Agents of DebAIt

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Abstract

Social platforms are where people exchange opinions on a wide array of topics with varying intensities. The underlying psychology of how people's opinions evolve over social media is a vast domain to explore for all the sciences. We chose ChangeMyView - an active community on Reddit, where users post their views and opinions on a subject, invite others to participate in discussions to challenge their original opinions and acknowledge when the arguments put forth caused a change of view within a moderated environment - as the platform to work on and attempted to train various agents of Dialog encoding-based Artificial Intelligence tasks (DebAIt) to take part in such a debate environment. We made use of ParlAI (Miller et al. [2017]) - a framework for language models built by Facebook research - to train, evaluate and have a chat/debate with trained agents.

1 Introduction

Persuasive arguments are a commonplace occurrence in several walks of life ranging from political to marketing campaigns to mere simple conversations with friends. The existence of several intelligent voice assistants and chat bots, give the impression that longer and more meaningful conversations could be possible with such agents. Prominently, due to the rise in the number of social media platforms, we are able to observe debates and discussions on substantially large scales. This allows us to circumvent some of the limitations of laboratory experiments and makes room for several questions regarding dynamics in real discussions. One such debate and discussion platform is ChangeMyView, which is a Reddit community for civil discourse. Here, users who are open to a change in opinion post their views and encourage others to contest their opinions and ideas in an attempt to change the view of the original poster (OP). All such discussions ensue within a well-regulated setup, with any comment or post that does not meet the documented rules of the subreddit being deleted by the moderators of the subreddit. If a user's comments manage to change the view of the OP, she or he is awarded a Δ (delta) by one of the automated moderators called DeltaBot. DeltaBot maintains a count of the number of Δs earned by a user which also adds to the credibility and reputation of the user on the subreddit.

The name of our project is an allusion to ParlAI (Miller et al. [2017]) - a unified framework for training, sharing and evaluating AI models on various openly available dialog datasets implemented in Python by Facebook Research. It provides multi-task training over many datasets at once and is easily integrable with Amazon Mechanical Turk for data collection and human evaluation. It supports several widely used conversational datasets such as SQuAD (Rajpurkar et al. [2016]), bABI (Bordes et al. [2016]), Cornell Movie (Suhr et al. [2018]) and PersonaChat (Zhang et al. [2018]). The aim of the framework is for the number of tasks and agents that train on them to grow as a shared community. As young researchers, with the ChangeMyView dataset, we hope to add to the list of conversational tasks at the disposal of ParlAI.

Tan et al. [2016] have worked on the ChangeMyView dataset and have performed a predictive analysis on what causes an argument to be persuasive. Musi [2018] tries to get answers by analyzing the semantic and pragmatic properties of concessions, and their argumentative role in the same subreddit. Jo et al. [2018] modeled the interplay between the original poster's view and a challenger's argument predicting if a change of view occurred or not. However, all of these works passively examine the flow of arguments and make predictions. In our work, we aim to train an agent to be an active participant in a real debate environment. Although the dataset has been reviewed previously, the task we set out to achieve with it is interesting and has not been worked upon before.

In this report, we describe the dataset, collecting the data and handling the complications by refining. In the subsequent sections, we describe the models used to predict the data, and the experimental results describing the performance. We further elaborate on the possible explorations in creating agent-vs-agent tasks and an extension to Reinforcement Learning.

2 Dataset

The subreddit `/r/changemyview` is a forum for users to participate in a healthy dialog with an aim to change a person's opinion. The intuition behind debating agents is that changing a person's mind requires her or him to accept and understand different perspectives with an open mind. Thus, this dataset allows us to create an agent that can learn to generate a contradicting opinion by comprehending the OP's point of view. This requires a great deal of learning content and argue constructively with another individual. As shown in the figure, the dataset forms a comment tree for

Figure 1: Example post from `r/changemyview` subreddit

every post including an original post as the root, followed by each user's comment and their replies as subsequent nodes of a discreet path. The DeltaBot, as shown in the figure, awards a Δ to the user who has successfully been able to change the opinion of the OP, after the OP signals an agreement. There is also a score associated with each comment and reply that is counted as per the number of upvotes to the respective comment.

2.1 Data Collection

We chose to scrape `/r/changemyview` posts dated from 01/01/2013 to 09/01/2015 in order to stay consistent with the dataset used by Tan et al. [2016]. We did so by making use of PRAW, a Python Reddit API Wrapper. This allowed us to extract the top 1000 most recent posts with the name of the subreddit being the key value. However, with ChangeMyView being a very active subreddit, for our choice of dates we were unable to scrape the required posts. Therefore, we made use of the Pushshift Reddit API that enabled us to obtain the required unique post IDs. On feeding these post IDs as key values to PRAW, we were able to extract the contents of corresponding posts and the associated comments and replies.

2.2 Refining

In order to make full use of the comment tree, we managed to format dialogs by taking each example of the training data to be of the form of a root-to-leaf-node path in the comment tree. While doing this, every comment/reply of the comment tree was chosen as a `[text]` as well as `[label]` for the previous comment.

We observed that there could be several discrepancies between the required format for ParlAI since the subreddit contained comments to the original post and replies instead of proper dialogues. This included quoting other comments and comments by moderators/DeltaBot. For this, we replaces strings of the form `>No way!` to `"No way!"`. A dataset with all lower-case characters was also generated since a dictionary with unique words was used during training.

There were several moderator posts that were made to explain the rules and changes in policies which were not required for the tasks and were deleted. Apart from this, `[deleted]` posts were ignored.

3 Proposed Approach

In order to generate convincing dialogs, our initial task was to generate the next dialog utterance, given the original post. Thus, we were required to train an agent using a language model that predicts the next statement. For this, we used two sequence models that have been proven to show excellent results:

3.1 Seq2seq

Luong et al. [2015]'s model encodes the input sequence and decodes the output by means of one of several flavors of RNN. It then uses a linear layer, whose weights can be shared with the embedding layer, to convert the RNN output states into output tokens. This model supports greedy decoding, selecting the highest probability token at each time step, as well as beam search.

At each time step t in the decoding phase, the hidden state h_t is taken as input at the top layer of a stacking LSTM. The goal is then to derive a context vector c_t that captures relevant source-side information to help predict the current target word y_t. Given the target hidden state h_t and the source-side context vector c_t, a simple concatenation layer is used to combine the information from both vectors to produce an attentional hidden state as follows :

$$\tilde{\mathbf{h_t}} = \tanh(\mathbf{W_c}[\mathbf{c_t};\mathbf{h_t}])$$

The attentional vector $\tilde{h_t}$ is then fed through the softmax layer to produce the predictive distribution formulated as :

$$p(y_t|y_{<t},x) = \text{softmax}(\mathbf{W_s}\tilde{\mathbf{h_t}})$$

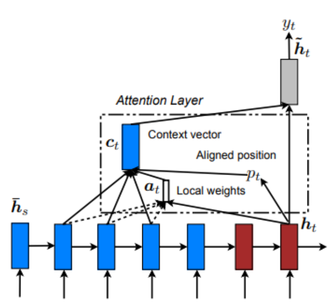

Figure 2: Local attention based seq2seq model (Luong et al. [2015])

We make use of local attention as the model first generates an aligned position p_t for each target word at time t. The context vector c_t is then derived as a weighted average over the set of source hidden states within the window $[p_t - D; p_t - D]$, where $2D (= 48)$ is the chosen attention window size.

3.2 Transformer

Recurrent models perform computations with respect to the positions of symbols in input and output sequences. They then generate a sequence of hidden states h_t as a function of the previous hidden state h_{t-1} and the input for position t. This sequential nature of processing would make its training more tedious as memory constraints limit batching across examples. Vaswani et al. [2017]'s Transformer is a network architecture that does away with recurrences and convolutions, and allows for more parallelization during training. It is based solely on attention mechanisms that draw global dependencies between input and output sequences. Further, Transformer also employs a self-attention mechanism wherein a representation of a single sequence is computed by relating different positions within it.

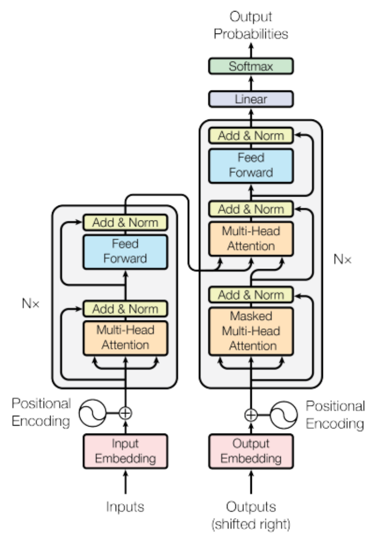

Figure 3: Transformer architecture (Vaswani et al. [2017])

4 Experimental Setup

After formatting the dataset to be integrated with ParlAI, we noted that we had $\sim$ 2.5 million examples. We trained our models on Nvidia Tesla P40 GPUs made available on the Prince cluster. However, due to limited time and insufficient compute resources, we reduced our dataset to $\sim$ 37k examples and $\sim$ 73k examples for separate trials. For similar reasons, we also resorted to limiting the length of comment threads to 7 comments with the length of each comment being no longer than 120 characters. In addition to this, we experimented with different batch sizes ranging from 2 to 10 and number of training epochs ranging from 5 to 15.

5 Results and Conclusion

As seen in the table 1, we can assert from the cross-entropy loss and F1 score that the Generic Seq2seq model performs better than the Transformer on the given dataset. The training and the validation loss curves for this model also seem to converge towards 0 as shown in Figure 4.

In Figure 5, we show a dialog conversation between a human and the seq2seq model trained on a $\sim$ 37k examples. The model generates an output of "`I ' m not sure`" repeatedly. Also, the model seems to give one of two answers for every given text. This is a common problem in language models and is empirically seen to get reduced with more training (data & epochs), and also changing hyperparameters like learning rate.

Table 1: Test data evaluation

Loss metrics	**Generic seq2seq**		**Transformer**	
	∼37k (5ep)	∼73k, (15ep)	∼37k, (5ep)	∼73k (15ep)
F1 score	0.03805	0.08841	0.00074	0
Cross-entropy loss	7.259	6.916	923.0	4118.0

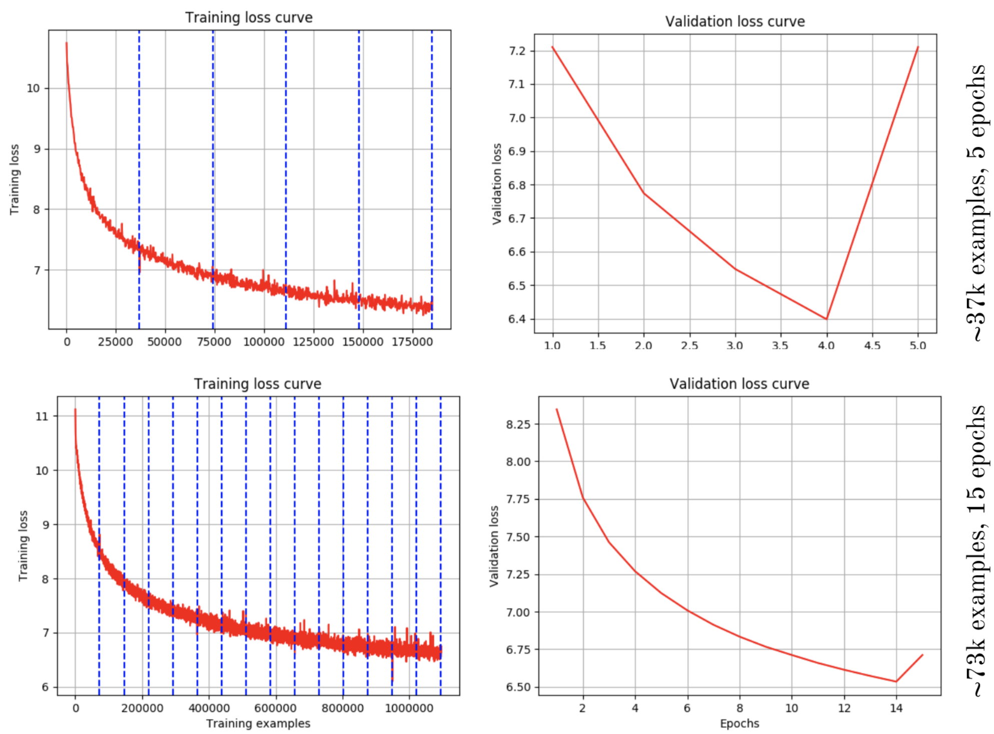

Figure 4: Plot of training loss and validation loss curves

The answer to every given text also hints at what the model understands from the content of the data provided. We seem to think that although the model is grammatically sound, it is still building an opinion, saying "`I ’ m not sure`" which could be a common statement in the dataset.

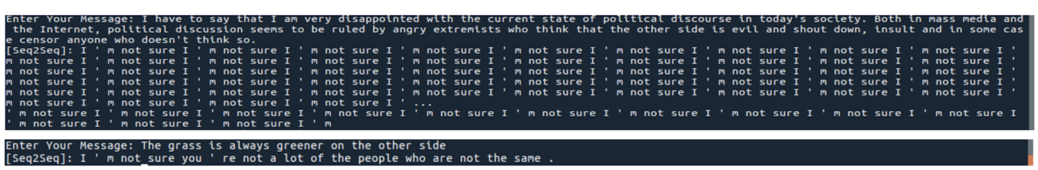

Figure 5: Interactive dialog example with the trained seq2seq model

6 Discussion and Further Work

In order to improve upon our current results, we plan to tweak the attention window size being used. Further, we plan to use a global attention mechanism in order to better capture long term dependencies which would also be a trade-off with the computation time. We also intend on trying out various language models such as Gehring et al. [2017] convolutional seq2seq Sukhbaatar et al. [2015]'s memory network and Wu et al. [2017]'s StarSpace.

As a follow-up to this phase, we aim to train our agent to be able to put forth meaningful arguments in debates in the context of specific topics and even bring about a change of mind of the OP. We intend to relax the unavailability of the Δ signal from the DeltaBot and use it as a reward, thus rendering our task more of a reinforcement learning problem.

As a final goal, we have our sights set on creating an environment wherein two artificial agents will have a conversations/debates with each other, without any human interference, through the agents of DebAIt.

7 Acknowledgements

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