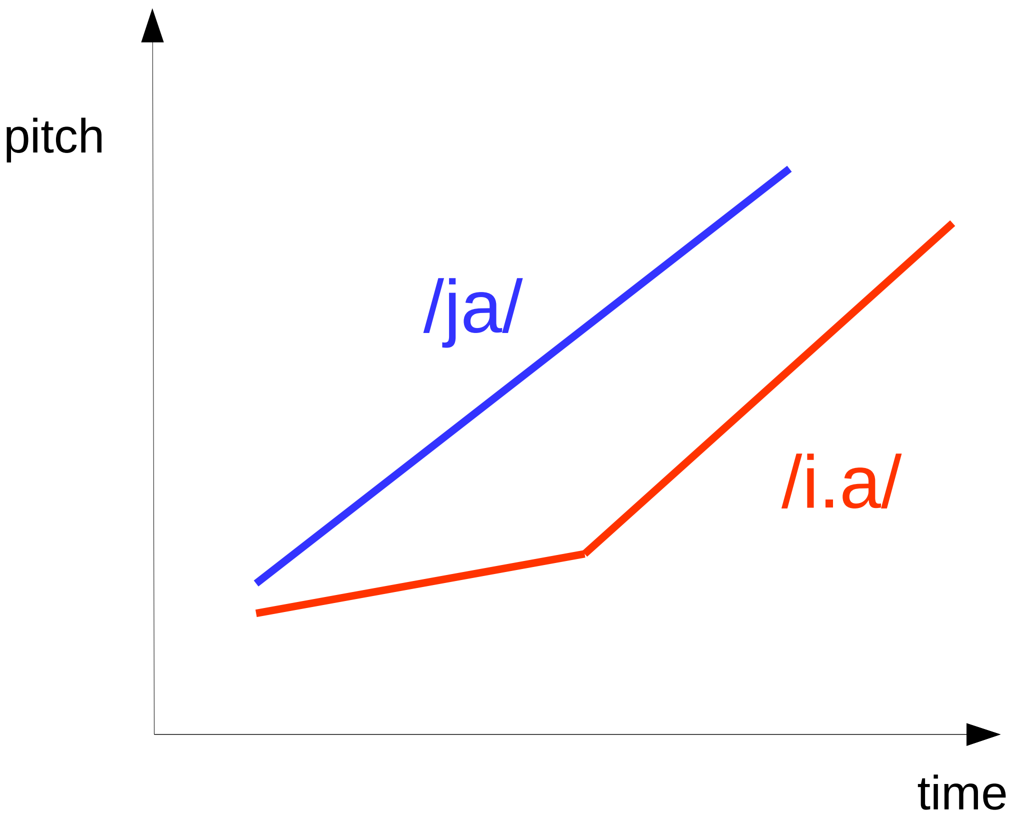
Modelling time-varying features of speech: tools and methods

Michele Gubian

Institute of Phonetics and Speech Processing
LMU Munich, Germany

Graz, October 2020

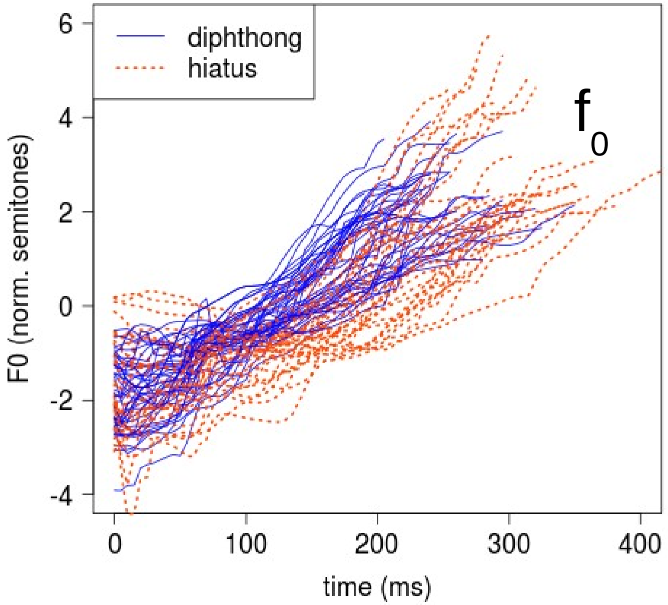
Alignment of rising pitch accents in Spanish



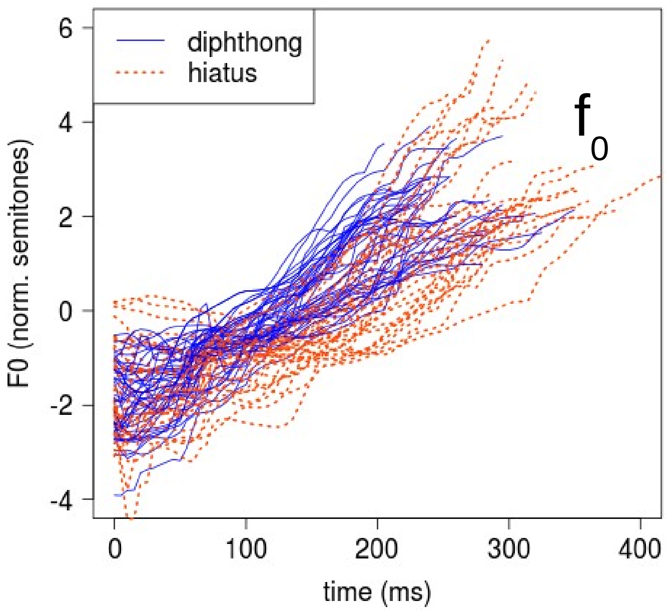
- European Spanish
- **Diphthong**: /ja/

  e.g. *Emil<u>ia</u>na*
- **Hiatus** /i.a/

  e.g. *p<u>ia</u>no*
- Rising pitch accent should align to syllabic structure



- Read speech
- 9 participants
- 20 Diphthongs +
  20 Hiatuses each

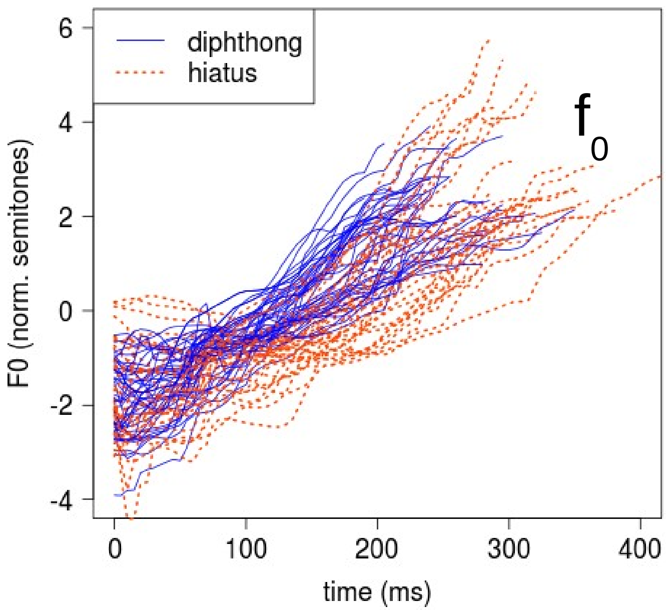


LMER

- Read speech
- 9 participants
- 20 Diphthongs +
  20 Hiatuses each

CURVES

NUMBERS



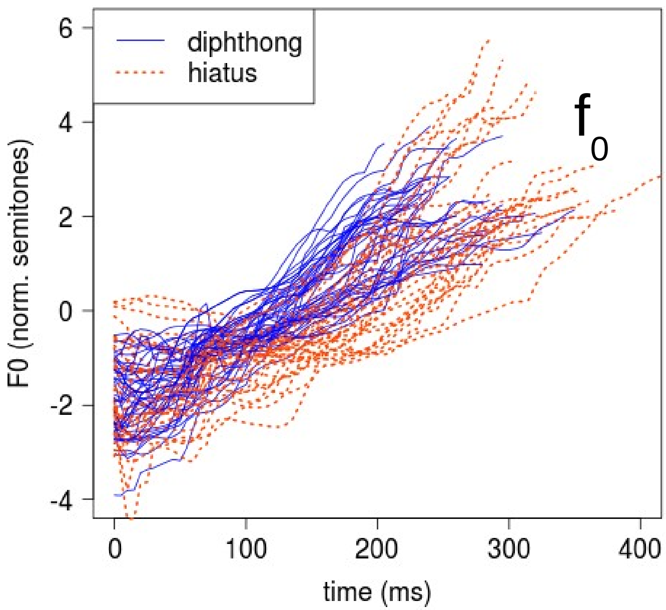
MIND THE GAP

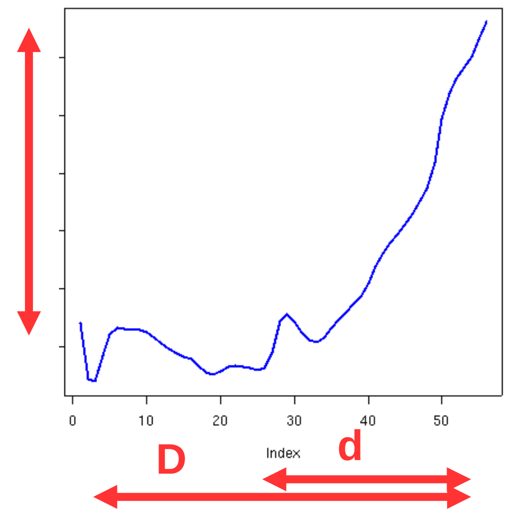
LMER

- Read speech
- 9 participants
- 20 Diphthongs + 20 Hiatuses each

CURVES

NUMBERS





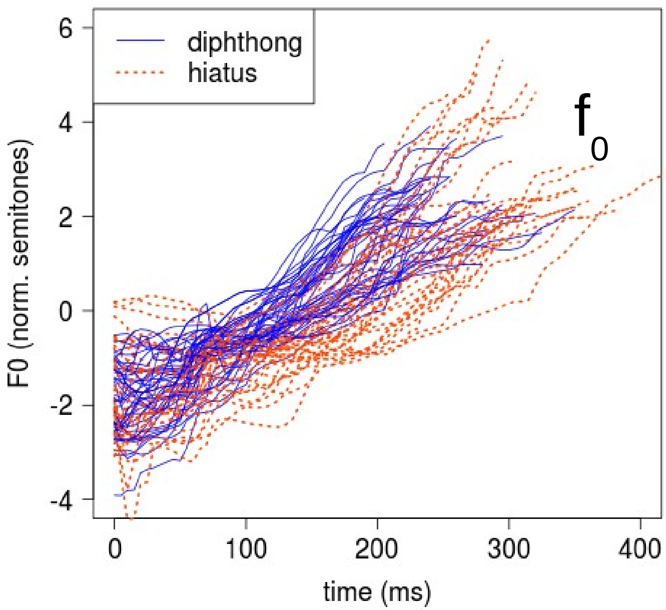
LMER

- Read speech
- 9 participants
- 20 Diphthongs + 20 Hiatuses each

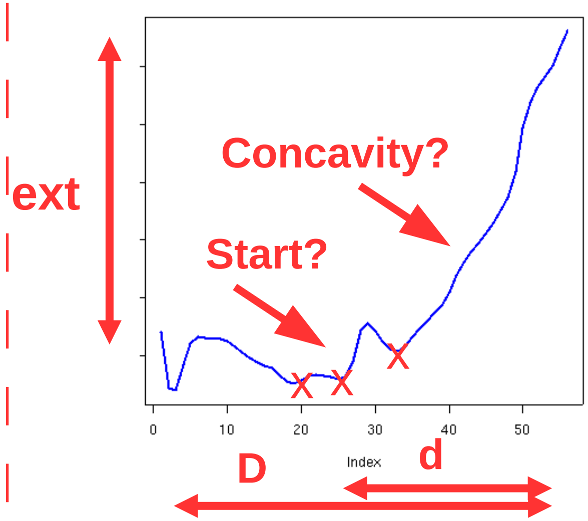
ext (st)	d/D	Cat.
5.3	0.9	D
4.6	0.7	H
...	...	...

CURVES

NUMBERS



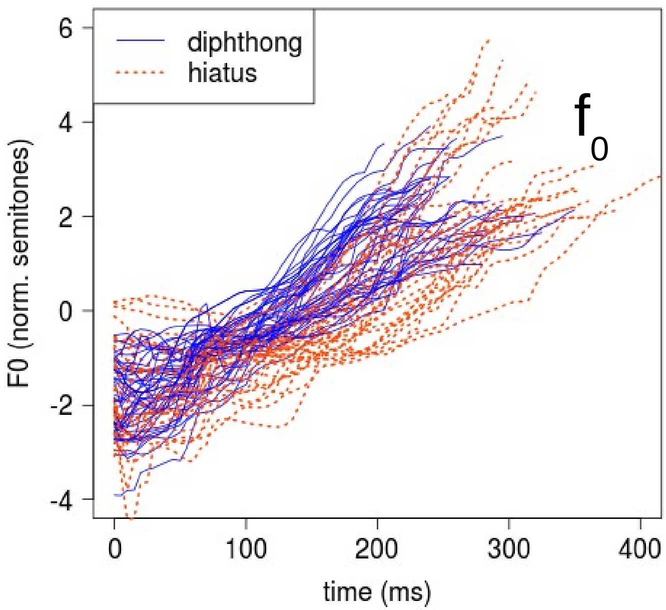
- Read speech
- 9 participants
- 20 Diphthongs + 20 Hiatuses each



ext (st)	d/D	Cat.
5.3	0.9	D
4.6	0.7	H
...	...	...

CURVES

NUMBERS



DCT

LMER

k0	k1	k2	...
...	...	...	...
...	...	...	...
...	...	...	...

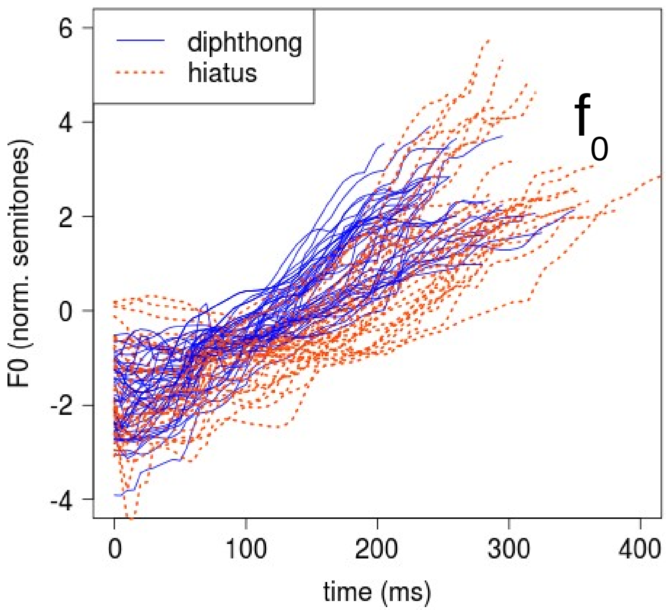
- Read speech
- 9 participants
- 20 Diphthongs +
  20 Hiatuses each

DCT limitations

- DCT does not (easily) encode time-localised information, e.g. a small hump
- Typically only k0, k1 and k2 are used, which have a geometric interpretation (mean, slope, curvature)
- Extracting several k's brings up the need of PCA
- In general, not effective to encode long signals

CURVES

NUMBERS



GAMM

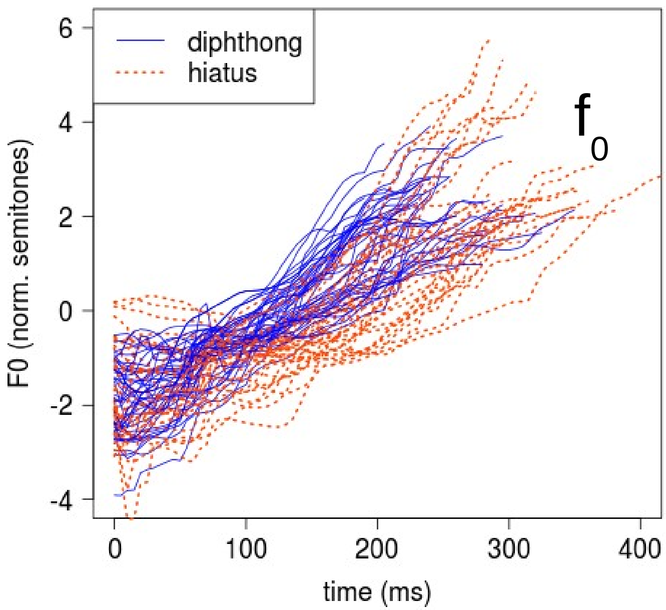
- Read speech
- 9 participants
- 20 Diphthongs +
  20 Hiatuses each

GAMMs

- **PRO**
  - LMER directly on curves
  - Good R packages (e.g. mgcv)
  - Good tutorials (e.g. Wieling, Soskuthy)
- **CON**
  - No easy way to analyse multidimensional signals
  - Computationally heavy
  - LMER directly on curves :D

CURVES

NUMBERS



- Read speech
- 9 participants
- 20 Diphthongs + 20 Hiatuses each

FPCA

s1	s2	s3	...
...	...	...	...
...	...	...	...
...	...	...	...

LMER

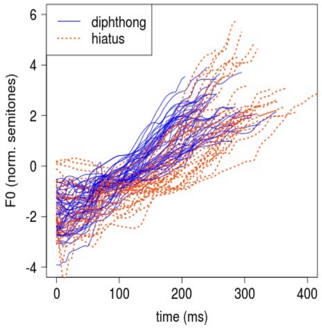
FPCA

- **PRO**
  - Computationally light
  - Interpretable
  - Easy to analyse multidimensional signals
  - Allows you to use LMER
- **CON**
  - Suboptimal with respect to GAMMs
  - Can fail with many categories
  - Can fail when noise is linearly related to variation of interest

Road map

CURVES

NUMBERS



Interpolate using a function basis

Dimensionality reduction tool

LMER

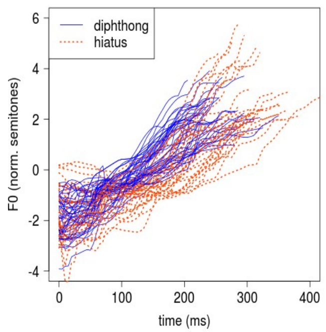
- Data driven

- Few parameters
- Interpretable

Road map

CURVES

NUMBERS



Interpolate using a function basis

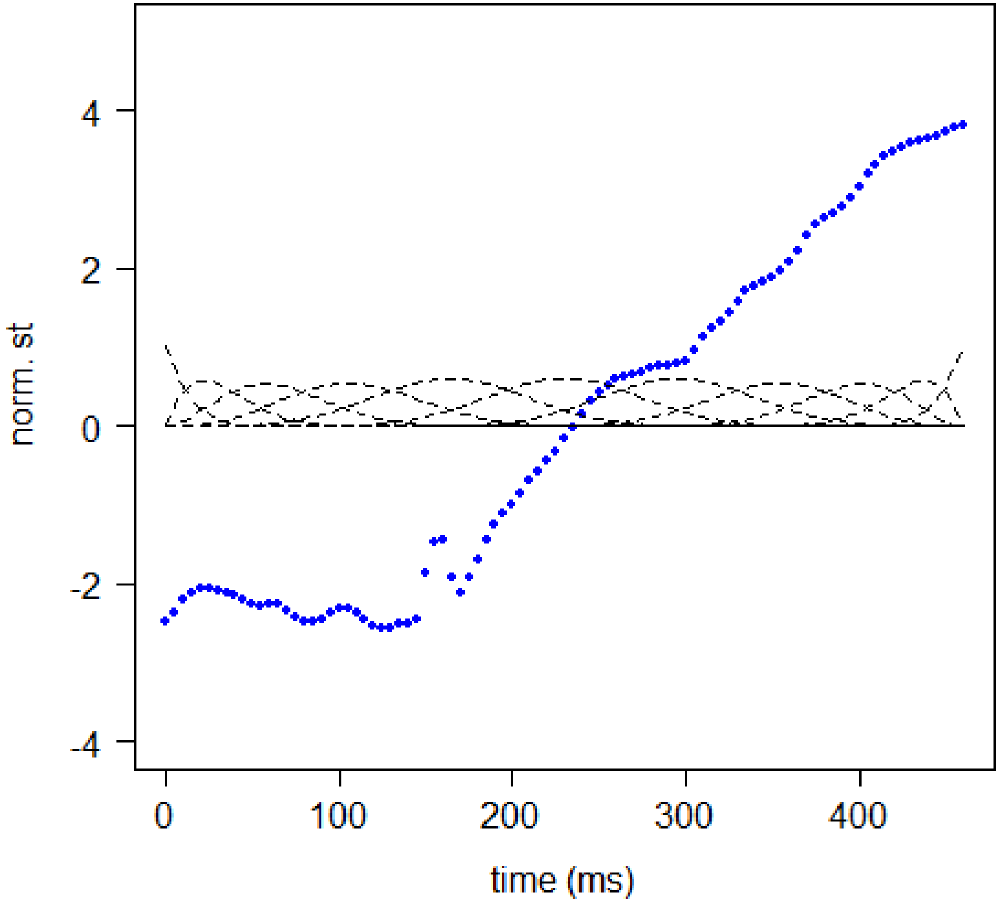
Dimensionality reduction tool

LMER

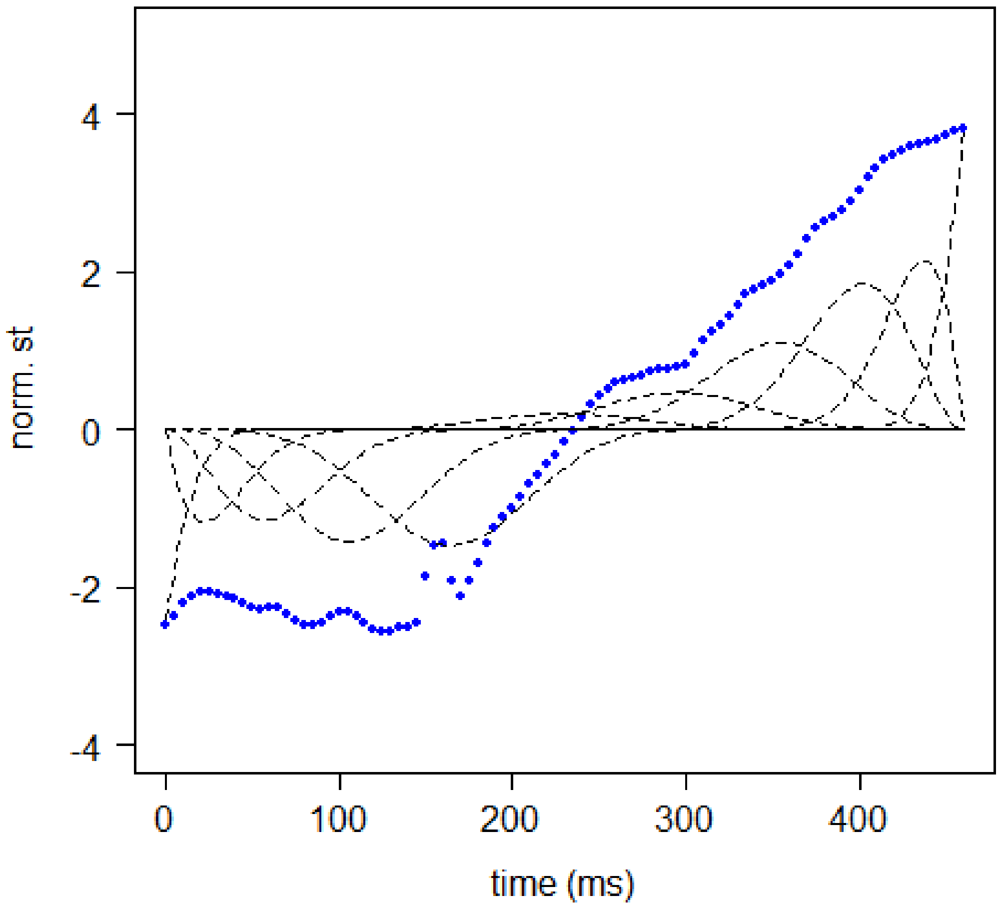
- Data driven

- Few parameters
- Interpretable

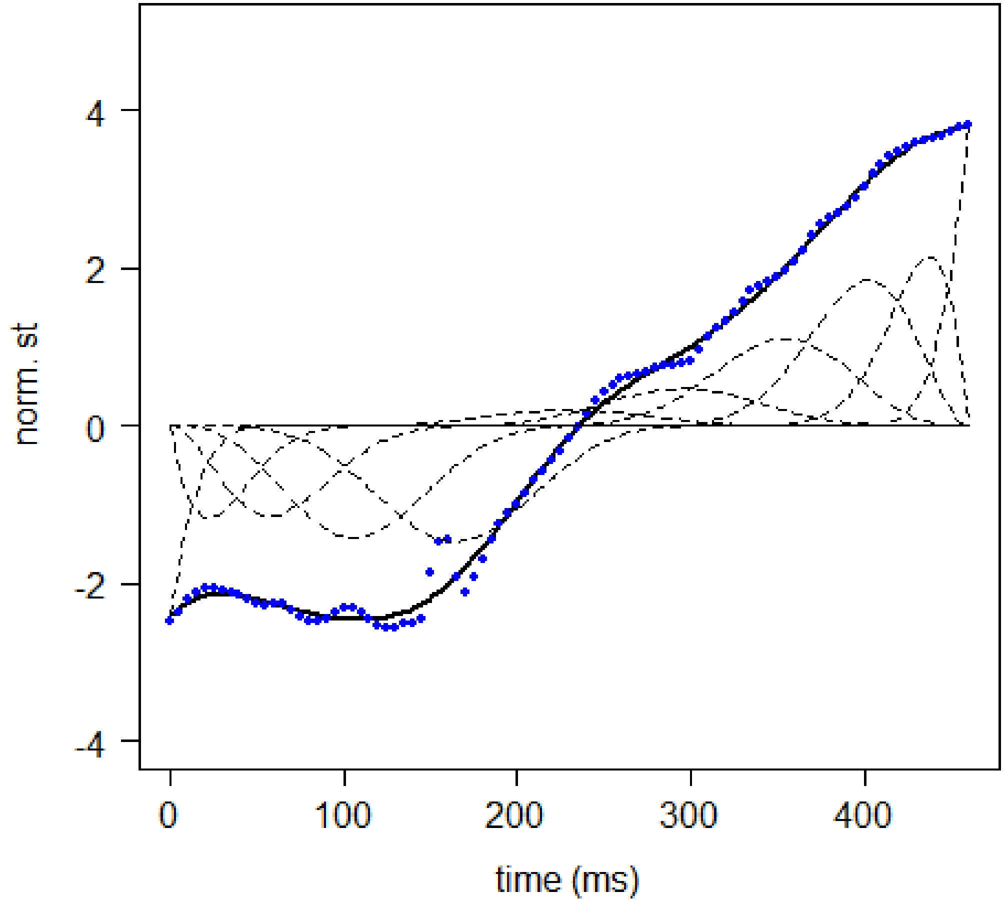
Interpolation with B-splines



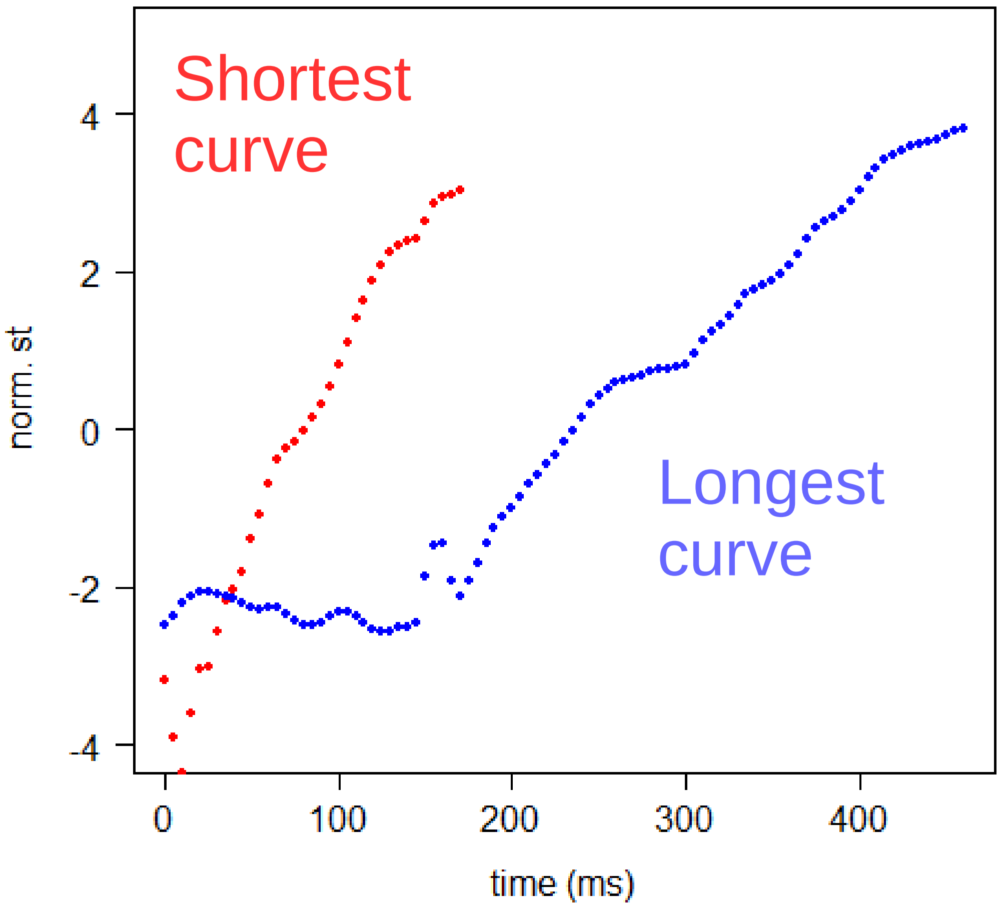
Interpolation with B-splines



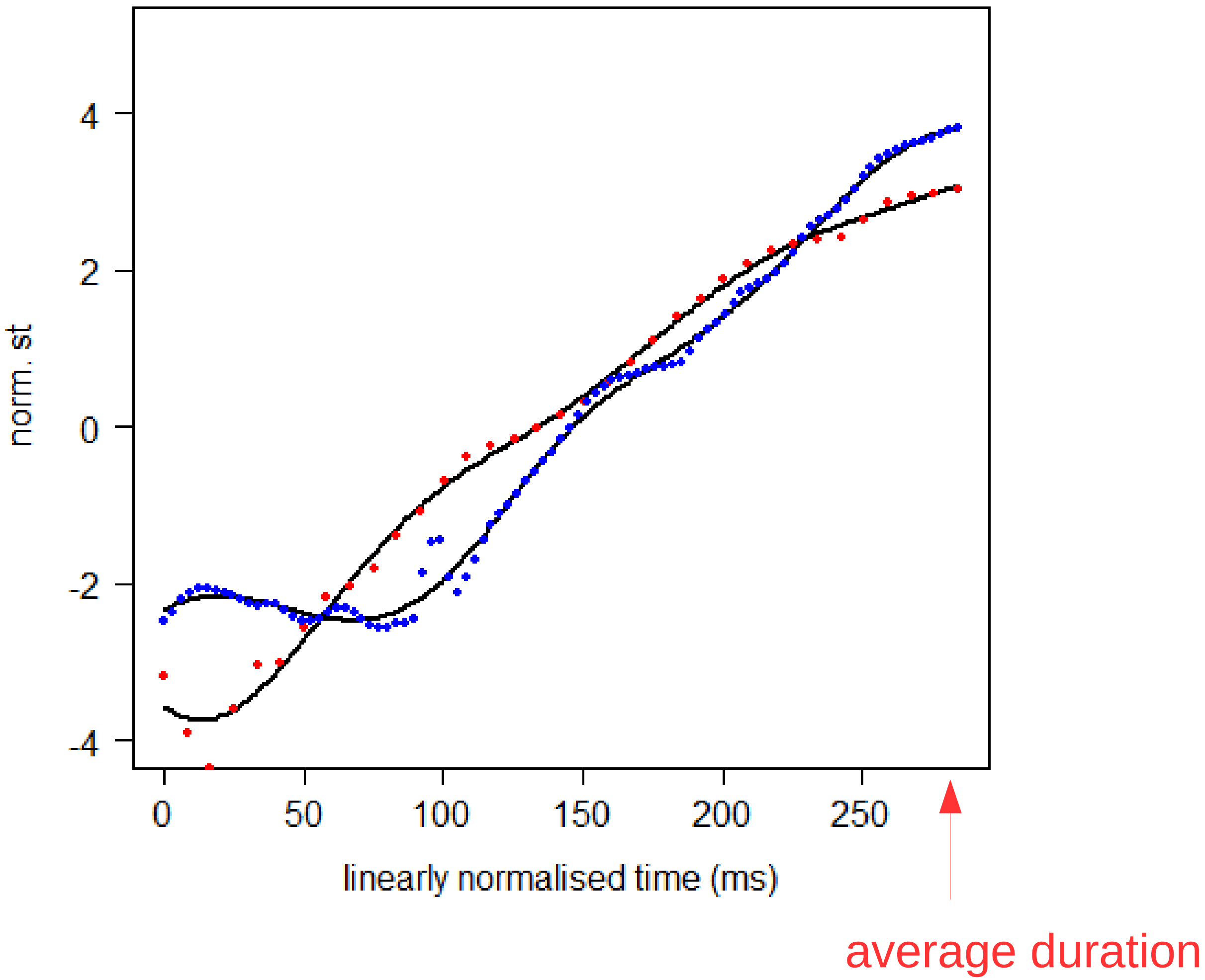
Interpolation with B-splines



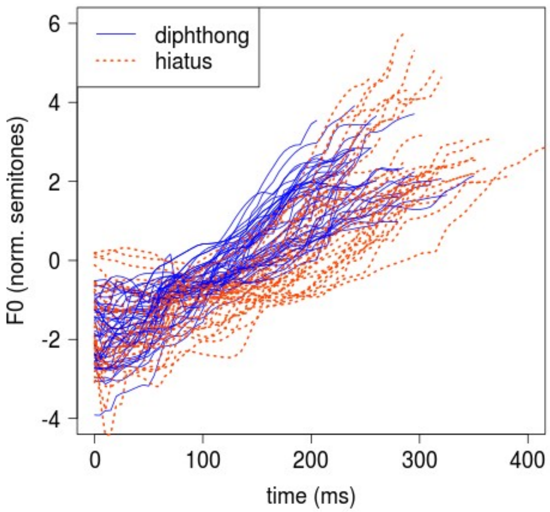
Different durations



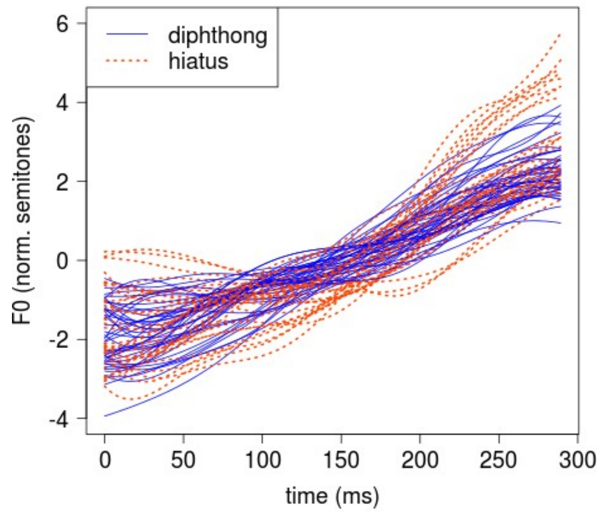
Linear time normalisation



Linear time normalisation



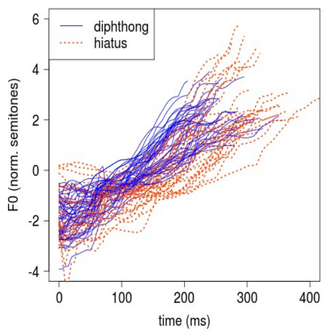
Interpolate to
<u>the same</u>
time interval



- We must use <u>the same</u> time interval
- This implies linear time normalisation
- Durations have to be reintroduced at the end of the analysis

Road map

CURVES



Interpolate to
<u>the same</u>
time interval

Dimensionality
reduction tool

LMER

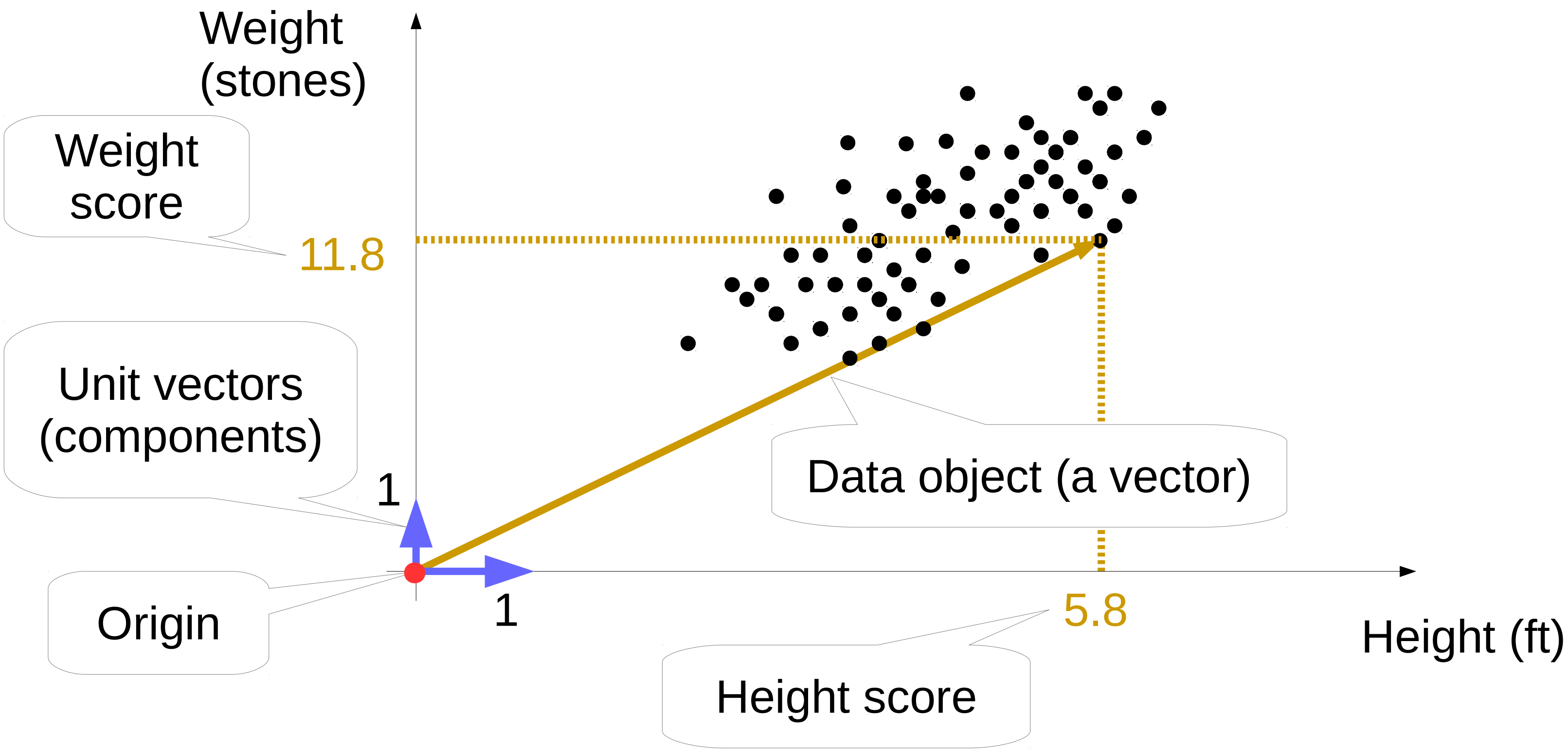
NUMBERS

- Data driven

- Few parameters
- Interpretable

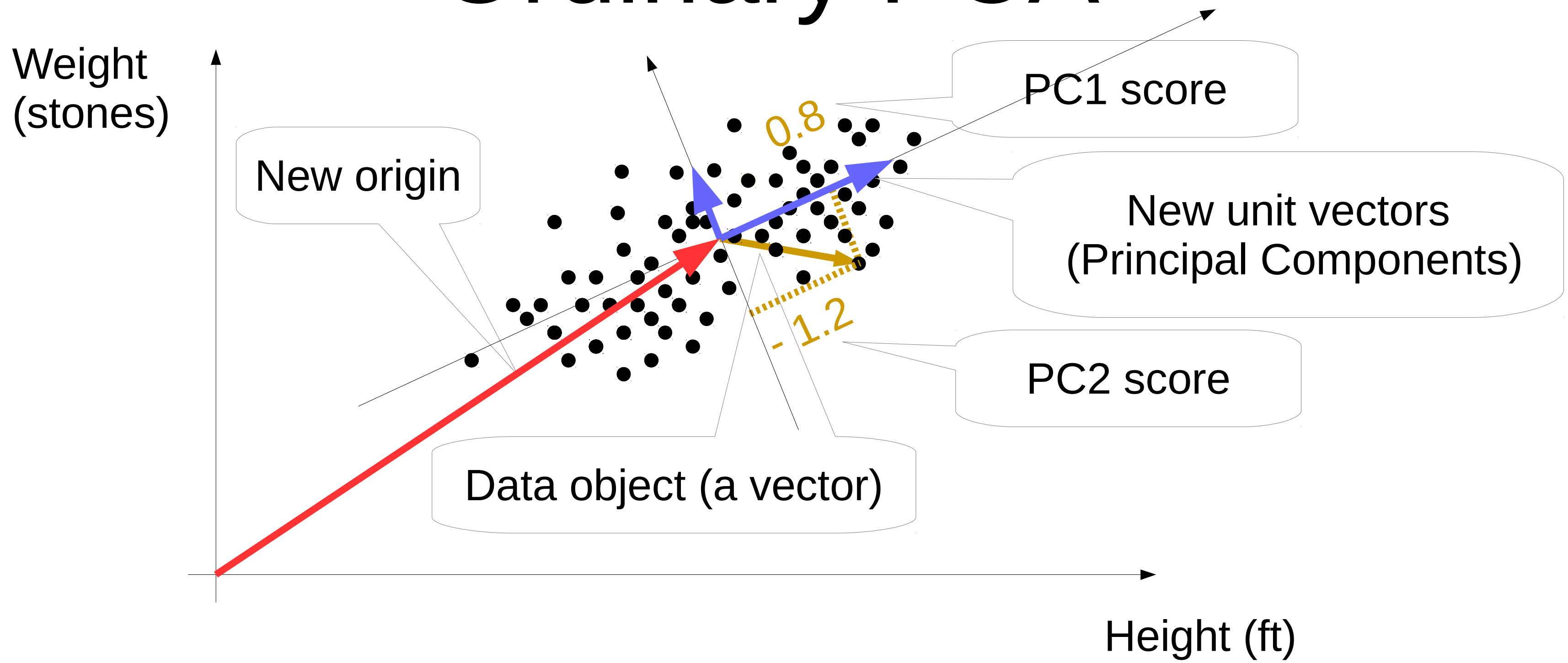
Introducing
Functional PCA

Vectors



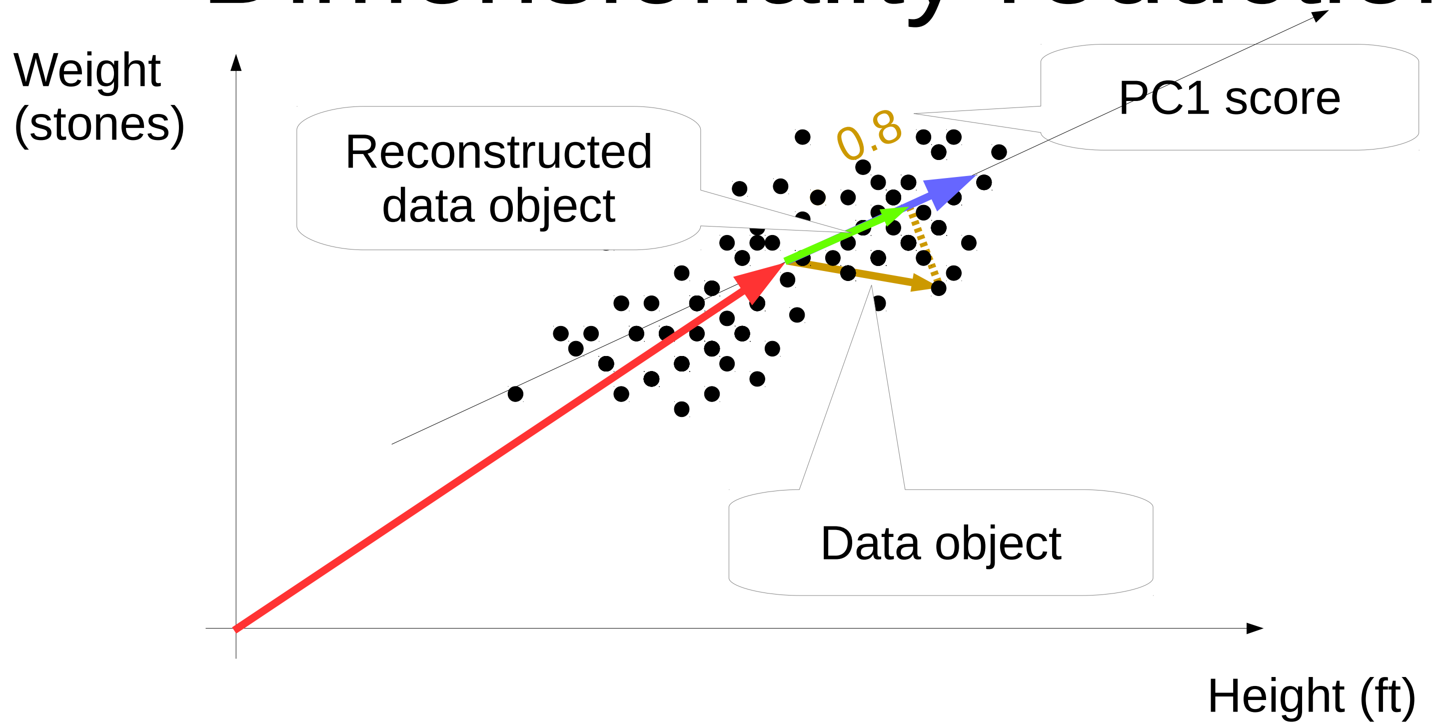
- Data objects and components are vectors
- From scores (numbers) we can reconstruct data objects (vectors)

Ordinary PCA

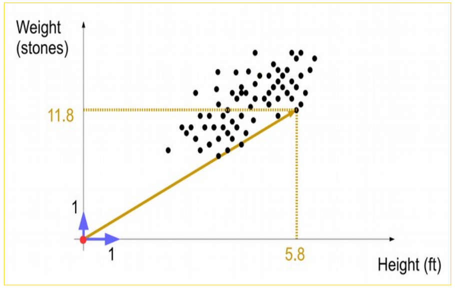


- PCA computes new origin and unit vectors which best suit the data
- From PC scores we can reconstruct data objects

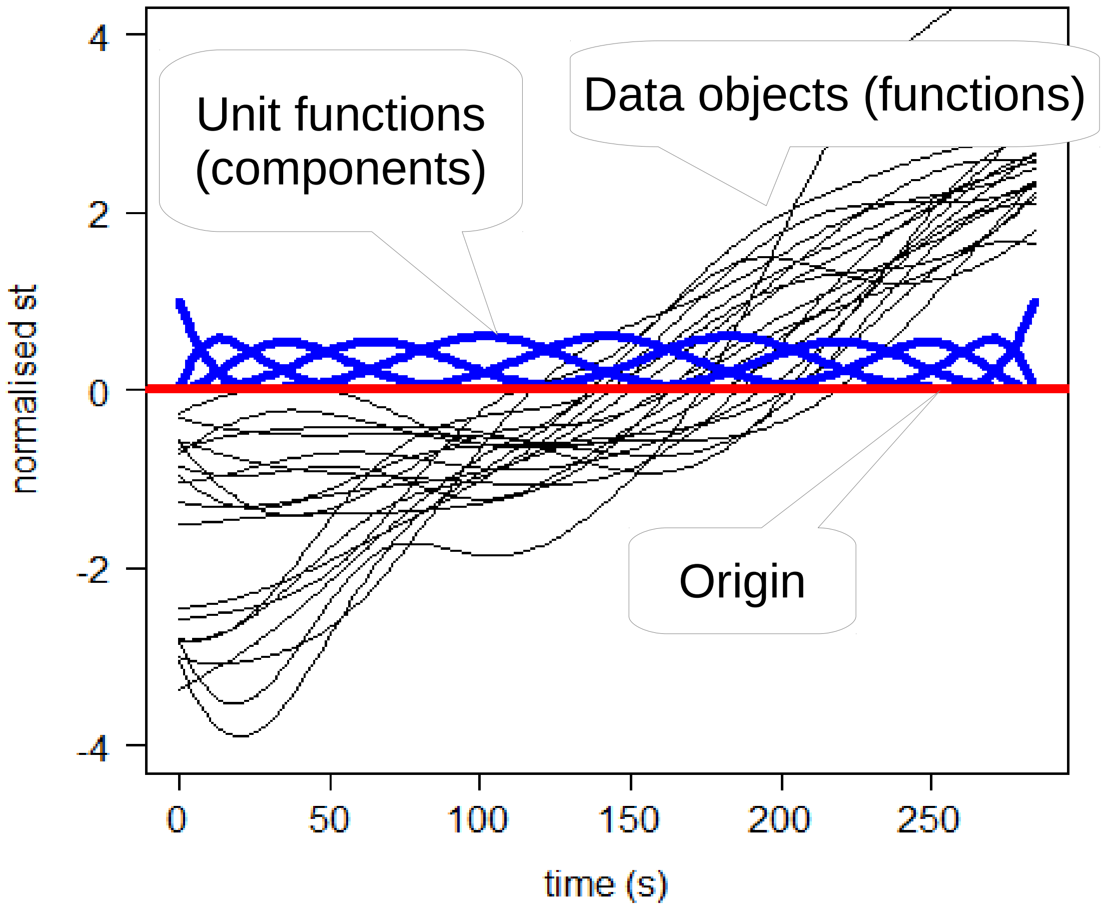
Dimensionality reduction



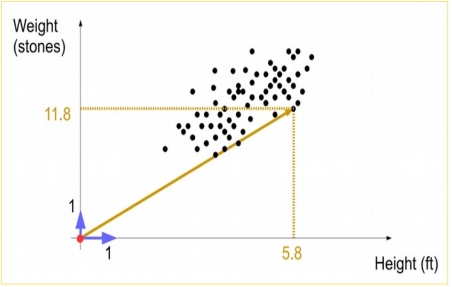
- We can use only part of the PCs
- This reduces the data dimensionality
- But introduces reconstruction errors too



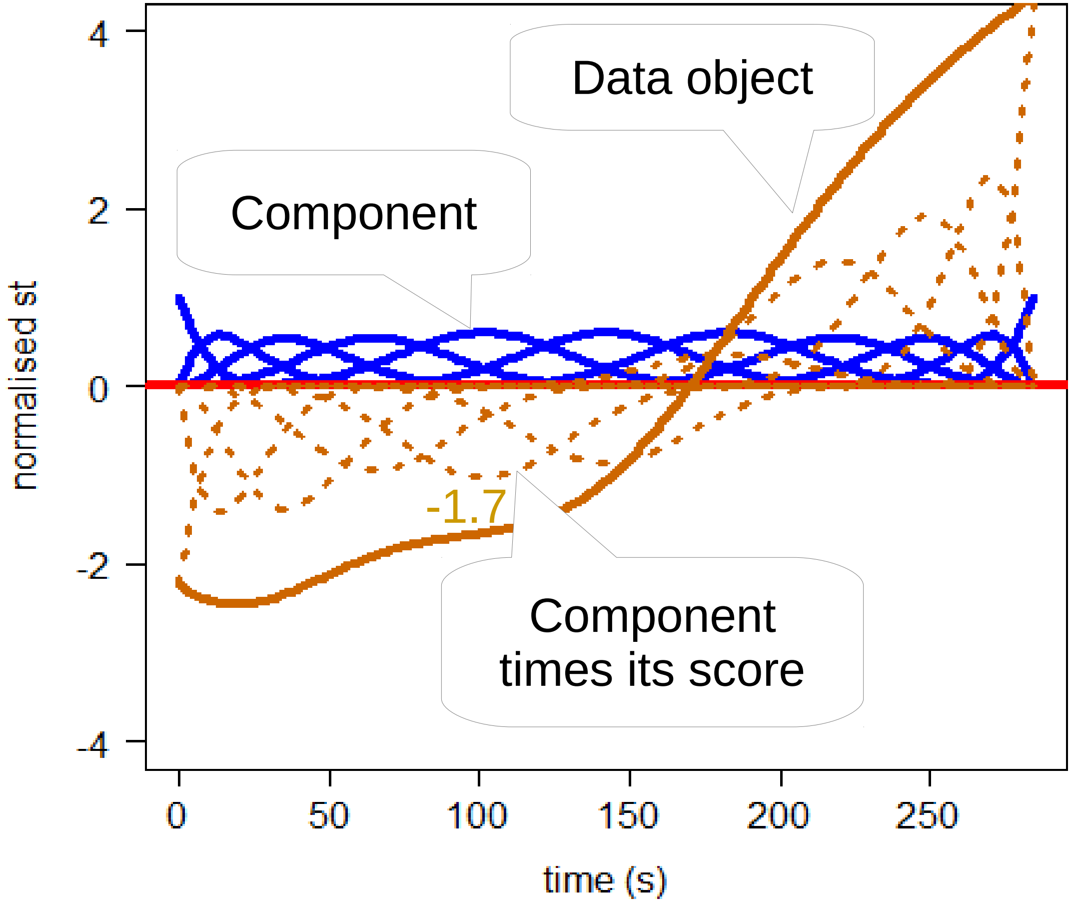
Functions (curves)



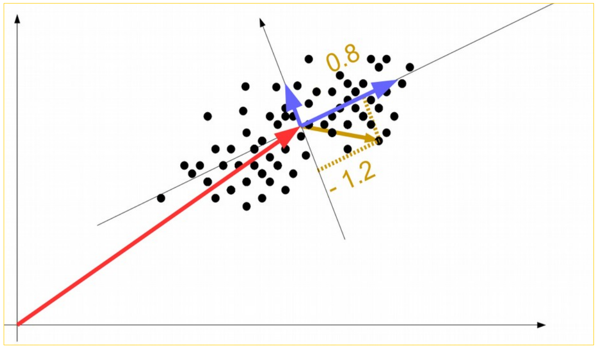
- Origin, components and data objects are functions
- Origin is a flat line
- Components are 11 B-spline curves



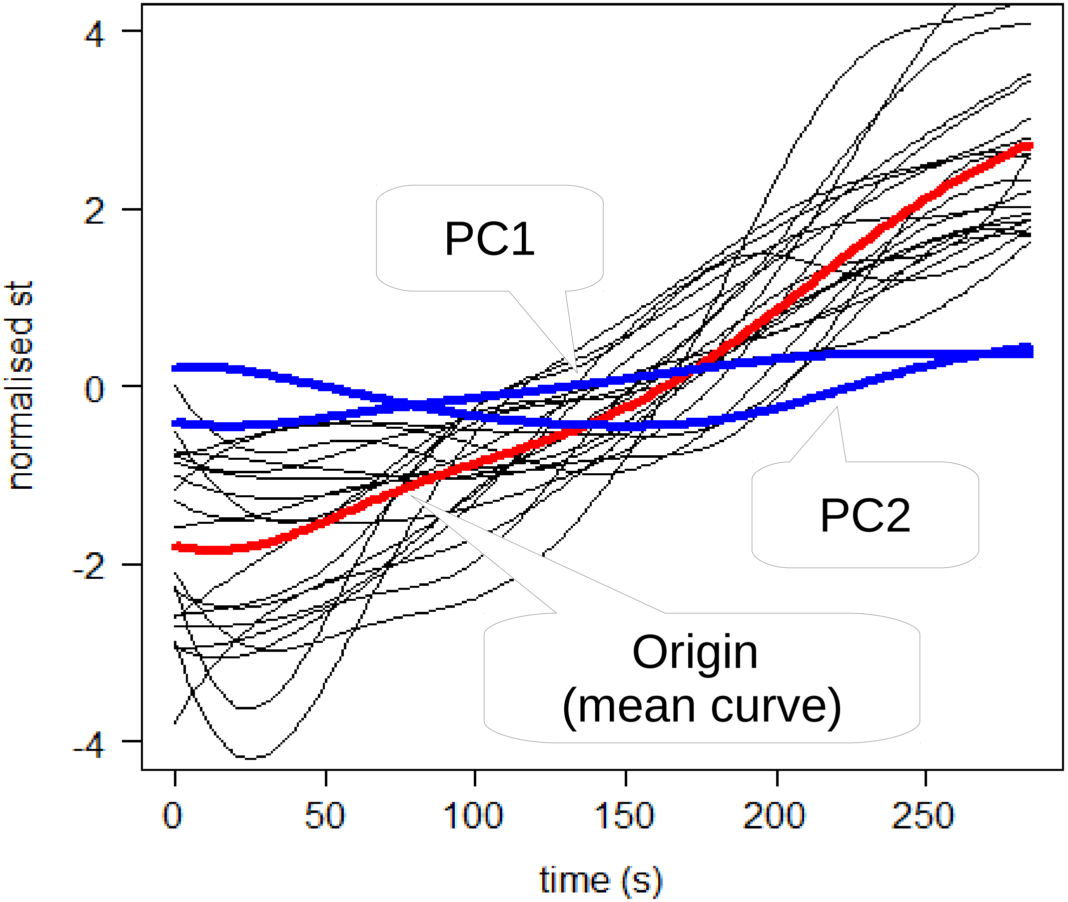
Functions (curves)



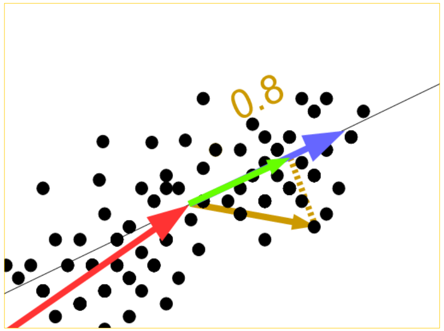
- Each of the 11 components is multiplied by a score
- These are summed together to obtain a data object



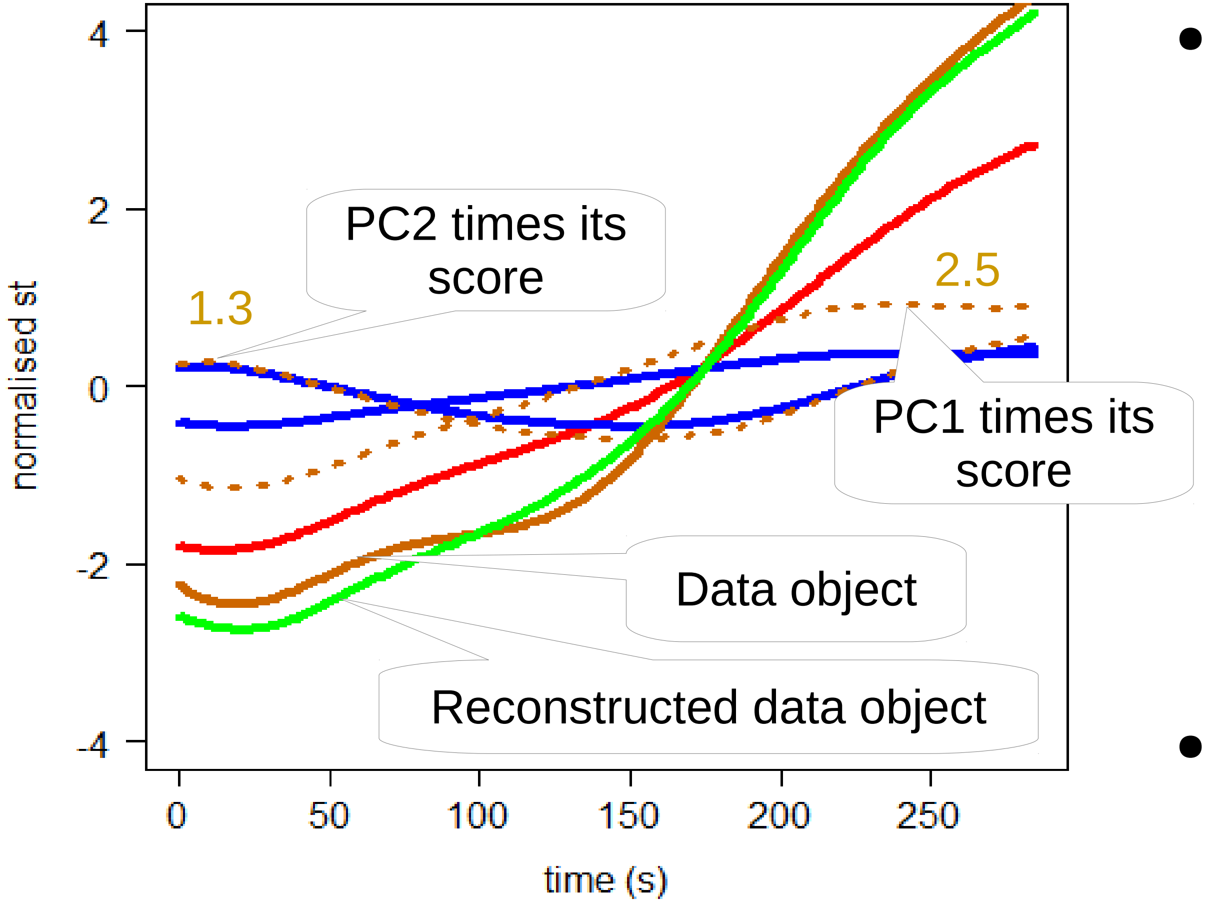
Functional PCA



- FPCA computes new origin and component functions which best suit the data



Functional PCA



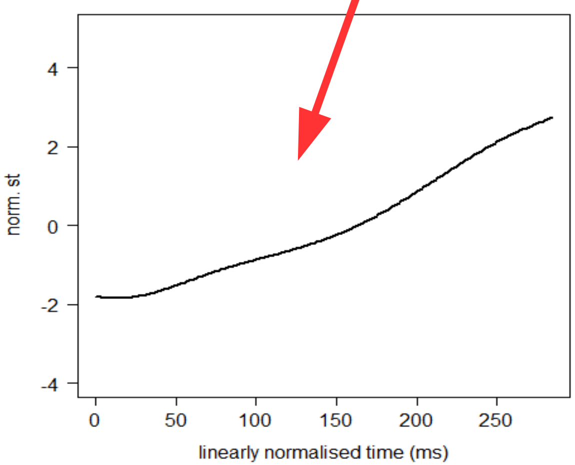
- The sum of origin (mean) curve + PCs times their scores gives an approx reconstruction of the original curve
- Dimensions from 11 (B-splines) down to 2 (PCs)

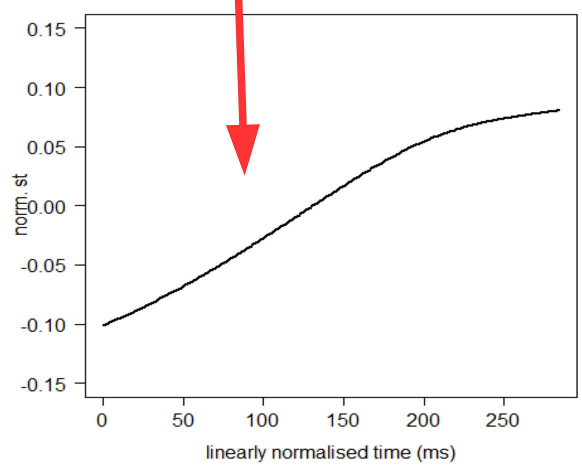
Functional PCs

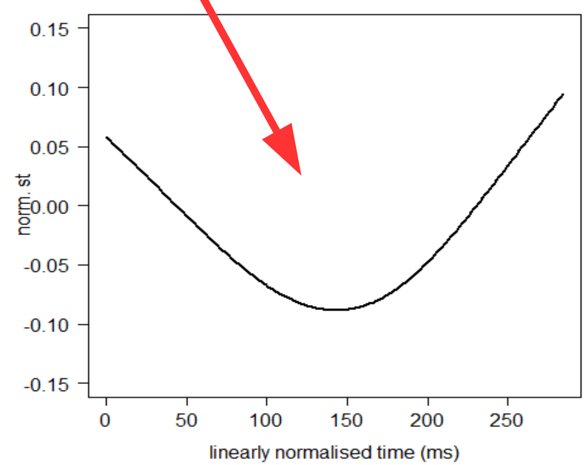
$$\boxed{f(t) \approx \mu(t) + s_1 \cdot PC1(t) + s_2 \cdot PC2(t) + \cdots}$$

PC1 score

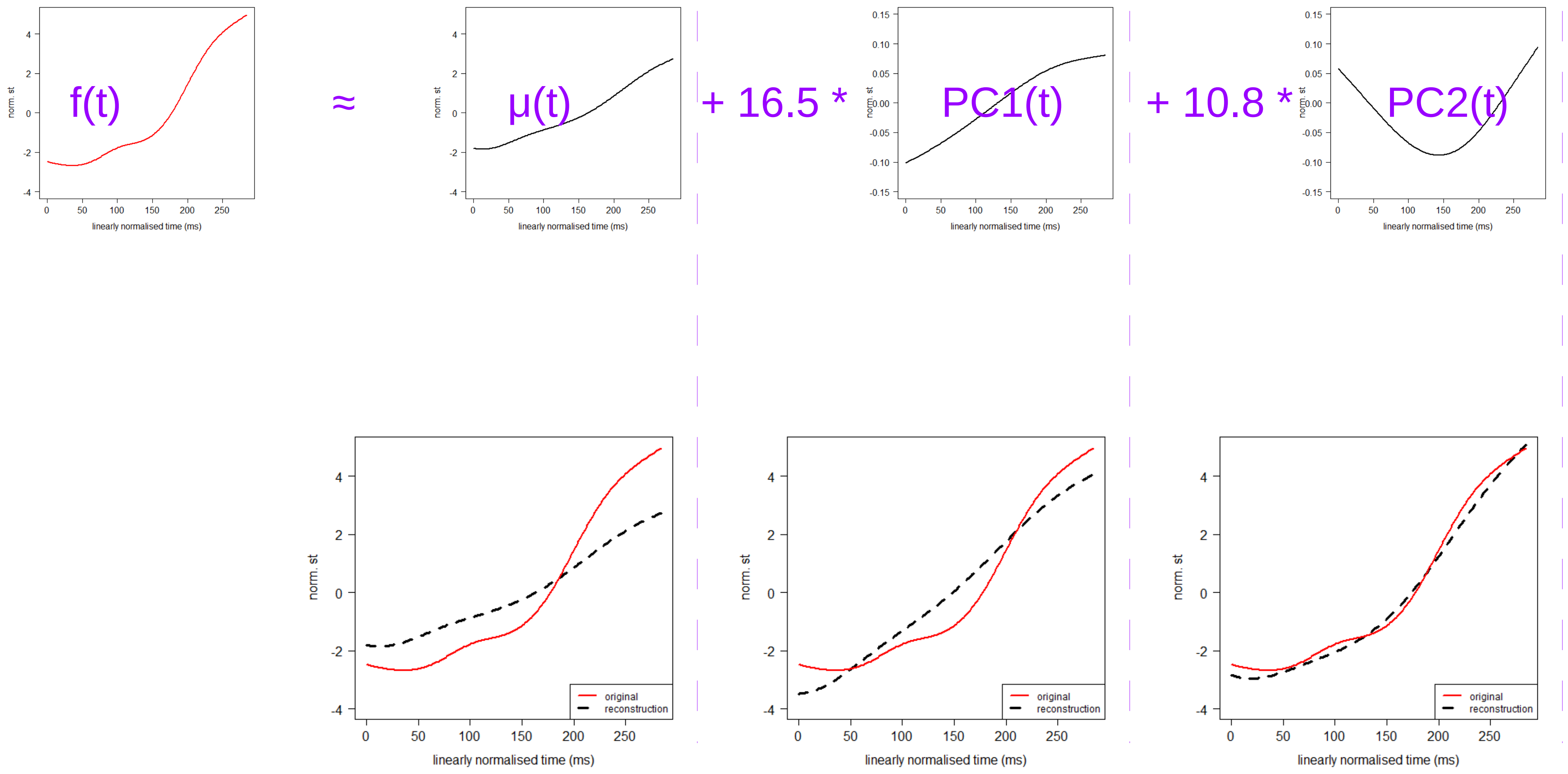
PC2 score



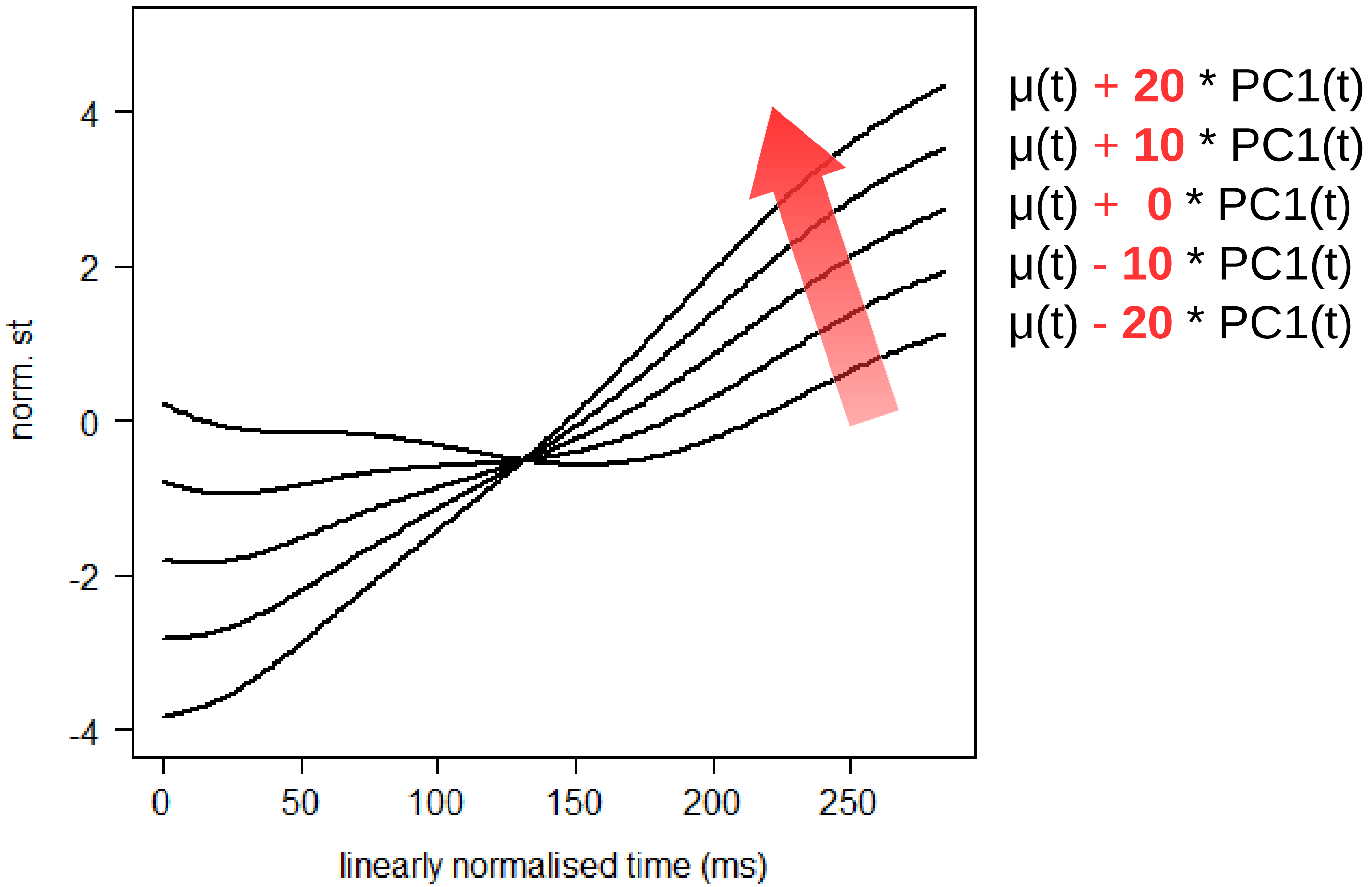




Curve reconstruction

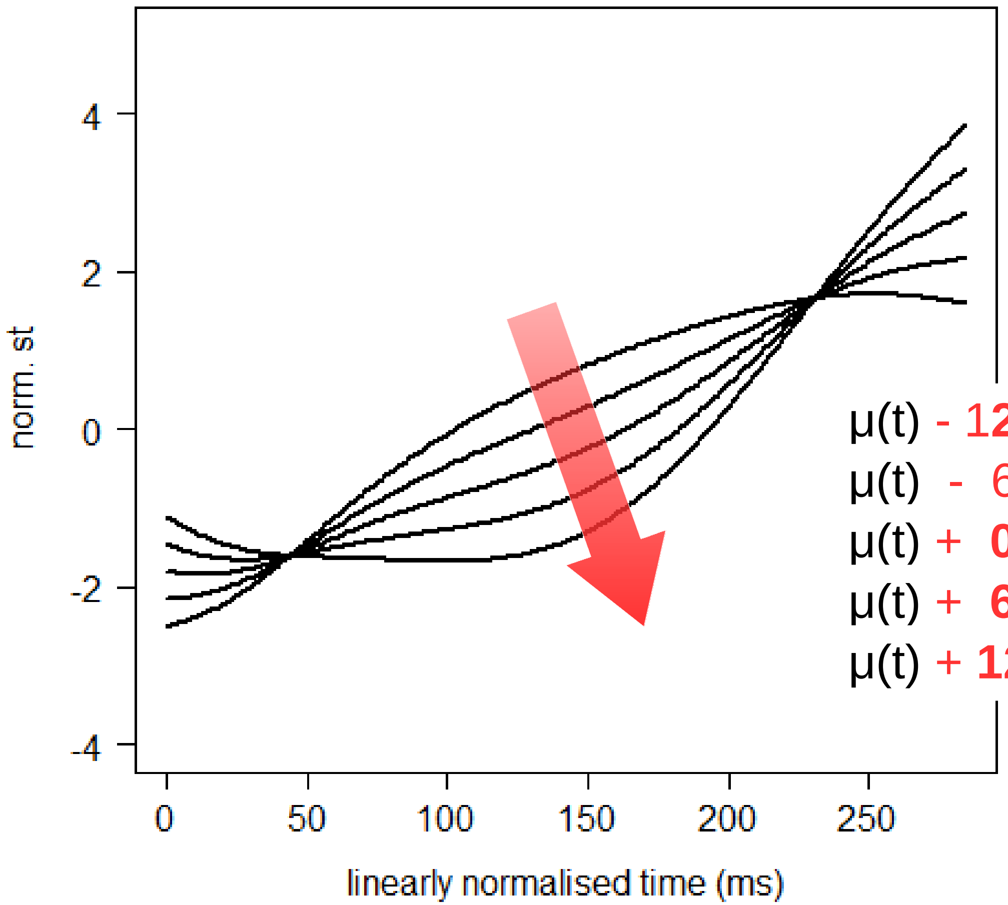


PC1 scores



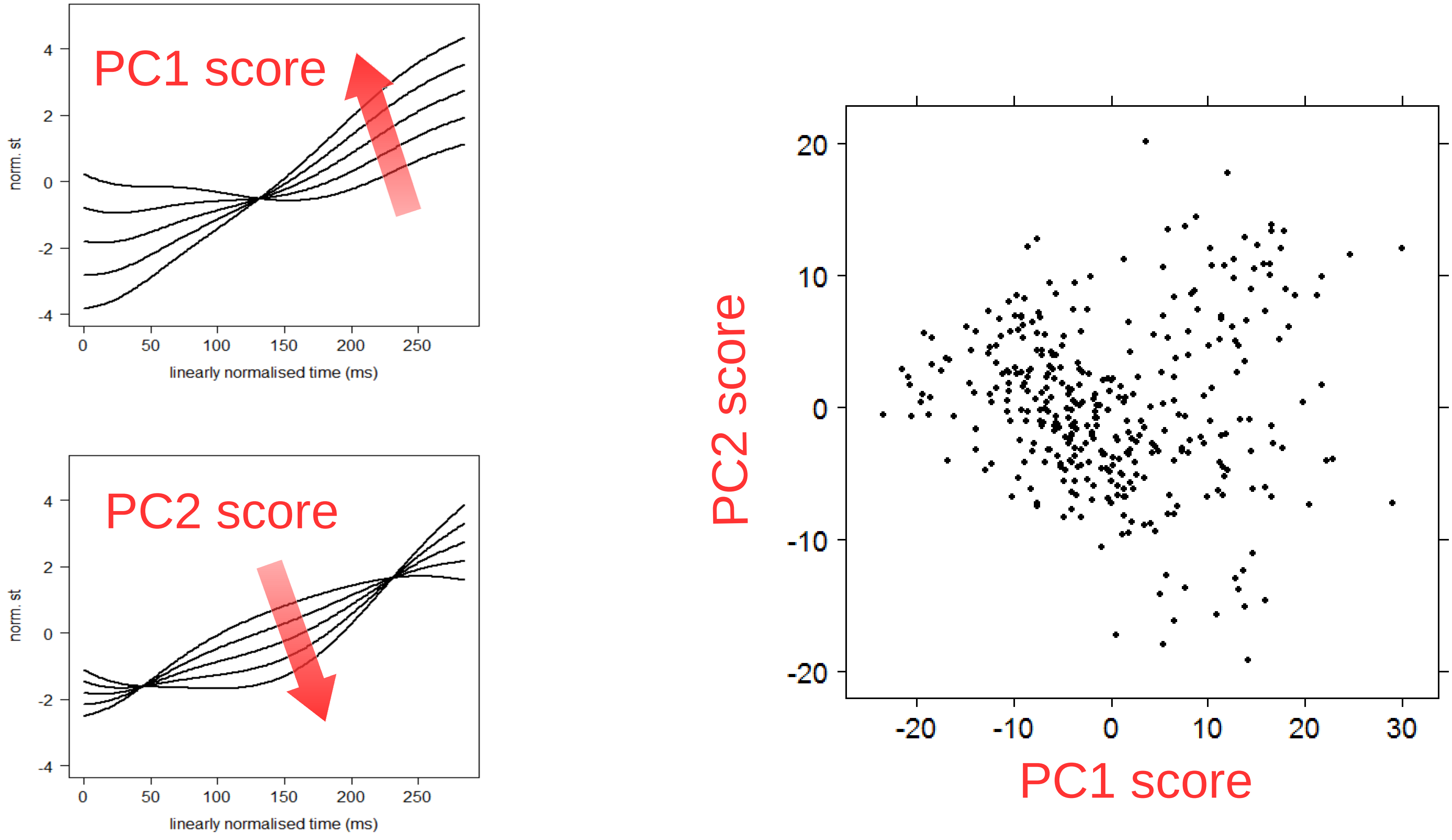
norm. st
4
2
0
-2
-4
0
50
100
150
200
250
linearly normalised time (ms)
μ(t) + 20 * PC1(t)
μ(t) + 10 * PC1(t)
μ(t) + 0 * PC1(t)
μ(t) - 10 * PC1(t)
μ(t) - 20 * PC1(t)

PC2 scores

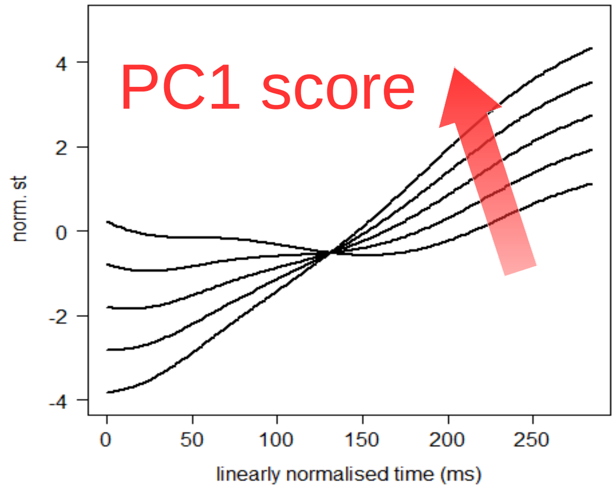


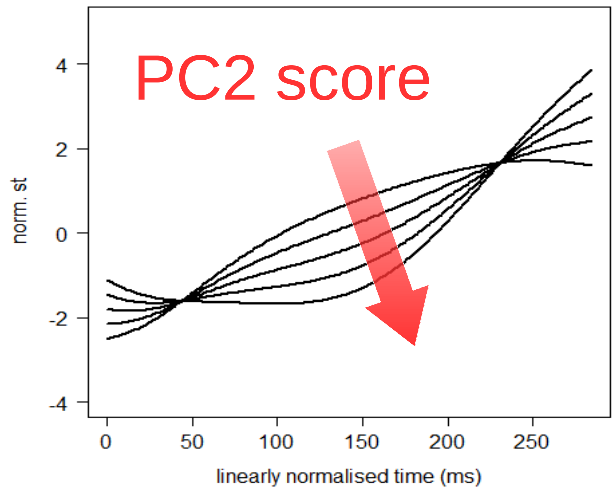
μ(t) - 12 * PC2(t)
μ(t) - 6 * PC2(t)
μ(t) + 0 * PC2(t)
μ(t) + 6 * PC2(t)
μ(t) + 12 * PC2(t)

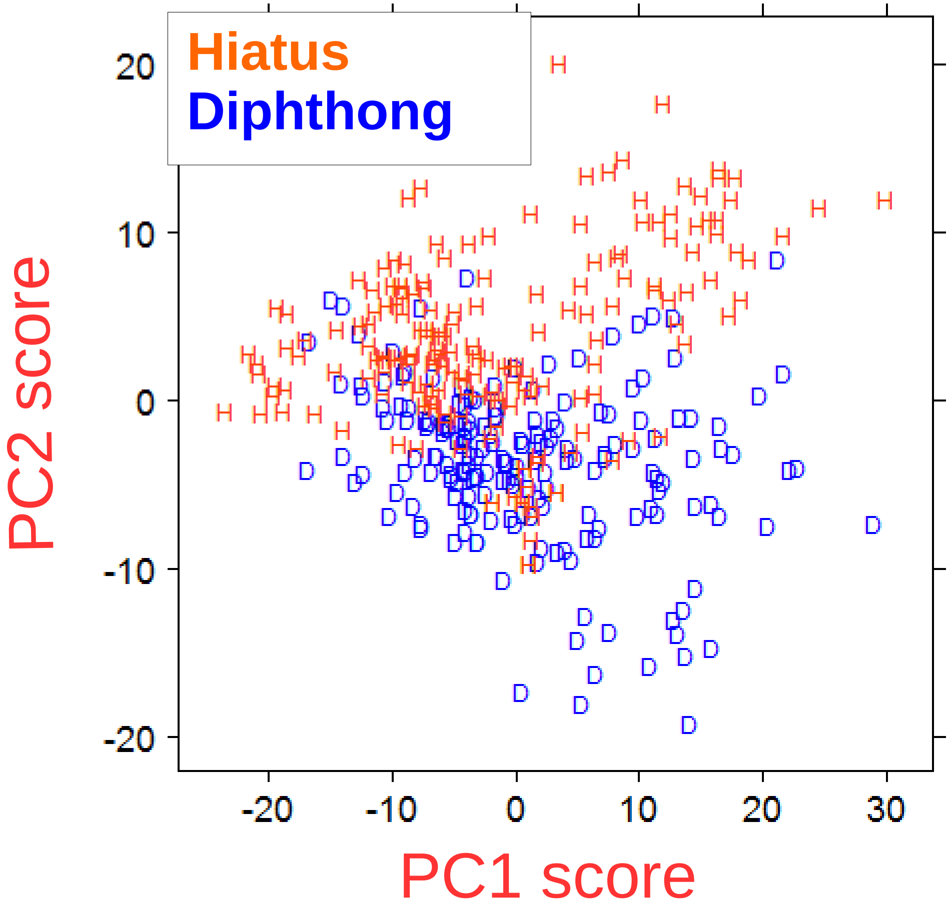
Curve parametrisation



Curve parametrisation

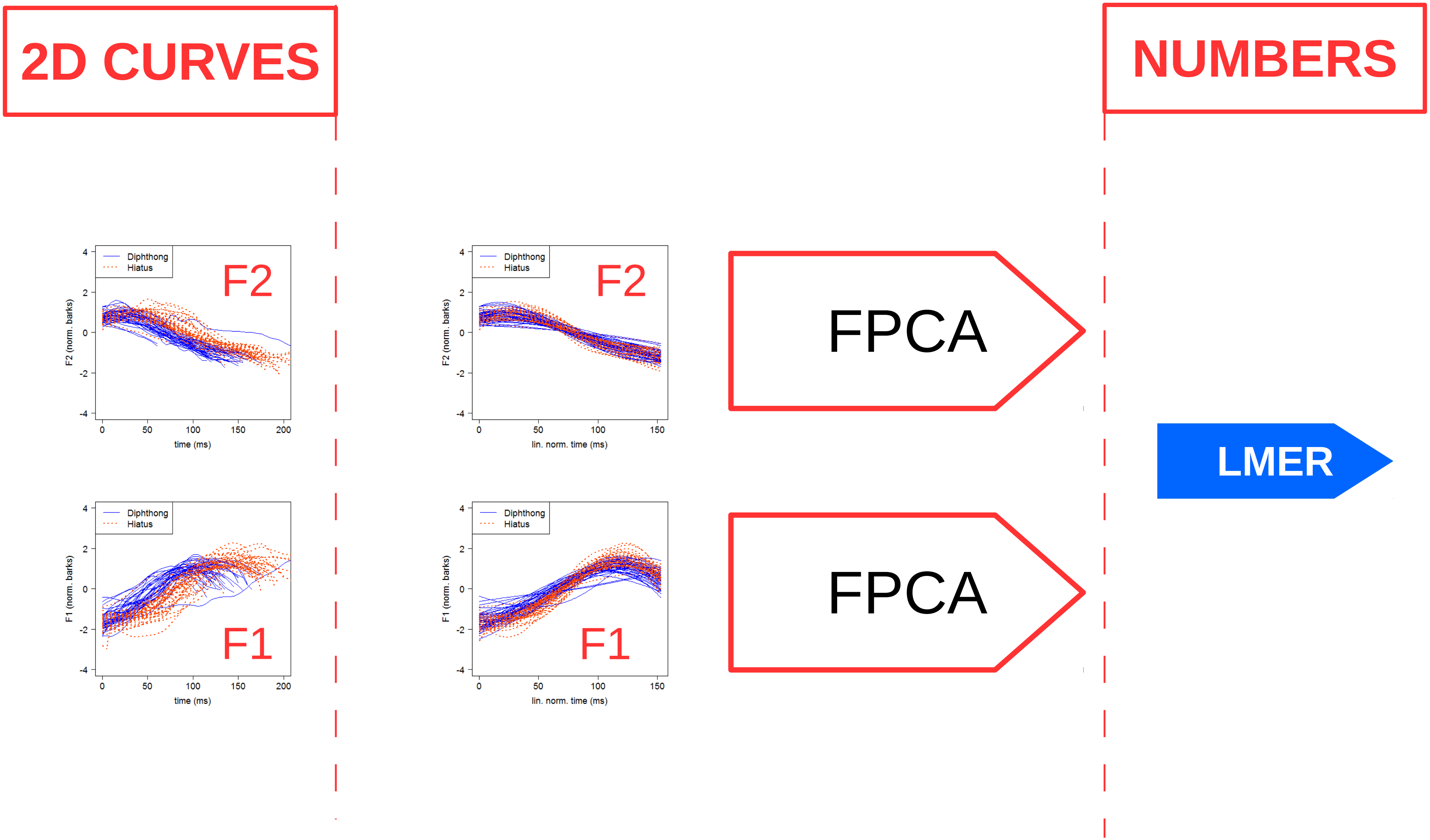






Multidimensional signals

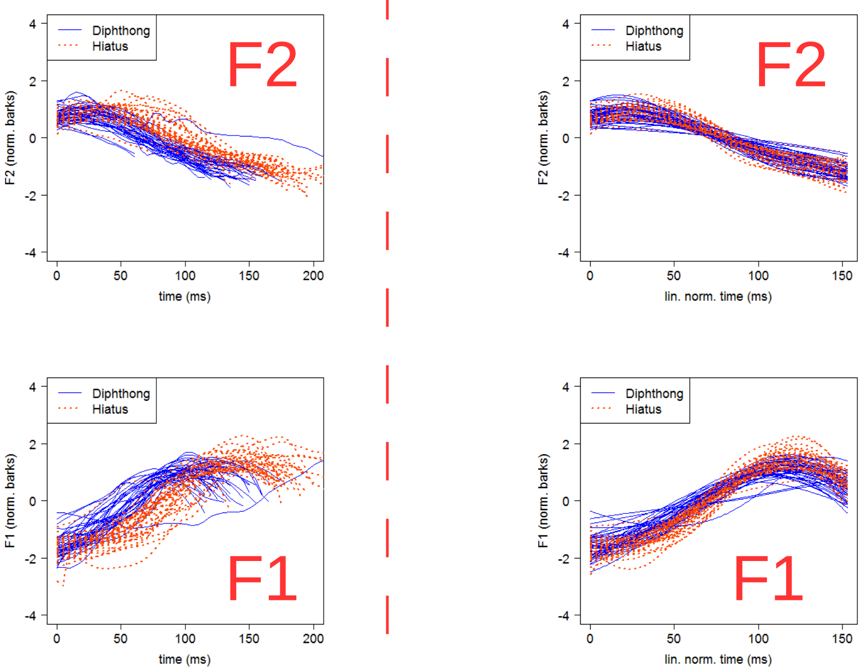
Formants


2D CURVES
NUMBERS
Diphthong
Hiatus
F2
F2 (norm. barks)
time (ms)
Diphthong
Hiatus
F2
F2 (norm. barks)
lin. norm. time (ms)
FPCA
LMER
Diphthong
Hiatus
F1
F1 (norm. barks)
time (ms)
Diphthong
Hiatus
F1
F1 (norm. barks)
lin. norm. time (ms)
FPCA

Formants

2D CURVES

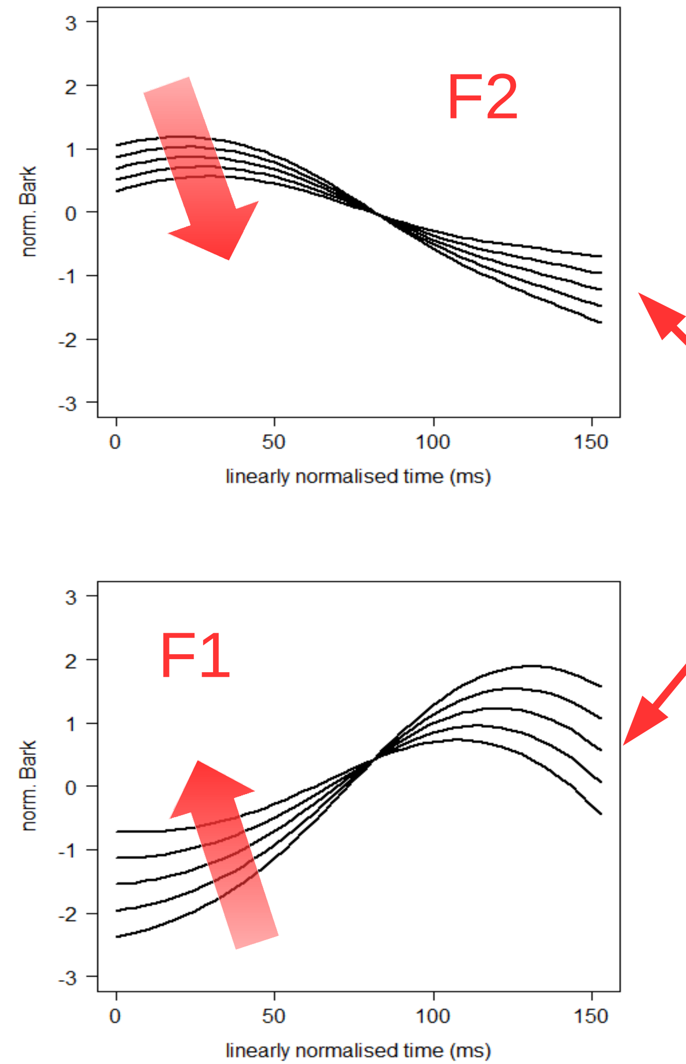
NUMBERS



2D FPCA

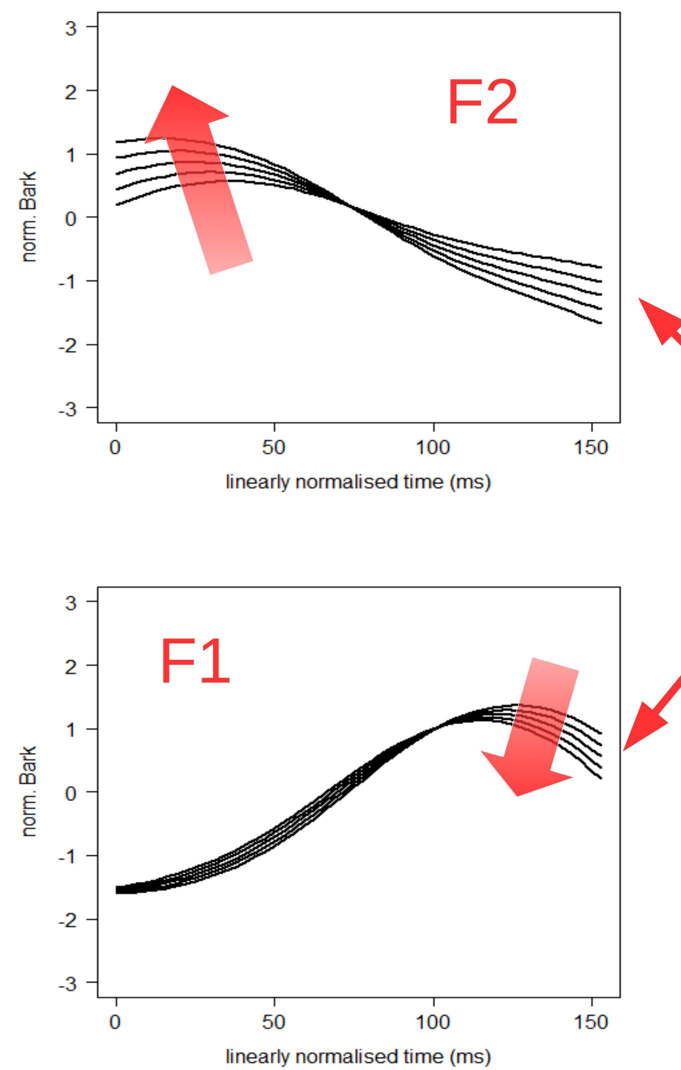
LMER

PC1 scores



$$\mu(t) + 8 * PC1(t)$$
$$\mu(t) + 4 * PC1(t)$$
$$\mu(t) + 0 * PC1(t)$$
$$\mu(t) - 4 * PC1(t)$$
$$\mu(t) - 8 * PC1(t)$$

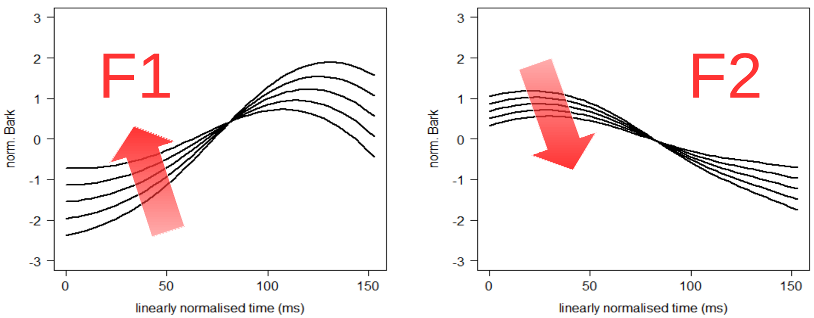
PC2 scores



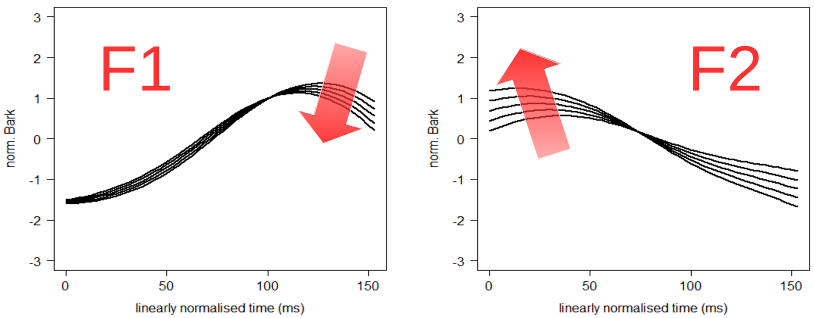
$\mu(t) + 4 * PC1(t)$
$\mu(t) + 2 * PC1(t)$
$\mu(t) + 0 * PC1(t)$
$\mu(t) - 2 * PC1(t)$
$\mu(t) - 4 * PC1(t)$

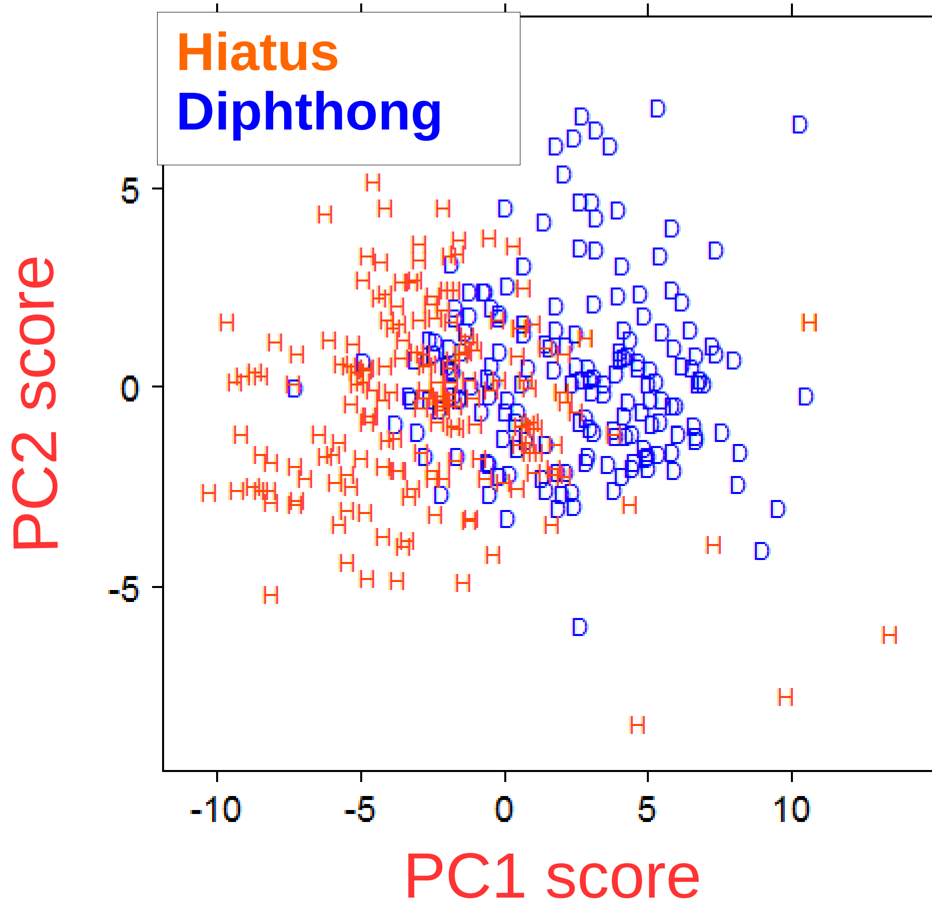
2D curve parametrisation

PC1 score



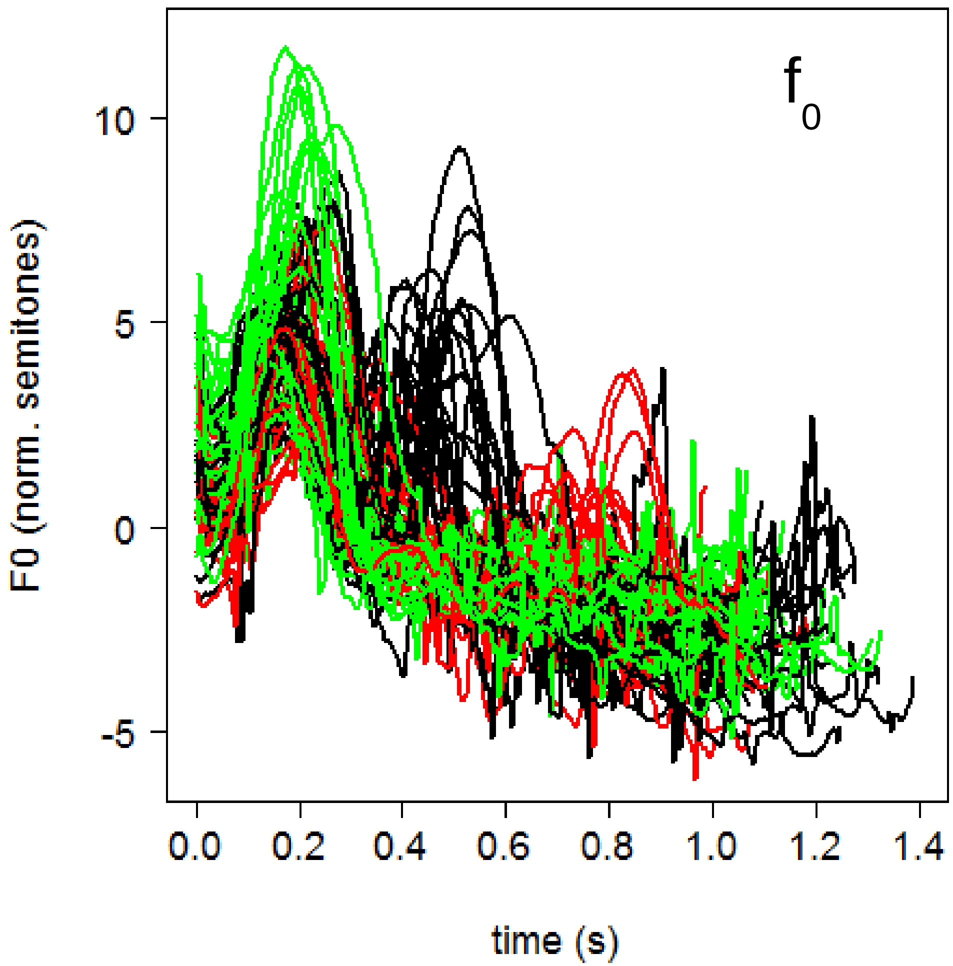
PC2 score





Long signals

Many segments



- Narrow focus in Neapolitan Italian
- Focus on

  Subject, **Verb** or **Prop. Phrase**

  Danilo vola da Roma

  (Danilo flies from Rome)
- 8 CV syllables

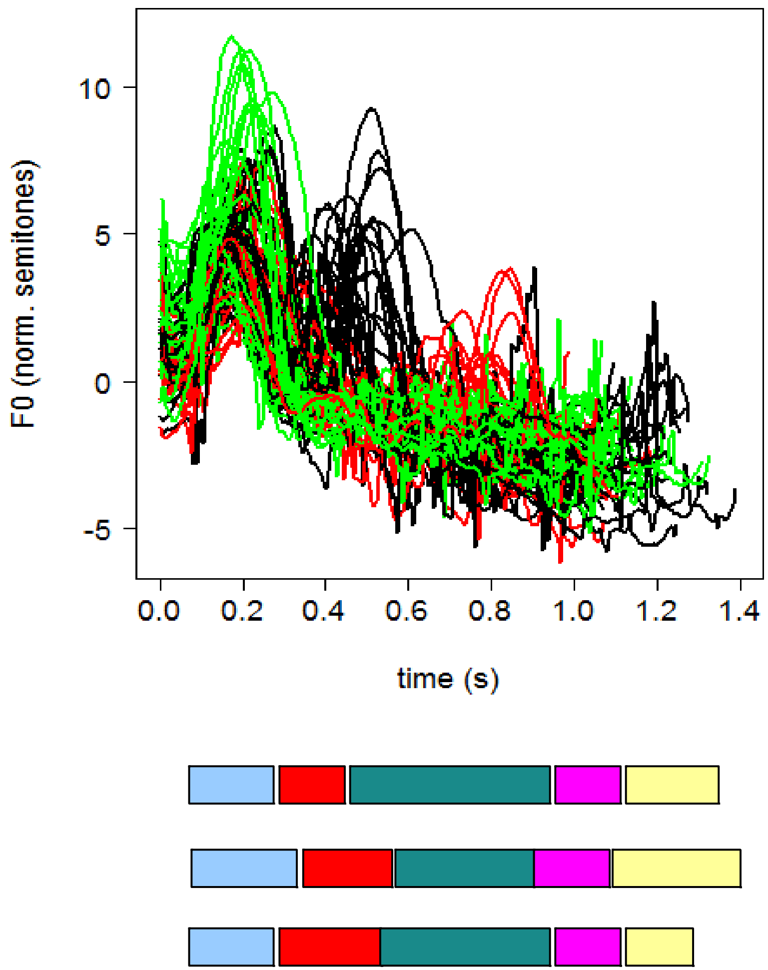
  first C was excluded (too short)

  VCVCV CVCV CV CVCV

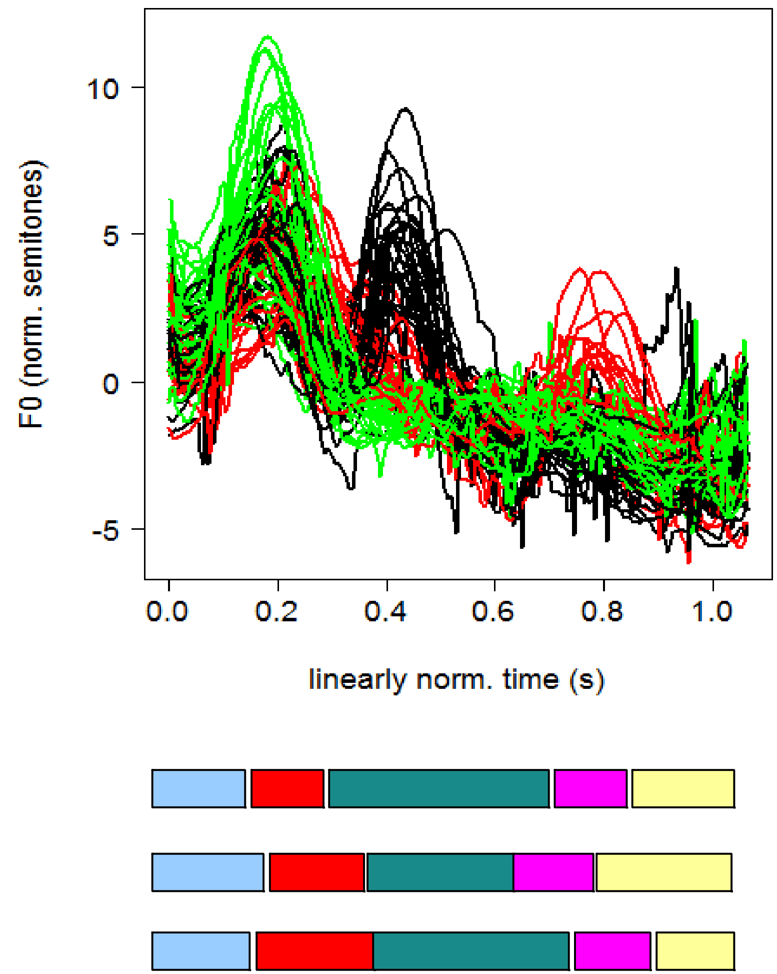
... 15 segments!

Linear time normalisation

BEFORE

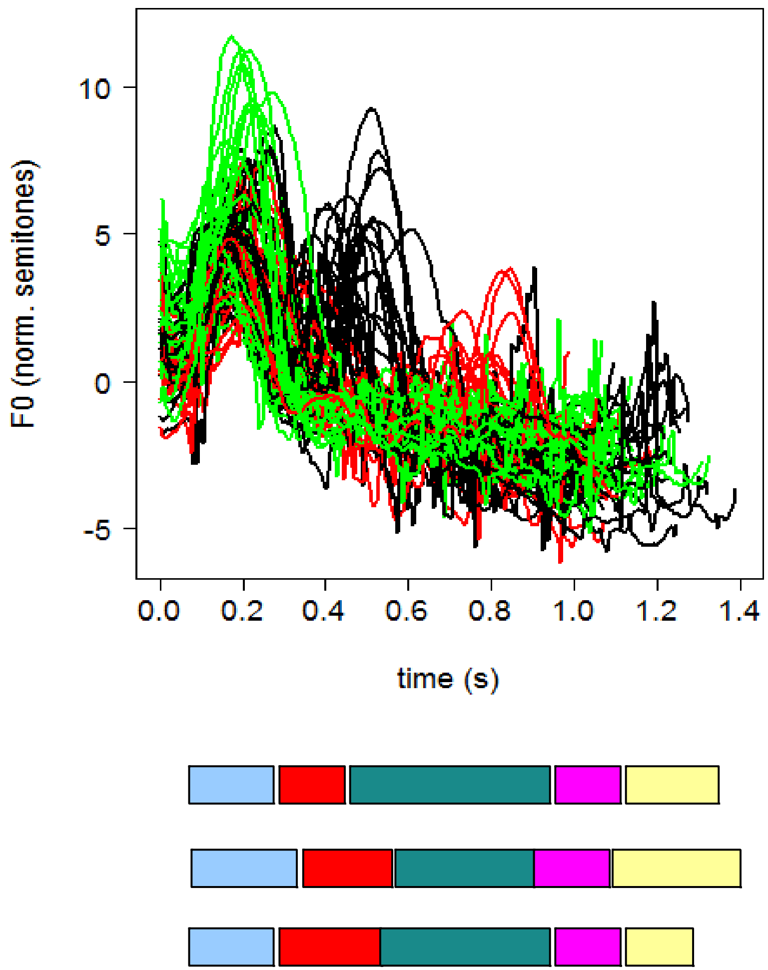


AFTER

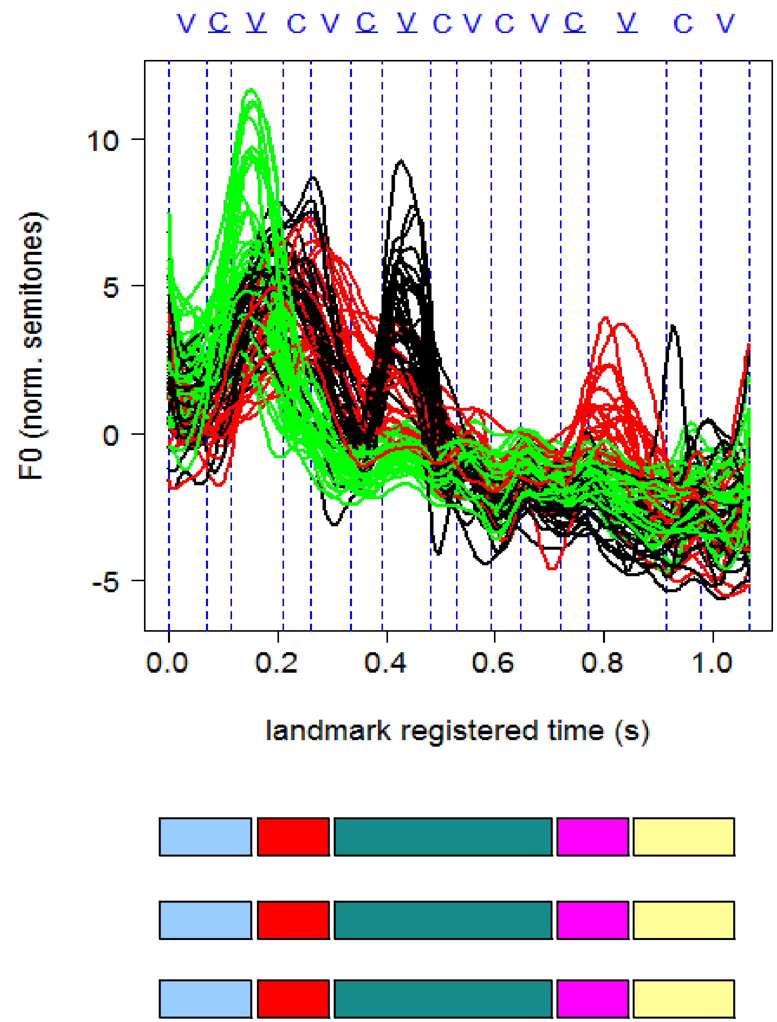


Landmark registration

BEFORE



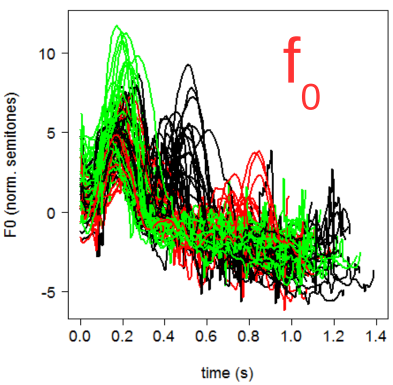
AFTER

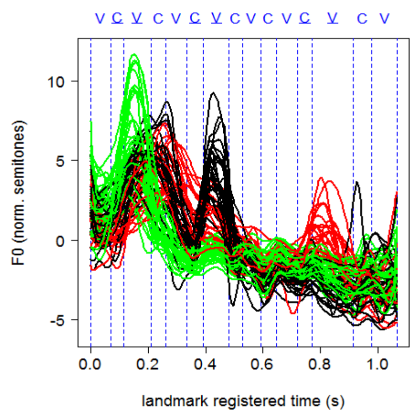


Using landmark registration

CURVES

NUMBERS





segment durations

d1	d2	...	d15
...	...	...	...
...	...	...	...
...	...	...	...

FPCA

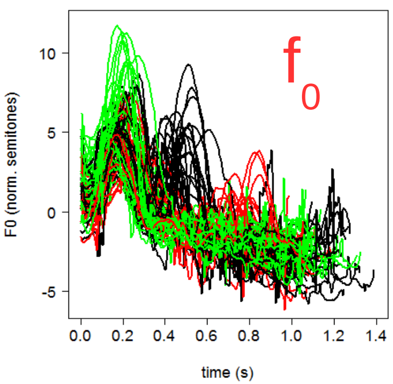
PCA

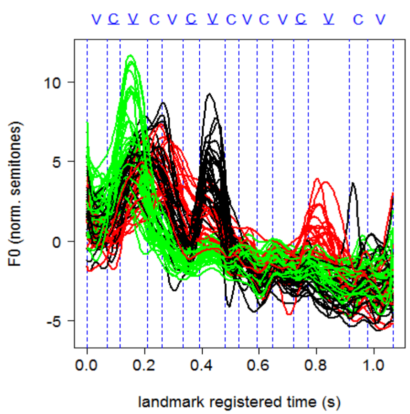
LMER

Using landmark registration

CURVES

NUMBERS





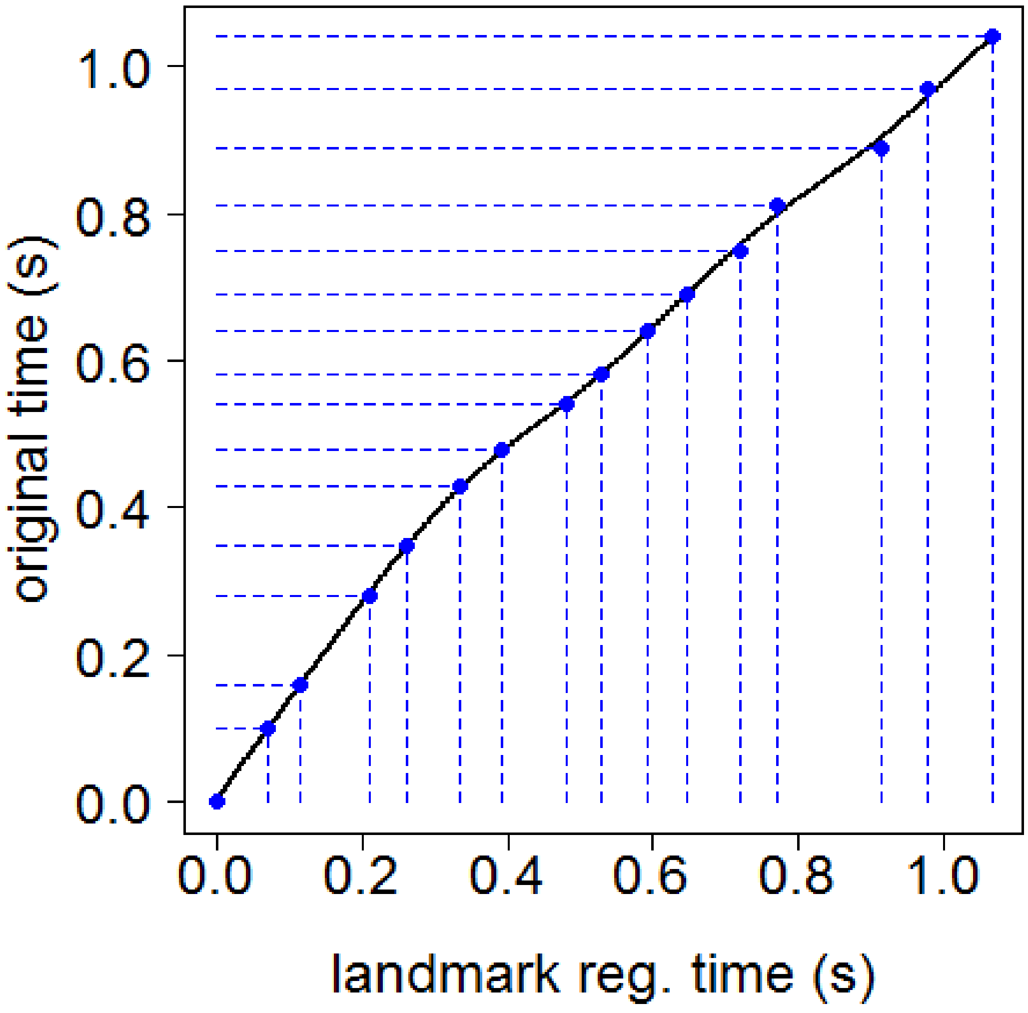
d1	d2	...	d15
...	...	...	...
...	...	...	...
...	...	...	...

segment durations

FPCA

LMER

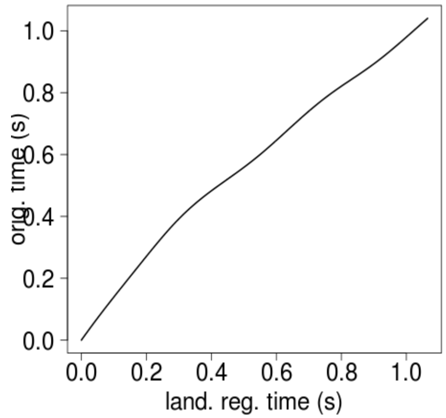
Inside landmark registration



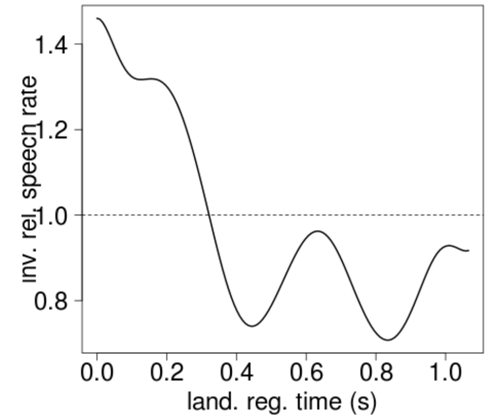
h(t)

Relative log rate

1 h(t)



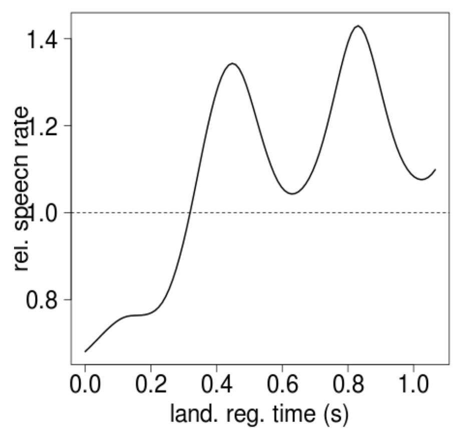
2 dh(t)/dt



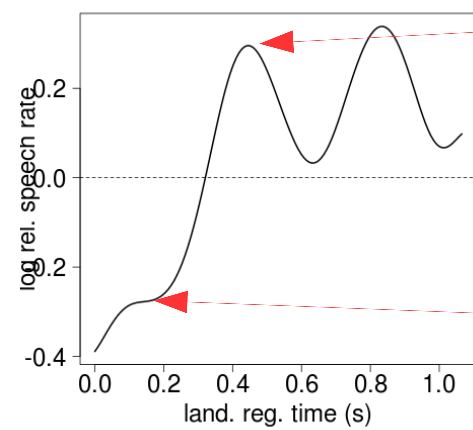
REVERSIBLE!

1 ⟷ 4

3 - dh(t)/dt



4 - log dh(t)/dt



+ 0.25 → duration / 1.28

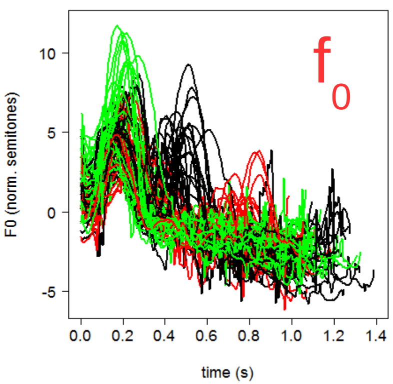
0 → same duration

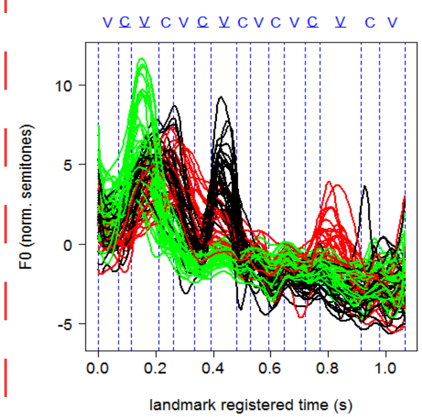
- 0.25 → duration * 1.28

Using log rates

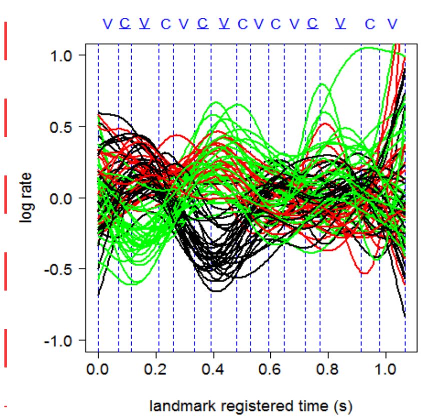
CURVES

NUMBERS





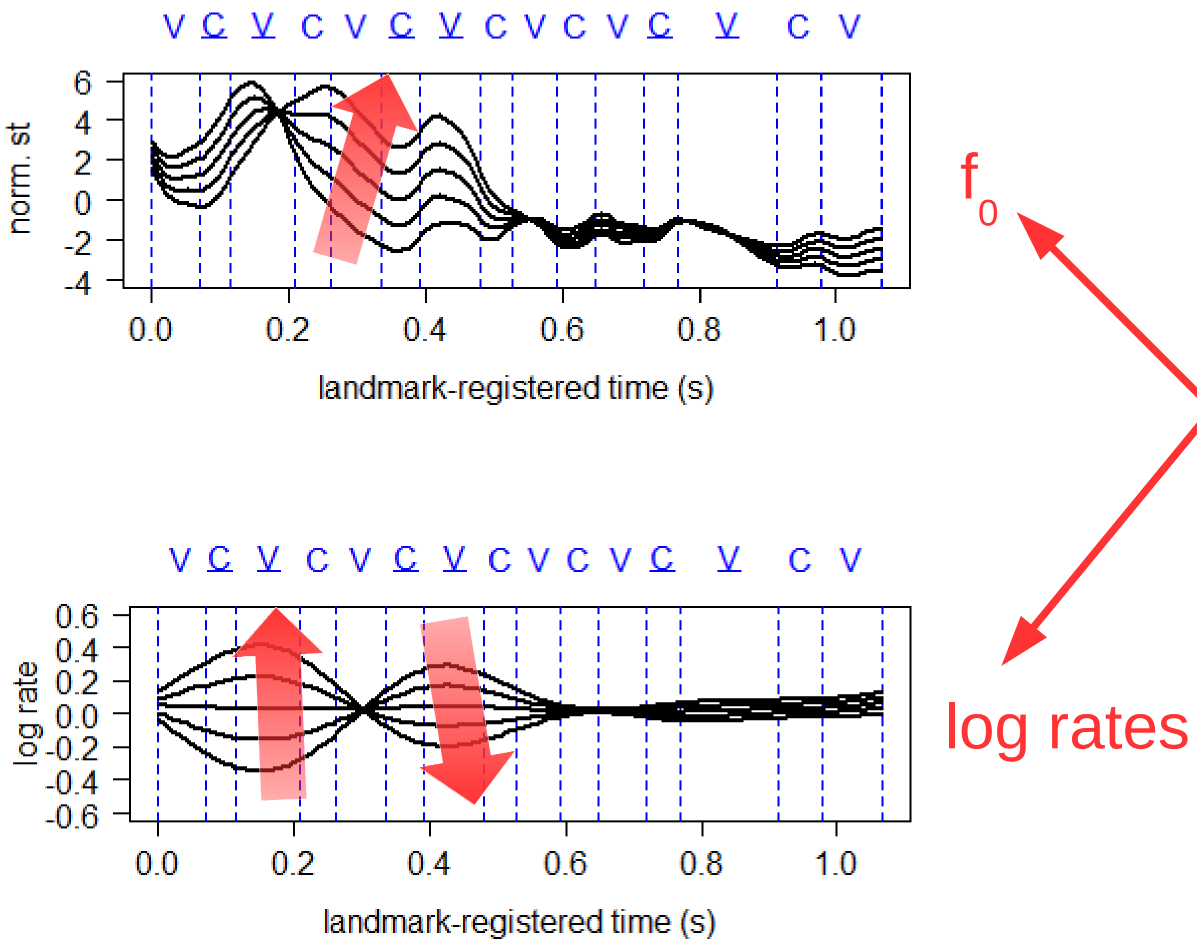
log rates



2D
FPCA

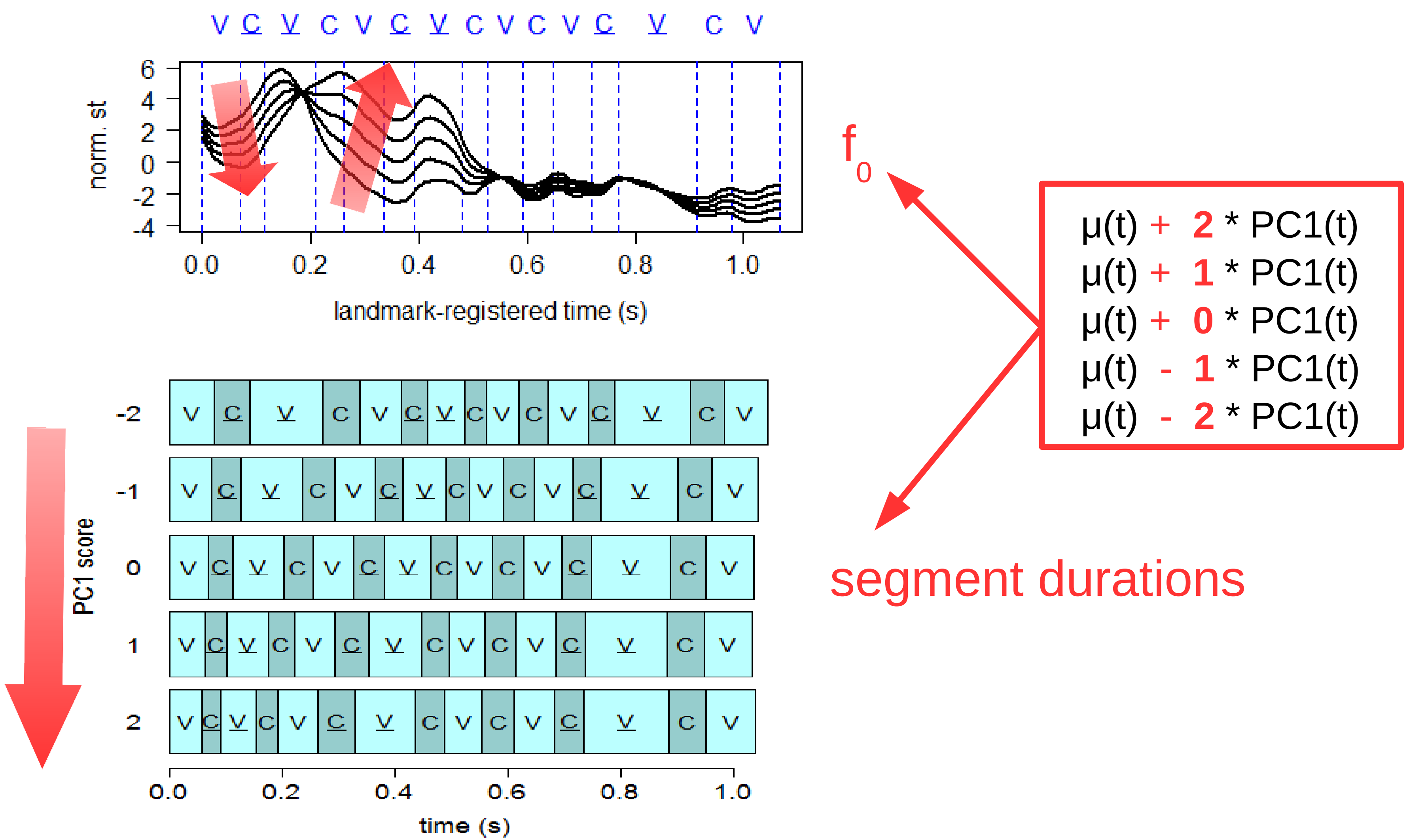
LMER

PC1 scores



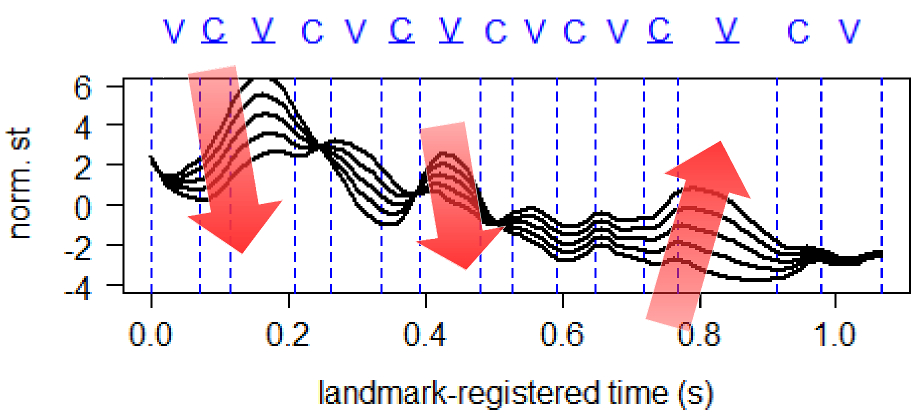
$\mu(t) + 2 * PC1(t)$
$\mu(t) + 1 * PC1(t)$
$\mu(t) + 0 * PC1(t)$
$\mu(t) - 1 * PC1(t)$
$\mu(t) - 2 * PC1(t)$

PC1 scores



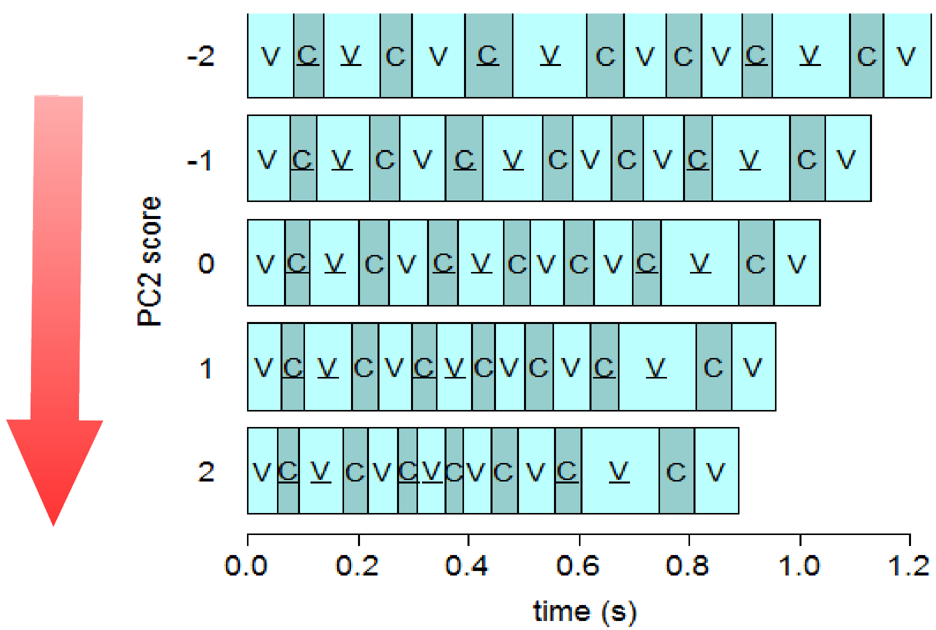
V C V C V C V C V C V C V C V
norm. st
landmark-registered time (s)
f0
μ(t) + 2 * PC1(t)
μ(t) + 1 * PC1(t)
μ(t) + 0 * PC1(t)
μ(t) - 1 * PC1(t)
μ(t) - 2 * PC1(t)
segment durations
PC1 score
-2
-1
0
1
2
time (s)

PC2 scores



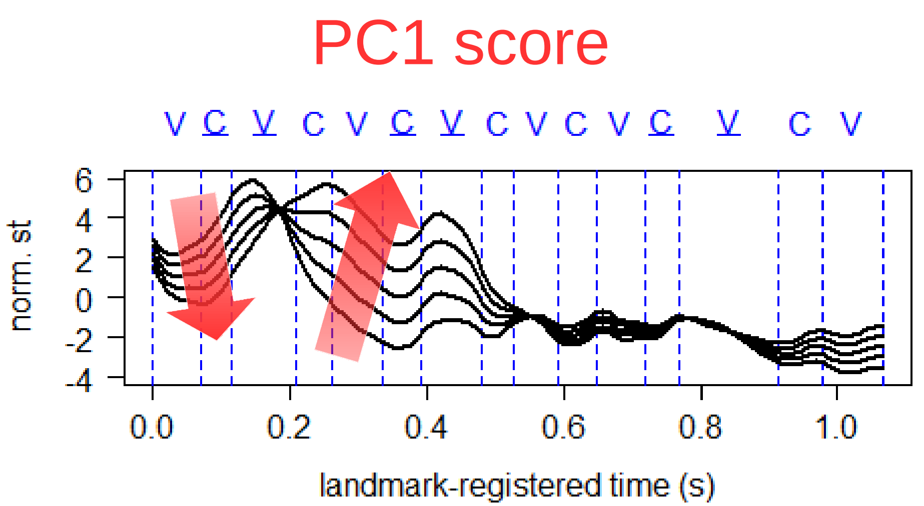
f_0

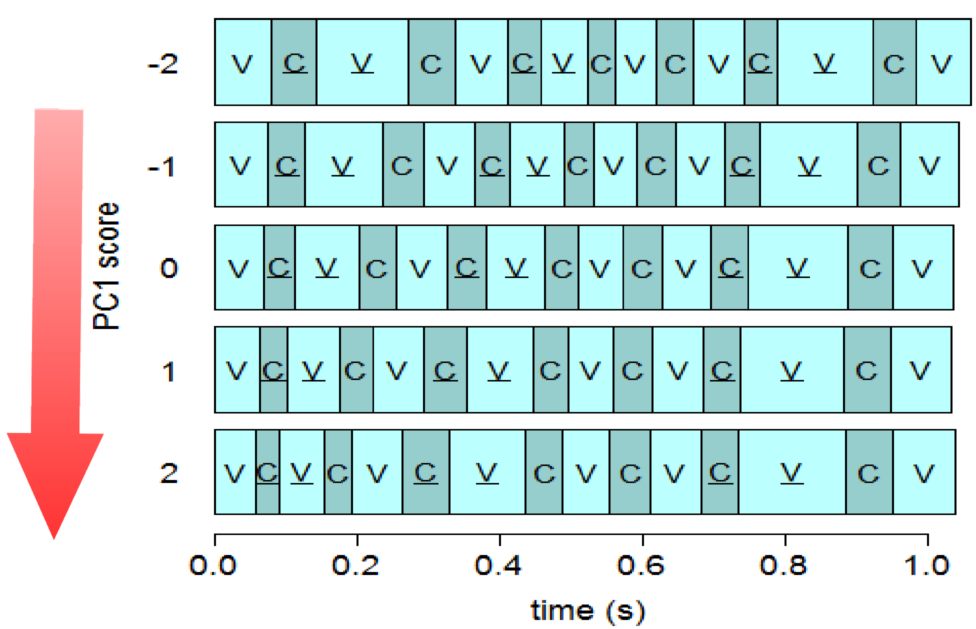
$\mu(t) + 2 * PC1(t)$
$\mu(t) + 1 * PC1(t)$
$\mu(t) + 0 * PC1(t)$
$\mu(t) - 1 * PC1(t)$
$\mu(t) - 2 * PC1(t)$

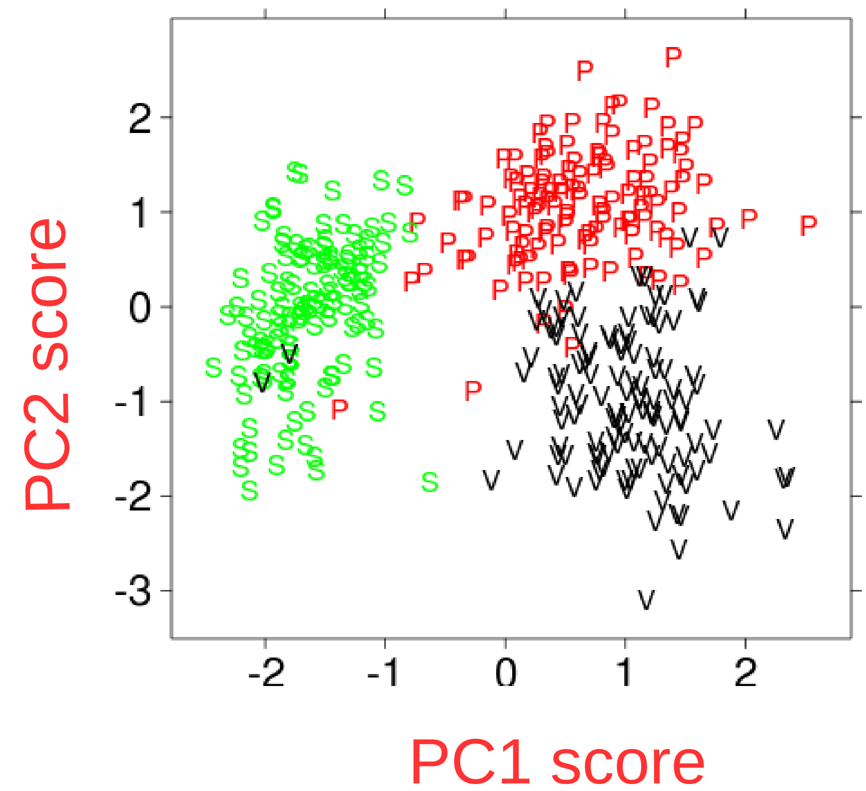


segment durations

multi-segment curve parametrisation

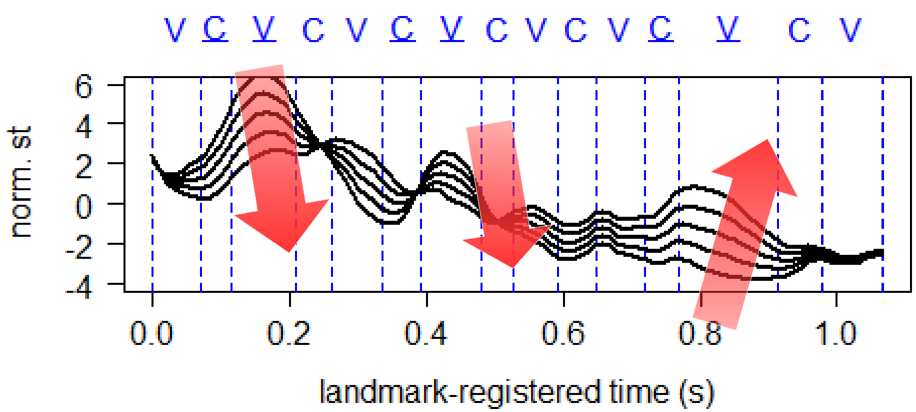


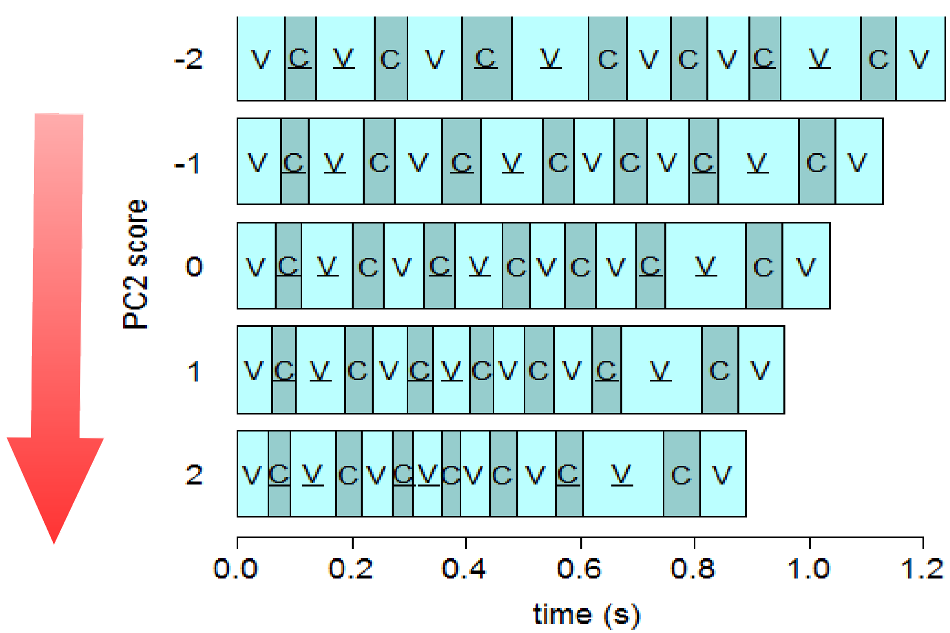


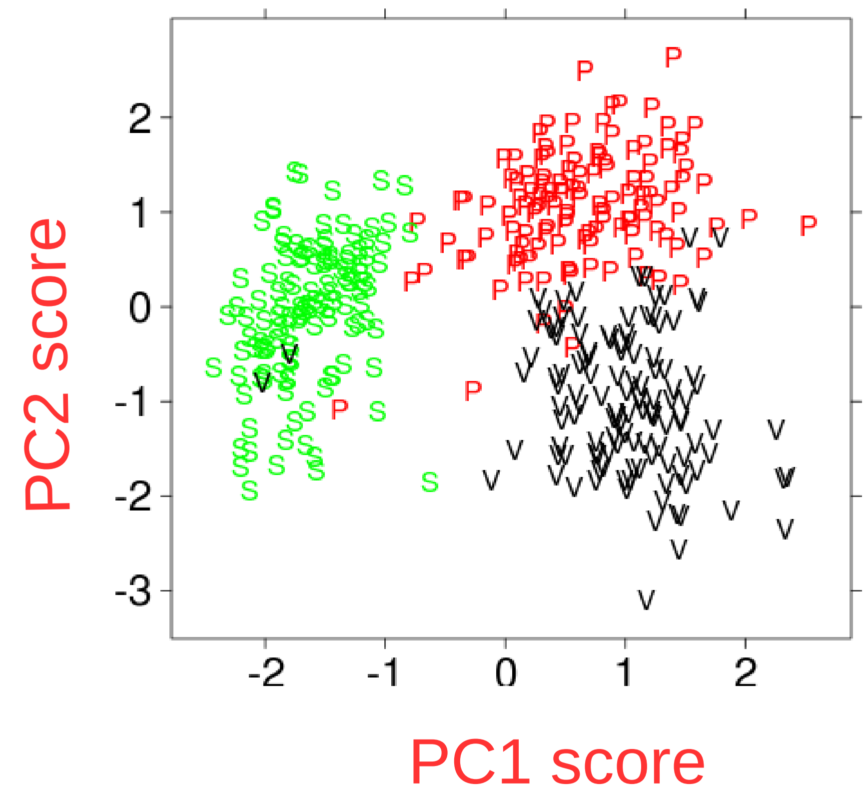


multi-segment curve parametrisation

PC2 score

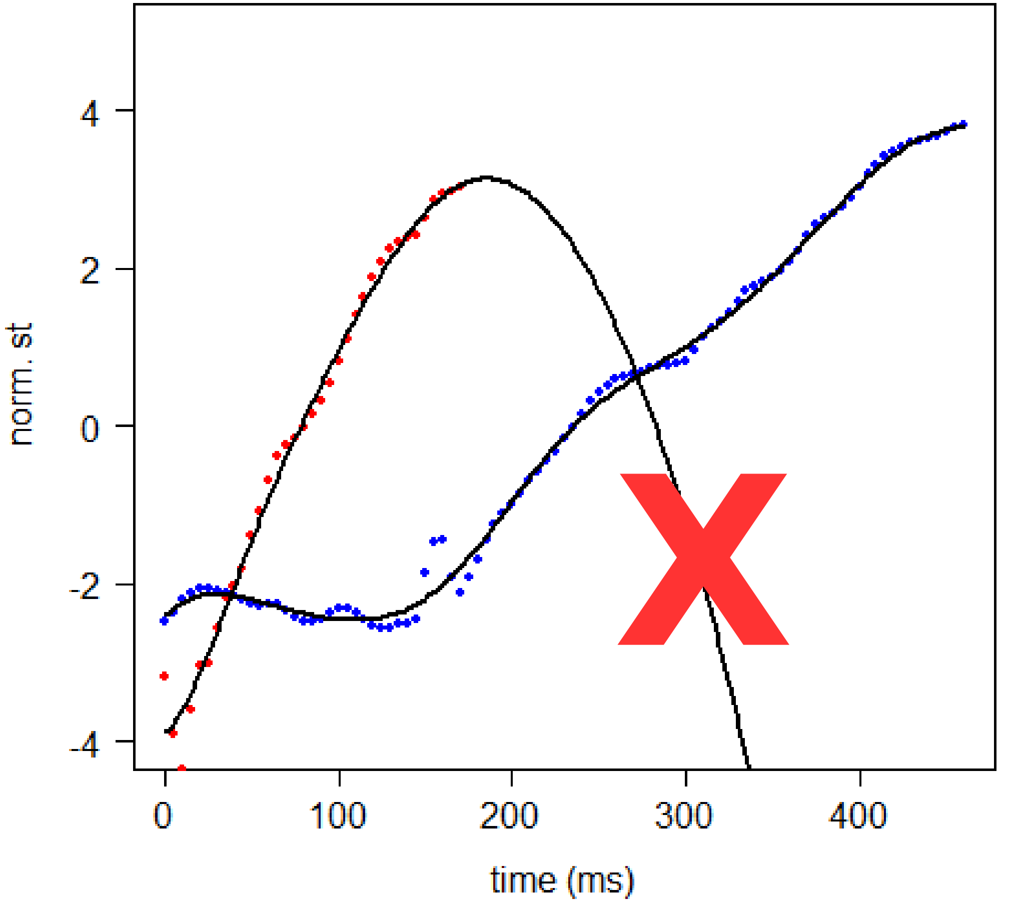




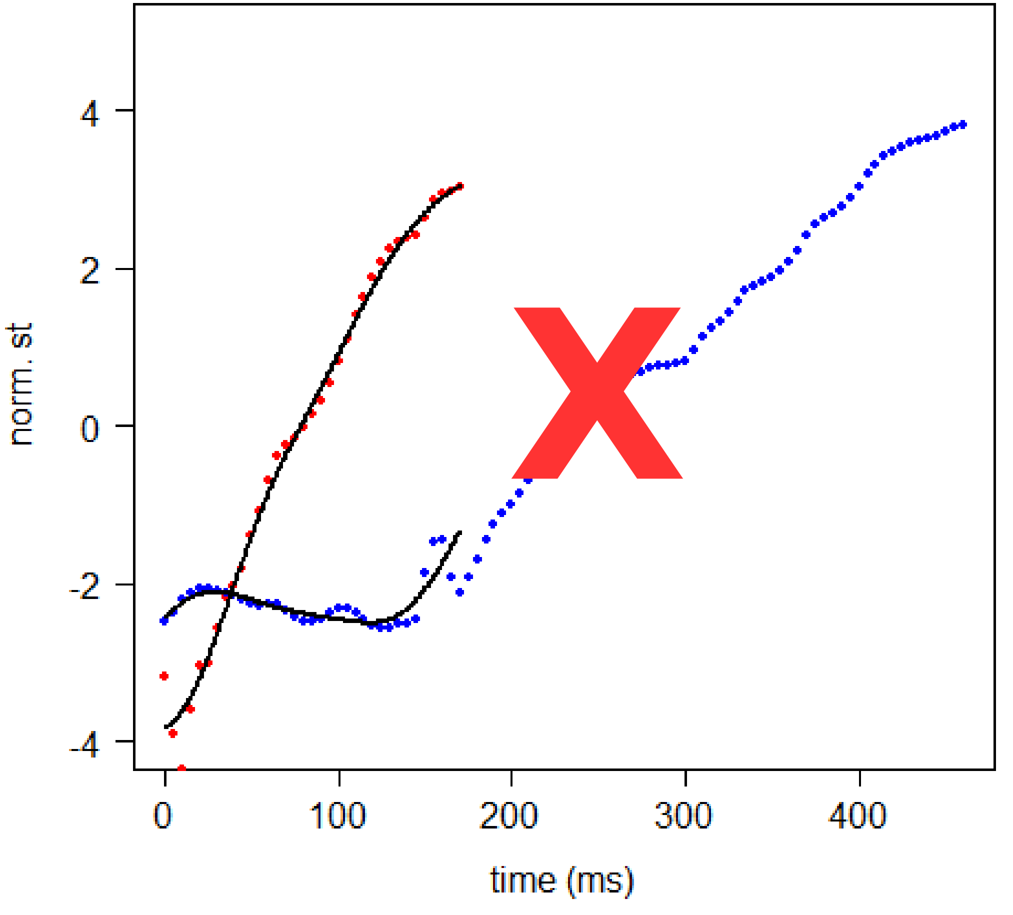


Extra slides

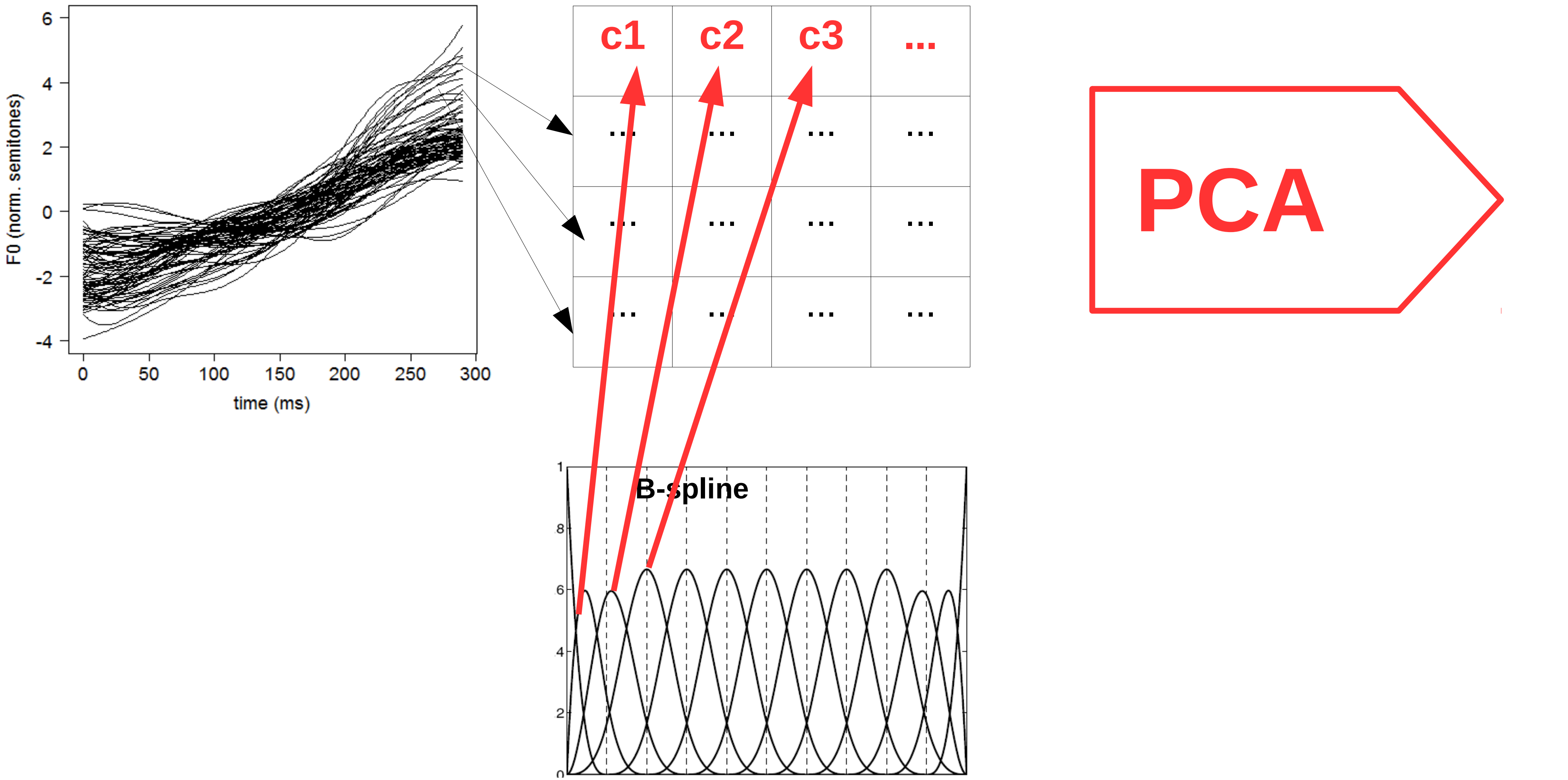
Take longest duration



Take shortest duration



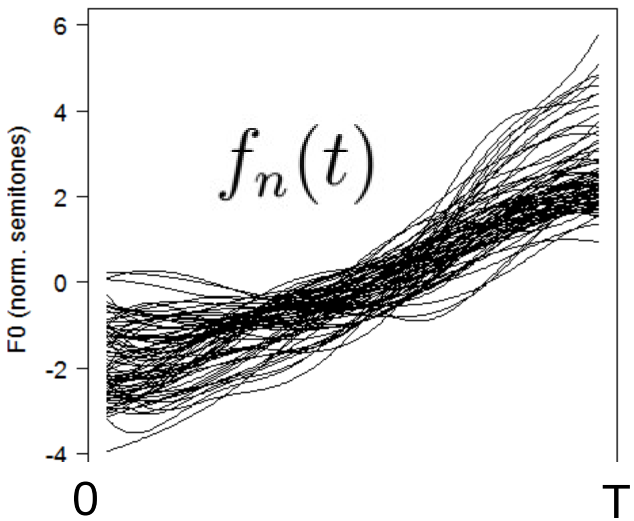
Principal Component Analysis



PCA limitations

- PCA does not use any explicit information related to the curve shapes or the B-splines shapes
- e.g. the sequence of coefficients c1, c2,.. reflects time adjacency of polynomial components, i.e. overlapping 'hills'

Functional PCA



$$\max\left\{ var_n \left(\int_0^T PC1(t) f_n(t)\,dt \right) \right\}$$

$$\text{subject to } \int_0^T PC1^2(t) = 1$$

- FPCA definition uses the input curves $f_n(t)$
- FPCA is independent of the B-splines used to smooth $f_n(t)$