# The Devil's in the Data 

Mapping and Generating Datasets for Robust Generalization

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## Moore's Law for Everything

by Sam Altman

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## Natural Language Inference

Given a premise, is a hypothesis true, false or neither?

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```
Premise
A dog is chasing birds on the
    shore of the ocean.
```



## Natural Language Inference

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Given a premise, is a hypothesis true, false or neither?

A dog is chasing birds on the shore of the ocean.

The birds are being
Hypothesis
chased by a cat.

Stanford NLI [Bowman et al., 2015]
$\sim 0.5 \mathrm{~m}$ instances

MultiNLI [Williams et al., 2018]
$\sim 0.4 \mathrm{~m}$ instances

OTrue
( False
O Cannot Say $\rightarrow$ Neutral

## MultiNLI leaderboard results from paperswithcode.com [March 2022]



## MultiNLI leaderboard results from paperswithcode.com [March 2022]




## contradiction



## contradiction

## Neutral

RoBERTa-Large [Liu et al. 2019]
Trained on MultiNLI + SNLI

contradiction

Contradiction


Neutral

Contradiction

People are reading, and the cat is napping on the couch.

The cat is not reading on the couch.

Entailment

Contradiction

RoBERTa-Large [Liu et al. 2019]
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contradiction



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RoBERTa-Large [Liu et al. 2019]

Trained on SNLI + MultiNLI

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??
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Trained on SNLI + MultiNLI

??

Contradiction
??

Contradiction
??

## Contradiction



RoBERTa-Large [Liu et al. 2019]

Trained on SNLI + MultiNLI



# How can we better analyze the model-data relationship? 

## Model Training Dynamics

## Model Training Dynamics



## Model Training Dynamics

$$
\hat{\mu}_{i}=\frac{1}{E} \sum_{e=1}^{E} p_{\theta^{(e)}}\left(y_{i}^{*} \mid x_{i}\right)
$$

confidence

Mean
probability
of the true class


## Model Training Dynamics

$$
\hat{\mu}_{i}=\frac{1}{E} \sum_{e=1}^{E} p_{\theta^{(e)}}\left(y_{i}^{*} \mid x_{i}\right)
$$

confidence

## Mean

probability
of the true
class


$$
\hat{\sigma}_{i}=\sqrt{\frac{\sum_{e=1}^{E}\left(p_{\theta^{(e)}}\left(y_{i}^{*} \mid x_{i}\right)-\hat{\mu}_{i}\right)^{2}}{E}} \quad \begin{gathered}
\text { Standard deviation of the } \\
\text { true class probability }
\end{gathered}
$$

## Model Training Dynamics

$$
\hat{\mu}_{i}=\frac{1}{E} \sum_{e=1}^{E} p_{\theta^{(e)}}\left(y_{i}^{*} \mid x_{i}\right)
$$

confidence

## Mean

probability
of the true class


## correctness

- 0.0
* 0.2
- 0.3
- 0.5
- 0.7
$\triangle \quad 0.8$
- 1.0

Ratio at
which
model prediction
matches
true class

$$
\hat{c}_{i}=\frac{1}{E} \sum_{e=1}^{E} 1\left[y_{i}^{*}=\arg \max _{y} p_{\theta^{(e)}}\left(y \mid x_{i}\right)\right]
$$

$$
\hat{\sigma}_{i}=\sqrt{\frac{\sum_{e=1}^{E}\left(p_{\theta^{(c)}}\left(y_{i}^{*} \mid x_{i}\right)-\hat{\mu}_{i}\right)^{2}}{E}} \quad \begin{gathered}
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Original (100\% Train)
Random (33\%)
Ambiguous (33\%) SNLI Test

##  <br> In-Distribution Performance

Diagnostics [Wang et al., 2019]



Original (100\% Train)
Random (33\%)
Ambiguous (33\%) SNLI Test


Diagnostics [Wang et al., 2019]


Out-of-Distribution Performance

SNLI-RoBERTa Data Map


SNLI-RoBERTa Data Map


An expression gathered there that I can only describe as half puzzled, and half relieved.

The expression on their face was puzzled and relieved.

SNLI-RoBERTa Data Map


An expression gathered there that I can only describe as half puzzled, and half relieved.

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Neutral



Not all training instances contribute equally to model learning

## AAlso see

Understanding Dataset Difficulty with $\mathscr{V}$-Usable Information
[Ethayarajh, Choi \& Swayamdipta, ICML 2022]



Can we leverage data maps to improve dataset collection?





Might introduce heuristics leading to annotation artifacts



Can be easily modified for diverse generations

MultiNLI-RoBERTa Data Map


GPT-3


MultiNLI-RoBERTa Data Map


GPT-3


GPT-3 $\qquad$

GPT-3 $\qquad$




About 1,000 people are diagnosed with chronic myeloid leukemia each year. Implication: About 9,000 people are not diagnosed with chronic myeloid leukemia each year.


About 1,000 people are diagnosed with chronic myeloid leukemia each year. Implication: About $\mathbf{9 , 0 0 0}$ people are not diagnosed with chronic myeloid leukemia each year.




He has never smoked, and he doesn't drink. Implication: He has smoked and he has drank.

1 percent of the seats were vacant.
Implication: 99 percent of the seats were occupied.


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$\left.\begin{array}{l}\text { instruction } \\ \text { nearest neighbors to } \\ \text { seed example } \\ \text { seed ambiguous example MultiNLI - RoBERTa }\end{array}\right\}$



\section*{Also see

Reframing Human-Al for Generating Free-Text Explanations
[Wiegreffe, Hessel, Swayamdipta, Riedel \& Choi, NAACL 2022]




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## GPT-3

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GPT-3

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Filter
1 percent of the seats were vacant.
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## Worker-AI Collaborative NLI: WANLI

万理

Ten thousand reasoning

## Worker-AI Collaborative NLI: WANLI

WaNLI Data Size


## Worker-AI Collaborative NLI: WANLI

WaNLI Data Size


RoBERTa-Large models

## RoBERTa-Large models



## RoBERTa-Large models



## RoBERTa-Large models



Please see paper for more comparisons
WANLI [Liu., Swayamdipta, Smith and Choi, ArXiV 2022]


MultiNLI-RoBERTa


MultiNLI-RoBERTa


WANLI-RoBERTa

A dog and cat are snuggling up during a nap.

Dogs and cats rarely, if ever, snuggle.

Neutral Contradiction

Neutral
Neutral


As a result of the disaster, the city was rebuilt and it is now one of the most beautiful cities in the world.

WANLI Hypothesis A disaster made the city better.

As a result of the disaster, the city was rebuilt and it is now one of the most beautiful cities in the world.

WANLI Hypothesis
A disaster made the city better.



Entailment
Also see
6
[Pavlick \& Kwiatkowski, 2019; Chen et al., 2020; Zhou et al., 2022; Davani et al., 2021]


Mapping large datasets to discover regions which are challenging to models


Mapping large datasets to discover regions which are challenging to models

## GPT-3



Generating new challenging instances via a collaboration of humans and models


## GPT-3



Generating new challenging instances via a collaboration of humans and models

Rethinking data by shifting the focus to data quality over quantity



WANLI


Cartography


