ERP analysis with generalized additive models

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September 26, 2011

Outline

1. **Introduction to generalized additive models**

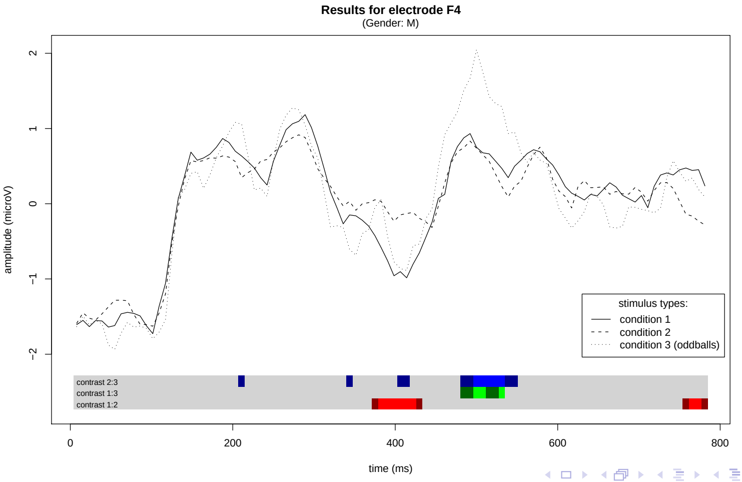
2. An application: prepositional phrases

Introduction to GAMs: introduction

- Central question: how to analyze ERPs in language processing studies?

Introduction to GAMs: introduction

- Traditional analyses:
  - dichotomize predictors
  - look at ERPs in a piecemeal fashion



Introduction to GAMs: introduction

- Problems:
  - dichotomizing predictors can mask non-linear effects in the predictor dimension
  - piecemeal analysis over time can mask or obscure non-linear effects in the time dimension

Introduction to GAMs: GAMs

- Proposed analysis method: generalized additive models (Hastie & Tibshirani, 1986; Wood, 2006)
- GAMs are a non-linear extension of simple regression models
- GAM structure:

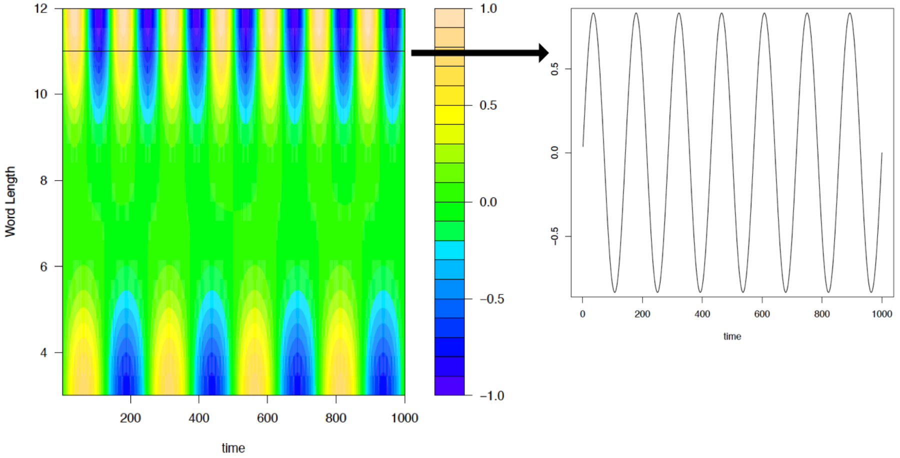
$$y = X\beta + f_i(x_1, x_2, \ldots, x_n) + \ldots + \varepsilon$$

- f_i are smooth functions without any predefined structure
- x_1 to x_n are covariates
- GAMs are capable of capturing non-linearities in both the time and predictor dimension

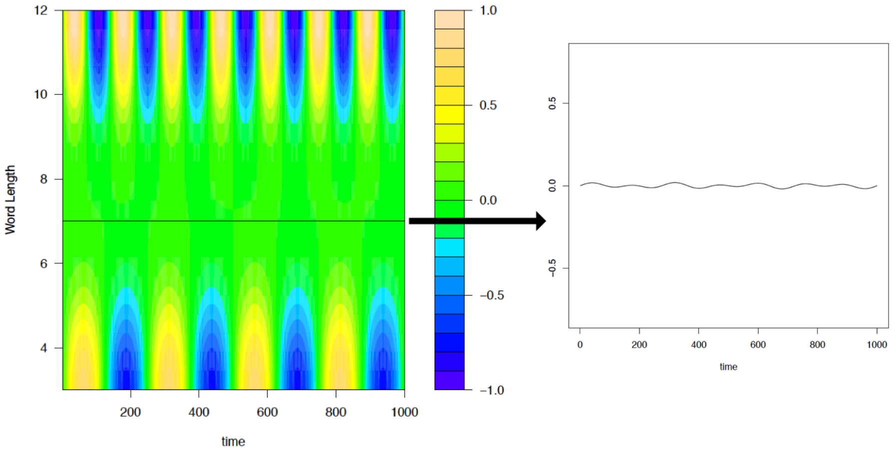
Introduction to GAMs: an example

- A simulation example: an oscillatory effect of Word Length over time (0-1000 ms)
- Word Length: a numerical variable that ranges from 3 to 12
- Low values of Word Length: oscillatory activity at 4 Hz
- High values of Word Length: oscillatory activity at 7 Hz

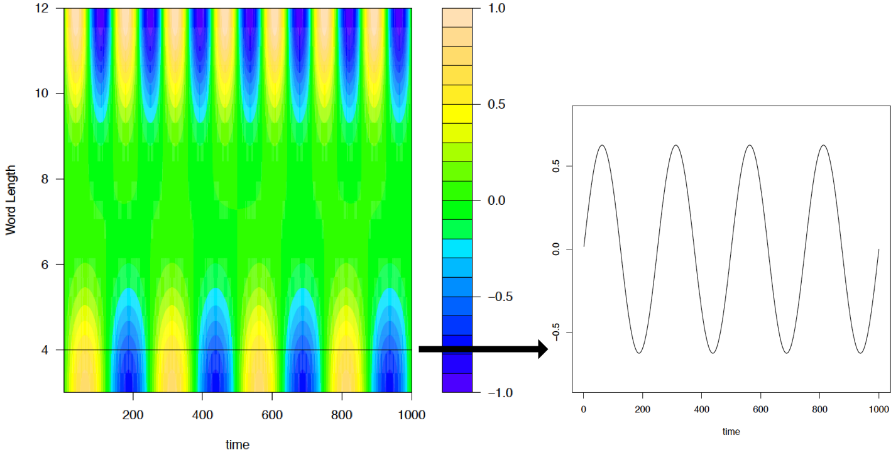
Introduction to GAMs: an example



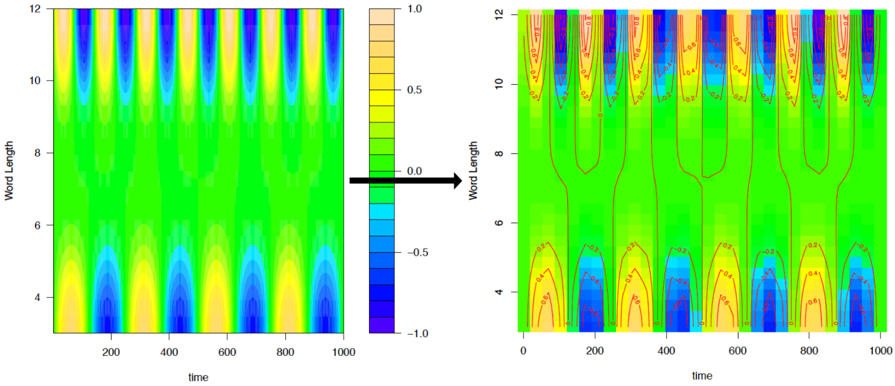
Introduction to GAMs: an example



Introduction to GAMs: an example



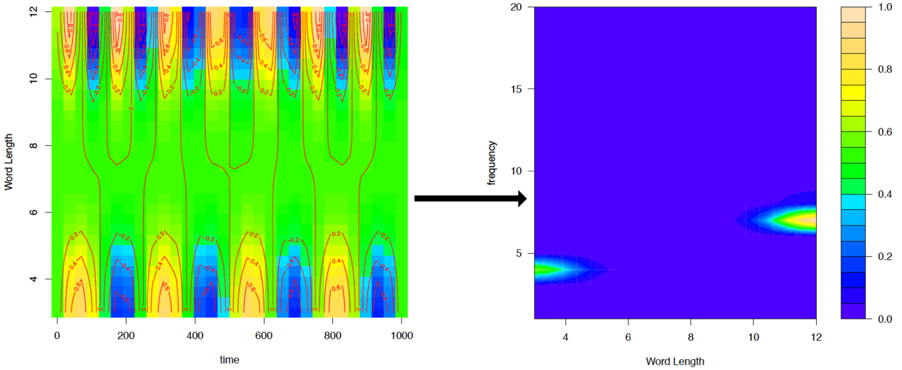
Introduction to GAMs: an example



Introduction to GAMs: an example

- The nature of oscillations is not always easily interpretable in the time domain
- To overcome this a discrete Fourier transform (DFT) can be used
- A DFT transforms the signal from the time domain to the frequency domain

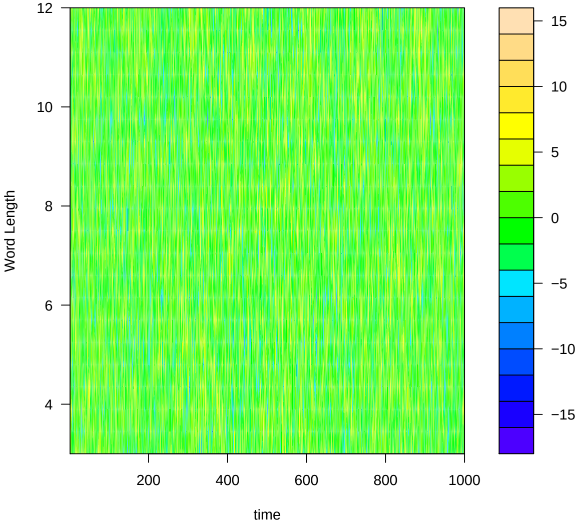
Introduction to GAMs: an example



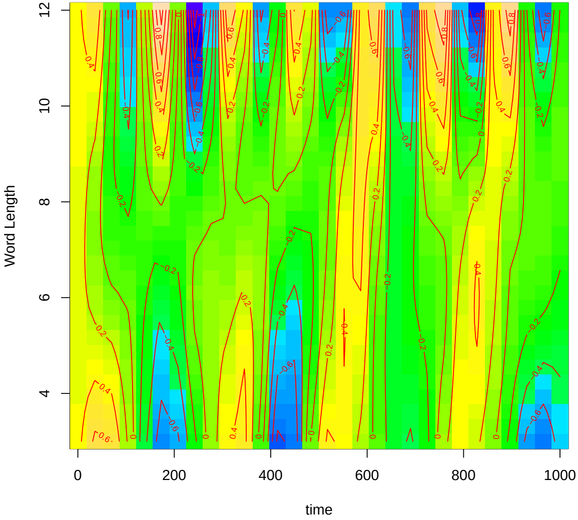
Introduction to GAMs: an example

- Real-life signals are not as clean as the oscillations in the previous simulation
- How do GAMs perform with extremely noisy signals?

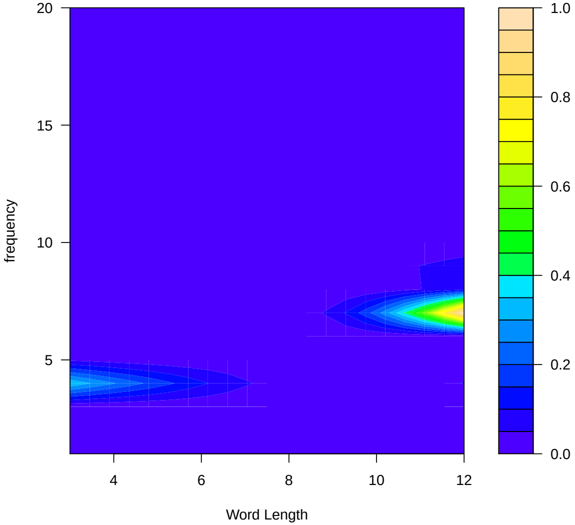
Introduction to GAMs: an example



Introduction to GAMs: introduction



Introduction to GAMs: introduction



Introduction to GAMs: introduction

- GAMs are capable of capturing non-linearities in two dimensions
- GAMs perform well with noisy signals

Outline

1. Introduction to generalized additive models

2. An application: prepositional phrases

Prepositional phrases: introduction

- Experimental items:
  - Primes: preposition + definite article (e.g.; “in the”, “above the”)
  - Targets: photographs of nouns (e.g.; STRAWBERRY, SAW)
- Task: picture naming

Prepositional phrases: example item

+

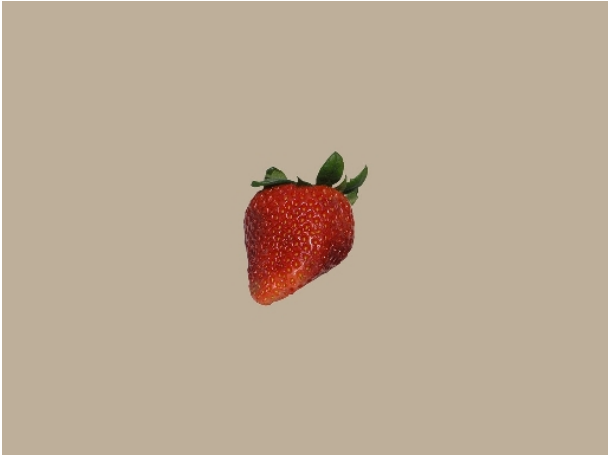
Prepositional phrases: example item

on the

Prepositional phrases: example item

+

Prepositional phrases: example item



Prepositional phrases: example item

+

Prepositional phrases: example item

in the

Prepositional phrases: example item

+

Prepositional phrases: example item

Prepositional phrases: experimental questions

Two experimental questions:

1. What is the nature of phrase frequency effects?
2. Do we find a prototypicality effect for prepositional phrases?

Prepositional phrases: question 1

- What is the nature of phrase frequency effects?

Prepositional phrases: question 1

- Phrasal decision latencies are shorter for high frequency phrases than for low frequency phrases
- The nature of this effect is unclear
- Hypothesis 1: whole phrase storage
  Under this hypothesis similar ERP signatures for word and phrase frequency effects are expected
- Hypothesis 2: decomposition
  Under this hypothesis qualitatively different ERP signatures for word and phrase frequency effects are expected

Prepositional phrases: question 1

- Three predictors:
  1. Preposition frequency
  2. Word frequency
  3. Phrase frequency
- All frequencies were derived from the Google 1T n-gram data
- Phrases were selected at the quantiles of the phrase frequency distribution for a given noun
- Example for “saw”:
  - “into the saw” (frequency: 2061, 25% of phrase frequency distribution)
  - “from the saw” (5358, 50 % of ...)
  - “to the saw” (9781, 75% of ...)
  - “with the saw” (20464, 100% of...)
- Number of phrases: 272

Prepositional phrases: question 1

- All frequencies were log-transformed to remove right-ward skew
- Phrase frequency was decorrelated from word and preposition frequency and did not correlate significantly with component bigram frequencies

Prepositional phrases: question 2

- Do we find a prototypicality effect for prepositional phrases?

Prepositional phrases: question 2

- Effects of prototypicality have been documented at the word level
- We used the Relative Entropy measure to find out if there is a similar prototypicality effect for prepositional phrases
- Relative Entropy indicates how similar the distribution of prepositional phrase frequencies for a given noun is to the distribution of preposition frequencies in the language as a whole

Prepositional phrases: question 2

- Given estimated probabilities p (relative frequencies) of prepositional phrases for a given noun and estimated probabilities q (relative frequencies) of prepositions across all nouns, relative entropy is defined as

$$\text{Relative Entropy} = \sum_{i=1}^{n} (p_i * \log_2 (p_i / q_i))$$

  where n is the number of prepositions in the language
- Values for Relative Entropy are low for nouns with prototypical prepositional phrase frequency distributions and high for nouns with non-prototypical prepositional phrase frequency distributions
- Relative Entropy was decorrelated from word and phrase frequency

Prepositional phrases: experiment setup

- Participants: 30 right-handed native speakers of English (mean age: 20.4)
- ERPs recorded at 32 electrodes (international 10/20 system)
- Preprocessing:
  - downsampling (to 256 Hz)
  - band-pass filter (0.5 to 50 Hz)
  - baseline correction (-200 to 0 ms interval)
  - re-referencing to the average of the left and right mastoids
  - eye-movement and eye-blink correction

Prepositional phrases: pre-analysis

- 12 items corresponding to 3 problematic photographs were excluded from the data
- Incorrect naming responses were removed from the data (7.61%)

Prepositional phrases: analysis

- Analysis method: two stratum hierarchical generalized additive models (GAMs)
- Stratum 1: a GAM modeling the main trend over time as well as the effects of Trial, Participant and Item
- Stratum 2: predictor GAMs on the residuals of the stratum 1 model to look at the effect of predictors over time

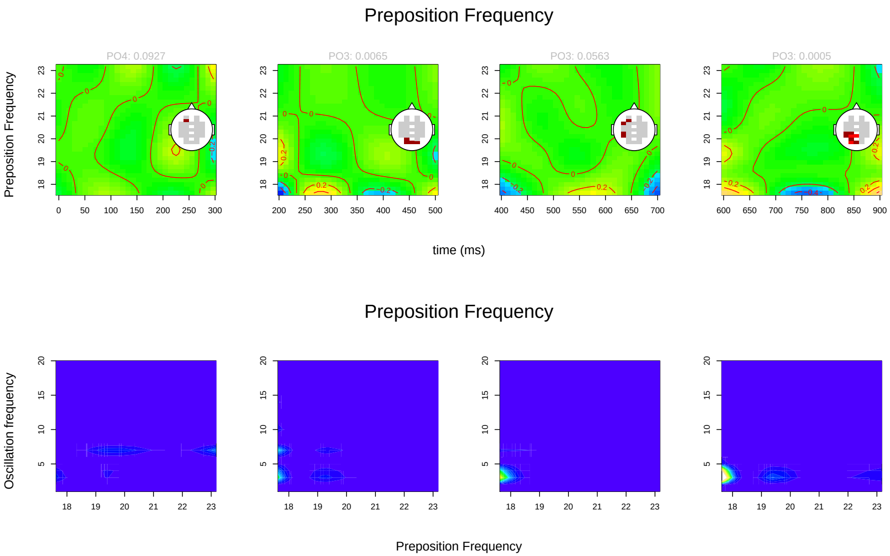
Prepositional phrases: analysis

- GAM models were fitted on 300 ms time windows for computational reasons
  - Time windows: 0-300, 200-500, 400-700 and 600-900 ms
  - 100 ms overlap between time windows to verify consistency of results
- Bonferroni-corrected significance level of 0.0004 (32 electrodes, 4 epochs)

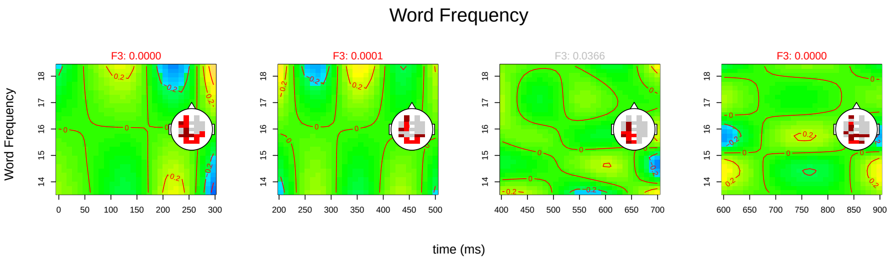
Prepositional phrases: results

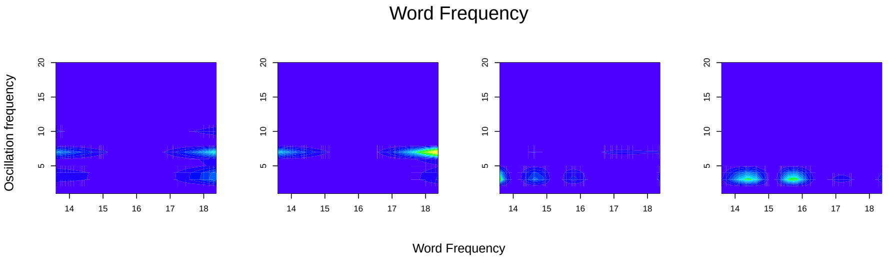
- What is the nature of phrase frequency effects?
- Hypothesis 1: whole phrase storage
  Similar ERP signatures for word and phrase frequency effects are expected
- Hypothesis 2: decomposition
  Different ERP signatures for word and phrase frequency effects are expected

Prepositional phrases: results

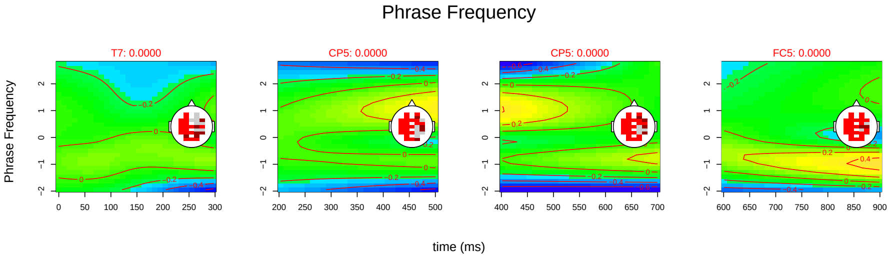


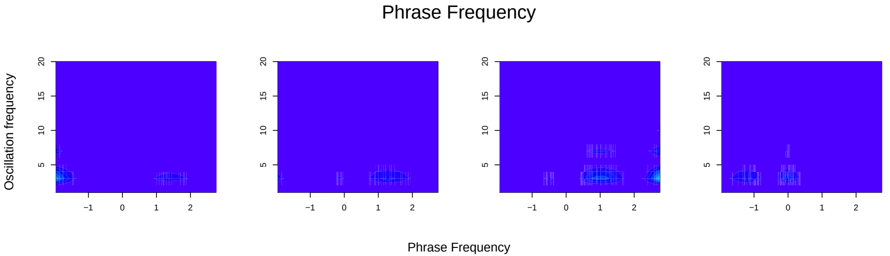
Prepositional phrases: results





Prepositional phrases: results





Prepositional phrases: results

- The ERP signatures for preposition and word frequency are characterized by theta range oscillations
- The ERP signature for phrase frequency shows an inverse U-shaped effect that persists over time
- This suggests distinct cognitive mechanisms underlie the effects for word frequency and phrase frequency

Prepositional phrases: results

- These results do not fit well with an explanation of phrase frequency effects in terms of whole phrase representations
- The results fit more readily with a decompositional view
- An example of such a model is the Naive Discriminative Reader (NDR) model

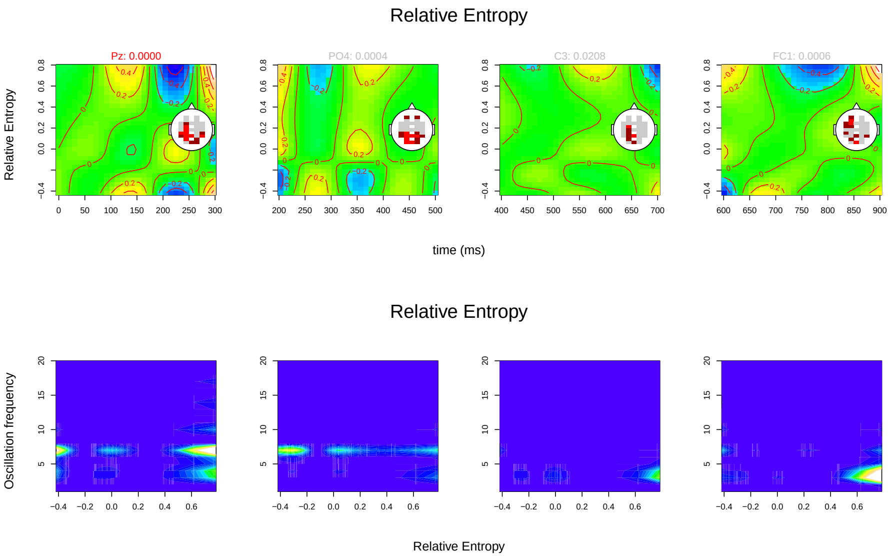
Prepositional phrases: results

- The NDR is a full decomposition model that directly maps orthographic input features onto meanings, without positing representations for morphemes, complex words or phrases
- Nonetheless, the NDR correctly simulates the whole phrase frequency effects reported in the lexical decision literature
- In the NDR phrase frequency effects emerge as a result of integration over decomposed meanings

Prepositional phrases: results

- Do we find a prototypicality effect for prepositional phrases?

Prepositional phrases: results



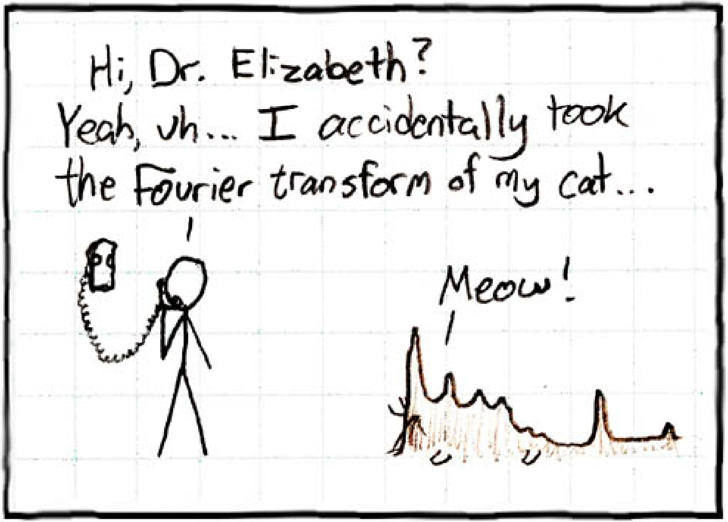
Prepositional phrases: results

- The ERP signature for Relative Entropy shows theta range oscillations related to prepositional phrase prototypicality
- Two qualitatively different processes seem to be at work:
  1. An early posterior effect
  2. A late left-anterior effect
- The early effect may be related to lexical access, whereas the later effect could reflect a higher level evaluation process

Summary

- GAMs provide an analysis method that retains the richness of information in ERP signals
- GAMs reliably capture non-linearities in both the time and the predictor dimension
- GAMs perform well with noisy signals

Summary



Hi, Dr. Elizabeth?
Yeah, uh... I accidentally took the Fourier transform of my cat...
Meow!