Natural Language Inference
(and the representation of sentences)

Computational Semantics 2021

Adam Ek

Plan

- Part 1: Natural Language Inference
- Part 2: Sentence embeddings and Natural Language Inference Models

$\rightarrow$ 15 min break $\leftarrow$

- Part 3: Where are we?
- Part 4: Moving forward?

Languages in this course

English

Natural Language Inference (1)

- The task of Natural Language Inference (NLI) is finding the relationship between two sentences
- A NLI example contains a *premise* (P) and a *hypothesis* (H)

Natural Language Inference (1)

- The task of Natural Language Inference (NLI) is finding the relationship between two sentences
- A NLI example contains a *premise* (P) and a *hypothesis* (H)
- The relations we are interested in are:
  - Entailment: the hypothesis is true given the premise
  - Contradiction: the hypothesis is false given the premise
  - Neutral: the hypothesis may be true given the premise

Natural Language Inference (2)

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- The task is to determine the relationship between H and P

Natural Language Inference (2)

- The task is to determine the relationship between H and P
- For example, what is the relationship of the H given P below:

P A cat and a dog are playing hockey

H1 Two pets are playing hockey

H2 Two animals are playing hockey

H3 Three animals are playing hockey

Natural Language Inference (3)

- Approaches
  - First-order logic, lambda calculus etc
  - Statistical and Neural methods

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- Approaches
  - First-order logic, lambda calculus etc
  - Statistical and Neural methods
- "Tasks" needed to perform NLI (very broadly)
  - Common-sense knowledge
  - Syntactic understanding
  - Semantic understanding
  - How two sentences relate to each other

Neural NLI

- To tackle this problem with neural networks we will use *sentence representations* of the *hypothesis* and *premise* to determine which class the pair belongs to.
- Mainly then, we need to construct good *sentence representations* and *combine* them.

Sentence representations

- We've seen one sentence representation already: the final *hidden state*

Sentence representations

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**What you can cram into a single $&!#* vector:
Probing sentence embeddings for linguistic properties**

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- Setup: Train models on different NLP tasks and investigate how well they predict linguistic properties

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- Setup: Train models on different NLP tasks and investigate how well they predict linguistic properties
- Use the last *hidden state* or *max pooling* (similar to what we did in the Word2Vec lab)

Predicting linguistic properties

Task	SentLen	WC	TreeDepth	TopConst	BShift	Tense	SubjNum	ObjNum	SOMO	CoordInv
Baseline representations										
Majority vote	20.0	0.5	17.9	5.0	50.0	50.0	50.0	50.0	50.0	50.0
Hum. Eval.	100	100	84.0	84.0	98.0	85.0	88.0	86.5	81.2	85.0
Length	**100**	0.2	18.1	9.3	50.6	56.5	50.3	50.1	50.2	50.0
NB-uni-tfidf	22.7	**97.8**	24.1	41.9	49.5	77.7	68.9	64.0	38.0	50.5
NB-bi-tfidf	23.0	95.0	24.6	53.0	**63.8**	75.9	69.1	65.4	39.9	**55.7**
BoV-fastText	66.6	91.6	**37.1**	**68.1**	50.8	**89.1**	**82.1**	**79.8**	**54.2**	54.8
BiLSTM-last encoder										
Untrained	36.7	43.8	28.5	76.3	49.8	84.9	84.7	74.7	51.1	64.3
AutoEncoder	**99.3**	23.3	35.6	78.2	62.0	84.3	84.7	82.1	49.9	65.1
NMT En-Fr	83.5	**55.6**	42.4	81.6	62.3	88.1	89.7	89.5	52.0	71.2
NMT En-De	83.8	53.1	42.1	81.8	60.6	88.6	89.3	87.3	51.5	**71.3**
NMT En-Fi	82.4	52.6	40.8	81.3	58.8	88.4	86.8	85.3	52.1	71.0
Seq2Tree	94.0	14.0	**59.6**	**89.4**	**78.6**	**89.9**	**94.4**	**94.7**	49.6	67.8
SkipThought	68.1	35.9	33.5	75.4	60.1	89.1	80.5	77.1	**55.6**	67.7
NLI	75.9	47.3	32.7	70.5	54.5	79.7	79.3	71.3	53.3	66.5
BiLSTM-max encoder										
Untrained	73.3	**88.8**	46.2	71.8	70.6	89.2	85.8	81.9	73.3	68.3
AutoEncoder	**99.1**	17.5	45.5	74.9	71.9	86.4	87.0	83.5	73.4	71.7
NMT En-Fr	80.1	58.3	51.7	81.9	73.7	89.5	90.3	89.1	73.2	75.4
NMT En-De	79.9	56.0	52.3	82.2	72.1	90.5	90.9	89.5	73.4	**76.2**
NMT En-Fi	78.5	58.3	50.9	82.5	71.7	90.0	90.3	88.0	73.2	75.4
Seq2Tree	93.3	10.3	**63.8**	**89.6**	**82.1**	**90.9**	**95.1**	**95.1**	73.2	71.9
SkipThought	66.0	35.7	44.6	72.5	73.8	90.3	85.0	80.6	**73.6**	71.0
NLI	71.7	87.3	41.6	70.5	65.1	86.7	80.7	80.3	62.1	66.8

Predicting acceptability

- But for semantics (and NLI) we are interested in more than linguistic properties

Predicting acceptability

- But for semantics (and NLI) we are interested in more than linguistic properties
- In particular, we hope that a model gives us representations that allow the model to predict how *acceptable* (or reasonable) humans consider sentences.

Predicting acceptability

Language Modeling with Syntactic and Semantic Representation for Sentence Acceptability Predictions

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- We investigate if the probabilities a LM assign correlate with human judgments

  $$SLOR_M = \frac{log(P_M(s)) - log(P_U(s))}{len(s)}$$

Can we really predict acceptability

- In particular, we investigate whether semantic or syntactic information helps us:

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Table 2: Weighted Pearson correlation between prediction from different models on the SMOG1 dataset. * indicates that the tags have been shuffled.

	HUMAN	LSTM	+SYN	+SYN*	+SEM	+SEM*	+DEPTH	+DEPTH*
HUMAN	1.00							
LSTM	**0.58**	1.00						
+SYN	0.55	0.96	1.00					
+SYN*	0.39	0.76	0.75	1.00				
+SEM	0.54	0.81	0.78	0.61	1.00			
+SEM*	0.52	0.81	0.78	0.63	0.96	1.00		
+DEPTH	0.56	0.97	0.97	0.74	0.79	0.79	1.00	
+DEPTH*	0.46	0.87	0.85	0.73	0.72	0.72	0.86	1.00

Natural Language Inference for Neural Networks

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- A problem with neural networks is that we need **a lot** of data for systems to work well
- Previous NLI datasets were small with carefully selected examples (FraCas), which made them unfit for neural networks (but excellent for evaluation)

Natural Language Inference for Neural Networks

- In 2015, we got SNLI with 550k examples and in 2018 MNLI with 440k examples

A large annotated corpus for learning natural language inference

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A Broad-Coverage Challenge Corpus for Sentence Understanding through Inference

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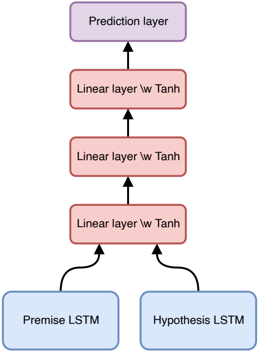
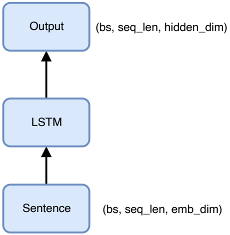
Neural Networks for Natural Language Inference

- A general architecture for NLI problems was first proposed in the SNLI paper:



But what is a sentence representation...

- If we use a LSTM to encode a sentence, we get one representation for each token:



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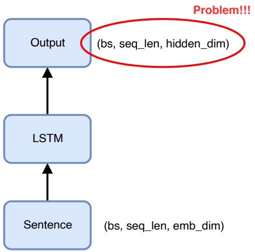

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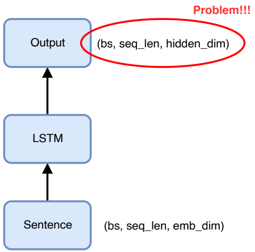
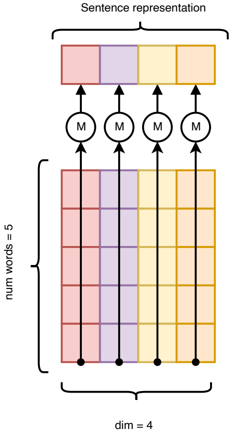


- to predict a class we need *one* embedding...

Compressing a sequence of token representations

- To solve this issue, we can use some form of *pooling*:



- Max
- Sum
- Mean
- ...

Neural Networks for Natural Language Inference (2)

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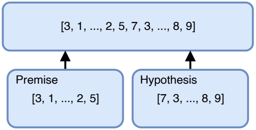
- What we could do is concatenating the representations:



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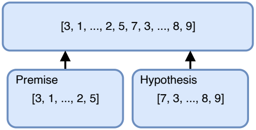

- But this has problems for example if the sentence is long.

Universal Sentence Representations from NLI

Supervised Learning of Universal Sentence Representations from Natural Language Inference Data

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Model	**dim**	**NLI dev**	**NLI test**
LSTM	2048	81.9	80.7
GRU	4096	82.4	81.8
BiGRU-last	4096	81.3	80.9
BiLSTM-Mean	4096	79.0	78.2
Inner-attention	4096	82.3	82.5
HConvNet	4096	83.7	83.4
BiLSTM-Max	4096	**85.0**	**84.5**

- Evaluate different model architectures on the same data
- This gives us a "estimation" of which architecture produce the best representations

A more advanced approach to NLI

- Instead of just concatenating H and P, we also consider the element-wise subtraction (vector contraction) and multiplication (vector scaling)

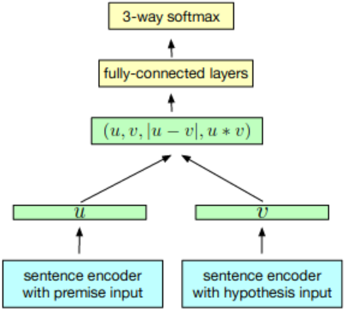
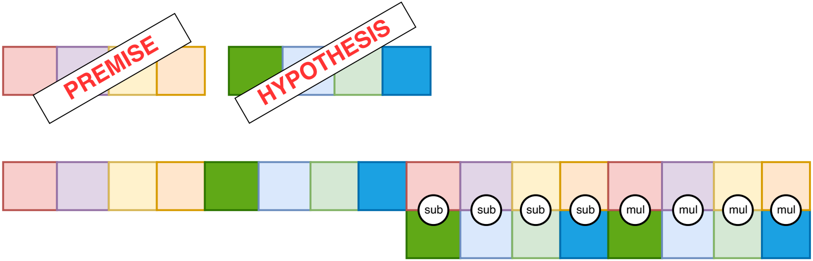


Figure 1: **Generic NLI training scheme.**

Combining sentences



Using attention

A Decomposable Attention Model for Natural Language Inference

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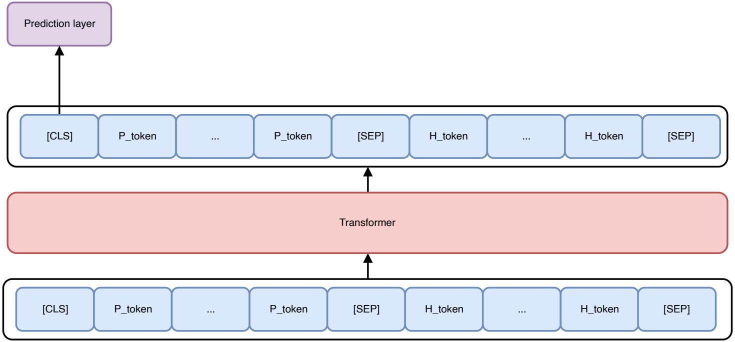
	a	cat	runs
a			
animal			
is			
running			

Transformers for Natural Language Inference



- We take the representation of *both sentences*, the CLS-token and use it to predict the relationship between the premise and hypothesis.

Transformers for Natural Language Inference

- Why don't we combine the representation of the premise and the hypothesis in the transformer?

Transformers for Natural Language Inference

- Why don't we combine the representation of the premise and the hypothesis in the transformer?
- In the transformer we consider both sentences *jointly*, i.e. the token representations are already conditioned on each other.

Next up...

Meta-overview

- We train some neural network to predict some classes over a large dataset
- But semantic problems (or tasks) usually contain complex reasoning involving commonsense knowledge
- To annotate datasets of NLI (and other NLU tasks) we use human labor

The state of NLI

- We've seen fancy models of inference (BERT/LSTM)
- They appear to work well, getting over 80-90% accuracy on NLI datasets

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- They appear to be great! We've solved NLI!
- But people started to look at the predictions and noticed, we can't explain why the system does x, y or z
- and people noted that "easy" examples were not solved by NLI systems, but they appear to solve more "difficult" examples

Hypothesis-only baseline

Hypothesis Only Baselines in Natural Language Inference

Adam Poliak[1] **Jason Naradowsky**[1] **Aparajita Haldar**[1,2]
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- What happens if we only consider the hypothesis?

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- What happens if we only consider the hypothesis?

P None

H The cats are playing

Label Contradiction

Does considering just the hypothesis work?

	DEV				TEST					
Dataset	Hyp-Only	MAJ	$\lvert\Delta\rvert$	$\Delta\%$	Hyp-Only	MAJ	$\lvert\Delta\rvert$	$\Delta\%$	Baseline	SOTA
SNLI	69.17	33.82	+35.35	+104.52	69.00	34.28	+34.72	+101.28	78.2	89.3
MNLI-1	55.52	35.45	+20.07	+56.61	–	35.6	– –		72.3	80.60
MNLI-2	55.18	35.22	+19.96	+56.67	–	36.5	–	–	72.1	83.21

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MNLI-2	55.18	35.22	+19.96	+56.67	–	36.5	–	–	72.1	83.21

- The results show that it's possible to predict the relation based only on the hypothesis. But how does this make sense? (it shouldn't work at all)
- The hypothesis contain implicit signals that can be used to predict its class

Sensitivity to word-order

- The success of the transformer models for NLU has been attributed to it's ability to model complex *syntactic and semantic dependencies* between words

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Masked Language Modeling and the Distributional Hypothesis: Order Word Matters Pre-training for Little

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Adina Williams[†] **Douwe Kiela**[†]

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Some results

- Setup: train RoBERTa (Liu et al. 2019) on a dataset containing sentence-permutations: permute *n*-grams of size 1, 2, 3, and 4

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  The cat is super tall and fancy $\rightarrow$ The cat (super tall) is fancy
- Evaluate on the GLUE benchmark

GLUE benchmark

- GLUE is a collection of datasets used to measure "success" in a variety of NLU tasks (including NLI)

Corpus	|Train|	|Test|	Task	Metrics	Domain
			Single-Sentence Tasks		
CoLA	8.5k	**1k**	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
			Similarity and Paraphrase Tasks		
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	**391k**	paraphrase	acc./F1	social QA questions
			Inference Tasks		
MNLI	393k	**20k**	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	**146**	coreference/NLI	acc.	fiction books

Table 1: Task descriptions and statistics. All tasks are single sentence or sentence pair classification, except STS-B, which is a regression task. MNLI has three classes; all other classification tasks have two. Test sets shown in bold use labels that have never been made public in any form.

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  The cat is super tall and fancy → The cat (super tall) is fancy
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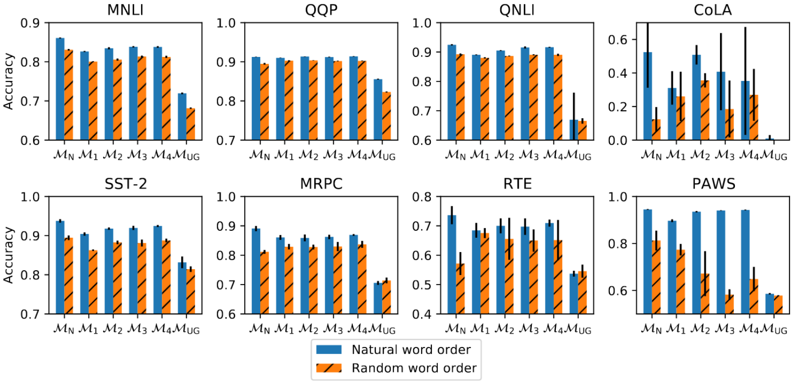

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- For example in English, word order gives *meaning* rather than morphology (like Turkish)
- The authors show that models use higher-order *distributional statistics* to construct *meaning* (simply put, the transformer puts the words in the right order)
- Consequently, it appears that transformers don't really consider the classical NLP pipeline (using human syntactic and semantic mechanisms)
- We need better evaluation datasets, that can't be solved by distributional statistics.

Let's replace some words!

- What happens if we remove entire word-classes from the dataset?

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NLI Data Sanity Check: Assessing the Effect of Data Corruption on Model Performance

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Let's replace some words!

- What happens if we remove entire word-classes from the dataset?

NLI Data Sanity Check: Assessing the Effect of Data Corruption on Model Performance

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- Setup: Train a BERT model on a corrupted version of the dataset and test it

Data corruption

	Premise	Hypothesis
Contradiction	*He was hardly more than five ~~feet~~, four ~~inches~~, but carried himself with great ~~dignity~~.*	*The ~~man~~ was 6 ~~foot~~ ~~tall~~.*
Entailment	*Two ~~plants~~ died on the long ~~journey~~ and the third one found its way to ~~Jamaica~~ exactly how is still shrouded in ~~mystery~~.*	*The third ~~plant~~ was a different ~~type~~ from the first two.*
Neutral	*In a ~~couple~~ of ~~days~~ the ~~wagon~~ ~~train~~ would head on north to ~~Tucson~~, but now the ~~activity~~ in the ~~plaza~~ was a ~~mixture~~ of ~~market~~ ~~day~~ and ~~fiesta~~.*	*They were ~~south~~ of ~~Tucson~~.*

Table 1: Sentence pairs from a corrupted MNLI training dataset where nouns have been removed.

What happens :(

Data	CORRUPT-TRAIN	Δ	CORRUPT-TEST	Δ	CORRUPT-TRAIN AND TEST	Δ
MNLI-NUM	82.37%	-1.37	81.71%	-2.03	81.87%	-1.87
MNLI-CONJ	83.09%	-0.65	82.75%	-0.99	83.10%	-0.64
MNLI-ADV	80.21%	-3.53	72.41%	-11.33	75.69%	-8.05
MNLI-PRON	83.27%	-0.47	81.98%	-1.75	82.65%	-1.09
MNLI-ADJ	81.67%	-2.07	74.61%	-9.13	76.44%	-7.30
MNLI-DET	83.15%	-0.59	79.29%	-4.44	81.32%	-2.42
MNLI-VERB	81.40%	-2.34	73.96%	-9.78	76.30%	-7.44
MNLI-NOUN	80.72%	-3.02	69.80%	-13.94	73.38%	-10.35
MNLI-NOUN-PRON	79.74%	-4.00	68.41%	-15.33	72.14%	-11.60
NOUN+PRON+VERB	72.55%	-11.19	54.59%	-29.15	62.18%	-21.56
NOUN+ADV+VERB	67.58%	-16.16	62.58%	-21.16	67.58%	-16.16
NOUN+VERB	71.14%	-12.60	52.90%	-30.84	61.31%	-22.43
NOUN+VERB+ADJ	75.54%	-8.20	61.90%	-21.84	68.20%	-15.54
NOUN+VERB+ADV+ADJ	79.81%	-3.93	71.81%	-11.93	76.29%	-7.45

Table 2: Prediction accuracy (%) for the BERT-base model fine-tuned on CORRUPT-TRAIN and tested on the original MNLI-matched evaluation (dev) set (columns 2 and 3); fine-tuned on the original MNLI data and tested on CORRUPT-TEST; fine-tuned on CORRUPT-TRAIN and tested on CORRUPT-TEST (columns 6 and 7). The delta shows the difference in accuracy compared to the model fine-tuned on the original MNLI training set and evaluated on the MNLI-matched development set (83.74%).

The case of punctuation

How does Punctuation Affect Neural Models in Natural Language Inference

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- Is BERT and LSTM models for NLI sensitive to punctuation?

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MODEL	TEST	MA	MM
BiLSTM_{orig}		.724	.723
BiLSTM_{p}	p	.723	.724
BiLSTM_{p}	$\neg p$	.428	.414
$\text{BiLSTM}_{\neg p}$	$\neg p$	.714	.727
$\text{BiLSTM}_{\neg p}$	p	.424	.430
HBMP_{orig}		.729	.733
HBMP_{p}	p	.728	.729
HBMP_{p}	$\neg p$	.430	.408
$\text{HBMP}_{\neg p}$	$\neg p$	.729	.732
$\text{HBMP}_{\neg p}$	p	.436	.427
BERT_{orig}		.833	.839
BERT_{p}	p	.835	.837
BERT_{p}	$\neg p$	.816	.822
$\text{BERT}_{\neg p}$	$\neg p$	.819	.820
$\text{BERT}_{\neg p}$	p	.830	.833

Taking a step back

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- Annotators have biases and use shortcuts when annotating (such as "give-away")
- Models exploit this!

Adversarial datasets

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  E.g. ANLI
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  E.g. ANLI
  (`https://github.com/facebookresearch/anli`)
- Humans generate a dataset with examples that fool the model
- we then train and evaluate on this and construct new models that "solve" these adversarial examples

Is adversarial datasets the solution?

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

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- Quote: *Evaluation for many natural language understanding (NLU) tasks is broken*

Taking a step back

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- Large-scale evaluation and models trained on huge dataset deviate from classical linguistics
  - Solutions tried so far: adversarial (ANLI) and out-of-domain test sets (MNLI)
  - But these methods inevitably obscure the models abilities
  - as examples are constructed to explicitly fool models, not represent actual inference problems
- Where do we go from here??? That's currently a work-in-progress :)

  (i.e. a great time to get into NLP and NLU)