An Illustration of Model-Based Cognitive Neuroscience

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model-based cognitive neuroscience
Traditional Computational Neuroscience

start with detailed circuit-level models of neurons and networks, which could include specifying receptor and spiking dynamics

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Model-based Cognitive Neuroscience

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Traditional Computational Neuroscience

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Model-based Cognitive Neuroscience

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- evaluate competing hypotheses about mechanisms by testing nested or non-nested architectures based on statistical criteria
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Model-based Cognitive Neuroscience

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evaluate competing hypotheses about mechanisms by testing nested or non-nested architectures based on statistical criteria

predicted temporal markers and patterns of brain activity and test hypotheses about global network properties
Model-based Cognitive Neuroscience

start with a model of detailed behavior, often a model with significant generalizability and practical applicability

Cognitive Psychometrics: characterize individual differences in cognitive performance (education, workforce training, remediation) in terms of parameters of cognitive models rather than purely statistical models of behavioral measures

Computational Psychiatry: characterize individual differences caused by disease or injury in terms of parameters of cognitive models rather than classical psychiatric or neuropsychological tests
From circuits to behavior: a bridge too far?

Matteo Carandini

Neuroscience seeks to understand how neural circuits lead to behavior. However, the gap between circuits and behavior is too wide. An intermediate level is one of neural computations, which occur in individual neurons and populations of neurons. Some computations seem to be canonical: repeated and combined in different ways across the brain. To understand neural computations, we must record from a myriad of neurons in multiple brain regions. Understanding computation guides research in the underlying circuits and provides a language for theories of behavior.
accumulation of evidence models
accumulation of evidence models
accumulation of evidence models

perceptual processing time
perceptual processing time

accumulation of evidence models

motor response

time
accumulation of evidence models

perceptual processing time

motor response

time
accumulation of evidence models

perceptual processing time

motor response

drift

$a$

$\text{z}$

$T_R$

$T_M$

time

e.g., Brown & Heathcote 2008; Busemeyer & Townsend 1993; Laming 1968; Link 1975; Nosofsky & Palmeri 1997; Palmeri 1997; Ratcliff & Rouder 1998; Ratcliff & Smith 2004; Smith & Van Zandt 2000; Usher & McClelland 2001
accumulation of evidence models

\[ \frac{\text{sim}(\text{target})}{\text{sim}(\text{other})} = \text{drift rate} \]

\[ T_R \]

\[ T_M \]

\[ \text{motor response} \]

e.g., Nosofsky & Palmeri, 1997, 2015; Palmeri 1997
accumulation of evidence models

e.g., Mack & Palmeri, 2010
accumulation of evidence models

e.g., Purcell et al., 2010, 2012
neural data

behavioral data

perceptual processing time

motor response

e.g., Forstmann et al 2008, Mansfield et al 2013, White et al 2012
neural data

behavioral data

joint Bayesian modeling

e.g., Turner et al 2013, 2015
Neuron types are determined by their response characteristics during an initial memory-guided saccade task. Cognitive models account for individual subject behavior.

**Behavioral Data**

- **PDF Distribution**
  - Easy: Peak at 150 ms, decreasing to 0 at 500 ms
  - Hard: Peak at 300 ms, decreasing to 0 at 500 ms

**Neural Data**

- Spikes/sec: 150 spikes/sec
- Time from target (ms): -300 to 150
- Time from saccade (ms): 100 to 500
Neuron types are determined by their response characteristics during an initial memory-guided saccade task.

Braden Purcell Gordon Logan Jeff Schall
predicting the neural and behavioral dynamics of perceptual decisions by awake behaving monkeys

where and when to move the eyes
brainstem
oculomotor
saccade system
visually-responsive neurons

- respond to task-defined targets
- respond whether a saccade is made or not
- magnitude of response varies with similarity

e.g., Bruce & Goldberg 1985; Bichot et al 1996; Bichot & Schall 1999
- hitting "threshold" triggers saccade
- ramping to threshold is not ballistic

movement-related neurons

visually-responsive neurons

target in RF
distracter in RF

behavioral response time

spike rate

time

e.g., Bruce & Goldberg 1985; Hanes & Schall 1996
- hitting "threshold" triggers saccade movement-related neurons
- ramping to threshold is not ballistic

visually-responsive neurons

target in RF
distracter in RF

behavioral response time

spike rate vs. time

e.g., Bruce & Goldberg 1985; Hanes & Schall 1996
perceptual processing time

motor response

movement-related neurons

visually-responsive neurons

target in RF

distracter in RF

spike rate

time

Purcell et al 2010 Psy Review

Purcell et al 2012 J of Neurosci
perceptual processing
time

motor response

T

TR

TM

target in RF
distracter in RF

visually-responsive neurons

neural data constrains the cognitive model

model parameters are replaced by observed neural recordings

movement-related neurons

behavioral response time

time

spike rate

spike rate

time

spike rate

time

spike rate

spike rate

motor response

T_M
perceptual processing time  

a

TRT

behavioral response time  

predicts when and where the monkey moves its eyes

neural data constrains the cognitive model

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movement-related neurons

spike rate

time

visually-responsive neurons

spike rate

time

spike rate

time

target in RF

distracter in RF

neural data constrains the cognitive model

model parameters are replaced by observed neural recordings

motor response

T_M

target in RF

distracter in RF
stochastic accumulator for each object location in the visual array

Target

Distractor

accumulator for saccade to target location

accumulator for saccade to distractor location

saccade execution
Target stochastic accumulator for each object location in the visual array

Distractor accumulator for saccade to target location

Target

Distractor

stochastic accumulator for each object location in the visual array
stochastic accumulator for each object location in the visual array

accumulator for saccade to target location

m_T

accumulator for saccade to distractor location

m_D
test competing model architectures for perceptual decisions

multiple independent artificial neurons
more complex models

test competing model architectures for perceptual decisions

more complex models
gated accumulator model
\[ dm_i(t) = \frac{dt}{\tau} \left[ (v_i(t) - \sum_{i' \neq i} u_{i'} v_{i'}(t) - g)^+ - \sum_{i' \neq i} \beta_d m_{i'}(t) - k \cdot m_i(t) \right] + \sqrt{\frac{dt}{\tau}} \xi \]
Accuracy
Correct RTs
Error RTs

Purcell et al 2012, J of Neurosci
successful models predict behavior: quantitative model fitting and model comparison

Purcell et al 2012, J of Neurosci
Accuracy

Correct RTs

Error RTs

Time

Spike rate

Predicts when and where the monkey moves its eyes

Model parameters are replaced by observed neural recordings
Model parameters are replaced by observed neural recordings, which predicts when and where the monkey moves its eyes.
The diagram illustrates the spike rate of neurons over time, with arrows indicating the direction of predictions:

- Target in RF predicts dynamics of movement-related neurons.
- Distracter in RF predicts when and where the monkey moves its eyes.
- Model parameters are replaced by observed neural recordings.

Accuracy, Correct RTs, and Error RTs are shown in separate plots, indicating the predictive nature of the neural recordings on behavior and movement.
successful models predict neural dynamics: compare model dynamics with neural dynamics
successful models predict neural dynamics: compare model dynamics with neural dynamics

we wanted to go beyond merely showing that neural “squiggles” look like model “squiggles”
successful models predict neural dynamics: compare model dynamics with neural dynamics
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successful models predict neural dynamics: compare model dynamics with neural dynamics

![Graph showing time activity with Fast RT, Medium RT, and Slow RT categories]
successful models predict neural dynamics: compare model dynamics with neural dynamics

how does onset vary with RT?

Woodman et al 2008
successful models predict neural dynamics: compare model dynamics with neural dynamics

we can measure this in neurons and accumulators
successful models predict neural dynamics: compare model dynamics with neural dynamics

- Fast RT
- Medium RT
- Slow RT

Activity over time
successful models predict neural dynamics: compare model dynamics with neural dynamics

Fast RT

Medium RT

Slow RT

activity

time
successful models predict neural dynamics:
compare model dynamics with neural dynamics
successful models predict neural dynamics: compare model dynamics with neural dynamics

how does rate vary with RT?
successful models predict neural dynamics: compare model dynamics with neural dynamics

we can measure this in neurons and accumulators
successful models predict neural dynamics: compare model dynamics with neural dynamics

how does baseline vary with RT?
successful models predict neural dynamics:
compare model dynamics with neural dynamics

how does threshold vary with RT?
models predict neural dynamics: compare model dynamics with neural dynamics

parameter-free predictions of neural data by a gated accumulator model fitted to behavioral data

Purcell et al 2010, Psy Rev
Purcell et al 2012, J of Neurosci
models predict neural dynamics: compare model dynamics with neural dynamics

parameter-free predictions of neural data by a gated accumulator model fitted to behavioral data

Purcell et al 2010, Psy Rev
Purcell et al 2012, J of Neurosci
models predict neural dynamics: compare model dynamics with neural dynamics

parameter-free predictions of neural data by a gated accumulator model fitted to behavioral data

Purcell et al 2010, Psy Rev
Purcell et al 2012, J of Neurosci
use neural data for model selection:
only some models make correct qualitative and quantitative predictions of neural dynamics
use neural data for model selection: only some models make correct qualitative and quantitative predictions of neural dynamics

non-gated accumulator

gated accumulator

Purcell et al 2010, Psy Rev
use neural data for model selection: only some models make correct qualitative and quantitative predictions of neural dynamics

non-gated accumulator

gated accumulator

Purcell et al 2010, *Psy Rev*
Purcell et al 2012, *J of Neurosci*
Accuracy
Correct RTs
Error RTs

predicts dynamics of movement-related neurons

time
spike rate

predicts when and where the monkey moves its eyes

Accuracy
Correct RTs
Error RTs

model parameters are replaced by observed neural recordings

T_M

target in RF
distracter in RF

spike rate
time
Neuron types are determined by their response characteristics during an initial memory-guided saccade task.
Memory Task

Neuron types are determined by their response characteristics during an initial memory-guided saccade task.
Neuron types are determined by their response characteristics during an initial memory-guided saccade task.
perceptual processing time

motor response

T_R

T_M
perceptual processing time

motor response

spike rate

time

perceptual processing time

motor response

T_R

T_M

z

drift

a
perceptual processing time

motor response

Zandbelt et al. 2014 PNAS
Activation

Time from target

Zandbelt et al 2014 PNAS
Ensemble Size

[Diagram showing network structure with nodes and connections labeled A₁, A₂, I₁, I₂, etc., with arrows indicating direction of information flow. The diagram also illustrates the concept of ensemble size, with different levels of network complexity depicted.]
1 accumulator per choice

N accumulators per choice

Zandbelt et al 2014 PNAS
$N$ accumulators (1 – 1000)
accumulation rate correlation, $r_v$
Pooling Mechanism

e.g., Wong & Wang, 2006
Polling Mechanism
(termination rule, $p_N$ accumulators hit threshold)

predicted response
time distribution
Predicted Response Time Distribution

\[ f(t) \]

time (t)
Predicted Response Time Distribution
Termination rule, $p$

Accumulation rate correlation, $r$

Zandbelt et al 2014 PNAS
Zandbelt et al. 2014, PNAS

Termination rule, p

RT (ms)

0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0

10% first 20% 30% 40% 50% 60% 70% 80% 90% 100% mean

Accumulation rate correlation, r

N accumulators

1 10 100 1000

quintile RT
Zandbelt et al. 2014
PNAS
correlation

Termination rule

$r_V = 0.2 \quad p_N = 30\%$

Zandbelt et al 2014 PNAS
Accumulation rate correlation, $r_v$

Termination rule, $p_N$

$r_V = 0.2 \quad p_N = 30\%$
Termination rule, $p_N$

Accumulation rate correlation, $r$

RT (ms)

Accumulation rate: 'first' - 'pool'

10% - 100%
predicted RT distributions from ensembles of accumulators are invariant to ensemble size so long as there is some degree of correlation in accumulation rates and so that RT is not driven by the fastest or slowest accumulator to hit threshold.
Termination rule, \( p_N \)

Predicted RT distributions from ensembles of accumulators are invariant to ensemble size above a small number of accumulators so long as there is some degree of correlation in accumulation rates and so that RT is not driven by the fastest or slowest
only with no rate correlation and extreme termination rules do predicted RT distributions vary systematically with ensemble size
Neuron types are determined by their response characteristics during an initial memory-guided saccade task.
Neuron types are determined by their response characteristics during an initial memory-guided saccade task.

Braden Purcell
Akash Umakantha Purcell
time
spike rate
behavioral response
time
deficit
motor response
perceptual processing time
T_R
T_M
the most complex structure in the known universe with uncountable structural, biophysical, and biochemical parameters

fairly abstract cognitive model that generalizes widely across subjects, tasks, and modalities with few parameters
the most complex structure in the known universe with numerous structural, biophysical, and biochemical parameters

tens of thousands of accumulating neurons per potential response

fairly abstract cognitive model that generalizes widely across subjects, tasks, and modalities with few parameters

one simulated accumulator unit per potential response
the most complex structure in the known universe with numerous structural, biophysical, and biochemical parameters

tensof thousands of accumulating neurons per potential response

behavior emerges from a highly complex nonlinear nonstationary stochastic system

fairly abstract cognitive model that generalizes widely across subjects, tasks, and modalities with few parameters

one simulated accumulator unit per potential response

predictions often derived from a closed-form mathematical equation
Data

response probabilities and distributions of error and correct response times

Predictions

response probabilities and distributions of error and correct response times
neural data

behavioral data

e.g., Forstmann et al 2008, Mansfield et al 2013, White et al 2012
Data

response probabilities and distributions of error and correct response times

Predictions

response probabilities and distributions of error and correct response times

drift rate

threshold

experimental manipulation

experimental manipulation

perceptual processing time

motor response

T_R

T_M

z

a
Data

response probabilities and distributions of error and correct response times

Predictions

response probabilities and distributions of error and correct response times
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

Umakantha et al 2015
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

- thousands of spiking neurons
- dozens of parameters
- time-intensive simulation

- one stochastic accumulator
- handful of parameters
- closed form mathematical solution
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

**Data**

response probabilities and distributions of error and correct response times

**Predictions**

response probabilities and distributions of error and correct response times
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

**Input Sensitivity vs. Mean RT**
- Neural network
- Diffusion model

**Accuracy vs. Input Sensitivity**
input sensitivity

mean

RT

accuracy

Neural network

Diffusion model

51.2%

25.6%

12.8%

6.4%

3.2%

0%

coherence

51.2% coherence

25.6% coherence

12.8% coherence

6.4% coherence

3.2% coherence

0% coherence

Correct cells

Error cells

input sensitivity

input sensitivity

mean RT

accuracy
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

I1

I2

1

2

NS

**Input sensitivity**

**Accuracy**

**Mean RT**

**Input sensitivity**
Spiking Neural Network Model  
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model  
Ratcliff & Rouder 1998 *Psych Sci*

- **Input sensitivity**
- **Mean RT**
- **Accuracy**

- Faster
- More Accurate
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

Threshold vs. input sensitivity:
- Threshold remains constant across different input sensitivities.

Drift rate slope vs. input sensitivity:
- Drift rate slope increases linearly with input sensitivity.
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

I1, I2

Input sensitivity

Threshold

Drift rate slope

Motor response

Perceptual processing time

Drift

Input sensitivity

T_R

T_M
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

threshold

threshold

input sensitivity

input sensitivity

Drift rate slope
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

**Spiking Neural Network Model**

- **I_1**
- **I_2**
- **NS**
- **I**
- **w_+**
- **Background**

**Drift Diffusion Model**

- **perceptual processing time**
- **drift**
- **a**
- **motor response**
- **T_R**
- **T_M**

**Graph**

- **Firing rate (Hz)**
- **Time (ms)**
- **Threshold**
- **Toward RF**
- **Away RF**
- **c' = 51.2%**
- **c' = 0%**

---

*Images and diagrams representing spiking neural network and drift diffusion models.*
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

- **I**
- **NS**
- **1**
- **2**

Firing rate (Hz) vs. Time (ms)

Threshold

- **Toward RF**
- **Away RF**

- **c' = 51.2%**
- **c' = 0%**

- **T_R**
- **T_M**

- **motor response**
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

**Firing rate (Hz)**
- **Threshold:**
  - **Toward RF:**
    - $c' = 51.2\%$
  - **Away RF:**
    - $c' = 0\%$

**Time (ms)**
- $0 - 2000$

**Variables:**
- $I_1$, $I_2$
- $w_+$
- **Background**
- $T_R$, $T_M$
- $a$, $z$
- Motor response
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

- Faster
- Less Accurate

- Slower
- More Accurate
Spiking Neural Network Model
Wong & Wang 2006 J of Neurosci

Drift Diffusion Model
Ratcliff & Rouder 1998 Psych Sci

- Threshold
- Drift rate slope
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

- **I** _1_ → **NS** → **I** → **I** _2_
- **I** _1_ → Background

- **T_\text{R}**
- **T_\text{M}**
- **a**
- **z**

- **Neural network**
- **Diffusion model**

<table>
<thead>
<tr>
<th>Neural network</th>
<th>Diffusion model</th>
</tr>
</thead>
<tbody>
<tr>
<td>51.2%</td>
<td>-</td>
</tr>
<tr>
<td>25.6%</td>
<td>-</td>
</tr>
<tr>
<td>12.8%</td>
<td>-</td>
</tr>
<tr>
<td>6.4%</td>
<td>-</td>
</tr>
<tr>
<td>3.2%</td>
<td>-</td>
</tr>
<tr>
<td>0.0%</td>
<td>-</td>
</tr>
</tbody>
</table>

Graphs showing:
- Mean RT vs. recurrent excitation
- Accuracy vs. recurrent excitation

- Faster
- Less Accurate
Spiking Neural Network Model
Wong & Wang 2006 J of Neurosci

Drift Diffusion Model
Ratcliff & Rouder 1998 Psych Sci

<table>
<thead>
<tr>
<th>threshold</th>
<th>drift rate slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.14</td>
<td>0.02</td>
</tr>
<tr>
<td>0.10</td>
<td>0.01</td>
</tr>
<tr>
<td>0.06</td>
<td>0.01</td>
</tr>
</tbody>
</table>

1.65  1.70  1.75  1.65  1.70  1.75  
recurrent excitation  recurrent excitation
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*
Spiking Neural Network Model
Wong & Wang 2006 J of Neurosci

Drift Diffusion Model
Ratcliff & Rouder 1998 Psych Sci

Threshold

Mean RT

Accuracy

Faster

Less Accurate

NMDA conductance
Spiking Neural Network Model
Wong & Wang 2006 J of Neurosci

Drift Diffusion Model
Ratcliff & Rouder 1998 Psych Sci

threshold

0.14
0.12
0.10
0.08
0.06

1.63
1.65
1.67

NMDA conductance

drift rate slope

0.02
0.01

1.63
1.65
1.67

NMDA conductance
Spiking Neural Network Model
Wong & Wang 2006 *J of Neurosci*

Drift Diffusion Model
Ratcliff & Rouder 1998 *Psych Sci*

perceptual processing

motor response

$I_1$ $w_+$

$I_2$ $w_+$

NS

$T_0$

$T_M$

$a$
perhaps not surprisingly, there is a **many-to-one** mapping between parameters of a neural model and parameters of a cognitive model, but this need *not* be a **many-to-many** mapping
perhaps not surprisingly, there is a many-to-one mapping between parameters of a neural model and parameters of a cognitive model, but this need not be a many-to-many mapping

also, at least when it comes to modeling behavior alone (educational, clinical, practical applications), the cognitive model may be sufficient to capture the important regularities produced by neural mechanisms
Illustration of Model-based Cognitive Neuroscience

abstract cognitive neural ensemble

behavioral data

neural data

Illustration of Model-based Cognitive Neuroscience

Illustration of Model-based Cognitive Neuroscience
Illustration of Model-based Cognitive Neuroscience

cognitive models account for individual subject behavior

abstract cognitive neural ensemble

behavioral data

neural data
Illustration of Model-based Cognitive Neuroscience

cognitive models account for individual subject behavior

neural data can inform and constrain cognitive models

behavioral data

abstract cognitive

neural ensemble

neural data
Illustration of Model-based Cognitive Neuroscience

cognitive models account for individual subject behavior

neural data can inform and constrain cognitive models

abstract cognitive
neural ensemble

behavioral data

scaling simple cognitive models can provide insight into properties of neural ensembles
Illustration of Model-based Cognitive Neuroscience

cognitive models account for individual subject behavior

neural data can inform and constrain cognitive models

abstract cognitive neural ensemble

scaling simple cognitive models can provide insight into properties of neural ensembles

linking cognitive models with neural models can highlight regularities across levels as well as limitations on inference