Capacity Constraints in Cognitive Function

Outline

- Multitasking and Control
- Miller's Law

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☞
- **Multitasking and Control**
- **Miller’s Law**

Cognitive Control

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There are even *laws* prohibiting allocation of control
to more than one task at a time:

Talking on a cell phone and driving

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What is its *cause,* and *why* is it so *restrictive?*

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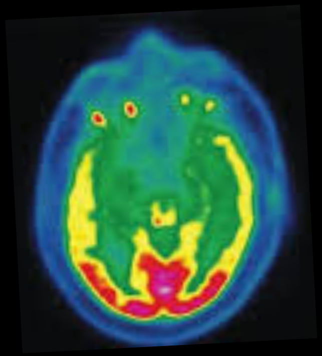

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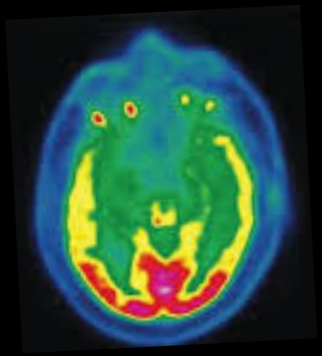

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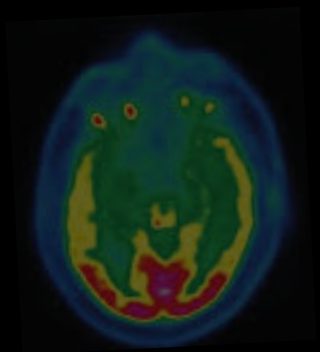

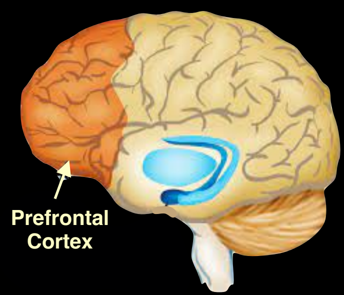

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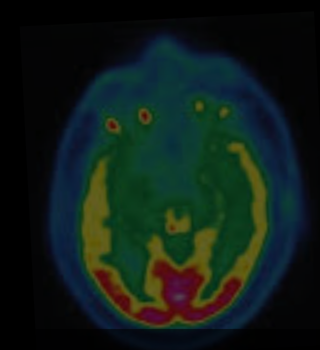

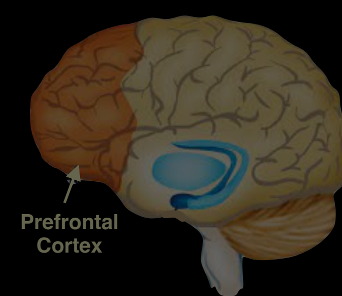

- **The question begs a more rational explanation…**

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    - **Beg the question: *why that architecture?***

Shared Representation vs. Multitasking

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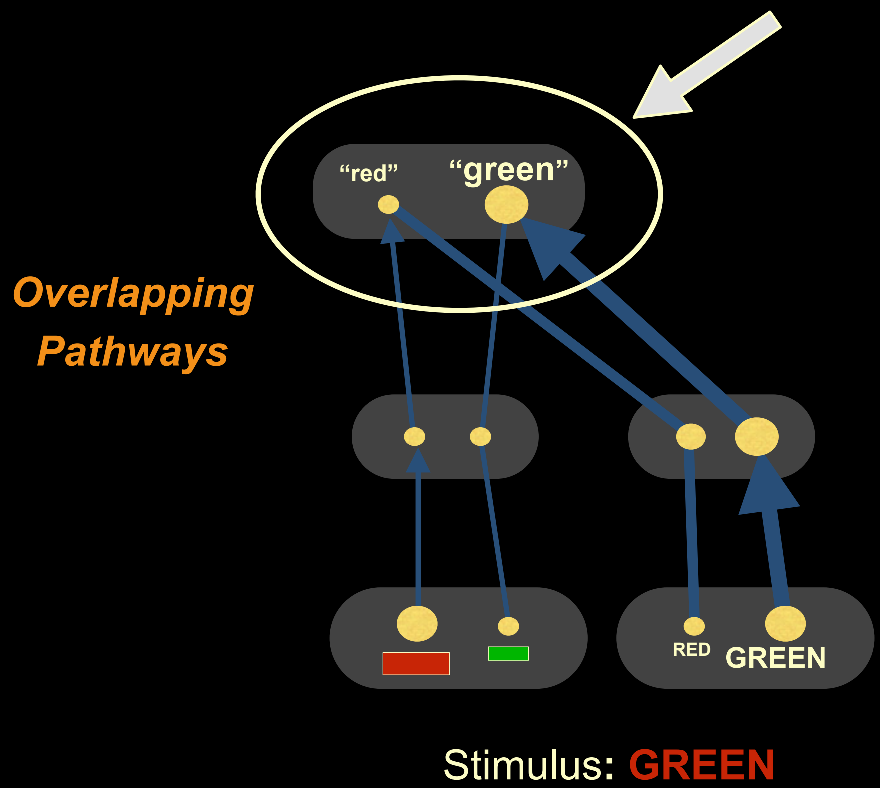
  - **Pathway overlap (shared representations) introduces potential for *cross-talk***



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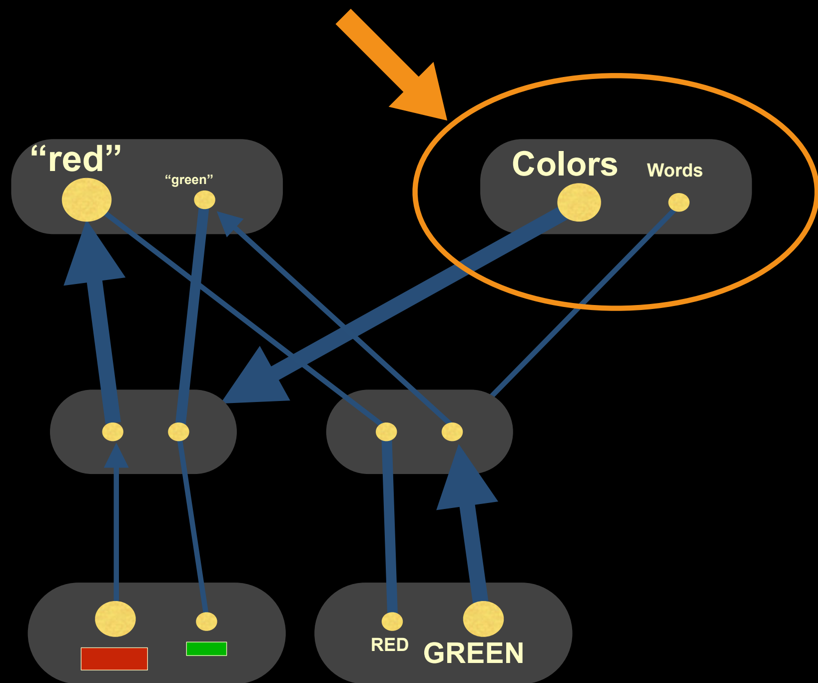
Overlapping Pathways



Stimulus: GREEN

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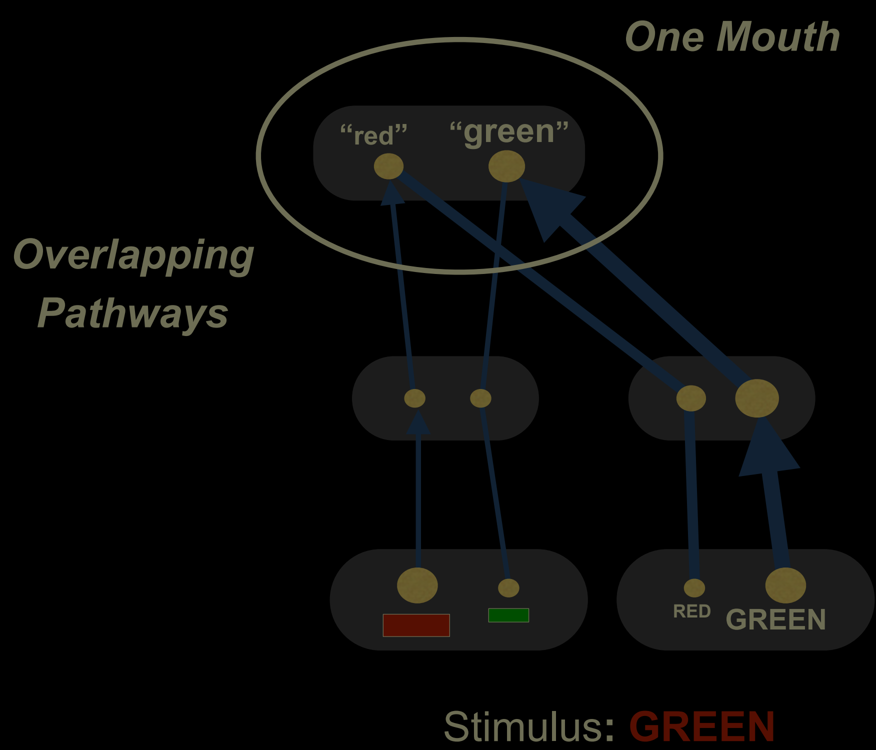

Shared Representation vs. Multitasking

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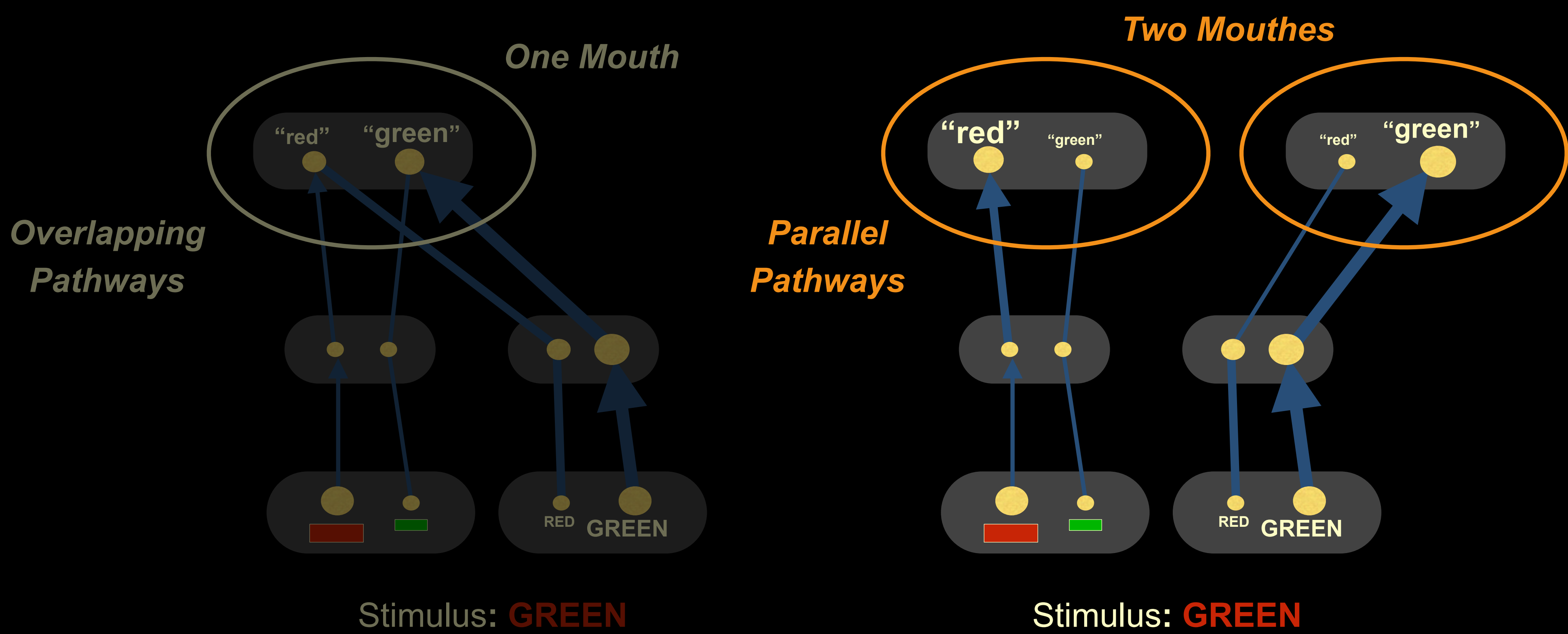
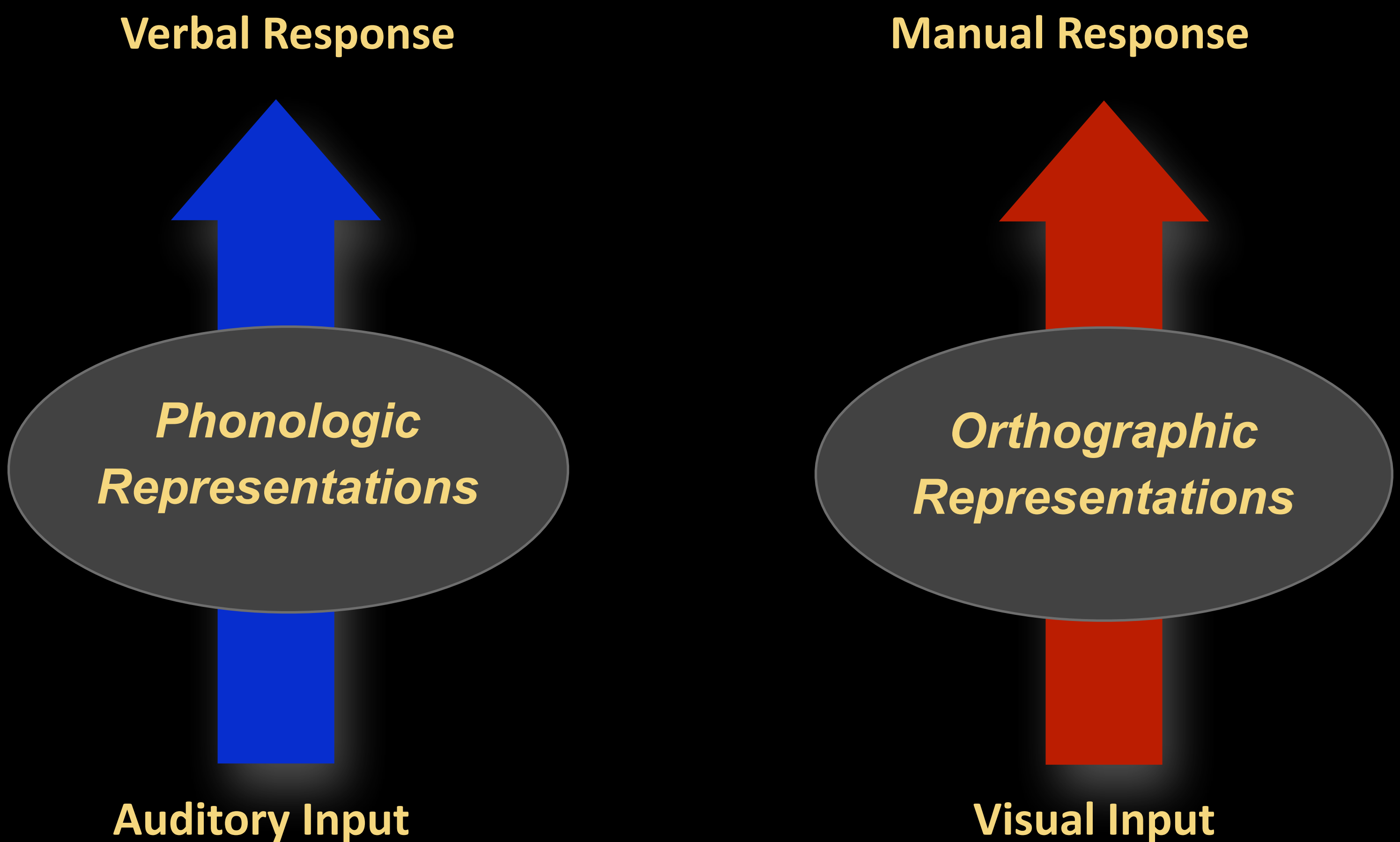


Shared Representation vs. Multitasking

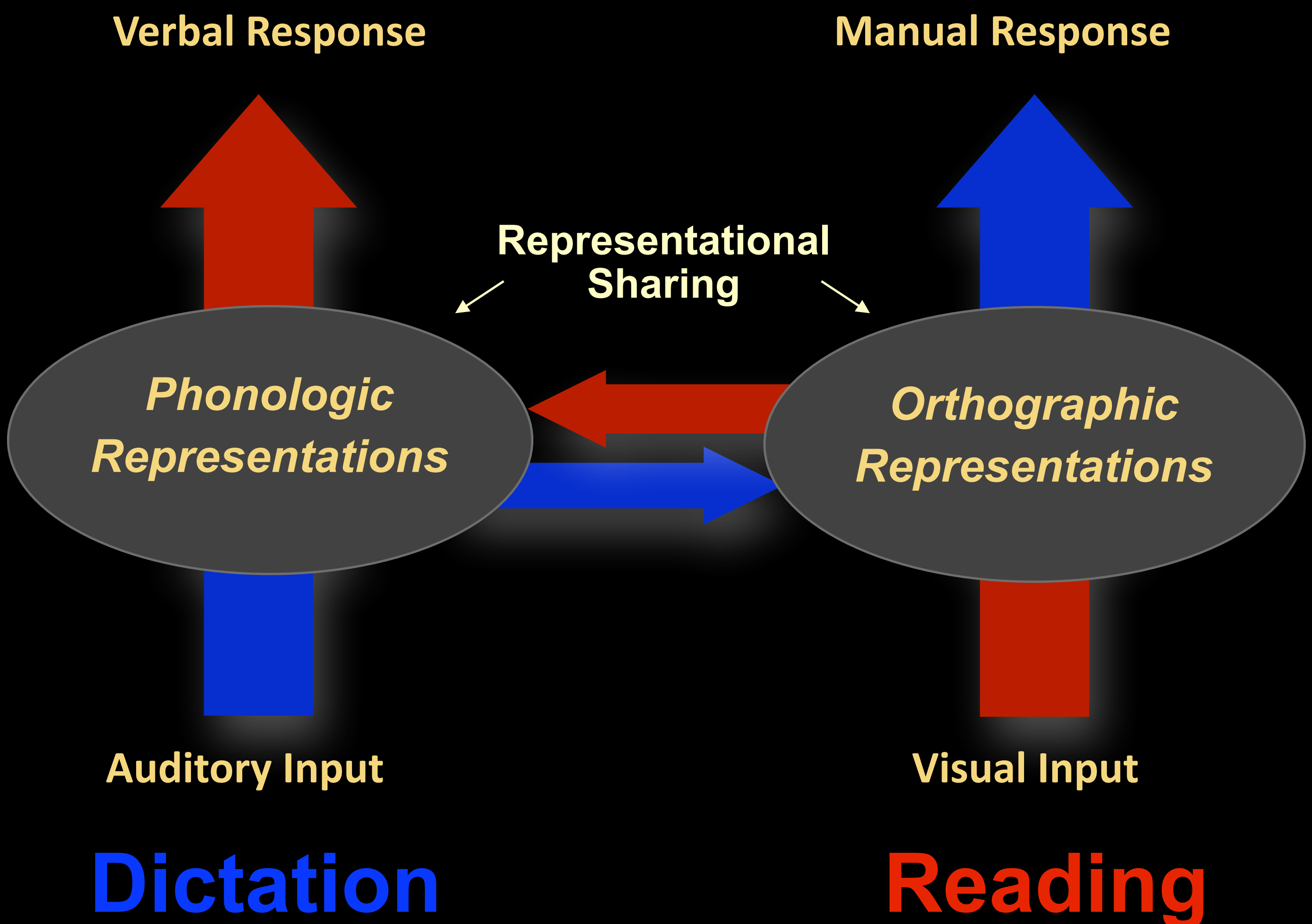
- **Classic illustration:**
  (Shaffer et al., 1975)
  - ***echoing*** **a speech stream while** ***copy-typing*** **(easy) vs.**
  - ***dictation*** **while** ***reading aloud*** **(hard)**

Shared Representation vs. Multitasking



Echoing **Copy-Typing**

Shared Representation vs. Multitasking



Crossings

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Control reflects ***bound on rational processing***

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- **Descendant of the Multiple Resources theory of attention**
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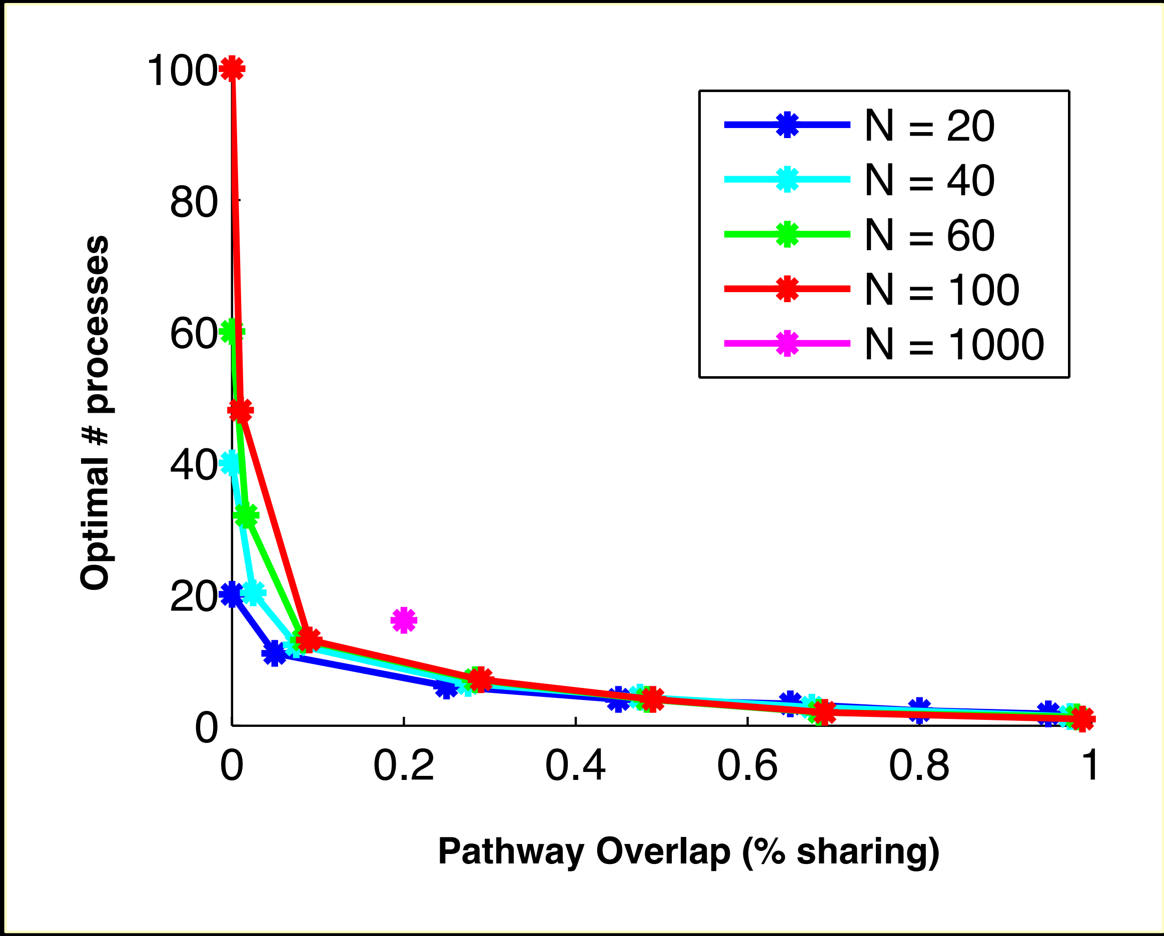
- **Formal treatment:**
  - **Numerical analysis** (simulations in a variety of network architectures)
  - **Mathematical analysis** (graph theoretic analyses)

Pathway Overlap (Shared Representation)



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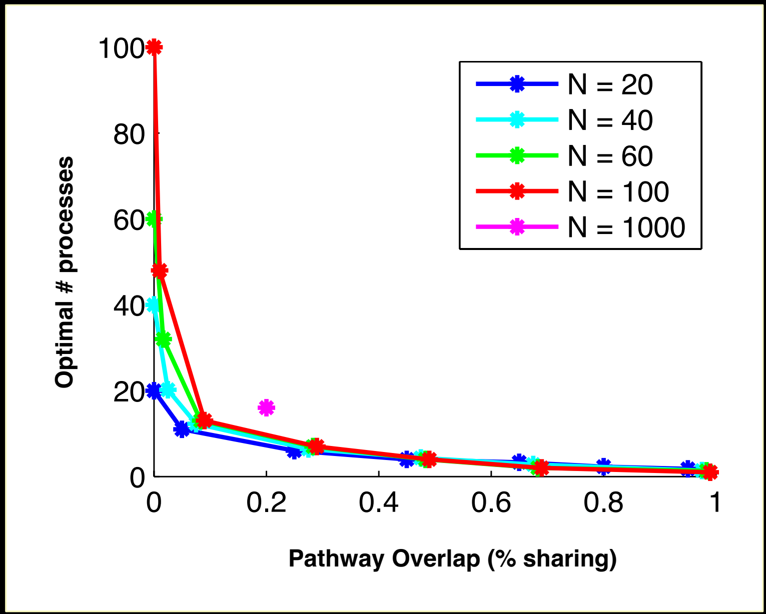

Why Shared Representations?

Why Shared Representations?

- Learning benefits by shared representations

Why Shared Representations?

- **But this costs us in the ability to multitask** *(i.e., do two control-demanding tasks at once)*

Why Shared Representations?

- To see this, let's do a little demonstration…

Color Naming + Location Pointing

Name the <u>color</u> of the stimulus and
at the same time point to <u>where</u> it is…

BLUE

YELLOW

Word Mapping

Point **left** if the written word is

⬅ RED

Point **right** if the written word is

GREEN ➡

GREEN

RED

Color Naming + Word Mapping

Name the color of the following stimulus
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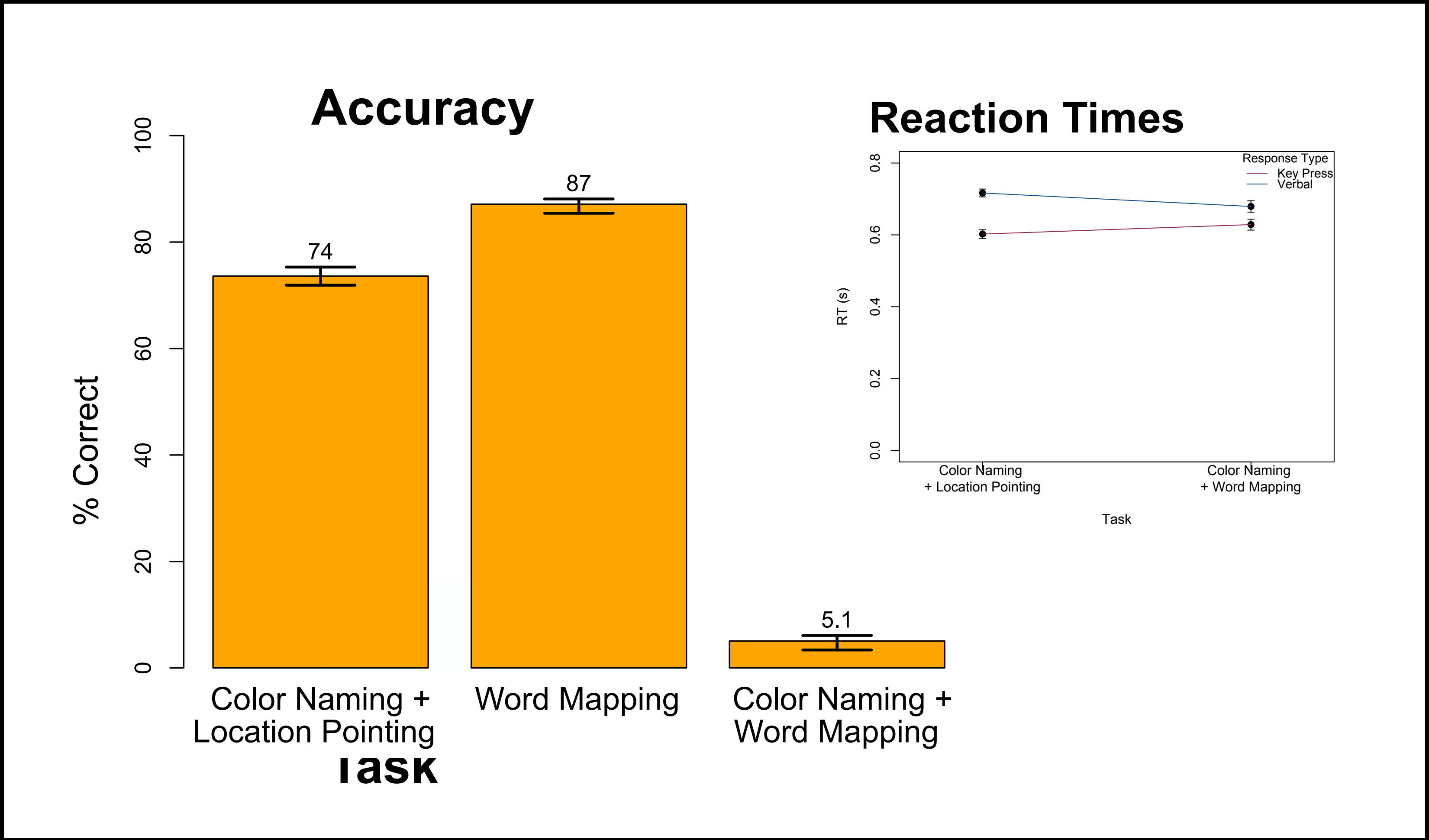
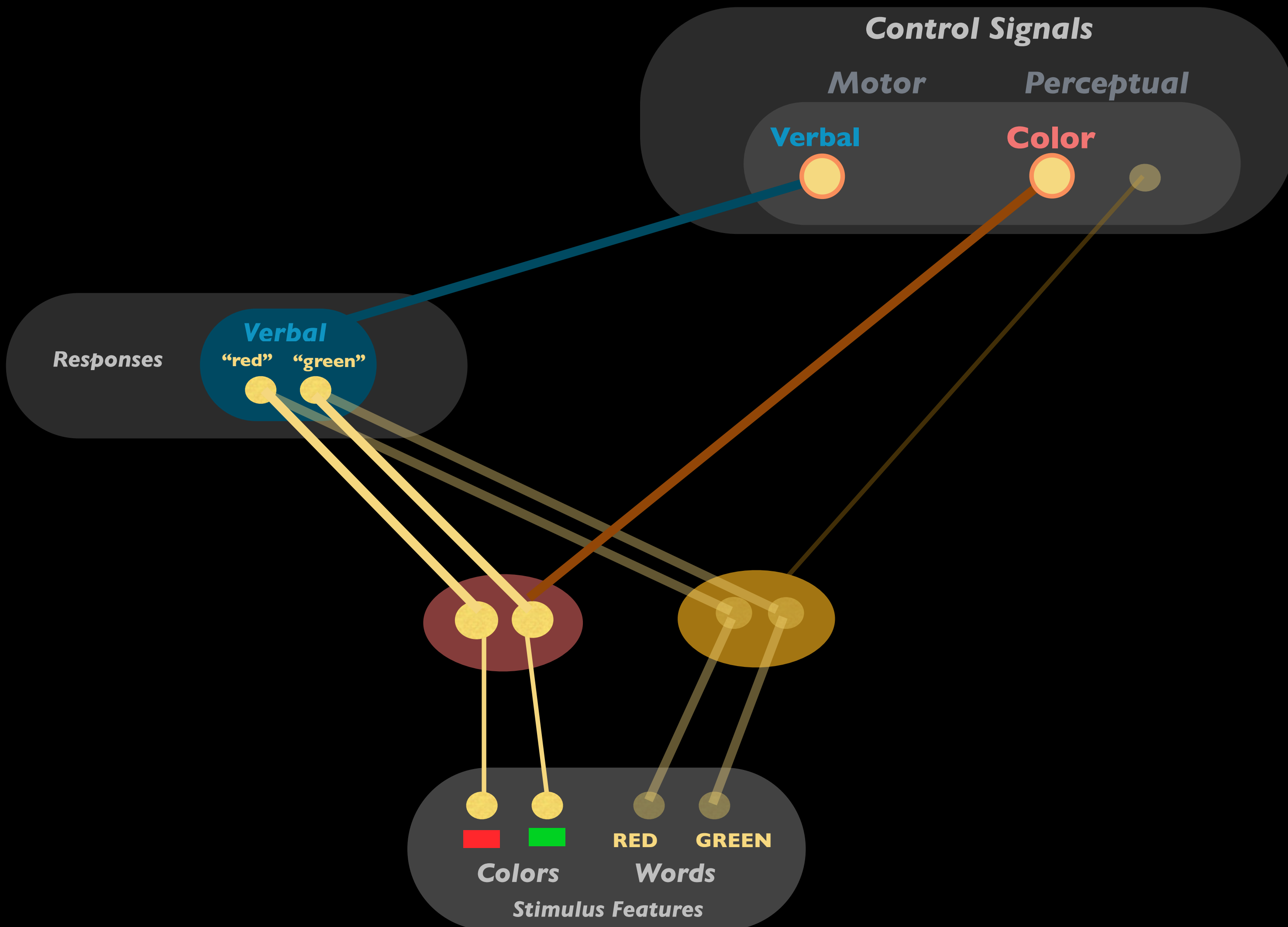
GREEN

RED

Learning and Multitasking

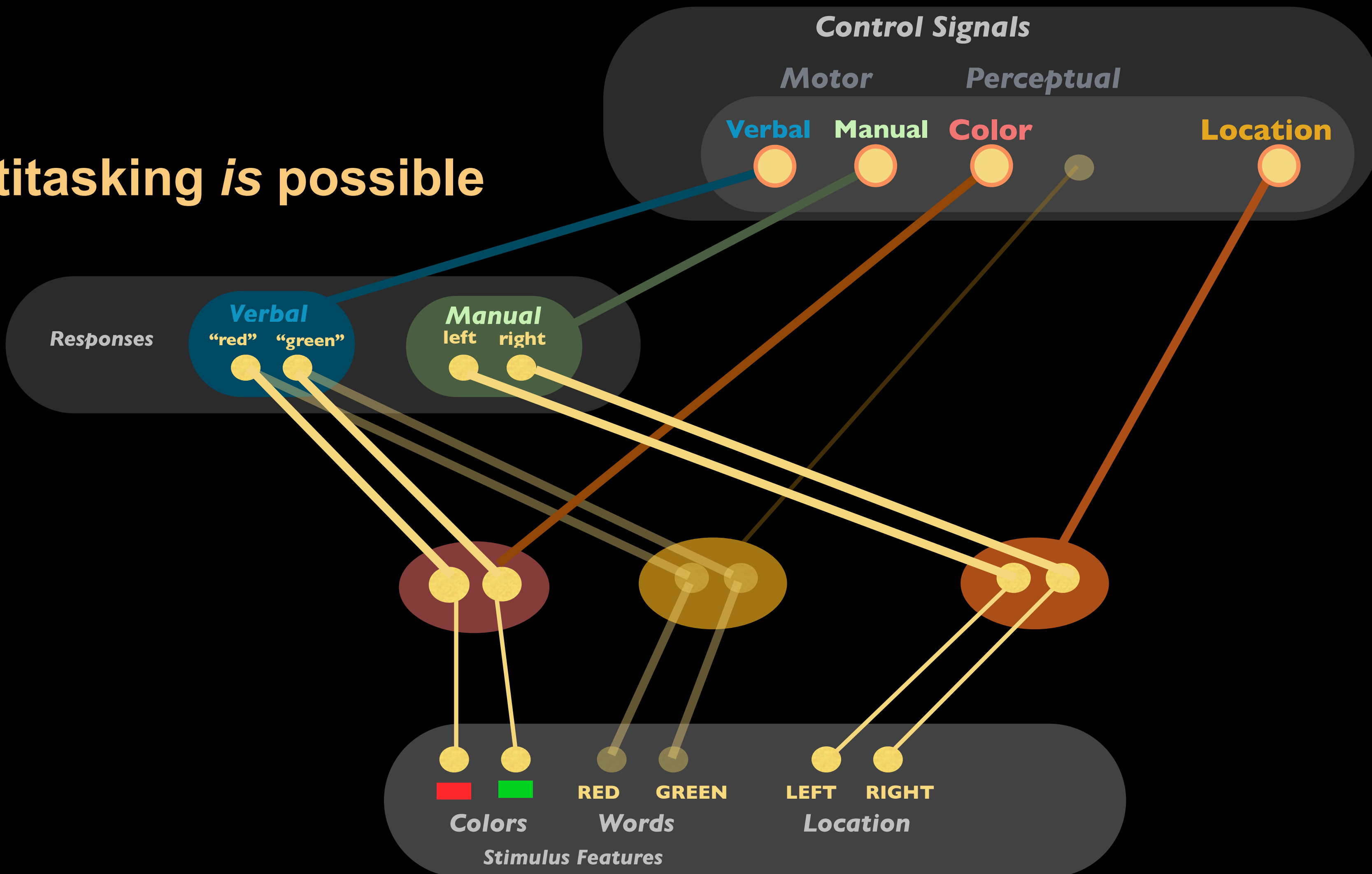


Color Naming



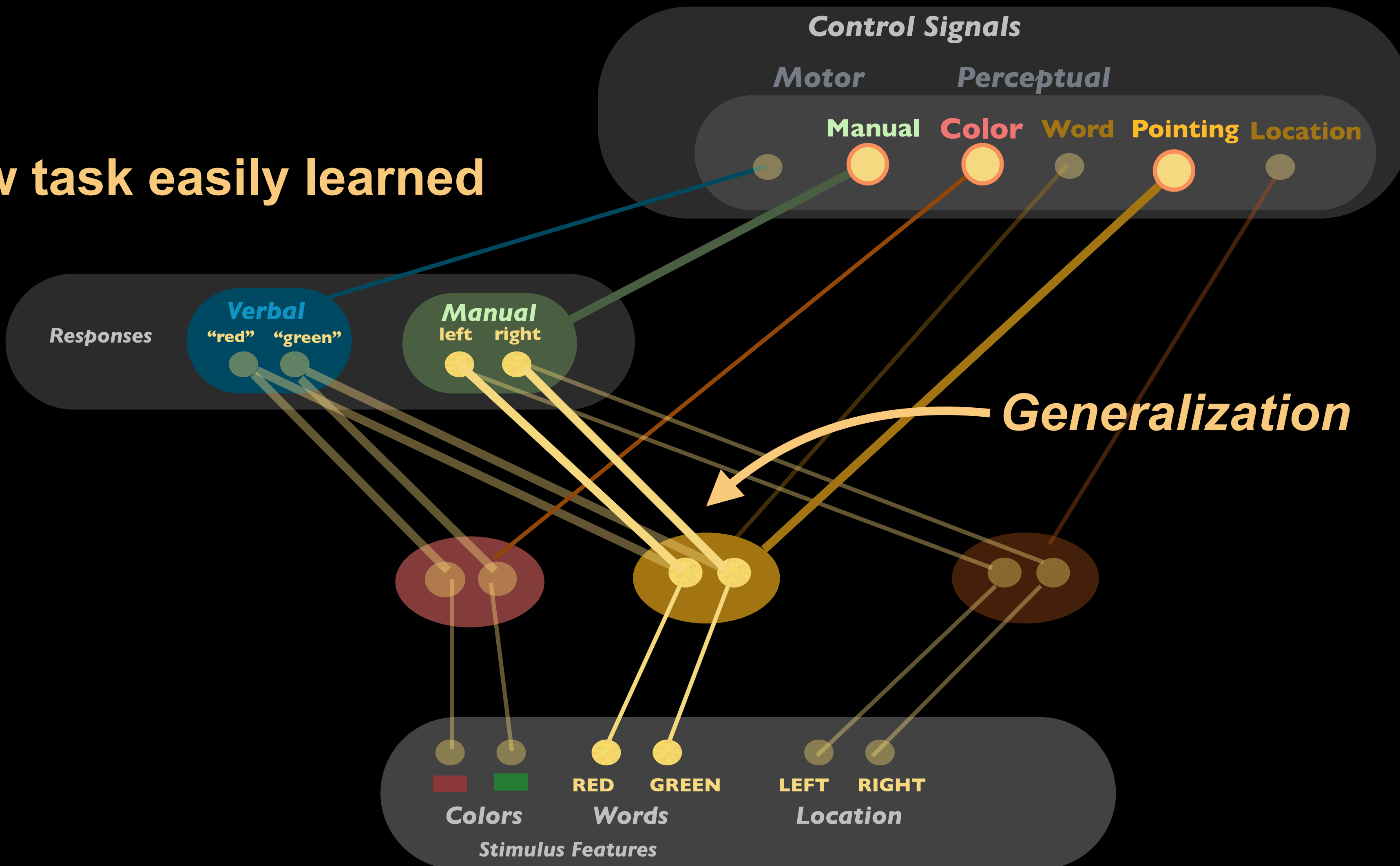
Color Naming + Location Pointing

Multitasking *is* possible



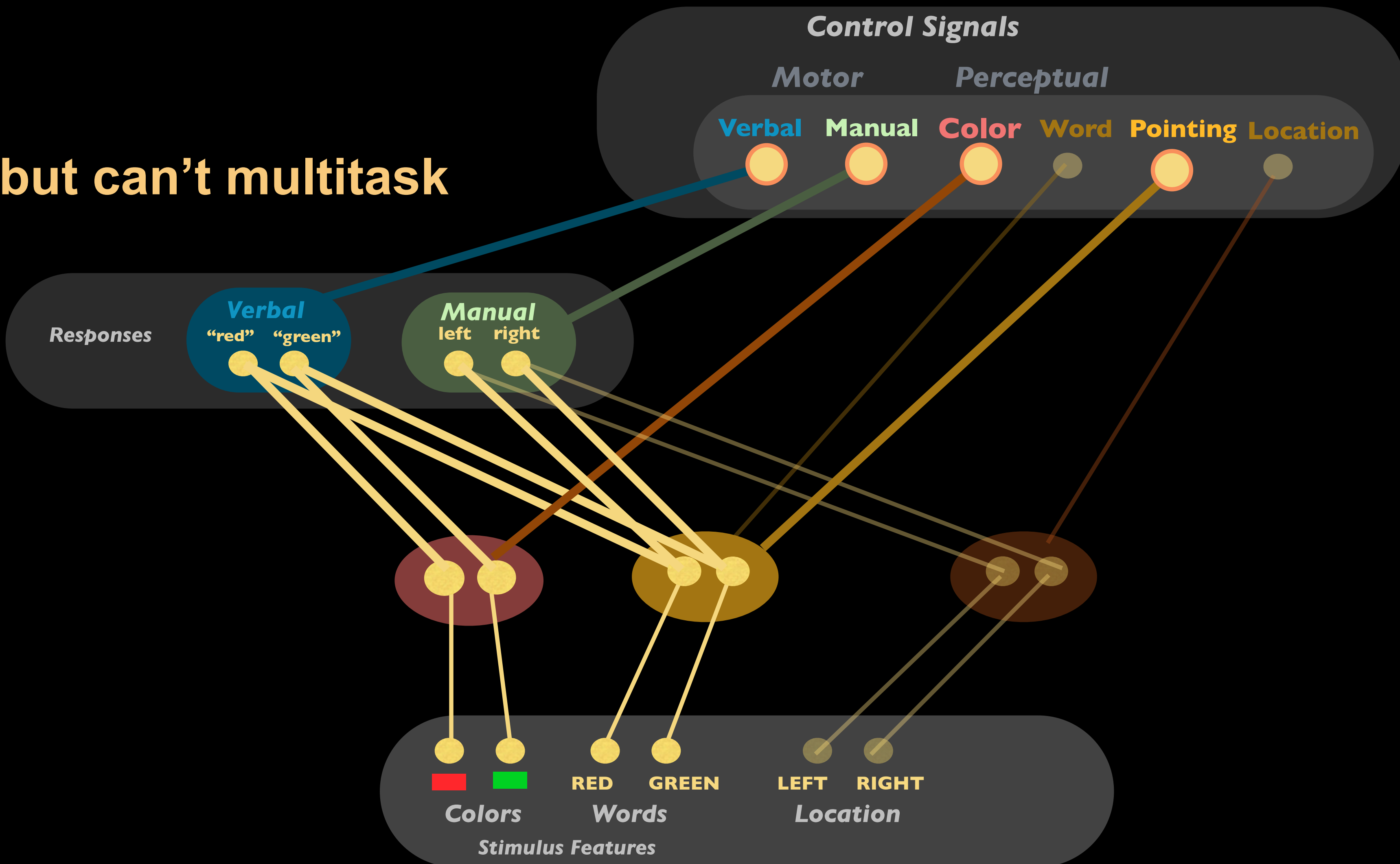
Word Mapping

New task easily learned



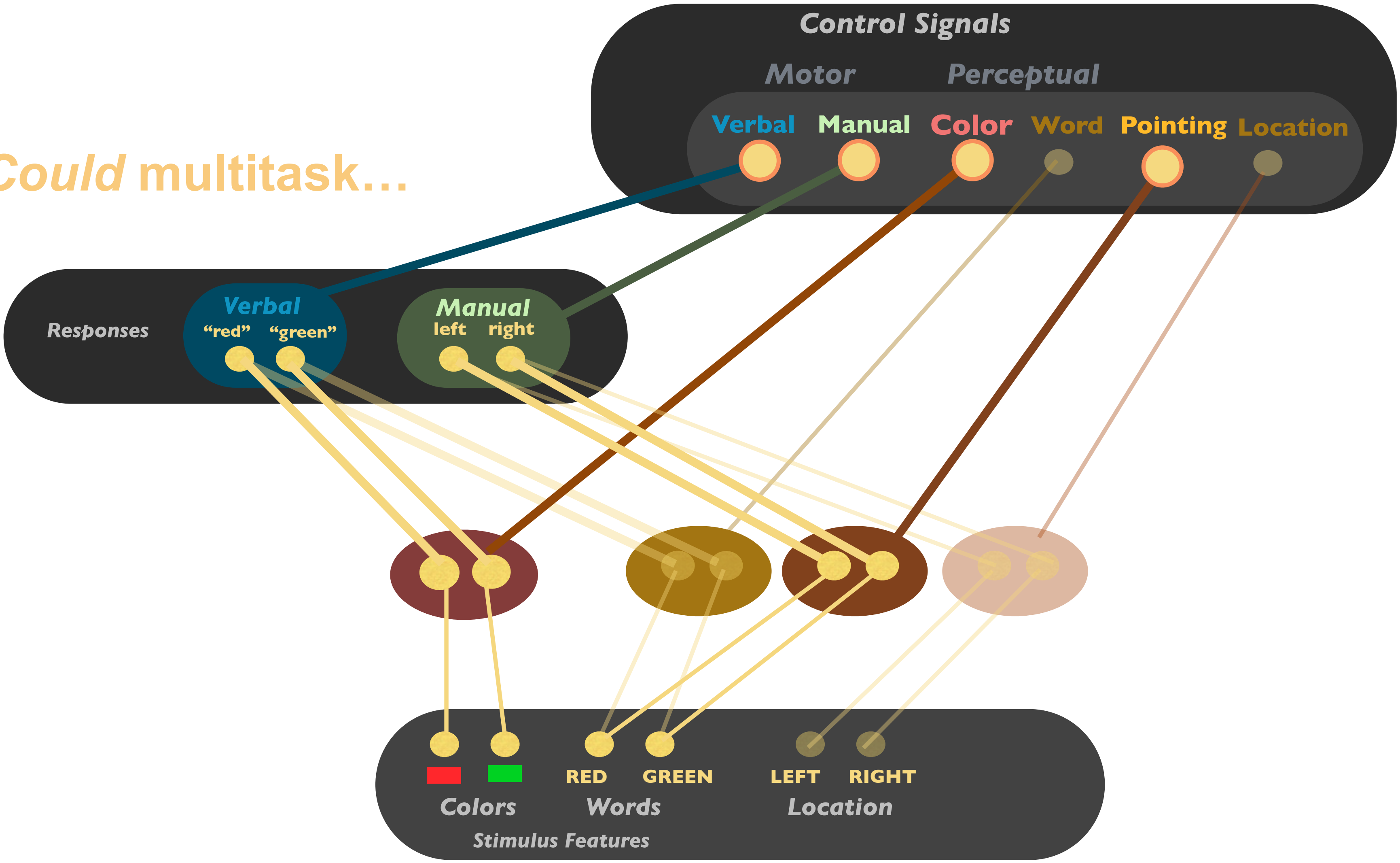
Color Naming + Word Mapping

…but can't multitask



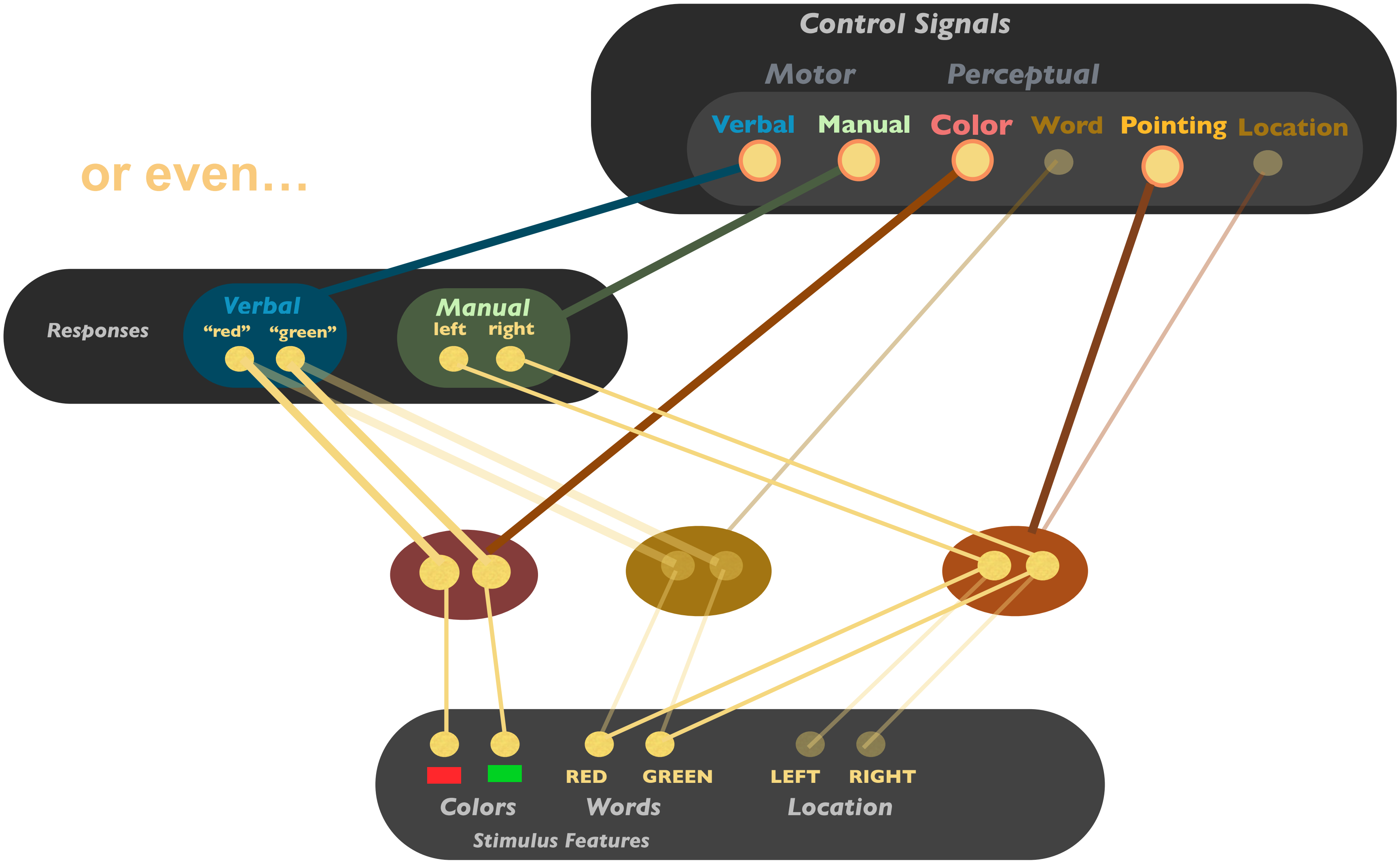
Color Naming + Word Mapping

Could multitask…

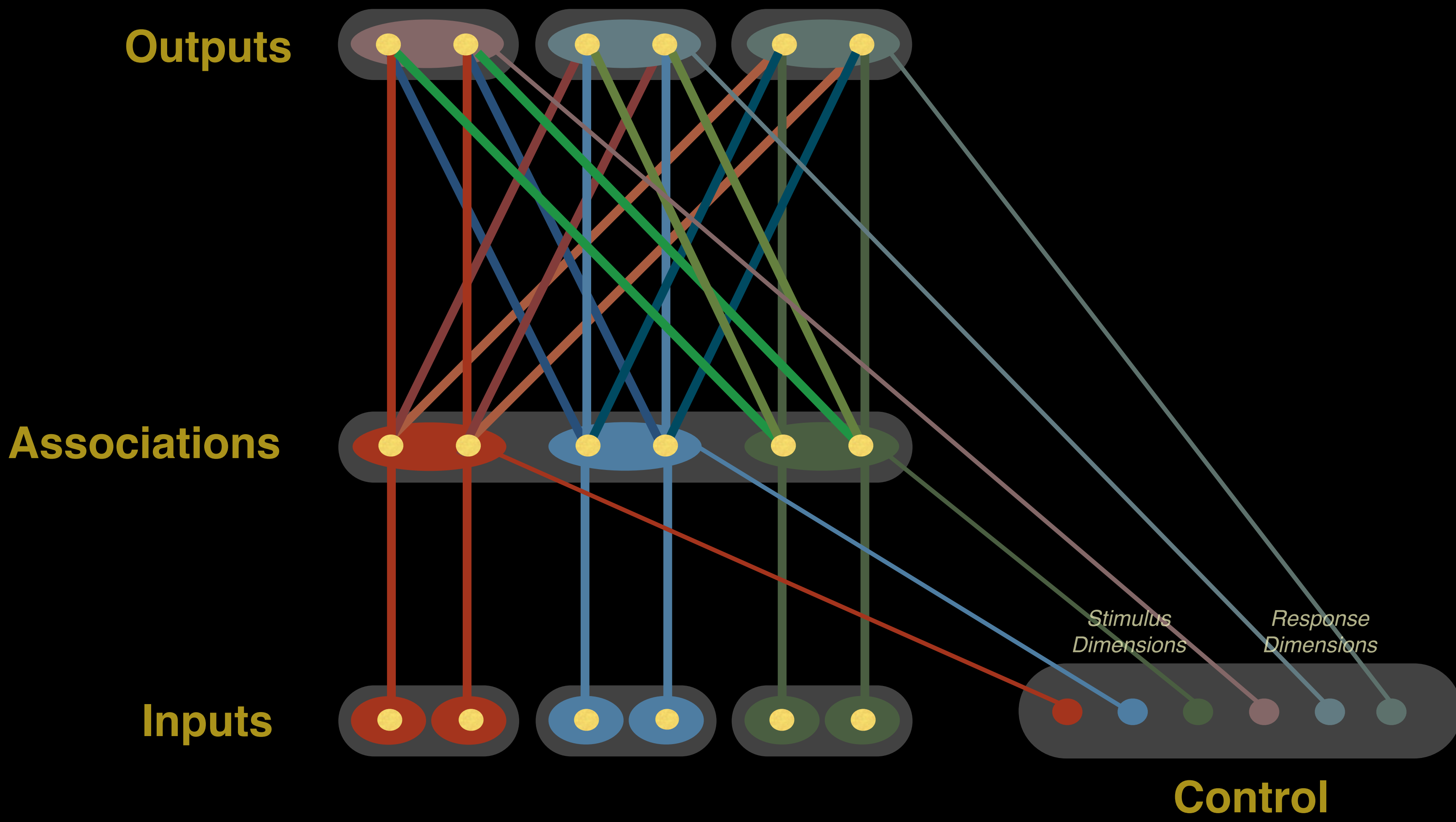


Color Naming + Word Mapping

or even…



Network Representation of Multiple Tasks



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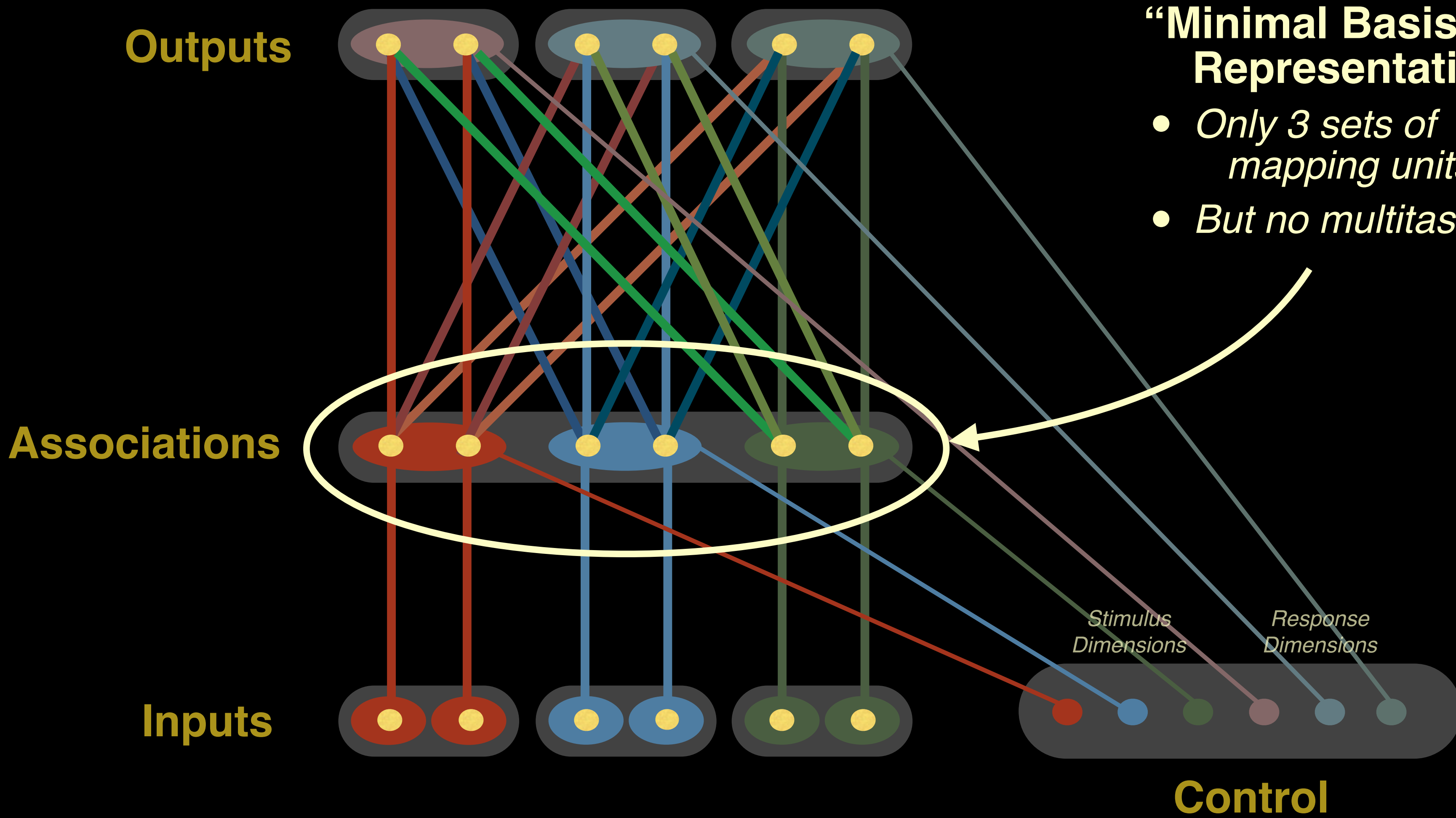
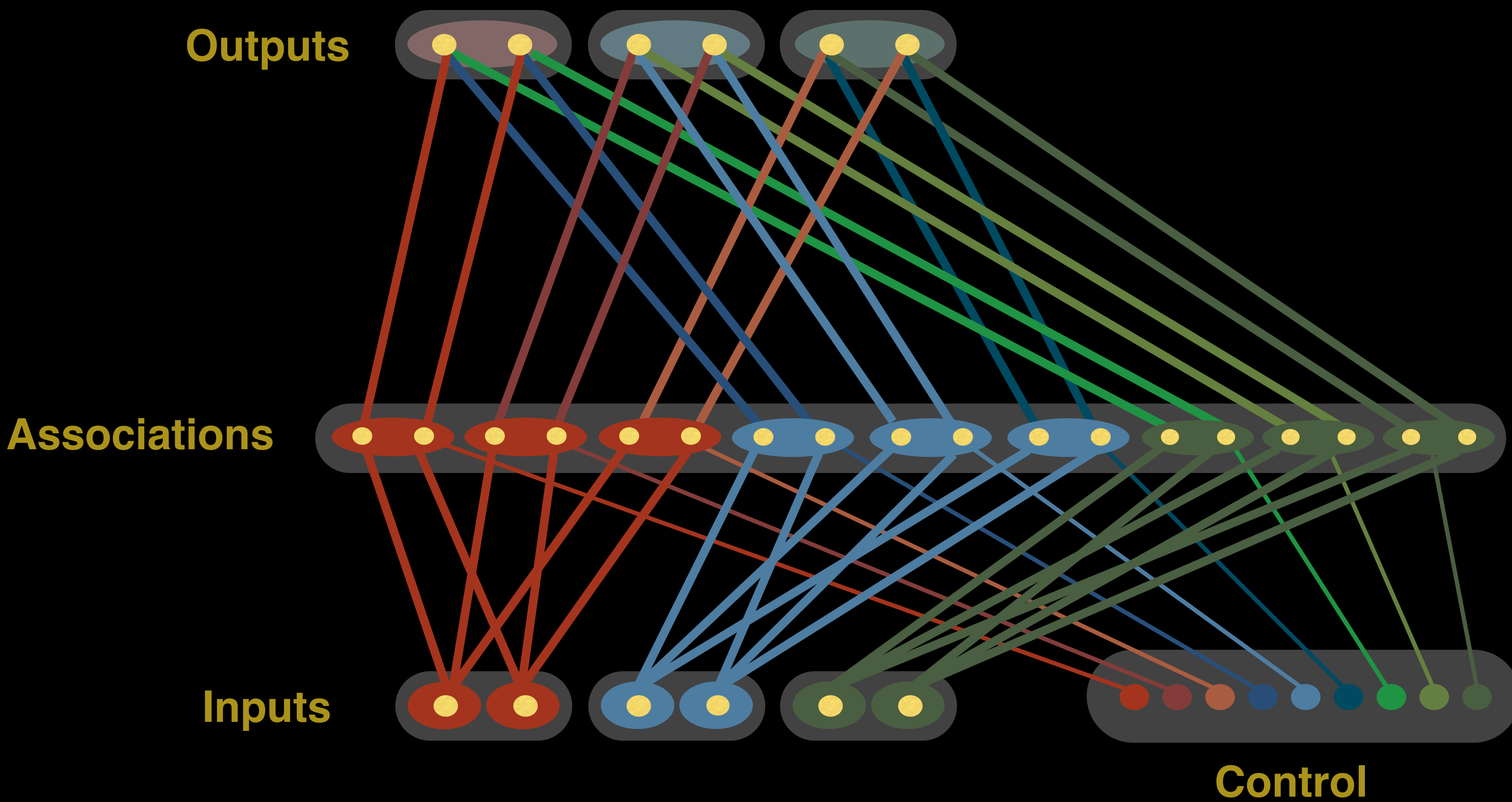


"Minimal Basis Set" Representation

- *Only 3 sets of mapping units*
- *But no multitasking*

Network Representation of Multiple Tasks



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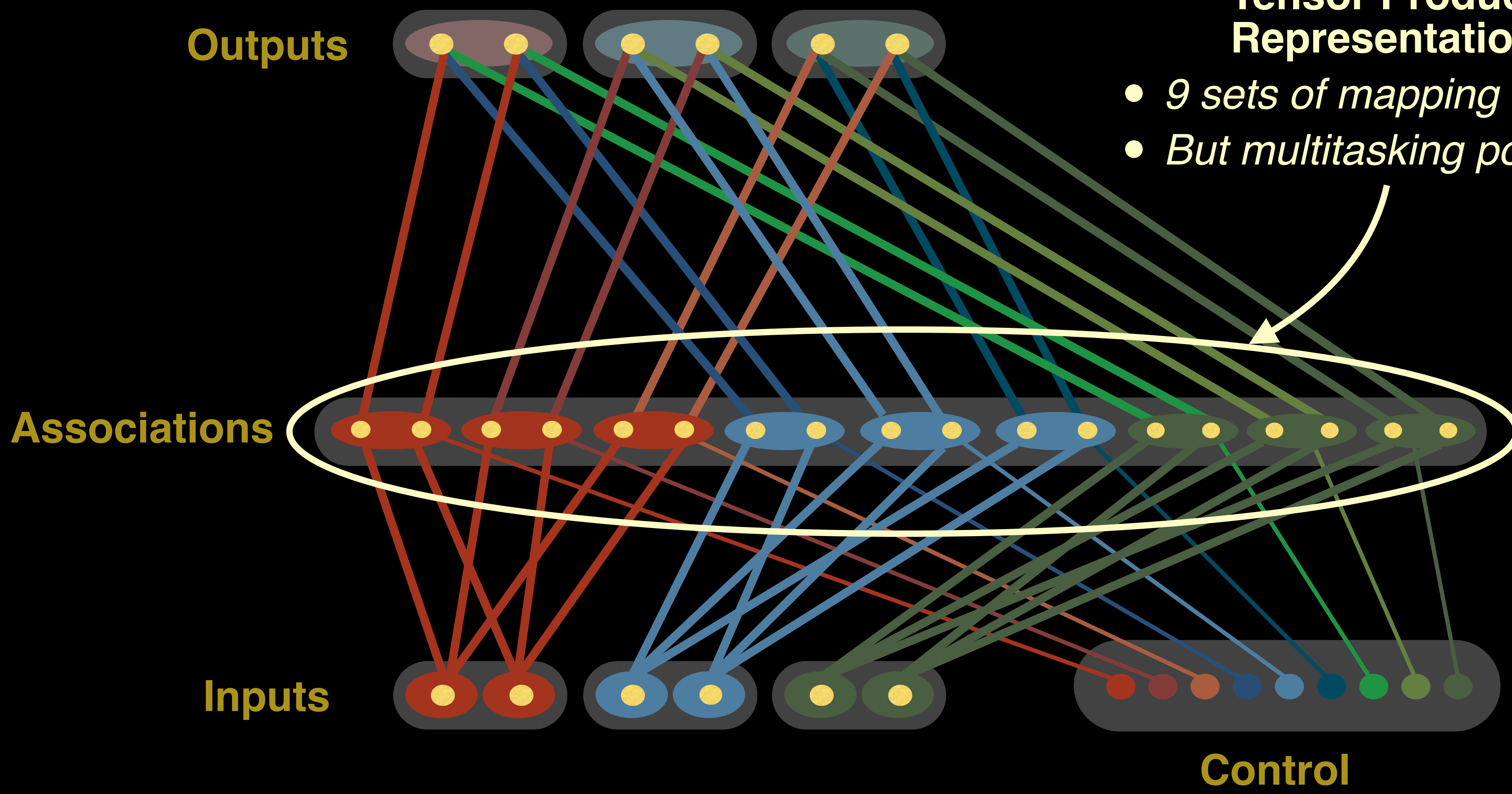
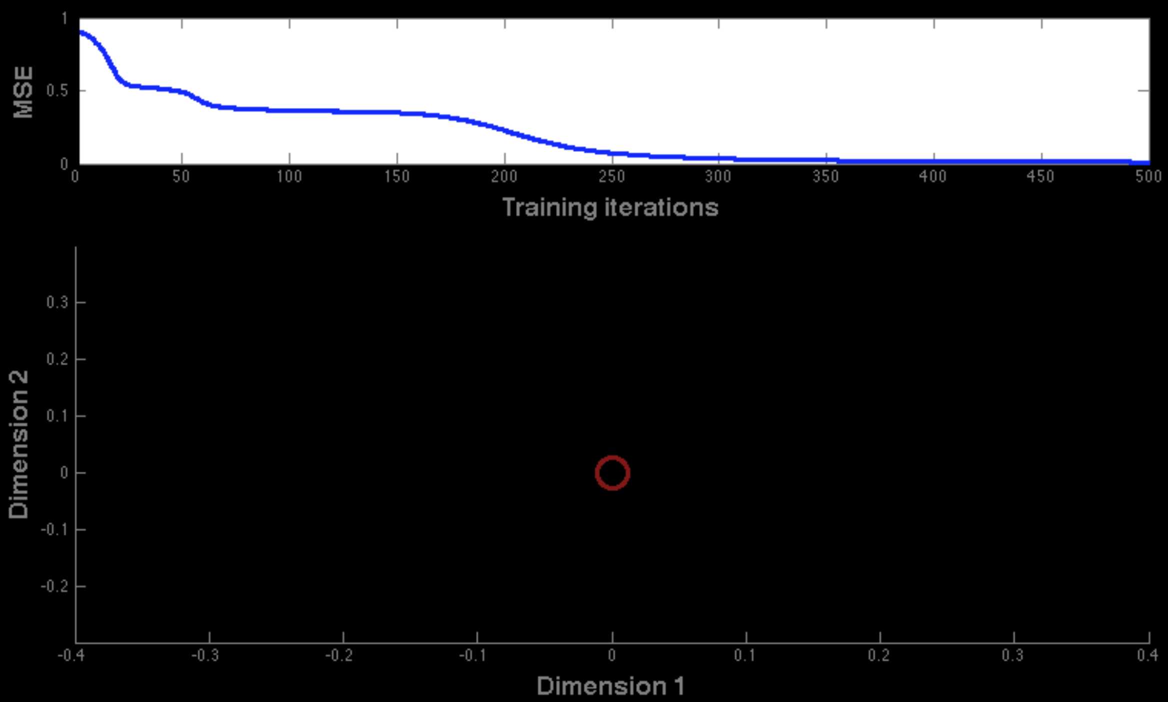


"Tensor Product" Representation

- *9 sets of mapping units*
- *But multitasking possible*

Single Task Training



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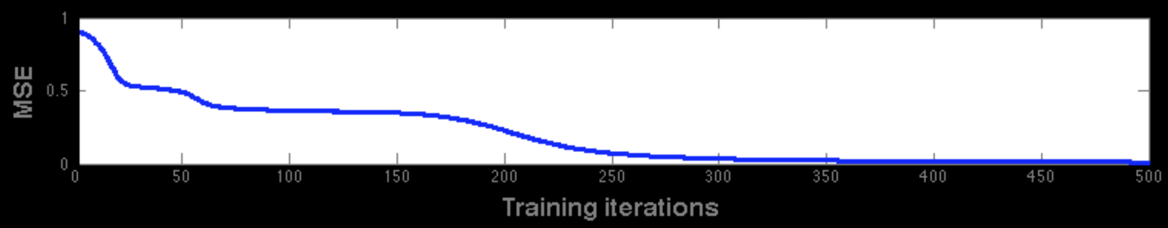
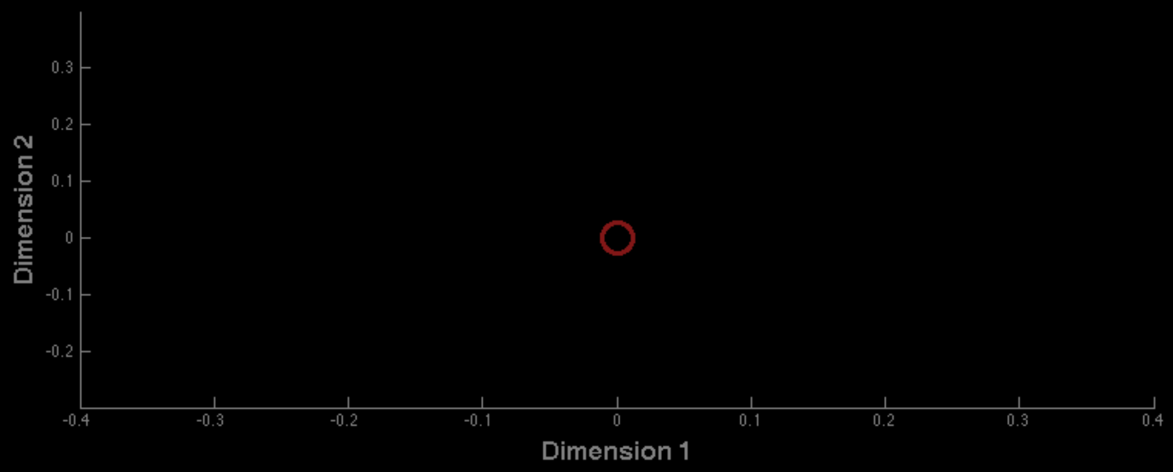
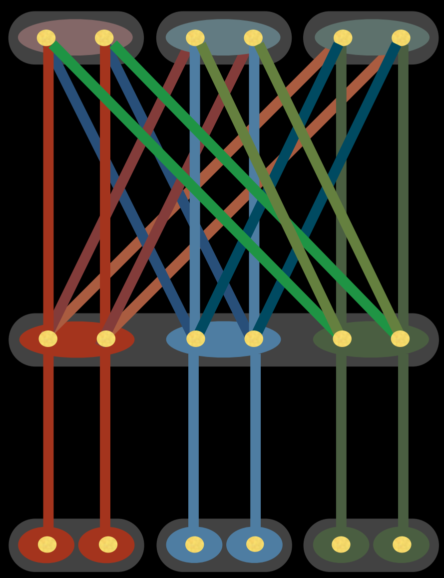
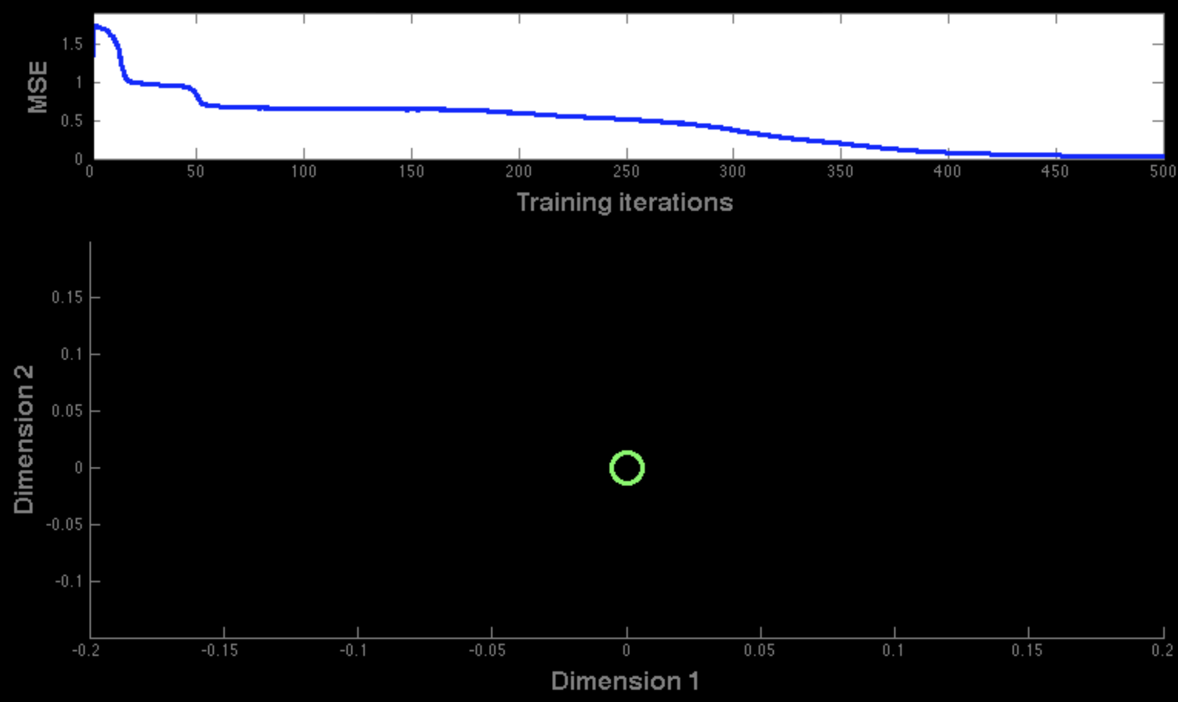






Single + Multitask Training



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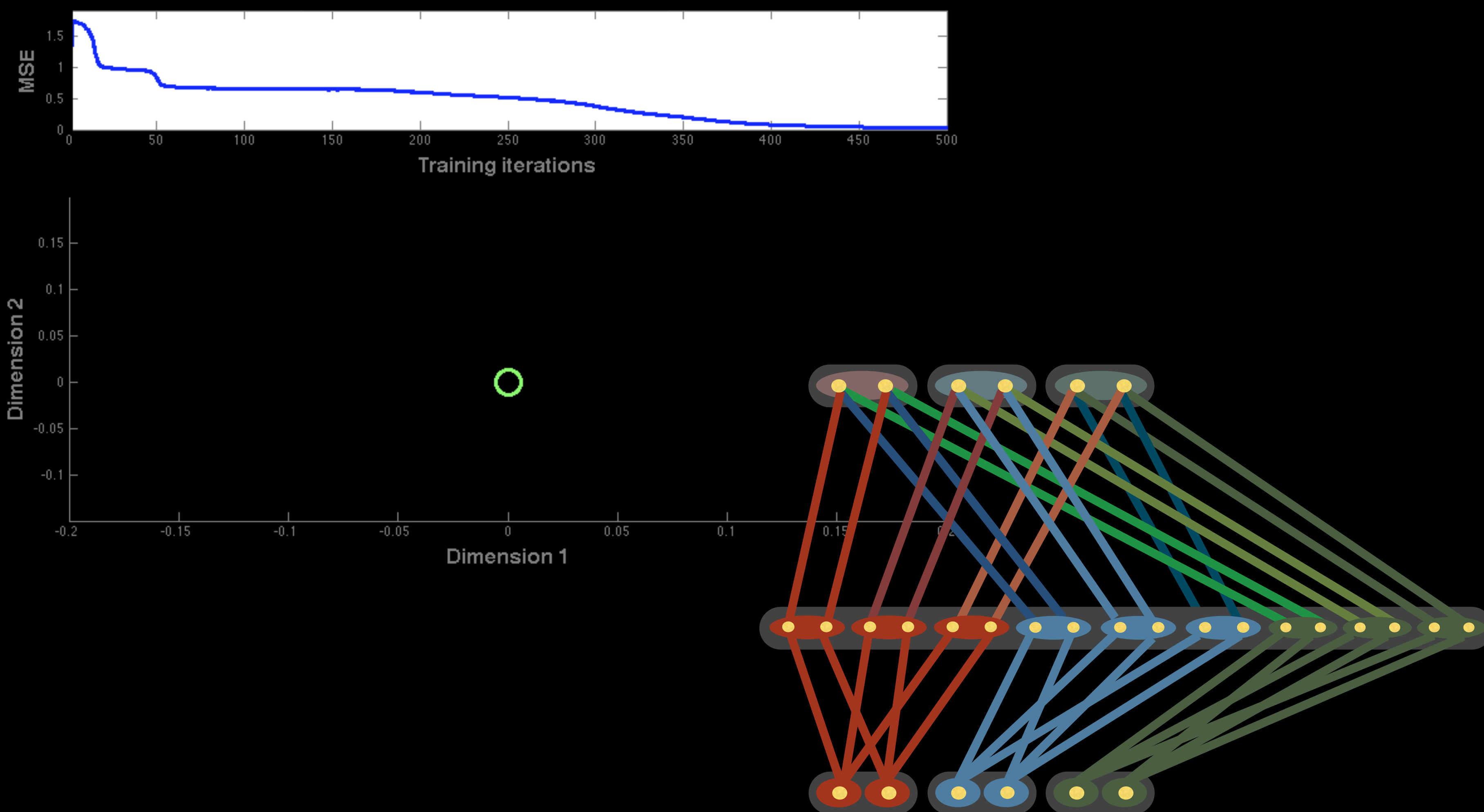

Example

JANUARY, 1923 SCIENTIFIC AMERICAN 17

Doing Two Things at Once

Multiple Consciousness, or Reflex Action of Unaccustomed Range?

By Dr. Alfred Gradenwitz

Thea Alba

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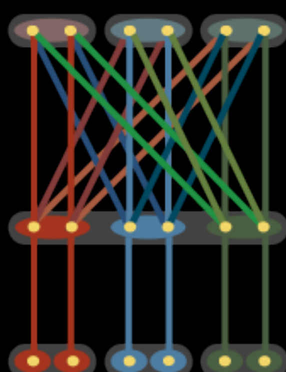
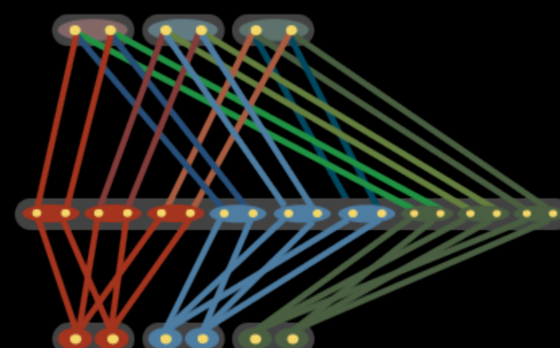
Empirical Implications

Multipurpose but serial



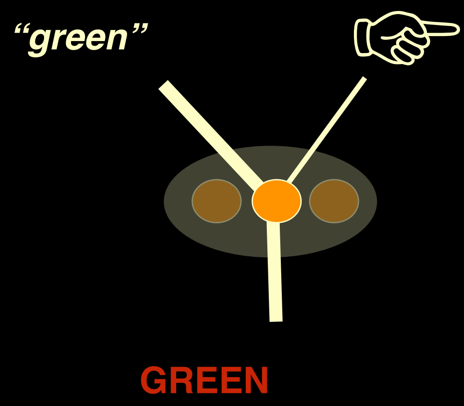
Learning

Multitasking and parallel



Empirical Study

Shared Representation
(can't* multitask with color naming*)



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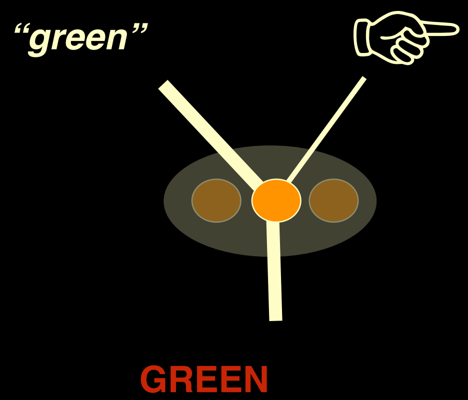
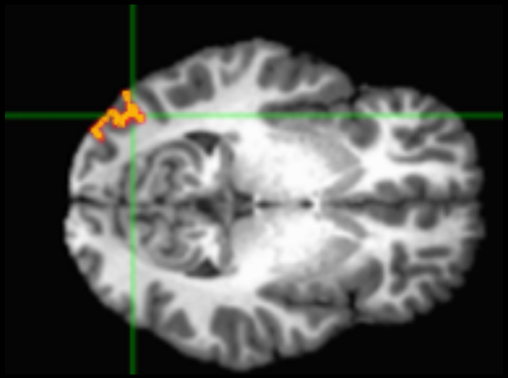


Predicted results



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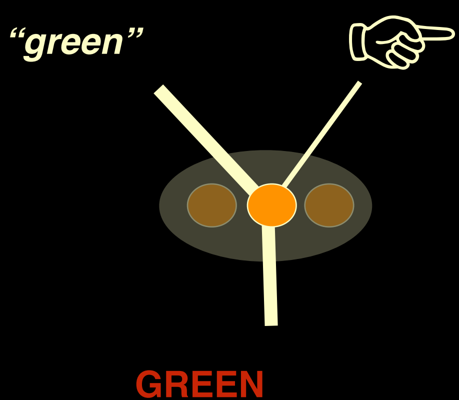

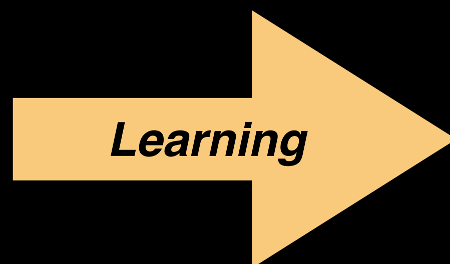

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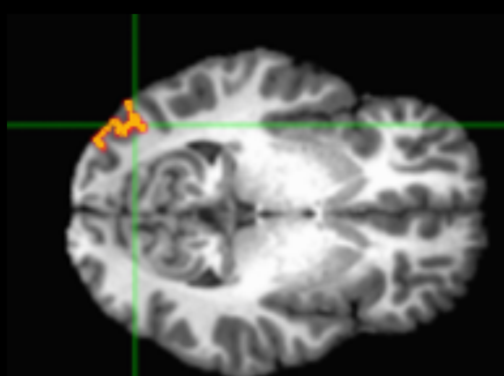
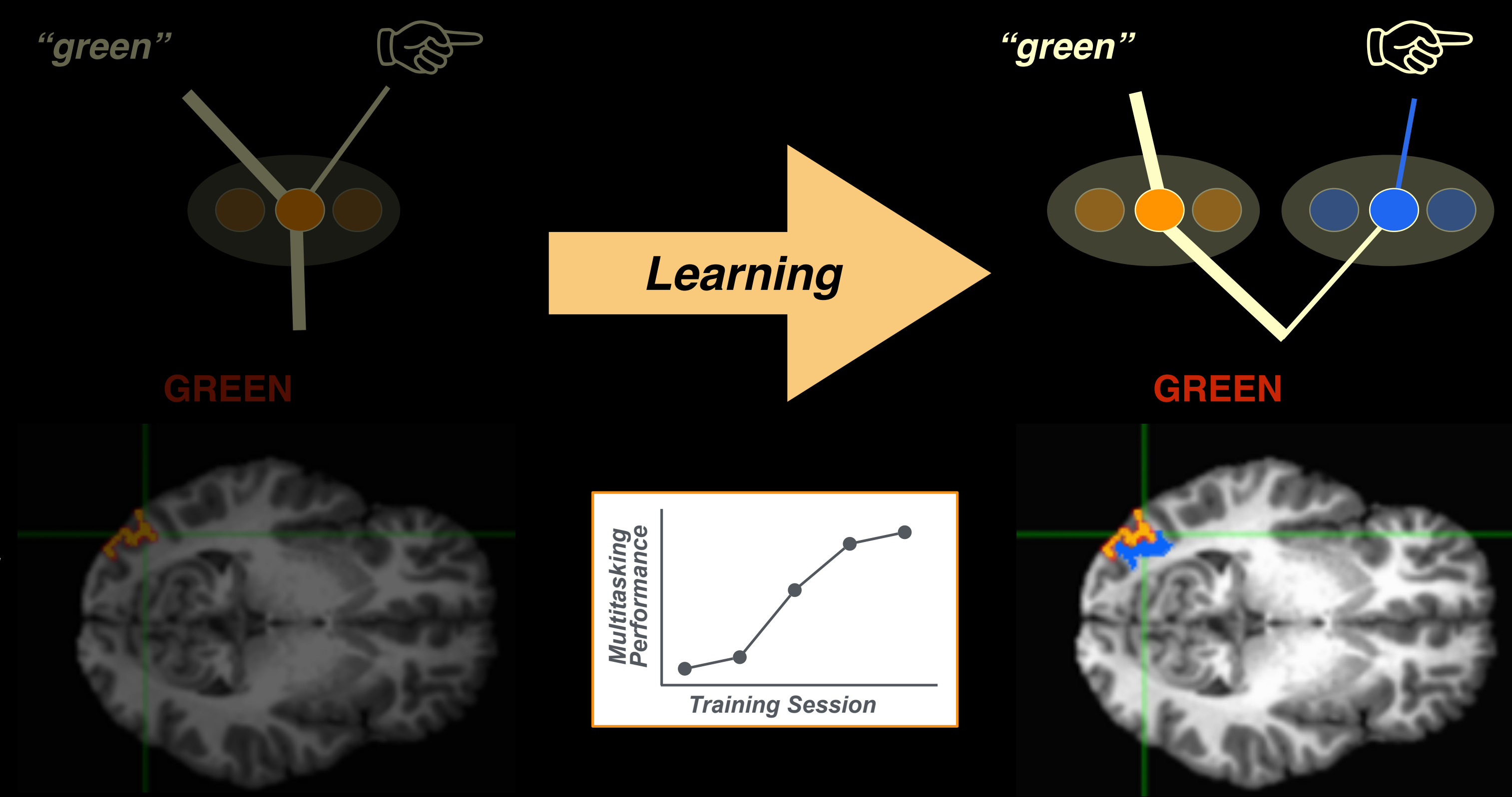


Empirical Study

Shared Representation
(*can't* multitask with color naming)

Separated Representation
(*can* multitask with color naming)



Predicted results

Summary

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- Modest amounts of cross-talk produce a radical constraint on parallelism:
  - Need to go “serial” with even modest pathway overlap

    ⇒constraints on multitasking capacity

Summary

- Modest amounts of cross-talk produce a radical constraint on parallelism:
  - Need to go "serial" with even modest pathway overlap

    ⇒constraints on multitasking capacity

- Control architecture is adapted to this constraint:
  - reflects optimization of tradeoff between *shared* of representations and *processing efficiency*

Learning vs. Performance

Learning vs. Performance

- **Fundamental tradeoff:**

SHARED representations
generalization & flexibility:
learning efficiency

vs.

SEPARATED representations
multitasking:
performance efficiency

Learning vs. Performance

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BIAS

SHARED **representations**

generalization & flexibility: ***vs.***

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    - *purpose of cognitive control rather than a limitation*

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  - **Other fundamental psychological phenomena:**
    - *attention & "binding"*
  - **Defines an intertemporal choice between "getting by" and "getting trained"**
    - *how does the system decide this?*
    - *how can this be formalized?*

Fundamental Tension

- *Interactive* Parallelism

- *Independent* Parallelism

Fundamental Tension

- *Interactive* Parallelism
  - many small *interacting* computations in the service of some *single* coherent higher level process

- *Independent* Parallelism

Fundamental Tension

- *Interactive* Parallelism
  - at the core of *PDP* (and now deep learning)
- *Independent* Parallelism

Fundamental Tension

- *Interactive* Parallelism

  – relies on *shared representations* *(learning efficiency)*

- *Independent* Parallelism

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  - requires "protection" from interference ⇒ *control-dependent*
- *Independent* Parallelism

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  - many *separate* unrelated computations

Fundamental Tension

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  - requires "protection" from interference ⇒ *control-dependent*
- *Independent* Parallelism
  - at the core of traditional *"embarrassing" parallelism* (e.g., MPI)

Fundamental Tension

- *Interactive* Parallelism
  - requires "protection" from interference ⇒ *control-dependent*
- *Independent* Parallelism
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Fundamental Tension

- *Interactive* Parallelism
  - requires “protection” from interference ⇒ *control-dependent*
- *Independent* Parallelism
  - allows “multitasking” ⇒ *automaticity* *(processing efficiency)*

Outline

- Multitasking and Control
- ☞ Miller's Law

VOL. 63, NO. 2 MARCH, 1956

THE PSYCHOLOGICAL REVIEW

THE MAGICAL NUMBER SEVEN, PLUS OR MINUS TWO: SOME LIMITS ON OUR CAPACITY FOR PROCESSING INFORMATION[1]

GEORGE A. MILLER

Harvard University

My problem is that I have been persecuted by an integer. For seven years this number has followed me around, has intruded in my most private data, and has assaulted me from the pages of our most public journals. This number assumes a variety of disguises, being sometimes a little larger and sometimes a little smaller than usual, but never changing so much as to be unrecognizable. The persistence with which this number plagues me is far more than a random accident. There is, to quote a famous senator, a design behind it, some pattern governing its appearances. Either there really is something unusual about the number or else I am suffering from delusions of persecution. . . .

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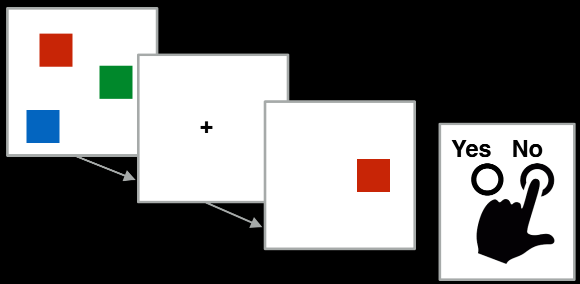
- Visual Working Memory Task



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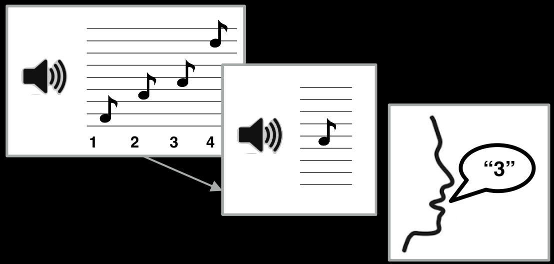
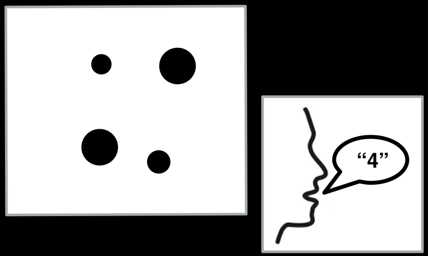


- Numerosity Estimation ("subtilizing")



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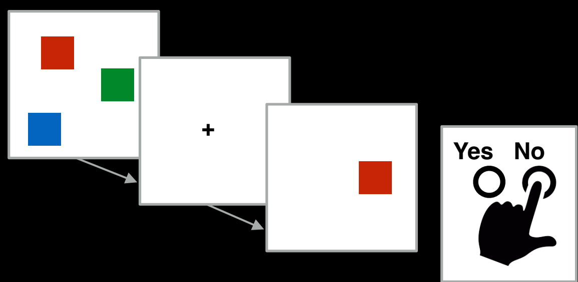

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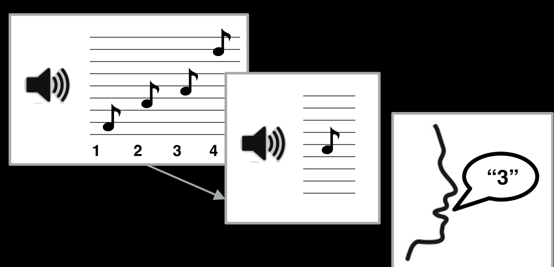

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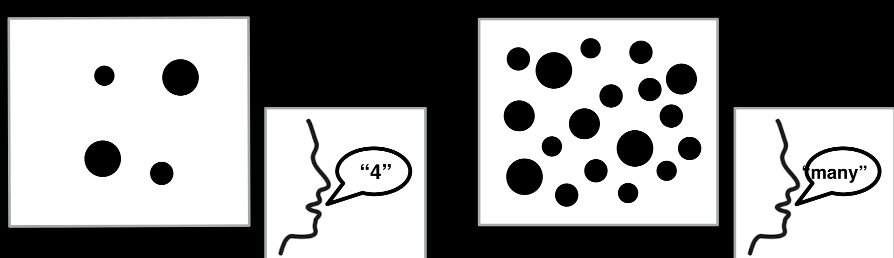

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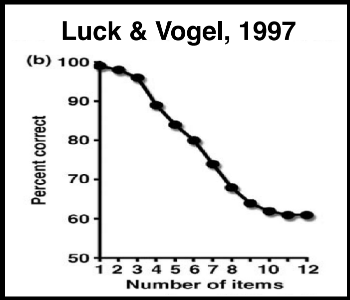

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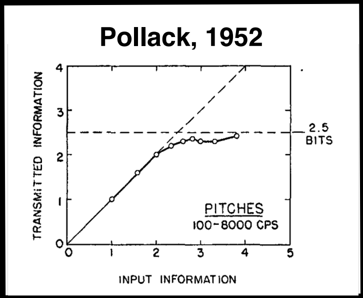

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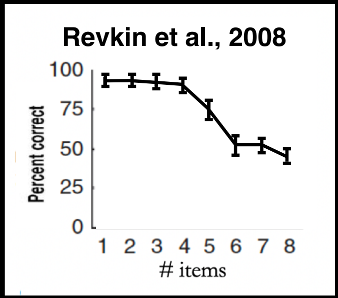

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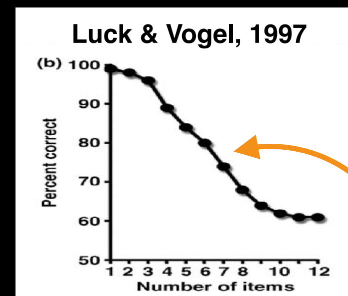

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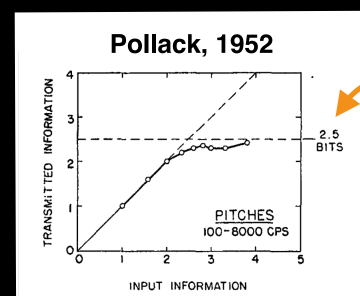

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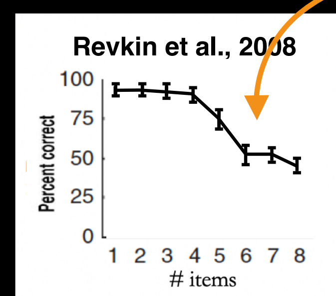

7 +/- 2

(~2.5 bits)

Vol. 63, No. 2 March, 1956

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. . . For the present I propose to withhold judgment. Perhaps there is something deep and profound behind all these sevens, something just calling out for us to discover it. But I suspect that it is only a pernicious, Pythagorean coincidence.

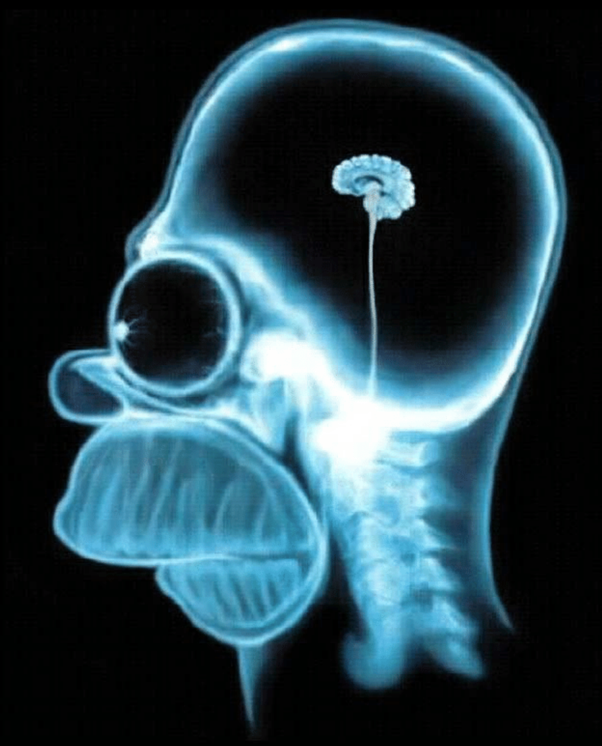
And the list goes on…

- **Classic verbal short-term memory task**
  (Sternberg, 1966)

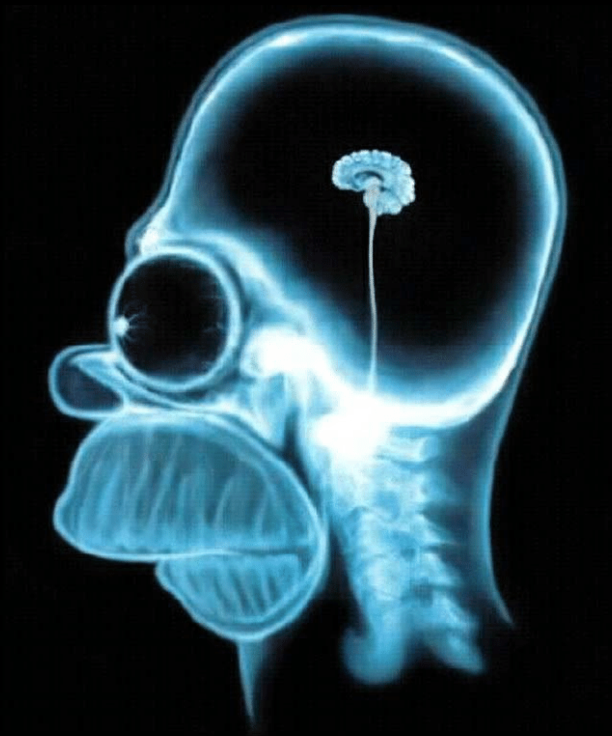
- **Classic working memory tasks**
  (Baddeley, 1990; Cowan, 1999; Luck & Vogel, 1997)

- **Attention / visual search tasks**
  (Shiffrin & Schneider, 1977; Treisman & Gelade, 1980)

- **Control-dependent processing**
  (Posner & Snyder,1975; Pashler, 1994)



And the list goes on…



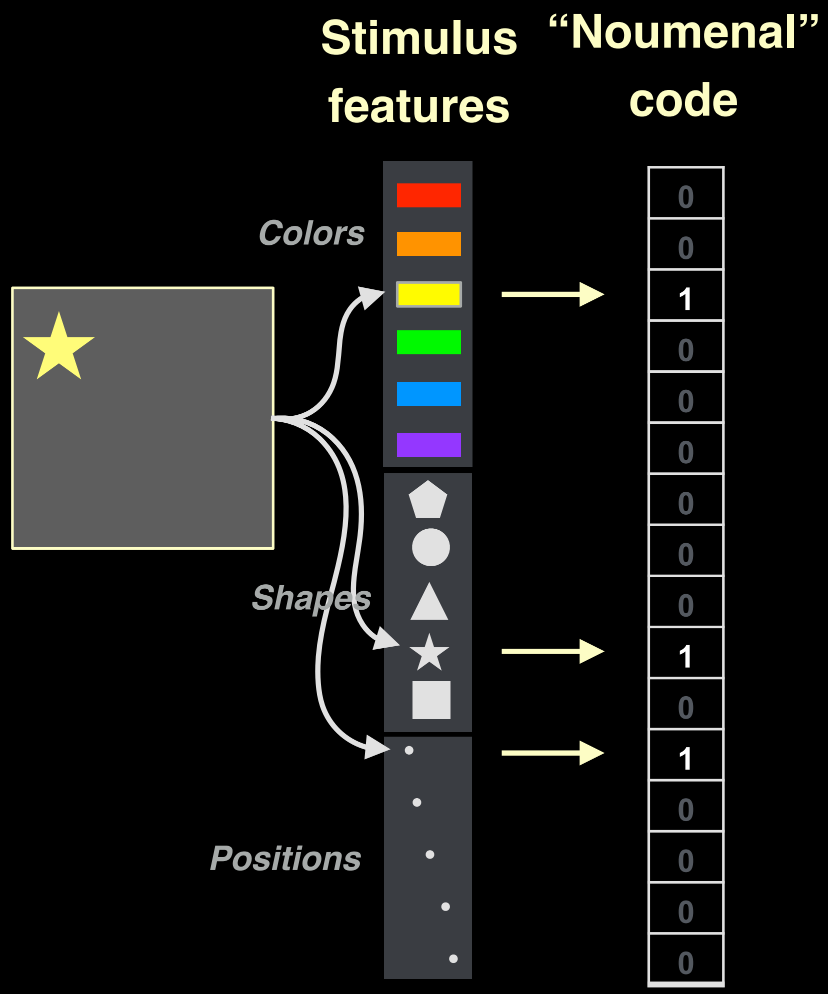
- All exhibit ≤ 2½ bit capacity limit

And the list goes on…

- But for the same reason?

An Information Theoretic Perspective

Empirical State



An Information Theoretic Perspective

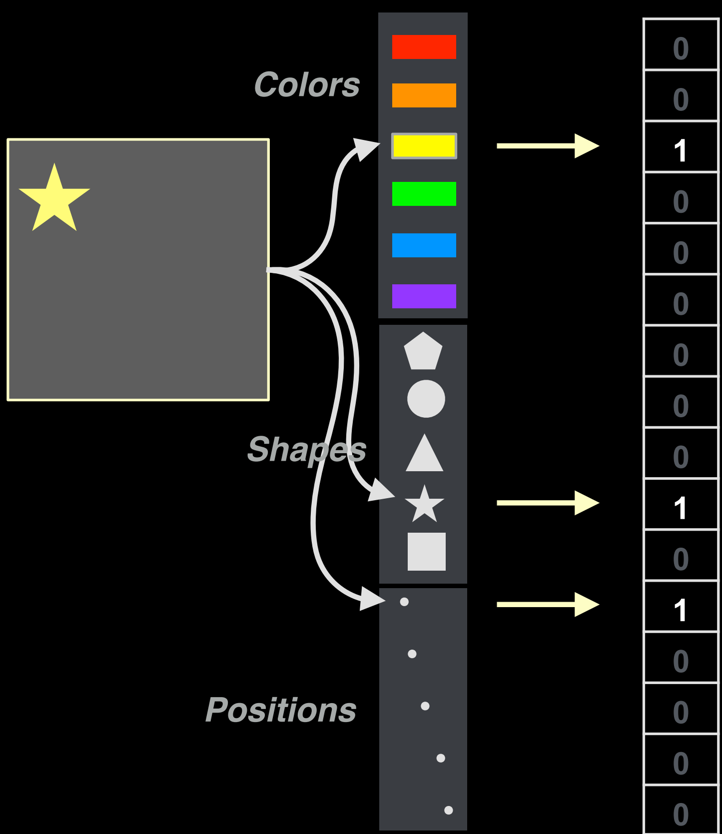
Empirical State

Internal Representation

Stimulus features

"Noumenal" code

"Phenomenal" code



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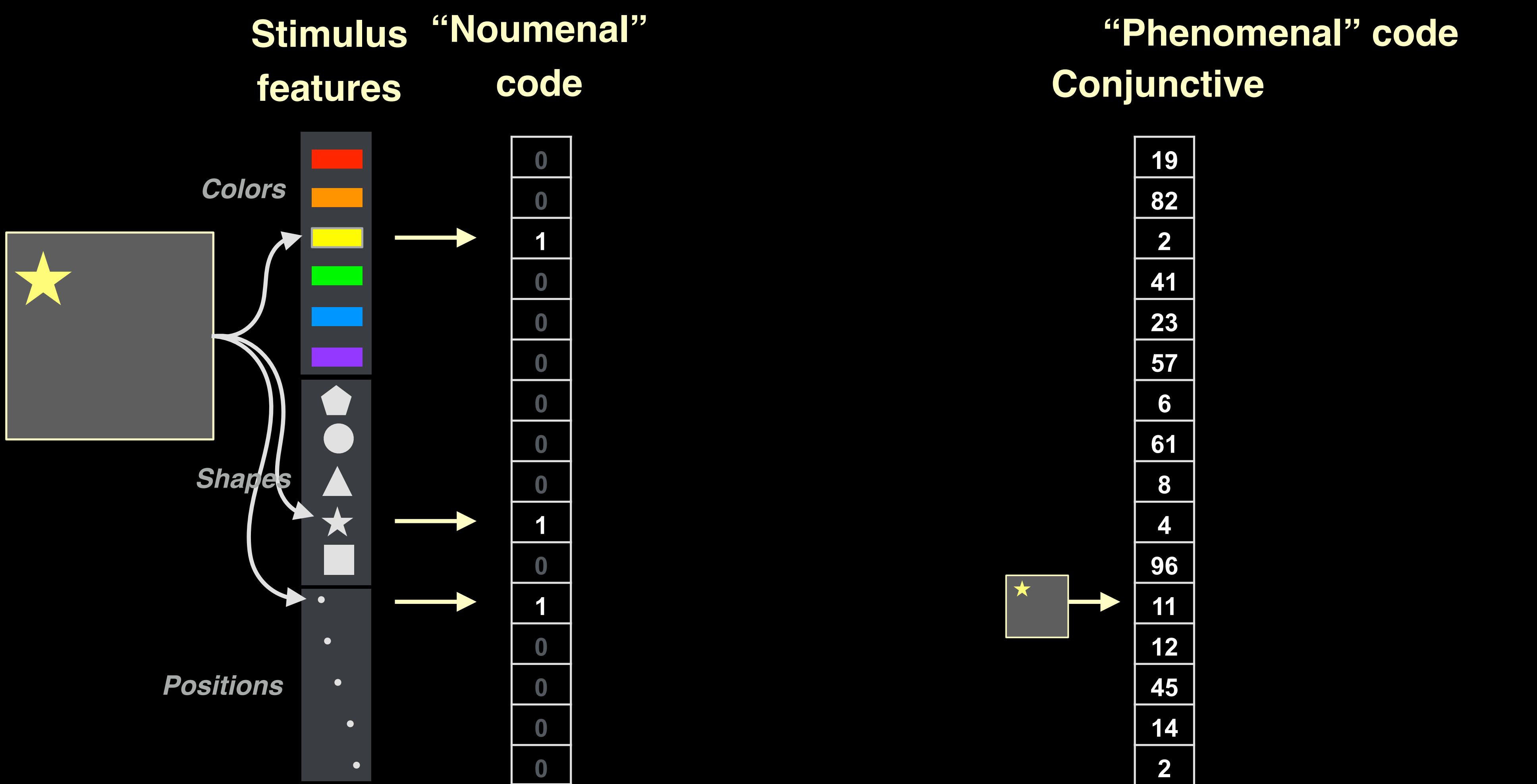

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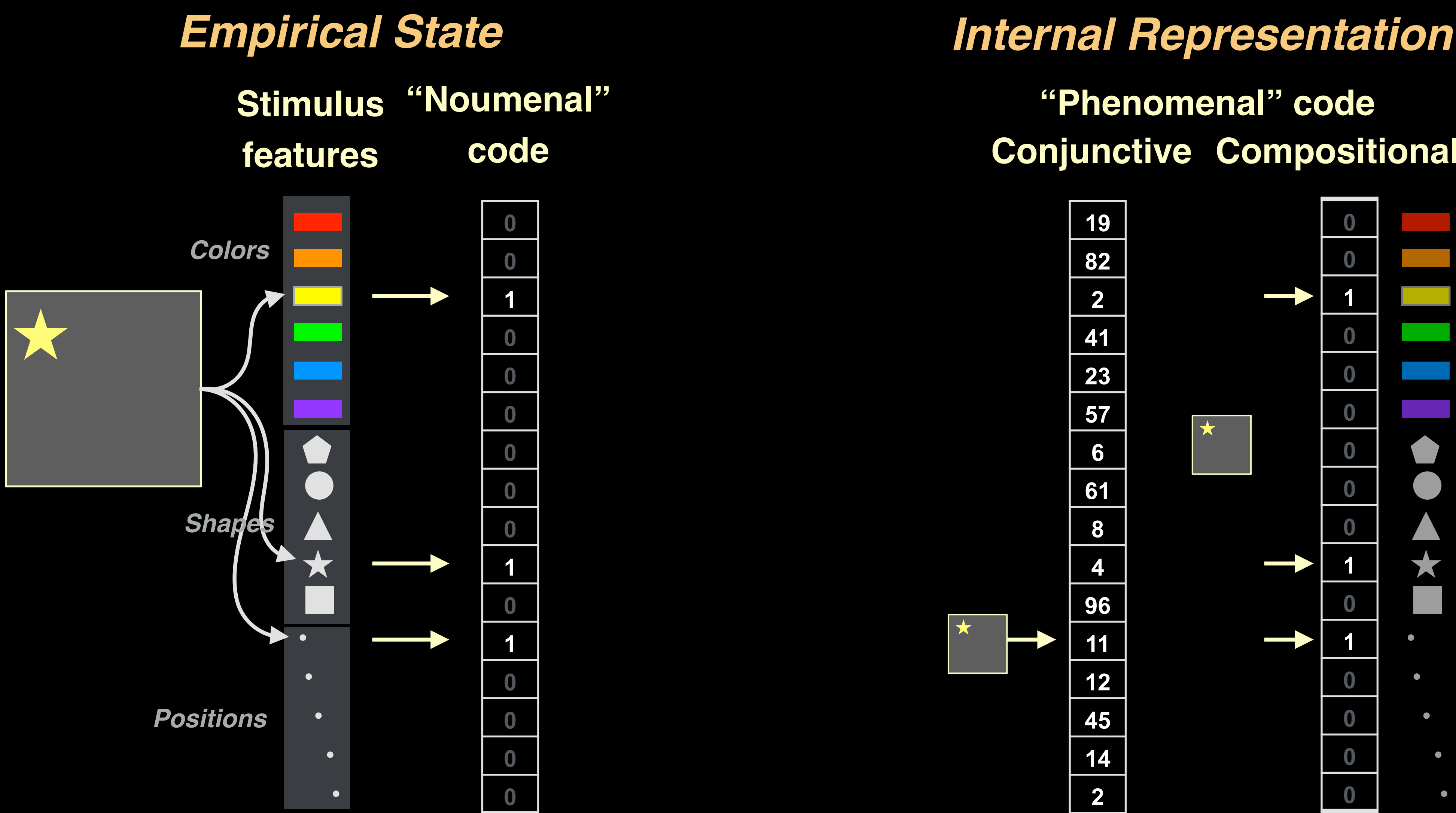

An Information Theoretic Perspective

Empirical State

Internal Representation

"Noumenal" code	"Phenomenal" code: Conjunctive	"Phenomenal" code: Compositional
0	19	0
0	82	0
1	2	1
0	41	0
0	23	0
0	57	0
0	6	0
0	61	0
0	8	0
1	4	1
0	96	0
1	11	1
0	12	0
0	45	0
0	14	0
0	2	0

—— *Transmission* ⟶

***Capacity*:**

⟵ **Mutual Information** ⟶

$H(X) + H(Y) - H(X,Y)$

Semanticity of Codes

Conjunctive Code

1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Semanticity of Codes

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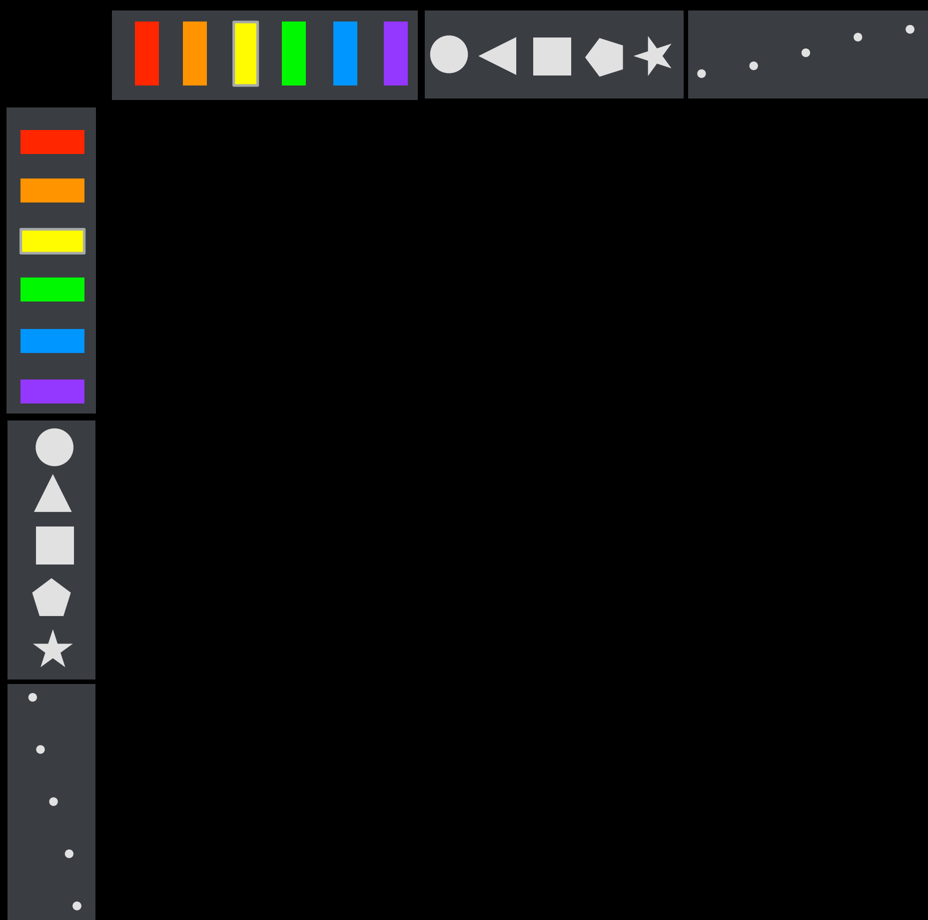

Semantic + Compositional Code

1	.3	.1	0	0	.1	0	0	0	0	0	0	0	0	0	0
.3	1	.3	.1	0	0	0	0	0	0	0	0	0	0	0	0
.1	.3	1	.3	.1	0	0	0	0	0	0	0	0	0	0	0
0	.1	.3	1	.3	.1	0	0	0	0	0	0	0	0	0	0
0	0	.1	.3	1	.3	0	0	0	0	0	0	0	0	0	0
.1	0	0	.1	.3	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	.1	0	.2	0	0	0	0	0	0
0	0	0	0	0	0	.1	1	.8	.4	.3	0	0	0	0	0
0	0	0	0	0	0	0	.8	1	.1	.1	0	0	0	0	0
0	0	0	0	0	0	.2	.4	.1	1	.9	0	0	0	0	0
0	0	0	0	0	0	0	.3	.1	.9	1	0	0	0	0	0
0	0	0	0	0	0	0	0	.4	.6	0	1	.8	.6	.4	.2
0	0	0	0	0	0	0	0	0	.4	0	.8	1	.8	.6	.4
0	0	0	0	0	0	0	0	0	0	0	.6	.8	1	.8	.6
0	0	0	0	0	0	0	0	0	0	0	.4	.6	.8	1	.8
0	0	0	0	0	0	0	0	0	0	0	.2	.4	.6	.8	1

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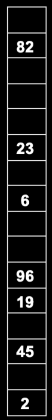

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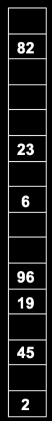

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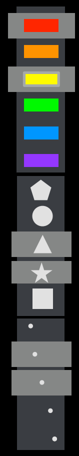

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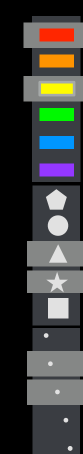
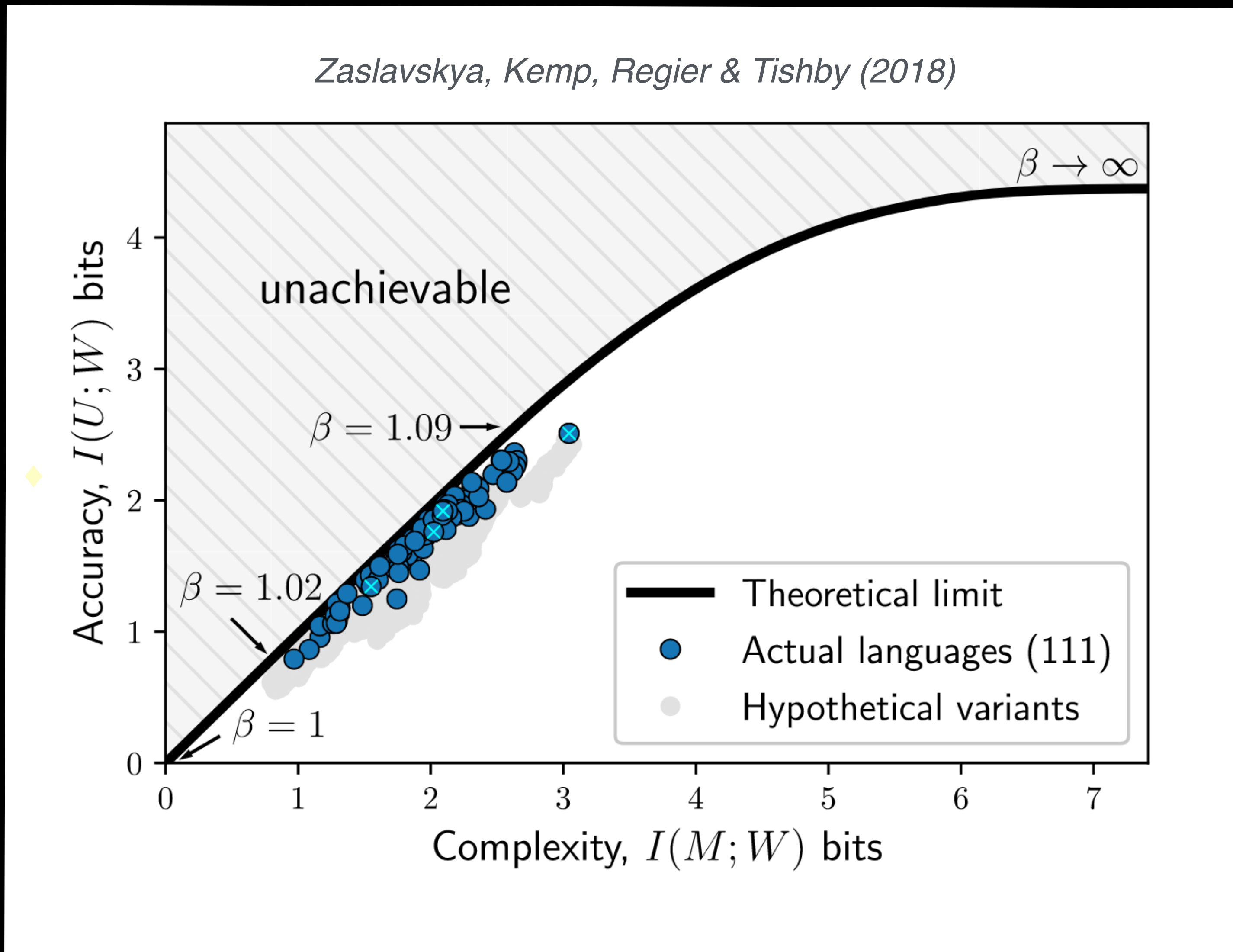


Information Bottleneck

Tishby, Naftali, Pereira & William Bialek (2000)



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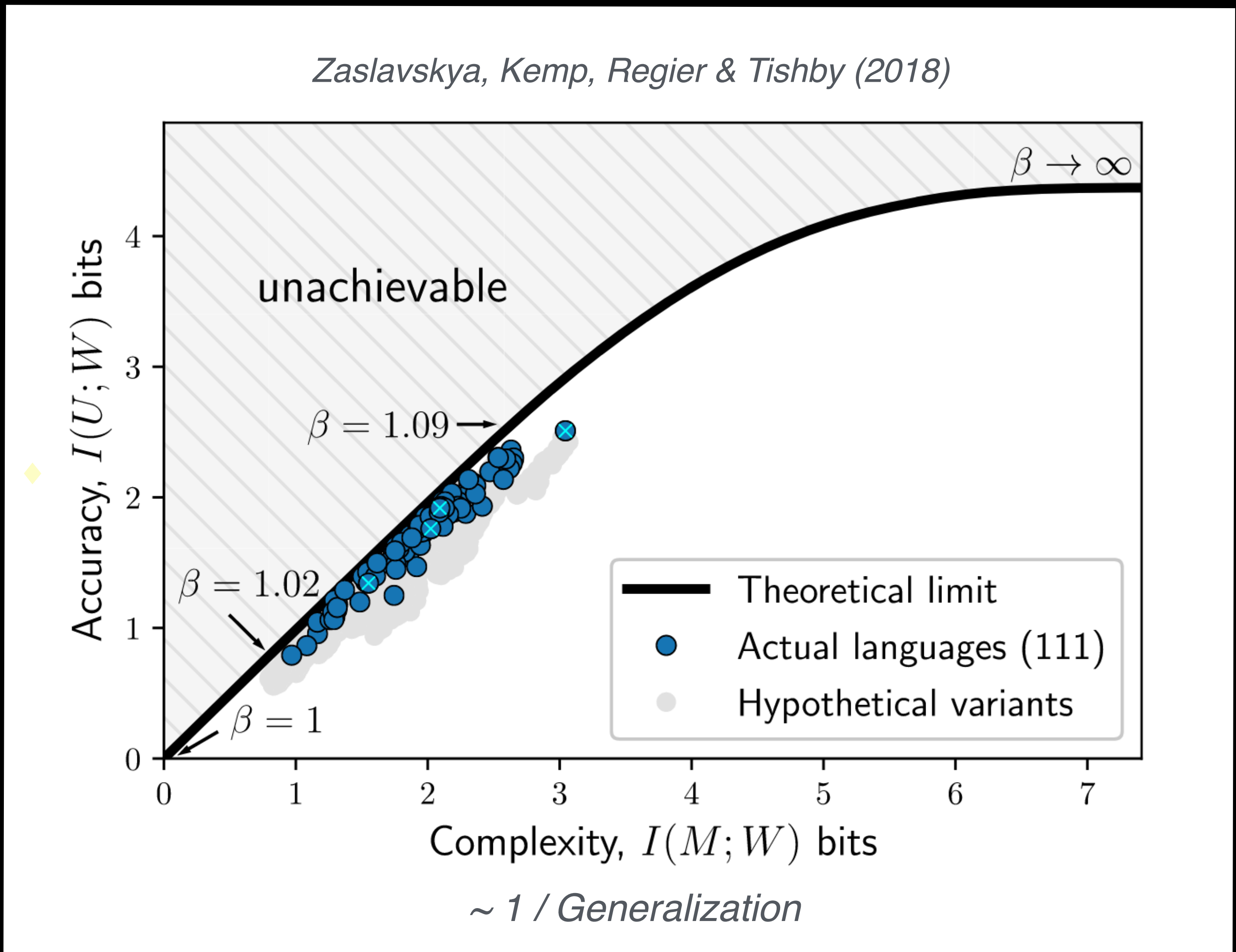

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    indexes *representational capacity* *(as a function of coding structure)*
  - **Identification task:**

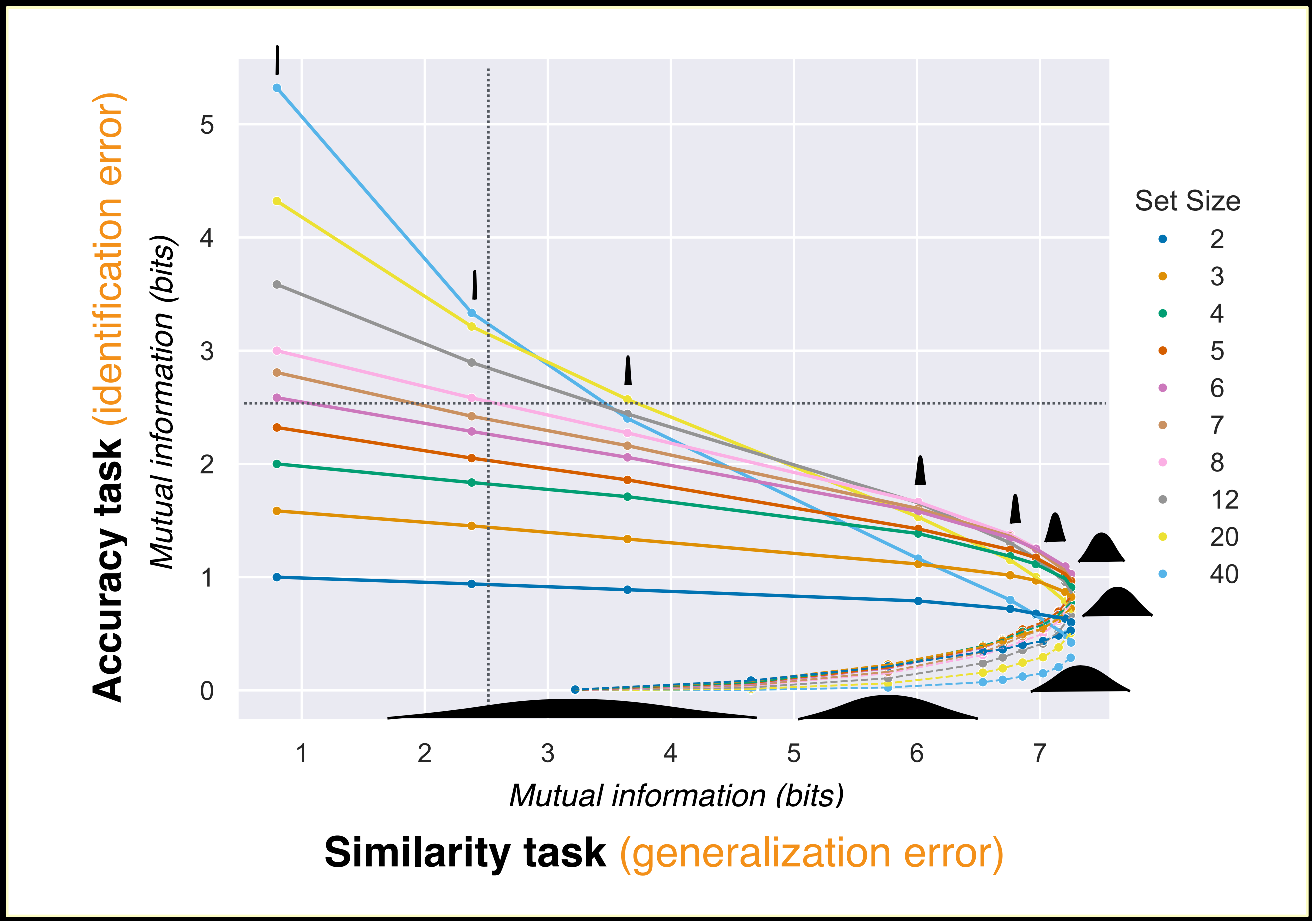
    identify probed item (based on one of its features)

    indexes *processing capacity* *(as a function of # items = set size)*

Miller's Law

Frankland, Webb, Lewis & Cohen (2025)

Identification Error ~1/∝ Generalization Error



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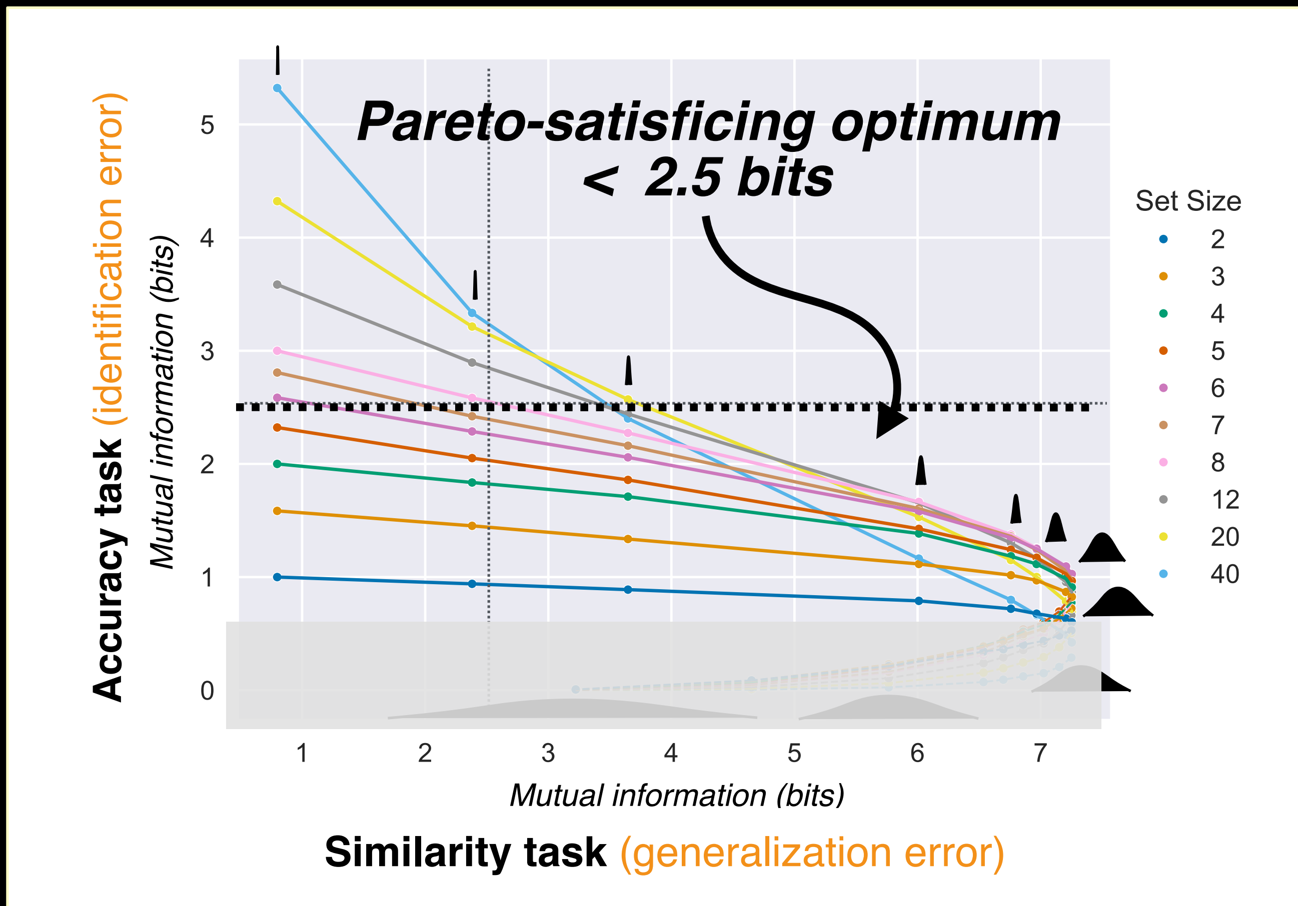
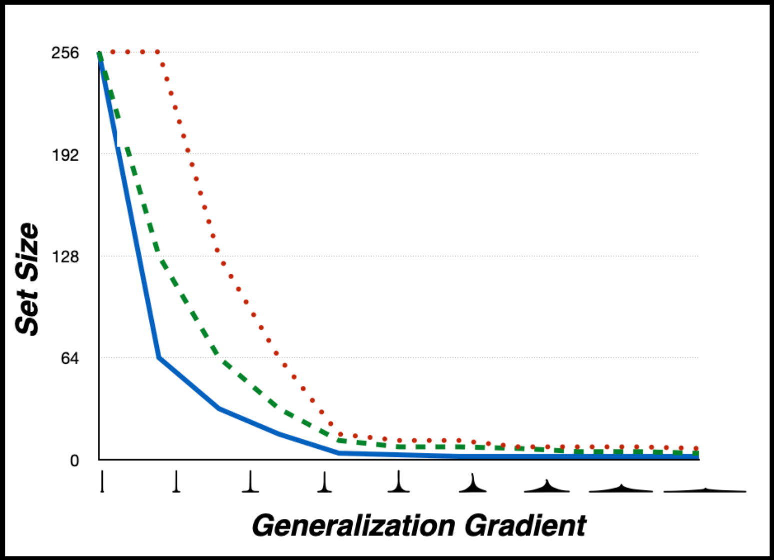


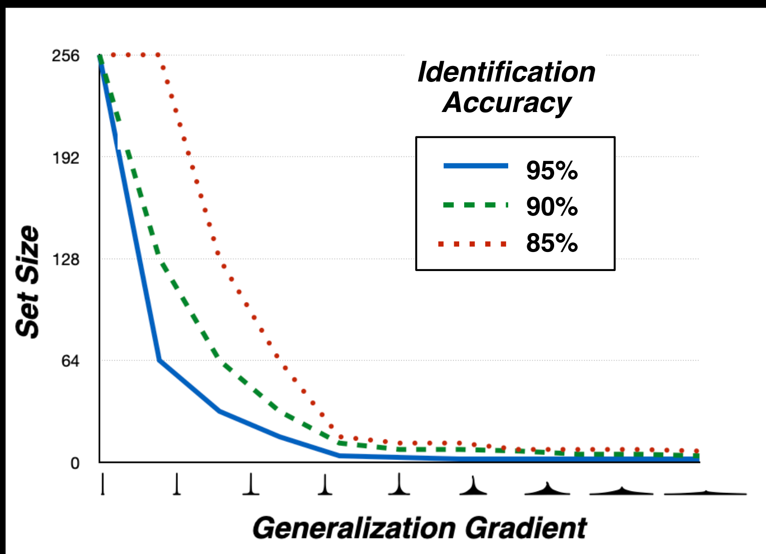
Ubiquitous Effect



Ubiquitous Effect

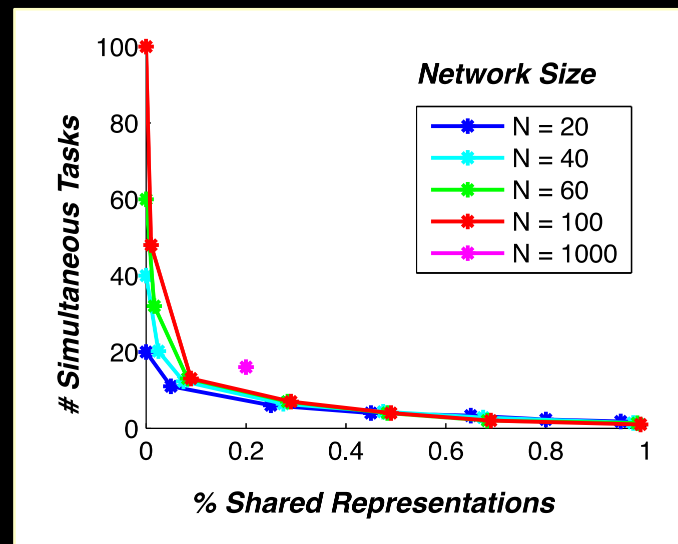
Inference

(Frankland et al., 2024)

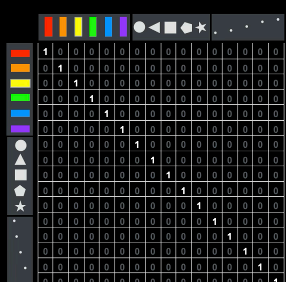


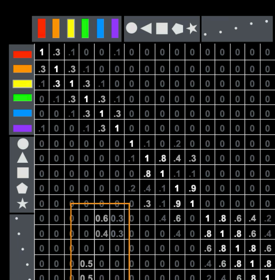
Affordance

(Musslick et al., 2023)

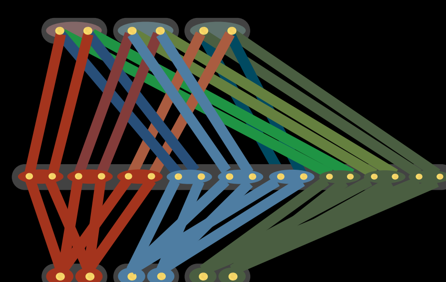


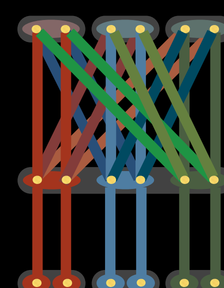
Conjunctive *vs.* ***Conjunctive***





Conjunctive *vs.* ***Conjunctive***





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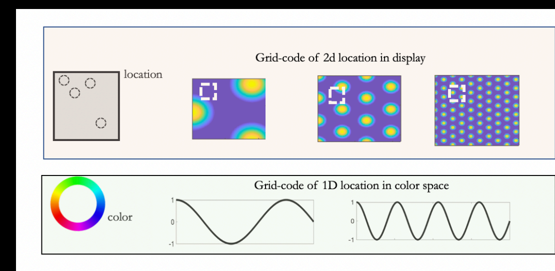
- **Case study:** ***"Miller's tasks"***

Mechanistic Process Model

Steven Frankland
Dartmouth University



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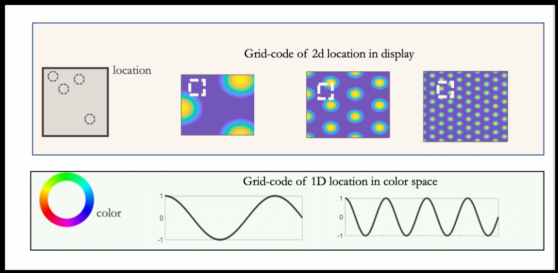

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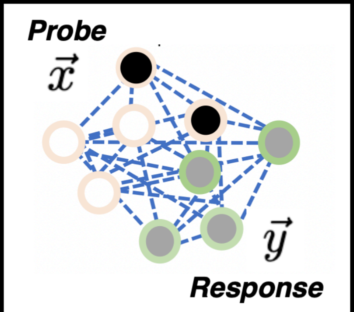

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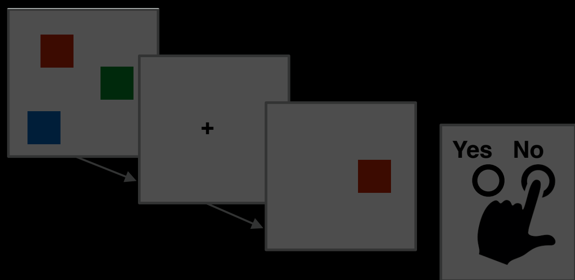
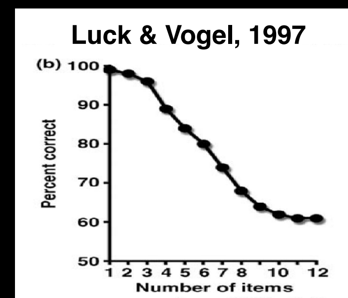
- **Processing**
  - embed items
  - encode in associative memory
  - clamp probe
  - settle to convergence (accuracy ≈ cross-entropy; cycles ≈ reaction time)
  - evaluate as a function of set size

Miller's Tasks

Data

- Visual Working Memory Task





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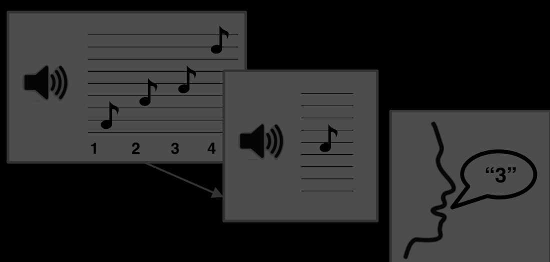
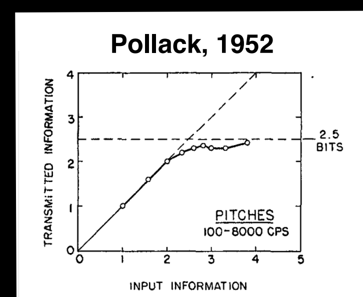
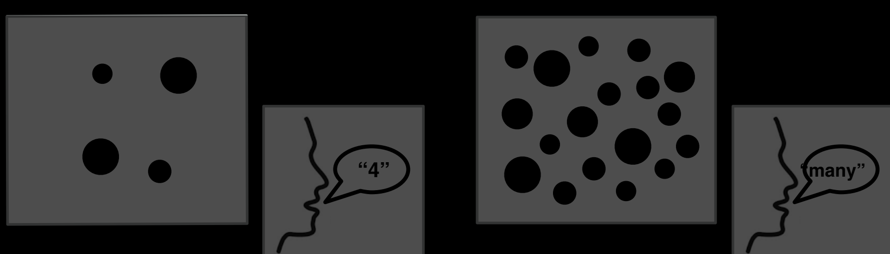
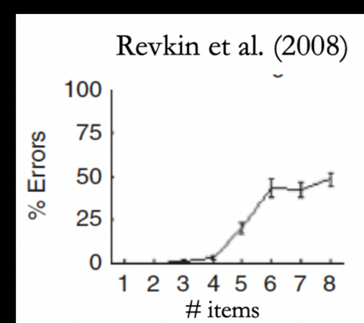




- Numerosity Estimation ("subtilizing")





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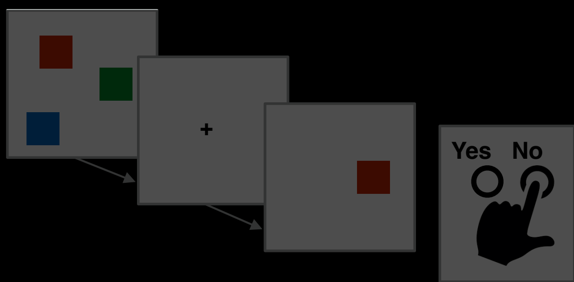

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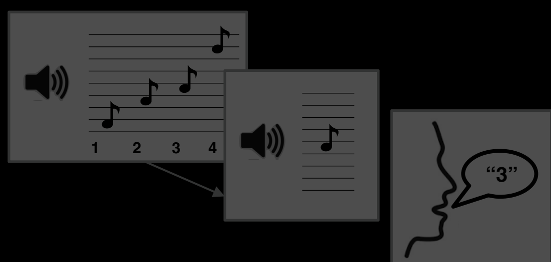

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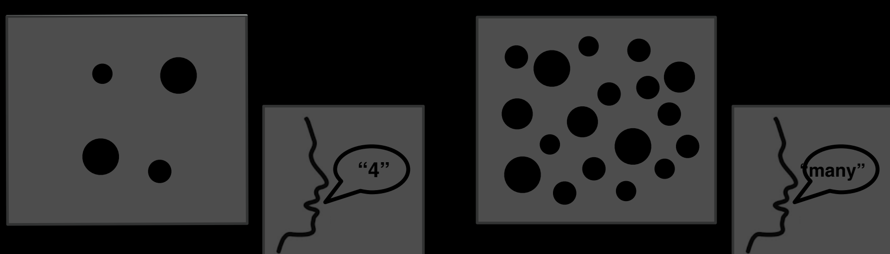

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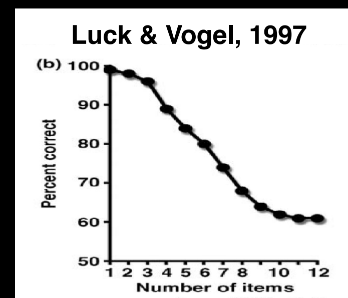

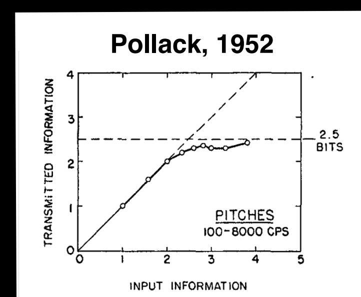

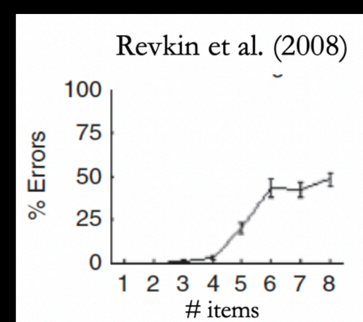

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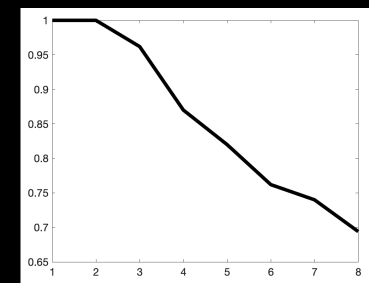

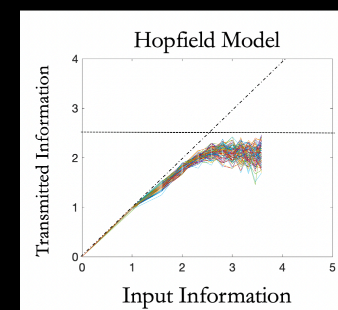

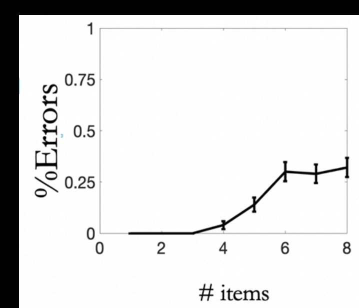

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  - **Serial search** *(compositional coding & the "Binding problem")*
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- **Performance: Automaticity and Control** *(Musslick et al, 2024)*
  - **Control-dependent, serial processing** *(shared, compositional reps)*
  - **Automatic, parallel multitasking** *(separated conjunctive reps)*

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and Artificial Minds

Declan Campbell
Princeton Neuroscience

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Response: There are 6 boats in the image

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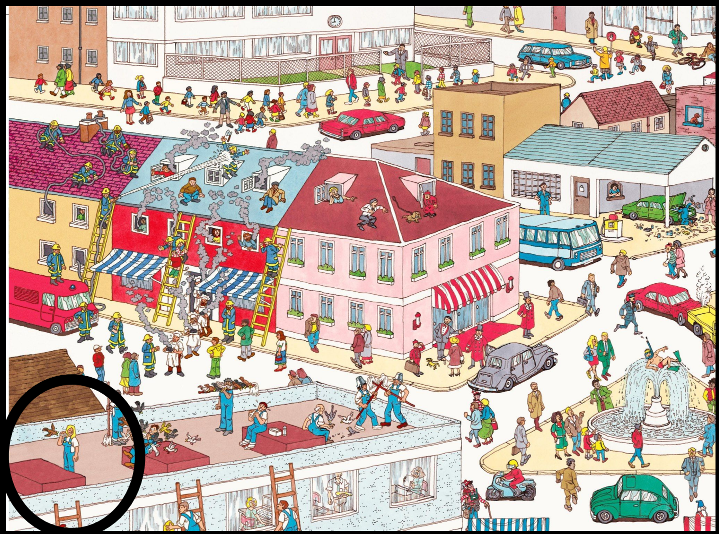

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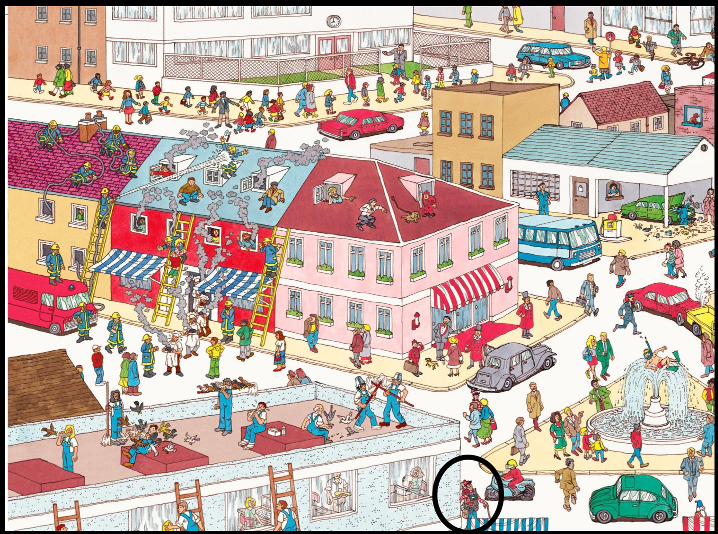

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