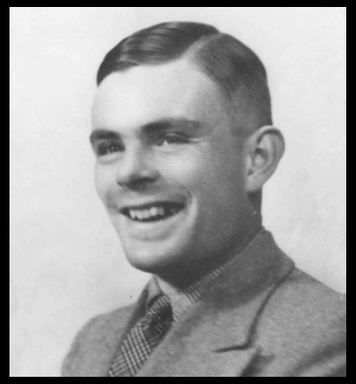
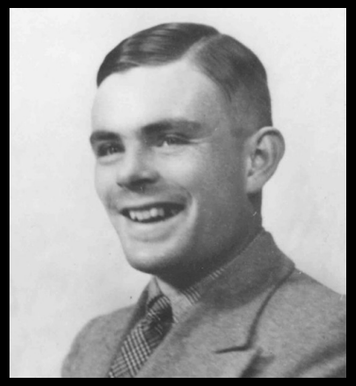
How to make computers work like the brain

(without really solving the brain)

Dileep George



“a single special machine can be made to do the work of all. It could in fact be made to work as a model of any other machine.”
Alan Turing 1937



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Mathematics
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Video
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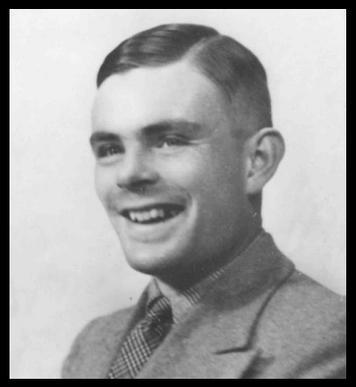

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Visual perception
Auditory perception
Somatosensory perception
Languages
Adaptive behavior
Planning, thinking,

Intelligence paradigms

Intelligence paradigms

- Early AI (1940s to 1970s)

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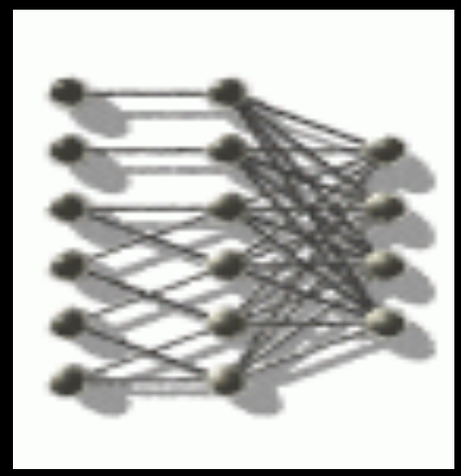
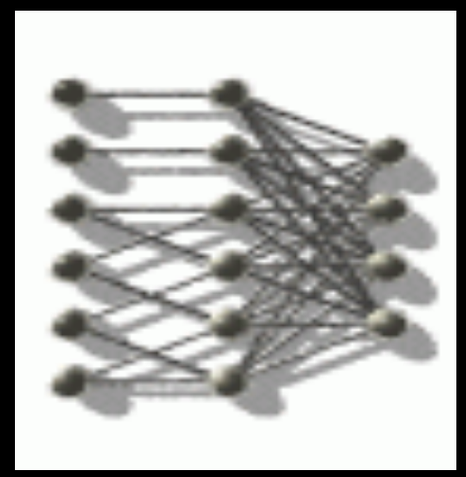
Intelligence Paradigms



Intelligence Paradigms

- Neural Networks (1980s and 1990s)

Intelligence Paradigms



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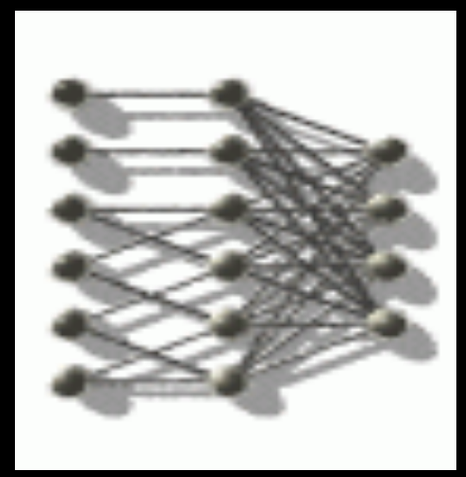
Intelligence Paradigms



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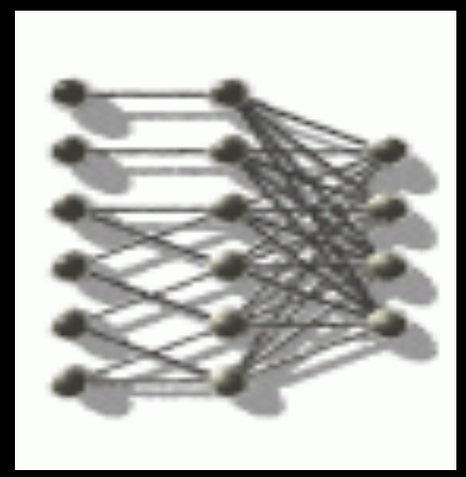

- Neural Networks (1980s and 1990s)
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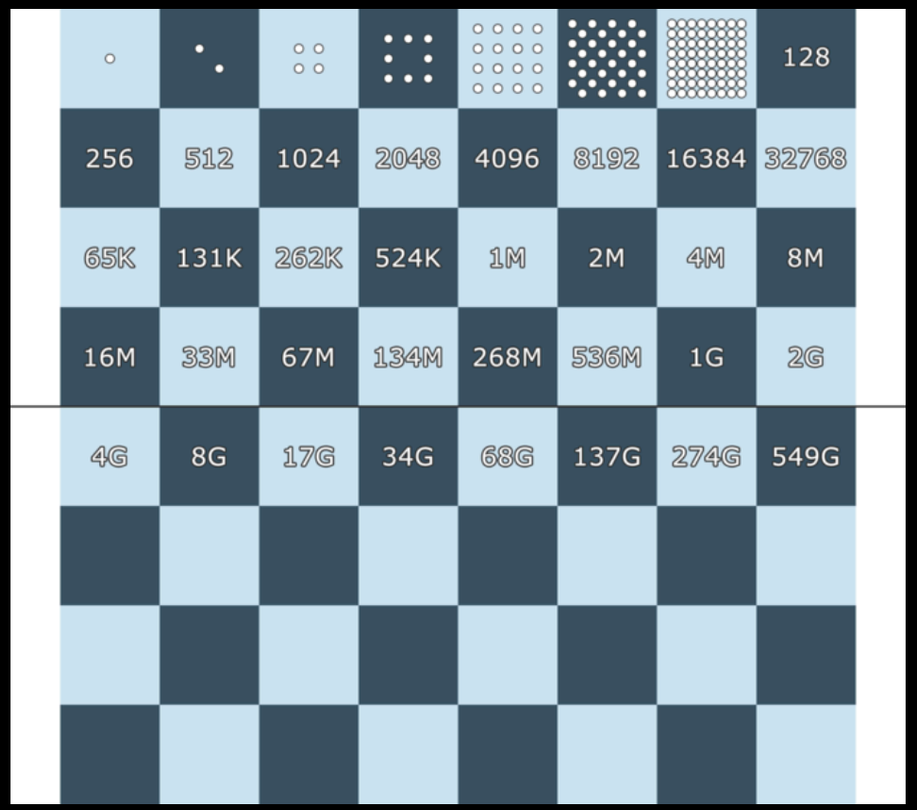
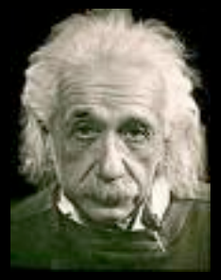
- The problem of scale

Story of chess..



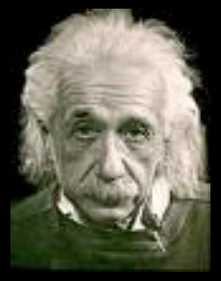
Sample complexity of learning



Face Non-face

256^1024

Sample complexity of learning



Face

Non-face

256^1024

256^1024=

256^1024=

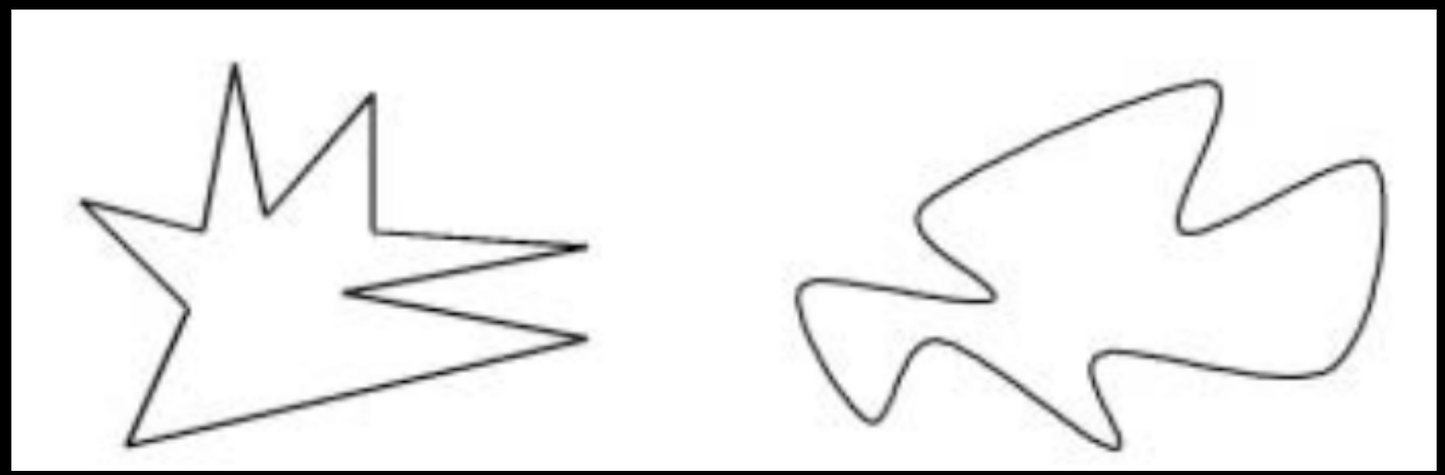
- 1090748135619415929462984244733782862448264161996232692431832786189721331849119295216264234525201987223957291796157025273109870820177184063610979765077554799078906298842192989538609825228048205159696851613591638196771886542609324560121290553901886301017900252535799917200010079600026535836800905297805880952350501630195475653911005312364560014847426035293551245843928918752768696279344088055617515694349945406677825140814900616105920256438504578013326493565836047242407382442812245131517757519164899226365743722432277368075027627883045206501792761700945699168497257879683851737049996900961120515655050115561271491492515342105748966629547032786321505730828430221664970324396138635251626409516168005427623435996308921691446181187406395310665404885739434832877428167407495370993511868756359970390117021823616749458620969857006263612082706715408157066575137281027022310927564910276759160520878304632411049364568754920967322982459184763427383790272448438018526977649410727156115804346908274593399919614142427414105991174260605564837637563145276113626586283833686211579936380208785376755453367899156942344339556663150700872135354702556703120041307254958345083574396538289360770809785505789129679073527800549356215610907958451729541159729274798775277385600082041185589300047777487277618538135104938405818615986522116059603083564059418211897140378687262194814987276036536162988561748224130334854387853240247514194171830122810782097293035373728045743720952287036227763639452908698062584223551485075710396193874496298668081887696628157781530793931790931436483407617385818195630029944227907549550612888183084300796486932321791587659180355652161571154029921202761556078731079374774668415283629877086994501520312318625942030856938389446570613462367042340268211029589549511970870765461866227962945364516207565093510189060237738215395327762086769785897319663303088933046651694361850783506415683369445300514374913112988343672652385954049042734559287239495252271846174043678547546104743770197680255766058810380772707077179422219770903854385858440954921160998525389039746557039439730860909305969633607675299649384145981857059637545614973558278136238332889063090042880173214248086639626713335280092327583508730596141187237814221014601986157473868550968960891891804413395585248228675411132126387936755676503403629700319300233978284653185472382442320280151896896604188229760008154376106522542701635956508754338511471232142272666054035817814690908065764689505876619971865056654757157928961

256^1024=

- 10907481356194159294629842447337828624482641619962326924318327861897213318491192952162642345252019872239572917961570252731098708201771840636109797650775547990789062988421929895386098252280482051596968516135916381967718865426093245601212905539018863010179002525357999172000100796000265358368009052978058809523505016301954756539110053123645600148474260352935512458439289187527686962793440880556175156943499454066778251408149006161059202564385045780133264935658360472424073824428122451315177575191648992263657437224322773680750276278830452065017927617009456991684972578796838517370499969009611205156550501155612714914925153421057489666295470327863215057308284302216649703243961386352516264095161680054276234359963089216914461811874063953106654048857394348328774281674074953709935118687563599703901170218236167494586209698570062636120827067154081570665751372810270223109275649102767591605208783046324110493645687549209673229824591847634273837902724484380185269777649410727156115804346908274593399919614142427414105991174260605564837637563145276113626586283833686211579936380208785376755453367899156942344339556663150700872135354702556703120041307254958345083574396538289360770809785505789129679073527800549356215610907958451729541159729274798775277385600082041185589300047777487277618538135104938405818615986522116059603083564059418211897140378687262194814987276036536162988561748224130334854387853240247514194171830122810782097293035373728045743720952287036227763639452908698062584223551485075710396193874496298668081887696628157781530793931790931436483407617385818195630029944227907549550612888183084300796486932321791587659180355652161571154029921202761556078731079374774668415283629877086994501520312318625942030856938389446570613462367042340268211029589549511970870765461866227962945364516207565093510189060237738215395327762086769785897319663303088933046651694361850783506415683369445300514374913111298834367265238595404904273455928723949525227184617404367854754610474377019768025576605881038077270707717942221977090385438585844095492116099852538903974655703943973086090930596963360767529964938414598185705963754561497355827813623833288906309004288017321424808663962671333528009232758350873059614118723781422101460198615747386855096896089189180441339558524822867541113212638793675567650340362970031930023397828465318547238244232028015189689660418822976000815437610652254270163595650875433851147123214227266605403581781469090806576468950587661997186505665475715792896

Number of seconds in a human’s life: 3153600000

Origins of Language..

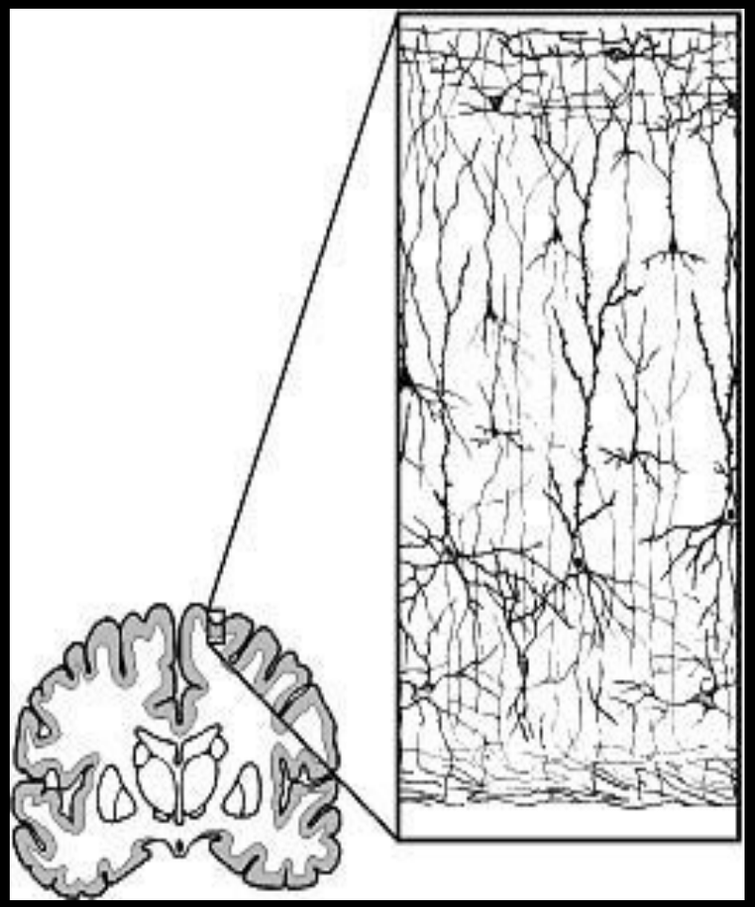


Ramachandran and Hubbard, 2001

Bouba

Kiki

Laminar structure



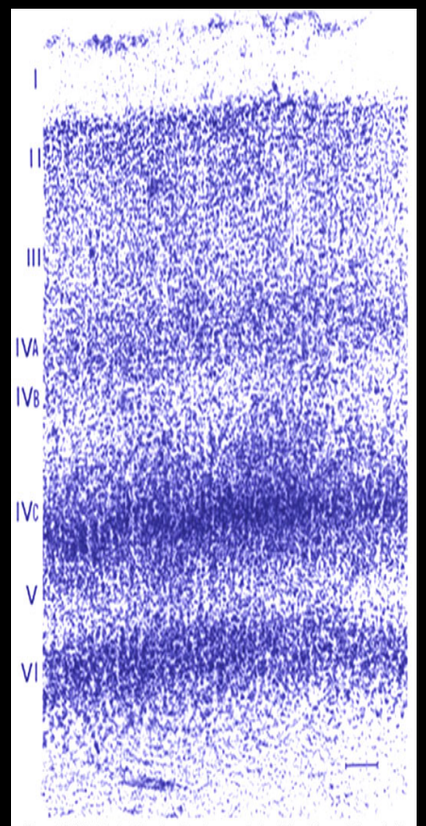


Figure 13. Nissl stain of the visual cortex reveals the different layers I through VI quite clearly.

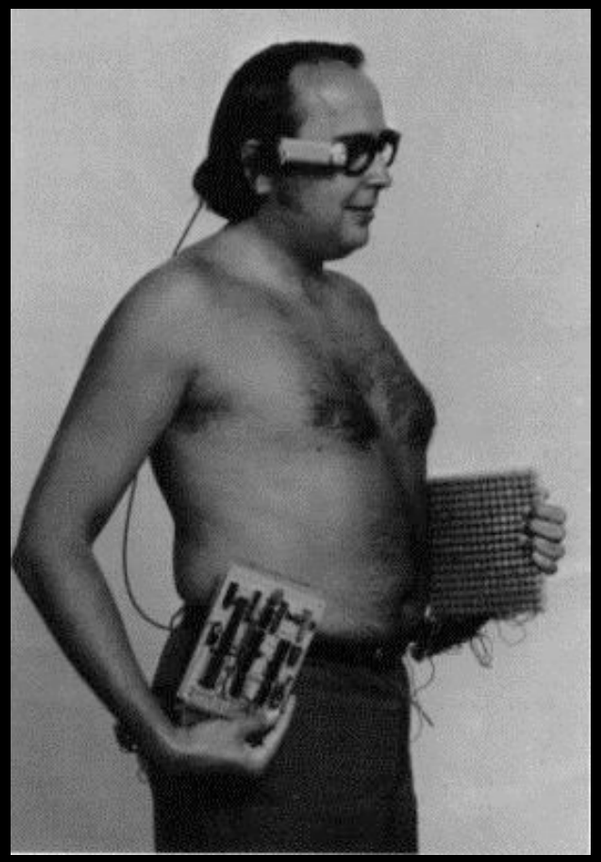
Common cortical algorithm: Supporting evidence

“Seeing in the Sound Zone," by Michael Merzenich, *Nature*, Vol. 404, April 20, 2000, pp. 820-821.

"Induction of visual orientation modules in auditory cortex," by Jitendra Sharma, Alessandra Angelucci and Mriganka Sur, *Nature*, Vol. 404, April 20, 2000, pp. 841-847

sensory substitution

sensory substitution



A sensorimotor account of vision and visual consciousness,
Kevin O’Regan and Alva Noe.
Photograph courtesy: P Bach-y-Rita

Neocortex

- Assume that:
  - Neocortex uses the same algorithm to learn different modalities
  - Neocortex learns efficiently

The No Free Lunch Theorem

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No learning algorithm has an inherent superiority over other learning algorithms for all problems.
(Wolpert, 1995)

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An algorithm's superiority comes from the assumptions that it makes about the problem

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Neocortex

- Assume that:
  - Neocortex uses the same algorithm to learn different modalities
  - Neocortex learns efficiently

=> Data from different modalities must have the same underlying statistical structure

The right question to ask..

- Are there assumptions we can make about the world that are

1. General enough to be applied to be a large number of problems
2. Specific enough to make learning possible ??

High-level properties of the neocortex

- Hierarchical organization
  - Spatial and temporal
- Using time as a supervisor
- Ability to make predictions
- Sparse Distributed Representations
- Feed-forward and feedback connections
- Sensori-motor

Abstraction levels

Consciousness
Cognitive models
Perception
Connections
High-level anatomical structure
Micro-circuit structure
Neuron models
Dendrites
Learning rules
Synapses
Ion channels
Proteins
Glia

Neocortex

Source of assumptions and constraints

World's Data (Visual/Auditory etc...)

To find correspondence with Neocortex properties

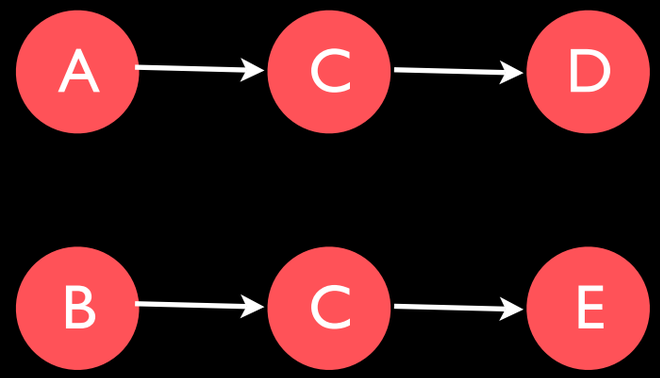
Computational Principles (Machine Learning/Graphical Models etc..)

To understand why brain does what it does in that particular way

If you are not computationally grounded,
looking into biology is like looking into a religious text.
You will always find what you are looking for.

Temporal learning example

Suppose A-C-D and B-C-E
are frequent in the data



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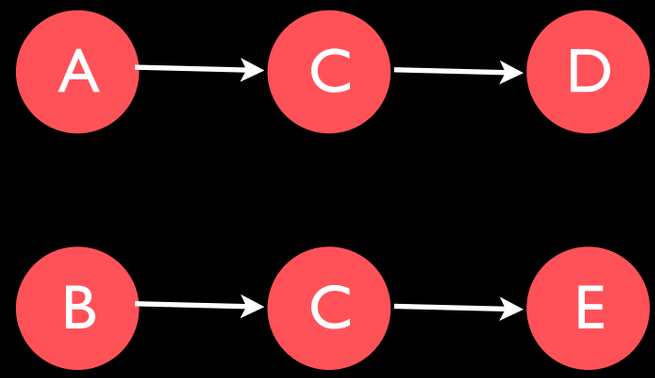
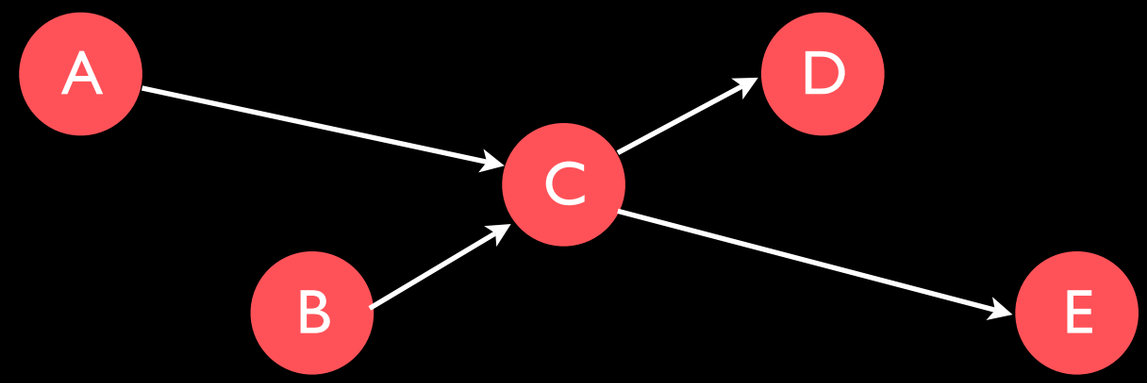


First-order model

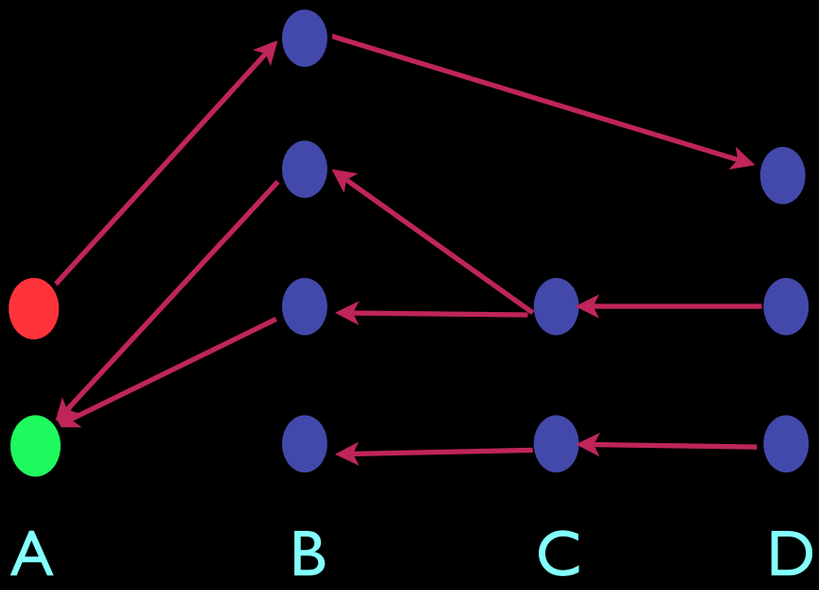


Temporal Models

N^2, but can initialize from data to create a sparse model

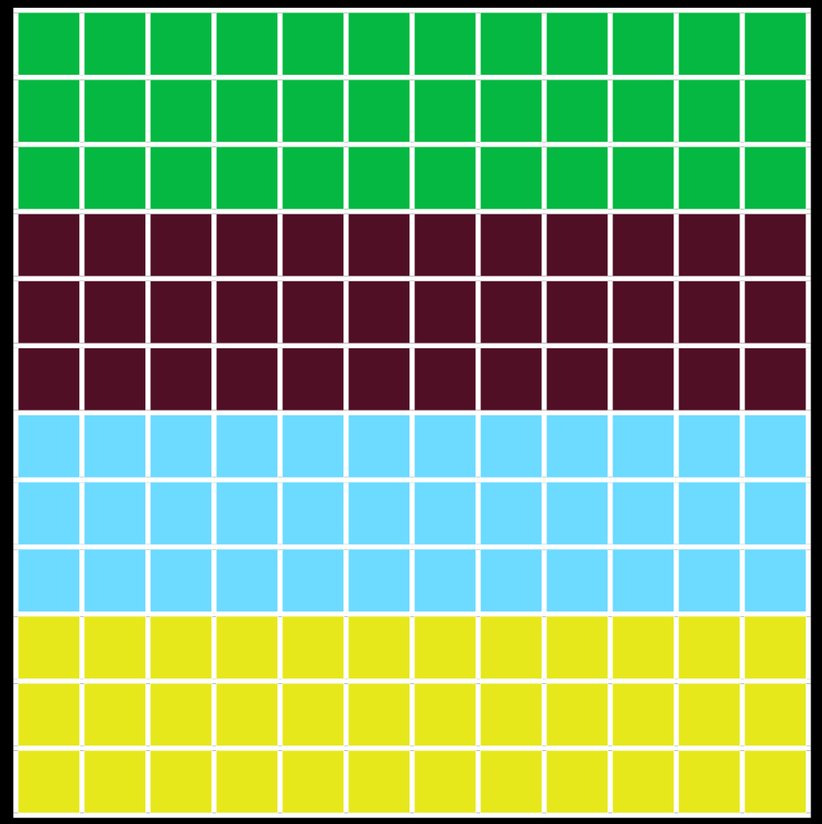
Not a scalable way to build higher order models

Variable order sequences



t

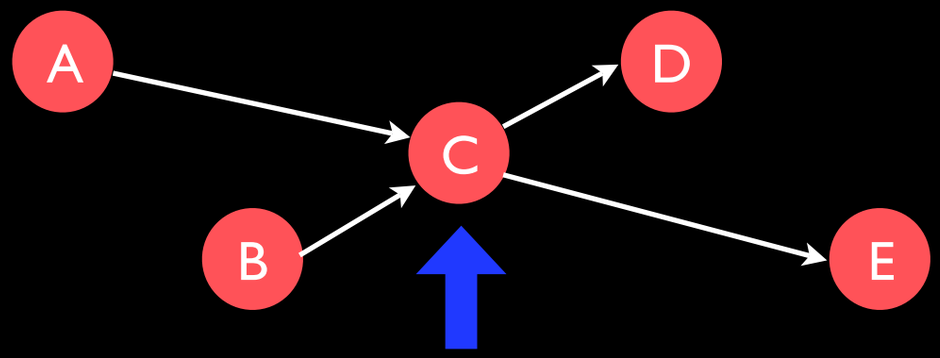
t-1



(kN)^2

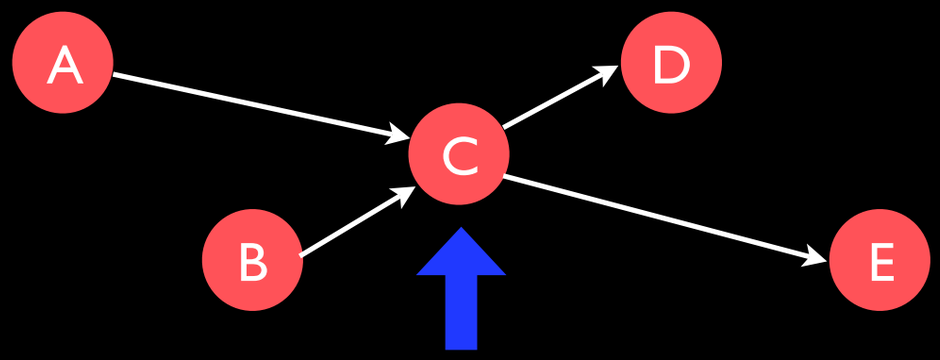
State-splitting model

First order model

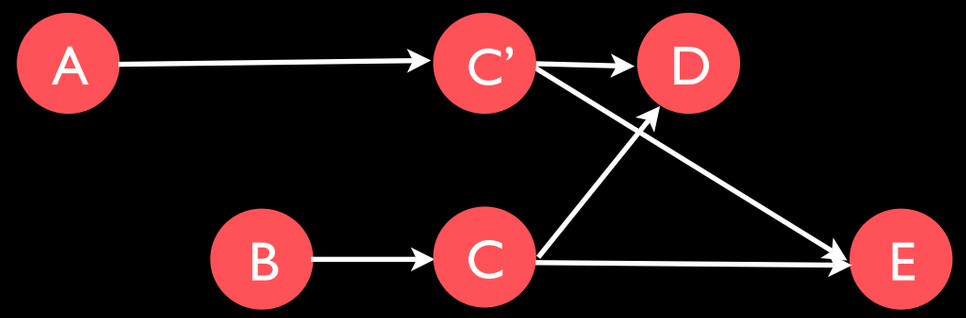


State-splitting model

First order model

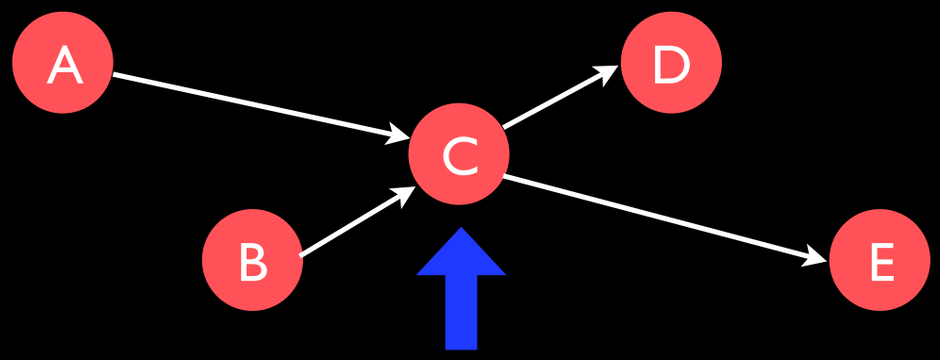


Model with replicated states

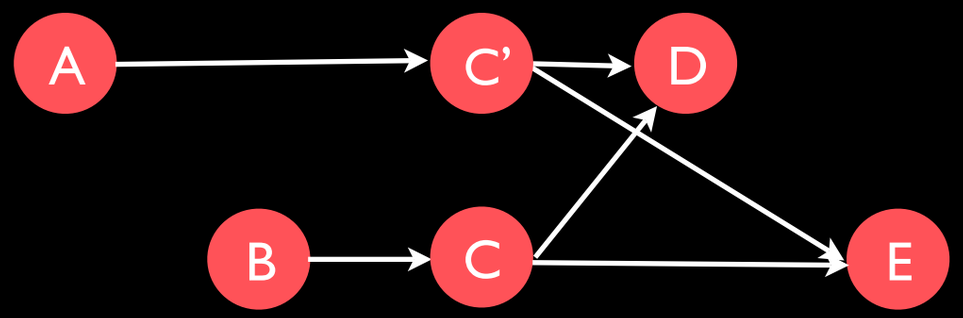


State-splitting model

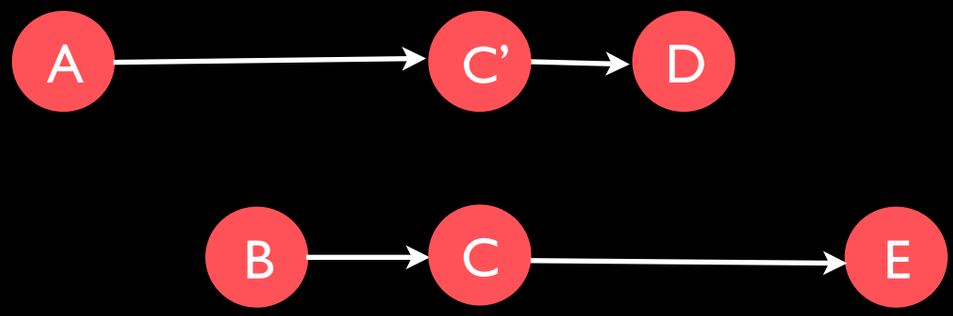
First order model



Model with replicated states



Model after further learning



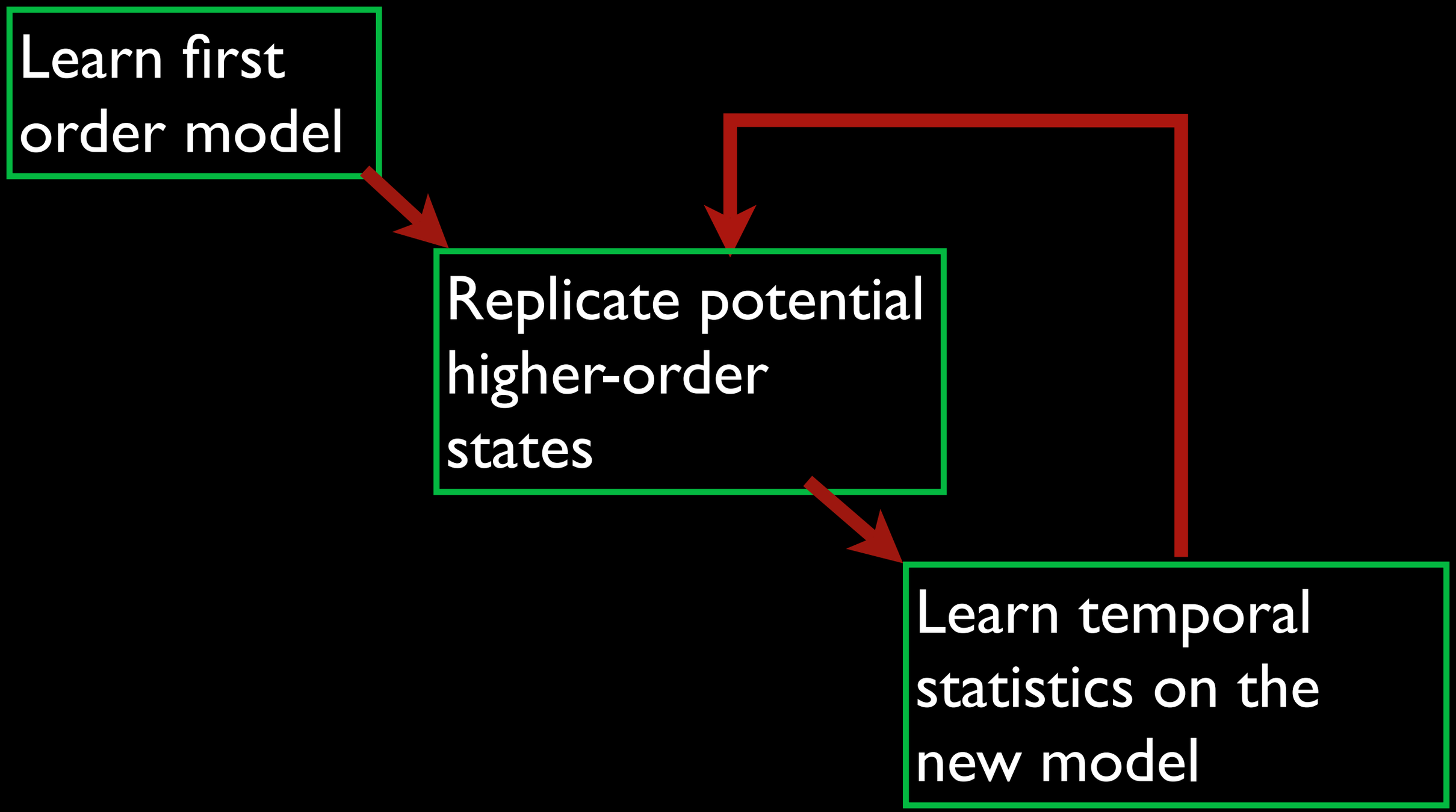
State-splitting model

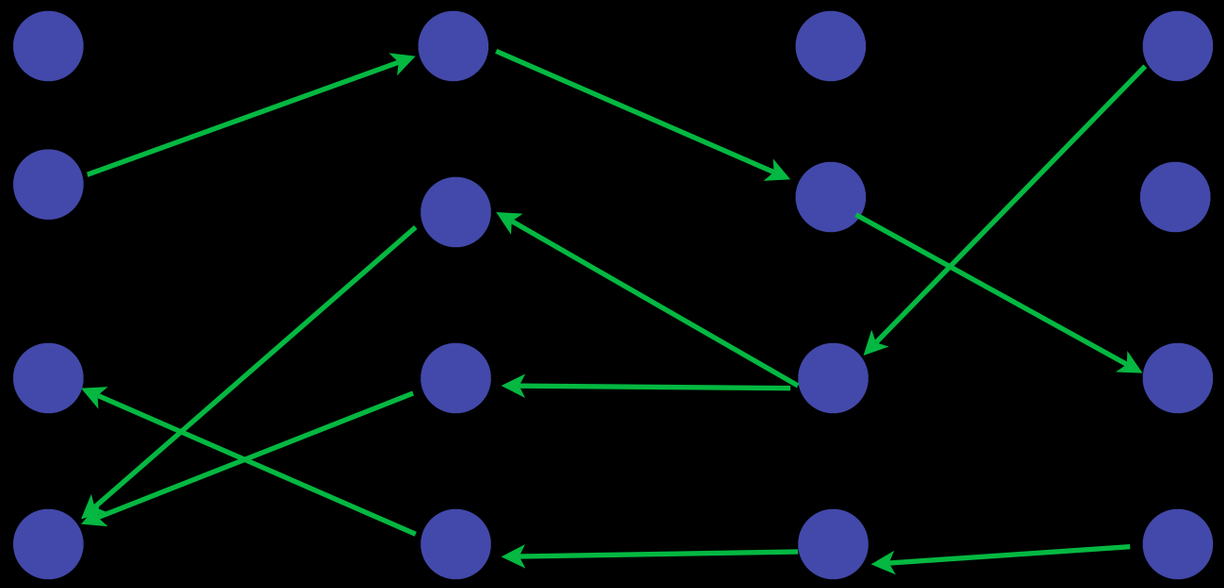
Learn first order model

Replicate potential higher-order states

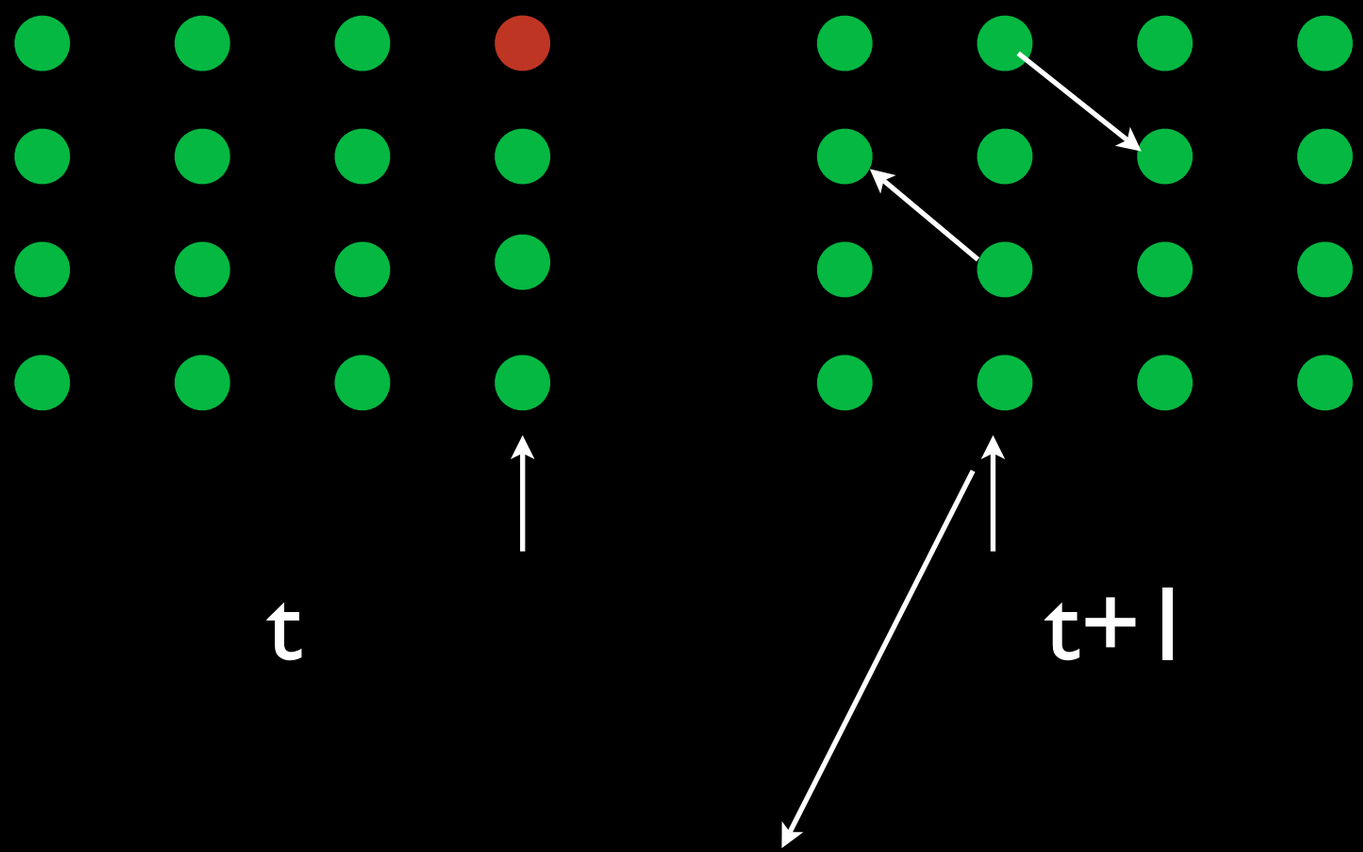
Learn temporal statistics on the new model

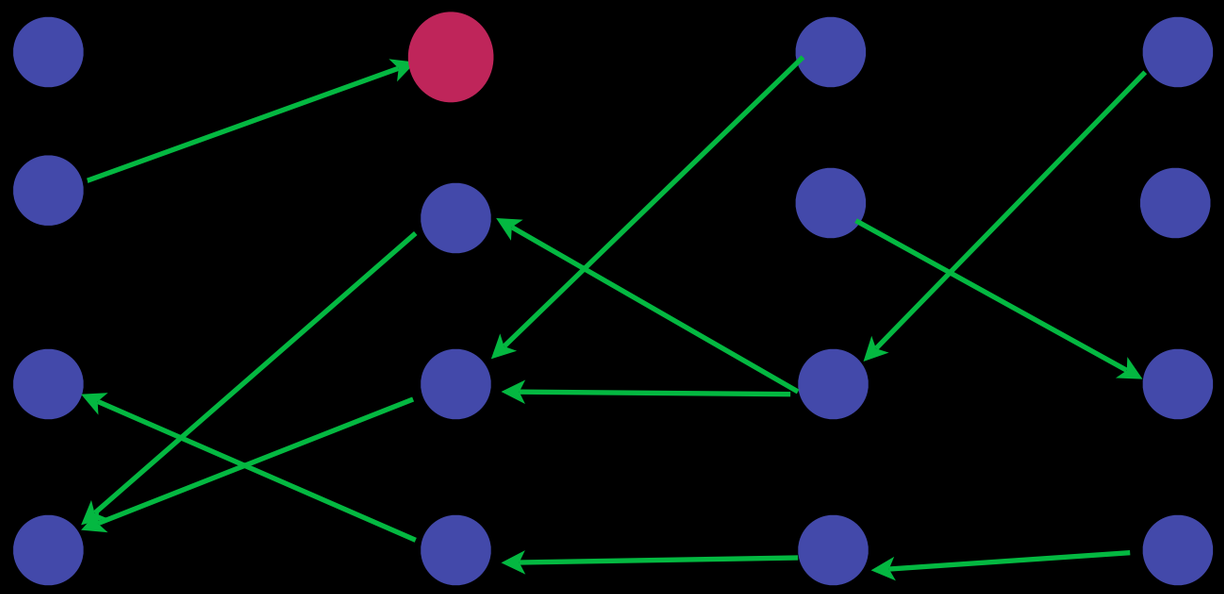
State-splitting model



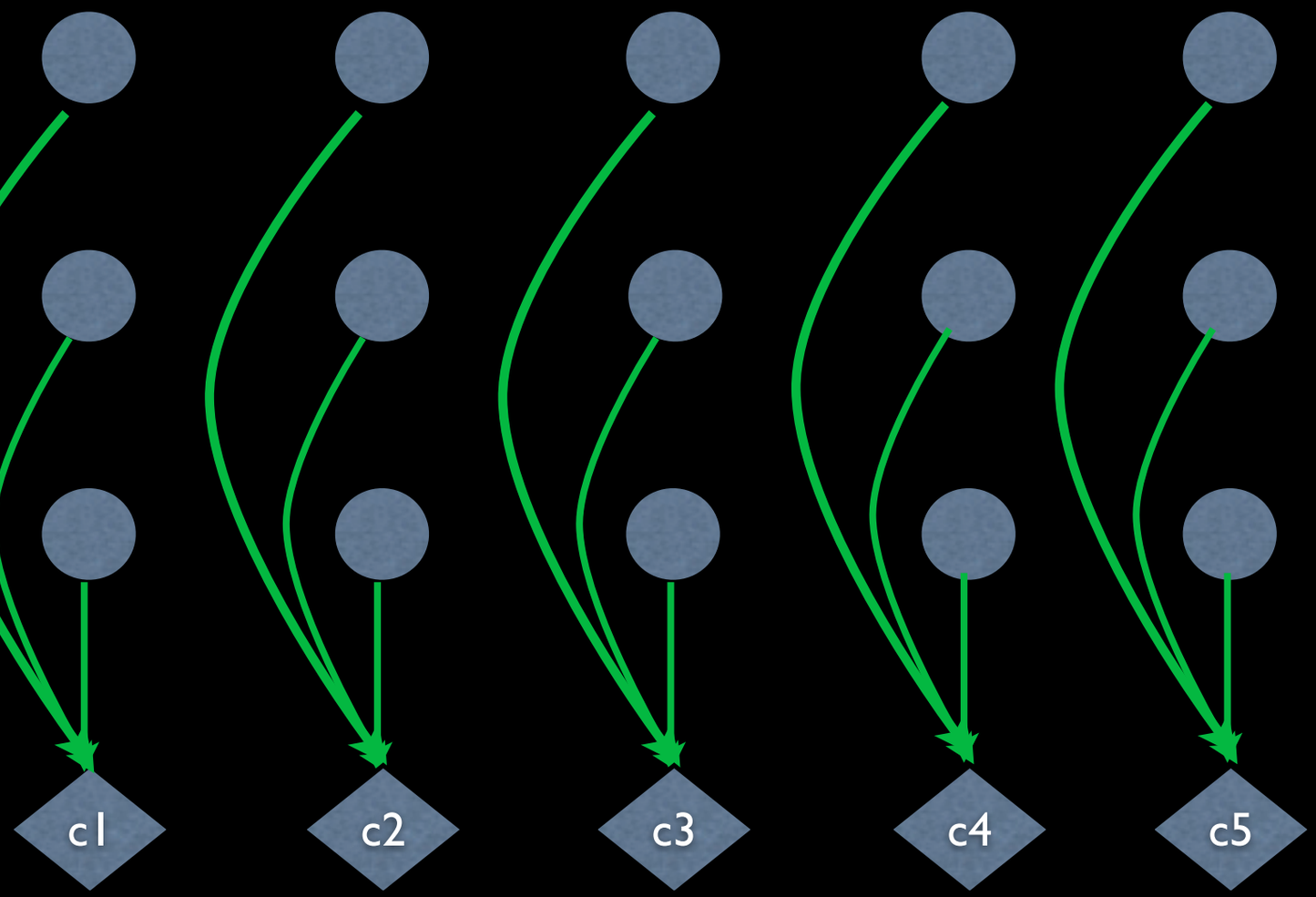


- Start with replicated states
- Should be online
- Should still be sparse and efficient


t
t+1
Which cell in this column do we connect to?



Connection to HMM



HMM and Forward-Backward

- Forward-backward algorithm
- On the restricted HMM, works very well in finding the higher-order states
- Can be made online by making reducing the look-ahead
- One step look-ahead works quite well
- Zero look-ahead (pure Hebbian learning) doesn't work well.

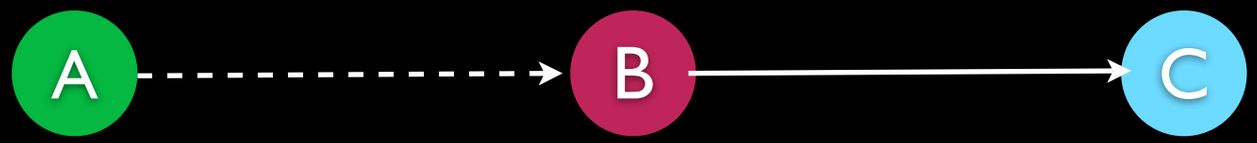
t

t+1

t+2

Which cell in this column do we connect to?

Biological implication



Can A know whether B was
successful in firing C?

The answer is YES

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Enhancement of presynaptic neuronal excitability by correlated presynaptic and postsynaptic spiking

Karunesh Ganguly[1,2], Laszlo Kiss[2] and Mu-ming Poo[1,2]

[1] *Program in Neuroscience, University of California at San Diego, La Jolla, California 92093-0357, USA*

[2] *Department of Biology, University of California at San Diego, La Jolla, California 92093-0357, USA*

The first two authors contributed equally to this work

Correspondence should be addressed to M.-m.P. (mpoo@ucsd.edu)

Use-dependent modifications, such as long-term potentiation (LTP) of synaptic efficacy, are believed to be essential for information storage in the nervous system. Repetitive correlated spiking of presynaptic and postsynaptic neurons can induce LTP at excitatory glutamatergic synapses. In cultured hippocampal neurons, we show that repetitive correlated activity also results in a rapid and

tion; the increased frequency of presynaptic firing following eEF
related spiking may facilitate the induction of bursting-like behavior and enhance the reliability of signal transmission[35]. Enhancement of presynaptic neuronal excitability will also affect the plasticity of 'upstream' synapses made onto the presynaptic neuron by facilitating the initiation of backpropagating action potentials[6,11,36].

The idea of replicated states for learning higher order

Neocortex
Source of assumptions and constraints

HMM model. Why one-step look-ahead is required. "Predicted" a computational property of neurons

Nature of higher-order sequences

World's Data (Visual/Auditory etc...)
To find correspondence with Neocortex properties

Computational Principles (Machine Learning/Graphical Models etc..)
To understand why brain does what it does in that particular way

Recipe for building brain-like computers

- Accept the broad biological constraints
  - Hierarchy, time as supervisor, sparse distributed representations, sensori-motor interactions....
- Have a biological circuit model for the learned system
  - Put in biological details you can computationally justify
- Get to the biological circuit model using the most expedient learning algorithm
  - Need not be biological. In fact, being biological can be a disadvantage.
- Work on a real problem

On to the paper....

- Can we come to a set of mathematical equations that model cortical function?

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    - Something like Maxwell's equations for electromagnetic waves

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  - Assigns functions/equations for laminar circuits

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    - Assigns functions/equations for laminar circuits

    -

Hierarchical Temporal Memory

Mathematical Expression of Theory

+

Hierarchical Temporal Memory

Mathematical Expression of Theory

Biological Data

Constraints on connectivity, placement

Hierarchical Temporal Memory

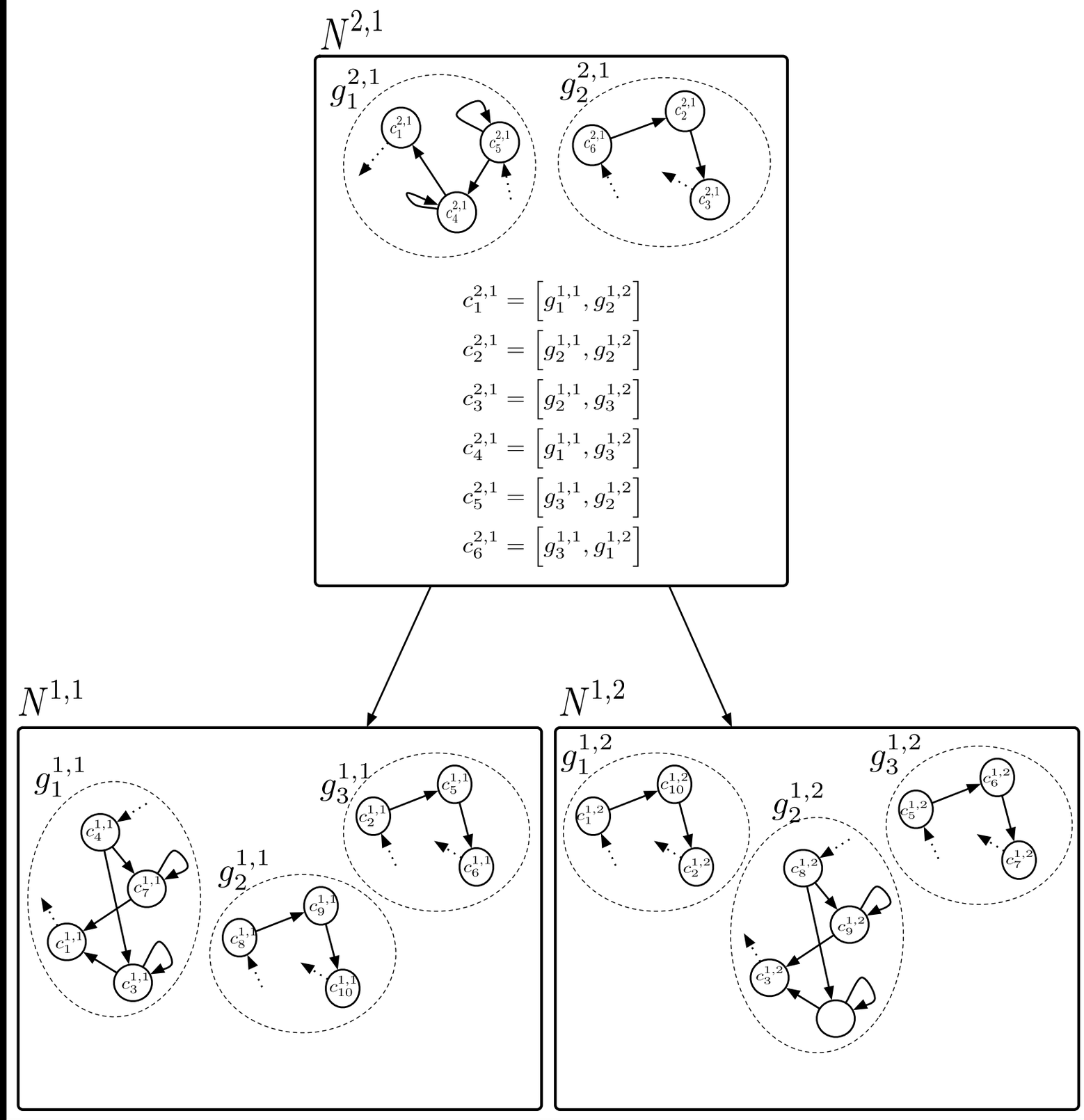
Mathematical Expression of Theory

Biological Data

Constraints on connectivity, placement

+

Laminar Cortical Circuit Model


$N^{2,1}$
$g_1^{2,1}$
$g_2^{2,1}$
$c_1^{2,1}$
$c_5^{2,1}$
$c_4^{2,1}$
$c_2^{2,1}$
$c_6^{2,1}$
$c_3^{2,1}$
$c_1^{2,1} = \left[g_1^{1,1}, g_2^{1,2}\right]$
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$N^{1,1}$
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$g_1^{1,1}$
$g_3^{1,1}$
$g_2^{1,1}$
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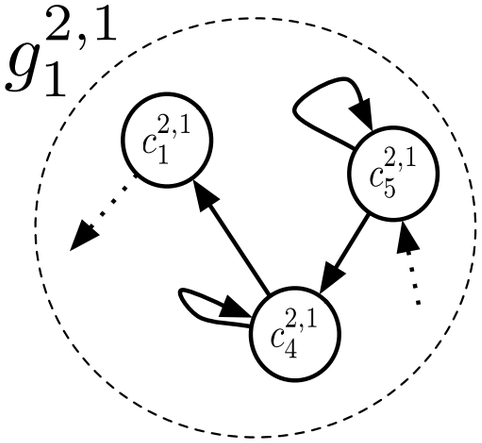
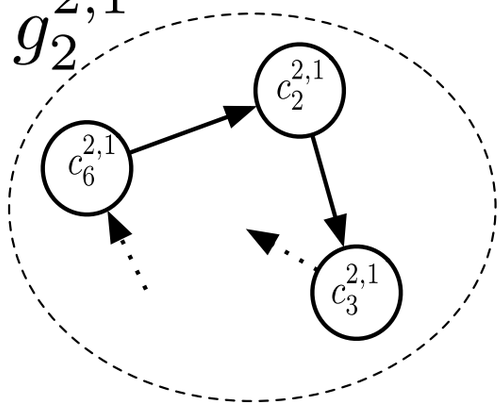
$g_3^{1,2}$
$g_2^{1,2}$

$N^{2,1}$

$g_1^{2,1}$



$g_2^{2,1}$



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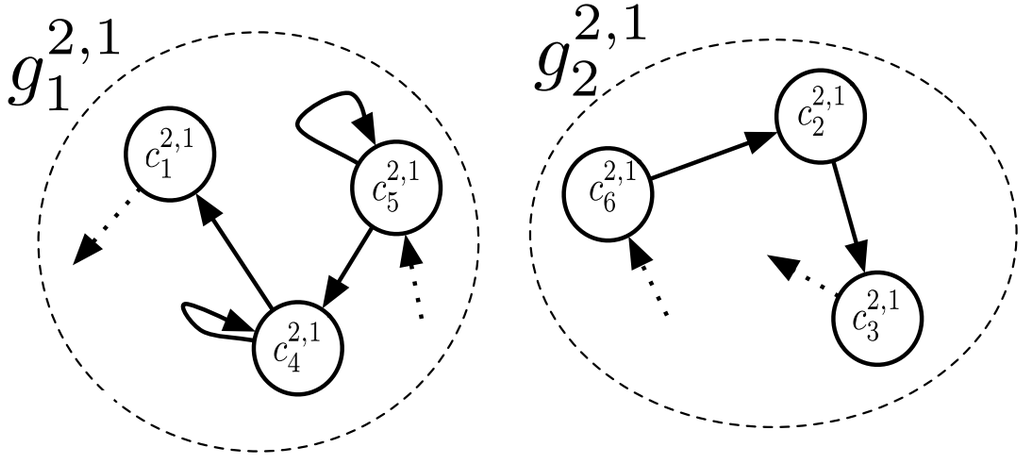
Markov chains
(sequences)

Coincidence patterns

$N^{2,1}$



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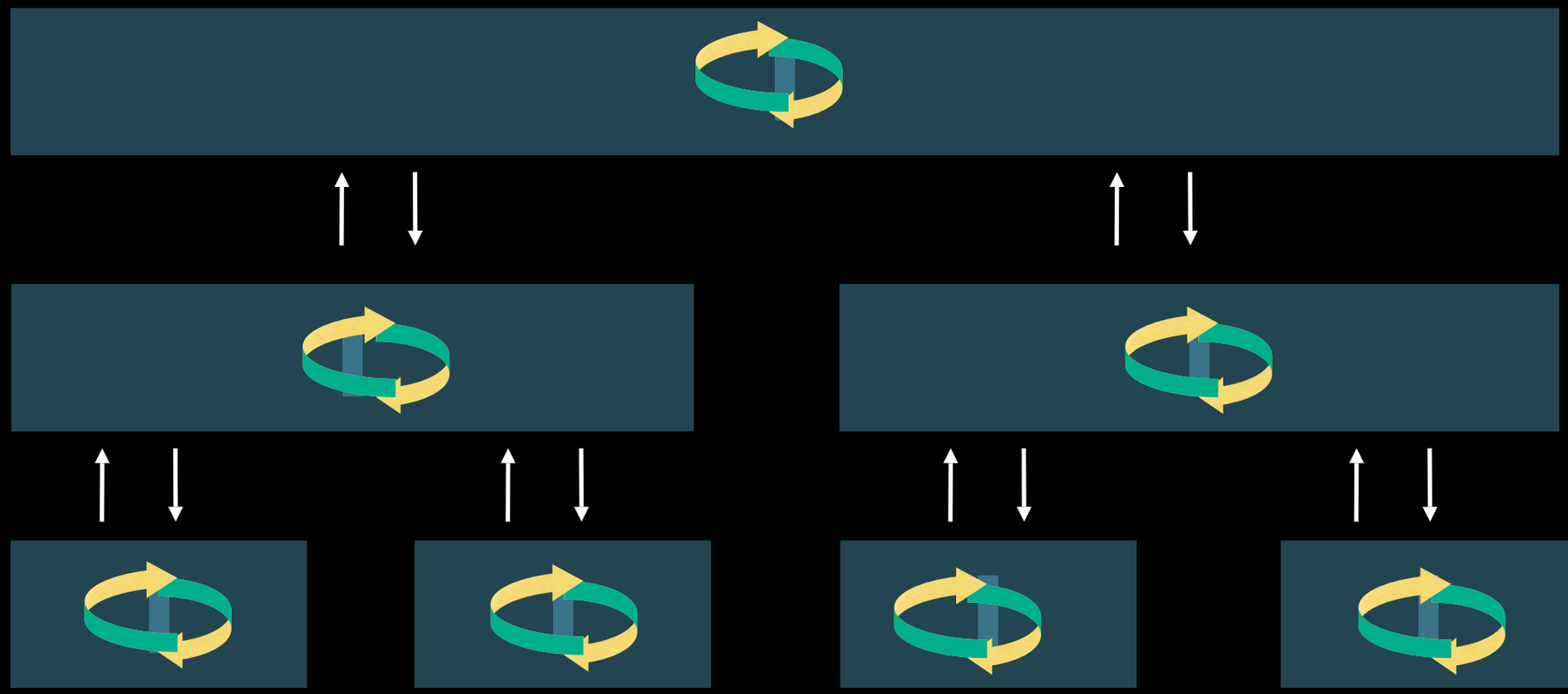
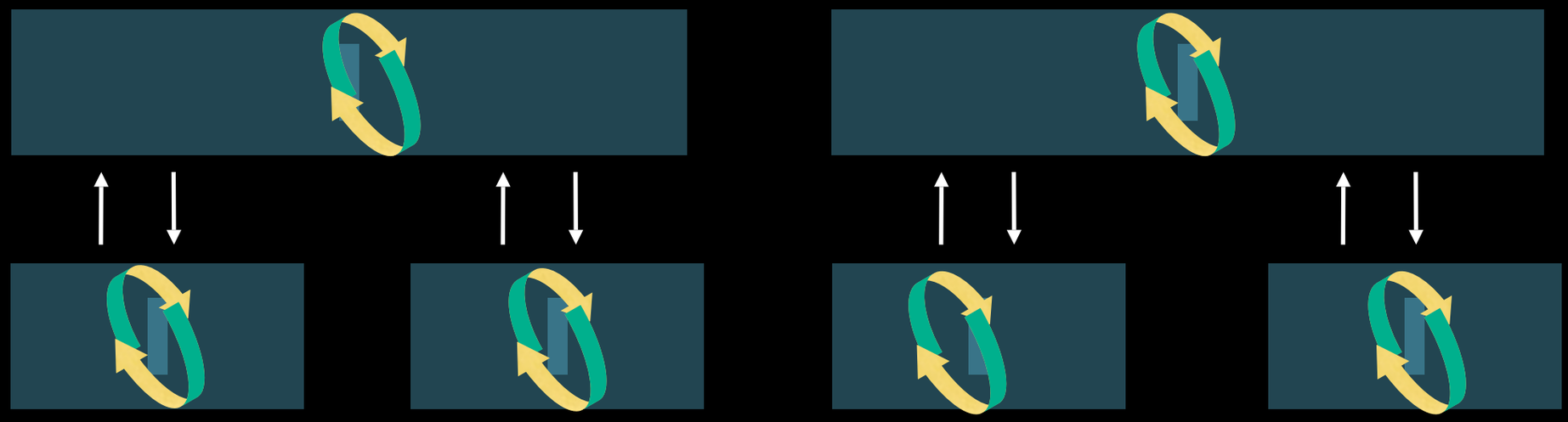
Largel Spatial Scales/ Slow temporal scales.



Small Spatial Scales/ Fast temporal scales.

Largel Spatial Scales/ Slow temporal scales.

Small Spatial Scales/ Fast temporal scales.



1. Mathematical expression of HTM inference

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2. Abstract neural implementation of equations

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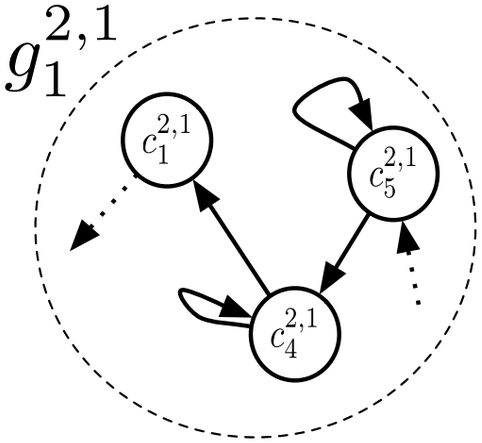
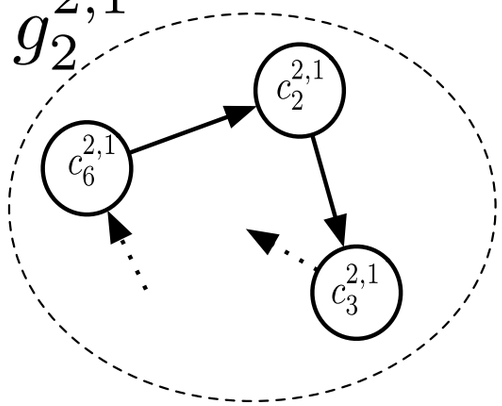
$N^{2,1}$

$g_1^{2,1}$



$g_2^{2,1}$



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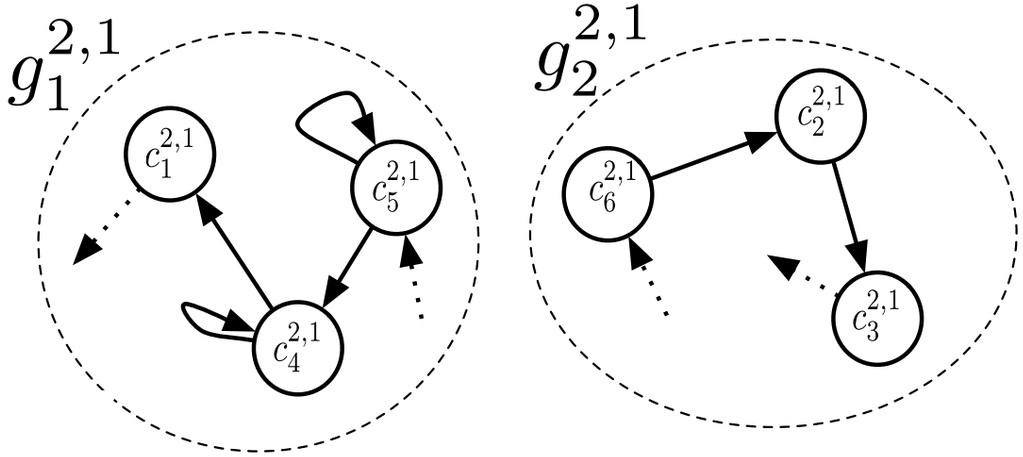
Markov chains
(sequences)

Coincidence patterns

$N^{2,1}$



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2 Calculate likelihood of Markov chains

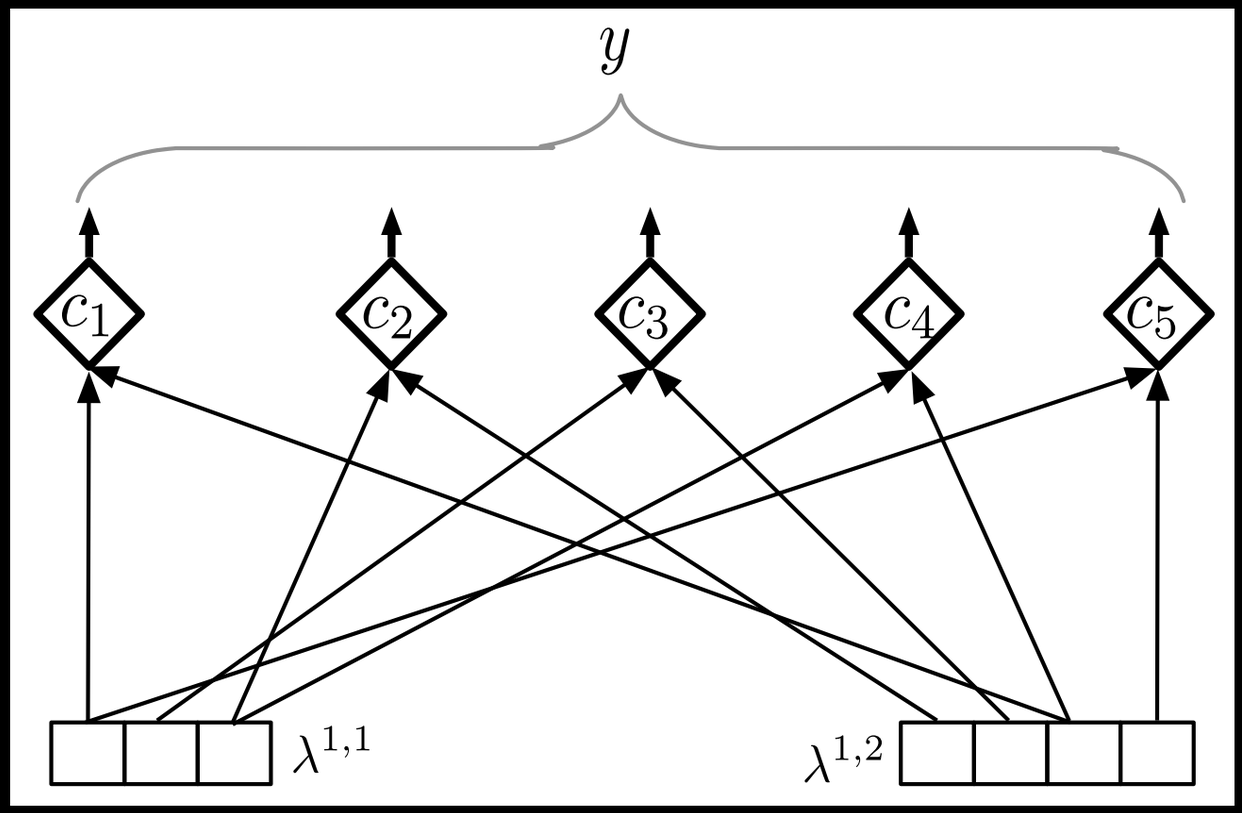
3 Calculate belief of coincidence patterns

1 Calculate likelihood of coincidence

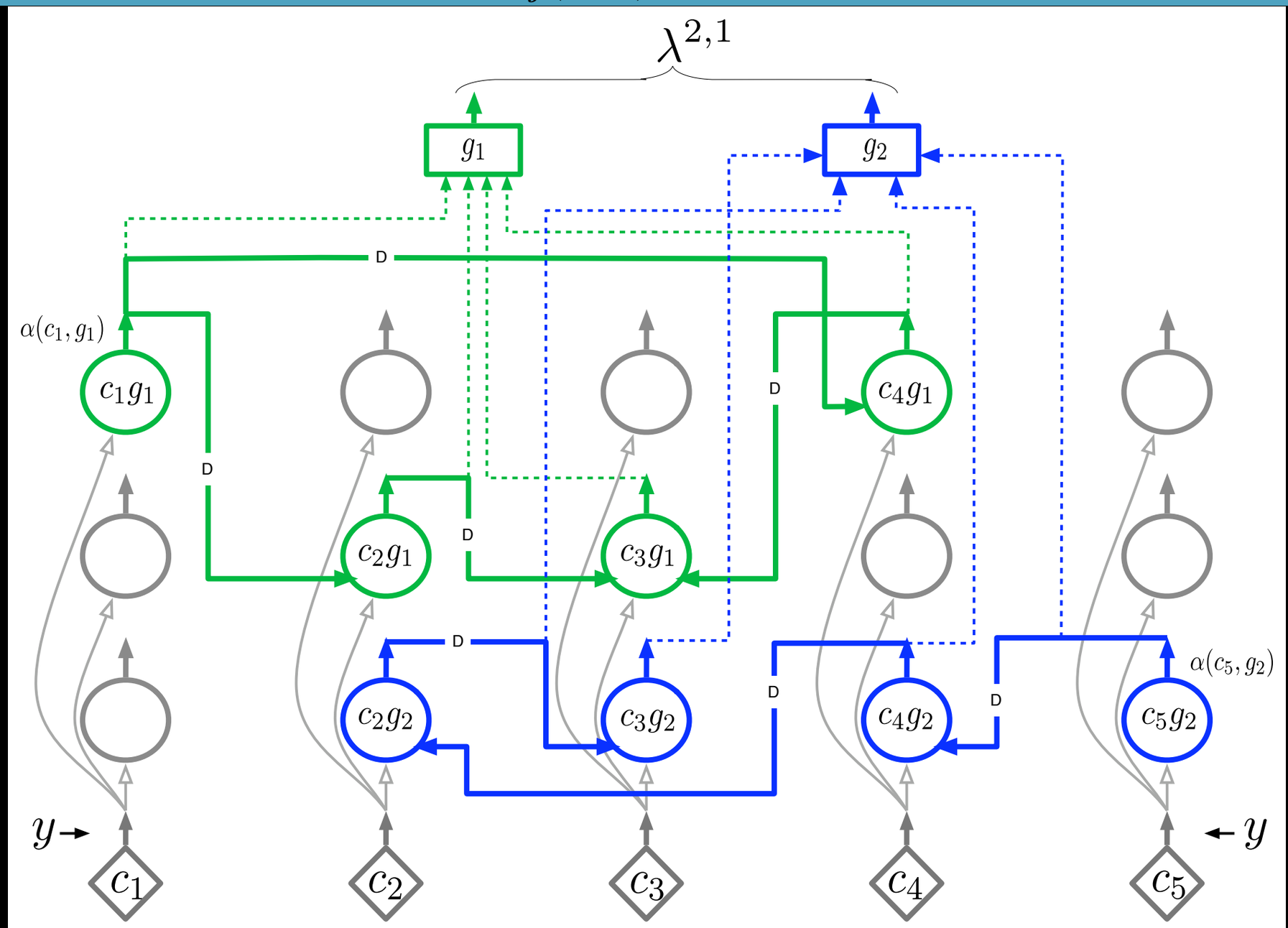
4 Calculate probability of Markov chains

(1) Coincidence likelihood	$$y_t(i) = P(^{-}e_t \mid c_i(t)) \propto \prod_{j=1}^{M} \lambda_t^{m_j}(r_i^{m_j}) \quad (1)$$ where coincidence-pattern c_i is the co-occurrence of $r_i^{m_1}$'th Markov chain from child 1, $r_i^{m_2}$'th Markov chain from child 2, $\cdots$, and $r_i^{m_M}$'th Markov chain from child M.
(2) Markov chain likelihood	$$\lambda_t^k(g_r) = P(^{-}e_0^t \mid g_r(t)) \propto \sum_{c_i(t) \in C^k} \alpha_t(c_i, g_r) \quad (2)$$ $$\alpha_t(c_i, g_r) = P(^{-}e_t \mid c_i(t)) \sum_{c_j(t-1) \in C^k} P(c_i(t) \mid c_j(t-1), g_r) \alpha_{t-1}(c_j, g_r) \quad (3)$$ $$\alpha_0(c_i, g_r) = P(^{-}e_0 \mid c_i(t=0)) P(c_i(t=0) \mid g_r) \quad (4)$$
(3) Coincidence Belief	$$Bel_t(c_i) \propto \sum_{g_r \in G^k} P(g_r \mid ^{+}e_0) \beta_t(c_i, g_r) \quad (5)$$ $$\beta_t(c_i, g_r) = P(^{-}e_t \mid c_i(t)) \sum_{c_j(t-1) \in C^k} P(c_i(t) \mid c_j(t-1), g_r) \beta_{t-1}(c_j, g_r) \quad (6)$$ $$\beta_0(c_i, g_r) = P(^{-}e_0 \mid c_i(t=0)) P(c_i(t=0) \mid g_r, ^{+}e_0) \quad (7)$$
(4) Feedback messages	$$\pi^{child}(g_m) \propto \sum_{i \forall i} I(c_i) Bel(c_i) \quad (8)$$ where $$I(c_i) = \begin{cases} 1, & \text{if } g_m^{child} \text{ is a component of } c_i \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

$$y_t(i) = P(^{-}e_t|c_i(t)) \propto \prod_{j=1}^{M} \lambda_t^{m_j}(r_i^{m_j})$$



$$\alpha_t(c_i, g_r) = P(^{-}e_t|c_i(t)) \sum_{c_j(t-1)\in C^k} P(c_i(t)|c_j(t-1), g_r)\alpha_{t-1}(c_j, g_r)$$



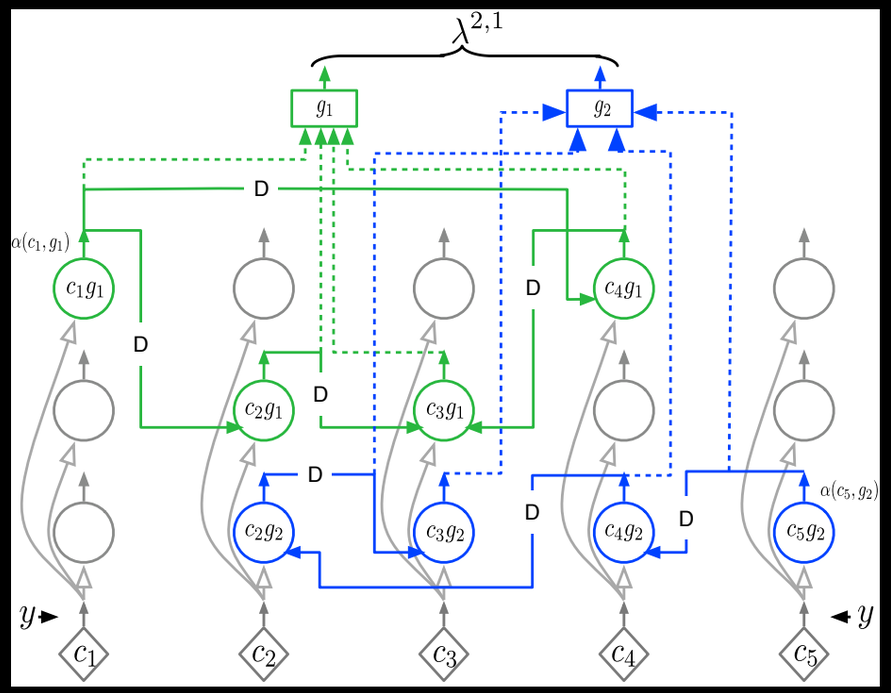
2 Calculate likelihood of Markov chains

3 Calculate belief of coincidence patterns

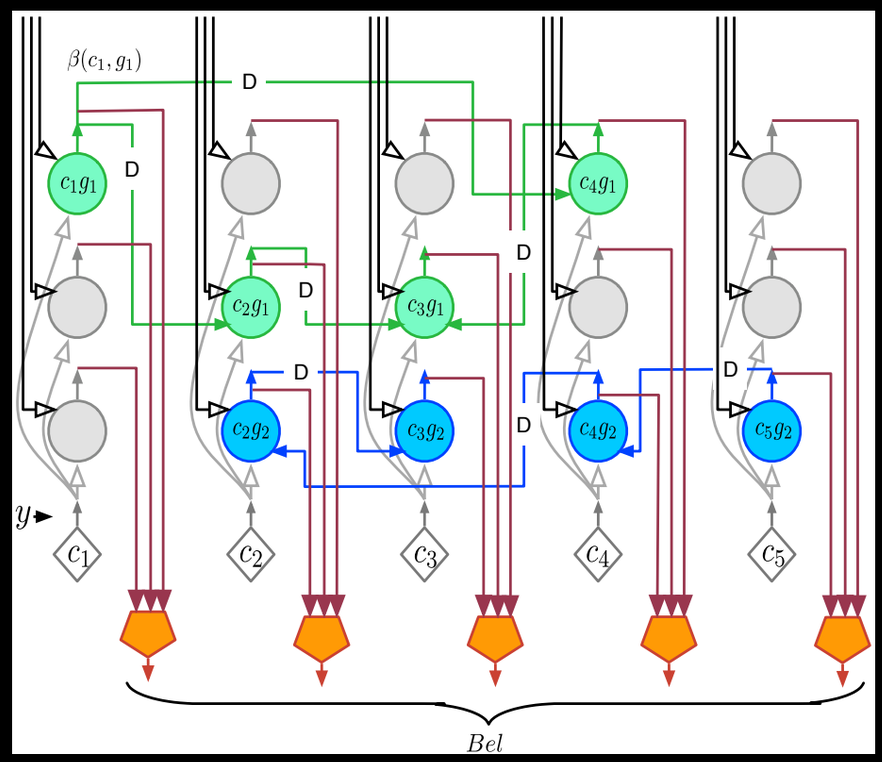
1 Calculate likelihood of coincidence

4 Calculate probability of Markov chains

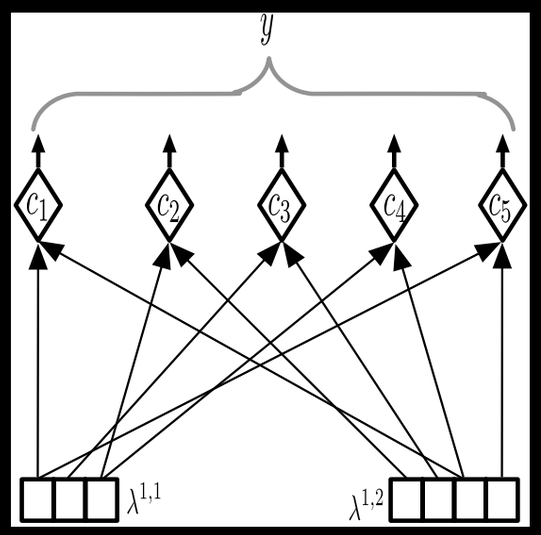
2


$\lambda^{2,1}$
g_1
g_2
D
$\alpha(c_1, g_1)$
c_1g_1
c_2g_1
c_3g_1
c_4g_1
c_2g_2
c_3g_2
c_4g_2
c_5g_2
$\alpha(c_5, g_2)$
y
c_1
c_2
c_3
c_4
c_5

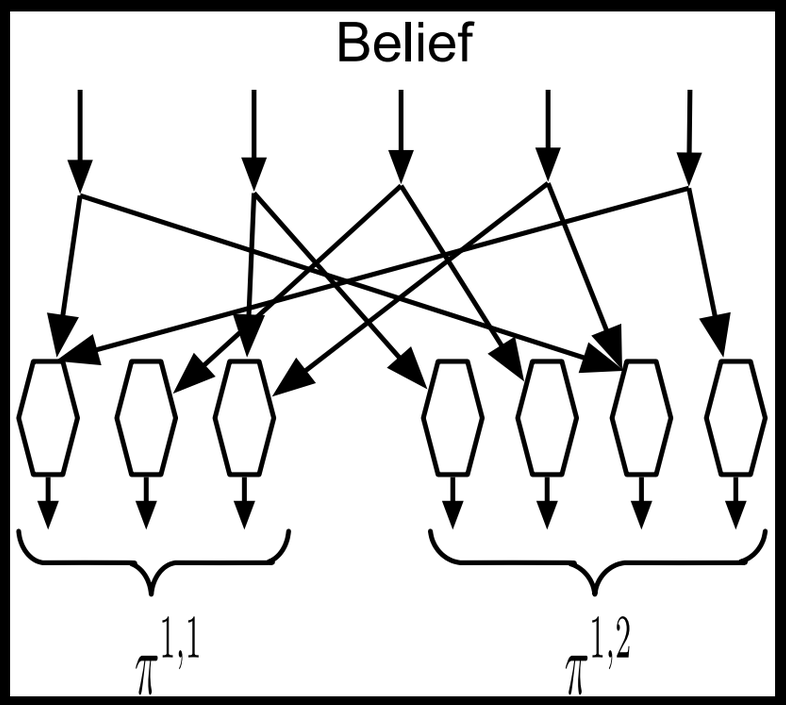
3


$\beta(c_1, g_1)$
D
c_1g_1
c_2g_1
c_3g_1
c_4g_1
c_2g_2
c_3g_2
c_4g_2
c_5g_2
y
c_1
c_2
c_3
c_4
c_5
Bel

1


y
c_1
c_2
c_3
c_4
c_5
$\lambda^{1,1}$
$\lambda^{1,2}$

4


Belief
$\pi^{1,1}$
$\pi^{1,2}$

1. Mathematical expression of HTM inference

2. Abstract neural implementation of equations

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1

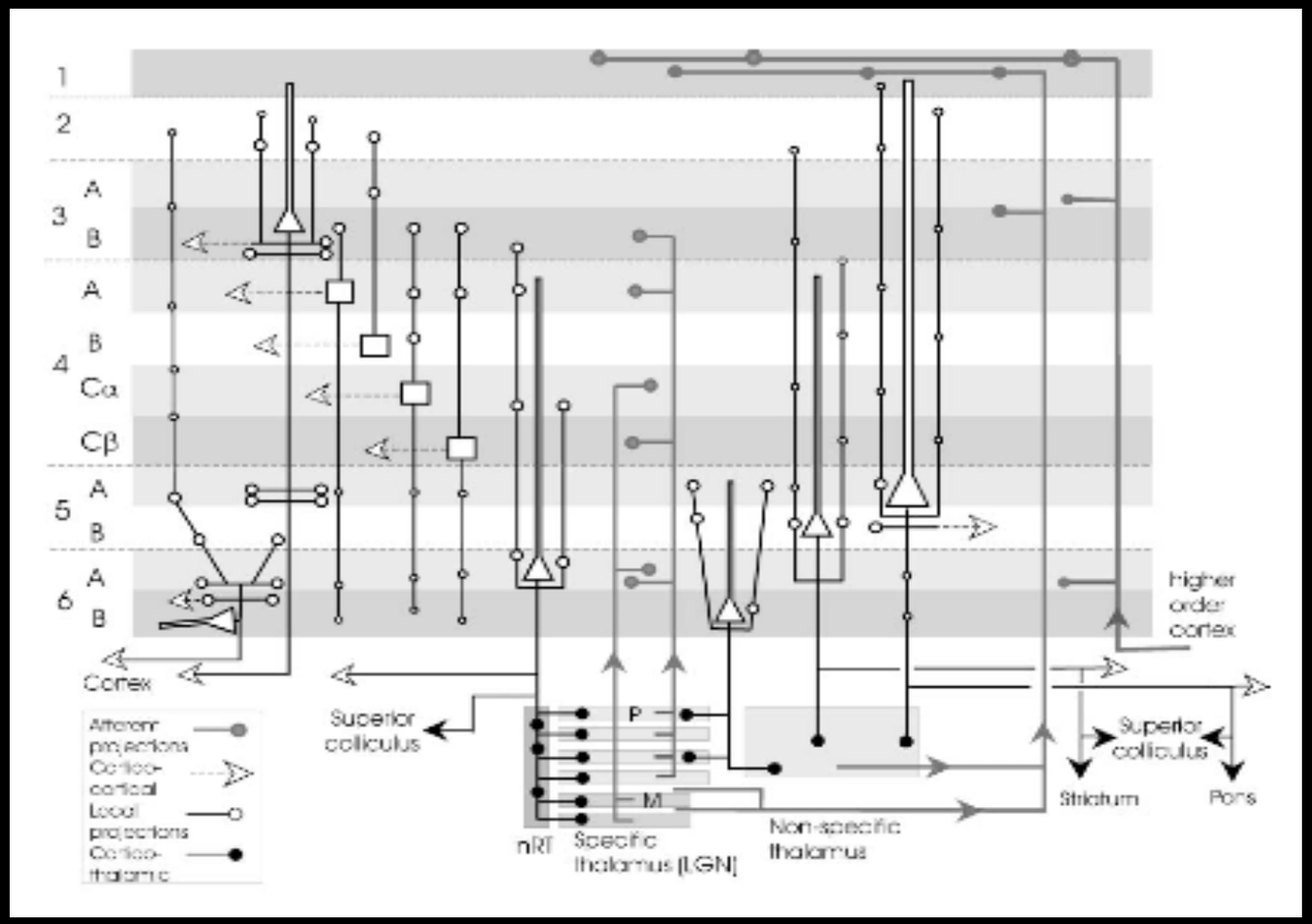
2

3

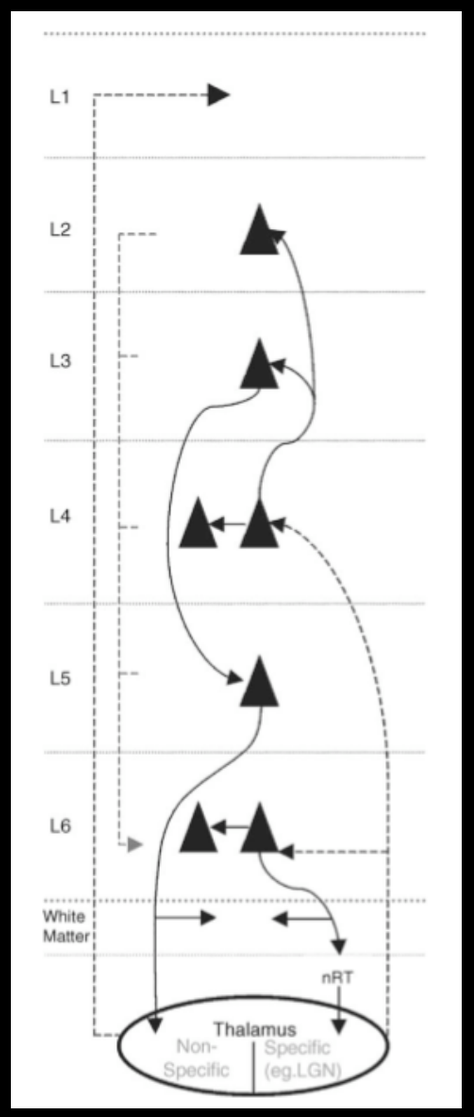
4

5

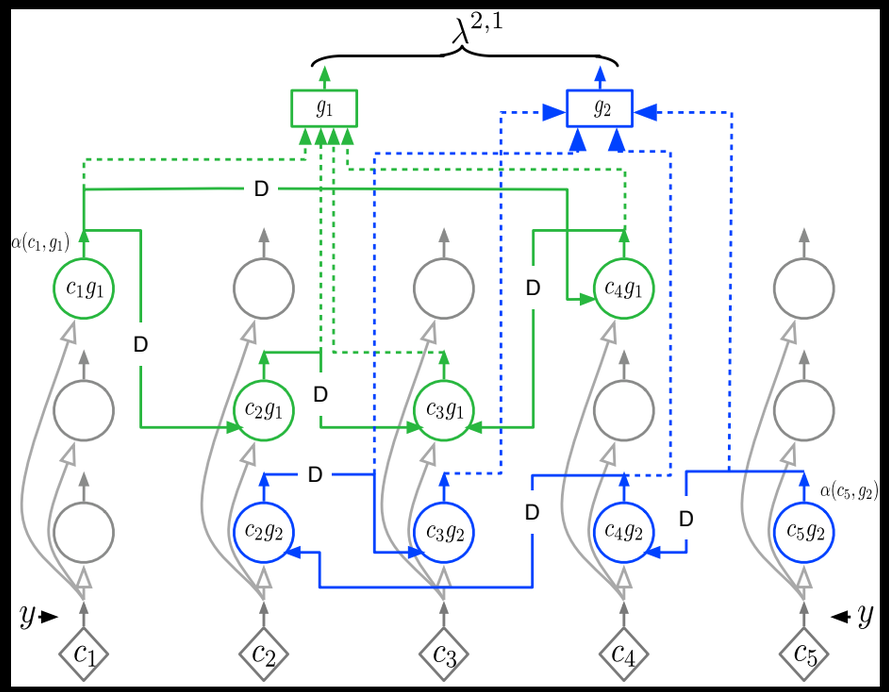
6

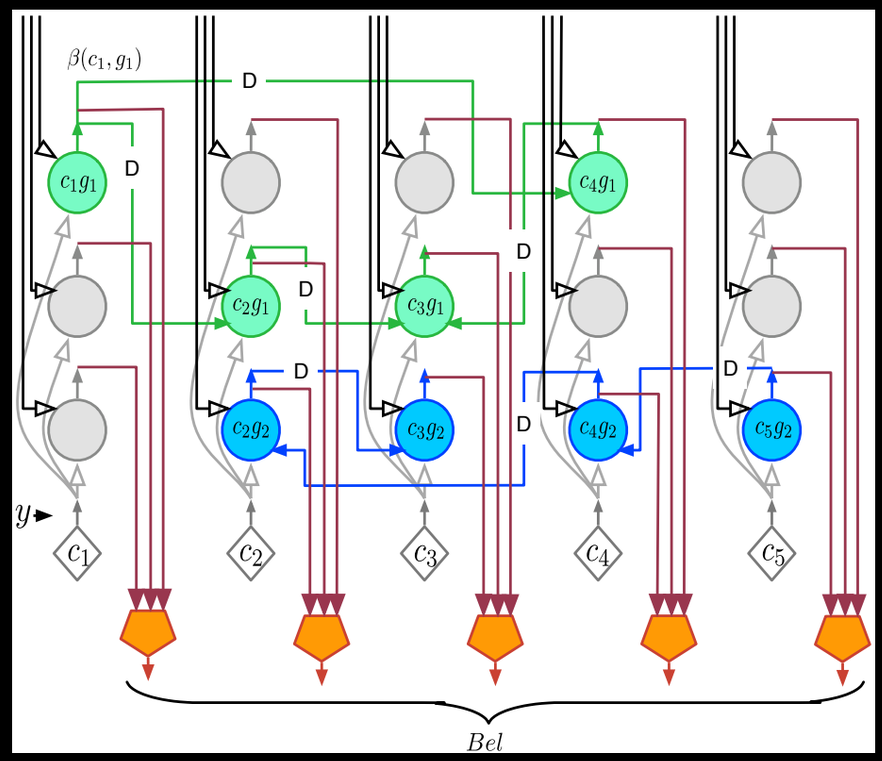


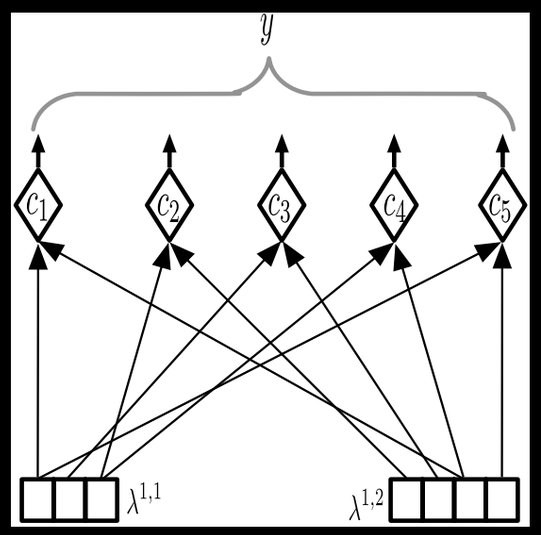
Alex M. Thomson and A. Peter Bannister. Interlaminar connections in the neocortex. *Cerebral cortex (New York, N.Y. : 1991)*, 13(1):5–14, 2003.

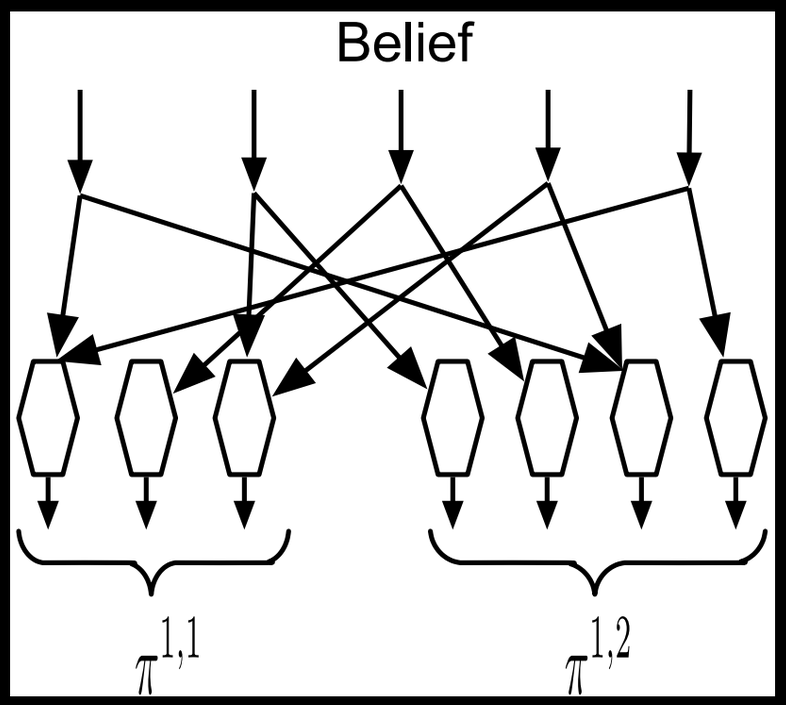


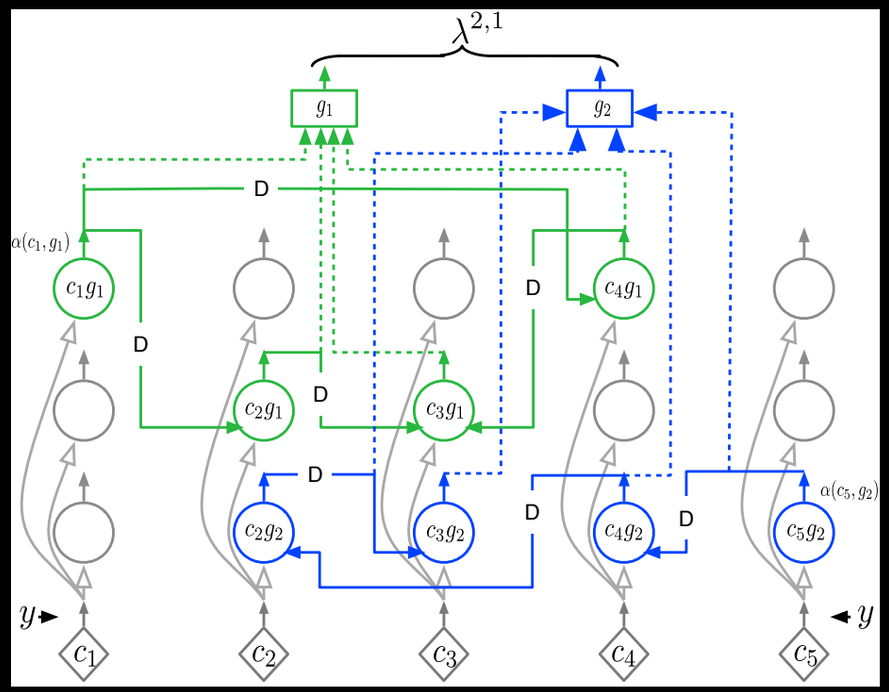
Bannister 2003

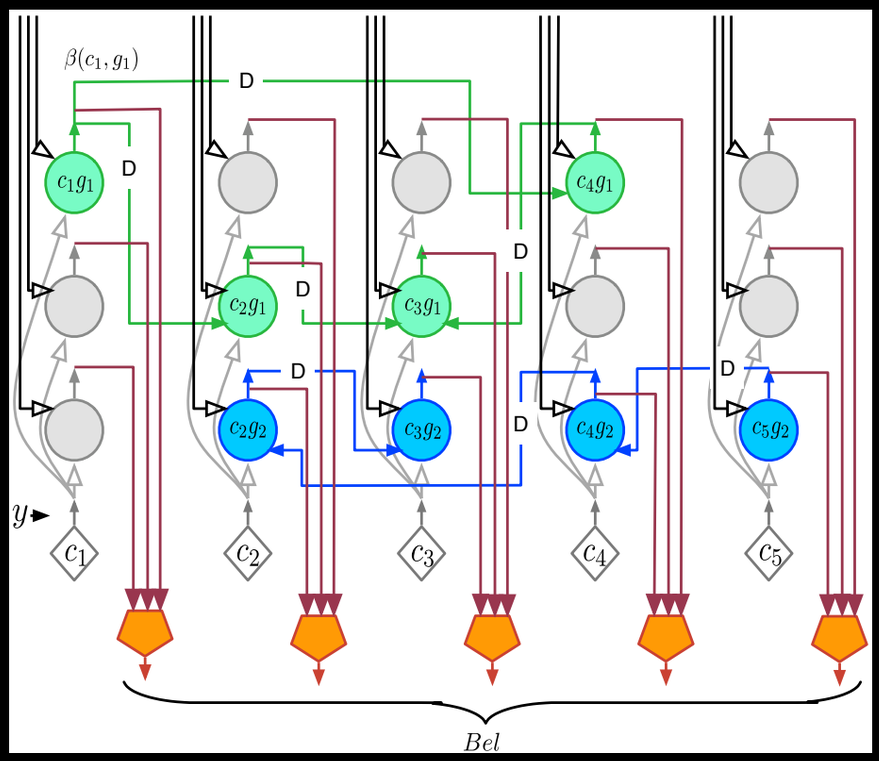

$\lambda^{2,1}$
g_1
g_2
D
$\alpha(c_1, g_1)$
c_1g_1
c_2g_1
c_3g_1
c_4g_1
c_2g_2
c_3g_2
c_4g_2
c_5g_2
$\alpha(c_5, g_2)$
y
c_1
c_2
c_3
c_4
c_5

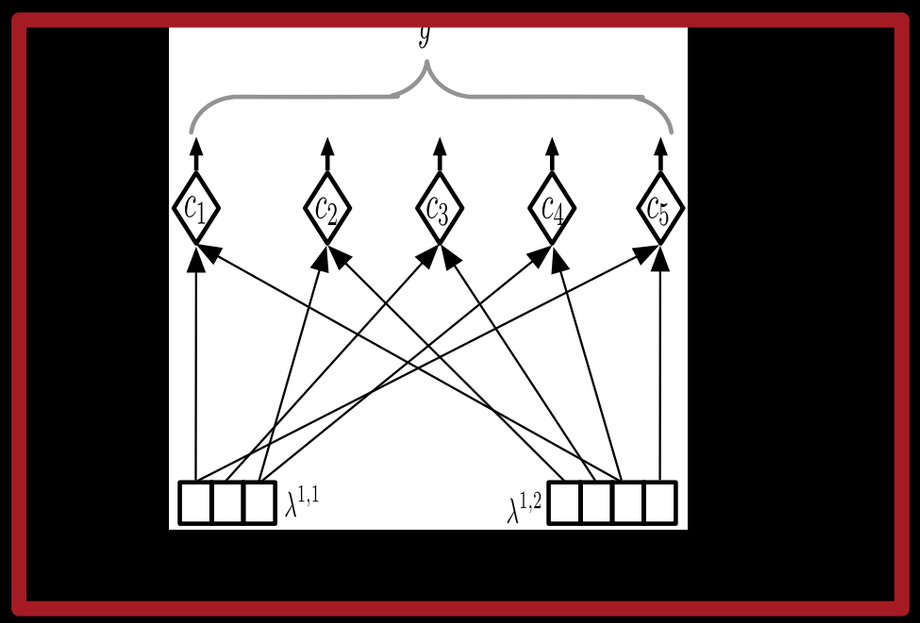

$\beta(c_1, g_1)$
D
c_1g_1
c_2g_1
c_3g_1
c_4g_1
c_2g_2
c_3g_2
c_4g_2
c_5g_2
y
c_1
c_2
c_3
c_4
c_5
Bel

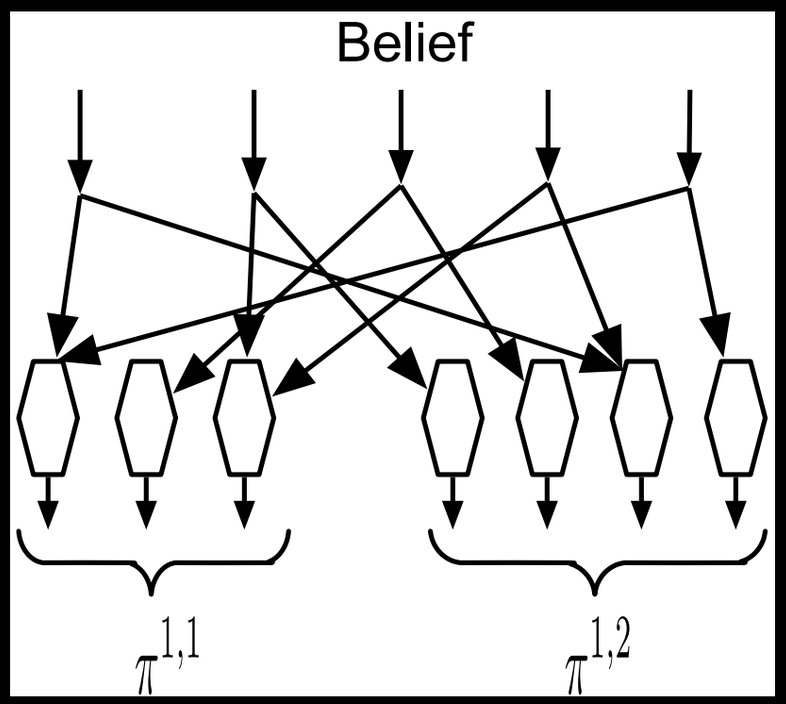

y
c_1
c_2
c_3
c_4
c_5
$\lambda^{1,1}$
$\lambda^{1,2}$


Belief
$\pi^{1,1}$
$\pi^{1,2}$


$\lambda^{2,1}$
g_1
g_2
D
$\alpha(c_1, g_1)$
c_1g_1
c_2g_1
c_3g_1
c_4g_1
c_2g_2
c_3g_2
c_4g_2
c_5g_2
$\alpha(c_5, g_2)$
y
c_1
c_2
c_3
c_4
c_5


$\beta(c_1, g_1)$
D
c_1g_1
c_2g_1
c_3g_1
c_4g_1
c_2g_2
c_3g_2
c_4g_2
c_5g_2
y
c_1
c_2
c_3
c_4
c_5
Bel


y
c_1
c_2
c_3
c_4
c_5
$\lambda^{1,1}$
$\lambda^{1,2}$


Belief
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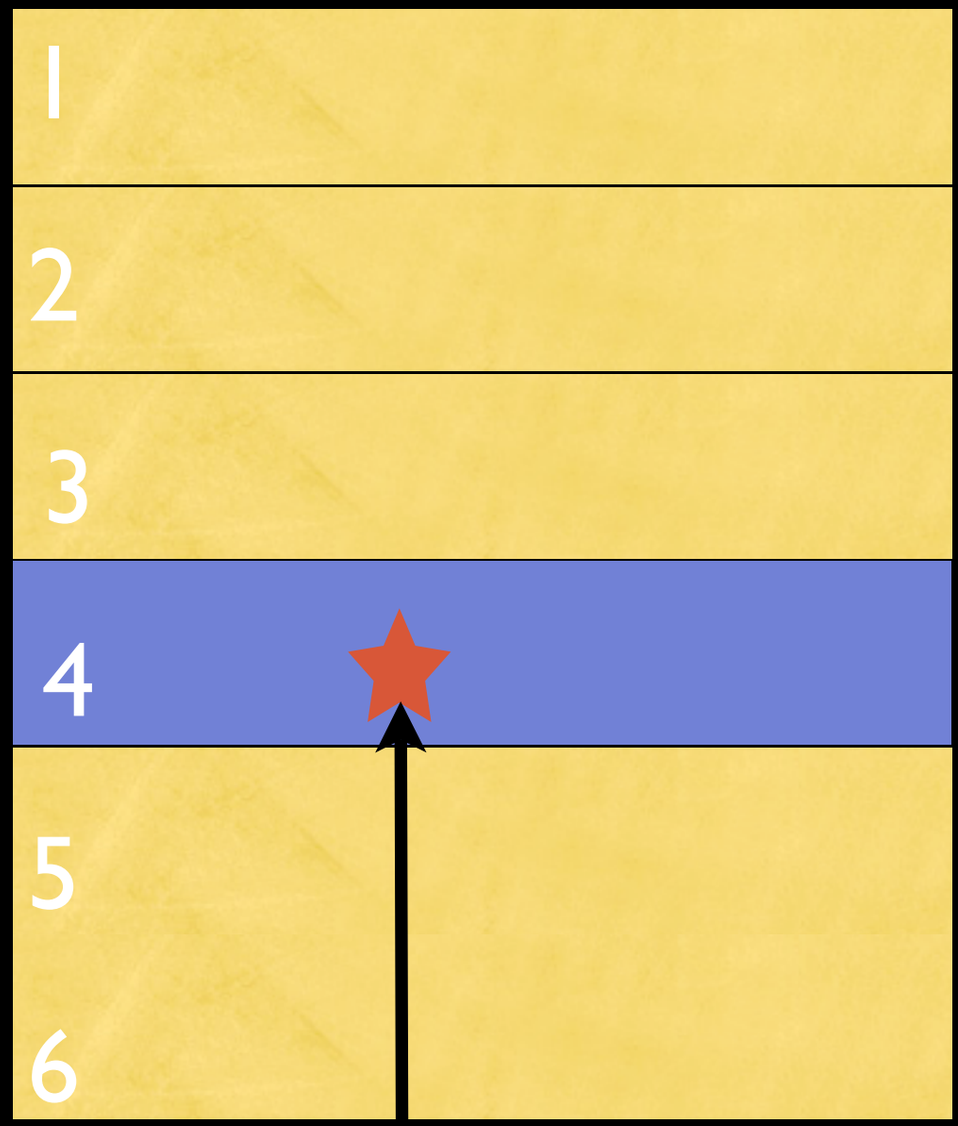
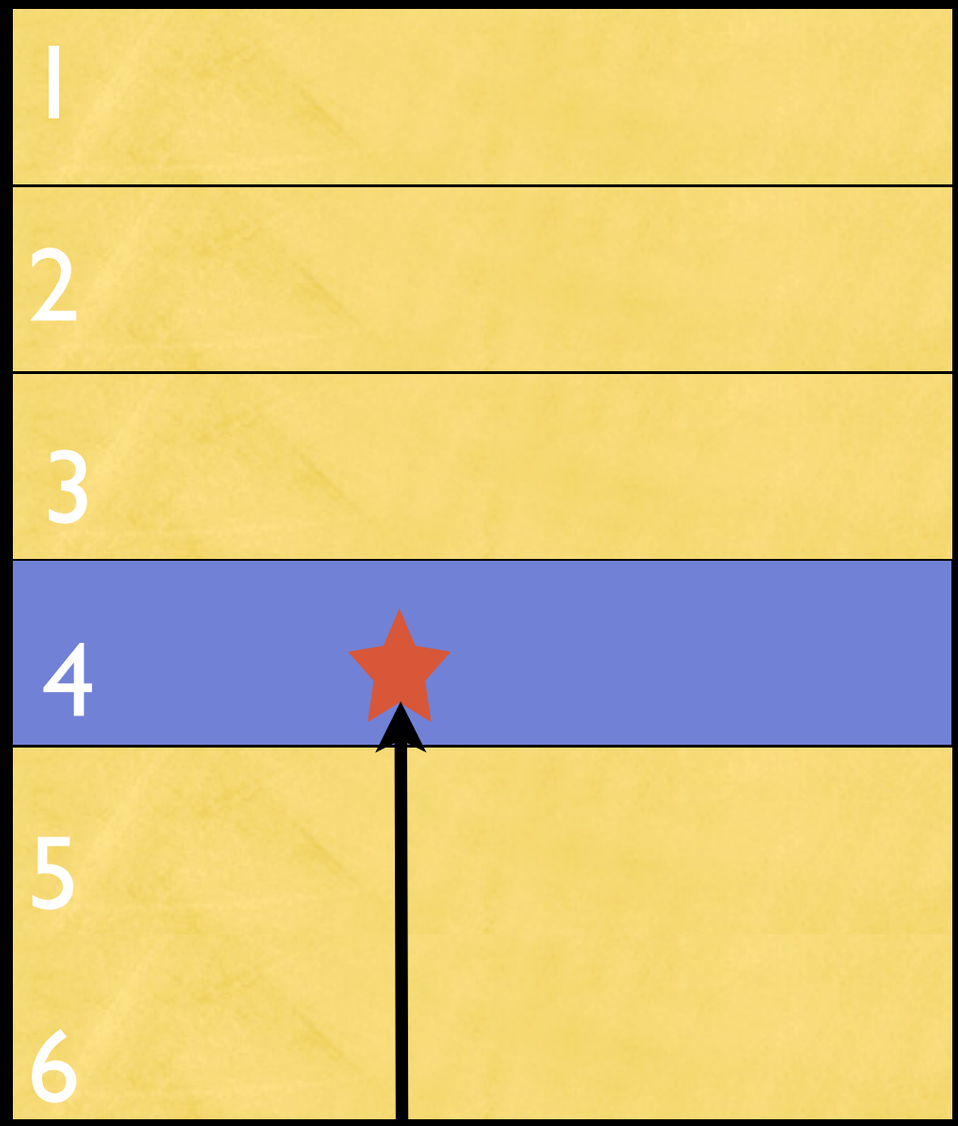
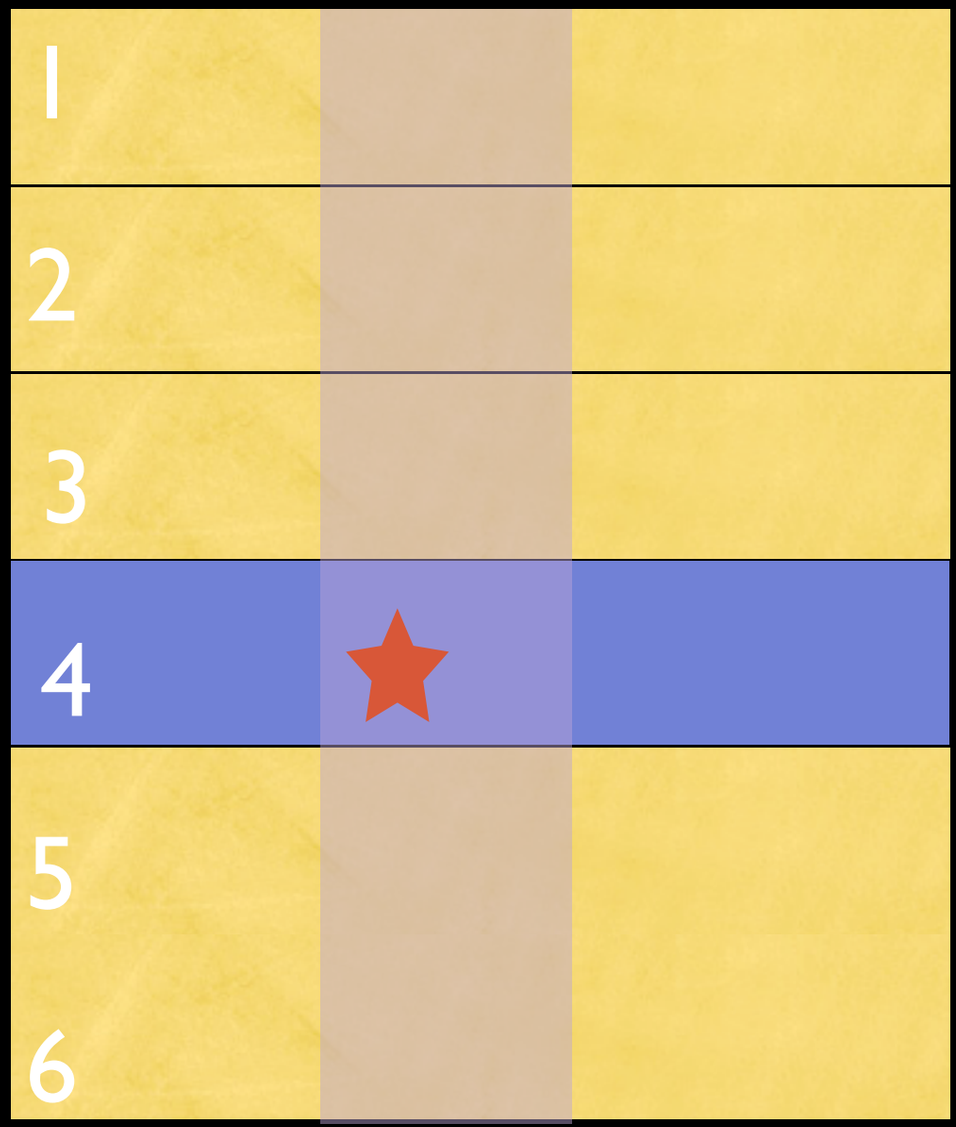
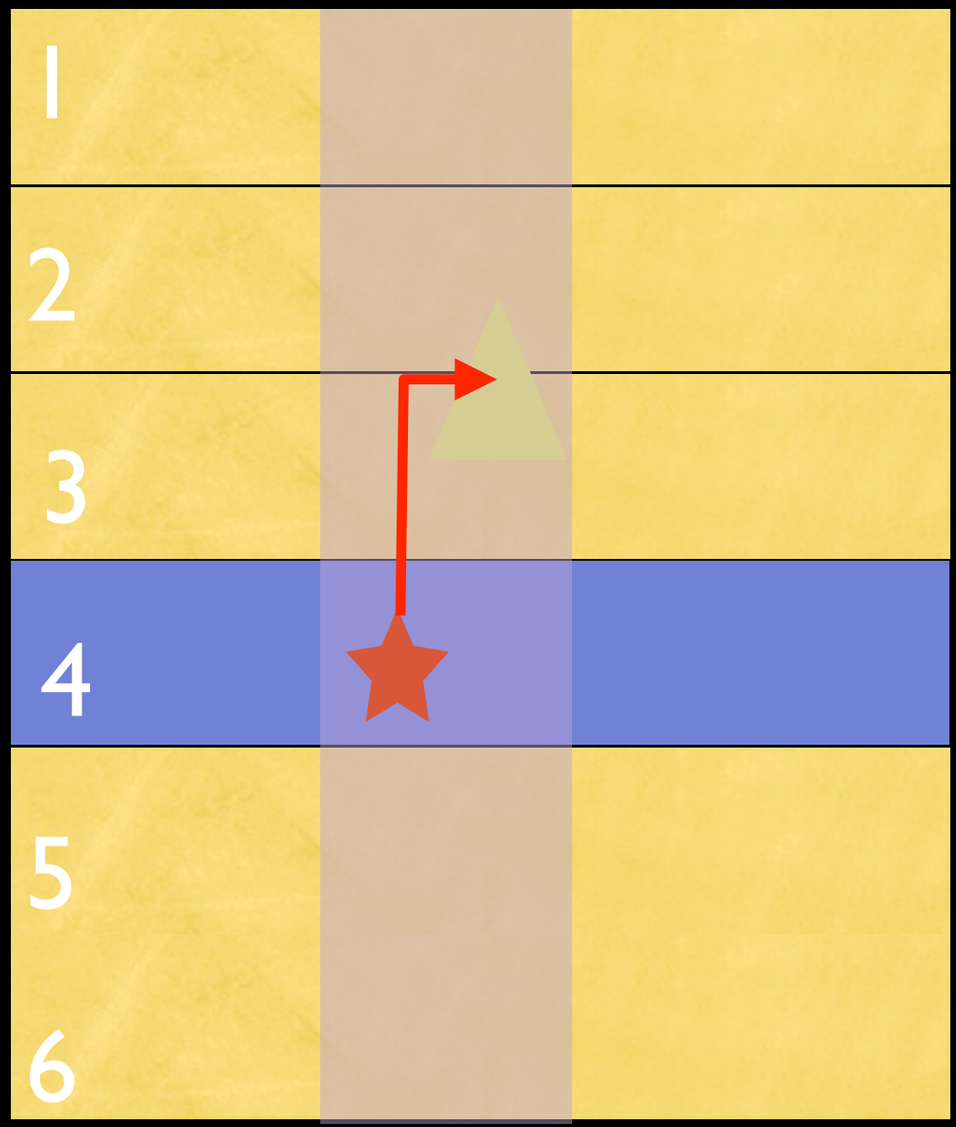

1
2
3
4
5
6

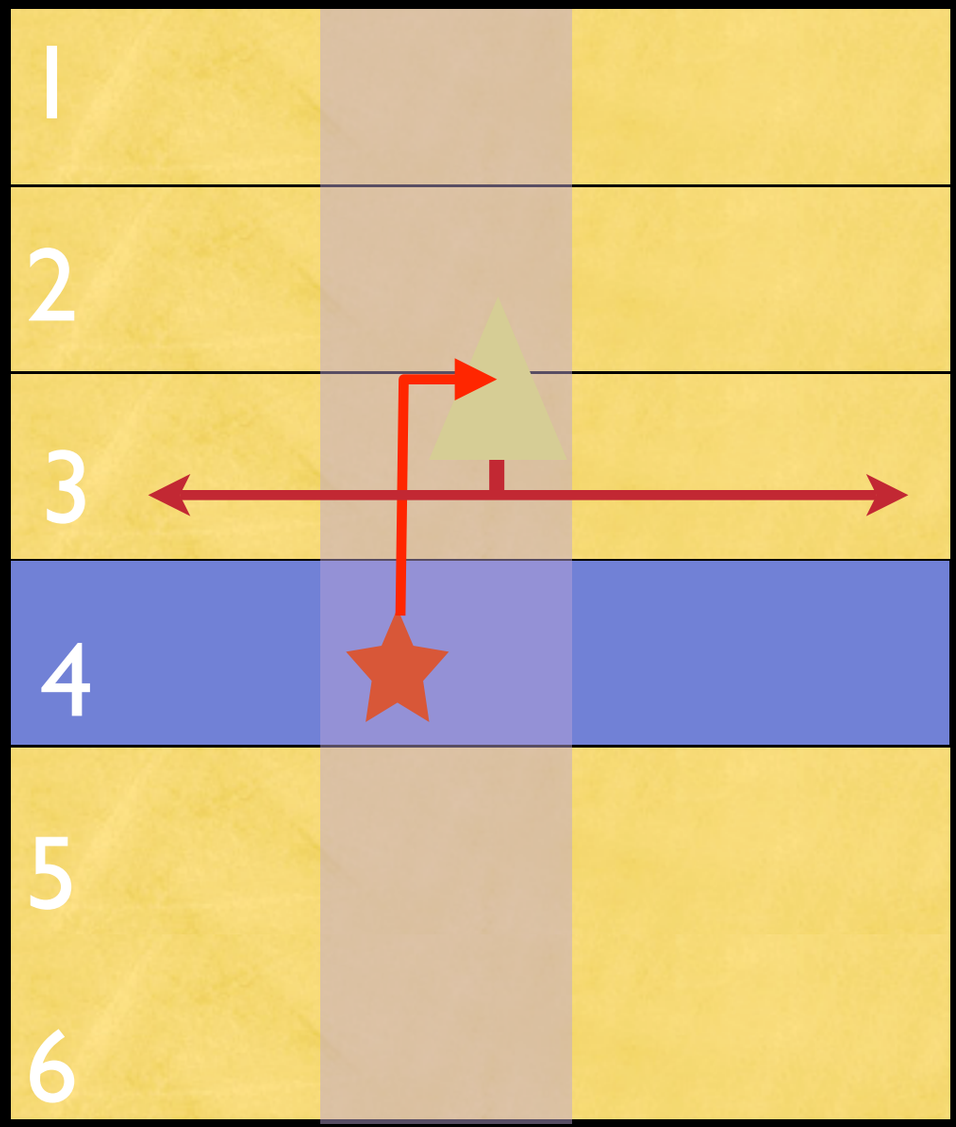


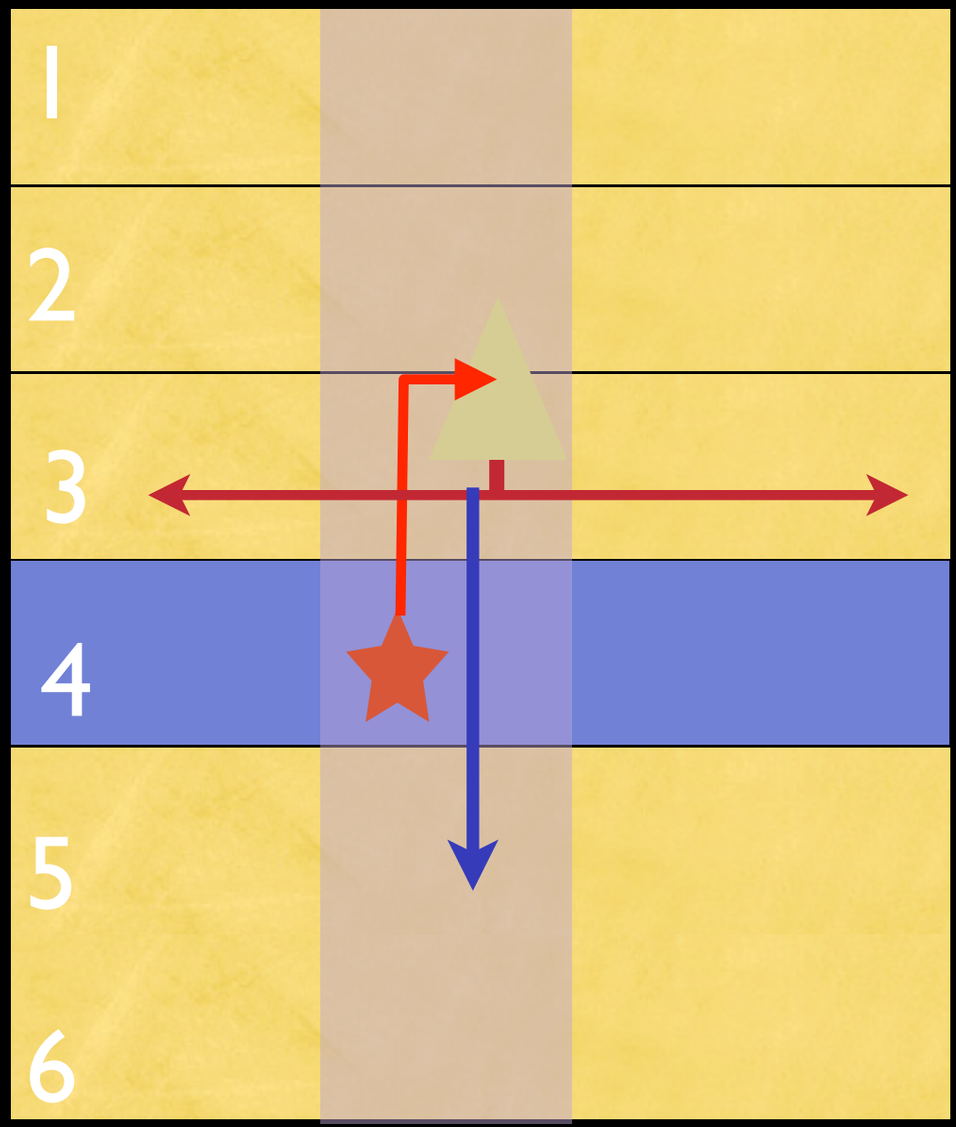
Why Layer 4?

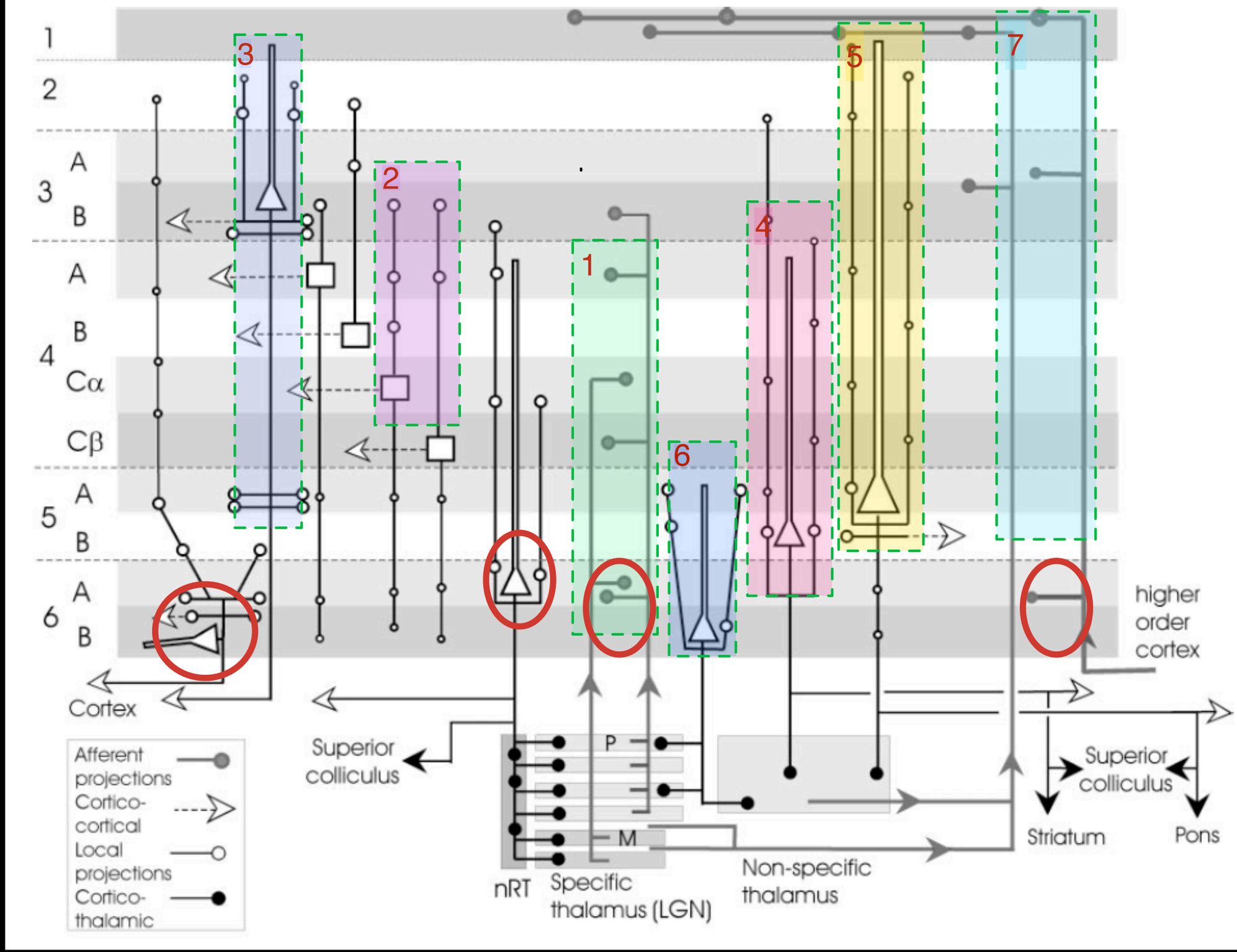
Thalamo-cortical inputs go to layer 4

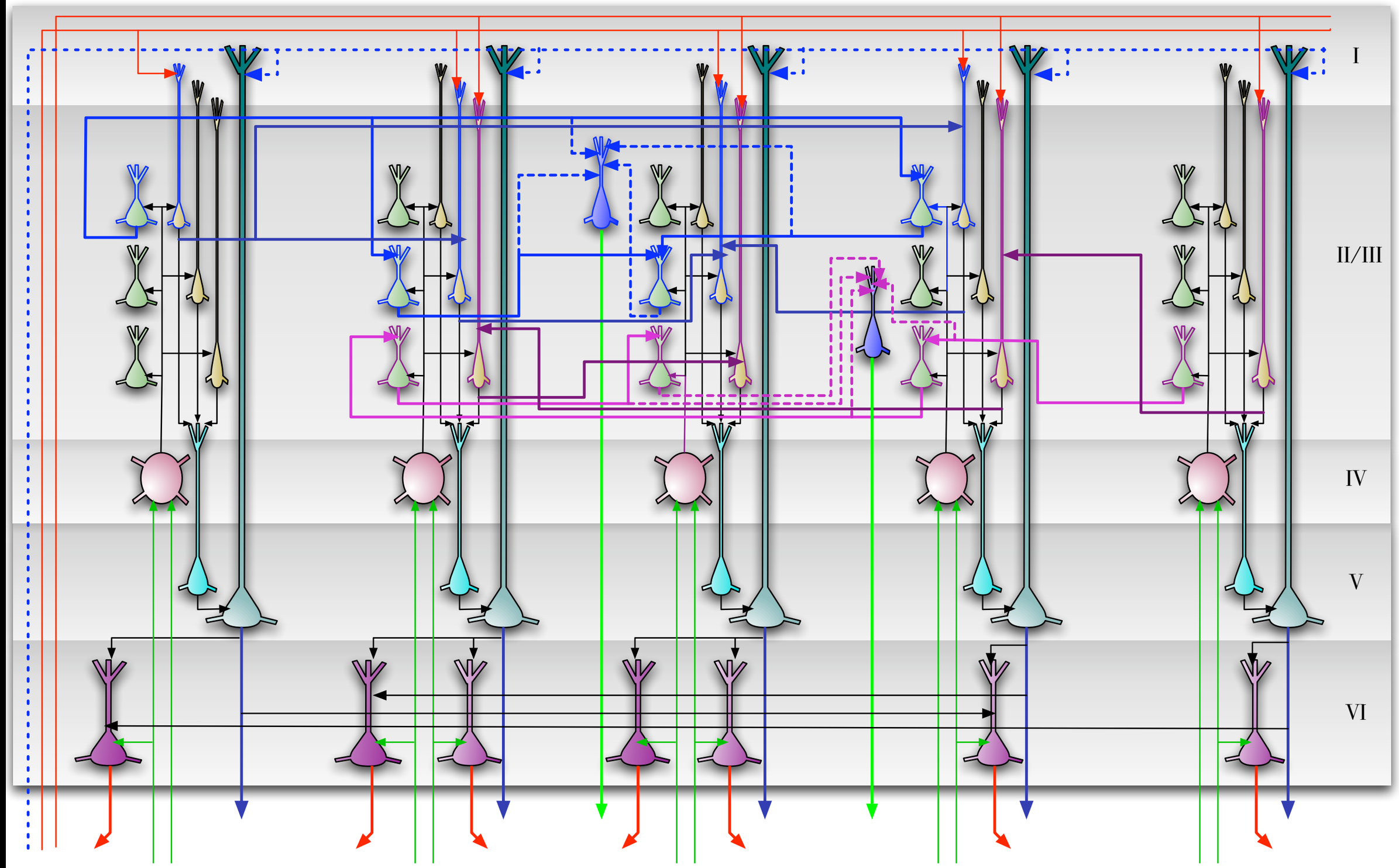

1
2
3
4
5
6


1
2
3
4
5
6


1
2
3
4
5
6


1
2
3
4
5
6


1
2
3
A
B
4
Cα
Cβ
5
A
B
6
A
B
Cortex
3
2
1
4
5
7
6
higher
order
cortex
Superior
colliculus
P
M
nRT
Specific
thalamus (LGN)
Non-specific
thalamus
Striatum
Superior
colliculus
Pons
Afferent
projections
Cortico-
cortical
Local
projections
Cortico-
thalamic


I
II/III
IV
V
VI

Images

17 of 57

Recognize

Continuous Recognition

Distortions

Undo

Revert

Results

attention/sr/attention-sr-fullFeedback

Categories Inspect

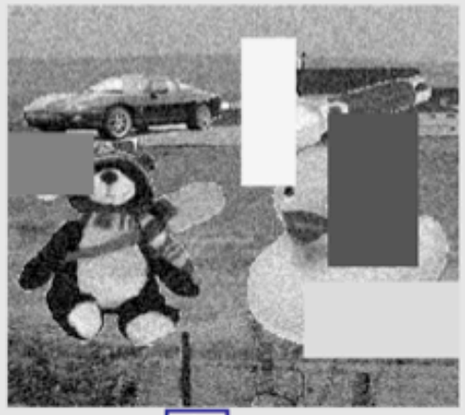
car sneaker flashlight pineapple rubber duck

Gabor responses

Gabor responses

Images

27 of 57



Recognize

Continuous Recognition

Distortions

Undo

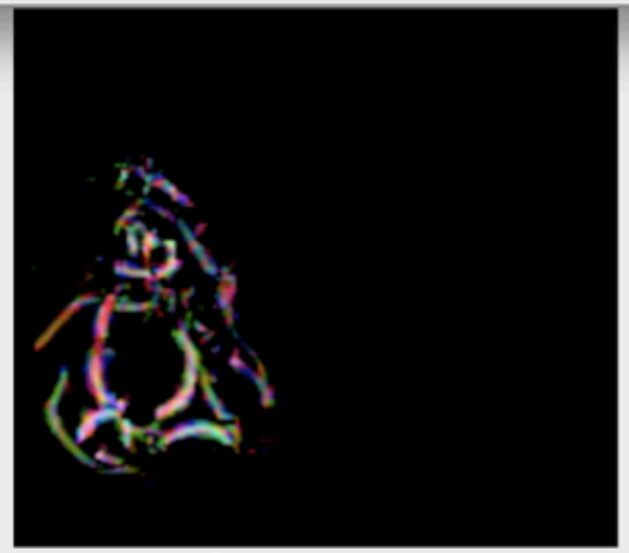
Revert

Results

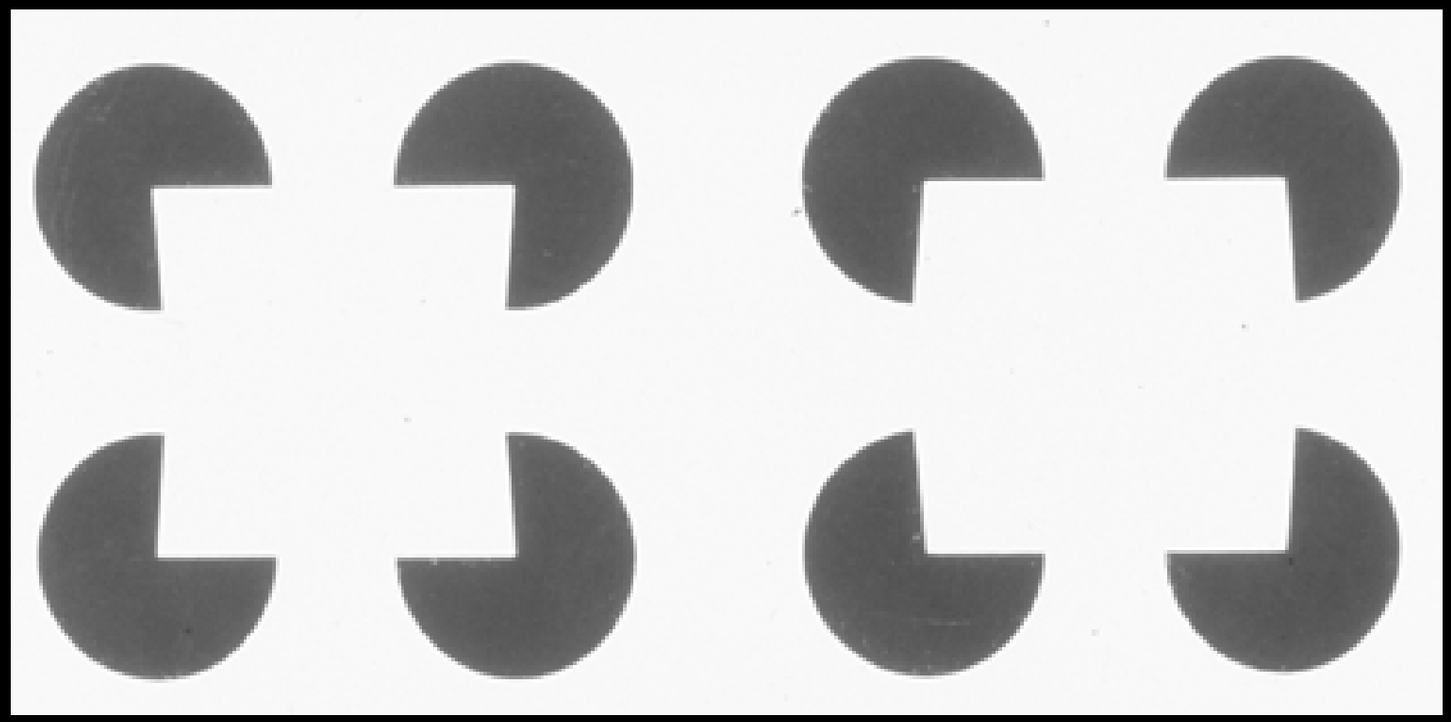
attention/sr/attention-sr-fullFeedback

Categories Inspect

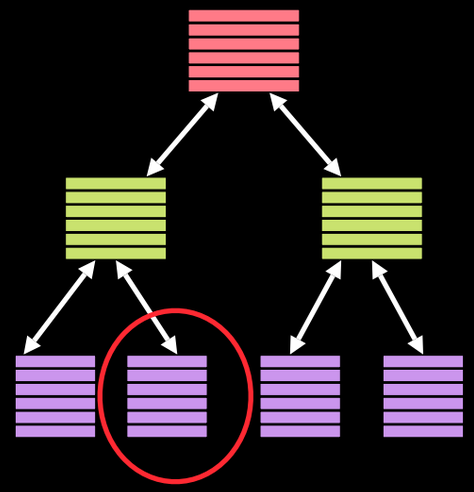
teddy bear flashlight cell phone car pineapple



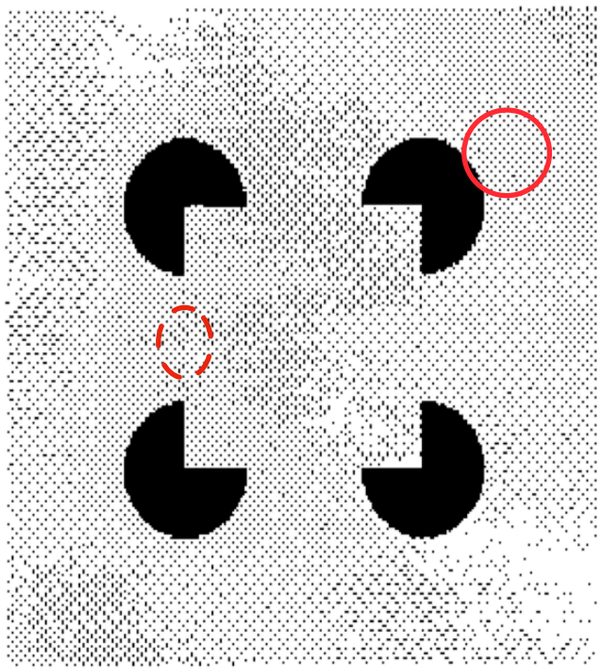
Gabor responses



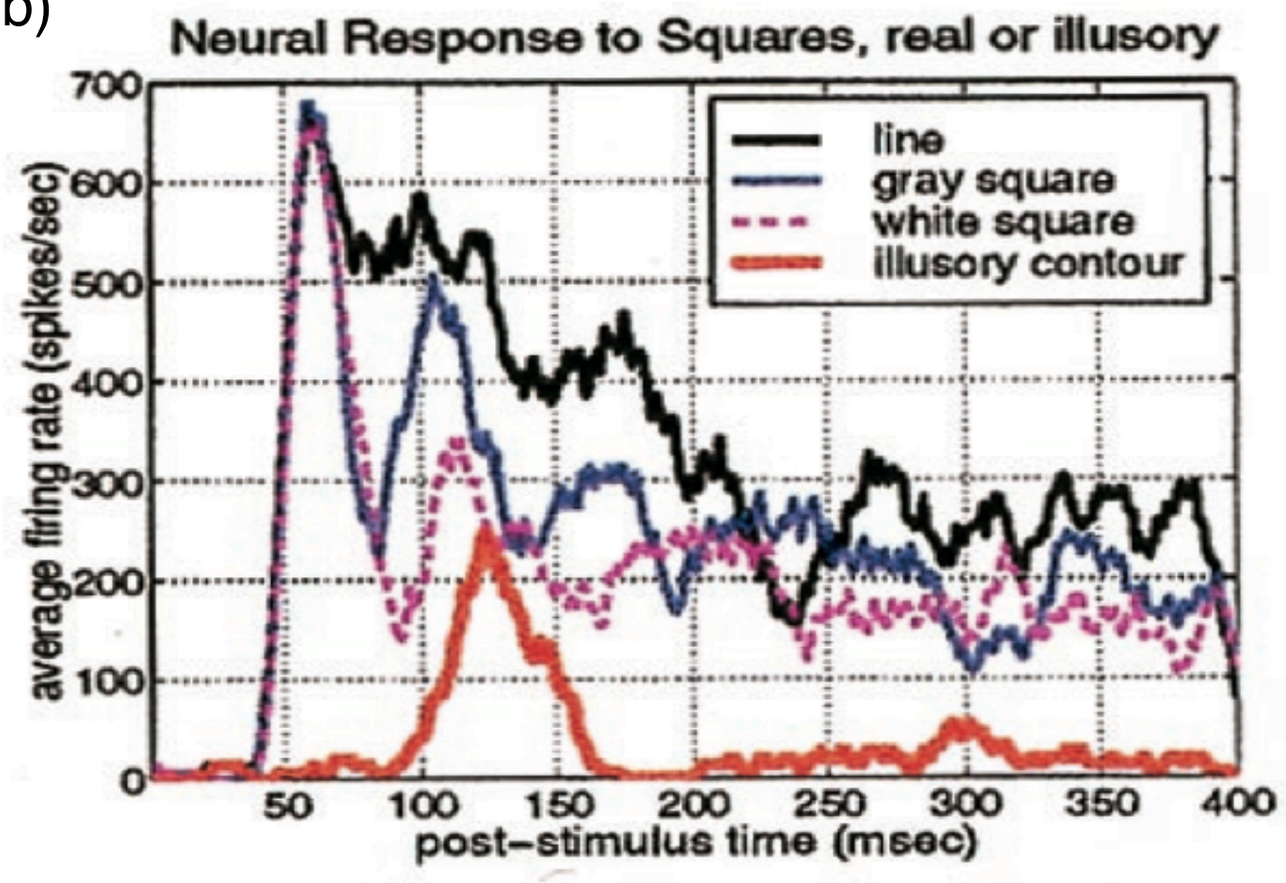
Lee and Mumford, J.Opt. Soc. America. July 2003



(a)



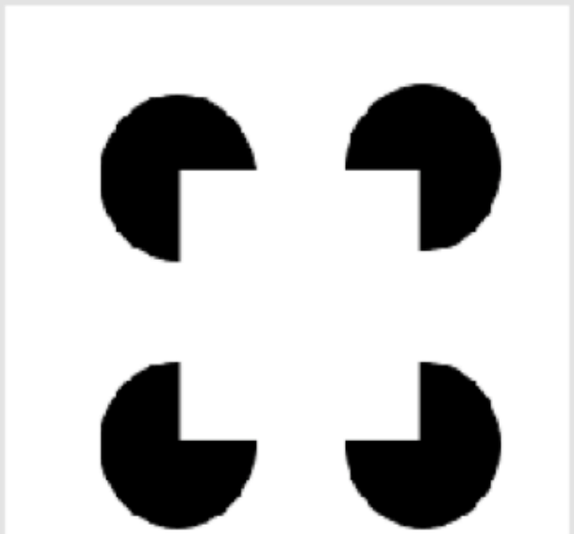
(b)


Neural Response to Squares, real or illusory
line
gray square
white square
illusory contour
average firing rate (spikes/sec)
0
100
200
300
400
500
600
700
50
100
150
200
250
300
350
400
post–stimulus time (msec)

Numenta Vision Test App – Subjective1.png

Images

1 of 1



Recognize

Continuous Recognition

Distortions

Undo

Revert

Results

attention/sr/subjectiveContours

Categories

Inspect

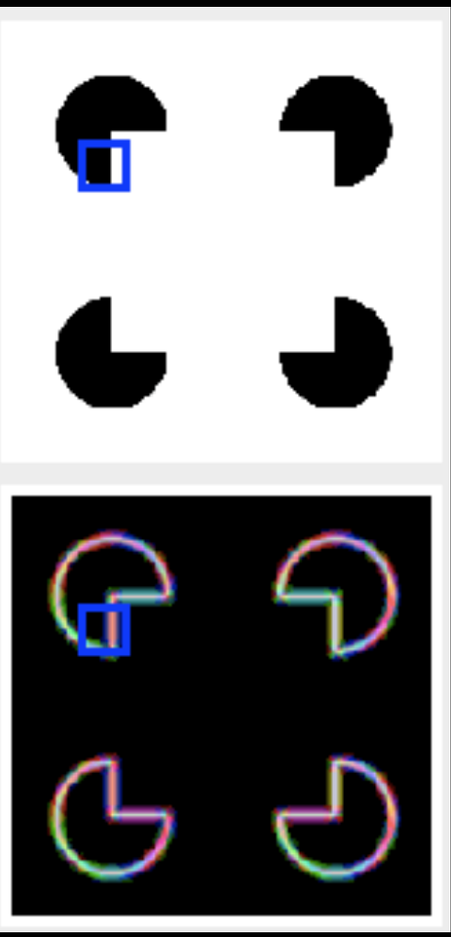
rectangle

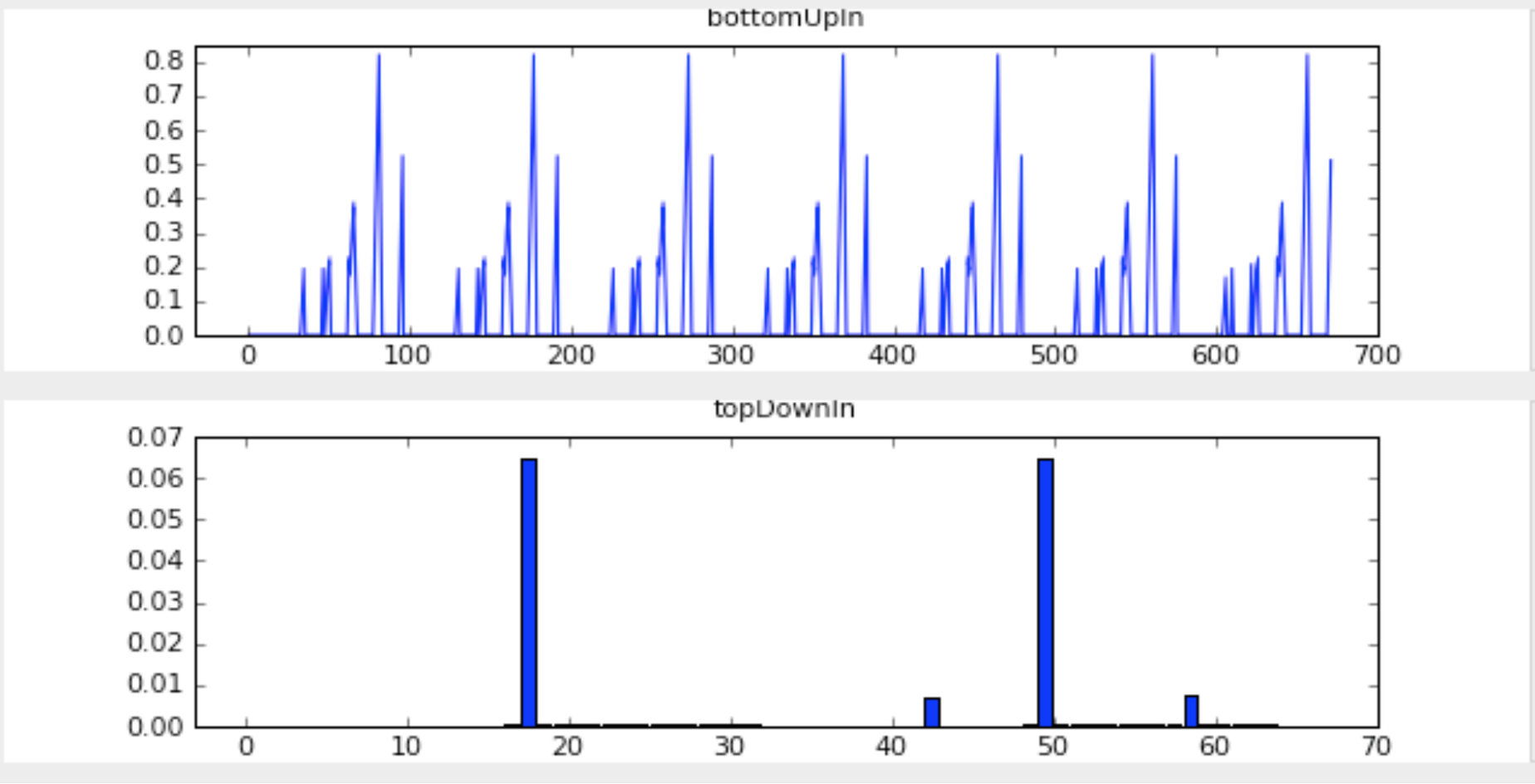
cell phone

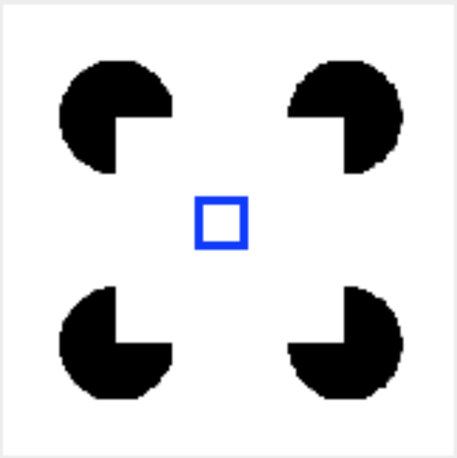
binocular

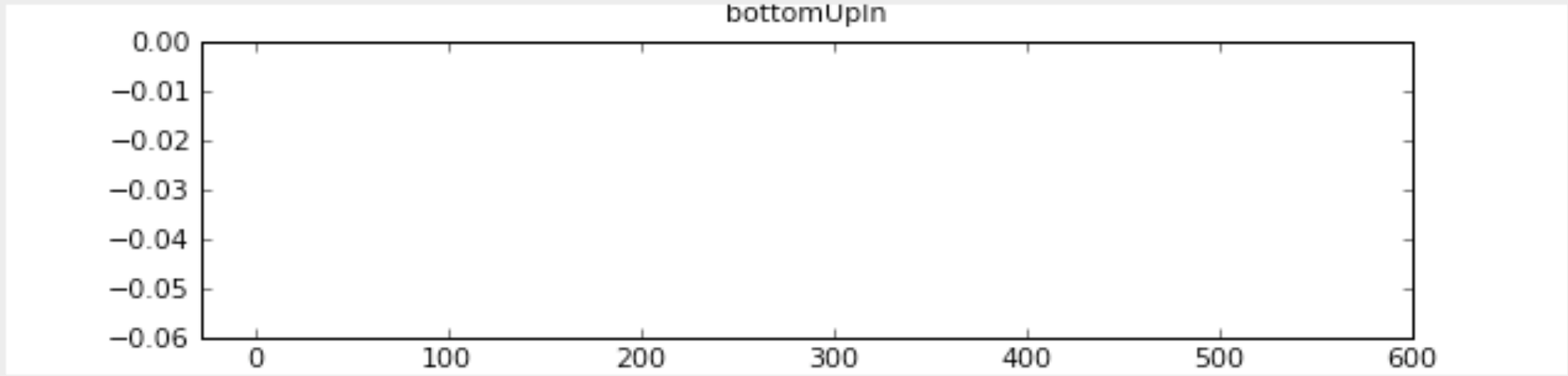
rubber duck

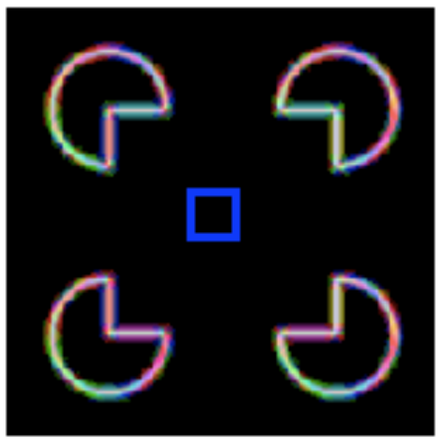
car

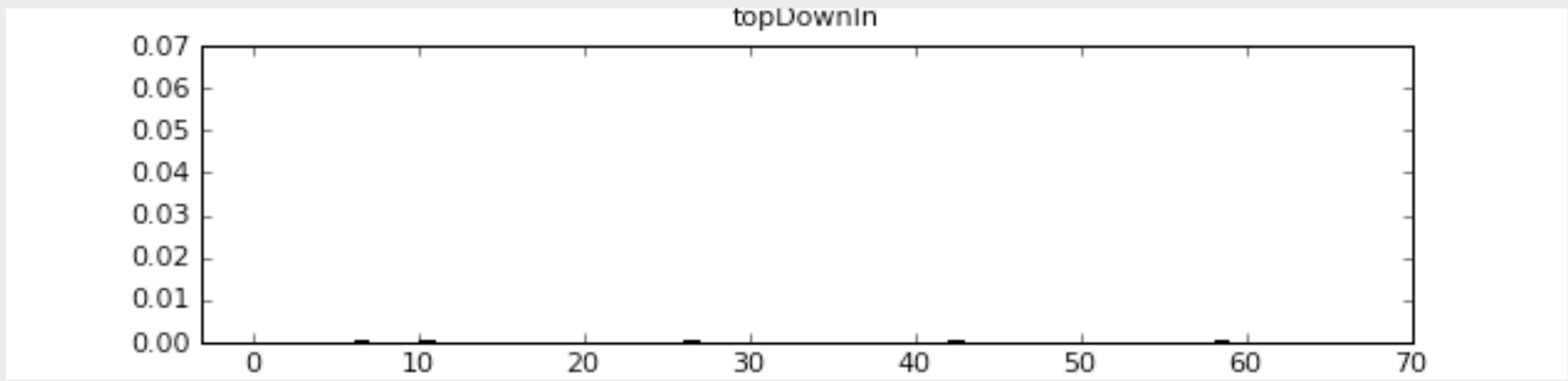



bottomUpIn
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
100
200
300
400
500
600
700
topDownIn
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
10
20
30
40
50
60
70




bottomUpIn
0.00
−0.01
−0.02
−0.03
−0.04
−0.05
−0.06
0
100
200
300
400
500
600




topDownIn
0.07
0.06
0.05
0.04
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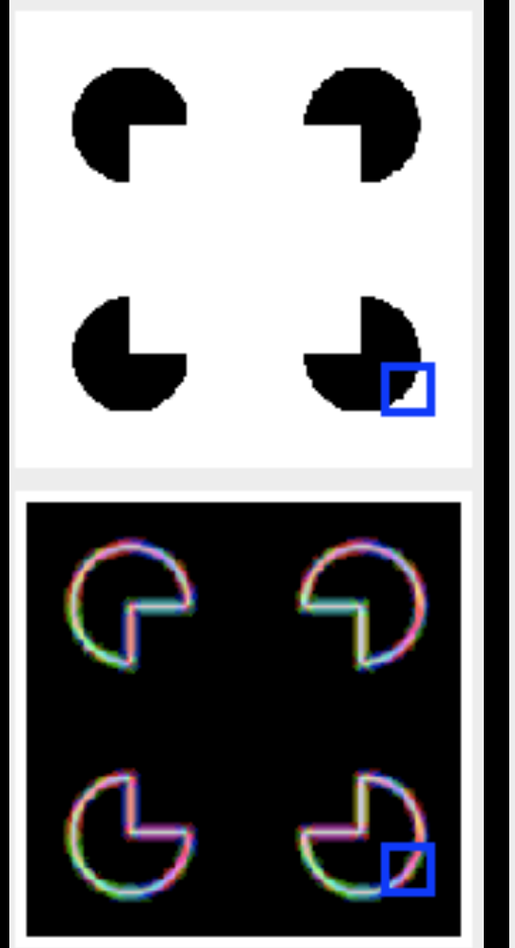
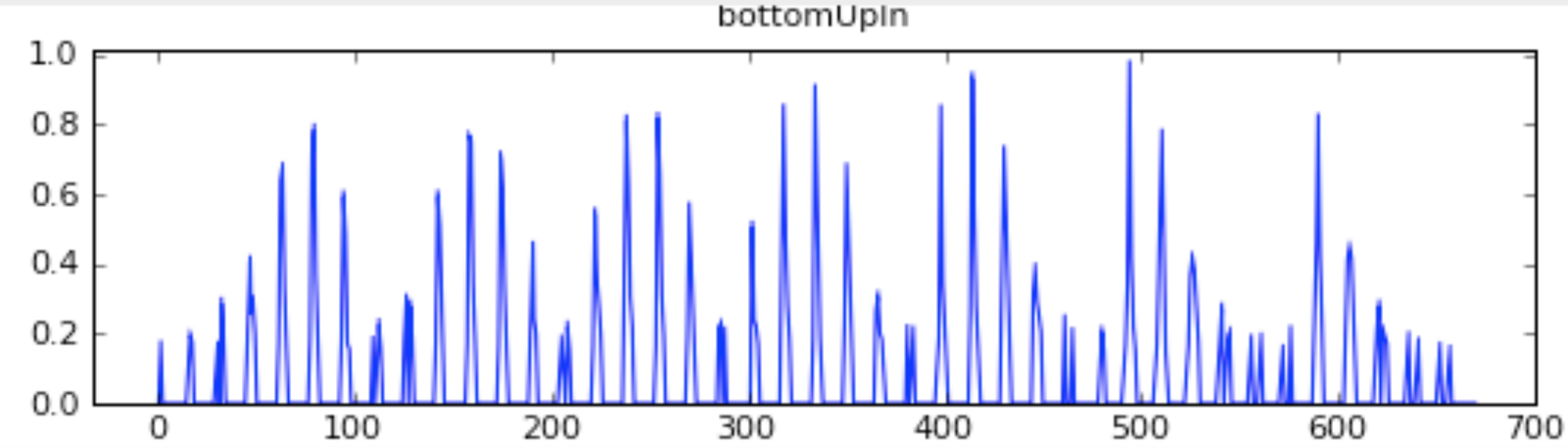
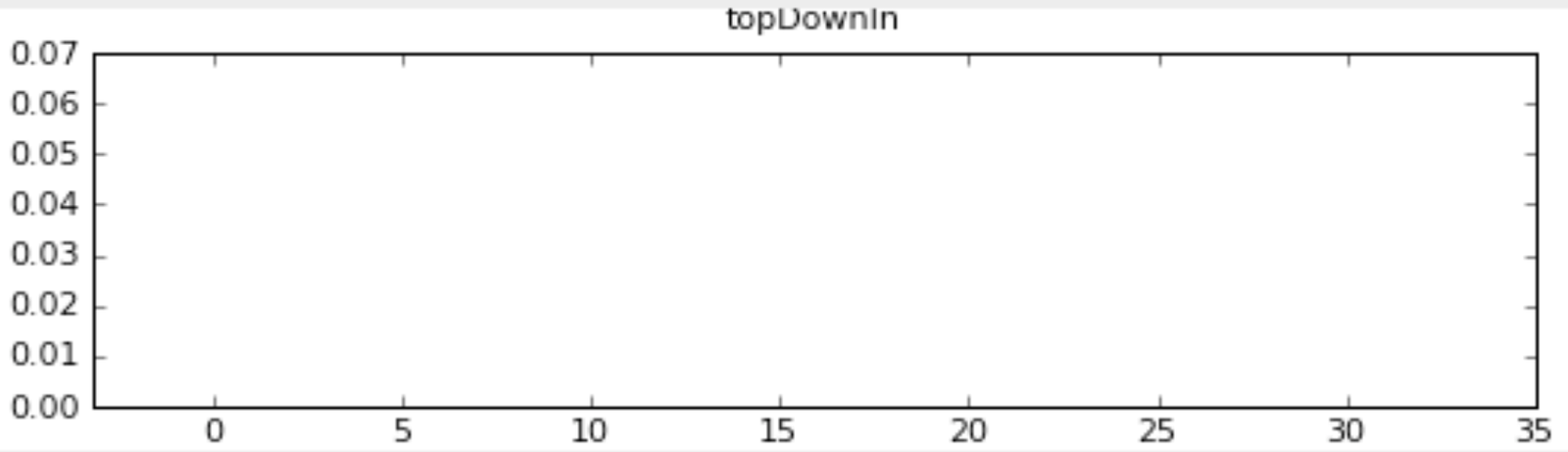
0.01
0.00
0
10
20
30
40
50
60
70




bottomUpIn
1.0
0.8
0.6
0.4
0.2
0.0
0
100
200
300
400
500
600
700


topDownIn
0.07
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5
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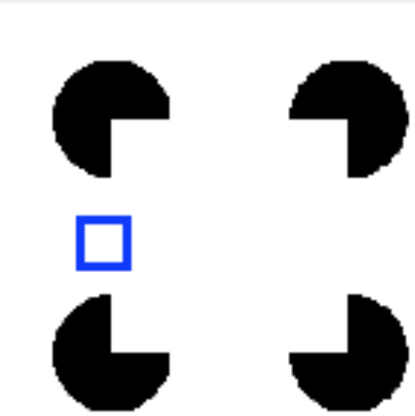
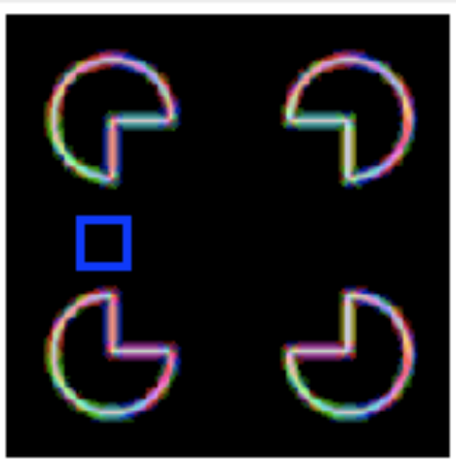
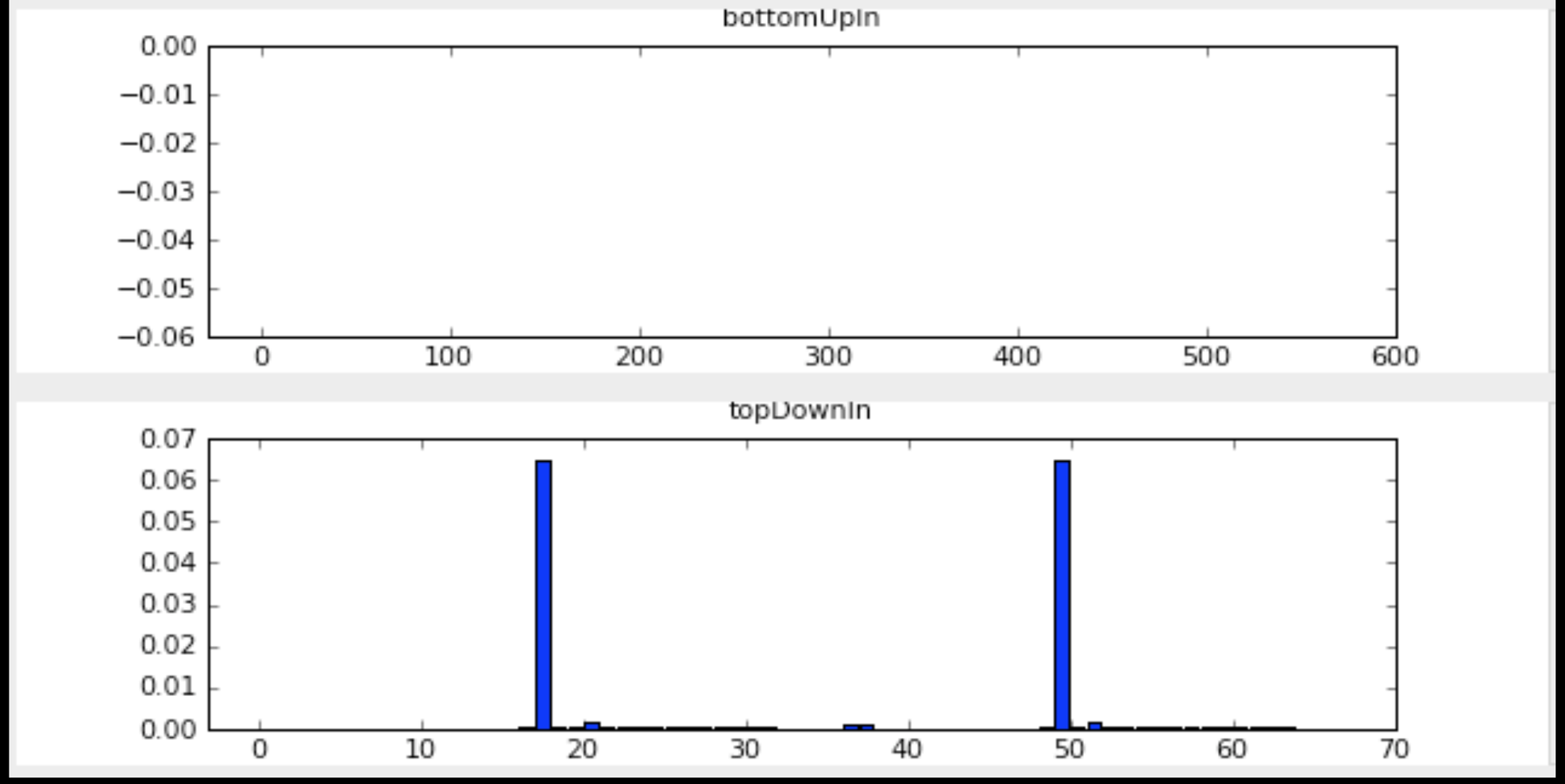
20
25
30
35






bottomUpIn
0.00
−0.01
−0.02
−0.03
−0.04
−0.05
−0.06
0
100
200
300
400
500
600
topDownIn
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
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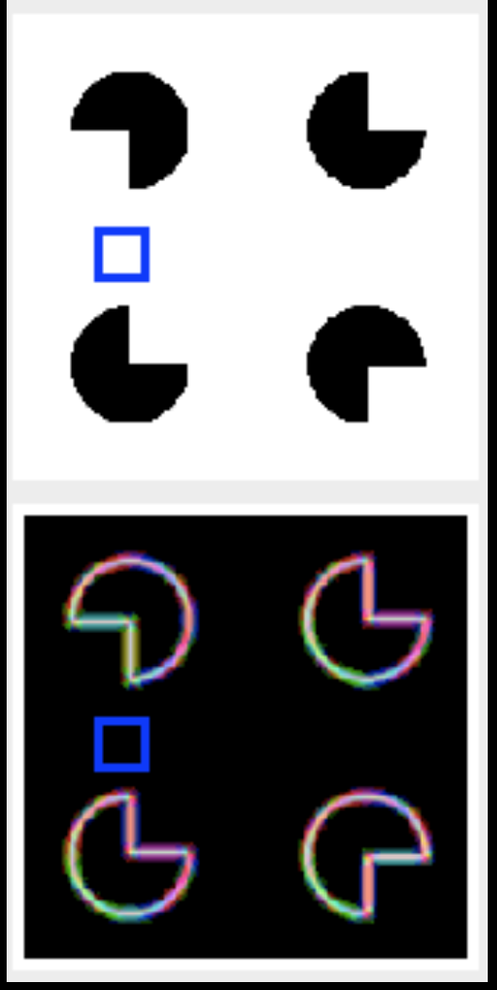
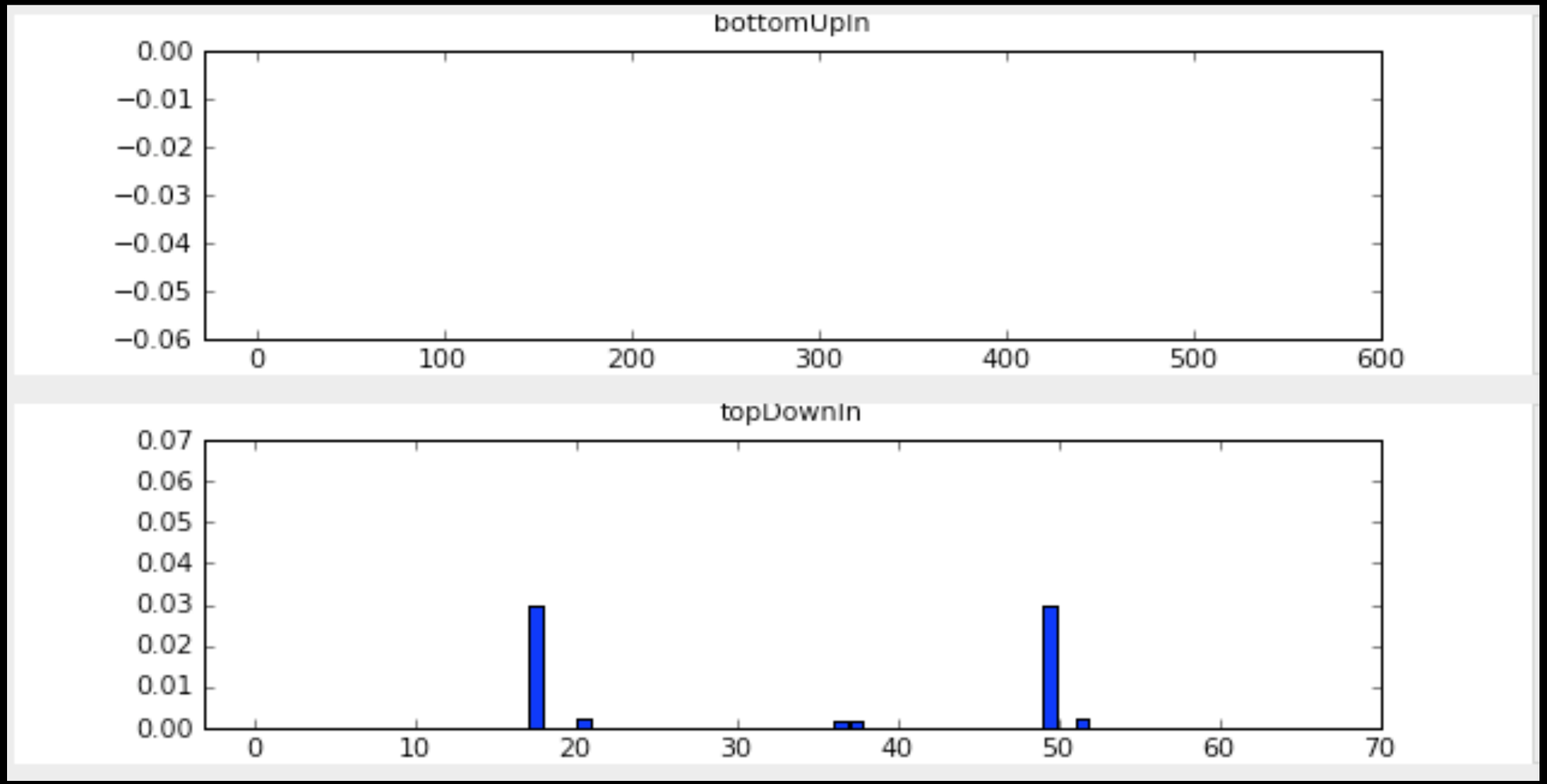
40
50
60
70




bottomUpIn
0.00
−0.01
−0.02
−0.03
−0.04
−0.05
−0.06
0
100
200
300
400
500
600
topDownIn
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
10
20
30
40
50
60
70

Thank You

Papers, thesis etc. www.dileepgeorge.com