

Speech Segmentation

Informatics 1 CG: Lecture 8

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Reading:

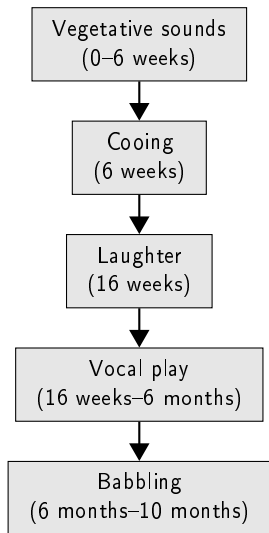
M. R. Brent and T. A. Cartwright (1996). Distributional regularity and phonotactic constraints are useful for segmentation. Cognition 61, 93–125.

T. Harley (2001). The Psychology of Language, Chapter 4.

- We have so far looked at the words and rules theory.
- Different models of past tense formation.
- Perceptrons and neural networks.
- Watch Pinker discuss his book at:
<https://www.youtube.com/watch?v=mqDGdgmUmvc>

Back to language and how words emerge in the first place. We will look at **speech segmentation**.

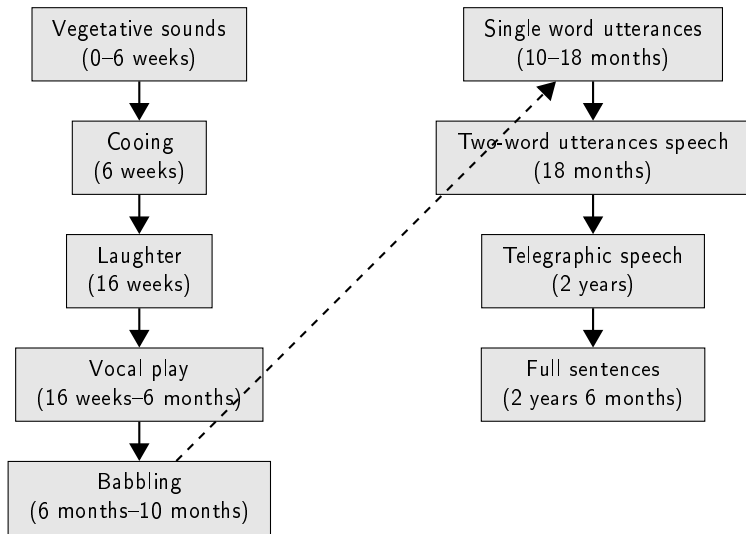
The Development of Language



<https://www.youtube.com/watch?v=YI1aPCdJaMw>

http://www.youtube.com/watch?v=_JmA2ClUvUY

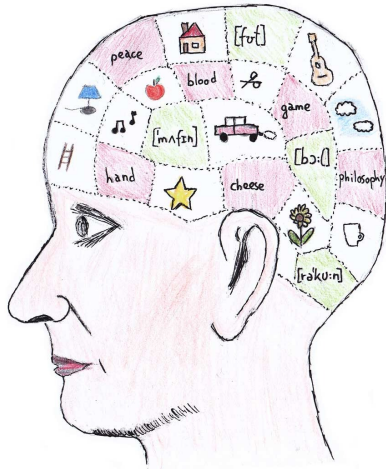
The Development of Language



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How Do We Learn Words?



- Knowing a language implies having a **mental lexicon**
- Memorized set of associations among sound sequences, their meanings, and their syntax.
- Speech stream lacks any acoustic analog of the **blank spaces** between printed words.
- Basic units of linguistic input are not words but **entire utterances**.
- Child's task: to **discover the words** themselves in addition to meaning and syntax.

What do Infants Hear?

Where are you going?

How does a bunny rabbit walk?

Does he walk like you or does he go hophophop?

What are you doing?

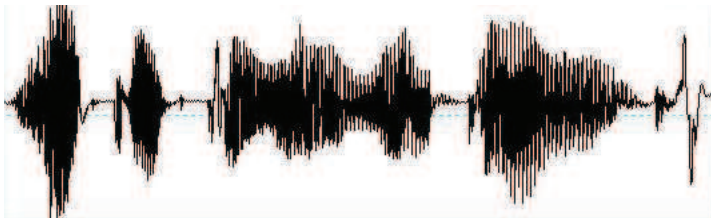
Sweepbroom.

Is that a broom?

It though 'twas a brush.

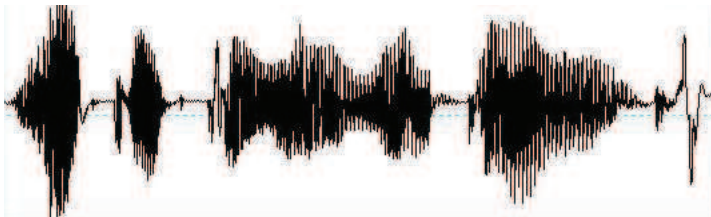
Adam's mother (Brown, 1973)

Where Are the Words?



THEREDONATEAKETTLEOFTENCHIPS

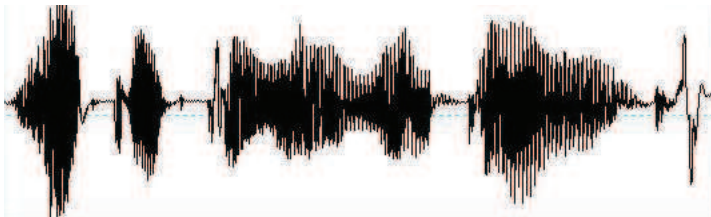
Where Are the Words?



THEREDONATEAKETTLEOFTENCHIPS

THE RED ON A TEA KETTLE OFTEN CHIPS

Where Are the Words?

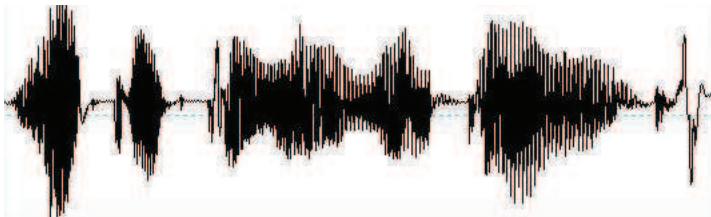


THEREDONATEAKETTLEOFTENCHIPS

THE RED ON A TEA KETTLE OFTEN CHIPS

THERE, DON ATE A KETTLE OF TEN CHIPS

Where Are the Words?



THEREDONATEAKETTLEOFTENCHIPS

THE RED ON A TEA KETTLE OFTEN CHIPS

THERE, DON ATE A KETTLE OF TEN CHIPS

THERE, DONATE A KETTLE OF TEN CHIPS

- How does an infant divide the input into reusable units?
- How does she represent those units?
- What does she know about them and when?

Not an end in itself: provides **useful units** (Peters, 1983) for learning a grammar: lexicon, morphosyntax, phonology.

How do Infants Segment Speech?

Infants make use of **multiple cues** in the input, most popularly:

- **Stress patterns:** English usually stresses 1st syllable, French always the last; final syllables of words are longer (*hamster* vs. *ham*).
- **Phonotactic constraints:** every word must contain a vowel, finite set of consonant clusters that can occur at the beginning of a word, before the first vowel (*gdog* is not a possible English word).
- **Statistical regularities:** within words, there is a consistent sequence of elements.
- **Bootstrapping** from known words.

Words create **regularities** in the sound sequences of a language.

- There is a **consistent sequence** of elements within words
- Sequences that don't occur within words can only occur at word boundaries.
- Sequences that don't occur within a word will tend to occur infrequently.
- Thus, we can find word boundaries by looking for **unlikely transitions**.

Transitional Probability

$$P(y|x) = \frac{p(x,y)}{p(x)} \approx \frac{\text{freq}(x,y)}{\text{freq}(x)}$$

Suppose the phoneme [ð] occurs 200,000 times in a text:

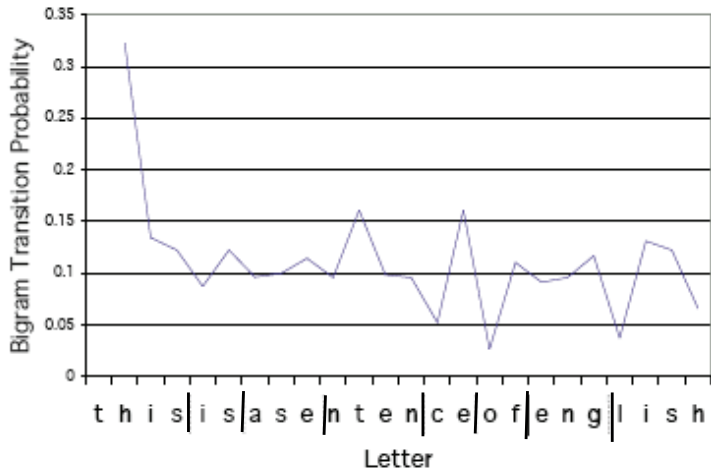
- 190,000 times are before a vowel (as in *the*, *this*);
- 200 times are before [m].

Transitional Probability

$$p(\text{vowel}|\text{ð}) = \frac{190,000}{200,000} = .95$$

$$P(m|\text{ð}) = \frac{200}{200,000} = .001$$

Transitional Probability



Saffran et al. (1996) asked whether 8-month-old infants can extract information about word boundaries solely on the basis of statistical information.

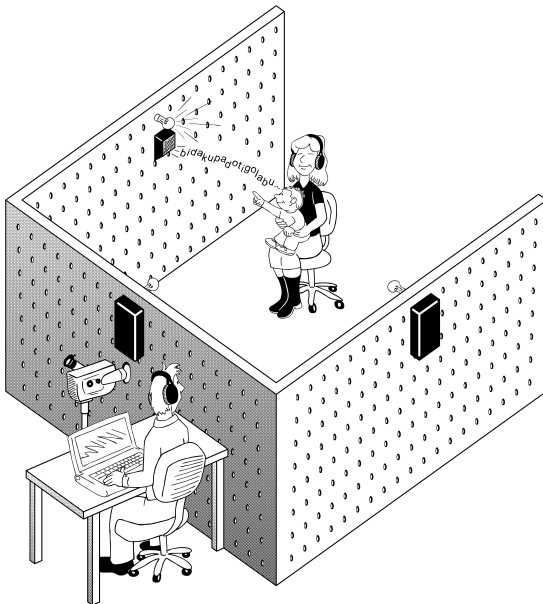
- 1 Create “language” from nonsense words.
- 2 Infants listen to synthesized language (*tokibu, gikoba*).
- 3 Then, test: can infants distinguish words (*tokibu*) vs. part-words (*bugiko*)?

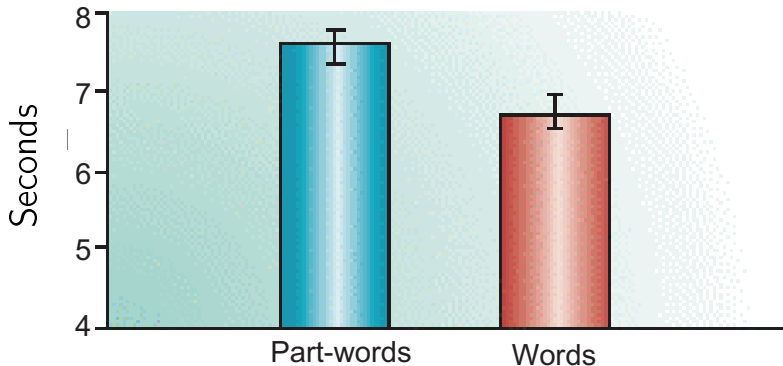
tokibugikobagopilatipolutokibu
gopilatipolutokibugikobagopila
gikobatokibugopilatipolugikoba
tipolugikobatipolugopilatipolu
tokibugopilatipolutokibugopila
tipolutokibugopilagikobatipolu
tokibugopilagikobatipolugikoba
tipolugikobatipolutokibugikoba
gopilatipolugikobatokibugopila

tokibgikobagopilatipolutokibu
gopilatipolutokibugikobagopila
gikobatokibugopilatipolugikoba
tipolugikobatipolugopilatipolu
tokibugopilatipolutokibugopila
tipolutokibugopilagikobatipolu
tokibugopilagikobatipolugikoba
tipolugikobatipolutokibugikoba
gopilatipolugikobatokibugopila

- Infants are exposed for 2 minutes to nonsense language (*tokibu, gopila, gikoba, tipolu*).
- Only **statistical cues** to word boundaries
- Then record how long they attend to novel sets of stimuli that either do or do not share some property with the familiarization data.
- Discrimination between *words* and *part-words* (sequences spanning word boundaries)
- If **there's a difference**, there has been some **learning** during familiarization.

Headturn Preference Procedure





- Infants show longer listening times for part-words
- Infants can extract information about sequential statistics of syllables (input contained no pauses, intonational patterns)

- Humans can use statistical information to segment speech.
- But all words were trisyllabic
- So, transitional probabilities were either 1 or .33
- Will this work if these are varied in a more naturalistic way?

Patricia Kuhl: The genius of babies

https://www.ted.com/talks/patricia_kuhl_the_linguistic_genius_of_babies

- The use of transitional probabilities to do word segmentation ignores the fact that **words** are being **learned at the same time**.
- There are statistical methods for speech segmentation that incorporate the learning of a lexicon as a sub-component.
- Brent and Cartwright (1996): find the **lexicon** which **minimizes the description** of the observed data

Minimum Description Length

$$\text{size}(\text{description}) = \text{size}(\text{lexicon}) + \text{size}(\text{data-encoding})$$

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- The MDL principle minimizes the length of words
shorter words are more plausible
- Minimizes the number of different words
try to make use of words you already know
- Maximizes the probability of each word
words recur as often as possible

Brent and Cartwright (1996)

Input

doyouseethekitty

seethekitty

doyoulikethekitty

Brent and Cartwright (1996)

Input

doyouseethekitty

seethekitty

doyoulikethekitty

Segmentation 1

do you see thekitty

see thekitty

do you like thekitty

Brent and Cartwright (1996)

Input

doyouseethekitty

seethekitty

doyoulikethekitty

Segmentation 1

do you see thekitty

see thekitty

do you like thekitty

Lexicon 1

1 do 2 thekitty 3 you

4 like 5 see

Brent and Cartwright (1996)

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Segmentation 1

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4 like 5 see

Derivation 1

1 3 5 2

5 2

1 3 4 2

Brent and Cartwright (1996)

Input

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Segmentation 1

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1 3 5 2
5 2
1 3 4 2

Minimum Description Length

$\text{size}(\text{description}) =$
 $\text{size}(\text{lexicon}) + \text{size}(\text{data-encoding})$

$\text{size}(\text{lexicon}) =$ number of characters
characters = letters and digits

$\text{size}(\text{data-encoding}) =$ number of
characters in derivation

Brent and Cartwright (1996)

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seethekitty
doyoulikethekitty

Segmentation 1

do you see thekitty
see thekitty
do you like thekitty

Lexicon 1

1 do 2 thekitty 3 you
4 like 5 see

Derivation 1

1 3 5 2
5 2
1 3 4 2

Minimum Description Length

$\text{size}(\text{description}) =$
 $\text{size}(\text{lexicon}) + \text{size}(\text{data-encoding})$

$\text{size}(\text{lexicon}) =$ number of characters
characters = letters and digits

$\text{size}(\text{data-encoding}) =$ number of
characters in derivation

Length: $25 + 10 = 35$

Brent and Cartwright (1996)

Input

doyouseethekitty

seethekitty

doyoulikethekitty

Segmentation 2

do you see thekitty

see the kitty

do you like the kitty

Lexicon 2

1 do 2 the 3 you

4 like 5 see 6 kitty

Derivation 2

1 3 5 2 6

5 2 6

1 3 4 2 6

Minimum Description Length

$\text{size}(\text{description}) =$
 $\text{size}(\text{lexicon}) + \text{size}(\text{data-encoding})$

$\text{size}(\text{lexicon}) =$ number of characters
characters = letters and digits

$\text{size}(\text{data-encoding}) =$ number of
characters in derivation

Brent and Cartwright (1996)

Input

doyouseethekitty
seethekitty
doyoulikethekitty

Segmentation 2

do you see thekitty
see the kitty
do you like the kitty

Lexicon 2

1 do 2 the 3 you
4 like 5 see 6 kitty

Derivation 2

1 3 5 2 6
5 2 6
1 3 4 2 6

Minimum Description Length

$\text{size}(\text{description}) =$
 $\text{size}(\text{lexicon}) + \text{size}(\text{data-encoding})$

$\text{size}(\text{lexicon}) =$ number of characters
characters = letters and digits

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characters in derivation

Length: $26 + 13 = 39$

- MDL model is tested on (phonetically) transcribed speech from the CHILDES corpus.
- An **idealization of** the raw **acoustic signal**.
- Model searches for segmentation of the input with least MDL.
- Search algorithm is **not incremental**; it reads in the entire input before segmenting any part of it.
- Approach does not rely on language-specific input!
- Computational simulations systematically explore hypothesis that distributional regularity is useful for word segmentation.

In order to acquire a lexicon young children segment speech into words using multiple sources of support; focused on distributional regularities.

- transitional probability provides cues
- verified by Saffran et al. (1996) experiments
- computational model of word segmentation
- based on Minimum Description Length Principle

Next lecture: word learning.