ACDA: Automatic Contextual Data Augmentation.

A data augmentation procedure which scans the hypothesis sentence for nouns, and queries WordNet synsets for a replacement word. It then swaps each one of the nouns at a time and composes new hypotheses for replacement words. It then swaps each one of the nouns at a time and composes new hypotheses for replacement words. ACDA yields a high number of new training examples from the most problematic areas of the decision boundary, which can now be used as part of training to incentivise the model against the reliance on dataset artifacts. The resulting augmentation benefits from being both fully automatic, as it does not require manual writing of new hypothesis or label annotation, while at the same time being non-trivial. It is also computationally efficient, as it adds no overhead to the training cost.

ACDA generates a dataset which is up to 10 times larger than the original one, while remaining computationally efficient. It generates adversarial examples which form instance bundles in areas of the decision boundary.

Hybrid Loss further optimizes the learning process by ensuring we retain the benefits of Contrastive Learning without losing learning generalization. The contrastive learning optimization technique re-focuses training in the localities of the current batch, but there lies the danger of the model learning to overfit these localities, while not being able to correctly classify examples that it has not seen and are further apart in decision space. Our Hybrid Loss combines Cross Entropy Loss and NLL Loss in a weighted average manner.

The framework that we used to create our label generation rules for ACDA.

The pre-trained models that we used to train our label generation rules for ACDA.

The large lexical database of English that we used to create our label generation rules for ACDA.

The programming language that we used.

A crowd-sourced collection of 433000 sentence pairs which cover a range of genres of spoken and written text, and support a distinctive cross-genre generalization evaluation.

A small set of hand-annotated adversarial examples which we created.

Python 3.9: The programming language that we used.

These were used to train our label generation rules for ACDA.

The framework that we used to train our label generation rules for ACDA.

The adversarial dataset: A small set of hand-annotated adversarial examples which we created.

Contrastive Learning takes advantage of the instance bundles generated by ACDA in order to optimize the learning process. Recent research shows that a model may achieve high performance on a dataset by learning spurious correlations, which are called dataset artifacts, but it is then expected to fail in settings where these artifacts are not present, such as adversarial cases.

ACDA: Automatic Contextual Data Augmentation.

A learning optimization technique which further incentivises the model to learn the nuances of the decision boundary. For this purpose, the model has to see instance bundles during training, that is, examples that are close together and belong to a specific area of the decision boundary in the same training batch. Since ACDA places the augmented examples right after each original one, the dataset batches provided to the model in each iteration will consist of some number of original examples and their augmentations. This way, we manage to have a dataset consisting of multiple instance bundles and therefore, we gain the maximum benefit from contrastive learning.

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Hybrid Loss further optimizes the learning process by ensuring we retain the benefits of Contrastive Learning without losing learning generalization. The contrastive learning optimization technique re-focuses training in the localities of the current batch, but there lies the danger of the model learning to overfit these localities, while not being able to correctly classify examples that it has not seen and are further apart in decision space. Our Hybrid Loss combines Cross Entropy Loss and NLL Loss in a weighted average manner. This way, we manage to retain the advantages of both loss functions. The Cross Entropy Loss ensures that part of the loss signal will be directly relevant to the shortcomings of the model in the localities of the decision boundary, enabling contrastive learning, while the NLL Loss will incentivise generalization in areas that the model has not seen, learning rules that can only be inferred by looking at unrelated examples.