Estimating Semantic Similarity between In-Domain and Out-of-Domain Samples

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Abstract

Prior work typically describes out-of-domain (OOD) or out-of-distribution (OODist) samples as those that originate from dataset(s) or source(s) different from the training set but for the same task. When compared to in-domain (ID) samples, the models have been known to usually perform poorer on OOD samples, although this observation is not consistent. Another thread of research has focused on OOD detection, albeit mostly using supervised approaches. In this work, we first consolidate and present a systematic analysis of multiple definitions of OOD and OODist as discussed in prior literature. Then, we analyze the performance of a model under ID and OOD/OODist settings in a principled way. Finally, we seek to identify an unsupervised method for reliably identifying OOD/OODist samples without using a trained model. The results of our extensive evaluation using 12 datasets from 4 different tasks suggest the promising potential of unsupervised metrics in this task.

1 Introduction

What happens when you train a machine learning model on a dataset and use it to predict a sample whose source is unknown? Would you fully rely on the model's prediction on the test sample? Basically, this situation is encountered in most real-world scenarios where the test sample may differ considerably from the training samples. Recent works show that models perform poorer on the samples that come from a different distribution (Gokhale et al., 2022). In many real-world scenarios, such as health and law, false predictions or misclassified results could have significant consequences, and as such identifying out-of-domain or out-of-distribution data beforehand is critical.

Previous works have defined OOD and OODist data in different ways or used them interchangeably. Early works define data that comes from a related but different domain as OOD (Dai et al., 2007), whereas OODist data has been defined as the data that might have been collected at a different time (Ovadia et al., 2019). In recent studies, (Chrysostomou and Aletras, 2022) use the term OOD to describe different datasets for the same task (e.g., SST, IMDb, and Yelp for sentiment classification), whereas (Lin et al., 2022) use OODist to describe the datasets that are not in the training set, including those that are subsets of the same dataset (e.g., PDTB 2.0 (Carlson et al., 2002)). In this paper, we first present a focused analysis of all the various terminologies used in this context in recent works.

Another thread of research has focused on identifying OOD/OODist samples, mostly through supervised methods (Varshney et al., 2022; Chiang and Lee, 2022; Gokhale et al., 2022). However, considering that trained models may not always be available, we take a complementary approach in this work to identify metric(s) that may be able to support OOD detection in an *unsupervised* manner.

The first part of our methodology focuses on establishing to what extent performance (e.g., accuracy) can inform the detection of OOD samples[1]. Our results indicate that indeed performance can serve as a reliable metric for estimating OODness, however, this requires a supervised model. To address this limitation, in the second part of this work, we explore several unsupervised metrics for estimating semantic similarity between the training and test samples. We hypothesize that an unsupervised metric which sufficiently correlates with performance, may be considered as a feasible alternative for detecting OOD samples.

The major contributions of this paper are:

- an in-depth exploration of the usage of the terms OOD and OODist in recent works;
- a systematic assessment of the effectiveness

[1]As formally distinguishing between the two terms remains beyond the scope of this paper, in this work we use the terms OOD and OODist interchangeably.

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Paper	Setup	Term	Metrics	Task
Chrysostomou and Aletras (2022)	A	OOD	-	Sentiment classification
Le Berre et al. (2022)	A	OOD	Accuracy	MCQ
Lin et al. (2022)	A	OODist	-	Extractive QA
Nejadgholi et al. (2022)	A	OOD	AUC, F1	Sentiment classification
Chiang and Lee (2022)	A	OODist	Cosine similarity, Confidence score, Probability distribution	Sentiment classification
Mishra and Arunkumar (2022)	A	OODist	NLI diagnostics	NLI
Varshney et al. (2022)	A	OOD	Accuracy	NLI, Duplicate detection, Sentiment analysis, MCQ, Commonsense Reasoning
Omar et al. (2022)	A	OODist	Accuracy, Success rate, Error rate, Diversity, Fairness, IBP tightness, Robustness	Classification, Paraphrasing, NLI
Adila and Kang (2022)	A	OODist	Confidence, Variability	NLI
Singhal et al. (2022)	A	OOD	Accuracy	NLI, Phrase identification
Agrawal et al. (2022)	A	OOD	Accuracy	Visual QA
Aghazadeh et al. (2022)	A, B	OODist	Accuracy	Metaphorical knowledge
Chen et al. (2023)	A, B	OODist	Accuracy	Sentiment analysis, Toxicity detection, News Classification, Dialogue Intent Classification
Mai et al. (2022)	B	OODist	-	Anomaly detection
Garg et al. (2022)	B	OOD	Accuracy	Rating generation, Toxicity classification
Jin et al. (2021)	B	OOD	False Positive Ratio, AUROC, AUPR	Text Classification
Atwell et al. (2022)	C	OOD	h-discrepancy	Discourse parsing
Gokhale et al. (2022)	C	OOD	Accuracy, EM	NLI, QA, Image classification

Table 1: A survey of recent works using various setups to study OODist or OOD settings. Here, **A** describes the cases where the train set is from one dataset, and the test set from another dataset; **B** describes the scenario where the train and test sets are two subsets of the same dataset; and **C** is a combination of both A and B. The "Metrics" column represents the metrics, while the "Task" column lists the tasks studied in these papers. Note that several papers whose setup can be described as **A** use different terms.

of performance in estimating OODness, and an investigation of unsupervised approaches for identifying OODness;

- an extensive evaluation across four different tasks using a total of twelve datasets; we will also make our code available for facilitating reproducibility.

2 Related Work

Prior research has often used the terms OOD and OODist interchangeably. In some works, dataset X is described to be OODist to dataset Y if they are different datasets, but support the same task (Lin et al., 2022; Aghazadeh et al., 2022; Chiang and Lee, 2022; Mishra and Arunkumar, 2022; Omar et al., 2022; Adila and Kang, 2022), while in other works, the term OOD is used to describe the similar

Task	Datasets	train/ val/ test
Sentiment	IMDb, SST2, Yelp	3310/ 428/ 909
MCQ	SCIQ, CS, QASC	8134/ 926/ 920
Extractive QA	SQUAD, News, Trivia	61688/ -/ 4212
NLI	MNLI, WNLI, QNLI	635/ 71/ 146

Table 2: Task and dataset details

setting (Chrysostomou and Aletras, 2022; Le Berre et al., 2022; Nejadgholi et al., 2022; Varshney et al., 2022). Beyond that, while some consider different subsets of the same dataset to be OODist (Mai et al., 2022; Garg et al., 2022; Jin et al., 2021), others refer to these as OOD to describe distributionally different datasets (Atwell et al., 2022; Gokhale et al., 2022).

When it comes to detecting OOD or OODist samples, using the model's accuracy (Le Berre et al., 2022; Aghazadeh et al., 2022; Gokhale et al., 2022; Omar et al., 2022), input features, hidden features representations, and output probability distribution of the network layers (Chiang and Lee, 2022), or AUC and F1 score (Nejadgholi et al., 2022) have been well-studied. Table 1 presents a brief summary of some recent works.

3 Method

3.1 Problem Definition

Given two datasets, $\mathcal{X} = \{x_1, ..., x_m\}$ and $\mathcal{Y} = \{y_1, ..., y_m\}$, the goal is to assess the correlation between the performance of the two datasets under ID/OOD settings and their (semantic) similarity. The performance is measured by training a model on one of the datasets, say, $\mathcal{X}_{train}$ and testing it on the test set $\mathcal{X}_{test}$ which represents the ID setting, and $\mathcal{Y}_{test}$ representing the OOD setting. The ID similarity is computed by averaging the similarity between the instances of $\mathcal{X}_{train}$ and $\mathcal{X}_{test}$, while OOD similarity is measured between $\mathcal{X}_{train}$ and $\mathcal{Y}_{test}$.

3.2 Datasets

We study four different tasks using a total of 12 datasets (3 datasets for per task). We include the most common tasks that have been used in prior work.

(i) Sentiment Analysis: given a text, classify its sentiment as negative or positive.

(ii) Multiple Choice Question Answering (MCQ): given a question and a context, select the correct answer from a pool of possible answers.

(iii) Extractive Question Answering (QA): given a question and a context, find the answer to the question from the context.

(iv) Natural Language Inference (NLI): given a premise and a hypothesis, determine whether the hypothesis contradicts, entails, or is neutral with respect to the premise.

Table 2 presents the details of the datasets and the tasks. For sentiment classification, we use IMDb (Maas et al., 2011), SST2 (Socher et al., 2013), and Yelp (Zhang et al., 2015) datasets. We experiment with SCIQ (Welbl et al., 2017), CommonsenseQA (CS) (Talmor et al., 2019), and QASC (Khot et al., 2020) for the MCQ task. For the Extractive QA task, SQUAD, News, and Trivia (Fisch et al., 2019) datasets are selected from the MRQA dataset (note that since these datasets do not have a separate test set, we use the validation data as the test set). The NLI datasets include MNLI, QNLI, and WNLI from the GLUE benchmark (Wang et al., 2018). All the other datasets were accessed from the HuggingFace repository[2].

Data preparation: Prior work has largely overlooked the effect of an important aspect – dataset size – in such studies. As such, we control the dataset size as a variable in our study by maintaining the size of all train, validation (when available), and test splits for all three datasets per task by downsampling them to match the size of the **smallest dataset in each set**. For instance, all the splits of all three sentiment analysis datasets are downsampled to be of equal size. Additionally, we balance the number of instances for each class when possible (e.g., in the sentiment datasets).

3.3 Metrics

We use three categories of metrics, one for measuring the performance of the model, another for estimating the similarity between the two datasets,

[2] https://huggingface.co/datasets/

and the third for computing the correlation between performance and similarity.

Performance Metrics. We report accuracy for the classification tasks, i.e., sentiment analysis, MCQ, and NLI tasks, and F1 score for extractive Question Answering task to measure the correctness of model predictions.

Similarity Metrics. To estimate the closeness among the ID and OOD datasets, we use metrics related to semantic similarity (higher value means the samples are from nearby distributions) and semantic distance (higher value indicates less similarity). These include: ***(i) Cosine Similarity***: measures the distance between the samples from two sources[3]. ***(ii) Mauve Score***: measures the similarity between two texts[4] (Pillutla et al., 2021). ***(iii) Wasserstein Distance (Wstn)***: measures the distance between the two distributions and if the distributions overlap enough, then they are close to each other[5] (Weng, 2019). ***(iv) Jensen Shannon Distance (JSD)***: quantifies the similarity between two probability distributions, where the smaller the value, the closer the distributions[6] (Manning and Schutze, 1999).

Correlation Metrics. Lastly, we use two commonly used correlation metrics – Kendall Tau and Pearson[7] (we also experimented with Spearman which gave similar results), with the goal of understanding the relationship between performance and similarity of datasets under ID/OOD settings.

3.4 Measuring Performance and Similarity

For measuring the performance, we fine-tune a BERT `base` uncased model for 2 epochs on each $\mathcal{X}_{train}$ and test it on $\mathcal{X}_{test}$ (ID) and $\mathcal{Y}_{test}$ (OOD). For estimating the similarity between the ID and OOD datasets, we randomly sample two sets of 20 instances, $\mathcal{X}_{train20}$ and $\mathcal{Y}_{test20}$, and estimate pairwise similarity between all of these samples, obtaining a total of 400 similarity scores which are then averaged to compute the similarity.

4 Results and Discussion

Performance analysis: Table 3 presents the results of the performance experiments, where we observe that the model performance under ID settings is generally better than under OOD settings, except for three exceptions, suggesting that performance can indeed serve as a reasonably dependable met-

Trained on	Tested on	Performance
IMDb-train	IMDb-test	0.90
	Yelp-test	0.87
	SST2-test	0.17
SST2-train	SST2-test	0.89
	IMDb-test	0.21
	Yelp-test	0.16
Yelp-train	Yelp-test	0.93
	IMDb-test	0.86
	SST2-test	0.19
SCIQ-train	SCIQ-test	0.64
	QASC-test	0.18
	CS-test	0.34
CS-train	CS-test	0.49
	SCIQ-test	0.58
	QASC-test	0.84
QASC-train	QASC-test	0.92
	SCIQ-test	0.51
	CS-test	0.48
SQUAD-train	SQUAD-test	0.86
	News-test	0.51
	Trivia-test	0.55
News-train	News-test	0.66
	SQUAD-test	0.77
	Trivia-test	0.56
Trivia-train	Trivia-test	0.66
	SQUAD-test	0.52
	News-test	0.31
MNLI-train	MNLI-test	0.57
	WNLI-test	0.56
	QNLI-test	0.54
WNLI-train	WNLI-test	0.42
	MNLI-test	0.26
	QNLI-test	0.47
QNLI-train	QNLI-test	0.83
	MNLI-test	0.43
	WNLI-test	0.56

Table 3: Performance results under different ID/OOD settings. Instances where ID performance is better than OOD performance are indicated in blue.

[3] We estimate this using `word2vec` embeddings.

[4] We use the default embeddings (GPT-2) https://pypi.org/project/mauve-text/.

[5] We use the universal sentence encoder for estimating this.

[6] We used `word2vec` embeddings.

[7] https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.corr.html

ric for detecting OOD. However, this requires a supervised model, which motivates us to explore unsupervised approaches for estimating OODness. It is worth noting that while Garg et al. (2022) found that OOD accuracy is less than the ID accuracy, this observation does not always hold true according to our analysis.

Correlation between performance and similarity: Figure 1 presents the heatmap visualizing the correlation (Kendall and Pearson) between performance and similarity metrics, across all 12 datasets for the four tasks (the full set of results is included in Appendix A). In looking at the results, we observe that according to Kendall Tau correlation analysis, Wasserstein distance (Wstn) shows the most consistent correlation (in 10 out of 12 cases), whereas according to Pearson correlation, both Wasserstein and Cosine are acceptable metrics (in 9 out of 12 cases). In all the scenarios, however, JSD is clearly the least correlated metric. This suggests the potential of unsupervised approaches in estimating OOD samples.

5 Conclusion

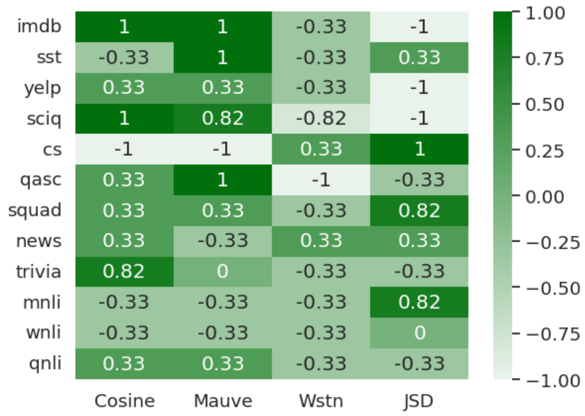
In this work, we aim to identify unsupervised approaches for identifying OOD samples. We conducted an in-depth analysis of different unsupervised similarity metrics and estimated their correlation with performance of a model under ID/OOD settings. Our findings indicate that Wasserstein distance presents a promising metric for determining OOD samples. The natural question of how to determine the appropriate threshold, however, remains to be explored in future work. Another direction worth exploring is to verify the robustness of these similarity metrics when estimated using different embeddings.

Limitations

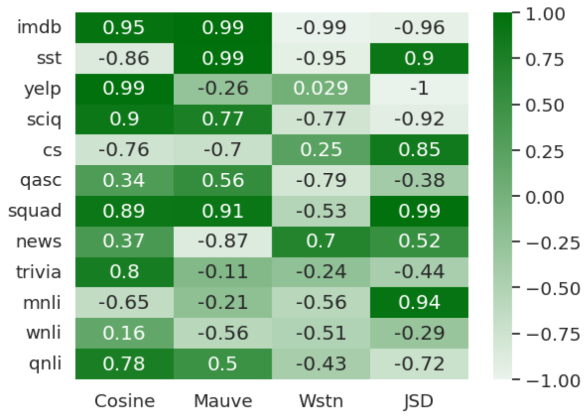
While our analysis suggests some promising results, we acknowledge some limitations of this work such as:

- on some datasets, the ID performance was observed to be less than the OOD performance, and further investigation is needed to study this observation in detail and bring additional insights.

- all the analysis in this study focuses on datasets in English language, and it will be interesting to investigate whether our findings will generalize to other languages.



(a)



(b)

Figure 1: (a) Kendall and (b) Pearson correlation between performance and dataset similarity, evaluated over 12 datasets with each serving as an ID dataset once. For Cosine and Mauve, darker shades are desirable, whereas for Wstn and JSD, lighter shades indicate better correlation.

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A Experimental Results

Trained	Tested	Model Accuracy	Cosine	Mauve	Wstn	JSD
IMDb	IMDb	0.90	0.92	1	0.004	0.21
IMDb	Yelp	0.87	0.87	0.91	0.0039	0.26
IMDb	SST2	0.17	0.78	0.42	0.0052	0.36
SST2	SST2	0.89	0.66	0.99	0.0032	0.46
SST2	IMDb	0.21	0.77	0.22	0.0051	0.38
SST2	Yelp	0.16	0.72	0.004	0.0046	0.41
Yelp	Yelp	0.93	0.86	0.98	0.0036	0.26
Yelp	IMDb	0.86	0.87	0.76	0.0041	0.27
Yelp	SST2	0.19	0.73	0.94	0.0038	0.4
SCIQ	SCIQ	0.64	0.82	1	0.004	0.33
SCIQ	QASC	0.18	0.66	0.01	0.008	0.46
SCIQ	CS	0.34	0.78	1	0.004	0.37
CS	CS	0.49	0.71	0.94	0.003	0.45
CS	SCIQ	0.58	0.62	0.01	0.007	0.48
CS	QASC	0.84	0.61	0.004	0.005	0.49
QASC	QASC	0.92	0.75	1	0.003	0.4
QASC	SCIQ	0.51	0.78	0.99	0.004	0.38
QASC	CS	0.48	0.66	0.004	0.006	0.48
SQUAD	SQUAD	0.86	0.84	0.99	0.0037	0.34
SQUAD	NEWS	0.51	0.82	0.32	0.0041	0.33
SQUAD	TRIVIA	0.55	0.81	0.04	0.0059	0.33
NEWS	NEWS	0.66	0.89	0.91	0.0036	0.23
NEWS	SQUAD	0.77	0.86	0.11	0.0046	0.31
NEWS	TRIVIA	0.56	0.84	0.89	0.0039	0.27
TRIVIA	TRIVIA	0.66	0.88	0.99	0.0031	0.23
TRIVIA	SQUAD	0.52	0.82	0.04	0.0062	0.34
TRIVIA	NEWS	0.31	0.82	0.99	0.0042	0.29
MNLI	MNLI	0.57	0.72	0.97	0.0035	0.43
MNLI	WNLI	0.56	0.71	0.27	0.0032	0.43
MNLI	QNLI	0.54	0.73	0.99	0.0037	0.42
WNLI	WNLI	0.42	0.74	0.79	0.0032	0.41
WNLI	MNLI	0.26	0.68	0.66	0.0036	0.46
WNLI	QNLI	0.47	0.67	0.004	0.0035	0.46
QNLI	QNLI	0.83	0.75	0.97	0.0036	0.41
QNLI	MNLI	0.43	0.64	0.66	0.0039	0.45
QNLI	WNLI	0.56	0.58	0.01	0.0034	0.48

Table 4: The results for the sentiment, MCQ, extractive QA, and NLI datasets.