Bootstrapping into Filler-Gap: An Acquisition Story

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What is Bootstrapping?

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Bootstrapping

The use of a weak ability to improve another weak ability and vice versa

What is Filler-Gap?

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A non-local dependency that potentially spans an unbounded # of words.

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e.g. That's {the ball} John kicked ___.
e.g. That's {the ball} Mary said John kicked ___.

What is Filler-Gap?

Filler-Gap

A non-local dependency that potentially spans an unbounded # of words.

e.g. That's {the ball} John kicked ___.
e.g. That's {the ball} Mary said John kicked ___.

This is hard because:

- Filler must be remembered
- Where is the gap?

Motivation

How could children learn this?

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Goal

- Simple model of filler-gap

Types of Filler-Gap (for us)

Questions

Wh-S: {What} ___ ate the apple?

Types of Filler-Gap (for us)

Questions

Wh-S: {What} ___ ate the apple?

Wh-O: {What} did the monkey eat ___?

Types of Filler-Gap (for us)

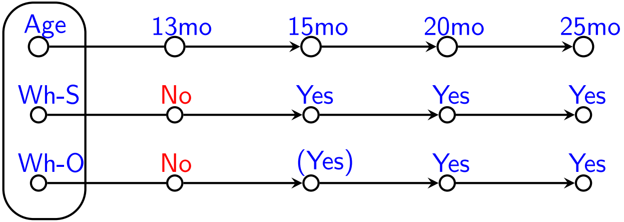
Questions

Wh-S: {What} ___ ate the apple?
Wh-O: {What} did the monkey eat ___?

Relatives

- Find {the boy} who ___ bumped the girl.
- Find {the boy} who the girl bumped ___.
- Find {the boy} that ___ bumped the girl.
- Find {the boy} that the girl bumped ___.

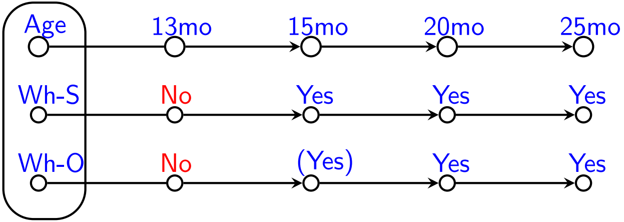
Filler-gap Timeline



Developmental timeline of wh- question comprehension
Parentheses = marginal comprehension

[Seidl et al., 2003, Gagliardi et al., 2014]

Filler-gap Timeline



Developmental timeline of wh- question comprehension

Parentheses = marginal comprehension

That-relatives acquired slower than wh-relatives

[Seidl et al., 2003, Gagliardi et al., 2014]

Gertner and Fisher (2012)

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The boy/girl is gorping.

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The girl and the boy are gorping.

Gertner and Fisher (2012)

The girl and the boy are gorping.

Acquisition Pattern

1-1 Role Bias

Subject Object

- John gorped

Acquisition Pattern

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Subject Object

- John gorped
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Acquisition Pattern

1-1 Role Bias

Subject Object

- John gorped
- Mary gorped John
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Interpreted by Gertner and Fisher (2012) as 'Agent-first bias'

Acquisition Pattern

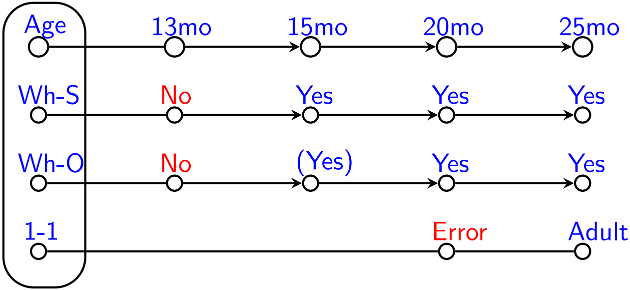
1-1 Role Bias

Subject Object

- John gorped
- Mary gorped John
- John and Mary gorped

Interpreted by Gertner and Fisher (2012) as ‘Agent-first bias’
But we will show: can be modeled as 1-1 role bias

Acquisition Pattern



Developmental timeline of 1-1 role bias errors (21, 25)
Children stop this error by 25 months
[Naigles, 1990, Gertner and Fisher, 2012]

Model Motivation

What are children learning?

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Complex Grammatical Constraints

Under certain conditions:

Arguments may occur in non-canonical syntactic positions.

e.g., questions introduce an expected future gap (SLASH, A-bar).

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Problem:

Syntax isn't great yet

- Role conjunction not comprehended

  [Gertner and Fisher, 2012]

- Ditransitives not generalized until later

  [Goldberg et al., 2004, Bello, 2012]

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Different Possible Orderings

The flower **hit** the apple.
What **hit** the apple.
What did the flower **hit**?

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Plausible:
Word ordering patterns are fairly widespread (e.g. SOV, SVO, etc)

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Different Possible Orderings

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What **hit** the apple.
What did the flower **hit**?

Plausible:
Word ordering patterns are fairly widespread (e.g. SOV, SVO, etc)

Previously used in BabySRL [Connor et al., 2008, 2009, 2010]

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Motivation

How could children learn this using word ordering?

Goals

- Simple model of filler-gap
  - Object filler-gap harder than subject
  - *That*-relatives harder than *Wh*-relatives
  - Children initially make 1-1 role bias error
  - After learning, stop making 1-1 role bias error

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Assumptions

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- (14m) Children can chunk nouns [Waxman and Booth, 2001]

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- (4-5y) Children are bad at recursion [Diessel and Tomasello, 2001]

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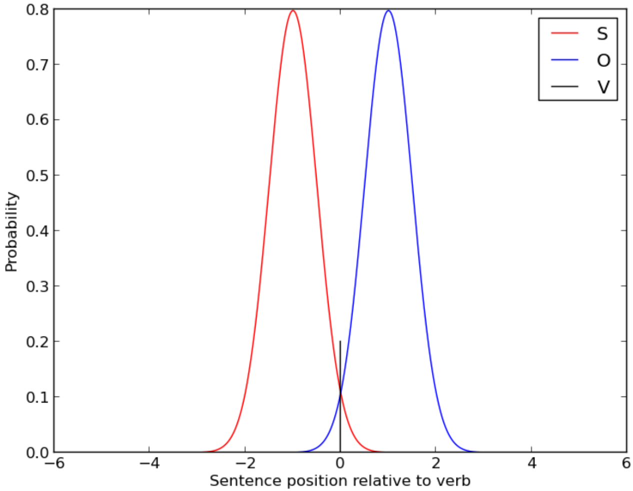
Implementation Assumptions

- Sampled from Gaussian distributions

Model


0.8
0.7
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0.4
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Probability
−6
−4
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0
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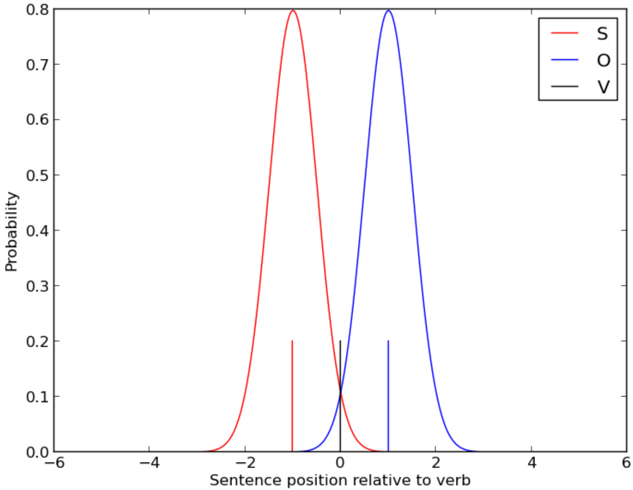
4
6
Sentence position relative to verb
S
O
V

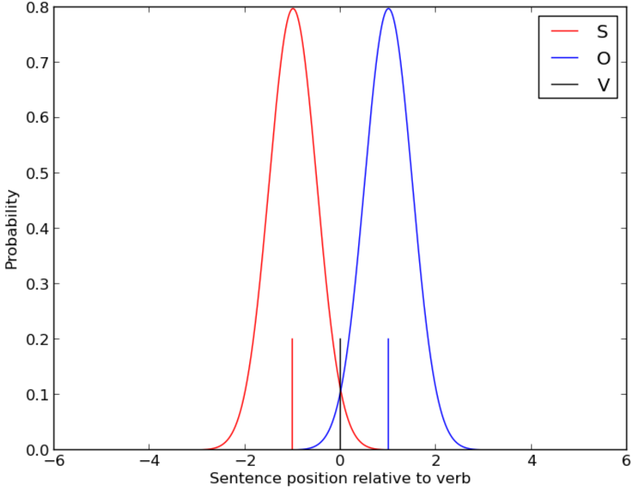
Model



$$P(-1 \mid S) \cdot P(1 \mid O)$$

The cat bumped the dog.

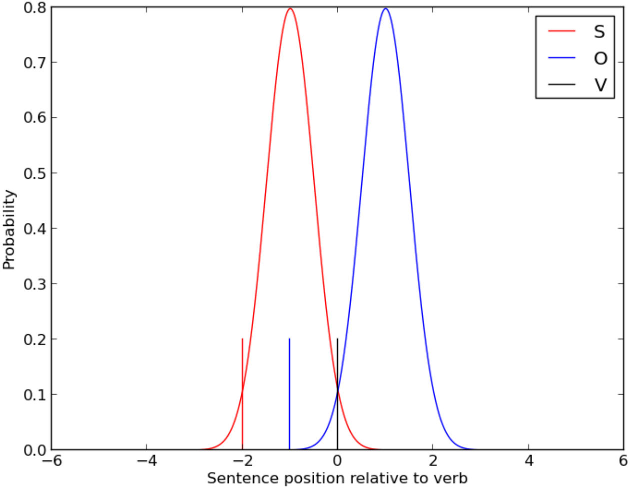
Model



$$P(-1 \mid S) \cdot P(1 \mid O)$$

Wh-S: Which cat bumped the dog?

Model



$P(-3 \mid S) \cdot P(-1 \mid O)$

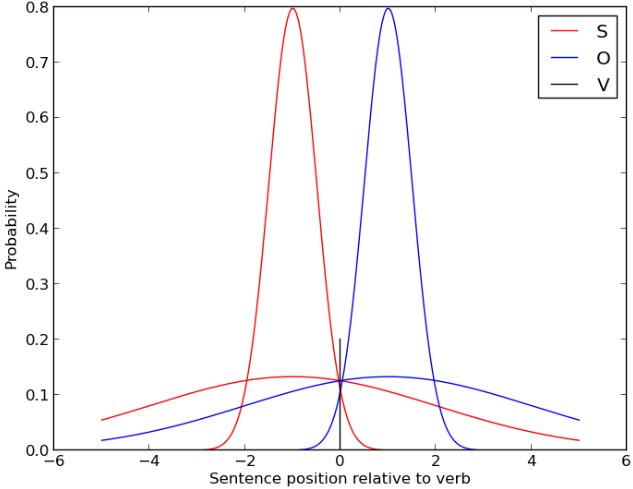
Wh-O: Which cat did the dog bump?*

Model

Initialization 2.0

- Split distributions into mixtures of distributions
  - 1) strong due to canonical evidence
  - 2) weak, but finds arguments from anywhere

Model



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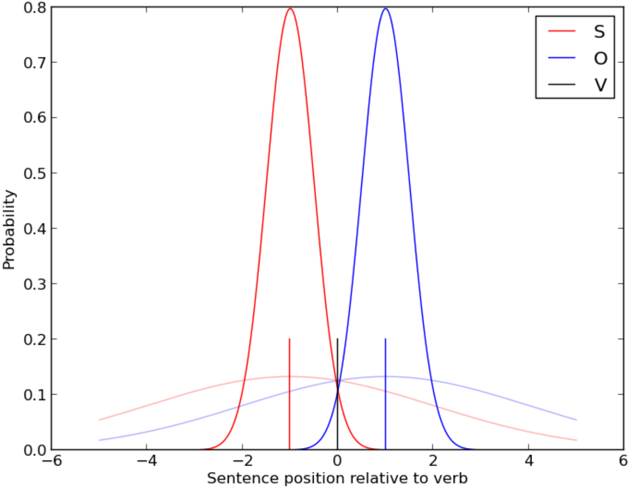
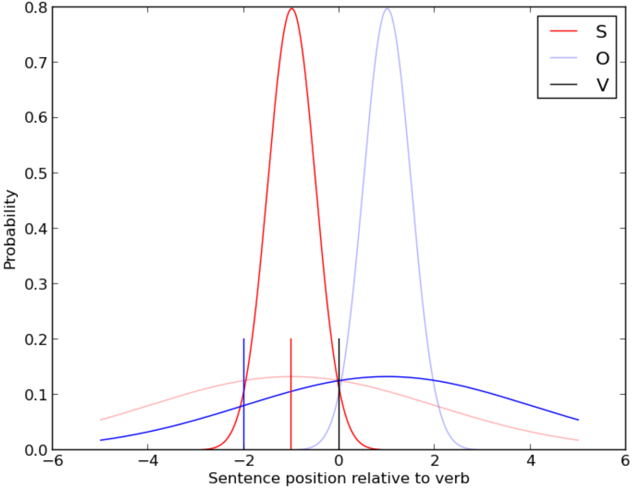


$$P(-1 \mid S_C) \cdot P(1 \mid O_C)$$

Wh-S: Which cat bumped the dog?

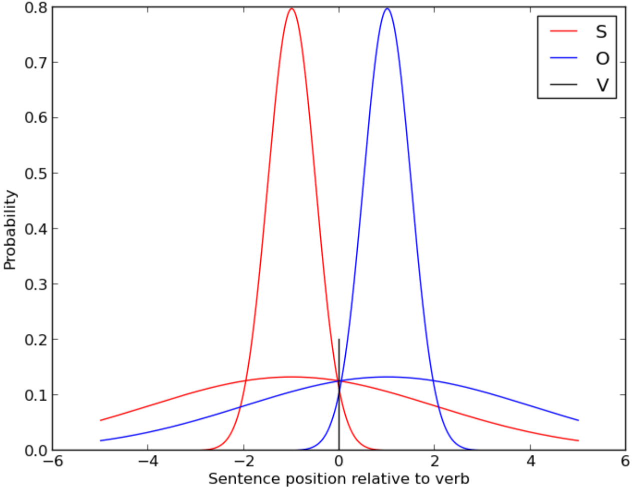
Model



$$P(-3 \mid O_N) \cdot P(-1 \mid S_C)$$

Wh-O: Which cat did the dog bump?

Model



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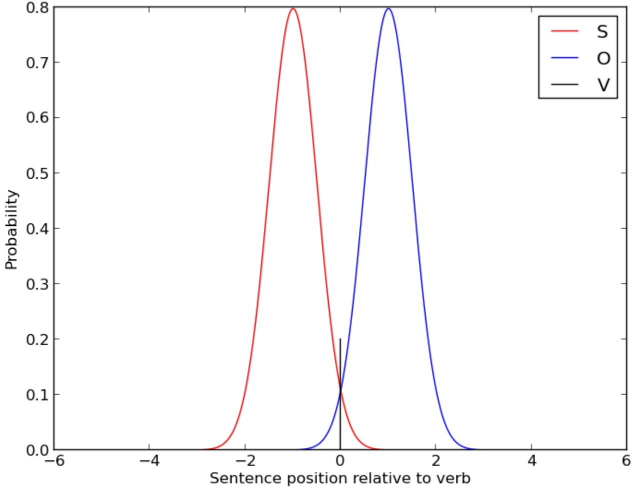

With priors, our initial model looks like this.

Evaluation

1. Extract CDS from Eve corpus
   (‘you’, ‘S’) (‘get’, ‘V’) (‘one’, ‘O’) .
   (‘what’, ‘O’) are (‘you’, ‘S’) (‘doing’, ‘V’) ?
   (‘you’, ‘S’) (‘have’, ‘V’) another (‘cookie’, ‘O’) right on the table .

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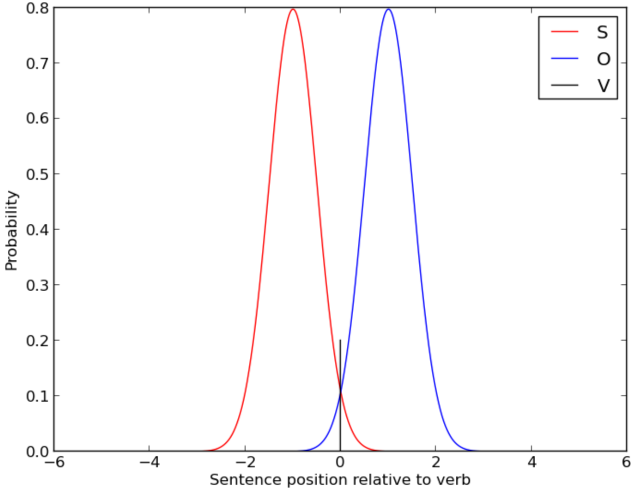
   ('what', 'O') are ('you', 'S') ('doing', 'V') ?
   ('you', 'S') ('have', 'V') another ('cookie', 'O') right on the table .
2. Chunk nouns (NLTK)
   (N;you)(V;get)(N;one) .
   (N;what)(X;are)(N;you)(V;doing) ?
   (N;you)(V;have)(N;cookie)(X;right)(X;on)(N;table) .

Results



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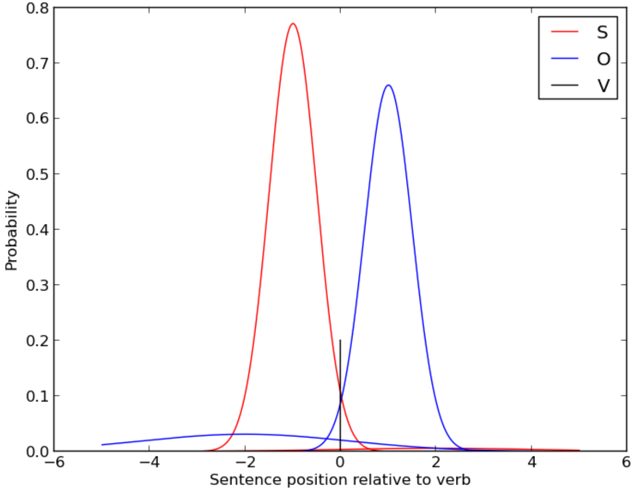

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Results: Filler-gap

Filler-gap Corpora

* ($p < .01$)

Results: Filler-gap

Filler-gap Corpora

	P	R	F
Initial	.53	.57	.55
Trained	**.55**	**.67**	**.61***

Eve FG (n = 1345)

* ($p < .01$)

Results: Filler-gap

Filler-gap Corpora

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Initial	.53	.57	.55
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Eve FG (n = 1345)

	P	R	F
Initial	.53	.52	.52
Trained	**.54**	**.63**	**.58***

Adam FG (n = 1287)

* ($p < .01$)

Results: Quantitative

Eve FG Corpus

Subject/Object

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Eve FG Corpus

Subject/Object

	P	R	F
Initial	**.66**	**.83**	**.74**
Trained	.64	.84	.72†

Subject (n = 691)

	P	R	F
Initial	.35	.31	.33
Trained	**.45**	**.52**	**.48***

Object (n = 654)

* ($p < .01$) † ($p < .05$)

Results: Quantitative

Eve FG Corpus

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Trained	**.45**	**.52**	**.48***

Object (n = 654)

That/Wh-

	P	R	F
Initial	.63	.45	.53
Trained	**.73**	**.75**	**.74***

Wh- (n = 689)

	P	R	F
Initial	.43	.48	.45
Trained	**.44**	**.57**	**.50**†

That (n = 125)

* ($p < .01$) † ($p < .05$)

1-1 Role Bias

How often is NNV labelled as SOV? (1-1 role bias error)

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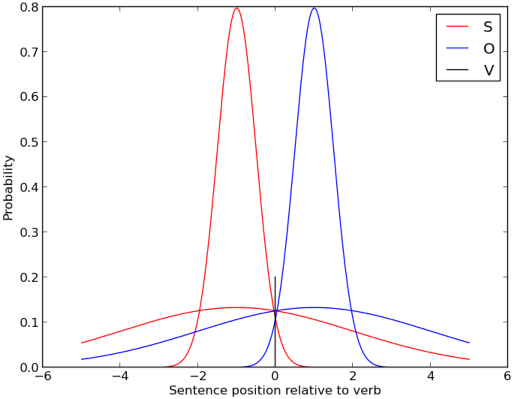
- Our trained model: 13% error (1-1 bias)

Is non-canonical subject useful?



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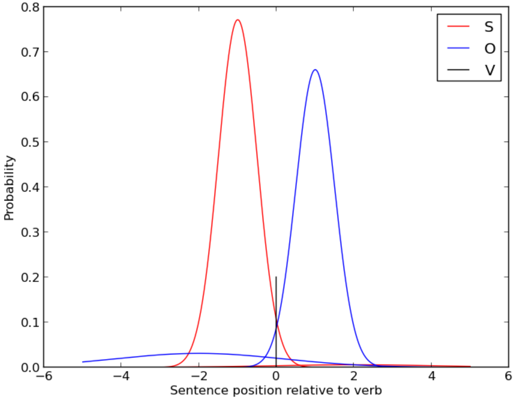

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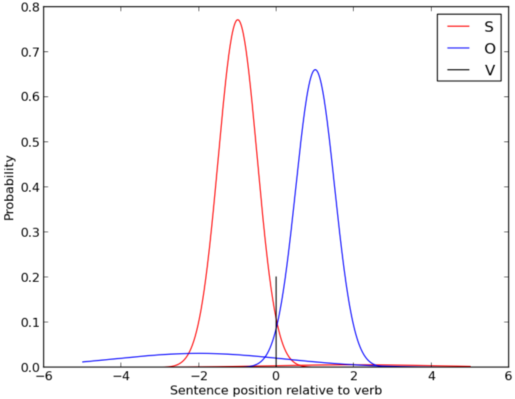

"Helps" capture imperatives...

'Put the cookie on the table!'

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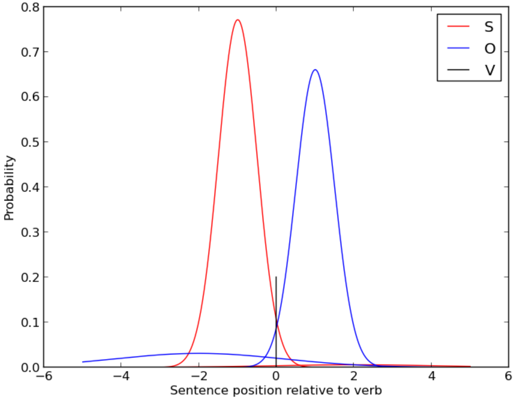

"Helps" capture imperatives. . .
But kids know imperatives. . .

'Put the cookie on the table!'
'[You] put the cookie on the table!'

Future Work

- Add lexicalization
- Dynamically generate Gaussians
- Model non-English (verb-medial) languages
- Bootstrap linear grammar into hierarchic grammar

Conclusion

It is possible to acquire filler-gap without (complex) syntax.

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Conclusion

It is possible to acquire filler-gap without (complex) syntax.
The current model offers additional benefits:

- Reflects developmental S-O asymmetry
- Reflects developmental That-Wh asymmetry
- Robust to varied initializations

Questions?

Joint work with Micha Elsner

Thanks to:

- Peter Culicover
- William Schuler
- Laura Wagner
- Attendees of the OSU 2013 Fall Ling. Colloquium Fest

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Results: 1-1 bias

How often NNV is labelled SOV

Current Model

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Current Model

	Error Rate
Initial	.66
Trained	.13

(n = 1000)

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Current Model

	Error Rate
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(n = 1000)

Trained Baby SRL

	Error Rate
Arg-Arg	.65
Arg-Verb	0

[Connor et al., 2008]

	Error Rate
Arg-Arg	.82
Arg-Verb	.63

[Connor et al., 2009]

Results: 1-1 bias

Agent Prediction

Results: 1-1 bias

Agent Prediction

	Recall
Initial	.67
Trained	.65

Transitive ($n = 1000$)

	Recall
Initial	1
Trained	.96

Intransitive ($n = 1000$)

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Agent Prediction

	Recall
Initial	.67
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Transitive (n = 1000)

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Intransitive (n = 1000)

[Connor et al., 2010]

	Recall
Weak (10) lexical	.71
Strong (365) lexical	.74
Gold Args	.77

Transitive

	Recall
Weak (10) lexical	.59
Strong (365) lexical	.41
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Intransitive

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- Connor et al. (2010): 41-59%
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Intransitives (1513 sents)

- Connor et al. (2010): 41-59%
- Initial current model: 100%
  Trained current model: 96%

Current model is comparable to Baby SRL for transitives

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Intransitives (1513 sents)

- Connor et al. (2010): 41-59%
- Initial current model: 100%
  Trained current model: 96%

Current model is comparable to Baby SRL for transitives
Current model does much better on intransitives

Bibliography I

Bello, S. (2012).
Identifying indirect objects in French: An elicitation task.
In *Proceedings of the 2012 annual conference of the Canadian Linguistic Association*.

Connor, M., Gertner, Y., Fisher, C., and Roth, D. (2008).
Baby srl: Modeling early language acquisition.
In *Proceedings of the Twelfth Conference on Computational Natural Language Learning*.

Connor, M., Gertner, Y., Fisher, C., and Roth, D. (2009).
Minimally supervised model of early language acquisition.
In *Proceedings of the Thirteenth Conference on Computational Natural Language Learning*.

Bibliography II

Connor, M., Gertner, Y., Fisher, C., and Roth, D. (2010).
Starting from scratch in semantic role labelling.
In *Proceedings of ACL 2010*.

Diessel, H. and Tomasello, M. (2001).
The acquisition of finite complement clauses in english: A corpus-based analysis.
Cognitive Linguistics, 12:1–45.

Gagliardi, A., Mease, T. M., and Lidz, J. (2014).
Discontinuous development in the acquisition of filler-gap dependencies: Evidence from 15- and 20-month-olds.
Harvard unpublished manuscript:
http://www.people.fas.harvard.edu/∼gagliardi.

Bibliography III

Gertner, Y. and Fisher, C. (2012).
Predicted errors in children's early sentence comprehension.
Cognition, 124:85–94.

Goldberg, A. E., Casenhiser, D., and Sethuraman, N. (2004).
Learning argument structure generalizations.
Cognitive Linguistics, 14(3):289–316.

Naigles, L. R. (1990).
Children use syntax to learn verb meanings.
The Journal of Child Language, 17:357–374.

Seidl, A., Hollich, G., and Jusczyk, P. W. (2003).
Early understanding of subject and object wh-questions.
Infancy, 4(3):423–436.

Bibliography IV

Waxman, S. R. and Booth, A. E. (2001).
Seeing pink elephants: Fourteen-month-olds' interpretations of novel nouns and adjectives.
Cognitive Psychology, 43:217–242.

Xu, F. (2002).
The role of language in acquiring object kind concepts in infancy.
Cognition, 85:223–250.