Review of a lecture 2 - A Diversity-Promoting Objective Function for Neural Conversation Models

summary 1

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Topic	We suggest that the traditional objective function, i.e., the likelihood of output (response) given input (message) is unsuited to response generation tasks. Instead we propose using **Maximum Mutual Information (MMI)** as the objective function in neural models.
Dataset	Twitter Conversation Triple Dataset, OpenSubtitles dataset,
Github	Torch implementation
Conclusion	We show that use of MMI results in a clear decrease in the proportion of generic response sequences, generating correspondingly more varied and interesting outputs
Analys 1	

Model	BLEU	*distinct-1*	*distinct-2*
SEQ2SEQ	1.28	0.0056	0.0136
MMI-antiLM	1.74 (+35.9%)	0.0184 (+228%)	0.066 (407%)
MMI-bidi	1.44 (+28.2%)	0.0103 (+83.9%)	0.0303 (+122%)

Table 3: Performance of the SEQ2SEQ baseline and two MMI models on the OpenSubtitles dataset.

Problem

- In part at least, this behavior can be ascribed to the relative frequency of generic responses like I don't know in conversational datasets, in contrast with the relative sparsity of more contentful alternative responses

Intuition

- Intuitively, it seems desirable to take into account not only the dependency of responses on messages, but also the inverse, the likelihood that a message will be provided to a given response.s

MMI Criterion

- $\frac{p(S,T)}{p(S)p(T)} = argmax\{logp(T|S) - logp(T)\}$
- Current research only used the criterion in testing time
- reason 1 : nontrivial to calculate it
- reason 2 : time consuming

generalization of MMI

$argmax\{logp(T|S) - \lambda logp(T)\} = argmax\{(1-\lambda)log(T|S) + \lambda logp(S|T) - \lambda logp(S)\}$

MMI-antiLM

- $logp(T|S) - \lambda logp(T)$
- limit : ungrammatical responses
- It penalizes not only high-frequency, generic responses, but also fluent ones and thus can lead to ungrammatical outputs
- solution : we replace the language model p(T) with U(T)
- $U(T) = \prod p(t_k|t_1, ..., t_{k-1}) * g(k)$ where $g(k) = 1$ if $k \leq \gamma$ $g(k) = 0$
- intuition : Thanks to memory-loss property of seq-2-seq models, first few sentences determine the decoded sentences. Therefore, penalizing only those is valid.

MMI-bidi

- $(1-\lambda)logp(T|S) + \lambda logp(S|T)$
- limit : decoding intractable
- Reason's simple. We literally can't compute $logp(S|T)$
- solution : Pick N-best lists from $logp(T|S)$ and compute $log(S|T)$

Decoding techniques

MMI-antiLM

- length of the sequences is Important
- Score(T) = $p(T|S) - \lambda U(T) + \gamma U(T)$
- hyperparams γ and λ
- optimize by MERT with N-best lists by beam search.

MMI-bidi

- hyperparams γ and λ
- optimize by MERT with N-best lists by beam search.