

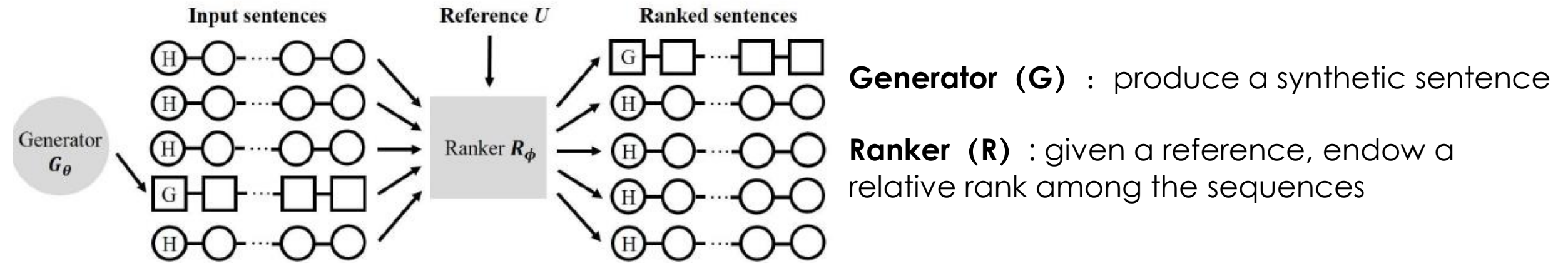
ADVERSARIAL RANKING FOR LANGUAGE GENERATION

NIPS 2017

OVERVIEW

- **Conventional Gan:**
 - The discriminator is train to assign absolute binary predict for individual data sample;
 - The diversity and richness inside the sentences are constrained.
- **Their proposed framework:**
 - Relax the training of the discriminator to a learning-to-rank optimization problem.
 - Adversarial network: a generation and a ranker.

MODEL



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

MODEL

- Generator: LSTM
- Ranker:

$$y_s = \mathfrak{F}(s)$$

$$\alpha(s|u) = \text{cosine}(y_s, y_u) = \frac{y_s \cdot y_u}{\|y_s\| \|y_u\|}$$

$$P(s|u, \mathcal{C}) = \frac{\exp(\gamma \alpha(s|u))}{\sum_{s' \in \mathcal{C}'} \exp(\gamma \alpha(s'|u))}$$

$$R_\phi(s|U, \mathcal{C}) = \mathbb{E}_{u \in U} [P(s|u, \mathcal{C})]$$

TRAINING

- **Generator:** Policy Gradient + Monte Carlo rollout

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

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

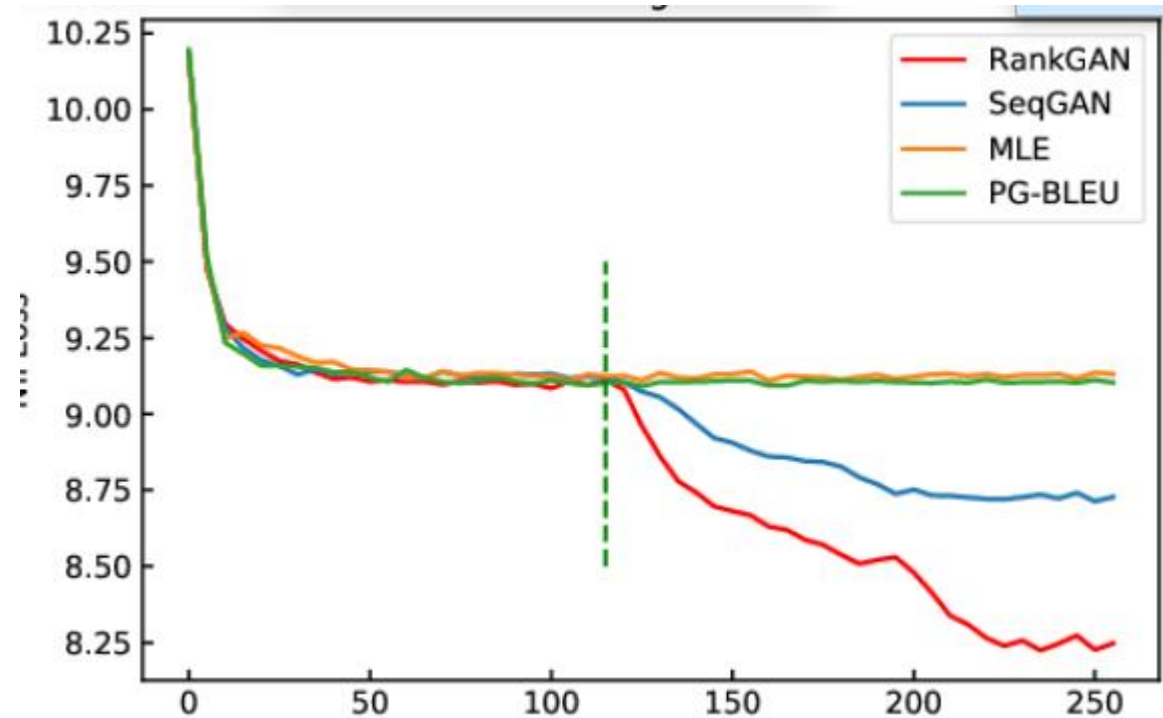
TRAINING

- **Ranker:**

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

EXPERIMENT

- Dataset: Chinese poems, COCO captions, Shakespeare's play
- Baselines: MLE, PG-BLEU, SeqGAN



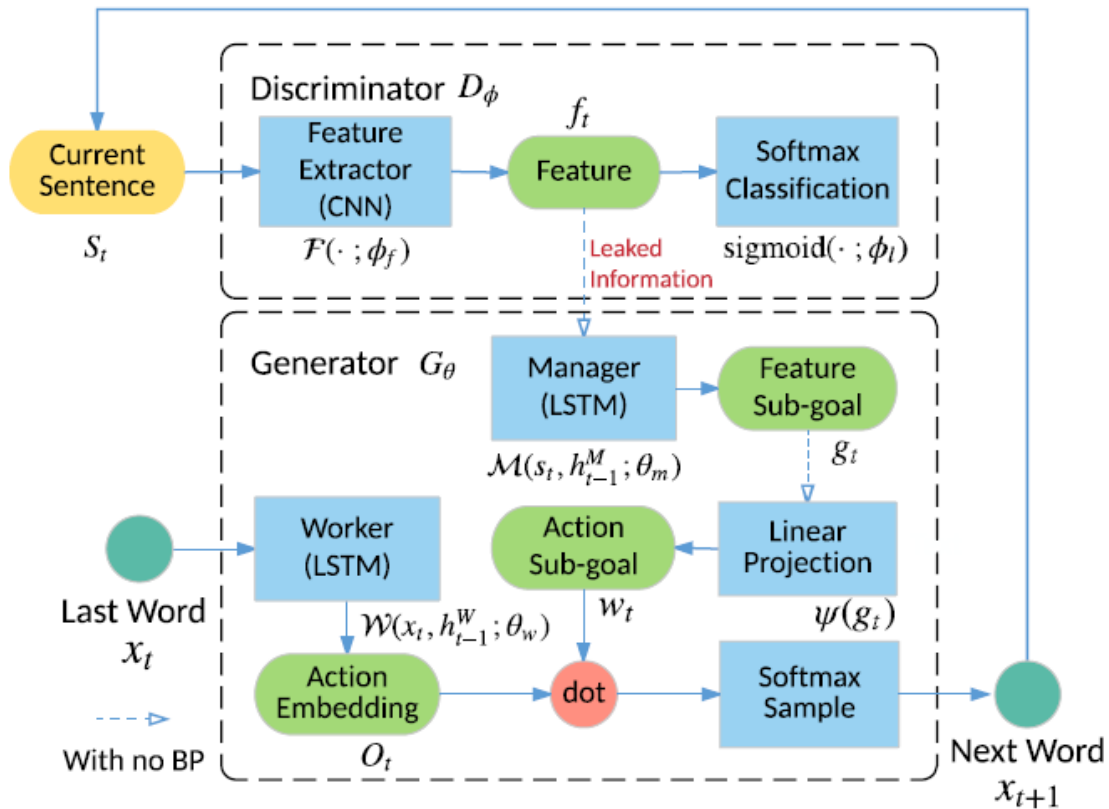
LONG TEXT GENERATION VIA ADVERSARIAL TRAINING WITH LEAKED INFORMATION

AAAI 2018

MOTIVATION

- **Conventional Gan:**
 - The scalar guiding signal lacks intermediate information during the generative process
 - The binary signal is sparse
- **Insight**
 - Hierarchy: decomposing the whole generation task into sub-tasks

OVERVIEW



Hierarchical Generator:

- a high-level MANAGER module
- a low-level WORKER module

MODEL

- **Leaked Features** from D as Guiding Signals

$$D_\phi(s) = \text{sigmoid}(\phi_l^\top \mathcal{F}(s; \phi_f)) = \text{sigmoid}(\phi_l^\top f),$$

- Hierarchical generator G

- **Manager**

$$\hat{g}_t, h_t^M = \mathcal{M}(f_t, h_{t-1}^M; \theta_m),$$

$$g_t = \hat{g}_t / \|\hat{g}_t\|,$$

$$(2) \quad w_t = \psi\left(\sum_{i=1}^c g_{t-i}\right) = W_\psi\left(\sum_{i=1}^c g_{t-i}\right). \quad (4)$$

(3)

- **Worker**

$$O_t, h_t^W = \mathcal{W}(x_t, h_{t-1}^W; \theta_w),$$

$$G_\theta(\cdot | s_t) = \text{softmax}(O_t \cdot w_t / \alpha),$$

TRAINING

- Manager and worker are trained separately
- **Manager:**

$$\nabla_{\theta_m}^{\text{adv}} g_t = -Q_{\mathcal{F}}(s_t, g_t) \nabla_{\theta_m} d_{\cos}(f_{t+c} - f_t, g_t(\theta_m)),$$

$$Q_{\mathcal{F}}(s_t, g_t) = Q(\mathcal{F}(s_t), g_t) = Q(f_t, g_t) = \mathbb{E}[r_t]$$

$$\nabla_{\theta_m}^{\text{pre}} g_t = -\nabla_{\theta_m} d_{\cos}(\hat{f}_{t+c} - \hat{f}_t, g_t(\theta_m)),$$

TRAINING

- **Worker**

$$\begin{aligned} & \nabla_{\theta_w} \mathbb{E}_{s_{t-1} \sim G} \left[\sum_{x_t} r_t^I \mathcal{W}(x_t | s_{t-1}; \theta_w) \right] \\ &= \mathbb{E}_{s_{t-1} \sim G, x_t \sim \mathcal{W}(x_t | s_{t-1})} [r_t^I \nabla_{\theta_w} \log \mathcal{W}(x_t | s_{t-1}; \theta_w)], \\ & r_t^I = \frac{1}{c} \sum_{i=1}^c d_{\cos} \left(f_t - f_{t-i}, g_{t-i} \right). \end{aligned}$$

TRAINING TECHNIQUES

- Bootstrapped rescaled activation

$$R_i^t = \sigma \left(\delta \cdot \left(0.5 - \frac{\text{rank}(i)}{B} \right) \right),$$

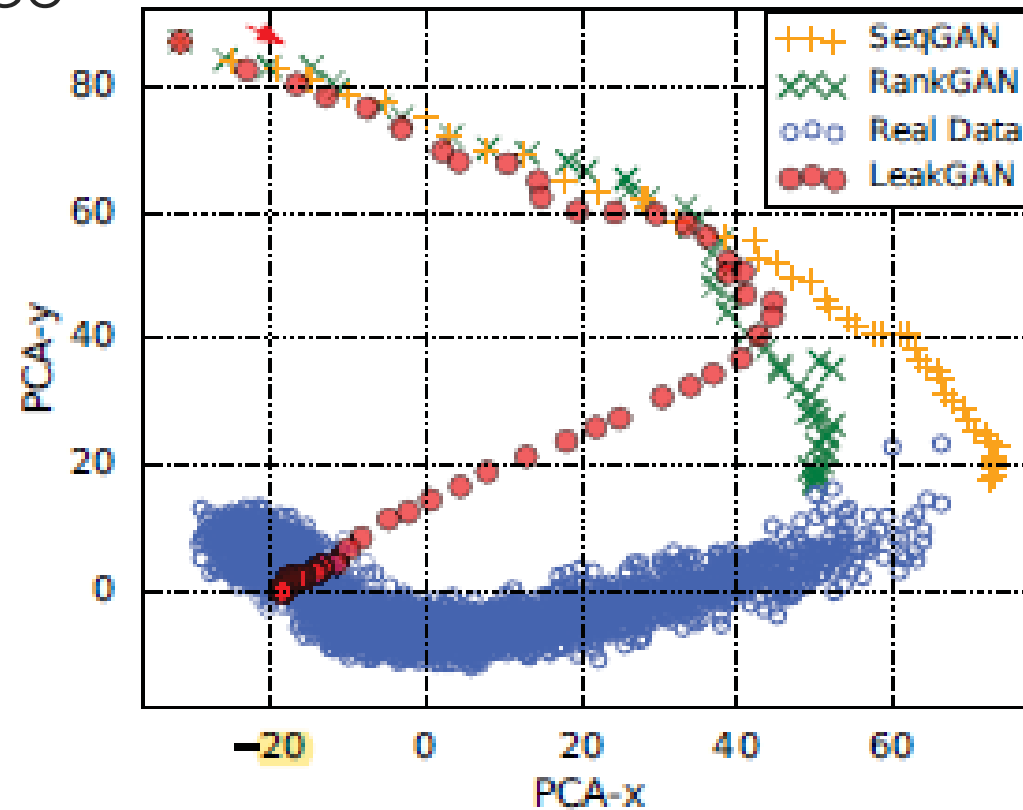
- Interleaved Training
- Temperature Control

EXPERIMENT

- Baselines: MLE, SeqGAN, RankGAN
- Datasets:
 - long text – wmt news;
 - middle text – coco captions;
 - Short text – Chinese Poems

MODEL EXPLANATION

- Feature Trace



MODEL EXPLANATION

- Behaviors of Worker and Manager

