In and Out-of-Domain Text Adversarial Robustness via Label Smoothing

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Abstract

Recently it has been shown that state-of-the-art NLP models are vulnerable to adversarial attacks, where the predictions of a model can be drastically altered by slight modifications to the input (such as synonym substitutions). While several defense techniques have been proposed, and adapted, to the discrete nature of text adversarial attacks, the benefits of general-purpose regularization methods such as label smoothing for language models, have not been studied. In this paper, we study the adversarial robustness provided by various label smoothing strategies in foundational models for diverse NLP tasks in both in-domain and out-of-domain settings. Our experiments show that label smoothing significantly improves adversarial robustness in pre-trained models like BERT, against various popular attacks. We also analyze the relationship between prediction confidence and robustness, showing that label smoothing reduces over-confident errors on adversarial examples.

1 Introduction

Neural networks are vulnerable to adversarial attacks: small perturbations to the input ,which do not fool humans (Szegedy et al., 2013; Goodfellow et al., 2014; Madry et al., 2017). In NLP tasks, previous studies (Alzantot et al., 2018; Jin et al., 2019; Li et al., 2020; Garg and Ramakrishnan, 2020) demonstrate that simple word-level text attacks (synonym substitution, word insertion/deletion) easily fool state-of-the-art models, including pre-trained transformers like BERT (Devlin et al., 2019; Wolf et al., 2020). Further, it has recently been shown models are overconfident[1] on examples which are easy to attack (Qin et al., 2021) and indeed, such over-confident predictions plague

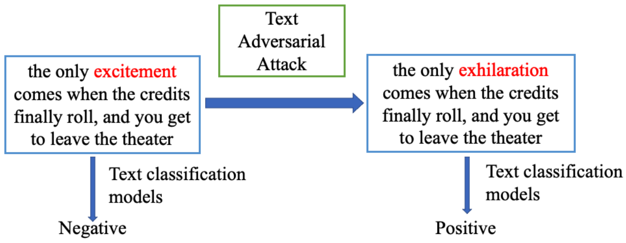

Figure 1: Here we show an example generated by word-level adversarial attack TextFooler (Jin et al., 2019) on SST-2 data. By replacing excitement with its synonym exhilaration, the text classification models changes its prediction from Negative to Positive, which is incorrect.

much of modern deep learning (Kong et al., 2020; Guo et al., 2017; Nguyen et al., 2015; Rahimi et al., 2020). Label smoothing is a regularization method that has been proven effective in a variety of applications, and modalities (Szegedy et al., 2016; Chorowski and Jaitly, 2017; Vaswani et al., 2017). Importantly, it has been shown to reduce overconfident predictions and implicitly produce better confidence calibrated classifiers (Muller et al., 2019; Zhang et al., 2021; Dan and Roth, 2021; Desai and Durrett, 2020; Huang et al., 2021; Liu and JaJa, 2020).

In this work, we focus on the question: *does label smoothing also implicitly help in adversarial robustness?* While there has been some investigation in this direction for adversarial attacks in computer vision, (Fu et al., 2020; Goibert and Dohmatob, 2019; Shafahi et al., 2019), there is a gap in understanding of whether it helps with discrete, text adversarial attacks used against NLP systems. With the increasing need for robust NLP models in safety-critical applications and a lack of generic robustness strategies,[2] there is a need to understand inherent robustness properties of popular label smoothing strategies, and the interplay between confidence and robustness of a model.

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[1]Confidence on an example is the highest softmax score of the classifier prediction on that example.

[2]which are flexible, simple and not over-specialized to very specific kinds of text adversarial attacks.

In this paper, we extensively study standard label smoothing and its adversarial variant, covering robustness, prediction confidence, and domain transfer properties. We observe that label smoothing provides implicit robustness against adversarial examples. Particularly, we focus on pre-trained transformer models and test robustness under various kinds of word-level attacks in both in-domain and out-of-domain scenarios. Our experiments show that label smoothing (1) improves robustness to text adversarial attacks, (2) mitigates over-confident errors on adversarial examples, and (3) improves adversarial accuracy for high-confidence examples. Analysing the adversarial examples along various quality dimensions reveals the remarkable efficacy of label smoothing as a general robustness tool.

2 Background

2.1 Text Adversarial Attacks

Our experiments evaluate the robustness of text classification models under two state-of-the-art text adversarial attacks TextFooler and BAE, described below. For a particular victim NLP model and a raw text input, the attack produces semantically-similar adversarial text as output. Importantly, only those examples are attacked, which are originally correctly predicted by the victim model. The attacks considered are word-level, i.e. they replace important words in a clean text with their synonyms to maintain the meaning of the clean text, but change the prediction of the victim models; and black-box, i.e., they do not need access to the victim model gradients.[3]

- **TextFooler**: (Jin et al., 2019) proposes an attack which determines the word importances in a sentence, and then replaces the important words with qualified synonyms.
- **BAE**: (Garg and Ramakrishnan, 2020) uses masked pre-trained language models like BERT to generate replacements for the important words until the victim model's prediction is incorrect.

2.2 Label Smoothing

Label Smoothing is a modified fine-tuning procedure to address overconfident predictions. It introduces uncertainty to smoothen the posterior distribution over the target labels. Label smoothing has been shown to implicitly calibrate neural networks on out-of-distribution data, where *calibration* measures how well the model confidences are aligned with the empirical likelihoods (Guo et al., 2017).

- **Standard Label Smoothing (LS)** (Szegedy et al., 2013; Muller et al., 2019) constructs a new target vector (y_i^{LS}) from the one-hot target vector (y_i), where $y_i^{LS} = (1-\alpha)y_i + \alpha/K$ for a K class classification problem. α is a hyperparameter selection and its range is from 0 to 1.
- **Adversarial Label Smoothing (ALS)** (Goibert and Dohmatob, 2019) constructs a new target vector (y_i^{ALS}) with a probability of $1-\alpha$ on the target label and α on the label to which the classification model assigns the minimum softmax scores, thus introducing uncertainty.

For both LS and ALS, the cross entropy loss is subsequently minimized between the model predictions and the modified target vectors y_i^{LS}, y_i^{ALS}.

3 Experiments

In this section, we present a thorough empirical evaluation on the effect of label smoothing on adversarial robustness for two pre-trained transformer models: BERT and its distilled variant, distilBERT, which are the victim models.[4] We attack the victim models using TextFooler and BAE [5]. For each attack, we present results on both the standard models and the label-smoothed models on various classification tasks: text classification (sentiment and topic classification) and natural language inference. For each dataset we evaluate on a randomly sampled subset of the test set (1000 examples), as done in prior work (Li et al., 2021; Jin et al., 2019; Garg and Ramakrishnan, 2020). We choose label smoothing factor $\alpha = 0.45$ for standard label-smoothed models in our experiments. We evaluate on the following tasks, and other details about the training procedure can be found in Appendix A.3:

- **Text Classification**: We evaluate on movie review classification using Movie Review (MR) (Pang and Lee, 2005) and Stanford Sentiment Treebank (SST2) (Socher et al., 2013) (both

[3] The black-box attacks keep trying multiple adversarial examples via substitutions until the victim model is fooled, or a max number of attempts is reached. Further details of the attacks are in (Jin et al., 2019; Garg and Ramakrishnan, 2020).

[4] Additional results on more datasets and models are presented in the Appendix. All pretrained models and fine-tuning are implemented using Huggingface (Wolf et al., 2020).

[5] TextFooler attack and BAE attack in our experiments are implemented using TextAttack (Morris et al., 2020), a Python framework for NLP adversarial attack.

SST-2	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.45	0	0.45	0	0.45
TextFooler	91.97	**92.09**	96.38	**88.92**	78.43	**63.62**
BAE	91.97	**92.09**	57.11	**53.42**	86.92	**68.35**
distilBERT(α)	0	0.45	0	0.45	0	0.45
TextFooler	89.56	**89.68**	96.29	**89.77**	76.28	**61.6**
BAE	89.56	**89.68**	59.28	**57.4**	83.55	**66.11**

AG_news	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.45	0	0.45	0	0.45
TextFooler	**94.83**	94.67	88.26	**77.45**	59.02	**42.46**
BAE	**94.83**	94.8	74.83	**62.82**	61.36	**43.98**
distilBERT(α)	0	0.45	0	0.45	0	0.45
TextFooler	**94.73**	94.47	90.11	**74.52**	57.6	**41.4**
BAE	**94.73**	94.47	77.79	**63.65**	60.01	**42.74**

Yelp	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.45	0	0.45	0	0.45
TextFooler	97.7	97.7	99.27	**92.90**	65.21	**55.36**
BAE	97.7	97.7	54.72	**45.14**	68.25	**57.38**
distilBERT(α)	0	0.45	0	0.45	0	0.45
TextFooler	97.5	97.63	99.59	**99.01**	61.78	**60.32**
BAE	97.5	97.4	55.9	**50.05**	64.03	**62.77**

SNLI	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.45	0	0.45	0	0.45
TextFooler	**90.0**	89.23	96.26	**96.15**	68.71	**52.61**
BAE	**90.0**	89.23	75.15	**74.82**	75.85	**57.42**
distilBERT(α)	0	0.45	0	0.45	0	0.45
TextFooler	**87.33**	87.1	97.56	**96.86**	65.27	**50.84**
BAE	**87.33**	87.1	74.48	**72.91**	72.65	**55.49**

Table 1: Comparison of standard models and models fine-tuned with standard label smoothing techniques (LS) against various attacks for in-domain data. We here reported clean accuracy, attack success rate and average confidence on successful adversarial texts. For each dataset, the left column are the results for standard model, and the right column are for LS models where α denotes the label smoothing factor (α=0: no LS). ↑ (↓) denotes higher (lower) is better respectively.

binary classification datasets), restaurant review classification: Yelp Review (Zhang et al., 2015a) (binary classification), and news category classification: AG News (Zhang et al., 2015b) (having the following four classes: World, Sports, Business, Sci/Tech).

- **Natural Language Inference:** We investigate two datasets for this task: the Stanford Natural Language Inference Corpus (SNLI) (Bowman et al., 2015) and the Multi-Genre Natural Language Inference corpus (MNLI) (Williams et al., 2018), both having three classes. For MNLI, our work only evaluates performance on the matched genre test-set in the OOD setting presented in subsection 3.2 .

3.1 In-domain Setting

In the in-domain setting, the pre-trained transformer models are fine-tuned on the train-set for each task and evaluated on the corresponding test-set. For each case, we report the clean accuracy, the adversarial attack success rate (percentage of misclassified examples after an attack) and the average confidence on successfully attacked examples (on which the model makes a wrong prediction).[6] Table 1 shows the performance of BERT and distilBERT, with and without label-smoothing.

We see that the label-smoothed models are more robust for every adversarial attack across different datasets in terms of the attack success rate, which is a standard metric in this area (Li et al., 2021; Lee et al., 2022). Additionally, the higher confidence of the standard models on the successfully attacked examples indicates that label smoothing helps mitigate overconfident mistakes in the adversarial setting. Importantly, the clean accuracy remains almost unchanged in all the cases. We also perform hyperparameter sweeping for label smoothing factors to investigate their impact to model accuracy and adversarial robustness. Figure 2 shows that the attack success rate gets lower as we increase the label smooth factor when fine-tuning the model while the test accuracy is comparable[7]. However, when the label smoothing factor is larger than 0.5, there is no further improvement on adversarial robustness in terms of attack success rate. We also observe that label smoothing has much more positive impact on adversarial robustness for AG_News (4-class classification tasks) compared to binary classification tasks like SST-2.

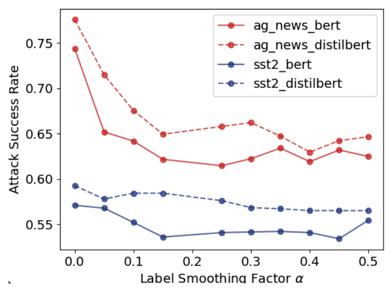

Figure 2: Adversarial success rate versus label smoothing factors (on AG News and SST-2 with BAE attack.)

[6]Details of each metric are presented in Appendix A.1.

[7]More results are in Appendix A.6

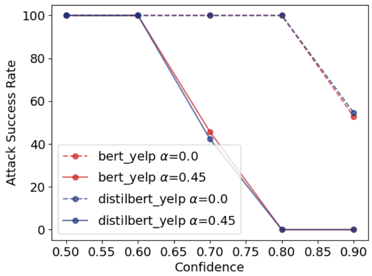

Figure 3: Adversarial success rate versus confidence for in-domain (Yelp) inputs. (Number of buckets: 10 and the number of instances in first 5 buckets [0-0.5] are 0).

Moreover, we bucket the examples based on the confidence scores, and plot the bucket-wise attack success rate (of the BAE attack on the Yelp dataset) versus confidence in Figure 3. We observe that the label smoothing technique improves the adversarial robustness for high confidence score samples significantly. In future work, we plan to investigate the variations of robustness in label-smoothed models as a function of the model size.

We additionally investigate the impact of adversarial label smoothing and we show that the adversarial label smoothed methods also improves model's robustness for TextFooler attack in Table 2, although the gains are similar compared to standard label smoothing.

SNLI	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.1	0	0.1	0	0.1
TextFooler	90.2	**90.8**	95.79	**94.93**	69.28	**67.32**
BAE	90.2	**90.8**	**74.83**	76.65	76.77	**73.83**

Table 2: Comparison of standard models versus models trained with ALS against various attacks on SNLI. ↑ (↓) denotes higher (lower) is better respectively.

3.2 Out-of-Domain setting

We now evaluate the benefits of label smoothing for robustness in the out-of-domain (OOD) setting, where the pre-trained model is fine-tuned on a particular dataset and is then evaluated directly on a different dataset, which has a matching label space. Three examples of these that we evaluate on are the Movie Reviews to SST-2 transfer, the SST-2 to Yelp transfer, and the SNLI to MNLI transfer.

In Table 3, we again see that label-smoothing helps produce more robust models in the OOD setting. This is a challenging setting, as evidenced by the significant performance drop in the clean accuracy as compared to the in-domain setting. We also

MR→SST2	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.2	0	0.2	0	0.2
TextFooler	92.89	**93.35**	93.21	**92.01**	70.24	**66.64**
BAE	92.89	**93.35**	57.28	**54.18**	77.32	**72.03**
distilBERT(α)	0	0.2	0	0.2	0	0.2
TextFooler	90.48	**90.6**	93.92	93.92	65.89	**63.66**
BAE	90.48	**90.6**	58.81	**58.48**	73.08	**69.25**
SNLI → MNLI	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.45	0	0.45	0	0.45
TextFooler	**73.4**	71.9	94.82	**92.79**	58.04	**46.43**
BAE	**73.4**	71.9	82.56	**80.72**	63	**49.45**
distilBERT(α)	0	0.45	0	0.45	0	0.45
TextFooler	**65.4**	62.1	94.5	**92.59**	54.54	**44.81**
BAE	**65.4**	62.1	77.68	**75.52**	58.88	**47.83**
SST-2 → Yelp	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.45	0	0.45	0	0.45
TextFooler	**92.5**	92.4	99.57	**98.27**	60.8	**54.28**
BAE	**92.5**	92.4	63.68	**60.71**	64.27	**55.66**
distilBERT(α)	0	0.45	0	0.45	0	0.45
TextFooler	**91.7**	91.1	99.78	**98.02**	59.12	**53.3**
BAE	**91.7**	91.1	68.7	**63.45**	61.37	**54.21**

Table 3: Comparison of standard models and models fine-tuned with standard label smoothing techniques (LS) against various attacks for OOD data where α denotes the label smoothing factor (α=0: no LS). ↑ (↓) denotes higher (lower) is better respectively.

see that the standard models make over-confident errors on successfully attacked adversarial examples, when compared to label-smoothed models.

3.3 Qualitative Results

In this section, we try to understand how the generated adversarial examples differ for label smoothed and standard models. First we look at some qualitative examples and then do a quality-assessment of adversarial examples along various dimensions. In Table 4 we show some examples (clean text) for which the different attack schemes fails to craft an attack for the label smoothed model but successfully attacks the non-label smoothed model.

Victim	Attack	Text	
SST2	BAE	clean text	at once half-baked and overheated.
BERT		adv text	at once warm and over-heated .
MR	TextFooler	clean text	no surprises .
dBERT		adv text	no surprise .

Table 4: Examples for which an attack could be found for the standard model but not for the label smoothed model. The Victim column shows the dataset and the pretrained model (dBERT denotes distilBERT).

We also performed automatic evaluation of the quality of the adversarial examples for standard and label smoothed models, adopting standard metrics from previous studies (Jin et al., 2019; Li et al., 2021). The reported scores for each metric are computed over only the successful adversarial examples, for each attack and model type.[8]

SST-2	Perplexity (↑)		Similarity Score (↓)		Grammar Error (↑)	
BERT (α)	0	0.45	0	0.45	0	0.45
TextFooler	400.31	**447.58**	0.800	**0.779**	0.33	**0.38**
BAE	300.74	**305.28**	0.867	**0.855**	−0.05	−**0.04**
AG_News	Perplexity (↑)		Similarity Score (↓)		Grammar Error (↑)	
BERT (α)	0	0.45	0	0.45	0	0.45
TextFooler	342.02	**355.87**	0.782	**0.772**	1.37	**1.40**
BAE	169.37	**170.73**	0.851	**0.845**	0.97	**1.00**

Table 5: Evaluation of adversarial text examples. The results in bold indicates worse adversarial attack quality.

Table 5 shows that the quality of generated adversarial examples on label smoothed models is worse than those on standard models for different metrics, which further demonstrates that label smoothing makes it harder to find adversarial vulnerabilities.

4 Conclusion

We presented an empirical study to investigate the effect of label smoothing techniques on adversarial robustness for various NLP tasks. Our results demonstrate that label smoothing imparts implicit robustness to models, even under domain shifts. This, complemented with prior work on label smoothing and implicit calibration, can guide research on developing robust, reliable models.

[8]Additional details, plots can be found in Appendix A.8.

5 Limitations

One limitation of our work is that we focus on robustness of pre-trained transformer language models against word-level adversarial attacks, which is the most common setting in this area. Future work could extend this empirical study to other types of attacks (for example, character-level and sentence-level attacks) and for diverse types of architectures. Further, it will be very interesting to theoretically understand how label smoothing provides (1) the implicit robustness to text adversarial attacks and (2) mitigates over-confident predictions on the adversarially attacked examples.

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A Appendix

A.1 Evaluation Metrics

The followings are details of evaluation metrics from previous work (Lee et al., 2022; Li et al., 2021):

Clean accuracy = $\frac{\text{\# of correctly predicted clean examples}}{\text{\# of clean examples}}$

Attack Succ Rate = $\frac{\text{\# of successful adversarial examples}}{\text{\# of correctly predicted clean examples}}$

where successful adversarial examples are derived from correctly predicted examples

Adv Conf = $\frac{\text{sum of confidence of successful adversarial examples}}{\text{\# of successful adversarial examples}}$

A.2 Additional results on Movie Review Dataset

Here we provide results of movie review datasets under in-domain setting.

MR	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.2	0	0.2	0	0.2
TextFooler	83.8	**84.2**	94.51	**92.87**	70.01	**66.89**
BAE	83.8	**84.2**	58.23	**55.46**	76.44	**71.89**
distilBERT(α)	0	0.2	0	0.2	0	0.2
TextFooler	83.0	**83.3**	95.78	**94.72**	65.67	**63.42**
BAE	83.0	**83.3**	61.45	**59.78**	71.82	**68.81**

Table 6: Comparison of standard models and label smoothed models against various attacks for Movie Review dataset.

A.3 Dataset Overview and Experiments Details

Dataset	No. of classes	Train/Test size	Avg. Length
MR	2	8530/1066	18.64
SST-2	2	6.7e4/872	17.4
Yelp	2	5.6e5/3.8e4	132.74
AG_news	4	1.2e5 /7600	38.68
SNLI	3	5.5e5 /1e4	22.01
MNLI	3	3.9e5/ 9815	28.96

Table 7: Summary of datasets

All models are fine-tuned for 3 epochs using AdamW optimizer (Loshchilov and Hutter, 2017) and the learning rate starts from $5e{-}6$. The training and attacking are run on an NVIDIA Quadro RTX 6000 GPU (24GB). The reported numbers are the average performance over 3 random runs of the experiment

A.4 Additional results of $\alpha = 0.1$

Table 8 and 9 are the additional results to show when label smoothing $\alpha = 0.1$, how the adversarial robustness of fine-tuned language models changes.

SST-2	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.1	0	0.1	0	0.1
TextFooler	91.97	**92.2**	96.38	**94.4**	78.43	**74.39**
BAE	91.97	**92.2**	57.11	**55.22**	86.92	**82.29**
distilBERT(α)	0	0.1	0	0.1	0	0.1
TextFooler	89.56	**89.68**	96.29	**95.14**	76.28	**70.77**
BAE	89.56	**89.68**	59.28	**58.44**	83.55	**78.16**
AG_news	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.1	0	0.1	0	0.1
TextFooler	94.9	95.2	88.62	**76.68**	58.96	**55.54**
BAE	94.9	95.2	74.39	**64.18**	61.36	**57.18**
distilBERT(α)	0	0.1	0	0.1	0	0.1
TextFooler	**94.9**	94.6	91.15	**81.4**	57.81	**53.31**
BAE	**94.9**	94.6	77.56	**67.55**	60.26	**55.14**
Yelp	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.1	0	0.1	0	0.1
TextFooler	97.7	**97.67**	99.27	**97.92**	65.21	**62.99**
BAE	97.7	**97.67**	54.72	**52.52**	68.25	**65.82**
distilBERT(α)	0	0.1	0	0.1	0	0.1
TextFooler	97.5	97.63	99.59	**99.01**	61.78	**60.32**
BAE	97.5	97.4	55.9	**50.05**	64.03	**62.77**
SNLI	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.1	0	0.1	0	0.1
TextFooler	**90.0**	89.13	**96.26**	96.9	68.71	**64.85**
BAE	**90.0**	89.13	75.15	**74.91**	75.85	**72.38**
distilBERT(α)	0	0.1	0	0.1	0	0.1
TextFooler	**87.33**	87.3	97.56	**96.83**	65.27	**62.5**
BAE	**87.33**	87.3	74.48	**74.24**	72.65	**69.27**

Table 8: Comparison of standard models and label smoothed models against various attacks for in-domain data where α denotes the label smoothing factor, 0 indicating no LS. [9] ↑ (↓) denotes higher (lower) is better respectively.

SNLI → MNLI	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.1	0	0.1	0	0.1
TextFooler	**73.4**	71.9	**94.82**	94.85	58.04	**48.56**
BAE	**73.4**	71.9	82.56	**77.19**	63	**49.3**
distilBERT(α)	0	0.45	0	0.45	0	0.45
TextFooler	**65.4**	65.2	94.5	**94.17**	54.54	**52.63**
BAE	**65.4**	65.2	77.68	**75.15**	58.88	**56.16**
SST-2 → Yelp	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
BERT (α)	0	0.1	0	0.1	0	0.1
TextFooler	**92.5**	92.0	99.57	**99.13**	60.8	**58.13**
BAE	**92.5**	92.0	63.68	**63.37**	64.27	**60.63**
distilBERT(α)	0	0.45	0	0.45	0	0.45
TextFooler	**91.7**	91.4	99.78	**99.34**	59.12	**56.42**
BAE	**91.7**	91.4	68.7	**67.07**	61.37	**57.73**

Table 9: Comparison of standard models versus label smoothed models against various attacks for OOD data where α denotes the label smoothing factor (α=0: no LS). ↑ (↓) denotes higher (lower) is better respectively.

A.5 Additional results on ALBERT

In this section, we include experiment results for standard ALBERT and label smoothed ALBERT in Table 10. We observe that the label smoothing technique also improves adversarial robustness of ALBERT model across different datasets.

MR	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
α	0	0.1	0	0.1	0	0.1
TextFooler	**86.3**	85.9	**89.22**	90.45	76.78	**69.6**
BAE	**86.0**	85.7	58.95	**58.46**	83.27	**76.4**
SST-2	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
α	0	0.1	0	0.1	0	0.1
TextFooler	92.2	**92.78**	93.41	**86.9**	94.1	**84.94**
BAE	92.2	**92.78**	59.33	**55.01**	96.93	**87.32**
AG_news	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
α	0	0.1	0	0.1	0	0.1
TextFooler	**97.4**	96.5	68.69	**64.87**	75.75	**71.01**
BAE	**95.4**	94.2	55.03	**50.11**	77.31	**72.63**
SNLI	Clean Acc (↑)		Attack Success Rate (↓)		Adv Conf (↓)	
α	0	0.1	0	0.1	0	0.1
TextFooler	89.9	**90.0**	95.88	**93.89**	85.12	**79.26**
BAE	**90.6**	89.9	77.26	**76.2**	88.64	**81.86**

Table 10: Comparison of standard models and label smoothed models against TextFooler and BAE attacks for ALBERT model.

A.6 Attack success rate versus label smoothing factors

As mentioned in Section 3.1, we plot the attack success rate of BAE attack versus the label smoothing factors. Here, we plot the results for TextFooler attack and observe the same tendency as we discussed above.

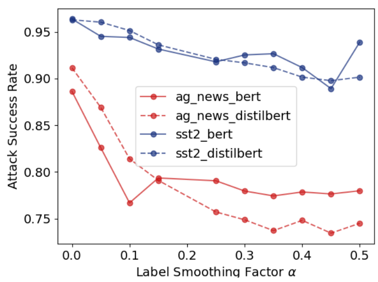

Figure 4: Adversarial success rate versus label smoothing factors (on AG News and SST-2 with TextFooler attack.)

A.7 Average number of word change versus Confidence

Word change rate is defined as the ratio between the number of word replaced after attack and the total number of words in the sentence. Here we plot the bucket-wise word change ratio of adversarial attack versus confidence, and observe that the word change rate for high-confident examples are higher for label smoothed models compared to standard models in most cases. This indicates that it is more difficult to attack label smoothed text classification models. Also note that there is the word change rate is zero because there is no clean texts fall into those two bins.

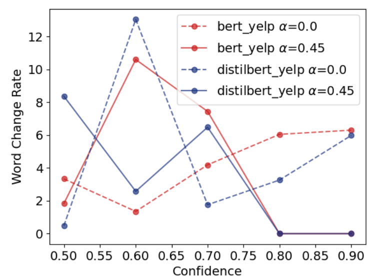

Figure 5: Average word change ratio versus confidence for in-domain inputs (No. of buckets: 10 and the number of instances in first 5 buckets [0-0.5] are 0)

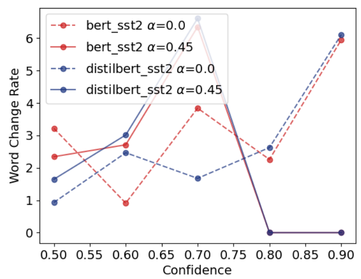

Figure 6: Average word change ratio versus confidence for out-of-domain inputs (No. of buckets: 10 and the number of instances in first 5 buckets [0-0.5] are 0)

Additionally, we also plot the relationship between adversarial success rate and confidence for each bucket in Figure 7, and observe a large drop for adversarial success rate on high-confidence text adversarial examples as previously seen in the in-domain setting.

A.8 Attack evaluation

We performed automatic evaluation of adversarial attacks against standard models and label smoothed models following previous studies (Jin et al., 2019; Li et al., 2021). Following are the details of the metrics we used in Table 5:

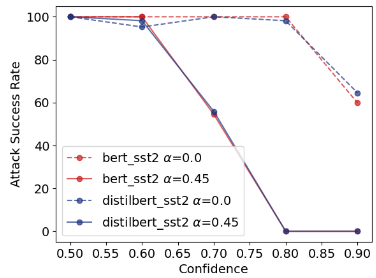

Figure 7: Adversarial success rate versus confidence for OOD inputs in the SST-2 → Yelp transfer setting.

Perplexity evaluates the fluency of the input using language models. We use GPT-2 (Radford et al., 2019) to compute perplexity as in (Li et al., 2021) .

Similarity Score determines the similarity between two sentences. We use Sentence Transformers (Reimers and Gurevych, 2019) to compute sentence embeddings and then calculate cosine similarity score between the clean examples and the corresponding adversarially modified examples.

Grammar Error The average grammar error increments between clean examples and the corresponding adversarially modified example.[10]

[10]we use https://pypi.org/project/language-tool-python/ to compute grammar error.