

# Clustering Classical Music Performances

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## Why?

- Easy to describe musical characteristics you like: “up-tempo,” “strong beat,” “good lyrics,” “jazzy,” etc.
- Harder to describe characteristics of a **performance** that you like.
- In classical music, there are hundreds or thousands of recordings of the **same** piece.
- Why do we like some better than others?

## What’s different?

- 1 Mistakes
- 2 Extraneous noise
- 3 Recording quality
- 4 Articulation/Legato/Bowing/Breathing
- 5 Dynamics
- 6 Rubato/Tempo

The first three are mostly uninteresting, but the rest are about **interpretation**.

We like performances with “better” interpretations.

## Piano music

With piano, can focus on **dynamics** and **tempo**

We have quantitative data on **everything** from a specially equipped piano.

This piano records keystroke velocity, pedaling, timing, duration.

It lives in a studio at the IU Jacobs School of Music.

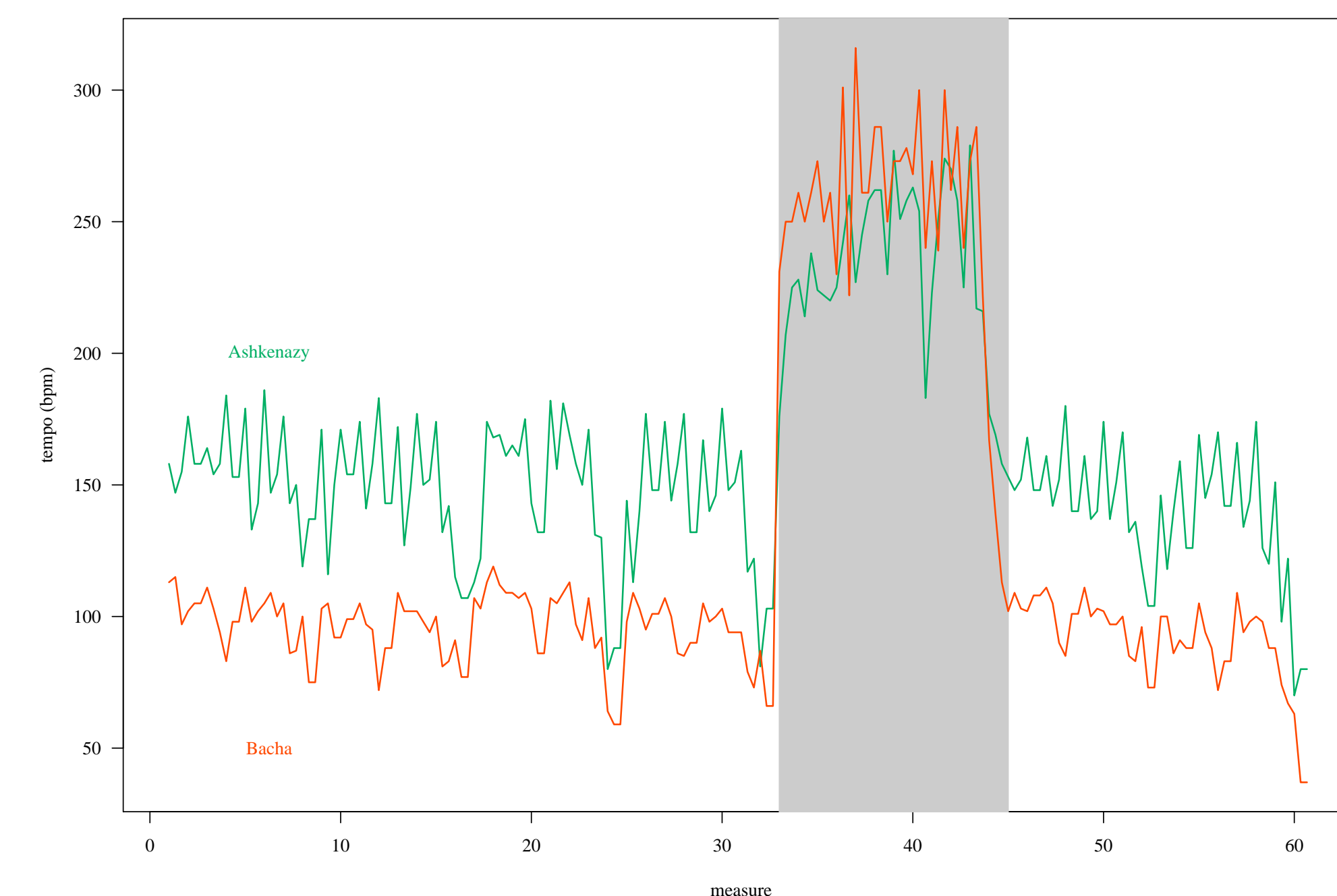


## Data

### Source and nature

- CHARM Mazurka Project
- Focus on timing only (dynamics also available)
- 50 recordings: Chopin Mazurka Op. 68 No. 3
- Recorded between 1931 and 2006
- 45 different performers

### Functional data



Time points are highly correlated due to musical structure

Treat as **functions**  $y_i(t)$  rather than vectors

### Structure

measure 1 9 17 25 | 33 37 41 | 45 53 |  
section a a' b a' pedal c c' a a'

**Allegro ma non troppo.** (♩ = 132.)

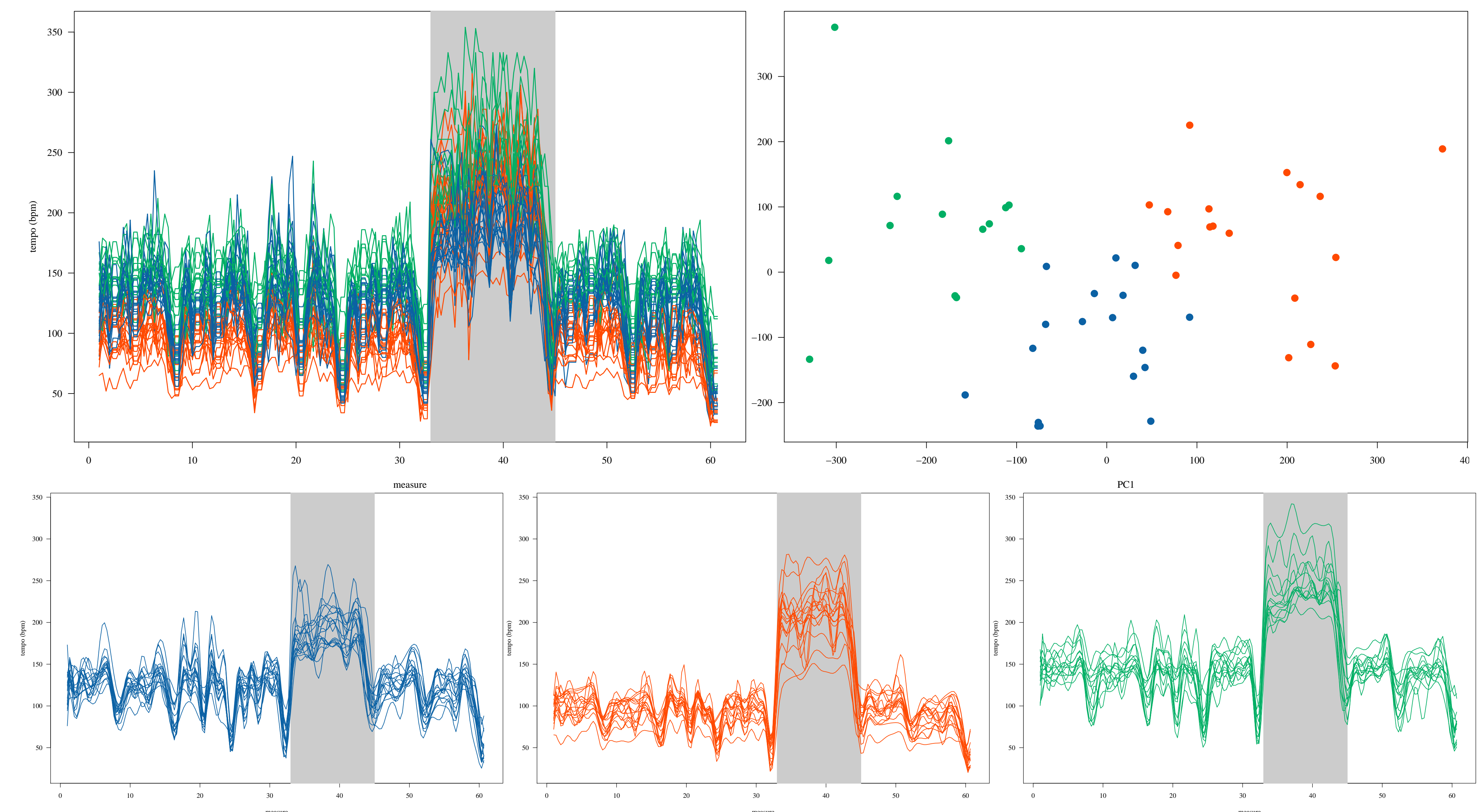
### Preprocessing

- Regress functions on orthogonal basis
- Use estimated coefficients as feature vector
- “Decorolates” the temporal dependence

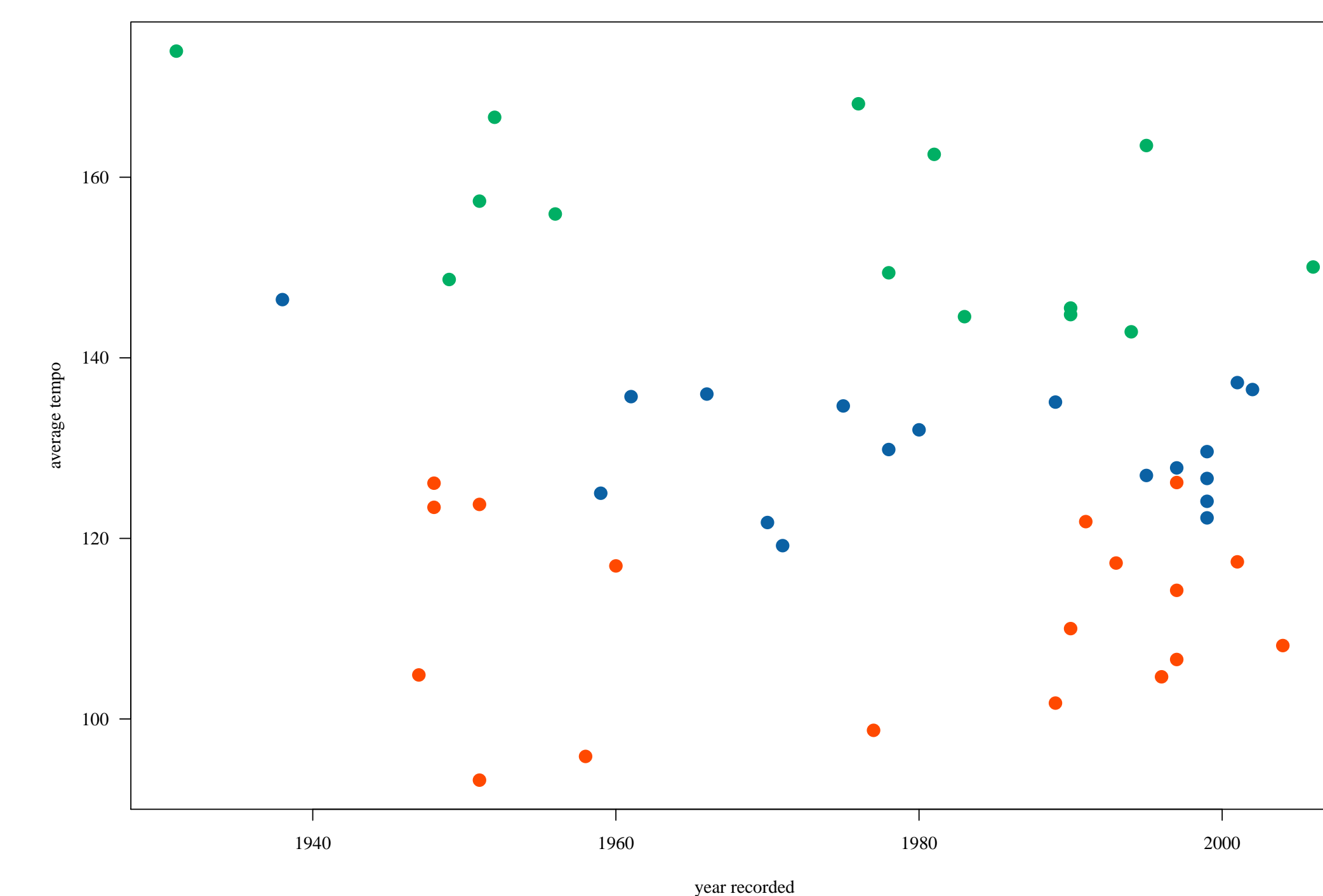
## Methodological details

- Use Cubic B-splines evaluated at knots  $t_1, \dots, t_{\nu+4}$ ; take  $x_i(t) = \sum_{j=1}^{\nu+4} \hat{\beta}_{ij} B_j(t)$ .
- Knot placement follows from musical structure
- Choose # of knots via GCV  $\nu^* = \operatorname{argmin}_n \frac{1}{n} \sum_{k=1}^n \left( \frac{y_i(t_k) - x_i(t_k)}{1 - \nu/n} \right)^2$ ; here  $\nu^* = 60$ : 1 knot/measure
- PCA on **coefficient** matrix  $\Phi := (\hat{\beta}_{ij}) = UDV^\top$  (functional PCA)
- Keep the leading eigenvectors and eigenvalues; used first 10  $U_{[1:10]}$
- $K$ -means clustering on the projection  $U_{[1:10]} D_{[1:10]}$ , take  $K = 3$

## Recovered clusters



## Chronological relationship?



## Future work

- Using dynamic information
- Model based rather than nonparametric functional preprocessing
- Functional data on a manifold
  - Use Diffusion Map rather than PCA
  - Theoretical implications
- Musical structure recovery (Ren et. al. (JASA 2010))
  - Looking at tempo tracks for multiple recordings displays obvious structure
- Testing in real people