Multi-step Prediction

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Skilled perception and action…learned without labels

Labels are are a crutch, a cheat

- The right representations must *already be in the unlabeled data!*
- Where do you think the labelers get them?
- We will never learn how to perceive properly until we stop relying on labels
- This is a fundamental weakness

Definitions

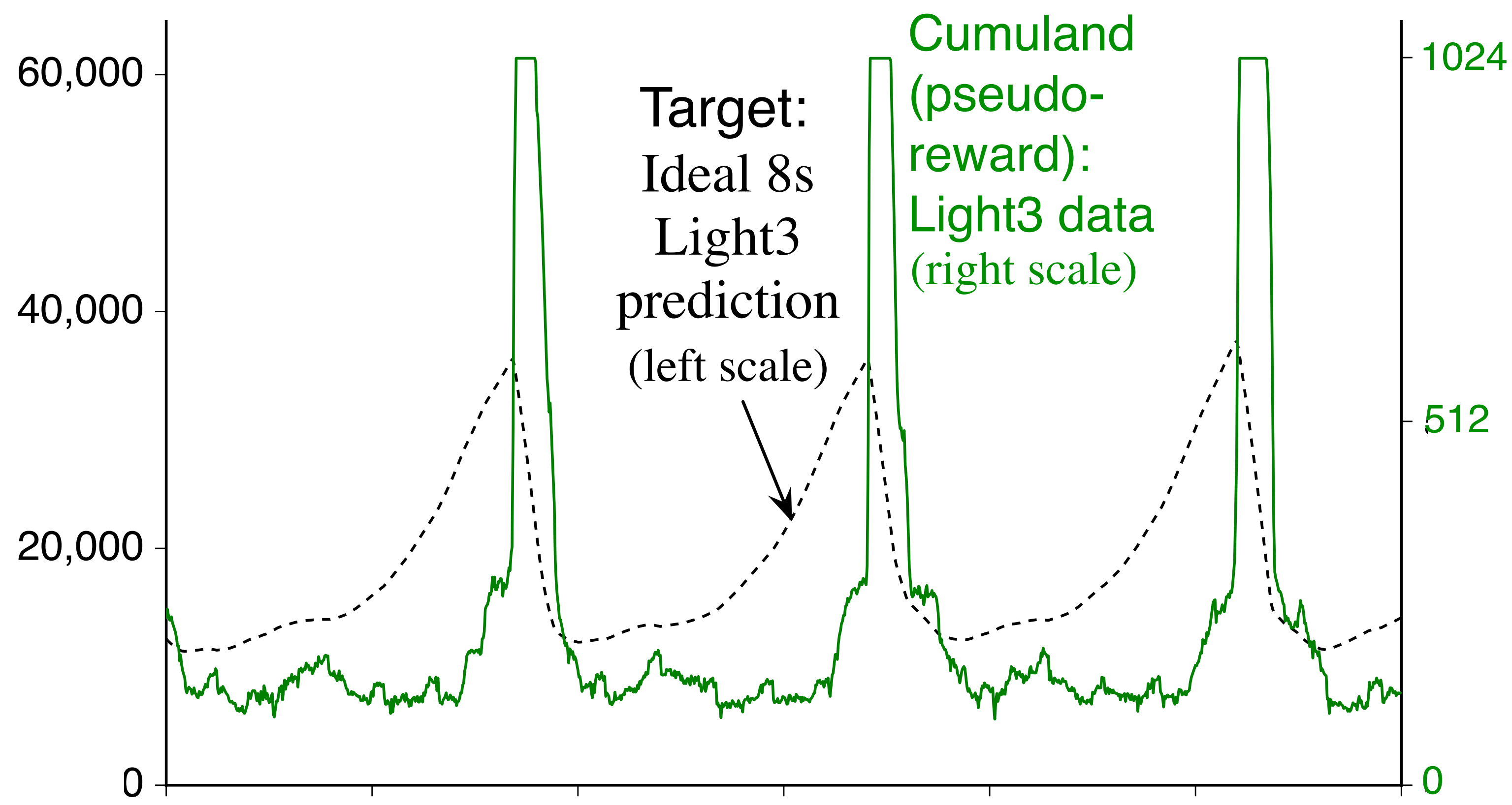
- Every 10ms or so we observe a new sensory vector and emit a new motor vector; this is the *data*
- By *prediction* I mean a statement at time *t* about what will happen at times >*t*
- I assume *repeated* prediction—at *each* time *t* we say something about the future
- If, at each *t*, we say something only about *t+1*, then that is a *one-step prediction*
- Everything else is a *multi-step prediction*

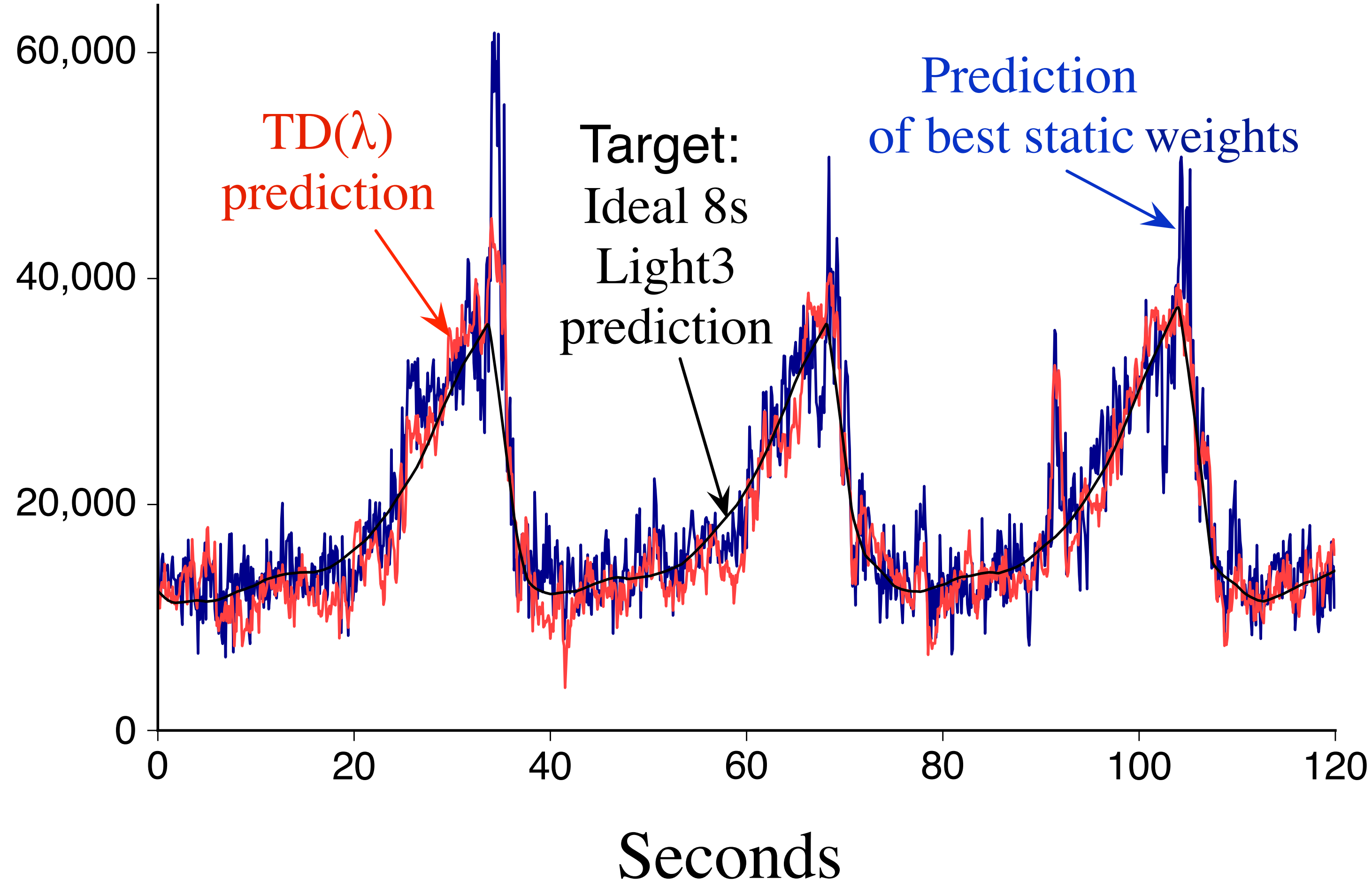
Examples of multi-step prediction

- Predicting the outcome of a game, like chess or backgammon
- Predicting what a stock-market index will be at the end of the year, or in six months
- Predicting who will be the next US president
- Predicting who the US will next go to war against
  - or how many US soldiers will be killed during a president's term
- Predicting a sensory observation, in 10 steps, in roughly 10 steps, or when something else happens
- Predicting discounted cumulative reward conditional on behavior

For Example: Predicting the discounted sum of future light-sensor readings

with a time constant of 8 seconds (80 steps, infinite span)





Predictive span

- The *span of a prediction* is the maximum number of time steps that might elapse between making a prediction and completely observing the outcome, or *target*
- One-step predictions have unit span
- Multi-step predictions have span > 1
- We are particularly interested in predictions that can be learned with computational complexity that is *independent of span*

Do we need to think about multi-step predictions?

- Can’t we just learn one-step predictions, and then iterate them (compose them) to produce multi-step predictions when needed?
- Can’t we just think of the multi-step as one big step, and then use one-step methods?
- No, we really can’t (and shouldn’t want to)

Can’t we learn one-step predictions, and iterate them to get multi-step predictions?

- Yes, sort of, but ultimately No, very much No
- Yes in the sense that if we have learned one-step predictions that are exactly correct, then they are informationally sufficient to make all multi-step predictions exactly correct; we would not have to learn cached answers to each one individually, we could just compute them on the fly
- However, computing the multi-step predictions involves a branching process (if the world is stochastic or we have action choices); the complexity of making the prediction is *exponential* in the span
- If there is any error in the one-step predictions, then the error will propagate and *expand exponentially* with span; the multistep predictions will be poor approximations, much poorer than if they were learned directly

Can’t we just use our familiar one-step learning methods?

- Can’t we just wait until the target is known, then use a one-step method? (reduce to input-output pairs)
    - E.g., wait until the end of the game, then regress to the outcome
- No, not really; there are significant computational costs to this
    - memory is O(span)
    - computation is poorly distributed over time
- These can be avoided with learning methods specialized for multi-step
- Also, sometimes the target is never known (off-policy)
- We should not ignore these things; they are not nuisances, they are <u>clues</u>, hints from nature

Every prediction has both a *question* and an *answer*

- Q: How much rain will fall in the next 24 hours? A: 0.5 centimeters
- Q: Will i win this chess game? A: with Probability 0.9
- Q: What will the dow jones index be at the end of the year? A: 18,000
- Q:What will be the discounted sum of rewards from here forward? A: 5.7 (or whatever the value of the state is)

- The question describes the procedure for calculating the target
- The answer is the expected value of the target (say)
- The answer process is familiar; it might be a deep/neural network
- The question process is less familiar, possibly more important

Generalized value functions (GVFs)

- A particular class of predictive questions
  - Inspired by the value functions of optimal control/RL
  - Whose answers can be learned in a computationally efficient way
    - independent of span and taking advantage of the state property (approximate Markov)
  - Linked to planning via dynamic programming and ‘option’ models

The question part of a GVF

- Given
  - a policy $\pi : \mathcal{A} \times \mathcal{S} \rightarrow [0, 1]$
  - a signal to be added up, the *cumuland* $R_t \in \Re$
  - a termination or discounting condition $\gamma : \mathcal{S} \rightarrow [0, 1]$
- The target is the sum of the cumuland signal up until termination, if the policy is followed:

$$G_t = \frac{\pi(A_t|S_t)}{\mu(A_t|S_t)} \Big(R_{t+1} + \gamma(S_{t+1}) G_{t+1} \Big)$$

behavior policy

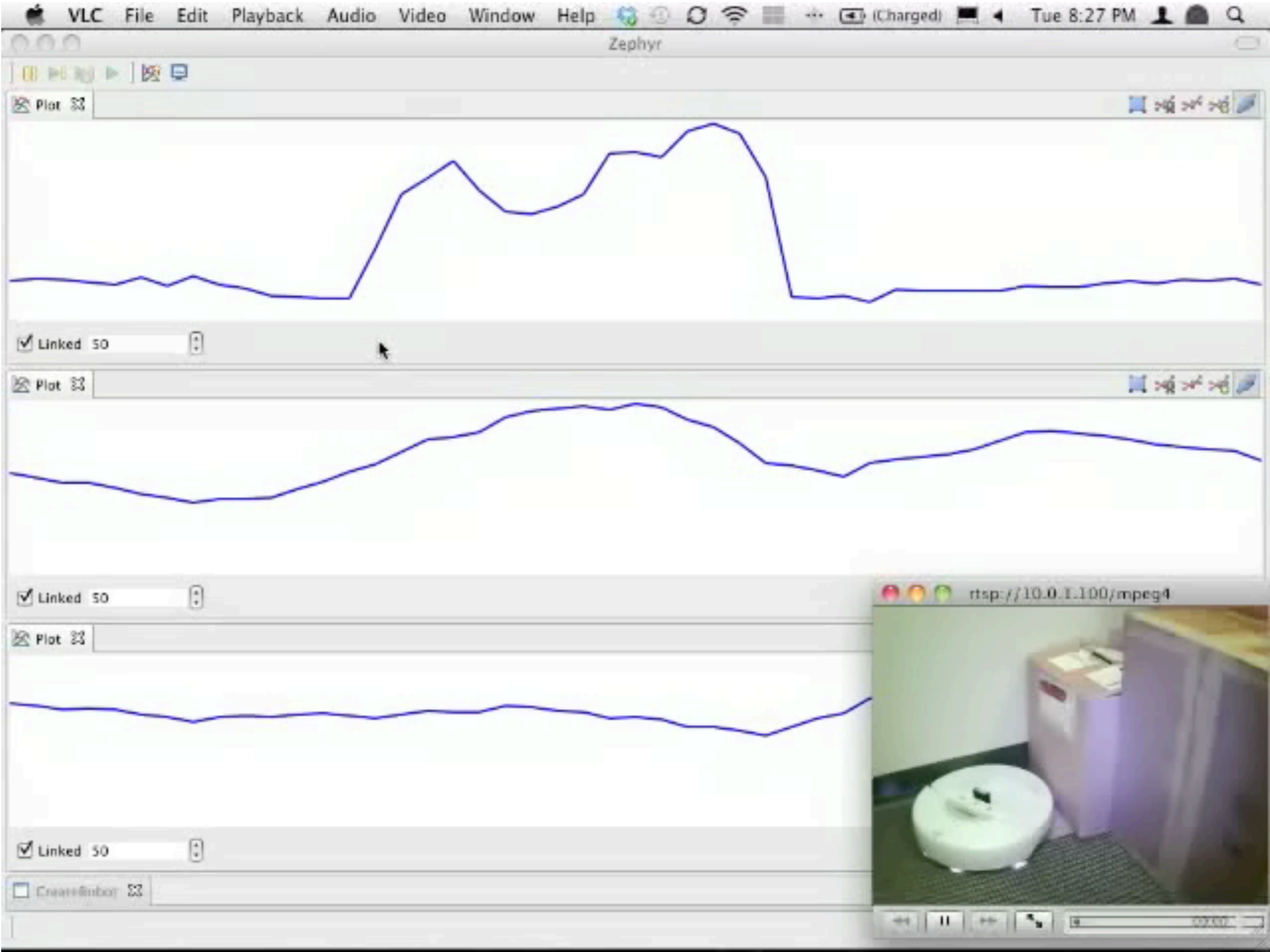
The answer part of a GVF

(determines the nature of the approximation)

- Given:
  - a parameterization (e.g., the features of a linear approximation, the structure of a deep net) $\hat{v} : \mathcal{S} \times \Re^n \rightarrow \Re$
  - a bootstrapping function $\lambda : \mathcal{S} \rightarrow [0,1]$
  - an interest function $i : \mathcal{S} \rightarrow \Re_+$
  - a source of data (e.g., behavior policy) $\mu : \mathcal{A} \times \mathcal{S} \rightarrow [0,1]$
- Find $\boldsymbol{\theta}$ to minimize: $\sum_{s \in \mathcal{S}} d_\mu(s) i(s) \Big(\hat{v}(s, \boldsymbol{\theta}) - \mathbf{E}_\pi \big[G_t^\lambda | S_t = s \big] \Big)^2$

where:

$$G_t^\lambda = R_{t+1} + \gamma(S_{t+1}) \Big((1 - \lambda(S_{t+1})) \hat{v}(S_{t+1}, \boldsymbol{\theta}) + \lambda(S_{t+1}) G_{t+1}^\lambda \Big)$$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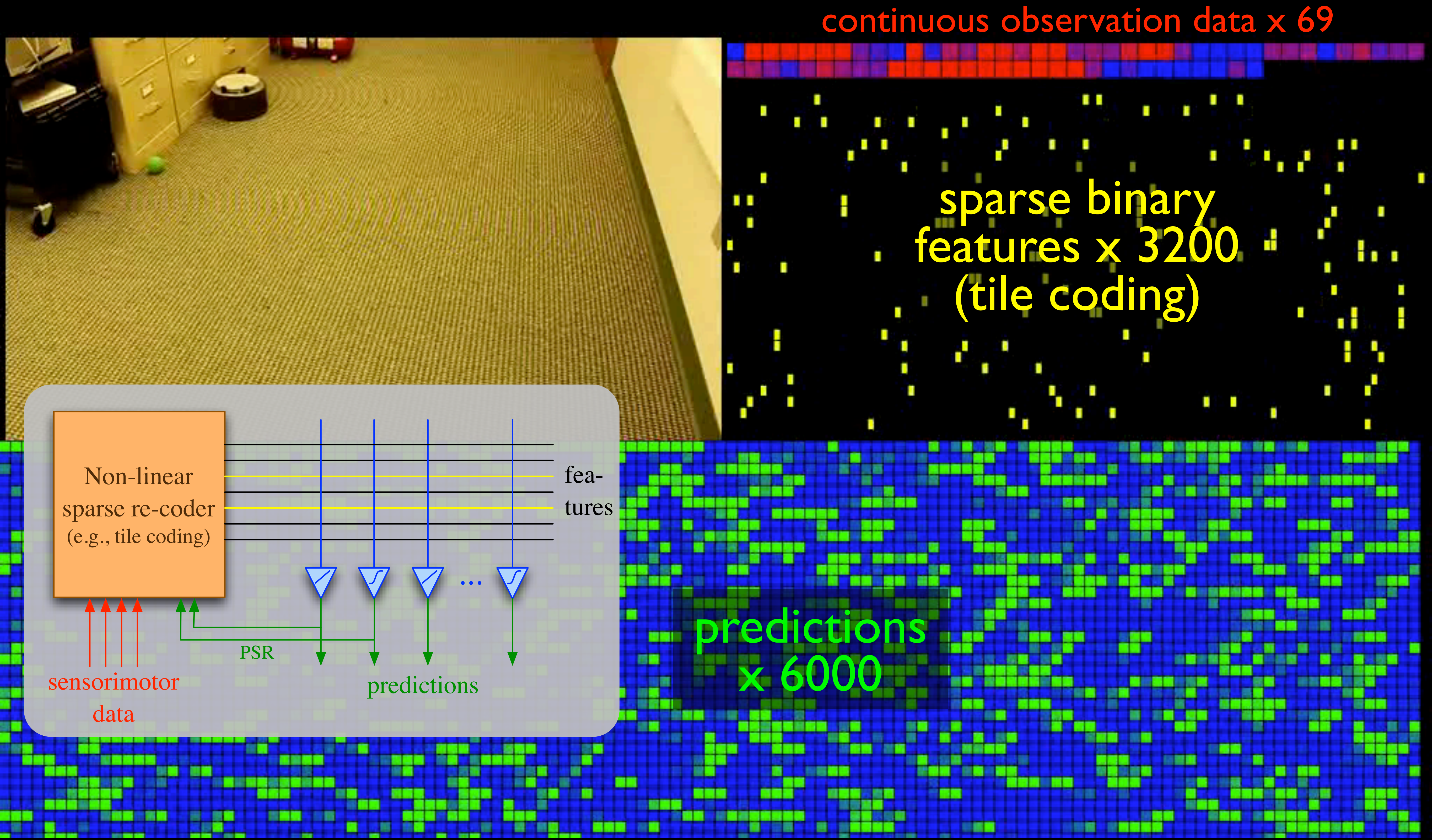
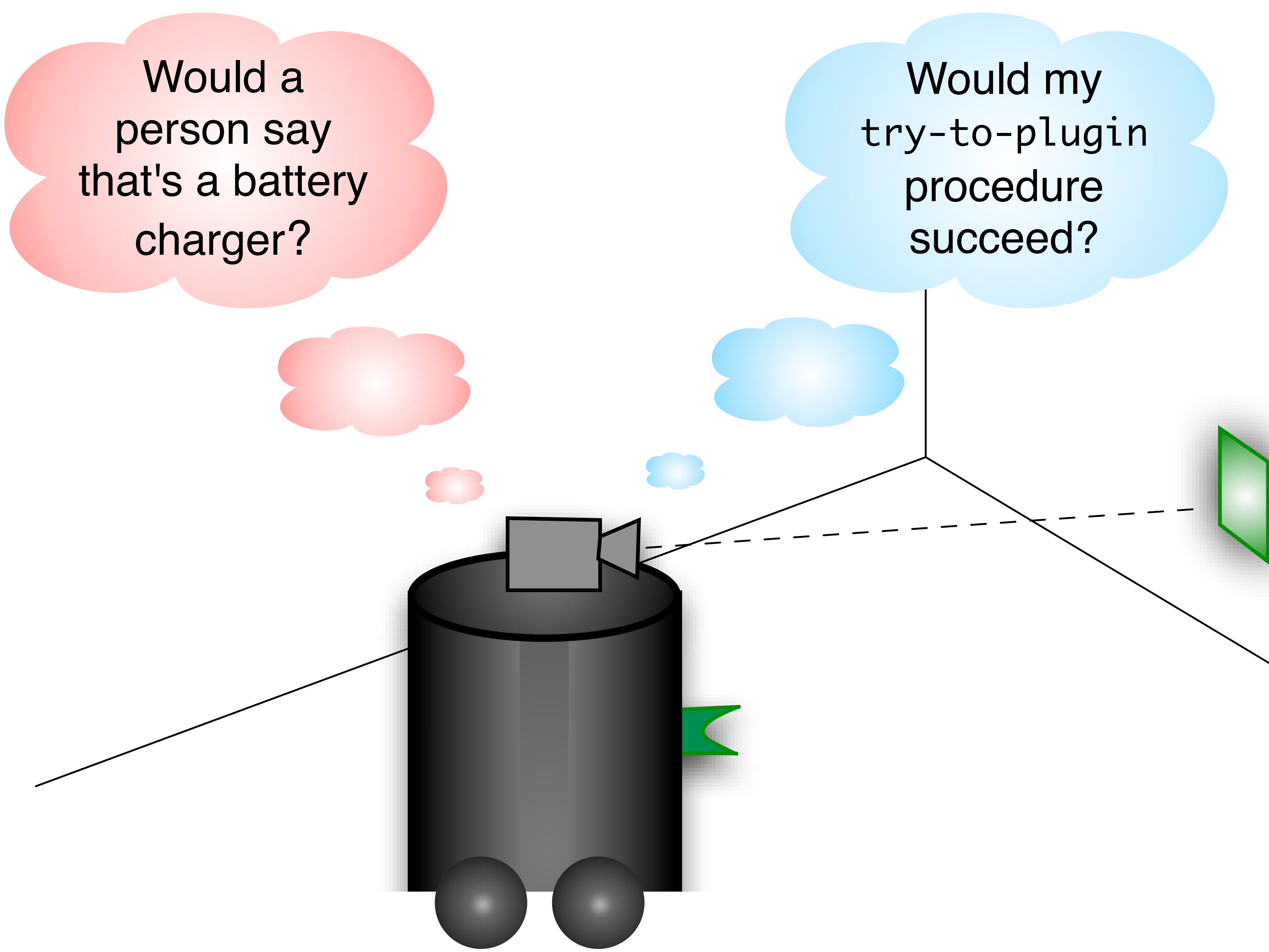
Massive real-time prediction learning
Up to one billion weight updates/second



The power of policy conditioning



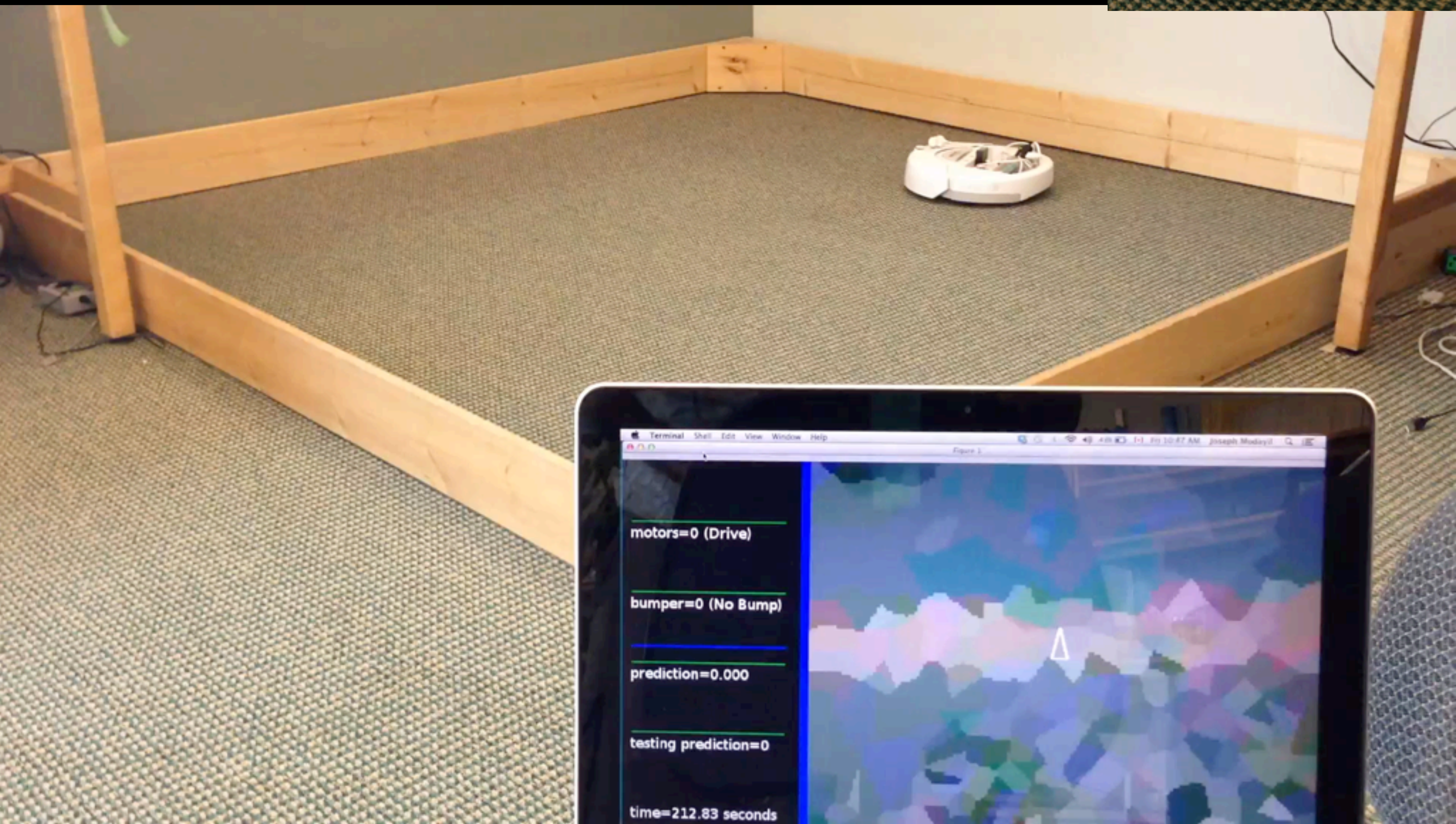
Multi-step predictions represent more interesting perceptual concepts

- They include physical things, like distance and weight
- But also higher-level, more abstract and cognitive things, like functions and opportunities, possibilities
  - a pitch I can hit, a girl I can kiss, a thing I can sit on, a way to get my email…
- cf. correlations between simultaneous signals
- cf. information theory, compression
- cf. invariances

Algorithmic issues in multi-step prediction

- eligibility traces
- temporal-difference learning
- off-policy learning and importance sampling
    - a very challenging technical problem with new methods still being proposed
- supporting composition and planning

An example of using the predictions for control



In conclusion, why do multi-step predictions matter?

- They are another source of data for perceptual learning
  - from sensory or sensorimotor (robot) streams
  - these are potentially *huge and scalable*
- They yield *higher-level concepts* than do one-step predictions
- Their questions can be represented *in the machine*
- Different algorithms are needed to learn them efficiently in both data and computation

Thank you for your attention

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