Obfuscating Web User Search Queries via Generative Adversarial Privacy

EE 599 Final Project

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AOL Dataset

UserID	Query	QueryTime	Rank	Link
81943	are people who have asthma prone to get lung cancer	3/7/06 23:26	2	http://kidshealth.org
81943	is pronounced lung cancer leaded into lung cancer	3/7/06 23:33		
81943	if you have asthma can it lead to lung cancer	3/7/06 23:35	6	http://www.lungusa.org

- Preprocessing:
  - Filter the dataset by keywords from two topic: cancer, pregnancy.
  - Classify the dataset into three categories: cancer related, pregnancy related, and other.
  - Each category contains 1000 users, with queries related to each topic.
- Goal:
  - Mutate word tokens in web search queries
  - Decrease its privacy risk: category inference accuracy
  - Maintain its stealthiness (utility metric1): the obfuscated query should be meaningful instead of random words
  - Reduce obfuscation cost (utility metric2): the maximum likelihood estimation loss

Motivation

- Baseline solution:
  - Delete words with high privacy risk (e.g. cancer, pregnancy)
  - Mutate words randomly
  - Mutate words with differential privacy
- Limitations:
  - May not capture the correlation among words in the query
  - Context-free, no adversary

Our approach: SeqGAN with multiple objectives

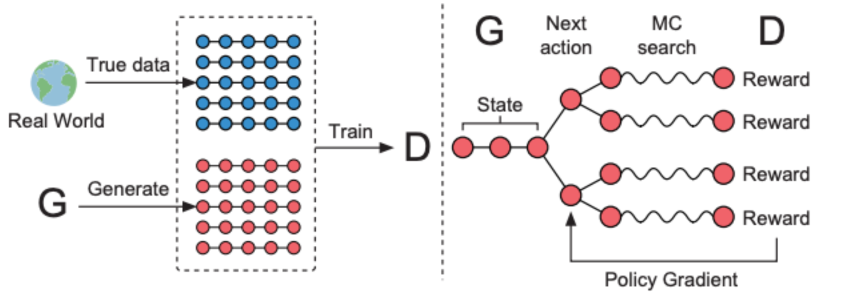


Figure 1: The illustration of SeqGAN. Left: D is trained over the real data and the generated data by G. Right: G is trained by policy gradient where the final reward signal is provided by D and is passed back to the intermediate action value via Monte Carlo search.

Fig. 1. Original SeqGAN (single objective).

* Discriminator: predict where a query is real, to make the obfuscated query meaningful.

* Adversary: predict the category of a query, to enhance the privacy of user query.

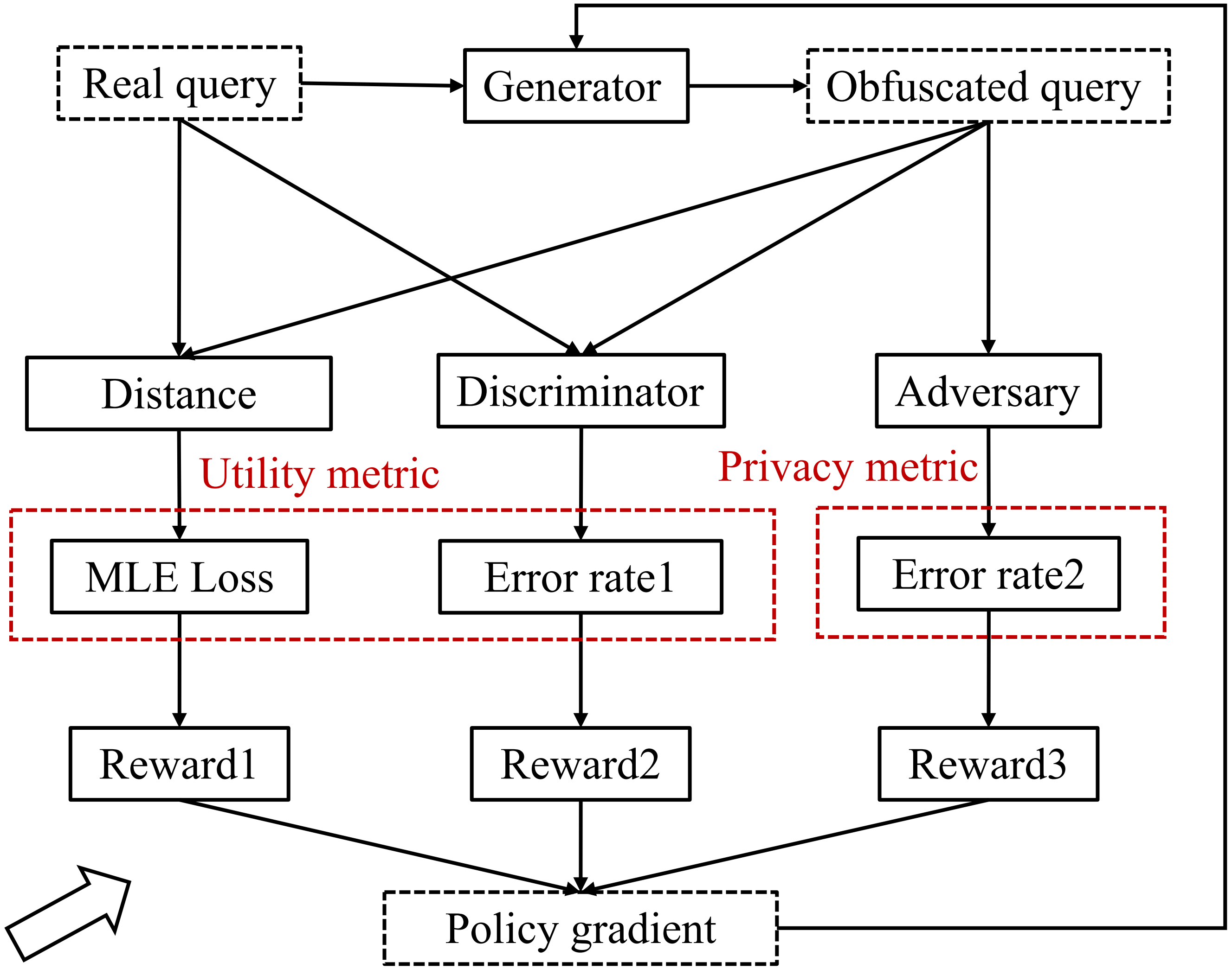


Fig. 2. Our SeqGAN with multiple objectives.

Policy gradient (theory part)

$$J(\theta) = \mathbb{E}[R_T|s_0, \theta] = \sum_{y_1 \in \mathcal{Y}} G_\theta(y_1|s_0) \cdot Q_{D_\phi}^{G_\theta}(s_0, y_1), \qquad (1)$$

$$Q_{D_\phi}^{G_\theta}(a = y_T, s = Y_{1:T-1}) = D_\phi(Y_{1:T}). \qquad (2)$$

$$\left\{Y_{1:T}^1, \ldots, Y_{1:T}^N\right\} = \mathbf{MC}^{G_\beta}(Y_{1:t}; N), \qquad (3)$$

$$Q_{D_\phi}^{G_\theta}(s = Y_{1:t-1}, a = y_t) = \qquad (4)$$
$$\begin{cases} \frac{1}{N}\sum_{n=1}^{N} D_\phi(Y_{1:T}^n),\ Y_{1:T}^n \in \mathbf{MC}^{G_\beta}(Y_{1:t}; N) & \text{for} \quad t < T \\ D_\phi(Y_{1:t}) & \text{for} \quad t = T, \end{cases}$$

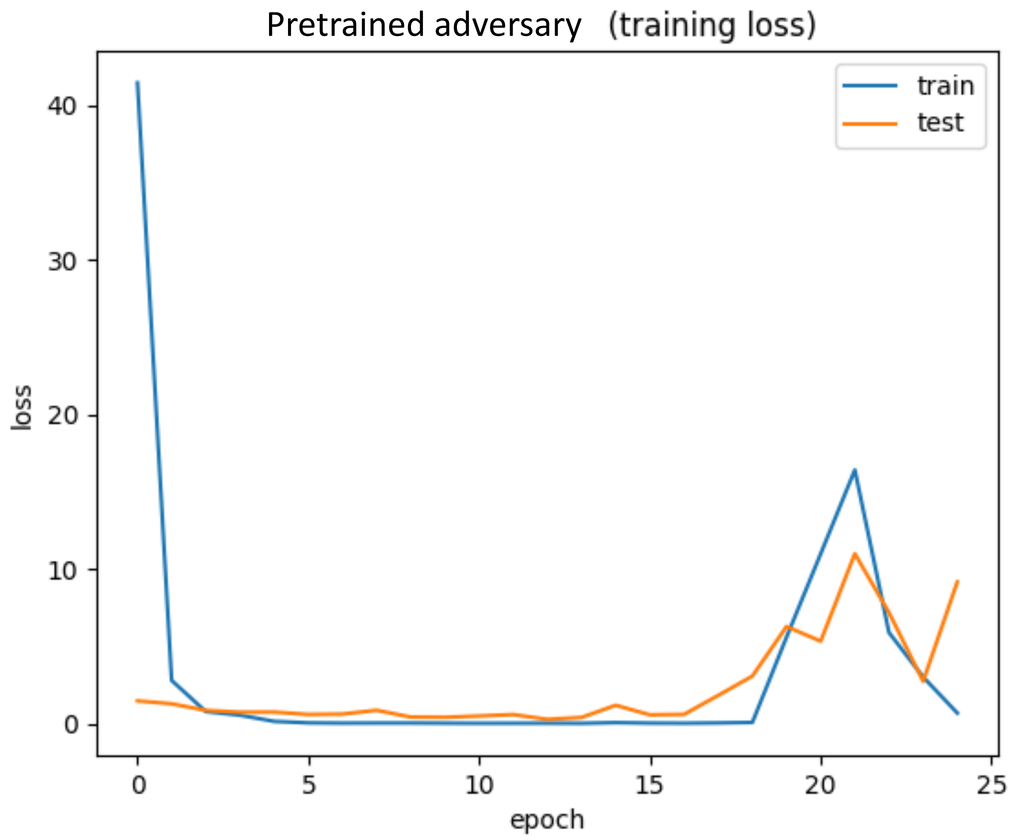
$$\min_\phi -\mathbb{E}_{Y\sim p_{\text{data}}}[\log D_\phi(Y)] - \mathbb{E}_{Y\sim G_\theta}[\log(1 - D_\phi(Y))]. \qquad (5)$$

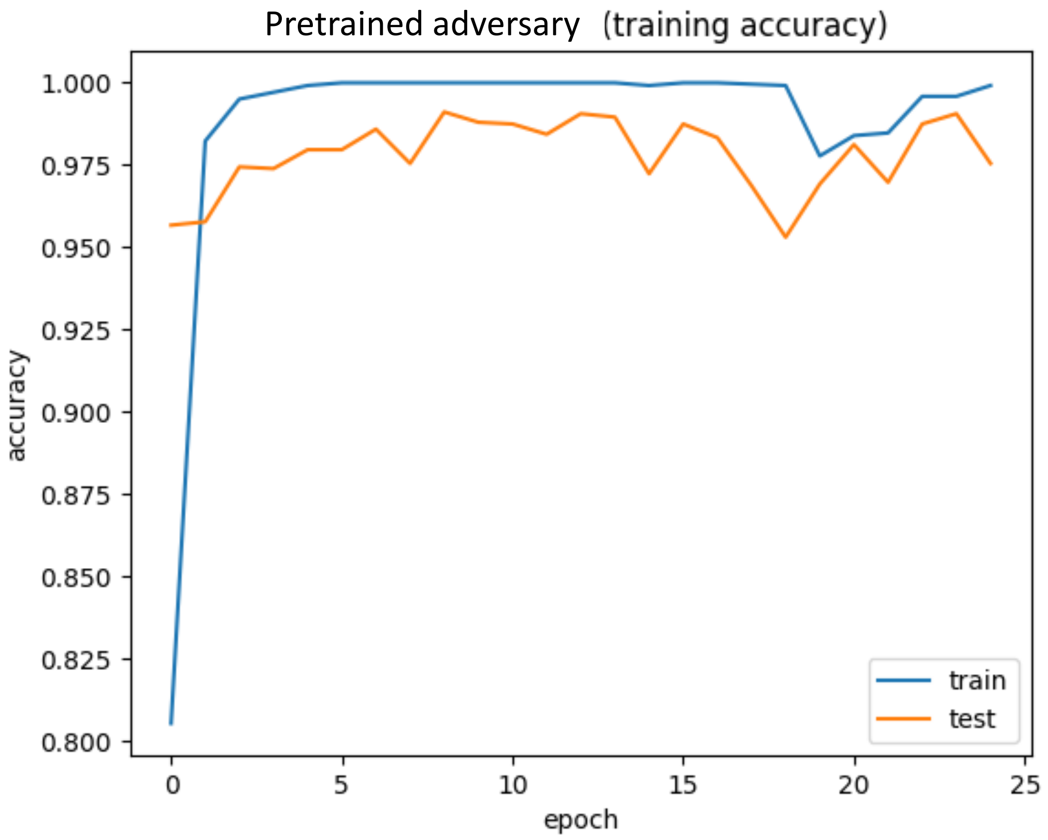
$$\nabla_\theta J(\theta) = \sum_{t=1}^{T} \mathbb{E}_{Y_{1:t-1}\sim G_\theta}\Big[\sum_{y_t \in \mathcal{Y}} \nabla_\theta G_\theta(y_t|Y_{1:t-1}) \cdot Q_{D_\phi}^{G_\theta}(Y_{1:t-1}, y_t)\Big]. \qquad (6)$$

$$\nabla_\theta J(\theta) \simeq \sum_{t=1}^{T} \sum_{y_t \in \mathcal{Y}} \nabla_\theta G_\theta(y_t|Y_{1:t-1}) \cdot Q_{D_\phi}^{G_\theta}(Y_{1:t-1}, y_t) \qquad (7)$$
$$= \sum_{t=1}^{T} \sum_{y_t \in \mathcal{Y}} G_\theta(y_t|Y_{1:t-1}) \nabla_\theta \log G_\theta(y_t|Y_{1:t-1}) \cdot Q_{D_\phi}^{G_\theta}(Y_{1:t-1}, y_t)$$
$$= \sum_{t=1}^{T} \mathbb{E}_{y_t\sim G_\theta(y_t|Y_{1:t-1})}[\nabla_\theta \log G_\theta(y_t|Y_{1:t-1}) \cdot Q_{D_\phi}^{G_\theta}(Y_{1:t-1}, y_t)],$$

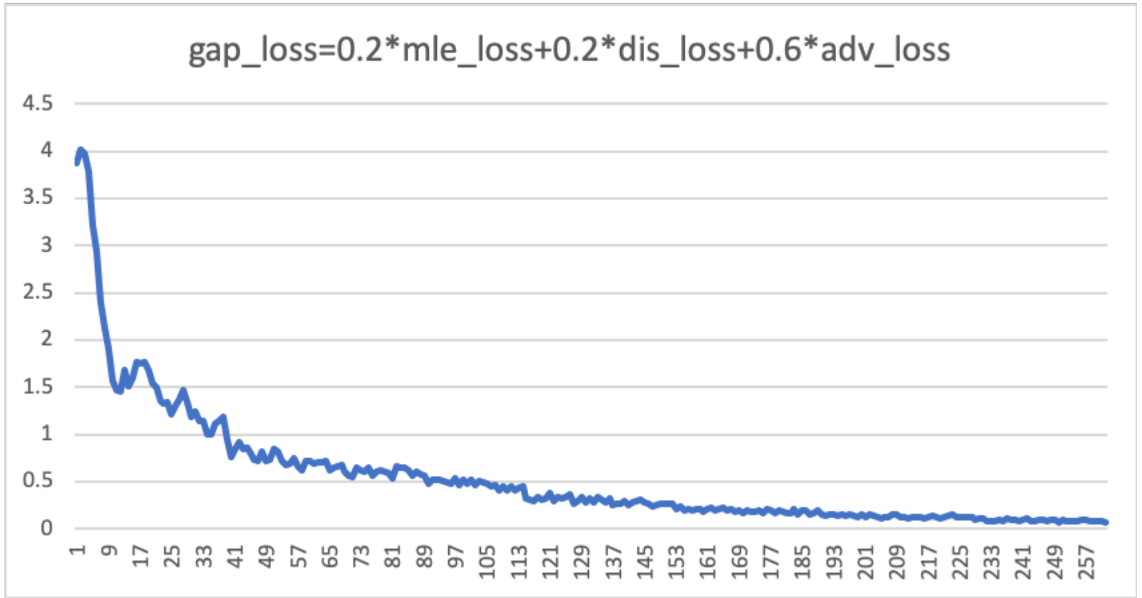
$$\theta \leftarrow \theta + \alpha_h \nabla_\theta J(\theta), \qquad (8)$$

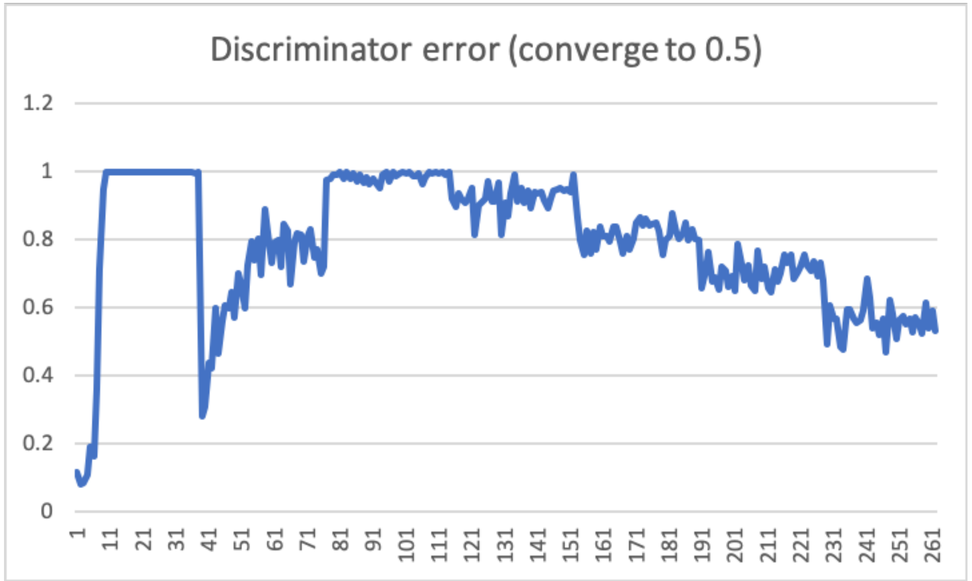
Pretrained Result (Adversary)





Evaluation






```
[INFO] Target query:  ['<SOS>', 'baby', 'modeling', '<POS>', 'baby', 'modeling', 'agency', '<POS>', 'baby', 'photo'
, 'contest', '<POS>', 'baby', 'photo', 'contest', '<EOS>', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '
*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '
*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*']
[INFO] Predicted query:  ['<SOS>', 'baby', 'modeling', '<POS>', 'baby', 'modeling', 'agency', '<POS>', 'baby', 'pho
to', 'contest', '<POS>', 'baby', 'photo', 'contest', '<EOS>', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*'
, '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*'
, '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*', '*']
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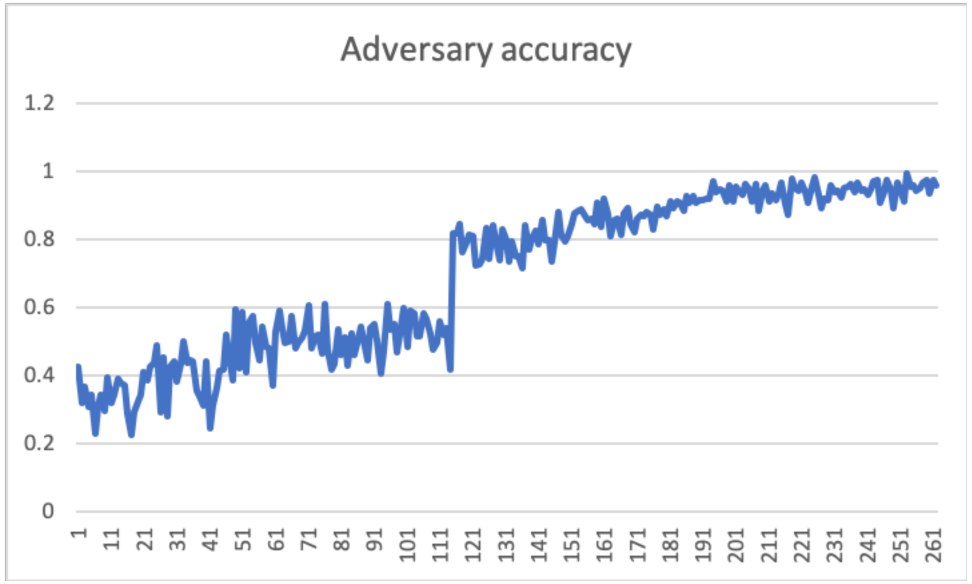

Explanation: MLE loss -> 0 (Identity transformation)

To do:

- Change the weights of each part in loss function

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Introduction

Conclusion