

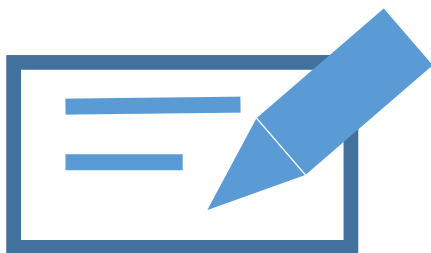
Exploring the Pareto-Optimality between Quality and Diversity in Text Generation Models

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- Problem & Formalization
- Theoretical Analysis
- Conclusion

Background – Text Generation Tasks



Machine Writing

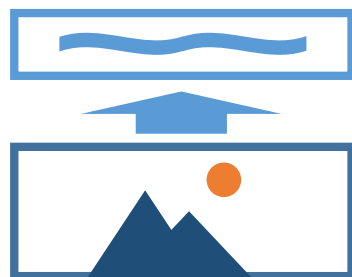
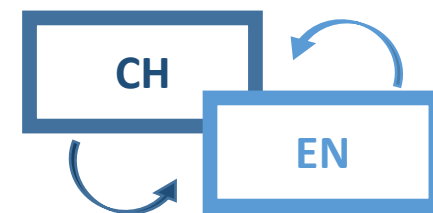
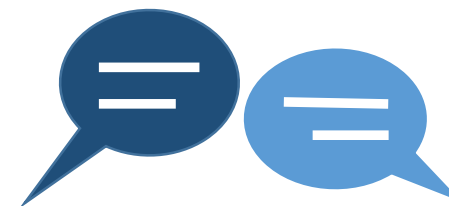


Image Captioning



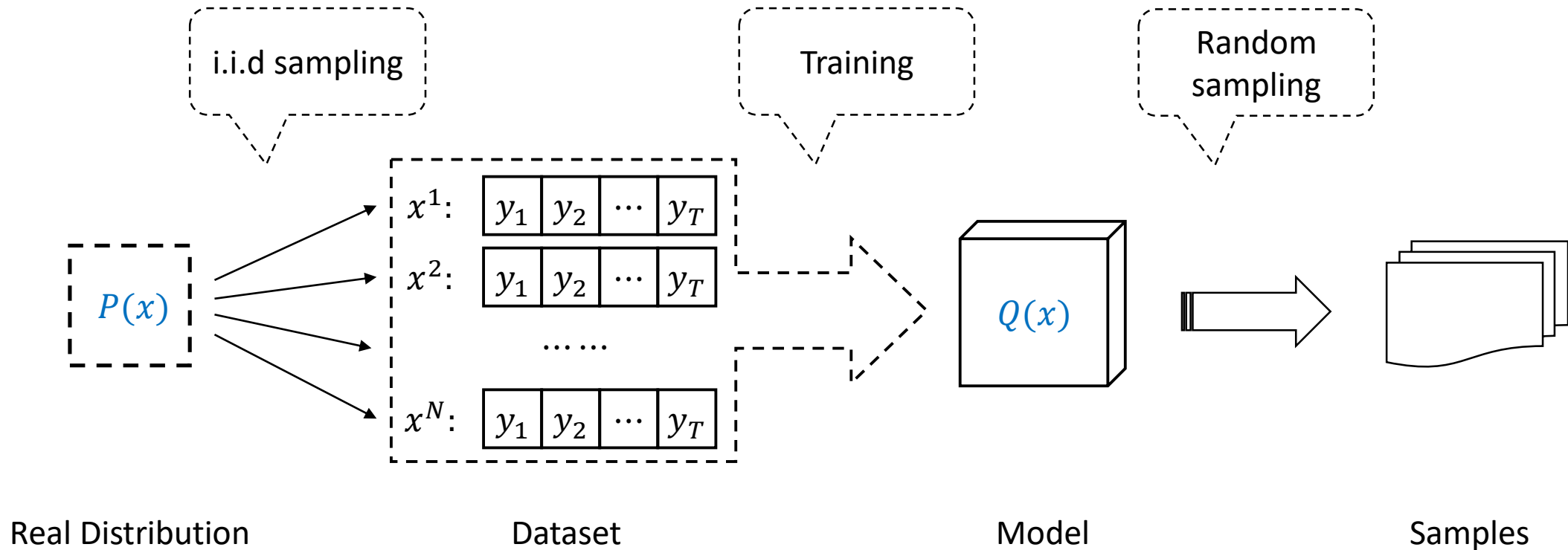
Machine Translation



Chatbot

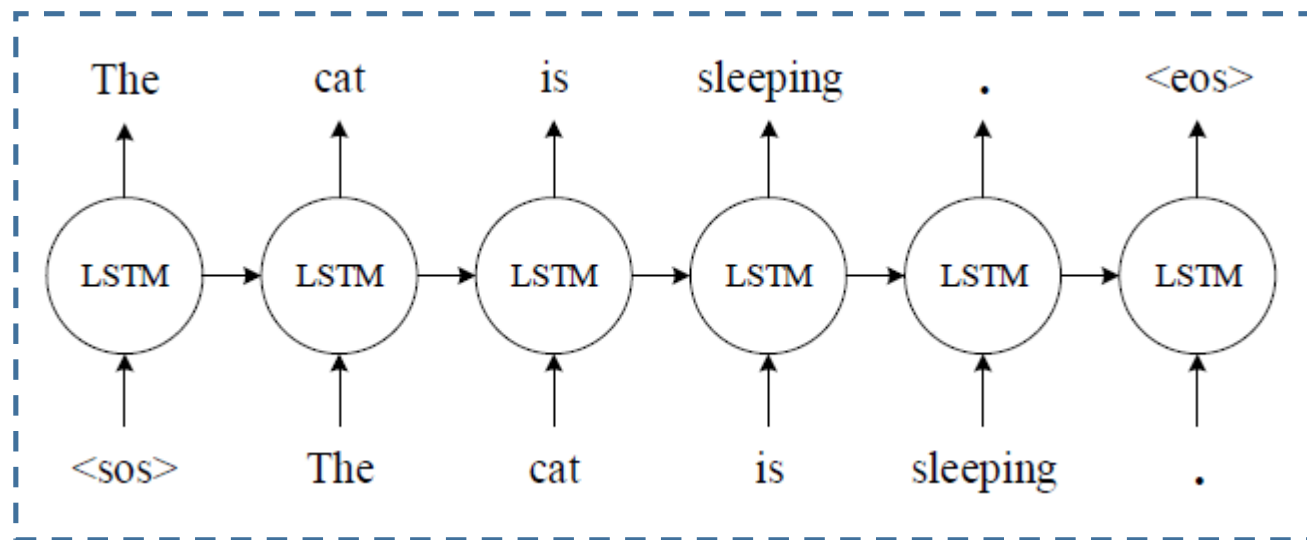
Background – Unconditional Text Generation

- Given a text dataset, build a model $Q(x)$ for text generation.



Background – RNN-based Language Model

- Most widely used method for text generation



Probability Decomposition:

$$x := Y_{1:T}$$
$$Q(Y_{1:T}) = \prod_{i=1}^T Q(y_t | Y_{1:t-1})$$

- Training by **Maximum Likelihood Estimation** (MLE)

$$\max_Q \mathbb{E}_{x \sim P} \log Q(x) \iff \min_Q D_{KL}(P || Q) \implies Q^* = P$$

Background – Evaluation

- **Divergence**: How close is it between distribution Q and P
 - **Perplexity(PPL)**: How likely are validation data to be generated by the model
- **Quality**: How likely are generated samples to be real ones
 - **NLL-oracle**: How likely are generated samples to appear in the real distribution
 - **BLEU**: N-gram overlap between generated samples and validation data
- **Diversity**: How much difference are there between generated samples
 - **Distinct**: Percentage of unique N-grams within generated sample
 - **Self-BLEU**: N-gram overlap within generated sample

Problem & Formularization

Problem

- What is the relationship between **quality** and **diversity**?
 - **Quality** and **diversity** seem to be a trade-off in practice, but there is no theoretical explanation.
- Can **quality** and **diversity** be used to evaluate **divergence**?
 - Calculation of **divergence** may not be tractable, so **quality** and **diversity** are usually used instead in practice. It is not clear if they are sufficient.
- How to balance the **quality** and **diversity** in practice?
 - Some tasks focus more on higher **quality** (or **diversity**). There is currently no method that maximize one metric while keeping another above a threshold.

Formularization – Notations

- Given the real distribution P and model distribution Q
 - $P = (P_1, \dots P_N)$
 - $Q = (Q_1, \dots Q_N)$
- Quality metric: $U(Q)$
- Diversity metric: $V(Q)$

Formularization – Special cases

- **LL-SE** metric:

- Log-likelihood with oracle: $U(Q) = \mathbb{E}_{x \sim Q} \log P(x) = \sum_{i=1}^N Q_i \log P_i$
- Shannon Entropy: $V(Q) = -\mathbb{E}_{x \sim Q} \log Q(x) = -\sum_{i=1}^N Q_i \log Q_i$

- **CR-NRR** metric:

- Coverage Rate: $U(Q) = \mathbb{E}_{x \sim Q} P(x) = \sum_{i=1}^N Q_i \cdot P_i$
- Negative Repeat Rate: $V(Q) = -\mathbb{E}_{x \sim Q} Q(x) = -\sum_{i=1}^N Q_i^2$

Formularization – General

- **Quality** metric:

- $U(Q) = U(Q; P) = \sum_{i=1}^N Q_i \cdot f(P_i)$
- Generating more samples with higher real probability yields higher overall quality
- $\Rightarrow f(x)$ is strictly monotonically increasing w.r.t x

- **Diversity** metric:

- $V(Q) = \sum_{i=1}^N g(Q_i)$
- Distribute the probability more equally yields higher overall diversity
- $\Rightarrow g(x)$ is strictly concave w.r.t x

Formularization – MOP

- The Multi-Objective Programming problem

$$\begin{aligned} \max_Q & (U(Q), V(Q)) \\ \text{s.t.} & \sum_{i=1}^N Q_i = 1 \end{aligned}$$

- The relationship between **quality** and **diversity** lies in the solution of this MOP

Theoretical Analysis

What is the relationship between **quality** and **diversity**?

$$\begin{aligned} \max_Q & (U(Q), V(Q)) \\ \text{s.t.} & \sum_{i=1}^N Q_i = 1 \end{aligned}$$

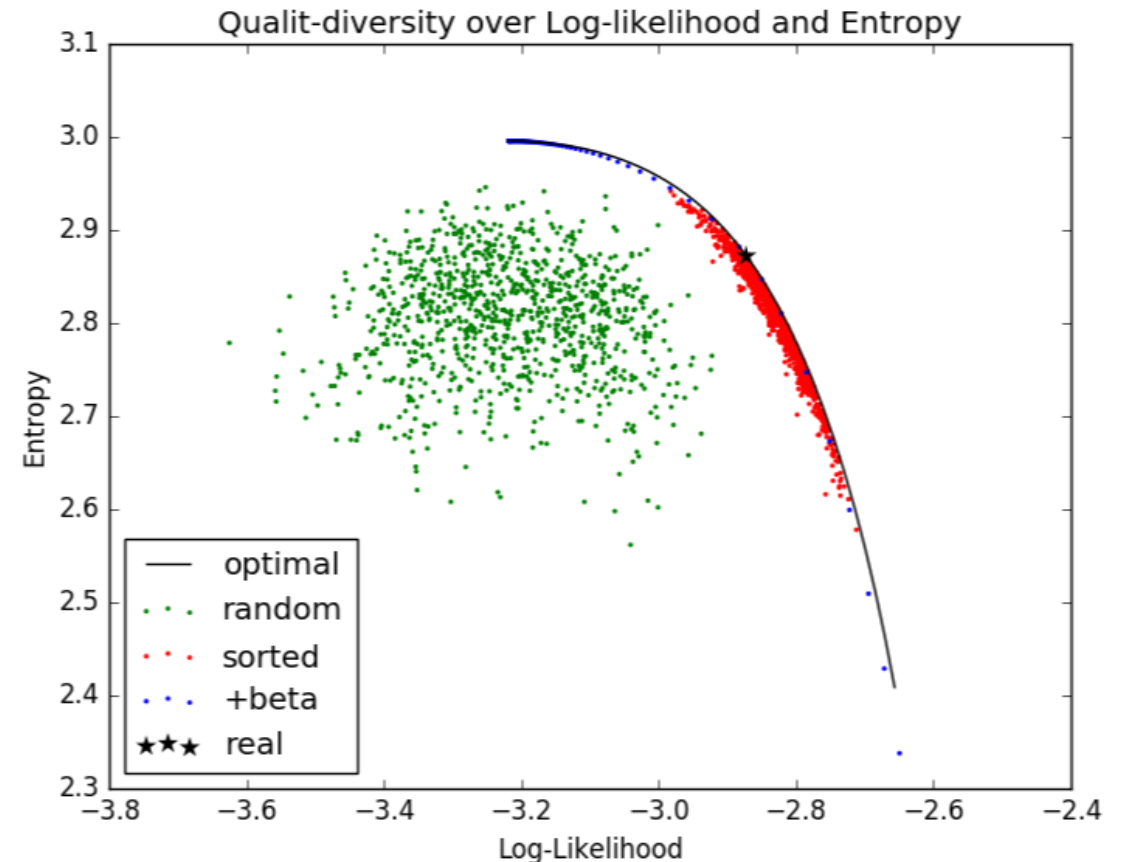
Analysis – Pareto Optimality

$$\begin{aligned} & \max_Q (U(Q), V(Q)) \\ & s.t. \sum_{i=1}^N Q_i = 1 \end{aligned}$$

- **Pareto-optimum**
 - A solution in MOP that no other solution can outperform it over all objectives
- **Pareto-frontier**
 - The set containing all the Pareto-optima

Analysis – Case Study

- Each point represents a distribution (model)
- Black: Pareto-frontier
- Star: Real distribution P
- Green: Random distributions
- Red: Sorted random distributions
- Blue: Optima from other metrics



Analysis – Pareto Optimum

- Properties of the Pareto-optima
 - The model distribution is **order-preserving**
 - The model distribution satisfies the following form:

$$Q_i = \hat{g}'^{-1}[w \cdot f(P_i) + b], \quad w \leq 0$$

$$\hat{g}'^{-1}(x) = \begin{cases} g'^{-1}(x) & \text{if } x < g'(0), \\ 0 & \text{if } x \geq g'(0). \end{cases}$$

$$U(Q) = U(Q; P) = \sum_{i=1}^N Q_i f(P_i), \quad V(Q) = \sum_{i=1}^N g(Q_i).$$

Analysis – Case Study

- **LL-SE** metric [$f(x) = \log x, g(x) = -x \log x$]:

$$Q_i = \frac{P_i^\beta}{Z}, \quad Z = \sum_{i=1}^N P_i^\beta, \quad \beta \geq 0,$$

$$w = -\beta, \quad b = 1 + \log Z.$$

- **CR-NRR** metric [$f(x) = x, g(x) = -x^2$]:

$$Q_i = \frac{\max(P_i + \gamma, 0)}{Z}, \quad Z = \sum_{i=1}^N \max(P_i + \gamma, 0), \quad \gamma > -\max_i P_i,$$

$$w = -\frac{2}{Z}, \quad b = -\frac{2\gamma}{Z}.$$


Analysis – Trade-off

- The Pareto-frontier contains infinite elements
 - b is determined by w
 - For any $B \leq w \leq 0$, w leads to a different distribution
 - As w grows, the **quality** $U(Q)$ decreases and the **diversity** $V(Q)$ increases
 - Each Pareto-optimum corresponds to a solution which maximizes

$$W(Q) = \alpha U(Q) + (1 - \alpha)V(Q), \quad \alpha = \frac{w}{w - 1}$$

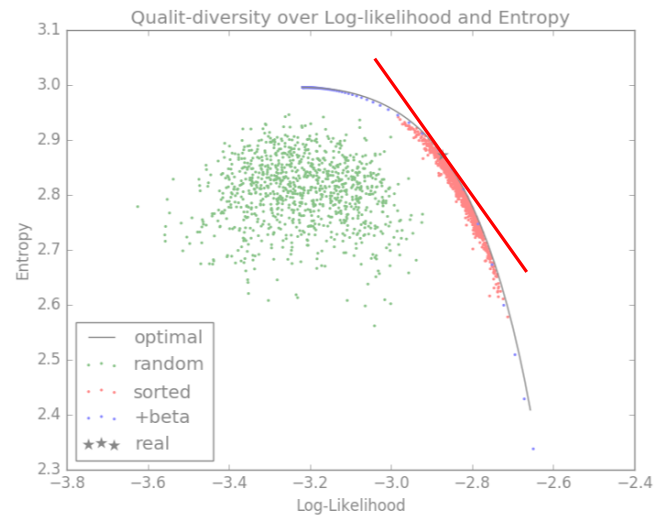
$$Q_i = \hat{g}'^{-1}[w \cdot f(P_i) + b], \quad w \leq 0$$

$$\hat{g}'^{-1}(x) = \begin{cases} g'^{-1}(x) & \text{if } x < g'(0), \\ 0 & \text{if } x \geq g'(0). \end{cases}$$



There is a trade-off
between quality and
diversity!

Can **quality** and **diversity** be used to evaluate **divergence**?



Analysis – Relationship with Divergence

- The following condition is both sufficient and necessary for $Q = P$ to be in the Pareto-frontier

$$g(x) = w_0 \int f(x) dx + b_0 x, \quad w_0 \leq 0.$$

$$\text{LL-SE: } f(x) = \log x, g(x) = -x \log x$$

$$\text{CR-NRR: } f(x) = x, g(x) = -x^2$$

- If so, then $D(P||Q) = W(P) - W(Q)$ is a divergence metric

- $W(Q) = \alpha U(Q) + (1 - \alpha)V(Q), \quad \alpha = \frac{w_0}{w_0 - 1}$

- LL-SE: $D(P||Q) = \frac{1}{2} \sum_{i=1}^N Q_i \cdot \log \frac{Q_i}{P_i}$

- CR-NRR: $D(P||Q) = \frac{1}{3} \sum_{i=1}^N (P_i - Q_i)^2$

Quality and diversity metrics should be chosen carefully to recover the divergence

How to balance the **quality** and **diversity** in practice?

$$Q_i = \hat{g}'^{-1}[w \cdot f(P_i) + b], \quad w \leq 0$$

Analysis – Algorithm

- We can reach a Pareto-optimum by using the following training objective:

$$\min_Q \mathbb{E}_{x \sim P} h[Q(x)],$$
$$h(x) = \int \frac{c}{f^{-1}\left[\frac{g'(x)-b}{w}\right]} dx, \quad c > 0.$$

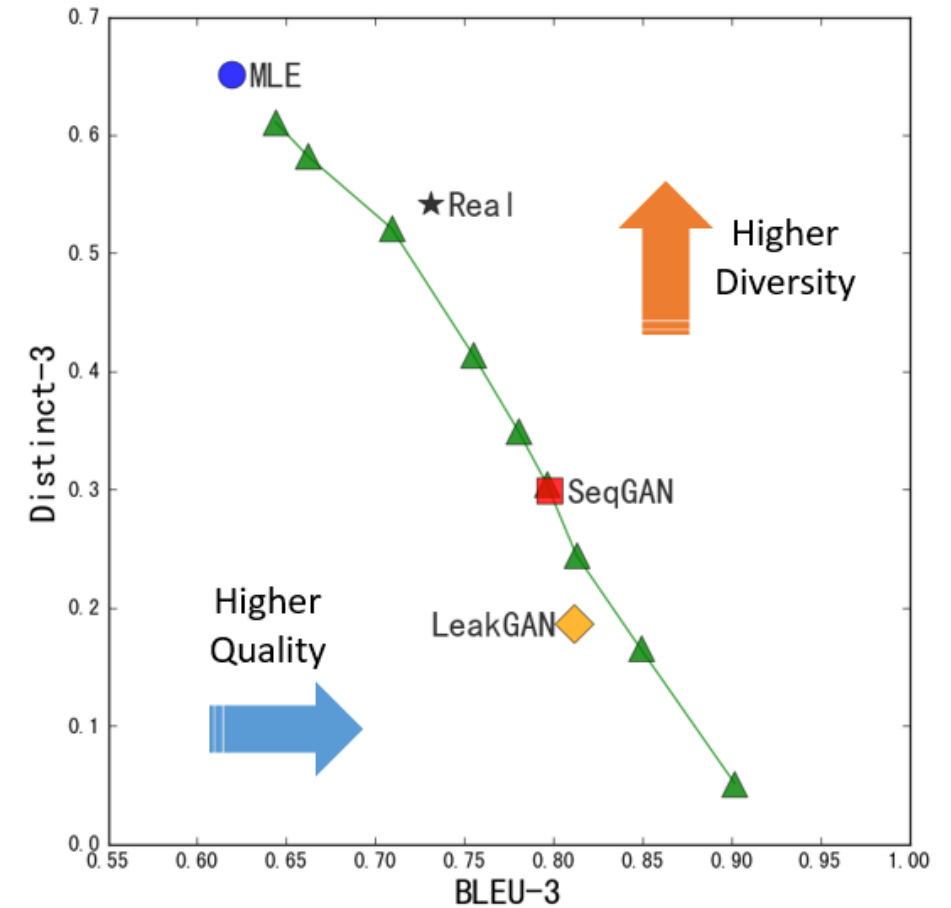
MLE:

$$\max_Q \mathbb{E}_{x \sim P} \log Q(x)$$

- Two cases feasible to be used in practice:
 - $f(x) = \log x$ $h(x, w, b, c) = h_1(x, w) \cdot h_2(w, b) \cdot c$
 - $f(x) = x^a$ $h(x, w, b, c) = h_3(x, b) \cdot h_4(w, b) \cdot c$

Analysis – Case Study

- Each point represents a distribution (model)
- **Green**: Proposed method (LL-SE)
- Star: Real distribution P



Conclusion

Conclusion

- We prove in theory that **quality** and **diversity** act as trade-off under unconditional text generation settings.
- We show that **quality** and **diversity** can recover the **divergence** with a linear combination, only if the metrics are carefully chosen.
- We derived a algorithm that can control the degree of **quality-diversity** trade-off.



Thank you!  Q&A



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