SARG: A Novel Semi Autoregressive Generator for Multi-turn Incomplete Utterance Restoration

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Abstract

Dialogue systems in the open domain have achieved great success due to large conversation data and the development of deep learning, but multi-turn scenarios are still a challenge because of the frequent coreference and information omission. In this paper, we investigate the incomplete utterance restoration since it has brought general improvement over multi-turn dialogue systems in recent studies. Inspired by the autoregression for generation and the sequence labeling for text editing, we propose a novel semi autoregressive generator (SARG) with the high efficiency and flexibility. Moreover, experiments on Restoration-200k show that our proposed model significantly outperforms the state-of-the-art models with faster inference speed.1

1 Introduction

Dialogue systems in open-domain have attracted increasing attention (Li, 2020; Huang et al., 2020), and been widely utilized in real-world applications, such as chatbot (Adiwardana et al., 2020), intelligent customer support systems (Gong et al., 2019), virtual assistants (Hewitt and Beaver, 2020), etc. However, due to frequently occurred coreference and information omission, there still exists a major challenge: it is hard for machines to understand the real intention from the original utterance without the context. A series of models of retrieval-based and generative-based have been studied for multi-turn systems (Yan et al., 2016; Zhang et al., 2018; Zhou et al., 2018; Wu et al., 2016b), and they generally combine the context and the original utterance as input to retrieve or generate responses. However, these methods lack great generalizations with a strong reliance on the history of dialogue. In other words, they are only suited for the applications where the appropriate multi-turn dialogue corpus can be available.

Su et al. 2019 and Pan et al. 2019 propose their utterance restoration models, respectively, which are aimed at restoring the semantic information based on the history of the session from a different perspective. Restoration methods decouple multi-turn systems into the single-turn problems and alleviate dependence on multi-turn dialogue corpus, and they can also achieve leading performance.

| Utterance 1 (Translation) | Context 1                      |
|--------------------------|-------------------------------|
| Human: 为什么?           | Human: Why?                   |
| Utterance 2              | Chatbot: 这个你得问李淳风呀。Chatbot: You’ll have to ask Li Chunfeng about that. |
| Utterance 3              | Human: 去问他。                |
| Utterance 3′             | Human: 我会问李淳风。          |
| Utterance 3′             | Human: I’ll ask Li Chunfeng.   |
| Utterance 1              | Human: 你最喜欢什么电影?      |
| Utterance 2              | Chatbot: 泰坦尼克。Chatbot: Titanic. |
| Utterance 3              | Human: 为什么呢?              |
| Utterance 3′             | Human: Why?                   |
| Utterance 3′             | Human: Why do you like Titanic most? |

Table 1: An example of utterance restoration in human-machine dialogue system. Utterance 3’ is the restored sentence based on Utterance 3. Red means coreference and blue means omission.

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1The code will be released soon.
Specifically, Su et al. 2019 employ transformer-based architecture and pointer network to rewrite the original utterance, and they split the whole session into history and original utterance for capturing different attentions. Pan et al. 2019 propose a cascade frame of pick-and-combine to restore the incomplete utterance from history. And both methods generate restored utterance from scratch using a complete autoregression, which is highly time-consuming during inference.

In the task of text generation with overlapped sources and targets, Malmi et al. 2019 introduce LaserTagger, a sequence labeling method, which casts text generation as a text editing task. However, the insertions of LaserTagger are restricted to a fixed phrase vocabulary that is derived from the training data. In multi-turn dialogue, some rare phrases are habitually omitted by the speaker without affecting the listening comprehension; as shown in Table 1, “Li Chunfeng” is a rare phrase and omitted in Utterance 3. And LaserTagger cannot solve such a coreference problem well, since the rare phrase is discarded when constructing the fixed phrase vocabulary.

In this paper, we propose a semi autoregressive generator (SARG), which cleverly combines the sequence labeling and autoregression well to address the challenges brought by high time-consuming and rare words or phrases discard. SARG retains the flexibility of autoregression and takes advantage of the fast inference speed of sequence labeling.

First, we employ a tagger to predict the editing labels, which involves three main operations: keep a token, delete a token, change a token with other phrases. Then, instead of adding phrases from a pre-defined phrase vocabulary, we utilize an autoregressive decoder based on a shallow LSTM with copy mechanism for generation. Moreover, inspired by the great success of the pre-trained transformer models, we also design an encoder based on BERT (Devlin et al., 2018) to obtain the contextual encodings. Finally, we perform experiments on the Restoration-200k (Pan et al., 2019), and SARG shows the superiorities on the automatic evaluation, the human evaluation, and the inference speed respectively. In summary, our contributions are:

- The ingenious combination of the advantages of sequence labeling and autoregression;
- The end-to-end transfer of pretrained BERT weights, which is beneficial to the overall system;
- The competitive performance and faster inference speed, which are both important for the incomplete utterance restoration task.

2 Related Work

2.1 Multi-turn Dialogue systems

Recently, building a chatbot with data-driven approaches in open-domain has drawn significant attention (Ritter et al., 2011; Ji et al., 2014; Athreya et al., 2018). Most work of conversational systems includes retrieval-based methods (Ji et al., 2014; Yan et al., 2016; Zhou et al., 2016; Wu et al., 2016a,b; Zhou et al., 2018; Zhang et al., 2018) and generation-based methods (Serban et al., 2016; Xing et al., 2016; Serban et al., 2017; Zhao et al., 2020; Lin et al., 2020).

In multi-turn dialogue systems, current models are still far from satisfactory compared to single-turn dialogue modeling, since the coreference and information omission frequently occur in our daily conversation, which makes machines hard to understand the real intention (Su et al., 2019). Recent studies suggest simplifying the multi-turn dialogue modeling into a single-turn problem by restoring the incomplete utterance (Su et al., 2019; Pan et al., 2019). Su et al. 2019 rewrite the utterance based transformer-based Seq2Seq and pointer network from context with two-channel attentions. Pan et al. 2019 propose a cascaded “pick-and-combine” model to restore the incomplete utterance from its context. Moreover, Pan et al. 2019 release the high quality datasets Restoration-200k for the study of incomplete utterance restoration in open-domain dialogue systems.

2.2 Sentence Rewriting

Sentence rewriting is a general task which has high overlap between input text and output text, such as: text summarization (See et al., 2017; Chen and Bansal, 2018; Cao et al., 2018), text simplification (Wubben et al., 2012; Zhang and Lapata, 2017), grammatical error correction (Ng et al., 2014; Ge et al., 2018; Chollampatt and Ng, 2018; Zhao et al., 2019) and sentence fusion (Thadani and McKeown, 2013; Lebanoff et al., 2019), etc. Seq2Seq models, which provide a powerful framework for learning
to translate source texts into target texts, is the main approach for sentence rewriting. However, conventional Seq2Seq approaches are hard to control and to constrain to desirable outputs, and require large amounts of training data.

Malmi et al. 2019 propose a text-editing approach for sentence rewriting that casts text generation as a text editing task. And the method is enough faster at inference time with performance comparable to the state-of-the-art Seq2Seq models. Due to some limitations of the pure sequence labeling approaches, our method combines autoregressive generation and sequence labeling for the trade-off between inference time and model flexibility.

3 Methodology

In this section, we demonstrate our proposed SARG for the multi-turn incomplete utterance restoration. By convention, the bold letters represent the vectors, the capital letters represent the matrices and others represent the scalars. The restoration problem can be denoted as $f(H, U) = R$, where $H = \{h_1, h_2, ..., h_m\}$ means the history (context) of dialogue, $U = \{u_1, u_2, ..., u_n\}$ denotes the original utterance (source) to be rewritten and $R$ is the restored utterance (target). Instead of generating the restored utterance from scratch, we first determine the editing operation sequence across the original utterance; then generate the potential phrases according to the operation sequence, and finally convert the operation sequence and the generated phrases to text. The detailed descriptions are as follows.

3.1 Tagging Operations

First of all, meaningless dummy tokens are inserted between every two tokens in the original utterance, as shown in Figure 1. The benefit of inserting dummy token is that we can directly add the phrases in the gaps between every two tokens, which reduces the ambiguity of possible editing operations to some extent. Moreover, we stipulate that the original tokens can only be kept or deleted, and the dummy tokens can only be deleted or replaced by other phrases.

Formally, three editing operations are defined in this work: KEEP, DELETE, CHANGE. Their physical meaning is straightforward, KEEP means the token remains in the restored utterance, DELETE means that the token is undesired, and CHANGE means that the token should be replaced by the informative phrase $A$.

In the process of constructing labels: (1) the longest common subsequence (LCS) between original and restored utterance is computed first; (2) then we greedily attempt to align the above three sequences; (3) and finally replace the undesired tokens in original utterance with the added tokens in restored utterance.

| Added Phrase | Restored Utterance |
|--------------|--------------------|
| Avg. length  | 3.1                |
|              | 12.4               |

Table 2: Comparison of the average length between the added phrase and the restored utterance.

The detailed descriptions are demonstrated in Algorithm 1, and the constructed labels can be referenced in Figure 1. Specifically, the first column of labels is used to supervise the tagger and other columns are used for the decoder. Moreover, the comparison of average length between added phrase and the restored utterance is listed in Table 2, which indicates that SARG saves at least three-quarters of the time for decoding compared to those complete autoregressive model.

3.2 Encoder

Pretrained transformers (Vaswani et al., 2017) are shown to be beneficial in many downstream NLP tasks (Radford et al., 2018; Devlin et al., 2018). In this work, we utilize the standard transformer blocks as the backbone of the encoder.

In the embedding module, we concatenate the history $H$ and the original utterance $U$ (involved dummy tokens) as the input sequence $W = \{w_1, w_2, ..., w_k\}$, then embed them into continuous space by looking up the following embedding tables:

- **Word Embedding**: the word embedding table is built on a pre-defined Chinese character vocabulary from pretrained transformers.
- **Position Embedding**: the position embedding table is also initialized by pretrained transformers.
- **Turn Embedding**: turn embedding is used to indicate which turn each token belongs to. The looking-up table is randomly initialized.

For each token $w_i$, we sum and normalize (Ba et al., 2016) the above three embeddings, then
Figure 1: The overall architecture of proposed SARG. In the constructed label, \( \text{L} \) means the \( \text{DELETE} \) operation, \( \text{K} \) means the \( \text{KEEP} \), \( \text{C} \) means the \( \text{CHANGE} \) and the \( \text{Li Chunfeng} \) is the added phrase subordinate to this \( \text{CHANGE} \) operation. In the input, the blue words are the history of the session, the red words are the original utterance and the \( < \text{ui}> \) is the dummy token. In the dataflow, the black means encoding, the orange means tagging, the green means decoding, and the blue means the realization.

Algorithm 1: Convert the target to label

**Input:** \( S \): the original utterance  
\( T \): the restored utterance  

**Output:** \( L \): the supervised label

1. Insert dummy tokens in \( S \)
2. \( j = 0; k = 0; A = [ ] \)
3. Compute the longest common subsequence \( K \) between \( S \) and \( T \)

for \( i \in [1, 2n + 1] \) do

if \( S[i] = K[k] \) then

\( L[i] = \text{KEEP} \)

while \( T[j] \neq K[k] \) do

\( A = A + T[j] \)

\( j = j + 1 \)

end

\( k = k + 1 \)

if \( A \neq \emptyset \) then

\( L[i - 1] = \text{CHANGE} \ A \)

\( A = [ ] \)

end

end

if \( T[j :] \neq \emptyset \) then

\( A = T[j :] \)

\( L[-1] = \text{CHANGE} \ A \)

end

return \( L \)

acquire the input embedding:

\[
E_i^{(0)} = \text{LN}(WE(w_i) + PE(w_i) + TE(w_i))
\]

where \( WE \) is the word embedding, \( PE \) is the position embedding and \( TE \) is the turn embedding.

Once the input embedding is acquired, we can feed such representation into the \( L \) stacked transformer blocks for the self-attention based encoding:

\[
E^{(l)} = \text{TransformerBlock}(E^{(l-1)})
\]

At last, we obtain the final encodings \( E^{(L)} \), which can be further divided into two parts according to the partitions of history and original utterance:

\[
\hat{H} = \{\hat{h}_1, \hat{h}_2, ..., \hat{h}_m\}
\]

\[
\hat{U} = \{\hat{u}_1, \hat{u}_2, ..., \hat{u}_{2n+1}\}
\]

where \( \hat{H} \) is the encodings of history and \( \hat{U} \) is the encodings of original utterance. There are \( n + 1 \) dummy tokens in the original utterance, which collect the information from those original tokens by the self attention.

3.3 Tagger

Tagger takes the encodings \( \hat{U} \) as the input and predicts the editing labels on each token in original
utterance. In our setting, a single linear transformation layer with softmax activation function is employed for projecting the encoding to the space of editing labels, the formula is as follows:

\[ p(y_i | \hat{u}_i) = \text{softmax}(W_t \cdot \hat{u}_i + b_t). \]

Finally, the loss provided by the tagger is defined as negative log-likelihood:

\[ \text{loss}_{\text{tag}} = - \sum_i \log p(y_i | \hat{u}_i). \]

where \( i \) is corresponding to the index of token in original utterance.

### 3.4 Decoder

In general text generation, decoder horizontally performs autoregressive decoding from scratch. However, in our setting, the decoder vertically generates the added phrases, and the generation only happens in the tokens which get CHANGE operations.

For the sake of efficiency, we employ one layer of unidirectional LSTM (Hochreiter and Schmidhuber, 1997) as the backbone of our decoder. For each token in original utterance, the related initial short-term memory \( \bar{h}_0 \) and long-term memory \( \bar{c}_0 \) are initialized with the according hidden representation \(^2\):

\[ \bar{h}_0 = \bar{c}_0 = \hat{u}_i \in \hat{U} \]

Then the vertical autoregressive generation is described as follows:

\[ \bar{h}_t, \bar{c}_t = \text{LSTM}(WE(x_t), \bar{h}_{t-1}, \bar{c}_{t-1}) \]

where \( x_t \) is the output of decoder in the previous step, \( WE \) is the word embedding, and the \( x_1 \) is initialized by a special start token.

Moreover, to dynamically choose copying from the history \( H \) or sampling from overall vocabulary, we introduce the recurrent attention and coverage mechanism as in pointer-generator network (See et al., 2017). At each decoding step, we utilize the output \( \bar{h}_t \) to collect information from the encodings of history \( \bar{H} \). The detailed calculations are as follows:

\[ e^t_j = \sigma^T \tanh(W_h \bar{h}_t + W_h^\dagger \bar{h}_j + \nu_c e_j^t + b_{\text{attn}}) \]

\[ a^t_i = \text{softmax}(e^t_i) \]

where \( j \) is corresponding to the index of token in the history, \( t \) is corresponding to the decoding steps and the \( e^t_i \) is the coverage vector in \( t \)-th step. Specifically, the coverage vector is initialized by zero at the beginning of decoding and accumulated as follow:

\[ c^t_j = \sum_{\nu' = 0}^{t-1} a^{t'\nu} \]

Once the normalized weights \( a^t_i \) is obtained, we can calculate the results of attention:

\[ h^*_t = \sum_j a^t_j \cdot \bar{h}_j \]

Then, the \( h^*_t \) is forwarded into the subsequent modules for acquiring the predicted word:

\[ g = \text{sigmoid}(w_{k^s} h^*_t + w_{h} \bar{h}_t + w_{WE}WE(x_t) + b_g) \]

\[ p_{\text{vocab}} = \text{softmax}(W_v \cdot h^*_t + b_v) \]

\[ p(x_t) = g \cdot p_{\text{vocab}} + (1 - g) \sum_{j : y_j = x_t} a^t_j \]

where the \( g \) is the gate to make a trade-off between copying and generating, the \( p(x_t) \) is the final probability distribution of generated word at \( t \)-th decoding step. Moreover, the coverage loss is introduced to penalize repeatedly attending:

\[ \text{covloss}_t = \sum_j \min(a^t_j, c^t_j) \]

Finally, the loss of the decoder is the weighted sum of negative log-likelihood and the coverage loss:

\[ \text{loss}_{\text{dec}} = \sum_i \sum_t - \log p(x^t_i) + \lambda \text{covloss}_t^i \]

where \( i \) is corresponding to the index of token in original utterance, \( \lambda \) is the hyperparameter for adjusting the weight.

### 3.5 Joint Training

The model is optimized jointly. Once the loss of tagger and the loss of decoder are obtained, we sum and backward propagate the total loss as below:

\[ \text{loss} = \alpha \text{loss}_{\text{tag}} + \text{loss}_{\text{dec}} \]

where \( \alpha \) is also the hyperparameter for adjusting the weight.
3.6 Realization

In the phase of realization, we convert the predicted editing labels and the generated phrases to a complete utterance. It is straightforward, we remain the token in original utterance which is assigned by KEEP operation, delete the token which is assigned by DELETE and replace the token which is assigned by CHANGE A with the generated phrase A.

4 Experiments

In this section, we first detail the experimental settings and the compared methods, then the main results and ablation study are described, finally, we report the human evaluation results and additional analysis based on some cases. Our experiments are conducted on the Restoration-200K (Pan et al., 2019). The overall statistics of the dataset is shown in Table 3.

|            | train | val  | test |
|------------|-------|------|------|
| # conversations | 194k  | 5k   | 5k   |
| Incomplete ratio (%) | 60.1  | 59.4 | 58.8 |
| Avg. history length | 25.9  | 25.8 | 25.7 |
| Avg. original length | 8.62  | 8.53 | 8.60 |
| Avg. restored length | 12.4  | 12.3 | 12.4 |

Table 3: Statistics of Restoration-200k. The incomplete ratio refers to the ratio of conversations that contains incomplete utterance.

4.1 Experiment Settings

We initialize the SARG with RoBERTa-wwm-ext (Cui et al., 2019), the hidden size is set to 768, the number of attention layers to 12, and the size of Chinese vocabulary to 21128. Adam optimizer is utilized, the loss of tagger weighted to $\alpha = 3$, the initial learning rate is 5e-5 and the batch size is 64. For the model with coverage mechanism, we first optimize the model 14000 steps with no coverage loss and then train it until convergence with coverage loss weighted to $\lambda = 1$. The above hyperparameters are all tuned on the standard validation data.

The same automatic evaluation metrics are utilized as in PAC (Pan et al., 2019), which contain BLEU, ROUGE, and restoration score. Specifically, the n-gram restoration precision, recall, and F-score are calculated as:

$$p_n = \frac{|\{\text{restored} \ n\text{-grams}\} \cap \{\text{n-grams in ref}\}|}{|\{\text{restored} \ n\text{-grams}\}|}$$

$$f_n = 2 \cdot \frac{p_n \cdot r_n}{p_n + r_n}$$

4.2 Compared Methods

We compare the performance of our proposed SARG with the following methods:

- **PAC** (Pan et al., 2019): this model restores the incomplete utterance in a cascade way: first, select the remained words by finetuning BERT, then roughly concatenate the selected words, history, original utterance and feed them into a standard pointer-generator network.

- **T-Ptr-$\lambda^3$** (Su et al., 2019): this model solves such restoration task in an end-to-end way. It employs six layers of transformer blocks as encoder and further six layers of transformer blocks as pointer decoder. Moreover, to emphasize the difference between history and utterance, it takes two individual channels in the encoder-decoder attention.

- **Seq2Seq-Uni**: traditional Seq2Seq has the isolated transformer encoder and decoder, which is not convenient for loading the weights from a pretrained model like BERT. Thus, we employ unified transformer blocks (Dong et al., 2019), which supports both bi-directional encoding and uni-directional decoding flexibly via specific attention masks, as the backbone of Seq2Seq.

4.3 Main Results

The main results on the automatic metric are shown in Table 4, and we also report the time which is consumed by making inference on the test set.

From the aspect of automatic metrics, we can make the following observations:

- **SARG** achieves the best results on 6 of 7 automatic metrics. And PAC is 1.2 higher than SARG on restoration $f_1$ score but 3.0 and 6.1 lower on $f_2$ and $f_3$ separately. The possible reason is that the $f_1$ score pays more attention to those tokens restored from history than others from the original utterance.

We re-implement the transformer-based method and evaluate on the same blind test set for the fair comparison.
Table 4: Main results of our method and other SOTA methods. Inference time is evaluated on the same blind test set (5104 examples) with one Nvidia Tesla P40.

| Model               | $f_1$  | $f_2$  | $f_3$  | BLEU-1 | BLEU-2 | ROUGE-1 | ROUGE-2 | Time |
|---------------------|--------|--------|--------|--------|--------|---------|---------|------|
| PAC (greedy)        | 61.1   | 46.9   | 37.7   | 89.5   | 85.7   | 91.2    | 82.2    | -    |
| PAC (n_beam=5)      | **63.7** | 49.7   | 40.4   | 89.9   | 86.3   | 91.6    | 82.8    | -    |
| T-Ptr-λ (greedy)    | 47.1   | 37.5   | 31.3   | 88.3   | 85.7   | 90.5    | 83.8    | 522 s|
| T-Ptr-λ (n_beam=5)  | 51.0   | 40.4   | 33.3   | 90.3   | 87.4   | 90.1    | 83.0    | 602 s|
| Seq2Seq-Uni (greedy)| 55.2   | 44.8   | 38.3   | 90.1   | 87.5   | 91.4    | 84.9    | 321 s|
| Seq2Seq-Uni (n_beam=5)| 56.8   | 46.4   | 39.8   | 90.8   | 88.3   | 91.4    | 85.0    | 467 s|
| SARG (greedy)       | 62.4   | 52.5   | 46.3   | **92.2** | **89.6** | **92.1** | **86.0** | 50 s  |
| SARG (n_beam=5)     | 62.3   | **52.5** | **46.4** | 91.4   | 88.9   | 91.9    | 85.7    | 70 s  |

In other words, though PAC can recall appropriate restored tokens from history, which cannot place the restored tokens in their right position well. We also exemplify such problem in the subsection 4.6.

- **T-Ptr-λ** performs far from the expectation. The reasons are two-fold: one is that T-Ptr-λ only copies words from either history or original utterance; however, some target words can only be generated by sampling the overall vocabulary; the other is that T-Ptr-λ do not enjoy the benefit from pretrained transformers. By contrast, the architecture of Seq2Seq-Uni is promising. It provides a convenient way of loading pretrained weights in Seq2Seq model and reduces the calculation amount.

- Beam-search brings pretty significant improvements on these complete autoregressive models, but less obvious improvements on our model. PAC gains 2.6 points, T-Ptr-λ gains 3.9 points, and Seq2Seq-Uni gains 1.6 points on restoration $f_1$ score through the beam-search; by contrast, SARG gains only 0.1 points on the restoration $f_3$ score. Moreover in SARG, we find that beam-search can recall more restored tokens which includes some undesired ones and harms the BLEU and ROUGE to some extent.

From the aspect of inference time\(^4\), we can make the following observations:

- Compared to the complete autoregressive methods, our model takes less time for inference. SARG is near 10x times as fast as T-Ptr-λ and 6x times as fast as Seq2Seq-Uni. Such observation demonstrates that the way of semi autoregressive can bring considerable improvements to the speed of inference.

- Seq2Seq-Uni is consistently faster than T-Ptr-λ. Though such two methods are both complete autoregressive, the T-Ptr-λ takes more multi-head attention calculations in its decoder.

- Beam-search increases the burden on inference. It needs more time and more memory for maintaining the candidate beams. Generally, the incomplete utterance restoration is required to be time-efficient as the intermediate subtask of multi-turn dialogue task, and it is unpractical to maintain plenty of beams in decoding. Therefore, we tend to choose the model which is less dependent on the beam-search, like the SARG.

Through the above analysis, SARG has advantages in automatic evaluation and computation complexity.

### 4.4 Ablation Study

In this subsection, we analyze the design choices crucial for the good performance of our proposed SARG, which includes pretrained weights (WEIGHT), copy mechanism (COPY), and generation from vocabulary (GEN). Table 5 shows the importance of each component with a series of ablation experiments.

As can be seen from Table 5, in the above three components, GEN plays the least important role in our model. By contrast, the absence of COPY or WEIGHT may raise a substantial lack of performance. Following our previous experimental setting as in 4.1, the above two variant models

\(^4\)We do not consider the inference speed of PAC, because the cascade way takes lower efficiency than other end-to-end methods.
|          | \( f_1 \) | \( f_2 \) | \( f_3 \) | BLEU-1 | BLEU-2 | ROUGE-1 | ROUGE-2 |
|----------|----------|----------|----------|--------|--------|---------|---------|
| SARG     | 62.4     | 52.5     | 46.3     | 92.2   | 89.6   | 92.1    | 86.0    |
| w/o WEIGHT | 52.8   | 41.1     | 33.8     | 89.2   | 86.7   | 89.9    | 83.6    |
| w/o COPY  | 55.6     | 38.9     | 32.8     | 89.4   | 85.6   | 89.9    | 81.7    |
| w/o GEN   | 56.2     | 48.0     | 42.9     | 90.4   | 88.2   | 91.4    | 85.6    |

Table 5: Ablation study of proposed model on the test set. The beam size is fixed to 1.

both can not converge well. Without the COPY, the model only selects words from pre-defined vocabulary, and the decoder is more difficult to be trained well. Without the WEIGHT, the model needs to be optimized from scratch.

To further investigate how the WEIGHT influences the overall model, we also compare the output of tagger among the above listed models. An observation is that the tagger without WEIGHT is conservative on predicting the CHANGE operations; by contrast, the decoder without WEIGHT is less affected and has normal-appearing. Therefore, in some cases, even though the decoder produces the right restored words, the model still cannot output the correct answers because the tagger does not produce the corresponding CHANGE operations.

### 4.5 Human Evaluation

|          | Quality | Fluency |
|----------|---------|---------|
| SARG     | 2.70    | 2.85    |
| PAC      | 2.67    | 2.83    |
| T-Ptr-\( \lambda \) | 2.58 | 2.80 |
| Seq2Seq-Uni | 2.65 | 2.87 |

Table 6: Human evaluation of the restoration quality and language fluency. Both quality and fluency score adopt a 3-point scale.

In the phase of human evaluation, we employ three experienced workers to score the restoration quality and sentence fluency separately on 200 randomly selected samples. The final results are shown in Table 6.

In Table 6, SARG obtains the highest restoration quality score among the compared methods, which is consistent with the results of automatic evaluation. However, in the aspect of fluency score, Seq2Seq-Uni achieves the best performance. The reasons are two-fold: one is that Seq2Seq-Uni takes a way of complete autoregression, which can complete the causal language modeling well.

### 4.6 Case Study

In this subsection, we observe the prediction results among different models, and then select several representative examples to illustrate the superiority of our proposed model as Table 7 shows.

As can be seen in Example 1, the first three models can restore the action “cry out”, but only SARG can restore the predicate “hire you”, which is important to understand the direction of the action.

In Example 2, the four models restored the keyword “constellation” correctly. However, in the results of T-Ptr-\( \lambda \) and Seq2Seq-Uni, undesired words “not believing” are also restored, which changes the intention of utterance. In PAC, we can find the keyword “constellation” is placed in a wrong position, which leads to the difficulty in understanding. Moreover, for the restoration scores, the wrong position problem have no effect on \( f_1 \) but damage \( f_2 \) and \( f_3 \). That is a possible reason, compared with SARG, PAC has higher \( f_1 \) but lower \( f_2 \) and \( f_3 \) in the automatic evaluation.

Finally Example 3 demonstrates the ability of SARG to restore utterance from distant context. Specifically, the keyword “skin” appears in \( A_1 \), and the model is required to restore it after three utterances. We observe that only our model can restore the “skin” from a distant context.

### 5 Conclusion

In this paper, we propose a novel semi autoregressive generator for multi-turn incomplete utterance restoration. The proposed model takes in the high efficiency of inference time from sequence labeling and the flexibility of generation from autoregressive modeling. Experimental results on Restoration-200k demonstrate that the proposed model is significantly superior to other state-of-the-art methods and an appropriate model of ut-
Table 7: Examples for incomplete utterance restoration. $A_1$ to $B_2$ is the history of conversation, $A_3$ is the original utterance.

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