Parkinson's disease and dopamine (DA) control of movement

• Standard account is that DA directly boosts movement performance

• Models suggest that DA modulates motivational incentive and learning, too.
What is dopamine doing?

Dopamine carries the brain's reward signal.
Reinforcement learning and dopamine: prediction errors

Schultz, Satoh, Roessl, Zaghoul, Glimcher, Hyland, and many more
Basic Data: VTA dopamine firing in Conditioning

Schultz, Montague & Dayan, 2007
Temporal Difference Learning: Equations

Value function, sum of discounted future rewards:

\[ V(t) = \langle \gamma^0 r(t) + \gamma^1 r(t+1) + \gamma^2 r(t+2) + \cdots \rangle \]

(1)

\[ \langle \cdots + (t+1)\gamma^0 + (t+2)\gamma^1 + (t+3)\gamma^2 \rangle = (t)\Lambda \]

(1)
Value function, sum of discounted future rewards:

\[ V(t) = \langle \gamma_0 r(t) + \gamma_1 r(t+1) + \gamma_2 r(t+2) + \ldots \rangle \]

Recursive definition:

\[ V(t) = \langle r(t) + \gamma V(t+1) \rangle \]

Equation 2:

\[ \langle (1 + \gamma) \Lambda + \gamma \Lambda \rangle = (1 + \gamma) \Lambda \]

Equation 1:

\[ \langle \cdots + \gamma^2 \Lambda + (1 + \gamma) \Lambda + \gamma \Lambda \rangle = (1 + \gamma) \Lambda \]

Temporal Difference Learning: Equations
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Value function, sum of discounted future rewards:

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(1)

Recursive definition:

$$V(t) = \langle r(t) + \gamma V(t+1) \rangle$$

(2)

Error in predicted reward (from previous to next time-step):

$$\delta(t) = \langle r(t) + \gamma \hat{V}(t+1) \rangle - \hat{V}(t)$$

(3)

Rewritten equation:

$$(t) \Delta - (\langle 1 + t \rangle \Delta \hat{\gamma} + (t) \Delta \hat{y}) = (t) \delta$$

(4)

Value function, sum of discounted future rewards:

$$\langle \cdots (2 + t) \Delta \hat{\gamma} + (1 + t) \Delta \hat{y} + (t) \Delta \hat{y} \rangle = (t) \Lambda$$

(5)
Temporal Difference Learning: Equations

Value function, sum of discounted future rewards:

\[ V(t) = \langle \gamma^0 r(t) + \gamma^1 r(t+1) + \gamma^2 r(t+2) + \ldots \rangle \]  

Recursive definition:

\[ V(t) = \langle r(t) + \gamma V(t+1) \rangle \]  

Error in predicted reward (from previous to next time-step):

\[ \delta(t) = \langle r(t) + \gamma \hat{V}(t+1) \rangle - \hat{V}(t) \]  

Update value estimate:

\[ \hat{V}(t) \leftarrow \hat{V}(t) + \alpha \delta(t) \]  

\( \alpha = \) learning rate

Equations:

\[ \langle (I + \gamma) \Lambda^\uparrow + (\gamma) \cdot \rangle = (\gamma)^0 \]  

Recursive definition:

\[ \langle \cdots (2 + \gamma) \cdot \Lambda^\uparrow + (I + \gamma) \cdot \Lambda^\uparrow + (\gamma) \cdot \rangle = (\gamma) \Lambda \]  

Value function, sum of discounted future rewards:

Temporal Difference Learning: Equations
Burst/Pause correlations with Rew Prediction Errors

Bayer et al. 2007 JNeurophys
How are dopamine-based RPE signals used to select actions?
What Do the Basal Ganglia Do?
What Do the Basal Ganglia Do?

- Hardly Anything: BG do not directly implement any cognitive (or motor) process.

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What Do the Basal Ganglia Do?

• **Hardly Anything:** BG do not directly implement any cognitive (or motor) process.

• **Almost Everything:** BG modulate activity in multiple cortical areas: affects motor, implicit, learning, motivation, decision making and executive function processes.

Parkinson’s disease (PD), ADHD: DA depletion in BG, resulting deficits in all above domains.
### What Do the Basal Ganglia Do?

- **Hardly Anything**: BG do not directly implement any cognitive (or motor) process.

- **Almost Everything**: BG modulate activity in multiple cortical areas: affects motor, implicit learning, motivation, decision making and executive processes.

  - Parkinson’s disease (PD), ADHD: DA depletion in BG, resulting deficits in all above domains.

  - Excess DA can induce impulsivity, e.g., pathological gambling, compulsive shopping (for review Dagher & Robbins, 2009).
Fronto-basal ganglia circuits in motivation, action, cognition,
BG damage \( \Rightarrow \) deficits in motor, learning, motivation, working memory, cognitive control

The Basal Ganglia as a Gate: Action Selection

- BG selectively facilitates (gates) one action while suppressing others (Mink, 1996; Frank et al., 2001; Cauda et al., 2004).

- Gating occurs in proportion to relative probability of positive-negative outcomes for each action, learned via dopamine...
Striato-Cortical Functional Circuitry

Basal Ganglia

Pre/motor cortex

Thalamus

Response 1
Response 2

Excitatory
Inhibitory
Modulatory
Striato-Cortical Functional Circuitry

- Striatum
- SNc
- SNr/GPi
- GPe
- STN
- Go
- NoGo
- Pre/motor cortex
- Thalamus

Excitatory and inhibitory connections.
Neural circuit model of BG in learning / decision making

Integrates a wide range of physiological data into a single coherent framework

Frank, 2005, 2006; Franklin & Frank, 2016
Striato-Cortical Functional Circuitry

- Excitatory
- Inhibitory
- Modulatory

- SNr/GPi
- Thalamus
- Pre/motor cortex

Tonic activity
Simultaneous Simulation of Striato-Cortical Functional Connectivity

Thalamus → SNr/GPi

SNr/GPi → Cortex (Pre/Motor) → Thalamus

Tonically active modulatory excitatory pathways

---

Striato-Cortical Functional Connectivity
Striato-Cortical Functional Circuitry

- **Excitatory**
- **Inhibitory**
- **Modulatory**

- **Striatum**
- **Thalamus**
- **Pre/motor cortex**
- **SNr/GPi**
- **Go**

**Direct**

**Disinhibition**

- **Striato-Cortical Functional Circuitry**
Striato-Cortical Functional Circuitry

Excitatory
Inhibitory
Modulatory

Striatum
Thalamus
Pre/motor cortex
SNr/GPi

"Disinhibition"

Simulation
Disinhibition as a gating mechanism

Hikosaka and colleagues; Chevalier & Deniau, 90 etc
Striato-Cortical Functional Circuitry

- Striatum
- Pre/motor cortex
- SNr/GPi
- GPe
- GO
- NoGo
- Direct
- Indirect
- Thalamus

Modulatory interactions indicated by the modulatory symbol (↑), inhibitory interactions indicated by the inhibitory symbol (●), and excitatory interactions indicated by the excitatory symbol (→).
Striato-Cortical Functional Circuitry

Simulation

Striatum

SNr/GPi

Direct

Indirect

Thalamus

Pre/motor cortex

Excitatory

Inhibitory

Modulatory
Striato-Cortical Functional Circuitry

- Striatum
- SNc
- SNr/GPi
- GPe
- thalamus

- Direct
- Indirect

- pre/motor cortex

- Go

- excitatory
- inhibitory
- modulatory

- dopamine
Evidence for go/nogo mechanism:

Optogenetic stimulation of direct and indirect pathways

Kravitz et al, 2010, Nature
• Go/NoGo terminology is misleading (implies "act" vs. "not act")
• Benefit vs. cost of alternative actions (both at the same time!)
• Phasic DA signals drive learning via modulation of activation dynamics
D1 effects on BG Learning: Positive PE
D1 effects on BG learning: Positive PE

Three factor learning: presynaptic, postsynaptic and DA
D2 effects on BG learning: Negative PE

- Originally: prediction based on computation (function) and circumstantial data
- D2 weights accumulate with experience - learned Parkinsonism

Frank et al., 2004; 2005
D2 effects on BG learning: Negative PE

Zalocusky et al, 2016
Samejima et al., 2005 Science

Separate striatal populations code for pos/neg action values
• uses DA RPE to drive contrastive Hebbian learning

• No supervised target; just reward-DA driven learning

• But still XCAL / CHL at level of synapse - activity dependent learning

• Note: wiki version is yet more simplified for demo

BC.Proj
Simulating Probabilistic Classification

Frank, 2005, J Cog Neurosci

Capturing experimental data in same task.

- PD nets were impaired due to reduced dynamic range of DA.
- Go/NoGo representations.

Intact nets extracted probabilistic structure by resolving differences in

Probabilistic Classification

![Graph showing trial number vs. percent error for different conditions: intact, PD, No Indir, Global Nogo.](image)
Simulating human learning and DA meds
Simulating human learning and DA meds

DA dips from inducing NoGo learning.

Medication: ↓ DA levels, but tonic stimulation of D2 receptors prevents

Cools et al., 2001; Frank, 2005
Model predictions supported by rodent D1/D2 manipulations
also monkey dl/d2 pharmacology, e.g. Nakamura & Hikosaka 06
Pitting action against RL accounts of D1/D2

Yttri & Dudman, 2016, Nature
Blocking neurotransmission in mouse Go/NoGo pathways

Hikida et al., 2010, Neuron

Direct pathway

Indirect pathway

Reward

Avoid

Reward
Reward prediction error and human functional imaging

O'Doherty et al., 2004; McClure et al., 2003; Daw et al., 2006; Caplin et al., 2010; Badre & Frank, 2011
Human probabilistic reinforcement learning

Avoid B?

Choose A?

Train

Test

A > CDEF

B > CDEF

E (60/40) F (40/60)

C (70/30) D (30/70)

A (80/20) B (20/80)

A > CDEF

B < CDEF

Choose A?
Testing the model:
Parkinson's and medication effects

(See also: Cools et al., 06, Frank et al., 07, Moustafa et al., 08, Bodi et al., 09, Palminteri et al., 09, Voon et al., 10, etc.)

Frank, Seeberger & O'Reilly (2004)

Parkinson's and medication effects
Testing the model.
BG model: DA modulates learning from pos/neg PE's

- Go learning to positive S-R requires sufficient phasic DA bursts
- NoGo learning to negative S-R requires sufficiently low DA during pauses
Pause duration facilitates NoGo learning (D2) •

Burst magnitude facilitates Go learning (D1) •

BG model: DA modulates learning from pos/neg PEs's

BG model: DA modulates learning from pos/neg PEs's
DA stimulation vs. D2 blockade on go/no go learning

Filled bars = medicated (l-dopa or D2 blockade)
Open bars = unmedicated

Palminteri et al., 2009

see Wiecki et al., 2009 for model of D2 blockade effects on Nogo learning in rats
Genetics of striatal dopamine function and model-based predictions
Genetics of striatal dopamine function and model-based predictions

DARPP-32: protein concentrated in striatum, required for D1-dependent plasticity (Calabresi et al. 00, Stipanovich et al. 08)

Meier-Lindeberg et al, 2007
Genetics of striatal dopamine function and model-based predictions

Model: $D_1 = \text{probabilistic Go learning}$

Dylan quotes Aristotle quotes Plato on DARPP-32!

Meyer-Lindenburg et al, 2007

$D_1$-dependent plasticity (Calabresi et al 00, Stipanovich et al 08)

DARPP-32: protein concentrated in striatum, required for DARPP-32
Hirvonen et al., 2009

DRD2 gene affects striatal D2 receptor function.
DRD2 gene: affects striatal D2 receptor function

Hirvonen et al., 2009 and here's what the red hot chili peppers have to say about this gene.
DRD2 gene affects striatal D2 receptor function

Hirvonen et al., 2009

Model: D2 = probabilistic NoGo learning

Heres what the red hot chilli peppers have to say about this gene
Frank et al. 07, PNAS

DA genes and probabilistic learning
Converging evidence in human probabilistic RL

Frank et al. (2004, 2006, 2007), Cockburn et al. 2014, Cox et al. 2015...

Test Condition

<table>
<thead>
<tr>
<th>PD OFF</th>
<th>PD ON</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD OFF</td>
<td>PD ON</td>
</tr>
</tbody>
</table>

Choose Pos - Avoid Neg (%)

Parkinson's patients on/off meds

Accuracy
Not just learning: striatal DA modulates "incentive salience"

Also: risky decision making, Floresco, Rutledge etc; effort/reward choice tasks, L-maze etc.

Collins & Frank, Psych Rev, 2014

(Da) Contributions to Learning vs. Choice Incentive

(Opal model)
Dissecting DA contributions to learning vs. choice incentive

(OpAL model)
Dissecting DA contributions to learning vs. choice incentive (OpAL model)

Collins & Frank, Psych Rev, 2014
Dissecting DA contributions to learning vs. choice incentive (OpAL model)

Collins & Frank, Psych Rev, 2014
Dissecting DA contributions to learning vs. choice incentive

(OpAL model)

Collins & Frank, Psych Rev, 2014
Back to reversal learning: DA-mediated Go/NoGo learning alone is limited

- Simulated D2 agonists prevent learning in D2 MSNs
- Intact BG model learns probabilistic reversal, but not optimally

Back to reversal learning: DA-mediated Go/NoGo learning alone is limited

Back to reversal learning: DA-mediated Go/NoGo learning alone is limited

Cools et al., 2001; Frank, 2005

Motivates need for dynamic learning rate...

• Simulated D2 agonists prevent learning in D2 MSNs
• Intact BG model learns probabilistic reversal, but not optimally

⇒ motivates need for dynamic learning rate...

Simulated D2 agonists prevent learning in D2 MSNs

Cools et al., 2001; Frank, 2005
Bayesian approach to dynamic learning
Bayesian approach to dynamic learning
Bayesian approach to dynamic learning
Bayesian approach to dynamic learning

Learning from individual noisy outcomes should depend on uncertainty (cf Kalman filter).

Bayesian approach to dynamic learning
Bayesian approach to dynamic learning

• Learning from individual noisy outcomes should depend on uncertainty

For choice tasks, uncertainty in A > B (overlap)

Bayesian approach to dynamic learning
\[ p_a(t) = \sum_i y_a(i) / \sum_i y_a(i) \]

\[ H = - \sum_{t} p_a(t) \sum_a \log_2 p_a(t) \]

\[ \text{MSN population entropy indexes choice uncertainty} \]

Diagram showing low and high entropy states with time indicated vertically.
Role for cholinergic interneurons in modulating learning?

- DA
- TAN
- TANs gate plasticity (e.g., Graybiel, Bergman, Craige et al.)
- TAN ablations impair reversal learning (e.g., Witten et al. 2010)
- Striatal M1 blockade impairs reversal learning (McCool et al. 08)

Morris et al., 2004
TAN effects on network learning

- TANs modulate MSN excitability during phasic DA signal (e.g., Koos)
- Long pause → disinhibitor corticostriatal input across population, more learning

TAN effects on network learning
TANs moderate divergence in MSN weights with learning and population entropy

- TAN pauses modulate MSN excitability during phasic DA (via M1, presynaptic M2 and nicotinic effects on GABA-internurons)
- Long pause → larger population of MSNs learn from DA
- Short pause → learning focused on sparse population

⇒ TAN pause modulates effective learning rate

TAN pauses modulate MSN excitability during phasic DA (via M1, presynaptic M2, and nicotinic effects on GABA-internurons)
MSN entropy $\rightarrow$ longer TAN pauses

MSN-TAN collaterals: Bolam et al. '86; Chuhma et al. '11; Gonzalez et al. '13

MSN-TAN feedback circuit for adaptive learning rates
TAN/MSN/DA interactions optimize learning across levels of

Stochasticity & Volatility

Self-regulating pause optimizes learning/reversal overall

- Benefit of long/short pause depends on level of stochasticity
- 85/15 vs. 40/10 environments
- Franklin & Frank, 2015, eLife
Bayesian approach to dynamic learning

• How do deal with volatility?
Bayesian approach to dynamic learning

How do deal with volatility?

Bayesian approach to dynamic learning
Franklin & Frank 2015, eLife

approximate Bayesian approach to dynamic learning

- Add uncertainty to belief distributions (decay counts)
- Regulate trade off by dynamically changing decay according to changes in choice uncertainty

![Graph showing learning curves with different decay rates.](image)
BG-TAN net is analogous to Bayesian uncertainty-driven learner.
same result in OpAL formulation
DA-mediated Go/NoGo learning alone is limited:

**Probabilistic reversal**

- Simulated D2 agonists prevent learning in D2 MSNs
- Intact BG model learns probabilistic reversal, but not optimally

⇒ motivates need for dynamic learning rate...

![Graph showing BG model performance](image)
Cools et al., 2001; Frank, 2003
Bayesian approach to dynamic learning
Bayesian approach to dynamic learning
Bayesian approach to dynamic learning
Bayesian approach to dynamic learning

Learning from individual noisy outcomes should depend on uncertainty.

Bayesian approach to dynamic learning
Bayesian approach to dynamic learning

- Learning from individual noisy outcomes should depend on uncertainty.

For choice tasks, uncertainty in $A > B$ (overlap)

Bayesian approach to dynamic learning
Bayesian approach to dynamic learning

- How do deal with volatility?
Bayesian approach to dynamic learning

How do deal with volatility?

Bayesian approach to dynamic learning
e.g., Yu et al. 2005; Behrens et al. 2007; Nassar et al. 2010; Mathys et al. 2011
approximate Bayesian approach to dynamic learning

Franklin & Frank 2015, eLife

in choice uncertainty
regulate trade off by dynamically changing decay according to changes

add uncertainty to belief distributions (decay counts)
\[
\sum_{i} \frac{y_{a}(t)}{\sum_{MSN} y_{a}(t)} = H
\]

\[
\sum_{i} / (t) \sum_{MSN} y_{a}(t) = (t)^{npd}
\]
Role for cholinergic interneurons in modulating learning?

- Striatal M1 blockade impairs reversal learning (Mccool et al 08)
- TAN ablations impair reversal learning (e.g., Witten et al 2010)
- TAN gate plasticity (e.g., Graybiel, Bergman, Crager etc)

Morris et al., 2004

Images depicting neural activity in TAN and DA neurons with labels for Reward and Cue.
TAN effects on network learning

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MSN-TAN feedback circuit for adaptive learning rates

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TAN/MSN/DA interactions optimize learning across levels of stochasticity & volatility.

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- 85/15 vs 40/10 environments.

Franklin & Frank, 2015, eLife.
BG-TAN net is analogous to Bayesian uncertainty-driven learner
same result in OpAL formulation
Deep Brain Stimulation of the Subthalamic Nucleus (STN) for treatment of Parkinson's disease

Video #1: http://ski.clps.brown.edu/dbs.mp4
Video #2: http://ski.clps.brown.edu/dbs2.mp4
But not all is grand in the world of DBS...
But not all is grand in the world of DBS...

Hi, I found your email address in an article I was reading about DBS surgery for Parkinson's. My dad had the surgery last May and we have a mess on our hands. Two months following the surgery, we began to notice some personality changes. He became impulsive, forgetful, has lied, has no empathy, he uses foul language, has become more detailed and now he is sloppy, and he is spending a lot of money. He has cancelled his 2 follow up dr appointments, he was always very detailed, oriented and now he is sloppily and he is spending a lot of money. He has NOT gone one day without buying something. He can't sit still, he's always moving somewhere and buying something. He has NOT gone one day without buying something. He can't sit still, he's always moving.
But not all is grand in the world of DBS...

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STN-DBS dramatically improves PD motor symptoms, but can induce impulsivity...
From reinforcement learning...
Neural circuit model of BC in learning / decision making

Frank, 2005, 2006 J Cog Neurosci, Neural Networks
Anatomy of BG gating: without STN
Anatomy of BG gating: with subthalamic nucleus (STN)

- PFC-STN provides an override mechanism
Subthalamic Nucleus: Dynamic modulation of decision threshold

Conflict (entropy) in choice prob: ⇒ Hold Your Horses!
STN and frontal cortex are directly connected via white matter

Aron et al. (2007), J. Neurosci
Neural model and STN ephys: decision conflict

Data from Isoda & Hikosaka 2008

Wiecki & Frank, 2013 Psych Review

Spike rate: Data vs Model
Neural model and STN ephys: decision conflict

Wiecki & Frank, 2013 Psych Review

Data from Isoda & Hikosaka 2008

Behavior:

Spike rate:

Neural model and STN ephys: decision conflict
Human probabilistic reward/choice conflict

Low Conflict: e.g., 80 vs 30%

\[ H(P_{\text{softmax}}) = 0.6 \]

High Conflict: e.g., 80 vs 70%

\[ H(P_{\text{softmax}}) = 0.84 \]

A (80%) B (20%)
C (70%) D (30%)
E (60%) F (40%)
Human probabilistic reward/choice conflict

Need STN to prevent impulsive responses

Low Conflict: e.g., 80 vs 30%

\[ \max \{ p_{\text{softmax}} \} H = 0.6 \]

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Human probabilistic reward/choice conflict

Low Conflict: e.g., 80 vs 30%

\[ H(\text{softmax}_p) = 0.6 \]

High Conflict: e.g., 80 vs 70%

\[ H(\text{softmax}_p) = 0.84 \]

Need STN to prevent impulsive responses
human STN spiking, Zaghloul et al., 2012
STN-DBS reverses conflict RT adjustments

see also Wylie et al 10; Halbij et al 09; Cavanagh et al 11; Coulthard et al 12; Green et al 13

Frank, Samanta, Moustafa & Sherman (2007)
Interim Summary

• DBS induces speeded responding in conflict conditions

  Simulations: STN modulates decision threshold × cortical conflict
Interim Summary

- DBS induces speeded responding in conflict conditions
- Simulations: STN modulates decision threshold as a function of mediofrontal conflict
- More precise predictions to be tested:
  - Does mediofrontal cortex and STN represent reinforcement conflict?
  - Does STN-DBS alter this relationship?

Simulations: STN modulates decision threshold as a function of mediofrontal conflict
- DBS induces speeded responding in conflict conditions
Abstraction: the drift diffusion model
Abstraction: the drift diffusion model

- Provides quantitative fits to error rates and RT distributions in many tasks
- Allows estimation of decision threshold ($a$), separately from other factors ($v$, $z$, $T_{ef}$)

E.G. Ratcliff & McKoon, 2008
Abstraction: the drift diffusion model

- Provides quantitative fits to error rates and RT distributions in many tasks
- Allows estimation of decision threshold \( \theta \) separately from other factors
Contrasting drift rate vs threshold

More Errors
Slower Responses
Response Time (Seconds)
Mechanism

Subthalamic nucleus stimulation reverses mediofrontal influence over decision threshold.
Hierarchical interactions in BG-FG circuits:

PFC & cognitive control influences on learning

Collins & Frank 2013, Psych Rev; Frank & Badre 2012
Broader speculations:

Why does motor control develop so slowly in humans?

Fourth trimester

Standard story: Infants born early due to large head, small birth canal.

•
Broader speculations:

Why does motor control develop so slowly in humans?

But 3 month old infants still pretty incompetent (from babycenter.com):

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Broader speculations:

Why does motor control develop so slowly in humans?

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Fourth trimester.

But 3-month-old infants still pretty incompetent (from babycenter.com):

"You no longer need to support his head. When he's on his stomach, he can lift his head and chest. He can open and close his hands."

"But 3-month-old infants still pretty incompetent (from babycenter.com):"

Standard story: Infants born early due to large head, small birth canal.

Broader speculations:

Why does motor control develop so slowly in humans?
Broader speculations:

Why does motor control develop so slowly in humans?

Hypothesis: Human brain is wired to discover generalizable structure.

But 3 month old infants still pretty incompetent (from babycenter.com):

• You no longer need to support his head. When he's on his stomach, he can lift his head and chest. He can open and close his hands.

• Fourth trimester

Standard story: Infants born early due to large head, small birth canal
which is initially inefficient.
Abstracting Task-sets rules
Abstracting Task-sets Rules
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Abstracting Task-sets rules

TS_{new} \rightarrow S_{i1} \rightarrow A_{i1}

TS_{i2} \rightarrow S_{i2} \rightarrow A_{i2}

TS_{i1} \rightarrow S_{i1} \rightarrow A_{i1}
See also Gershman et al. 2010.

- $\alpha > 0$: Clustering parameter

$$\frac{\lambda}{(1+u)} \log \frac{S_L}{S_L} \frac{\lambda}{\lambda} = \left\{ \begin{array}{ll} 1+u & \text{if } S_L = S_L \neq \emptyset \\ 1+u & \text{if } S_L = S_L \emptyset \end{array} \right\} = (1+u) \log = S_L \frac{\lambda}{\lambda}$$

Prior prob on TS space given a new C.

Task-sets are clustered.

C-TS model
Implimentation

Neurobiologically plausible
Implementation
Neurobiologically plausible
Neurobiologically plausible implementation
Implenentation
Neuropathologically plausible
Predicts positive, negative transfer

The network learns efficiently unsupervised.

Neural Network - Results
MRI evidence: Badre & Frank 2012

Collins & Frank 2013, Psych Rev; Collins et al, 2014, J Neurosci; Collins & Frank, in review

Re-using and creating task-sets
Model mimicry: C-TS and Hierarchical BG-PFC network

- MRI evidence for Hierarchical PFC-BG mechanisms Badre & Frank 2012
- Both models are approximations of the same process: building TS structure
- Sparseness of context-PFC connectivity matrix is linked to TS clustering

Collins & Frank 2013 Psych Rev