Sentence Understanding with Neural Networks and Natural Language Inference

Sam Bowman
Asst. Prof. of Linguistics and Data Science, NYU

CLASP Seminar, University of Gothenburg

Context: Deep learning in NLP

As in vision and elsewhere, deep learning techniques have yielded very fast progress on a few important data-rich tasks:

- **Reading comprehension questions**
    - Near human performance (but brittle)
- **Translation**
    - Large, perceptually obvious improvements over past systems.
- **Syntactic parsing**
    - Measurable improvements on a longstanding state of the art

The Question

Can current neural network methods learn to do anything that resembles *compositional semantics*?

The Question

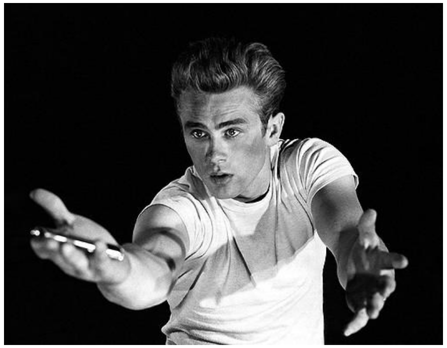
Can current neural network methods learn to do anything that resembles *compositional semantics*?

If we take this as *a goal to work toward*, what's our metric?

Proposal: Natural language inference as a research task

Natural Language Inference (NLI)

also known as recognizing textual entailment (RTE)



James Byron Dean refused to move without blue jeans

{**entails**, contradicts, neither}

James Dean didn't dance without pants

Example: MacCartney thesis '09

Judging Understanding with NLI

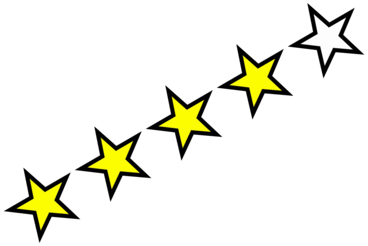
To reliably perform well at NLI, your representations of meaning must handle with the full complexity of compositional semantics:*

- Lexical entailment (*cat* vs. *animal*, *cat* vs. *dog*)
- Quantification (*all*, *most*, *fewer than eight*)
- Lexical ambiguity and scope ambiguity (*bank*, ...)
- Modality (*might*, *should*, ...)
- Common sense background knowledge

…

* without grounding to the outside world.

Why not Other Tasks?

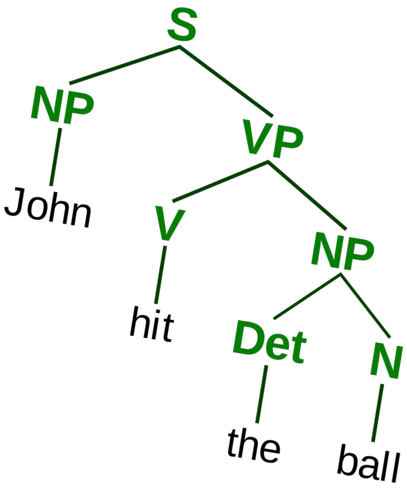


Many tasks that have been used to evaluate sentence representation models don’t require all that much language understanding:

- Sentiment analysis
- Sentence similarity

…

Why not Other Tasks?



NLI isn’t the only task to require high-quality natural language understanding, see also:

- Machine translation
- Question answering
- Goal-driven dialog
- Semantic parsing
- Syntactic parsing

…

But it’s the easiest of these.

Outline

- **Background:** NLI as a research task for NLU
- **Part 1** Preliminaries: Artificial language results
- **Part 2** The Stanford NLI Corpus
- **Part 2** The MultiNLI Corpus
- **Conclusion**

Part I

Natural (?) Language Inference
on Artificial Languages

Bowman, Potts & Manning '15a,b

Can standard NNs learn, *with arbitrarily clean and abundant data*, to perform NLI with perfect precision?

Artificial Data Experiments

Experimental paradigm:

- *Train on relational statements generated from some formal system.*
- *Test on other such relational statements.*

NLI and Natural Logic

Research in **Natural Logic** formally characterizes sound inference patterns over natural language.

dance $\sqsubset$ *move*

so...

James Dean danced $\sqsubset$ *James Dean moved*

but...

James Dean ***didn't*** *dance* $\sqsupset$ *James Dean* ***didn't*** *move*

Sánchez-Valencia, '91; MacCartney, '09; Icard & Moss '13

Experiment I: Lexical relations

Training data

dance	***entails***	*move*
tango	***entails***	*dance*
sleep	***contradicts***	*dance*
waltz	***entails***	*dance*

Test data

sleep	***?***	*waltz*

Artificial data methods: relation types

MacCartney’s seven possible relations between phrases/sentences:

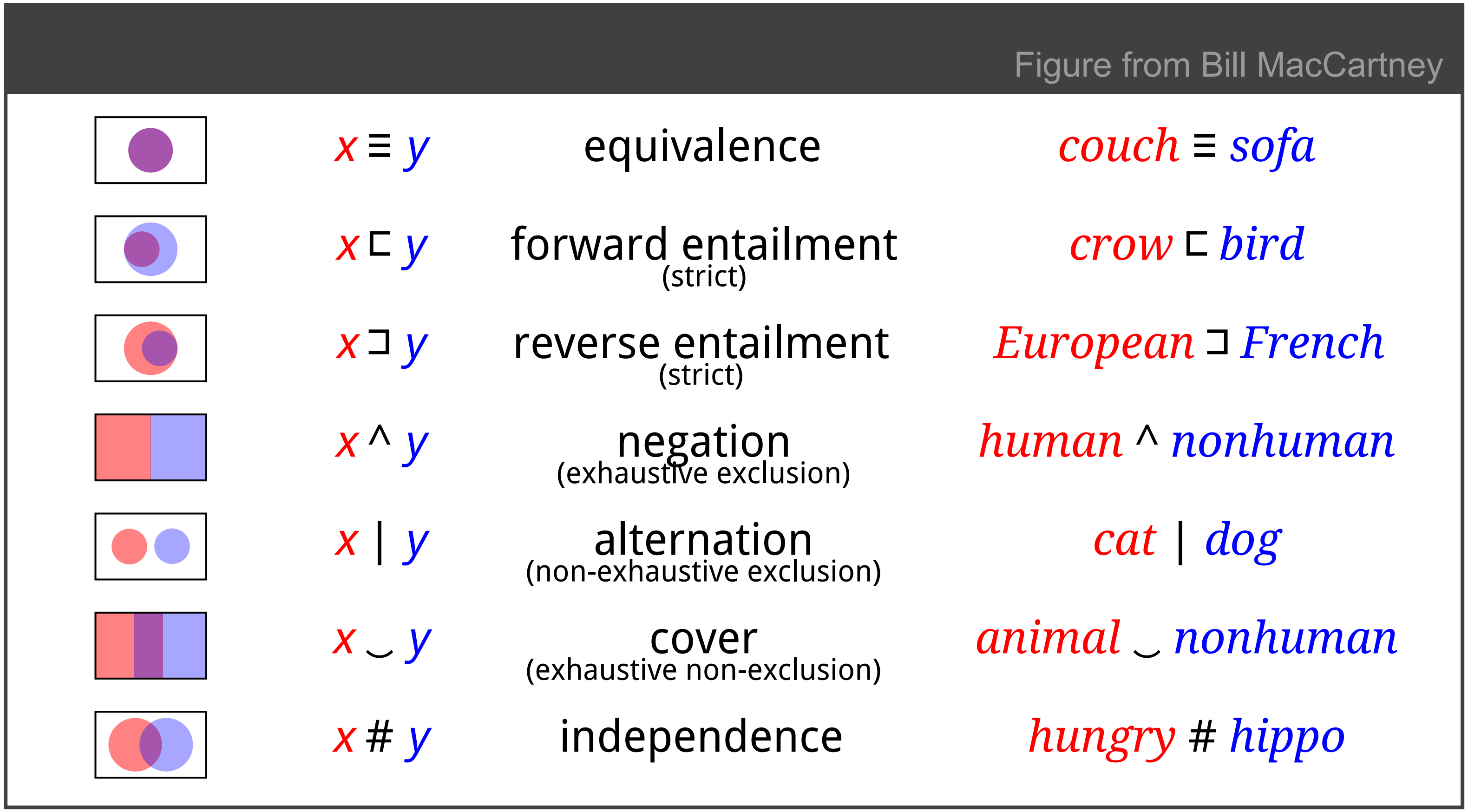


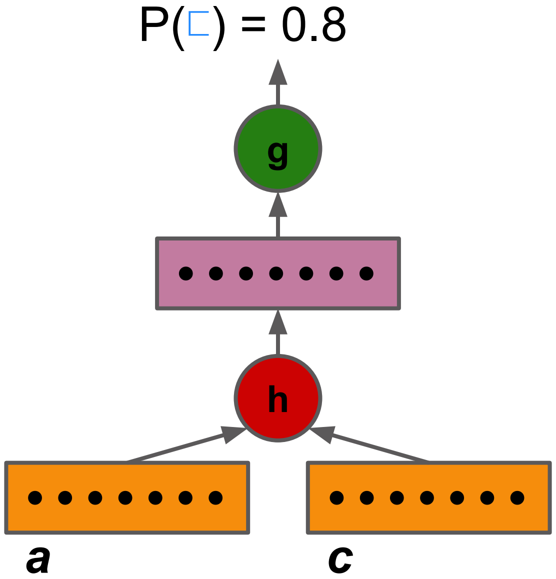
Figure from Bill MacCartney

$x \equiv y$	equivalence	*couch* ≡ *sofa*
$x \sqsubset y$	forward entailment (strict)	*crow* ⊏ *bird*
$x \sqsupset y$	reverse entailment (strict)	*European* ⊐ *French*
$x \wedge y$	negation (exhaustive exclusion)	*human* ^ *nonhuman*
$x \mid y$	alternation (non-exhaustive exclusion)	*cat* | *dog*
$x \smile y$	cover (exhaustive non-exclusion)	*animal* ‿ *nonhuman*
$x \# y$	independence	*hungry* # *hippo*

Lexical relation data

TRAIN	TEST
a ≡ a	a ≡ b
a ^ f	a ⌣ d
b ⌣ c	a ⊐ e
b ⌣ d	b ⊐ e

The simplest viable model



Lexical relations

Success!

15D bilinear comparison function: **99.6%** test accuracy

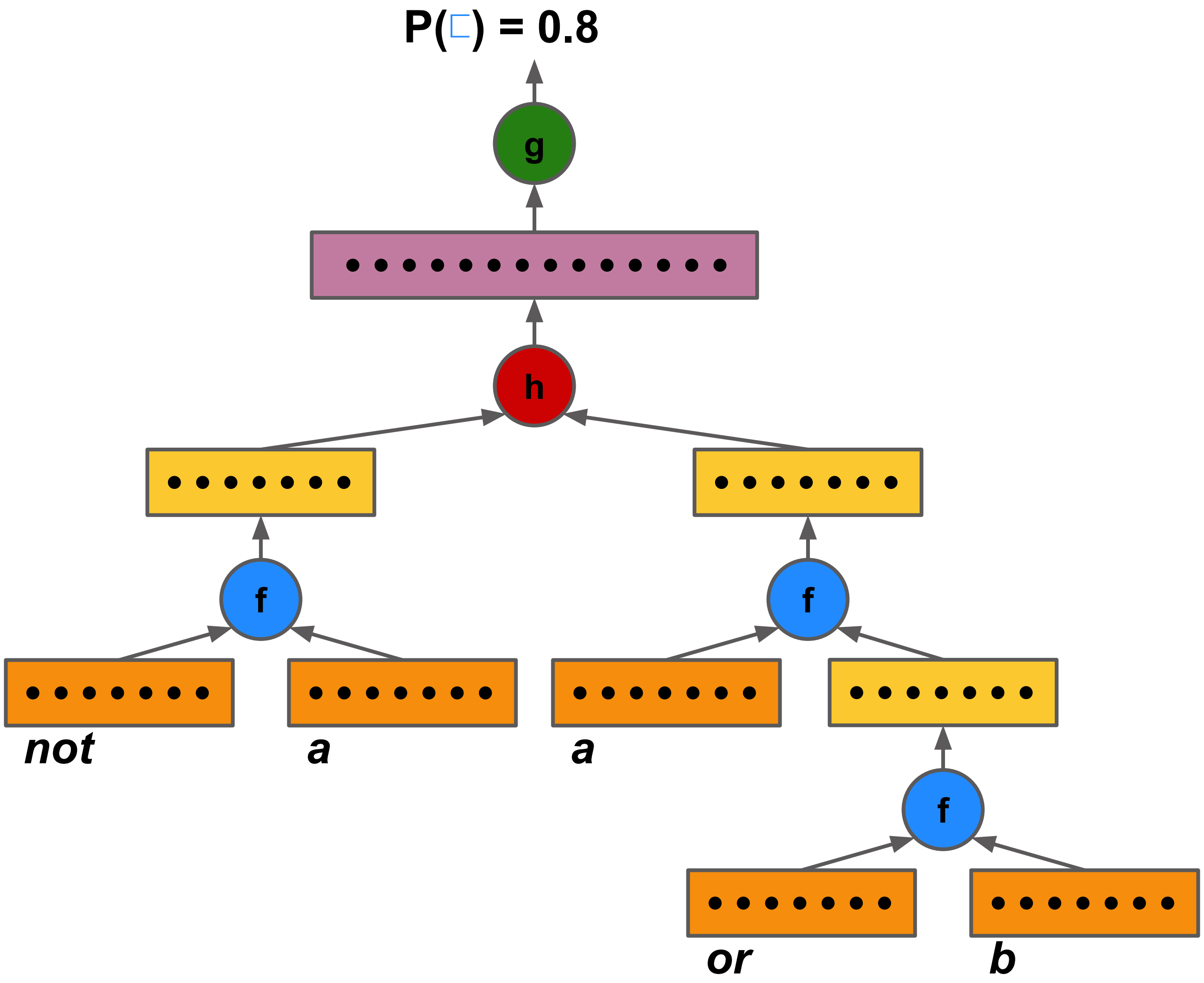
15D linear comparison function: 94.0%

Fine print: 80 symbols, 50% of pairs held out for testing w/ cross-validation, discarding examples not solvable by natural logic.

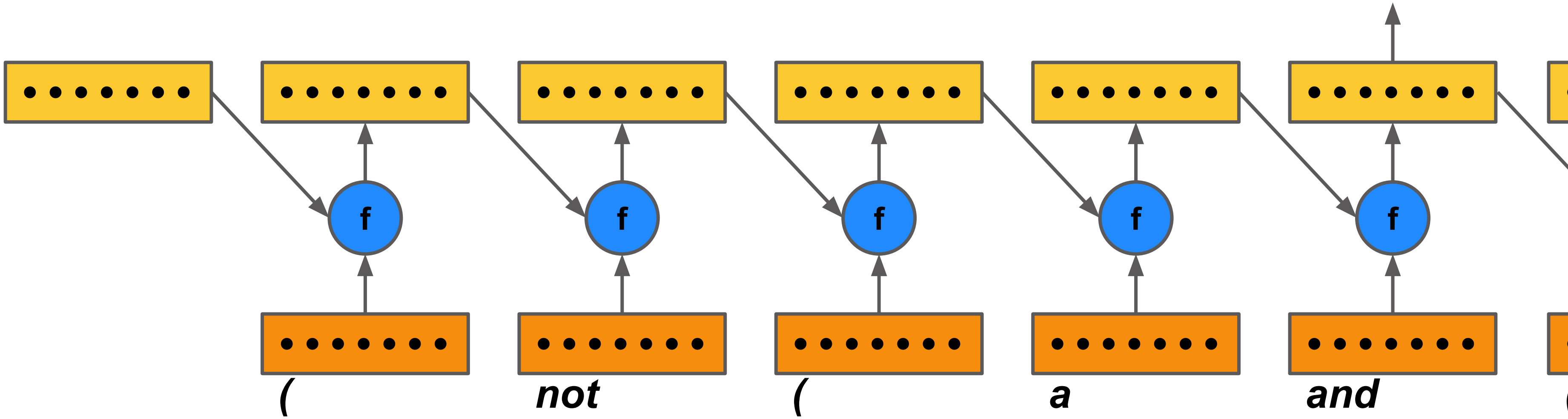
Experiment II: A simple recursive language

TRAIN			TEST		
b	≡	b	not a	^	a
not (not a)	≡	a	c or d	⊐	d
c	⊐	b and c	not not b	≡	b
			not (not a and not d)	≡	a or d

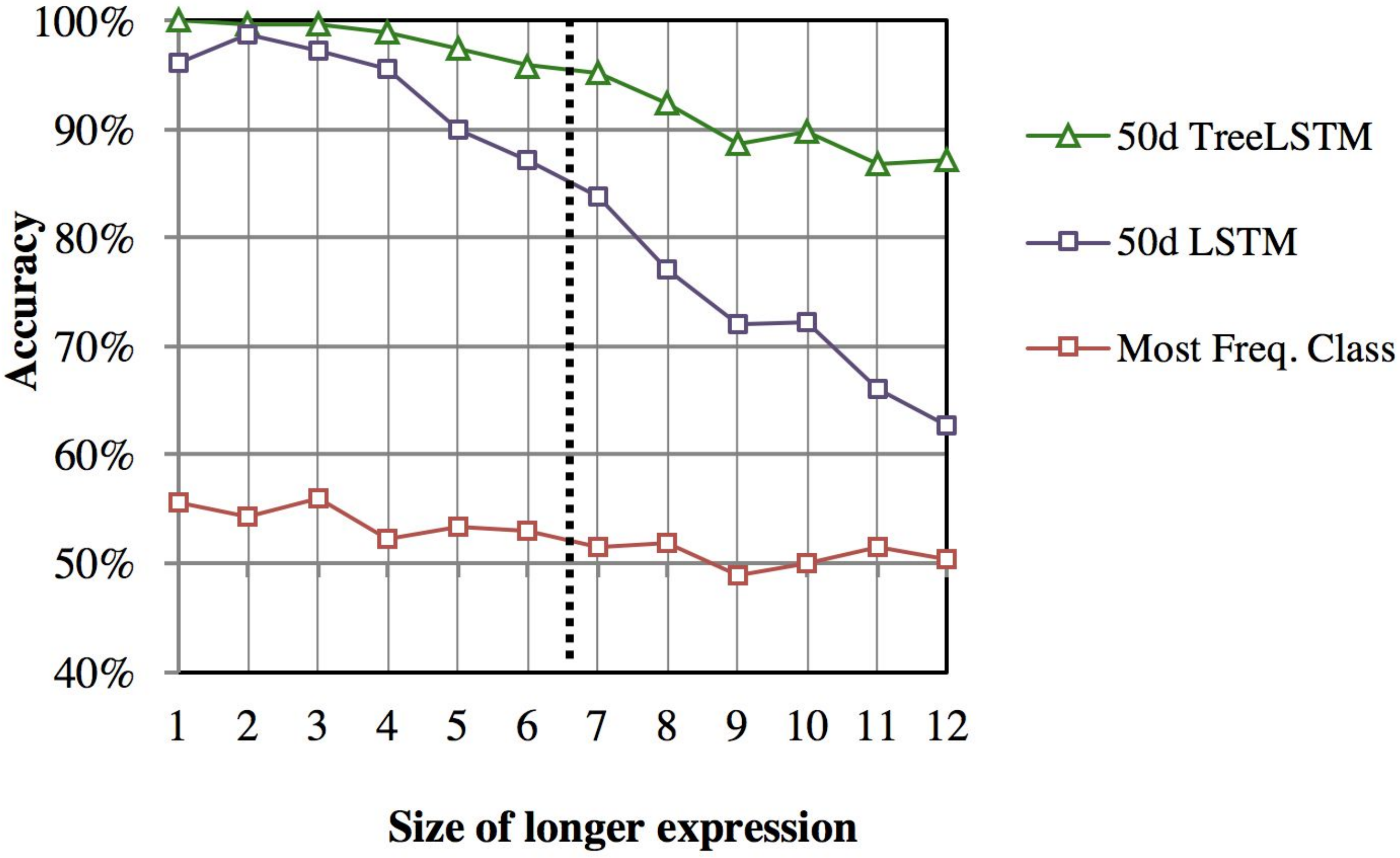
Composition Mechanism: TreeLSTM



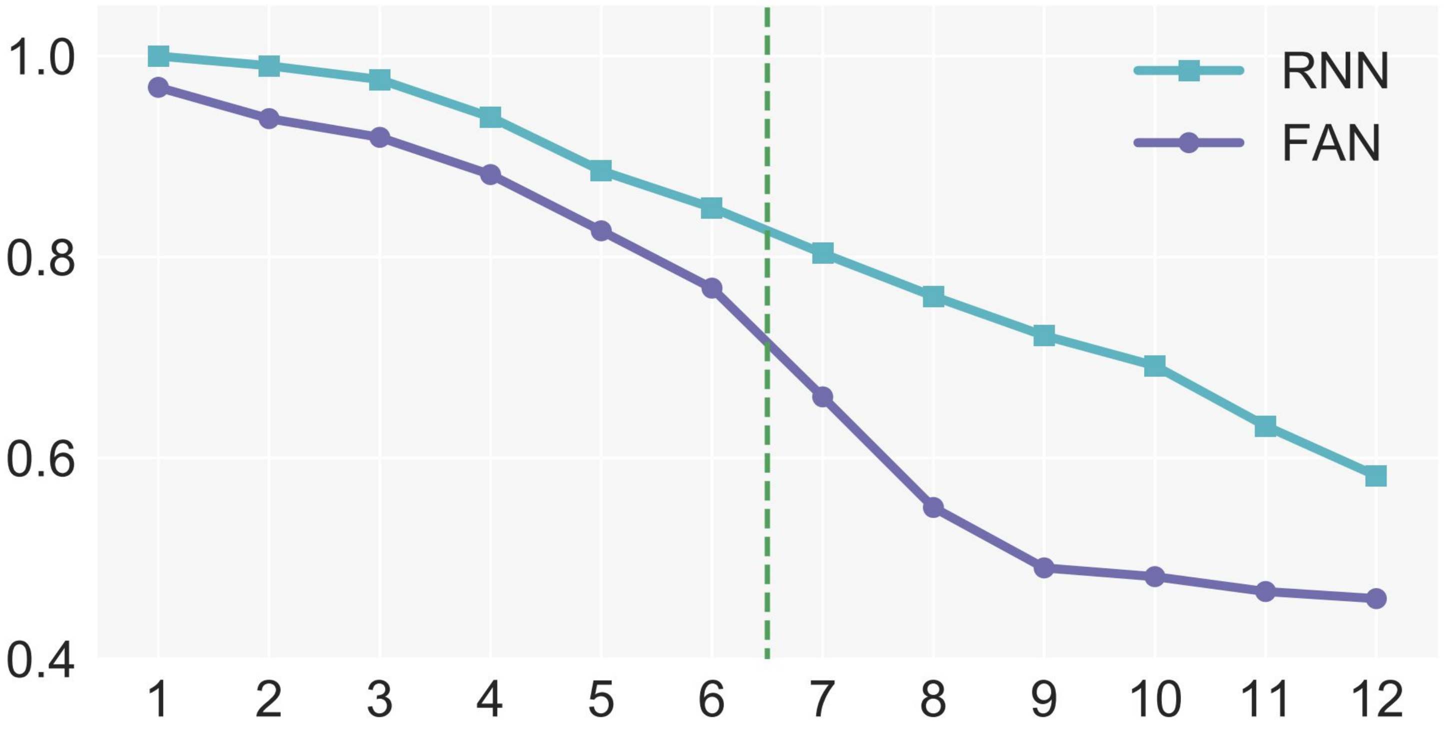
Composition Mechanism:
LSTM RNN with bracketing



Function words and infinite languages



Aside: Attention can't Replace Recurrence



Tran, Bisazza & Monz '18

Success?

Part II

The Stanford NLI Corpus

EMNLP '15 Best New Data Set Award

Samuel R. Bowman
Gabor Angeli
Christopher Potts
Christopher D. Manning

Natural Language Inference Data

Corpus	Size	Natural	Validated
FraCaS	.3k	~	✓
RTE	7k	✓	✓
SICK	10k	✓	✓
DG	728k	~	
Levy	1,500k		
PPDB2	100,000k	~	

Natural language inference data

The current data is not sufficient to train neural networks for NLI:

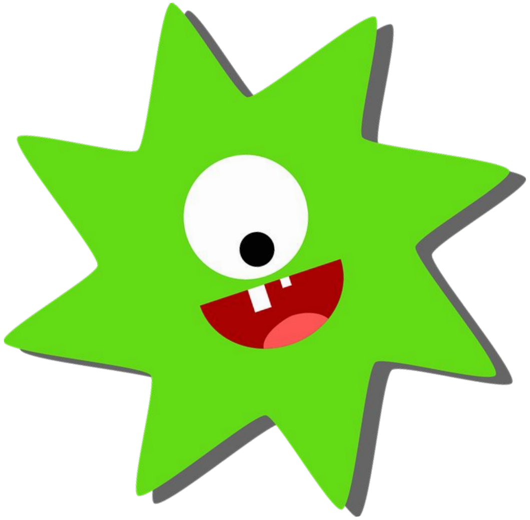
- No successful prior applications of NNs to NLI

SemEval-2014 Task 1

Natural Language Inference Data

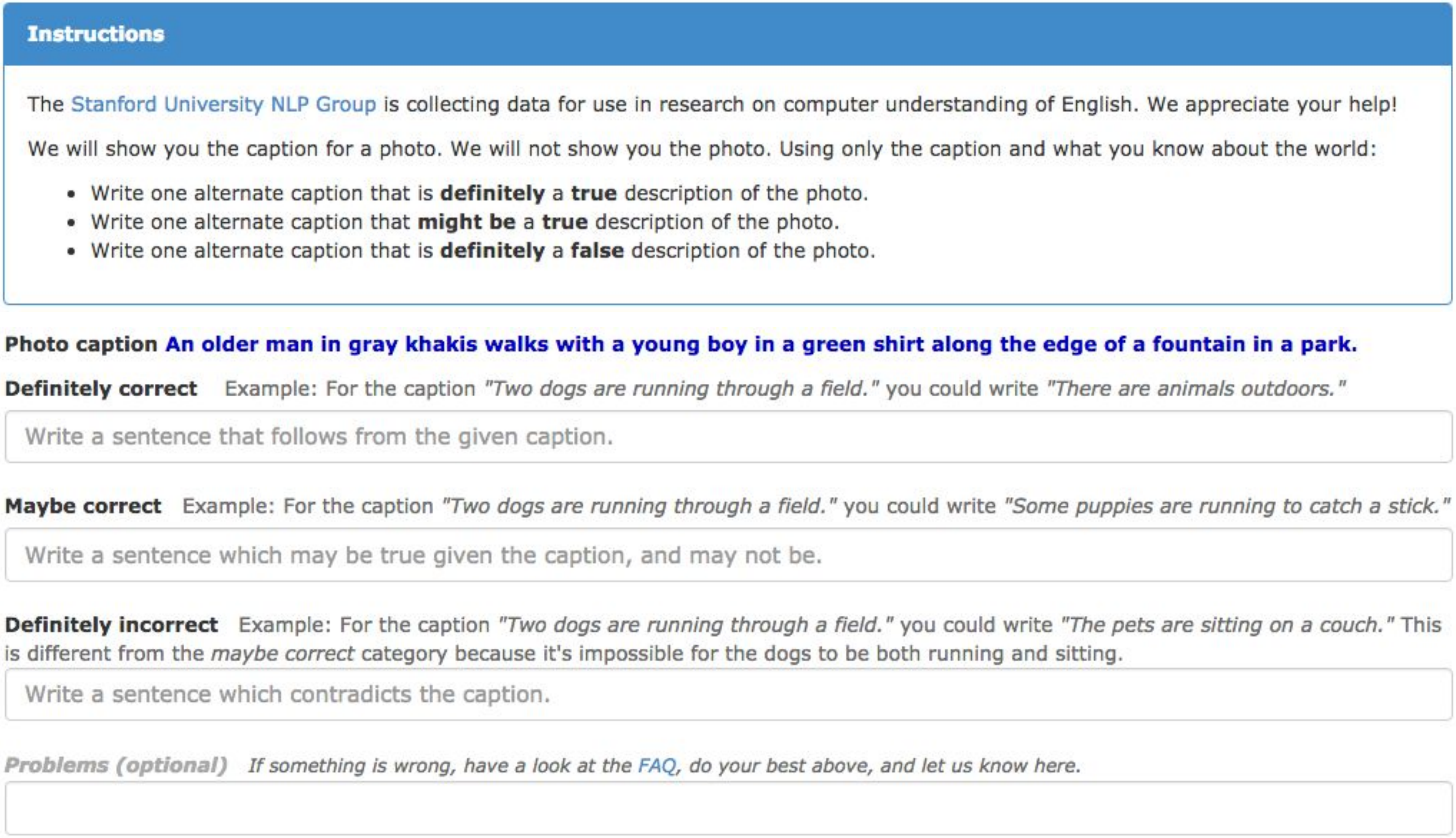
Corpus	Size	Natural	Validated
FraCaS	.3k	~	✓
RTE	7k	✓	✓
SICK	10k	✓	✓
DG	728k	~	
Levy	1,500k		
PPDB2	100,000k	~	

Natural Language Inference Data



Corpus	Size	Natural	Validated
FraCaS	.3k	~	✓
RTE	7k	✓	✓
SICK	10k	✓	✓
SNLI	570k	✓	✓
DG	728k	~	
Levy	1,500k		
PPDB2	100,000k	~	

Our data collection prompt



Instructions

The Stanford University NLP Group is collecting data for use in research on computer understanding of English. We appreciate your help!

We will show you the caption for a photo. We will not show you the photo. Using only the caption and what you know about the world:

- Write one alternate caption that is **definitely** a **true** description of the photo.
- Write one alternate caption that **might be** a **true** description of the photo.
- Write one alternate caption that is **definitely** a **false** description of the photo.

Photo caption **An older man in gray khakis walks with a young boy in a green shirt along the edge of a fountain in a park.**

Definitely correct Example: For the caption *"Two dogs are running through a field."* you could write *"There are animals outdoors."*

Write a sentence that follows from the given caption.

Maybe correct Example: For the caption *"Two dogs are running through a field."* you could write *"Some puppies are running to catch a stick."*

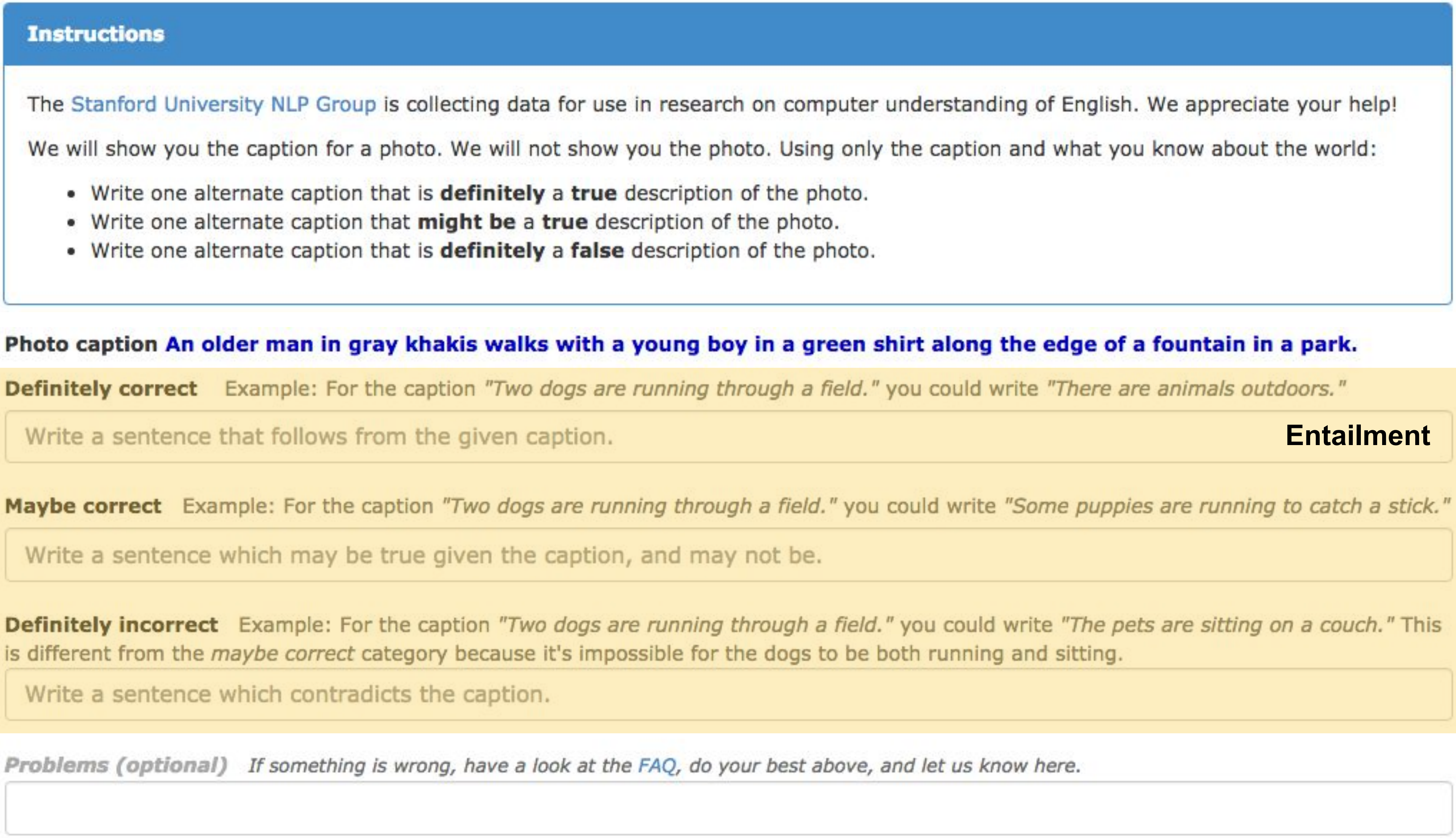
Write a sentence which may be true given the caption, and may not be.

Definitely incorrect Example: For the caption *"Two dogs are running through a field."* you could write *"The pets are sitting on a couch."* This is different from the *maybe correct* category because it's impossible for the dogs to be both running and sitting.

Write a sentence which contradicts the caption.

Problems (optional) *If something is wrong, have a look at the FAQ, do your best above, and let us know here.*

Source captions from Flickr30k: Young, Lai, Hodosh, and Hockenmaier, TACL ‘14



Instructions

The Stanford University NLP Group is collecting data for use in research on computer understanding of English. We appreciate your help!

We will show you the caption for a photo. We will not show you the photo. Using only the caption and what you know about the world:

- Write one alternate caption that is **definitely** a **true** description of the photo.
- Write one alternate caption that **might be** a **true** description of the photo.
- Write one alternate caption that is **definitely** a **false** description of the photo.

Photo caption **An older man in gray khakis walks with a young boy in a green shirt along the edge of a fountain in a park.**

Definitely correct Example: For the caption *"Two dogs are running through a field."* you could write *"There are animals outdoors."*

Write a sentence that follows from the given caption.

Entailment

Maybe correct Example: For the caption *"Two dogs are running through a field."* you could write *"Some puppies are running to catch a stick."*

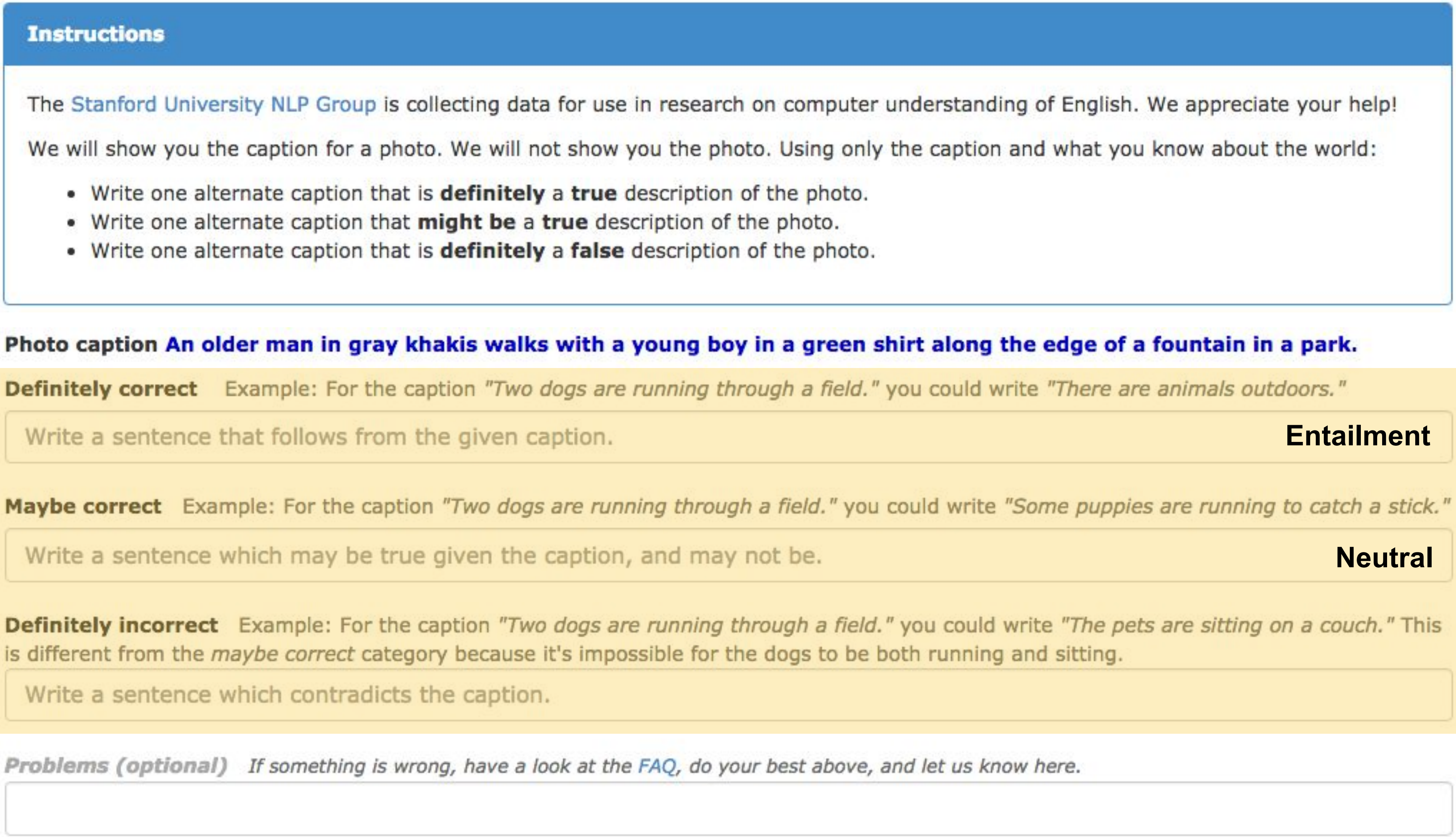
Write a sentence which may be true given the caption, and may not be.

Definitely incorrect Example: For the caption *"Two dogs are running through a field."* you could write *"The pets are sitting on a couch."* This is different from the *maybe correct* category because it's impossible for the dogs to be both running and sitting.

Write a sentence which contradicts the caption.

Problems (optional) *If something is wrong, have a look at the FAQ, do your best above, and let us know here.*

Source captions from Flickr30k: Young, Lai, Hodosh, and Hockenmaier, TACL ‘14



Instructions

The Stanford University NLP Group is collecting data for use in research on computer understanding of English. We appreciate your help!

We will show you the caption for a photo. We will not show you the photo. Using only the caption and what you know about the world:

- Write one alternate caption that is **definitely** a **true** description of the photo.
- Write one alternate caption that **might be** a **true** description of the photo.
- Write one alternate caption that is **definitely** a **false** description of the photo.

Photo caption **An older man in gray khakis walks with a young boy in a green shirt along the edge of a fountain in a park.**

Definitely correct Example: For the caption *"Two dogs are running through a field."* you could write *"There are animals outdoors."*

Write a sentence that follows from the given caption.

Entailment

Maybe correct Example: For the caption *"Two dogs are running through a field."* you could write *"Some puppies are running to catch a stick."*

Write a sentence which may be true given the caption, and may not be.

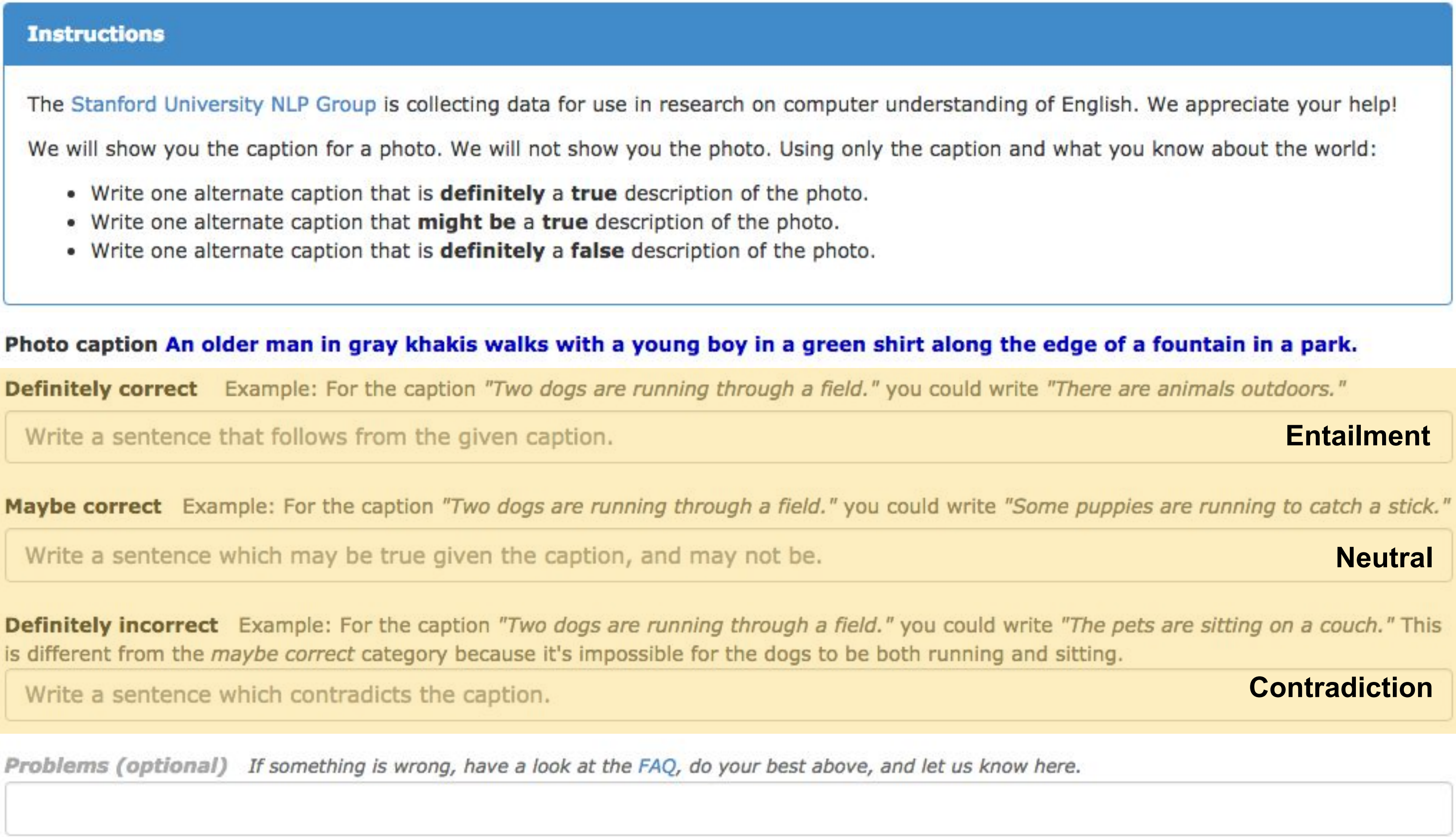
Neutral

Definitely incorrect Example: For the caption *"Two dogs are running through a field."* you could write *"The pets are sitting on a couch."* This is different from the *maybe correct* category because it's impossible for the dogs to be both running and sitting.

Write a sentence which contradicts the caption.

Problems (optional) *If something is wrong, have a look at the FAQ, do your best above, and let us know here.*

Source captions from Flickr30k: Young, Lai, Hodosh, and Hockenmaier, TACL ‘14



Instructions

The Stanford University NLP Group is collecting data for use in research on computer understanding of English. We appreciate your help!

We will show you the caption for a photo. We will not show you the photo. Using only the caption and what you know about the world:

- Write one alternate caption that is **definitely** a **true** description of the photo.
- Write one alternate caption that **might be** a **true** description of the photo.
- Write one alternate caption that is **definitely** a **false** description of the photo.

Photo caption **An older man in gray khakis walks with a young boy in a green shirt along the edge of a fountain in a park.**

Definitely correct Example: For the caption *"Two dogs are running through a field."* you could write *"There are animals outdoors."*

Write a sentence that follows from the given caption.

Entailment

Maybe correct Example: For the caption *"Two dogs are running through a field."* you could write *"Some puppies are running to catch a stick."*

Write a sentence which may be true given the caption, and may not be.

Neutral

Definitely incorrect Example: For the caption *"Two dogs are running through a field."* you could write *"The pets are sitting on a couch."* This is different from the *maybe correct* category because it's impossible for the dogs to be both running and sitting.

Write a sentence which contradicts the caption.

Contradiction

Problems (optional) *If something is wrong, have a look at the FAQ, do your best above, and let us know here.*

Source captions from Flickr30k: Young, Lai, Hodosh & Hockenmaier ‘14

What we got

Some Sample Results

Premise: *Two women are embracing while holding to go packages.*

Hypothesis: *Two woman are holding packages.*

Label: Entailment

Some Sample Results

Premise: *A man in a blue shirt standing in front of a garage-like structure painted with geometric designs.*

Hypothesis: *A man is repainting a garage*

Label: Neutral

Some Sample Results

Premise: *A man selling donuts to a customer during a world exhibition event held in the city of Angeles*

Hypothesis: *A woman drinks her coffee in a small cafe.*

Label: Contradiction

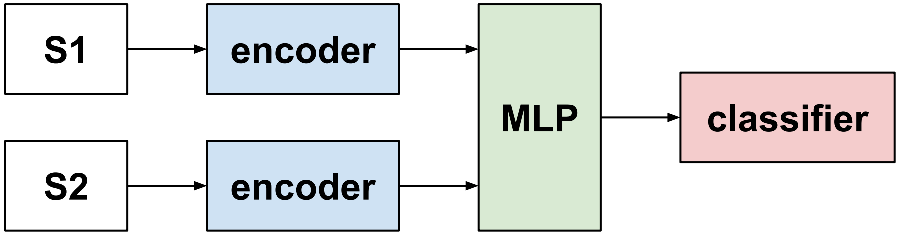
Results on SNLI

Some Results on SNLI

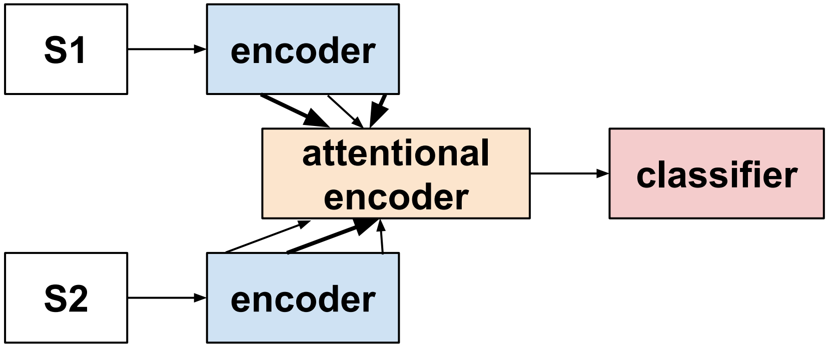
Model	Test accuracy
Most frequent class	34.2%
Big lexicalized classifier	78.2%

Two Classes of Neural Network

- Sentence encoder-based models



- Attention and memory models



Some Results on SNLI

Model	Test accuracy
Most frequent class	34.2%
Big lexicalized classifier	78.2%
300D CBOW	80.6%
300D BiLSTM	81.5%

Some Results on SNLI

Model	Test accuracy
Most frequent class	34.2%
Big lexicalized classifier	78.2%
300D CBOW	80.6%
300D BiLSTM	81.5%
REINFORCE-Trained Self-Attention (Tao Shen et al. ‘18)	86.3%
Self-Attention/Cross-Attention + Ensemble (Yi Tay et al. ‘18)	**89.3%**

Success?

- We’re not at human performance yet…
- ...but with 100+ published experiments, the best systems rarely stray too far from the standard toolkit:
  - LSTMs
  - Attention
  - Pretrained word embeddings
  - Ensembling

Part III

The Multi-genre NLI Corpus

Adina Williams
Nikita Nangia
Samuel R. Bowman

SNLI is Showing its Limitations

- Little headroom left:
  - SotA: **89.3%**
  - Human performance: ~96%
- Many linguistic phenomena underattested or ignored
  - Tense
  - Beliefs
  - Modality (possibility/permission)

    …

SNLI is Showing its Limitations

Gururangan et al. ‘18:

- Some cues in SNLI hypotheses give clues to the label:
  - Negation is most common with *contradiction*
  - Some content words more common in *contradiction* (‘sleeping’)
  - Very short sentences tend to be *entailment*
- A trained NN classifier can reach 67% *without access to the premise.*

The MultiGenre NLI Corpus

Genre	Train	Dev	Test
Captions (SNLI Corpus)	(550,152)	(10,000)	(10,000)
Fiction	77,348	2,000	2,000
Government	77,350	2,000	2,000
Slate	77,306	2,000	2,000
Switchboard (Telephone Speech)	83,348	2,000	2,000
Travel Guides	77,350	2,000	2,000

The MultiGenre NLI Corpus

Genre	Train	Dev	Test
Captions (SNLI Corpus)	(550,152)	(10,000)	(10,000)
Fiction	77,348	2,000	2,000
Government	77,350	2,000	2,000
Slate	77,306	2,000	2,000
Switchboard (Telephone Speech)	83,348	2,000	2,000
Travel Guides	77,350	2,000	2,000
9/11 Report	0	2,000	2,000
Face-to-Face Speech	0	2,000	2,000
Letters	0	2,000	2,000
OUP (Nonfiction Books)	0	2,000	2,000
Verbatim (Magazine)	0	2,000	2,000
Total	**392,702**	**20,000**	**20,000**

The MultiGenre NLI Corpus

Genre	Train	Dev	Test
Captions (SNLI Corpus)	(550,152)	(10,000)	(10,000)
Fiction	77,348	2,000	2,000
Government	77,350	2,000	2,000
Slate	77,306	2,000	2,000
Switchboard (Telephone Speech)	83,348	2,000	2,000
Travel Guides	77,350	2,000	2,000
9/11 Report	0	2,000	2,000
Face-to-Face Speech	0	2,000	2,000
Letters	0	2,000	2,000
OUP (Nonfiction Books)	0	2,000	2,000
Verbatim (Magazine)	0	2,000	2,000
Total	**392,702**	**20,000**	**20,000**

genre-matched evaluation

genre-mismatched evaluation

What we got

Typical Dev Set Examples

Premise: *In contrast, suppliers that have continued to innovate and expand their use of the four practices, as well as other activities described in previous chapters, keep outperforming the industry as a whole.*

Hypothesis: *The suppliers that continued to innovate in their use of the four practices consistently underperformed in the industry.*

Label: Contradiction

Genre: Oxford University Press (Nonfiction books)

Typical Dev Set Examples

Premise: *someone else noticed it and i said well i guess that’s true and it was somewhat melodious in other words it wasn’t just you know it was really funny*

Hypothesis: *No one noticed and it wasn’t funny at all.*

Label: Contradiction

Genre: Switchboard (Telephone Speech)

Typical Dev Set Examples

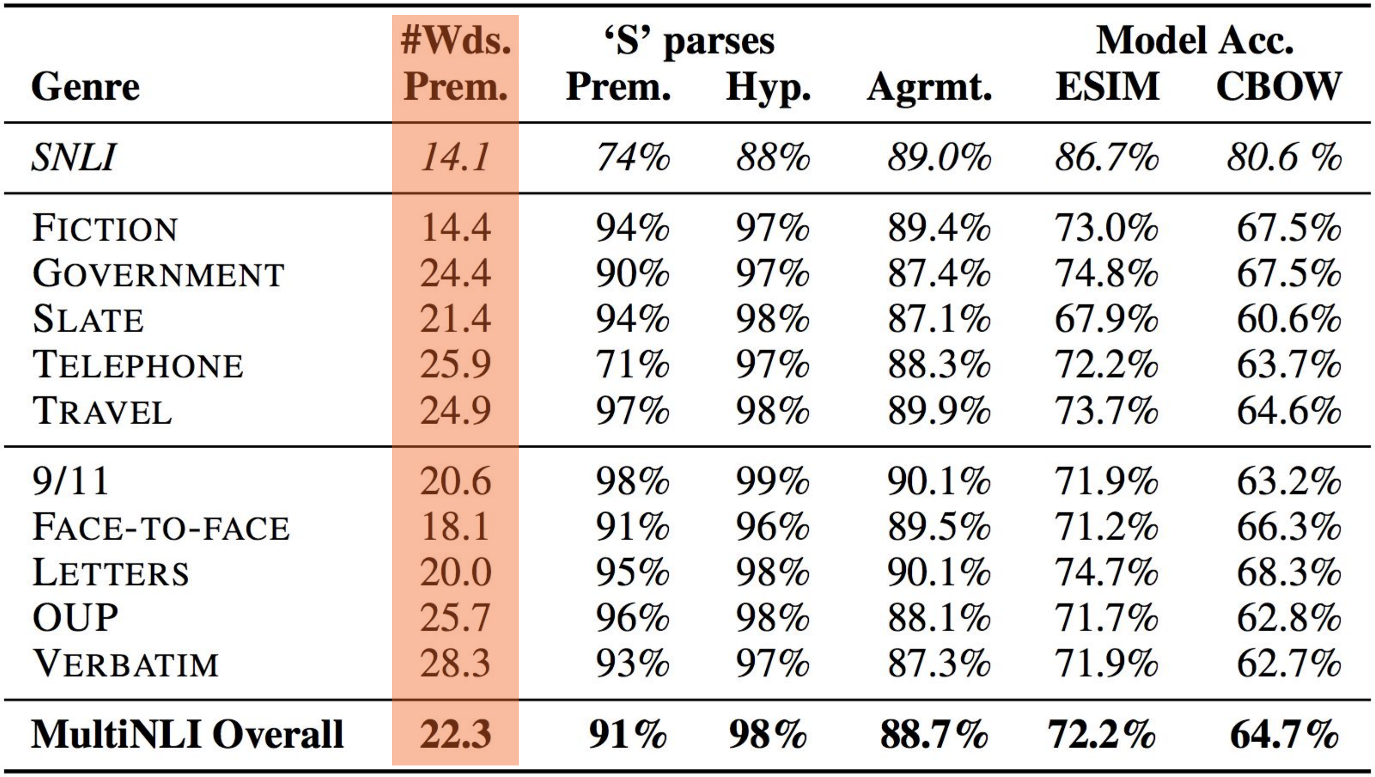
Premise: *The father can beget new offspring safe from Macbeth's hand; the son is the palpable threat.*

Hypothesis: *The son wants to kill him to marry his mom*

Label: Neutral

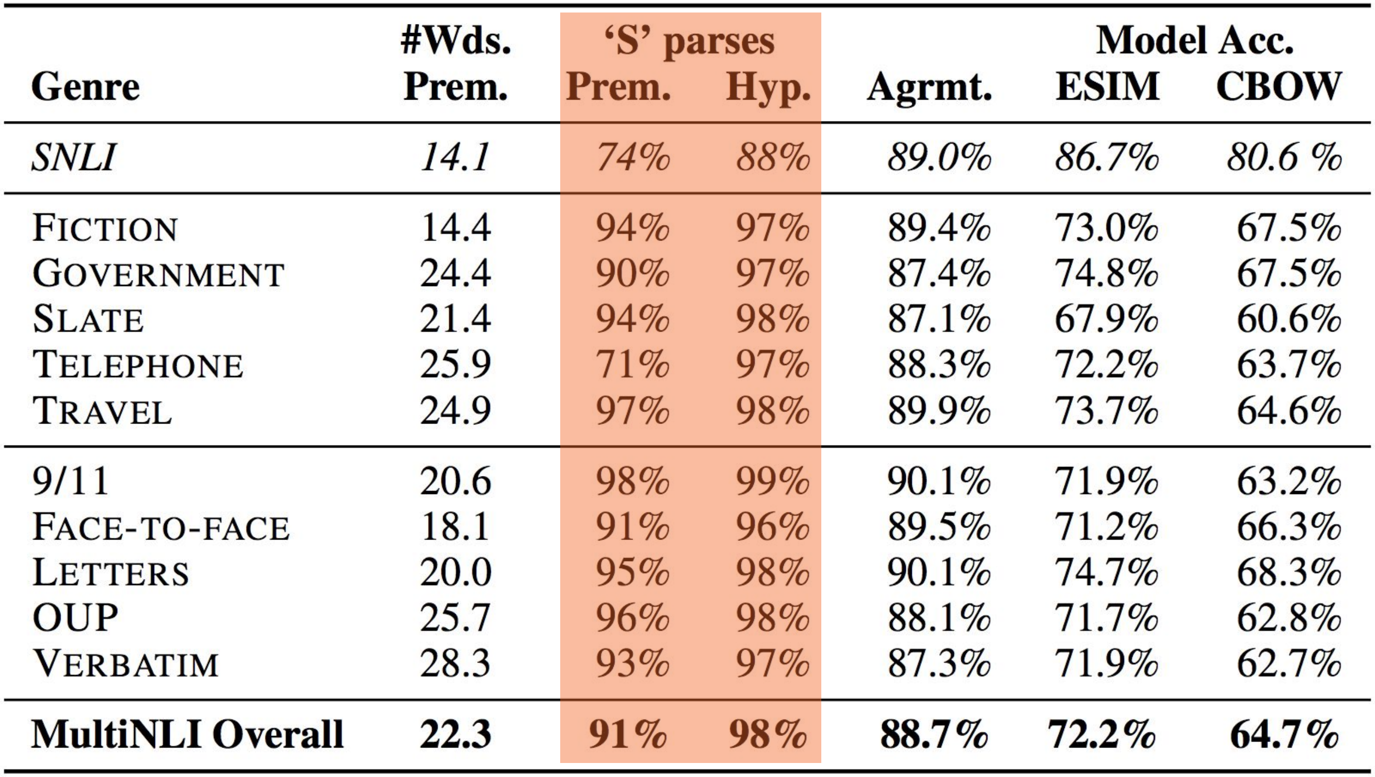
Genre: Verbatim (Magazine)

Key Figures



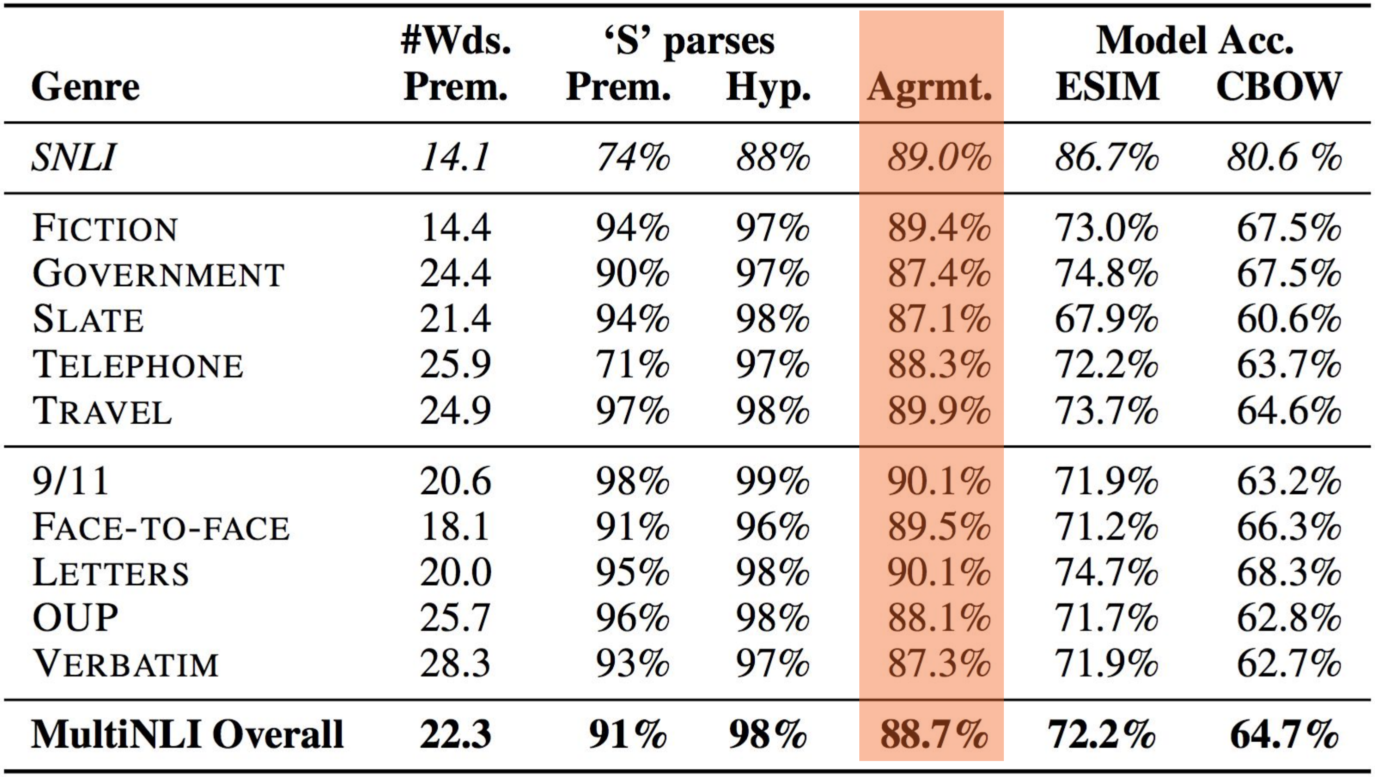
	#Wds.	'S' parses			Model Acc.	
Genre	**Prem.**	**Prem.**	**Hyp.**	**Agrmt.**	**ESIM**	**CBOW**
SNLI	*14.1*	*74%*	*88%*	*89.0%*	*86.7%*	*80.6 %*
Fiction	14.4	94%	97%	89.4%	73.0%	67.5%
Government	24.4	90%	97%	87.4%	74.8%	67.5%
Slate	21.4	94%	98%	87.1%	67.9%	60.6%
Telephone	25.9	71%	97%	88.3%	72.2%	63.7%
Travel	24.9	97%	98%	89.9%	73.7%	64.6%
9/11	20.6	98%	99%	90.1%	71.9%	63.2%
Face-to-face	18.1	91%	96%	89.5%	71.2%	66.3%
Letters	20.0	95%	98%	90.1%	74.7%	68.3%
OUP	25.7	96%	98%	88.1%	71.7%	62.8%
Verbatim	28.3	93%	97%	87.3%	71.9%	62.7%
MultiNLI Overall	**22.3**	**91%**	**98%**	**88.7%**	**72.2%**	**64.7%**

Key Figures



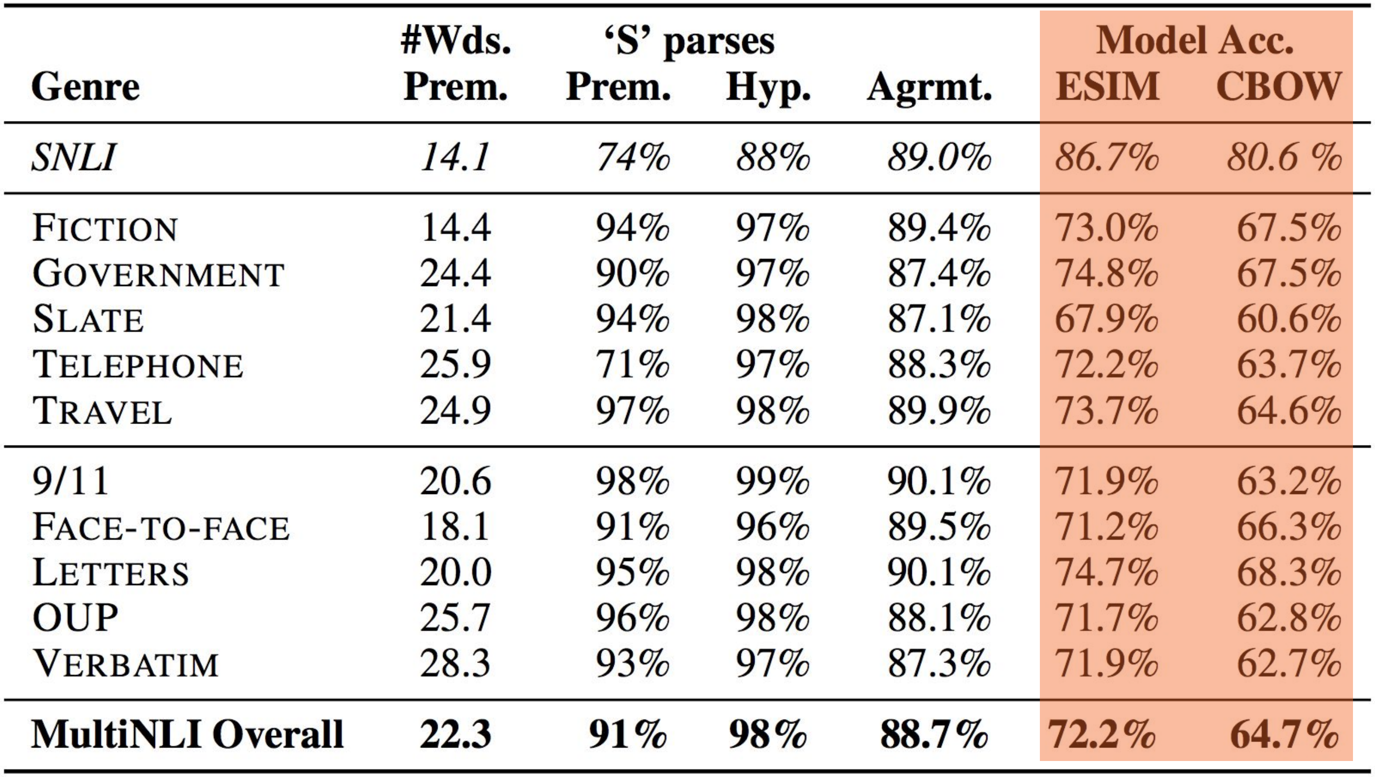
Genre	#Wds.	'S' parses		Agrmt.	Model Acc.	
	Prem.	Prem.	Hyp.		ESIM	CBOW
SNLI	*14.1*	*74%*	*88%*	*89.0%*	*86.7%*	*80.6 %*
FICTION	14.4	94%	97%	89.4%	73.0%	67.5%
GOVERNMENT	24.4	90%	97%	87.4%	74.8%	67.5%
SLATE	21.4	94%	98%	87.1%	67.9%	60.6%
TELEPHONE	25.9	71%	97%	88.3%	72.2%	63.7%
TRAVEL	24.9	97%	98%	89.9%	73.7%	64.6%
9/11	20.6	98%	99%	90.1%	71.9%	63.2%
FACE-TO-FACE	18.1	91%	96%	89.5%	71.2%	66.3%
LETTERS	20.0	95%	98%	90.1%	74.7%	68.3%
OUP	25.7	96%	98%	88.1%	71.7%	62.8%
VERBATIM	28.3	93%	97%	87.3%	71.9%	62.7%
MultiNLI Overall	**22.3**	**91%**	**98%**	**88.7%**	**72.2%**	**64.7%**

Key Figures



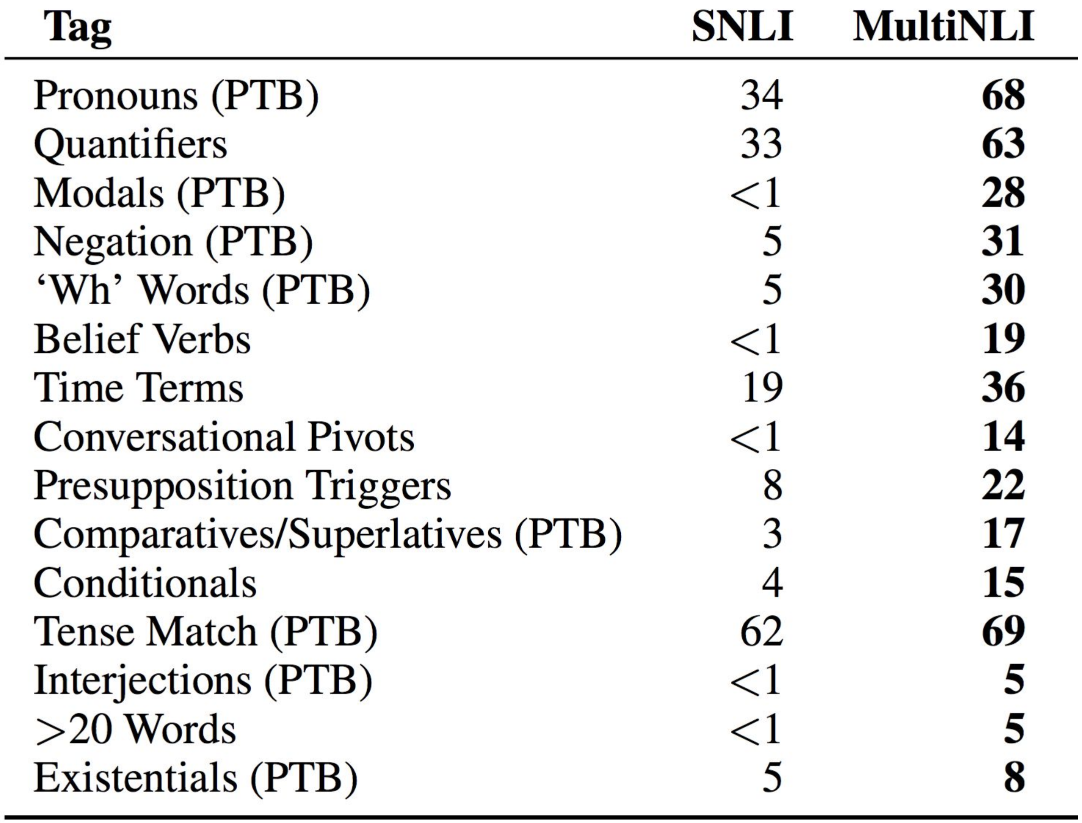
	#Wds.	‘S’ parses			Model Acc.	
Genre	**Prem.**	**Prem.**	**Hyp.**	**Agrmt.**	**ESIM**	**CBOW**
SNLI	*14.1*	*74%*	*88%*	*89.0%*	*86.7%*	*80.6 %*
Fiction	14.4	94%	97%	89.4%	73.0%	67.5%
Government	24.4	90%	97%	87.4%	74.8%	67.5%
Slate	21.4	94%	98%	87.1%	67.9%	60.6%
Telephone	25.9	71%	97%	88.3%	72.2%	63.7%
Travel	24.9	97%	98%	89.9%	73.7%	64.6%
9/11	20.6	98%	99%	90.1%	71.9%	63.2%
Face-to-face	18.1	91%	96%	89.5%	71.2%	66.3%
Letters	20.0	95%	98%	90.1%	74.7%	68.3%
OUP	25.7	96%	98%	88.1%	71.7%	62.8%
Verbatim	28.3	93%	97%	87.3%	71.9%	62.7%
MultiNLI Overall	**22.3**	**91%**	**98%**	**88.7%**	**72.2%**	**64.7%**

Key Figures



	#Wds.	‘S’ parses			Model Acc.	
Genre	**Prem.**	**Prem.**	**Hyp.**	**Agrmt.**	**ESIM**	**CBOW**
SNLI	*14.1*	*74%*	*88%*	*89.0%*	*86.7%*	*80.6 %*
Fiction	14.4	94%	97%	89.4%	73.0%	67.5%
Government	24.4	90%	97%	87.4%	74.8%	67.5%
Slate	21.4	94%	98%	87.1%	67.9%	60.6%
Telephone	25.9	71%	97%	88.3%	72.2%	63.7%
Travel	24.9	97%	98%	89.9%	73.7%	64.6%
9/11	20.6	98%	99%	90.1%	71.9%	63.2%
Face-to-face	18.1	91%	96%	89.5%	71.2%	66.3%
Letters	20.0	95%	98%	90.1%	74.7%	68.3%
OUP	25.7	96%	98%	88.1%	71.7%	62.8%
Verbatim	28.3	93%	97%	87.3%	71.9%	62.7%
MultiNLI Overall	**22.3**	**91%**	**98%**	**88.7%**	**72.2%**	**64.7%**

Key Figures



Tag	SNLI	MultiNLI
Pronouns (PTB)	34	**68**
Quantifiers	33	**63**
Modals (PTB)	<1	**28**
Negation (PTB)	5	**31**
‘Wh’ Words (PTB)	5	**30**
Belief Verbs	<1	**19**
Time Terms	19	**36**
Conversational Pivots	<1	**14**
Presupposition Triggers	8	**22**
Comparatives/Superlatives (PTB)	3	**17**
Conditionals	4	**15**
Tense Match (PTB)	62	**69**
Interjections (PTB)	<1	**5**
>20 Words	<1	**5**
Existentials (PTB)	5	**8**

Some Results

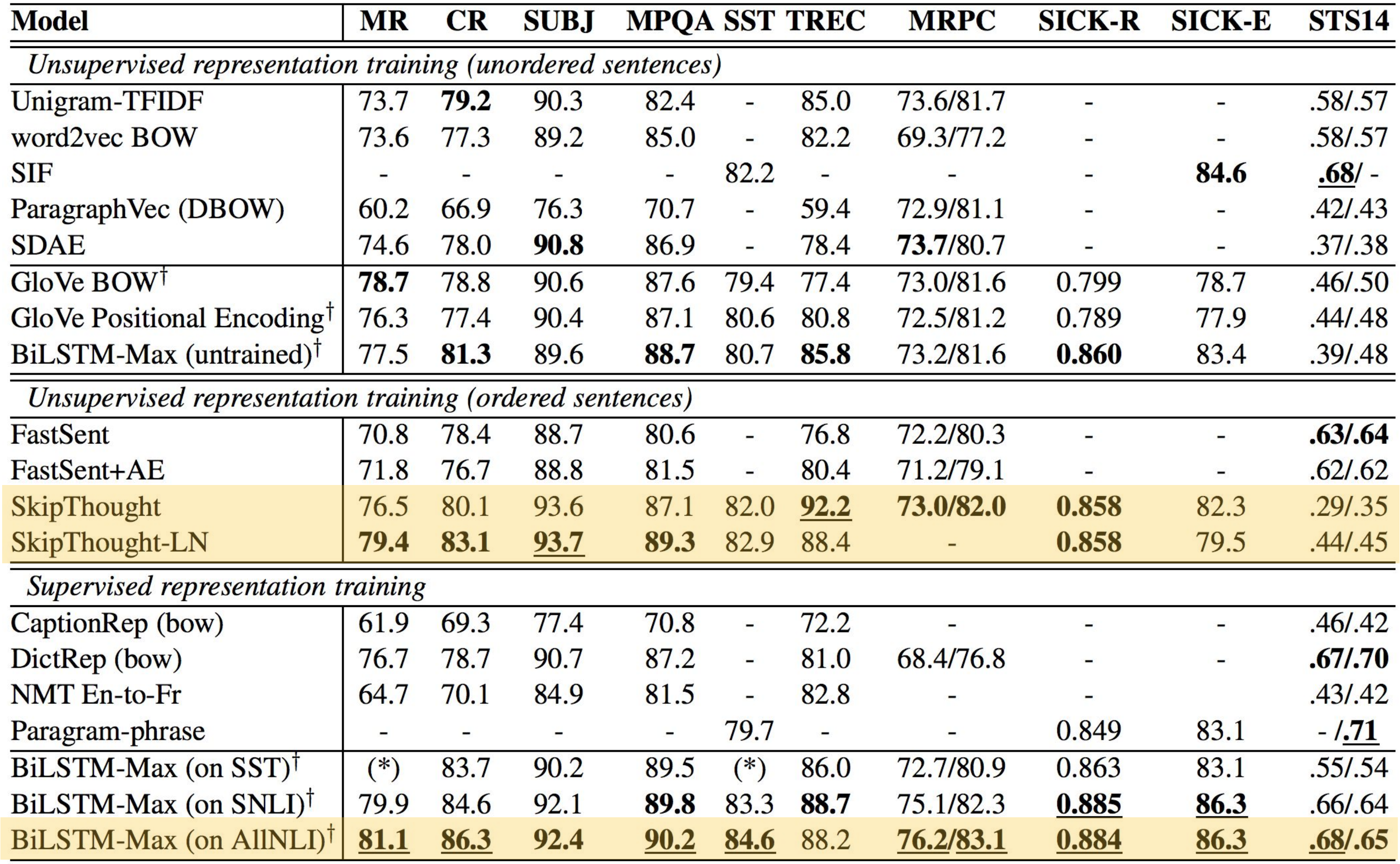
Model	**Matched Test Acc.**	**Mismatched Test Acc.**
Most frequent class	36.5%	35.6%
CBOW	65.2%	64.6%
Deep BiLSTM+ (Chen et al. ‘17)	74.9%	74.9%
Attention+convolutions (Gong et al. ‘18)	80.0%	78.7%

Fewer Clues in the Hypotheses

Gururangan et al. ‘18:

- Fewer clues to pair label in hypothesis sentences.
- NN classifier performance without access to premise:
    - SNLI: 67% (vs. SotA 89%)
    - MultiNLI: 54/52% (vs. SotA 80/79%)
- Why? No deliberate intervention, but…
    - More diverse content (fewer content cues)
    - More diverse hypothesis structure (fewer structural cues)
    - More communication with annotators

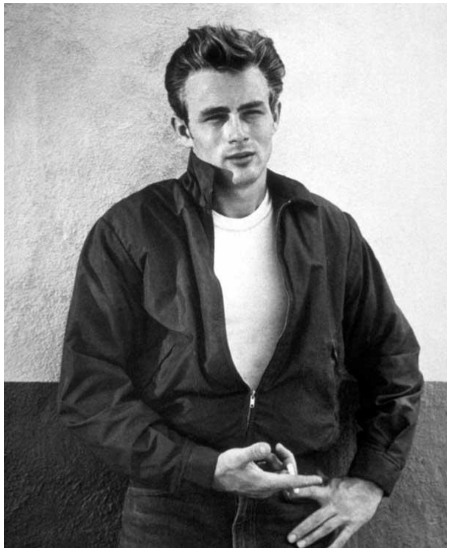
NLI as a Pretraining Task



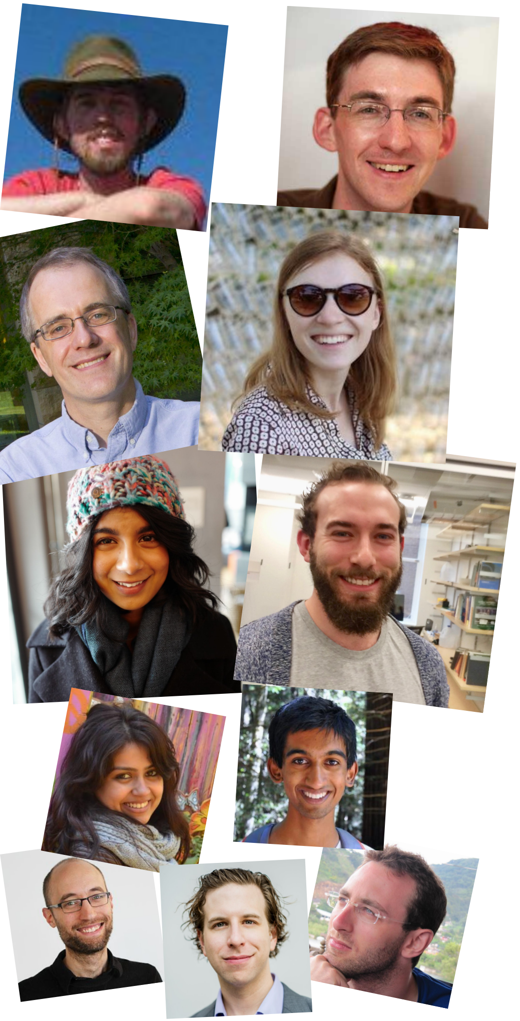
Model	MR	CR	SUBJ	MPQA	SST	TREC	MRPC	SICK-R	SICK-E	STS14
Unsupervised representation training (unordered sentences)										
Unigram-TFIDF	73.7	**79.2**	90.3	82.4	-	85.0	73.6/81.7	-	-	.58/.57
word2vec BOW	73.6	77.3	89.2	85.0	-	82.2	69.3/77.2	-	-	.58/.57
SIF	-	-	-	-	82.2	-	-	-	**84.6**	**.68**/ -
ParagraphVec (DBOW)	60.2	66.9	76.3	70.7	-	59.4	72.9/81.1	-	-	.42/.43
SDAE	74.6	78.0	**90.8**	86.9	-	78.4	**73.7**/80.7	-	-	.37/.38
GloVe BOW†	**78.7**	78.8	90.6	87.6	79.4	77.4	73.0/81.6	0.799	78.7	.46/.50
GloVe Positional Encoding†	76.3	77.4	90.4	87.1	80.6	80.8	72.5/81.2	0.789	77.9	.44/.48
BiLSTM-Max (untrained)†	77.5	**81.3**	89.6	**88.7**	80.7	**85.8**	73.2/81.6	**0.860**	83.4	.39/.48
Unsupervised representation training (ordered sentences)										
FastSent	70.8	78.4	88.7	80.6	-	76.8	72.2/80.3	-	-	**.63/.64**
FastSent+AE	71.8	76.7	88.8	81.5	-	80.4	71.2/79.1	-	-	.62/.62
SkipThought	76.5	80.1	93.6	87.1	82.0	**92.2**	**73.0/82.0**	**0.858**	82.3	.29/.35
SkipThought-LN	**79.4**	**83.1**	**93.7**	**89.3**	82.9	88.4	-	**0.858**	79.5	.44/.45
Supervised representation training										
CaptionRep (bow)	61.9	69.3	77.4	70.8	-	72.2	-	-	-	.46/.42
DictRep (bow)	76.7	78.7	90.7	87.2	-	81.0	68.4/76.8	-	-	**.67/.70**
NMT En-to-Fr	64.7	70.1	84.9	81.5	-	82.8	-	-		.43/.42
Paragram-phrase	-	-	-	-	79.7	-	-	0.849	83.1	- /**.71**
BiLSTM-Max (on SST)†	(*)	83.7	90.2	89.5	(*)	86.0	72.7/80.9	0.863	83.1	.55/.54
BiLSTM-Max (on SNLI)†	79.9	84.6	92.1	**89.8**	83.3	**88.7**	75.1/82.3	**0.885**	**86.3**	.66/.64
BiLSTM-Max (on AllNLI)†	**81.1**	**86.3**	**92.4**	**90.2**	**84.6**	88.2	**76.2/83.1**	**0.884**	**86.3**	**.68**/.65

Conneau et al. ‘17; see also Subramanian et al. ‘18

Discussion: NLI



- NLI lets you judge the degree to which models can learn to understand natural language sentences.
- With SNLI, it’s now possible to train low-bias machine learning models like NNs on NLI.
- MultiNLI makes it possible to test models’ ability to understand American English in nearly its full range of uses.
- Sentence encoders trained on NLI, like InferSent, are likely among the best general-purpose encoders we have.



Thanks!

- Data, leaderboards, and papers:
    - ○ https://nlp.stanford.edu/projects/snli/
    - ○ https://nyu.edu/projects/bowman/multinli/
- Adina Williams is seeking a postdoc position!

These projects were supported in part by a Google Faculty Research Award, gifts from Tencent Holdings and NVIDIA, and a grant from Samsung Research.