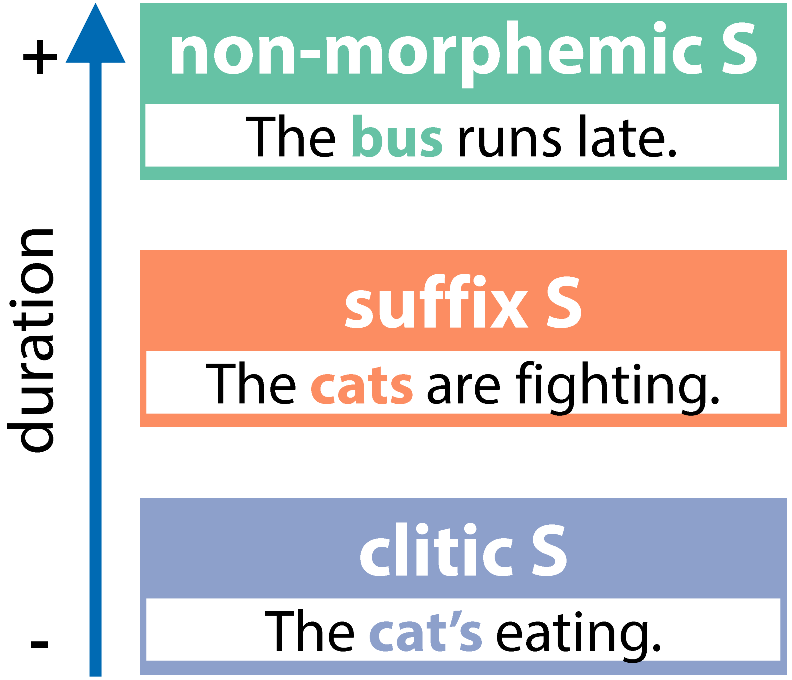
Durational differences of homophonous suffixes emerge from the lexicon:

Evidence from nonce words

Dominic Schmitz, Ingo Plag, Dinah Baer-Henney

Starting point

- Zimmermann (2016)
- Plag et al. (2017)
- Tomaschek et al. (2019)
- Schmitz et al. (2020) on nonce words



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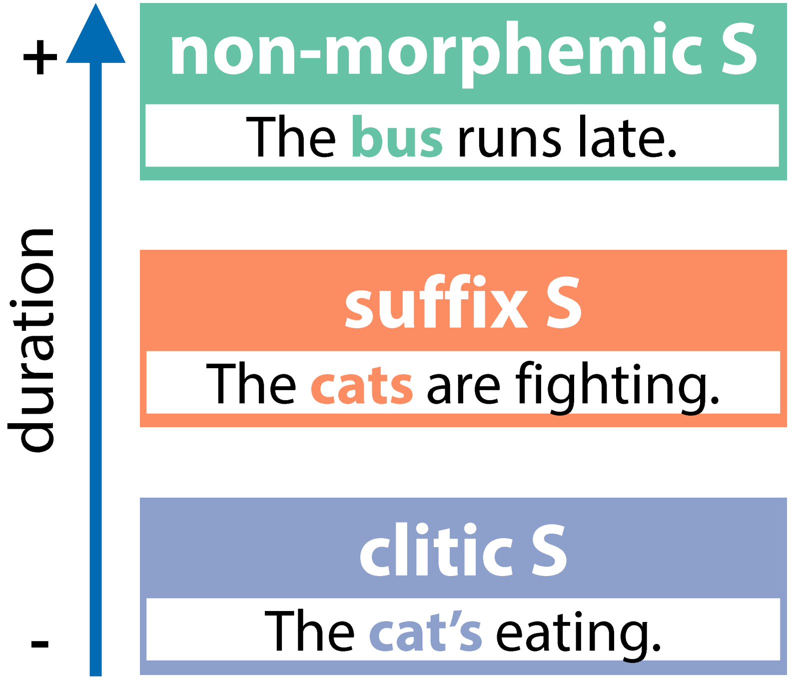

How do such differences come to existence?

Linear Discriminative Learning – LDL

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- **LDL** takes **lexomes** as the basic units for lexical processing
- each lexome is connected to a **semantic vector** containing the **association strengths** of its **lexome** with each of the other **lexomes**
- **lexomes** and their **association strengths** can then be used to obtain a number of **LDL measures**

How do we obtain LDL measures?

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- $\boxed{\text{data}}$

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Word	Base	Affix	Transcription
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students	student	PL	stjudHts
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- pseudowords (Schmitz et al., 2020)

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bloups	bloups	NA	bl6ps
bloups	bloup	PL	bl6ps
pleeps	pleeps	NA	plips
pleeps	pleep	PL	plips

1. From data to matrices

[C]ue matrix

- contains the triphones of all **word forms**

	#mi	mil	il#	mit	it#
/mil/	1	1	1	0	0
/mit/	1	0	0	1	1
/stjudHt/	0	0	0	0	0
/tiJ@R/	0	0	0	0	0

1. From data to matrices

[S]emantic matrix

- there is a number of options when it comes to semantics, i.e. whether to use real (Chuang et al., 2020) or simulated (Baayen et al., 2018) semantics for parts of or all data
- today:
  - Simulated semantic vectors for real words and/or pseudowords
    → real and/or pseudowords contain some sort of semantics

1. From data to matrices

[S]emantic matrix

- contains semantic vectors for all **word forms**

	classroom	college	cook	eat	vegetable	PL
/mil/	0.003	0.0005	0.9	0.8	0.7	0.2
/mit/	0.0006	0.0002	0.8	0.9	0.5	0.04
/stjudHt/	0.9	0.8	0.05	0.1	0.005	0.7
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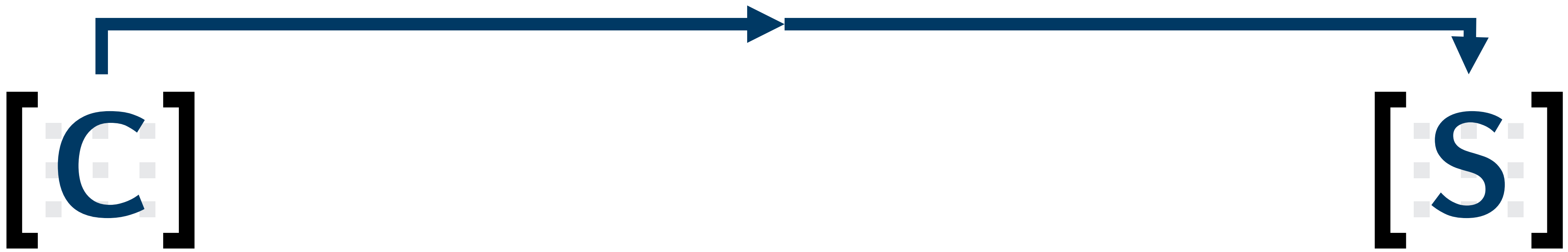

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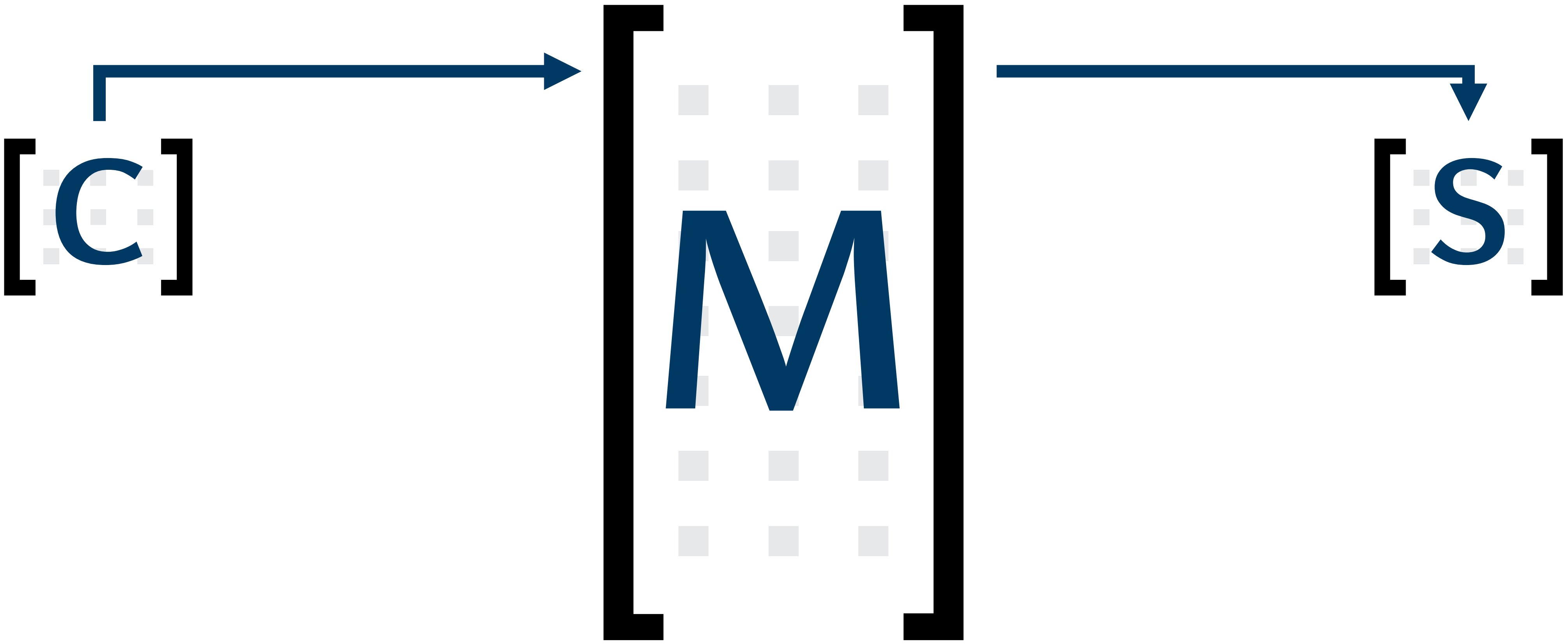

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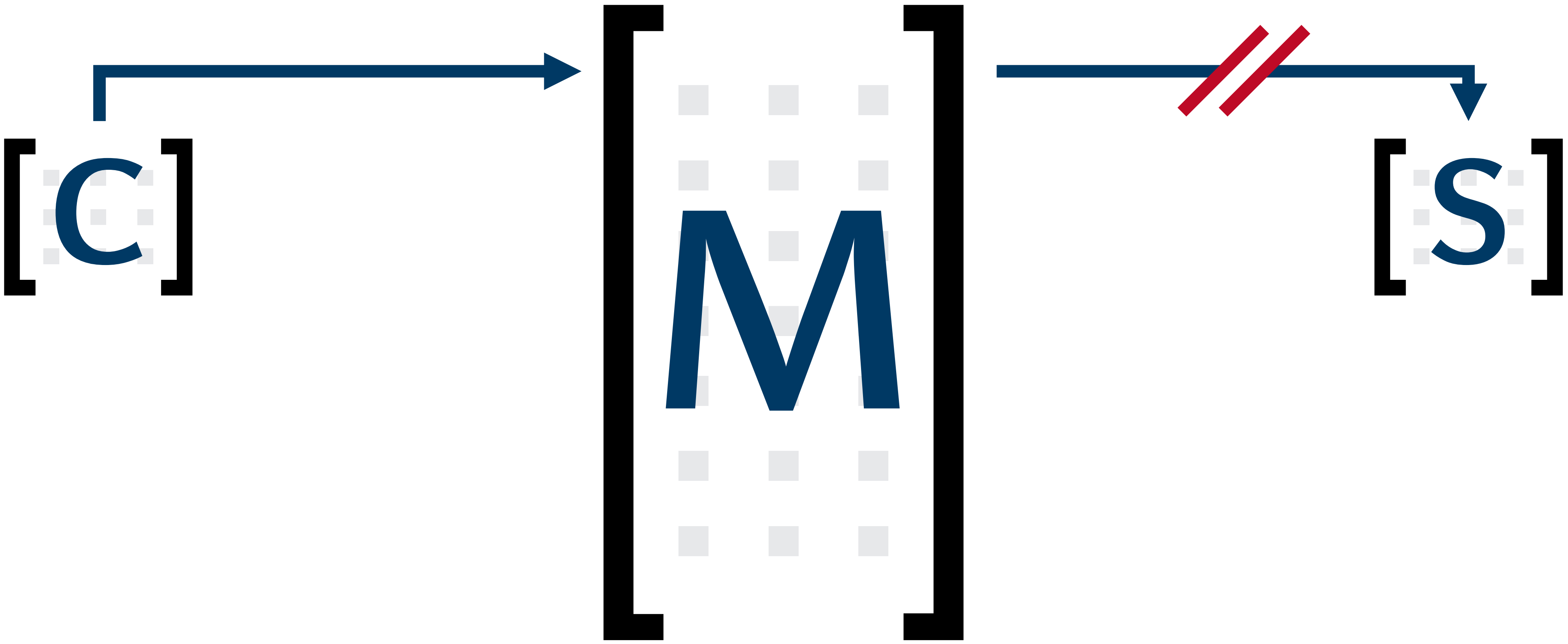

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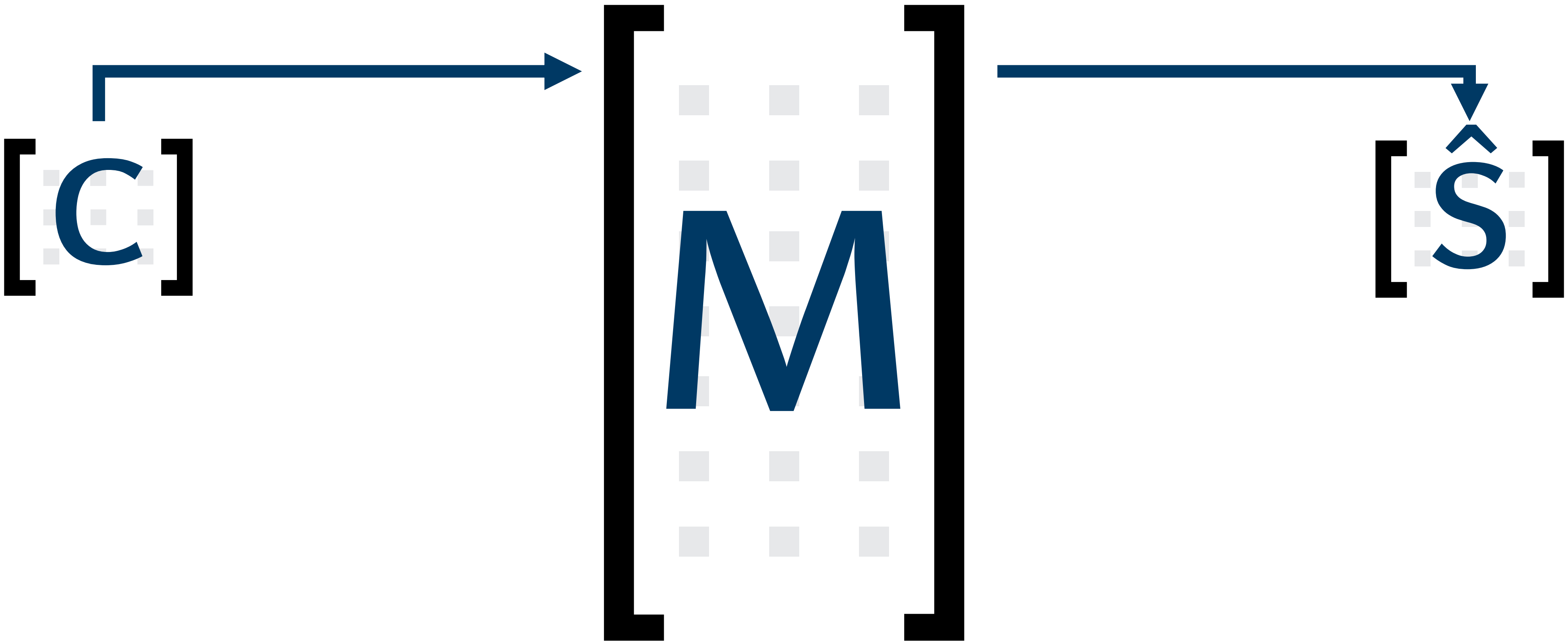

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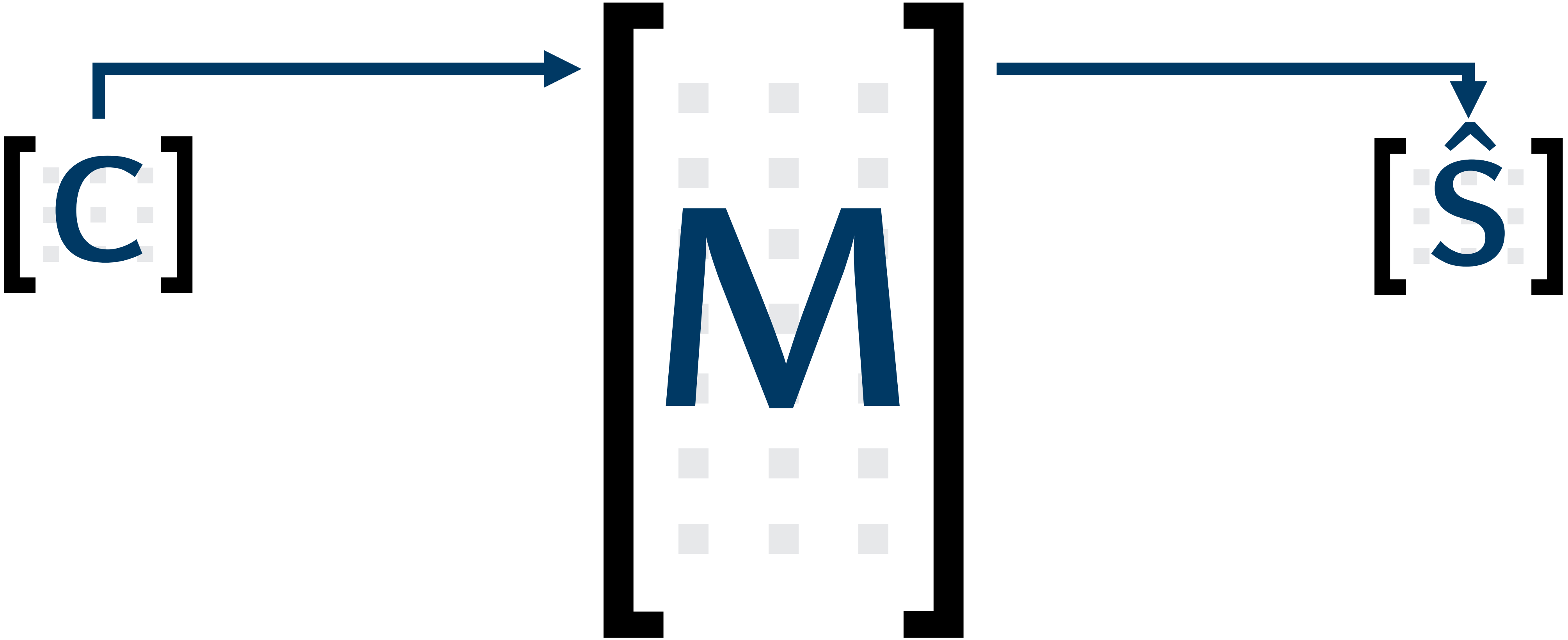

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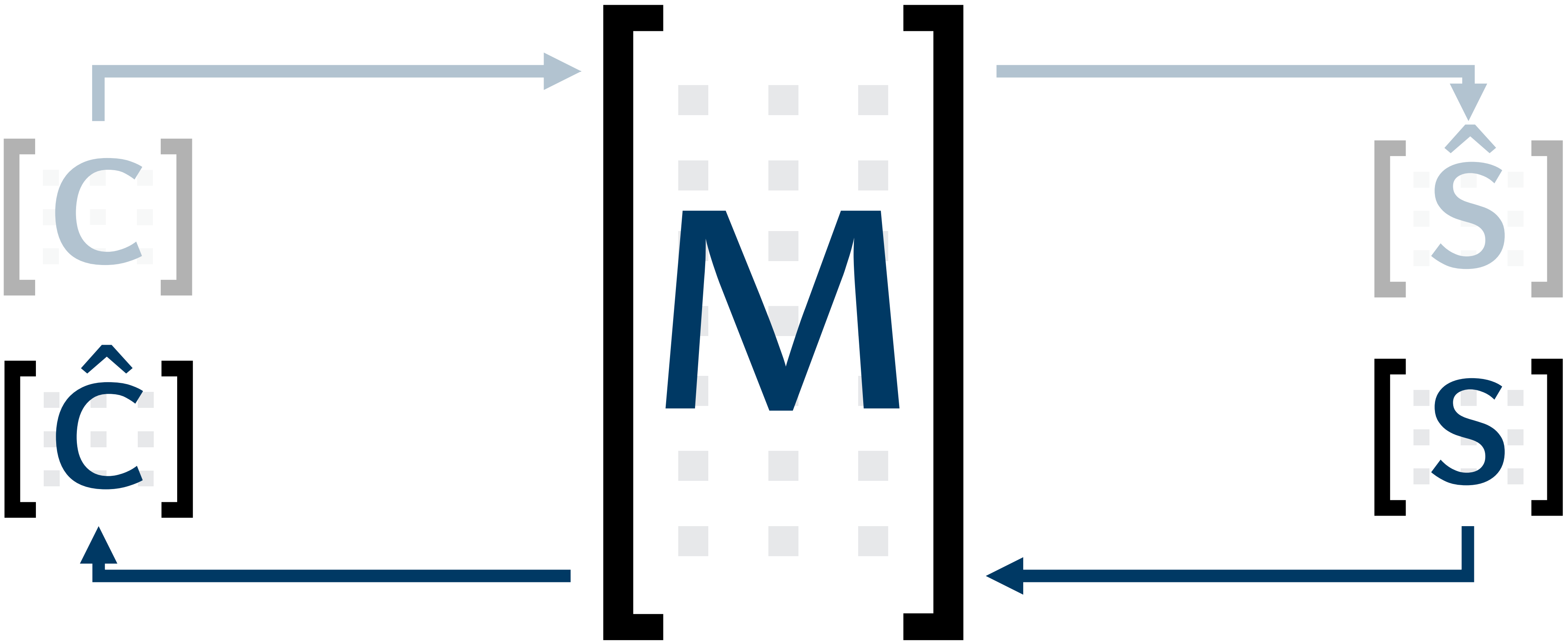

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2. From matrices to comprehension & production
3. From comprehension & production to measures

4. From comprehension to measures

$[C] \rightarrow [M] \rightarrow [\hat{S}]$

&

$[S]$

&

data

comp measures

4. From production to measures

[S] → [M] → [Ĉ]

&

[C]

&

data

prod measures

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a) Pseudowords

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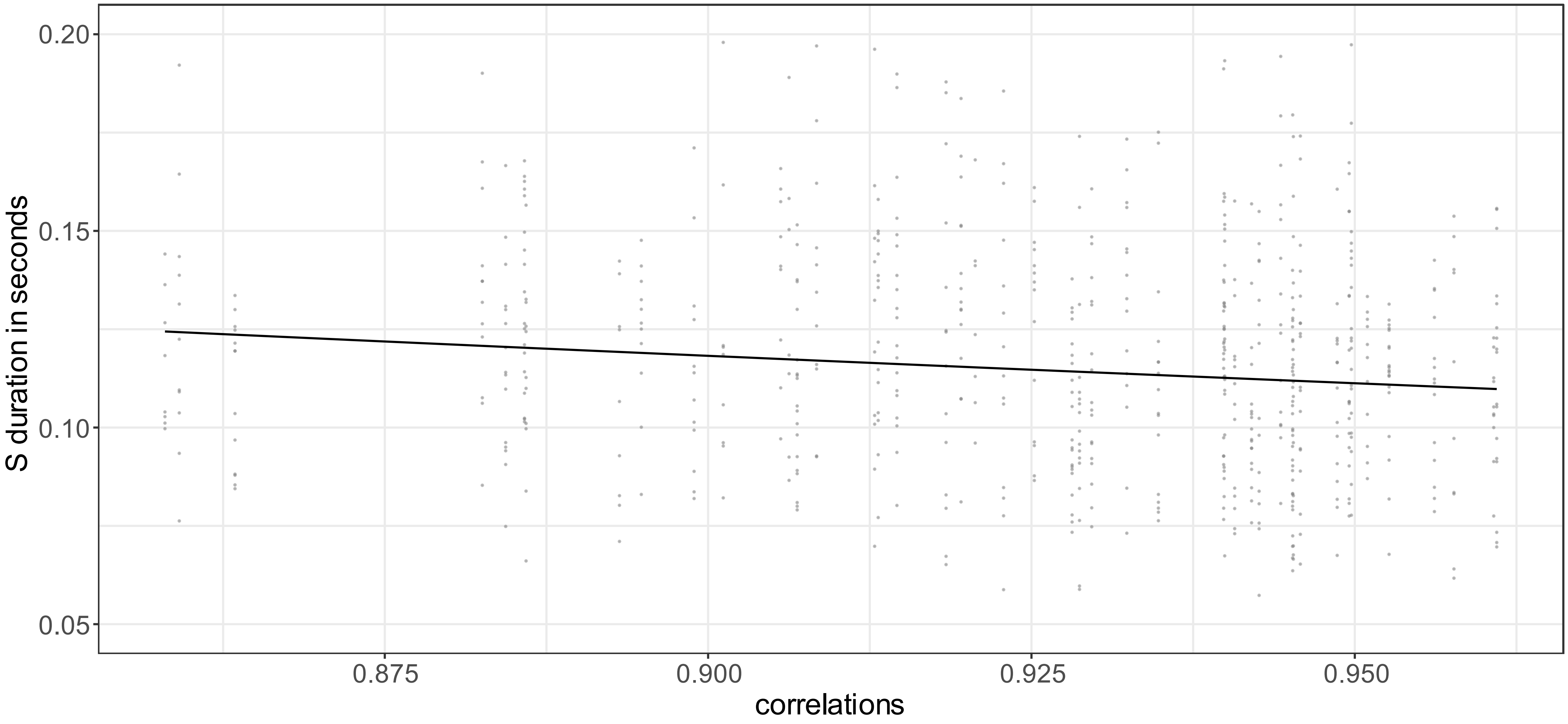

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a) Pseudowords

b) Real + Pseudowords

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  - **PATH_SUM** the summed support for the predicted path:

    $\xrightarrow{1} \#bl \xrightarrow{1} bli \xrightarrow{1} lip \xrightarrow{1} ips \xrightarrow{1} ps\#$

    $\sum = 5 \longrightarrow$ high support
  - PAUSEBIN
  - FOLTYPE
  - SPEAKINGRATELOG
- random intercept:
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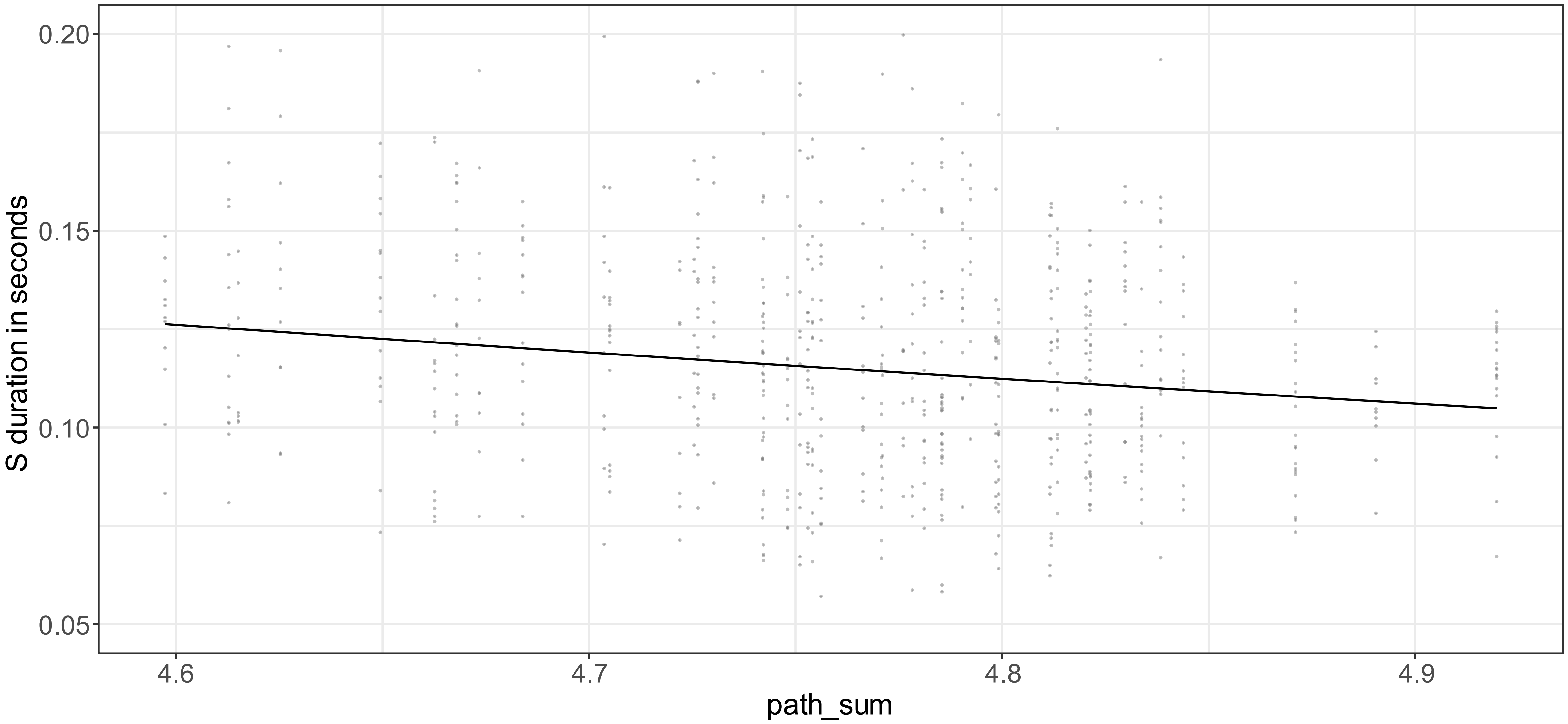

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correlations	path_sum	/s/ duration
high	high	short
low	low	long

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plural	high	high	short
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- remaining questions:
  - *Why are predicted paths of plurals more correlated to their targeted semantic vectors?*
  - *Why is the certainty in plurals higher than in monomorphemic words?*

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- Some LDL measures appear to be predictable for differences in /s/ durations, thus durational differences in word-final /s/ appear to emerge from the lexicon
- However, further steps are necessary
  - use more data for mapping
  - use real semantics for real words, and derived semantics for pseudowords
  - analyse LDL measures not only for predicting /s/ durations in pseudowords but also for real words

Thank you!

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