Harvard John A. Paulson School of Engineering and Applied Sciences

JOHNS HOPKINS UNIVERSITY

Don’t Take the Premise for Granted: Mitigating Artifacts in Natural Language Inference

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NLU as Relationship Identification

Natural language inference (entailment)

Premise: A woman is running in the park with her dog

Hypothesis: A woman is sleeping

Relation: entailment, neutral, contradiction

[Sources: Hill+ ‘16, Zhang+ ‘16]

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Reading comprehension

"No," he replied, "except that he seems in a great hurry." "That's just it," Jimmy returned promptly. "Did you ever see him hurry unless he was frightened?" Peter confessed that he never had.

Q: "Well, he isn't _____ now, yet just look at him go"

A: Do, case, confessed, frightened, mean, replied, returned, said, see, thought

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Visual question answering

Q: Is the girl walking the bike?

A: Yes, No

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Assumption: Identifying the relationship requires deep language understanding

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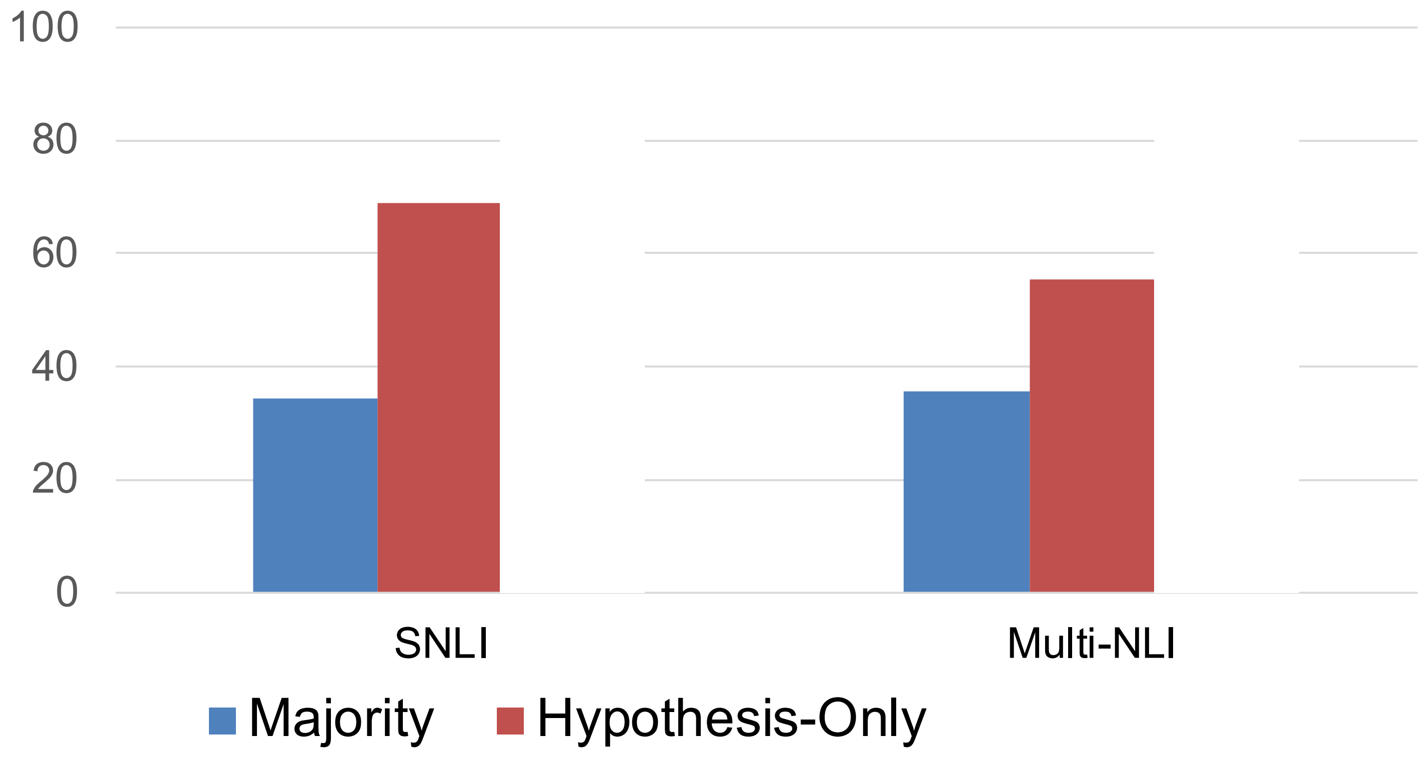

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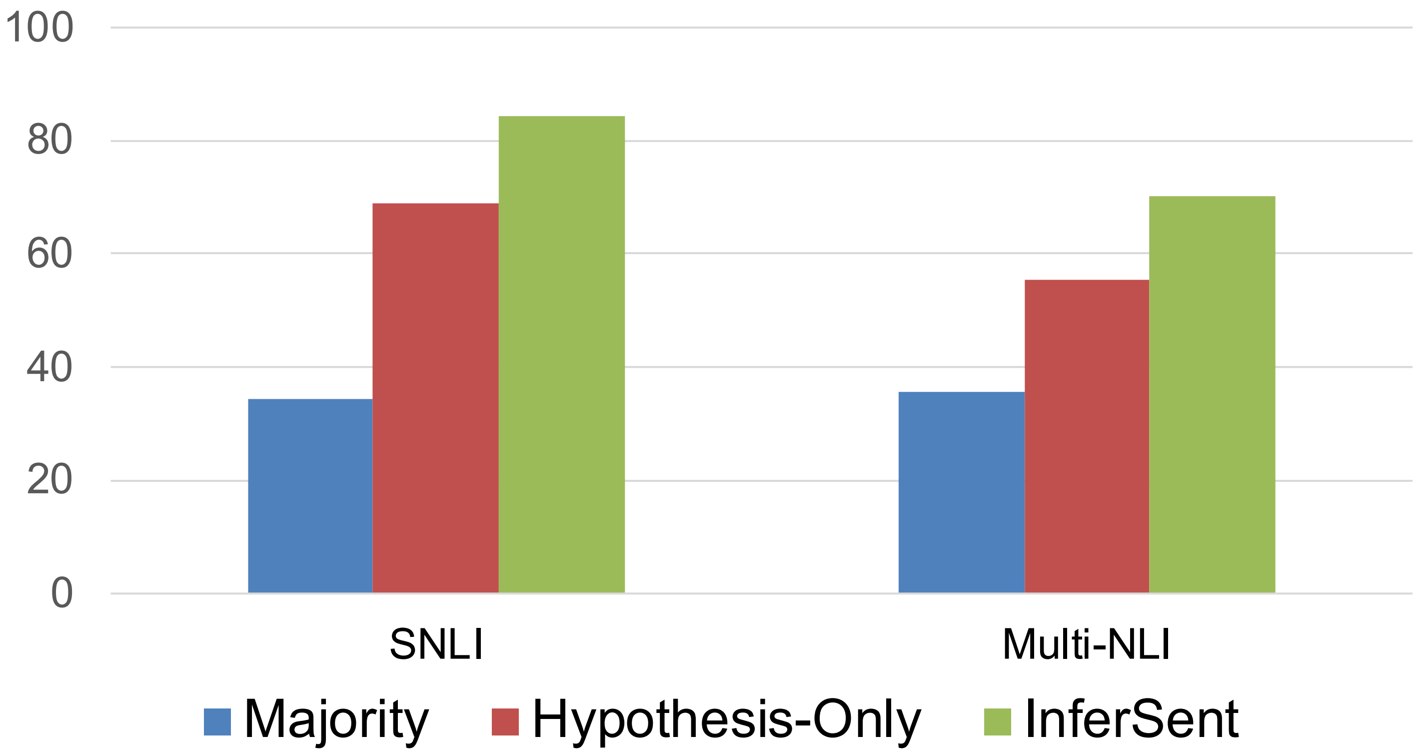

One-Sided Biases

- Hypothesis-only NLI (Poliak+ ‘18; Gururangan+ ’18; Tsuchia ‘18)
- Reading comprehension (Kaushik & Lipton ‘18)
- Visual question answering (Zhang+ ’16; Kafle & Kanan ’16; Goyal+ ’17; Agarwal+ ’17; *inter alia*)
- Story cloze completion (Schwartz+ ‘17, Cai+ ’17)

Problem:

One-sided biases mean that models may not learn the true relationship between premise and hypothesis

Strategies for dealing with dataset bias

- Construct new datasets (Sharma+ ‘18)
    - $$$
    - Other bias

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  - $$$
  - Other bias
- Filter “easy” examples (Gururangan+ ‘18)
  - Hard to scale
  - May still have biases (see SWAG → BERT → HellaSWAG)
- Forgo datasets with known biases
  - Not all bias is bad
  - Biased datasets may have other useful information

Our approach:

Design models
that facilitate learning
less biased representations

A Generative Perspective

- Typical NLI models maximize the discriminative likelihood

$$p_\theta(y|P, H)$$

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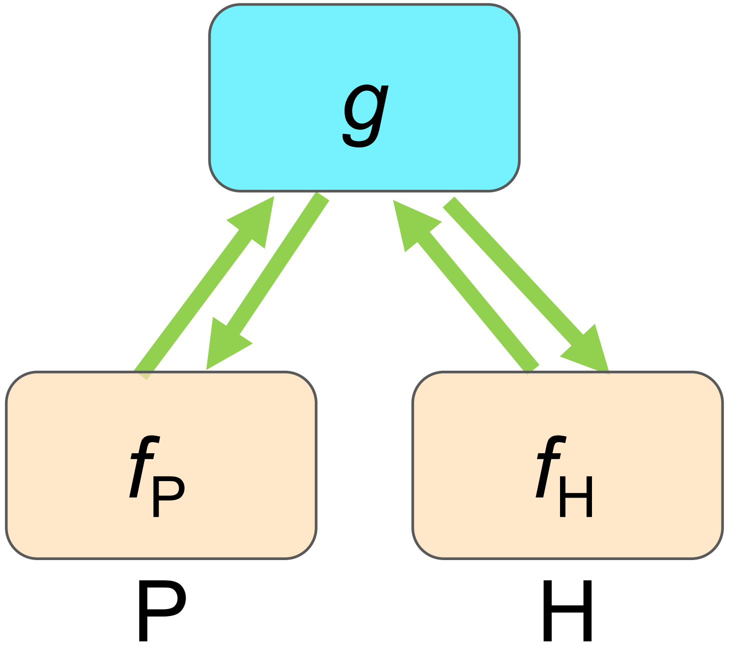

g – classifier

f_P, f_H – encoders

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- Our key idea: If we **generate** the premise, it cannot be ignored
- We will maximize the likelihood of generating the premise

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Premise: A woman is running in the park with her dog

Premise: A woman sings a song while playing piano

Premise: This woman is laughing at her baby

⋮

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$$\log p(P|y,H) = \log \frac{p_\theta(y|P,H)p(P|H)}{p(y|H)}$$

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- Assume $p(P|H)$ is constant
- We have $\log p_\theta(y|P, H) - \log p(y|H)$

Need to estimate this

Method 1: Auxiliary Hypothesis Classifier

- Learn a new estimator $p_{\phi,\theta}(y|H)$
  - Share the hypothesis-encoder
  - Learn an additional classification layer
  - Multi-task objective function

$$\max_{\theta} L_1(\theta) = \log p_\theta(y|P,H) - \alpha \log p_{\phi,\theta}(y|H)$$

$$\max_{\phi} L_2(\phi) = \beta \log p_{\phi,\theta}(y|H)$$

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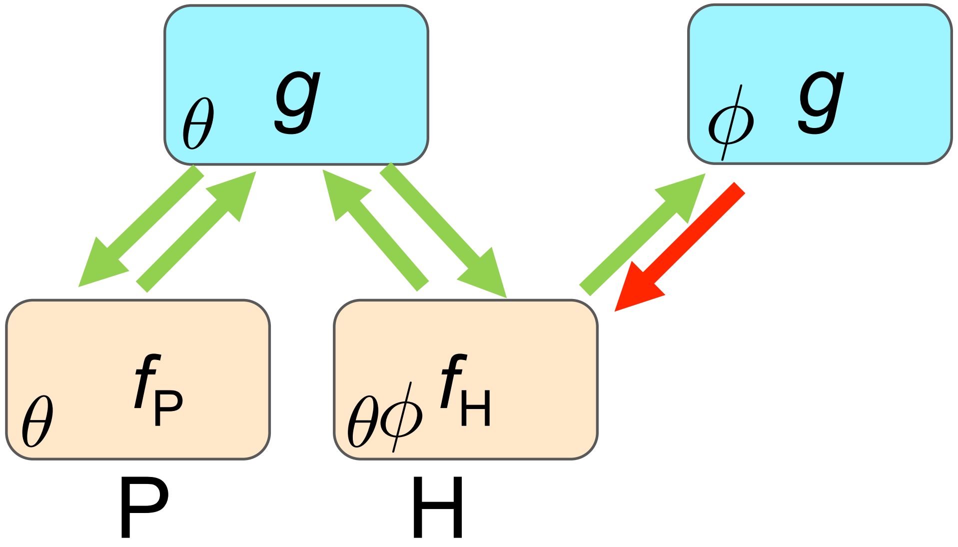

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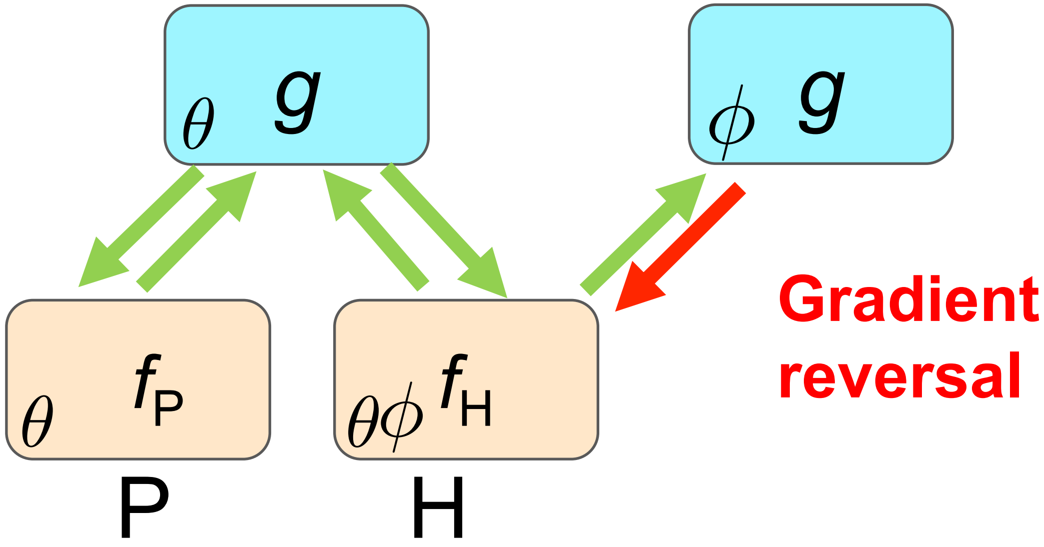

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$$\begin{aligned}-\log p(y \mid H) &= -\log \sum_{P'} p(P' \mid H) p(y \mid P', H) \\ &= -\log \mathbb{E}_{P'} p(y \mid P', H) \geq -\mathbb{E}_{P'} \log p(y \mid P', H),\end{aligned}$$

  - Lower bound from Jensen’s inequality
  - Approximate the expectation with uniform samples *P’*

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\end{aligned}
$$

  - Lower bound from Jensen's inequality
  - Approximate the expectation with uniform samples *P'*
  - Multi-task objective function

$$
\max_{\theta} L_1(\theta) = (1-\alpha) \log p_{\theta}(y|P,H) - \alpha \log p_{\phi,\theta}(y|P',H)
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\max_{\phi} L_2(\phi) = \beta \log p_{\phi,\theta}(y|P',H)
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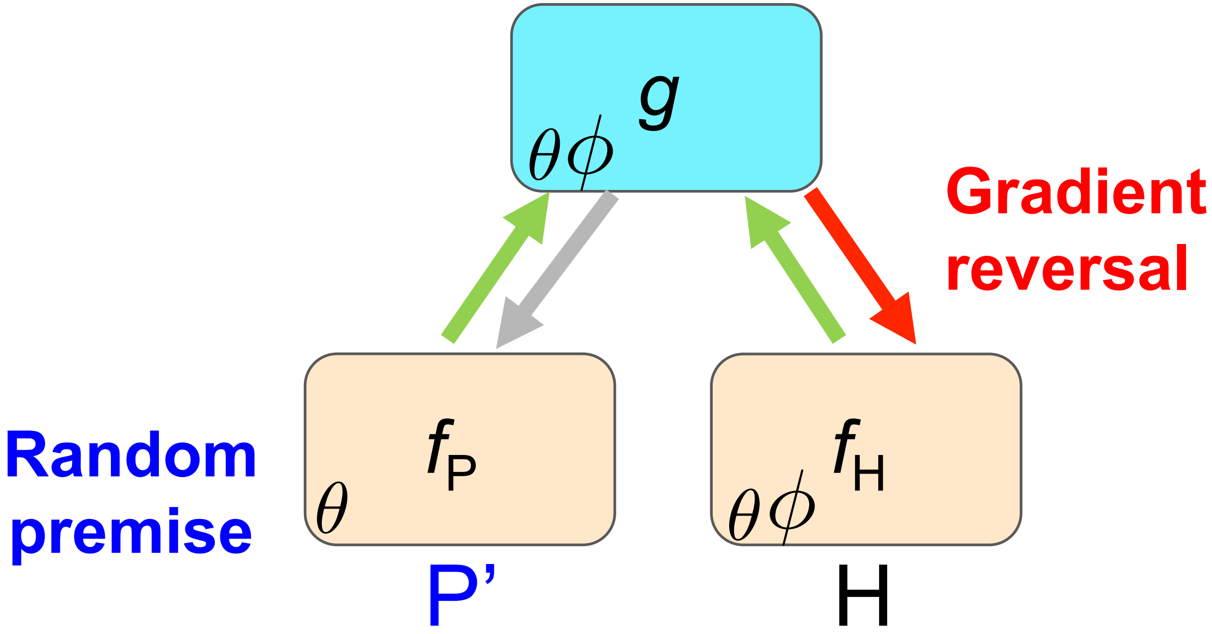

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What is this good for?

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Are less biased models
more transferable?

A Toy Example

Synthetic dataset (unbiased)

$$(a, a) \rightarrow \textsc{True} \qquad (a, b) \rightarrow \textsc{False}$$

$$(b, b) \rightarrow \textsc{True} \qquad (b, a) \rightarrow \textsc{False}$$

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Synthetic dataset (biased)

$$(a, ac) \rightarrow \textsc{True} \qquad (a, b) \rightarrow \textsc{False}$$
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Synthetic dataset (unbiased)

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$$(a, \cancel{a}c) \rightarrow \textsc{True} \qquad (a, b) \rightarrow \textsc{False}$$
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Models transfer well on synthetic data

β	α = 0.1	0.25	0.5	1	2.5	5
0.1	50	50	50	50	50	50
0.5	50	50	50	50	50	50
1	50	50	50	50	50	50
1.5	50	50	50	50	50	100
2	50	50	50	50	100	100
2.5	50	50	100	75	100	100
3	50	100	100	100	100	100
3.5	100	100	100	100	100	100
4	100	100	100	100	100	100
5	100	100	100	100	100	100
10	100	100	100	100	100	100
20	100	100	100	100	100	100

Method 1: Auxiliary Hypothesis Classifier

Models transfer well on synthetic data

β	α				
	0.1	0.25	0.5	0.75	1
0.1	50	50	50	50	50
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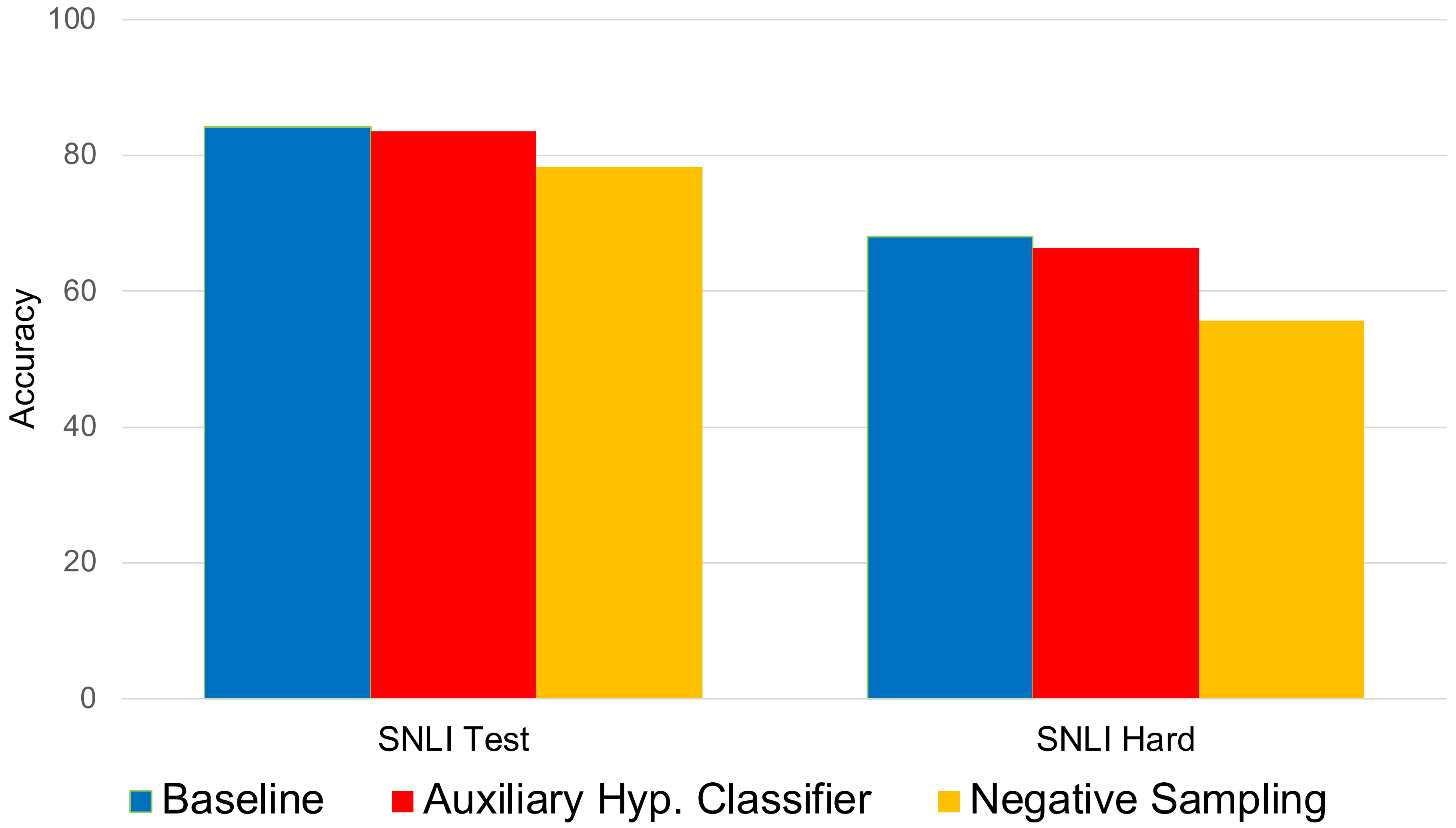
3	50	50	100	50	50
3.5	50	50	100	50	50
4	50	100	100	50	50
5	50	50	100	100	50*
10	75	100	100	100	50*
20	100	100	100	50*	50*

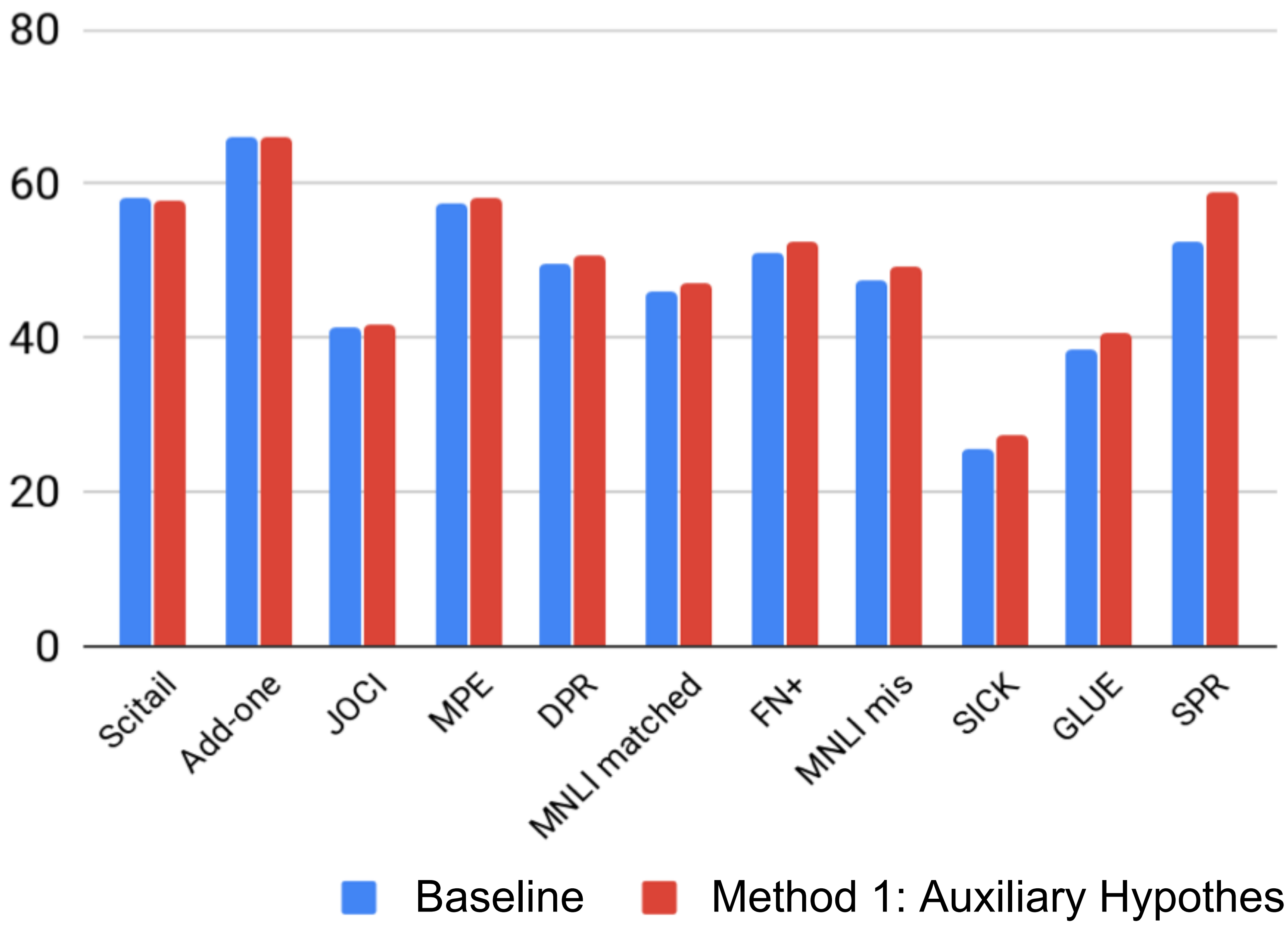
Method 2: Negative Sampling

Do the models transfer well
on standard NLI datasets?

Degradation in domain

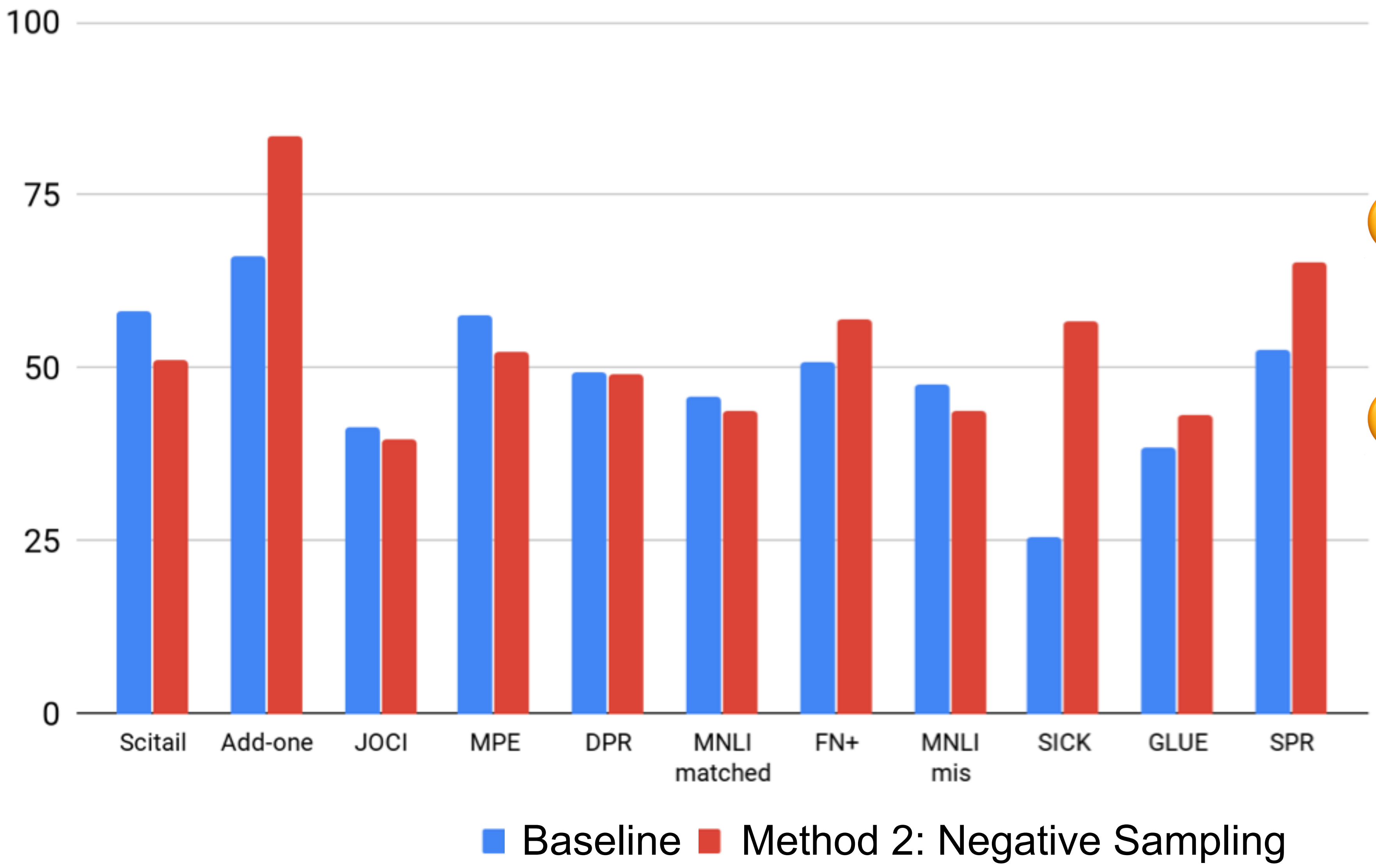


Transfer to other datasets



😀 **Improvements in 9/11 datasets**

Transfer to other datasets



🙁 **Less consistent improvements**

😀 **When it works, it works well**

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- Usually, more improvement from our methods
- But not always

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Q: Do stronger hyper-parameters help?

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- More transferability, but worse in-domain performance

Q: What if we get a bit of out-of-domain training data?

A: Pre-training with our methods still helps

- Especially with datasets with different biases

More Analysis

Q: Are biases really removed from the hidden representations?

A: Some, but not all

- See our recent work: *On Adversarial Removal of Hypothesis-only Bias in NLI, *SEM 2019*

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Q: Does this approach work for other tasks?

A: Seems to work for VQA (Ramakrishnan+ ‘18)

A: But there are shortcomings

- See our recent work: *Adversarial Regularization for VQA: Strengths, Shortcomings, and Side Effects, SiVL 2019*

Contributions

- Our approach may aid with one-sided biases in NLI and other tasks
  - Reduces the amount of bias
  - Improves transferability

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- Our approach may aid with one-sided biases in NLI and other tasks
  - Reduces the amount of bias
  - Improves transferability
- Our analysis shows that the methods should be handled with care
  - Not all bias may be removed
  - Some other information may also be removed
  - The goal matters: bias may sometimes be helpful

Acknowledgements: