Modelling word-final /s/ duration in pseudowords with LDL

Dominic Schmitz, Ingo Plag, Dinah Baer-Henney

Previous findings on /s/ duration

non-morphemic S

The bus runs late.

suffix S

The cats are fighting.

clitic S

The cat's eating.

- duration +

- Zimmermann (2016); Plag et al. (2017); Tomaschek et al. (2019); Schmitz et al. (2020)
- but also: Walsh & Parker (1983); Hsieh et al. (1999); Seyfarth et al. (2017); Plag et al. (2020)

Previous findings on /s/ duration

Heinrich Heine Universität Düsseldorf

non-morphemic S

The glaips calls his mum.

plural S

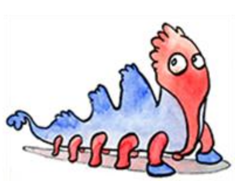
The glaips called their mum.

clitic S

The glaip's called his mum several times.

\- duration +

a glip



a pleets

a clook

a prufs

a bloup

a glait

Previous findings on /s/ duration

non-morphemic S

The glaips calls his mum.

plural S

The glaips called their mum.

clitic S

The glaip's called his mum several times.

\-

duration

\+

How to explain such differences?

- standard feed-forward theories of morphology-phonology interaction (e.g. Chomsky & Halle, 1968; Kiparsky, 1982)
  - bracket erasure: simplex and complex word forms are the same to production
- psycholinguistic models of speech production (e.g. Levelt et al., 1999; Roelofs & Ferreira, 2019)
  - phonological forms without morphological info are used in speech production

Alternative: Discriminative Learning

- Can we use measures derived from discriminative networks to model /s/ duration?
  - Yes: Tomaschek et al. (2019) reproduce the differences in /s/ duration found by Plag et al. (2017) by means of NDL measures
- Can we use pseudowords?
  - Yes: Chuang et al. (2020) successfully implement LDL with real and nonce words; pseudowords resonate with the lexicon = show semantics

Can we implement LDL with real and nonce words and use measures derived from such an implementation to model /s/ durations? If so, how can we interpret these LDL measures?

Can we **implement LDL with real and nonce words** and use measures derived from such an implementation to model /s/ durations? If so, how can we interpret these LDL measures?

LDL Basics

- **lexome**
  basic semantic units corresponding to words or morphological functions

$$\text{cat} = \overrightarrow{cat} \qquad \& \qquad \text{cats}_{\text{plural}} = \overrightarrow{cat} + \overrightarrow{plural}$$

- **cue matrix C**
  encodes the forms of words in a binary fashion, giving information on which triphones are part of which word

	#k{	k{t	{t#	#bV
cat	1	1	1	0

- **semantic matrix S**
  contains semantic vectors of word forms on basis of their corresponding lexomes

	bus	eel
k{t	0.7	0.2

LDL: Real Words

- C and S matrix are easily created with WpmWithLdl package (Baayen et al., 2019)
- C matrix:
  - based on 8362 words taken from MALD corpus (Tucker et al., 2019)
- S matrix:
  - based on semantic vectors created based on TASA corpus (Ivens & Koslin, 1991) by Baayen et al. (2019)

LDL: Real Words

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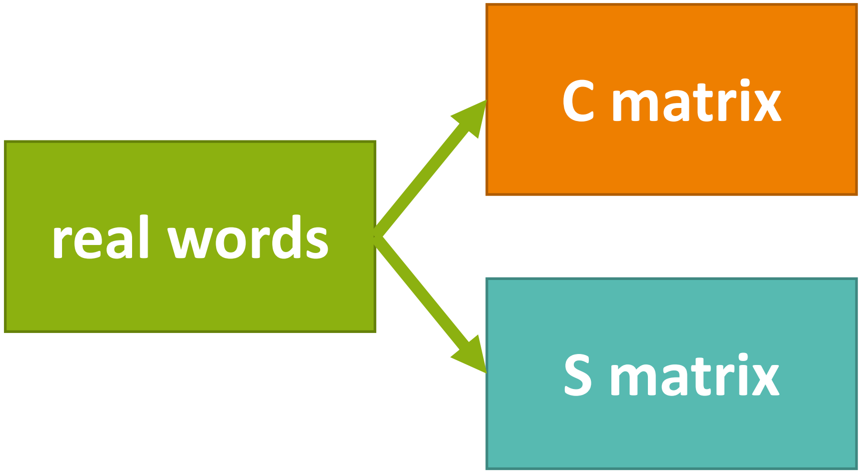
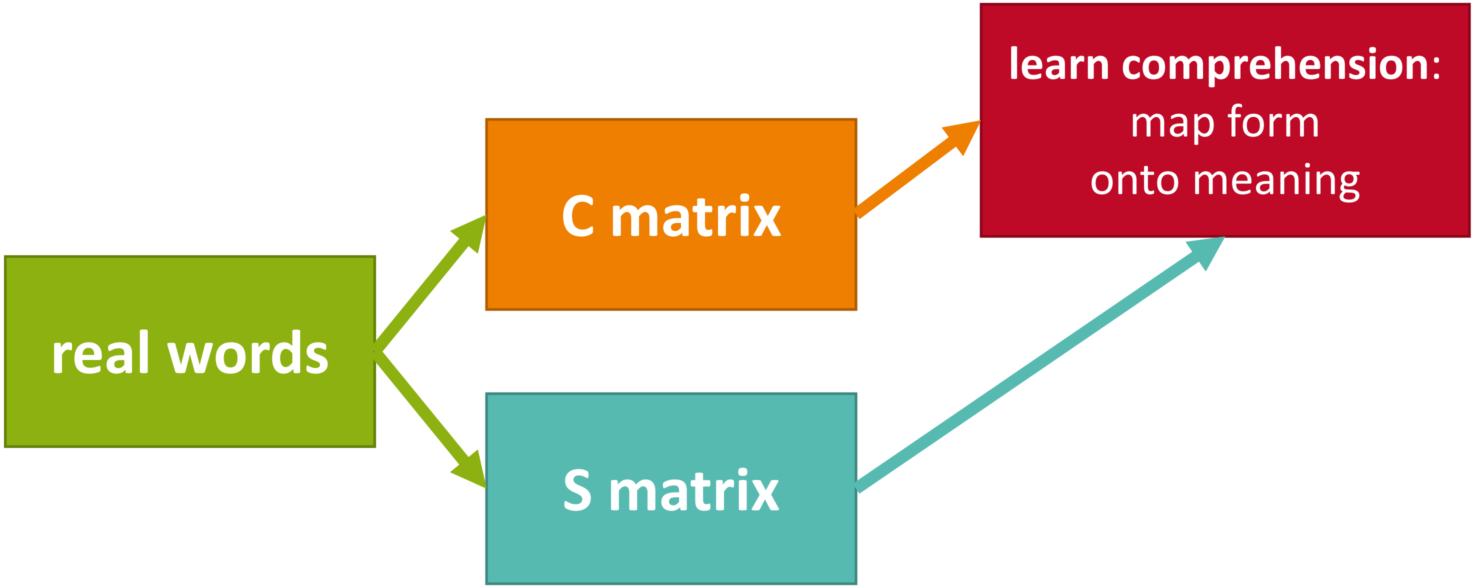
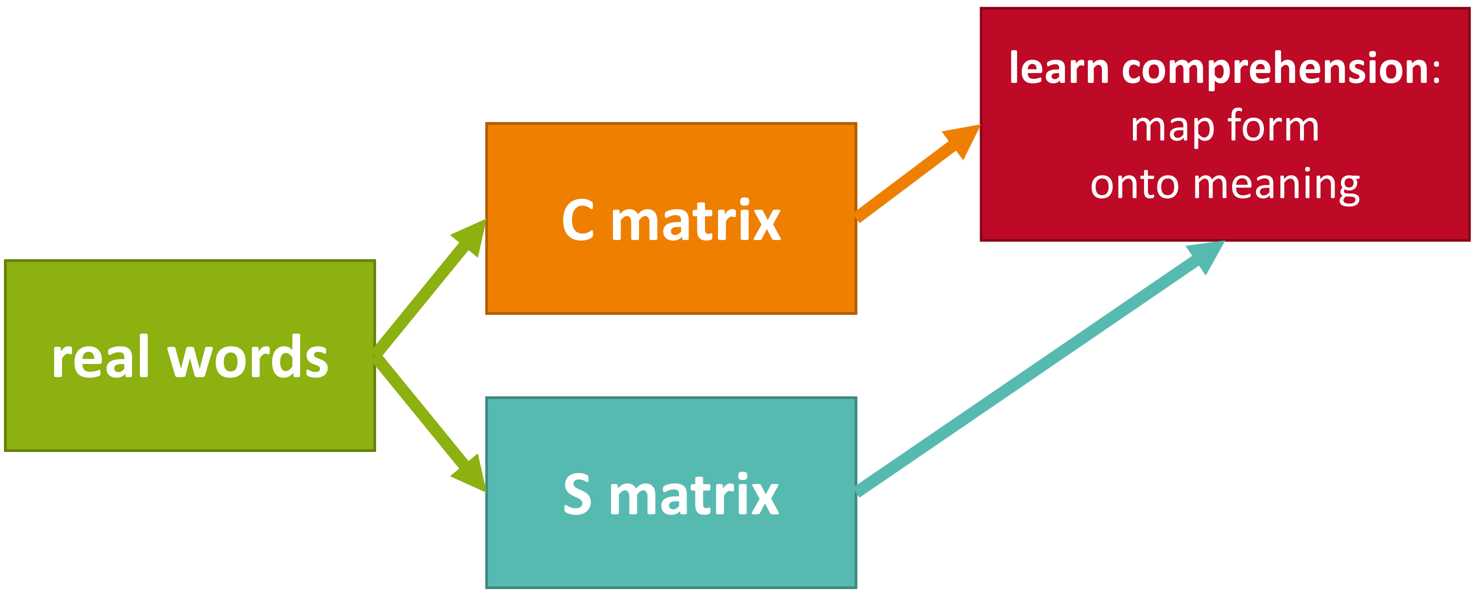


LDL: Real Words



LDL: Real Words

$$CF = S$$



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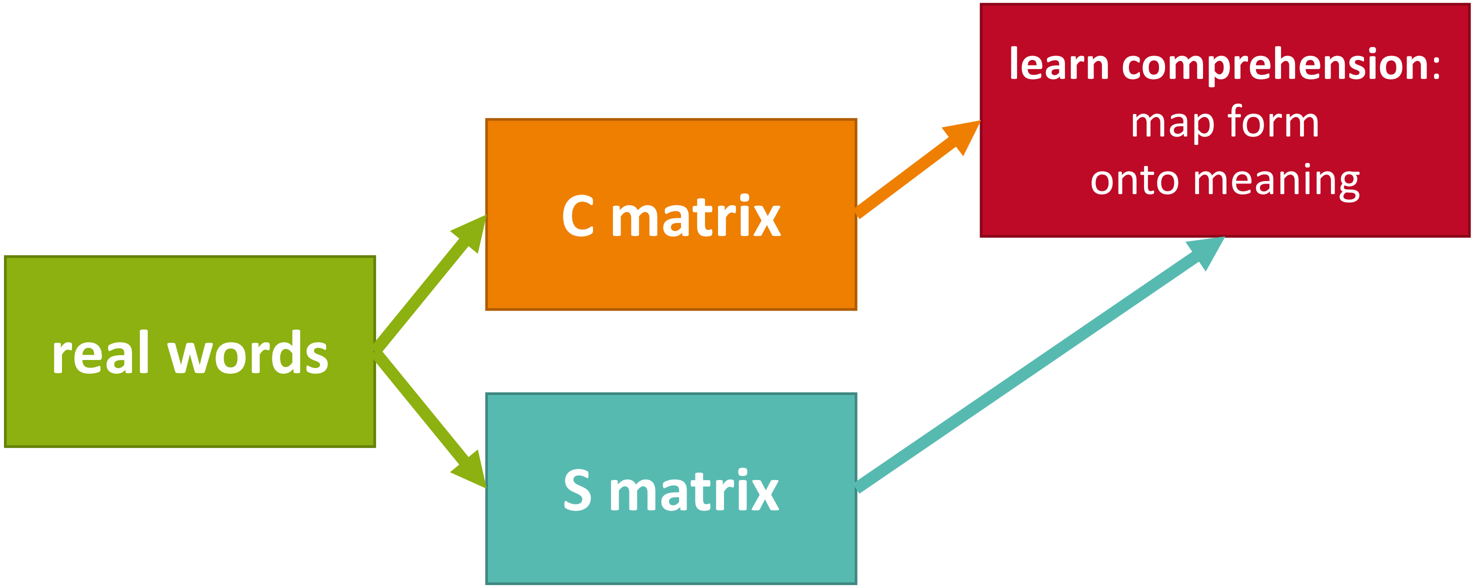
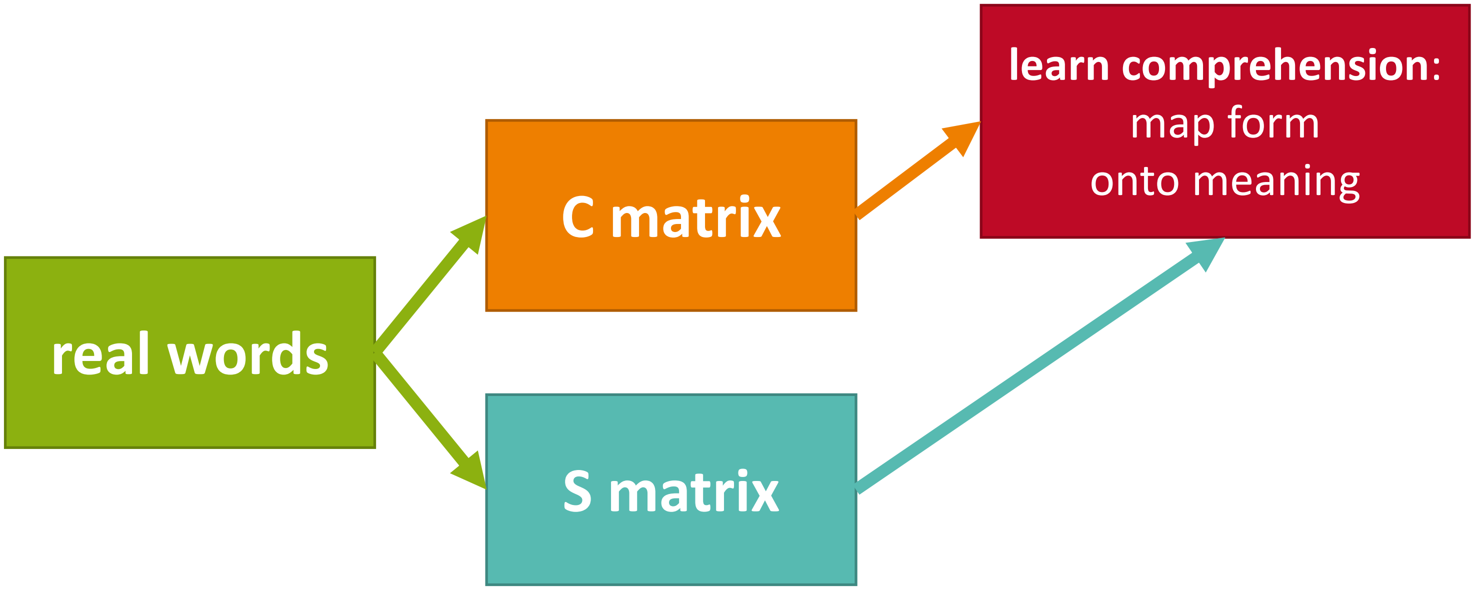


$$CF = S$$

$$F = C'S$$

LDL: Real Words

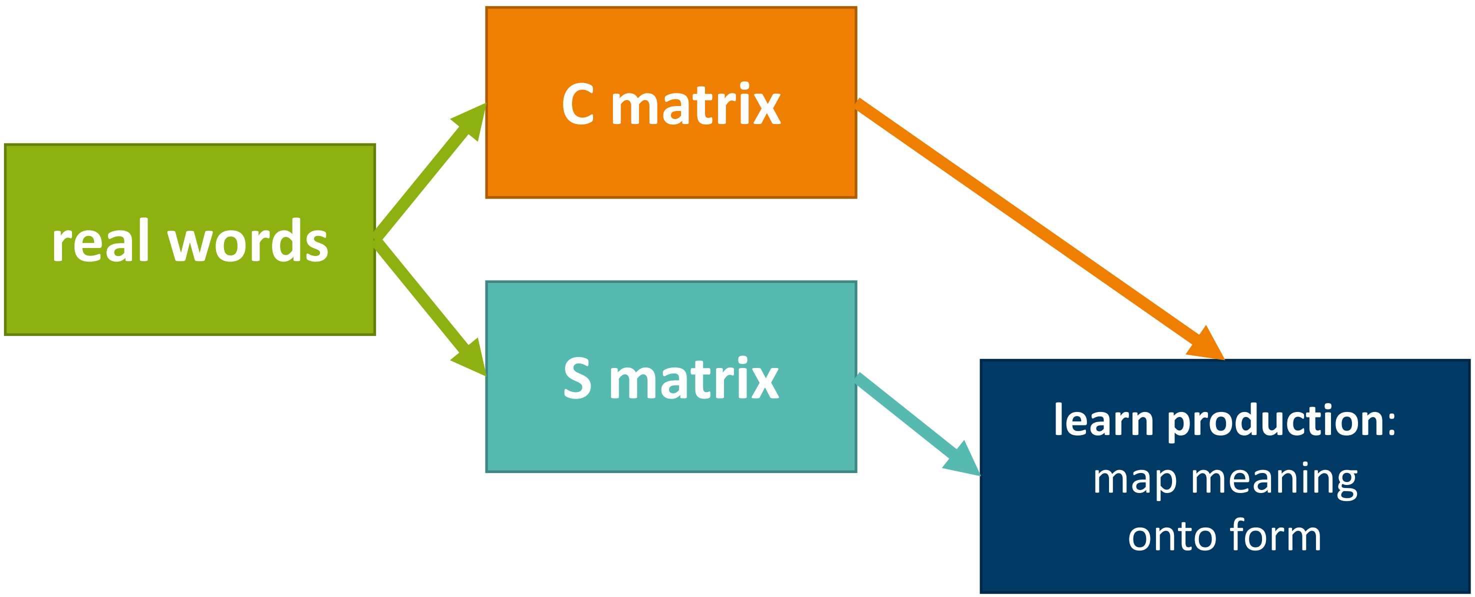


$$\boldsymbol{CF} = \boldsymbol{S}$$

$$\boldsymbol{F} = \boldsymbol{C'S}$$

$$\boldsymbol{CF} = \boldsymbol{\hat{S}}$$

LDL: Real Words

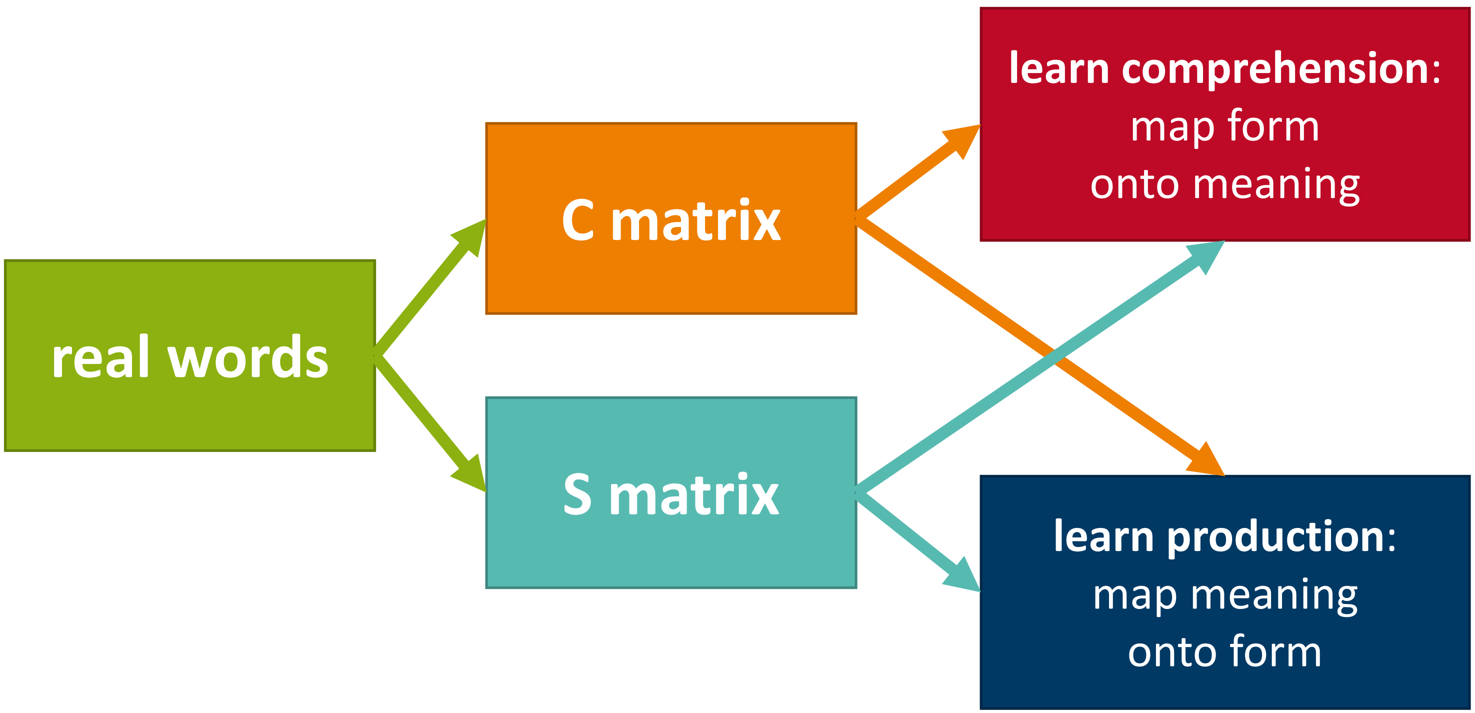


$$SG = C$$

$$G = S'C$$

$$SG = \hat{C}$$

LDL: Real Words



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$$\boldsymbol{CF} = \widehat{\boldsymbol{S}}$$

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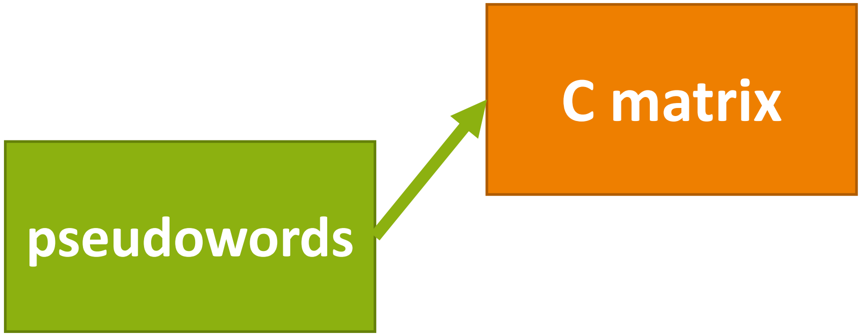
$$\boldsymbol{SG} = \widehat{\boldsymbol{C}}$$

LDL: Pseudowords

- C matrix is easily created with WpmWithLdl package (Baayen et al., 2019)
- C matrix:
  - based on 48 pseudowords with 72 phonological forms taken from the ENGS production experiment (Schmitz et al., 2020)
- S matrix:
  - ...well, what about the S matrix?

LDL: Pseudowords

LDL: Pseudowords



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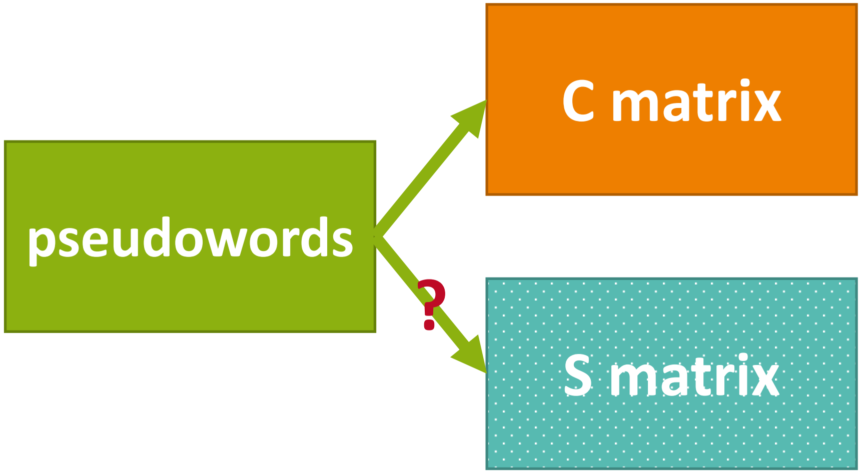

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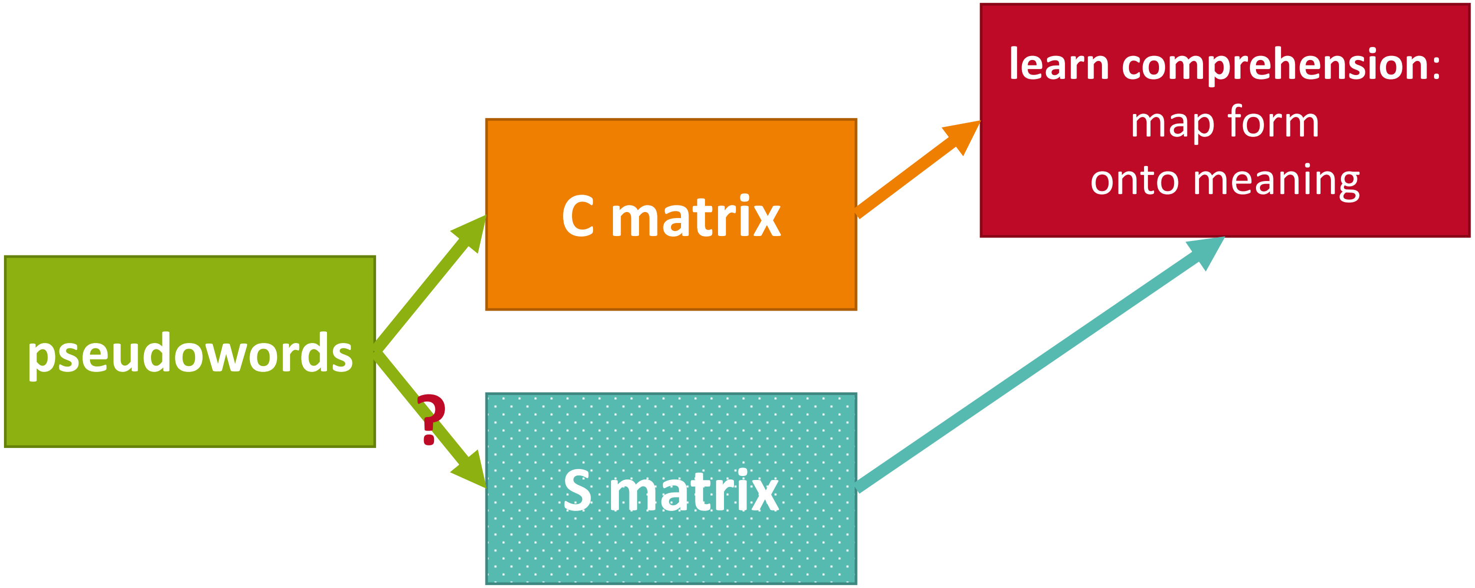
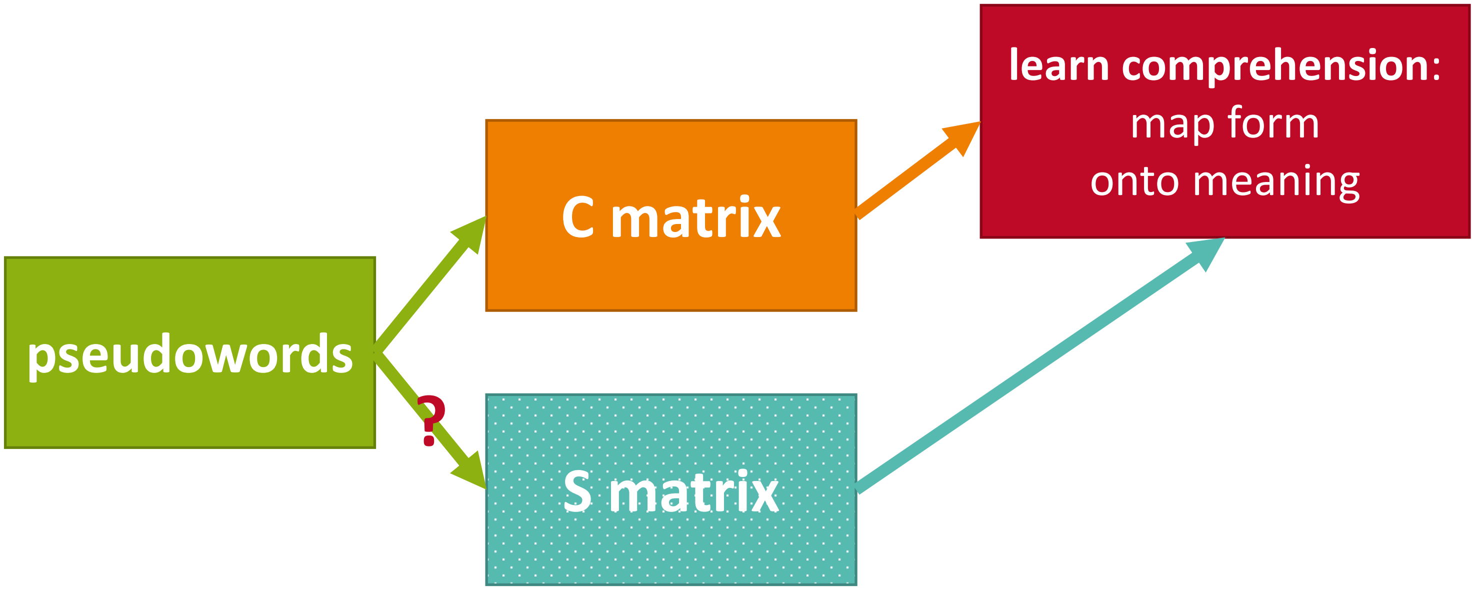


$$CF = S$$

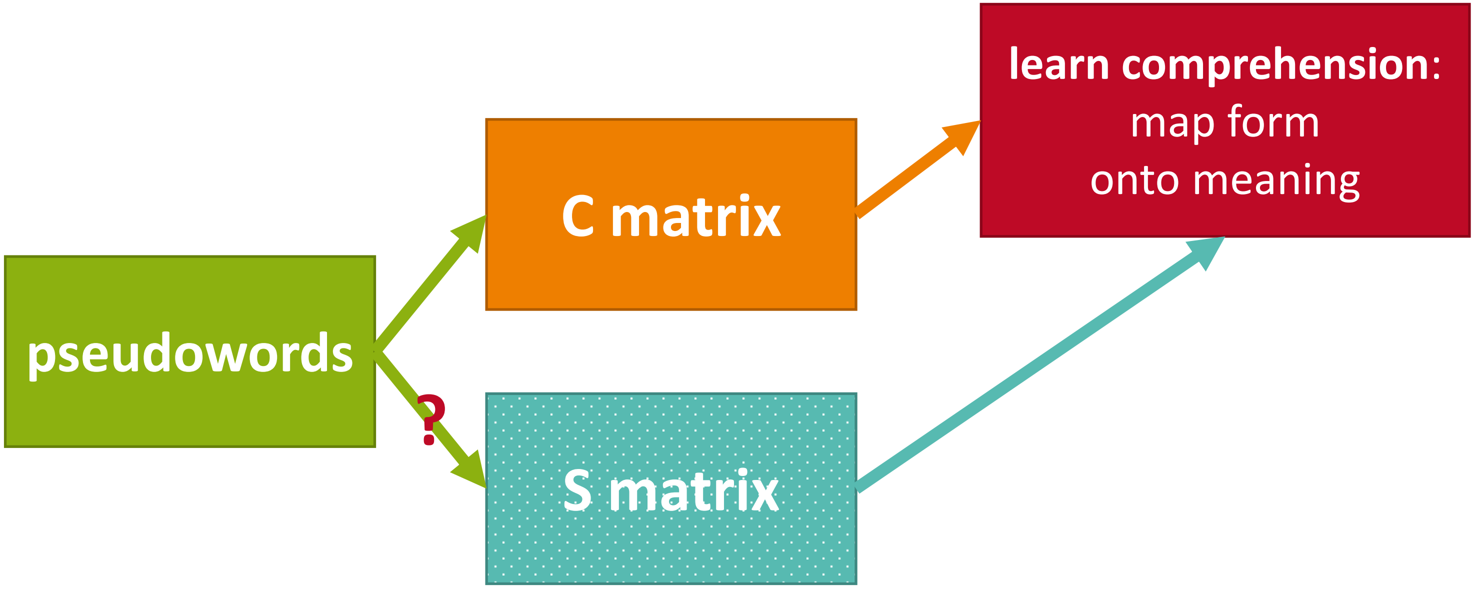
LDL: Pseudowords

$$\boldsymbol{CF = S}$$



LDL: Pseudowords

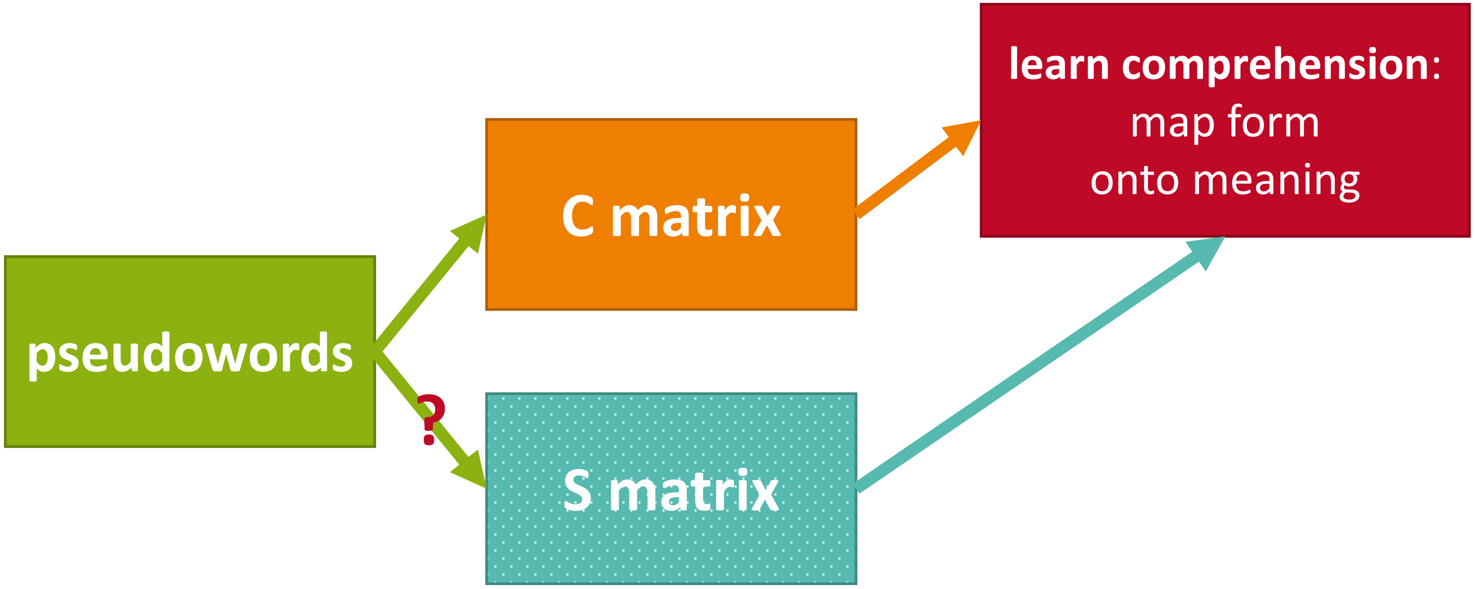
$CF = S$



LDL: Pseudowords

use the F found by mapping real words

$$\boldsymbol{C}\boldsymbol{F} = \boldsymbol{S}$$



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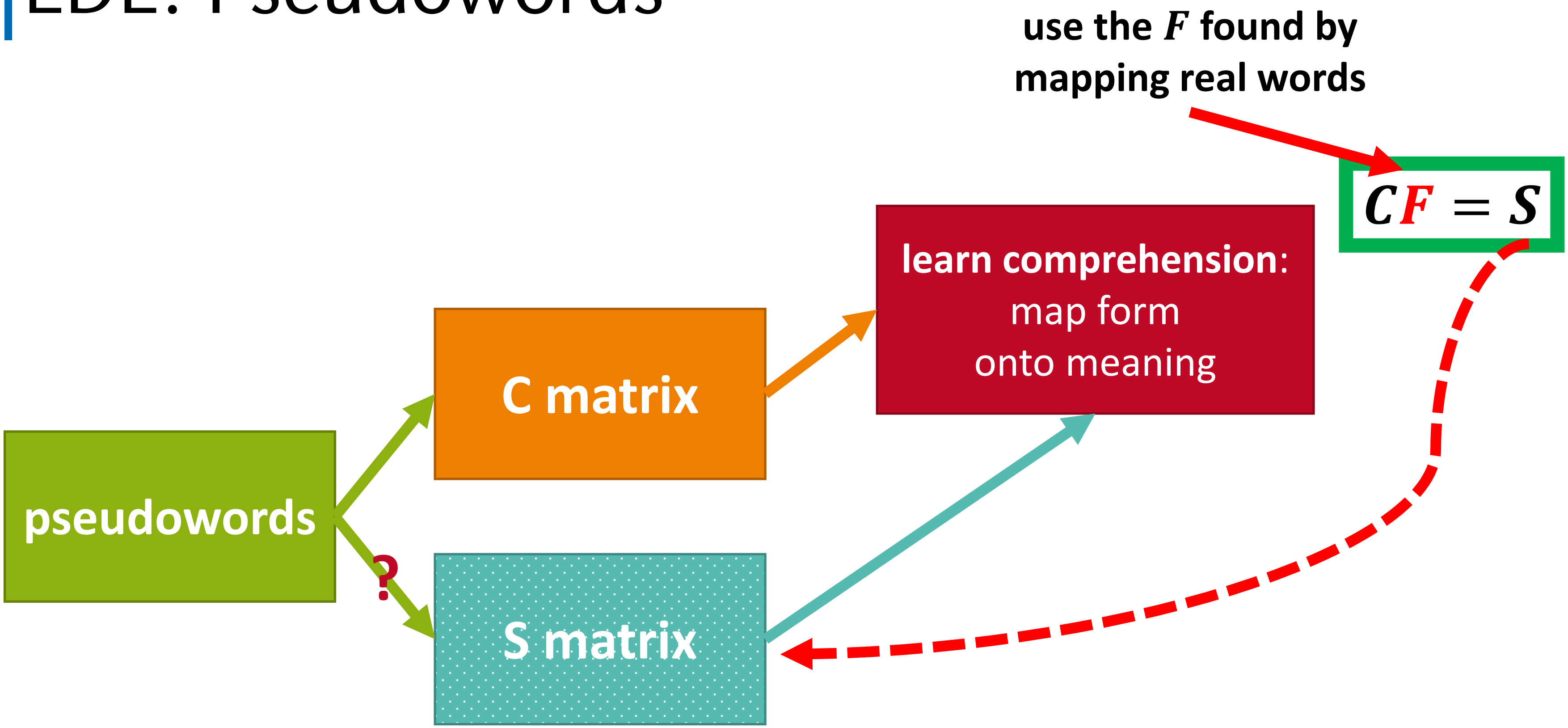

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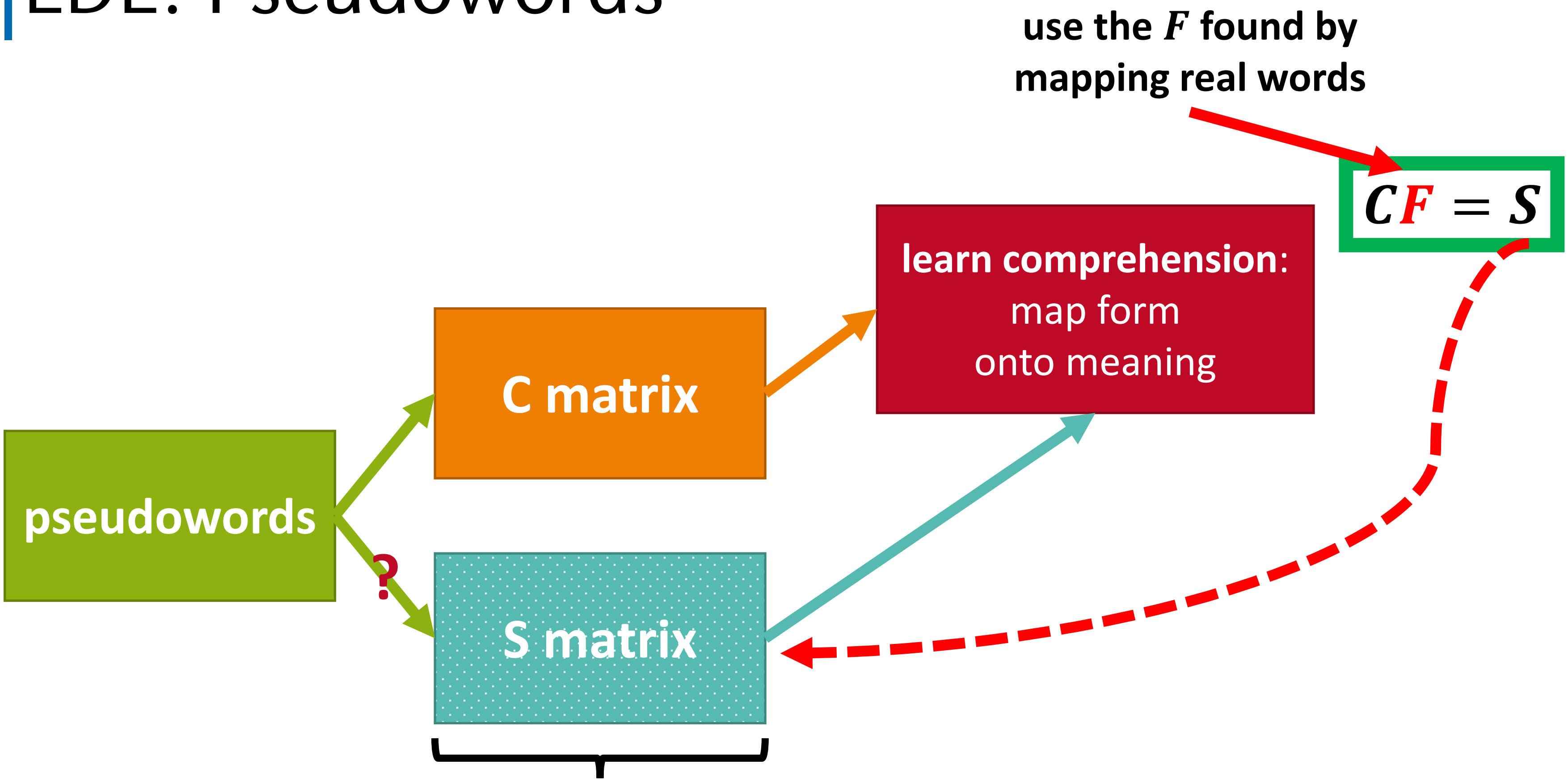
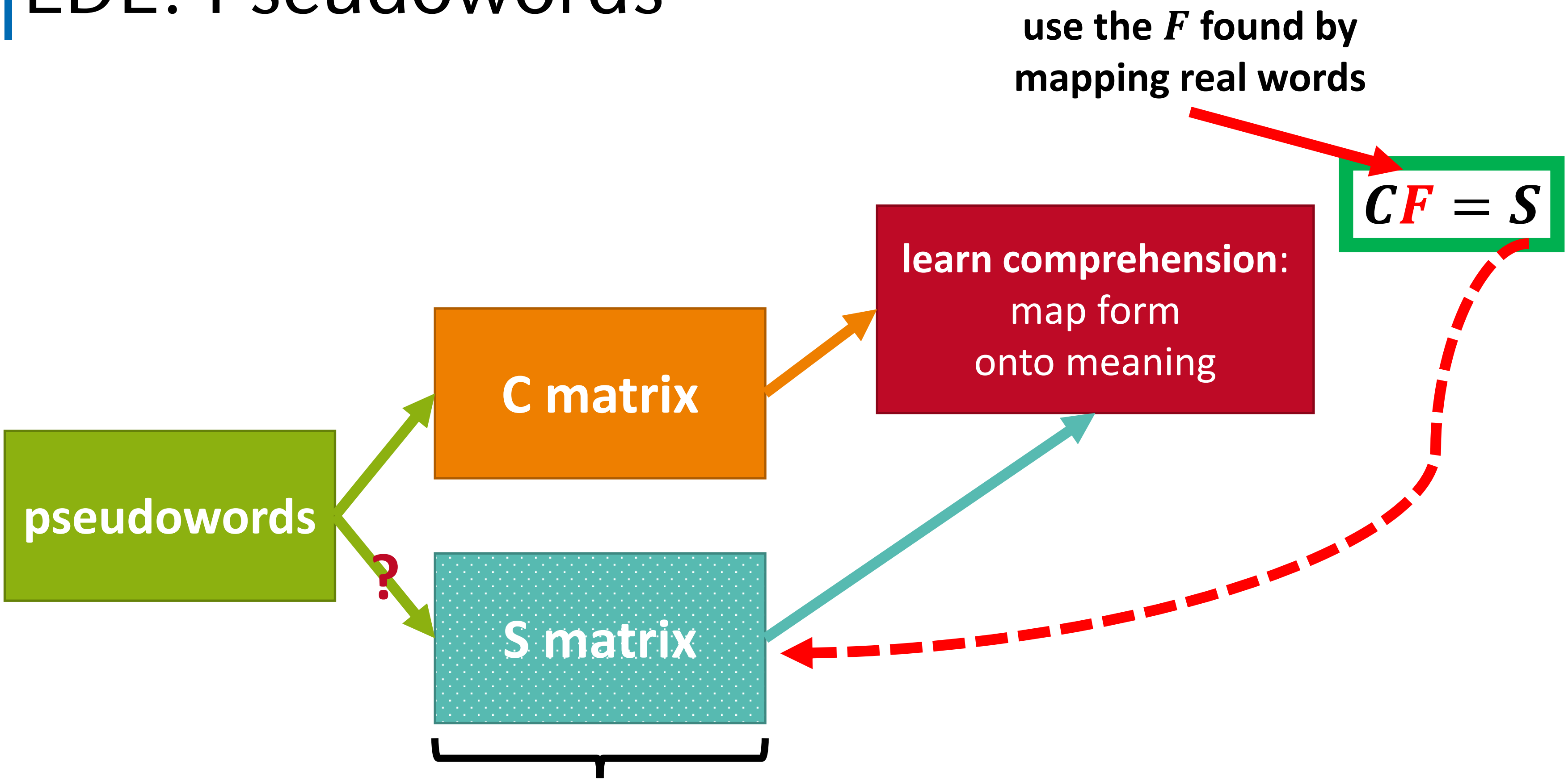


		cat	bus	eel
monomorphemic	glaips	0.4	0.7	0.2
plural	glaips	0.4	0.7	0.2

LDL: Pseudowords



		cat	bus	eel
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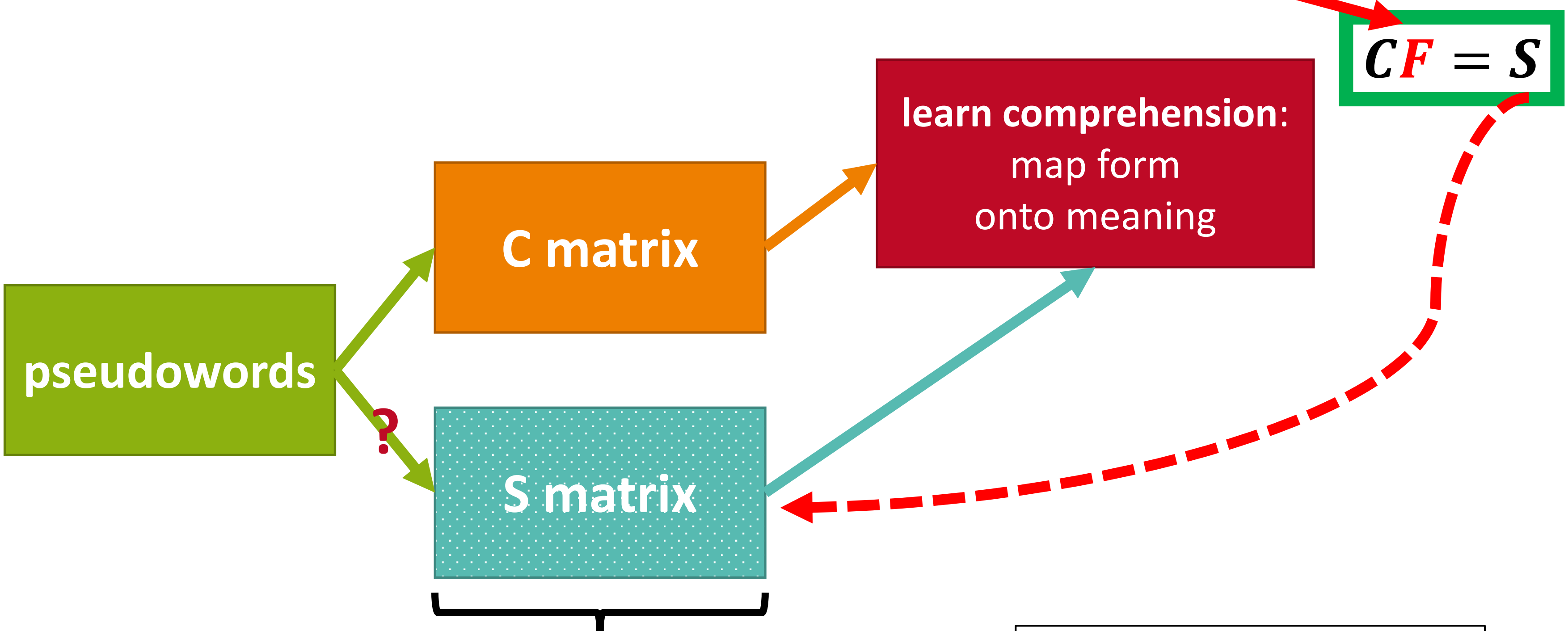
add the semantic vector of the plural lexome to all plural pseudowords

LDL: Pseudowords

use the F found by mapping real words



		cat	bus	eel
monomorphemic	glaips	0.4	0.7	0.2
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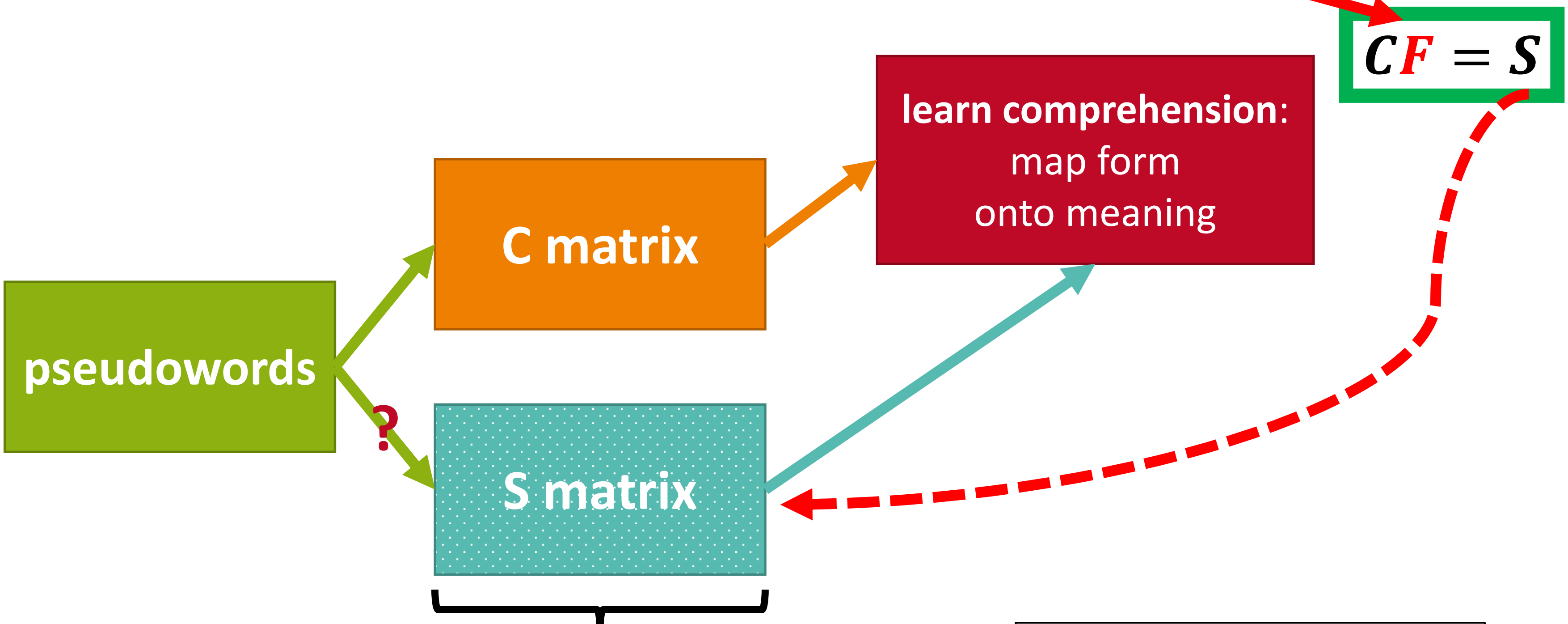
cat = $\overrightarrow{cat}$

cats$_{\text{plural}}$ = $\overrightarrow{cat} + \overrightarrow{plural}$

add the semantic vector of the plural lexome to all plural pseudowords

LDL: Pseudowords

use the F found by mapping real words



		cat	bus	eel
monomorphemic	glaips	0.4	0.7	0.2
plural	glaips	0.5	0.3	0.8

add the semantic vector of the plural lexome to all plural pseudowords

cat = $\overrightarrow{cat}$
$\text{cats}_{\text{plural}} = \overrightarrow{cat} + \overrightarrow{plural}$

LDL: Real + Nonce Words

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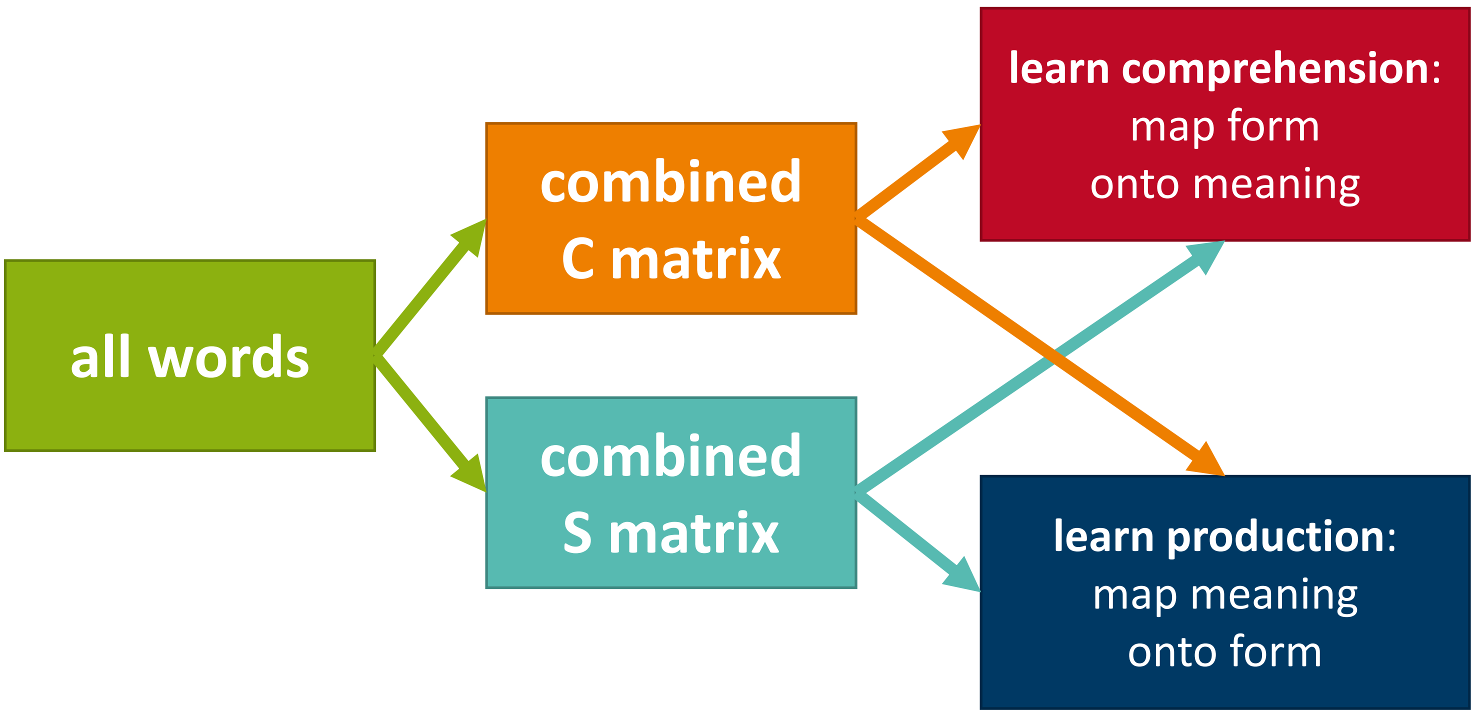

$$\boldsymbol{CF} = \boldsymbol{S}$$

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$$\boldsymbol{CF} = \widehat{\boldsymbol{S}}$$

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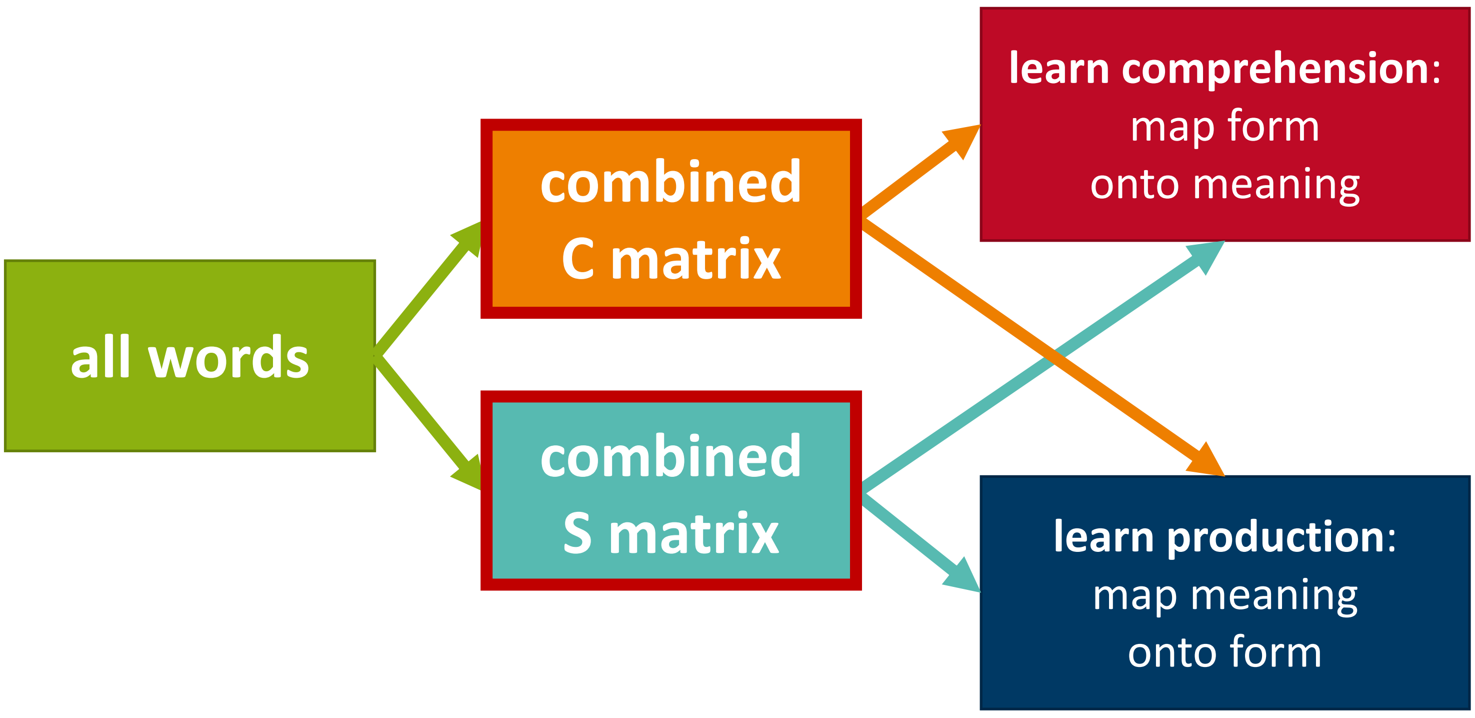
LDL: Real + Nonce Words



$$CF = S$$

$$F = C'S$$

$$CF = \boxed{\hat{S}}$$

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$$SG = \boxed{\hat{C}}$$

Can we **implement LDL with real and nonce words** and use **measures derived from such an implementation** to model /s/ durations? If so, how can we interpret these LDL measures?

LDL: Measures

- 17 measures derived from LDL implementation in total
  - 13 as part of the WpmWithLdl package (Baayen et al., 2019)
  - 4 of those introduced by Chuang et al. (2020)

- let's see whether (some of) these measures are useful when modelling /s/ durations

Can we **implement LDL with real and nonce words** and use **measures derived from such an implementation** to **model /s/ durations**?

If so, how can we interpret these LDL measures?

Two Models

- we use linear mixed-effects regression models, following standard procedures (e.g. log-transformation; stepwise backward model selection; trimming of residuals)
- all initial models share the same non-lexical covariates, e.g. speaking rate, pause, following segment type
- **Model 1**:
  model containing LDL measures and the categorical variable 'type of S'
- **Model 2:**
  model containing LDL measures only

Principal Component Analyses

- the 17 LDL measures & ‘type of S’ show a total of 16 correlations with $r \geq 0.5$
- two separate PCAs are computed as ‘type of S’ is one of the highly correlated variables
- Why two PCAs?
  - remember: we want to create two models, i.e. one with
    - LDL measures with ‘type of S’
    - LDL measures without ‘type of S’

Can we **implement LDL with real and nonce words** and use **measures derived from such an implementation** to **model /s/ durations**?

If so, **how can we interpret these LDL measures**?

Model 1: LDL + ‘type of S’

- variables showing significant effects are

  1. base duration
  2. pause
  3. Component4Bin
  4. segmental class of the following segment
  5. speaking rate
  6. Component3
  7. consonant preceding the /s/

Model 1: LDL + ‘type of S’

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    7. consonant preceding the /s/

Model 1: LDL + ‘type of S’

Component4Bin

- strongly correlated with
  - **type of S**
  - **ALC**

Model 1: LDL + ‘type of S’

Component4Bin

- strongly correlated with
  - **type of S**
    - categorical variable: non-morphemic vs. plural /s/
  - **ALC**

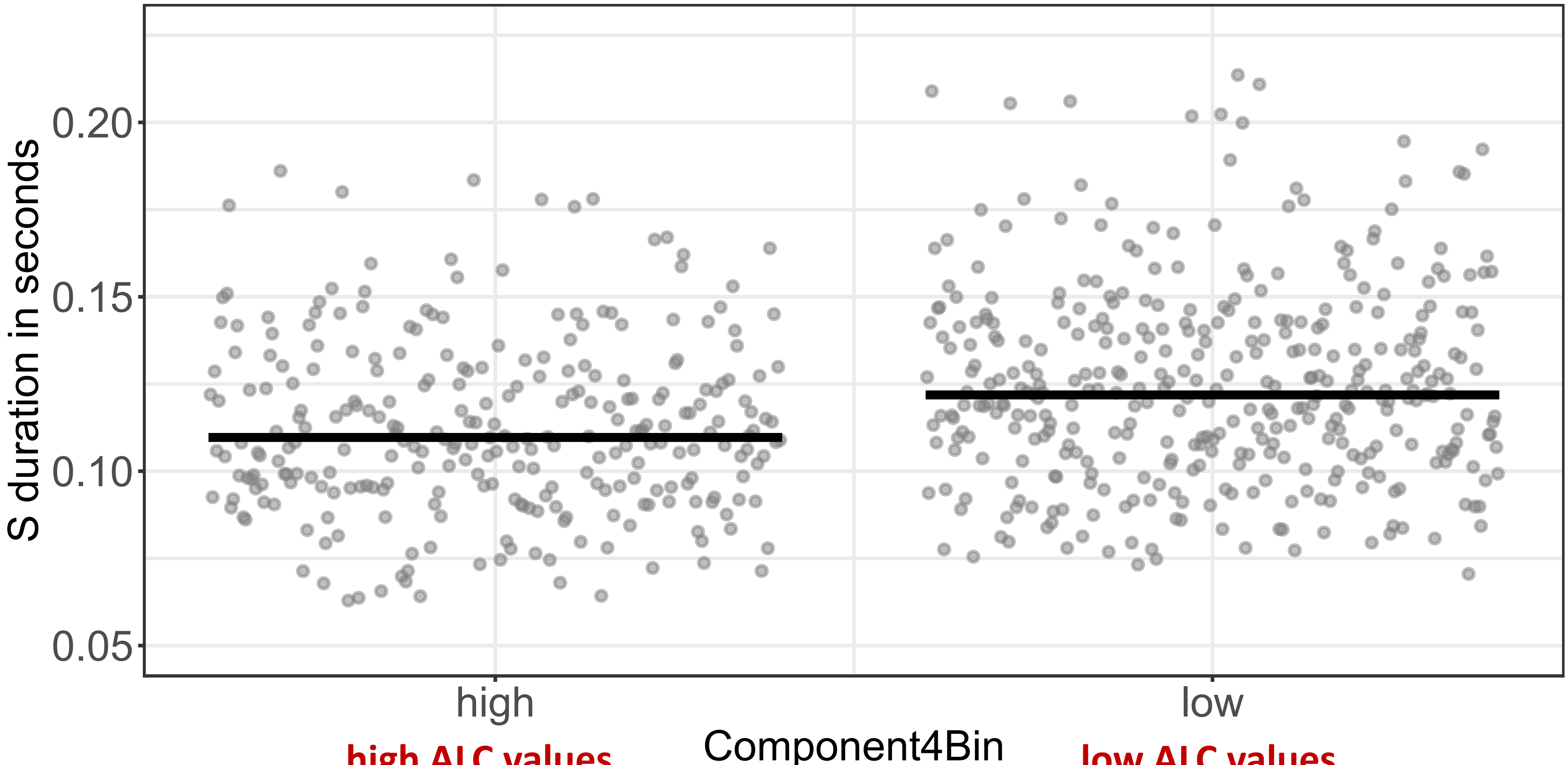
Model 1: LDL + ‘type of S’

Component4Bin

- strongly correlated with
  - **type of S**
    - categorical variable: non-morphemic vs. plural /s/
  - **ALC – Average Lexical Correlation**
    - mean value of all correlation values of a pseudoword’s estimated semantic vector with each of the real word semantic vectors
    - higher values indicate that a pseudoword vector has “landed” in a denser semantic neighbourhood
    - may be interpreted as a measure of semantic activation diversity for pseudowords

Model 1: LDL + ‘type of S’

Component4Bin



high ALC values
high semantic activation diversity

low ALC values
low semantic activation diversity

Model 1: LDL + ‘type of S’

Component4Bin

- strongly correlated with
  - **type of S**
    - categorical variable: non-morphemic vs. plural /s/
  - **ALC**
    - may be interpreted as a measure of semantic activation diversity for pseudowords
- **general pattern**: plurals show higher ALC values

  monomorphemics show lower ALC values
- presence of plural makes words semantically more similar

  → plurals live in a space of greater semantic activation diversity

Model 1: LDL + ‘type of S’

- variables showing significant effects are
  1. base duration
  2. pause
  3. Component4Bin
  4. segmental class of the following segment
  5. speaking rate
  6. Component3
  7. consonant preceding the /s/

Model 1: LDL + ‘type of S’

Component3

- strongly correlated with
  - **l1norm**
  - **l2norm**

Model 1: LDL + ‘type of S’

Component3

- strongly correlated with
  - **l1norm**
    - the sum of the absolute values of vector elements of a given word’s predicted semantic vector, i.e. its city-block distance
  - **l2norm**

Model 1: LDL + ‘type of S’

Component3

- strongly correlated with
  - **l1norm**
    - the sum of the absolute values of vector elements of a given word’s predicted semantic vector, i.e. its city-block distance
  - **l2norm**
    - the square root of the sum of the squared values of a given word’s predicted vector, i.e. its Euclidian distance

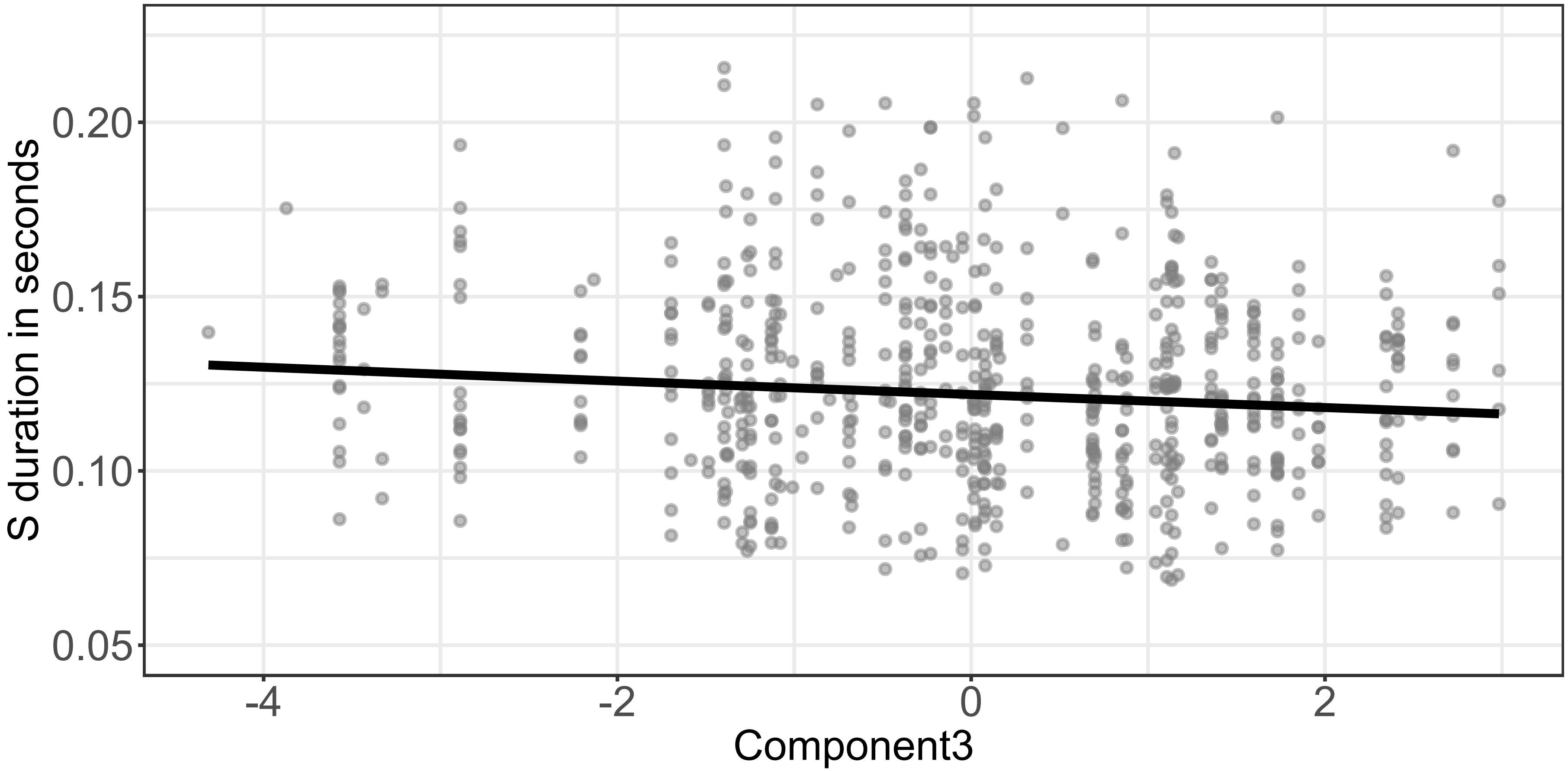
Model 1: LDL + 'type of S'

Component3

- strongly correlated with
  - **l1norm**
    - the sum of the absolute values of vector elements of a given word's predicted semantic vector, i.e. its city-block distance
  - **l2norm**
    - the square root of the sum of the squared values of a given word's predicted vector, i.e. its Euclidian distance
  - higher values imply more strong links to many other lexomes
  - both measures may be interpreted as semantic activation diversity

Model 1: LDL + ‘type of S’

Component3



low **semantic activation diversity** **high**

Model 1: LDL + ‘type of S’

Component3

- strongly correlated with
  - **l1norm**
  - **l2norm**
  - both measures may be interpreted as semantic activation diversity,
- some sort of general semantic activation diversity effect:
  - higher activation diversity leads to shorter /s/ durations

Model 2: LDL only

- variables showing significant effects are
    1. base duration
    2. pause
    3. segmental class of the following segment
    4. speaking rate
    5. Component.woA.4
    6. consonant preceding the /s/

Model 2: LDL only

- variables showing significant effects are
  1. base duration
  2. pause
  3. segmental class of the following segment
  4. speaking rate
  5. Component.woA.4
  6. consonant preceding the /s/

Model 2: LDL only

Component.woA.4

- strongly correlated with
  - **density**
  - **ALC**
  - **ALDC**

Model 2: LDL only

Component.woA.4

- strongly correlated with
  - **density**
    - mean correlation to eight closest semantic neighbours
    - higher values indicate a denser semantic neighbourhood
    - may be interpreted as a measure of semantic activation diversity
  - **ALC**
  - **ALDC**

Model 2: LDL only

Component.woA.4

- strongly correlated with
  - **density**
    - may be interpreted as a measure of semantic activation diversity
  - **ALC – Average Lexical Correlation**
    - mean value of all correlation values of a pseudoword's estimated semantic vector with each of the real word semantic vectors
    - higher values indicate that a pseudoword vector has "landed" in a denser semantic neighbourhood
    - may be interpreted as a measure of semantic activation diversity for pseudowords
  - **ALDC**

Model 2: LDL only

Component.woA.4

- strongly correlated with
  - **density**
    - may be interpreted as a measure of semantic activation diversity
  - **ALC**
    - may be interpreted as a measure of semantic activation diversity for pseudowords
  - **ALDC – Average Levensthein Distance of Candidates**
    - the mean of all Levenshtein distances of a word and its candidate forms

target	candidates	distance	ALDC
prVps	prVts	1	1

Model 2: LDL only

Component.woA.4

- strongly correlated with
  - **density**
    - may be interpreted as a measure of semantic activation diversity
  - **ALC**
    - may be interpreted as a measure of semantic activation diversity for pseudowords
  - **ALDC – Average Levensthein Distance of Candidates**
    - the mean of all Levenshtein distances of a word and its candidate forms

target	candidates	distance	ALDC
prVps	prVts	1	1
pli:ps	pli:ts	1	1.5
	pri:ts	2	

Model 2: LDL only

Component.woA.4

- strongly correlated with
  - **density**
    - may be interpreted as a measure of semantic activation diversity
  - **ALC**
    - may be interpreted as a measure of semantic activation diversity for pseudowords
  - **ALDC – Average Levensthein Distance of Candidates**
    - the mean of all Levenshtein distances of a word and its candidate forms
    - conceptual similar to classical measures of phonological neighbourhood density
    - may be interpreted as a measure of phonological certainty, i.e.
      higher values = less similar neighbours = higher degree of certainty

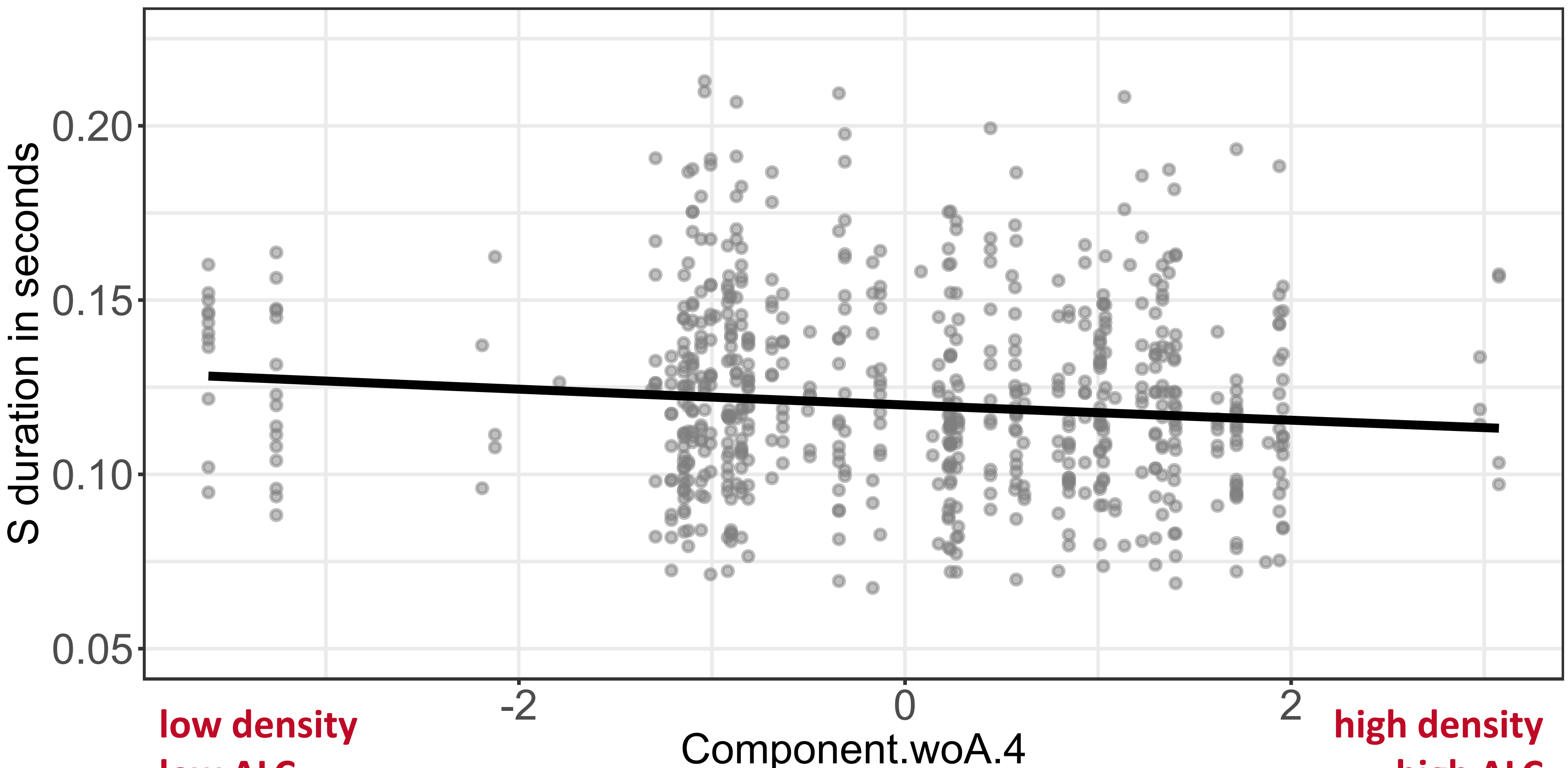
Model 2: LDL only

Component.woA.4

- strongly correlated with
  - **density**
    - may be interpreted as a measure of semantic activation diversity
  - **ALC**
    - may be interpreted as a measure of semantic activation diversity for pseudowords
  - **ALDC – Average Levensthein Distance of Candidates**
    - may be interpreted as a measure of phonological certainty

Model 2: LDL only

Component.woA.4



low density
low ALC
high ALDC

high density
high ALC
low ALDC

Model 2: LDL only

Component.woA.4

- strongly correlated with
  - **density & ALC**
    - may be interpreted as a measure of semantic activation diversity
  - **ALDC**
    - may be interpreted as a measure of phonological certainty
- some sort of general semantic activation diversity effect:
  - higher activation diversity leads to shorter /s/ durations
- more phonological certainty = longer /s/ durations

Can we **implement LDL with real and nonce words** and use **measures derived from such an implementation** to **model /s/ durations**?

If so, **how can we interpret these LDL measures**?

Discussion

- higher activation diversity leads to shorter /s/ durations
  - a prolongation of the acoustic signal is dysfunctional if the prolongation maintains or increases the discrimination problem instead of contributing to resolving it (Tomaschek et al., 2019)
- more phonological certainty = less similar neighbours = longer /s/ durations
  - in line with results on pseudoword word durations modelled by LDL measures (Chuang et al., 2020)
  - such effects of phonological neighbourhood density on articulation were found before (e.g. Gahl et al., 2012)

Thank you!

References I

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