Generating Natural Language Adversarial Examples on a Large Scale with Generative Models

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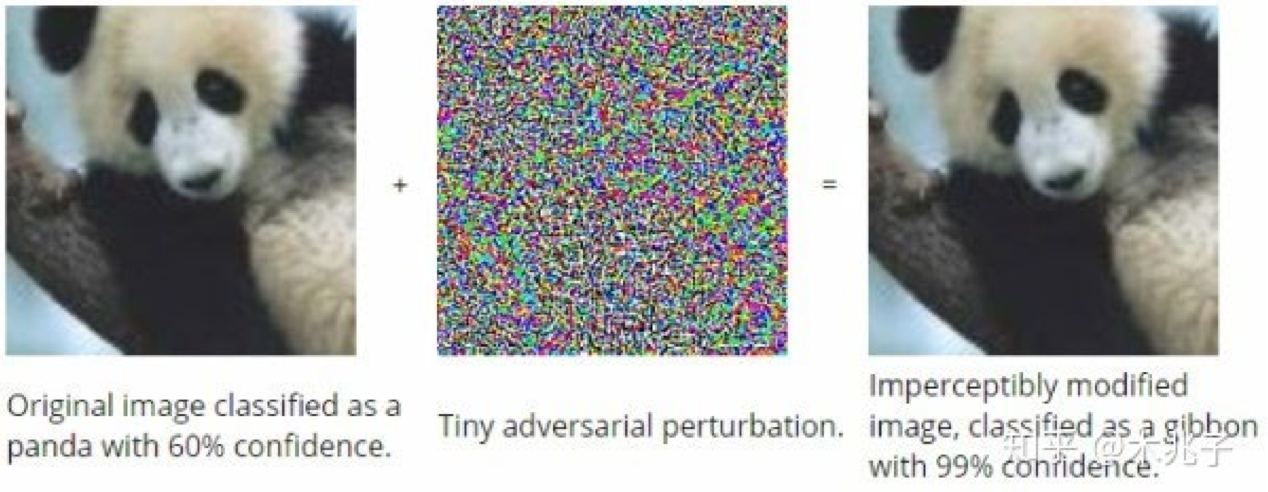
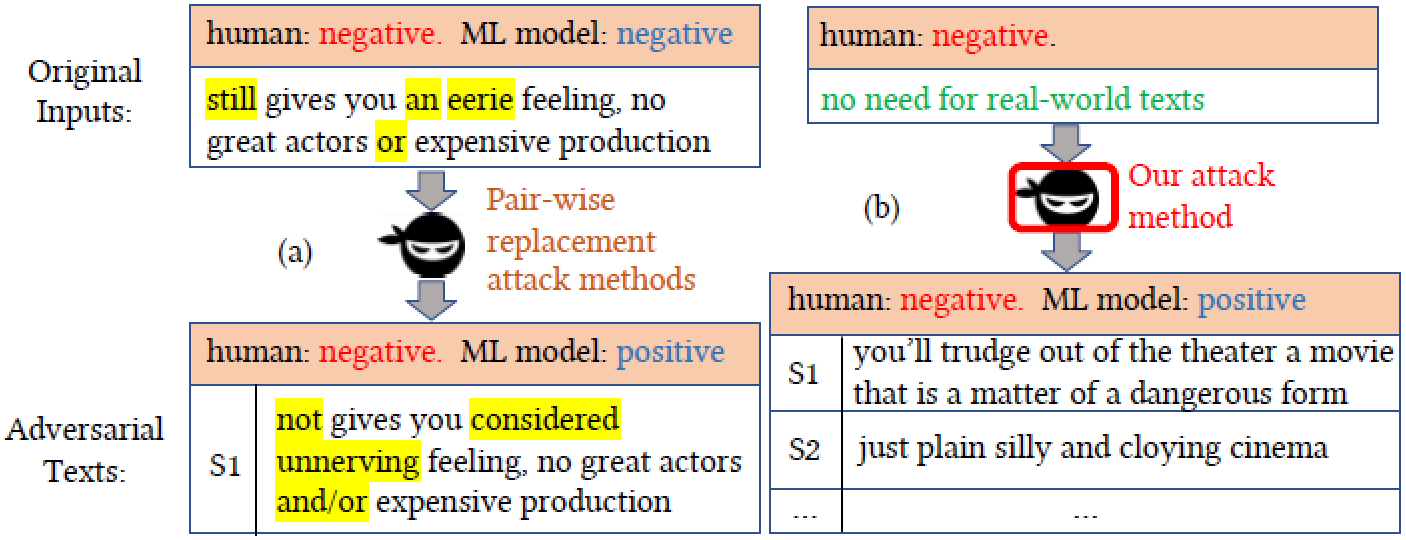
Background：Adversarial Examples



Adversarial Examples Are Not Bugs,
They are features.

Background: Adversarial Examples Generation in NLP

Traditional: pair-wise



Proposed method: from scratch

Contributions

- generate text adversarial examples from scratch
- a novel method :VAE+GAN+ adversarial loss
- Some interesting experiments

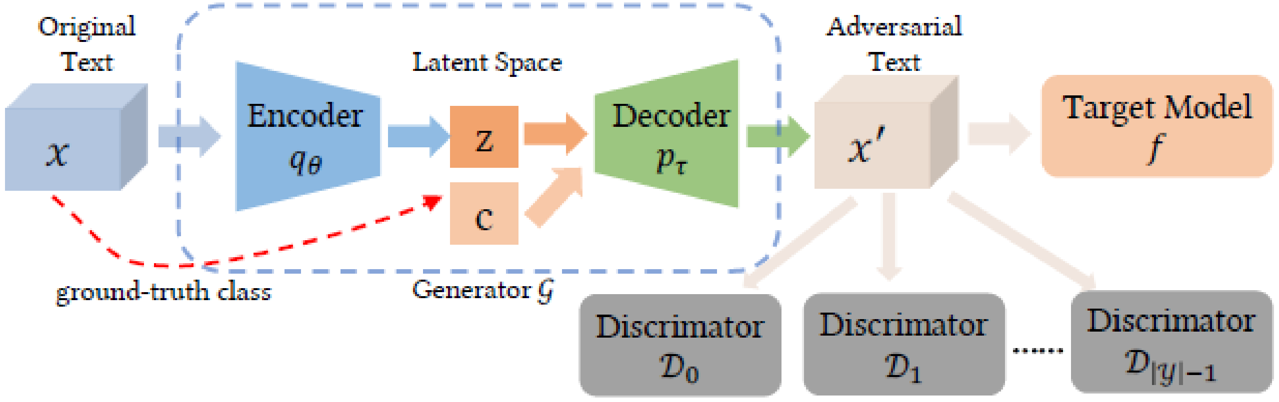
Methodology: overview

- three components:

  a generator G, discriminators D, and a targeted model

$$\mathcal{L}_{VAE}(\theta,\phi) = -\mathbb{E}_{q_\theta(z|x)}(\log p_\tau(x|z)) + \alpha \mathbb{KL}(q_\theta(z|x)||p(z))$$

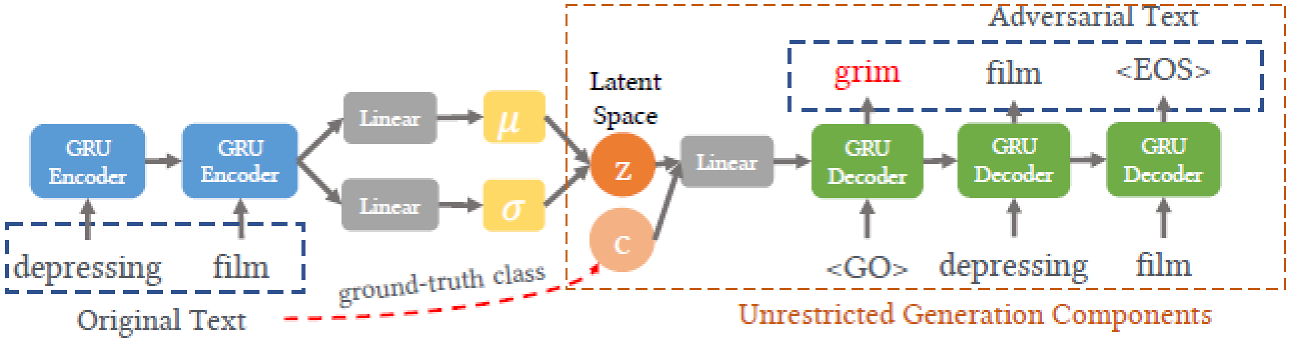
$$\mathcal{L}_{adv} = -\mathbb{E}_{p_\tau(x|z)}(\log P_{target}(y_t))$$

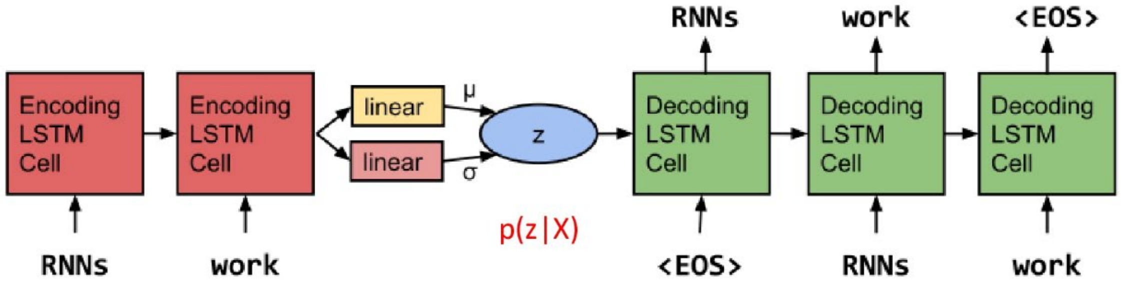


$$\mathcal{L}^k_{disc} = \mathbb{E}_{x\sim X_k}[\log(\mathcal{D}_k(x))] + \mathbb{E}_{x'\sim X_k'}[\log(1-\mathcal{D}_k(x'))]$$

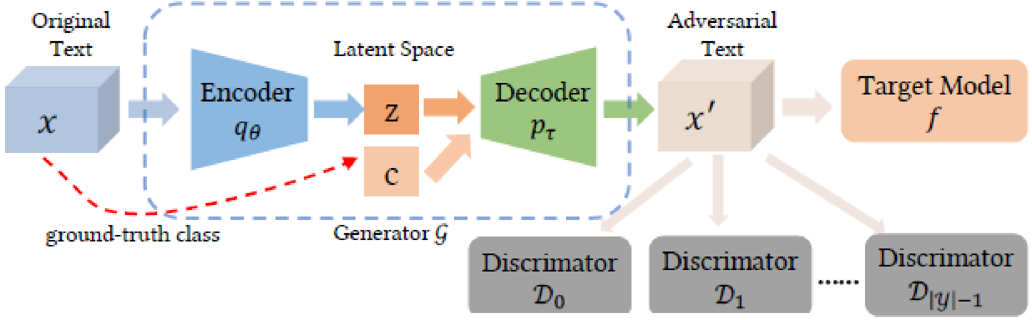
Methodology: generator

$$\mathcal{L}_{VAE}(\theta,\phi) = -\mathbb{E}_{q_\theta(z|x)}(\log p_\tau(x|z)) + \alpha\mathbb{KL}(q_\theta(z|x)||p(z))$$





Methodology： Model Training



$$\mathcal{L}_{VAE}(\theta, \phi) = -\mathbb{E}_{q_\theta(z|x)}(\log p_\tau(x|z)) + \alpha \mathbb{KL}(q_\theta(z|x)||p(z))$$

$$\mathcal{L}_{adv} = -\mathbb{E}_{p_\tau(x|z)}(\log P_{target}(y_t))$$

$$\mathcal{L}_{disc}^{k} = \mathbb{E}_{x \sim X_k}[\log(\mathcal{D}_k(x))] + \mathbb{E}_{x' \sim X_k'}[\log(1 - \mathcal{D}_k(x'))]$$

$$\mathcal{L}_{joint} = \mathcal{L}_{VAE} + \phi \mathcal{L}_{adv} + \sum_{k=1}^{|\mathcal{Y}|-1} \mathcal{L}_{disc}^{k}$$

Algorithm 1 Text Adversarial Examples Generation

Input: Training data of different classes $\mathbf{X}_0$, ..., $\mathbf{X}_{|\mathcal{Y}|-1}$
Output: Text Adversarial Examples

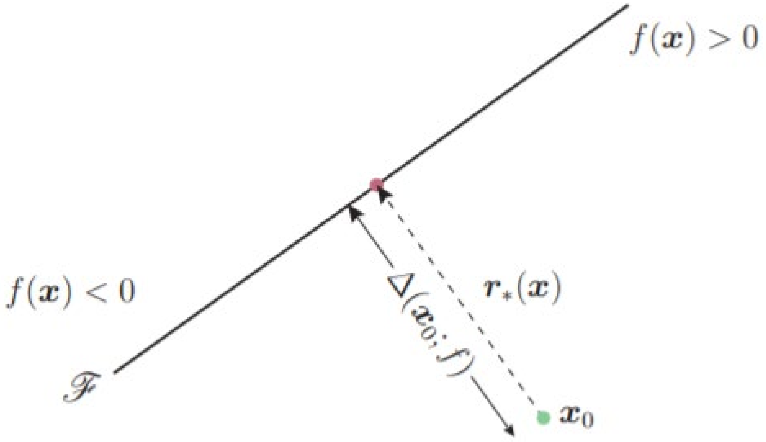
Train a VAE by minimizing $\mathcal{L}_{VAE}$ on $\mathbf{X}_0$, ..., $\mathbf{X}_{|\mathcal{Y}|-1}$ with KL-annealing mechanism and word drop
Initialize $\mathcal{G}$ with the pretrained VAE
Initialize the targeted model with a pretrained TextCNN
Freeze the weights of the targeted model
repeat
  for $y_k = y_0, y_1, ..., y_{|\mathcal{Y}|-1}$ **do**
    sample a batch of n texts $\{x_i\}_{i=0}^{n}$ of class y_k from $\mathbf{X}_k$
    $\mathcal{G}$ generates $\{x'\}_{i=0}^{n}$ with condition c_k
    Compute $\mathcal{L}_{disc}^{k} = \frac{1}{n}\sum_{i=1}^{n} \log \mathcal{D}_k(x) + \frac{1}{n}\sum_{i=1}^{n} \log(1 - \mathcal{D}_k(x'))$
  end for
  Update weights of $\mathcal{D}_0$, $\mathcal{D}_1$, ..., $\mathcal{D}_{|\mathcal{Y}|-1}$ by minimizing $-\sum_{k=1}^{|\mathcal{Y}|-1} \mathcal{L}_{disc}^{k}$
  Update weights of $\mathcal{G}$ by minimizing $\mathcal{L}_{joint}$
until convergence
if With inputs for the encoder **then**
  Encode inputs and decode the corresponding adversarial texts
else
  Randomly sample $z \in \mathcal{N}(0, 1)$ and choose a class $y_k \in \mathcal{Y}$
  The decoder takes $[z, c_k]$ and generates the adversarial text from scratch

Related Work

- gradient-based replacement methods
  - FSGM（Fast Gradient Sign Method）

$$x' = x + \varepsilon \cdot sign(\nabla_x J(x, y))$$

  - DeepFool



核心思想：最小程度的扰动来获得良好性能的对抗性样例。（可评估分类模型鲁棒性）

添加扰动之后将x0映射到分类边界的投影点p，即 $\boldsymbol{p} = \boldsymbol{x_0} + \boldsymbol{r}(\boldsymbol{x_0})$

- gradient-free replacement methods
  - TextBugger

基于梯度的攻击：FSGM. https://www.cnblogs.com/tangweijqxx/p/10615950.html

- TextBugger（白盒设定）

  - 使用雅克比矩阵找到最重要的单词排序

TABLE I. EXAMPLES FOR FIVE BUG GENERATION METHODS.

Original	Insert	Delete	Swap	Sub-C	Sub-W
foolish	f oolish	folish	fooilsh	fo0lish	silly
awfully	awfull y	awfuly	awfluly	awfu1ly	terribly
cliches	clich es	clichs	clcihes	c1iches	cliche

  - TEXTBUGGER的五种错误生成方法:
    (1)插入:插入一个空格到单词中。
    (2)删除:删除除第一个字符和最后一个字符外的任意字符。
    (3)交换:在单词中随机交换两个相邻的字母，但不改变第一个或最后一个字母。
    (4) Substitute-C (Sub-C):用视觉上相似的字符(例如，用“0”代替“o”，用“1”代替“l”，用“@”代替“a”)或键盘上相邻的字符(例如，用“n”代替“m”)代替字符。
    (5)Sub-W:在上下文感知的词向量空间中，用它的最近邻替换一个词。

  - 根据置信度的变化选择bug（选变化最大的）。用最优的bug来替换这个单词，得到一个新的文本。我们重复上述步骤来替换下一个单词，直到找到解决方案（攻击成功），或者未能找到一个**保留语义的对抗样本。**

TextBugger. https://www.cnblogs.com/shona/p/11809257.html

4 Experiment

4.1 Experiment Setup and Details

Two popular public benchmark datasets， both widely used in sentiment analysis and adversarial example generation

Rotten Tomatoes Movie Reviews (RT)： 5331 positive and 5331 negative processed movie reviews

80% of the dataset as the training set, 10% as the development set and 10% as the test set

IMDB： 50000 movie reviews from online movie websites

50% for training 50% are for testing.

Holdout 20% of the training set as a validation set.

4.2 Comparing With Pair-wise Methods

Representative methods as baselines：

Random： Select 10% words randomly and modify them.

FSGM

DeepFool

TextBugger

Generation Speed

Table 2. Time cost of generating one adversarial text.

Method	FGSM+NNS	TextBugger	Ours ($\phi = 5$)
Time	0.7s	0.05s	**0.014s**

Take the FGSM method as the representative of gradient-based methods, as FGSM is the fastest among them.

Measure the time cost of generating 1000 adversarial examples and calculate the average time of generating one.

Faster->Trained beforehand

Attack Success Rate

Table 1. Attack success rate of transforming given texts in a pair-wise way.

Method	RT	IMDB
Random	1.5%	1.3%
FGSM+NNS	25.7%	36.2%
DeepFool+NNS	28.5%	23.9%
TextBugger	85.1%	90.5%
Ours ($\phi = 5$)	**87.1%**	**92.8%**

Dataset: RT. **Method:** Ours(ϕ = 9). **Ground-truth:** Positive. **Original prediction:** 0.95 Positive. **Adversarial prediction:** 0.68 Negative.

Text: ~~Inside~~ one the films ~~conflict~~ like powered plot there is a decent moral trying to get out but its not that it's the ~~tension~~ first that ~~keeps~~ makes you ~~in~~ feel your seat affleck and jackson ~~are good~~ is magnificent sparring partners

Dataset: IMDB. **Method:** Ours(ϕ = 9). **Ground-truth:** Negative. **Original prediction:** 0.98 Negative. **Adversarial prediction:** 0.94 Positive.

Text: i ~~read the novel~~ love the book some years ago and i ~~liked~~ loved it a lot when i ~~saw the~~ read this movie i ~~couldnt believe~~ was cared it ~~they changed~~ was thrown everything i ~~liked~~ expected about the ~~novel~~ book even the plot i wonder ~~what~~ if did isabel allende ~~author~~ did say about ~~the~~ this movie but i think it sucks

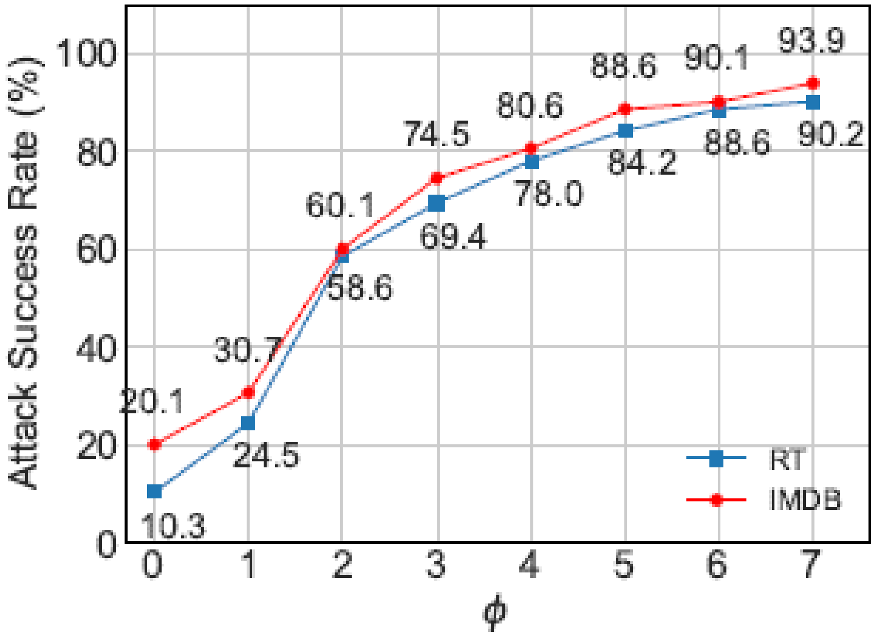
Dataset: IMDB. **Method:** TextBugger. **Ground-truth:** Negative. **Original prediction:** 0.99 Negative. **Adversarial prediction:** 0.81 Positive.

Text: I love these ~~awful~~ awf ul 80's summer camp movies. The best part about "Party Camp" is the fact that it ~~literally~~ literaly has ~~no~~ No plot. The ~~cliches~~ clichs here are limitless: the nerds vs. the jocks, ..., the secretly horny camp administrators, and the ~~embarrassingly~~ embarrassing1y ~~foolish~~ fo0lish sexual innuendo littered throughout. This movie will make you laugh, but never intentionally. I repeat, never.

Figure 4. Adversarial texts generated in a pair-wise way. In texts, the crossed out contents are from the original texts, while the red texts are the substitute contents in the adversarial examples.

4.3 Unrestricted Adversarial Text Generation

Attack Success Rate



(a) Attack Success Rate

The attack success rate of the vanilla VAE is only 10.3% and 20.1% respectively, this implies **that only randomly generating texts can hardly fool the targeted model.**

When φ is greater than 0, the attack success rate is consistently better than the vanilla VAE. This reflects the importance of $\mathbf{L_{adv}}$.

Adversarial Examples

Dataset: RT. **Method:** Vanilla VAE ($\phi = 0$). **Chosen Emotional Class:** Negative. **Model prediction:** 0.53 Positive.

Text: this is the kind of movie that might have been benefited from a movie that is not more than a movie

Dataset: IMDB. **Method:** Vinilla VAE ($\phi = 0$). **Chosen Emotional Class :** Positive. **Model prediction:** 0.54 Negative.

Text: i had never heard of this movie until the end of the first half hour or minutes we were glued to the edge of your seat throughout the entire movie i thought it was going to be a good idea to see a movie about a bunch of people trying to find out what happened to their ... see if you want to see a movie that is going to happen next to the end

Dataset: RT. **Method:** Ours ($\phi = 1$). **Chosen Emotional Class :** Positive. **Model prediction:** 0.99 Negative

Text: theres no reason to be disappointed

Dataset: RT. **Method:** Ours ($\phi = 7$). **Chosen Emotional Class :** Negative. **Model prediction:** 0.89 Positive

Text: sandra bullock fish out into a dark and poorly executed story about about about which he doesnt manage to be a joyful teacher

Dataset: IMDB. **Method:** Ours ($\phi = 1$). **Chosen Emotional Class :** Negative. **Model prediction:** 0.97 Positive

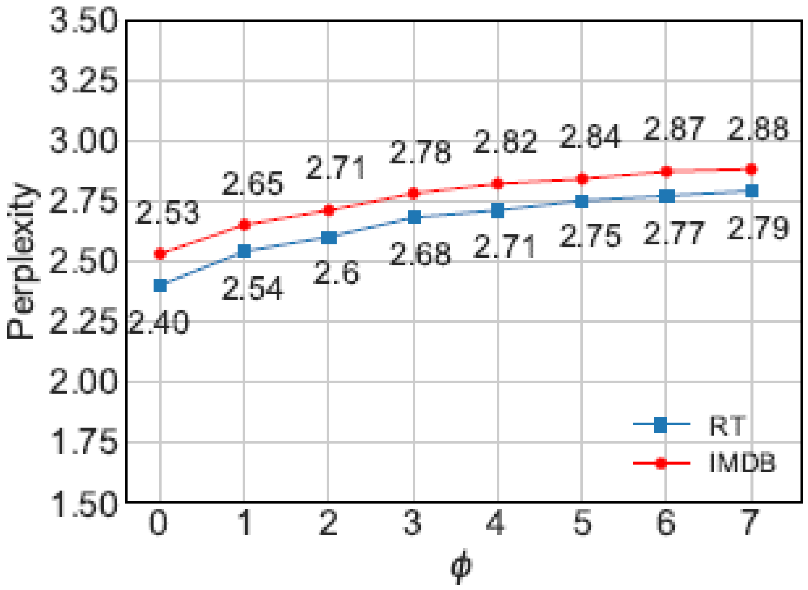
Text: this was the first time i saw this movie when i was a kid i was expecting it to be the first time i saw this movie i was thoroughly impressed with this movie was that it was so bad

Dataset: IMDB. **Method:** Ours ($\phi = 7$). **Chosen Emotional Class :** Positive. **Model prediction:** 0.93 Negative

Text: a lot of fun to watch this movie is about a virus who crashes in the himalayas unlucky enough to take a trip to the old house in the woods in the himalayas unlucky enough to be a photographer and wanted to prevent the freezing man in a limb in a limb in a limb in a limb in a limb in his assignment to stop him he decides to take him out of his apartment with his wife

Figure 6. Adversarial examples generated from scratch unrestrictedly. Humans should classify adversarial texts as the chosen emotional class y_k.

Quality of the generated adversarial texts 1 : **Perplexity**



(b) Perplexity

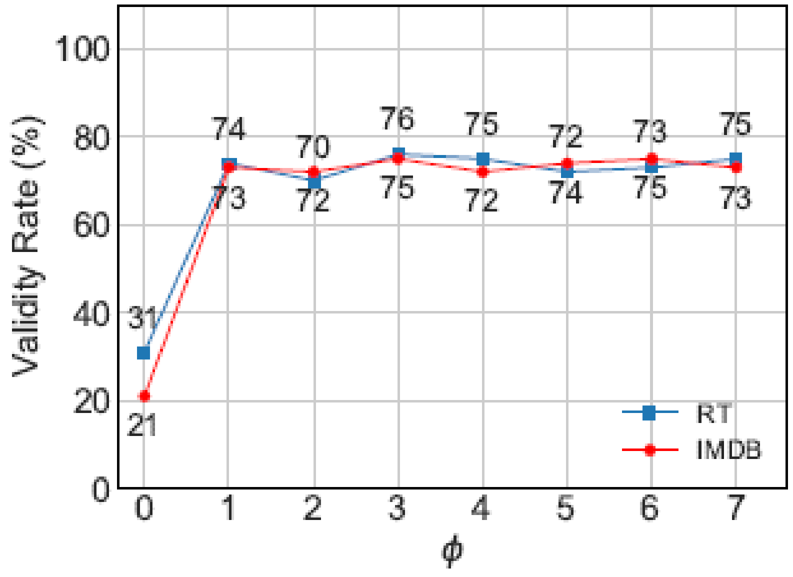
$$Perplexity = -\frac{1}{|word\_num|}\sum_{x \in X'}\sum_{j=1}^{V}\log P(x'_j|x'_0, ..., x'_{j-1}) \quad (15)$$

A low perplexity indicates the language model is good at predicting the sample. (fluency)

The quality of generated texts are acceptable: only a bit higher than the original data's

As φ gets larger, the perplexity gets bigger. This is perhaps because **L_{adv} can distort the generated texts.**

Quality of the generated adversarial texts 2 : **Validity**



(c) Validity Rate

A valid generated adversarial text is supposed to be classified as class yk by humans but be classified as class yt≠yk by the targeted model.

higher than 70% and much higher than that of the vanilla VAE.

Ablation Study (4.4)

Table 3. Performance of our model trained with and without $\mathcal{L}_{disc}$.

Dataset	Method	Attack Success Rate	Perplexity	Validity
RT	with $\mathcal{L}_{disc}$	90.2%	2.79	75%
	without $\mathcal{L}_{disc}$	94.1%	7.32	15%
IMDB	with $\mathcal{L}_{disc}$	93.9%	2.88	73%
	without $\mathcal{L}_{disc}$	94.3%	7.41	12%

The attack **success rates** of models trained with and without L_{disc} are **close**.

But the **validity** of the model trained without L_{disc} is **much lower** than that of the model with L_{disc}.

Discriminators to draw distribution of adversarial texts close to the distribution of real data.

This shows that **discriminators loss can improve the validity greatly.**

Quality of the generated adversarial texts 3 : **Diversity**

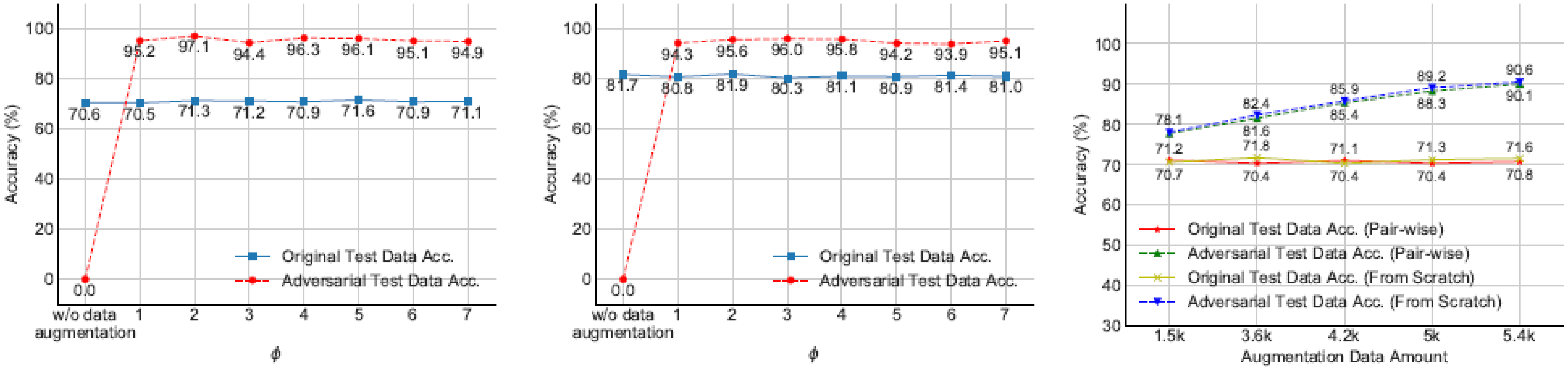
We first **generate one million adversarial texts**.

To compare generated texts with train data, we **extract all 4-grams of train data and generated texts.** On average, for each generated text, **less than 18% of 4-grams can be found in all 4-grams of train data on all datasets**. This shows that there exists some similarity and our model **can also generate texts with different words combinations**.

To compare generated texts with each other, **we suppose that if over 20% of 4-grams of one generated text don't exist at the same time in any one of the other generated texts, the text is one unique text.** We observe more than **70% of generated texts are unique**. This proved that the generated texts are diverse.

4.5 Defense With Adversarial Training

Using the adversarial examples to augment the training data can make models more robust, this is called **adversarial training**.



(a) RT (b) IMDB (c) Data augmentation compare

Figure 7. Defense with adversarial training in different settings. (a) and (b) On RT and IMDB datasets, data augmentation with adversarial data generated from scratch under different ϕ. (c) On RT dataset, accuracy of models trained with equal size of augmentation adversarial data, which is generated in pair-wise way and unrestricted generation way respectively.