# Dynamic Ensemble Modeling Approach to Nonstationary Neural Decoding in Brain-Computer Interfaces

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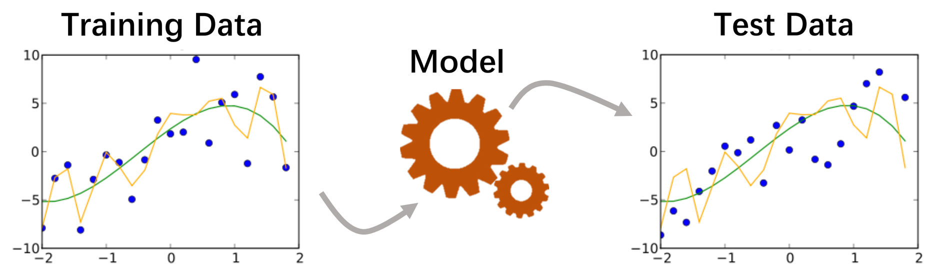
## Problem and objective

### Problem: Dynamic world and static models

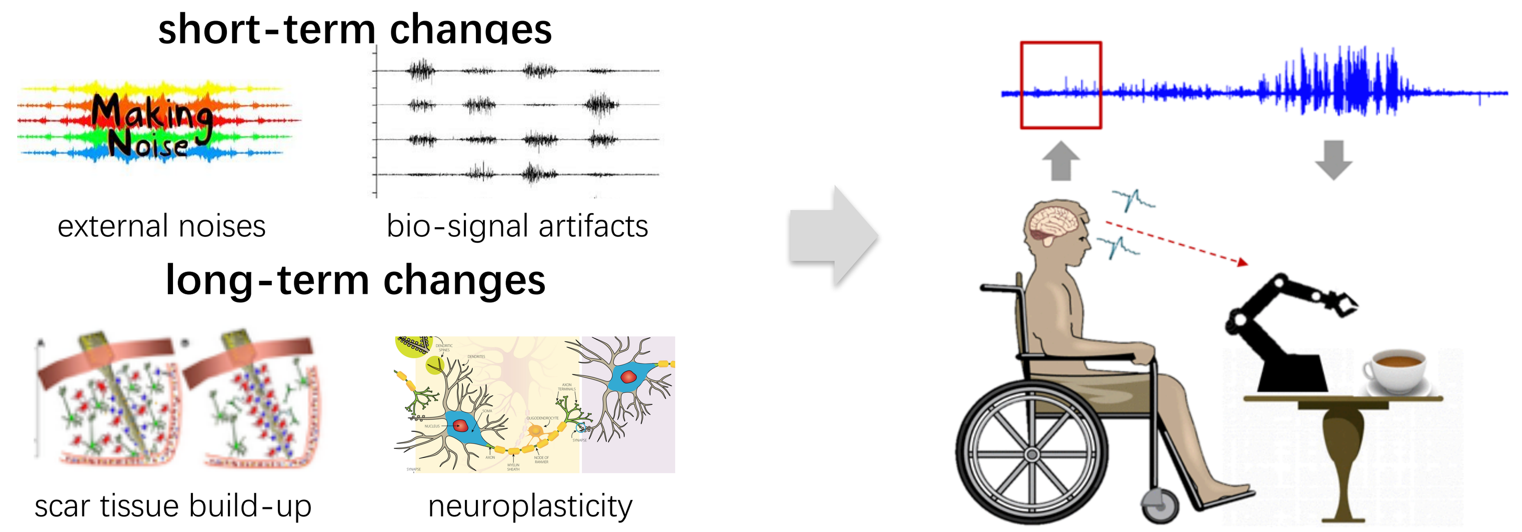



**Typical model training pipeline**

- use a static model
- assumes the data distribution is fixed and stable in time

It would fail if the assumption is not satisfied …

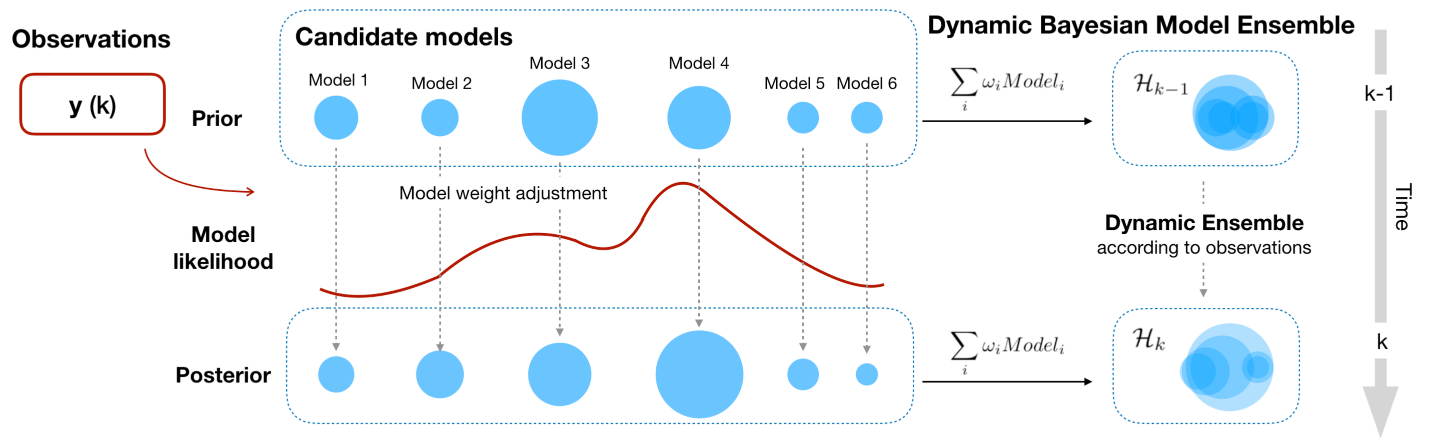
### Brain signals are typical nonstationary data




## Main insights

| Problems to solve | Proposed solution | |
|---|---|---|
| Formulation: State-space model with dynamic observation function | Classic state-space model $\mathbf{x}_k = f(\mathbf{x}_{k-1}) + \mathbf{v}_{k-1}$, $\mathbf{y}_k = h(\mathbf{x}_k) + \mathbf{n}_k$, | Dynamic observation function $\mathbf{x}_k = f(\mathbf{x}_{k-1}) + \mathbf{v}_{k-1}$, $\mathbf{y}_k = h_{\mathcal{H}_k}(\mathbf{x}_k) + \mathbf{n}_k$, |
| Model construction: A Dynamic Bayesian Model Ensemble Approach | Fixed model of $h(\mathbf{x}_k)$ | Dynamic ensemble of multiple model candidates |
| State estimation: A particle filter algorithm | Only estimate state x | Estimate both state x and observation model $h_{\mathcal{H}_k}$ |

## Method: Dynamic model ensemble (DyEnsemble)




$$\mathbf{x}_k = f(\mathbf{x}_{k-1}) + \mathbf{v}_{k-1}, \quad \mathbf{y}_k = h_{\mathcal{H}_k}(\mathbf{x}_k) + \mathbf{n}_k,$$

$$p(\mathbf{x}_k|\mathbf{y}_{0:k}) = \sum_{m=1}^{M} \underbrace{p(\mathbf{x}_k|\mathcal{H}_k = m, \mathbf{y}_{0:k})}_{\text{the posterior probability of x given } \mathcal{H}_k = m} \underbrace{p(\mathcal{H}_k = m|\mathbf{y}_{0:k})}_{\text{the posterior probability of the m-th hypothesis}}$$

**Step 1.** Particle based estimation of $p(\mathbf{x}_k|\mathcal{H}_k = m, \mathbf{y}_{0:k})$

$$\omega^i_{m,k} \propto \omega^i_{k-1} p_m(\mathbf{y}_k|\mathbf{x}^i_k), \ \textstyle\sum_{i=1}^{N_s} \omega^i_{m,k} = 1.$$

$$p(\mathbf{x}_k|\mathcal{H}_k = m, \mathbf{y}_{0:k}) \approx \sum_{i=1}^{N_s} \omega^i_{m,k} \delta(\mathbf{x}_k - \mathbf{x}^i_k),$$

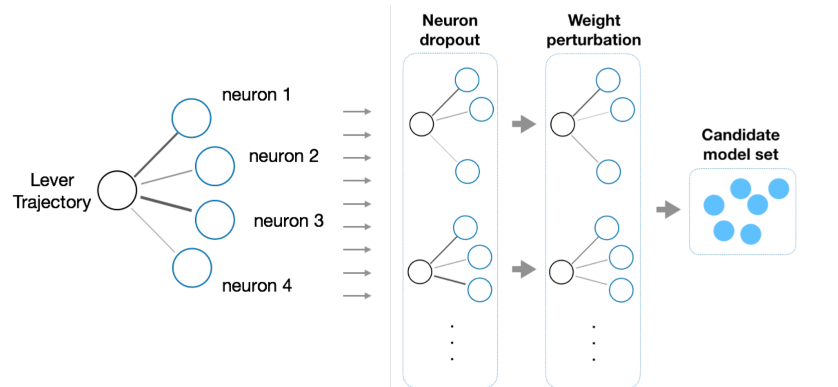
**Step 2.** Particle based estimation of $p(\mathcal{H}_k = m|\mathbf{y}_{0:k})$

$$p(\mathcal{H}_k = m|\mathbf{y}_{0:k-1}) = \frac{p(\mathcal{H}_{k-1} = m|\mathbf{y}_{0:k-1})^\alpha}{\sum_{j=1}^{M} p(\mathcal{H}_{k-1} = j|\mathbf{y}_{0:k-1})^\alpha}$$

$$p_m(\mathbf{y}_k|\mathbf{y}_{0:k-1}) \approx \sum_{i=1}^{N_s} \omega^i_{k-1} p_m(\mathbf{y}_k|\mathbf{x}^i_k)$$

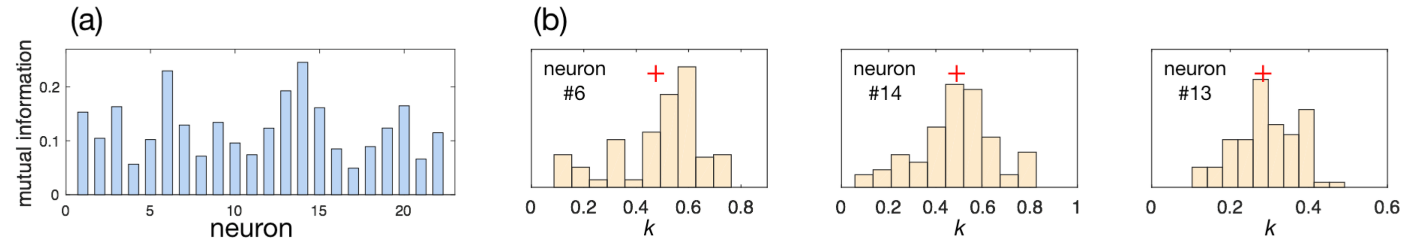
$$p(\mathcal{H}_k = m|\mathbf{y}_{0:k}) = \frac{p(\mathcal{H}_k = m|\mathbf{y}_{0:k-1}) p_m(\mathbf{y}_k|\mathbf{y}_{0:k-1})}{\sum_{j=1}^{M} p(\mathcal{H}_k = j|\mathbf{y}_{0:k-1}) p_j(\mathbf{y}_k|\mathbf{y}_{0:k-1})}$$

## Candidate model generation strategy




**Algorithm 1** Candidate Model Generation Strategy.

```
s: model size, M: model number, p: weight perturbation factor
D: training data, N: neuron set
Init M = {}
for i = 1, ..., M do
    N_subset = Neuron-dropout(N, s)
    h_i = Train-model(D, N_subset)
    for w in weights of h_i do
        w = Weight-perturbation(w, p)
    end for
    Add h_i to M
end for
```

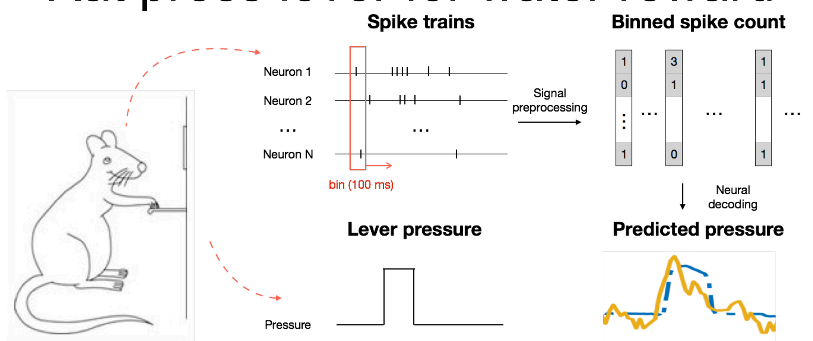



## Experiments

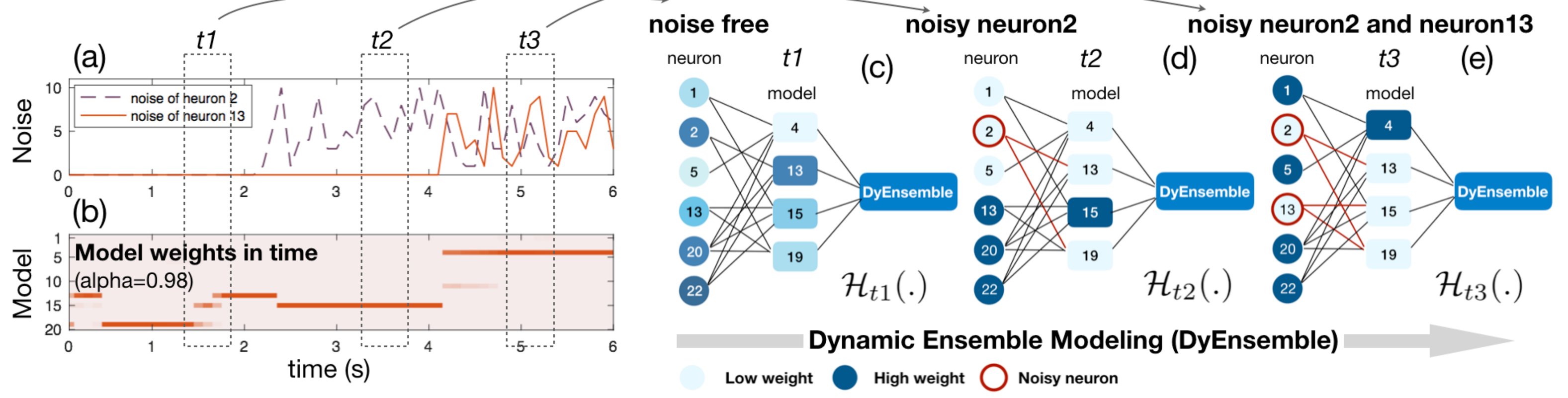
### Neural signal dataset

| | # neuron | train data | test data |
|---|---|---|---|
| Rat 1 | 22 | 200 s | 100 s |
| Rat 2 | 58 | 200 s | 100 s |

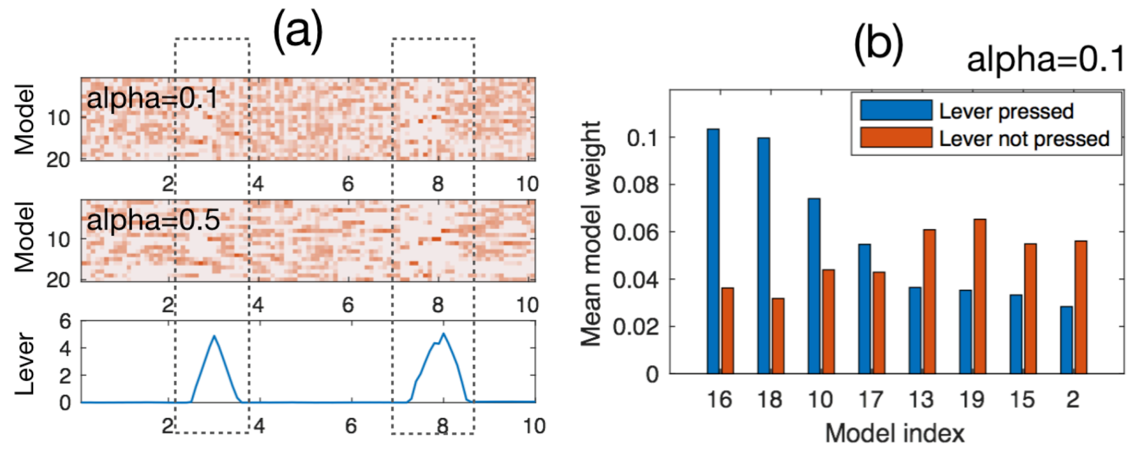
Rat press lever for water reward




### Model switching along with changing noises




### Model switching along with task behaviors




During lever pressing, only a certain set of candidate models are selected.

### Comparison with other approaches

Table 1: Correlation coefficient with different numbers of noisy neurons.

| Method | Rat 1 | | | Rat 2 | | |
|---|---|---|---|---|---|---|
| | Original | Noisy (#2) | Noisy (#4) | Original | Noisy (#2) | Noisy (#4) |
| Kalman filter | 0.777±0.000 | 0.696±0.012 | 0.560±0.009 | 0.798±0.000 | 0.580±0.039 | 0.381±0.093 |
| LSTM | 0.753±0.017 | 0.687±0.033 | **0.617±0.045** | **0.846±0.021** | 0.551±0.127 | 0.338±0.050 |
| Dual decoder | **0.779±0.000** | 0.694±0.010 | 0.575±0.013 | **0.803±0.000** | **0.585±0.025** | 0.387±0.030 |
| DyEnsemble (w/o P, w/o D) | 0.776±0.002 | 0.684±0.014 | 0.558±0.009 | 0.798±0.002 | 0.579±0.066 | 0.377±0.155 |
| DyEnsemble (P(0.1), w/o D) | 0.780±0.008 | 0.711±0.004 | 0.557±0.035 | 0.780±0.006 | 0.665±0.024 | 0.472±0.080 |
| DyEnsemble-2 (P(0.1), D(2)) | **0.799±0.012** | **0.735±0.006** | 0.583±0.090 | 0.788±0.009 | **0.633±0.064** | **0.516±0.092** |
| DyEnsemble-5 (P(0.1), D(5)) | 0.775±0.015 | **0.739±0.021** | **0.671±0.039** | **0.803±0.009** | 0.584±0.035 | **0.596±0.035** |

* w/o: without; P($k$): weight perturbation with p=$k$; D($l$): neuron dropout with $l$ neurons dropped.