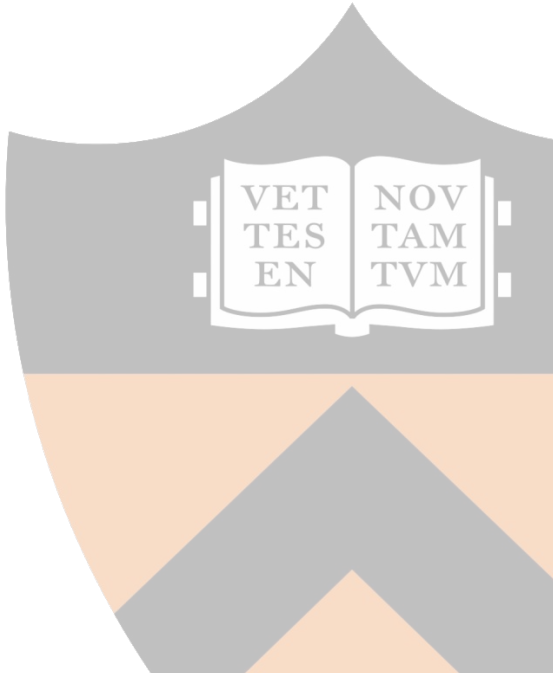
Direct fit

an ecological perspective on biological and artificial neural networks

Samuel A. Nastase
Princeton Neuroscience Institute
snastase@princeton.edu



@samnastase

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Uri Hasson

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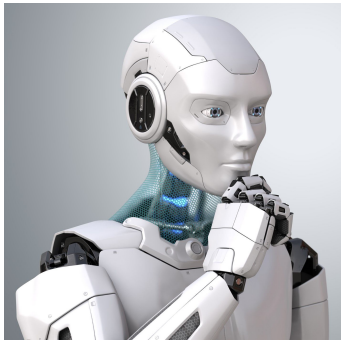
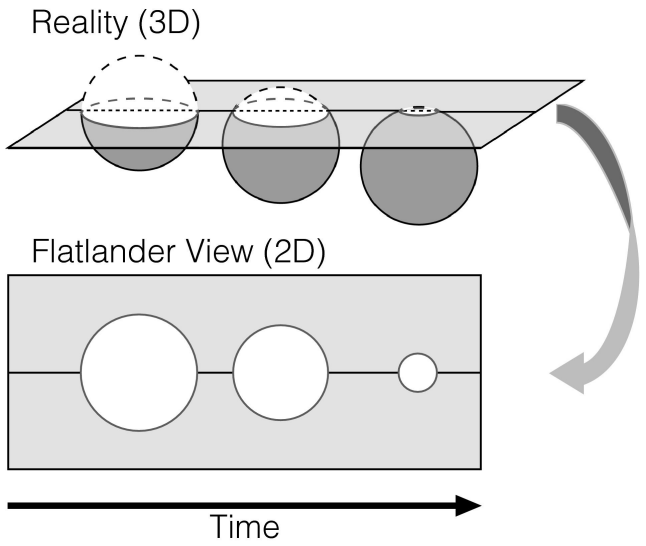


@samnastase

Toward a more ecological neuroscience

Confronted with the complexity of brain and behavior, neuroscientists traditionally design controlled experiments to reduce the dimensionality of the problem to a few intuitive factors.

Meehl, *Psychol Rep*, 1990
Rozenblit & Keil, *Cogn Sci*, 2002
Jolly & Chang, *Topics Cogn Sci*, 2019



Toward a more ecological neuroscience

Models developed under tightly-controlled experimental manipulations are typically tested in more naturalistic, ecological contexts…

…but results have been mixed

Reinagel, *Curr Opin Neurobiol*, 2001
Simoncelli et al., *Annu Rev Neurosci*, 2001
Bartels & Zeki, *Hum Brain Mapp*, 2004
David et al., *Nature*, 2004
Hasson et al., *Science*, 2004
Kayser et al., *Curr Opin Neurobiol*, 2004
Felsen & Dan, *Nat Neurosci*, 2005
Spiers & Maguire, *Trends Cogn Sci*, 2007
Haxby et al., *Neuron*, 2011
Hasson & Honey, *NeuroImage*, 2012
Maguire, *NeuroImage*, 2012
Hamilton & Huth, *Lang Cogn Neurosci*, 2018
Haxby, Nastase et al., *NeuroImage*, 2020

Toward a more ecological neuroscience

Models developed under tightly-controlled experimental manipulations are typically tested in more naturalistic, ecological contexts…

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"We can rightfully claim to understand only 10% to 20% of how V1 actually operates under normal conditions."

Olshausen & Field, *Neural Comput*, 2005

—biased sampling in neural measurement

—biased sampling of stimuli and tasks

—bias toward simple, interpretable theories

—interdependence of neural variables and context

—publication bias

Toward a more ecological neuroscience

Models developed under tightly-controlled experimental manipulations are typically tested in more naturalistic, ecological contexts…

…but results have been mixed

"We can rightfully claim to understand only 10% to 20% of how V1 actually operates under normal conditions."

Olshausen & Field, *Neural Comput*, 2005

"In order to behave like scientists, [experimental psychologists] must construct situations in which our subjects are totally controlled, manipulated and measured. We must cut our subjects down to size. We construct situations in which they can behave as little like human beings as possible and we do this in order to allow ourselves to make statements about the nature of their humanity."

Bannister, *Bull Br Psychol Soc*, 1966

A brief history of “ecological validity”

“Ecological validity”—coined by Egon Brunswik in 1947

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…to mean something else (¬_¬)

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Representative design

—psychology maintains a “double standard” in the application of sampling theory

—subjects are sampled with the goal of generalizing to the population, whereas stimuli and tasks generally are not

—ecological generalizability demands a “representative sampling of situations” where “situational instances in an ecology are analogous to individuals in a population”

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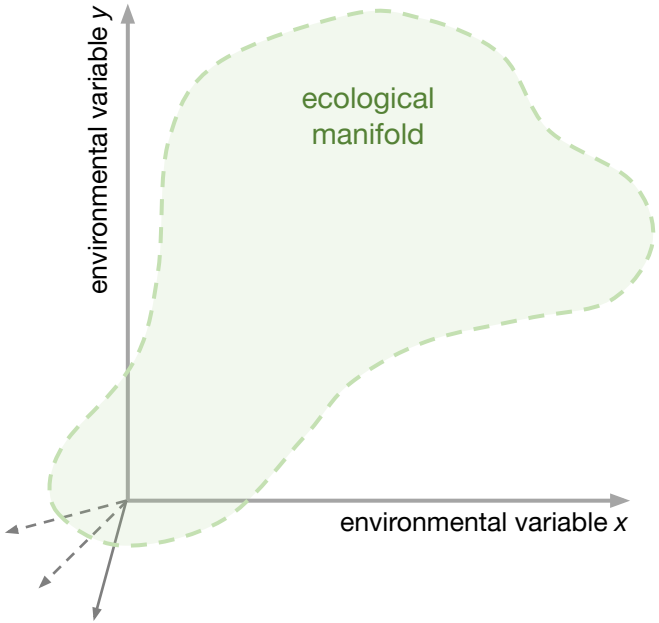

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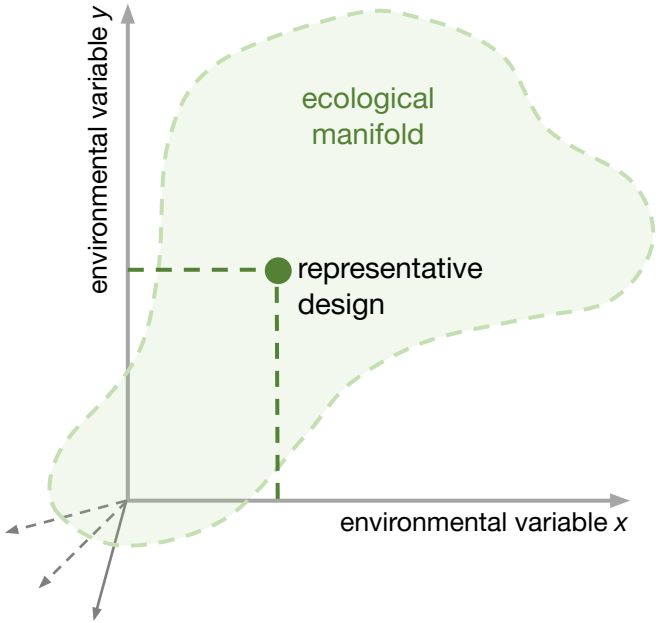

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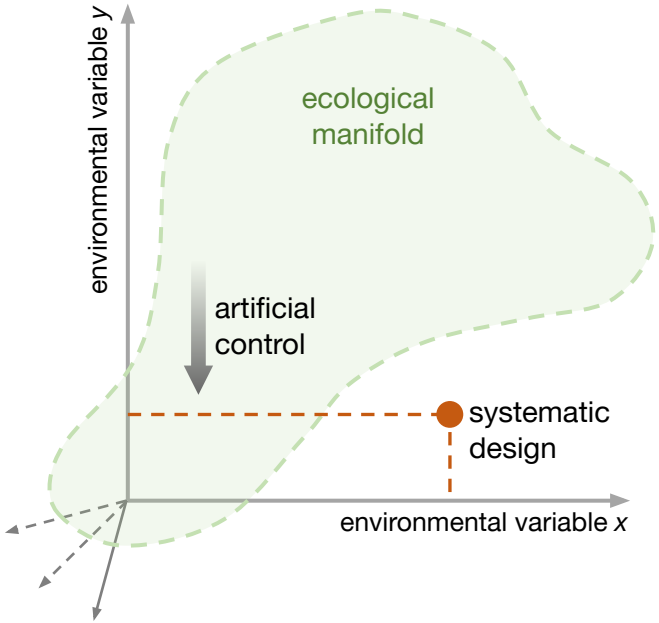

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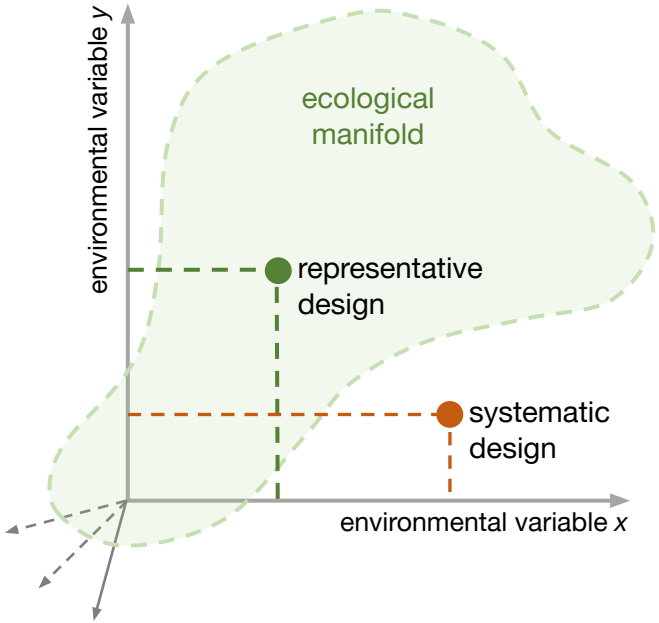

Nastase, S. A., Goldstein, A., & Hasson, U. (2020). Keep it real: rethinking the primacy of experimental control in cognitive neuroscience. *PsyArXiv*.

The “direct fit” model of biological learning

Relinquishing control—machine learning

Modern artificial neural networks leverage millions of noisy, real-world samples to achieve shockingly good performance at a variety of “cognitive” tasks…

—how is this possible?

—**and why do neuroscientists find this so unsatisfying?**

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Statistical Science
2001, Vol. 16, No. 3, 199–231

Statistical Modeling: The Two Cultures

Leo Breiman

Choosing Prediction Over Explanation in Psychology: Lessons From Machine Learning

Perspectives on Psychological Science
2017, Vol. 12(6) 1100–1122
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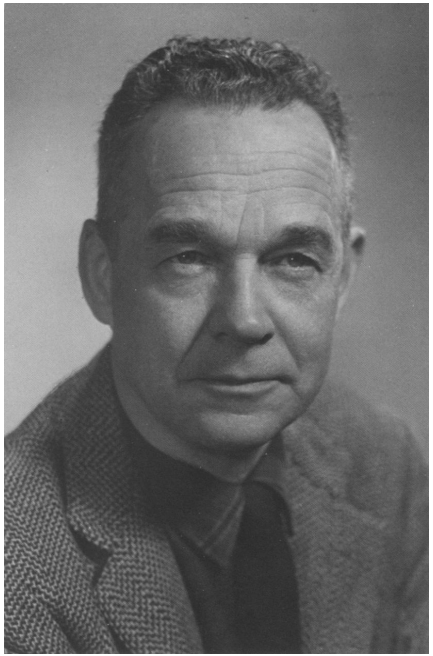
DOI: 10.1177/1745691617693393
www.psychologicalscience.org/PPS
SAGE

Tal Yarkoni and Jacob Westfall
University of Texas at Austin

The “direct fit” model of biological learning

The *meaningful* environment

“The *affordances* of the environment are what it *offers* the animal, what it *provides* or *furnishes*, either for good or ill. The verb to *afford* is found in the dictionary, but the noun *affordance* is not. I have made it up.” —James J. Gibson (1979)



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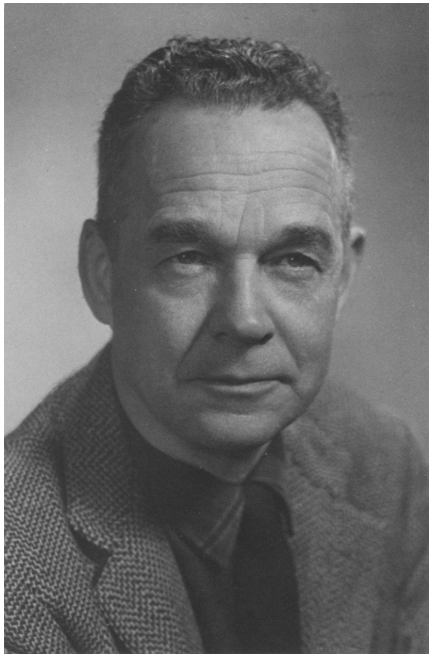
Ecological psychology and “direct perception”

—organisms “directly” perceive opportunities for **adaptive behavior** encoded in the environment—or “affordances”

—organism and environment are inextricably coupled

—perception and action are inextricably coupled



The “direct fit” model of biological learning

“In perception, perhaps the nearest anyone came to the level of computational theory was Gibson (1966). However, although some aspects of his thinking were on the right lines, he did not understand properly what information processing was, which led him to seriously underestimate the complexity of the information-processing problems involved in vision and the consequent subtlety that is necessary in approaching them.” —David Marr (1982)

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Direct-fit learning

Neural networks rely on “mindless” overparameterized optimization to map millions of noisy, real-world samples along task-relevant objective functions—providing a mechanistic basis for Gibson’s “direct perception.”

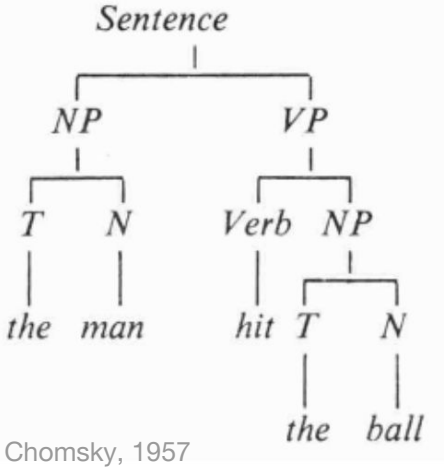
Hasson, U., Nastase, S. A., & Goldstein, A. (2020). Direct fit to nature: an evolutionary perspective on biological and artificial neural networks. *Neuron*, *105*(3), 416–434.

What makes a good model?

Scientists favor concise, interpretable models with an emphasis on explanatory power over predictive power.

Sentence

NP + VP	(i)
T + N + VP	(ii)
T + N + Verb + NP	(iii)
the + N + Verb + NP	(iv)
the + man + Verb + NP	(v)
the + man + hit + NP	(vi)
the + man + hit + T + N	(ii)
the + man + hit + the + N	(iv)
the + man + hit + the + ball	(v)



Chomsky, 1957

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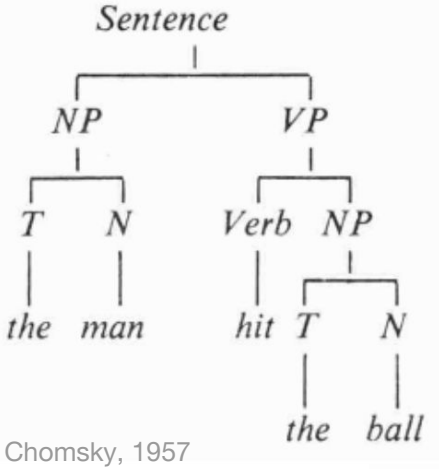
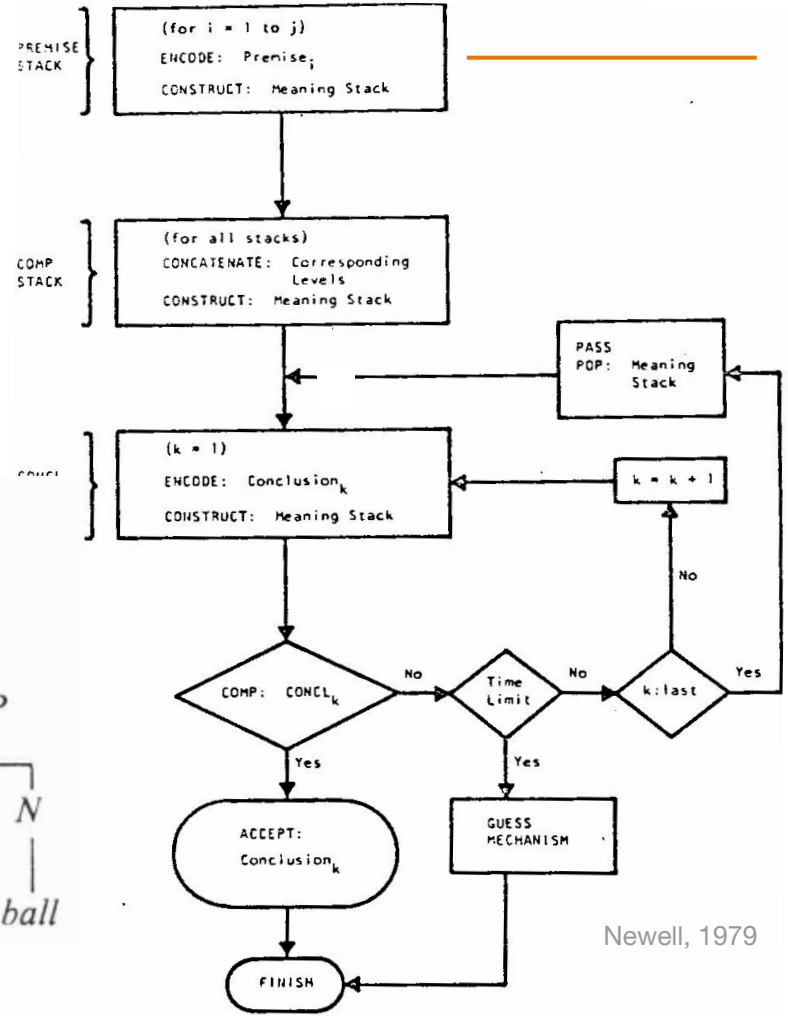


Chomsky, 1957



Newell, 1979

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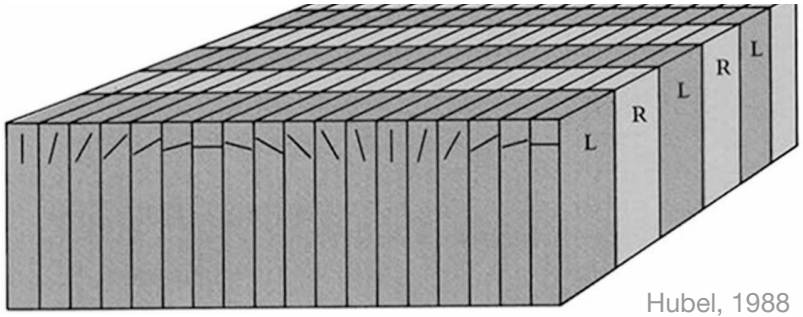
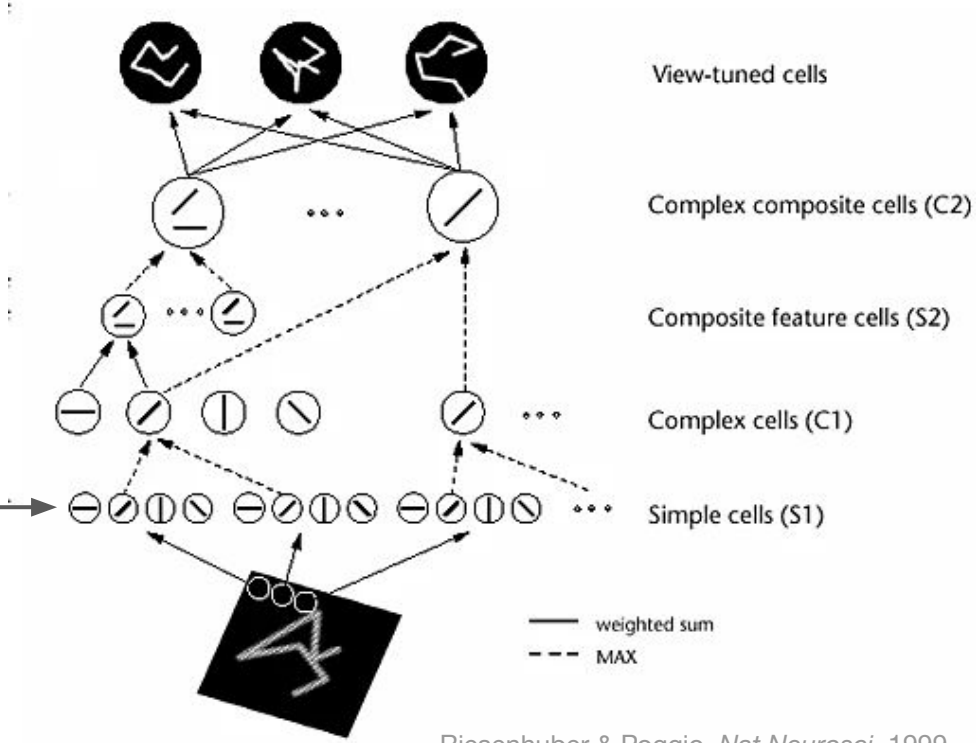


Hubel, 1988



Riesenhuber & Poggio, *Nat Neurosci*, 1999

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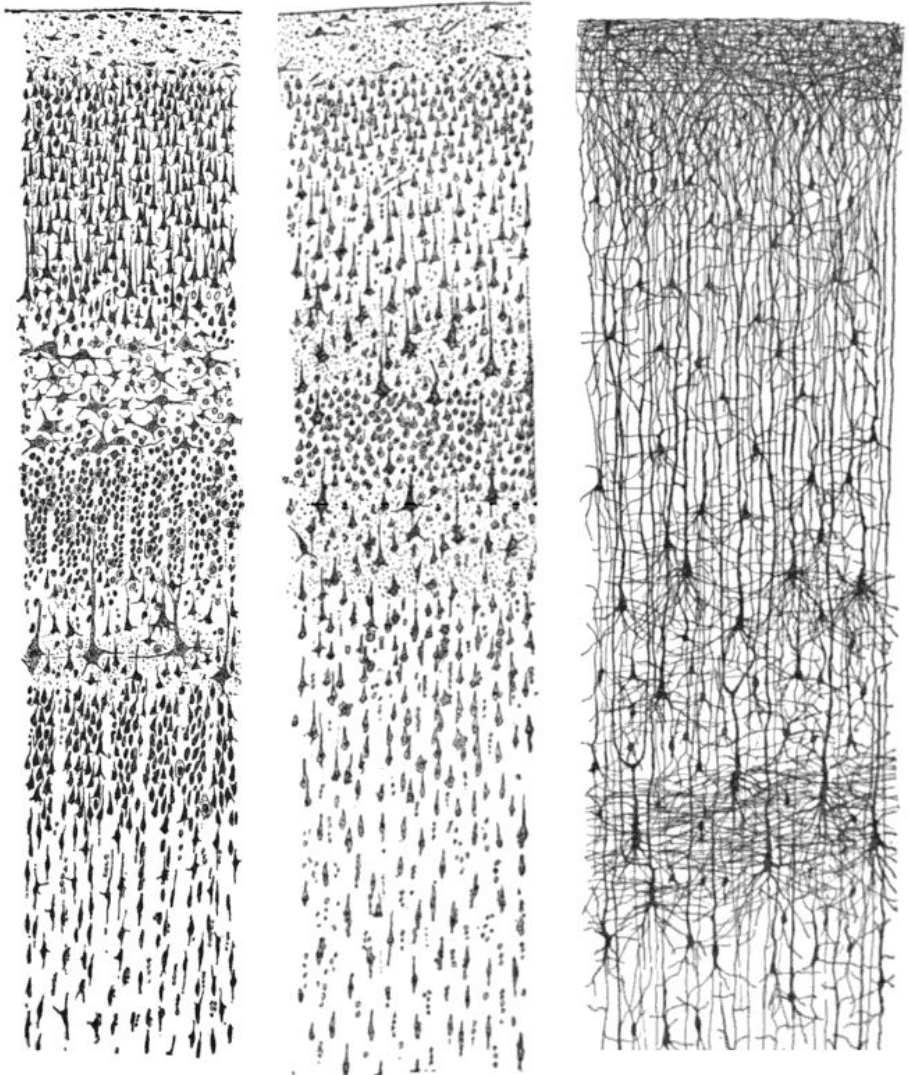
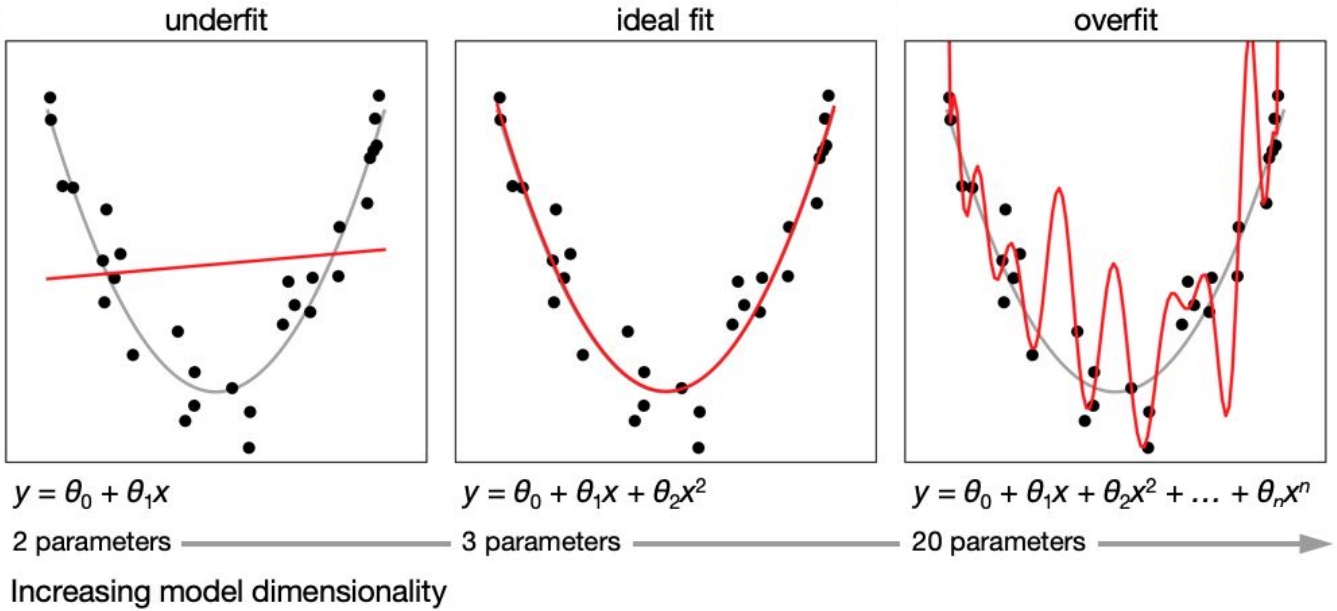


Ramon y Cajal, 1899

What makes a good model?

The textbook example of underfitting/overfitting

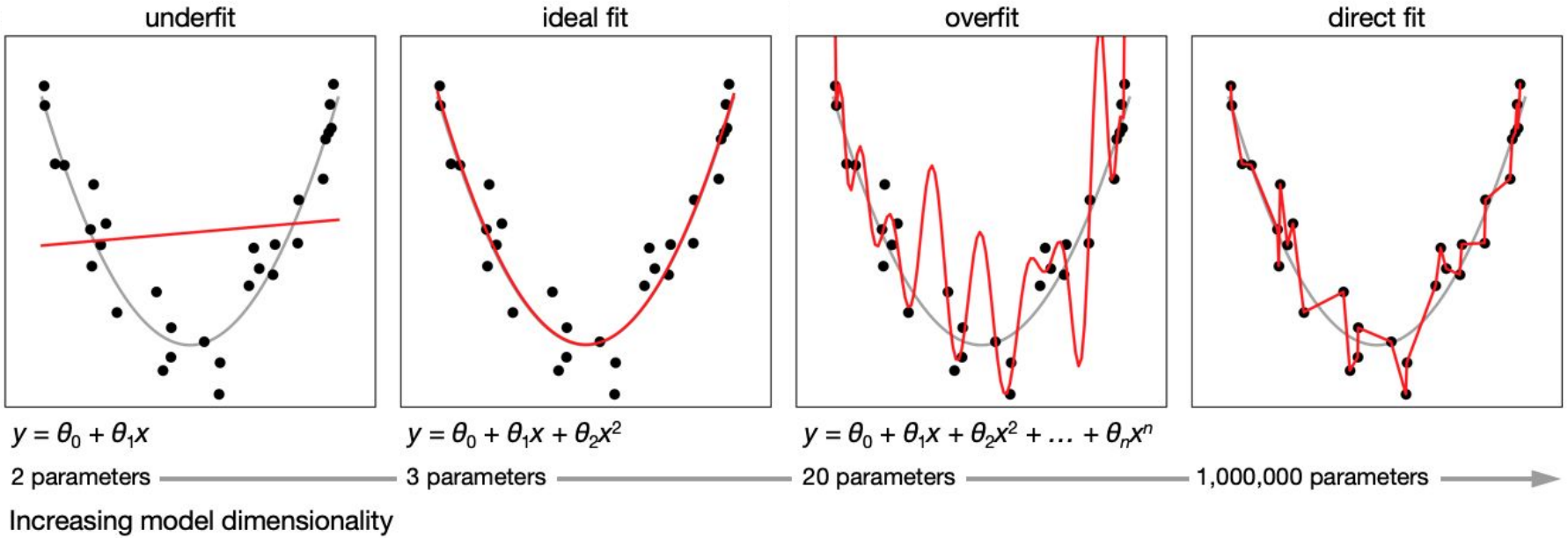
—overly simplistic models will underfit the data, whereas overly complex models will overfit



What makes a good model?

The textbook example of underfitting/overfitting

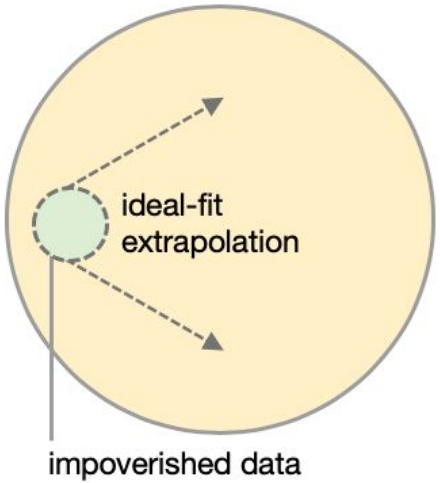
—overly simplistic models will underfit the data, whereas overly complex models will overfit—**right?**



Rethinking overparameterized models

Two types of generalization: interpolation and extrapolation

—experimentalists typically operate in a well-controlled, narrow sampling aperture and seek to discover simple models that will **extrapolate** to novel contexts



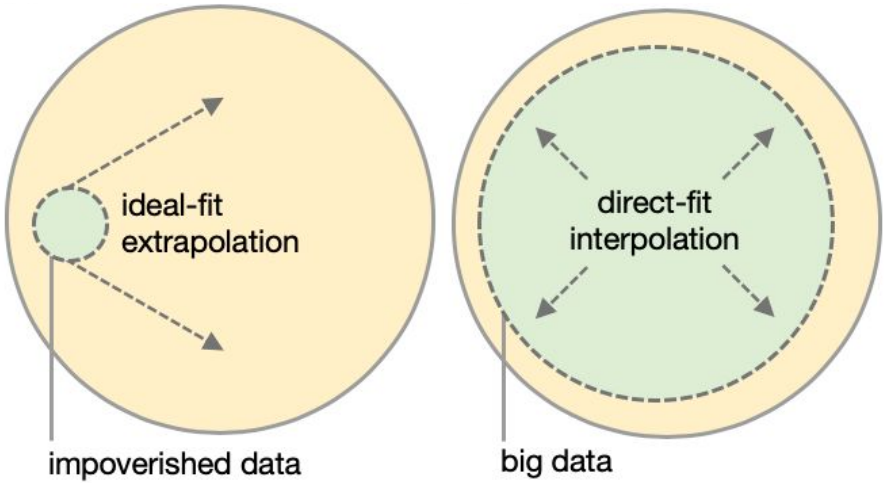
In this constrained sampling regime, ideal-fit **extrapolation** is required for generalization. **Interpolation** only provides weak generalization.

Rethinking overparameterized models

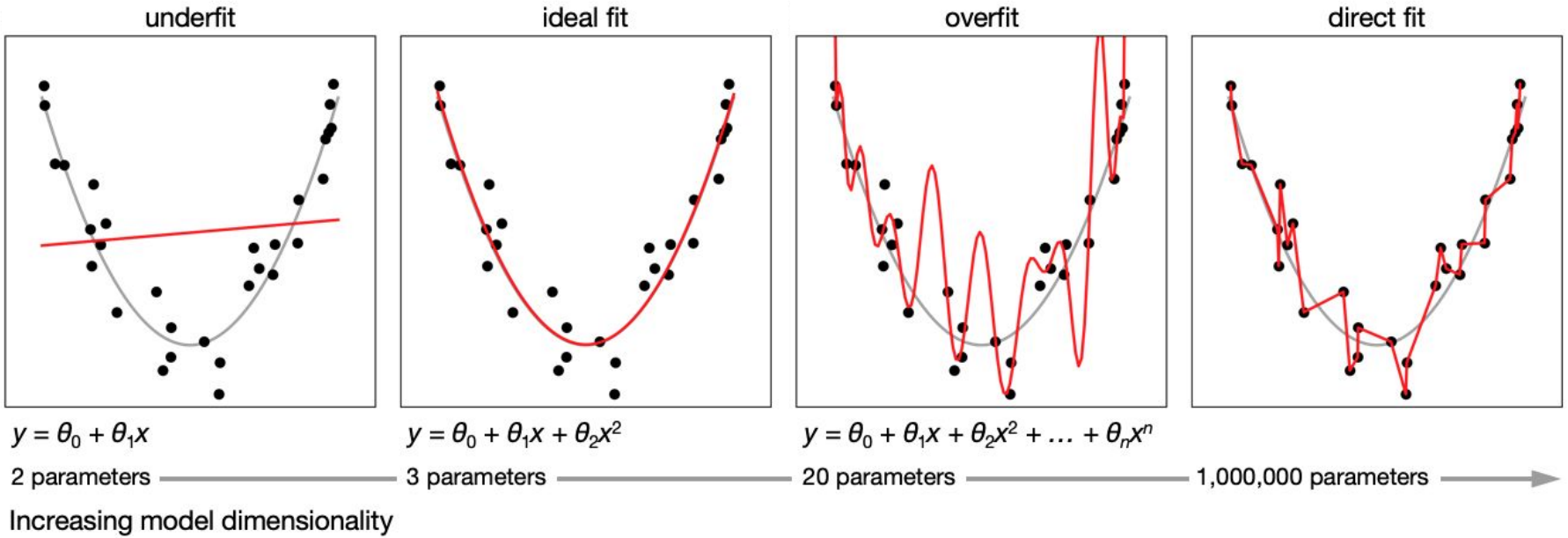
Two types of generalization: interpolation and extrapolation

—experimentalists typically operate in a well-controlled, narrow sampling aperture and seek to discover simple models that will **extrapolate** to novel contexts

—machine learning research leverages “big data” and overparameterized models to expand the **interpolation zone**



Rethinking overparameterized models



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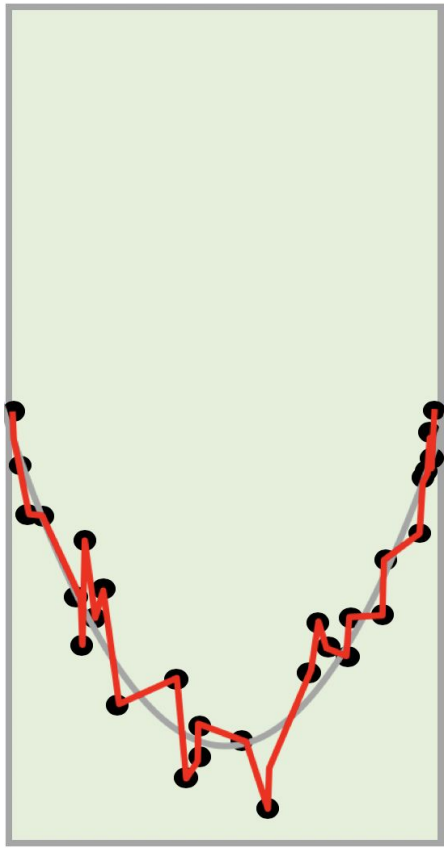
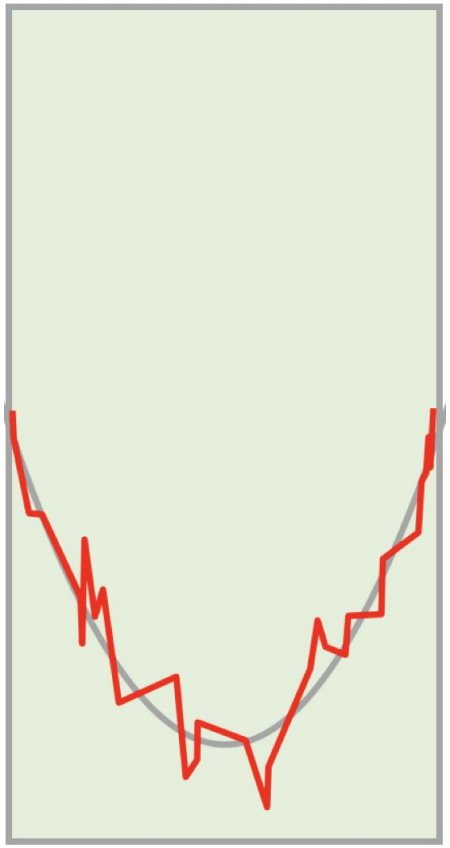


● many training samples

Rethinking overparameterized models

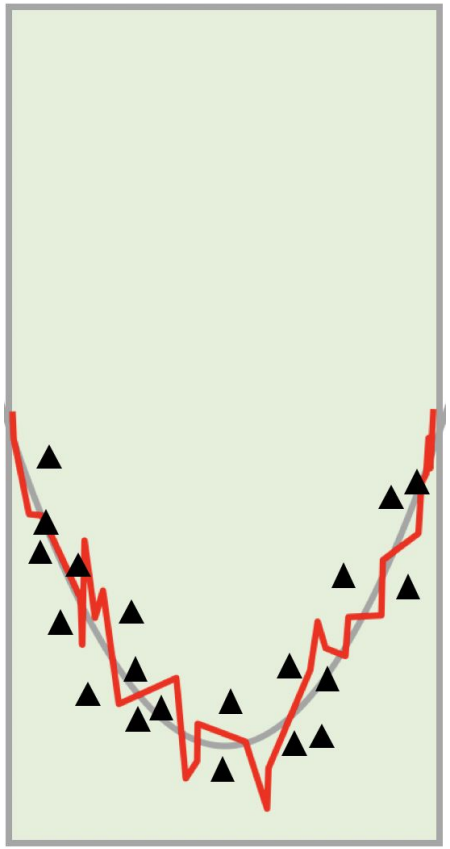


Which is the better model?

ideal model

direct-fit model

Rethinking overparameterized models



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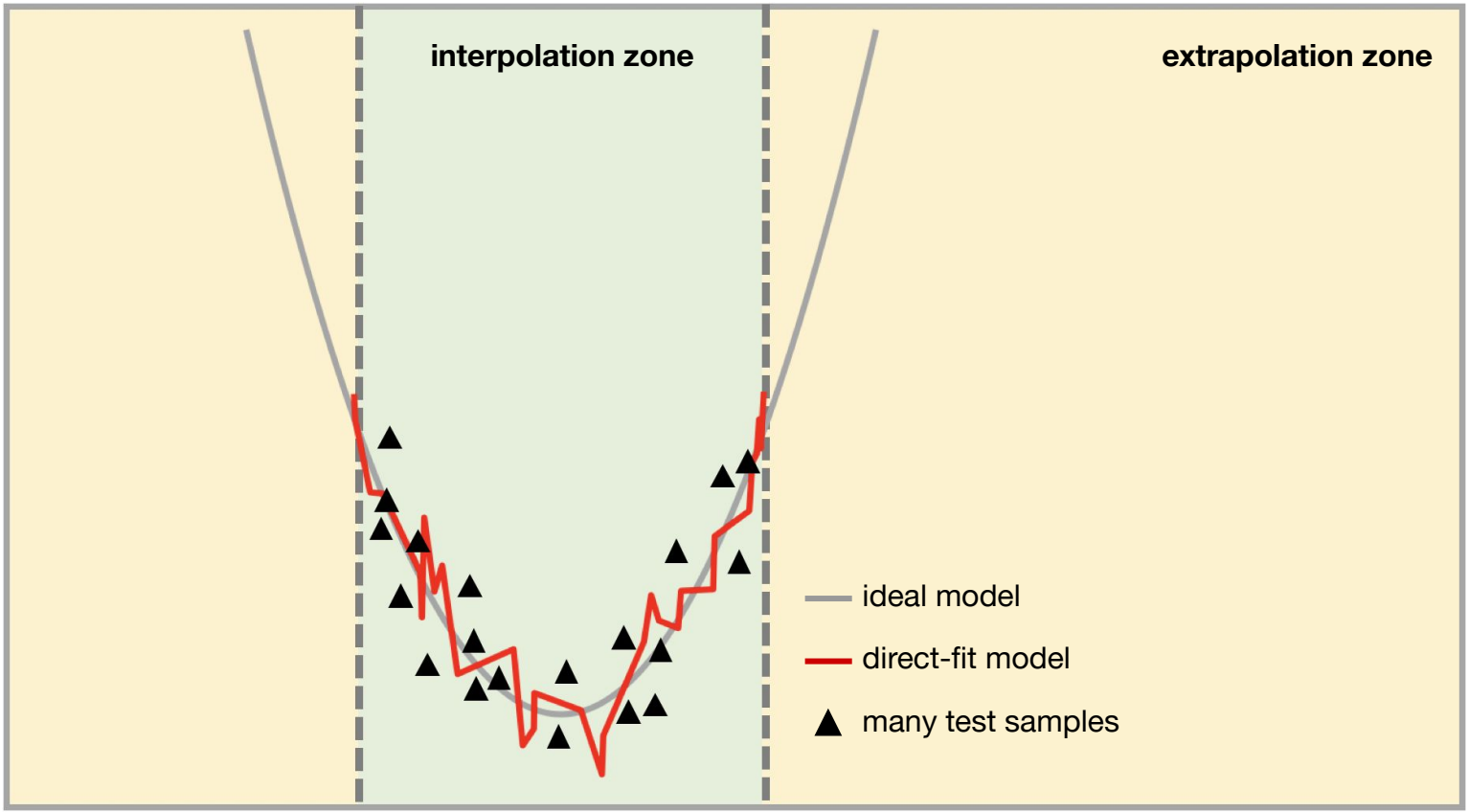

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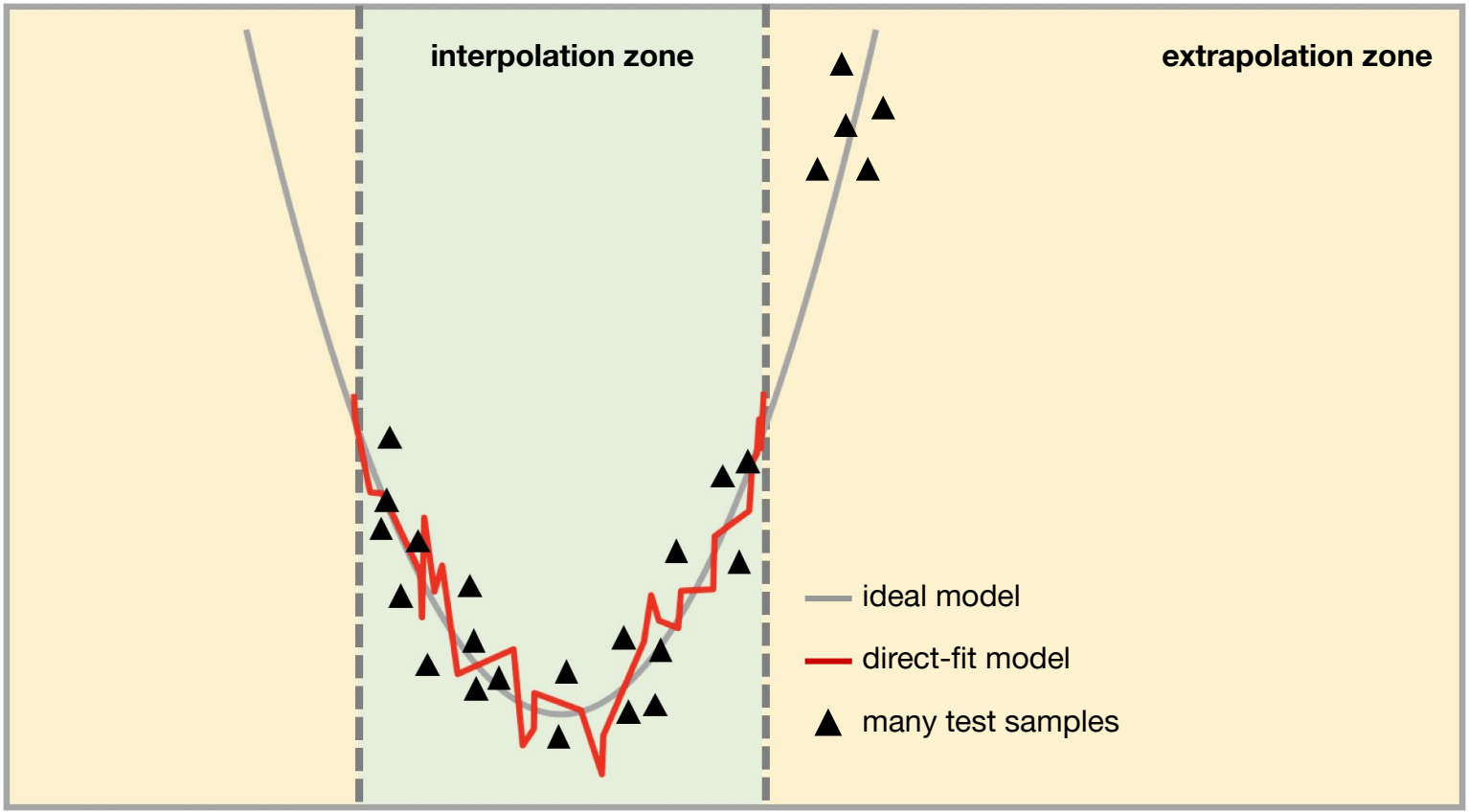

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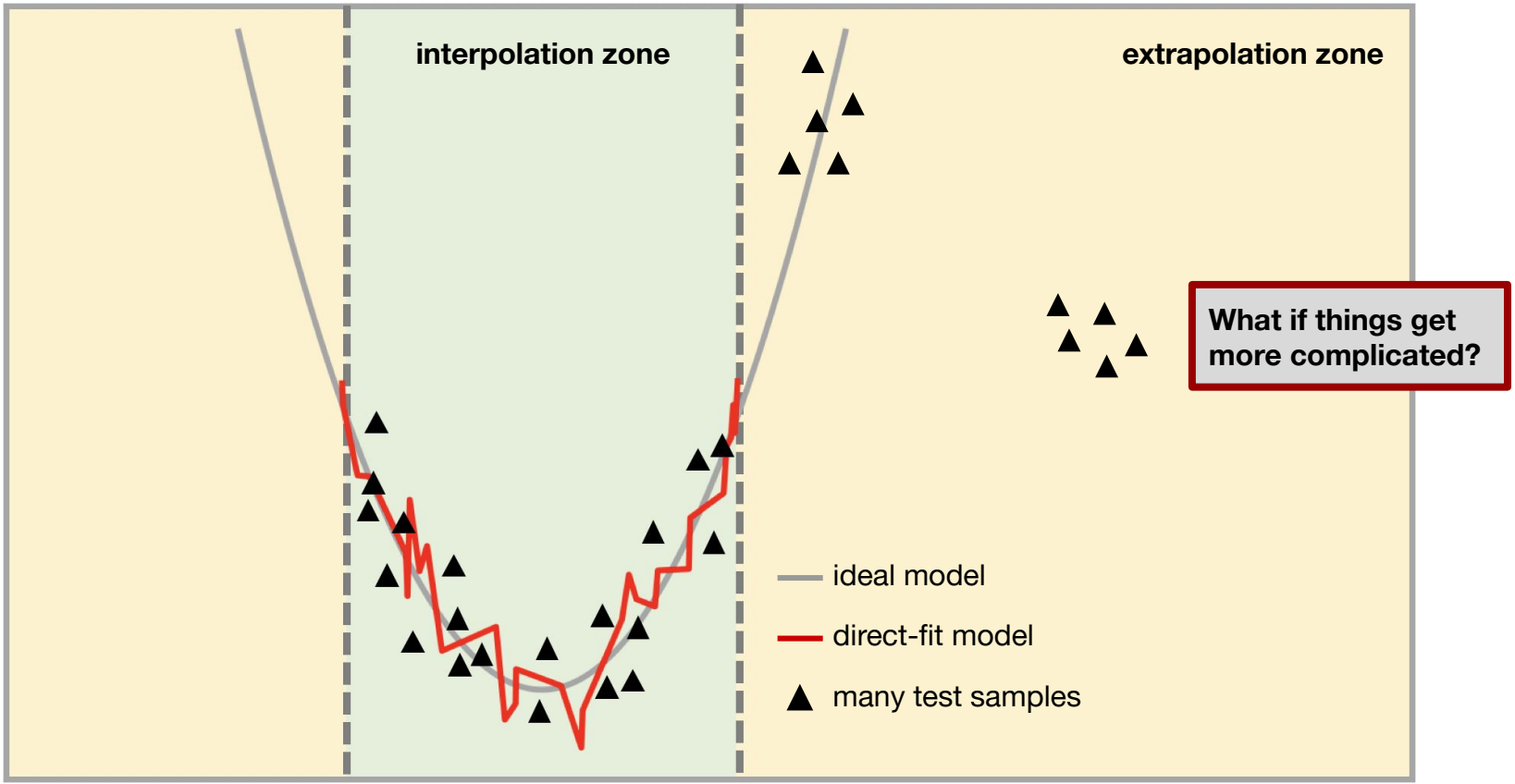
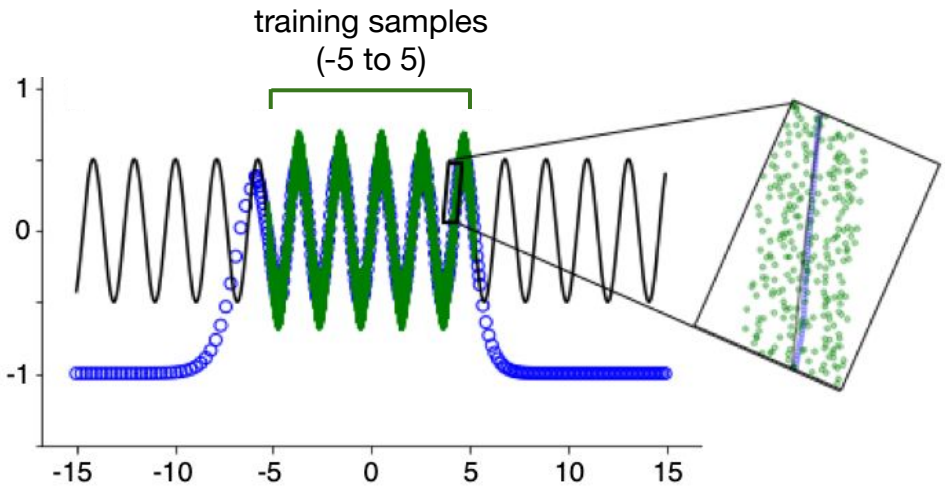


Interpolation and extrapolation

Example—interpolation over space

—simple ANN with 1 input unit, 1 output unit, and three fully connected hidden layers with 300 units each (180,600 parameters)

—trained to predict *y* values from *x* values given input–output mappings reflecting by a sine function: **training samples** (even values), **test samples** (odd values)



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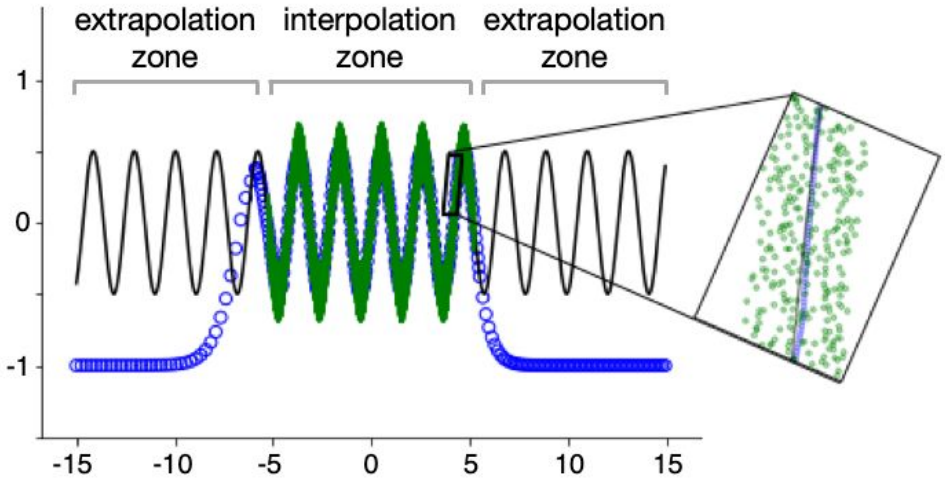

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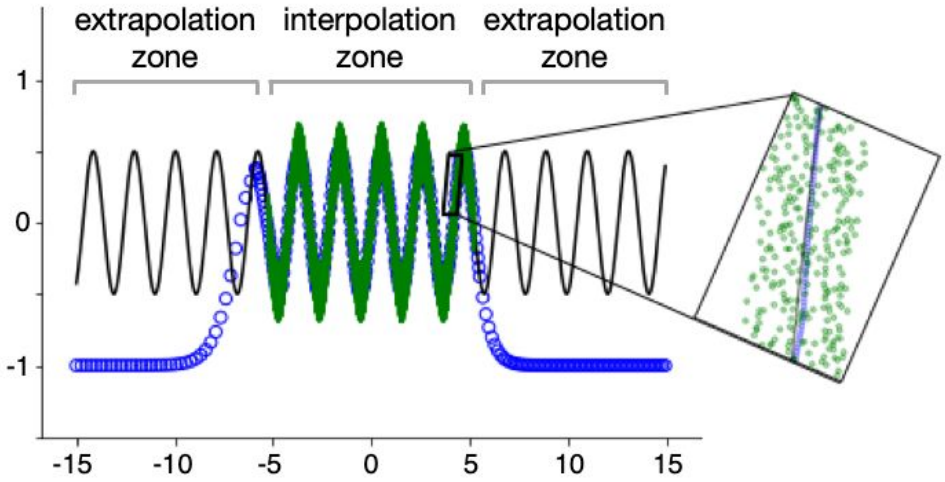
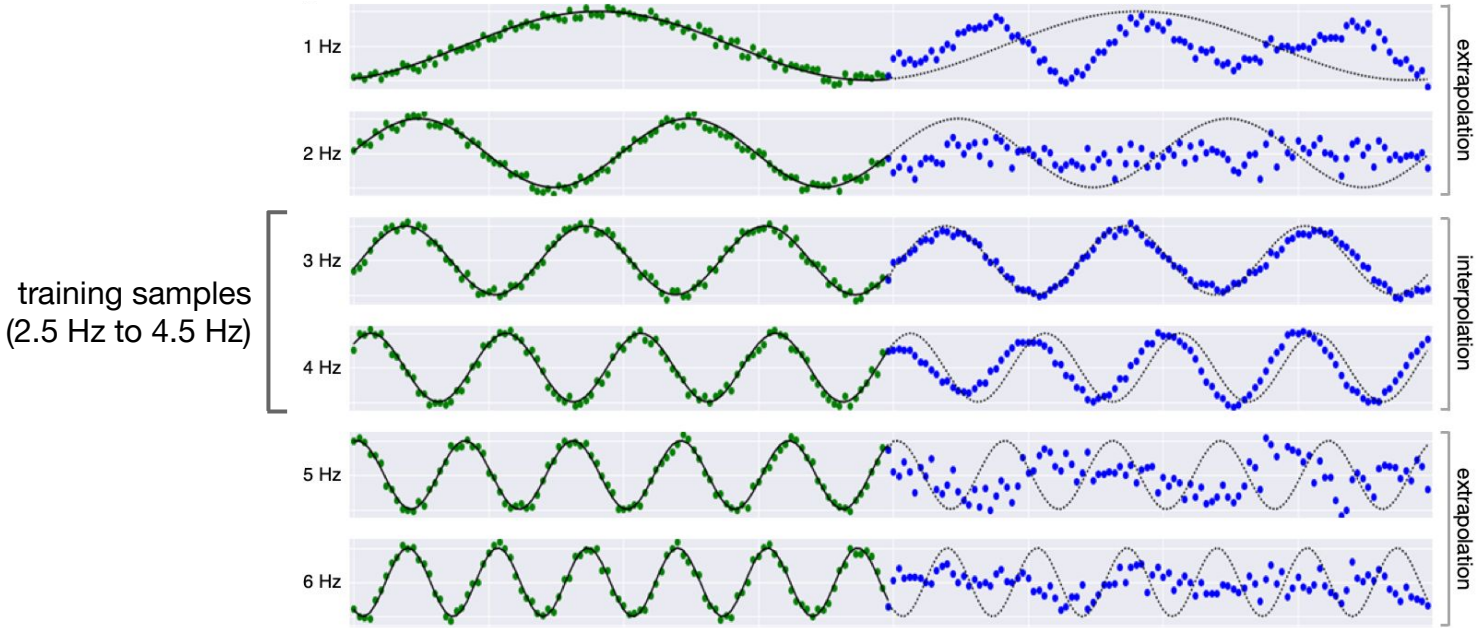


This overparameterized model generalizes well within the scope of the training sample—i.e., the **interpolation zone**. However, the model does not actually learn the ideal sine function necessary for generalization into the **extrapolation zone**.

Interpolation and extrapolation

Example—interpolation over time

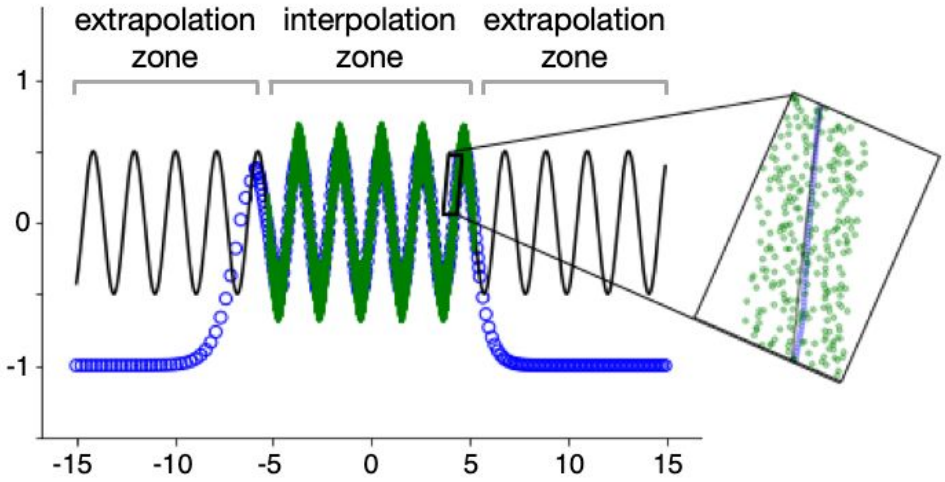
—simple RNN (LSTM) trained to predict the **future sequence** of *y* values based on the **preceding sequence** of 100 *y* values sampled within a 1-second input window



The robustness of direct fit

Has this neural network “learned” the sine function?

The model may *appear* to learn the sine function (in the interpolation zone), but this is an incidental byproduct of the input and the fitting procedure.



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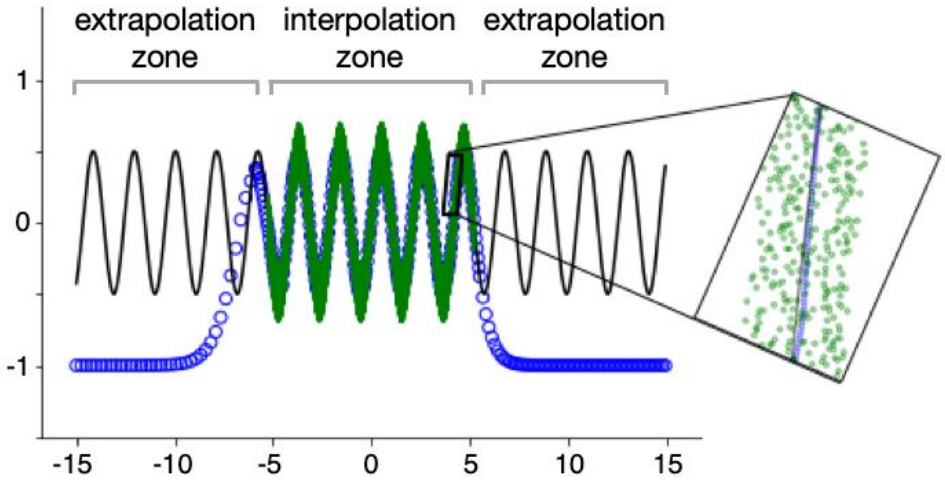
The model may *appear* to learn the sine function (in the interpolation zone), but this is an incidental byproduct of the input and the fitting procedure.

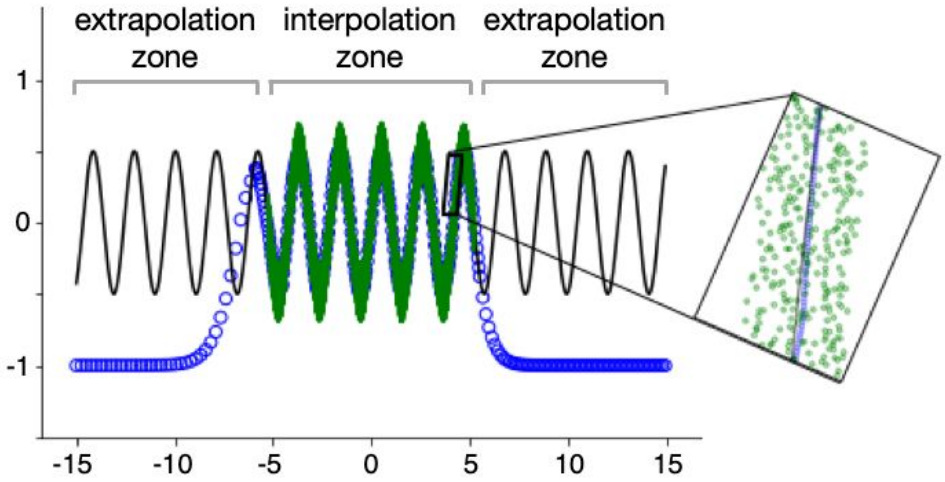
We can interrogate the model for “representations” of the sine function, but these only exist because we injected them into the training data.



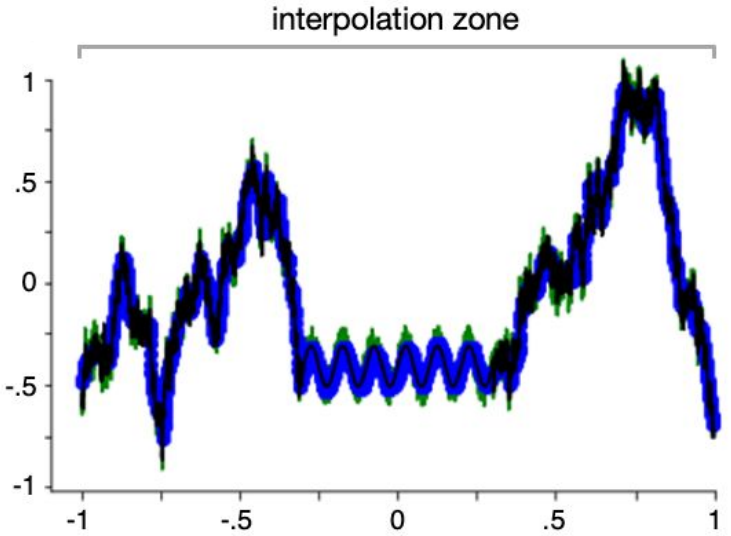
The robustness of direct fit

What's the benefit of interpolation-based direct-fit learning?

—in a more naturalistic "big data" regime, the overparameterized model can learn the structure of a more complex world



Meanwhile—outside the laboratory...



Face recognition in the wild

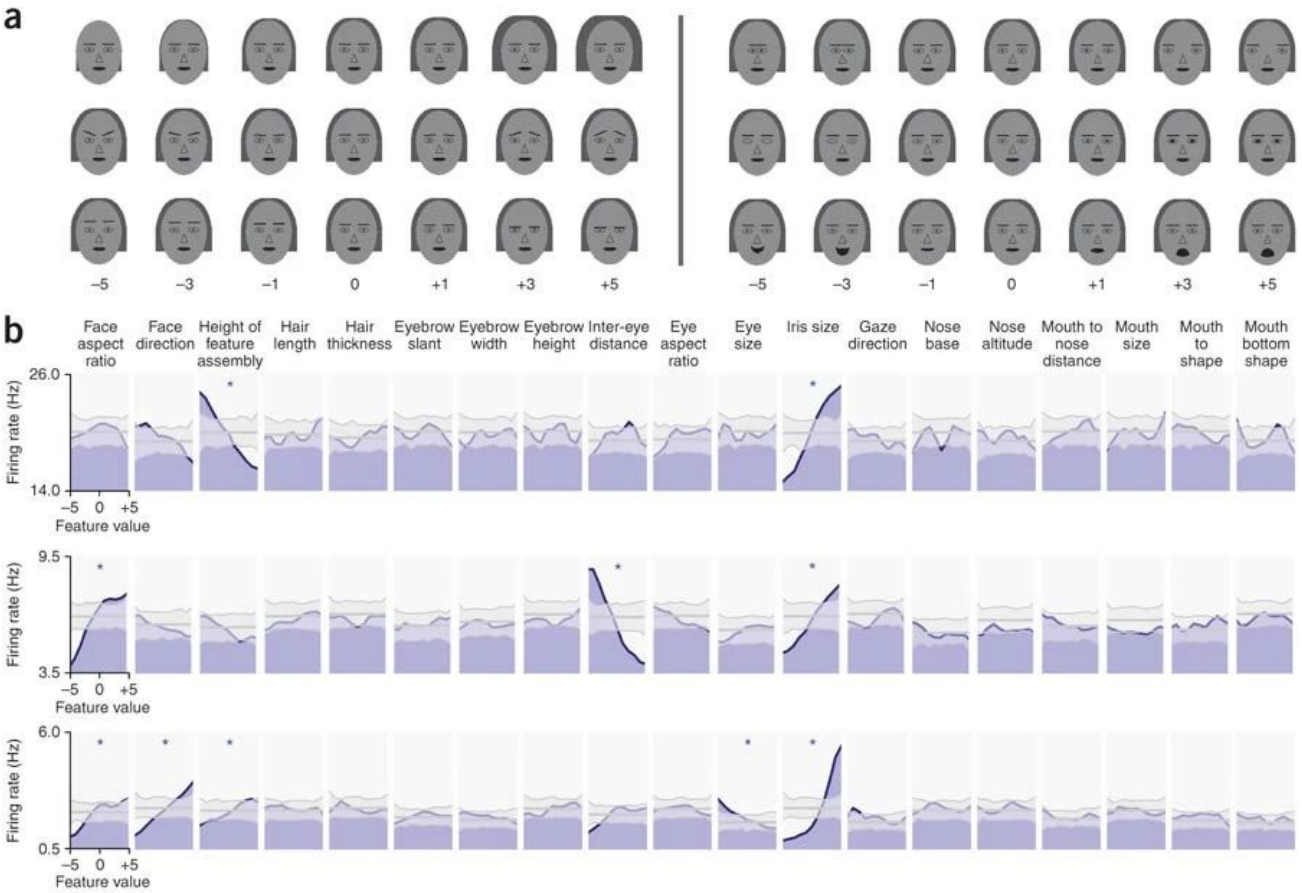
FaceNet—an example at scale

Superhuman performance (95%+ accuracy) based on dense training set of 200 million faces comprising 8 million identities.

Schroff et al, *CVPR*, 2015

layer	size-in	size-out	kernel	param	FLPS
conv1	220×220×3	110×110×64	7×7×3, 2	9K	115M
pool1	110×110×64	55×55×64	3×3×64, 2	0	
rnorm1	55×55×64	55×55×64		0	
conv2a	55×55×64	55×55×64	1×1×64, 1	4K	13M
conv2	55×55×64	55×55×192	3×3×64, 1	111K	335M
rnorm2	55×55×192	55×55×192		0	
pool2	55×55×192	28×28×192	3×3×192, 2	0	
conv3a	28×28×192	28×28×192	1×1×192, 1	37K	29M
conv3	28×28×192	28×28×384	3×3×192, 1	664K	521M
pool3	28×28×384	14×14×384	3×3×384, 2	0	
conv4a	14×14×384	14×14×384	1×1×384, 1	148K	29M
conv4	14×14×384	14×14×256	3×3×384, 1	885K	173M
conv5a	14×14×256	14×14×256	1×1×256, 1	66K	13M
conv5	14×14×256	14×14×256	3×3×256, 1	590K	116M
conv6a	14×14×256	14×14×256	1×1×256, 1	66K	13M
conv6	14×14×256	14×14×256	3×3×256, 1	590K	116M
pool4	14×14×256	7×7×256	3×3×256, 2	0	
concat	7×7×256	7×7×256		0	
fc1	7×7×256	1×32×128	maxout p=2	103M	103M
fc2	1×32×128	1×32×128	maxout p=2	34M	34M
fc7128	1×32×128	1×1×128		524K	0.5M
L2	1×1×128	1×1×128		0	
total				140M	1.6B

Face recognition ~~in the wild~~



Freiwald et al,
Nat Neurosci, 2009

Face recognition in the wild

How many unique individuals are in this set of images?

Jenkins et al, *Cognition*, 2011

Face recognition in the wild

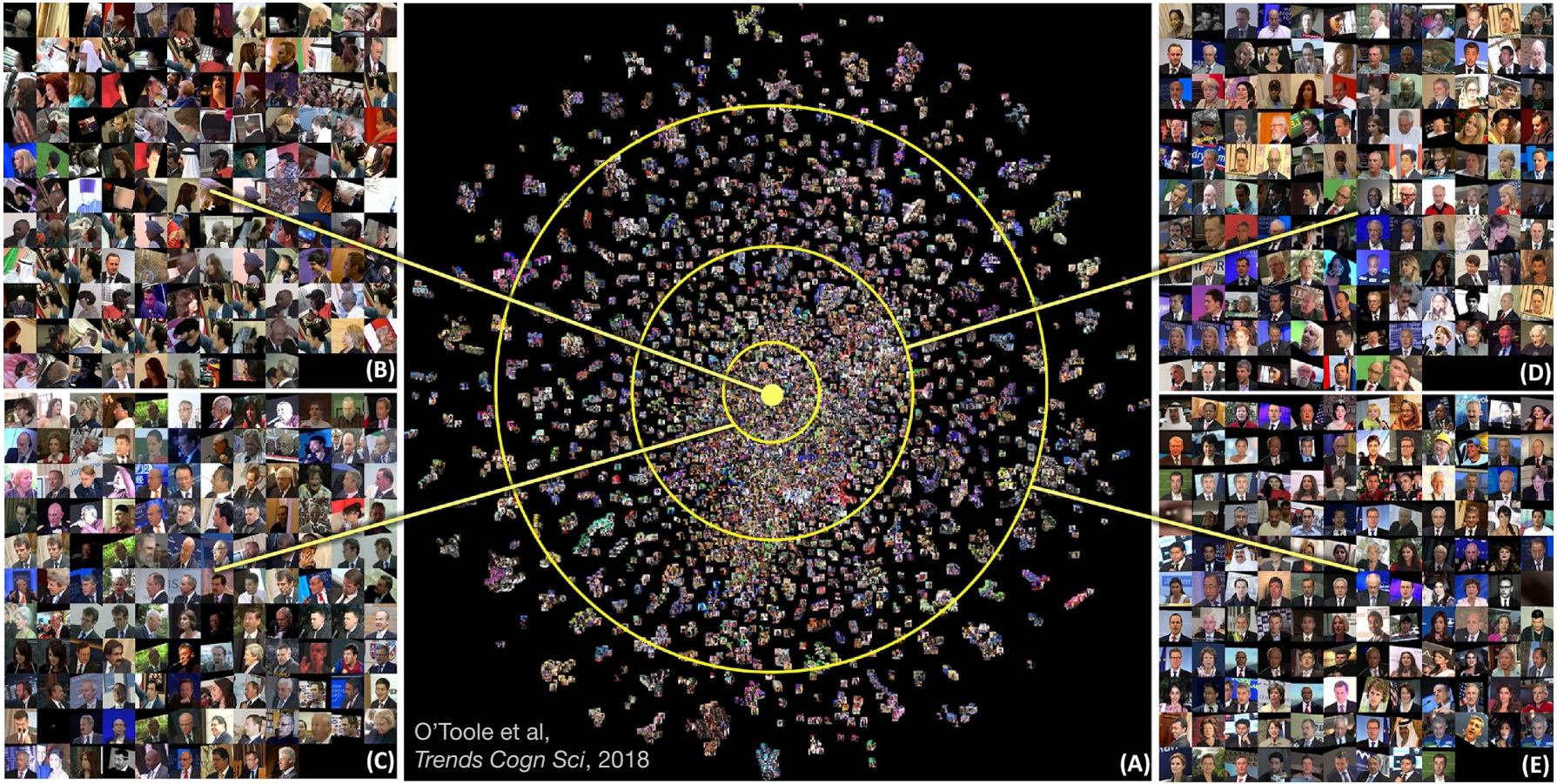
How many unique individuals are in this set of images?

Jenkins et al, *Cognition*, 2011

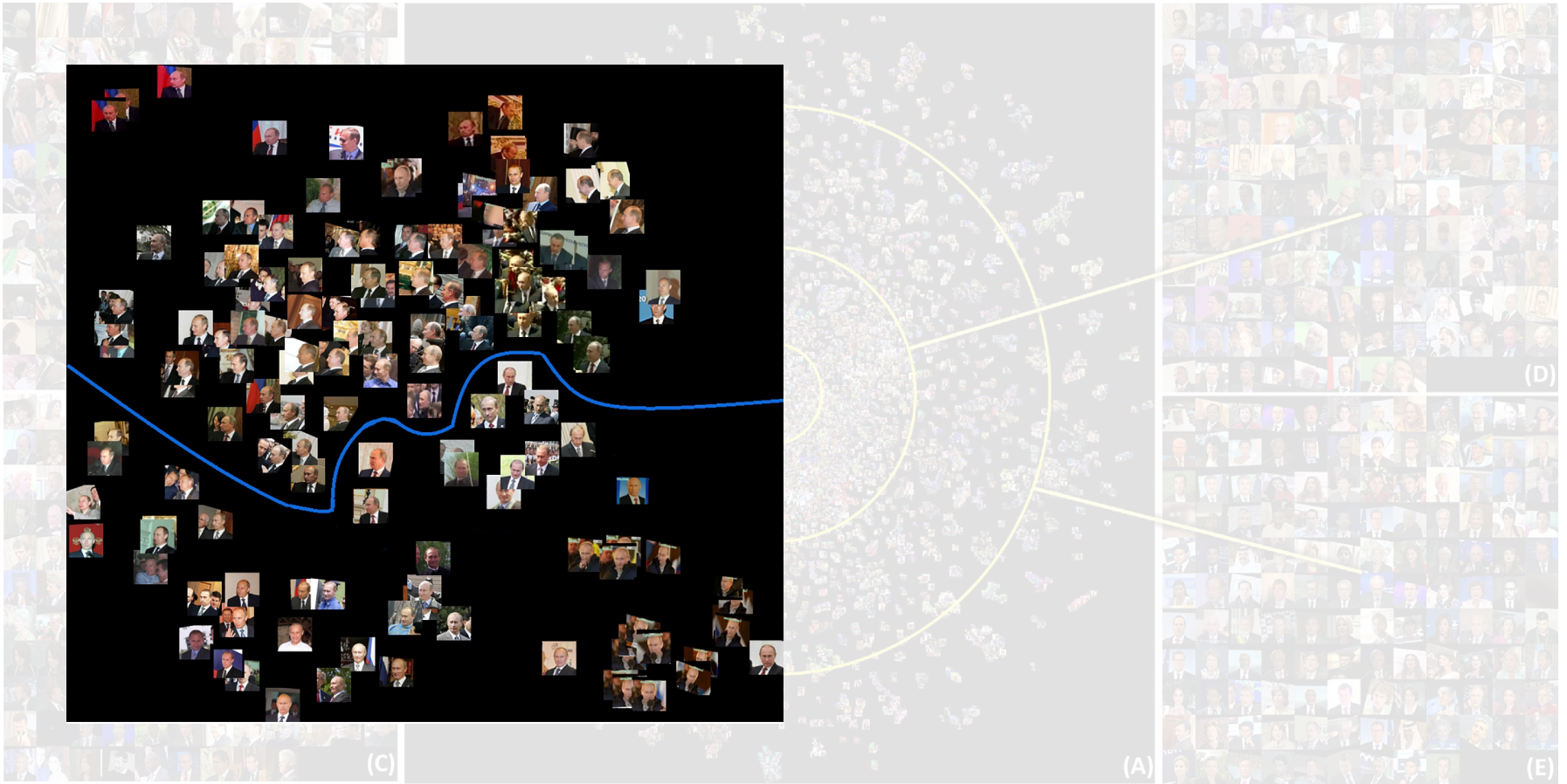
People know roughly 5,000 faces.

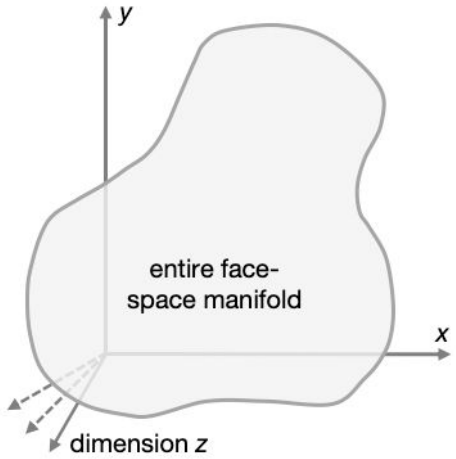
Jenkins et al, *Proc R Soc Lond B Biol Sci*, 2018

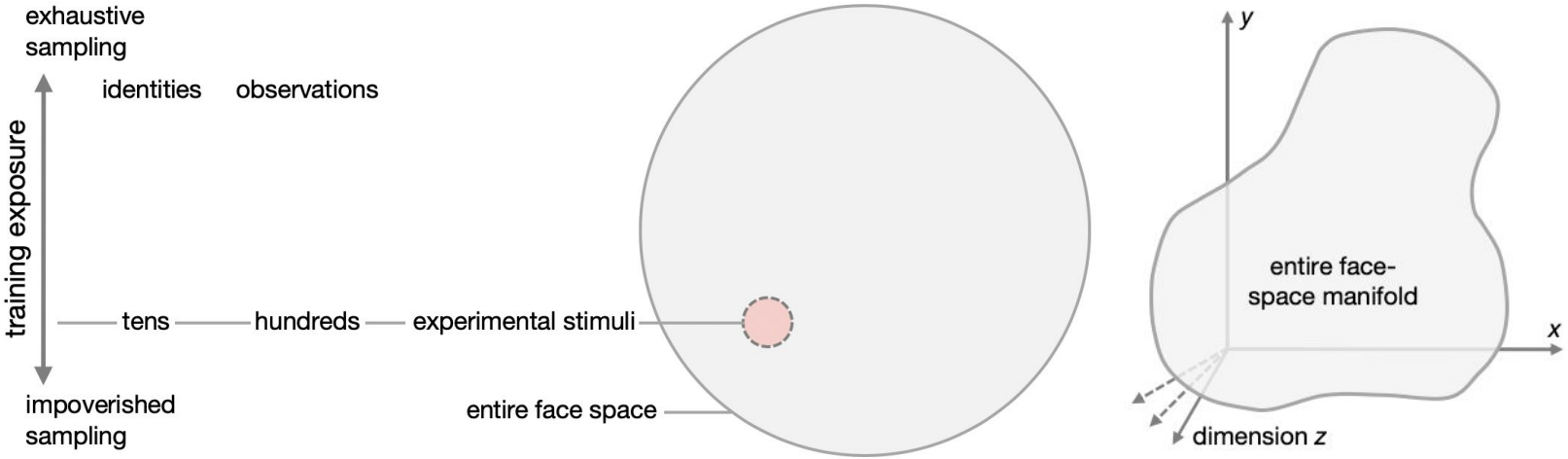
Face recognition in the wild



Face recognition in the wild




y
entire face-
space manifold
x
dimension z


exhaustive
sampling
identities
observations
training exposure
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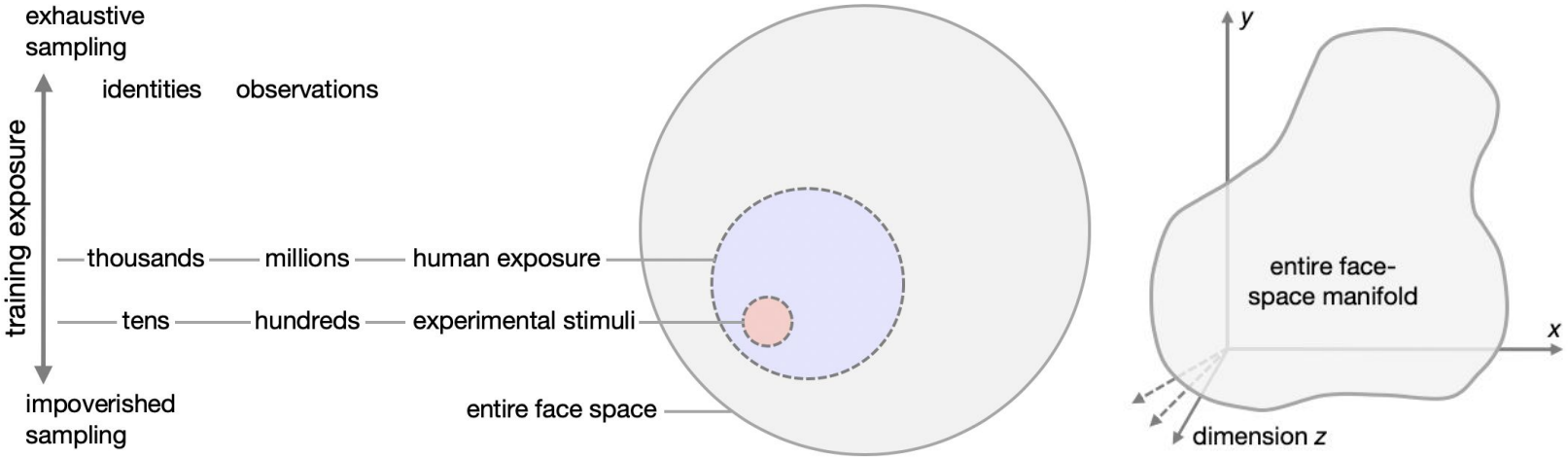
experimental stimuli
impoverished
sampling
entire face space
y
entire face-
space manifold
x
dimension z


exhaustive sampling
identities
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training exposure
thousands
millions
human exposure
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hundreds
experimental stimuli
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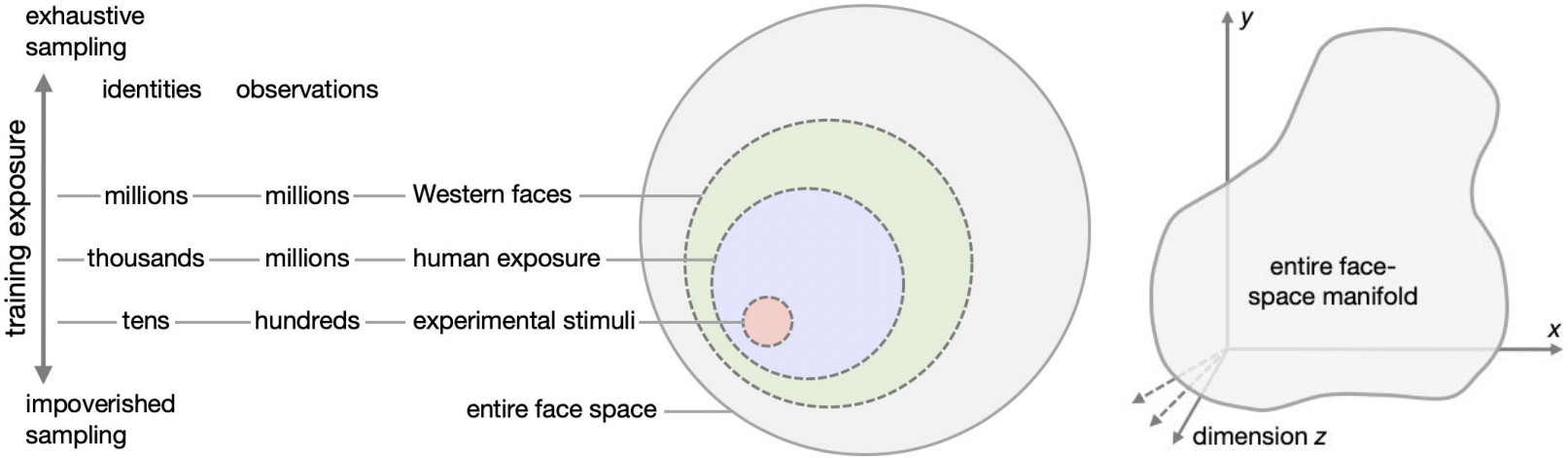
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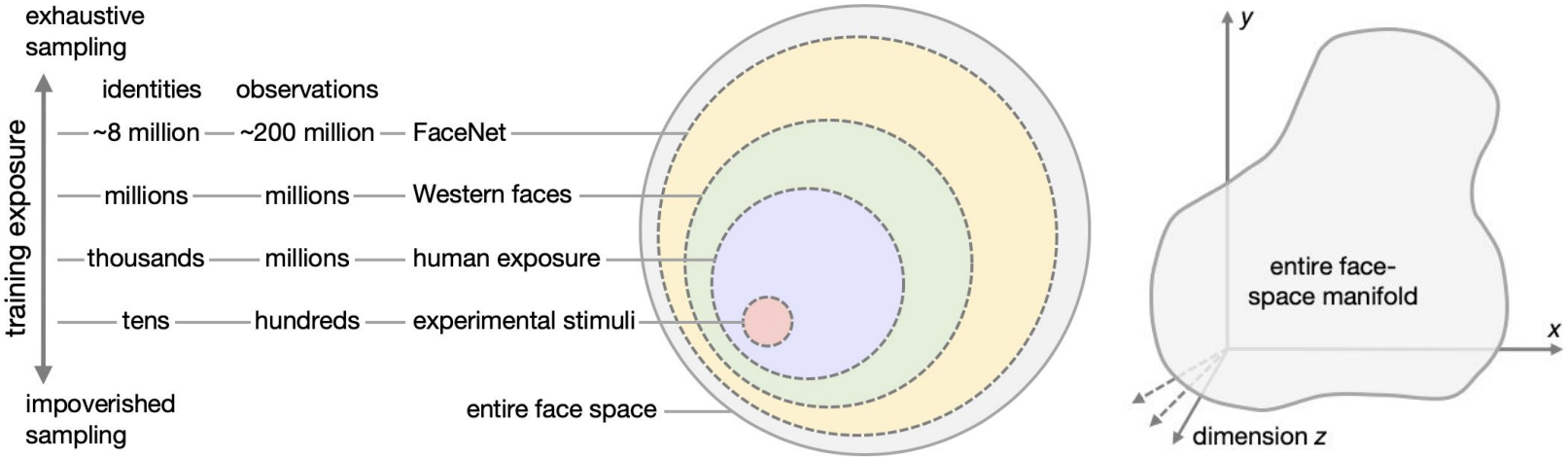
tens
hundreds
experimental stimuli
impoverished sampling
entire face space
y
entire face-space manifold
x
dimension z


exhaustive sampling
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observations
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FaceNet
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millions
Western faces
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human exposure
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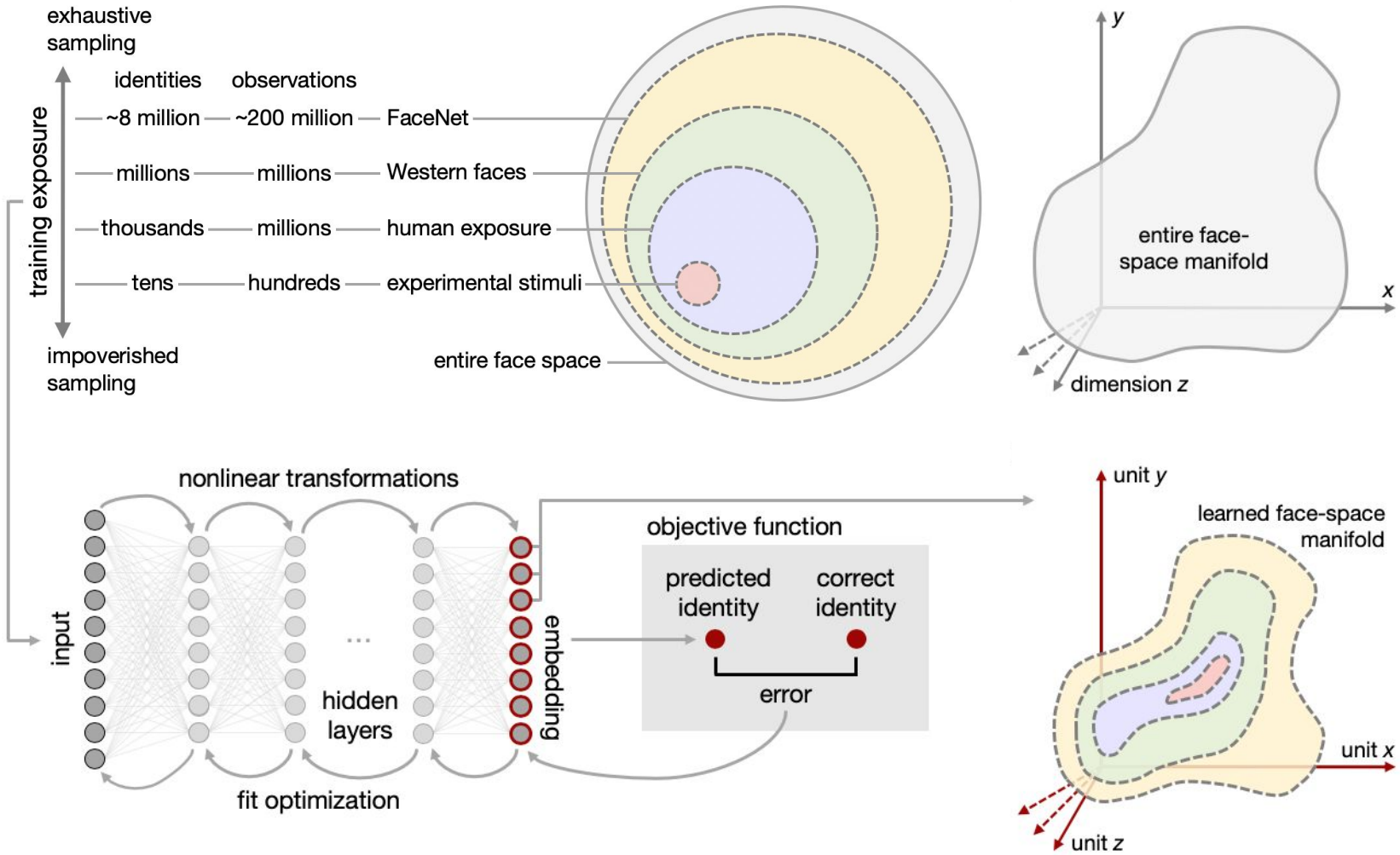
hundreds
experimental stimuli
entire face space
impoverished sampling
y
x
entire face-space manifold
dimension z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entire face space
y
entire face-space manifold
x
dimension z
nonlinear transformations
input
hidden layers
embedding
objective function
predicted identity
correct identity
error
fit optimization
unit y
learned face-space manifold
unit x
unit z

The “direct fit” model of biological learning

Relinquishing control—machine learning

Modern artificial neural networks leverage millions of noisy, real-world samples to achieve shockingly good performance at a variety of “cognitive” tasks…

—how is this possible?

—**and why do neuroscientists find this so unsatisfying?**

The “black box” argument

Artificial neural networks provide an input–output mapping with no explanation of their internal workings. We have simply duplicated the original problem by creating one more black box.

Ashby, 1956
McCloskey, *Psychol Sci*, 1991

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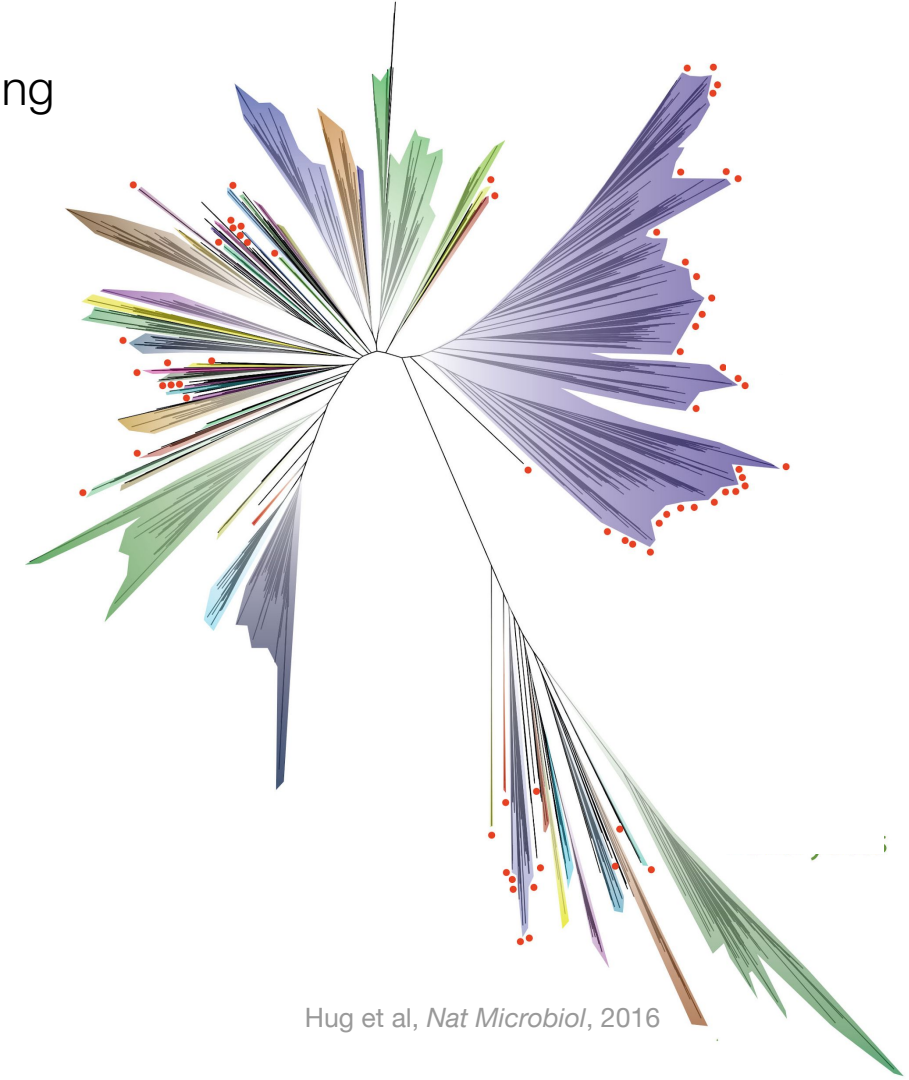
…because we didn’t find what we were looking for

Neuroscientists find this unsatisfying because we **assume** that to perform “cognitive” tasks, a neural network must learn concise, human-interpretable rules about the world.

Parallels between evolution and direct-fit learning

Evolution relies on “blind” optimization to produce complex organisms that over many generations become adapted to an ecological niche.

Evolution does not rely on idealized or interpretable model of the world, but relies on local interpolation to capitalize on “affordances” of the environment.



Hug et al, *Nat Microbiol*, 2016

Parallels between evolution and direct-fit learning

Evolution	Learning
Over-production with variation. Over-production of organisms with variation is drives adaptation by sampling the space of feasible solutions for fitting to the environment.	**Over-sampling with variation.** Dense and broad sampling of observations expands the interpolation zone and allows the learner to effectively mimic extrapolation.

Parallels between evolution and direct-fit learning

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Inheritance. Genes provide a stable substrate for accumulating adaptations (via mutation), thus optimizing the organism to the structure of the world over generations.	**Plasticity.** Neural circuits provide a stable substrate for accumulating knowledge over the lifespan of an organism, thus optimizing synaptic weights to support adaptive behavior.

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Combinatorial genetic code. The genetic code shared by all organisms is sufficiently high dimensional to express diverse organisms adapted to diverse ecological niches.	**Combinatorial neural code.** High-dimensional neural networks support a broad solution space and are expressive enough to learn complex, multidimensional structure in the world.

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Natural selection. External forces and ecological constraints guide evolution by punishing for maladaptive variations.	**Objective functions.** Self-supervised and externally-supervised objective functions guide learning by differentially adjusting synaptic weights to reinforce adaptive behaviors.

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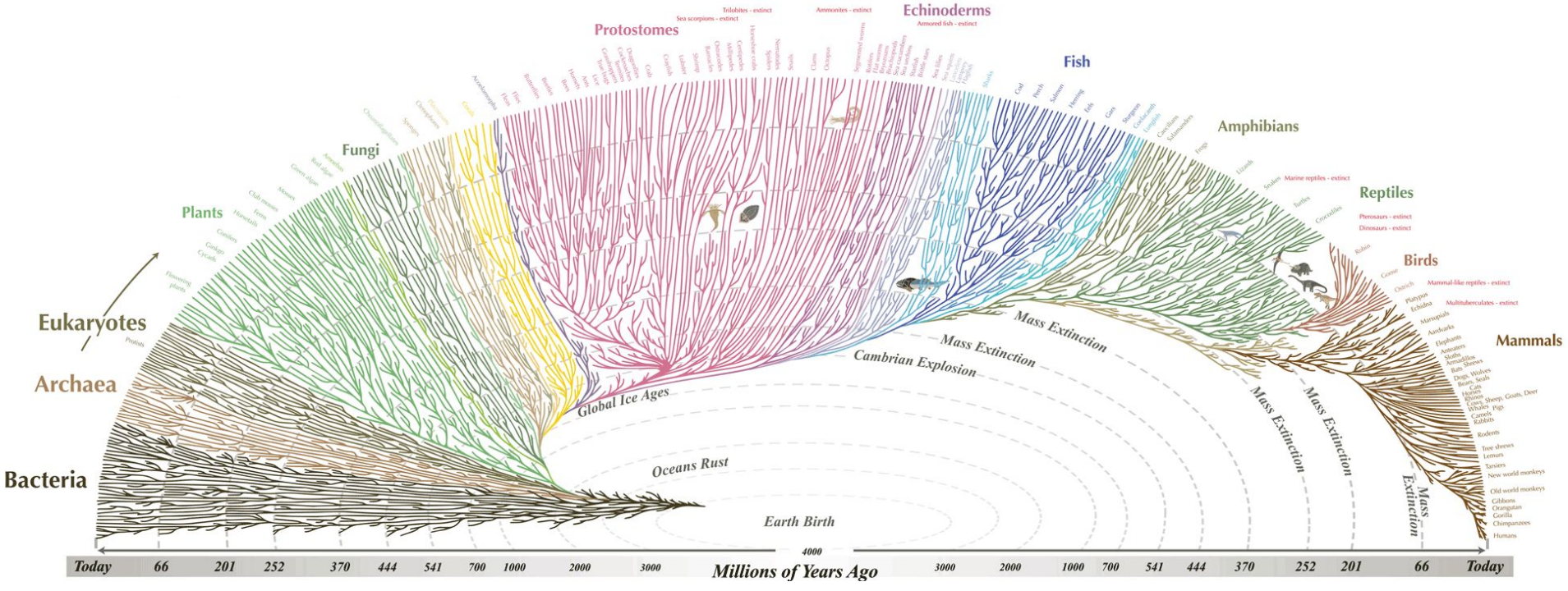
Natural selection. External forces and ecological constraints guide evolution by punishing for maladaptive variations.	**Objective functions.** Self-supervised and externally-supervised objective functions guide learning by differentially adjusting synaptic weights to reinforce adaptive behaviors.
Iteration over generations. Evolution is an iterative optimization process across generations that yields diverse organisms adapted to their ecological niche over billions of years.	**Iteration over samples.** Direct-fit learning is an iterative optimization process over many percepts and actions over the lifespan that affords an organism flexible, adaptive behavior within an ecological niche.

Parallels between evolution and direct-fit learning

Evolutionary theory—an elegant model?

Evolution does not have the luxury of operating in an idealized, highly controlled parameter space (like the experimenter's laboratory) and neither does biological learning.



Ecological learning and embodiment

Neural networks still have a long way to go

—current models are very limited and brittle

—current models rely on ad hoc domain-specific engineering “tricks”

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—current models rely on ad hoc domain-specific engineering “tricks”

Evolution, embodiment, and the primacy of action

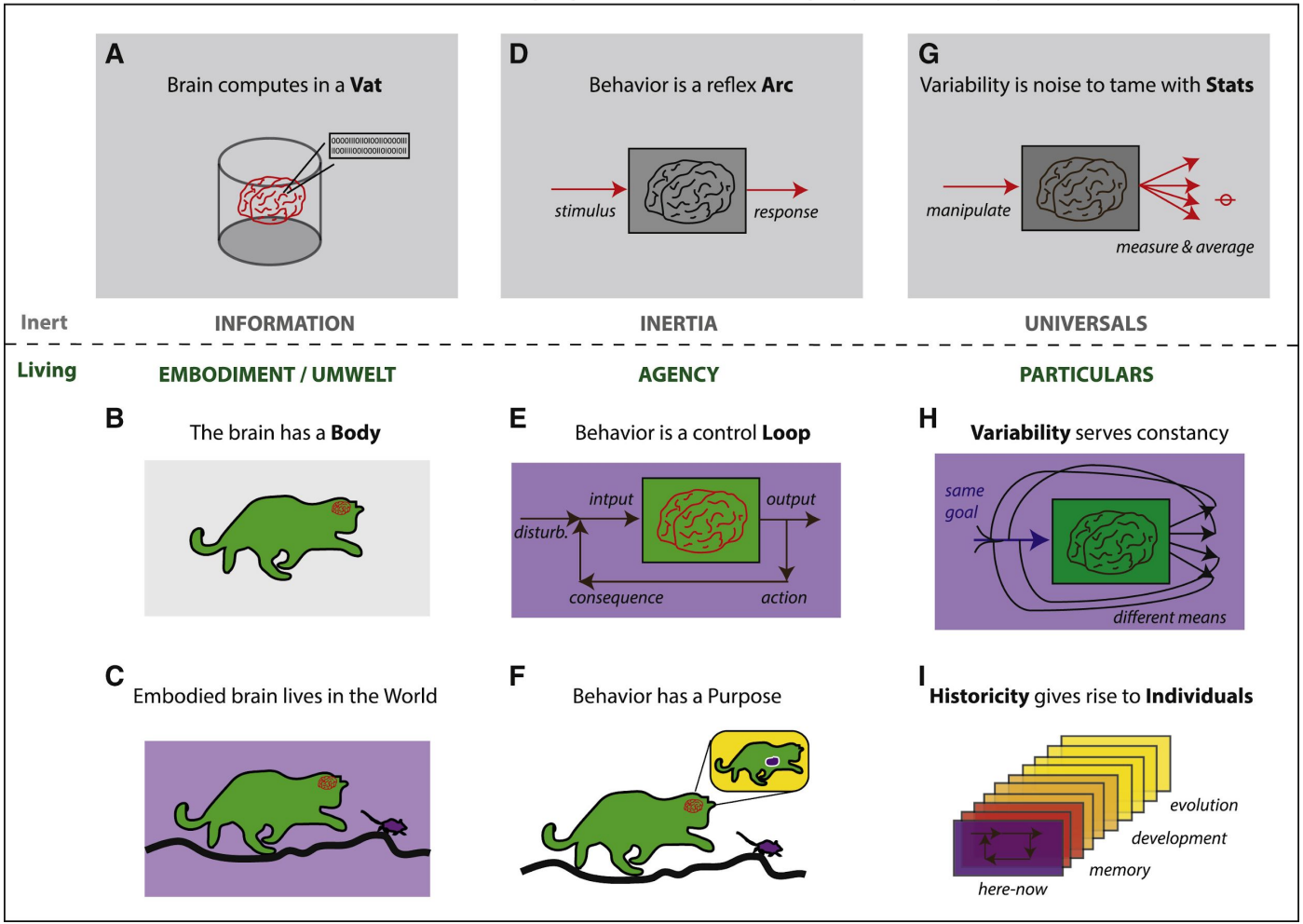
—all biological learning systems were designed by evolution to produce adaptive behavior

—evolution and learning are continuous organism–environment feedback loops

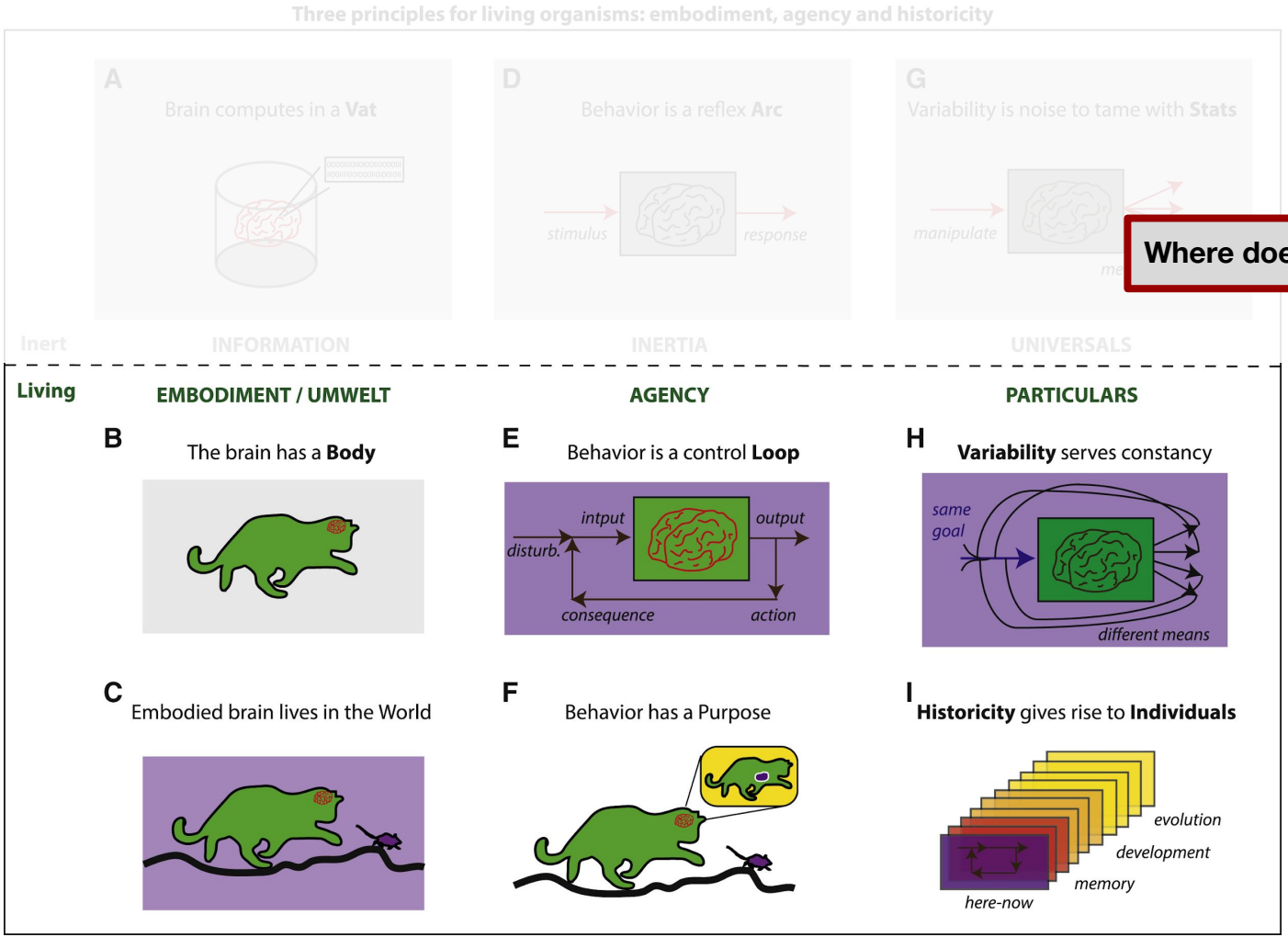
—we may need to reorient our criteria for “understanding” neural networks

Richards et al, *Nat Neurosci*, 2019

Three principles for living organisms: embodiment, agency and historicity



Gomez-Marin & Ghazanfar, *Neuron*, 2019



Where does "System 2" emerge?

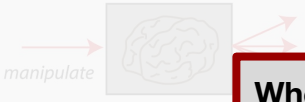
Gomez-Marin & Ghazanfar, *Neuron*, 2019

Three principles for living organisms: embodiment, agency and historicity

A
Brain computes in a **Vat**

D
Behavior is a reflex **Arc**

G
Variability is noise to tame with **Stats**



Where does “System 2” emerge?

Inert | INFORMATION | INERTIA | UNIVERSALS

Living | EMBODIMENT / UMWELT | AGENCY | PARTICULARS

B
The brain has a **Body**

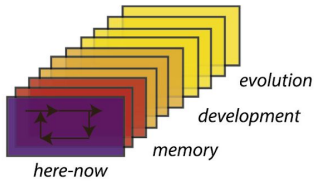
E
Behavior is a control **Loop**

H
Variability serves constancy

C
Embodied brain lives in the World

F
Behavior has a Purpose

I
Historicity gives rise to **Individuals**



Gomez-Marin & Ghazanfar, *Neuron*, 2019

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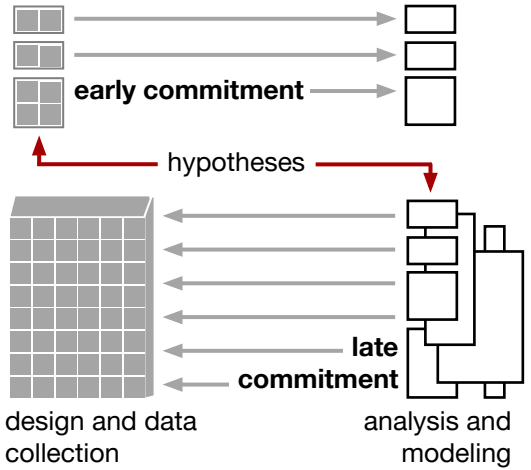
Where now for the neuroscientist?

—ecological considerations must play a central role in both model development and model evaluation to avoid confining ourselves to a “self-created ivory tower ecology”

—in the context of representative design, the “challenge of further [isolating variables] must be met by after-the-fact, mathematical means”

Brunswik, 1955



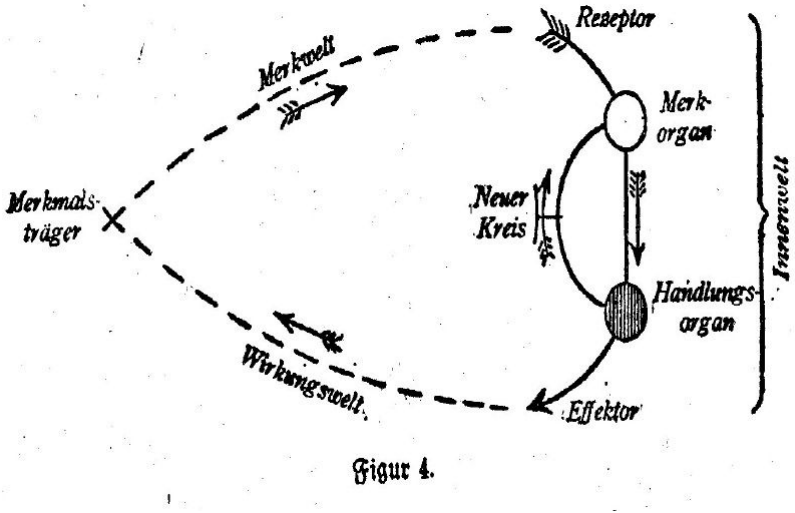
Nastase, S. A., Goldstein, A., & Hasson, U. (2020). Keep it real: rethinking the primacy of experimental control in cognitive neuroscience. *PsyArXiv*.

The “direct fit” model of biological learning

Exiting the Cartesian Theater

Biological systems are not obligated to learn human-interpretable *rules*, *representations*, or *maps*—there is no “little scientist” inside the organism following the rules or reading the map.

Ryle, 1949
Gibson, 1979
Dennett, 1991



Figur 4.

The “direct fit” model of biological learning

Exiting the Cartesian Theater

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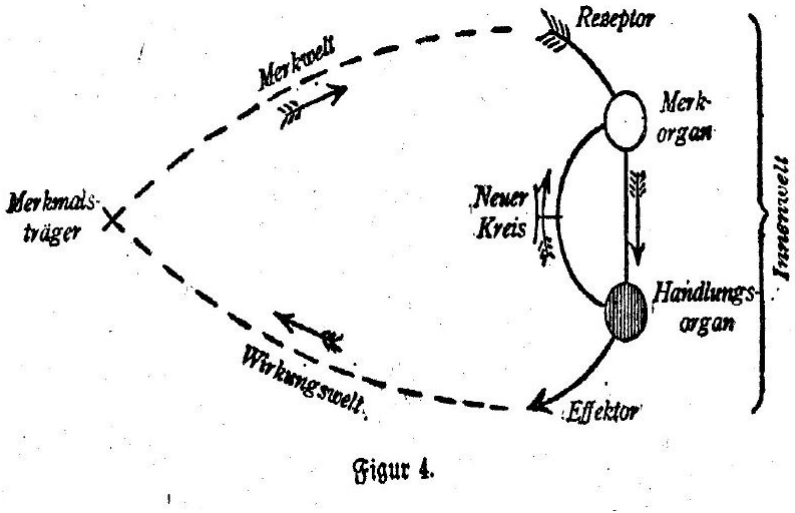
The meaningful environment (or *Umwelt*)

The organism cannot be decoupled from its environment—biological (and artificial) neural networks rely on local interpolation to capitalize on “affordances” of the environment.

von Uexküll, 1967
Gibson, 1979
Gomez-Marin & Ghazanfar, *Neuron*, 2020



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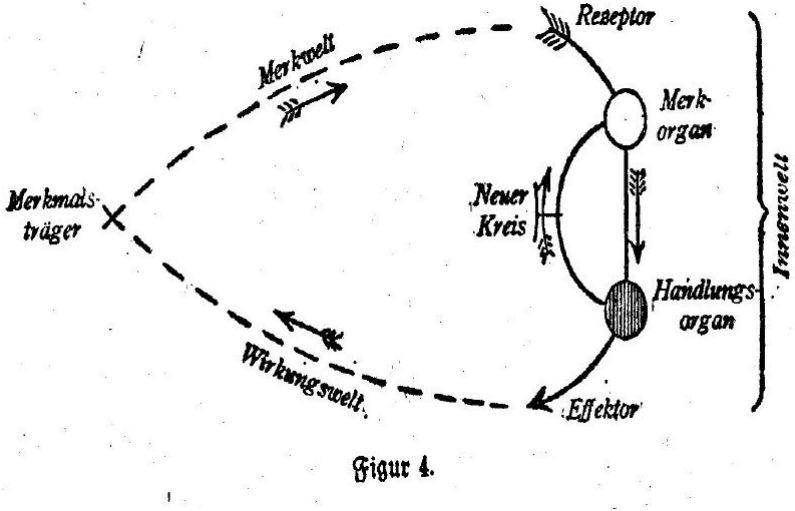
“There is grandeur in this view of life…”

Both evolution and direct-fit learning models produce solutions that may be mistakenly interpreted in terms of elegant design principles, but in fact reflect the interdigitation of “mindless” optimization processes and the structure of the world.

Darwin, 1859
Dawkins, 1986
Dennett, 1995, 2017



Figur 4.

Thanks!

Uri Hasson
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Yun-Fei Liu
Hanna Hillman
Asieh Zadbood
Liat Hasenfratz
Neggin Keshavarzian
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Christopher J. Honey
Mai Nguyen
Claire H. C. Chang
Christopher Baldassano
James V. Haxby
M. Ida Gobbini
Yaroslav O. Halchenko
Feilong Ma
J. Swaroop Guntupalli
Andrew C. Connolly

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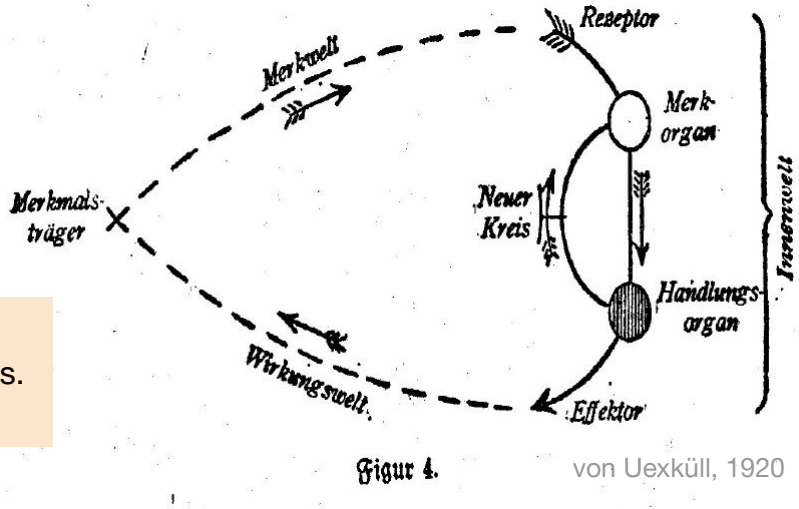

Figur 4. von Uexküll, 1920

Hasson, U., Nastase, S. A., & Goldstein, A. (2020). Direct fit to nature: an evolutionary perspective on biological and artificial neural networks. *Neuron*, *105*(3), 416–434.