**RRL**

In the text classification system, the classifier is the main part. The classifier performance quality is directly related to the efficiency and effect of text classification. Most of theclassifiers are based on the methods from information retrieval and the machine learning algorithms that are introduced for text classification purpose [7]

L. Wei, B. Wei, B. Wang Text classification using support vector machine with mixture of kernel Journal of Software Engineering and Applications, 5 (2012), p. 55

Logistic Regression Quick to train data,Work well forcategorical data,Simple parameterEstimation,Better for linear data. Not better for non-lineardata,Required large sample size

Sayar Ul Hassan, Jameel Ahamed, Khaleel Ahmad, Analytics of machine learning-based algorithms for text classification, Sustainable Operations and Computers, Volume 3, 2022, Pages 238-248, ISSN 2666-4127, https://doi.org/10.1016/j.susoc.2022.03.001.

The multilayer perceptron [172] and the recursive neural network [173] are the first two deep learning approaches used for the text classification task, which improves performance compared with traditional models. Then, CNNs, Recurrent Neural Networks (RNNs), and attention mechanisms are used for text classification [101, 174, 175].

172 M. k. Alsmadi, K. B. Omar, S. A. Noah, and I. Almarashdah, “Performance comparison of multi-layer perceptron (back propagation, delta rule and perceptron) algorithms in neural networks,” in 2009 IEEE International Advance Computing Conference, pp. 296–299, 2009.

173 S. Pouyanfar, S. Sadiq, Y. Yan, H. Tian, Y. Tao, M. E. P. Reyes, M. Shyu, S. Chen, and S. S. Iyengar, “A survey on deep learning: Algorithms, techniques, and applications,” ACM Comput. Surv., vol. 51, no. 5, pp. 92:1–92:36, 2019.

174 L. Qin,W. Che, Y. Li, M. Ni, and T. Liu, “Dcr-net: A deep co-interactive relation network for joint dialog act recognition and sentiment classification,” in The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020, pp. 8665–8672, 2020.

175 Z. Deng, H. Peng, D. He, J. Li, and P. S. Yu, “Htcinfomax: A global model for hierarchical text classification via information maximization,” in Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021 (K. Toutanova, A. Rumshisky, L. Zettlemoyer, D. Hakkani-Tür, I. Beltagy, S. Bethard, R. Cotterell, T. Chakraborty, and Y. Zhou, eds.), pp. 3259–3265, Association for Computational Linguistics, 2021.

**Proposed solution**

we propose a two classifiers of these comments

the other using a deep learning approach particularly an LSTM Neural Network model and the other a simple generalized version of logistic regression called the Softmax Regression model suited best for multi class classification

because machine leraning models work on numbers the next problem was how would we feed words to a model such that it was able to detect sentences or phrases that were known to either be derogatory, non-derogatory, offensive, or homonymous

**Word Embeddings**

these are a way to represent words numerically in a d-dimensional vector space

According to Ameida, F. & Xexeo, G. (2019) the task of representing words and documents is part and parcel of most, if not all, Natural Language Processing (NLP) tasks. In general, it has been found to be useful to represent them as vectors, which have an appealing, intuitive interpretation, can be the subject of useful operations (e.g. addition, subtraction, distance measures, etc) and lend themselves well to be used in many Machine Learning (ML) algorithms and strategies.

They also state that words with similar contexts (other words) have the same meaning. For example, the words Dostoevsky and Tolstoy may be words that appear in the context of Russian related literature, hypothetically when these words are represented as vectors in a 2-dimensional space they might appear closer to each other.

Almeida, Felipe & Xexéo, Geraldo. (2019). Word Embeddings: A Survey.

On A side note we can represent these embeddings in a lower dimensional such that words can be visualized in a 2D plane or 3D plane. T-distributed Stochastic Neighbor Embedding (T-SNE) is a machine learning algorithm for data visualization, which is based on a nonlinear dimensionality reduction technique. The basic idea of t-SNE is to reduce dimensional space keeping relative pairwise distance between points. In other words, the algorithm maps multi-dimensional data to two or more dimensions, where points which were initially far from each other are also located far away, and close points are also converted to close ones. It can be said that t-SNE looking for a new data representation where the neighbourhood relations are preserved.

More recently ways of creating embeddings have surfaced, which rely not on neural networks and embedding layers but on leveraging word-context matrices to arrive at vector representations for words. Among the most influential models is that of the GloVe model by Pennington, J., et al. (2014).

Jeffrey Pennington, Richard Socher, and Christopher Manning. October 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for Computational Linguistics.

Another model proposed was named ELMo (Embedding from language models) looks at the entire sentence as it assigns each word an embedding. It uses a bi‐directional recurrent neural network (RNN) trained on a specific task to create the embeddings. Since it uses a bidirectional architecture, the embedding is based on both the next and previous words in the sentence.

M.E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, L. Zettlemoyer, Deep contextualized word representations, in: Proc. of NAACL, 2018

Which is useful given that words more often than not have their meaning dependent upon the context they are in or the words surrounding them.

Many of the suggested advances seen in the literature have been incorporated in widely used toolkits, such as Word2Vec, gensim, FastText, and GloVe, resulting in ever more accurate and faster word embeddings to be used in NLP.

Almeida, Felipe & Xexéo, Geraldo. (2019). Word Embeddings: A Survey.

While various models have been proposed to train embeddings of numerous words such as Word2Vec, GloVe, ELMo etc., sometimes sparsity in data can occur, and deciding to train such word embeddings from scratch may not be wise because it can be difficult with merely a few say thousand words to train a model that represents these words in a vector of high-dimensional space. Fortunately, open source and publicly pre-trained embeddings can be of great use to an individual looking to use the vector representation of the words they have in their vocabulary or corpus

with the use of these word embeddings particularly GloVe the one we propose to use in this problem we can represent the words in our corpus in a vector space such that it is useful later on in the two models we have chosen to classify and detect certain phrases with derogatory, non-derogatory, offensive, or homonymous words.

In particularly the pre-trained word embeddings we've chosen to use is that of the common crawl pre-trained word vectors also by Pennington, J., et al. (2014), which contain over 42 billion tokens, 1.9 million uncased words in its vocabulary, each with vector representations of 300 dimensions.