Using Adversarial Examples in Natural Language Processing

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Abstract

Machine learning models have been providing promising results in many fields including natural language processing. These models are, nevertheless, prone to adversarial examples. These are artificially constructed examples which evince two main features: they resemble the real training data but they deceive already trained model. This paper investigates the effect of using adversarial examples during the training of recurrent neural networks whose text input is in the form of a sequence of word/character embeddings. The effects are studied on a compilation of eight NLP datasets whose interface was unified for quick experimenting. Based on the experiments and the dataset characteristics, we conclude that using the adversarial examples for NLP tasks that are modeled by recurrent neural networks provides a regularization effect and enables the training of models with greater number of parameters without overfitting. In addition, we discuss which combinations of datasets and model settings might benefit from the adversarial training the most.

Keywords: Neural networks, Adversarial examples, Natural Language Processing, Regularization, Evaluation

1. Introduction

In recent years, deep learning has outperformed many of other machine learning models in various tasks of natural language processing (Amodei et al., 2016; Wang et al., 2017; Yin et al., 2015; Collobert and Weston, 2008). Many of these models have been completely trained in end-to-end manner without any need for hand-crafting. These models are usually very complex and tend to overfit easily, especially in cases of small datasets. For that reason, regularization techniques are often employed in order to prevent overfitting. A popular solution to the lack of data and to model overfitting is dataset augmentation (Simard et al., 2003). This technique automatically generates similar training instances to the ones already present in the dataset, which effectively results in the dataset size increase. While augmenting the visual data is straightforward, the augmentation of text data is non-trivial. Lately, a novel method for creating so called adversarial examples was introduced (Goodfellow et al., 2014b; Szegedy et al., 2013). These examples reveal that the models do not fulfill the smoothness assumption, i.e. the adversarial examples are very similar to the examples in the training dataset, but the already trained models classify them differently than the very similar ones in the training data. When generating such examples during training and employing them in the process of model parameters update, they function as strong regularization. Generating adversarial examples can be understood as a form of dataset augmentation. The aim of this paper is to evaluate the effect of using the adversarial examples during training of the deep recurrent neural networks which process natural language in the form of written text. More specifically, we intend to perturb trainable word/character embeddings (Mikolov et al., 2013) in a way the network is confused, although the new embeddings are extremely close to the original ones.

Our contribution is threefold:

• We prepared, selected and preprocessed a collection of eight distinct NLP datasets.
• Employing the collected datasets, we evaluate the effects of using the adversarial examples during the deep learning model training. We include significance tests in order to support our claims.
• We discuss which datasets in general can benefit most from the adversarial examples.

2. Related Work

Neural networks are commonly regularized by a handful of standard techniques. Apart from traditional shrinkage techniques such as $L_2$ and $L_1$ regularization, the most used regularization technique is dropout (Hinton et al., 2012) which randomly selects a subset of neurons that are disabled in a following training iteration. Additional techniques include batch normalization (Ioffe and Szegedy, 2015) and layer normalization (Ba et al., 2016) which normalize the layer activation. Notably, recurrent neural networks greatly benefit from the latter approach. Further techniques include weight normalization (Salimans and Kingma, 2016), batch renormalization (Ioffe, 2017) and self normalizing networks (Klambauer et al., 2017).

Adversarial examples have been mostly studied in the context of image processing, especially for image classification. Goodfellow et al. (2014b), by following the work of Szegedy et al. (2013), show that not only highly non-linear models such as deep neural networks have adversarial examples, but also much more linear and simpler models such as logistic regression do too.

Moosavi-Dezfooli et al. (2016a) introduce a heuristic technique which develops such a perturbation that, when applied to almost any image in the dataset, misleads the model. They name this established perturbation as universal. In addition, the authors discover that this perturbation...
affects various models trained on the same dataset. Therefore, the universality is twofold. Nguyen et al. (2015) use a different approach by generating the adversarial examples by an evolution algorithm instead of by using gradient descent. This approach provides adversarial examples even in the environments in which the neural network cannot be trained via back-propagation, since the target variables remain unknown.

Jia and Liang (2017) used (Miyato et al., 2016b, Eq. 3,4). The authors evaluated five which introduces a new loss term based on KL-divergence adversarial perturbations of word embeddings. In addition, the Miyato et al. (2016b) were the first who constructed adversarial embeddings. Nonetheless, the results of their experiments did not support any hypothesis of the method usefulness.

Moosavi-Dezfooli et al. (2016b), Papernot et al. (2016b) and Papernot et al. (2016a). Regarding adversarial examples used in the context of NLP, there is much less published research. Caswell et al. (2016) have been, to our knowledge, the first who experimented with using adversarial embedding perturbations. The IMDB dataset (Maas et al., 2011) was used as a binary sentiment classification task. The authors introduced visualization techniques in order to understand the effect of constructed adversarial embeddings. Nonetheless, the results of their experiments did not support any hypothesis of the method usefulness.

Miyato et al. (2016b) were the first who constructed adversarial perturbations of word embeddings. In addition, the authors employed a so-called virtual adversarial training which introduces a new loss term based on KL-divergence (Miyato et al., 2016b) Eq. 3.4). The authors evaluated five data sources and both adversarial and virtual adversarial learning outperformed the state-of-the-art models.

Jia and Liang (2017) used adversarial generation of the source text instead of embeddings. They introduced various methods fooling the models for Standford Question Answering Dataset (Rajpurkar et al., 2016) by generating additional sentences to the original source text. Doshi-Velez and stalks (2017) aimed for adversarial examples detection in the context of Generative Adversarial Networks (GANs) (Goodfellow et al., 2014a). In addition, Miyato et al. (2016a) employed RNN-based GANs to semi-supervised text classification. Adversarial examples are often created as a perturbation of the original input. Goodfellow et al. (2014b) and Szegedy et al. (2013) work with a deterministic perturbation which “damages” the current model the most. Contrary to them, using random perturbations has various theoretical implications and is commonly employed (Matsuoka, 1992; Bishop, 1995; Grandvalet et al., 1997)

3. Adversarial Examples

Adversarial examples are artificially constructed inputs that are very similar to some example from the training set, but they fool an already trained model. Adversarial examples can be employed during the model training in order to supply new training data from which the model might benefit. Let us assume a classification task. Given a trained model representing function f and a training example (x, y), the adversarial example is such x + Δ which fools the model, i.e. f(x) = y while f(x + Δ) ≠ y. The difference Δ is called the perturbation and its magnitude can be limited subject to some metric. In our case, Δ is a deterministic perturbation which is constructed subject to the gradient updates of the network.

We focus on NLP tasks in which the input is encoded as a sequence of word/character embeddings. The perturbation Δ slightly modifies the embeddings of the input sequence. The described process can be understood as a modification of the original example text, however, the final perturbed embedding does not correspond to a particular word (besides exceptional cases), since the perturbations are arbitrary. Nevertheless, it is easy to find a nearest neighbor embedding and its corresponding word. Understandably, such nearest word does not necessarily behave the same as the perturbed embedding.

Since it is expected that the nearest neighbor is the original embedding without any perturbation applied, the adversarial examples in the context of NLP are difficult to interpret. One possible intuition is that the adversarial example replaces each word with a “new word” which is supposed to have a similar semantics to the original one, even though it is uninterpretable to human.

Apart from the proof of various machine learning models instability, Goodfellow et al. (2014b) demonstrated that employing the adversarial examples during the training of gradient-based models functions as a regularization technique whose effect is comparable to dropout (Hinton et al., 2012).

The main principle lies in online generation of adversarial examples throughout the training of the model. These generated examples are similar to the training instances, which might improve model smoothness and generalization, by enforcing the model to behave similarly on a similar input (Goodfellow et al., 2014b).

This modification of the training effectively extends the training data, hence it can be understood as an augmentation technique.

Given a training pair (x, y) and current model parameters Θ, the cost function J might be linearly approximated on the neighborhood of Θ.

Assuming the prior conditions, gradient ∇ΘJ(x, y; Θ) can be easily estimated (e.g. by back-propagation). Based on the explanation of (Goodfellow et al., 2014b), a possible way of perturbation computation is using the estimated gradients. Considering the fact that the gradient might be arbitrarily large and the perturbation is thought to be small, the authors approximate the gradient by a vector of {−1, 0, +1} by applying the sign function. The total magnitude of the perturbation might be then controlled by a (small) multiplicative constant ε > 0. This approach was named fast gradient sign method and is defined by Equa-

\[ \text{Equation} \]
4. Datasets

A collection of eight datasets in total was selected in order to evaluate the adversarial training in the context of NLP. In order to provide further complexity of the evaluation, we selected datasets that differ in multiple characteristics. However, due to limited resources, the selected datasets do not cover the whole characteristic space.

All datasets were provided with a unified interface so that they could be easily experimented with. Goodfellow et al. (2014b) proposed a modification of the optimization algorithm based on back-propagation which employs the adversarial examples. The authors define a new loss function $\tilde{J}$ which regards both the original loss and the loss computed on an adversarial example (based on the currently processed pattern). The definition of $\tilde{J}$ for training pair $(x, y)$ and parameters $\Theta$ is given by Equation (1)

$$
\Delta = \varepsilon \cdot \text{sign} (\nabla_{\Theta} J(x, y; \Theta))
$$

$$
\tilde{J}(x, y; \Theta) = \alpha J(x, y; \Theta) + (1 - \alpha) J(x + \Delta, y; \Theta)
$$

$$
= \alpha J(x, y; \Theta) + (1 - \alpha) \cdot J(x + \varepsilon \cdot \text{sign}(\nabla_{\Theta} J(x, y; \Theta)), y; \Theta)
$$

Equation (2)

5. Evaluation

Each dataset was split into three distinct parts: training, validation and testing. The training part was used for the model parameter estimation, the validation for the best model selection and the testing for the final result reports. We employ the testing losses in order to perform significance of the performance improvement.

5.1. Model Selection

The neural networks are typically trained in several epochs. After each epoch, the model loss is evaluated both on training and validation data. While the validation loss represents an independent estimation of the model generalization capability, both losses are used together for overfitting detection.

In order to select the epoch in which the model achieved the best performance, we select the one in which the loss was the least on the validation data. The final performance is then reported on testing dataset, which is completely held-out until the final model is selected.

Since the validation and test datasets were constructed by randomly choosing examples, the test performance on the model is conditionally independent on the validation performance given the model parameters. However, the test performance is expected to be slightly worse in comparison to the validation performance since the model was chosen to achieve the best validation performance regardless the test evaluation.

The use of loss instead of other metrics such as accuracy or F-measure is supported by the fact that the loss itself
models the actual behavior of the model. In contrast, in a classification problem, the accuracy of the model does not express its behavior in a sufficient detail.

5.2. Testing Significance
In order to evaluate whether the adversarial training has a significantly positive effect on model performance, we perform the paired t-test on the testing losses as follows. Comparing two experiments given a single dataset, we train appropriate network architectures independently with the same train/valid/test data split. Then, we select the best models using the validation dataset. Finally, we evaluate and compare the testing losses between the corresponding testing examples. This leads to a paired t-test using these two sets of losses pairs.

5.3. Experiment Setup
A model processes tokenized text with special tokens indicating the beginning and the ending of a sequence. In case there is a token in the validation or testing dataset which was not present in the training dataset, it is replaced with the unknown token symbol. In order to adapt to texts containing such unknown tokens, the tokens used for training are usually uniformly randomly replaced with the unknown token during each training epoch. The uniformity is employed since many of the datasets were collected automatically and contain various typing errors, which are believed to be distributed uniformly. Afterwards, each token is translated into its corresponding embedding. The embeddings are uniformly randomly initialized without any pretraining and being updated during the model training. In some experiments, we apply dropout with 50% keep probability to the embeddings. Once the sequence of embeddings is constructed, a recurrent cell is applied to it. We employ either GRU (Cho et al., 2014) or LSTM (Hochreiter and Schmidhuber, 1997) cells in the following experiments. We use the last output of the cell (the concatenation of both last outputs in the case of bi-directional RNN) as the input to a multilayer perceptron (MLP) which contains a single hidden layer. In some experiments, we apply dropout with 50% keep probability to the hidden layer of the MLP.

By using a fully connected layer, we transform the output vector cell so that the final dimension matches the desired number of output neurons.

5.4. Model Training
The final output vector is trained to minimize categorical cross-entropy error function, in which the index of the target class is provided as the ground truth. The models are trained via mini-batch gradient descent with Adam gradient update (Kingma and Ba, 2014). The learning rates have been chosen from the interval 0.001–0.003 without major performance influence.

We experimented also with additional loss functions such as mean-square error applied to the sigmoid of the final output vector and one-hot encoded ground truth, however, we observed no major difference.

5.5. Results
During the evaluation, we focus on the testing loss improvement in comparison with the original vanilla model. We do not aim to compare our results with state-of-the-art results that usually employ additional (possibly hand-crafted) techniques during the training. All our results are presented in Table 1

At least two models differing in the number of parameters (referred to as the big and small models) were trained for each experiment. Throughout our experiments, the smaller models tend to underfit the given task and the use of adversarial examples had no effect. In contrast, the bigger models tend to overfit massively which made regularization methods such as dropout or the adversarial examples effective. In the following text, we report only the results of the big models.

In addition, we experimented with both LSTM and GRU recurrent cells which, to our knowledge, did not affect the overall model performance. The presented results represent the models which employ bidirectional GRU recurrent cells.

All experiments compare four models (see Table 1):
1. the vanilla model (without any regularization),
2. the same model trained with dropout (embedding layer, MLP hidden layer),
3. the same model trained with adversarial examples,
4. the same model trained with both adversarial examples and dropout.

We start by evaluating the bAbI datasets, namely bAbI #1, #2 and #6. In all bAbI experiments we use a model which employs embeddings of dimension 100, which we experimentally discovered to be sufficient (increasing the dimension does not affect training). The GRU dimension is set to 400 and MLP hidden layer dimension is set to 512. Focusing mainly on the test performance which represents the actual model generalization, we observe that the employment of the adversarial perturbations together with dropout provides approximately 22% accuracy improvement in the case of bAbI #6. On the contrary, the employment of dropout provides only approximately 10% accuracy gain.

In contrast with the previous experiment, the employment of the adversarial examples damaged the model performance in the case of bAbI #1. However, the dataset accuracy benefited from using both adversarial training and dropout by approximately 4%.

For both experiments, we tested the testing loss difference between the vanilla model and the one employing the adversarial training. All measurements indicate that the testing losses significantly differ at the significance level α = 0.05, which was set in advance (p-values 0.003 and 0.001, respectively).

Both datasets outperformed the baselines set by Weston et al. (2015) when evaluating the weakly supervised cases. The final selected bAbI dataset (#2) which represents more

5 All reported improvements are absolute. The testing accuracies and losses are presented in Table 1 The baseline provided by Weston et al. (2015) yielded 48% when using the weakly supervised LSTM.
challenging questions has not significantly benefited from the employment of the adversarial examples.

The next evaluated dataset is the Movie Review dataset for subjectivity detection. We use a model which employs embeddings of dimension 200; the GRU dimension is set to 200 and MLP hidden layer dimension is set to 256. We observe that employing both adversarial examples and dropout during training stabilizes it. Approximately 0.3% increase in accuracy is achieved, however, the testing loss is significantly smaller (p-value 0.039) than the testing loss yielded by the model with only dropout. We suggest that the model is more confident of its responses.

Then, we evaluated the three Czech/Slovak sentiment analysis datasets. We used all four classes (positive, negative, neutral, bi-polar) and trained models using the their phonetic transcriptions. We have experimented also with stemming instead of phonetic transcriptions, however, the performance was poor and all models tended to overfit in early epochs.

The Social Media dataset benefited from the adversarial training by 0.05% increase in F1-score and the testing loss significantly decreases either with or without using dropout (p-values 0.009 and 0.026, respectively). We observe similar gain in F1-score (+0.15%) in the case of omitting the bi-polar class. For these experiments we employ embeddings of dimension 200; the GRU dimension is set to 400 and MLP hidden layer dimension is set to 512.

The sentiment analysis dataset (Movie Review) has not significantly benefited from the adversarial examples. The performance of the final sentiment analysis dataset (Product Review) surprisingly decreased in all our experiments when using the adversarial examples even though it is similar to the previous two datasets. The main difference is the size of the dataset as the Product Reviews contains neutral, bi-polar) and trained models using the their phonetic transcriptions. We have experimented also with stemming instead of phonetic transcriptions, however, the performance was poor and all models tended to overfit in early epochs.

The conducted experiments lead us to the following claims. Firstly, we observe that the employment of adversarial examples improves the model loss on majority of datasets of our collection.\(^6\)

We conclude that the models whose capacity is sufficient so that they overfit the training data (the number of their parameters is large) can benefit from using adversarial examples. In these cases, we claim that employing adversarial examples during training acts as a regularization technique. Furthermore, our preliminary hypotheses on the trends between the dataset characteristics and the effect of using the adversarial examples are as follows. Note that a wider collection of datasets would be required to make our propositions more credible.

English datasets exhibited better performance from the adversarial examples than the Czech or Slovak ones. We hypothesize that this effect might be caused by the fact that the Slavic languages feature a more complex morphology

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\(^6\)We support the claim of Caswell et al. (2016) and Miyato et al. (2016) who suggest that the use of adversarial examples during the training might be beneficial even for recurrent networks.

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| Task Type          | Dataset  | Vanilla Perf | Dropout Perf | Adversarial Perf | Advers. examples Perf + Dropout | Drop | Advers. examples Drop |
|--------------------|----------|--------------|--------------|------------------|--------------------------------|------|-----------------------|
| Question Reasoning | bAbI #1  | 73.8%        | 73.8%        | 68.3%            | 77.5%                          | 0.592| 0.925                 |
|                    | bAbI #2  | 30.8%        | 30.6%        | 30.8%            | 29.9%                          | 1.435| 1.399                 |
|                    | bAbI #6  | 47.9%        | 45.5%        | 56.2%            | 69.8%                          | 0.662| 0.636                 |
| Subjectivity      | Movie Review | 64.4% | 61.6%        | 63.5%            | 64.7%                          | 0.617| 0.606                 |
| Detection         | Movie Review | 42.5% (F1)  | 43.0% (F1)   | 42.0% (F1)       | 40.6% (F1)                     | 0.592| 1.076                 |
|                   | DSL 10k  | 41.9% (F1)   | 42.1%        | 42.7%            | 57.7%                          | 0.676| 0.676                 |
|                   | DSL 70k  | 74.3%        | 73.4%        | 72.1%            | 1.098                          | 0.619| 0.619                 |
|                   | DSL 130k | 55.3%        | 55.9%        | 57.0%            | 53.0%                          | 0.891| 0.912                 |
|                   | DSL 190k | 51.8%        | 51.8%        | 51.8%            | 51.8%                          | 0.543| 0.543                 |
| Language Detection| DSL 10k  | 73.4%        | 71.6%        | 66.7%            | 66.6%                          | 0.579| 0.579                 |
|                   | DSL 70k  | 35.3%        | 4.53%        | 4.53%            | 4.53%                          | 0.579| 0.579                 |
|                   | DSL 130k | 73.4%        | 56.7%        | 56.7%            | 56.7%                          | 0.579| 0.579                 |
|                   | DSL 190k | 77.8%        | 1.435        | 1.024            | 78.6%                          | 0.579| 0.579                 |

Table 1: The first and second columns describe the task type and the dataset name, respectively. The final four columns demonstrate the testing accuracies or F1-scores and the mean testing losses. The bold formatting indicates the loss which is the best among the dataset experiment.
and a greater number of distinct words (tokens). Nevertheless, even though strict stemming was employed, we did not achieve such performance improvement compared to the one we have observed in other English datasets.

Furthermore, we claim that the networks trained on artificial data (such as bAbI tasks \cite{Weston2015}) with a rather small number of distinct tokens are more likely to be vulnerable to adversarial examples and their use during training prevents the model from overfitting particularly efficiently.

Based on our experiments, we observe that the impact of the studied technique decreases as the size of the training dataset increases. We conclude that this phenomenon supports the hypothesis that adversarial training serves as a regularization technique, which is usually less effective in case more training data is available.

We provide novel evidence that the adversarial perturbation of character embeddings can also lead to performance improvement when used in the process of training character-level models.

7. Conclusion

This paper focuses on employing adversarial examples during training of deep recurrent neural networks. The contribution of this paper is threefold.

Firstly, we compiled a collection of eight datasets for which a unified stream interface was created. The datasets were chosen in order to represent a distinct set of characteristics which were chosen in advance.

Secondly, the employment of adversarial examples during the network training was evaluated in various settings. We focused on embeddings which are randomly initialized at the beginning of the training.

Finally, we have proposed several hypotheses about relations between the dataset characteristics and the effect of model training when using adversarial examples. In some cases, we outperformed the baselines provided by the authors of the dataset publications.

We conclude that the adversarial training can function as a regularization for RNNs processing natural text. This is a direct extension of the work of Miyato et al. \cite{Miyato2016a} who have experimented with pretrained embeddings.

7.1. Future Work

We consider the following possible research directions in our future work regarding the adversarial examples.

Firstly, additional datasets might be evaluated in order to provide more detailed study. In particular, tasks such as machine translation, which do not aim to classify the input, could be studied. For this purpose, supplementary architectures such as sequence-to-sequence models shall be evaluated.

Secondly, our further research will focus on the embedding structure analysis, primarily on the changes caused by employing the adversarial examples. Even though we have not been able to prove a significant change in their structure yet, we hope the interpretation of the embedding differences might be found. In addition, we will study the stability of training when using adversarial examples.

Furthermore, supplementary techniques for adversarial example creation will be analyzed, notably Generative Adversarial Networks \cite{Goodfellow2014a}. Another approach could employ genetic algorithms for embedding perturbations.

Finally, additional types of machine learning, such as (deep) reinforcement learning (RL) could be examined. Focusing on NLP, the end-to-end neural dialogue systems are suitable for further analysis.

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