‘Hardness’ of Samples Need to be Quantified for a Reliable Evaluation System: Exploring Potential Opportunities with a New Task

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Abstract

Evaluation of models on benchmarks is unreliable without knowing the degree of sample hardness; this subsequently overestimates the capability of AI systems and limits their adoption in real world applications. We propose a Data Scoring task that requires assignment of each unannotated sample in a benchmark a score between 0 to 1, where 0 signifies easy and 1 signifies hard. Use of unannotated samples in our task design is inspired from humans who can determine a question difficulty without knowing its correct answer. This also rules out the use of methods involving model based supervision (since they require sample annotations to get trained), eliminating potential biases associated with models in deciding sample difficulty. We propose a method based on Semantic Textual Similarity (STS) for this task; we validate our method by showing that existing models are more accurate with respect to the easier sample-chunks than with respect to the harder sample-chunks. Finally we demonstrate five novel applications.

1 Introduction

Empirical justification of model superiority without theoretical proof can be unreliable. Suppose model $M_1$ has higher accuracy than model $M_2$ on a dataset $D_1$. In order to confirm if we should choose $M_1$ over $M_2$, we can train and evaluate both models on $D_2$, $D_3$ and $D_4$. Even if $M_1$ has higher accuracy than $M_2$ on all the three datasets, we cannot say that $M_1$ is always better; we may then evaluate both models on Out of Distribution (OOD) (Quionero-Candela et al., 2009) datasets (usually done zero-shot (Bras et al., 2020)) $D_5$ and $D_6$ to find their generalization performance. Suppose that $M_1$ still performs better than $M_2$ in $D_5$ and $D_6$. Is that enough to justify the superiority of $M_1$, or do we need further experimentation on a wider range of datasets? Often, $M_1$ will not be a clear winner in all six datasets, making this evaluation even harder.

Justifying superiority as above requires analysis of ‘hardness’ of questions that models are answering. For instance, $D_1$-$D_4$ may contain ‘easy’ questions on which $M_1$ excels and ‘hard’ questions on which it fails. It is also possible that $M_2$ answers more ‘hard’ questions than $M_1$, while the overall count of correctly answered questions for $M_2$ is lower, so $M_1$ has better accuracy. In that case, zeroshot OOD performance can help identify the winner, assuming that OOD samples are harder samples that diverge from the training set.

Consequently, a clear definition of the ‘hardness’ of data items is useful in better analyzing empirical results. It will help in the design of a futuristic testbed consisting of a hierarchy of question sets with increasing levels of difficulty, similar to hierarchical testbeds used in software engineering (Barreiros et al., 2011) and in competitive examinations such as GRE. This will further allow us to quantify the weightage assigned to each question based on its hardness and assign weighted score to models based on their performance across various datasets, instead of the average sample performance typically calculated within a dataset and average dataset performance calculated in a benchmark (e.g. GLUE score (Wang et al., 2018)). Additionally, defining OOD in terms of ‘hardness’ allows for the representation of such samples as extensions of IID (independent and identically distributed)–‘very hard’ samples– and also for the implicit identification of OOD.

Swayamdipta et al. (2020) uses annotated datasets to find sample hardness with a model-dependent method; however knowledge of correct answers is not a prerequisite for humans to decide on question ‘hardness’ (and subsequent distribution shift). Also, a model based and annotation dependent method can contain artifact as a sample which is easy for this model may be difficult for
another model. To the best of our knowledge, we do not have a measure to find hardness of unannotated data. This motivates us to propose a Data Scoring Task and a STS based method that assigns each unannotated sample a score between 0 (‘easy’) and 1 (‘hard’), and explains distribution shift, thus quantifying the degree of OOD characteristics. Here, ‘hardness’ is considered to be inversely proportional to model predictability. For instance, if question $q_1$ is a random sample from set $s_1$, and $q_2$ is a random sample from set $s_2$ such that $s_2$ is harder than $s_1$, then the probability that $q_1$ will be correctly answered by a model $M$ is higher than for $q_2$, i.e., model predictability of $q_1$ is higher than that of $q_2$.

**Contributions:** In summary, the contribution of this work are as follows: (i) We propose a Data Scoring task realizing the need for quantification of ‘hardness’ of samples to build a reliable evaluation system, (ii) We propose an STS based approach that gives strong results, specially on recent transformers, (iii) We demonstrate five novel applications and opportunities associated with this task.

## 2 Our Approach:

First, we propose an annotation-agnostic measure that quantifies a sample’s relative predictability (‘hardness’), and explains relative distribution shift.

We experiment with ten models across an IID-OOD dataset pair, using STS (Semantic Textual Similarity) of test samples with respect to the training set for our task, and find it a strong indicator of predictability in regular/zero shot OOD settings.

We analyze several recent works (Hendrycks et al., 2020; Bras et al., 2020; Hendrycks and Dietterich, 2019; Talmor and Berant, 2019) involving datasets that have been paired with an OOD counterpart. Identification of OOD datasets as well as how to break ties if $M_1$ and $M_2$ excel on equal numbers of the OOD datasets used for evaluation, have remained unanswered. To address this, we divide the datasets into several hierarchies, based on STS. We can therefore reasonably identify samples within a dataset, which have higher OOD characteristic levels. This allows the same dataset to be used to evaluate OOD. STS can thus be used to draw a boundary between IID and OOD, and to control the degree of OOD characteristics in a dataset.

Next, we formulate an equitable evaluation metric Weighting Out of Distribution Score (WOOD Score), that weights each test sample in proportion to its degree of OOD characteristics (‘hardness’) and penalizes incorrect answers, such that ‘hard’ samples are both ‘high risk’ and ‘high gain’. This compels a model to solve ‘hard’ questions and thus generalize in order to dominate leaderboards.

Models that surpass human performance are often found to depend on spurious bias—unintended correlation between input and output, (Bras et al., 2020)– instead of truly learning the task (Gururangan et al., 2018; Kaushik and Lipton, 2018), and thus fail to generalize on OOD data (Eykholt et al., 2018; Jia and Liang, 2017), leading to overestimation of AI (Sakaguchi et al., 2019; Hendrycks et al., 2019). WOOD Score shows a decrease in model performance, thus addressing model inflation.

Conventionally, MaxProb is used as a strong baseline (Hendrycks and Gimpel, 2016a) for misclassification and OOD detection. However, it requires data annotation/running models; thus it cannot be used in our model/annotation-agnostic task. We find that STS indicates relative distribution of MaxProb across a dataset, and can therefore be used instead of MaxProb in various tasks e.g. selective answering (Kamath et al., 2020; Varshney et al., 2020).

Our task also allows for the selection of question subset for annotation–’hard’ questions require explicit annotation– to maintain a desired data quality level. This drastically reduces heavy resource investment in annotating and wastage (Bras et al., 2020; Mishra and Sachdeva, 2020) due to sample deletion (to get rid of spurious bias). This also allows for the recommendation of ‘hard’ question creation by experts, if such questions are found to be lacking in scored datasets. This can be further extended to potentially create a hierarchical testbed, where samples from different datasets are pooled and ranked based on their hardness, leading to a new demarkation of dataset boundaries. This will ensure reliable and standardized model evaluation.

## 3 Data Scoring with STS

We use two movie review datasets: SST-2 (Socher et al., 2013) and IMDB (Maas et al., 2011), which contain succinct expert reviews and full length general reviews respectively. We utilize IMDB as the IID dataset and SST-2 as the OOD dataset, and evaluate them using ten models: Bag-of-words (BoW) model (Harris, 1954), word embedding - word2vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014) encoded with three models.
-word averages (Wieting et al., 2015), LSTM (Hochreiter and Schmidhuber, 1997) and CNN (LeCun et al., 1995), and pretrained transformer models -BERT Base and Large (Devlin et al., 2018) along with GELU (Hendrycks and Gimpel, 2016b) and RoBERTA (Liu et al., 2019), following a recent work on OOD Robustness (Hendrycks et al., 2020).

**Implementation:** We use Spacy’s (Honnibal and Montani, 2017) BERT STS implementation to find the similarity between every pair of train-test set samples. We sort samples of the test set in a descending order, based on the average STS value with varying percentages of the SST-2 train set samples. We consider the top 1% – 100% of the training data (obtained by sorting train set samples in descending order of STS against each test set sample) with nine total steps $^1$, as similarity between the train and test sets is a task dependent hyperparameter, that trades off between inductive bias and spurious bias (Mishra et al., 2020). We train models on the IID data (IMDB) and evaluate on both the IID test set (IMDB) and the OOD test set (SST-2). We compare model predictions with the average STS value for each sample.

**Results:** We find three broad patterns: (i) Sample-chunks with higher average STS (‘easier samples’) have fewer percentage of incorrect predictions (Figure 1); in Figure 2, we show that for transformer models (in both datasets) and word2vec embedding models (in IMDB) exhibit this behavior. Our observation of STS accurately explaining predictability of transformers may indicate that Transformers are better at leveraging training data for memorization. (ii) IID sample-chunks have higher average STS than OOD (Figure 8); STS therefore helps in drawing a boundary between IID and OOD, and (iii) Samples with higher average STS value are classified correctly with higher confidence, and incorrectly with lower confidence (Figure 7).$^2$

**Figure 1:** Percentage of incorrect classifications using BERT-Base model across test samples of SST-2 and IMDB in decreasing order of train (IMDB)-test similarity. Monotonic increase in slope is desirable.

**Figure 2:** Percentage of incorrect classifications across test samples of SST-2 and IMDB in decreasing order of train (IMDB)-test similarity.

### 4 WOOD Score for Equitable Evaluation

We propose *equitable data evaluation* using WOOD Score, in lieu of a conventional evaluation metric (e.g. accuracy) that weights all samples uniformly.

**Formalization:** Let $X$ represent a dataset where $X_{Test}$ is the test set spanned by $i$ and $X_{Train}$ is the train set. $E$ represents the evaluation metric (which depends on the application– here we consider +1 for correct answers and a -1 penalty for incorrect answers). $p$ is the degree of OOD characteristics (i.e., data score) a sample has, and $S$ represents STS. $a$ allows for the control of $p$ based on $S$, $b$ is the number of train samples considered that have higher similarity values than rest of the dataset. $W_{opt}$ represents our proposed metric in generic form, and $W_{acc}$ is the proposed accuracy metric in this paper. We divide the dataset into three sample-chunks, $c_1$, $c_2$, $c_3$ having the highest, moderate, and lowest degrees of OOD characteristics respectively.

\[
W_{opt} = \frac{\sum_{X_{Test}} E_i p_i}{\sum p_i} \\
p = \frac{\alpha}{\sum_{X_{Train}} \max_b S}
\]

$^1$1%,5%,10%,25%,30%,40%,50%,75%,100%

$^2$More details in Supplementary Material
Figure 3: Accuracy and WOOD Score of SST-2 and IMDB across models. **WOOD Score** is significantly lower than accuracy for both datasets, with greater decrease seen for OOD data. Ranking changes for 9/10 models in IMDB (IID) and 3/10 models in SST-2 (OOD).

\[ W_{\text{acc}} = \frac{\sum X_{\text{test}} E_i p_i}{\sum p_i} \text{, where (based on max } S) \]

\[ p_i = \begin{cases} 
3 & \text{if } i \in c_1 \\
2 & \text{if } i \in c_2 \\
1 & \text{if } i \in c_3 
\end{cases} \]

**Controlling Benchmark Accuracy Using Hyperparameters**: Benchmark accuracy can be controlled using \( a \) and \( b \) appropriately. \( E \) controls penalties imposed for incorrect answers (e.g. safety critical applications require higher penalties). Using \( W_{\text{acc}} \) for both datasets across ten models has resulted in a significant reduction in accuracy, thus addressing model performance inflation (Table 3, where \( a \) is 1 and \( b \) is taken as 0.1; however similar observations are noted for all hyperparameters). We also note that the WOOD score rankings significantly differ from that with accuracy.

5 Discussion

**Data Annotation and Creation**: Figure 5 shows the distribution of STS values across both datasets, and hierarchical testbed creation. Assuming that these data are unannotated, authors can decide to annotate only the hard samples (e.g. below
Figure 5: Percentage of samples in IMDB and SST-2 with STS value within threshold bins, with hierarchical testbed formation, from ‘easy’ (B1) to ‘hard’ (B7).

STS threshold of 0.7) as easy samples won’t be really help to increase performance of a model already trained with varieties of dataset of the same task (sentiment analysis). Similarly, authors may decide to manually create hard samples (e.g. STS <0.5) since they are limited in both datasets. This technique can be helpful in the learning from instruction paradigm (Mishra et al., 2022b; Wei et al., 2021; Sanh et al., 2021; Ouyang et al., 2022; Mishra et al., 2022a; Parmar et al., 2022) because of the implicit setting which is low resource with annotated data.

6 Conclusion

We propose a Data Scoring measure that quantifies the hardness of each sample in an unannotated dataset based on STS, and show its applications in various domains. We further show that STS sometimes fails to appropriately indicate model predictability, demonstrating room for future research on this unexplored task.

7 Limitations

Augmenting STS: STS may not follow monotonic behavior with model performance for certain cases, as illustrated in Figure 6. Similarity across several granularities – such as word, bigram, and trigram – can be used to augment STS and increase the robustness of ‘hardness’ evaluation.

Strengthening ‘in-house’ IID (acting OOD): We further observe that, IID data, even with STS calibration, may not represent many properties of an OOD data sample – such as variations in writing style, topic, vocabulary, sentence length, and number of sentences. We recommend that dataset creators go beyond the common patterns found in a dataset, and draw patterns from other datasets intended for the same task, while creating contrast sets (Gardner et al., 2020), to address this.

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A Analysis

Figure 7: Average MaxProb of correct classifications using BERT-Base model across test sample-chunks of SST-2 and IMDB in decreasing order of train (IMDB)-test similarity. Monotonic slope decrease is desirable.

D STS’s correlation with MaxProb Across Models

Similar to our observation in Figure 2 of the main paper, here also we see that, in transformers, STS better correlates with MaxProb in comparison with other classes of models. This may further indicate the effectiveness of transformers in utilizing training data. Als, this observation opens up opportunity for further research as MaxProb has its own limitations and is not the ideal indicator of model confidence (Kamath et al., 2020; Varshney et al., 2022).

B Infrastructure Used

All the experiments were conducted on “TeslaV100-SXM2-16GB”; CPU cores per node 20; CPU memory per node: 95,142 MB; CPU memory per core: 4,757 MB. This configuration is not a necessity for these experiments as we ran our operations with NVIDIA Quadro RTX 4000 as well with lesser memory. We used AllenNLP (Gardner et al., 2018) for our implementations.

C Another Case of STS Failure:

Similar to Figure 6 of the main paper, we show a case for RoBERTA-Large where STS does not monotonically correlate with accuracy.
Figure 6: The top \( b\% \) of training samples is obtained by sorting in descending order of STS with each test set sample; test set samples are then divided into seven splits, based on decreasing STS averaged over the top \( b\% \) of training samples considered, for BERT-BASE over the SST-2 dataset.

Figure 9: The top \( b\% \) of training samples is obtained by sorting in descending order of STS with each test set sample; test set samples are then divided into seven splits, based on decreasing STS averaged over the top \( b\% \) of training samples considered, for BERT-BASE over the SST-2 (top) and IMDB (bottom) datasets.
Figure 10: The top $b\%$ of training samples is obtained by sorting in descending order of STS with each test set sample; test set samples are then divided into seven splits, based on decreasing STS averaged over the top $b\%$ of training samples considered, for ROBERTA-LARGE over the SST-2 (top) and IMDB (bottom) datasets.

Figure 11: Confidence of incorrect classifications across test samples of SST-2 and IMDB in decreasing order of train (IMDB)-test similarity.