DynaSent: A Dynamic Benchmark for Sentiment Analysis

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Abstract

We introduce DynaSent ('Dynamic Sentiment'), a new English-language benchmark task for ternary (positive/negative/neutral) sentiment analysis. DynaSent combines naturally occurring sentences with sentences created using the open-source Dynabench Platform, which facilities human-and-model-in-the-loop dataset creation. DynaSent has a total of 121,634 sentences, each validated by five crowdworkers, and its development and test splits are designed to produce chance performance for even the best models we have been able to develop; when future models solve this task, we will use them to create DynaSent version 2, continuing the dynamic evolution of this benchmark. Here, we report on the dataset creation effort, focusing on the steps we took to increase quality and reduce artifacts. We also present evidence that DynaSent's Neutral category is more coherent than the comparable category in other benchmarks, and we motivate training models from scratch for each round over successive fine-tuning.

1 Introduction

Sentiment analysis is an early success story for NLP, in both a technical and an industrial sense. It has, however, entered into a more challenging phase for research and technology development: while present-day models achieve outstanding results on all available benchmark tasks, they still fall short when deployed as part of real-world systems (Burn-Murdoch, 2013; Grimes, 2014, 2017; Gossett, 2020) and display a range of clear shortcomings (Kiritchenko and Mohammad, 2018; Hanwen Shen et al., 2018; Wallace et al., 2019; Tsai et al., 2019; Jin et al., 2019; Zhang et al., 2020).

In this paper, we seek to address the gap between benchmark results and actual utility by introducing version 1 of the DynaSent dataset for English-language ternary (positive/negative/neutral) senti-
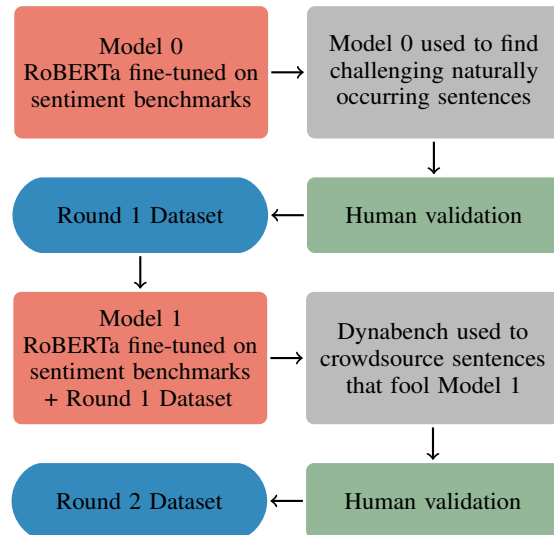

Figure 1: The DynaSent dataset creation process. The human validation task is the same for both rounds; five responses are obtained for each sentence. On Dynabench, we explore conditions with and without prompt sentences that workers can edit to achieve their goal.

ment analysis.[1] DynaSent is intended to be a *dynamic* benchmark that expands in response to new models, new modeling goals, and new adversarial attacks. We present the first two rounds here and motivate some specific data collection and modeling choices, and we propose that, when future models solve these rounds, we use those models to create additional DynaSent rounds. This is an instance of "the 'moving post' dynamic target" for NLP that Nie et al. (2020) envision.

Figure 1 summarizes our method, which incorporates both naturally occurring sentences and sentences created by crowdworkers with the goal of fooling a top-performing sentiment model. The starting point is Model 0, which is trained on standard sentiment benchmarks and used to find challenging sentences in existing data. These sentences are fed into a human validation task, leading to

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[1]https://github.com/cgpotts/dynasent

the Round 1 Dataset. Next, we train Model 1 on Round 1 data in addition to publicly available datasets. In Round 2, this model runs live on the Dynabench Platform for human-and-model-in-the-loop dataset creation;[2] crowdworkers try to construct examples that fool Model 1. These examples are human-validated, which results in the Round 2 Dataset. Taken together, Rounds 1 and 2 have 121,634 sentences, each with five human validation labels. Thus, with only two rounds collected, DynaSent is already a substantial new resource for sentiment analysis.

In addition to contributing DynaSent, we seek to address a pressing concern for any dataset collection method in which workers are asked to construct original sentences: human creativity has intrinsic limits. Individual workers will happen upon specific strategies and repeat them, and this will lead to dataset artifacts. These artifacts will certainly reduce the value of the dataset, and they are likely to perpetuate and amplify social biases.

We explore two methods for mitigating these dangers. First, by harvesting naturally occurring examples for Round 1, we tap into a wider population than we can via crowdsourcing, and we bring in sentences that were created for naturalistic reasons (de Vries et al., 2020), rather than the more artificial goals present during crowdsourcing. Second, for the Dynabench cases created in Round 2, we employ a 'Prompt' setting, in which crowdworkers are asked to modify a naturally occurring example rather than writing one from scratch. We compare these sentences with those created without a prompt, and we find that the prompt-derived sentences are more like naturally occurring sentences in length and lexical diversity. Of course, fundamental sources of bias remain – we seek to identify these in the Datasheet (Gebru et al., 2018) distributed with our dataset – but we argue that these steps help, and can inform crowdsourcing efforts in general.

As noted above, DynaSent presently uses the labels Positive, Negative, and Neutral. This is a minimal expansion of the usual binary (Positive/Negative) sentiment task, but a crucial one, as it avoids the false presupposition that all texts convey binary sentiment. We chose this version of the problem to show that even basic sentiment analysis poses substantial challenges for our field. We find that the Neutral category is especially dif-

ficult. While it is common to synthesize such a category from middle-scale product and service reviews, we use an independent validation of the Stanford Sentiment Treebank (Socher et al., 2013) dev set to argue that this tends to blur neutrality together with mixed sentiment and uncertain sentiment (Section 5.2). DynaSent can help tease these phenomena apart, since it already has a large number of Neutral examples and a large number of examples displaying substantial variation in validation. Finally, we argue that the variable nature of the Neutral category is an obstacle to fine-tuning (Section 5.3), which favors our strategy of training models from scratch for each round.

2 Related Work

Sentiment analysis was one of the first natural language understanding tasks to be revolutionized by data-driven methods. Rather than trying to survey the field (see Pang and Lee 2008; Liu 2012; Grimes 2014), we focus on the benchmark tasks that have emerged in this space, and then seek to situate these benchmarks with respect to challenge (adversarial) datasets and crowdsourcing methods.

2.1 Sentiment Benchmarks

The majority of sentiment datasets are derived from customer reviews of products and services. This is an appealing source of data, since such texts are accessible and abundant in many languages and regions of the world, and they tend to come with their own author-provided labels (star ratings). On the other hand, over-reliance on such texts is likely also limiting progress; DynaSent begins moving away from such texts, though it remains rooted in this domain.

Pang and Lee (2004) released a collection of 2,000 movie reviews with binary sentiment labels. This dataset became one of the first benchmark tasks in the field, but it is less used today due to its small size and issues with its train/test split that make it artificially easy (Maas et al., 2011).

A year later, Pang and Lee (2005) released a collection of 11,855 sentences extracted from movie reviews from the website Rotten Tomatoes. These sentences form the basis for the Stanford Sentiment Treebank (SST; Socher et al. 2013), which provides labels (on a five-point scale) for all the phrases in the parse trees of the sentences in this dataset.

Maas et al. (2011) released a sample of 25K labeled movie reviews from IMDB, drawn from

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1–4-star reviews (negative) and 7–10-star reviews (positive). This remains one of largest benchmark tasks for sentiment; whereas much larger datasets have been introduced into the literature at various times (Jindal and Liu, 2008; Ni et al., 2019), many have since been removed from public distribution (McAuley et al., 2012; Zhang et al., 2015). A welcome exception is the Yelp Academic Dataset,[3] which was first released in 2010 and which has been expanded a number of times, so that it how has over 8M review texts with extensive metadata.

Not all sentiment benchmarks are based in review texts. The MPQA Opinion Corpus of Wiebe et al. (2005) contains news articles labeled at the phrase-level by experts for a wide variety of subjective states; it presents an exciting vision for how sentiment analysis might become more multidimensional. SemEval 2016 and 2017 (Nakov et al., 2016; Rosenthal et al., 2017) offered Twitter-based sentiment datasets that continue to be used widely despite their comparatively small size (≈10K examples). And of course there are numerous additional datasets for specific languages, domains, and emotional dimensions; Google's Dataset Search currently reports over 100 datasets for sentiment, and the website Papers with Code gives statistics for dozens of sentiment tasks.[4]

Finally, sentiment lexicons have long played a central role in the field. They are used as resources for data-driven models, and they often form the basis for simple hand-crafted decision rules. The Harvard General Inquirer (Stone and Hunt, 1963) is an early and still widely used multidimensional sentiment lexicon. Other important examples are OpinionFinder (Wilson et al., 2005), LIWC (Pennebaker et al., 2007), MPQA, Opinion Lexicon (Liu, 2011), SentiWordNet (Baccianella et al., 2010), and the valence and arousal ratings of Warriner et al. (2013).

2.2 Challenge and Adversarial Datasets

Challenge and adversarial datasets have risen to prominence over the last few years in response to the sense that benchmark results are overstating the quality of the models we are developing (Linzen, 2020). The general idea traces to Winograd (1972), who proposed minimally contrasting examples meant to evaluate the ability of a model to capture specific cognitive, linguistic, and social phenomena (see also Levesque 2013).

This guiding idea is present in many recent papers that seek to determine whether models have met specific learning targets (Alzantot et al., 2018; Glockner et al., 2018; Naik et al., 2018; Nie et al., 2019). Related efforts reveal that models are exploiting relatively superficial properties of the data that are easily exploited by adversaries (Jia and Liang, 2017; Kaushik and Lipton, 2018; Zhang et al., 2020), as well as social biases in the data they were trained on (Kiritchenko and Mohammad, 2018; Rudinger et al., 2017, 2018; Sap et al., 2019; Schuster et al., 2019).

For the most part, challenge and adversarial datasets are meant to be used primarily for evaluation (though Liu et al. (2019a) show that even small amounts of training on them can be fruitful in some scenarios). However, there are existing adversarial datasets that are large enough to support full-scale training efforts (Zellers et al., 2018, 2019; Chen et al., 2019; Dua et al., 2019; Bartolo et al., 2020). DynaSent falls into this class; it has large train sets that can support from-scratch training as well as fine-tuning. Our approach is closest to, and directly inspired by, the Adversarial NLI (ANLI) project, which is reported on by Nie et al. (2020) and which continues on Dynabench. In ANLI, human annotators construct new examples that fool a top-performing model but make sense to other human annotators. This is an iterative process that allows the annotation project itself to organically find phenomena that fool current models. The resulting dataset has, by far, the largest gap between estimated human performance and model accuracy of any benchmark in the field right now. We hope DynaSent follows a similar pattern, and that its naturally occurring sentences and prompt-derived sentences bring beneficial diversity.

2.3 Crowdsourcing Methods

Within NLP, Snow et al. (2008) helped establish crowdsourcing as a viable method for collecting data for at least some core language tasks. Since then, it has become the dominant mode for dataset creation throughout all of AI, and the scientific study of these methods has in turn grown rapidly. For our purposes, a few core findings from research into crowdsourcing are centrally important.

First, crowdworkers are not fully representative of the general population: they are, for example, more educated, more male, more technologically enabled (Hube et al., 2019). As a result, datasets

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[3]https://www.yelp.com/dataset
[4]https://paperswithcode.com/task/sentiment-analysis

	SST-3		Yelp		Amazon	
	Dev	Test	Dev	Test	Dev	Test
Positive	444	909	9,577	10,423	130,631	129,369
Negative	428	912	10,222	9,778	129,108	130,892
Neutral	228	389	5,201	4,799	65,261	64,739
Total	1,100	2,210	25,000	25,000	325,000	325,000

Table 1: External assessment datasets used for Model 0 and Model 1. SST-3 is the ternary version of SST as described in Table 2a but with only the sentence-level phrases included. For the Yelp and Amazon datasets, we split the test datasets of Zhang et al. 2015 in half by line number to create a dev/test split.

created using these methods will tend to inherit these biases, which will then find their way into our models. DynaSent's naturally occurring sentences and prompt sentences can help, but we acknowledge that those texts come from people who write online reviews, which is also a special group.

Second, any crowdsourcing project will reach only a small population of workers, and this will bring its own biases. The workers will tend to adopt similar cognitive patterns and strategies that might not be representative even of the specialized population they belong to (Gadiraju et al., 2017). This seems to be an underlying cause of many of the artifacts that have been identified in prominent NLU benchmarks (Poliak et al., 2018; Gururangan et al., 2018; Tsuchiya, 2018; Belinkov et al., 2019).

Third, as with all work, quality varies across workers and examples, which raises the question of how best to infer individual labels from response distributions. Dawid and Skene (1979) is an early contribution to this problem leveraging Expectation Maximization (Dempster et al., 1977). Much subsequent work has pursued similar strategies; for a full review, see Zheng et al. 2017. Our corpus release uses the true majority (3/5 labels) as the gold label where such a majority exists, leaving examples unlabeled otherwise, but we include the full response distributions in our corpus release and make use of those distributions when training Model 1. For additional details, see Section 3.3.

3 Round 1: Naturally Occurring Sentences

We now begin to describe our method for constructing DynaSent (Figure 1). We begin with an initial model, Model 0, and use it to harvest challenging examples from an existing corpus. These examples are human-validated and incorporated into the training of a second model, Model 1. This model

is then loaded into Dynabench; Round 2 of our data collection (Section 4) involves crowdworkers seeking to create examples that fool this model.

3.1 Model 0

Our Model 0 begins with the RoBERTa-base parameters (Liu et al., 2019b) and adds a three-way sentiment classifier head. The model was trained on a number of publicly-available datasets, as summarized in Table 2a. The Customer Reviews (Hu and Liu, 2004) and IMDB (Maas et al., 2011) datasets have only binary labels. The other datasets have five star-rating categories. We bin these ratings by taking the lowest two ratings to be negative, the middle rating to be neutral, and the highest two ratings to be positive. The Yelp and Amazon datasets are those used in Zhang et al. 2015; the first is derived from an earlier version of the Yelp Academic Dataset, and the second is derived from the dataset used by McAuley et al. (2012). SST-3 is the ternary version of the SST; we train on the phrase-level version of the dataset (and always evaluate only on its sentence-level labels). For additional details on how this model was optimized, see Appendix A.

We evaluate this and subsequent models on three datasets (Table 1): SST-3 dev and test, and the assessment portion of the Yelp and Amazon datasets from Zhang et al. 2015. For Yelp and Amazon, the original distribution contained only (very large) test files. We split them in half (by line number) to create dev and test splits.

In Table 2b, we summarize our Model 0 assessments on these datasets. Across the board, our model does extremely well on the Positive and Negative categories, and less well on Neutral. We trace this to the fact that the Neutral categories for all these corpora were derived from three-star reviews, which actually mix a lot of different phenomena:

	CR	IMDB	SST-3	Yelp	Amazon
Positive	2,405	12,500	42,672	260,000	1,200,000
Negative	1,366	12,500	34,944	260,000	1,200,000
Neutral	0	0	81,658	130,000	600,000
Total	3,771	25,000	159,274	650,000	3,000,000

(a) Model 0 training data. CR is the Customer Reviews dataset from Hu and Liu 2004, IMDB is from Maas et al. 2011, SST-3 is the phrase-level ternary SST (labels 0–1 = Neg; 2 = Neu; 3–4 = Pos), and Yelp and Amazon are from Zhang et al. 2015 (1–2-star reviews = Neg; 3-star = Neutral; 4–5-star = Pos).

| | SST-3 | | Yelp | | Amazon | | Round 1 | | Round 2 | |
	Dev	Test	Dev	Test	Dev	Test	Dev	Test	Dev	Test
Positive	85.1	89.0	88.3	90.5	89.1	89.4	33.3	33.3	58.4	63.0
Negative	84.1	84.1	88.8	89.1	86.6	86.6	33.3	33.3	61.0	63.1
Neutral	45.4	43.5	58.2	59.4	53.9	53.7	33.3	33.3	38.4	44.3
Macro avg	71.5	72.2	78.4	79.7	76.5	76.6	33.3	33.3	52.6	56.8

(b) Model 0 performance (F1 scores) on external assessment datasets (Table 1). We also report on our Round 1 dataset (Section 3.4), where performance is at chance by construction, and we report on our Round 2 dataset (Section 4) to further quantify the challenging nature of that dataset.

Table 2: Model 0 summary.

neutrality, mixed sentiment, and (in the case of the reader judgments in SST) uncertainty about the author's intentions. We return to this issue in Section 5.2, arguing that DynaSent marks progress on creating a more coherent Neutral category.

Finally, Table 2b includes results for our Round 1 dataset, as we are defining it. Performance is at chance across the board by construction (see Section 3.4 below). We include these columns to help with tracking the progress we make with Model 1. We also report performance of this model on our Round 2 dataset (described below in Section 4), again to help with tracking progress and understanding the two rounds.

3.2 Harvesting Sentences

Our first round of data collection focused on finding naturally occurring sentences that would challenge our Model 0. To do this, we harvested sentences from the Yelp Academic Dataset, using the version of the dataset that contains 8,021,122 reviews.

The sampling process was designed so that 50% of the sentences fell into two groups: those that occurred in 1-star reviews but were predicted by Model 0 to be Positive, and those that occurred in 5-star reviews but were predicted by Model 0 to be Negative. The intuition here is that these would likely be examples that fooled our model. Of course, negative reviews can (and often do) contain

positive sentences, and vice-versa. This motivates the validation stage that we describe next.

3.3 Validation

Our validation task was conducted on Amazon Mechanical Turk. Workers were shown ten sentences and asked to label them according to the following four categories, which we give here with the glosses that were given to workers in instructions and in the annotation interface:

Positive: The sentence conveys information about the author's positive evaluative sentiment.

Negative: The sentence conveys information about the author's negative evaluative sentiment.

No sentiment: The sentence does not convey anything about the author's positive or negative sentiment.

Mixed sentiment: The sentence conveys a mix of positive and negative sentiment with no clear overall sentiment.

We henceforth refer to the 'No sentiment' category as 'Neutral' to remain succinct and align with standard usage in the literature.

For this round, 1,978 workers participated in the validation process. In the final version of the

Sentence	Model 0	Responses
Good food nasty attitude by hostesses .	neg	**mix, mix, mix**, neg, neg
Not much of a cocktail menu that I saw.	neg	**neg, neg, neg, neg, neg**
I scheduled the work for 3 weeks later.	neg	**neu, neu, neu, neu**, pos
I was very mistaken, it was much more!	neg	neg, **pos, pos, pos, pos**
It is a gimmick, but when in Rome, I get it.	neu	**mix, mix, mix**, neu, neu
Probably a little pricey for lunch.	neu	mix, **neg, neg, neg, neg**
But this is strictly just my opinion.	neu	**neu, neu, neu, neu**, pos
The price was okay, not too pricey.	neu	mix, neu, **pos, pos, pos**
The only downside was service was a little slow.	pos	**mix, mix, mix**, neg, neg
However there is a 2 hr seating time limit.	pos	mix, **neg, neg, neg**, neu
With Alex, I never got that feeling.	pos	**neu, neu, neu, neu**, pos
Its ran very well by management.	pos	**pos, pos, pos, pos, pos**

Table 3: Round 1 train set examples, randomly selected from each combination of Model 0 prediction and majority label, but limited to examples with 30–50 characters. Appendix E provides fully randomly selected examples.

corpus, each sentence is validated by five different workers. To obtain these ratings, we employed an iterative strategy. Sentences were uploaded in batches of 3–5K and, after each round, we measured each worker's rate of agreement with the majority. We then removed from the potential pool those workers who disagreed more than 80% of the time with their co-annotators, using a method of 'unqualifying' workers that does not involving rejecting their work or blocking them (Turk, 2017). We then obtained additional labels for examples that those 'unqualified' workers annotated. Thus, many examples received more than five responses over the course of validation. The final version of DynaSent keeps only the responses from the highest-rated workers. This led to substantial increase in dataset quality by removing a lot of labels that seemed to us to be randomly assigned. Appendix B describes the process in more detail, and our Datasheet enumerates the known unwanted biases that this process can introduce.

3.4 Round 1 Dataset

The resulting Round 1 dataset is summarized in Table 4. Table 3 provides train-set examples for every combination of Model 0 prediction and majority validation label. The examples were randomly sampled with a restriction to 30–50 characters. Appendix E provides examples that were truly randomly selected.

Because each sentence has five ratings, there are two perspectives we can take on the dataset:

	Dist	Majority Label		
	Train	Train	Dev	Test
Positive	130,045	21,391	1,200	1,200
Negative	86,486	14,021	1,200	1,200
Neutral	215,935	45,076	1,200	1,200
Mixed	39,829	3,900	0	0
No Majority	–	10,071	0	0
Total	472,295	94,459	3,600	3,600

Table 4: Round 1 Dataset. 'Dist' refers to the individual responses (five per example). We omit the comparable Dev and Test numbers to save space. The Majority Label is the one chosen by at least three of the five workers, if there is such label. For Majority Label Train, the Positive, Negative, and Neutral categories contain a total of 80,488 examples.

Distributional Labels   We can repeat each example with each of its labels. For instance, the first sentence in Table 3 would be repeated three times with 'Mixed' as the label and twice with 'Negative'. For many classifier models, this reduces to labeling each example with its probability distribution over the labels. This is an appealing approach to creating training data, since it allows us to make use of all the examples,[5] even those that do not have a majority label, and it allows us to make maximal use of the labeling information. In our experiments, we found that training on the distributional labels consistently led to slightly better models.

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[5]For 'Mixed' labels, we create two copies of the example, one labeled 'Positive', the other 'Negative'.

	CR	IMDB	SST-3	Yelp	Amazon	Round 1
Positive	2,405	12,500	128,016	29,841	133,411	339,748
Negative	1,366	12,500	104,832	30,086	133,267	252,630
Neutral	0	0	244,974	30,073	133,322	431,870
Total	3,771	25,000	477,822	90,000	400,000	1,024,248

(a) Model 1 training data. CR and IMDB are unchanged from Table 2a. SST-3 is processed the same way as before, but we repeat the dataset 3 times to give it more weight. For Yelp and Amazon, we include only 1-star, 3-star, and 5-star reviews, and we subsample from those categories, with the goal of down-weighting them overall and removing ambiguous reviews. Round 1 here uses distributional labels and is copied twice.

| | SST-3 | | Yelp | | Amazon | | Round 1 | | Round 2 | |
	Dev	Test	Dev	Test	Dev	Test	Dev	Test	Dev	Test
Positive	84.6	88.6	80.0	83.1	83.3	83.3	81.0	80.4	33.3	33.3
Negative	82.7	84.4	79.5	79.6	78.7	78.8	80.5	80.2	33.3	33.3
Neutral	40.0	45.2	56.7	56.6	55.5	55.4	83.1	83.5	33.3	33.3
Macro avg	69.1	72.7	72.1	73.1	72.5	72.5	81.5	81.4	33.3	33.3

(b) Model 1 performance (F1 scores) on external assessment datasets (Table 1), as well as our Round 1 and Round 2 datasets. Chance performance for this model on Round 2 is by design (Section 4.5).

Table 5: Model 1 summary.

Majority Label We can take a more traditional route and infer a label based on the distribution of labels. In Table 4, we show the labels inferred by assuming that an example has a label just in case at least three of the five annotators chose that label. This is a conservative approach that creates a fairly large 'No Majority' category. More sophisticated approaches might allow us to make fuller use of the examples and account for biases relating to annotator quality and example complexity (see Section 2.3). We set these options aside for now because our validation process placed more weight on the best workers we could recruit (Section 3.3).

The Majority Label splits given by Table 4 are designed to ensure five properties: (1) the classes are balanced, (2) Model 0 performs at chance, (3) the review-level rating associated with the sentence has no predictive value, (3) at least four of the five workers agreed, and (5) the majority label is Positive, Negative, or Neutral. (This excludes examples that received a Mixed majority and examples without a majority label at all.)

Over the entire round, 47% of cases are such that the validation majority label is Positive, Negative, or Neutral and Model 0 predicted a different label.

3.5 Estimating Human Performance

Table 6 provides a conservative estimate of human F1 in order to have a quantity that is comparable to our model assessment metrics. To do this, we randomize the responses for each example to create five synthetic annotators, and we calculate the precision, recall, and F1 scores for each of these annotators with respect to the gold label. We average those scores. This is a conservative estimate of human performance, since it heavily weights the single annotator who disagreed for the cases with 4/5 majorities. We can balance this against the fact that 614 workers (out of 1,280) *never* disagreed with the majority label (see Appendix B for the full distribution of agreement rates). However, it seems reasonable to say that a model has solved the round if it achieves comparable scores to our aggregate F1 – a helpful signal to start a new round.

4 Round 2: Dynabench

In Round 2, we leverage the Dynabench platform to begin creating a new dynamic benchmark for sentiment analysis. Dynabench is an open-source application that runs in a browser and facilitates dataset collection efforts in which workers seek to construct examples that fool a model (or ensemble of models) but make sense to other humans.

4.1 Model 1

Model 1 was created using the same general methods as for Model 0 (Section 3.1): we begin with RoBERTa parameters and add a three-way senti-

	Dev	Test
Positive	88.1	87.8
Negative	89.2	89.3
Neutral	86.6	86.9
Macro avg	88.0	88.0

Table 6: Estimates of human performance (F1 scores) on the Round 1 dataset. The estimates come from comparing random synthesized human annotators against the gold labels using the response distributions in the dataset. The Fleiss Kappas for the dev and tests set are 0.616 and 0.615, respectively. We offer F1s as a way of tracking model performance to determine when the round is "solved" and a new round of data should be collected. However, we note that 614 of our 1,280 workers never disagreed with the gold label.

ment classifier head. The differences between the two models lie in the data they were trained on.

Table 5a summarizes the training data for Model 1. In general, it uses the same datasets as we used for Model 0, but with a few crucial changes. First, we subsample the large Yelp and Amazon datasets to ensure that they do not dominate the dataset, and we include only 1-star, 3-star, and 5-star reviews to try to reduce the number of ambiguous examples. Second, we upsample SST-3 by a factor of 3 and our own dataset by a factor of 2, using the distributional labels for our dataset (Section 3.4). This gives roughly equal weight, by example, to our dataset as to all the others combined. This makes sense given our general goal of doing well on our dataset and, especially, of shifting the nature of the Neutral category to something more semantically coherent than what the other corpora provide.

Table 5b summarizes the performance of our model on the same evaluation sets as are reported in Table 5b for Model 0. Overall, we see a small performance drop on the external datasets, but a huge jump in performance on our dataset (Round 1). While it is unfortunate to see a decline in performance on the external datasets, this is expected if we are shifting the label distribution with our new dataset – it might be an inevitable consequence of hill-climbing in our intended direction.

4.2 Dynabench Interface

Appendix C provides the Dynabench interface we created for DynaSent as well the complete instructions and training items given to workers. The

essence of the task is that the worker chooses a label y to target and then seeks to write an example that the model (currently, Model 1) assigns a label other than y but that other humans would label y. Workers can try repeatedly to fool the model, and they get feedback on the model's predictions as a guide for how to fool it.

4.3 Methods

We consider two conditions:

Prompt Workers are shown a sentence and given the opportunity to modify it as part of achieving their goal. Prompts are sampled from parts of the Yelp Academic Dataset not used for Round 1.

No Prompt Workers wrote sentences from scratch, with no guidance beyond their goal of fooling the model.

We piloted both versions and compared the results. Our analyses are summarized in Section 5.1. The findings led us to drop the No Prompt condition and use the Prompt condition exclusively, as it clearly leads to examples that are more naturalistic and linguistically diverse.

For Round 2, our intention was for each prompt to be used only once, but prompts were repeated in a small number of cases. We have ensured that our dev and test sets contain only sentences derived from unique prompts (Section 4.5).

4.4 Validation

We used the identical validation process as described in Section 3.3, getting five responses for each example as before. This again opens up the possibility of using label distributions or inferring individual labels. 395 workers participated in the validation process for Round 2. See Appendix B for additional details.

4.5 Round 2 Dataset

Table 7 summarizes our Round 2 dataset. Overall, workers' success rate in fooling Model 1 is about 19%, which is much lower than the comparable value for Round 1 (47%). There seem to be at least three central reasons for this. First, Model 1 is hard to fool, so many workers reach the maximum number of attempts. We retain the examples they enter, as many of them are interesting in their own right. Second, some workers seem to get confused about the true goal and enter sentences that the model

| | Dist | Majority Label | | |
	Train	Train	Dev	Test
Positive	32,551	6,038	240	240
Negative	24,994	4,579	240	240
Neutral	16,365	2,448	240	240
Mixed	18,765	3,334	0	0
No Majority	–	2,136	0	0
Total	92,675	18,535	720	720

Table 7: Round 2 splits using the framework described in Section 4.5 and the criteria specified in Section 4.5.

in fact handles correctly. Some non-trivial rate of confusion here seems inevitable given the cognitive demands of the task, but we have taken steps to improve the interface to minimize this factor. Third, a common strategy is to create examples with mixed sentiment; the model does not predict this label, but it is chosen at a high rate in validation.

Despite these complicating factors, we can construct splits that meet our core goals: (1) Model 1 performs at chance on the dev and test sets, and (2) the dev and test sets contain only examples where the majority label was chosen by at least four of the five workers. In addition, (3) our dev and test sets contain only examples from the Prompt condition (the No Prompt cases are in the train set, and flagged as such), and (4) all the dev and test sentences are derived from unique prompts to avoid leakage between train and assessment sets and reduce unwanted correlations within the assessment sets. Table 7 summarizes these splits.

Table 8 provides train examples from Round 2 sampled using the same criteria we used for Table 3: the examples are randomly chosen to show every combination of model prediction and majority label, with the restriction that the examples be 30–50 characters long. (Appendix E gives fully randomly selected examples.)

4.6 Estimating Human Performance

Table 9 provides estimates of human F1 for Round 2 using the same methods as described in Section 3.5 and given in the corresponding table for Round 1 (Table 6). We again emphasize that these are very conservative estimates. We once again had a large percentage of workers (116 of 244) who never disagreed with the gold label on the examples they rated, suggesting that human performance can approach perfection. Nonetheless, the

estimates we give here seem useful for helping us decide whether to continue hill-climbing on this round or begin creating new rounds.

5 Discussion

We now address a range of issues that our methods raise but that we have so far deferred in the interest of succinctly reporting on the methods themselves.

5.1 The Role of Prompts

As discussed in Section 4, we explored two methods for collecting original sentences on Dynabench: with and without a prompt sentence that workers could edit to achieve their goal. We did small pilot rounds in each condition and assessed the results. This led us to use the Prompt condition exclusively. This section explains our reasoning more fully.

First, we note that workers did in fact make use of the prompts. In Figure 2a, we plot the Levenshtein edit distance between the prompts provided to annotators and the examples the annotators produced, normalized by the length of the prompt or the example, whichever is longer. There is a roughly bimodal distribution in this plot, where the peak on the right represents examples generated by the annotator tweaking the prompt slightly and the peak on the left represents examples where they deviated significantly from the prompt. Essentially no examples fall at the extreme ends (literal reuse of the prompt; complete disregard for the prompt).

Second, we observe that examples generated in the Prompt condition are generally longer than those in the No Prompt condition, and more like our Round 1 examples. Figure 2b summarizes for string lengths; the picture is essentially the same for tokenized word counts. In addition, the Prompt examples have a more diverse vocabulary overall. Figure 2c provides evidence for this: we sampled 100 examples from each condition 500 times, sampled five words from each example, and calculated the vocabulary size (unique token count) for each sample. (These measures are intended to control for the known correlation between token counts and vocabulary sizes; Baayen 2001.) The Prompt-condition vocabularies are much larger, and again more similar to our Round 1 examples.

Third, a qualitative analysis further substantiates the above picture. For example, many workers realized that they could fool the model by attributing a sentiment to another group and then denying it, as in "They said it would be great, but they were

Sentence	Model 1	Responses
The place was somewhat good and not well	neg	**mix, mix, mix, mix**, neg
I bought a new car and met with an accident.	neg	**neg, neg, neg, neg, neg**
The retail store is closed for now at least.	neg	**neu, neu, neu, neu, neu**
Prices are basically like garage sale prices.	neg	neg, neu, **pos, pos, pos**
That book was good. I need to get rid of it.	neu	**mix, mix, mix**, neg, pos
I REALLY wanted to like this place	neu	mix, **neg, neg, neg**, pos
But I'm going to leave my money for the next vet.	neu	neg, **neu, neu, neu, neu**
once upon a time the model made a super decision.	neu	**pos, pos, pos, pos, pos**
I cook my caribbean food and it was okay	pos	**mix, mix, mix**, pos, pos
This concept is really cool in name only.	pos	mix, **neg, neg, neg**, neu
Wow, it'd be super cool if you could join us	pos	**neu, neu, neu, neu**, pos
Knife cut thru it like butter! It was great.	pos	**pos, pos, pos, pos, pos**

Table 8: Round 2 train set examples, randomly selected from each combination of Model 1 prediction and majority label, but limited to examples with 30–50 characters. Appendix E provides fully randomly selected examples.

	Dev	Test
Positive	91.0	90.9
Negative	91.2	91.0
Neutral	88.9	88.2
Macro avg	90.4	90.0

Table 9: Estimates of human performance (F1 scores) on the Round 2 dataset using the procedure described in Section 3.5. The Fleiss Kappas for the dev and tests set are 0.681 and 0.667, respectively. The F1s are conservative estimates; 116 of our 244 workers never disagreed with the gold label for this round..

wrong". As a result, there are dozens of examples in the No Prompt condition that employ this strategy. Individual workers hit upon more idiosyncratic strategies and repeatedly used them. This is just the sort of behavior that we know can create persistent dataset artifacts. For this reason, we include No Prompt examples in the training data only, and we make it easy to identify them in case one wants to handle them specially.

5.2 The Neutral Category

For both Model 0 and Model 1, there is consistently a large gap between performance on the Neutral category and performance on the other categories, but only for the external datasets we use for evaluation. For our dataset, performance across all three categories is fairly consistent. We hypothesized that this traces to semantic diversity in the Neutral categories for these external datasets. In review corpora, three-star reviews can signal neutrality, but they are also likely to signal mixed sentiment or uncertain overall assessments. Similarly, where the ratings are assigned by readers, as in the SST, it seems likely that the middle of the scale will also be used to register mixed and uncertain sentiment, along with a real lack of sentiment.

To further support this hypothesis, we ran the SST dev set through our validation pipeline. This leads to a completely relabeled dataset with five ratings for each example and a richer array of categories. Table 10 compares these new labels with the labels in SST-3. Overall, the two label sets are closely aligned for Positive and Negative. However, the SST-3 Neutral category has a large percentage of cases falling into Mixed and No Majority, and it is overall by far the least well aligned with our labeling of any of the categories. Appendix D gives a random sample of cases where the two label sets differ with regard to the Neutral category. It also provides all seven cases of sentiment confusion. We think these comparisons favor our labels over SST's original labels.

5.3 Fine-Tuning

Our Model 1 was trained from scratch (beginning with RoBERTa) parameters. An appealing alternative would be to begin with Model 0 and fine-tune it on our Round 1 data. This would be more efficient, and it might naturally lead to the Round 1 data receiving the desired overall weight relative to the other datasets. Unfortunately, our attempts to fine-tune in this way led to worse models, and the
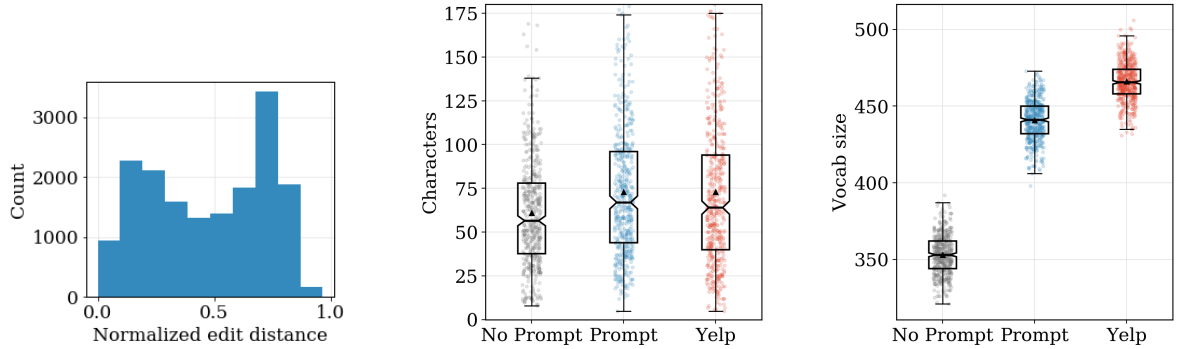
(a) Normalized edit distances between the prompt and the example.

(b) String lengths. The picture is essentially the same for tokenized word counts.

(c) Vocabulary sizes in samples of 100 examples (500 samples with replacement).

Figure 2: The 'Prompt' and 'No Prompt' conditions.

| | SST-3 | | |
	Positive	Negative	Neutral
Positive	367	2	64
Negative	5	359	57
Neutral	23	8	44
Mixed	34	35	39
No Majority	15	24	25

Table 10: Comparison of the SST-3 labels (dev set) with labels derived from our separate validation of this dataset.

problems generally traced to very low performance on the Neutral category.

To study the effect of our dataset on Model 1 performance, we employ the "fine-tuning by inoculation" method of Liu et al. (2019a). We first divide our Round 1 train set into small subsets via random sampling. Then, we fine-tune our Model 0 using these subsets of Round 1 train with non-distributional labels. We early-stop our fine-tuning process if performance on the Round 0 dev set of Model 0 (SST-3 dev) has not improved for five epochs. Lastly, we measure model performance with Round 1 dev (SST-3 dev plus Round 1 dev) and our external evaluation sets (Table 1).

Figure 3 presents F1 scores for our three class labels using this method. We observe that model performance on Round 1 dev increases for all three labels given more training examples. The F1 scores for the Positive and Negative classes remain high, but they begin to drop slightly with larger samples. The F1 scores on SST-3 dev show larger perturbations. However, the most striking trends are for the Neutral category, where the F1 score on Round 1

dev increases steadily while the F1 scores on the three original development sets for Model 0 decrease drastically. This is the general pattern that Liu et al. (2019a) associate with dataset artifacts or label distribution shifts.

Our current hypothesis is that the pattern we observe can be attributed, at least in large part, to label shift – specifically, to the difference between our Neutral category and the other Neutral categories, as discussed in the preceding section. Our strategy of training from scratch seems less susceptible to these issues, though the label shift is still arguably a factor in the relatively poor performance we see on this category with our external validation sets.

6 Conclusion

We presented DynaSent, as the first stage in what we hope is an ongoing effort to create a dynamic benchmark for sentiment analysis that responds to scientific advances and concerns relating to real-world deployments of sentiment analysis models. DynaSent contains 121,634 examples from two different sources: naturally occurring sentences and sentences created on the Dynabench Platform by workers who were actively trying to fool a strong sentiment model. All the sentences in the dataset are multiply-validated by crowdworkers in separate tasks. In addition, we argued for the use of prompt sentences on Dynabench to help workers avoid creative ruts and reduce the rate of biases and artifacts in the resulting dataset. We hope that the next step for DynaSent is that the community responds with models that solve both rounds of our task. That will in turn be our cue to launch another round of data collection to fool those models and push the field of sentiment forward by another step.
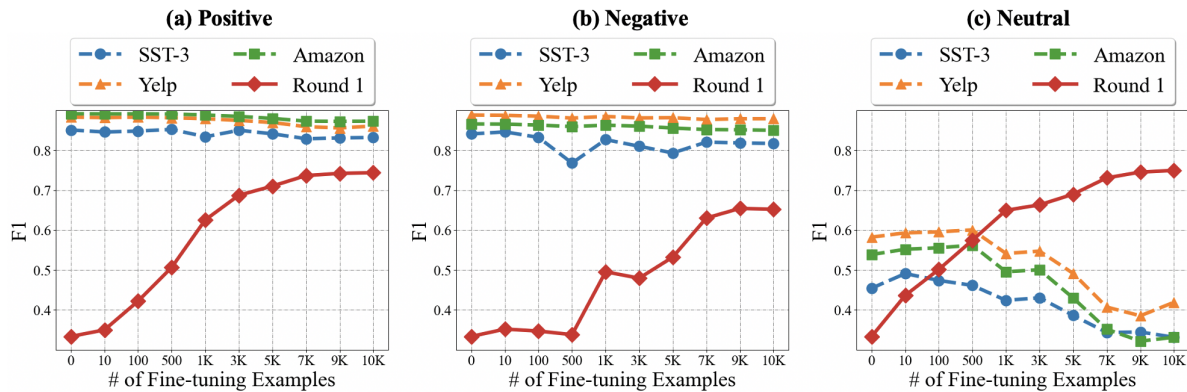
Figure 3: Inoculation by fine-tuning results with different number of fine-tuning examples. (a-c): F1 score on different development sets for three categories: Positive, Negative and Neutral.

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Appendix

A   Model 0

To train our Model 0, we import weights from the pretrained RoBERTa-base model.[6] As in the original RoBERTa-base model (Liu et al., 2019b), our model has 12 heads and 12 layers, with hidden layer size 768. The model uses byte-pair encoding as the tokenizer (Sennrich et al., 2016), with a maximum sequence length of 128. The initial learning rate is $2e-5$ for all trainable parameters, with a batch size of 8 per device (GPU). We fine-tuned for 3 epochs with a dropout probability of 0.1 for both attention weights and hidden states. To foster reproducibility, our training pipeline is adapted from the Hugging Face library (Wolf et al., 2019).[7] We used $6 \times$ GeForce RTX 2080 Ti GPU each with 11GB memory. The training process takes about 15 hours to finish.

B   Additional Details on Validation

B.1   Validation Interface

Figure 4 shows the interface for the validation task used for both Round 1 and Round 2. The top provides the instructions, and then one item is shown. The full task had ten items per Human Interface Task (HIT). Workers were paid US$0.25 per HIT, and all workers were paid for all their work, regardless of whether we retained their labels.

B.2   Worker Selection

Examples were uploaded to Amazon's Mechanical Turk in batches of 3–5K examples. After each round, we assessed workers by the percentage of examples they labeled for which they agreed with the majority. For example, a worker who selects Negative where three of the other workers chose Positive disagrees with the majority for that example. If a worker disagreed with the majority more than 80% of the time, we removed that worker from the annotator pool and revalidated the examples they labeled. This process was repeated iteratively over the course of the entire validation process for Round 1. Thus, many examples received more than 5 labels; we keep only those by the top-ranked workers according to agreement with the majority. We observed that this iterative process led to

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[6]https://dl.fbaipublicfiles.com/fairseq/models/roberta.base.tar.gz
[7]https://github.com/huggingface/transformers

substantial improvements to the validation labels according to our own intuitions.

To remove workers from our pool, we used a method of 'unqualifying', as described in (Turk, 2017). This method does no reputational damage to workers and is often used in situations where the requester must limit responses to one per worker (e.g., surveys). We do not know precisely why workers tend to disagree with the majority. The reasons are likely diverse. Possible causes include inattentiveness, poor reading comprehension, a lack of understanding of the task, and a genuinely different perspective on what examples convey. While we think our method mainly increased label quality, we recognize that it can introduce unwanted biases. We acknowledge this in our Datasheet, which is distributed with the dataset.

B.3   Worker Distribution

Figure 5 show the distribution of workers for the validation task for both rounds. In the final version of Round 1, the median number of examples per worker was 45 and the mode was 11. For Round 2, the median was 20 and the mode was 1.

B.4   Worker Agreement with Gold Labels

Figure 6 summarizes the rates at which individual workers agree with the gold label. Across the dev and test sets for both rounds, substantial numbers of workers agreed with the gold label on all of the cases they labeled, and more than half were above 95% for this agreement rate for both rounds.

C   Additional Details on Dynabench Task

C.1   Interface for the Prompt Condition

Figure 7 shows an example of the Dynabench interface in the Prompt condition.

C.2   Instructions

Figure 8 provides the complete instructions for the Dynabench task, and Table 11 provides the list of comprehension questions we required workers to answer correctly before starting.

C.3   Data Collection Pipeline

For each task, a worker has ten attempts in total to find an example that fools the model. A worker can immediately claim their payments after submitting a single fooling example, or running out of attempts. The average number of attempts per task is two before the worker generates an example

that they claim fools the model. Workers are paid US$0.30 per task.

A confirmation step is required if the model predicts incorrectly: we explicitly ask workers to confirm the examples they come up with are truly fooling examples. Figure 7 shows this step in action.

To incentives workers, we pay a bonus of US$0.30 for each truly fooling example according to our separate validation phase.

We temporarily disallow a worker to do our task if they fail to answer correctly to all our onboarding questions as in Table 11 within five attempts. We also temporarily disallow a worker to do our task if they consistently cannot come up with truly fooling examples validated by us.

A worker must meet the following qualifications before accepting our tasks. First, a worker must reside in U.S. and speak English. Second, a worker must have completed at least 1,000 tasks on Amazon Mechanical Turk with an approval rating of 98%. Lastly, a worker must not be in any of our temporarily disallowing worker pools.

We adapt the open-source software package Mephisto as our data collection tool for Amazon Mechanical Turk.[8]

D SST-3 Validation Examples

Table 12 provides selected examples comparing the SST-3 labels with our revalidation of that dataset's labels.

E Randomly Selected Corpus Examples

Table 13 provides 10 truly randomly selected examples from each round's train set.

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[8]https://github.com/facebookresearch/Mephisto

Instructions

You will be shown 10 sentences from reviews of products and services. For each, your task is to choose from one of four labels:

- `Positive` : The sentence conveys information about the author's **positive evaluative sentiment**.
- `Negative` : The sentence conveys information about the author's **negative evaluative sentiment**.
- `No sentiment` : The sentence **does not convey anything** about the author's positive or negative sentiment.
- `Mixed sentiment` : The sentence conveys **a mix of positive and negative sentiment** with **no clear overall sentiment**.

Here are some simple examples of the labels:

- Sentence: This is an under-appreciated little gem of a movie.
  This is `Positive` because it expresses a positive overall opinion.
- Sentence: I asked for my steak medium-rare, and they delivered this perfectly!
  This is `Positive` because it puts a positive spin on an aspect of the author's experience.
- Sentence: The screen on this device is a little too bright.
  This is `Negative` because it negatively evaluates an aspect of the product.
- Sentence: The book is 972 pages long.
  This is `No sentiment` because it describes a factual matter with no evaluative component.
- Sentence: The waiting room is drab but the examination rooms are cheery enough.
  This is `Mixed sentiment` because two different sentiment evaluations are balanced against each other.
- Sentence: The entrees are delicious, but the service is so bad that it's not worth going.
  This is `Negative` because the negative statement outweighs the positive one.

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Sentence: The host did a great job of making me feel unwanted.

○ `Positive` : **The sentence conveys information about the author's positive evaluative sentiment.**

○ `Negative` : **The sentence conveys information about the author's negative evaluative sentiment.**

○ `No sentiment` : **The sentence does not convey anything about the author's positive or negative sentiment.**

○ `Mixed sentiment` : **The sentence conveys a mix of positive and negative sentiment with no clear overall sentiment.**
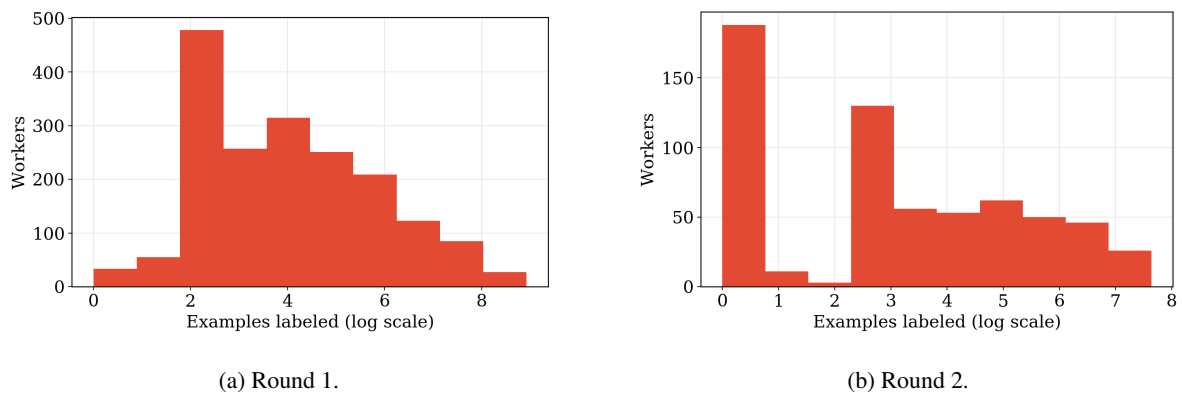
Figure 4: Validation interface.

(a) Round 1.

(b) Round 2.

Figure 5: Worker distribution for the validation task.
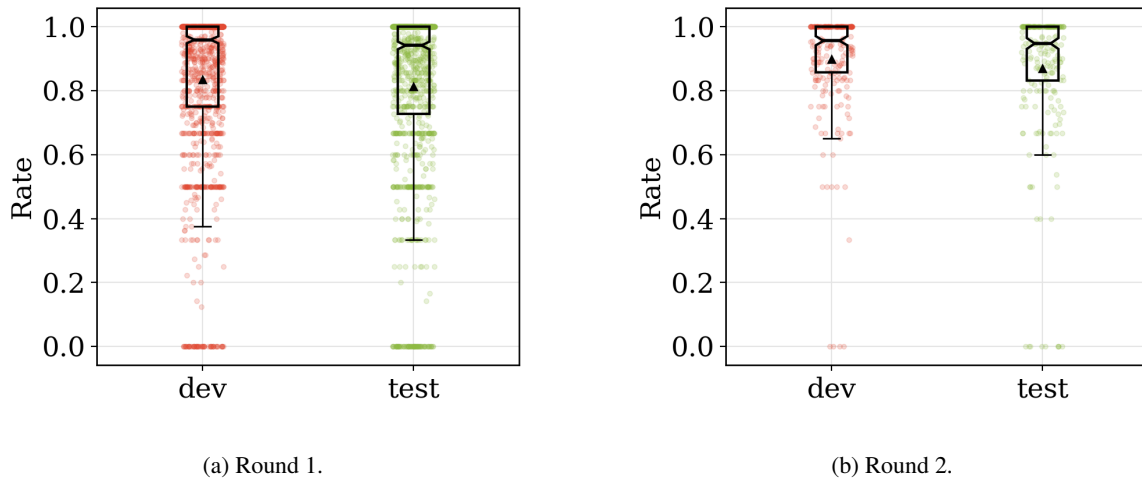
(a) Round 1.

(b) Round 2.

Figure 6: Rates at which individual worker agree with the majority label. The y-axis gives, for each worker, the total number of examples for which they chose the majority label divided by the total number of cases they labeled over all.

Figure 7: Dynabench interface.

In this task, you will be asked to find examples that fool an AI model into making the wrong prediction.

This AI model has been trained to predict whether a sentence is either **positive, neutral or negative**. It is a very strong model, so we will provide you with prompt sentences that might suggest effective strategies for fooling it. The prompt sentences will not always have the same sentiment as your target sentiment, but they might be useful nonetheless.

For example, you might be given the prompt sentence:

"The team did a great job."

and, if your goal is to create a **negative** sentence that fools the model, you might modify it to:

"The host did a great job of making me feel unwanted."

which seems **negative**, and then you should check that the model wrongly predicts it to be **positive or neutral**.

Figure 8: Dynabench instructions.

	Questions	Answers
Q1	You are asked to write down one sentence at each round.	False, **True**
Q2	You will not know whether you fool the model after you submit your sentence.	**False**, True
Q3	You may need to wait after you submit your result.	False, **True**
Q4	The goal is to find an example that the model gets right but that another person would get wrong.	**False**, True
Q5	You will be modifying a provided prompt to generate your own sentence.	False, **True**
Q6	Here is an example where a powerful model predicts positive sentiment: "The restaurant is near my place, but the food there is not good at all."	**False**, True
Q7	Suppose the goal is to write a positive sentence that fools the model into predicting another label. The sentence provided is "That was awful!", and the model predicts negative. Does this sentence meet the goal of the task?	Yes, **No**
Q8	Suppose the goal is to write a negative sentence that fools the model into predicting another label. The sentence provided is "They did a great job of making me feel unwanted", and the model predicts positive. Does this sentence meet the goal of the task?	**Yes**, No

Table 11: A list of comprehension questions we asked workers to answer correctly with a maximum of 5 retires. Correct answer is bolded.

	SST-3	Responses
Moretti 's compelling anatomy of grief and the difficult process of adapting to loss.	neg	neu, **pos, pos, pos, pos**
Nothing is sacred in this gut-buster.	neg	neg, neg, **pos, pos, pos**

(a) All examples for which the SST-3 label is Negative and our majority label is Positive.

	SST-3	Responses
... routine , harmless diversion and little else.	pos	mix, mix, **neg, neg, neg**
Hilariously inept and ridiculous.	pos	mix, **neg, neg, neg, neg**
Reign of Fire looks as if it was made without much thought – and is best watched that way.	pos	mix, **neg, neg, neg, neg**
So much facile technique, such cute ideas, so little movie.	pos	mix, mix, **neg, neg, neg**
While there 's something intrinsically funny about Sir Anthony Hopkins saying 'get in the car, bitch,' this Jerry Bruckheimer production has little else to offer	pos	mix, **neg, neg, neg, neg**

(b) All examples for which the SST-3 label is Positive and our majority label is Negative.

	SST-3	Responses
Returning aggressively to his formula of dimwitted comedy and even dimmer characters, Sandler, who also executive produces, has made a film that makes previous vehicles look smart and sassy.	neu	**neg, neg, neg, neg, neg**
should be seen at the very least for its spasms of absurdist humor.	neu	**pos, pos, pos, pos, pos**
A workshop mentality prevails.	neu	**neu, neu, neu, neu, neu**
Van Wilder brings a whole new meaning to the phrase ' comedy gag . '	neu	mix, neu, **pos, pos, pos**
' They' begins and ends with scenes so terrifying I'm still stunned.	neu	neu, neu, **pos, pos, pos**
Barely gets off the ground.	neu	**neg, neg, neg, neg, neg**
As a tolerable diversion, the film suffices; a Triumph, however, it is not.	neu	**mix, mix, mix, mix**, neg
Christina Ricci comedy about sympathy, hypocrisy and love is a misfire.	neu	**neg, neg, neg, neg, neg**
Jacquot's rendering of Puccini's tale of devotion and double-cross is more than just a filmed opera.	neu	neg, neu, **pos, pos, pos**
Candid Camera on methamphetamines.	neu	**neg, neg, neg**, neu, pos

(c) A random selection of 10 examples for which SST-3 label is Neutral and our validation label is not.

Table 12: Comparisons between the SST-3 labels and our new validation labels.

Sentence	Model 1	Responses
We so wanted to have a new steak house restaurant.	pos	**neu, neu, neu, neu,** pos
As a foodie, I can surely taste the difference.	pos	**neu, neu, neu, pos,** pos
There was however some nice dinner table chairs that I liked a lot for $35 a piece and for the quality and style this was a very nice price for them.	pos	**pos, pos, pos, pos, pos**
The waitress helped me pick from the traditional menu and I ended up with chilli chicken.	pos	neu, neu, **pos, pos, pos**
I have had lashes in the past and have used some of those Living Social deals.	pos	**neu, neu, neu, neu,** pos
Lots of trash cans.	neu	mix, **neu, neu, neu, neu**
They were out the next day after my call to do the inspection and same for the treatment.	pos	mix, **neu, neu, neu,** pos
When we walked in no one was there to sit us, I waited for a minute and then decided just to take a seat.	neg	mix, **neg, neg, neg, neg**
Driver was amazing!	pos	**pos, pos, pos, pos, pos**
We tried:\n\nChampagne On Deck - Smooth and easy to drink.	pos	neu, neu, **pos, pos, pos**

(a) Randomly sampled Round 1 train cases.

Sentence	Model 1	Responses
The menu was appealing.	pos	**pos, pos, pos, pos, pos**
Our food took forever to get home.	neg	**neg, neg, neg, neg,** neu
Our table was ready after 90 minutes and usually I'd be mad but the scenery was nice so it was an okay time.	pos	**mix, mix, mix, mix,** pos
I left feeling like an initiator in a world of books that I never even knew existed.	pos	mix, neu, **pos, pos, pos**
I decided to go with josh wilcox, only as a last resort	neu	mix, neg, **neu, neu, neu**
:] Standard ask if the food is a great happening!	neu	**neu, neu, neu, neu,** pos
The car was really beautiful.	pos	neu, **pos, pos, pos, pos**
Food is a beast of its own, low-quality ingredients, typically undercooked, and a thin, very simple menu.	neg	**neg, neg, neg, neg,** neu
I want to share a horrible experience here.	neg	**neg, neg, neg, neg, neg**
I tried a new place. The entrees were subpar to say the least.	neg	**neg, neg, neg, neg, neg**

(b) Randomly sampled Round 2 train cases.

Table 13: Randomly sampled Round 1 and Round 2 train cases.