

# ACTORS IN TYPOLOGICAL STRUCTURE

## A PLAY IN THREE ACTS

Jeffrey Heinz

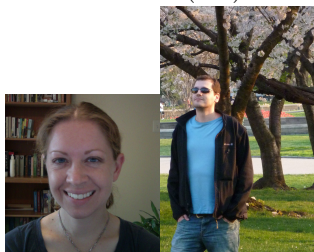


Stony Brook University

Workshop on Analyzing Typological Structure  
Stanford University  
September 22, 2018

# ACKNOWLEDGMENTS

- Alëna Askënova (Stony Brook)
- Jane Chandlee (Haverford)
- Aniello DeSanto (Stony Brook)
- Hossep Dolatian (Stony Brook)
- Rémi Eyraud (Marseilles)
- Thomas Graf (Stony Brook)
- Hyun Jin Hwangbo (CUNY)
- Bill Idsardi (UMCP)
- Adam Jardine (Rutgers)
- Regine Lai (HKU)
- Kevin McMullin (Ottawa)
- Jon Rawski (Stony Brook)
- Jim Rogers (Earlham)
- Kristina Strother-Garcia (UD)
- Herbert G. Tanner (UD)
- Mai Ha Vu (UD)



# STUDYING LINGUISTIC TYPOLOGY

Requires two books:

- “encyclopedia of categories”
- “encyclopedia of types”



Wilhelm Von  
Humboldt

# THESIS

Theoretical computer science provides a useful “encyclopedia of categories.”

- This encyclopedia is both about representations and computational power.
- This encyclopedia is not complete and we can help write it.
- The categories in this encyclopedia are not in competition with statistics or probabilities. They complement it.
- Each entry in this encyclopedia can be viewed as a linguistic hypothesis with consequences for psychology, typology, and learnability.

# Act I

## Phonological Generalizations are Regular

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Johnson 1972, Koskeniemi 1983, Kaplan and Kay 1994, Beesley and  
Karttunen 2003

# REGULAR GRAMMARS FOR SETS AND TRANSFORMATIONS

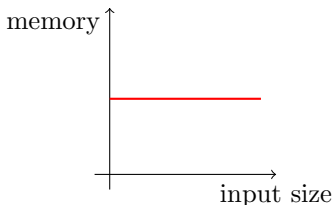
1. Regular expressions
2. Finite-state machines
3. Monadic Second Order (MSO)-definability

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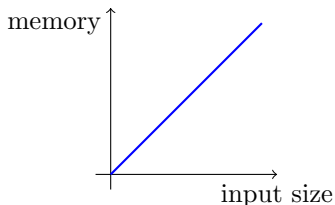
Kleene 1956, Scott and Rabin 1959, Büchi 1960, Engelfriedt and Hoogeboom  
2001

# WHAT “REGULAR” MEANS

A set, relation, or function is regular provided **the memory required for the computation is bounded by a constant, regardless of the size of the input.**



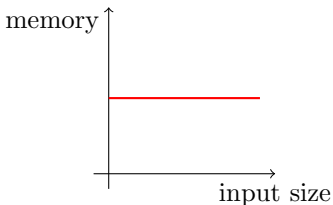
Regular



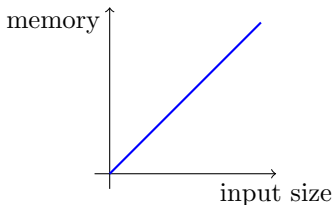
Non-regular

# SOME COMPUTATIONS IMPORTANT TO GRAMMAR

- For given constraint  $C$  and any representation  $w$ :
  - Does  $w$  violate  $C$ ? How many times?
- For given grammar  $G$  and any underlying representation  $w$ :
  - What surface representation(s) does  $G$  transform  $w$  to? With what probabilities?



Regular



Non-regular



# EXAMPLE: VOWEL HARMONY

## Progressive

*Vowels agree in backness with the first vowel in the underlying representation.*

## Majority Rules

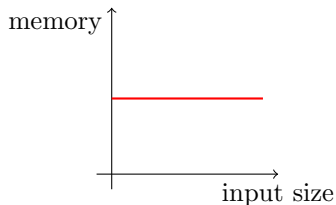
*Vowels agree in backness with the majority of vowels in the underlying representation.*

UR	Progressive	Majority Rules
/nokelu/	nok <u>o</u> lu	nok <u>o</u> lu
/nokeli/	nok <u>o</u> li	nikeli
/pidugo/	pid <u>i</u> ge	p <u>u</u> dugo
/pidugomemi/	pid <u>i</u> gememi	pid <u>i</u> gememi

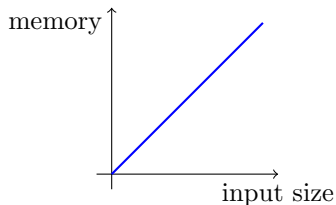
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(Lombardi 1999, Bakovic 2000, Finley 2008, 2011, Riggle 2004, Heinz and Lai 2013)

# PROGRESSIVE AND MAJORITY RULES HARMONY



Regular  
Progressive



Non-regular  
Majority Rules

# SOME PERSPECTIVE

**TYPOLOGICAL:** With one potential counterexample (Bowler 2013),  
Majority Rules is unattested.  
(Lombardi 1999, Bakovic 2000)

**PSYCHOLOGICAL:** Human subjects fail to learn Majority Rules in  
artificial grammar learning experiments, unlike  
progressive harmony. (Finley 2008, 2011)

**COMPUTATIONAL:** Majority Rules is not regular.  
(Riggle 2004, Heinz and Lai 2013)

# WHETHER A FUNCTION IS REGULAR IS INDEPENDENT OF ITS CO-DOMAIN.

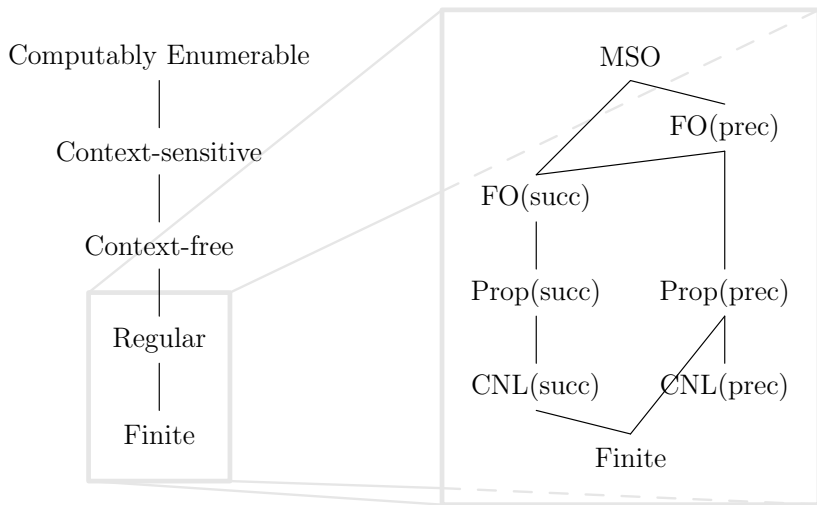
Function	Description
$f : \Sigma^* \rightarrow \{0, 1\}$	Binary classification (well-formedness)
$f : \Sigma^* \rightarrow \mathbb{N}$	Maps strings to numbers (counting violations)
$f : \Sigma^* \rightarrow [0, 1]$	Maps strings to real values (gradient well-formedness)
$f : \Sigma^* \rightarrow \Delta^*$	Maps strings to strings (single-valued transformation)
$f : \Sigma^* \rightarrow \wp(\Delta^*)$	Maps strings to sets of strings (multi-valued transformation)

TABLE: Functions from strings to various co-domains

## Act II

### Representation and Computational Power (with examples from phonotactics)

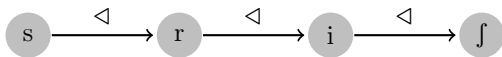
# THE CHOMSKY HIERARCHY



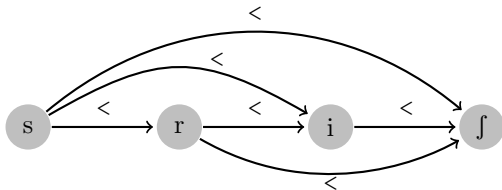
# MODEL THEORETIC REPRESENTATION OF ORDER IN WORDS

hypothetical [sriʃ]

Successor



Precedence



# REPRESENTATIONS AND POWER

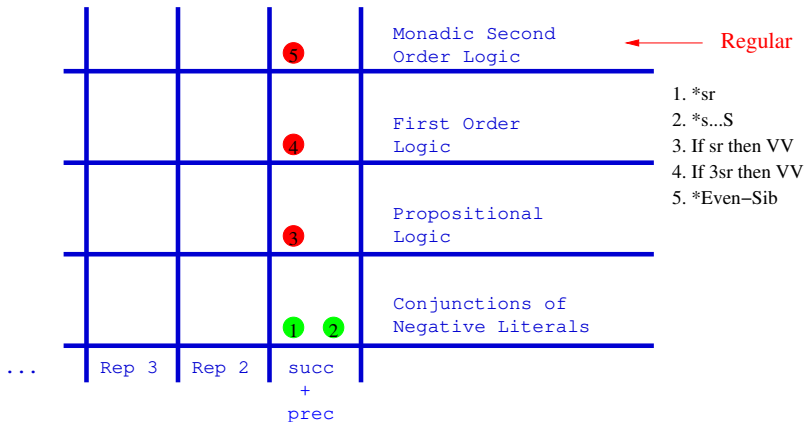
				Monadic Second Order Logic	← Regular
				First Order Logic	
				Propositional Logic	
				Conjunctions of Negative Literals	
...	Rep 3	Rep 2	Rep 1		



# WITH SUCCESSOR

			5	2	Monadic Second Order Logic	← Regular
			4		First Order Logic	1. *sr 2. *s...S 3. If sr then VV 4. If 3sr then VV 5. *Even-Sib
			3		Propositional Logic	
			1		Conjunctions of Negative Literals	
...	Rep 3	Rep 2	succ			

# WITH SUCCESSOR AND PRECEDENCE



# SOME LESSONS OF THIS STORY

1. Precedence is the transitive closure of successor.
2. Providing the power of transitive closure (MSO-definability) yields power to do lots of other things (so expands the typology undesirably)
3. Putting precedence directly into the representation allows a restricted expansion of the typology in a more desirable way.
4. The restriction to  $CNL(X)$  also has provable learnability benefits.
5. Makes strong psychological predictions.

# LEST THERE BE ANY MISUNDERSTANDING

1. I am not claiming that order (successor and precedence) is all that matters.
2. I am using an example to make a point about the interplay of representation and power.
3. Generally, this model-theoretic perspective provides a systematic way to explore what De Lacy (2011) calls “Constraint Definition Languages” (CDLs).

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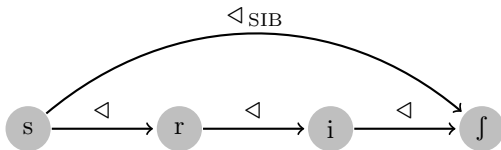
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A coda:

1. Many more representations to explore!
2. Theories with optimization also can check whether these CDLs are closed under optimization or not...

# PHONOLOGICAL TIERS

Locality on the tier



**PHONOLOGICAL THEORY:** Goldsmith 1976, Rose and Walker 2004, McMullin 2016, Aksënova and Deshmukh 2018, a.o.

**COMPUTATIONAL ANALYSIS:** Heinz et al. 2011, De Santo 2016

**LEARNING WITH TIERS:** Hayes and Wilson 2008, Wilson and Gallagher 2018, a.o.

**LEARNING TIERS THEMSELVES:** Jardine and McMullin 2017, a.o.

**EXTENSIONS TO MORPHOLOGY:** Graf 2017 (CLS), Askënova et al. 2016, Askënova and De Santo 2017

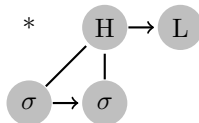
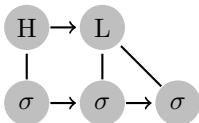
# AUTOSEGMENTAL REPRESENTATIONS

1. Jardine (2016, 2017) examines autosegmental representations (ASRs), where the sub-structures are now sub-graphs of the autosegmental structure.
2. He argues that a theory of tonal surface patterns as CNL(ASR) captures the typology better than both Zoll 2003 and earlier derivational approaches.
3. He shows that his grammars can be learned from strings (not ASRs!) because ASRs are fundamentally stringlike (Jardine and Heinz 2015).

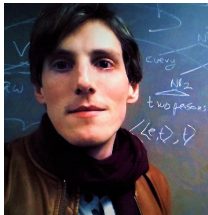


Adam Jardine

[félàmà]  
'junction'  
(Mende)

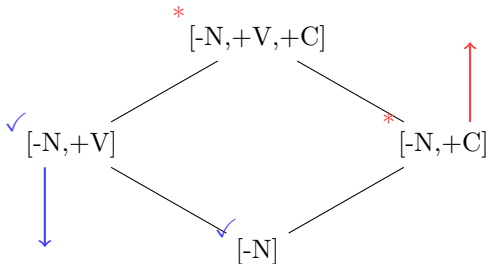


# STRUCTURE IN PHONOLOGICAL REPRESENTATIONS



Jon Rawski

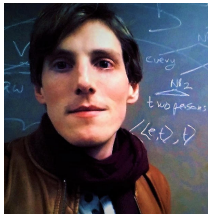
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2. From a learning perspective, this structure provides entailment relations, which helps prune the search space (cf. Tesar 2014, Antilla and Magri 2018).



Joint work with Jane Chandlee, Rémi Eyraud, and Adam Jardine.

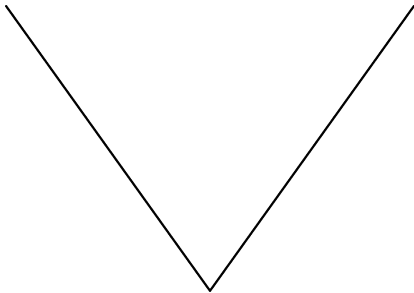


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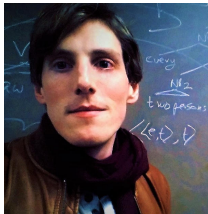


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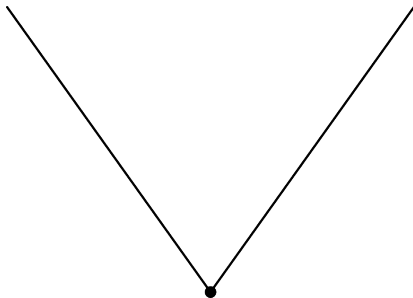


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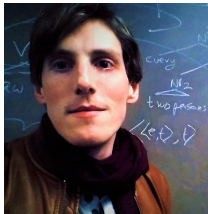


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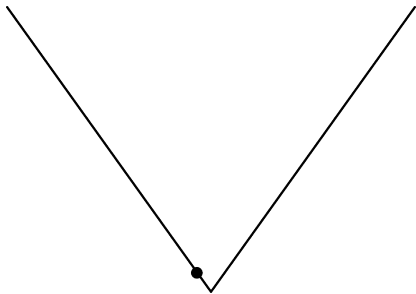


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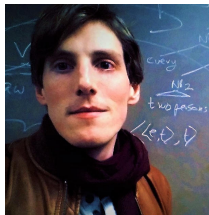


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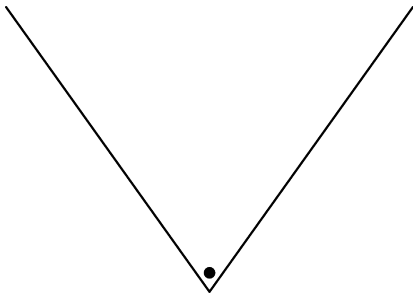


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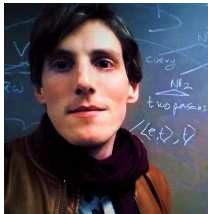


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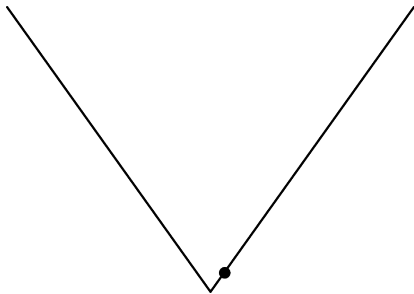


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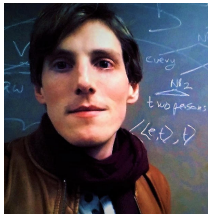


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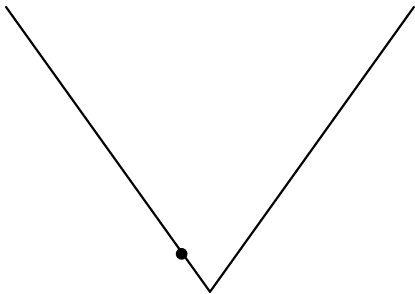


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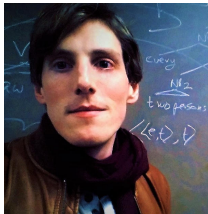


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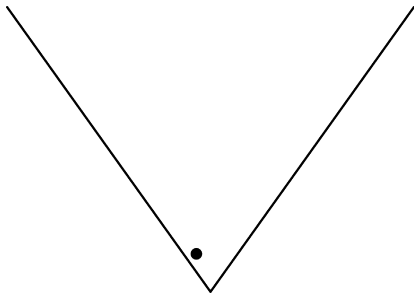


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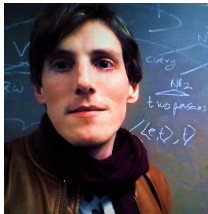


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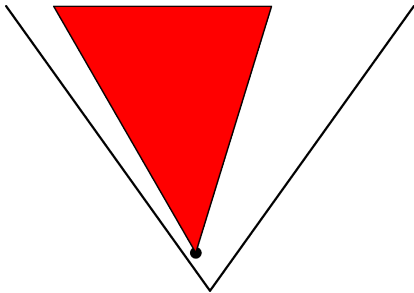


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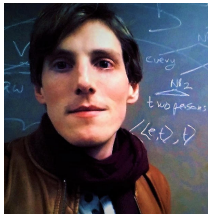
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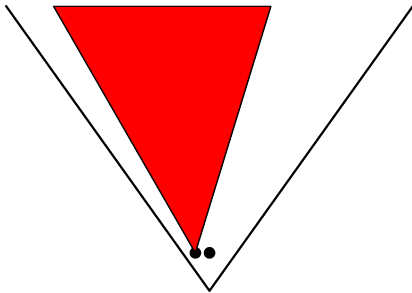


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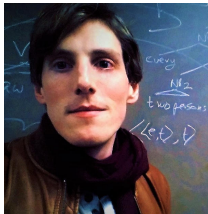


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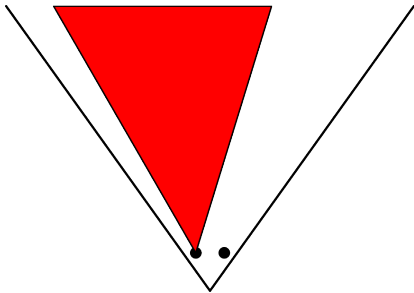


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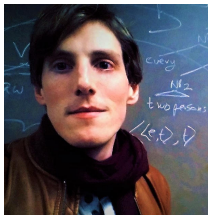


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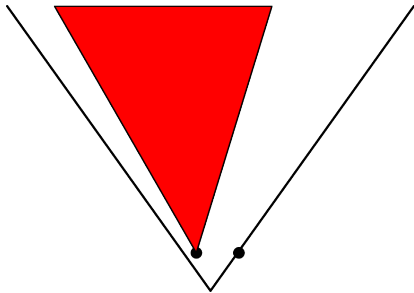


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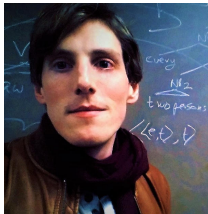


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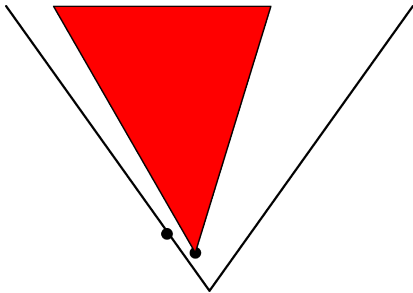


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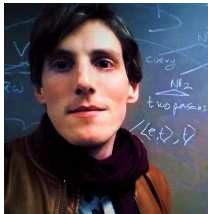


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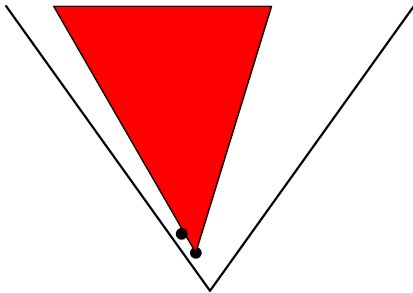


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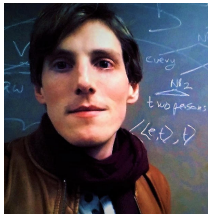


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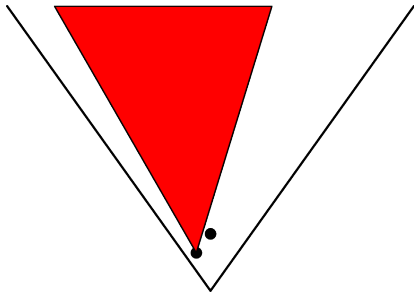


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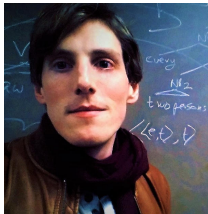


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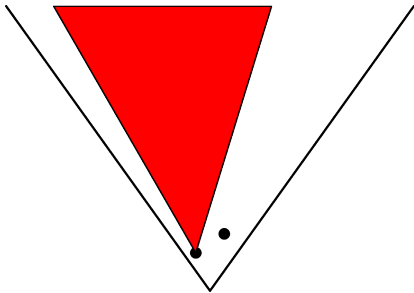


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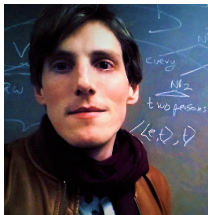


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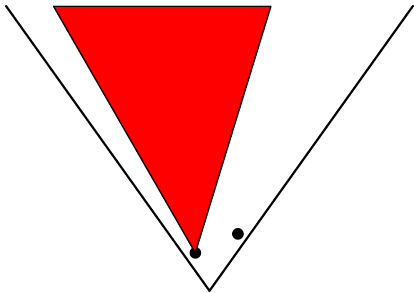


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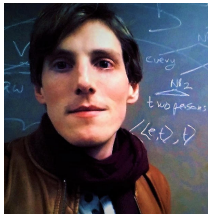
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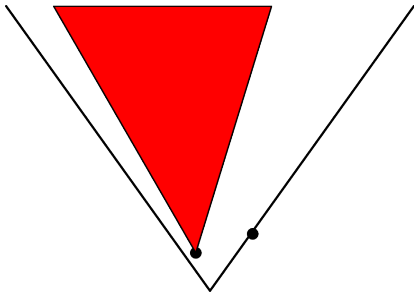


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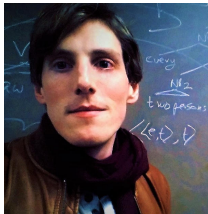


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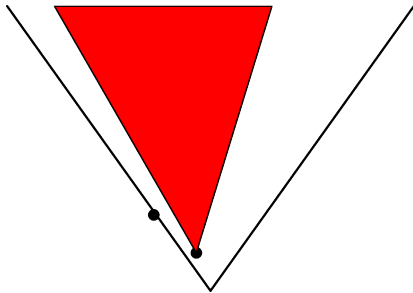


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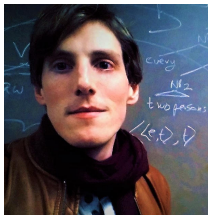


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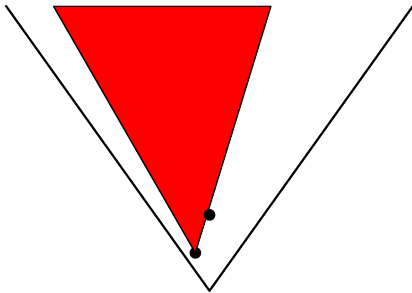


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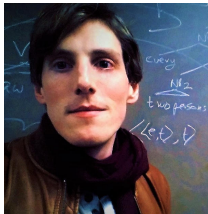


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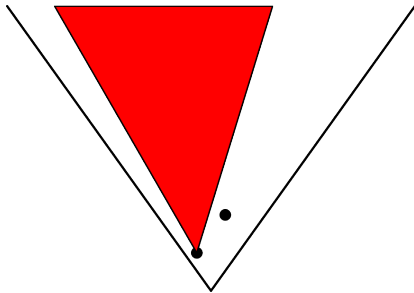


# STRUCTURE IN PHONOLOGICAL REPRESENTATIONS

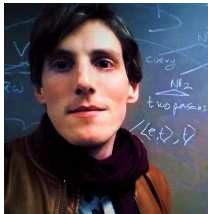


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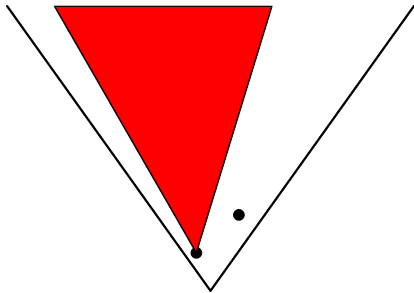


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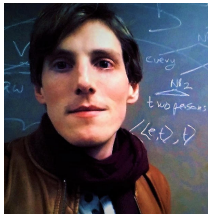


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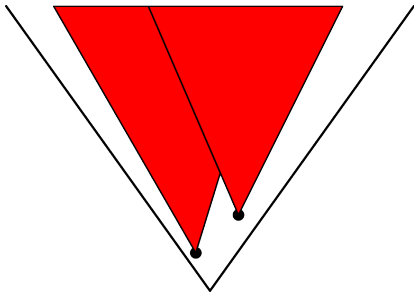


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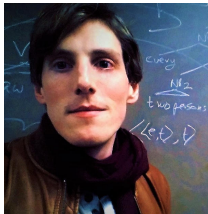


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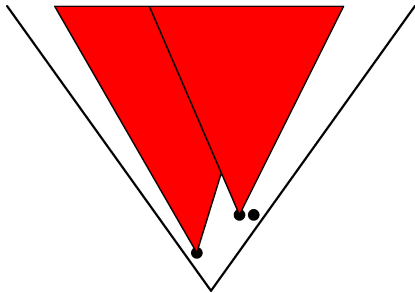


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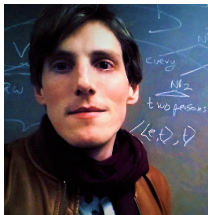


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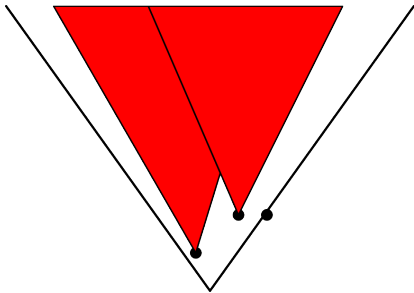


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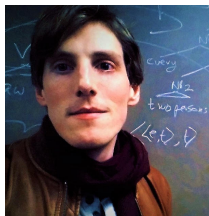
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# STRUCTURE IN PHONOLOGICAL REPRESENTATIONS



Jon Rawski

What has been done

- Provably correct bottom-up learning algorithm

Goals of the Project

- Model Efficiency
- Model Implementation (integration with MaxEnt, MLE, etc.)
- Model Testing - large linguistic datasets

Broader Impacts

- Learner that takes advantage of data sparsity
- applicable on any representational structures of sequential data (language, genetics, robotic planning, etc.)
- implemented, open-source code

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Joint work with Jane Chandlee, Rémi Eyraud, and Adam Jardine.

# THE END OF ACT II

The typological hypothesis which emerges from these studies is

**Phonotactics is CNL(X) with the right representations X.**

This is *not* a claim about categoricity vs. gradience. It is *independent* of that distinction.

# Intermission

What about statistics and probability?

# LOTS OF POSSIBILITIES

- Maximum Entropy
- Maximum Likelihood Estimate
- Bayesian Inference
- Minimum Description Length
- Markov Logic Networks
- Support Vector Machines (Empirical Risk Minimization)
- Neural Networks
- ...

In every case, it is worthwhile to think carefully about the family of distributions these methods are being used on.

---

Goldwater and Johnson 2003, Hayes and Wilson 2008, Jarosz 2006, Goldwater 2006, Solomnoff 1964, Goldsmith 1999, Rasin and Katzir 2016, Vu et al. 2018, Shaw and Taylor 2005, Goldberg 2017, a.o.

# MAXIMUM LIKELIHOOD ESTIMATE

$$\hat{\Theta} = \arg \max_{\Theta} (L(D | \Theta))$$

The family of distributions really matters!

1. CNL(succ) = Strictly k-Local  $\rightarrow$  stochastic SL / n-gram model
2. CNL(prec) = Strictly k-Piecewise  $\rightarrow$  stochastic SP models
3. For same data D, the MLE returns different functions because the parameters mean different things.

# COMPARING REPRESENTATIONS WITHIN A STATISTICAL MODEL

Hayes and Wilson maxent models	$r$
features & complement classes	0.946
no features & complement classes	0.937
features & no complement classes	0.914
no features & no complement classes	0.885

**TABLE:** From Hayes and Wilson (2008: Table 5) and Koirala and Heinz 2010: Table 4): Correlations of different versions of HW maxent model with Scholes data.

# COMPARING STATISTICAL MODELS WITHIN A REPRESENTATION

models	$r$
HW MaxEnt w/no features & no complement classes	0.885
N-gram model (MLE)	0.877

**TABLE:** From Hayes and Wilson (2008: Table 5): Correlations of different models with Scholes data.

Open question: How to find MLE of feature-based representations.  
What is this family of distributions?

# RESEARCH ON LEARNING LARGE FAMILIES OF DISTRIBUTIONS

Deterministic regular stochastic functions

- ALEGRIA (Carrasco and Oncina 1994, 1999, de la Higuera and Thollard 2000)

Non-deterministic regular stochastic functions

- Clark and Thollard (2004)
- Spectral learning (Hsu et al. 2009, Baille et al. 2014)

None of these have been applied to phonological learning to my knowledge. How can they be generalized to other phonological representations?



# CONCLUSION TO THE INTERMISSION

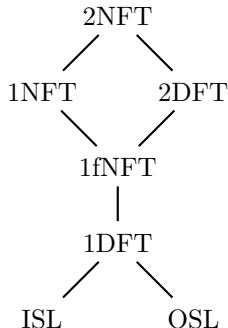
1. The choice of statistical learning methods is distinct from the choice of representation and the family of stochastic models.
2. Both matter and both must be attended to when making comparisons.
3. Many more models out there!

## Act III

# Morpho-phonological Transformations

# THE ENCYCLOPEDIA OF CATEGORIES FOR MAPS

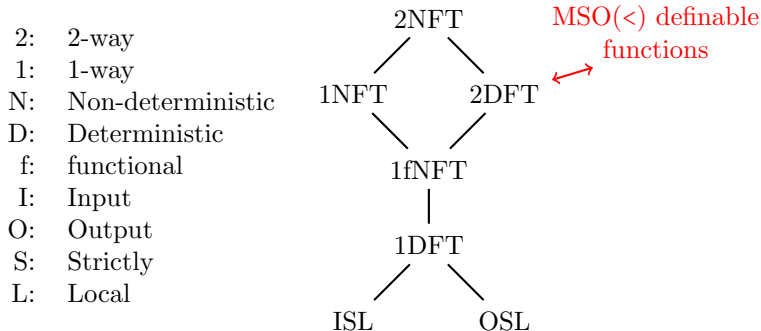
2: 2-way  
1: 1-way  
N: Non-deterministic  
D: Deterministic  
f: functional  
I: Input  
O: Output  
S: Strictly  
L: Local



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Engelfriedt and Hoozeboom 2001, Chandler 2014, Filiot and Reynier 2016,  
Chandler and Lindell, forthcoming

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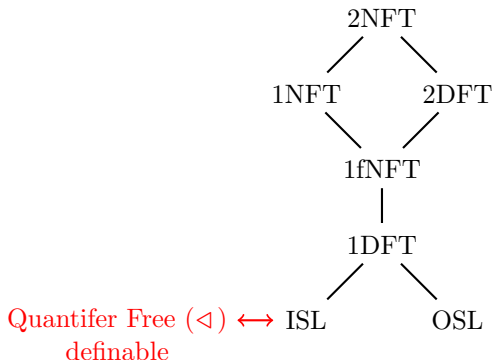


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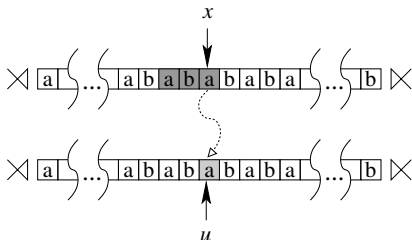
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# INPUT STRICTLY LOCAL MAPS

For every Input Strictly Local function, the output string  $u$  of each input element  $x$  depends only on  $x$  and  $k - 1$  input elements previous to  $x$ . Here  $k = 3$  so the contents of the lightly shaded cell only depends on the contents of the darkly shaded cells.



Jane Chandlee



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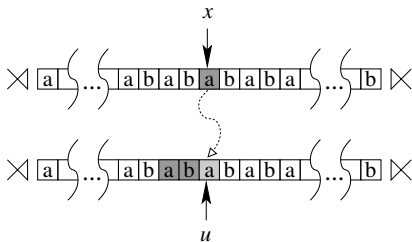
Chandlee 2014, Chandlee et al. 2014, Chandlee and Heinz 2018, Chandlee et al. 2018

# OUTPUT STRICTLY LOCAL MAPS

For every Output Strictly Local function, the output string  $u$  of each input element  $x$  depends only on  $x$  and the last  $k-1$  elements written to the output. Here  $k = 3$  so the contents of the lightly shaded cell only depends on the contents of the darkly shaded cells.



Jane Chandlee



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Chandlee 2014, Chandlee et al. 2015, Chandlee and Heinz 2018, Chandlee 2018 (AMP)

# ISL AND OSL

## ISL is *input-oriented*

1. Maps describable with a rule  $R: A \longrightarrow B / C \text{ — } D$  where  $CAD$  is a finite set and  $R$  applies simultaneously
2. Approximately 95% of the individual processes in P-Base (v.1.95, Mielke (2008))
3. Many *opaque* transformations without any special modification.

## OSL is *output-oriented*

1. Spreading processes
2. ...

Neither can describe long-distance consonantal harmony

---

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**Learnability:**  $k$ -ISL and  $k$ -OSL are learnable with quadratic time and data by ISLFIA and OSLFIA, respectively.

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Chandlee 2014, Chandlee et al. 2014, 2015, Chandlee and Heinz 2018,  
Chandlee et al. 2018

# SYLLABIFICATION



Kristina  
Strother-Garcia

1. Translations between different syllabic representations are Quantifier Free interpretations.
2. Syllabification in IT Berber is also Quantifier Free, with a “window size” of 3.

She concludes “...syllabification in ITB can be represented by a QF graph transduction, a formalism restricted to substantially lower computational complexity than [traditional] phonological grammars... Establishing that ITB syllabification is QF highlights an insight not apparent from [those traditional] grammatical formalisms...”

# COMPUTATIONAL TYPOLOGY OF REDUPLICATION



Hossep Dolatian

REDTYP: <https://github.com/jhdeov/RedTyp>

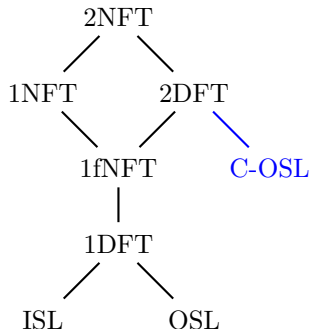
- SQL database of reduplicative processes
- Modeled 138 reduplicative processes across 90 languages using 57 2-way FSTs
- Average number of states: 8.8
- Largest number of states: 30 (1000s for 1-way FSTs)

## Contributions

1. 2-way FSTs can model virtually all reduplication patterns.
2. ~87% belongs to a subclass which can be described as the “Concatenation of two OSL functions” (C-OSL).
3. Simple learning algorithm for C-OSL which uses OSLFIA but also a boundary-enriched sample.

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Engelfriedt and Hoozeboom 2001, Chandler 2014, Filiot and Reynier 2016,  
Dolati and Heinz 2018a,b

# WHO ARE THE ACTORS IN PHONOLOGICAL TYPOLOGY?

- Representation
- Logical power
- Grammatical structure
- Statistics

And... Curtain!

Thanks!