Classificaion for fMRI curves with similar mean, different variation

2024-04-30

Functional GLM with sparse group lasso penalty

다음의 functional GLM에서

$$g(\mu) = \beta_0 + \sum_{j=1}^{p} \int X_i^j(t)\beta^j(t)dt \approx \beta_0 + \sum_{j=1}^{p} \sum_{k=1}^{K_j} \xi_{ik}^j \beta_k^j$$

아래의 sparse group lasso penalty를 주어 loss를 minimize.

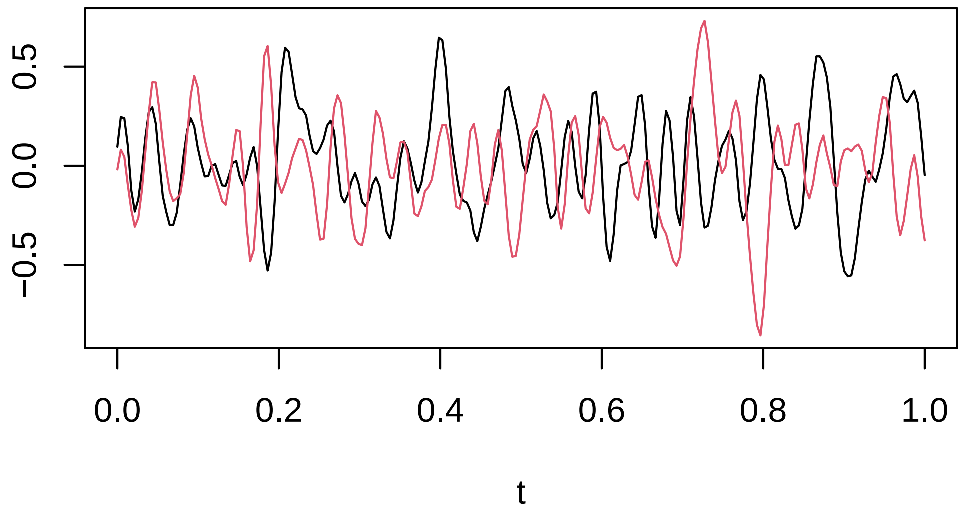
$$P(\lambda) = (1-\alpha)\lambda \sum_{j=1}^{p} \sqrt{K_j} \|\beta^j\|_2 + \alpha\lambda\|\beta\|_1$$

결과

		FGLM		FLasso	
# of basis		B-spline	FPCA	B-spline	FPCA
		Train:Test = 80:20			
FVE = 0.9 # of knots = 20	Accuracy	0.489	0.503	0.586	0.584
FVE = 0.8 # of knots = 50	Accuracy	0.524	0.509	0.585	0.581
K = 5 # of knots = 5	Accuracy	0.501	0.512	0.587	0.583
K = 3 # of knots = 3	Accuracy	0.509	0.501	0.588	0.582
$\alpha = 0.05$ FVE = 0.7 # of knots = 40	Accuracy	0.500	0.497	0.584	0.584
		Train:Test = 70:30			
$\alpha = 0.1$ FVE = 0.7 # of knots = 30	Accuracy	0.486	0.499	0.576	0.581
	Sensitivity	0.479	0.483	0.025	0.014
	Specificity	0.490	0.510	0.963	0.980
$\alpha = 0.2$ FVE = 0.7 # of knots = 30	Accuracy	0.486	0.499	0.576	0.580
	Sensitivity	0.479	0.483	0.025	0.016
	Specificity	0.490	0.510	0.962	0.977

문제점

- Group lasso를 준 `FLasso`의 경우, optimal λ가 큰 값을 가질 때 10-fold CV error가 가장 작은 값을 가지게 됨
  - 이 때문에 모든 $\beta = 0$으로 shrinkage 되어 prediction을 1개 class로만 분류해버림 (control의 비율이 높기 때문에 control로 모두 classify해버림)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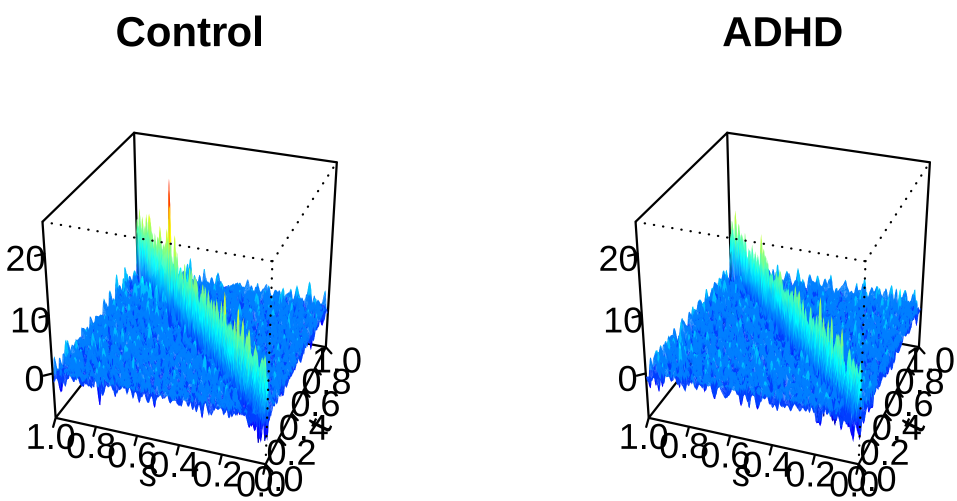
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