presentation Text Analysis project

0. Hello to everyone, I'm Giovanna Ferraro and this is my project for the course Text Analytics and language understanding.

1. During the presentation we will go through a Twitch overview; a brief introduction to emotes; the project goal and its' challenges; data collection and lexica used; the model development and the steps made to deliver the project; I'll show you the results of the work with a short discussion; finally, some of the predictions made by the model and some failures of the current implementation.

2. Twitch community is long-lasting and live chats are one of the most interesting features of the platform, gathering thousands of people watching the same thing and commenting together.
   Through time, people started to create communities with their way of talking, creating a real new language where emotes are a crucial aspect of this new language.

3. This is a set of some of the most used emotes on Twitch (courtesy of the official Twitch page). They are made of textual and graphical descriptions.
   Each Twitch community has its' own set of emotes, although there are many emotes common to all communities.
   The interesting thing is that every single emote has a sentiment embedded. Research has been conducted to create a lexicon of emotes; however, sentiment related to emotes is context-specific and the emote can be either positive or negative.
   For example, Trihard is a quite famous emote: its first meaning was excitement or hype, but over time it took on a racist connotation about which there are still some debates today. The same happens with the emote cmonbruh, which sentiment is negative either in its first meaning (confusion) or the new racist address.
   Twitch allows streamers to moderate their live chats via bots and

moderators, but chats get hectic easily and it's hard to handle a huge amount of comments.

4. For this reason, studying emotes, and their meaning in a specific context and finding a way to make the moderation process automatic is a compelling aspect and the reason why I choose to work on this topic.
   So, the project goal is to make a sentiment analysis of League of Legends comments on Twitch as League of Legends is known to have quite a polarized community.
   The challenges relates to this work were emotes related, as there aren't many lexicons. The sentiment is context-dependent, the language used is short and repeated words to comment stand out among the others.
   Finally, there's no specific grammar that can be analyzed in the comments.

5. The data collection is based on unlabeled Twitch comments from the 10 more active League of Legends streamers. The weakly labeled comments were obtained using a rule-based classification. In addition to this, a hard-labeled dataset was used. Both datasets were used to obtain the final dataset of approx 30.000 entries.

6. The first step of the model involved using a distribution-based classifier with a probabilistic approach to predict the sentiment of comments.
   This indeed produces good results but the accuracy is slightly above the random guess.
   This felt not enough for sentiment analysis and I choose to take a step further and adopt a deep learning approach.
   Simply put, I used a RNN with a first layer of embedding, then several LSTM cells, and for last a fully connected layer.
   LSTM cells are a particular implementation of RNN that resolve the vanishing of the gradient peculiar to RNN. They are also able to learn order dependencies, face the problem of missing grammar for Twitch comments, and are very important in learning from the context of a comment.
   BiLSTM is just LSTM that goes back and forth in the comment, making the analysis more robust.

7. We start analyzing the LSTM model.
   From the confusion matrix, it's clear that the model is pretty accurate, having both recall and precision quite high.
   The loss/accuracy curve is impressive, showing how much the network learned from the dataset.
   Almost the same results are obtained with the BiLSTM, which slightly improved the results of the simple LSTM.
   The model can distinguish the sentiment of "kill strike" with is negative, and "kill strike pog" which in a gaming context is positive.
   However, those results are clearly showing some overfitting, as the model is experimentally proven to predict well some comments and predict others quite bad others.
   This is probably due to the structure of the comment, quite short and with repeated emotes that may have polluted the final prediction. Also, chats are constantly moderated so many negative/hateful patterns in comments have been removed by the streamer.
   All considered, this project taught me the importance of preserving context while making text analysis and this field of research is quite new so further effort can be made in this direction. Related work can be working on sentiment or hate speech in live chats, removing the burden of live chat moderation from streamers.