Word segmentation (example paper presentation)

Topics in Cognitive Modelling
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Sharon Goldwater
School of Informatics
University of Edinburgh
sgwater@inf.ed.ac.uk

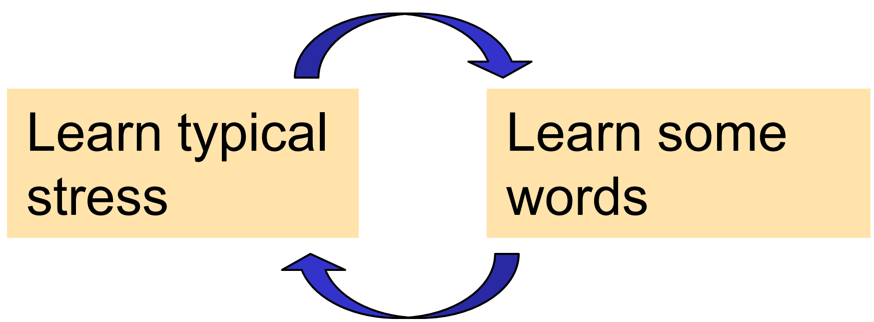
Word segmentation

- One of the first problems infants must solve when learning language: where are the word boundaries?

- May be similar to segmenting other kinds of sequences (e.g., actions) and visual scenes.

Cues to word segmentation

- Infants make use of many different cues.
  - Phonotactics (which sound sequences are legal?)
    - *sound* vs. *ndsequen*
  - Stress patterns
    - English usually stresses 1st syllable, French always the last.
  - Etc.
- But specifics differ between languages, presenting a chicken-and-egg problem:



Statistical word segmentation

- In *any* language, words create statistical regularities in the sequences of sounds in the language.
- Experimental work (Saffran et al. 1996) focuses on transitional probabilities between syllables.
  - Idea: $P(syl_i \mid syl_{i\text{-}1})$ is often lower at word boundaries.

"pretty baby": P(by|ba) > P(ba|ty)

Experimental evidence

- Infants (and adults) can learn word-like units in a nonsense language based on statistics alone.

Lexicon:

pabiku
tibudo
golatu
daropi

→

Training stimulus:

…pabikudaropigolatutibudodaropitibudogolatu
pabikudaropigolatupabikutibudogolatupabikud
aropitibudo...

- After training, test: Can subjects distinguish *words* (pabiku) vs. *part-words* (kudaro)?

Questions raised

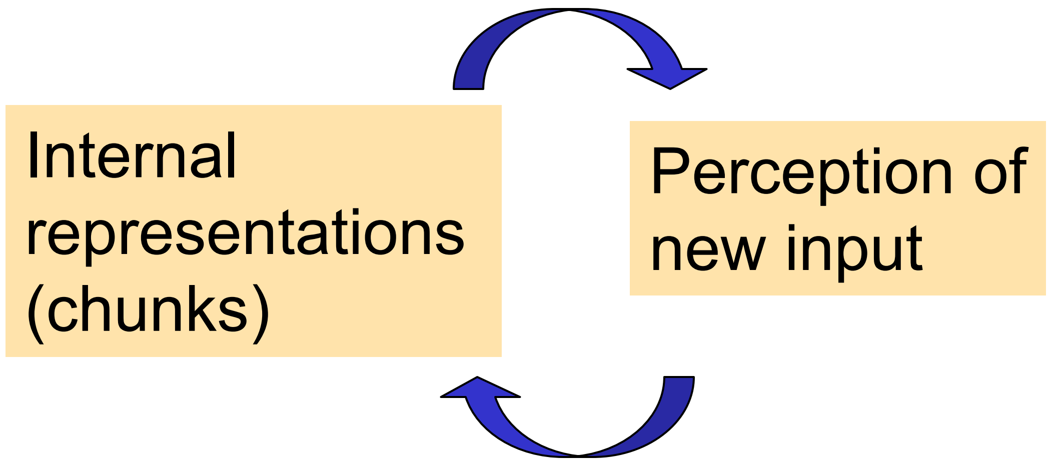
- What statistical information is actually being used?
    - Transitional probabilities or something else?
- Does the mind represent and compute with these statistics directly, or is it doing something else?
- Are listeners finding boundaries or finding words?
- What happens with more realistic linguistic input?

Today's models

- PARSER (Perruchet and Vinter, 1998)
  - Humans are not tracking boundary statistics; segmentation results from general properties of attention, perception, and memory.
- Bayesian model (Goldwater, Griffiths, and Johnson, 2007)
  - What kind of information would be useful for segmenting from more realistic input? What would result, if humans use the information optimally?
- Both models focus on words, not boundaries.
- Both use little or no domain-specific information.

PARSER

- Main thesis: No special mechanism is needed for word segmentation; it results from interaction of perception and internal representation.



PARSER

- Main thesis: No special mechanism is needed for word segmentation; it results from interaction of perception and internal representation.
  - Initially, input is perceived and chunked randomly into units.
  - Units are encoded in memory.
  - Memory decays rapidly.
  - Uncommon units disappear, common units are reinforced.
  - Units in memory influence perception and encoding of new input (input is segmented into existing units).

Representation

- Units are stored in “Percept Shaper” (PS): set of units and their weights (~strength in memory).
  - PS starts with set of primitive units (syllables), weight =1.
  - Units with weight 1 or more can “shape perception”

pa	1
bi	1
ku	1
ti	1
bu	1
do	1
...	

Processing

- On each cycle:
  - One “percept” is seen: 1, 2, or 3 units in size.
  - Add new unit to PS, or increment weight of existing unit.
  - All units in PS decay, overlapping units interfere: decrease weights.

pa	1
bi	1
ku	1
ti	1
bu	1
do	1
...	

Input: pabikudaropigolatutibudodaropitibudo...

Percept: pabi

Over time

- Frequent subsequences reinforce units in PS
- Infrequent subsequences disappear from PS.
- Words are more frequent, so will dominate.

pa	1
bi	1
ku	1
ti	1
bu	1
do	1
...	

pabiku	14.1
pabi	12.8
tibudo	11.8
bikutibudo	3.1
gola	3.0
pa	2.4
...	

pabiku	67.4
tibudo	63.2
golatu	59.1
daropi	55.2
tibudopabiku	1.3

Experiments

- Experiment 1, 2, and 4 show:
  - Using same input stimulus as Saffran et al. experiments, PARSER learns the lexicon.
  - Can also do so while simulating lowered attention (like humans).
  - Predicts that different word lengths should present no problem (since then, this has been verified in humans).

Issues

- Would it work on realistic input data?
  - Discussion suggests not (unless modified).
- Experiment 3: simulating infant study.
  - Uses 4 lexical items instead of 6.
  - Performance actually goes down: pairs of words are found more commonly (*pabikutibudo*), interfere with single words.
  - Fixes this by changing model parameters – “infants have more limited memory” – but this is done post-hoc.
  - Still predicts that adults would have more trouble with 4 lexical items than 6.

Summary

- PARSER provides a mechanistic account of word segmentation based on general principles of attention, perception, and memory.
- No explicit tracking of statistics is needed.
- Works on experimental stimuli but might need modifications for realistic language.
- Probably would work in other domains.
- Smaller vocabulary is harder than larger one??
- Lots of parameters – how sensitive to these?

Bayesian model

- An ideal observer analysis: what words would be learned if statistical information is used optimally, and the learner assumes:
  a) Words are defined as statistically independent units in the input (i.e., randomly ordered, as in experimental stimuli)?
  b) Words are defined as units that help predict other units?
- Is (a) sufficient? I.e., what kind of prior does the learner need?

Two kinds of models

- Unigram model: words are independent.

$$P(w_1 \ldots w_n) = \prod_{i=1}^{n} P(w_i)$$

Two kinds of models

- Unigram model: words are independent.

$$P(w_1 \dots w_n) = \prod_{i=1}^{n} P(w_i)$$

- Bigram model: words depend on other words.

$$P(w_1 \dots w_n) = \prod_{i=1}^{n} P(w_i | w_{i-1})$$

Data:

lookatthedoggie
seethedoggie
shelookssofriendly
…

Hypotheses:

lookatthedoggie
seethedoggie
shelookssofriendly
…

l o o k a t t h e d o g g i e
s e e t h e d o g g i e
s h e l o o k s s o f r i e n d l y
…

look at thed oggi e
se e thed oggi e
sh e look ssofri e ndly
…

look at the doggie
see the doggie
she looks so friendly
…

$P(d|h)=1$

i like pizza
what about you
…

abc def gh
ijklmn opqrst uvwx
…

$P(d|h)=0$

Bayesian segmentation

- Data: unsegmented corpus (transcriptions).
- Hypotheses: sequences of word tokens.

$$\underbrace{P(h|d)}_{\text{posterior}} \propto \underbrace{P(d|h)}_{\text{likelihood}} \underbrace{P(h)}_{\text{prior}}$$

= 1 if concatenating words forms corpus,
= 0 otherwise.

Encodes assumptions of learner.

- Optimal solution is the segmentation with highest prior probability.

Bayesian model

Assumes word w_i is generated as follows:

1. Is w_i a novel lexical item?

$$P(yes) = \frac{\alpha}{n+\alpha}$$

$$P(no) = \frac{n}{n+\alpha}$$

Fewer word types =
Higher probability

Bayesian model

Assume word w_i is generated as follows:

2. If novel, generate phonemic form $x_1 \ldots x_m$:

$$P(w_i = x_1 \ldots x_m) = \prod_{i=1}^{m} P(x_i)$$

Shorter words =
Higher probability

If not, choose lexical identity of w_i from previously occurring words:

$$P(w_i = w) = \frac{n_w}{n}$$

Power law =
Higher probability

Experiments

- Input: phonemically transcribed infant-directed speech.

```
yuwanttusiD6bUk
lUkD*z6b7wIThIzh&t
&nd6dOgi
yuwanttulUk&tDIs
...
```

- Optimal segmentation is found using a standard optimization algorithm (Gibbs sampling).
- Compare to bigram model (developed using similar maths).

Example output

Unigram model:

```
youwant to see thebook
look theres aboy with his hat
and adoggie
you wantto lookatthis
lookatthis
havea drink
okay now
whatsthis
whatsthat
whatisit
look canyou take itout
...
```

Bigram model:

```
you want to see the book
look theres a boy with his hat
and a doggie
you want to lookat this
lookat this
have a drink
okay now
whats this
whats that
whatis it
look canyou take it out
...
```

- Quantitative comparison verifies bigram is better.

What's wrong with unigrams?

- Model assumes (falsely) that words have the same probability regardless of context.

$P(\texttt{that}) = .024$ $P(\texttt{that}|\texttt{whats}) = .46$ $P(\texttt{that}|\texttt{to}) = .0019$

- Positing amalgams allows the model to capture word-to-word dependencies.
- Paper argues that this is a general property of unigram models, not specific to this one.

Summary

- Good segmentations of naturalistic data can be found using fairly weak/domain-general prior assumptions.
  - Utterances are composed of discrete units (words).
  - Units tend to be short.
  - Some units occur frequently, most do not.
  - Units tend to come in predictable patterns.
- More sophisticated use of information works better.
  - But still possible that simpler learner is enough to start learning other language-specific cues.

Issues

- No direct comparison to humans.
  - Is there evidence that human performance is consistent with Bayesian predictions? [Later paper suggests: yes]
  - Are humans able to use bigram information?
- Algorithm iterates multiple times over the entire corpus – are more cognitively plausible algorithms possible?

Conclusion

- Models have different emphasis:
  - PARSER: mechanistic explanation; experimental data.
  - Bayesian model: ideal observer analysis; naturalistic data.
- But some similar ideas/conclusions:
  - Segmentation is about building a lexicon, not finding boundaries.
  - Built on domain-general principles.
- Open questions:
  - Relationship to adult speech processing?
  - Multiple cues?

References

Goldwater, S., Griffiths, T. L., and Johnson, M. (2007). Distributional cues to word segmentation: Context is important. *Proceedings of the 31st Boston University Conference on Language Development*, pp. 239-250. Somerville, MA: Cascadilla Press.

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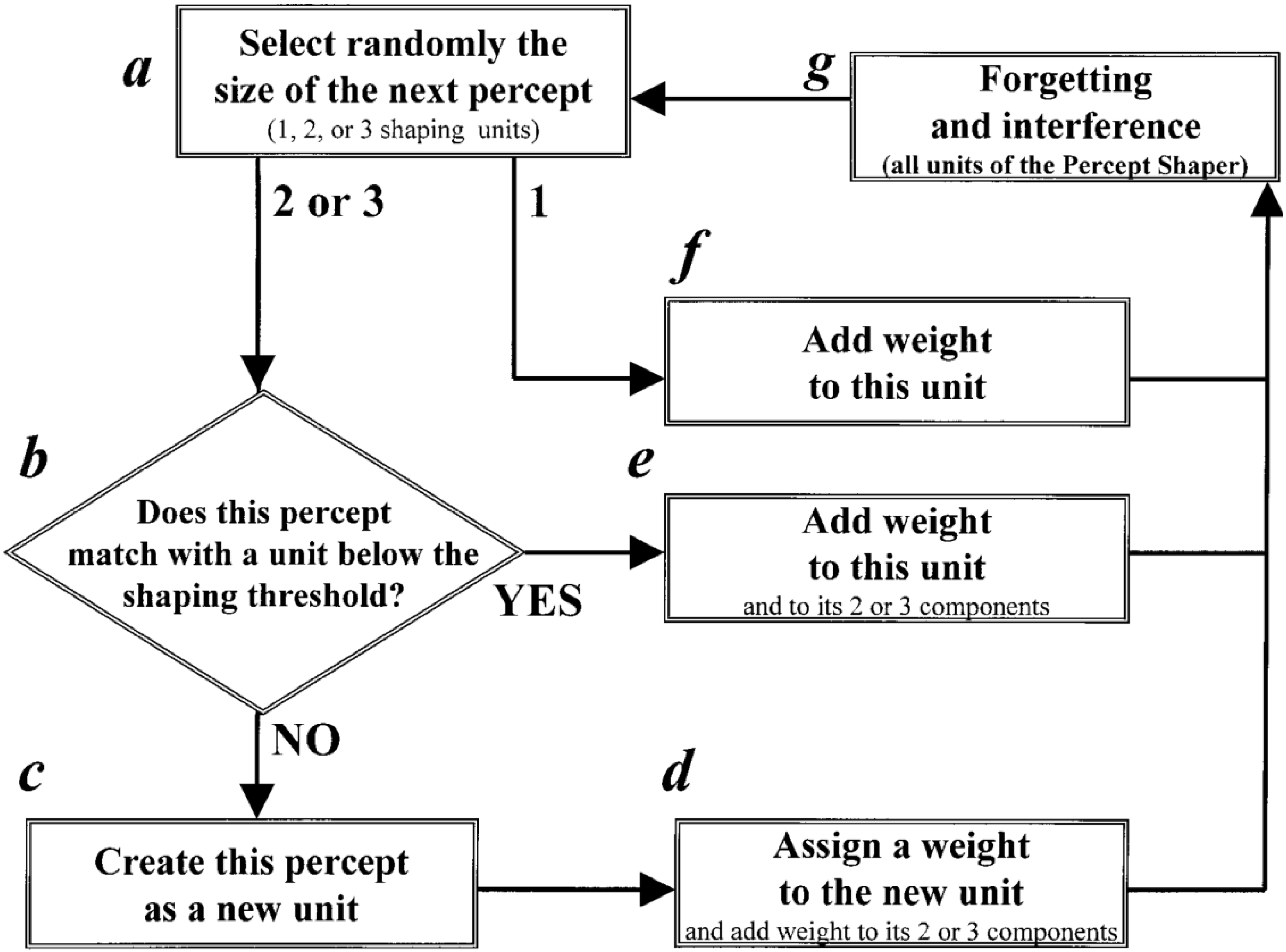


Figure: Perruchet and Vinter (1998)

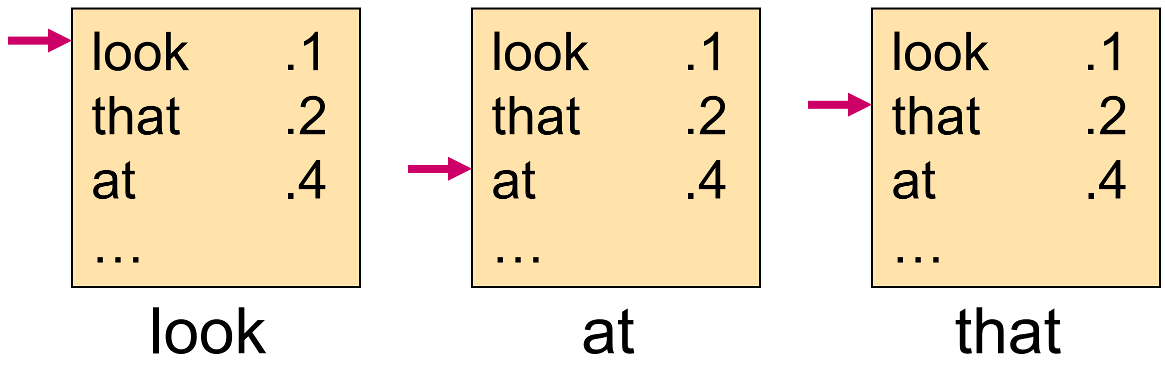
Bayesian learning

- Want to find an explanatory linguistic hypothesis that
  - accounts for the observed data.
  - conforms to prior expectations.

$$P(h \mid d) \propto P(d \mid h) P(h)$$

Two kinds of models

- Unigram model: words are independent.
  - Generate a sentence by generating each word independently.



Two kinds of models

- Bigram model: words predict other words.
  - Generate a sentence by generating each word, conditioned on the previous word.