Outline for Maria’s thesis proposal

Aliens & CHaRLy: Part of the RO1

SLCN project: 2 separate pages

# Specific aims

(1 page)

## Introductory paragraph

* Opening sentence:
  + Abstract, hierarchical thinking is a crucial ability of humans, defines human intelligence
  + Compromised in neural and psychiatric conditions (long-term planning, abstract thinking)
* Current knowledge:
  + RL models have revolutionized our understanding of human cognition and brain function
  + Humans think hierarchically and abstractly (e.g., goals & sub-goals), but most current computational models do not take this into account
  + Only few, but promising, recent advances incorporate hierarchy into RL models:
    - Collins & Frank model about hierarchically-organized BG-PFC loops
    - Options are powerful in ML (Sutton, Precup, Singh)
* Gap in knowledge base / unmet need:
  + The Collins & Frank model, although built on top of plenty of evidence, has not been tested empirically. The options framework, although powerful in ML, has not been tested in humans.

## What, why, who paragraph

* Long-term goal: Understand the computational structure of abstract, hierarchical thinking, a hallmark of intelligence; understand how this is implemented in the brain; how problems with abstract hierarchical thinking can arise (and be cured); and understand the purpose of abstract thinking.
* Objective of this application: Develop specific, testable computational models of simplified tasks that require abstract hierarchical thinking; verify these models with human behavior; and identify neural correlates of hierarchical thinking in these tasks.
* Central hypothesis
  + Humans create hierarchical structure in a process involving curiosity, hypothesis formation, and skill learning, which can be formalized in the options framework
  + Hierarchical thinking is implemented in PFC-BG loops, whose activity can be measured from EEG signals
  + Humans’ use of hierarchical thinking is beneficial because it affords advantages in compositional environments and produces transferable skills
* Rationale (“why do I want to conduct the research?”): This research will produce objective, computational models of human hierarchical thinking. These models will capture the cognitive steps humans take when learning hierarchical representations, will explain brain activity associated with hierarchical thinking, and will shed light on the benefits of hierarchical thinking.

## Specific aims paragraph

**Aim 1. Understand how humans build hierarchical reasoning structures on-line**. [CHaRLy (& Nora’s sub-goals?)] The working hypothesis for this aim is that the creation of structure is driven by humans’ curiosity about novel events, in conjunction with the motivation to understand the mechanisms underlying such events, which leads to skills learning. Such a process can be modeled within the options framework of reinforcement learning.

**Aim 2. Identify the neural mechanisms that underlie hierarchical reasoning**. [Aliens EEG (& Nora EEG?)]

**Aim 3. Explain the benefits of hierarchical reasoning**. [Aliens (and CHaRLy?) in different environments -> when is hierarchy beneficial?]

## Payoff paragraph

* Expected outcomes: The proposed research will produce computational models of hierarchical, abstract thinking that can be used as process models (explaining human abstract thinking), elucidate the neural systems underlying abstract thinking, and shed light on its benefits.
* Generality regarding positive impact: Models will elucidate intelligence, and help cure diseases.

# Significance

(0.5-0.75 pages)

***Part 1: Statement of the problem and need for the research***.

The application of computational models has revolutionized our understanding of human an animal cognition as well as brain function (Schultz, 1997; Huys, …; Daw, ….; Tenenbaum / Griffiths). Reinforcement learning algorithms can reproduce human and animal decision making, and therefore serve as models for the underlying cognitive processes (Huys, Daw, Balleine). In addition, specific brain areas show responses that correspond to the crucial components of reinforcement learning computations, suggesting that the brain implements similar processes (Schultz, 1997; some human study).

Reinforcement learning models have revolutionized our understanding of simple, non-hierarchical learning and decision making. Nevertheless, a hallmark of human cognition is the ability to represent hierarchical structures and allow for abstract thought (Cohen? Old cognitive scientists? Chomsky? Miller?). Humans have the ability to break down tasks into goals and sub-goals (cite), and to reason about problems at different time scales, for example. *More research is needed in this field* because despite their importance, these crucial abilities are missing from most current reinforcement learning models.

A small number of recent studies has aimed to incorporate hierarchy into reinforcement learning models, with promising results (cite a few: casino, sub-goals, etc.). The *contribution of the proposed research* is to explain the cognitive processes involved in the creation of hierarchical structure, and to show that reinforcement learning occurs simultaneously at different levels of abstraction, thereby addressing the above-mentioned need.

***Part 2: Statement of significance***.

*Our proposed research will be significant because it will equip reinforcement learning models, which have provided elegant explanations for simple cognitive and neural processes, with hierarchical structure, a crucial element of human thought.*

***Part 3: Positive effect***.

The creation of such models is expected to have positive impact. It will further our understanding of complex human thought, and provide an explanatory and process model. It will advance research in the cognitive science, and maybe also in CS / ML / AI.

Many neurological and psychiatric conditions are associated with problems of abstract hierarchical thinking: PTSD, schizophrenia, ADHD, depression, etc. This is a huge problem for our society. Computational models of these functions will lead to the detailed understanding of the underlying mechanisms and potential sources of problems. They could be used to diagnose problems and to develop targeted treatments.

They can also be used to learn about the underlying brain function. This knowledge is crucial to diagnose neurological conditions.

# Innovation

(0.5-0.75 pages)

# Approach

(6 pages: 2 per project)

## Aim 1: Understand how humans build hierarchical reasoning structures on-line

***Introduction***. In order to reason hierarchically, humans need to infer the underlying hierarchical structure of a problem first. The *objective of this aim* is to understand how humans create such structure. To attain the objective of this aim, we will test the *hypothesis* that the creation of structure is driven by humans’ curiosity about unexpected outcomes, in conjunction with the motivation to understand the mechanisms underlying such outcomes, which leads to skills learning. We will test our hypothesis by using the *approach* of behavioral analysis and computational modeling. We will collect human data on a task that has an underlying hierarchical structure, and analyze behavioral markers of hierarchical reasoning to assess whether participants form hierarchical structure. We will then create a computational model of the task that aims to produce human-like behavior, showing the same learning trajectories, and making similar decisions. This model will be used to model the underlying human thought processes. The *rationale* for this aim is that successful completion of the proposed research will contribute a missing, fundamental element to our base of knowledge, without which the human ability to create abstract representations cannot be understood. The acquisition of such knowledge is critical to the development of improved therapeutic strategies for diseases related to abstract reasoning and decision making. When the proposed studies for aim 1 have been completed, it is our *expectation* that the created computational model will closely reproduce human hierarchical reasoning. The model will achieve this by combining curiosity and skills learning within the options framework of reinforcement learning. Such a finding would be of importance because it would allow, for the first time, to investigate the mechanisms underlying the creation of hierarchical structure. This key faculty is compromised in various psychiatric conditions, and mechanistic insight is a necessary step toward eventual treatment of such conditions.

***Justification & feasibility***.

*Background*. In recent years, reinforcement learning (RL) theory has allowed for breakthroughs in the fields of artificial intelligence and machine learning as well as cognitive and brain science, by proposing a precise computational model of learning and decision making. Nevertheless, the RL framework has some crucial limitations. Specifically, learning is driven entirely by “rewards”, i.e., those signals from the environment that the agent tries to maximize (e.g., food, praise, money, etc.).

*Problem*. This formulation of RL leads to two particular problems. First, traditional RL frameworks cannot explain how agents learn in environments that provide no rewards, or even in environments that are sparse in rewards, because learning cannot occur without reward signals. Nevertheless, biological systems excel at learning in such situations (just imagine high school as an example). Second, RL cannot explain how structured learning processes can arise in which simpler skills are acquired before, and facilitate learning of, more abstract skills, while the (reward) structure of the environment remains the same. Nevertheless, many biological systems, including humans, show this kind of hierarchical learning.

*Proposed solution*. We propose that both shortcomings arise because of the way rewards are usually implemented in RL frameworks, and that both can be resolved if rewards are implemented in a different, more flexible way. In current RL applications, rewards are hard-coded into the task environment, such that agents have no access to the reward function. We propose a formulation in which the reward function is instead created by the agent, and can be adapted flexibly. This allows for learning to occur in environments that would otherwise be sparse in rewards, because the agent can add rewards. It also allows for hierarchical learning because the reward structure can be adjusted to reward more difficult behaviors once simpler ones have been acquired. The challenge for this approach is to create an agent that will set the rewards in the places that actually facilitate learning. We propose that curiosity can provide this information, as will be explained below.

*Rationale of the proposed research*. The goal of our proposed research is twofold. First, we want to provide a proof of concept for our proposed adapted reinforcement learning mechanism, by implementing it and verifying that it shows the expected benefits. This part is a crucial step in the overall research program and could hinder the progress of the remaining projects. It has therefore been completed as part of our prior work, as detailed below. The second goal of the proposed research is to understand the processes underlying human hierarchical learning, and to link these to the mechanisms implemented in the algorithm.

*Preliminary results*.

*Problem formulation*. In order to test the proposed algorithm, we first created a hierarchical learning environment that would be abstract enough to encompass a broad variety of learning problems, ranging from the domain of motor skills (e.g., learning to grasp objects before stacking objects, before playing the violin) to cognitive skills (e.g., learning to recognize an object before recognizing a scene of multiple objects). We formulated the environment as a semi-Markov Decision Problem (semi-MDP), which is a formal description of an environment’s structure and used in most RL algorithms. In the semi-MDP, the agent selects an action and the environment responds with an outcome, which might be determined by a whole sequence of past actions, before the agent selects another action, etc. The problem is hierarchical in that all action sequences that elicit responses are composed of shorter action sequences that also elicit (different) responses. In other words, shorter action sequences are the building blocks for longer action sequences. This problem is meant to capture the structure of a number of hierarchical learning problems encountered by humans. For example, in the domain of motor learning, simpler motor actions (e.g., grasping) are combined to achieve more complex actions (e.g., stacking objects), which are combined to achieve more complex actions (e.g., playing the violin), etc.

*Implementation of the agent*. The crucial feature of the RL agent is that it constructs its own reward function, based on curiosity, as mentioned above. Specifically, the agent is maximally “curious” about environmental responses that is has rarely seen and becomes less curious the more often it has seen them. This mechanism assures that at the beginning, the agent seeks out those environmental outcomes that are elicited by simple and short action sequences, and then gradually moves on to learn more and more complex ones. The action sequences themselves are acquired through standard hierarchical RL (options framework).

*Results*. This agent indeed showed superior learning compared to classic RL agents. It acquired a larger number of meaningful action sequences, which was evident in that the agent consistently elicited a larger number of environmental responses at all levels of abstraction (Fig. xyzA), and also discovered a larger number of meaningful action sequences overall (Fig. xyzB). In other words, the agent became more efficient at controlling its environment, i.e., at eliciting those responses that it deemed worthwhile. The mechanisms underlying this behavior were also evident in the changes in curiosity over time. Whereas curiosity about the outcomes of basic action sequences increased and decreased very rapidly, curiosity about more abstract outcomes changed more slowly (Fig. xyz), such that the agent set its own goals in a way that maximized potential learning.

***Proposed research***.

*Task design*. In order to assess human hierarchical reinforcement learning, we will present research participants with a behavioral task that is an instance of the abstract semi-MDP described above. In the computerized task, participants will perform sequences of actions (button presses), one at a time, and observe environmental responses (objects appearing on the computer screen). Like above, environmental responses will depend on hierarchical action sequences, which the participants can learn. Crucially, this task does not contain any explicit rewards. We expect that human participants will still learn action sequences that lead to specific responses, using their curiosity to guide the selection of goals (i.e., to set rewards).

*Data collection*. Participants will be recruited through UC Berkeley’s research participation pool (RPP). Data collection will take approximately 60 minutes per participant. We are planning to enroll 40 participants for the study.

*Planned analyses and expected results*. We are planning to analyze the data form this experiment in two ways, using traditional behavioral methods and computational modeling using our algorithm described above.

*Behavioral analysis*. We will first verify that participants indeed acquired action sequences. One piece of evidence for this is a pattern of response times in which actions within the same sequence are executed with short delays, whereas transitions between different sequences lead to longer delays. Another piece of evidence can come from patterns of transition probabilities between actions, with higher probabilities for actions within the same sequence than for actions in different sequences.

Having confirmed that participants acquire action sequences, we next want to investigate the hierarchical aspect of learning, i.e., how simple action sequences are combined into more complex ones. We expect that over time, the response times at the borders of component action sequences will decrease, eventually leading to a homogeneous distribution of responses times over long and complex action sequences. We expect similar, correlated changes in transition probabilities. Crucially, we expect that the changes in response times and transition probabilities will be correlated within the same action sequences, but will not be correlated with other ones. In this way, different action sequences can serve as mutual control conditions.

Lastly, we will compare action sequences at different levels of abstraction (different lengths). We expect that the sequences at the lower levels will be learned sooner that the ones at the higher levels, if only because participants will receive more feedback and experience shorter delays between two subsequent executions because the sequences themselves are shorter. It is an open question though whether learning progresses equally fast at all levels of abstraction after controlling for these factors. We will assess this question using regression models with these factors as predictors of no interest, and expect that learning indeed progresses equally fast at all levels, indicative of the same learning mechanism that underlies everything.

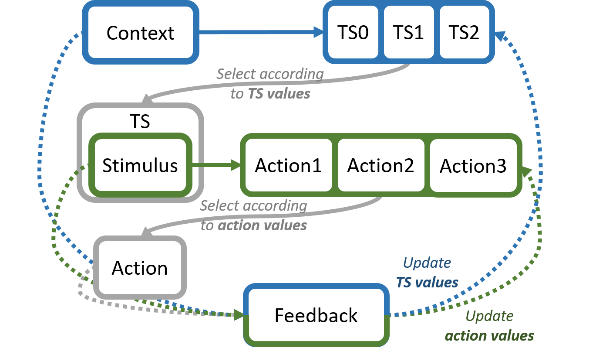
*Computational modeling*.

*Potential problems & alternative strategies*.

## Aim 2: Identify the neural mechanisms that underlie hierarchical reasoning

***Introduction***.

***Justification & feasibility***.

Review of relevant literature.

* Specifically, the brain’s Basal Ganglia show responses that correspond to reward prediction errors, and the Prefrontal Cortex shows responses that correspond to so-called *Q*-values.
* Reinforcement learning theory explains how agents acquire preferences ( “*Q*-values”) through interaction with their environment and how they make decisions based on these *Q*-values (Sutton & Barto). Reinforcement learning agents adjust their *Q*-values continuously in order to approximate the true contingencies of their environment. *Q*-values are adjusted based on a reward signal *r* that the environment produces in response to the agent’s action *a* in state *s*, *Q(s,a)=Q(s,a)+α(r-Q(s,a))*, whereby *r-Q(s,a)* is the reward prediction error, and *α* is the agent’s learning rate.

Figure : The hierarchical reinforcement learning model proposed by Collins & Frank.

* Collins and Frank (…) have proposed that the Prefrontal Cortex and the Basal Ganglia are connected through multiple “loops”, allowing for reinforcement learning at multiple levels of abstraction. The theory is based on ample neural as well as behavioral evidence (see Collins & Frank, …), but has not been tested formally yet. One *contribution of the proposed research* is to apply this model to human decision making in a hierarchical task.
* Another, formal, approach to hierarchical reinforcement learning is the options framework, developed as a tool for artificial intelligence (Sutton, Precup, Singh). Many powerful artificial-intelligence algorithms have been shown to have counterparts in human cognition (cite actor-critic; feature-based RL), but the options framework has not been tested yet in humans. The proposed research will also apply this model to human cognition.

Preliminary studies and results.

Analyzing human behavior during hierarchical reasoning.

*Rationale*. Previous research has shown that humans condense behavioral knowledge into latent underlying rule structures, called Task Sets (TS). A TS is a form of abstract knowledge that can be applied in a number of different contexts. For example, the abstract TS of using a Windows machine can be applied to any concrete Windows machine, and a rule that is learned on one Windows machine is immediately generalized to all Windows machines. Although there is evidence that humans use TS (Collins & Frank), it is unknown how humans make the decision which TS to apply to a given situation. This problem is in fact computationally intractable, demanding research into what cognitive and brain mechanisms allow humans to solve this problem so well.

*Predictions*. We suggest that, just like TS are acquired through RL, the selection of TS is also guided by RL. This view has been proposed in a novel theory and is supported by a large collection of neural and behavioral evidence. In order to test this theory, we designed a behavioral task in which human participants first acquired three TS, and where then asked to indicate their preferences between the TS, and to select a TS for a novel context. Crucially, we had designed the task such that the three TS differed in RL values. The two tests therefore allowed us to assess whether participants acquired values for TS, as predicted by the theory, and whether they used these values to select TS in potentially new situations.

*Task design*. We designed the behavioral task in the following way.

*Results*. In accordance with our predictions, participants showed a preference for those contexts that had been associated with higher-valued TS compared to contexts associated with lower-valued TS (Fig. xyz). This shows that participants were sensitive to TS values, a novel prediction of our theory. Participants also preferred higher-valued TS to lower-valued ones in the generalization test of the experiment (Fig. xyz), i.e., participants preferentially applied higher-valued TS to novel contexts. This shows that TS values indeed guided action selection. Another piece of evidence for the influence of TS values comes from the analysis of participants’ errors. We found that the value of a TS was associated with the number of intrusion errors from a given TS, such that responses that were correct in higher-valued TS were more often incorrectly applied in other TS than responses that were correct in lower-valued TS. In addition, learning speed was associated with TS values, such that higher-valued TS were acquired faster than lower-valued ones. All of the results remained after controlling for the values of the stimuli themselves.

Taken together, the results support our theory. TS values influence TS selection.

* Behavioral markers (CogSci results)
* Computational model (what I have + what I’m planning)

***Research design***.

* Study 1: Behavioral markers and computational model of the creation of hierarchical structure
  + Task; RL values at different levels
  + Behavioral analysis
  + Computational model
  + Detailed expectations
* Study 2: Brain activity associated with the creation of hierarchical structure

***Expected outcomes***.

* Behavioral markers (CogSci results)
* Computational model (what I have + what I’m planning)
* EEG analyses (what I’m planning)

***Potential problems & alternative strategies***.

## Aim 3: computational purpose of hierarchical thinking

Rationale

Procedure: Aliens task and CHaRLy

Predictions / hypotheses: Hierarchical algorithms perform better than non-hierarchical algorithms in environments with certain characteristics (compositionality; transferability of skills). Do humans adjust their use of hierarchy to the situation, or do they always reason hierarchically?

Data analysis methods:

* Computational simulations
* Human behavior
* Human computational modeling

Alternative outcomes

# SLCN adult part

Background

Methods

Hypotheses / expected results