Motor Control and Reinforcement Learning

Computational Cognitive Neuroscience
Randall O'Reilly

Learning Rules Across the Brain

	Learning Signal			Dynamics		
Area	Reward	Error	Self Org	Separator	Integrator	Attractor
Primitive Basal Ganglia	+++			++	-	
Cerebellum		+++		+++		
Advanced Hippocampus						
Neocortex	++	+++	++		+++	+++

+ = has to some extent ... +++ = defining characteristic – definitely has - = not likely to have ... --- = definitely does not have

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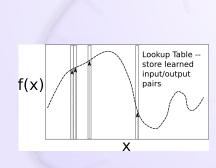
Primitive, Basic Learning..

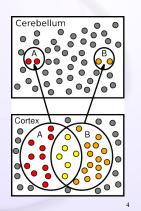
	Learning Signal			Dynamics		
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Cerebellum		+++		444		

- Reward & Error = most basic learning signals (self organized learning is a luxury..)
- Simplest general solution to any learning problem is a lookup table = separator

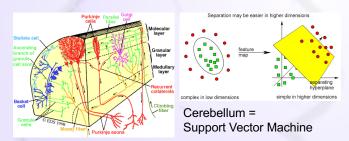
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Lookup Table & Pattern Separation





Cerebellar Error-driven Learning



- Granule cells = high-dimensional encoding (separation)
- Purkinje/Olive = delta-rule error-driven learning
- Classic ideas from Marr (1969) & Albus (1971)

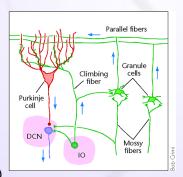
Cerebellum is Feed Forward

Feedforward circuit:

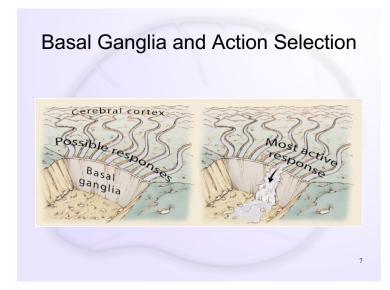
- Input (PN) -> granules -> Purkinje -> Output (DCN)
- Inhibitory interactions no attractor dynamics
- Key idea: does delta-rule learning bridging small temporal gap:

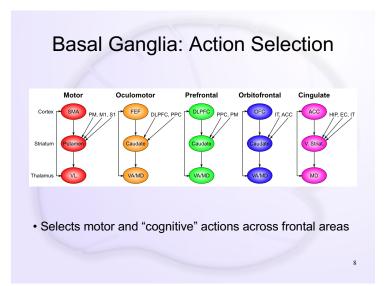
S(t-100) -> R(t)

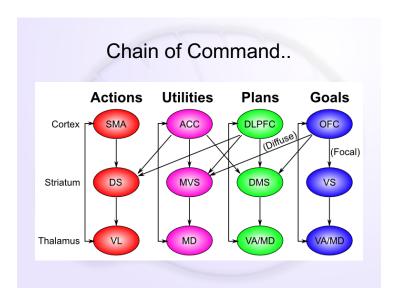
^ Error(t+100)

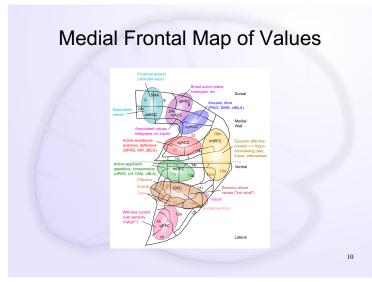


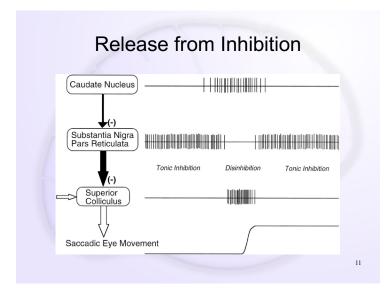
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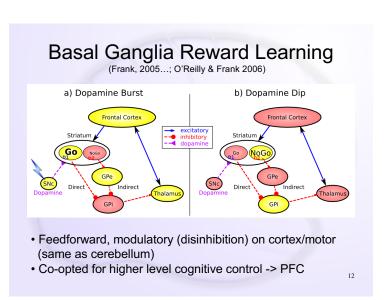




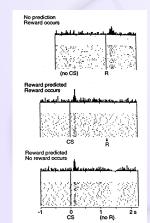








Reinforcement Learning: Dopamine



Rescorla-Wagner / Delta Rule:

•
$$\delta = r - \hat{r}$$

• $\delta = r - \sum xw$

But no CS-onset firing – need to Anticipate the future!

•
$$\delta = (r+f) - \hat{r}$$

CS-onset = future reward = f

Temporal Differences Learning
$$\bullet V(t) = r(t) + \gamma^1 r(t+1) + \gamma^2 r(t+2) \dots$$

$$\bullet \hat{V}(t) = r(t) + \gamma \hat{V}(t+1)$$

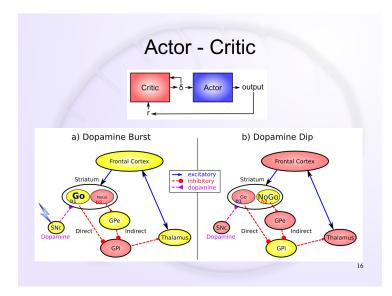
$$\bullet 0 = \left(r(t) + \hat{V}(t+1) \right) - \hat{V}(t)$$

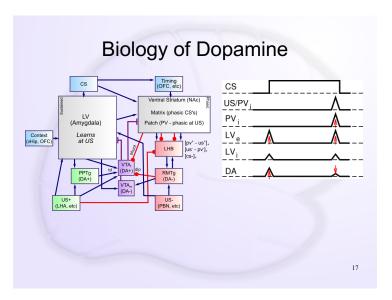
$$\bullet \delta = \left(r(t) + \hat{V}(t+1) \right) - \hat{V}(t)$$

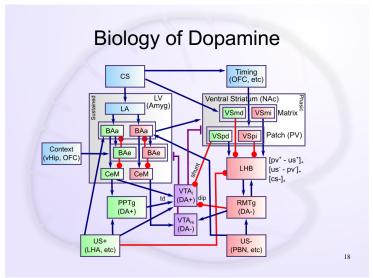
<- this is the future!

• $f = \gamma \hat{V}(t+1)$

Network Implementation Output Description Network Implementation







BG + Cerebellum Capacities

- Learn what satisfies basic needs, and what to avoid (BG reward learning)
 - And what information to maintain in working memory (PFC) to support successful behavior
- Learn basic Sensory -> Motor mappings accurately (Cerebellum error-driven learning)
 - Sensory -> Sensory mappings? (what is going to happen next..)

BG + Cerebellum Incapacities

- Generalize knowledge to novel situations
 - Lookup tables don't generalize well..
- Learn abstract semantics
 - Statistical regularities, higher-order categories, etc
- Encode episodic memories (specific events)
 - Useful for instance-based reasoning
- Plan, anticipate, simulate, etc...
 - Requires robust working memory

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