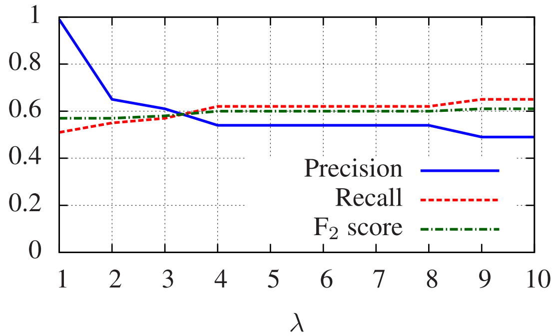

Figure 5: Results for different values of λ (parameter to filter out noise).

evance to words not in the USW list.

Conclusion

We have presented a new approach to extend word highlighting in multiparticipant chat. GWRH can find word relations using a graph-based unsupervised learning algorithm. Our results show that, for one corpus (concerning technical support), it outperforms two baseline approaches that are similar to current state-of-the-art chat client capabilities.

While GWRH increases recall for our task, there are some types of messages that it would not easily be able to find. One example is messages that use pronouns to refer to Unity. Another is messages that use a misspelling that forms another correctly-spelled word (e.g., "unify" instead of "unity").

In our future research, we will first try to extend the corpus, allowing for formal validation of our hypothesis. As it took three weeks to validate the 8675 messages in our test set, we would then expect it to take many months to annotate enough messages to allow for cross-validation. To alleviate this, we are investigating how to leverage crowd sourcing for annotating chat messages. In addition to annotating a longer series of messages in time, we will also obtain annotations for additional topics (i.e., other than Unity).

One possible extension for GWRH is to consider conversation threads. We could use these to train the model. When looking at Figure 3, the unlabeled data could be disentangled using a thread disentanglement method (Elsner and Charniak 2010; Wang and Oard 2009) prior to being passed to the unsupervised learner. Instead of changing weights by examining only a single message in a vacuum, we could change the weights by examining the message in context to its given conversation. As a part of thread disentanglement, we will also consider disambiguating pronouns. As discussed before, finding related words will not always help when Unity is referred to by a pronoun.

Another interest is extending GWRH to be a lifelong learner, as we want it to learn new terminology as they are introduced. Most of our approach is suitable to lifelong learning, though adjustments need to be made to prevent the graph from growing too large. The graph created for these experiments included 35,281 vertices and 1,699,164 edges. Of these edges, 65.8% have a weight of 1, meaning the two vertices of the edge have only been seen once together. It could be possible then to prune such edges over time, and even remove vertices once they no longer have any edges. Additionally, the approach needs to be modified so it can "forget" relations since terminology changes with time.

Finally, these ideas of extending word highlighting will be evaluated through human subject studies in a simulated Navy environment. As mentioned earlier, our work addresses a problem in the US Navy of chat and information overload. We hope that our results will show that extending word highlighting can assist Navy watchstanders with finding messages of interest in a fast-paced environment.

Acknowledgments

Thanks to NRL for funding this research. David Uthus performed this work while an NRC postdoctoral fellow located at the Naval Research Laboratory. The views and opinions contained in this paper are those of the authors and should not be interpreted as representing the official views or policies, either expressed or implied, of NRL or the DoD.

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