

Inducing Phonological Rules: Perspectives from Bayesian Program Learning

Kevin Ellis and Timothy O'Donnell and Joshua B. Tenenbaum
and Armando Solar-Lezama

MIT

2017

A language learning experiment

xau

man

kwaj

çin

A language learning experiment

xau xauxaudə

man manmandə

kwaj kwajkwajdə

çin çinçində

A language learning experiment

xau xauxaudə

man manmandə

kwaj kwajkwajdə

çin çinçində

lej

A language learning experiment

xau xauxaudə

man manmandə

kwaj kwajkwajdə

çin çinçində

lej lejlejdə

A language learning experiment

xau xauxaudə

man manmandə

kwaj kwajkwajdə

çin çinçində

lej lejlejdə

$A \rightarrow AA + d\text{ə}$

A language learning experiment

dom

kot

lut

vus

wuk

bur

A language learning experiment

dom domi

kot koti

lut lodi

vus vozi

wuk wugi

bur bori

A language learning experiment

dom domi

kot koti

lut lodi

vus vozi

wuk wugi

bur bori

rogi

A language learning experiment

dom domi

kot koti

lut lodi

vus vozi

wuk wugi

bur bori

ruk rogi

A language learning experiment

dom domi

kot koti

lut lodi

vus vozi

wuk wugi

bur bori

ruk rogi

$A \rightarrow A + /i/$

$o \rightarrow u / _ [-\text{nasal} + \text{voice}] \#$

$[-\text{sonorant}] \rightarrow [-\text{voice}] / _ \#$

ABA (same/different/same)

wofewo

lovido

fimufi

ABA (same/different/same)

wofewo

lovido

fimufi

$$\emptyset \rightarrow \sigma_i / \sigma_i \sigma _$$

$$/\text{wofe}/ \rightarrow [\text{wofewo}]$$

Motivation

Problem: Understand the principles that underlie linguistic generalization.

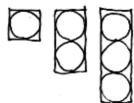
Approach: Triangulate these inductive principles with a wide variety of problems/data sets

A (reverse) engineering problem

How is it possible to learn a large number of diverse natural and artificial grammars from relatively small data sets?

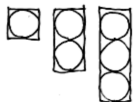
Bayesian Program Learning (BPL)

Bayesian Program Learning (BPL)



```
for (i < 3)
  rectangle(3*i,-2*i+4,
            3*i+2,6)
  for (j < i + 1)
    circle(3*i+1,-2*j+5)
```

Bayesian Program Learning (BPL)



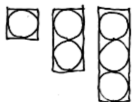
```
for (i < 3)
  rectangle(3*i,-2*i+4,
            3*i+2,6)
  for (j < i + 1)
    circle(3*i+1,-2*j+5)
```

Input	Output
"1/21/2001"	"01"



```
substr(pos('0',-1),-1)  "last 0 til end"
const('01')             "output 01"
substr(-2,-1)            "take last two"
```

Bayesian Program Learning (BPL)



```
for (i < 3)
  rectangle(3*i,-2*i+4,
            3*i+2,6)
for (j < i + 1)
  circle(3*i+1,-2*j+5)
```

Input	Output
"1/21/2001"	"01"

```
substr(pos('0',-1),-1)  "last 0 til end"
const('01')             "output 01"
substr(-2,-1)           "take last two"
```

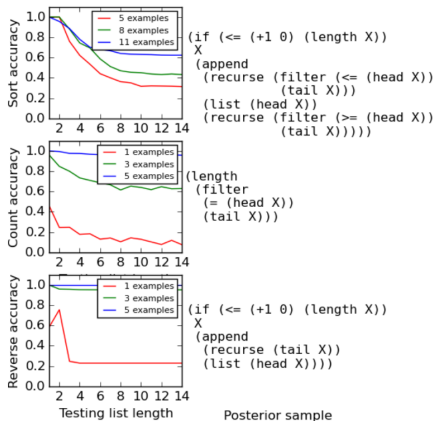


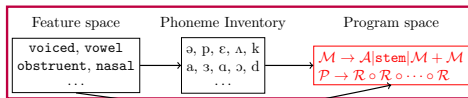
Figure 9: Learning to manipulate lists. Trained on lists of length ≤ 3 ; tested on lists of length ≤ 14 .

Talk roadmap

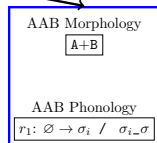
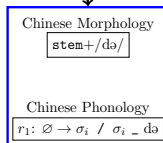
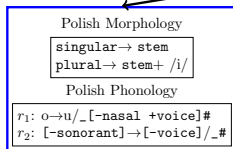
- ▶ Bayesian program learning (BPL) for phonology
- ▶ Artificial grammar learning: using BPL as a tool for studying simplicity trade-offs
- ▶ Phonological rules in natural language: BPL as a tool for explaining a breadth of phenomena
- ▶ Simplicity metrics and universal grammar
- ▶ A problem with minimum description length as a simplicity metric

Bayesian Program Learning (BPL) for phonology

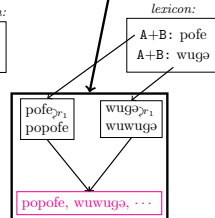
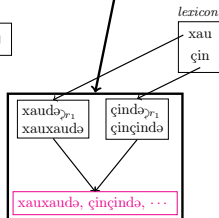
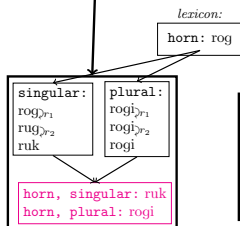
Programming language
(Universal Grammar)



Language-specific
morphophonology



Observed data



What makes a good model?

Probable \iff low description length \iff simple

$$\text{descriptionLength}(\text{randomEvent}) = -\log \mathbb{P}[\text{randomEvent}]$$

What makes a good model?

Probable \iff low description length \iff simple

$$\text{descriptionLength}(\text{randomEvent}) = -\log \mathbb{P}[\text{randomEvent}]$$

$$\begin{aligned} \text{descriptionLength}(\text{model}; \text{data}) &= \text{descriptionLength}(\text{model}) \\ &+ \sum_{x \in \text{data}} \text{descriptionLength}(x; \text{model}) \end{aligned}$$

What makes a good model?

Probable \iff low description length \iff simple

$$\text{descriptionLength}(\text{randomEvent}) = -\log \mathbb{P}[\text{randomEvent}]$$

$$\begin{aligned} \text{descriptionLength}(\text{model}; \text{data}) &= \text{descriptionLength}(\text{model}) \\ &+ \sum_{x \in \text{data}} \text{descriptionLength}(x; \text{model}) \end{aligned}$$

$$\text{descriptionLength}(\text{model}) \sim \text{program size}$$

What makes a good model?

Probable \iff low description length \iff simple

$$\text{descriptionLength}(\text{randomEvent}) = -\log \mathbb{P}[\text{randomEvent}]$$

$$\begin{aligned} \text{descriptionLength}(\text{model}; \text{data}) &= \text{descriptionLength}(\text{model}) \\ &+ \sum_{x \in \text{data}} \text{descriptionLength}(x; \text{model}) \end{aligned}$$

$$\text{descriptionLength}(\text{model}) \sim \text{program size}$$

$\text{descriptionLength}(x; \text{model}) = \text{size of } x\text{'s UR in model}$

$$\text{descriptionLength}([\text{pofepo}]; \text{ABA}) = \text{len}(/ \text{pofe} /) = 4$$

(see Richard Futrell's talk)

What makes a good model?

Probable \iff low description length \iff simple

$$\text{descriptionLength}(\text{randomEvent}) = -\log \mathbb{P}[\text{randomEvent}]$$

$$\begin{aligned} \text{descriptionLength}(\text{model}; \text{data}) &= \text{descriptionLength}(\text{model}) \\ &+ \sum_{x \in \text{data}} \text{descriptionLength}(x; \text{model}) \end{aligned}$$

$$\text{descriptionLength}(\text{model}) \sim \text{program size}$$

$\text{descriptionLength}(x; \text{model}) = \text{size of } x\text{'s UR in model}$

$$\text{descriptionLength}([\text{pofepo}]; \text{ABA}) = \text{len}(/ \text{pofe} /) = 4$$

(see Richard Futrell's talk)

Bayesian Program Learning framed as compression

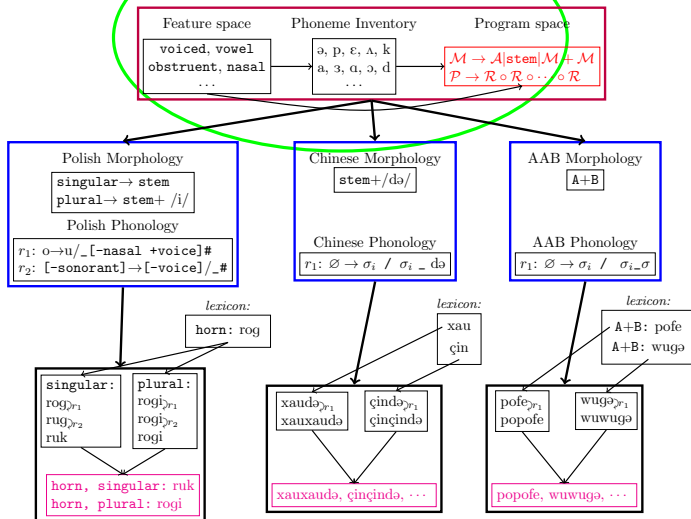
Old idea from Solomonoff

The program space

Programming language
(Universal Grammar)

Language-specific
morphophonology

Observed data



The program space: SPE-style context-sensitive rewrites

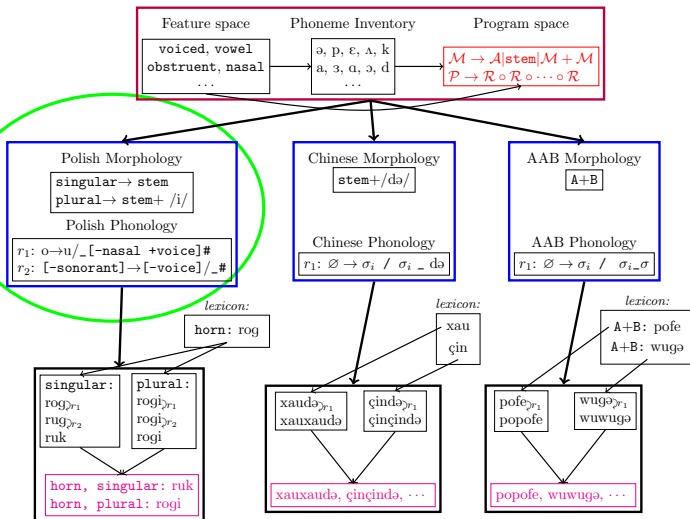
Grammar rule	English description
$\mathcal{P} \rightarrow \mathcal{R} \circ \mathcal{R} \circ \dots \circ \mathcal{R}$	P honology is compositions of r ewrites
$\mathcal{R} \rightarrow \mathcal{F} \longrightarrow \mathcal{C} / \mathcal{T} _ \mathcal{T}$	Rewrite f ocus to c hange between t riggers
$\mathcal{T} \rightarrow \# \mathcal{T}' \mathcal{T}'$	T riggers optionally match end of string, #
$\mathcal{T}' \rightarrow \epsilon \mathcal{X} \mathcal{T}' \mathcal{X}^* \mathcal{T}'$	T riggers are sequences of matrices \mathcal{X}
$\mathcal{X} \rightarrow a t s \dots$	Matrices can be constant phonemes
$\mathcal{X} \rightarrow [\pm \mathcal{E} \pm \mathcal{E} \dots \pm \mathcal{E}]$	Matrices check features \mathcal{E}
$\mathcal{E} \rightarrow \text{voice} \text{nasal} \dots$	Standard phonological f eatures
$\mathcal{F} \rightarrow \mathcal{X}$	Focus can be a feature matrix
$\mathcal{F} \rightarrow \mathbb{Z}$	Focus can be one of the triggers (copies it)
$\mathcal{F} \rightarrow \emptyset$	Insertion rule
$\mathcal{C} \rightarrow \mathcal{X}$	Structural change can be a feature matrix
$\mathcal{C} \rightarrow \emptyset$	Deletion rule
$\mathcal{C} \rightarrow \mathbb{Z}$	Structural change constrained to match a triggering feature matrix

The programs

Programming language
(Universal Grammar)

Language-specific
morphophonology

Observed data



The programs

- ▶ Morphology: Simple concatenative rules combining underlying forms of morphemes based on morphological function.

SING: # + rog + #

PLURAL: # + rog + i + #

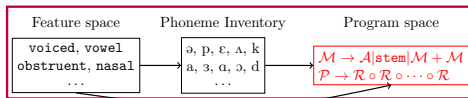
- ▶ Phonology: Ordered rules that transform resulting phone sequences.

$o \rightarrow u / _ [-\text{nasal} \text{ +voice}] \#$

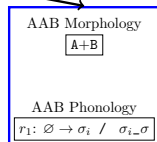
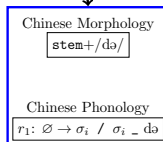
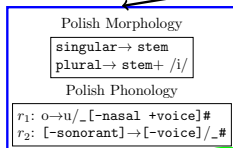
$\text{obstruent} \rightarrow [-\text{voice}] / _ \#$

The lexicon

Programming language
(Universal Grammar)

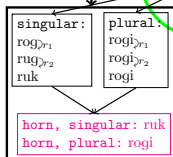


Language-specific
morphophonology



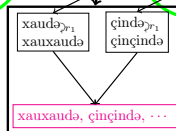
lexicon:

horn: rog



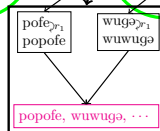
lexicon:

xau
çin



lexicon:

A+B: pofe
A+B: wugə



Observed data

The lexicon

Inventory of stems (“underlying representations”)

Polish:

rog

klub

dvon

...

AAB:

pofe

wuga

...

Shorter stem \iff Better compression \iff Higher likelihood of
data

But how do you find any good programs in the first place?

The search problem

program synthesis techniques from Armando Solar-Lezama

SAT/SMT solving:

```
Program ::= i
| nand(Program, Program)
```

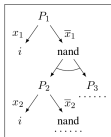
(a) Sketch

```
Program(i = 0) = 1
```

(d) Specification

```
x1 = 0, x2 = 1, x3 = 1
Program = nand(i, i)
```

(c) A constraint solution; $|x| = 3$ bits



(b) Program space

```
 $i \Leftrightarrow 0 \wedge P_1 \Leftrightarrow 1$ 
 $x_1 \Rightarrow (P_1 \Leftrightarrow i)$ 
 $\bar{x}_1 \Rightarrow (P_1 \Leftrightarrow \overline{P_2 \wedge P_3})$ 
 $x_2 \Rightarrow (P_2 \Leftrightarrow i)$ 
 $\bar{x}_2 \Rightarrow (P_2 \Leftrightarrow \overline{P_4 \wedge P_5})$ 
 $x_3 \Rightarrow (P_3 \Leftrightarrow i)$ 
.....
```

(c) Constraints for SAT solver

Figure 2: Synthesizing a program via sketching and constraint solving. Typewriter font refers to pieces of programs or sketches, while math font refers to pieces of a constraint satisfaction problem. The variable i is the program input.

Sketch:

```
generator int rec(int x, int y, int z){
    int t = ??;
    if(t == 0){return x;}
    if(t == 1){return y;}
    if(t == 2){return z;}
}
```

```
int a = rec(x,y,z);
```

```
int b = rec(x,y,z);
```

```
if(t == 3){return a * b;}
if(t == 4){return a + b;}
if(t == 5){return a - b;}
}
```

```
harness void sketch( int x, int y, int z ){
    assert rec(x,y, z) == (x + x) * (y - z);
}
```

The search problem

program synthesis techniques from Armando Solar-Lezama

SAT/SMT solving:

Program ::= i
| nand(Program, Program)

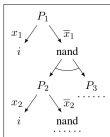
(a) Sketch

Program($i = 0$) = 1

(d) Specification

$x_1 = 0, x_2 = 1, x_3 = 1$
Program = nand(i, i)

(c) A constraint solution; $|x| = 3$ bits



(b) Program space

$i \Leftrightarrow 0 \wedge P_1 \Leftrightarrow 1$
 $x_1 \Rightarrow (P_1 \Leftrightarrow i)$
 $\bar{x}_1 \Rightarrow (P_1 \Leftrightarrow \bar{P}_2 \wedge \bar{P}_3)$
 $x_2 \Rightarrow (P_2 \Leftrightarrow i)$
 $\bar{x}_2 \Rightarrow (P_2 \Leftrightarrow \bar{P}_4 \wedge \bar{P}_5)$
 $x_3 \Rightarrow (P_3 \Leftrightarrow i)$
.....

(c) Constraints for SAT solver

Figure 2: Synthesizing a program via sketching and constraint solving. Typewriter font refers to pieces of programs or sketches, while math font refers to pieces of a constraint satisfaction problem. The variable i is the program input.

Sketch:

```
generator int rec(int x, int y, int z){  
    int t = ??;  
    if(t == 0){return x;}  
    if(t == 1){return y;}  
    if(t == 2){return z;}  
}
```

```
int a = rec(x,y,z);
```

```
int b = rec(x,y,z);
```

```
if(t == 3){return a * b;}  
if(t == 4){return a + b;}  
if(t == 5){return a - b;}  
}
```

```
harness void sketch( int x, int y, int z ){  
    assert rec(x,y, z) == (x + x) * (y - z);  
}
```

✓ Guarantee: Exact optimization

✗ No guarantee: runtime

The search problem

program synthesis techniques from Armando Solar-Lezama

SAT/SMT solving:

Program ::= i
| $\text{nand}(\text{Program}, \text{Program})$

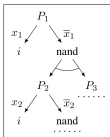
(a) Sketch

Program($i = 0$) = 1

(d) Specification

$x_1 = 0, x_2 = 1, x_3 = 1$
Program = $\text{nand}(i, i)$

(c) A constraint solution; $|x| = 3$ bits



(b) Program space

$i \Leftrightarrow 0 \wedge P_1 \Leftrightarrow 1$
 $x_1 \Rightarrow (P_1 \Leftrightarrow i)$
 $\bar{x}_1 \Rightarrow (P_1 \Leftrightarrow \bar{P}_2 \wedge \bar{P}_3)$
 $x_2 \Rightarrow (P_2 \Leftrightarrow i)$
 $\bar{x}_2 \Rightarrow (P_2 \Leftrightarrow \bar{P}_4 \wedge \bar{P}_5)$
 $x_3 \Rightarrow (P_3 \Leftrightarrow i)$
.....

(c) Constraints for SAT solver

Figure 2: Synthesizing a program via sketching and constraint solving. Typewriter font refers to pieces of programs or sketches, while math font refers to pieces of a constraint satisfaction problem. The variable i is the program input.

Sketch:

```
generator int rec(int x, int y, int z){  
  int t = ??;  
  if(t == 0){return x;}  
  if(t == 1){return y;}  
  if(t == 2){return z;}  
}
```

```
int a = rec(x,y,z);
```

```
int b = rec(x,y,z);
```

```
if(t == 3){return a * b;}  
if(t == 4){return a + b;}  
if(t == 5){return a - b;}  
}
```

```
harness void sketch( int x, int y, int z ){  
  assert rec(x,y, z) == (x + x) * (y - z);  
}
```

✓ Guarantee: Exact optimization

✗ No guarantee: runtime

2 rules, 1 inflection:

$\geq (10^{18}\text{rules})^2 \times (10^8\text{morphologies}) = 10^{42}\text{models}$

Artificial Grammar Learning

Widely studied.

Fundamental hypothesis: AGL engages some shared resources with first language acquisition

- ▶ ABA (same/different/same): wofewo, pikæpi, gugagu
- ▶ ABB (different/same/same): wowofe, pipikæ, guguga
- ▶ Pig Latin
- ▶ ...

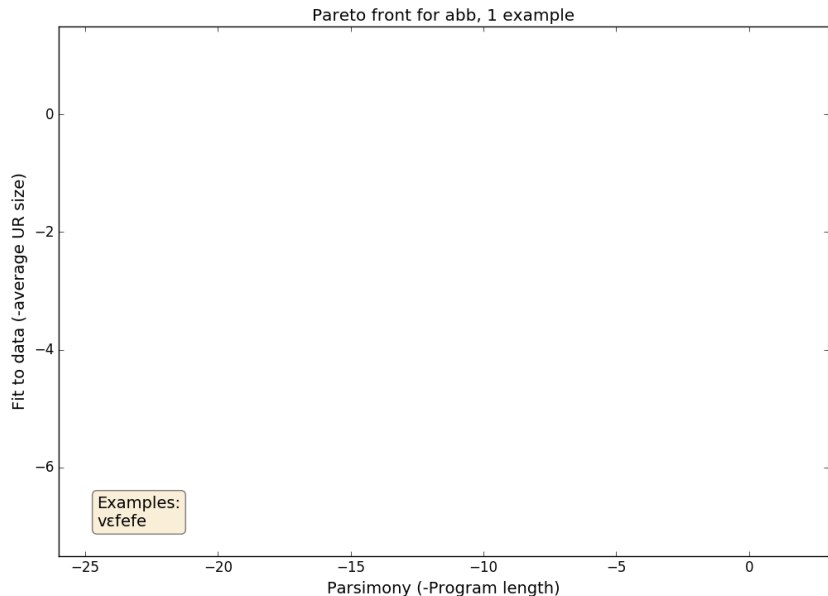
Artificial Grammar Learning

Grammar	Example input to learner	MAP grammar	Natural language analogues
ABA (same/different/same) Marcus et al. 1999.	wofewo lovilo fimufi	$\emptyset \rightarrow \sigma_i / \#_ \sigma \sigma_i$	Reduplication (eg, Tagalog)
ABB (different/same/same) Marcus et al. 1999.	wofefe lovivi fimumu	$\emptyset \rightarrow \sigma_i / \sigma_i _ \#$	Reduplication (eg, Tagalog)
ABx (different/different/constant)	wofeka lovika fimuka	$\emptyset \rightarrow x / _ \#$	concatenative morphology
AAx (same/same/constant) Gerken 2006.	wowoka loloka fikika	$\emptyset \rightarrow \sigma_i / \#_ \sigma_i$ $\emptyset \rightarrow x / _ \#$	reduplication concatenative morphology
AxA (same/constant/same) Gerken 2006.	wokawo lokalo fikafi	$\emptyset \rightarrow a / \# _$ $\emptyset \rightarrow k / \# _$ $\emptyset \rightarrow \sigma_i / \# _ \sigma \sigma_i$	Infixing Reduplication
Pig Latin	pig→igpe latm→atile æsk→æske	$\emptyset \rightarrow C_i / \# C_i [\] * _ \#$ $\emptyset \rightarrow e / _ \#$ $C \rightarrow \emptyset / \# _$	

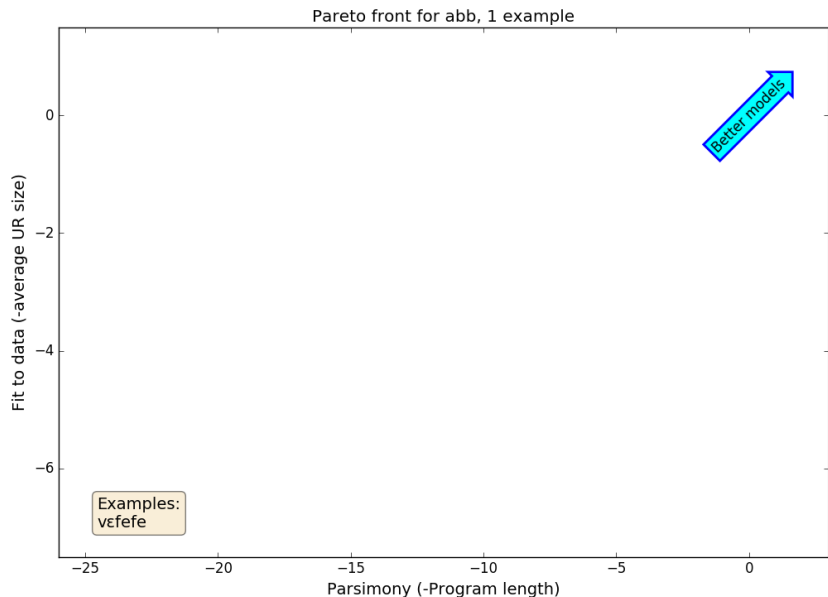
Marcus 1999: Babies learn these grammars

Gerken 2006: Babies learn these grammars *from only a few examples*

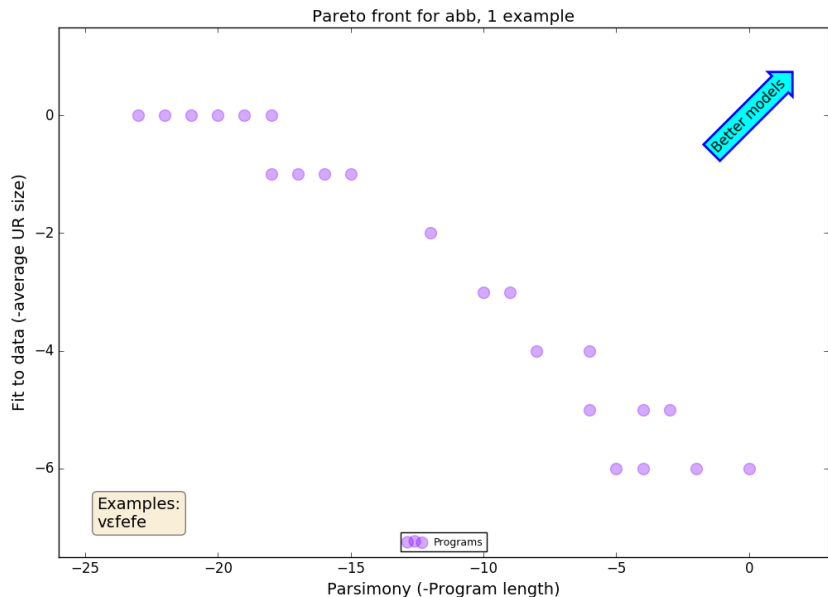
Optimal simplicity front for learning ABB from 1 example



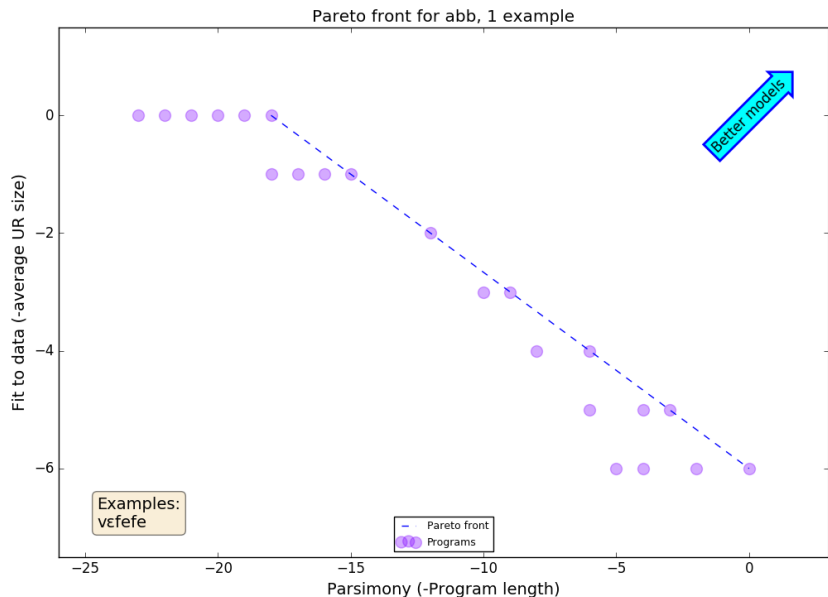
Optimal simplicity front for learning ABB from 1 example



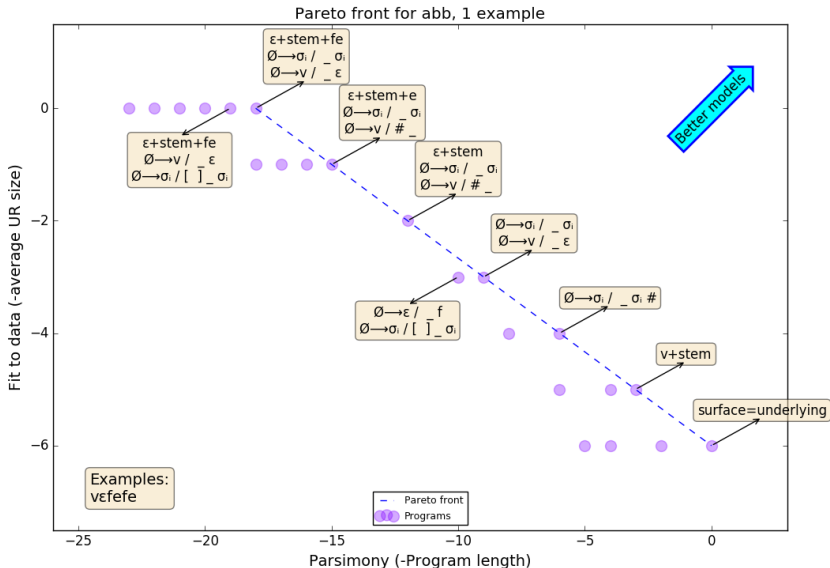
Optimal simplicity front for learning ABB from 1 example



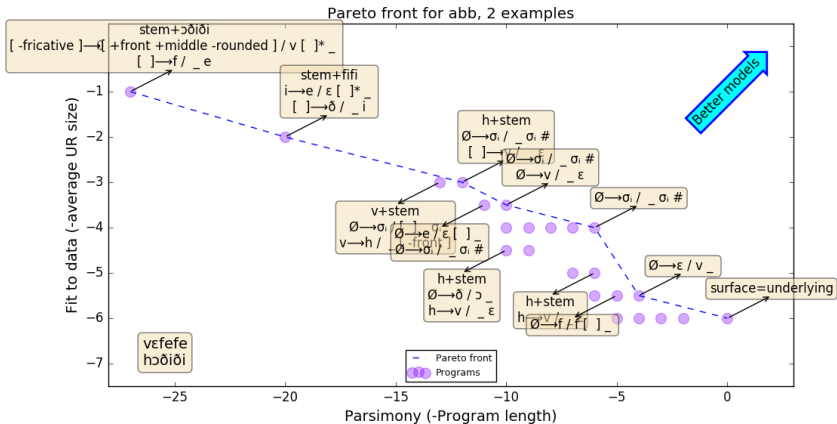
Optimal simplicity front for learning ABB from 1 example



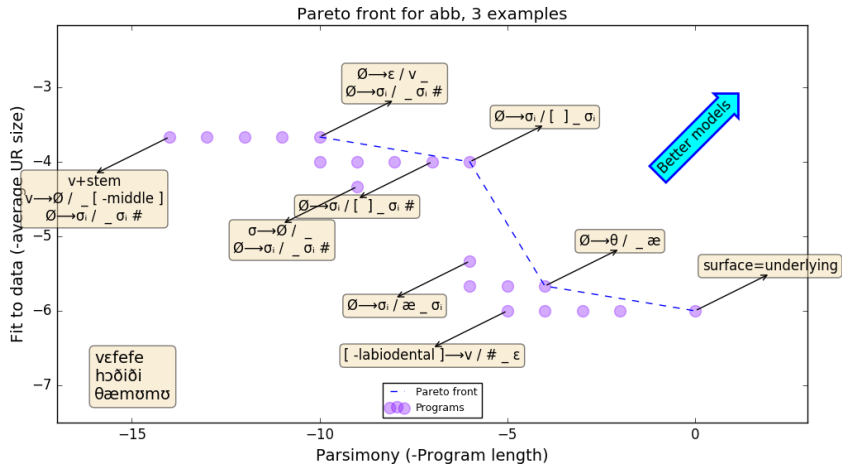
Optimal simplicity front for learning ABB from 1 example



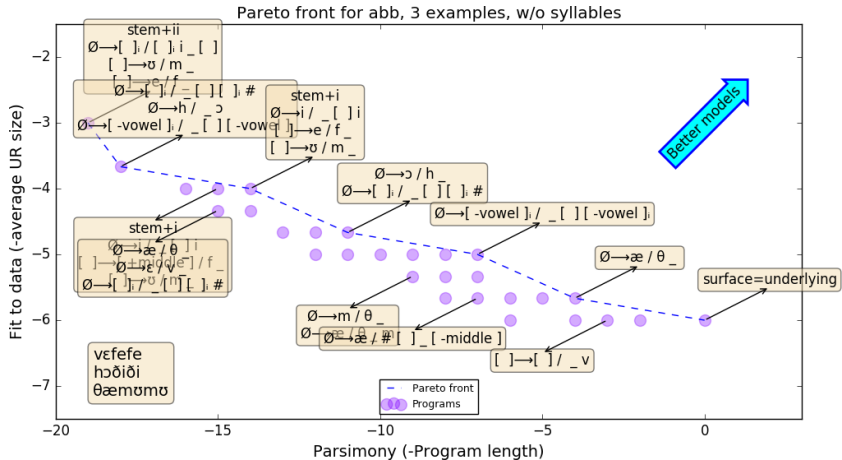
Optimal simplicity front for learning ABB: 2 examples



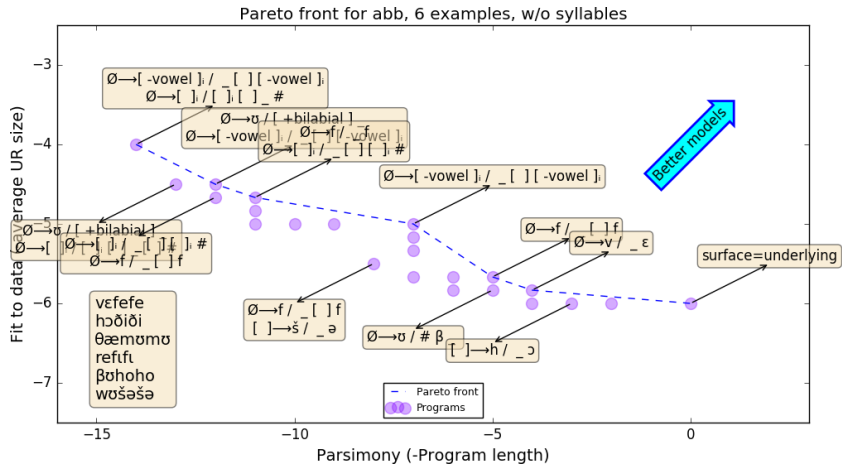
Optimal simplicity front for learning ABB: 3 examples



Optimal simplicity front for learning ABB without syllables,
3 examples



Optimal simplicity front for learning ABB without syllables, 6 examples



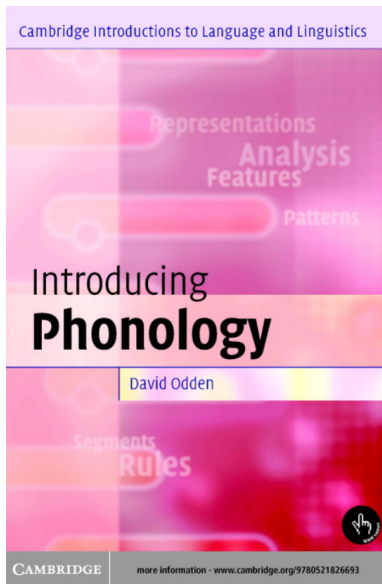
Learning natural language phonology

The vision: Induce programs describing diverse phonological systems from many languages. Imagine getting data from field linguists

Ours is not the first linguistic rule learner: Ezer Rasin & Roni Katzir (this workshop); Albright & Hayes 2003; Yip & Sussman 1996; Constantine Lignos & Charles Yang 2010; Doyle & Bicknell & Levy 2014; Colin Wilson 2006

What is a good stepping stone toward this vision?

Doing your phonology homework



Doing your phonology homework

Exercises

1 Axininca Campa

Provide underlying representations and a phonological rule which will account for the following alternations:

toniro	'palm'	notoniroti	'my palm'
yaarato	'black bee'	noyaaratoti	'my black bee'
kanari	'wild turkey'	noyanariti	'my wild turkey'
kosiri	'white monkey'	noyosiriti	'my white monkey'
pisiro	'small toucan'	nowisiroti	'my small toucan'
porita	'small hen'	noworitati	'my small hen'

Cambridge Introduction

Introduction Phonology

David Odden

Segments
Rules

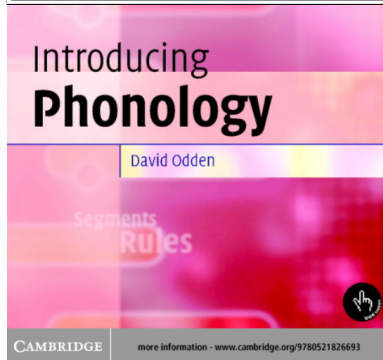


CAMBRIDGE

more information - www.cambridge.org/9780521826693

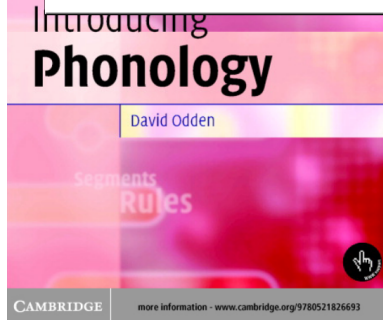
Doing your phonology homework

Language	Example data			Phonology	Morphology	Phenomena
Makonde	amáŋga	amíle	áma	$[] \rightarrow [-\text{stress}] / _ [] * [+\text{stress}]$ $[+\text{middle} \text{ } -\text{stress}] \rightarrow a / _ []$	stem+áŋga stem+íle stem+a	Stress patterns Neutralizing rule
	akáŋga	akíle	áka			
	aváŋga	avíle	óva			
	amáŋga	amíle	óma			
	utáŋga	utíle	úta			
	aváŋga	avíle	éva			
	taváŋga	tavíle	táva			
	uŋgáŋga	uŋgíle	úŋga			
	patáŋga	patíle	póta			



Doing your phonology homework

Language	Example data			Phonology	Morphology	Phenomena
	amángga	amíle	áma			
	akángga	akíle	áka			
Language	Example data			Phonology	Morphology	
Ma	kubala	kubalana	kubalila	kubalilana	ku+stem+a	
	kugaya	kugayana	kugayila	kugayilana	ku+stem+ana	
	kubála	kubálana	kubálila	kubálilana	ku+stem+ila	
Kerewe	kutúbála	kukibála	kutúbálila	kukítúbalila	ku+stem+ilana	
	kutúgáya	kukígáya	kutúgáyila	kukítúgayila	kutú+stem+a	
	kutúbála	kukibála	kutúbálila	kukítúbalila	kukí+stem+a	
					kutú+stem+ila	
					kukítú+stem+ila	



Doing your phonology homework

Language	Example data			Phonology	Morphology	Phenomena
Ma	amángga	amíle	áma			
	akángga	akíle	áka			
Language	Example data			Phonology	Morphology	
Ma	kubala	kubalana	kubalila	kubalilana	ku+stem+a	
					ku+stem+ana	
Language	Example data			Phonology	Morphology	Phenomena
Hungarian	a:g ^y	a:g ^y ban	ak ^y to:l	a:g ^y nak		
	ör	örben	örtö:l	örnek	V→[+mid +tense +front]/	
	ku:t	ku:dban	ku:ttö:l	ku:tnak	[+front] [*] _	stem
	re:s	rezben	restö:l	re:snak	[]→[+voice]/	stem+ban
	rab	rabban	raptö:l	rabnak	_ [+bilabial]	stem+to:l
	vi:z	vizben	vistö:l	vi:znak	[-sonorant]→[-voice]/	stem+nak
	fal	falban	faltö:l	falnak	_ [-voice]	
	test	tezdben	testtö:l	testnek		



What it can do right now

- ▶ **Kikurai:** fricatives alternate with stops after nasals
- ▶ **Farsi:** Trills alternate with flaps
- ▶ **Amharic:** alternation between ə & ε
- ▶ **Gen:** l/r alternation
- ▶ **Greek:** Velar stops alternate with palatalized versions before front vowels
- ▶ **Osage:** coronal stops become dentals before central vowels
- ▶ **Kishambaa:** voiced/unvoiced nasals alternate
- ▶ **Thai:** stops are unreleased word finally
- ▶ **Palauan:** a word initial neutralizing rule
- ▶ **Quechua:** Velar becomes uvular when followed by uvular (spreading)
- ▶ **Lhasa Tibetan:** no contrast between velar/uvular, or voiced/voiceless stops or fricatives
- ▶ **Axininca Campa:** stops become glides
- ▶ **Kikuyu:** infinitive prefix can surface as either k or γ
- ▶ **Korean:** vowel harmony, aspiration only surfaces in certain contexts
- ▶ **Hungarian:** vowel harmony and voicing assimilation
- ▶ **Kikuria:** vowel harmony
- ▶ **Farsi:** a deletion rule explains singular/plural
- ▶ **Tibetan:** initial consonant cluster reduction explains counting system
- ▶ **Makonde:** stress patterns; unstressed vowels are neutralized
- ▶ **North Saami:** 3 neutralization rules explain nominative sg essive
- ▶ **Samoa:** 2 deletion rules that explain words that sound the same in one inflection being different in another
- ▶ **Russian:** devoicing of word final obstruent
- ▶ **English:** verbal inflections (voicing assimilation, epenthesis)
- ▶ **Finnish:** nominative/partive explained by vowel raising and vowel harmony
- ▶ **Kerewe:** Interacting tone rules
- ▶ **Polish:** vowel alternations interacting with devoicing of word final obstruent in singular/plural
- ▶ **Ancient Greek:** voicing assimilation, deaspiration, deletion rule. Order matters.
- ▶ **Serbo-Croatian:** predictable stress, devoicing, neutralizing, epenthesis
- ▶ **Artificial grammar learning:** Pig Latin, ABB, ABA, AxA, ABx, AAX, Chinese duplication

What it can do right now

Handles 60%
of the
textbook

- ▶ **Kikurai:** fricatives alternate with stops after nasals
- ▶ **Farsi:** Trills alternate with flaps
- ▶ **Amharic:** alternation between ə & ε
- ▶ **Gen:** l/r alternation
- ▶ **Greek:** Velar stops alternate with palatalized versions before front vowels
- ▶ **Osage:** coronal stops become dentals before central vowels
- ▶ **Kishambaa:** voiced/unvoiced nasals alternate
- ▶ **Thai:** stops are unreleased word finally
- ▶ **Palauan:** a word initial neutralizing rule
- ▶ **Quechua:** Velar becomes uvular when followed by uvular (spreading)
- ▶ **Lhasa Tibetan:** no contrast between velar/uvular, or voiced/voiceless stops or fricatives
- ▶ **Axininca Campa:** stops become glides
- ▶ **Kikuyu:** infinitive prefix can surface as either k or γ
- ▶ **Korean:** vowel harmony, aspiration only surfaces in certain contexts
- ▶ **Hungarian:** vowel harmony and voicing assimilation
- ▶ **Kikuria:** vowel harmony
- ▶ **Farsi:** a deletion rule explains singular/plural
- ▶ **Tibetan:** initial consonant cluster reduction explains counting system
- ▶ **Makonde:** stress patterns; unstressed vowels are neutralized
- ▶ **North Saami:** 3 neutralization rules explain nominative sg essive
- ▶ **Samoa:** 2 deletion rules that explain words that sound the same in one inflection being different in another
- ▶ **Russian:** devoicing of word final obstruent
- ▶ **English:** verbal inflections (voicing assimilation, epenthesis)
- ▶ **Finnish:** nominative/partive explained by vowel raising and vowel harmony
- ▶ **Kerewe:** Interacting tone rules
- ▶ **Polish:** vowel alternations interacting with devoicing of word final obstruent in singular/plural
- ▶ **Ancient Greek:** voicing assimilation, deaspiration, deletion rule. Order matters.
- ▶ **Serbo-Croatian:** predictable stress, devoicing, neutralizing, epenthesis
- ▶ **Artificial grammar learning:** Pig Latin, ABB, ABA, AxA, ABx, AAX, Chinese duplication

Polish: Final devoicing + Rule ordering

singular	plural
dom	domi
kot	koti
lut	lodi
vus	vozi
wuk	wugi
ruk	rogi
bur	bori
vsum	vsumi

Polish: Final devoicing + Rule ordering

singular	plural
dom	domi
kot	koti
lut	lodi
vus	vozi
wuk	wugi
ruk	rogi
bur	bori
vsum	vsumi

$o \rightarrow u / _ [-\text{nasal} +\text{voice}] \#$

$[-\text{sonorant}] \rightarrow [-\text{voice}] / _ \#$

singular: stem

plural: stem + /i/

TOOLKIT: Scaling program synthesis to learn large grammars

Exercises

1 Serbo-Croatian

These data from Serbo-Croatian have been simplified in two ways, to make the problem more manageable. Vowel length is omitted, and some stresses are omitted. The language has both underlying stresses whose position cannot be predicted – these are not marked in the transcriptions – and a predictable “mobile” stress which is assigned by rule – these are the stresses indicated here. Your analysis should account for how stress is assigned in those words marked with a rule-governed stress: you should not try to write a rule that predicts *whether* a word has a stress assigned by rule versus an underlying stress. Ignore the stress of words with no stress mark (other parts of the phonology of such words must be accounted for). Past-tense verbs all have the same general past-tense suffix, and the difference between masculine, feminine and neuter past-tense involves the same suffixes as are used to mark gender in adjectives.

Adjectives

Masc	Fem	Neut	Pl	
mlád	mladá	mladó	mladí	‘young’
túp	tupá	tupó	tupí	‘blunt’
blág	blagá	blagó	blagi	‘mild’
grúb	grubá	grubó	grubí	‘coarse’
béo	belá	beló	belí	‘white’
veseo	vesela	veselo	veseli	‘gay’
debéo	debelá	debeló	debelí	‘fat’
mío	milá	miló	milí	‘dear’
zelén	zelená	zelenó	zelení	‘green’
kradén	kradená	kradenó	kradení	‘stolen’
dalék	daleká	dalekó	dalekí	‘far’
visók	visoká	visokó	visokí	‘high’
dubók	duboká	dubokó	dubokí	‘deep’

križan	križana	križano	križani	‘cross’
sunčan	sunčana	sunčano	sunčani	‘sunny’
svečan	svečana	svečano	svečani	‘formal’
bogat	bogata	bogato	bogati	‘rich’
rapav	rapava	rapavo	rapavi	‘rough’
yásan	yasná	yasno	yasni	‘clear’
vážan	važná	važno	važni	‘important’
sítan	sitná	sitno	sitni	‘tiny’
ledan	ledna	ledno	ledni	‘frozen’
tának	tanká	tankó	tankí	‘slim’
kráta	kratká	kratkó	kratkí	‘short’
blízak	bliská	bliskó	bliski	‘close’
úzak	uská	uskó	uski	‘narrow’
dóbar	dobrá	dobro	dobri	‘kind’
óštar	oštrá	oštro	oštri	‘sharp’
bodar	bodra	bodro	bodri	‘alert’
ustao	ustala	ustalo	ustali	‘tired’
múkao	muklá	mukló	mukli	‘hoarse’
óbao	oblá	obló	oblí	‘plump’
pódao	podlá	podló	podli	‘base’

Verbs

1 sg pres	Masc past	Fem past	Neut past	
tepém	tépao	teplá	tepló	‘wander’
skubém	skúbao	skublá	skubló	‘tear’
tresém	trésao	treslá	tresló	‘shake’
vezém	vézao	vezlá	vezló	‘lead’

Investigating the inductive bias over grammars

Motivation: Counting in Tibetan

7 Tibetan

Numbers between 11 and 19 are formed by placing the appropriate digit after the number 10, and multiples of 10 are formed by placing the appropriate multiplier before the number 10. What are the underlying forms of the basic numerals, and what phonological rule is involved in accounting for these data?

ju	'10'	jiŋ	'1'	juŋjiŋ	'11'
ši	'4'	juβši	'14'	šibju	'40'
gu	'9'	juŋgu	'19'	gubju	'90'
ŋa	'5'	juŋa	'15'	ŋabju	'50'

Motivation: Counting in Tibetan

Number	Pronunciation
1	ṣig
4	ši
10	ṣu
11	ṣu+gṣig (10+1)
40	ši+bṣu (4+10)

Motivation: Counting in Tibetan

Number	Pronunciation
1	ǰig
4	ši
10	ǰu
11	ǰu+gǰig (10+1)
40	ši+bǰu (4+10)

Explanation:

ǰig ("1") is really gǰig

ǰu ("10") is really bǰu

Program:

$C \rightarrow \emptyset / \# _ C$

(Delete initial cluster of consonants)

Counting in Tibetan

Number	Pronunciation
1	ǰig
4	ši
10	ǰu
11	ǰu+gǰig (10+1)
40	ši+bǰu (4+10)

Explanation:

ǰig ("1") is really gǰig

ǰu ("10") is really bǰu

Program:

[-nasal] → ∅ / # _

Delete initial nonnasal???

Problem:

Probable grammar \neq grammars children/linguists prefer

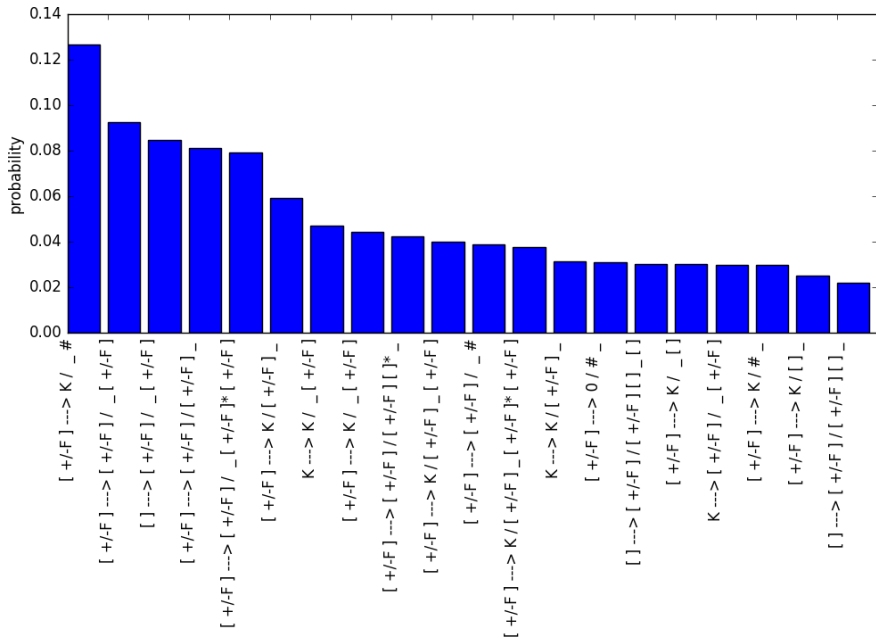
Problem:

Probable grammar \neq grammars children/linguists prefer

Solution:

Get a better inductive bias (a better universal grammar)

Learning what rules look like



Learning a (fragment) grammar over grammars

Fragment grammars: O'Donnell 2011

FEATUREMATRIX \rightarrow [-voice]
FEATUREMATRIX \rightarrow [-sonorant]
FEATUREMATRIX \rightarrow [+voice]
FEATUREMATRIX \rightarrow [+tense]
FEATUREMATRIX \rightarrow [+highTone]
FEATUREMATRIX \rightarrow [+middle]
TRIGGER \rightarrow [+sibilant]
TRIGGER \rightarrow [] [+highTone]
TRIGGER \rightarrow [+stop +voice]
TRIGGER \rightarrow [-low]
TRIGGER \rightarrow []* FEATUREMATRIX
RULE \rightarrow [-vowel] \rightarrow \emptyset / TRIGGER _ TRIGGER
RULE \rightarrow [+low] \rightarrow CONSTANT / []* FEATUREMATRIX _
RULE \rightarrow [] \rightarrow [+voice] / _ TRIGGER
RULE \rightarrow CONSTANT \rightarrow CONSTANT / [] _ TRIGGER
RULE \rightarrow [] \rightarrow [-highTone] / TRIGGER _ TRIGGER
RULE \rightarrow [-sonorant] \rightarrow [-voice] / _ #
RULE \rightarrow [] \rightarrow FC / TRIGGER _ [] FEATUREMATRIX

Learning a (fragment) grammar over grammars

Fragment grammars: O'Donnell 2011

FEATUREMATRIX \rightarrow [-voice]

FEATUREMATRIX \rightarrow [-sonorant]

FEATUREMATRIX \rightarrow [+voice]

FEATUREMATRIX \rightarrow [+tense]

FEATUREMATRIX \rightarrow [+highTone]

FEATUREMATRIX \rightarrow [+middle]

TRIGGER \rightarrow [+sibilant]

TRIGGER \rightarrow [] [+highTone]

TRIGGER \rightarrow [+stop +voice]

TRIGGER \rightarrow [-low]

TRIGGER \rightarrow []* FEATUREMATRIX

RULE \rightarrow [-vowel] \rightarrow \emptyset / TRIGGER _ TRIGGER

RULE \rightarrow [+low] \rightarrow CONSTANT / []* FEATUREMATRIX _

RULE \rightarrow [] \rightarrow [+voice] / _ TRIGGER

RULE \rightarrow CONSTANT \rightarrow CONSTANT / [] _ TRIGGER

RULE \rightarrow [] \rightarrow [-highTone] / TRIGGER _ TRIGGER

RULE \rightarrow [-sonorant] \rightarrow [-voice] / _ #

RULE \rightarrow [] \rightarrow FC / TRIGGER _ [] FEATUREMATRIX

Learning a (fragment) grammar over grammars

Fragment grammars: O'Donnell 2011

FEATUREMATRIX \rightarrow [-voice]

FEATUREMATRIX \rightarrow [-sonorant]

FEATUREMATRIX \rightarrow [-voice]

FEATUREMATRIX

FEATUREMATRIX

FEATUREMATRIX

FEATUREMATRIX

TRIGGER \rightarrow

TRIGGER \rightarrow [-vowel] $\rightarrow \emptyset$ / # - [-vowel]

TRIGGER \rightarrow [+stop +voice]

TRIGGER \rightarrow [-low]

TRIGGER \rightarrow []* FEATUREMATRIX

RULE \rightarrow [-vowel] $\rightarrow \emptyset$ / TRIGGER _ TRIGGER

RULE \rightarrow [+low] \rightarrow CONSTANT / []* FEATUREMATRIX _

RULE \rightarrow [] \rightarrow [+voice] / _ TRIGGER

RULE \rightarrow CONSTANT \rightarrow CONSTANT / [] _ TRIGGER

RULE \rightarrow [] \rightarrow [-highTone] / TRIGGER _ TRIGGER

RULE \rightarrow [-sonorant] \rightarrow [-voice] / - #

RULE \rightarrow [] \rightarrow FC / TRIGGER _ [] FEATUREMATRIX

In light of this UG, the system revises its rule for Tibetan to match the good linguistics students judgment:

Problems with minimum description length

Problems with compression

varit	varihin
oahpis	oahpisin
bissobeahrtset	bissobeahrtsehin
yaaʔmin	yaaʔmimin
gahpir	gahpirin
gaauhtsis	gaauhtsisin
beštor	beštorin
heevemeahhtun	heevemeahhtunin
bissomeahtun	bissomeahtumin
laðas	laðasin
heanʒkan	heanʒkanin
yaman	yamanin

Problems with compression

varit	varihin
oahpis	oahpisin
bissobeahrtset	bissobeahrtsehin
yaaʔmin	yaaʔmimin
gahpir	gahpirin
gaauhtsis	gaauhtsisin
beštor	beštorin
heevemeahhtun	heevemeahhtunin
bissomeahtun	bissomeahtumin
laðas	laðasin
heanʔkan	heanʔkanin
yaman	yamanin

stem+/in/

m→n word finally

yaaʔmim→yaaʔmin

yaaʔmim+in→yaaʔmimin

Problems with compression

varit	varihin
oahpis	oahpisin
bissobeahrtset	bissobeahrtsehin
yaaʔmin	yaaʔmimin
gahpir	gahpirin
gaauhtsis	gaauhtsisin
beštor	beštorin
heevemeahhtun	heevemeahhtunin
bissomeahtun	bissomeahtumin
laðas	laðasin
heanʔkan	heanʔkanin
yaman	yamanin

stem+/in/

m→n word finally

yaaʔmim→yaaʔmin

yaaʔmim+in→yaaʔmimin

Problems with compression

varit

oahpis

bissobeahrtset

yaaʔmin

gahpir

gaauhtsis

beštor

heevemeahhtun

bissomeahtun

laðas

heagkkan

yaman

varihin

oahpisin

bissobeahrtsehin

yaaʔmimin

gahpirin

gaauhtsisin

beštorin

heevemeahhtunin

bissomeahtumin

laðasin

heagkkanin

yamanin

stem+/**i**m/

m→n word finally

yaaʔmim→yaaʔmin

yaaʔmim+**i**m→

yaaʔmimim→

yaaʔmimin

Problems with compression

varit

oahpis

bissobeahrtset

yaaʔmin

gahpir

gaauhtsis

beštor

heevemeahhtun

bissomeahtun

laðas

heanjkan

yaman

varihin

oahpisin

bissobeahrtsehin

yaaʔmimin

gahpirin

gaauhtsisin

beštorin

heevemeahhtunin

bissomeahtumin

laðasin

heanjkanin

yamanin

stem+/im/

m→n word finally

yaaʔmim→yaaʔmin

yaaʔmim+im→

yaaʔmimim→

yaaʔmimin

MDL

unchanged!

Problems with compression

varit
oahpis
bissobeahrtset

yaa?min

gahpir
gaauhtsis
beštor

heevemeahhtun

bissomeahtun

laðas

heanjkan

yaman

varihin
oahpisin
bissobeahrtsehin

yaa?mimin

gahpirin
gaauhtsisin
beštorin

heevemeahhtunin

bissomeahtumin

laðasin

heanjkanin

yamanin

stem+/im/

m→n word finally

yaa?mim→yaa?min

yaa?mim+im→

yaa?mimim→

yaa?mimin

MDL

unchanged!

$\text{cost}(\text{model}; \text{data}) =$

$\text{cost}(\text{model}) + \sum_{x \in \text{data}} \text{cost}(x; \text{model}) + \text{runtimeCost}(x; \text{model})$

Contributions

Engineered new approaches to grammar learning drawn from program synthesis. Allows exact study of simplicity trade-offs between different grammars.

A system that can learn many morphophonologies, both natural and artificial, from relatively small amounts of data

Learning to learn phonological rules as a way of estimating and probing universal grammar

Contributions

Engineered new approaches to grammar learning drawn from program synthesis. Allows exact study of simplicity trade-offs between different grammars.

A system that can learn many morphophonologies, both natural and artificial, from relatively small amounts of data

Learning to learn phonological rules as a way of estimating and probing universal grammar

The end.