Sentiment Analysis of Customer Feedback

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Overview

Analysis of the Problem Statement

Objective of the problem

Sentiment analysis is the process of analysing textual data and inferring the general mood of the text.

- Our task involves the follows
  - We are required to develop a robust model that can analyse verbatim feedback from customers and label them as per their sentiment.
  - The model must be **quick, efficient** and also **easily extendable** to different languages and domains.

Analysis of the Problem Statement

Analysing the dataset

- The data provided to us has positive labels and negative labels.
- There are some outliers in the data as well , which have no sort of tone whatsoever.

For example ”Convolve 2023” was a feedback given, and yes that has no relevance to the product or service .

Approach

To solve this problem, we have tried a variety of approaches from different angles .

In this section we will have a brief look at our various attempts, and the best solution to the problem with a justification for the same.

Data Processing

In order to judge anything we need some things as a baseline, so at first, we tried approaching the problem by traditional ML methods. First, we split our data into train set and validation set with a ratio of **85: 15**

Approach

Text Processing

- One must first process the text into a vector of numbers. These are called **embeddings** and can be done using a variety of approaches.
- We tried out methods such as **Bag-of-Words and TFIDF vectorization**. We could not achieve best results using the above methodologies. The final approach will be described in a while.

Approach

Baseline Models Implemented

- We tokenised our text using the techniques described in the previous slide
- Training of the vectors was done on linear models and **Ensemble** Techniques. Upon observation, TFIDF vectorisation was clearly better.
- Post this, models like **RandomForest, XGB** were trained. XGBoost outperformed all ensembling techniques like Decision Trees and CatBoost. Logistic Regression could not improve the accuracy.
- Best score using the TFIDF embeddings were obtained using Random Forest , which was about 60% in terms of validation F_1 score.

Approach

Deep Learning Approach

- Now in order to improve the accuracy, we tried taking a Deep Learning Approach using **LSTM**(Long-Short-Term-Memory) on pre-trained word-embeddings like **glove-embeddings** and spacy embeddings.
- These were chosen as they have been trained with billions of words and often produce rich-quality embeddings. Fresh embeddings were also created by us but as expected , our embeddings were of much lower quality than the above mentioned.
- Using Glove-Embeddings and LSTM , we were able to achieve an F_1 score of about 80%

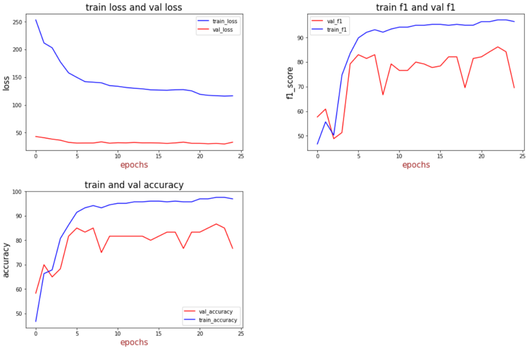
Approach

Transformers

- **Transformers** have recently caused a buzz in the world of NLP and are regarded as the best language model with high parellisability, long-range dependency capturing and ease of training.
- As many pre-trained models exist on Hugging face, **Mini LM-6, distill-roberta** were tried on the data with **mean pooling** and fine tuning of the final layer.

Approach
Plots

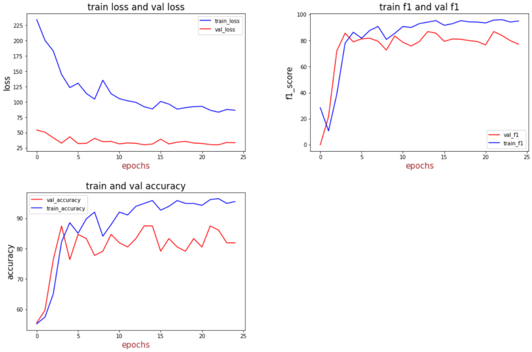
Figure: *distill-roberta training curve*



Approach

Plots

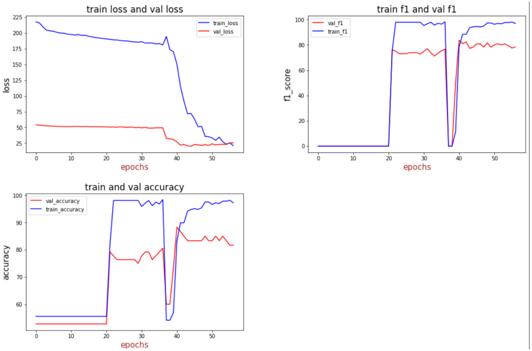
Figure: *mini-lm6 training curve*



Approach

Plots

Figure: *multi-qa-mpnet training curve*



Towards our final architecture

- Combining the word embeddings into **document embeddings**(which serve as a feature vector for the entire sentence(s)) required more detailing.
- Simple Mean Pooling of words would **not** serve well as the sequential context of words is lost.
- However RNNs serve as a good network to combine these feature vectors of words into a single dense representation of the text.
- An LSTM network was chosen over GRU due to the short length of text, and required lesser training.

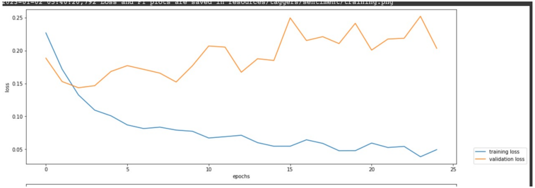
Classification

- The classifier we used is a simple **feed-forward neural network** with dropout layers for regularisation.
- **LayerNormalisation** is done in the RoBERTa framework for better generalisation.
- Ensemble methods like AdaBoostClassifier were not able to capture features correctly. We believe this is because AdaBoost uses **"stumps"** which are single heighted decision trees which are often used only for sparse encodings.

Hyperparameters

1. The training pipeline was created using **Flair** an open source library, which consists of various state-of-the-art NLP frameworks.
2. Various trials were conducted to determine the optimal parameters for our model.

Figure: ***overfitting*** *due to poor choice of parameters*



Hyperparameters

Optimal Hyperparameters

Learning Rate

Learning Rate $= 10^{-6}$

Scheduler

CosineAnnealing with $T_{max} = 30$

Cross-Entropy Loss was used as the loss function.

Optimizer

AdamW with *weight decay* $= 0.1$

Results & Inferences

F_1 Metrics

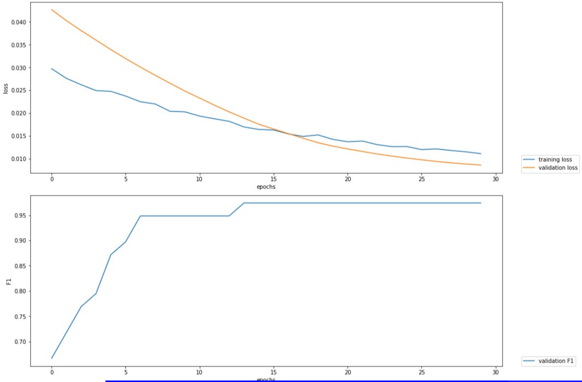
1. Train F_1 score $= 0.9799$
2. Validation F_1 score $= 0.9744$

twitter-RoBERTa-base was used as our transformer taking into consideration the short length of tweets and high correlation of social media posts with emotion.

Results & Inferences

Model Convergence

Figure: *Final Model*



What makes our model better?

- Large Language Models such as RoBERTa do **not** require end-to-end training for performing any particular task. Simply fine-tuning the last few layers is more than sufficient. This is commonly known as **Transfer Learning**.
- RoBERTa has been trained for **multiple languages** and for different domains. So, our model can be easily **extended** to work in various languages as per your needs.
- Our model has very **low inference latency**, order of tens of milliseconds($\sim 30ms$). Hence, the model can manage large volumes of data.

Github Repo

Solution Report, Code and this Presentation can be viewed here

Thank You