1 Introduction

Language is very powerful. One can convey the same meaning/content with different styles e.g. brief/verbose, colloquial/professional and etc. Recently there have been different attempts to transfer the style but preserve the content of text corpora without having parallel data. For example transferring Shakespeare’s plays to modern English spoken today. This is an instance of a broad family of problems including machine translation. Having parallel data makes the problem much easier and almost trivial with the use of neural networks, however parallel data is usually not available, forcing us to use non-parallel data. This project is an attempt to use structured features such as Entity Recognition and Relation Extraction to improve the transferred results. In this paper we will report the first steps taken to solve this problem.

2 Method

After thoroughly going through previous works mentioned in the project survey, work done by (Shen et al., 2017) was chosen as the base model and also for the baseline. This work has been used as baseline for few other works and their approach is very clear and reasonable. Below is a summary of their approach:

They learn an encoder that takes a sentence and its original style indicator as input, and maps it to a style-independent content representation. This is then passed to a style-dependent decoder for rendering. In order to align the latent content representations across the corpora they introduce a refined alignment using an adversarial approach. More detailed description of the model was presented in the class. Figure 1 illustrates this model.

3 Results

After finding their code and going through it and understanding it, we trained the model on Yelp reviews with different options. However because of some constraints, limit on the number of GPUs (2) and maximum runtime allowed for jobs (24 hours), we were not able to train the model completely. We also looked for the pre-trained model to get the final transferred sentences. We were able to find it, however the model took too long to load and we ended up looking at the intermediate results obtained (The model is still being trained on the server for the final results). A few examples of the transferred sentences are presented in table 1. These samples are chosen from the incorrect outputs of the model, in order to understand the shortcomings and look for ways to improve it.

Some of the samples reported in table 1 are not fluent and this could be caused by the fact that the model is not trained until convergence and these are intermediate results. We will look back at this issue when the final results are ready. Another issue observed in samples 2 and 6 is that the content has changed in the transferred sentence. Our idea is to add the important entities to the set of features passed as input, in that way the model would learn to keep those entities throughout the transfer. For example in sample 2, burrito is the
From negative to positive

clearly their aggressive pricing comes with poor quality.
really good food for the food .
not impressed , the burritos were small , lukewarm , and sort of bland .
is really good , the food and always fresh and fresh and friendly .
the customer service is nonexistent !
the food is great !
it was definitely not worth the price at all .
it was really worth the good .
ugh messed up my night .
will recommend my money .
i came here on a whim today with a craving for mexican food .
i have recommend a of time for a good food with a good price .

Table 1: Sentiment transfer results by (Shen et al., 2017). First sentence is the original negative review and the second sentence is it’s transferred generated positive review.

entity that should be preserved, in sample 3, customer service is that entity and in sample 6 Mexican food is that entity.

4 Future Work

After receiving the final results obtained from the fully trained model, we need to check the transferred sentences for fluency. Afterwards we will train a separate model to get Entity Recognition and Relation Extraction and POS tagging and add them to the set of features used for style transfer and check if any of them could improve the results. One other possible improvement is to use Bert’s (Devlin et al., 2018) pre-trained embedding instead of random initialization.

After these steps the results could be re-evaluated to see what other aspects could be improved.

References
