

How Cognitive Biases Do (and Do Not) Shape Lexicons

Two Computational Studies

David R. Mortensen

July 19, 2022

Language Technologies Institute Carnegie Mellon University

Introduction

No system that learns from data is free from bias—not even very general learners like neural networks—but different systems have different biases.

It follows that human language users, which learn from data, learn in ways that reflect their cognitive capacities, however general.

Many Classes of Cognitive Biases Have Been Proposed

- All statistical learners are subject to fundamental information-theoretic factors (so general that we many not even think of them as "cognitive")
- Other types of biases are more clearly cognitive properties of language users:
 - PROCESSING BIASES (including factors influencing lexical access and recognition), which skew the distribution of the data from which learners acquire language
 - LEARNING BIASES that influence how language users will make inferences about target outputs in the face of incomplete information

In this talk, I will discuss some recent work regarding how cognitive biases may influence the lexicons (including the collections of multiword expressions) in human languages, especially how they develop over time Cognitive Processing Affects Lexical Decline

Why Do Some Words Persist while Others Decline?



Lexicons and Natural Selection

Many researchers, from Schleicher up to the present, have drawn analogies between **biological evolution** and the **evolution of languages**. Following Schleicher:

Language	:	Biology	::
Languages	:	Ecosystems	::
Lexicons	:	Populations	::
Words	:	Organisms	

A kind of natural selection, he argued, applies to both.

(Schleicher, 1863; Croft, 2000; Oudeyer & Kaplan, 2007; Atkinson, Meade, Venditti, Greenhill, & Pagel, 2008; Thanukos, 2008; Turney & Mohammad, 2019)

Group	Factor	Predicted Corr. w/Decline
semantic	semantic density concreteness number of meanings	+ - -
distributional	contextual diversity	_
phonological	phon typicality phon density phon complexity	- - +

Hypothesis: Cognitive Pressures Influence Lexical "Success"



Density of Semantic Neighborhoods

- Less evidence: semantic density facilitates access
- More evidence: it is INHIBITORY due to COMPETITION

PREDICTION

more semantic neighbors \Rightarrow accessed less \Rightarrow observed less \Rightarrow learned by fewer people \Rightarrow used less frequently

(Buchanan, Westbury, & Burgess, 2001; Marslen-Wilson, 1990; Dahan, Magnuson, Tanenhaus, & Hogan, 2001; Vejdemo & Hörberg, 2016)

10 Nearest Neighbors of Magnesium and Secrets



t-SNE projection of the 10-closest neighbors in the semantic space of the matched words *magnesia* (dec):*secrets* (stb). The semantic neighborhood of 'magnesia' (left) is denser, compared to that of 'secrets' (right).

Psycholinguistic studies: concrete words are learned and retrieved more easily than abstract ones

PREDICTION

more concrete \Rightarrow learned by more people, retrieved more frequently \Rightarrow occurs more frequently

(James, 1975; De Groot & Keijzer, 2000)

More POLYSEMOUS words are easier to access

$\label{eq:prediction} \mbox{PREDICTION} \\ \mbox{more senses} \Rightarrow \mbox{more aggregate access} \Rightarrow \mbox{greater frequency} \\ \end{tabular}$

(Jastrzembski, 1981; Rood, Gaskell, & Marslen-Wilson, 2002; Vejdemo & Hörberg, 2016)

Words that occur in more varied contexts are easier both to LEARN and to ACCESS and words with broader topical dissemination tend to become more ROBUSTLY ENTRENCHED into the lexicon

PREDICTION

more varied contexts \Rightarrow more frequent access, robustness to change \Rightarrow greater frequency

(Johns, Dye, & Jones, 2016; McDonald & Shillcock, 2001; Altmann, Pierrehumbert, & Motter, 2011; Stewart & Eisenstein, 2018)

Phonologically typical words are easy to process/recognize.

$\label{eq:prediction} \mbox{PREDICTION} \\ \mbox{recognized more} \Rightarrow \mbox{learned by more people} \Rightarrow \mbox{more frequent} \\ \label{eq:prediction}$

(Vitevitch, Luce, Pisoni, & Auer, 1999; Yates, Locker, & Simpson, 2004; Vitevitch, 2002; Marian & Blumenfeld, 2006)

Dense phonological neighborhoods FACILITATE lexical processing.

$\label{eq:prediction} \begin{array}{l} \mbox{PREDICTION} \\ \mbox{easier to process} \Rightarrow \mbox{used more} \Rightarrow \mbox{more frequent} \end{array}$

(Vitevitch et al., 1999; Yates et al., 2004; Vitevitch, 2002; Marian & Blumenfeld, 2006)

To control for confounders, we studied (declining:stable) pairs, using an experimental design from psycholinguistics.

Potential Confounder	Interaction
initial frequency	correlated with subsequent frequency
word length	correlated with frequency and number of
	senses
part of speech	interacts with patterns of decline

We studied pairs of words (declining:stable) matched according to these variables.

Selecting Declining and Stable Words

Two sets of words were selected from Google ngrams dataset (years/yearly word frequencies accumulated into decades, our unit of analysis).

- 1. Declining words Common from 1800–1810; less common now.
- 2. Stable words Common from 1800–1810; still common now.



(Michel et al., 2011)

Examples of Stable and Declining Pairs

En	glish	French		Ger	man
dec	stb	dec	stb	dec	stb
verdure	criminals	industrieux	législative	tugendhaft	schwarzer
impracticable	unreasonable	évacuations	inventions	dünkt	hängen
unexampled	invaluable	estimable	acquises	endigen	brauche
dignities	extinction	intrépidité	irrégularité	hernach	innen
insensibility	embarrassment	factieux	habituel	mannigfaltige	gegenseitigen
amusements	foundations	mâchoire	surprise	füglich	dringend
illustrious	successful	magnésie	désert	siebenten	tägliche
necessaries	repetition	réfraction	conversion	redlichen	einseitigen
sublimity	attainment	sulfurique	naturelles	erstlich	einziges
whence	highly	prairial	arbitraire	dermalen	halbes

Semantic Density (SemDens) The average similarity of a word to its 10 nearest neighbors in semantic space.

Concreteness (Conc) Values from Snefjella, Généreux, and Kuperman with missing values inferred using the technique from Tsvetkov, Mukomel, and Gershman (English only).

Number of Meanings (NMngs) Number of senses in the Historical Thesaurus of English (HTE) (English only).

(Snefjella et al., 2019; Tsvetkov et al., 2013; Kay et al., 2019)

Contextual Diversity (CDiv) How much the local context (w_{i-1}, w_{i+1}) of the target word w_i deviates from the distribution of words in the language as a whole. Stated in terms of KL divergence (*w* is target, *c* is context):

$$D_{KL}(P(c|w)||P(c)) = \sum P(c|w) \log \frac{P(c|w)}{P(c)}$$

Contextual diversity of a word w at time period t is defined as:

$$\texttt{CDiv}^t(w) \!=\! \exp(-D_{KL}^t(w))$$

(McDonald & Shillcock, 2001)

Phonological Typicality (PhonTyp) Estimated using a phoneme-based LSTM language model:

$$\texttt{PhonTyp}(w) {=} \frac{\sum_{i=1}^k \log P(c_i \mid c_1,..,c_{i-1})}{k}$$

Phonological Density (PhonDens) The sum of distances of its IPA transcription to that of all other word types:

$$\texttt{PhonDens}(w) = \sum_{v \in L} \exp(-d(w,v))$$

Phonological Complexity (PhonComp) Ratio of syllables to IPA segments*.

*This, we are aware, is terrible.

(Hochreiter & Schmidhuber, 1997; Bailey & Hahn, 2001)

Factor	severest (D)	longest (S)	solicitude (D)	marriages (S)	ornamented (D)	attracted (S)
SemDens	0.61	0.41	0.50	0.48	0.69	0.51
Conc	0.50	0.77	0.48	0.59	0.90	0.78
NMngs	4.59	4.59	2.00	4.59	1.00	1.00
CDiv	0.52	0.95	1.31	1.81	1.80	4.40
PhonTyp	-2.93	-2.24	-3.40	-0.98	-1.62	—1.35
PhonDens	6.02	5.76	5.87	5.88	6.03	6.03
PhonComp	0.60	0.40	0.80	0.75	0.40	0.37

Examples of English word-pairs with varying initial frequency, POS, and length, along with their predictor values. Differences in the expected direction are **boldfaced**.

For convenience, $\mathtt{CDiv}{ imes}10^3$ and $\mathtt{PhonDens}{ imes}10^{-3}$ values are presented.

	Engli	ish	Fren	ch	Germ	ian
Factor	dec	stb	dec	stb	dec	stb
SemDens	0.55** (±0.07)	0.52 (±0.07)	0.65** (±0.10)	$0.53 (\pm 0.07)$	N/A	N/A
Conc	0.53^{*} (± 0.15)	$0.57 (\pm 0.16)$	N/A	N/A	N/A	N/A
NMngs	3.91** (±2.21)	5.26 (±4.02)	N/A	N/A	N/A	N/A
CDiv	1.97** (±4.10)	2.93 (±7.72)	0.88** (±2.82)	1.20 (±3.30)	1.47** (±2.01)	$2.01(\pm 4.05)$
PhonTyp	-2.02*	-1.85	-2.27**		-1.83**	-1.73
	(± 0.85)	(± 0.71)	(±0.84)	(± 0.86)	(±0.47)	(± 0.46)
PhonDens	5.90 (± 0.12)	5.92 (±0.12)	5.37 (± 0.11)	5.38 (±0.12)	8.65 (± 0.27)	$8.65(\pm 0.26)$
PhonComp	0.38^{*} (±0.07)	$0.35 (\pm 0.07)$	$0.38 (\pm 0.10)$	$0.37 (\pm 0.09)$	$0.45 \ (\pm 0.09)$	$0.44 (\pm 0.09)$

Mean (\pm SD) of factor values for declining (dec) and stable (stb) words.

Were Our Predictions Borne Out?

		Predicted Corr.	
Group	Factor	w/Decline	
	semantic density	+	[√en][√fr]
semantic	concreteness	_	[✔en]
	number of meanings	_	[✔en]
distributional	contextual diversity		[✔en][✔fr][✔de]
	phon typicality	—	[√en][√fr][√de]
phonological	phon density	—	[? en][? fr][? de]
	phon complexity	+	[? en][? fr][? de]

The psycholinguistic literature made correct predictions wherever results were significant.

Why were phonological factors (other than typicality) not stronger predictors?

- Words selected by language users according to MESSAGE more than MEDIUM?
- Processing effects for phonology relatively weak compared to those for semantics/lexical distribution?
- PhonComp formulation sub-optimal?

Although lexical decline is multifaceted, COGNITIVE FACTORS—in an EVOLUTIONARY LINGUISTICS framework—can explain to a surprising degree why some words persist while others fall out of use.

But note: some of these COGNITIVE FACTORS can also be framed in INFORMATION-THEORETIC TERMS that don't make reference to specific cognitive architectures (e.g., phonological typicality, contextual diversity, and semantic density)



https://github.com/ellarabi/linguistic_decline

Ordering of Coordinate Constructions May Run Counter to Proposed Formal Biases

Elaborate Expressions (EEs) and Coordinate Compounds (CCs)

- Productive classes of multiword expressions (AB₁AB₂ or B₁B₂) in languages of East and Southeast Asia
- Coordinate structure with two related words B_1 and B_2 .
- (1) cho phô? cho dì people pile people lump
 'a throng of people'
- (2) kawm ntaub kawm ntawv study cloth study paper
 'to learn to read and write; to become educated'
- (3) *tiān dì* heaven earth

'universe'

They have interesting and unconventional linguistic properties.

(Lahu EE)

(Hmong EE)

(Chinese CC)

Ordering of EEs and CCs

	Hmong EEs		(tone)	
Constituent words in 🗸	Lahu EEs	\rangle appear to be ordered by a \langle	rhyme	hierarchy (Ting, 1975; Dai, 1986;
	Chinese CCs	J	tone ,	
Mortensen, 2006).				

	kawm ntau b kawm ntaw \mathbf{v}	Order	Tone
		1	-j
	study cloth study paper	2	-b
Hmong Elaborate	<i>y</i>	3	-m
Expression		4	-S
LAPIESSION	* house atom house atom	5	-v
	^RAWM NTAW V RAWM NTAU D	6	-g
	* ctudy papar ctudy cloth	7	-Ø
	Sludy paper sludy cloth -		

Who Made these Claims?



- The sounds in words do not determine word order (Chomsky, 1981, 1995) (phonology is conditioned upon syntax, not syntax upon phonology)
- Grammatical patterns involving sound (phonology) have a phonetic basis (Chomsky & Halle, 1968; Becker, Ketrez, & Nevins, 2011; Hayes & White, 2013) (phonology is phonetically natural/grounded)

It has been proposed that learners rely on these biases in order to acquire language (and that languages that defy these tendencies would be difficult or impossible to learn).

Contention: When learners model word order, they limit themselves to (morpho)syntactic information. Phonology may not even be accessible to syntax.



In Hmong, Lahu, and Chinese EEs and CCs, word order appears to be affected by phonology.

Hmong Order of EEs largely predictable based on tone.
Lahu Order of EEs somewhat predictable based on vowel quality/rhyme.
Chinese Order of CCs predictable based on tone, especially in earlier stages of Chinese—Old Chinese and Middle Chinese (Ting, 1975).

For Hmong, in particular, these effects are claimed to be strong (Mortensen, 2006).

Previous works have found that word order can be sensitive to phonology:

- Coordinate compound in Jingpho (Dai, 1986)
- Echo reduplication in Japanese and Korean (Kwon & Masuda, 2019)
- Noun-adjective order in Tagalog (Shih, 2017; Shih & Zuraw, 2017)
- Binomial expressions in English (Morgan & Levy, 2016; Benor & Levy, 2006)

EEs and CCs in Hmong, Lahu and Chinese would enrich the body of evidence.

EEs and CCs Violate the Assumption of Phonetic Naturalness

Typologically, we expect rules like:

i[m]possible i[n]tolerant i[ŋ]glorious

and not the formally equivalent:

i[n]possible i[ŋ]tolerant i[m]glorious

For this reason, many assume that **there is a naturalness bias in phonological learning**. The tone and rhyme hierarchies that determine word order in EEs and CCs are phonetically **unnatural**.

Order	Orthography	IPA	Description
1	-j	Y	high falling
2	-b	٦	high
3	-m	1	low creaky
4	-S	4	low
5	-V	1	rising
6	-g	1	falling breathy
7	-Ø	+	mid

A vocal minority of phonologists have long argued that **phonetic biases in phonology were epiphenomenal** (Fudge, 1967; Hyman, 1970; Hale & Reiss, 2000).

The ARTIFICIAL GRAMMAR LEARNING literature suggests that **biases based on substance** (phonetics) are less important than biases toward formal or structural simplicity in phonological learning (Moreton & Pater, 2012b, 2012a)

If we can show that the unnatural patterns in Hmong, Lahu, and Chinese **can be learned by models** from naturally-occurring data, it would be suggestive evidence against the majority (phonetic bias) position.

- 1. To what extent can the ordering of constituent words in EEs and CCs be learned by computational models?
- 2. What role does phonology play in this ordering effect?

Hypotheses:

- 1. The order of Hmong and Lahu EEs and Chinese CCs can be predicted phonologically
- 2. The "phonetically unnatural" phonological scales predict the ordering of EEs in Hmong and Lahu and CCs in Chinese
- 3. These scales can be learned by decision tree classifiers

Hmong	Elaborate expressions extracted manually from the SCH corpus, manually annotated	3254 elaborate expressions, all in ABAC form
Lahu	Elaborate Expressions extracted from Matisoff's (1988) dictionary	elaborate expressions in ABAC and ABCB form
Chinese	Antonymic coordinate compounds with Mandarin and Middle Chinese pronunciations from Wiktionary	254 coordinate compounds

- \cdot Add fake EEs by swapping the order
- $\cdot\,$ Occasionally both orders are attested
- Some B₁B₂ pairs are very frequent We report results with duplicate pairs removed so the model cannot memorize them

AB_1AB_2	Attested
AB_2AB_1	Fake
C_1DC_2D	Attested
C_2DC_1D	Fake

Classification Features: One-Hot Phoneme Vectors

- One-hot features for all onsets, rhymes, and tones, for each word.
 - "Word A has hm- onset"
 - "Word B_1 has -j tone"
- E.g. for Hmong: (7 tones + 14 rhymes + 58 onsets) × 3 words = 237 features
- Classifiers:
 - Decision Tree (best interpretability)
 - SVM (best performance)
 - Rules (proposed by linguists)

Hmong hmoob onset rhyme tone

Result (with Duplicates Removed)



The Learned Trees Look Remarkably Like the Proposed Hierarchies



Language		Order	
Hmong	Linguist Dec. Tree	$ \begin{array}{l} j \prec b \prec m \prec s \prec v \prec g \prec \emptyset \\ j \prec b \prec m \prec v \prec s \prec g \prec \emptyset \end{array} $	
Lahu	Linguist Dec. Tree	ο ⊣ u ⊣ i ⊣ i ⊣ ə ⊣ ɔ ⊣ e ⊣ ε ⊣ a o ⊣ u ⊣ ⊣ e ⊣ ɔ ⊣ ε ⊣ a	
МС	Linguist Dec. Tree	ping ≺ shang ≺ qu ≺ ru ping ≺ shang ≺ qu ≺ ru	

For Hmong, the one deviation may be due to a dialect difference between the corpus and the data on which the scale was based (see below).

Hypotheses:

- The order of Hmong and Lahu EEs and Chinese CCs can be predicted phonologically. (Robustly, even with duplicates removed)
- ✓ The "phonetically unnatural" phonological scales predict the ordering of EEs in Hmong and Lahu and CCs in Chinese. (Well above 70%, in all cases)
- ✓ These scales can be learned by decision tree classifiers (strikingly similar scales are learned)

Can models recognize EEs and their ordering patterns in context, in a naturalistic corpus? (Only Hmong from now on)

Hypothesis:

Phonological information facilitates the recognition of correctly and incorrectly ordered Hmong EEs in context.

Setup: Sequence Labeling

	yav	0	yav	0
	tag	0	tag	0
	los	0	los	0
	nej	0	nej	0
 Predict {B, I, 0} tag for each token. 	twb	0	twb	0
	hais	0	hais	0
Sequence labeling models:	tias	0	tias	0
• Bi-ISTM	cov	0	COV	0
	laus	0	laus	0
• CNN	no	0	no	0
 Simple Baseline: any ABAC 4-gram is an EE. 	tsi	в	tsi	<mark>B-</mark> fake
Improved Baseline: see next slide	txawj	I	ntse	I-fake
• Improved baseline. see next slide.	tsi	IX	tsi	I-fake
• Also: Swap half of EEs and change their tags to B-fake		I	🌂 txawj	I-fake
	thiaj	0	thiaj	0
and I-fake	1i	0	li	0
 Identify EEs and detect whether the order has been 	coj	0	coj	0
identity LES and detect whether the order has been	tsis	0	tsis	0
changed at the same time	tau	0	tau	0
	hmoob	0	hmoob	0
	no	0	no	0
	nes	0	nes	0

Simple baseline, with 3 tricks to improve the performance:

Assume any AB₁AB₂ 4-gram is an EE. (100% recall but poor precision). Then:

- Ensure A, B₁, and B₂ are proper Hmong syllables parsable by a regular expression (Hmong orthography is well-defined)
- 2. B1 and B2 have word2vec cosine similarity > 0.4 (an empirically determined threshold)
- 3. B1 and B2 follow the tonal scale proposed in the literature

Sequence Labeling Results



- Both Bi-LSTM and CNN beat the baselines
- With half of the EEs swapped and tags changed (+clf), the performance of the CNN model does not degrade much—it is able to tag real vs fake EEs in context
- In-context classification accuracy is 99.5%
- Phoneme features don't help in any of the settings

What is the Model Learning?



The UMAP projections contrast the embeddings learned by the tagger with skipgram embeddings trained on the same corpus.

- \cdot Words occurring first in an EE (B $_1)$ are shown in cyan
- \cdot Words ocurring second in an EE (B₂) are shown in gold
- In the tagger embeddings, there is a clear separation, but not in the skipgram embeddings
- The tagging model learns **lexical representations** of the B₁ and B₂ words that are different **with no phonological information**

First Position and Second Position Words

The model learned the separation of "first position" vs "second position" words from occurrence of these words in the corpus.

For example, many B_1B_2 pairs occur independently as CCs in Hmong

The model picked up on this fact and used it to detect properly/improperly ordered EEs in the test set.

Note: the splits are made so that test set EEs never occur in the training corpus, but the component words still occur.



Hypothesis:

Phonological information facilitates the recognition of correctly and incorrectly ordered Hmong EEs in context. (Lexical information is sufficient)

Experiment 3: Using Learned Embeddings in Classification

- Embeddings from tagger show a clear separation
- Use the tagger's embedding layer as classification features in addition to one-hot features for all onsets, rhymes, and tones, for each word.
- Do phonemes add extra information? Do embeddings add extra information?



Results of Classification with Learned Embeddings



Observations:

- Embeddings alone are as good as phonemes alone.
- Embeddings + phonemes together create the best performance.
- Embeddings from Skipgram are trained on general semantics, while embeddings from the tagger are trained to identify EEs.

Tone is Important if there are Few Features, Lexical Features if there are Many



- The classification model disproportionately chooses tones (red) as classification features, especially when the number of features is small
- Onsets (orange) are of moderate importance in the mid range
- The test accuracy is impressively 84% with only 12 features, 40% of which are tones.
- As *k* increases, word embedding features start to gain importance.

Bringing Everything Together

What features are useful for predicting the ordering effect?	Phonemes	Tagger Embeddings	
Exp 1: Classification	 Image: A second s	-	
Exp 2: Seq Tagging	×	✓	
Exp 3: Classification w/ wv	1	1	

We have shown two independent routes to arrive at the ordering effect: phonology-based features and lexical distributions.

Both contribute to the identification of correctly ordered EEs, but the information is not completely redundant. The unnatural phonological hierarchy is very robust, **but this does not falsify a naturalness bias, since—in context—learners can rely on other information to learn the pattern**.

A Diachronic (Historical) Story

- 1. Once upon a time, the phonological hierarchies were phonetically grounded—language users ordered CCs and EEs based on phonetic, rather than structural, considerations.
- 2. This affected the distribution of words within these MWEs and across the languages
 - 2.1 Learners "phonologized" the tendencies into structural patterns \rightarrow syntactic bias weak
 - 2.2 Related words in CCs and EEs came to fall into "first position" and "second position" categories on the basis of distribution → phonology becomes lexical
- 3. The phonetics of the tones (and rhymes) shifted around; this is pervasive in tone systems of East and Southeast Asia and in vowel systems of the world
- 4. The result was typologically unusual phonological hierarchies latent in the data—which may or may not be learned by language users—in spite of any bias against unnatural phonology

Hmong-Mien	W Hmongic	Dananshan	Mong Leng	Hmong Daw
Λ	A2	√ falling	۱ high falling	۱ high falling
A	A1	۱ high falling	l high	1 high rising
D	D2	∤ rising	J low falling	J low falling
D	D1	H mid	4 low	4 low
R	B2	J low falling breathy	J low falling breathy	-low
D	B1	1 high	1 rising	1 rising
C	C2	<i>يا</i> low rising breathy	실 low falling breathy	្ឆlow falling breathy
C	C1	1 high	H mid	⊣ mid

If this story is correct, it means that, if language learners are biased against seeking a phonological explanation for a syntactic fact, this bias is not overwhelming.

It is difficult to understand EE and CC ordering patterns if learners are biased against accounting for word order patterns with phonology.

- The unnatural hierarchies can be learned by a classifier, given the data, and are extremely predictive
- This phonological information does contribute information to classification that embeddings from the tagger do not
- But, in context, phonological information (and the unnatural hierarchies) are not needed to achieve strong results

This Is a Wug

Ultimately, the only way to determine whether the unnatural phonological hierarchies from Mortensen (2006) are learned by language users is through **psycholinguistic experiments using nonce words**—the same kind of experiment that uncovered the biases in the first study.



However, NLP-inspired studies like this one demonstrate that there is a hypothesis worth investigating.

The Full Paper



Conclusion

I have presented two, related but distinct studies:

- One which sought to explain patterns in lexical change in terms of documented cognitive biases
- One which questioned two other cognitive biases regarding the phonology and syntax of certain multiword expressions, with mixed results

Takeaway: Language and language change is shaped, in many respects, by the cognitive properties of humans as language users and this is true of the lexicon as much as of other aspects of language. But data-driven methods allow investigators to critically examine proposed cognitive biases in new ways.

Thanks to My Collaborators



Suzanne Stevenson



Ella Rabinovich



Fahar Samir



Chenxuan Cui



Katherine Zhang



David Francis

Questions?

References

Altmann, E. G., Pierrehumbert, J. B., & Motter, A. E. (2011). Niche as a determinant of word fate in online groups. PLoS ONE, 6(5). doi: https://doi.org/10.1371/journal.pone.0019009 Atkinson, Q. D., Meade, A., Venditti, C., Greenhill, S. J., & Pagel, M. (2008). Languages evolve in punctuational bursts. Science, 319(5863), 588–588. doi:

http://doi.org/10.1126/science.1149683

Bailey, T. M., & Hahn, U. (2001). Determinants of wordlikeness: Phonotactics or lexical neighborhoods? Journal of Memory and Language, 44(4), 568–591. doi: https://doi.org/10.1006/jmla.2000.2756

Becker, M., Ketrez, N., & Nevins, A. (2011). The surfeit of the stimulus: Analytic biases filter lexical statistics in turkish laryngeal alternations. Language, 84–125.

Benor, S. B., & Levy, R. (2006). The chicken or the egg? a probabilistic analysis of english binomials. Language, 82(2), 233-278.

Buchanan, L., Westbury, C., & Burgess, C. (2001). Characterizing semantic space: Neighborhood effects in word recognition. Psychonomic Bulletin & Review, 8(3), 531–544. doi: https://doi.org/10.3758/BF03196189

Chomsky, N. (1981). Lectures on government and binding: The pisa lectures. de Gruyter.

Chomsky, N. (1995). The minimalist program. MIT Press.

Chomsky, N., & Halle, M. (1968). The sound pattern of English. ERIC.

Croft, W. (2000). Explaining language change: An evolutionary approach. New York: Pearson Education.

Dahan, D., Magnuson, J. S., Tanenhaus, M. K., & Hogan, E. M. (2001). Subcategorical mismatches and the time course of lexical access: Evidence for lexical competition. Language and Cognitive Processing, 16(5/6), 507–534. doi: https://doi.org/10.1080/01690960143000074

Dai, Q. (1986). Jingpo yu binglie jiegou fuheci de yuanyin hexie. Minzu Yuwen, 1986(5), 23–29.

De Groot, A. M. B., & Keijzer, R. (2000). What is hard to learn is easy to forget: The roles of word concreteness, cognate status, and word frequency in foreign-language vocabulary learning and forgetting. Language Learning, 50(1), 1-56. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/0023-8333.00110 doi: 10.1111/0023-8333.00110

Fudge, E. C. (1967). The nature of phonological primes. Journal of Linguistics, 3(1), 1–36.

Hale, M., & Reiss, C. (2000). "substance abuse" and "dysfunctionalism": current trends in phonology. Linguistic inquiry, 31(1), 157-169.

Hayes, B., & White, J. (2013, 01). Phonological Naturalness and Phonotactic Learning. Linguistic Inquiry, 44(1), 45-75. Retrieved from https://doi.org/10.1162/LING_a_00119 doi: 10.1162/LING_a_00119

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780. doi: https://doi.org/10.1162/neco.1997.9.8.1735

Hyman, L. M. (1970). How concrete is phonology? Language, 58-76.

- James, C. T. (1975). The role of semantic information in lexical decisions. Journal of Experimental Psychology: Human Perception and Performance, 1(2), 130. doi: https://doi.org/10.1037/0096-1523.12.130
- Jastrzembski, J. E. (1981). Multiple meanings, number of related meanings, frequency of occurrence, and the lexicon. Cognitive Psychology, 13(2), 278–305. doi: 10.1016/0010-0285(81)90011-6
- Johns, B. T., Dye, M., & Jones, M. N. (2016). The influence of contextual diversity on word learning. Psychonomic Bulletin & Review, 23(4), 1214–1220. doi: https://doi.org/10.3758/s13423-015-0980-7
- Kay, C., Alexander, M., Dallachy, F., Roberts, J., Samuels, M., & Wotherspoon, I. (2019). The historical thesaurus of english, version 4.21. Glasgow: University of Glasgow. Retrieved from https://ht.ac.uk/
- Kwon, N., & Masuda, K. (2019). On the ordering of elements in ideophonic echo-words versus prosaic dvandva compounds, with special reference to korean and japanese. Journal of East Asian Linguistics, 28(1), 29–53. doi: 10.1007/s10831-019-09189-1
- Marian, V., & Blumenfeld, H. (2006). Phonological neighborhood density guides lexical access in native and non-native language production. Journal of Social and Ecological Boundaries, 2(1), 3–35.
- Marslen-Wilson, W. (1990). Activation, competition, and frequency in lexical access. In Cognitive models of speech processing: Psycholinguistic and computational perspectives. (pp. 148–172). Cambridge, MA, US: The MIT Press. doi: https://doi.org/10.7551/mitpress/1889.003.0008
- McDonald, S. A., & Shillcock, R. C. (2001). Rethinking the word frequency effect: The neglected role of distributional information in lexical processing. Language and Speech, 44(3), 295–322. doi: https://doi.org/10.1177/00238309010440030101
- Michel, J.-B., Shen, Y. K., Aiden, A. P., Veres, A., Gray, M. K., Pickett, J. P., ... others (2011). Quantitative analysis of culture using millions of digitized books. Science, 331(6014), 176–182. doi: https://doi.org/10.1126/science.1199644
- Moreton, E., & Pater, J. (2012a). Structure and substance in artificial-phonology learning, part ii: Substance. Language and Linguistics Compass, 6(11), 702–718. doi: 10.1002/lnc3.366 Moreton, E., & Pater, J. (2012b). Structure and substance in artificial-phonology learning, part i: Structure. Language and Linguistics Compass, 6(11), 686–701. doi: 10.1002/lnc3.363 Moretan, E., & Levy, R. (2016). Abstract knowledge versus direct experience in processing binominal expressions. Comition, 157, 384–402.
- Mortensen, D. R. (2006). Logical and substantive scales in phonology (Doctoral dissertation, University of California, Berkeley). Retrieved from

https://escholarship.org/uc/item/0sp1b9w8

Oudeyer, P.Y., & Kaplan, F. (2007). Language evolution as a Darwinian process: computational studies. Cognitive Processing. doi: https://doi.org/10.1007/s10339-006-0158-3 Rood, J., Gaskell, G., & Marslen-Wilson, W. (2002). Making sense of semantic ambiguity: Semantic competition in lexical access. Journal of Memory and Language, 46, 245-266. doi:

https://doi.org/10.1006/jmla.2001.2810

- Schleicher, A. (1863). Die darwinsche theorie und die sprachwissenschaft: Offenes sendschreiben an herrn dr. ernst häcke. Weimar: Böhlau.
- Shih, S. S. (2017). Phonological influences in syntactic alternations. In The morphosyntax-phonology connection: Locality and directionality at the interface (pp. 223–252). doi: 10.1093/acprof.oso/9780190210304.001.0001
- Shih, S. S., & Zuraw, K. (2017). Phonological conditions on variable adjective and noun word order in tagalog. Language, 93(4), e317-e352. doi: 10.1353/lan.2017.0075

- Snefjella, B., Généreux, M., & Kuperman, V. (2019). Historical evolution of concrete and abstract language revisited. Behavior Research Methods, 51(4), 1693–1705. doi: https://doi.org/10.3758/s13428-018-1071-2
- Stewart, I., & Eisenstein, J. (2018). Making "fetch" happen: The influence of social and linguistic context on nonstandard word growth and decline. In Proceedings of the 2018 conference on empirical methods in natural language processing (pp. 4360–4370). Retrieved from https://www.aclueb.org/anthology/D18-1467
- Thanukos, A. (2008, July). A Look at Linguistic Evolution. Evolution: Education and Outreach, 1(3), 281–286. Retrieved from https://doi.org/10.1007/s12052-008-0058-3 doi: 10.1007/s12052-008-0058-3
- Ting, P.-H. (1975). Tonal relationship between the two consistuent of the coordinate construction in the analects, the meng-tze, and the book of odes. Bulletin of the Institute of History and Philology, Academia Sinica, 47(1), 17–52.
- Traugott, E. C., & Dasher, R. B. (2001). Regularity in semantic change (Vol. 97). Cambridge: Cambridge University Press.
- Tsvetkov, Y., Mukomel, E., & Gershman, A. (2013). Cross-lingual metaphor detection using common semantic features. In Proceedings of the first workshop on metaphor in nlp (pp. 45-51). Retrieved from https://www.aclweb.org/anthology/W13-0906
- Turney, P. D., & Mohammad, S. M. (2019). The natural selection of words: Finding the features of fitness. PLoS ONE, 14(1). Retrieved from

https://doi.org/10.1371/journal.pone.0211512

Vejdemo, S., & Hörberg, T. (2016). Semantic factors predict the rate of lexical replacement of content words. PLoS ONE, 11(1). Retrieved from

https://doi.org/10.1371/journal.pone.0147924

- Vitevitch, M. S. (2002). The influence of phonological similarity neighborhoods on speech production. Journal of Experimental Psychology: Learning, Memory, and Cognition, 28(4), 735. Retrieved from https://doi.org/10.1037//0278-7393.28.4.735
- Vitevitch, M. S., Luce, P. A., Pisoni, D. B., & Auer, E. T. (1999). Phonotactics, neighborhood activation, and lexical access for spoken words. Brain and Language, 68(1-2), 306–311. doi: https://dx.doi.org/10.1006\%2Fbrln.1999.2116
- Yates, M., Locker, L., & Simpson, G. B. (2004). The influence of phonological neighborhood on visual word perception. Psychonomic Bulletin & Review, 11(3), 452–457. Retrieved from https://doi.org/10.3758/BF03196594