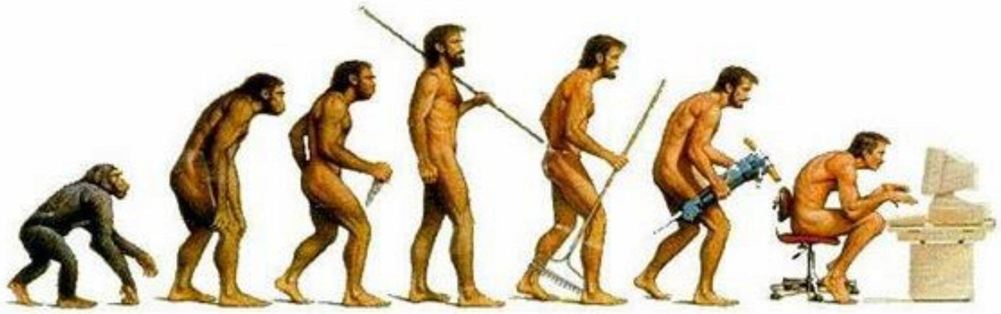
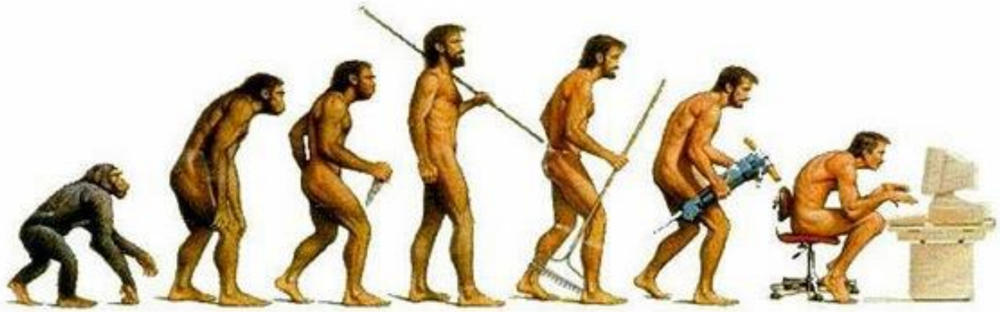
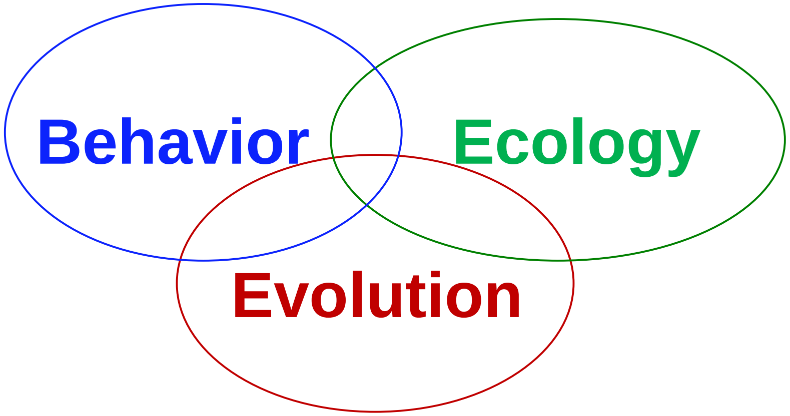
Social learning and cognitive evolution



Arnon Lotem
Tel-Aviv University

Social learning and cognitive evolution

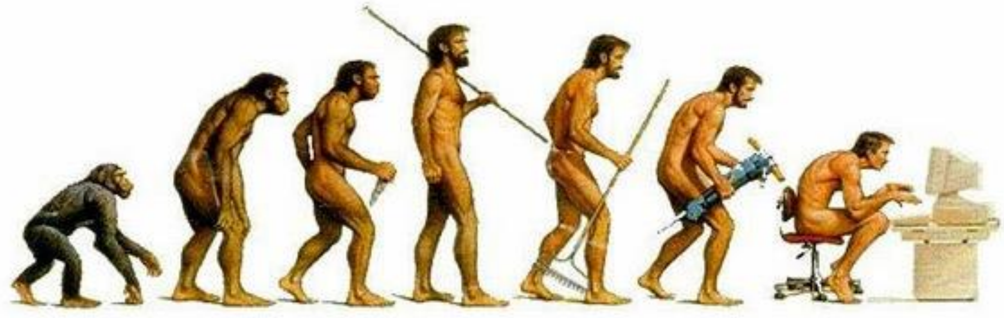




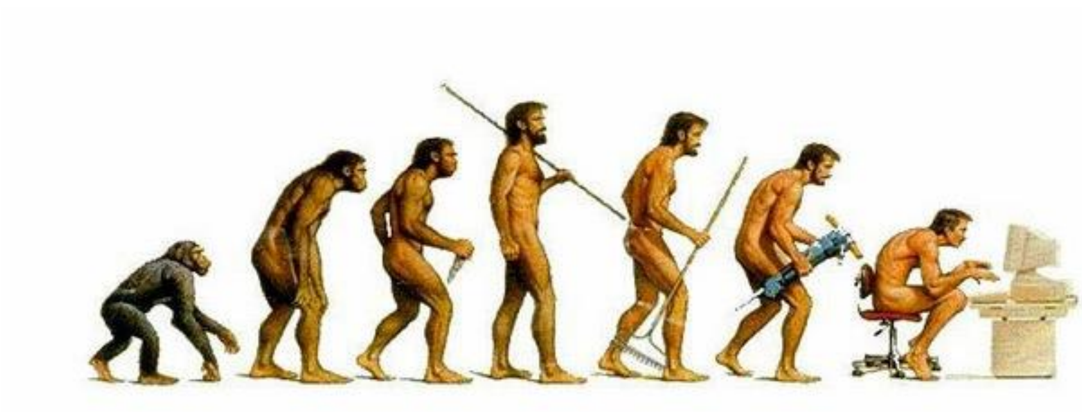
Behavioral Ecology:

Arnon Lotem
Tel-Aviv University

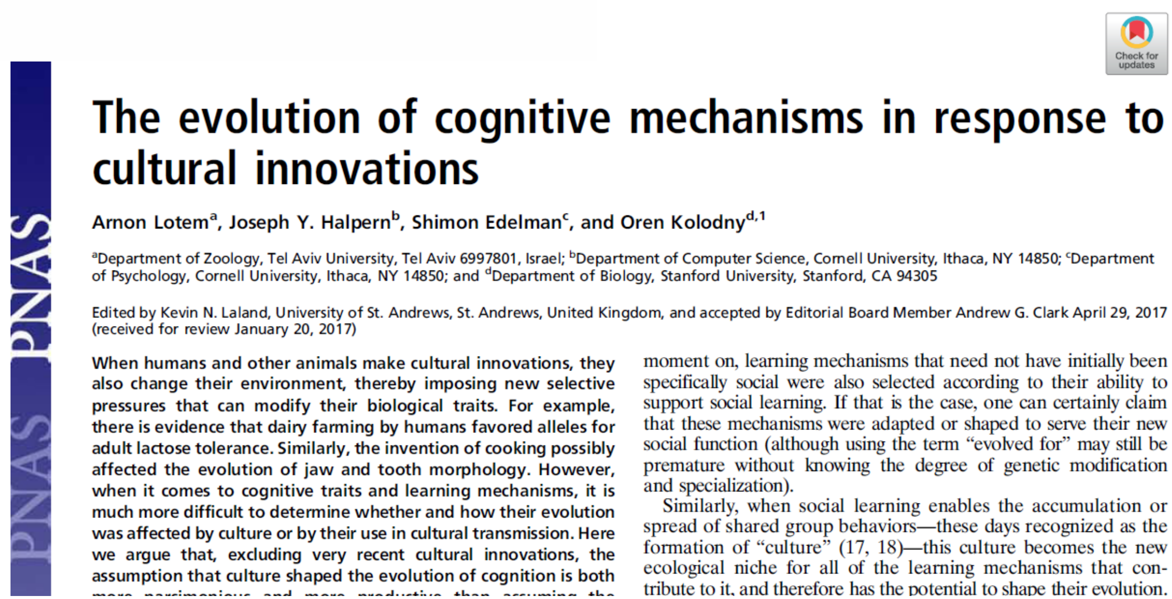
Social learning and cognitive evolution



Social learning and cognitive evolution



Humans in the Context of Evolutionary Transitions



PNAS PNAS

The evolution of cognitive mechanisms in response to cultural innovations

Arnon Lotem[a], Joseph Y. Halpern[b], Shimon Edelman[c], and Oren Kolodny[d,1]

[a]Department of Zoology, Tel Aviv University, Tel Aviv 6997801, Israel; [b]Department of Computer Science, Cornell University, Ithaca, NY 14850; [c]Department of Psychology, Cornell University, Ithaca, NY 14850; and [d]Department of Biology, Stanford University, Stanford, CA 94305

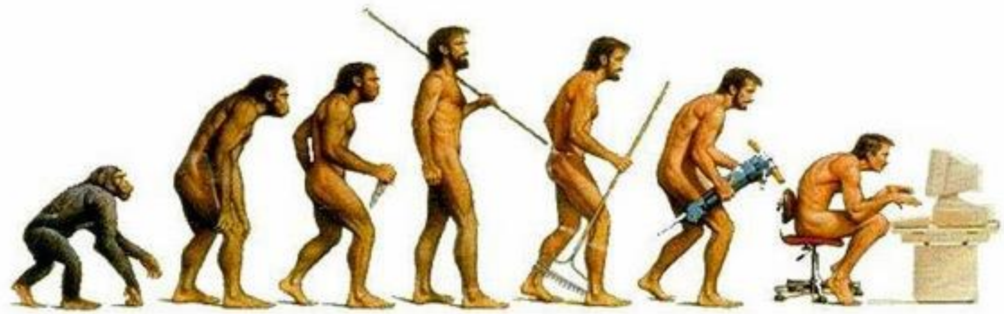
Edited by Kevin N. Laland, University of St. Andrews, St. Andrews, United Kingdom, and accepted by Editorial Board Member Andrew G. Clark April 29, 2017 (received for review January 20, 2017)

When humans and other animals make cultural innovations, they also change their environment, thereby imposing new selective pressures that can modify their biological traits. For example, there is evidence that dairy farming by humans favored alleles for adult lactose tolerance. Similarly, the invention of cooking possibly affected the evolution of jaw and tooth morphology. However, when it comes to cognitive traits and learning mechanisms, it is much more difficult to determine whether and how their evolution was affected by culture or by their use in cultural transmission. Here we argue that, excluding very recent cultural innovations, the assumption that culture shaped the evolution of cognition is both

moment on, learning mechanisms that need not have initially been specifically social were also selected according to their ability to support social learning. If that is the case, one can certainly claim that these mechanisms were adapted or shaped to serve their new social function (although using the term "evolved for" may still be premature without knowing the degree of genetic modification and specialization).

Similarly, when social learning enables the accumulation or spread of shared group behaviors—these days recognized as the formation of "culture" (17, 18)—this culture becomes the new ecological niche for all of the learning mechanisms that contribute to it, and therefore has the potential to shape their evolution.

1. Cognitive evolution in response to culture



PNAS PNAS

The evolution of cognitive mechanisms in response to cultural innovations

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Humans in the Context of Evolutionary Transitions

1. Cognitive evolution in response to culture

2. Can humans and other animals learn (from experience) what is beneficial for the “higher level” of organization?

3. Can cost-free virtual communication be reliable?

PNAS

Crowd wisdom enhanced by costly signaling in a virtual rating system

Ofer Tchernichovski[a,1], Lucas C. Parra[b], Daniel Fimiarz[c], Arnon Lotem[d], and Dalton Conley[e,1]

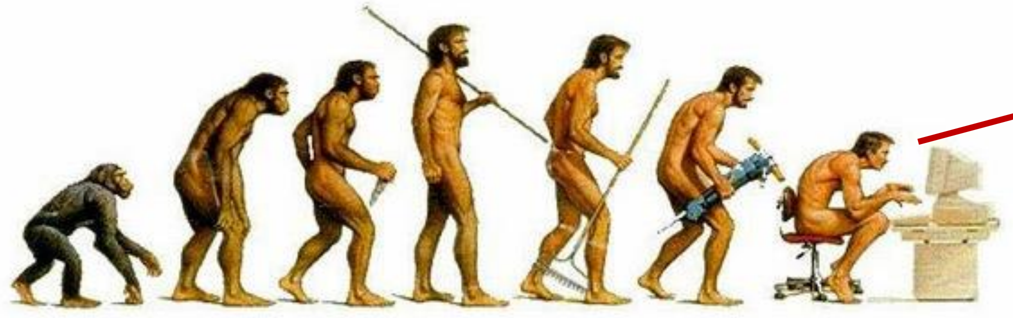
[a]Department of Psychology, Hunter College, The City University of New York, New York, NY 10065; [b]Department of Biomedical Engineering, City College, The City University of New York, New York, NY 10031; [c]Science Division, City College, The City University of New York, New York, NY 10031; [d]School of Zoology, Tel Aviv University, Tel Aviv, Israel 61000; and [e]Department of Sociology and Office of Population Research, Princeton University, Princeton, NJ 08544

Contributed by Dalton Conley, February 26, 2019 (sent for review October 9, 2018; reviewed by Damon Centola and Rufus A. Johnstone)

Costly signaling theory was developed in both economics and biology and has been used to explain a wide range of phenomena. However, the theory's prediction that signal cost can enforce in-

cheating. But even if there is no motivation to cheat, there is, at best, ambiguous direct benefit to the rater in providing an accurate assessment of provider quality (16). Therefore, especially

1. Cognitive evolution in response to culture



Intelligence

Working memory

Poor memory

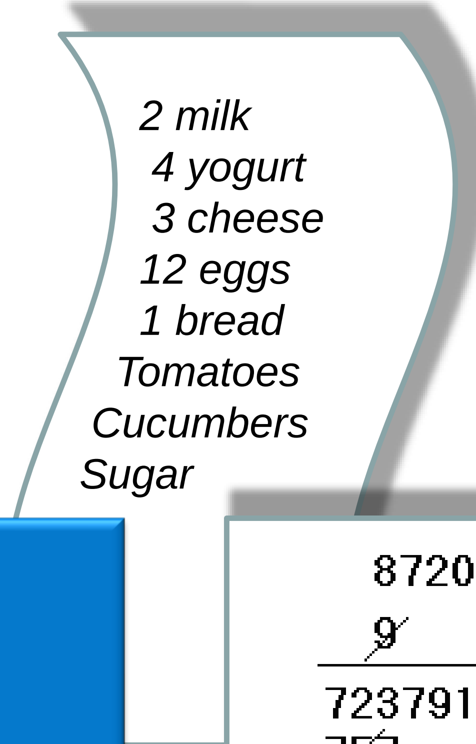
Slow learning

2 milk
4 yogurt
3 cheese
12 eggs
1 bread
Tomatoes
Cucumbers
Sugar
….

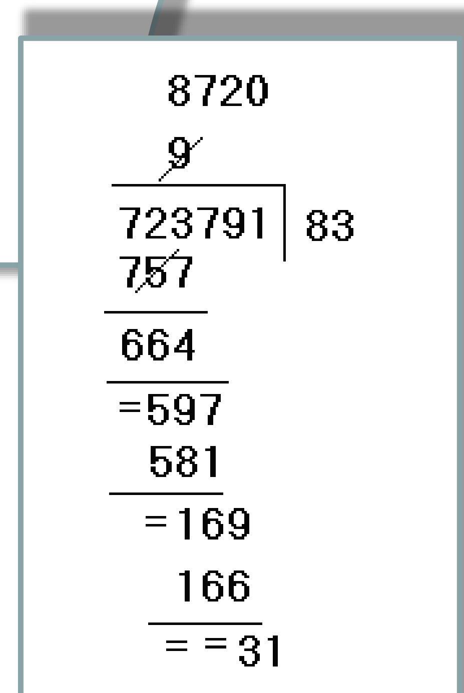
8720
$\cancel{9}$
723791 | 83
7$\cancel{5}$7
664
=597
581
=169
166
= =31

Why can’t we have a better memory?

There is evidence for genetic heritability in various types of memory (in humans and animals)



Memory can evolve !



Mueller ST, … decay hypot… 53:14–25.

Cui J, Gao D, … early-school-age children with Asperger’s syndrome. J Autism Dev Disord 40:958–967.

Blokland GAM, et al. (2011) Heritability of working memory brain activation. J Neurosci 31:10882–10890.

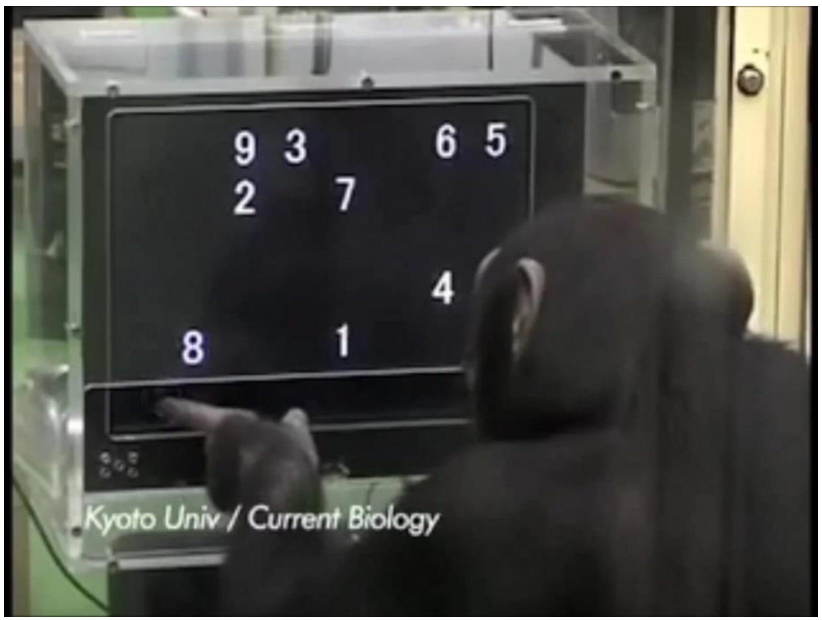
Vogler C, et al. (2014) Substantial SNP-based heritability estimates for working memory performance. Transl Psychiatry 4:e438.

…….

Working memory of numerals in chimpanzees

Inoue & Matsuzawa 2007.

Current Biology



Why can’t we have a (slightly) better memory?

Joseph Y. Halpern
Computer Science, Cornell

Shimon Edelman
Psychology, Cornell

Oren Kolodny
(just back from Stanford)

Lotem A, Halpern JY (2008) Cornell Univ. Computing and Information Sci. Techl Reports.

Goldstein MH, et al. (2010) **Trends Cogn Sci** 14:249–258.

Lotem A, Halpern JY (2012) **Philos Trans R Soc Lond B Biol Sci** 367: 2686–2694.

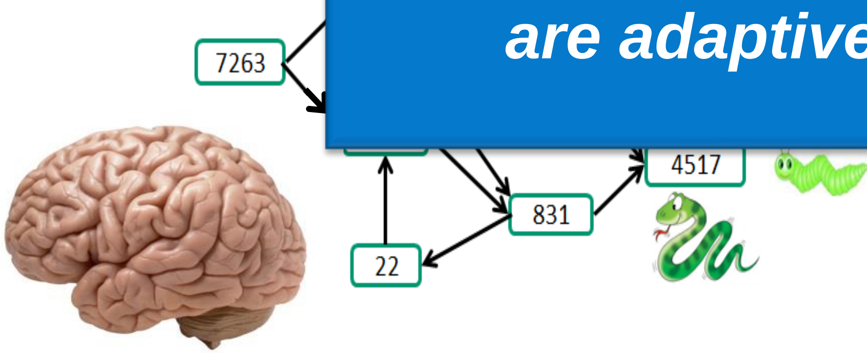
Kolodny O, Edelman S, Lotem A (2014) **J R Soc Interface** 11:20131091.

Kolodny O, Edelman S, Lotem A (2015) **Proc Biol Sci** 282: 20150353.

ny O, Lotem A, Edelman S (2015) **itive Science** 39:227–267.

ny O, Edelman S, Lotem A (2015) **Zool** 61:350–367.

Lotem A., Halpern JY, Edelman S & Kolodny O, (2017). ***PNAS***

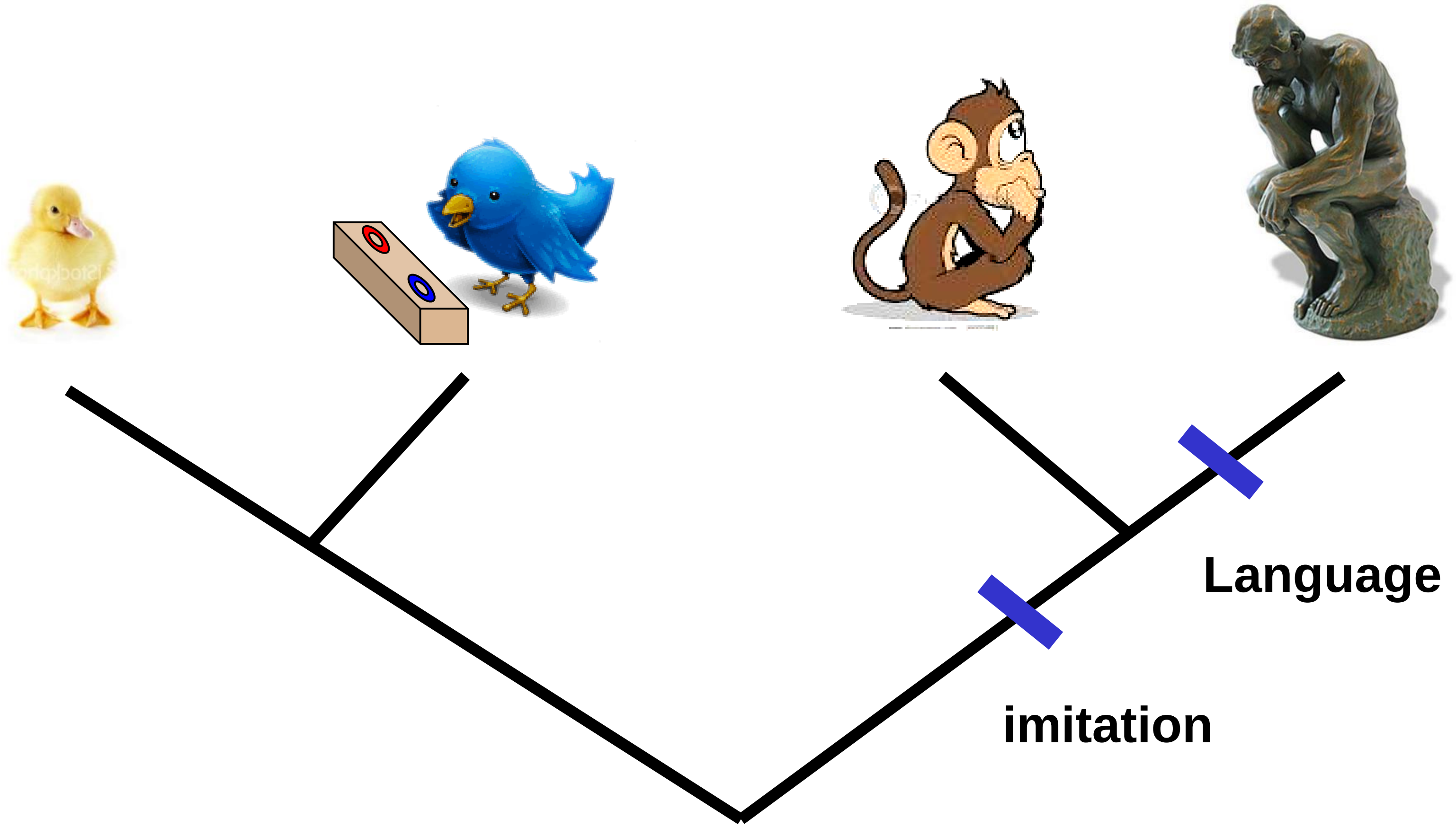


Memory limitations are adaptive !

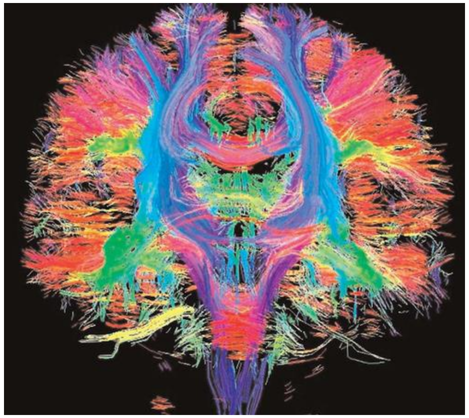
Cognitive evolution from animal foraging to human language

A model for cognitive evolution?

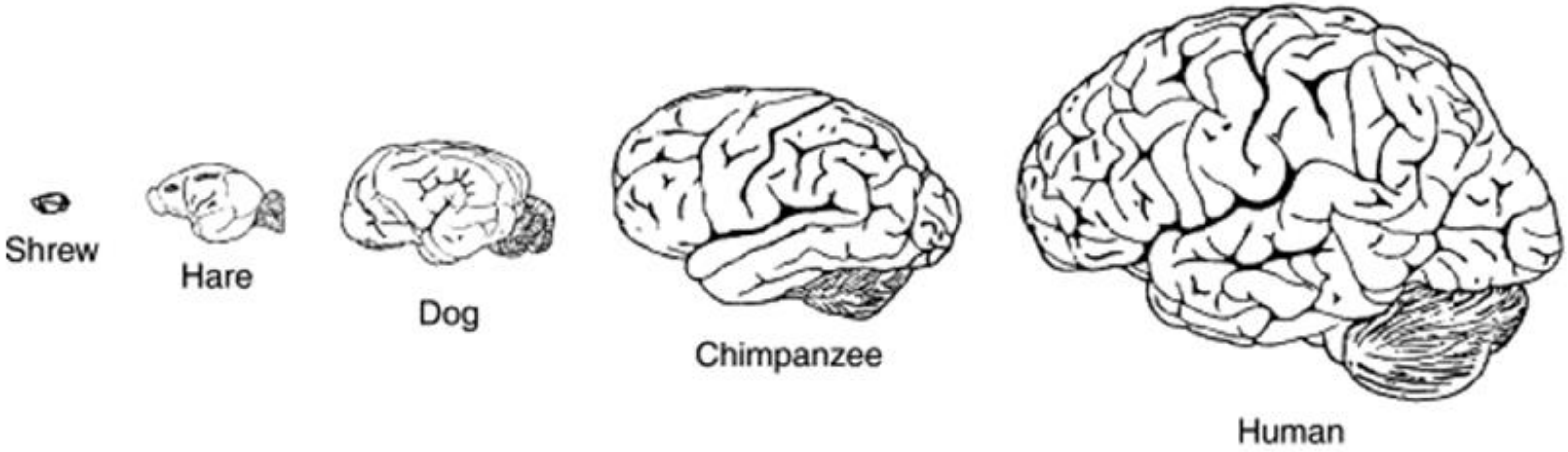
A model for cognitive evolution?



A model for cognitive evolution?



How small genetic modifications make a better brain?



A model for cognitive evolution?

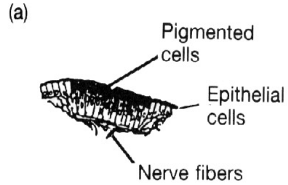
How small genetic modifications make a better brain?

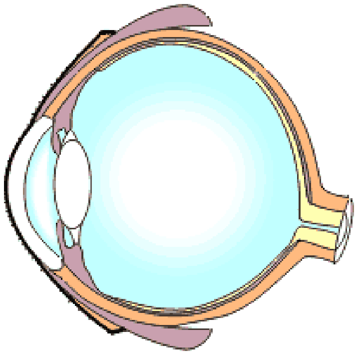
A model for cognitive evolution?

A model for ….the brain

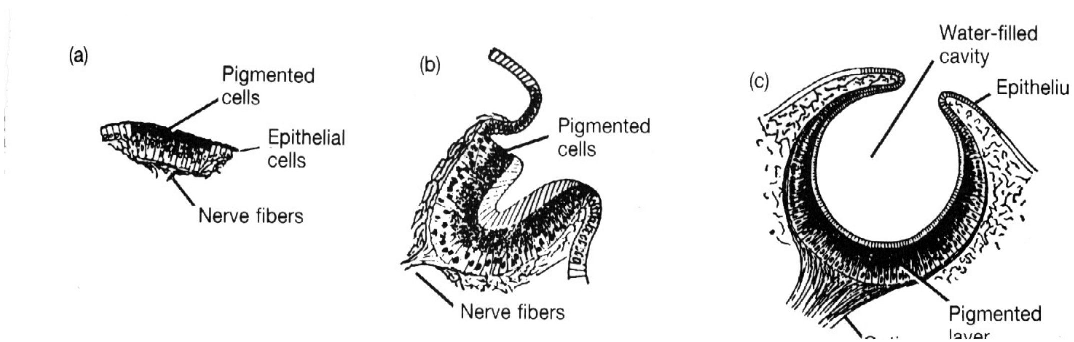
How small genetic modifications make a better brain?

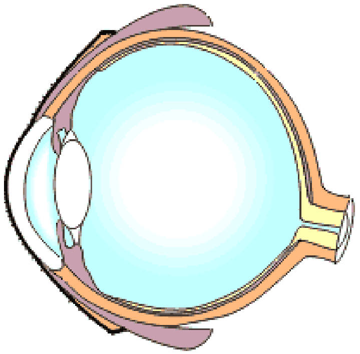
How small genetic modifications make a better eye?





How small genetic modifications make a better eye?





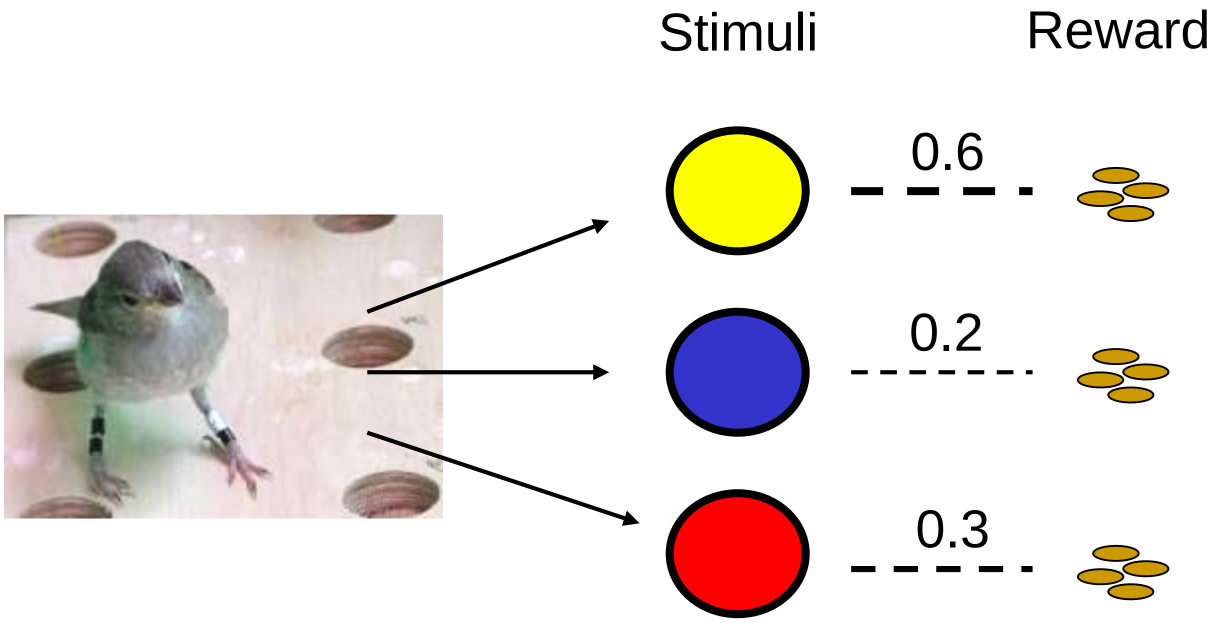
learning

How small genetic modifications make a better brain?

Algorithms

Networks

A typical learning model:



Data is given


Where is the food?

Where is the food?

91726397976123437568270768397564833198984657465338394793698372639837
08357028750298986756128736597912341324512344491989827875628712873985
26192739127396919287390128726387391872983691287319827398273618723643 4

Where is the food?

9172639797612343756827076839756448 31989846574653383947936983726398 37

0835702875029898 75612873659791234132451234449198982 87562871287398 5

261927391273969192873901287263873918729836912873198273982736187236434

The simple way

(associate nearby data)

Where is the food?

917263979761234375682707683975648 31<u>9898</u>4657465338394793698372639837
0835702875029898 7561287365979123413245123444919898 2 875628712873985
261927391273969192873901287263873918729836912873198273982736187236434

The simple way

(associate nearby data)

Where is the food?

917263979761234375682707683975648 319898465746533839479369837263983 7
0835702875029898 7561287365979123413245123444919898 2 875628712873985
261927391273969192873901287263873918729836912873198273982736187236434

The simple way
(associate nearby data)

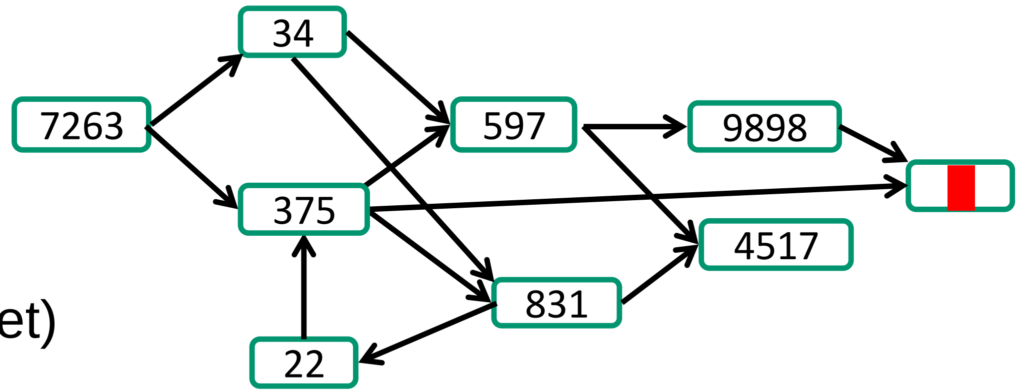
The “expensive” way
(learn the entire data set)

Where is the food?

917263979761234375682707683975648 3198984657465338394793698372639837
0835702875029898 756128736597912341324512344491989822 87562871287398 5
2619273912739691928739012872638739187298369128731982739827361872364 34

The simple way

The “expensive” way
(learn the entire data set)



The problem of correct segmentation (or chunking)

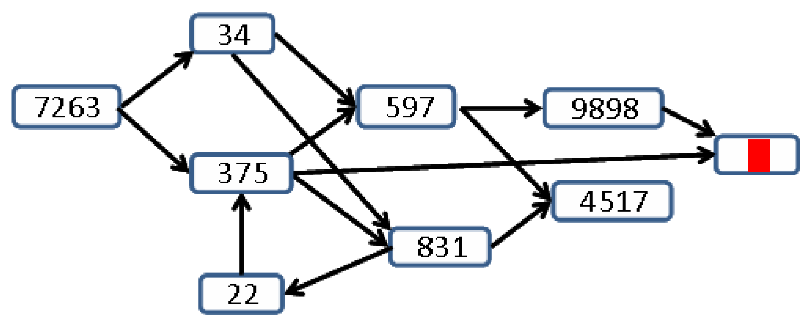
There are ways to solve this….

917263979761234375682707683975648319898465746533839479369837263983 7
0835702875029898756128736597912341324512344491989828756287128739 85
261927391273969192873901287263873918729836912873198273982736187236434

The simple way

The “expensive” way

Our model:



…through co-evolution of learning and data acquisition mechanisms

The main idea:

375682707683975648 36799984657465338394793698320847979357398753739 75
283083702847502834750835702875029 8 756128739182736 9 8756287391287398
261927391273969192873912873928739187236912873198273982736187236402834

Acquire “relevant” data → Determined by the “data acquisition mechanisms”

Innate templates
Innate reinforcers
(food, danger, social)
Learned (secondary) reinforcers

↓

The distribution of data input

The main idea:

Acquire “relevant” data

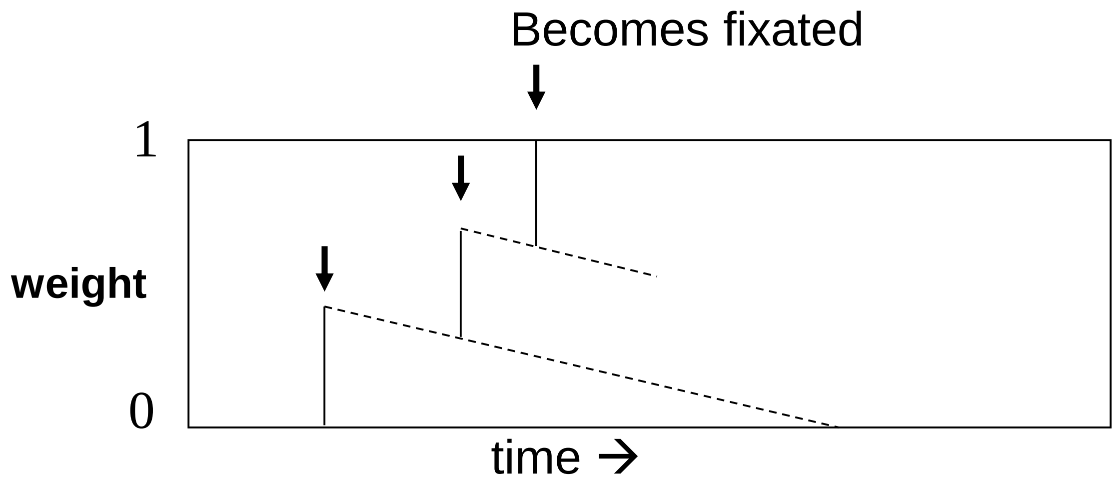
756

The main idea:

Acquire “relevant” data

756
. . .
. . .
756
. . .
756

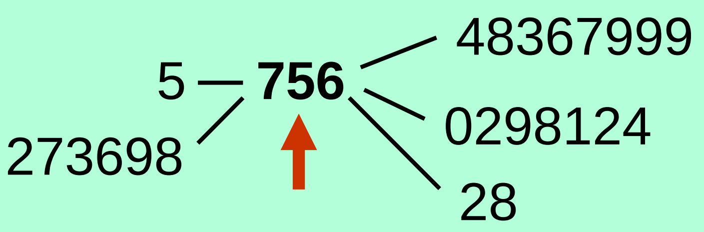
756 **is a significant item**



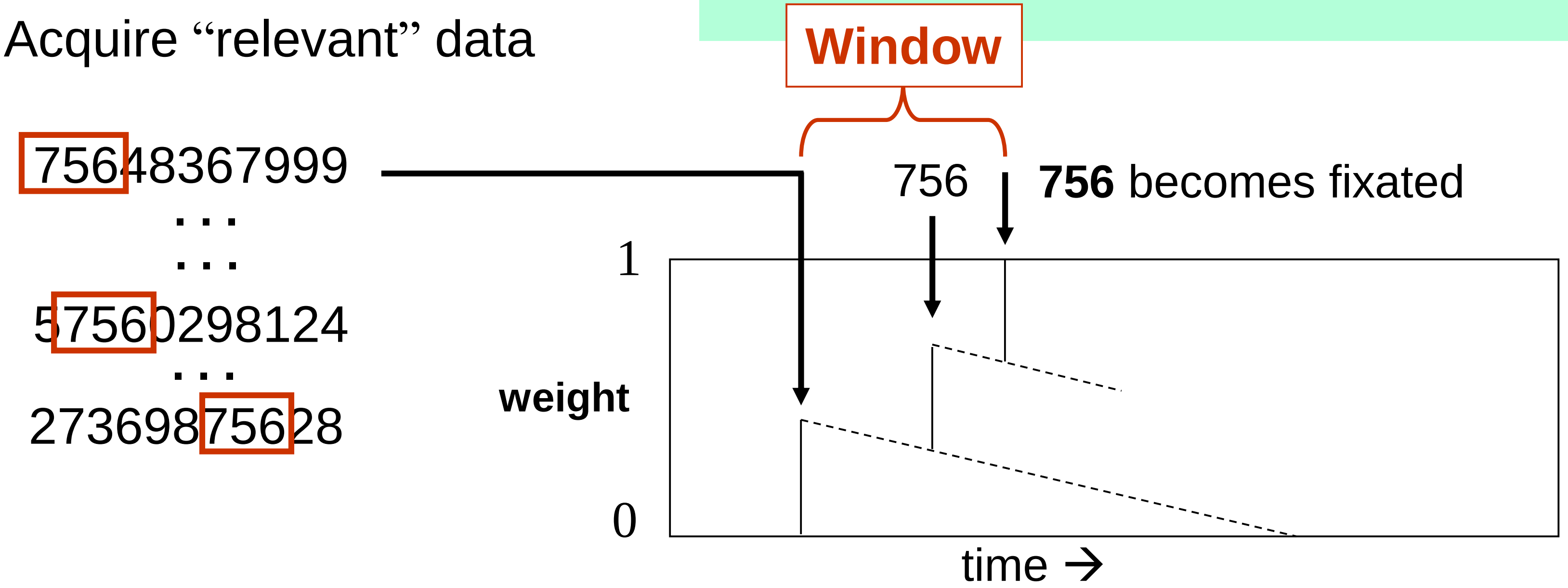
Memory parameters: weight increase and decrease (decay)

The main idea:

A network in memory representation



Acquire “relevant” data



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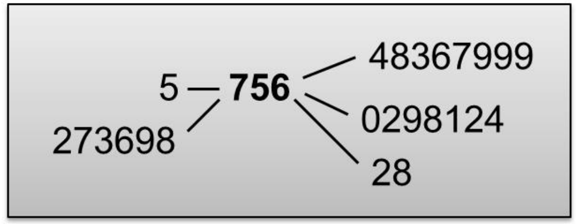


75648367999

57560298124

Acquire “relevant” data

75648367999

. . .

75648367999

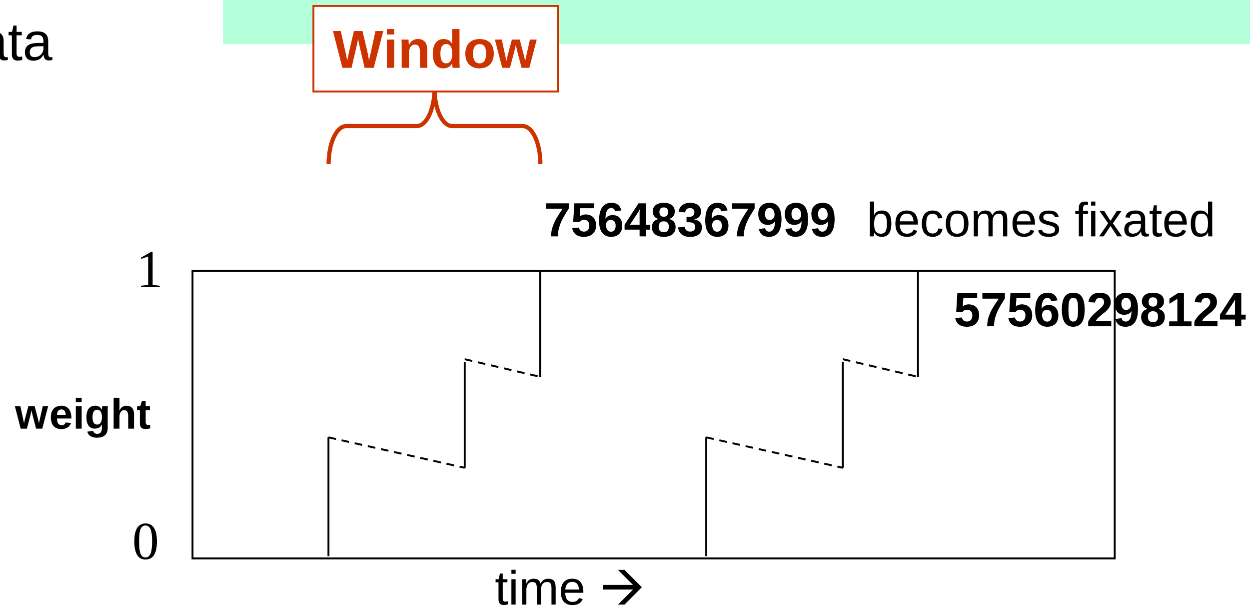
. . .

75648367999

57560298124

57560298124

57560298124



Memory parameters: weight increase and decrease (decay)

The main idea:

A network in memory representation

Acquire “relevant” data

75648367999

. . .

. . .

. . .

. . .

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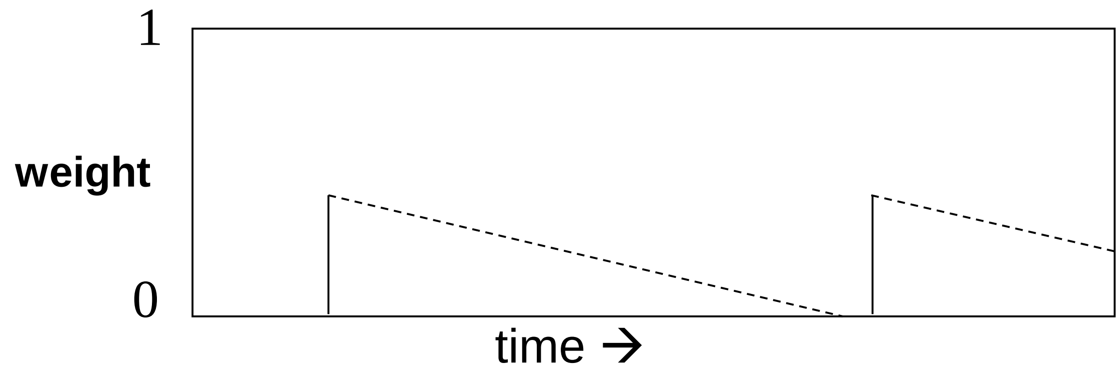
. . .

. . .

57560298124

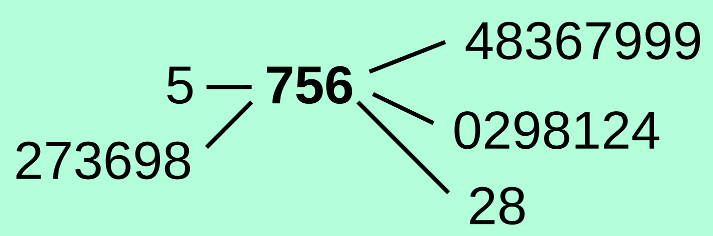
Window



Memory parameters: weight increase and decrease (decay)

The main idea:

A network in memory representation



Acquire "relevant" data

$\boxed{756}48367999$

...

...

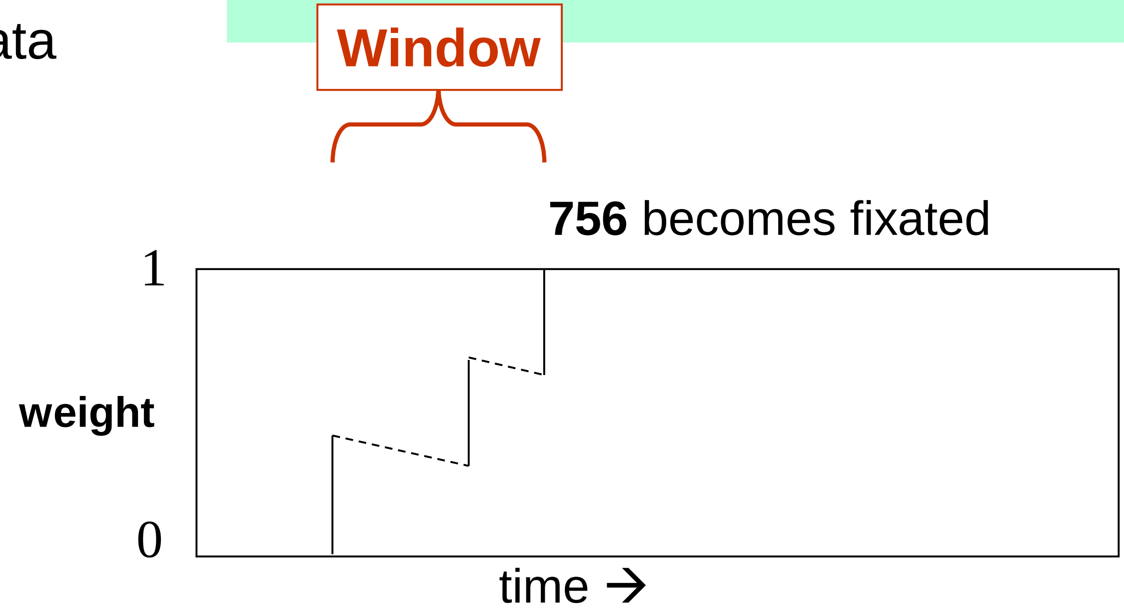
$5\boxed{756}0298124$

...

$273698\boxed{756}28$

Data acquisition mechanisms

co-evolve



Memory parameters: weight increase and decrease (decay)

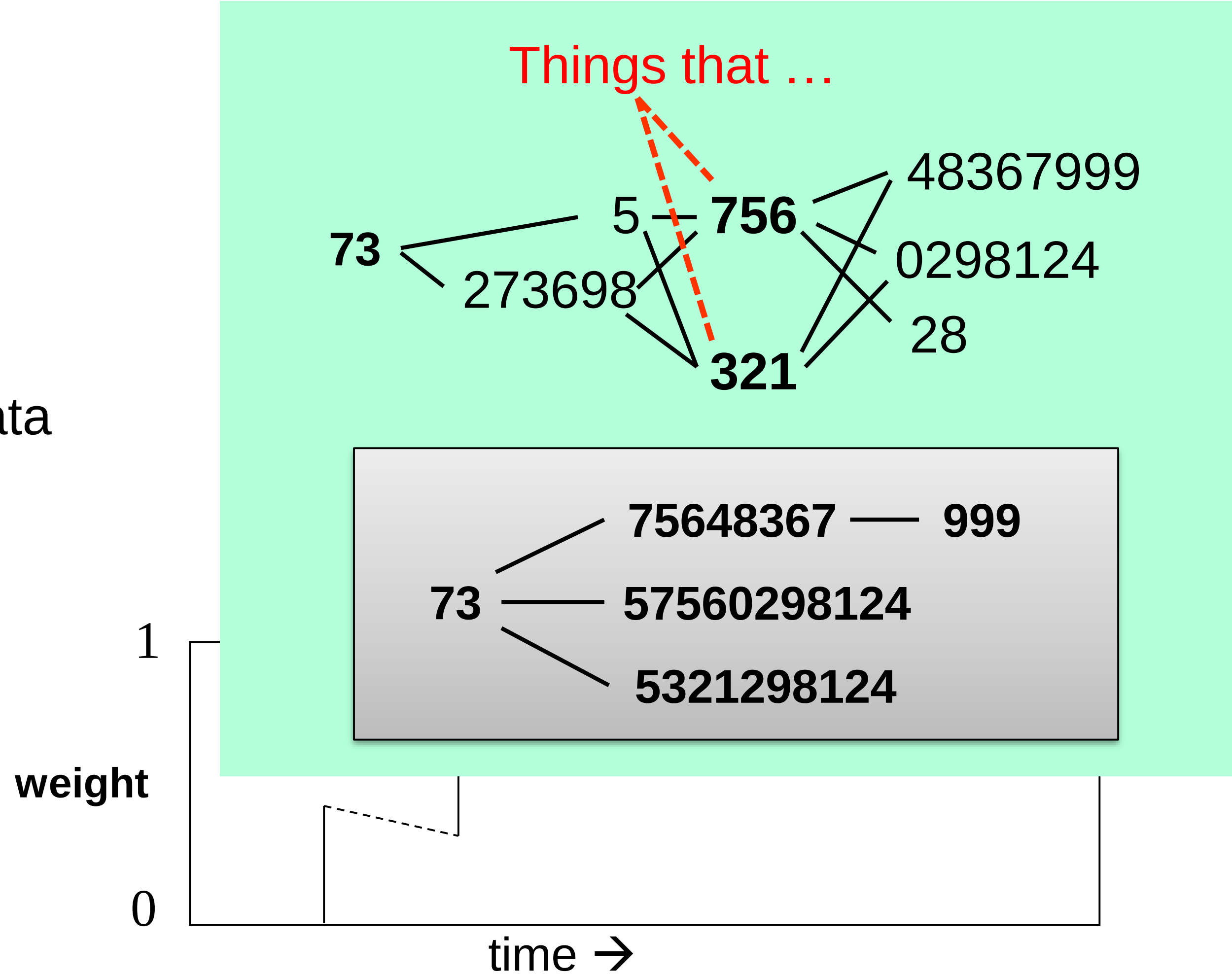
The main idea:

Acquire “relevant” data

756[48367999]
. . .
. . .
5756[0298124]
. . .
273698756[28]

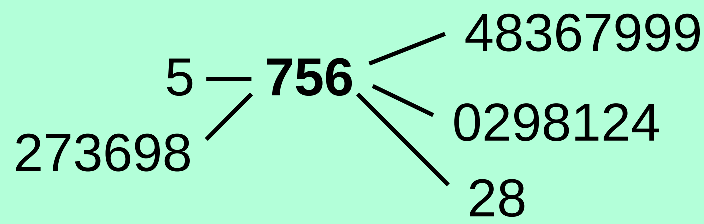
Data acquisition mechanisms

co-evolve



Memory parameters: weight increase and decrease (decay)

The main idea:



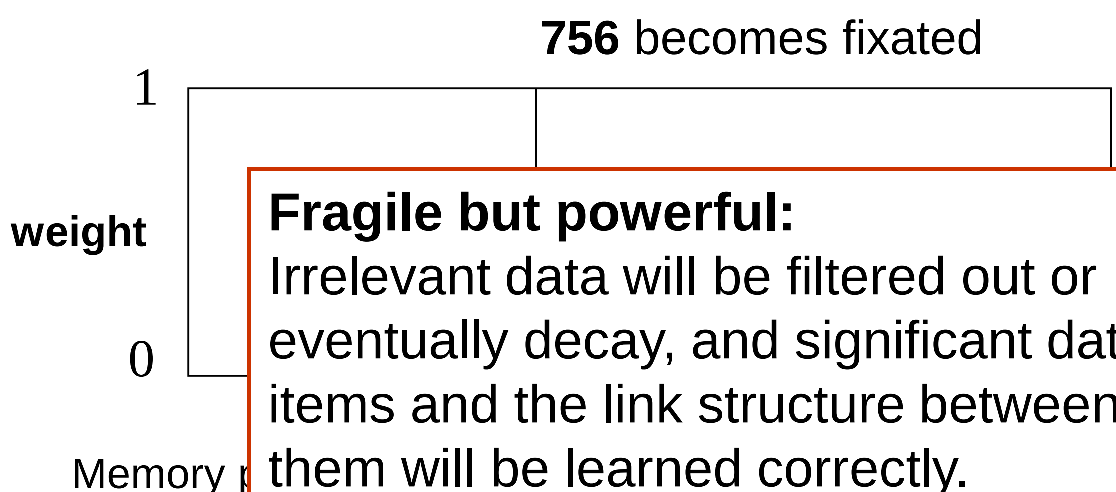
Acquire “relevant” data

75648367999
. . .
. . .
57560298124
. . .
27369875628

Data acquisition mechanisms

co-evolve

Window



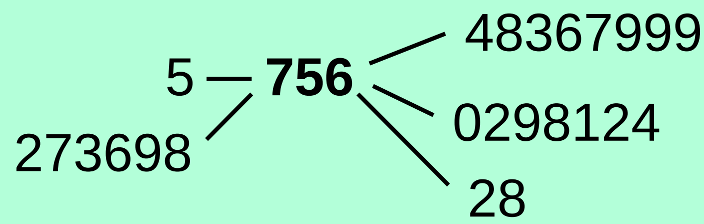
Fragile but powerful:
Irrelevant data will be filtered out or eventually decay, and significant data items and the link structure between them will be learned correctly.

- requires less memory and computation

explains why memory has to be limited

and it is also evolvable

The main idea:



Acquire “relevant” data

756483679999

...

...

57560298124

...

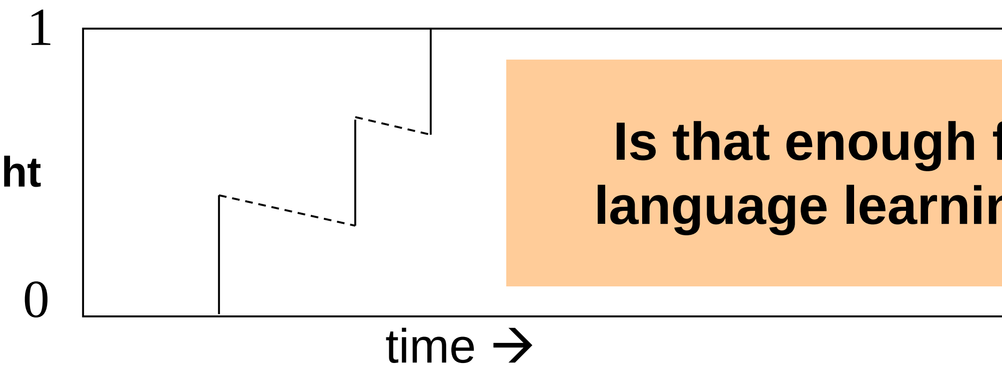
2736987562 8

Data acquisition mechanisms

co-evolve

Window

756 becomes fixated



Is that enough for language learning?

Memory parameters: weight increase and decrease (decay)

- requires less memory and computation

(explains why memory has to be limited)

and it is also evolvable

The main idea:

5 — **756**
273698
48367999
0298124
28

Acquire "relevant

756 48367999
. . .
. . .
5 756 0298124
. . .
2736987 56 28

Data acquisition mechanisms

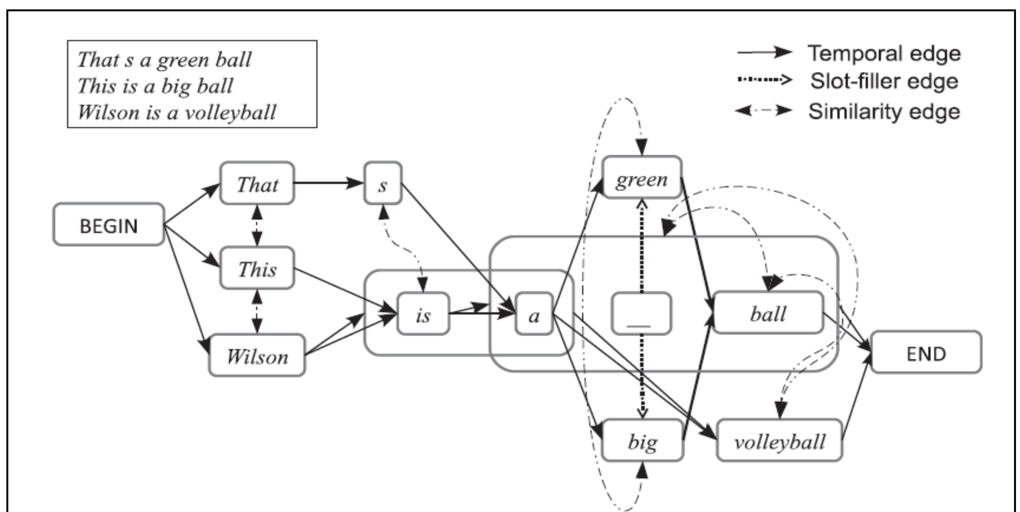
co-evolve

COGNITIVE SCIENCE
A Multidisciplinary Journal

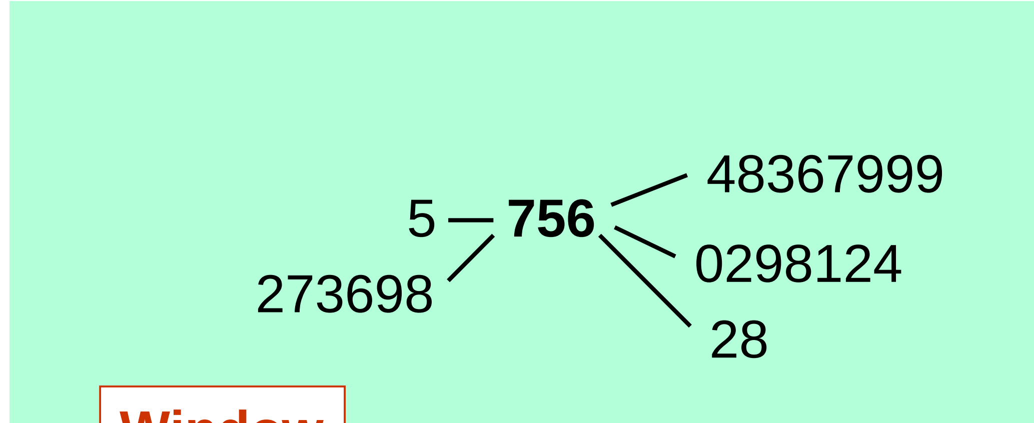
Cognitive Science 39 (2015) 227–267

Learning a Generative Probabilistic Grammar of Experience: A Process-Level Model of Language Acquisition

Oren Kolodny[a], Arnon Lotem[a], Shimon Edelman[b]



The main idea:



Acquire “relevant” data

75648367999

. . .

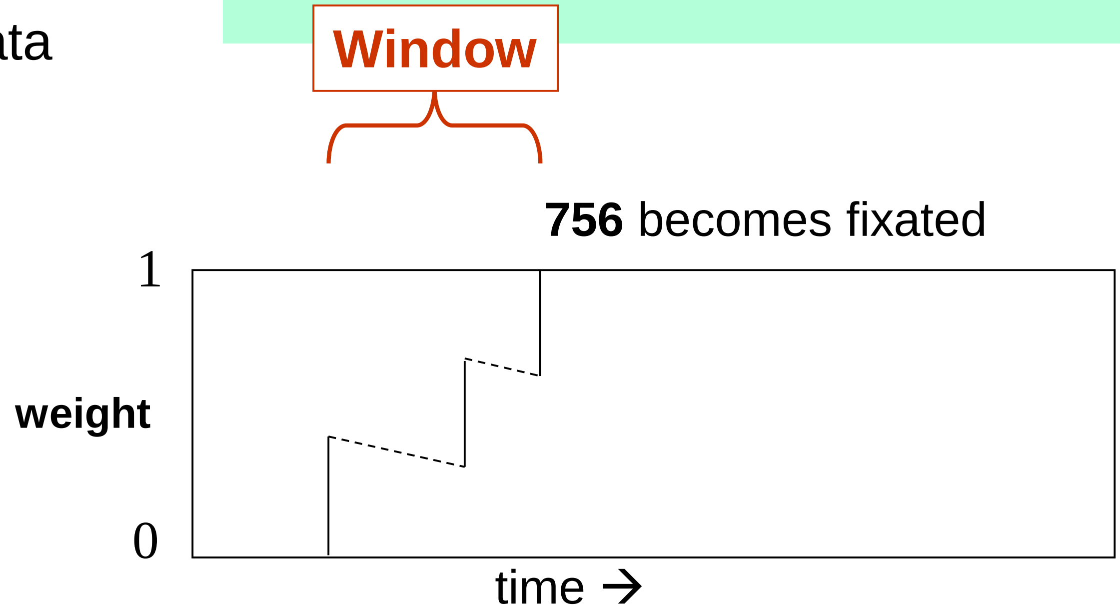
. . .

57560298124

. . .

27369875628

Data acquisition mechanisms



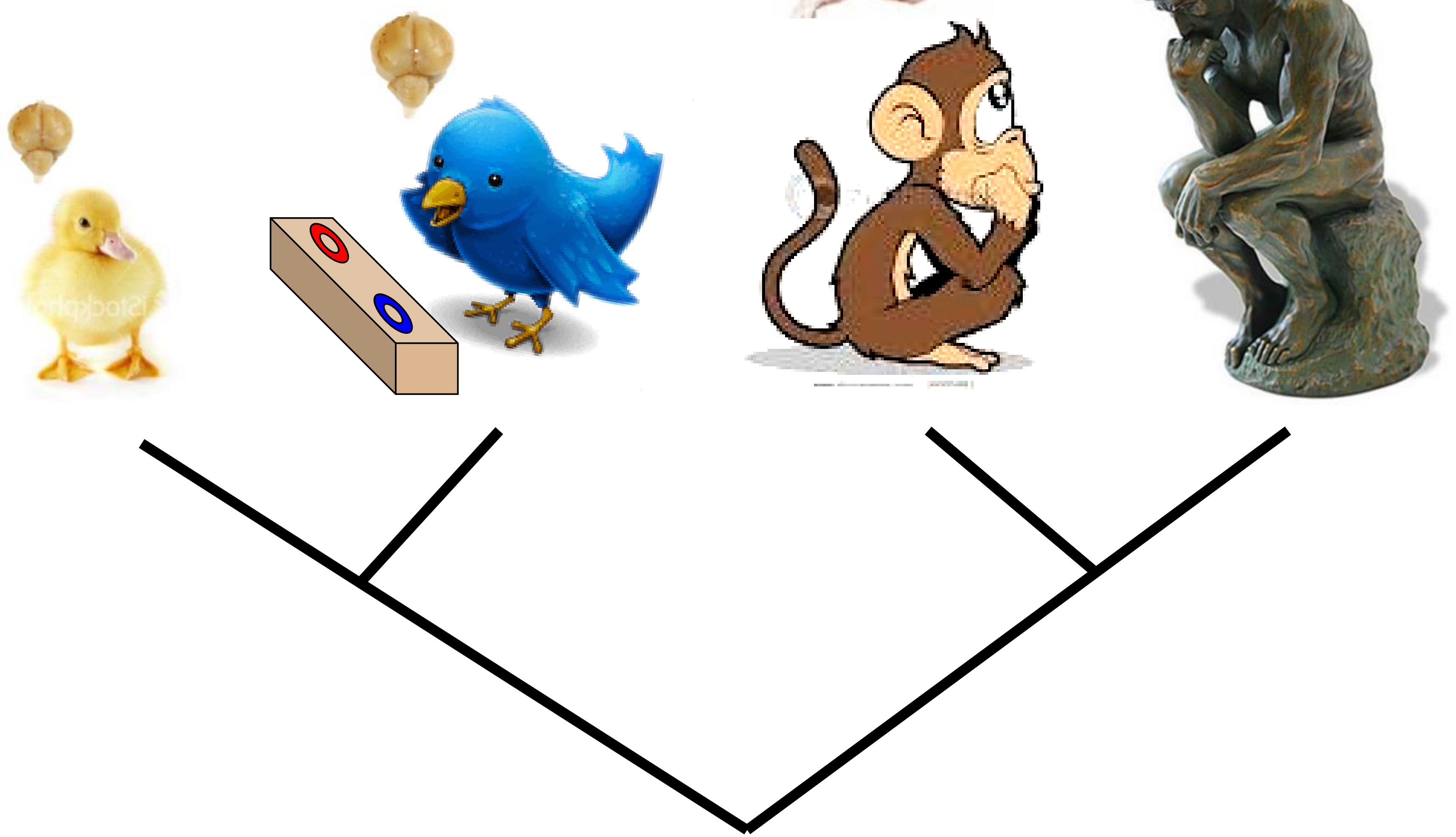
Memory parameters: weight increase and decrease (decay)

co-evolve

Not just the type and amount of data

The distribution of data input

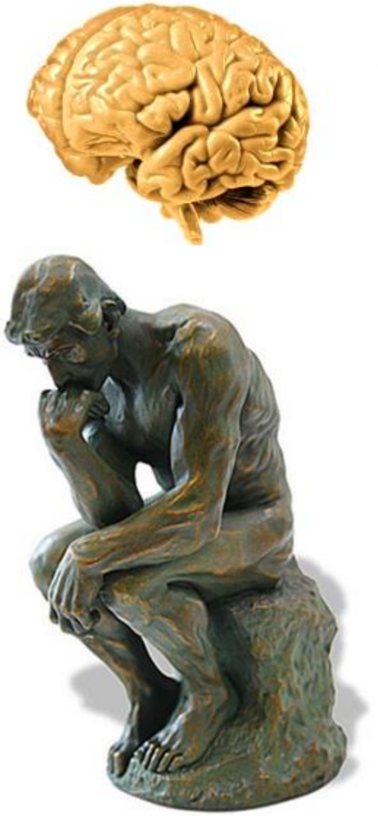
Learning parameters



Not just the type and amount of data

The distribution of data input

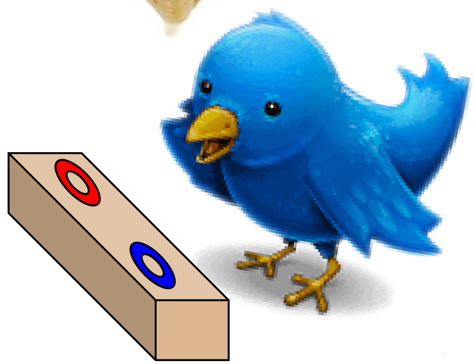
Learning parameters



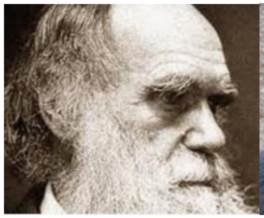
Not just the type and amount of data

The distribution of data input

Learning parameters



- **The “chimp memory test” paradox**



The problem of correct <u>segmentation</u> (or chunking)

The number of possible chunks in a linear sequence = N(N-1)/2

2619273912739691928739012872638739187298369128731982739827361872

The problem of correct <u>segmentation</u> (or chunking)

The number of possible chunks in a linear sequence = N(N-1)/2

2619273912739691928739012872638739187298369128731982739827361872

N=5
10 chunks

2619273912739691928739012872638739187298369128731982739827361872

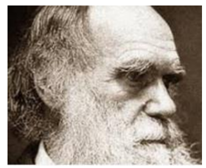
N=10
45 chunks

2619273912739691928739012872638739187298369128731982739827361872

N=15
105 chunks

The problem of correct <u>segmentation</u> (or chunking)

2619273912739691928739012872638739187298369128731982739827361872

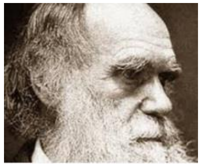
Thenumberofpossiblechunksinalinearsequence = N(N-1)/2

המספרהאפשרישלצ'אנקיםברצףלינארי = N(N-1)/2

線形シーケンス内の可能なチャンク数 = N(N-1)/2

The problem of correct <u>segmentation</u> (or chunking)

2619273912739691928739012872638739187298369128731982739827361872



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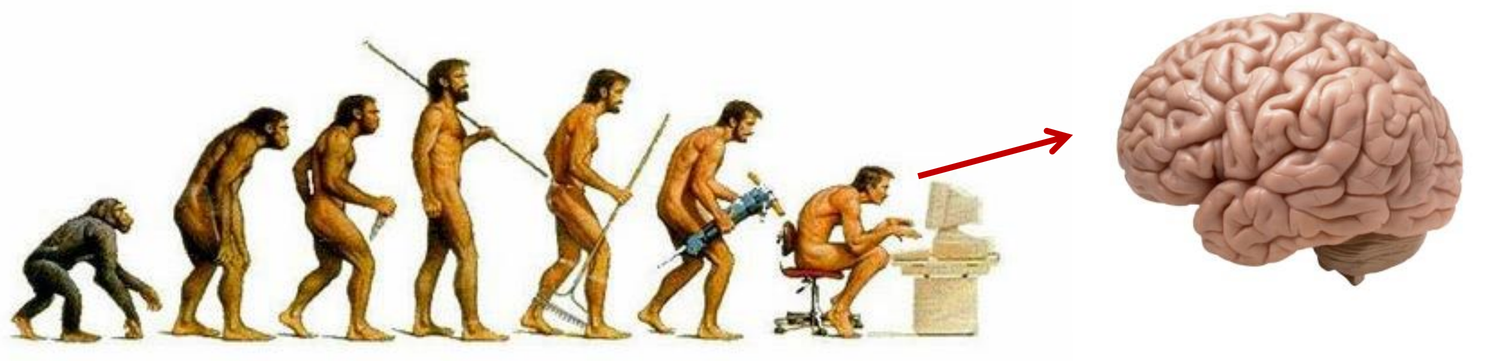
線形シーケンス内の可能なチャンク数 = N(N-1)/2

Memory limitations may be adaptive for handling computational challenges during data segmentation

and for testing the statistical significance of segments and patterns that are candidates to be represented in memory



2. Can humans and other animals learn (from experience) what is beneficial for the "higher level" of organization?

Do you believe in global warming ?

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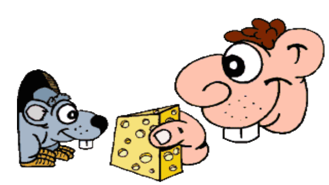
The description–experience gap in risky choice

R Hertwig, I Erev - Trends in cognitive sciences, 2009 - Elsevier

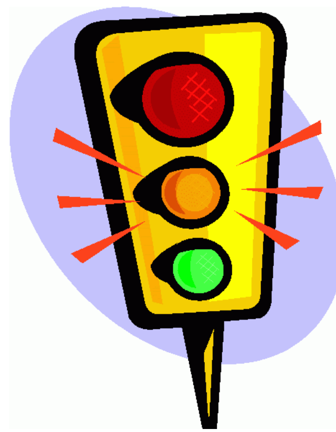
Nature, June 2008

Perceptual accuracy and conflicting effects of certainty on risk-taking behaviour

Sharoni Shafir[1], Taly Reich[2], Erez Tsur[1], Ido Erev[2] & Arnon Lotem[3]



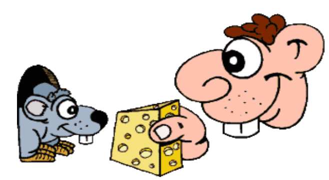
Listen to me !!
I have experience….



Nature, June 2008

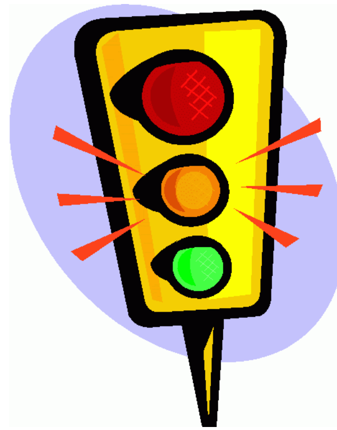
Perceptual accuracy and conflicting effects of certainty on risk-taking behaviour

Sharoni Shafir[1], Taly Reich[2], Erez Tsur[1], Ido Erev[2] & Arnon Lotem[3]



… develop a preference for the option that was better most of the time

Listen to me !!
I have experience….



What can we do?

Wait for genetic evolution to catch up with technology ?

A possible (partial) solution:

We can learn from experience
NOT to trust our (previous) experience !!!

Science education:

Don’t just tell them…,

- Let them do the experiment
- Let them do the math

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3. Can cost-free virtual communication be reliable?

Ofer Tchernichovski
CUNY, Hunter

PNAS

Crowd wisdom enhanced by costly signaling in a virtual rating system

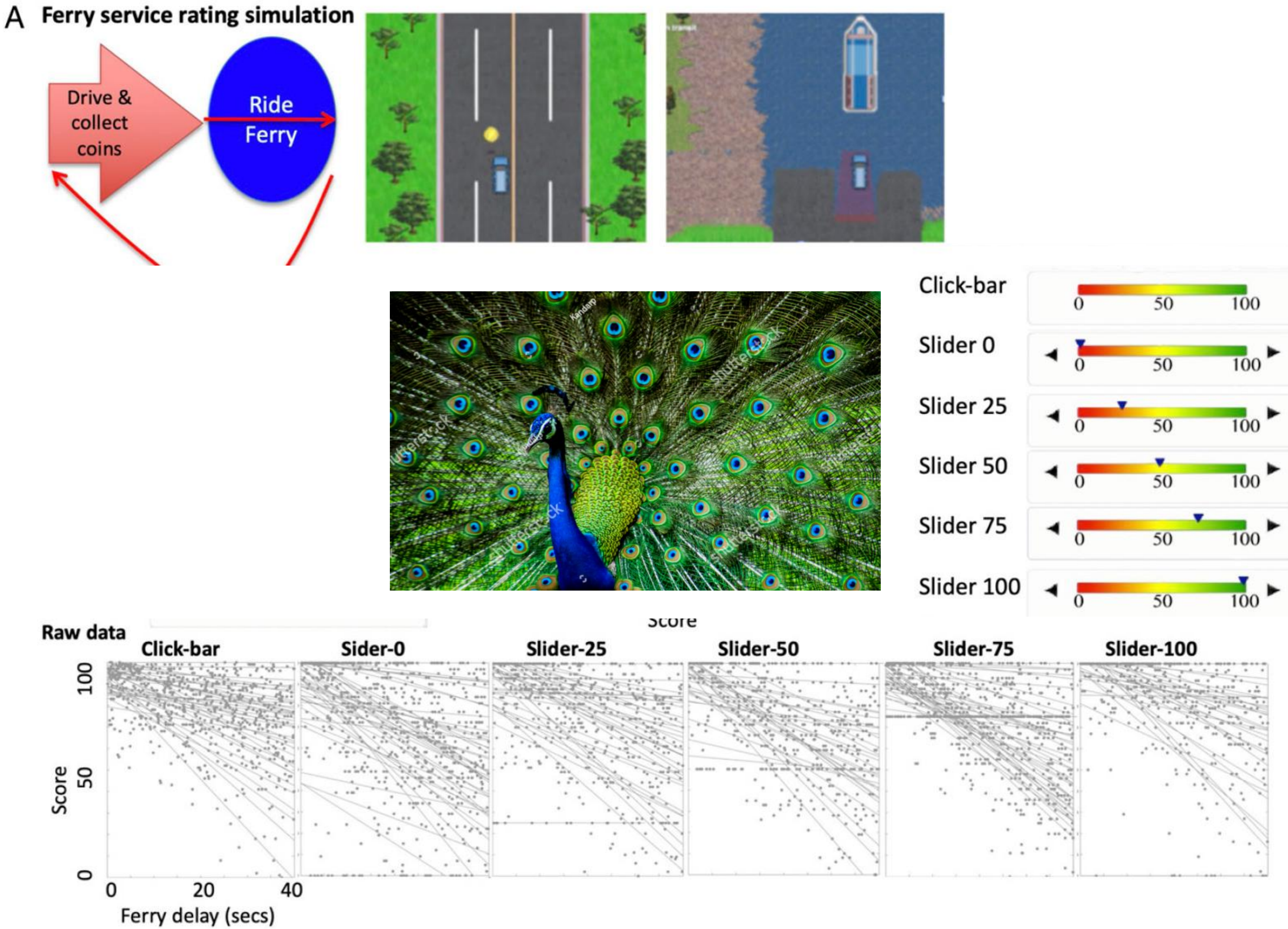
Ofer Tchernichovski[a,1], Lucas C. Parra[b], Daniel Fimiarz[c], Arnon Lotem[d], and Dalton Conley[e,1]

[a]Department of Psychology, Hunter College, The City University of New York, New York, NY 10065; [b]Department of Biomedical Engineering, City College, The City University of New York, New York, NY 10031; [c]Science Division, City College, The City University of New York, New York, NY 10031; [d]School of Zoology, Tel Aviv University, Tel Aviv, Israel 61000; and [e]Department of Sociology and Office of Population Research, Princeton University, Princeton, NJ 08544

Contributed by Dalton Conley, February 26, 2019 (sent for review October 9, 2018; reviewed by Damon Centola and Rufus A. Johnstone)

Costly signaling theory was developed in both economics and biology and has been used to explain a wide range of phenomena. However, the theory's prediction that signal cost can enforce in-

cheating. But even if there is no motivation to cheat, there is, at best, ambiguous direct benefit to the rater in providing an accurate assessment of provider quality (16). Therefore, especially


A
Ferry service rating simulation
Drive & collect coins
Ride Ferry
Click-bar
0 50 100
Slider 0
0 50 100
Slider 25
0 50 100
Slider 50
0 50 100
Slider 75
0 50 100
Slider 100
0 50 100
Score
Raw data
Click-bar
Sider-0
Slider-25
Slider-50
Slider-75
Slider-100
100
50
0
Score
0 20 40
Ferry delay (secs)

Thank you