I. ABSTRACT

While great advances are made in pattern recognition and machine learning, the successes of such fields remain restricted to narrow applications and seem to break down when training data is scarce, a shift in domain occurs, or when intelligent reasoning is required for rapid adaptation to new environments. In this work, we list several of the shortcomings of modern machine-learning solutions, specifically in the contexts of computer vision and in reinforcement learning and suggest directions to explore in order to try to ameliorate these weaknesses.

II. Introduction

The Selective Tuning Attentive Reference (STAR) model of attention is a theoretical computational model designed to reproduce and predict the characteristics of the human visual system when observing an image or video, possibly with some task at hand. It is based on psycho-physical observations and constraints on the amount and nature of computations that can be carried out in the human brain. The model contains multiple sub-modules, such as the Visual Hierarchy (VH), visual working memory (vWM), fixation controller (FC), and other. The model describes flow of data between different components and how they affect each other. As the model is given various tasks, an executive controller orchestrates the action of the different modules. This is viewed as a general purpose processor which is able to reason about the task at hand and formulate what is called Cognitive Programs (CP). Cognitive Programs are made up of a language describing the set of steps required to control the visual system, obtain the required information and track the sequence of observations so that the desired goal is achieved. In recent years, methods of pattern recognition have taken a large step forward in terms of performance. Visual recognition of thousands of object classes as well as detection and segmentation have been made much more reliable than in the past. In the related field of artificial intelligence, progress has been made by the marriage of reinforcement learning and deep learning, allowing agents to successfully play a multitude of game and solve complex environments without the need for manually crafting feature spaces or adding prior knowledge specific to the task. There is much progress still to be made in all of the above mentioned models, namely

(1) a computational model of the human visual system (computer vision) and (3) intelligent agents. The purpose of this work is to bridge the gap between the worlds of machine learning and modeling of the way human beings solve visual tasks. Specifically, providing a general enough solution to the problem of coming up with Cognitive Programs which will enable solving visual tasks given some specification.

We make two main predictions:

1) Many components of the STAR model can benefit greatly from modern machine learning tools and practices.

2) Constraining the machine learning methods used to solve tasks, using what is known on biological vision will benefit these models and, if done right, improve their performance and perhaps allow us to gain further insights.

The next sections will attempt to briefly overview the STAR model as well as the recent trends in machine learning. In the remainder of this report, we shall show how the best of both worlds of STAR and Machine Learning can be brought together to create a working model of an agent which is able to perform various visual tasks.

III. Selective Tuning & Cognitive Programs

The Selective Tuning (ST) [1, 2, 3, 4] is a theoretical model set out to explain and predict the behavior of the human visual system when performing a task on some visual input. Specifically, it focuses on the phenomena of visual attention, which includes overt attention (moving the eyes to fixate on a new location), covert attention (internally attending to a location inside the field of view without moving the eyes) and neural modulation and feedback that facilitates these processes. The model is derived from first principles which involve analysis of the computational complexity of general vision tasks, as well as biological constraints known from experimental observation on human subjects. Following these constraints, it aims to be biologically plausible while ensuring a runtime which is practical (in terms of complexity) to solve various vision tasks. In [5], ST has been extended to the STAR (Selective Tuning Attentive Reference) model to include the capacity for cognitive programs.

We will now describe the main components of STAR. This description is here to draw a high-level picture and is by no means complete. For a reader interested in delving into further details, please refer to [4] for theoretical justifications and a broad discussion and read [5] for further
description of these components. The ST model described here is extended with a concept of Cognitive Programs (CP) which allows a controller to break down visual tasks into a sequence of actions designed to solve them.

Fig. 1 describes the flow of information in the STAR architecture at a high-level. Central to this architecture is the Visual Hierarchy. The VH is meant to represent the ventral and dorsal streams of processing in the brain and is implemented as a neural network with feedforward and recurrent connections. The structure of the VH is designed to allow recurrent localization of input stimuli, as well as discrimination, categorization and identification. While a single feed-forward pass may suffice for some of the tasks, for other, such as visual search, multiple forward-backward passes (and possibly changing the focus of attention) may be required. Tuning of the VH is allowed so it will perform better on specific tasks. The recurrent tracing of neuron activation along the hierarchy is performed using a \( \Theta \)-WTA decision process. This induces an Attentional Sample (AS) which represents the set of neurons whose response matches the currently attended stimulus.

The Fixation Control mechanism has two main components. The Peripheral Priority Map (PPM) represents the saliency of the peripheral visual field. The History Biased Priority Map (HBPM) combines the focus of attention derived from the central visual field (cFOA) and the foci of attention derived from the peripheral visual field (pFOA). Together, these produce a map based on the previous fixations (and possibly the current task), setting the priority for the next gaze.

A. Cognitive Programs

To perform some task, the Visual Hierarchy and the Fixation Controller need to be controlled by a process which receives a task and breaks it down into a sequence of methods, which are basic procedures commonly used across the wide range of visual tasks. Each method may be applied with some degree of tuning to match it to the specific task at hand, whereas it become an executable script. A set of functional sub-modules is required for the execution of CP’s.

The controller orchestrating the execution of tasks is called the Visual Task Executive (vTE). Given a task (from some external source), the vTE selects appropriate methods, tunes them into scripts and controls the execution of these scripts by using several sub-modules. Each script initiates an attentive cycle and sends the element of the task required for attentive tuning to the Visual Attention Executive (vAE). The vAE primes the Visual Hierarchy (VH) with top-down signals reflecting the expectations of the stimulus or instructions and sets required parameters. Meanwhile, the current attention is disengaged and any feature surround suppression imposed for previous stimuli is lifted. Once this is completed, a feed-forward signal enters the tuned VH. After the feed-forward pass is completed, the \( \Theta \)-WTA process selects the makes a decision as to what to attend and passes on this choice from the next stage. The vTE, monitoring the execution of the scripts, can decide based on this information whether the task is completed or not.

The selection of the basic methods to execute a task is done by using the Long Term Memory for Method (mLTM). This is an associative memory which allows for fast retrieval of methods.

The Visual Working Memory (vWM) contains two representations: the Fixation History Map stores the last several fixation locations, each decaying over time. This allows for location based Inhibition of Return (IOR). The second representation is the Blackboard (BB), which store the current Attentional Sample (AS).

Task Working Memory (tWM) includes the Active Script NotePad which itself might have several compartments. One such compartment would store the active scripts with pointers to indicate progress along the sequence. Another might store information relevant to script progress including the sequence of attentional samples and fixation changes as they occur during the process of fulfilling a task. Another might store relevant world knowledge that might be used in executing the CP. The Active Script NotePad would provide the vTE with any information required to monitor task progress or take any corrective actions if task progress is unsatisfactory.

Finally, the Visual Attention Executive contains a Cycle Controller, which is responsible for starting and terminating each stage of the ST process. The vAE also initiates and monitors the recurrent localization process in the VH [6]. A detailed view of the entire architecture can be seen in Fig 2.

The Selective Tuning with Cognitive Programs framework allows a very rich set of visual tasks to be solved, given the correct sequence of methods is performed. A recent realization of Cognitive Programs in challenging environments has been presented in [7] where an agent is able to successfully play two video games by using a set of methods to control and tune the Visual Hierarchy and decide on the next move for the player.

Nevertheless, some open questions remain, which are (1) how to design the structure and parameters of the VH so that it can, given the proper task-biasing / priming, deal with a broad range of visual inputs? (2) How does one learn the type of tuning that is to applied to VH for each given task (3) How to create a visual task executive which is able to appropriately select a set of methods which will accomplish a visual task.

It seems that the main questions posed here have to do with control and with planning solution given some set of tools, as well as fitting models to a complex data (such as images). It is only natural to proceed with the recent trends in machine learning which can facilitate the solution of such problems. The following descriptions are not meant as very in-depth descriptions of the respective methods,
Figure 1. High-level view of the STAR architecture. Reproduced from [5]

but more as a high-level overview, elaborating on details as required. Importantly, we highlight shortcomings that these methods face and suggest solutions for some.

IV. Machine Learning

In this section, we provide an overview of the main methods in machine learning which are relevant to require some intelligent agent to observe the world and perform various given complex tasks. This seems like a very broad subject, certainly one which is yet to be fully solved (as having this fully solved would mark the start of a general AI). Yet, notable progress has been made in recent years in machine learning and pattern recognition. In this short exposition, we mention the two main methods of interest which we deem relevant to the current goal of this work.

A. Deep Learning

Deep learning is certainly not a new field and has its roots set back in the 1960’s. Due to various reasons which are out of the scope of this work, it has not always been as popular as today and certainly there are still those that claim that the current hype around it is exaggerated. A turning point responsible for its current surge in popularity is the 2012 paper [8] which won the ImageNet [9] large-scale visual recognition challenge. This is a massive benchmark for computer-vision methods where a classifier is required to predict the class of an object in an image out of a possible 1000 different classes. Significantly outperforming all other results, the work spurred an avalanche of follow-ups and modifications, both from an optimization point of view and of different architectures, as well as theoretical works attempting to justify the success of such methods over others. To date, it is rare to see a leading method in computer vision which is not based on deep learning, be it in the sub-tasks for object recognition, detection (i.e, localization), segmentation, tracking, 3D-reconstruction, face recognition, fine-grained categorization and others. Specifically, deep convolutional neural networks, a certain form of neural nets which exploits assumptions about the structure of natural images, is a main class in deep networks. The success of deep learning has also spread to other media such as audio (e.g, speech recognition), natural language processing (translation) and other sub-fields involving pharmaceutical and medical applications, etc. The literature in recent years on Deep Learning is vast and the reader is encouraged to turn to it for more
in depth information. [10, 11].

The crux of the various deep-learning based methods lie in their need for massive amounts of supervised data. To obtain good performance, tens of thousands (sometimes more) of example are required. While some semi-supervised methods are being suggested, none have approached the performance of fully supervised ones. This is not to say that their utility is discarded - on the contrary, we believe that they will play a major role in the developments of the near future. Additional issue lies in their current seemingly inherent inability to adjust to new kinds of data or apply compositions of already learned solutions to new problems [12]. Further weaknesses of deep learning systems are discussed in [13] and [14], as well as a discussion about some major differences between the way humans and machines solve problems [15].

1) Semi-supervised and Unsupervised Learning: One variant of machine learning potentially holds some promise to ameliorate the need for supervision at scale which is required by methods such as Deep Learning. Such methods attempt to perform learning by receiving a much smaller amount of supervision. For example, learning how to distinguish the data into two classes, but doing so by learning on a datasets where only 10% is labeled and the rest is not.

This can be done by exploiting observed similarities in the underlying data and / or assuming some regularities such as smoothness, etc. An extreme case would be using no labeled data at all, however, as at some point there will be a task where a system should learn in a supervised manner, the utility of the unsupervised learning will be measured by finding how it benefits the supervised learner. Another form of unsupervised learning is Generative Models, which is able to produce at test time data points whose properties ideally resemble those observed at training time, though of course not identical to them. An example of Semi-supervised Learning is Ladder-Networks [16], where an unsupervised loss is added to the network in addition to the supervised loss. A notable method which has recently gained popularity are Generative Adversarial Networks (GAN) [17], where two networks constantly compete: the goal of the Generator network is to generate images which are as realistic as possible in the sense that they resemble images from the training set and a Discriminator network whose goal is to tell apart the images from the Generator and the images from the real dataset. This has quickly evolved to produce impressive results, a recent one due to [18], see Fig. 3 for some results.
B. Deep Reinforcement Learning

Reinforcement Learning (RL) refers to a set of classical and well studied methods in the field of control systems and artificial intelligence. The general setting is that of an agent who is supposed to take actions in some given environment. As a result the agent may encounter new situations and be given some reward (or penalty). The actions of the agent may affect the environment. The agent does not necessarily see the entire environment at all times, rather have access to some input which is its current observation. Through this loop of act-observe-receive reward the agent must increase its total future reward. This setting is very general in the sense that it is limited only by the richness of the environment and of the agent. For an extreme example, we may say that the environment is planet Earth and the agent is some human being or animal. As simulating either of these seems like a virtual impossibility one can model e.g., robots in closed and well defined environments, or anything in between. Much research has gone into making agents which can learn and are able to perform well in various environments, as well as making robust control systems. RL was also one of the fields to benefit and regrow in popularity following the success of deep learning, leading to a new method called Deep Reinforcement Learning. The first widely known success of this new method has been published in [19], where an agent was shown to be able to learn how to perform well in multiple Atari video games, outperforming many previous methods. Notably, the system was learned end-to-end without any input except the raw pixel data and the score of the game. In some cases, it has even learned to outperform human players. The reported performance was a result of using a
single architecture (except the number of output variables where games had different number of possible controls) and set of hyper-parameters. Although there were many game on which the method performed poorly at the time (and still does), this was a significant results which lead to others, such as beating a human expert in the game of GO [20] which is widely acknowledged as a long standing challenge for the artificial intelligence community. For a recent overview on this subject, please refer to [21].

Formally, RL assumes the following setting: an agent may interact with an environment at each time \( t \) by applying an action \( a_t \), given an observation \( s_t \). Note that the entire state of the environment may not be observed, and in this context the state \( s_t \) represents only the observation of the agent - it is all that it can directly measure. The interaction \( a_t \) of the agent leads to another state \( s_{t+1} \), where the agent may perform another action \( a_{t+1} \), and so on. A Markov Decision Process (MDP) is defined as an environment where the probability of the next state is fully determined by the current state and the action:

\[
P_{ss'} = P(r_{t+1} = s' | s_t = s, a_t = a)
\]

i.e., the probability of state \( s' \) following state \( s \) after action \( a \).

Note that this has the Markov property, i.e., that each state is dependent only on the previous one and not on ones before that. For example, in a game of Chess, where the entire board is observed as the state, nothing needs to be known about previous steps of the game to determine the next move. For each action the agent receives a reward \( r_t \), which is a real scalar that can take on any value, be it positive, negative or zero. Hence, the entire sequence of \( n \) actions of an agent in an environment is

\[
s_0, a_0, r_1, s_1, a_1, r_2, s_2, a_2, r_3, \ldots, s_{n-1}, a_{n-1}, r_n, s_n
\]

Where \( s_n \) is the terminal reward (win/lose/terminate). The goal of the agent is to maximize the total future reward: assuming that the agent performed \( n \) steps and at each step received a reward \( r_t \) the total reward is

\[
R = \sum_{t=1}^{n} r_t
\]

The total future reward from time \( t \) is

\[
R_t = \sum_{i=1}^{n-t} r_{t+i}
\]

However, as the close future holds less uncertainty, it is common to consider the discounted future reward, that is a reward which is exponentially decayed over time:

\[
R_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots + \gamma^{n-t} r_n
\]

\[
= r_t + \gamma (r_{t+1} + \gamma (r_{t+2} + \ldots))
\]

\[
= r_t + \gamma R_{t+1}
\]

The strategy that the agent uses to determine the next action is called a policy, and is usually denoted by \( \pi \). A good policy would maximize the discounted future reward. A value-action function \( Q \) is defined as a function which assigns the maximum discounted future reward for an action \( a_t \) performed at a state \( s_t \):

\[
Q(s_t, a_t) = \max_a R_{t+1}
\]

Given this function, the optimal policy can simply choose for each state \( s \) the action \( a \) which maximizes \( Q \):

\[
\pi(s) = \arg \max_a Q(s, a)
\]

From Eq. 7 the following relation holds:

\[
Q(s, a) = r + \gamma \max_{a'} Q(s', a')
\]

Meaning that if we find a function \( Q \) for which the above holds, we can use it to generate an optimal policy. For a discrete number of states and actions, a simple method known as value iteration is know converge to the optimal policy [22], given that each state/action pair is visited an infinite number of times. This is simply implemented as continuously updating \( Q \), until some stopping criteria is met:

\[
Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_t + \gamma \max_a Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)].
\]

Such methods can work well for a finite number of states and actions. However, for many interesting environments it is challenging to define the states as a discrete set, and doing so naively would result in an exponential number. For example, if the task is to play a video game, while the available actions form a small set, enumerating the number of possible stimuli would easily lead to intractable numbers, that is, all possible combinations of pixel values on the screen.

With this in mind, we turn to Deep Reinforcement Learning. Here, instead of representing each state explicitly as some symbol in a large set, a neural network is learned to predict the \( Q \)-value from the state, by being applied directly to each input frame (or set of a few consecutive ones to capture motion). Hence the state is represented implicitly by the network’s weights and structure. This allows the agent to learn how to act in the environment without having privileged knowledge about its specific inner workings. There are many variants and improvements on this idea, though the basic setting remains the same. In what follows, we highlight some of the challenges and shortcomings of the current approaches of Deep RL.

1) Efficient Exploration: A very big challenge currently holding back RL methods is the huge exploration space that should potentially be sought in order to produce a good policy. This is a chicken and egg problem of sorts: exploration is needed to find out a good policy and a good policy is required to be able to do sufficient exploration; consider even a simple game such as Atari Breakout, where the player is able to move a paddle left or right and hit...
the ball so it doesn’t fall off the bottom of the screen. If nothing else is known, it would take some amount of exploration to find out the paddle should bounce the ball to avoid losing. Before that, the agent will probably start off just moving randomly to the left and right. As the rewards of the game are sparse, it will not be until the agent encounters its first reward that it will be able to update its policy. For this reason, it will take many iterations until it can start learning how to act to avoid losing quickly. Only then can it continue to explore further states of the game, which could not even be reached if it had not passed the very first steps of hitting the ball. The greedy strategy somewhat improves on this problem by choosing a random move with a probability of $\epsilon$, a hyper-parameter which is usually decayed over time as the system learns. This helps getting out of local minima in the exploration space, though the general problem described here is certainly not solved.

2) Exploration vs Representation: The problem of exploration is exacerbated for the case of Deep RL. In a discrete search space, each state is well recognized once encountered. When the state space is represented implicitly by a deep network, the evolution of the Q function is tied with the representation of the environment by the Deep network. This means that updating the Q function can lead to unstable results. One strategy to address this is by reducing the frequency in which the network which updates the Q function is tied with the representation of the environment by the Deep network. This helps getting out of local minima in the exploration space, though the general problem described here is certainly not solved.

A strong visual representation: the visual system of human beings is a strong one and is able to represent stimuli very robustly, owing both to evolution and learning from prior experience. An agent usually learns the visual representation of the environment from scratch. Certainly, being able to robustly represent the observations right from the start would allow the agent to focus more on planning and less on learning the representation. Nevertheless, the representation may continue evolving as the agent encounters new situations. One way to allow this is to use as a starting point a pre-trained visual representation, be it in a supervised or unsupervised manner, and adapt it as needed for the task.

Symbolic representation: allowing the agent to group observations into equivalence classes by assigning symbols or compact representations to them would allow policies to be learned more efficiently and probably converge to a higher level of performance. This can be done in an implicit manner by attempting to cluster the representation of the environment into few informative clusters which carry the maximal information with respect to the task. More explicitly, the observation can be somehow parsed into objects, background, possibly other agents, etc. The representation of the scene will then be made up of the properties (speed, location, state) of the constituents of the scene. While the latter would probably carry more meaning (and presumably lead to higher performance), it seems hard to do so in a purely data-driven approach without external knowledge about the world.

3) Prior and External Knowledge: A child is able to learn how to play a game reasonably well within a few minutes (a few tens of thousands of frames). Current methods require many millions of frames to do so, if they succeed at all. Why is this so? Besides the reasons stated above, we claim that additional forms of prior experience are useful.

One form of experience is having solved tasks in the past which may be related to the current task. Indeed, this has been recently shown to be effective in [23] where a single network learns to mimic the behaviour of multiple expert networks, each of which was pre-trained on a single tasks. Thus the new network represents simultaneously the knowledge to solve all of the learned tasks in a relatively compact manner. In most cases, such a network was shown to learn new tasks much faster than a randomly initialized version as well as converge in a more stable manner.

World knowledge also plays a major role in understanding a new situation. The factual knowledge we gain from experience, if written as a list of many different facts and rules, would probably make a very long one. Here are a few examples:

- An intuitive understanding of Newtonian Physics - even children understand that object tend to continue in their general direction, tend to fall down after going up, may move if pushed by some external force, etc.
- Relations and interactions between objects: doors require keys to be opened
- Survival: falling off a cliff is usually a bad idea; if an opponent comes your way, you’d better avoid it or terminate it
- General facts: roses are red. Violets are blue. Gold gives you points.

It is difficult to imagine how all of this is learned and stored in our brains and how the relevant facts come into play in the abundance of different situations that we encounter. Being able to effectively utilize such a vast knowledge-base about the behavior of the world would no doubt aid intelligent agents in many environments. Attempts at using external knowledge to aid tasks have already been made in Computer Vision for image captioning and Visual Question Answering (VQA) [24], Zero-Shot Learning (ZSL) [25] and in general to gain knowledge about unseen objects or categories by comparing their detected attributes to those of known ones [26]. Such worldknowledge is collected either by data-driven approaches such as word2vec (a learned vector space representation of words) [27] or word relation graphs (WordNet [28]), datasets collected manually or by scanning online knowledge collections such as Wikipedia, such as ConceptNet [29].

Such collections of linguistic and factual knowledge can certainly help an agent quickly reason about its surrounding environment - only if it is able to link its observations to items in the knowledge base. It is interesting to ask...
how a person acquires such knowledge in the first years of his/her lifetime, through an experience which is quite different that simply being exposed to millions of online articles. Somehow a collection of useful facts and rules is picked up from experience despite being drowned in a pool of distracting and noisy signals.

Some recent work by [30] has demonstrated that prior knowledge is quite critical to the success of humans in simple games. The work devises a few ways to remove the semantics from gameplay by replacing graphical elements in the game by semantically meaningless ones. For example, switch each piece of texture in the game to a random one (but do so consistently). This makes the game screen appear meaningless to the human observer. The performance of humans in such modified games dropped signficantly while that of the tested machine-learning based method remained the same. Another type of modification was switching elements with elements of different meaning. An example is replacing the appearance of a ladder to be climbed to a column of flames, or transposing the screen so gravity appears to work sideways. Though there is a one-to-one translation between the original and modified version of the game, human players did much worse on these semantically modified examples, and on others. This demonstrates the heavy reliance humans have on prior knowledge. In this context, learning a game from scratch without prior knowledge is “unfair” for machine-learning methods.

Nevertheless, such knowledge bases still do not account for an intuitive physical understanding, which seems to require some other type of experience. Such knowledge can either be pre-injected into the agent but, as children do not come equipped with such knowledge, we believe that the agent should learn the rules of physical interactions from its own experience or observations. An interesting attempt at this direction can be seen in [31] where robots gain a reportedly “intuitive” understanding of physical interactions by attempting to perform simple tasks on objects such as moving them around.

4) High Level Reasoning and Control: Planning can be performed at several levels of granularity. Certainly, a human being or animal does not think in terms of the force that needs to be applied by each of the muscles in order to pick up some object. It rather seems that plans are made at a higher level of abstraction and some process then breaks them down to motor commands and everything that is required for them to be carried out. The motor commands can also be grouped into logical units above the most basic ones, such as “fully stretch out left arm”, which is only then translated to low level commands. Newborns are not able to control their limbs and fingers immediately, but over time they acquire this ability and perform tasks with seamless movements, usually dedicating little or no concious thought to the movement of muscles. Similarly, exploration which goes on early on in the “life” of an agent should allow the agent to learn how to perform simple and common actions and store these as routines to be later used in more elaborate plans. End-to-end learning of motor policies from raw pixel data is attempted in [32].

The above was only the simplest level of high-level control. Further advances would require strategic thinking in terms of long-range goals and actions. We claim that this cannot be done effectively without first obtaining a hierarchy of basic control over the agents actions and being able to predict quite reliably their immediate future effect.

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