An open-ended learning architecture to face the
REAL 2020 simulated robot competition

Emilio Cartoni¹, Davide Montella¹, Jochen Triesch², and Gianluca Baldassarre¹

¹Institute of Cognitive Sciences and Technologies, CNR, Rome, Italy
²Frankfurt Institute for Advanced Studies, Frankfurt am Main, Germany

Abstract

Open-ended learning is a core research field of machine learning and robotics aiming to build learning machines and robots able to autonomously acquire knowledge and skills and to reuse them to solve novel tasks. The multiple challenges posed by open-ended learning have been operationalized in the robotic competition REAL 2020. This requires a simulated camera-arm-gripper robot to (a) autonomously learn to interact with objects during an intrinsic phase where it can learn how to move objects and then (b) during an extrinsic phase, to re-use the acquired knowledge to accomplish externally given goals requiring the robot to move objects to specific locations unknown during the intrinsic phase. Here we present a ‘baseline architecture’ for solving the challenge, provided as baseline model for REAL 2020. Few models have all the functionalities needed to solve the REAL 2020 benchmark and none has been tested with it yet. The architecture we propose is formed by three components: (1) Abstractor: abstracting sensory input to learn relevant control variables from images; (2) Explorer: generating experience to learn goals and actions; (3) Planner: formulating and executing action plans to accomplish the externally provided goals. The architecture represents the first model to solve the simpler REAL 2020 ‘Round 1’ allowing the use of a simple parameterised push action. On Round 2, the architecture was used with a more general action (sequence of joints positions) achieving again higher than chance level performance. The baseline software is well documented and available for download and use at https://github.com/AIcrowd/REAL2020_starter_kit
1 Introduction

In many organisms, the satisfaction of biological and social needs are major drives for learning. Along these drives, more sophisticated animals, in particular humans, have evolved other drives, such as curiosity and intrinsic motivations, able to guide the acquisition of knowledge and skills that are only later used to satisfy biological needs (Berlyne 1960; Baldassarre 2011; Gottlieb et al. 2013). In the last fifteen years, increasingly sophisticated learning algorithms and robots have been proposed to mimic such processes and undergo ‘open-ended learning’, that is, a cumulative autonomous acquisition of knowledge and skills in the absence of pre-defined reward functions, tasks, and goals (Baldassarre and Mirolli 2013). The technological relevance of this endeavour is the possibility of building intelligent machines and robots able to autonomously acquire knowledge and skills in unstructured, non-engineered environments, where it is impossible to directly program the systems as such environments pose challenges unknown at design time. Open-ended learning could offer a solution to this difficulty as one could allow the robots to autonomously acquire knowledge and skills in a certain environment (say in a construction site or a house) for a prolonged time and then ask them to use such knowledge to solve goals relevant for the user.

The autonomous acquisition of knowledge and skills in an open-ended learning fashion has been studied under different headings. The field of developmental robotics (Lungarella et al. 2003; Cangelosi and Schlesinger 2015) has developed algorithms for autonomous learning based on intrinsic motivations (e.g., Barto et al. 2004; Schembri et al. 2007; Oudeyer et al. 2007; Schmidhuber 2010; Zhao et al. 2012; Santucci et al. 2014b; Tanneberg et al. 2019; Eckmann et al. 2020). More recently, also machine learning and robotics have started to propose systems to face the challenges of open-ended learning see Section 2, in particular based on reinforcement learning algorithms (Sutton and Barto 1998; Barto and Mahadevan 2003).

An important trend within both fields has been the use of intrinsic motivations not to directly learn skills but rather to guide the self-generation or discovery of goals, namely internal representations of the world that might drive the agent’s actions to realize these world states (Santucci et al. 2013a, 2014a; Forestier et al. 2017; Nair et al. 2018a). This idea, also fostered by whole projects dedicated to this end, is that the autonomous setting of goals can support open-ended learning.

---

1See for example the EU project GOAL-Robots – Goal-based Open-ended Autonomous Learning, [www.goal-robots.eu](http://www.goal-robots.eu)
as it allows the autonomous generation of tasks which in turn can drive the acquisition of the skills directed to pursue the goals. An increasing number of works thus focus on the development of agents able to autonomously form new goals and learn the associated skills for realizing these goals (Held et al., 2017; Meeden and Blank, 2017; Nair et al., 2018a; Rolf and Asada, 2014; Santucci et al., 2016; Seepanomwan et al., 2017) based on the saliency of world states (Barto et al., 2004), the change of states (Santucci et al., 2016; Sperati and Baldassarre, 2018), eigenoptions (Machado et al., 2017), density models (Bellemare et al., 2016), entropy (Eysenbach et al., 2018), and variational inference (Achiam et al., 2018). While these are important developments, as discussed below, at present we still do not have a system that is able to undergo truly open-ended learning.

One way to promote research in this area is the introduction of benchmarks and competitions that facilitate comparison of competing approaches. Video games, such as Atari’s, have been profitably used in AI research, but they involve simplified actuators with respect to robotic setups and they are usually used to accomplish externally defined tasks. Some existing competitions face issues relevant for open-ended learning. For example, the AutoML for Lifelong Machine Learning\(^2\) competition aims to develop systems able to acquire an increasing amount of knowledge. However, it aims to build systems that can learn increasing amounts of input-output data furnished externally, rather than on embodied systems interacting with a physical world to actively generate new experience. Animal-AI Olympics\(^3\) are focused on simulated animal-like robots interacting with physical environments. However, these robots are tested with a set of specific tasks defined through reward functions, rather than requiring the autonomous generation of tasks. The ICDL MODELbot Challenge\(^4\) is focused on developmental processes. However, it also involves social tasks (e.g., imitation, social learning), and is not focused on a specific benchmark but rather on an article-based jury’s evaluation of the scientific quality of the reproduction of a target empirical database chosen from three possible experiments.

Thus we still lack a benchmark of open-ended learning encompassing all challenges that make it interesting. We have thus organised a new competition, called REAL 2020 – Robot open-Ended Autonomous Learning and now at its second edition\(^5\), that aims to create an open-ended learning

---

\(^2\)http://automl.chalearn.org/life-long-learning
\(^3\)http://animalaiolympics.com
\(^4\)https://icdl-epirob2019.org/modelbot-challenge
\(^5\)https://www.aicrowd.com/challenges/real-robots-2020
benchmark to more clearly identify the challenges posed by open-ended learning and to attract work of the community on them and allow a rigorous measurement of the performance of different systems. The core structure of the competition is based on two phases (Cartoni et al., 2020; Baldassarre et al., 2019): an intrinsic phase of learning and an extrinsic phase of testing. In the intrinsic phase, the robot can autonomously interact with the environment for a long time during which it should acquire, in a fully autonomous way, as much knowledge and skills as possible to best solve the tasks in the succeeding extrinsic phase. During this extrinsic phase, the knowledge acquired during the intrinsic phase is evaluated with tasks unknown during the intrinsic phase. The competition involves a ‘Round 1’ allowing the use of a simple parameterised push action and other simplifications, and a ‘Round 2’ where this is not allowed. The competition structure and the general setting is reviewed in Section 3 (see also Cartoni et al., 2020 for more detail on the competition). Here, we present a first ‘baseline model’ that achieves a score well beyond chance level by managing to drive one object to desired positions.

The architecture is modular to facilitate further development. It is formed by three components implementing the following functions important for open-ended learning: (1) Abstractor: abstraction of sensory inputs to learn relevant control variables, for example learning from images where the objects are located; (2) Explorer: generation of experience to learn goals and actions; (3) Planner: formulation and execution of action plans to accomplish the extrinsic goals. Preliminary tests of the architecture shows that it is able to accomplish a performance well above the chance level, and to exhibit a coherent behaviour.

The rest of the paper is organised as follows. In Section 2 we review related previous work on open-ended learning. In Section 3 we present the general setting and the REAL 2020 competition. In Section 4 we present our baseline model for the REAL 2020 competition. In Section 5 we evaluate the model. Finally, in Section 6 we draw conclusions.

2 Related Work

Recently, quite a few articles have appeared in the deep-learning literature that address the challenges presented by the REAL 2020 competition. Some of these works have focused on exploration: for example, Pathak et al. (2017), Burda et al. (2018) and Pathak et al. (2019) train a policy to explore unknown environments
using images only, by providing a reward based on prediction errors: i.e. the policy is reward if it goes in places where a predictor gives an error \cite{Pathak2017, Burda2018}, or where an ensemble of predictors do not agree \cite{Pathak2019}; in \cite{Sekar2020} they further augment this exploration strategy by adding planning - instead of computing the prediction error retrospectively, they add a planning step where the consequences of the current policy from the current starting state are imagined using a world model, and then the policy is optimized to seek ‘novel states’ before executing it in the environment to explore.

To learn a world model and optimize the policy using imagined trajectories, they rely on the work of \cite{Hafner2019} that showed the advantages of learning long-horizon behaviors purely by latent imagination. However, \cite{Pathak2017, Burda2018} and \cite{Pathak2019} assume a discrete set of actions. While a solution to generalize to continuous action has been proposed \cite{Pathak2019}, to our knowledge it has not been applied yet in practice. \cite{Pong2019} has also focused on the exploration problem, but in this case the images are first processed by a variational autoencoder (VAE, \cite{Kingma2013}, and then the exploration is done by drawing from the VAE latent space, using biased-weights to encourage exploration of less drawn areas. The same approach, of using the latent space of a VAE, has been applied earlier in \cite{Nair2018}. While \cite{Nair2018} did not use biased-weights, it showed a full application of the concept on a robotic scenario: starting with a first set of images to train the VAE (given or possibly obtained by random exploration) the robot automatically sampled new images from the VAE and then trained itself to achieve them. While the above works base their exploration on the state ‘novelty’, \cite{Florensa2017} instead progressively train their agent by using a network to predict state of ‘intermediate difficulty’, i.e. states where the agent find hard to reach; this latter work thus bases its exploration on ‘competence’ instead of ‘novelty’ \cite{Santucci2013}.

Other relevant works have focused instead on learning suitable representations to enable planning in an unknown environment directly from images \cite{Ding2020, Laskin2019, Wang2019, Yang2020, Yu2019}. \cite{Ding2020} use a mutual information constraint between observations and latent state to train the latent space representations, optimizing at the same time for the rewards; the authors provide experiment that show how the learned representation are robust to distractors that do not alter the dynamics of the task. \cite{Yu2019} focus on learning a representation that leads to a metric
space indicating the distance to the goal and provide a comparison against agents using a VAE. Yang et al. (2020) also learns a goal metric starting from a graph of experienced actions and then generalizing. Laskin et al. (2019) instead builds a graph-based memory and keeps it as a graph, pruning redundant nodes to enable fast planning and assuming a low-level controller that learns to move between the nodes. Wang et al. (2019) also uses a low-level controller to execute the plan but the plan itself is done on the latent representation created by a CIGAN, a Causal InfoGAN network that learns to predict which states can be successors of another state; from the CIGAN representation a plan is obtained (using A* with Euclidian distance in the latent space as heuristic) and then the plan is decoded into images that a visual-tracker (the low-level controller) will follow.

All these works might be applied to the REAL competition to try and solve various parts of it (i.e. to achieve better exploration or to learn better representations), however, with the exception of Nair et al. (2018b), no other work offers a complete solution that could be readily applied to solve the competition from intrinsic phase up to the extrinsic phase.

### 3 Experimental Setup

Autonomous open-ended learning requires skills without external guidance, i.e. with an external assigned task or reward for doing specific actions. In the competition, this is emphasized by having two different phases: one phase, the *intrinsic phase*, where the robot is free to explore the environment, with no task or reward assigned; then, in a second phase, the *extrinsic phase*, a task is assigned to check if the robot was able to learn how to control the world it was put in. More specifically, in the REAL2020 competition the robot is composed by a 7 DoF Kuka arm, coupled with a 2 dof gripper standing near a table which has a shelf and 1 to 3 objects (a cube, a tomato can and a mustard bottle, see Figure 1a). In the following experiments, 1 object only is used (the cube) unless differently specified. The robot can be controlled using joint angles, Cartesian coordinates (see ...) or a ‘macro_action’ (see also below). The robot has the following sensors: a camera offering a top-view of the table (see Figure 1a), joint angles sensors and touch sensors inside the gripper. During the extrinsic phase, the robot is also given a ‘goal’ image that specifies how the objects should be arranged on the table to reach the goal. The intrinsic phase lasts 15 million
timesteps (each timestep corresponds to 5 milliseconds, so about 21 hours of real time). The extrinsic phase is divided into 50 trials, each lasting 10 thousand timesteps. At the start of every trial, the objects are put into a different position and a new goal image is sent to the robot (see Figure 1b). All the trials are scored using the following formula:

$$M_g = \sum_{o=1}^{n} \left[ e^{-c||p_o^*-p_o||} \right]$$

where $n$ is the number of objects (1, 2, or 3), $p_o^*$ is the $(x, y, z)$ position vector of the mass center of object $o$ in the target goal, $p_o$ is the position of the object at the end of the task after the robot attempts to bring it to the goal position, $c$ is a constant ensuring that this part of the score will be 0.25 if the distance to the goal position is 0.10 (10 cm). The metric ranges in $(0, 1]$ for each object, and is equal to 1.0 if the object is exactly at the goal position, and decays exponentially with an increasing distance from it. Placing all 3 objects exactly in the overall goal configuration yields a maximum score of 3.0. The total Score $M$ of a certain system is the average of its scores across the $G$ ($G = 50$) overall goals:

$$M = \frac{1}{G} \sum_{g=1}^{G} M_g$$
4 Baseline architecture

The proposed baseline architecture has a modular structure. The architecture is composed of the following modules: Abstractor, Explorer, and Planner, as illustrated in Figure 2.

The baseline agent queries the Explorer module to know which actions it should perform during the intrinsic phase. In theory, the Explorer module should direct the exploration to maximize the ability of the agent to learn new skills during the intrinsic phase. However, in this version of the baseline we simply used a random exploration, which was enough to pick up some skills in the setting with just one object. All the actions performed by the agent during the intrinsic phase are stored as triplets \((pre, action, post)\), where \(pre\) is the status of the sensors before doing the action, \(action\) is the action that was performed and \(post\) is the sensors readings after the action is completed. At the end of each action the robot always goes back to its ‘home’ position, which is a position that is assumed not to cause further changes to the environment (i.e. it sets the arm straight up, away from the table). All the triplets are sent to the Abstractor, which tries to learn useful control variables from the sensors. This variables are then used by the Planner. In theory, they could also be learned during the intrinsic phase and used by the Explorer, although this is not the case in the current version.

The current Abstractor version does the following: we first discard all sensor readings except the images - joint angles and touch sensors would not add anything since we take the sensor readings at the start and at the end of the action, when the robot is always in the home position, so it has always the same
joint angles and it is not touching anything. The images are then processed with the OpenCV MOG2 computer vision algorithm (Zivkovic 2004; Zivkovic and van der Heijden 2006) that filters the background. We filter the background because we assume that the robot is interested in learning about things that change in the environment, so the static portion of the image can be removed. A Variational Autoencoder is then trained on the background-filtered images, thus converting all the pre and post images into latent variables. The latent variables are then sent to the Dynamic abstractor, which is a further abstraction layer used to facilitate the planning process. The output of the Dynamic Abstractor is a nxm array, where n is the number of abstraction levels desired (200 in the following experiments) and m is the number of latent variables. For each level of abstraction, the Dynamic Abstractor gives m values which represent the threshold below which two states are considered the same (see Algorithm 1). The lowest level utilizes as threshold the minimum differences found in each latent variables between all the pre and post states of each experienced action. The maximum level of abstraction instead uses the biggest difference that was experienced between each pre and post. The idea is that for the minimum level of abstraction, it would not make sense to distinguish between two states that are less different than the minimum change that the robot was able to produce in its experience. The higher abstraction levels progressively uses bigger differences, where the scale is also determined by what was experienced, thus allowing the Dynamic abstractor to work unsupervised without specific tuning to the environment. As we will see below the Dynamic abstractor is invoked by the Planner to know which state can consider the same, both to know which actions can be done in the current state and to know if the goal state was achieved. Without the Dynamic Abstractor, the Planner would only be able to construct a plan if the current state exactly matches one the experienced pre states, and the available actions would be only those that start with that pre state. By using the Dynamic Abstractor, the Planner will be able to consider nearby state (those within the threshold of the chosen level of abstraction) thus generalizing the actions to other states and allowing for more planning options. However, the generalization can ‘fail’ as with higher level of abstraction progressively different states are considered the same even though they do not lead to the same outcome.

---

6 We are arbitrarily using seven latent variables in the VAE, which are more than those needed by a robot that knows the task in advance; knowing the task in advance two would probably suffice to convert the images to latents representing an x-y coordinate position of the object.
when performing a certain action. This is why the Planner always starts with the lowest level of abstraction.

The Planner uses the triplets \((\phi_{pre}, \text{action}, \phi_{post})\) to find a plan of actions that transforms the current state into a state that matches the goal, where \(\phi_{pre}\) and \(\phi_{post}\) are the pre and post states abstracted using the Abstractor module. It uses A* planning with a depth limit that varies as the trial progresses\(^7\); the heuristic used for the A* search is the Manhattan distance to the goal state in latent space. The states are initially abstracted at ‘abstraction level 1’ (see Dynamic abstractor above): if the plan is found, it is executed, otherwise the planner tries again to find a plan with an higher level abstraction. If it reaches the maximum abstraction level without finding a plan, the robot will just stay still. If a plan is found, the first action is executed, then the Planning is invoked again to remake the plan again based on the state obtained after the first action (see Agent flowchart in Figure 6 of the Supplemental Material).

Algorithm 1: Dynamic Abstractor

1. Input: \((\phi_{pre}, \text{action}, \phi_{post})\) triplets, max_abstractions;
2. Output: abstraction_distances vector;
3. foreach \((\phi_{pre}, \text{action}, \phi_{post}) \in \text{triplets}\) do
   4. difference_vector \(\leftarrow |\phi_{pre} - \phi_{post}|\);
   5. for \(k \leftarrow 1\) to \(n_{\text{latents}}\) do
      6. variable_differences\([k]\).append(difference_vector\([k]\));
   7. for \(k \leftarrow 1\) to \(n_{\text{latents}}\) do
      8. sort(variable_differences\([k]\));
   9. for \(k \leftarrow 1\) to \(n_{\text{latents}}\) do
      10. \(k \leftarrow 0\);
   11. for \(i \leftarrow 1\) to \(\text{max\_abstractions}\) do
      12. abstraction_distances\([i]\) \(\leftarrow\) variable_differences\([i]\)[\(k\)];
      13. \(k \leftarrow k + \text{length(triplets)} / \text{max\_abstractions}\);

---

\(^7\)i.e. if there are only 4000 timesteps remaining in the trial the maximum depth is 4, as each action lasts 1000 timesteps.
Figure 3: Dynamic abstraction process in planning: as progressively higher abstraction levels are used, multiple states will be considered ‘the same’ by the planner; this enables a single state to reach more states.

5 Results

We applied the baseline to both Round 1 and Round 2 of the REAL 2020 competition.

Figure 4: REAL 2020 scores plotted as averages distances to the goals. On both Round 1 and Round 2 the baseline reaches higher than random scores, using ‘macro_action’ and joints control respectively.

On Round 1, the baseline was configured to use the ‘macro_action’. The ‘macro_action’ was a simplification available in Round 1 that allowed participants to control the robot by specifying the starting and ending positions of a pre-defined push movement. The robot lowered its gripper vertically on the specified (x, y) starting location, then it moved it along the table up to the (x, y) ending position and then returned the arm to the home position (i.e. the arm being all vertical).8 We achieved a score on the REAL 2020 benchmark of 0.211, which significantly higher than a random controller, which would only achieve 0.022 (see Figure 4). The score of the baseline is equivalent to putting the cube always at a distance of 11 cm from the goal on all the 50 goals. In reality, some of the

8See video at: https://www.youtube.com/watch?v=k126SyGAYK
goals cannot be reached by the ‘macro_action’, since it cannot reach the shelf. The performance on the first 25 goals, which are guaranteed to be on the shelf is about the double (above 0.4), equivalent to an accuracy of about 6.5 cm overall. Indeed, the system was able to place the object within 10 cm 21 times out of 25.

Figure 5 shows the score achieved by different runs of the baseline with different lengths of the intrinsic phase, using 100 goals on the lower part of the table. As it can be seen, the baseline achieves a significant score even with shorter intrinsic phases than the one allowed by the competition.

We also tried the baseline using multiple objects, achieving an average score of 0.095 with 2 objects (cube and tomato can) and 0.127 with 3 objects (cube, tomato can, mustard). The performance dropped, due to the inability of the Planner to find suitable plans. Indeed, as the Planner uses monolithic states, it becomes increasingly difficult to find in the experienced triples a \textit{pre} state that matches the current disposition of all 3 objects.

On Round 2, the ‘macro_action’ simplification was no longer available: participants can only use Cartesian or joint control. It is forbidden by the rule
to create a pre-defined action, however, it is possible to return to the ‘home’ position periodically. Building on this, we configured the baseline to perform a random sequence joint positions between consecutive returns to the home position. The baseline returns to the home position every 1000 timesteps, with the command to return to the home lasting 150 timesteps to ensure that the robot has gone back to home. The remaining 850 timesteps between two home commands, are divided into 1 to 10 parts, with each part being used to reach a different joint position. We have thus constructed a 1000 timestep action that is general enough not to violate the rules, but still contains the concept of ‘doing something and then returning to the home position’ so that the logic of the baseline can still be applied. As in Round 1, the actions performed by the Explorer are random, this time drawing 1 to 10 random positions in the joints space.

Figure 4 shows that even with this new general action the baseline achieves good results for a score of 0.155, equivalent to keeping an accuracy of about 13 cm.

6 Conclusions

Human’s ability for open-ended learning of virtually countless skills is still unmatched by Artificial Intelligence. Here, we have highlighted the need for benchmarks of open-ended learning to allow comparing competing approaches and measuring progress in the field. We have reviewed one such benchmark, the REAL 2020 competition focusing on robotic manipulation tasks, and we have proposed a baseline open-ended learning system for this challenge. This baseline system has a modular architecture consisting of 1) an “Abstractor” module to learn compact representations of the state of the world, 2) an “Exploerer” module to generate experience and discover useful learning goals, and 3) a “Planner” module to formulate and execute action plans to achieve externally provided goals. Our results demonstrate that this baseline system performs well on both Round 1 and Round 2 of the REAL 2020 challenge, where objects needs to be moved to specified locations.
Acknowledgment

This research was supported by the European Union’s Horizon 2020 Research and Innovation Programme under Grant Agreement No 713010, Project “GOAL-Robots – Goal-based Open-ended Autonomous Learning Robots”.

References

Achiam, J., Edwards, H., Amodei, D., Abbeel, P., 2018. Variational option discovery algorithms. arXiv 1807.10299.

Baldassarre, G., 2011. What are intrinsic motivations? A biological perspective, in: Proceedings of the International Conference on Development and Learning (ICDL-2011).

Baldassarre, G., Lord, W., Granato, G., Santucci, V.G., 2019. An embodied agent learning affordances with intrinsic motivations and solving extrinsic tasks with attention and one-step planning. Frontiers in Neurorobotics 13, e1–26. doi:10.3389/fnbot.2019.00045

Baldassarre, G., Mirolli, M. (Eds.), 2013. Intrinsically motivated learning in natural and artificial systems. doi:10.1007/978-3-642-32375-1

Barto, A., Mahadevan, S., 2003. Recent advances in hierarchical reinforcement learning. Discrete event dynamic systems 13, 41–77.

Barto, A., Singh, S., Chentanez, N., 2004. Intrinsically motivated learning of hierarchical collections of skills, in: ICDL-2004.

Bellemare, M., Srinivasan, S., Ostrovski, G., Schaul, T., Saxton, D., Munos, R., 2016. Unifying count-based exploration and intrinsic motivation, in: NIPS, pp. 1471–1479.

Berlyne, D.E., 1960. Conflict, arousal, and curiosity. McGraw-Hill Book Company.

Burda, Y., Edwards, H., Pathak, D., Storkey, A., Darrell, T., Efros, A.A., 2018. Large-Scale Study of Curiosity-Driven Learning URL: http://arxiv.org/abs/1808.04355 arXiv:1808.04355

Cangelosi, A., Schlesinger, M., 2015. Developmental robotics. MIT Press.
Cartoni, E., Mannella, F., Santucci, V.G., Triesch, J., Rueckert, E., Baldassarre, G., 2020. Real-2019: Robot open-ended autonomous learning competition, 142–152.

Ding, Y., Clavera, I., Abbeel, P., 2020. Mutual Information Maximization for Robust Plannable Representations, 1–5. URL: http://arxiv.org/abs/2005.08114, arXiv:2005.08114.

Eckmann, S., Klimmasch, L., Shi, B.E., Triesch, J., 2020. Active efficient coding explains the development of binocular vision and its failure in amblyopia. Proceedings of the National Academy of Sciences 117, 6156–6162.

Eysenbach, B., Gupta, A., Ibarz, J., Levine, S., 2018. Diversity is all you need: Learning skills without a reward function. arXiv 1802.06070.

Florensa, C., Held, D., Geng, X., Abbeel, P., 2017. Automatic Goal Generation for Reinforcement Learning Agents. URL: http://arxiv.org/abs/1705.06366, arXiv:1705.06366.

Forestier, S., Mollard, Y., Oudeyer, P., 2017. Intrinsically motivated goal exploration processes with automatic curriculum learning. arXiv 1708.02190.

Gottlieb, J., Oudeyer, P., Lopes, M., Baranes, A., 2013. Information-seeking, curiosity, and attention. Trends in Cognitive Science 17, 585–593.

Hafner, D., Lillicrap, T., Ba, J., Norouzi, M., 2019. Dream to Control: Learning Behaviors by Latent Imagination. URL: http://arxiv.org/abs/1912.01603, arXiv:1912.01603.

Held, D., Geng, X., Florensa, C., Abbeel, P., 2017. Automatic goal generation for reinforcement learning agents. arXiv 1705.06366.

Kingma, D.P., Welling, M., 2013. Auto-Encoding Variational Bayes. Preprint arXiv 1312.6114v10.

Laskin, M., Emmons, S., Jain, A., Kurutach, T., Abbeel, P., Pathak, D., 2019. Sparse Graphical Memory for Robust Planning arXiv:2003.06417v2.

Lungarella, M., Metta, G., Pfeifer, R., Sandini, G., 2003. Developmental robotics: A survey. Connection Science 15, 151–190.

Machado, M.C., Bellemare, M.G., Bowling, M., 2017. A laplacian framework for option discovery in reinforcement learning. arXiv 1703.00956.
Meeden, L., Blank, D., 2017. Developing grounded goals through instant replay learning, in: ICDL-2017.

Nair, A., Pong, V., Dalal, M., Bahl, S., Lin, S., Levine, S., 2018a. Visual reinforcement learning with imagined goals, in: LLRLA2018 (at FAIM2018).

Nair, A., Pong, V., Dalal, M., Bahl, S., Lin, S., Levine, S., 2018b. Visual Reinforcement Learning with Imagined Goals URL: http://arxiv.org/abs/1807.04742, arXiv:1807.04742.

Oudeyer, P., Kaplan, F., Hafner, V., 2007. Intrinsic motivation systems for autonomous mental development. IEEE transactions on evolutionary computation 11.

Pathak, D., Agrawal, P., Efros, A.A., Darrell, T., 2017. Curiosity-driven Exploration by Self-supervised Prediction URL: http://arxiv.org/abs/1705.05363, arXiv:1705.05363.

Pathak, D., Gandhi, D., Gupta, A., 2019. Self-supervised exploration via disagreement. 36th International Conference on Machine Learning, ICML 2019 2019-June, 8887–8896. arXiv:1906.04161.

Pong, V.H., Dalal, M., Lin, S., Nair, A., Bahl, S., Levine, S., 2019. Skew-Fit: State-Covering Self-Supervised Reinforcement Learning URL: http://arxiv.org/abs/1903.03698, arXiv:1903.03698.

Rolf, M., Asada, M., 2014. Autonomous development of goals: From generic rewards to goal and self detection, in: ICDL-2014.

Santucci, V., Baldassarre, G., Mirolli, M., 2013a. Intrinsic motivation signals for driving the acquisition of multiple tasks: a simulated robotic study, in: ICCM-2013.

Santucci, V.G., Baldassarre, G., Mirolli, M., 2013b. Which is the best intrinsic motivation signal for learning multiple skills? Frontiers in Neurorobotics 7, e1–14. doi:10.3389/fnbot.2013.00022.

Santucci, V.G., Baldassarre, G., Mirolli, M., 2014a. Autonomous selection of the “what” and the “how” of learning: an intrinsically motivated system tested with a two armed robot, in: ICDL-2014.
Santucci, V.G., Baldassarre, G., Mirolli, M., 2014b. Cumulative learning through intrinsic reinforcements, in: Evolution, Complexity and Artificial Life. Springer.

Santucci, V.G., Baldassarre, G., Mirolli, M., 2016. GRAIL: A goal-discovering robotic architecture for intrinsically-motivated learning. IEEE Transactions on Cognitive and Developmental Systems 8, 214–231.

Schembri, M., Mirolli, M., Baldassarre, G., 2007. Evolving internal reinforcers for an intrinsically motivated reinforcement-learning robot, in: ICDL-2007.

Schmidhuber, J., 2010. Formal theory of creativity, fun, and intrinsic motivation (1990–2010). IEEE Transactions on Autonomous Mental Development 2, 230–247.

Seepanomwan, K., Santucci, V., Baldassarre, G., 2017. Intrinsically motivated discovered outcomes boost user’s goals achievement in a humanoid robot, in: ICDL-2017.

Sekar, R., Rybkin, O., Daniilidis, K., Abbeel, P., Hafner, D., Pathak, D., 2020. Planning to Explore via Self-Supervised World Models arXiv:2005.05960v2

Sperati, V., Baldassarre, G., 2018. Bio-inspired model learning visual goals and attention skills through contingencies and intrinsic motivations. IEEE Transactions on Cognitive and Developmental Systems 10, 326–344.

Sutton, R.S., Barto, A.G., 1998. Reinforcement learning: An introduction. MIT press.

Tanneberg, D., Peters, J., Rueckert, E., 2019. Intrinsic motivation and mental replay enable efficient online adaptation in stochastic networks. Neural Networks 109, 67–80.

Wang, A., Kurutach, T., Liu, K., Abbeel, P., Tamar, A., 2019. Learning Robotic Manipulation through Visual Planning and Acting URL: http://arxiv.org/abs/1905.04411, arXiv:1905.04411

Yang, G., Zhang, A., Morcos, A.S., Pineau, J., Abbeel, P., Calandra, R., 2020. Plan2Vec: Unsupervised Representation Learning by Latent Plans 120, 1–19. URL: http://arxiv.org/abs/2005.03648, arXiv:2005.03648
Yu, T., Shevchuk, G., Sadigh, D., Finn, C., 2019. Unsupervised Visuomotor Control through Distributional Planning Networks URL: http://arxiv.org/abs/1902.05542, arXiv:1902.05542.

Zhao, Y., Rothkopf, C.A., Triesch, J., Shi, B.E., 2012. A unified model of the joint development of disparity selectivity and vergence control, in: 2012 IEEE International Conference on Development and Learning and Epigenetic Robotics (ICDL), IEEE. pp. 1–6.

Zivkovic, Z., 2004. Improved adaptive gaussian mixture model for background subtraction, in: In Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on, volume, IEEE. pp. 28–31.

Zivkovic, Z., van der Heijden, F., 2006. Efficient adaptive density estimation per image pixel for the task of background subtraction, 773–780.
Supplementary material

Agent state machine

The overall agent is composed by a state-machine that orchestrates the coordination between all the three modules. The states are as illustrated in Figure 6. The agent starts with the state ActionStart that based on the presence of a goal in the observation will go to explore or to plan. In the case the goal don’t exists, it generates an action with the Explorer through the ProposeAction state. If instead there is a goal, it will query the Planner for a plan through PlanAction. In both cases an action is executed with DoAction, unless the planning had no success; in this last case it will wait the next goal through WaitForGoal. After it executes the action the robot will go into the in EndAction state and save the triplet (pre, action, post containing the states before and after the action and the parameters of the executed action.

Figure 6: Agent flow

Planning

This section reports additional data on the functioning of the Planner component. In particular, Figure 7 reports the branching factor of the planning process dependent on different levels of abstraction. Figure 8 reports the number of states experienced during the intrinsic phase that the system considers as different depending on the abstraction level.
Figure 7: Branching factor in function of the abstraction level. As the abstraction level goes up, it is possible to reach multiple states from the same state.
Figure 8: Number of states that are considered different as a function of the abstraction level.