Another Diversity-Promoting Objective Function for Neural Dialogue Generation

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Neural Dialogue Generation

- An open-domain dialogue system that generates a response word by word using a trained neural network (e.g., seq2seq)
- Generation-base is more flexible than retrieval-base, but fluency, consistency are not good

- In particular, the generated response has **low diversity** and tends to be a generic response like "I don’t know." Why?
During training

- Frequent words in training set supply more training penalties than rare words
- Therefore, large occurrence probabilities is assigned to frequent words

one-hot target distribution

wrong model distribution

data distribution

Stupid is as stupid as stupid does.
During evaluation

- Dialogue generation is a **many-to-many** transduction task in which contents vary depending on the context.
- Frequent words are applicable in any context, so they tend to be candidates for generation.
- As a result, only the most likely response is generated.

**Data transduction**

- **Hey, what’s up?**
  - **Hi, Sean. How are you doing?**
    - MAP prediction after MLE training
  - **Not much.**
    - enormous candidates in real dialogue
- **Hey, Erin. What’s up?**
  - **Do you have any plans tonight?**
Break down low diversity problem

During training

No suggestion. We challenged it!

• Frequent words supply more penalties than rare words
• Due to lack of data and data imbalance (Serban et al. 2016)
• Softmax Cross-Entropy (SCE) loss is not good because all words are handled equally regardless of lack and imbalance

During evaluation

Measures already suggested

• Maximum A-Posteriori (MAP) predicts the most likely response only
• A way to generate unlikely response using Maximum Mutual Information (MMI) is reported in (Li et al. 2016)
Previous research

- Maximum Mutual Information (Li et al. 2016)

\[
\hat{T} = \text{argmax} \{ \log p(T|S) - \lambda \log p(T) \},
\]

- MMI-antiLM suppresses language model-like generation by subtracting a language model term \( \log p(T) \) from transduction model term \( \log p(T|S) \).

- They used MLE during training and used MMI-antiLM during evaluation.

- In practice, MMI-antiLM generates token \( y \):

\[
y = \text{argmax} \{ \log \text{softmax}(x - \lambda u) \},
\]
Proposed method

Softmax Cross-Entropy loss

- SCE loss treats each token class equally

\[ L_{\text{sce}} = - \log \left( \frac{\exp(x_c)}{\sum_{k}^{\mid V \mid} \exp(x_k)} \right) \]

Inverse Token Frequency Frequency loss

- ITF loss scales smaller loss for frequent token classes

\[ L_{\text{tfd}} = w_c L_{\text{sce}} \]
\[ w_c = \frac{1}{\text{freq(token}_c)\lambda} \]

You
do
not
talk
about
Fight
Club
.

You
do
not
talk
about
Fight
Club
.

https://arxiv.org/abs/1811.08100
Advantages compared to previous works

• No special inference method. You can use common greedy search

• ITF loss can be easily incorporated. Just replace loss function!

• Training with ITF loss is as stable as training with SCE loss.

• ITF models yield state-of-the-art diversity and maintains quality.
Code examples with PyTorch

```python
cse_loss = nn.NLLLoss(weight=None)

def get_weights(_lambda):
    weights = torch.zeros(vocab_size)
    for token, index in token2index.items():
        weight = 1 / (token2freq[token]**_lambda)
        weights[index] = weight
    return weights

weights = get_weights(_lambda=0.4)

itf_loss = nn.NLLLoss(weight=weights)
```

SCE loss

Inverse Token Frequency

ITF loss
Experiment setups

Datasets
• OpenSubtitles (En)  5M turns and 0.4M episodes
• Twitter (En/Ja)     5M/4.5M turns and 2.5M/0.7M episodes

Baselines
• Seq2Seq            4 layers Bi-LSTM w/ residual connections
• Seq2Seq + Attention
• Seq2Seq + MMI
• MemN2N             considering dialogue history using memory

Evaluation metrics
• BLEU-1/2           n-grams matching between all hypo. and all ref.
• DIST-1/2           distinct n-grams in all generated responses
Result on OpenSubtitles

![Graph showing results on OpenSubtitles]

- Human
- Seq2Seq
- MemN2N
- S2S+Attn
- Ours (S2S+MMI)
- Previous (S2S+ITF)

Legend:
- BLEU-2
- DIST-1

Graph metrics:
- Y-axis: 0-10
- X-axis: Human, Seq2Seq, MemN2N, S2S+Attn, Ours (S2S+MMI), Previous (S2S+ITF)

Source: Another Diversity-Promoting Objective Function for Neural Dialogue Generation (Nakamura et al. 2018)
Result on Twitter

- ITF models outperform the MMI on both of BLEU-2 and DIST-1
- ITF model achieves a ground truth-level DIST-1 score of 16.8 on Japanese Twitter Dataset
A generated sample on OpenSubtitles

<table>
<thead>
<tr>
<th>SRC</th>
<th>Does he know what’s going on?</th>
</tr>
</thead>
<tbody>
<tr>
<td>TGT</td>
<td>He knows he’s leaving.</td>
</tr>
<tr>
<td>MLE</td>
<td>No.</td>
</tr>
<tr>
<td>MMI</td>
<td>No.</td>
</tr>
<tr>
<td>ITF</td>
<td>He’s got a lot of trouble.</td>
</tr>
</tbody>
</table>
A generated sample on Twitter

<table>
<thead>
<tr>
<th>SRC</th>
<th>12 gb ram at 384 gb/sec (gddr5x)... if this is true than damn!... you want</th>
</tr>
</thead>
<tbody>
<tr>
<td>TGT</td>
<td>eurogamer also said that it speculates 384 and 12 gb of ram by placement of ram in original video</td>
</tr>
<tr>
<td>MLE</td>
<td>i’m not sure if it is worth it.</td>
</tr>
<tr>
<td>MMI</td>
<td>mwr gpu is the best.</td>
</tr>
<tr>
<td>ITF</td>
<td>rambo is a newer one with chromebook7 connector, laptop router, hdmi cables.</td>
</tr>
</tbody>
</table>
Summary

- SCE loss + MAP prediction ⇒ Low diversity ⇒ Dull Response
- SCE loss + MMI inference ⇒ High diversity and good quality

Diversity-Promoting Objective Function for Neural Conversation Models

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ITF loss + MAP prediction ⇒ Very high diversity and good quality

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