Example of applying GAM: Articulography

Martijn Wieling and Jacolien van Rij

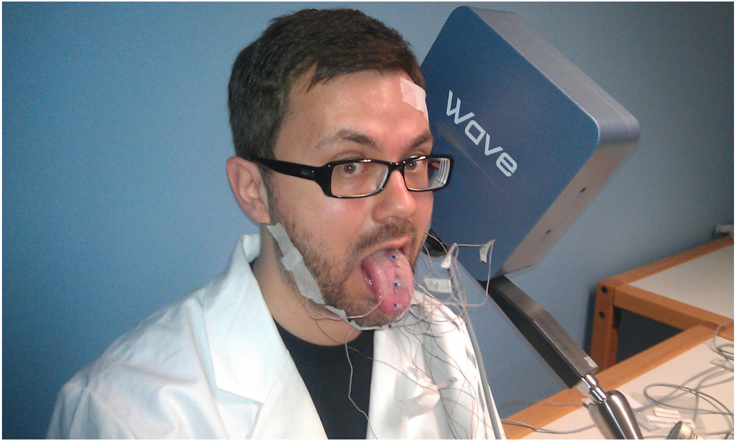
University of Groningen/Tübingen

LSA Institute 2015, Chicago, July 7

This lecture

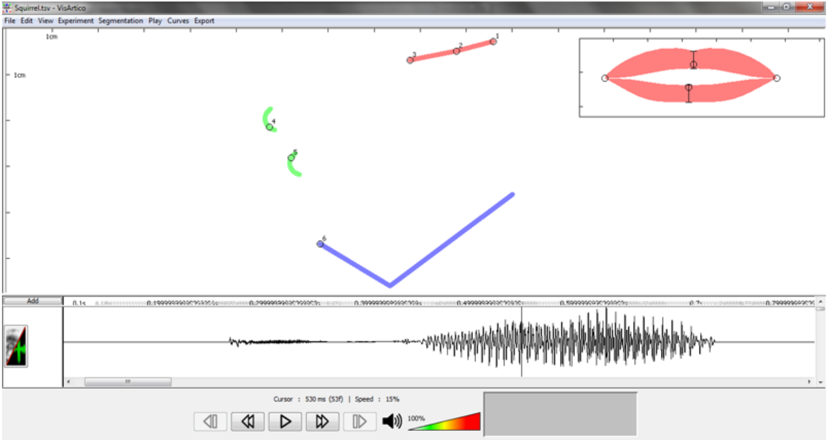
- Introduction
  - Articulography
  - Using articulography to study L2 pronunciation differences
- Design
- Methods: R code
- Results
- Discussion

Articulography



Obtaining data

Recorded data



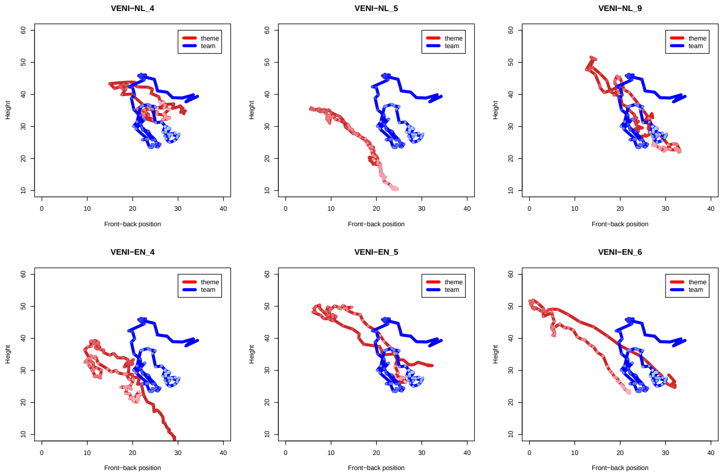
Study setup: differences between native and non-native English

- 19 native Dutch speakers from Groningen
- 22 native Southern Standard British English speakers from London
- Material:
  - 10 minimal pairs [t]:[θ] repeated twice:
    - 'fate'-'faith', 'forth'-'fort', 'kit'-'kith', 'mitt'-'myth', 'tent'-'tenth'
    - 'tank'-'thank', 'team'-'theme', 'tick'-'thick', 'ties'-'thighs', 'tongs'-'thongs'
    - Note that the sound [θ] does not exist in the Dutch language
    - The pronunciation of the words was preceded and followed by /ə/
- Goal: compare distinctions between both sound contrasts for both groups

Data overview

```
> load('art.rda')

> head(art)

Word          Axis  Sensor Participant    RecBlock
@_faith_@     X     TB     VENI-EN_1       6
@_faith_@     X     TB     VENI-EN_1       6
@_faith_@     X     TB     VENI-EN_1       6
@_faith_@     X     TB     VENI-EN_1       6
@_faith_@     X     TB     VENI-EN_1       6
@_faith_@     X     TB     VENI-EN_1       6

Time.normWord  SeqNr   Position.norm Sound Group
0.002777711    21      84.22126      TH    EN
0.010648939    21      84.40235      TH    EN
0.018520166    21      84.30614      TH    EN
0.026391394    21      84.23431      TH    EN
0.034262621    21      84.19509      TH    EN
0.042133849    21      83.93635      TH    EN

> dim(art)
[1] 342850     10
```

Much individual variation and noisy data



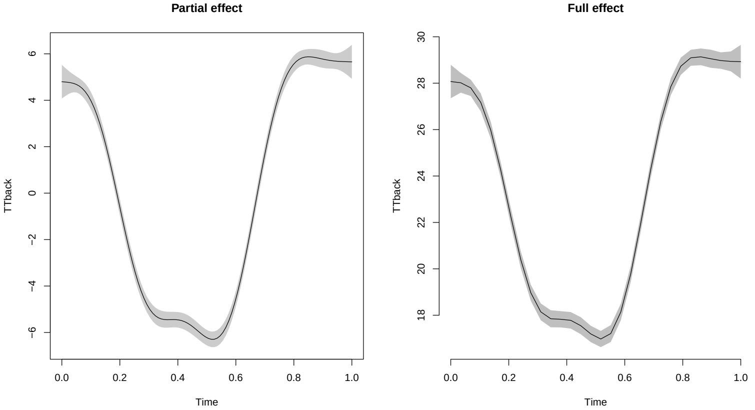
A first model: tongue backness for *theme* and *team*

```
> library(mgcv) # GAM package, version 1.8.6
> library(itsadug) # plotting package, version 0.93
> tm = art[art$Word %in% c('@_theme_@','@_team_@') & art$Sensor == 'TT' &
           art$Axis == 'X',]
> tm$TTback = tm$Position
> m0 = bam(TTback ~ s(Time), data = tm)
> summary(m0)

Family: gaussian
Link function: identity

Formula:
TTback ~ s(Time)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 23.27250    0.06208   374.9   <2e-16 ***

Approximate significance of smooth terms:
          edf Ref.df     F p-value
s(Time) 8.732  8.979 649.7  <2e-16 ***

R-sq.(adj) =   0.24   Deviance explained = 24.1%
fREML =  65527  Scale est. = 71.078    n = 18448
```

Visualizing the non-linear time pattern of the model

(Interpreting GAM results **always** involves visualization)

```
> par(mfrow=c(1,2)) # 2 plots in one window
> plot(m0, rug=F, shade=T, main='Partial effect', ylab='TTback')
> plot_smooth(m0, view='Time', rug=F, main='Full effect')
```



Check for additional wigglyness

(if p-value is low and edf close to k')

```
> gam.check(m0)

Method: fREML   Optimizer: perf newton
full convergence after 10 iterations.
Gradient range [-9.676733e-06,8.869831e-06]
(score 65527.35 & scale 71.07836).
Hessian positive definite, eigenvalue range [3.770432,9223.002].
Model rank =  10 / 10

Basis dimension (k) checking results. Low p-value (k-index<1) may
indicate that k is too low, especially if edf is close to k'.

           k'   edf k-index p-value
s(Time) 9.000 8.732   0.999    0.45
```

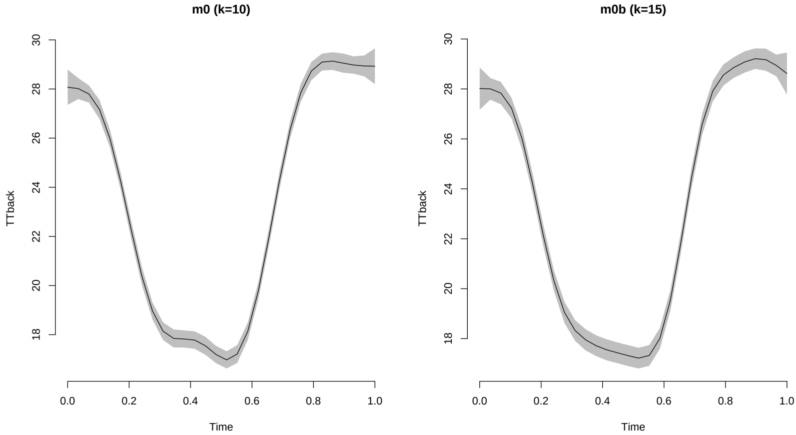
Increasing the wigglyness of a smooth with *k*

(double *k* if higher *k* is needed, but do not set it too high, i.e. max $\frac{1}{2} \times$ unique time points)

```
> m0b = bam(TTback ~ s(Time,k=15), data=tm) # 30 values => max(k)=15
> summary(m0b)

Family: gaussian
Link function: identity

Formula:
TTback ~ s(Time, k = 15)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 23.27236    0.06208   374.9   <2e-16 ***

Approximate significance of smooth terms:
          edf Ref.df     F p-value
s(Time) 11.93   13.3 439.2  <2e-16 *** # edf was 8.732

R-sq.(adj) =   0.24   Deviance explained = 24.1%
fREML =  65527  Scale est. = 71.058    n = 18448
```

Effect of increasing *k*

```
> par(mfrow=c(1,2)) # 2 plots in one window
> plot_smooth(m0, view='Time', rug=F, main='m0 (k=10)')
> plot_smooth(m0b, view='Time', rug=F, main='m0b (k=15)')
```



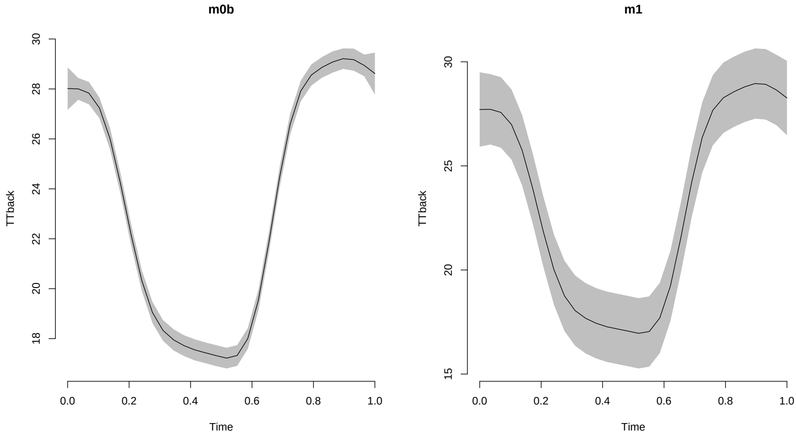
Taking into account individual variation

Mixed-effects regression: adding a random intercept

```
> m1 = bam(TTback ~ s(Time,k=15) + s(Participant,bs='re'), data=tm)
> summary(m1)

...
Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)  22.9974     0.8468   27.16   <2e-16 ***

Approximate significance of smooth terms:
edf Ref.df     F p-value
s(Time)        12.57  13.64 720.8  <2e-16 ***
s(Participant) 39.86  40.00 314.5  <2e-16 ***

R-sq.(adj) =  0.549   Deviance explained =   55% # was 24.1%
fREML =  60846  Scale est. = 42.238    n = 18448
```

Effect of including a random intercept

```
> par(mfrow=c(1,2)) # 2 plots in one window
> plot_smooth(m0b, view='Time', rug=F, main='m0b')
> plot_smooth(m1, view='Time', rug=F, main='m1', rm.ranef=T)
```



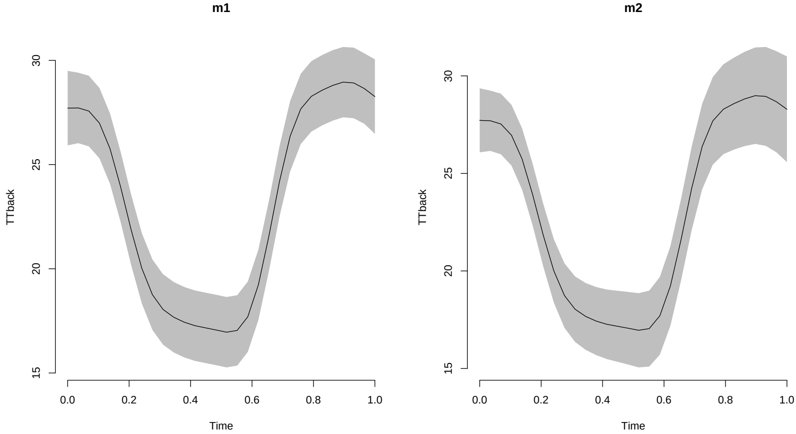
Taking into account individual variation

Mixed-effects regression: adding a random slope

```
> m2 = bam(TTback ~ s(Time,k=15) + s(Participant,bs='re') +
                    s(Participant,Time,bs='re'), data=tm)
> summary(m2)

...
Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  22.9984     0.9461   24.31   <2e-16 ***

Approximate significance of smooth terms:
                         edf Ref.df       F p-value
s(Time)                12.66  13.69   718.9  <2e-16 ***
s(Participant)         39.42  40.00 44340.0  <2e-16 ***
s(Participant,Time)    39.15  40.00 37387.2  <2e-16 ***

R-sq.(adj) =   0.59   Deviance explained = 59.2% # was 55%
fREML =  60043  Scale est. = 38.394    n = 18448
```

Effect of including a random slope

```
> par(mfrow=c(1,2)) # 2 plots in one window
> plot_smooth(m1, view='Time', rug=F, main='m1', rm.ranef=T)
> plot_smooth(m2, view='Time', rug=F, main='m2', rm.ranef=T)
```



Taking into account individual variation

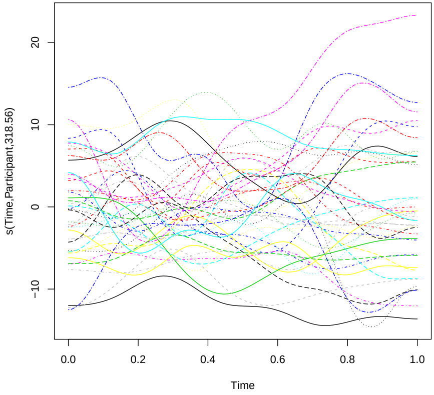
Adding a non-linear random effect

- The effect of time is non-linear and may vary non-linearly per subject
- We need a random intercept/slope which is non-linear
  - (instead of random intercept and random slope of time per subject)

```
> m3 = bam(TTback ~ s(Time,k=15) + s(Time,Participant,bs='fs',m=1), data=tm)
> summary(m3)

...
Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    23.05       1.16   19.86   <2e-16 ***

Approximate significance of smooth terms:
                      edf Ref.df     F p-value
s(Time)              12.4  13.34 28.55  <2e-16 ***
s(Time,Participant) 318.6 368.00 68.22  <2e-16 ***

R-sq.(adj) =  0.678   Deviance explained = 68.4% # was 59.2%
fREML =  58146  Scale est. = 30.087    n = 18448
```

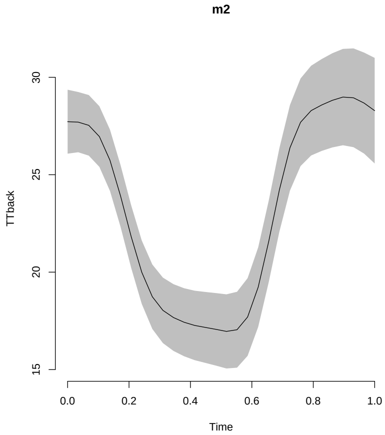
Visualization of individual variation

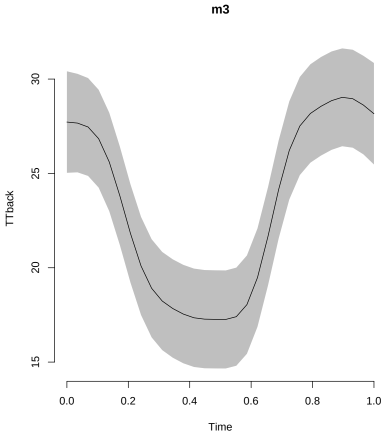
```
> plot(m3, select=2)
```



Effect of including a random non-linear effect

```
> par(mfrow=c(1,2))
> plot_smooth(m2, view='Time', rug=F, main='m2', rm.ranef=T)
> plot_smooth(m3, view='Time', rug=F, main='m3', rm.ranef=T)
```





Comparing *theme* and *team*

(smooths are centered, so the factorial predictor also needs to be included in the fixed effects)

```
> m4 = bam(TTback ~ s(Time,k=15,by=Word) + Word +
                    s(Time,Participant,bs='fs',m=1), data=tm)
> summary(m4)

...

Parametric coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     25.16649    1.16592   21.59   <2e-16 ***
Word@_theme_@   -4.18243    0.07096  -58.94   <2e-16 ***

Approximate significance of smooth terms:
                            edf Ref.df     F p-value
s(Time):Word@_team_@      11.81  13.04 19.27  <2e-16 ***
s(Time):Word@_theme_@     12.48  13.46 45.02  <2e-16 ***
s(Time,Participant)      327.48 368.00 89.87  <2e-16 ***

R-sq.(adj) =  0.755   Deviance explained = 75.9%
fREML =  55718  Scale est. = 22.948    n = 18448
```

- Does the correct-incorrect distinction improve the model?

Comparing *theme* and *team*

(smooths are centered, so the factorial predictor also needs to be included in the fixed effects)

```
> m4 = bam(TTback ~ s(Time,k=15,by=Word) + Word +
                    s(Time,Participant,bs='fs',m=1), data=tm)
> summary(m4)

...

Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   25.16649    1.16592   21.59   <2e-16 ***
Word@_theme_@ -4.18243    0.07096  -58.94   <2e-16 ***

Approximate significance of smooth terms:
                          edf Ref.df     F p-value
s(Time):Word@_team_@    11.81  13.04 19.27  <2e-16 ***
s(Time):Word@_theme_@   12.48  13.46 45.02  <2e-16 ***
s(Time,Participant)    327.48 368.00 89.87  <2e-16 ***

R-sq.(adj) =  0.755   Deviance explained = 75.9%
fREML =  55718  Scale est. = 22.948    n = 18448
```

- Does the correct-incorrect distinction improve the model?

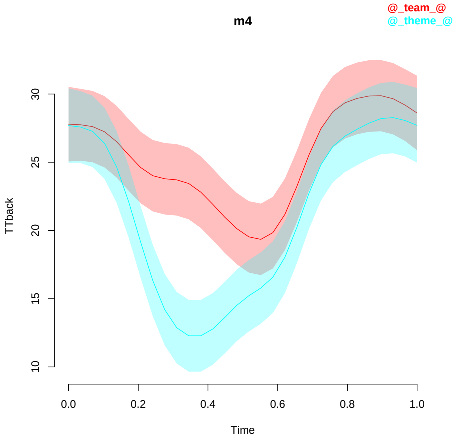
Assessing model improvement

```
> compareML(m3,m4)

m3: TTback ~ s(Time, k = 15) + s(Time, Participant, bs = "fs", m = 1)

m4: TTback ~ s(Time, k = 15, by = Word) + Word +
             s(Time, Participant, bs = "fs", m = 1)

Chi-square test of fREML scores
-----
  Model    Score Edf    Chisq    Df  p.value Sig.
1    m3 58145.79   5
2    m4 55718.06   8 2427.731 3.000  < 2e-16  ***

AIC difference: 4975.26, model m4 has lower AIC.
```

- Model `m4` is much better (AIC decrease > 2)!

Visualizing the two patterns

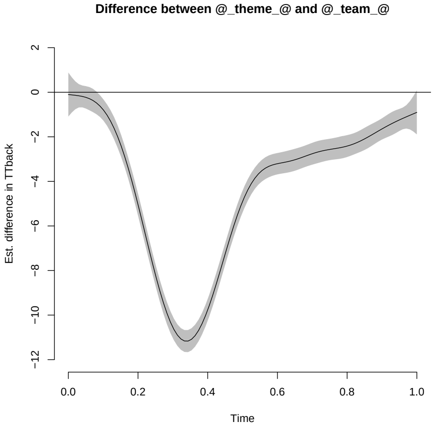
```
> plot_smooth(m4, view='Time', rug=F, plot_all='Word', main='m4',
              rm.ranef=T)
```



Visualizing the difference

(no individual variation w.r.t. the difference is taken into account: confidence bands **too** thin)

```
> plot_diff(m4, view='Time', comp=list(Word=c('@_theme_@','@_team_@')),
            ylim=c(-12,2), rm.ranef=T)
```

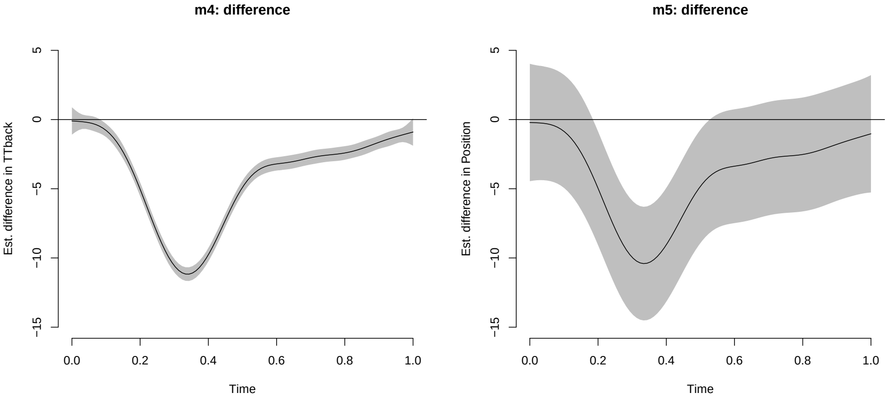


Including individual variation for *theme* vs. *team*

```
> tm$ParticipantWord = interaction(tm$Participant,tm$Word) # new factor
> m5 = bam(TTback ~ s(Time,k=15,by=Word) + Word +
                    s(Time,ParticipantWord,bs='fs',m=1), data=tm)
> summary(m5)

...
Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)    25.121      1.245  20.181   <2e-16 ***
Word@_theme_@  -4.098      1.761  -2.327     0.02 *

Approximate significance of smooth terms:
                           edf Ref.df     F p-value
s(Time):Word@_team_@     12.09  13.05 14.17  <2e-16 ***
s(Time):Word@_theme_@    12.76  13.45 30.61  <2e-16 ***
s(Time,ParticipantWord) 666.57 736.00 91.66  <2e-16 ***

R-sq.(adj) =  0.853   Deviance explained = 85.8% # was 75.9%
fREML =  51660  Scale est. = 13.759    n = 18448
```

More uncertainty in the difference

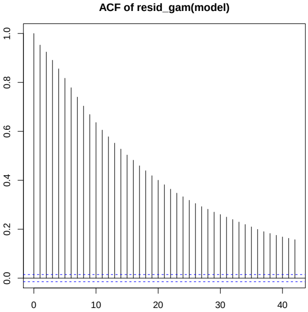
```
> par(mfrow=c(1,2))
> plot_diff(m4, view='Time', comp=list(Word=c('@_theme_@','@_team_@')),
            ylim=c(-15,5), main='m4: difference', rm.ranef=T)
> plot_diff(m5, view='Time', comp=list(Word=c('@_theme_@','@_team_@')),
            ylim=c(-15,5), main='m5: difference', rm.ranef=T)
```



Autocorrelation in the data is a problem!

(residuals should be independent, otherwise the standard errors and *p*-values are wrong)

```
# It is essential that the data is sorted per individual trajectory
> tm = start_event(tm, event=c("Participant","Word","RecBlock"))

> m5acf = acf_resid(m5) # show autocorrelation
> rhoval = m5acf[2]
> rhoval
[1] 0.9527261 # correlation of residuals at time t with those at time t-1
```

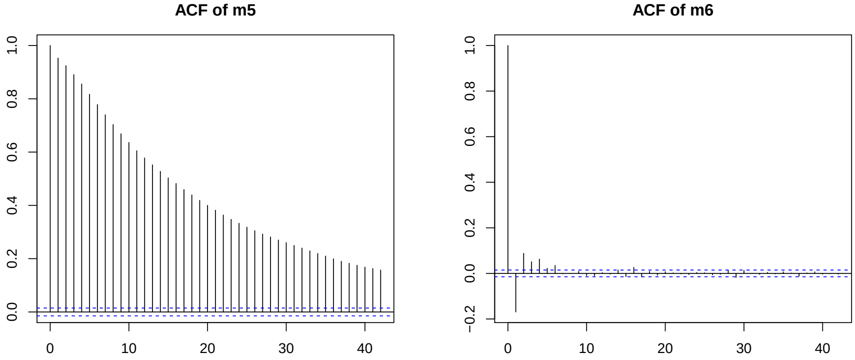


Correcting for autocorrelation

```
> m6 = bam(TTback ~ s(Time,k=15,by=Word) + Word +
                    s(Time,ParticipantWord,bs='fs',m=1), data=tm,
           rho=rhoval, AR.start=start.event)

> summary(m6)

...
Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)     25.193      1.167  21.595   <2e-16 ***
Word@_theme_@   -4.068      1.650  -2.465   0.0137 *

Approximate significance of smooth terms:
                          edf Ref.df     F p-value
s(Time):Word@_team_@     12.41  13.32 14.86  <2e-16 ***
s(Time):Word@_theme_@    12.95  13.59 32.27  <2e-16 ***
s(Time,ParticipantWord) 555.16 736.00  5.51  <2e-16 ***

R-sq.(adj) =  0.842   Deviance explained = 84.7%
fREML =  26710  Scale est. = 10.473    n = 18448
```

Autocorrelation has been removed

```
> par(mfrow=c(1,2))
> acf_resid(m5, main='ACF of m5')
> acf_resid(m6, main='ACF of m6')
```



Clear model improvement

```
> compareML(m5,m6)

m5: Position ~ s(Time, k = 15, by = Word) + Word +
               s(Time, ParticipantWord, bs = "fs", m = 1)

m6: Position ~ s(Time, k = 15, by = Word) + Word +
               s(Time, ParticipantWord, bs = "fs", m = 1)

Model m6 preferred: lower fREML score (24950.265), and equal df (0.000).
-----
  Model     Score Edf Difference    Df
     m5 51660.09   8
1    m6 26709.83   8 -24950.265 0.000

Warning message:
In compareML(m5, m6) :
   AIC is not reliable, because an AR1 model is included
   (rho1 = 0.000000, rho2 = 0.952726).
```

Distinguishing the two speaker groups

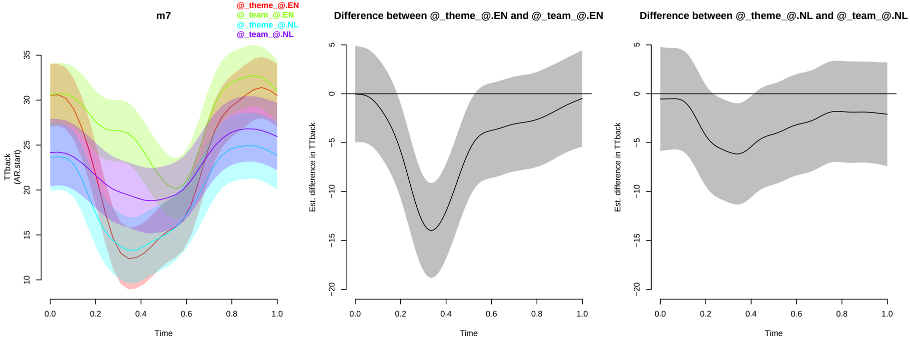
```
> tm$WordGroup = interaction(tm$Word,tm$Group)
> m7 = bam(TTback ~ s(Time,k=15,by=WordGroup) + WordGroup +
                     s(Time,ParticipantWord,bs='fs',m=1), data=tm,
           rho=rhoval, AR.start=start.event)
> summary(m7)

...
Parametric coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)             27.497      1.452  18.938  < 2e-16 ***
WordGroup@_theme_@.EN   -4.944      2.055  -2.406 0.016135 *
WordGroup@_team_@.NL    -4.896      2.132  -2.297 0.021640 *
WordGroup@_theme_@.NL   -7.987      2.134  -3.742 0.000183 ***

Approximate significance of smooth terms:
                                  edf Ref.df      F  p-value
s(Time):WordGroup@_team_@.EN   12.308  13.28 12.884  < 2e-16 ***
s(Time):WordGroup@_theme_@.EN  12.781  13.53 27.256  < 2e-16 ***
s(Time):WordGroup@_team_@.NL    9.026  10.75  4.531 9.89e-07 ***
s(Time):WordGroup@_theme_@.NL  11.365  12.69  9.777  < 2e-16 ***
s(Time,ParticipantWord)       535.302 734.00  4.789  < 2e-16 ***

R-sq.(adj) =  0.843   Deviance explained = 84.8%
```

The difference between EN and NL is necessary

```
> compareML(m6,m7)

m6: TTback ~ s(Time, k = 15, by = Word) + Word +
             s(Time, ParticipantWord, bs = "fs", m = 1)

m7: TTback ~ s(Time, k = 15, by = WordGroup) + WordGroup +
             s(Time, ParticipantWord, bs = "fs", m = 1)

Chi-square test of fREML scores
-----
  Model     Score Edf  Chisq     Df   p.value Sig.
     m6 26709.83   8
1    m7 26694.00  14 15.826 6.000 1.902e-05  ***

Warning message:
In compareML(m6, m7) :
   AIC is not reliable, because an AR1 model is included
   (rho1 = 0.952726, rho2 = 0.952726).
```

Visualizing the patterns

```
> plot_smooth(m7, view='Time', rug=F, plot_all='WordGroup', main='m7',
              rm.ranef=T)
> plot_diff(m7, view='Time', rm.ranef=T, ylim=c(-20,5),
            comp=list(WordGroup=c('@_theme_@.EN','@_team_@.EN')))
> plot_diff(m7, view='Time', rm.ranef=T, ylim=c(-20,5),
            comp=list(WordGroup=c('@_theme_@.NL','@_team_@.NL')))
```



The full tongue tip model: all words and both axes

(Word is now a random-effect factor, Sound distinguishes T from TH words)

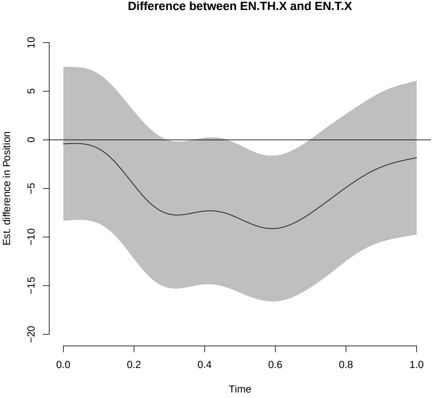
```
> tt = art[art$Sensor == 'TT',]
> tt$GroupSoundAxis = interaction(tt$Group,tt$Sound,tt$Axis)
> tt$WordGroupAxis = interaction(tt$Word,tt$Group,tt$Axis)
> tt$PartSoundAxis = interaction(tt$Participant,tt$Group,tt$Axis)
> tt = start_event(tt, event=c("Participant","Word","RecBlock","Axis"))

> model = bam(Position ~ s(Time,k=15,by=GroupSoundAxis) + GroupSoundAxis +
                         s(Time,PartSoundAxis,bs='fs',m=1) +
                         s(Time,WordGroupAxis,bs='fs',m=1), data=tt,
              rho=rhoval, AR.start=start.event)
```

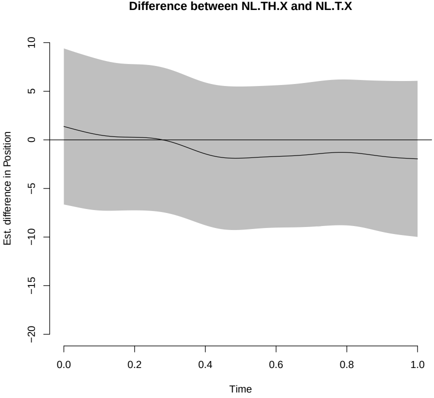
The full tongue tip model: all words and both axes

```
> summary(model)
...
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)                74.053      2.040  36.297  < 2e-16 ***
GroupSoundAxisNL.T.X       -3.191      2.932  -1.088 0.276508
GroupSoundAxisEN.TH.X      -4.333      2.902  -1.493 0.135410
GroupSoundAxisNL.TH.X      -1.742      2.745  -0.635 0.525590
GroupSoundAxisEN.T.Z      -12.419      2.926  -4.245 2.19e-05 ***
GroupSoundAxisNL.T.Z      -11.099      3.010  -3.688 0.000226 ***
GroupSoundAxisEN.TH.Z     -17.338      2.923  -5.932 2.99e-09 ***
GroupSoundAxisNL.TH.Z     -14.069      3.009  -4.676 2.93e-06 ***

Approximate significance of smooth terms:
                                    edf   Ref.df       F  p-value
s(Time.normWord):GpSdAxEN.T.X     7.059    7.310   3.566 0.000651 ***
s(Time.normWord):GpSdAxNL.T.X     5.703    6.022   0.985 0.433398
s(Time.normWord):GpSdAxEN.TH.X    7.686    7.883   6.689 1.23e-08 ***
s(Time.normWord):GpSdAxNL.TH.X    1.003    1.006   1.627 0.201799
s(Time.normWord):GpSdAxEN.T.Z     8.828    8.862 135.188  < 2e-16 ***
s(Time.normWord):GpSdAxNL.T.Z     8.483    8.576  38.591  < 2e-16 ***
s(Time.normWord):GpSdAxEN.TH.Z    8.657    8.722 117.599  < 2e-16 ***
s(Time.normWord):GpSdAxNL.TH.Z    8.429    8.530  40.308  < 2e-16 ***
s(Time.normWord,PartSoundAxis) 1276.029 1396.000  22.022  < 2e-16 ***
s(Time.normWord,WordGroupAxis)  618.503  712.000  58.318  < 2e-16 ***
```

A clear L1-based pattern

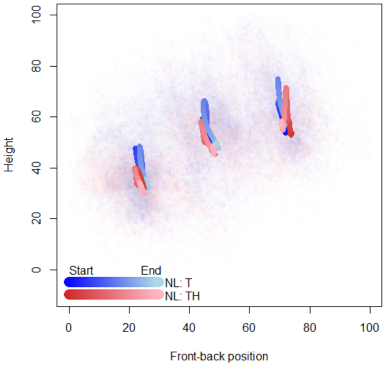
```
> par(mfrow=c(1,2))
> plot_diff(m8, view='Time', rm.ranef=T, ylim=c(-20,10),
          comp=list(GroupSoundAxis=c('EN.TH.X','EN.T.X')))
> plot_diff(m8, view='Time', rm.ranef=T, ylim=c(-20,10),
          comp=list(GroupSoundAxis=c('NL.TH.X','NL.T.X')))
```

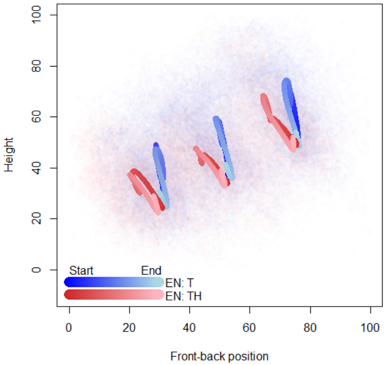




2D visualization

```
> source('plotArt2D.R')
> plotArt2D(m, catvar="GroupSoundAxis", catlevels.x=c("NL.T.X","NL.TH.X"),
            catlevels.y=c("NL.T.Z","NL.TH.Z"),collabels=c("NL: T","NL: TH"))
# repeated for models for TM and TB (with parameter add=T)
```





Discussion

- Native English speakers appear to make the /t/-/θ/ distinction, whereas Dutch L2 speakers of English generally do not
- Obviously, the model could be improved by separating minimal pairs into two categories (which?)

Recap

- We have applied GAMs to articulography data and learned how to:
  - use `s(Time)` to model a non-linearity over time
  - use the `k` parameter to control the ‘wigglyness’ of the non-linearity
  - use the plotting functions `plot_smooth` and `plot_diff`
  - use the parameter setting `bs="re"` to add random intercepts and slopes
  - add non-linear random effects using `s(Time,...,bs="fs",m=1)`
  - use the `by`-parameter to obtain separate non-linearities
    - note that the factorial predictor used for the `by`-part needs to be included as fixed-effect factor as well!
  - use `compareML` to compare models

Thank you for your attention!