Dynamic Ensemble Modeling Approach to Nonstationary Neural Decoding

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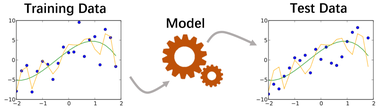
Problem and objective

Problem: Dynamic world and static models

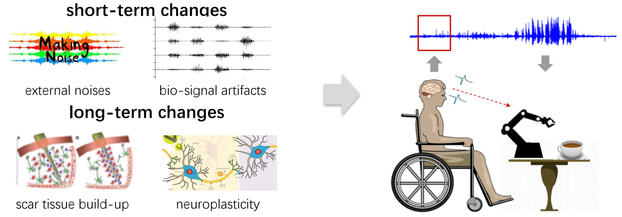


Typical model training pipeline

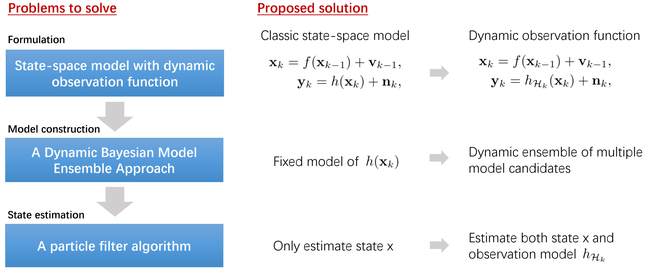
- use a static model
- assumes the data distribution is fixed and stable in time

It would fail if the assumption is not satisfied ...

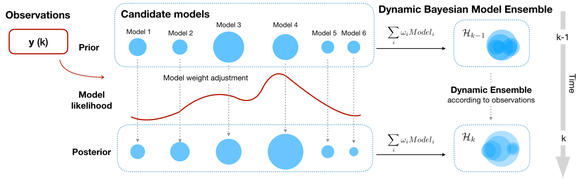
Brain signals are typical nonstationary data



Main insights



Method: Dynamic model ensemble (DyEnsemble)



$$\mathbf{x}_k = f(\mathbf{x}_{k-1}) + \mathbf{v}_{k-1}, \quad \mathbf{y}_k = h_{\mathcal{H}_k}(\mathbf{x}_k) + \mathbf{n}_k, \quad \Rightarrow \quad p(\mathbf{x}_k|\mathbf{y}_{0:k}) = \sum_{m=1}^{M} p(\mathbf{x}_k|\mathcal{H}_k = m, \mathbf{y}_{0:k}) p(\mathcal{H}_k = m|\mathbf{y}_{0:k})$$

the posterior probability of x given $\mathcal{H}_k = m$

the posterior probability of the m-th hypothesis

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

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

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

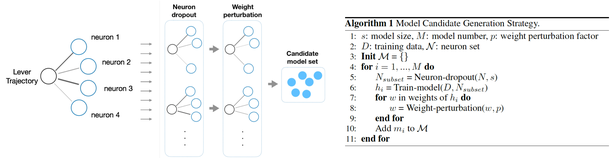
Step 2. Particle based estimation of $p(\mathcal{H}_k = m|\mathbf{y}_{0:k})$

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

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

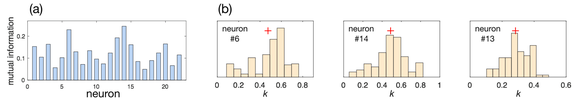
$$p(\mathcal{H}_k = m|\mathbf{y}_{0:k}) = \frac{p(\mathcal{H}_k = m|\mathbf{y}_{0:k-1}) p_m(\mathbf{y}_k|\mathbf{y}_{0:k-1})}{\sum_{j=1}^{M} p(\mathcal{H}_k = j|\mathbf{y}_{0:k-1}) p_j(\mathbf{y}_k|\mathbf{y}_{0:k-1})}$$

Candidate model generation strategy



Algorithm 1 Model Candidate Generation Strategy.

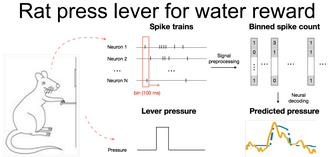
1: s: model size, M: model number, p: weight perturbation factor
2: D: training data, $\mathcal{N}$: neuron set
3: **Init** $\mathcal{M} = \{\}$
4: **for** $i = 1, ..., M$ **do**
5: N_{subset} = Neuron-dropout(N, s)
6: h_i = Train-model(D, N_{subset})
7: **for** w in weights of h_i **do**
8: w = Weight-perturbation(w, p)
9: **end for**
10: Add m_i to $\mathcal{M}$
11: **end for**



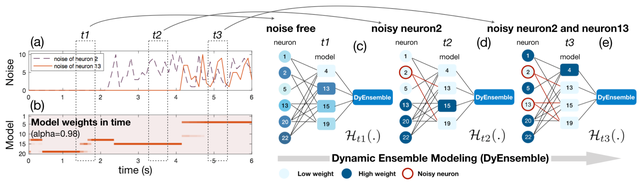
Experiments

Neural signal dataset

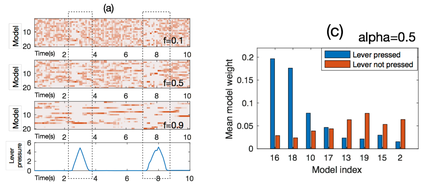
	# neuron	train data	test data
Rat 1	22	200 s	100 s
Rat 2	58	200 s	100 s



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.