

Introduction

- Generate natural language descriptions similar to human-written.
- Existing GANs restrict the discriminator to be a binary classifier.
- The proposed RankGAN learns from relative ranking between machine- and human-written sentences in an adversarial framework.

Adversarial Ranking

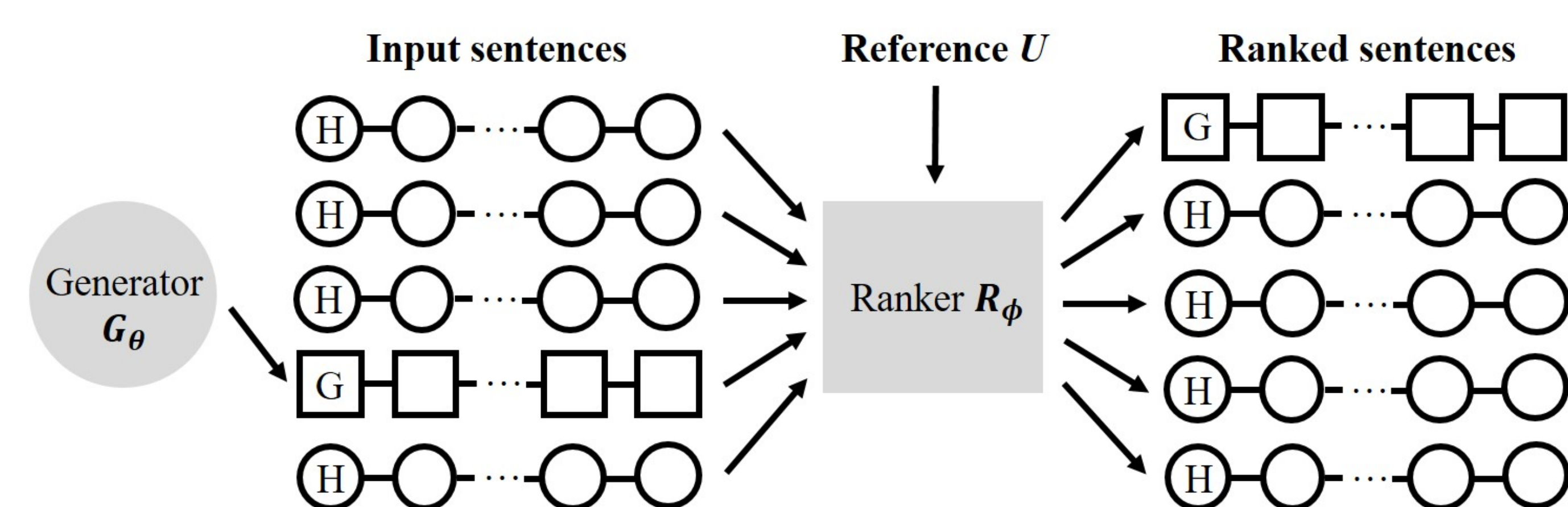


Figure 1: **H** denotes the sentence sampled from the human-written sentences. **G** is the sentence generated by the generator G_θ . It is illustrated that the generator tries to fool the ranker and let the synthetic sentence to be ranked at the top with respect to the reference sentence.

MinMax game:

$$\min_{\theta} \max_{\phi} \mathcal{L}(G_\theta, R_\phi) = \mathbb{E}_{s \sim \mathcal{P}_h} [\log R_\phi(s|U, \mathcal{C}^-)] + \mathbb{E}_{s \sim G_\theta} [\log(1 - R_\phi(s|U, \mathcal{C}^+))]$$

where U is the reference set used for estimating relative ranks, and \mathcal{C}^+ , \mathcal{C}^- are the comparison set with regard to input sentences s .

Ranking score:

$$\log R_\phi(s|U, \mathcal{C}) = \mathbb{E}_{u \in U} \log \left[\frac{\exp(\gamma \alpha(s|u))}{\sum_{s' \in \mathcal{C}'} \exp(\gamma \alpha(s'|u))} \right]$$

$\alpha(s|u)$ computes cosine similarity between reference u and input sequence s . \mathcal{C}' denotes all sentences to be ranked. γ is a hyperparameter.

Ranking score for partial sentence:

$$V_{\theta, \phi}(s_{1:t-1}, U) = \mathbb{E}_{s_r \sim G_\theta} [\log R_\phi(s_r|U, \mathcal{C}^+, s_{1:t-1})]$$

where s_r is a simulated sentence by Markov rollout method.

Policy gradient for generator G_θ :

$$\nabla_{\theta} \mathcal{L}_{\theta}(s_0) = \mathbb{E}_{s_{1:T} \sim G_\theta} \left[\sum_{t=1}^T \sum_{w_t \in V} \nabla_{\theta} \pi_{\theta}(w_t | s_{1:t-1}) V_{\theta, \phi}(s_{1:t}, U) \right]$$

where w_t is the next token sampled by policy π_{θ} .

Synthetic Data Experiments

Method	MLE	PG-BLEU	SeqGAN	RankGAN
NLL	9.038	8.946	8.736	8.247

Table 1: The performance comparison of different methods on the synthetic data [SeqGAN, AAA17] in terms of the negative log-likelihood (NLL) scores. The lower the NLL score is, the higher chance the synthesized sentences will pass Turing test.

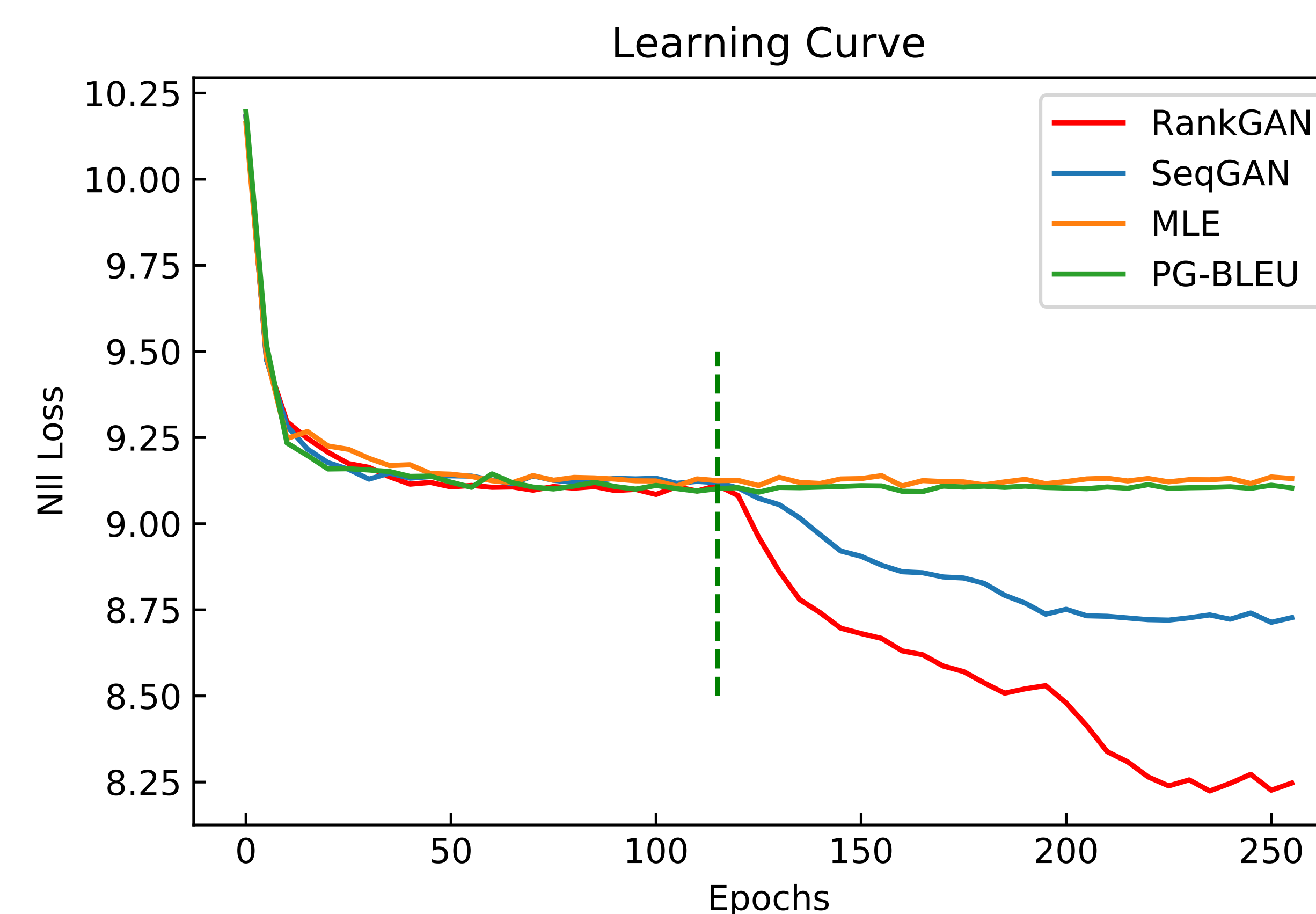


Figure 2: Learning curves of different methods on the simulation of synthetic data with respect to different training epochs. Note that the vertical dashed line indicates the end of the pre-training of PG-BLEU, SeqGAN and RankGAN.

Results on Chinese Poems Composition

Method	BLEU-2	Method	Human score
MLE	0.667	SeqGAN	3.58
SeqGAN	0.738	RankGAN	4.52
RankGAN	0.812	Human-written	6.69

Table 2: The performance comparison of different methods on the Chinese poem generation in terms of the BLEU scores and human evaluation scores.

Results on COCO image captions

Method	BLEU-2	BLEU-3	BLEU-4	Method	Human score
MLE	0.781	0.624	0.589	SeqGAN	3.44
SeqGAN	0.815	0.636	0.587	RankGAN	4.61
RankGAN	0.845	0.668	0.614	Human-written	6.42

Table 3: The performance comparison of different methods on the COCO captions in terms of the BLEU scores and human evaluation scores.

Human-written

Two men happily working on a plastic computer.
The toilet in the bathroom is filled with a bunch of ice.
A bottle of wine near stacks of dishes and food.

SeqGAN (Baseline)

A baked mother cake sits on a street with a rear of it.
A tennis player who is in the ocean.
A highly many fried scissors sits next to the older.

RankGAN (Ours)

Three people standing in front of some kind of boats.
A bedroom has silver photograph desk.
The bears standing in front of a palm state park.

Table 4: Example of the generated descriptions with different methods. Note that the language models are trained on COCO caption dataset without the images.

Results on Shakespear's Plays

Method	BLEU-2	BLEU-3	BLEU-4
MLE	0.796	0.695	0.635
SeqGAN	0.887	0.842	0.815
RankGAN	0.914	0.878	0.856

Table 5: The performance comparison of different methods on Shakespeare's play *Romeo and Juliet* in terms of the BLEU scores.