Caminhos Cruzados Entre Visão Computacional e Visão Biológica

Ricardo Marroquim

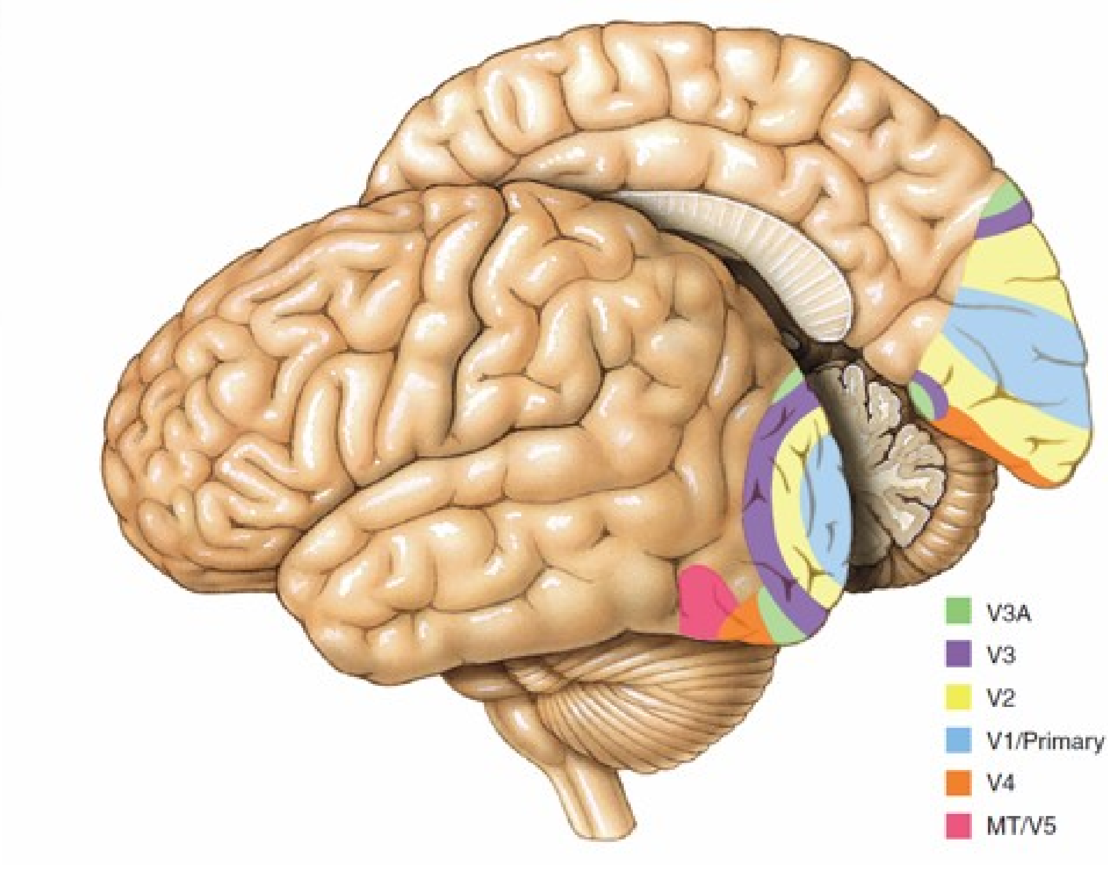
www.lcg.ufrj.br/marroquim

Laboratório de Computação Gráfica

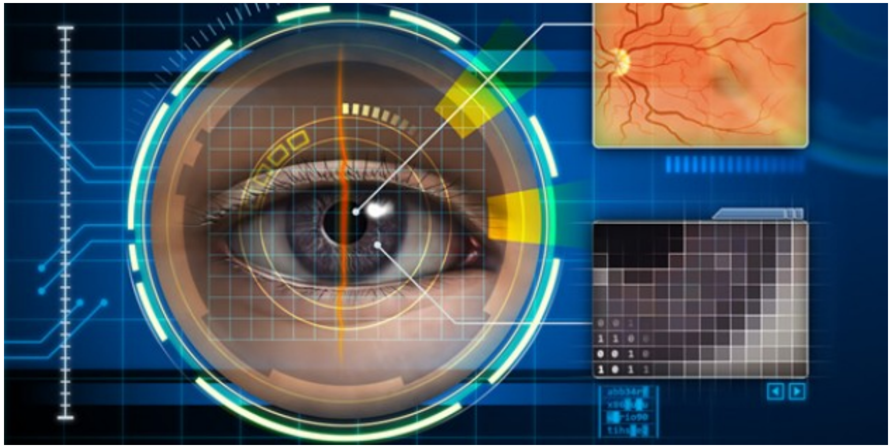
PESC
Programa de Engenharia de Sistemas e Computação

Cefet/RJ – V Workshop da Escola de Informática & Computação – 26 outubro 2017

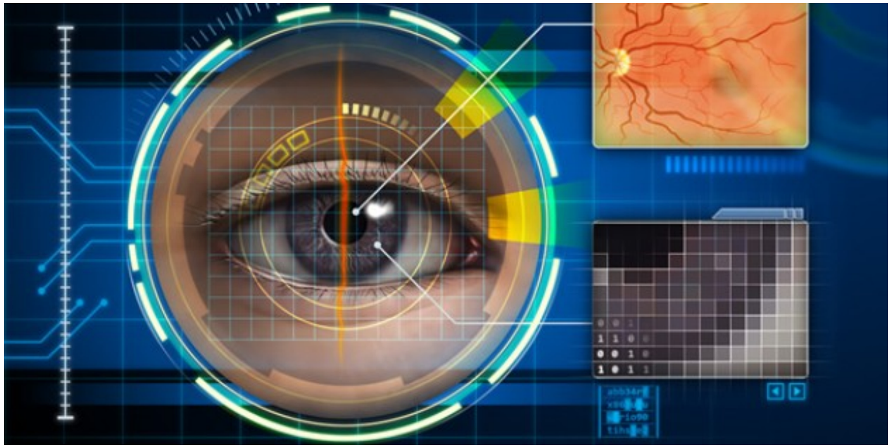
how do we see?

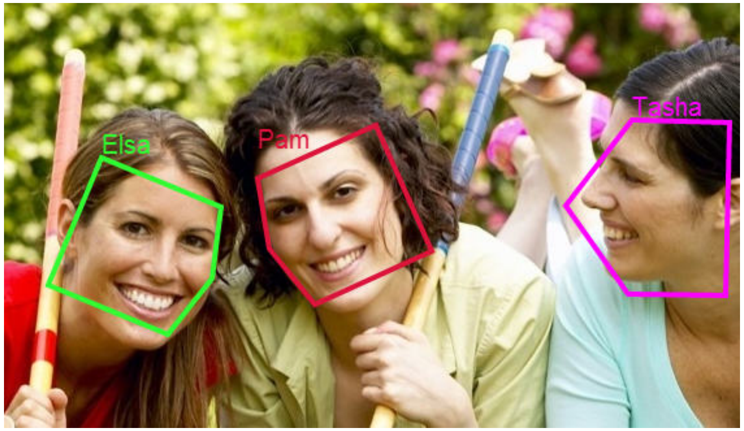


how computers see?

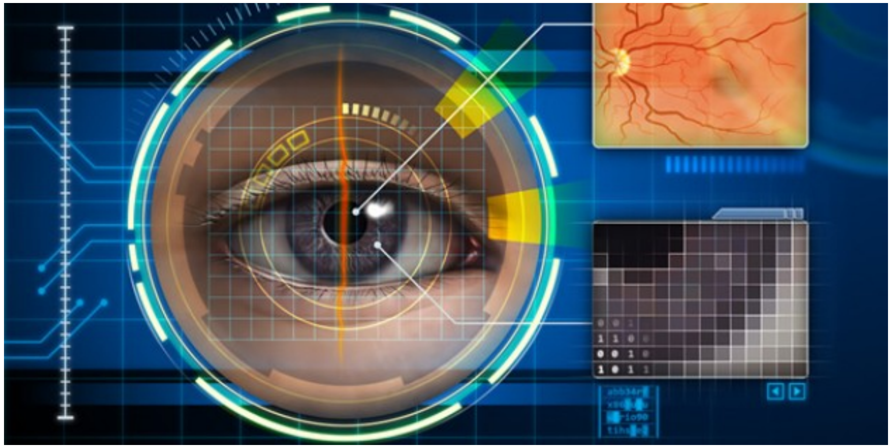


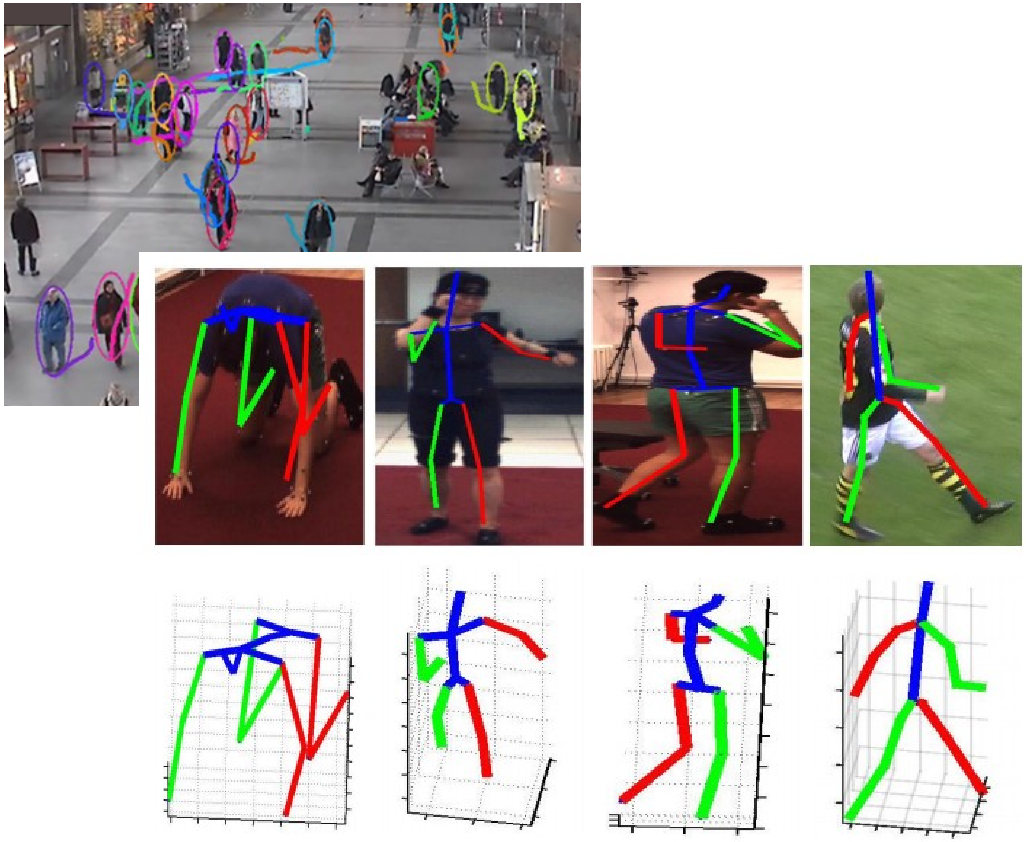
computer vision

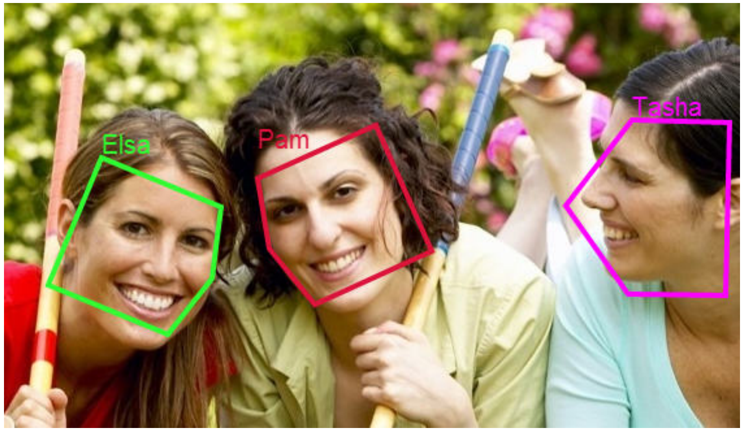




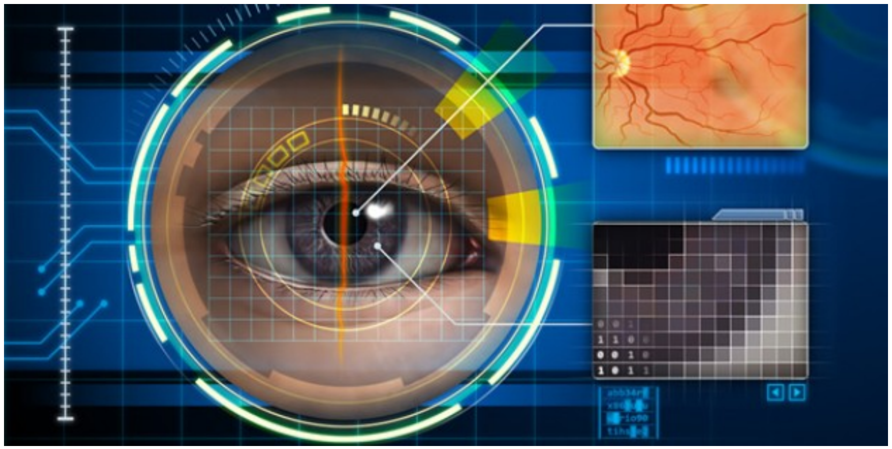
computer vision

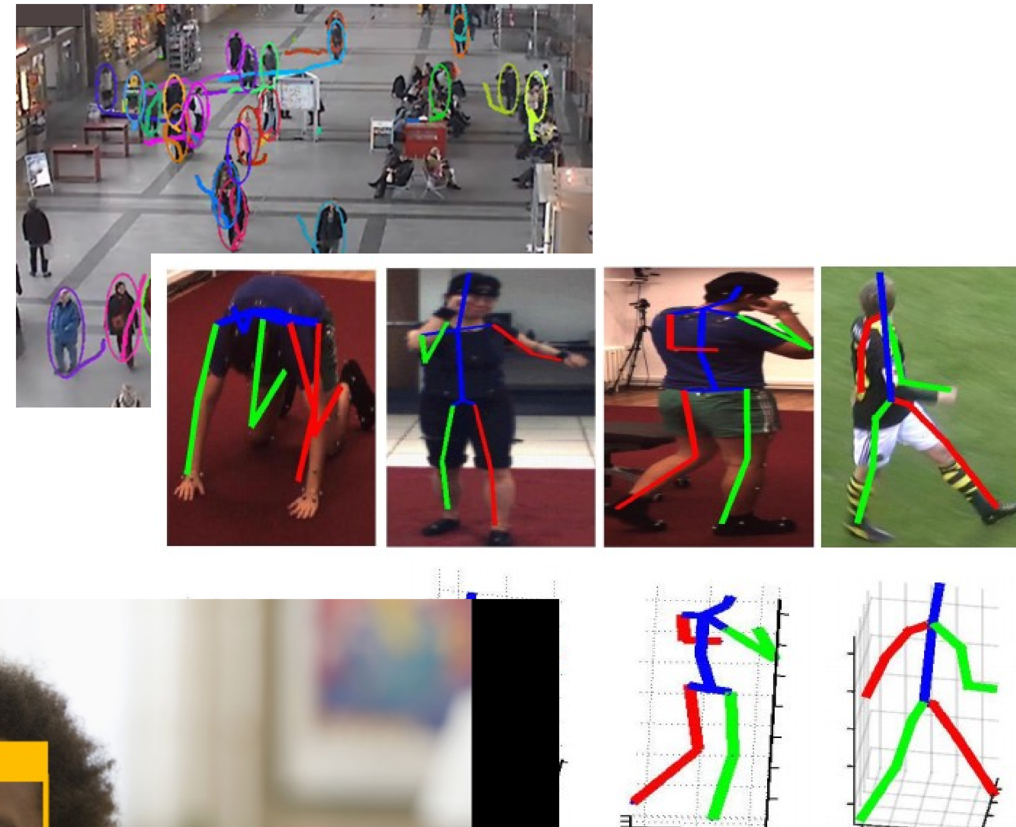


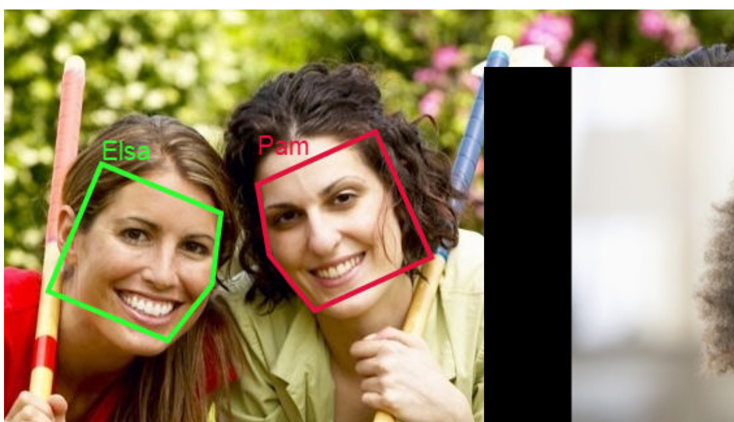


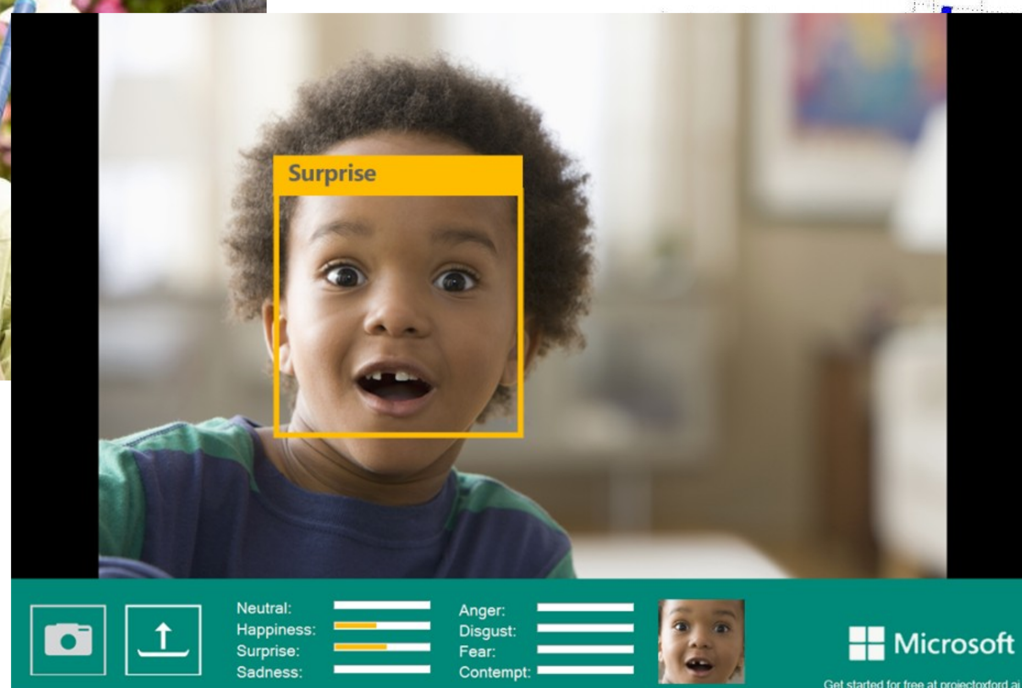


computer vision

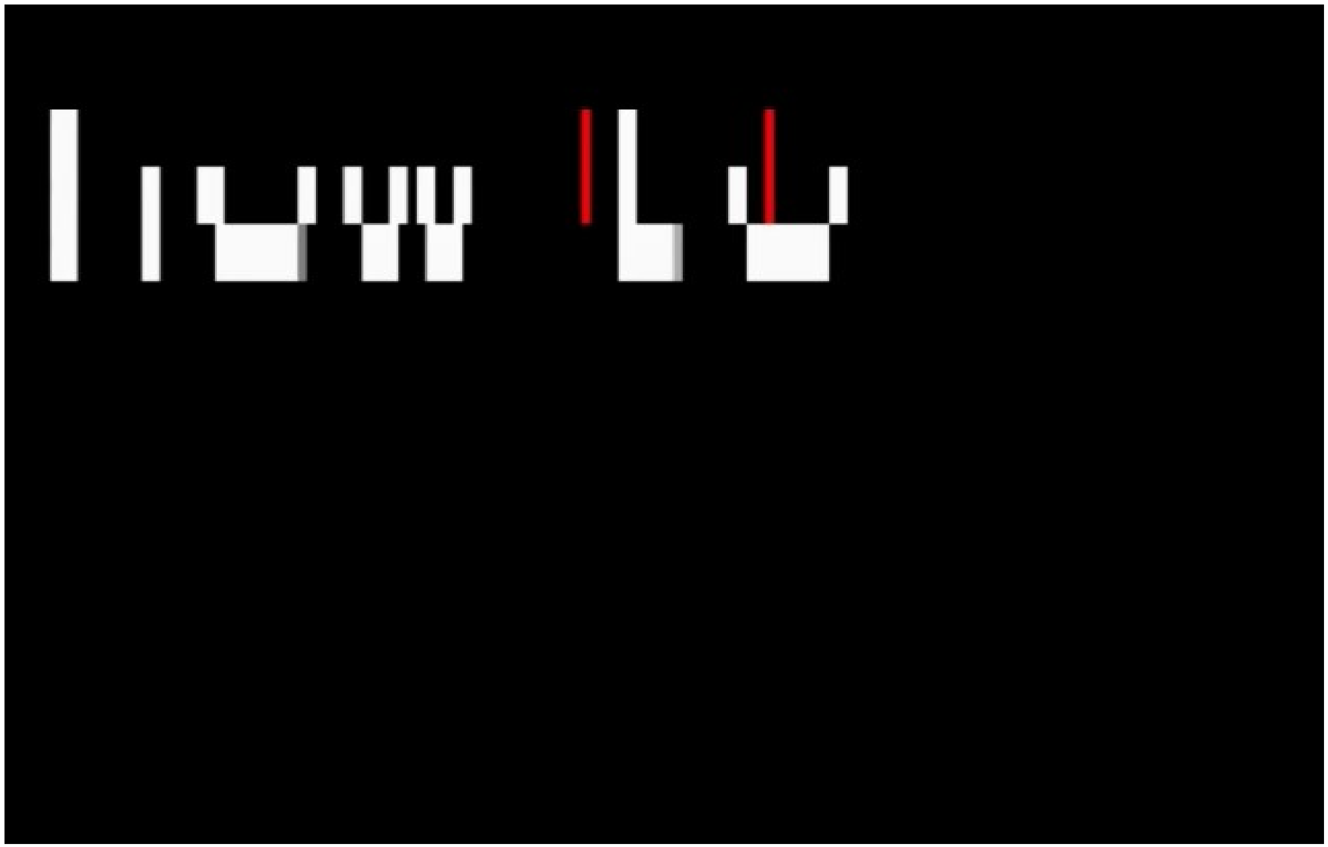






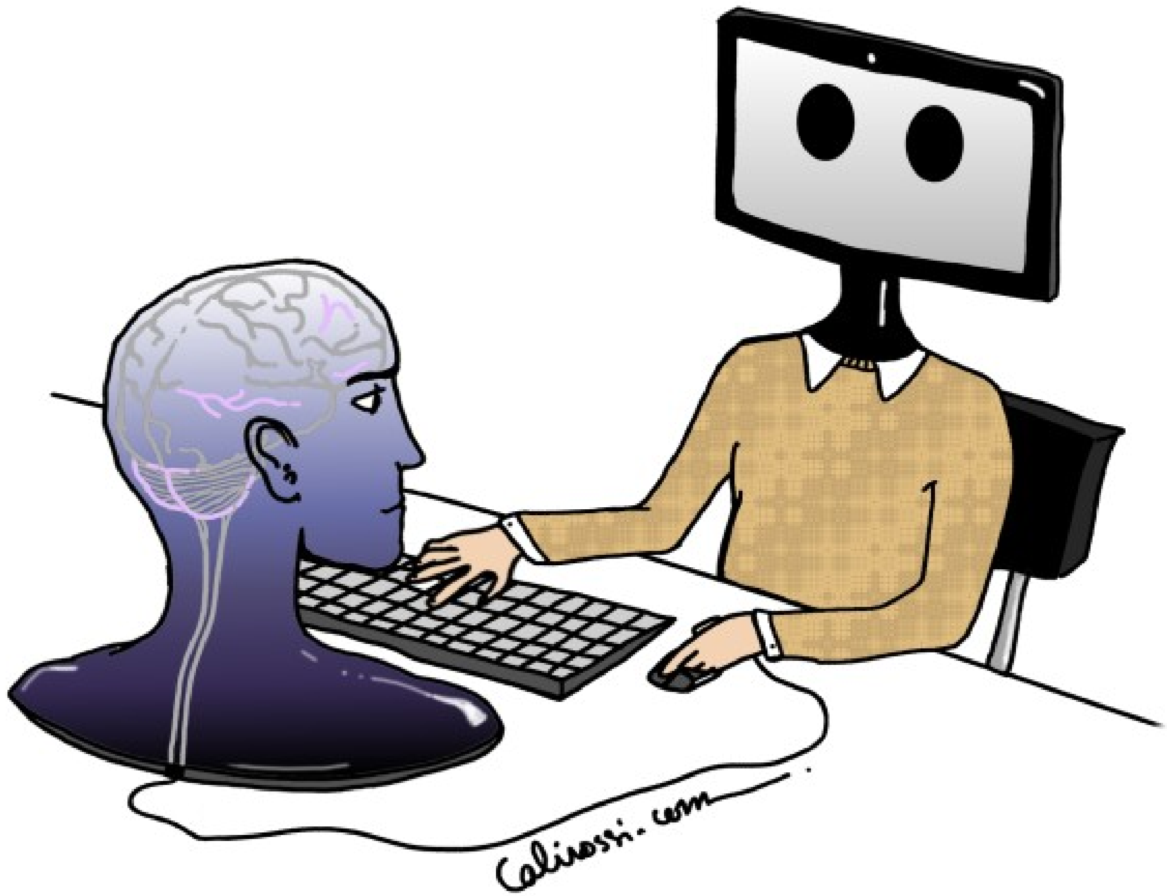


computer vision



https://www.youtube.com/watch?v=eQLcDmfmGB0

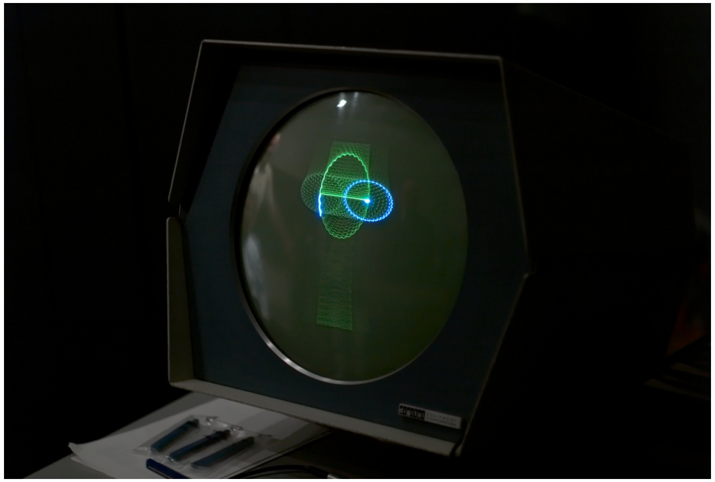
humans vs computers

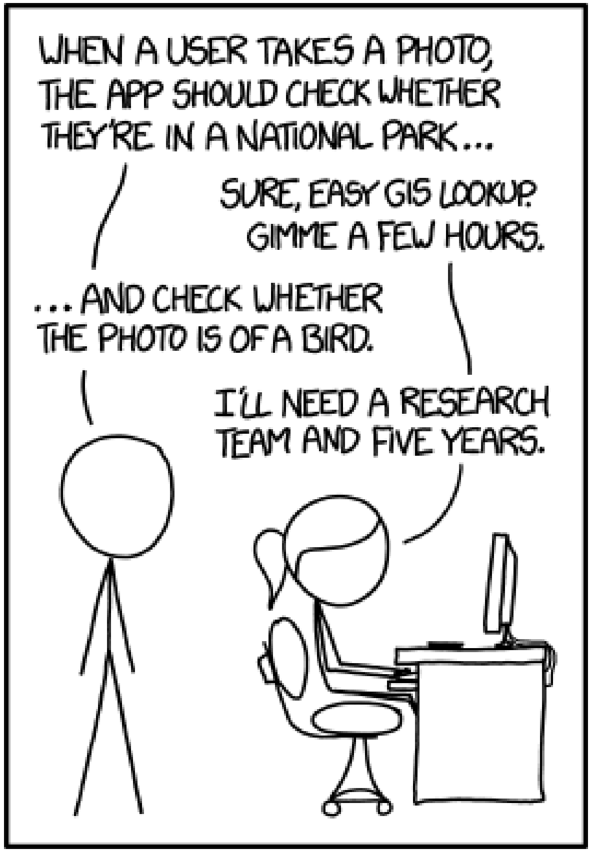


http://benedicterossi.com/

Marvin Minsky

- pioneer: Perceptrons, Logo turtle, Head-mounted display …
- 1969: Turing Award

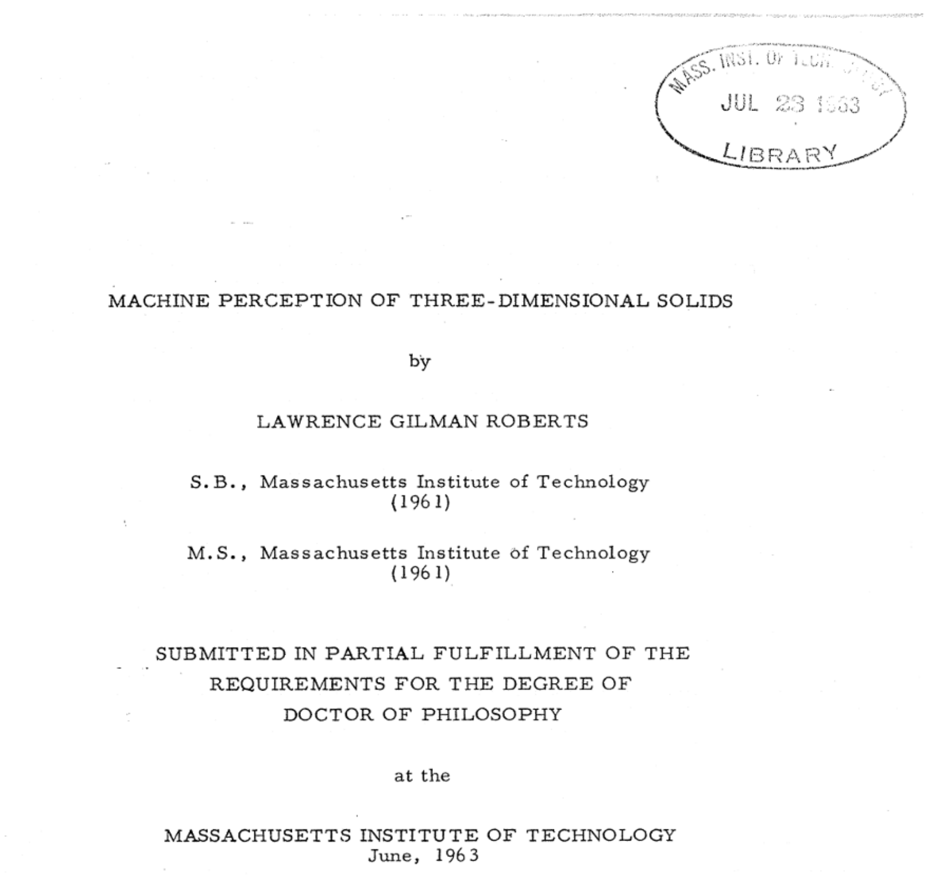




IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

Larry Roberts

- 1963 - PhD Thesis: Machine Perception of Three-Dimensional Solids



MACHINE PERCEPTION OF THREE-DIMENSIONAL SOLIDS

by

LAWRENCE GILMAN ROBERTS

S.B., Massachusetts Institute of Technology
(1961)

M.S., Massachusetts Institute of Technology
(1961)

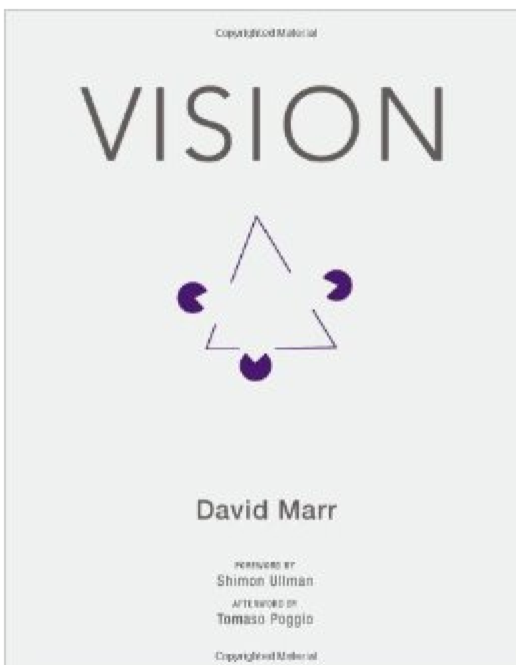
SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

at the

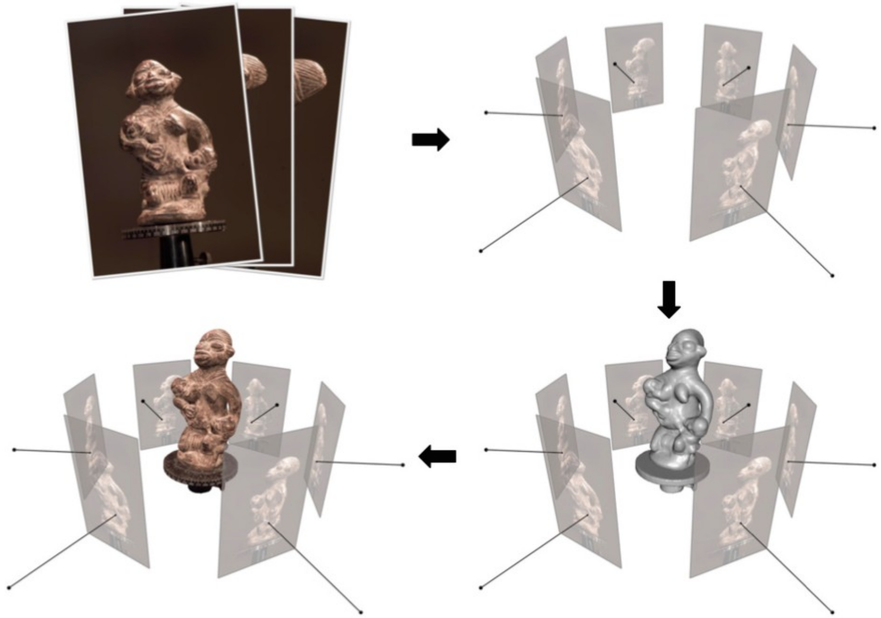
MASSACHUSETTS INSTITUTE OF TECHNOLOGY
June, 1963

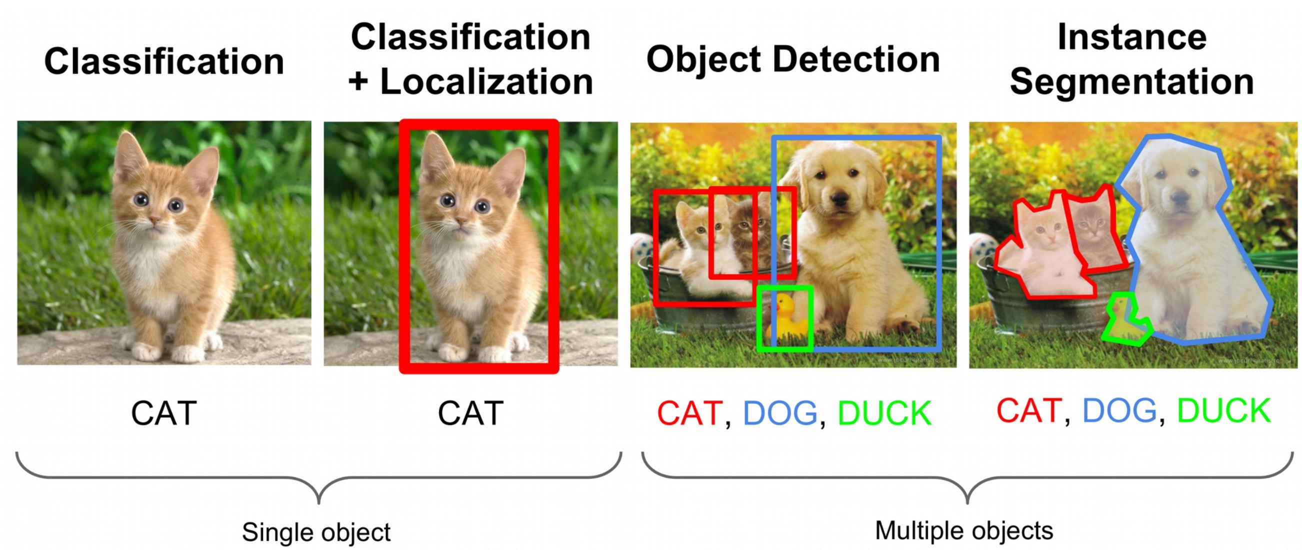
David Marr

- 1982 - David Marr - Vision: A Computational Investigation into the Human Representation and Processing of Visual Information

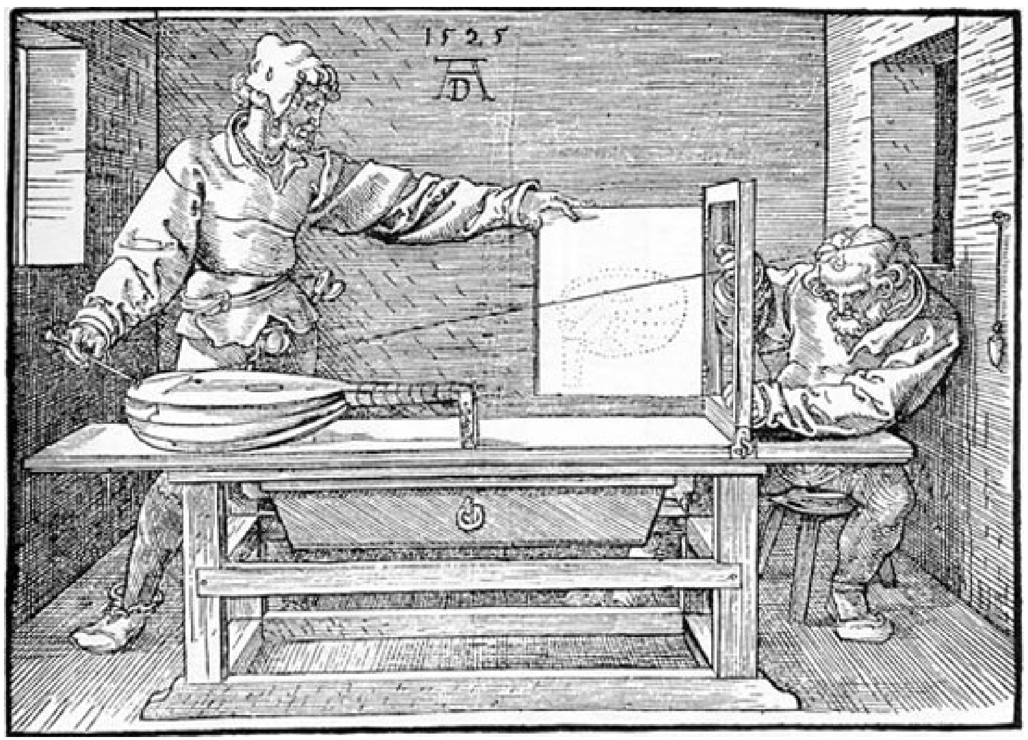


computer vision





projective geometry



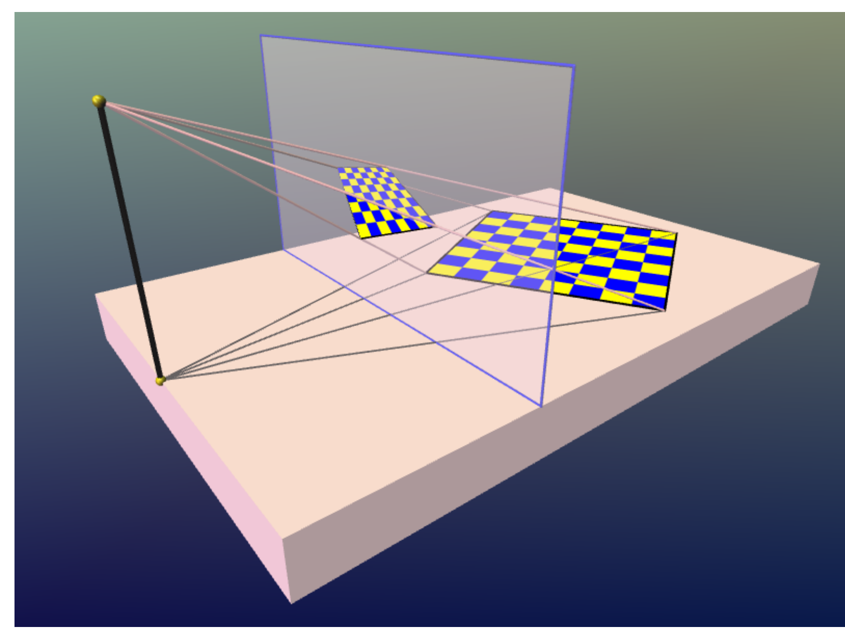
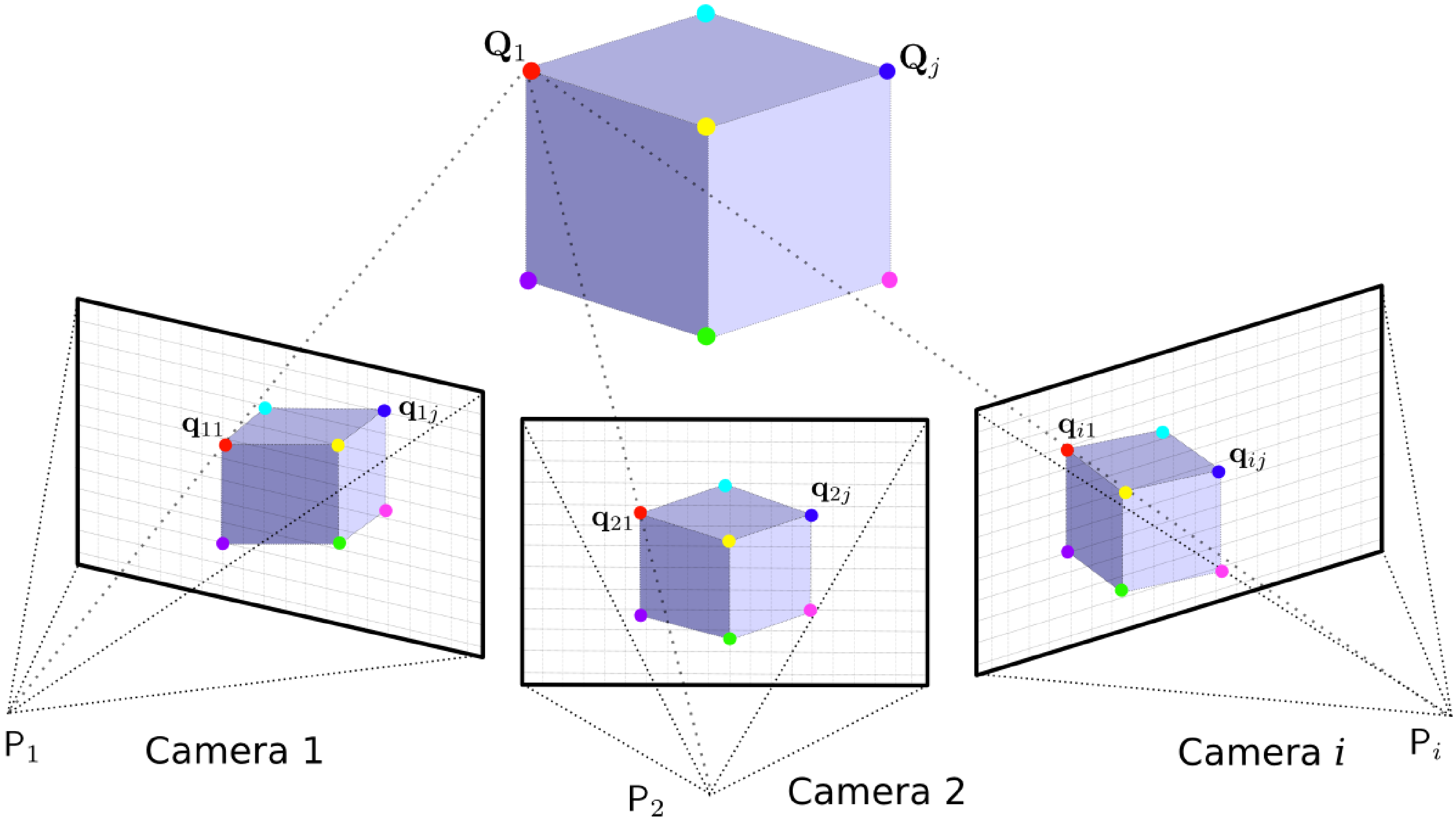


photo pop-up

http://dhoiem.cs.illinois.edu/projects/popup/

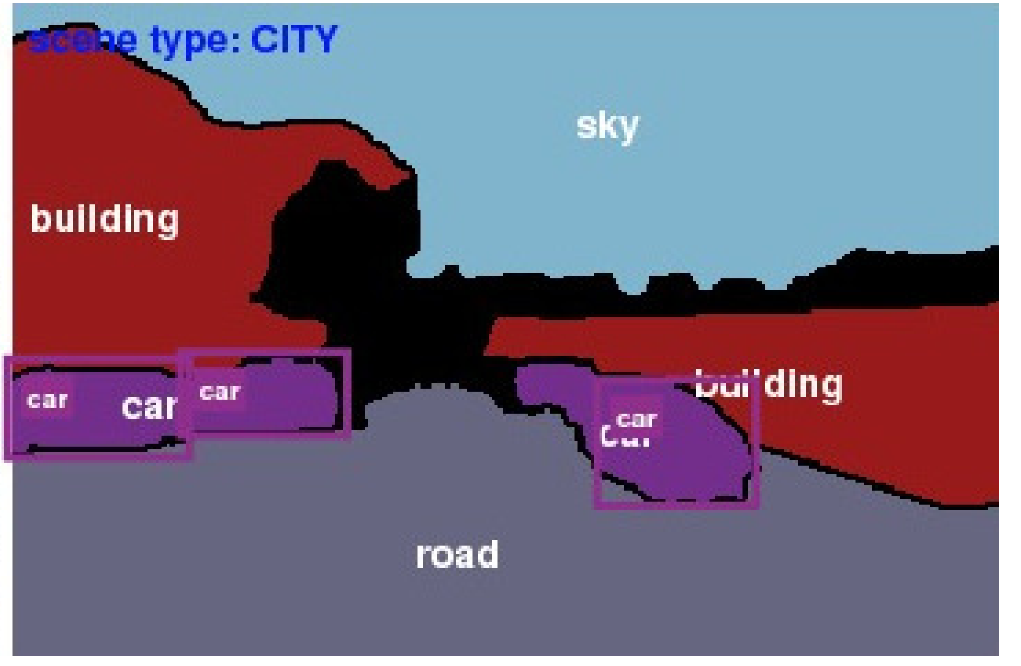
projective geometry



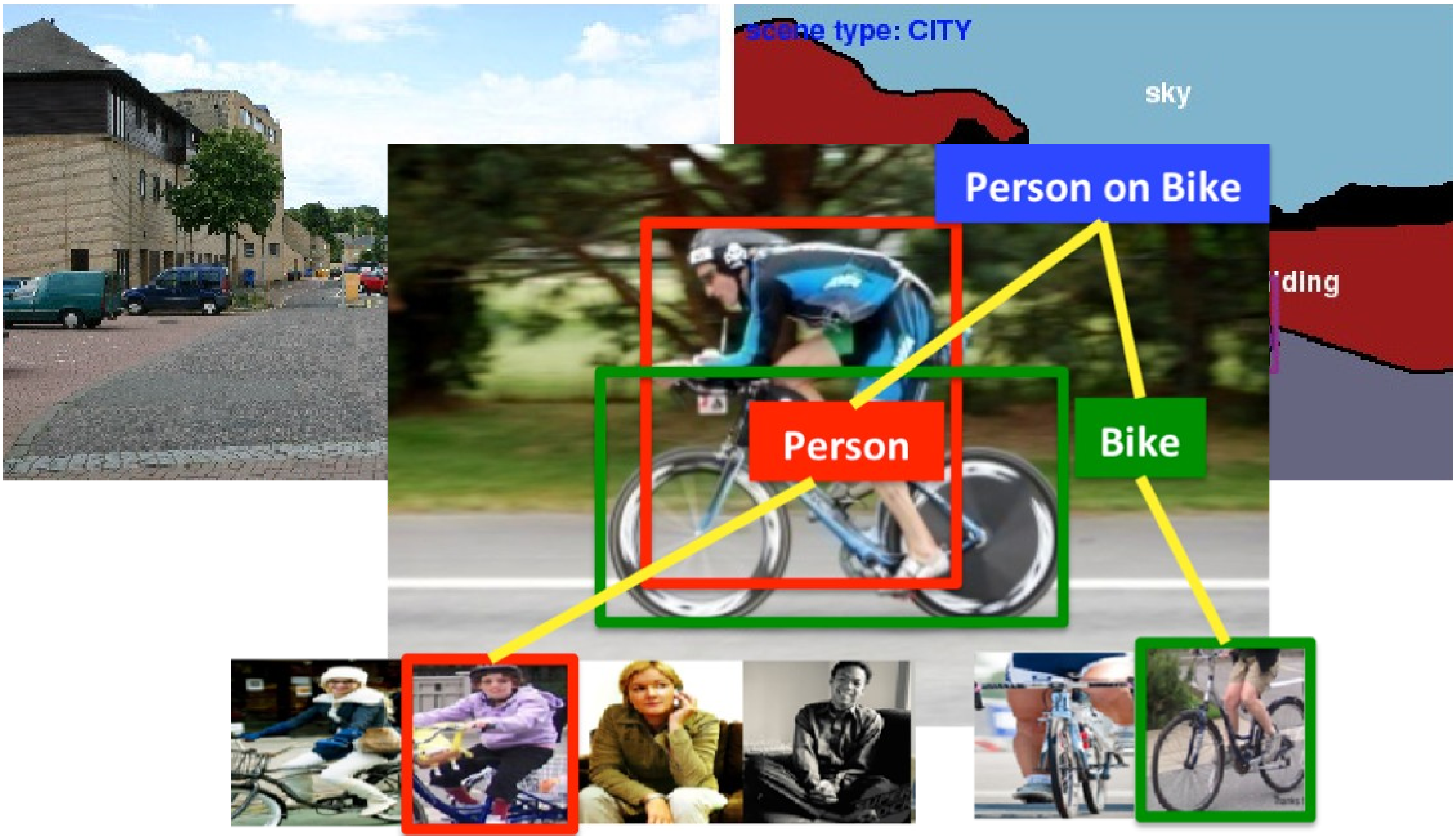
3D reconstruction

http://www.3dflow.net/

understanding



understanding



understanding

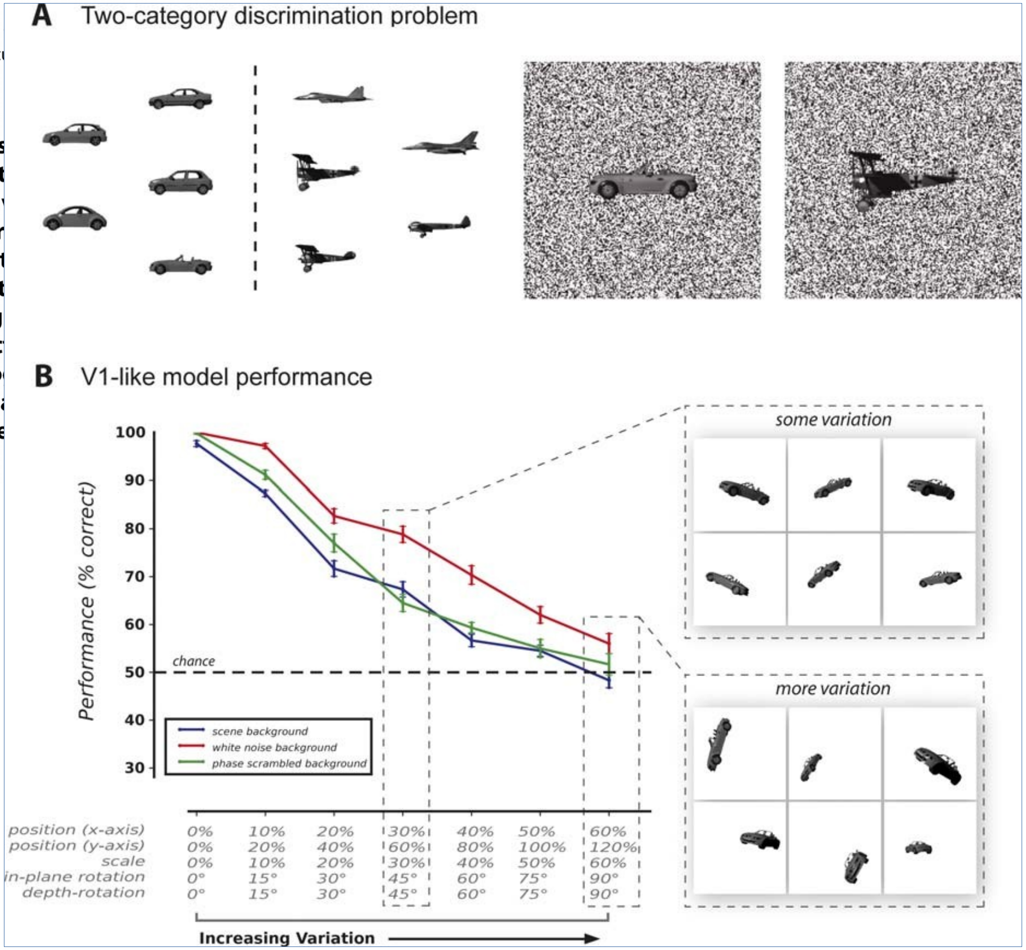
OPEN ACCESS Freely available online PLoS COMPUTATIONAL BIOLOGY

Why is Real-World Visual Object Recognition Hard?

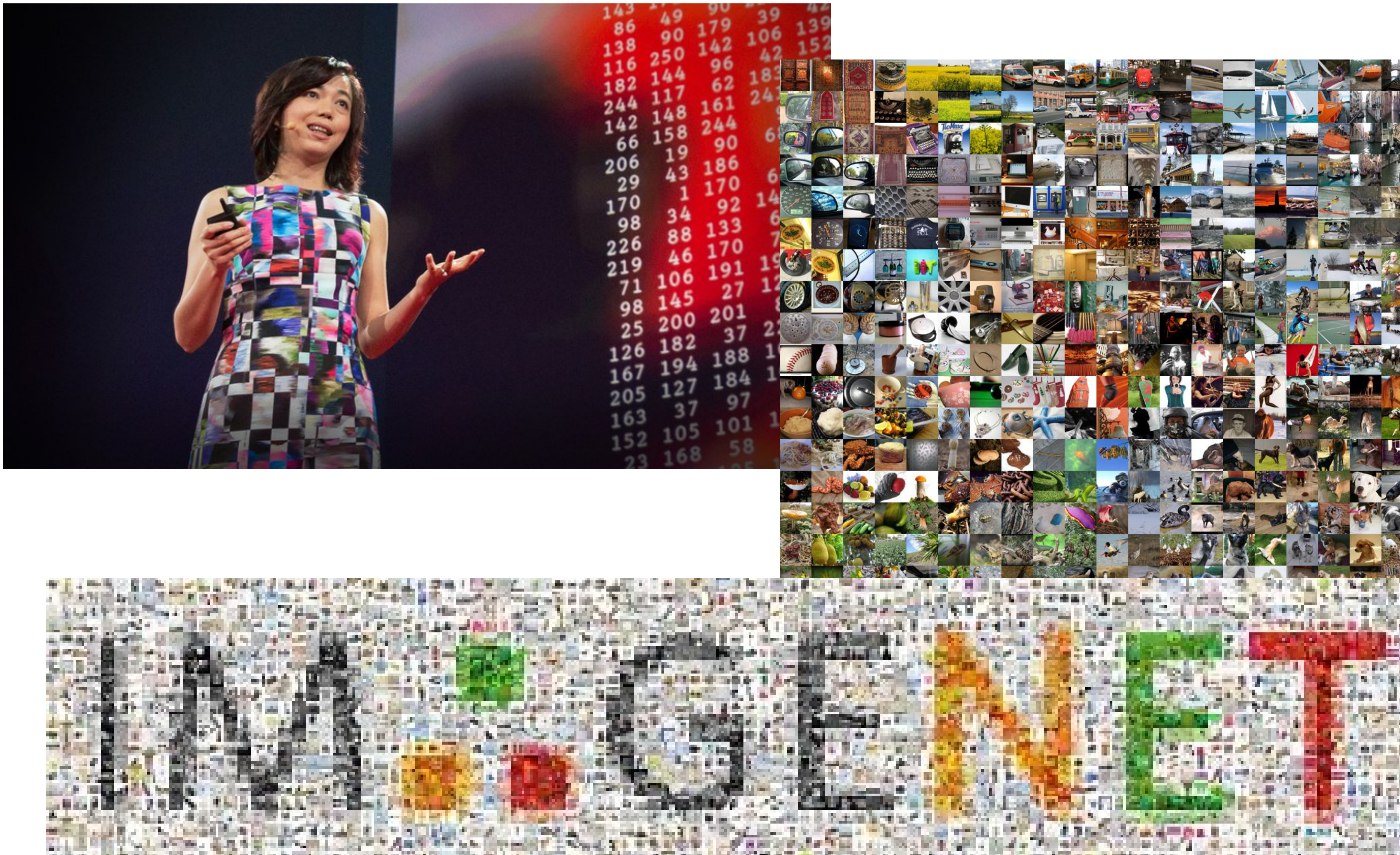
Nicolas Pinto[1,2], David D. Cox[1,2,3], James J. DiCarlo[1,2*]

1 McGovern Institute for Brain Research, Massachusetts Institute of Technology, Cambridge, Massachusetts, United States
Sciences, Massachusetts Institute of Technology, Cambridge, Massachusetts, United States of America, 3 The Rowland Institu
States of America

Progress in understanding the brain mechanisms underlying vision requires the cons that not only emulate the brain's anatomy and physiology, but ultimately match it recent years, "natural" images have become popular in the study of vision and ha impressive progress in building such models. Here, we challenge the use of uncontr that progress. In particular, we show that a simple V1-like model—a neuroscient perform poorly at real-world visual object recognition tasks—outperforms state-of-t (biologically inspired and otherwise) on a standard, ostensibly natural image recog designed a "simpler" recognition test to better span the real-world variation in objec show that this test correctly exposes the inadequacy of the V1-like model. Taken to that tests based on uncontrolled natural images can be seriously misleading, potenti direction. Instead, we reexamine what it means for images to be natural and argue problem of object recognition—real-world image variation.



Fei Fei Li



https://www.ted.com/talks/fei_fei_li_how_we_re_teaching_computers_to_understand_pictures

deep learning

ImageNet Classification with Deep Convolutional Neural Networks

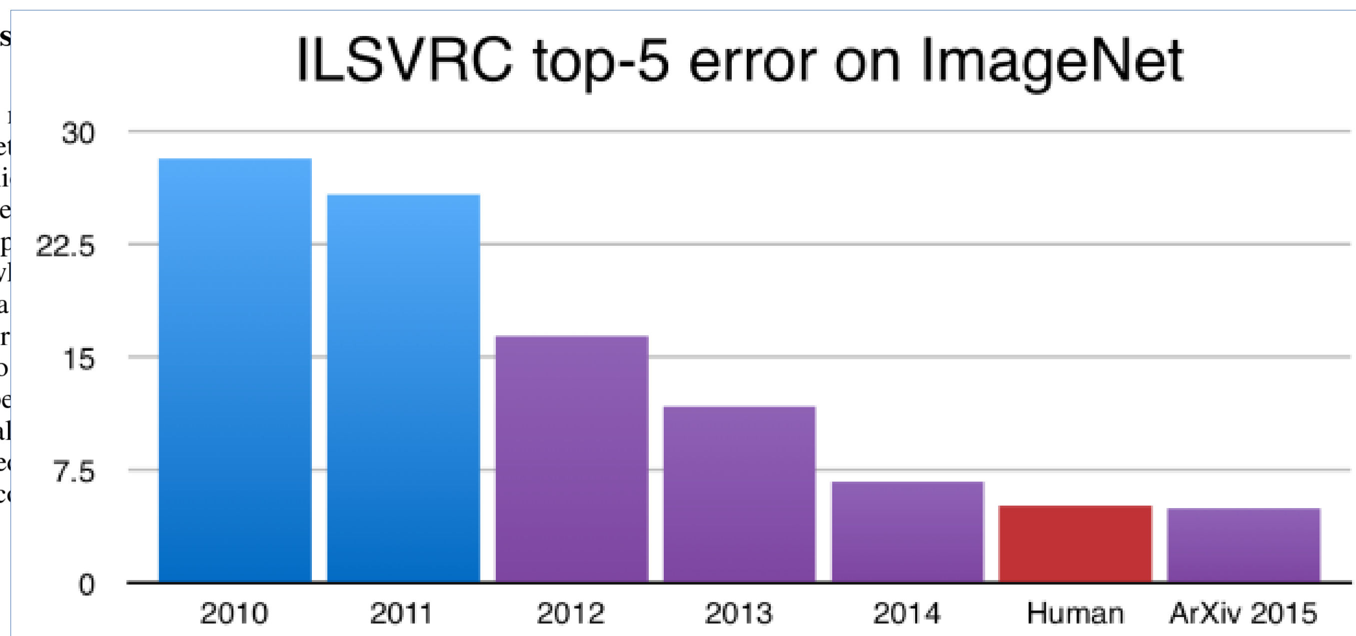
Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

Abs

We trained a large, deep convolutional
high-resolution images in the ImageNet
ferent classes. On the test data, we achi
and 17.0% which is considerably bette
neural network, which has 60 million p
of five convolutional layers, some of wh
and three fully-connected layers with a
ing faster, we used non-saturating neur
tation of the convolution operation. To
layers we employed a recently-develope
that proved to be very effective. We al
ILSVRC-2012 competition and achieved
compared to 26.2% achieved by the sec



deep learning

DenseCap: Fully Convolutional Localization Networks for Dense Captioning

Justin Johnson* Andrej Karpathy* Li Fei-Fei
Department of Computer Science, Stanford University
{jcjohns,karpathy,feifeili}@cs.stanford.edu

Abstract

We introduce the dense captioning task, which requires a computer vision system to both localize and describe salient regions in images in natural language. The dense captioning task generalizes object detection when the descriptions consist of a single word, and Image Captioning when one predicted region covers the full image. To address the localization and description task jointly we propose a Fully Convolutional Localization Network (FCLN) architecture that processes an image with a single, efficient forward pass, requires no external regions proposals, and can be trained end-to-end with a single round of optimization. The architecture is composed of a Convolutional Network, a novel

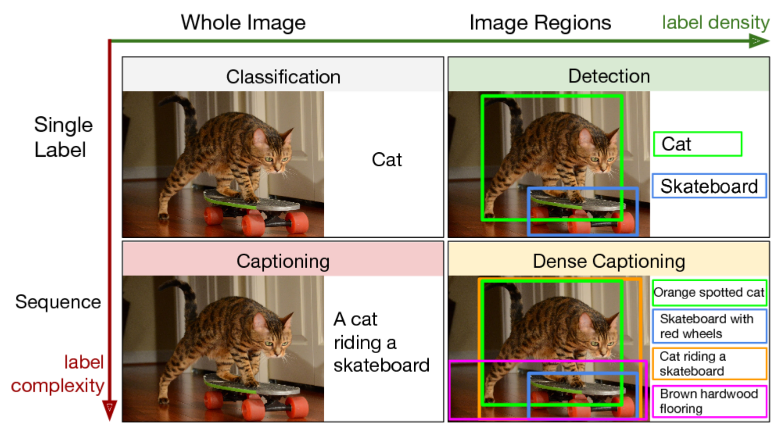


Figure 1. We address the Dense Captioning task (bottom right) with a model that jointly generates both dense and rich annotations in a single forward pass.

deep learning

DenseCap: Fully Convolutional Localization Networks for Dense Captioning

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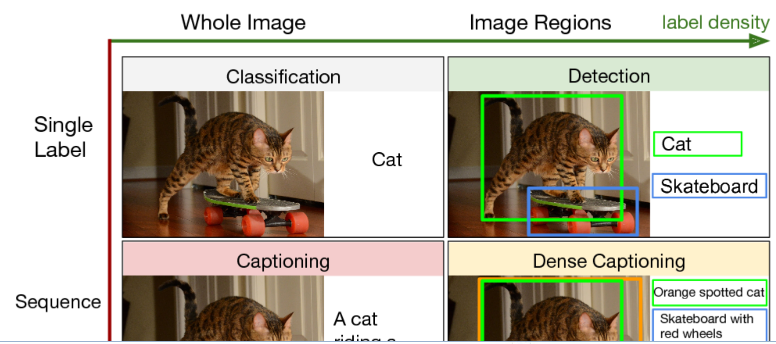
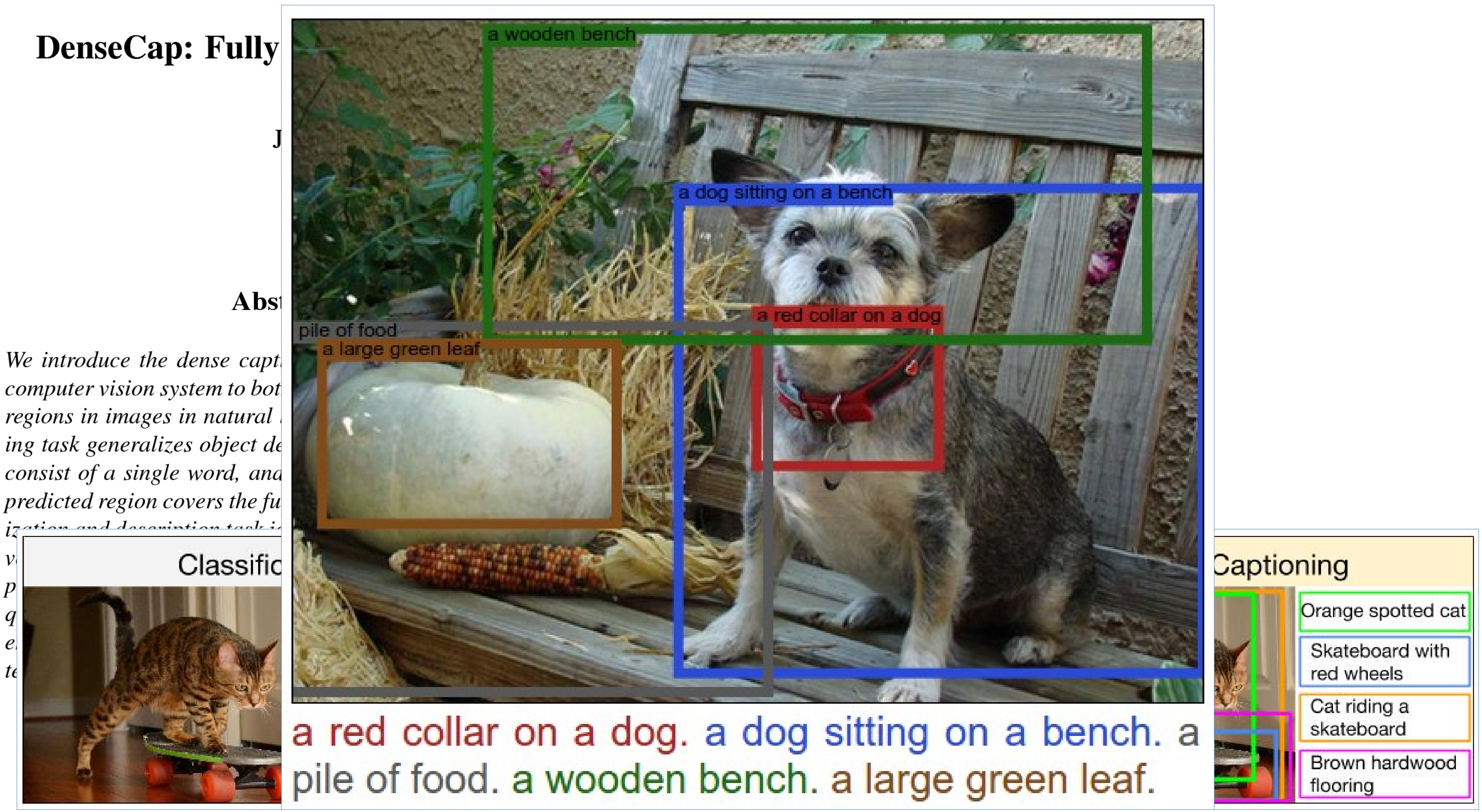
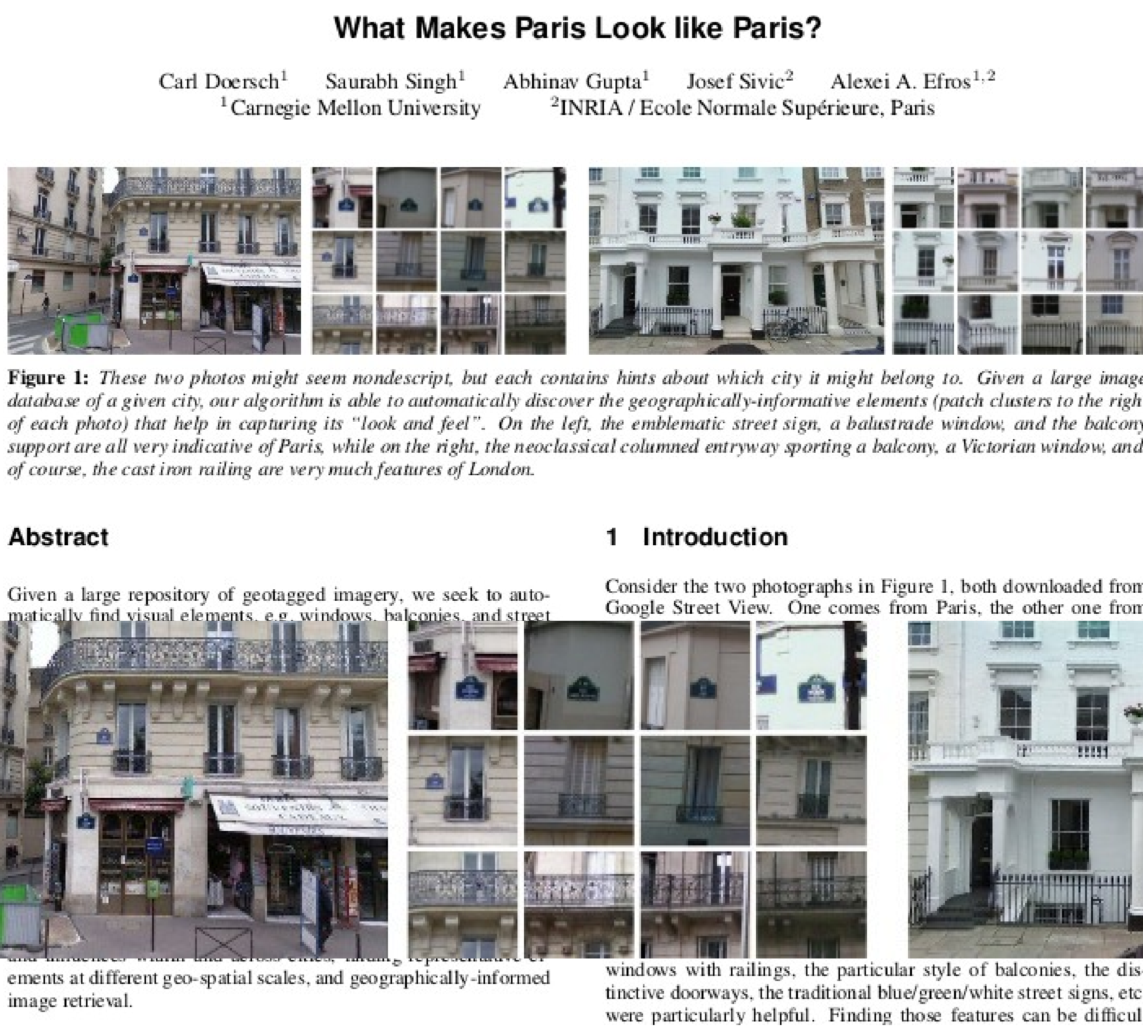


deep learning



ACM Prize in Computing



What Makes Paris Look like Paris?

Carl Doersch[1] Saurabh Singh[1] Abhinav Gupta[1] Josef Sivic[2] Alexei A. Efros[1,2]
[1]Carnegie Mellon University [2]INRIA / Ecole Normale Supérieure, Paris

Figure 1: *These two photos might seem nondescript, but each contains hints about which city it might belong to. Given a large image database of a given city, our algorithm is able to automatically discover the geographically-informative elements (patch clusters to the right of each photo) that help in capturing its "look and feel". On the left, the emblematic street sign, a balustrade window, and the balcony support are all very indicative of Paris, while on the right, the neoclassical columned entryway sporting a balcony, a Victorian window, and, of course, the cast iron railing are very much features of London.*

Abstract

Given a large repository of geotagged imagery, we seek to automatically find visual elements, e.g. windows, balconies, and street

ements at different geo-spatial scales, and geographically-informed image retrieval.

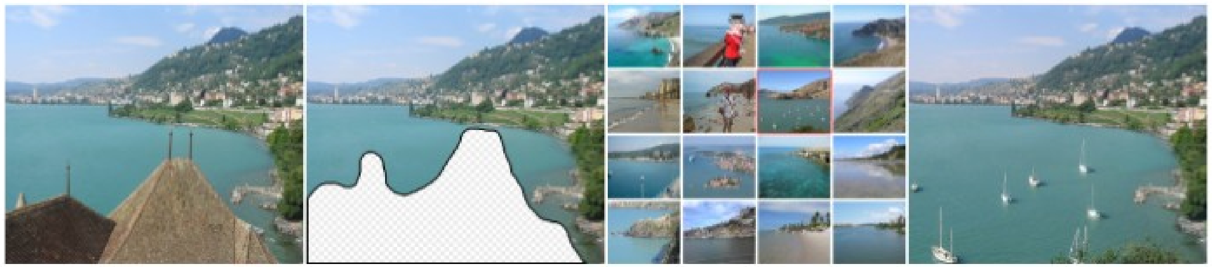
1 Introduction

Consider the two photographs in Figure 1, both downloaded from Google Street View. One comes from Paris, the other one from

windows with railings, the particular style of balconies, the distinctive doorways, the traditional blue/green/white street signs, etc. were particularly helpful. Finding those features can be difficult

Scene Completion Using Millions of Photographs

James Hays Alexei A. Efros
Carnegie Mellon University



Original Image Input Scene Matches Output

Figure 1: Given an input image with a missing region, we use matching scenes from a large collection of photographs to complete the image.

Abstract

What can you do with a million images? In this paper we present a new image completion algorithm powered by a huge database of photographs gathered from the Web. The algorithm patches up holes in images by finding similar image regions in the database that are not only seamless but also semantically valid. Our chief insight is that while the space of images is effectively infinite, the space of semantically differentiable scenes is actually not that large. For many image completion tasks we are able to find similar scenes which contain image fragments that will convincingly complete the image. Our algorithm is entirely data-driven, requiring no annotations or labelling by the user. Unlike existing image completion methods, our algorithm can generate a diverse set of results for each input image and we allow users to select among them. We demonstrate the superiority of our algorithm over existing image completion approaches.

Keywords: Image Completion, Image Database, Image Com-

There are two fundamentally different strategies for image completion. The first aims to reconstruct, as accurately as possible, the data that *should have been* there, but somehow got occluded or corrupted. Methods attempting an accurate reconstruction have to use some other source of data in addition to the input image, such as video (using various background stabilization techniques, e.g. [Irani et al. 1995]) or multiple photographs of the same physical scene [Agarwala et al. 2004; Snavely et al. 2006].

The alternative is to try finding a plausible way to fill in the missing pixels, hallucinating data that *could have been* there. This is a much less easily quantifiable endeavor, relying instead on the studies of human visual perception. The most successful existing methods [Criminisi et al. 2003; Drori et al. 2003; Wexler et al. 2004; Wilczkowiak et al. 2005; Komodakis 2006] operate by extending adjacent textures and contours into the unknown region. This idea is derived from example-based texture synthesis [Efros and Leung 1999; Efros and Freeman 2001; Kwatra et al. 2003; Kwatra et al.

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Colorful Image Colorization

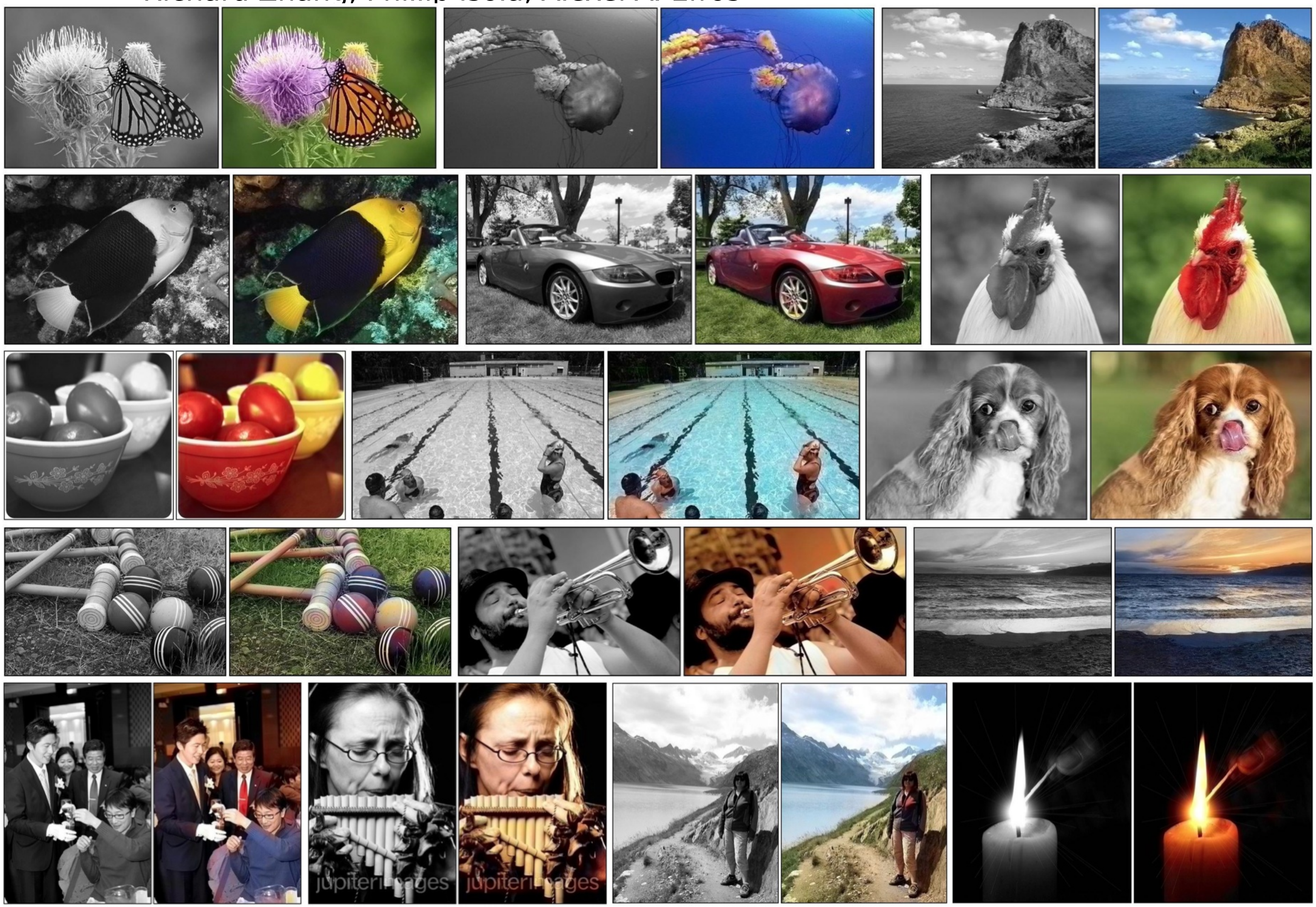
Richard Zhang, Phillip Isola, Alexei A. Efros
{rich.zhang,isola,efros}@eecs.berkeley.edu

University of California, Berkeley

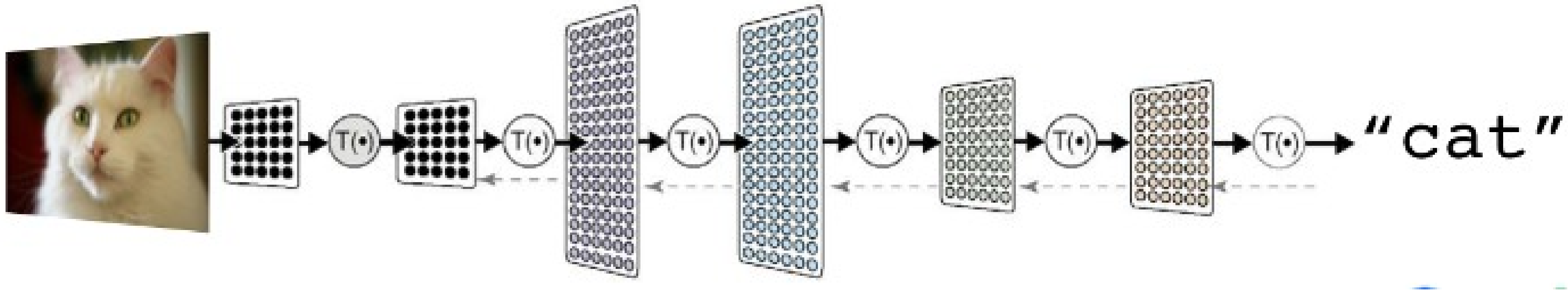
Abstract. Given a grayscale photograph as input, this paper attacks the problem of hallucinating a *plausible* color version of the photograph. This problem is clearly underconstrained, so previous approaches have either relied on significant user interaction or resulted in desaturated colorizations. We propose a fully automatic approach that produces vibrant and realistic colorizations. We embrace the underlying uncertainty of the problem by posing it as a classification task and use class-rebalancing at training time to increase the diversity of colors in the result. The system is implemented as a feed-forward pass in a CNN at test time and is trained on over a million color images. We evaluate our algorithm using a "colorization Turing test," asking human participants to choose between a generated and ground truth color image. Our method successfully fools humans on 32% of the trials, significantly higher than previous methods. Moreover, we show that colorization can be a powerful pretext task for

Colorful Image Colorization

Richard Zhang, Phillip Isola, Alexei A. Efros

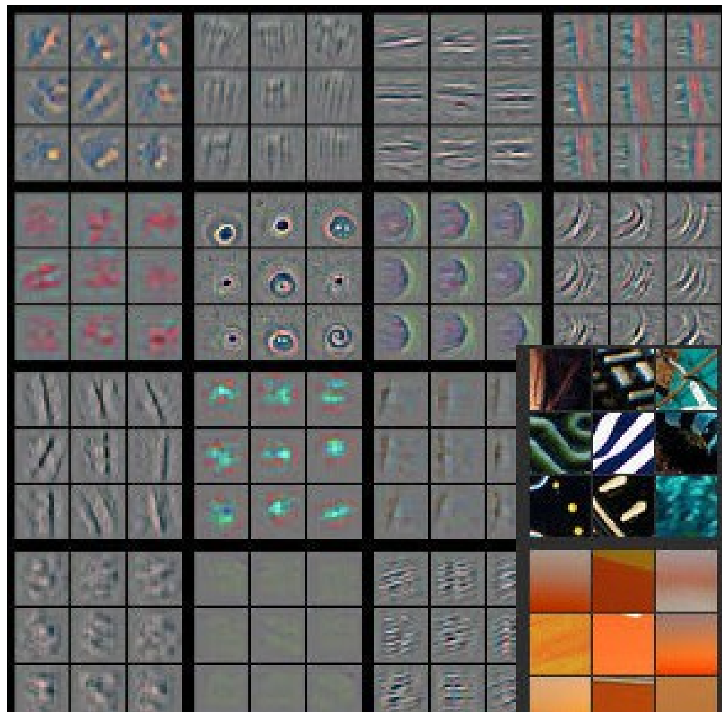


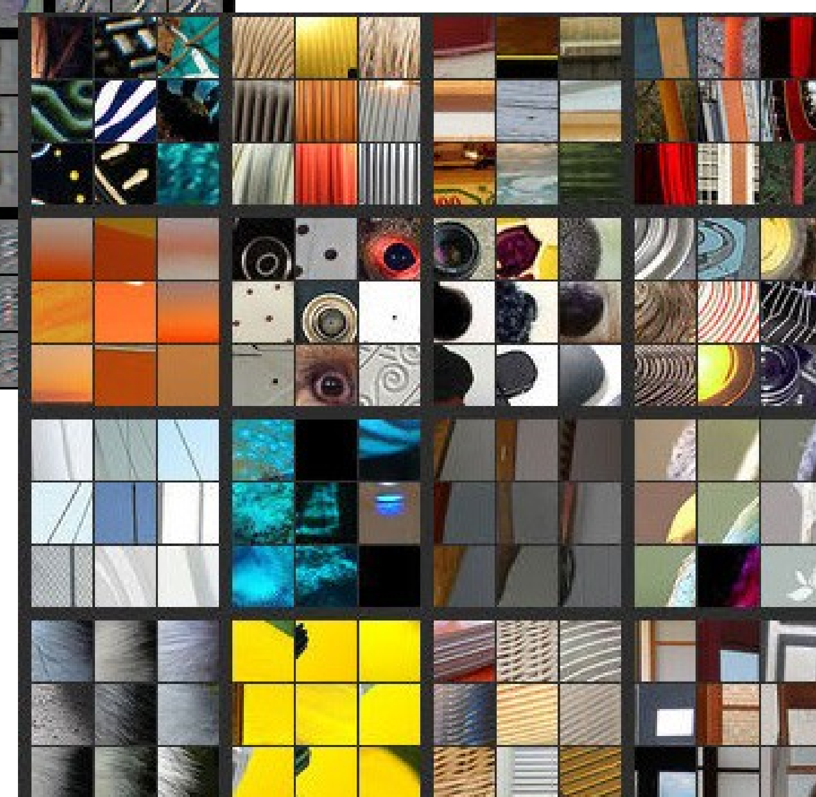
deep learning



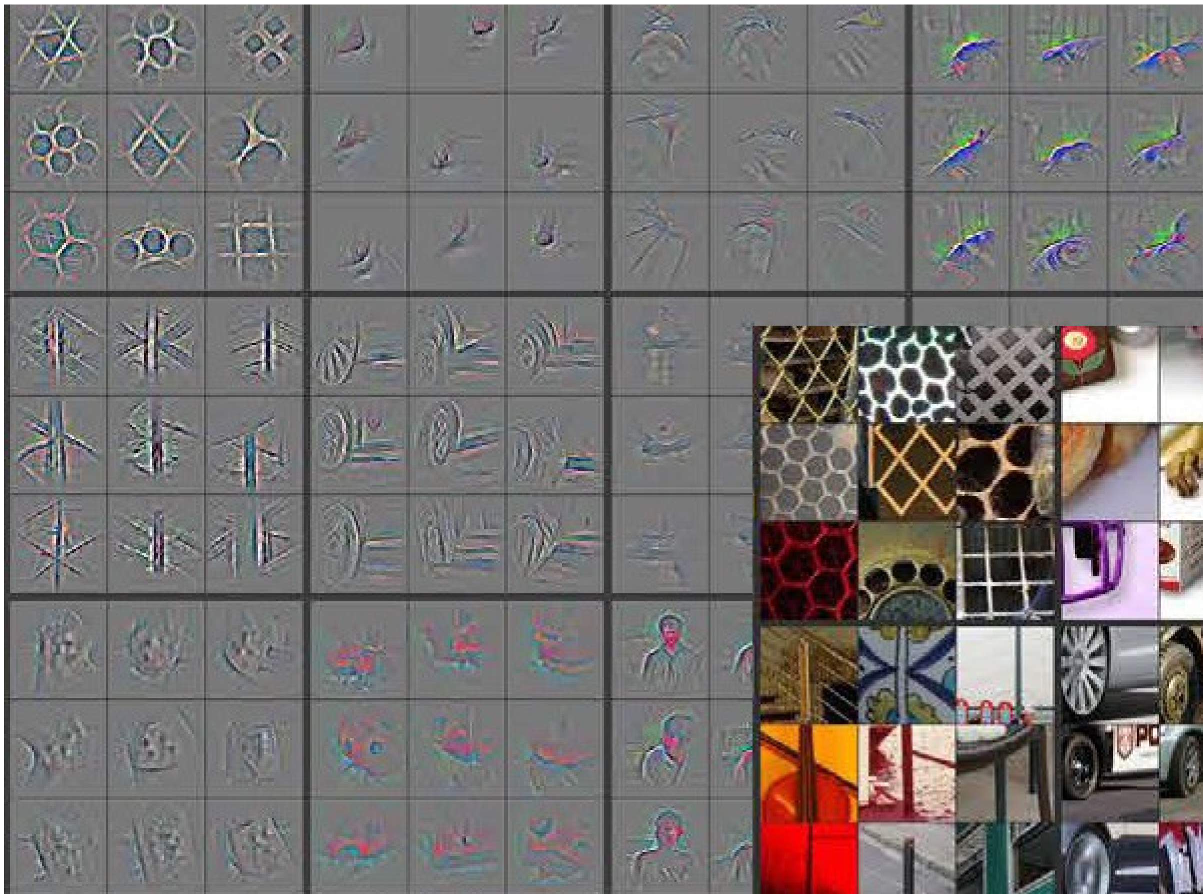
Alchemy or Chemistry?

deepvis

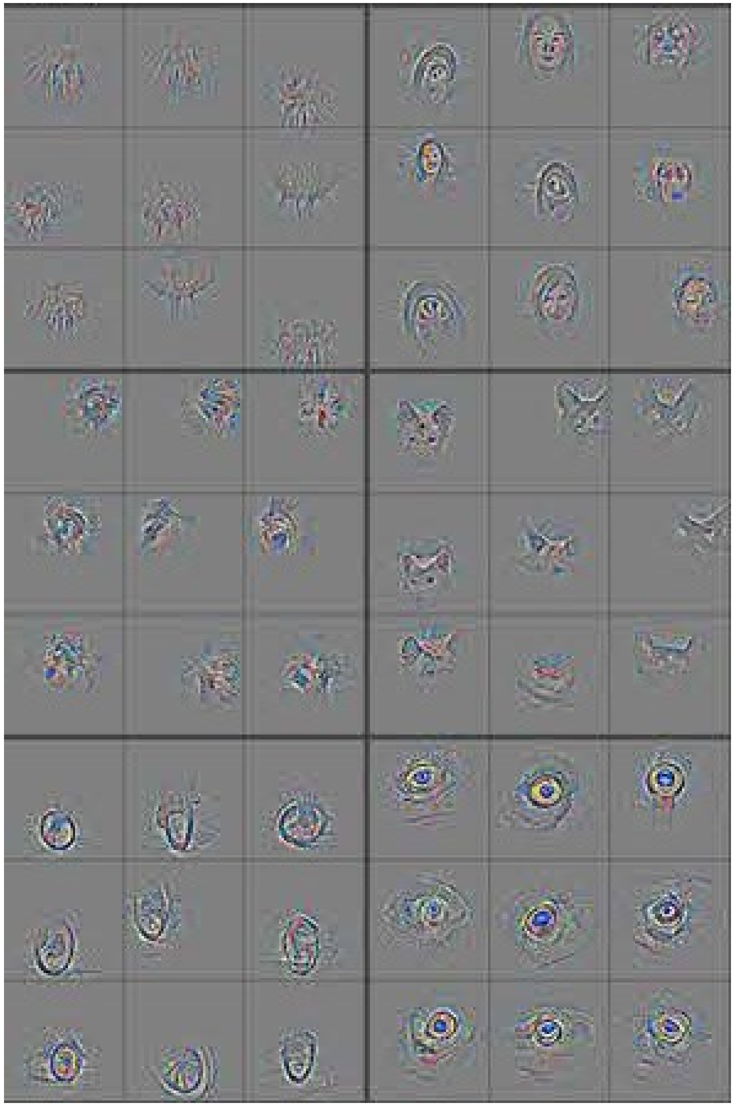




deepvis



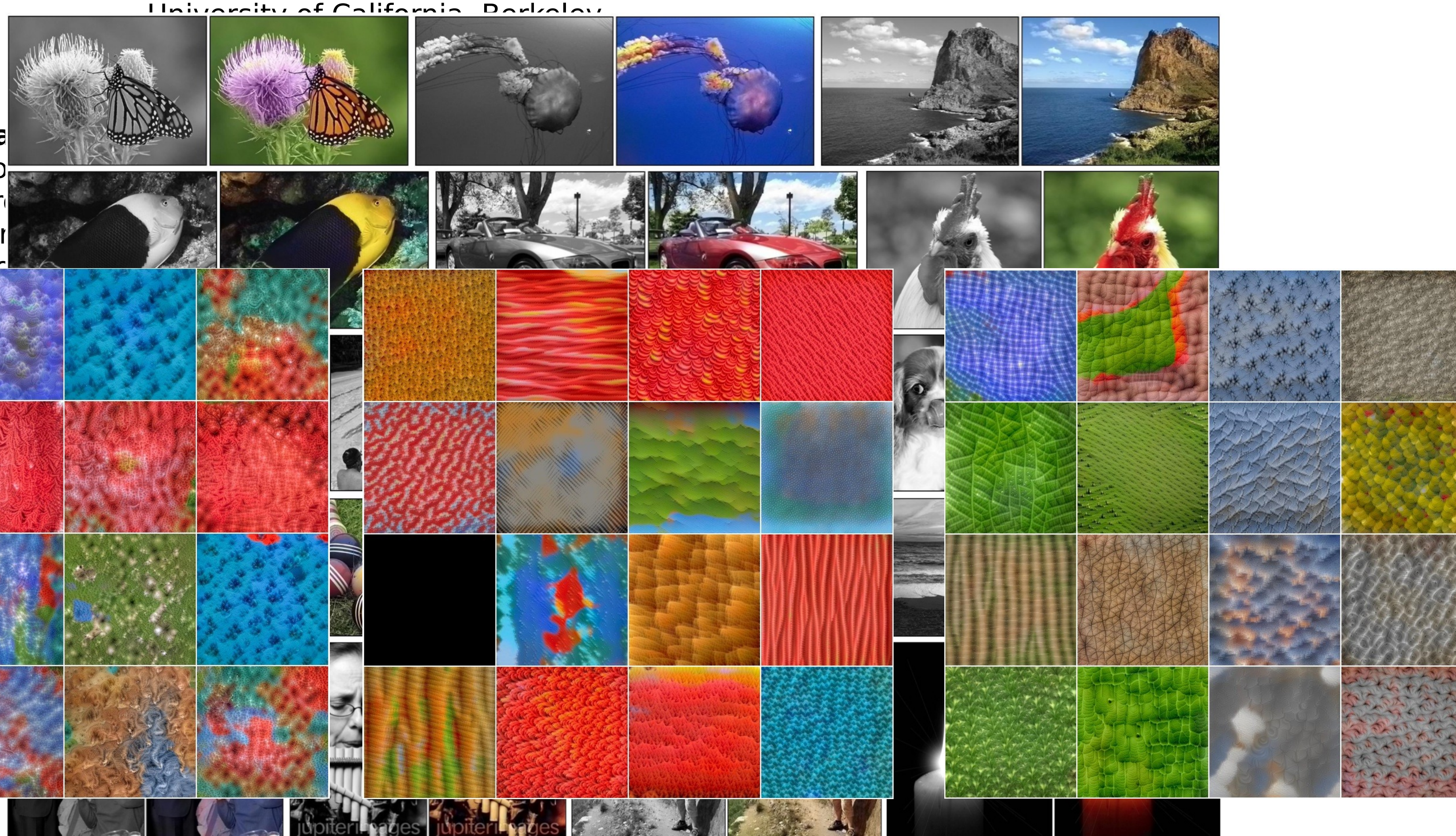
deepvis



Colorful Image Colorization

Richard Zhang, Phillip Isola, Alexei A. Efros
{rich.zhang,isola,efros}@eecs.berkeley.edu

University of California, Berkeley



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deep dreams

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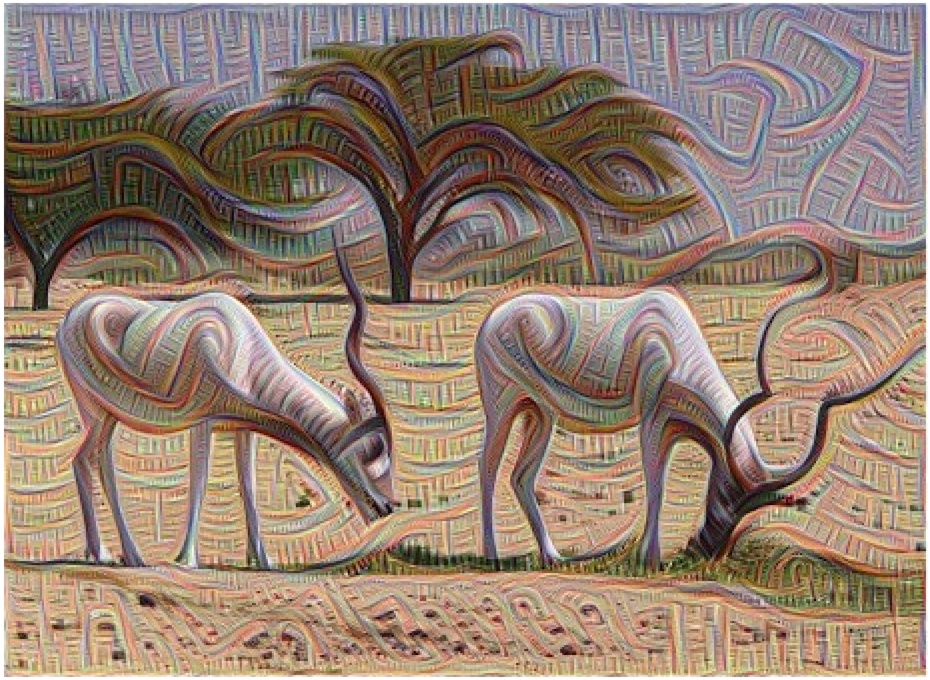
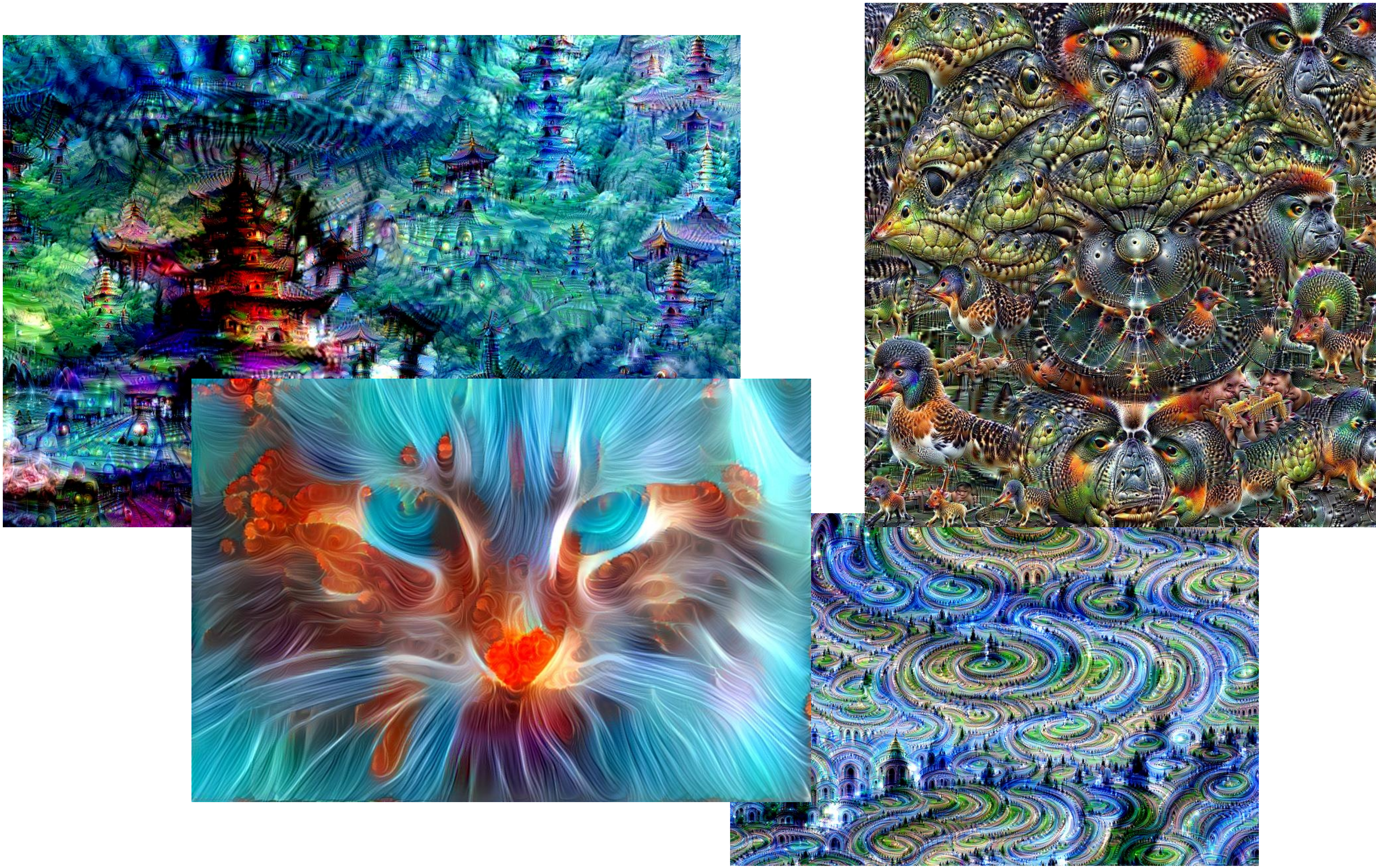
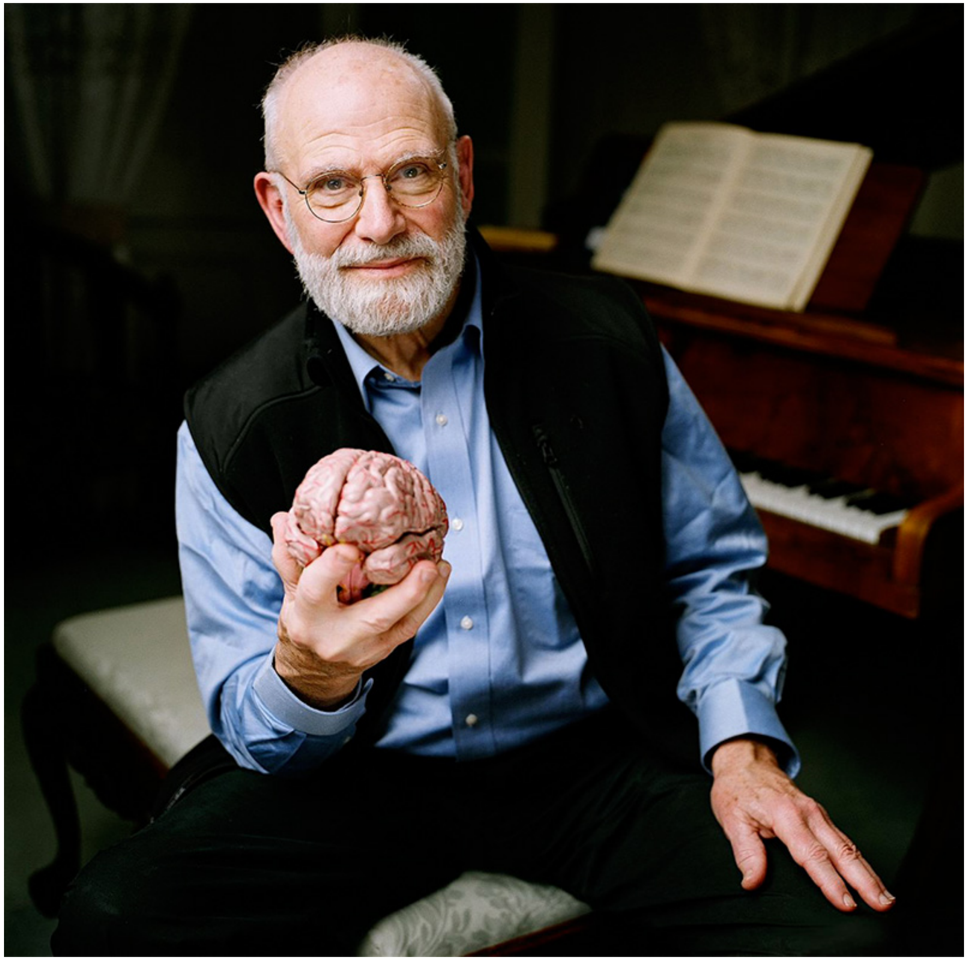


deep dreams

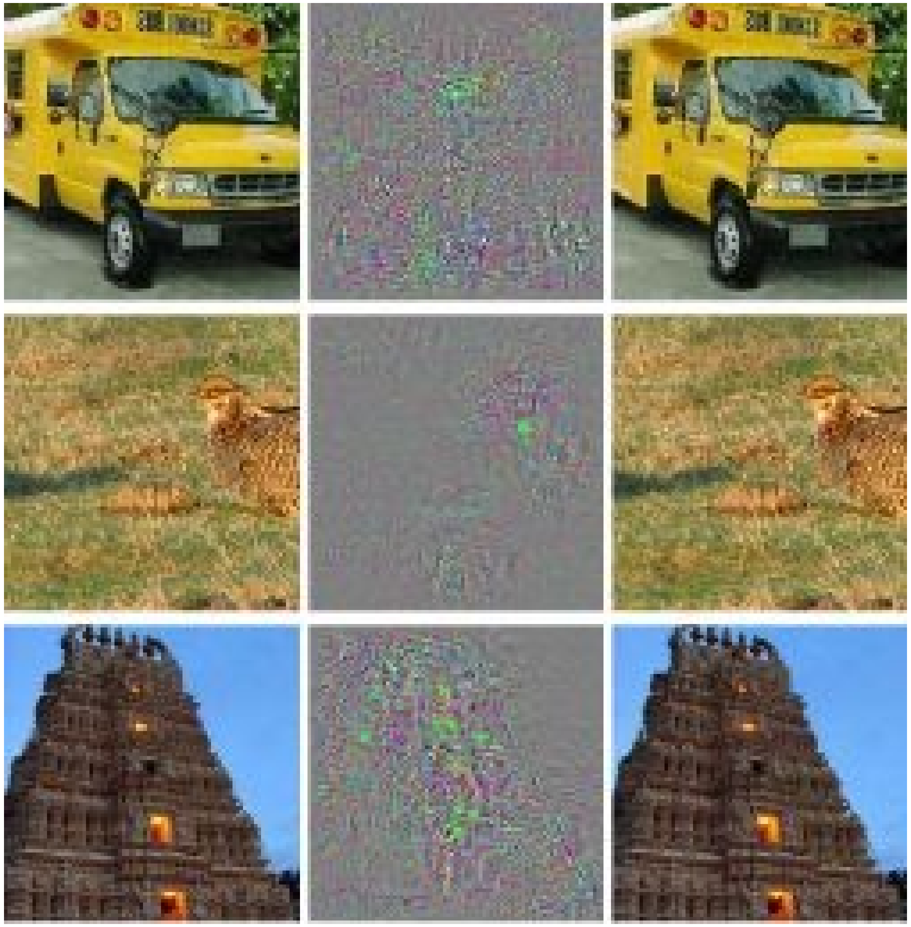


real deep dreams?



https://www.ted.com/talks/oliver_sacks_what_hallucination_reveals_about_our_minds

human vs machine



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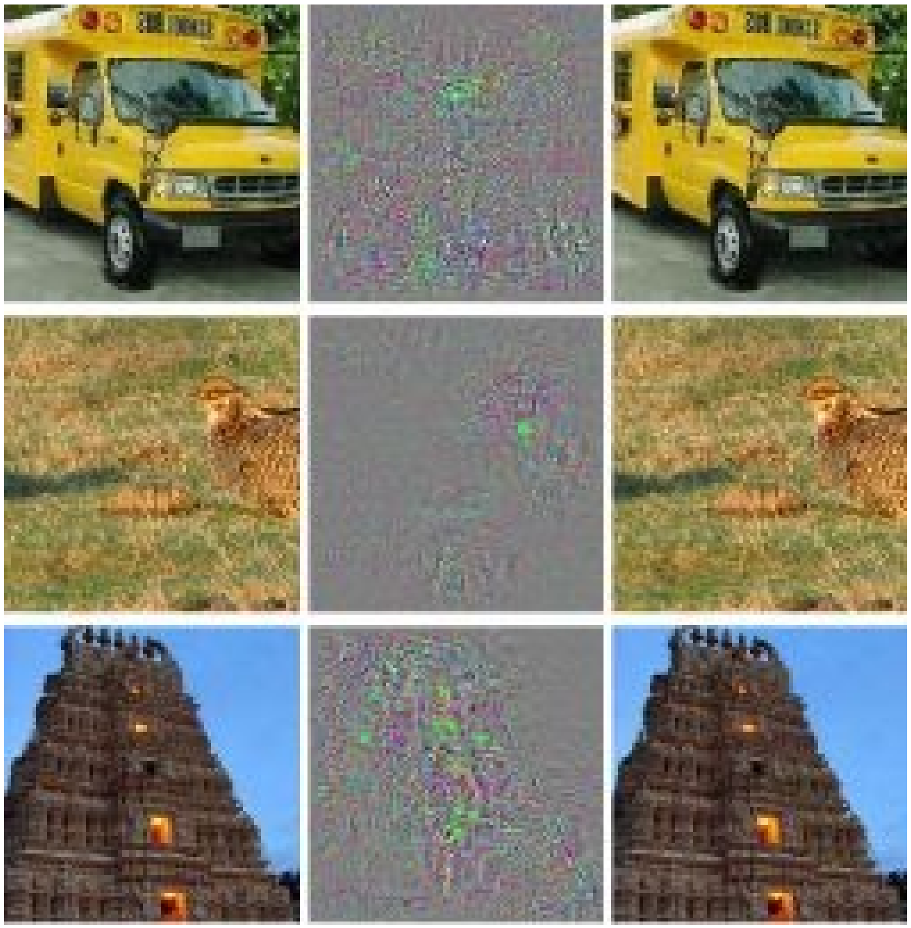

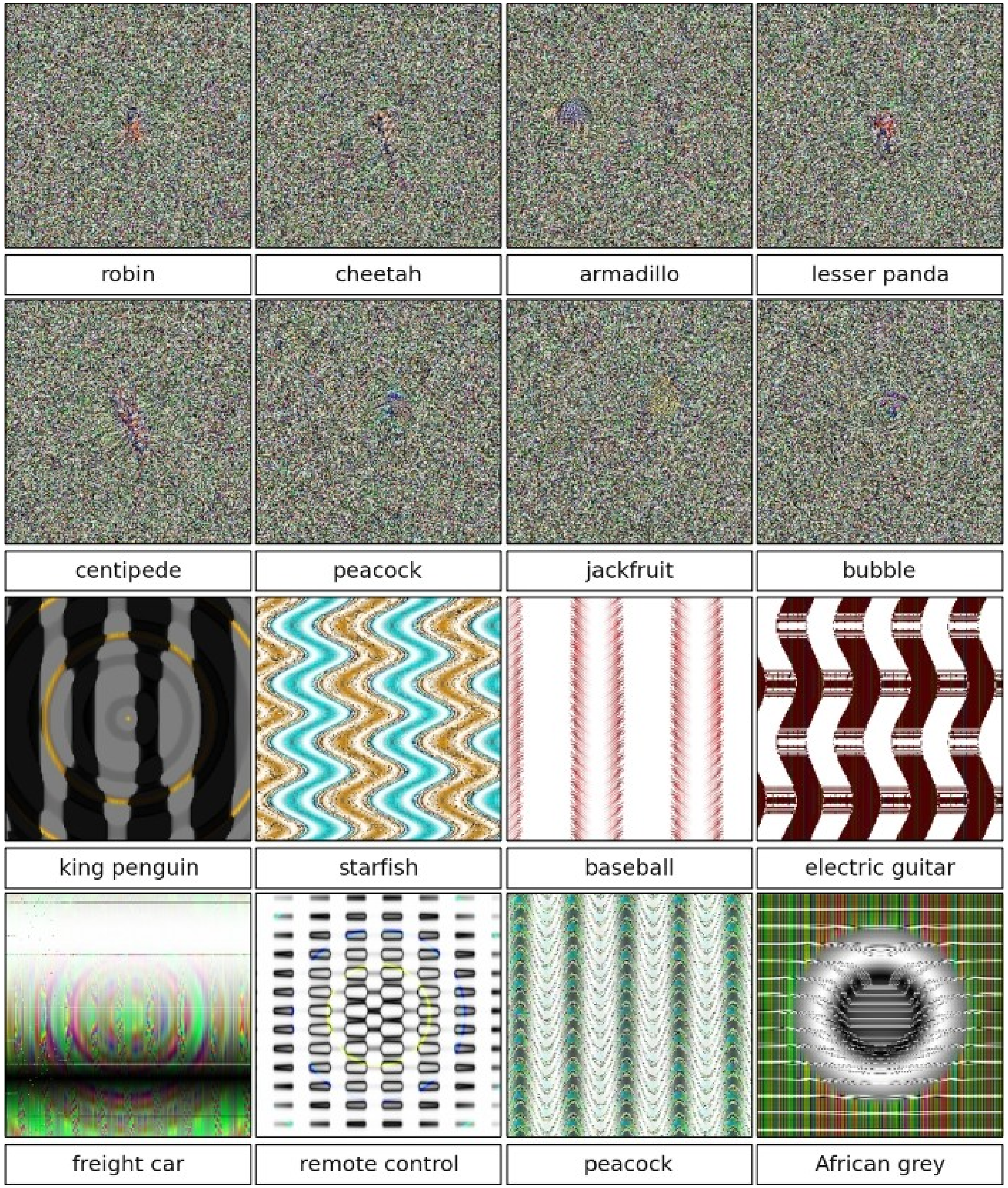

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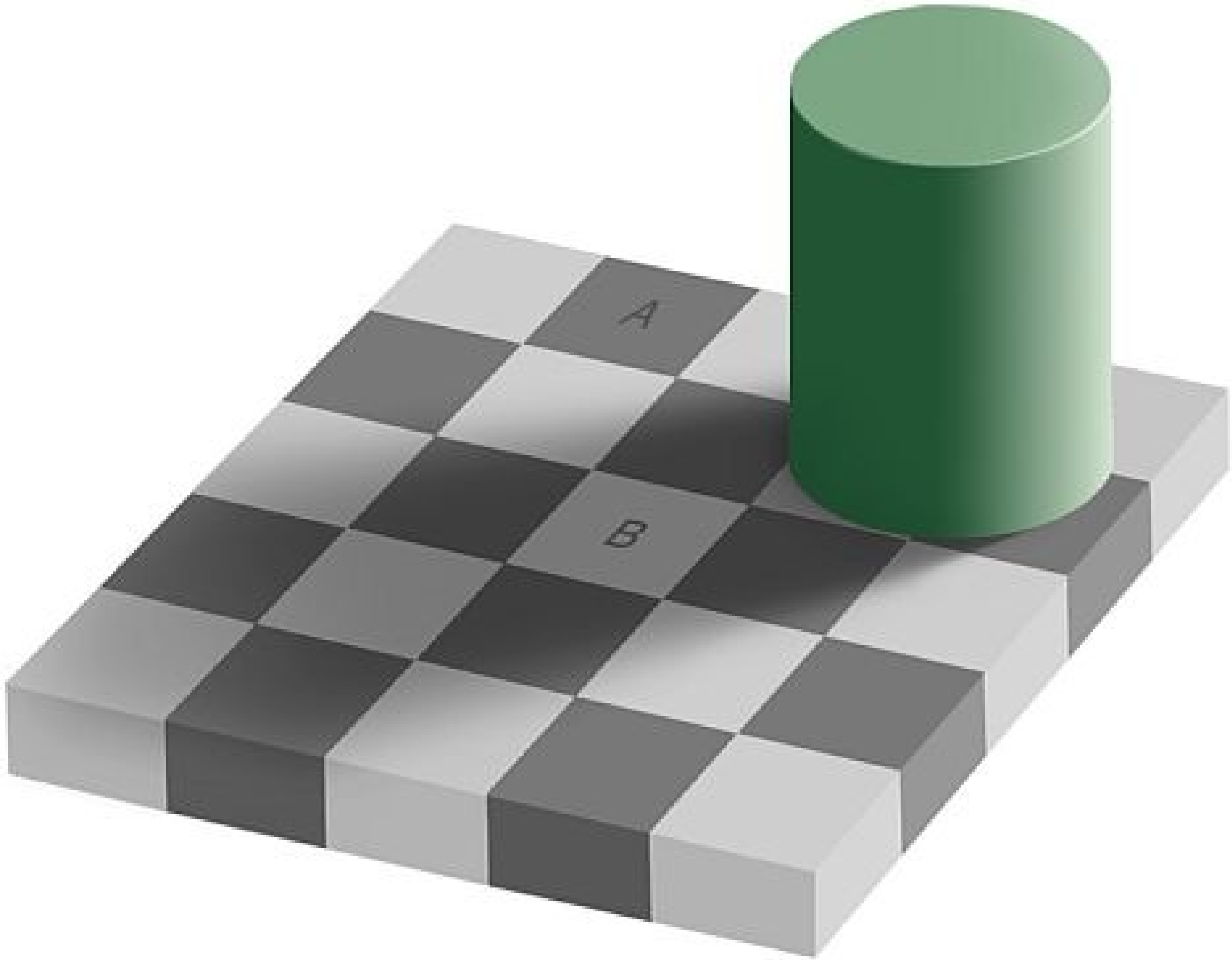

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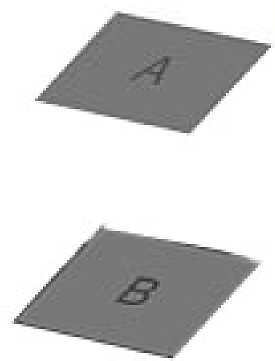
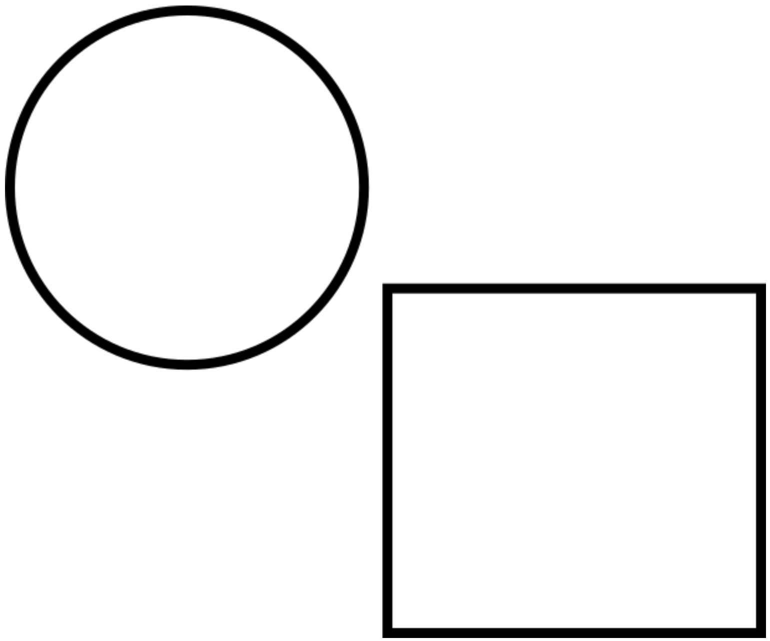
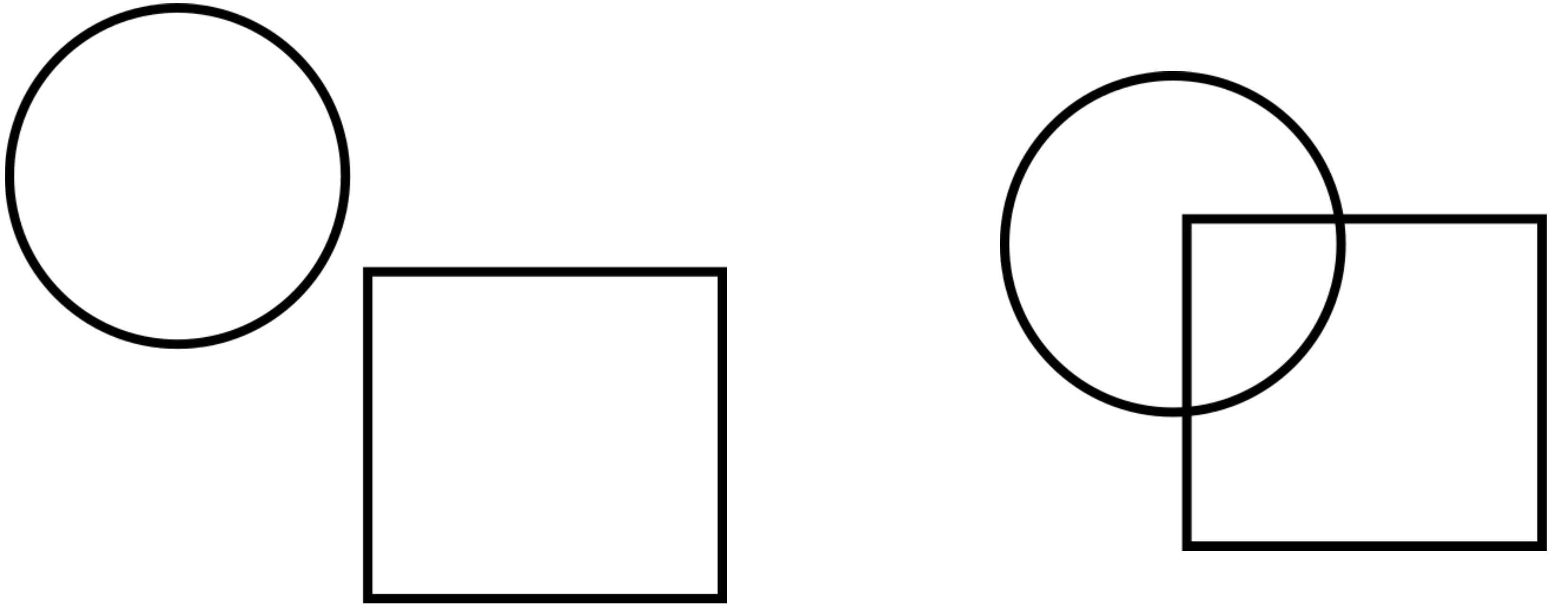


learning to see



https://www.ted.com/talks/pawan_sinha_on_how_brains_learn_to_see

learning to see



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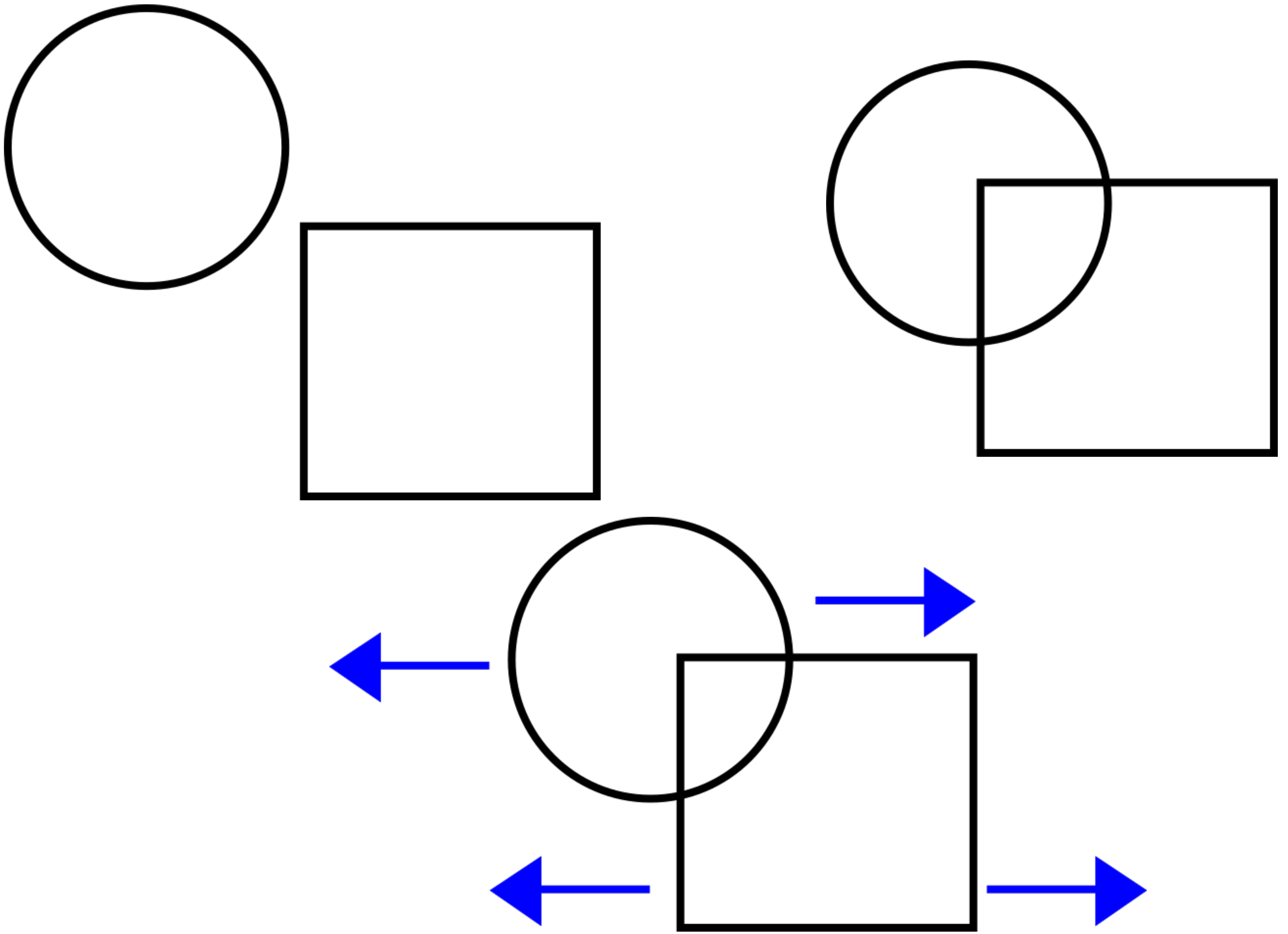
learning to see



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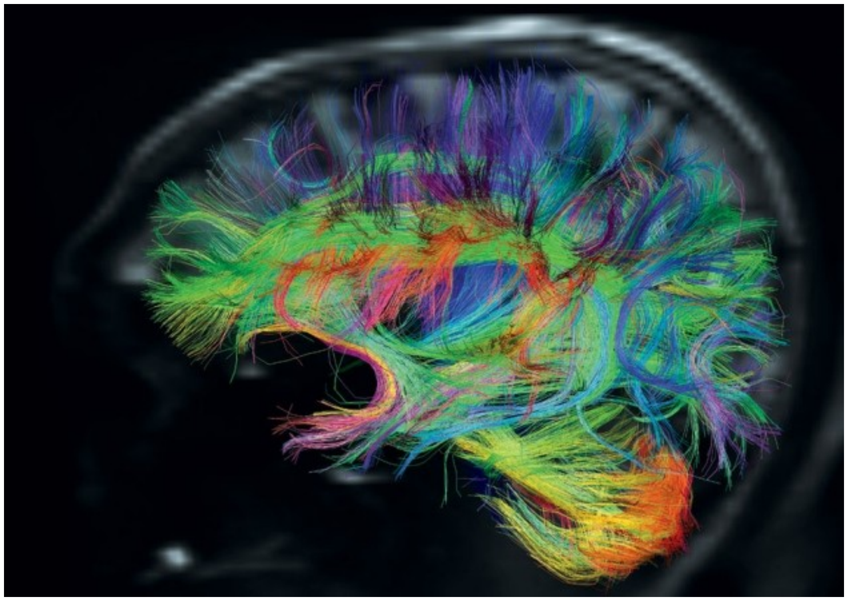
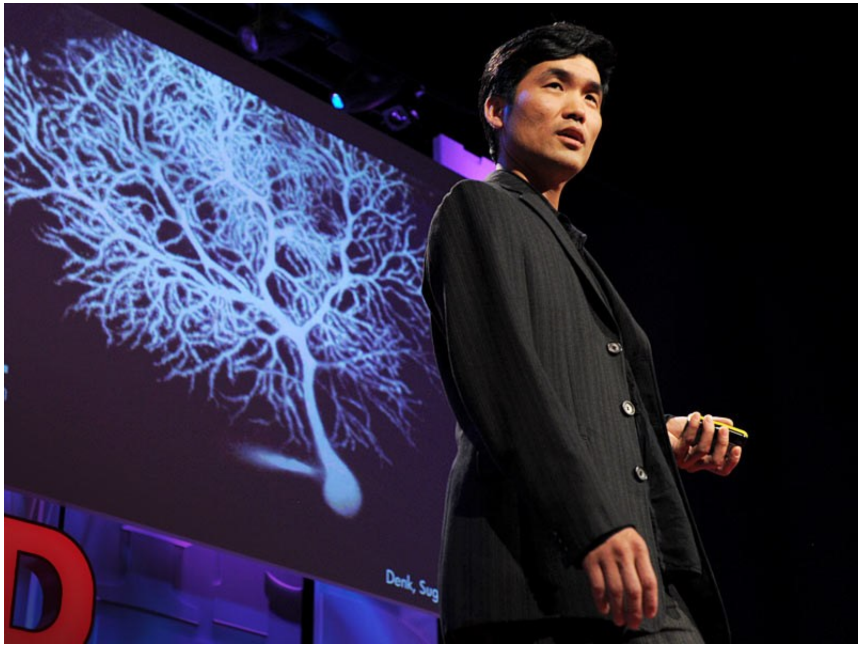
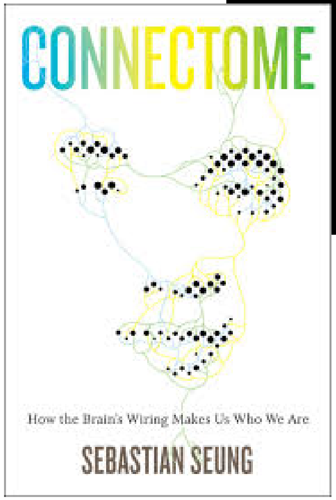
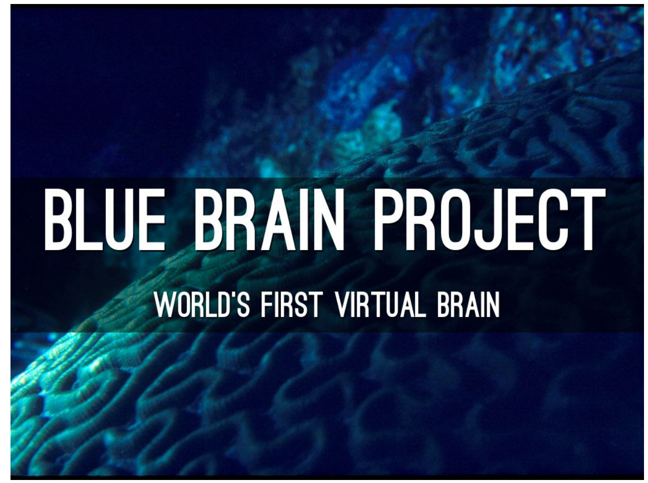
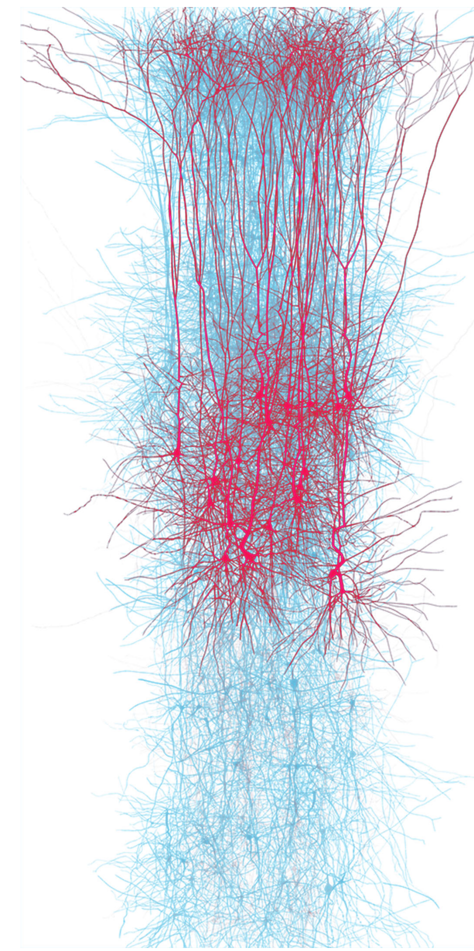






Blue Brain Project





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https://www.youtube.com/watch?time_continue=2&v=2qTuZlMvFgY

The Big and the Small: Challenges of Imaging the Brain's Circuits

Jeff W. Lichtman[1]* and Winfried Denk[2]*

The relation between the structure of the nervous system and its function is more poorly understood than the relation between structure and function in any other organ system. We explore why bridging the structure-function divide is uniquely difficult in the brain. These difficulties also explain the thrust behind the enormous amount of innovation centered on microscopy in neuroscience. We highlight some recent progress and the challenges that remain.

A central theme of biology is the relation between the structure and function of things. By structure, we mean the physical form of something, a property that humans can apprehend by touch (if the object is big enough) or by sight. Right now, the leading edge of this effort is the field known by the general name "structural biology" but is focused

tem, where much progress has been made at the molecular and functional level. But notwithstanding the extraordinary insights of neurobiology's foremost structural biologist, Cajal, our understanding of the relation between the structure and function of the brain remains primitive, especially when compared to other organ systems. There is no other organ system where so

research to determine the full extent of cell-type diversity in this small part of the nervous system, because the range of cell types continues to grow as the analysis becomes more refined. Moreover, neuronal cellu

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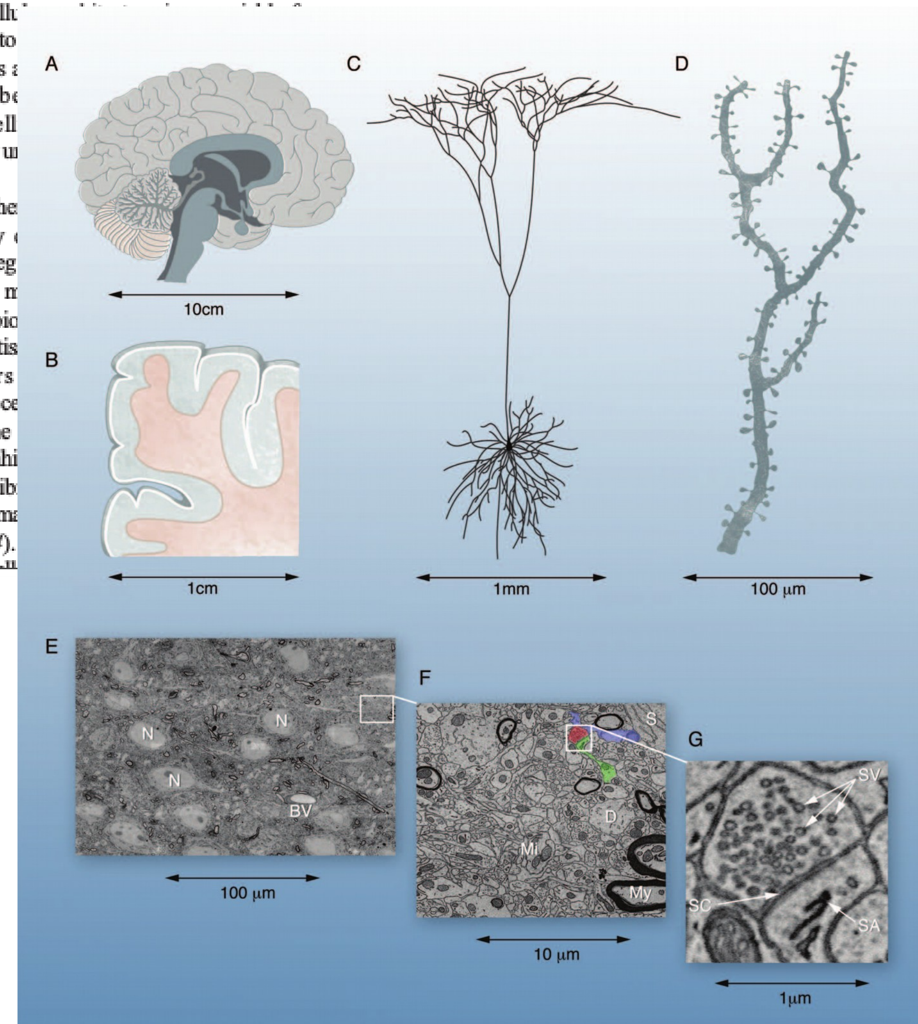
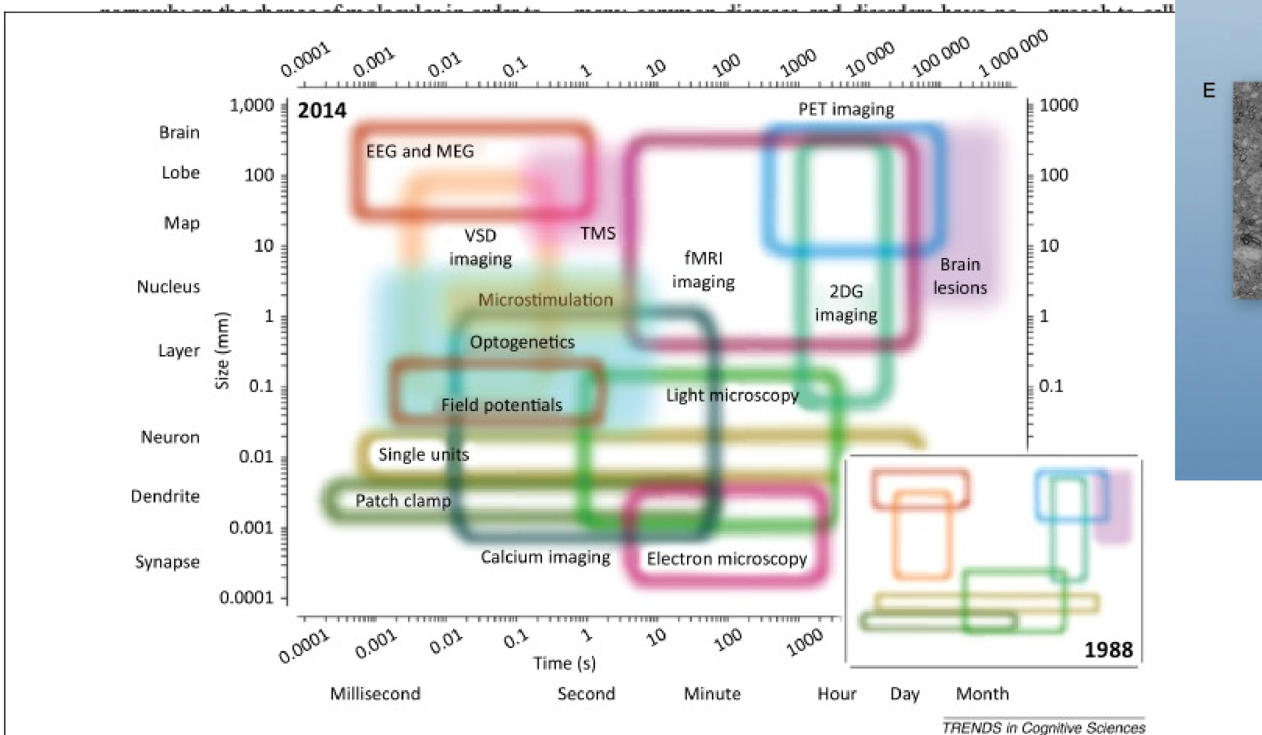
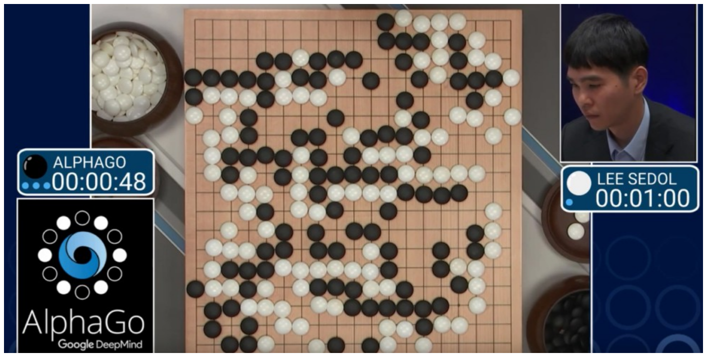




applications



TensorFlow

IBM Watson

Google's Neural Machine Translation

...reduced translation errors by an average of 60% when compared to the prior Google Translate technology

https://www.ted.com/talks/jeremy_howard_the_wonderful_and_terrifying_implications_of_computers_that_can_learn

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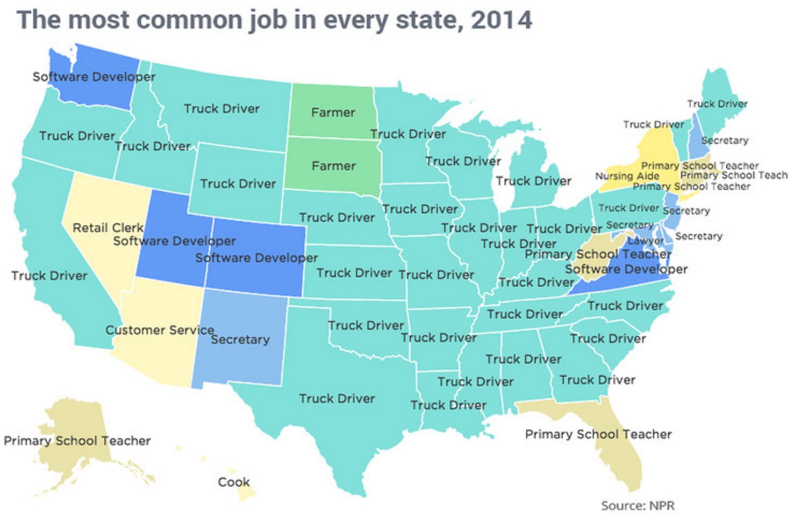
Moshe Vardi


The most common job in every state, 2014
Software Developer
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Primary School Teacher
Nursing Aide
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Primary School Teacher
Truck Driver
Truck Driver
Secretary
Retail Clerk
Software Developer
Truck Driver
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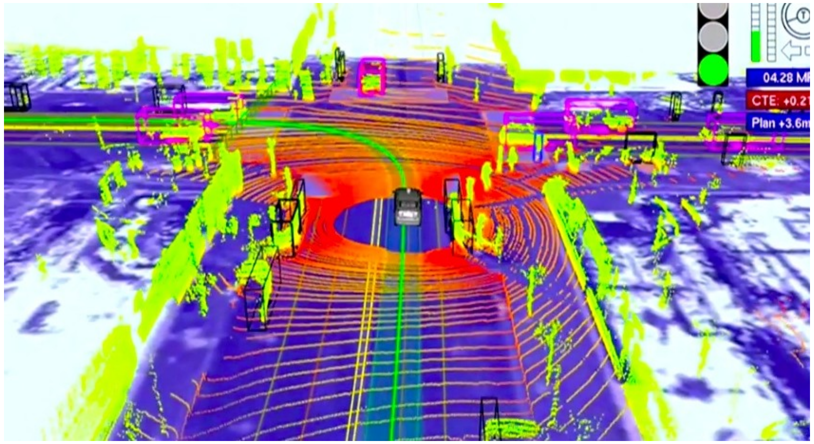
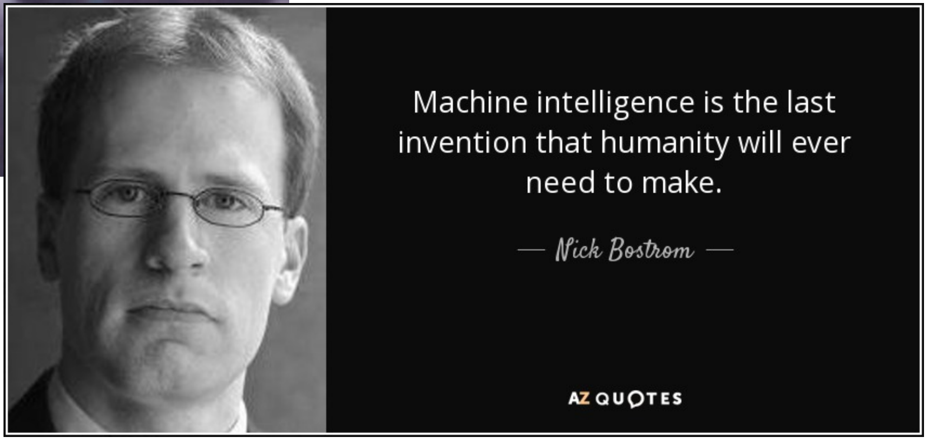


Nick Bostrom



https://www.ted.com/talks/nick_bostrom_what_happens_when_our_computers_get_smarter_than_we_are

See eye to eye!

Ricardo Marroquim

www.lcg.ufrj.br/marroquim

Laboratório de Computação Gráfica

PESC
Programa de Engenharia de Sistemas e Computação

Cefet/RJ – V Workshop da Escola de Informática & Computação – 26 outubro 2017

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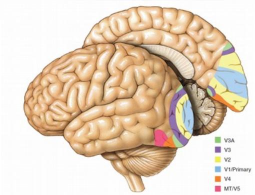

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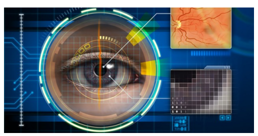

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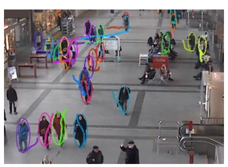

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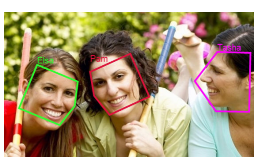

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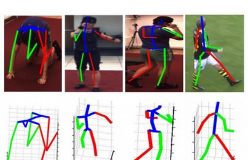

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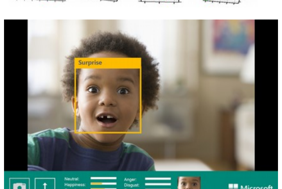

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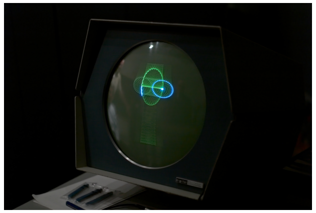

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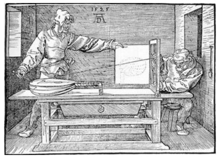

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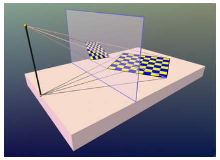

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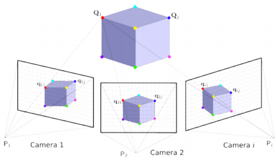

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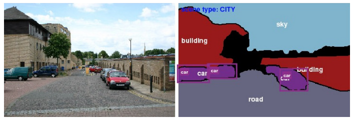

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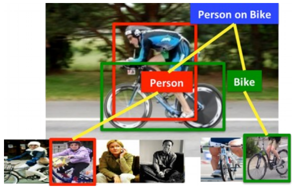

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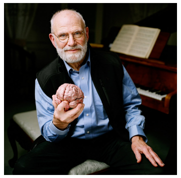

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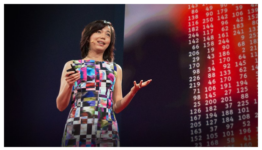

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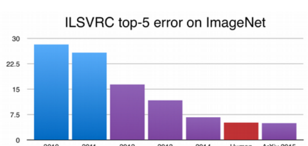

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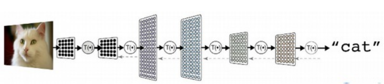

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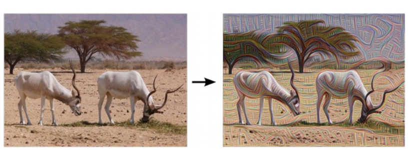

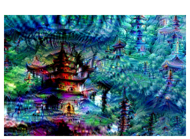

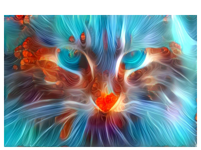

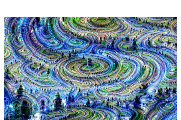

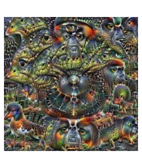

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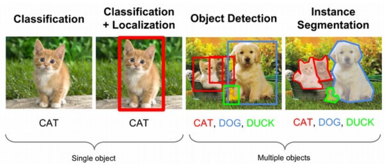

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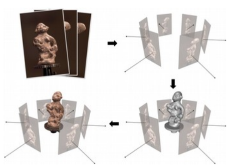

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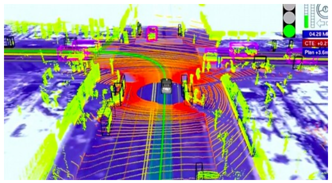

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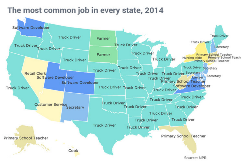

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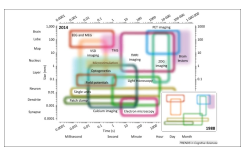
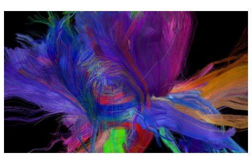


Self-portraits of the brain: cognitive science, data visualization, and communicating brain structure and function



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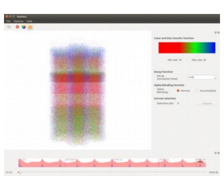

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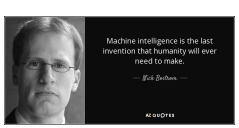

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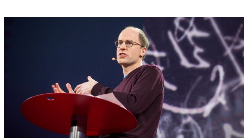

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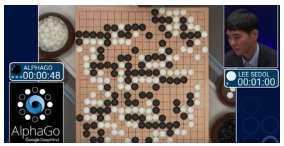

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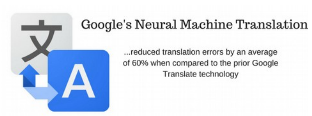

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