

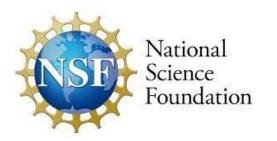
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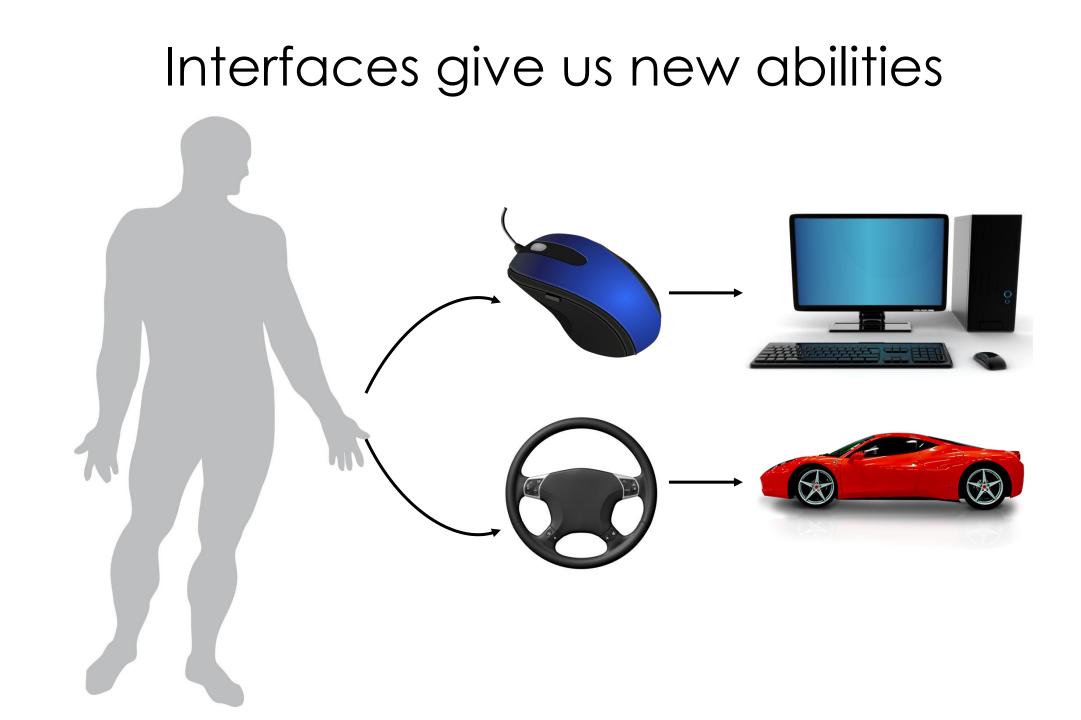
# Towards Real-time Brain Computer Interfaces Development -Data, Algorithms, and Hardware Lauren Peterson (A3D3 PostBac),

auren Peterson (A3D3 PostBac Si Jia Li, Amy Orsborn (PI)

July 10, 2023







# Neural Interfaces can restore abilities





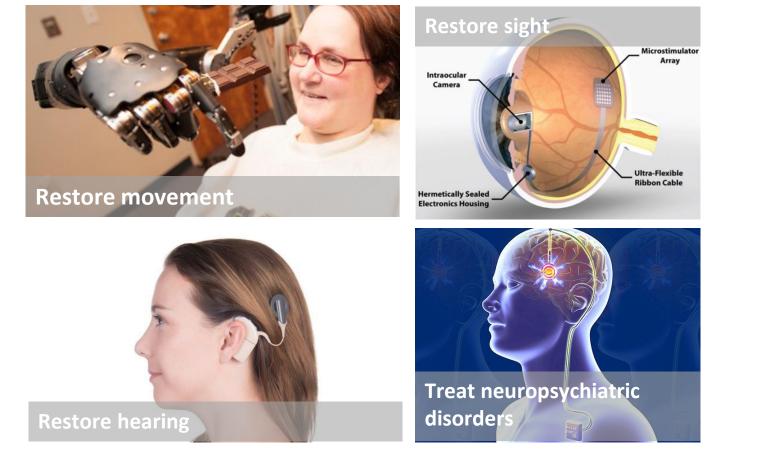
Brain-machine interfaces restore movement to people with paralysis



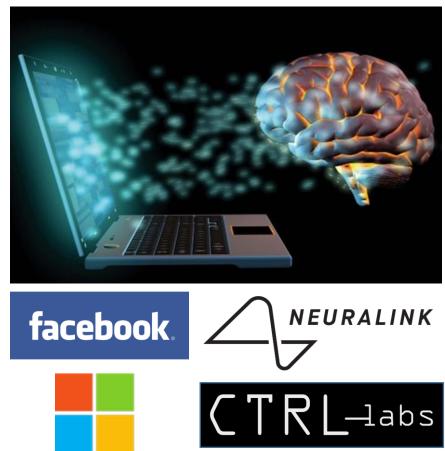
Collinger et al., Lancet 2012

# Huge range of applications & implications

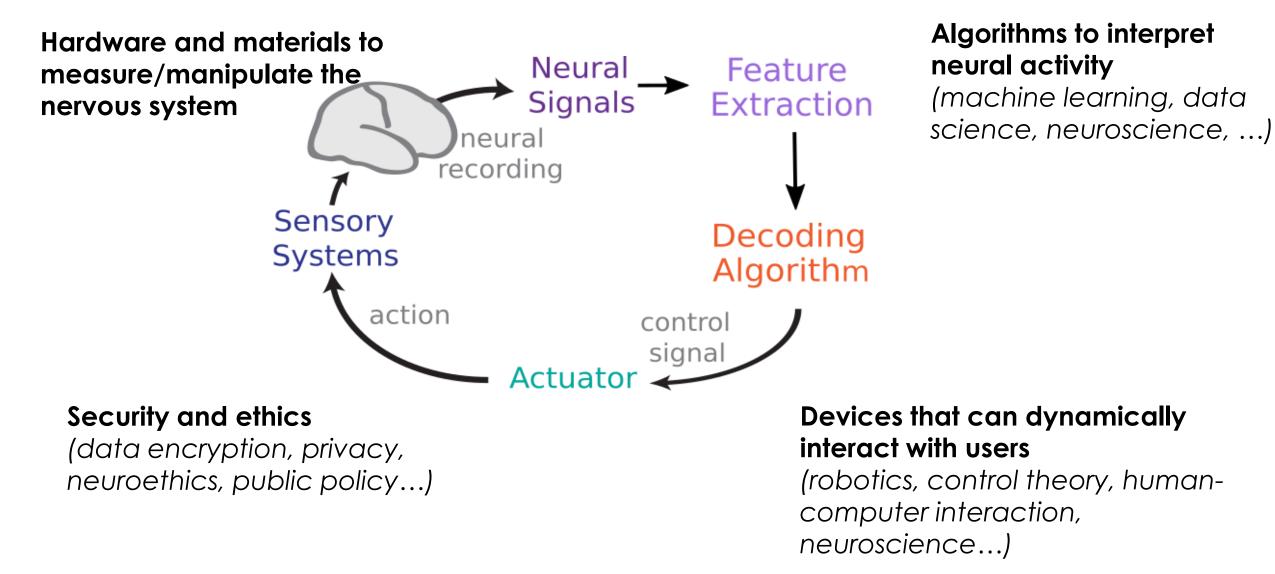
#### Revolutionizing healthcare...



#### **Revolutionizing HCI...**

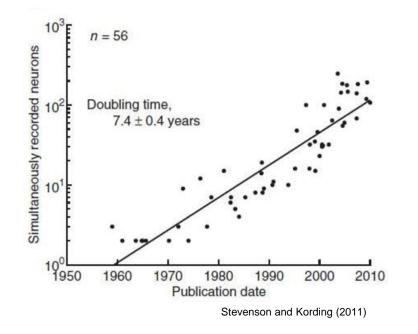


# Requires interdisciplinary engineering

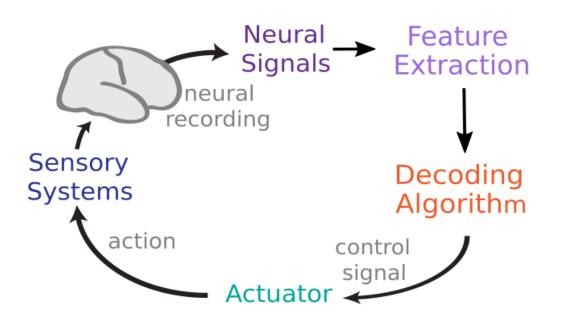


Neuroengineering needs high-throughput and real-time AI

Rapid increase in number, type of measurements

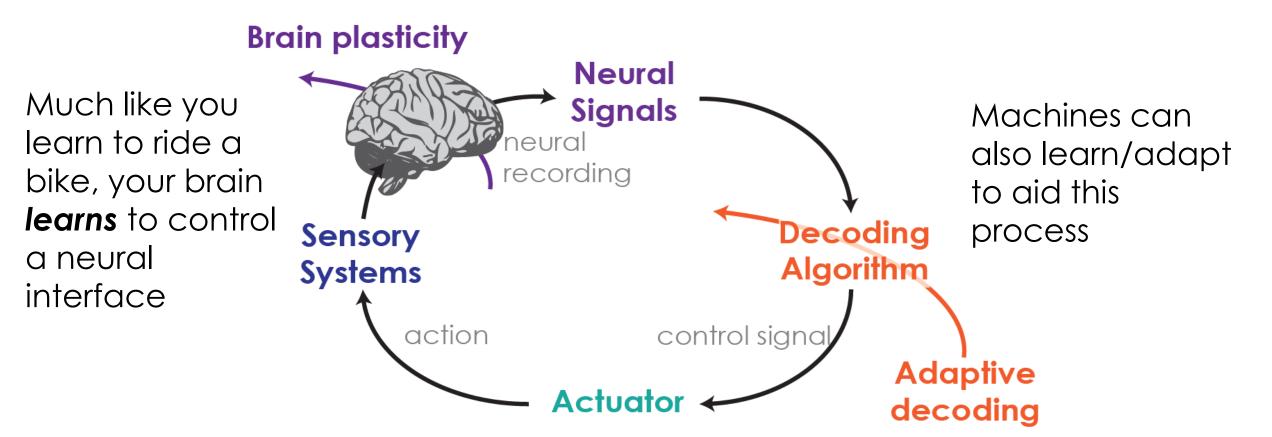


Algorithms must interact with the brain and control device in real-time



Need: data-driven discovery of relevant features, structure in data

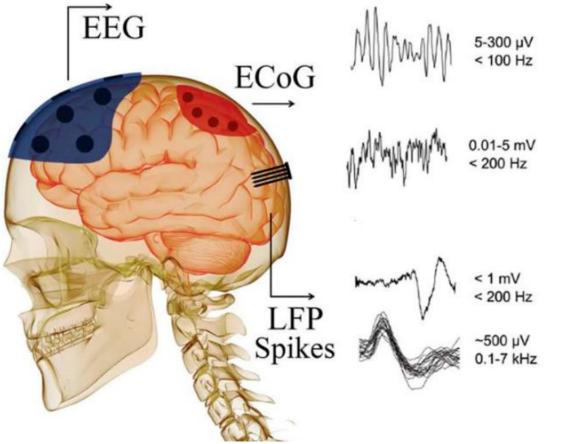
Need: low-latency algorithms (<1ms) How do we make machine learning that interacts with the brain?



# Assuring both learners work *together* requires understanding the intersection of neuroscience and machine learning

Madduri, Burden, and Orsborn, Curr Op BME 2023 (in press)

#### We record different types of neural signals

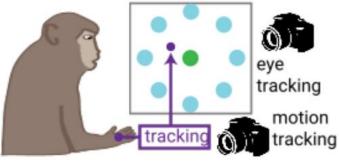


- Electrocorticograph: **continuous** surface potentials
- Local field potentials (LFPs):
  continuous measurement
- Spikes: **discrete** measurement (action potentials of neurons)

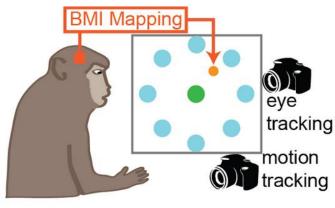
Each type of recording gives rise to many types of neural features.

#### A spectrum of tasks and data structures

more constrained, structured data, less time (1hr/day)



Manual center-out reaching



BMI center-out reaching

less constrained, unstructured data, more time

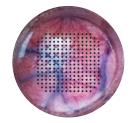


In cage wireless recording

Berger et al., (2020)

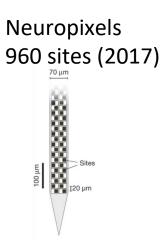
## Data-driven discovery of relevant features, structure in data

Electrocorticography 244 Electrodes



What are the task-relevant electrodes/features?

What are the underlying dynamics?



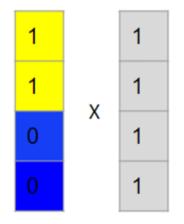
What are the electrodes to stream as the user learns?

# Convex feature objective that optimizes for sparseness, smoothness, and relevance

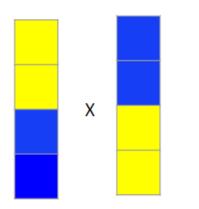
 $\min_{\theta_i} \quad \lambda \theta_i^T \mathbf{1}$ 

s.t. 
$$0 \le \theta_{i,m} \le 1$$





Maximize feature selection smoothness

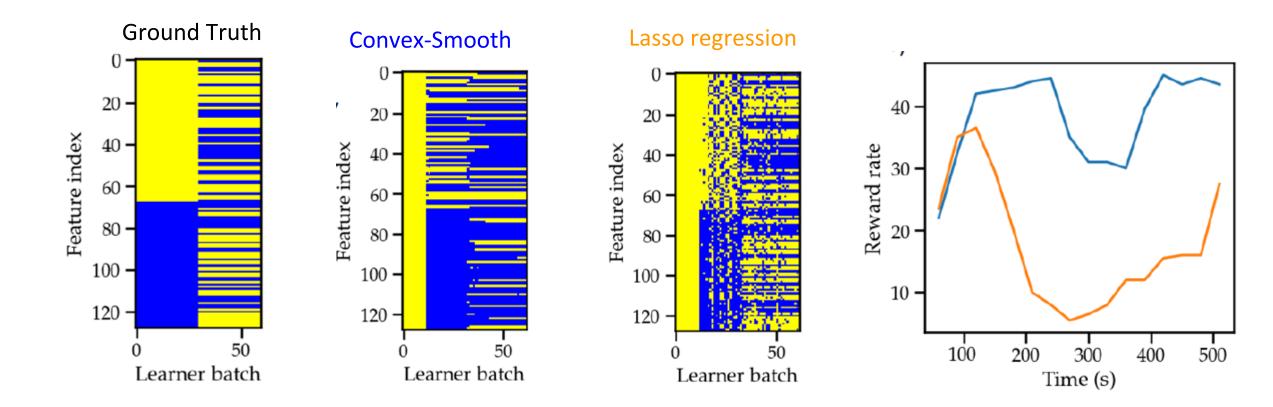


Maximize feature relevance by measuring weight to noise ratio

Convert to a convex optimization problem that is easier to solve (Joshi and Boyd, 2006)

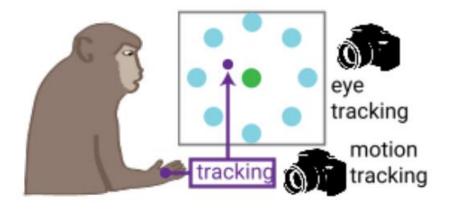
Si Jia Li et al., in prep

#### Smooth objective helps with online task performance

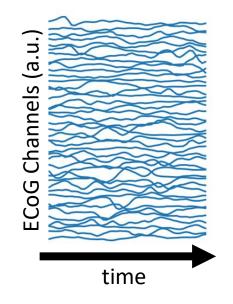


#### Feature selection applications

Implement in animal experiments



Data driven selection of ECoG features

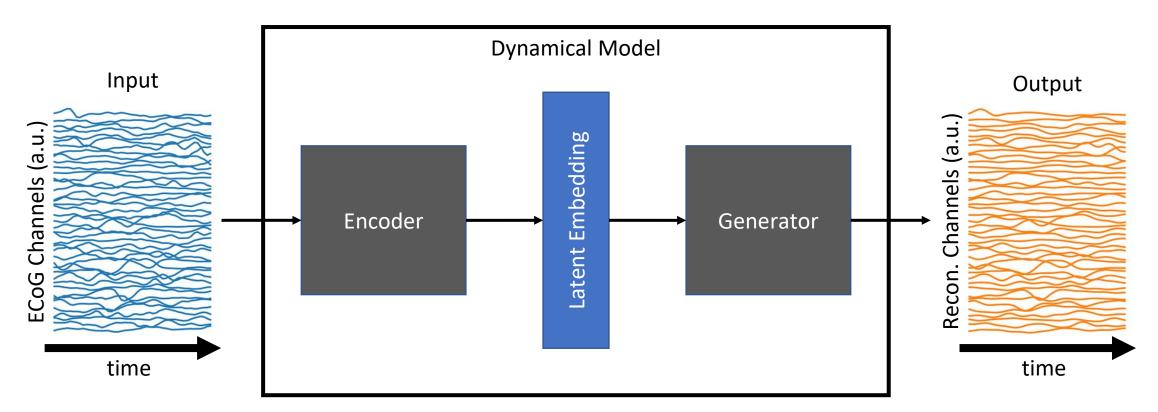


# ECoG Signal Reconstruction

How do we build models of neural signal dynamics?

based on work from "Multi-block RNN Autoencoders Enable Broadband ECoG Signal Reconstruction", preprint: doi: https://doi.org/10.1101/2022.09.07.507004

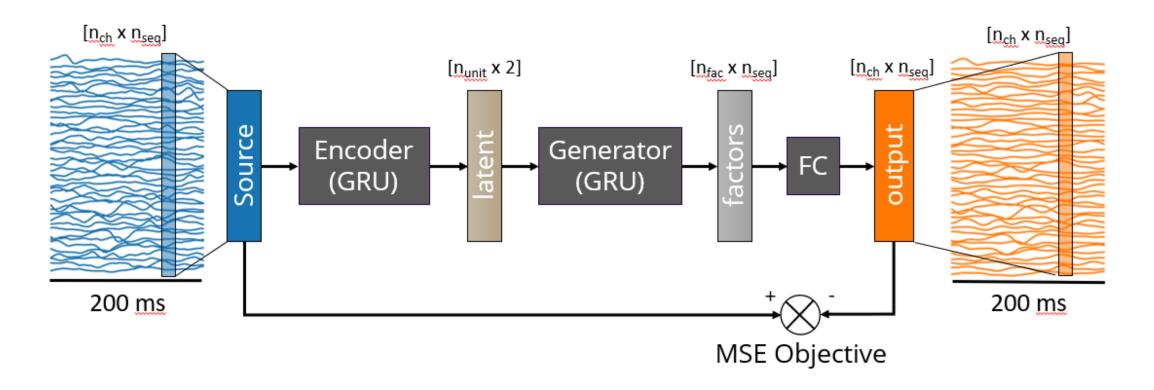
#### Modeling Neural Dynamics: Recurrent Autoencoders



- Current models have been useful for neuroscience research
- What happens when we use a broadband signal?

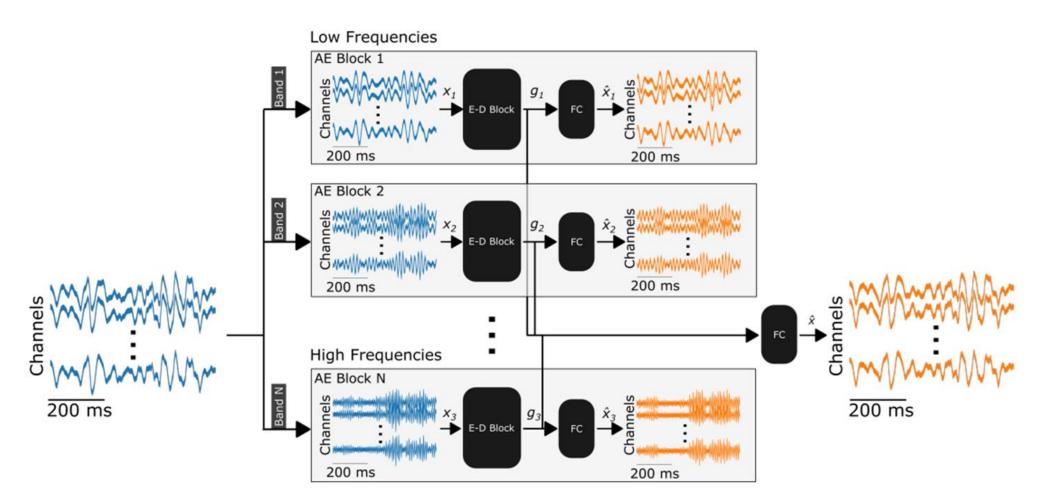
(arXiv:1608.06315)

#### **RNN** Autoencoder Models (RAE)



- We make some minor adjustments to handle broadband
- Increasing model size improves performance

#### Multi-block RAE (MRAE)



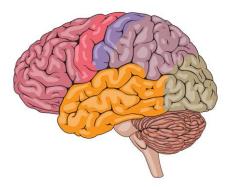
• Performance improves with model size, and scalability is good

from "Multi-block RNN Autoencoders Enable Broadband ECoG Signal Reconstruction"

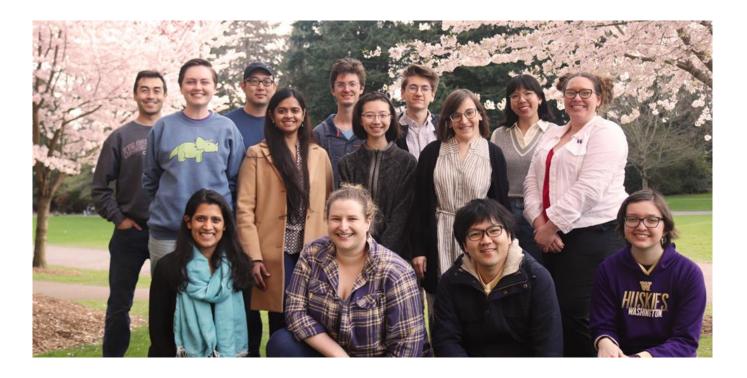
#### **Real-time Applications**

- FPGA implementation is in the works
- Collaborating with Shlizerman, Hauck labs to improve performance and latency
- MRAE is scalable, but other emerging technologies (e.g. transformers) might improve reconstruction and prediction, and help us determine which features are the most important





# Acknowledgements



Thanks to NSF and A3D3 (OAC-2117997) for funding this research







# Backup slides

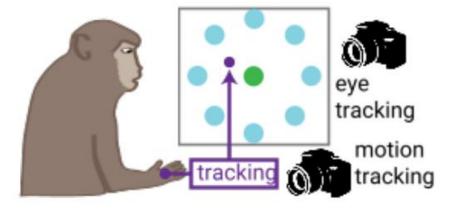
### **Experimental Subjects**

There are 5 monkeys in the lab:

- A & B: brain-computer interface, neuropixels, center-out task
- C: behavioral tasks; will add neural in ~6 months
- D & E: currently used in other projects

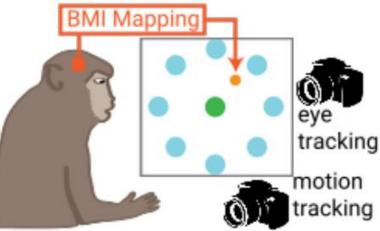
#### Manual Center-out

- Hand position (3D space) controls cursor position (2D plane) via mapping
  - Subject wears a glove with IR panels, recorded by motion-tracking cameras
  - Cursor position recorded directly
  - Eye tracking recorded by cameras (I currently can't answer questions about this)
- Brain activity (electrode array) recorded, but not used as input
- Can change the mapping to see how subject adapts and learns a new mapping
- Associated metadata includes:
  - Time stamps, trial tags (trial begin/end, etc)
  - Sampling rate
  - Cursor size, target size, target position
  - Number of channels/samples



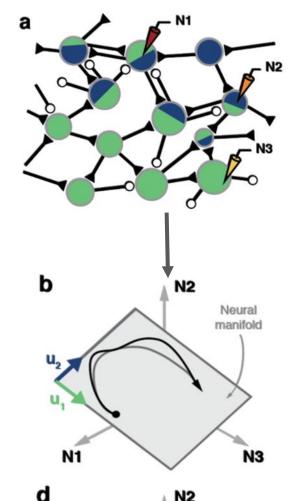
# **BCI** Center-out

- Hand is somewhat restricted
- Neural activity (recorded from electrode array) used as input
  - High frequencies used in linear regression decoder
- Experiment proceeds the same way otherwise
- Same metadata, but no hand position recorded



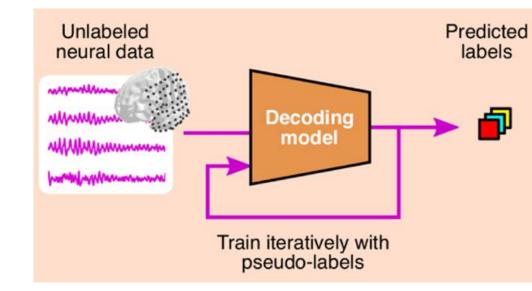
#### Example types of AI applications in neuroscience

1. Identify relevant features of neural activity (latent structure)



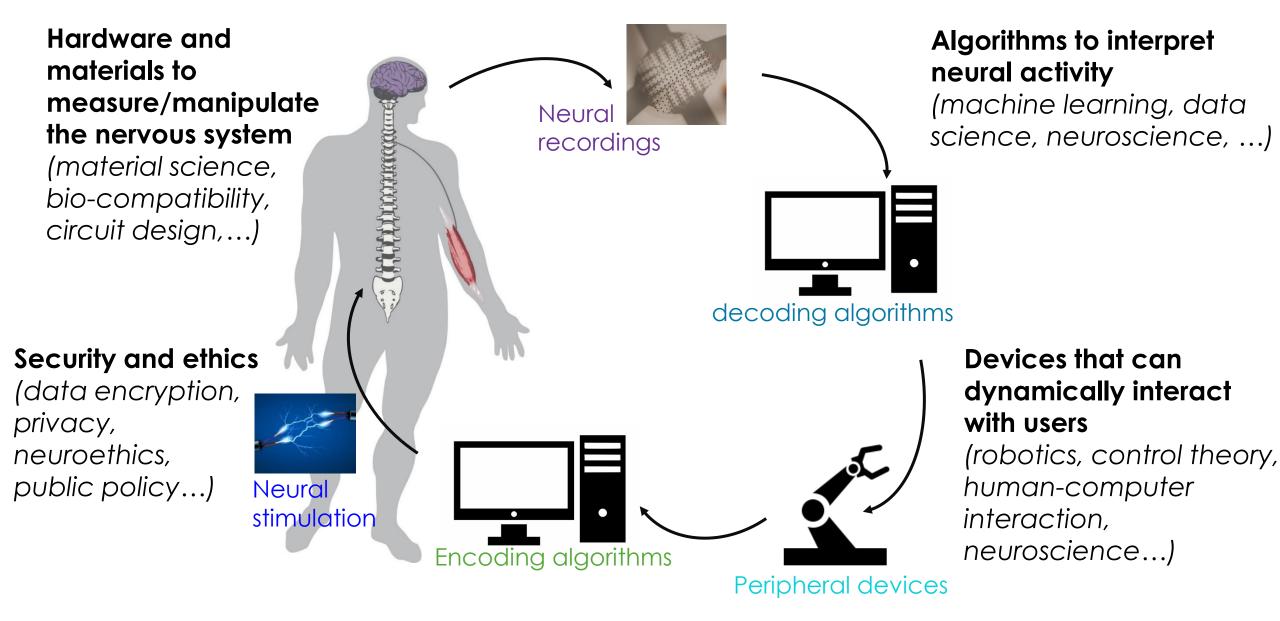
2. Relate neural features to behavior

3. Decode behavior in real-time to restore function





# Requires interdisciplinary engineering



#### Neural recording hardware

