Learning About Sensorimotor Data

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with thanks to

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Outline

- The sensorimotor approach to knowing
- Robot experiments
  - the need for multi-step prediction
- The Horde-of-demons architecture
- Remarks on gradient-TD algorithms

Intelligence

- Knowing a lot
- Being able to use what you know flexibly to achieve goals (maximize reward)

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Knowledge should be

1. *Learnable*—from low-level sensorimotor data
2. *Expressive*—able to express abstract, high-level facts as well as specific, low-level facts
3. *Useful*—for action and planning

"The problem of knowing"

Examples of stuff to know

- Twitching this muscle lifts that finger
- There is a wall behind me
- The toilet is down the hall on the left
- The shape of a teacup
- Knowing how to ride a bike
- Knowing how to call a taxi
- My keys are in my pocket
- There is an apple in the box
- There is a book on the table
- My car is red
- People usually have two feet
- The Eiffel tower is in Paris
- John has the flu

The Sensorimotor View

- In which an agent's knowledge is viewed as facts about the statistics of its sensorimotor data stream
- This point of view is interesting because
  - it is reductionist and demystifies world knowledge
  - it provides a clear way of thinking about semantics
  - it implies that knowledge can be verified and learned from data – "the knowledge is in the data"

Thus "Learning About Sensorimotor Data"

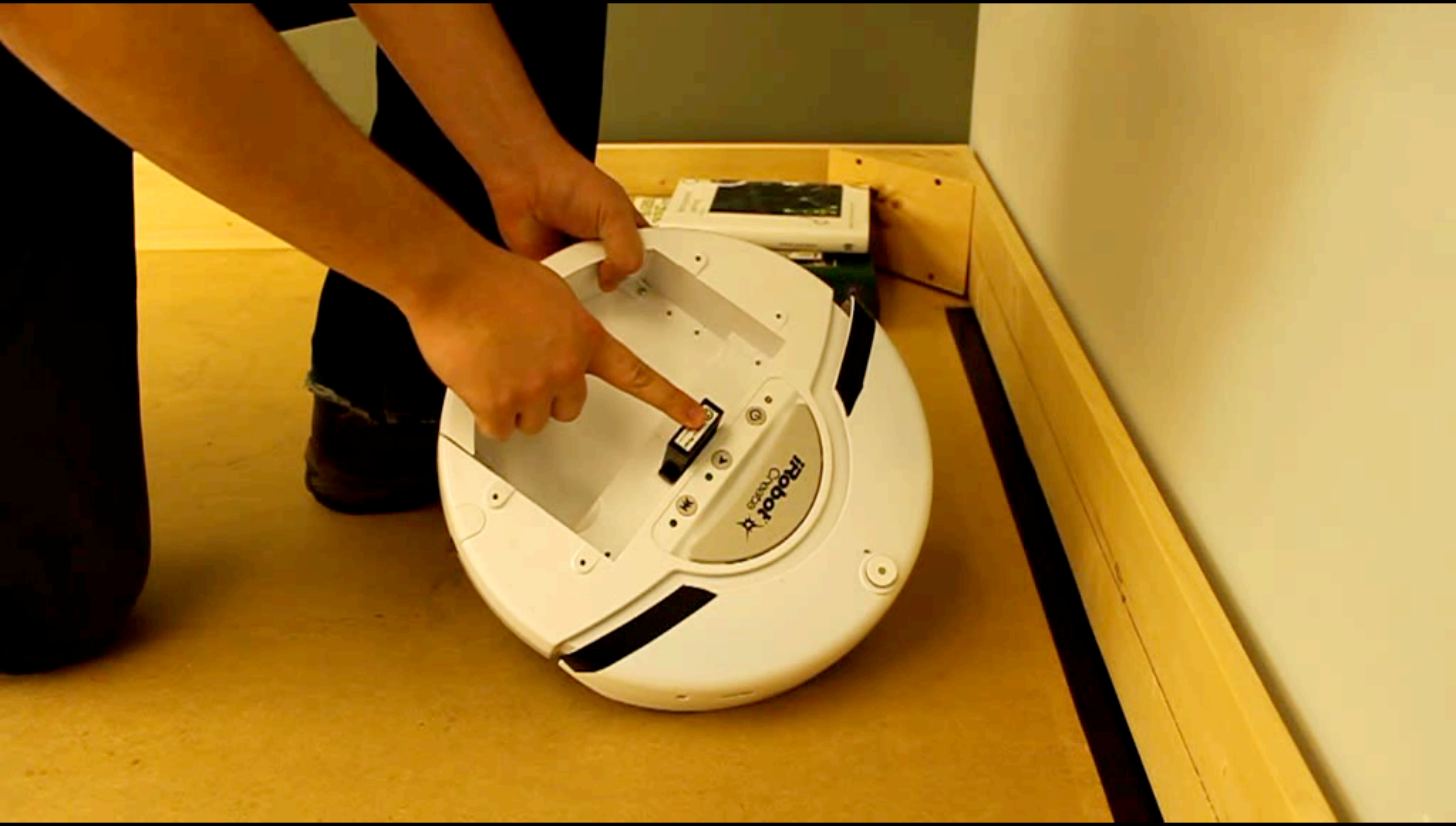
It's hard to implement the Sensorimotor View well

- Where "well" means such that it is
  - sound, stable, and efficient with function approximation
  - scalable to large numbers of predictions learned in parallel from the same experience
  - real time (online with many updates/second)
  - captures multi-step facts
- Achieving these modest goals is highly constraining

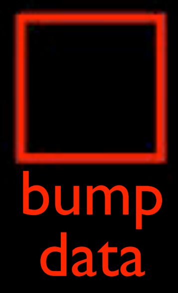
Thus a successful implementation can be informative

Robot experiments

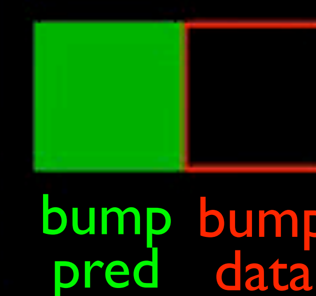
The iRobot Create



“Wall ahead” is a sensorimotor fact



Predicting: Will rolling forward soon result in a bump?



Predicting right and left bumps

pred data

left bump

both bump

right bump

Strategy

- To understand the world is to have *many predictions* about your sensorimotor data stream
- The predictions must be multi-step and policy contingent
  - because almost all interesting predictions are more-than-one-step and policy-contingent
- You must be able to learn from partial executions
  - because then you can learn about *many policies in parallel*
  - this will require *TD* and *off-policy* learning, and *FA*

Temporal-difference (TD) learning

- The core learning algorithm of online reinforcement learning
  - model-free dynamic programming
- Learning driven by TD errors (changes in prediction from one time to the next)
  - learning a guess from a guess

TD Learning in Engineering and Biology

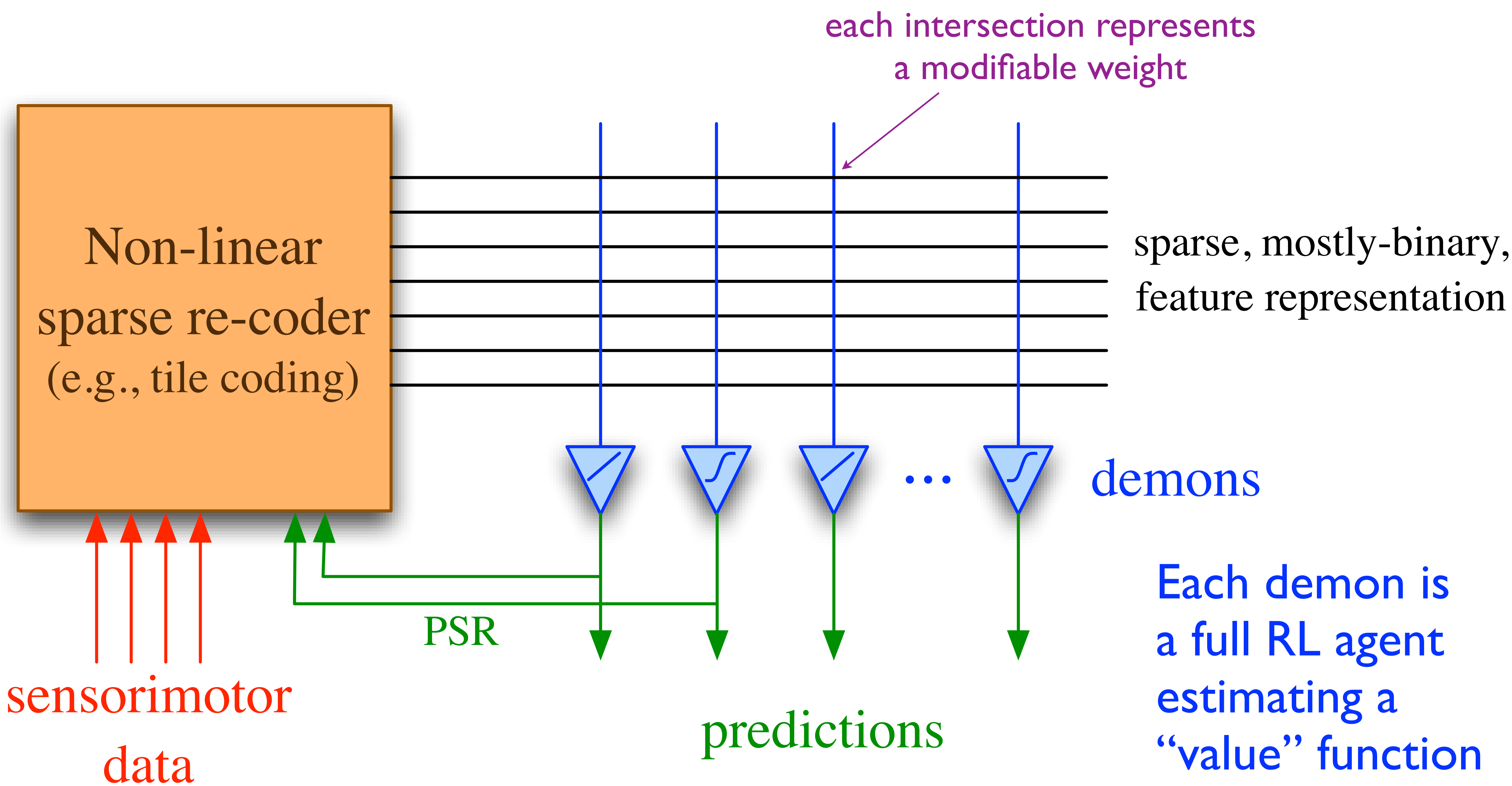
- TD algorithms are the standard model of reward-based learning in both
  - *engineering* (artificial intelligence and optimal control)
  - *biology* (neuroscience and psychology)
- TD algorithms have been *independently validated* in four distinct fields
- This is an unprecedented convergence

TD is in no way specific to reward

- TD is a real-time prediction-learning method
- suitable for predicting any signal, not just reward

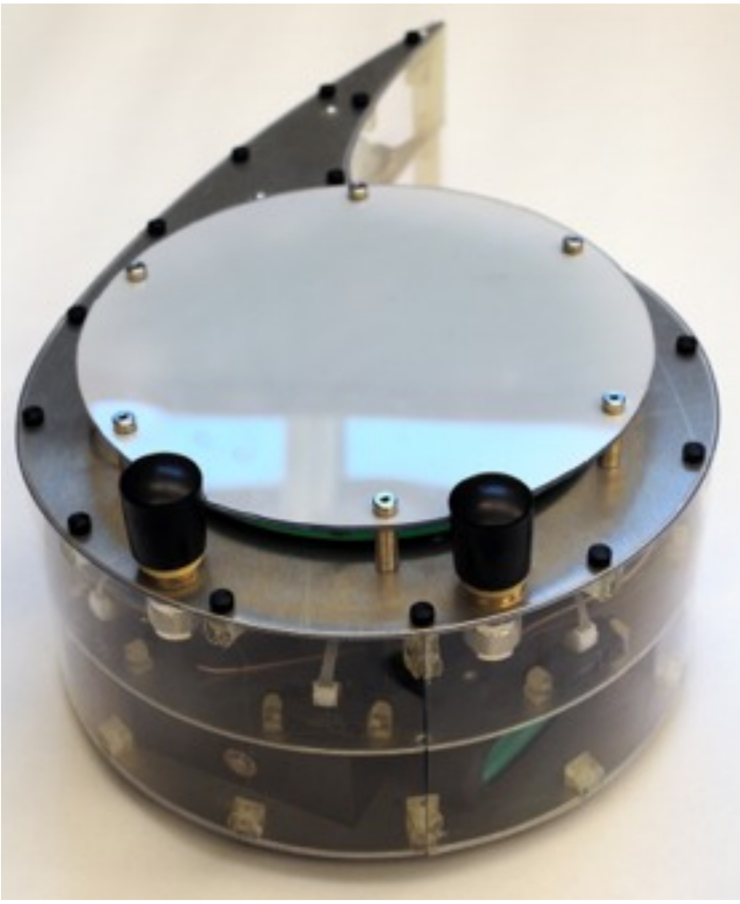
- it is a candidate for a universal prediction-learning algorithm

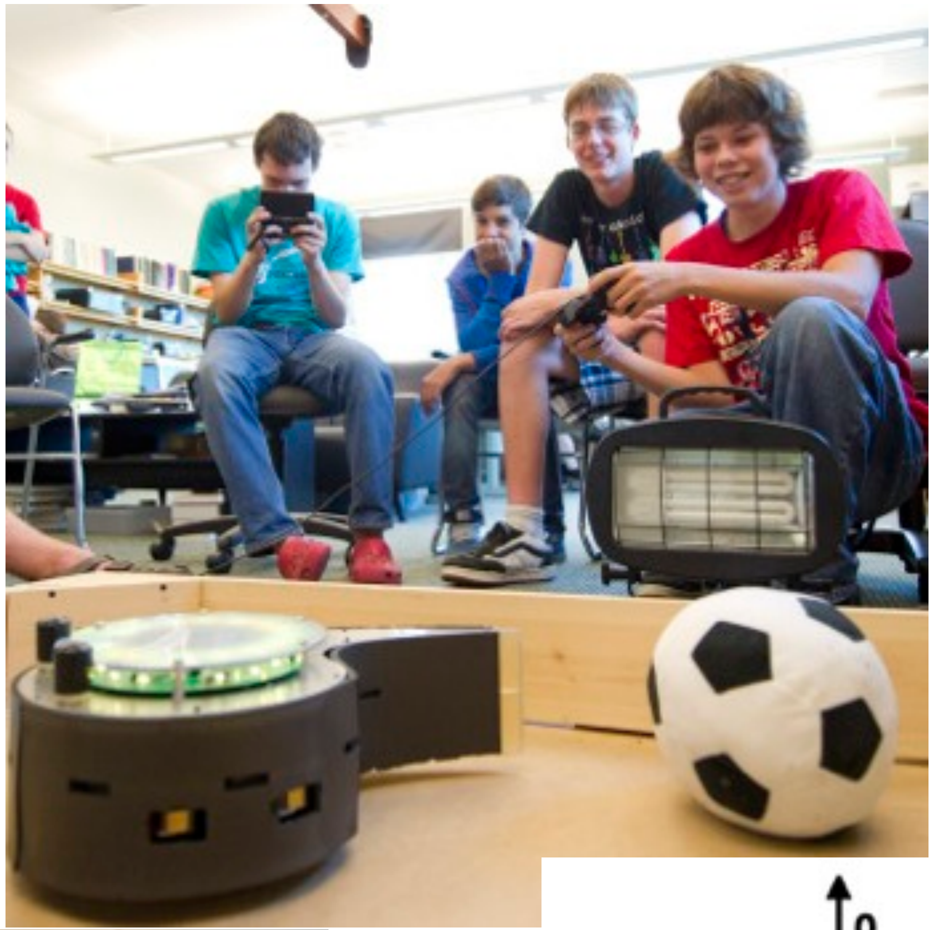
The Horde Architecture

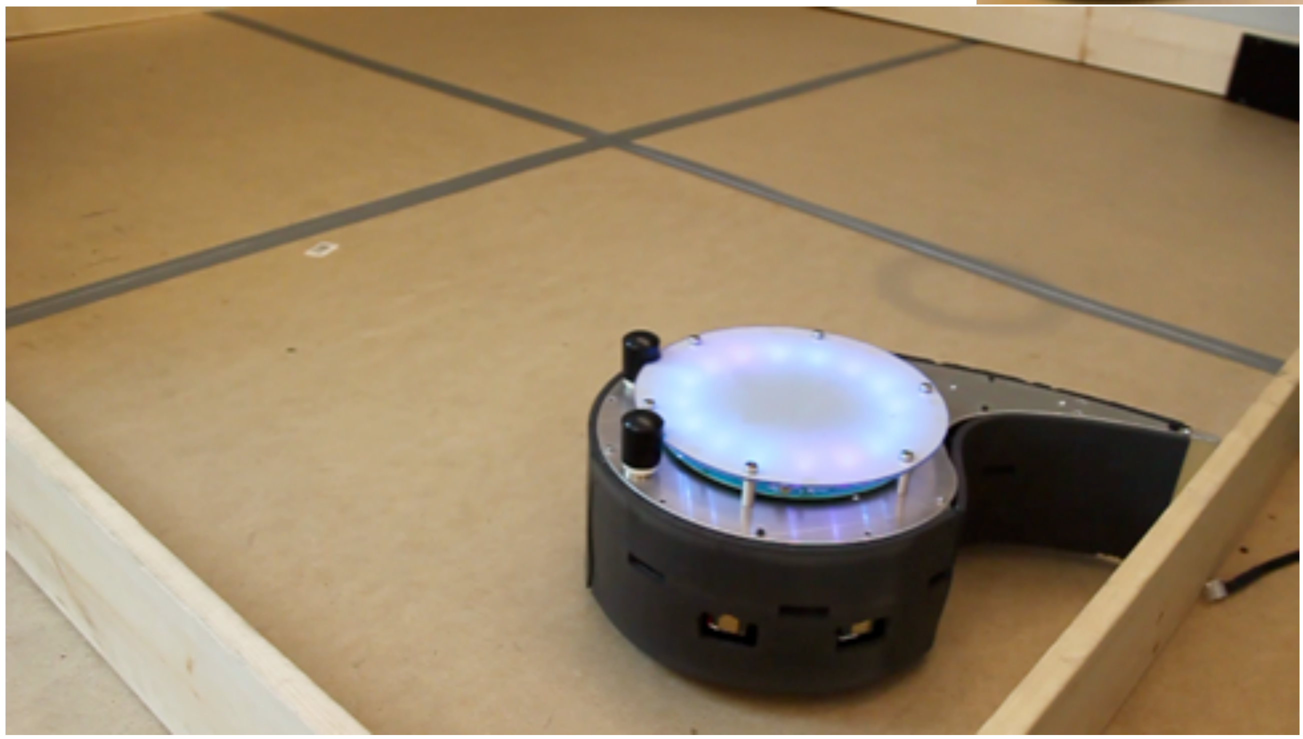


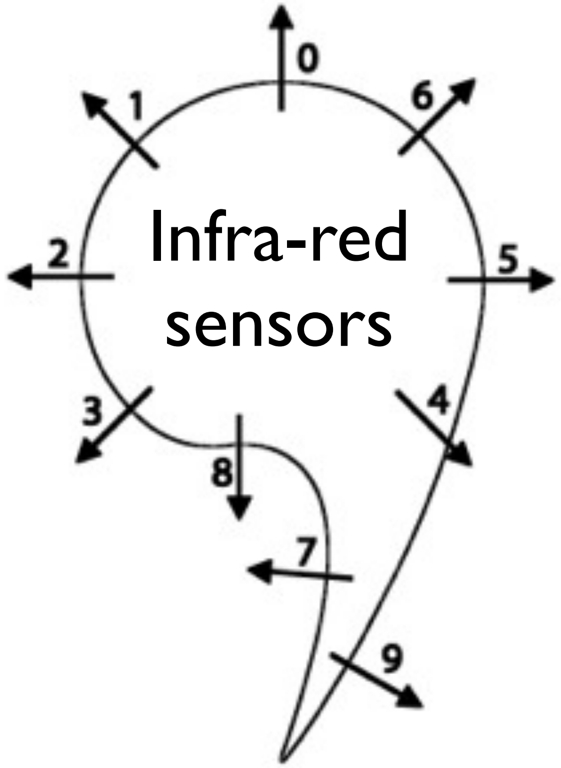
Each demon is
a full RL agent
estimating a
"value" function

The Critterbot

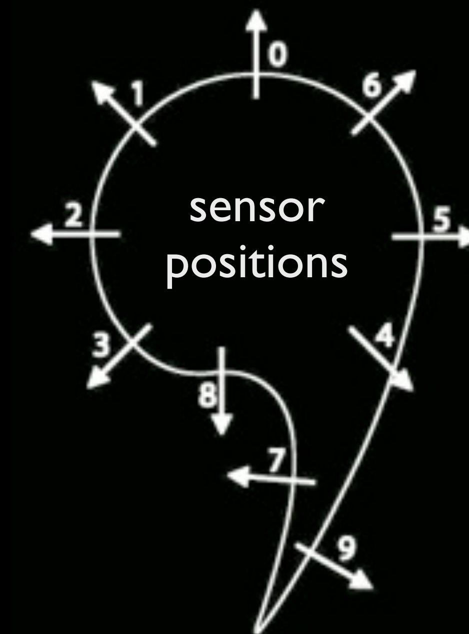


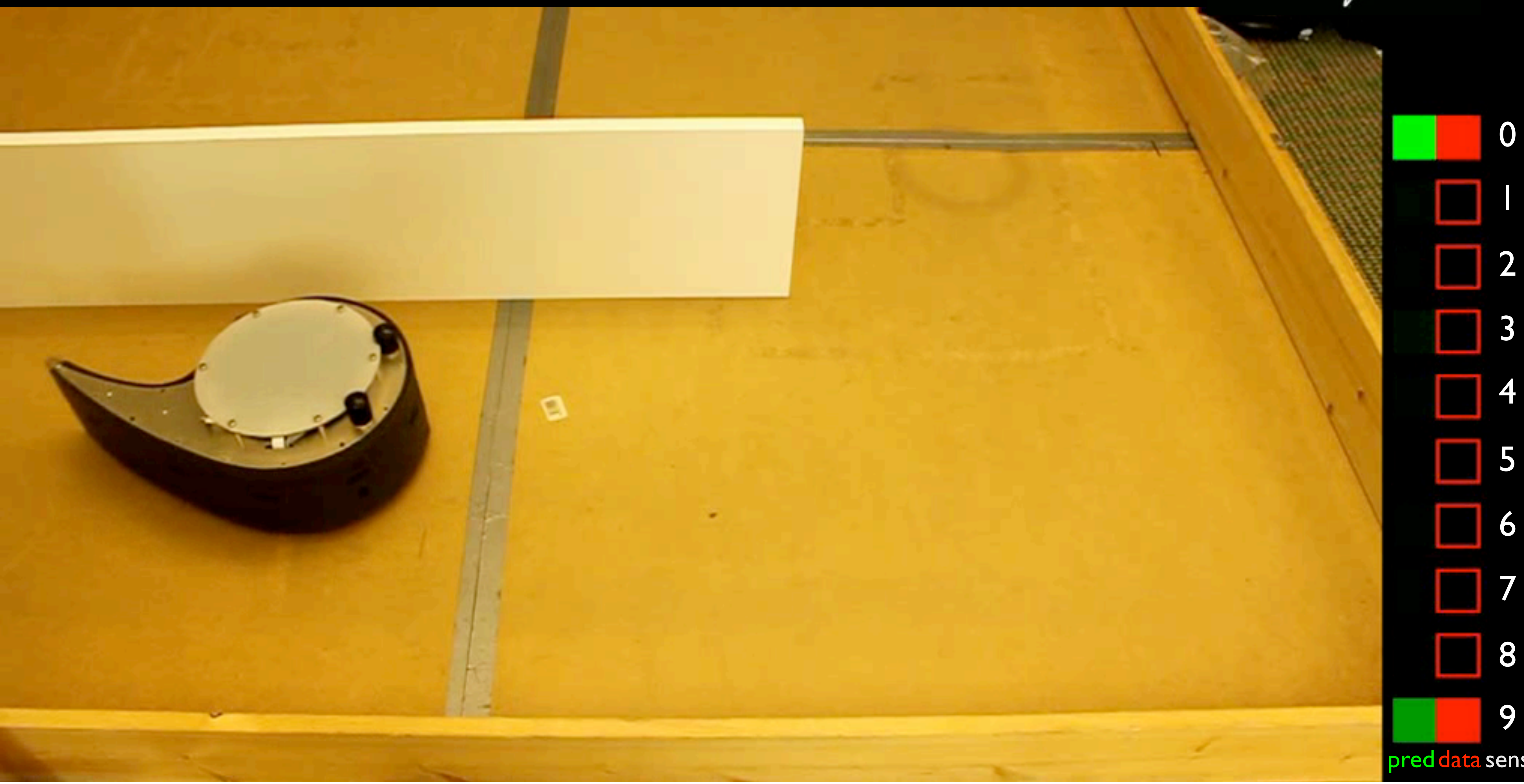




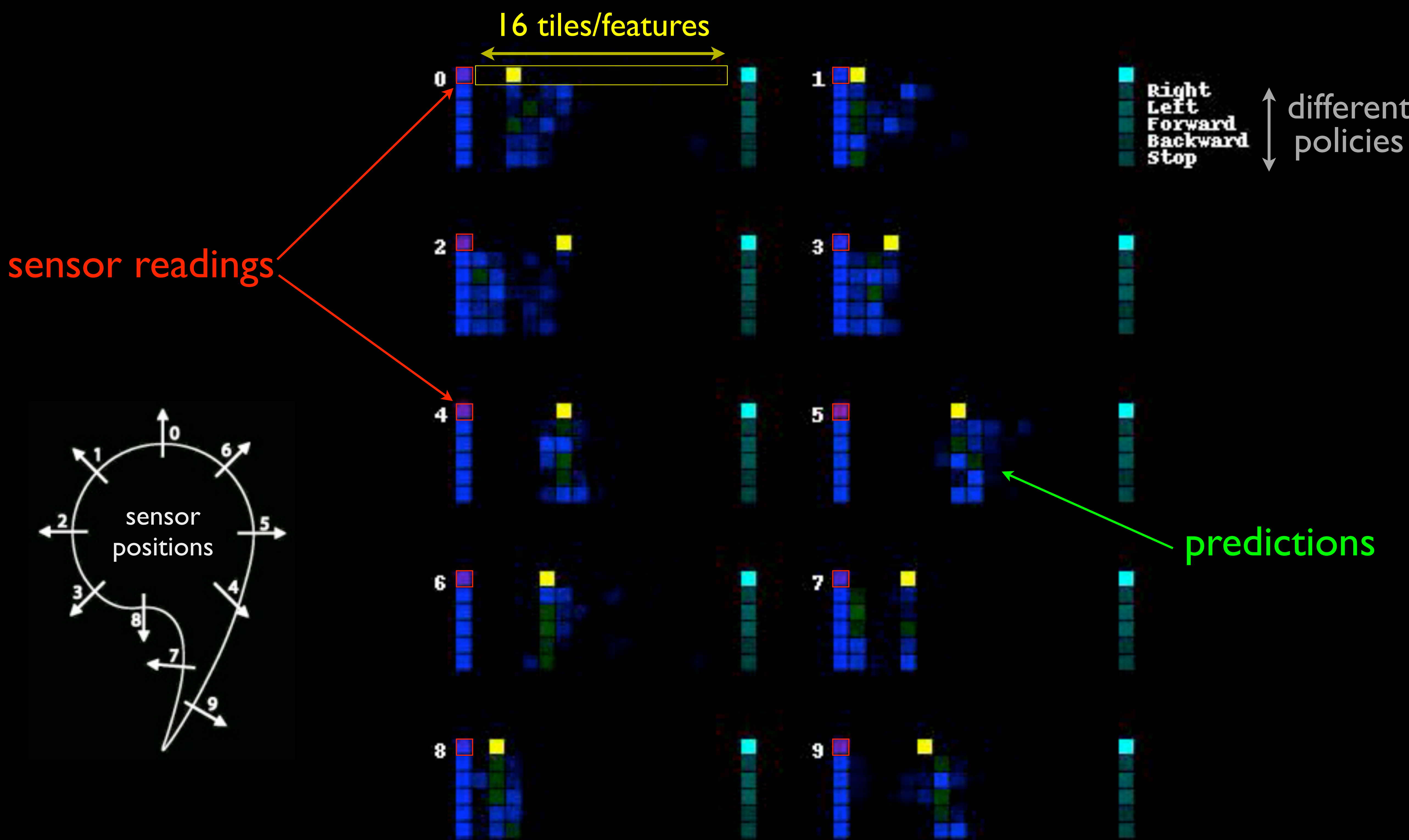


Infrared-sensor data and predictions



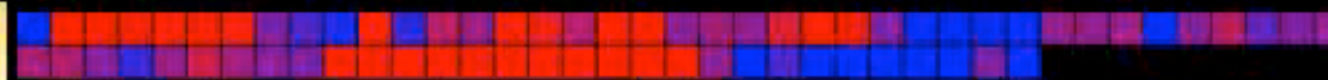


Scaling up: IR predictions for multiple tiles and policies



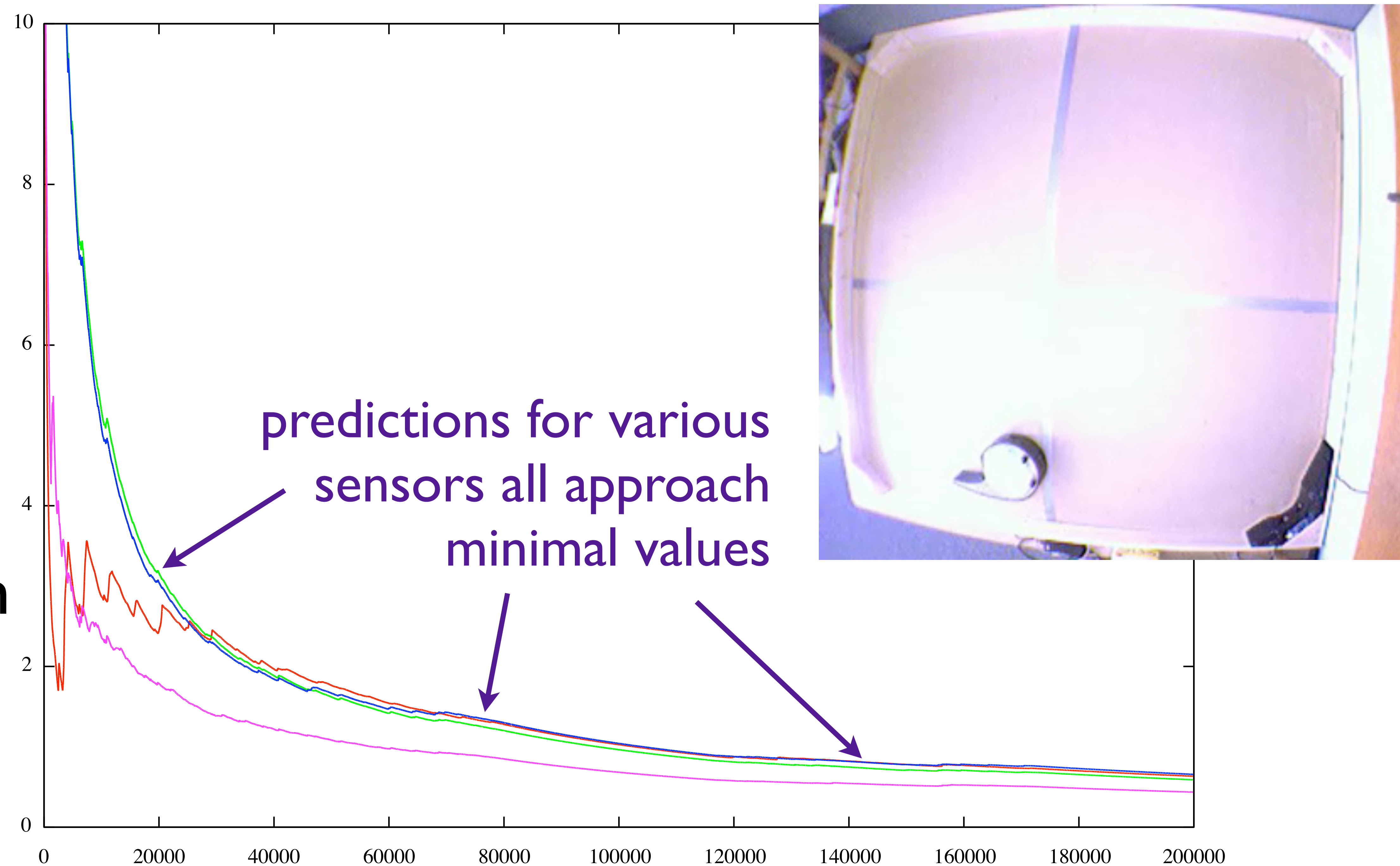
Scaling Up

continuous observation data x 69



Learning is fast enough

Mean-square error in prediction



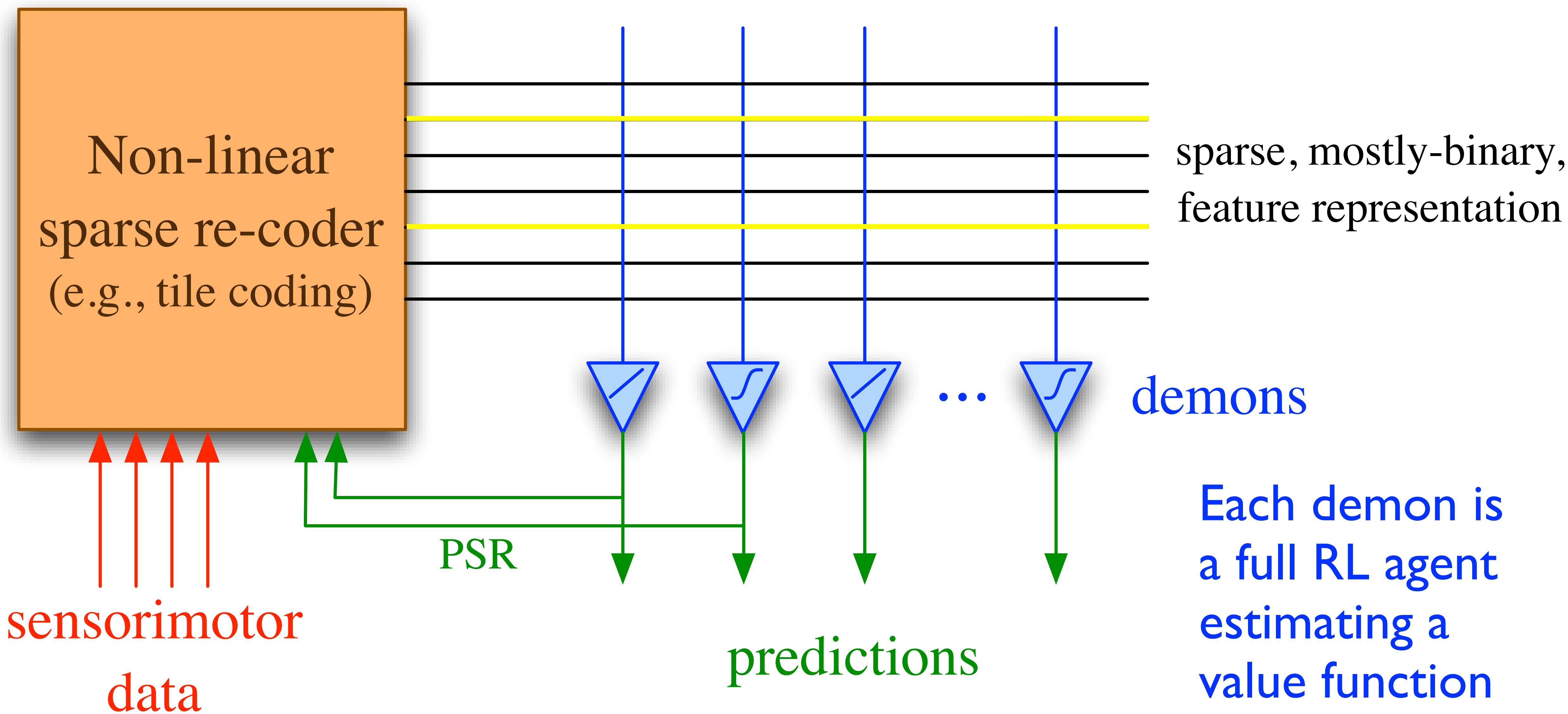
5 hours of training (100ms time steps)

Conclusions from robot experiments

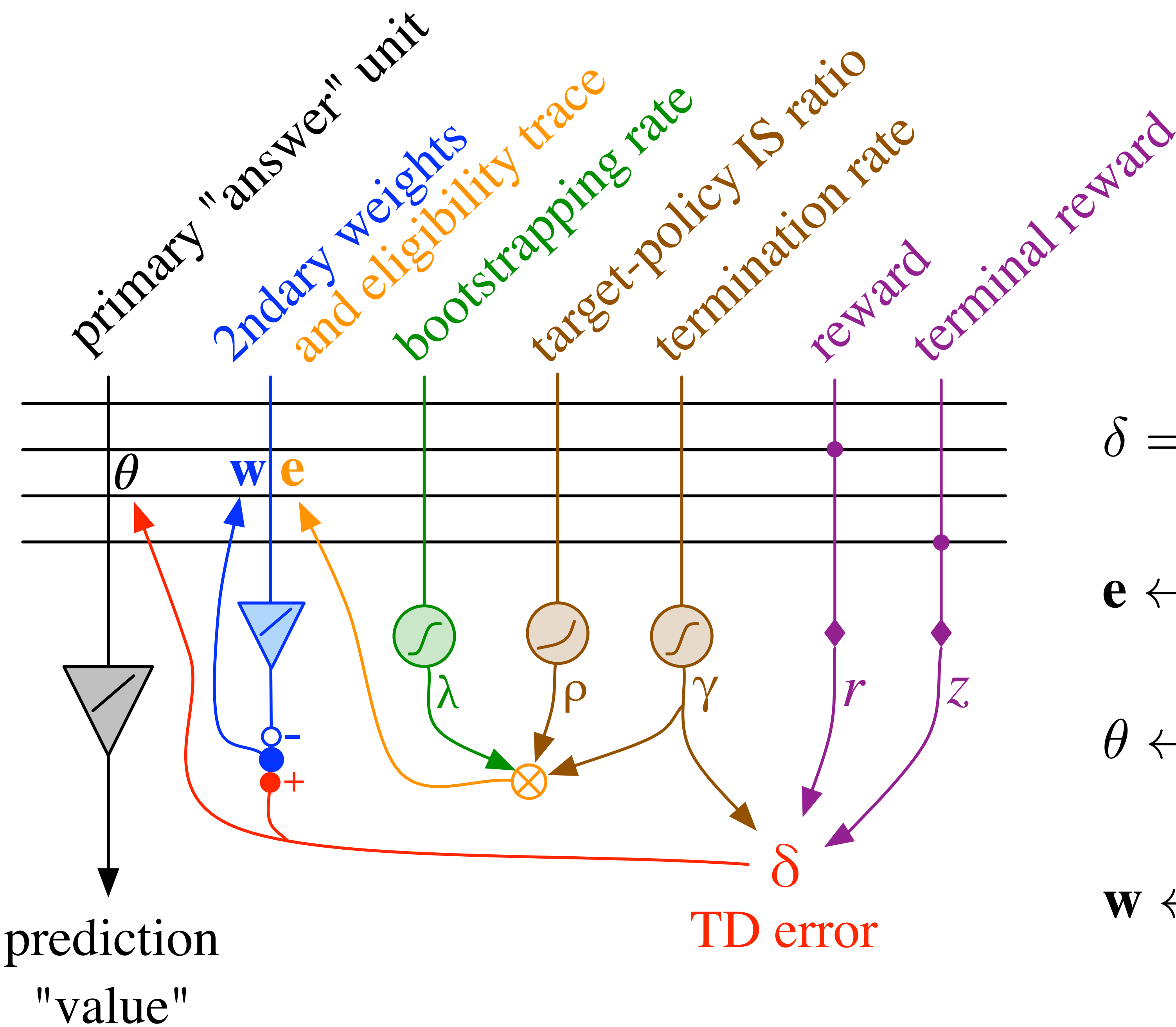
- Thousands of accurate multi-step predictions can be made and learned in real time at 10/second by linear TD algorithms
  - This could not have been done in any other way
- Model-free algorithms can learn fast enough to be useful
- *Real-time learning of sensorimotor knowledge is practical and scalable*

The Horde-of-demons architecture

The Horde Architecture



Inside a GTD(λ) Demon



$$\phi \xrightarrow[\rho,\gamma,\lambda]{r,z} \phi'$$

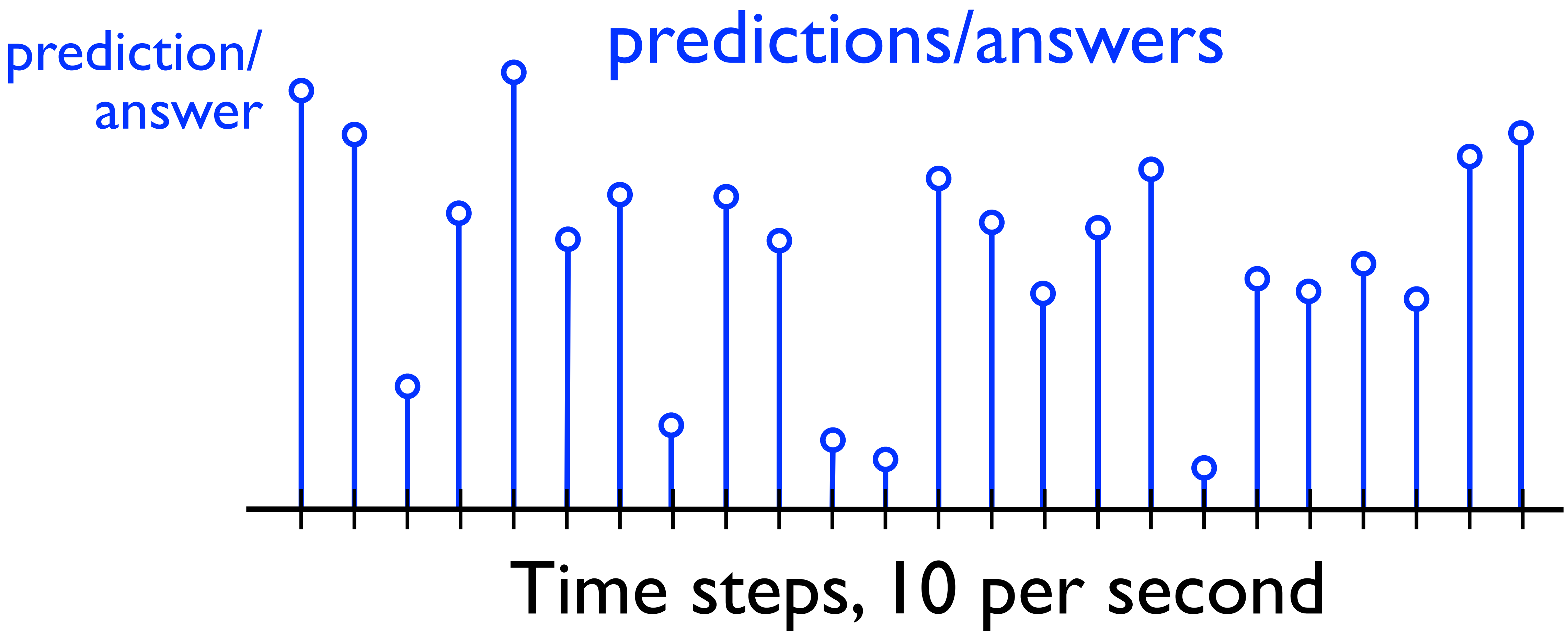
$$\delta = r + (1-\gamma)z + \gamma\theta^\top\phi' - \theta^\top\phi$$

$$\mathbf{e} \leftarrow \rho\left(\phi + \gamma\lambda\,\mathbf{e}\right)$$

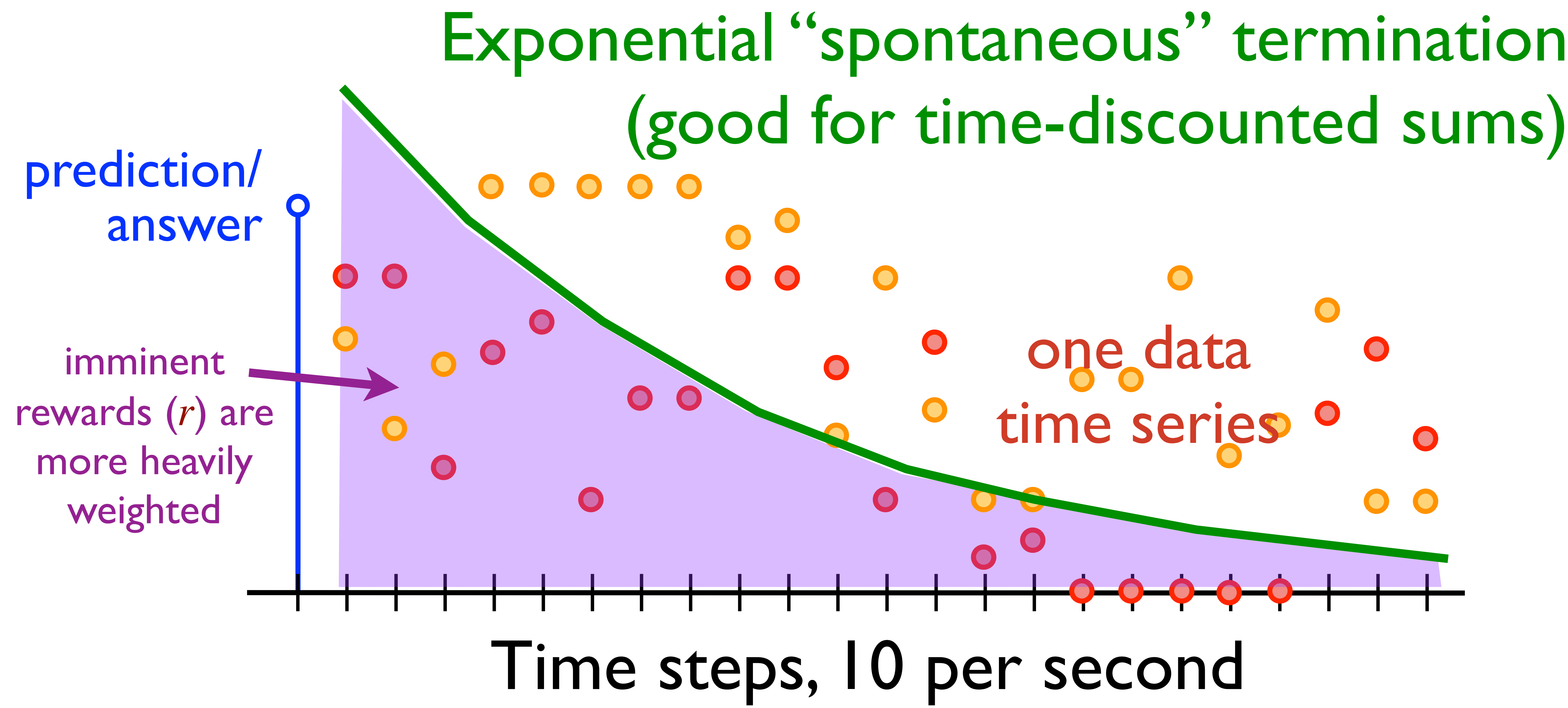
$$\theta \leftarrow \theta + \alpha\left[\delta\mathbf{e} - \gamma\left(1-\lambda\right)\left(\mathbf{w}^\top\mathbf{e}\right)\phi'\right]$$

$$\mathbf{w} \leftarrow \mathbf{w} + \beta\left[\delta\mathbf{e} - \left(\mathbf{w}^\top\phi\right)\phi\right]$$

General value functions as a language for multi-step predictive *questions*

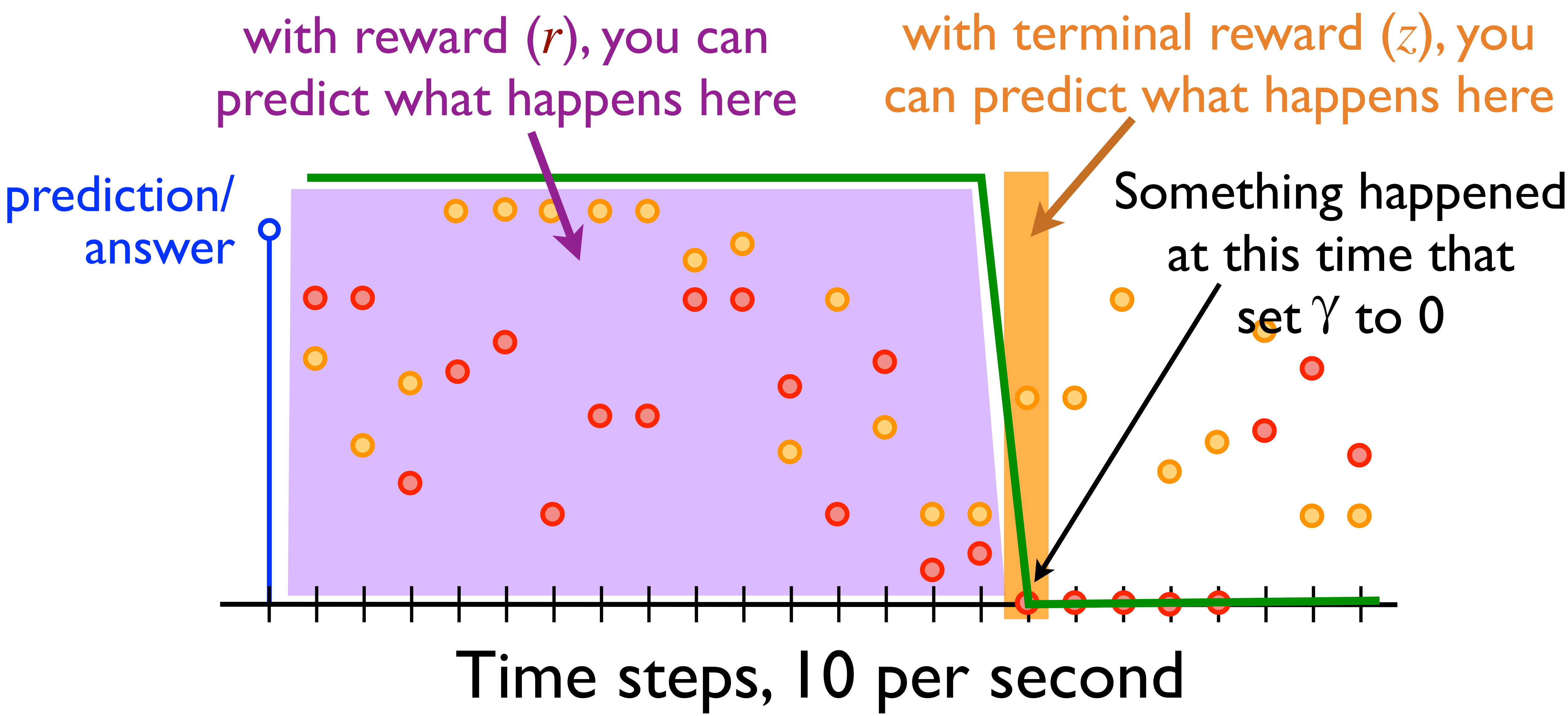


General value functions as a language for multi-step predictive <u>*questions*</u>



$$\theta^\top \phi(s) \;\approx\; V^{\pi,\gamma,r,z}(s) \;=\; \mathbb{E}[r(S_1) + \cdots + r(S_T) + z(S_T) \mid S_0 = s, T \sim \gamma, A_{0:T-1} \sim \pi]$$

General value functions as a language for multi-step predictive *questions*



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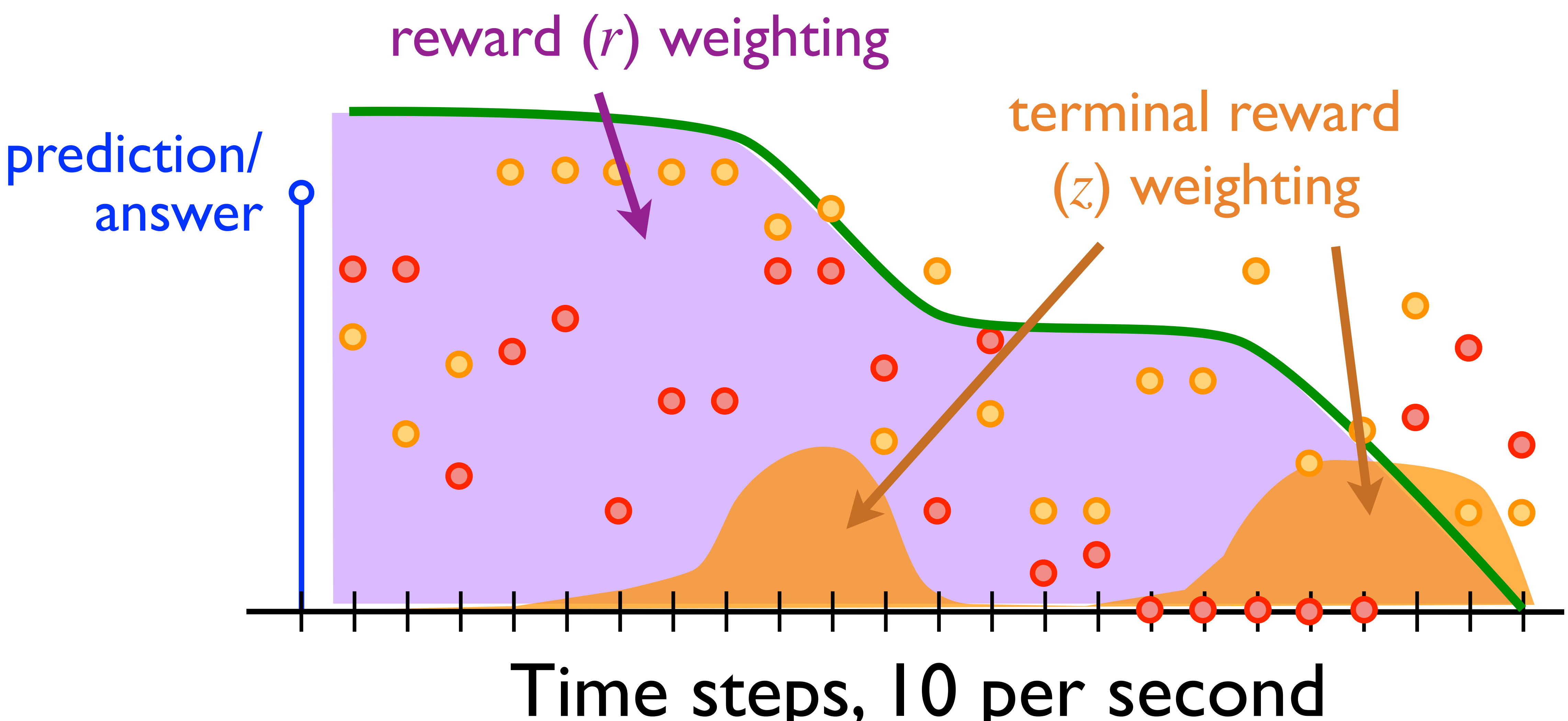

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General value functions—Fundamental or idiosyncratic?

- GVFs are a powerful rep'n language for the semantics of sensorimotor knowledge
  - GVFs seem powerful enough to encode all scientific knowledge (knowledge with experimentally testable predictions)
  - But we don't yet have extensive experience; some changes will probably be needed
- Crafted for efficient recursive computations
- Proven utility in control, planning, neuroscience

Remarks on gradient-TD algorithms

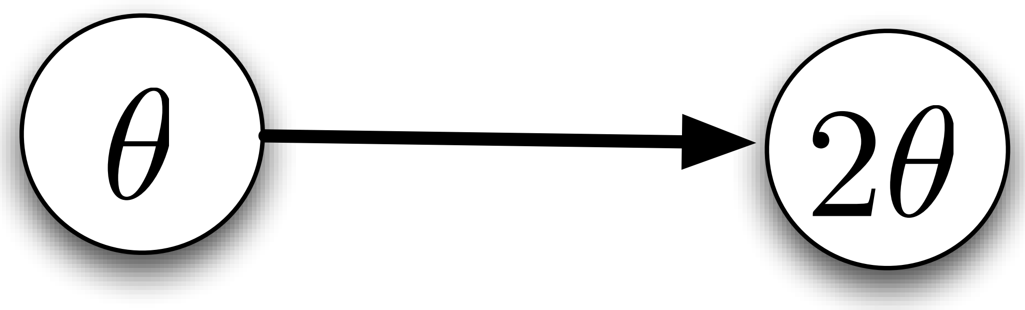
TD with FA

- TD with function approximation (FA) has historically been problematic:
  - for linear FA, there has been no TD algorithm with linear complexity that is sound under off-policy training
    - Q-learning diverges with linear FA
  - for non-linear FA, there has been no sound algorithm with constant per-step comp.
- The root problem is that there have been no true *gradient-descent* TD algorithms

TD and GD: Headlines

- Convention gradient-based TD algorithms are not true GD (because they ignore the effect on the new guess)
  - guaranteed convergent on-policy but not off-policy
- Baird's Residual Gradient and VAPS methods are GD in the wrong objective
  - converge to the wrong thing even in tabular case
- Precup's Importance Sampling methods too slow
  - too slow to benefit from parallel off-policy learning
- New true-GD methods (Maei, Szepesvari, Sutton et al.)

TD(0) can diverge: A simple example



$$
\begin{aligned}
\delta &= r + \gamma\theta^\top\phi' - \theta^\top\phi \\
&= 0 + 2\theta - \theta \\
&= \theta
\end{aligned}
$$

TD update: $\Delta\theta = \alpha\delta\phi$

$= \alpha\theta$ Diverges!

TD fixpoint: $\theta^* = 0$

TD with FA: Non-GD solutions?

- Linear least-squares methods: LSTD, LSPI
  - complexity is $O(n^2)$/step
- Gordon's averagers, Gaussian Processes
  - require storing examples—not scalable FA
- Policy-Gradient methods
  - RL not TD; don't learn multi-step facts
- Model-based methods
  - non-starter for the sensorimotor approach

The Gradient-TD Family

- GTD(λ) and GQ(λ), for learning GVF V and Q
- Developed by Maei, Szepesvari, Sutton, Precup, Bhatnagar, Silver, Wiewiora 2008-11
- Solve two open problems:
  - convergent linear-complexity off-policy TD learning
  - convergent non-linear TD
- True gradient-descent algorithms

Gradient-TD convergence theorem

The weights of Gradient TD methods follow the gradient of a projected-Bellman-error objective function in expected value:

step size

Bellman operator

vector of estimated values, one per state

$$E_D[\Delta\theta] = -\alpha \nabla_\theta \| V_\theta - \Pi T V_\theta \|_D^2$$

expectation under data distribution

gradient vector of partial derivatives

projection back into the space of representable functions

2-norm under the data distribution

which guarantees convergence to the TD fixpoint (under step-size conditions)

TD vs Gradient-TD

- TD error:

$$\delta_t = r_{t+1} + \gamma\theta_t^\top\phi_{t+1} - \theta_t^\top\phi_t$$

- Linear TD(0):

$$\theta_{t+1} = \theta_t + \alpha\delta_t\phi_t$$

- Importance sampling ratio:

$$\rho_t = \frac{\pi_{\text{target}}(s_t, a_t)}{\pi_{\text{behavior}}(s_t, a_t)}$$

- Off-policy linear GTD(0)

$$\theta_{t+1} = \theta_t + \alpha\rho_t\left[\delta_t\phi_t - \gamma\left(\mathbf{w}_t^\top\phi_t\right)\phi_{t+1}\right]$$

$$\mathbf{w}_{t+1} = \mathbf{w}_t + \beta\left(\rho_t\delta_t - \mathbf{w}_t^\top\phi_t\right)\phi_t$$ 2nd weight vector

My message in one sentence

If it's important for your AI agent to know a lot,

and you take the sensorimotor approach,

then you are forced to multi-step predictions,

and to policy-contingent predictions,

which require TD (a new reason for TD!),

and, in fact, a new kind of gradient-TD,

if you want to proceed in a practical and scalable way (linear-complexity function approximation).

Further frontiers

- Learning directing action: Curiosity, intrinsic motivation
- Discovering features and questions
- Better gradient-TD algorithms
- Parallel learning by policy-gradient (actor-critic) methods?
- Models and planning
- It will be interesting just to keep scaling

Questions?

- What is the latest on Gradient-TD algs?
- Where do the questions come from?
- How do you know off-policy predictions are accurate?
- How can you be abstract when predictions are about low-level data?
- Can you give a simple example/intuition of why conventional TD methods diverge?
- Can you show us the simplest gradient-TD algorithm
- How can the predictions be used for action?
- How can GVFs form a world model for planning?

Thank you for your attention

- And thanks again to Adam White, Joseph Modayil, Thomas Degris, and the RLAI group