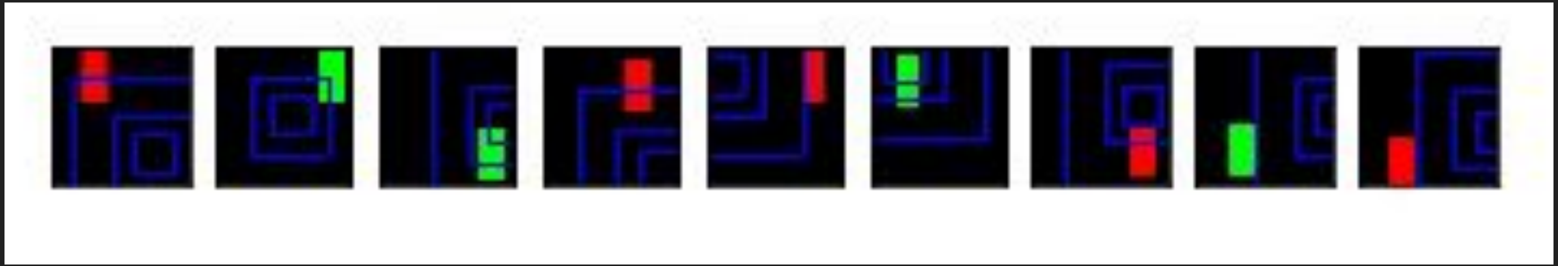
Building and Replicating Models of Visual Search Behavior



with Tensorflow and the Scientific Python Stack

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Acknowledgements

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Prinz

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Acknowledgements

pygame

pandas

Joblib

imageio

Introduction

Visual search:

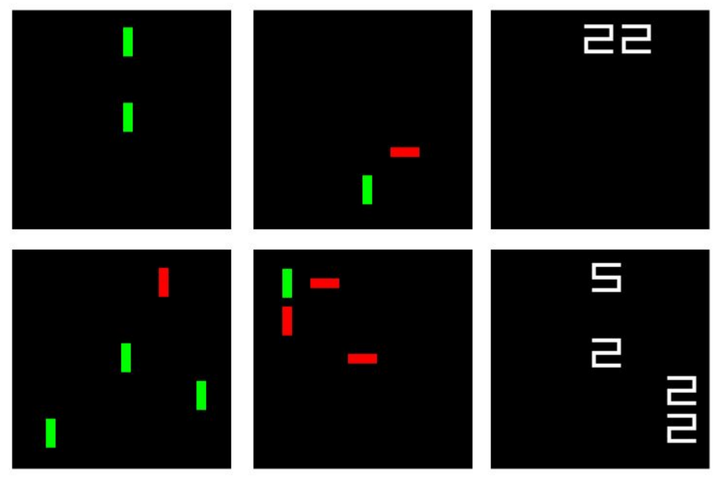
- in the real world

http://info.ni.tu-berlin.de/photodb/

Introduction

Visual search:

- in the real world
- in the lab



Introduction

Why build models of visual search **behavior**?

1. understand brain mechanisms of **goal-driven perception**

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    - Does the model we build with this mechanism **behave** like humans and other animals?

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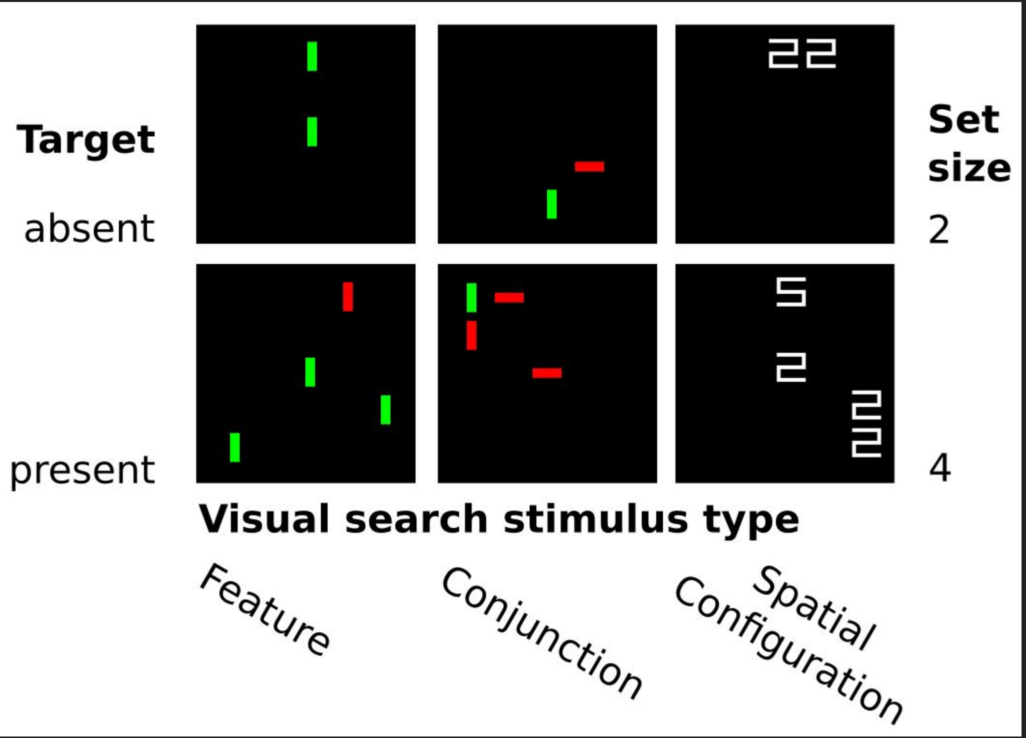
Why build models of visual search **behavior**?

1. understand brain mechanisms of **goal-driven perception**
    - Does the model we build with this mechanism **behave** like humans and other animals?
2. design artificial intelligence algorithms that draw from these mechanisms
    - Does our agent **behave** like humans and other animals?

Introduction

The *discrete item display visual search* task



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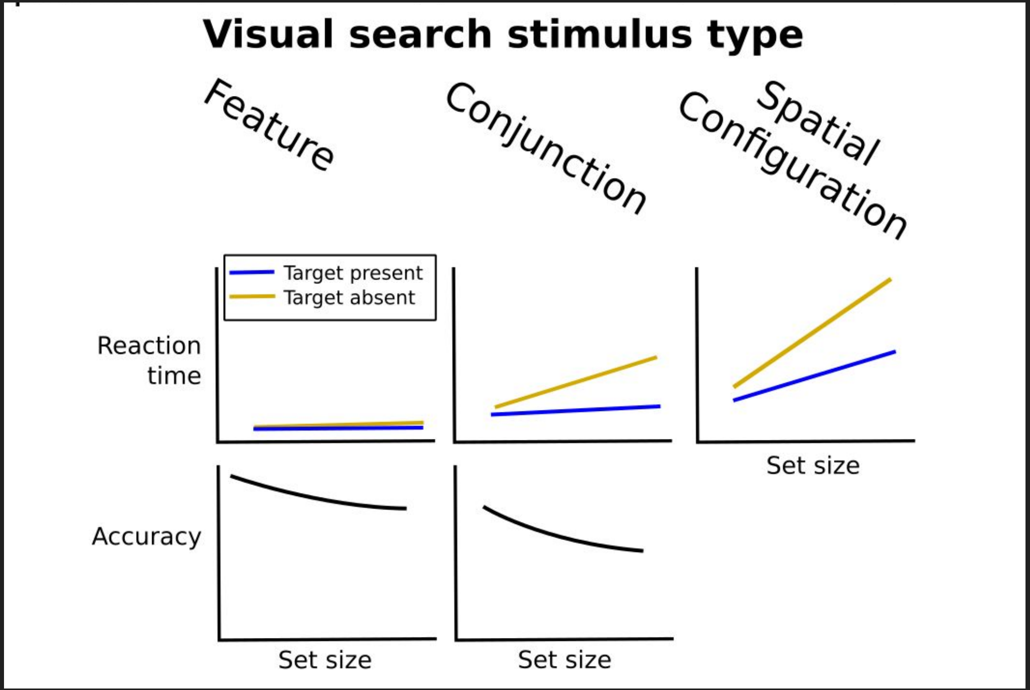
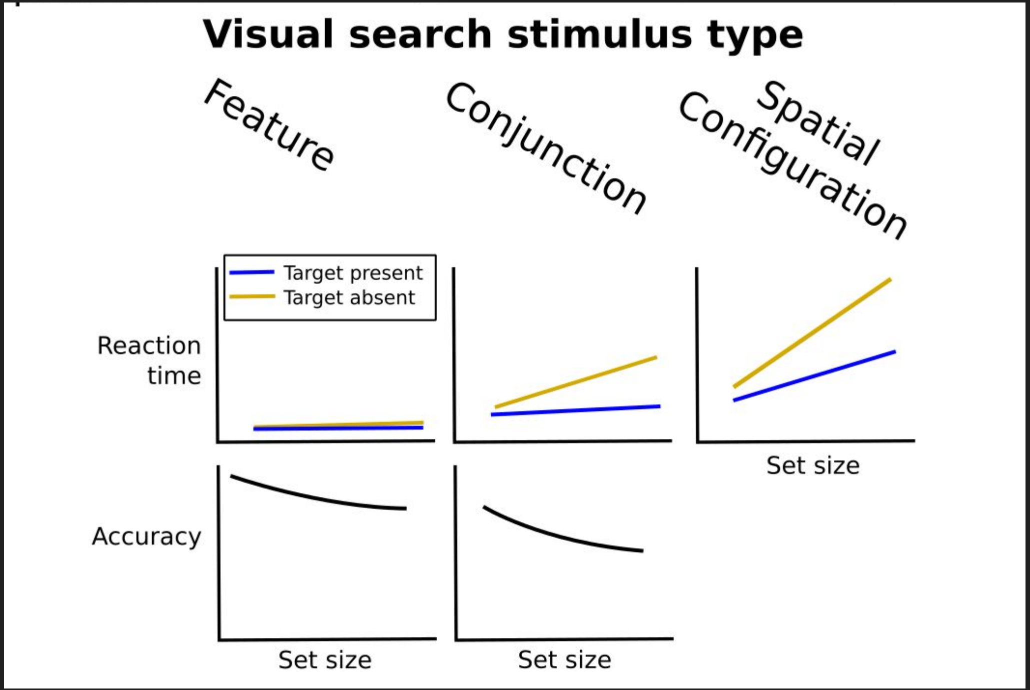


Introduction

***Models* of the *discrete item display visual search* task**



Models of
capacity limitations

serial, attention-limited
- e.g. Guided Search

parallel, noise-limited
- Signal Detection Theory-based models

Introduction

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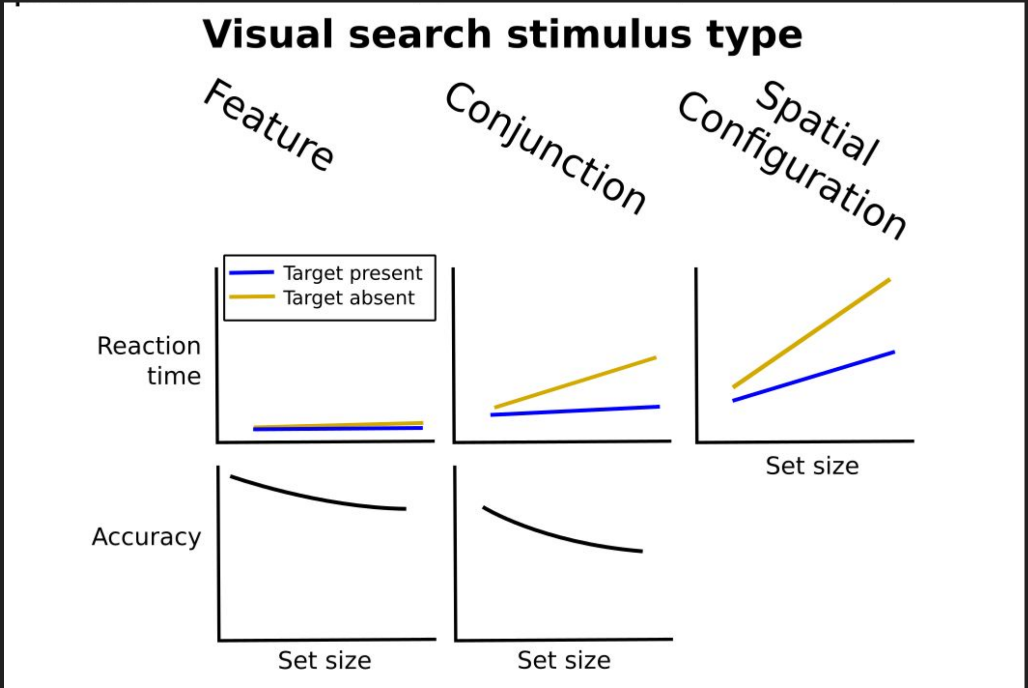


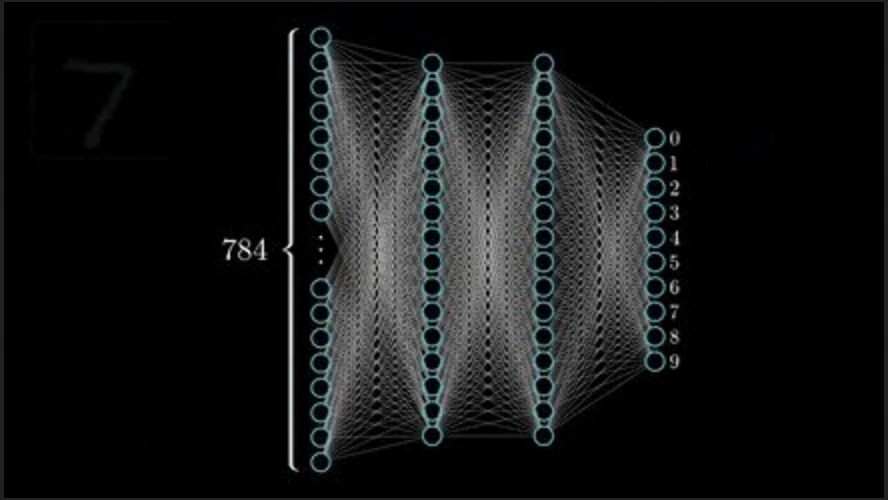
Models of
capacity limitations

None of these models are
"pixels-in, behavior out"

Introduction

Neural networks as models of the visual system

What I mean by "neural networks"



https://www.youtube.com/watch?v=aircAruvnKk

Introduction

Neural networks as models of the visual system

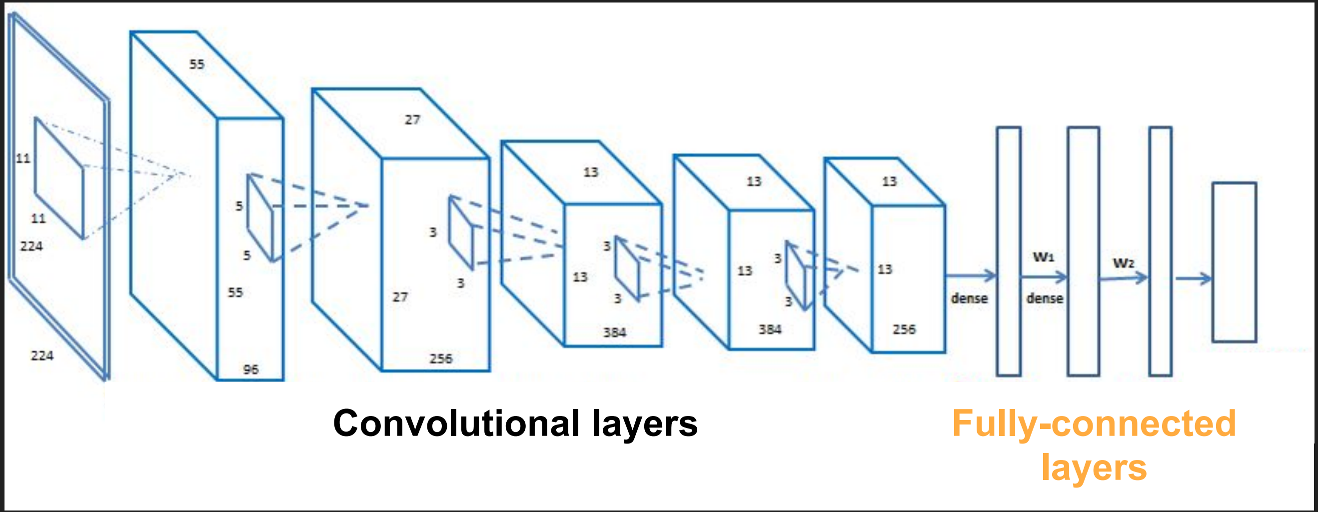
Specifically, **convolutional neural networks (CNNs)**

https://cs.nyu.edu/~fergus/tutorials/deep_learning_cvpr12/

Introduction

Neural networks as models of the visual system

The architecture of CNNs resembles the visual system



AlexNet (Krizhevsky et al. 2012). Adapted from Wang et al. 2015

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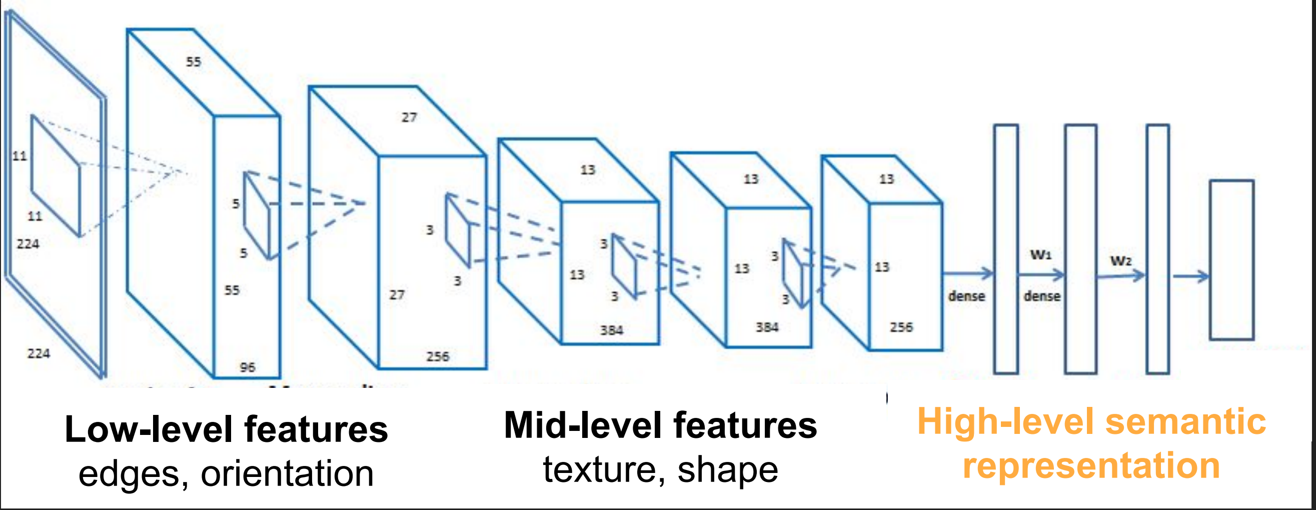
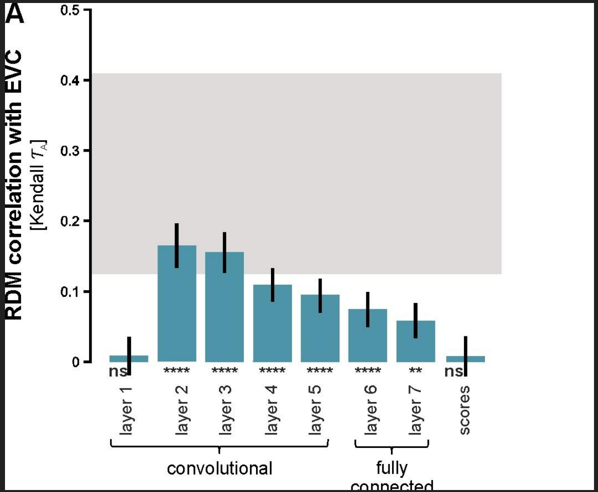


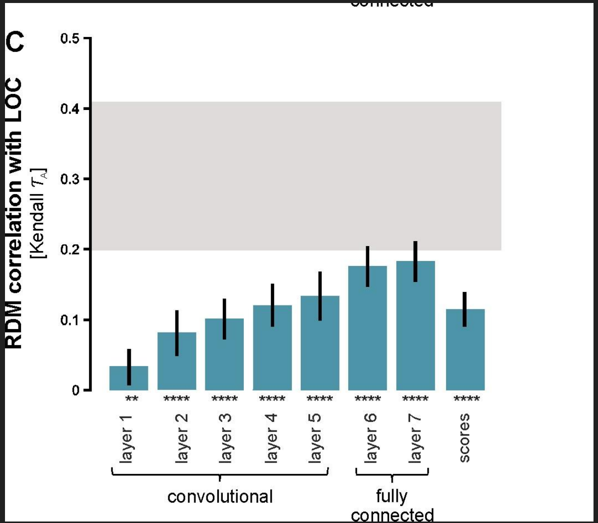
"the (primate) visual system"

Introduction

Neural networks as models of the visual system

Task-optimized CNNs learn representations similar to those in the visual system of the (primate) brain





Khaligh-Razavi, Kriegeskorte 2014

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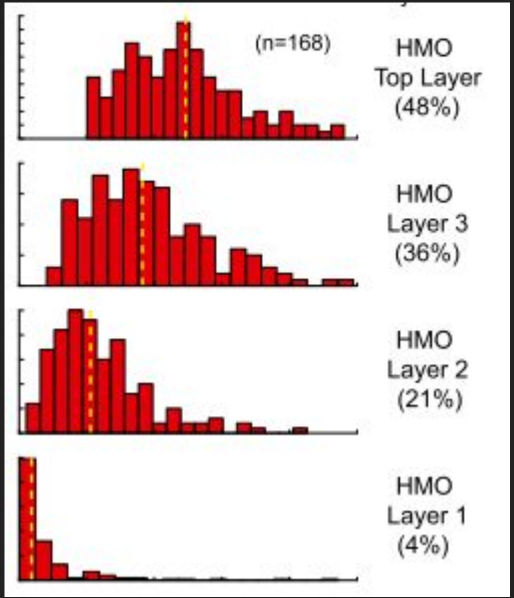

Yamins DiCarlo 2014

Introduction

Neural networks as brain models

Hypothesis: if CNNs are using representations similar to those in the (primate) visual system, then they should **behave** like humans when performing related tasks

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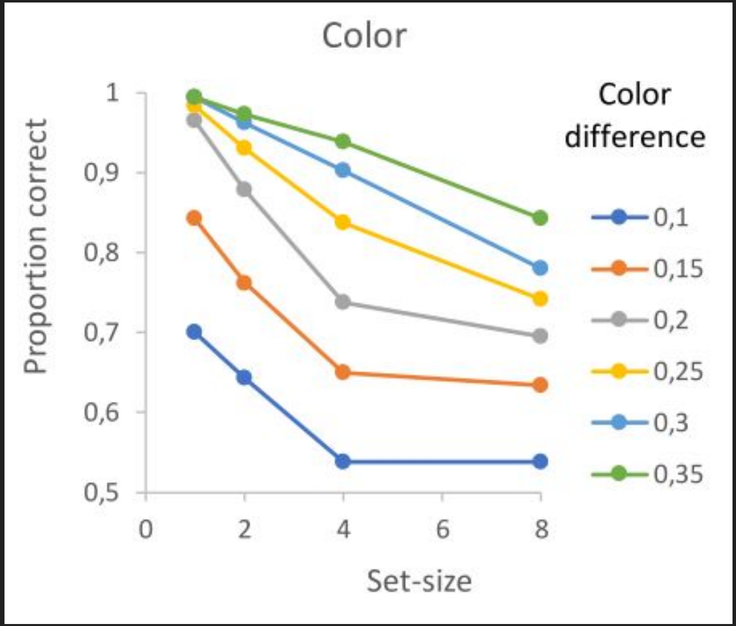

Põder, 2017. "Capacity limitations of visual search in deep convolutional neural network"

Experiment 1: replicate fine-tuning approach

Methods

- use AlexNet and VGG16 architecture with **weights pre-trained on ImageNet dataset**

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- generate visual search stimuli with `searchstims`, a Python package built with PyGame (https://github.com/NickleDave/searchstims)

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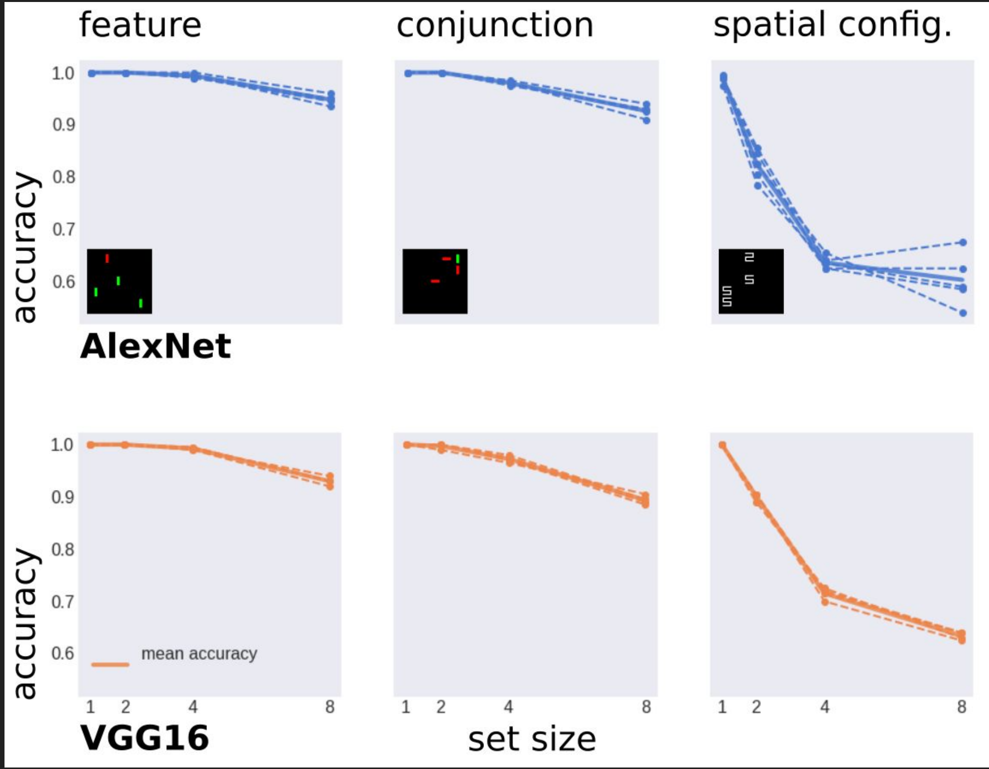
- apply base learning rate to other layers: `1e-20`
- generate visual search stimuli with `searchstims`, a Python package built with PyGame (https://github.com/NickleDave/searchstims)
- train 5 replicates of each network on a dataset with 6400 samples of a **single visual search stimulus**, balanced across "set size"
- measure accuracy on separate 800 sample test set

Experiment 1: replicate fine-tuning approach

Results

- Both AlexNet and VGG16 show human-like drop in accuracy when trained this way



Experiment 1: replicate fine-tuning approach

Results

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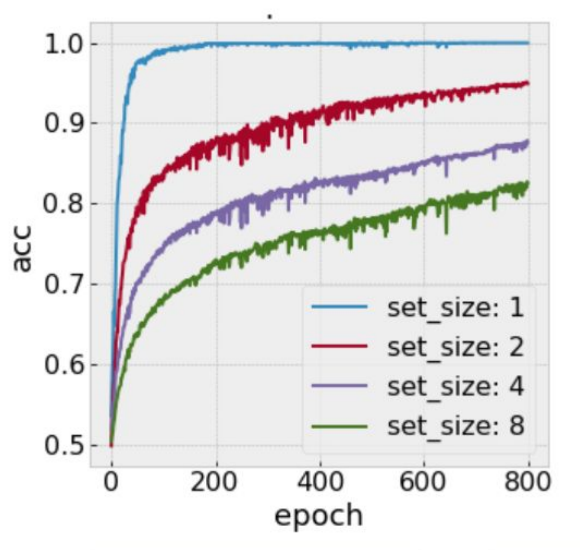
- **but** training histories suggest model has not converged

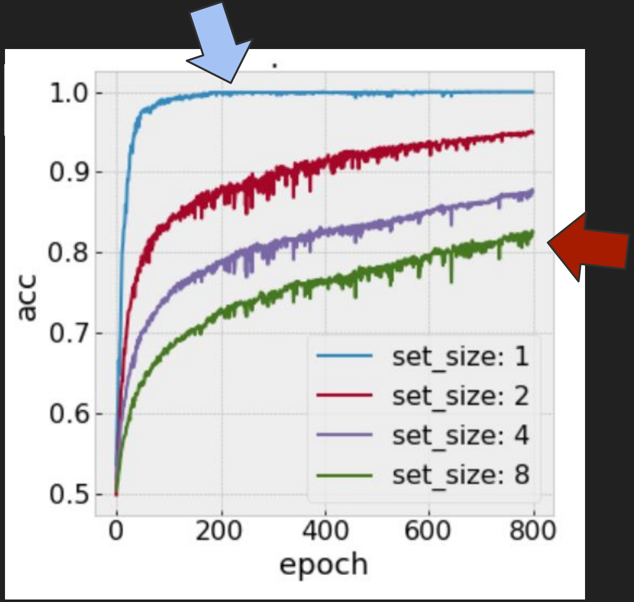


Experiment 1: replicate fine-tuning approach

Results

- notice **different rates of convergence** across set sizes:

  1 > 2 > 4 > 8



Experiment 2: typical learning rate, augment data

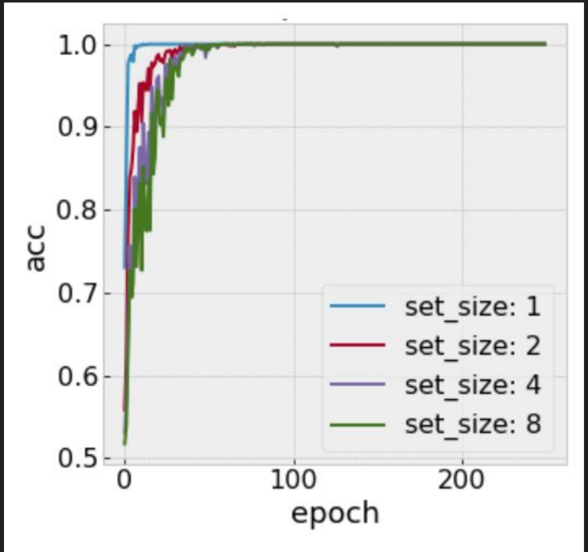
Methods

- train **fully-connected layers** with typical learning rate: `0.001`
- **freeze** weights in other layers pre-trained on ImageNet; no "base" rate
- **increase** number of training examples for larger set sizes

Experiment 2: typical learning rate, augment data

Results

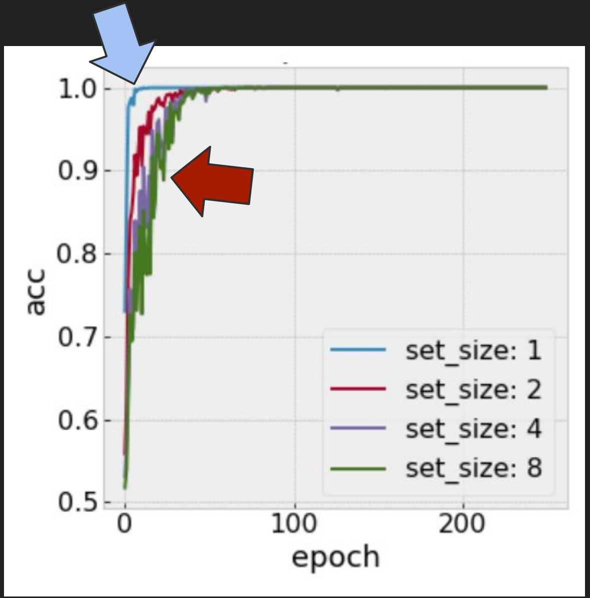
- training histories show that accuracy of models now converge on asymptotic value



Experiment 2: typical learning rate, augment data

Results

- training histories show that accuracy of models now converge on asymptotic value
- but still see different rates of convergence



Experiment 2

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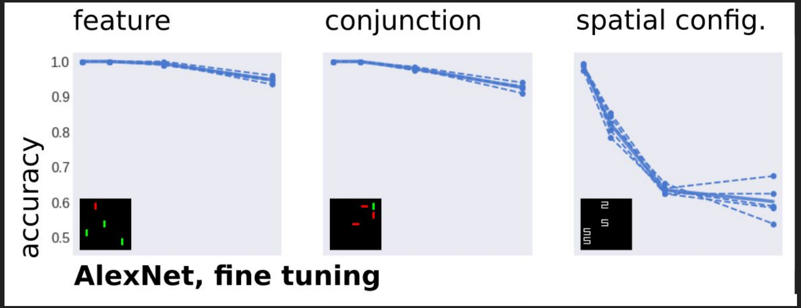

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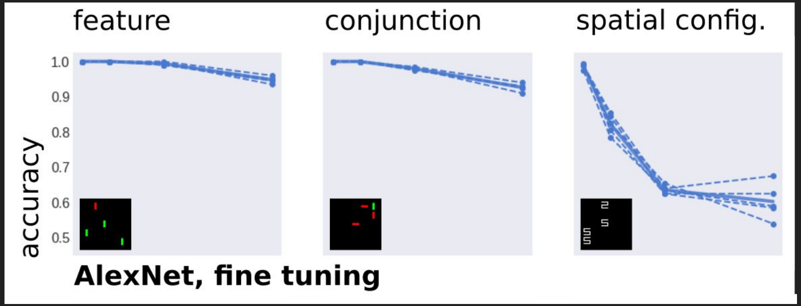
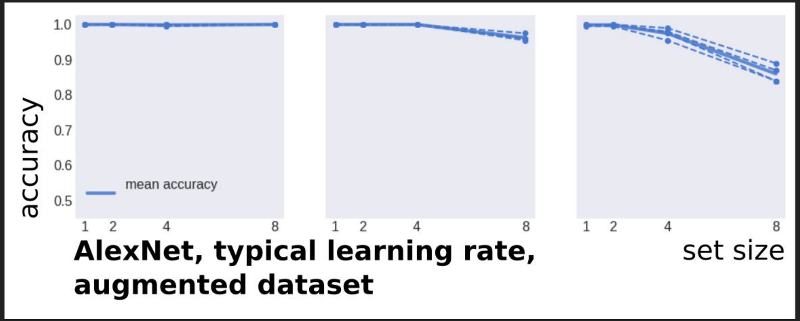
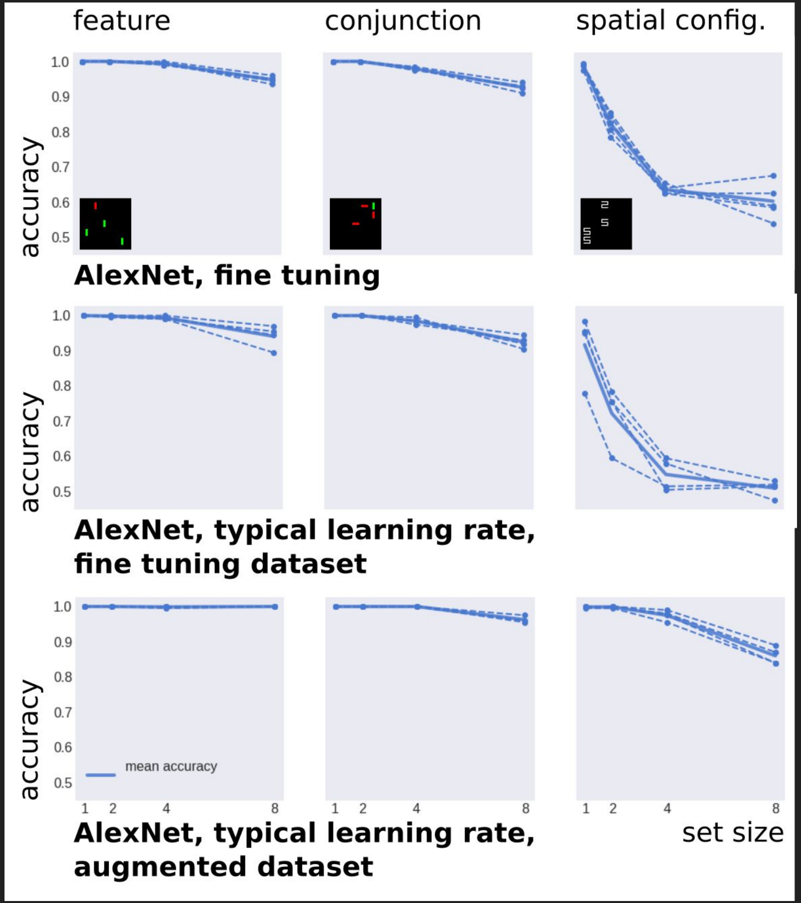




Experiment 2

Results:

- improvement comes from augmented data



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Results:

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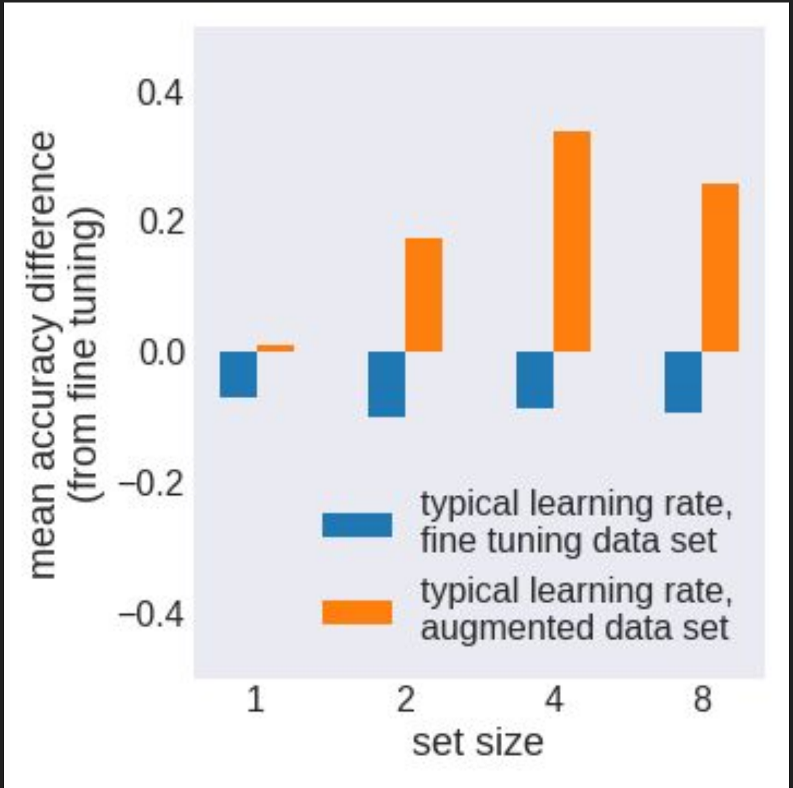


Discussion

implications for artificial intelligence:

- **translational invariance** is still an issue
- possible solutions:
  - spatial transformer networks (Jaderberg 2015)
  - **dynamic routing** with capsules (e.g. Sabour et al. 2017)
- are these mechanisms competitive with just augmenting the dataset?

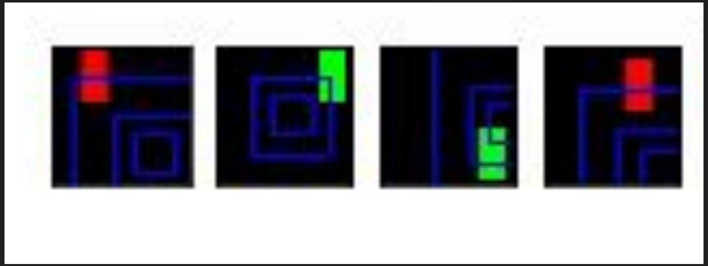
Discussion

Implications for neuroscience

- "training" the visual system may include "augmentation" to induce translational invariance
  - e.g. see just a few objects but from many different perspectives
  - cf. work by Linda Smith et al.
- visual system has other mechanisms to enable translational invariance
  - such as: moving the eyes
- hard to compare behavior of deep learning models with behavior of animals when tasks measure factors that **impair** performance
  - do we have a good model or just bad training?
  - but this is important to do; can't ignore tasks with clear effects

Questions, comments

please check out:
https://github.com/NickleDave/thrillington



https://www.nengo.ai/
https://www.nengo.ai/nengo-dl/

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http://unsupervisedthinkingpodcast.blogspot.com/