Phoneme Serialisation in Speech Production

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ACTION!!!

NOT

TIONCASH!!!
Serial Order in Speech

- Common Task Demands:
  - System designed to recall a sequence of words
  - System designed to recall a sequence of sounds or phonemes

- Speech
  - the human brain is required to complete both tasks:
    - sequencing phonemes in order to form word
    - sequencing words in order to form coherent sentences

- Romani (Dec 2010)
  - Parsimonious argument
    - Same mechanisms underlie both operations.
Short Term Memory Solutions

- Substantial literature investigating our ability to recall word series from short term memory (STM)
  - Henson 1998

- Relatively little is known about mechanisms underlying ability to recall and order phonemes in word production

- Aim:
  - Use solutions to the problem of serial order within the phonological short term memory literature, to assess evidence for the presence of similar mechanisms in the sequencing of phonemes within word production.
Error Patterns

- Powerful means by which models can be assessed
  - (Glasspool, 1998; Glasspool & Houghton, 2005)
  - Intuitive that accurate model should provide error patterns that fit experimental data

- However:
  - control groups do not produce errors when performing familiar word repetition tasks

- Romani (2010):
  - Aphasic patients do provide error patterns in such tasks
Candidate Models

- Three distinct solutions (Henson, 1998)
  - Chaining
  - Ordinal
  - Positional

- Compare the strength of evidence within aphasic phonological error data, in support of underlying chaining and positional based mechanisms
  - Information Theoretic approach (Burnham & Anderson, 1998)
Formalisation

- **Constraints:**
  - $P(X) =$ probability of the next phoneme $(x)$ in sequence being correct
  - Covariates limited to values derived from patient data found in Romani et al (2010)
  - Representative of the assigned theoretical perspective
  - Parameters are limited to minimally sufficient set
Simple Chaining

- Chaining
  - Simple & intuitive solution
  - Influential in earlier literature
  - Largely unsuccessful in modelling serial recall (Henson 1998).
Simple Chaining

\[ P(X) = \beta_1(x_1) + \beta_2(x_1 \cdot x_2) \]

where:

- \( x_1 = \) binary value representing successful production of previous phoneme
- \( x_2 = \) binary value indicating initial phoneme
- \( x_3 = \) word frequency taken from Barcelona corpus, 1998.
Compound Chaining

- **Cue:**
  - Association between element and preceding elements
- Avoids recovery limitations of simple chaining
- Limited success in modelling serial recall
  - (Baddeley, 1996; Henson, 1996).
Compound Chaining

\[ P(X) = \beta_1 \sum_{i=1}^{n} \left( \frac{x_{1,i}}{1 + x_{2,i} \beta_2} \right) + \beta_3(x_3) + \beta_4(x_4) \]

where:

\( n = \text{position within word of previously produced phoneme} \)
\( x_1 = \text{value representing production of correct phoneme at position } i \)
\( x_2 = \text{distance of phoneme } i \text{ from current position} \)
\( x_3 = \text{binary value indicating initial phoneme} \)
\( x_4 = \text{word frequency taken from Barcelona corpus, 1998} \).
Positional

- Capture key characteristics of serial recall
- Positional mechanism + competitive queuing framework
  - Common to group of models with success in modelling experimental data across multiple domains
  - (Glasspool et al, 2005).
Positional

\[ P(X) = \beta_1 \left( \frac{x_1}{1 + x_2 \beta_2} \right) + \beta_3 \left( \frac{1}{1 + x_3 \beta_4} \right) + \beta_5 \left( \frac{1}{1 + x_4 \beta_6} \right) + \beta_7(x_5) \]

where:

- \( x_1 \) = phoneme of same type previously displayed within response
- \( x_2 \) = distance from current position to previous occurrences of phoneme in response
- \( x_3 \) = distance from first phoneme
- \( x_4 \) = distance from final phoneme
- \( x_5 \) = word frequency taken from Barcelona corpus, 1998.
Fitting

- Exponent relationships
  - required to capture defining characteristics of theoretical perspectives

- Log Likelihood function Maximised

- optimisation algorithm:
  - variant of a simulated annealing (Belisle, 1992)

- Likelihood = response - model output

  - Model output = probability of the next phoneme in sequence being correct

  - Response = phoneme in sequence correctly produced
Patient Data

- Romani et al (2010)
  - All patients were Italian speaking
  - Selected for study due to phonological errors made in speech production.
    - articulatory planning difficulties (apraxia)
    - difficulty retrieving phonological representations (phonological),
  - Word repetition task.
    - Response:
      - successfully produced (1) = match target
      - unsuccessfully produced (0).
Artificial Data

- Models assessed on their ability to identify the underlying mechanism used to produce artificially generated data.

- Three artificial data sets produced using a Monte Carlo method
  - Simple Chaining, Compound Chaining & Positional

- Akaike’s Information Criteria:
  - selects ‘best’ model irrespective of the quality of the models with candidate set

- Can models produce distinct data sets?

- Can Information Theoretic approach correctly identify underlying mechanism?
Selection

- Information Theoretic approach

- Burnham & Anderson (1998)

- Allows models to be ranked according to AIC

  - An estimate of the fitted model’s expected distance from the unknown true mechanism that underlies the observed data

  - Effective measure when models are not hierarchically related
Results

Results of fitting models to patient data are not currently available
Table 1: Regression coefficients for models fit to artificial data sets

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Model</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>( \beta_5 )</th>
<th>( \beta_6 )</th>
<th>( \beta_7 )</th>
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</thead>
<tbody>
<tr>
<td>Basic Chaining</td>
<td>True*</td>
<td>0.300</td>
<td>0.000</td>
<td>0.070</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>Basic Chaining</td>
<td>0.305</td>
<td>-0.095</td>
<td>0.069</td>
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<tr>
<td></td>
<td>Compound Chaining</td>
<td>0.541</td>
<td>5.609</td>
<td>-0.068</td>
<td>0.072</td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td>Positional</td>
<td>-0.109</td>
<td>4.288</td>
<td>-0.065</td>
<td>2.733</td>
<td>0.024</td>
<td>2.600</td>
<td>0.097</td>
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<td>Compound Chaining</td>
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<td>0.300</td>
<td>2.000</td>
<td>0.000</td>
<td>0.070</td>
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<td></td>
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<tr>
<td></td>
<td>Basic Chaining</td>
<td>0.039</td>
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<td>0.089</td>
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<tr>
<td></td>
<td>Compound Chaining</td>
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<td>1.881</td>
<td>0.042</td>
<td>0.078</td>
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<td>Positional</td>
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<td>-0.090</td>
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<td>0.057</td>
<td>4.038</td>
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<td>2.000</td>
<td>0.270</td>
<td>2.000</td>
<td>0.070</td>
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<td>Compound Chaining</td>
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<td></td>
<td>Positional</td>
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<td>2.018</td>
<td>0.260</td>
<td>2.165</td>
<td>0.263</td>
<td>4.103</td>
<td>0.071</td>
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</tbody>
</table>

* ‘True’ indicates coefficients used in the creation of artificial data sets, they do not represent the true values for artificially created data sets due to the randomising procedures used in the data creation process.
Results

Table 2: Likelihood and AIC values for models fit to artificial data sets

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Model</th>
<th>Likelihood</th>
<th>K</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic Chaining</td>
<td>True*</td>
<td>-3025.597</td>
<td>3</td>
<td>6057.19</td>
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<td>Basic Chaining</td>
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<td>Compound Chaining</td>
<td>-3029.349</td>
<td>4</td>
<td>6066.7</td>
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<td>Positional (SEM)</td>
<td>-3267.722</td>
<td>7</td>
<td>6549.44</td>
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<td>Compound Chaining</td>
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<tr>
<td></td>
<td>Basic Chaining</td>
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<td>6900.7</td>
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<td></td>
<td>Compound Chaining</td>
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<td>Positional (SEM)</td>
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<td>Positional (SEM)</td>
<td>-3701.070</td>
<td>7</td>
<td>7416.14</td>
</tr>
</tbody>
</table>

* 'True' indicates coefficients used in the creation of artificial data sets, they do not represent the true values for artificially created data sets due to the randomising procedures used in the data creation process.
Results

Accuracy of phoneme production in relative word locations for models fit to artificial Basic Chaining data

![Graph showing the accuracy of phoneme production in relative word locations for models fit to artificial Basic Chaining data. The graph plots the probability of producing correct phoneme against the location of phoneme as a percentage of word length. The graph includes data for Artificial Data, Basic Chain, Comp Chain, and Positional models.]
Results

Accuracy of phoneme production in relative word locations for models fit to artificial Compound Chaining data
Results

Accuracy of phoneme production in relative word locations for models fit to artificial Positional data
Discussion

- Fitting models to artificial data:
  - Models based on positional and chaining processes are able to produce distinct data sets
  - Model fitting and selection process applied provides valid insight into the mechanisms that underlie data production
Discussion

‘Best’ model selected:

- Do models capture theoretical perspective
- Applying similar models and procedures to analyse STM data may provide an insightful means of assessing the quality of models defined in this study.
Discussion

- Improvements to fitting procedure:
  - Re-writing R scripts to exploit the most efficient functions and data structures within the language
  - Examining the true function to inform selection of initial parameters
  - Condense patient data, e.g. calculate probabilities for accuracy at each position within a word for each word length
  - Simplify models
Discussion

- Extend analysis to entire patient data set

- Inform our understanding of variation in the mechanisms underlying patient error both within and between patient categories.
Skills Developed

- Competence in formalisation
- Fit and evaluation of mathematical models
- Proficiency in the use of statistics program R to construct and analyse model performance
- Ability to interpret and evaluate model performance in the context of behavioural data and assess wider theoretical implications