Adversarial Training with Contrastive Learning in NLP

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Introduction

- **Task**: Language modeling (LM) and Neural Machine Translation (NMT).

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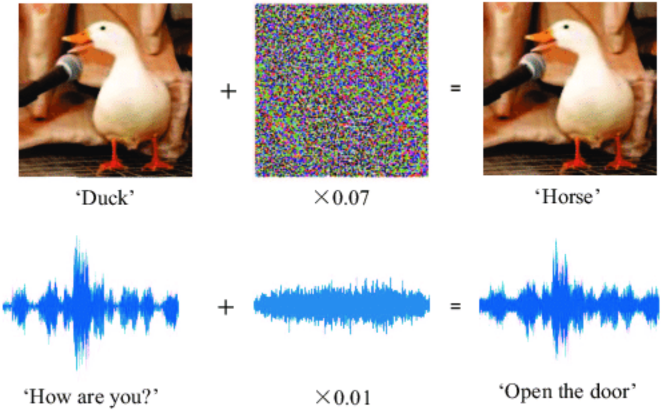
- **Goal**: Improve models so that they are semantically more robust:

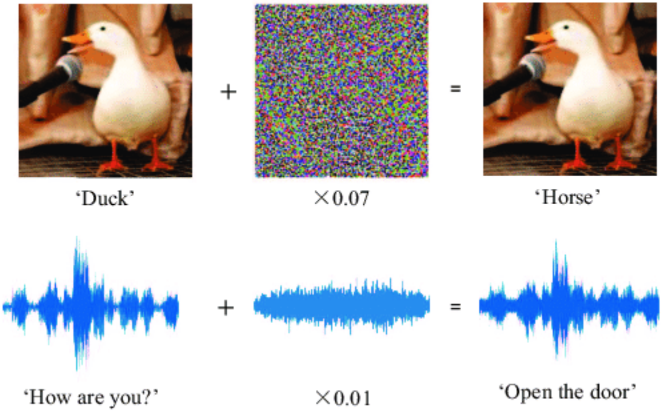
$$\text{Similar inputs} \implies \text{Similar outputs}$$

Tools

Adversarial Training



Adversarial Training



How does adversarial training help our models ?

Adversarial examples creation techniques

- Visual techniques: (Morris u. a., 2020).

Original Input	This film has a special place in my heart	Positive
Adversarial example	This film has a special plcae in my herat	Negative

Table 1: Example extracted from (Gao u. a., 2018)

- Semantic:(Jin u. a., 2019).

Original
<u>**Perfect**</u> performance by the actor → **Positive (99%)**

Adversarial
<u>**Spotless**</u> performance by the actor → **Negative (100%)**

Figure 1: Example extracted from (Jin u. a., 2019)

Our adversarial examples

Given a sequence of tokens $s = \{x_1, \ldots, x_T\}$

1. We map each discrete token to an embedded representation in the continuous space

$$\mathbf{E}x_i = e_i.$$

2. We add a little perturbation to the embedding

$$e_i' = e_i - \epsilon \frac{\nabla_{e_i} J(s, \theta)}{\|\nabla_{e_i} J(s, \theta)\|_2}.$$

Current loss function:

$$\mathcal{J}(\theta) = \sum_{s} \mathcal{L}(s, \theta) + \alpha \sum_{s'} \mathcal{L}_{adv}(s', \theta), \quad \alpha \in [0, 1].$$

Example

Original: Elephant. Positive: Tiger. Negative: Pizza.

Definition (Contrastive loss)

Let a_i be the original inputs, p_{a_i} positive examples and n_a negative examples. The contrastive loss is defined as follows:

$$\mathcal{L}_{cont} = -\sum_{a_i \in A} \log \frac{\exp(a_i \cdot p_{a_i}/\tau)}{\sum_{n_a \in A-\{a_i\}} \exp(a_i \cdot n_a/\tau)}$$

Framework

Adversarial Training with Contrastive Learning (ATCL)

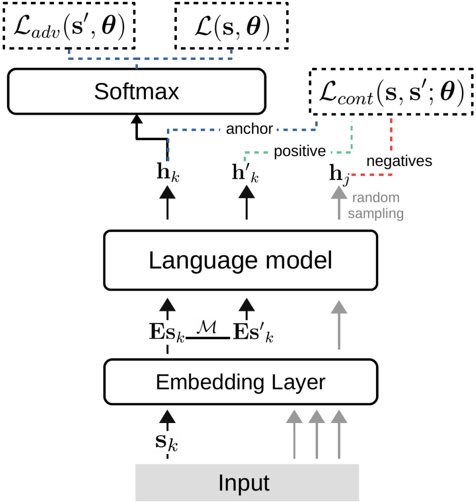


Figure 2: ACTL Framework. Image obtained from the original paper (Rim u. a., 2021).

Considerations about ATCL

Definition (ATCL's loss function)

The used loss function to train ATCL is:

$$\mathcal{J}(\theta)_{ATCL} = (\mathcal{L} + \alpha\mathcal{L}_{adv} + \beta\mathcal{L}_{cont})$$

Experiments and results

Language modeling

Model and Training	Wikitext 103		Penn Tree Bank	
	Validation	Test	Validation	Test
T XL base	23.10	24.00	56.72	54.52
T XL +TT	23.61	25.70	57.90	55.40
Baseline TT	22.70	22.42	41.91	36.13
Baseline +Adv. only	21.75	21.67	42.68	36.46
Baseline +ATCL (n=5)	22.79	22.59	37.93	32.89
Baseline +ATCL (n=10)	21.75	21.67	**35.29**	**29.08**
Baseline +ATCL (n=20)	**20.73**	**20.61**	42.52	36.85

Table 2: Perplexity achieved.

Language modeling

Word	Baseline	+Adv. only	+ATCL
friend	‘brother’, ‘daughter’, ‘understanding’, **‘director’**	‘cousin’, ‘colleague’, **‘knowledge’**, ‘mentor’	‘cousin’, ‘fellow’, ‘partner’, ‘colleague’
hate	‘admit’, ‘prejudice’, ‘troubled’, ‘regret’	**‘loving’**, ‘hurt’, **‘embrace’**, ‘committing’	‘dirty’, ‘poison’, ‘regret’, ‘shame’

Table 3: Four closest neighbors of some words in the vocabulary of the WikiText-103. Table from (Rim u. a., 2021).

Model name	En-De	De-En	En-Fr	Fr-En
Baseline (Transformer S)	24.61	30.34	35.23	34.51
Baseline +Adv	25.04	30.36	35.02	**35.97**
Baseline +ATCL	24.63	**31.34**	**36.40**	35.35
	25.26	30.36	35.60	35.48
	24.74	30.13	35.38	35.46

Table 4: BLEU test scores for the IWSLT dataset. Table from (Rim u. a., 2021).

Conclusions

- Usage of two general machine learning techniques applied to natural language processing.
- Applying this method has a similar effect to regularization.
- Results are promising in Language modeling, but not so much in Neural Machine Translation.

Thank you for your attention.

References

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[Jin u. a. 2019] Jin, Di ; Jin, Zhijing ; Zhou, Joey T. ; Szolovits, Peter: Is BERT Really Robust? Natural Language Attack on Text Classification and Entailment. (2019). – URL http://arxiv.org/abs/1907.11932

[Morris u. a. 2020] Morris, John X. ; Lifland, Eli ; Yoo, Jin Y. ; Qi, Yanjun: TextAttack: A Framework for Adversarial Attacks in Natural Language Processing. (2020). – URL https://arxiv.org/abs/2005.05909

[Rim u. a. 2021] Rim, Daniela N. ; Heo, DongNyeong ; Choi, Heeyoul: Adversarial Training with Contrastive Learning in NLP. (2021). – URL https://arxiv.org/abs/2109.09075

Elements

We consider:

- $\mathbf{S} = \{s_1, \ldots, s_B\}$ a set of sentences, where each sentence $s_k = \{x_{k1}, \ldots, x_{kN}\}$ contains N tokens.
- $\mathbf{E}s_k = \{\mathbf{E}x_{k1}, \ldots, \mathbf{E}x_{kN}\} = \{e_{k1}, \ldots e_{kN}\}$ the continuous space embedding of each sentence.
- The vocabulary $\mathcal{V}$ and a **restricted** subset from it in which we exclude incomplete words (single characters or symbols) $\mathcal{V}_R$
- The restriction function from $\mathcal{V}$ to $\mathcal{V}_R$:

$$\mathcal{M}(\mathbf{E}x_{ki}) = \begin{cases} 1 & \text{if } x_{ki} \in \mathcal{V}_R \\ 0 & \text{otherwise} \end{cases}$$

  (this function avoids taking senseless adversarial candidates).
- h_{kj} the representation of each sentence s_k.