Text Data Augmentation: Towards better detection of spear-phishing emails

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Abstract. Text data augmentation, i.e. the creation of synthetic textual data from an original text, is challenging as augmentation transformations should take into account language complexity while being relevant to the target Natural Language Processing (NLP) task (e.g. Machine Translation, Question Answering, Text Classification, etc.) [8]. Motivated by a business application of Business Email Compromise (BEC) detection, we propose a corpus and task agnostic text augmentation framework combining different methods, utilizing BERT language model [10], multistep back-translation and heuristic. We show that our augmentation framework improves performances on several text classification tasks using publicly available models and corpora (SST2 [53] and TREC [33]) as well as on a BEC detection task. We also provide a comprehensive argumentation about the limitations of our augmentation framework.

Keywords: Email Security · Business Email Compromise · Spear Phishing · Email Spoofing · Artificial Intelligence · Supervised Learning · Data Augmentation · Text Augmentation · NLP.

1 Introduction

It is important for machine learning models to generalize outside the training data. Achieving such a generalization is often challenging because of limited data amount, annotated data acquisition being costly. Data augmentation which consists in creating new samples from existing ones, pushes toward generalization by increasing samples diversity and reinforcing data characteristics such as invariances.

Ubiquitous in computer vision and audio analysis, data augmentation contribution to benchmark results is significant [45,51,56]. These data augmentation techniques usually involve relatively simple operations (e.g. light distortion, frequency modulation, image rotation, wavelength shifting, etc) leveraging data continuity and our knowledge about invariances regarding the end task (e.g. object detection, voice recognition, etc). Data augmentation, however, has had

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1 Approach to solve a problem employing a practical method that is not guaranteed to be optimal.
limited application in Natural Language Processing (NLP). Guaranteeing augmented texts readability, intelligibility, grammatical correctness and relevance to a given NLP task is a difficult challenge often involving domain or corpus dependent methods \cite{12,26,61}. Indeed, text processing operates in a discrete space of words and cope with natural language complexity (e.g. polysemy, ambiguity, common-sense knowledge \cite{39} usage, long range dependencies between words, etc.).

Recently, language representation models \cite{10,32,47,64} leveraging transfer learning have emerged, helping improve model generalization on NLP tasks. For instance, BERT \cite{10} or XLNet \cite{64} have been successfully finetuned improving state-of-the-art NLP results without requiring data augmentation. However, text augmentation still seems relevant in domains where annotated data collection associated cost is particularly high. It is the case of Business Email Compromise (BEC) detection.

BEC are among the most advanced email attacks relying on social engineering and human psychology to trick their targeted victim \cite{22,38,46}. BEC emails convey attacks through their textual content (e.g. impersonation, request of payment, of sensitive information, etc) almost indistinguishable from legitimate content (see Figure 1), evading traditional email filtering methods \cite{20,31,31,42,43}. Examples of BEC categories are given in Table 12. BEC emails targeted and elaborate content drives their rarity \cite{7,17}.

Subject: Same day payment

Hi Harry,
Hope your day is going on fine. I need you to make a same day UK payment for me. Kindly email me the required details you will need to send out the payment. I will appreciate a swift email response.
Kind regards,
Jack

Fig. 1: Example of CEO fraud email
For these reasons BEC are particularly difficult to detect and a well conducted attack can lead to substantial financial losses. "In 2018, the IC3 received 20,373 BEC/E-mail Account Compromise (EAC) complaints with adjusted losses of over $1.2 billion." Collecting BEC is very challenging as there is no public corpora, and, in addition to being rare, BEC are not often reported. We developed a framework which combines methods to anonymize and augment our corpus made of BEC and short benign texts extracted from emails. This text augmentation framework is corpus and task agnostic so it can be easily used in other contexts (e.g. movie reviews sentiment analysis with Stanford Sentiment Treebank (SST-2), or question classification with Trec REtrieval Conference (TREC-6)). Examples of augmentations obtained using our framework are presented in Table 1. We leverage this framework to tackle BEC detection. Indeed we generate augmentations with the objective of improving our email text classifier (see Section 4), part of our BEC detection pipeline.

| Dataset | Original text | Augmented text |
|---------|---------------|----------------|
| SST-2   | the entire movie establishes a wonderfully creepy mood | the whole movie creates a wonderfully scary mood |
| BEC     | Hello Cassie, I need you to update my bank account on record, also what pay date will the change be effective? Please advise so that i will furnish you with my new account details. | Hello Maureen, I have to update my bank ACCT in the register, also on what date of payment will the modification be effective? Please contact me for my new ACCT details. |

Table 1: Augmentation examples

The contributions of our paper are the following:

- We propose a corpus and task agnostic framework that can be easily used to augment any English text corpus without the need to train or finetune models. Our framework leverages an ensemble of methods (e.g. translation, heuristics, BERT “Masked LM”, WordNet replacements, etc) combined for the first time, to the best of our knowledge.
- We assess the contribution of our framework to public datasets. Datasets description, and experimental results are presented in Section 4.
- Finally, we provide a discussion on the limitations of our framework in Section 5.

## 2 Related Work

Text augmentation is usually applied in a discrete space of words, in which a simple change implies to change a whole word. Such changes lead to the use of word replacements methods to augment texts. Those replacements are valid if
they preserve data characteristics which can be achieved in supervised learning settings guaranteeing augmented texts compatibility to their labels.

Preserving texts meaning through the augmentation may be sufficient to satisfy label compatibility in many contexts. Thus, some works rely on WordNet to find synonyms replacements, while others leverage word embeddings and latest pretrained language models such as BERT. Our work profits from both methods. Besides word replacements, other operations at word level have been explored such as word dropout or word swap. However, these operations do not guarantee sentence readability or syntax validity, potentially bringing discrepancy between augmented texts and original ones. We chose not to use such operations in this work.

Natural language generation can also be used to augment text, however guaranteeing label compatibility implies control over the generation process. Paraphrase generation has been widely studied and may provide sufficient control over the generation process. For instance, Gupta et al. use a Variational Autoencoder (VAE) conditioned on the original text in their paper, and Li et al. propose to use a generator and evaluator network with a supervised training and Reinforcement Learning finetuning. These works have shown promising results but there is still a gap in term of readability and relevance between generated and ground truth paraphrases. Moreover, these architectures can be complex to implement (e.g. several training phases, different networks).

An alternative to paraphrase generation is back-translation. Machine translation has significantly improved in the last years. This improvement is due to the growing use of Neural Machine Translation. Neural Machine Translation relies on Seq2Seq model compressing the source language text before generating the target language text. Through multiple compressions and generations with different translation models, back-translation allows to generate paraphrases. This method has already been successfully used for text augmentation or paraphrase generation. We implemented our version of a multi-step back-translation.

Some works also explored augmentation in word embedding space. In such a space, texts are represented as a concatenation of continuous word vectors referred to as word embeddings. This continuous text representation can then be used to feed NLP models. Similarly to computer vision where noise can be applied to augment images in the continuous pixel space, Zhang and Yang study the addition of noise in the continuous word embedding space. Noise or small variations can occur on image pixels due to sensor uncertainty or adversarial attacks, consequently noise augmentation improve model robustness to small variations. However, in natural language, the word embedding for a same word in a same context will not vary as the word embedding is the output of a deterministic model. We argue that adding noise to words embeddings may bring discrepancy as the augmented word embeddings cannot exist "naturally". We chose not to explore augmentation in the embedding space.

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2 Tag associated to each data sample in regards to a task.
It is possible to combine different text augmentation methods. For instance, the study of Giridhara et al. [14] combines augmentation at word level and word embedding level, and the work of Wei et Zou [59] combines different simple text editing methods. As in computer vision, we argue that combining different augmentation methods help to improve augmented text diversity. Our proposed framework uses an ensemble of augmentation methods.

3 Method

We propose a new data augmentation framework that combines existing techniques while ensuring that augmented texts are good candidates to improve the original dataset and the generalization of machine learning models trained on it. Indeed, it is paramount to ensure that augmented data does not “poison” this original dataset.

Our proposed augmentation framework generates an augmentation pipeline for each augmentation attempt as the one shown in Figure 2. Such an augmentation pipeline includes:

- A normalization module that tokenizes and anonymizes the input text.
- A number $k$ of successive transformation modules randomly selected that augments the text.

Fig. 2: Generic augmentation pipeline for each augmentation attempt. $k$ is generated based on the initial text length.
A validation module that filters out the augmented text candidate.

At the end of the pipeline the augmented text may be kept or discarded. Consequently, as we parameterize the number of augmentation pipeline generated per initial text, the number of augmented texts is limited and might vary for each initial text.

This architecture allows us to easily tune the different modules (adding blocks, adjusting them or removing them) without impacting the rest of the augmentation algorithm. We now describe each module in details.

3.1 Normalization

Textual data, as part of any natural language processing pipeline, must be normalized. This is important as textual data might come from different sources, in different format. Normalization helps parsing the text into separate tokens representing words or punctuation marks and ensures correct encoding for those tokens. Our normalization module also includes further text processing by providing additional characteristics about each identified token (e.g. Part-Of-Speech (POS) tagging, Named Entities Recognition, stemming [8, 37]). These characteristics are leveraged by transformation modules but also to perform text anonymization (see Section A for details).

Indeed, in the context of BEC detection, we are often dealing with confidential data (i.e. person to person emails in different contexts such as business or private communication) which is often a concern for companies. To use such data, we anonymize each email content. Consequently our normalization module tackles text anonymization. It includes the recognition and replacement of some named entities with generic placeholders (e.g. “John” will be replaced with “ENTITY FIRST NAME MALE 0”, see Section A.1 for examples and the list of entities anonymized). Those placeholders are eventually substituted with randomly generated replacements, while the sentence coherence remains thanks to the suffixed number used. Text anonymization is disabled for data with no privacy concerns such as public corpora.

3.2 Transformation

As mentioned in Section 2 several augmentation techniques have been presented before but never combined to this extend, to the best of our knowledge. We propose to randomly apply several textual transformations, combining existing approaches and new ones, such as:

- The use of multiple steps of machine translation applied to the text.
- The replacement of words leveraging BERT model, and WordNet lexical database.
- The generation of abbreviations and misspellings relying on heuristics.

Text transformations can be applied \{0..n\} times. However, some transformations must be processed in a specific order (e.g. misspelling words may affect
the ability of some other transformations to process the text correctly). We de-
tail in subsections below our different transformations, more examples of each
transformation can be found in Section A.

Word replacements: We consider three kinds of replacements:

- **Abbreviations replacement**: Abbreviations are quite common in natural lan-
guage, so a word or group of words may be replaced by an abbreviation and vice versa (e.g. “IMO” stands for “In my opinion”). We perform abbreviation replacements from expanded to abbreviated form and inversely relying on respective word-pair dictionaries. An abbreviation may correspond to different expended forms based on the context (e.g. “PM” → {“Post Meridiem”, “Project Manager”, “Prime Minister”, etc.}). We excluded these context dependent abbreviations from our replacement mappings not to make inconsistent replacements and change the text meaning. We make the assumption that abbreviation replacements are useful or at least not harmful to most NLP tasks.

- **Misspellings replacement**: Misspellings are quite common in natural language as they are often accidental. However, it is unlikely that they appear with our other types of replacements. We generate misspellings relying on a heuristic to simplify misspellings occurrence and letter replacements. Through these generations we also make the assumption that misspellings are useful or at least not harmful to most NLP tasks. Moreover, in our context of fraud detection, misspellings are important for two reasons:
  - They can convey a sense of urgency,
  - They are traditionally used to evade security technologies based on text analysis [18,58].

- **Other words replacements**: For these replacements our goal is to paraphrase the input sentence, consequently we want to replace words by synonyms or near-synonyms [54]. To do so we developed two different methods leveraging pretrained BERT [10] to increase replacements diversity.
  
  For the first method we randomly masked a chosen proportion of words in the original sentence. We then used pretrained BERT to output a probability distribution over the vocabulary for each masked word. Eventually we chose the replacement candidate sampling over the distribution due to the inherent uncertainty of masked word prediction task. In order to improve replacements, we added conditions on masking and sampling operations taking into account POS tags for syntax continuity and cosine similarity between original word and replacement candidate embeddings. If the conditions are not met, the replacement candidate is discarded.
  
  For the second method we use both WordNet [41] and BERT. Similarly, the first step is to pick randomly a chosen proportion of words to replace. For each word to replace, we obtain a list of replacement candidates using WordNet synsets and words POS tags. We then filter the list of candidates with BERT by computing the cosine similarity between the original word embedding and the replacement candidate embedding. We only keep candidates
whose cosine similarity is above a chosen threshold. Eventually we randomly choose a replacement from the filtered list of WordNet candidates.

As mentioned in Section 2, other works use language models (e.g. BERT) to perform word replacements in text augmentation context [26,28,61]. However these methods are not corpus agnostic as language models are finetuned, conditioning replacements on text labels. Our methods do not involve any finetuning and can directly be used on any text corpus.

**Multiple steps of translation:** As mentioned in Section 2, back-translation has been used in the context of text augmentation [12,52,63], we propose a method relying on multiple steps of machine translation. Our method uses a strongly connected translation graph such as the one represented in Figure 3. Each node $L_i$ represents a language, and each edge $MT_{ij}$ represents a machine translation engine able to translate from $L_i$ to $L_j$. We generate a cycle originating from and terminating to the English node and passing through several intermediate languages, achieving a multi-steps back-translation. Numerous constraints can be applied on the generation of cycles (e.g. length of the cycle, performance of its edges, etc) affecting back-translated texts quality and diversity. In our settings, we use Google Translate engine 3 for all our edges. We limit the cycle maximum length to 3 (i.e. simple and 2-steps back-translation possible), for instance a path may be: English $\rightarrow$ German $\rightarrow$ Danish $\rightarrow$ English. Additionally we only consider nodes among best performing translation pairs with English. Because our augmentation framework includes a validation module we aim toward a trade-off between augmentation validity and diversity for back-translations instead of prioritizing validity only. Indeed keeping only the best performing nodes with English may improve validity (e.g. label compatibility) but reduce diversity, while limiting the cycle length to 3 instead of 2 may increase the diversity but will add uncertainty on the validity.

### 3.3 Data validation

Each augmented text is validated with the objective of improving the original dataset and the generalization of machine learning models trained on it. Ideally an augmented text should ensure label compatibility and bring an added value to the dataset. Making the assumption that diverse paraphrases satisfy these two objectives, the goal of our validation module is to discard augmentations that may be too dissimilar or too redundant when compared to the original text. To do so we trained a text pair classifier on an internal dataset composed of sentences pairs labeled as redundant, valid, invalid or dissimilar (see Section A.4). Each text pair is mapped to a feature vector using a set of similarity metrics. We considered the following similarity metrics: BLEU score [44], METEOR score [2], bag of word representation with cosine similarity [19], corpus knowledge-based text semantic similarity [40], sentence similarity based on semantic nets.

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3 https://cloud.google.com/translate

4 https://www.teachyoubackwards.com/
and corpus statistics [34], BERT embeddings with Word Mover Distance [10, 29], BERT embeddings with cosine similarity, Universal Sentence Representation with cosine similarity [9], and Sentence Embeddings with cosine similarity [49]. For metrics leveraging corpus statistics [34, 40], we used the Brown corpus, a standard corpus of American English [13]. We initially chose similarity metrics different enough to increase their potential complementary. Thus we considered metrics leveraging WordNet knowledge base [34, 40], metrics based on words or n-grams co-occurrence [19, 44], metrics leveraging language models [9, 49]. We eventually refine the set of metrics to use, with the objective of improving text pair classifier performance under constraints of storage and computation time. Our validation module accepts an augmented text candidate if the text pair classifier predicts the label valid, the candidate is discarded otherwise.

4 Experiments

In order to evaluate our data augmentation framework, we performed several experiments with publicly available models and corpora from text augmentation state-of-the-art. Additionally, we present results obtained for our use case of BEC detection.

5 Some of the aforementioned metrics are not named and are referenced using the title of the paper in which they are introduced.
4.1 Datasets

The benchmark datasets used are SST-2 [53] and TREC-6 [33]. SST-2 is a dataset made of movie reviews with two labels (positive or negative). TREC-6 is a multi-label-questions dataset, each label corresponding to a question type (e.g. Abbreviation, Description and abstract concepts, Entities, etc).

We also used a private dataset for BEC detection. This dataset is composed of anonymized texts labeled as suspicious through different BEC typologies (e.g. ceofraud, w2fraud, payrollfraud) or nonsuspicious, all extracted from emails. BEC corpus labels definitions can be found in Section A.5. Our BEC detection dataset is highly unbalanced, as mentioned in Section 1, BEC emails texts are not common. Class imbalance is a known issue in Machine Learning [4,27] as most models assume data to be equally distributed which results in poor performances on minority classes. To address this imbalance we use our augmentation framework only on minority classes (i.e. BEC typologies) samples referred as BEC* in Table 2.

| Dataset | \(c\) | \(l\) | \(N\) | \(|V|\) |
|---------|-----|------|------|------|
| SST-2   | 2   | 9    | 613  | 16185|
| TREC-6  | 6   | 10   | 952  | 9592 |
| BEC     | 6   | 48   | 1224 | 8042 |
| BEC*    | 5   | 38   | 115  | 1153 |
| Table 2: Datasets statistics |

Table 2 contains for each dataset the number of classes \(c\), the average sentence length \(l\), the total number of texts for each dataset \(N\), and the vocabulary size \(|V|\) (Detailed class repartition for each dataset can be found in Section A.5).

These datasets are diverse in terms of samples number and texts length allowing us to study the impact of these factors on the added value of our augmentations.

Intuitively we expect a stronger added value on a small dataset with long texts as the space of possible augmentations is constrained by the text length. Moreover, a large dataset might sufficiently achieve good generalization.

Besides samples number and texts length, the complexity of the classification task must be taken in account. As mentioned in Section 2 augmented texts must ensure label compatibility to be relevant. If the natural language task is complex (e.g. involves figurative language, is sensitive to small changes on specific syntactic components) augmented texts may hardly ensure label compatibility which, in the end, would reduce augmentation added value.

We argue that we also have a diversity in terms of task complexity as can be seen in Table 2:

- TREC-6 questions are divided into broad semantic categories, questions are both short and objective;
| Dataset  | \textit{Label}_1: Sample_1                                      | \textit{Label}_2: Sample_2                                        |
|----------|----------------------------------------------------------------|------------------------------------------------------------------|
| TREC-6   | \textit{Locations}: “What is the capital of Zimbabwe?”        | \textit{Abbreviation}: “What does the abbreviation SOS mean?”   |
| SST-2    | \textit{Negative}: “it feels like a community theater production of a great Broadway play even at its best, it will never hold a candle to the original” | \textit{Positive}: “few films this year have been as resolute in their emotional nakedness” |
| BEC      | \textit{ceofraud}: “I need you to process a payment for me, let me know if you’re available, so I can send the account info. Regards” | \textit{nonsuspicious}: “I will pay this invoice per Randy. If you need anything else just let me know. Thanks.” |

Table 3: Classification task complexity

- SST-2 implies figurative language;
- BEC classification is sensitive to both syntax and semantic as a suspicious email will contain a request on some specific topics (e.g. payment, sharing of sensitive information, etc).

Thus we analyze the resilience of our augmentation framework to different kinds of classification tasks and complexity.

In order to respect the classification task associated with public corpus, we use the provided train/test split for TREC-6 and SST-2 datasets. For our BEC detection task we apply a 70%/30% stratified split.

We only apply our augmentation framework to the train split of each dataset.

### 4.2 Models

To study our augmentation contribution on different text classification tasks, we use the \textit{CNN for sentence classification} \cite{24}. This model has smaller capacity\footnote{Measure of the complexity, richness, flexibility of the space of functions that can be learned by a machine learning model.} than recent language models \cite{10, 47, 64}, however it has been widely used in text augmentation state-of-the-art \cite{26, 59, 61, 65}. For the BEC dataset, we also assess our augmentation contribution fine-tuning \textit{BertForSequenceClassification} implemented in HuggingFace’s \cite{60} transformer package \footnote{https://github.com/huggingface/transformers}. In our configuration, \textit{BertForSequenceClassification} is composed of the pretrained BERT \textit{base uncased} model followed by a linear classifier taking as input the first BERT token output (i.e. \texttt{[CLS]} token embedding). Following \cite{24} we train our classification models using early stopping on a development set (\textit{dev set}). For SST-2 the dev set is provided, for TREC-6 and BEC detection datasets we generated it with respectively a 90%/10% and 80%/20% stratified split of the train set.

Moreover, we leverage different models in our augmentation framework. As described in Section 3 BERT is used for word replacements, more specifically the pretrained \textit{BertForMaskedLM base uncased} from HuggingFace’s transformer
package. BertForMaskedLM is used as a denoising autoencoder to predict masked tokens from an input text, “Masked LM” being one of the pretraining tasks of BERT \cite{10}. When BERT word replacement method is chosen (Section 3) we leverage BertForMaskedLM to output a probability distribution over the vocabulary for each masked token. We also use this model to output word embeddings (i.e. last hidden state). As described in Section 3 word embeddings are necessary to filter out replacement candidates. For our validation engine we trained a LinearSVM on our internal dataset of text pairs described in Section A.4.

4.3 Data augmentation

We performed augmentation on each dataset using our framework. We generated 10 augmentation pipelines for each sample, as mentioned in (Section 3), the number of achieved augmentations per text varies. The average number of effective augmentations per sample (i.e. augmentation factor) is recorded in Table 4. We argue that the difference between augmentation factors is driven by the average text size of those datasets (see l in Table 2). Consequently, the augmentation contribution potential is higher on BEC than on SST-2 or TREC-6.

| Dataset | Augmentation factor |
|---------|---------------------|
| TREC-6  | 3.4                 |
| SST-2   | 4.7                 |
| BEC*    | 8.3*                |

Table 4: Average augmentation factor per dataset. For BEC dataset only minority classes are considered.

4.4 Impact of data size

We analyzed our augmentations contribution through different data regimes. For this purpose, TREC-6 and SST-2 datasets are augmented. Figure 4 depicts the results obtained by training a model on three types of data:

- **Originals**, corresponding to samples from TREC-6 or SST-2 datasets;
- **Augmentations**, corresponding to all samples generated by our augmentation framework using the samples present in Originals;
- **Merged**, containing all samples from Originals and Augmentations.

The proportion of Originals samples used to create datasets related to each data regime varies from 10% to 100%. For each proportion a new data trio (Originals, Augmentations, Merged) is generated and used to train the CNN \cite{24}. For instance, we may consider a 10% subsampling of TREC-6 dataset, i.e. Originals, from this subsample generate augmentations, i.e. Augmentations, and combine
the subsample and related augmentations into a single dataset $\textit{Merged}$. Evaluation is performed on test sets provided with public corpora. Figure 4 validates that our augmentations preserve label compatibility on different task complexities as there is no significant performance drop when training models solely on augmented samples (i.e. $\textit{Augmentations}$). Figure 4 also shows the contribution of our augmentations specially in low-data regimes. This is depicted by the positive and decreasing performance gap between $\textit{Merged}$ and $\textit{Originals}$. We could argue that our augmentation benefit goes beyond low-data regime (e.g. until 50% and 80% of TREC-6 and SST-2 datasets respectively), however performances are model dependent. Indeed, $\textit{CNN for sentence classification}$, widely used in text augmentation state-of-the-art, is outperformed by latest language models [5,48,55] leveraging transfer learning. These models show excellent generalization reducing augmentations added value [28].

4.5 Impact of augmented data size

To improve our text classifier generalization, we augmented our BEC corpus (Table 2) on minority classes. In this experiment we consider the whole BEC corpus. To comply with our previous definitions, we refer to as $\textit{Merged}$ the dataset containing BEC corpus and all related augmentations. On average 8.3 augmentations were generated for each sample (see Table 4), which significantly increases minority classes weight in the learning phase. To dissociate classes weight effect from our augmentations contribution we created a BEC "duplicated" corpus ($\textit{Duplicated}$) where each minority class sample is duplicated to replicate the augmentations number in $\textit{Merged}$. 

Fig. 4: Performances on SST-2 and TREC-6 as a function of dataset size
To analyze augmentation factor impact, we capped\footnote{A capping factor in the number of augmentation only guarantees that the maximum number of augmented texts generated from an original text is equal to the factor, but it does not constrain the minimum number of augmentations.} the augmentations per sample from 0 to 10 and trained CNN on each data type (i.e. Original, Duplicated and Merged). The results obtained when training CNN for text classification are shown in Figure 5.

Our augmentations contribution is significant in this low-data regime. We can notice a large gap between Merged and the other data types capping over 2 augmentations per sample. However, contrary to BEC duplicated data, performances with BEC augmented data does not improve above a cap of 6 (i.e. no added value above 6 augmentations per sample). This limitation might result from the difficulty for our framework to continuously produce both diverse and label compatible augmentations. Limited diversity among augmentations is a good candidate to explain this lack of improvements as we validated previously label compatibility preservation in different contexts. However, a lack of improvement could also be explained by factors external to our augmentations such as the classifier model capacity. For this reason, we performed a human evaluation on augmentations related to randomly selected Original samples. This evaluation pointed out a limited diversity among augmentations, examples of redundant augmentations are shown in Section A.6.

4.6 Our use case with class imbalance

In this experiment BertForSequenceClassification is also considered besides CNN for sentence classification. As mentioned previously, pretrained general language
models have improved state-of-the-art on different NLP tasks. Leveraging self-supervised pretraining and Transformer architecture [57] these models are able to learn and transpose natural language concepts to specific tasks, achieving excellent generalization. Table 5 regroups the best results obtained when varying the augmentations cap per sample.

As shown previously (Figure 5) augmentations are key for CNN model generalization, with a contribution well above classes weight. With \textit{BertForSequenceClassification}, while being less significant, augmentations still have a positive impact over class weights. Thus we exemplified that leveraging pretrained language models such as BERT, data augmentation stays relevant for finetuning in low data regimes.

5 Further analysis

5.1 Corpus agnostic framework

We choose to design our augmentation framework to be corpus agnostic to address the diversity of use cases within our company. Initially motivated by the challenging task of BEC detection, the development of our framework evolved toward an internal service exposed as an API to augment English texts in several contexts (e.g. BEC detection, email generation for user security awareness training, fraud simulation, etc). We recognize that being corpus agnostic degrades augmented texts’ quality (i.e. label compatibility and diversity) as it prevents the use of context specific methods, such as model finetuning [26, 60, 61]. We proposed several workarounds to mitigate this negative effect. Firstly, as detailed in Section 3 we constrain words replacement. Replacement candidates must preserve their original initial POS tags and are filtered based on cosine similarity measurements of BERT embeddings. This creates some control which reduces inconsistent replacements, however it is not optimal. Indeed, BERT embeddings are not optimized for cosine similarity measurements which suppose that all dimensions have equal weights \(^9\), and both methods may discard some valid replacements. Additionally, we developed a validation module called at the end of the augmentation pipeline (Section 3) to reduce the risk of compromising labels. This module is further discussed in the following subsection. Results in Section 4 have shown in different text classification contexts that our framework produces label compatible augmentations despite being corpus agnostic.

\(^9\) https://github.com/UKPLab/sentence-transformers/issues/80

| Dataset     | CNN 24 | \textit{BertForSequenceClassification} |
|-------------|--------|---------------------------------------|
| Original    | 0.560  | 0.903                                 |
| Duplicated  | 0.629  | 0.918                                 |
| Augmented   | 0.795  | 0.942                                 |

Table 5: BEC detection balanced accuracy
5.2 Augmentation limitation

**Diversity:** The goal of data augmentation is to reinforce patterns and characteristics associated to the data. However, one caveat of this is to capture specificity of the training data and reinforce them. This can only be avoided by injecting diversity in the original data when augmenting it while still preserving the original features of the data.

![2D visualization of some augmented classes from BEC corpus and average similarity between samples.](image)

| similarity<sub>ori-ori</sub> | similarity<sub>ori-aug</sub> |
|-------------------------------|-------------------------------|
| 0.47                          | 0.81                          |

(e) Average similarities

Fig. 6: 2D visualization of some augmented classes from BEC corpus and average similarity between samples.
projecting each text to an embedding space \cite{49} and leveraging t-SNE \cite{36} for 2D visualization.\footnote{2D visualization implies a significant loss of information about data representation due to the substantial dimension reduction.} Moreover, we compare similarities between samples (Figure 6 - Table 6e) by considering all BEC corpus augmented classes. The metric \textit{similarity}_{ori-ori} corresponds to the average similarity between \textit{Original} samples of the same class, and \textit{similarity}_{ori-aug} corresponds to the average similarity between each \textit{Original} sample and their related \textit{Augmentations}. The similarity metric used is the cosine similarity between text embeddings \cite{49}. Detailed results for each BEC corpus augmented class is provided in Section A.6.

Visualization and similarity values (Figure 6) suggest that augmentations, while bringing diversity, are restricted to the neighborhood of original samples they relate to. The challenge of diversity is to expand these neighborhoods while preserving augmentations validity. We argue that using an ensemble of augmentations methods rather than a single one, helps increase diversity. Our experiments (Section 4) exhibit the ability and limitations of our framework to produce diverse augmentations. These limitations will be addressed in future work improving our existing modules and leveraging new techniques such as natural language generation.

**Validation:** As mentioned earlier, it is important to ensure that augmentations have enough diversity while preserving data characteristics, which is challenging in our corpus agnostic setting.

Indeed, we cannot guarantee that our augmentation techniques (e.g. constrained words replacements, multi-steps back-translation) always preserve data characteristics. For this purpose, we use a validation module constraining our augmentations to be paraphrases. We made the assumption that paraphrasing original texts brings sufficient control to prevent data poisoning, this assumption will be discussed in the following subsection. Moreover, as presented in Section 3 our validation module also discards detected near duplicates of original texts to augment data diversity.

However, we are aware that this validation module is not an oracle, measuring text similarity still being an open problem in NLP \cite{35}. Additionally, our validation module relevance depends on different factors such as our sentence pairs dataset quality or our design choice of relying on similarity metrics combination.

**Task influence:** Data augmentation is strongly linked to the task performed. Similarly to what is done for image or sound augmentation, it is important to consider how data is processed and what is required by the task before considering augmentation.

Our framework being corpus and task agnostic, this preliminary analysis is not possible. Moreover, paraphrasing to prevent data poisoning may not bring sufficient control in all contexts.

For example, if the task is authorship attribution (i.e. the process of determining the writer of a document), using back-translation to augment texts may
poison the data, altering some writer style characteristics (e.g. vocabulary distribution or syntax representation). Similarly, if the task is to identify pairs of sentences, preserving label compatibility is challenging as considering sentences independently may bring inconsistency between augmented sentence pairs and their labels. The modular design of our framework brings flexibility helping to cope with some specific contexts. Through the configuration it is possible to disable components, for instance we may not consider multi-step back-translation in case of authorship attribution.

6 Closing remarks

Using supervised learning to tackle BEC detection presents the contradiction of requiring large quantity of data while BEC are extremely rare. This paradox can be mitigated leveraging data augmentation. Usually text data augmentation relies on a single method, limiting generated data diversity. Furthermore, latest works often leverage corpus dependent techniques (e.g. language model finetuning) increasing the complexity of using augmentation techniques.

We present a new text augmentation framework that is corpus and task agnostic. This framework combines several augmentation techniques and can be easily applied to different NLP projects. Experiments have shown that our augmentation framework improves significantly machine learning models generalization in different low-data regimes contexts. Our analysis on limitations provides additional guidelines on future work. Thus we will consider adding new techniques (e.g. natural language generation) and improving existing ones (e.g. word replacements monitoring, validation module) aiming toward a better trade-off between augmentations diversity and validity (i.e. label compatibility in supervised settings).

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A Appendices

A.1 Example of normalization

If we consider the following text:

| Dear Maxime,  
| Attached, please find new invoices for your kind attention.  
| Thank you.  
| Best regards,  
| Luke |

The textual content is normalized and anonymized as follows:

| Dear ENTITY_FIRST_NAME_MALE_0,  
| Attached, please find new invoices for your kind attention.  
| Thank you.  
| Best regards,  
| ENTITY_FIRST_NAME_MALE_1 |

Table[6] lists entities considered for anonymization. To ensure the consistency of the text, the placeholders are suffixed with a zero based index number.
| Placeholder                      | Description       | Example       |
|---------------------------------|-------------------|---------------|
| ENTITY_FIRST_NAME_MALE          | A man first name  | John          |
| ENTITY_FIRST_NAME_FEMALE        | A woman first name| Melania       |
| ENTITY_LAST_NAME                | A last name       | Sinatra       |
| ENTITY_FINANCIAL_AMOUNT         | A financial amount| 16.45 $       |
| ENTITY_DATE                     | A calendar date   | May 5th 2018  |
| ENTITY_TIME                     | A time            | 5 pm          |
| ENTITY_YEAR                     | A recent year     | 2019          |
| ENTITY_DAY                      | A weekly day      | Monday        |
| ENTITY_ULTIMATUM_DELAY          | A short duration  | 3 days        |
| ENTITY_PHONE_NUMBER             | A phone number    | +1 514 559 2408|
| ENTITY_ADDRESS                  | A physical address| 4220 Queen St, H2W 2E7 Montreal |
| ENTITY_COMPANY_NAME             | A company name    | Vade Secure   |
| ENTITY_URL                      | A web URL         | https://vadesecure.com |
| ENTITY_BITCOIN_ADDRESS          | A bitcoin wallet address | 3FZbg29cjq[***]JnkLtktZc5 |
| ENTITY_EMAIL_ADDRESS            | An email address  | john.doe@anonymous.com |
| ENTITY_PASSWORD                 | A password        | qwertyuiop    |
| ENTITY_ONLINE_USERID            | An online user id | jdoe42        |
| ENTITY_WEB_DOMAIN               | A web domain      | vadesecure.com |

Table 6: Placeholders for entities anonymization

A.2 Examples of text replacements

If we consider the text:

Mary,
Please do you have a moment? Am tied up in a meeting and there is something I need you to take care of ASAP. We have a pending invoice from our vendor. I have asked them to email me a copy of the invoice. I will be highly appreciative if you can handle it before the close of banking transactions for 3:10 pm. I can’t take calls now so an email will be fine.
John

Then applying several word replacements can produce the following augmented text:

Mary,
Please do you have a moment? Am tied up in a meeting and there is something I need you to take care of as soon as possible. We have a new invoice from our vendor. I have asked them to give me a copy of the invoice. I will be very appreciative if you can handle it before the start of banking transactions for 3:10 pm. I can’t take message now so an email will be fine.
John
Table 7 presents the different replacements performed.

| Original element | Replaced element          | Transformation          |
|------------------|---------------------------|-------------------------|
| transactions     | transactions              | MisspellingReplacement  |
| ASAP             | as soon as possible       | AbbreviationsReplacement|
| pending          | new                       | OtherWordsReplacements  |
| email            | give                      | OtherWordsReplacements  |
| highly           | very                      | OtherWordsReplacements  |
| start            | close                     | OtherWordsReplacements  |
| calls            | message                   | OtherWordsReplacements  |

Table 7: Replacements performed
A.3 Example of multistep translation graph

If we consider the text:

Mary,
Please do you have a moment?
Am tied up in a meeting and there is something I need you to take care of as soon as possible.
We have a new invoice from our vendor.
I have asked them to give me a copy of the invoice.
I will be very appreciative if you can handle it before the start of banking transactions for 3:10 pm.
I can’t take message now so an email will be fine.
John

By applying back-translation with the graph represented in Figure 7 we obtain the following augmented texts.

Maria,
Heb je even tijd?
Ik zit vast in een vergadering en er is iets waar je zo snel mogelijk voor moet zorgen.

Translations made here using https://translate.google.com

11 Translations made here using https://translate.google.com
We hebben een nieuwe factuur van onze leverancier.
Ik heb hen gevraagd om mij een kopie van de factuur te geven.
Ik zal het zeer op prijs stellen als u het voor het begin van de banktransacties om 15.10 uur kunt afhandelen.
Ik kan nu geen bericht opnemen, dus een e-mail komt goed.
John

Maria,
Har du et øjeblik?
Jeg sidder fast i et møde, og der er noget, du har brug for at tage sig af så hurtigt som muligt.
Vi har en ny faktura fra vores leverandør.
Jeg bad dem give mig en kopi af fakturaen.
Jeg vil sætte stor pris på det, hvis du kan håndtere det inden banktransaktionens start kl. 15.10.
Jeg kan ikke optage en besked nu, så en e-mail vil være i orden.
John

Maria,
Do you have a moment?
I’m stuck in a meeting and there’s something you need to take care of as soon as possible.
We have a new invoice from our supplier.
I asked them to give me a copy of the invoice.
I would really appreciate it if you can handle it before the start of the banking transaction. 10.15.
I can’t record a message now, so an email will be fine.
John

The reader can notice that:

- The misspelling word “transactions” has been corrected during the back-translation.
- The back-translation can add imperfections to the text e.g. “for 3:10 pm.” replaced by “10.15.”.
A.4 Validation engine dataset

We built an internal dataset to train our validation engine model. This dataset is composed of text pairs labeled as redundant, valid, invalid or dissimilar. Considering texts (text$_A$, text$_B$) we define the pair as:

- **redundant**: if text$_B$ is almost identical to text$_A$ and includes minor change.
- **valid**: if text$_B$ keeps text$_A$ meaning but contain potentially significant vocabulary changes, changes in text structure, sentence reordering, etc.
- **invalid**: if text$_B$ contains some element of text$_A$ but has a different meaning.
- **dissimilar**: if text$_B$ is far from text$_A$ both in terms of meaning and construction.

Table 8 gives an example where text$_A$ is the reference and different text$_B$ are given for each label.

| text$_A$                                      | text$_B$ - Redundant            | text$_B$ - Valid                                      | text$_B$ - Invalid                       | text$_B$ - Dissimilar                   |
|-----------------------------------------------|--------------------------------|-------------------------------------------------------|-----------------------------------------|-----------------------------------------|
| Hi Sarah! Can you please send me the SSN of all employees ASAP. Thanks! | Hello Sarah! Can you please send me the SSN of all employees ASAP. Thank you! | Hello Sarah! it is urgent, can you send the social security number of the whole staff? Thank you! | Hi Sarah! Can you please send me the picture we took with all employees ASAP. Thanks! | Spring is coming, my favorite time of the year. |

Table 8: Validation engine dataset
A.5 Detailed datasets

| SST-2 | 0   | 1   |
|--------|-----|-----|
| trainOriginals | 3 305 | 3 606 |
| trainAugmentations | 17 007 | 15 760 |
| test set | 912 | 909 |
| Table 9: SST-2 class repartition |

| TREC-6 | ABBR | DESC | ENTY | HUM | LOC | NUM |
|--------|------|------|------|-----|-----|-----|
| trainOriginals | 86   | 1 150 | 1 244 | 1 210 | 823 | 854 |
| trainAugmentations | 262  | 3 353 | 4 894 | 4 147 | 3 034 | 2 702 |
| test set | 9    | 138  | 94   | 65  | 81  | 113 |
| Table 10: TREC-6 class repartition |

| BEC | areyouavailable | ceofraud | giftcardscam | payrollfraud | w2fraud | nonsuspicious |
|-----|----------------|----------|---------------|--------------|---------|---------------|
| trainOriginals | 43       | 26       | 15            | 9            | 27      | 808           |
| trainAugmentations | 340     | 226      | 126           | 79           | 183     | 0             |
| test set | 18       | 11       | 6             | 10           | 4       | 347           |
| Table 11: BEC class repartition |
| Label       | Definition                                                                 | Example                                                                                                                                 |
|-------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| areyouavailable | Short email asking for the availability of the recipient, usually with a sense of urgency. One of the goal of this kind of email is to initiate a communication with the victim without using suspect keywords. BEC detection technologies may whitelist an email address after a couple of emails have been exchanged, hence this trick. | “I need you to get a task done for me promptly. Let me know if you are unoccupied”                                                       |
| ceofraud    | CEO fraud is a threat consisting in the impersonation of a position of authority (e.g. CEO) asking a financial action (wire transfer, check, etc) from a company employee with a sense of urgency. It usually targets finance department. The threat relies on the fear of failing to please an authoritative power. | “Please process immediately a wire transfer payment to $45,000. It is an urgent invoice from the business attorney. Banking instructions attached. Thanks” |
| giftcardscam | Gift card scam is a threat consisting in the impersonation of an executive requesting the purchase of gift cards for a special occasion. The message will often tell the victim to stay quiet, trying to make it appear as a surprise. | “Hi, I have a request. I’m planning to surprise some of the staff with gifts, are you available to get a purchase done for me? I will appreciate your assistance and confidentiality. Email me once you get this.” |
| payrollfraud | Payroll fraud is a threat consisting in the impersonation of an employee asking to change direct deposit information. It usually targets HR or finance departments. The goal for the fraudster is to replace in the payroll system the impersonated employee bank account by a fraudulent bank account. | “I have recently changed banks and need to change my direct deposit for payroll. I need your prompt assistance in this matter and when this will take effect.” |
| w2fraud     | W2 fraud is a threat consisting in the impersonation of an executive asking for documents (e.g. W-2 forms) containing employees confidential information, such as SSN. | “I have an important meeting at 10:30 and I need the W-2s of the staff ASAP. Please upload the files to https://drop.box.it for security purposes. Thanks!” |
| nonsuspicious | This label corresponds to all emails we decided not to flag in our BEC detection context, i.e. emails that do not belong to previous labels. There are two types of emails in this category: benign emails that have similar topics (invoice, sense of urgency, etc.), and benign emails that do not have any similar topics (majority of the corpus). | “I will pay this invoice per Randy. If you need anything else just let me know. Thanks.” |

Table 12: BEC corpus labels definition
A.6 Augmentations diversity

Table 13 shows examples of redundancy between augmentations for different Original samples.

| Original sample                                                                 | Augmentation₁                                                                 | Augmentation₂                                                                 |
|---------------------------------------------------------------------------------|-------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| “Hi Stacy. I need you to handle a piece of work for me. Send me your cell # and look forward to my text. Thanks, Joaquin” | “Hi Chris. I need you to handle a job for me. Send me your cell number and wait for my text. Thank you, Ryan” | “Hi John. I need you to handle a job for me. Send me your cell number and wait for my call. Thank you, Alex” |
| “Hello Aurora, Are you available now? Get back to me as soon as this message is received, I need you to handle a purchase. ASAP. P.S: I’m busy now and can’t talk, just reply back. Regards.” | “Hello, Carol, Are you available now? Contact me as soon as this message is received, I need you to manage a purchase, as soon as possible. P.S: I’m busy now and can’t speak, just answer. Best regards” | “Hello Lela, Are you available now? Contact me as soon as this message is received, I need you to manage a purchase, as quickly as possible. P.S: I’m busy now and I can’t speak, just answer. Cordially.” |
| “Emilio, I need the w2 forms for the last five years. We have an audit starting tomorrow and I want to review the forms tonight. Please upload the documents to http://stpkwcyunz.com. Thanks! Randal” | “Matthew, I need the w2 forms for the last five years. We have an audit starting tomorrow and I want to review the documents online. Upload the files to http://shombvtd.com. Thank you! Bryant” | “Leon, I need the w2 forms for the last five years. We have an audit starting tomorrow and I want to review the documents myself. Please upload to https://retshxqigmp.com. Thanks! Guillermo” |

Table 13: Redundancy among augmentations

Table 14 presents detailed similarities for each augmented class in BEC corpus using cosine similarity between text embeddings \cite{49}. similarity\textsubscript{ori-ori} corresponds to the average similarity between Original samples of the same class, and similarity\textsubscript{ori-aug} corresponds to the average similarity between each Original sample and their related Augmentations.
| Augmented Class | similarity_{ori-ori} | similarity_{ori-aug} |
|----------------|----------------------|---------------------|
| areyouavailable | 0.44                 | 0.80                |
| ceofraud       | 0.50                 | 0.81                |
| giftcardscam   | 0.50                 | 0.83                |
| payrollfraud   | 0.62                 | 0.87                |
| w2fraud        | 0.46                 | 0.80                |

Table 14: Detailed similarity between samples for each BEC* corpus labels