

Diversity-Promoting GAN: A Cross-Entropy Based Generative Adversarial Network for Diversified Text Generation

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Abstract

- **Task:**
 - Text Generation.
- **Problem:**
 - Existing text generation methods tend to produce **repeated and “boring”** expressions.
- **Proposal:**
 - We propose a new model, called Diversity-Promoting Generative Adversarial Network (**DP-GAN**) for diversified text generation.
 - The proposed model assigns low reward for repeatedly generated text and high reward for “novel” and fluent text.
 - Moreover, we propose a novel **language model based discriminator** without the saturation problem.

Approach

Our model contains a **generator** and a **discriminator**. The sketch is shown in Figure 1.

- The **generator** G_θ is responsible for generating text, which is based on a sequence-to-sequence structure.
- The **discriminator** D_ϕ is a language model.
- We define **cross entropy** as the reward to train the generator.

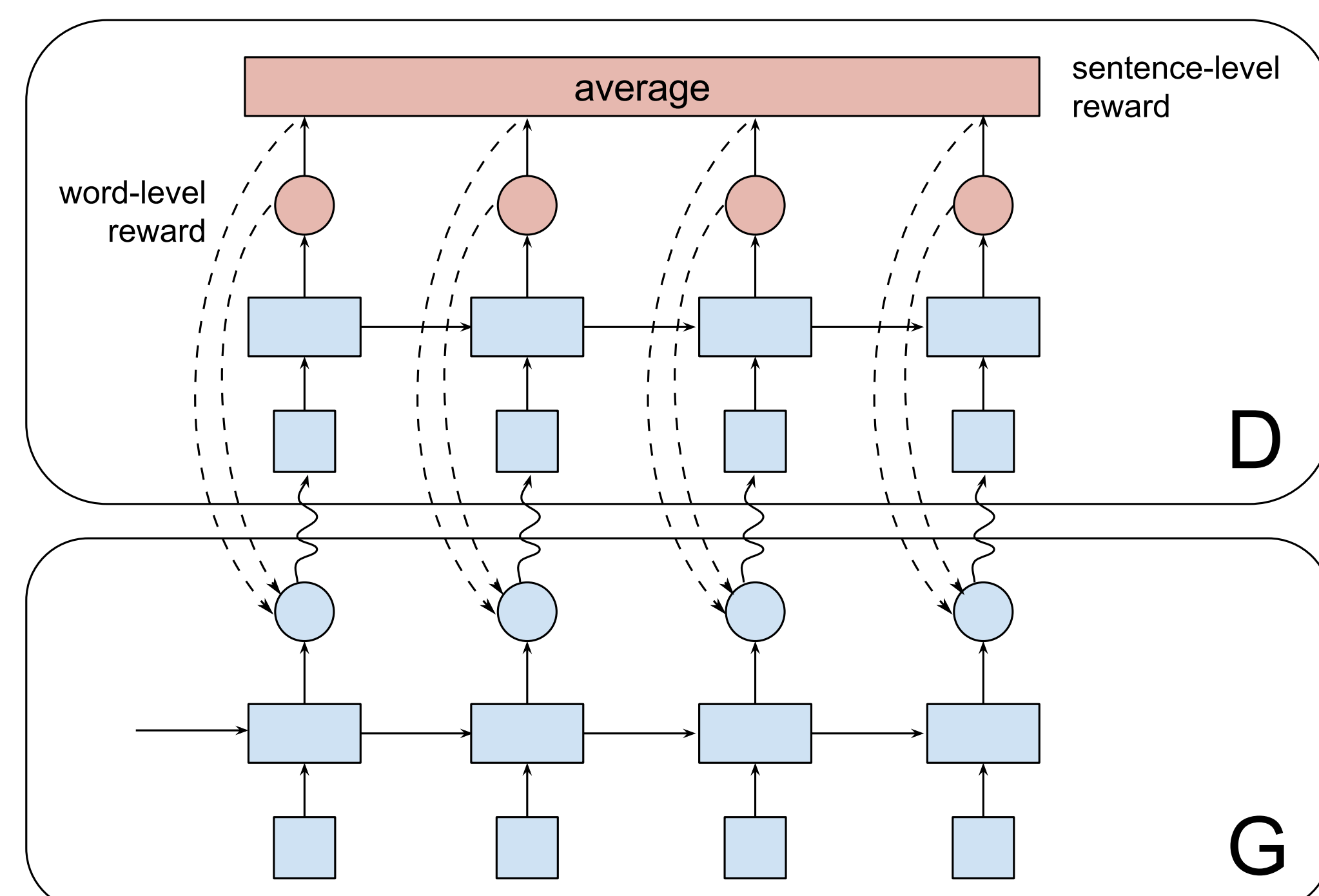


Figure 1: Illustration of DP-GAN. Lower: The generator. Upper: The discriminator.

Rewards

Our reward function consists of two parts:

▪ Sentence-Level Reward

For a sentence y_t of K words, the reward at the sentence level is the averaged reward of each word:

$$R(y_t) = -\frac{1}{K} \sum_{k=1}^K \log D_\phi(y_{t,k}|y_{t,<k}) \quad (1)$$

▪ Word-Level Reward

Considering that the reward for different words in a sentence y_t should be different, we further propose to use the reward at the word level as follows:

$$R(y_{t,k}|y_{t,<k}) = -\log D_\phi(y_{t,k}|y_{t,<k}) \quad (2)$$

Policy Gradient Training

Adversarial reinforcement training:

- 1: Initialize G_θ, D_ϕ with random weights θ, ϕ
- 2: Pre-train G_θ using MLE on a sequence dataset $\mathcal{D} = (X, Y)$
- 3: Generate samples using G_θ for training D_ϕ
- 4: Pre-train D_ϕ
- 5: $N =$ number of training iterations
- 6: $M =$ number of training generator
- 7: $K =$ number of training discriminator
- 8: **for** each $i = 1, 2, \dots, N$ **do**
- 9: **for** each $j = 1, 2, \dots, M$ **do**
- 10: Generate a sequence $Y_{1:T} \sim G_\theta$
- 11: Update generator via policy gradient
- 12: Sample a sequence $Y_{1:T} \sim \mathcal{D}$
- 13: Update generator parameters
- 14: **end for**
- 15: **for** each $j = 1, 2, \dots, K$ **do**
- 16: Generate samples using G_θ
- 17: Train discriminator D_ϕ
- 18: **end for**
- 19: **end for**

Experiment Dataset

Task:

- Review generation: Yelp & Amazon.
- Dialogue generation: OpenSub.

Results

Automatic evaluation results:

Yelp	Token	Dist-1	Dist-2	Dist-3	Dist-S
MLE	151.2K	1.2K	3.9K	6.6K	3.9K
PG-BLEU	131.1K	1.1K	3.3K	5.5K	3.1K
SeqGAN	140.5K	1.1K	3.5K	6.1K	3.6K
DP-GAN	406.8K	3.4K	22.3K	49.6K	17.3K

Dialogue	Token	Dist-1	Dist-2	Dist-3	Dist-S
MLE	81.1K	1.4K	4.4K	6.3K	4.1K
PG-BLEU	97.9K	1.2K	3.9K	5.5K	3.3K
SeqGAN	83.4K	1.4K	4.5K	6.5K	4.5K
DP-GAN	97.3K	2.1K	10.8K	19.1K	8.0K

Human evaluation results:

Yelp	Relevance	Diversity	Fluency	All
MLE	1.49	1.73	1.78	1.89
PG-BLEU	1.47	2.59	1.38	2.22
SeqGAN	1.48	2.40	1.54	2.12
DP-GAN	1.32	1.23	1.66	1.51

Dialogue	Relevance	Diversity	Fluency	All
MLE	1.19	1.84	1.37	1.87
PG-BLEU	1.13	1.85	1.21	1.75
SeqGAN	1.13	1.71	1.20	1.64
DP-GAN	1.13	1.50	1.30	1.55

Analysis

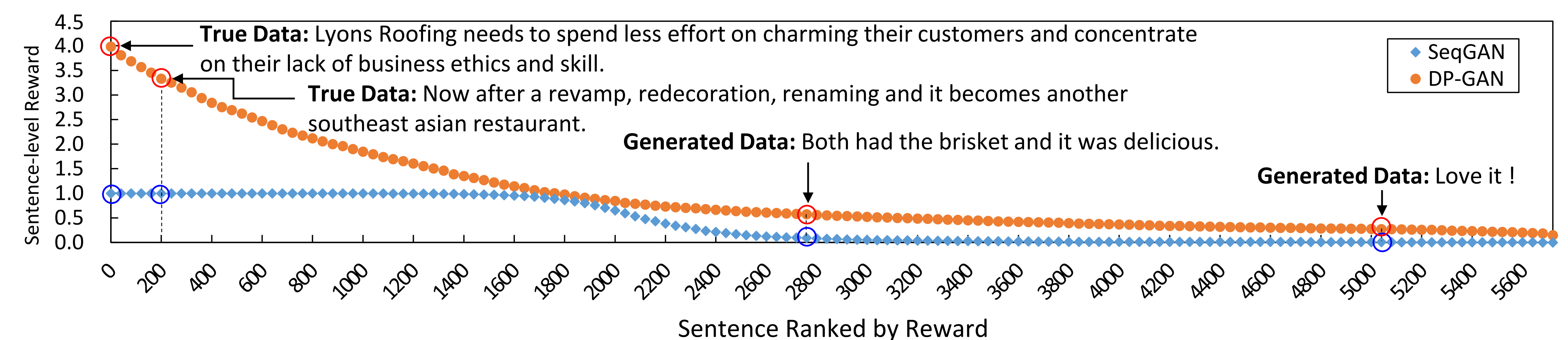


Figure 2: Distribution of rewards between SeqGAN and DP-GAN. The upper two sentences are sampled from the real-world data and the lower two sentences are sampled from the generated data.

Contributions

- We propose a new model, called DP-GAN, for diversified text generation, which assigns low reward for repeated text and high reward for novel and fluent text.
- We propose a novel language-model based discriminator that can better distinguish novel text from repeated text without the saturation problem.
- The experimental results on review generation and dialogue generation tasks show that our method can generate substantially more diverse and informative text than existing methods.