Graph pattern learning for long-distance phonotactics

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NAPhC 9
May 7, 2016

Introduction

- Languages have long-distance phonotactic patterns, especially in tone (Yip, 2002; Hyman, 2011)
- Dependencies between non-adjacent units can make the learning problem difficult (Hayes and Wilson, 2008)
- How are these patterns learned?

Introduction

- Computationally local string learners form a strong theory of phonotactic learning, including many long-distance patterns (Heinz, 2009, 2010; Jardine and Heinz, 2016)
- Some tone patterns are beyond these learners

Introduction

- These can be learned with a local **autosegmental** learner
- Idea: learn banned **subgraphs**
- Local autosegmental learning provides a strong theory of tone learning
- May be extended to long-distance segmental phonology as well

Computational locality

- **Strictly Local (SL)** stringsets are those describable by a finite set of *banned substrings* (Rogers and Pullum, 2011)

Computational locality

- Kagoshima Japanese
  (Hirayama, 1951; Haraguchi, 1977; Kubozono, 2012)

a.	hána	‘nose’	HL
b.	sakúra	‘cherry blossom’	LHL
c.	kagaríbi	‘watch fire’	LLHL
d.	kagaribí-ga	‘watch fire’ + NOM	LLLHL
			...
e.	haná	‘flower’	LH
f.	usagí	‘rabbit’	LLH
g.	kakimonó	‘document’	LLLH
h.	kakimono-gá	‘document’ + NOM	LLLLH
			...

Computational locality

$$KJ = \{ \begin{array}{ll} \text{\#HL\#}, & \text{\#LH\#}, \\ \text{\#LHL\#}, & \text{\#LLH\#}, \\ \text{\#LLHL\#}, & \text{\#LLLH\#}, \\ \ldots & \end{array} \}$$

- $G_{KJ} = \{\text{HLL, HH, HLH, LL\#}\}$

Computational locality

$$KJ = \{ \begin{array}{ll} \#HL\#, & \#LH\#, \\ \#LHL\#, & \#LLH\#, \\ \#LLHL\#, & \#LLLH\#, \\ \ldots & \end{array} \}$$

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*#HLLLL#, *#HLLHL#

Computational locality

$$KJ = \{ \#HL\#, \quad \#LH\#, \quad \#LHL\#, \quad \#LLH\#, \quad \#LLHL\#, \quad \#LLLH\#, \quad ... \}$$

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Computational locality

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- G_{KJ} = {HLL, HH, HLH, LL#}

*#HLLLL#, *#HLLHL#, *#LLHHL#, *#LHLHL#, *#LLLLL#, ...

Computational locality

Learning SL patterns

- Fix k

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- $\texttt{substr}_3(\text{\#LLHL\#}) = \{\text{\#LL, LLH, LHL, HL\#}\}$

Computational locality

Learning SL patterns

- Fix k

$$\texttt{substr}_k(w) = \{u \mid u \text{ is a } k\text{-substring of } w\}$$

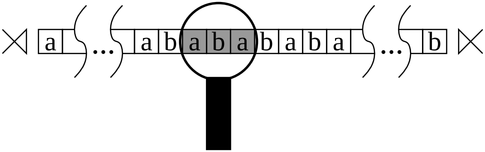
$$\texttt{substr}_k(D) = \bigcup_{w \in D} \texttt{substr}_k(w)$$

- $\texttt{substr}_3(\text{\#LLHL\#}) = \{\text{\#LL, LLH, LHL, HL\#}\}$

Computational locality

Learning SL patterns

- `substr`$_k$ scans each input string with a window of size k



Rogers and Pullum (2011); Rogers et al. (2013)

Computational locality

Learning SL patterns

- Let S_k be the set of all possible k-substrings
- Learner: $G_0 = S_k$
  $G_n = S_k - \texttt{substr}_k(\{d_1, d_2, ..., d_n\})$

Computational locality

Learning SL patterns

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- *KJ*: $k = 3$

  $G_0 =$ { #LL, LLL, LLH, LHL, HLL, HLH, ..., LH#}

Computational locality

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G_1 = { #LL, LLL, LLH, LHL, HLL, HLH, ..., LH#}

Time	Datum	$\texttt{substr}_3$
1	#LLHL#	{#LL, LLH, LHL, HL#}

Computational locality

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$G_2 = \{$ #LL, LLL, LLH, LHL, HLL, HLH, ..., LH# $\}$

Time	Datum	$\texttt{substr}_3$
1	#LLHL#	{#LL, LLH, LHL, HL#}
2	#LLLH#	{#LL, LLL, LLH, LH#}

Computational locality

Learning SL patterns

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Time	Datum	$\texttt{substr}_3$
1	#LLHL#	{#LL, LLH, LHL, HL#}
2	#LLLH#	{#LL, LLL, LLH, LH#}
3	#LLLLHL#	{#LL, LLL, LLH, LHL, HL#}

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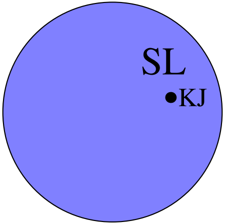
- There will always be some n for which G_n describes *KJ* (García et al., 1990; Heinz, 2010, 2011)

Tone patterns and stringset classes



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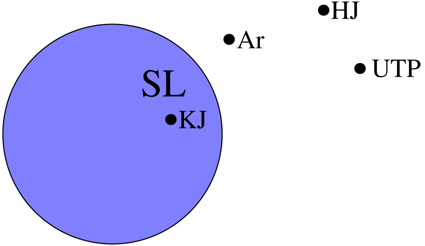
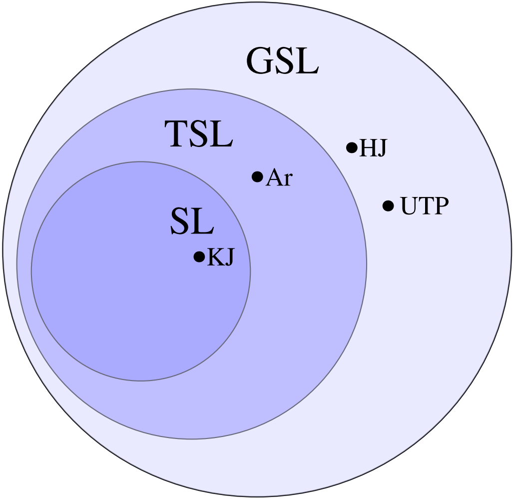


Tone patterns and stringset classes



Non-local tone patterns

- Arigibi (Donohue, 1997): **At most one H**

a.	naː L	'finish'	e.	umú LH	'dog'	j.	olaʔolá LLLH	'red'
b.	tutuː LL	'long'	f.	nímo HL	'louse'	k.	tuniʔʌ́ʔʌ LLHL	'all'
c.	vovoʔo LLL	'bird'	g.	mudɛbɛ́ LLH	'claw'	l.	idómai LHLL	'eye'
d.	ɛlaila LLLL	'hot'	h.	ivío LHL	'sun'	m.	núʔʌtama HLLL	'bark'
			i.	ŋgíʔɛpu HLL	'heart'			

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- **Not** SL
- *H...H; {HH, HLH, HLLH, HLLLH, ...}

Non-local tone patterns

- Arigibi: **At most one H**
- Hirosaki J. (Haraguchi, 1977):
  Exactly one H or F; F word-final

a.	‘chicken’	niwatorí	LLLH
b.	‘lightening’	kaminarî	LLLF
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- *H...H, *H...F, *L^n, *FL, etc.

Non-local tone patterns

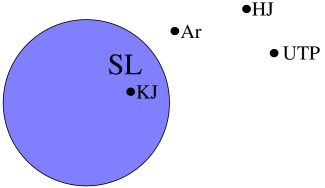
- Arigibi: **At most one H**
- Hirosaki J.: **Exactly one H or F; F word-final**
- Unbounded Tone Plateauing (Hyman, 2011; Jardine, to appear):
  At most one plateau of H

a.	‘chopper’	mutéma	LHL
b.	‘log’	kisikí	LLH
c.	‘log chopper’	mutémá+bísíkí	LHHHHH
d.	″ ″	*mutéma+bisikí	*LHLLLH

(Luganda; Hyman, 2011; Hyman and Katamba, 2010)

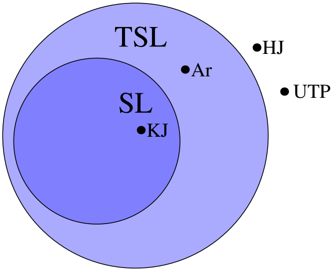
Non-local tone patterns

- Arigibi: **At most one H** (*Ar*)
- Hirosaki J.: **Exactly one H or F; F word-final** (*HJ*)
- Unbounded Tone Plateauing: **At most one plateau of H** (*UTP*)



Non-local tone patterns

- **Tier-based SL** (Heinz et al., 2011): Banned substrings evaluated over one subset or **tier** of alphabet
- Arigibi: $G = \{\text{HH}\}$ when L is ignored;
  *HLH, *LLHLLLH, ...



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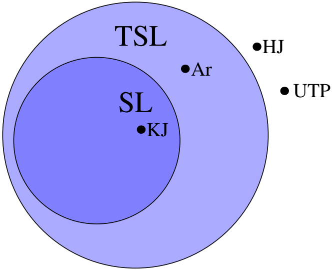

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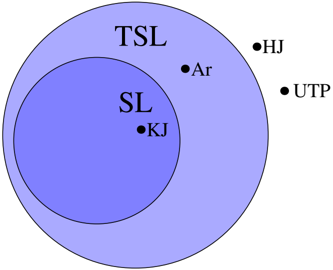

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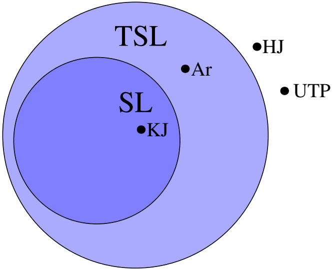
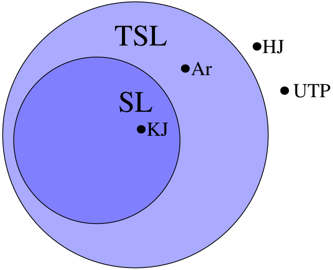


- Tier and grammar are learnable (Jardine and Heinz, 2016)

Non-local tone patterns

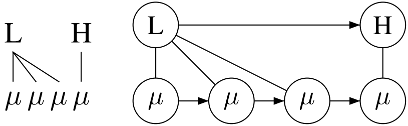
- For *HJ* (exactly one H; F word-final), can't ignore Ls: *FLL...
- For *UTP* (at most one H plateau), can't posit *HH



Computational locality for autosegmental representations

- Autosegmental representations are **graphs** (Goldsmith, 1976; Coleman and Local, 1991)

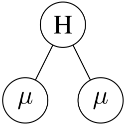
olaʔolá LLLH 'red'
(Arigibi)

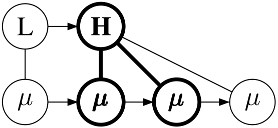


- We can instead consider banned sub**graph** grammars

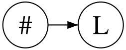
Computational locality for autosegmental representations

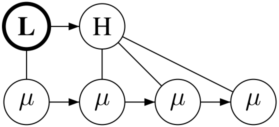
- Let a **subgraph** be some finite, connected piece of a graph





- Subgraphs may refer to boundaries on each tier (not depicted in full graphs)

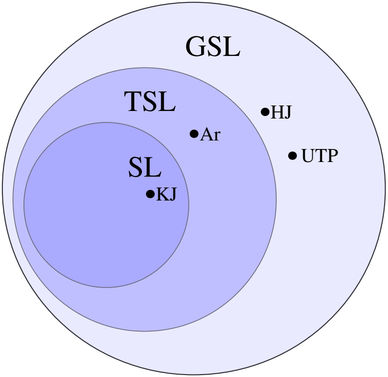




- k is the number of nodes

Computational locality for autosegmental representations

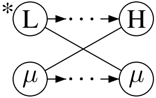
- **Graph SL**: Describable by banned subgraph grammars



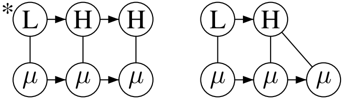
- These grammars are learnable in a similar way to SL grammars

Some assumptions

- Association preserves precedence relations **(the No-Crossing Constraint (NCC))**



- Adjacent nodes on tonal tier cannot be identical **(the Obligatory Contour Principle (OCP)**

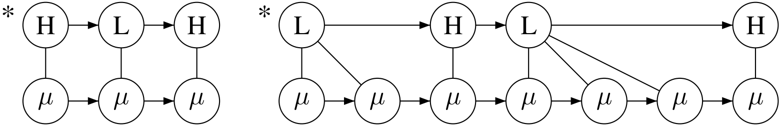


- Such representations can be generated from strings (Jardine and Heinz, 2015)

Banned subgraph analyses

Arigibi: At most one H

- *HLH, *HLLH, *LLHLLLH, ...



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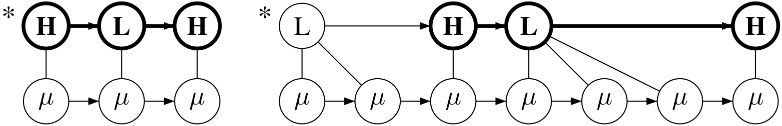
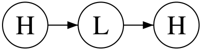
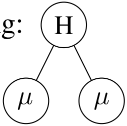
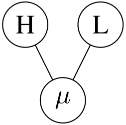


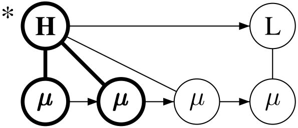
- First banned subgraph: 

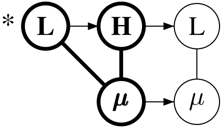
Banned subgraph analyses

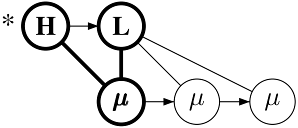
Arigibi: At most one H

- Spreading: 

- Contours: 

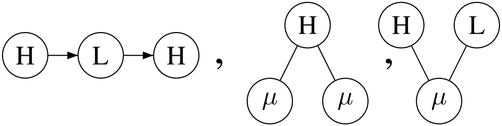
*HHHL 

*RL 

*FLLL 

Banned subgraph analyses

Arigibi: At most one H

- $G_{Ar} = \{$ 

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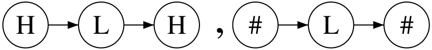
Banned subgraph analyses

Hirosaki Japanese: Exactly one H or F; F is word-final

- *HLLF, *LLLL
- 

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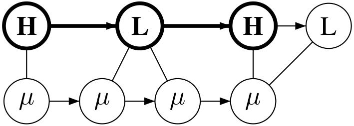

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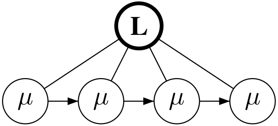

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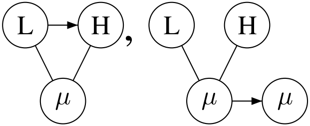
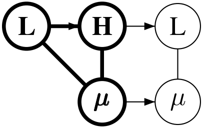
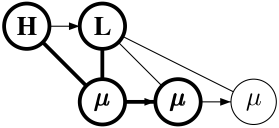
- Contours: 

*RL * 

*FLLL * 

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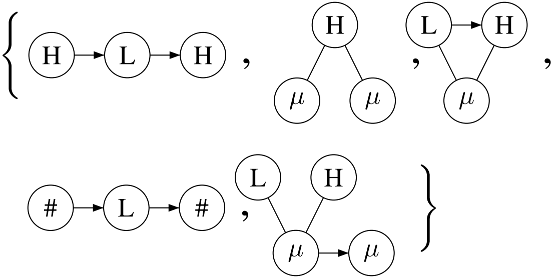
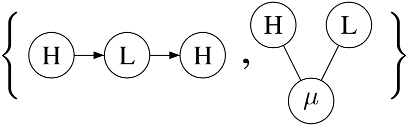
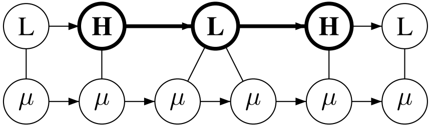
- $G_{HJ} =$ 

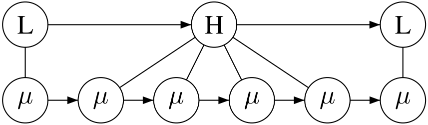
Banned subgraph analyses

UTP: At most one plateau of H

- $G_{UTP} =$ 

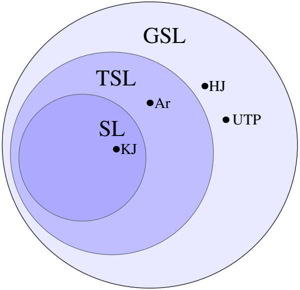
- *LHLLHL, LHHHHL

* 



Banned subgraph analyses

- Arigibi: **At most one H** (*Ar*)
- Hirosaki J.: **Exactly one H or F; F word-final** (*HJ*)
- Unbounded Tone Plateauing: **At most one plateau of H** (*UTP*)



Learning GSL

- Fix k

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$$\texttt{subg}_k(g) = \{s |\ s \text{ is a } k\text{-subgraph of } g\}$$

Learning GSL

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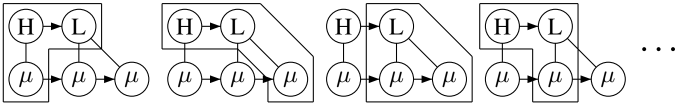
$$\texttt{subg}_k(g) = \{s |\ s \text{ is a } k\text{-subgraph of } g\}$$

$$\texttt{subg}_k(D) = \bigcup_{g \in D} \texttt{subg}_k(g)$$

Learning banned GSL

- Cognitive interpretation of $\texttt{subg}_k$ is the same as $\texttt{substr}_k$: scan input structures, remembering substructures of size k



Learning GSL

- Let S_k be the set of all possible k-sub**graphs**
- Learner: $G_0 = S_k$
  $G_n = S_k - \texttt{subg}_k(\{d_1, d_2, ..., d_n\})$

Learning GSL

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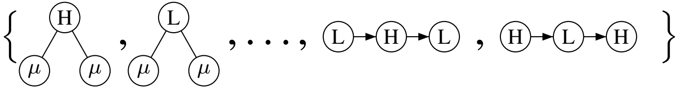
- *Ar*: $k = 3$

$G_0 =$



Learning GSL

- Let S_k be the set of all possible k-sub**graphs**
- Learner: $G_0 = S_k$
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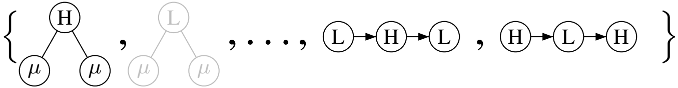
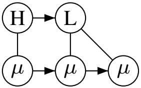
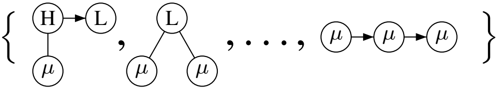
- *Ar*: $k = 3$

$G_1 =$

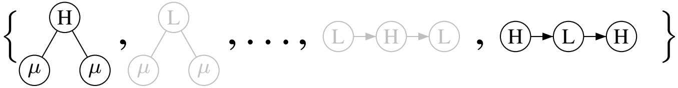


Time	Datum	$\texttt{subg}_3$
1		

Learning GSL

- Let S_k be the set of all possible k-sub**graphs**
- Learner: $G_0 = S_k$

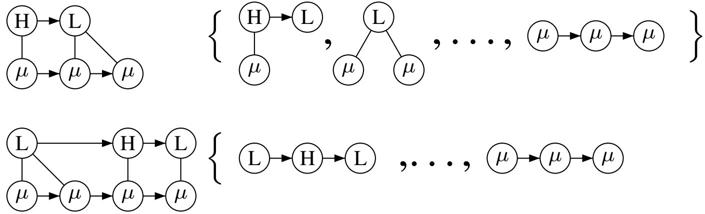
  $G_n = S_k - \texttt{subg}_k(\{d_1, d_2, ..., d_n\})$
- *Ar*: $k = 3$

$G_2 =$ 

Time | Datum | $\texttt{subg}_3$

1

2



Learning GSL

- Let S_k be the set of all possible k-sub**graphs**
- Learner: $G_0 = S_k$

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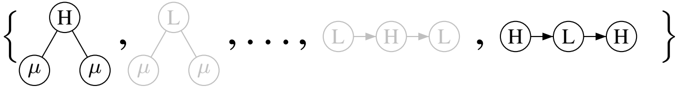
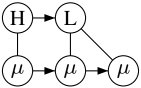
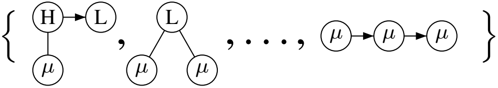
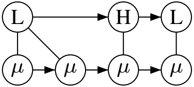
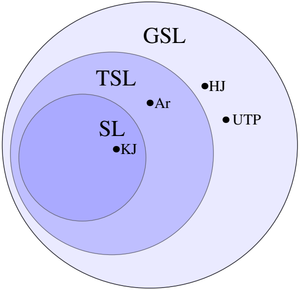
$G_2 =$ 

Time	Datum	$\texttt{subg}_3$
1		
2		

...

Learning GSL

- There will always be some n for which G_n describes Ar
- Searching for k connected subgraphs is tractable (Ferreira, 2013)
- Can learn from string input (Jardine and Heinz, 2015)



Conclusions

- Tone includes many long-distance patterns, including some that are outside of the range of established string-based learners
- A graph-based learner can learn these patterns
- This is thanks to a computational notion of **locality** extended to autosegmental representations
- Future work: how can this result be extended to representations in other domains (segmental, metrical)?

Acknowledgments

Thanks to Jeff Heinz, Rémi Eyraud, and the members of the UD Speech, Phonetics, and Phonology Lab

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