

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

The effects of N-gram probabilistic measures on the recognition and production of four-word-sequences.

Eberhard Karls Universität Tübingen

Course: Frequency effects of multi-word sequences

Lecturer: Hendrix-Sun, June , Ph.D.

Student: Johannes Krämer

SS 2017

How to read the title?

Title interpretation

Methods

frequency
probability
MI

What to measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- Effects of [...] probabalistic measures [...]

How to read the title?

Title interpretation

Methods

frequency
probability
MI

What to measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- Effects of [...] probabalistic measures [...]
→ it's about the methods:

How to read the title?

Title interpretation

Methods

frequency
probability
MI

What to measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- Effects of [...] probabalistic measures [...]
 - it's about the methods:
 - how was it measured?
 - which probabalitic methods were used?
 - which are the best methods?

Which methods were used?

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

Methods = Predictors

- frequency of occurrence
- log probability of occurrence
- mutual information

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- frequency of occurrence

in more detail...

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- frequency of occurrence
- $$\frac{\text{freq} - \text{of} - \text{event}}{\text{all} - \text{possible} - \text{events}}$$

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- probability of occurrence

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- probability of occurrence
- $P(W_i | W_{i-2}, W_{i-1})$

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- probability of occurrence
- $P(W_i | W_{i-2}, W_{i-1})$
- what is more propable?
 - wit OR with
 - given that previous words are...

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- probability of occurrence
- $P(W_i | W_{i-2}, W_{i-1})$
- what is more propable?
 - wit OR with
 - given that previous words are...
 - I like pizza

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- probability of occurrence
- $P(W_i | W_{i-2}, W_{i-1})$
- what is more propable?
 - wit OR with
 - given that previous words are...
 - I like pizza

(this example is from Mr. Cöltekens SNLP Course)

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- probability of occurrence
- $P(W_i | W_{i-2}, W_{i-1})$
- what is more propable?
 - wit OR with
 - given that previous words are...
 - I like pizza

(this example is from Mr. Cöltekens SNLP Course)

- log is for scaling
 - fitting more on the same plot

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- mutual information

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- mutual information
- how much do we know about a fact given another fact
- correlation of variables

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- mutual information
- how much do we know about a fact given another fact
- correlation of variables
- $I(X; Y)$

in more detail...

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- mutual information
- how much do we know about a fact given another fact
- correlation of variables
- $I(X; Y)$
- how much do we now about the gender given the name of a person?

in more detail...

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- mutual information
- how much do we know about a fact given another fact
- correlation of variables
- $I(X; Y)$
- how much do we now about the gender given the name of a person?
- how much do we know about FreqAB given FreqA

What is measured?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- onset latency

What is measured?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- onset latency
- production duration

Why do such a experiment in the first place?

What inspired them?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- no one did it before

Why do such a experiment in the first place?

What inspired them?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- no one did it before
 - Baayen, Kuperman, Bertram (2010):
 - found interaction between measures of different linguistic units
- claim: multiple sources of linguistic information are processed in parallel

This study: Find out the following questions

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- whether freq., log prob., MI of 1-4grams affect onset latency and production duration

This study: Find out the following questions

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- whether freq., log prob., MI of 1-4grams affect onset latency and production duration
- Which is the better predictor for:
 - onset latency
 - production duration

This study: Find out the following questions

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- whether freq., log prob., MI of 1-4grams affect onset latency and production duration
- Which is the better predictor for:
 - onset latency
 - production duration
- Are there (linear) interactions between predictors?

Conclusion spoiler

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- MI not very predictive

Conclusion spoiler

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- MI not very predictive
 - leaves us with:
 - frequency of occurrence
 - log probability of occurrence

Conclusion spoiler

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- MI not very predictive
 - leaves us with:
 - frequency of occurrence
 - log probability of occurrence
- prob. measures up to 4-grams all interact with each other

Conclusion spoiler

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- MI not very predictive
 - leaves us with:
 - frequency of occurrence
 - log probability of occurrence
- prob. measures up to 4-grams all interact with each other
 - but how strong?
 - for which N-gram does it work best?
 - what does it mean if they interact?

Setup of the Experiment

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- participants:
 - 17 Students (10 female, 7 male)
 - University of Alberta
 - paid: yes

Setup of the Experiment

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- participants:
 - 17 Students (10 female, 7 male)
 - University of Alberta
 - paid: yes
- material:
 - extracted 112 most freq. 4grams from BNC (100 mio words)

Setup of the Experiment

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- participants:
 - 17 Students (10 female, 7 male)
 - University of Alberta
 - paid: yes
- material:
 - extracted 112 most freq. 4grams from BNC (100 mio words)
 - frequency: 12 - 117 per million words (?)

Setup of the Experiment

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- participants:
 - 17 Students (10 female, 7 male)
 - University of Alberta
 - paid: yes
- material:
 - extracted 112 most freq. 4grams from BNC (100 mio words)
 - frequency: 12 - 117 per million words (?)
 - random selection of 320 4grams:
 - frequency: 0.3 - 11 per million words

Setup of the Experiment

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- participants:
 - 17 Students (10 female, 7 male)
 - University of Alberta
 - paid: yes
- material:
 - extracted 112 most freq. 4grams from BNC (100 mio words)
 - frequency: 12 - 117 per million words (?)
 - random selection of 320 4grams:
 - frequency: 0.3 - 11 per million words
 - total: 432 4grams

Where did the data come from?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- most freq. items from BNC

Where did the data come from?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- most freq. items from BNC
- frequencies of the items taken from COCA
 - COCA = The Corpus of Contemporary American and English
 - COCA size: 385 mio. words

Where did the data come from?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- most freq. items from BNC
- frequencies of the items taken from COCA
 - COCA = The Corpus of Contemporary American and English
 - COCA size: 385 mio. words
- don't, you've, wasn't → one word
- data was randomized for every participant

What was the technological setup for the experiment?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- 4gram preceded by a fixation cross

What was the technological setup for the experiment?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- 4gram preceded by a fixation cross
- cross for 500ms → black screen 20ms → 4gram 1500ms

What was the technological setup for the experiment?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- 4gram preceded by a fixation cross
- cross for 500ms → black screen 20ms → 4gram 1500ms
- interstimulus 1000ms

What was the technological setup for the experiment?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- 4gram preceded by a fixation cross
- cross for 500ms → black screen 20ms → 4gram 1500ms
- interstimulus 1000ms
- read out loud aqap ;)

What was the technological setup for the experiment?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- 4gram preceded by a fixation cross
- cross for 500ms → black screen 20ms → 4gram 1500ms
- interstimulus 1000ms
- read out loud aqap ;)
- 2 possible breaks (most of the participants didn't make use of it)

What was the technological setup for the experiment?

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- 4gram preceded by a fixation cross
- cross for 500ms → black screen 20ms → 4gram 1500ms
- interstimulus 1000ms
- read out loud aqap ;)
- 2 possible breaks (most of the participants didn't make use of it)
- 2 microphones

What was the technological setup for the experiment?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- 4gram preceded by a fixation cross
- cross for 500ms → black screen 20ms → 4gram 1500ms
- interstimulus 1000ms
- read out loud aqap ;)
- 2 possible breaks (most of the participants didn't make use of it)
- 2 microphones
 - onset latency recording
 - speech recording

The problem of collinearity

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- W is our outcome

The problem of collinearity

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- W is our outcome
- X and Z are predictors

The problem of collinearity

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- W is our outcome
- X and Z are predictors
- if X, Z correlated \rightarrow can't tell whether W is due to X or to Z

The problem of collinearity

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- W is our outcome
- X and Z are predictors
- if X, Z correlated \rightarrow can't tell whether W is due to X or to Z
- draw on blackboard!

How to handle Collinearity?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- detect collinearity

How to handle Collinearity?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- detect collinearity
- reduce collinearity

How to handle Collinearity?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- detect collinearity
- reduce collinearity
 - centering

How to handle Collinearity?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- detect collinearity
- reduce collinearity
 - centering
 - residualization

Remove bad data points

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- total: 7344 data points (17×432)

Remove bad data points

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- total: 7344 data points (17×432)
- removed: $2251 = 30,7\%$

Remove bad data points

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- total: 7344 data points (17×432)
- removed: $2251 = 30,7\%$
- WHY?
 - 5 items had $p = 0$ in COCA \rightarrow 85 data points | $1,2\%$

Remove bad data points

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- total: 7344 data points (17×432)
- removed: $2251 = 30,7\%$
- WHY?
 - 5 items had $p = 0$ in COCA \rightarrow 85 data points | 1,2%
 - 1 Participant had too many errors \rightarrow 35 data points | 0.5%

Remove bad data points

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- total: 7344 data points (17×432)
- removed: $2251 = 30,7\%$
- WHY?
 - 5 items had $p = 0$ in COCA \rightarrow 85 data points | 1,2%
 - 1 Participant had too many errors \rightarrow 35 data points | 0.5%
 - not triggered sound \rightarrow 869 data points | 11,8%

Remove bad data points

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- total: 7344 data points (17×432)
- removed: $2251 = 30,7\%$
- WHY?
 - 5 items had $p = 0$ in COCA \rightarrow 85 data points | 1,2%
 - 1 Participant had too many errors \rightarrow 35 data points | 0.5%
 - not triggered sound \rightarrow 869 data points | 11,8%
 - research assistants removed \rightarrow 1258 data points | 17,1%

Other independent variables

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- trials 1-432

Other independent variables

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- trials 1-432
- Manner
 - stop
 - approximant
 - vowel
 - fricative
 - nasal

Other independent variables

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- trials 1-432
- Manner
 - stop
 - approximant
 - vowel
 - fricative
 - nasal
- NumSyll

Other independent variables

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- trials 1-432
- Manner
 - stop
 - approximant
 - vowel
 - fricative
 - nasal
- NumSyll
- PhraseABCD

Other independent variables

Title
interpretation

Methods

frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- trials 1-432
- Manner
 - stop
 - approximant
 - vowel
 - fricative
 - nasal
- NumSyll
- PhraseABCD
 - 117 phrase
 - 310 non-phrase

Interpretation of data

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- We will look together at the plots and figger out whats going on there.

Why does FreqB have such a big impact?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- B-gram appeared at position of fixation cross

Why does FreqB have such a big impact?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- B-gram appeared at position of fixation cross
- WordTypeB as influencer?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- look at the results together!

What do the two tables mean?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- onset latency \rightarrow log probability of occurrence

What do the two tables mean?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- onset latency \rightarrow log probability of occurrence
 \rightarrow 'recognition is mainly underpinned by a mechanism whereby a target N-gram competes with its family members'

What do the two tables mean?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- onset latency → log probability of occurrence
→ 'recognition is mainly underpinned by a mechanism whereby a target N-gram competes with its family members'
- production duration → frequency of occurrence (amount of experience)

What do the two tables mean?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- onset latency → log probability of occurrence
→ 'recognition is mainly underpinned by a mechanism whereby a target N-gram competes with its family members'
- production duration → frequency of occurrence (amount of experience)
- most important among: unigrams, bigrams, trigrams, quadgrams

What do the two tables mean?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- onset latency → log probability of occurrence
→ 'recognition is mainly underpinned by a mechanism whereby a target N-gram competes with its family members'
- production duration → frequency of occurrence (amount of experience)
- most important among: unigrams, bigrams, trigrams, quadgrams
 - onset latency?

What do the two tables mean?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

- onset latency → log probability of occurrence
→ 'recognition is mainly underpinned by a mechanism whereby a target N-gram competes with its family members'
- production duration → frequency of occurrence (amount of experience)
- most important among: unigrams, bigrams, trigrams, quadgrams
 - onset latency?
→ trigrams

What do the two tables mean?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- onset latency → log probability of occurrence
→ 'recognition is mainly underpinned by a mechanism whereby a target N-gram competes with its family members'
- production duration → frequency of occurrence (amount of experience)
- most important among: unigrams, bigrams, trigrams, quadgrams
 - onset latency?
→ trigrams
 - production duration?

What do the two tables mean?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- onset latency → log probability of occurrence
→ 'recognition is mainly underpinned by a mechanism whereby a target N-gram competes with its family members'
- production duration → frequency of occurrence (amount of experience)
- most important among: unigrams, bigrams, trigrams, quadgrams
 - onset latency?
→ trigrams
 - production duration?
→ unigrams

What do the two tables mean?

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots

FreqB

Conclusion

- onset latency → log probability of occurrence
→ 'recognition is mainly underpinned by a mechanism whereby a target N-gram competes with its family members'
- production duration → frequency of occurrence (amount of experience)
- most important among: unigrams, bigrams, trigrams, quadgrams
 - onset latency?
→ trigrams
 - production duration?
→ unigrams
- BUT they still interact → what does it mean?

The very conclusion

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

'Finally, the finding that probabilistic measures tied to N-grams up to four-words long **interacted** with each other in the onset latency and production duration analyses suggests that they are **processed in parallel** in both recognition and production.'

Reference:

Title
interpretation

Methods
frequency
probability
MI

What to
measure

Motivation

Goals

Spoiler

Experiment

Data

Technics

Problems

Collinearity

Noisy data

more var

Plots
FreqB

Conclusion

Antoine Tremblay and Benjamin V. Tucker. 'The effects of N-gram probabilistic measures on the recognition and production of four-word sequences.' IWK Health Center / University of Alberta.