Diverse dialogue generation with context dependent
dynamic loss function

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Abstract

Dialogue systems using deep learning have achieved generation of fluent response sentences to
user utterances. Nevertheless, they tend to produce responses that are not diverse and which are
less context-dependent. To address these shortcomings, we propose a new loss function, an In-
verse N-gram Frequency (INF) loss, which incorporates contextual fluency and diversity at the
same time by a simple formula. Our INF loss can adjust its loss dynamically by a weight using
the inverse frequency of the tokens’ n-gram applied to Softmax Cross-Entropy loss, so that rare
tokens appear more likely while retaining the fluency of the generated sentences. We trained
Transformer using English and Japanese Twitter replies as single-turn dialogues using different
loss functions. Our INF loss model outperformed the baselines of SCE loss and ITF loss models
in automatic evaluations such as DIST-N and ROUGE, and also achieved higher scores on our
human evaluations of coherence and richness.

1 Introduction

Recently, many reports have described studies using deep learning for dialogue systems that have
achieved good performance. They can generate fluent sentences based on a user’s utterances
(Vinyals and Le, 2015; Shang et al., 2015; Serban et al., 2016). Nevertheless, such neural dialogue systems tend
to generate phrases such as “Yes” and “I do not know” frequently in non-task-oriented dialog systems,
referred to as the low diversity issue and the generic response issue. After training by a loss function of
similarity with gold standard reference sentences, frequent phrases are more likely to be assigned a large
occurrence probability than rare phrases are.

Nakamura et al. (2018) proposed an Inverse Token Frequency (ITF) loss, which multiplies the Soft-
max Cross-Entropy (SCE) loss by weights based on the inverse of the frequency of tokens. This ITF loss
incorporates the frequency distribution of token classes so that rare tokens become more likely to appear.

However, sentence diversity is based not only on individual tokens, but also on the token sequence.
We are able to compute weights for loss functions dynamically, depending on the context, while retaining
the fluency of generated sentences. We propose such a loss function, Inverse N-gram Frequency (INF)
loss, which uses the inverse of the frequency of the n-gram of the tokens, rather than the token frequency.
We built a neural dialogue system trained by INF loss using huge amounts of dialogue data extracted
from Twitter. After comparing models using the SCE loss, the ITF loss, and the INF loss, we evaluated
their diversity and fluency. Results show that our proposed INF loss model outperformed the SCE loss
and ITF loss models for most automatic assessment measures such as DIST-N (Li et al., 2016) and
ROUGE (Lin, 2004). Our INF loss model also achieved higher scores on our human evaluations of
coherence and richness.

2 Related Work

The diversity of neural dialogue generation has been studied actively. Li et al. (2016) first addressed this
problem using Maximum Mutual Information (MMI) as the objective function of the neural model.
Takayama and Arase (2019) used Positive Pointwise Mutual Information (PPMI) to identify keywords

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in the dialogue corpus that were likely to appear both in response utterances and their input utterances. Xing et al. (2017) proposed a model that uses topic words extracted from conversations to simulate human prior knowledge, generating informative and interesting responses. In addition, Variational AutoEncoder (VAE) and Generative Adversarial Network (GAN), which were proposed originally for image generation, have also been applied to text and dialogue generation (Kingma and Welling, 2014; Bowman et al., 2016; Xu et al., 2018). Although GAN helps to reduce response text ambiguity, their primary purpose was not diversity. Zhang et al. (2018) proposed and demonstrated the effectiveness of Adversarial Information Maximization (AIM) as a new method for generating informative and diverse conversational responses. Their work also resolved instability that arose when training the GAN model.

3 Loss Functions

3.1 Softmax Cross-Entropy Loss

The SCE loss, which is often used to train a sequence-to-sequence (Seq2Seq) model (Sutskever et al., 2014), is expressed as \( L_{SCE} = -\log \left( softmax_c \right) \), where \( softmax_c = \frac{e^{d_c}}{\sum_{k \in V} e^{d_k}} \). Therein, \( V \) represents the lexicon;\( d_k \) denotes the \( k \)-th element of the output \( d \in \mathbb{R}^{|V|} \).

3.2 Inverse Token Frequency Loss

Nakamura et al. (2018) defined Inverse Token Frequency (ITF) loss as shown below.

\[
L_{ITF} = w_c L_{SCE}, \quad w_c = \frac{1}{freq(token_c)^\lambda}
\]

Therein, where \( w_c \) represents an element of the weight \( w \in \mathbb{R}^{|V|} \) of the token class \( c \), \( token_c \) is a token of token class \( c \), \( freq(token_c) \) stands for a function that counts \( token_c \) in the training data, \( \lambda \) denotes a hyper-parameter that adjusts the frequency. The ITF loss at \( \lambda=0 \) is equivalent to SCE loss.

3.3 Inverse N-gram Frequency Loss

We propose our Inverse N-gram Frequency (INF) loss as a new loss function that replaces the ITF loss. Our INF loss is defined as presented below.

\[
L_{INF} = w_c L_{SCE}, \quad w_c = \frac{1}{freq(ngram_c(n))^{\lambda}}
\]

Therein, \( ngram_c(n) \) represents \( n \) consecutive \( (n \in \mathbb{N}, n \geq 2) \) tokens in the training data, where \( c \) is the first token of \( ngram_c(n) \). Therefore, \( w_c \) is expected to differ considerably depending on the context.

Special symbols such as \(<BOS>\) (beginning of sentence) and \(<EOS>\) (end of sentence) are treated similarly to other ordinary tokens. However, because \(<BOS>\) and \(<EOS>\) occur in every sentence, we set the weight of the loss function as very small value for these special characters.

A special symbol, \(<NORM>\), was added \( n-1 \) times to the beginning of the sentence and to the end of the sentence respectively to represent padding.

4 Experiments

The SCE model and the ITF model were used as baseline models. Experiment settings are the same among these models and our proposed INF model, except for loss functions.

4.1 Dataset

Japanese and English Twitter conversations were extracted from Twitter replies, adjacent tweets as pairs of [utterance, response] to construct a single-turn dialogue dataset of one million dialogue pairs for each language. SentencePiece (Kudo and Richardson, 2018) was trained using a dataset with a vocabulary of 32,000 for both Japanese and English data. We then used these SentencePiece models to tokenize the training set into subwords. Each of the verification set and the test set consists of 1024 pairs.

4.2 Model Setting

Both the encoder and decoder are six-layer Transformer (Vaswani et al., 2017), the number of heads of Multi-Head Attention is 8, the token embedding dimension is 512, and the ratio of Dropout is 0.1. Adam
INF with a similar pattern: generated responses of our two models. Table 1 shows our human evaluation results obtained using Japanese and English models. For each dataset, 100 dialogue tweet pairs were presented to five human evaluators. Responses for each pair include responses of four patterns: generated responses of our three models and the original tweet reply. Evaluators ranked the responses generated by the respective models in terms of coherence and richness, with scores of 1, 2, and 3. Richness was defined as whether the models would achieve the best scores for DIST-N and ROUGE. The length of the generated sentences was greater in the order INF > SCE > ITF. Overall, the INF model at $\lambda = 0.2$ is superior in the metric-based evaluation. The English dataset yielded similar results: the INF model was superior.

| model | $\lambda$ | perplexity | BLEU-1 | BLEU-2 | DIST-1 | DIST-2 | ROUGE-1 | ROUGE-2 | length |
|-------|----------|-------------|--------|--------|--------|--------|----------|----------|--------|
| SCE   | -        | 60.572*     | 15.19  | 0.049  | 1.376* | 7.949* | 3.781    | 0.421    | 8.013* |
| ITF   | 0.2      | 16.512*     | 15.32  | 0.016  | 1.303* | 6.592* | 3.775    | 0.357*    | 7.513* |
|       | 0.4      | 9.401*      | 15.78  | 0.033  | 0.524* | 2.594* | 2.916*   | 0.305*    | 7.737* |
|       | 0.6      | 7.511*      | 15.15  | 0.034  | 0.245* | 1.309* | 2.308*   | 0.181*    | 6.002* |
|       | 0.8      | 7.341*      | 13.71  | 0.082  | 0.155* | 0.697* | 1.873*   | 0.096*    | 6.350* |
| INF   | 0.2      | 11.045      | 13.97  | 0.049  | 3.265* | 15.285 | 3.877    | 0.445     | 10.253 |
|       | 0.4      | 5.936       | 12.35  | 0.049  | 1.401  | 5.661  | 2.482    | 0.295     | 10.521 |
|       | 0.6      | 4.413       | 12.12  | 0.033  | 2.001  | 6.981  | 2.633    | 0.234     | 10.114 |
|       | 0.8      | 3.890       | 12.32  | 0.033  | 2.039  | 6.681  | 1.348    | 0.085     | 9.998  |

Table 3: Human evaluation.

(Japanese/English)
be willing to talk to that systems in the future. A smaller score denotes a better evaluation rank. We used a model setting with the best metric-based evaluation score for each loss function model, i.e. $\lambda=0.4$ for the ITF model and $\lambda=0.2$ for the INF model. Table 3 presents the average human evaluation rankings. These results demonstrate that INF was best in terms of both coherence and richness, followed by ITF and SCE.

### 6 Discussion

Results show that INF produced superior perplexity values compared to SCE and ITF. Therefore, INF produces more fluent sentences than the baselines. BLEU and ROUGE often showed good results in SCE and ITF. BLEU calculates n-gram precision between generated and target sentences, which does not incorporate recall. Therefore, SCE and ITF can obtain better performance because their generated sentence lengths were shorter. They are not directly comparable with the INF of the longer sentences. Also, INF presents excellent values for the diversity in both DIST-1 and DIST-2. Particularly, the INF of DIST-2 for the Japanese model and the Japanese dataset was 15.285, which is much higher than SCE and ITF. This result demonstrates that INF can generate responses that are more diverse, which also incorporate sequential information of tokens.

Table 4 presents example dialogue pairs, where SRC is the input sentence to the model and TGT is the target sentence, i.e. an original reply tweet. The $\lambda$ values of ITF and INF are the same as the model used for human evaluation. Regarding the example ID1J, INF generated a rich contextual response, whereas the responses generated by SCE and ITF were less context-dependent. In the ID2J dialogue, all three models generated responses that make sense as replies to the input, but they generated different tokens. In such cases, automatic evaluation using a single reference output might not be meaningful. In the ID1E dialogue, SCE generated a sentence that does not make sense. INF generated a meaningful sentence related to a song probably because “SUPERNOVA” was interpreted as a Korean dance group, although it differs from the human reference response. In the ID2E dialogue, responses that are more relevant are potentially available because its input sentence is ambiguous; SCE and ITF were unable to generate any meaningful conversation, although INF was able to generate them.

Overall, all three models generated semantically relevant responses, but INF generates a wider variety of responses with longer sentences.

### 7 Conclusion

We proposed a weighted INF loss based on the inverse of the frequency of token n-grams, which can generate diverse responses while retaining fluency. Comparison to baseline methods revealed that our automatic and human evaluation scores obtained using our proposed method generated more diverse responses with improved contextual consistency. Future works are expected to include a tri-gram version of our INF model and the use of deep learning models other than Transformer.
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