Computing Graphical Perception

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Fig. 1. Here is a fish.

Abstract—TODO

Index Terms—Machine Perception, Deep Learning

1 Introduction

Artificial intelligence has taken the world of technology by storm. Deep multilayer neural networks are being successfully applied in a wide range of applications that are regularly outperforming humans in object recognition [13, 20, 21]. Originally inspired by neuroscientific discoveries, the recent advances in deep learning have been the direct results of engineering efforts, more specifically in convolutional neural networks (CNNs). While there has been significant advancement, this does not mean we understand what CNNs are doing and we are in fact treating them as blackboxes without detracting from their success [7, 19]. Our current knowledge of biological vision suggests that modern machine learning models indeed mimic the underlying biology by abstracting the many details of biological neural networks [9, 24].

Despite tremendous research efforts and generating massive datasets, we are far from fully understanding biological vision. Similarly, we are constantly developing inventive features for deep artificial networks without truly understanding it in its entirety. As a result, a double discrepancy is observed. Advances in neuroscience can revolutionize machine learning by reverse-engineering neural circuits, yielding new classifiers which, in turn, can help process the massive biological data. There are many existing questions which must be answered in order to fill this gap of our understanding.

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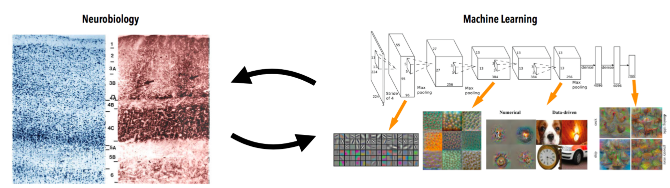

Fig. 2. The Biological Vision (schematic)

We focus on perception... experiments from cleveland mcgill..

1.1 Biological Vision

Biological vision is an extremely powerful system which allows humans the ability, and seemingly without effort, to recognize an enormous amount of distinct objects in the world. Object detection is extremely difficult and therefore is especially impressive as light intensities can change by levels of magnitude and contrast between foreground and background is so often low. In addition, the visual scene changes every time the human body or human eyes move. This visual system exhibits a very noisy structure but because it is organized by layers it has inspired the mathematical theory of multilayer neural networks. What is remarkable is that even though current machine learning models do not resemble the complexity of its biological pendant, they inherently generalize extremely well. Neural networks trained on one specific task can be used to perform detection or segmentation of, seemingly, unrelated objects with relatively minor retraining. The reported classification performance is superior to that of humans and the question in regards to their functionality opens an interesting research topic.

GOALS ...reduce the gap between neurobiology and data science to advance the understanding of visual cortex inspired machine learning

CONTRIBUTIONS

Fig. 3. The Classifiers...

Fig. 5. The Position-Length Experiment

Fig. 4. The Position-Angle Experiment

Fig. 6. The Bars and Framed Rectangles Experiment

- experiments of cleveland mcgill with systematic parametrization and evaluation
- ranking like cleveland mcgill for machine perception?
- many other insights?
- framework

2 Related Work

[3] Clevenland McGill experiments

[10] Heer and Bostock, CHI 2010 — Crowdsourcing Graphical Perception: Using Mechanical Turk to Assess Visualization Design

[22] Comparing linegraph vs. scatterplot

[4] [6] [14] 2D vs. 3D Evaluation (vector fields)

[12] [17] [23] [18] color maps

2d vs. 3d + color [1]

black hat vis [5]

timeseries [11]

munzner [15]

open vs. closed shaped [2]

visualization ranking [8]

Pineo et al. [16] present a method to automatically evaluating and optimizing visualizations using a computational model of human vision, based on a neural network simulation of the early perceptual processing in the retina and primary visual cortex. [JT] Copied from their abstract.

3 Experimental Setup

3.1 Measures

3.2 Classifiers

4 Elementary Perceptual Tasks

THe Figure 1 of Cleveland McGill

4.1 Parametrization

Here we show each of Figure 1 with its parametrization.

5 Position-Angle Experiment

This is pie chart vs bar chart

6 Position-Length Experiment

This is the one where we estimate two selected bars compared to the longest one

7 Bars and Framed Rectangles Experiment

7.1 Weber's Law

8 Results and Discussion

Cleveland McGills Ranking - can we observe something similar?

1. Position along a common scale e.g. scatter plot
2. Position on identical but nonaligned scales e.g. multiple scatter plots
3. Length e.g. bar chart
4.Angle & Slope (tie) e.g. pie chart
5. Area e.g. bubbles
6. Volume, density, and color saturation (tie) e.g. heatmap
7. Color hue e.g. newsmap

9 Conclusions

Future work: allow insights for infovis for machines

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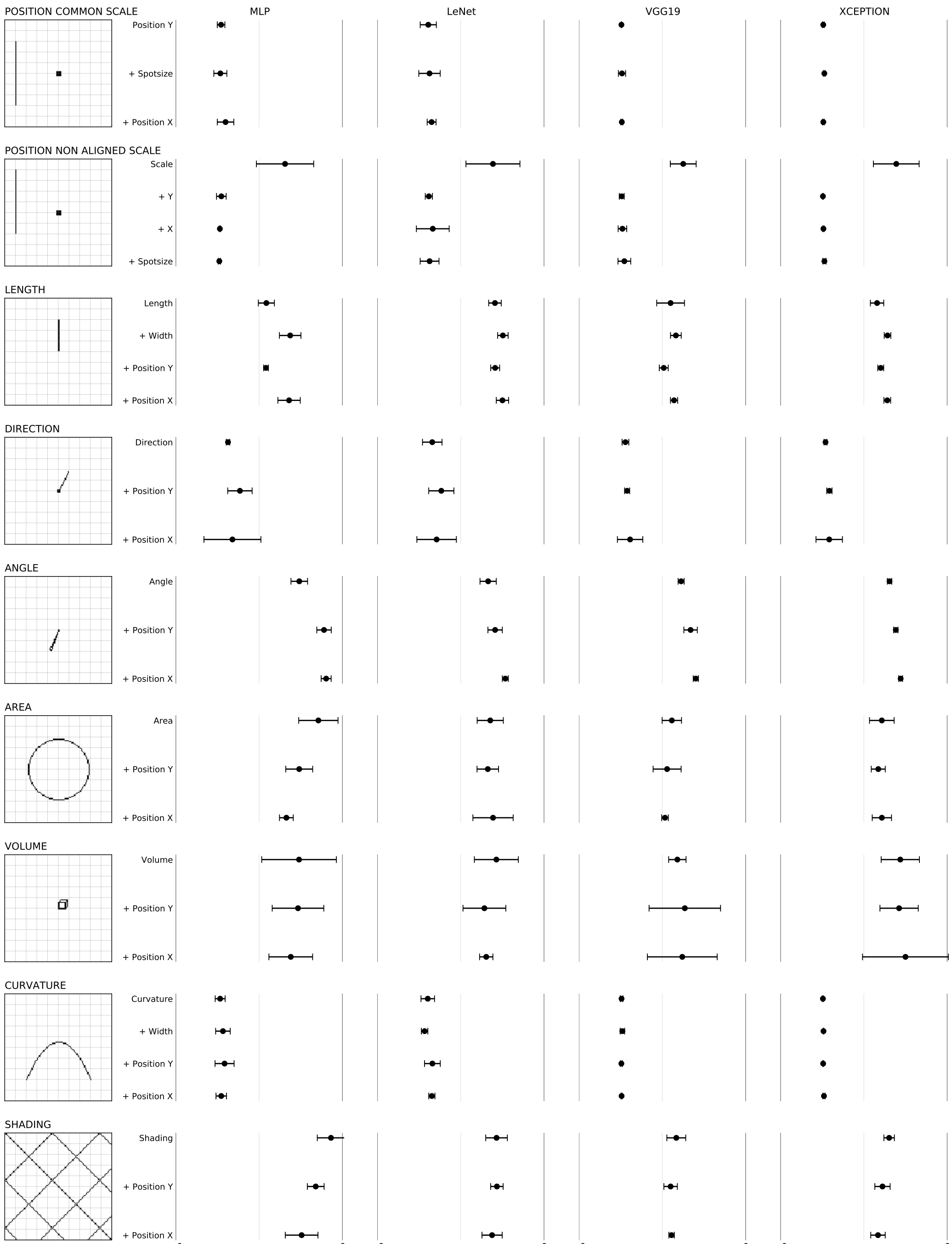

Fig. 7. The Bars and Framed Rectangles Experiment