

Reinforcement learning's connection to quantum mechanics via the Schrödinger equation

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Abstract. This paper contains enough details for implementation, and a prototype system is currently under development. We adopt an abstract style of exposition so that the reader can understand there is a large number of variations possible under this architecture.

Keywords: cognitive architecture, reinforcement learning, deep learning, logic-based artificial intelligence

0 Summary

We propose an AGI architecture:

1. With **reinforcement learning** (RL) as top-level framework
 - The external environment is turned “inward”
 - State space = mental space
2. **Logic** structure is imposed on the **knowledge representation** (KR)
 - State transitions are given by logic rules
 - Actions in RL = right-hand side of logic rules
3. The set of logic rules is approximated by a deep-learning neural network (**deep NN**)
 - Logic conjunctions are **commutative**, so the NN should be made **symmetric** using an algebraic trick (§??)
 - **Policy-gradient** methods (and variants) may be employed to speed up learning
 - Logic propositions are embedded in “continuous” space, so we have **continuous actions** in RL. The probability distribution over actions can be modeled by **Gaussian kernels** (radial basis functions).

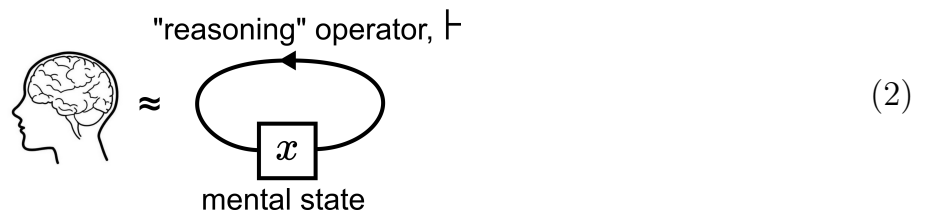
The rest of this paper will explain these design features in detail.

1 Reinforcement-learning architecture

The **metaphor** in the title of this paper is that of RL controlling an autonomous agent to navigate the maze of “thoughts space”, seeking the optimal path:



The main idea is to regard “thinking” as a **dynamical system** operating on **mental states**:



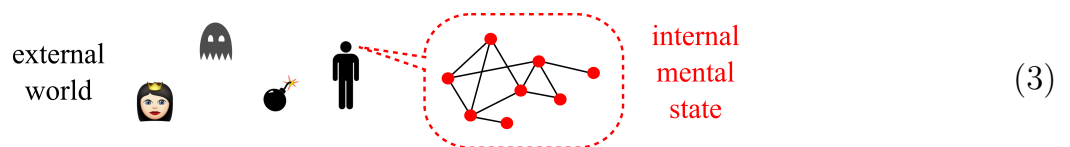
A mental state is a **set of propositions**, for example:

- I am in my room, writing a paper for AGI-2019.
- I am in the midst of writing the sentence, “I am in my room, ...”
- I am about to write a gerund phrase “writing a paper...”

Thinking is the process of **transitioning** from one mental state to another. As I am writing now, I use my mental states to keep track of where I am at within the sentence’s syntax, so that I can construct my sentence grammatically.

1.1 “Introspective” view of reinforcement learning

Traditionally, RL deals with acting in an *external* environment; value / utility is assigned to *external* states. In this view, the *internal* mental state of the agent may change without any noticeable change externally:

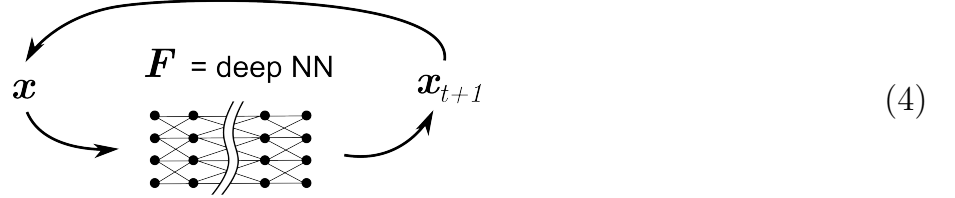


1.2 Actions = cognitive state-transitions = “thinking”

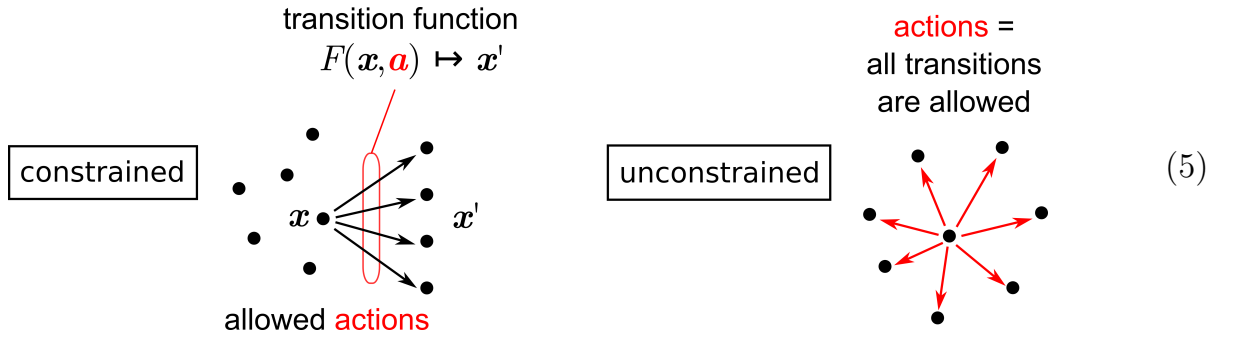
Our system consists of two main algorithms:

1. Learning the transition function \vdash or $\mathbf{F} : \mathbf{x} \mapsto \mathbf{x}'$. \mathbf{F} represents the **knowledge** that constrains thinking. In other words, the learning of \mathbf{F} is the learning of “static” knowledge.
2. Finding the optimal trajectory of the state \mathbf{x} . This corresponds to optimal “thinking” under the constraints of static knowledge.

In our architecture, \mathbf{F} can implemented as a simple feed-forward neural network (where “deep” simply means “many layers”):



In traditional reinforcement learning (left view), the system chooses an action \mathbf{a} , and the transition function \mathbf{F} gives the probability of reaching each state \mathbf{x} given action \mathbf{a} . In our model (right view), all possible cognitive states are potentially **reachable** from any other state, and therefore the action \mathbf{a} coincides with the next state \mathbf{x}' .



1.3 Comparison with AIXI

AIXI’s environmental setting is the same as ours, but its agent’s internal model is a universal Turing machine, and the optimal action is chosen by maximizing potential rewards over all programs of the UTM. In our (minimal) model, the UTM is restricted to a neural network, where the NN’s **state** is analogous to the UTM’s **tape**, and the optimal weights (program) are found via Bellman optimality.

1.4 Infinite-dimensional control

The cognitive state is a vector $\mathbf{x} \in \mathbb{X}$ where \mathbb{X} is the space of all possible cognitive states, the reasoning operator \vdash or \mathbf{F} is an **endomorphism** (an **iterative map**) $\mathbb{X} \rightarrow \mathbb{X}$.

Mathematically this is a **dynamical system** that can be defined by:

$$\boxed{\text{discrete time}} \quad \mathbf{x}_{t+1} = \mathbf{f}(\mathbf{x}_t) \quad (6)$$

$$\text{or } \boxed{\text{continuous time}} \quad \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) \quad (7)$$

where \mathbf{f} and \mathcal{f} are different but related ¹. For ease of discussion, sometimes I mix discrete-time and continuous-time notations.

A **control system** is a dynamical system added with the control vector $\mathbf{u}(t)$:

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t) \quad (8)$$

The goal of control theory is to find the optimal $\mathbf{u}^*(t)$ function, such that the system moves from the initial state \mathbf{x}_0 to the terminal state \mathbf{x}_\perp .

A typical control-theory problem is described by:

$$\boxed{\text{state equation}} \quad \dot{\mathbf{x}}(t) = \mathbf{f}[\mathbf{x}(t), \mathbf{u}(t), t] \quad (9)$$

$$\boxed{\text{boundary condition}} \quad \mathbf{x}(t_0) = \mathbf{x}_0, \mathbf{x}(t_\perp) = \mathbf{x}_\perp \quad (10)$$

$$\boxed{\text{objective function}} \quad J = \int_{t_0}^{t_\perp} L[\mathbf{x}(t), \mathbf{u}(t), t] dt \quad (11)$$


and we seek the optimal control $\mathbf{u}^*(t)$.

According to control theory, the condition for **optimal path** is given by the Hamilton-Jacobi-Bellman equation:

$$\boxed{\text{Hamilton-Jacobi-Bellman}} \quad 0 = \frac{\partial J^*}{\partial t} + \min_u H \quad (12)$$

$$\frac{d}{dt} V(x, t) = \min_u \{C(x, u) + \langle \nabla V(x, t), f(x, u) \rangle\} \quad (13)$$

1.5 Reinforcement learning / dynamic programming

Reinforcement learning is a branch of machine learning that is particularly suitable for controlling an **autonomous agent** who interacts with an **environment**. It uses **sensory perception** and **rewards** to continually modify its **behavior**. The exemplary image you should invoke in mind is that of a small insect that navigates a maze looking for food and avoiding predators: 

A reinforcement learning system consists of a 4-tuple:

$$\boxed{\text{reinforcement learning system}} = (\mathbf{x} \in \text{States}, \mathbf{u} \in \text{Actions}, R = \text{Rewards}, \pi = \text{Policy}) \quad (14)$$

For details readers may see my *Reinforcement learning tutorial* [YanRLtutorialEN].

U is the total rewards of a sequence of actions:

$$\begin{array}{ccc} \text{total value of state 0} & & \text{reward at time } t \\ & \swarrow & \nearrow \\ U(\mathbf{x}_0) & = & \sum_t R(\mathbf{x}_t, \mathbf{u}_t) \end{array} \quad (15)$$

¹ They are related by: $\mathbf{x}(t+1) = \mathbf{x}(t) + \mathcal{f}(\mathbf{x}(t))$, $\mathbf{x}^{-1}(\mathbf{x}(t)) = t = \int_{\mathbf{x}_0}^{\mathbf{x}_t} \frac{d\mathbf{x}}{\mathcal{f}(\mathbf{x}(t))}$, and $\mathbf{f}(\mathbf{x}) = \frac{1}{(\mathbf{x}^{-1})'(\mathbf{x}(t))}$.
So we can just solve the functional equation $\mathbf{x}^{-1}(\mathbf{x} + \mathcal{f}(\mathbf{x})) - \mathbf{x}^{-1}(\mathbf{x}) = 1$. See [3] §8.2.3.

For example, the value of playing a chess move is not just the immediate reward of that move, but includes the consequences of playing that move (eg, greedily taking a pawn now may lead to checkmate 10 moves later). Or, faced with delicious food, some people may choose not to eat, for fear of getting fat.

The goal of **reinforcement learning** is to learn the **policy function**:

$$\text{policy} : \text{state} \xrightarrow{\text{action}} \text{state}' \quad (16)$$

when we are given the **state space**, **action space**, and **reward function**:

$$\text{reward} : \boxed{\text{state}} \times \boxed{\text{action}} \rightarrow \mathbb{R} \quad (17)$$

The action a is the same notion as the control variable u in control theory.

The central idea of **Dynamic programming** is the **Bellman optimality condition**, which says: “if we cut off a tiny bit from the endpoint of the optimal path, the remaining path is still an optimal path between the new endpoints.”

$$\begin{array}{ccccc} \text{value of entire path} & & \text{reward of choosing } \mathbf{u} \text{ at current state} & & \text{value of rest of path} \\ & \swarrow & & \searrow & \\ \boxed{\text{Bellman equation}} & & U^*(\mathbf{x}) = \max_{\mathbf{u}} \{ R(\mathbf{u}) + U^*(\mathbf{x}_{t+1}) \} & & \end{array} \quad (18)$$

This seemingly simple formula is the entire content of dynamic programming; What it means is that: When seeking the path with the best value, we cut off a bit from the path, thus reducing the problem to a smaller problem; In other words, it is a **recursive relation** over time.

In AI reinforcement learning there is an oft-employed trick known as Q -learning. Q value is just a variation of U value; there is a U value for each state, and Q is the **decomposition** of U by all the actions available to that state. In other words, Q is the utility of doing action \mathbf{u} in state \mathbf{x} . The relation between Q and U is:

$$U(\mathbf{x}) = \max_{\mathbf{u}} Q(\mathbf{x}, \mathbf{u}) \quad (19)$$

The advantage of Q is the ease of learning. We just need to learn the value of actions under each state. This is so-called “**model free learning**”.

The **Bellman equation** governs reinforcement learning just as in control theory:

$$\boxed{\text{optimal path}} = \text{choose max reward on current path segment} + \boxed{\text{the rest of optimal path}} \quad (20)$$

In math notation:

$$U_t^* = \max_{\mathbf{u}} \{ \boxed{\text{reward}(\mathbf{u}, t)} + U_{t-1}^* \} \quad (21)$$

where U is the “long-term value” or **utility** of a path.

1.6 Connections with Hamiltonian and quantum mechanics

This section is optional.

In **reinforcement learning**, we are concerned with two quantities:

- $R(\mathbf{x}, \mathbf{u}) = \text{reward}$ of doing action \mathbf{u} in state \mathbf{x}
- $U(\mathbf{x}) = \text{utility}$ or **value** of state \mathbf{x}

Simply put, **utility** is the integral of instantaneous **rewards** over time:

$$\boxed{\text{utility } U} = \int \boxed{\text{reward } R} dt \quad (22)$$

In **control-theoretic** parlance, it is usually defined the **cost functional**:

$$\boxed{\text{cost } J} = \int L dt + \Phi(\mathbf{x}_{\perp}) \quad (23)$$

where L is the **running cost**, ie, the cost of making each step; Φ is the **terminal cost**, ie, the value when the terminal state \mathbf{x}_{\perp} is reached.

In **analytical mechanics** L is known as the **Lagrangian**, and the time-integral of L is called the **action**:

$$\boxed{\text{action } S} = \int L dt \quad (24)$$

Hamilton's **principle of least action** says that S always takes the **stationary value**, ie, the S value is extremal compared with neighboring trajectories.

The **Hamiltonian** is defined as $H = L + \frac{\partial J^*}{\partial \mathbf{x}} \mathbf{f}$, which arises from the method of **Lagrange multipliers**.

All these refer to essentially the same thing, so we have the following correspondence:

Reinforcement learning	Control theory	Analytical mechanics
utility or value U	cost J	action S
instantaneous reward R	running cost	Lagrangian L
action a	control u	(external force?)

 (25)

Interestingly, the reward R corresponds to the **Lagrangian** in physics, whose unit is “energy”; In other words, “desires” or “happiness” appear to be measured by units of “energy”, this coincides with the idea of “positive energy” in pop psychology. Whereas, long-term value is measured in units of [energy \times time].

This correspondence between these 3 theories is explained in detail in Daniel Liberzon's book [7]. The traditional AI system is discrete-time; converting it to continuous-time seems to

increase the computational burden. The recent advent of **symplectic integrators** [6] are known to produce better numerical solutions that retain qualitative features of the exact solution, eg. quasi-periodicity.

An interesting insight from control theory is that our system is a Hamiltonian dynamical system in a broad sense.

Hamilton's **principle of least action** says that the trajectories of dynamical systems occurring in nature always choose to have their action S taking **stationary values** when compared to neighboring paths. The action is the time integral of the Lagrangian L :

$$\boxed{\text{Action } S} = \int \boxed{\text{Lagrangian } L} dt \quad (26)$$

From this we see that the Lagrangian corresponds to the instantaneous “rewards” of our system. It is perhaps not a coincidence that the Lagrangian has units of **energy**, in accordance with the folk psychology notion of “positive energy” when we talk about desirable things.

The **Hamiltonian** H arises when we consider a typical control theory problem; The system is defined via:

$$\text{state equation:} \quad \dot{\mathbf{x}}(t) = \mathbf{f}[\mathbf{x}(t), \mathbf{u}(t), t] \quad (27)$$

$$\text{boundary condition:} \quad \mathbf{x}(t_0) = \mathbf{x}_0, \mathbf{x}(t_\perp) = \mathbf{x}_\perp \quad (28)$$

$$\text{objective function:} \quad J = \int_{t_0}^{t_\perp} L[\mathbf{x}(t), \mathbf{u}(t), t] dt \quad (29)$$

The goal is to find the optimal control $\mathbf{u}^*(t)$.

Now apply the technique of **Lagrange multipliers** for finding the maximum of a function, this leads to the new objective function:

$$U = \int_{t_0}^{t_\perp} \{L + \boldsymbol{\lambda}^T(t) [f(\mathbf{x}, \mathbf{u}, t) - \dot{\mathbf{x}}]\} dt \quad (30)$$

So we can introduce a new scalar function H , ie the Hamiltonian:

$$H(\mathbf{x}, \mathbf{u}, t) = L(\mathbf{x}, \mathbf{u}, t) + \boldsymbol{\lambda}^T(t) f(\mathbf{x}, \mathbf{u}, t) \quad (31)$$

Physically, the unit of \mathbf{f} is velocity, while the unit of L is energy, therefore $\boldsymbol{\lambda}$ should have the unit of **momentum**. This is the reason why the phase space is made up of the diad of (position, momentum).

According to control theory, the **optimal path** is given by the Hamilton-Jacobi-Bellman equation:

$$\boxed{\text{Hamilton-Jacobi-Bellman}} \quad 0 = \frac{\partial S^*}{\partial t} + \min_u H. \quad (32)$$

With the substitution $\Psi = e^{iS/\hbar}$ into the Hamilton-Jacobi equation, one can obtain the **Schrödinger equation** in quantum mechanics:

$$\boxed{\text{Hamilton-Jacobi}} \quad \frac{\partial S}{\partial t} = -H \quad \xrightarrow{\Psi = \exp\{iS/\hbar\}} \quad i\hbar \frac{\partial \Psi}{\partial t} = H\Psi \quad \boxed{\text{Schrödinger}} \quad (33)$$

which suggests that techniques in quantum mechanics can be applied to solve our AGI problem.

1.7 Diffusion equation

Recently, I accidentally discovered [9]² a precise transition from the classical H-J equation to the **Schrödinger equation** in quantum mechanics, via a simple substitution $\Psi = e^{iS/\hbar}$,

$$\boxed{\text{Hamilton-Jacobi}} \quad \frac{\partial S}{\partial t} = -H \quad \xrightarrow{\Psi = \exp\{iS/\hbar\}} \quad i\hbar \frac{\partial \Psi}{\partial t} = H\Psi \quad \boxed{\text{Schrödinger}}. \quad (34)$$

This implies that the Schrödinger equation is an alternative way of expressing the optimality condition for RL! It is also known that the Schrödinger equation in *imaginary time* becomes the **diffusion equation** and is related to stochastic processes (*cf* [8] Ch.6); This may lead to new algorithms.

We can also express J using the quantum-mechanical notation:

$$J = \langle \Psi | i\hbar \log \Psi | \Psi \rangle \quad (35)$$

All these “physical” ideas flow automatically from our definition of **rewards**, without the need to introduce them artificially. But these ideas seem not immediately useful to our project, unless we are to explore **continuous-time** models.

2 Weyl correspondence

Weyl proposed the following very general quantization rule: to a classical observable $a(x, p)$ depending on the position and momentum coordinates, one should associate an operator defined by

$$a_{\text{Weyl}}(\hat{x}, \hat{p}) = \frac{1}{2\pi\hbar} \int e^{\frac{i}{\hbar}(x\hat{x} + p\hat{p})} F a(x, p) dp dx \quad (36)$$

where F is the Fourier transform; this operator is formally obtained by replacing the variables x and p in the Fourier inversion formula by the non-commuting variables \hat{x} and \hat{p} used by Born, Jordan, and Heisenberg. Some easy algebra shows that if we quantize a classical Hamiltonian function

$$H = \frac{p^2}{2m} + V(x) \quad (37)$$

using Weyl’s rule one obtains the operator

$$H(\hat{x}, \hat{p}) = -\frac{\hbar^2}{2m} \frac{\partial^2}{\partial x^2} + V(x) \quad (38)$$

which is the same as the one appearing in Schrödinger’s equation. So far, so good. The rub comes from the following observation: if we apply Weyl’s rule to the monomials $x^r p^s$ considered by Born, Jordan, and Heisenberg, we get the correspondence

$$x^r p^s \longrightarrow \frac{1}{2^s} \sum_{k=0}^s \binom{s}{k} \hat{p}^{s-k} \hat{x}^r \hat{p}^k \quad (39)$$

² The relation $S = i\hbar \log \Psi$ appeared in one of Schrödinger’s 1926 papers, but is dismissed by him as “incomprehensible”. This formula seems to be overlooked by physicists since that time, possibly including Feynman. I have yet to discuss / verify this with physicists.

where the $\binom{s}{k}$'s are the binomial coefficients; as is immediately seen by simple inspection, this rule is fundamentally different from Born and Jordan's quantization rule, as soon as $r, s \geq 2$. Thus, if one wants to extend the Schrödinger picture to observables which are arbitrary functions of the variables x and p one obtains two different results depending on which quantization rule one uses. This fact has the following unwanted consequence: if one uses Weyl quantization, the Born-Jordan and Schrödinger pictures are no longer equivalent, and we thus have two different quantum mechanics.

— Maurice A. de Gosson, Born-Jordan Quantization

2.1 Prior art: other cognitive architectures

The minimalist architecture based on reinforcement learning has been proposed by Itamar Ariel from Israel, in 2012 [2], and I also independently proposed in 2016 (precursor of this paper). The prestigious researcher of signal processing, Simon Haykin, recently also used the “RL + memory” design, cf. his 2012 book *Cognitive dynamic systems* [4]. Vladimir Anashin in the 1990's also proposed this kind of cognitive architecture [1]. There may exist more precedents, eg: [5].

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