Gestalt Phenomenon & Neural Networks

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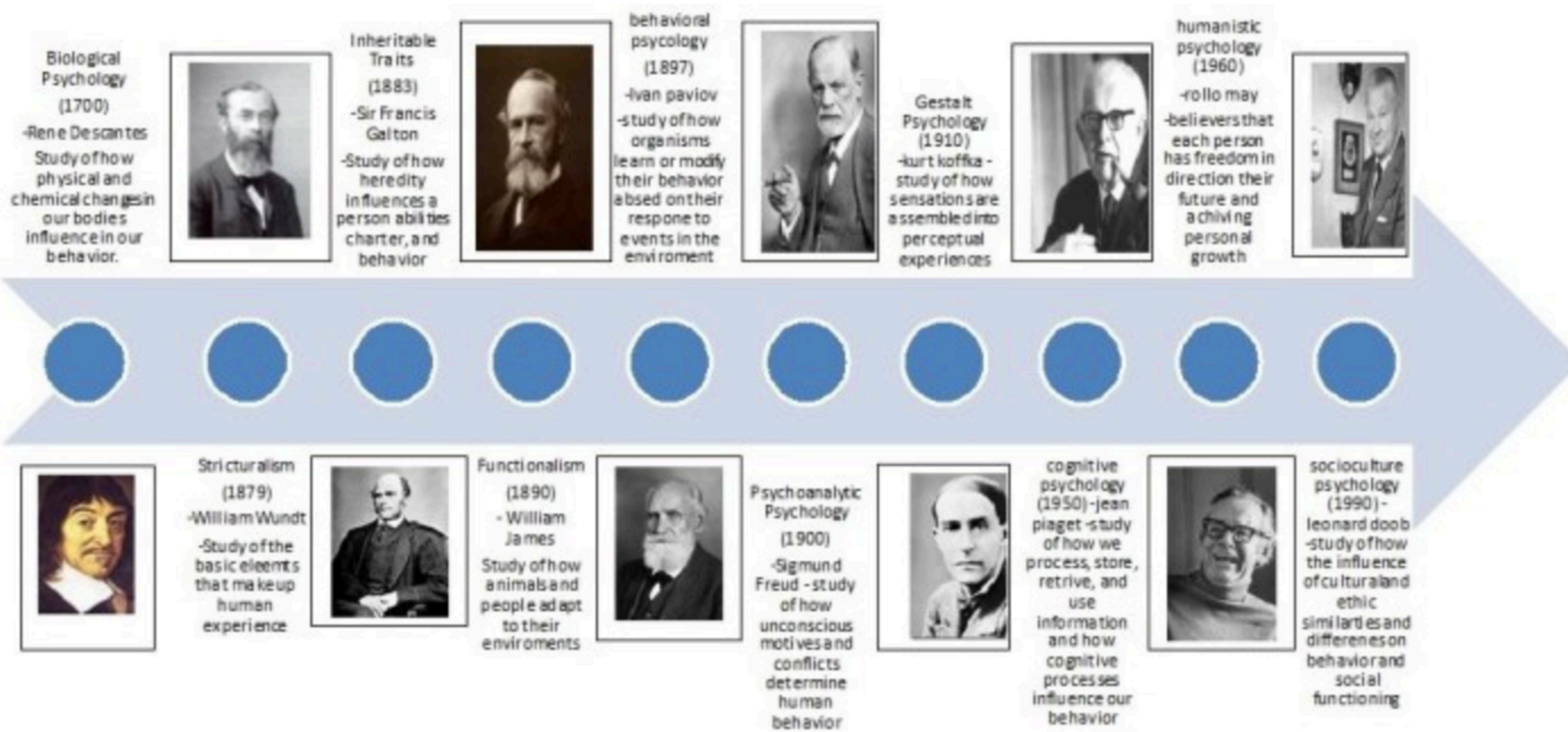
History of Psychology



Gestalt Psychology

Gestalt Psychology

Gestalt Psychology

“The whole is something else than the sum of its parts” - Kurt Koffka

Gestalt Psychology

Gestalt Principles

- Principles governing organization of perceptual scenes
- Utilized in design, Photography

Gestalt Principles

- Figure/Ground
- Similarity
- Proximity
- Closure
- Continuation

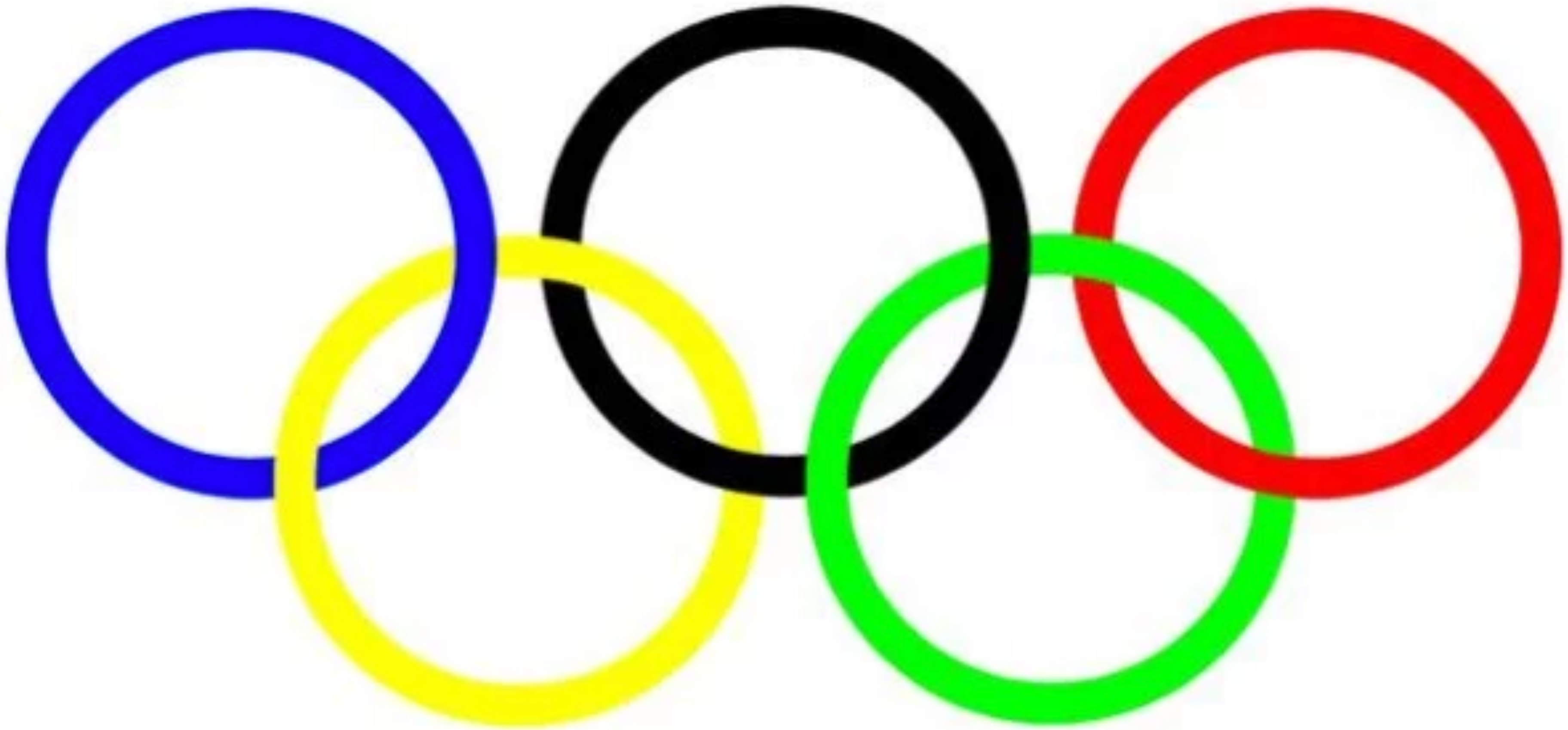
Gestalt Principles

- Figure/Ground

Pittsburgh Zoo
& PPG Aquarium

Gestalt Principles

- Proximity



Gestalt Principles

- Closure

Research Paper

- Authors: Been Kim and colleagues at Google Brain
- Tested various neural networks using a methodology inspired by human experiments
- Answer the question -

Research Paper

Do Neural Networks Show Gestalt Phenomena? An Exploration of the Law of Closure

"A natural question is whether image recognition networks show similar effects. Our paper investigates one particular type of Gestalt phenomenon, the law of closure, in the context of a feedforward image classification neural network"

Training Images

How to test for the law of closure?

Three sets of Training Images:

- Set complete - full triangles
- Illusory - triangles with open space
- Non-Illusory - triangles with open space, but the corners have been rotated

Training Images

Set complete - full triangles

Set C

<u>All sets of images were varied</u>

- Rotation
- Background color
- Image position
- Rotation of image

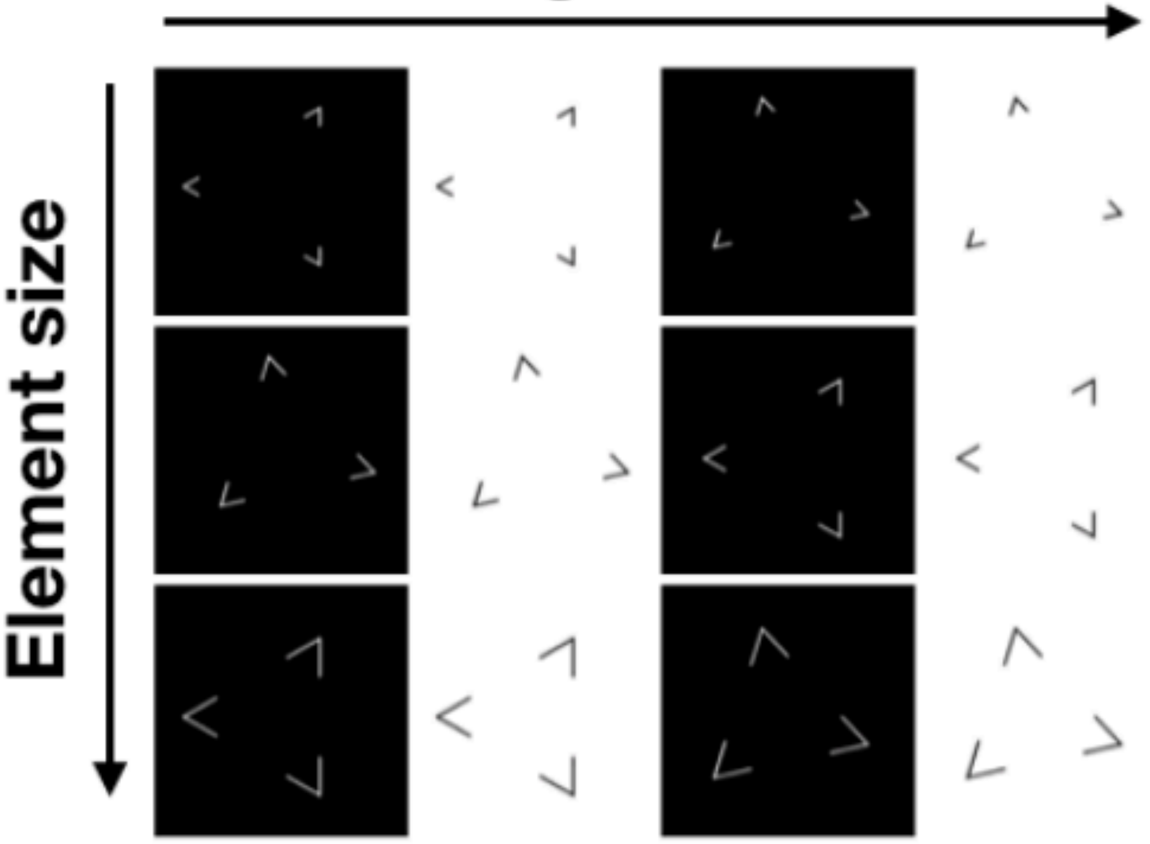
Training Images

Illusory & Non-illusory

Set I

Set Illusory

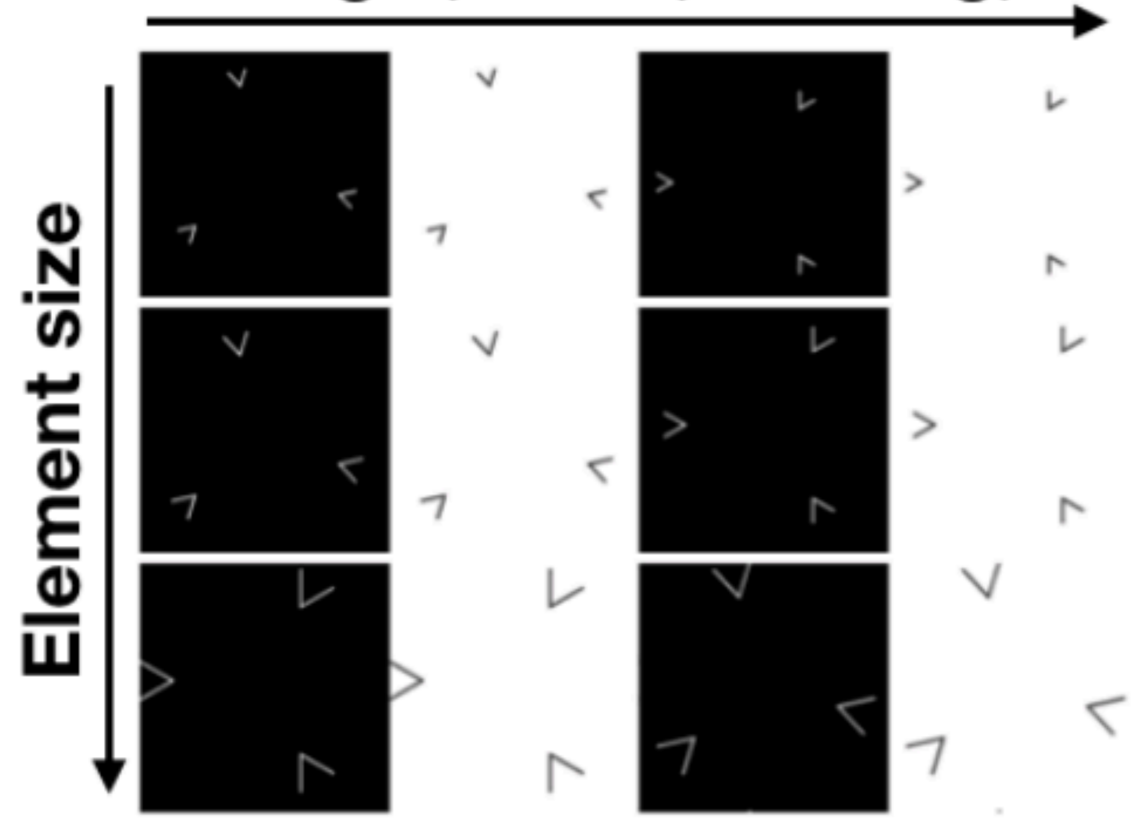
Rotation angle, color, shifting



Set NI

Set Non-illusory

Rotation angle, color, shifting, theta



Training Images

<u>Key Independent Variable - Element Size:</u>

- Research has shown closure effect is highly dependent upon the size of the remaining corners
- As element size increases, it becomes easier to perceive a whole triangle
- Element size was varied in both the I and NI sets

Neural Network Experimental Paradigm

Simple Technique to measure closure effect:

- Observe activations in intermediate layers of the network
- Compare network's responses between the various sets of triangles
- If network's response to set C are more similar to set I than set NI, then it suggests the presence of the closure effect

Raw Closure Measurement

How to measure similarity in responses?

Raw closure measurements For two inputs x and y, we define the *response similarity* in layer l as the cosine similarity between the activations during inference:

$$r_l(x, y) = \frac{f_l(x) \cdot f_l(y)}{|f_l(x)||f_l(y)|} .$$

$f_l : \mathbb{R}^n \to \mathbb{R}^m$

$\boldsymbol{x} \in \mathbb{R}^n$

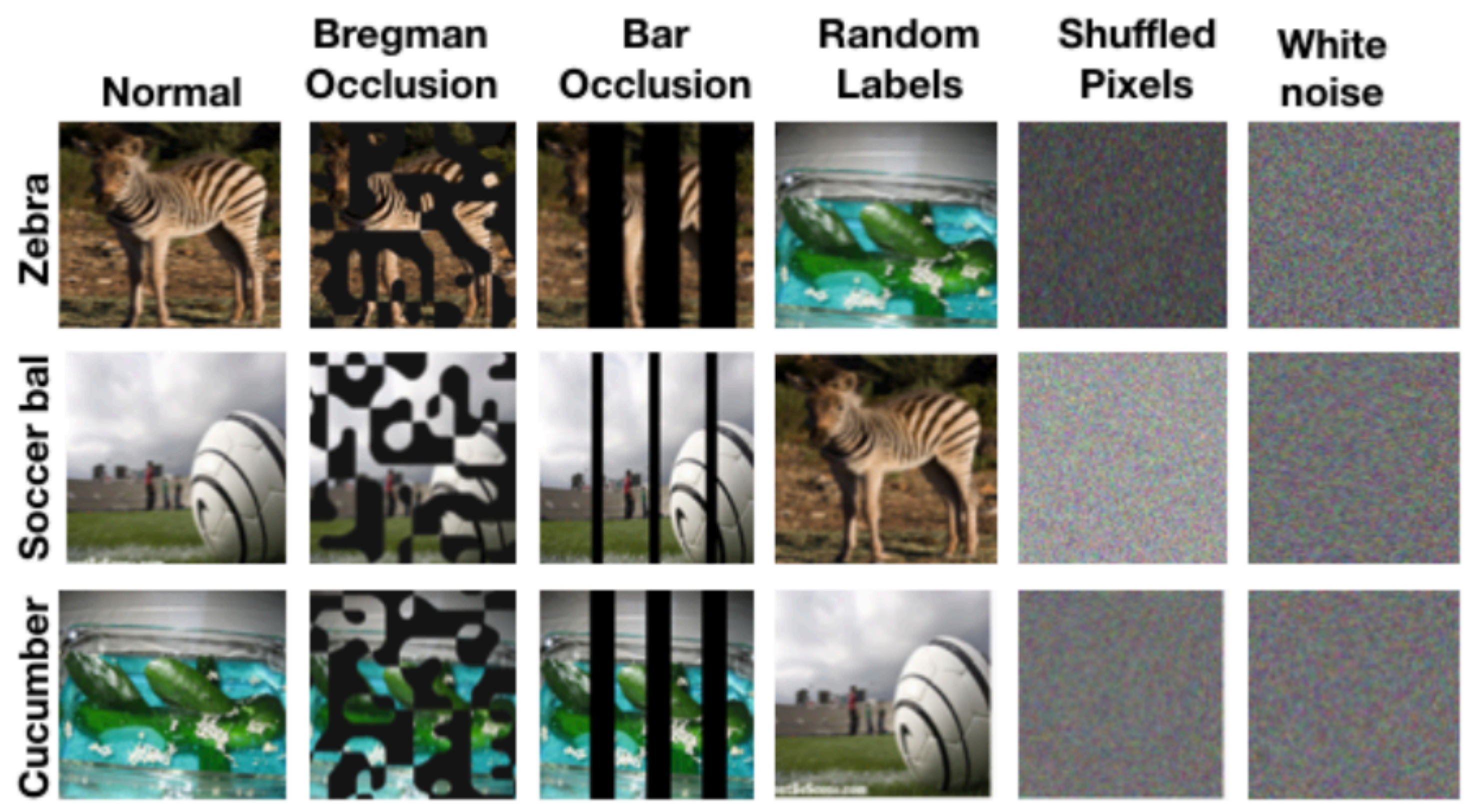
- Activation function within layer L
- Network inputs

Raw Closure Measurement

$$\text{Closure}_l^{\text{raw}} = \frac{1}{n} \sum_{V(C,I)} r_l(x, y) - \frac{1}{n} \sum_{V(C,NI)} r_l(x, y)$$

- V(C,I) & V(C,NI) - Valid pairs from the different sets
- Comparison of average differences between valid pairs

Neural Networks Trained



Type	Trained
NORMAL	with 600 images for each nc classes
BREGMAN OCCLUSION	with images occluded by structured noise patterns (Bregman, 2017)
BAR OCCLUSION	with images occluded by vertical black bars
RANDOM LABELS nc	with randomly labeled images of nc classes
RANDOM LABELS 1000	with randomly labeled images of 1000 classes
SHUFFLED PIXELS	with images of nc classes. Pixels are shuffled across channels.
WHITE NOISE	with random white noise images.
UNTRAINED	is an untrained network.
SMALL DATA	with one image for each nc classes.

Figure 4. Descriptions of running conditions and a subset of training data used to test hypotheses

9 Different running conditions

- Normal
- Bregman Occlusion
- Bar Occlusion
- Random labels nc
- Random Labels 1000
- Shuffled Pixels
- Untrained
- Small Data

Each condition is trained with convolutional layers and fully-connected layer only (FC-only) networks

Hypotheses

H1:The closure effect is associated with generalization.

H2:The closure effect is stronger in higher layers than lower layers.

H3: The closure effect will generally increase during training before convergence.

H4: The closure effect is NOT arbitrarily influenced by simple input manipulations (e.g., brightness).

H5. The closure effect is stronger in deeper networks.

H6. The closure effect is stronger when trained with intentionally occluded images.

H7. The closure effect is stronger with convolutional operators than without.

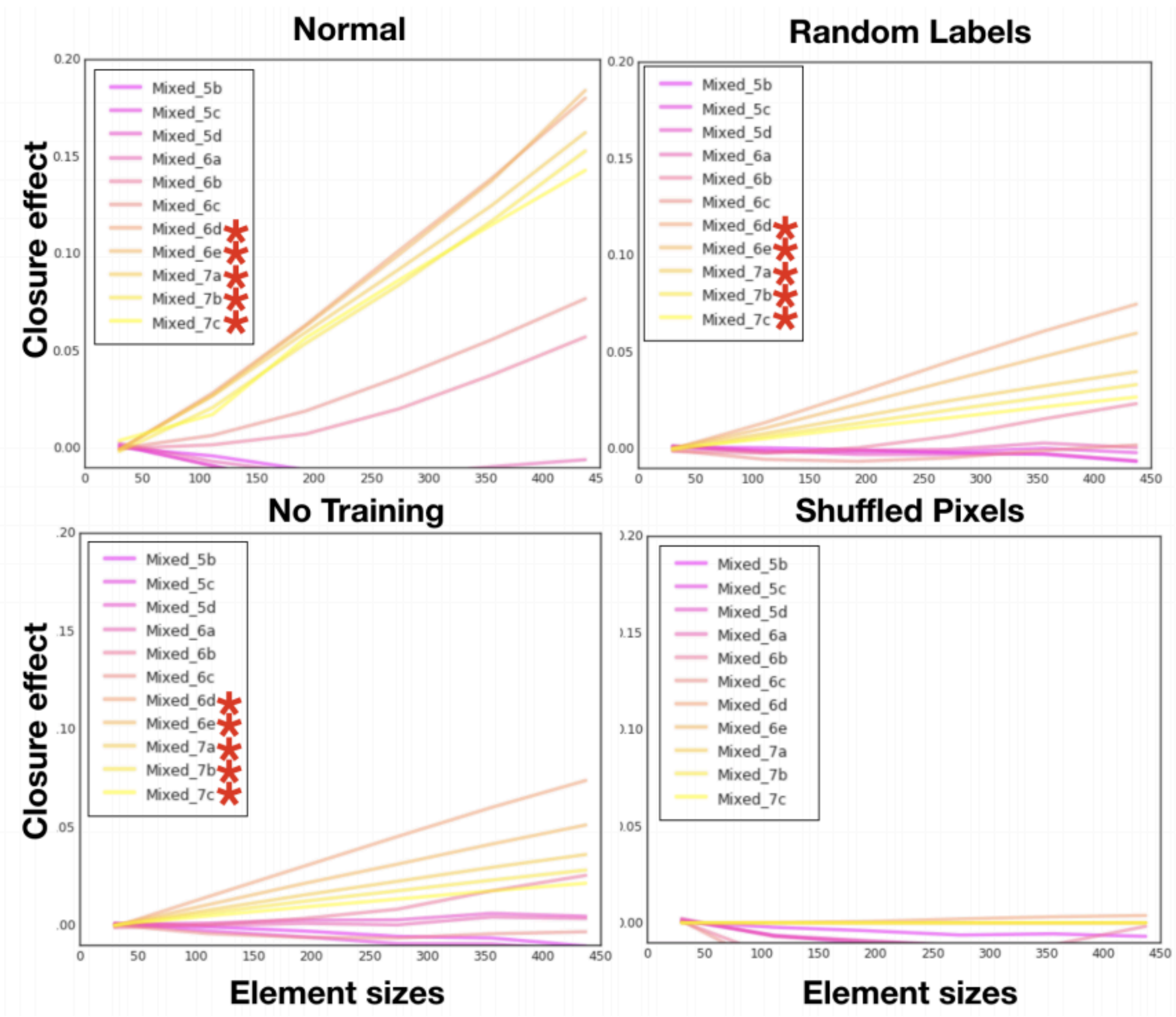
Hypotheses

H1:The closure effect is associated with generalization.

H2:The closure effect is stronger in higher layers than lower layers.

H7. The closure effect is stronger with convolutional operators than without.

Hypothesis 1: The closure effect is associated with generalization



Conclusions:

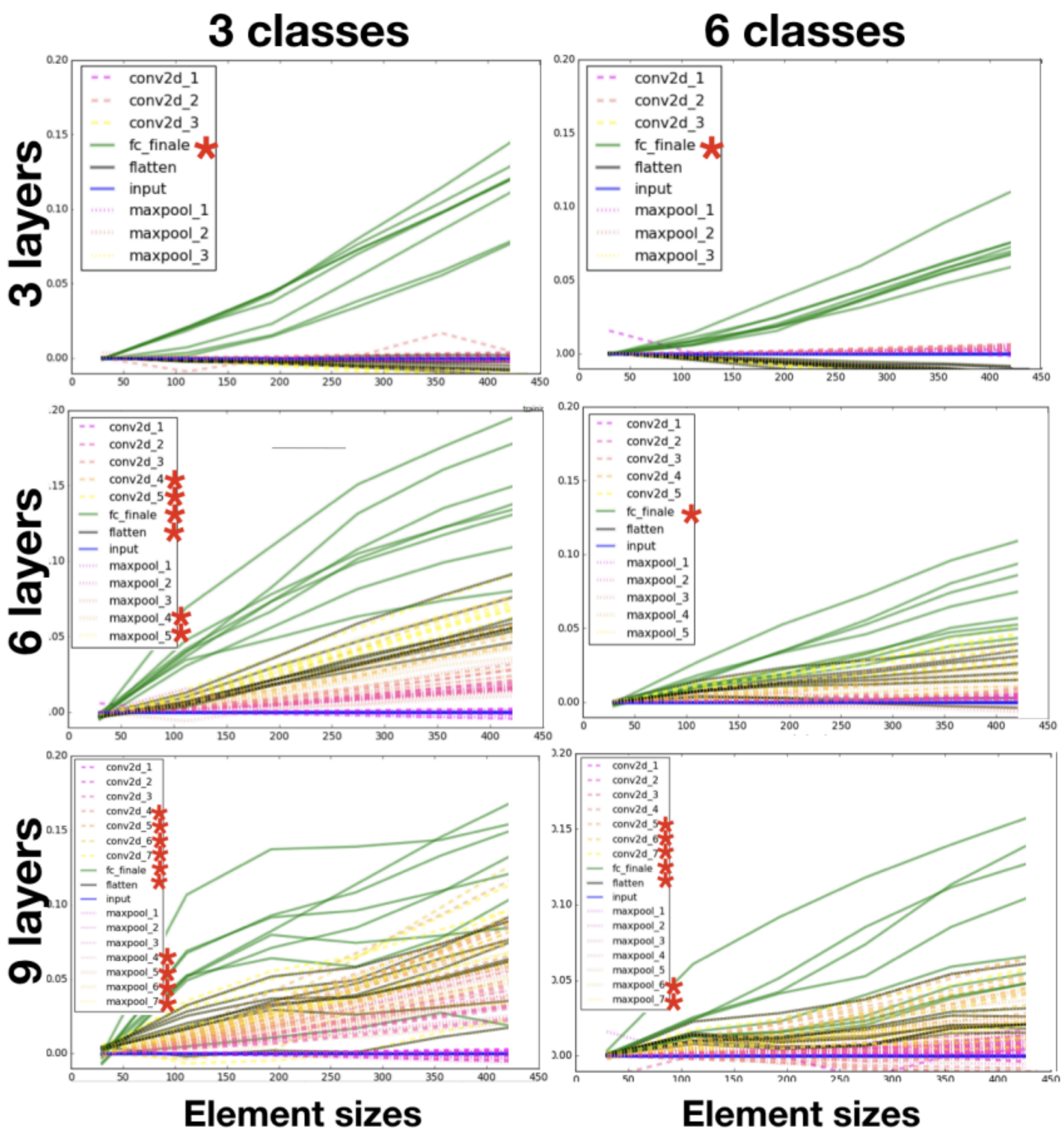
- Ability to generalize and to extract common features
- Normal network possesses the strongest closure effect
- Untrained and Random labels networks show the closure effect?

Hypothesis 1: The closure effect is associated with generalization

Untrained networks show the closure effect?

- Coincides with recent discoveries
- Ulyanov, 2018, Untrained networks are already good feature extractors
- Shuffled Pixels Network - feature extraction ability has been destroyed - features cannot be extracted from degenerate data

Hypothesis 2: Is the closure effect stronger in higher layers than lower layers?



Conclusions:

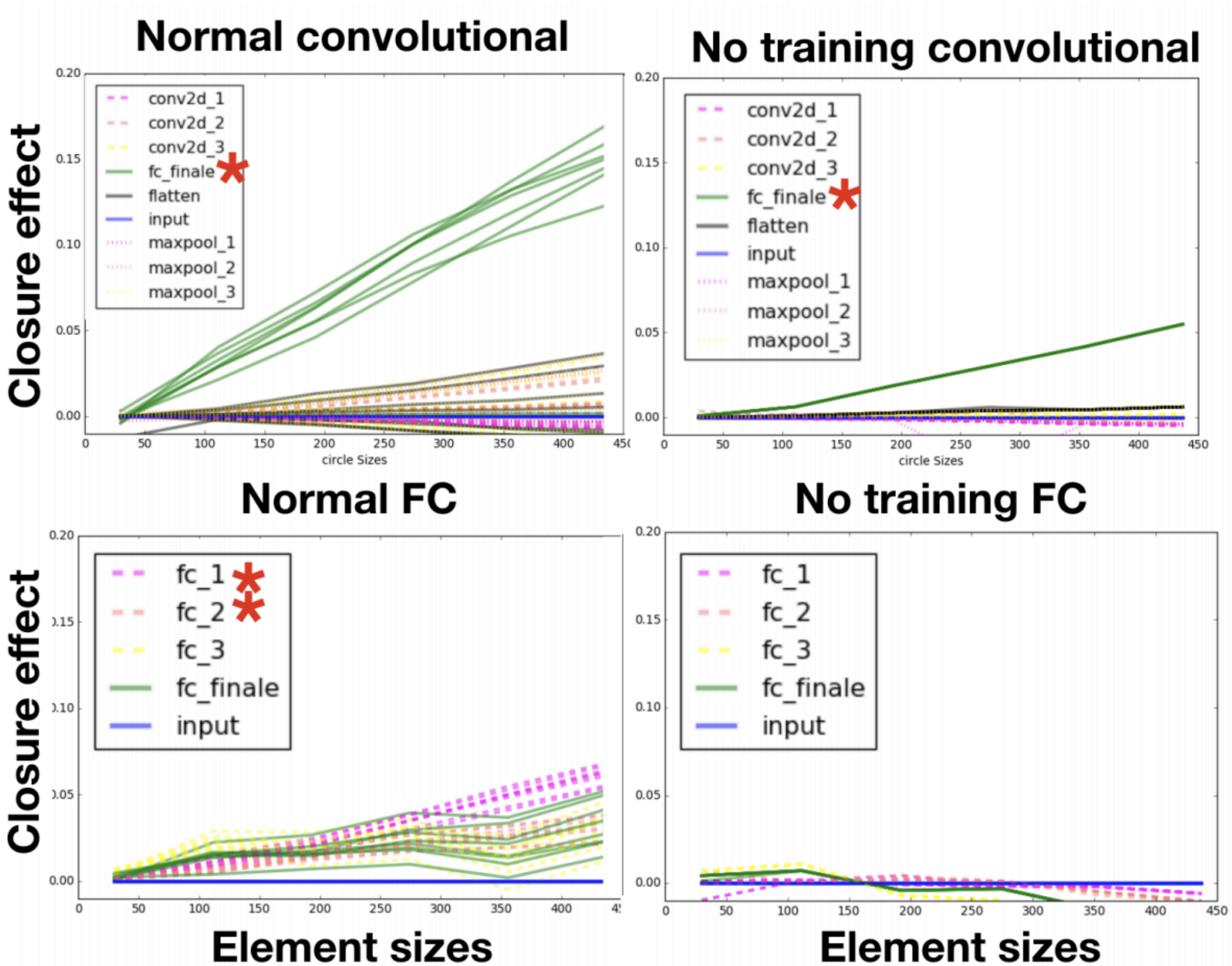
- Layers closer to prediction layer typically exhibit stronger closure effect
- Each Network seems to have a threshold layer after which all are statistically significant

Hypothesis 2: Is the closure effect stronger in higher layers than lower layers?

Conclusions:

- Coincide with - “The whole is different from the sum of its parts”
- Bau, 2017 - lower layers extract lower features & higher levels learn higher level features
- Lower levels - “parts”
- Closure effect must occur when the “whole” is detected in higher layers

H7. The closure effect is stronger with convolutional operators than without.



Conclusions:

- Having convolutional layers correlates with stronger closure effect.

Questions?

References

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