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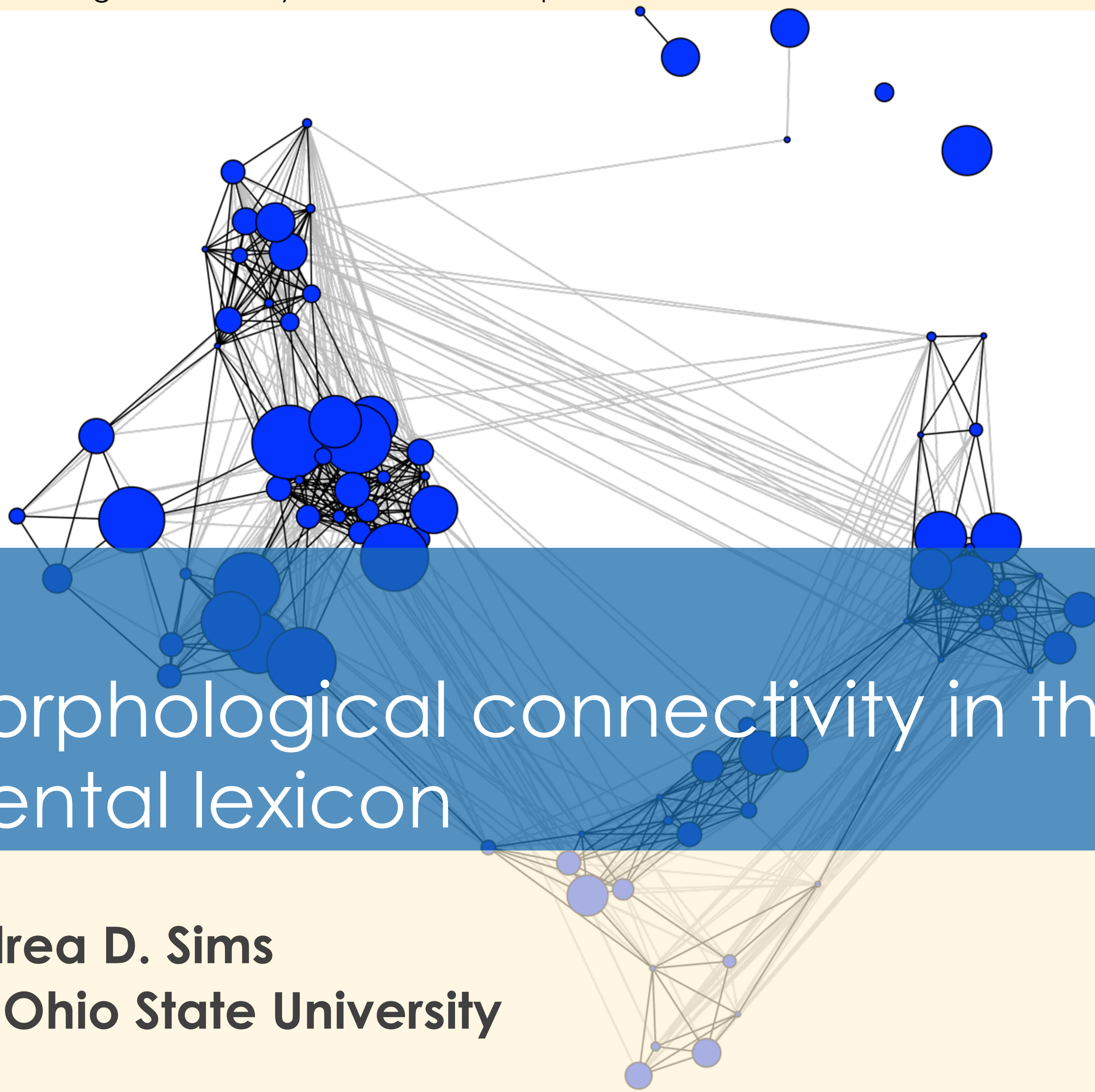


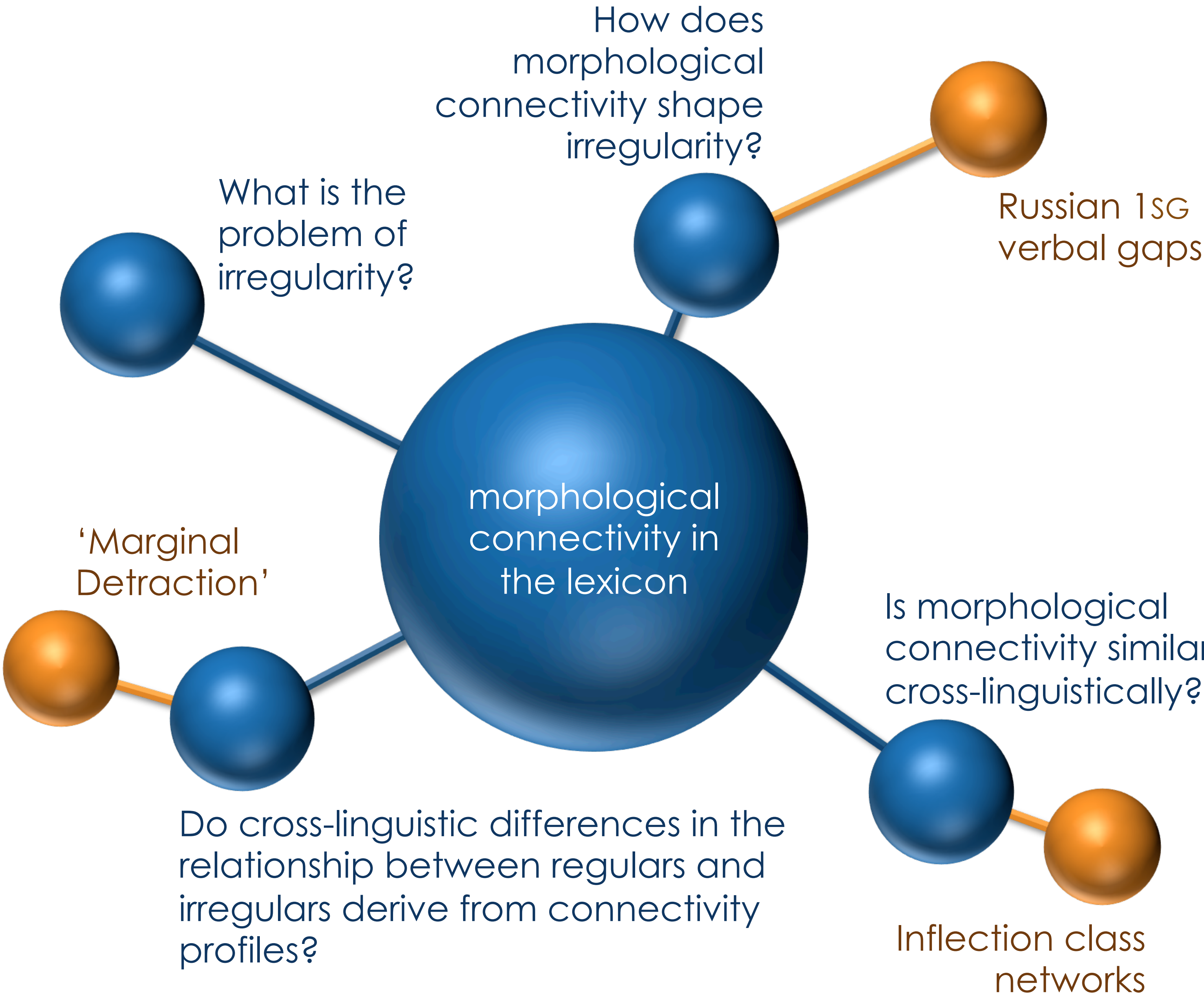
Morphological connectivity in the mental lexicon

Andrea D. Sims
The Ohio State University

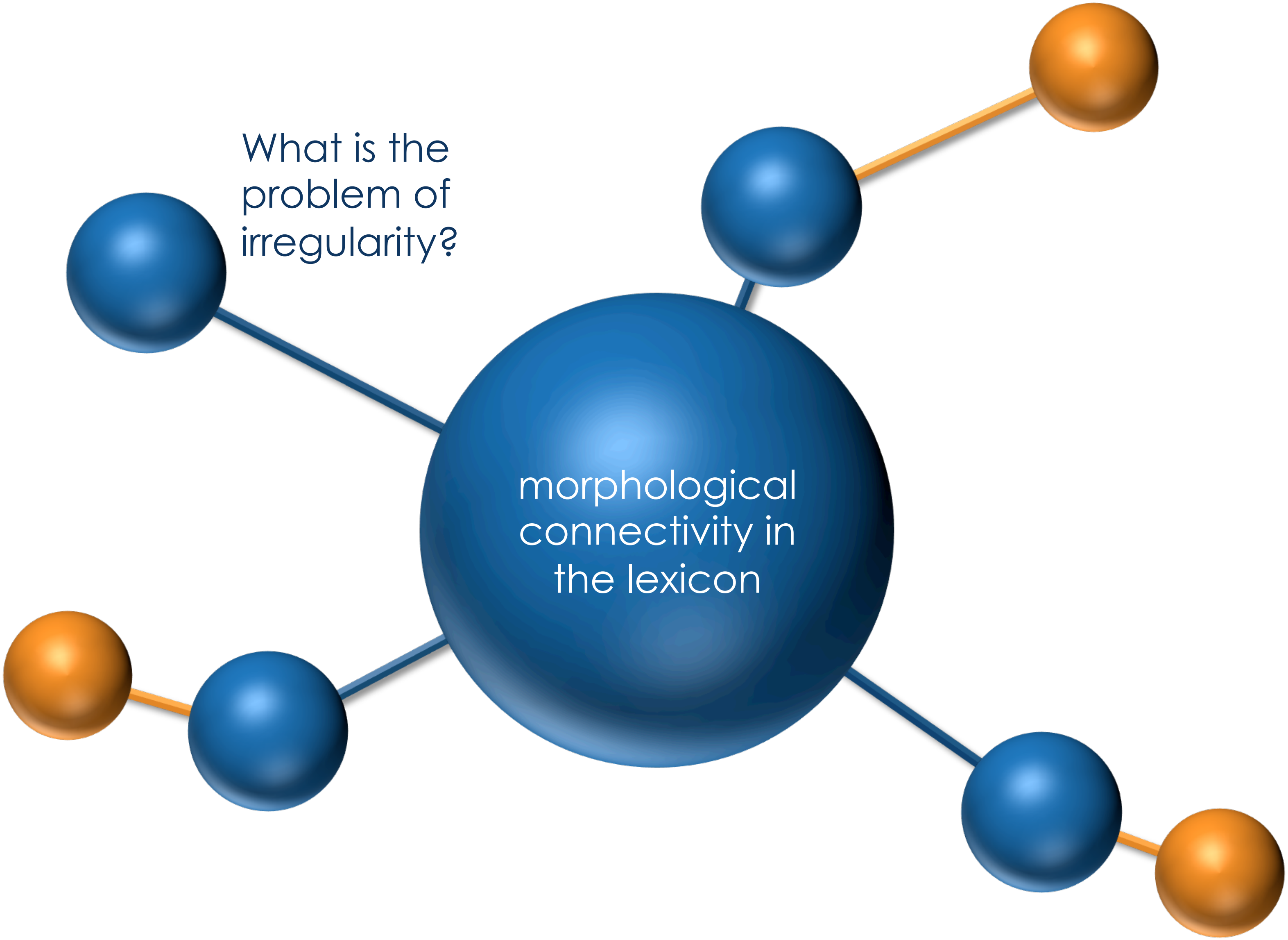
A (too) big question

How does the relationship between individual elements within morphological systems relate to 'global' properties of inflectional organization?

OUTLINE



How does morphological connectivity shape irregularity?
Russian 1SG verbal gaps
What is the problem of irregularity?
'Marginal Detraction'
morphological connectivity in the lexicon
Is morphological connectivity similar cross-linguistically?
Do cross-linguistic differences in the relationship between regulars and irregulars derive from connectivity profiles?
Inflection class networks


What is the problem of irregularity?
morphological connectivity in the lexicon

Irregularity as lawlessness?

The lexicon "... is incredibly boring by its very nature... Those objects that it does contain are there because they fail to conform to interesting laws. The lexicon is like a prison -- it contains only the lawless, and the only thing its inmates have in common is lawlessness."
(Di Sciullo and Williams 1987:3)

Irregularity as lawlessness?

irregularity

regularity

Irregularity as lawlessness?

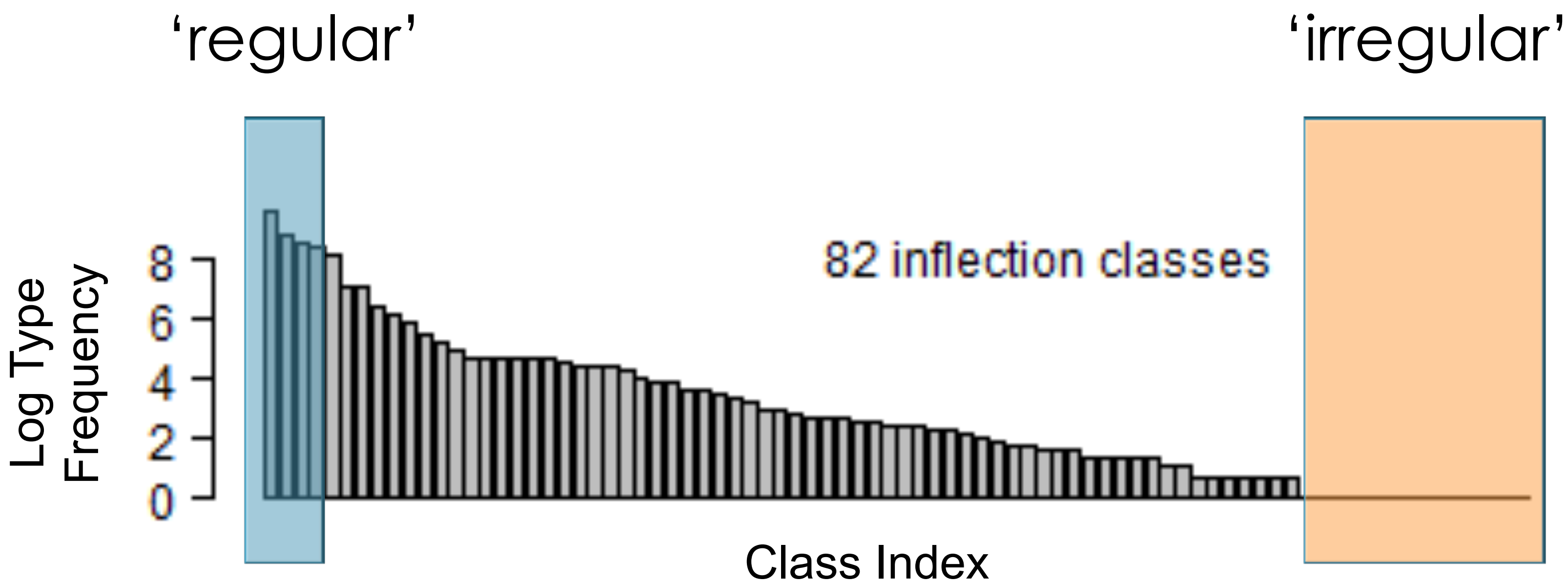
lexicon

morphology

Four-class description of Russian nouns

	Class I ZAKAZ 'order'	Class IV BLJUDO 'dish'	Class II KNIGA 'book'	Class III TETRAD' 'exercise book'
NOM SG	zakáz	bljúd-o	kníg-a	tetrád'
ACC SG	zakáz	bljúd-o	kníg-u	tetrád'
GEN SG	zakáz-a	bljúd-a	kníg-i	tetrád-i
DAT SG	zakáz-u	bljúd-u	kníg-e	tetrád-i
LOC SG	zakáz-e	bljúd-e	kníg-e	tetrád-i
INST SG	zakáz-om	bljúd-om	kníg-oj	tetrád'-ju
NOM PL	zakáz-y	bljúd-a	kníg-i	tetrád-i
ACC PL	zakáz-y	bljúd-a	kníg-i	tetrád-i
GEN PL	zakáz-ov	bljúd	kníg	tetrád-ej
DAT PL	zakáz-am	bljúd-am	kníg-am	tetrádj-am
LOC PL	zakáz-ax	bljúd-ax	kníg-ax	tetrádj-ax
INST PL	zakáz-ami	bljúd-ami	kníg-ami	tetrádj-ami

Distribution of Russian noun classes



Source: Sims and Parker (2016)

Dimensions of Russian noun exponence: suffixes, stem changes, stress alternations, defectiveness

The problem of irregularity

	gospodin 'lord/sir'
NOM SG	gospod-ín
ACC SG	gospod-ín-a
GEN SG	gospod-ín-a
DAT SG	gospod-ín-u
LOC SG	gospod-ín-e
INST SG	gospod-ín-om
NOM PL	gospod-á
ACC PL	gospód
GEN PL	gospód
DAT PL	gospod-ám
LOC PL	gospod-áx
INST PL	gospod-ámi

- Type frequency = 1

The problem of irregularity

	gospodin 'lord/sir'
NOM SG	gospod-ín
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NOM PL	gospod-á
ACC PL	gospód
GEN PL	gospód
DAT PL	gospod-ám
LOC PL	gospod-áx
INST PL	gospod-ámi

- Type frequency = 1
- Most of the inflectional exponents are regular

The problem of irregularity

	gospodin 'lord/sir'	krest'janin 'peasant'	professor 'professor'
NOM SG	gospod-ín	krest'ján-in	proféssor
ACC SG	gospod-ín-a	krest'ján-in-a	proféssor-a
GEN SG	gospod-ín-a	krest'ján-in-a	proféssor-a
DAT SG	gospod-ín-u	krest'ján-in-u	proféssor-u
LOC SG	gospod-ín-e	krest'ján-in-e	proféssor-e
INST SG	gospod-ín-om	krest'ján-in-om	proféssor-om
NOM PL	gospod -á	krest'ján -e	professor-á
ACC PL	gospód	krest'ján	professor-óv
GEN PL	gospód	krest'ján	professor-óv
DAT PL	gospod -ám	krest'ján -am	professor-ám
LOC PL	gospod -áx	krest'ján -ax	professor-áx
INST PL	gospod -ámi	krest'ján -ami	professor-ámi

The problem of irregularity

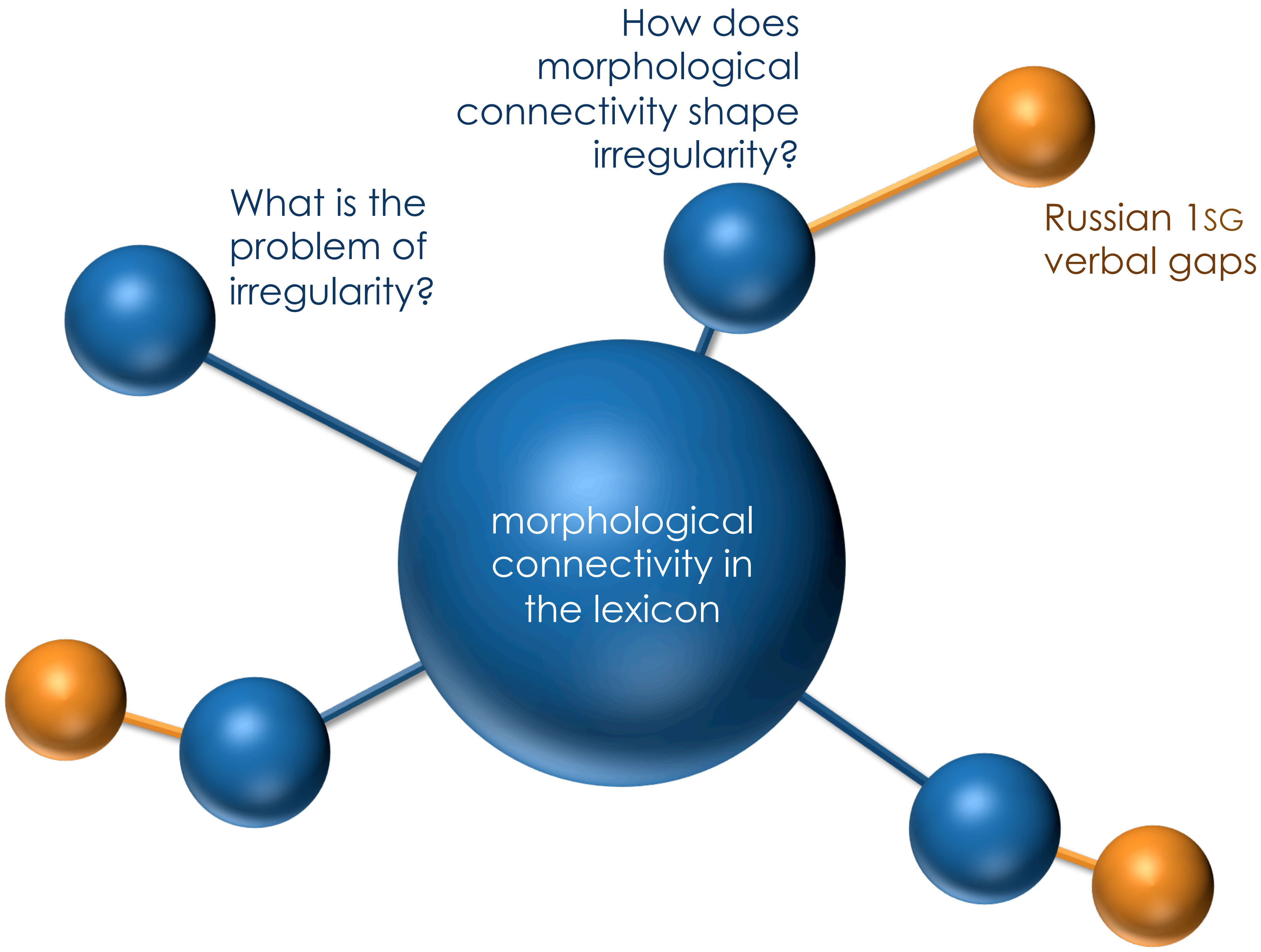
	gospodin 'lord/sir'
NOM SG	gospod-ín
ACC SG	gospod-ín-a
GEN SG	gospod-ín-a
DAT SG	gospod-ín-u
LOC SG	gospod-ín-e
INST SG	gospod-ín-om
NOM PL	gospod-á
ACC PL	gospód
GEN PL	gospód
DAT PL	gospod-ám
LOC PL	gospod-áx
INST PL	gospod-ámi

- None of the exponents are idiosyncratic
  - All occur in class patterns
- Only the *combination* of exponents is unique

Irregularity as network embedding

- Irregularity is not *fundamentally* different from regularity
  - It's about the distribution of information, not the information itself

- 'Irregularity' = a question of how words are embedded in lexical networks, and the relationship between words in a network
  - Brown and Hippisley 2012, Dressler et al. 2006
  - Albright and Hayes 2002, Bybee and Slobin 1982, Bybee 1985, Pierrehumbert 2012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Sources and collaborators

Robert Daland

Janet Pierrehumbert

Daland, Robert, Andrea D. Sims, and Janet Pierrehumbert. 2007. Much ado about nothing: A social network model of Russian paradigmatic gaps. *Association for Computational Linguistics Proceedings* 45: 936-943.

Sims, Andrea D. 2015. *Inflectional defectiveness*. Cambridge: Cambridge University Press.

Paradigmatic gaps in Russian 1SG

	SINGULAR	PLURAL			SINGULAR	PLURAL
1ST	sprošu	sprosim		1ST	--	ubedim
2ND	sprosiš'	sprosite		2ND	ubediš'	ubedite
3RD	sprosit	sprosjat		3RD	ubedit	ubedjat

SPROSIT' – 'ask'

UBEDIT' – 'convince'

missing inflected form = paradigmatic gap

More examples of Russian 1SG gaps

bdet'	'keep watch'	*pobedit'*	'conquer'
buzit'	'protest'	*rysit'*	'trot'
galdet'	'make a hubbub'	*sosedit'*	'be a neighbor'
derzit'	'be imprudent'	*pobedit'*	'conquer'
dudet'	'play the pipe'	*umiloserdit'*	'take pity on'
erundit'	'do funny things'	*čudesit'*	'do magic'
čudit'	'to behave oddly'	*očutit'sja*	'find o.s. to be'
oščutit'	'to feel'	*škodit'*	'misbehave'

Stem-final C	/d^j/	/t^j/	/z^j/	/s^j/	/st^j/
gaps / all 2nd conj	**13.3%** (19/143)	**12.4%** (14/118)	**11.9%** (5/42)	**4.8%** (3/62)	**4.3%** (2/47)

A short history

- In mid-19th c., competing alternations in 1SG
  - Native East Slavic (and modern standard) alternation (e.g. d^j ~ ž)
  - Church Slavonic (CS) alternation (e.g. d^j ~ žd^j)
  - Non-alternation (e.g. d^j ~ d^j)
- Baerman (2008)
  - As CS alternation and non-alternation fell out of developing standard, some lexemes were 'stranded'
  - Gaps in 1SG first noted by Pavskij (1841)
  - Gaps synchronically (mostly) remnants

The learning problem

	High Token Frequency	Low Token Frequency
High Type Frequency	✔	✔ (Hare & Elman 1995)
Low Type Frequency	✔ (Bybee & Slobin 1982, Hare et al. 1995)	**1SG gaps in Russian**

Bayesian inference: It's about observations

UBEDIT' 'convince'	Raw #	Relative Freq	Neighbors
1SG	1	0.2%	12%
2SG	53	11.7%	7%
3SG	210	46.4%	39%
1PL	27	6.0%	11%
2PL	71	15.7%	10%
3PL	91	20.1%	21%

Observations given relatively greater weight in inferences about high frequency verbs (→ word-specific learning)

Bayesian inference: It's about expectations

PROROČIT' 'prophesize'	Raw #	Relative Freq	Neighbors
1SG	0	0%	12%
2SG	2	13.3%	7%
3SG	6	40.0%	39%
1PL	3	20.0%	11%
2PL	0	0%	10%
3PL	4	26.7%	21%

Expectations given relatively greater weight in inferences about low frequency verbs (→ analogical learning)

Bayesian inference: It's about expectations

Prior probability distribution

=

Expectations

$$p(h \mid D) = \frac{\boxed{p(h)} \times p(D \mid h)}{p(D)}$$

Neighbors
12%
7%
39%
11%
10%
21%

Neighbors based on stem-final C

Remember the distributional facts…

bdet'	'keep watch'	*pobedit'*	'conquer'
buzit'	'protest'	*rysit'*	'trot'
galdet'	'make a hubbub'	*sosedit'*	'be a neighbor'
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gaps / all 2nd conj	**13.3%** (19/143)	**12.4%** (14/118)	**11.9%** (5/42)	**4.8%** (3/62)	**4.3%** (2/47)

Bayesian inference: It's about expectations

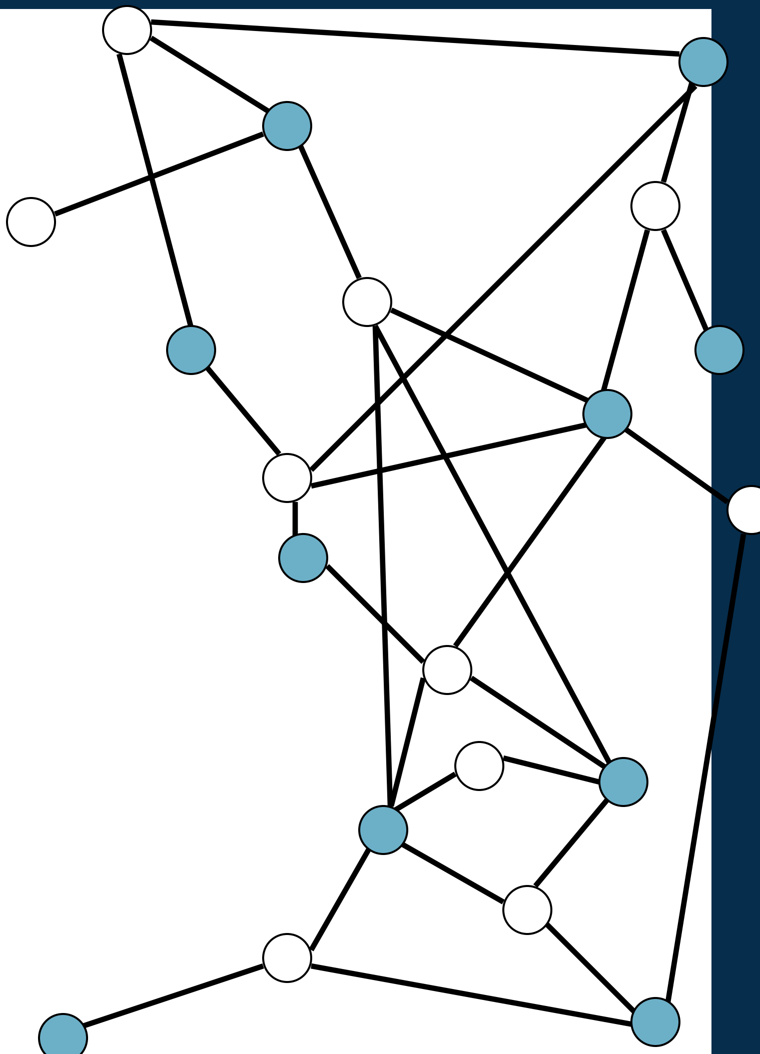
Neighbors (GALDET')
9%
7%
43%
9%
9%
23%

Higher expectation of 1SG gap for GALDET' than for PROROČIT'

Neighbors (PROROČIT')
12%
7%
39%
11%
10%
21%

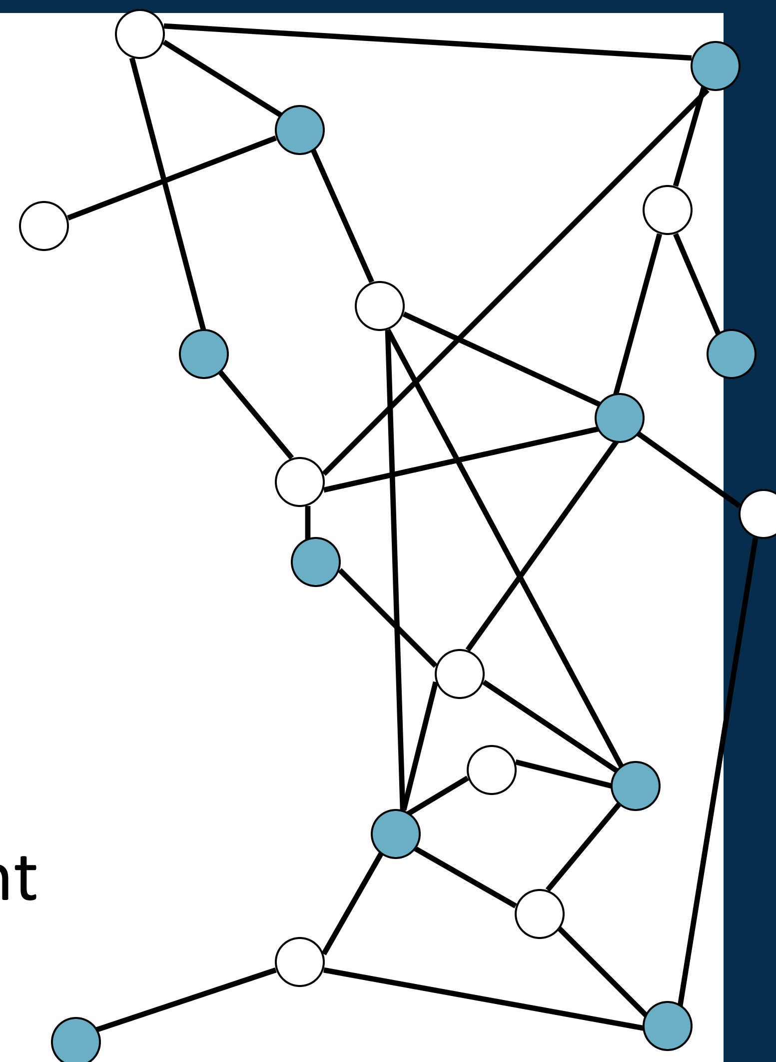
A computational test

- "Adult" agents talk, "child" agents listen
- **Bayesian inference to determine frequency if use of all cells of all verbs**
- Child agents mature; new children introduced
- **Speech of new adults based on sampling from the grammar that they learned**



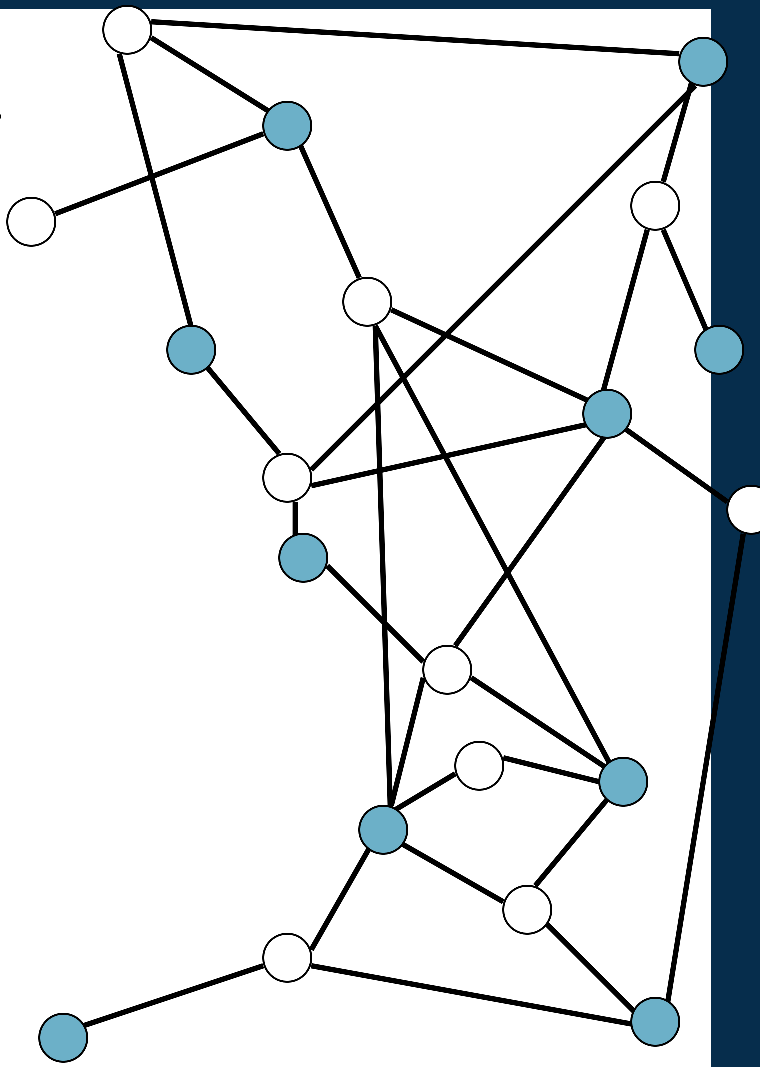
A computational test

- Eight conditions
  - **4 strength of analogy levels**
    - "beta"
  - **2 neighborhood levels**
    - Weighted by similarity of stem-final consonant
    - Unweighted



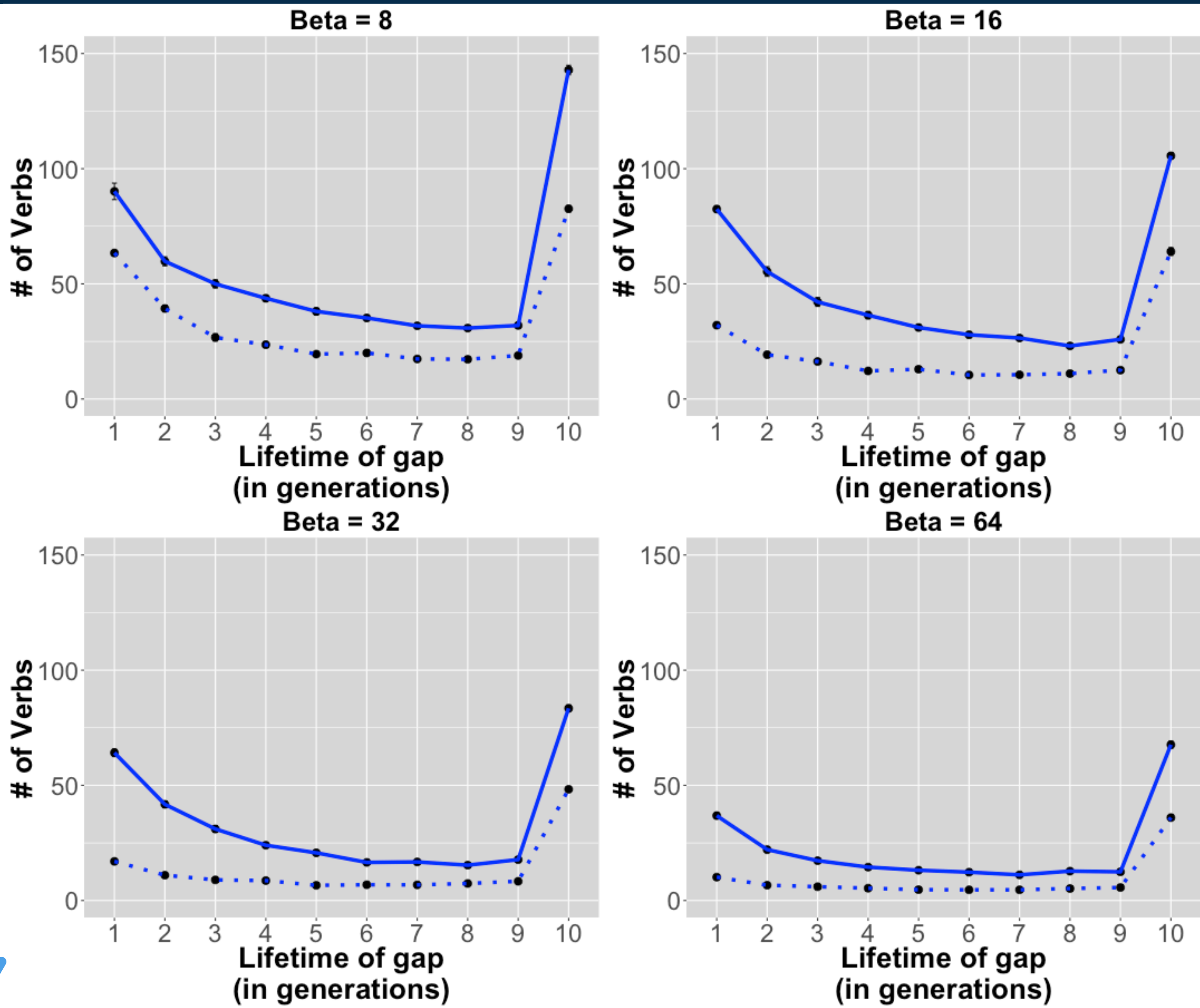
A computational test

- Seeded based on sampling of Russian National Corpus
- At end of each generation, verbs with 1SG gaps counted based on confidence algorithm



'Lifetime' of gaps

increasing analogical strength



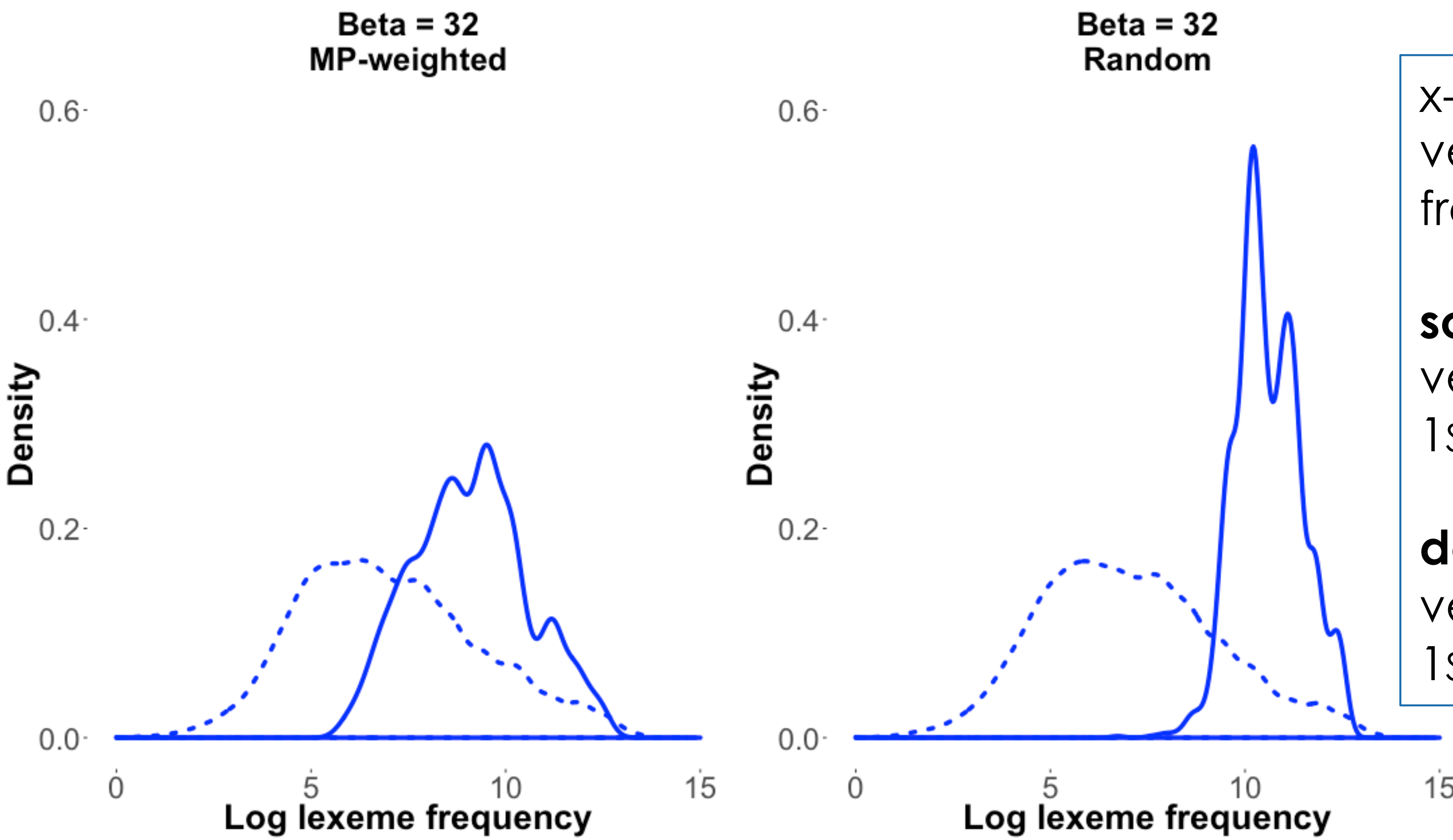
x-axis = gap 'lifetime'

y-axis = number of verbs

solid line = weighted neighbors

dashed = unweighted neighbors

Distribution of gaps by frequency



x-axis = log verb frequency

solid line = verbs w/ 1SG gaps

dashed = verbs w/o 1SG gaps

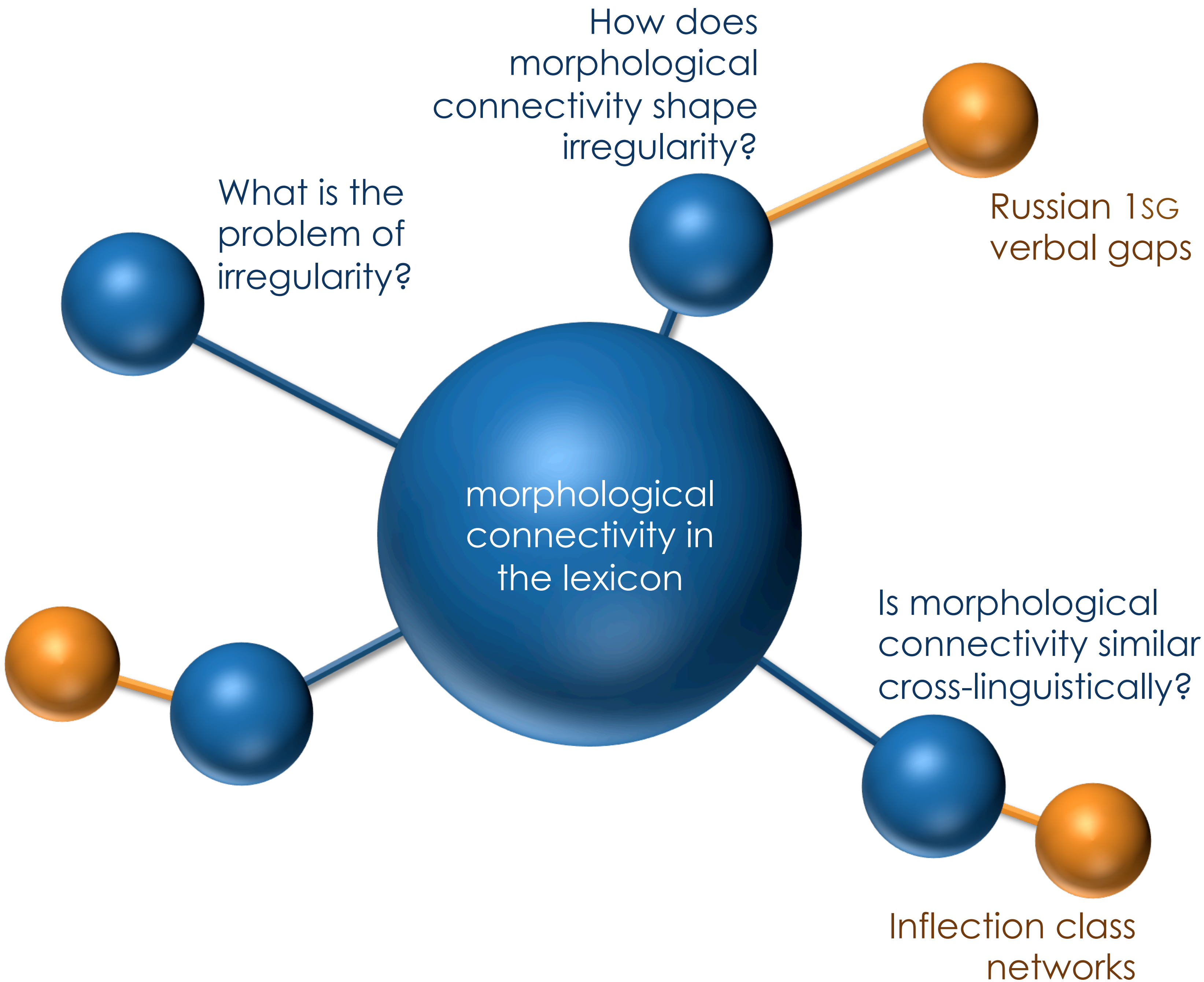
Neighbors weighted by morphophonological similarity

Neighbors unweighted

Morphological connectivity and the 1SG gaps

- Morphophonological neighborhood density is crucial to the learnability and persistence of the Russian 1SG gaps
  - Effect strongest in mid-frequency verbs
  - A lexical gang effect
- Defective and non-defective patterns directly compete in the hypothesis space
  - Defectiveness as a productive pattern
- Russian 1SG gaps as a self-reinforcing pattern that emerges from how verbs are embedded in the lexical network, in the context of analogical learning

OUTLINE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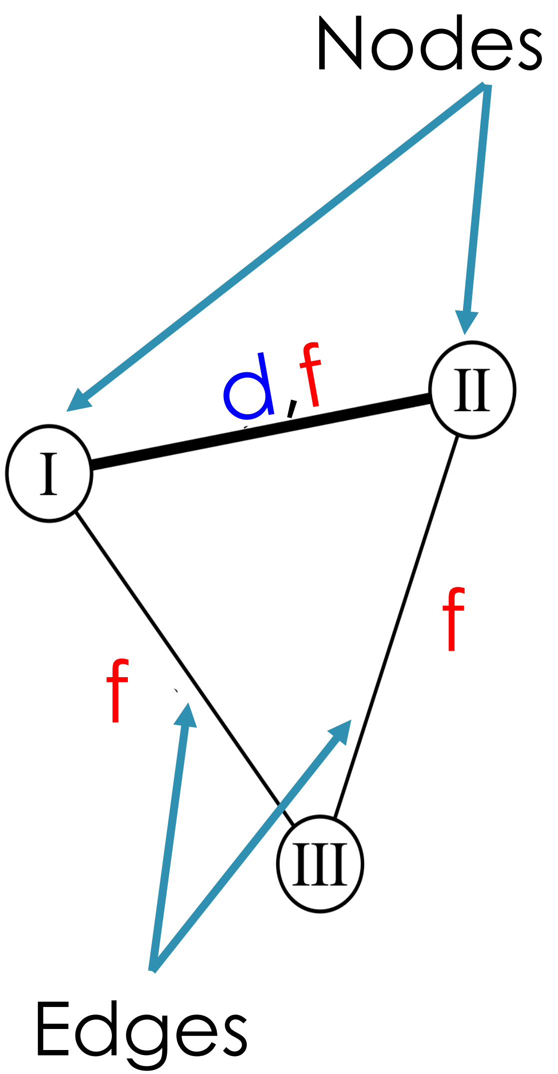
Is morphological connectivity similar cross-linguistically?
Inflection class networks

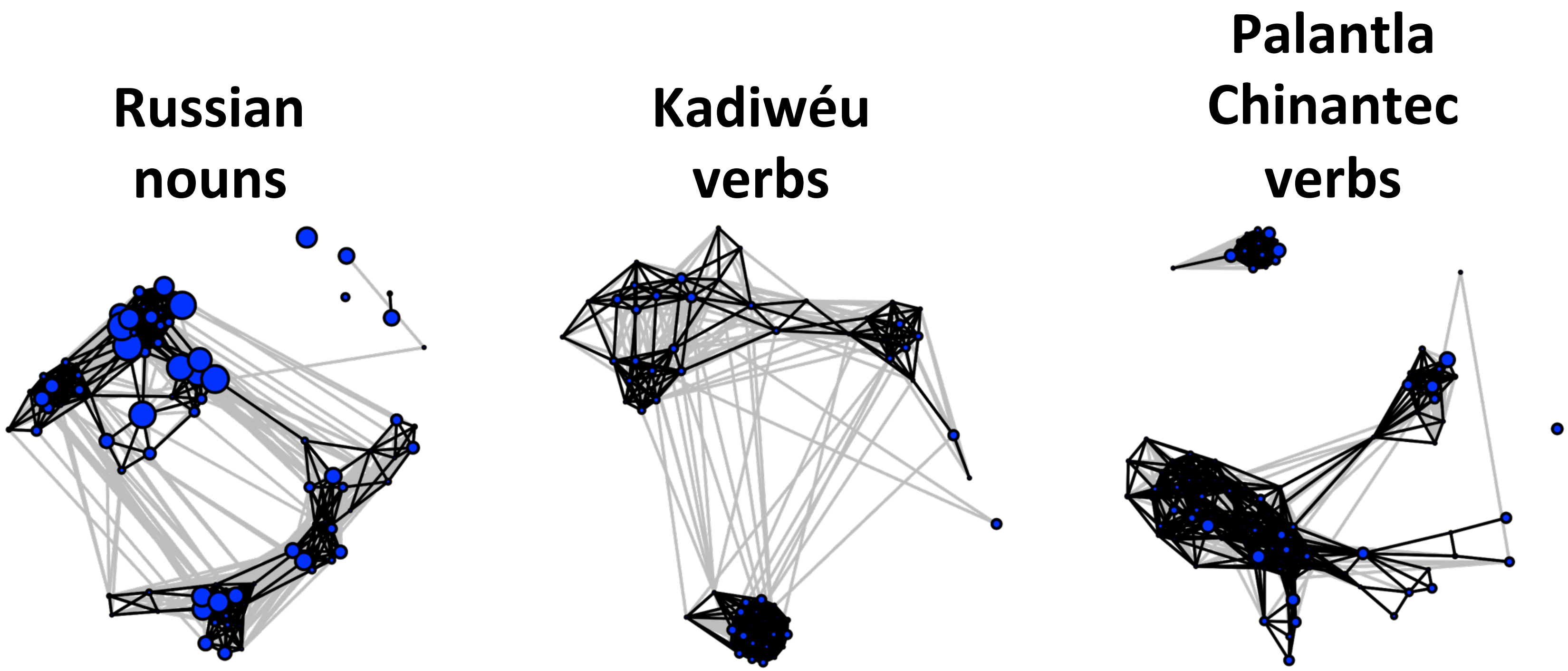
Inflection class systems as networks

Node size

	Word Type Freq.	MSPS X	MSPS Y	MSPS Z
Class I	6	a	d	f
Class II	3	b	d	f
Class III	1	c	e	f



What real languages look like



High node clustering = closely related microclasses that group into macroclasses

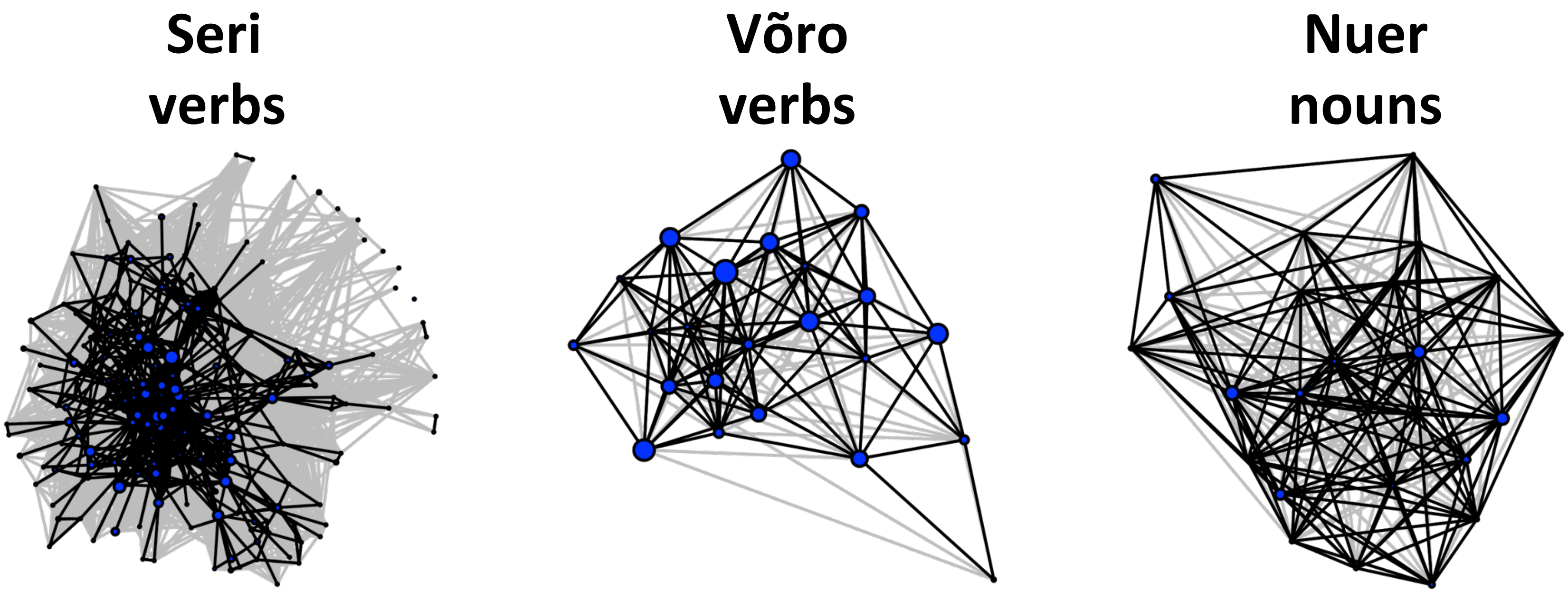
Data sources: Baerman et al. (2015), Griffiths (2002), Merrifield & Anderson (2007), Zaliznjak (1977)

What real languages look like

Weak connectivity = inflection classes are more distinct (good for predictability)

Data sources: Stump & Finkel (2013), Triantafillidis Institute (1998)

What real languages look like

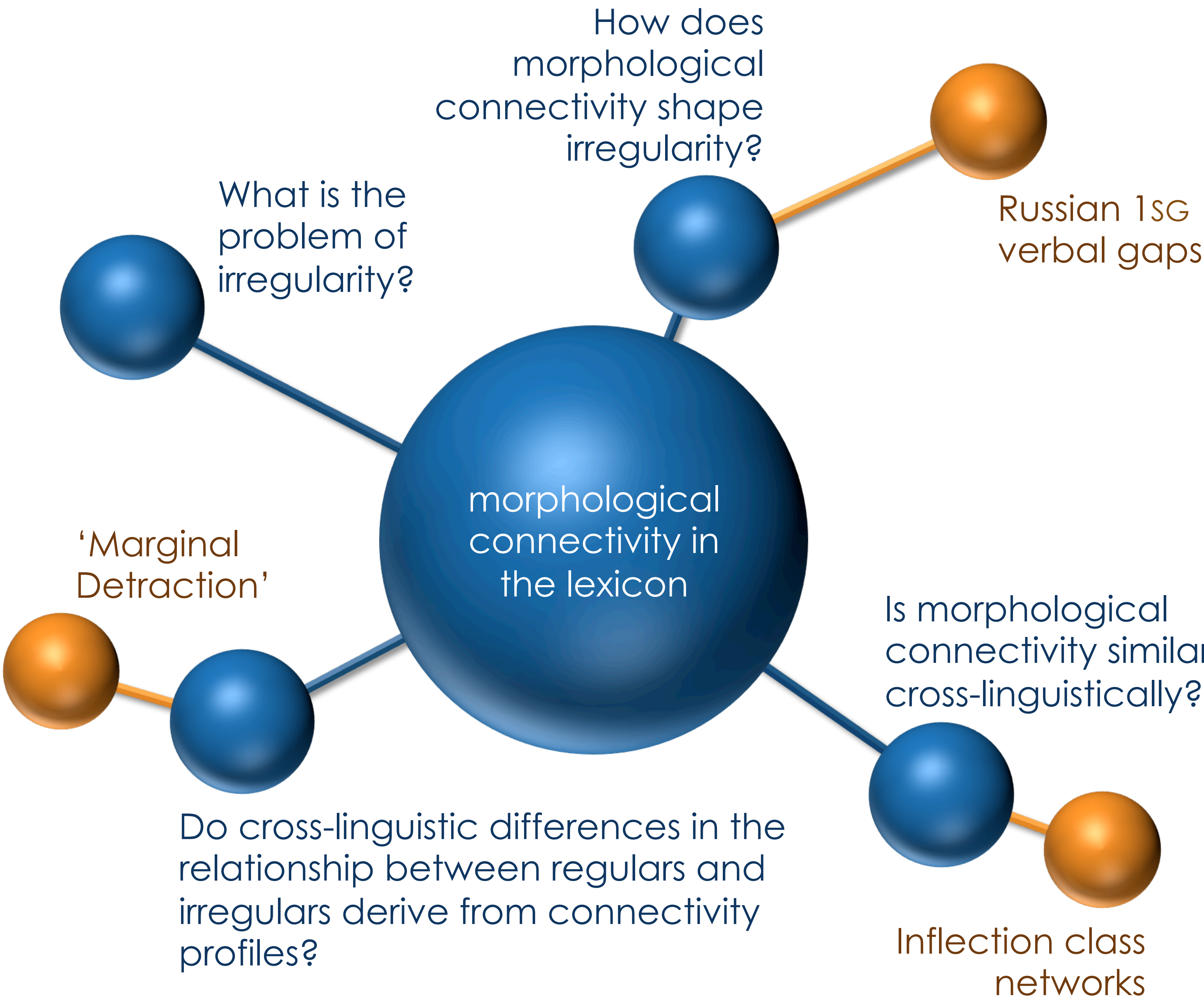


Heavy inflection class overlap = inflected forms are bad predictors of inflection class

Data sources: Baerman (2012, 2014, 2016), Frank (1999), Iva (2007), Moser & Marlett (2010)

Cross-linguistic differences in connectivity

- Languages differ in how classes are embedded within inflection class networks
- Are there consequences of the different connectivity profiles for the relationship between elements *within* a given system?



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Sources and collaborators

Jeff Parker

Robert Reynolds

Sims, Andrea D. and Jeff Parker (2016). How inflection class systems work: On the informativity of implicative structure. *Word Structure* 9(2): 215-239.

Parker, Jeff and Andrea D. Sims (submitted). Irregularity, paradigmatic layers, and the complexity of inflection class systems: A study of Russian nouns.

Parker, Jeff, Robert Reynolds and Andrea D. Sims (in prep). Network properties of inflection class systems.

- A classic story: Irregulars persist because have high token frequency and this allows them to resist the forces of analogy
  - I.e., we tend to think about irregulars in fundamentally individualistic terms
- But analogical pressure is about the distributional properties of the system

Marginal Detraction Hypothesis

"Marginal I[nflection] C[lasses] tend to detract most strongly from the IC predictability of other ICs."

(Stump and Finkel 2013:225)

marginal = low type frequency

Information and inference

	Class I	Class IV	Class II	Class III
NOM SG	/-Ø/	/-o/	/-a/	/-Ø/
ACC SG	/-Ø/	/-o/	/-u/	/-Ø/
GEN SG	/-a/	/-a/	/-i/	/-i/
DAT SG	/-u/	/-u/	/-e/	/-i/
LOC SG	/-e/	/-e/	/-e/	/-i/
INST SG	/-om/	/-om/	/-ej/	/-ju/
NOM PL	/-i/	/-a/	/-i/	/-i/
ACC PL	/-i/	/-a/	/-i/	/-i/
GEN PL	/-ov/	/-Ø/	/-Ø/	/-ej/
DAT PL	/-am/	/-am/	/-am/	/-am/
LOC PL	/-ax/	/-ax/	/-ax/	/-ax/
INST PL	/-am^{j}i/	/-am^{j}i/	/-am^{j}i/	/-am^{j}i/

Really informative! Must be class II.

Somewhat informative. Must be I or IV.

Not at all informative. Could be any class!

Russian noun inflection classes

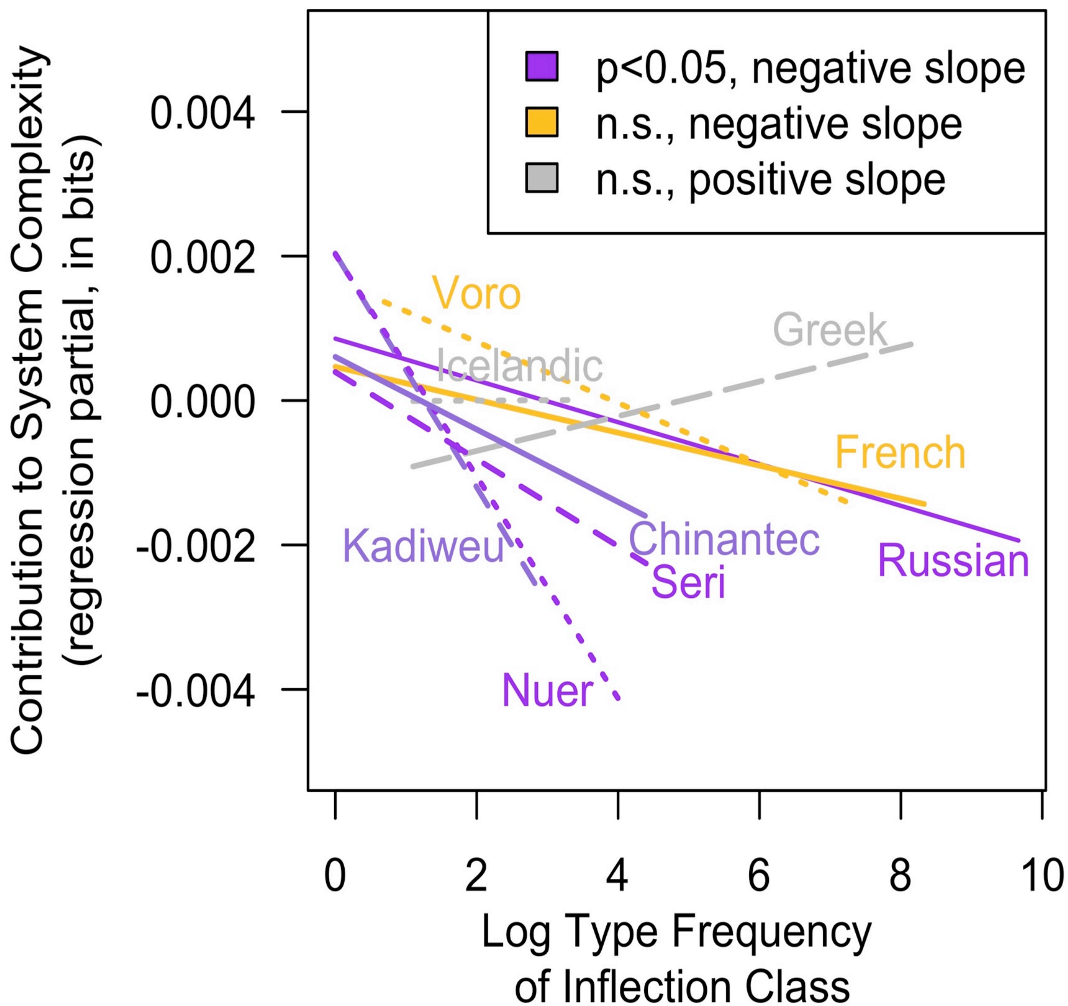
Information and inference

	Class I	Class IV	Class II	Class III
NOM SG	/-Ø/	/-o/	/-a/	/-Ø/
ACC SG	/-Ø/	/-o/	/-u/	/-Ø/
GEN SG	/-a/	/-a/	/-i/	/-i/
DAT SG	/-u/	/-u/	/-e/	/-i/
LOC SG	/-e/	/-e/	/-e/	/-i/
INST SG	/-om/	/-om/	/-oj/	/-ju/
NOM PL	/-i/	/-a/	/-i/	/-i/
ACC PL	/-i/	/-a/	/-i/	/-i/

Conditional Entropy

$$H(A|B) = \sum_{b \in B, a \in A} p(b,a) \log_2 \frac{p(b)}{p(b,a)}$$

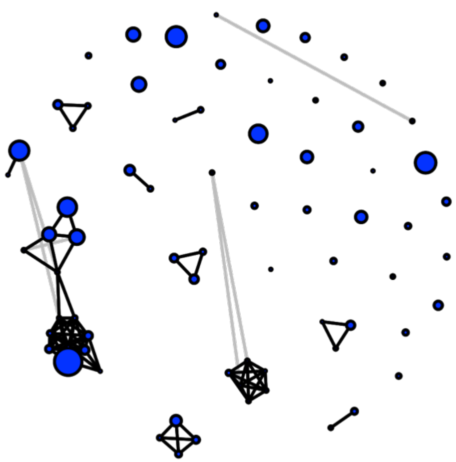
Evidence for marginal detraction



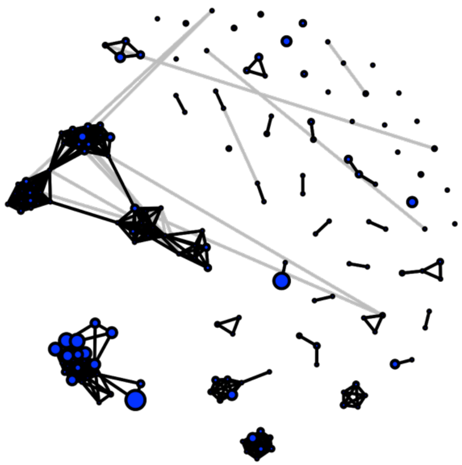
- Negative slope = marginal detraction
- 7 of 9 with negative slopes (5 significant)
- Confirms and extends evidence for marginal detraction
- Also suggests marginal detraction may not hold for all languages

What real languages look like

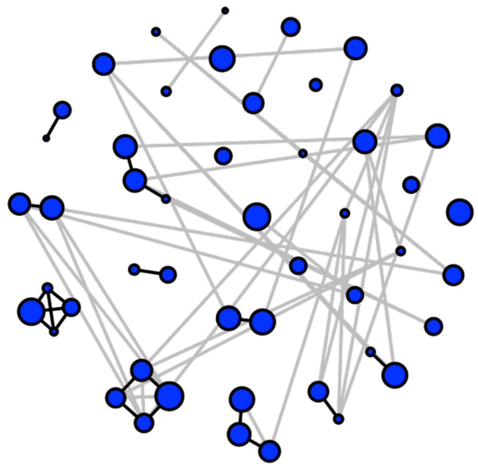
French verbs



Icelandic verbs



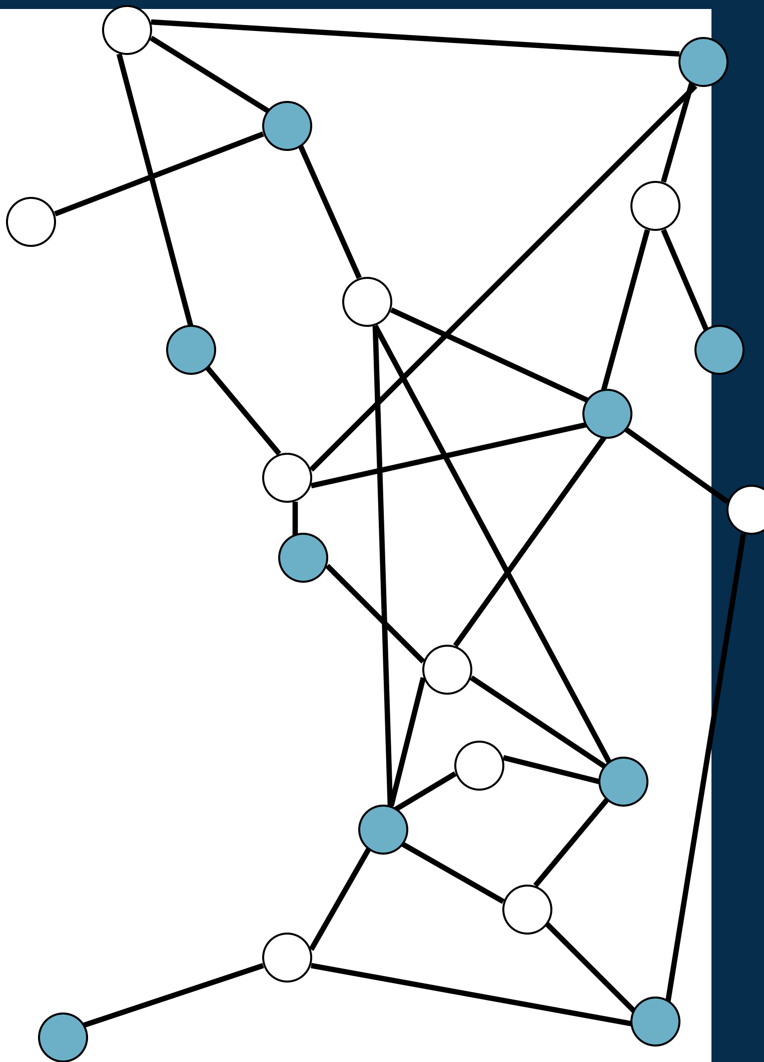
Modern Greek nouns



Weak connectivity = inflection classes are more distinct (good for predictability)

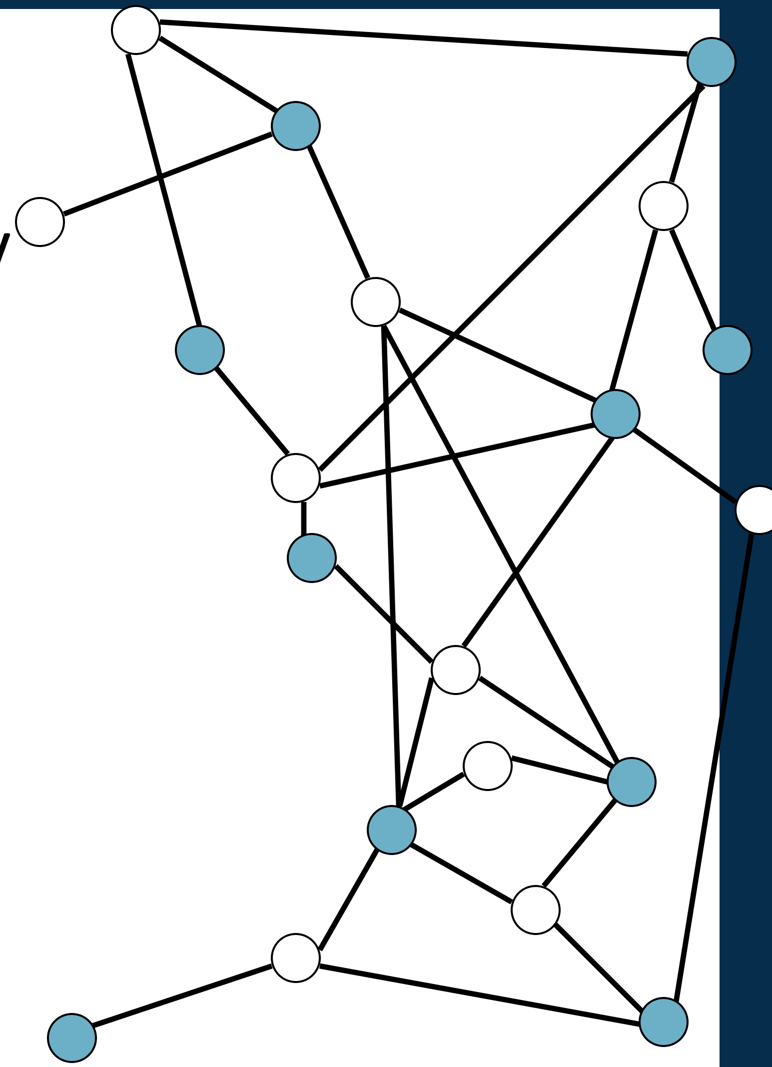
A computational test

- "Adult" agents talk, "child" agents listen
- **Bayesian inference to determine all forms of all lexemes**
- Child agents mature; new children introduced
- **Speech of new adults based on sampling from the grammar that they learned**



A computational test

- Lexemes distributed Zipfianly across classes
- **All lexemes produced with equal probability**
  - MSPS also equally probable

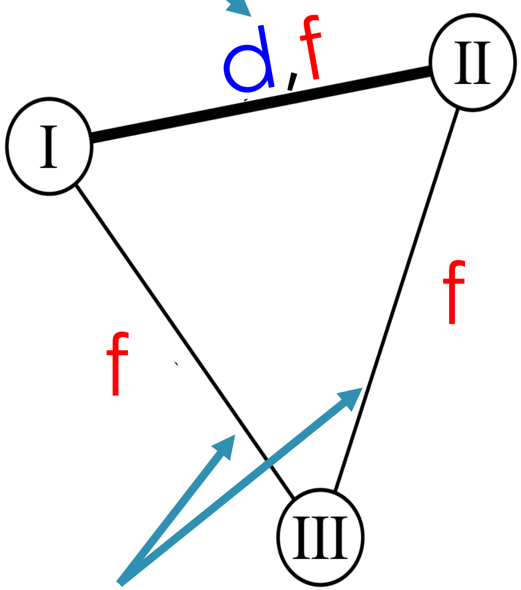


Node properties

(Node size)

	Word Type Freq.	MSPS X	MSPS Y	MSPS Z
Class I	6	a	d	f
Class II	3	b	d	f
Class III	1	c	e	f

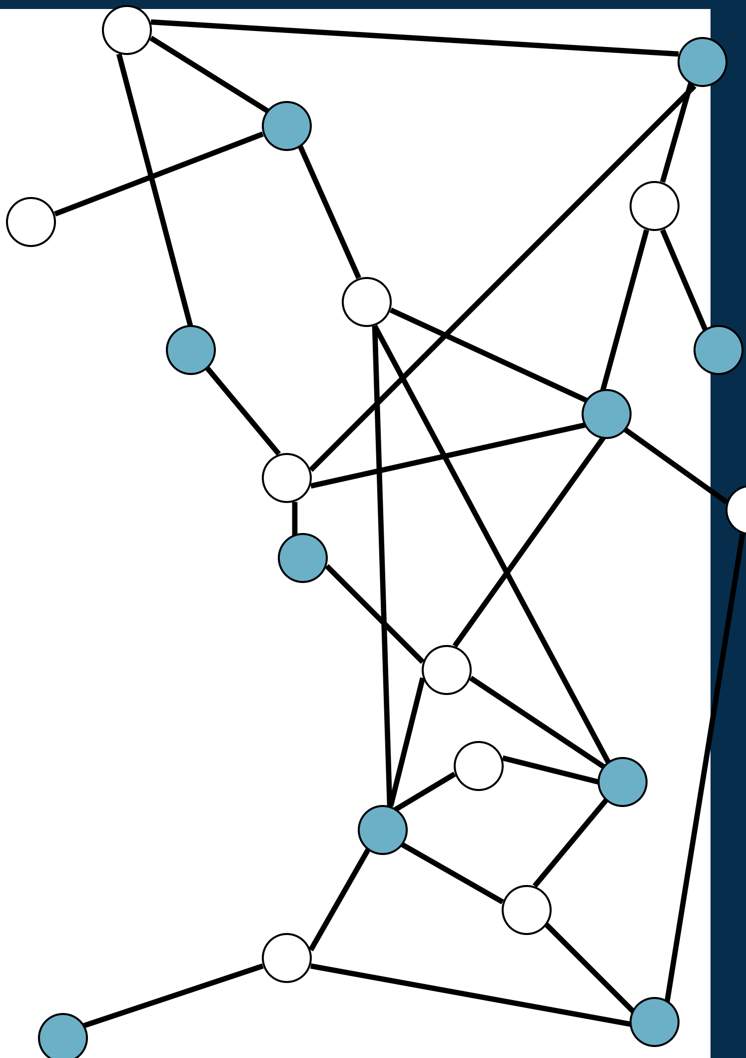
Edge weight = # of overlapping cells



Degree = # of node's edges

A computational test

- 10 input data sets
  - Connected graphs
  - 24 classes and 6 morpho-syntactic property sets
  - In a given input, each node has same degree and average edge weight
- **Degree and average edge weight varied across inputs**



Sample input

	MSPS				
Class	**A**	**B**	**C**	**D**	**E**
I	a	ppp	x	ff	mmmm
II	a	i	xxx	ff	nn
III	aaa	i	q	ffff	nn
IV	b	iii	q	y	nnnn
V	b	j	qqq	y	gg
VI	bbb	j	r	yyy	gg
VII	c	jjj	r	z	gggg
VIII	c	k	rrr	z	hh

Subset of Input Set 2

Degree = 2

Edge weight = 2

Bayesian inference: It's about observations

Productions heard by child agents
=
Observations

$$p(h\,|D) = \frac{p(h) \times \boxed{p(D\,|\,h)}}{p(D)}$$

A | B = i	Lexeme Observations
a	15%
aaa	85%
b	0%
bbb	0%
c	0%

Distribution of observations matters, but number of observations constant

Bayesian inference: It's about expectations

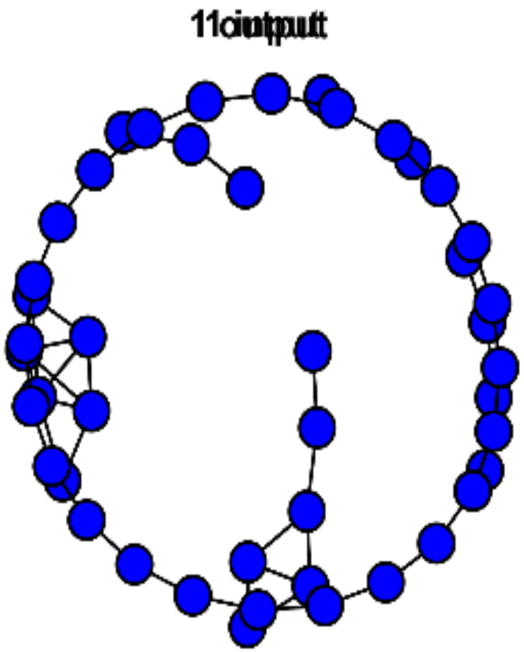
Prior probability
of hypotheses
=
Expectations

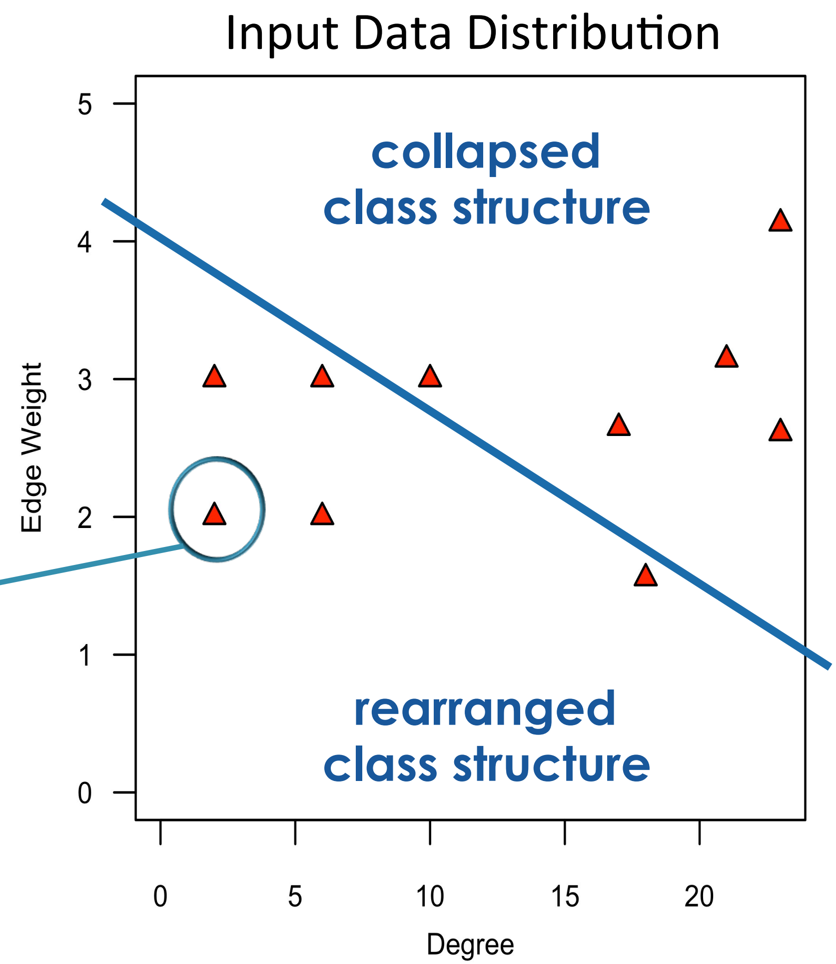
$$p(h \mid D) = \frac{\boxed{p(h)} \times p(D \mid h)}{p(D)}$$

A | B = i	Mean Neighbor Behavior
a	75%
aaa	25%
b	0%
bbb	0%
c	0%

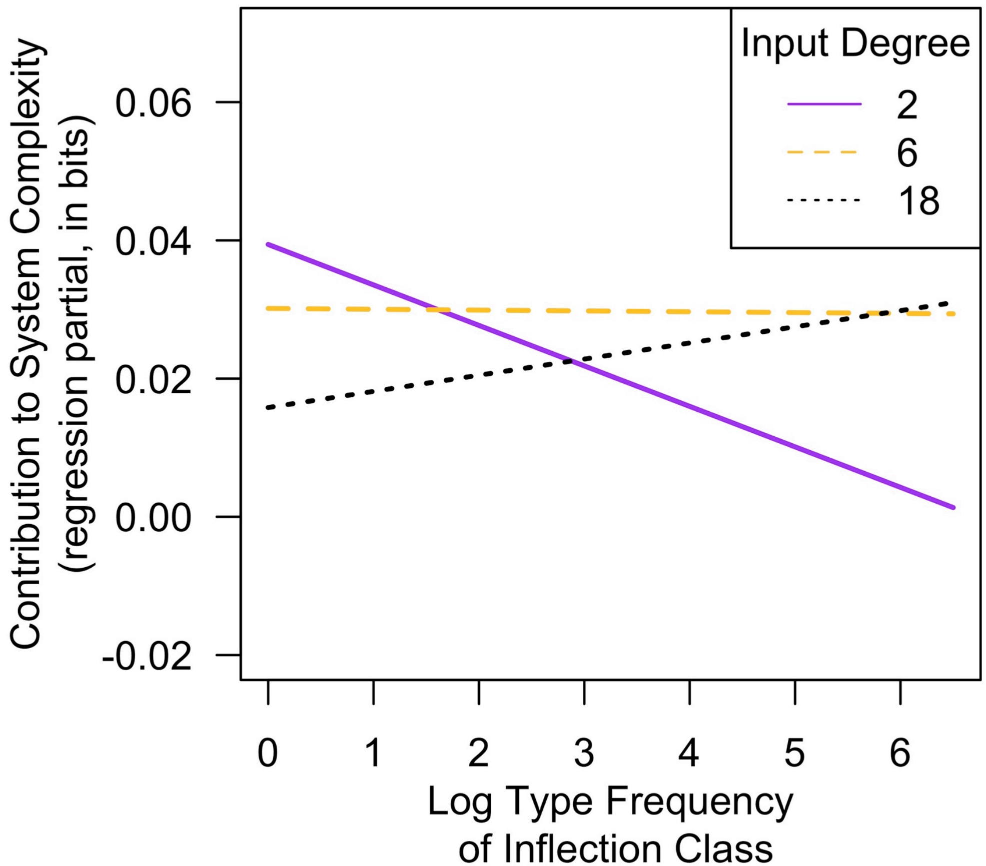
Neighbors based on shared conditioning cell exponent

Distribution of input





Modeling Marginal Detraction



As input node degree increases, slope increases

Low degree → Marginal Detraction

Why marginal detraction?

	MSPS				
Class	A	B	C	D	E
I	aa	b	c	d	e
II	a	bb	c	d	e
III	a	b	cc	d	e
IV	a	b	c	dd	e
V	a	b	c	d	ee
VI	a	b	c	d	e
VII	gg	b	c	d	e
VIII	a	hh	c	d	e

Subset of Input Data 10

More neighbors exerting analogical pressure

→ less likely to maintain unique exponents

Why marginal detraction?

	MSPS				
Class	A	B	C	D	E
I	a	ppp	x	ff	mmmm
II	a	i	xxx	ff	nn
III	aaa	i	q	ffff	nn
IV	b	iii	q	y	nnnn
V	b	j	qqq	y	gg
VI	bbb	j	r	yyy	gg
VII	c	jjj	r	z	gggg
VIII	c	k	rrr	z	hh

Subset of Input Set 2

Low degree + low type frequency

→ few neighbors exerting analogical pressure

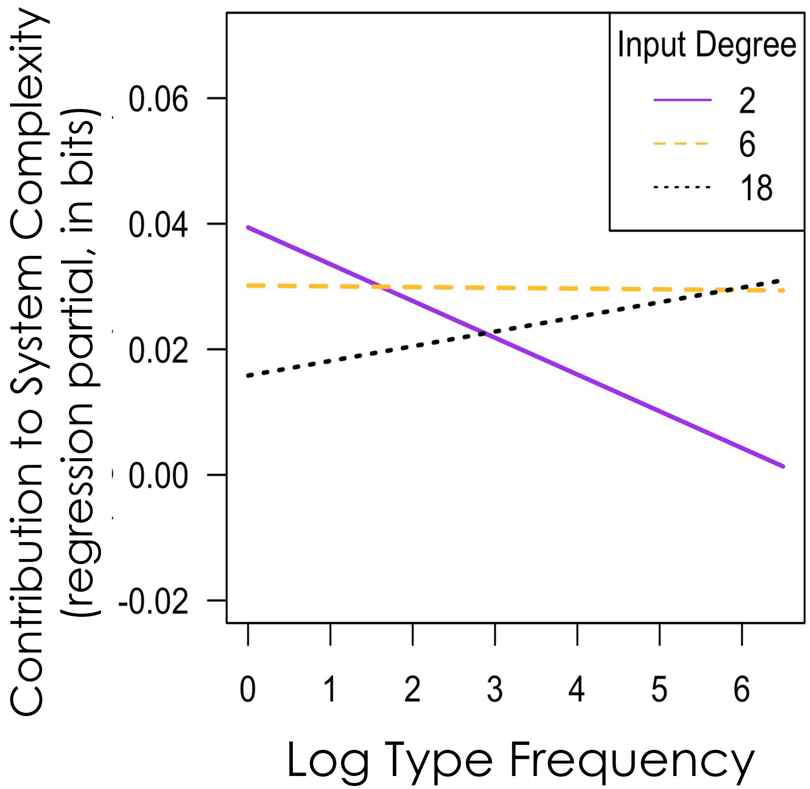
→ more likely to maintain unique exponents

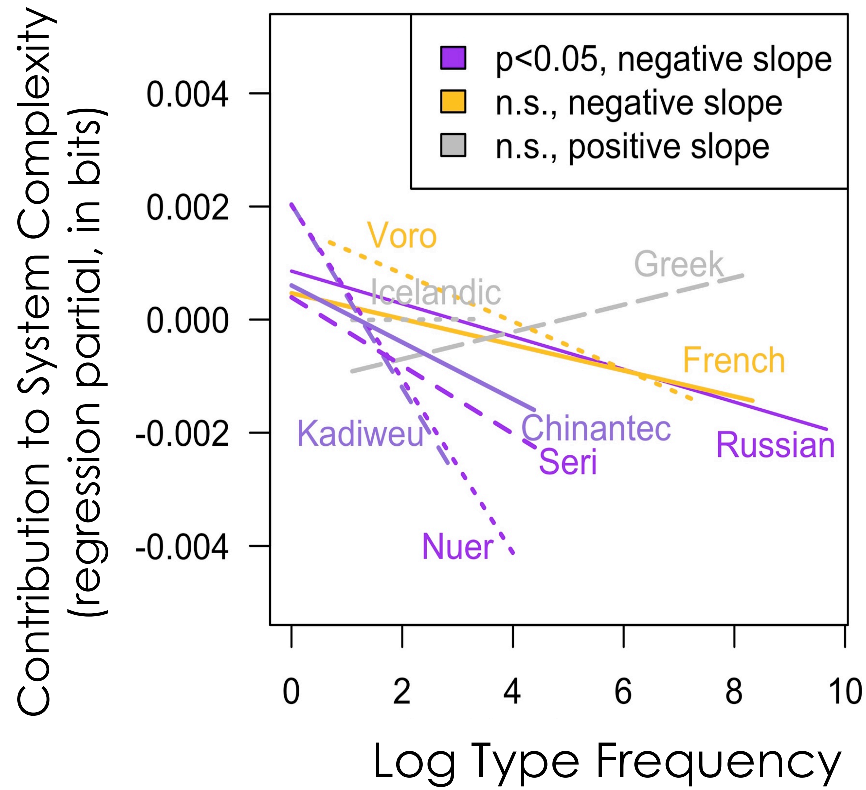
→ detract from the predictability of other classes

Relationship between regulars and irregulars

- In low degree systems, low type frequency classes are more likely to maintain unique exponents (‘irregularity’) and thus detract disproportionately from the predictability of inflected forms (‘marginal detraction’)
- Irregularity modeled without reference to token frequency

Hmmm…





In the model, low degree
→ marginal detraction

In real languages, high degree
→ marginal detraction

Ongoing work…

- Cue strength? (speculation in Sims & Parker 2016)
  - The real-world inflectional systems differ in how much ‘work’ implicative structure does
- Token frequency?
  - Of lexemes and/or inflected forms
- Clustering?
  - High marginal detraction languages are also high marginal detraction
- ??

Conclusions

The problem of irregularity, redux

- Data dovetail with other work on role of morphological connectivity (lexical neighborhoods) in reinforcing irregular inflectional morphology
- A systems-oriented perspective also raises new questions about the emergence of the organizational properties of inflectional systems
  - Cross-linguistic similarities and differences
  - System-internal differentiation of connectivity profiles
- We should ask how words are connected (embedded) in lexical networks and how the interaction among elements may differ depending on network structures, and in the context of environmental factors (e.g. learning principles)

Thank you!

References

- Albright, Adam and Bruce Hayes. 2002. Modeling English past tense intuitions with minimal generalization. In *Proceedings of the Sixth Meeting of the Association for Computational Linguistics Special Interest Group in Computational Phonology*, ed. By Michael Maxwell, 58-69. Cambridge, MA: ACL.
- Baerman, Matthew. 2008. Historical observations on defectiveness: The first singular non-past. *Russian Linguistics* 32(1): 81-97.
- Baerman, Matthew 2012. Paradigmatic chaos in Nuer. Language 88(3): 467–494.
- Baerman, Matthew 2014. Covert systematicity in a distributionally complex system. Journal of Linguistics 50(1): 1–47.
- Baerman, Matthew. 2016. Seri verb classes: Morphosyntactic motivation and morphological autonomy. *Language* 92(4): 792-823.
- Baerman, Matthew, Dunstan Brown, Roger Evans, Greville G. Corbett & Lynne Cahill 2015. Surrey morphological complexity database. Online resource, University of Surrey. www.smg.surrey.ac.uk/complexity/

References

- Brown, Dunstan and Andrew Hippisley. 2012. *Network morphology: A defaults-based theory of word structure*. Cambridge: Cambridge University Press.
- Bybee, Joan and Dan Slobin. 1982. Rules and schemas in the development and use of the English past tense. *Language* 58(2): 265-289.
- Bybee, Joan. 1985. *Morphology: A study of the relation between meaning and form*. Philadelphia: John Benjamins.
- Daland, Robert, Andrea D. Sims and Janet Pierrehumbert. 2007. Much ado about nothing: A social network model of Russian paradigmatic gaps. *Association for Computational Linguistics Proceedings* 45: 936-943.
- Di Sciullo, Anna Maria and Edwin Williams. 1987. *On the definition of word*. Cambridge: CUP.
- Dressler, Wolfgang U., Marianne Kilani-Schoch, Natalia Gagarina, Lina Pestal and Markus Pöchtrager. 2006. On the typology of inflection class systems. *Folia Linguistica* 40(1-2): 51-74.

References

- Frank, Wright 1999. Nuer noun morphology. M.A. thesis, University of New York at Buffalo.
- Griffiths, Glyn 2002. Diciona´rio da lı´ngua Kadiwe´u. Cuiaba´, MT: SIL.
- Hare, Mary and Jeffrey L. Elman. 1995. Learning and morphological change. *Cognition* 56: 61-98.
- Hare, Mary, Jeffrey L. Elman and Kim G. Daugherty. 1995. Default generalization in connectionist networks. Language and Cognitive Processes 10(6): 601-630.
- Iva, Sulev 2007. Vo˜ru kirjakeele so˜namuutmissu¨steem. Ph.D. dissertation, University of Tartu.
- Lexiko´ tı¯s koinı¯s neoellı¯nikı¯s 1998. Thessaloniki: Triantafillidis Institute, Aristoteleio Panepistimio Thessalonikis
- Merrifield, William R. & Alfredo B. Anderson 2007. Diccionario Chinanteco de la dia´spora del pueblo antiguo de San Pedro Tlatepuzco, Oaxaca. 2nd ed. Mexico DF: Instituto Lingu¨ ı´stico de Verano.

References

- Moser, Mary B. & Stephen A. Marlett 2010. Comcaac Quih Yaza Quih Hant Ihiip Hac = Diccionario Seri-Espan˜ol-Ingle´s. Mexico City and Sonora: Plaza y Valde´s Editores and Universidad de Sonora.
- Parker, Jeff. 2016. *Inflectional complexity and cognitive processing: An experimental and corpus-based investigation of Russian nouns.* Ph.D. dissertation, The Ohio State University.
- Pavskij, G.P. 1841. *Filologičeskie nabljudenija nad sostavom russkogo jayzka, tom 3: O glagole*. Sankt-Peterburg.
- Pierrehumbert, Janet. 2012. The dynamic lexicon. In *The Oxford handbook of laboratory phonology*, ed. by Abigail C. Cohn, Cécile Fougeron, and Marie K. Huffman, 173-183. Oxford: OUP.
- Russian National Corpus. www.ruscorpora.ru. Accessed February 2007.
- Sims, Andrea D. 2015. *Inflectional defectiveness.* Cambridge: CUP.
- Sims, Andrea D. and Jeff Parker. 2016. How inflection class systems work: On the informativity of implicative structure. *Word Structure* 9(2): 215-239.

References

- Stump, Gregory T. and Raphael Finkel. 2013. *Morphological typology: From word to paradigm*. Cambridge: CUP.
- Zaliznjak, Andrei A. 1977. Grammaticˇeskij slovar’ russkogo jazyka. Moskva: Russkij jazyk.
- Zaliznjak, A.A. 1977. *Grammatičeskij slovar’ russkogo jazyka: Slovoizmenenie.* Moskva: Russkij jazyk.