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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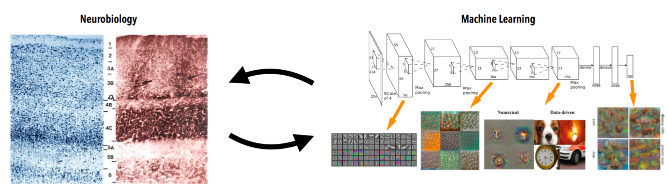

Fig. 2. The Biological Vision (schematic)

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

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

2 Previous Work

Graphical Perception. Cleveland and McGill [3] introduced the concept of *graphical perception* and investigated how different visual attributes and encodings are perceivable by humans. They define *elementary perceptual tasks* as mental-visual stimuli to understand encodings in visualizations.

[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]

Visual Cortex Inspired Machine Learning. LeNet etc and work from THomas Serre

Computing Perception.

Pineo et al. [16] present a method to automatically evaluate and optimize 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

The experiments shown in this paper are either regression or classification tasks. We formulate any estimation of quantities (e.g. angles, positions, lengths etc.) as a regression problem between 0 and 1. The output indicates the percentage in regards to the degrees of freedom of the individual experiment. If the experiment involves a choice, we formulate it as a classification problem.

3.1 Measures

Accuracy. We use the same metric as Cleveland McGill to measure accuracy.

$$\log_2(|\text{predicted percent} - \text{true percent}| + .125) \tag{1}$$

Efficiency. We use the convergence rate based on the decrease of loss per training epoch as an indicator for the efficiency of the classifier in combination with a visual encoding. For regression tasks the loss is defined as mean squared error (MSE) and for classification tasks the loss is categorical cross-entropy.

3.2 Classifiers

Our classifiers are built upon a multilayer perceptron (MLP) which is a feedforward artificial neural network. We combine this MLP with different convolutional neural networks (CNNs) for preprocessing and feature generation. These include the traditional LeNet trained from scratch, as well as VGG19 and Xception trained using ImageNet.

Multilayer Perceptron. The multilayer perceptron in this paper has 256 neurons which are activated as rectified linear units (Fig. 3). We then add a dropout layer to prevent overfitting and compute linear regression or classification (softmax).

Convolutional Neural Networks. We use CNNs to generate additional features as input to the MLP. We train the *LeNet* classifier with tune it specifically towards each visualization. For *VGG19* and *Xception*, we generate features using previously trained weights on ImageNet.

Table 1. We use different feature generators as input to a multilayer perceptron which performs linear regression or the classification task. This yields different sets of trainable parameters. We also train the MLP directly on the visualizations without any additional feature generation.

Classifier	Trainable Parameters	Optimization
MLP	2,560,513	SGD (Nesterov momentum)
LeNet + MLP	8,026,083	Learning rate: 0.0001
VGG19 + MLP	21,204,545	Momentum: 0.9
Xception + MLP	25,580,585	Batchsize: 32
		Epochs: 1000 (Early Stopping)

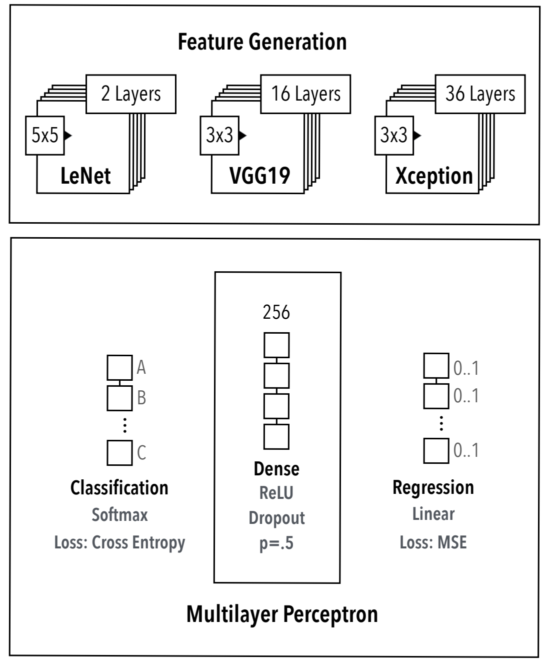

Fig. 3. The multilayer perceptron (MLP) in our experiments has 256 neurons which are activated as rectified linear units (ReLU). We use Dropout regularization to prevent overfitting. We learn categorical and unordered dependent variables using the softmax function and perform linear regression for continuous variables. The MLP can learn the visualizations directly but we also learn features generated by LeNet (2 conv. layers, filter size 5), VGG19 trained on ImageNet (16 conv. layers, filter size 3×3), or Xception trained on ImageNet (36 conv. layers, filter size 3×3) to increase the number of trainable parameters.

Optimization. All networks are optimized using stochastic gradient descent with Nesterov momentum using fixed parameters (Table 1). We train for 1000 epochs but stop early if the loss does not decrease for ten epochs.

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

Fig. 4. The Position-Angle Experiment

Fig. 5. The Position-Length Experiment

Fig. 6. The Bars and Framed Rectangles Experiment

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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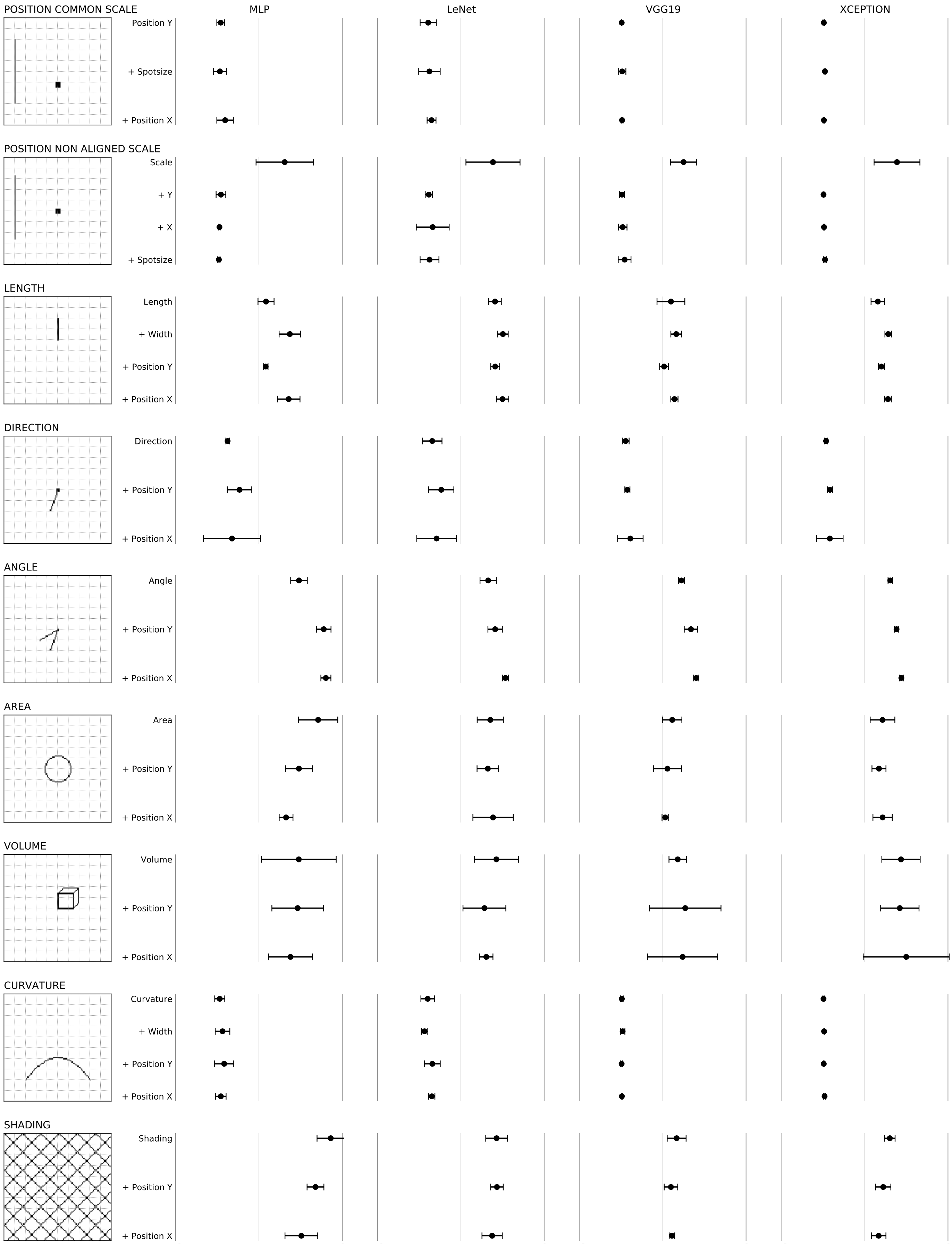

Fig. 7. Log absolute error means and 95% confidence intervals for computed perception of different classifiers on the *elementary perceptual tasks* introduced by Cleveland and McGill 1984 [3]. We test the performance of a Multi-layer Perceptron (MLP), the LeNet Convolutional Neural Network, as well as feature generation using the VGG19 and Xception networks trained on ImageNet.

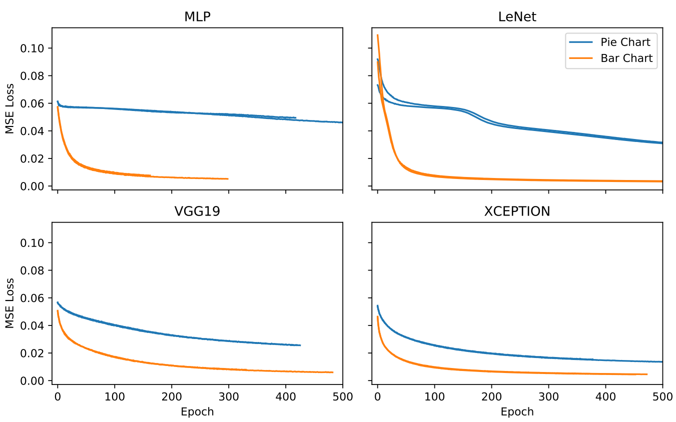

Fig. 8. Mean Square Error (MSE) loss for the *position-angle experiment* as described by Cleveland and McGill [3] which compares the visualization of pie charts and bar charts. We report the MSE measure for both encodings of four different classifier on previously unseen validation data.

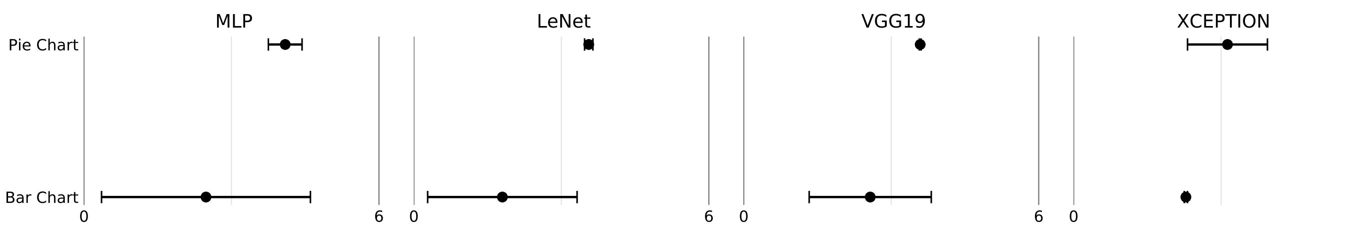

Fig. 9. Log absolute error means and 95% confidence intervals for the *position-angle experiment* as described by Cleveland and McGill [3]. We test the performance of a Multi-layer Perceptron (MLP), the LeNet Convolutional Neural Network, as well as feature generation using the VGG19 and Xception networks trained on ImageNet.