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FOR2373

Using linear discriminative learning to model the acoustic duration of English derived words

EDLL 2022

August 1–3, 2022

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 directly mapping forms and meanings onto each other
- meanings are incrementally learned based on error-driven learning
- dynamic association strengths instead of fixed form-meaning units

- In LDL, morphological effects on phonetic detail can be explained by its underlying principles of learning and experience.

cf. Baayen et al. 2019b

How can LDL explore morphological structure?

We treat all words as idiosyncratic.	We take words to share morphological categories.
We remain agnostic with regards to morphology, it's semantics all the way down.	We categorize words according to phonological and semantic similarities.

Both perspectives assume that there are no fixed units below the word level which are separately represented in the lexicon.

- Let's explore both options empirically!

e.g., Matthews 1991

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{plnls	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{plnls	-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
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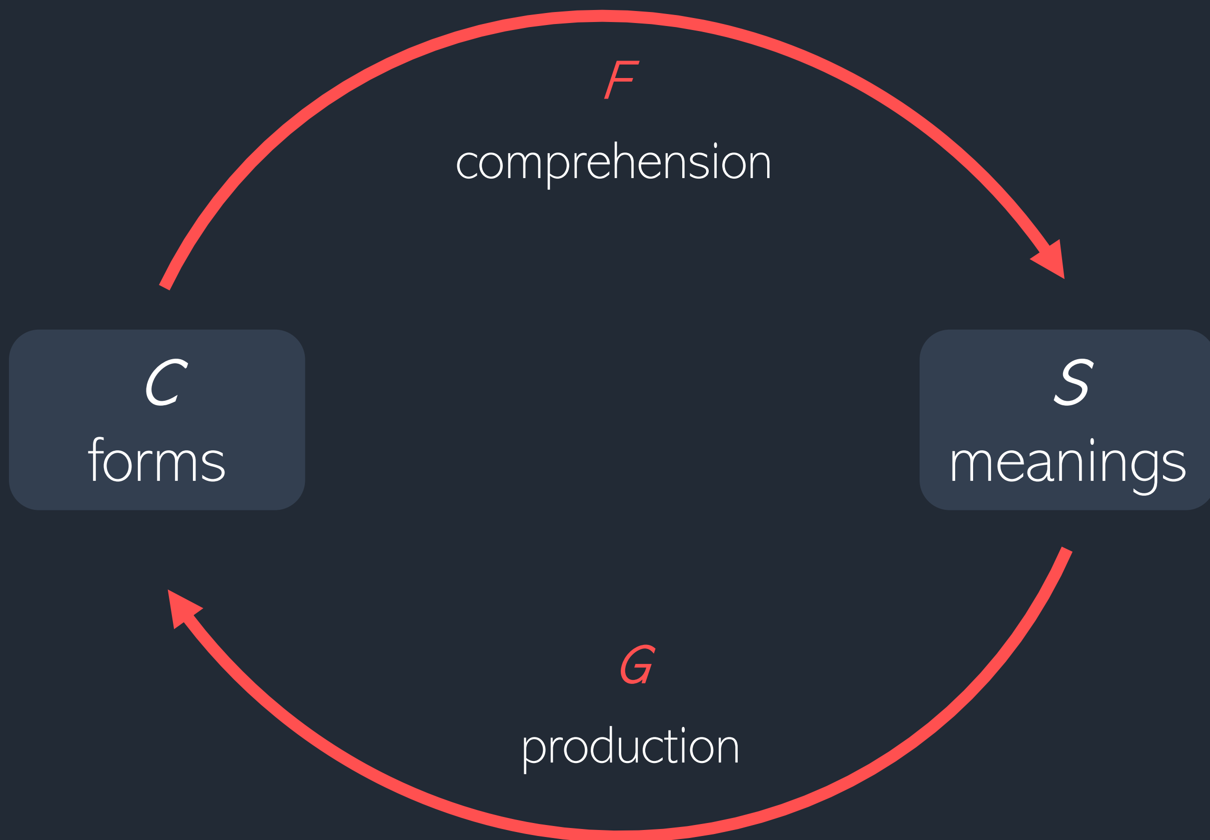
Baayen et al. 2019b

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

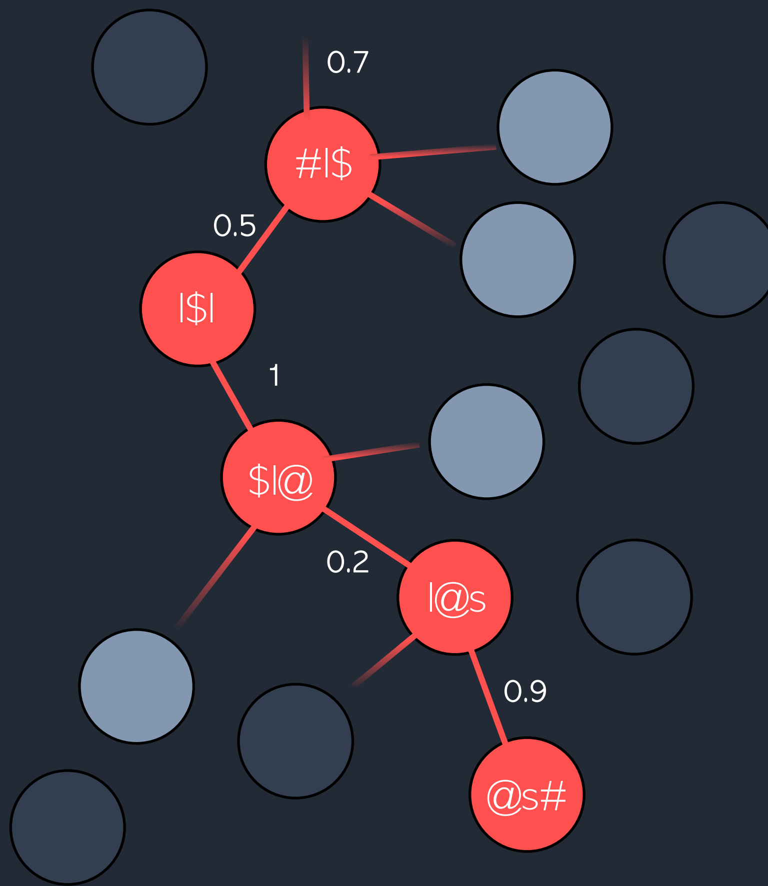
traditional model with
WORD FREQUENCY, RELATIVE FREQUENCY, BIGRAM FREQUENCY, BIPHONE PROBABILITY, AFFIX, SPEECH RATE

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

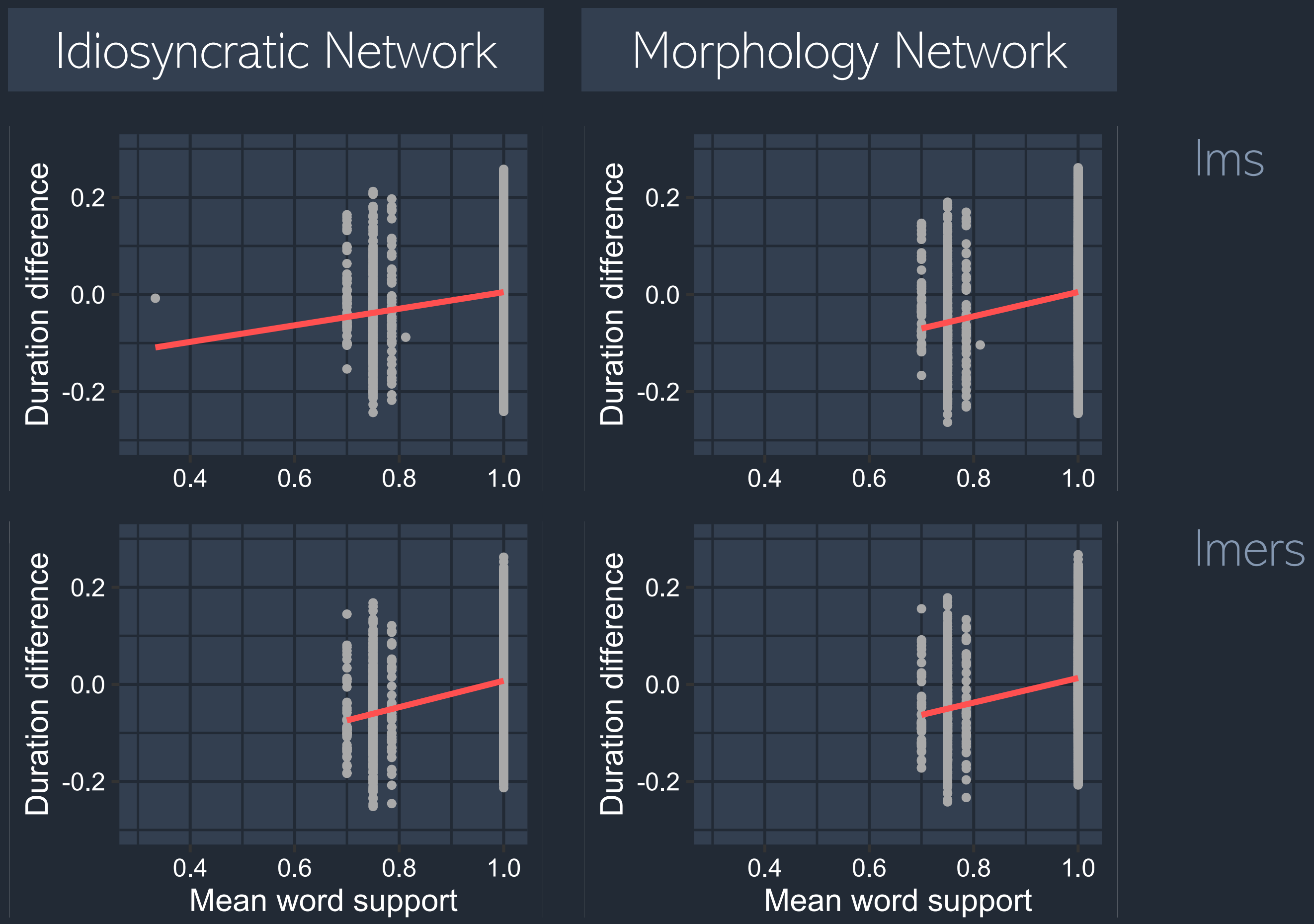
MEAN WORD SUPPORT

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

can represent
articulatory certainty



MEAN WORD SUPPORT

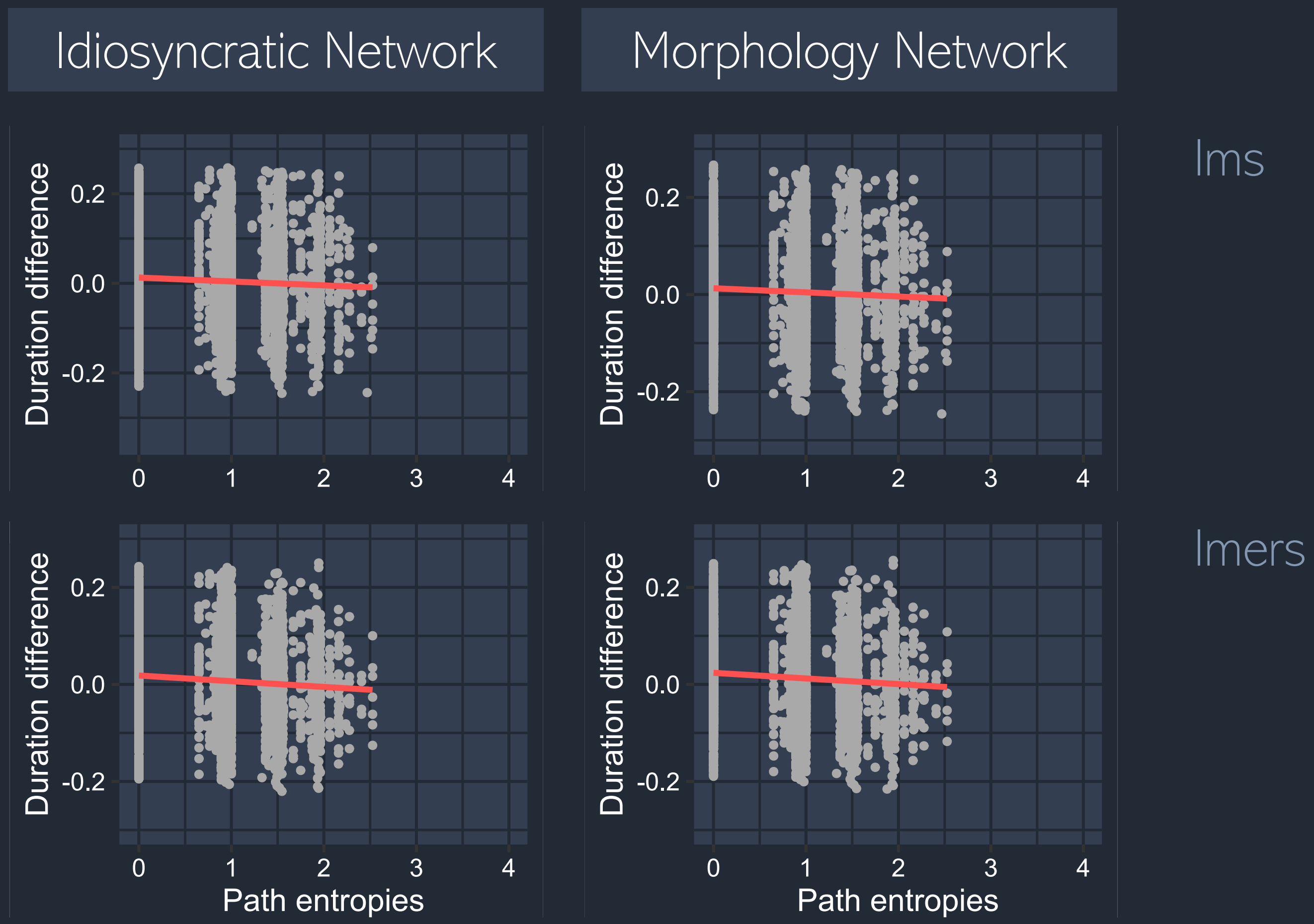


PATH ENTROPIES

Shannon entropy
of path supports

can represent
articulatory uncertainty

PATH ENTROPIES

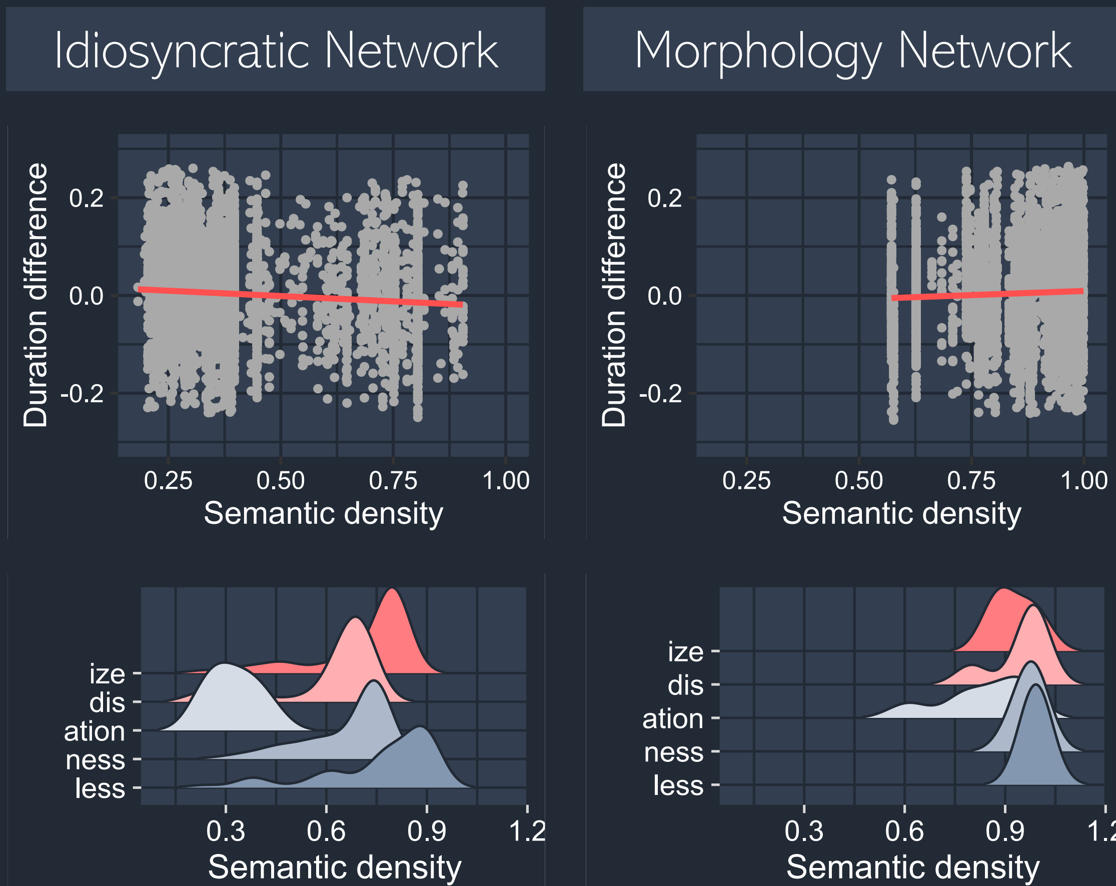


SEMANTIC DENSITY

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

can represent semantic transparency

SEMANTIC DENSITY



lms

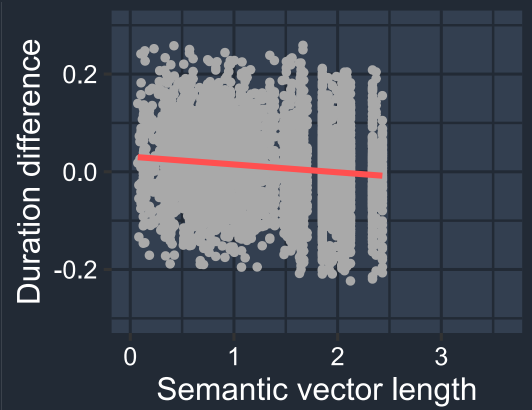
SEMANTIC VECTOR LENGTH

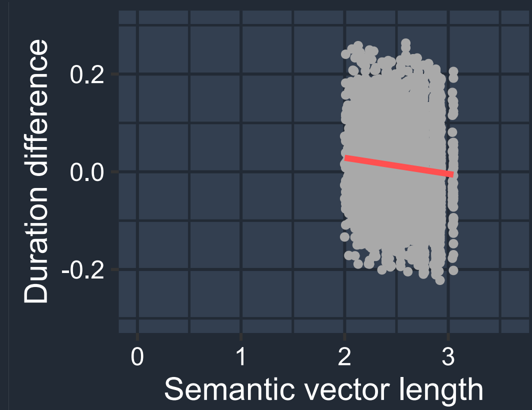
L1 distance of $\hat{s}$

can represent
activation diversity or polysemy

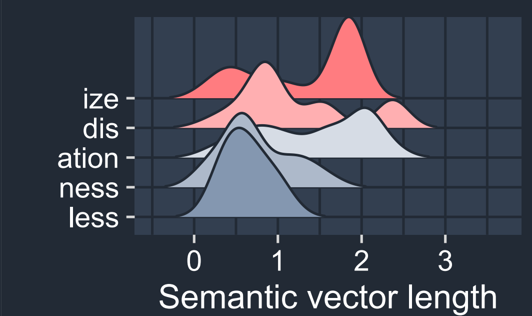
SEMANTIC VECTOR LENGTH

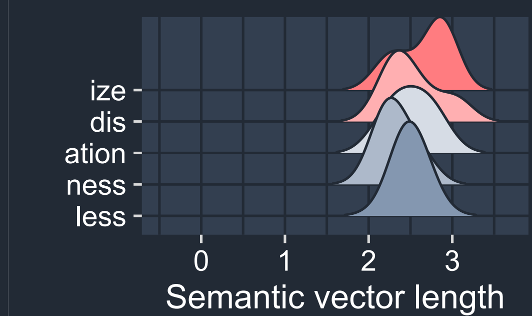
Idiosyncratic Network	Morphology Network





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 error-driven, discriminative learning 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*).

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

- The phonetics of derived words can be modeled successfully with an approach based on error-driven learning, linear discriminative learning.
- 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

Data

Types and tokens before excluding outliers

	Tokens	Types
DIS	233	35
NESS	344	49
LESS	145	31
ATION	3403	209
IZE	405	39

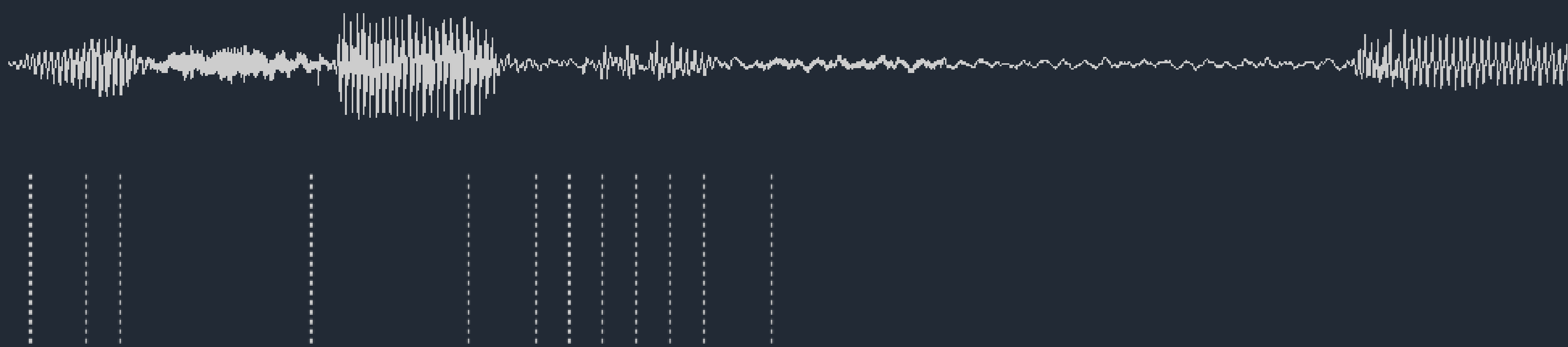
Segmentation

Example of a token of *happiness*

<table>
<tr><td colspan="2">put</td><td colspan="2">it</td><td></td><td colspan="7">happiness</td><td colspan="5">amongst</td></tr>
<tr><td colspan="2">put</td><td colspan="2">it</td><td></td><td colspan="7">happiness</td><td colspan="5">amongst</td></tr>
<tr><td>U</td><td>t</td><td>I</td><td>t</td><td></td><td>h</td><td>{</td><td>p</td><td>I</td><td>n</td><td>I</td><td>s</td><td>@</td><td>m</td><td>V</td><td>N</td><td>s</td></tr>
<tr><td colspan="2">’pUt</td><td colspan="2">’It</td><td></td><td colspan="2">’h{</td><td colspan="2">pI</td><td colspan="3">nIs</td><td>@</td><td colspan="4">’mVNst</td></tr>
</table>

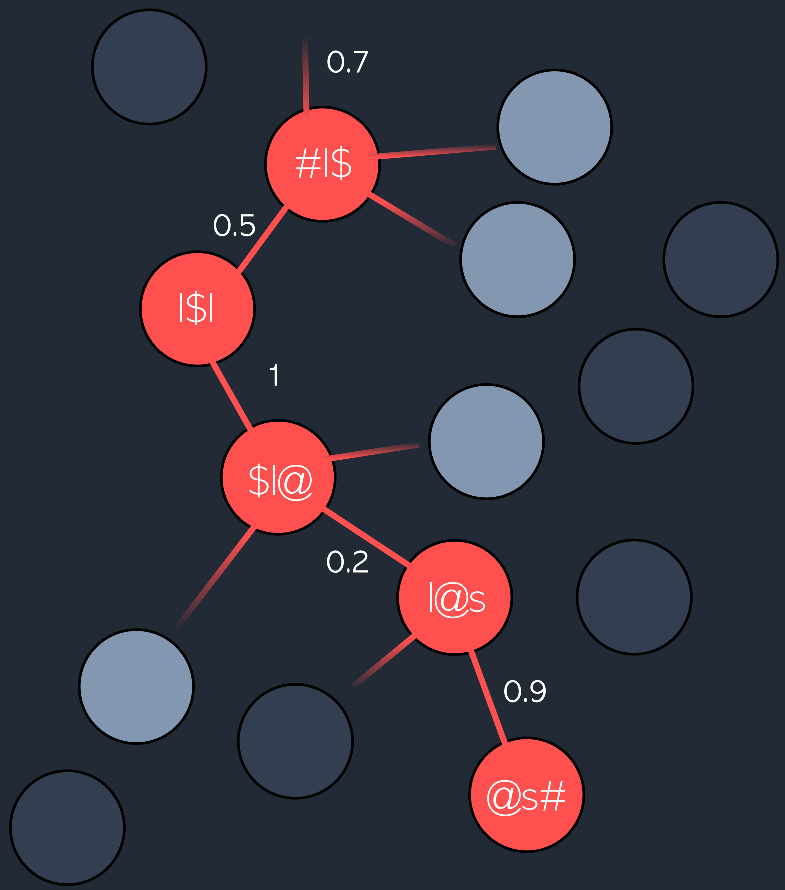
Segmentation

Example of a token of *sadness*



	the		sadness						and -			
	the		sadness						and			
	D	i	s	{	d	n	I	s	{	n	d	
	’Di		’s{d			nIs			’{nd			

Graph-based triphone sequencing



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

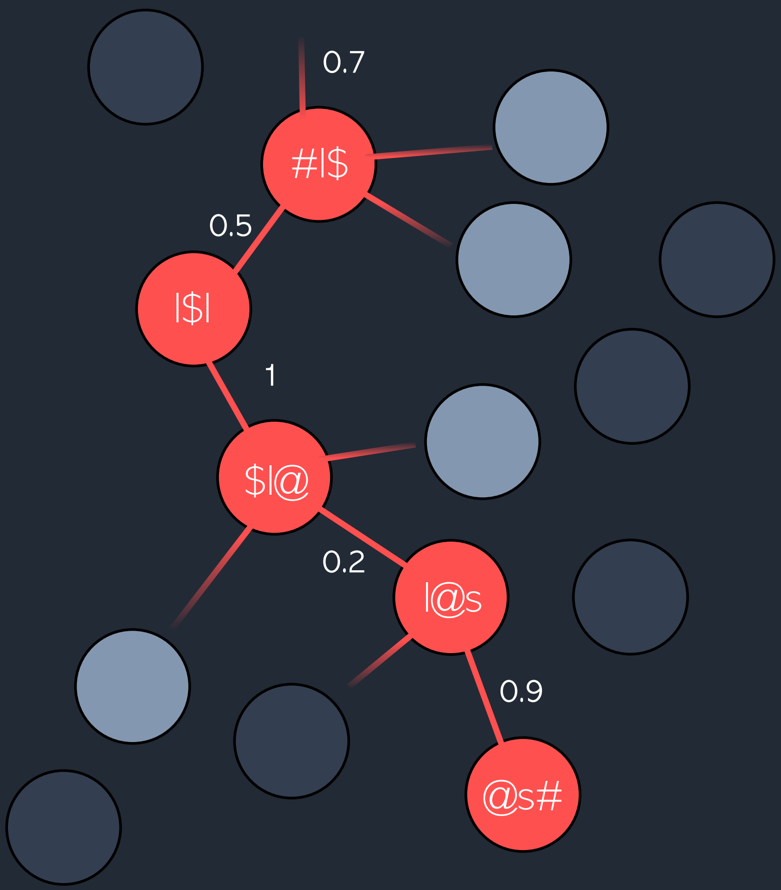
traditional model with
WORD FREQUENCY, RELATIVE FREQUENCY, BIGRAM FREQUENCY, BIPHONE PROBABILITY, AFFIX, SPEECH RATE

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

MEAN WORD SUPPORT

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

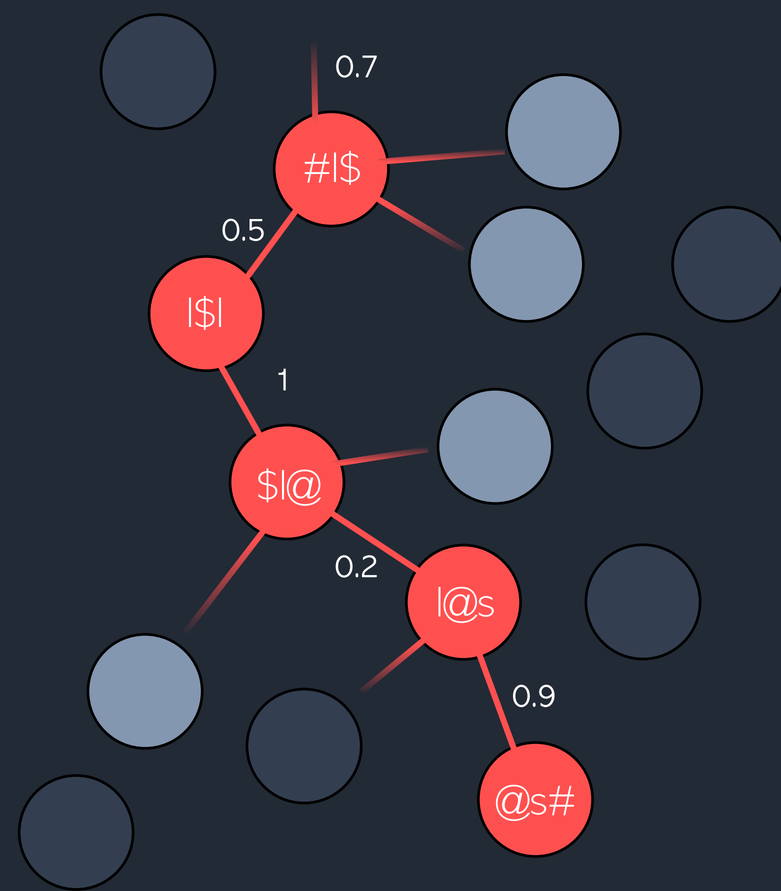
can represent
articulatory certainty



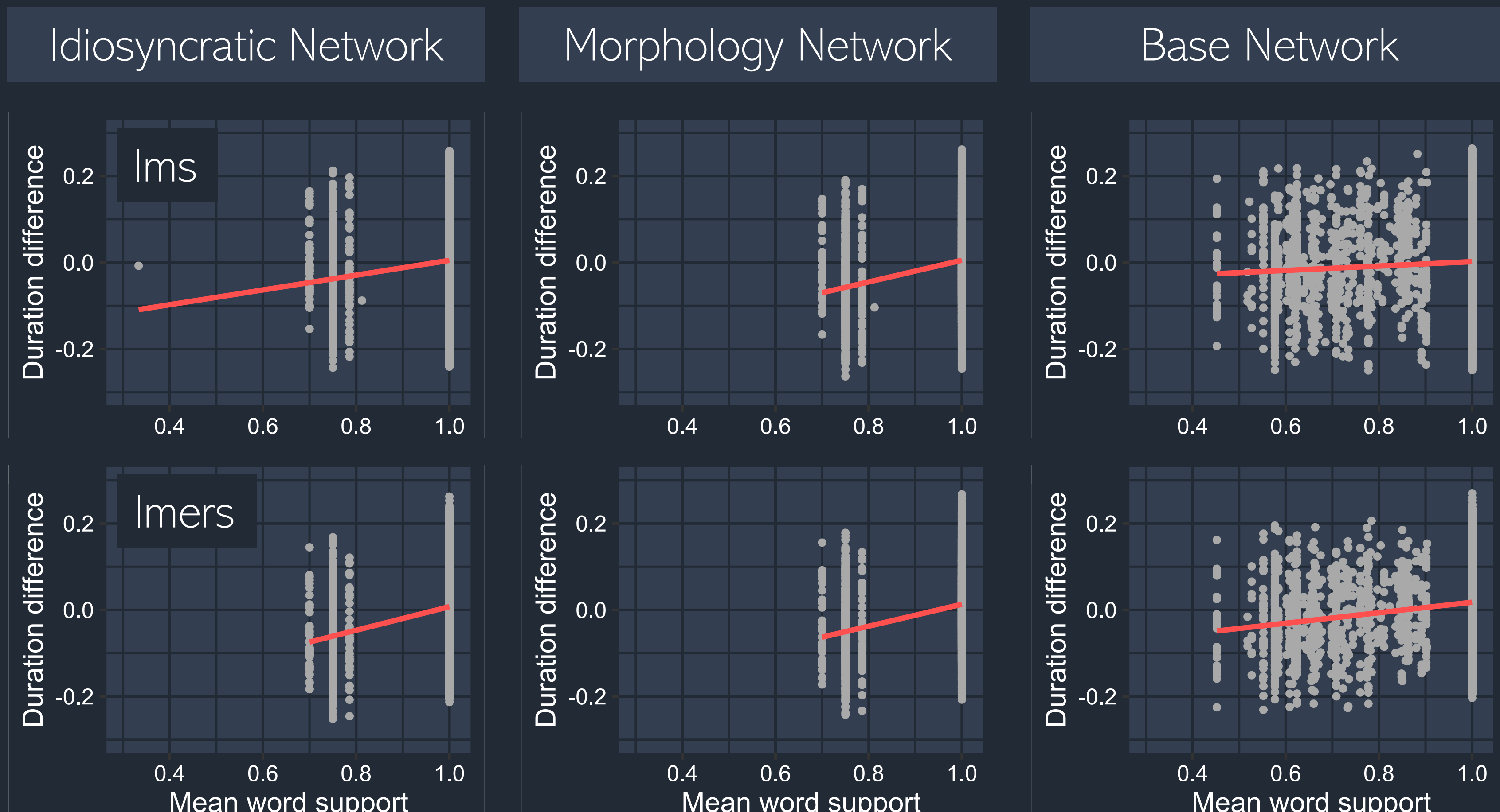
PATH ENTROPIES

Shannon entropy
of path supports

can represent
articulatory uncertainty

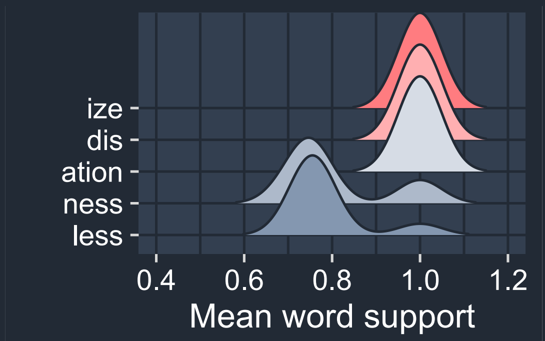


MEAN WORD SUPPORT



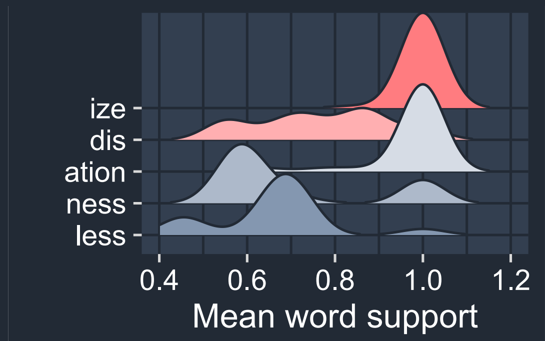
MEAN WORD SUPPORT

Idiosyncratic Network

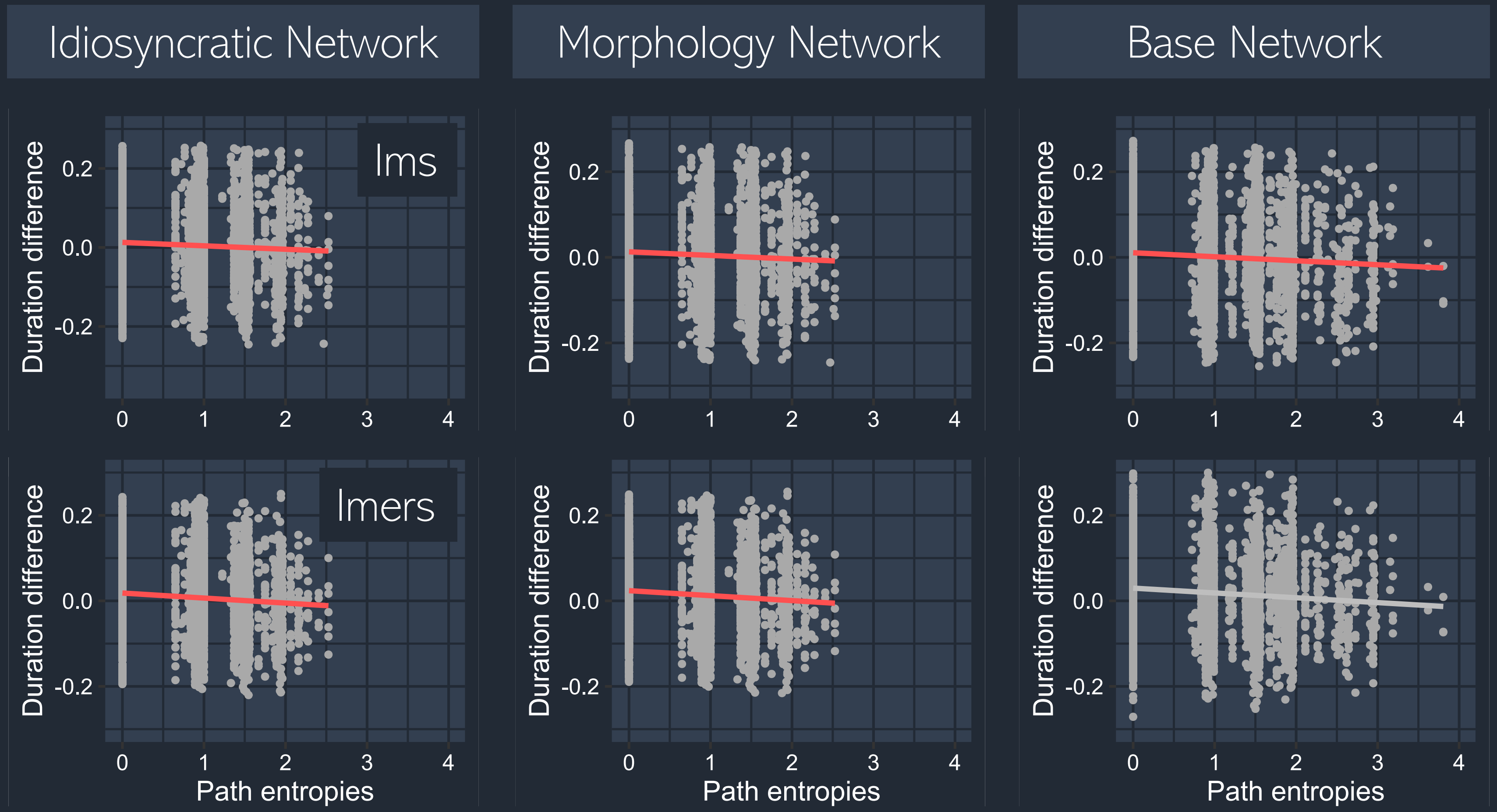


Morphology Network

Base Network

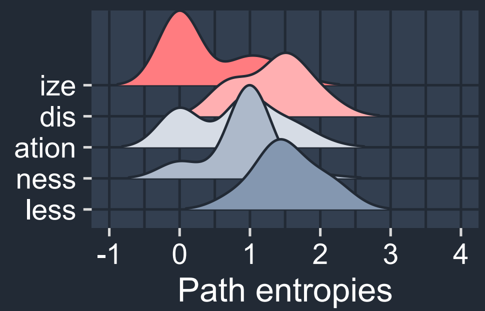


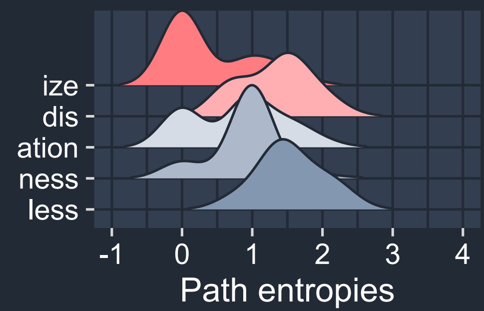
PATH ENTROPIES

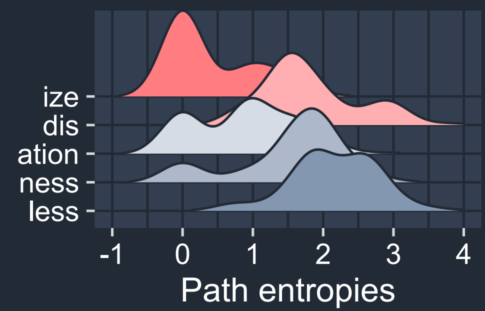


PATH ENTROPIES

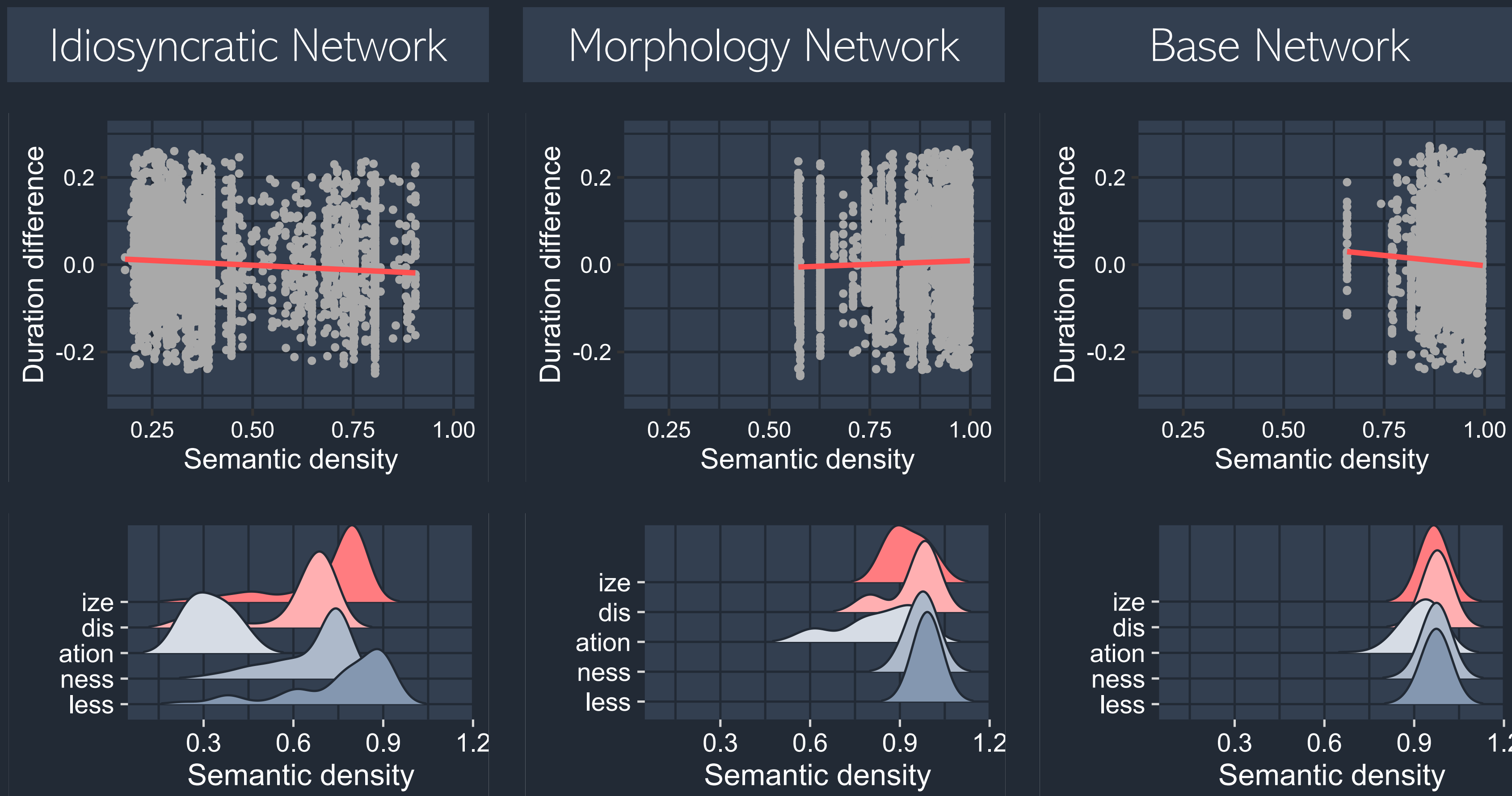
Idiosyncratic Network	Morphology Network	Base Network



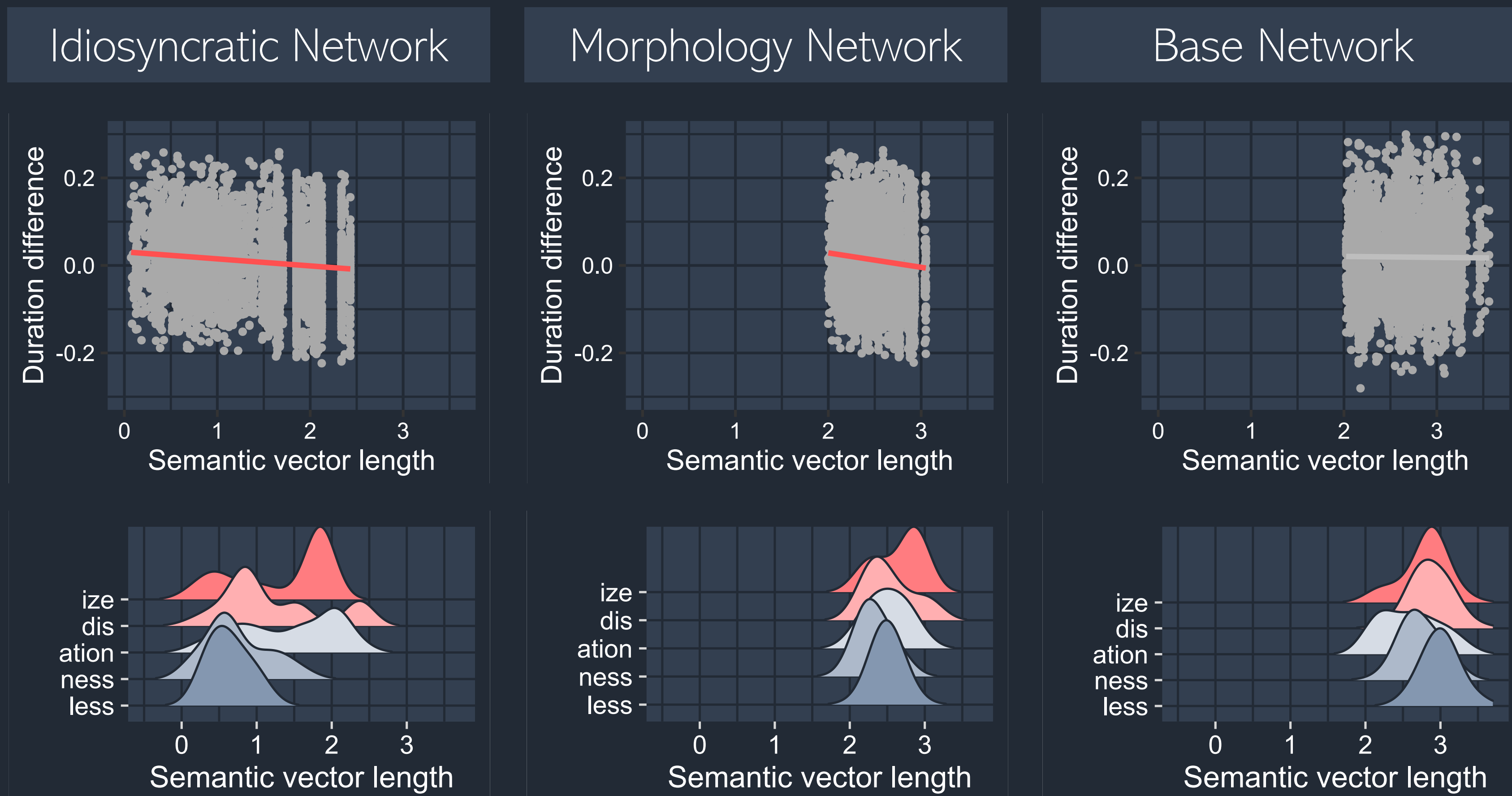




SEMANTIC DENSITY lms



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		

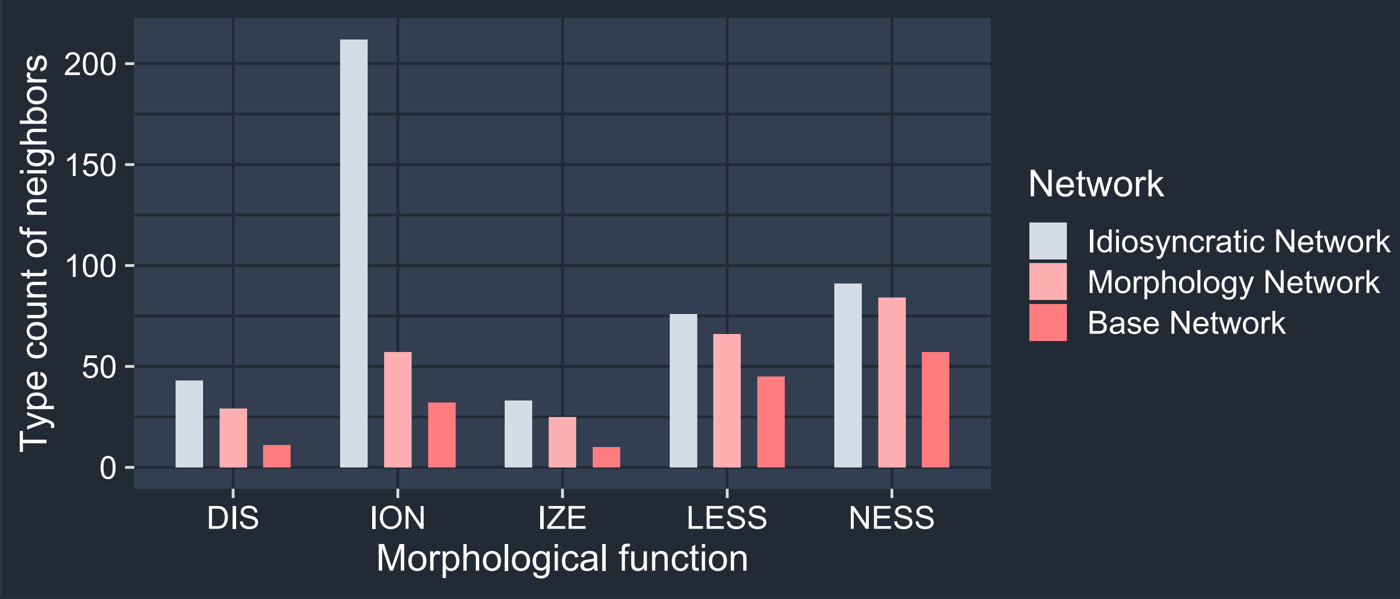
Traditional models

	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

Type count of top 8 neighbors



Extract from closest semantic neighbors of DIS words

Word	Phones	Neighbors						
Idiosyncratic Network								
disarm	dls,m	mayday	quint	wham	mambo	cranky	nosy	blankly
disband	dlsb{nd	mayday	quint	blankly	wham	mambo	cranky	pippin
discard	dlsk,d	disarray	distaste	discredit	disgrace	discomfort	awl	disobey
discharge	dlsJ,=	dislike	dishonest	distrust	disagree	discomfort	disgrace	discontent
disclose	dlskl5z	mayday	quint	mambo	wham	blankly	nosy	shit
discount	dlsk6nt	dishonest	discomfort	disgrace	discontent	distrust	distaste	disguise
discourse	dlsk$s	disarray	distaste	discredit	disgrace	discomfort	disparity	dislodge
disease	dlziz	discover	disappear	disorder	discharge	dislike	discount	disagree
disgrace	dlsgr1s	distaste	discomfort	disarray	discredit	disobey	dislodge	disparity
Morphology Network								
disarm	dls,m	disunity	disown	disband	disarray	discredit	disparity	disobey
disband	dlsb{nd	disunity	disown	disarm	disarray	discredit	disobey	disparity
discard	dlsk,d	discomfort	disgrace	distaste	dishonest	disarray	discontent	dislodge
discharge	dlsJ,=	dislike	dishonest	distrust	disagree	discomfort	disgrace	discontent
disclose	dlskl5z	disarray	disown	disarm	discredit	disunity	disband	disparity
discount	dlsk6nt	discomfort	dishonest	disgrace	dislike	disagree	distrust	disguise
discourse	dlsk$s	discomfort	disgrace	distaste	dishonest	discontent	disarray	disregard
disease	dlziz	discover	disappear	disorder	discharge	dislike	discount	disagree
disgrace	dlsgr1s	distaste	discomfort	disarray	discredit	disobey	dislodge	disparity
Base Network								
disarm	dls,m	disguise	disparity	disgust	disarray	dislike	disobedience	displace
disband	dlsb{nd	disguise	disparity	disarray	disgust	dislike	displace	disobedience
discard	dlsk,d	disguise	disparity	disgust	disarray	disobedience	dislike	displace
discharge	dlsJ,=	disguise	disparity	disgust	disarray	dislike	disobedience	dishonest
disclose	dlskl5z	disguise	disparity	disgust	disarray	dislike	disobedience	dislodge
discount	dlsk6nt	disguise	disparity	disgust	disarray	disobedience	dislike	dishonest
discourse	dlsk$s	disguise	disparity	disgust	disarray	displace	disobedience	dishonest
disease	dlziz	disguise	disparity	disgust	disarray	disobedience	dislike	dishonest
disgrace	dlsgr1s	disguise	disparity	disgust	disarray	dislike	disobedience	dishonest