Preface

Arrogance and ambition: In praise of outsider AI

- AGI is outsider AI
- Outsiders do better at
  - thinking for themselves
  - questioning the status quo
  - seeing the obvious
- AGI is on the hairy edge between arrogance and ambition

seeing what is obvious, and therefore invisible

- The discovery of gravity, by Isaac Newton
- The discovery of air/vacuum
- The discovery of reinforcement learning, by Harry Klopf, in the 1970s
  - RL was born seemingly in rude arrogance, by a total outsider

Harry Klopf
1941–1997

My conclusion

- Outsider AI is good
- Questioning the problem is often the best way to make the important advances

Personal perspective

- There is a *science of mind* that is neither natural science nor applications technology
  - as in, e.g., Marr's "computational theory"
- "Minds" can be defined as things more usefully thought of in terms of goals than of mechanisms
  - goals can be well thought of as rewards
- Reinforcement learning is part of the beginning of a science of mind

Toward Learning Human-level Predictive Knowledge

Rich Sutton
Reinforcement Learning and Artificial Intelligence Lab
University of Alberta, Canada

with thanks to
Hamid Maei, Csaba Szepesvari, Doina Precup, Shalabh Bhatnagar, David Silver, Michael Delp, Eric Weiwiora, and Mark Ring

The problem

- *How we can know lots of stuff* about how the world works and what we can do, and apply it efficiently to maximize reward
- We know so much! So much sensori-motor stuff
- How can we relate higher-level knowledge to the low-level sensorimotor stuff?
- How can it all be organized and maintained? What are the principles?

Much of mind is about prediction

- *Perception* and *state representation* can be thought of as making predictions
- *Models the world* and *cause and effect* can be thought of in terms of predictions
- *Planning* can be thought of as composing predictions to anticipate possible futures, and then choosing among them
- *Predictions are the coin of the mental realm*

World knowledge

- Much knowledge is *about the world*
  - but not all, e.g., mathematics, memories
- All knowledge about the world is *predictive*, meaning that it can be translated into statements about future experience
- Such statements are the content of the knowledge
- They make the knowledge potentially verifiable

Predictions can be more powerful than you think

- Not just a "saying before" of what the sensory signals will be
- All scientific knowledge can be expressed as predictions
- Predictions can be about the outcomes of extended courses of behavior (options)
- All the little things you know can be well thought of as prediction

Predictions are signals

- They have a value that varies from time to time
- Their statement about the world is always relative to the current time
- Each prediction is a signal, a time series

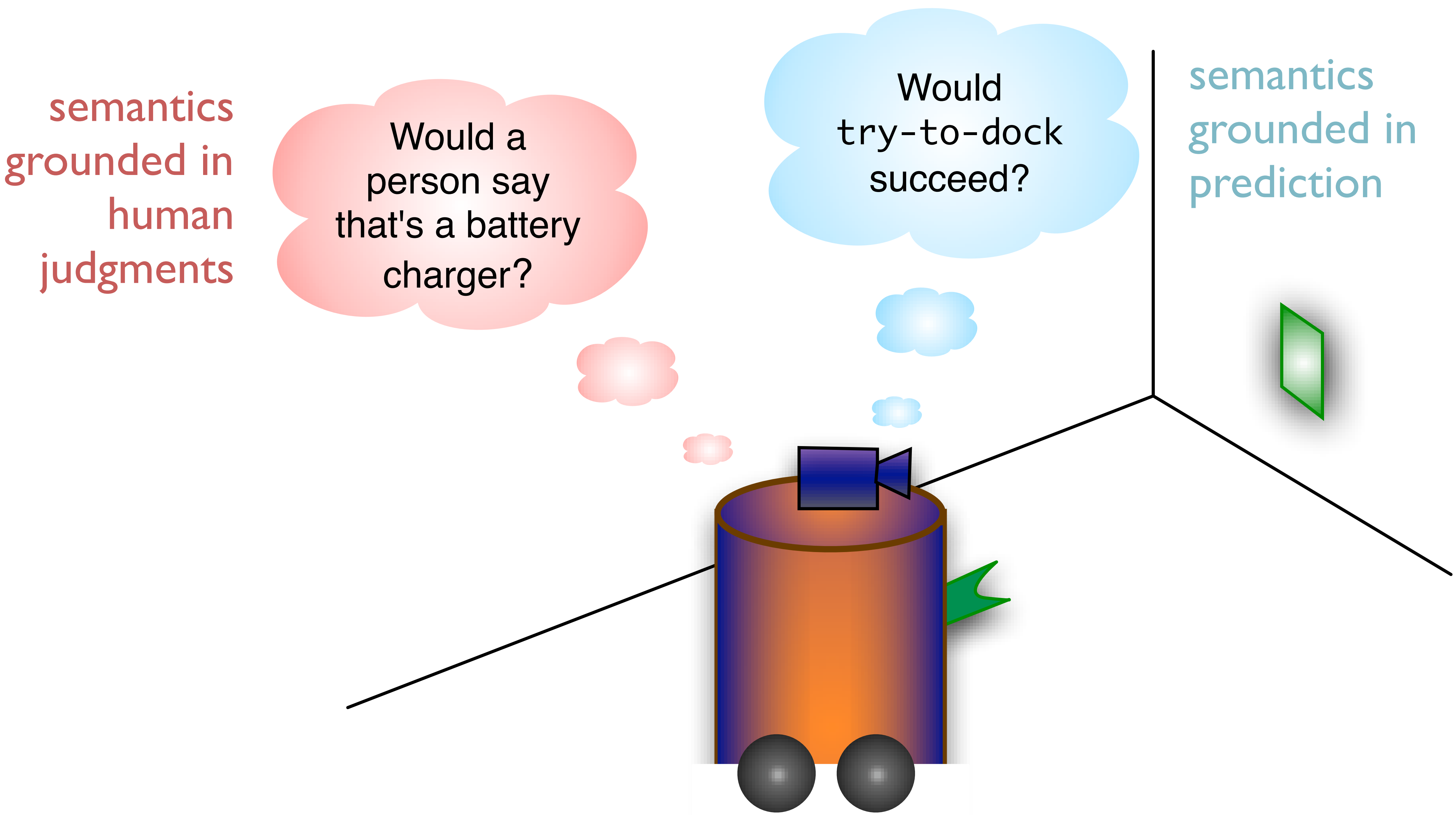
Predictions have two parts: a “*question*” and an “*answer*”

- Question: will the sun rise tomorrow?
  Answer: yes
- Question: will i win this backgammon game?
  Answer: probability 0.6
- The question is future oriented whereas the answer is strictly a function of the past
- The question is the semantics of the prediction; it is needed for learning and verification, but not for performance

Questions are more important, more mysterious, more often overlooked; answers are relatively straightforward

- E.g., flipping a coin
  - Question: what is the probability of heads
  - Answer: 0.5
- How to represent *flipping*, *coin*, and *heads*?

The robot and the battery charger



Only the predictive question can be autonomously verified

Desiderata: Predictive knowledge should be

1. Useful, e.g., for planning
2. Expressive (powerful, abstract, human-level)
3. Autonomously verifiable
4. Suitable for efficient learning with approximations

The theory of options from 1999 satisfies all but the last.
Today, instead, we will talk of value functions

Outline

✔ • *The problem* of learning predictive knowledge

- *Value functions* have been key to RL
- *General value functions* may be key to the problem of human-level predictive knowledge
  - many things work out neatly
- But learning must be *off-policy* and use function approximation; using the *new GQ algorithm* this can, at last, be done efficiently

Value functions

Value functions

- Value functions provide moment-to-moment estimates of the total future reward an AI agent can expect to receive
- They are predictions!
  - Question: how much total reward will i receive? Answer: a single real number (at each time)
- There are both true value functions and estimated value functions

Target value functions

- A *state*-value function maps states to values, given a policy

$$V^{\pi}(s) \quad = \quad \mathbb{E}\left[r_1 + \gamma r_2 + \gamma^2 r_3 + \cdots \mid s_0 = s, a_{0:\infty} \sim \pi\right]$$

policy · state · expectation · scalar rewards · discount factor <1 · actions

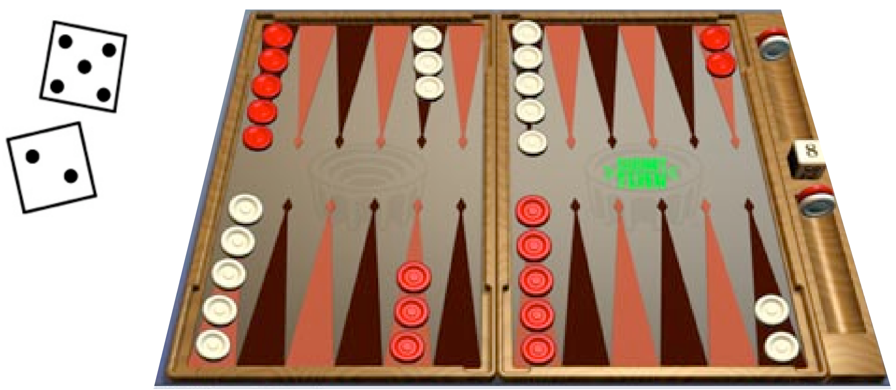
- An *action*-value function is the same except it commits to the first action as well

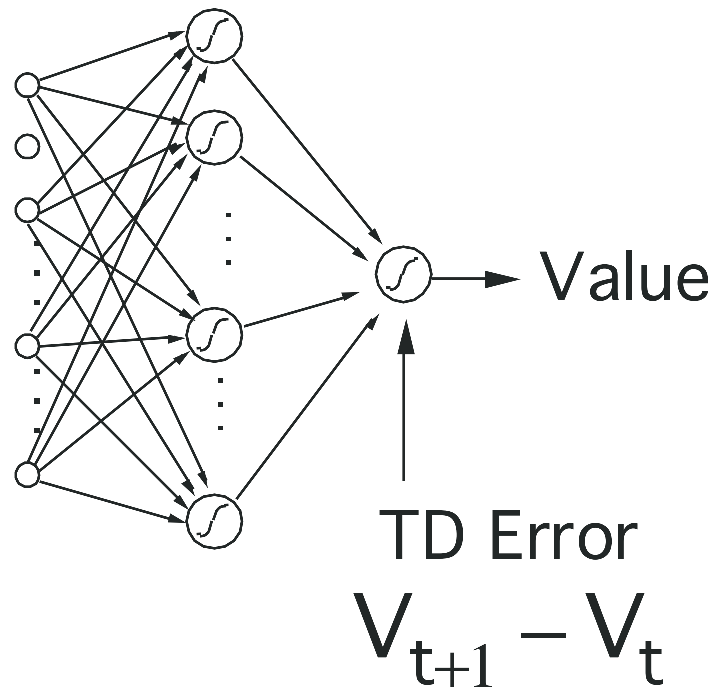
$$Q^{\pi}(s, a) \quad = \quad \mathbb{E}\left[r_1 + \gamma r_2 + \gamma^2 r_3 + \cdots \mid s_0 = s, a_0 = a, a_{1:\infty} \sim \pi\right]$$

first action

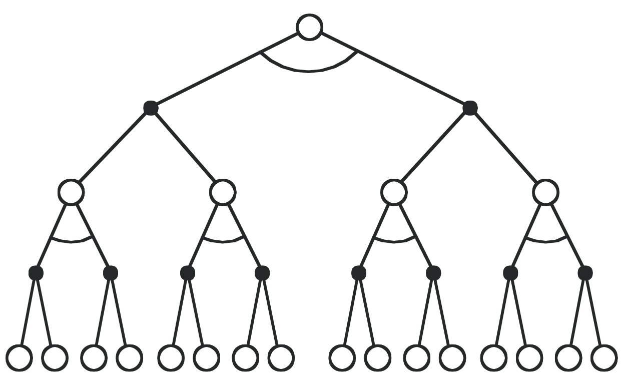
TD-Gammon

Tesauro, 1992-1995





Action selection by 2-3 ply search



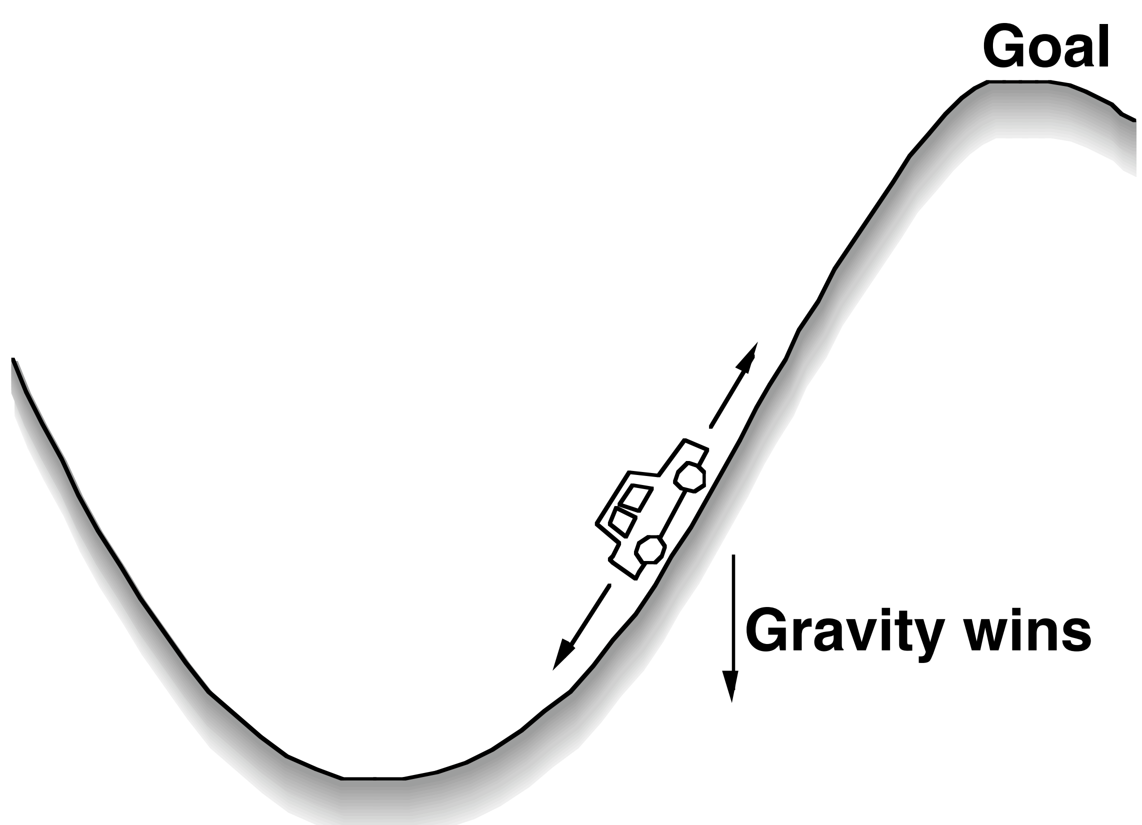
Start with a random Network

Play millions of games against itself

Learn a value function from this simulated experience

Six weeks later it's the best player of backgammon in the world

The Mountain Car Problem



Minimum-Time-to-Goal Problem

<u>SITUATIONS</u>: car's position and velocity

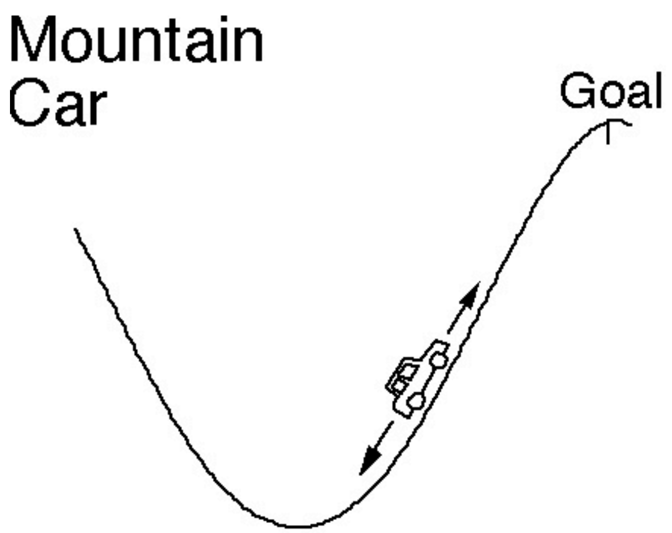
<u>ACTIONS</u>: three thrusts: forward, reverse, none

<u>REWARDS</u>: always –1 until car reaches the goal

No Discounting

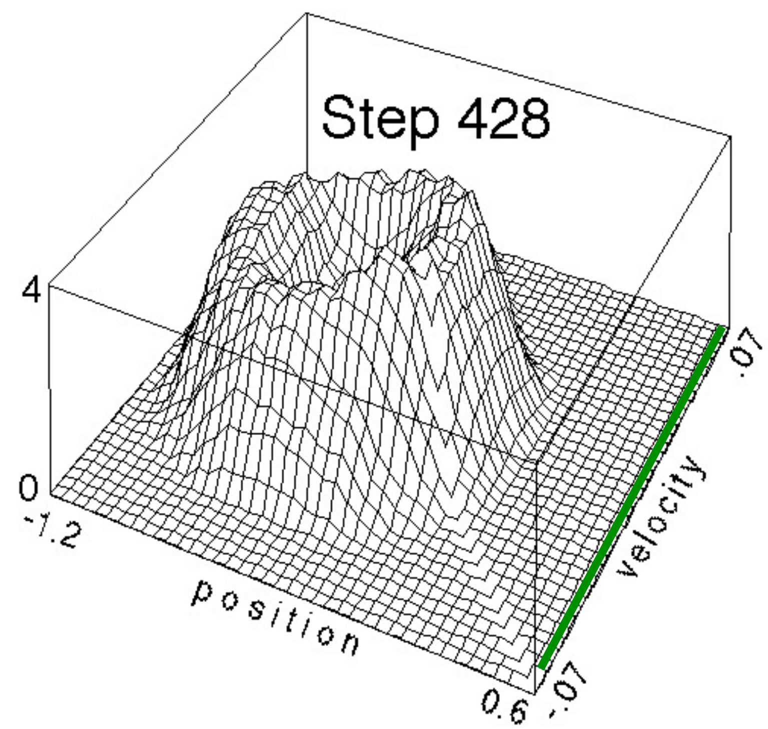
Moore, 1990

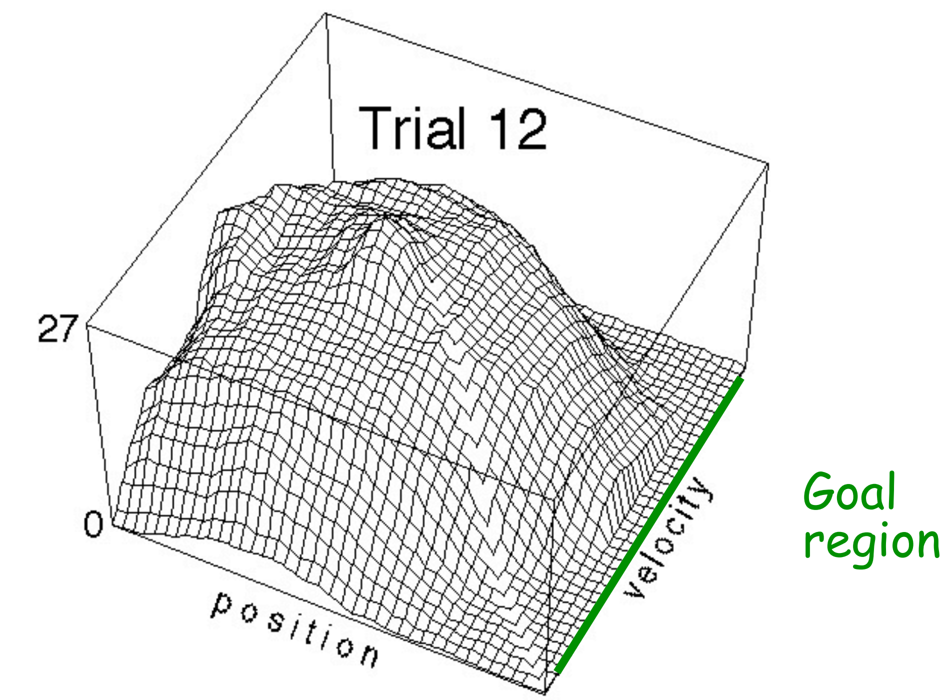
Value Functions Learned while solving the Mountain Car problem

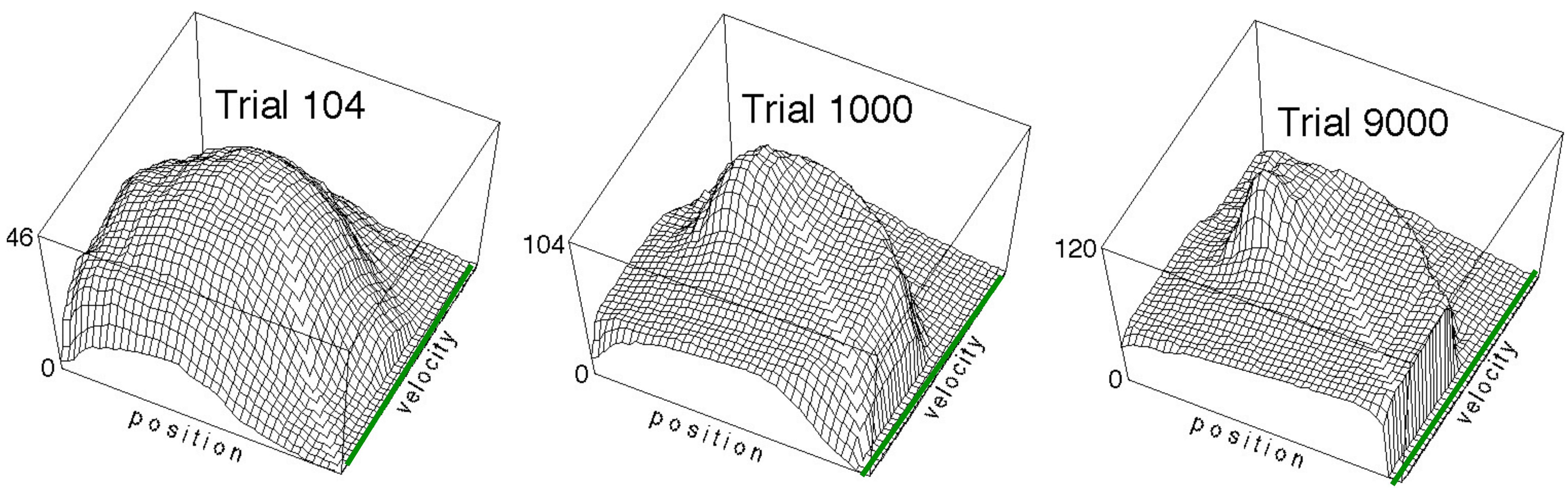


Minimize Time-to-Goal

Value = estimated time to goal







The value-function hypothesis

All efficient methods for solving sequential decision problems estimate value functions as an intermediate step

Value-function approximation

- Value-function learning is sometimes done in a table-lookup context - where every state is distinct and treated totally separately
- But really, to be powerful, we must generalize between states
  - the same state never occurs twice
- We use parameterized function approximators, and learn the parameters, aka weights

For example, linear value-function approximation in Computer Go

state

s

feature vector   parameter vector

$$\begin{bmatrix}0\\1\\0\\0\\0\\1\\1\\0\end{bmatrix} \times \begin{bmatrix}0.1\\-2\\0\\0.5\\0\\0\\5\\-.4\end{bmatrix} = -2 + 0 + 5 = 3 = \mathbf{w}^\top \mathbf{f}$$

$\mathbf{f}(s)$ $\mathbf{w}$

estimated value

10^{35} states 10^{6} binary features and weights

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General value functions

Multiple value functions as a knowledge rep'n language

- Value functions are predictions, long-term predictions
- They predict reward, but couldn't we pretend anything is reward, and learn a value function for getting it?
  - if i open it the fridge, will i see a beer?
  - if i take out my wallet, will i see any euros?
  - if i do what i usually do, will the sun rise tomorrow?

Termination tricks

- It is common in RL problems to have terminal values, e.g., +1/-1 for winning or losing a game
- Termination means complete instantaneous discounting, together with a special terminal value that can depend on the state
- We can use pretend termination to escape from exponential discounting
  - Will sweden or norway be the next to win a gold medal? (no discounting until one wins, then complete discounting/termination)

General value functions

- Conventional value functions are predictions wrt the rewards, discount, and terminal values of the problem, for a given policy

$$
\begin{aligned}
Q^\pi(s,a) &= \mathbb{E}\left[r_1 + \gamma r_2 + \gamma^2 r_3 + \cdots \mid s_0 = s, a_0 = a, a_{1:\infty} \sim \pi\right] \\
&= \mathbb{E}[r_1 + \cdots + r_k + z_k \mid s_0 = s, a_0 = a, a_{1:k} \sim \pi, k \sim \gamma]
\end{aligned}
$$

- *General value functions* are predictions wrt to four given functions

$$
Q^{\pi,r,\gamma,z}(s,a) = \mathbb{E}[r(s_1) + \cdots + r(s_k) + z(s_k) \mid s_0 = s, a_0 = a, a_{1:k} \sim \pi, k \sim \gamma]
$$

↑ these four functions define the semantics of the prediction

General value functions

$$Q^{\pi,r,\gamma,z}(s,a) \quad = \quad \mathbb{E}[r(s_1) + \cdots + r(s_k) + z(s_k) \mid s_0 = s, a_0 = a, a_{1:k} \sim \pi, k \sim \gamma]$$

these four functions define the semantics of the prediction

policy $\pi : \mathcal{A} \times \mathcal{S} \longrightarrow [0,1]$

reward $r : \mathcal{S} \longrightarrow \mathbb{R}$

termination $\gamma : \mathcal{S} \longrightarrow [0,1]$

terminal value $z : \mathcal{S} \longrightarrow \mathbb{R}$

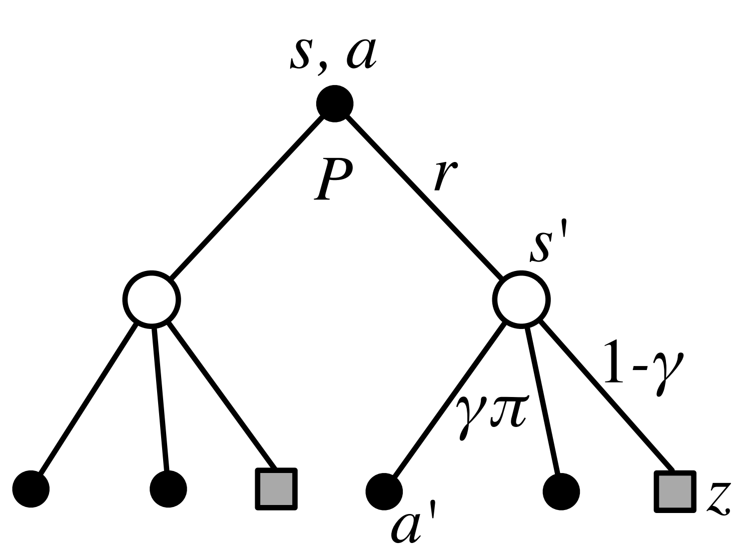
These are the prediction's question!

General value functions

$$Q^{\pi,r,\gamma,z}(s,a) \quad = \quad \mathbb{E}[r(s_1)+\cdots+r(s_k)+z(s_k) \mid s_0\!=\!s, a_0\!=\!a, a_{1:k}\!\sim\!\pi, k\!\sim\!\gamma]$$

There is also a Bellman equation for GVFs:

$$Q^{\pi,r,\gamma,z}(s,a) \quad = \quad \sum_{s'} P(s'|s,a)\left[r(s')+\gamma(s')\sum_{a'}\pi(a'|s')Q^{\pi,r,\gamma,z}(s',a')+(1-\gamma(s'))z(s')\right]$$



General value functions

$$Q^{\pi,r,\gamma,z}(s,a) \quad = \quad \mathbb{E}[r(s_1) + \cdots + r(s_k) + z(s_k) \mid s_0 = s, a_0 = a, a_{1:k} \sim \pi, k \sim \gamma]$$

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and a TD (temporal difference) error:

$$\delta_t \quad = \quad r(s_{t+1}) + \gamma(s_{t+1}) \sum_{a'} \pi(a'|s_{t+1}) \hat{Q}(s_{t+1},a') + (1-\gamma(s_{t+1}))\, z(s_{t+1}) - \hat{Q}(s_t,a_t)$$

thus there will be simple, cheap, TD learning algorithms

General value functions

and a TD (temporal difference) error:

$$\delta_t = r(s_{t+1}) + \gamma(s_{t+1}) \sum_{a'} \pi(a'|s_{t+1}) \hat{Q}(s_{t+1}, a') + (1 - \gamma(s_{t+1}))\, z(s_{t+1}) - \hat{Q}(s_t, a_t)$$

thus there will be simple, cheap, TD learning algorithms

e.g., tabular GQ:

$$\Delta \hat{Q}(s_t, a_t) = \alpha \delta_t$$

(generalizes tabular Q-learning)

step size

with function approximation, there are also simple methods, but just like for regular value functions, conventional methods are stable only for the linear, on-policy case

if we can't learn off-policy it spoils everything!

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Off-policy learning with GQ

Off-policy learning

- Off-policy learning is learning about a policy different than that used to generate actions
  - Most often arises when learning an optimal policy while following an exploratory policy, or from a pre-collected data set
- We are envisioning learning about many policies, so it will have to be off-policy (or else the policies have to take turns ☹)
- Off-policy learning is roughly the same as learning from incomplete trajectories

Parallel prediction demons

- We should be able to learn lots of value functions at once, in parallel
  - we call them *parallel prediction demons*
- *Every* demon should be able to learn on *every* step
- This has always been the promise of off-policy temporal-difference learning

But this promise has been unfulfilled

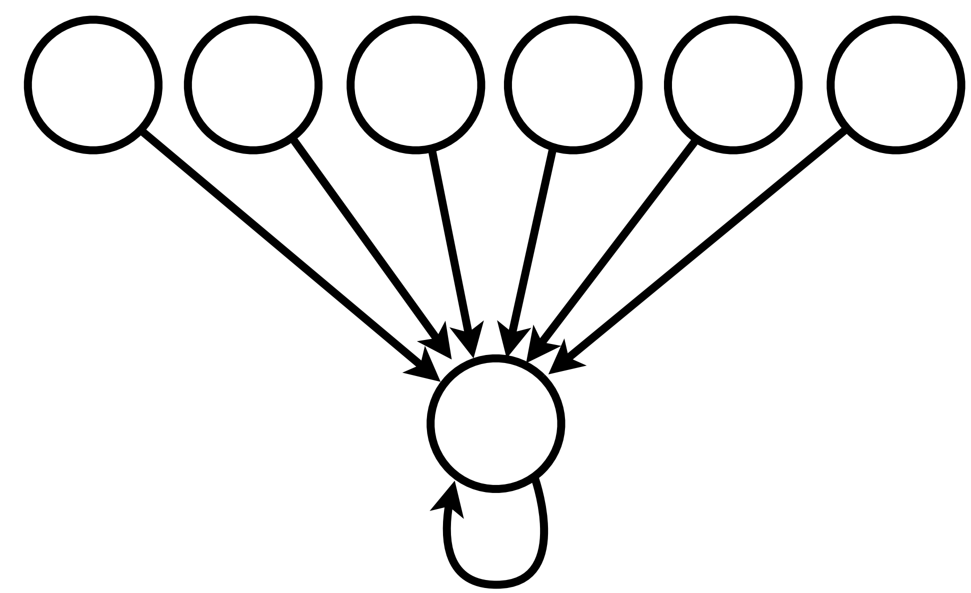
- There has been no practical algorithm for parallel prediction learning
  - Previous methods were too complex (LSTD, iLSTD), restricted to table lookup (Q-learning), not parallel (Monte Carlo, Sarsa), too slow (importance sampling), or had weak approximators (averaging)

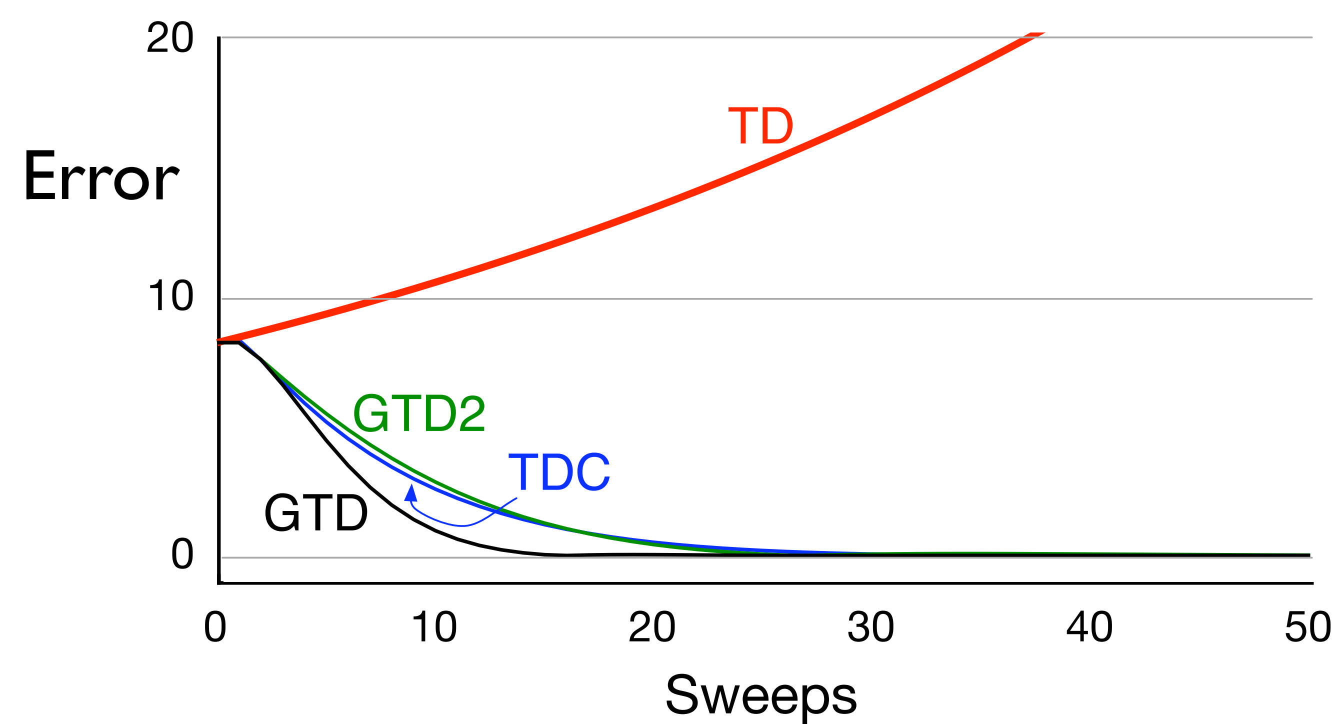
Until now

- Now, for the first time, it is practical and straightforward to do massive, in parallel, prediction learning
- With new gradient-based TD algorithms
  - GTD, TDC (NIPS-08, ICML-09, NIPS-09)
  - GQ(λ) (AGI-10)

Baird's counterexample

- A simple Markov chain
- Linear FA, all rewards zero
- Deterministic, expectation-based full backups (as in DP)
- Each state updated once per sweep (as in DP)
- Weights can diverge to $\pm\infty$





Linear GQ(0)

Linear approximation of the GVF:

$$\hat{Q}(s,a) \quad = \quad \mathbf{w}^\top \mathbf{f}(s,a) \quad \approx \quad Q^{\pi,r,\gamma,z}(s,a)$$

Learning:

$$\Delta \mathbf{w}_t \quad = \quad \alpha \delta_t \mathbf{f}(s_t,a_t) - \alpha\gamma(s_{t+1})(\mathbf{v}_t^\top \mathbf{f}(s_t,a_t)) \sum_a \pi(a|s_{t+1})\mathbf{f}(s_{t+1},a)$$

$$\Delta \mathbf{v}_t \quad = \quad \beta \left(\delta_t - \mathbf{v}_t^\top \mathbf{f}(s_t,a_t)\right) \mathbf{f}(s_t,a_t)$$

2nd step size

a separate set of weights used only for learning

It's one more step bring in eligibility traces...

Linear GQ(λ)

Linear approximation of the GVF:

$$\hat{Q}(s,a) \quad = \quad \mathbf{w}^\top \mathbf{f}(s,a) \quad \approx \quad Q^{\pi,r,\gamma,z}(s,a)$$

Learning:

$$\Delta \mathbf{w}_t \quad = \quad \alpha \delta_t \mathbf{e}_t - \alpha \gamma(s_{t+1})(\mathbf{v}_t^\top \mathbf{e}_t) \sum_a \pi(a|s_{t+1}) \mathbf{f}(s_{t+1}, a)$$

$$\Delta \mathbf{v}_t \quad = \quad \beta \left(\delta_t \mathbf{e}_t - \mathbf{v}_t^\top \mathbf{f}(s_t, a_t) \mathbf{f}(s_t, a_t) \right)$$

a separate set of weights used only for learning

$$\mathbf{e}_t \quad = \quad \gamma(s_t) \lambda(s_t) \frac{\pi(a_t|s_t)}{b(a_t|s_t)} \mathbf{e}_{t-1} + \mathbf{f}(s_t, a_t)$$

eligibility traces

the *behavior policy*, the policy actually picking the actions

Stability and convergence theorem for GQ(λ)

There exists a projected-Bellman-error objective function

vector of general values, one per state

$$J(\mathbf{w}) = \left\| \hat{Q}_w - \Pi T^{\pi,r,\gamma,z} \hat{Q}_w \right\|_b^2$$

generalized Bellman operator

projection back into the space of representable functions

such that

$$E_b[\Delta \mathbf{w}] = -\alpha \nabla_{\mathbf{w}} J(\mathbf{w})$$

expectation under the behavior policy

gradient vector of partial derivatives

which guarantees convergence to $J(\mathbf{w}) = 0$ (under step-size conditions)

Further results with new *gradient-descent TD* methods

- Convergence with nonlinear function approximators (e.g., neural networks)
- Empirical on-policy learning rate comparable to that of linear and nonlinear TD on 9x9 Computer Go
- First convergence result for the control case (changing target policy π)
- One-time-scale proofs of convergence for all algorithms; constant second step-size

Application to computational curiosity

- Imagine *one million prediction demons*, all learning in parallel
  - for various random or cleverly chosen GVFs
- Imagine each can measure its learning progress
- Use the *sum-total learning progress* as intrinsic reward to direct the behavior policy
- Weed and refine the set of demons, then repeat

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Conclusions

- The new gradient TD algorithms are a breakthrough in RL (two open probs solved)
- Function approximation in RL is now nearly as straightforward as supervised learning
- General value functions turn out to be a very expressive knowledge rep'n language
  - their underlying Bellman equation makes (TD) learning them computationally efficient
  - they take us from values to knowledge very economically, with few new ideas

What is new?

- Efficient off-policy learning is new
- General value functions are a new, simpler way to present the ideas of options and option models
- Applications to computational curiosity are new and ongoing
- Applications to representation change and state discovery are starting

In its ambitions, AGI should be...

(a) Arrogant and abrasive

(b) Audacious

(c) Appropriate

✓ (d) All of the above

- thank you for your attention