



# Annotation Artifacts in Natural Language Inference Data

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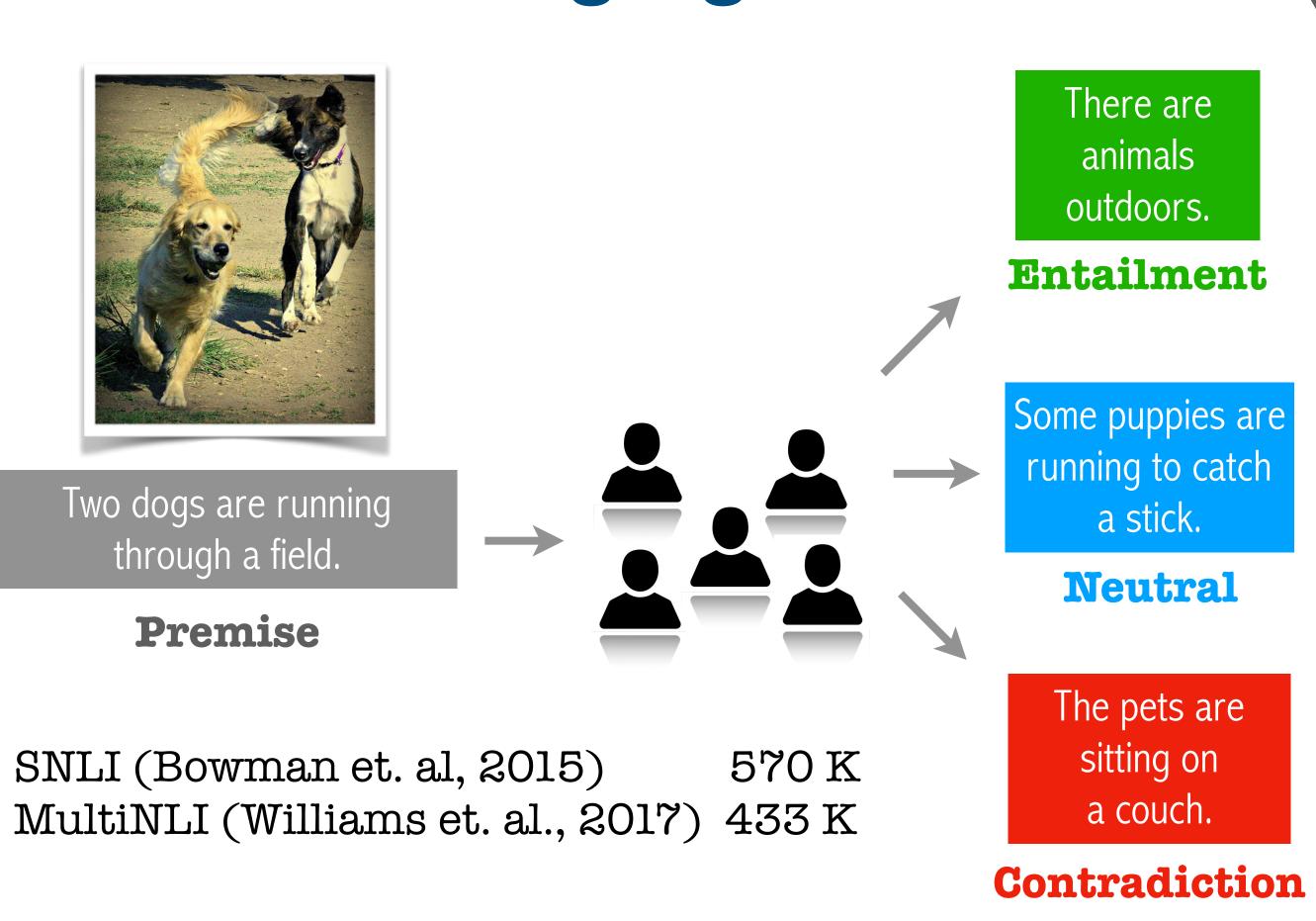
\* equal contribution





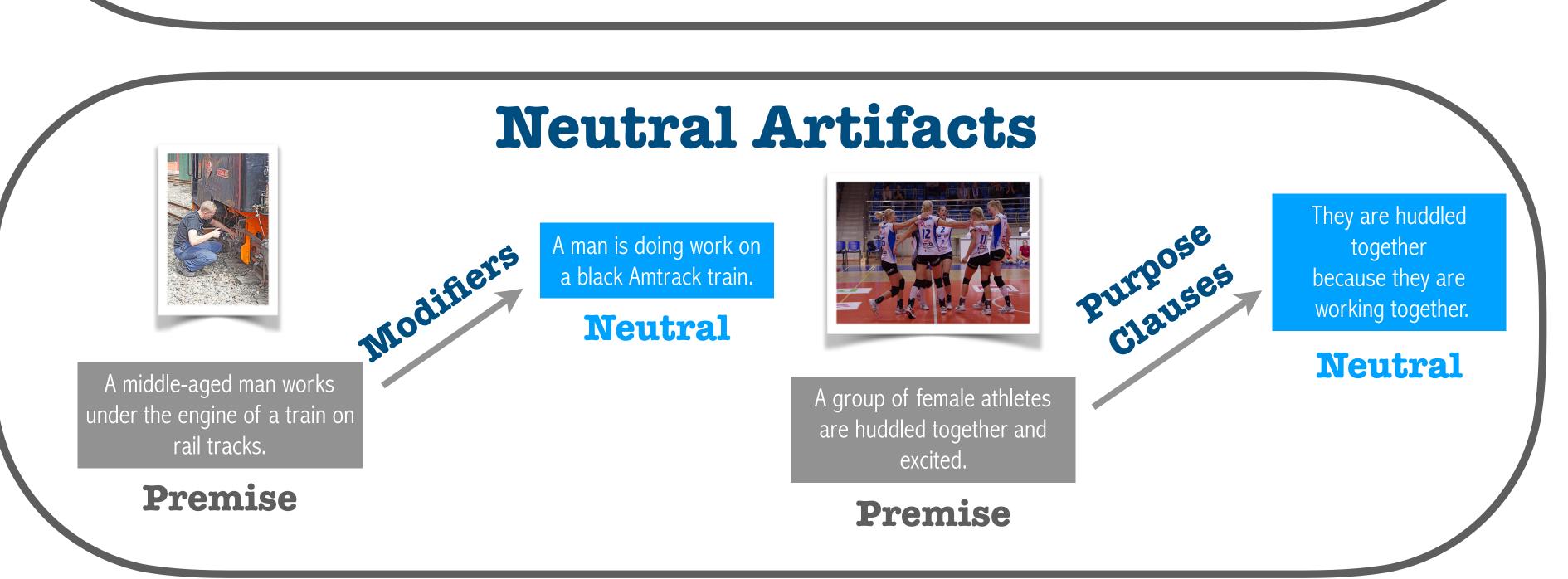
**Easy** 

### Natural Language Inference

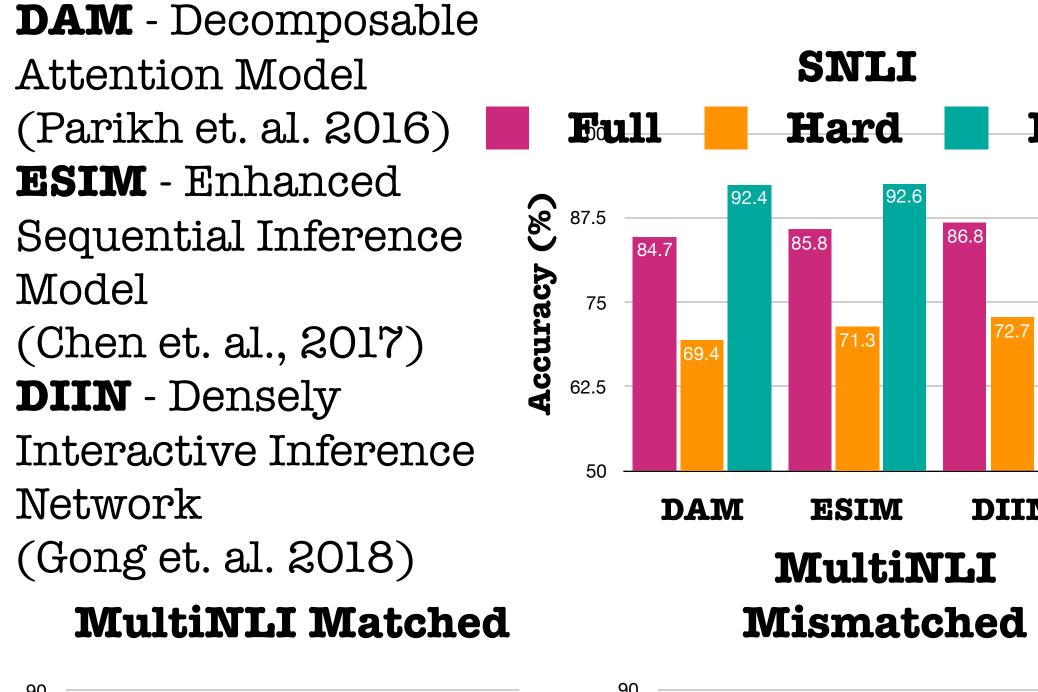


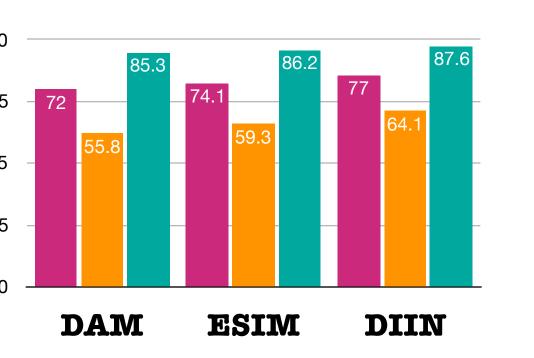
SNLI premises are Flickr captions. MultiNLI premises are collected from diverse genre. Hypotheses are crowdsource-generated.

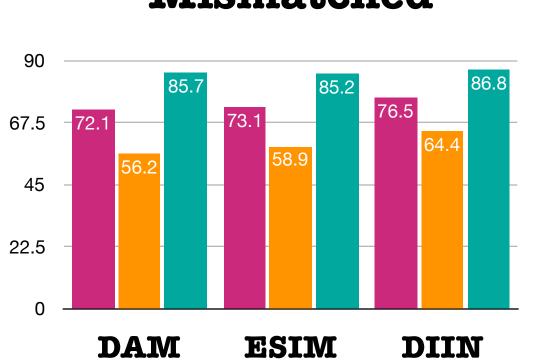
#### Entailment Artifacts A person in red is cutting the grass on a outdoors. riding mower. Entailment Entailment person in a red shirt i nowing the grass with a playing frisbee in a grassy Premise **Premise**



## What are NLI models really learning?

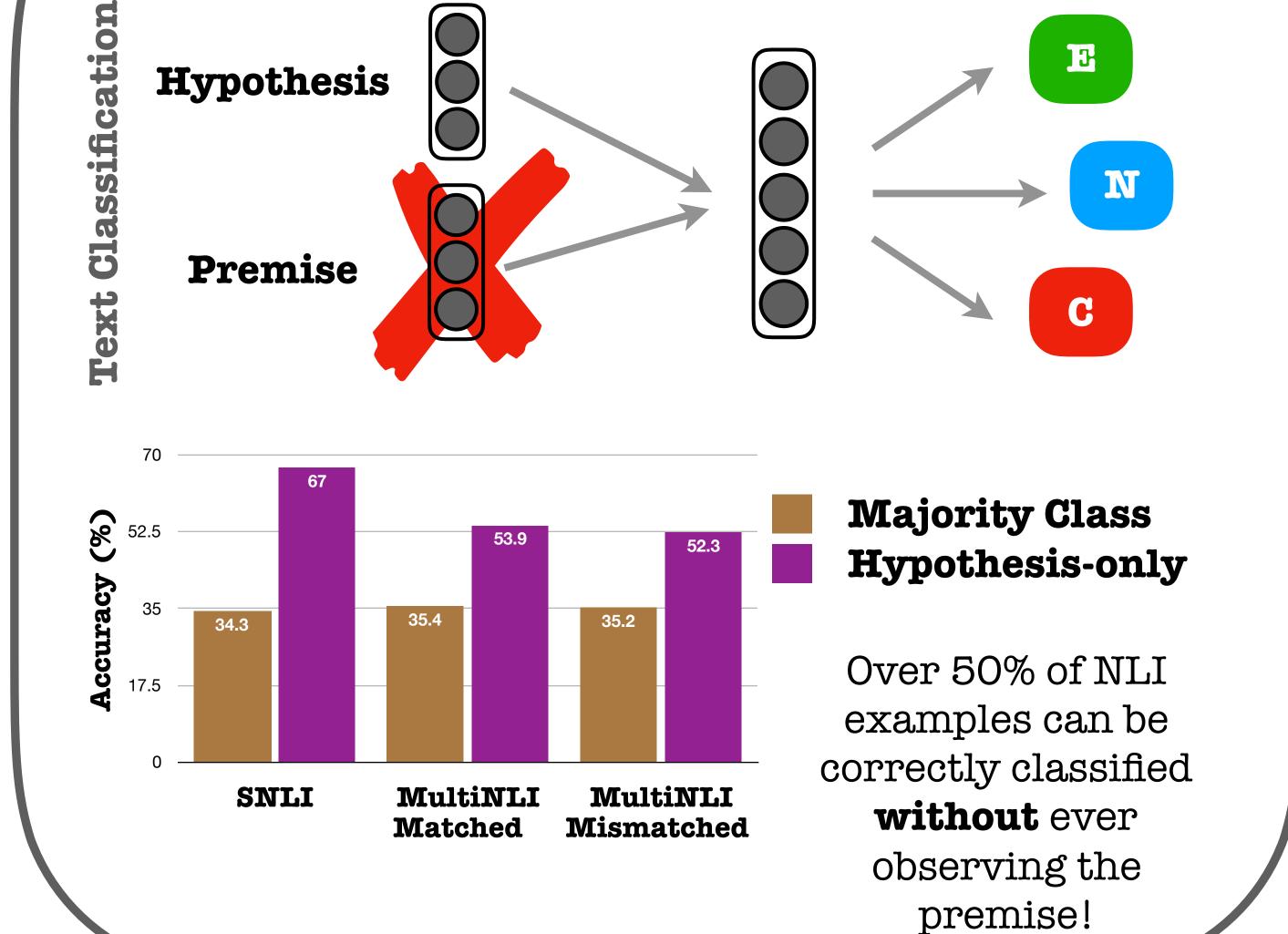




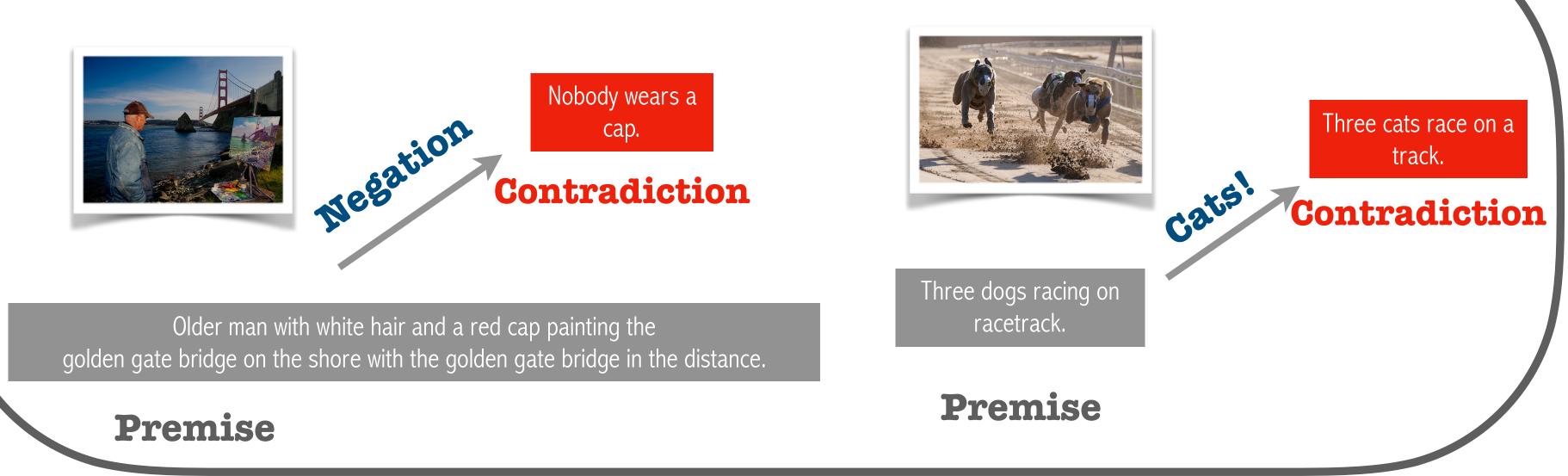


NLI models learn from lexical cues rather than entailment semantics.

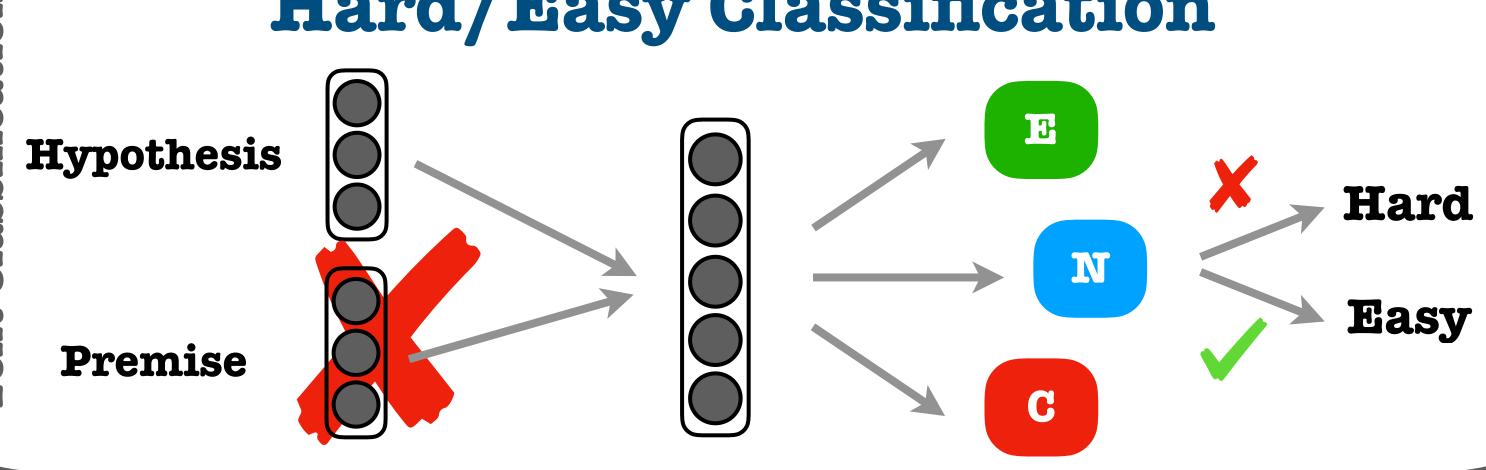
## Kicking out Premises...



#### Contradiction Artifacts



# Hard/Easy Classification



### Takeaways

- \*Results consistent with numerous findings of issues with NLP datasets like ROC (Cai et. al., 2017) and VQA (Agrawal et. al., 2016).
- \*Annotation artifacts could be addressed by improving annotation protocols preemptively to correct for common biases.

#### Resources

- \* Hard benchmarks for MultiNLI: www.kaggle.com/c/multinli-matched-open-hard-evaluation/
- \* Hard benchmark for SNLI: www.nlp.stanford.edu/projects/snli/snli\_1.0\_test\_hard.jsonl