

[EX 16]

Fill up the functions *build_model* and *train_model* to build and train up your own model (you can use whatever model you desire) and plot the main model metrics and defend, on the report, why you have chosen that model (from model selection to hyperparameters selection) based on graphics and metrics.

In exercise 16, I have built a Recurrent Neural Network since we are interested in the whole meaning of the commentary, so we need to keep in memory the computations of the previous words. In my case, I have used a LSTM model (Long short-term memory), that takes the 128 dimensions from the Embedding layer and gives it back to the two final Dense layers, that end up classifying between the different classes of comments that we receive: good, natural, and bad. As an optimizer I declined myself to Adam's since it gave me better results overall. The number of epochs is set to 20 since it is about that number that the model converges to a loss and accuracy value.

Model: "sequential_2"

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, None, 128)	128000
lstm_2 (LSTM)	(None, 32)	20608
dense_4 (Dense)	(None, 16)	528
dense_5 (Dense)	(None, 3)	51
Total params: 149,187		
Trainable params: 149,187		
Non-trainable params: 0		

[EX 21]

Save the *data_report*, *mainwords_count_df*, *mainwords_conversation_df*, *relatedword_per_mainword_df* and build up a dashboard with the idea of help to Customer Service to quickly understand what customers think about their product, identify those unsatisfied customers and see the main and related words

For this exercise 21 of pr9, I have created a dashboard in Tableau that can be accessed through the following link:

<https://public.tableau.com/profile/aran3436#!/vizhome/Pr9TextAnalyticsforCustomerCare/Dashboard1>

In the dashboard we can see on the top right plot, the 10 most important words for each of the sentiment's comments. The dimensionality of the size is proportional to the total count of the word. We can appreciate that the words product, sound, and qualiti are considerably big in all three sentiments.

Right below, in a stacked bar plot, the comments count of each of the main words, differentiating the sentiment on their appearance. From this plot we can conclude that the main words retrieved count for good feedback comments, followed by neutral ones.

Finally, at the bottom of the dashboard, we observe the MainWords and their RelativeWords that are used to explain the different sentiments. For example, the main word 'best' does not matter what its relative is since the sentiment it shows is 'good'. That may be something expected, but as stated in the first plot, the main word 'good' is used for explaining the three of the sentiments without taking into account the relative word. As a curiosity, 'ear' is used for neutral comments, and 'month' ends up in bad feedback comments.

