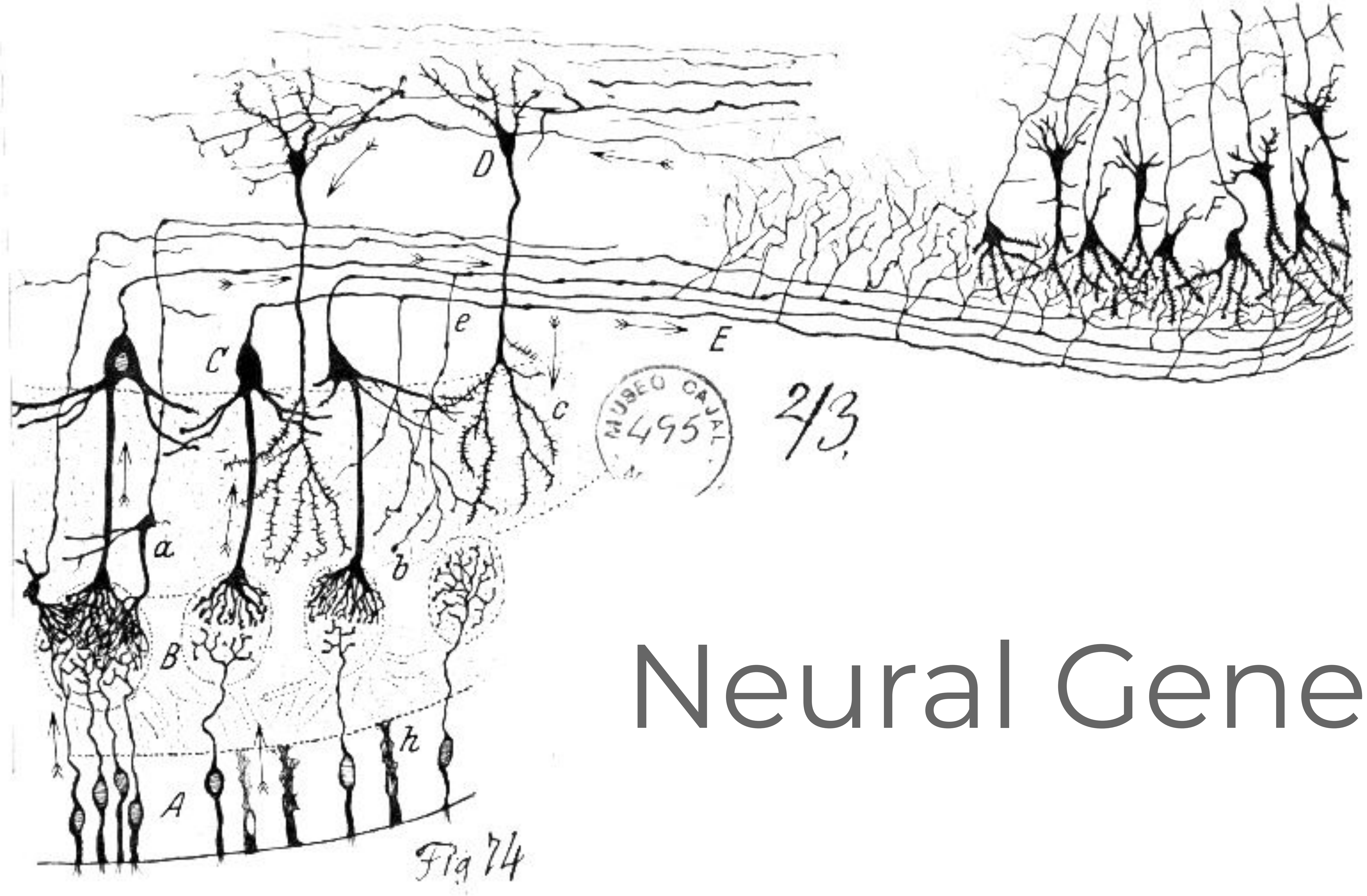


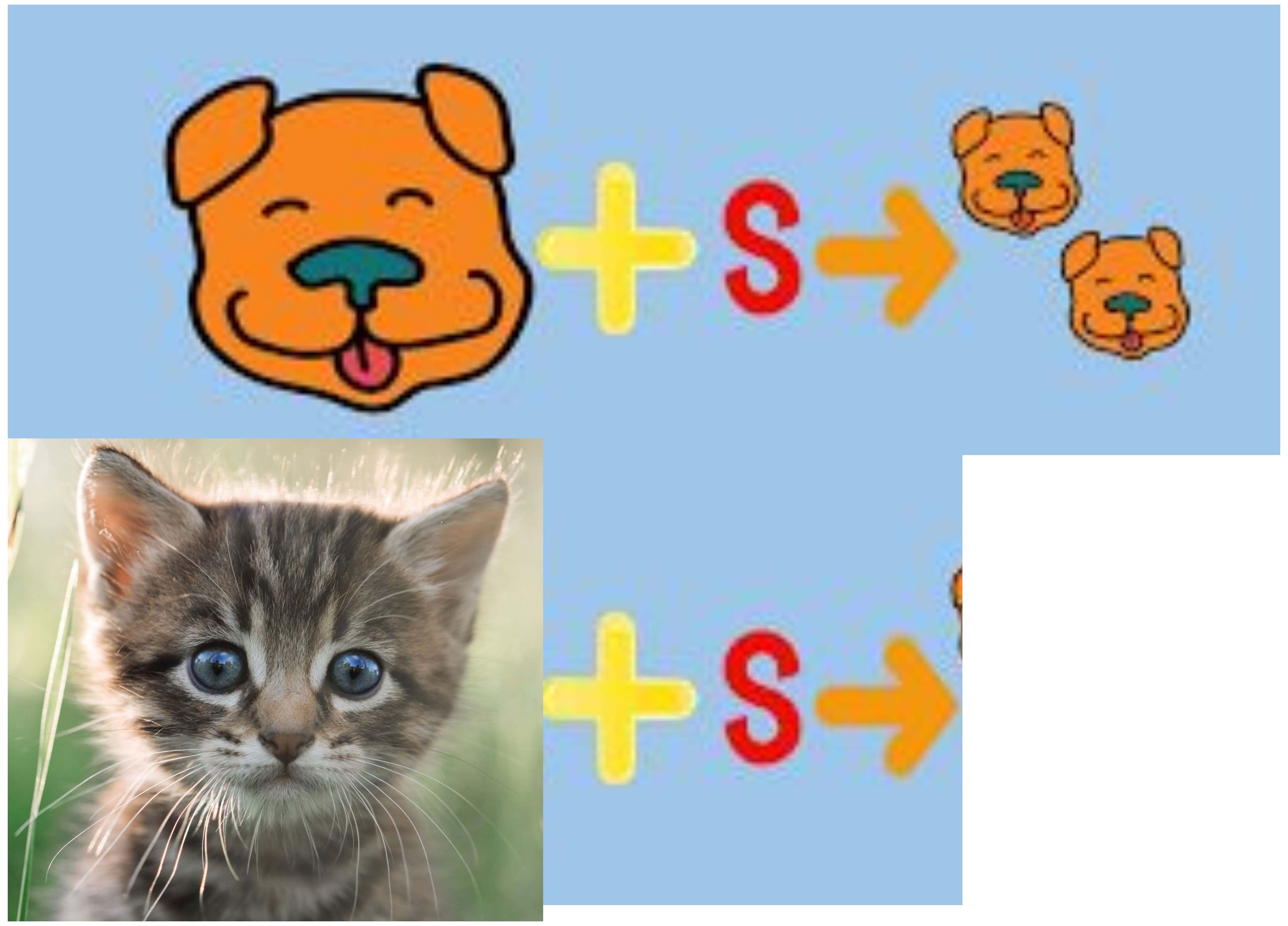
Neural Generalization

Image: Santiago Ramón y Cajal (1891; edited)

Generalizable generalization

Bartlett 1932

rodents (Murphy et al., 2008)
birds (Vaughan, 1988, Soto 2014)
monkeys (Minamimoto et al., 2010)
Humans (personal observations)



Children's word plurality generalization (Berko 1958)

Children's word / shape generalization (Landau 1988)

What is the benchmark?

Infants don’t generalize some motor behaviors (Rovee-Collier 1997)

Infants don’t generalize crib colors (Borovsky 1990)

Infants and toddlers learn actions from observation
but don’t generalize when the object is changed (Hayne 2000)
small change disrupted 6 and 12mo, but not 18mo
larger change disrupted 18 but not 21mo

Adults struggle to generalize puzzles with the same solution but different shapes (Newell and Simon 1972)

Context driven recall (Godden and Baddeley 1975)

Examples or Abstractions?

Exemplar theory
(Nosofsky 1986)

Prototype theory
(Reed 1972; Posner 1968)

figure from Zeithamova et al 2019

The brain represents exemplars: Mack et al 2013

Participants trained to categorize items

Neural data supported exemplar models

Network of brain regions:
- Occipital
- Parietal
- right lPFC

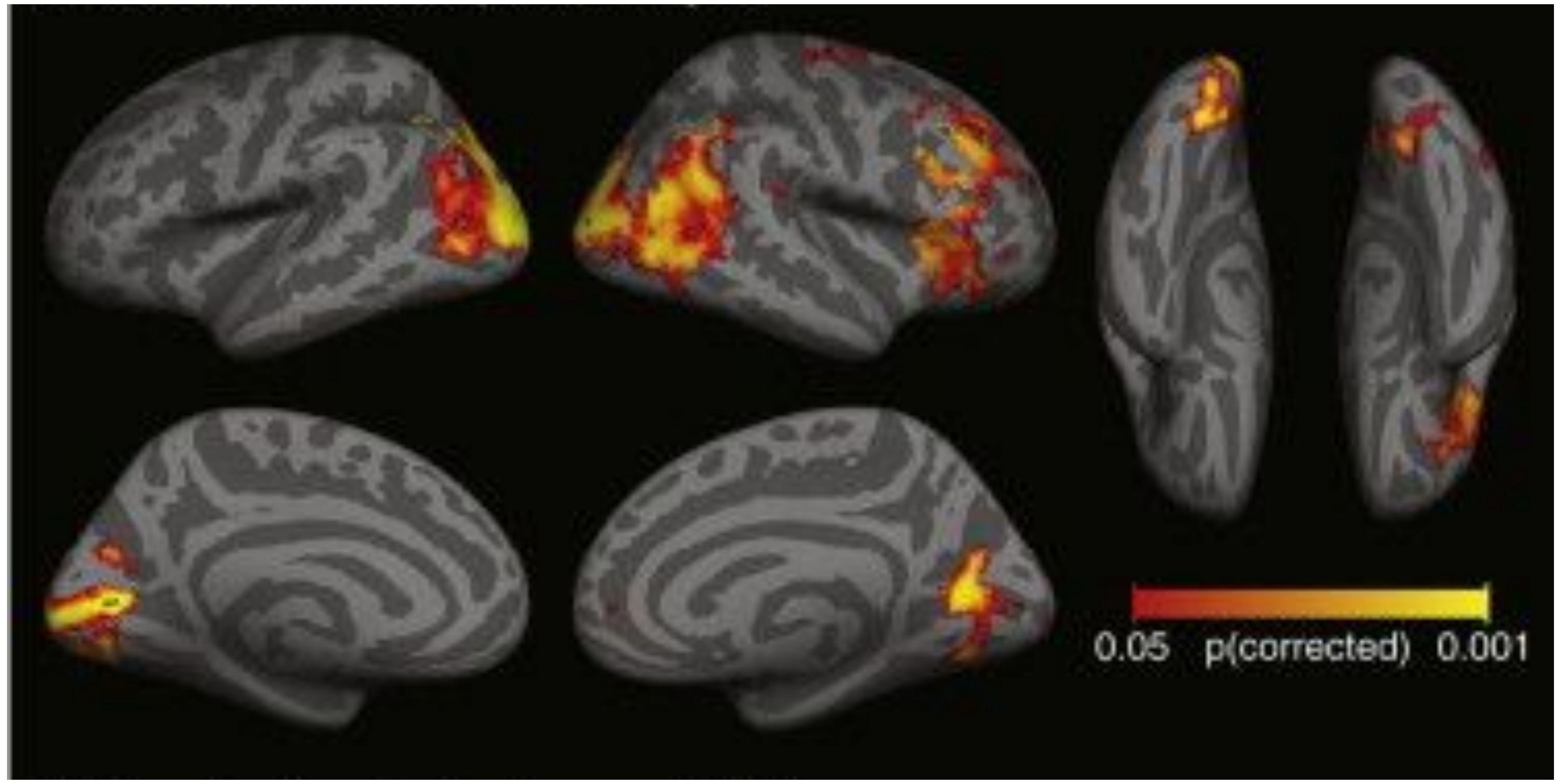


Figure from Mack et al 2013

...and prototypes: Bowman et al 2018, 2019

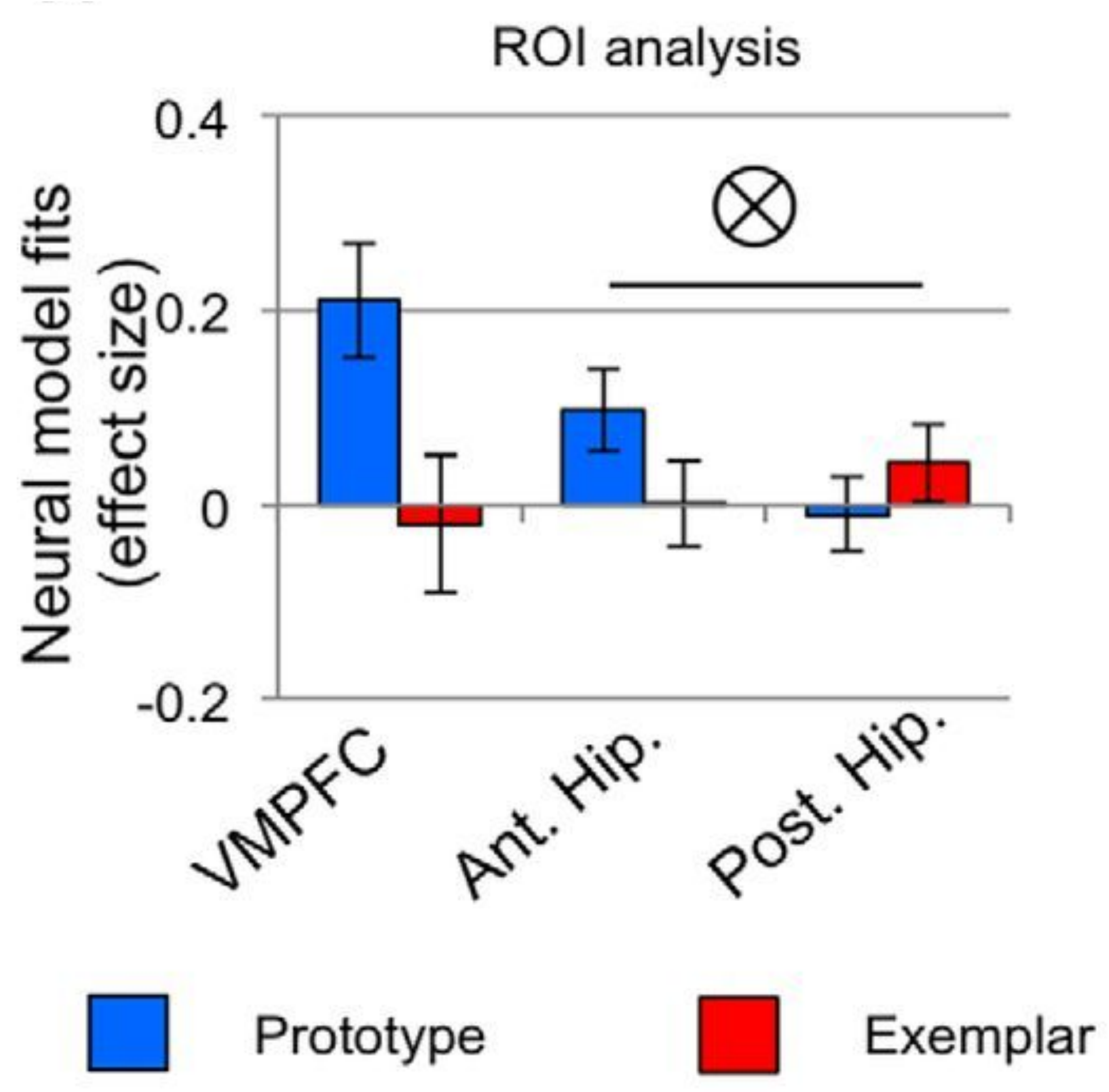
Mack et al task may be constrained

Use more distinct stimuli categories

Prototype model supported

New network of brain regions:
  hippocampus
  vmPFC

Category coherence is critical



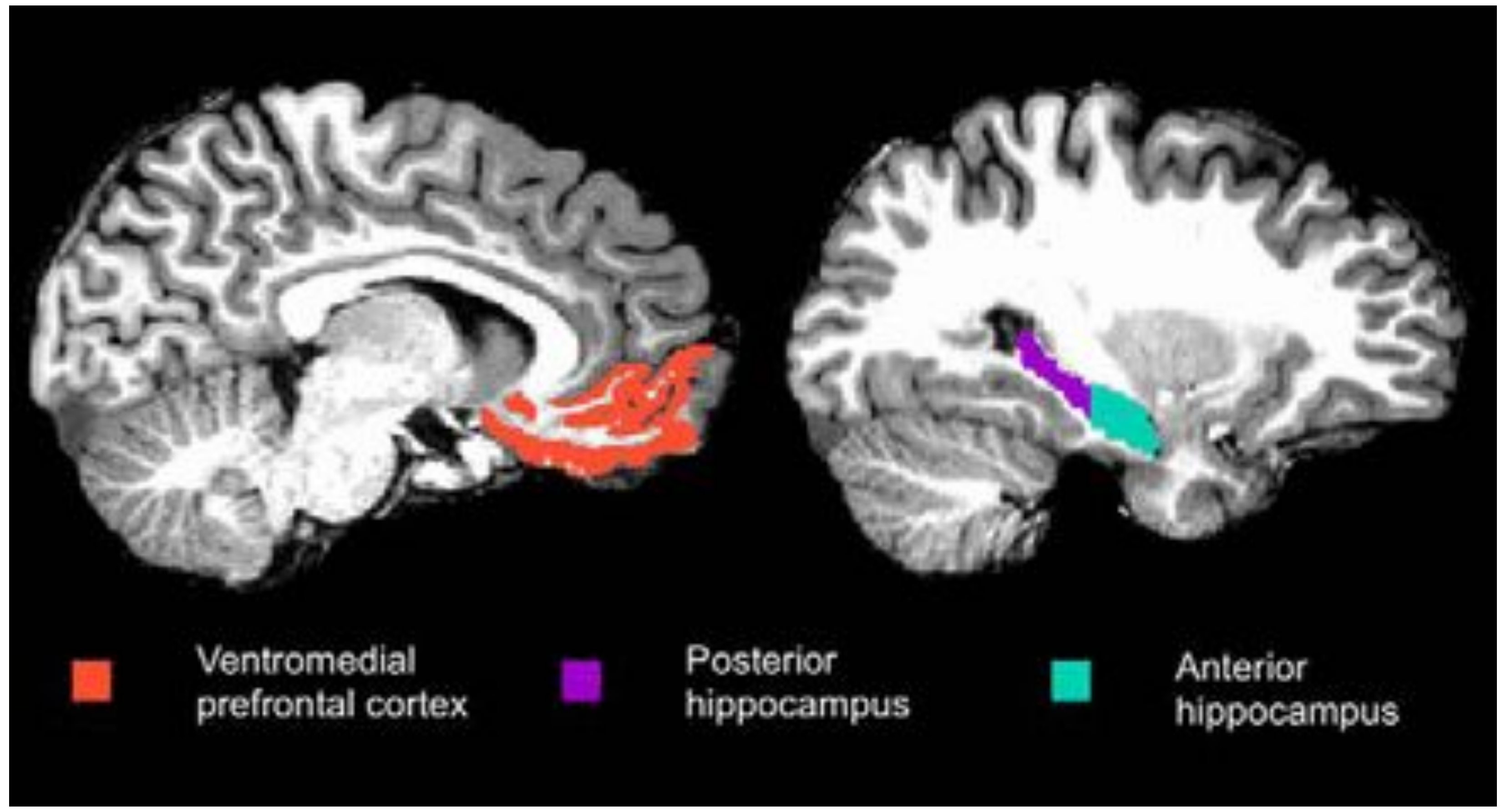


Figure from Bowman et al 2018

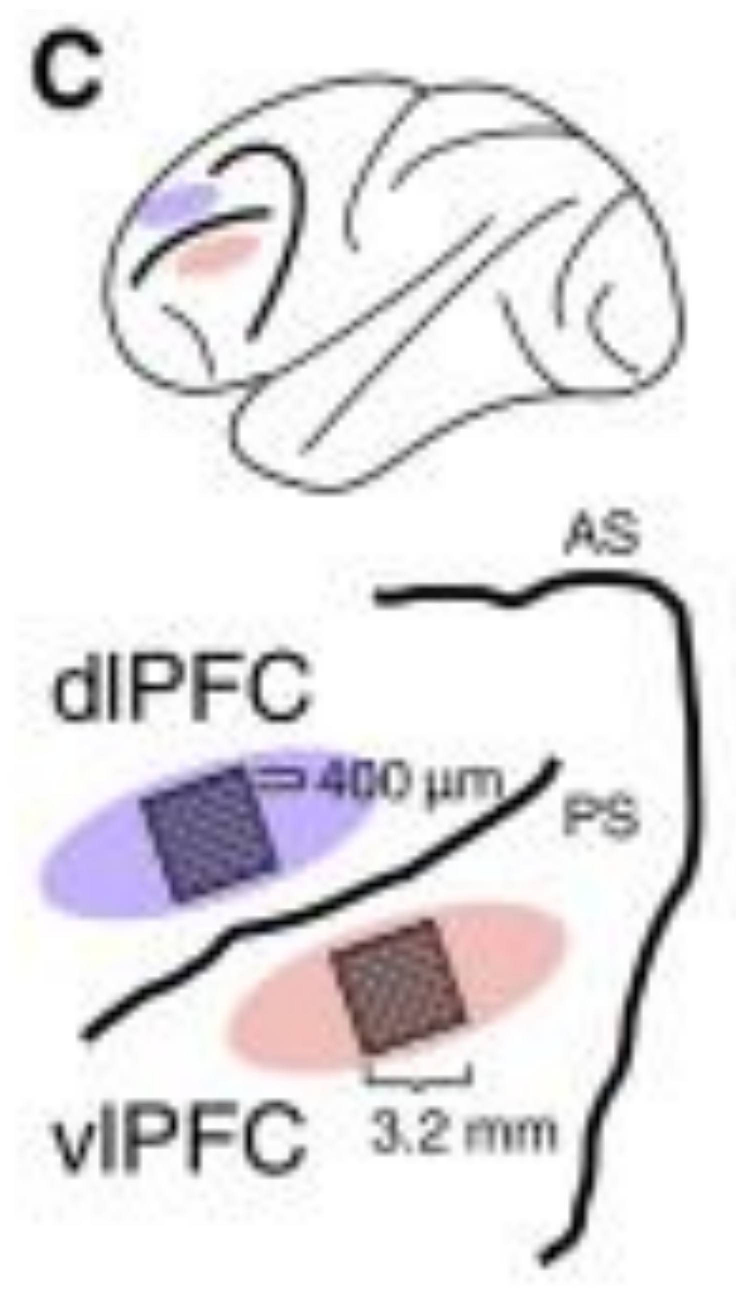
Deeper dive into PFC: Wutz et al 2018

Monkey categorization task

Varied abstraction level

vlPFC gamma: sensory matching

dlPFC beta: generalization



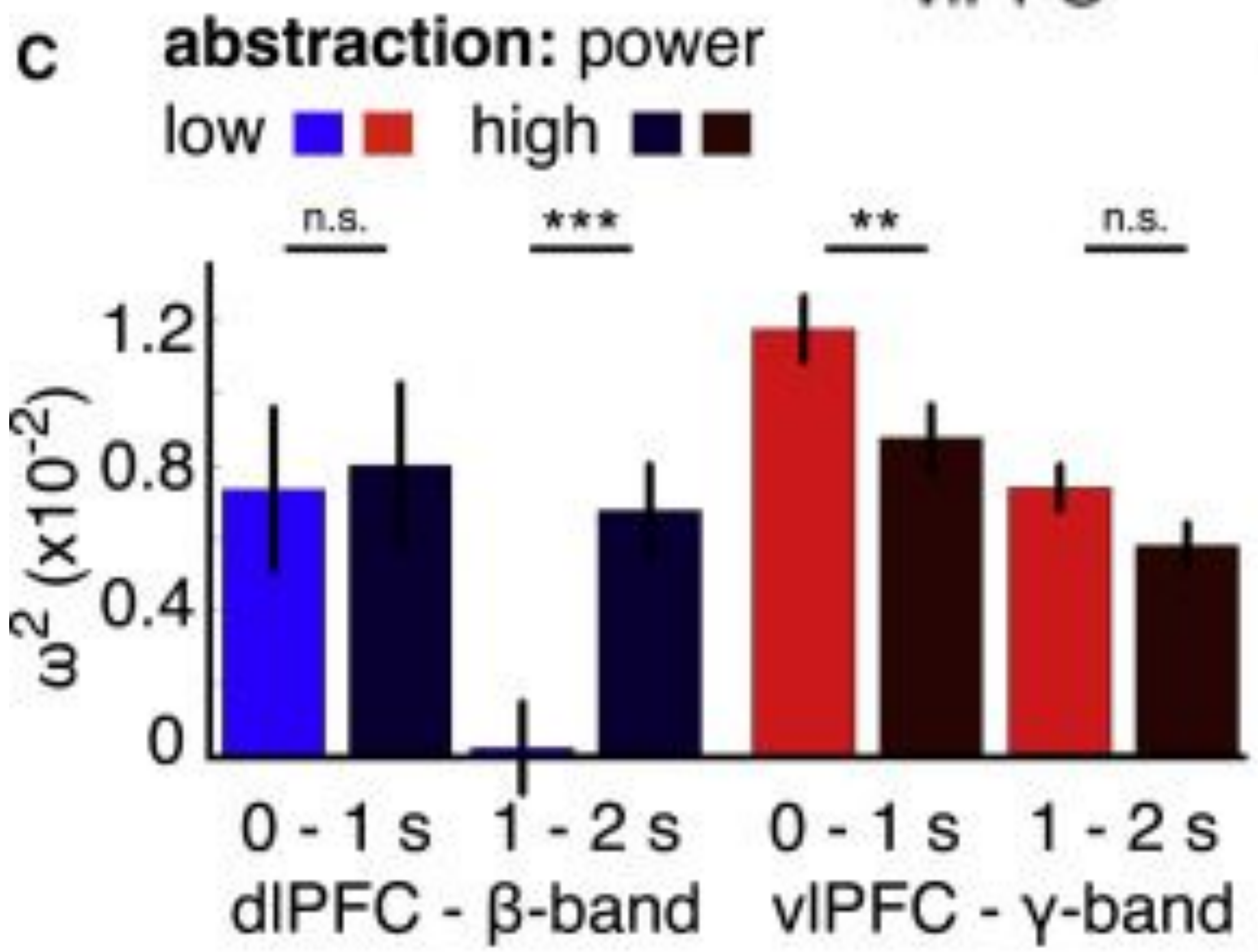


Figure from Wutz et al 2018

Slightly more of the iceberg...

Coherent sets are more efficient, but variable sets lead to better generalization
(Hintzman, 1984; Homa & Vosburgh, 1976; Posner & Keele, 1968)

Prototypes tend to require more samples
(Minda & Smith, 2001; Murdock, 1962)

Specialized and abstract representations form simultaneously
(Brunec et al., 2018; Collin, Milivojevic, & Doeller, 2015, Hassabis, & Kumaran, 2016)

Consolidation may lend to generalization

Vincenzo Lomonaco
@v_lomonaco

Continual Learning and Sequence Learning are two sides of the same coin. I predict they will be connected more and more in the near future.

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Continual Learning and Sequence Learning are two sides of the same coin. I predict they will be connected more and more in the near future.

CATASTROPHIC INTERFERENCE IN CONNECTIONIST NETWORKS: THE SEQUENTIAL LEARNING PROBLEM

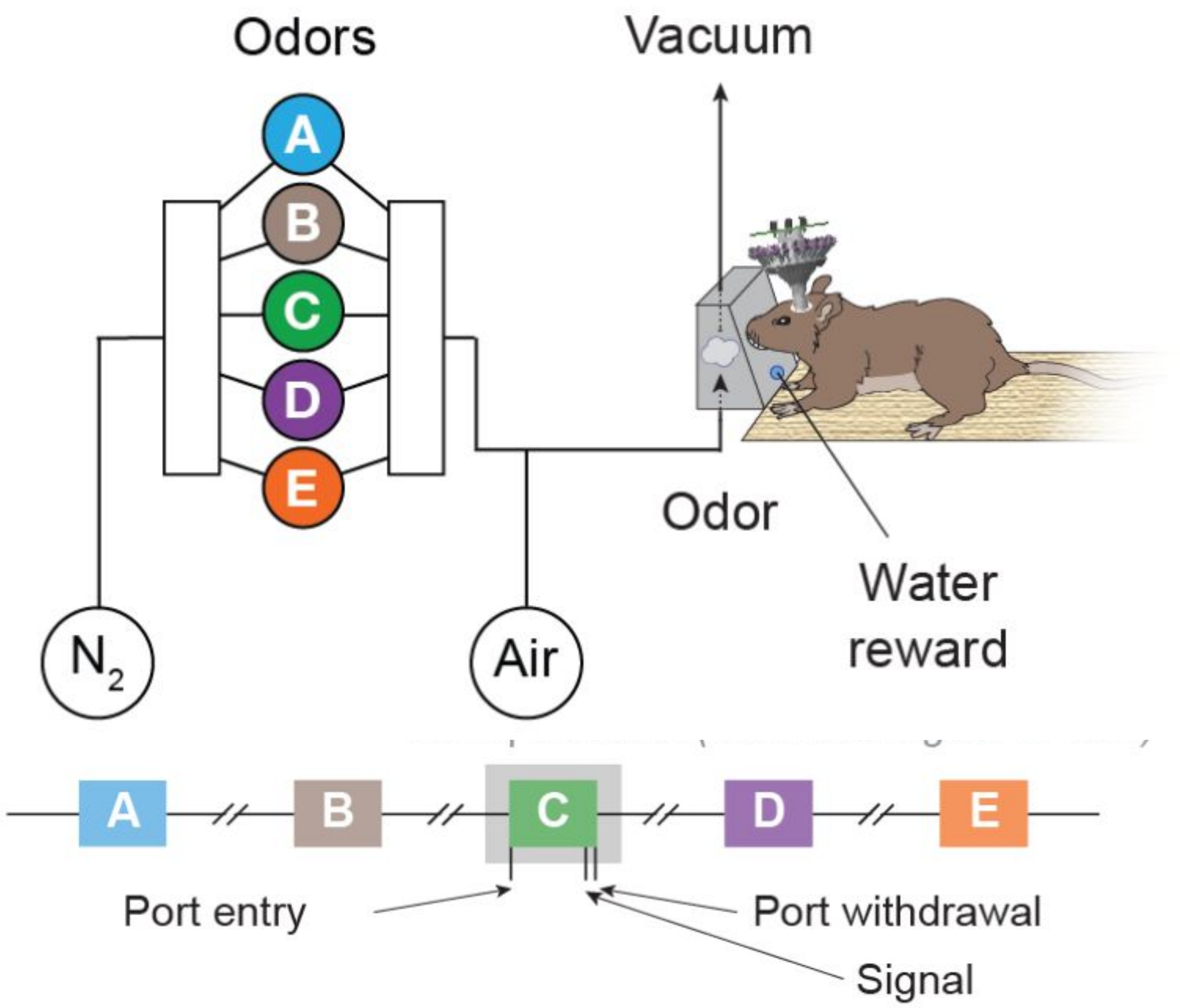
Michael McCloskey
Neal J. Cohen

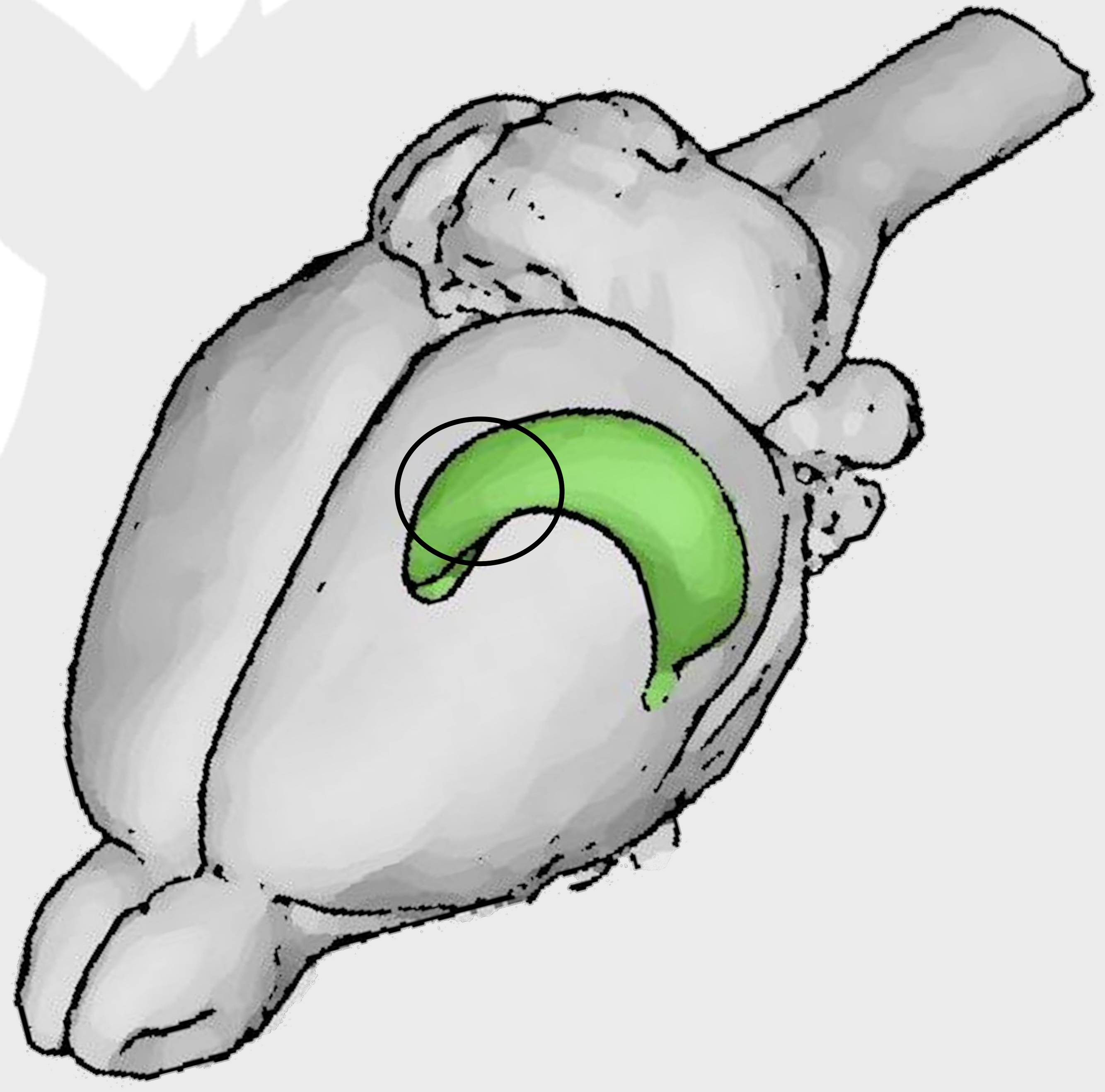
I. Introduction

Connectionist networks in which information is stored in weights on connections between simple processing units have attracted considerable interest in cognitive science (e.g., Rumelhart, McClelland, & the PDP Research Group, 1986; McClelland, Rumelhart, & the PDP Research Group, 1986). Much of the interest centers around two characteristics of these networks. First, the weights on connections between units need not be prewired by the model builder but rather may be established through training in which items to be learned are presented repeatedly to the network and the connection weights are adjusted in small increments according to a learning algorithm (e.g., Ackley, Hinton, & Sejnowski, 1985; Rumelhart, Hinton, & Williams, 1986; Hinton & Sejnowski, 1986). Second, the networks may represent information in a distributed fashion. That is, the representation of an item may be spread, or distributed, across many different processing units and connections, and each unit and connection may be involved in representing many different items.

Distributed representations established through the application of learning algorithms have several properties that are claimed to be desirable from the standpoint of modeling human cognition (e.g., Hinton, McClelland, & Rumelhart, 1986; McClelland, Rumelhart, & Hinton, 1986; but see Prince & Pinker, 1988; Fodor & Pylyshyn, 1988; Lachter &

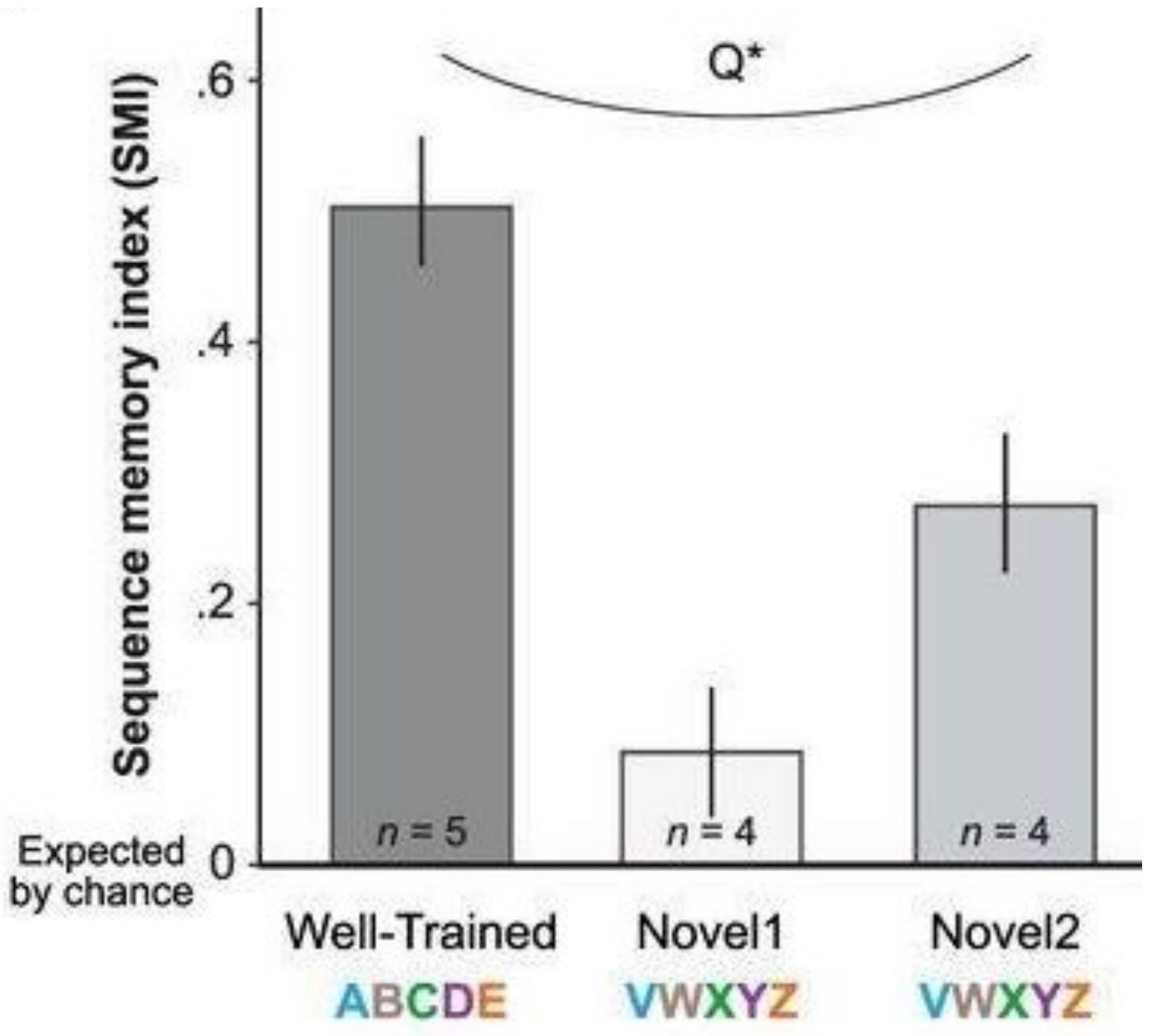
Odor Sequence Task





Allen et al 2016 (J Neurosci); Shahbaba et al 2019 (Under Review)

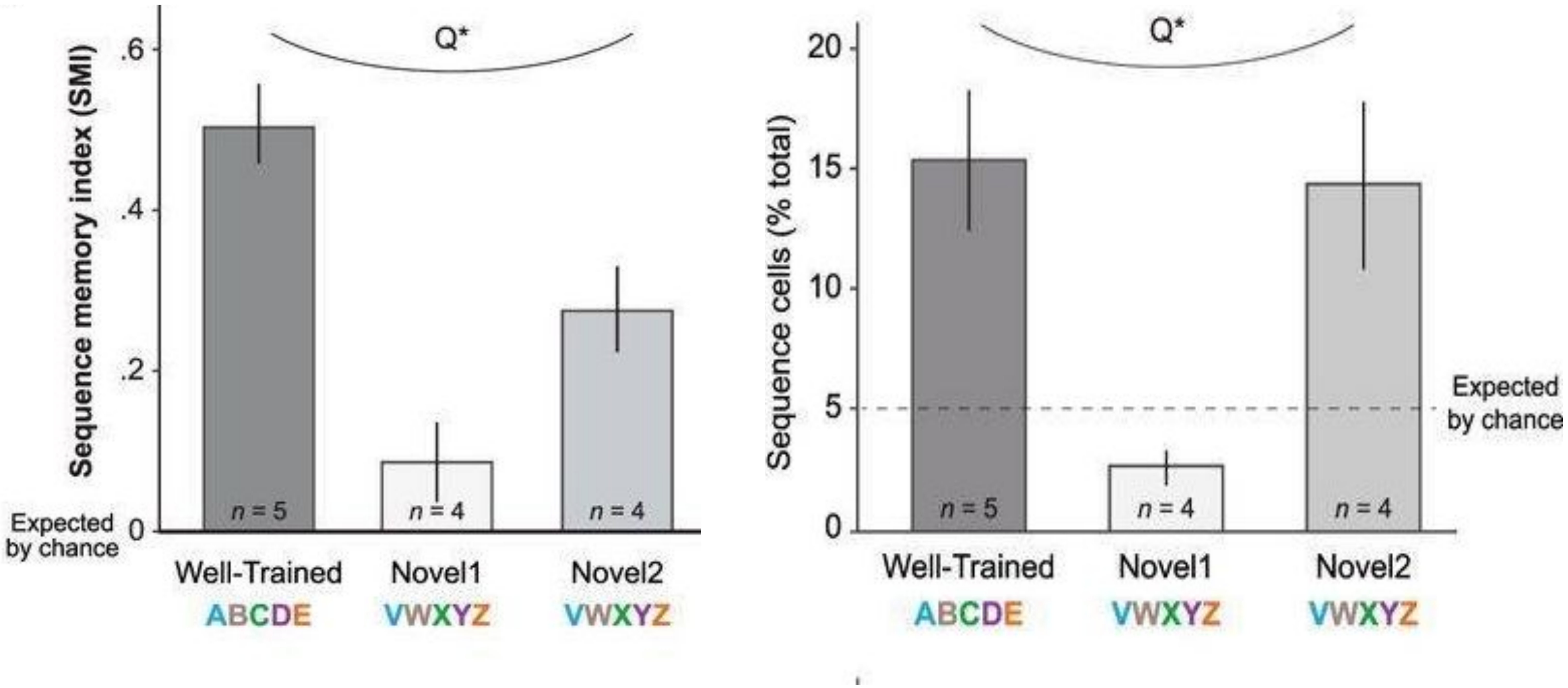
Sequence generalization



Fast generalization to new sequences

Figure from Allen et al 2015; Gattas 2020 (preprint)

Sequence generalization

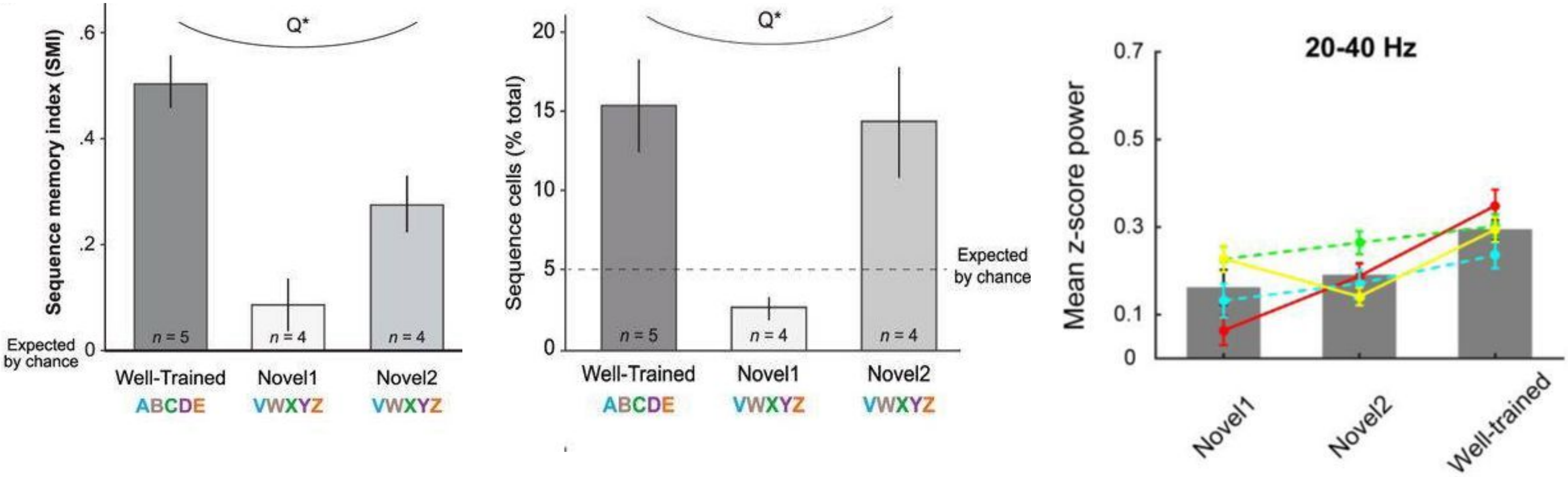


Fast generalization to new sequences

Rapid return of sequence cells

Figure from Allen et al 2015; Gattas 2020 (preprint)

Sequence generalization



Fast generalization to new sequences

Rapid return of sequence cells

Beta dynamics track sequence knowledge

Figure from Allen et al 2015; Gattas 2020 (preprint)

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ContinualAI

Norbert Fortin

Bruce McNaughton

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And many more...

Feel free to reach out!