# Functional Data Analysis (Lecture 6) - Regularized functional PCA

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## One-page summary

- Last time:
  - functional PCA (=:fPCA),
  - $var_x \langle w, x \rangle \rightarrow \max_{w: \|w\|_2 = 1}$ .

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  - functional PCA (=:fPCA),
  - $var_x \langle w, x \rangle \rightarrow \max_{w: ||w||_2 = 1}$ .
- Today:
  - regularized fPCA.

# Regularized fPCA: objective

- Idea: modify the fPCA objective with a smoothness term.
- Old objective:

$$J_0(w) = var_X \langle w, x \rangle \rightarrow \max_{w: \|w\|_2 = 1}.$$

• New objective  $(\lambda > 0)$ :

$$J(w) = \frac{var_{x} \langle w, x \rangle}{\|w\|^{2} + \lambda PEN_{2}(w)} \to \max_{w},$$
$$PEN_{2}(w) = \|D^{2}w\|^{2}.$$

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$$= \mathbf{b}^T \underbrace{\left[ \int \phi(t) \phi^T(t) dt \right]}_{=:\mathbf{J}} \mathbf{c}_i,$$

$$var_{x} \langle \mathbf{w}, \mathbf{x} \rangle = \frac{1}{n} \sum_{i=1}^{n} \left( \mathbf{b}^{T} \mathbf{J} \mathbf{c}_{i} \right) \left( \mathbf{c}_{i}^{T} \mathbf{J} \mathbf{b} \right)$$

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Using

$$w(t) = \mathbf{b}^{\mathsf{T}} \phi(t) = \sum_{j} b_{j} \phi_{j}(t),$$

$$\|\mathbf{w}\|^2 = \int \mathbf{b}^T \phi(t) \phi(t)^T \mathbf{b} dt$$

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#### Regularized fPCA: collect the terms

Until now:

$$\operatorname{var} \langle w, x \rangle = \mathbf{b}^T \mathbf{J} \mathbf{V} \mathbf{J} \mathbf{b},$$
  
 $\|\mathbf{w}\|^2 = \mathbf{b}^T \mathbf{J} \mathbf{b},$   
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Thus

$$J(w) = \frac{var_{x} \langle w, x \rangle}{\|w\|^{2} + \lambda PEN_{2}(w)} = \frac{\mathbf{b}^{T} \mathbf{J} \mathbf{V} \mathbf{J} \mathbf{b}}{\mathbf{b}^{T} \mathbf{J} \mathbf{b} + \lambda \mathbf{b}^{T} \mathbf{K} \mathbf{b}}.$$

## Regularized fPCA: final eigenproblem

The objective function:

$$J(w) = \frac{\mathbf{b}^T \mathsf{J} \mathsf{V} \mathsf{J} \mathbf{b}}{\mathbf{b}^T \mathsf{J} \mathbf{b} + \lambda \mathbf{b}^T \mathsf{K} \mathbf{b}},$$

which is equivalent to the eigenproblem

$$\mathbf{JVJb} = \lambda(\mathbf{J} + \lambda\mathbf{K})\mathbf{b}.$$

$$\mathbf{J} = [\langle \phi_i, \phi_j \rangle] = [\delta_{ij}] = \mathbf{I},$$

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Here, with 
$$\phi_{2j-1}(t)=\sin{(2\pi jt)}$$
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In case of Fourier basis simplifications happen.

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For fixed smoothing parameter  $(\lambda)$ :

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$$\{x_i\}_{i=1}^n \setminus \{x_i\} \rightarrow \text{eigenfunctions: } \{w_j^i(\lambda)\}_{j=1}^d.$$

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• *d*-independent cross-validation  $(d \le n-1)$ :

$$CV(\lambda) = \sum_{d} CV_{d}(\lambda).$$



# Summary

- Functional PCA (pca\_fd).
- Old objective + smoothing term  $(\lambda)$ ,
- Eigenvalue problem.
- $\bullet$   $\lambda$  choice: cross-validation.

We covered Chapter 9 in [1], 'fPCA part' of Chapter 7 in [2].