Modeling derivative durations with linear discriminative learning

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Ingo Plag

PROJECT VAR 1

DFG Deutsche Forschungsgemeinschaft
FOR2373

Previously on VAR 1

Derived English words from three corpora

AudioBNC | Quakebox | ONZE

Modeling durations with:

- morphological segmentability (relative frequency)
- other frequency measures (word frequency, base frequency)
- informativity (semantic information load, affix probability)
- prosodic structure (pword integration)
- a number of "traditional" covariates

  - In a nutshell: These variables produce very inconsistent results.
  - Both effects and null results are often not well explained at the (traditional) theoretical level.

LDL

We need to explore whether LDL is a fruitful alternative for predicting our data.

- How well can it account for the durational variation of derivatives?
- What do effects of LDL-derived measures tell us about speech production?
- What does LDL tell us about the role of morphological categories?

Dataset

		tokens	*types*	*derivational functions*
AudioBNC	audio data	4530	363	DIS, NESS, LESS, ATION, IZE

Dataset

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AudioBNC	audio data	4530	363	DIS, NESS, LESS, ATION, IZE
AudioBNC TASA Baayen et al. 2019	training data		363 + 4813	DIS, NESS, LESS, ATION, IZE, AGAIN, AGENT, EE, ENCE, FUL, IC, INSTRUMENT, ISH, IST, IVE, LY, MENT, MIS, NOT, ORDINAL, OUS, OUT, SUB, UNDO, Y, MONOMORPHEMIC

Matrices

Schematic examples

C matrix

	#k{	k{t	{t#	#h{	h{p
k{t	1	1	1	0	0
h{plnls	0	0	0	1	1
w$k	0	0	0	0	0
lEm@n	0	0	0	0	0

S matrix

	CAT	HAPPINESS	NESS	WALK
k{t	0.000000	-6.24E-05	-0.0003179	4.71E-05
h{plnls	-0.00056	0.0346008	0.032476	7.26E-05
w$k	0.000304	-0.0002334	-9.76E-06	0.00000
lEm@n	-7.28E-05	-2.41E-07	-0.0001247	-2.68E-05

Matrices

Schematic examples

NDL network in TASA

Baayen et al. 2019

lexome-to-lexome matrix

	CAT	HAPPINESS	NESS	WALK
CAT	0.000000	-6.24E-05	-0.0003179	4.71E-05
HAPPINESS	-0.000110	0.00000000	0.032476	0.000194
NESS	-0.000450	0.0346008	0.000000	-0.0001
WALK	0.000304	-0.0002335	-9.76E-06	0.000000
LEMON	-7.28E-05	-2.41E-07	-0.0001247	-2.68E-05

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Building the S matrices

Two networks

M-Network

$\overrightarrow{happiness} + \overrightarrow{NESS}$

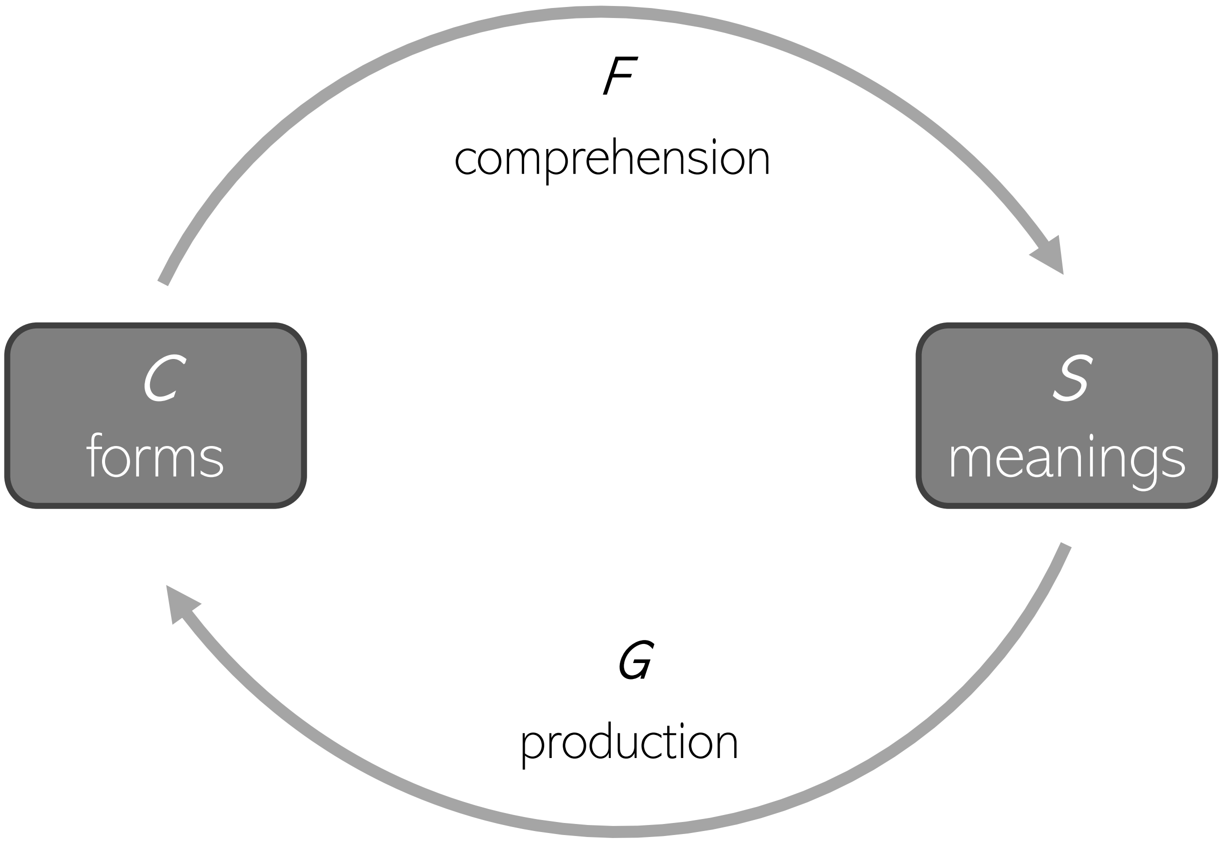
Vectors contain idiosyncratic information and information about morphological category.

I-Network

$\overrightarrow{happiness}$

Vectors contain only idiosyncratic information.

Comprehension and production mapping



Obtaining estimated vectors

predicting meanings

$$\hat{S} = CF$$

predicting forms

$$\hat{C} = SG$$

Predictor variables

predictor	defined as	represents

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MEAN WORD SUPPORT	$\frac{sum\ of\ path\ supports}{number\ of\ path\ nodes}$	articulatory certainty

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SEMANTIC DENSITY	mean correlation of $\hat{s}$ with top 8 neighbors	semantic transparency

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TARGET CORRELATION	correlation between $\hat{\boldsymbol{s}}$ and $\boldsymbol{s}$	accuracy in predicting meaning from form

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TARGET CORRELATION	correlation between $\hat{s}$ and s	accuracy in predicting meaning from form
SPEECH RATE	$\frac{number\ of\ syllables}{utterance\ duration}$	

Response variable

DURATION DIFFERENCE

residuals of a linear model absolute duration ~ baseline duration

absolute duration = actual acoustic duration

baseline duration = sum of mean segment durations in corpus

Performance

Network accuracy

M-Network

Comprehension	82 %
Production	99 %

I-Network

Comprehension	81 %
Production	99 %

traditional model with RELATIVE FREQUENCY, BIGRAM FREQUENCY, BIPHONE PROBABILITY, AFFIX, SPEECH RATE: 37 %

Explained variance of variables predicting duration

M-Network

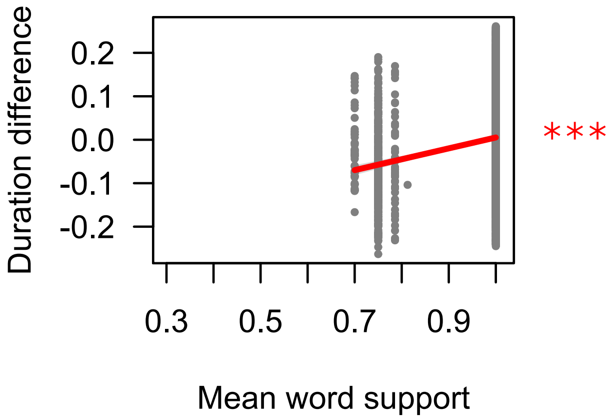
Adjusted R^2 37 %

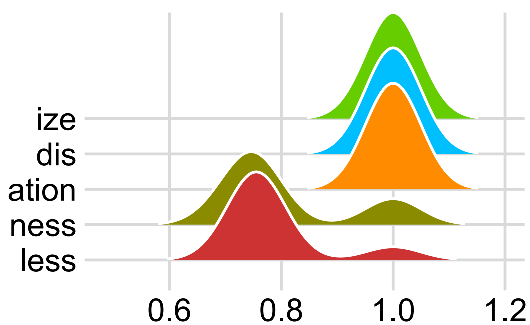
I-Network

Adjusted R^2 38 %

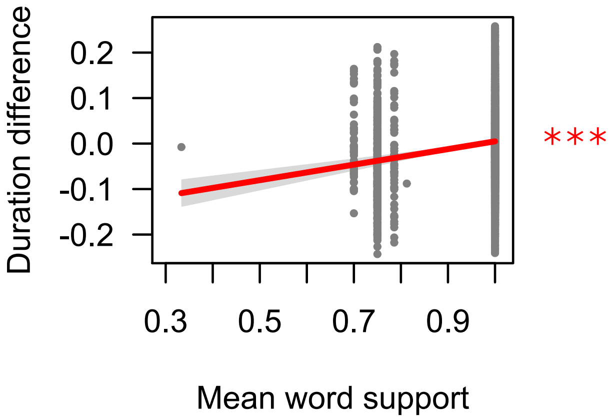
MEAN WORD SUPPORT

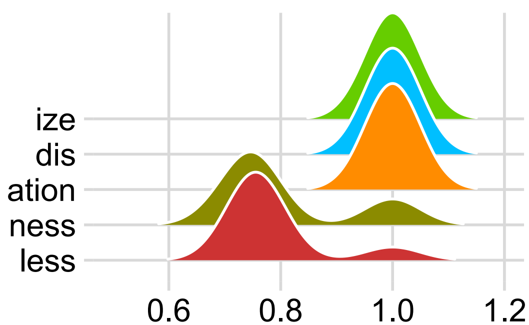
M-Network





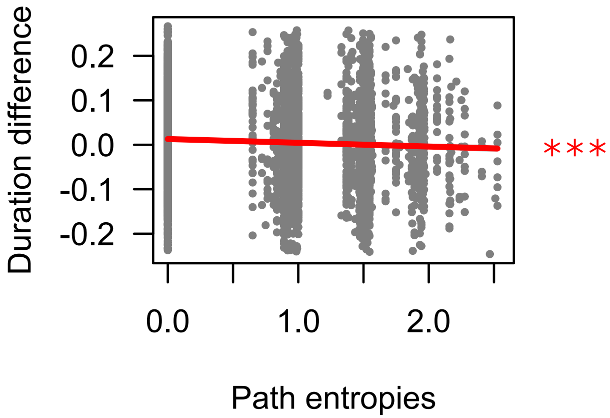
I-Network

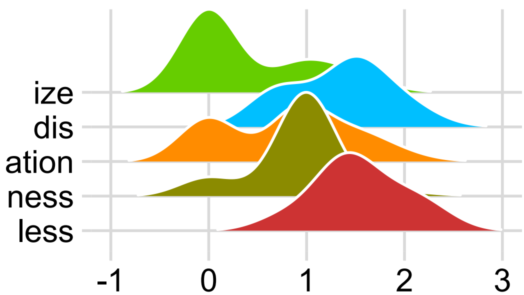




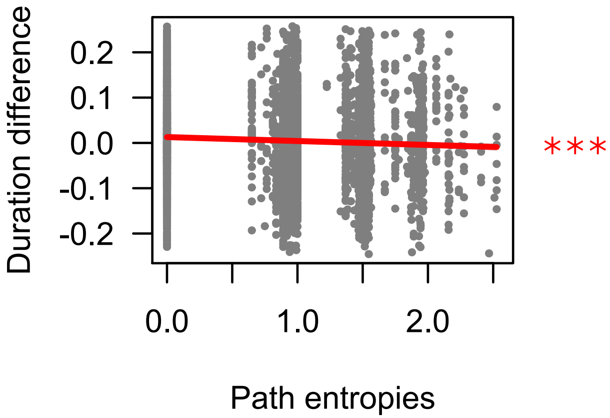
PATH ENTROPIES

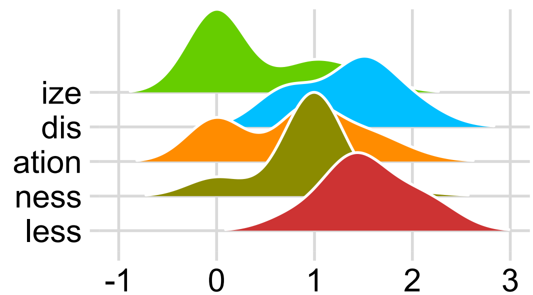
M-Network





I-Network

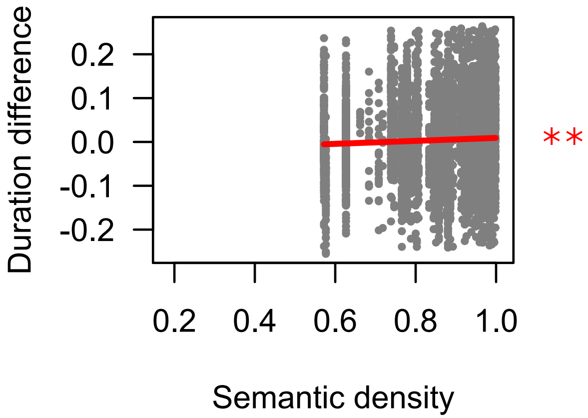


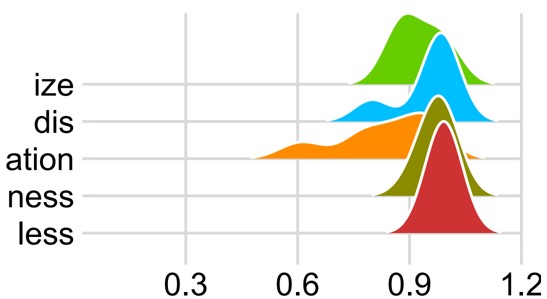


Results

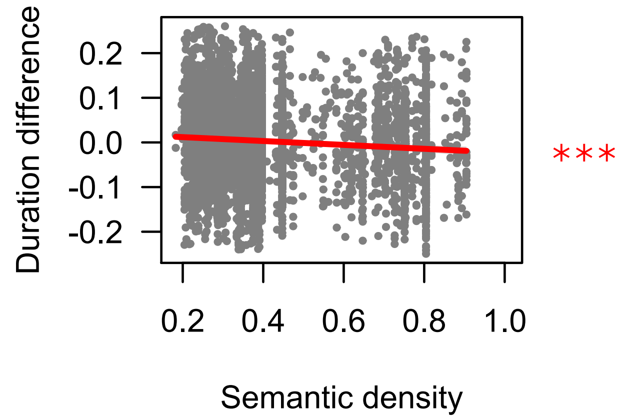
SEMANTIC DENSITY

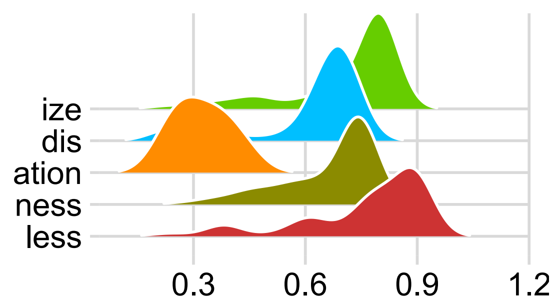
M-Network





I-Network

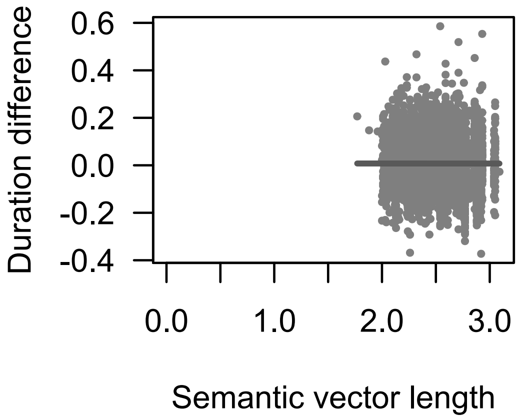


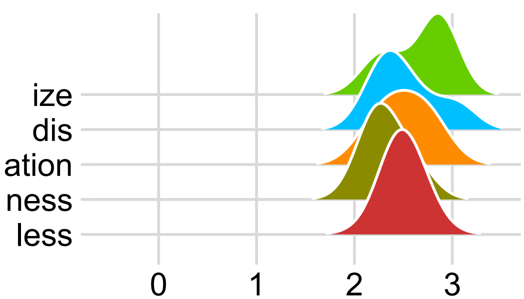


Results

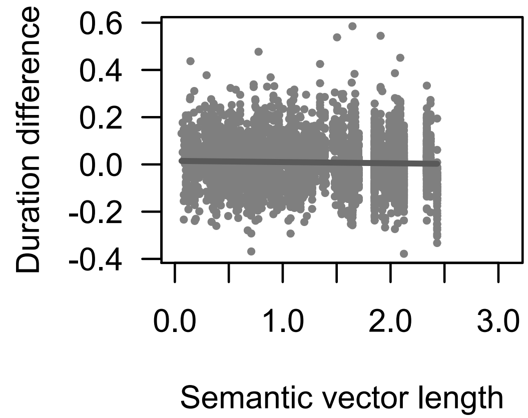
SEMANTIC VECTOR LENGTH

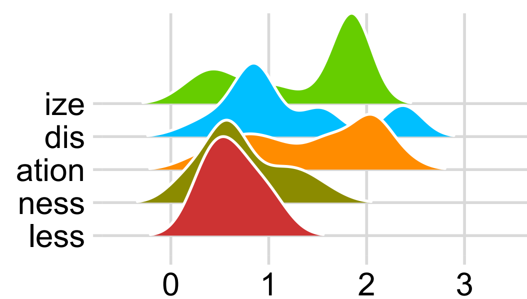
M-Network





I-Network

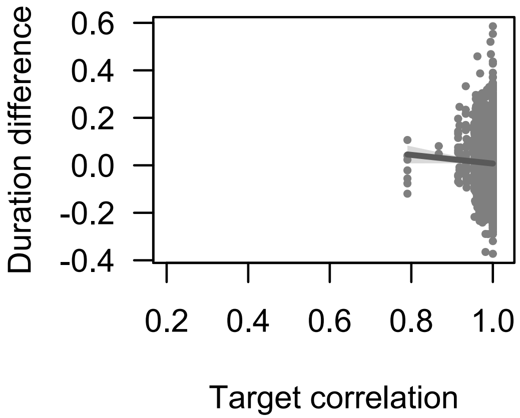


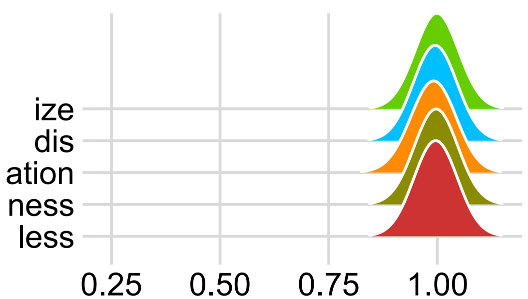


Results

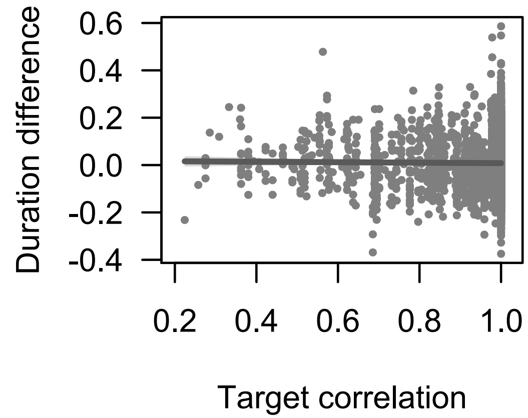
TARGET CORRELATION

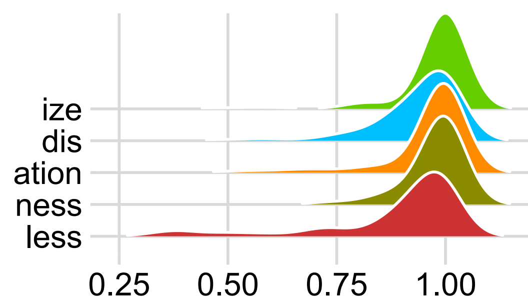
M-Network





I-Network





General implications

LDL-derived variables are successful in predicting derivative durations.

- This is further evidence that discriminative models are a promising approach to speech production where morpho-phonetic effects are not unexpected.
  cf., e.g., Baayen et al. 2019, Chuang et al. 2020, Tomaschek et al. 2019, Tucker et al. 2019

LDL can discriminate derivational functions from sublexical and contextual cues.

- This provides more support for the idea that morphology is possible without morphemes.

Effects on duration

Higher certainty is associated with lengthening.

- In the discussion of whether certainty has an effect of enhancement or reduction, much recent evidence points towards enhancement.
  cf. Tomaschek et al. 2019, Kuperman et al. 2007, Cohen 2014, Cohen 2015, Tucker et al. 2019, this study

Higher semantic transparency can be associated with lengthening and with shortening.

- Traditional lines of argumentation would expect lengthening.
  cf. Hay 2003, 2007, Plag and Ben Hedia 2018, Zuraw et al. 2020
- If interpreted with regards to activation diversity, we could also expect shortening.
  cf. Tucker et al. 2019

Differences between morphological functions

Differences between morphological categories can emerge even from the network without any information about derivational functions.

Some of these differences mirror traditional classifications from the literature.

- Semantic density is higher for words with NESS, LESS and DIS than for words with ATION.
  - *-ness*, *-less* and *dis-* are regarded as producing more transparent derivatives than *-ation* (exception: IZE vs. *-ize*).
    cf. Bauer et al. 2013; Plag 2018
- Semantic vector length was highest for IZE and ATION words.
  - *-ize* and *-ation* are traditionally described as having highly multifaceted semantics, while *-less*, *dis-*, and to a lesser extent *-ness* have clearer and narrower semantics.
    cf. Bauer et al. 2013; Plag 2018

Future directions

We think it could be worthwhile to…

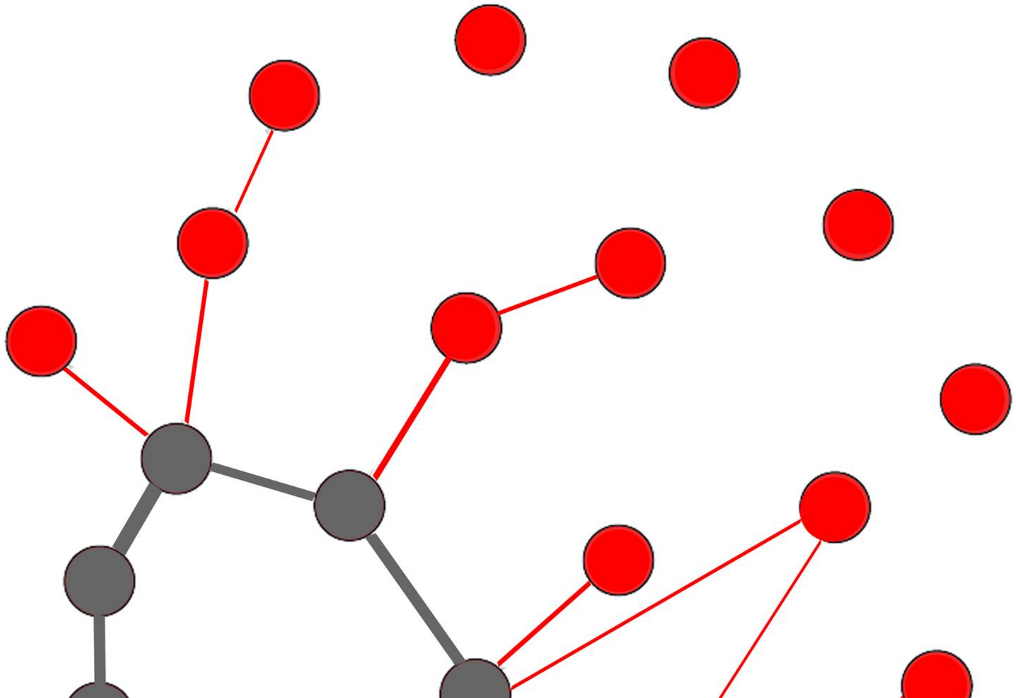
- analyze durations for a larger dataset with more derivational functions.
- somehow control the response variable for segmental makeup without referring to segments.
- explore how to build vectors for words with multiple derivational functions.

We also need to think about how to interpret semantic transparency effects:

- Why does articulation slow down both with high and with low semantic density, and is fastest for medium densities?
- Which behavior would be expected based on which theoretical perspective, and why?

Future directions

Thank you for listening.



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Models

M-Network

	Estimate	*Std. Err.*	*t-value*	*Pr(>|t|)*	
Intercept	0.090708	0.025887	3.504	0.000463	***
MEAN WORD SUPPORT	0.250262	0.020700	12.090	< 2e-16	***
SEMANTIC DENSITY	0.033868	0.012372	2.737	0.006217	**
PATH ENTROPIES	-0.008442	0.002309	-3.656	0.000259	***
SPEECH RATE	-0.058602	0.001159	-50.579	< 2e-16	***

I-Network

	Estimate	*Std. Err.*	*t-value*	*Pr(>|t|)*	
Intercept	0.216901	0.026210	8.276	< 2e-16	***
MEAN WORD SUPPORT	0.170726	0.023507	7.263	4.45e-13	***
SEMANTIC DENSITY	-0.043545	0.008925	-4.879	1.10e-06	***
PATH ENTROPIES	-0.008688	0.002242	-3.875	0.000108	***
SPEECH RATE	-0.058757	0.001148	-51.186	< 2e-16	***

Models

Traditional model

	Estimate	Std. Err.	t-value	Pr(>|t|)	
Intercept	3.299e-01	1.086e-02	30.379	< 2e-16	***
RELATIVE FREQUENCY	-2.383e-05	4.167e-05	-0.572	0.567504	
BIGRAM FREQUENCY	-4.169e-07	6.135e-07	-0.680	0.496818	
MEAN BIPHONE PROBABILITY	-4.835e+00	8.661e-01	-5.583	2.51e-08	***
AFFIX less					
ness	2.921e-03	9.242e-03	0.316	0.751941	
ation	5.843e-02	8.201e-03	7.125	1.21e-12	***
dis	6.504e-02	1.016e-02	6.399	1.73e-10	***
ize	3.451e-02	9.222e-03	3.742	0.000185	***
SPEECH RATE	-5.885e-02	1.161e-03	-50.680	< 2e-16	***

Models

Traditional model

	Df	*Sum Sq*	*Mean Sq*	*F-value*	*Pr(>F)*	
RELATIVE FREQUENCY	1	0.018	0.0182	2.1070	0.14669	
MEAN BIPHONE PROBABILITY	1	0.043	0.0433	5.0118	0.02522	*
AFFIX	4	0.581	0.1452	16.8251	1.069e-13	***
SPEECH RATE	1	22.223	22.2229	2574.5115	< 2.2e-16	***
BIGRAM FREQUENCY	1	0.004	0.0040	0.4618	0.49682	

Comparing matrices

M-Network

$\overrightarrow{happiness} + \overrightarrow{NESS}$

Vectors contain idiosyncratic information and information about morphological category.

I-Network

$\overrightarrow{happiness}$

Vectors contain only idiosyncratic information.

B-Network

$\overrightarrow{happy} + \overrightarrow{NESS}$

Vectors contain information about morphological category and the base, but no idiosyncratic information.

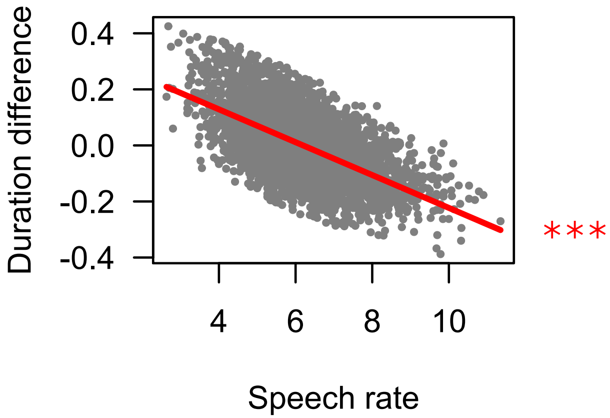
r = 0.08

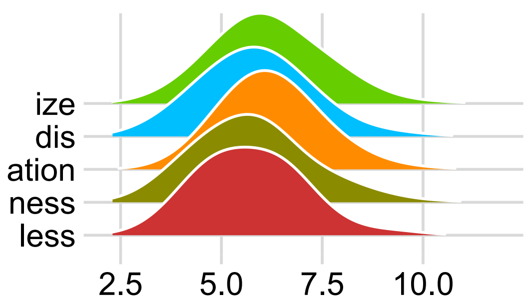
r = 0.1

r = 0.9

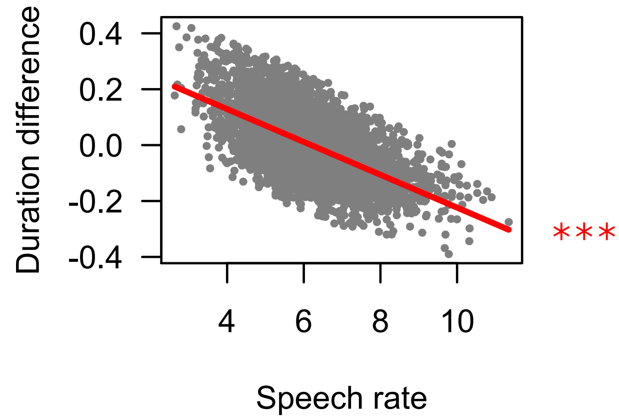
SPEECH RATE

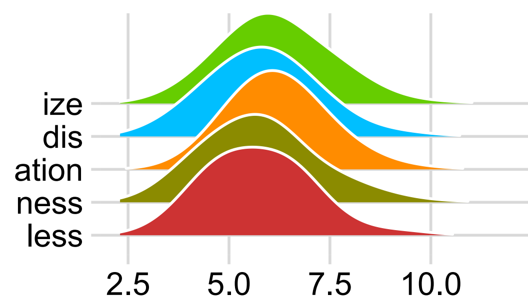
M-Network





I-Network





Path supports

Toy example