FEEL-IT: Emotion and Sentiment Classification for the Italian Language

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Abstract

Sentiment analysis is a common task to understand people’s reactions online. Still, we often need more nuanced information: is the post negative because the user is angry or because they are sad? An abundance of approaches has been introduced for tackling both tasks. However, at least for Italian, they all treat only one of the tasks at a time. We introduce FEEL-IT, a novel benchmark corpus of Italian Twitter posts annotated with four basic emotions: anger, fear, joy, sadness. By collapsing them, we can also do sentiment analysis. We evaluate our corpus on benchmark datasets for both emotion and sentiment classification, obtaining competitive results. We release an open-source Python library, so researchers can use a model trained on FEEL-IT for inferring both sentiments and emotions from Italian text.

1 Introduction

Emotions shape our lives and the way we communicate. We can be happy, sad, or angry, and we can let others know of our emotional state through language. Thus, efficiently detecting emotion in text is essential for analyzing people’s position towards a topic. Product and service companies frequently use emotion and sentiment data to inform advertising campaigns and measure customer satisfaction (Ahmad et al., 2020). Emotions have a central role in a political campaigns, and political discourse in particular (Huguet Cabot et al., 2020). Emotion and sentiment recognition can also aid in the critical decision-making process of crisis management or emergency scenarios (Stowe et al., 2016; Desai et al., 2020).

*Both authors contributed equally to this research and are ordered alphabetically.

| anger | fear | joy | sadness | Total |
|-------|------|-----|---------|-------|
| 912   | 103  | 728 | 294     | 2037  |

Table 1: FEEL-IT corpus statistics.

Despite the huge interest of the Natural Language Processing community, the majority of benchmark datasets have been proposed for English (Calefato et al., 2017; Abdul-Mageed and Ungar, 2017; Akhtar et al., 2019, inter alia) showing a limited interest for other languages, such as German (Troiano et al., 2019), Chinese (Wang et al., 2018), Spanish (Navas-Loro and Rodríguez-Doncel, 2019), Italian (Barbieri et al., 2016; Sprugnoli, 2020), and multiple languages in shared tasks (Mohammad et al., 2018; Pontiki et al., 2016). Moreover, they are usually collected either via hashtags and emojis for distant supervision (Abdul-Mageed and Ungar, 2017; Mohammad, 2012; Pak and Paroubek, 2010; Lamprinidis et al., 2021), or via very specific topics (Khanpour and Caragea, 2018; Chang et al., 2018; Nozza et al., 2017). The first causes noisy training data (Bing et al., 2015), the second results in highly domain-specific datasets.

This paper presents FEEL-IT, a novel benchmark corpus of Italian Twitter posts annotated with four basic emotions (Ekman, 1992): anger, fear, joy, sadness. To the best of our knowledge, no other Italian dataset with a broad topic and domain coverage for emotion and sentiment classification exists. Beyond releasing benchmark results on FEEL-IT, we evaluate recent neural models trained on our corpus for emotion recognition.

1We focus on these emotions because they appear most frequently in text.
on the MultiEmotions-It dataset (Sprugnoli, 2020). It contains comments on music videos and advertisements posted on YouTube and Facebook. We also test performance on sentiment classification by collapsing positive and negative emotions on the SENTIPOLC16 benchmark dataset (Barbieri et al., 2016). It comprises both general and political topics. The best-performing models are released as part of a Python library to foster and facilitate research on the topic.

Contributions. We present FEEL-IT, a new corpus on Italian tweets, annotated with four basic emotions (anger, fear, joy, sadness). We demonstrate that we can effectively predict sentiments and emotions in text by training prediction models on this corpus. We release an open-source Python library\(^2\) that researchers can use to classify their text.

2 Data Collection and Annotation
We retrieved the data by monitoring trending topics each day between 20\(^{th}\) August to 12\(^{th}\) October 2020, using the Twitter API. For each day, we sampled 1000 tweets. This approach allowed us to get data from a range of different topics that span over many weeks.

The two first authors labeled the complete set of posts. Both are native Italian speakers with a strong NLP background. Eventually, the number of annotated tweets that contained an emotion was 2037 tweets (we removed tweets that did not contain any emotion, that is, most of them). This process involves a lot of data that has been discarded, and it is time-consuming, but the upside of it is that the collected tweets are from diverse domains and are high quality.

We computed our inter-rater agreement on a shared set of 220 tweets, annotated both with emotions and with none (i.e., no emotion found). We reached an agreement of 0.6 (Krippendorff’s Alpha). Once none tweets were removed, the agreement on the remaining 68 annotated tweets was 0.8 (Krippendorff’s Alpha).

Corpus Analysis Table 1 shows the label distribution of the FEEL-IT corpus for the four basic emotions considered. Examples for each class are shown in Table 2.

Similar to other realistic emotion classification datasets (Sprugnoli, 2020; Mohammad et al., 2018; Nozza et al., 2017; Mohammad, 2012), the dataset is imbalanced. The distribution is similar to the SemEval-2018 Task 1 dataset (Mohammad et al., 2018), where anger and joy account for the majority of tweets, and fear is the least frequent emotion.\(^3\)

In FEEL-IT, topics vary both with respect to domains and time. Topic domains ranges from health (#covid19, #mascherinamask) to sports (#F1, #Juventus), from social issues (#scuola) to TV shows (#GFvip, #pomeriggio5), from individuals (#DiMaio, #Suarez) to generic targets (#negazionisti/negationists). Each topic is associated with a time range that greatly varies with subject. TV shows are cited when they are broadcast, e.g., #domenicalive, literally Sunday live is mainly commented on Sunday. Some events, like soccer matches or celebrity birthdays, are mentioned only one day, e.g., the hashtag of the soccer match #BeneventoInter appears 371 times, but only the 31\(^{st}\) September. Tweets related to COVID-19 are present every observed day, with some peaks for specific events (e.g., on the 2\(^{nd}\) October, we recorded a peak of 132 tweets due to the news of US president Trump testing positive for COVID-19).

3 Experiments
We use experimental evaluation to (i) show that our classifier can predict emotions in tweets and (ii)

\(^2\)https://github.com/MilaNLProc/feel-it

\(^3\)Note that in other datasets, joy is the most frequent emotion, because of their focus on music or movies.
that FEEL-IT can also be used to perform sentiment classification with competitive results.

## 3.1 Emotion Classification

We first experiment with emotion recognition in the FEEL-IT dataset. Contextualized representations, such as BERT (Devlin et al., 2019) have obtained a lot of attention due to the great results (Rogers et al., 2021; Nozza et al., 2020) on multiple languages and on different tasks (Scarlini et al., 2020; Mass and Roitman, 2020; Du et al., 2020; Pasini et al., 2020; Peinelt et al., 2020; Bianchi et al., 2021; Nozza et al., 2021, inter alia). In this paper, we use the Italian BERT model UmBERTo trained on Commoncrawl ITA.4

As the first experimental condition, we fine-tune the UmBERTo model for the task of emotion classification with the considered training data (UmBERTO-FT).

As additional experimental frameworks, we use three different approaches to represent tweets: (i) We collect pre-trained UmBERTo representations using average pooling of the last layer (UmBERTO-PT); (ii) we use an Italian word2vec model (W2V) and create the representation of the tweet as the average of the word embeddings; (iii) we use a TF-IDF baseline with bi-grams to represent tweets. To make TF-IDF and W2V as competitive as possible, we apply a pre-processing pipeline to the text: (1) replace URLs and mentions with unique tokens; (2) replace emojis with a description of the emoji (Leonardelli et al., 2020), (3) split hashtags on camel case (#HappyBirthday becomes Happy Birthday); (4) remove punctuation. Given the representations, we use logistic regression with a softmax and with instance-weight balancing for classification. We test the models in a 10-fold cross-validation setting. We use the Most Frequent Class (MFC) as the baseline method.

### Results

Table 3 reports Precision, Recall, F1-score, and Accuracy of the cross-validated emotion classification on FEEL-IT.

| Model        | P  | R  | F1 | Acc |
|--------------|----|----|----|-----|
| UmBERTO-FT   | 0.72 | 0.73 | 0.71 | 0.82 |
| UmBERTO-PT   | 0.64 | 0.67 | 0.65 | 0.76 |
| W2V          | 0.57 | 0.62 | 0.58 | 0.76 |
| TF-IDF       | 0.72 | 0.60 | 0.64 | 0.74 |
| MFC          | 0.11 | 0.25 | 0.15 | 0.45 |

**Table 3**: Precision (P), Recall (R), F1-score (F1), and Accuracy (Acc) of the cross-validated emotion classification on FEEL-IT.

| Model        | anger | fear | joy | sadness |
|--------------|-------|------|-----|---------|
| UmBERTO-FT   | 0.88  | 0.51 | 0.87 | 0.60   |
| UmBERTO-PT   | 0.85  | 0.38 | 0.86 | 0.51   |
| W2V          | 0.80  | 0.31 | 0.76 | 0.42   |
| TF-IDF       | 0.80  | 0.51 | 0.80 | 0.46   |

**Table 4**: F1-score per class of the cross-validated emotion classification on FEEL-IT.

perform best. Again, UmBERTO-FT is the model with the highest overall performance.

The only emotion for which UmBERTO-FT obtains lower equal to TF-IDF is fear. It should be noted that this is the least frequent class in the dataset and, therefore, the more difficult to capture. The different prediction behavior on this class is also why the large difference in precision in Table 3. Indeed, precision for the class fear is 0.76 for TF-IDF, 0.55 for UmBERTO-FT, and 0.33 for UmBERTO-PT, while recall is 0.38, 0.52, and 0.53, respectively. This discrepancy means that, while TF-IDF is more cautious on assigning the label fear, UmBERTO-FT and UmBERTO-PT have a high number of false positives (see Appendix B for confusion matrices). From a qualitative perspective, we see that many of these false-positive tweets could be associated with fear, even if the most prevalent emotion is anger or sadness. This correspondence indicates that tweet authors tend to communicate their fears by other, less intimate, emotions. Examples are “Siete un branco di egoisti che pensa solo al proprio, fregandosi di mettere a rischio la vita di tutti gli altri” (You are a bunch of selfish people who only think about themselves, not caring about putting everyone else’s life at risk) and “Ogni giorno compilo il mio excel sulla situazione in Veneto...e ogni giorno lo chiudo pensando Speriamo che domani ci siano dati un po’ più incoraggianti” (Every day I fill an excel file on the situation in Veneto...and every day I close it thinking “Let’s hope that tomorrow we are going to have more encouraging data”).

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4https://github.com/musixmatchresearch/umberto
5http://vectors.nlpl.eu/repository/20/52.zip, see (Fares et al., 2017)
### 3.2 Sentiment Analysis

We test on SENTIPOLC16 (SP16) (Barbieri et al., 2016) to evaluate the performance of sentiment classification models trained on FEEL-IT. We collapsed the FEEL-IT classes into 2 by mapping joy to the positive class and anger, fear, and sadness into the negative class. We use the fine-tuned UmBERTo model (UmBERTo-FT) and the logistic regression classifier applied to its representations (UmBERTo-PT).

SP16 also comes with a training set. We fit a classifier on this data to see whether it is better to train on FEEL-IT or SP16. Eventually, we also combine the two datasets to see if we can get the best of both worlds. SP16 comprises tweets that could be both positive and negative; in our experiment, we exclude the tweets that were labeled both positive and negative. Thus, SP16 training contains 4154 examples, while the test contains 1050 samples.

**Results.** Table 5 shows the results for the sentiment classification task. They demonstrate that our proposed corpus is useful for sentiment prediction. While FEEL-IT contains roughly half of the tweets that SP16 has, the performance obtained with FEEL-IT on the SP16 test set is the best. Interestingly, using a more sophisticated model (UmBERTo-FT) leads to narrowing the differences between performance. This result confirms that our dataset can 1) be used for sentiment analysis and 2) obtains state-of-the-art performances on the current benchmark for Italian sentiment analysis. Note that the combination between SP16 and FEEL-IT brings good recall, with a slight drop in Precision and F1-score.

| Training data | P   | R   | F1  | Acc |
|---------------|-----|-----|-----|-----|
| FT SP16      | 0.79| 0.84| 0.80| 0.82|
| FEEL-IT      | 0.82| 0.80| 0.81| 0.84|
| SP16+FEEL-IT | 0.80| 0.84| 0.81| 0.82|
| FT SP16      | 0.77| 0.82| 0.77| 0.77|
| FEEL-IT      | 0.81| 0.80| 0.80*| 0.84|
| SP16+FEEL-IT | 0.78| 0.83| 0.79| 0.80|

Table 5: Precision (P), Recall (R), F1-score (F1), and Accuracy (Acc) of sentiment classification on SENTIPOLC16 using UmBERTo-FT and UmBERTo-PT model. We tested the statistical significance of the *F1-score for UmBERTo-PT trained on FEEL-IT showing that it is significantly better than the one trained on SP16 (bootstrap sampling $p < 0.05$).

### 4 Use-cases: COVID-19 and MultiEmotions-It

To further validate our approach, we showcase the results of emotion recognition models trained on FEEL-IT and tested on two topic-specific datasets: MultiEmotions-It (Sprugnoli, 2020) and a dataset of 662 tweets about COVID-19.

MultiEmotions-It (ME) (Sprugnoli, 2020) is a linguistic resource for Italian which comprises comments of music videos and advertisements posted on YouTube and Facebook. Each text is manually annotated according to four different dimensions: i.e., relatedness, opinion polarity, emotions, and sarcasm. This dataset differs from FEEL-IT both in terms of topic variety and considered social media. Among all the emotion classes considered in ME, we removed the ones not pertaining to our set of emotions. After this process, we are left with 304 comments.

As before, we pick UmBERTo-FT and UmBERTo-PT as our champion models. To give a point of reference, we also show the Most Frequent Class (MFC) baseline results.

**Results.** Table 6 shows that training on FEEL-IT brings stable performance even on datasets from different contexts. Note that the MFC accuracy is high because both datasets contain a wide range of emotions annotated as anger.

| Model          | Testing | P   | R   | F1  | Acc |
|----------------|---------|-----|-----|-----|-----|
| UmBERTo-FT ME | ME      | 0.56| 0.59| 0.57| 0.73|
| UmBERTo-PT ME | ME      | 0.56| 0.66| 0.57| 0.69|
| MFC ME        | ME      | 0.16| 0.25| 0.20| 0.64|
| UmBERTo-FT C19| C19     | 0.56| 0.56| 0.56| 0.69|
| UmBERTo-PT C19| C19     | 0.53| 0.53| 0.50| 0.60|
| MFC C19       | C19     | 0.15| 0.25| 0.19| 0.60|

Table 6: Precision (P), Recall (R), F1-score (F1), and Accuracy (Acc) of emotion recognition on use-cases using UmBERTo model.

### 5 Related Work

Different works have explored emotion recognition approaches. However, few of them incorporate text in Italian. Indeed, currently, no general-purpose dataset for emotion recognition has been proposed for the Italian language. However, for Italian, there is a dataset for emotion recognition limited to Youtube and Facebook comments (Sprugnoli, 2020), and one for sentiment analysis SENTIPOLC16 (Barbieri et al., 2016). We used these datasets in the experimental evaluation to show that
our model can also perform sentiment prediction.

Regarding other languages, Abdul-Mageed and Ungar (2017) proposes EmoNet, an English emotion dataset that has been collected using a keyword-based approach (e.g., tweets are retrieved using #happy as a marker for joy). The authors have obtained high accuracy with this dataset. Alternatively, we approach the problem annotating manually and without using distant supervision. EmoTxt (Calefato et al., 2017) is an open-source toolkit for emotion prediction supporting prediction for different emotions for the English language: love, joy, surprise, anger, sadness, and fear. Nozza et al. (2017) propose a English corpus of tweets that comprises five different views for each message, i.e. subjective/objective, sentiment polarity, implicit/explicit, irony, emotion. Lamprinidis et al. (2021) introduce a novel dataset that covers multiple languages extracted from Facebook posts. Troiano et al. (2019) introduce a dataset in two languages, English and German, obtained through crowd-sourcing. Interestingly, Akhtar et al. (2019) propose a multi-model architecture that combines visual, auditory, and text information for both emotion and sentiment prediction in English.

6 Conclusions

We present FEEL-IT, a new corpus for emotion classification on Italian Twitter data, and release an open-source Python library to run both emotion and sentiment classification. Future work will focus on the extension of this dataset, considering other emotions and languages.

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A Data Statement

We follow Bender and Friedman (2018) on providing a Data Statement for the proposed FEEL-IT corpus.

Data has been annotated by two native Italian speakers, age group in 25-35, both with experience in computational linguistics. The data we share is not sensitive to personal information, as it does not contain information about individuals. Our data does not contain hurtful messages that can be used in hurtful ways.

B Additional results

As follows, we show the confusion matrices for UmBERTo-FT (Figure 1), UmBERTo-PT (Figure 2) and TF-IDF (Figure 3) representation models for the experiments in emotion recognition task with 10-fold cross validation on FEEL-IT.
|        | anger | fear | joy | sadness |
|--------|-------|------|-----|---------|
| anger  | 825   | 5    | 33  | 48      |
| fear   | 46    | 39   | 5   | 13      |
| joy    | 147   | 3    | 530 | 48      |
| sadness| 133   | 4    | 38  | 119     |

Figure 3: Confusion matrix of TF-IDF predictions of cross-validated emotion classification on FEEL-IT.