# A Survey on Data Augmentation for Text Classification<sup>1</sup>

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Data augmentation, the artificial creation of training data for machine learning by transformations, is a widely studied research field across machine learning disciplines. While it is useful for increasing the generalization capabilities of a model, it can also address many other challenges and problems, from overcoming a limited amount of training data over regularizing the objective to limiting the amount data used to protect privacy. Based on a precise description of the goals and applications of data augmentation (C1) and a taxonomy for existing works (C2), this survey is concerned with data augmentation methods for textual classification and aims to achieve a concise and comprehensive overview for researchers and practitioners (C3). Derived from the taxonomy, we divided more than 100 methods into 12 different groupings and provide state-of-the-art references expounding which methods are highly promising (C4). Finally, research perspectives that may constitute a building block for future work are given (C5).

• Computing methodologies ~ Machine learning ~ Machine learning algorithms ~ Regularization • Computing methodologies ~ Machine learning approaches ~ Neural networks • Computing methodologies ~ Artificial intelligence ~ Natural language processing

Additional Keywords and Phrases: Data Augmentation, Low Data Regimes, Small Data Analytics

## **1 INTRODUCTION**

An increase in training data does not always result in a solution for the learning problem. Nevertheless, the data is still decisive for the quality of a supervised classifier. Originating from the field of computer vision, there exist many different methods to artificially create such data, which is called *data augmentation*. With regard to images, transformations such as rotations or changes of the RGB channel are sensible, as for these the model should be invariant. Similar to computer vision, speech recognition uses procedures that change, for example, the sound or speed. In contrast, research on data augmentation in Natural Language Processing (NLP) has the difficulty of establishing universal rules for transformations of textual data that can be executed automatically while the quality of labeling is also maintained [1], [2]. That is why the research in this field before 2019 was much more limited, although there also exist extensive areas of application [3].

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Nowadays, this challenge still remains but is being addressed by many scientists in different research directions. Within these directions, various goals are followed, e.g., generating more data for low-data regimes, balancing imbalanced dataset classes or security against adversarial examples. Thus, textual data augmentation comes in many contrasting forms that are grouped and explained in this survey. We give an in-depth analysis and also try to relate the methods to the state-of-the-art, as the methods face another challenge due to the rise of transfer learning. For example, Longpre et al. [4] show that many data augmentation methods are not able to achieve gains when using large pre-trained language models, as they are already invariant to various transformations by themselves. They hypothesize that data augmentation methods can only be really beneficial if they are creating new linguistic patterns that have not been seen before. Keeping this in mind, the survey is closed with a meta perspective on the methods. Thus, this survey pursues the following contributions:

- Goals and applications (C1). We highlight the goals and applications of data augmentation that we derive from the comprehensive review. These have only been presented to a limited and incomplete extent in previous research papers.
- Taxonomy and categorization (C2). The text classification data augmentation methods will be clustered according to a high-level taxonomy and then subdivided into more fine-grained groups. This is also present in the surveys from Shorten and Khoshgoftaar [5] and Wen et al. [6] and is now adapted for the text classification domain.
- Overview and in-depth details (C3). The textual data augmentation methods are explained in a clear form with the
  details necessary for delimitation and comparison with each other. Contrasting other works, our extensive study
  contains 12 groups with more than 100 different approaches.
- State of the art review (C4): Within the literature survey we try to examine latest state-of-the-art considerations, as, for example, the limited benefit of textual data augmentation methods with large pre-trained models, that are often neglected in current works.
- Future research perspectives (C5). We identify future research opportunities that are either necessary for a state-ofthe-art comparison or sensible to look into because of current challenges for textual data augmentation.

The survey paper is structured as follows: The paper introduces the foundations of data augmentation in Section 2. This section is then broadened by the consideration of the goals and applications. Section 3 is subdivided into the various data augmentation groups and contains the explanations as well as tabular overviews of the methods. In Section 4, an analysis of the data augmentation methods from a more global perspective is given and various future research directions are discussed. Section 5 outlines the limitations of data augmentation and concludes this survey.

## 2 BACKGROUND: FOUNDATIONS, GOALS, AND APPLICATIONS OF DATA AUGMENTATION

In many machine learning scenarios, not enough data is available to train a high-quality classifier. To address this problem, data augmentation can be used. It artificially enlarges the amount of available training data by means of transformations [7]. Already in the well-known LeNet by LeCun et al. [8], early versions of data augmentation can be observed. The notion of data augmentation is broad and comprises various research in different sub-areas of machine learning. Many scientific works merely relate data augmentation to deep learning, yet it is frequently applied in the entire context of machine learning. Therefore, this paper adopts the notion of data augmentation as a broad concept, encompassing any method that enables the transformation of training data. However, following common understanding in research, semi-supervised learning is not regarded as a form of data augmentation and only thematized if sensible in the context of this survey.

When talking about data augmentation, an important term is label preservation, which describes transformations of training data that preserve class information [9]. For example, in sentiment analysis, an entity replacement within a sentence

is often sufficient for label preservation but the random addition of words may result in an alteration of the sentiment (e.g., an additional "not" could invert the meaning of a sentence). In many research works, the term of label preservation is adapted to cover also transformations changing the class information if the label is adjusted correctly. Additionally, many transformations maintain the right class not in every case but with a high probability. Shorten and Khoshgoftaar [5] define this probability as the safety of a data augmentation method. When this uncertainty is known, it could be directly integrated in the label. Otherwise, methods like label smoothing [10] can model a general uncertainty.

The goals of data augmentation are manifold and encompass different aspects. As mentioned above, training data is essential for the quality of a supervised machine learning process. Banko and Brill [11] show that only the creation of additional data can improve the quality of a solution in the confusion set disambiguation problem, while the choice of the classifier does not lead to a significant change. The model-selection and -development will remain a crucial aspect of machine learning. Yet, scholars express the suggestion that in some situations the choice for higher investments in algorithm-choice and -development instead of corpus-development should be carefully considered [11]. Closely connected to this is the big data wall problem, which Coulombe [9] mentions in his work on data augmentation. It describes that big companies benefit from the special advantage of having access to a big amount of training data. As a result, the already large GAFAM-Companies (Google, Amazon, Facebook, Apple, and Microsoft) expand their predominance over smaller businesses due to their data superiority. An ideal data augmentation method could approach these points and decrease the dependency of training data even though full elimination is not likely.

Additionally, the creation of training data for various classification problems is accompanied by high labelling costs. In many instances, assessment and labelling by experts is necessary to prevent incorrect training examples. This can, for example, be especially stressed for the field of crisis informatics [12]. The creation of relevance classifiers for emergency services and helpers is only possible during the occurrence of the crisis situations. It requires otherwise needed personal resources and time, which can in the worst-case cost lives. In a similar way, training data for medical image processing is very valuable. Due to the rareness of certain diseases, the privacy of patients, and the requirement of medical experts, it is challenging to provide medical datasets [5]. With regard to classification problems of such kind, data augmentation could help to minimize the required amount of data that needs to be labelled and to solve interlinked problems.

Especially in the area of deep learning, data augmentation methods play a special role. As Srivastava et al. [13] demonstrated, deep neural networks are particularly powerful but they also encompass a tendency to overfit; faced with unseen instances, they might generalize badly. This observation can be illustrated with help of the bias variance dilemma. On the one hand, deep learning algorithms are, due to their deep and non-linear layers, very strong models with a lower bias-error. On the other hand, they show a high variance for different subsets of training data [14]. This problem can be solved by arranging the algorithm to prefer simple solutions or by providing a bigger amount of training data. The first option is aimed at methods of regularization, such as dropout or the addition of a L2 norm via the model's parameters in the loss-function. The second option is frequently realized by means of data augmentation and could in this context also be considered as a kind of regularization. According to Hernandez-Garcia and König [15], data augmentation is a favorable method of regularization, as it achieves generalization without degrading the representational capacity of the model and without re-tuning other hyperparameters. While the other methods reduce the bias error, data augmentation has the goal of keeping it constant; it is used to solve the problem at the root [5]. Nonetheless, data augmentation is still dependent on the underlying classification problem. Hence, it cannot be effectively applied under all circumstances.

Moreover, in context of deep learning models, so called adversarial examples/ attacks are generated more and more frequently. These are little changes in the input data, almost unrecognizable to humans, that mislead the algorithms to wrong predictions [16]. Figure 1 shows two different genuine examples in which smallest changes in the texts alter the

classification prediction. Alzantot et al. [17] also present an algorithm that generates semantically and syntactically similar instances of the training data, successfully outwitting sentiment analysis and entailment models. With the help of adversarial training, these automatic adversarial example generators can be used as data augmentation methods, as done, for example, in [18], [7], [19], or [20], so that deep learning models are less susceptible to such easy alterations.

If the amount of data is taken into consideration, it stands out that certain classification problems are often heavily unbalanced, for instance, only a small amount is relevant or positive while the irrelevant or negative data is prevalent [21]. For example, in an entire corpus available for topic classification or crisis identification, only few data actually relate to the topics or the crisis in question. Zhong et al. [22] term a dataset as unbalanced if the distribution of classes within it is not approximately equally balanced. Data augmentation may help to enhance the amount of data for a certain class so that balanced class distribution is present and thus a classifier can be modelled more robustly [23], [24].

Data augmentation can also be helpful in sensitive domains. Dealing with confidential or privacy-related data, one can lower the usage of real-world data by crafting artificial data. It is even possible to just train the algorithm on the newly created data in order to prevent drawing any conclusions on non-artificial training data from a deployed model. For example, Carlini et al. [25] showed a method for extracting training data from large language models that could contain private information. For training such a privacy ensuring model, special data augmentation techniques that are able to anonymize the data have to be used.

Original text	Altered text
South Africa's historic Soweto township marks its 100th	South Africa's historic Soweto township marks its 100th
birthday on Tuesday in a mood of optimism.	birthday on Tuesday in a mooP of optimism.
57% World	95% Sci/Tech
Chancellor Gordon Brown has sought to quell speculation	Chancellor Gordon Brown has sought to quell speculation
over who should run the Labour Party and turned the	over who should run the Labour Party and turned the
attack on the opposition Conservatives.	attack on the oBposition Conservatives.
75% World	94% Business

#### Figure 1: Examples for Adversarial Attacks adapted from Ebrahimi et al. [16]

Data augmentation exists in different types and areas of application. A taxonomy of the types in the textual domain can be seen in Figure 2. The augmentation methods can be divided into the transformation of raw data (data space) and processed representations of data (feature space) [5]. These representations are transformed types of data, for example, activation vectors of a neuronal network, the encoding of an Encoder Decoder Network, or LSTM hidden states, respectively embeddings of the data. Abstracting from the textual realm, in many cases, data augmentation is dependent on the underlying problem (text classification, image recognition, etc.); therefore, it is applied in different manners in diverse areas. Procedures generic enough to be used across different areas are for the most part limited to the feature space.

The most substantial research on data augmentation exists in the field of computer vision. This is due to the intuitive construction of simple label preserving transformations. Data augmentation methods in computer vision are, among other, geometric transformations [7], [19], neural style transfers [26]–[28], interpolation of images [29], random partial deletions [30], and generative adversarial network data generation [16]. Sophisticated techniques can additively improve the accuracy baseline for different problems around 10 to 15 percent [30]. Another area of application for data augmentation is speech processing. Researchers successfully used acoustic transformations of the input data. Ko et al. [31] achieved with modification of the speed up to 4.3 % better accuracy values. Furthermore, interferences of the vocal tract length [30] or

the addition of noise [29] may also enhance the quality of the classifiers. The application of data augmentation in the textual realm is considered a difficult task since textual transformations preserving the label are difficult to define [1], [2]. Nevertheless, several simple and sophisticated methods have been developed in this and adjacent research areas.

## **3 TEXTUAL DATA AUGMENTATION METHODS**

In the following, different data augmentation methods for textual data are summarized, explained, and subdivided in different groupings. Methods that focus on the application of text classification are mainly included, although augmentation methods for other tasks in the textual realm are also mentioned if they fit the group. For a more general perspective on NLP augmentations we advise the reader to look at the work from Feng et al. [32], which is not as detailed in text classification as our work but has a broader task view. This way, the reader can get insights into how a data augmentation technique might be adjusted so that it is fitting for a very specific problem.

In the next paragraph, data augmentation methods relevant in textual contexts are summarized and grouped. Generally, the methods are described in a sensible order for the specific group. In groups with many similar approaches, we try to summarize the most valuable information in form of tables. We also try to extract information about the improvements. The improvement indications should give a quick overview how well a method can perform, while they are not in-depth informative and comparable on their own. For a more detailed perspective, the models and datasets are also given. This should provide a more holistic perspective, although in-depth information has to be extracted from the papers itself.

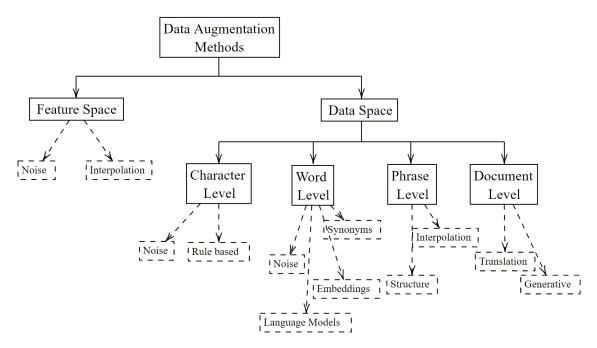


Figure 2: Taxonomy and grouping for different data augmentation methods

## 3.1 Data Space

Augmentation in the data space deals with the transformation of the input data in the raw form, which in the case of this survey is the readable textual form of the data.

### 3.1.1Character Level

#### 3.1.1.1 Noise Induction

The addition of noise to the input data is one of the data augmentation methods with the smallest alterations, especially when applied on a character level. As further described in this paper, the induction of noise can also be used at the word level and in the feature space.

The basic idea of the method of Belinkov and Bisk [33] is to add artificial and natural noise to the source training data so that in their case neural machine translation models (NMT) are less susceptible for adversarial examples. Belinkov and Bisk [33] describe operations like the random switching of single letters ("cheese" -> "cehese"), the randomization of the mid part of a word ("cheese" -> "ceehse"), the complete randomization of a word ("cheese", "eseehc"), and the replacement of one letter with a neighboring letter on the keyboard ("cheeae") as artificial noise [33]. Similarly, Feng et al. [34] randomly delete, swap, and insert characters of texts (the prompt portion) that are used for finetuning text generators. For this, they also ignore the first and last character of a word. To measure the suitableness for text generators, they intrinsically measure the diversity, fluency, semantic context preservation, and sentiment consistency. The used method beats the baseline in every metric. These augmentations are also usable in the text classification domain. Ebrahimi et al. [16] used an existing model, trained with the initial dataset, to generate adversarial examples. They used the direct input data to flip a letter if the change enhances the loss of the existing model. If a new model is trained with the additional data once again, the error rate is improved and the success of adversarial attacks is clearly mitigated. Furthermore, they compared their approach with the adversarial method from the before mentioned work of Belinkov and Bisk [33] and the feature space method from Miyato et al. [35] (see Section 3.2.1). Based on a CharCNN-LSTM on the AG News dataset, they achieve the best improvement in the accuracy by gaining 0.62% additively. While the method of Miyato et al. [35] only improved the score by 0.24% additively, it is interesting to see that the method of Belinkov and Bisk [33] even decreased the accuracy by 0.33%. Coulombe [9] describes the injection of weak textual sounds as the before mentioned change, deletion, and addition of letters in words as well as additionally the change of case and the modification of punctuation. With regard to the best baseline (XGBoost), they get the best absolute accuracy improvement by 2.5%. However, the evaluation was performed with very basic architectures and no embeddings, wherefore further studies need to be performed to validate the usefulness in a current setting.

Natural noise, as defined by Belinkov and Bisk [33], covers spelling mistakes that are often occurring in the respective language based on spelling mistake databases. Every word associated with a common mistake is replaced by the misspelled word and if more than one exists the mistake is randomly sampled. Belinkov and Bisk [33] receive varying BLEU scores with their artificial and natural noise methods; most noise operations made the model more robust against attacks with similar operations. Most importantly, natural noise almost consistently worsens a translation model with regards to the baseline. Analogous to the natural noise defined by Belinkov and Bisk [33], Coulombe [9] also adds common spelling mistakes in the textual data and achieves good improvements when added to classifiers. The best baseline (XGBoost) was improved by an additive of 1.5%. With such transformations, learners can cope with spelling mistakes in prospective texts better, even though the mistakes were not present in the original training data set. This variant of data augmentation may, for example, be of interest when dealing with texts originating from social networks

#### 3.1.1.2 Rule-based Transformations

Coulombe [9] implements rule-based transformations with the usage of regular expressions. He describes that such rules are not established easily, as many surface-level transformations necessitate deeper changes so that the grammar is preserved and other transformations are dependent on the language. Valid transformations are, for example, the injection

of spelling mistakes, data alterations, entity names, and abbreviations. He concretely implements the transformation of verbal short forms to their long forms and vice versa ("I am" <-> "I'm"). In English, this is semantically invariant if ambiguities are preserved [9]. This form of data augmentation achieves very good results in the work of Coulombe [9]. The best baseline model (XGBoost) gained additively 0.5% in the accuracy.

## 3.1.2Word Level

#### 3.1.2.1 Noise Induction

Noise induction can also be applied on the word level. For example, the method of Xie et al. [30] encompasses two noise patterns. With "unigram noising", words in the input data get replaced by another word with a certain probability. With "blank noising", words get replaced with "\_". The adoption of both patterns led to improved results in the experiments.

Li et al. [36] are using syntactic and semantic methods as well as word dropout for the generation of noise. Syntactic noise is realized via the shortening of sentences and methods like the switching of adjectives or the relativization of modifiers. The authors generate semantic noise by the lexical substitution of word synonyms (see 3.1.2.2). In contrast to both methods, word dropout is more clearly comparable to noise. Random input neurons or rather words get masked out during the training of the network. The authors state that in general their proposed methods achieve an improvement. Especially a combination of all methods could reach a relative improvement of up to 1,7% with regard to the accuracy.

Two of the four sub-methods of the EDA method by Wei and Zou [2], random swap and deletion, should also be mentioned as methods of noise induction. A combination of both sub-methods led to an increase in performance of the used classifier. EDA is very popular in the research and was used as a method and for comparisons in the works of Qiu et al. [37], Huong and Hoang [38], Anaby-Tavor et al. [39], Kumar et al. [40], Feng et al. [34], Luu et al. [41], and Kashefi and Hwa [42]. Wei and Zou [2] report that for a small dataset these two methods gain higher improvements than the other two sub-methods that are based on synonym replacement and insertion (see Section 3.1.2). Nevertheless, Qiu et al. [37], Anaby-Tavor et al. [39], Bayer et al. [43], and Luu et al. [41] also report some cases in which EDA as a whole data augmentation method decreases the classification score. This behaviour can be expected, as the two methods are not label preserving. For example, for sentiment classification: "I did not like the movie but the popcorn was good" -random\_swap-> "I did like the movie but the popcorn was not good".

The training instances of one batch have to be of same length when being fed into a neural network. For this, the sequences are often zero-padded on the left or right side. Rizos et al. [44] propose a specific noise induction method to augment the training data by shifting the instances within the confines of their padding so that the padding is not solely on one side. Evaluated on a hate speech detection dataset, the authors show that this method achieves additive performance gains of more than 5.8% (Macro-F1). Sun and He [45] also translate the instances by adding either to the beginning or end meaningless words. Unfortunately, they do not evaluate the impact of this method in isolation.

Xie et al. [46] propose a TF-IDF based replacement method in which they are replacing uninformative words of an instance with other uninformative words. As the authors are combining this technique with round trip translation (see Section 3.1.4) and unsupervised data augmentation, it is not clear to which degree it benefits the task.

More data augmentation methods related to other tasks can be found in the works of Cheng et al. [47], Li et al. [36], Wang et al. [48], Andreas [49], Guo et al. [50], Kashefi and Hwa [42], Sun and He [43], and Kurata et al. [51].

#### 3.1.2.2 Synonym Replacement

This very popular form of data augmentation describes the paraphrasing transformation of text instances through replacements of synonyms of certain words. One of the first applications of this substitution in the data augmentation realm

was researched by Kolomiyets et al. [52] with regard to temporal expressions. They substituted temporal expressions with potential synonyms from WordNet [53]. As the authors argue, the replacement of one original token in a sentence will mostly preserve the semantics. Based on the time expression recognition task, the authors propose to replace the headword, since temporal trigger words usually occur there. However, it showed no substantial improvements, but the authors also proposed a language model replacement method that was more suited for the task at hand (see Section 3.1.2.4).

In later years, many researchers experimented with word replacements based on thesauri. The works of Li et al. [36], Mosolova et al. [54], X. Wang et al. [55], and many more partially or primarily execute synonym substitution. They differ with regard to the words that are getting substituted, the synonyms that come into question, and the utilization of different databases. For example, X. Zhang et al. [56] and Marivate and Sefara [57] choose the synonyms for substitution on basis of the geometric distribution by which choosing a more distant synonym becomes less probable. Furthermore, several approaches exclude stop words or words with certain POS-tags from the set of words that would come into question for replacement. Interesting is also the second sub-method of EDA from Wei and Zou [2], where the synonyms are not replaced but randomly inserted into the instance. A summary of the replacement method, synonym selection, database, and improvements of the various approaches is listed in Table 1.

	Synonym Database	Replacement Method	Synonym Selection	Model Base	Dataset	Improvements
[52]	WordNet	Headword replacement	Not stated	Logistic Regression	TempEval Reuters (12) Wikipedia (1)	-1 (F1) -0.6 -0.1
[56], [58]	mytheas (LibreOffice) WordNet- based	Randomly choose number of words based on geometric distribution	Randomly based on geometric distribution	Character CNN	AG News DBP. Yelp P. Yelp F. Yahoo A. Amazon F. Amazon P.	[56] / [58] (Acc.) -0.38 / -0.57 +0.05 / +0.13 -0.03 / +0.36 +0.22 / 0.65 +0.1 / 0.1 -0.17 / -0.17
[36]	WordNet	Substitutable words are nouns, verbs, adjectives, or adverbs and not part of a named entity. Each candidate is replaced with a probability.	The remaining probability of substation is shared among the synonyms based on a language model score	CNN	MR CR Subj SST MR/CR CR/MR	+0.8 (Acc.) +1.2 +0.5 +0.1 0.9 0.3
[9]	WordNet	Only adverbs and adjectives, sometimes nouns, more rarely verbs	Most similar companion information of the synonym with the context of the chosen word.	XGBoost MLP (2 hidden layer)	IMDB	+0.5 (Acc.) +4.92
[54]	WordNet	No pronouns, conjunctions, prepositions, and articles for replacement. Choosing uniform randomly.	Uniform random	CNN with word embeddings	Toxic Comment Classification	-0.09/-0.21 (AUC)

Table 1: Overview of different approaches of the synonym replacement method.

[55]	HIT IR-Lab Tongyici Cilin (Extended) (Chinese)	No time words, prepositions, and mimetic words. Chi-square statistics method.	Chi-square statistics method	Character CNN-SVM	Hotel R. Laptop R. Book R.	~+1 (Acc.) ~+1 ~+0.25
[57]	WordNet	Verbs, nouns, and the combination of them. Geometric distribution.	Geometric distribution	DNN	AG News Sentiment Hate Speech	~+0.4 (Acc.) ~+0 ~-0.8
[59]	WordNet & Thesaurus.com	For Minibatch: Augmentation with probability. Replacement of those words that belong to certain POS- tags. One replacement of a word per sentence that maximizes loss.	Synonym that maximizes the loss.	Kim CNN	TREC	+1.2 (Acc.)
[2]	WordNet	No stop words. Choosing n random words to be replaced (SR) or from which the synonyms are insert at a random position (RI)	Uniform random	CNN	5 classification tasks (500) (2000) (5000) (full)	SR / RI (Acc.) ~+1.9 / ~+2.0 ~+1.2 / ~+0.9 ~+0.7 / ~+0.6 ~+1.0 / ~+0.9
[1]	WordNet	Replacement of a word based on a probability	Temperature hyperparameter learned while training	CNN	SST-5 SST-2 Subj MPQA RT TREC	-0.6 (Acc.) +0.5 +0 +0.2 +0.1 -0.4
[37]	WordNet	Replacement of a word based on a probability	Temperature hyperparameter learned while training	TextRCNN	ICS NEWS	-0.26 (Macro F1) +1.63
[45]	Not stated	Filtering words according to their POS-tag. Selecting a fixed or variable number of words	Specific or variable number of synonyms	LSTM- CNN	Tan NLPCC	Results only in combination with other methods
[60]	WordNet	Not stated	Not stated	BERT	SST-5 (40) IMDB (40) TREC (40)	-0.87 (Acc.) -0.87 +0.01
[61]	WordNet	No Stopwords. 10% of documents randomly selected	Not stated	M-BERT	CodiEsp-D CodiEsp-P	+0.6 (F1) -0.7 (F1)
[34]	WordNet	Keywords replaced are ordered by their RAKE score (e.g. the probability of being a keyword).	Randomly selected. Replacement only with same POS- tag.	No model (intrinsic evaluation with different metrics)	Yelp-LR (small subset of Yelp Reviews)	+0.015 (SBLEU) -0.018 (UTR) -0.02 (TTR) -0.016 (RWords) 0 (SLOR) -0.007 (BPRO) +0.001 (SStd) 0 (SDiff)

[42]	WordNet	No stop words. Uniform random until 20%	Uniform random	CNN	Yelp P.	Only against other data
		of the words in a sentence are			augmentation	
		changed				methods

Interesting is also the more sophisticated integration into the learning process, as described by Jungiewicz and Pohl [59]. The authors only replace words with synonyms if the replacement and the chosen synonym maximize the loss of the current state of the classifier model. There are also approaches that adapt the general idea of thesauri-based replacements to perform augmentation on specific tasks, for example, in Kashefi and Hwa [42] and Feng et al. [34].

#### 3.1.2.3 Embedding Replacement

Comparable to synonym substitution, embedding replacement methods search for words that fit as good as possible into the textual context and additionally do not alter the basic substance of the text. To achieve this, the words of the instances are translated into a latent representation space, where words of similar contexts are closer together. Thus, these latent spaces are based on the distributional hypothesis, almost in every case now in the form of embedding models. Choosing words that underlie this hypothesis and that are, thus, near in the representation space, implies that the newly created instances maintain a grammatic coherence, as it can be seen in the example of Figure 3. Besides this advantage, Rizos et al. [44] argue that the "method encourages the downstream task to place lower emphasis on associating single words with a label and instead place higher emphasis on capturing similar sequential patterns, i.e., the context of hate speech". Benefits of this data augmentation technique in comparison to the synonym substitution method are that techniques based on the distributional hypothesis are more general and the context of texts is taken into consideration. This means that substitutions are not limited by a database, like WordNet, and that grammatically more correct sentences can be generated [62]. Furthermore, the general form of this approach can be beneficial for languages which have no large thesauri but a lot of general text resources, on the basis of which the self-supervised embedding models can be easily trained [9].



Figure 3: Example of a sentence with predicted words that can be used to replace a word in the sentence [1]

Wang and Yang [63] use this kind of augmentation to better classify annoying tweets. They utilize k-nearest-neighbor to identify the best embeddings as a substitution of the training data words. Compared to the baseline, they achieve an additive improvement of up to 2.4% in the F1-Score with logistic regression. Marivate and Sefara [57], Rizos et al. [44], Huong and Hoang [38], and others also utilize the embedding replacement in very similar ways. The strongest differences with regard to the method stem from the selection of the words to be replaced (e.g., POS-tag based) and the selection of the replacing words based on the embeddings. The differences can be found in Table 2.

	Replacement Selection	Embedding Selection	Model Base*	Dataset	Embedding Model	Improvements
[63]	Not stated	K-nearest- neighbor and	Logistic regression	Petpeeve dataset	UrbanDictionary W2V Twitter W2V	+0.3 (F1) +1.7
		cosine similarity			GoogleNews W2V	+2.4
[57]	Random	Random with	DNN	AG News	Wikipedia W2V	~0 (Acc.)
		probability		Sentiment	Wikipedia W2V	~+0.5
		proportional to		Hate	GloVe Twitter	~-0.3
		cosine similarity		Speech		
[44]	Every word	Cosine similarity	CNN+LSTM/GRU	HON	Word2Vec Hate Speech	-22.7 (Macro F1)
		threshold + POS-			FastText Wikipedia	+1.0
		tag matching			GoogleNews W2V	-3.3
					GloVe Common Crawl	+0.3
				RSN-1	GloVe Common Crawl	-0.2
				RSN-2	GloVe Common Crawl	0
[45]	<ol> <li>Method:</li> <li>Filtering words according to their POS-tag.</li> <li>Selecting a fixed or variable number of words.</li> <li>Method:</li> <li>Replacing adverbial phrases (Chinese related)</li> </ol>	Own similarity measure and specific or variable number of replacements	LSTM-CNN	Tan	W2V self-pretrained	Results only in combination with other word level augmentation methods
[36]	Substitutable words are nouns, verbs, adjectives, or adverbs and not part of a named entity. Each candidate is replaced with a probability.	Embeddings are found with the counter-fitting method. Each candidate is replaced with a probability. The remaining probability of substation is shared among the embeddings based on a language model score	CNN	MR CR Subj SST MR/CR CR/MR	GoogleNews W2V	-0.6/-4.2 (Acc +0.1/-3.7 +0.2/-1.4 -0.4/-4.2 +1.9/+0.4 +0.1/-3.0
[38]	Not stated	Cosine similarity	Random Forest, Naïve Bayes, SVM	Vietnamese comments	W2V Vietnamese	Results only in combination
[17]	Random sampling with probabilities proportional to the neighbors each word has within the counter-fitted	1. K-nearest- neighbors with Euclidean distance + counter-fitting method	LSTM	IMDB	GloVe	Adversarial training: No improvements but safer mode

	embedding space + exclude common articles and prepositions	<ol> <li>Google LM to filter out words</li> <li>Pick the one word that will maximize the target label</li> </ol>				
		prediction probability				
[64]	Only for multi- piece words. Random probability for	Random embedding of the k nearest	Small transformer model	Various GLUE tasks	GloVe	No augmentation baseline comparisons
[65]	replacement. No stop-words or symbolic and	Cosine similarity threshold of 0.97	Manhattan LSTM model	Thai text similarity	Thai2fit (Thai language)	+1.71

A major factor for bad results is that the embedding replacement does not necessarily guarantee that the meaning of the instances will be preserved, which could in turn lead to distortions of the label, e.g., "the movie was fantastic" and "the movie was horrible" are valid transformations but the sentiment is the opposite. A way to address this issue is the use of the counter-fitting method of Mrkšić et al. [66] for synonym embedding substitution, as for example done by Li et al. [36]. Counter-fitting is an approach that depicts word embeddings on the basis of a target function in a way that similarities between synonyms are rewarded and similarities between antonyms are sanctioned [66]. Li et al. [36] extend this approach by selecting the most fitting words with a higher possibility for the replacement. This is done by leveraging a language model that can give an indication how well a given word fits into the sequence. However, the authors achieve only mixed results with this method. The counter-fitting method offers much less replacement possibilities due to the fact that the embeddings have to be trained on the downstream task, leading to a smaller coverage of their corpora words. Alzantot et al. [17] also use this method and a language model filtering in their adversarial example generator. They extend the approach by only incorporating the words that are maximizing the target label prediction probability (label preservation) of an already trained classifier. The authors report no improvements with regard to the task testing set, but they show that the model is safer with respect to their adversarial attacks. Embedding replacement methods are also used in specific task-dependent ways, as, for example, by Kashefi and Hwa [42].

## 3.1.2.4 Replacement by Language Models

Language models are able to represent language by predicting next or missing words given the previous or surrounding context (classical and respectively masked language modelling). This way, the models can, for example, be used to filter unfitting words, as already discussed in Section 3.1.2.3 with the work of Alzantot et al. [17]. The authors generate similar words with GloVe embeddings and the counter-fitting method and utilize a language model to only choose words with a high fitting probability. In contrast to embedding replacements by word embeddings that take in a global context, language models enable a more localized replacement [57]. Utilizing the next word prediction, language models can also be used as the main augmentation method. Kobayashi [1] is, for example, using an LSTM language model to identify substitution words. However, language models do not only substitute words with similar meanings but also words that fit in principle to the context [1]. This trait is encompassed with a greater risk of label distortion. To prevent the attachment of wrong labels to the new training data due to the changed semantic, Kobayashi [1] modifies the language model so that it allows

the integration of the label in the model for the word prediction (label-conditional language model). Inspired by this approach, Wu et al. [67] alter the architecture of the language model BERT [68] so that it is label conditional (c-BERT). In an evaluation with different tasks the authors showed that in comparison to Kobayashi [1] and other approaches they were able to increase the performance of a classifier the most (see Table 3). However, the c-BERT approach also has the drawbacks that the language model is fixed when applied and in case of low-data regimes the augmentation might not be label preserving anymore [60]. That is why Hu et al. [60] include the c-BERT method in a reinforcement learning scheme, which learns the task in a normal supervised fashion but is also able to simultaneously fine-tune the c-BERT LM. With this adaption, the authors significantly outperform the normal c-BERT approach in a low-data regime setting. The results can be found in Table 3 together with the results of Anaby-Tavor et al. [39], who evaluated c-BERT as comparison, and Qu et al. [69], who employed the c-BERT model with supervised consistency training (see 3.4) on the MLNI-m task.

Publication	Method	Dataset	Improvements (Accuracy)
[67]	c-BERT	SST-5	+0.8 (CNN)/+1.3 (RNN)
		SST-2	+0.2 (CNN)/ +0.5 (RNN)
		Subj	+0.5 (CNN)/ +0.4 (RNN)
		MPQA	+0.5 (CNN)/ +0.7 (RNN)
		RT	+0.8 (CNN)/ +0.6 (RNN)
		TREC	+0.8 (CNN)/ +0.2 (RNN)
[69]	c-BERT with consistency training	MLNI-m	+0.4 (RoBERTa-Base)
[39]	c-BERT	ATIS	-1.9 (BERT) / -0.8 (SVM) / -5.8 (LSTM)
		TREC	+1.1 (BERT) / +1.1 (SVM) / +6.5 (LSTM
		WVA	+0.2 (BERT) / 0.5 (SVM) / +2.4 (LSTM)
[60]	c-BERT integrated in reinforcement	SST-5 (42)	+1.17 (BERT) / +2.19 (normal c-BERT)
	learning scheme	IMDB (45)	+1.97 (BERT) / +1.97 (normal c-BERT)
		TREC (45)	+0.73 (BERT) / +0.87 (normal c-BERT)
[64]	c-BERT and embedding substitution for	MNLI-m	+2.3 (TinyBERT)
	multiple-pieces words	MNLI-mm	+1.9 (TinyBERT)
		MRPC	+3.4 (TinyBERT)
		CoLA	+21.0 (TinyBERT)

Table 3: Evaluation results for the state-of-the-art language substition method c-BERT

Jiao et al. [64] take the already improved method by Wu et al. [67] and adjusted it in their work on TinyBERT. The scholars realized that the quality of the data generated with BERT is low if the words include many multiple-pieces words. To mitigate this problem, they propose to perform a embedding substitution on the base of GloVe embeddings [70] for such words. Further language model augmentations for different tasks are proposed by Gao et al. [71], Ratner et al. [72], Fadaee et al. [73], and Kashefi and Hwa [42].

## 3.1.3Phrase Level

## 3.1.3.1 Structure-based Transformation

Structure-based approaches of data augmentation may utilize certain features or components of a structure to generate modified texts. Such structures can be based on grammatical formalisms, for example, dependency and constituent grammars or POS-tags. They are naturally more limited to certain languages or tasks. Sahin and Steedman [74] are, for example, concerned with the augmentation of datasets from low resource languages for POS-tagging. With "cropping", sentences get shortened by putting the focus on subjects and objects. With the "rotation" technique, flexible fragments get

rotated around the root. The authors state that this method is dependent on the language and may likely only generate noise in the English language. Both methods are well suited to a multitude of low resource languages. The method was also tested by Vania et al. [75] who are using it to augment the training data for dependency parsers for low-resource data.

Feng et al. [76] propose a method for changing the semantics of a text while trying to preserve the fluency and sentiment. Given a set of phrases (replacement entities) to every instance, the Semantic Text Exchange method first identifies phrases in the original text that can be replaced by a replacement entity based on the constituents. Then similar phrases to the identified phrases are replaced by a masked token. This is then filled by an attention-based language model so that the similar words better suit the replacement entity. Feng et al. [34] adapt this approach by automatically choosing the 150 of the 200 most frequent nouns of the Semantic Text Exchange training set for the replacement entity candidates and breaking their Yelp Review dataset into windows, as the method is only suited for short texts. In an analysis with this dataset Feng et al. [34] report that the Semantic Text Exchange method decreases fluency, diversity, and semantic content preservation.

An important work was proposed by Min et al. [77] who show that inversion (swapping the subject and object part) and passivation result in a higher generalization capability in natural language inference. In fact, preliminary work [78]–[80] in combination with this work suggests that BERT is able to extract the relevant syntactic information from the instances but is unable to use this information in the task, as there are too few examples in the MNLI dataset demonstrating the necessity of syntax. Even a limited utilization of their data augmentation methods already helps to mitigate this problem.

#### 3.1.3.2 Interpolation

In numerical analysis, interpolation is a procedure to construct new data points from existing points [81]. While the formal interpolation versions are found in the feature space section, a sensible definition of interpolation in the data space of text is hard to construct. However, the SUB<sup>2</sup> method by Shi et al. [82] is here regarded as one of them due to its resemblance to the feature space methods. SUB<sup>2</sup> substitutes substructures (dependents, constituents, or POS-tag sequences) of the training examples if they have the same tagged label (for example, "a [DT] cake [NN]" in an instance can be replaced with "a [DT] dog [NN]" of another instance). The variant adapted for classification views all text spans of an instance as structures and is constrained by replacement rules that can be combined or completely left out. The replacement rules are only replacing (1) same lengths spans, (2) phrases with phrases, (3) phrases of the same constituency label, and (4) spans that come from instances with the same class label. The authors show that their methods outperform the baseline when applied to low resource tasks. Their classification variant is able to nearly double the accuracy on a subsample of the SST-2 and AG News datasets. They also achieve better results than the language model augmentation c-BERT (Section 3.1.2.4).

### 3.1.4Document Level

#### 3.1.4.1 Round-trip Translation

Round-trip translation<sup>3</sup> is an approach to get paraphrases with the help of translation models. A word, phrase, sentence or document gets translated to another language (forward translation) and afterwards translated back to the source language (back translation) [83]. The rationale behind this is that translations of texts are often not unique as of the complexity of natural language [9], which leads to various possibilities. The process is depicted in Figure 4 by Yu et al. [84].

<sup>&</sup>lt;sup>3</sup> Even though Coulombe [9], Yu et al. [84], Xie et al. [46], Qu et al. [68], and more use the term backtranslation for their data augmentation works as well, these approaches are assigned to the round-trip translation approaches because they execute forward and back translation.

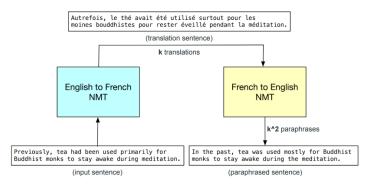


Figure 4: Round-trip translation process [84]

The approach is promising because of its good inherent label preserving and highly valuable paraphrasing capabilities. Translating instances retains the meaning of them but, for example, stylistic features based on the traits of the author are excluded [85]. Some translation systems can propose several translation options; this is hinted in Figure 3. Yu et al. [84], Aroyehun and Gelbukh [62], Coulombe [9], Kruspe et al. [86], and others use this technique to generate artificial training data. Their works differ with regard to the used language and the subsequently applied filtering methods. These filtering methods are important, as the process of the twofold translation may be faulty [62]. Furthermore, Xie et al. [46] as well as Chen et al. [87] change the normal beam search generation strategy to random sampling with a temperature parameter to ensure a greater diversity. The results of the round-trip translation applications are presented in Table 4.

	Translation Model	Languages	Filtering	Model	Dataset	Improvements
[84]	Google's NMT [88]	en -> fr -> en	No filtering	Convolution and self- attention model	SQuAD	+1.5 (EM) / +1.1 (F1)
[9]	Google Translate API	Not stated	Excluding identical instances. Similarity threshold based on lengths.	XGBoost MLP 2 hidden layer	IMDB	+0 (Acc.) +5.8
[62]	Google Translate API	en -> fr, es, de, hi -> en	No filtering	NBSVM CNN LSTM BiLSTM CNN-LSTM LSTM-CNN CNN-BiLSTM BiLSTM-CNN	Aggression Detection	+0.19 (Macro F1) +5.31 +7.39 +5.6 +5.94 +19.45 +14.33 +6.87
[86]	Google Translate	Randomly selected	No filtering	Fusion CNN	TREC Incident Streams track	~-1.2 (F1)
[57]	Google Translate API & Amazon translate	en -> fr, de -> en	"We ensured that the [] texts carry the same meaning as the source text"	DNN	AG News Hate Speech	~+0.33 (Acc.) ~-2.3
[46]	WMT'14 English-French	en -> fr -> en	No filtering	Randomly initialized transformer	Yelp-5	+1.65 (Acc.)

Table 4: Overview of the round-trip translation approaches

	translation model						
[69]	WMT19 released FairSeq	and in	en -> de -> en	No filtering	RoBERTa	MLNI-m	+0.9 (Acc.)
[89]*	Not stated		Not stated	No filtering	Transformer	MNLI	+0.9 (Acc)
					base with	QNLI	+0.6 (Acc)
					consistency	QQP	-0.2 (Acc)
					training	RTE	+5.1 (Acc)
						SST-2	+0.7 (Acc)
						MRPC	+2.6 (F1)
						CoLA	+1.4 (Mcc)
						STS-B	+0.4 (Corr)
[90]	MarianMT		en -> fr, de,	(Word sense disambiguation)	MT-DNN	SemEval-2013 +	No baseline
			es -> en	Retaining those where the		SemEval-2015 +	comparisons
			Chained:	target word occurs exactly		Senseval-2 +	
			en -> es -> fr	once (in both original and		Senseval-3	
			-> en	augmented instance)			

\* trained with supervised consistency training

#### 3.1.4.2 Generative Methods

Generative methods are becoming more and more interesting in recent data augmentation research. As the capabilities of language generation increased significantly, the models are able to create very diverse texts and can thus incorporate new information. For example, Qiu et al. [37] propose, besides noise generation techniques, a variational autoencoder (VAE) based method that is used for text generation in their system. VAEs are probabilistic neural network structures that consist of an encoder network, which transforms input data into a latent representation, and of a decoder-network, which transforms the latent representations back. The authors differentiate between unconditional and conditional VAEs. With unconditional VAEs, separate text generation models are trained for all classes, whereas with conditional VAEs, label information is fed into the model as an additional input. Furthermore, they distinguish between sampling from the prior distribution, leading to greatly diverse instances, and the posterior distribution, creating text that is semantically closer to the training data. With the unconditional VAE and sampling from the prior distribution, they achieve the highest improvements of up to 2 F1-points (see Table 5). Malandrakis et al. [91] make similar efforts by evaluating VAEs for augmentation. While their objective is more narrowed, as they are interested in natural language understanding with limited resources, they analyze a broader variety of VAE augmentation variants. They also propose augmentation by conditional and unconditional VAEs with sampling from the posterior or prior distribution. Furthermore, they test two different learning objectives, where in the first the VAEs try to reconstruct the input and in the second the VAEs take an instance from a certain class and try to construct another instance from that class. They also experiment with the addition of a discriminator network to the VAE that predicts from which class an output appears to be. In intrinsic and extrinsic evaluations, the conditional VAEs with the reconstruction task are best performing. The discriminator variant achieves poor results, which stem from the little amount of available training data for the many different classes. Contrary to the improvements of Qiu et al. [37], the CVAEs outperform the VAE generation. An excerpt of the extrinsic evaluation results is given in Table 5. However, one has to keep in mind that the task at hand is very specific (intent classification).

VEAs are also a main component in the NeuralEditor proposed by Guu et al. [92] that generates new texts based on edition vectors. For the training of the generative model, they take pairs of instances x' and x in the training data that are

lexically similar, encode the differences of them and noise into an edition vector z, and try to generate x based on x' and z. It should be noted that the lexical similarity is just a rough approximation of semantic similarity, which is the reason why it could happen that instances are, for example, negated which in turn weakens the label preservation capabilities of this approach. This suffices the purposes of the authors of the paper, as they only use the method for language modeling. Specifically in this domain, they report improvements with regard to the generation quality and the perplexity. Raille et al. [93] propose Edit-transformer, which is an adaptation of the NeuralEditor with the ability to function cross domain, so that the learned edits of a large dataset can be transferred to a small dataset. Besides the improvements in speed and language modeling, they also apply their method on three different classification tasks. The results are shown in Table 5.

Rizos et al. [44] create an RNN that, depending on a specific class, learns language modelling to generate training data thereafter. The class specific RNN for augmentation is primed with a random start word from the class specific training data. However, the authors state that this method achieves the worst results compared to embedding substitution and noise generation. In a similar sense, Ollagnier and Williams [61] also perform text generation using a language model. Their model is based on an LSTM-CNN architecture. In contrast, they split each document in a minibatch into sentences, then generate new sentences for 30% of them and utilize 30% of the beginning of a given sentence as priming.

Sun and He [45] used the seqGAN architecture [94] to generate artificial data on basis of a generative adversarial network (GAN). Comparable to computer vision, seqGAN consists of a generator network creating texts and a discriminator network examining the authenticity of the generated texts next to the real instances. As the discriminator network can only prove the authenticity after a sequence of words and thus gives delayed feedback to the generator, the generator network is trained as a reinforcement learning agent. Utilizing the method as a data augmentation technique, the authors only receive minor improvements of classification quality.

Wang and Lillis [95], Anaby-Tavor et al. [39], Abonizio and Junior [96], Bayer et al. [43], and Liu et al. [97] use the GPT model of Radford et al. [98], which achieves very good results in text generation, to create new complete instances. Concerning the adoption of the method, Wang and Lillis [95] only describe that they use rare instances as dependent examples for the generation. Anaby-Tavor et al. [39], on the other hand, develop a method that increases the safety with regard to label preservation. First, they further train the GPT-2 model with training data of a certain task (finetuning). In the process, they concatenate the respective label to every instance in order to facilitate the generation of new data for the respective class afterwards. Finally, a classifier determines which generated instances can actually be assigned to the class stated. The authors manage to achieve significant improvements in the classification of sentences. They show that their method outperforms conditional VAEs (unfortunately no sampling technique is described) and even EDA (Section 3.1.1.1) and c-BERT (Section 3.1.2.4) when applied to a severe low data regime. The results of their LAMBADA approach and CVEA implementation is given in Table 5. Abonizio and Junior [96] try to improve this approach by concatenating three random samples for the priming of the generation. Furthermore, they are using DistilGPT2 by Sanh et al. [99], which is substantially faster and smaller. As can be seen in Table 5, the method consistently outperforms the baseline. While LAMBADA and PREDATOR are only applicable to short texts as instances, Bayer et al. [43] design a GPT-2 based approach to augment short as well as long text tasks. They want to achieve a very high label preservation and diversity by finetuning the language model on the class specific data, generating data primed with specialized training data tokens and a document embedding based filtering method. They can achieve high improvements for constructed and real-world low data regimes. However, they also discuss where their method is limited and for which datasets and tasks it may be especially helpful. The results can also be seen in Table 5. Liu et al. [97] use a reinforcement learning component after the softmax prediction of the GPT-2 model to be able to predict the tokens conditional on the class for that the instance should be generated. The authors tested their method with many model architectures. It consistently improved all of them on all tasks, especially the larger pre-trained models, like BERT and XLNet. The results for XLNet are shown in Table 5.

In the generative method proposed by Lee et al. [100], a first step is to subdivide the data into different slices (informed or based on the labels). Then a generative model is trained on these slices that is supposed to predict an instance in the slice based on a subsample of instances in this slice. This model is then used to generate new data for underrepresented slices by priming it with data instances from it. This way, the authors can gain several improvements in text classification, intent classification, and relation extraction task with new state-of-the-art results for the latter two. Furthermore, Ding et al. [101] and Chang et al. [102] proposed methods using generative models for tasks other than text classification.

Publication	Method	ethod Model Dataset			
[37]	VAE	Ensemble of BiLSTM, TextCNN,	ICS (Zh)	+0.04 (F1)	
		TextRCNN, and FastText with	News Category Dataset (EN)	+2.02	
	CVAE + prior	XGBoost as top-level classifier	ICS (Zh)	-0.13	
	sampling		News Category Dataset (EN)	+1.55	
	CVAE + posterior		ICS (Zh)	-0.06	
	sampling		News Category Dataset (EN)	+1.88	
[91]	VAE	BiLSTM	Movie	+4.0 (Macro F1)	
			Movie + Live Entertainment	-0.5	
	CVAE + prior		Movie	+5.9	
	sampling		Movie + Live Entertainment	+1.7	
	CVAE + posterior		Movie	+5.6	
	sampling		Movie + Live Entertainment	+0.6	
[103]	CVAE	BERT	SNIPS (few shot)	+8.00	
			SNIPS	+0.06 (Acc.)	
			FBDialog (few shot)	+7.42	
			FBDialog	+0.0	
[93]	Transformer-based	CNN	Subj (20%)	+1.71 (Acc.)	
	sentence editor	CNN	Subj (100%)	+1.62	
		CNN	SST-2 (20%)	+0.87	
		CNN	SST-2 (100%)	-0.84	
		LSTM	Amazon Reviews (1%)	+1.12	
		LSTM Amazon Reviews (4%)		+0.41	
[44]	RNN LM with random	CNN+LSTM + GloVe++	HON	-1.8 (Micro-F1)	
	start word priming		RSN-1	+8.2	
			RSN-2	-7.4	
[61]	CNN-LSTM LM with	CNN-LSTM	CodiEsp-P	+3.1 (F1)	
	30% of a given				
	sentence for priming				
[45]	GAN (seqGAN)	LSTM + pretrained embeddings	Tan's task	+1.06 (F1)	
		CNN + pretrained embeddings		+0.9	
		LSCNN + pretrained embeddings		+0.8	
[95]	GPT-2 for rarer	Logistic regression/biLSTM/ Bi-	Alerting	No comparative	
	instances without	attentive classification+ELMo +	Information Feed	results	
	filtering	GloVe	Prioritisation		
[39]	CVAE	BERT	ATIS (5)	+7.3 (Acc.)	
			TREC (5)	+0.8	
			WVA (5)	-1.8	

Table 5: Overview of the	e text generation methods

[39]	LAMBADA – GPT-2	BERT	ATIS (5)	+22.4 (Acc.)
	generation and		ATIS (20)	~0
	classifier filtering		ATIS (50)	~+2.0
			ATIS (100)	~+0.5
			TREC (5)	+4.0
			WVA (5)	+1.4
[96]	PREDATOR -	BERT	AG-NEWS	+0.61 (Acc.)
	DistilGPT2 generation	CNN	CyberTrolls	+0.45
	and classifier filtering	BERT	SST-2	+1.63
[43]	GPT-2 with	ULMFit	SST-2 (100)	+15.53 (Acc.)
	conditional finetuning,		SST-2 (700)	-0.19 (Acc.)
	special priming and		Layoff	+4.84 (F1)
	document embedding		Management Change	+3.42 (F1)
	filtering		Mergers & Acquisitions	+1.42 (F1)
			Flood	+0.25 (F1)
			Wildfire	+0.44 (F1)
			Boston Bombings	+2.44 (F1)
			Bohol Earthquake	+2.05 (F1)
			West Texas Explosions	+3.81 (F1)
			Dublin	-2.54 (F1)
			New York	+0.44 (F1)
[97]	GPT-2 with a	XLNet	Offense Detection (20%)	+1.3 (F1)
	reinforcement learning		Offense Detection (40%)	+4.3
	component for class		Sentiment Analysis (20%)	+1.2
	conditional		Sentiment Analysis (40%)	+1.4
	generation.		Irony Classification (20%)	+1.0
			Irony Classification (40%)	+2.3

## 3.2 Feature Space

Data augmentation in the feature space is concerned with the transformation of the feature representations of the input data.

#### 3.2.1Noise induction

As in the data space, noise can also be introduced in several variants in the feature space. For example, Kumar et al. [103] employ four such techniques for the ultimate goal of intent classification. One of those methods applies random multiplicative and additive noise to the feature representations, as is done in [51]. However, in contrast, they are not transforming the created representations back into the data space. Another method called Linear Delta calculates the difference between two instances and adds it to a third (all from the same class). The third method interpolates instances, which fits to Section 3.2.2.2 (see Table 7). Furthermore, for their fourth method, they are adapting the Delta-Encoder by Schwartz et al. [104] for textual data. There, an autoencoder model learns the deltas between instance pairs of the same class, what is then utilized to generate instances of a new unseen class. In a normal testing setting, the augmentation methods only slightly improve the classification results, while in a few-shot setting all methods are highly beneficial.

Several feature space data augmentation methods stem from the adversarial training research field. As explained in the background section, the models are trained with adversarial examples, i.e., little perturbed training data instances that would change the prediction or maximize the loss. This can be formally written as follows [105]:

$$\min_{\boldsymbol{\theta}} \mathbb{E}_{(\mathbf{Z},\mathbf{y}) \sim \mathbf{D}} \left[ \max_{||\boldsymbol{\delta}|| \leq \epsilon} \mathcal{L}(\mathbf{f}_{\boldsymbol{\theta}}(\mathbf{X} + \boldsymbol{\delta}), \mathbf{y}) \right],$$

where  $\Theta$  are the model parameters and  $\delta$  the perturbation noise added to the original instances (within a norm ball). Further, D is the data distribution, y the label, and L a loss function. The training of the network (outer minimization) can still be solved by SGD, while the search for the right perturbations (i.e., inner maximization) is non-concave [105]. As described by Zhu et al. [105], PGD [106], [107] can be used to solve this. Unfortunately, several steps (K) for converging to a good result makes it computationally expensive [105]. Shafahi et al. [108] and Zhang et al. [109] proposed two methods that use the idea to calculate the gradient with respect to the input (for PGD) on the same backward pass as the gradient calculations with respect to the network parameters during a training step. This mitigates additional calculation overhead of PGD. In detail, FreeAT by Shafahi et al. [108] trains the same batch of training examples K times so that several adversarial updates can be performed. YOPO by Zhang et al. [109] accumulates the gradients with respect to the parameters from the K steps and updates the parameters with them after the steps. Zhu et al. [105] also propose a method called FreeLB, which is similar to YOPO, as it also accumulates the parameter gradients. On several tasks, this method consistently exceeds the results of the baseline and the other two methods. The results of the GLUE dataset are given in Table 6. Miyato et al. and Miyato et al. [35], [110] change the normal adversarial training rule so that no label information is needed and call it virtual adversarial training. Without going into exact details, virtual adversarial training regularizes the standard training loss with a KL divergence loss of the distribution of the predictions with and without perturbations, where the perturbations are chosen to maximize the KL divergence. While the adversarial training method is suitable for semi-supervised learning, we are particularly interested in the supervised setting. Their method improves the supervised DBpedia topic classification task baseline classifier by 0.11 points of accuracy. Their method gains additively 0.03% accuracy in comparison to the conventional adversarial training method. Jiang et al. [111] propose the adversarial method SMART, which relies on the virtual adversarial training regularization. They introduce the utilization of the Bregman proximal point optimization with momentum to solve the virtual adversarial training loss, which prevents the model from aggressive updates [35]. The authors show in their experiments that the method significantly improves the baseline and is also able to achieve better results than the other methods discussed in this paragraph (see Table 6). Furthermore, they demonstrate the robustness enhancement and domain adaption capabilities in several evaluation applications.

Wang et al. [112] and Liu et al. [113] developed methods for enhancing the pre-training of language models with adversarial training. Wang et al. [112] simply generate adversarial examples on the output embeddings in the softmax function of the language models. The authors can reduce the perplexity of the AWD-LSTM and QRNN model on different datasets; for example, a reduction by 2.29 points on the Penn Treebank dataset with the AWD-LSTM model. However, it is not clear how the training of bigger pre-trained language models like BERT and RoBERTa would have been influenced by the method. This is addressed in the work of Liu et al. [113] with their method called ALUM. ALUM introduces noise to the input embeddings. The authors build their system upon the virtual adversarial training by Miyato et al. [35], as they noticed that it is superior to conventional adversarial training for self-supervision. They also found out that they can omit the Bregman proximate point method and the free adversarial training proposed by Jiang et al. [111] and Shafahi et al. [108] when they are using curriculum learning, where the model is first trained with the standard objective and then with virtual adversarial training. They report promising generalization and robustness improvements with the largest transformer models. For example, RoBERTa models can be improved with the ALUM continual pretraining by +0.7% (absolute) on the MNLI task, while standard continual pretraining does not introduce further gains. The results on the GLUE dataset are given in Table 6. They also tested the robustness of the models with three different adversarial datasets. ALUM achieves in all tasks significant improvements. In another evaluation setting they combined adversarial pretraining with adversarial finetuning. ALUM improves all the evaluation scores of the standard pretrained models. This model reaches the best performances and outperforms the other models substantially across the tested tasks, e.g., with an accuracy of +0.4% more than without fine-tuning the SNLI dataset. The improvement on the MNLI task is given in Table 6.

With regard to the generative adversarial training methods of the feature space, it is also of interest to investigate how to transform the newly created examples to the data space to enable their inspection. This is done in the works of Liu et al. and Wan et al. [114], [115]. Wan et al. try to improve the classification behavior of a grammatical error correction system by training with adversarial examples. Such an example, made from applying loss increasing noise in the hidden representation of a transformer encoder, is mapped to the data space by a transformer encoder that was trained autoregressively. Then they use a similarity discriminator based on the model to filter instances that are not similar to their initial counterparts. Liu et al. [114] also use a transformer autoencoder architecture to get data space instances. In contrast to the work of Wan et al. [115], they generate the noisy instances from the input embeddings, filter instances based on unigram word overlap and try to improve machine ready question generation and question answering tasks. Both methods significantly improve the baselines and other augmentation methods.

Given the constraint that adversarial training can be computationally expensive, Shen et al. [89] propose three simple and efficient data augmentation methods of the feature space (see Figure 5). Token cutoff sets a whole embedding of an individual word to 0, while feature cutoff sets one embedding dimension of every word in the input to 0. The third method, span cutoff, employs token cutoff across a coherent span of words. With every method, several different slightly changed instances can be created, which the authors see as different perspectives/views that can be integrated in a multi-view learning fashion through consistency training. This means that the model should predict similar outputs across different views (details can be found in Section 3.4). The authors evaluate their model on the GLUE task and compare it with adversarial training algorithms as well as round-trip translation. In three out of eight tasks, an improvement over all other methods could be achieved (see Table 6). They extend the cutoff strategies to work with natural language generation, and they significantly outperform the baseline as well as the adversarial training method of Wang et al. [112].

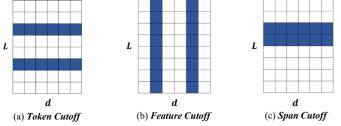


Figure 5: Visualization of the different cutoff methods [89]

Table 6: Comparison of different noise inducing methods on the GLUE task

	Model	SST-2	STS-B	MNLI-	QQP	RTE	QNLI	MRPC	CoLA
		Acc	P/S Corr	m/mm-	Acc	Acc	Acc	F1	Mcc
				Acc					
Baseline	RoBERTa-L	96.4	92.4	90.2	92.2	86.6	94.7	90.9	68.0
Adversarial	PGD	96.4	92.4	90.5	92.5	87.4	94.9	90.9	69.7
Training	FreeAT	96.1	92.4	90.0	92.5	86.7	94.7	90.7	68.8
	FreeLB	96.7	92.7	90.6	92.6	88.1	95.0	91.4	71.1
	ALUM*	96.6	92.1	90.9	92.2	87.3	95.1	91.1	68.2
	ALUM	-	-	91.4	-	-	-	-	-
	SMART	96.9	92.8	91.1	92.4	92.0	95.6	92.1	70.6
Cutoff**	Token	96.9	92.5	91.0	92.3	90.6	95.3	93.2	70.0

100	ature 97	<b>7.1</b> 92		90.9	92.4	90.9	95.2	93.4 ′	71.1
Spa	an 96	5.9 <b>9</b> 2	2.8 9	91.1	92.4	91.0	95.3	93.8	71.5

\*only adversarial pre-training

\*\* supervised consistency training

## 3.2.2 Interpolation methods

For textual data, interpolation methods are mostly limited to the feature space since there is no intuitive way for combining two different text instances. Nevertheless, the application in the feature space seems reasonable, as the interpolation of hidden states of two sentences creates a new one with the meaning of both original sentences [87], [116]. Besides this, interpolation methods have a high value for machine learning models from the learning-based perspective. Possible explanations for the success of interpolation methods, which are described in the following, may stem from the balancing of classes, the smoothening of the decision border (regularization) [117], and the improvement of the representations [118].

For example, the SMOTE approach in its original context was developed to oversample the minority class, which, as described in the background section, inherently leads to better classification performances. In fact, a balancing of a class can easily be achieved by simply copying the minority class. However, Chawla et al. [117] show that simple oversampling leads to more specific decision boundaries than applying SMOTE for balancing the classes. Interpolation methods can smoothen the boundary as it is shown in Figure 6. Smoothened and more general decision borders signify that an algorithm can generalize better and, in relation to training data, is accompanied by less overfitting. Furthermore, when applying interpolation methods to representations of the input data, Verma et al. [118] empirically and theoretically prove that the representations are flattened with regard to the number of directions with significant variance. This is desirable since the data representations capture less space, meaning that a classifier is more uncertain for randomly sampled representations and a form of compression is achieved which leads to generalization [118]–[120].

#### 3.2.2.1 SMOTE Interpolation

The Synthetic Minority Over-sampling Technique (SMOTE) is an interpolation method of feature space representations of the input data. With SMOTE, various neighbors that are as close as possible to a specific instance are searched within the feature space in order to be interpolated with the following formula:

$$\tilde{x} = x_i + \lambda * dist(x_i, x_i),$$

where  $(x_i, y_i)$  is the source instance and  $(x_j, y_i)$  is a close neighbour with the same class label. dist(a, b) is a distance measure and  $\lambda \in [0,1]$ . Unlike with mixup, only instances of the same class get interpolated. The rationale behind the calculation of neighbors with the same class labels is that the interpolations tend to be class preserving, leading to a higher safety of the technique. However, this has the effect that the novelty and diversity of the created instances is limited.

SMOTE is rudimentarily illustrated in Figure 6. In the illustration, a binary classification problem in which a learning algorithm has learned the specific decision border is shown. To achieve a balanced class distribution, a new instance is added to the blue class by utilizing SMOTE. This addition achieves, apart from a balancing of the dataset, an adjustment of the decision boundary. The new boundary is less specific and thus contributes to more general decisions.

SMOTE in combination with textual data augmentation is, for instance, applied in the work of Wang and Lillis [95]. Unfortunately, the authors do not describe how and on which point in the network the method is applied.

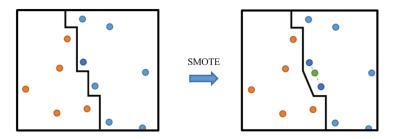


Figure 6: Illustration of the interpolation method SMOTE

#### 3.2.2.2 Mixup Interpolation

Mixup by Zhang et al. [121] is an interpolation method similar to SMOTE. In the simplest adoption, the convex interpolation is implemented with the following formulas:

 $\tilde{x} = \lambda x_i + (1 - \lambda) x_j$ , whereas  $x_i, x_j$  are input vectors  $\tilde{y} = \lambda y_i + (1 - \lambda) y_j$ , whereas  $y_i, y_j$  are one-hot-coded labels

 $(x_i, y_i)$  and  $(x_j, y_j)$  randomly drawn from the training data and  $\lambda$  is either fixed in [0,1] or  $\lambda \sim \text{Beta}(\alpha, \alpha)$ , for  $\alpha \in (0, \infty)$ .

Mixup is a general technique that can be applied to all kinds of equal dimensional data. However, text cannot trivially be represented in equal dimensions [122]. As a very general method, Verma et al. [118] propose the idea of applying mixup within a randomly selected hidden layer of a neural network. Despite the fact that the authors only perform the tests on image datasets, this approach paves the way for applying mixup for many textual related tasks. The results are very promising, and for textual evaluations we advise the reader to look at the methods described in the following (Table 7), which oftentimes can be seen as specializations of the approach by Verma et al. [118] for textual data. Marivate and Sefara [57] state that they use mixup on representations of bag of word models, TF.IDF models, word embeddings, and language models. Unfortunately, the authors do not explicitly describe how the interpolation is done. This raises questions about how to interpolate instances of different sizes, when, for example, word embedding vectors are used. Marivate and Sefara [57] report about 0.2, 0.4, and 0 points gain for the AG News, Sentiment 140, and Hate Speech detection task. In contrast to this work, Qu et al. [69] describe how their interpolation is performed internally. For the interpolation, they draw two instances from a mini-batch and linearly combine their input embedding matrices in the above described way. They improve the baseline on the MNLI-m task additively by about 0.6% accuracy. Guo et al. [123] propose two variants, wordMixup and senMixup, where the interpolation is applied in the word embedding space and on the final hidden layer of the neural network before it is passed to a softmax layer. For wordMixup the sequences have to be zero padded so that the dimensions are the same. For senMixup this is not necessary, as the hidden embeddings generated are of the same length each. The improvement results of both methods with regard to the CNN model with pretrained GloVe embeddings (trainable), which is the best baseline, is given in Table 7. In [124], Guo further advances the wordMixup approach by using a nonlinear interpolation policy. The policy is constructed to mix every dimension of each of the word embeddings separately in a given sentence. Furthermore, the labels are also nonlinearly interpolated while it is adaptively learned based on the embeddings mixing. This way, a much larger variety of generated examples can be created. While this procedure outperforms the other two variants in most tasks, it can also have a negative effect on the classification quality, as shown in Table 7. Similar to the senMixup method, L. Sun et al. [122] apply mixup to the output of transformer models. Furthermore, they only activate mixup in the last half of the training epochs to first learn good representations. The improvements on the GLUE benchmark are listed in Table 7. In a very similar way, Chen et al. [87] propose TMix, which is also able to interpolate the hidden representations of an encoder. Indeed, TMix is able to interpolate at every layer of the encoder, similar to Verma et al. [118]. Based on the work of Jawahar et al. [125], who analyzed which types of information is learned in the different layers of BERT, the authors narrowed their approach down and chose 7, 9, and 12 as interpolation layers as they contain the syntactic and semantic information. The improvements of TMix are also shown in Table 7.

Method	Technique for textual application	Model	Datasets	Improvements
mixup by Marivate	Not stated	DNN	AG News	+0.2 (Acc.)
and Sefara [57]			Sentiment 140	+0.4
			Hate Speech	+0
[103]	Interpolation of the BERT CLS output	BERT-base-english-	SNIPS (few shot)	+8.36 (Acc.)
		uncased	SNIPS	+0.0
			FBDialog (few shot)	+7.92
			FBDialog	+0.08
[69]	Interpolation of the embedding matrices	RoBERTa-base	MNLI-m	+0.6 (Acc.)
wordMixup by Guo	Word embeddings that are zero-padded	CNN	Trec	+1.6 (Acc.)
et al. [123]			SST-1	+1.9
			SST-2	+0.2
			Subj	+0.3
			MR	+1.5
senMixup by Guo et	Interpolation on the final hidden layer	CNN	Trec	+1.2 (Acc.)
al. [123]	-		SST-1	+2.3
			SST-2	+0.3
			Subj	+0.5
			MR	+0.8
Nonlinear Mixup by	Padded word embeddings are	CNN	Trec	+2.6 (Acc.)
Guo [124]	nonlinearly interpolated		SST-1	+3.0
			SST-2	+2.3
			Subj	-0.5
			MR	+3.6
Mixup-Transformer	Interpolation after last layer of the	BERT-large	CoLA	+2.68 (Corr.)
by Sun et al. [122]	transformer		SST-2	+0.81 (Acc.)
			MRPC	+1.72 (Acc.)
			STS-B	+0.89 (Corr.)
			QQP	+0.42 (Acc.)
			MNLI-mm	-0.01 (Acc.)
			QNLI	+0.13 (Acc.)
			RTE	+0.37(Acc.)
TMix by Chen et al.	Interpolation of the m-th BERT layer (7,	BERT-based-	AG News (10)	+4.6 (Acc.)
[87]	9, and 12 randomly chosen per batch)	uncased + d average	AG News (2500)	+0.2
		pooling + two-layer	DBPedia (10)	+1.6
		MLP	DBPedia (2500)	+0.0
			Yahoo! (10)	+2.4
			Yahoo! (2500)	+0.3
			IMDB (10)	+1.8
			IMDB (2500)	+0.5
Intra-LADA [126]	Interpolating an instance with a	BERT-base-	CoNLL (5%)	+0.24 (F1)
	randomly reordered version of itself	multilingual-cased +	CoNLL (100%)	+0.03 (*)
	-	linear layer	GermEval (5%)	+0.29
		-	GermEval (100%)	+0.04 (*)

Table 7: Overview of different approaches of the replacement method "mixup interpolation"

Inter-LADA [126]	Interpolating nearest neighbors and	BERT-base-	CoNLL (5%)	+1.32 (F1)
	sometimes randomly selected instances.	multilingual-cased +	CoNLL (100%)	+0.64
		linear layer	GermEval (5%)	+0.49
			GermEval (100%)	+0.33
Intra-Inter-LADA	Combination of Intra- and Inter-LADA	BERT-base-	CoNLL (5%)	+1.57 (F1)
[126]		multilingual-cased +	CoNLL (30%)	+0.59
		linear layer	GermEval (5%)	+0.53
			GermEval (30%)	+0.78

\* included in the pretraining

Chen et al. [126] similarly propose an interpolating augmentation method in which the hidden layer representations of two samples are interpolated. However, they noticed that this method is not suitable for sequence tagging tasks. That is why they propose Intra- and Inter-LADA. Intra-LADA aims to reduce noise from interpolating unrelated sentences by only interpolating an instance with a randomly reordered version of itself. This way, they can increase the performance on every tested task (see Table 7). However, Chen et al. [126] also hypothesize that their Intra-LADA algorithm is limited in producing diverse examples. This limitation leads to Inter-LADA, which sets a trade-off between noise and regularization by interpolating instances that are close together. The closeness is estimated through kNN based on sentence-BERT [127] embeddings and widened through occasionally sampling two instances completely at random. As it can be seen in Table 7, Inter-LADA oftentimes performances better than Intra-LADA. The combination of both can further improve the results.

### 3.3 Combination of Augmentation Methods

In augmentation research, a common technique is to combine several data augmentation methods to get more diversified instances [128]. The combination can either be several methods separately applied to the data or stacked onto each other. For the first kind, Sun and He [45] propose word-level and phrase-level methods that they apply separately. While the results of the word-level and phrase-level methods were insignificantly different, both groups of methods together produced very good results. Similarly, Li et al. [36] combined their proposed methods, which led to better results for the in-domain evaluations. The method of stacking methods, on the other hand, is not always feasible. It is, for example, in most cases not possible to first apply a feature space method and then a data space method. Qu et al. [69] experimented this with round-trip translation, cutoff and adversarial examples. Round-trip translation and the training with adversarial examples produced the best results. Marivate and Sefara [57] stack round-trip translation, synonym and embedding replacement with mixup. In two out of three evaluation settings, this procedure reduces the minimal error.

For the combination of augmentation methods, the meta-learning augmentation approach by Ratner et al. [72] is also interesting. It describes the utilization of a neural network to learn data augmentation transformations [5]. Specifically, Ratner et al. use a GAN to generate sensible sequences of transformations that were defined beforehand. This approach is usable for image as well as text datasets and the authors show that it can achieve a significant improvement when applied to a relation extraction task with augmentations based on language model replacements.

### 3.4 Training Strategies

While semi-supervision is not considered as data augmentation in this work, it can still be sensibly combined through consistency training. In its origin, consistency training is used to make predictions of classifiers invariant to noise [46]. This can be enforced by minimizing the divergences between the output distributions of real and noised instances. Additionally, because only the output distributions are included in the process, this consistency can be trained with unlabeled data. Several authors analyze how consistency training behaves when data augmentation methods are used for

noise. This process can be illustrated as taking an instance from which the label is unknown, applying a label preserving data augmentation method and then learning the model to predict the same label for both instances. This way, the model can learn the invariances and is able to generalize better. Xie et al. [46] show that by employing consistency training with round-trip translation and a TF-IDF based replacement method, they achieve very good results, with, for example, an absolute improvement of 22.79% accuracy on an artificially created low-data regime based on the Amazon-2 dataset with BERT base. They are also able to outperform the state of the art in the IMDb dataset with only 20 supervised instances. Chen et al. [87] even extend this approach within their MixText (TMix) system. First of all, they generate new instances with round-trip translation. Then, they are guessing the label of the original and augmented instances by taking a weighted average of the predictions of all of them. In the training, they randomly sample two instances and mix them together with TMix. If one of the two instances is from the original data, they are using the normal supervised loss, but if both instances are from the unlabeled or augmented data, they use the consistency loss, like Xie et al. [46].

Consistency training can also be applied in a supervised fashion as an additional term in the training objective to enforce the predictions to be equal. This is, for example, used in the cutoff method by Shen et al. [89]. They show in their ablation studies that this consistency term improves the accuracy results additively by 0.15%. Qu et al. [69] combine this supervised consistency training with contrastive training, which should bring the original and augmented instances closer together relative to the other instances in the representation space. This contrastive term alone (without consistency) improves the accuracy of a RoBERTa base classifier of the SST-2 and RTE dataset absolutely by 0.5% and 3.3%. Combined with augmented data and consistency training, they achieve further improvements (e.g., +1% for SST-2 with RoBERTa large).

Other training strategies in which the order of how the training examples are presented to the learning algorithm is altered are for example employed by Liu et al. [113] and Yang et al. [129]. Liu et al. [113] adopt a curriculum learning approach, which means the algorithm should at first learn the less difficult instances. Transferred to the data augmentation topic, the model is first trained with the original data and then with the augmented data. Yang et al. [129] reverse this step and first train the model with the augmented data and then with the original data. This way, the model can correct unfavorable behavior that it learned through noisy augmented data. They also tried an importance-weight loss in which the weights of the synthetic instances are lower than the original but find that the other training method performs better.

#### 3.5 Filtering Mechanisms

Mechanisms that filter the generated instances are especially important for methods that are not perfectly label-preserving. A simple mechanism is, for example, employed by Liu et al. [114], who remove generated instances based on the unigram word overlap to their original counterparts. Similarly, other metrics could also be used, e.g., Levenshtein distance, Jaccard similarity coefficient, or Hamming distance. Wan et al. [115] use in their work a similarity discriminator (natural language inference model) proposed by Parikh et al. [130], which also measures the similarity of two sentences.

The generative methods by Anaby-Tavor et al. [39] and Abonizio and Junior [96] filter instances based on a classifier that was trained on the class data. This majorly reduces the diversity of the samples, and the classifier cannot really be improved because it is already confident with those instances. Bayer et al. [43] improve this by using embeddings to measure the quality of the generated instances with regard to the class and more importantly incorporating the human expert in the loop who needs to determine the right threshold. However, Yang et al. [129] consider another filtering mechanism in their work that does not need any human assistance and is sophisticated by incorporating two perspectives. Generally, Yang et al. [129] propose a generative method that is suited for increasing the dataset size for question answering tasks. While they propose to utilize language models for finetuning and generating questions and answers, their filtering methods can be adapted for the other data augmentation methods as well. A first filtering mechanism determines whether a generated

instance is detrimental by measuring whether the validation loss increases when including the artificial instance. As this would require retraining the model with every generated example, the authors propose to use influence functions [131], [132] to approximate the validation loss change. Furthermore, they firstly train on the augmented instances and then on the original training data so that the model can adjust itself when unfavorable noise is included in the augmented instances. The other filtering mechanism tries to favor diversity by selecting examples that maximize the number of unique unigrams.

### 4 DISCUSSION: A RESEARCH AGENDA FOR TEXTUAL DATA AUGMENTATION

One has to keep in mind that the results reported by the authors of the approaches that are linked in this survey paper are restricted in their expressiveness and only show one perspective. Many results are limited to special kinds of models and datasets. However, based on our findings, we identified an agenda for future research on data augmentation as follows:

**Developing evaluation criteria for data augmentation research**. A general problem in data augmentation research is that mostly only improvements with regard to the prediction performance on specific datasets are presented. While this metric is probably the most important one, there are other metrics, like the time and resource usage, language variety, or configurability, that are important for practitioners as well as researchers. For example, the generative approaches based on GPT-2 seem to be very promising when considering the prediction performance gain. Nevertheless, the language variety is narrowed down, as the model is mostly just trained on English data. Furthermore, only few authors discuss the time required for the application of their data augmentation methods. The GPT-2 based method of Bayer et al. [43] takes up to 30 seconds for generating one example, leading to several computing days for a 10 times augmentation of a small dataset. For instance, in the context of crisis informatics this might be too long, as the classifiers have to be created fast for quick incident management. For this reason, we urge scientists developing data augmentation techniques to consistently describe the limitations of their approaches.

Researching the merits of data augmentation in the light of large pre-trained language models. Generally, it is not possible to determine which augmentation method works best for a given dataset, nor predict which research direction will be the most appealing in the future. Nevertheless, there are some patterns in the current state of the approaches that hint into the directions research can follow to overcome obstacles and challenges. One of the most important challenges, formulated by Longpre et al. [4], is that the usage of large pre-trained language models makes the utilization of several data augmentation methods obsolete. This is the reason why especially experiments with BERT or other bigger language models are of interest. Concurring, several studies [39], [43], [60], [97], [114] show that methods transforming the instances only slightly with random behavior, like synonym replacement (Section 3.1.2.2), EDA (synonym replacement, random swap, deletion, and insertion in one) (Section 3.1.2.1), or spelling error insertion (Section 3.1.1.1), tend to be less beneficial in this setting than more elaborate ones. Particularly adversarial training (Section 3.2.1), cutoff (Section 3.2.1), interpolation (Section 3.1.3.2 and 3.2.2), and some generative methods (Section 3.1.4.2) show significant improvements with large pre-trained language models. While the replacement methods based on embeddings (Section 3.1.2.3) and especially language models (c-BERT) (Section 3.1.2.4) also can gain improvements in combination with those pre-trained models, several studies [39], [57], [69], [97] show that the former mentioned methods can get better results in most cases. This is also apparent when approaching the challenge of Longpre et al. [4] from an intuitive perspective. Large language models map the data into a latent space with representations nearly invariant to some transformations. For example, the synonym replacement methods only replace words that are by definition very close in the representation space, leading to instances that are almost identical [54]. As Longpre et al. [4] hypothesize, data augmentation methods can only be helpful if they are able to introduce new linguistic patterns. There, the mentioned methods and especially the usage of generative methods might be sensible, as they are based on other large language models that can introduce a high novelty. However, the challenge proposed by Longpre et al. [4] does not have to be universally true, as, for example, the SUB<sup>2</sup> by Shi et al. [82] just interpolates phrases from the training data and thus does not include unseen linguistic patterns but also achieves high gains with a pre-trained model.

**Finetuning existing data augmentation approaches**. In general, most of the promising data augmentation methods have limits and challenges that may be overcome due to further research. The generative models or their output needs to be conditioned on the specific class, otherwise the created instances might not preserve the label. This conditioning is oftentimes reached through training a model, which in turn needs enough data to be consistent. Bayer et al. [43] show that the conditional model can replicate the data class better if the problem definition and task data is relatively narrow. Tasks with a broad variety of topics in the data seem to be less suitable. This problem might be mitigated by new conditioning methods. Currently most approaches are extended by filter mechanisms. The existing mechanisms, detailed in Section 3.5, have some drawbacks, which might be reduced in the future. Another obstacle is that the generative models can require many resources and time to create new instances [43]. Therefore, lightweight alternatives need to be tested in this setting, what might prevent a high dependence on resources, described as the high resource wall problem by Bayer et al. [43]. Furthermore, methods like round-trip translation are limited by the underlying model. For example, Marivate and Sefara [57] hypothesize that they might not be good for social media data, where the error of the translations increases. This problem will be addressed, as machine translation models get more capable in translating these difficult instances.

For adversarial examples, Liu et al. [113], hypothesize that the good generalizability performance stems from the perturbation of the embedding space in contrast to the input space. However, the data space adversarial training methods should not be disregarded too early, as, for example, Ebrahimi et al. [16] show that their data space method achieves better results than the virtual adversarial training by Miyato et al. [35]. A general challenge with adversarial training is that they can disturb the true label space in the training data. For example, adversarial example generators often rely on the belief that close input data points tend to have the same labels [105]. Concerning the data space methods, this is often not true for natural language tasks, where few words or even characters determine the class affiliation (e.g., sentiment classification: "I can't like the movie" -small\_transformation-> "I can' like the move"). Whether this applies to the adversarial example generators in the feature space needs to be evaluated. If so, research needs to find a way to exclude the cases where small transformations disturb the labels and at best include cases where stronger transformations still preserve the labels. For this, the inspection of feature space methods would be helpful, which is difficult due to their high dimensional numerical representation. The same applies to the interpolation methods of the feature space, where a back transformation to the data space is not trivial. Nevertheless, there exist approaches such as those from Liu et al. and Wan et al. [114], [115], which use encoder-decoder architectures that are able to transform the newly created instances to the data space. An inspection of interpolated instances could lead to interesting insights. This opens another research direction where the interpolation of instances in the data space could be further investigated. A method that initially implements this behavior is SUB<sup>2</sup> (Section 3.1.3.2), which interpolates instances of the data space through sub-phrase substitutions. This, however, does not result in a high diversity, which is particularly interesting. In this regard, a further analysis of the GPT-3 language model by Brown et al. [133] could be valuable, as it shows very interesting interpolation capabilities in the data space.

However, even avoidably inferior methods can achieve better results if they are integrated sensibly. The work of Jungiewicz and Pohl [59] can serve as an example. They perform synonym substitution only if it increases the loss of the model. There we can see that some data augmentation techniques proposed in the different groups are advanced, sometimes adopting existing methods and refining them. We try to highlight some of those works in Table 8 to show which research directions can be considered in the future. We want to mention that these methods are not necessarily the best in their groups. The selection is made by the author team on the basis of the information gathered during writing this survey.

Space	Group	Work	Method description	Improvement
	Character	[16]	Flip a letter if it maximizes the loss	+0.62 Acc. (LSTM)
	Level Noise			
	Synonym	[59]	Only replace words with a synonym if it maximizes	+1.2 Acc. (Kim CNN)
	Replacement		the loss	
Data Space	Embedding Replacement	[17]	Choosing embeddings based on the counter-fitting method	-0.6 – +1.9 Acc. (CNN)
		[36]	Counter-fitting, language model selection and maximizing the prediction probability	Safer model (LSTM)
	Language Model Replacement	[60]	c-BERT integrated in reinforcement learning scheme	+0.73 - +1.97 Acc. (BERT)
		[64]	c-BERT and embedding substitution for compound words	+1.9 - +21.0 Acc. (TinyBERT)
	Phrase Level Interpolation	[82]	Substitutes substructures	+20.6 - +46.2 Acc. (XLM-R)*
	Round-trip Translation	[46]	Random sampling with a temperature parameter	+1.65 Acc.
	Generative	[43]	Conditional GPT-2 with human assisted filtering	-2.54 F1 - +15.53 Acc. (ULMFit)*
	Methods	[97]	GPT-2 with a reinforcement learning component	+1.0 - +4.3 F1 (XLNet)*
Feature	Noise	[111]	Virtual adversarial training with special optimization	+0.5 - +5.4 Acc. (RoBERTa-l)
		[113]	Virtual adversarial training with curriculum learning	-0.3 Corr +1.2 Acc. (RoBERTa-l)
		[89]	Embedding noising	+0.0 Corr +4.4 Acc. (RoBERTa-1)
Space		[122]	Interpolation after last layer of the transformer	-0.01 Acc +2.68 Corr. (BERT-l)
	Interpolation	[87]	Interpolation of a random BERT layer	+0.0 - +4.6 Acc. (BERT-b)*
		[126]	Interpolating neighbors and reordered versions	+0.53 - +1.57 F1 (BERT-b)*

Table 8: Collection of some of the most advanced data augmentation techniques for text classification

\* Results contain tests on low data regime datasets

## **5** CONCLUSION

This survey gives an overview over data augmentation approaches suited for the textual domain. Data augmentation is helpful for reaching many goals, including regularization, minimizing label effort, lowering the usage of real-world data in sensitive domains, balancing unbalanced datasets, and increasing robustness against adversarial attacks (see Section 2). On a high level, the data augmentation methods are differentiated into methods applied in the feature and in the data space. These methods are then subdivided into more fine-grained groups, from noise induction to the generation of completely new instances. In addition, we propose several promising research directions that are relevant for future work. Especially in this regard, a holistic view on the current state of the art necessary. For example, the increasing usage of transfer learning methods make some of the data augmentation methods obsolete as they follow similar goals. Hence, there is a need for more sophisticated approaches that, for example, are capable of introducing new linguistic patterns not seen during pre-training, as suggested by Longpre et al. [4].

While data augmentation is increasingly researched and very promising, it also has several limitations. For instance, many data augmentation methods can only create high quality augmented data if the original amount of data is large enough. Furthermore, like Shorten and Khoshgoftaar [5] describe, data augmentation is not capable to cover all transformation possibilities and to eliminate all kind of biases in the original data. Adopting the example of Shorten and Khoshgoftaar [5], in a news classification task in which there are no articles containing sports, the standard data

augmentation methods will most certainly also not create sport articles, even though this would be necessary. In contrast, data augmentation might induce new undesirable biases. For instance, language models like GPT-2 can contain biases that are then propagated into the dataset [134]. The wide variety of techniques and some very sophisticated methods also bring another layer of complexity that needs to be understood. Moreover, data augmentation can take a lot of time, making not all methods feasible for time critical machine learning development domains, e.g., in some areas of crisis informatics. With data augmentation, there also comes a demand for more resources, especially in the context of training generative models.

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