

CS 686, Winter 2020

Project Proposal

- The application domain is **sentiment analysis/text classification**
- The data I will be using is the **Yelp dataset**, stored in JSON format. The following information is available
 - 200K businesses, with location data and categories
 - 6.7 million reviews, with full text data and ratings (1 - 5)
- The input variable is the **full review text**. For simplicity purpose, the target variable, **rating**, will be transformed into a binary class:
 - 1 - 2: negative (class 0)
 - 4 - 5: positive (class 1)
 - 3: neutral, discard
- I will be implementing and comparing the effectiveness of various machine learning/AI algorithms. Since this is a binary classification problem, I am considering the following:
 - Naive Bayes [1] [2]
 - Logistic regression [3] [4]
 - Tree-based ensemble models (e.g., LightGBM, XGBoost) [5] [6]
 - Long-short term memory (LSTM) [7] [8]
 - Bidirectional Encoder Representations from Transformers (BERT) [9] [10]
- The analytical aspect of this project would be on why certain algorithms out-perform/under-perform compared to the others
- Extension, if time permits - I will try to identify any common theme among positive reviews that businesses can leverage to achieve higher ratings

References

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