# A large annotated corpus for learning natural language inference

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**EMNLP 2015** 

- Natural Language Inference
- 2 Stanford Natural Language Inference Corpus
  - Coreference issue
  - Data collection & validation
- Methods
  - Feature-based
  - Sentence embedding
- 4 Results

# Natural Language Inference (NLI)

- a.k.a. recognising textual entailment (RTE)
- Does a piece of text follows from or contradict another?

## Example

Premise: A man inspects the uniform of a figure in some East Asian

country.

Hypothesis: The man is sleeping.

## Example

Premise: A soccer game with multiple males playing.

Hypothesis: Some men are playing a sport.

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contradiction

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entailment

- Bowman et al. 2015
- 570,152 pairs of sentences
- Collected over Amazon Mechanical Turk
  - Simple annotation guidelines
  - Captions from the Flickr30k corpus
  - 2,500 workers contributed
  - 30 trusted workers for validation
- https://nlp.stanford.edu/projects/snli/

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Coreference issue

## Example

A boat sank in the Pacific Ocean.

A boat sank in the Atlantic Ocean.

Do they contradict each other? or neutral?

Coreference issue

# Example

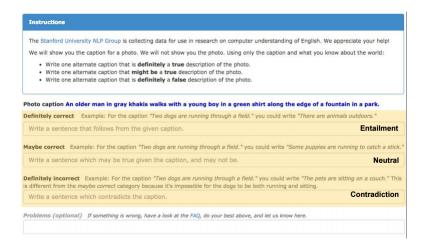
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#### Data collection



### Figure: Crowd-sourcing on Amazon Mechanical Turk<sup>1</sup>

### Data collection

Data set sizes:		
Training pairs	550,152	
Development pairs	10,000	
Test pairs	10,000	
Sentence length:		
Premise mean token count	14.1	
Hypothesis mean token count	8.3	
Parser output:		
Premise 'S'-rooted parses	74.0%	
Hypothesis 'S'-rooted parses	88.9%	
Distinct words (ignoring case)	37,026	

Figure: Key statistics for the raw sentence pairs in SNLI

# SNLI Corpus Data validation

Condition	% of pairs
5 vote unanimous agreement:	58.3%
3-4 vote majority for one label including author:	32.9%
3-4 vote majority for one label not including original author:	6.8%
No majority for any one label:	2.0%

Figure: Data validation with 10% held-out data<sup>2</sup>

<sup>&</sup>lt;sup>2</sup>https://www.nyu.edu/projects/bowman/cusp\_snli\_slides.pdf → ⟨ ≥ ⟩ ⟨ ≥

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## Feature-based

#### Feature selection

- BLEU score of the hypothesis with respect to the premise (n-gram =1..4)
- 2 Length difference between the hypothesis and the premise
- Count & percentage of overlapping words in the premise and hypothesis (all and just nouns, verbs, adjectives, and adverbs)
- Unigram and bigram in the hypothesis.
- Cross-unigrams: for every pair of words across the premise and hypothesis which share a POS tag.
- Cross-bigrams: for every pair of bigrams across the premise and hypothesis which share a POS tag on the second word.

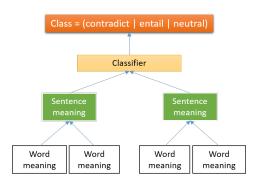
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Word embeddings

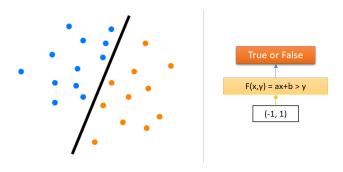
- Represent words as a vectors
  - $cat \Rightarrow [0.4, 0.3, ..., 0.1]$
  - $dog \Rightarrow [0.1, 0.5, ..., 0.2]$
- Word2vec Mikolov et al. 2013

Bowman et al. 2015



Neural network - a quick look

## Learning a function



Bowman et al. 2015

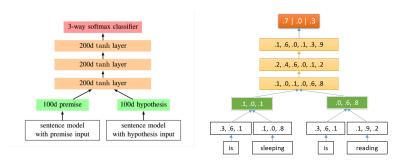


Figure: Neural network classification architecture

Bowman et al. 2015

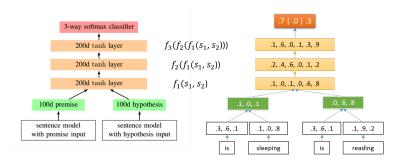


Figure: Neural network classification architecture

## Results

### Feature-based

System	SNLI		SICK	
	Train	Test	Train	Test
Lexicalized	99.7	78.2	90.4	77.8
Unigrams Only	93.1	71.6	88.1	77.0
Unlexicalized	49.4	50.4	69.9	69.6

Figure: Feature-based variants

## Results

### Feature-based vs. Sentence embedding

Model	% Accuracy (Test set)
Feature-based classifier	78.2
LSTM RNN sequence model	80.6

Figure: Results<sup>3</sup>

³https://nlp.stanford.edu/manning/talks/SIGIR2016-Deep-Learning=NLI.pdf == +0 a.@

# Summary

- A large-scale, naturalistic corpus of sentence pairs labeled for entailment, contradiction, and independence.
- Both simple lexicalised models and neural network models perform well.
- The RepEval 2017 Shared Task
  - https://repeval2017.github.io/shared/

## References I

- Bowman, Samuel R. et al. (2015). "A large annotated corpus for learning natural language inference". In: Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP).

  Association for Computational Linguistics.
- Mikolov, Tomas et al. (2013). "Distributed representations of words and phrases and their compositionality". In: *Advances in neural information processing systems*, pp. 3111–3119.