AI Autonomy: Self-Initiation, Adaptation and Continual Learning

Bing Liu, Sahisnu Mazumder, Eric Robertson, Scott Grigsby

1 University of Illinois at Chicago, USA
2 Intel Labs, USA
3 PAR Government Systems Corporation, USA
liub@uic.edu, sahisnu.mazumder@intel.com, {eric_robertson, scott_grigsby}@partech.com

Abstract
As more and more AI agents are used in practice, it is time to think about how to make these agents fully autonomous so that they can (1) learn by themselves continually in a self-motivated and self-initiated manner rather than being retrained offline periodically on the initiation of human engineers and (2) accommodate or adapt to unexpected or novel circumstances. As the real-world is an open environment that is full of unknowns or novelties, detecting novelties, characterizing them, accommodating or adapting to them, and gathering ground-truth training data and incrementally learning the unknowns/novelties are critical to making the AI agent more and more knowledgeable and powerful over time. The key challenge is how to automate the process so that it is carried out continually on the agent’s own initiative and through its own interactions with humans, other agents and the environment just like human on-the-job learning. This paper proposes a framework (called SOLA) for this learning paradigm to promote the research of building autonomous and continual learning enabled AI agents. To show feasibility, an implemented agent is also described.

1 Introduction
Classic machine learning (ML) makes the closed-world assumption, which means that what is seen by the system in testing or deployment must have been seen during training (Fei, Wang, and Liu 2016; Bendale and Boult 2015; Liu 2020), i.e., there is nothing unexpected or novel occurring in testing or deployment. This assumption is invalid in practice as the real world is an open environment that is full of unknowns or novel objects. For humans, novelties serve as an intrinsic motivation for learning. Human novelty detection results in a cascade of unique neural responses and behavioral changes that enable exploration and flexible memory encoding of the novel information. As learning occurs, this novelty response is soon lost as repeated exposure to novelty results in fast neural adaptation (Tulving and Kroll 1995; Murty et al. 2013). In order to make an AI agent thrive in the real open world, like humans, it has to detect novelties and learn them incrementally to make the system more knowledgeable and adaptable over time. It must do so on its own initiative on the job (after deployment) rather than relying on human engineers to retrain the system offline periodically. That is, it must learn in the open world in a self-motivated manner in the context of its performance task (the main task of the agent).

We use the hotel guest-greeting bot example from (Chen and Liu 2018) to illustrate the issues involved. The bot’s performance task is greeting hotel guests. When its vision system sees a guest (say, John) it has learned before, it greets him by saying,

“Hi John, how are you today?”

When it sees a new guest, it should detect this guest as new or novel. This is a novelty detection problem (also known as out-of-distribution (OOD) detection), upon discovering the novelty, the new guest, it needs to accommodate or adapt to the novel situation. The bot may say to the new guest

“Hello, welcome to our hotel! What is your name, sir?”

If the guest replies “David,” the bot takes some pictures of the guest to gather training data and then incrementally or continually learn to recognize David. The name “David” serves as the class label of the pictures taken. As for humans, the detected novelty serves as an intrinsic self-motivation for the agent/bot to learn. When the bot sees this guest again next time, it can say

“Hi David, how are you today?” /David is no longer novel

In an actual hotel, the situation is, however, much more complex than this. For example, how does the system know that the novel object is actually a person, not a dog? If the system can recognize the object as a person, how does it know that he/she is a hotel guest, not a service provider for services such as delivery or security? In order to adapt to the novel object or situation, the system must first characterize the novel object, as without it, the agent does not know how to adapt or respond. In this case, some classification or similarity comparison is needed to decide whether it is a person with luggage. If the object looks like a person but has no luggage, the bot will not respond or learn to recognize the person as it is irrelevant to its performance task. If the novel object looks like an animal, it should notify a hotel employee and learn to recognize the object so that it will no longer be novel when it is seen next time. In short, for each characterization, there is a corresponding response or adaptation strategy, which can be NIL (i.e., do nothing). This discussion shows that in order to characterize, the agent must already have rich world knowledge. Last but not least, there is also risk involved when making an incorrect decision.

As classic learning matures, we should go beyond the
existing paradigm to study how to enable an agent to learn and adapt by itself via its own interactions with humans and the environment, i.e., self-initiation, involving no engineers. This paper proposes a Self-initiated Open-world continual Learning and Adaptation (SOLA) framework to promote the research of autonomous AI agents so that they can face the real open world and learn by themselves. An example SOLA agent in the context of dialogue systems or chatbots that implements the SOLA framework is also discussed.

2 Comparison with Related Work

Open world learning has been studied by many researchers (Bendale and Boult 2015; Fei, Wang, and Liu 2016; Xu et al. 2019), but they mainly focused on novelty detection (Parmar et al. 2021), also called open set or out-of-distribution (OOD) detection. Some researchers have also studied learning the novel objects after they are detected (Bendale and Boult 2015; Fei, Wang, and Liu 2016; Xu et al. 2019) and manually labeled. A survey of the topic can be found in (Yang et al. 2021). A position paper presented some nice blue sky ideas about open world learning in (Langley 2020), but it does not have sufficient details or an implemented system. SOLA differs from the prior studies in many ways.

(1). SOLA stresses self-initiation in learning, which means that all the learning activities from start to end are self-motivated and self-initiated by the agent itself. The process involves no human engineers.

(2). Due to self-initiation, SOLA enables learning after the model deployment like human learning on the job or while working, which has barely been attempted before. In existing learning paradigms, after a model has been deployed, there is no more learning until the model is updated or retrained on the initiation of human engineers.

(3). SOLA is a lifelong and continual learning paradigm again because learning is self-initiated and unceasing. It is thus connected with lifelong and continual learning, which is an active research area (Chen and Liu 2018).

(4). SOLA involves online interactions of the learning agent and human users, other AI agents, and the environment. The purpose is to acquire ground-truth training data on the fly by itself. This is very similar to what we humans do when we encounter something novel or new and ask others interactively to acquire knowledge. It is very different from collecting a large amount of unlabeled data and asking human annotators to label the data. Also, it differs from active learning (Settles 2009; Ren et al. 2021) as active learning only focuses on acquiring labels from users for selected unlabeled examples in the given dataset. Furthermore, SOLA allows learning from other resources, e.g., the Web, to gain knowledge, like a human reading a book. Due to space limits, this paper will not focus on this type of learning (see an example in (Mitchell et al. 2015)).

(5). SOLA includes modules to characterize and to adapt to novel situations so that the agent can work in the open world environment and also continually learn in the process.

In summary, SOLA makes learning autonomous and self-initiated. We believe that SOLA is necessary for the next generation machine learning and AI agents. Finally, note that although SOLA focuses on self-initiated learning, it does not mean that the learning system cannot learn a task given by humans or other AI agents.

3 Lifelong and Continual Learning

Since SOLA at its core is a continual learning paradigm, this section introduces lifelong or continual learning (Chen and Liu 2018). To enable autonomous continual learning without the involvement of human engineers, other capabilities are needed, which we will discuss in subsequent sections.

The terms lifelong learning and continual learning have the same meaning and are used interchangeably now, but the past research under the two names has focused on different aspects of the same problem.

Lifelong Learning (LL)

LL is defined in (Chen and Liu 2018) as follows, which is based on the early definitions in (Thrun 1995; Silver, Yang, and Li 2013; Ruvolo and Eaton 2013; Mitchell et al. 2015):

Lifelong learning: At any time point, the learner has learned a sequence of $N$ tasks, $T_1, T_2, \ldots, T_N$. When faced with the $(N + 1)^{th}$ task $T_{N+1}$, the learner can leverage the knowledge in the knowledge base (KB) to help learn $T_{N+1}$. KB maintains the knowledge learned from the previous $N$ tasks. After the completion of learning $T_{N+1}$, KB is updated with the knowledge gained from learning $T_{N+1}$.

We can see the goal of LL is to leverage the knowledge learned in the past to learn the new task $T_{N+1}$ better, i.e., knowledge transfer. An implicit assumption of LL is that the tasks learned are very similar (Chen and Liu 2018).

Continual Learning (CL)

The term continual learning (CL) is more commonly used than LL in the deep learning community. The focus of CL has been on solving the catastrophic forgetting (CF) problem (Rusu et al. 2016; Kirkpatrick et al. 2017; Zenke, Poole, and Ganguli 2017; Rebuffi, Kolesnikov, and Lampert 2017; Shin et al. 2017; Serra et al. 2018; Lee, Stokes, and Eaton 2019; Chaudhry et al. 2020). CF refers to the phenomenon that when a neural network learns a sequence of tasks, the learning of each new task is likely to change the weights learned for previous tasks, which degrades the model accuracy for the previous tasks (McCloskey and Cohen 1989). Two CL settings have been studied extensively in the research literature.

Class continual learning (CCL). In CCL, each task consists of one or more classes to be learned together but only one model is learned to classify all classes so far. In testing, a test instance from any class may be presented to the model after the completion of learning.

Task continual learning (TCL). In TCL, each task is a separate classification problem (e.g., one classifying different breeds of dogs and one classifying different types of birds). TCL builds a set of classification models (one per task) in one neural network. In testing, the system knows which task each test instance belongs to and uses only the model for the task to classify the test instance. Note that classical LL
mainly works in this CL setting and assumes that the tasks are similar to enable knowledge transfer across them.

Ideally, we would like CL or LL to achieve both objectives i.e., (1) overcoming CF and (2) performing cross task knowledge transfer. For example, it is not obvious that different tasks or classes can help each other in CCL except feature sharing. For TCL, if the tasks are entirely different, it is hard to improve the new task learning via knowledge transfer either. For example, one task is to classify whether one has a heart disease or not and another is to classify whether a loan application should be approved or not. In these cases, CF is the only problem to solve. Recent research has shown that when a mixed sequence of similar and dissimilar tasks are learned in TCL, it is possible to perform selective knowledge transfer among similar tasks (Ke, Liu, and Huang 2020) and also to overcome CF for dissimilar tasks. Task similarity is detected automatically.

The architecture of CL/LL systems is given in Figure 1 without the orange-colored links. The orange-colored links will be discussed in the next subsection. Dealing with CF is not reflected in the architecture as it stays in the algorithm of the learner. Model_{N+1} includes all the models from T_1 to T_{N+1}, which may all be in one neural network. In the case of TCL, they may be separate models indexed by their task identifiers. In the case of CCL, Model_{N+1} is just one model that covers all classes of the tasks learned so far.

Limitation. One key limitation of the existing CL paradigm is that the tasks and their training data are given by the user. This means that the system is not autonomous and cannot learn by itself. In order to do that, we extend the CL architecture with the orange-colored links in Figure 1 to enable learning on the job to achieve full SOLA.

A New CL Architecture

The new architecture is the full diagram in Figure 1, which adds the orange-colored links to the traditional CL. These links enable the system to learn by itself to achieve autonomy in the full SOLA framework, i.e., to learn on the job during application or after model deployment.

The basic idea is that during application, if the system/agent encounters anything that is out-of-distribution or novel (a novelty), the system creates a new task to learn and also obtains the needed ground-truth training data to learn the task on the initiation of the system itself through interactions with the humans and the environment. Some new knowledge (or auxiliary knowledge) gained from the application can be added to the KB that may be leveraged in future learning or to improve the current model.

Below, we first discuss novelty, which serves as the motivation for learning, and then present the details of on-the-job learning in Section 5, which is the new SOLA paradigm.

4 Novelty

Novelty is an agent-specific concept. An object may be novel to one agent based on its partial knowledge of the world but not novel to another agent. We distinguish two types of novelty, absolute novelty and contextual novelty.

Absolute novelty. Absolute novelty represents something that the agent has never seen before. For example, in the context of supervised learning, the agent’s world knowledge is learned from the training data D_{tr} = \{(x_i, y_i)\}_{i=1}^{n} with x_i \in X and y_i \in Y_{tr}. Let h(x) be the latent or internal representation of x in the agent’s mind, h(D_{tr}) be the latent representation of the training data of class y_i, and k (= |Y_{tr}|) be the total number of training classes. We use \mu(h(x), h(D_{tr}))

Figure 1: Architecture of a typical lifelong learning framework incorporating on-the-job learning (best viewed in color). T_1, ..., T_N are the previously learned tasks, T_{N+1} is the current new task to be learned and D_{N+1} is its training data. The Learner learns by leveraging the relevant prior knowledge identified by the Task-based Knowledge Miner from the Knowledge Base (KB), which contains the retained knowledge in the past. Existing research on lifelong or continual learning does not have the orange-colored lines. The orange-colored lines are added for on-the-job learning in SOLA.
to denote the novelty score of a test instance \( x \) with respect to \( h(D_{tr}) \). The degree of novelty of \( x \) with respect to \( D_{tr} \),

\[
\mu(h(x), h(D_{tr})) = \min(\mu(h(x), h(D_{tr}^1)), \ldots, \mu(h(x), h(D_{tr}^k)))
\]

The novelty function \( \mu \) can be defined based on specific applications. For example, if the training data of each class follows the Gaussian distribution, one may use the distance from the mean to compute the novelty score.

**Novel instance:** A test instance \( x \) is novel if its novelty score \( \mu(x, \cdot) \) is greater than or equal to a threshold value \( \gamma \) such that \( x \) can be assigned a new class not in \( Y_{tr} \).

**Novel class:** A newly created class \( y_{new} \) (\( y_{new} \notin Y_{tr} \)) assigned to some novel instances is called a novel class (unknown or unseen class). The classes in \( Y_{tr} \) are called known or seen classes.

**Contextual novelty.** Based on the prior knowledge of the agent, the probability \( P(x|Q) \) of \( x \) occurring in a particular context \( Q \) is very low, but \( x \) has occurred in \( Q \), which is surprising or unexpected. If \( x \) has been seen before, it is not absolutely novel. A contextual novelty is also commonly called a surprise or unexpected event. In human cognition, surprise is an emotional response to an instance which greatly exceeds the expected uncertainty within the context of a task. The definitions of contextual novel instance and class are similar to those for absolute novelty.

Novelty is not restricted to the perceivable physical world but also includes the agent’s internal world, e.g., novel interpretations of world states or internal cognitive states that have no correspondence to any physical world state. Interested readers may also read (Boutil et al. 2021) for a more nuanced and perception-based study of novelty.

There are other related concepts to novelty, e.g., outliers and anomalies.

**Outlier and anomaly:** An outlier is a data point that is far away from the main data clusters, but it may not be unknown. For example, the salary of a company CEO is an outlier with respect to the distribution of company employees, but it is known and thus not novel. Unknown outliers are novel. Anomalies can be considered outliers or instances that are one off and never repeated. Though technically “novel” they may not need to result in a new class.

Note that this paper does not deal with various types of data shift such as covariate shift, prior probability shift and concept drift as a large amount of work has been done (Moreno-Torres et al. 2012).

We will not discuss novelty detection further because it has been studied extensively in the literature under the names of novelty detection, out-of-distribution detection, or open-world classification/recognition. Several excellent surveys exist (Pang et al. 2021; Parmar et al. 2021; Yang et al. 2021).

## 5 The Proposed SOLA Framework

An AI agent consists of a pair of key modules \( (T, S) \), where \( T \) is the primary task-performer that performs its performance task (e.g., the dialogue system of the greeting bot) and \( S \) is a set of supporting or peripheral functions (e.g., the vision system and the speech system of the bot) that supports the primary task-performer. The primary task-performer \( T \) or each supporting function \( S_i \in S \) may consist of ten sub-systems \((L, M, K, R, C, A, S, P, I, E)\). Figure 2 shows the relationships and functions of the sub-systems. We do not distinguish \( T \) and \( S_i \) in terms of techniques or subsystems as we believe they have no fundamental difference.

- **\( L \)** is the open world continual learner that builds models to not only classify the input into known classes but also detect novel objects that has not been seen in training. For example, for the greeting bot, \( L \) of the primary task performer \( T \) is a continual learning dialogue system similar to that in Section 6. For the supporting vision system, \( L \) is a continual learner that can learn to recognize guests and detect novel or unknown objects.

- **\( K \)** is the knowledge base & world model (KB) that is important for the performance task. It keeps the learned or prior knowledge of the domain and the world model. If needed, reasoning capability can be provided to help the other modules of the system. World model refers to the representation of the task environment and the commonsense knowledge about the objects and their relationships within.

- **\( M \)** is the model learned by \( L \). \( M \) takes the input or perception signals from the application environment to make a decision, which is used by the planner \( (P) \) to generate actions to be performed. \( M \) may also use some knowledge from the KB in decision making.

- **\( R \)** is the relevance or focusing mechanism that decides whether the detected novelty is relevant to the current task or not. If it’s relevant, the agent should respond to the novelty (discussed below); otherwise ignore. For example, in the greeting bot application, when it hears something from people who are chatting with each other, whether understandable or not, it will be ignored, i.e., irrelevant to
its intended application.

- **C** is the novelty characterizer that characterizes the detected novelty based on the KB and the world model so that the adaptor (below) can formulate a course of actions to respond or adapt to the novelty. For the characterizer **C** of **T** of the greeting bot, as **T** is a dialogue system, when it cannot understand the utterance (novelty) of a hotel guest, it may decide what it can and cannot understand (see Section 6) and ask the guest (see below). In the case of the supporting vision system, when a novel object it detected, the characterizer may decide what the object looks like and its physical attributes. For example, the novel object may look like a dog based on the greeting bot’s KB and the world model (see Section 5 for more discussions).

- **A** is the adaptor that adapts to or accommodates the novelty based on the characterization result. Given the characterization in the case of **T** above, **A** may adapt by asking the guest to clarify (see Section 6) and then learn to understand the utterance. In the case of the vision system, if the characterizer believes that the novel object looks like a dog, the adaptor may decide to report to a hotel employee and also learns the new object by taking some pictures as the training data and asking the hotel staff for the name of the object as the class label. In the latter two cases, **A** needs to invite **I** to interact with the human and **L** to learn the novelty so that it will not be novel in the future. That is, **A** is also responsible for creating new tasks (e.g., learning to recognize new objects in the greeting bot) on the fly and proceeds to acquire ground truth training data with the help of **I** (discussed below) to be learned by **L**. This adaptation process often involves reasoning.

- **S** is the risk assessment module. Novelty implies uncertainty in adapting to the novel situation. In making each response decision, risk needs to be assessed (see Section 5 for more discussions).

- **P** is the planner that produces a plan of actions for the executor **E** to perform. This paper will not discuss this component further as our focus is on learning.

- **I** is the interactive module for the agent to communicate with humans or other agents, e.g., to acquire ground-truth training data or to get instructions when the agent does not know what to do in a unseen situation. It may use the natural language (for interaction with humans) or an agent language (for interaction with other agents).

- **E** is the executor that performs the actions formulated by **P** based on decisions of **M** and **A**. The application environment may also give feedback to **E** and to **A**.

Several remarks need to be made. First, not all agents need all these sub-systems and some sub-systems may also be shared. For example, the primary task performer **T** in the greeting bot application is a dialogue system. Its interaction module **I** can use the same dialogue system. Second, as we will see, every sub-system can and should have its own local learning capability. Third, the interaction module **I** and the adapter **A** will create new tasks to learn and gather ground truth training data for learning. Fourth, most links in Figure 2 are bidirectional, which indicates that the sub-systems need to interact in order to perform their tasks.

Since the primary task performer **T** and each supporting sub-system **S** has the same components or sub-systems, we will discuss them in general rather than distinguishing them. Below, we first discuss the SOLA learner **L**.

### Open World Continual Learning

The classic ML makes the *i.i.d* assumption, which is often violated in practice. Here we first define several related concepts and then the proposed SOLA framework.

Let the training data that have been seen so far from previous tasks be \( D_{tr} = \{ (x_i, y_i) \}_{i=1}^n \) with \( x_i \in X \) and \( y_i \in Y_{tr} \). Let the set of class labels that may appear in testing or application be \( Y_{tst} \). Classical ML makes the closed-world assumption.

**Closed-world assumption**: There are no new or novel instances or classes that may appear in testing or application, i.e., \( Y_{tst} \subseteq Y_{tr} \). In other words, every class seen in testing or application must have been seen in training.

**Open world**: There are test classes that have not been seen in training, i.e., \( Y_{tst} \cap Y_{tr} = \emptyset \).

**Definition (closed-world learning)**: It refers to the learning paradigm that makes the closed-world assumption.

**Definition (open world learning)**: It refers to the learning paradigm that performs the following functions: (1) classify test instances belonging to training classes to their respective classes and detect novel or out-of-distribution instances, and (2) learn the novel classes labeled by humans in the identified novel instances to update the model using the labeled data. The model updating is initiated by human engineers and involves re-training or incremental learning.

**Definition (SOLA)**: SOLA is a learning paradigm that performs open-world learning but the learning process is initiated by the agent itself after deployment with no involvement of human engineers. The new task creation and ground-truth training data acquisition are done by the agent via its interaction with the user and the environment. The learning of the new task is incremental, i.e., no re-training of previous tasks/classes. The process is lifelong or continuous, which makes the agent more knowledgeable over time.

**Steps in learning in SOLA**. The main continual learning process in SOLA involves the following three steps, which can be regarded as part of the novelty adaptation or accommodation strategy (see Section 5).

**Step 1 - Novelty detection**. This step involves detecting data instances whose classes do not belong to \( Y_{tr} \). As mentioned earlier, a fair amount of research has been done on this under open-set classification or out-of-distribution detection (Pang et al. 2021).

**Step 2 - Acquiring class labels and creating a new learning task on the fly**: This step first clusters the detected novel instances. Each cluster represents a new class. It may be done automatically or through interactions with humans using the interaction module **I**. Interacting with human users should produce more accurate clusters and also obtain meaningful class labels. If the detected data is insufficient for building an accurate model to recognize the new classes, additional
ground-truth data may be collected via interaction with human users (and/or passively by downloading data from web like searching and scrapping images of objects of a given class). A new learning task is then created.

In the case of our hotel greeting bot, since the bot detects a single new guest (automatically), no clustering is needed. It then asks the guest for his/her name as the class label. It also takes more pictures as the training data. With the labeled ground-truth data, a new learning task is created to incrementally learn to recognize the new guest on the fly.

The learning agent may also interact with the environment to obtain training data. In this case, the agent must have an internal evaluation system that can assign rewards to different states of the world, e.g., for reinforcement learning.

**Step 3 - Incrementally learn the new task.** After ground-truth training data has been obtained, the learner $L$ incrementally learns the new task. This is continual learning (Chen and Liu 2018), which has been discussed earlier. We will not discuss it further as there are already numerous existing techniques (Parisi et al. 2019; Lomonaco et al. 2022). Many can leverage existing knowledge to learn the new task better (Chen and Liu 2018).

**Relevance of Novelty**

Due to the performance task, the agent should focus on novel values that are critical to the performance task. For example, a self-driving car should focus on novel objects or events that are or may potentially appear on the road in front of the car. It should not pay attention to novel objects in the shops along the street (off the road) as they do not affect driving. This relevance check involves gathering information about the novel object to make a classification decision.

**Novelty Characterization and Adaptation**

In a real-life application, classification may not be the primary task of an agent. For example, in a self-driving car, object classification supports its primary performance task of driving. To drive safely, the car has to take some actions to adapt or respond to novel/new objects, e.g., slowing down and avoiding the objects. In order to know what actions to take to adapt, the agent must characterize the new object. The characterization of a novel object is a description of the object based on the agent’s existing knowledge of the world. Based on the characterization, appropriate actions are formulated to adapt or respond to the novel object. The process may also involve learning.

Novelty characterization and adaptation (or response) form a pair $(c, r)$, where $c$ is the characterization of the novelty and $r$ is the adaptation response to the novelty, which is a plan of dynamically formulated actions based on the characterization of the novelty. The two activities go hand-in-hand. Without an adaptation strategy for a characterization, the characterization has no use. If the system cannot characterize a novelty, it takes a low risk-assessed default response. In our greeting bot example, when it can characterize a novelty as a new guest, its response is to say “Hello, welcome to our hotel! What is your name, sir?” If the bot has difficulty with characterization, it can take a default action, e.g., ‘do nothing.’ The set of responses are specific to the application. For a self-driving car, the default response to a novel object is to slow down or stop the car so that it will not hit the object.

In some situations, the agent must take an action under low confidence circumstances, the agents engage in reinforcement learning paradigm, trying actions and assessing outcomes.

Characterization can be done at different levels of detail, which may result in more or less precise responses. Based on an ontology and object attributes related to the performance task in the domain, the characterization can be described based on the type of the object and the attribute of the object. For example, in the greeting bot application, it is useful to determine whether the novel object is a human or an animal because the responses to them are different. For self-driving cars, when sensing a novel object on the road, it should focus on those aspects that are important to driving, i.e., whether it is a still or a moving object. If it is a moving object, the car should determine its direction and speed of moving. Thus, the classification of movement is needed in this case to characterize the novelty, which, in turn, facilitates determination of the agent’s responding action(s). For instance, if the novel object is a mobile object, the car may wait for the object to leave the road before driving.

Another characterization strategy is to compare the similarity between the novel object and the existing known objects. For example, if it is believed that the novel object looks like a dog (assuming the agent can recognize a dog), the agent may react like when it sees a dog on the road.

The above discussion implies that in order to effectively characterize a novelty, the agent must already have a great deal of world knowledge that it can use to describe the novelty. Additionally, the characterization and response process is often interactive in the sense that the agent may choose a course of action based on the initial characterization. After some actions are taken, it will get some feedback from the environment. Based on the feedback and the agent’s additional observations, the course of action may change.

**Learning to respond.** In some situations, the system may not know how to respond to a novel object or situation. It may try any of the following ways.

1. **Asking a human user.** In the case of the self-driving car, when it does not know what to do, it may ask the passenger using the interactive module $I$ in natural language and then follow the instruction from the passenger and also learn it for future use. For example, if the car sees a black patch on the road that it has never seen before, it can ask “What is that black thing in front?” The passenger may answer “That is tan.” If there is no ready response, e.g., no prior information on tan, the system may progress with a further inquiry, asking the passenger “What should I do?”

2. **Imitation learning.** On seeing a novel object, if the car in front drives through it with no issue, the car may choose the same course of action as well and also learn it for future use if the car drives through without any problem.

3. **Reinforcement learning.** By interacting with the environment through trial and error exploration, the agent learns a good response policy. This is extremely challenging as any action taken has consequences and cannot be reversed. For this to work, the agent must have an internal evaluation
system that can assign rewards to states.

If multiple novelties are detected at the same time, it is more difficult to respond as the agent must reason over the characteristics of all novel objects to dynamically formulate an overall plan of action that prioritizes the responses.

Risk Assessment and Learning

There is risk in achieving performance goals of an agent when making an incorrect decision. For example, classifying a known guest as unknown or an unknown guest as known may negatively affect guest impressions resulting in negative reviews. For a self-driving car, misidentifications can result in wrong responses, which could be a matter of life and death. Therefore, risk assessment must be made in making each decision. Risk assessment can also be learned from experiences or mistakes. In the example of a car passing over tar, after the experience of passing over shiny black surfaces safely many times, if the car slips in one instance, the car agent must assess the risk of continuing the prior procedure. Given the danger, a car may weight the risk excessively, slowing down on new encounters of shiny black surfaces.

6 CML: An Example SOLA System

Although novelty detection (Yang et al. 2021; Pang et al. 2021) and incremental or continual learning (Chen and Liu 2018; Parisi et al. 2019; Lomonaco et al. 2022) have been studied widely, little work has been done to build a SOLA system. Here we describe a dialogue system (called CML) that is based on the SOLA framework and performs each function in SOLA continually by itself on the job during conversation (Mazumder et al. 2020b). Another two related systems can be found in (Mazumder et al. 2019, 2020a), which are more sophisticated than CML in several aspects.

CML is a natural language interface like Amazon Alexa and Apple Siri. Its performance task is to take a user command in natural language (NL) and perform the user requested API action in the underlying application. Since it is a text based system, no other support function is needed. The key issue is how to understand paraphrased NL commands from the user in order to map a user command to a system’s API call. Novelty equates to the system’s failure in understanding a user command. After the system automatically detects a novelty (a hard-to-understand user command), it will try to understand the command and also learn the command so that it will be able to understand it and similar commands in the future. The system also assumes that every novelty is relevant to the application. The novelty characterization step of CML tries to identify the part of the user command that the system does not understand and how similar it is to some known commands. Based on the characterization, the system adapts by asking the user via an interactive dialogue to obtain the ground truth API action requested by the user, which also serves as a piece of training data for continual learning. In the adaptation or accommodation process, risk is also considered.

Consider the following example. The user issues the command “turn off the light in the kitchen” that the system does not understand (i.e., a novelty). Based on the current system state, it decides which part of the command it can understand, which part it has difficulty with, and what known commands are similar to the user command (i.e., characterization). Based on the characterization result, it provides the user a list of top-k predicted actions (see below) described in NL and asks the user to select the most appropriate action from the given list (i.e., adaptation).

Bot: Sorry, I didn’t get you. Do you mean to:

- **option-1.** switch off the light in the kitchen, or
- **option-2.** switch on the light in the kitchen.
- **option-3.** change the color of the light?

The user selects the desired action (option-1). The action API [say, SwitchOffLight(arg:place)] corresponding to the selected action (option-1) is retained as the ground truth action for the issued NL command. In subsequent turns of the dialogue, the agent can also ask the user questions to acquire ground truth values associated with arguments of the selected action, as defined in the API. This process is controlled by the action planner. CML then incrementally learns to map the original command “turn off the light in the kitchen” to the API action, SwitchOffLight(arg:place). This learning ensures that in the future the system will not have problem understanding the related commands.

Risk is considered in the system in two ways. First, it does not ask the user too many questions in order not to annoy the user. Second, when the characterization is not confident, the system simply asks the user to say his/her command again in an alternative way (which may be easier for the system to understand) rather than providing a list of random options to the user to choose from. If the options have nothing to do with the user command, the user may lose confidence in the system.

7 Key Challenges

Although novelty detection and continual learning have been researched extensively (Yang et al. 2021; Pang et al. 2021), they remain challenging. Limited work has been done to address the following (this list is by no means exhaustive):

Learning everything and everywhere. As indicated earlier, every module or sub-system in Figure 2 needs to learn continually, i.e., everywhere needs learning. Similarly, everything can be learned. For example, from each user’s dialogue history with a chatbot, the system can learn whether a user feels more excited or gets annoyed while conversing on a particular topic, what he/she likes and dislikes. The chatbot can then utilize this user’s profile in modeling future conversations to make them more engaging with the user.

In this paper, we focus only on the open world continual learning of the main task. A general framework is needed to integrate all the learning activities and their resulting knowledge to make the agent work even better.

Obtaining training data on the fly. One key feature of SOLA is the interaction with human users to obtain ground-truth training data, which needs a dialogue system. Building an effective dialogue system for this purpose is challenging. We are unaware of any such system for SOLA except
CML (Mazumder et al. 2020b), but CML is only for simple command learning.

**Few-shot continual learning.** It is unlikely for the learning agent to collect a large volume of training data via interaction with the user. Then, an effective and accurate few-shot continual/incremental learning method is necessary.

**Novelty characterization and adaptation.** Characterization is critical because it defines the characteristics used to recognize world state and determine the best response strategy. We have given several examples of characterization and adaptation in the domains of self-driving cars and greeting bots. However, little research has been done on the topics in the academic community. They are extremely challenging as they require the system to have a large amount of prior knowledge and a domain world model, and to reason based on this knowledge and the current observations.

**Learning to respond/adapt.** As indicated earlier, this is especially challenging in a physical environment (Dulac-Arnold et al. 2021). For example, due to safety concerns, learning during driving by a self-driving car using reinforcement learning (RL) is very dangerous because every action has potentially life and death consequences and cannot be undone. Furthermore, for RL to work, the agent must have a highly effective internal reward or evaluation system to assign rewards to actions and states and be aware of safety constraints automatically without detailed manual specifications. So far limited work has been done (Dulac-Arnold et al. 2021).

**Knowledge representation, reasoning, and revision.** SOLA has so many components, but it is not known what knowledge representation reasoning scheme best suits all modules and facilitates their integration. Further, it is inevitable that the system may misinterpret, generalize or otherwise assemble incorrect knowledge. A system must have a mechanism to detect and revise the inaccurate knowledge on its own. Little work has been done in this area.

### 8 Conclusion

A truly intelligent system must be able to learn autonomously and continually in the open world on its own initiative after deployment, adapt to the ever-changing world, and learn more and more to become more and more powerful over time. This paper proposed the self-initiated open world continual learning and adaptation (SOLA) framework for this purpose, and presented the concepts, steps and key challenges. An example SOLA system called CML in the context of dialogue systems is also described. Future research in SOLA will bring AI to the next level.

### Acknowledgments

This paper benefited from many discussions in DARPA SAIL-OFF Program meetings. This work was supported in part by a DARPA Contract HR001120C0023. Bing Liu was also partially supported by two National Science Foundation (NSF) grants (IIS-1910424 and IIS-1838770), and a Northrop Grumman research gift. The views expressed in this document are those of the authors and are not those of the funders.

### References

Bendale, A.; and Boult, T. 2015. Towards open world recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 1893–1902.

Boult, T.; Grabowicz, P.; Prijatelj, D.; Stern, R.; Holder, L.; Alспектor, J.; Jafarzadeh, M.; Ahmad, T.; Dhamija, A.; Li, C.; et al. 2021. Towards a Unifying Framework for Formal Theories of Novelty. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, 15047–15052.

Chaudhry, A.; Gordo, A.; Dokania, P. K.; Torr, P.; and Lopez-Paz, D. 2020. Using hindsight to anchor past knowledge in continual learning. *arXiv preprint arXiv:2002.08165*, 3.

Chen, Z.; and Liu, B. 2018. *Lifelong machine learning*. Morgan & Claypool Publishers.

Dulac-Arnold, G.; Levine, N.; Mankowitz, D. J.; Li, J.; Paduraru, C.; Gowal, S.; and Hester, T. 2021. Challenges of real-world reinforcement learning: definitions, benchmarks and analysis. *Machine Learning*, 2419–2468.

Fei, G.; Wang, S.; and Liu, B. 2016. Learning cumulatively to become more knowledgeable. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1565–1574.

Ke, Z.; Liu, B.; and Huang, X. 2020. Continual learning of a mixed sequence of similar and dissimilar tasks. *Advances in Neural Information Processing Systems*, 33: 18493–18504.

Kirkpatrick, J.; Pascanu, R.; Rabinowitz, N.; Veness, J.; Desjardins, G.; Rusu, A. A.; Milan, K.; Quan, J.; Ramalho, T.; Grabska-Barwinska, A.; and Others. 2017. Overcoming catastrophic forgetting in neural networks. *Proceedings of the National Academy of Sciences*, 114(13): 3521–3526.

Langley, P. 2020. Open-world learning for radically autonomous agents. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, 13539–13543.

Lee, S.; Stokes, J.; and Eaton, E. 2019. Learning shared knowledge for deep lifelong learning using deconvolutional networks. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence (IJCAI-19)*, 2837–2844.

Liu, B. 2020. Learning on the job: Online lifelong and continual learning. In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI-2020)*.

Lomonaco, V.; Pellegrini, L.; Rodriguez, P.; Caccia, M.; She, Q.; Chen, Y.; Jodelet, Q.; Wang, R.; Mai, Z.; Vazquez, D.; et al. 2022. CVPR 2020 continual learning in computer vision competition: Approaches, results, current challenges and future directions. *Artificial Intelligence*, 303: 103635.

Mazumder, S.; Liu, B.; Ma, N.; and Wang, S. 2020a. Continuous and Interactive Factual Knowledge Learning in Verification Dialogues. *NeurIPS-2020 Workshop on Human And Machine in-the-Loop Evaluation and Learning Strategies*.

Mazumder, S.; Liu, B.; Wang, S.; and Esmaeilpour, S. 2020b. An Application-Independent Approach to Building Task-Oriented Chatbots with Interactive Continual Learning. *NeurIPS-2020 Workshop on Human in the Loop Dialogue Systems*. 
Mazumder, S.; Liu, B.; Wang, S.; and Ma, N. 2019. Lifelong and Interactive Learning of Factual Knowledge in Dialogues. In SIGDIAL.

McCloskey, M.; and Cohen, N. J. 1989. Catastrophic interference in connectionist networks: The sequential learning problem. In Psychology of learning & motiv., volume 24.

Mitchell, T.; Cohen, W.; Hruschka, E.; Talukdar, P.; Betteridge, J.; Carlson, A.; Dalvi, B.; Gardner, M.; Kisiel, B.; Krishnamurthy, J.; Lao, N.; Mazaitis, K.; Mohamed, T.; Nakashole, N.; Platanios, E.; Ritter, A.; Samadi, M.; Settles, B.; Wang, R.; Wijaya, D.; Gupta, A.; Chen, X.; Saparov, A.; Greaves, M.; and Welling, J. 2015. Never-Ending Learning. In Proceedings of the AAAI Conference on Artificial Intelligence (AAAI-15).

Moreno-Torres, J. G.; Raeder, T.; Alaiz-Rodríguez, R.; Chawla, N. V.; and Herrera, F. 2012. A unifying view on dataset shift in classification. Pattern recognition, 45(1): 521–530.

Murty, V. P.; Ballard, I. C.; Macduffie, K. E.; Krebs, R. M.; and Adcock, R. A. 2013. Hippocampal networks habituate as novelty accumulates. Learning & Memory, 20(4): 229–235.

Pang, G.; Shen, C.; Cao, L.; and Hengel, A. V. D. 2021. Deep learning for anomaly detection: A review. ACM Computing Surveys (CSUR), 54(2): 1–38.

Parisi, G. I.; Kemker, R.; Part, J. L.; Kanan, C.; and Wermer, S. 2019. Continual lifelong learning with neural networks: A review. Neural Networks.

Parmar, J.; Chouhan, S. S.; Raychoudhury, V.; and Rathore, S. S. 2021. Open-world Machine Learning: Applications, Challenges, and Opportunities. arXiv preprint arXiv:2105.13448.

Rebuffi, S.-A.; Kolesnikov, A.; and Lampert, C. H. 2017. iCaRL: Incremental classifier and representation learning. In CVPR, 5533–5542.

Ren, P.; Xiao, Y.; Chang, X.; Huang, P.-Y.; Li, Z.; Gupta, B. B.; Chen, X.; and Wang, X. 2021. A survey of deep active learning. ACM Computing Surveys (CSUR), 54(9): 1–40.

Rusu, A. A.; Rabinowitz, N. C.; Desjardins, G.; Soyer, H.; Kirkpatrick, J.; Kavukcuoglu, K.; Pascanu, R.; and Hadsell, R. 2016. Progressive neural networks. arXiv preprint arXiv:1606.04671.

Ruvolo, P.; and Eaton, E. 2013. ELLA: An efficient lifelong learning algorithm. In ICML.

Serra, J.; Suris, D.; Miron, M.; and Karatzoglou, A. 2018. Overcoming catastrophic forgetting with hard attention to the task. In International Conference on Machine Learning, 4548–4557. PMLR.

Settles, B. 2009. Active learning literature survey.

Shin, H.; Lee, J. K.; Kim, J.; and Kim, J. 2017. Continual learning with deep generative replay. In NIPS, 2994–3003.

Silver, D. L.; Yang, Q.; and Li, L. 2013. Lifelong machine learning systems: Beyond learning algorithms. In 2013 AAAI spring symposium series.

Thrun, S. 1995. Is learning the n-th thing any easier than learning the first? Advances in neural information processing systems, 8.

Tulving, E.; and Kroll, N. 1995. Novelty assessment in the brain and long-term memory encoding. Psychonomic Bulletin & Review, 2(3): 387–390.

Xu, H.; Liu, B.; Shu, L.; and Yu, P. 2019. Open-world learning and application to product classification. In The World Wide Web Conference, 3413–3419.

Yang, J.; Zhou, K.; Li, Y.; and Liu, Z. 2021. Generalized out-of-distribution detection: A survey. arXiv preprint arXiv:2110.11334.

Zenke, F.; Poole, B.; and Ganguli, S. 2017. Continual learning through synaptic intelligence. In ICML, 3987–3995.