Differentiated Distribution Recovery for Neural Text Generation

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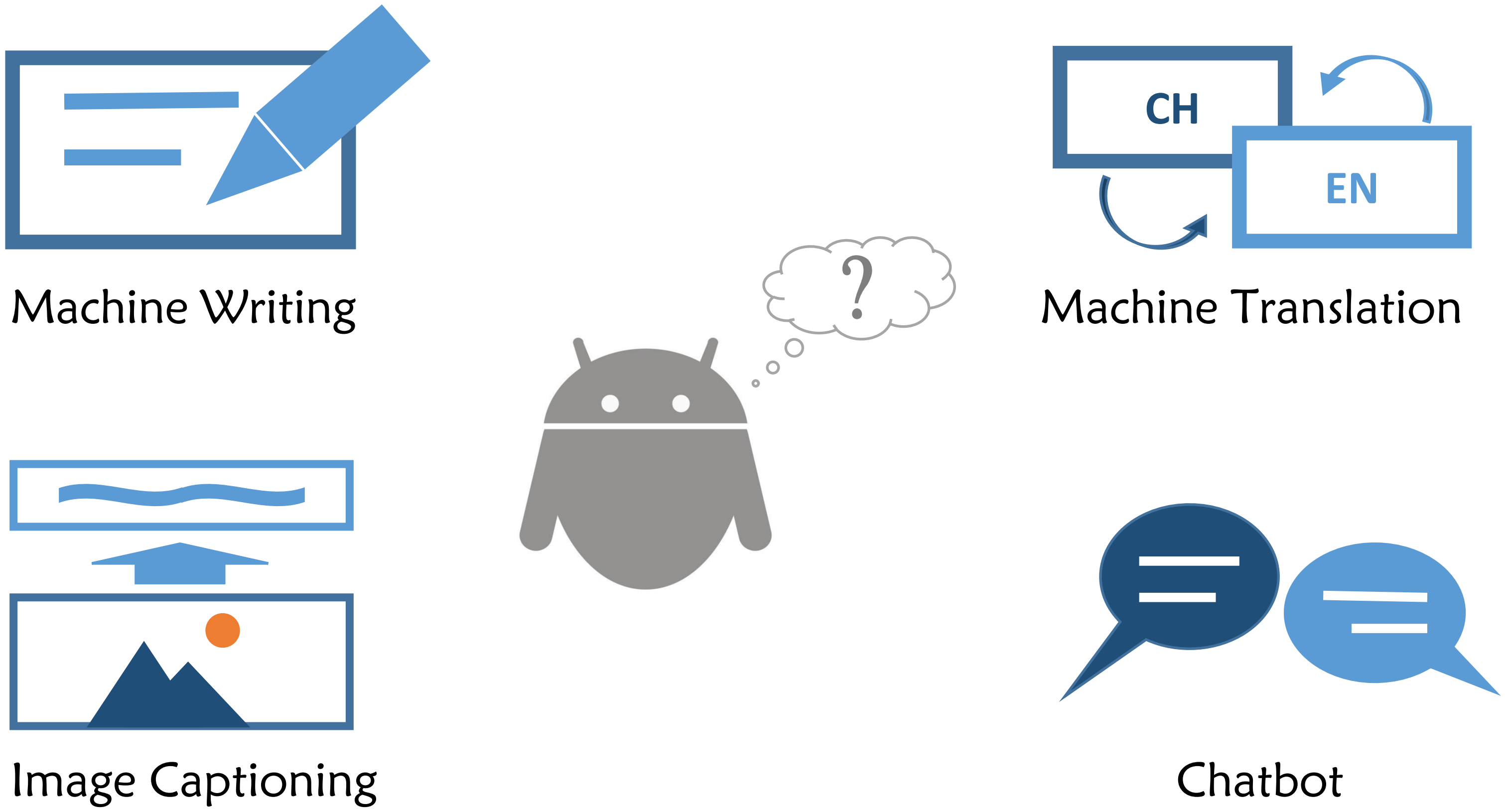
Background – Text Generation Tasks



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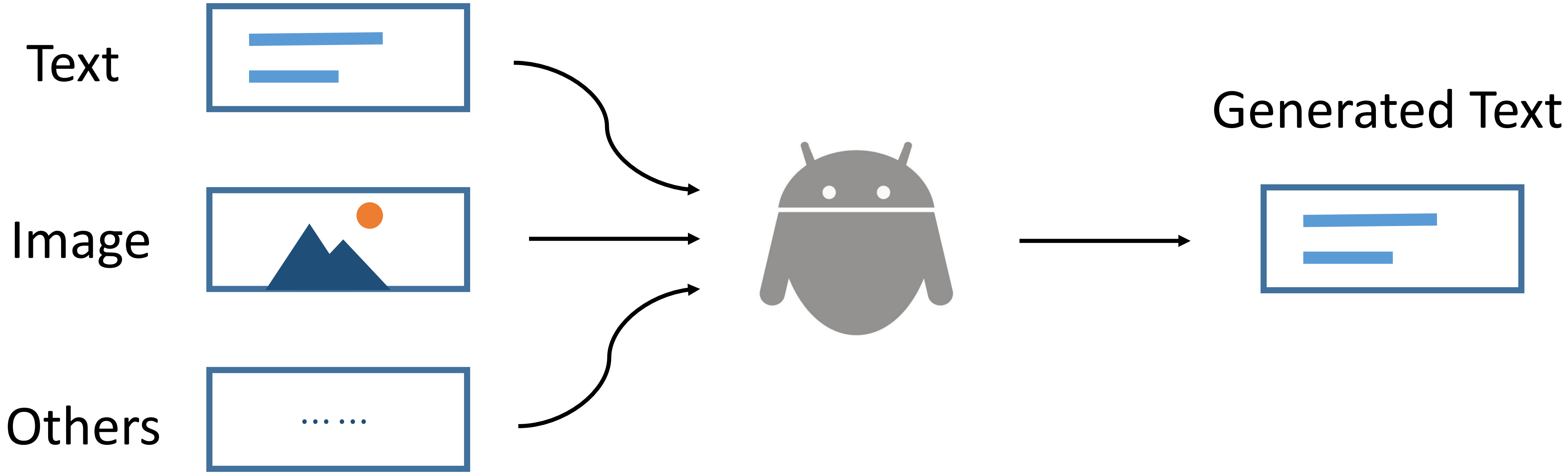

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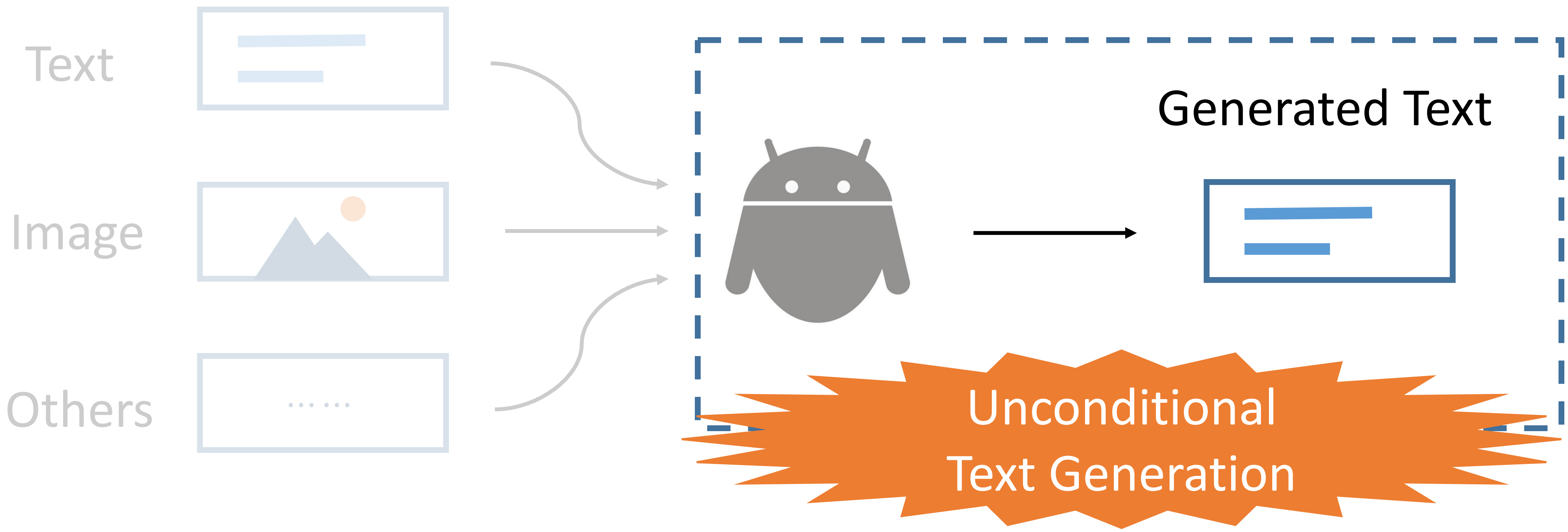
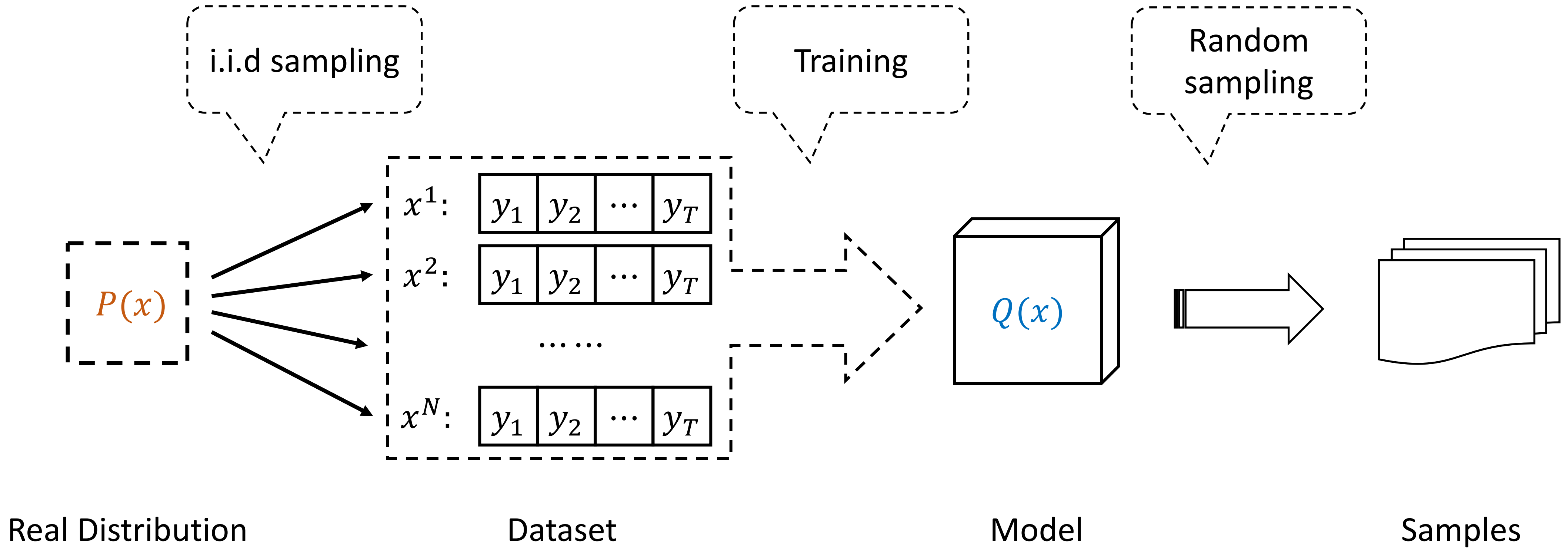


Task – Unconditional Text Generation

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



Task – Unconditional Text Generation

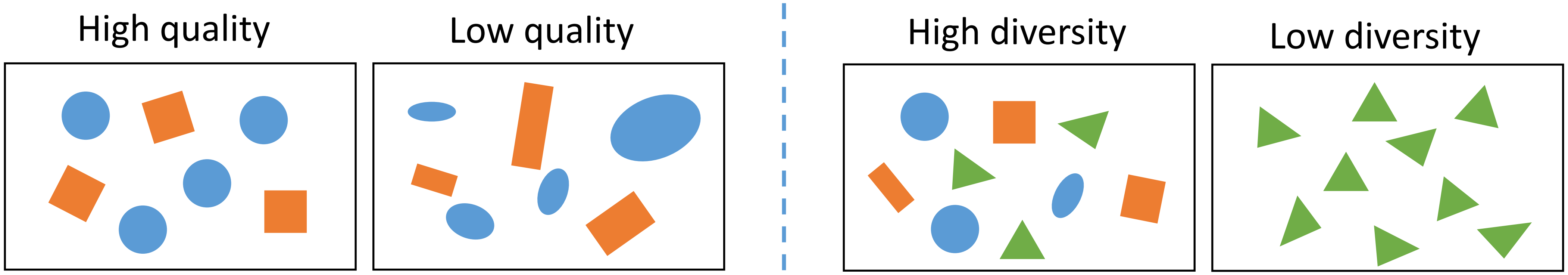
- Evaluation Metrics

  Quality: Generated text should contain less grammatical and logical errors.

  > Primary! We do not accept samples with errors.

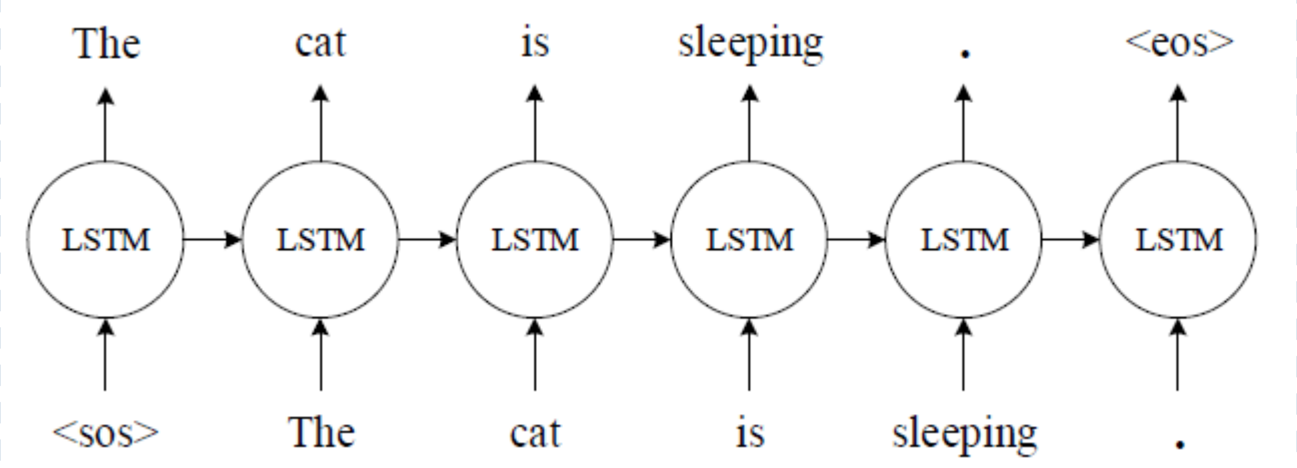
  Diversity: Generated text should not share similar words and structures.

  > Secondary. Similar samples are acceptable to some extent.



Baseline – RNN-based Language Model

- Use Recurrent Neural Networks (RNNs) to model sequential data



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)

$$\max_{Q} \mathbb{E}_{x\sim P} \log Q(x) \Longleftrightarrow \min_{Q} D_{KL}(P||Q) \Longrightarrow Q^* = P$$

Precise Distribution Recovery

Baseline – RNN-based Language Model

- RNNLM achieves only 49% Turing Test pass rate on MSCOCO dataset.
- Precise distribution recovery is sensitive to noises and rare patterns in training data.

Some common errors in MSCOCO dataset

A man is talking a picture of himself in the mirror.
A cat laying on top of a table trying to sleep.
A cat staring out a window at snow covered tree's.

Influence of noises should be minimized

How to neglect the impact of bad training data ?

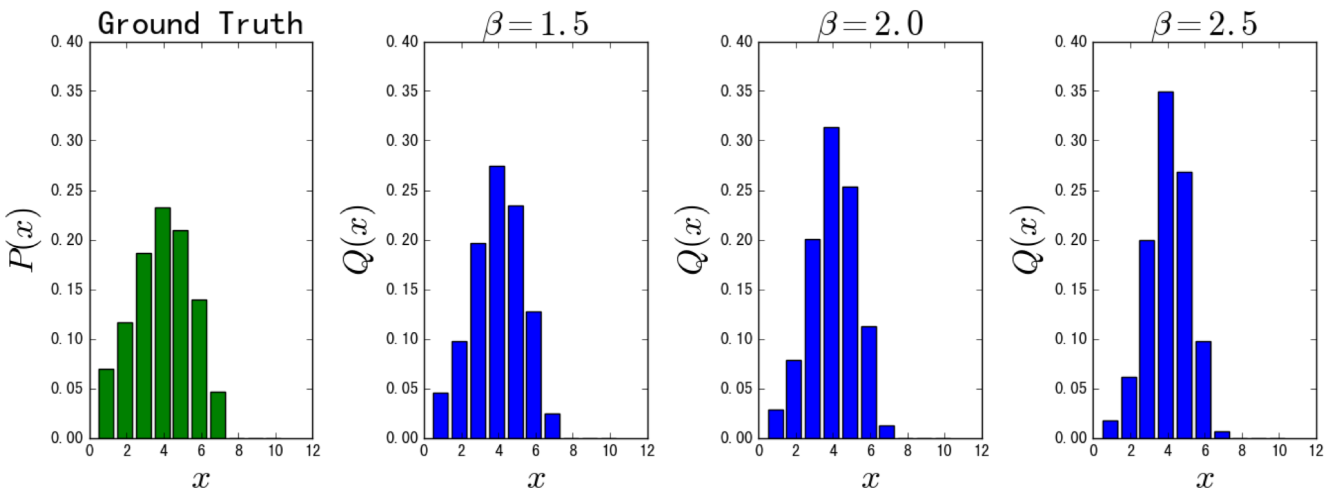
Use different strategy for different data !

Method – Differentiated Distribution Recovery

Assumption: Samples with lower probability under real distribution $P(x)$ are more likely to be bad samples.

Idea: Instead of making the model $Q(x)$ to precisely recover $P(x)$, we encourage samples with high probability and discourage samples with low probability.

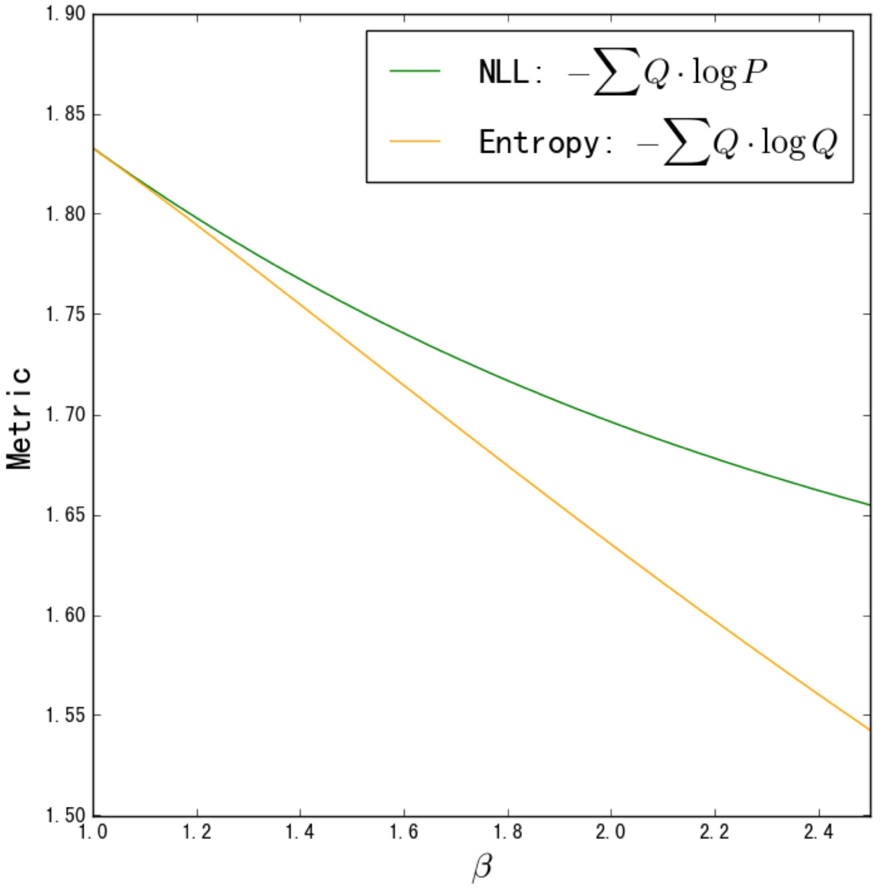
Differentiated Distribution Recovery (DDR):



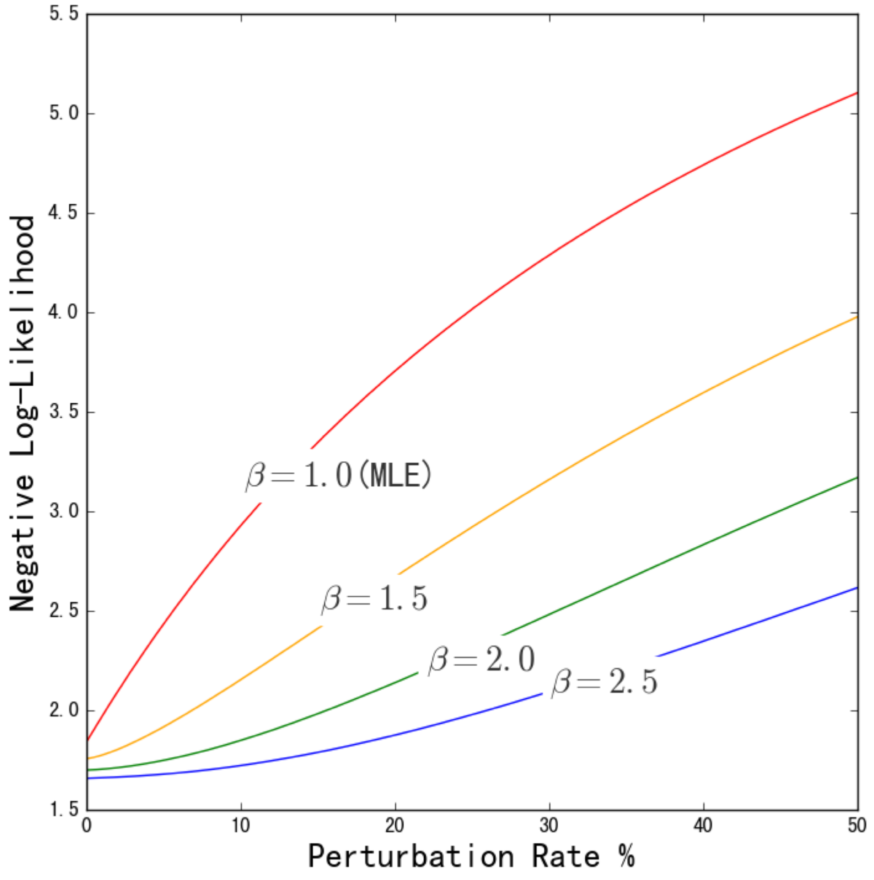
$$Q^*(x) \propto P(x)^\beta$$
$$\beta > 1$$

Method – Differentiated Distribution Recovery

Larger β leads to higher quality but lower diversity



Larger β is more robust to noises



How can we achieve Differentiated Distribution Recovery in practice?

$$\boxed{Q^*(x) \propto P(x)^{\beta}} \Rightarrow \boxed{Q^*(x) = \frac{P(x)^{\beta}}{\sum_x P(x)^{\beta}}}$$

Method – Implementation of DDR

Theorem

Let P and Q be two discrete distributions. With an objective defined as

$$\max_{Q} \mathbb{E}_{x\sim P}\, f[Q(x)]\,,$$

$$f(Q(x);\alpha) = \alpha \cdot Q(x)^{\frac{1}{\alpha}} - \alpha, \qquad \alpha > 1,$$

The optimal Q with respect to the objective can be written as:

$$Q^*(x) = \frac{P(x)^{\beta}}{\sum_x P(x)^{\beta}}, \qquad \beta = \frac{\alpha}{\alpha - 1}$$

Method – Implementation of DDR

Proof

This is a constrained optimization problem:

$$\max_{Q} \mathbb{E}_{x\sim P}\, f[Q(x)],$$
$$f(Q(x);\alpha) = \alpha \cdot Q(x)^{\frac{1}{\alpha}} - \alpha$$
$$s.t. \sum_x Q(x) = 1\,, 0 \le Q(x) \le 1$$

The Lagrange function is:

$$L(Q(x),\lambda,\gamma,\eta) =$$
$$\sum_x P(x) \cdot f[Q(x)] + \lambda[1 - \sum_x Q(x)] - \gamma Q(x) + \eta[Q(x) - 1]$$

Let the first derivative be zero:

$$P(x) \cdot f'[Q^*(x)] = constant,$$
$$\sum_x Q^*(x) = 1,$$
$$0 \le Q^*(x) \le 1$$

We get the optimal $Q(x)$:

$$Q^*(x) = \frac{P(x)^\beta}{\sum_x P(x)^\beta}, \qquad \beta = \frac{\alpha}{\alpha - 1}$$

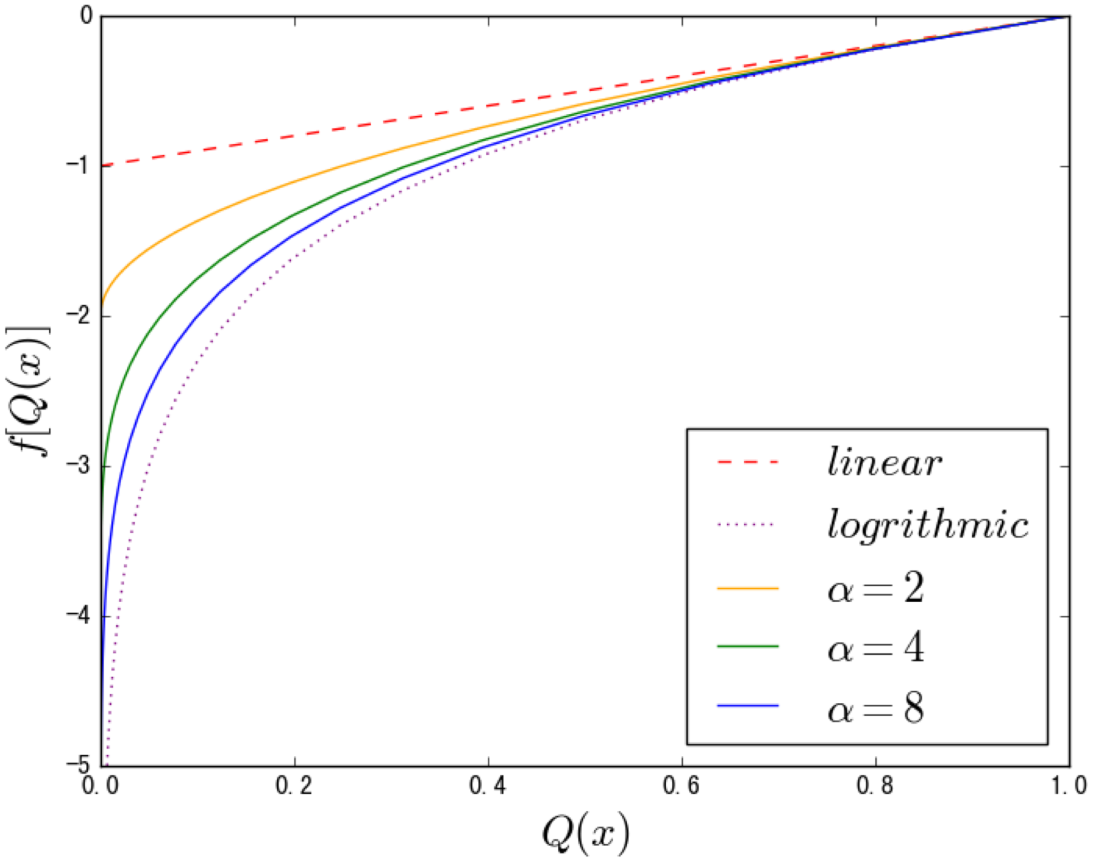
Method – Implementation of DDR

- DDR can be realized by using the following objective function

$$\max_{Q} \mathbb{E}_{x\sim P}\, f[Q(x)],$$
$$f(Q(x);\alpha) = \alpha \cdot Q(x)^{\frac{1}{\alpha}} - \alpha,$$
$$\alpha = \frac{\beta}{\beta - 1} > 1$$

Function f changes from linear to logarithm as α grows

$$f(Q(x);1) = Q(x) - 1,$$
$$\lim_{\alpha\to\infty} f(Q(x);\alpha) = \ln Q(x)$$



Method – Implementation of DDR

Loss function

$$\mathcal{L}(\mathcal{D};\alpha) = -\frac{1}{N}\sum_{i=1}^{N} \alpha \cdot Q\left(Y_{1:T}^{i}\right)^{\frac{1}{\alpha}}$$

$$= -\frac{\alpha}{N}\sum_{i=1}^{N}\prod_{t=1}^{T} Q\left(y_t^i \middle| Y_{1:t-1}^i\right)^{\frac{1}{\alpha}}$$

$$= -\frac{\alpha}{N}\sum_{i=1}^{N}\exp\left\{\frac{1}{\alpha}\sum_{t=1}^{T}\log Q\left(y_t^i \middle| Y_{1:t-1}^i\right)\right\}$$

Easy to implement

No extra training overhead

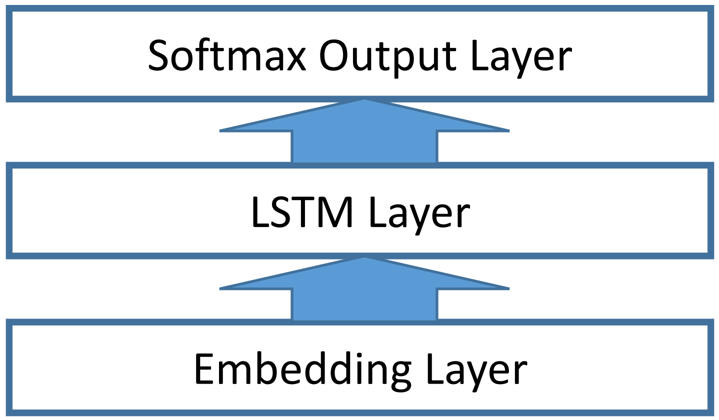
Comparison with Related works

RNNLM (Baseline)	GANs & RL methods	DDR (Ours)
• Low generation quality • Fast training speed • Hard to control the tradeoff between quality and diversity	• Improved generation quality • Low training speed • Hard to control the tradeoff between quality and diversity	• Improved generation quality • Fast training speed • Easy to control the tradeoff between quality and diversity

Experiments – Settings

- Datasets
  - Synthetic data
  - MSCOCO Image Caption dataset
  - EMNLP2017 WMT News dataset
- Baselines
  - RNNLM
  - SeqGAN (Yu et al. 2017)
  - LeakGAN (Guo et al. 2017)

General model architecture

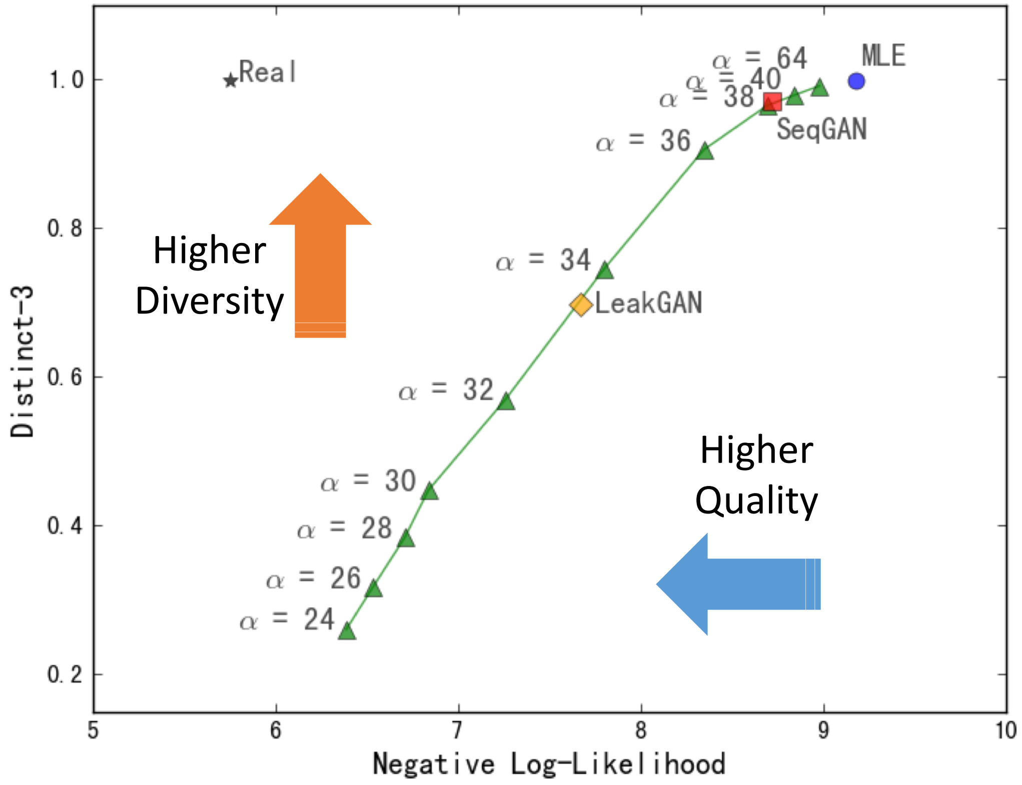


Experiments – Synthetic Data

- Use an oracle model (Yu et al. 2017) to generate data.
- Attributes
  - #Training data: 10000
  - Sequence length: 20
  - Vocabulary size: 5000
- Evaluation metrics:

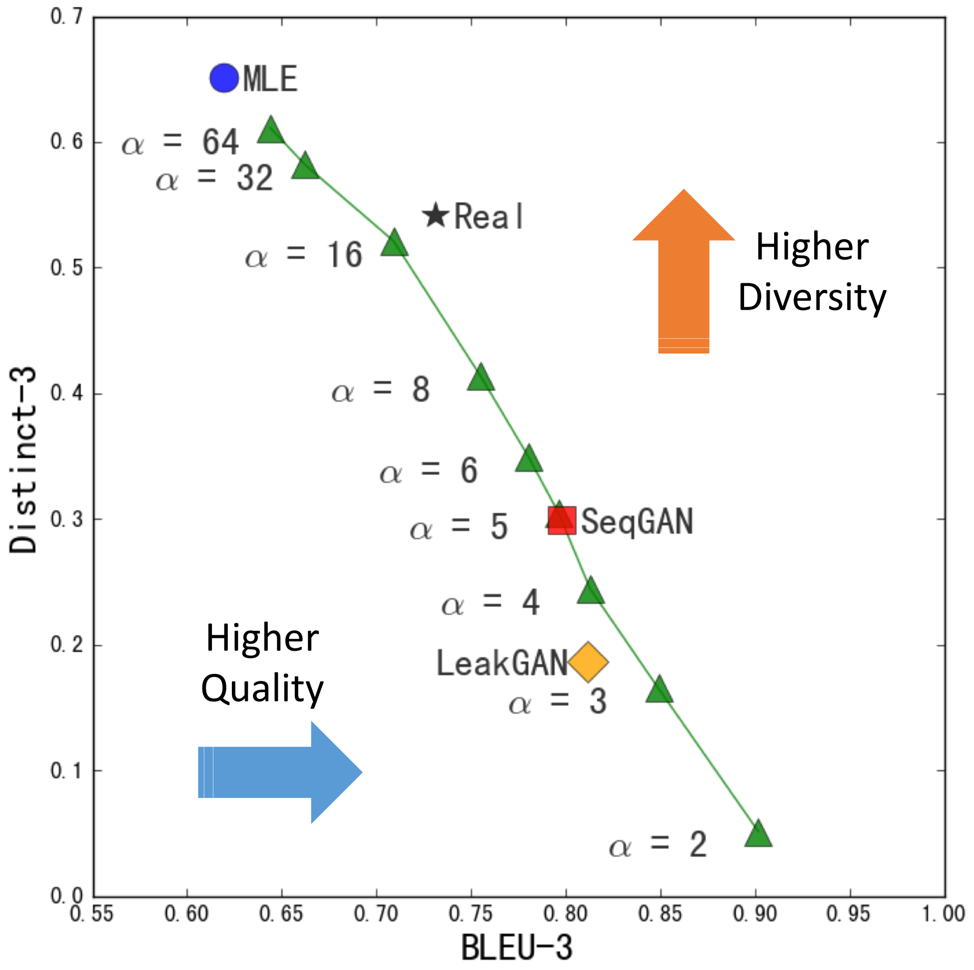
$$NLL = -\mathbb{E}_{Y_{1:T} \sim Q}\left[\sum_{t=1}^{T} \log G_{oracle}(y_t | Y_{1:t-1})\right]$$

$$Distinct\_n = \frac{\#\ \text{Unique}\ n\_grams}{\#\ Total\ n\_grams}$$

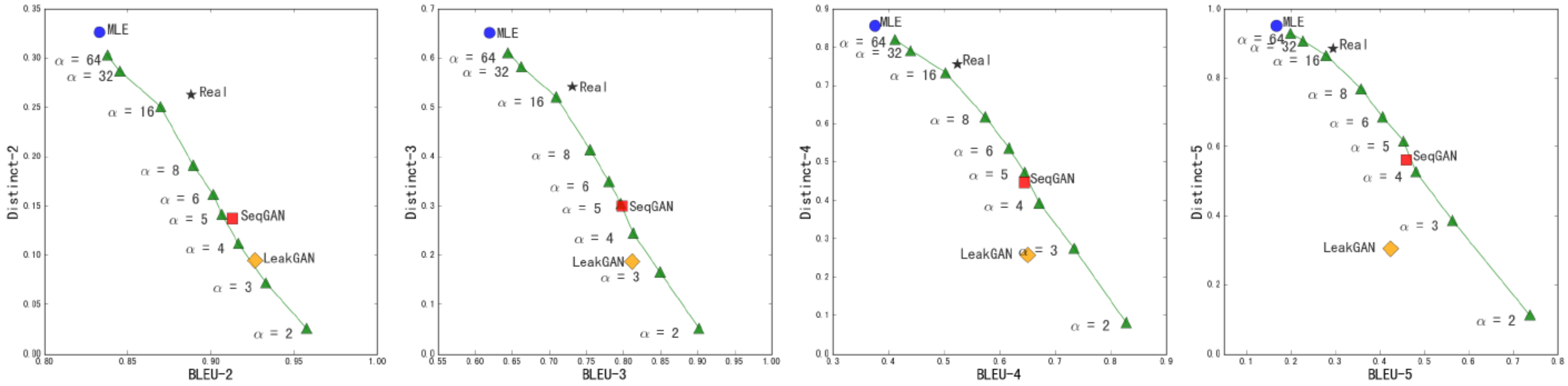


Experiments – Real World Datasets

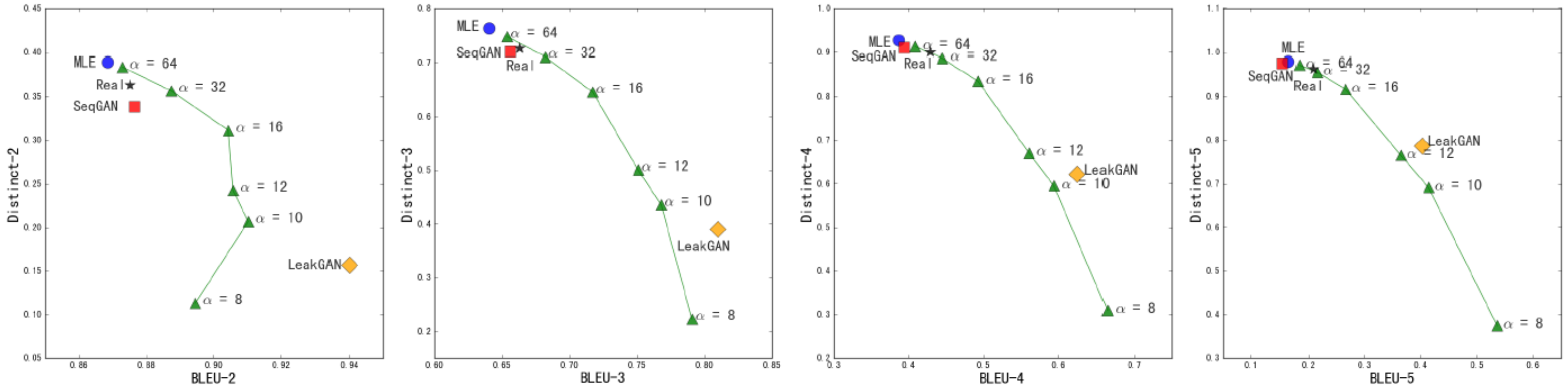
- MSCOCO Dataset
  - #Training/Test data: 80000/5000
  - Sequence length: 32
  - Vocabulary size: 4840
- WMT Dataset
  - #Training/Test data: 200000/10000
  - Sequence length: 50
  - Vocabulary size: 6655
- Evaluation Metrics:
  - BLEU-(2-5)
  - Distinct-(2-5)



Experiments – Real World Datasets



(a) MSCOCO dataset



(b) WMT dataset

Experiments – Generated Samples (MSCOCO)

Method	Generated samples
Real data	A cat stuck in a car with a slightly opened window . Bicycles , cars and a trash can in a garage . A lady talking a self portrait in a fancy bathroom . A man standing in a white kitchen with his arms folded .
MLE	Two young children playing a video game on the Nintendo Wii . Two pancakes on a white paper plate with sauce on the plate . A suitcase with vanilla and yellow markings on top of it . Birds flying on a stone bench next to the tree .
SeqGAN	A group of people standing on top of a snow covered mountain . Two people standing next to each other in the dirt . A brown horse standing next to a white fence on the beach . A cow standing in a grassy area near a body of water .
LeakGAN	A bicycle is locked to a fence by a truck . The interior of a bathroom with a long mirror and partially tiled walls . A small bathroom has toilet , medicine cabinet , and small sink . A woman riding a bicycle down a street in front of shops .

Method	Generated samples
DDR($\alpha=64$)	A woman wearing tennis gear holding a racket and her racquet . A dog sitting on a chair in front of a birthday cake . A bald man lays on a bed in the yellow floral pot . A girl is flying a kite in the sky into the airport .
DDR($\alpha=8$)	A man is sitting in a chair with a white cat . A guy is jumping in the air with a skateboard . A tall giraffe standing on top of a lush green field . Two women pose in front of a very tall building .
DDR($\alpha=2$)	A couple of young men playing a game of baseball . A couple of zebra standing on top of a lush green field . A red stop sign sitting on the side of a road . A man hitting a tennis ball with a tennis racquet .

Experiments – Human Turing Test

- Sample 50 sentences from each model, and mix all sentences together.
- 10 Ph.D students are invited to give scores individually for all samples.
- A sample get +1 score if one think it is possibly written by a human, otherwise get +0 score.

Method	Turing Test Score
Ground Truth	0.772
MLE	0.490
SeqGAN	0.706
LeakGAN	0.758
DDR($\alpha=64$)	0.586
DDR($\alpha=8$)	0.692
DDR($\alpha=2$)	**0.932**

Generation quality is significantly improved with DDR

Experiments – Robustness Test

- Add 10% random noises to MSCOCO dataset.
- See how many bad sentences are generated by models.
- A sample is regarded as bad if its BLEU-2 score is lower than 0.001

Method	Bad Samples %
MLE	8.0
SeqGAN	2.2
LeakGAN	**0.0**
DDR($\alpha=64$)	0.4
DDR($\alpha=32$)	0.1
DDR($\alpha=16$)	**0.0**
DDR($\alpha=8$)	**0.0**
DDR($\alpha=2$)	**0.0**

Model become more robust with DDR

Conclusion

- **Differentiated Distribution Recovery (DDR)** is an efficient way to promote generation quality for unconditional neural text generation.
- **DDR** provides an flexible control between generation quality and diversity through a hyper-parameter α.
- **DDR** makes the model more robust against noises in training data.

Thank you! Q&A

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