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

- Dopamine levels in a normal neuron and a Parkinson's disease neuron
- Changes in movement and other symptoms
What is Dopamine Doing?
Reinforcement learning and dopamine: prediction errors

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

Schultz, Montague & Dayan, 2007
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)

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

Temporal Difference Learning: Equations
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:

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

\[ (1) \]

\[ \langle \cdots + \gamma Z(t) + (1 + \gamma Z(t+1) + (1 + \gamma Z(t+2) + \ldots) \rangle = (\gamma) \Lambda \]

Termporal Difference Learning: Equations

Recursive definition:
Temporal Difference Learning: Equations

Value function, sum of discounted future rewards:

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

(3) \( (t) \Delta - ((1 + t) \Delta^\uparrow + (t) \Delta^\downarrow) = (t) \hat{\phi} \)

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

(2) \( \langle (1 + t) \Lambda^\uparrow + (t) \Lambda^\downarrow \rangle = (t) \Lambda \)

Recursive definition:

(1) \( \langle \cdots (2 + t) \Lambda^\uparrow + (1 + t) \Lambda^\downarrow + (t) \Lambda^\downarrow \rangle = (t) \Lambda \)

Value function, sum of discounted future rewards:

Temporal Difference Learning: Equations: Equations
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:

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

\[
\alpha = \text{learning rate}
\]

(1) (2) (3) (4)

Equations: Temporal Difference Learning
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.
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.

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

What Do the Basal Ganglia Do?
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 function processes. Parkinson’s disease (PD), ADHD: DA depletion in BG, resulting deficits in all above domains. Also: excess BG 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 ⇒ deficits in motor, learning, motivation, working memory, cognitive control.

Alexander, G. E. et al. (1986), "Parallel Organization of Functionally Segregated Circuits Within Basal Ganglia Architecture: Cortically Based Loops."
The Basal Ganglia as a Gate: Action Selection

Each action, learned via dopamine...

Gate occurs in proportion to relative probability of positive-negative outcomes for

Frank et al., 2001; Cunqueiro et al., 2001; Brown et al., 2004;...)

BG selectively facilitates (gates) one action while suppressing others (Mink, 1996;)

(figure borrowed from Ivry & Spencer, 2004)
Striato-Cortical Functional Circuity

- Basal Ganglia
- Pre/motor cortex
- Basal Ganglia
- Response 1
- Response 2
- Thalamus

Excitatory: →
Inhibitory: ◯
Modulatory: ——

Striato-Cortical Functional Circuitry
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

- Thalamus
- Pre/motor cortex
- SNr/GPi

Excitatory connections are indicated by arrows, while inhibitory connections are indicated by solid lines with arrows. Modulatory connections are indicated by dashed lines with arrows.
**Striato-Cortical Functional Circuitry**

- **Thalamus**
  - **SNr/GPi**
  - **Pre/motor cortex**
- **Simulation**
  - Tonic activity

Types of connections:
- Dashed line: Modulatory
- Solid line: Excitatory
- Red dot: Inhibitory
Striato-Cortical Functional Circuitry

- Excitatory
- Inhibitory
- Modulatory

Go

pre/motor cortex

striatum

thalamus

SNr/GPi

"Disinhibition"
Striato-Cortical Functional Circuitry

- Excitatory
- Inhibitory
- Modulatory

- Striatum
- Thalamus
- Premotor cortex
- SNr/GPi

"Disinhibition"
Disinhibition as a gating mechanism

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

- Excitatory
- Inhibitory
- Modulatory

Diagram shows connections between SNr/GPi, GPe, thalamus, pre/motor cortex, and striatum, indicating direct and indirect pathways.

Key nodes:
- SNr/GPi
- GPe
- Thalamus
- Pre/motor cortex
- Striatum
- Go/NoGo

Connection types:
- Direct
- Indirect
Striatocortical Functional Circuitry

Simulation

Thalamus 

Direct 

Indirect 

SNr/GPi

GPi

Striatum

Nogo

Go

Pre/motor cortex

Simulation modulatory
modulatory
inhibitory
inhibitory
excitatory
excitatory
Striato-Cortical Functional Circuitry

- **GPe**
- **D1**
- **D2**
- **excitatory**
- **inhibitory**
- **modulatory**
- **striatum**
- **SNc**
- **Indirect thalamus**
- **pre/motor cortex**
- **SNr/GPi**
- **Direct**
- **Indirect**
- **Go**
Evidence for go/no-go mechanism:

Optogenetic stimulation of direct and indirect pathways

Kravitz et al, 2010, Nature

Go inhibits SNr; NoGo ± excites SNr ... and induces/inhibits movement.
- Go/NoGo terminology is misleading (implies "act" vs. "not act")
- Benefit vs. cost of alternative actions (both at the same time?)
- Dual pathways in the BG: Cartoon Version

Phasic DA signals drive learning via modulation of activation dynamics
D1 effects on BC Learning: Positive PE
Three factor learning: presynaptic, postsynaptic and DA

D1 effects on BG learning: Positive PE
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
Separate striatal populations code for pos/neg action values

Samejima et al., 2005 Science
Note: wiki version is yet more simplified for demo

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

No supervised target; just reward-DA driven learning.

Uses DA RPE to drive contrastive Hebbian learning signal.
Simulating Probabilistic Classification

Frank, 2005, J Cog Neurosci

capturing experimental data in same task.

• Intact nets were impaired due to reduced dynamic range of DA.

• Go/NoGo representations.

Probabilistic Classification

10 50 100 150 200
Trial

0
Percent Error

0.0 0.1 0.2 0.3 0.4

Simulating Probabilistic Classification

Frank, 2005, J Cog Neurosci

capturing experimental data in same task.

• Intact nets extracted probabilistic structure by resolving differences in

• PD nets were impaired due to reduced dynamic range of DA.

• Go/NoGo representations.

Probabilistic Classification

10 50 100 150 200
Trial

0
Percent Error

0.0 0.1 0.2 0.3 0.4
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
Reward prediction error and human functional imaging

McClure et al., 2003; O’Doherty et al., 2004; Daw et al., 2005; Caplin et al., 2006; Badre & Frank, 2011, etc.
Human probabilistic reinforcement learning

Train

Test

Avoid B?

Choose A?

A > CDEF

B > CDEF

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

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

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

Choose A?

A > CDEF

B < CDEF

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

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

E (60/40) F (40/60)
Testing the model:

Parkinson's and medication effects

Probabilistic Selection
Test Performance

Choose A
Avoid B

Test Condition

Percent Accuracy

Seniors
PD OFF
PD ON

Frank, Seeberger & O'Reilly (2004)

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

Parkinson's and medication effects
Testing the model:
Go learning to positive S-R requires sufficient phasic DA bursts

NoGo learning to negative S-R requires sufficiently low DA during pauses

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

Pause duration facilitates NoGo learning (D2)

Burst magnitude facilitates Go learning (D1)

Burst magnitude facilitates Go learning (D1)
DA stimulation vs. D2 blockade on go/no go learning

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

See Wiecki et al., 2009 for model of D2 blockade effects on Nogo learning in rats

Palminteri et al., 2009
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)

Genetics of striatal dopaminergic function and model-based predictions

Meier-Lindenberg et al. 2007
Genetics of striatal dopamine function

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

• Meyer-Lindenberg et al, 2007

Dylan quotes Aristotle quotes Plato on DARPP-32!
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)

Dylan quotes Aristotle quotes Plato on DARPP-32!

⇒ Model: D1 = probabilistic Go learning

Meyer-Lindenberg et al. 2007
DRD2 gene affects striatal D2 receptor function

Hirvonen et al., 2009
D2D2 gene affects striatal D2 receptor function

and here's what the red hot chili peppers have to say about this gene

Hirvonen et al., 2009
DRD2 gene: affects striatal D2 receptor function

Model: D2 = probabilistic NoGo learning

Hirvonen et al., 2009

and here's what the red hot chili peppers have to say about this gene

Hirvonen et al., 2009
DA genes and probabilistic learning

Frank et al. 07, PNAS

Choose A Avoid B

Test Condition

60 65 70 75 80 85

Accuracy

C/C, C/T

T/T

Striatal Genes: DARPP-32

Choose A Avoid B

Test Condition

60 65 70 75 80 85

Accuracy

val/met, met/met

val/val

Go/NoGo Generalization

DRD2 gene

* 

Go/NoGo Generalization

COMT gene

Frank et al. 07, PNAS

DA genes and probabilistic learning
In humans: probabilistic reinforcement learning

Frank et al (04, 06, 07), Cockburn et al, Cox et al, 2015...
Not just learning: striatal DA modulates "incentive salience"

Also: risky decision making, Floresco, Rutledge etc; effort/reward choice tasks, T-maze etc.
Collins & Frank, Psych Rev, 2014

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)
Dissecting DA contributions to learning vs. choice incentive

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

(Copal model)
Back to reversal learning: DA-mediated Go/NoGo learning

alone is limited

...motivates need for dynamic learning rate...

⇒ intact BG model learns probabilistic reversal, but not optimally

• Simulated D2 agonists prevent learning in D2 MSNs

• Simulated DA Meds 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.

References:
- Yu & Dayan (2006)
- Behrens et al. (2007)
- Nassar et al. (2010)
- Mathys et al. (2011)
\[
(m(t))^{p} \log (m(t))^{p} \sum_{i=1}^{a} \sum_{j=1}^{t} - = H
\]

\[
\sum_{i=1}^{MSN} f_i / (m(t))^{p} \sum_{i=1}^{a} f_i = (m(t))^{p}
\]
Role for cholinergic interneurons in modulating learning?

- Striatal MI blockade impairs reversal learning (McCool et al 08)
- TAN ablations impair reversal learning (e.g., Witten et al 2010)
- TANs gate plasticity (e.g., Graybiel, Bergman, Cragg et al)
TAN effects on network learning

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

**Population entropy**

TANs moderate divergence in MSN weights with learning.
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
- 85/15 vs 40/10 environments
- Benefit of long/short pause depends on level of stochasticity
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 time vs. accuracy for Bayesian learners with variable and fixed decay models.](image-url)
BG-TAN net is analogous to Bayesian uncertainty-driven Learner
same result in OpAL formulation
DA-mediated Go/NoGo learning alone is limited:

motivates need for dynamic learning rate...

\[ \xrightarrow{\text{Intact BG model learns probabilistic reversal, but not optimally}} \]

\[ \implies \text{Simulated D2 agonists prevent learning in D2 MSNs} \]

Simulated D2 agonists prevent learning in D2 MSNs.
Deep Brain Stimulation of the Subthalamic Nucleus (STN) for treatment of Parkinson's disease

Video #1: https://ski.clps.brown.edu/dbs.mp4
Video #2: https://ski.clps.brown.edu/dbs2.mp4
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, cocky, oblivious to his surroundings, forgetful, has lied, he has no empathy, he uses foul language, canceled his 2 follow up dr appointments, he was always very detail oriented and now he is sloppy, 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. He can't sit still, he's always moving. Going 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...

Hi, I found your email address in an article I was reading about DBS surgery for Parkinsons. 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's always been detail-oriented and now he's sloppy, he has no empathy, he uses foul language... canceled his 2 follow up appointments, he was always very detailed about appointments, he was always very detailed, now he's not. He can't sit still, he's always on the move, going somewhere and buying something...}

STN-DBS dramatically improves PD motor symptoms, but can induce impulsivity (Saint-Cyr et al, 06; Frank et al, 07; Wyble et al, 10; Halbach et al, 09)
From Reinforcement Learning...
...to reinforcement conflict-based decision making
Frank, 2005, 2006 J Cog Neurosci, Neural Networks
Anatomy of BG gating: without STN
Anatomy of BG Gating: with subthalamic nucleus (STN)
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

Spike rate:

Data from Isoda & Hikosaka 2008

Wiecki & Frank, 2013 Psych Review
Neural model and STN ephys: decision conflict

Data from Isoda & Hikosaka 2008

Behavior:

Spike rate:

Wiecki & Frank 2013 Psych Review
Human probabilistic reward/conflict

A (80%) B (20%) C (70%) D (30%) E (60%) F (40%)

Low Conflict: e.g., 80 vs 30% $H(p_{\text{softmax}}) = 0.6$

High Conflict: e.g., 80 vs 70% $H(p_{\text{softmax}}) = 0.84$
Human probabilistic reward/choice conflict

Need STN to prevent impulsive responses

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

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

$H(softmax_{H})(p) = 0.84$

$H(softmax_{H})(p) = 0.96$
Human probabilistic reward/choice conflict

Need STN to prevent impulsive responses

\[ H_{\text{softmax}}(p) \]

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

\[ H_{\text{softmax}}(p) = 0.6 \]

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

\[ H_{\text{softmax}}(p) = 0.84 \]
human STN spiking, Zaghloul et al., 2012
STN-DBS reverses conflict RT adjustments

Frank, Samanta, Moustafa & Sherman (2007)

See also Wylie et al. 10; Habibis et al. 09; Cavannah et al. 11; Coulthard et al. 12; Green et al. 13
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

More precise predictions to be tested:

- Does DBS alter this relationship?
- Does STN-DBS alter the relationship?
- Does STN represent reinforcement conflict?
- Does mediofrontal cortex and STN represent reinforcement conflict?
- Does mediofrontal conflict vary as a function of mediofrontal conflict?

Simulations: STN modulates decision threshold × cortical 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 ($a$, $z$, $T_{rel}$) separately from other factors ($v$)

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 ($a$), separately from other factors
Contrasting drift rate vs threshold
Mediation of mitochondrial influence over decision threshold

Subthalamic nucleus stimulation reverses
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?
Broader speculations: Why does motor control develop so slowly in humans?

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

• "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."

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

Why does motor control develop so slowly in humans?

Hypothesis: Human brain is wired to discover generalizable structure....

‘Fourth trimester’

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

But 3 month old infants still pretty incompetent (from babycenter.com):
which is initially inefficient.
Abstracting Task-set rules

TS as abstract rule objects
Reverberi et al 2011
Woolgar et al 2011
TS\textsubscript{2}
TS\textsubscript{1}
S\textsubscript{12}
A\textsubscript{12}
S\textsubscript{11}
A\textsubscript{11}
Latent task-set space
Abstracting Task-sets Rules
Abstracting Task-sets rules
Abstracting Task-sets rules

TS₂ → S₁₂ → A₁₂
TS₁ → S₁ → A₁
Abstracting Task-sets rules
Abstracting Task-sets rules

Latent task-set space: Unknown size
Prior prob on TS space given a new C:

Task-sets are clustered

C-TS model

- Chinese Restaurant Process (Jordan, Blei 2005)
- \( \alpha > 0 \): Clustering parameter

\[
\frac{\lambda}{(1 + \alpha)} p(SL) \frac{\lambda}{\alpha} = \begin{cases} (1 + \alpha) p(SL) \frac{\lambda}{\alpha}, & \text{if } m_{eu} \neq m_A \\ (1 + \alpha) p(SL) \frac{\lambda}{\alpha}, & \text{if } m_{eu} = m_A \end{cases}
\]
Implementation
Neurobiologically plausible
Implementation
Neurobiological plausibly
Neurobiologically plausible
Implementation
Implimentation
Neurobiologically plausible
Predicts positive, negative transfer

The network learns efficiently unsupervised.

Neural Network – Results

NEW TS
OLD TS
new contexts:
Phase 2

Transfer Experiment
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 α clustering

Collins & Frank 2013 Psych Rev