Simulating Language Behavior

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Information science/Informatiekunde

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Outline

Tentative Plan

Week	Subject
3	Simulation of language change/diffusion Simulation of learning pronoun reference
4	Simulation of segmentation
5	Simulation of segmentation
6	Simulation of language comprehension Simulation of acquisition of words, morphology or syntax
7	Project presentations

Top candidates

- Segmentation
  - Christiansen et al. (1998)
  - Goldwater et al. (2009)
  - Johnson and Goldwater (2009);
  - Monaghan and Christiansen (2010)
  - Borschinger and Johnson (2011)
- Grammar induction
- Learning words/word meanings
- Simulation of learning regular/irregular forms.
- On nature–nurture debate, poverty of stimulus, and role of computational models/simulations
- Simulation of language diffusion
- Use of computational modeling in study of language.
- Methodological issues with simulation of human behavior, for example evaluation.

Project ideas: segmentation

- An new algorithm or method of segmentation, or modification of an existing method in an interesting way.
- Trying existing methods/tools on different languages.
- Different input representation. For example, adding noise or using phonetic features or non-segmental cues/information.
- Investigating role of a certain cue, for example lexical stress.
- Critical comparison/review of models in the literature.

Project ideas (2)

- Learning regular & irregular forms.
  - try existing methods on a different language.
  - implement a new method.
  - (formally) analyze new data (possibly different language).
- Grammar induction
  - morphology (?)
  - learnability related.
  - evaluation
- Simulating diffusion of language change
- Simulating another linguistic process: your ideas.

Modeling human behavior

Models: why and how

- Why do we model things at all?

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  - Study the model analytically.
  - Run simulations.

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> All models are wrong, some are useful.
> — *Box and Draper (1986, p. 424)*

Marr's three levels

Our modeling practice is affected by what type of questions we want to answer. Marr proposed three complementary levels of analysis to understand cognitive systems.

- **computational** level is concerned with the questions *what* problem the system solves and *why*.
- **algorithmic** level is concerned with the question *how*. How does the system solve the question, what processes and representations are employed?
- **implementation** level is concerned with how the system is physically realized.

Marr's three levels: an example

We can try to understand a calculator in three different levels.

- In computational level, we are concerned about what it does; e.g., addition.
- In algorithmic level we are interested in how it does it; e.g., uses base-10 representation and a particular algorithm for adding two numbers.
- In implementation level, we are interested in the physical components; e.g., whether it is a mechanical or electronic calculator.

Cognitively plausible models (of language acquisition)

- Learning from data compatible with data children receive (e.g., no newspaper text, no unrealistic annotations).
- Using realistic amount of data.
- Incremental processing/learning.
- Following the observed course of development, including the errors children make.
- Using limited resources (memory and processing).
- Learning from limited feedback.

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Do we have to meet all requirements to have 'useful' models?

Some challenges

- Lack of suitable data: it is often difficult to collect the right type of input data.
- Too many unknowns: we know very little about the processes that lead to our linguistic capabilities.
- Evaluation: it is difficult to set good criteria for deciding good performance from the model.

Modeling segmentation

Back to the puzzle: some cues

```
ljuuzuibutsjhiuljuuz
ljuuztbzjubhbjompwfljuuz
xibutuibu
ljuuz
epzpvxbounpsfnjmlipofz
ljuuzljuuzephhjf
opnjxibuepftbljuuztbz
xibuepftbljuuztbz
ephhjfeph
ephhjf
opnjxibuepftuifephhjftbz
xibuepftuifephhjftbz
mjuumfcbczcjsejf
cbczcjsejf
zpvepoumjlfuibupof
plbznpnnzublfuijtpvu
dpx
uifdpxtbztnppnpp
xibuepftuifdpxtbzopnj
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ljuuztbzjubhbjompwfljuuz
xibutuibu
ljuuz
epzpvxbounpsfnjmlipofz
ljuuzljuuzephhjf
opnjxibuepftbljuuztbz
xibuepftbljuuztbz
ephhjfeph
ephhjf
opnjxibuepftuifephhjftbz
xibuepftuifephhjftbz
mjuumfcbczcjsejf
cbczcjsejf
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- Acoustic cues, such as *pauses*, *stress*, *coarticulation*, *allophonic alternations*, *vowel harmony*

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opnjxibuepftbljuuztbz
xibuepftbljuuztbz
ephhjfeph
ephhjf
opnjxibuepftuifephhjftbz
xibuepftuifephhjftbz
mjuumfcbczcjsejf
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xibuepftbljuuztbz
ephhjfeph
ephhjf
opnjxibuepftuifephhjftbz
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mjuumfcbczcjsejf
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xibuepftbljuuztbz
ephhjfeph
ephhjf
opnjxibuepftuifephhjftbz
xibuepftuifephhjftbz
mjuumfcbczcjsejf
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- utterance boundaries

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ephhjfeph
ephhjf
opnjxibuepftuifephhjftbz
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opnjxibuepftbljuuztbz
xibuepftbljuuztbz
ephhjfeph
ephhjf
opnjxibuepftuifephhjftbz
xibuepftuifephhjftbz
mjuumfcbczcjsejf
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- lexical knowledge
- phonotactics
- utterance boundaries
- distributional regularities
- predictability

$$\mathrm{TP(ju)} = 11/27 = 0.40$$
$$\mathrm{TP(zu)} = 2/23 = 0.08$$

Segmentation: what do we know?

- Multiple cues are used by adults and children in this task.
- Most cues are language specific, but some are language neutral (such as predictability).

Modeling segmentation: some points of interest/concern

- Input
- Processing strategy
- Incrementality
- Search strategy & computational complexity
- Performance
- External constraints
- Explicit lexicon

The input

- Most interesting models use child-directed speech, e.g., from CHILDES database.
- Most of the current models use phonemically transcribed input.
- Some models use a phonetic feature vector for each phoneme.
- Use of acoustic cues in models of segmentation is rare.
- The data typically does not include noise, variation or (non-linguistic) contextual cues.

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In this talk we will use phonemically transcribed child-directed speech, with some use of lexical stress.

Processing strategy

There are mainly two approaches:

- **synthetic** models form lexical items from smaller units, such as syllables or phonemes.
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There is some evidence that children use a strategy similar to analytic approach. For example, there is evidence that their first 'words' are whole utterances or phrases. They analyze these into smaller units later.

Incremental or batch

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Are batch models completely uninteresting from a cognitive perspective?

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length (n)	substrings ($\frac{n(n+1)}{2}$)	segmentations (2^{n-1})
1	1	1
10	55	512
50	1275	562,949,953,421,312
100,000	5,000,050,000	$\approx 5.0 \times 10^{30102}$

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Which one is cognitively more plausible?

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In the absence of a better option, we generally compare our model’s performance with a theoretical gold standard.

Quantitative measures of success

		Gold std.	
		+	−
Model	+	TP	FP
	−	FN	TN

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 - score = 2\,\frac{Precision \times Recall}{Precision + Recall}$$

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precision is the ratio of correctly found 'items' to the total number of items found by the model.

recall is the ratio of correctly found 'items' to the total number of items that exist in real world.

f-score is the harmonic mean of the two.

Three types of success scores

In segmentation we can measure success in three different ways by counting different 'items':

boundaries
: BP, BR, BF: credits the system when it finds a boundary. Note that we should be careful not to give extra credit for boundaries that already exist in the input (e.g., utterance boundaries).

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word tokens
: WP, WR, WF: requires both boundaries to be found.

word types
: LP, LR, LF: counts each word found only once, measuring the differences in lexical units between gold standard and the model.

Boundary, type or token scores

In case of segmentation 'items' to count can be either *boundaries*, word *tokens* or word *types*.

An example:

Input	`kittysayitagainlovekitty`
Gold standard	`kitty say it again love kitty`
Segmentation	`kitty sayit aga inlove kitty`

	TP	FP	FN	precision	recall	f-score
Boundary (B)	3	1	2	$3/4 = 0.75$	$3/5 = 0.60$	0.66
Token (W)	2	3	3	$2/5 = 0.40$	$2/6 = 0.33$	0.35
Type (L)	1	3	4	$1/4 = 0.25$	$1/5 = 0.20$	0.22

Empty part of the glass

Sometimes it is more insightful to check where/how the model fails.

		Gold std. +	Gold std. −
Model	+	TP	FP
Model	−	FN	TN

$$Oversegmentation = \frac{FP}{FP + TN}$$

$$Undersegmentation = \frac{FN}{FN + TP}$$

Baselines: I got an F-score of 50, now what?

We typically compare the results of a simulation with

- A random segmentation.
- A trivial segmentation method. An informed random segmentation model is common in the literature, but 'no segmentation' and 'segment everywhere' baselines can also be insightful.
- State-of-the-art-models in the literature. (Note that comparing different models/simulations is not always straightforward).

Baseline segmentation models

An informed random model

- It is common in literature to compare results against a model that guesses boundaries with the probability of boundaries in the data.
- Note that this model is given too much information: number/probability of boundaries.

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	boundary			word			lexicon			error	
model	P	R	F	P	R	F	P	R	F	E_o	E_u
random	27.4	50.0	35.4	8.6	13.6	10.5	7.4	38.1	12.4	50.0	50.0
RM	27.4	27.0	27.2	12.6	12.5	12.5	6.0	43.6	10.5	27.1	73.0

A state-of-the-art baseline

- Most successful models of segmentation use a strategy based on so-called 'language models' in computational linguistics.
- Assign probabilities to the utterances using:

$$P(s) = \prod_{i=1}^{n} P(w_i)$$

$$P(w) = \begin{cases} (1-\alpha) f(w) & \text{if } w \text{ is known} \\ \alpha \prod_{i=1}^{m} P(a_i) & \text{if } w \text{ is unknown} \end{cases}$$

- Then the problem becomes a search problem: finding the best segmentation under these probability assignments.

Reference model: example probability assignments

utterance probabilities				word probabilities				
utterance	freq	rank	p	word	freq	rank	p_c	p_ℓ
`yu`	4	165	0.05	`t`	0	*NA*	0.09	0.07
`In`	0	*NA*	0.01	`6`	895	3	0.04	0.02
`WAts D&t`	208	2	0.0004	`yu`	1704	1	0.001	0.0002
`bItwin`	0	*NA*	.00003	`Z`	0	*NA*	.00002	0.0001
`WAt du yu want`	33	21	0.0000001	`WAts`	569	9	0.000002	0.0000003

Reference model: performance

	boundary			word			lexicon			error	
model	P	R	F	P	R	F	P	R	F	E_o	E_u
RM	27.4	27.0	27.2	12.6	12.5	12.5	6.0	43.6	10.5	27.1	73.0
LM	84.1	82.7	83.4	72.0	71.2	71.6	50.6	61.0	55.3	5.9	17.3
GW	90.3	80.8	85.2	75.2	69.6	72.3	63.5	55.2	59.1	–	–

GW: Goldwater et al. (2009)

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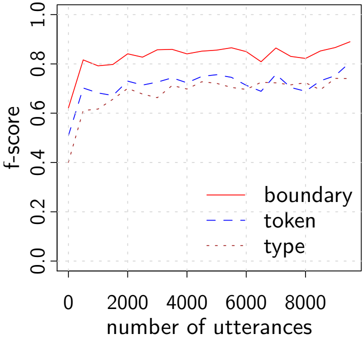

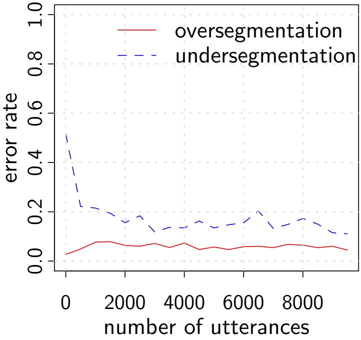

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- It is not clear how to incorporate more cues.

An alternative segmentation model

Everything being equal, we want our model to be

- incremental/online model.

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We will use,

- predictability
- common utterance beginnings and endings

to start finding boundaries, and we will make use of other lexical cues once we build a lexicon.

Putting it all together: a simple algorithm

foreach *utterance* **do**
    foreach *phoneme position in the utterance* **do**
        Get the majority vote of all measures calculated using context sizes one to four;
        if *majority vote is positive* **then**
            insert a boundary;
    output the segmented utterance ;

Alternative model: performance

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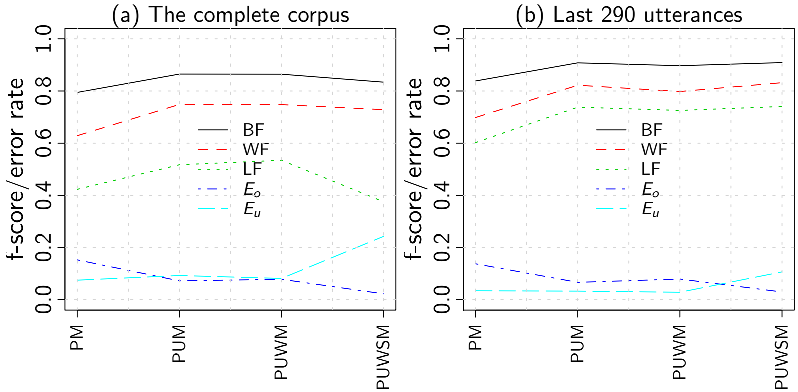
model	P	R	F	P	R	F	P	R	F	E_o	E_u
PM	69.6	92.5	79.5	56.9	70.2	62.9	36.7	49.8	42.3	15.3	7.5
UM	82.9	84.8	83.8	70.5	71.7	71.1	33.8	66.9	44.9	6.6	15.2
WM	77.5	71.3	74.3	60.6	57.2	58.9	18.3	47.7	26.4	7.8	28.7
SM	78.2	8.2	14.8	26.5	9.7	14.2	8.2	38.7	13.5	0.9	92.8
PUM	82.6	90.7	86.5	72.4	77.4	74.8	42.8	65.3	51.7	7.2	9.3
PUWM	83.7	91.2	87.3	74.1	78.8	76.4	43.9	67.7	53.3	6.7	8.8
PUWSM	92.8	75.7	83.4	78.3	68.1	72.9	26.8	62.7	37.5	2.2	24.3
RM	27.4	27.0	27.2	12.6	12.5	12.5	6.0	43.6	10.5	27.1	73.0
LM	84.1	82.7	83.4	72.0	71.2	71.6	50.6	61.0	55.3	5.9	17.3

Alternative model: more on performance



No conclusions (yet), but some points to discuss

- Which model is better? why?
- Remarks on cognitive plausibility?
- What does the simulation say about human performance?
- At what level (of Marr's) the alternative model provides analysis?
- What can be improved?