

Sequence to Sequence Generative Argumentative Dialogue Systems with Self Attention

Ademi Adeniji, Nathaniel Lee, Vincent Liu
ademi@stanford.edu
Stanford University Department of Computer Science



Overview

Problem

- Argument mining, a growing field in natural language generation, includes the automatic identification and generation of argumentative structures within conversation
- We experiment with various methods for creating a dialogue agent that can engage in argumentative discourse

Significance

- Utility in education and assessment as well as business use for investment decision
- Advances self-attention/transformer in argument NLG/NLU objectives

Existing Approaches

- Current state-of-the-art generative model: hierarchical recurrent neural network, encoding and decoding at one level and updating a conversation-level state at another
 Encoder: Bidirectional GRU encoder w/
 - conversation-level RNN memory
 - Decoder: Vanilla RNN
- Model often misinterprets arguments or produces irrelevant responses.

Data

$$\begin{split} d &= [\,p^{(1)}, p^{(2)}, ..., p^{(m)}\,]\\ p^{(i)} &= [\,w_1^{(i)}, w_2^{(i)}, ..., w_n^{(i)}\,] \end{split}$$

- Internet Argument Corpus Dataset-v1: 11,800 discussions w/~390,000 posts total
- Training instance: discussion, d (sequence of posts)
- · Gold instances are offset from train instances
- p is a padded sequence of tokens, w

Task

Given a post (w, w/o context), generate an appropriate adversarial argumentative response

Approach

Project Phases

- LSTM Seq2Seq model baseline, context-free argument generation
 - <u>Pure transformers</u> *context-free* argument generation
- 3. <u>Transformer with LSTM Session Memory</u> context-rich argument generation

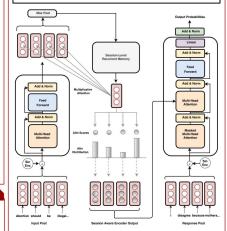


Figure 1. Transformer Model Architecture w/ LSTM. We borrow the Transformer architecture and use an LSTM between the encoder/decoder to encode session level memory.

Additional Tunings

- Hyperparameter search layers, dimensions, attention heads, learning rate, vocabulary size, min word count, etc.
- Pre-training with cross-argumentative embedding objective (Self-referential)
- 3. GloVe embeddings vs. training from scratch
- 4. <unk> thresholding, vocabulary pruning, etc. (16k size)

Results

Seq2seq (with char decoder) outputs

Query Output

I think the bible is read and it is most sure that you are not a christian, i do n't think it is a matter of the bible, i do n't think it is a matter of a person.

Woman's rights and suffrage

id on 't know what i said, but i do n't know should be upheld under the law is why our are talking about.

Transformer w/ LSTM

 Query
 Output

 i believe in god
 i 'm not sure what you mean by " god " well then, have you heard of the bible?

 i do n't think it 's a good idea .

Transformer w/o LSTN

Transformer w/o LSTM			
Query	Output		
I think that gun control has the potential to solve a lot of the problems with school shootings	i think that 's a good thing .		

Figure 2. Transformer w, w/o LSTM sample argumentation

Table 1. Transformer w/ LSTM validation metrics with tuned parameters

Epoch:	Perplexity	Accuracy	Loss
0	205.88	17.30%	5.33
4	84.21	24.83%	4.43
8	72.10	26.35%	4.28
12	65.65	27.36%	4.18
16	62.40	28.00%	4.13

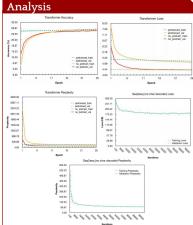


Figure 4. Training and validation metrics of pre-trained and from-scratch Transformer w/ LSTM models and Seq2Seq over 26

Conclusion

- From our qualitative results, we conclude that our dataset is ill-suited for generating more sophisticated language models typical of advanced argumentative discourse
- Our extensive hyperparameter search suggests that our cross entropy training objective is overly simplistic
 for more complex generation tasks. A more involved theoretical formulation of training loss could yield
 qualitative translation improvements
- We were impressed by the model's **ability to infer the underlying basis** of the human input arguments
- Additionally, the dialogue agent was proficient in establishing a sufficiently resolute position on many topics

Future Work

- Less primitive argumentation datasets increases language model expressivity
- Fine-tuning on pretrained contextual embeddings (BERT) captures word relationships more precisely for better NLG
- More sophisticated attention mechanisms may allow for a more informative signal for decoding

References

M Waller, J. F. Trox, P. Arand, R. Albest, and J. King, "A coppe for research on deliberation and defines," in Proceedings of the Eight International Conference on Language Resources and Evaluation (LERC-12), No. C. Chaile, K. Cholest, T. Decker, M. U. Dog, B. Meagand, J. Marin, A Morenzo, 1048), and S. Pjerdin, Eds., Isamball, Tarkey-European Language Resources Association (ELRA), May 2012, ISBN: 982-985/1868-73.

Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and J. Polosukhin, "Attention All You Need," no. Nips, 2017, ISSN: 1469-8714. DOI: 10.1017/ S0952523813000308. arXiv: 1706.03762. [Online]. Available: http://arxiv.org/abs/1706.03762.

D. Thu Le, C.-T. Nguyen, and K. Anh Nguyen, "Dave the debater: a retrieval-based and generative