# Counter-Contrastive Learning for Language GANs[1]

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[1] The work was done at Institute of Automation, Chinese Academy of Sciences (CASIA).

# Overview


1. Introduction
2. Methodology
3. Experiments
4. Conclusions

## Language GANs are an alternative to mitigate exposure bias.

1. Previous innovations adopt various approaches to enhance the learning signals for generators, such as using ranking or feature matching techniques. However, the problem of language GANs' training is far from being fully solved.
2. Inspired by the recent success in contrastive learning approaches in learning effective representations, we propose a **counter-contrastive learning** objective to aid the adversarial learning of sequence generators in language GANs.

## Language GAN

1. Train a language generator $G$ to compete with the discriminator $D$, *i.e.*, $D$ is to distinguish $G$'s output $x^-$ from real data $x^+$, while $G$ aims at preventing $x^-$ from being discriminated from $x^+$.
2. Language GANs target towards training a good $G$. Thus, we would like to support $G$, *i.e.*, **draw together the representation of $x^-$ and $x^+$ to cheat $D$**!

# Background: Contrastive Learning

Assuming a set of paired examples $\mathcal{D} = \{(x_i, x_i^+)\}_{i=1}^N$, where $(x_i, x_i^+)$ are positive pairs. Let the $\mathrm{h}_i$ and $\mathrm{h}_i^+$ denote the representations of $x_i$ and $x_i^+$, the contrastive learning training objective is:

$$\mathcal{L}_i^{\mathrm{CL}} = -\log \frac{e^{\mathrm{sim}(\mathrm{h}_i, \mathrm{h}_i^+)/\tau}}{\sum_{j=1}^N e^{\mathrm{sim}(\mathrm{h}_j, \mathrm{h}_j^+)/\tau}} \tag{1}$$

where $\tau$ is the temperature scalar, and $\mathrm{sim}(\cdot)$ is the cosine similarity operator.

Contrastive Learning **pulls together positive neighbors** $(x_i, x_i^+)$ and **pushes way non-neighbors** $(x_i^+, x_i^-)$ $\Rightarrow$ help to discriminate positive samples from negative ones, which exactly benefits the discriminator $\mathcal{D}$.

# Intuition: Counter-Contrastive Learning

## Contrastive Learning

1. Help $\mathcal{D}$ to discriminate positive samples from negative ones.
2. However, the generator $\mathcal{G}$ in language GANs aims to **cheat the discriminator** $\mathcal{D}$!

## Counter-Contrastive Learning

- Draw together the fake and real samples $(x_i, x_i^-)$ (to let the generator imitate the real sentences)
- Push away the real samples $(x_i, x_i^+)$ (to fool and hinder the discriminator training, thereby preventing it from fast convergence).

# Counter-Contrastive Learning (CCL)

Given the mini-batch of size $N$, we formulate the counter-contrastive learning objectives as:

$$\mathcal{L}_i = -\log \frac{e^{\mathrm{sim}(\mathrm{h}_i, \mathrm{h}_i^-)/\tau}}{\sum_{j=1}^{N} \left( e^{\mathrm{sim}(\mathrm{h}_j, \mathrm{h}_j^-)/\tau} + e^{\mathrm{sim}(\mathrm{h}_j, \mathrm{h}_j^+)/\tau} \right)} \tag{2}$$

where $\tau$ is the constant temperature.

# Contrastive Pair Construction

## Counter-Contrastive Learning

- **Negative pairs**: Sample the negative one from the $G$ and the positive one from real data.
- **Positive pairs**: Sample one real sentence from real data, but apply different dropout when computing their representations to increase the robustness. Refer to the paper for details.

# Data

| dataset | Synthetic data | MS COCO Image Caption | EMNLP2017 WMT News |
|---|---|---|---|
| vocabulary size | 5,000 | 4,657 | 5,255 |
| sequence length | 20 / 40 | 37 | 51 |
| training set | 10,000 | 10,000 | 278,586 |
| test set | 10,000 | 10,000 | 10,000 |

- **Synthetic data**, which is generated by an oracle single-layer LSTM. We use a randomly initialized single-layer LSTM as the oracle, and generate 10,000 discrete sequences of length 20 and 40 respectively as either training or test set.
- **Real data**. We use MS COCO Image Captions (only caption references are used) and EMNLP2017 WMT News dataset.

# Results

## Results on Synthetic Data

| Model | $\text{NLL}_{\text{oracle}}$ (20/40) | $\text{NLL}_{\text{gen}}$ (20/40) | $\text{NLL}_{\text{oracle}} + \text{NLL}_{\text{gen}}$ (20/40) |
|---|---|---|---|
| MLE | 9.05$\pm$0.03 / 9.84$\pm$0.02 | 5.96$\pm$0.02 / 6.55$\pm$0.02 | 15.02$\pm$0.03 / 16.39$\pm$0.01 |
| SeqGAN | 8.63$\pm$0.19 / 9.63$\pm$0.04 | 6.61$\pm$0.22 / 6.98$\pm$0.08 | 15.00$\pm$0.03 / 16.35$\pm$0.02 |
| RankGAN | 8.42$\pm$0.31 / 9.52$\pm$0.11 | 7.14$\pm$0.34 / 7.05$\pm$0.12 | 15.01$\pm$0.02 / 16.37$\pm$0.02 |
| MaliGAN | 8.74$\pm$0.16 / 9.67$\pm$0.03 | 6.62$\pm$0.25 / 7.14$\pm$0.09 | 15.03$\pm$0.03 / 16.39$\pm$0.03 |
| SAL | 7.71$\pm$0.17 / 9.31$\pm$0.03 | 6.58$\pm$0.15 / 6.97$\pm$0.05 | 14.29$\pm$0.11 / 16.24$\pm$0.03 |
| Ours | **6.77**$\pm$0.34 / **6.65**$\pm$0.14 | 6.91$\pm$0.62 / 7.68$\pm$0.79 | **13.69**$\pm$0.36 / **14.33**$\pm$0.76 |

# Results on Real Data

## MS COCO Image Captions

It achieves competitive results in terms of the sample **quality** (indicated by BLEU scores) while maintaining the **diversity** (indicated by $\mathrm{NLL}_{\mathrm{gen}}$).

| Model | BLEU-2 | BLEU-3 | BLEU-4 | BLEU-5 | $\mathrm{NLL}_{\mathrm{gen}}$ |
|---|---|---|---|---|---|
| MLE | 0.731 | 0.497 | 0.305 | 0.189 | 0.718 |
| SeqGAN | 0.745 | 0.498 | 0.294 | 0.180 | 1.082 |
| RankGAN | 0.743 | 0.467 | 0.264 | 0.156 | 1.344 |
| LeakGAN | 0.746 | 0.528 | 0.355 | 0.230 | 0.679 |
| RelGAN | 0.849±0.030 | 0.687±0.047 | 0.502±0.048 | 0.331±0.044 | 0.756±0.054 |
| SAL | 0.785±0.02 | 0.581±0.03 | 0.362±0.02 | 0.227±0.02 | 0.873±0.02 |
| Ours (CCL) | **0.871**±0.032 | **0.715**±0.050 | **0.538**±0.068 | **0.399**±0.082 | **0.630**±0.103 |

# Results on Real Data

## EMNLP2017 WMT News

| Model | BLEU-2 | BLEU-3 | BLEU-4 | BLEU-5 | $NLL_{gen}$ |
|---|---|---|---|---|---|
| MLE | 0.768 | 0.473 | 0.240 | 0.126 | 2.382 |
| SeqGAN | 0.777 | 0.491 | 0.261 | 0.138 | 2.773 |
| RankGAN | 0.727 | 0.435 | 0.209 | 0.101 | 3.345 |
| LeakGAN | 0.826 | 0.645 | 0.437 | 0.272 | **2.356** |
| RelGAN | 0.881±0.013 | 0.705±0.019 | 0.501±0.023 | 0.319±0.018 | 2.482±0.031 |
| SAL | 0.788±0.02 | 0.523±0.02 | 0.281±0.02 | 0.149±0.02 | 2.578±0.04 |
| Ours | **0.903**±0.016 | **0.749**±0.022 | **0.525**±0.017 | **0.324**±0.008 | 2.818±0.499 |

# Results

## Case Study

GANs with CCL tend to produce sentences with better diversity.

| model | Sample sentences |
|---|---|
| w/o CCL | a cat is sitting on a white plate .<br>a cat is sitting on a bathroom sink sitting inside of a toilet .<br>a black and white cat outside decorated in rustic kitchen .<br>a cat is sitting on a bathroom sink sitting in a bathroom .<br>a cat is sitting on a bathroom sink sitting on a bathroom counter .<br>a cat sitting on a gravel ground inside of a bathroom sink .<br>a cat is sitting on a bathroom sink sitting in a bathroom . |
| w/ CCL | a cat is sitting on top of a car .<br>a cat is sitting on top of a car cleaning itself .<br>a cat is sitting on top of a car roof .<br>a cat is sitting on top of a car hood .<br>a cat is sitting on top of a man 's head in front of a glass door .<br>a dog sitting on top of a parked car near a cat .<br>a cat in a white bathroom with a toilet paper beside a child . |

# Conclusion

- We introduce a counter-contrastive learning objective to advance the training of language GANs.
- It pulls the representation of generated and real samples together to promote the generator training, and pushes apart real sample pairs to depress the discriminator training as a competitor.

Thanks