

# A NEURAL MODEL OF ADAPTATION IN READING

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# THOUGHT EXPERIMENT

...cassowary ...

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...cassowary ...

...cassowary? ...

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...cassowary ...

...cassowary? ...

...cassowary ...

# THOUGHT EXPERIMENT

...cassowary ...

...cassowary? ...

...cassowary ...

...cassowary! ...

# THOUGHT EXPERIMENT

...cassowary ...

...cassowary? ...

...cassowary ...

...cassowary! ...

You are now less surprised when this person says 'Cassowary'

The



The soldiers

The soldiers warned

The soldiers warned about

The soldiers warned about the

The soldiers warned about the dangers

The soldiers warned about the dangers conducted

The soldiers warned about the dangers conducted the

The soldiers warned about the dangers conducted the raid.



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Unreduced: The soldiers (who were) warned about the dangers ...

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By end of experiment, subjects expected RRC more than at beginning

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By end of experiment, subjects expected RRC more than at beginning

- Humans adapt to syntactic structures

- Domain adaptation (Kuhn & de Mori, 1990; McClosky, 2010)  
News Model → Biomedical Text
- Handling unknown words (Grave et al., 2015)  
Learn new words from context
- Style adaptation (Jaech & Ostendorf, 2017)  
Lawyer A → Lawyer B

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But can we model human adaptation?

LSTM language model (Gives prob of next word in sequence)

Base Model: Trained on Wikipedia (90M words)

(Gulordava et al., 2018)

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- 1 Test on a sentence



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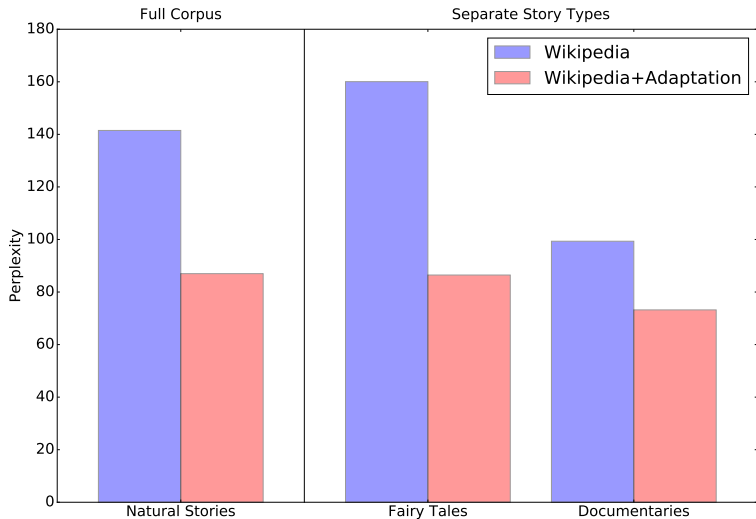
- 1 Test on a sentence
- 2 Update weights based on that sentence
- 3 Repeat on remaining sentences

Experiment 1 (standard):  
Does adaptation improve model accuracy?

Test data: Natural Stories Corpus (Futrell et al., 2017)

- 10 texts (485 sentences)
  - 7 Fairy Tales
  - 3 Documentaries

# ACCURACY RESULTS



Experiment 2:  
Evaluate model against human adaptation

Reading times can be predicted with surprisal (Smith and Levy, 2013)

$$\text{Surprisal}(w_i) = -\log P(w_i \mid w_{1..i-1})$$

- Timeline of adaptation is similar to human adaptation
- Adaptive surprisal predicts reading times better than non-adaptive surprisal



The soldiers (who were) warned about the dangers conducted the raid.

# EVALUATION: READING TIMES

The soldiers (who were) warned about the dangers conducted the raid.

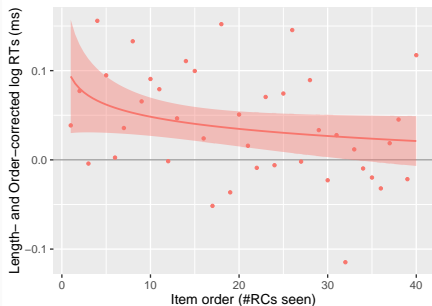


FIGURE 1: Human reading times

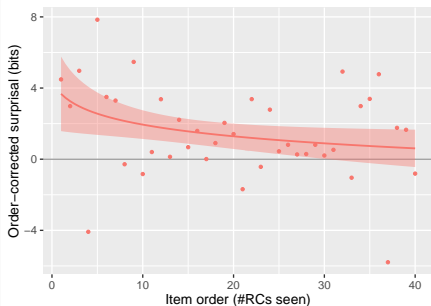
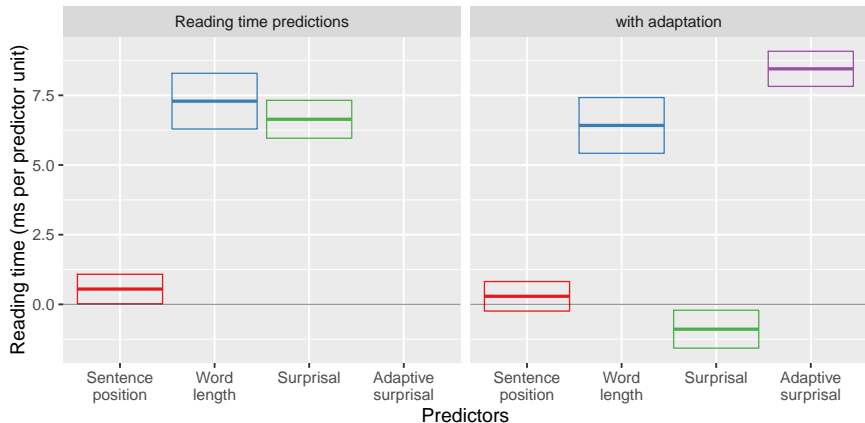


FIGURE 2: Adaptive model surprisal

# EVALUATION: READING TIMES



Experiment 3:

How sensitive is adaptation to different signals?

Vocabulary? Syntax?

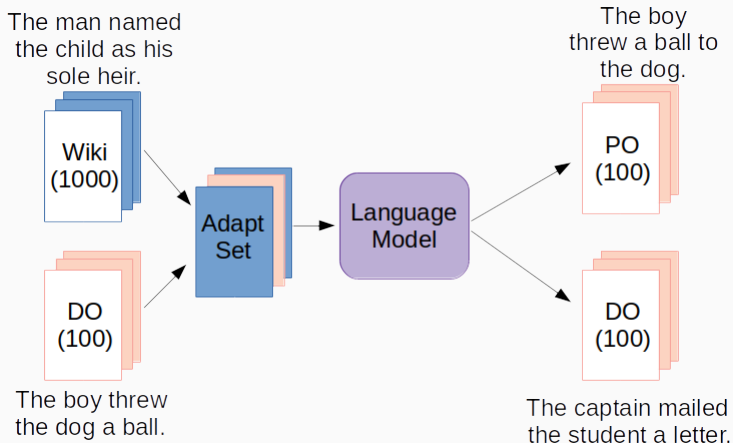
Prepositional Object (PO):

*The boy threw the ball to the dog.*

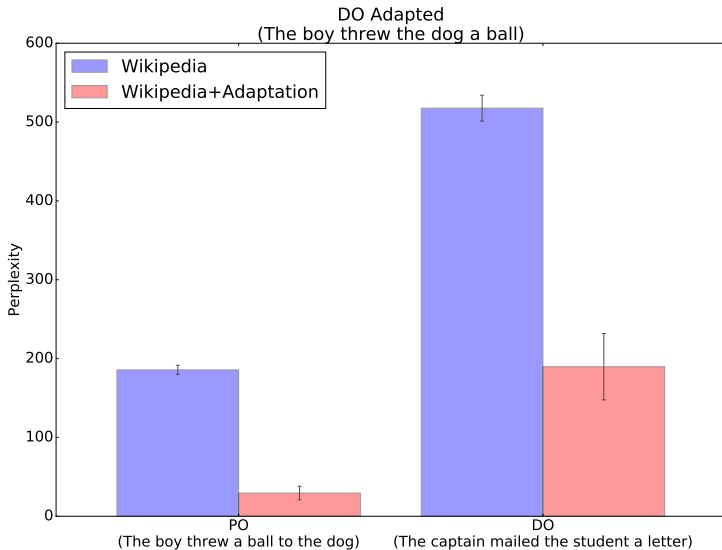
Double Object (DO):

*The boy threw the dog the ball.*

# DATIVE EVALUATION PARADIGM



# MODEL ADAPTS TO VOCABULARY AND SYNTAX



- Proposed a simple adaptation mechanism which
  - Is more accurate than a non-adaptive model
  - Makes more human-like predictions than a non-adaptive model



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  - Psycholinguistic experiments to probe signal sensitivity:  
Adaptation is sensitive to both vocabulary and syntax

Thanks!

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Split each domain into training and testing sets (1000 sentences each)

- 1 Adapt to a training domain

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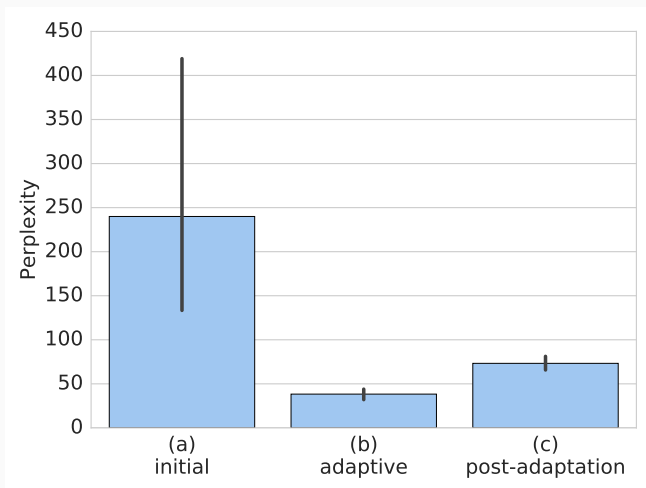
Split each domain into training and testing sets (1000 sentences each)

- 1 Adapt to a training domain
- 2 Adapt to a second training domain

Does the model forget the first adaptive training domain?



# CATASTROPHIC FORGETTING TEST



**FIGURE 3:** Perplexity on the held-out set of  $G_1$  (a) before adaptation, (b) after adaptation to  $G_1$ , (c) after adapting to  $G_1$  then adapting to  $G_2$ .

# MODEL ADAPTS TO VOCABULARY AND SYNTAX

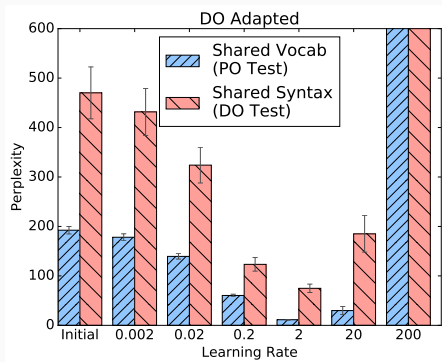


FIGURE 4: Learning rate influence over syntactic and lexical adaptation.

	$\hat{\beta}$	$\hat{\sigma}$	t
WITHOUT ADAPTIVE SURPRISAL:			
Sentence position	0.55	0.53	1.03
<b>Word length</b>	<b>7.29</b>	<b>1.00</b>	<b>7.26</b>
<b>Non-adaptive Surprisal</b>	<b>6.64</b>	<b>0.68</b>	<b>9.79</b>
WITH ADAPTIVE SURPRISAL:			
Sentence position	0.29	0.53	0.55
<b>Word length</b>	<b>6.42</b>	<b>1.00</b>	<b>6.40</b>
Non-adaptive Surprisal	-0.89	0.68	-1.31
<b>Adaptive Surprisal</b>	<b>8.45</b>	<b>0.63</b>	<b>13.42</b>

Fixed effects of linear mixed regression

The soldiers warned about the dangers conducted the raid.

# QUALITATIVE ADAPTATION TIMELINE

The soldiers warned about the dangers conducted the raid.

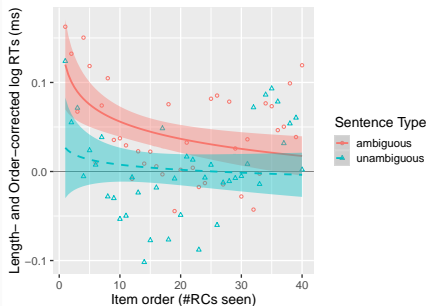


FIGURE 5: Human reading times

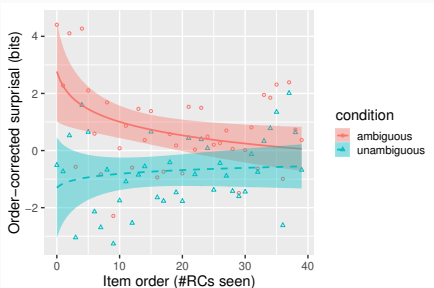


FIGURE 6: Adaptive model surprisal