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Summary of My Chosen ACL Paper

The paper that I chose to read and summarize is titled “So Different Yet So Alike! Constrained Unsupervised Text Style Transfer”. The authors of this paper are Abhinav Ramesh Kashyap, Devamanyu Hazarika, Min-Yen Kan, Roger Zimmermann, and Soujanya Poria. They are all affiliated with the University of Singapore.

Among the five authors, Roger Zimmermann has the most citations on Google Scholar. He has 490 citations. The first author, Abhinav Ramesh Kashyap, has the least amount of citations on Google Scholar with 12. Of the three remaining authors, Devamanyu Hazarika has 45 citations, Min-Yen Kan has 268 citations, and Soujanya Poria has 172 citations.

The paper discusses issues surrounding preserving semantic content as well as other attributes, such as style, when translating text from a source to a specific target domain. When it comes to prior work, modern neural networks are able to map data from 1 domain to another. Emoji creation from human faces is an example of this. The goal of these kinds of methods is typically to preserve the semantics of the data, the content, while changing some other properties such as formality, sentiment, or any other combination. Specifically, when it comes to text style transfer, unsupervised style transfer has been introduced which tries to avoid the costly annotation of parallel sentences. However, one drawback of this approach is the fact that unsupervised style transfer has routinely performed worse than supervised, or parallel, style transfer.

The main contribution of this paper is that it introduced a method for unsupervised text style transfer that greatly reduced the correlated loss in accuracy commonly associated with the process. The authors introduced two types of cooperative losses in place of the existing competing losses of the existing method. These cooperative losses work to reduce the same loss rather than competing with each other and increasing loss. The method used to bring semantically sentences across two domains closer together to be more similar stylistically. In the paper, the authors show how this method was able to better preserve stylistic attributes such as lexical constraints and syntactical constraints. This method accomplished the goal of improving text quality after transfer which the authors show through their evaluation methods.

The authors evaluated their work through both automatic and human methods. The first step of the automatic evaluation was keeping track of semantic differences between the source and target sentences. This was done using encoders rather than through the n-gram metrics we discussed in class. The second step of the automatic evaluation was transfer accuracy. This step just consisted of the authors keeping track of the percentage of transferred sentences that actually belonged to the target domain. The final step of the automatic evaluation was keeping track of fluency. In this context, fluency refers to whether or not the transferred sentence is grammatically correct. These 3 resulting scores were combined through a formula shown in the paper to come up with an overall score for the automatic evaluation. The human evaluation that the authors did consisted of them randomly sampling 100 of the transferred sentences from each of the datasets and hiring researchers to manually rate each sentence in regards to semantics, accuracy, and fluency.