

# Visualization for Machine Perception

Daniel Haehn, *Member, IEEE*, James Tompkin, and Hanspeter Pfister



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.

- Daniel Haehn, and Hanspeter Pfister are with the Paulson School of Engineering and Applied Sciences at Harvard University.  
E-mail: {haehn,pfister}@seas.harvard.edu.
- James Tompkin is with the Thomas J. Watson Sr. Center for Information Technology at Brown University.  
E-mail: james\_tompkin@brown.edu.

Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org.  
Digital Object Identifier: xx.xxx/TVCG.201x.xxxxxxx

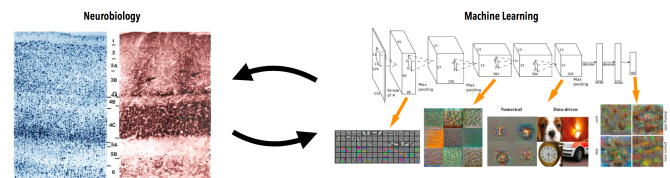


Fig. 2. The Biological Vision (schematic)

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] Cleveland 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

## REFERENCES

- [1] M. Borkin, K. Gajos, A. Peters, D. Mitsouras, S. Melchionna, F. Rybicki, C. Feldman, and H. Pfister. Evaluation of artery visualizations for heart disease diagnosis. *IEEE transactions on visualization and computer graphics*, 17(12):2479–2488, 2011.
- [2] D. Burlinson, K. Subramanian, and P. Goolkasian. Open vs. closed shapes: New perceptual categories? *IEEE Transactions on Visualization and Computer Graphics*, 24(1):574–583, Jan 2018. doi: 10.1109/TVCG.2017.2745086
- [3] W. S. Cleveland and R. McGill. Graphical perception: Theory, experimentation, and application to the development of graphical methods. *Journal of the American statistical association*, 79(387):531–554, 1984.
- [4] A. Cockburn and B. McKenzie. Evaluating the effectiveness of spatial memory in 2d and 3d physical and virtual environments. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '02, pp. 203–210. ACM, New York, NY, USA, 2002. doi: 10.1145/503376.503413
- [5] M. Correll and J. Heer. Black hat visualization. In *Workshop on Dealing with Cognitive Biases in Visualisations (DECISive)*, IEEE VIS, 2017.
- [6] A. Forsberg, J. Chen, and D. Laidlaw. Comparing 3d vector field visualization methods: A user study. *IEEE Transactions on Visualization and Computer Graphics*, 15(6), 2009.
- [7] I. Goodfellow, Y. Bengio, and A. Courville. *Deep Learning*. MIT Press, 2016. <http://www.deeplearningbook.org>.

- [8] L. Harrison, F. Yang, S. Franconeri, and R. Chang. Ranking visualizations of correlation using weber's law. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):1943–1952, Dec 2014. doi: 10.1109/TVCG.2014.2346979
- [9] D. Hassabis, D. Kumaran, C. Summerfield, and M. Botvinick. Neuroscience-inspired artificial intelligence. *Neuron*, 95(2):245–258, 2017.
- [10] J. Heer and M. Bostock. Crowdsourcing graphical perception: using mechanical turk to assess visualization design. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pp. 203–212. ACM, 2010.
- [11] J. Heer, N. Kong, and M. Agrawala. Sizing the horizon: The effects of chart size and layering on the graphical perception of time series visualizations. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '09, pp. 1303–1312. ACM, New York, NY, USA, 2009. doi: 10.1145/1518701.1518897
- [12] G. Kindlmann, E. Reinhard, and S. Creem. Face-based luminance matching for perceptual colormap generation. In *Proceedings of the Conference on Visualization '02*, VIS '02, pp. 299–306. IEEE Computer Society, Washington, DC, USA, 2002.
- [13] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, eds., *Advances in Neural Information Processing Systems 25*, pp. 1097–1105. Curran Associates, Inc., 2012.
- [14] D. H. Laidlaw, R. M. Kirby, C. D. Jackson, J. S. Davidson, T. S. Miller, M. da Silva, W. H. Warren, and M. J. Tarr. Comparing 2d vector field visualization methods: a user study. *IEEE Transactions on Visualization and Computer Graphics*, 11(1):59–70, Jan 2005. doi: 10.1109/TVCG.2005.4
- [15] T. Munzner. *Visualization Analysis and Design*. AK Peters Visualization Series. CRC Press, 2015.
- [16] D. Pineo and C. Ware. Data visualization optimization via computational modeling of perception. *IEEE Transactions on Visualization and Computer Graphics*, 18(2):309–320, Feb 2012. doi: 10.1109/TVCG.2011.52
- [17] P. Rheingans. Color, change, and control of quantitative data display. In *Visualization, 1992. Visualization'92, Proceedings., IEEE Conference on*, pp. 252–259. IEEE, 1992.
- [18] B. E. Rogowitz and A. D. Kalvin. The "which blair project": a quick visual method for evaluating perceptual color maps. *Proceedings Visualization, 2001. VIS '01.*, pp. 183–556, 2001.
- [19] R. Shwartz-Ziv and N. Tishby. Opening the black box of deep neural networks via information. *CoRR*, abs/1703.00810, 2017.
- [20] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.
- [21] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. Rethinking the inception architecture for computer vision. *CoRR*, abs/1512.00567, 2015.
- [22] Y. Wang, F. Han, L. Zhu, O. Deussen, and B. Chen. Line graph or scatter plot? automatic selection of methods for visualizing trends in time series. *IEEE Transactions on Visualization and Computer Graphics*, 24(2):1141–1154, Feb 2018. doi: 10.1109/TVCG.2017.2653106
- [23] C. Ware. Color sequences for univariate maps: Theory, experiments and principles. *IEEE Computer Graphics and Applications*, 8(5):41–49, 1988.
- [24] D. L. Yamins and J. J. DiCarlo. Using goal-driven deep learning models to understand sensory cortex. *Nature neuroscience*, 19(3):356, 2016.