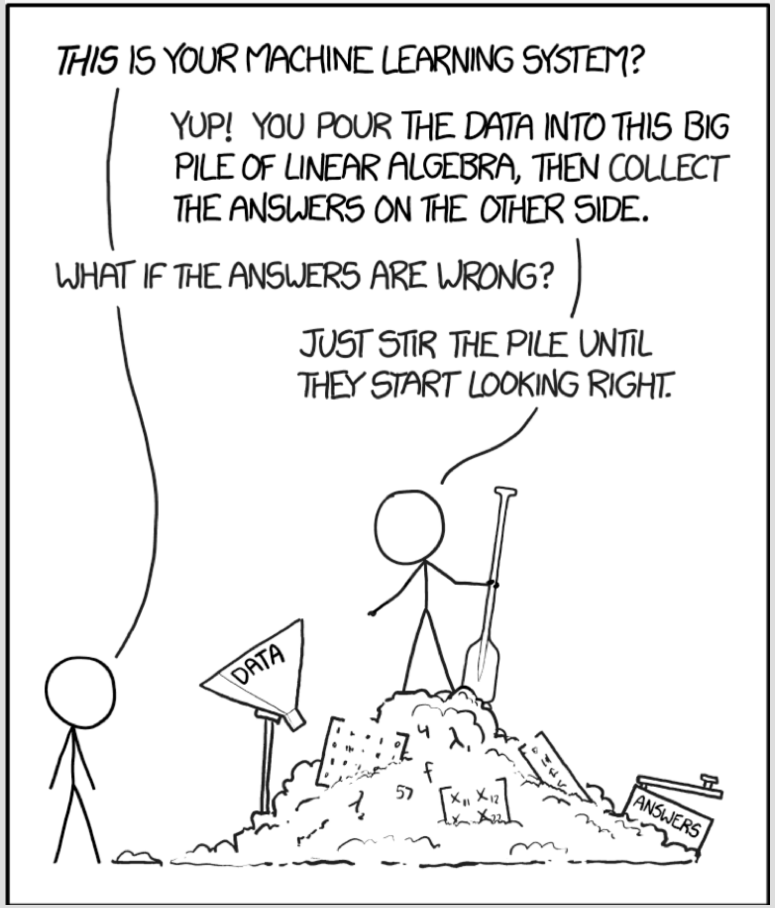
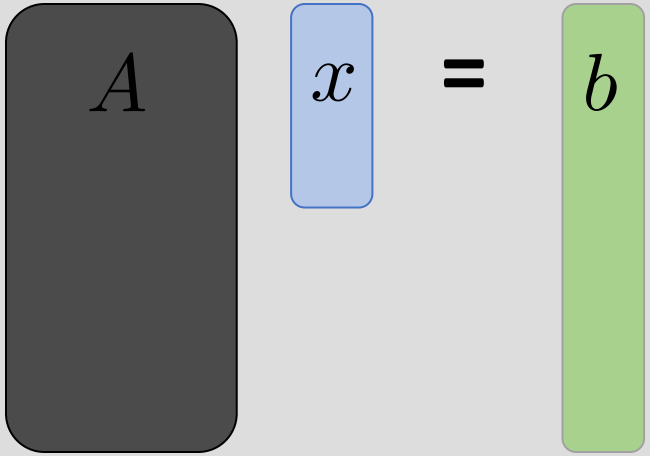


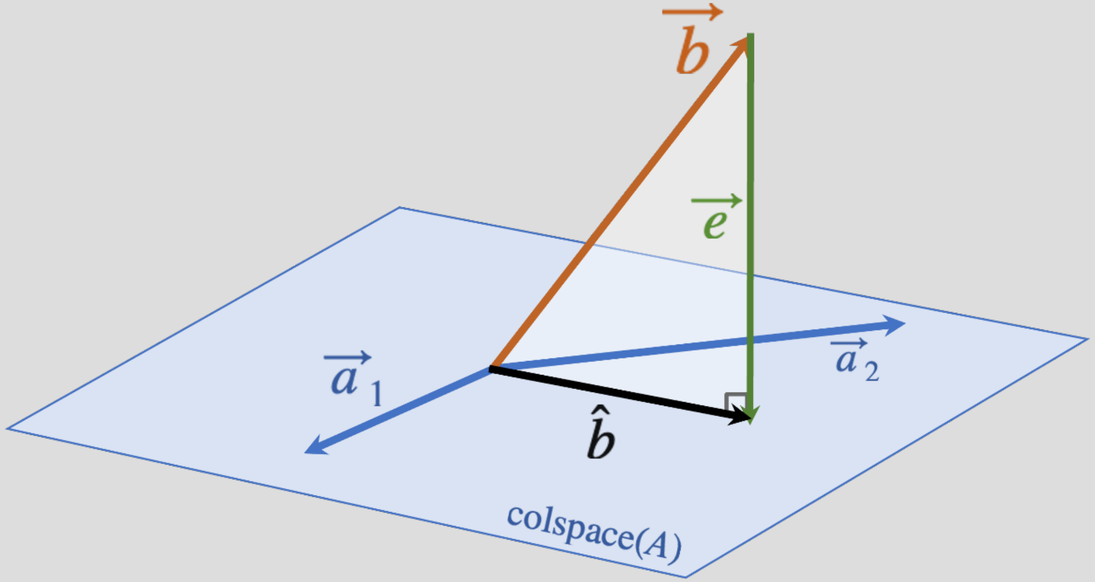
THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

EECS 16A

fun stuff!

*Over*determined system: use least squares

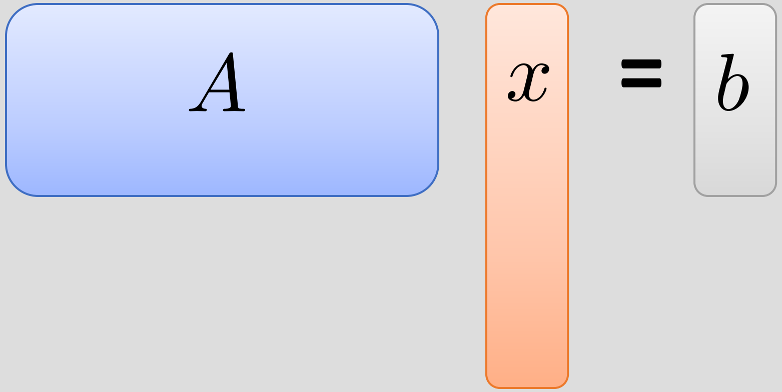


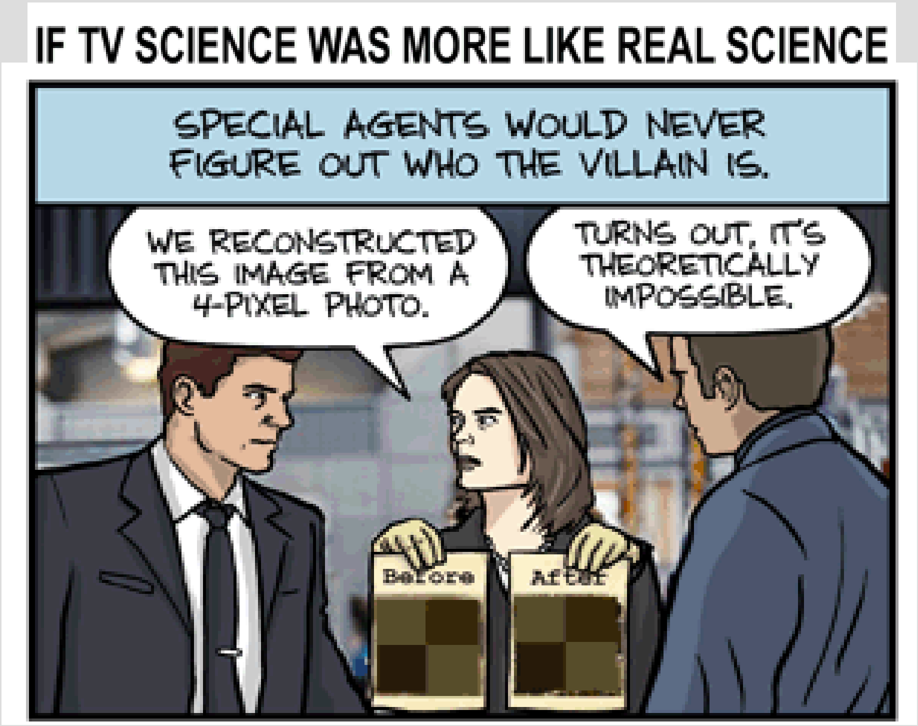


- the least-squares solution “minimally perturbs” b

$$\boxed{\hat{x} = (A^T A)^{-1} A^T \vec{b}}$$

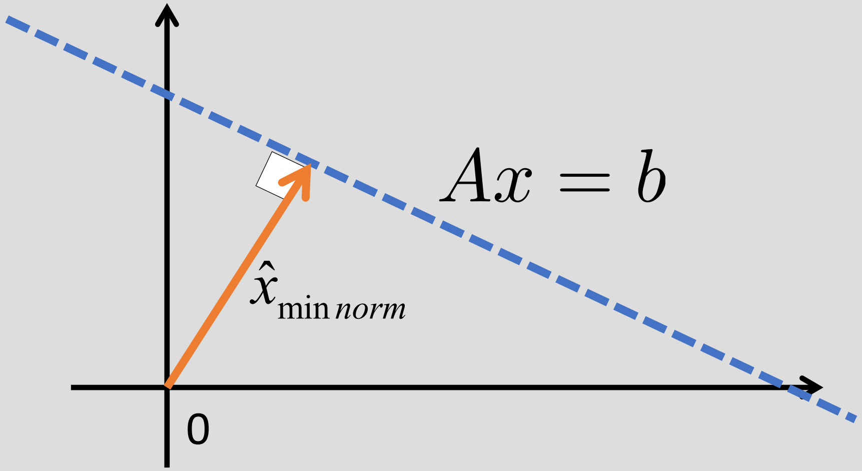
Underdetermined system: ????



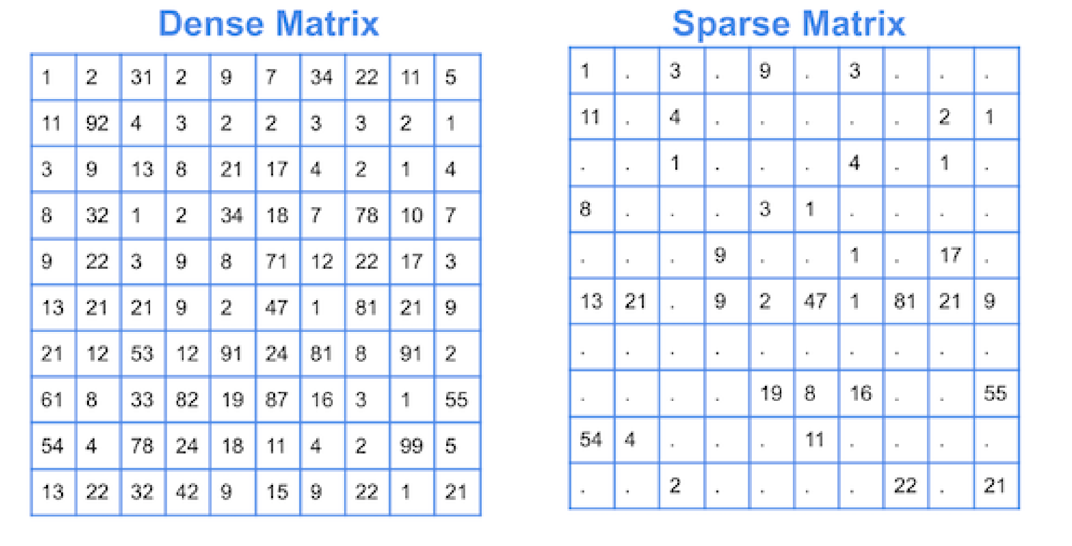

IF TV SCIENCE WAS MORE LIKE REAL SCIENCE
SPECIAL AGENTS WOULD NEVER FIGURE OUT WHO THE VILLAIN IS.
WE RECONSTRUCTED THIS IMAGE FROM A 4-PIXEL PHOTO.
TURNS OUT, IT'S THEORETICALLY IMPOSSIBLE.
Before
After

- Can be infinite valid solutions!
- Ideas: pick the 'smallest' one? The 'sparsest'?
  - e.g. min norm:

$$\hat{x}_{\min norm} = \mathbf{A}^T(\mathbf{A}\mathbf{A}^T)^{-1}\vec{b}$$



‘Sparsity’ tells us how ‘dense’ the solution is



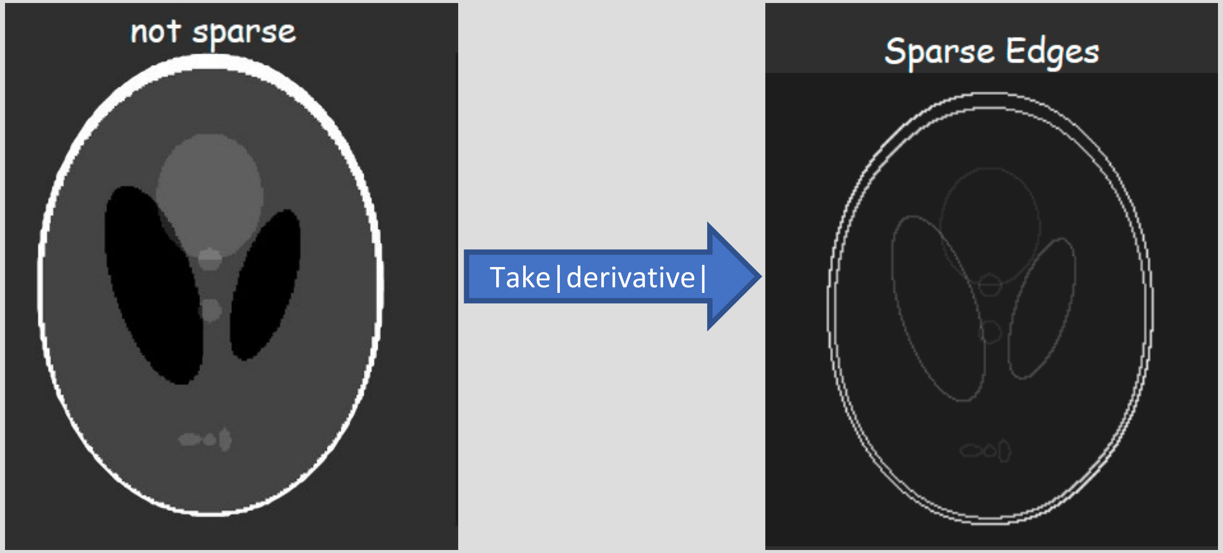
Dense Matrix

1	2	31	2	9	7	34	22	11	5
11	92	4	3	2	2	3	3	2	1
3	9	13	8	21	17	4	2	1	4
8	32	1	2	34	18	7	78	10	7
9	22	3	9	8	71	12	22	17	3
13	21	21	9	2	47	1	81	21	9
21	12	53	12	91	24	81	8	91	2
61	8	33	82	19	87	16	3	1	55
54	4	78	24	18	11	4	2	99	5
13	22	32	42	9	15	9	22	1	21

Sparse Matrix

1	.	3	.	9	.	3	.	.	.
11	.	4	.	.	.	.	.	2	1
.	.	1	.	.	.	4	.	1	.
8	.	.	.	3	1	.	.	.	.
.	.	.	9	.	.	1	.	17	.
13	21	.	9	2	47	1	81	21	9
.	.	.	.	.	.	.	.	.	.
.	.	.	.	19	8	16	.	.	55
54	4	.	.	.	11	.	.	.	.
.	.	2	.	.	.	.	22	.	21

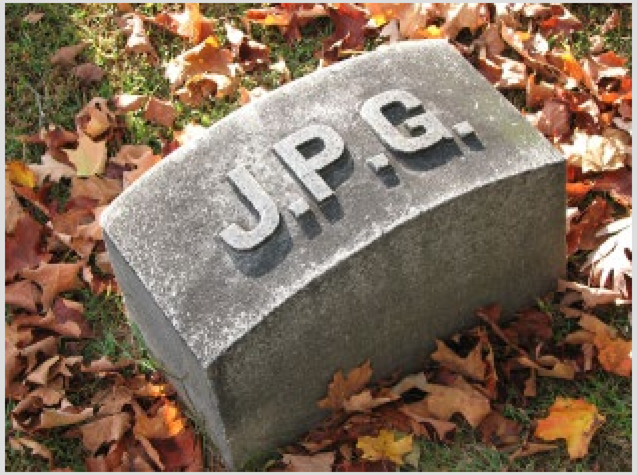
The fraction of non-zero elements in a matrix is called the ***sparsity***



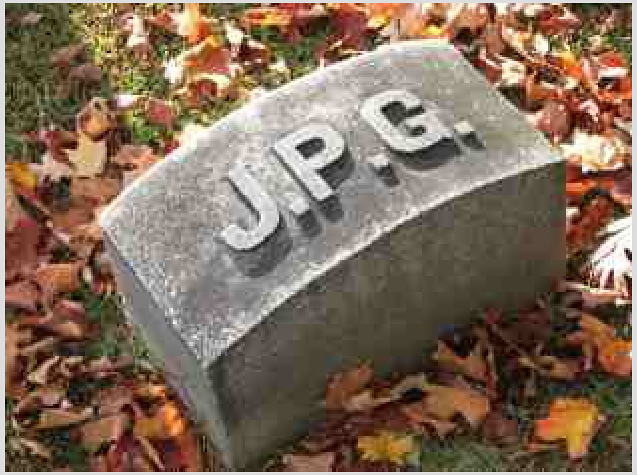
Sometimes things are sparse in a different way

Example: image compression

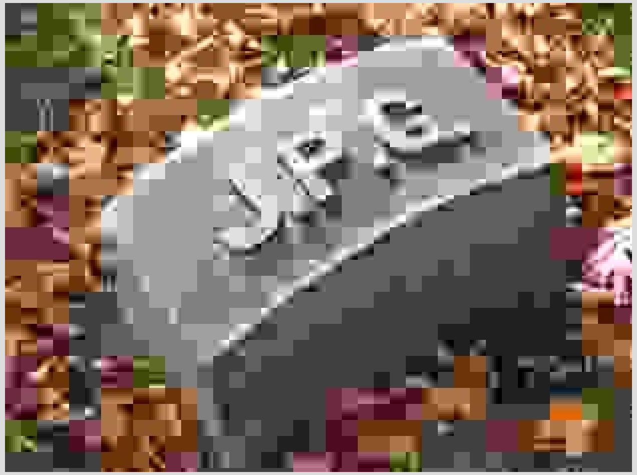
Reduce memory by smartly choosing which information to throw away



No compression

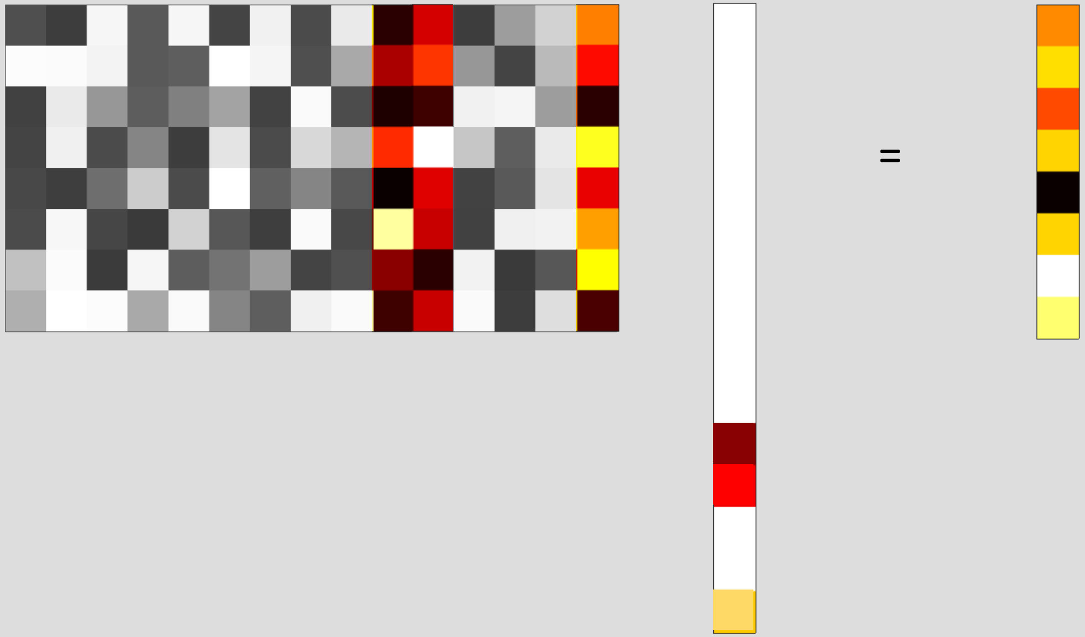


23:1 compression

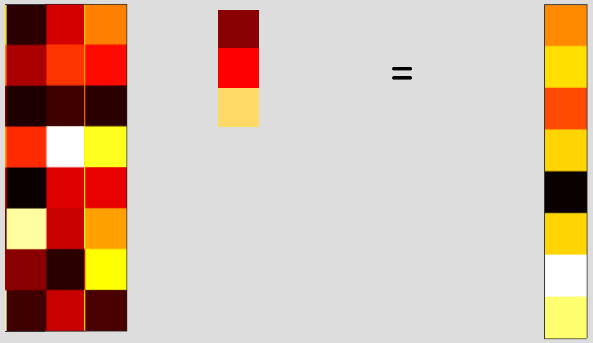


144:1 compression

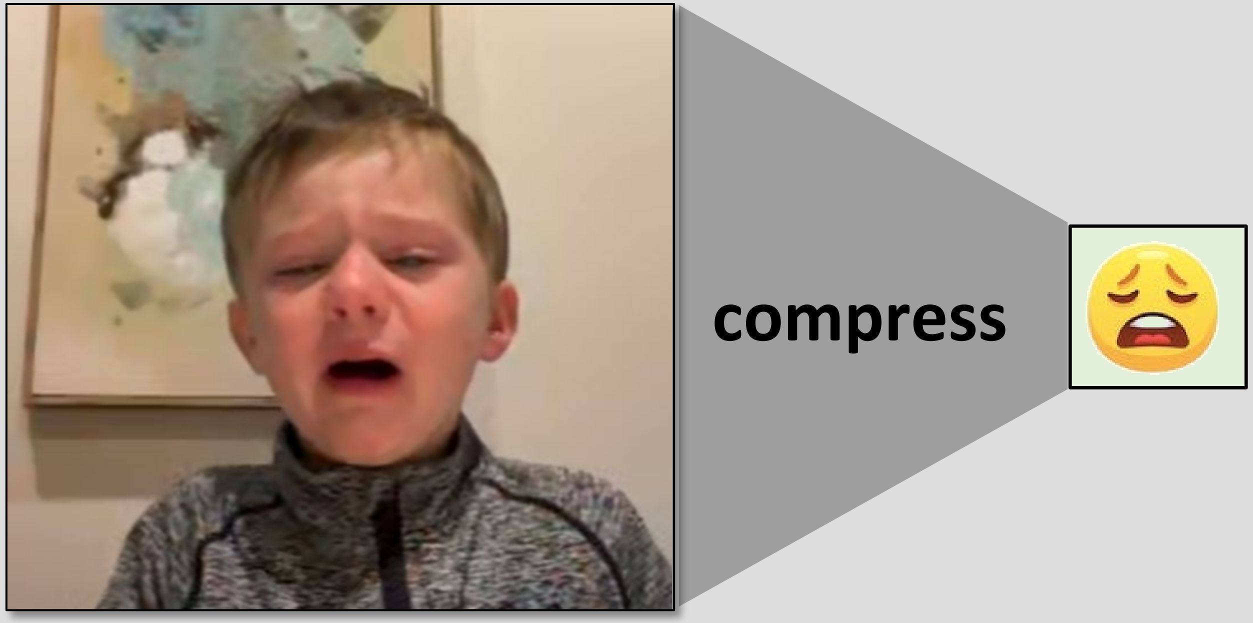
Sparse x means only a few columns of A ‘matter’



If we knew which elements were non-zero, we could solve a small least squares problem:

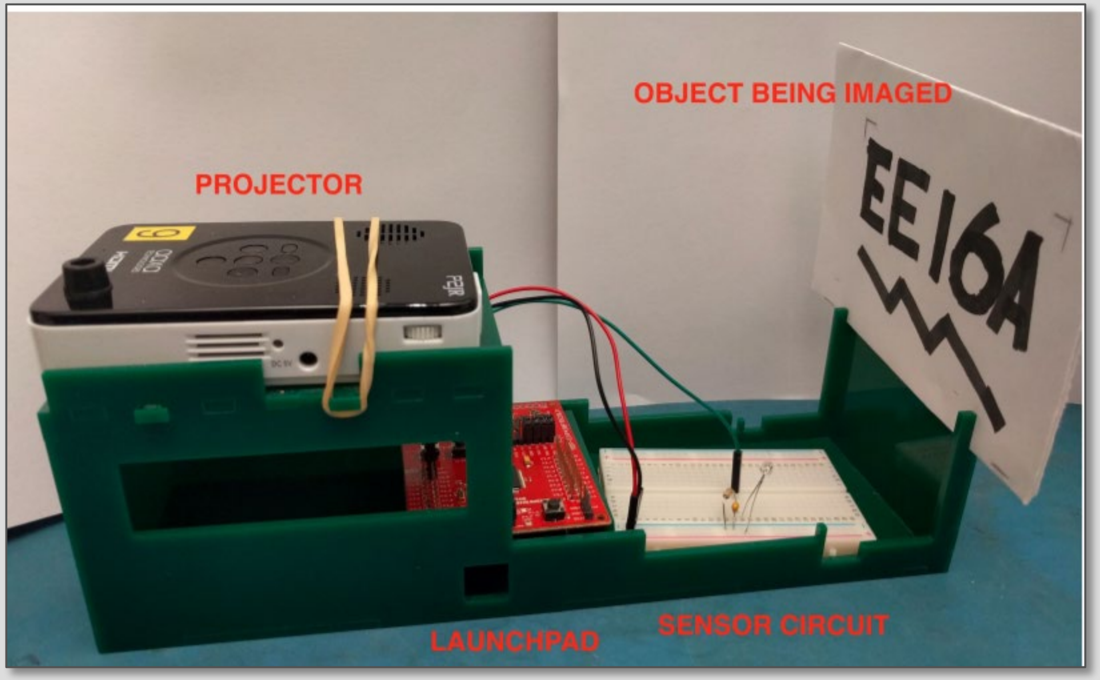


Can we compress data at the capture stage?

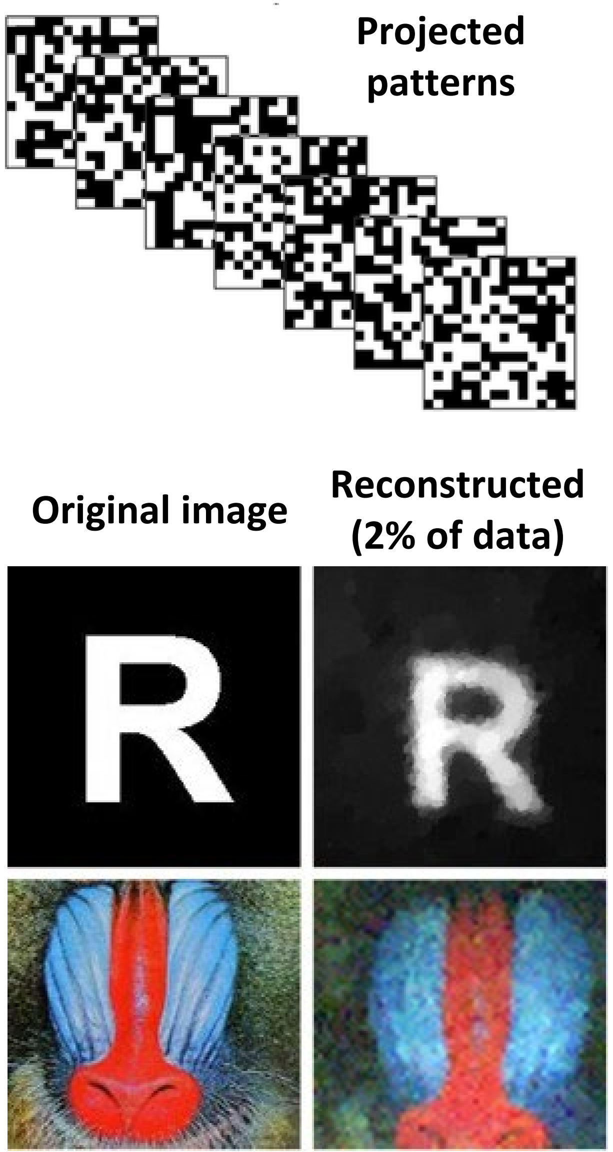


compress

Yes! With compressed sensing!
Example: single-pixel camera

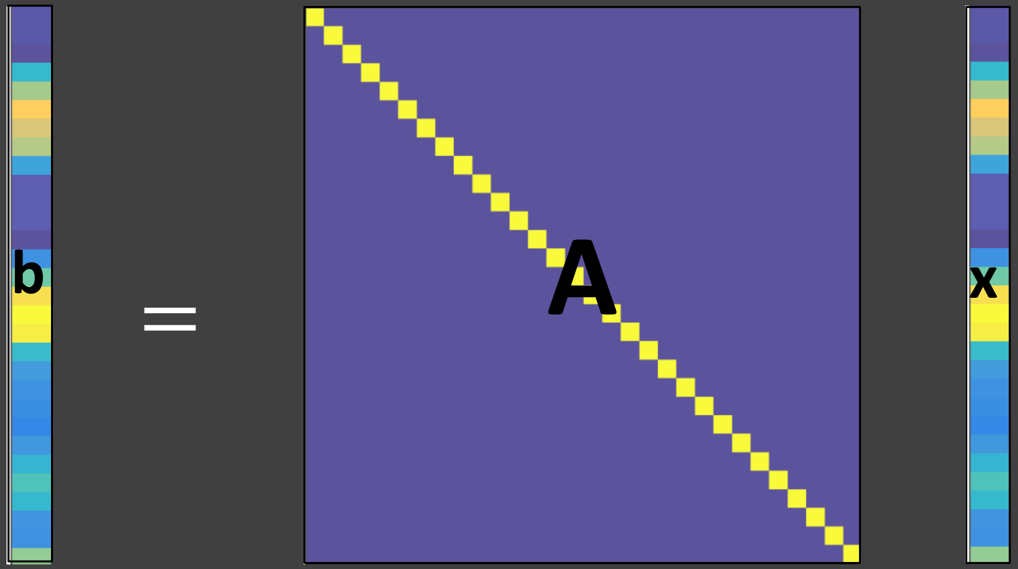


If you design the patterns on your imaging lab well, and images are compressible, you could solve with very little data!

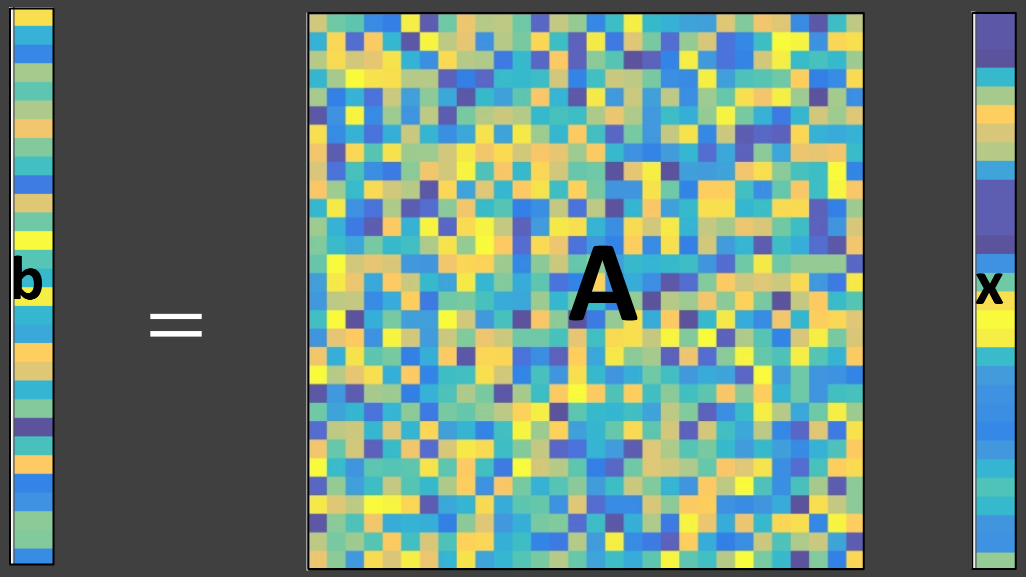


Barniauk et al., Rice University.

We usually take direct measurements

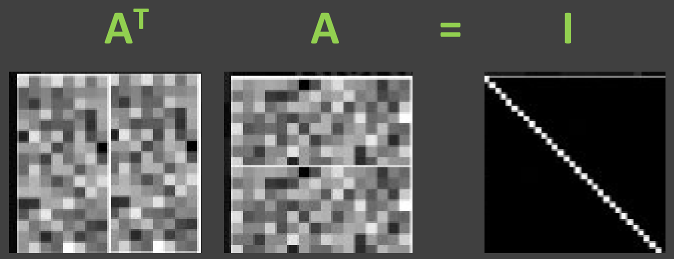


Multiplexed measurements

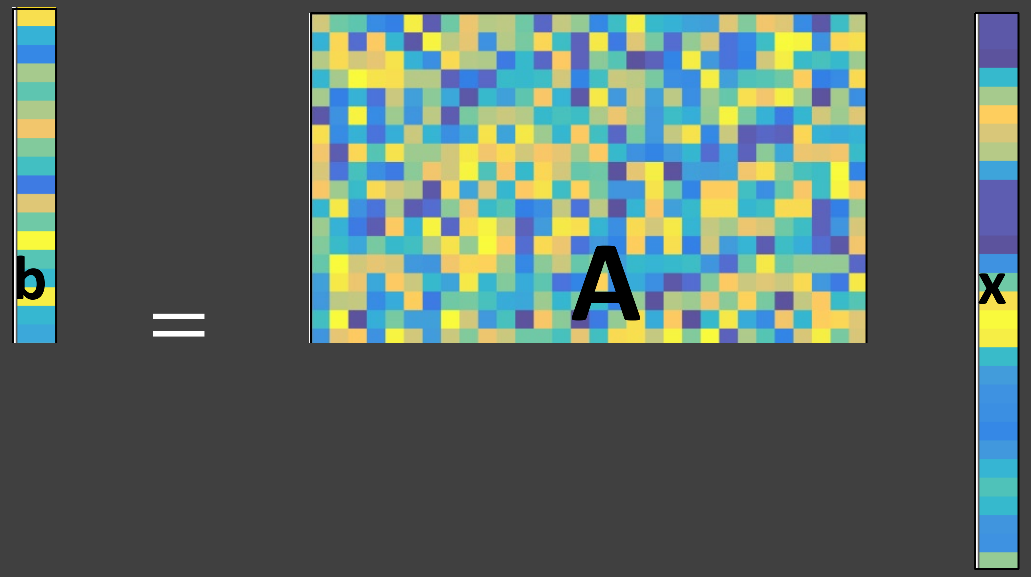


What makes a good A matrix?

A is “orthogonal”

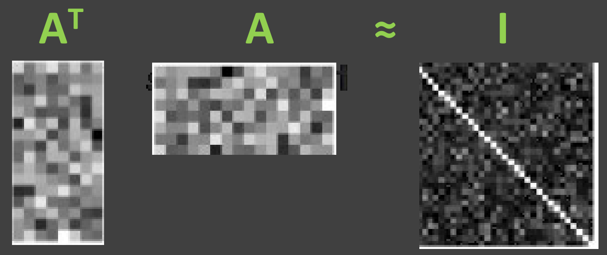


Compressed sensing solves underdetermined problems



What makes a good A matrix?

A is (almost) orthogonal



Computational Imaging

2019
iPhone 11 Pro
2029
iPhone 21 Pro

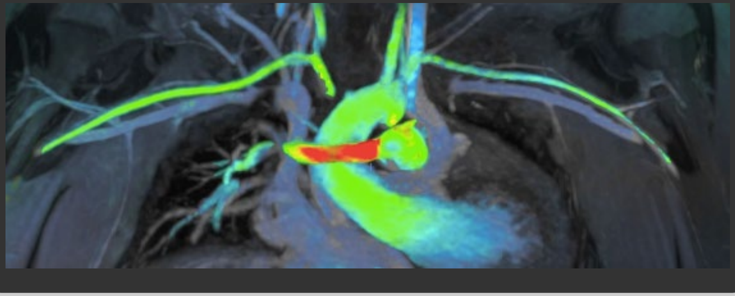
Computational Imaging @ Berkeley

Light Field Cameras

Ren Ng

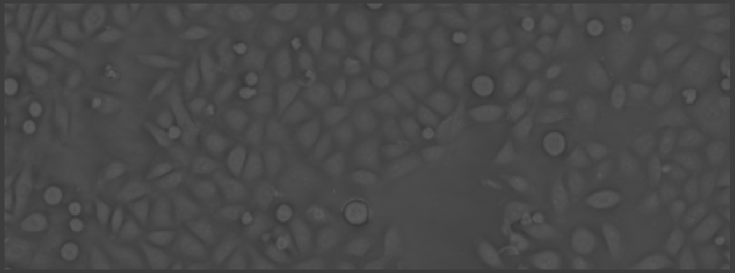
Compressed Sensing MRI

Michael Lustig



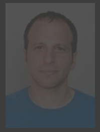
Comp. Illumination Microscopy

Laura Waller



Full-stack Optimization

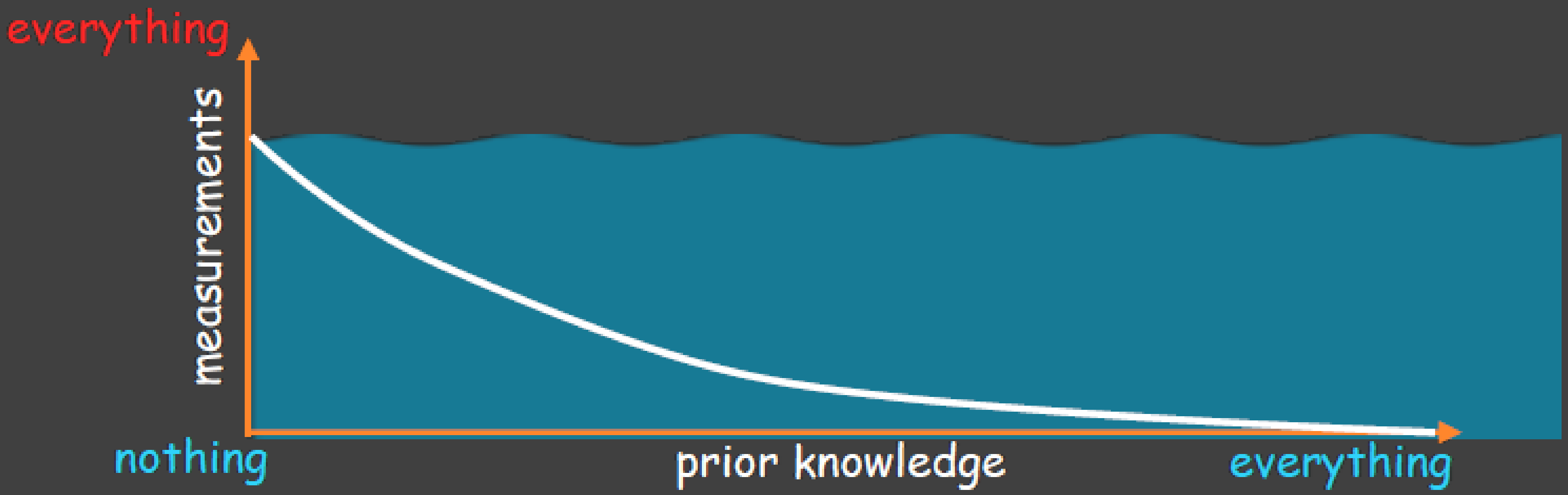
Ben Recht

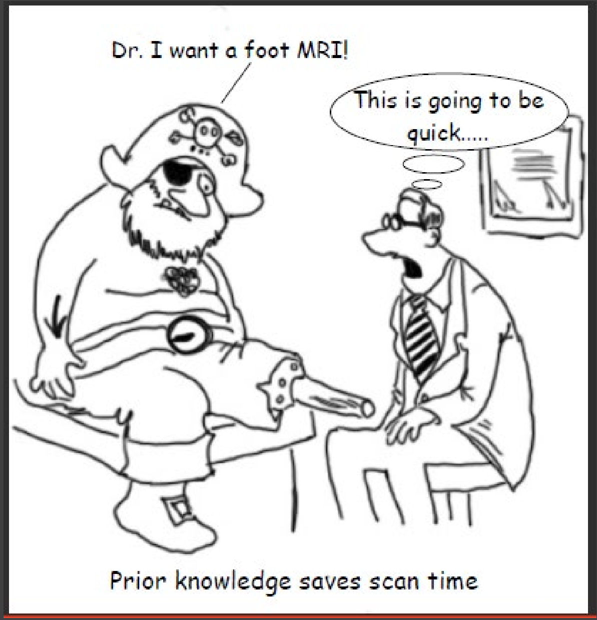


$$x(s) = \mathrm{PSF} \circledast \left\{ \sum_{j=1}^{k} c_j \delta(s - s_j) \right\}$$

Compressed sensing is all about using prior knowledge

- Redundancy reduces sampling requirements
  (The more you know, the less you need)



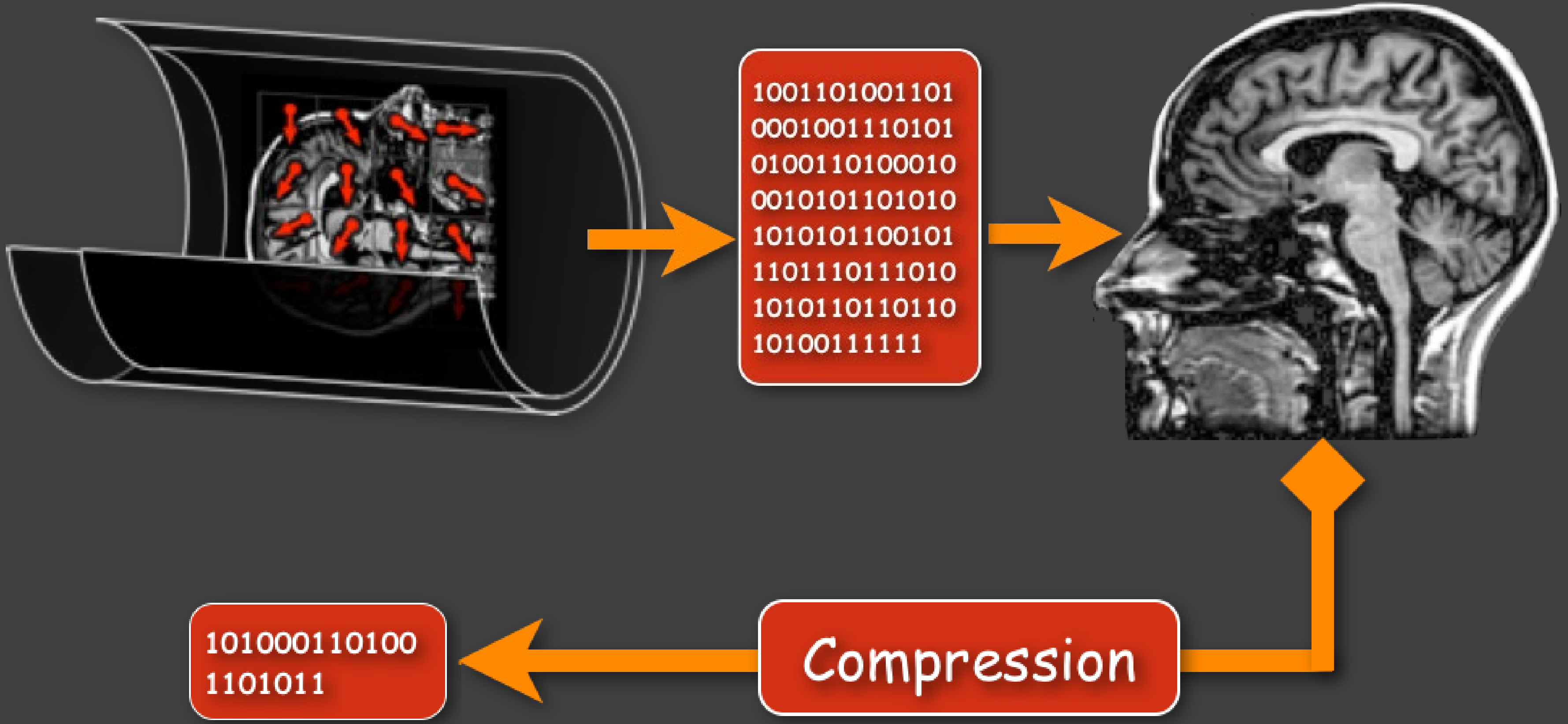

Dr. I want a foot MRI!
This is going to be quick.....
Prior knowledge saves scan time

M. Lustig, UC Berkeley

Compressed Sensing MRI

Medical images are compressible

- Standard approach: First collect, then compress



1001101001101
0001001110101
0100110100010
0010101101010
1010101100101
1101110111010
1010110110110
10100111111

Compression

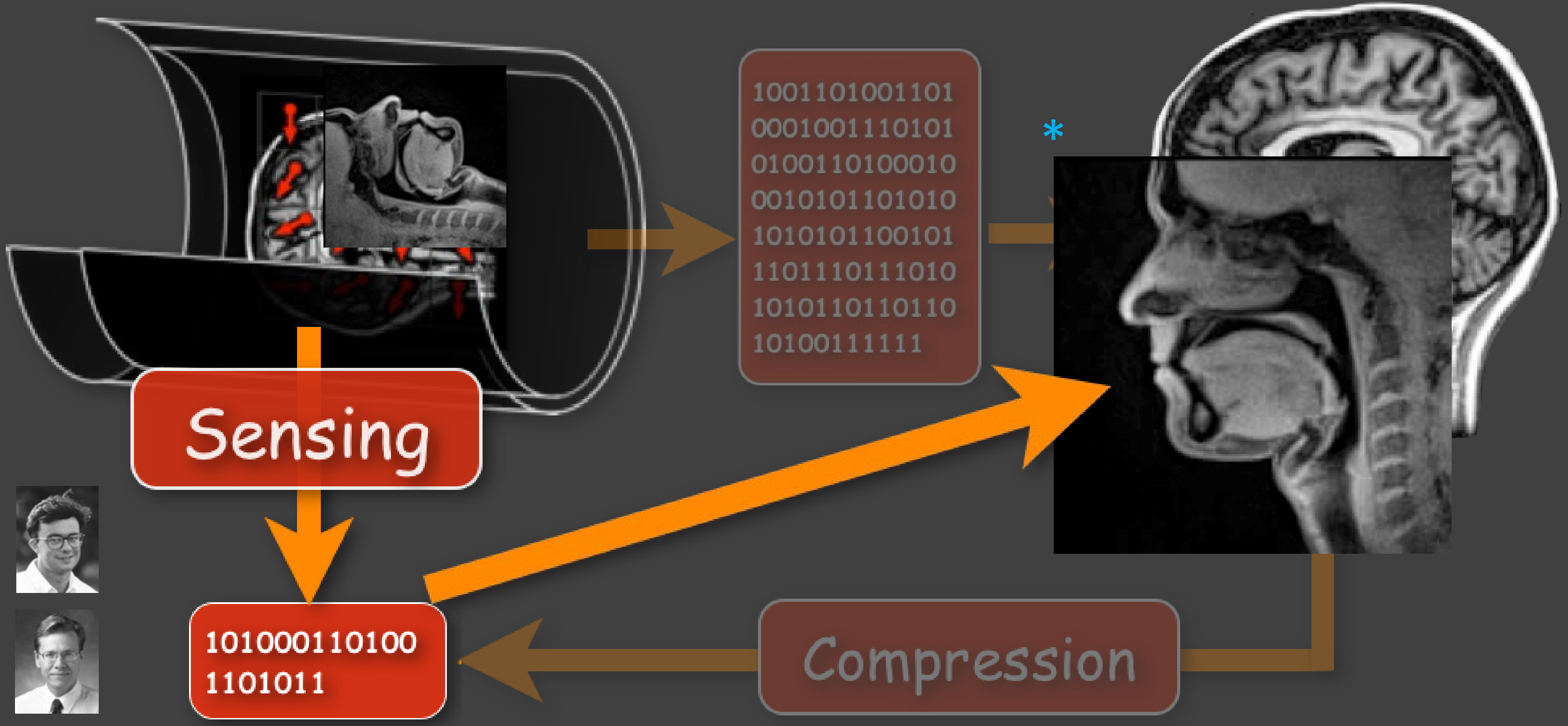
101000110100
1101011

Michael Lustig's Lab

Compressed Sensing MRI

Medical images are compressible

New approach: Acquire “compressed” data directly!



*Courtesy, M. Uecker, J. Frahm, Max Planck

Michael Lustig’s Lab

Computational Imaging @ Berkeley

Light Field Cameras

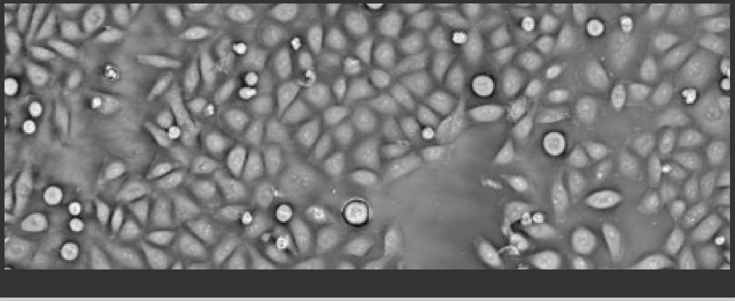
Ren Ng

Compressed Sensing MRI

Michael Lustig

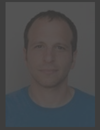
Comp. Illumination Microscopy

Laura Waller



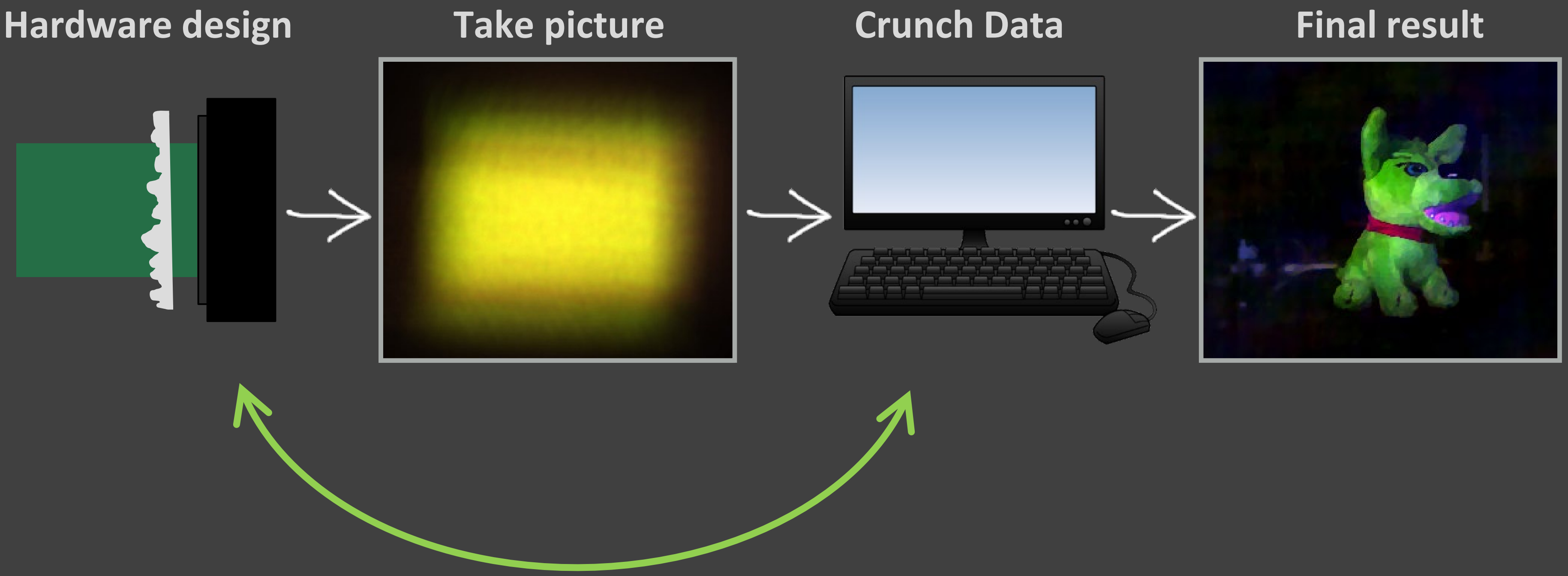
Full-stack Optimization

Ben Recht



$$x(s) = \mathrm{PSF} \circledast \left\{ \sum_{j=1}^{k} c_j \delta(s - s_j) \right\}$$

Computational imaging pipeline



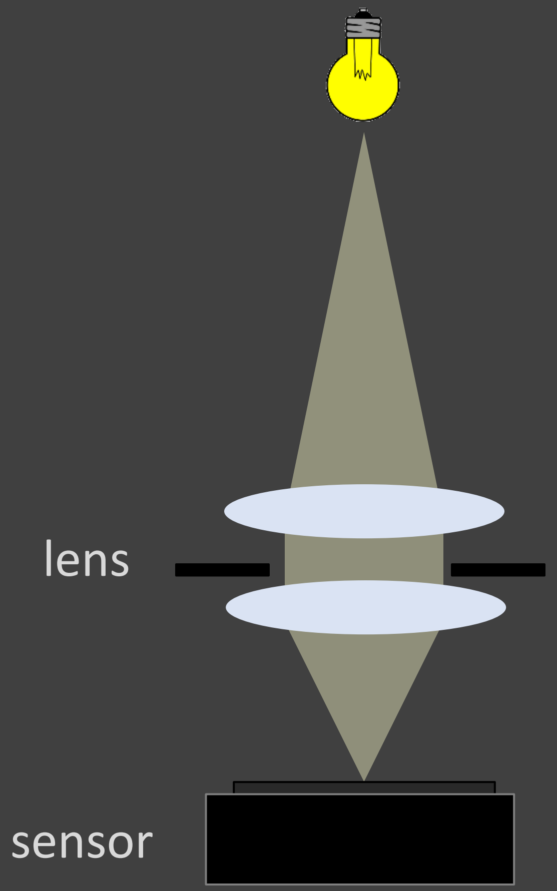
Hardware design

Take picture

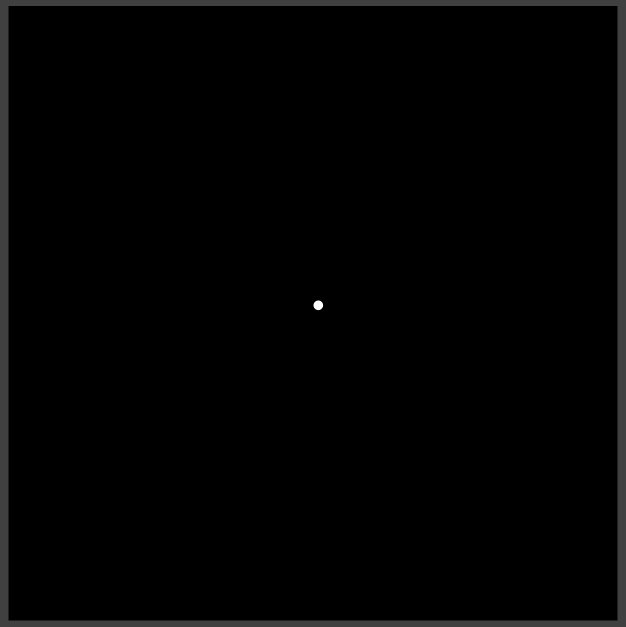
Crunch Data

Final result

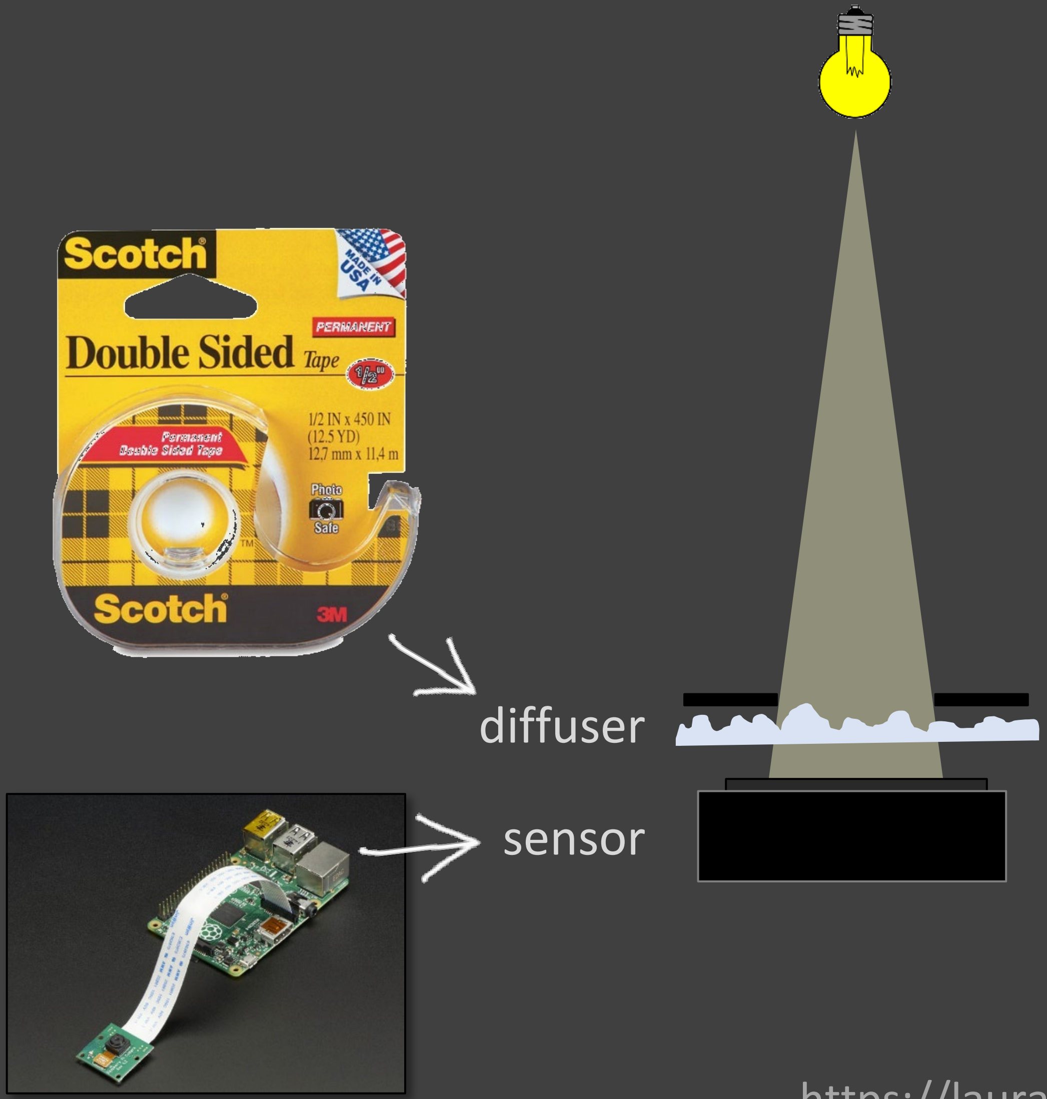
Lenses map points to points



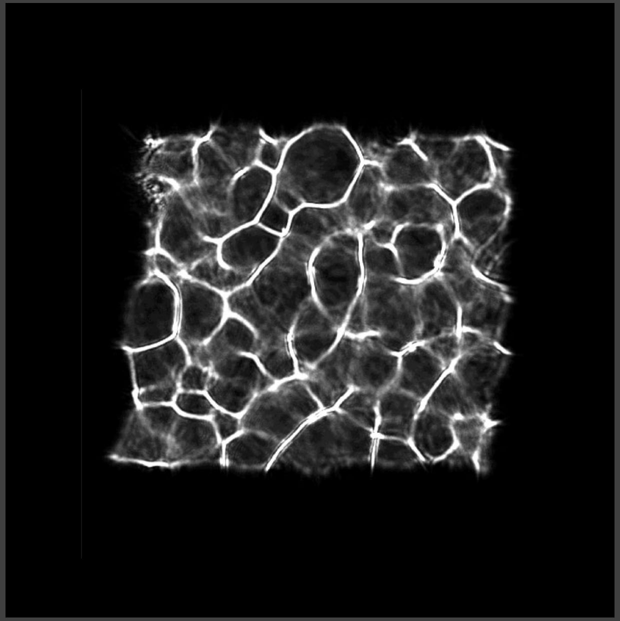
System response to point source



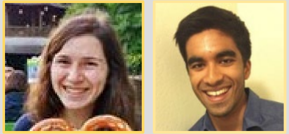
DiffuserCam: stick a scatterer on a sensor



System response to point source

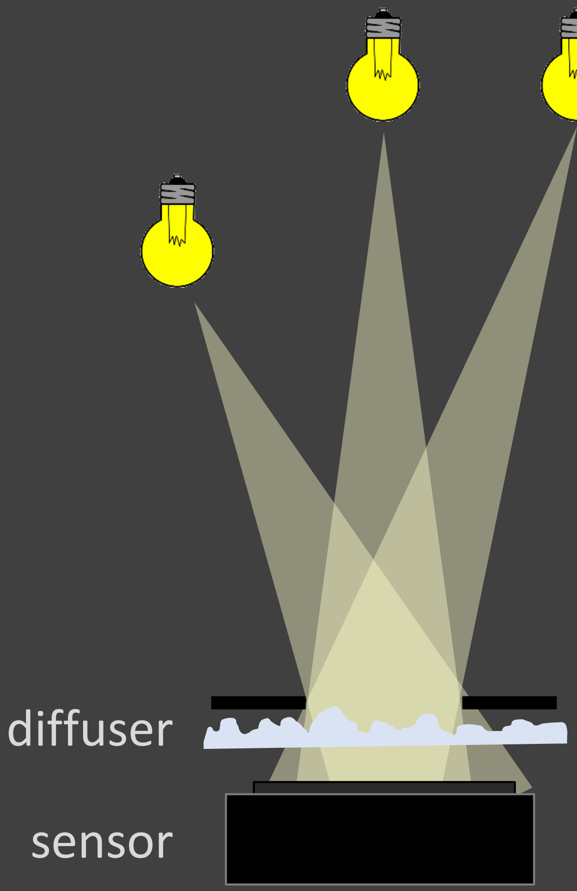


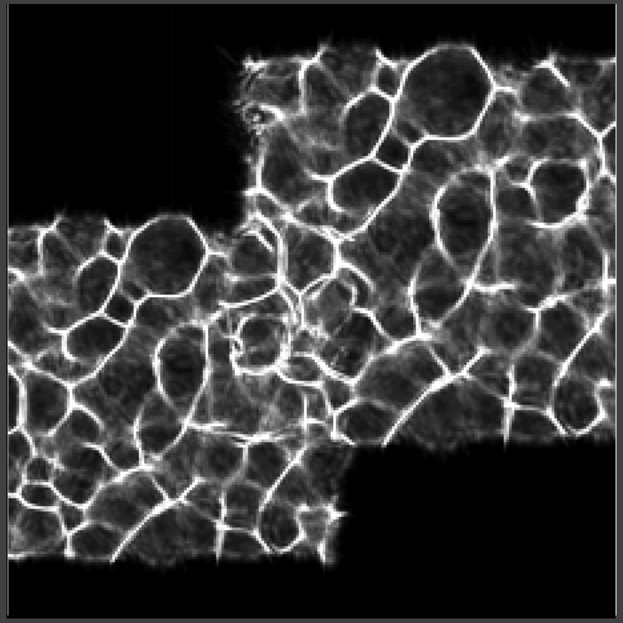
Camille Biscarrat
Shreyas Parthasarathy



https://laurawaller.com/opensource

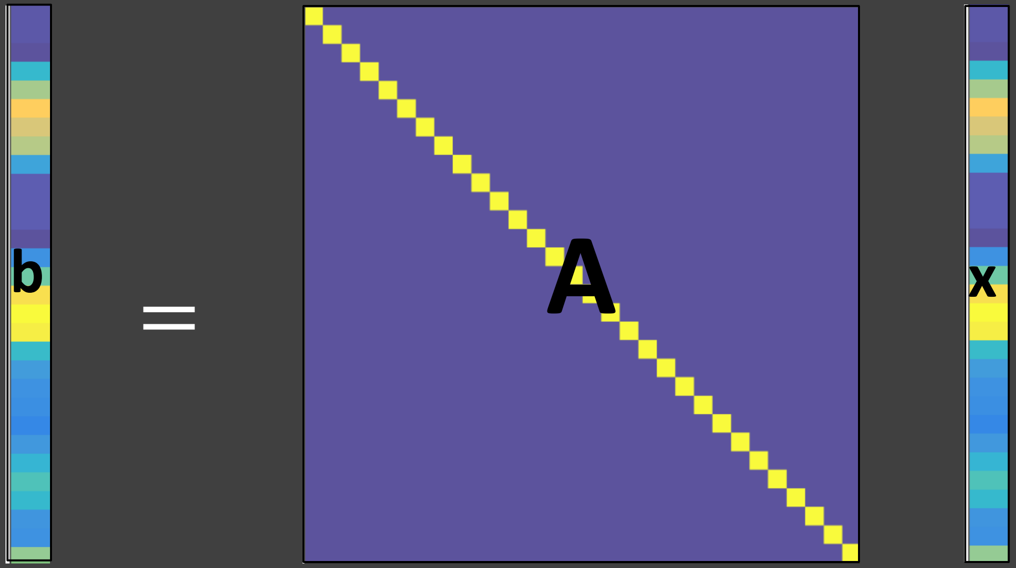
DiffuserCam: stick a scatterer on a sensor





Grace Kuo
Nick Antipa

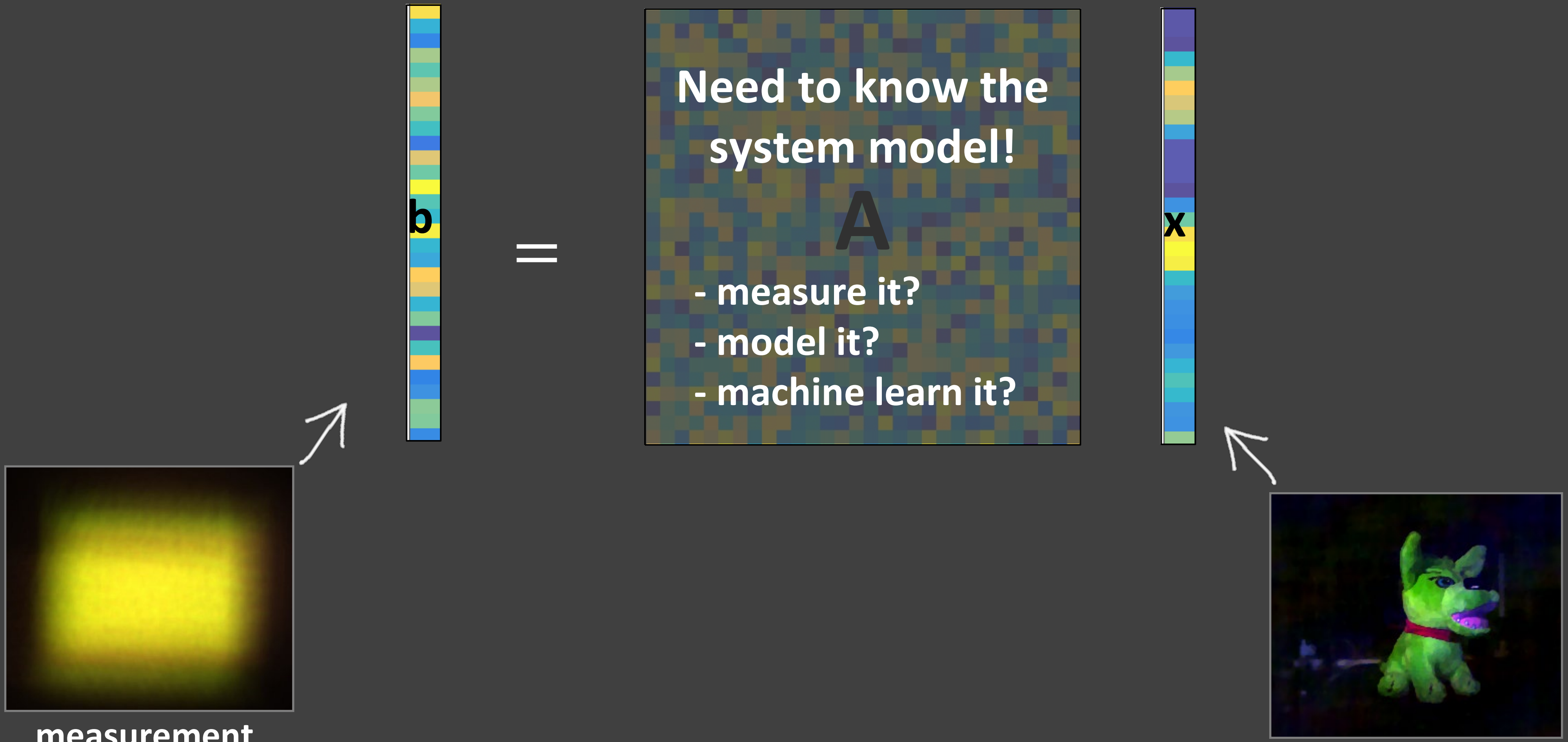
Traditional cameras take direct measurements



measurement

object

Computational cameras can multiplex



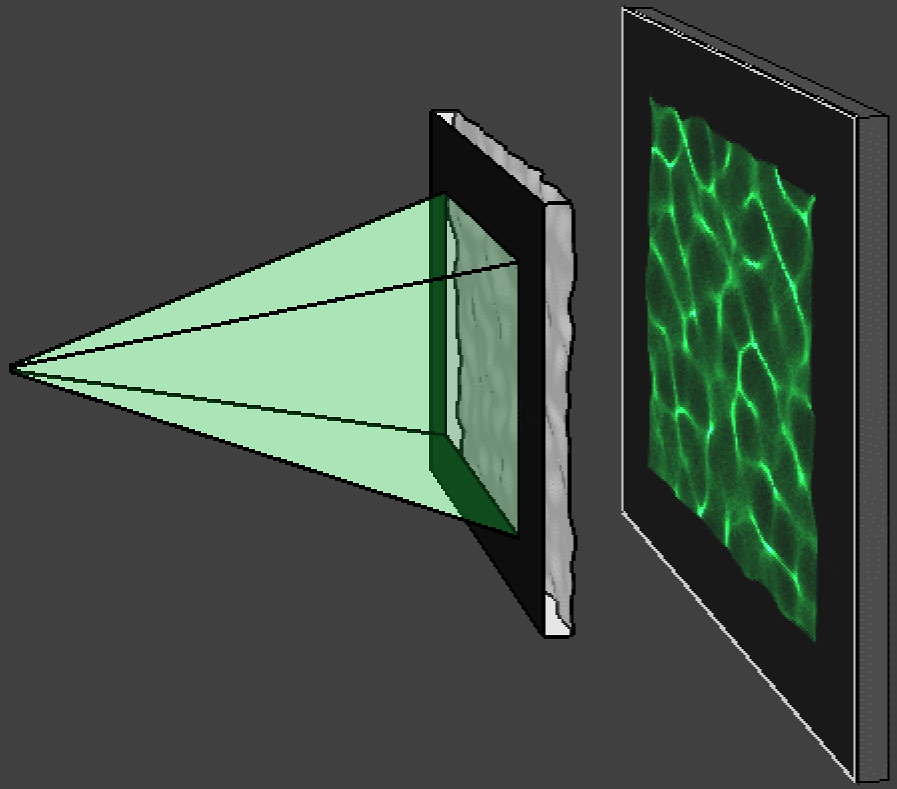
Need to know the system model!

- measure it?
- model it?
- machine learn it?

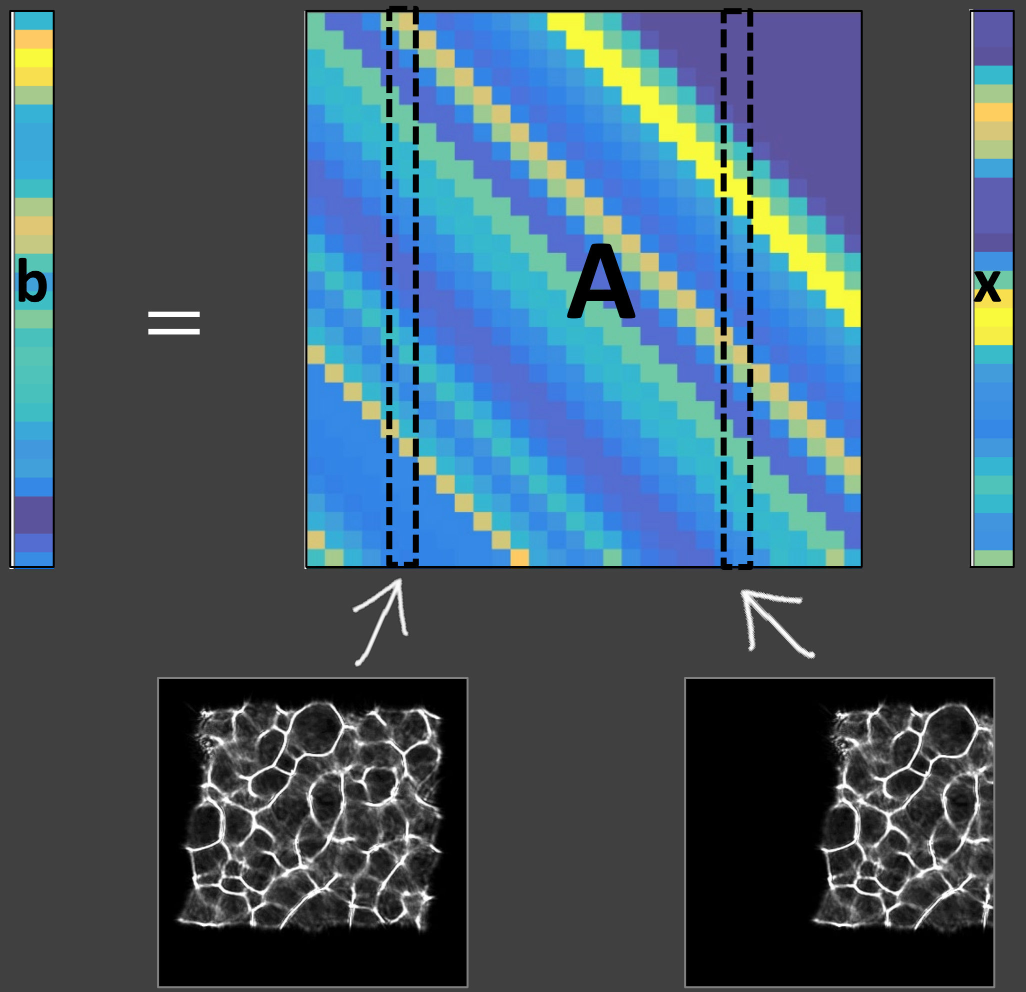
measurement

object

System response shifts with position

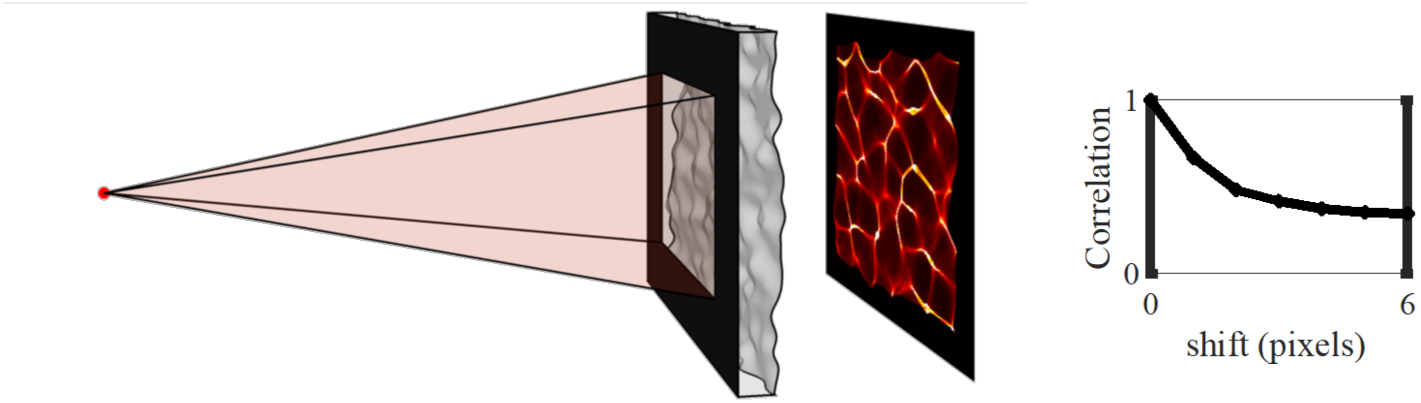


DiffuserCam system model is a ‘shift-invariant’



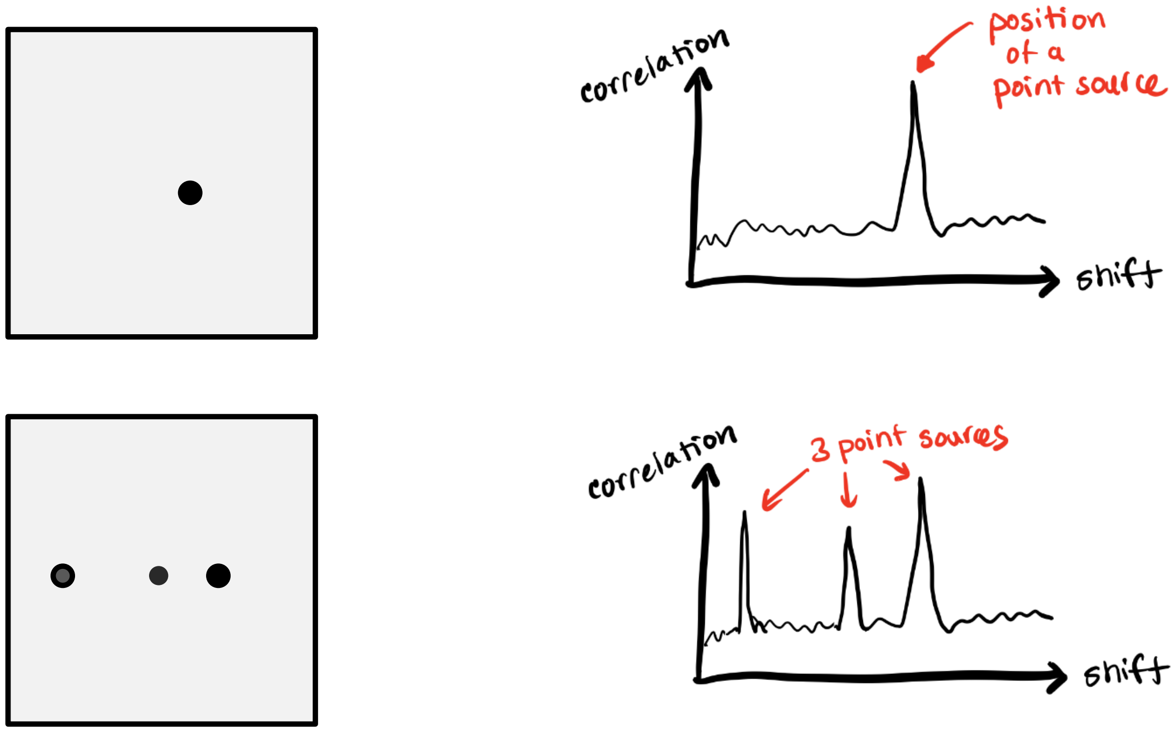
System response is same but shifted for different image pixels

We could find location of a point by correlating image captured with shifts in system response!

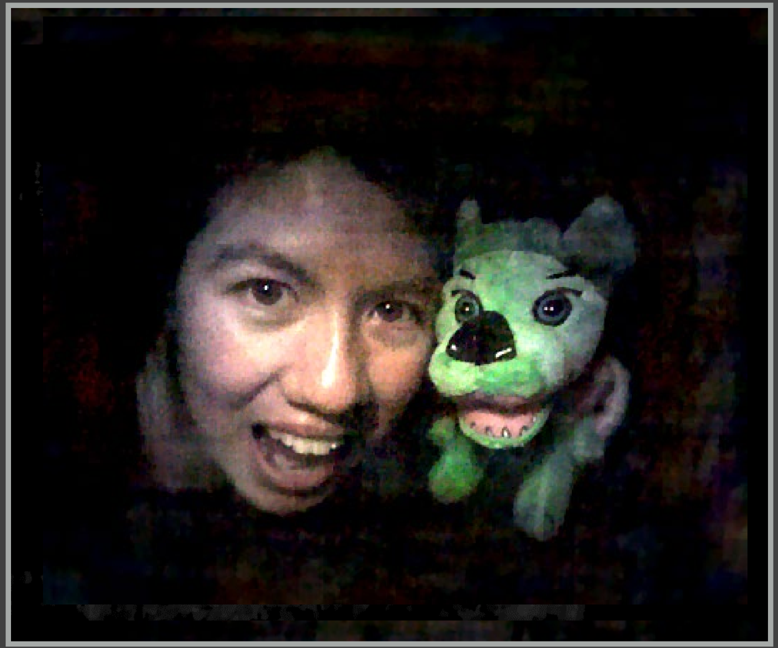


Reconstruction finds strength of each ‘point source’:

Looks a lot like our GPS problem! (especially if image is sparse)



raw sensor data

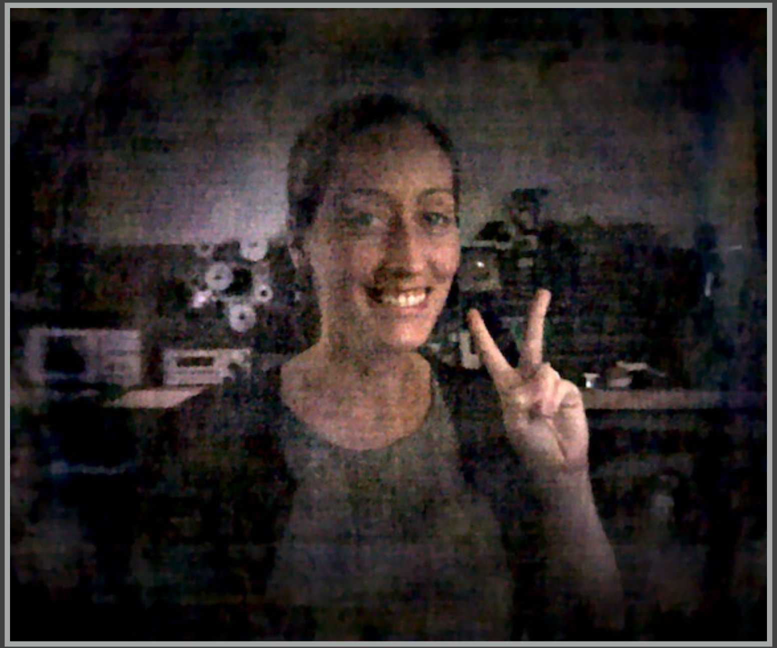


recovered scene

*solver is ADMM with TV reg in Halide

Grace Kuo
Nick Antipa

raw sensor data

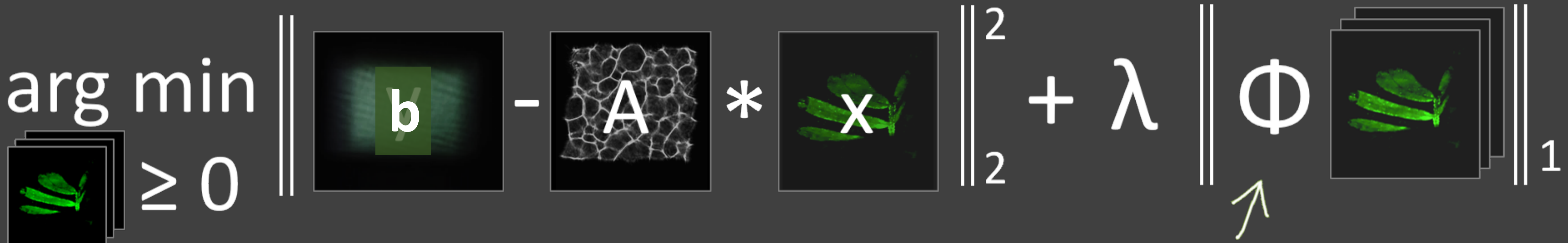


recovered scene

Grace Kuo
Nick Antipa

*solver is ADMM with TV reg in Halide

Image reconstruction is nonlinear optimization



$$\underset{x \geq 0}{\arg\min} \left\| b - A * x \right\|_2^2 + \lambda \left\| \Phi x \right\|_1$$

Sparsity basis

*solved with ADMM in Halide

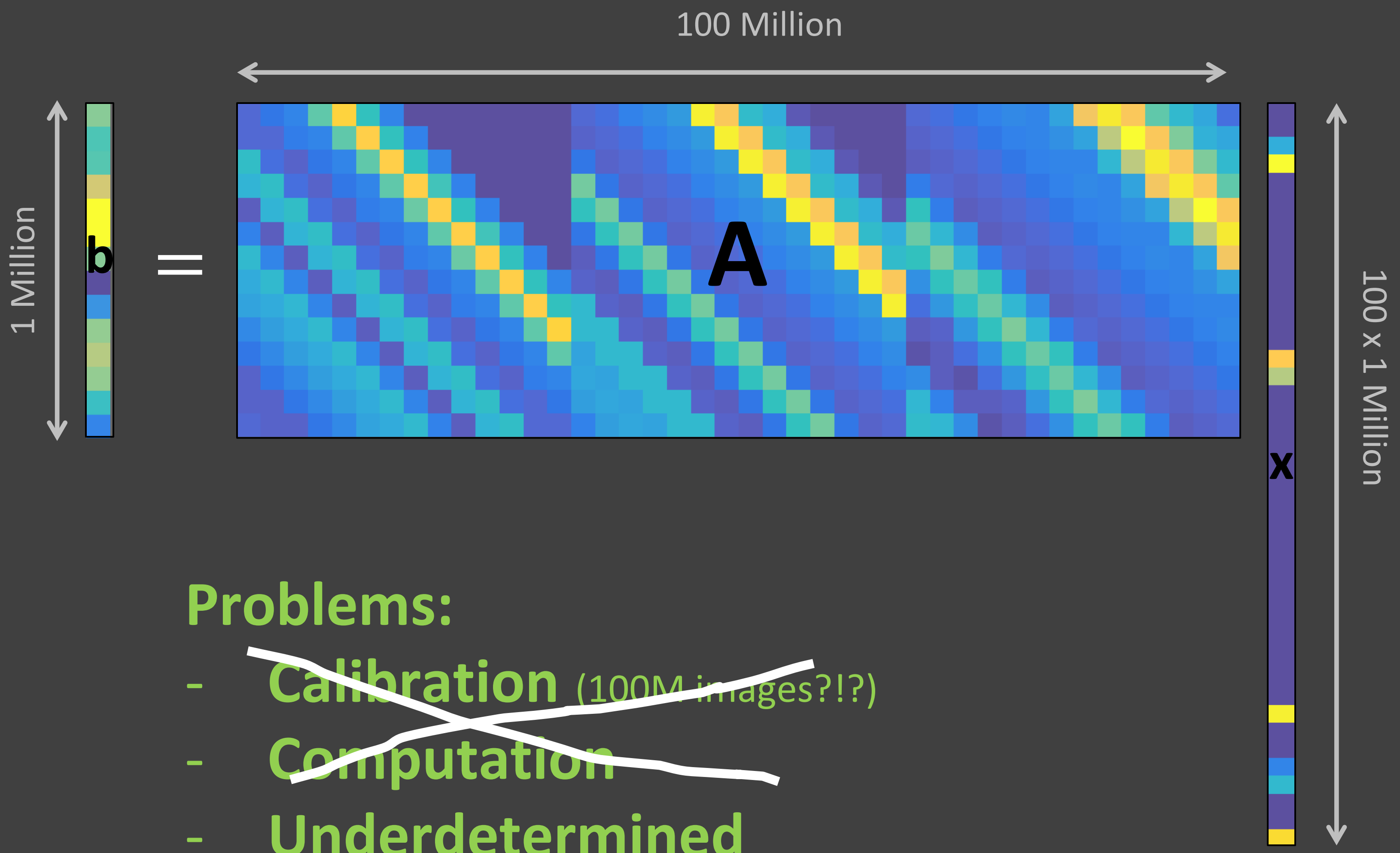
S. Boyd, et al. *Foundations and Trends in Machine Learning* (2011)

J. Ragan-Kelley, et al. *AMC SIGPLAN* (2013)

Cute! But what’s it good for?

2D →

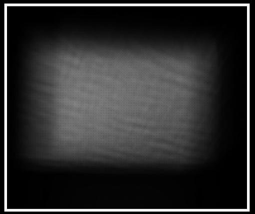
Single-shot 3D is underdetermined

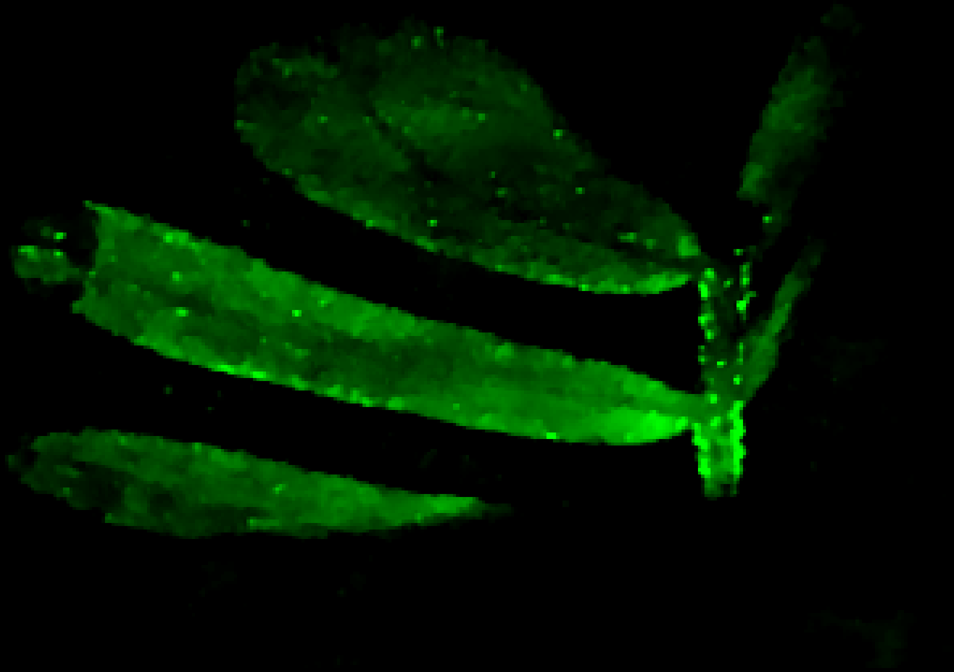


Problems:

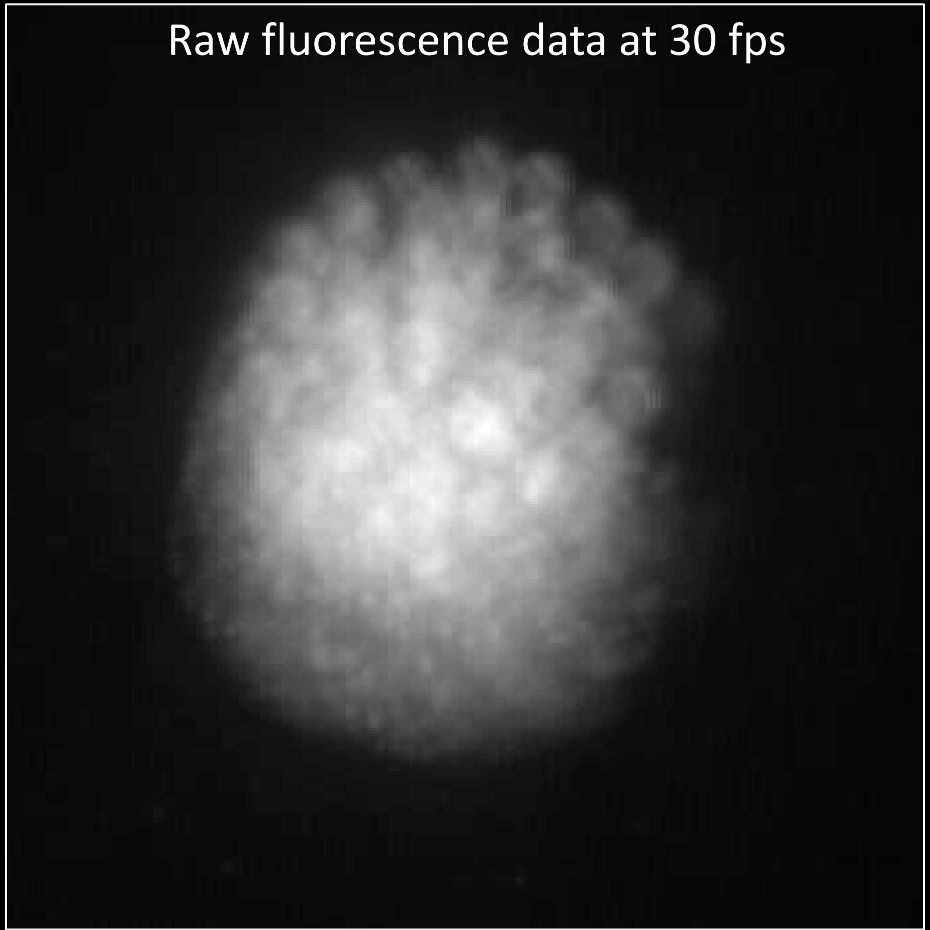
- ~~**Calibration** (100M images?!?)~~
- ~~**Computation**~~
- **Underdetermined**

128x more voxels for ***FREE!***



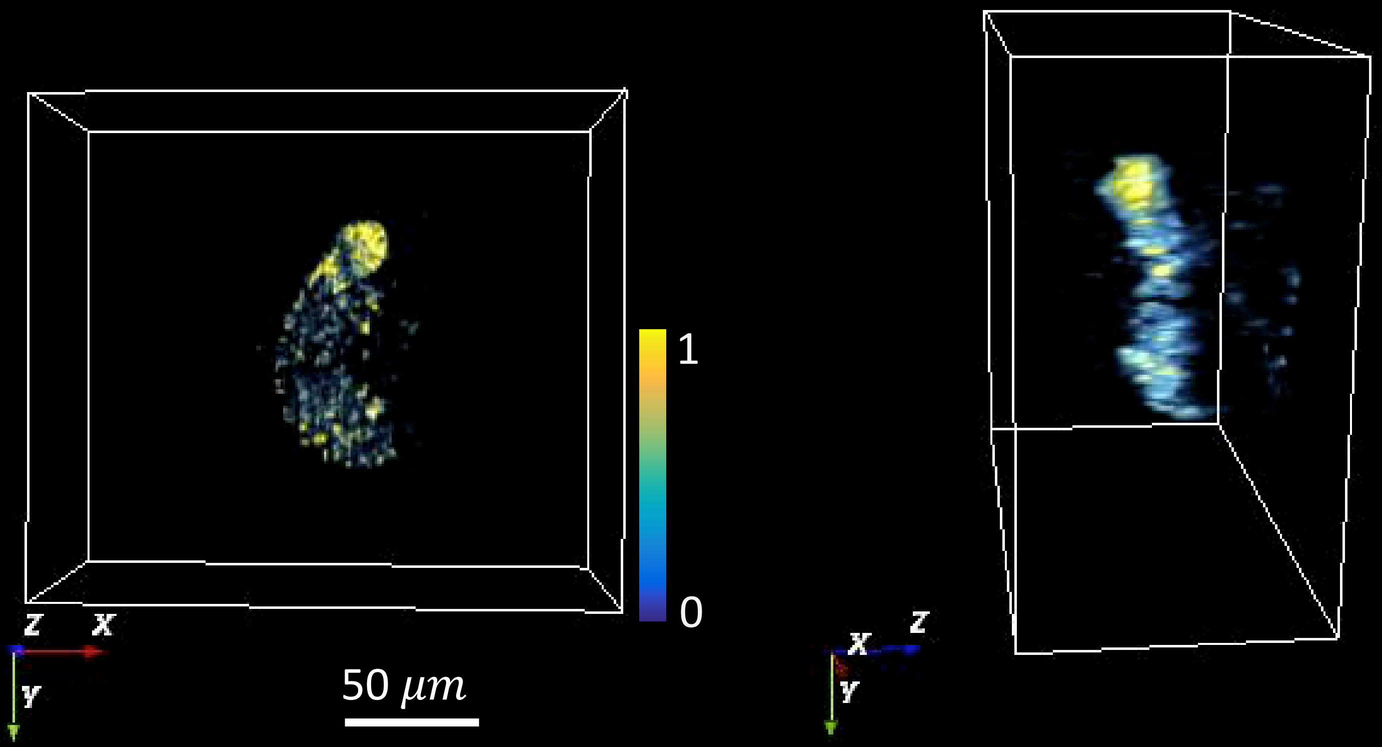


N. Antipa, G. Kuo, R. Heckel, E. Bostan, B. Mildenhall, R. Ng, L. Waller, *Optica* 5(1) (2017).

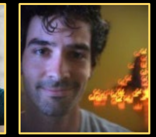


Raw fluorescence data at 30 fps

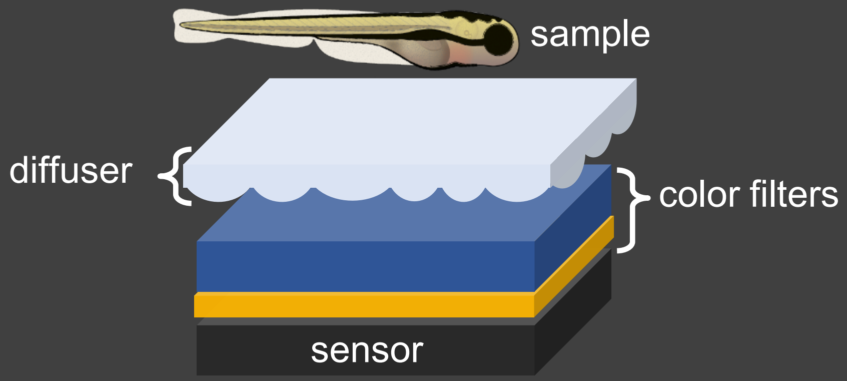
3D video reconstruction

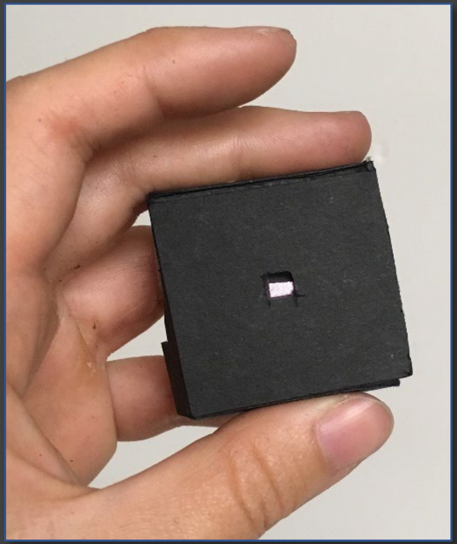


Kyrollos Yanny
Nick Antipa



Neural activity tracking with flat DiffuserScope

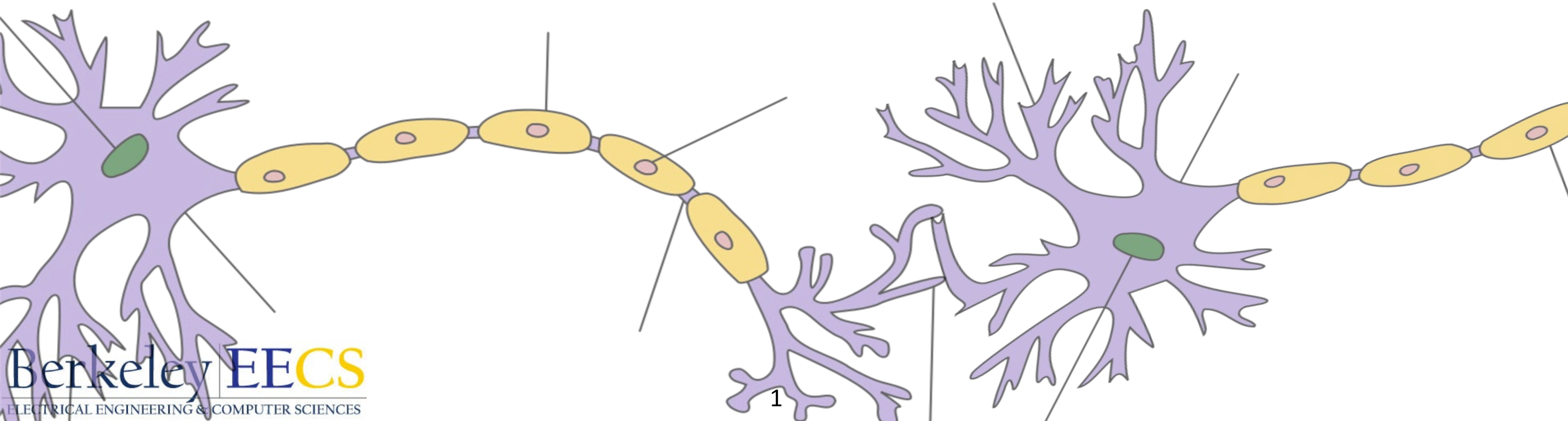




Grace Kuo

G. Kuo, F. Liu, I. Grossrubatscher, R. Ng, L. Waller, *Optics Express* (2020).

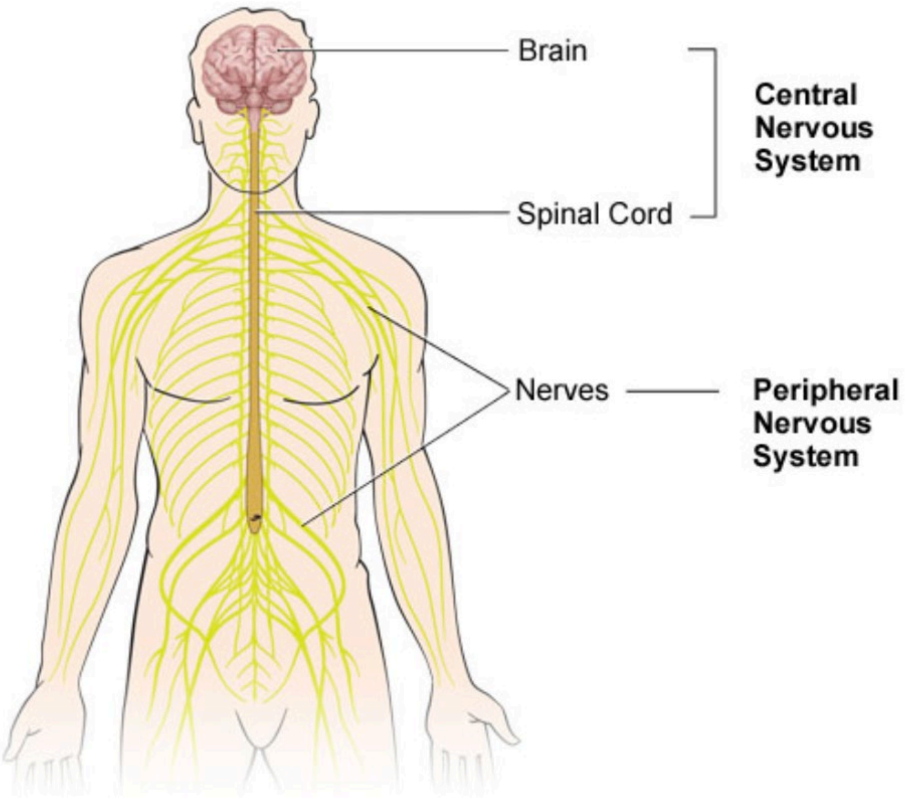
EECS 16A
Neurons are Circuits!



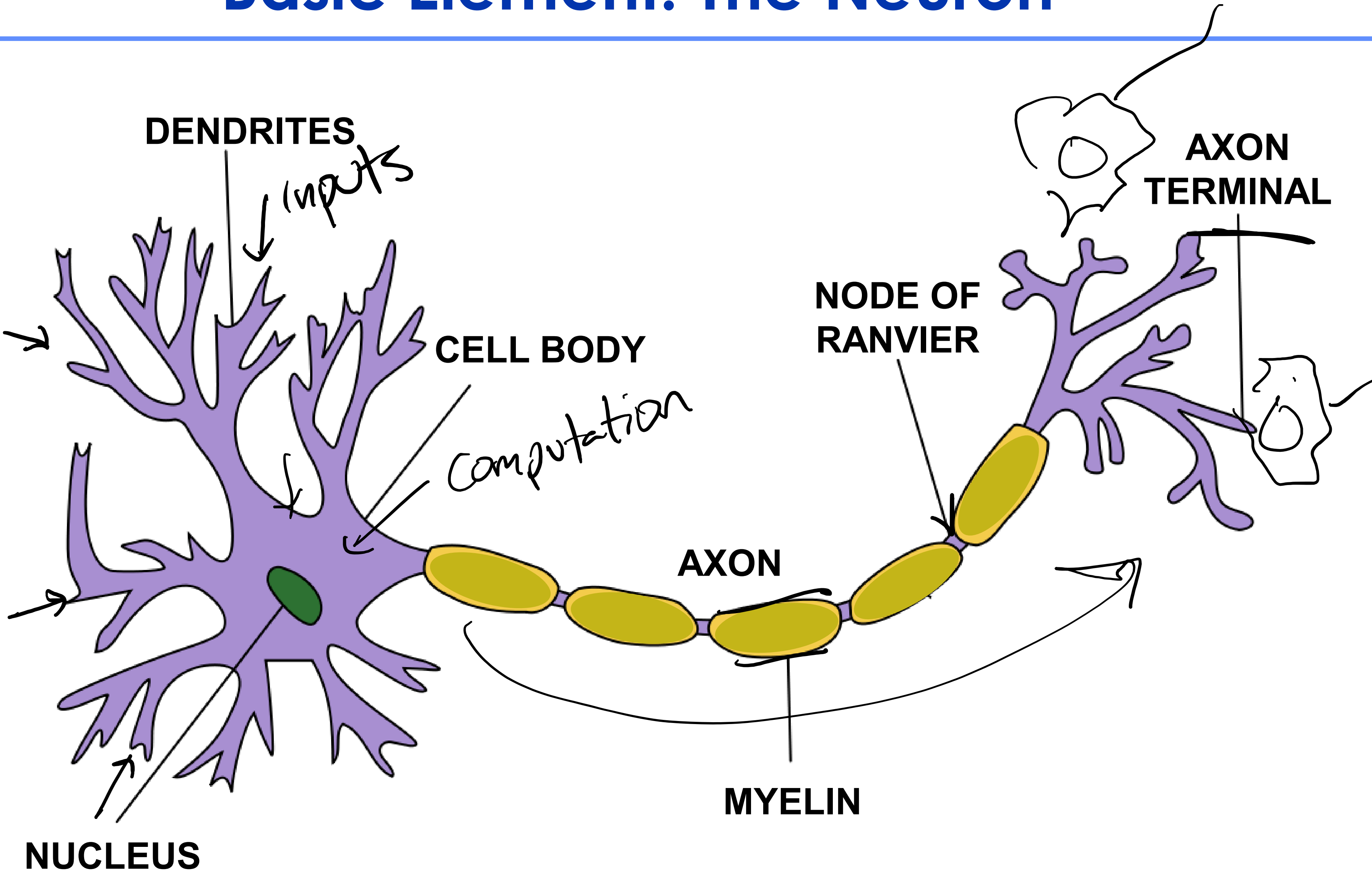
Berkeley EECS
ELECTRICAL ENGINEERING & COMPUTER SCIENCES

The Body Electric - Nervous System

- **There are two distinct parts of the nervous system**
  - Central Nervous system: Brain, Spinal Cord
  - Peripheral Nervous system: All other neural elements, including the peripheral nerves (motor and sensory) and the autonomic nerves (regulate internal organs)

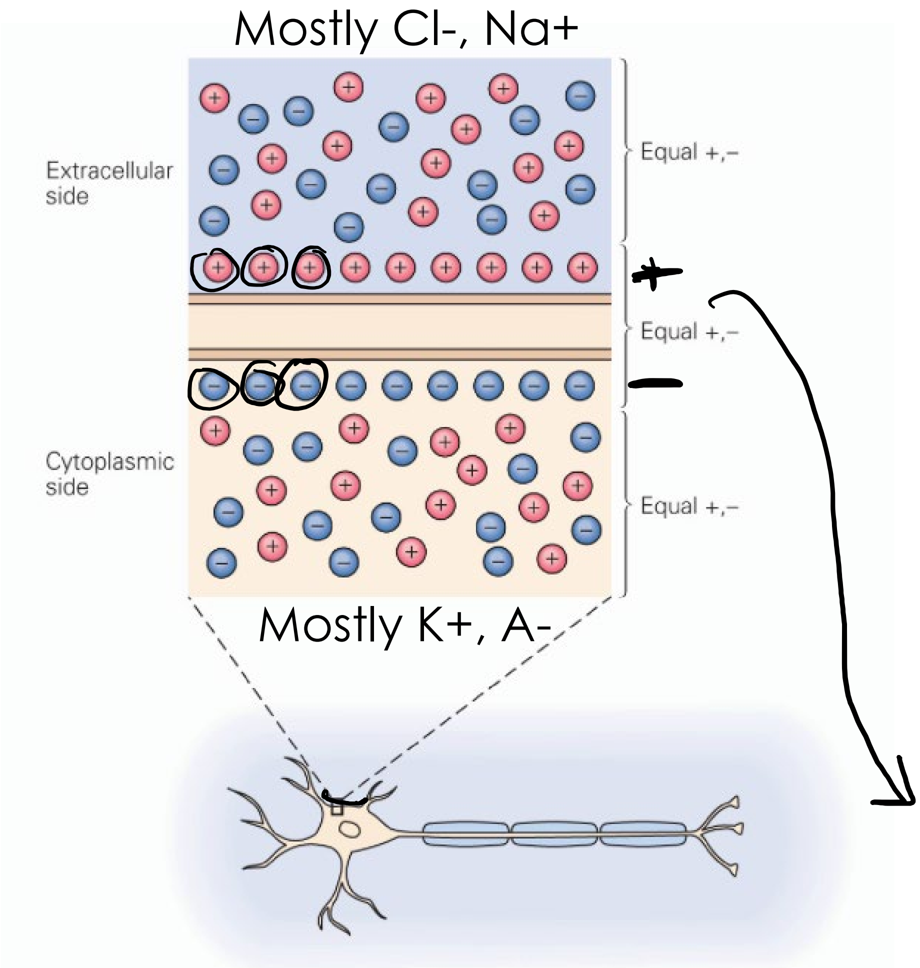


Basic Element: The Neuron



You have 100 billion of these

Resting Membrane Potential



- Nernst Equation (E → potential)

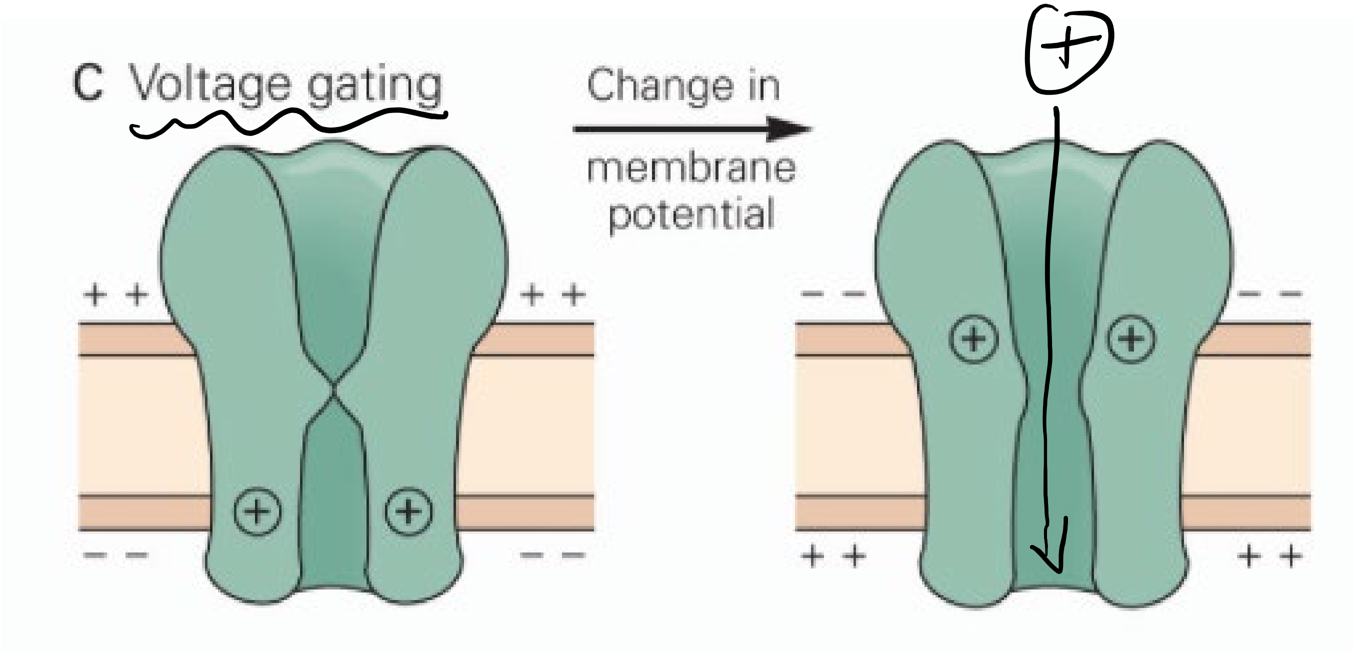
$$E_X = \frac{RT}{zF} \ln \frac{[X]_o}{[X]_i}$$

← concentration

- R – gas constant
- T – Temperature (K)
- F – Faraday constant
- z – Valence of ion
- RT/zF ~ 25mV at 25C, K+
  - Equivalent to kT/q!
- E_k is typically ~ -70 to -80mV

- Resting channels are permeable to K+ diffusing out of the cell causing (+) charges to accumulate at the cell surface and (–) charges inside
- This self limits when the electrical force negates the chemical force

Ion Channels (switches)

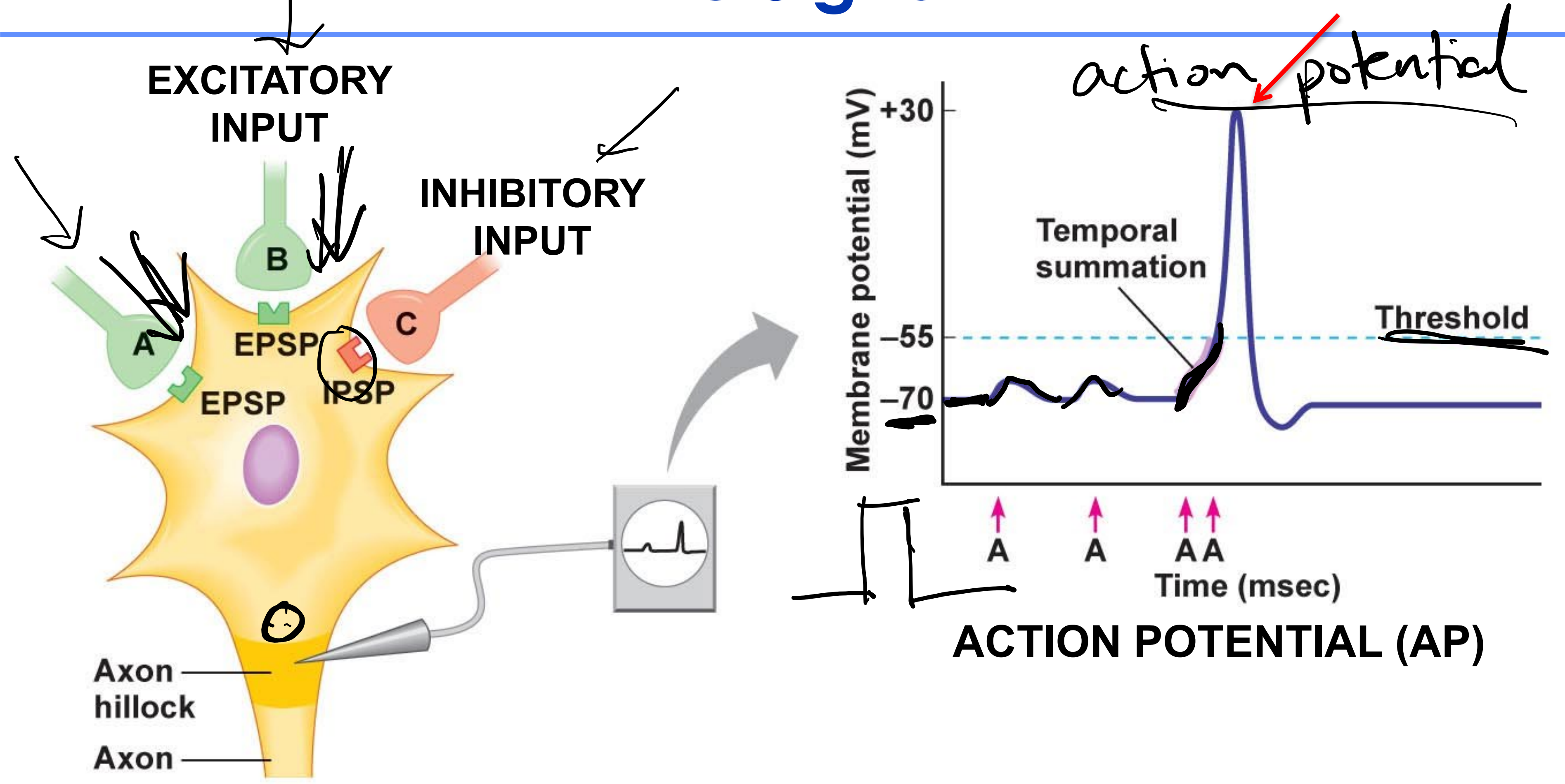


- **There are several types of stimuli controlling ion channels opening and closing**
  - These can be chemical, electrical or mechanical

Kandel, PONS

The Signal

CURRENT PULSE



ACTION POTENTIAL (AP)

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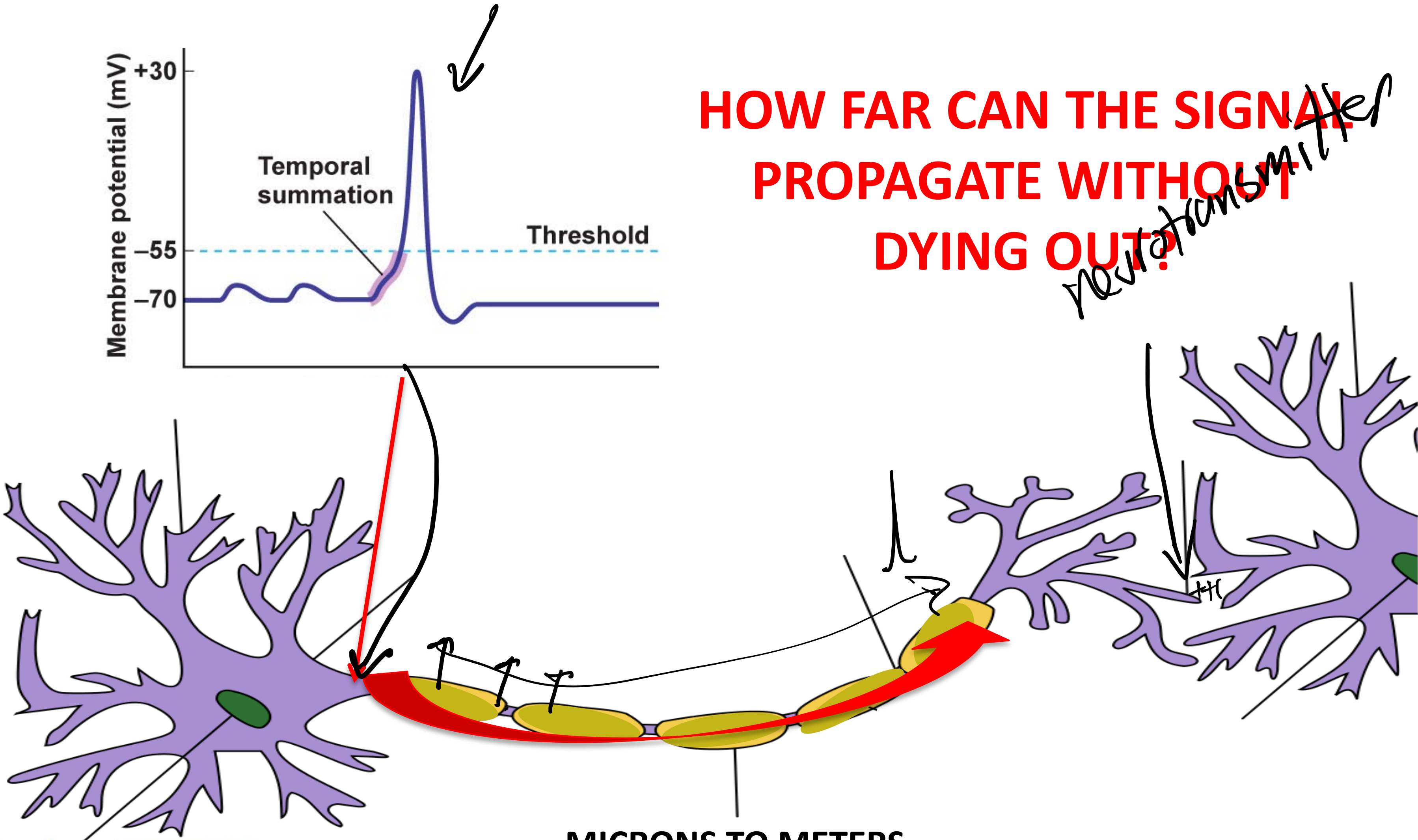
- Ion channels open in response to stimuli causing the cell to depolarize
- There is temporal and spatial summation
- Once the membrane potential goes above threshold, it starts an AP

Action Potential Propagation

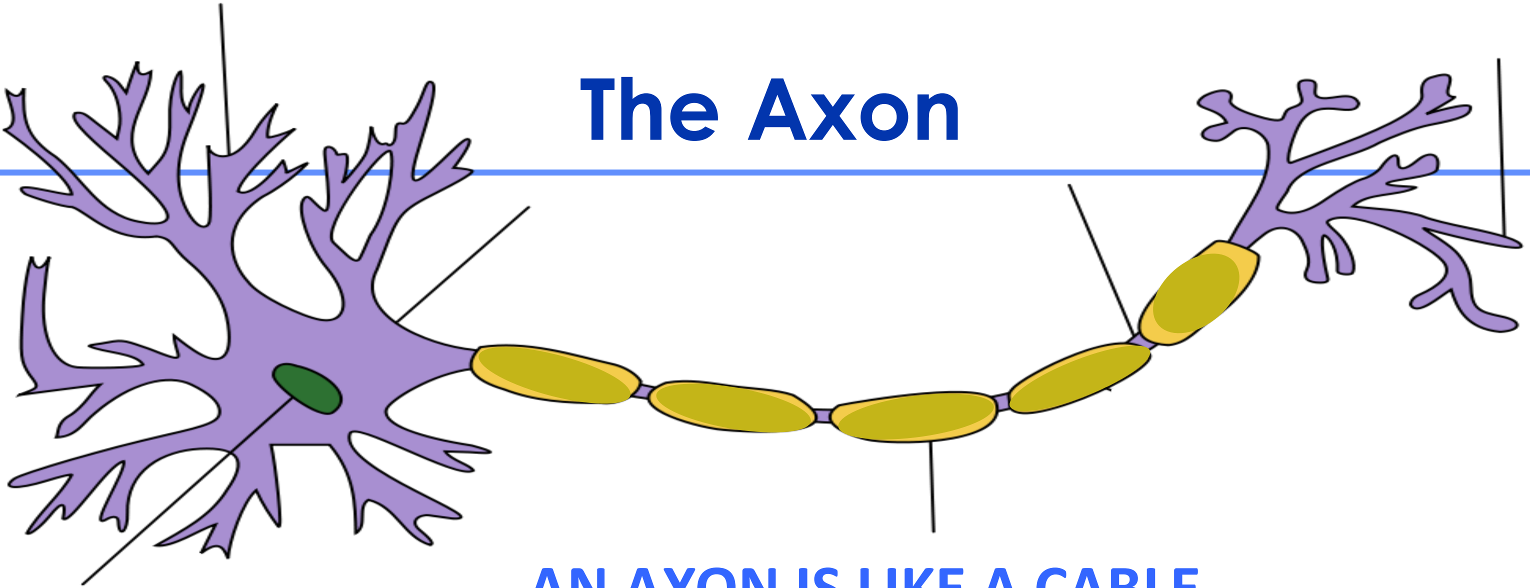


HOW FAR CAN THE SIGNAL PROPAGATE WITHOUT DYING OUT?

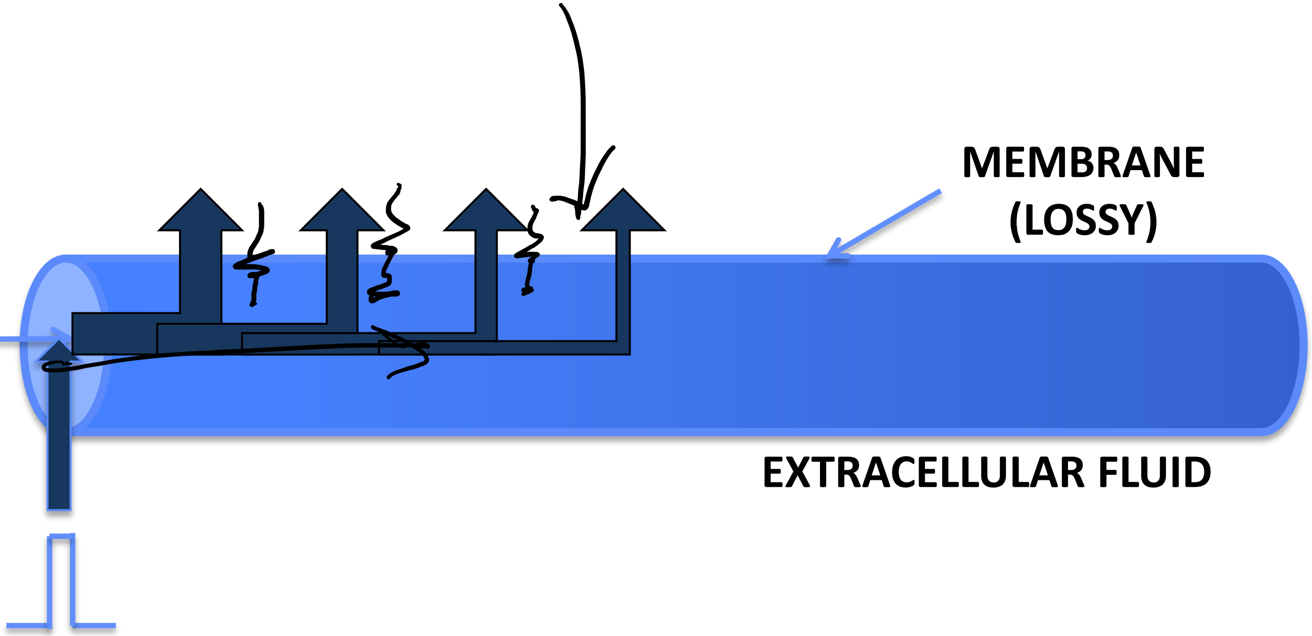
neurotransmitter

MICRONS TO METERS

The Axon



AN AXON IS LIKE A CABLE

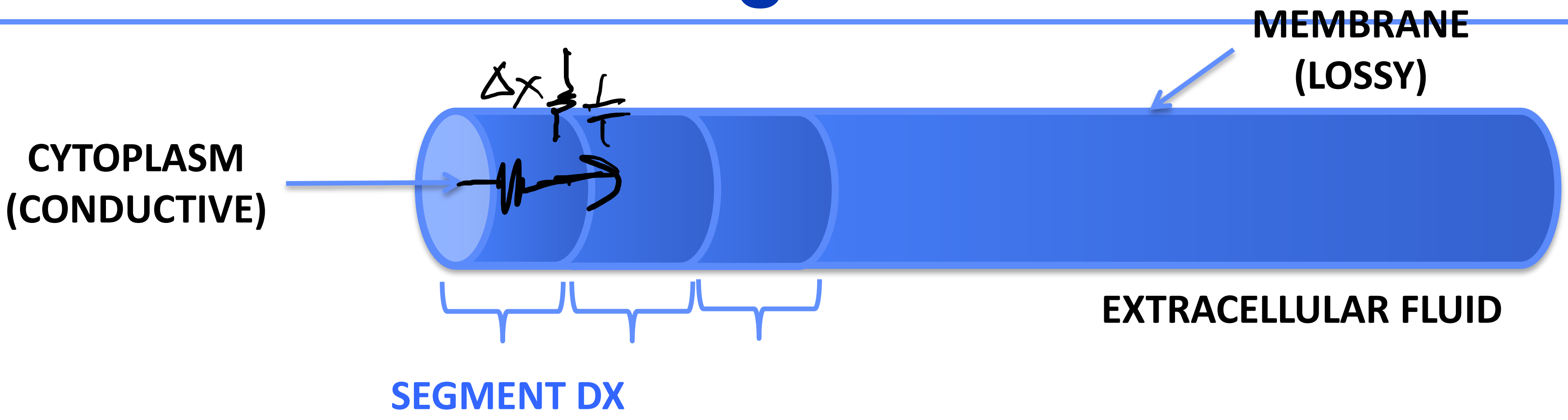


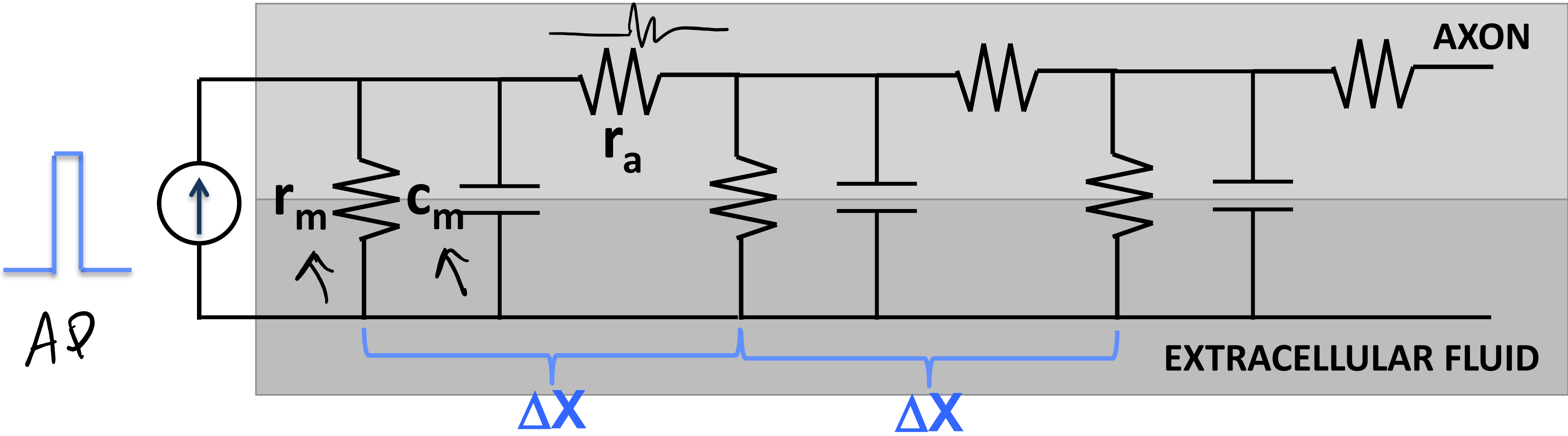
CYTOPLASM (CONDUCTIVE)

MEMBRANE (LOSSY)

EXTRACELLULAR FLUID

Modeling the Axon



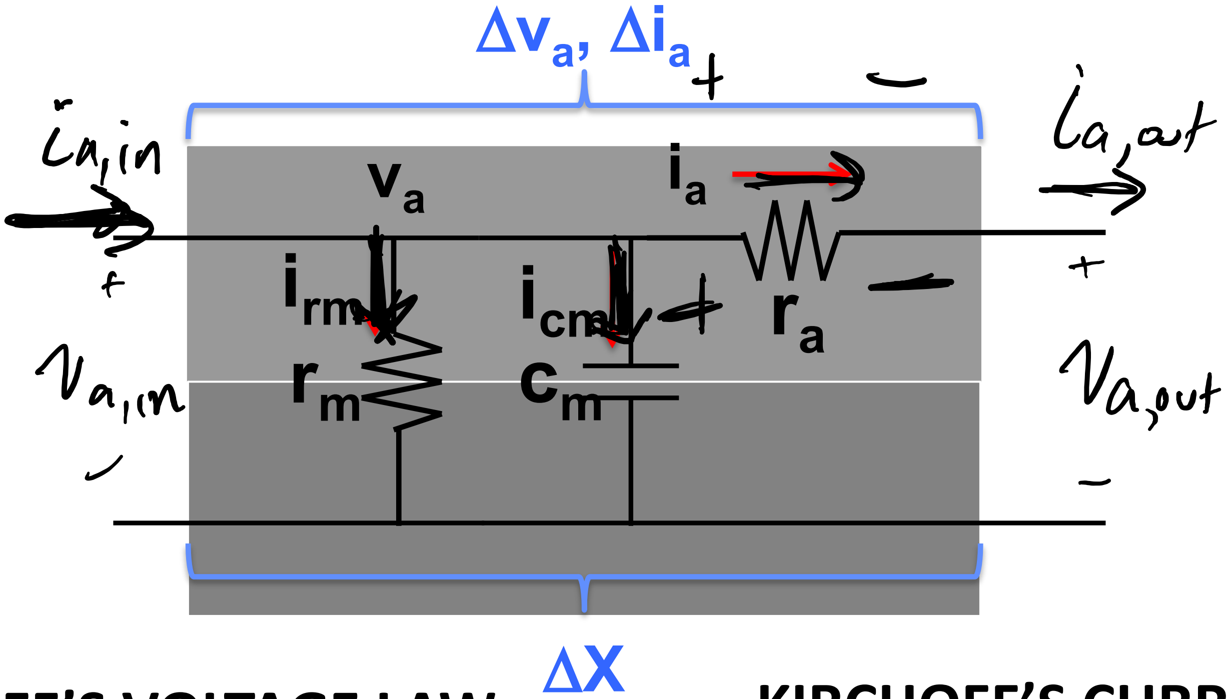


r_m = membrane resistance [Ω•m];

r_a = axon resistance [Ω/m]

c_m = membrane capacitance [F/m]

A Single Axon Segment



KIRCHOFF'S VOLTAGE LAW

$$\Delta v_a = -i_a r_a \Delta x$$

$$\boxed{\frac{\Delta v_a}{\Delta x} = -i_a r_a}$$

KIRCHOFF'S CURRENT LAW

$$\Delta i_a = (-i_{rm} - i_{cm})\Delta x$$

$I = C\frac{dV}{dt}$

$$\boxed{\frac{\Delta i_a}{\Delta x} = -\frac{v_a}{r_m} - c_m\frac{\partial v_a}{\partial t}}$$

The Rest is Math

→ EECS 16B
120

$$\frac{\Delta v_a}{\Delta x} = -i_a r_a$$

$$\frac{\Delta i_a}{\Delta x} = -\frac{v_a}{r_m} - c_m \frac{\partial v_a}{\partial t}$$

$$\underline{\Delta x} \to 0$$

$$-\frac{1}{r_a}\frac{\partial v_a}{\partial x} = i_a$$

$$\frac{\partial i_a}{\partial x} = -\frac{v_a}{r_m} - c_m \frac{\partial v_a}{\partial t}$$

$$-\frac{1}{r_a}\frac{\partial^2 v_a}{\partial x^2} = \frac{\partial i_a}{\partial x}$$

*

$$\boxed{-\frac{1}{r_a}\frac{\partial^2 v_a}{\partial x^2} = -\frac{v_a}{r_m} - c_m \frac{\partial v_a}{\partial t}}$$

The Equation

$$-\frac{1}{r_a}\frac{\partial^2 v_a}{\partial x^2} = -\frac{v_a}{r_m} - c_m \frac{\partial v_a}{\partial t}$$

REARRANGE TERMS

$$\underbrace{-\frac{r_m}{r_a}\frac{\partial^2 v_a}{\underline{\partial x^2}}}_{\text{SPACE DEPENDENT}} + c_m r_m \underbrace{\frac{\partial v_a}{\underline{\partial t}}}_{\text{TIME DEPENDENT}} + v_a = 0 \Bigg\} \text{final equation}$$

LET'S ANALYZE ONE AT A \underline{TIME}

Time Dependence

$$-\underbrace{\cancelto{0}{\frac{r_m}{r_a}\frac{\partial^2 v_a}{\partial x^2}}}_{\text{HOLD SPACE CONSTANT}}+c_m r_m\frac{\partial v_a}{\partial t}+v_a=0$$

$$c_m r_m\frac{\partial v_a}{\partial t}+v_a=0$$

ODE WITH STANDARD SOLUTION

$$\longrightarrow\boxed{v_a(t)=v_o e^{-t/\tau}}\qquad\boxed{\tau=r_m c_m}$$

TIME CONSTANT

Space Dependence

$$-\frac{r_m}{r_a}\frac{\partial^2 v_a}{\partial x^2} + \underbrace{\cancelto{0}{c_m r_m \frac{\partial v_a}{\partial t}}}_{\text{HOLD TIME CONSTANT}} + v_a = 0$$

$$-\frac{r_m}{r_a}\frac{\partial^2 v_a}{\partial x^2} + v_a = 0$$

ODE WITH STANDARD SOLUTION

$$\boxed{v_a(x) = v_o e^{-x/\lambda}} \qquad \boxed{\lambda = \sqrt{\frac{r_m}{r_a}}}$$

SPACE CONSTANT

What does it mean?

$$\lambda = \sqrt{\frac{r_m}{r_a}}$$

*SPACE CONSTANT

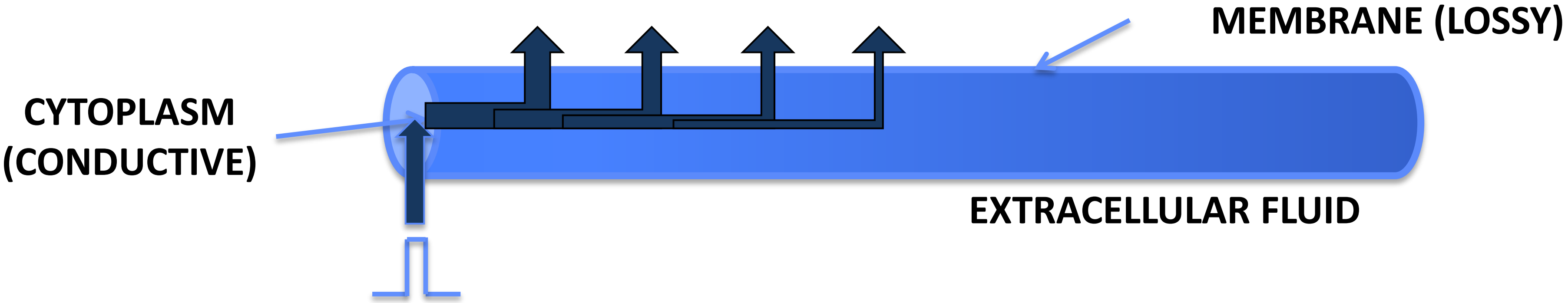
The distance it takes for a signal to decay away

↓ loss

$$\tau = \underline{r_m}\,\underline{c_m}$$

*TIME CONSTANT

The amount of time it takes for a signal to decay away



HOW CAN IT BE IMPROVED?

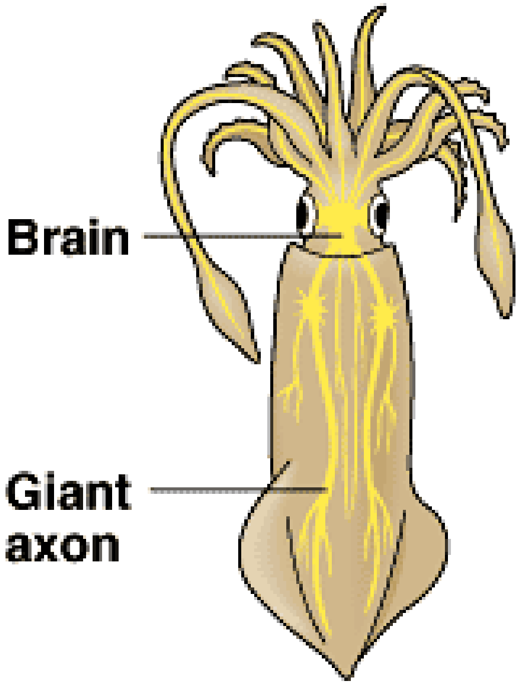
Evolution

$$\uparrow \lambda = \sqrt{\frac{r_m \uparrow}{r_a \downarrow}}$$

SPACE CONSTANT

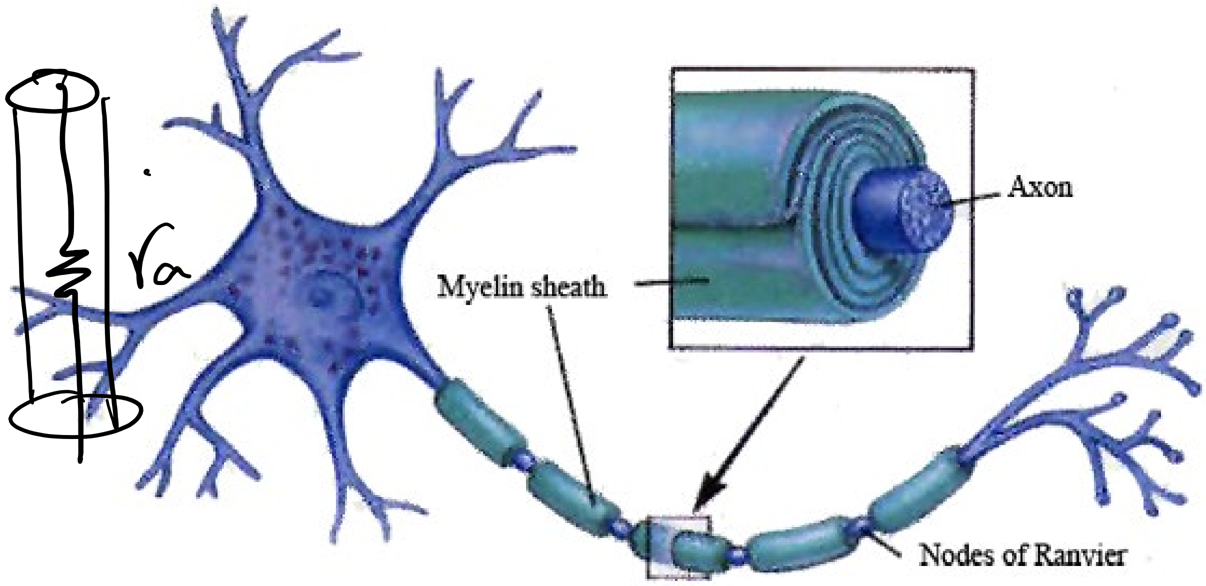
$$\uparrow \underline{\tau = r_m c_m}$$

TIME CONSTANT



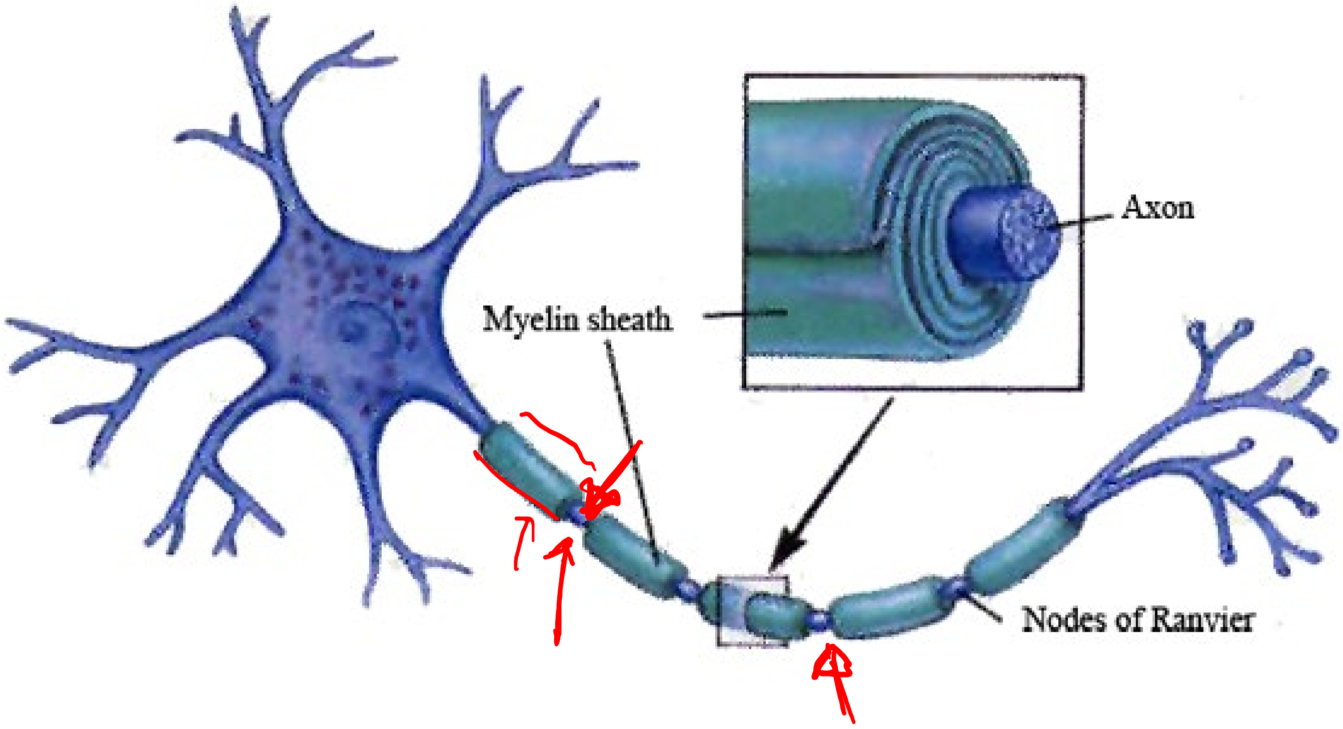
$$\underset{\sim}{r_a} \downarrow, \lambda \uparrow$$

MYELINATION



$$r_m \uparrow, c_m \downarrow, \lambda \uparrow$$

Nodes of Ranvier



What do you think Nodes of Ranvier are for?

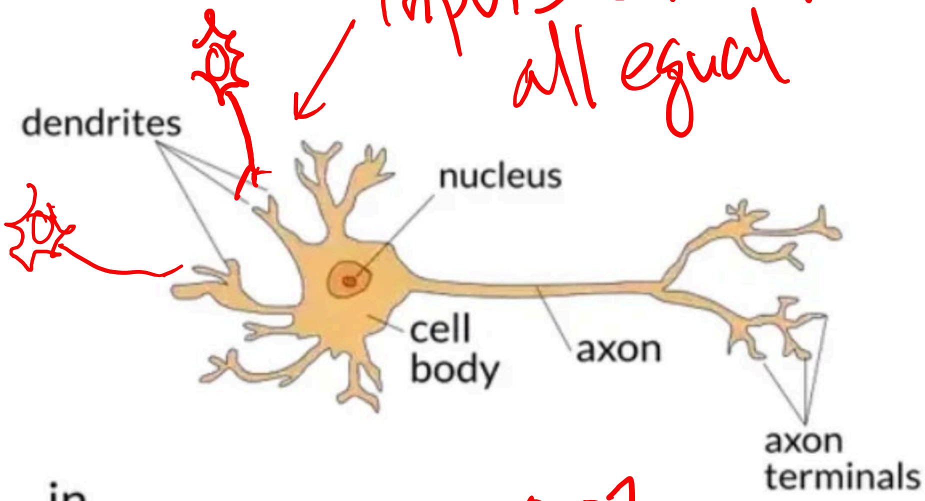
Hint: think about a digital signal propagating across a very long wire..

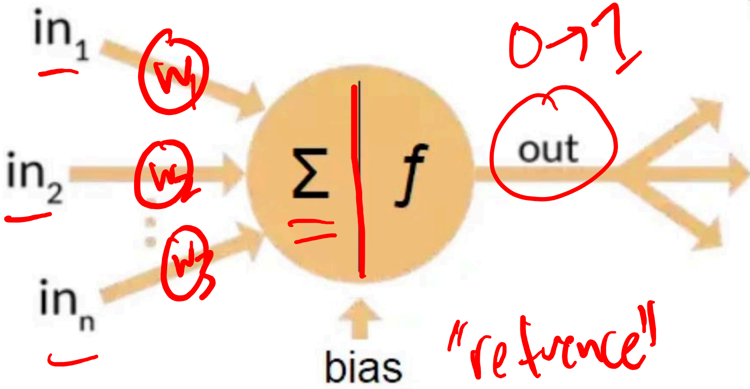
digital repeater
EECS 151

Berkeley EECS
ELECTRICAL ENGINEERING & COMPUTER SCIENCES

Neural Networks

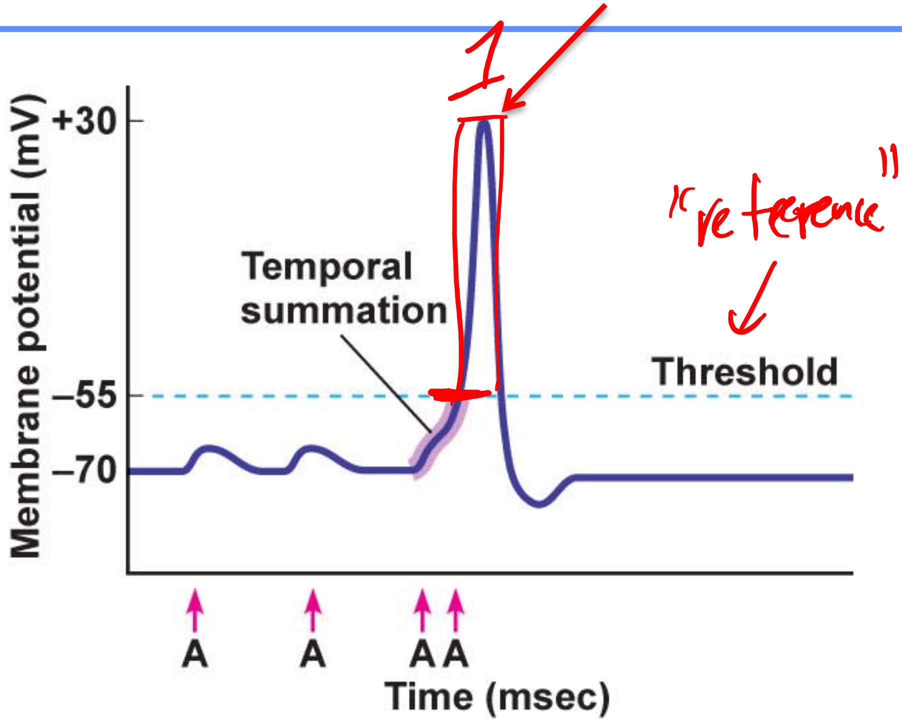
inputs are not all equal





"reference"

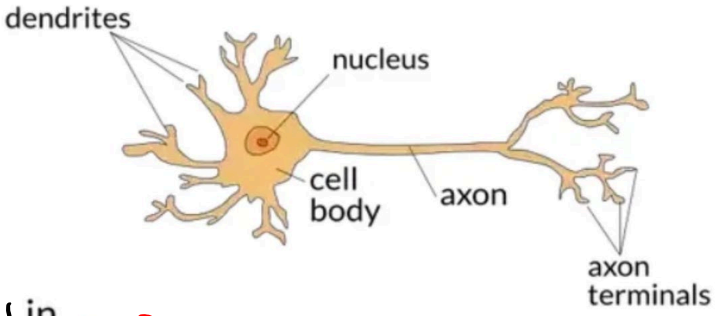
CURRENT PULSE

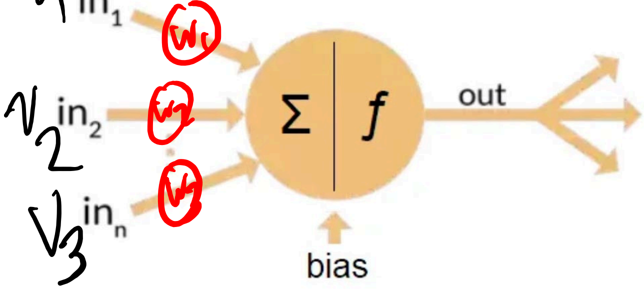


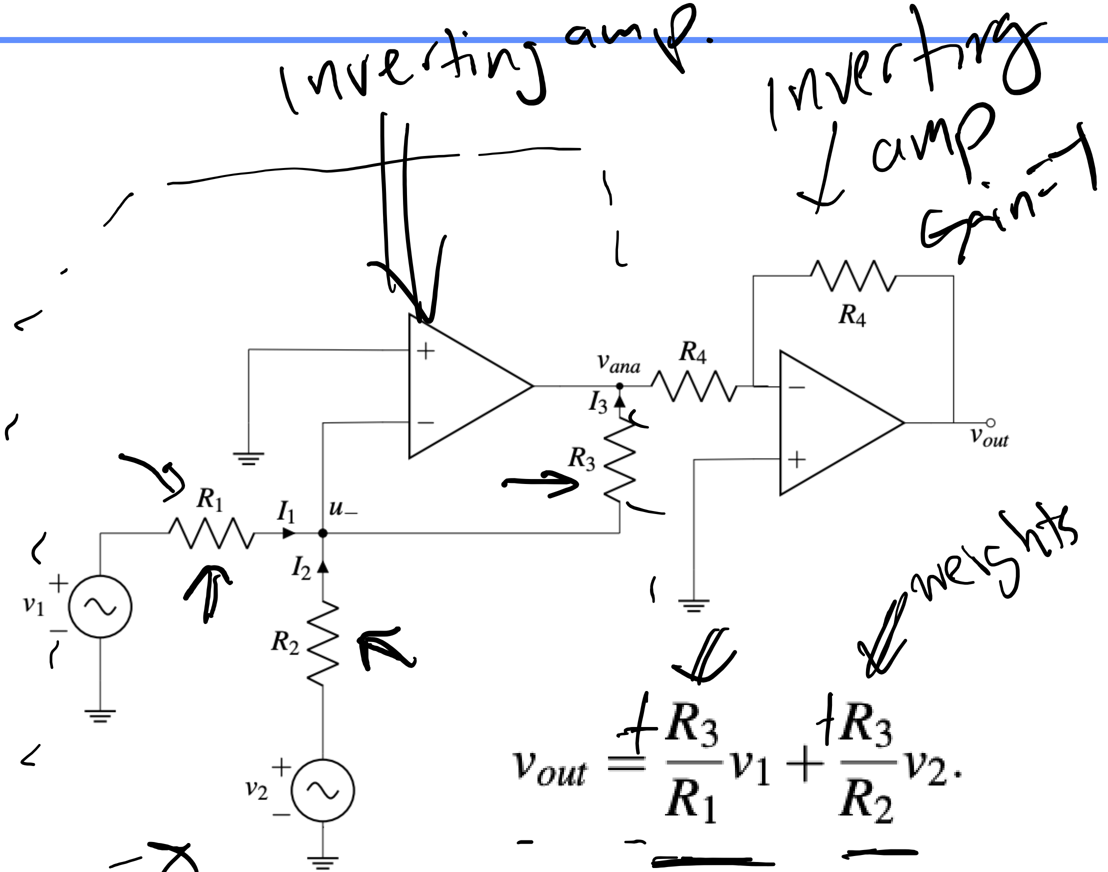
ACTION POTENTIAL (AP)

circuits?

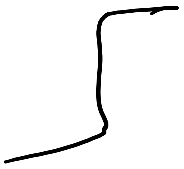
Artificial Neuron







$$v_{out} = \frac{R_3}{R_1}v_1 + \frac{R_3}{R_2}v_2.$$

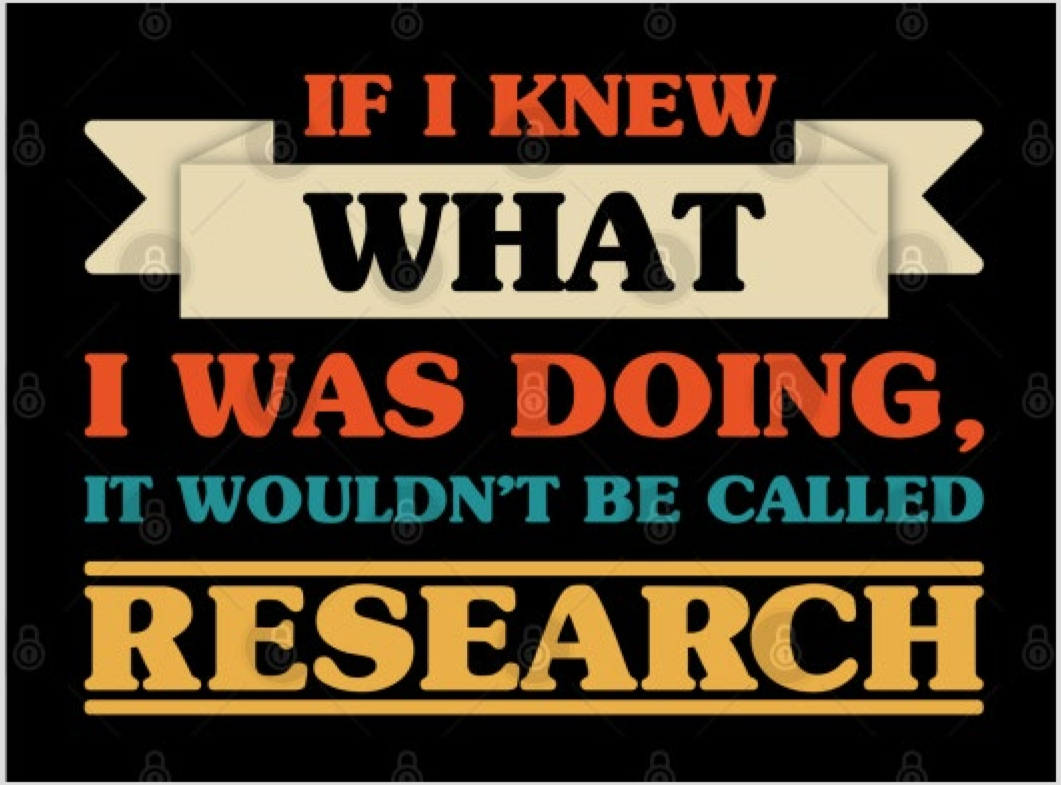


Note 19

"artifial neuron"

How to get involved in research

- If you’re interested in research:
  - Talk to your TAs
  - Talk to professors
  - Look for openings on Beehive/Dare/URAP websites



Enough about me…

- Congrats!
- What you have accomplished this semester:
  - Built a camera
  - Built two types of touchscreens
  - Built your own GPS system
- If you liked the class, please:
  - Thank your TAs!
  - apply to become one!

Learning Goals

Stuff We did:

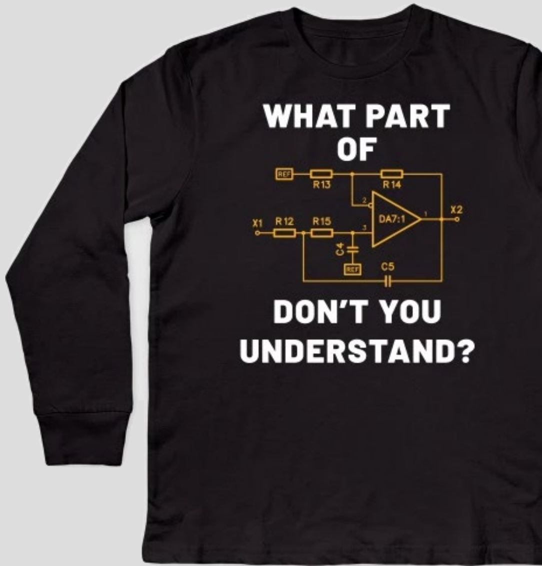
EECS 16A

- Module 1: Introduction to systems
  - How do we collect data? build a model?
- Module 2: Introduction to circuits and design
  - How do we use a model to solve a problem
- Module 3: Introduction Signal Processing and Machine Learning
  - How do we “learn” models from data, and make predictions?

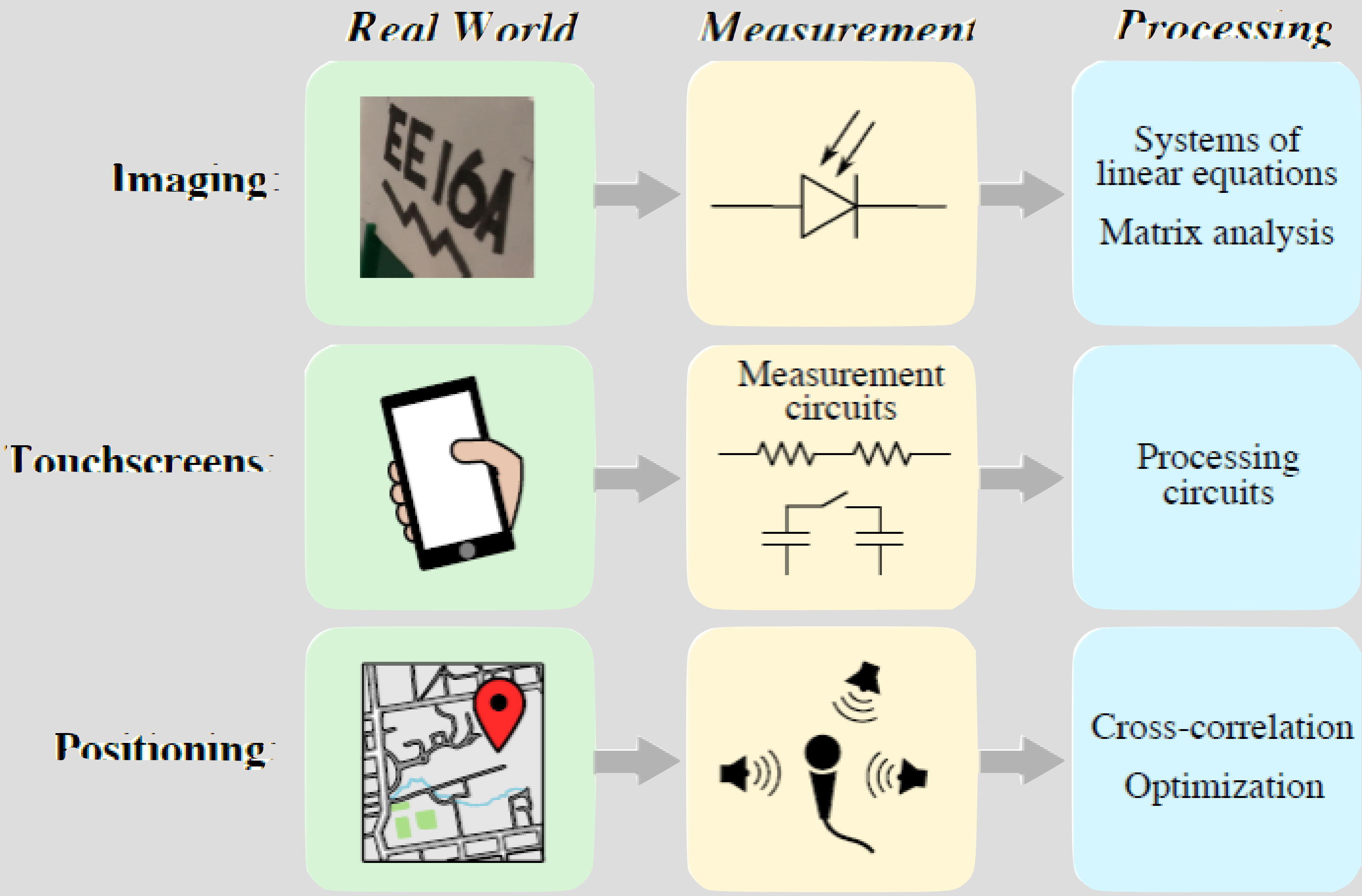
Stuff you will do next

EECS 16B

- Module 4: Advanced circuit design / analysis
- Module 5: Introduction to control and robotics
- Module 6: Introduction to data analysis and signal processing



What you built:



Real World | *Measurement* | *Processing*

Imaging:

Systems of linear equations

Matrix analysis

Touchscreens:

Measurement circuits

Processing circuits

Positioning:

Cross-correlation

Optimization

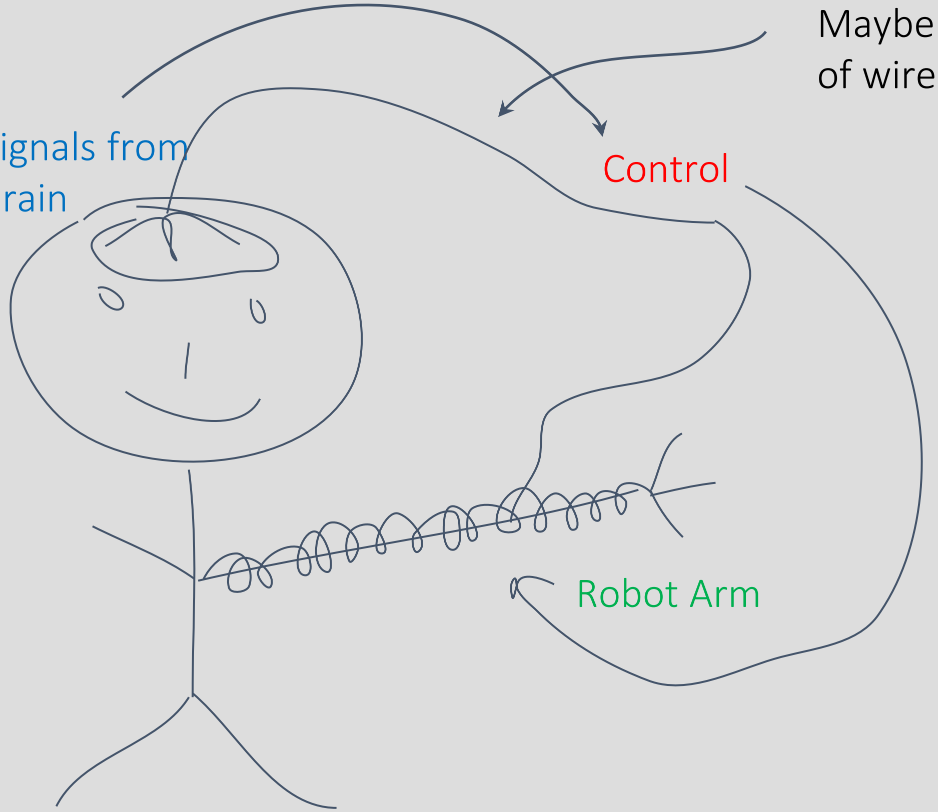
EECS16B: Designing Information Devices and Systems II

Big goal: Get signals from brain and interpret them

Module 1 – Circuits: Interfaces (brain, voice)

Module 2 – Control: Controls (feedback, stability)

Module 3 - Classification: Figuring out the intention



Signals from brain

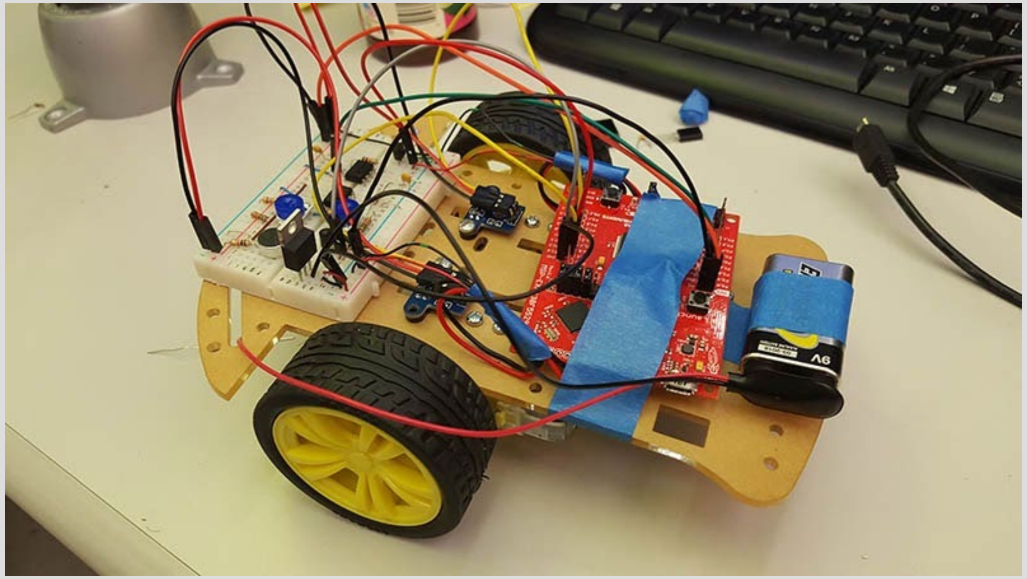
Control

Maybe get rid of wires too

Robot Arm

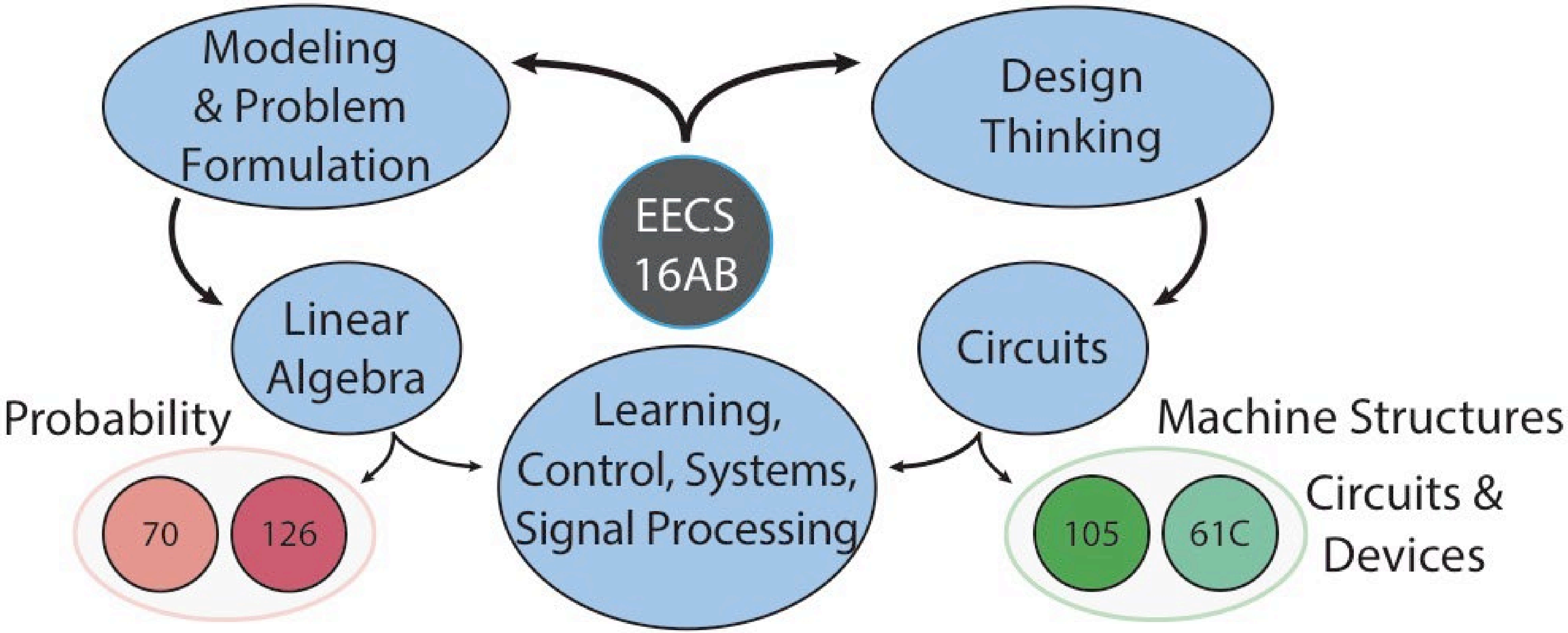
OpAmp Filters,
ADCs/DACs,
uController,
SysID,
Feedback,
SVD, PCA

Voice controlled robo car lab project – from scratch!



[Demo video]

Design Contest
(make our SIXT33N better!)

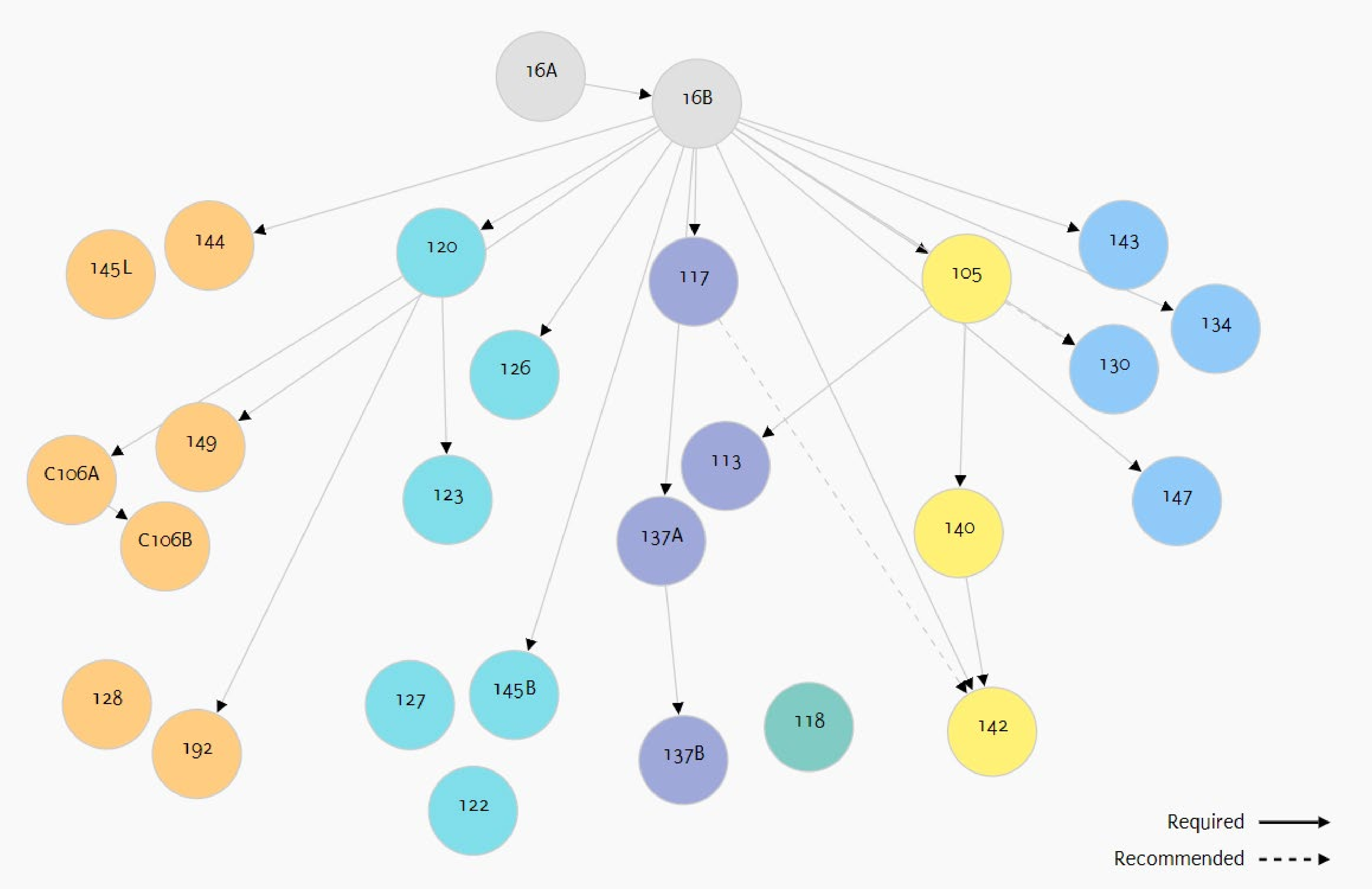


How to approach something unfamiliar
and systematically build understanding

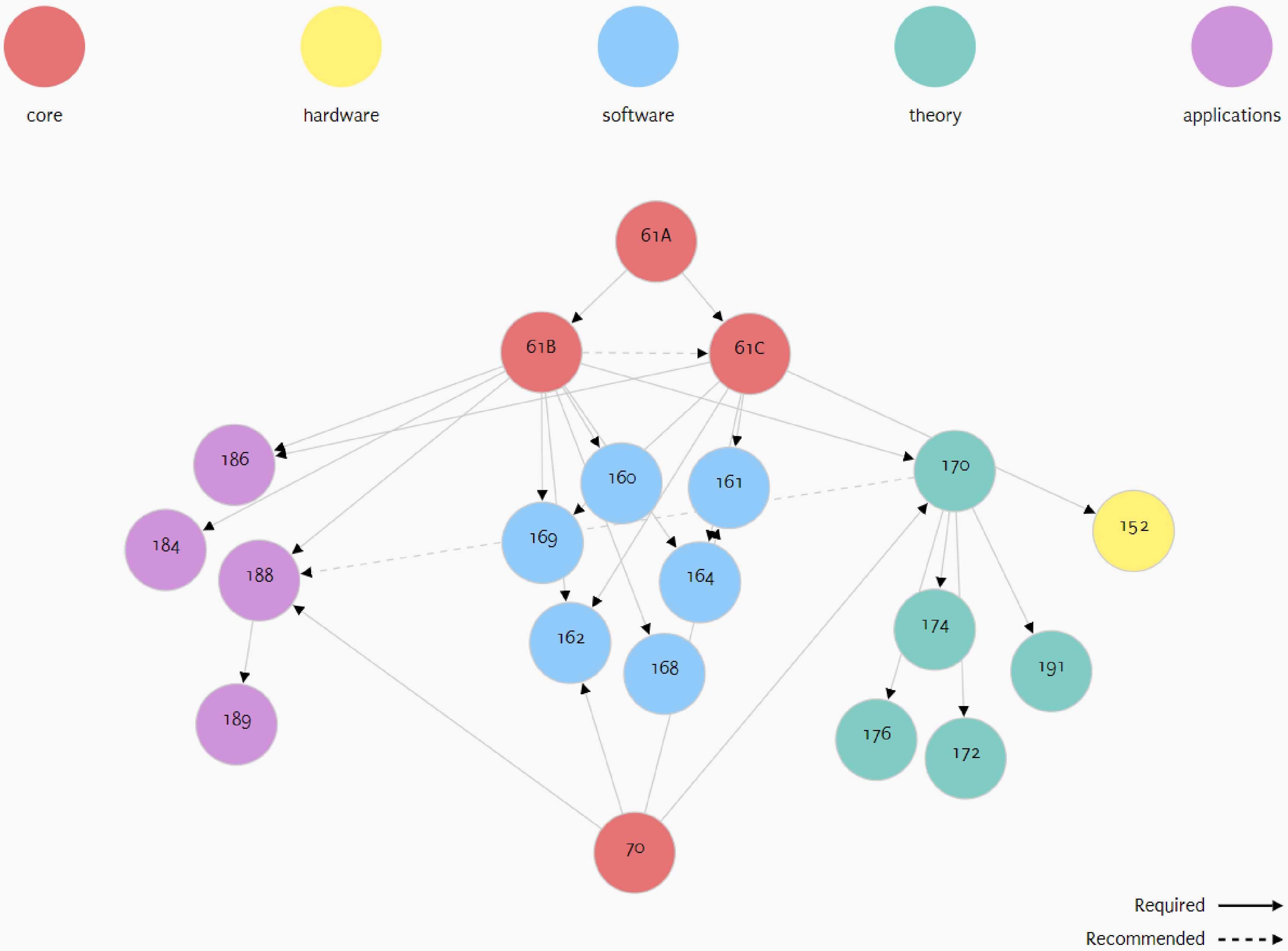
Linear Algebra: conceptual tools to model
Circuits: How to go from model to design, grounded in physical world

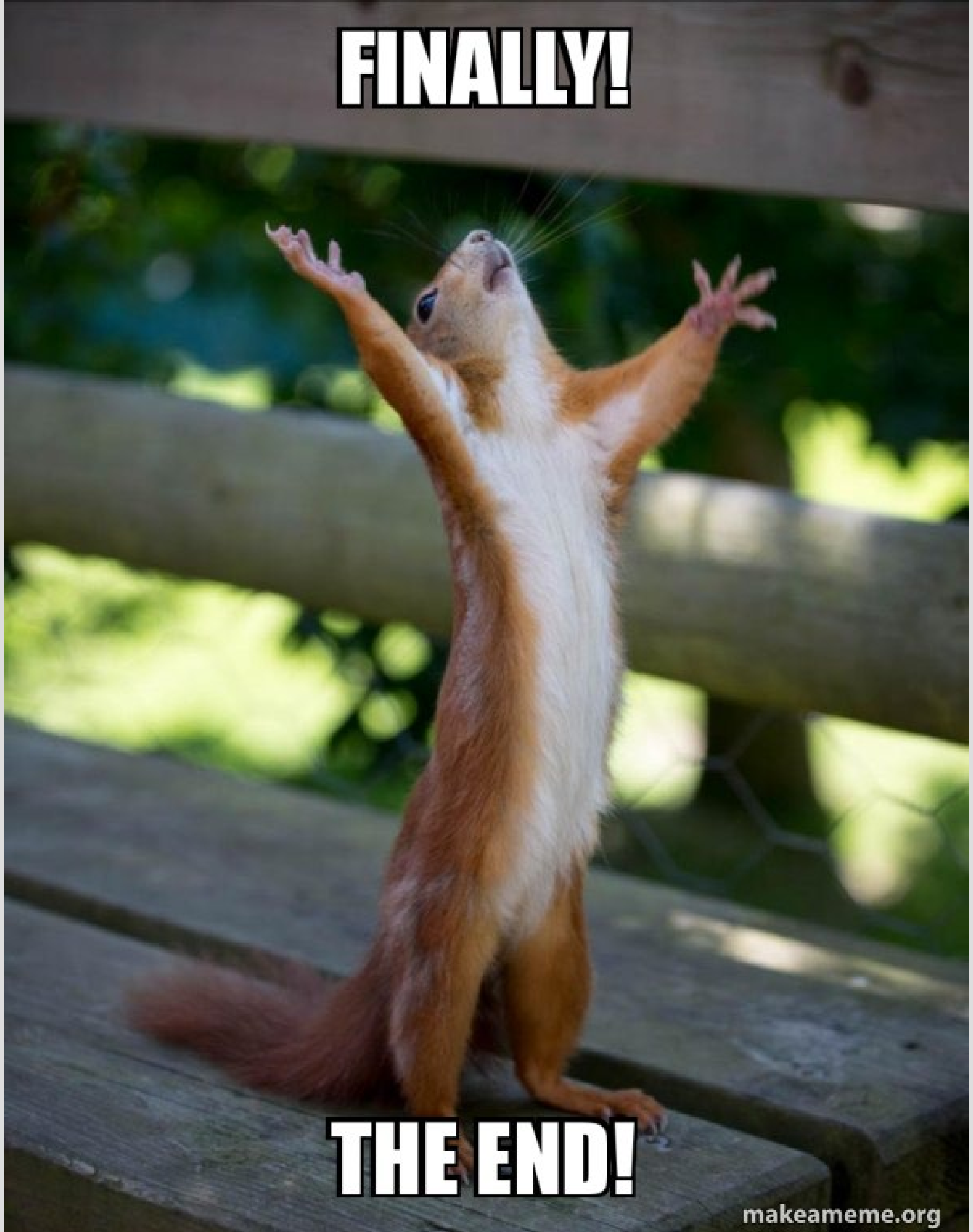
Intro to foundational concepts in Machine Learning

EECS course map



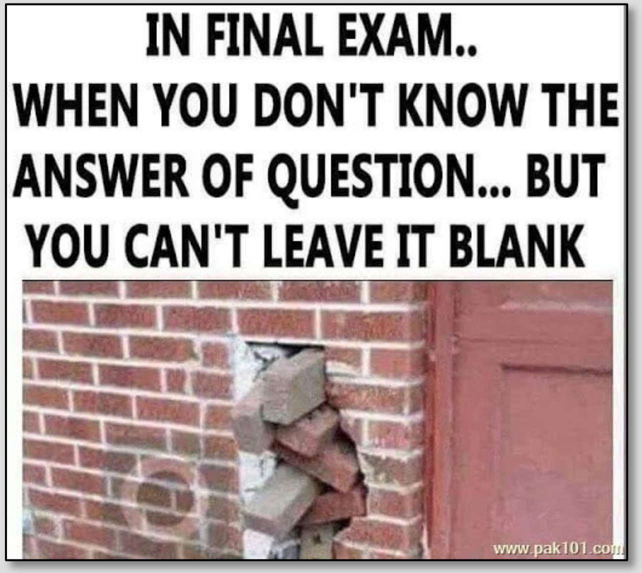
CS COURSE MAP





The End

Oh, except for the final exam…


IN FINAL EXAM..
WHEN YOU DON'T KNOW THE ANSWER OF QUESTION... BUT YOU CAN'T LEAVE IT BLANK
www.pak101.com