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Augmenty: A Python Library for Structured Text Augmentation

Kenneth Enevoldsen [1]

1 Center for Humanities Computing, Aarhus University, Aarhus, Denmark

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Software

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Summary

Text augmentation is useful for tool for training (Wei & Zou, 2019) and evaluating (Ribeiro et al., 2020) natural language processing models and systems. Despite its utility existing libraries for text augmentation often exhibit limitations in terms of functionality and flexibility, being confined to basic tasks such as text-classification or cater to specific downstream use-cases such as estimating robustness (Goel et al., 2021). Recognizing these constraints, `Augmenty` is a tool for structured text augmentation of the text along with its annotations. `Augmenty` integrates seamlessly with the popular NLP library `spaCy` (**honnibal_efficient_2020?**) and seeks to be compatible with all models and tasks supported by `spaCy`. Augmenty provides a wide range of augmenters which can be combined in a flexible manner to create complex augmentation pipelines. It also includes a set of primitives that can be used to create custom augmenters such as word replacement augmenters. This functionality allows for augmentations within a range of applications such as named entity recognition (NER), part-of-speech tagging, and dependency parsing.

Statement of need

Augmentation is a powerful tool within disciplines such as computer vision (Wang et al., 2017) and speech recognition (Park et al., 2019) and it used for both training more robust models and evaluating models ability to handle pertubations. Within natural language processing (NLP) augmentation has seen some uses as a tool for generating additional training data (Wei & Zou, 2019), but have really shined as a tool for model evaluation, such as estimating robustness (Goel et al., 2021) and bias (Lassen et al., 2023), or for creating novel datasets (Nielsen, 2023).

Despite its utility, existing libraries for text augmentation often exhibit limitations in terms of functionality and flexibility. Commonly they only provide pure string augmentation which typically leads to the annotations becoming misaligned with the text. This has limited the use of augmentation to tasks such as text classification while neglected structured prediction tasks such as named entity recognition (NER) or coreference resolution. This has limited the use of augmentation to a wide range of tasks both for training and evaluation.

Existing tools such as `textgenie` (Pandya, 2023), and `textaugment` (Marivate & Sefara, 2020) implements powerful techniques such as backtranslation and paraprashing, which are useful for augmentation for text-classification tasks. However, these tools neglect a category of tasks which require that the annotations are aligned with the augmentation of the text. For instance even simple augmentation such as replacing the named entity “Jane Doe” with “John” will lead to a misalignment of the NER annotation, part-of-speech tags, etc., which if not properly handled will lead to a misinterpretation of the model performance or generation of incorrect training samples.

Augmenty seeks to remedy this by providing a flexible and easy-to-use interface for structured text augmentation. Augmenty is built to integrate well with of the spaCy (**honnibal_efficient_2020?**) and seeks to be compatible with the broads set of tasks supported by spaCy. Augmenty provides augmenters which takes in a spaCy Doc-object (but works just as well with string-objects) and returns a new Doc-object with the augmentations applied. This allows for augmentations of both the text and the annotations present in the Doc-object.

Other tools for data augmentation focus on specific downstream application such textattack (Morris et al., 2020) which is useful for adversarial attacks of classification systems or robustnessgym (Goel et al., 2021) which is useful for evaluating robustness of classification systems. Augmenty does not seek to replace any of these tools but seeks to provide a general purpose tool for augmentation of both the text and its annotations. This allows for augmentations within a range of applications such as named entity recognition, part-of-speech tagging, and dependency parsing.

Features & Functionality

Augmenty is a Python library that implements augmentation based on spaCy's Doc object. spaCy's Doc object is a container for a text and its annotations. This makes it easy to augment text and annotations simultaneously. The Doc object can easily be extended to include custom augmention not available in spaCy by adding custom attributes to the Doc object. While Augmenty is built to augment Docs the object is easily converted into strings, lists or other formats. The annotations within a Doc can be provided either by existing annotations or by annotations provided by an existing model.

Augmenty implements a series of augmenters for token-, span- and sentence-level augmentation. These augmenters range from primitive augmentations such as word replacement which can be used to quickly construct new augmenters to language specific augmenters such as keystroke error augmentations based on a French keyboard layout. Augmenty also integrates with other libraries such as NLTK [bird2009natural] to allow for augmentations based on WordNet (Miller, 1994) and allows for specification of static word vectors [pennington-etal-2014-glove] to allow for augmentations based on word similarity. Lastly, augmenty provides a set of utility functions for repeating augmentations, combining augmenters or adjust the percentage of documents that should be augmented. This allow for the flexible construction of augmentation pipelines specific to the task at hand.

Augmenty is furthemore designed to be compatible with spaCy and thus its augmenters can easily be utilized during the training of spaCy models.

Example Use Cases

Augmenty have already seen used in a number of projects. The code base was initially developed for evaluating the robustness and bias of DaCy (Enevoldsen et al., 2021), a state-of-the-art Danish NLP pipeline. It is also continually used to evaluate Danish NER systems for biases and robustness on the DaCy website. Augmenty has also been used to detect intersectional biases (Lassen et al., 2023) and used within benchmark of Danish language models (Sloth & Rybner, 2023).

Besides its existing use-cases Augmenty could for example also be used to a) upsample minority classes without duplicating samples, b) train less biased models by e.g. replacing names with names of minority groups c) train more robust models e.g. by augmenting with typos or d) generate pseudo historical data by augmenting with known spelling variations of words.

Target Audience

The package is mainly targeted at NLP researchers and practitioners who wish to augment their data for training or evaluation. The package is also targeted at researchers who wish to evaluate their models either augmentations or generating new datasets.

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