

# Twitter Emotion Classification Challenge

**Github Repository:** [https://github.com/pilarguerreromorales/ml\\_emotions](https://github.com/pilarguerreromorales/ml_emotions)

**Command to install:**

pip install

[git+https://github.com/pat\\_11BEKAZVY02I0DXRoo3kot\\_KLcP7wdwVVREyz41DfUn7LUTKYOYxy3JiyIk4SpXr29H3JWLOXIJ3ryXoZd@github.com/pilarguerreromorales/ml\\_emotions.git](https://github.com/pat_11BEKAZVY02I0DXRoo3kot_KLcP7wdwVVREyz41DfUn7LUTKYOYxy3JiyIk4SpXr29H3JWLOXIJ3ryXoZd@github.com/pilarguerreromorales/ml_emotions.git)

## Approach and Methodology

My approach was to first explore the data. The first thing I noticed was that there was a slight class imbalance with labels 0 and 1 being more represented in the dataset than the rest. In terms of preprocessing I ensured normalizing tweet text to Unicode, putting everything in lowercase and stripping urls and mentions which the model may have trouble understanding. I also dealt with punctuation and hashtags and removed outliers which were too short or too long tweets to stabilise learning.

To address the previously mentioned imbalance I computed inverse-frequency class weights and used a WeightedRandomSampler in the training DataLoader. In this way I could ensure that all emotions were fairly represented when sampling.

In terms of model I used distil-roberta as I could not get enough power to finetune the full roberta with the GPU I had access to. The smaller distilled roberta however was easy to fine tune in kaggle and offered quite impressive results. The classification head was randomly initialized and then fine-tuned for 4 epochs so that it accurately classified each tweet into one of the classes. This proved to be a good choice as already in the first epoch I was getting a Val macro of 0.9132 which proved it was a good starting point for finetuning.

In terms of optimisation and regularisation I ended up using the AdamW optimizer with a linear warm-up, followed by cosine decay, a  $2e-5$  base learning rate, and gradient clipping at norm=1.0. Dropout also helped regularisation. I also used early stopping which ended kicking in in epoch 4 where the f1 val score did not improve and so the training stopped. The best model in terms of val f1 score was saved which was the one after epoch 3.

## Experimental Results

Trial	Description	Final Train Loss	Val F1 Score
1	Roberta - could not get it to work due to space constraints took too long but still attempted.		
2	Distil- Roberta, no regularisation and cross entropy loss	0.2578	0.914
3	Distil Roberta with	0.1005	0.9176

	regularisation, optimisers and scheduled learning rate. Maintained cross entropy loss.		
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## Training Curves

