Constrained Sentence Generation by Metropolis-Hastings Sampling

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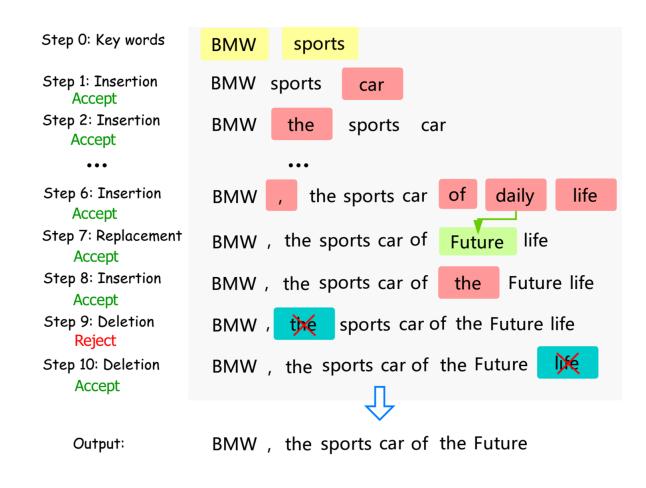


Motivation

- > We often need to add constrains to sentence generation
 - Hard constrains (eg. keyword2sentence)
 Juice -> Brand natural juice, specially made for you
 - Soft constrains (eg. paraphrase)
 The movie is a great success -> It is one of my favorite movies
- > Current methods don't work well in constrained sentence generation
 - It's difficult to add constraints to widely-used sequential sentence generation models, such as seq2seq and VAE.
 - Methods dedicated for constrained sentence generation can only handle a specific problem.
 - GBS and CBS can only generate sentence from certain keywords
 - VAE-SVG can only do paraphrase

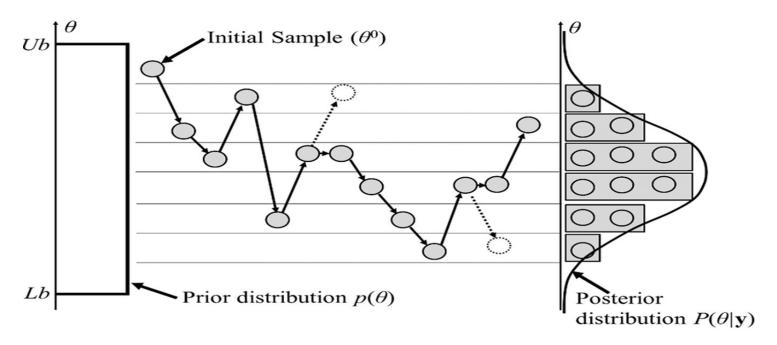
Introduction

- We need a practical method for sentence generation under both hard and soft constraint! So we propose Constrained Generation by Metropolis-Hastings sampling (CGMH).
- ➤ The main idea of CGMH is performing Metropolis-Hastings sampling directly in the space of sentences. The figure on right illustrates CGMH by an example of generating advertisement from keywords.



Metropolis-Hastings Sampling

- Metropolis-Hastings(MH) sampling is a 2-step Markov Chain Monte-Carlo (MCMC) algorithm
- MH first proposes a transition and then accepts or rejects the transition. (Gibbs sampling is a special case of MH sampling, which always accepts transitions.)



Method

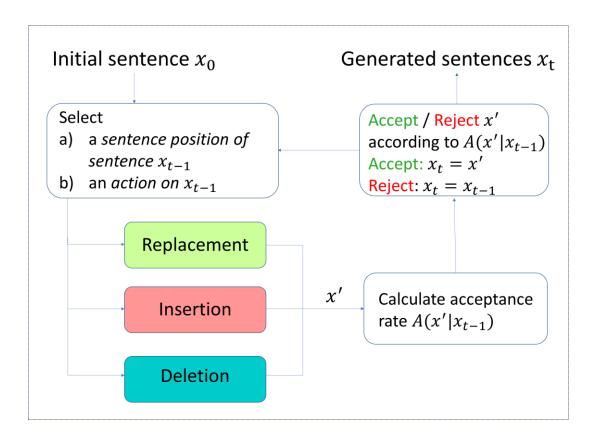
We set the stationary distribution as:

$$\pi(x) = p(x) \cdot \prod_{i} P_C^i(x)$$

- p(x) is the probability of sentence in a generalpurpose language model and $P_C^i(x)$ is the indicator function showing whether constraint i is satisfied.
- \triangleright We use MH algorithm to sample from $\pi(x)$
 - From a sentence x_{t-1} , we propose a new sentence x' by replacement/insertion/deletion of a position of x_{t-1}
 - Calculate the acceptance rate:

$$A(x'|x_{t-1}) = \min(1, \frac{\pi(x') \cdot g(x_{t-1}|x')}{\pi(x_{t-1}) \cdot g(x'|x_{t-1})})$$

• Accept x' with probability $A(x'|x_{t-1})$



Experiment - Keywords2Sentence Generation

> CGMH outperforms previous work in both NLL and human evaluations.

#keyword(s)		CGMH	GBS	sep-B/F	asyn-B/F
1	NLL	7.04	7.42	7.80	8.30
	Human	0.45	0.32	0.11	0.09
2	NLL	7.57	8.72	-	-
	Human	0.61	0.55	-	-
3	NLL	8.26	8.59	-	-
	Human	0.56	0.49	-	-
4	NLL	7.92	9.63	-	-
	Human	0.65	0.55	-	-

Keyword(s)	Generated Sentences
friends	My good friends were in danger.
project	The first project of the scheme .
have, trip	But many people have never
nave, urp	made the trip .
lottery, scholarships	But the lottery has provided
	scholarships .
decision, build,	The decision is to build a new
home	home .
attempt, copy,	The first attempt to copy the
painting, denounced	painting was denounced .

Experiment - Unsupervised Paraphrase Generation

> CGMH is the first unsupervised model to achieve comparable results with supervised models.

Model	BLEU-ref	BLEU-ori	NLL
Origin Sentence	30.49	100.00	7.73
VAE-SVG (100k)	22.50	-	-
VAE-SVG-eq (100k)	22.90	-	-
VAE-SVG (50k)	17.10	-	-
VAE-SVG-eq (50k)	17.40	-	-
Seq2seq (100k)	22.79	33.83	6.37
Seq2seq (50k)	20.18	27.59	6.71
Seq2seq (20k)	16.77	22.44	6.67
VAE (unsupervised)	9.25	27.23	7.74
CGMH w/o matching	18.85	50.28	7.52
w/KW	20.17	53.15	7.57
w/KW + WVA	20.41	53.64	7.57
w/KW + WVM	20.89	54.96	7.46
w/KW + ST	20.70	54.50	7.78

Type	Examples
Ori	what 's the best plan to lose weight
Ref	what is a good diet to lose weight
Gen	what 's the best way to slim down quickly
Ori	how should i control my emotion
Ref	how do i control anger and impulsive emotions
Gen	how do i control my anger
Ori	why do my dogs love to eat tuna fish
Ref	why do my dogs love eating tuna fish
Gen	why do some dogs like to eat raw tuna and raw fish

Experiment - Unsupervised Error Correction

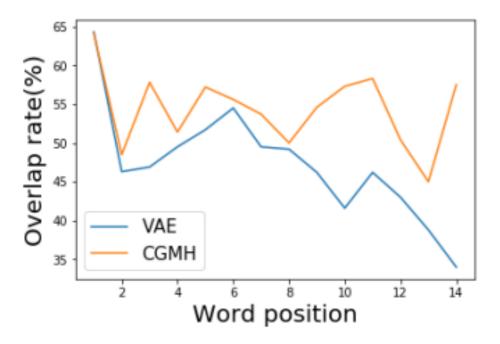
> CGMH outperforms some of the supervised models trained on large parallel corpus.

Model	#parallel data	GLEU
AMU	2.3M	44.85
CAMB-14	155k	46.04
MLE	720k	52.75
NRL	720k	53.98
CGMH	0	45.5

Ori	Even if we are failed, We have to try to get a new things.
Ref	Even if we all failed, we have to try to get new things.
Gen	Even if we are failing, We have to try to get some new things.
Ori	In the world oil price very high right now.
Ref	In today 's world, oil prices are very high right now.
Gen	In the world, oil prices are very high right now.

Analysis

- Why CGMH performs better than sequential models?
 - RNN can be thought of as an autoregressive Bayesian network generating words conditioned on previous ones. Hence error will accumulate during generation.
 - CGMH doesn't generate sequentially, so error won't accumulate.
 - At the same time, CGMH has the ability of selfcorrection. Please refer to the part of sentence correction.



Main Reference

- [1] Hokamp, C., and Liu, Q. 2017. Lexically constrained decoding for sequence generation using grid beam search. In ACL.
- [2] Li, Z.; Jiang, X.; Shang, L.; and Li, H. 2017. Paraphrase generation with deep reinforcement learning. arXiv preprint arXiv:1711.00279.
- [3] Gupta, A.; Agarwal, A.; Singh, P.; and Rai, P. 2017. A deep generative framework for paraphrase generation. *arXiv* preprint *arXiv*:1709.05074.
- [4] Mou, L.; Yan, R.; Li, G.; Zhang, L.; and Jin, Z. 2015. Backward and forward language modeling for constrained sentence generation. arXiv preprint arXiv:1512.06612.
- [5] Junczys-Dowmunt, M., and Grundkiewicz, R. 2016. Phrasebased machine translation is state-of-the-art for automatic grammatical error correction. *arXiv* preprint *arXiv*:1605.06353.
- [6] Felice, M.; Yuan, Z.; Andersen, Ø. E.; Yannakoudakis, H.; and Kochmar, E. 2014. Grammatical error correction using hybrid systems and type filtering. In *CoNLL*.
- [7] Napoles, C.; Sakaguchi, K.; Post, M.; and Tetreault, J. 2015. Ground truth for grammatical error correction metrics. In ACL.

THANKS.

Byte Dance 字节跳动