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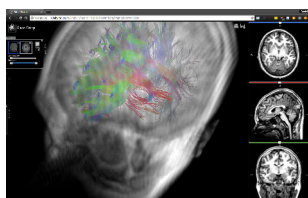**Video summary of my research**: https://danielhaehn.com/research.mp4

Research Statement

Artificial intelligence is loosely inspired by neuroscientific discoveries. However, existing methods are fragile and do not generalize well. In contrast, the brain allows humans to reliably recognize, extrapolate, and classify enormous amounts of stimuli–seemingly without effort. This difference in performance is likely the result of limited architectural correspondences between neurobiology and machine learning. With advances in computer science, my goal is *to reduce the gap between natural and artificial intelligence*: First, with bottom-up investigations for how visual computing methods can aid brain connectivity analysis, and in turn, how neurobiological insights can improve machine intelligence. Second, exploring top-down how perceptual studies can increase the comprehension of machine learning models, along with how explanatory analysis can lead to better applications of these algorithms.
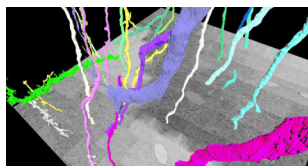
Analyzing Brain Connectivity

Connectivity analysis at different scales aims to demystify how the brain works. Macro-scale investigations focus on connections at the brain area level while micro-scale studies analyze neuronal connectivity at the synapse level. For both scales, I create visual computing methods to accelerate neuroscience research.

Macro-scale. Structural and functional magnetic resonance imaging paired with diffusion tensor imaging allows for connectivity analysis at (sub-)millimeter resolution. A variety of data formats, different radiological conventions, and the need for rapid analysis and diagnostics require visualization and processing methods that are fast, reliable, and collaborative. I designed XTK, the first neuroimaging framework for visualizing, interacting, and processing medical imaging data in the web browser. Building off this platform, my front-end application Slice:Drop provides a web-based graphical experience in 2D/3D comparable to traditional radiology workstations. My application enables real-time rendering and the sharing of standard medical data formats across multiple devices. This work has won several awards and contributed to medical advancement in brain development research. [Front. in Neuroinformatics 2012; SIGGRAPH Real-time Live! 2013; Cerebral Cortex 2012, 2015]

Micro-scale. In connectomics, modern electron microscopes produce petabyte volumes of brain images at nanometer resolution. The typical processing pipeline includes image acquisition, 3D volume registration, membrane segmentation of neurons, proofreading of labeling errors, and network graph analysis. Each step of this workflow requires automatic computing methods to handle vast amounts of data. Additionally, each step requires specialized visualization techniques to allow human verification. I created BUTTERFLY, a scalable platform for interactive web-based visualization and processing for every step of the connectomics pipeline. This platform
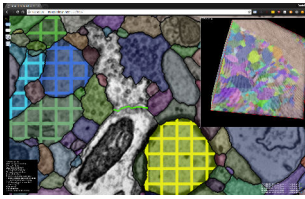

Slice:Drop visualizes MRI data in the web browser using volume rendering.

The twenty largest neurons in a 100µm cube of rat cortex processed with BUTTERFLY.
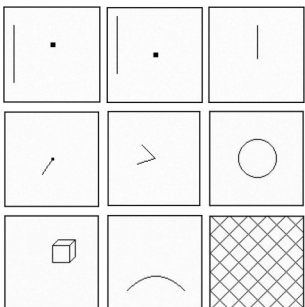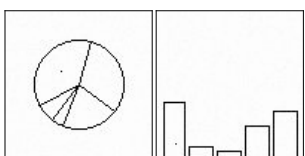
Web-based Dojo allows interactive proofreading of automatic neuron segmentations by multiple users in parallel.
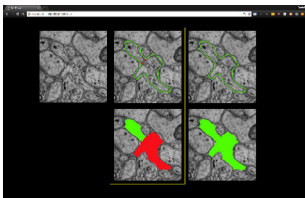
The Guided Proofreading system reduces error correction of segmentations to yes/no decisions by leveraging machine learning.

Convolutional neural networks are able to estimate elementary visual encodings but fail when slight variations are introduced.

Human perceptual capabilities favor bar charts over pie charts, which is also true for current artificial neural networks.

interfaces with Dojo, my web-based visual proofreading software, which allows novice users to interactively find and correct errors in automatic neuron segmentations. Further research then identified the visual search for these errors as the bottleneck for interactive corrections. Thus, I developed the Guided Proofreading system: a machine learning algorithm that automatically finds and recommends potential segmentation errors to the user. Corrections can then be performed with yes/no decisions which make it easier for both novices and experts to proofread successfully. Therefore, this reduces search and error correction times and allows faster generation of ground truth label data. [IEEE Vis 2014, 2016; Microscopy and Microanalysis 2016; MDPI Informatics 2017; CVPR 2018]

Future work. Neurobiological datasets will further increase in size, demanding improved automatic processing methods. However, such methods require large amounts of training data through expensive manual labeling. I aim to reduce this cost with active learning and semi-supervised methods. Yet, even with less manual labor, significant computational challenges remain, leaving the need for novel computer vision, visualization, and interaction methods to better understand neural connectivity and pathologies. Advancements here will allow us to better reverse-engineer neural circuits, yielding new artificial intelligence that, in turn, can improve the automatic processing of biological data.

Computing Machine Perception

Artificial neural networks have been successfully applied to a wide range of visual tasks but struggle to generalize when slight variations are introduced. For instance, I observed that convolutional neural networks (CNNs) are able to predict the length of an ordinary line with great precision but struggle if the width of the line is slightly varied across testing stimuli. This experiment is part of a series of questions I explore with modern neural networks by replicating Cleveland and McGill's seminal 1984 studies of human perception. In this work, I train neural networks to estimate elementary perceptual encodings including angles, curvature, volumes, and textures. I also compare machines against humans when measuring perceptual capabilities of more complex visualizations such as pie charts, bar charts, and point clouds. While under limited circumstances CNNs are able to meet or outperform human task performance, I have found that modern architectures do not match human graphical perception capabilities. [IEEE Vis 2018]

Future work. Systems for machine perception eventually need to be capable of abstraction and reasoning rather than applying memorization and interpolation. Promising approaches are capsule networks that include compartments for learning different visual attributes and the recent CORnet framework that replicates the ventral visual pathway. I aim to continue the systematic evaluation of existing and future neural network architectures to model human graphical perception. This requires artificial intelligence that is designed closer to its natural counterpart. Progress in neurobiology, hand in hand with machine perception research, is necessary to reach this goal.