict—hence, new behaviors develop that broaden the system’s understanding of the world. From this fact, the reward given to the predictor \(f_W\) and the reward given to the developing behavioral policy network \(f_{\pi^*_j+1}\) can not be and should not be the same. In fact, they exhibit an inverse variation phenomena, therefore, the reward for new behavioral policy networks must be derived from the prediction network’s ill-performance. An example reward structure that obeys this particular property is the Kullback-Leibler (KL) divergence given by,

\[
D(f_W(s, \rho_{|s|}) || s') = \sum_{i,j} f_W(s, \rho_{|s|})_{i,j} \log(f_W(s, \rho_{|s|})_{i,j} / s_{i,j}) — this particular quantity is ubiquitously used as a measure of the similarity between two distributions, describing relative entropy. Such metrics generally concern controlling the exploration and exploitation tradeoffs in learning architectures Levine et al. (2015). For instance, a number of approaches have used the KL-divergence to control policy update step sizes Peters et al. (2010); Levine and Abbeel (2014); Schulman et al. (2015); Akrour et al. (2016).

A key concern with this approach is the stability of the learned control policy under an ever-changing dynamics model may be compromised, especially when computing rewards in response to its predictive accuracy. To address this, it is wise to consider a target network paradigm like that of Mnih et al. (2015), except instead of freezing the target \(Q\) network for stability, one should consider freezing the affordance network \(f_W\) when computing rewards for the corresponding behavioral policy network. Since otherwise, these rewards will be drastically non-stationary and thus may have large implications on convergence issues.
5 Implications for Task Planning

Perhaps, one of the most recurrent themes throughout this manuscript is that there likely is not a single method capable of solving all problems, especially those that concern developing artificial intelligence for physical robotic systems. Similarly, we find that a candidate approach is the marriage between several theisms of thought. For instance, consider a lifelong learning framework that generates useful artifacts that task planners can exploit—in actuality, let us briefly entertain this idea. Quite obviously, we would like robots to perform useful tasks or missions in the real world given its massive repertoire of motor skills and precise, learned representation of interaction dynamics in the world. Because these representations and control policies are all derived by the robot through intrinsic motivation, it encodes inherent uncertainties that allow for robust plans and execution of actions. So evidently, it is up to task planners to find plans over these control skills and transition dynamics such that the robot will solve useful problems

Planning generally assumes some form of forward dynamics model, of how actions affect the state of the world—in this particular scenario, we suggest that a learned aspect transition network \( f_W \) will serve purposefully as it is a representation for forward dynamics. In other works, basic push motion planning was achieved using dynamics in the form of video prediction and visual foresight Finn and Levine (2016). In another study by Tamar et al. (2016), value iteration networks were presented as an architecture that allows systems with the capability of learning to plan by embedding the fully differentiable neural network with a “planning module.”

Interestingly, research has shown that an aspect geometry alone is sufficient in describing a number of complex robotic tasks Ruiken et al. (2016a). In particular, object identification and assembly tasks can be reconfigured into a model-referenced belief-space planner. The aspect definition prescribes sensory geometries to define a Markovian state described by an aspect node in a geometric structure outlining the geometric constellations under some field of view—thus, encoding latent affordances of entities in the world. The specific geometries of features embedded in the environment can be used to drive belief-space architectures into task-specific solutions. Simply in this setting, the artifacts produced by the approximations describe the networks \( f_\pi_T, f_\pi_*, f_\rho \) and \( f_W \), which are respectively the networks for control state prediction, complex behavioral policies, continuous control parameters, and world transition dynamics, can be used during planning rollouts (i.e. a Monte Carlo simulation of trajectories according to action-conditioned transition dynamics \( f_W \) via parameters \( f_\rho \)).

We decompose this task solution into a mathematical representation outlined by a (partially observable) Markov Decision Process. Firstly, Markovian state is given by the robot’s perception or raw sensory input. The set of actions in this case collectively describe the set of all control state predictors, control parameter learning networks, and complex policies given by the three set of networks: \( f_\pi_T, f_\pi_*, f_\rho \). And lastly, the transition dynamics are encoded through the aspect transition network \( f_W \), with actions being constrained through the \( \gamma^T \)-networks’ prediction that decides the likely control states at any given time instance.

In planning, one may simply perform rollouts over the Markovian state and predict likely candidate actions that can be executed. Many planning approaches at this point resort to sample techniques in conjunction with RRTs, preimage backchaining Kaelbling and Lozano-Pérez (2011), or large population of dynamics models Ruiken et al. (2016b). Instead, we have control state networks that specifically describe candidate control programs—for each of these actions, we rollout under the aspect transition network the candidate future states. A similar affordance model referenced Active Belief Planner Ruiken et al. (2016b) has been presented recently to solve object identification tasks. In fact, their planner uses these affordance representations as forward models during problem solving behavior in non-ideal contexts that include sensor noise, suboptimal lighting, missing information, and extraneous information arising from scenes that can contain multiple objects in initially unknown arrangements. Unfortunately, their methods requires that large populations of transition models are explicitly described—this population is what would be a useful structure to approximate using \( f_W \), the aspect transition network.

Evidently this roll out can be performed by a number of generic planners that expand states accordingly to their future dynamics. As such, a number of planners like A*, All-Domain Execution and Planning Technology (ADEPT) Ricard and Kolitz (2003), or Hierarchical Planning in the Now (HPN) Kaelbling and Lozano-Pérez (2011) can solve for task relevant plans while leveraging learned artifacts for additional robustness.

A fundamental problem with planners in general consist of the planning horizon and the branching factor prescribed by the possible number of actions at any given state. Hierarchy attempts to reduce the planning horizon by only planning to the first executable primitive. Still, hierarchical planning scales exponentially (number of operators to the shallowest abstraction level). Fortunately, the control state description networks \( f_\pi_T \) and complex behavioral policy networks \( f_\pi_* \) drastically helps reduce this planning complexity by in turn decreasing the depth at which the planner must roll out due to the consideration of more complex motions. Secondly, the possible actions at any given state is constrained by those physically plausible which is immediately evaluated by the approximator \( f_\pi_T \) for each control program \( \phi_i \)—quiescent actions should then not be considered.

Interestingly, another problem that arises is when a cognitive system increases its skill set, this in turn has monotonically increasing effects on the branching factor of planners. One may consider only feasible transitions to attack this phenomena—the feasibility of actions requires either geometric evaluations or explicitly defined dynamics models. For instance, HPN uses generators that reason over the geometry of entities in the world Kaelbling and Lozano-Pérez (2011). The concept of an aspect transition graph under planning frameworks do a good job of ensuring

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8While a complete review of all task planning frameworks is outside the scope of this paper, we discuss how lifelong learning artifacts can integrate with a number of selected planners to accomplish task-relevant solutions.
that only feasible actions are planned for by exploiting the likely transitions under learned object models Ruiken et al. (2016b). Similarly, the network variants are good candidates for quickly evaluating potential control contexts and feasibility of particular actions parameters.

Importantly, by no means do the control policies and transition dynamics learned through lifelong intrinsic motivation limit the use of more sophisticated planners. Dealing with unstructured and dynamic environments becomes a fundamental problem. Therein, a number of frameworks have been adjusted to operate over uncertainties like for example, the Active Belief Planner Ruiken et al. (2016b) and the Belief-space HPN Kaelbling and Lozano-Pérez (2013).

A key insight is that many of these video prediction paradigms (as described in Section 4) can be inferred as affordance models that predict all possible futures given interaction with the world—a promising advantage of using generative adversarial networks. As such, this inherently encodes the belief over many possible outcomes that may result in interaction and can be leveraged in planning. For instance, one can operate in the belief space of futures by observing the manifold on which the many futures lie. It appears that deep generative adversarial networks, like the future prediction networks trained adversarially, obey certain arithmetics Radford et al. (2015) and as a result can be used to discover such a futures manifold.

6 Conclusion

This paper has provided an initial survey of recent advances in deep learning applicable to mobile perceptual systems, namely pertaining to the robotics domain. We discuss a series of challenges that arise when applied to physical embodied systems that are otherwise unseen in strictly vision and simulation domains. And we have outlined these recent advances in detection, control, and future prediction problems that are most relevant to robotics and candidate planners in a new learning direction.

These advances were structured in this manuscript in such a way that implies a future direction in self-supervision and lifelong learning. Piecing together these individual research ideas, we indicate that the technologies currently may be ripe to design a lifelong self-supervised system to learn complex behaviors in the real world. As such, the acquisition over an extended period of learning can be leveraged in numerous robotics tasks both in research and industry by coupling these learned artifacts with existing task planners. As Silver et al. (2013) mentions, it is time to move on from task-specific machine learning—instead, learn over an extensive repertoire, over numerous tasks in order to acquire general intelligence.

However, with using physical hardware a concern revolving around exploration of control actions comes into play. One of the most fundamental concerns with learning systems considers the question of what constitutes a safe exploration paradigm. Rather, how does one ensure that the system does not perform catastrophic actions during exploration? Safe reinforcement paradigms have been outlined by Thomas (2015), discussing algorithms to search for new and refined policies while ensuring that the probability of bad policies are minimized. In these works, Thomas et al. (2015) presented a method using the trajectories of other policies that were executed in the past to efficiently, with high confidence, perform off-policy evaluations to gauge exploration candidates. With such an approach, it becomes possible to evaluate the performance of new policies without explicit execution. Perhaps, the future for self-supervised systems lies in the connection to metrics that safeguards the hardware while effectively evaluating its possible actions. Measures like these should be considered in order to built a system that learns over a lifetime of experiences.

Recently, the emergence of deep symbolic reinforcement learning may be a promising architecture by combining recent breakthroughs in deep reinforcement learning with classical symbolic artificial intelligence Garnelo et al. (2016). Simply, a neural network backend is used to extract useful symbolic representations which are then used by a symbolic frontend for action selection. Although the work is still at its infancy, a fundamental drawback is that alike the formulation of DQN, it requires that the system has a specified task that it is trying to solve in which reward can be evaluated from. In fact, the resulting artifact of this is a meta-policy composed of sub-policies under a specified task—these sub-policies are however locally optimal under any combination of interactions between entities. There are two evident issues consisting of scaling, due to the nature of considering all possible interactions, and troubles with global optima. However, insight from the two network approach, learning a value and a policy network, may help support some of these immediate issues. Perhaps as this idea develops, it may be considered as a module in lifelong self-supervision, due to its promising connections with symbolic hierarchical planning Kaelbling and Lozano-Pérez (2013).

An important aspect of reinforcement learning is the capability of transfer, both between systems and between task domains. Work by Devin et al. (2016) provided insight on the decomposition of network policies into robot-specific and task-specific modules that supported transfer between tasks and different robot morphologies (e.g. varying in number of links and joints). Interestingly, under the control basis formulation, parametrized controllers already supports generalization from robot to robot, with an assumption that the new system has sufficiently motor resources the same control objectives. As such, the high level behavioral networks, those that are composed of primitive parametrized controllers, too inherit this form of generalizability.

A good review by Lake et al. (2016) discusses the fundamental cognitive problems with building systems that expertly accomplish tasks by pattern recognition alone. Wherein to build cognitive systems that learn and think like people, they suggest that these systems must have the capability to support both explanation and understanding. Systems must be able to understand intuitive physics, have the capacity to learn to learn, and build grounded generalizations that span new tasks and situations—such a view is similar to the direction presented in this paper. Our survey is particularly tailored towards the connection of these ideas with physical robot systems. We suggest that perhaps the goal is not the build a system that exactly mimics human cognition and learning, but instead draw insight and
computational analogs from ideas in cognitive development. Robots are not humans and do not necessarily have to learn at their granularity nor produce the same artifacts through learning. But, we regard that studying the development of cognition in biological systems may be crucial in building algorithms for artificial systems.

In this manuscript, we outlined powerful nonlinear approximation tools with inspirations from cognitive development and control theory to produce a direction in which lifelong learning frameworks can be applied to autonomous systems that continuously acquire a hierarchy of complex motor behaviors in addition to a dynamics representation of interactions in the world. A number the ideas presented in this manuscript were influenced by the computational development of action and representation going back to Grupen and Huber (2005). Their work, however, assumes there exists some preordained developmental guideline under the notion of a Developmental Assembler that provides design constraints and developmental schedules. Such entities assigns task specific rewards that are the fundamental motivators to the acquisition of complex behaviors. In the case of our review, we outlined an example reward paradigm that computes reward that adhere to the system’s internal predictions of the world and of it evolution through interaction—tying together the dynamic modeling of action related complexes in the world. Further, we surveyed numerous deep learning advances pertaining to robotics and found a close connection between many deep reinforcement learning paradigms with classical concurrent control schemes under the control basis formulation. With this survey, we would like to acknowledge that deep learning should be considered as an hyperparametric approximation tool that alone is likely not capable of attacking all problems. And as such, we foresee a direction in which these powerful approximators are integrated with closed-loop control and optimization paradigms, driven by principled motivators, and inspired by insight from cognitive development to realize a robust lifelong self-supervised system.

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