

# Machine Learning in Imaging

BME 590L  
Roarke Horstmeyer

Lecture 24: Looking ahead and hyper-parameter optimization

## **Schedule for lectures and assignments**

- Tuesday 4/9: Guest lecture – Dr. Nikhil Naik, MIT Media Lab, Harvard, Salesforce
- Thursday 4/11: "Deep Imaging" Summary
- Tuesday 4/16: Guest lecture – Kevin Zhou, Deep Image Priors & Current GANs
- Saturday 4/20: Homework #5 due
- Monday 4/29, 9am – noon: Final project presentations

## **Components of final project**

Total grade % (after re-distribution of quizzes) – 41%

- 5 minute presentation (share slides afterwards) – 8%
- 3-6 page write up with at least 3 figures and 5 references – 20%
  - Introduction, related work, methods, results, discussion
- share code for submission – 9%
- brief website template & permission to share results – 5%
- shared annotated datasets & permissions – no grade, but would be much appreciated

Final webpage – I'll try to find a suitable template for you guys to fill out

# MoSculp: Interactive Visualization of Shape and Time

Xiuming Zhang<sup>1</sup>

Tali Dekel<sup>2</sup>

Tianfan Xue<sup>2</sup>

Andrew Owens<sup>3</sup>

Qiurui He<sup>1</sup>

Jiajun Wu<sup>1</sup>

Stefanie Mueller<sup>1</sup>

William T. Freeman<sup>1,2</sup>

<sup>1</sup> MIT CSAIL



<sup>2</sup> Google Research

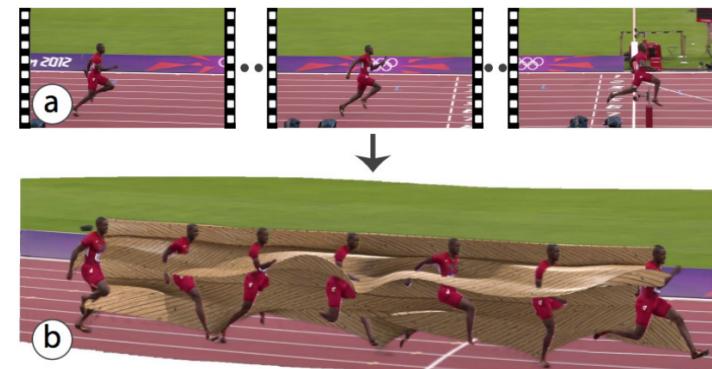


<sup>3</sup> UC Berkeley



## Abstract

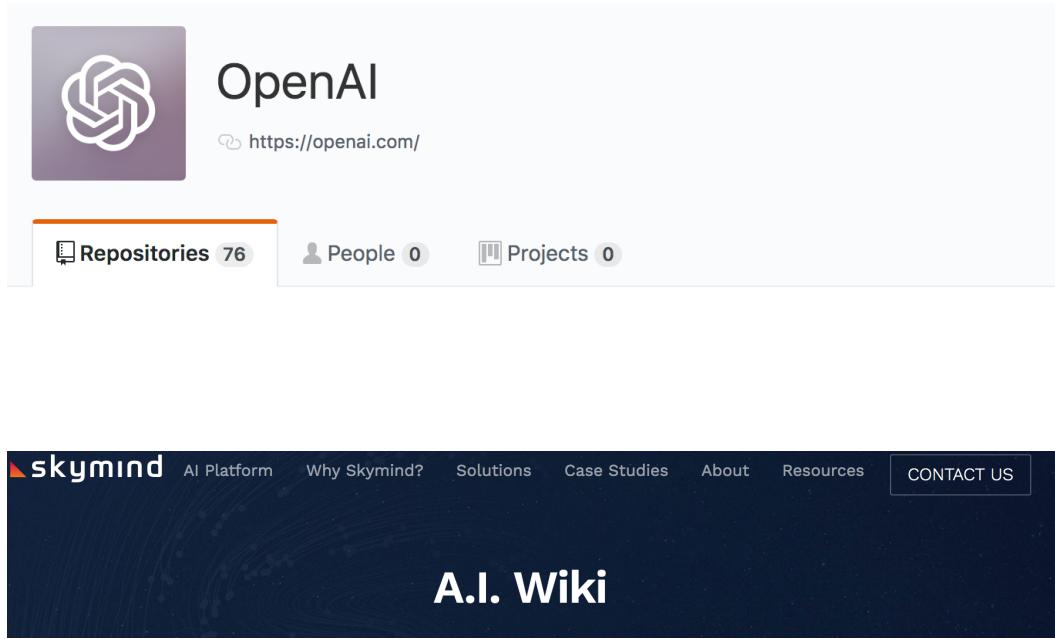
We present a system that visualizes complex human motion via 3D motion sculptures---a representation that conveys the 3D structure swept by a human body as it moves through space. Our system computes a motion sculpture from an input video, and then embeds it back into the scene in a 3D-aware fashion. The user may also explore the sculpture directly in 3D or physically print it. Our interactive interface allows users to customize the sculpture design, for example, by selecting materials and lighting conditions.



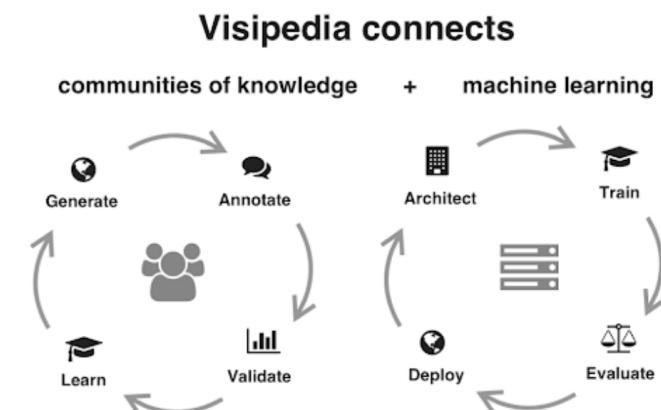
**Where are things going with Machine Learning and Imaging in 10 years?**

# Where are things going with Machine Learning and Imaging in 10 years?

1. Proliferation of trained models, similar datasets and shared goals



Visipedia

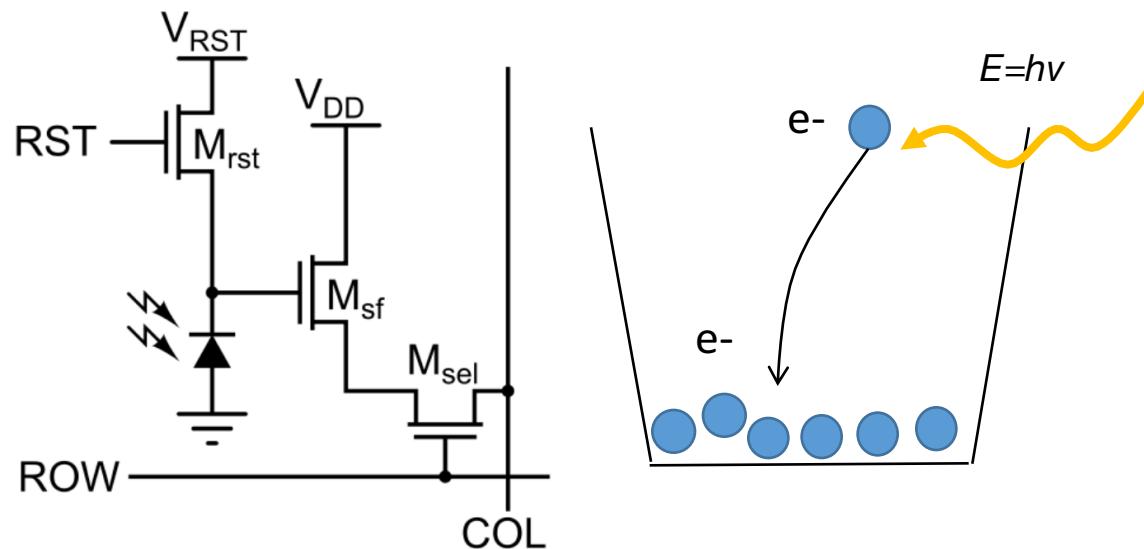


Caltech Visipedia

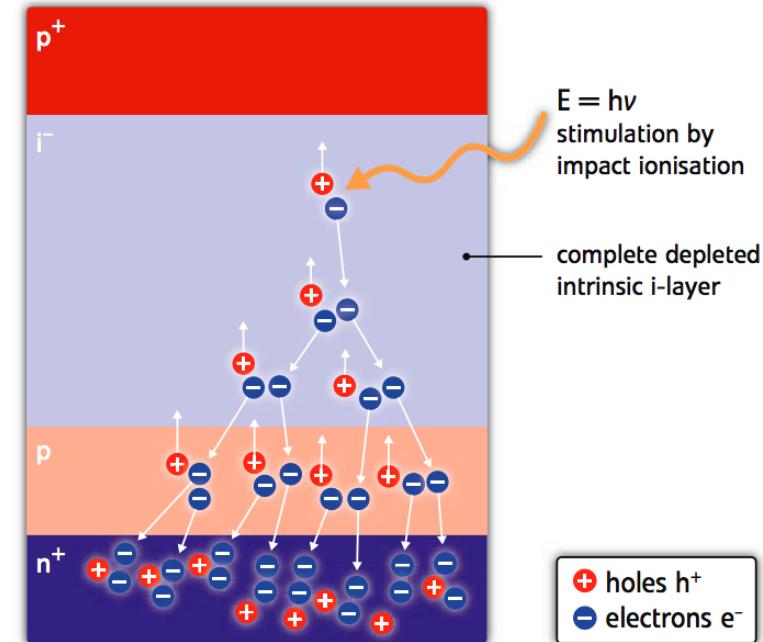
# Where are things going with Machine Learning and Imaging in 10 years?

## 2. “Cameras” on many devices & new types of sensors

Standard CMOS pixel = bucket that collects electrons

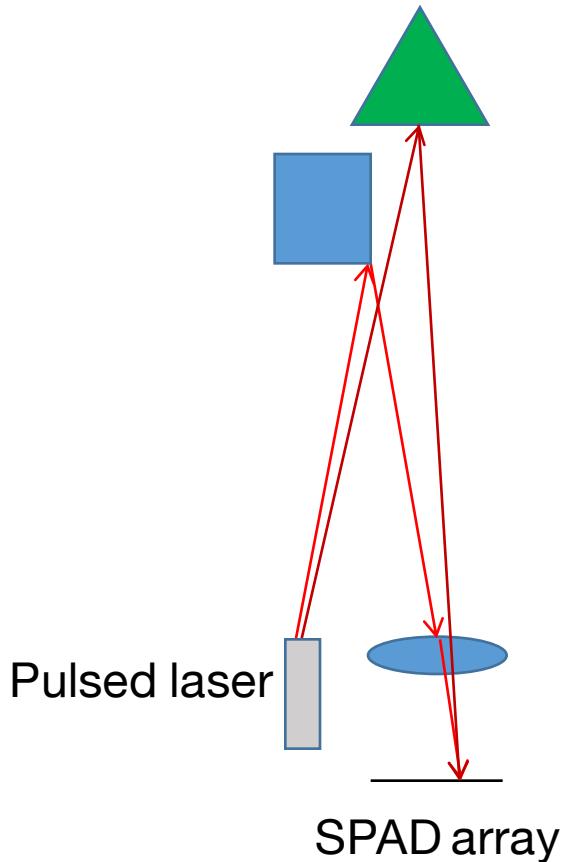


SPAD pixel: was there a photon or not?

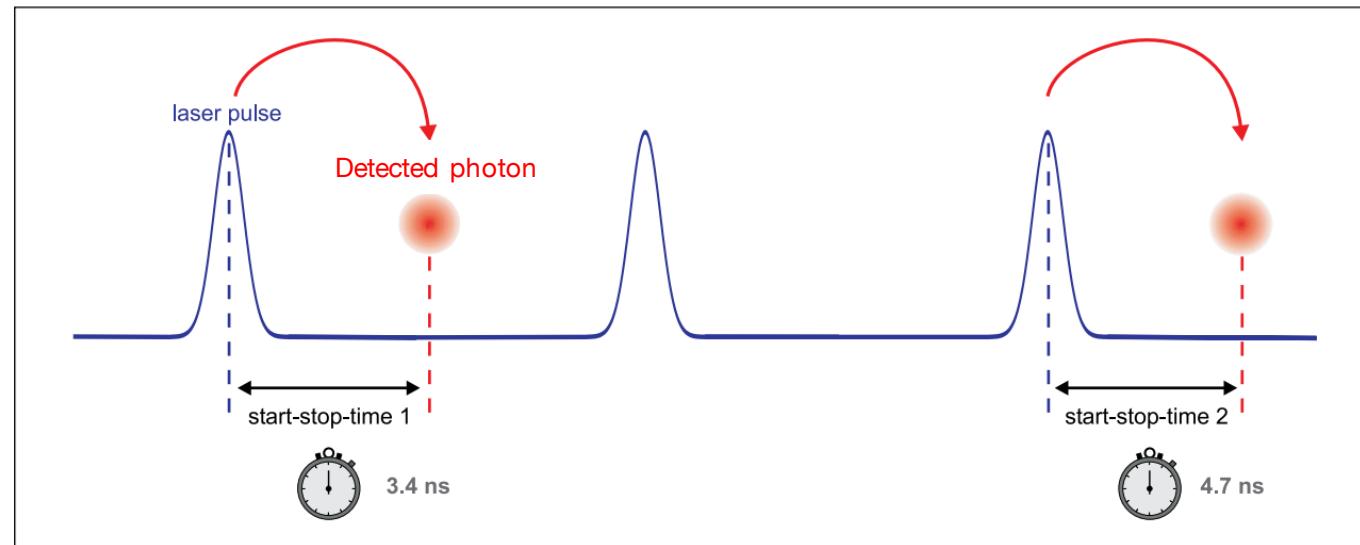


# Where are things going with Machine Learning and Imaging in 10 years?

## 2. “Cameras” on many devices & new types of sensors



- Light travels 1 ft in 1 ns.
- SPADs can precisely photon arrival time to measure travel distance (TOF)



# Where are things going with Machine Learning and Imaging in 10 years?

## 2. “Cameras” on many devices & new types of sensors

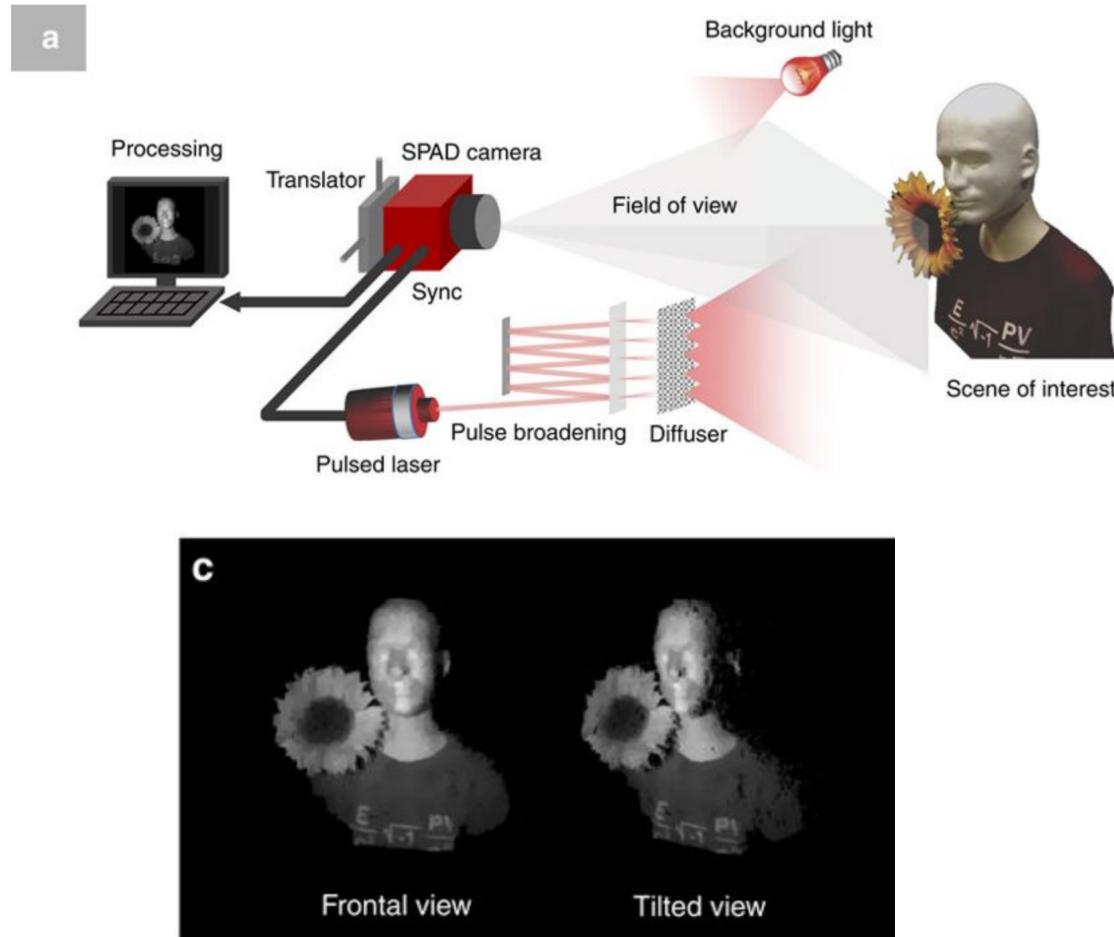
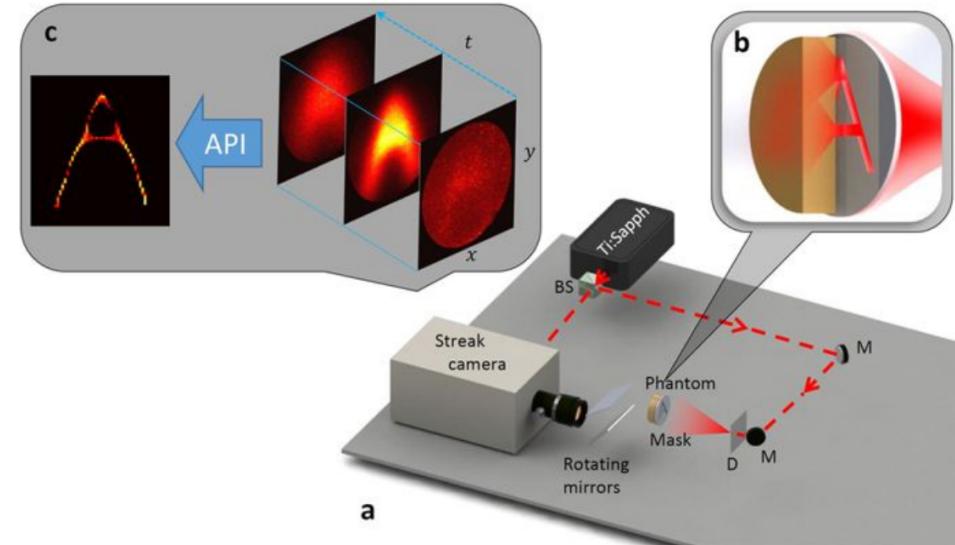


Figure 1: Imaging Through Thick Scattering.



G. Satat et al, <https://www.nature.com/articles/srep33946>

D. Shen et al, <https://www.nature.com/articles/ncomms12046>

# **Where are things going with Machine Learning and Imaging in 10 years?**

3. Beyond convolutions - new constructs for deep networks

# **Where are things going with Machine Learning and Imaging in 10 years?**

## **3. Beyond convolutions - new constructs for deep networks**

---

### **Dynamic Routing Between Capsules**

---

**Sara Sabour**

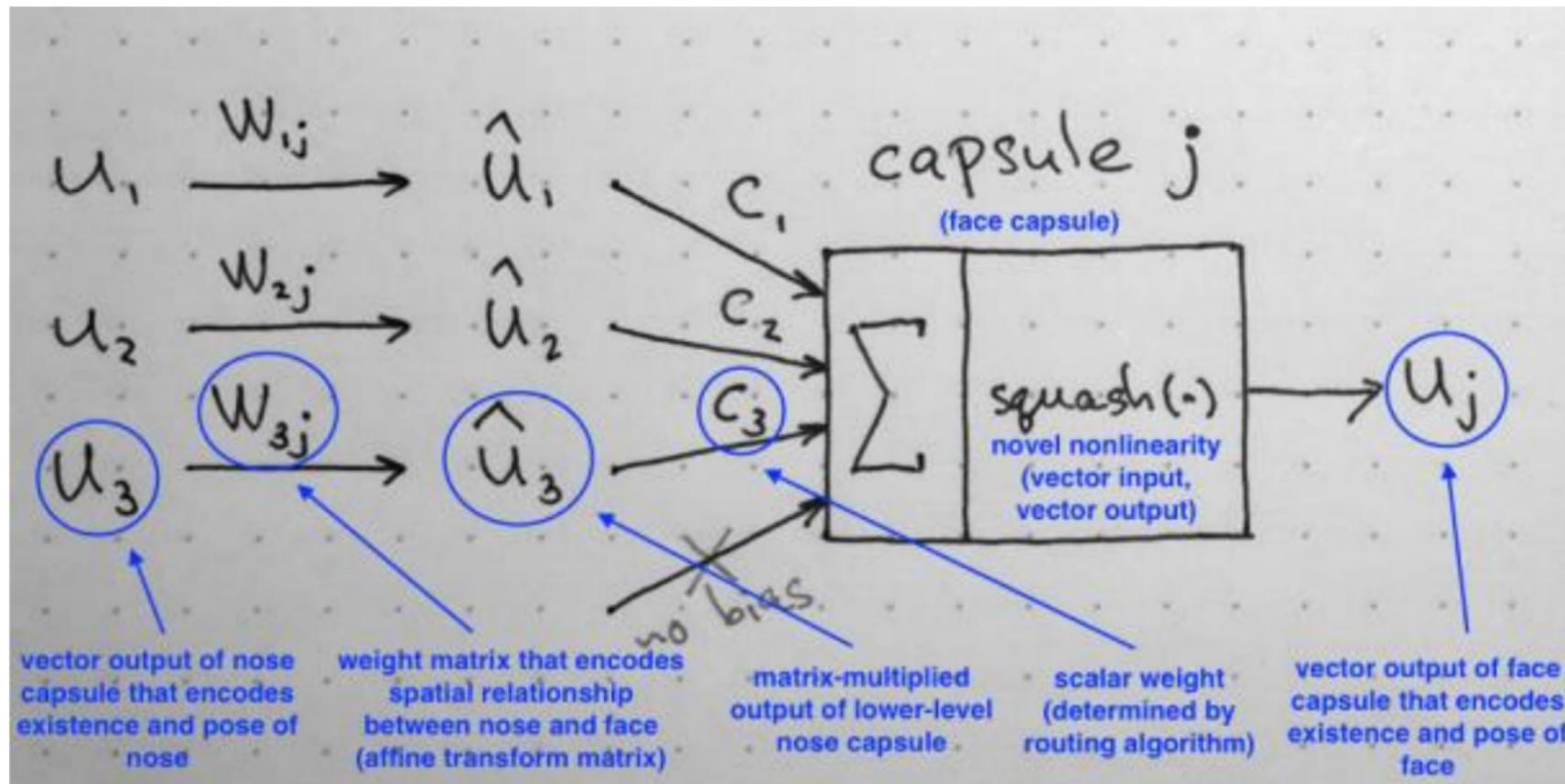
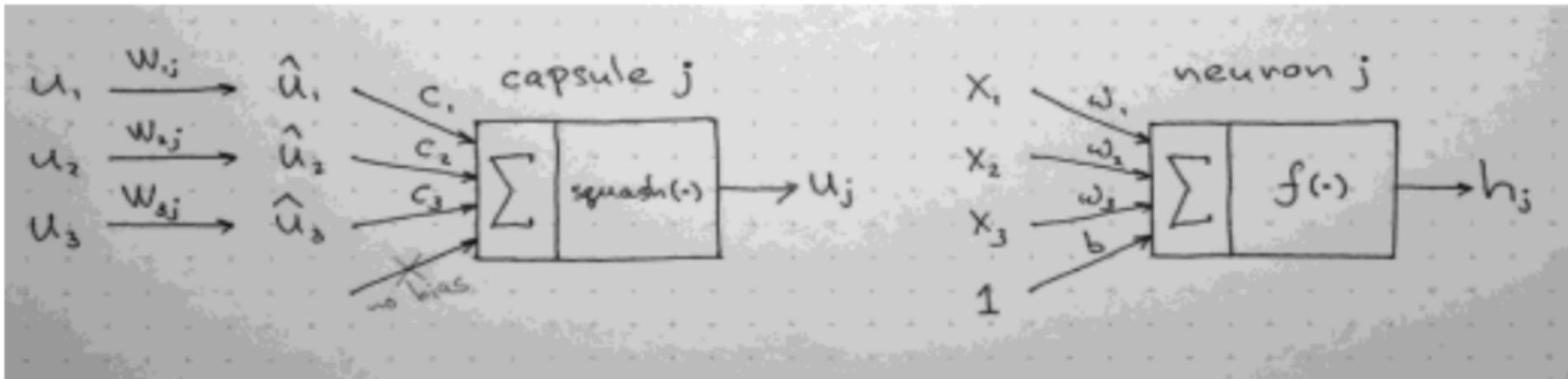
**Nicholas Frosst**

**Geoffrey E. Hinton**

Google Brain

Toronto

{sasabour, frosst, geoffhinton}@google.com



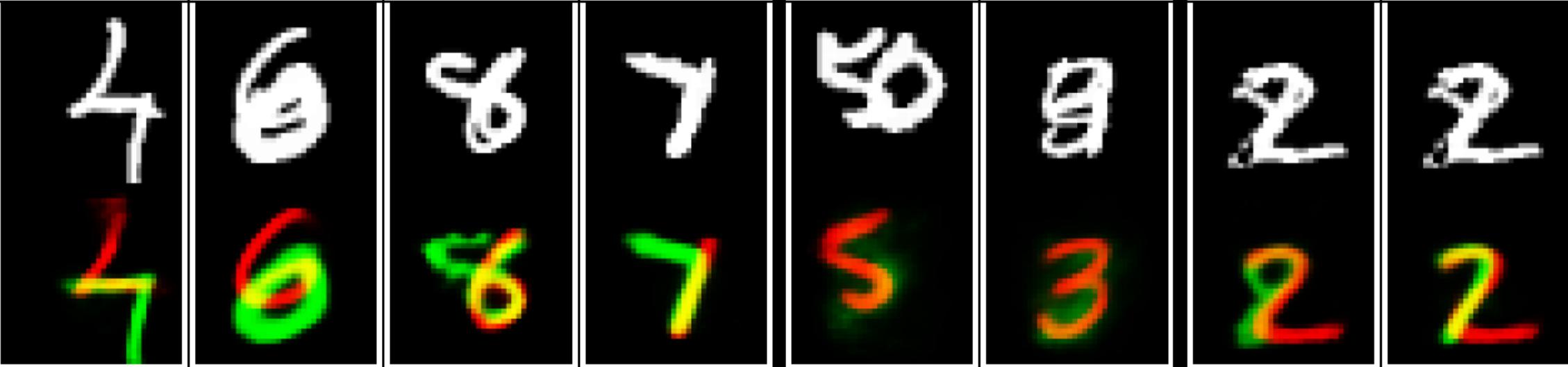
# Where are things going with Machine Learning and Imaging in 10 years?

## 3. Beyond convolutions - new constructs for deep networks

Capsule vs. Traditional Neuron			
Input from low-level capsule/neuron	vector( $\mathbf{u}_i$ )	scalar( $x_i$ )	
Operation	Affine Transform	$\hat{\mathbf{u}}_{j i} = \mathbf{W}_{ij}\mathbf{u}_i$	-
	Weighting	$\mathbf{s}_j = \sum_i c_{ij} \hat{\mathbf{u}}_{j i}$	$a_j = \sum_i w_i x_i + b$
	Sum		
	Nonlinear Activation	$\mathbf{v}_j = \frac{\ \mathbf{s}_j\ ^2}{1+\ \mathbf{s}_j\ ^2} \frac{\mathbf{s}_j}{\ \mathbf{s}_j\ }$	$h_j = f(a_j)$
Output	vector( $\mathbf{v}_j$ )	scalar( $h_j$ )	

3. Therefore R will not assign one pixel to two digits if one of them does not have any other support.

R:(2, 7) L:(2, 7)	R:(6, 0) L:(6, 0)	R:(6, 8) L:(6, 8)	R:(7, 1) L:(7, 1)	*R:(5, 7) L:(5, 0)	*R:(2, 3) L:(4, 3)	R:(2, 8) L:(2, 8)	R:P:(2, 7) L:(2, 8)
----------------------	----------------------	----------------------	----------------------	-----------------------	-----------------------	----------------------	------------------------



R:(8, 7) L:(8, 7)	R:(9, 4) L:(9, 4)	R:(9, 5) L:(9, 5)	R:(8, 4) L:(8, 4)	*R:(0, 8) L:(1, 8)	*R:(1, 6) L:(7, 6)	R:(4, 9) L:(4, 9)	R:P:(4, 0) L:(4, 9)
----------------------	----------------------	----------------------	----------------------	-----------------------	-----------------------	----------------------	------------------------

