Psych 156A/ Ling 150: Acquisition of Language II

Lecture 7
Words in Fluent Speech II

Announcements

Be working on HW2

Be working on word segmentation review questions

Midterm on Tuesday, 5/8

Computational Problem

Divide fluent speech into individual words

tuðəkǽsəlbijándðəgáblɪnsíɾi

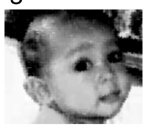
tu ðə kǽsəl bijánd ðə gáblɪn síɾi
to the castle beyond the goblin city

Recap: Saffran, Aslin, & Newport (1996)

Experimental evidence suggests that 8-month-old infants can track statistical information such as the transitional probability between syllables. This can help them solve the task of word segmentation.

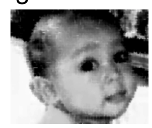
Evidence comes from testing children in an artificial language paradigm, with very short exposure time.

Computational Modeling Data (Digital Children)



Computational model: a program that simulates the mental processes occurring in a child. This requires knowing what the input and output are, and then testing the strategies that can take the given input and transform it into the desired output.

Computational Modeling Data (Digital Children)



For example, in word segmentation, the input could be a sequence of syllables and the desired output is words (groups of syllables).

Input: "un der stand my po si tion"
Desired Output: "understand my position"

How good is transitional probability on real data?

Gambell & Yang (2006): Computational model goal

Real data, Psychologically plausible learning algorithm

Realistic data is important to use since the experimental study of Saffran, Aslin, & Newport (1996) used artificial language data, and it's not clear how well the results they found will map to real language.

A psychologically plausible learning algorithm is important since we want to make sure whatever strategy the model uses is something a child could use, too. (Transitional probability would probably work, since Saffran, Aslin, & Newport (1996) showed that infants can track this kind of information in the artificial language.)

How do we measure word segmentation performance?

Perfect word segmentation:
- identify all the words in the speech stream (*recall*)
- only identify syllables groups that are actually words (*precision*)

ðəbígbǽdwʌ́lf
↓
ðə bíg bǽd wʌ́lf
the big bad wolf

How do we measure word segmentation performance?

Perfect word segmentation:
identify all the words in the speech stream (*recall*)
only identify syllables groups that are actually words (*precision*)

ðəbígbǽdwʌ́lf
↓
ðə bíg bǽd wʌ́lf
the big bad wolf

Recall calculation:
# of real words found / # of actual words
Identified 4 real words: the, big, bad, wolf
Should have identified 4 words: the, big, bad, wolf
Recall Score: 4 words found/4 should have found = 1.0

How do we measure word segmentation performance?

Perfect word segmentation:
identify all the words in the speech stream (*recall*)
only identify syllables groups that are actually words (*precision*)

ðəbígbǽdwʌ́lf
↓
ðə bíg bǽd wʌ́lf
the big bad wolf

Precision calculation:
# of real words found / # of words guessed
Identified 4 real words: the, big, bad, wolf
Identified 4 words total: the, big, bad, wolf
Precision Score: 4 real words found/4 words found= 1.0

How do we measure word segmentation performance?

Perfect word segmentation:
identify all the words in the speech stream (*recall*)
only identify syllables groups that are actually words (*precision*)

ðəbígbǽdwʌ́lf
↓
Error ðəbíg bǽd wʌ́lf
thebig bad wolf

How do we measure word segmentation performance?

Perfect word segmentation:
identify all the words in the speech stream (*recall*)
only identify syllables groups that are actually words (*precision*)

ðəbígbǽdwʌ́lf
↓
Error ðəbíg bǽd wʌ́lf
thebig bad wolf

Recall calculation:
Identified 2 real words: bad, wolf
Should have identified 4 words: the, big, bad, wolf
Recall Score: 2 real words found/4 should have found = 0.5

How do we measure word segmentation performance?

Perfect word segmentation:
- identify all the words in the speech stream (*recall*)
- only identify syllables groups that are actually words (*precision*)

ðəbígbǽdwʌ́lf

↓

Error ðəbíg bǽd wʌ́lf

thebig bad wolf

Precision calculation:

Identified 2 real words: bad, wolf

Identified 3 words total: thebig, bad, wolf

Precision Score: 2 real words/3 words identified = 0.666…

How do we measure word segmentation performance?

Perfect word segmentation:
- identify all the words in the speech stream (*recall*)
- only identify syllables groups that are actually words (*precision*)

Want good scores on both of these measures in order to be sure that word segmentation is really successful

Where does the realistic data come from?

CHILDES

Child Language Data Exchange System
http://childes.psy.cmu.edu/

Large collection of child-directed speech data (usually parents interacting with their children) transcribed by researchers. Used to see what children's input is actually like.

CHILDES Child Language Data Exchange System

Where does the realistic data come from?

Gambell & Yang (2006)

Looked at Brown corpus files in CHILDES (226,178 words made up of 263,660 syllables).

Converted the transcriptions to pronunciations using a pronunciation dictionary called the CMU Pronouncing Dictionary.

http://www.speech.cs.cmu.edu/cgi-bin/cmudict

The CMU Pronouncing Dictionary

Where does the realistic data come from?

Converting transcriptions to pronunciations

- **Look up words or a sentence (v. 0.7a)**

Look Up

☑ Show Lexical Stress

- the big bad wolf
- DH AH0 . B IH1 G . B AE1 D . W UH1 L F .

Gambell and Yang (2006) tried to see if a model learning from transitional probabilities between syllables could correctly segment words from realistic data.

the big bad wolf

DH AH0 . B IH1 G . B AE1 D . W UH1 L F .

ðə bíg bǽd wʌ́lf

Segmenting Realistic Data

Gambell and Yang (2006) tried to see if a model learning from transitional probabilities between syllables could correctly segment words from realistic data.

ðə bíg bǽd wʌ́lf

DH AH0 B IH1 G B AE1 D W UH1 L F

"There is a word boundary AB and CD if

TrProb(A --> B) > TrProb(B-->C) < TrProb(C --> D)."

Transitional probability minimum

Segmenting Realistic Data

Gambell and Yang (2006) tried to see if a model learning from transitional probabilities between syllables could correctly segment words from realistic data.

Desired word segmentation

ðə | bíg | bǽd | wʌ́lf

DH AH0 | B IH1 G | B AE1 D | W UH1 L F

the | big | bad | wolf

Modeling Results for Transitional Probability

Precision: 41.6%

Recall: 23.3%

A learner relying only on transitional probability does not reliably segment words such as those in child-directed English.

About 60% of the words posited by the transitional probability learner are not actually words (41.6% precision) and almost 80% of the actual words are not extracted (23.3% recall).

Why such poor performance?

"We were surprised by the low level of performance. Upon close examination of the learning data, however, it is not difficult to understand the reason….a sequence of monosyllabic words requires a word boundary after each syllable; a [transitional probability] learner, on the other hand, will only place a word boundary between two sequences of syllables for which the [transitional probabilities] within [those sequences] are higher than [those surrounding the sequences]..." - Gambell & Yang (2006)

Why such poor performance?

"We were surprised by the low level of performance. Upon close examination of the learning data, however, it is not difficult to understand the reason….a sequence of monosyllabic words requires a word boundary after each syllable; a [transitional probability] learner, on the other hand, will only place a word boundary between two sequences of syllables for which the [transitional probabilities] within [those sequences] are higher than [those surrounding the sequences]..." - Gambell & Yang (2006)

ðə bíg bǽd wʌ́lf

TrProb1 TrProb2 TrProb3

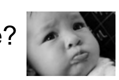
Why such poor performance?

"We were surprised by the low level of performance. Upon close examination of the learning data, however, it is not difficult to understand the reason….a sequence of monosyllabic words requires a word boundary after each syllable; a [transitional probability] learner, on the other hand, will only place a word boundary between two sequences of syllables for which the [transitional probabilities] within [those sequences] are higher than [those surrounding the sequences]..." - Gambell & Yang (2006)

ðə bíg bǽd wʌ́lf

0.6 0.3 0.7

Why such poor performance?



"We were surprised by the low level of performance. Upon close examination of the learning data, however, it is not difficult to understand the reason….a sequence of monosyllabic words requires a word boundary after each syllable; a [transitional probability] learner, on the other hand, will only place a word boundary between two sequences of syllables for which the [transitional probabilities] within [those sequences] are higher than [those surrounding the sequences]..." - Gambell & Yang (2006)

ðə bíg bǽd wʌ́lf

0.6 0.3 0.7

0.6 > 0.3 < 0.7

Why such poor performance?

"We were surprised by the low level of performance. Upon close examination of the learning data, however, it is not difficult to understand the reason….a sequence of monosyllabic words requires a word boundary after each syllable; a [transitional probability] learner, on the other hand, will only place a word boundary between two sequences of syllables for which the [transitional probabilities] within [those sequences] are higher than [those surrounding the sequences]..." - Gambell & Yang (2006)

learner posits one word boundary at minimum TrProb

ðə bíg ⋮ bǽd wʌ́lf

0.6 0.3 0.7

0.6 > 0.3, 0.3 < 0.7

Why such poor performance?

"We were surprised by the low level of performance. Upon close examination of the learning data, however, it is not difficult to understand the reason….a sequence of monosyllabic words requires a word boundary after each syllable; a [transitional probability] learner, on the other hand, will only place a word boundary between two sequences of syllables for which the [transitional probabilities] within [those sequences] are higher than [those surrounding the sequences]..." - Gambell & Yang (2006)

…but nowhere else

ðə bíg ⋮ bǽd wʌ́lf

0.6 0.3 0.7

0.6 > 0.3, 0.3 < 0.7

Why such poor performance?

"We were surprised by the low level of performance. Upon close examination of the learning data, however, it is not difficult to understand the reason….a sequence of monosyllabic words requires a word boundary after each syllable; a [transitional probability] learner, on the other hand, will only place a word boundary between two sequences of syllables for which the [transitional probabilities] within [those sequences] are higher than [those surrounding the sequences]..." - Gambell & Yang (2006)

…but nowhere else

ðə bíg ⋮ bǽd wʌ́lf

Why such poor performance?

"We were surprised by the low level of performance. Upon close examination of the learning data, however, it is not difficult to understand the reason….a sequence of monosyllabic words requires a word boundary after each syllable; a [transitional probability] learner, on the other hand, will only place a word boundary between two sequences of syllables for which the [transitional probabilities] within [those sequences] are higher than [those surrounding the sequences]..." - Gambell & Yang (2006)

…but nowhere else

ðəbíg ⋮ bǽdwʌ́lf

thebig ⋮ badwolf

Precision for this sequence: 0 words correct out of 2 found

Recall: 0 words correct out of 4 that should have been found

Why such poor performance?

"More specifically, a monosyllabic word is followed by another monosyllabic word 85% of the time. As long as this is the case, [a transitional probability learner] cannot work." - Gambell & Yang (2006)

Additional Learning Bias

Gambell & Yang (2006) idea
Children are sensitive to the properties of their native language like stress patterns very early on. Maybe they can use those sensitivities to help them solve the word segmentation problem.

Hypothesis: Unique Stress Constraint (USC)
Children think a word can bear at most one primary stress.

no stress	stress	stress	stress
ðə	bíg	bǽd	wʌ́lf
the	big	bad	wolf

Additional Learning Bias

Gambell & Yang (2006) idea
Children are sensitive to the properties of their native language like stress patterns very early on. Maybe they can use those sensitivities to help them solve the word segmentation problem.

Hypothesis: Unique Stress Constraint (USC)
Children think a word can bear at most one primary stress.

ðə	bíg	bǽd	wʌ́lf
the	big	bad	wolf

Learner gains knowledge: These must be separate words

Additional Learning Bias

Gambell & Yang (2006) idea
Children are sensitive to the properties of their native language like stress patterns very early on. Maybe they can use those sensitivities to help them solve the word segmentation problem.

Hypothesis: Unique Stress Constraint (USC)
Children think a word can bear at most one primary stress.

húz ə	fréd	əv	ðə	bíg	bǽd	wʌ́lf
who's a	fraid	of	the	big	bad	wolf

Get these boundaries because stressed (strong) syllables are next to each other.

Additional Learning Bias

Gambell & Yang (2006) idea
Children are sensitive to the properties of their native language like stress patterns very early on. Maybe they can use those sensitivities to help them solve the word segmentation problem.

Hypothesis: Unique Stress Constraint (USC)
Children think a word can bear at most one primary stress.

húz ə fréd əv ðə bíg bǽd wʌ́lf
who's a fraid of the big bad wolf

Can use this in tandem with transitional probabilities when there are weak (unstressed) syllables between stressed syllables.

Additional Learning Bias

Gambell & Yang (2006) idea
Children are sensitive to the properties of their native language like stress patterns very early on. Maybe they can use those sensitivities to help them solve the word segmentation problem.

Hypothesis: Unique Stress Constraint (USC)
Children think a word can bear at most one primary stress.

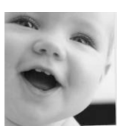
? ?
húz ə fréd əv ðə bíg bǽd wʌ́lf
who's a fraid of the big bad wolf

There's a word boundary at one of these two.

USC + Transitional Probabilities

Precision: 73.5%

Recall: 71.2%



A learner relying on transitional probability but who also has knowledge of the Unique Stress Constraint does a much better job at segmenting words such as those in child-directed English.

Only about 25% of the words posited by the transitional probability learner are not actually words (73.5% precision) and about 30% of the actual words are not extracted (71.2% recall).

Another Strategy

Using words you recognize to help you figure out words you don't recognize

Another Strategy: Algebraic Learning

Algebraic Learning (Gambell & Yang (2003))

Subtraction process of figuring out unknown words.

"Look, honey - it's a big goblin!"

bíggáblɪn

bíg = big (familiar word)

bíggáblɪn

_bíg______

gáblɪn = (new word)

Evidence of Algebraic Learning in Children

"Behave yourself!"
"I was have!"
(be-have = be + have)

"Was there an adult there?"
"No, there were two dults."
(a-dult = a + dult)

"Did she have the hiccups?"
"Yeah, she was hiccing-up."
(hicc-up = hicc + up)

Experimental Evidence of Algebraic Learning

Experimental studies show young infants can use familiar words to segment novel words from their language

-Bortfeld, Morgan, Golinkoff, & Rathbun 2005:
6-month-old English infants use their own name or *Mommy/Mama*

-Hallé, Durand, Bardies, & de Boysson 2008
11-month-old French infants use French articles like *le, les,* and *la*

-Shi, Werker, & Cutler 2006
11-month-old English infants use English articles like *her, its,* and *the*

-Shi, Cutler, Werker, & Cruickshank 2006
11-month-old English infants (but not 8-month-old English infants) use the English article *the*

Using Algebraic Learning + USC

WeakSyl	StrongSyl	StrongSyl	StrongSyl
the	big	bad	wolf
ðə	bíg	bǽd	wʌ́lf

"the big bad wolf"

Using Algebraic Learning + USC

Familiar word: “the” (algebraic learning)

WeakSyl	StrongSyl	StrongSyl	StrongSyl
the	big	bad	wolf
ðə	bíg	bǽd	wʌ́lf

“the big bad wolf”

Using Algebraic Learning + USC

USC says these must be separate words

WeakSyl	StrongSyl	StrongSyl	StrongSyl
the	big	bad	wolf
ðə	bíg	bǽd	wʌ́lf

“the big bad wolf”

Using Algebraic Learning + USC

Correct segmentation!

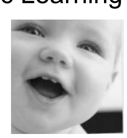
WeakSyl	StrongSyl	StrongSyl	StrongSyl
the	big	bad	wolf
ðə	bíg	bǽd	wʌ́lf

“the big bad wolf”

Algebraic Learning + USC

Precision: 95.9%

Recall: 93.4%



A learner relying on algebraic learning and who also has knowledge of the Unique Stress Constraint does a really great job at segmenting words such as those in child-directed English - even better than one relying on the transitional probability between syllables.

Only about 5% of the words posited by the transitional probability learner are not actually words (95.9% precision) and about 7% of the actual words are not extracted (93.4% recall).

Gambell & Yang 2006 Summary

Learning from transitional probabilities alone doesn't work so well on realistic data, even though experimental research suggests that infants are capable of tracking and learning from this information.

Models of children that have additional knowledge about the stress patterns of words seem to have a much better chance of succeeding at word segmentation if they learn via transitional probabilities.

However, models of children that use algebraic learning and have additional knowledge about the stress patterns of words perform even better at word segmentation than any of the models learning from the transitional probability between syllables.

Gambell & Yang 2006 Critiques

Do children have access to the Unique Stress Constraint (USC)?
-Children definitely use TPs & Algebraic Learning

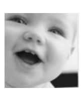
Does dictionary stress really match actual stress patterns?

Gambell & Yang: the *big bad wolf*
Typical speech: the big bad *wolf*

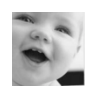
It's unclear how well this algorithm works with real stress patterns…

Pearl, Goldwater, & Steyvers 2011

What if children are capable of tracking more sophisticated distributional information (that is, they're not just restricted to transitional probability minima)? In that case, how well do they do on realistic data, if all they're using is statistical learning (no stress information)?



Pearl, Goldwater, & Steyvers 2011



What if children can use Bayesian inference?
Human cognitive behavior is consistent with this kind of reasoning. (Tenenbaum & Griffiths 2001, Griffiths & Tenenbaum 2005, Xu & Tenenbaum 2007)

Bayesian inference is a sophisticated kind of probabilistic reasoning that tries to find hypotheses that
(1) are consistent with the observed data
(2) conform to a child's prior expectations

Bayesian inference for word segmentation

What kind of hypotheses might a child have for word segmentation?

Observed data:
"to the ca stle be yond the go blin ci ty"

Hypothesis = sequence of vocabulary items producing this observable data

Some sample hypotheses

Hypothesis 1:
"tothe castle beyond thegoblin city"
Items: *tothe, castle, beyond, thegoblin, city*

Hypothesis 2:
"to the castle beyond the goblin city"
Items: *to, the, castle, beyond, goblin, city*
Note: the *is used twice*

Bayesian model: Pearl et al. 2011

Learner expectations about word segmentation:
(1) Words tend to be shorter rather than longer
(2) Vocabulary tends to be small rather than large

How would a Bayesian learner with these kind of expectations decide between the two hypotheses from before?

Hypothesis 1:
"tothe castle beyond thegoblin city"
Items: *tothe, castle, beyond, thegoblin, city*

How long are words? Between 4 and 9 letters
How large is the vocabulary? 5 words

Bayesian model: Pearl et al. 2011

Learner expectations about word segmentation:
(1) Words tend to be shorter rather than longer
(2) Vocabulary tends to be small rather than large

How would a Bayesian learner with these kind of expectations decide between the two hypotheses from before?

Hypothesis 2:
"to the castle beyond the goblin city"
Items: *to, the, castle, beyond, goblin, city*

How long are words? Between 3 and 6 letters
How large is the vocabulary? 6 words

Bayesian model: Pearl et al. 2010

Comparing hypotheses - which is most likely?

Hypothesis 1: longer words, but fewer words
How long are words? Between 4 and 9 letters
How large is the vocabulary? 5 words

Hypothesis 2: shorter words, but more words
How long are words? Between 3 and 6 letters
How large is the vocabulary? 6 words

A Bayesian learner makes a decision based on how important each of its expectations is (in this case, it's a balance of the two constraints: fewer words vs. shorter words).

Bayesian model: Pearl et al. 2010

Comparing hypotheses - which is most likely?

Hypothesis 1: longer words, but fewer words
How long are words? Between 4 and 9 letters
How large is the vocabulary? 5 words

Hypothesis 2: shorter words, but more words
How long are words? Between 3 and 6 letters
How large is the vocabulary? 6 words

There will be some probability the Bayesian learner assigns to each hypothesis. The most probable hypothesis will be the one the learner chooses.

Bayesian model: Pearl et al. 2010

Comparing hypotheses - which is most likely?

Hypothesis 1: longer words, but fewer words
How long are words? Between 4 and 9 letters
How large is the vocabulary? 5 words

Probability: 0.33

Hypothesis 2: shorter words, but more words
How long are words? Between 3 and 6 letters
How large is the vocabulary? 6 words

Probability: 0.67

There will be some probability the Bayesian learner assigns to each hypothesis. The most probable hypothesis will be the one the learner chooses.

Bayesian model: Pearl et al. 2010

Comparing hypotheses - which is most likely?

Hypothesis 1: longer words, but fewer words
How long are words? Between 4 and 9 letters
How large is the vocabulary? 5 words

Probability: 0.33

Hypothesis 2: shorter words, but more words
"to the castle beyond the goblin city"

Probability: 0.67

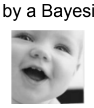
There will be some probability the Bayesian learner assigns to each hypothesis. The most probable hypothesis will be the one the learner chooses.

Realistic Bayesian Learners: Pearl et al. 2011

Pearl et al. 2011 tested their Bayesian learners on realistic data: 9790 utterances of child-directed speech from the Bernstein-Ratner corpus in CHILDES. (Average utterance length: 3.4 words)

Best performance by a Bayesian learner:

Precision: 72%
Recall: 74%



This is much better than what we found for a learner that hypothesizes a word boundary at a transitional probability minimum (41.6% precision, 23.3% recall). Statistical learning by itself isn't always so bad after all!

Model Comparison

So which model performs better?
-Rate only based on Recall and Precision scores?

Any model makes assumptions which should be included in analysis!

Gambell & Yang:
- Syllables, TPs, USC, Lexicon, Algebraic Learning, Dictionary Stress
- Less processing power

Pearl et al:
- Phonemes, TPs, Lexicon, Bayesian Inference, Bias for shorter/fewer words
- More processing power

Statistical Learning for Word Segmentation

Saffran et al. (1996) found that human infants are capable of tracking transitional probability between syllables and using that information to accomplish word segmentation in an artificial language.

Gambell & Yang (2006) found that this same statistical learning strategy (positing word boundaries at transitional probability minima) failed on realistic child-directed speech data.

Pearl et al. (2011) found that more sophisticated statistical learning (Bayesian inference) did much better on realistic child-directed speech data, suggesting that children may be able to use statistical learning to help them with word segmentation - even if they don't use other strategies like lexical stress.

Questions?

Use the remaining time to work on HW2 and the review questions for word segmentation.