CGMH: Constrained Sentence Generation by Metropolis-Hastings Sampling

Ning Miao, Hao Zhou, Lili Mou, Rui Yan, Lei Li

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  - Constrained generation is difficult for current methods
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  - Hard constrains (eg. keyword2sentence)

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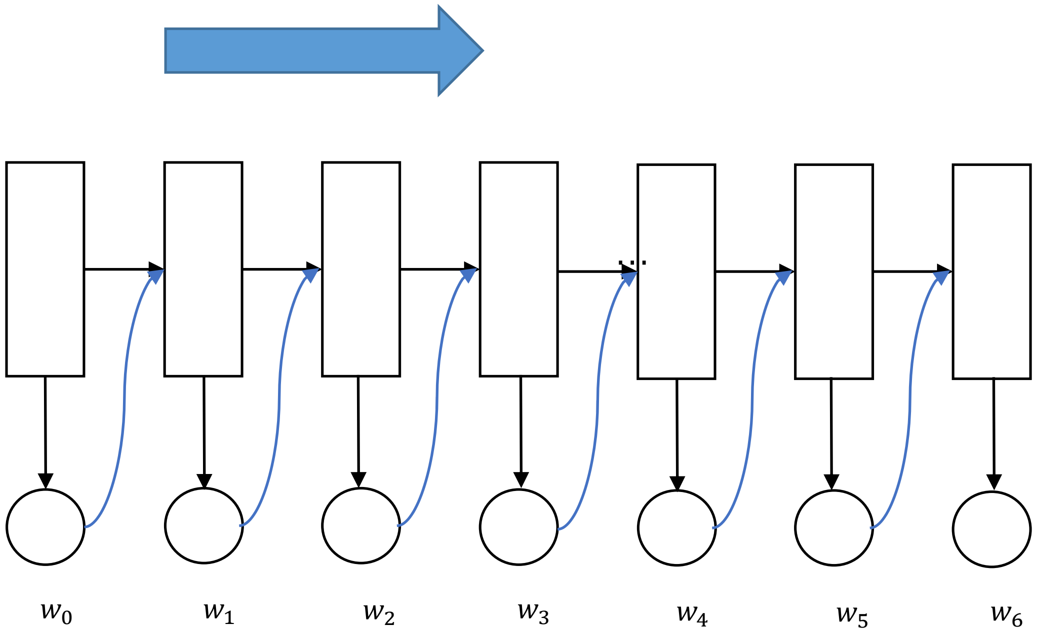
  - Hard constrains (eg. keyword2sentence)

    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

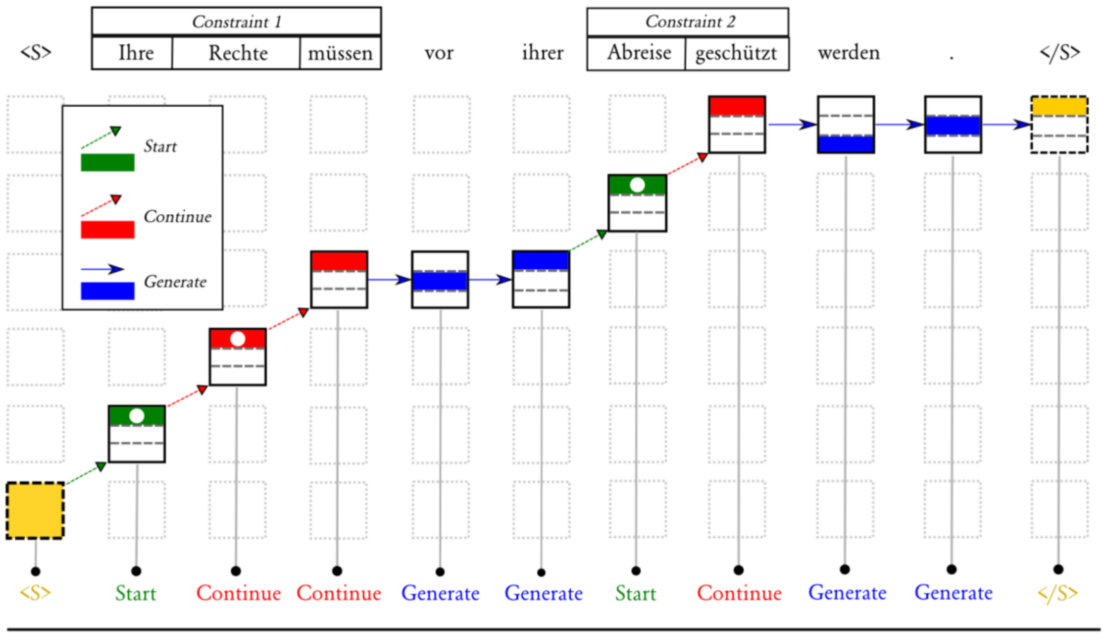
Motivation

- It's difficult to add constraints to sequential language models.



Motivation

- Methods dedicated for constrained sentence generation can only handle a specific kind of constraints.
  - Grid Beam Search(GBS)[1]
  - Constrained Beam Search(CBS)[2]



Input: Rights protection should begin before their departure .

Motivation

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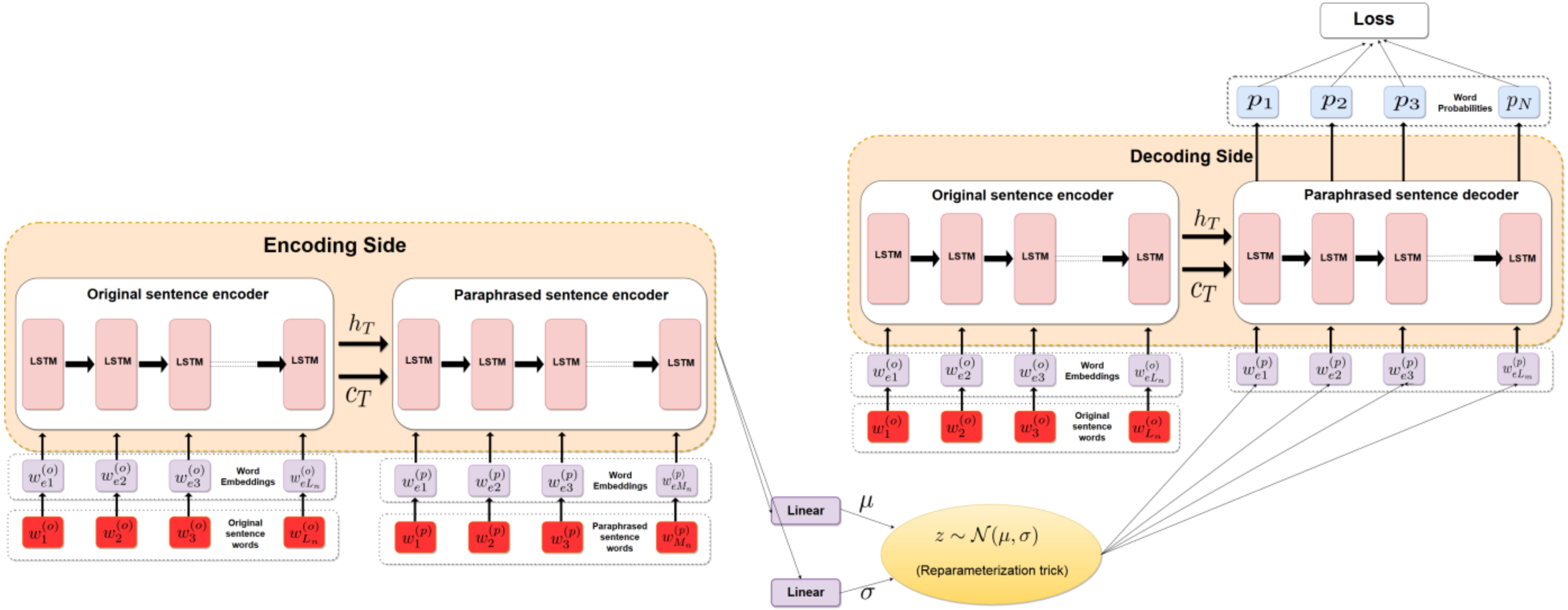
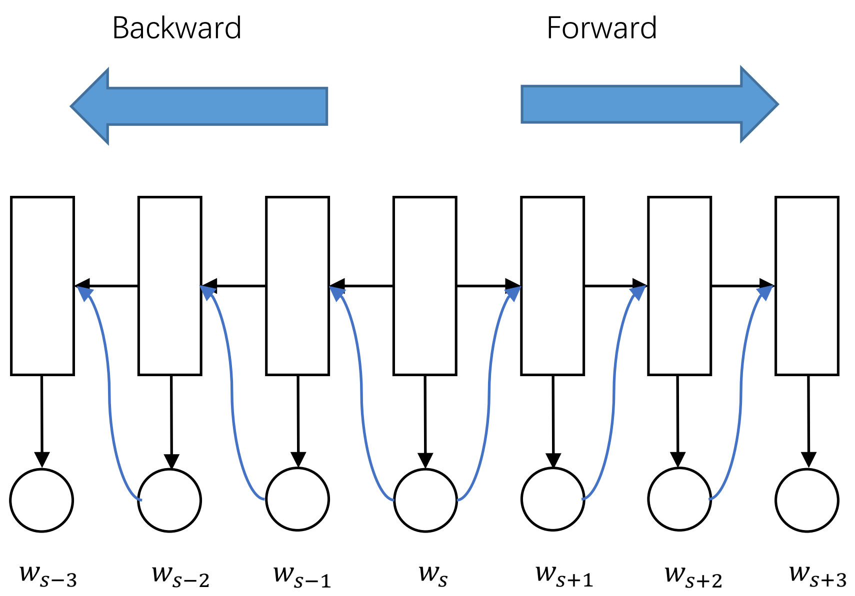
  - VAE-SVG[3]



Motivation

➢ Current models don’t perform well

- LSTM w/ sep-B/F[4] generates **independent backward and forward** sequences from the given word.



Eg: demand -> this is what it does in <u>demand</u> is very necessary .

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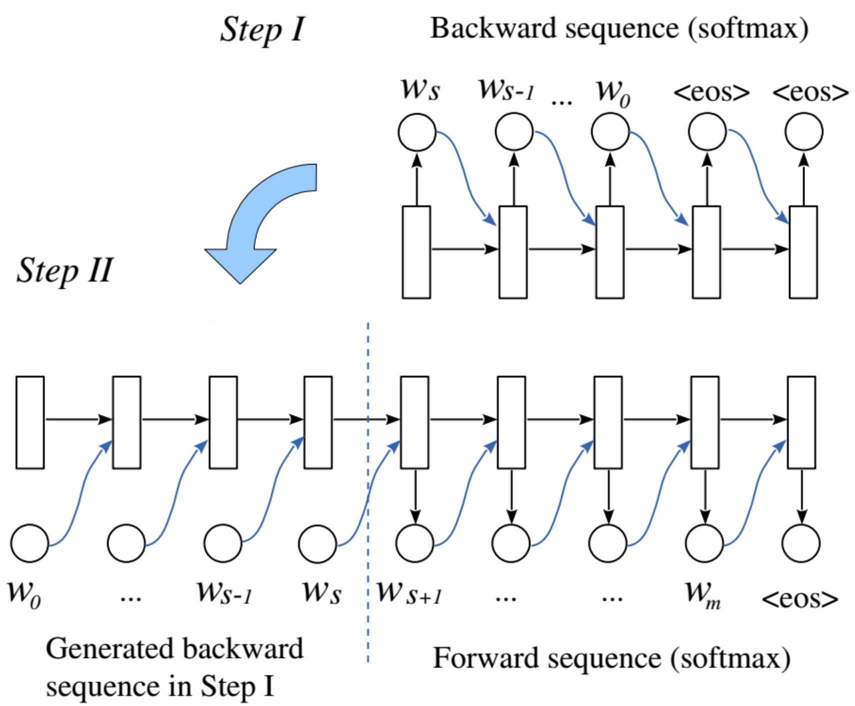
- LSTM w/ asyn-B/F[4] **first generates the first half of a sentence and then generates another half** conditioned on the first half.

Eg: player -> The best name of the <u>player</u> is not making a year .



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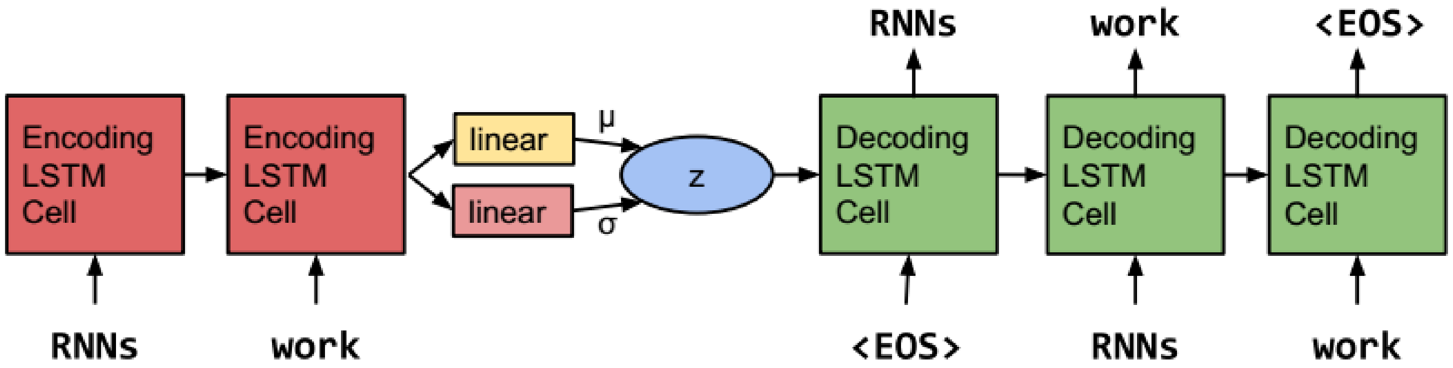
- VAE[5] - We can perform paraphrasing by
  1. Encode a sentence into a distributional representation
  2. Add some noise to the representation
  3. then decoding the disturbed representation.

Unfortunately, the generated sentences of this method is of low quality.

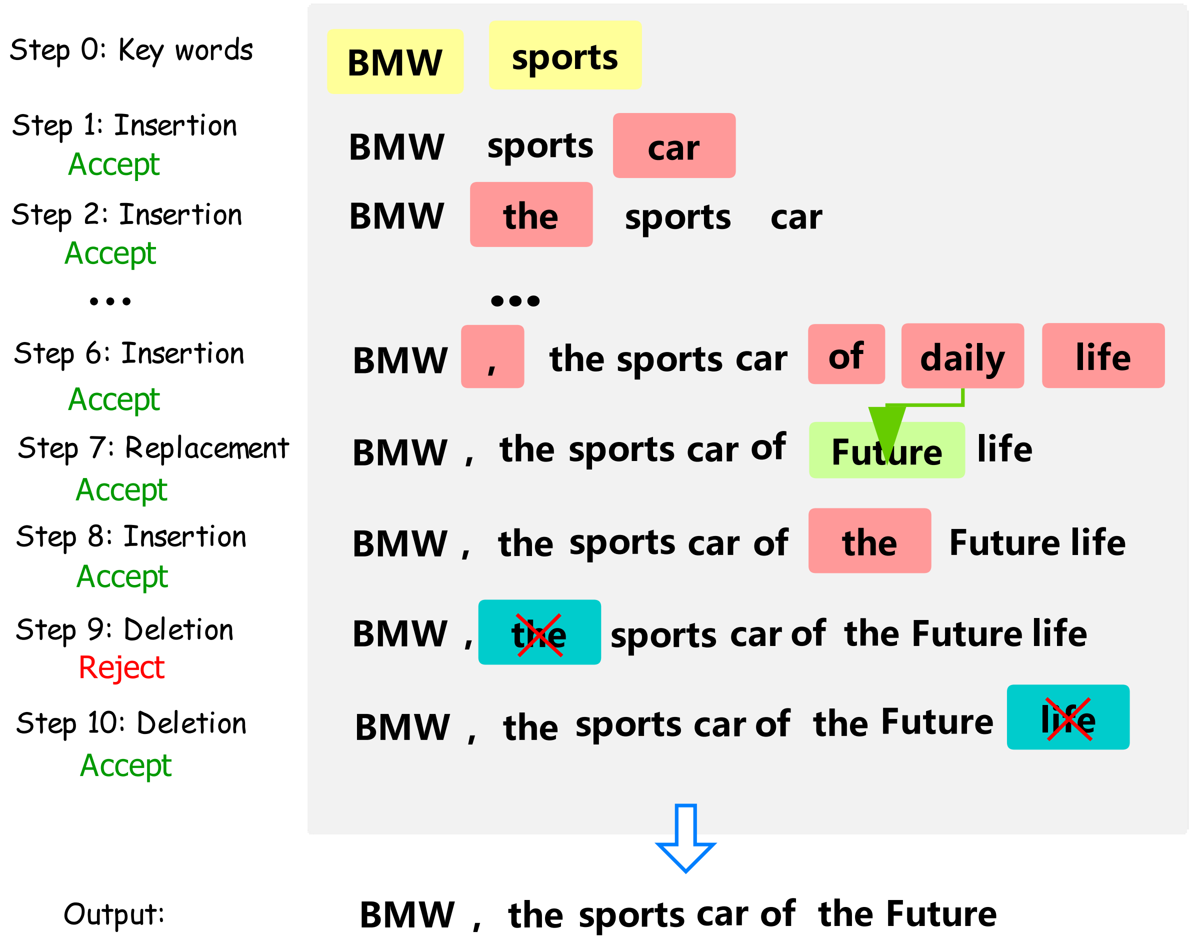


Motivation

- We need a practical method for sentence generation under both hard and soft constraints! So we propose **Constrained Generation by Metropolis-Hastings sampling (CGMH).**

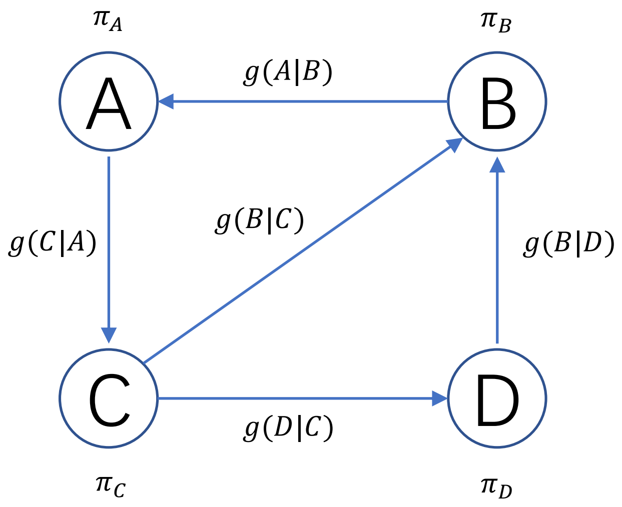
Introduction

- The main idea of CGMH is performing Metropolis-Hastings **sampling directly in sentence space**. The figure on the right illustrates CGMH by an example of generating advertisement from keywords.



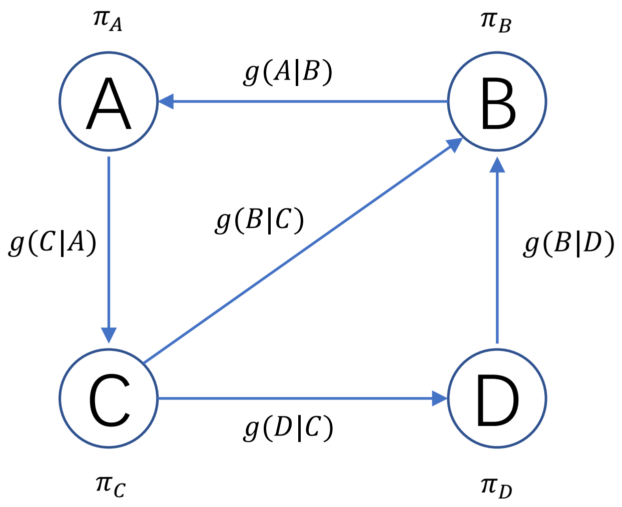
Introduction - Metropolis-Hastings Sampling

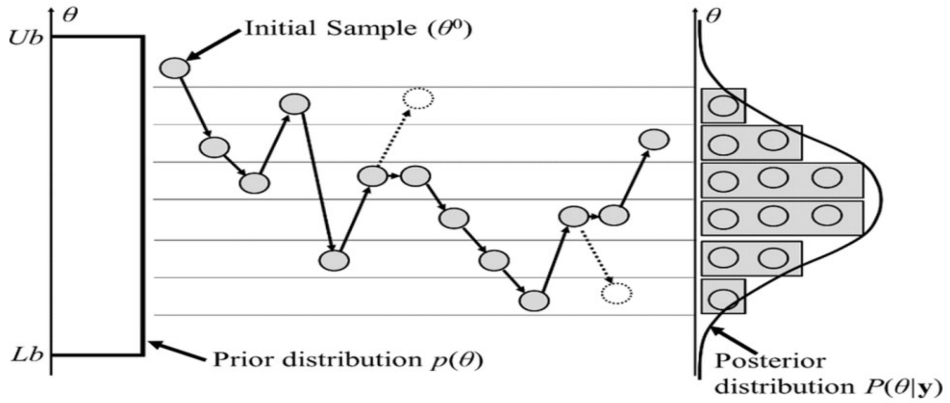
- Metropolis-Hastings(MH) sampling is a 2-step **Markov Chain Monte Carlo** (MCMC) algorithm



Introduction - 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 – Stationary Distribution

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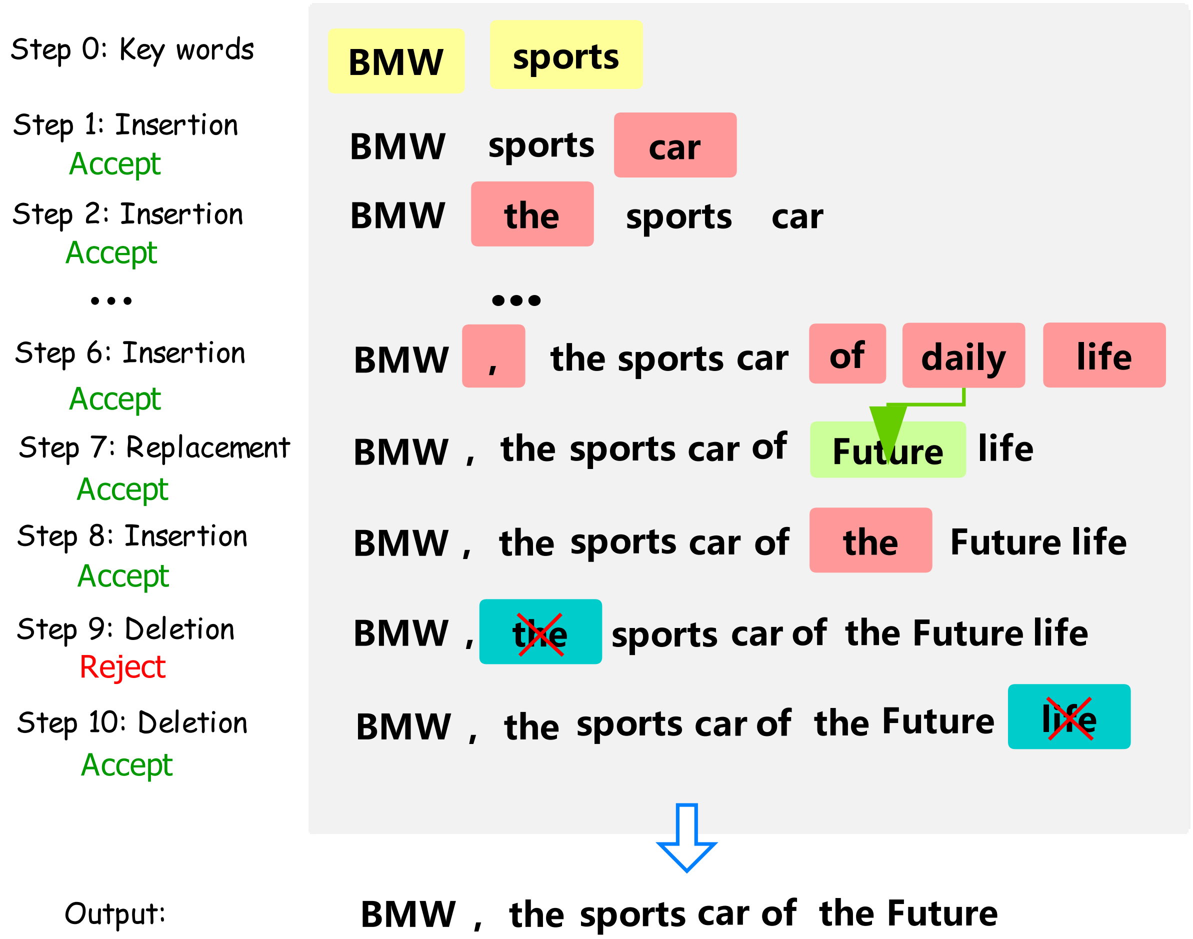
  - $P_C(x) = \prod_i P_C^i(x)$ is the indicator function showing whether constraints are satisfied.
  - For different tasks, we use different $P_C(x)$:
    - Keywords2Sentence: $P_C(x) = 1_{\{x \text{ contains the keywords}\}}$
    - Paraphrase: $P_C(x) = 1 \,/\, P_C^{KW}(x) \,/\, P_C^{KW}(x)\, P_C^{SIM}(x)$
    - Correction: $P_C(x) = 1 \,/\, P_C^{WMA}(x)$

Method – Proposal

- 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 from x_{t-1}



Method –Accept/Reject

- Calculate the acceptance rate:

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

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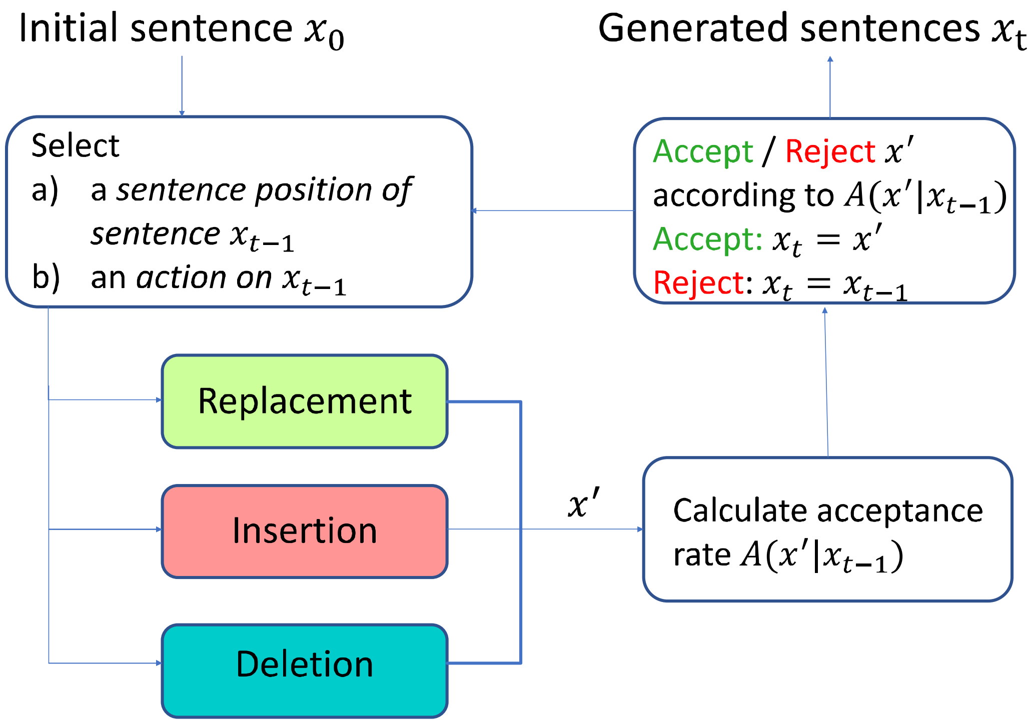

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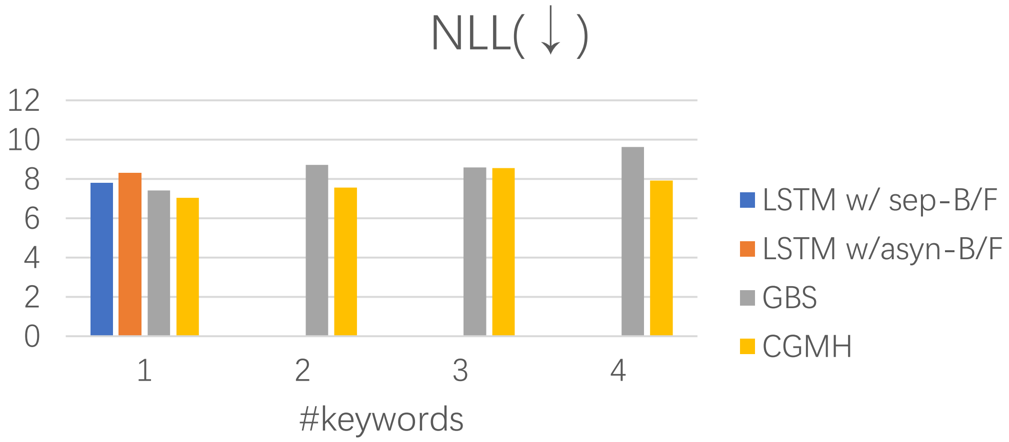
- **Unsupervised Paraphrase Generation**
  - Aim: To generate sentences with similar meaning of the given one.
  - Dataset: Quora(140k pairs of paraphrase sentences)
- **Sentence Correction**
  - Aim: To correct the errors in the given sentence.
  - Dataset: A subset of One-Billion-Word Corpus (5M, base language model) and JFLEG(1501 sentences, for test only)

Experiment - Keywords2Sentence Generation

- To generate sentences from a variable number of keywords, we simply start sampling from the given keywords. Experimental results show that CGMH outperforms previous work in both NLL and human evaluations.



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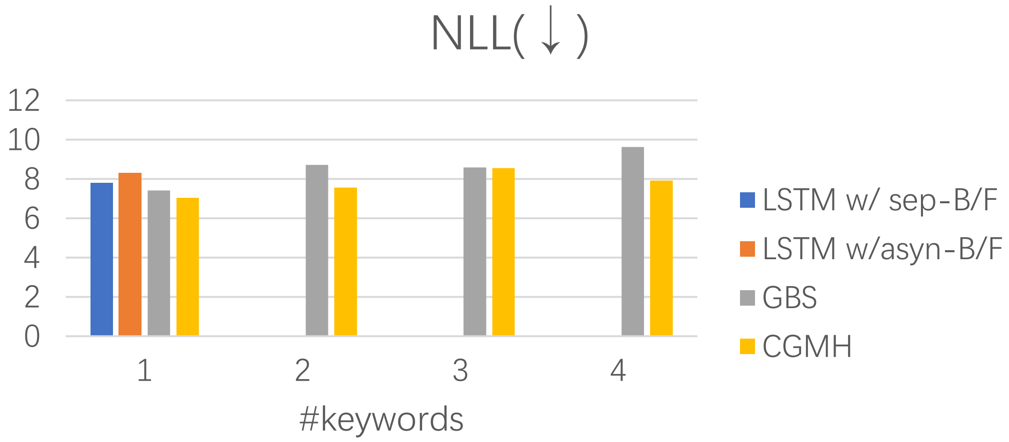

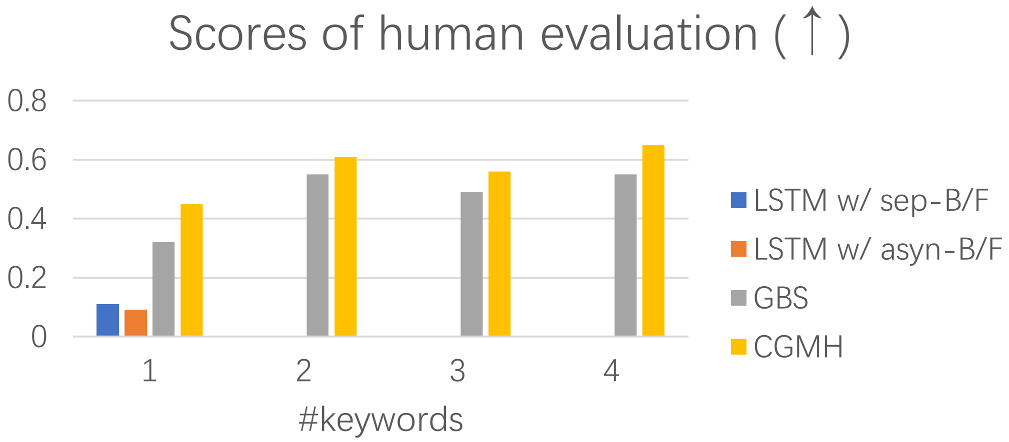

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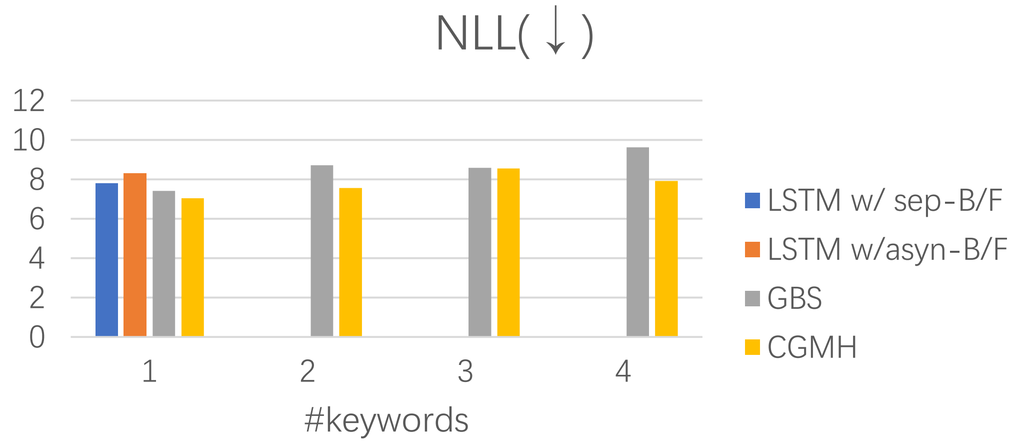

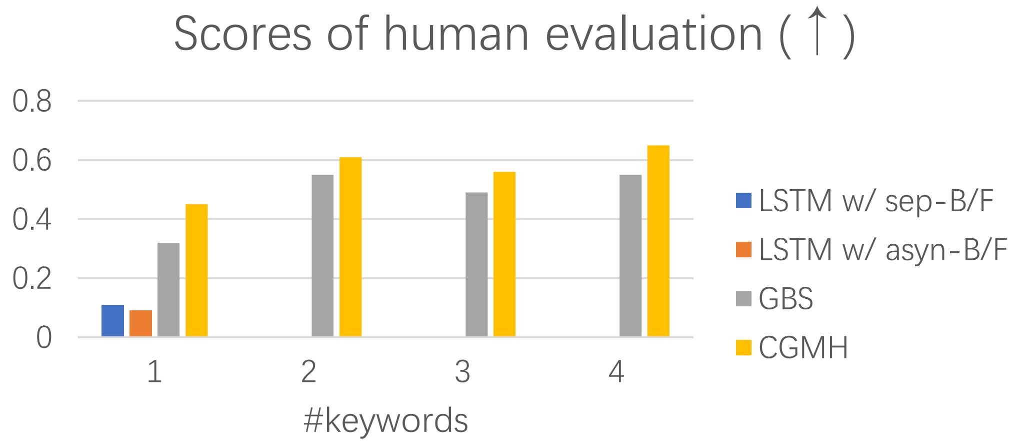

Keyword(s)	Generated Sentences
friends	My good friends were in danger .
project	The first project of the scheme .
have, trip	But many people have never made the trip .
lottery, scholarships	But the lottery has provided scholarships.
decision, build, home	The decision is to build a new home.
attempt,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

Experiment - Unsupervised Paraphrase Generation

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  - **CGMH w/ KW**, $P_C\ (x) = P_C^{KW}(x),\ P_C^{KW}(x)$=1 if x still contains the keywords of x_0, which ensures that important information of x_0 won't be forgotten.

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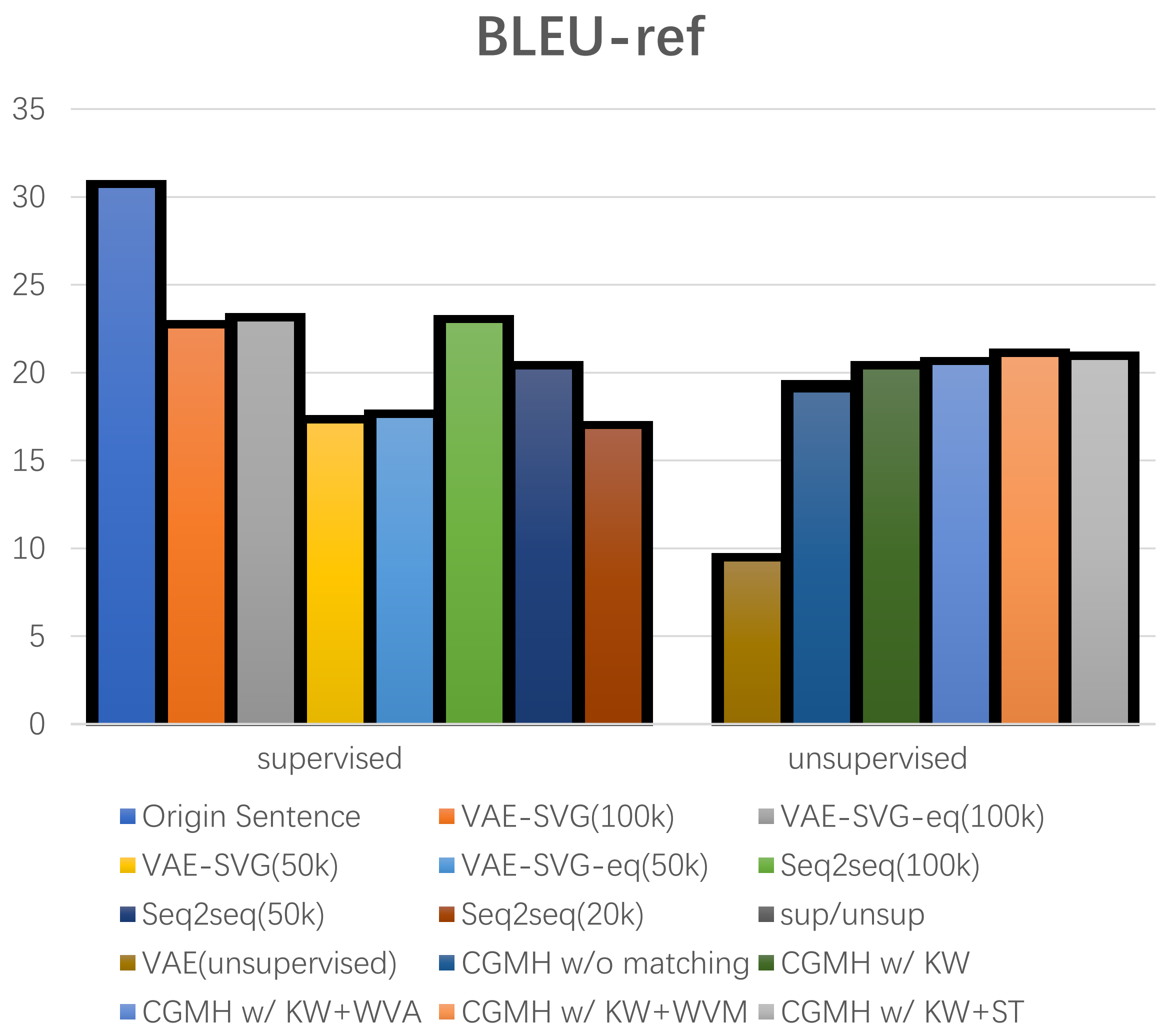
  - **CGMH w/ KW+**SIM, $P_C\ (x) = P_C^{KW}(x)\ P_C^{SIM}(x),\ P_C^{SIM}\ (x)$ is the cosine similarity of sentences embeddings. If SIM=**WVA**, sentence embeddings are calculated as the mean vectors of word embeddings. If SIM=**ST**, we get sentence embeddings by SkipThoughts. And if SIM=**WVM**, we calculate maximal word similarities between each word in x with words in x_0, and use their average value as $P_C^{WVM}(x)$.

Experiment - Unsupervised Paraphrase Generation

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



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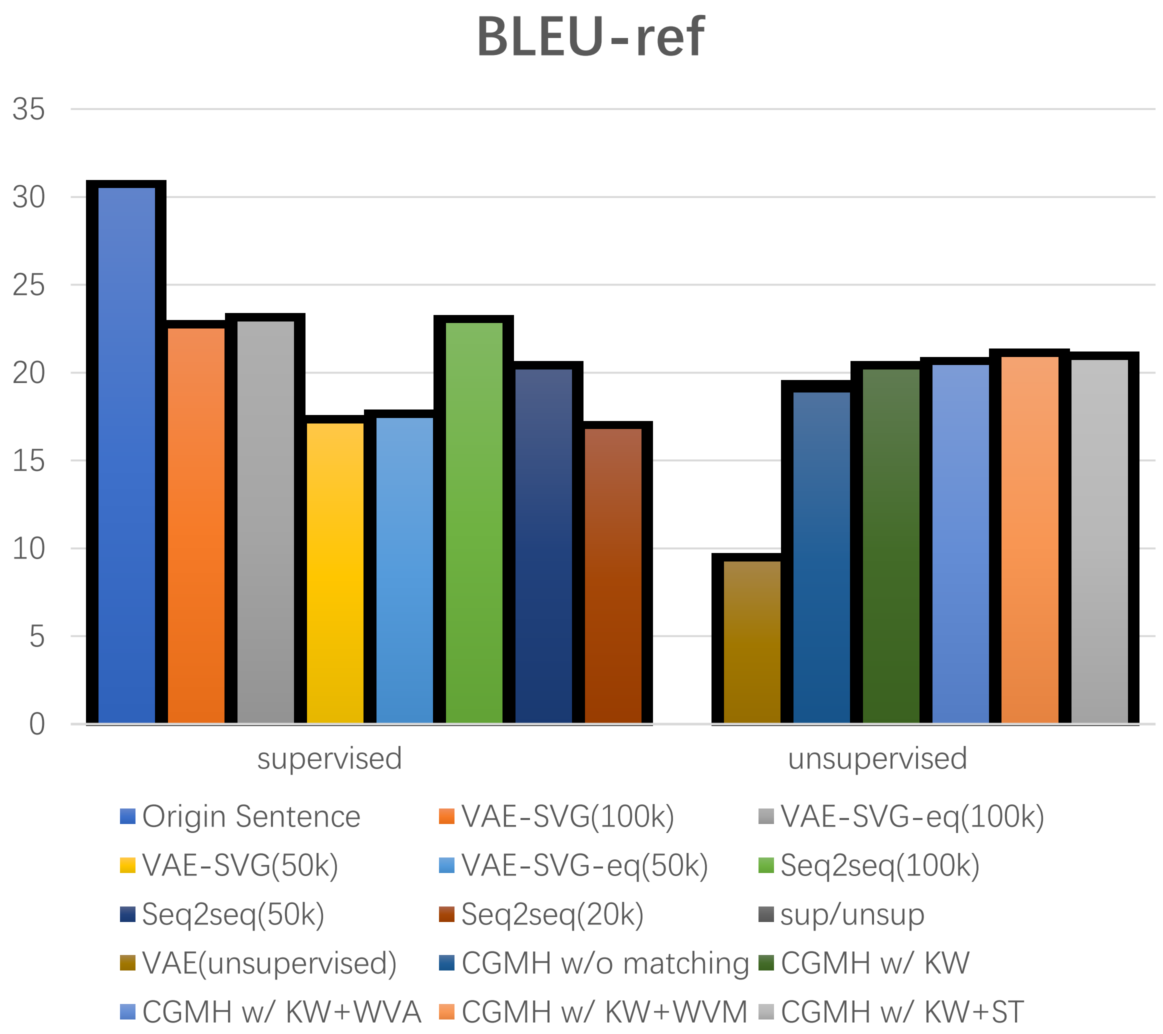


Examples

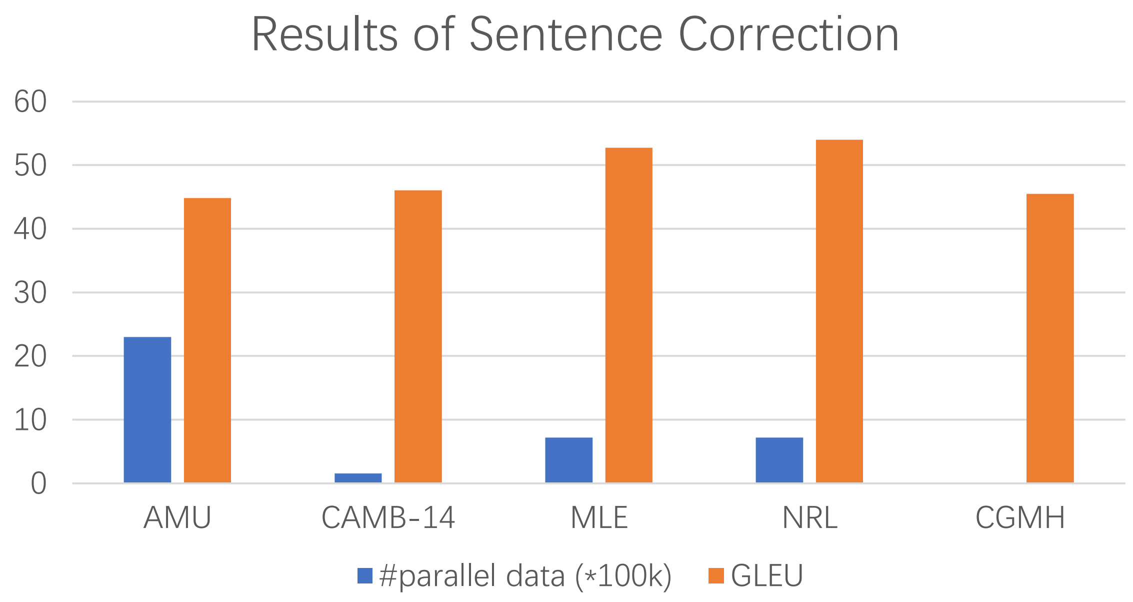
1,what ‘s the best plan to lose weight ->
what ‘s the best way to slim down quickly

2. how should i control my emotion ->
how do i control my anger

3. why do my dogs love to eat tuna fish ->
why do my 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.



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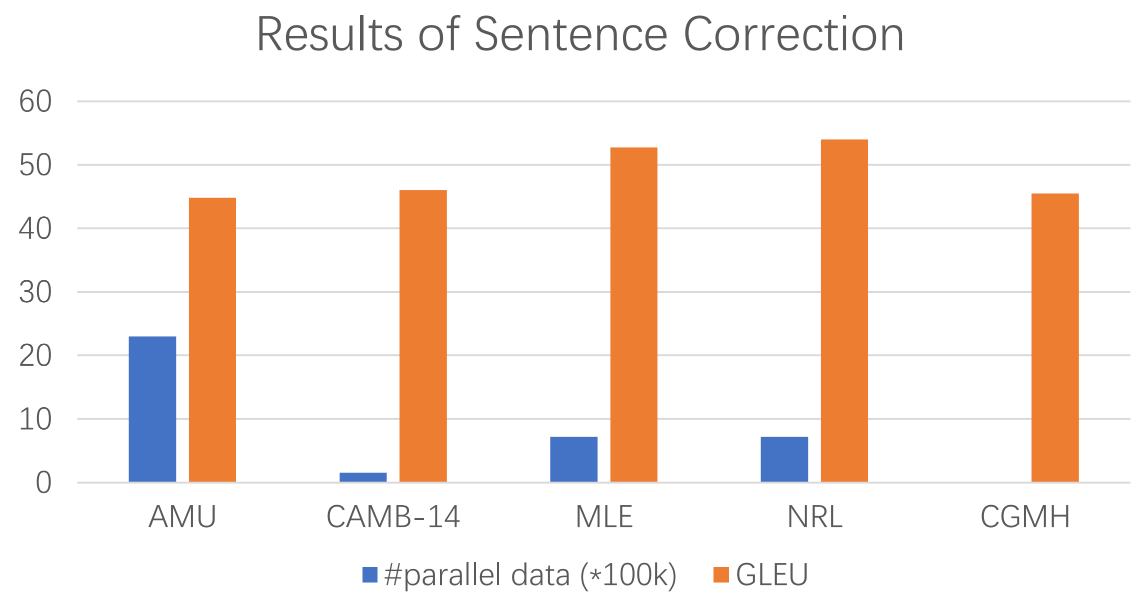
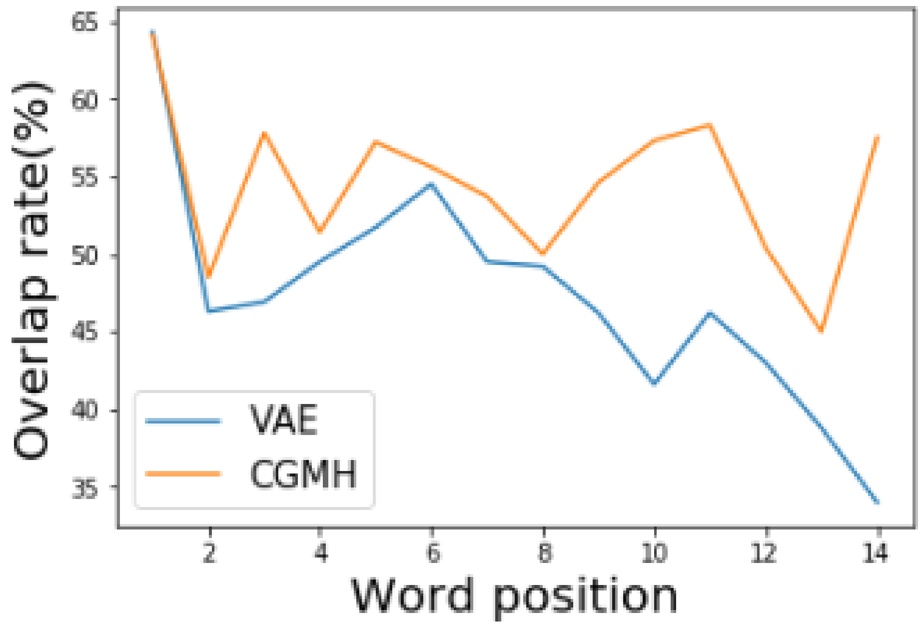


Erroneous sen1	**Even if we are failed , we have to try to get a new things .**
Reference sen1	Even if we all failed , we have to try to get new things .
Output sen1	Even if we are failing , we have to try to get some new things ..
Erroneous sen2	In the world oil price very high right now .
Reference sen2	In today 's world , oil prices are very high right now .
Output sen2	In the world , oil prices are very high right now .

Analysis

➢ Why CGMH outperforms sequential models?

- RNN can be thought of as an autoregressive Bayesian network generating words conditioned on previous ones. Hence **error will accumulate** during generation.



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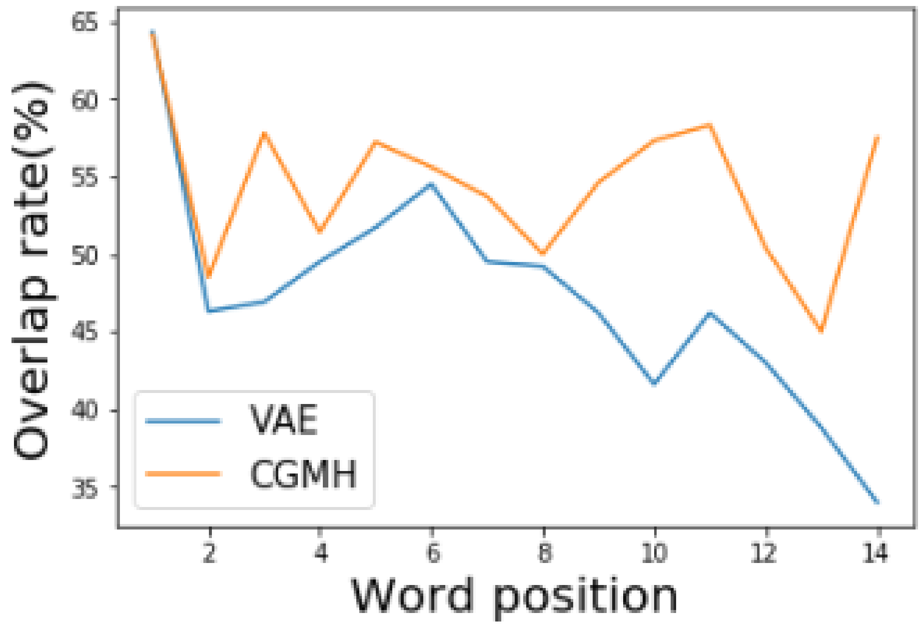

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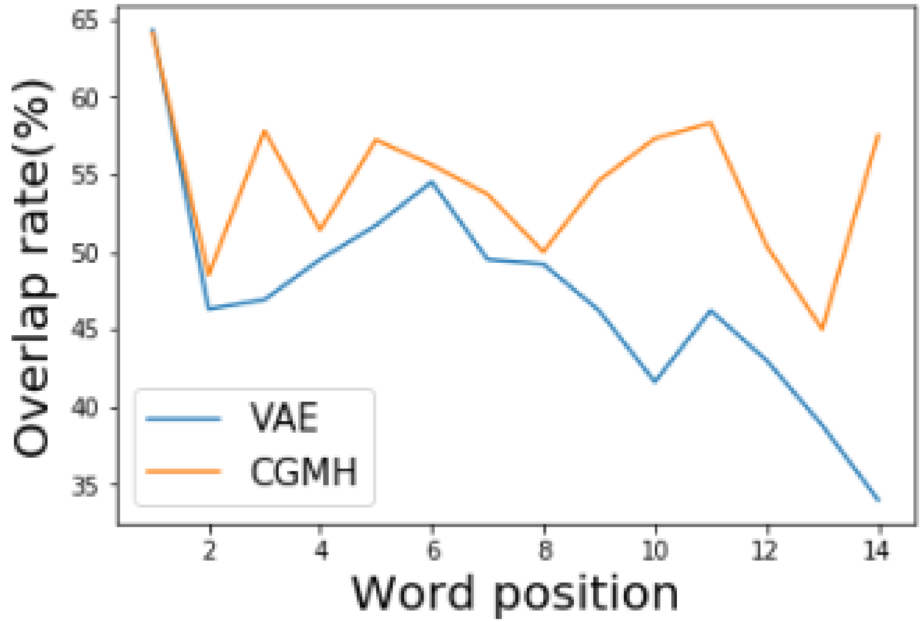
  - CGMH doesn't generate sequentially, so error won't accumulate.
  - At the same time, CGMH has the ability of **self-correction**. Please refer to the part of sentence correction.



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THANKS.

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