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Modeling the acoustic duration of English derivatives with linear discriminative learning

PaPe

June 21–23, 2021

Workshop: From speech technology to big data phonetics and phonology: A win-win paradigm

Background

Motivation

Phonetic detail varies by morphological structure.

- Morphological information must still be present at the phonetic level.

e.g., Plag et al. 2020, Zuraw et al. 2020,
Tomaschek et al. 2019, Ben Hedia 2019, Plag & Ben Hedia 2018,
Plag et al. 2017, Seyfarth et al. 2017, Ben Hedia & Plag 2017, Hay 2007, 2003

Many models of the morphology-phonology interaction and of speech production do not allow for post-lexical access to morphological information (e.g., bracket erasure).

- They cannot account for such findings.

e.g., Chomsky & Halle 1968, Kiparsky 1982, Dell 1986,
Levelt et al. 1999, Roelofs & Ferreira 2019, Turk & Shattuck-Hufnagel 2020

Linear discriminative learning

- end-to-end model
- associations between form and meaning
- learning and experience

- Morphological information can be expected to be reflected in phonetic detail.

cf. Baayen et al. 2019b

… a win-win paradigm?

psycholinguistic research on phonetic detail and phonetic-phonological interfaces	methods from computer linguistics, (discriminative) machine learning, “big data”, speech technology
explanandum: processing apparatus explanans: behavioral data	explanandum: behavioral data explanans: processing apparatus

- Linear discriminative learning is one example of this symbiosis.

Pirelli et al. 2020

Research questions

1. How well can LDL account for the durational variation of derivatives?
2. What do effects of LDL-derived measures tell us about speech production?
3. What does LDL tell us about the role of morphological functions?

Method

Data

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

Coleman et al. 2012

Data

		tokens	*types*	*derivational functions*
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

Coleman et al. 2012, Ivens & Koslin 1991, Baayen et al. 2019b

Matrices

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

Matrices

C matrix

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

S matrix

	CAT	HAPPINESS	WALK	LEMON
k{t	0.000000	-6.24e-05	4.71e-05	-0.000138
h{pInIs	-0.000110	0.0000000	0.000194	-2.20E-05
w$k	0.000304	-0.0002335	0.000000	-3.74E-05
lEm@n	-7.28e-05	-2.41e-07	-2.68e-05	0.00000

Matrices

learning algorithm in TASA
Baayen et al. 2019

752,130 sentences,
10,719,386 tokens

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

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

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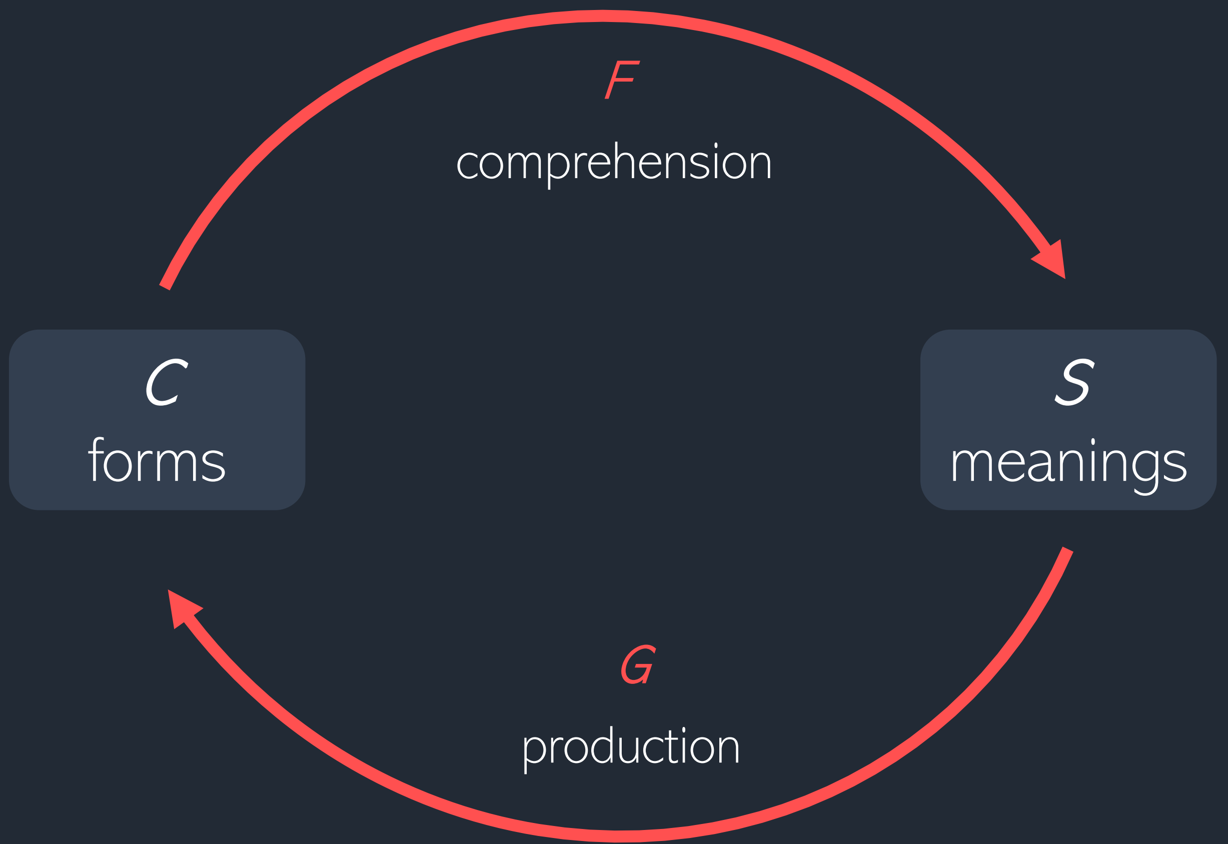
Baayen et al. 2019b

Two networks

Idiosyncratic Network	Morphology Network
$\overrightarrow{happiness}$	$\overrightarrow{happiness} + \overrightarrow{NESS}$
Vectors do not contain explicit information about morphological function	Vectors do contain explicit information about morphological function

Comprehension and production mapping



Comprehension and production mapping

predicting meanings

$$\hat{S} = CF$$

predicting forms

$$\hat{C} = SG$$

Modeling durations

linear models and mixed effects models with random intercept for word type

response variable

- DURATION DIFFERENCE
  residuals of a linear model OBSERVED DURATION ~ BASELINE DURATION

predictors

- MEAN WORD SUPPORT
- PATH ENTROPIES
- SEMANTIC VECTOR LENGTH
- SEMANTIC DENSITY
- TARGET CORRELATION
- SPEECH RATE

Results

Network accuracy

	Idiosyncratic Network	Morphology Network
comprehension	81 %	82 %
production	99 %	99 %

Explained variance of variables predicting duration

	Idiosyncratic Network	Morphology Network
R^2 adj. lm	.38	.37
R^2 mar. lmer	.37	.36

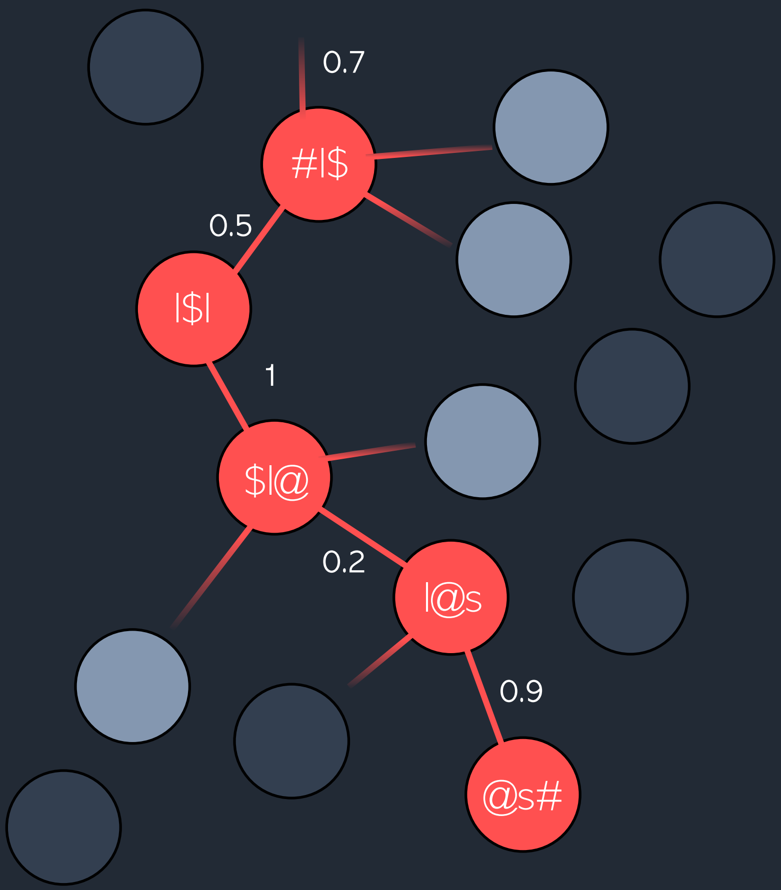
traditional model with
WORD FREQUENCY, RELATIVE FREQUENCY, BIGRAM FREQUENCY, BIPHONE PROBABILITY, AFFIX, SPEECH RATE

R^2 adj. lm	.37
R^2 mar. lmer	.37

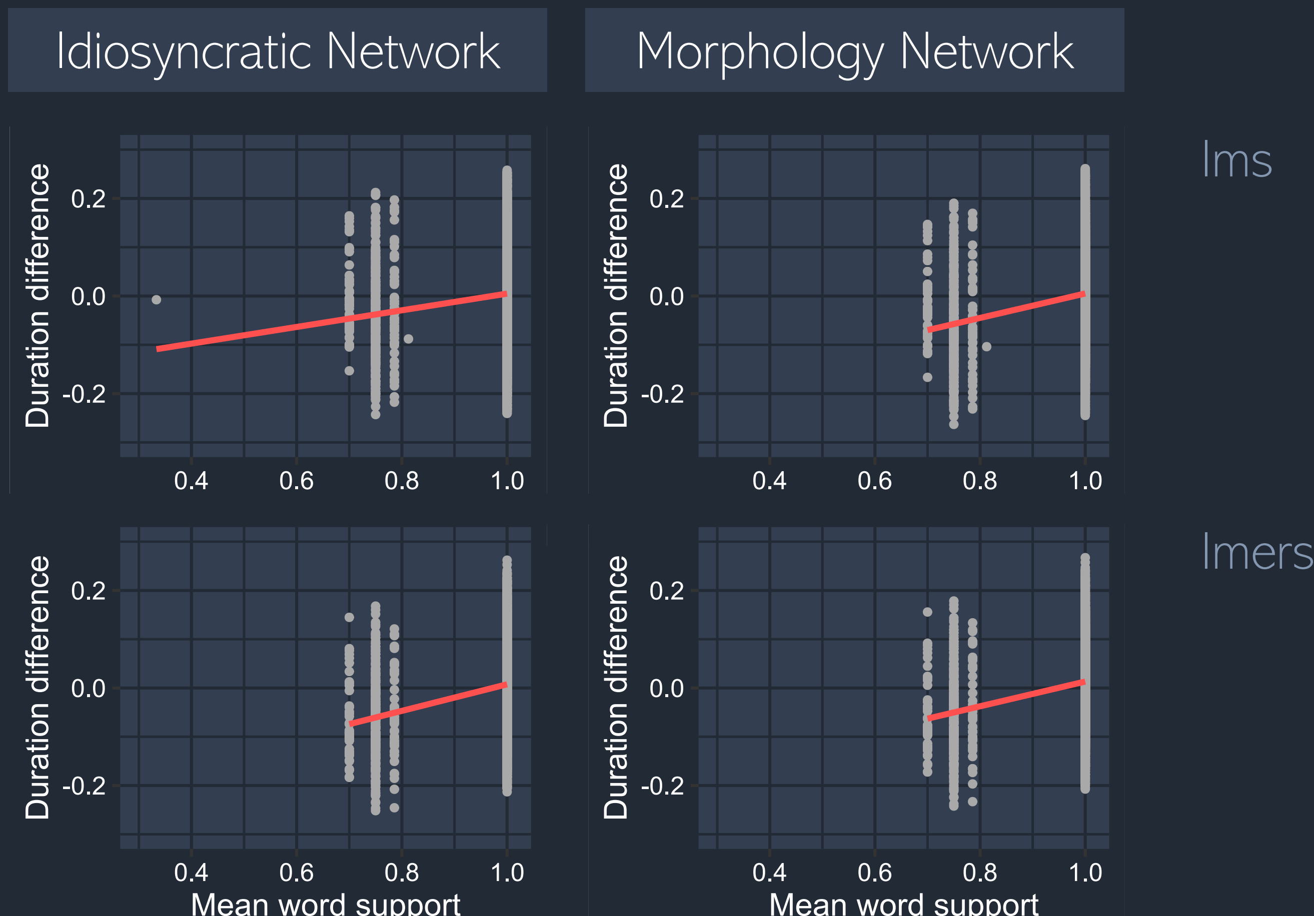
MEAN WORD SUPPORT

$$\frac{\textit{sum of path supports}}{\textit{number of path nodes}}$$

can represent
articulatory certainty



MEAN WORD SUPPORT

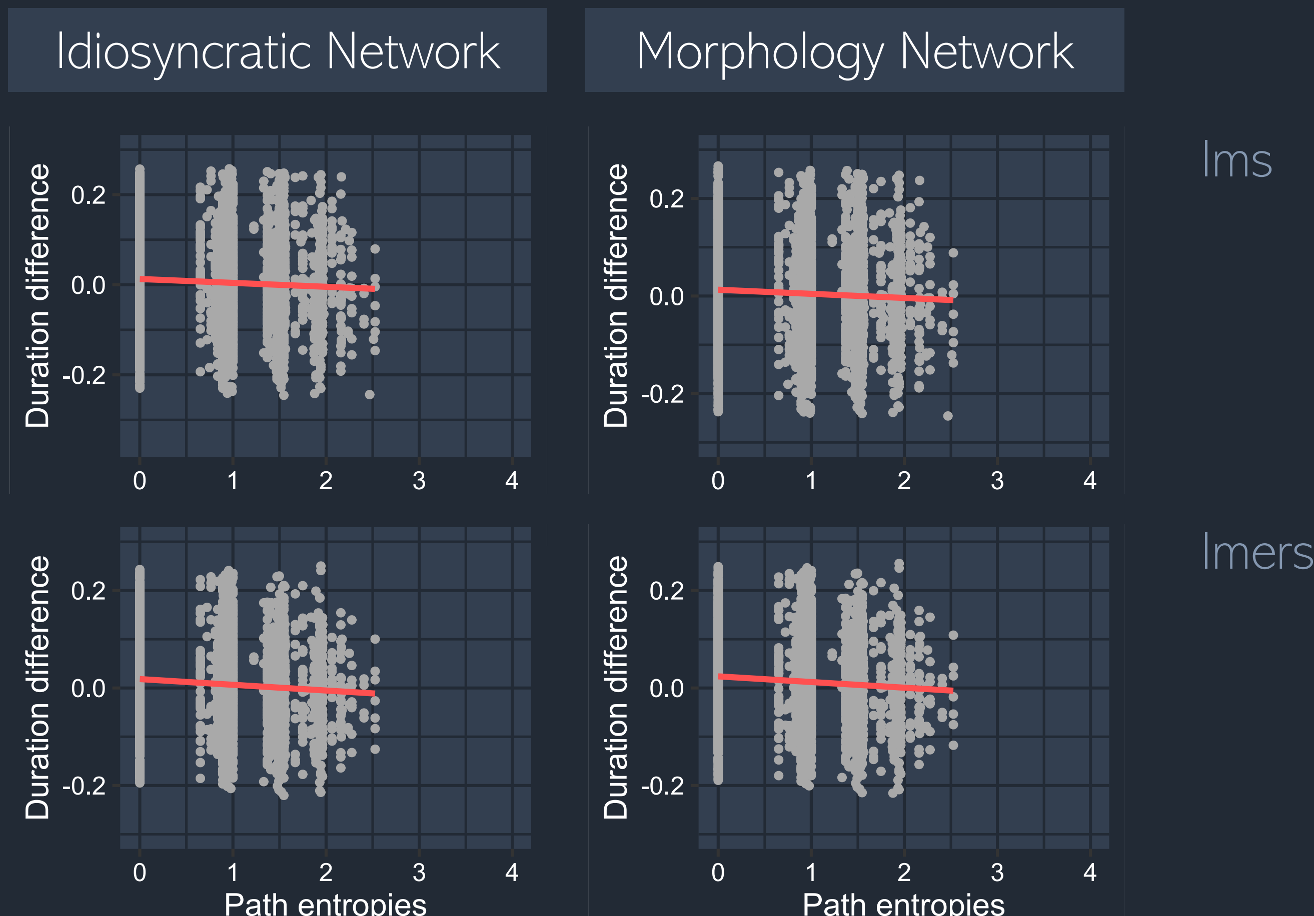


PATH ENTROPIES

Shannon entropy
of path supports

can represent
articulatory uncertainty

PATH ENTROPIES



SEMANTIC DENSITY

mean correlation of $\hat{s}$
with top 8 neighbors

can represent
semantic transparency

SEMANTIC DENSITY

Idiosyncratic Network	Morphology Network

lms

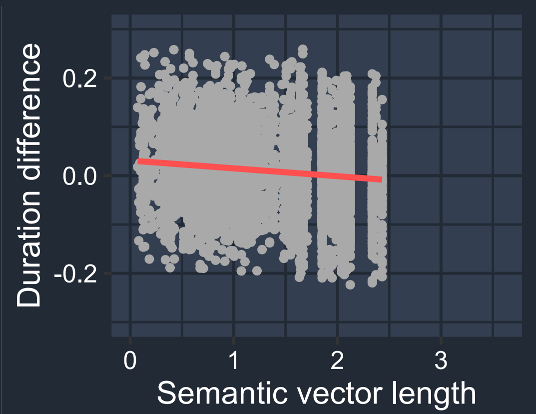
SEMANTIC VECTOR LENGTH

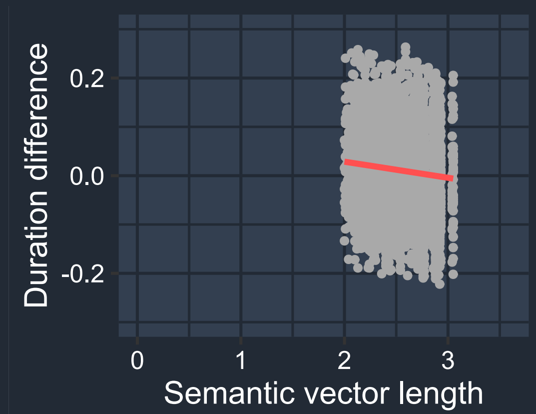
L1 distance of $\hat{s}$

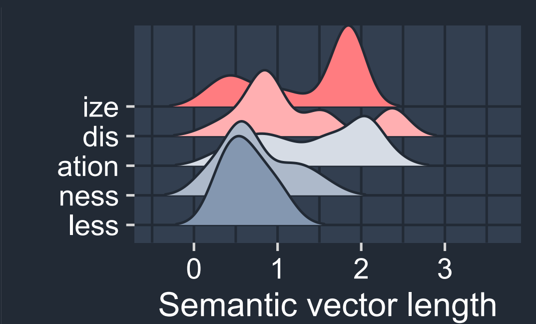
can represent
activation diversity or polysemy

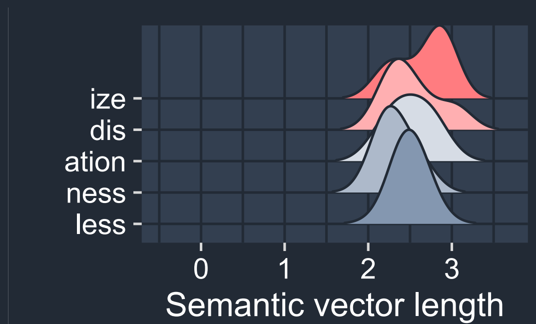
SEMANTIC VECTOR LENGTH

Idiosyncratic Network	Morphology Network









lmers

Discussion

1. How well can LDL account for the durational variation of derivatives?

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

2. What do effects of LDL-derived measures tell us about speech production?

Higher certainty is associated with lengthening, higher uncertainty is associated with shortening.

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.
There are different expectations in the literature.

cf. Hay 2003, 2007, Plag & Ben Hedia 2018, Zuraw et al. 2020; but cf. Tucker et al. 2019, Schreuder & Baayen 1997, Plag & Baayen 2009

Higher semantic activation diversity is associated with shortening.

cf. Tucker et al. 2019

3. What does LDL tell us about the role of morphological functions?

   Differences between morphological functions can emerge even from the Idiosyncratic Network without morphological function vectors.

   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 (cf. transparency of *-ness*, *-less*, and *dis-* vs. *-ation*).
   - Semantic vector length was highest for IZE and ATION words (cf. semantics of *-ize* and *-ation* vs. *-less*, *dis-*, and *-ness*).

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.
- train lexome-to-lexome vectors without coding for function lexomes in the first place.
- explore how to build vectors for words with multiple derivational functions.

Conclusion

Takeaways

- Phonetic data can be modeled successfully with a linear discriminative learning approach.
- Higher articulatory certainty is associated with lengthening, higher activation diversity with shortening.
- Differences between morphological functions are successfully captured by the semantic vectors in the network.

Thank you!

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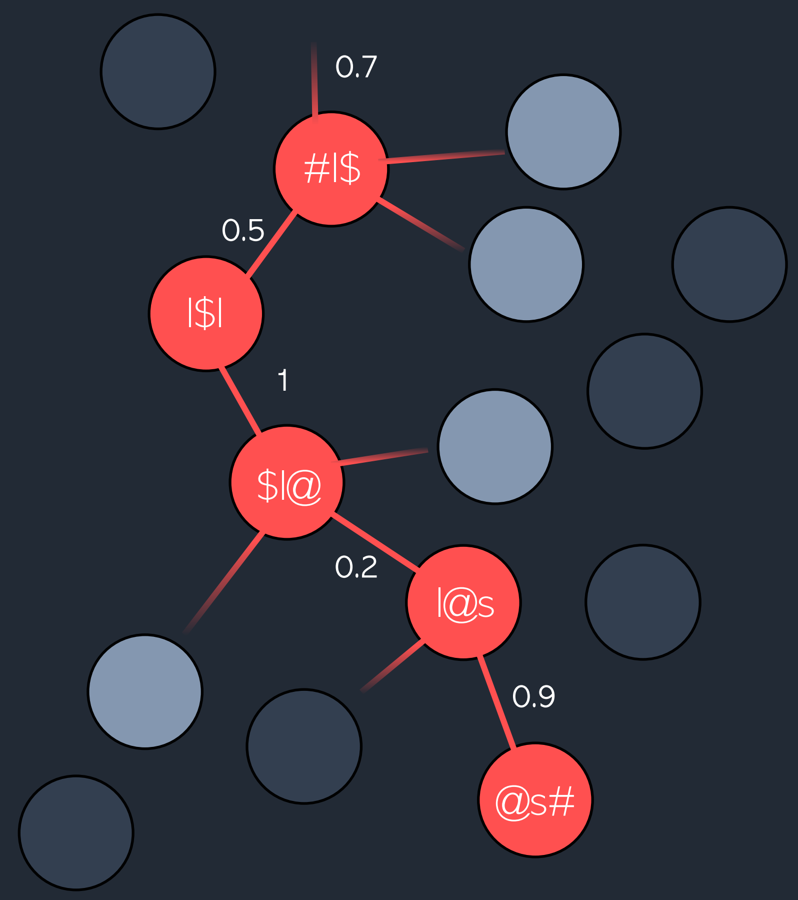
Appendix

MEAN WORD SUPPORT

$$\frac{\textit{sum of path supports}}{\textit{number of path nodes}}$$

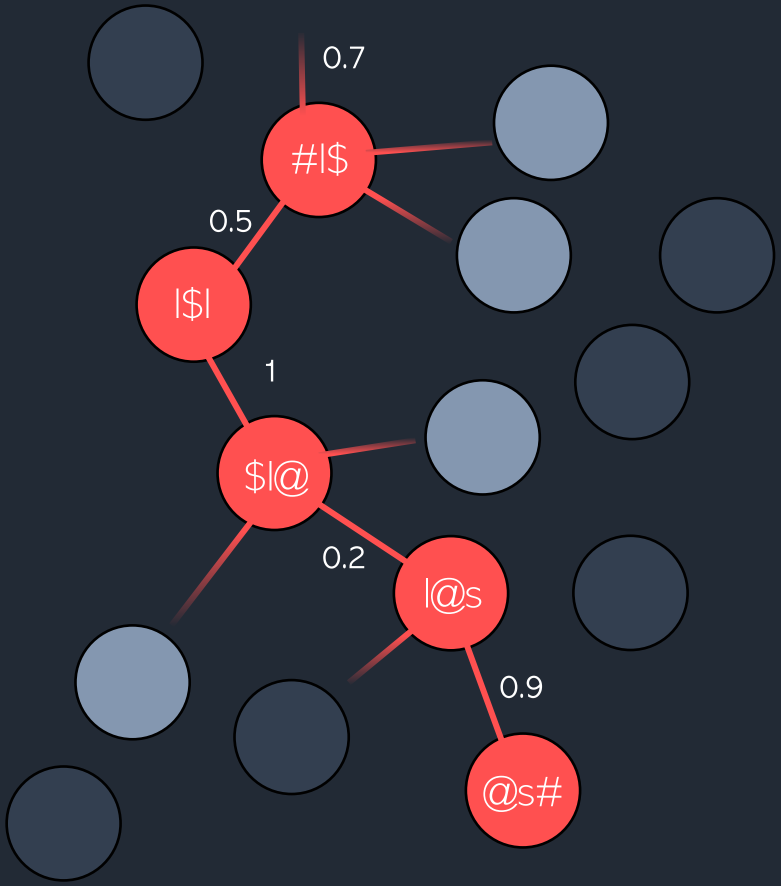
can represent
articulatory certainty



PATH ENTROPIES

Shannon entropy
of path supports

can represent
articulatory uncertainty



Three networks

Idiosyncratic Network	Morphology Network	Base Network
$\overrightarrow{happiness}$	$\overrightarrow{happiness} + \overrightarrow{NESS}$	$\overrightarrow{happy} + \overrightarrow{NESS}$
Vectors contain:	Vectors contain:	Vectors contain:
idiosyncratic information about derivative,	idiosyncratic information about derivative,	no idiosyncratic information about derivative,
no information about morphological function	information about morphological function	information about morphological function

Network accuracy

	Idiosyncratic Network	Morphology Network	Base Network
comprehension	81 %	82 %	83 %
production	99 %	99 %	98 %

Similarity of semantic matrices

Idiosyncratic Network ⟷ Morphology Network	r = .08
Idiosyncratic Network ⟷ Base Network	r = .1
Base Network ⟷ Morphology Network	r = .9

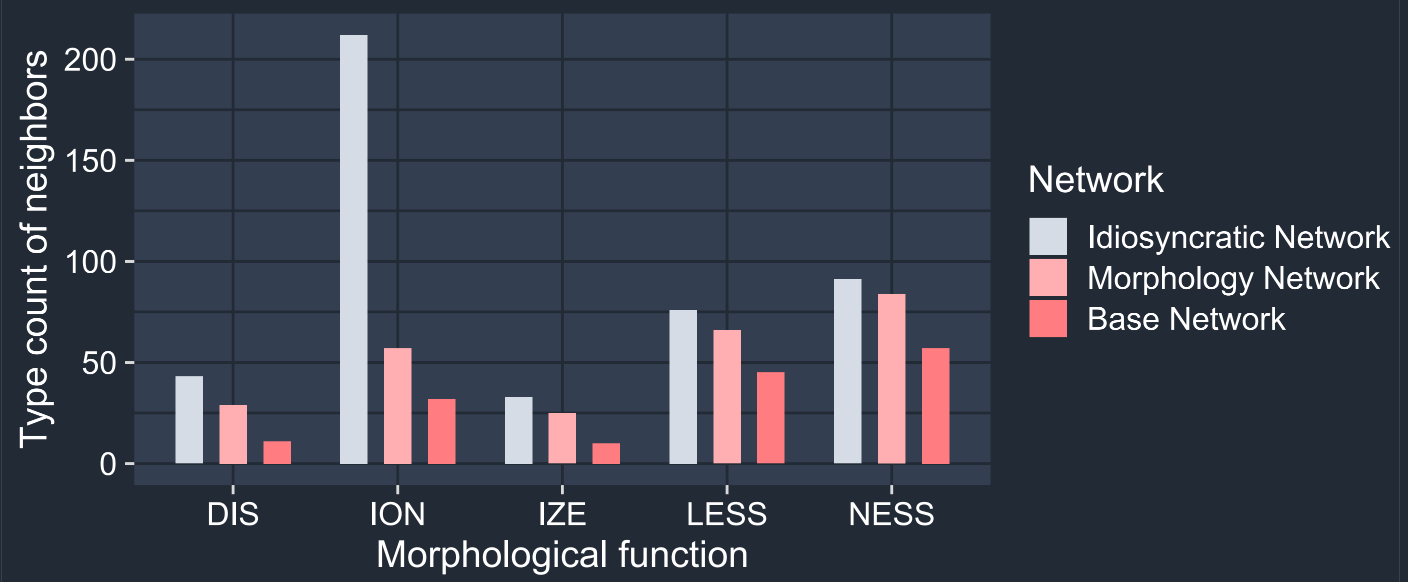
Explained variance of variables predicting duration

	Idiosyncratic Network	Morphology Network	Base Network
R^2 adj. lm	.38	.37	.36
R^2 mar. lmer	.37	.36	.35

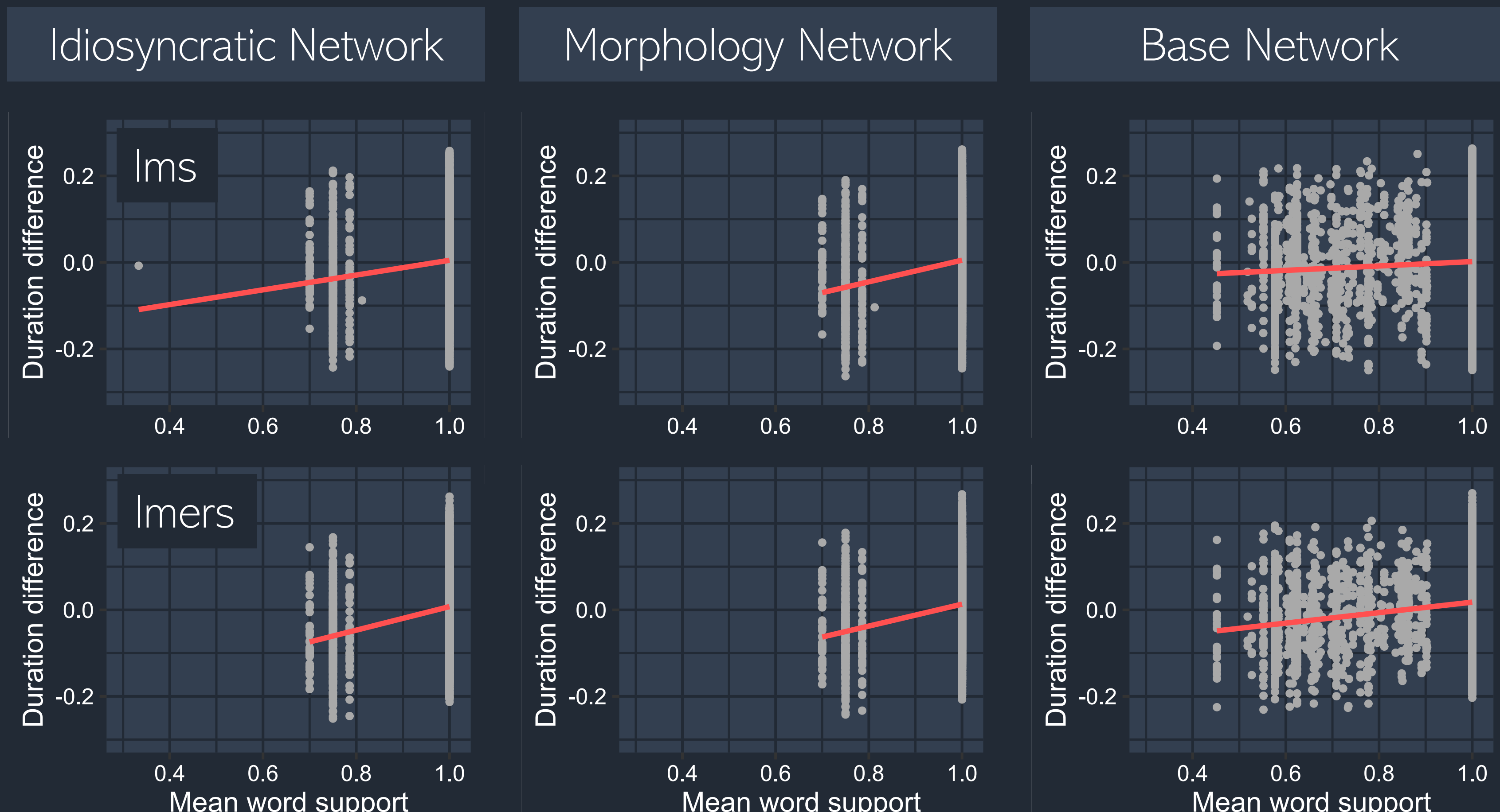
traditional model with
WORD FREQUENCY, RELATIVE FREQUENCY, BIGRAM FREQUENCY, BIPHONE PROBABILITY, AFFIX, SPEECH RATE

R^2 adj. lm	.37
R^2 mar. lmer	.37

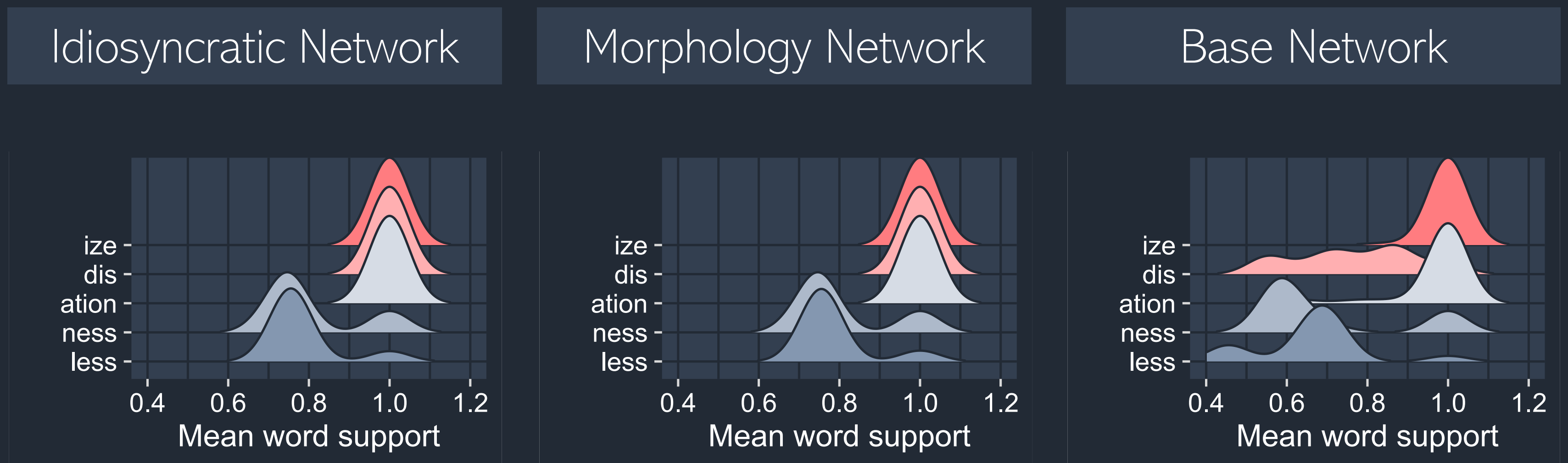
Type count of top 8 neighbors



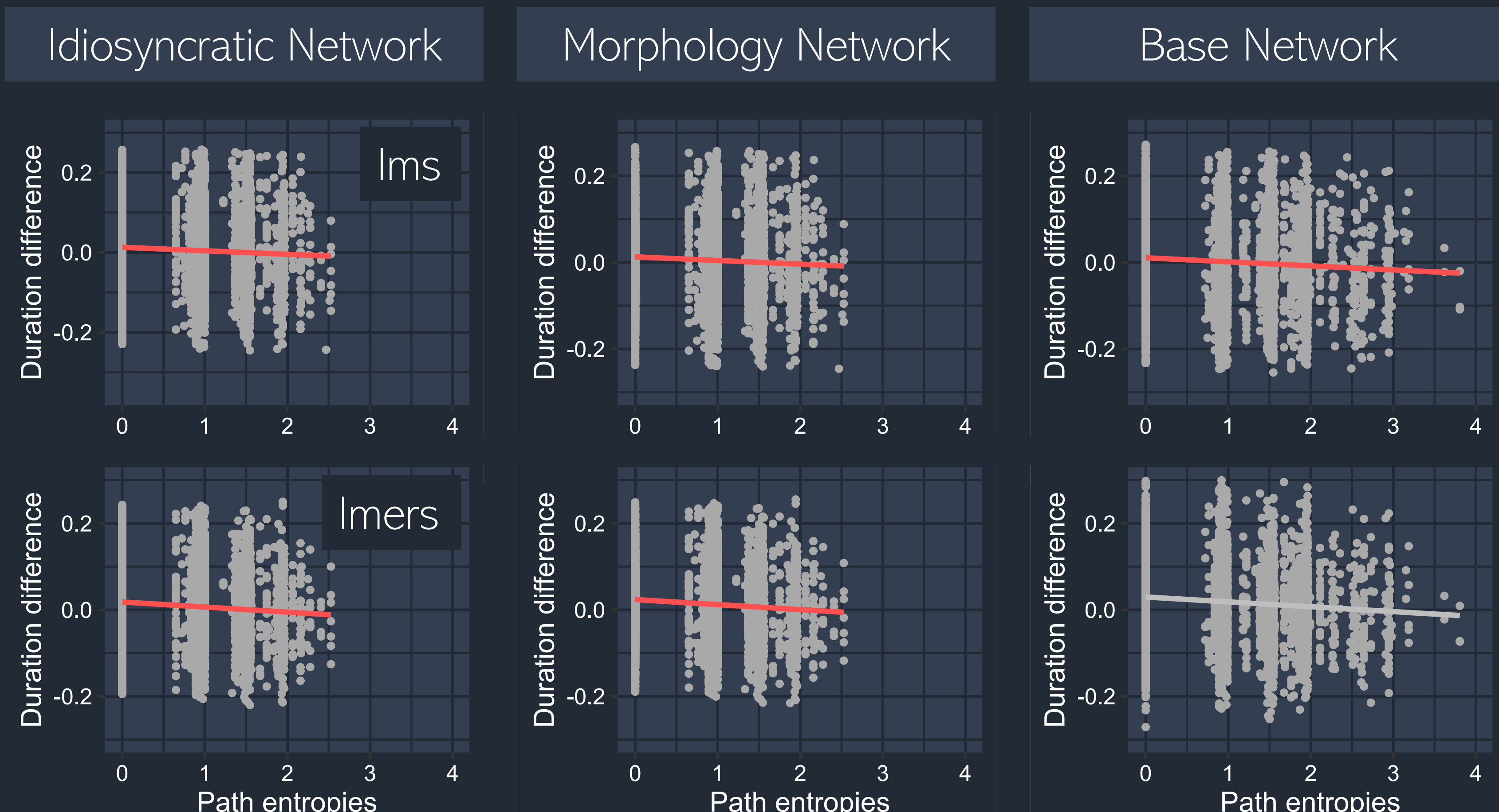
MEAN WORD SUPPORT



MEAN WORD SUPPORT

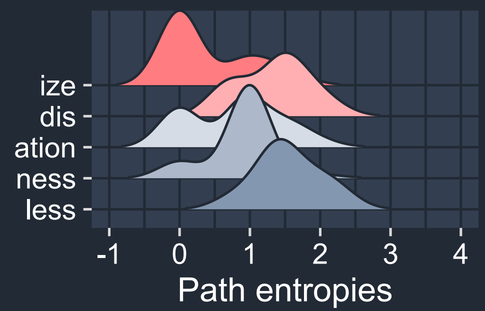


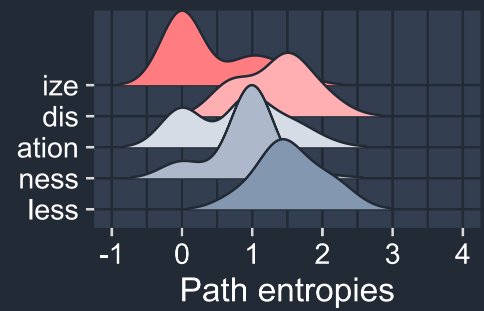
PATH ENTROPIES

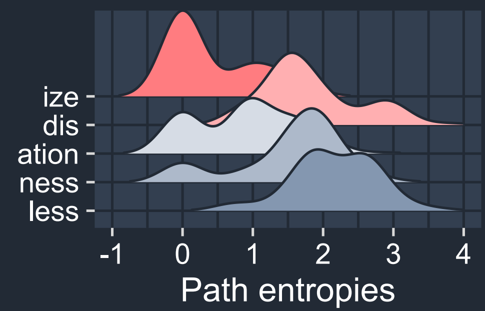


PATH ENTROPIES

Idiosyncratic Network	Morphology Network	Base Network

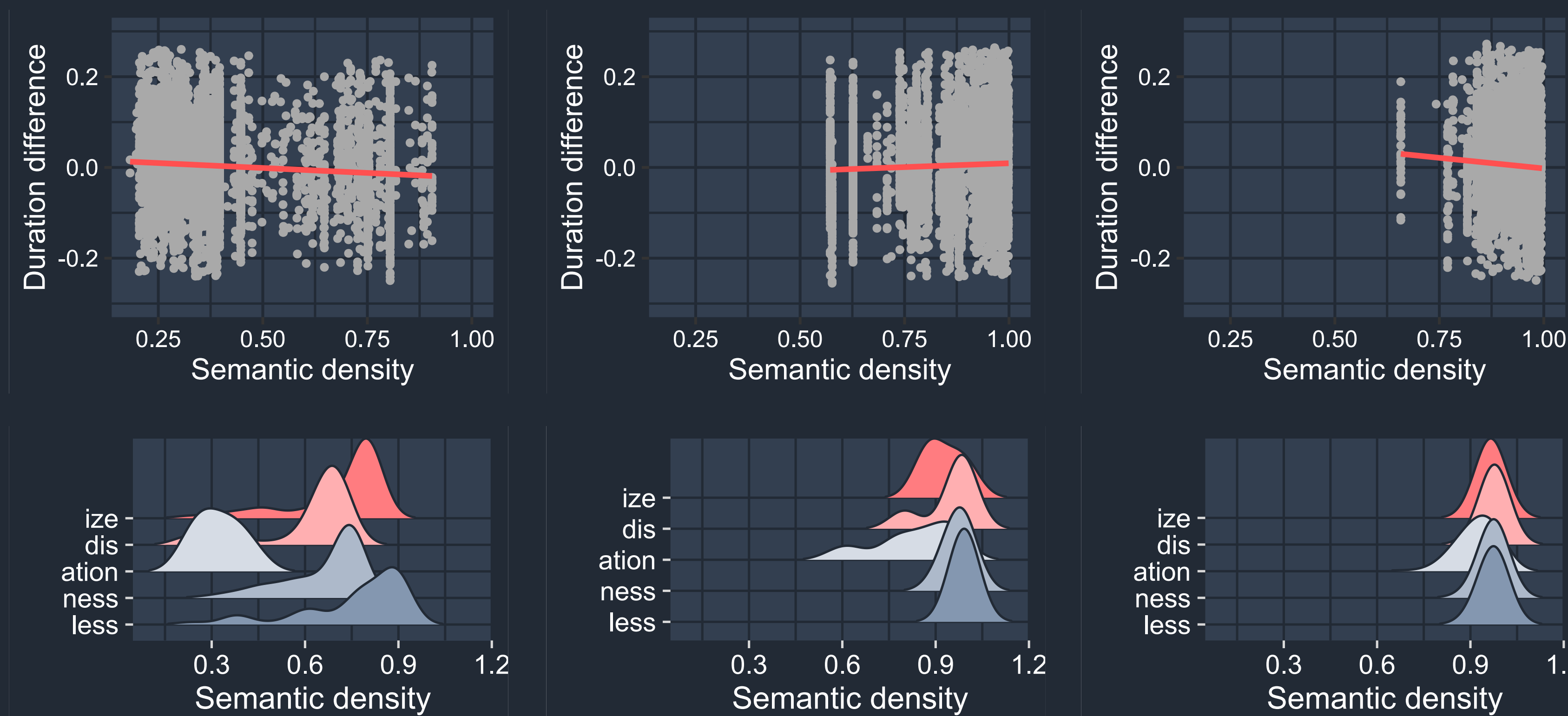




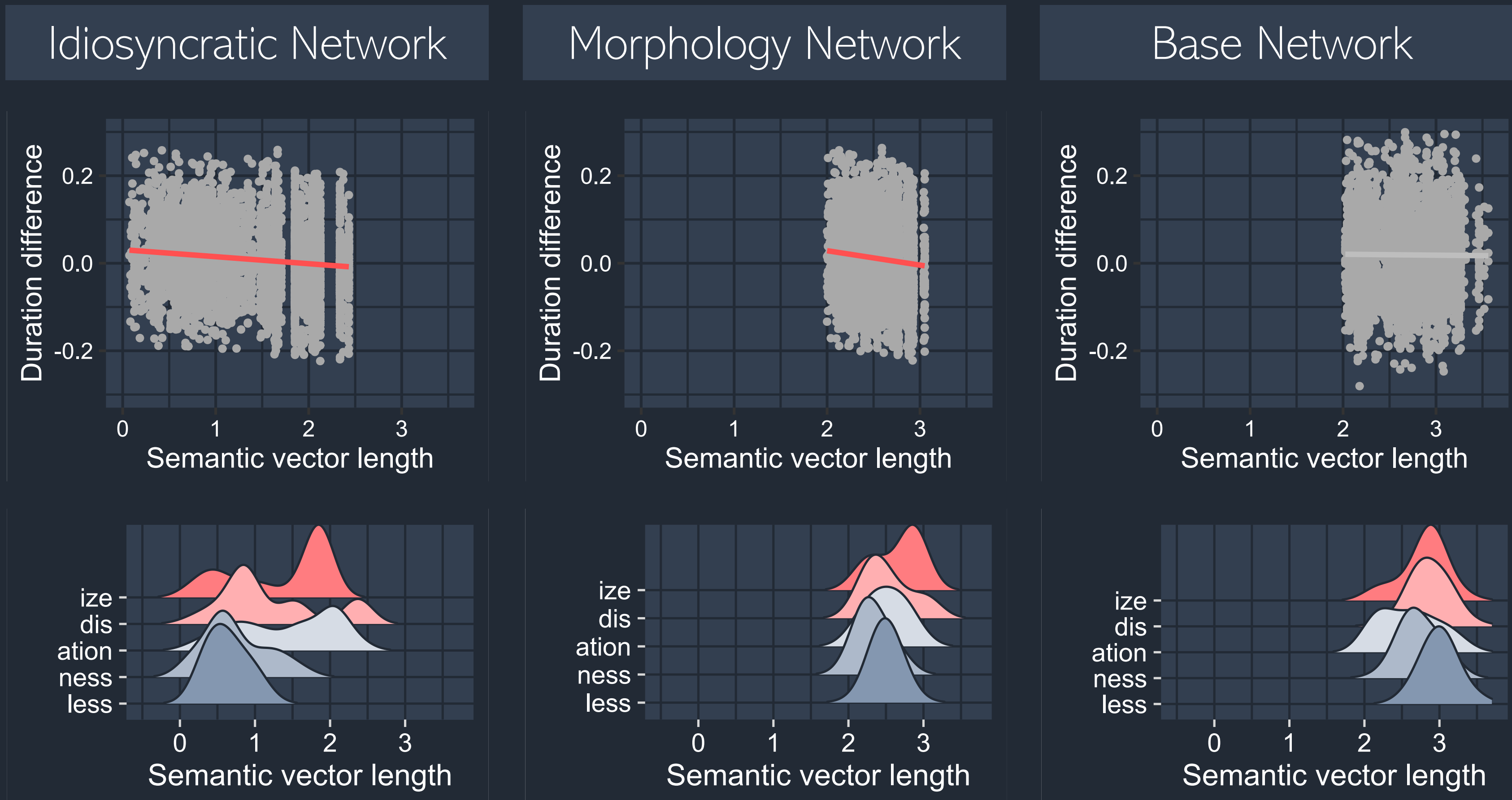


SEMANTIC DENSITY lms

Idiosyncratic Network | Morphology Network | Base Network



SEMANTIC VECTOR LENGTH lmers



Standard linear regression models

	Idiosyncratic Network model			Morphology Network model			Base Network model		
	Estimate	*SE*		*Estimate*	*SE*		*Estimate*	*SE*	
Intercept	0.216901	0.026210	***	0.090708	0.025887	***	0.408246	0.029999	***
MEAN WORD SUPPORT	0.170726	0.023507	***	0.250262	0.020700	***	0.050723	0.012716	***
PATH ENTROPIES	-0.008688	0.002242	***	-0.008442	0.002309	***	-0.009342	0.002259	***
SEMANTIC DENSITY	-0.043545	0.008925	***	0.033868	0.012372	**	-0.093906	0.025844	***
SPEECH RATE	-0.058757	0.001148	***	-0.058602	0.001159	***	-0.058702	0.001171	***
N	4448			4456			4456		
R^2 *adjusted*	0.3778			0.3742			0.3623		

Mixed-effects regression models

	Idiosyncratic Network model			Morphology Network model			Base Network model		
	Estimate	*SE*		*Estimate*	*SE*		*Estimate*	*SE*	
Intercept	1.328e-01	4.601e-02	**	2.146e-01	6.024e-02	***	2.595e-01	2.510e-02	***
MEAN WORD SUPPORT	2.722e-01	4.600e-02	***	2.535e-01	4.572e-02	***	1.211e-01	2.654e-02	***
PATH ENTROPIES	-1.173e-02	5.625e-03	*	-1.163e-02	5.633e-03	*			
SEMANTIC VECTOR LENGTH	-1.606e-02	6.860e-03	*	-3.294e-02	1.550e-02	*			
SPEECH RATE	-5.944e-02	1.116e-03	***	-5.937e-02	1.116e-03	***	-5.936e-02	1.117e-03	***
N	4357			4358			4357		
R^2 marginal	0.3690016			0.3638608			0.3487138		

Traditional models

	Traditional standard regression model			Traditional mixed-effects model		
	Estimate	*SE*		*Estimate*	*SE*	
Intercept	3.888e-01	8.345e-03	***	4.159e-01	1.106e-02	***
WORD FREQUENCY	4.970e-08	3.764e-08		-2.608e-07	2.328e-07	
RELATIVE FREQUENCY	-2.136e-05	4.166e-05		-1.446e-05	8.931e-05	
BIGRAM FREQUENCY	-6.542e-07	6.293e-07		7.978e-07	6.382e-07	
MEAN BIPHONE PROBABILITY	-5.188e+00	8.872e-01	***	-7.167e+00	1.545e+00	***
AFFIX ation						
dis	8.145e-03	6.700e-03		-1.405e-03	1.438e-02	
ize	-2.316e-02	5.251e-03	***	-1.491e-02	1.377e-02	
less	-5.749e-02	8.226e-03	***	-7.569e-02	1.524e-02	***
ness	-5.473e-02	5.700e-03	***	-3.630e-02	1.295e-02	**
SPEECH RATE	-5.893e-02	1.163e-03	***	-5.986e-02	1.116e-03	***
N	4450			4354		
R^2 adjusted/marginal	0.3731			0.3705799		
R^2 conditional				0.5344904		

Relative importance of variables

	Relative importance metrics (lmg)							
	Idiosyncratic Network		Morphology Network		Base Network		Traditional model	
	lm	lmer	lm	lmer	lm	lmer	lm	lmer
MEAN WORD SUPPORT	0.0089	0.1649	0.0148	0.0956	0.0025	0.1641		
PATH ENTROPIES	0.0023	0.0031	0.0023	0.0017	0.0030			
SEMANTIC DENSITY	0.0067		0.0020		0.0014			
SEMANTIC VECTOR LENGTH		0.0064		0.0399				
SPEECH RATE	0.3605	0.1946	0.3556	0.2266	0.3559	0.1845	0.3561	0.2140
WORD FREQUENCY							0.0007	0.0065
RELATIVE FREQUENCY							0.0006	0.0044
BIGRAM FREQUENCY							0.0007	0.0034
MEAN BIPHONE PROBABILITY							0.0025	0.1178
AFFIX							0.0136	0.0246
total variance explained	0.3778	0.3690	0.3742	0.3639	0.3623	0.3487	0.3731	0.3706

Extract from closest semantic neighbors of DIS words

Word	Phones	Neighbors						
Idiosyncratic Network								
disarm	dIs,m	m1d1	kInt	w{m	m{mb5	kr{NkI	n5zl	bl{NkIl
disband	dIsb{nd	m1d1	kInt	bl{NkIl	w{m	m{mb5	kr{NkI	plpIn
discard	dIsk,d	dIs@r1	dIst1st	dIskrEdIt	dIsgr1s	dIskVmf@t	$l	dIs@b1
discharge	dIsJ,=	dIsl2k	dIsQnIst	dIstrVst	dIs@gri	dIskVmf@t	dIsgr1s	dIsk@ntEnt
disclose	dIskl5z	m1d1	kInt	m{mb5	w{m	bl{NkIl	n5zl	SIt
discount	dIsk6nt	dIsQnIst	dIskVmf@t	dIsgr1s	dIsk@ntEnt	dIstrVst	dIst1st	dIsg2z
discourse	dIsk$s	dIs@r1	dIst1st	dIskrEdIt	dIsgr1s	dIskVmf@t	dIsp{r@tl	dIslQ=
disease	dIziz	dIskVv@R	dIs@p7R	dIs$d@R	dIsJ,=	dIsl2k	dIsk6nt	dIs@gri
disgrace	dIsgr1s	dIst1st	dIskVmf@t	dIs@r1	dIskrEdIt	dIs@b1	dIslQ=	dIsp{r@tl
Morphology Network								
disarm	dIs,m	dIsjun@tl	dIs5n	dIsb{nd	dIs@r1	dIskrEdIt	dIsp{r@tl	dIs@b1
disband	dIsb{nd	dIsjun@tl	dIs5n	dIs,m	dIs@r1	dIskrEdIt	dIs@b1	dIsp{r@tl
discard	dIsk,d	dIskVmf@t	dIsgr1s	dIst1st	dIsQnIst	dIs@r1	dIsk@ntEnt	dIslQ=
discharge	dIsJ,=	dIsl2k	dIsQnIst	dIstrVst	dIs@gri	dIskVmf@t	dIsgr1s	dIsk@ntEnt
disclose	dIskl5z	dIs@r1	dIs5n	dIs,m	dIskrEdIt	dIsjun@tl	dIsb{nd	dIsp{r@tl
discount	dIsk6nt	dIskVmf@t	dIsQnIst	dIsgr1s	dIsl2k	dIs@gri	dIstrVst	dIsg2z
discourse	dIsk$s	dIskVmf@t	dIsgr1s	dIst1st	dIsQnIst	dIsk@ntEnt	dIs@r1	dIsrIg,d
disease	dIziz	dIskVv@R	dIs@p7R	dIs$d@R	dIsJ,=	dIsl2k	dIsk6nt	dIs@gri
disgrace	dIsgr1s	dIst1st	dIskVmf@t	dIs@r1	dIskrEdIt	dIs@b1	dIslQ=	dIsp{r@tl
Base Network								
disarm	dIs,m	dIsg2z	dIsp{r@tl	dIsgVst	dIs@r1	dIsl2k	dIs@bidj@ns	dIspl1s
disband	dIsb{nd	dIsg2z	dIsp{r@tl	dIs@r1	dIsgVst	dIsl2k	dIspl1s	dIs@bidj@ns
discard	dIsk,d	dIsg2z	dIsp{r@tl	dIsgVst	dIs@r1	dIs@bidj@ns	dIsl2k	dIspl1s
discharge	dIsJ,=	dIsg2z	dIsp{r@tl	dIsgVst	dIs@r1	dIsl2k	dIs@bidj@ns	dIsQnIst
disclose	dIskl5z	dIsg2z	dIsp{r@tl	dIsgVst	dIs@r1	dIsl2k	dIs@bidj@ns	dIslQ=
discount	dIsk6nt	dIsg2z	dIsp{r@tl	dIsgVst	dIs@r1	dIs@bidj@ns	dIsl2k	dIsQnIst
discourse	dIsk$s	dIsg2z	dIsp{r@tl	dIsgVst	dIs@r1	dIspl1s	dIs@bidj@ns	dIsQnIst
disease	dIziz	dIsg2z	dIsp{r@tl	dIsgVst	dIs@r1	dIs@bidj@ns	dIsl2k	dIsQnIst
disgrace	dIsgr1s	dIsg2z	dIsp{r@tl	dIsgVst	dIs@r1	dIsl2k	dIs@bidj@ns	dIsQnIst