

Stimulus Representation in Temporal-difference Models of the Dopamine System

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joint work with Elliot Ludvig and Jim Kehoe

Outline

- General comments about modeling
- Overview of TD dopamine models
- Stimulus representations
- Core TD algorithm
- Reprise of CSC vs microstimuli comparison
- Conclusion



Reinforcement Learning and Artificial Intelligence



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INFORMATICS



CORE

CIRCLE OF RESEARCH EXCELLENCE

Reinforcement learning and temporal-difference learning

- Algorithms have been validated within four research communities
 - Artificial intelligence
 - Psychology
 - Operations research
 - Neuroscience

Marr's three levels of explanation for information-processing systems

- Computation theory

- *What* is computed?

Reward pred. (TD) error

- Algorithms

- *How* is it computed?

TD models

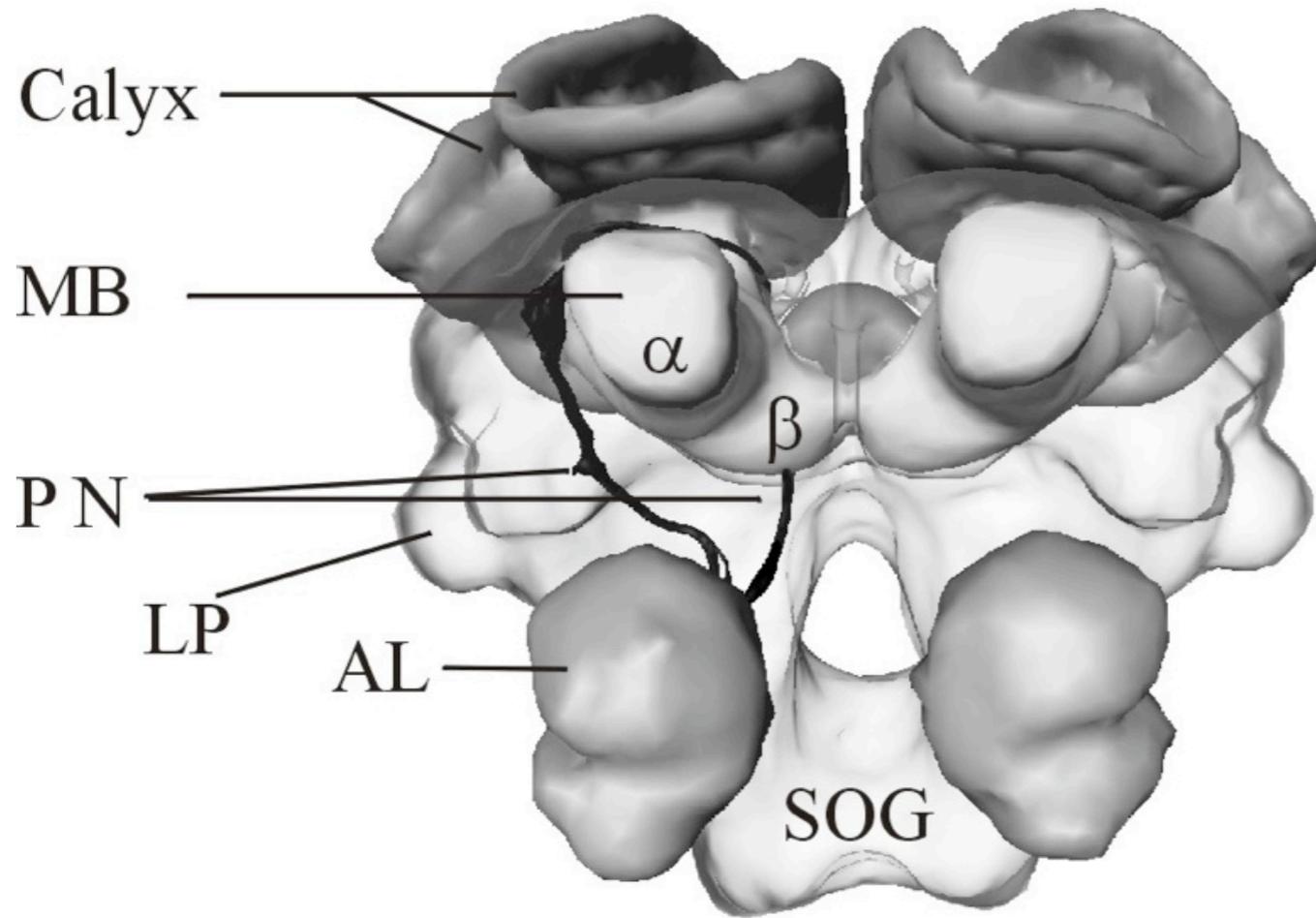
- Implementation

- Really, how is it done?

TD error = Dopamine

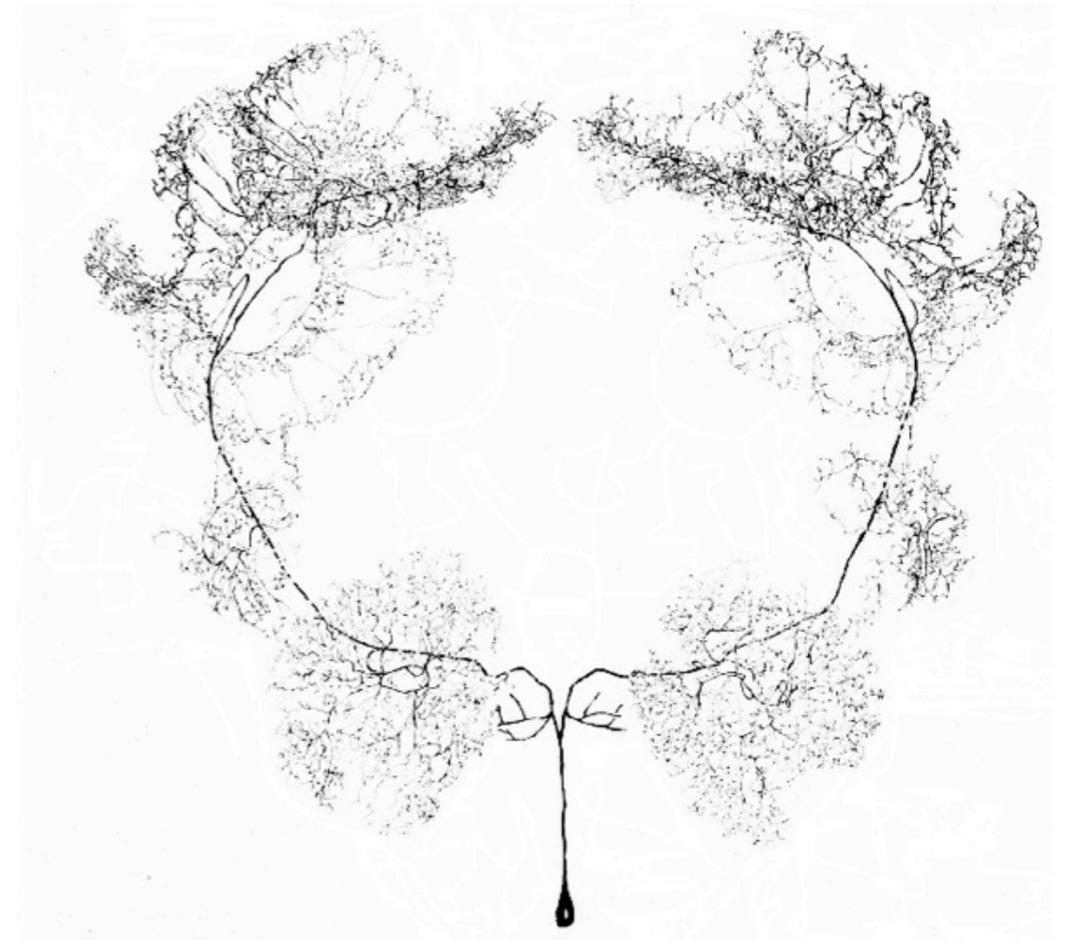
Levels can be validated independently

Brain Reward Systems

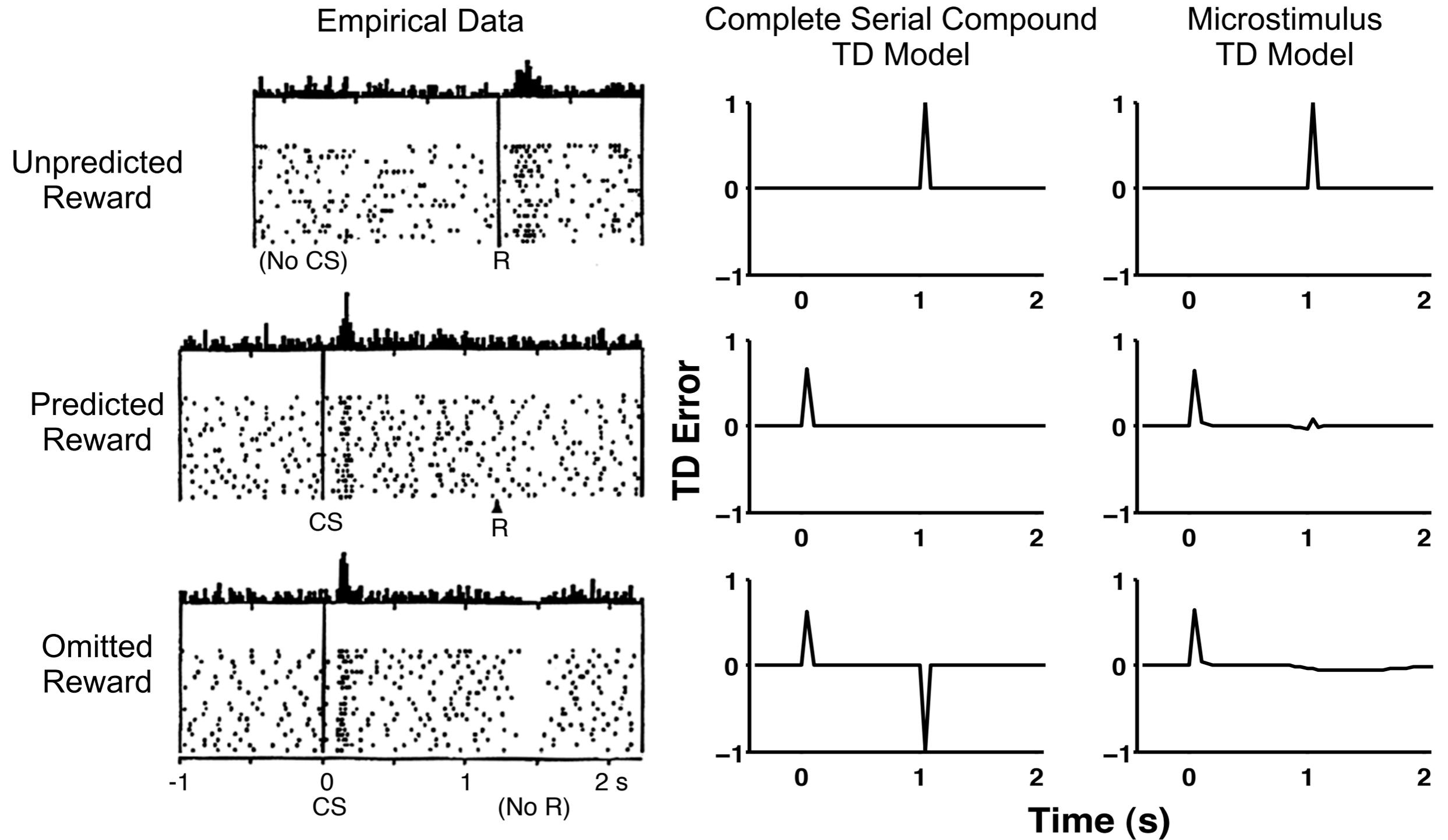


250 μm

Honeybee brain



VUM neuron



Schultz et al., 1997

Problems with current TD models of dopamine

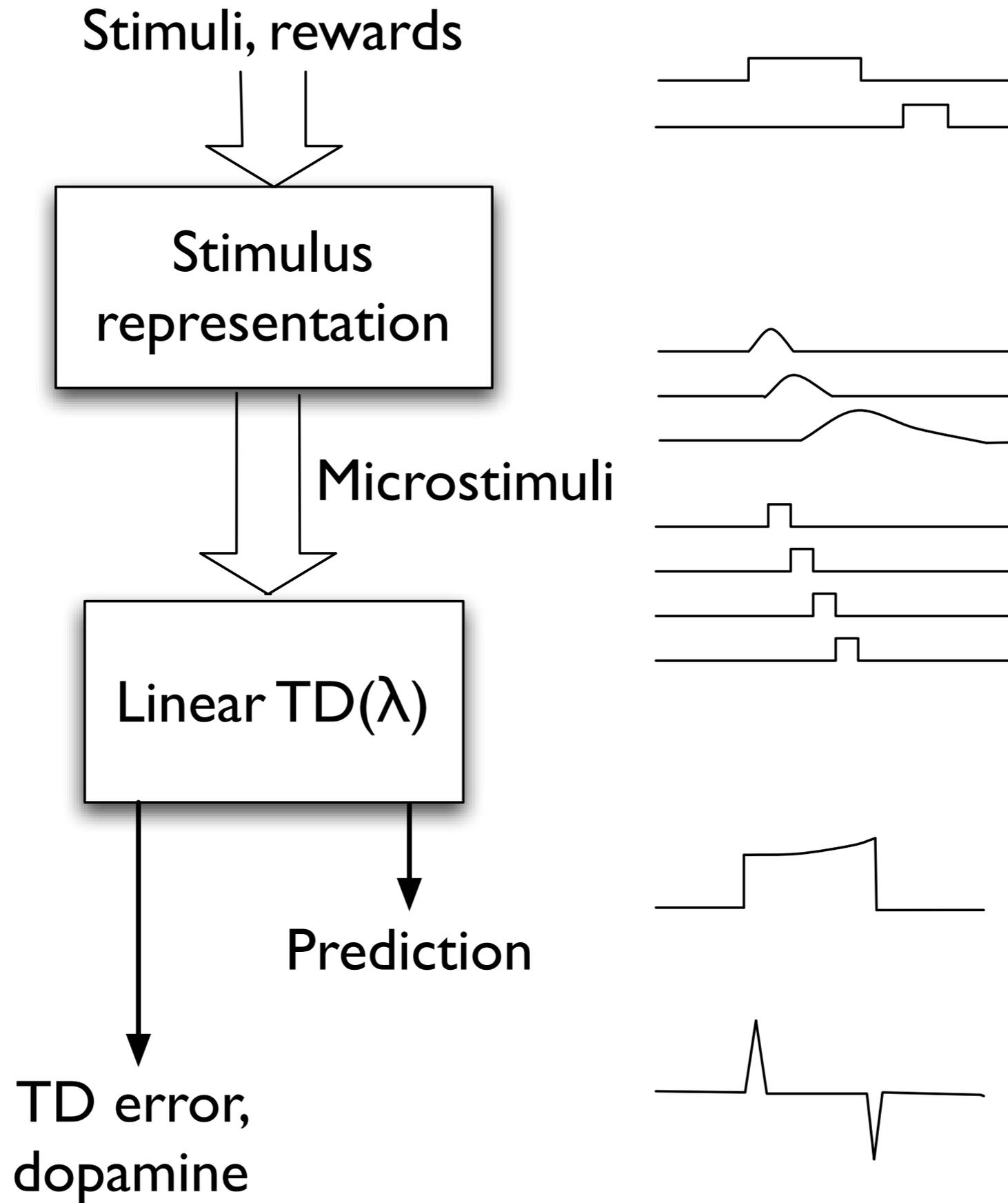
- Implausible clock-like mechanism
- Poor handling of variations in reward timing
- Predicts large negative error on reward omission
- Needs large (non-physiological) negative errors
- Complexity
- Changes in learning algorithm

Daw, 2006

Niv et al., 2005

Bayer & Glimcher, 2005

TD models



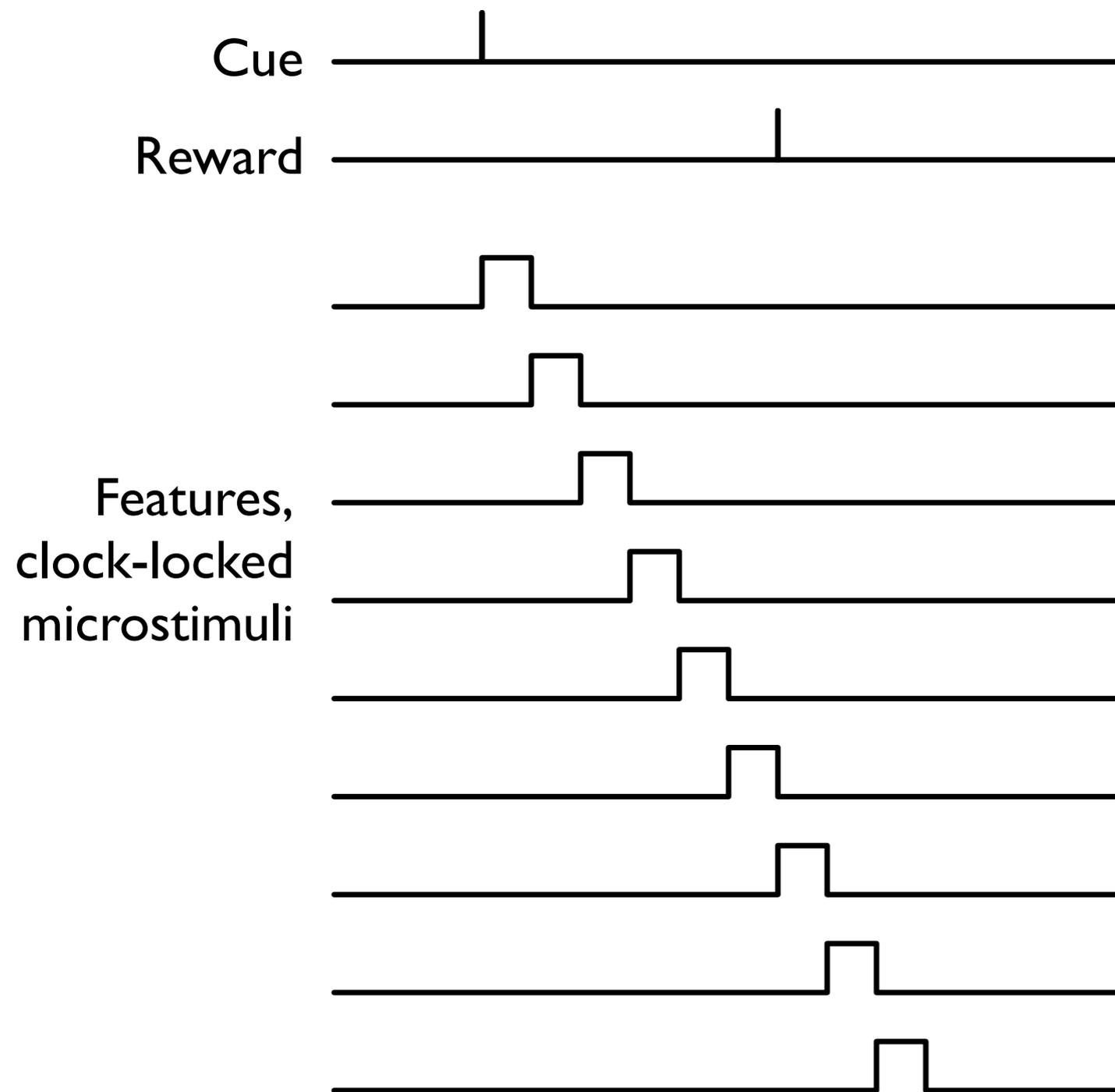
New model

- Temporal generalization via internal microstimulus representation of overt stimuli
- Cueing role for rewards
- Underlying learning algorithm unchanged
 - Retains abilities of previous TD models
- Extended eligibility traces

Stimulus representations

- Trial level
- Real time
 - Presence/absence
 - CSC (current standard TD model)
 - Microstimuli

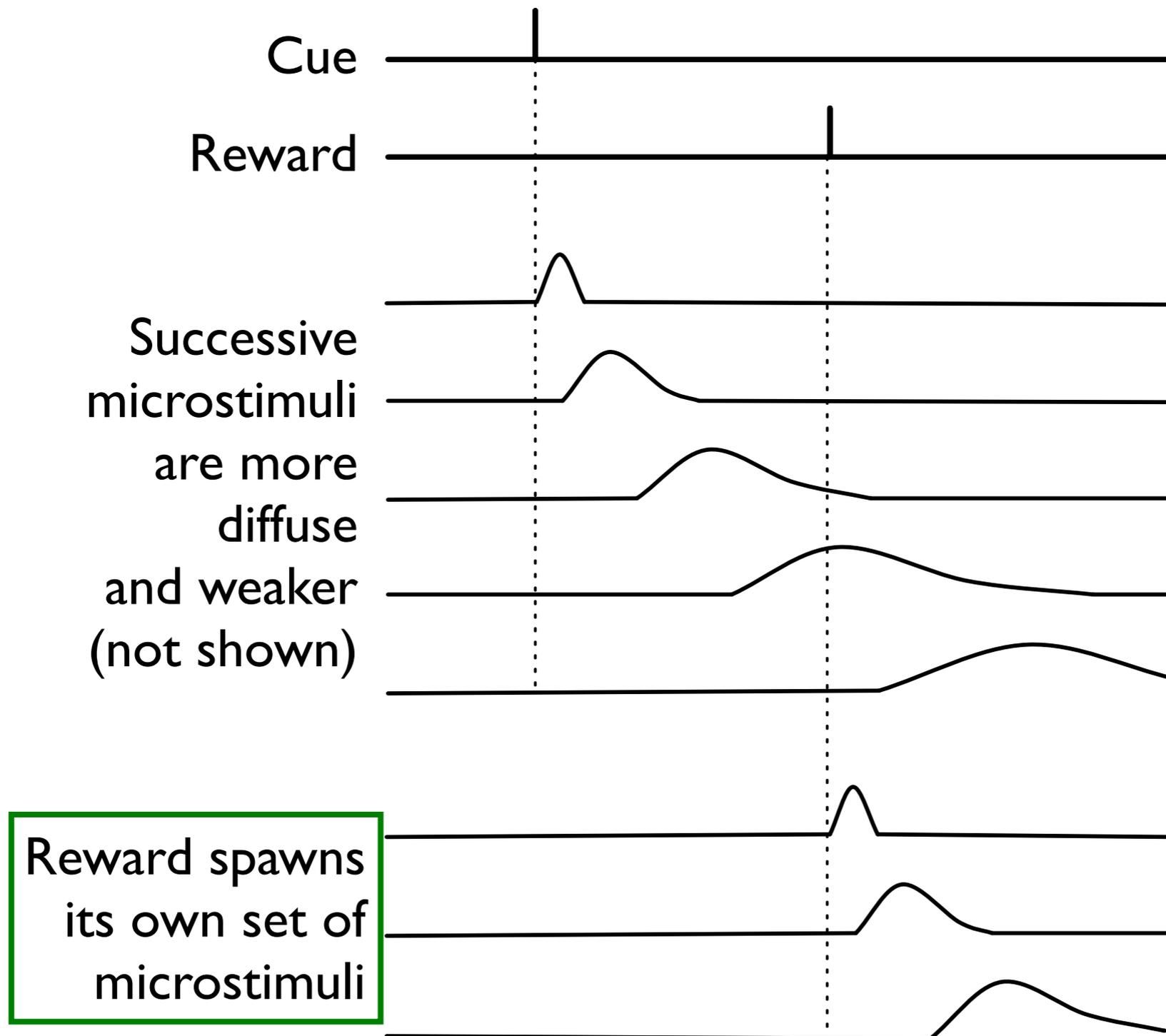
Complete Serial Compound (CSC) stimulus rep'n



No generalization
between time instants

No independent effect
of reward

Temporally-extended microstimuli

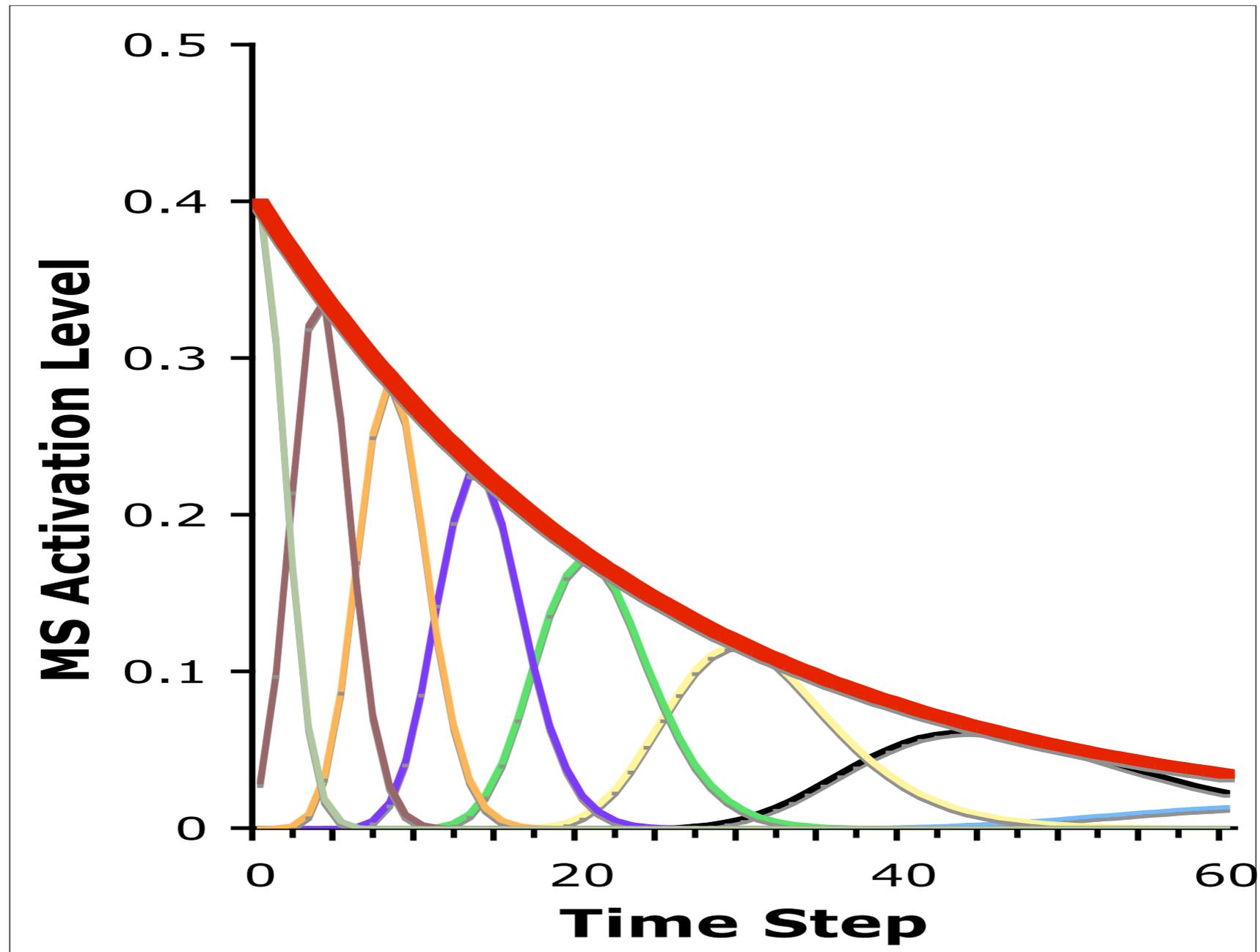


Generalization
across nearby
time instants

Temporal
uncertainty

cf. Machado, 1997
Grossberg & Schmayuk, 1989
Suri & Schultz, 1999

Successive microstimuli get weaker



you can understand everything in this talk at this level:

- Linear TD models can only add things to produce their predictions
- therefore, stimulus representations determine what can be learned
- TD(λ) is a magic thing that wants to predict the discounted future reward
- Dopamine is TD error is $\text{Reward} + \Delta\text{Prediction}$

- Linear models can only add things microstimuli

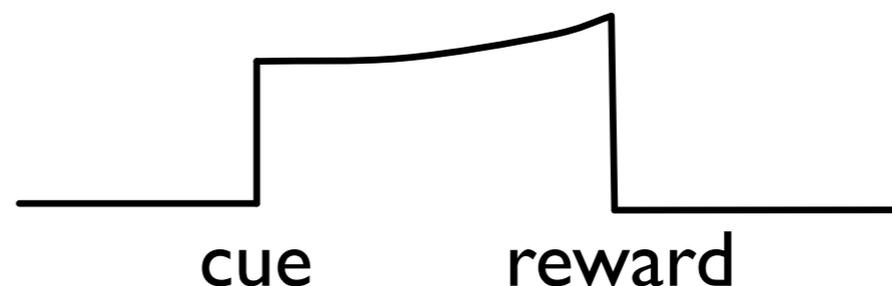
$$\text{Prediction} = \mathbf{w}_t^T \mathbf{x}_t = \sum_{i=1}^n w_t(i) x_t(i)$$

weights

- But they want to predict discounted reward

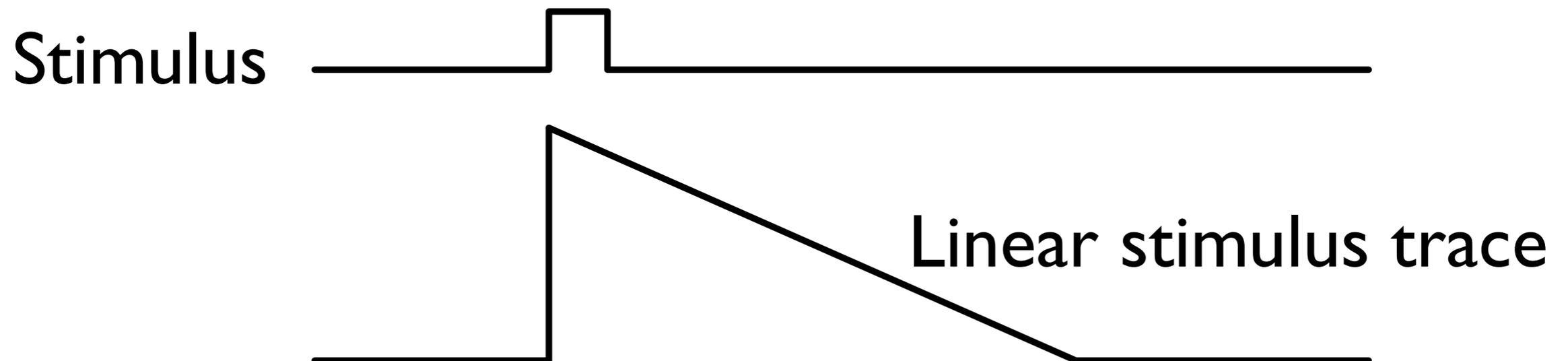
$$\text{Ideal prediction} = E \left[\sum_{k=1}^{\infty} \gamma^{k-1} r_{t+k} \right]$$

Ideal prediction
profile



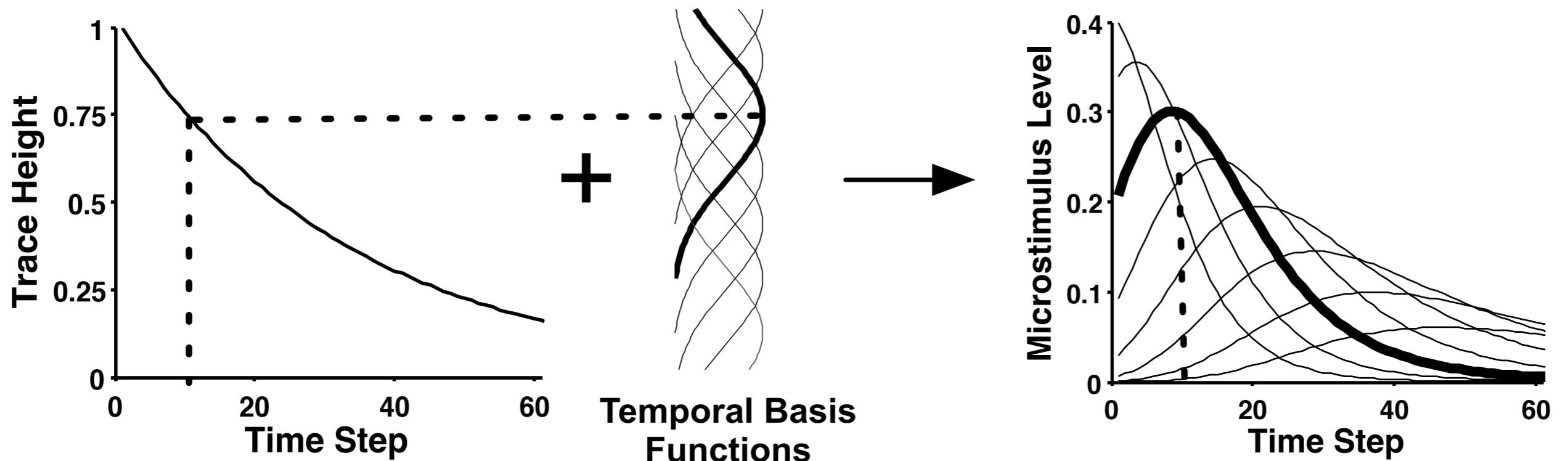
Making microstimuli with stimulus traces (I)

- Start with classical *stimulus trace* (Ebbinghaus, 1888)
- Stimuli leave behind a short term (seconds) representation of themselves

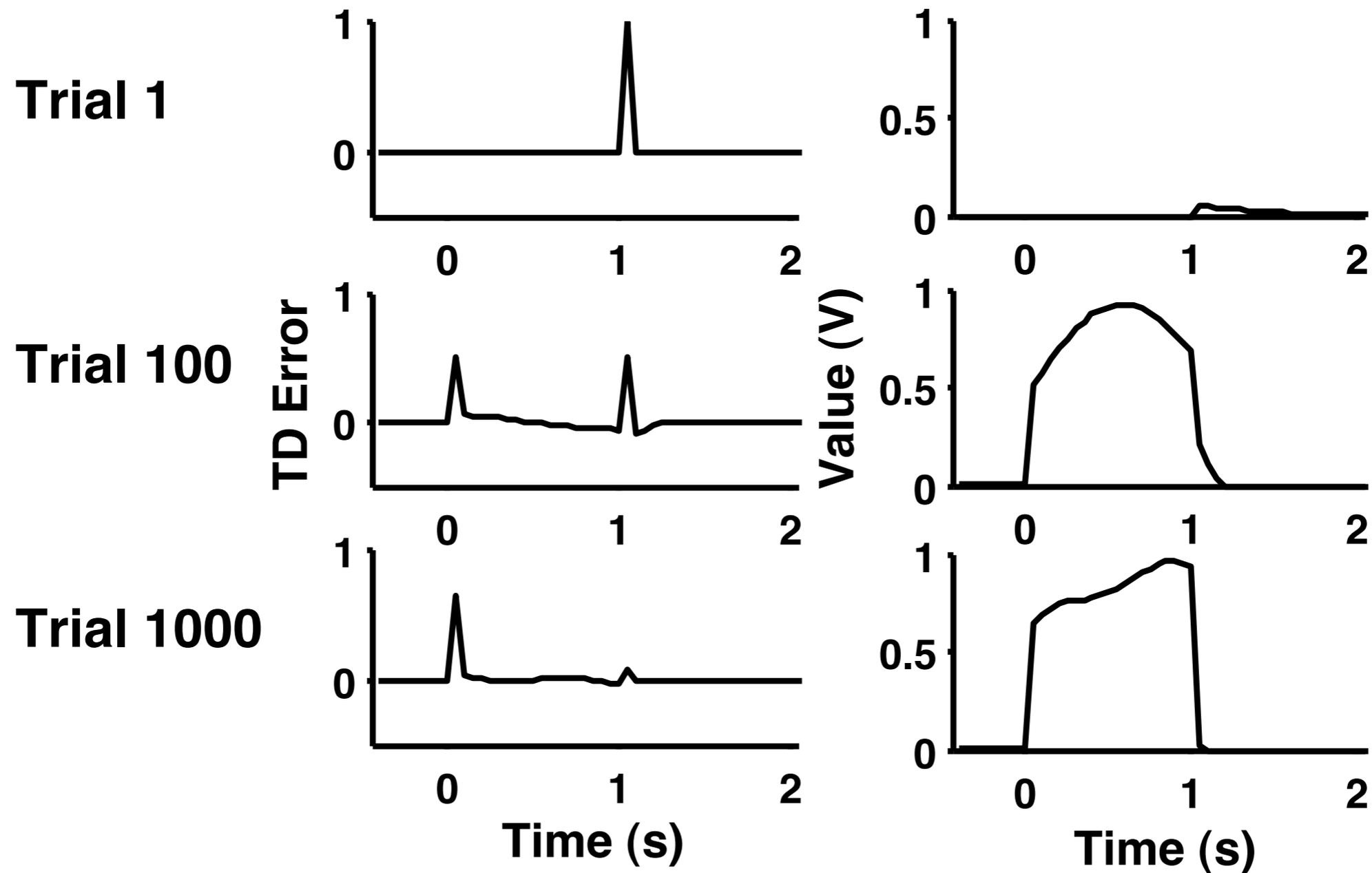


Making microstimuli with stimulus traces (2)

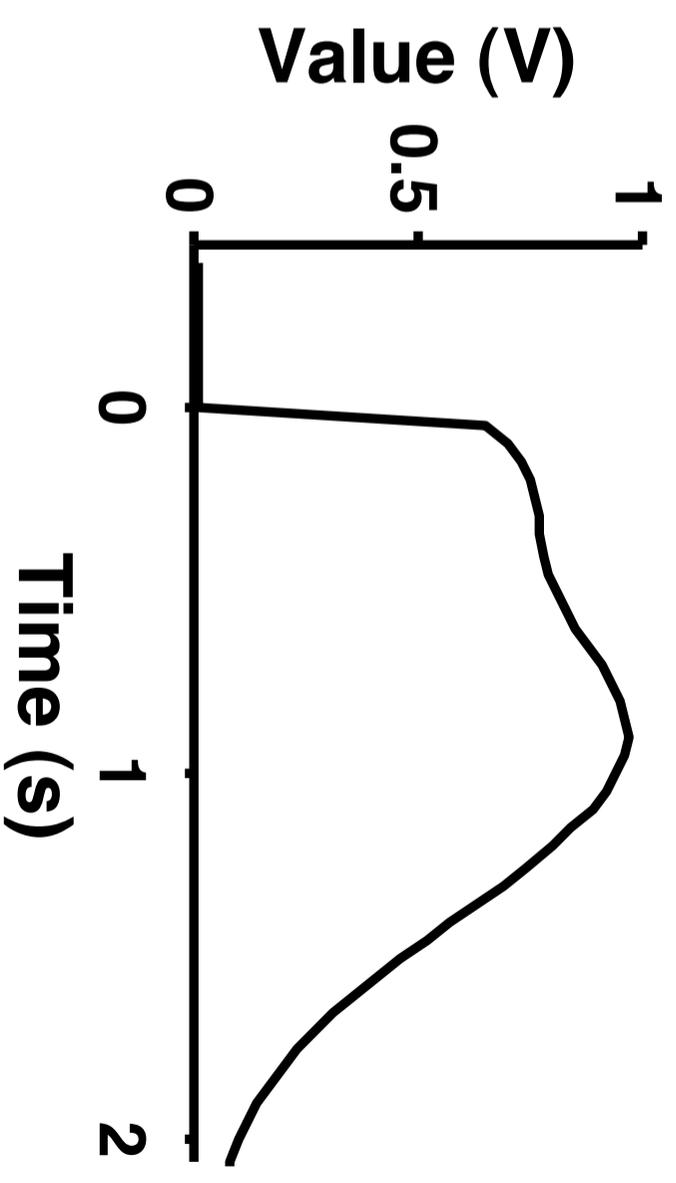
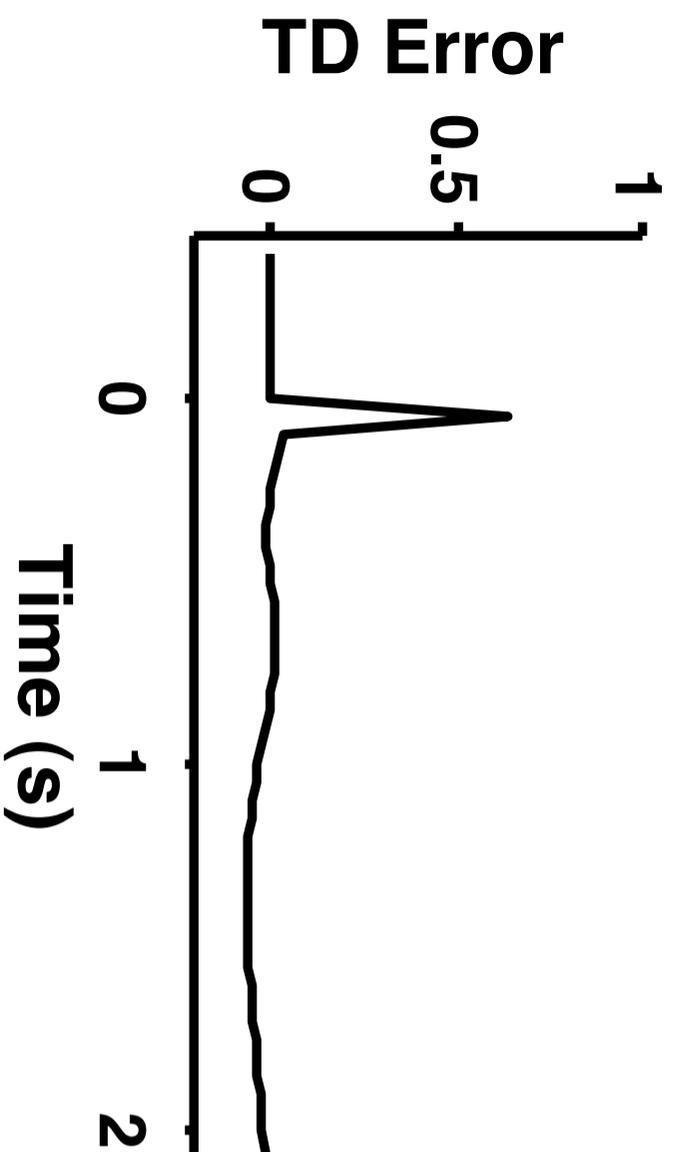
- Microstimuli represent the trace's height (coarsely)



MS model - acquisition



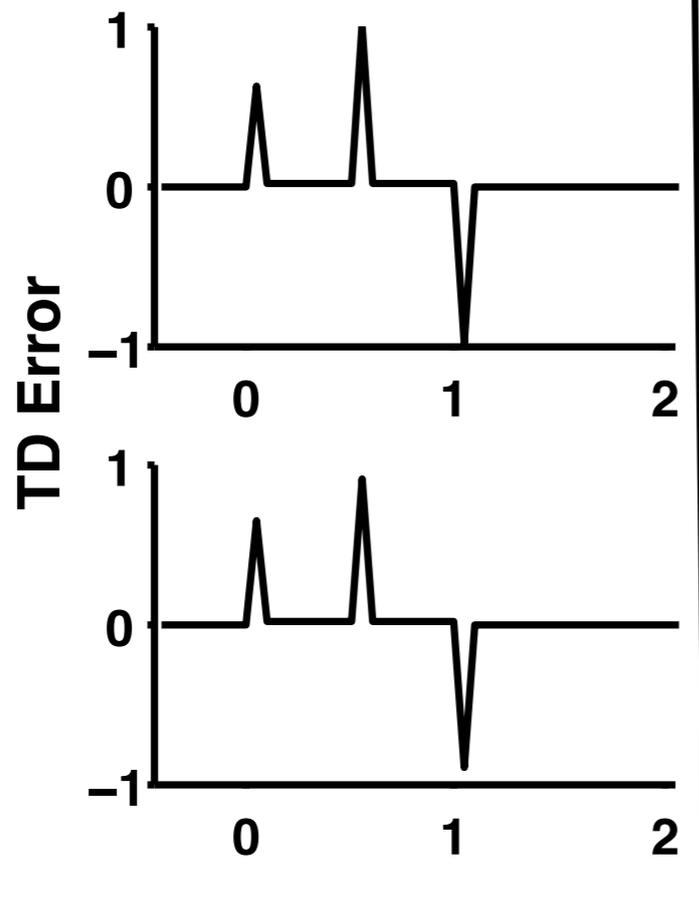
MS model - omission



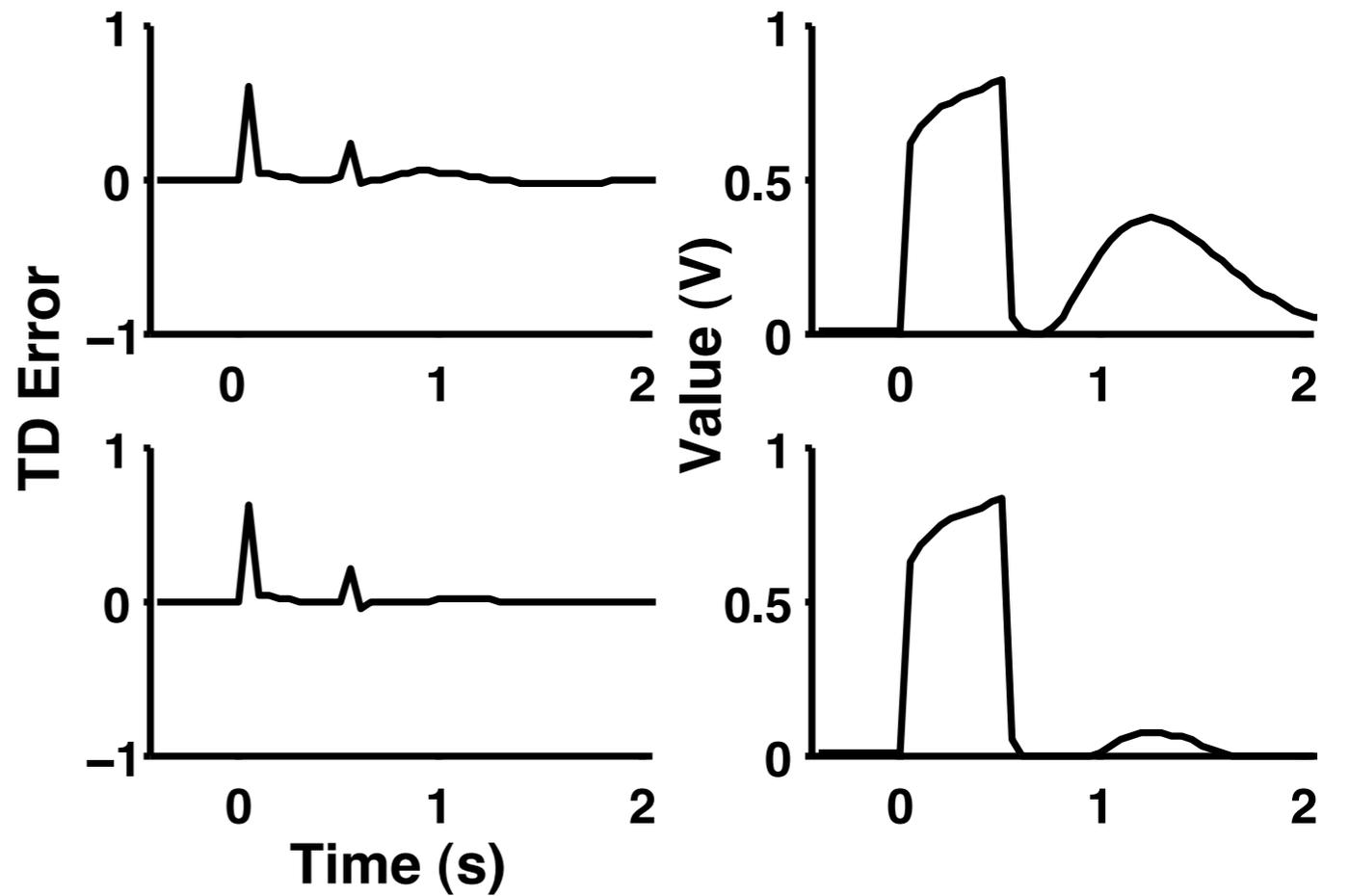
MS model - reward early

1 Probe

Complete Serial Compound TD Model



Microstimulus TD Model



Many Probes

Conclusion regards microstimuli + reward cues

- Benefits
 - more realistic, plausible, natural
 - handles variations in reward timing better
 - does not produce large negative TD errors
- Not tweaks to the TD model, not extensions
 - should be thought of not as adding something, but as taking away two artificial assumptions

Ongoing work

- Microstimuli + presence/absence
- Assessing effect of extended eligibility trace
- Response generation in classical conditioning
- Experimental work with Jim Kehoe, UNSW
 - Rabbit NMR
 - Detailed timing effects