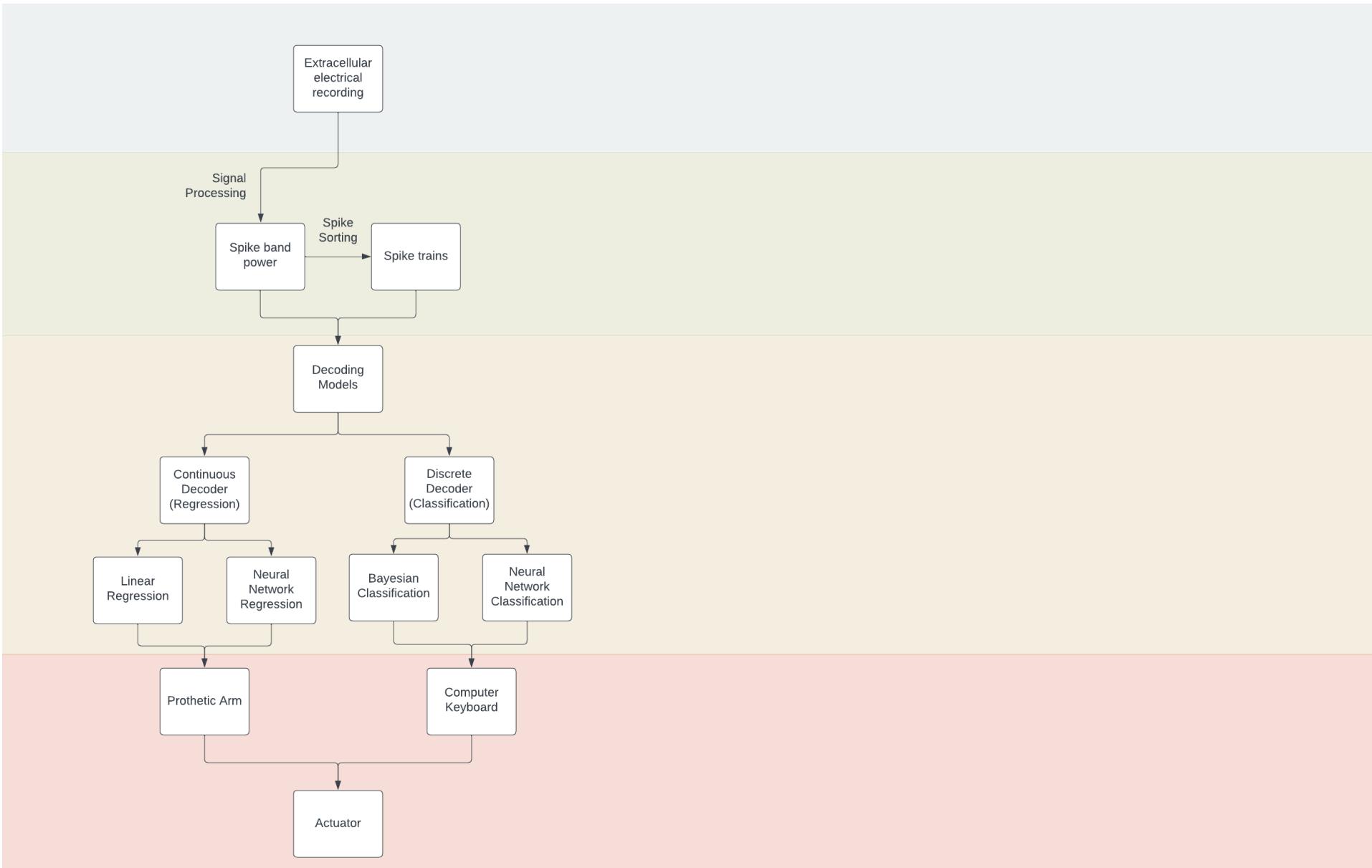
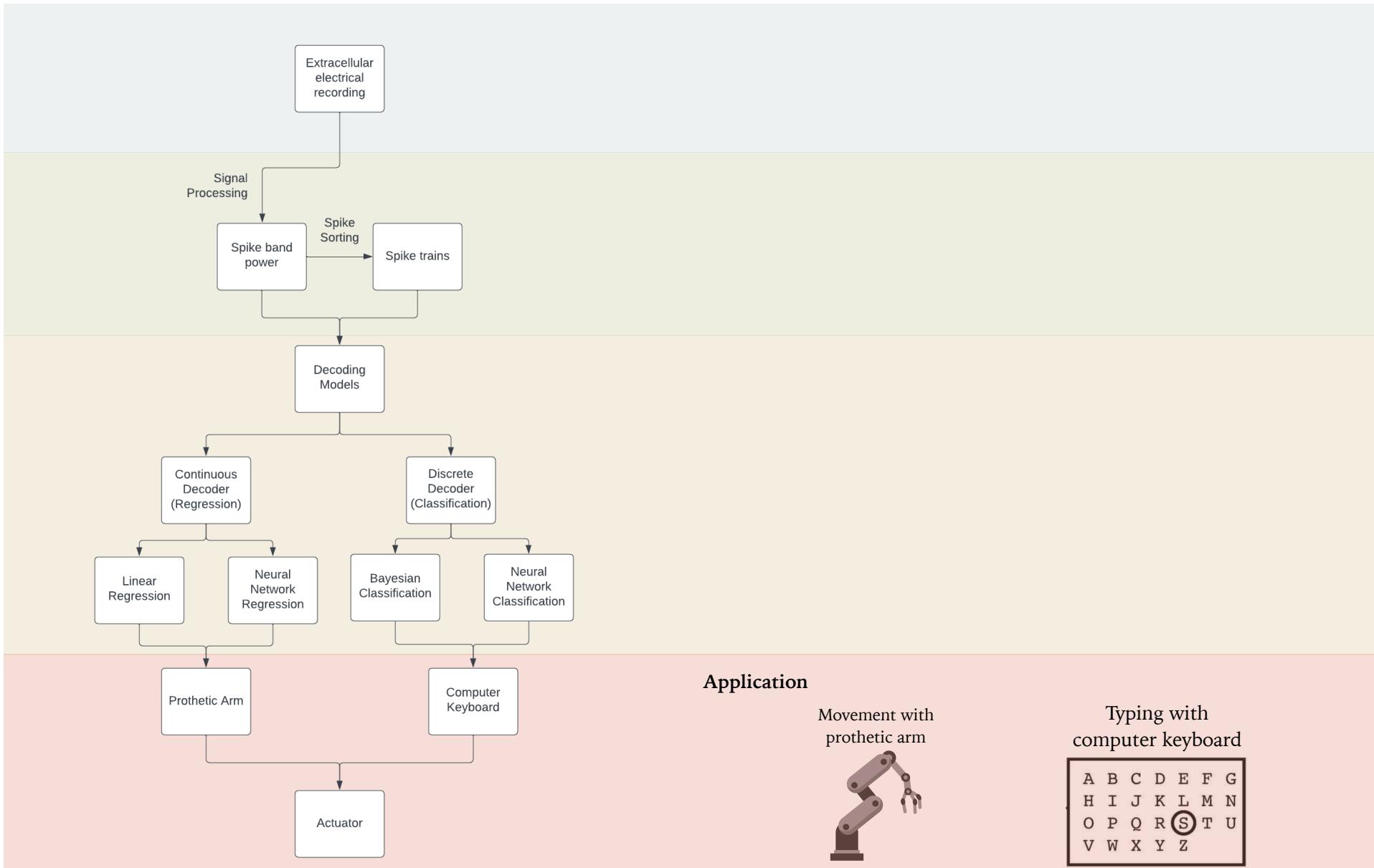


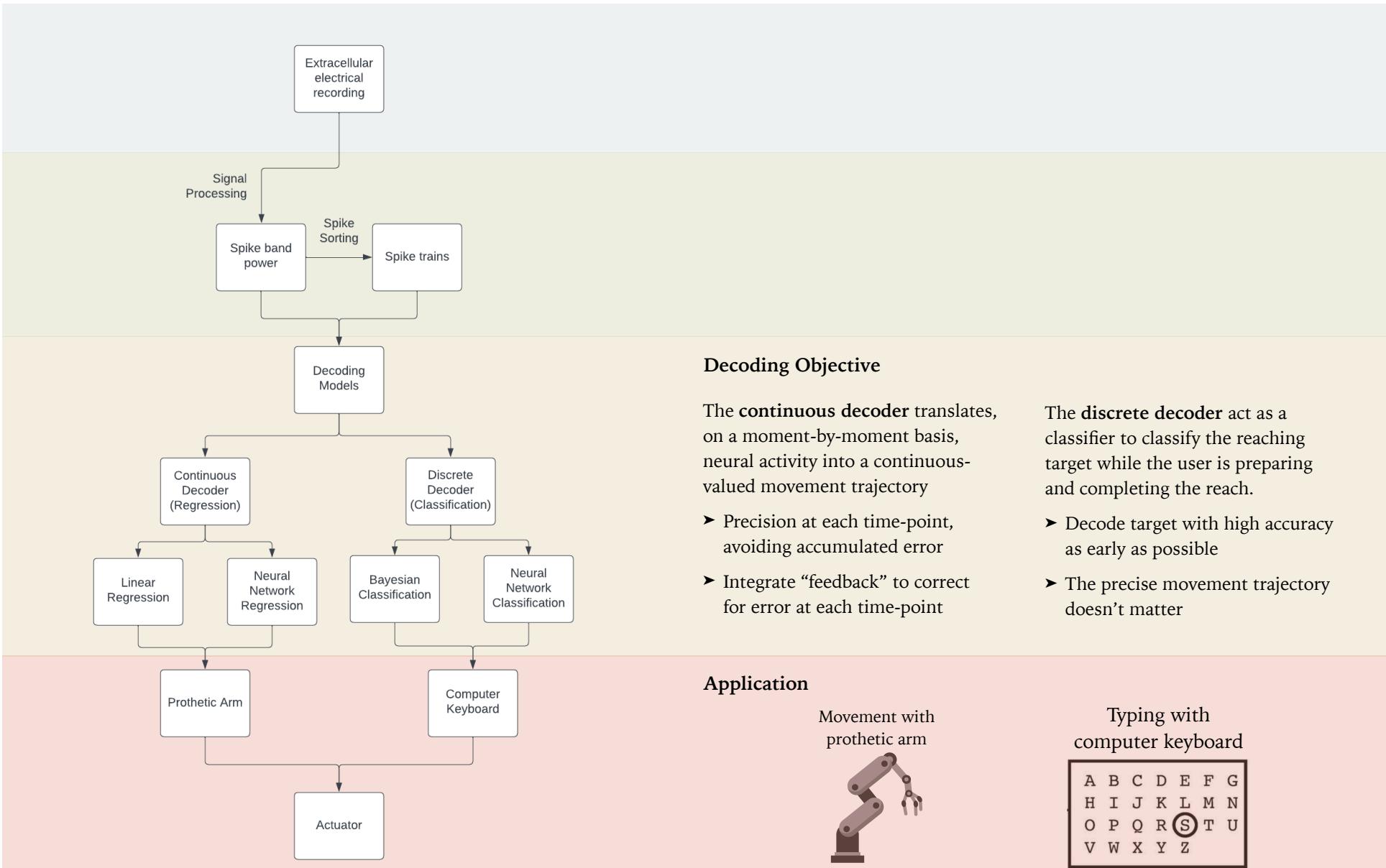
# Self-Guided Coding Session



# Formulate Decoding Problem Base on Target Application



# Formulate Decoding Problem Base on Target Application



# Formulate Decoding Problem Base on Target Application

Neural Decoding.ipynb ★

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Peristimulus Time Histogram (PSTH)

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- Dimensionality Reduction (Bin Neural Response)
- Decoding target with binned neural response
- Speed-accuracy trade-off for decoding target

Neural Network Classification

- Decoding Challenge - RNN: many-to-one

Define RNN Model: RNNClassifier

## Formulate the Neural Decoding Problem

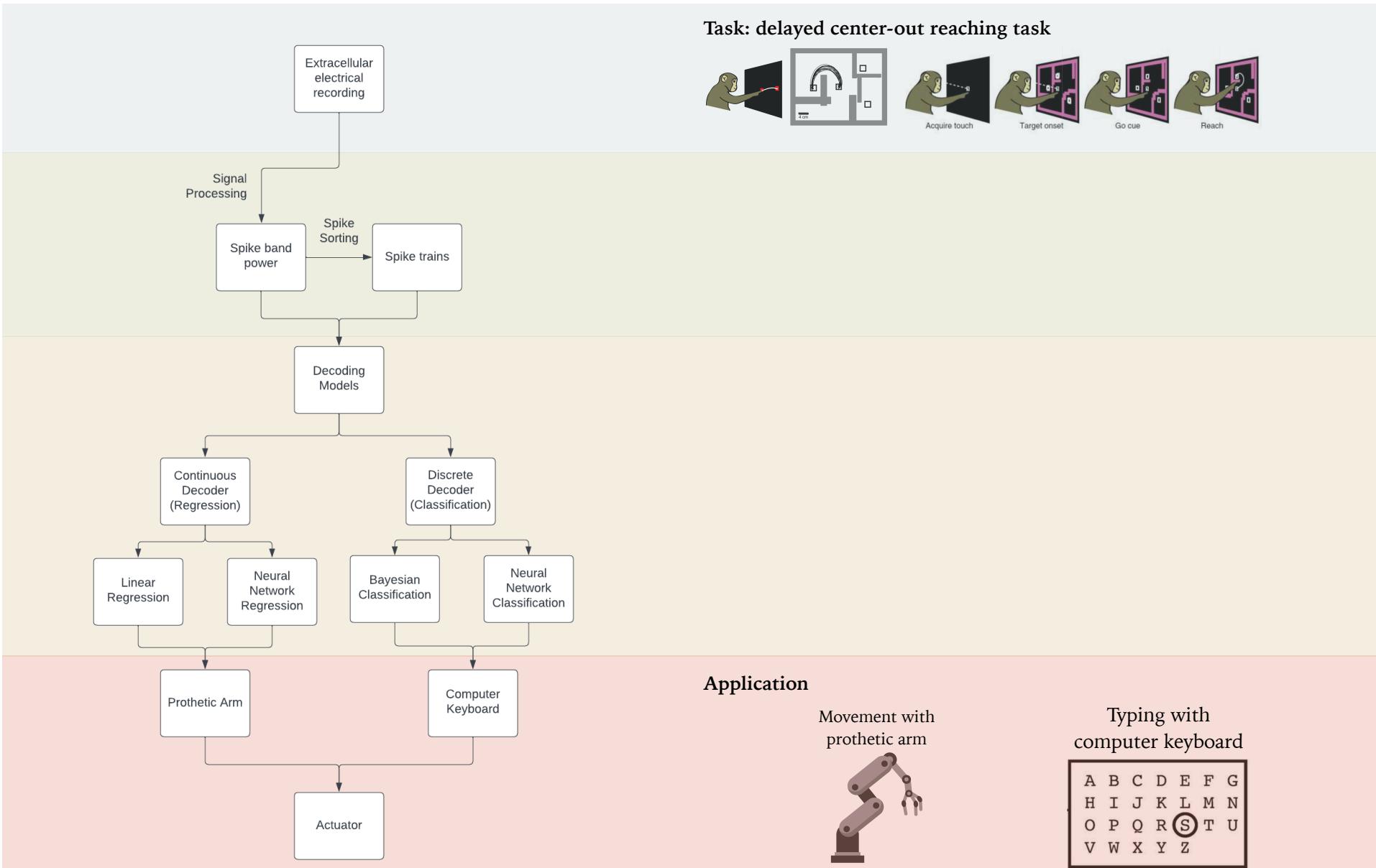
The primary goal of the neural decoding algorithm is to translate the electrical neural activity from the brain into control signals for guiding paralyzed upper limbs, prosthetic arms, and computer cursors to achieve user's movement intent. Neural decoding algorithms can be devised to decode the desired movement trajectory (continuous decoder) or movement target (discrete decoder) based on the pattern of neural activity.

To direct the prosthetic arm through space, the neural decoder must produce movement trajectories as accurately as possible to enact precisely the desired movement. The **continuous decoder** translates, on a moment-by-moment basis, neural activity into a continuous-valued movement trajectory.

In contrast, for neural decoder to direct the cursor for key selection on the keyboard, the precise trajectory moving through the keyboard is less important compare to the speed in decoding the target key. The **discrete decoder**, thus, act as a classifier to classify the reaching target while the user is preparing and completing the reach.

The diagram illustrates the neural decoding process for two different target applications. On the left, a continuous movement target is shown as a hand reaching from a starting circle to an ending circle. On the right, a discrete movement target is shown as a hand reaching from a starting circle to one of four possible circular targets on a keyboard. Above the targets, a brain model shows electrode placement in the Dorsal premotor cortex. Below the targets, two PSTH plots show neural activity over time for two trials. Trial 1 shows a continuous movement trajectory, while Trial 11 shows discrete target selection. Arrows point from the PSTH plots to the corresponding movement targets, indicating the mapping of neural activity to movement intent.

# MC\_Maze: Delayed Center-out Reaching Task Dataset



# MC\_Maze: Delayed Center-out Reaching Task Dataset

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+ Code + Text

Delayed Arm Reaching (MC\_Maze Dataset)

The MC\_Maze dataset encompasses recordings from sessions in which a macaque performed delayed center-out reaches, capturing neural activity from the primary motor and dorsal premotor cortices.

This dataset, featuring concurrent neural and reaching recordings, offers a means to comprehend the response characteristics of neurons during various reaching behaviors and explore the intricate relationship between this activity and the moment-to-moment reaching movements. This exploration serves as a foundational step toward the development of neural decoding methods, allowing for the extraction of the desired movement trajectory (continuous decoding) or movement target (discrete decoding) based on the neural activity patterns.

This data was provided by Krishna Shenoy, Mark Churchland, and Matt Kaufman from Stanford University, and you can learn more about the task design, data collection, and their analyses of the data in a number of papers, including this (Churchland et al. 2010).

## MC\_Maze

A brain visualization showing the distribution of neuron counts across different firing rates. The x-axis is labeled "Firing rate (spk/s)" and ranges from 0 to 20. The y-axis is labeled "Neuron count" and ranges from 0 to 60. A histogram shows a peak around 5 spk/s, with a blue shaded region highlighting the primary motor and dorsal premotor cortices.

Three small illustrations of a macaque's arm reaching for a target in a maze. The first illustration is labeled "Target onset", the second "Go cue", and the third "Target acquisition".

A Peristimulus Time Histogram (PSTH) showing neural activity over time. The x-axis is labeled "Time (ms)" with markers at -500, 0, 500, 1000, 1500, and 2000. The y-axis is labeled "Channels". The histogram shows a strong burst of activity starting at 0 ms, corresponding to the "Target onset" and "Go cue" stages shown above.

# Experiment Task Structure: Plan and Movement Activity

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Time Alignment

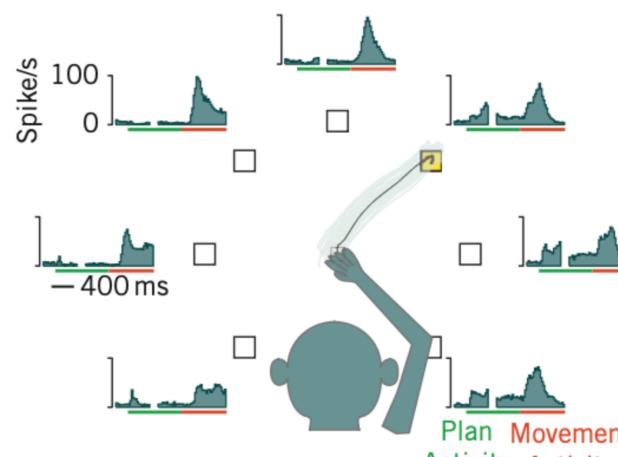
Plan and Movement Neural Activity

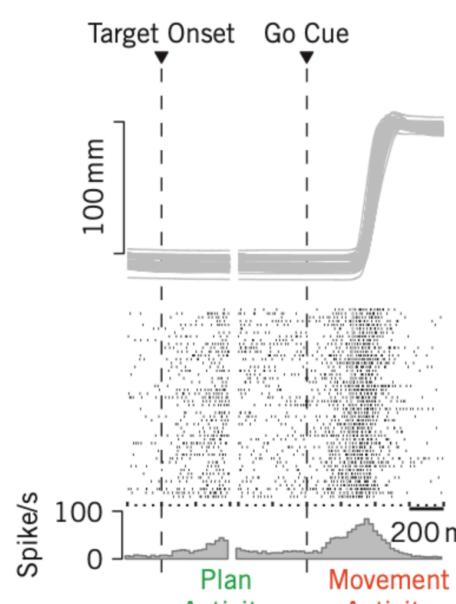
Two types of neural activity are commonly used for driving prosthetic systems: plan and movement activity.

- Plan Activity:** Plan activity is present before arm movements begin and is believed to reflect preparatory processing required for the fast and accurate generation of movement. Plan activity has been shown to reflect reach target, peak velocity, eye position and attention.
- Movement Activity:** Movement activity follows plan activity in a delayed reach task. Movement activity often exhibits a moment-to-moment correspondence with the intended trajectory of the hand's movement.

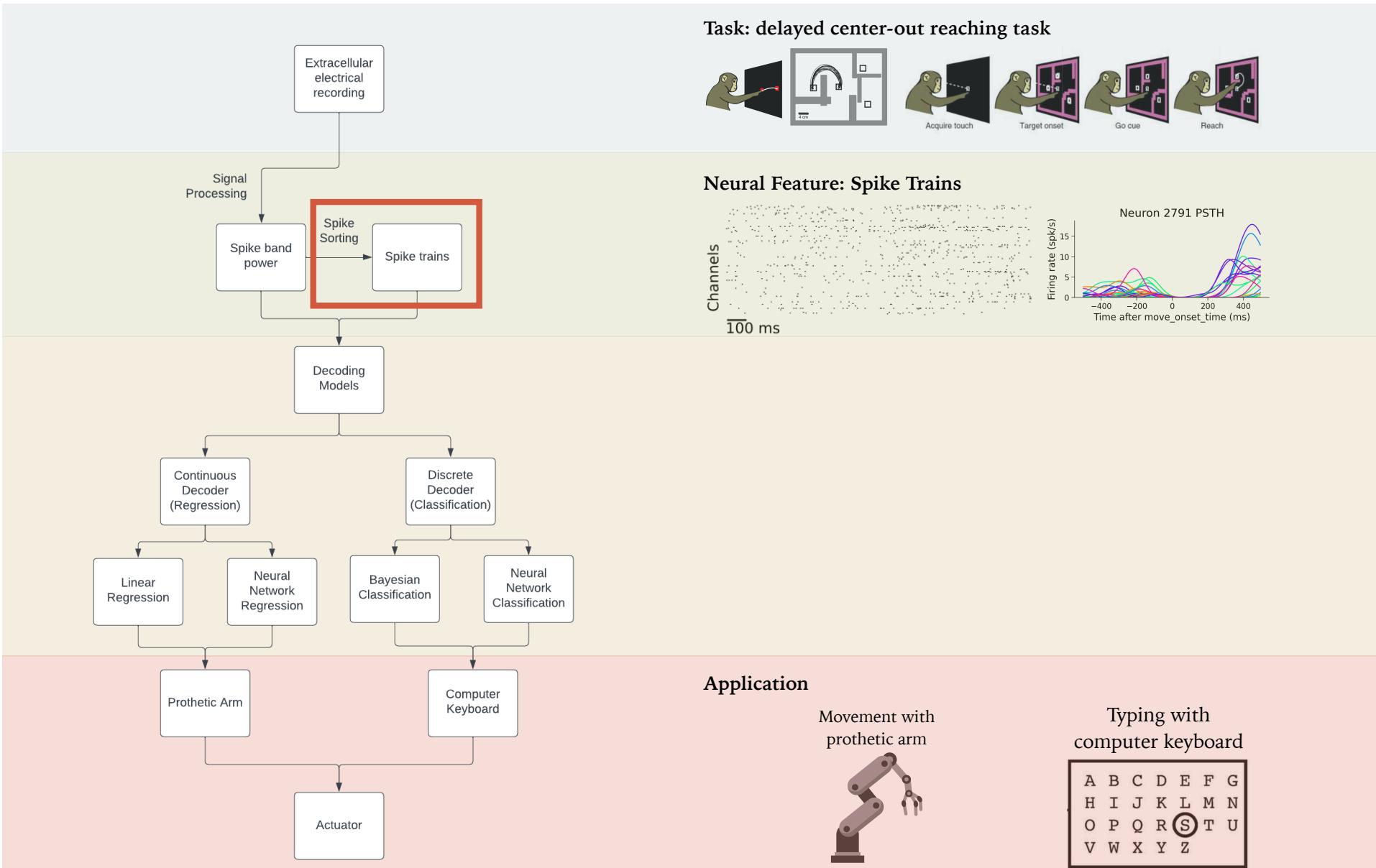
Localization of the neural activity for movement plan and control:

- PMd (dorsal premotor cortices) neurons** typically exhibit strong plan activity, as well as some movement activity
- M1 (Primary motor cortex) neurons** typically exhibit the opposite pattern





# Neural Feature: Spike Trains



# Neural Feature: Spike Trains

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Neural Recording

For these datasets, neural activity was recorded from two Utah arrays: one implanted in the dorsal premotor cortex, which is thought to play a role in movement planning, and one in the primary motor cortex.

This recorded data was spike sorted offline into the provided unit spike times.

- spikes | spike times binned at 1 ms

Single-neuron responses

Various aspects of movement (e.g. position, velocity, acceleration, and force) are encoded in the activity of neurons throughout the motor system. Even though our understanding of movement encoding in the motor system is incomplete (mechanism of cortex control for movement), there is usually a relationship between aspects of movement and neural activity. This reliable relationship allows us to estimate the desired movements from neural activity.

Consider the activity of an individual neuron across repeated movements (referred to as 'trials') to the same target. The activity of the neuron can be averaged across many trials to create a spike histogram for each target, often referred to as peristimulus time histogram (PSTH). By comparing the spike histograms for different target, one can characterize how the neuron's activity varies with the movement produced.

Given leftward and rightward arm reaching as an example, the firing rate of the neuron (approximated with spike histogram) shows statistical regularity across the two reach condition and across time.

- Distinct spike patterns for leftward and rightward arm reaching in both preparation and execution time period. On average, a greater level of preparation activity for leftward movements and a greater level of execution activity for rightward movements.
- Consistent moment-by-moment variability in spike patterns across trials of similar arm reaching indicates correlation between neural activity and arm trajectory across time.

The diagram illustrates two hand icons: one reaching left with an arrow pointing left, and another reaching right with an arrow pointing right. Below these is a stylized brain diagram with a green electrode probe inserted into the 'Dorsal premotor cortex' region.

Preparation Execution Preparation Execution

Trial 1 Trial 11

# Behavior: Reaching Trajectory and Hand Velocity

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Formulate the Neural Decoding Problem

Format the Data

+ Code + Text

## Behavior Recording

In addition to the neural data, cursor position and the monkeys' hand and gaze position were recorded during the experiment, and the hand velocity was estimated offline using the recorded hand position.

- cursor\_pos | x and y position of the cursor controlled by the monkey
- eye\_pos | x and y position of the monkey's point of gaze on the screen, in mm
- hand\_pos | x and y position of the monkey's hand, in mm
- hand\_vel | x and y velocities of the monkey's hand, in mm/s, computed offline using np.gradient

There are 27 different reach conditions in the MC\_Maze dataset. Here, we'll plot the average trajectory per condition to see what typical reaches look like.

```
[35] ## Plot trial-averaged reaches
# Find unique conditions
conds = dataset.trial_info.set_index(['trial_type', 'trial_version']).index.unique().tolist()

# Initialize plot
fig = plt.figure(figsize=(6, 6))
ax = fig.add_axes([0.1, 0.1, 0.8, 0.8])

# Loop over conditions and compute average trajectory
for cond in conds:
    # Find trials in condition
    mask = np.all(dataset.trial_info[['trial_type', 'trial_version']] == cond, axis=1)
    # Extract trial data
    trial_data = dataset.make_trial_data(align_field=data_align_field, align_range=data_align_range, ignored_trials=~mask)
    # Average hand position across trials
    traj = trial_data.groupby('align_time')[['hand_pos', 'x'], ('hand_pos', 'y')].mean().to_numpy()
    # Determine reach angle for color
    active_target = dataset.trial_info[mask].target_pos.iloc[0][dataset.trial_info[mask].active_target.iloc[0]]
    reach_angle = np.arctan2(*active_target[::-1])
    # Plot reach
    ax.plot(traj[:, 0], traj[:, 1], linewidth=0.7, color=plt.cm.hsv(reach_angle / (2*np.pi) + 0.5))
    ax.scatter(traj[-1, 0], traj[-1, 1], color=plt.cm.hsv(reach_angle / (2*np.pi) + 0.5))

plt.axis('off')
plt.show()
```



# Format Data to Data Tensor

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Continuous Decoder (Regression)

Machine Learning Regression

Ridge Regression

Neural Network Regression

Recurrent Neural Network

RNN(GRU): many-to-many

Training RNNRegressor

Pre-trained RNNRegressor

Evaluate the Model performance

+ Code + Text

Format the Data

Neuron (Firing rate)

Trial x T x nNeuron

Trial 1 Trial 2 Trial 3

Neurons 1 20

Conditions

Time

Behavior (Hand Velocity)

Trial x T x nBehavior (x and y velocity)

Trial 1 Trial 2 Trial 3

Behavior Variable 1 20

Conditions

Time

[21] # alignment parameter for this dataset  
data\_align\_field='move\_onset\_time'  
data\_align\_range = (-500, 500)  
# Decoding behavior with neural response preceding the behavior  
response\_delay = -70  
  
# Select hand velocity and hand position and behavior data  
behavior\_data\_fields = ['hand\_vel', 'hand\_pos']  
# Select smoothed spike train as neural feature  
neuron\_data\_fields = ['spikes\_rate']  
  
# Size of the time bin in (ms) for each time sample  
bin\_width = dataset.bin\_width  
# Number of discrete state  
n\_state = 6

[22] ## Load dataset

# Format Data to Data Tensor

Neural Decoding.ipynb ★

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Pre-trained RNNRegressor

Evaluate the Model performance

+ Code + Text

Format the Data

Neuron (Firing rate)

Trial x T x nNeuron

Trial 1 Trial 2 Trial 3

1 Neurons 20

Conditions Time

Behavior (Hand Velocity)

Trial x T x nBehavior (x and y velocity)

Trial 1 Trial 2 Trial 3

1 Behavior Variable 20

Conditions Time

Formatted Data are stored in data\_dict

```
print("====")
print("Key data fields in data_dict")
print("====")

for key in data_dict.keys():
    data_dict[key] = np.vstack(data_dict[key])
    print(f'{key}: {np.shape(data_dict[key])}')
    if key not in ['traj', 'pstb']:
        data_dict[key] = data_dict[key][trial_order]
data_dict['trial_id'] = np.array(trial_id)[trial_order]

=====
Key data fields in data_dict
=====
hand_vel: (250, 200, 2)
hand_pos: (250, 200, 2)
cond_label: (250, 2)
cond: (250, 1)
reach_angle: (250, 1)
spikes_rate: (250, 200, 152)
traj: (27, 200, 2)
pstb: (27, 200, 152)
state: (250, 1)

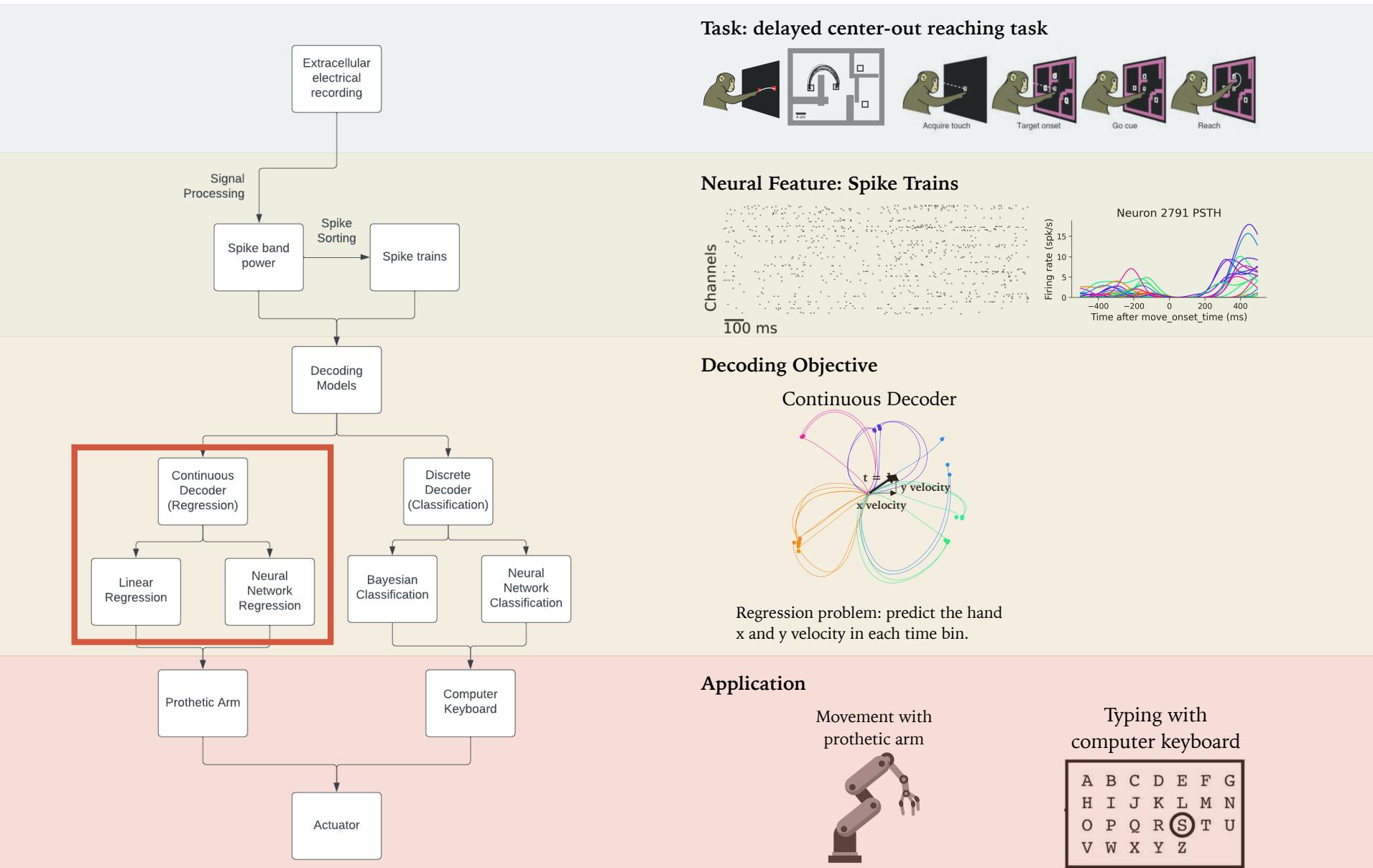
[21] # alignment parameter for this dataset
data_align_field='move_onset_time'
data_align_range = (-500, 500)
# Decoding behavior with neural response preceding the behavior
response_delay = -70

# Select hand velocity and hand position and behavior data
behavior_data_fields = ['hand_vel', 'hand_pos']
# Select smoothed spike train as neural feature
neuron_data_fields = ['spikes_rate']

# Size of the time bin in (ms) for each time sample
bin_width = dataset.bin_width
# Number of discrete state
n_state = 6

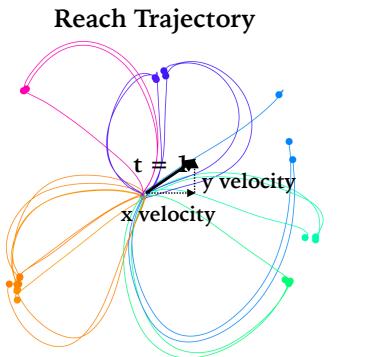
[22] ## Load dataset
```

# Continuous Decoder: Decoding Hand X and Y Velocity

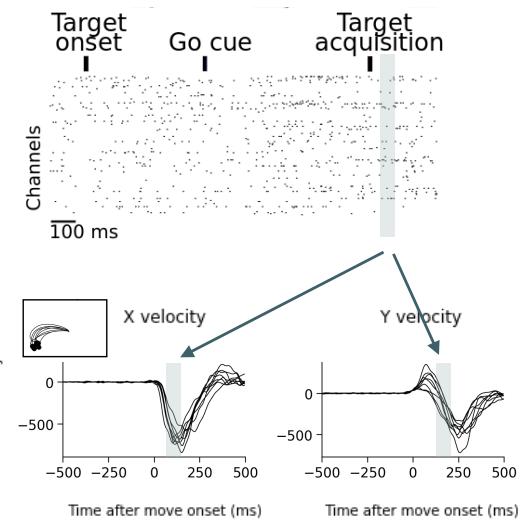


# Regression Problem: Decode Hand Velocity With Neural Firing Rate

## Regression Problem

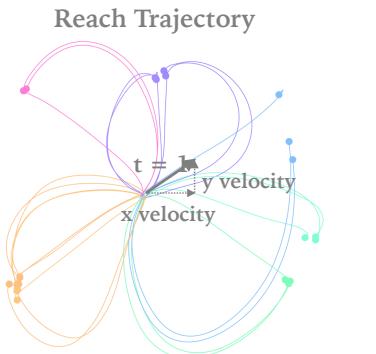


## Neural Spike Trains

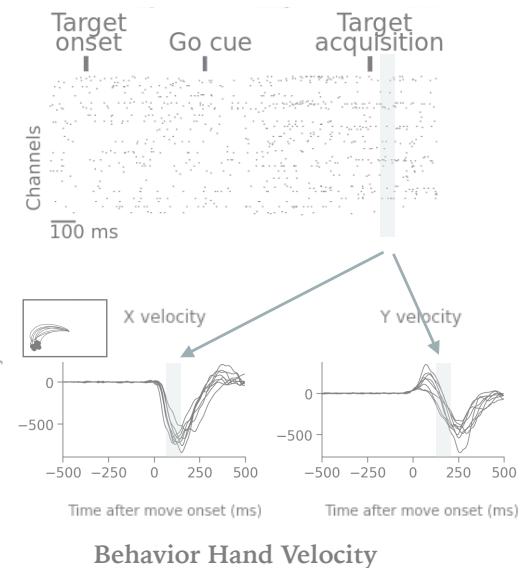


# Regression Problem: Decode Hand Velocity With Neural Firing Rate

## Regression Problem



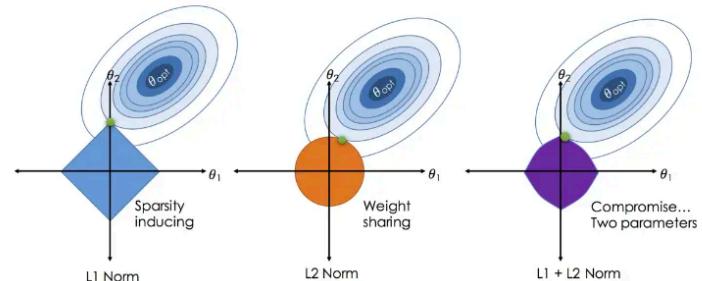
## Neural Spike Trains



## Regression Model

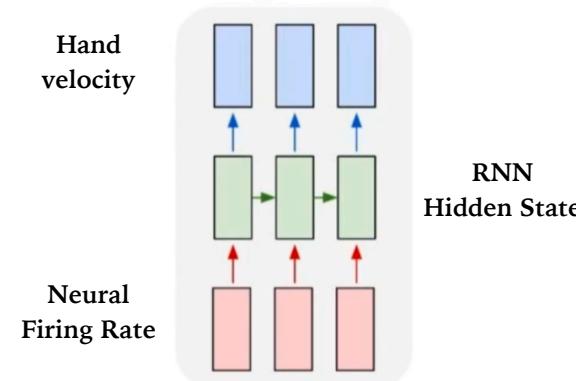
### Regularized Linear Regressor

Linear regression with L2 norm penalty for size of the weights to encourage a regression model that generate better at testing time



### RNN Regressor

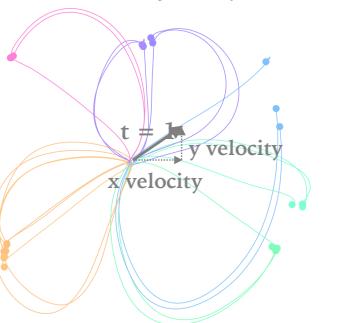
Many-to-many RNN regressor to predict the hand velocity at each corresponding time-point while accumulating trajectory information in the past with the hidden state



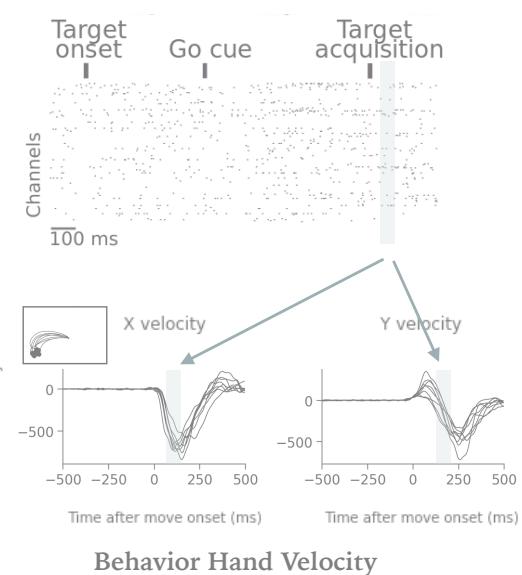
# Regression Problem: Decode Hand Velocity With Neural Firing Rate

## Regression Problem

### Reach Trajectory



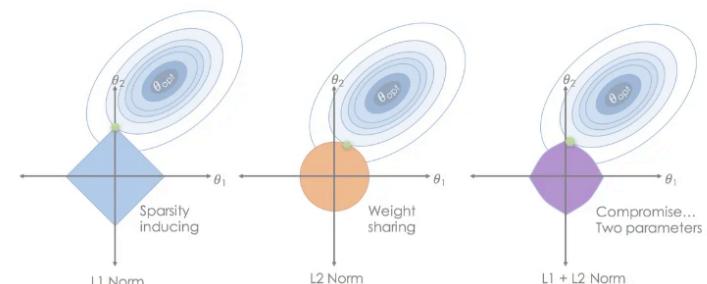
### Neural Spike Trains



## Regression Model

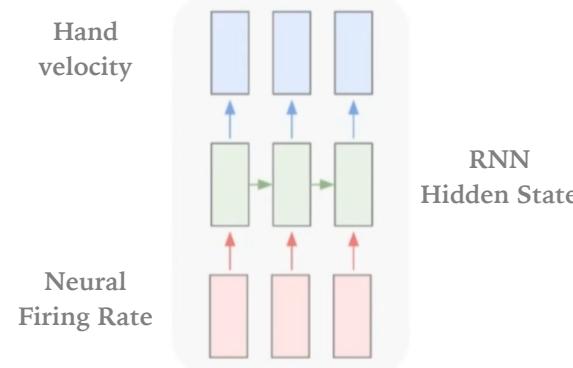
### Regularized Linear Regressor

Linear regression with L2 norm penalty for size of the weights to encourage a regression model that generate better at testing time



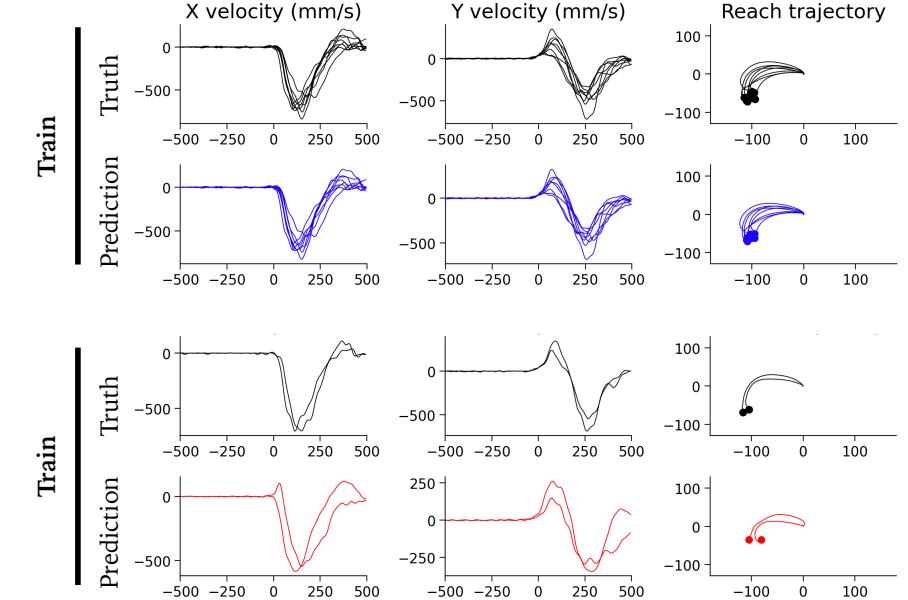
### RNN Regressor

Many-to-many RNN regressor to predict the hand velocity at each corresponding time-point while accumulating trajectory information in the past with the hidden state



## Model Evaluation

### Visualizing decoded hand trajectory (per condition, repeated trials)



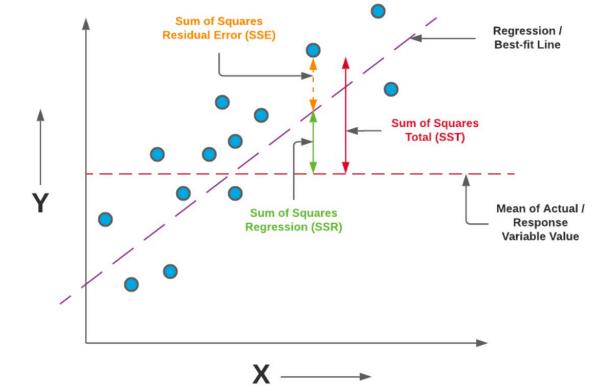
### Percentage of variance explained (R-squared)

$$R^2 = \frac{SSR}{SST} = \frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2}$$

$R^2$  = coefficient of determination

$SSR$  = sum of squares of residuals

$TSS$  = total sum of squares



# Regression Problem: Decode Hand Velocity With Neural Firing Rate

Neural Decoding.ipynb ★

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Machine Learning Regression

Ridge Regression

Model Fitting

Evaluation: Percentage of variance explained (R-squared)

Evaluation: Visualizing decoded hand trajectory (per condition, repeated trials)

Neural Network Regression

Recurrent Neural Network

RNN(GRU): many-to-many

Training RNNRegressor

Pre-trained RNNRegressor

Evaluate the Model performance

Discrete Decoder (Classification)

Machine Learning Classification

Dimensionality Reduction (Bin Neural Response)

Decoding target with binned neural response

Speed-accuracy trade-off

+ Code + Text

Continuous Decoder (Regression)

To predict the intended movement trajectories precisely, the continuous decoder translates, on a moment-by-moment basis, neural activity into a continuous-valued movement trajectory. In this case, the decoder solves a regression problem.

```
[24] import numpy as np
     import matplotlib.pyplot as plt
     from sklearn.linear_model import Ridge
     from sklearn.model_selection import GridSearchCV
     from sklearn.metrics import r2_score
     from sklearn.model_selection import train_test_split
```

Machine Learning Regression

Ridge Regression

Model Fitting

```
[25] ## Kinematic decoding
      nTrial, T, _ = np.shape(data_dict['spikes_rate'])

      # Train test split
      cond = data_dict['cond']
      reg_split = train_test_seq_split(data_dict, ['spikes_rate', 'hand_vel'], stratify=cond)

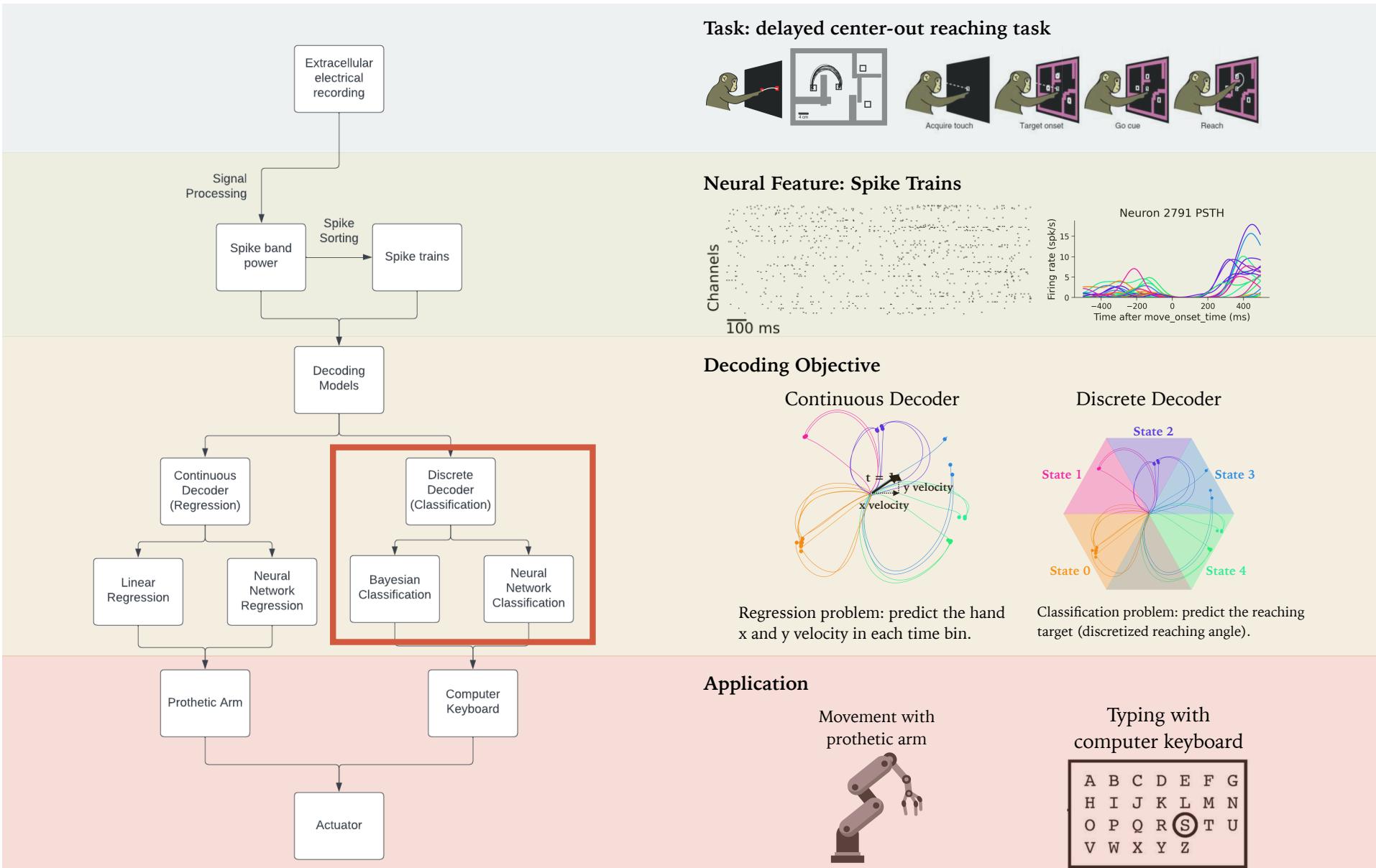
      # Fit and evaluate decoder
      gscv = GridSearchCV(Ridge(), {'alpha': np.logspace(-4, 0, 5)})

      gscv.fit(reg_split['train']['spikes_rate_flatten'], reg_split['train']['hand_vel_flatten'])

      === train Data ===
      Decoding R2: 0.9959651139415143
      === test Data ===
      Decoding R2: 0.04131468868461461
```

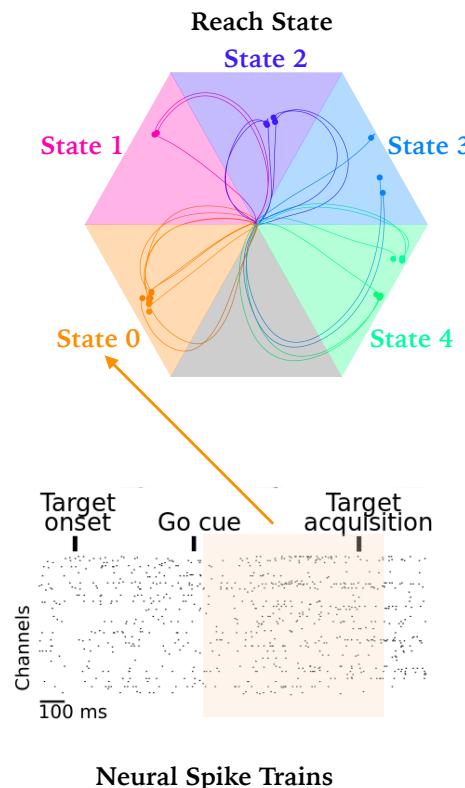
Evaluation: Percentage of variance explained (R-squared)

# Discrete Decoder: Decoding Reaching Target



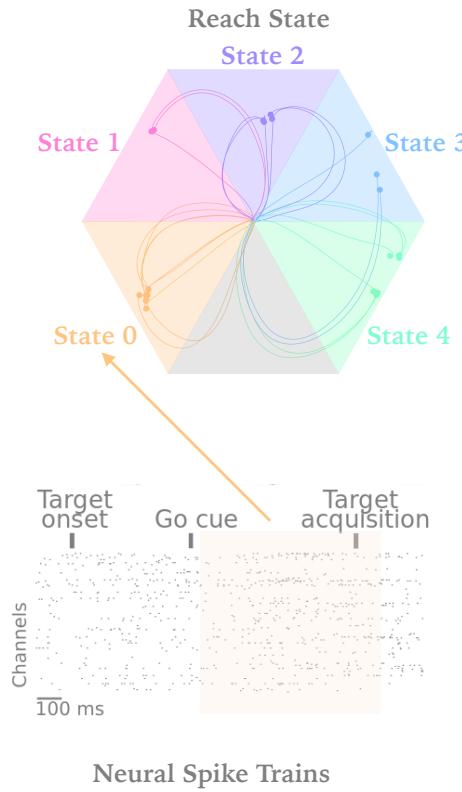
# Classification Problem: Decode Reaching Target With Neural Firing Rate

## Classification Problem



# Classification Problem: Decode Reaching Target With Neural Firing Rate

## Classification Problem

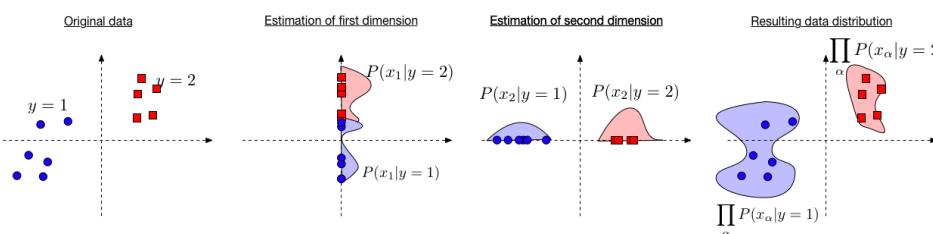


## Classification Model

### Naive Bayesian Classifier

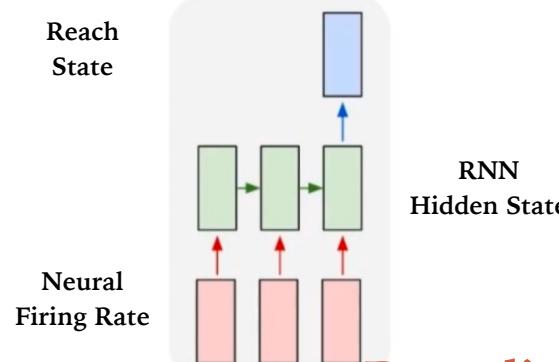
Estimate the class probability base on class prior  $p(y)$  and estimation of the class conditioned distribution  $p(x|y)$ , with naive assumption that each feature dimension is independent given the class label.

$$P(\mathbf{x}|y) = \prod_{\alpha=1}^d P(x_\alpha|y), \text{ where } x_\alpha = [\mathbf{x}]_\alpha \text{ is the value for feature } \alpha$$



### RNN Classifier

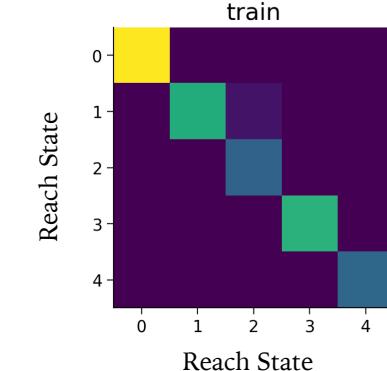
Many-to-one RNN Classifier to predict the reach target by integrating all observed neural firing rate from time 1 to t through the RNN hidden state.



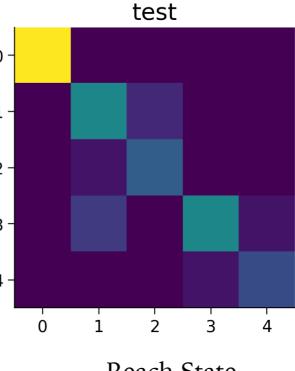
**Decoding Challenge**

## Model Evaluation

### Confusion Matrix

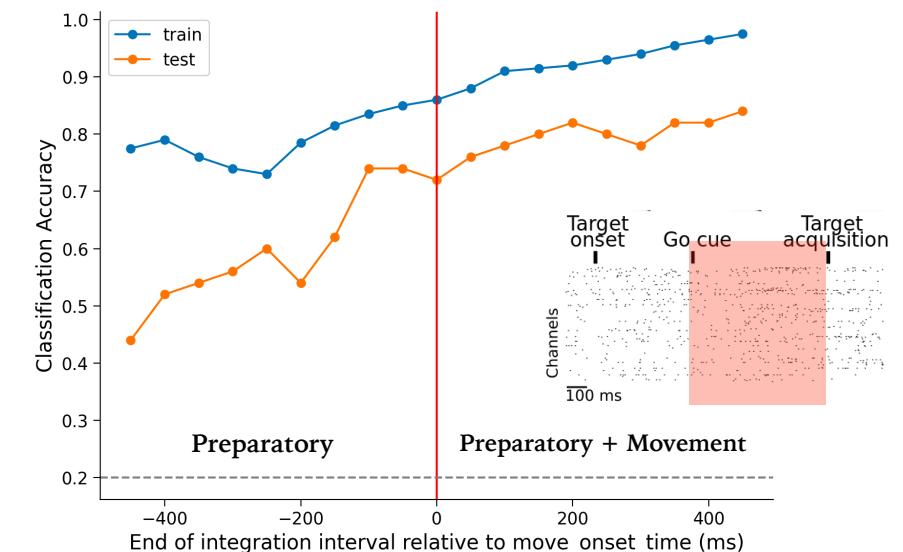


test



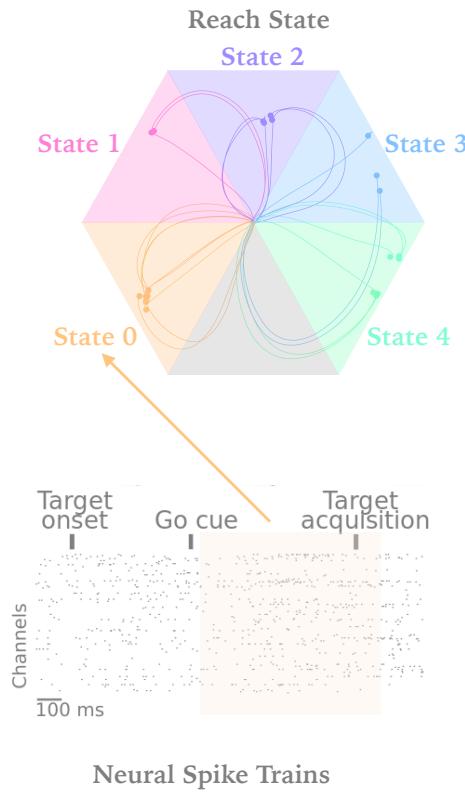
### Classification Accuracy

(As a function of integration window)



# Classification Problem: Decode Reaching Target With Neural Firing Rate

## Classification Problem

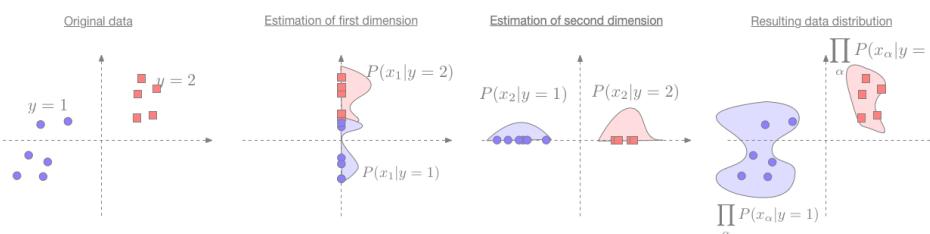


## Classification Model

### Naive Bayesian Classifier

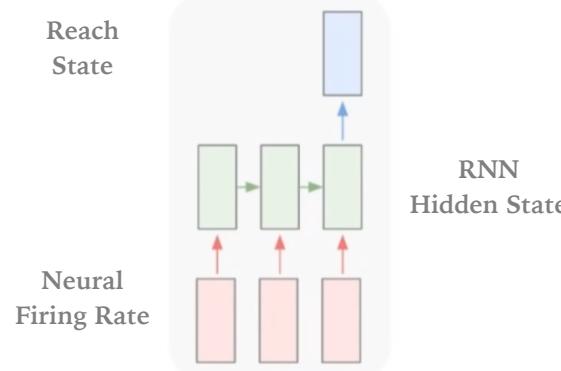
Estimate the class probability base on class prior  $p(y)$  and estimation of the class conditioned distribution  $p(x|y)$ , with naive assumption that each feature dimension is independent given the class label.

$$P(\mathbf{x}|y) = \prod_{\alpha=1}^d P(x_\alpha|y), \text{ where } x_\alpha = [\mathbf{x}]_\alpha \text{ is the value for feature } \alpha$$



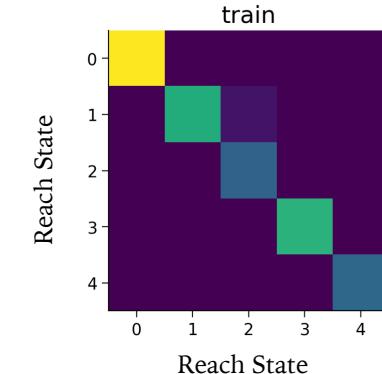
### RNN Classifier

Many-to-one RNN Classifier to predict the reach target by integrating all observed neural firing rate from time 1 to t through the RNN hidden state.

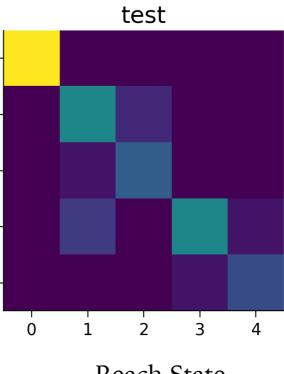


## Model Evaluation

### Confusion Matrix

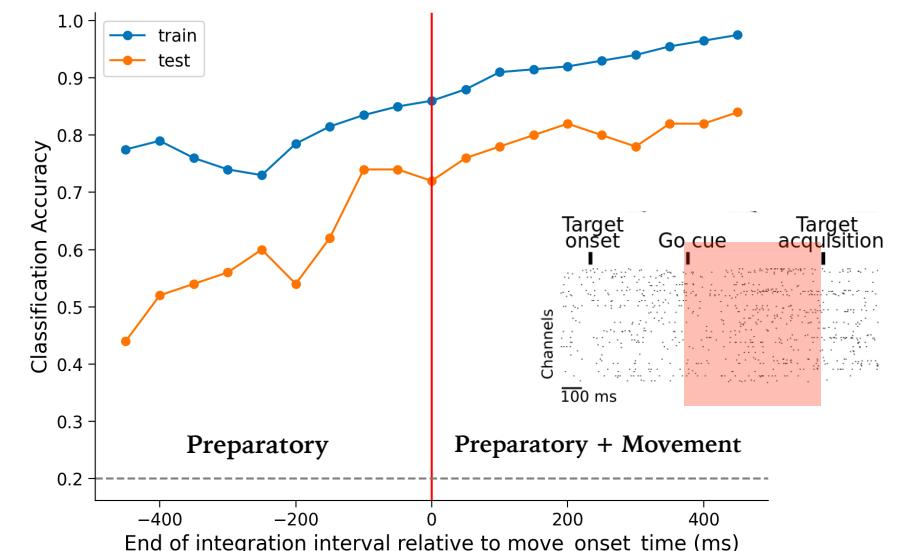


### test



### Classification Accuracy

(As a function of integration window)



# Classification Problem: Decode Reaching Target With Neural Firing Rate

Neural Decoding.ipynb ★

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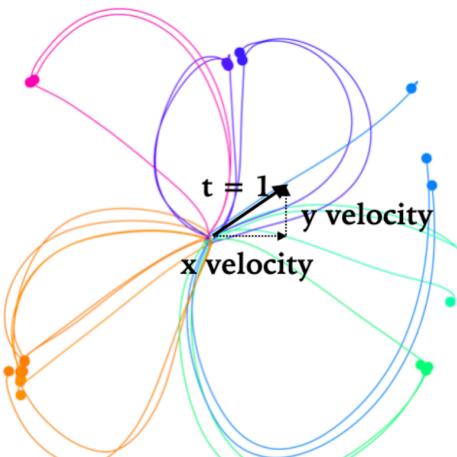
- RNN(GRU): many-to-many
- Training RNNRegressor
- Pre-trained RNNRegressor
- Evaluate the Model performance
- Discrete Decoder (Classification)**
- Machine Learning Classification
- Dimensionality Reduction (Bin Neural Response)
- Decoding target with binned neural response
- Speed-accuracy trade-off for decoding target
- Neural Network Classification
- Decoding Challenge - RNN: many-to-one
- Define RNN Model: RNNClassifier
- Define RNN training procedure
- RNNClassifier prediction helper function
- Prepare the Train and Test Dataset
- Define the parameter and start training
- Solution to the Decoding Challenge
- Evaluate the Model performance

+ Code + Text

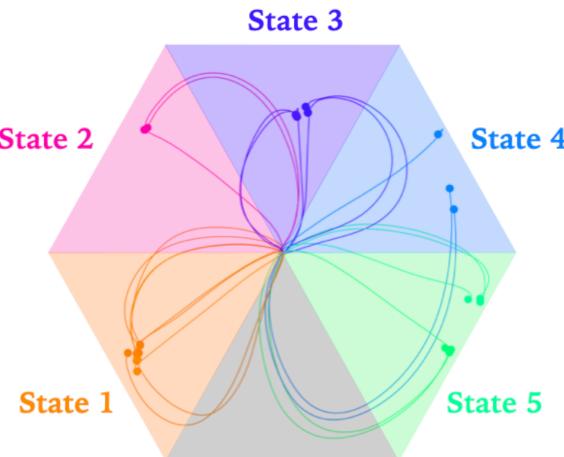
Discrete Decoder (Classification)

To predict the intended movement target, the discrete decoder integrate neural activity throughout time to predict the movement target. In this case, the decoder solves a classification problem.

## Continuous Decoder



## Discrete Decoder



[29] `from sklearn.naive_bayes import GaussianNB  
from sklearn.metrics import confusion_matrix  
from sklearn.metrics import accuracy_score`

# Self-Guided Coding Session

