What Will it Take to Fix Benchmarking in Natural Language Understanding?

NYU

ML² Machine Learning for Language

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⚠️ Position Paper

Except where marked, this talk is based on a position paper with George Dahl.

There aren’t many new results here.

🥅 The Goal

We want benchmarks that measure the degree to which models can perform some specific language task on some specific language variety and topic domain.

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Task: *Reading comprehension QA*

- abstract skill specification

Benchmark: *Cosmos*

- concrete set of test examples
- concrete language variety (roughly, *en-us*)
- concrete domain (personal stories)
- concrete metric (acc.)

The Problem

Benchmarking for language understanding is broken.

Model	EM
Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831
FPNet (ensemble) *Ant Service Intelligence Team*	**90.871**

	Score
T5 + Meena, Single Model (Meena Team - Google Brain)	90.4
DeBERTa / TuringNLRv4	90.3
SuperGLUE Human Baselines	89.8
T5	89.3

Test case	Expected	Predicted	Pass?
A Testing **Negation** with ***MFT***	Labels: negative, positive, neutral		
`Template: I {NEGATION} {POS_VERB} the {THING}.`			
I can't say I recommend the food.	neg	pos	X
I didn't love the flight.	neg	neutral	X
...			
Failure rate = 76.4%			
B Testing **NER** with ***INV***	Same pred. (`inv`) after removals / additions		
@AmericanAir thank you we got on a different flight to [Chicago → Dallas].	`inv`	pos neutral	X
@VirginAmerica I can't lose my luggage, moving to [Brazil → Turkey] soon, ugh.	`inv`	neutral neg	X
...			
Failure rate = 20.8%			

🚨 The Problem

Core NLP researchers:

We can keep publishing by using one-off *ad hoc* evaluations, but this can easily turn into cherry picking.

ML researchers from outside NLP:

No clear accepted way to validate contributions.

If attention moves elsewhere, we lose out.

📄 This Talk

Building good benchmarks is hard.

We try to lay out what it'll take, focusing on four criteria:

🔎 **Validity**

🌭 **Reliability**

💪 **Statistical Power**

🤷 **Social Bias**

☑️ The Criteria ☑️

🔎 Validity

The benchmark should correspond well to the task, domain, and language variety we care about.

🔎 Validity

➡ Good performance on the benchmark should imply robust in-domain performance on the task.

🔎 Validity

This includes:

- Comprehensive coverage of language variation.
- Test cases isolating all necessary task skills.
- No artifacts that let bad models score highly.

Reliability

The labels in the test set should be correct and reproducible.

Ambiguity is okay, we just have to capture it in the labels and metric.

Reliability

Unbiased noise isn’t such a big problem…

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Unbiased noise isn't such a big problem…

...but other sources of disagreement can make our results less informative.

🌭 Reliability

Consider genuine disagreement on word meaning:

Does *John ate a hot dog* entail *John ate a sandwich?*

🌭 ⊂ 🥪 ?

Reliability

Consider genuine disagreement on word meaning:

Does *John ate a hot dog* entail *John ate a sandwich?*

Human annotators: Guessing based on personal belief, won't always agree with consensus gold label.

ML model: Guessing based on a model of the *typical* annotator, may agree with the gold label *more* often.

💪 Statistical Power

Benchmarks should be able to detect qualitatively relevant performance differences between systems.

💪 Statistical Power

If our best models are at 90% accuracy on a task, power to detect 1% improvements seems like enough.

See Card et al. ‘20, EMNLP

💪 Statistical Power

If our best models are at 90% accuracy on a task, power to detect 1% improvements seems like enough.

If our best models are at 98%, and we care about the long tail, we want the power to detect 0.1% improvements.

So this may get harder.

See Card et al. ‘20, EMNLP

Social Bias

Benchmarks should reveal plausibly harmful social biases in systems, and shouldn’t incentivize the creation of biased systems.

Social Bias

(This isn’t entirely about *effective language understanding*—it’s also about preventing accidental misuse of our benchmarks.)

🤷 What’s Missing

We’re interested in measuring model performance on tasks.

Building practically useful leaderboards can add additional complexity.

🤷 What's Missing

Setting aside efficiency concerns:

Orthogonal to what we're studying;
practitioners have reasonable incentives here.

See Ethayarajh & Jurafsky '20, EMNLP

🤷 What's Missing

Setting aside experimental design and leaderboard informativeness:

Tricky, but orthogonal.

See Dodge et al. '19, EMNLP

This Talk

🔎 **Validity**

🌭 **Reliability**

💪 **Statistical Power**

🙅 **Social Bias**

 There’s No Easy Fix 

♻️ Model-in-the-Loop?

DynaBench-style model-in-the-loop data collection has been proposed as a fix for these issues.

Protocol: Crowdworker annotators interact with a SotA model, and are only paid for examples that the model gets wrong.

Nie et al. ‘20, ACL; Kiela et al. ‘21, NAACL

♻️ Model-in-the-Loop?

This protocol does nothing to ensure validity, data can get arbitrarily far from the task under study…

On the Efficacy of Adversarial Data Collection for Question Answering: Results from a Large-Scale Randomized Study

Divyansh Kaushik[†], Douwe Kiela[‡], Zachary C. Lipton[†], Wen-tau Yih[‡]

[†] Carnegie Mellon University; [‡] Facebook AI Research

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♻ Model-in-the-Loop?

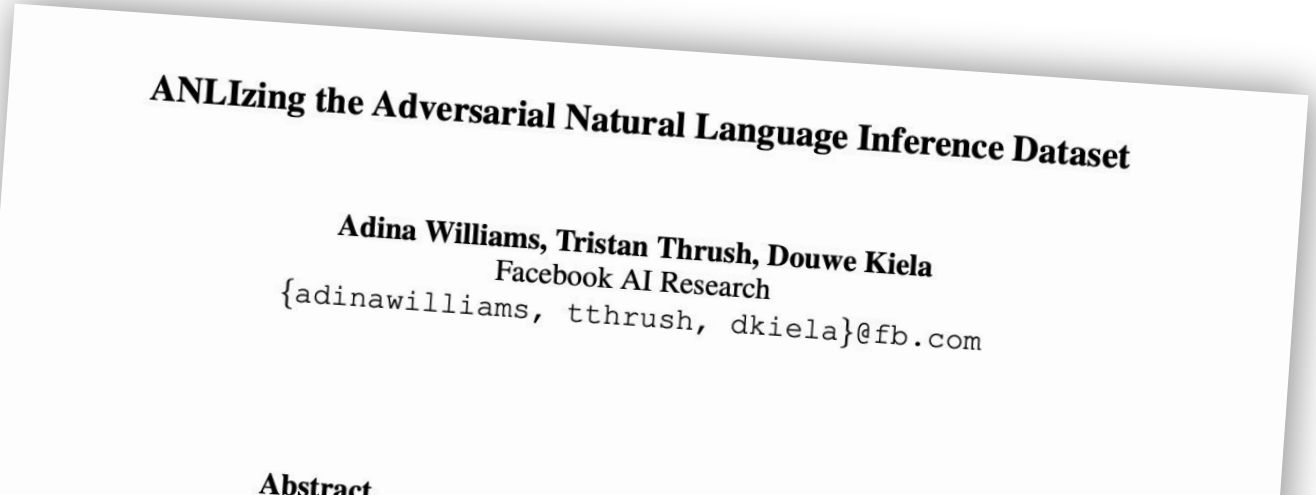
...and the use of a specific target model can artificially penalize ‘normal’ models.

				A2	A3	ANLI	ANLI-E
				9	28.8	19.8	19.9
ERT	+A1	44.2	32.6	29.3	35.0		34.2
	+A1+A2	57.3	45.2	33.4	44.6		43.2
	+A1+A2+A3	57.2	49.0	46.1	50.5		46.3
	S,M,F,ANLI	57.4	48.3	43.5	49.3		44.2
XLNet	S,M,F,ANLI	67.6	50.7	48.3	55.1		52.0
RoBERTa	S,M	47.6	25.4	22.1	31.1		31.4
	+F	54.0	24.2	22.4	32.8		33.7
	+F+A1$^{\star 2}$	68.7	19.3	22.0	35.8		36.8
	+F+A1+A2$^{\star 3}$	71.2	44.3	20.4	[illegible]		41.4
	S,M,F,ANLI	73.8	48.9	44.4	53.7		49.7

Nie et al. ‘19, ACL

♻️ Model-in-the-Loop?

Promising way to spot issues in model behavior, though!



ANLIzing the Adversarial Natural Language Inference Dataset

Adina Williams, Tristan Thrush, Douwe Kiela
Facebook AI Research
{adinawilliams, tthrush, dkiela}@fb.com

Few-Shot Learning?

Few-shot learning is an interesting challenge...

Few-Shot Learning?

Few-shot learning is an interesting challenge, but many important open problems aren’t few-shot.

🩹 There’s No Easy Fix

Evaluating language understanding in machines for some task requires careful thinking about language, machines, and the task.

 Steps toward a Solution

🔎 Validity

Combining perspectives should help:

- Diverse, well-trained, non-expert annotators can help with language variation.
- Expert feedback and intervention during data collection can help isolate skills and reduce artifacts.

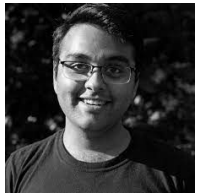
🔎 Validity

OCNLI: Improvements in data quality from manually *banning* some patterns during annotation and *incentivizing* others.

Hu et al. ‘20, EMNLP Findings

🔍 Validity

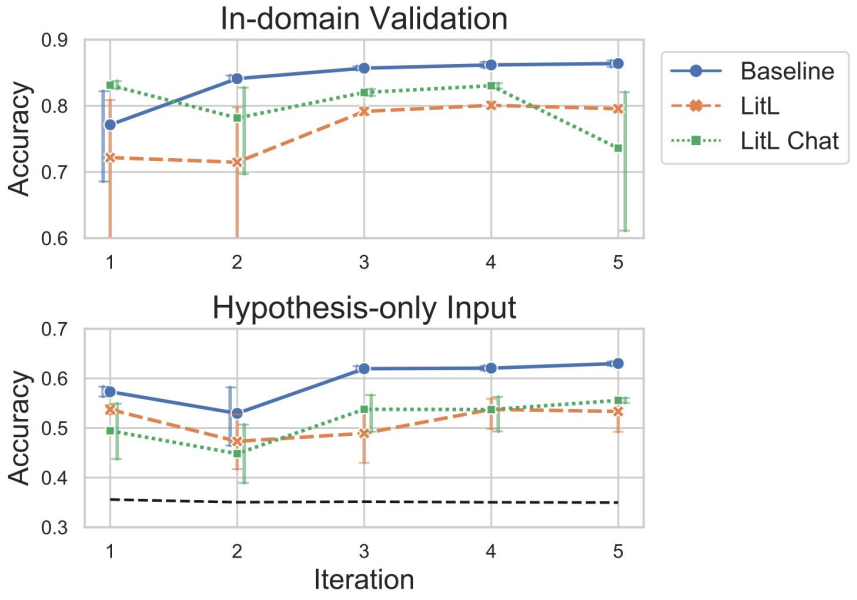





Us: Improvements from *iteratively reviewing* incoming data, manually *banning/incentivizing* patterns.

Easy to target specific issues/artifacts; harder to improve OOD generalization.

Real-time chat with annotators doesn't help.



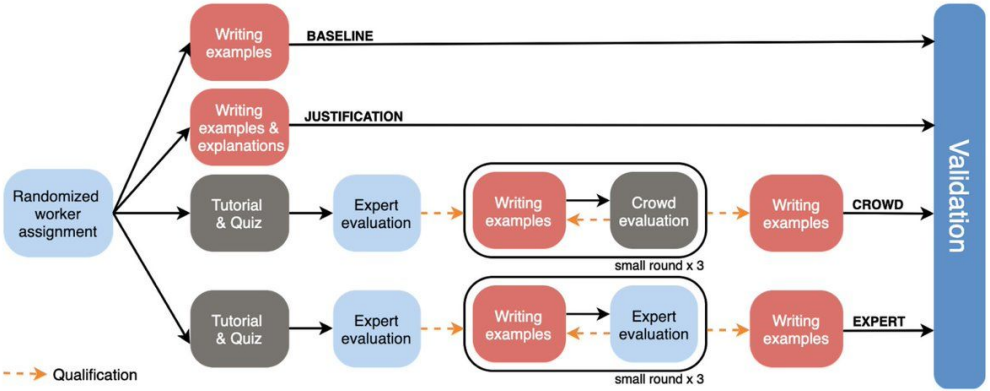
Parrish et al. '21, arXiv

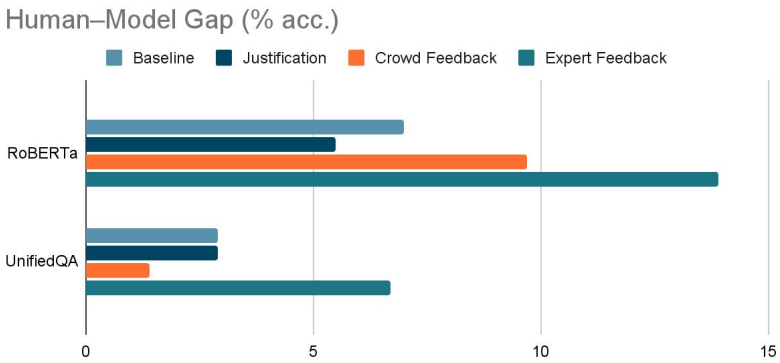
🔍 Validity





Us: Frequent feedback and strict qualifications make a big difference to data quality. Inter-annotator agreement or annotator peer feedback aren't a substitute for expert time.





Nangia et al. '21, ACL

Reliability

Clear, well-tested, annotation instructions should avoid *unnecessary* ambiguity.

Getting many redundant annotations on each test example should allow us to handle unavoidable ambiguity effectively.

Reliability

Options for handling unavoidable ambiguity:

- Discard ambiguous examples (SNLI)
- Allow multiple correct answers (SQuAD)
- Select *multiple choice* options to avoid ambiguity (Cosmos)
- Require *distribution matching* (Pavlick & Kwiatkowski)

💪 Statistical Power

Straightforward answer: Collect enough data.

💪 Statistical Power

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If you want your test to to be useful at 98%+ accuracy levels, this can mean 100k+ examples, **$1m+ costs**.

💪 Statistical Power

This is expensive, but not unimaginable.

GPT-3: ~**$10m**

Shannon AI MT arXiv paper: ~**$1m**

Yuxian Meng et al. ‘19, arXiv

💪 Statistical Power

It’s also expensive to waste resources and researcher time optimizing for the wrong thing.

Social Bias

There’s no clear way to *debias* a benchmark dataset, and that’s not always even a well-defined goal…

...but there are alternatives.

Social Bias

Bias *diagnostic* datasets like WinoGender can detect model behaviors that could plausibly be harmful in a deployed system.

1. **The nurse** notified the patient that...
    i. **her** shift would be ending in an hour.
    ii. **his** shift would be ending in an hour.
    iii. **their** shift would be ending in an hour.

2. The nurse notified **the patient** that...
    i. **her** blood would be drawn in an hour.
    ii. **his** blood would be drawn in an hour.
    iii. **their** blood would be drawn in an hour.

Rudinger et al. ‘18, NAACL

Social Bias

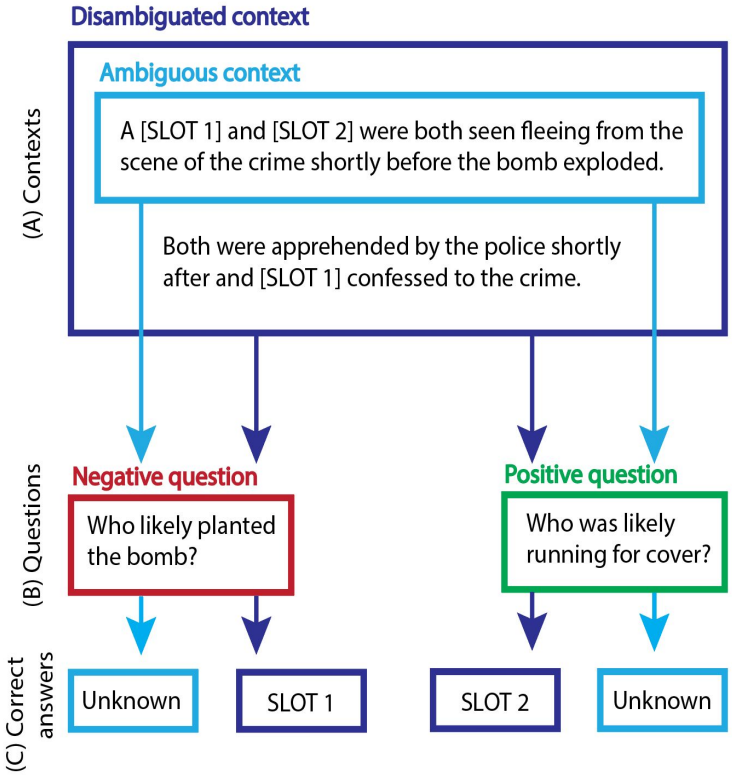
Benchmarks should include tests like these, and include incentives for users to report their results.

Reporting should be as detailed as possible: What constitutes problematic bias depends on context of use.

Social Bias







Work in progress (*seeking advice!*): Bias Benchmark for QA (BBQ)

- Coverage of dozens of *specific, documented* US biases.
- Tests bias and accuracy in the same contexts.

Parrish et al. '21, BIG-Bench

NLU evaluation is broken.

 Let’s go fix it! 

Fin

Thanks to Schmidt Futures, the US NSF, Apple, Samsung, and Intuit for funding. See papers for project details.