Analysing the Greek Parliament Records with Emotion Classification

Vanessa Lislevand
Stockholm University, Sweden
lislevand@dsv.su.se

John Pavlopoulos
Ca’ Foscari University of Venice, Italy
Stockholm University, Sweden
Athens University of Economics and Business, Greece
annis@aueb.gr

Abstract

In this project, we tackle emotion classification for the Greek language, presenting and releasing a new dataset in Greek. We fine-tune and assess Transformer-based masked language models that were pre-trained on monolingual and multilingual resources, and we present the results per emotion and by aggregating at the sentiment and subjectivity level. The potential of the presented resources is investigated by detecting and studying the emotion of ‘disgust’ in the Greek Parliament records. We: (a) locate the months with the highest values from 1989 to present, (b) rank the Greek political parties based on the presence of this emotion in their speeches, and (c) study the emotional context shift of words used to stigmatise people.

1 Introduction

Text emotion detection concerns the classification of a text based on specific emotion categories. The emotion categories are often defined by a psychological model (Oberländer and Klinger, 2018) and the field is considered a branch of sentiment analysis (Acheampong et al., 2020). Classifying a text as negative or positive may be a simpler task, but this coarse level of aggregation is not useful in tasks that require a subtle understanding of emotion expression (Demszky et al., 2020). As described by Seyeditabari et al. (2018), for example, although ‘fear’ and ‘anger’ express a negative sentiment, the former leans towards a pessimistic view (passive) while the latter with a more optimistic one that can lead to action. This has made the detection of emotions preferred over sentiment analysis for a variety of tasks, such as in political science (Ahmad et al., 2020), to measure customer satisfaction in marketing (Bagozzi et al., 1999), to use the emotional state of the user in recommendation systems (Brave and Nass, 2002), and to monitor the public sentiment during crisis (Kabir and Madria, 2021).

Most of the work in emotion detection concerns resource-rich languages and only few published studies concern emotion detection for under-represented languages (Ahmad et al., 2020). The same problem exists for the Greek language, for which there is no publicly available dataset for the task. This study focuses on the detection of the eight basic emotions from Plutchik’s Wheel (Plutchik, 1980), shown in Figure 1, for the Greek language. We developed a new Greek dataset which we release for public use.

Figure 1: Plutchik’s Wheel of emotions colored based on our sentiment aggregation. Green colour corresponds to positive sentiment, red to negative sentiment, and yellow to emotions that we didn’t include in the aggregation.

We used this dataset to benchmark a multilingual and a monolingual Transformer-based emotion classifier, and to assess them for emotion classification. Our results show that although our benchmarks achieve low to average results for most of the studied emotions, the performance for one of the emotions, vis. DISGUST, is much higher and comparable to the performance of sentiment and subjectivity classification when we aggregate the emotions accordingly.

By employing an emotion classifier trained on

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A. A. Oberländer and M. J. Klinger (2018). "The Darkening Course of the Emotion Experience." Psychology, 9(5), 219-226.
B. Acheampong, O. S., C. A., K. O., & T. A. (2020). "Sentiment Analysis: A Survey." Journal of Big Data, 7(1), 1-22.
C. A. Demszky, Z. A., Y. A., & C. A. (2020). "Emotion Recognition in Images Using Deep Learning Techniques." IEEE Access, 8, 54178-54191.
D. S. Seyeditabari, S. H. L., & R. A. S. (2018). "Emotion Recognition in Social Media Using Deep Learning." Computers & Electrical Engineering, 69, 291-304.
our data, we analysed the records of the Greek Parliament Corpus from 1989 to 2020 with regards to DISGUST, the most frequently occurring emotion in electoral data (Mohammad et al., 2015). First, we studied the points in time when this emotion was most frequently occurring in the Greek parliament records and we ranked the Greek political parties based on the detected score. Second, we used it to investigate the emotional context shift, focusing on words used to stigmatise. Our findings show that the records of the far right wing are relatively higher in DISGUST, when compared to the rest, and (b) words that could stigmatise people are being increasingly used in an emotional context related to DISGUST in the studied parliamentary records.

2 Related work

Emotion classification is a natural language processing (NLP) problem with various use cases (Oberländer and Klinger, 2018; Acheampong et al., 2020; Demszky et al., 2020; Seyeditabari et al., 2018; Sailunaz et al., 2018; Gaind, 2019). Following the introduction of Transformers (Vaswani et al., 2017), several Transformer-based monolingual and multilingual pre-trained language models (Devlin et al., 2018; Conneau et al., 2019) (PLMs) have been on the spotlight, leading to improvements for many NLP tasks through their fine-tuning, including emotion and sentiment classification. Kant et al. (2018) demonstrated that pre-training an attention-based Transformer network on Amazon reviews and then fine-tuning it on the ‘SemEval Task 1: E-c’ multilabel emotion classification training set offers benefits (Mohammad et al., 2018). We also explore the benefits of using this dataset, as we will discuss later. Desai et al. (2020) presented HURRICANE EMO, a dataset with 15,000 tweets, each annotated with emotions perceived after hurricanes. They suggested classification tasks to discriminate between coarse grained emotion groups and experimented with neural networks and PLMs.

Emotion detection in not well resourced settings

The above mentioned advancements have assisted research more broadly in NLP for high-resource languages such as English, but the challenge remains for the rest. Ranasinghe and Zampieri (2020) experimented with transfer learning from English to Bengali, Hindi and Spanish at the offensive language identification task. They showed the superiority of XLM-R (Conneau et al., 2019), a multilingual BERT-based PLM, compared to the best systems submitted to recent shared tasks in these three languages. Ahmad et al. (2020) implemented emotion detection in Hindi proposing a deep transfer learning framework from English which captures relevant information through the shared embedding space of the two languages.

Tela et al. (2020) compared the English XLNet (Yang et al., 2019), fine-tuned with the Tigrinya language with a new monolingual Transformer (TigXLNet), pre-trained on Tigrinya. Even though the XLNet was trained with only 10k examples of the Tigrinya sentiment analysis dataset, its results were comparable to the results of TigXLNet and it outperformed both BERT (Devlin et al., 2018) and mBERT (Devlin et al., 2018). Hedderich et al. (2020) evaluated transfer learning and distant supervision on mBERT and XLM-R, from English to three African languages Hausa, isiXhosa, and Yoruba, on named entity recognition and topic classification. They showed that even with a small amount of labeled data, a reasonable performance can be achieved. Pires et al. (2019) studied the performance of mBERT at zero-shot cross-lingual model transfer, by fine-tuning the model using task-specific supervised training data from one language, and evaluating on that task in a different language. They showed that transfer is possible even to languages in different scripts, and that better performance is achieved when the languages are typologically similar.

Lauscher et al. (2020) studied the effectiveness of cross-lingual transfer for distant languages through multilingual transformers. They detected a correlation between the performance of transfer-learning with: (1) the philological similarity between the source and the target languages, and (2) the size of the corpora used for pre-training on target languages, which highlighted the significance of few-shot transfer-learning. Das et al. (2021) showed that XLM-R outperformed various machine and deep learning, and Transformer-based approaches at the emotion classification task for the six basic emotions (i.e., ANGER, FEAR, DISGUST, SADNESS, JOY) and for SURPRISE for the Bengali language. Kumar and Kumar (2021) evaluated XLM-R with zero-shot transfer learning from

An older review of the field can by found in the work of Mohammad (2016).
English to Indian on the Benchmark ‘SemEval 2017’ dataset Task 4 A’ Rosenthal et al. (2017), and proved that the model compares favorably to state-of-the-art approaches.

**Emotion detection for the Greek language**

Although there are a few published studies focusing on sentiment analysis in Greek (Markopoulos et al., 2015; Athanasiou and Maragoudakis, 2017), limited published work concerns emotion detection, probably due to the lack of publicly available resources. Fortunate exceptions are the work of (Krommyda et al., 2020) and the work of (Palogianidi et al., 2016). The authors of the former study suggested the use of emoji in order to assign emotions to a text, but they didn’t share their dataset while this approach is expected to work only with emoji-rich corpora. We also experimented with a dataset created with indicators of emotions, which we release for public use. The latter study created an affective lexicon, which can lead to efficient solutions, but not useful to train machine and deep learning algorithms, such as BERT (Koutsikakis et al., 2020) that achieve the state of the art nowadays. Alexandridis et al. (2021) was the first to experiment with two BERT-based models, trained on a Greek emotion dataset. This dataset can be used to train supervised learning solutions, but unfortunately it is not publicly available. Upon communication with one of the authors, part of their data are comprised in our dataset. To the best of the authors’ knowledge, this is the first work focusing on emotion detection for the Greek language, employing (monolingual and multilingual) deep learning solutions, while releasing the developed datasets to promote future research.

### 3 Dataset development

This section presents our new dataset, comprising tweets annotated regarding the emotion of the author. We discuss its three parts, the evaluation (PALO.ES), the training (PALO.GR), and the one used for augmentation (ART). Also, we discuss how we extended a well-known English emotion detection dataset, used to fine-tune PLMs first in English, with neutral tweets, in order to adjust to a setting where the majority of tweets is characterised by lack of emotion.

**The artificial ART dataset** was developed by retrieving Greek tweets for several emotions using the Tweepy.3 In order to retrieve tweets per emotion, we used target words that could have been selected by users under specific emotional states. For example, in order to collect tweets related to JOY, we searched for tweets that contain words such as ‘I am happy’. The exact words that were used to retrieve tweets for each emotion are presented in Table 1.4

The **evaluation PALO.ES dataset** comprises Greek tweets provided by Palo Services,5 each annotated by two professional annotators employed by the company. Each tweet was annotated regarding ten emotion classes, which are presented in Table 2. As a first step, we shared a small sample of one hundred tweets to estimate inter-annotator agreement, providing no specific instructions. Cohen’s Kappa was found to be as low as 0.29. In a second annotation round, we provided the annotators with the guidelines suggested by Moham-

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3https://www.tweepy.org/

4We note that not all words referring to a specific emotion lead to the retrieval of tweets comprising that emotion. For example, searching for ‘χαίρομαι’ (‘I am happy’), we received emotionless tweets, such as ‘Η χαρά είναι ένα συναισθήμα που πρέπει να εκφράζεται στον ίδιο βαθμό όπως και τα υπόλοιπα.’ (‘Happiness is an emotion that must be expressed to the same degree as the rest.’).

5http://www.paloservices.com/

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| Class       | Emotions                      |
|-------------|-------------------------------|
| ANGER       | anger, annoyance, rage        |
| ANTICIPATION| anticipation, interest, vigilance |
| DISGUST     | disgust, disinterest, dislike, loathing |
| FEAR        | fear, apprehension, anxiety, terror |
| JOY         | joy, serenity, ecstasy        |
| SADNESS     | sadness, pensiveness, grief   |
| SURPRISE    | surprise, distraction, amazement |
| TRUST       | trust, acceptance, liking, admiration |
| OTHER       | sarcasm, irony, or other emotion |
| NONE        | no emotion                    |
mad et al. (2018) and asked two questions per tweet. Our first question was: Which of the following options best describes the emotional state of the tweeter?, seeking for the primary emotion of the respective tweet. The second question was: Which of the following options further describes the emotional state of the tweeter? Select all that apply., now allowing more than one emotions to be assigned. Tweets were provided to the annotators as examples per emotion (more details can be found in Table 7 of Appendix A). Cohen’s Kappa improved to 0.36 for the primary emotions while Fleiss Kappa (Fleiss and Cohen, 1973) was found to be 0.26 for the multi-label annotation setting.

A manual investigation of the annotations revealed that disagreement was often on tweets comprising news or announcements. Attempting to alleviate a possible misunderstanding, we updated the annotation guidelines so that the annotators were guided to classify tweets with news or announcements to the NONE class (more details can be found in Table 8 of Appendix A). With the updated guideline we proceeded to the final annotation round by providing both annotators with the same batch of 999 tweets and filtering out tweets that the annotators disagreed on. Cohen’s Kappa improved to 0.51 (+15) and Fleiss Kappa improved to 0.44 (+18). We kept 786 out of 999 tweets that annotators agreed on at least one emotion, rejecting 146 tweets with no agreement and 68 tweets labeled with the emotion OTHER. Due to its size and guaranteed quality, we employ PALO.ES only for evaluation purposes.

**The training PALO.GR dataset** follows the same annotation process as with PALO.ES, but each professional annotator was now given 1,000 different tweets. Out of the 2,000 annotated tweets, we excluded 135 (6.8%) that were labelled as OTHER, leaving 1,865 tweets in total. In order to augment the under-represented positive emotion classes (i.e., ANTICIPATION, JOY, SURPRISE, TRUST), we provided our annotators with 543 more tweets, which had been classified as positive with prior annotation efforts by the company. This led to a total of 2,408 tweets.

**Using an existing English dataset** can assist as a prior step, by fine-tuning multilingual PLMs in emotion detection in English, before moving to a resource-lean language, such as Greek. Mohammad et al. (2018) introduced such a dataset for the 1st SemEval E-c Task, a multi-dimensional emotion detection dataset, which can be used to fine-tune (multilingual or monolingual) PLMs in emotion classification in English. We will refer to this dataset as SE.EN. The task of the challenge was defined as: “Given a tweet, classify it as ‘neutral or no emotion’ or as one, or more, of eleven given emotions that best represent the mental state of the tweeter”. The dataset consisted of 7,724 tweets with binary labels for each of the eight categories of Plutchik (1980): ANGER, FEAR, SADNESS, DISGUST, SURPRISE, TRUST, and JOY, which were expanded with OPTIMISM, PESSIMISM, LOVE, and with NONE for the neutral tweets. These categories are not mutually exclusive, i.e., a tweet may belong to one or more categories. For example, the tweet: ‘Don’t be afraid to start. Be afraid not to start. #happiness’, belongs to two classes: FEAR and JOY.

Neutral SE.EN tweets (in train and dev sets) were 218 (2.8%), which means that it is assumed that most often tweets do comprise emotions. Although this may be simply due to the sampling of the data, we find that this assumption is weak. Depending on the domain, most often it is the lack of emotion that characterises a tweet. Based on this observation, and in order to better represent the neutral class, we enriched SE.EN with 795 neutral tweets that were taken from the timeline of the British newspaper ‘The Telegraph’, and provided by the online community Kaggle.

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We will refer to this extended English dataset as SE+."

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**Table 3**: The relative frequency per emotion (columns 1-8), or their absence (column 9), along with the total number of tweets (last column) per dataset. In bold are the highest values per class.

| Dataset | ANGER | ANTIC | DISGUST | FEAR | JOY | SADNESS | SURPRISE | TRUST | NONE | TOTAL |
|---------|-------|-------|---------|------|-----|---------|----------|-------|------|-------|
| SE.EN   | 37.0  | 14.3  | 37.8    | 17.6 | 37.2| 29.4    | 5.1      | 5.2   | 2.8  | 7,724 |
| SE+     | 33.6  | 12.9  | 34.3    | 16.0 | 33.8| 26.7    | 4.6      | 4.7   | 11.9 | 8,519 |
| ART     | 12.9  | 12.9  | 12.9    | 12.9 | 12.9| 10.9    | 11.7     | 12.9  | 7,753|
| PALO.GR | 9.8   | 9.8   | 24.2    | 0.7  | 16.2| 6.2     | 21.6     | 46.2  | 2,408|
| PALO.ES | 10.8  | 2.8   | 31.7    | 0.5  | 1.8 | 0.6     | 1.4      | 2.2   | 60.6 | 786  |

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6https://competitions.codalab.org/competitions/17751
7https://www.telegraph.co.uk/
8https://www.kaggle.com/
9Preliminary experiments with the dataset of Demszy et al. (2020) showed that it wasn’t beneficial.
The class support of all the datasets is presented in Table 3. SE+ has the highest total support and the highest percentage of the categories ANGER, ANTICIPATION, DISGUST, FEAR, JOY and SADNESS compared to the other datasets. The distribution of the support for the ART dataset is spread. For the PALO.GR and PALO.ES datasets a high percentage for the category DISGUST and especially for the category NONE. By adding more neutral tweets to SE.EN, the support for NONE increased from 2.8% to 11.9%, almost reaching that of ART (12.9%).

4 Empirical analysis

We preprocessed the tweets of all the datasets by removing all URLs and usernames (e.g., @Papadopoulos) while tokenisation was undertaken with respect to each model’s properties. We trained our systems in order to classify the tweet into one or more of the eight former emotion categories of Table 4, excluding NONE. The score for the NONE class was calculated as the complementary of the maximum probability of the other eight categories. In other words, if the maximum emotion score was lower than 0.5, the NONE class was assigned.

From emotions to subjectivity and sentiment

In order to study not only the emotions but also the sentiment of the tweets, we aggregated ANGER, FEAR, SADNESS, DISGUST into a ‘NEGATIVE’ sentiment category (in red in Fig. 1). TRUST and JOY were aggregated into a ‘POSITIVE’ category (in green in Fig. 1). The rest were considered as belonging to a ‘NEUTRAL’ category. ANTICIPATION and SURPRISE were not considered neither as POSITIVE nor as NEGATIVE, because we find that the sentiment that they express is ambiguous. To model subjectivity, we used the NONE emotion class, linking low NONE scores to the subjective class and high scores to the objective.

Opted evaluation measure

For evaluation, we report the Area Under Precision-Recall Curves (AUPRC) per emotion, sentiment and subjectivity category, which was preferred due to the highly imbalanced nature of our dataset.\(^\text{10}\)

4.1 Machine and deep learning benchmarks

We used six Transformer-based models, using one PLM pre-trained on multiple languages and one that was pre-trained on Greek. As a simpler baseline, we opted for Random Forests (RF:\(\text{PALO})).\(^\text{11}\) XLM-R (Conneau et al., 2019) is a Transformer-based multilingual PLM which leads to state-of-the-art performance on several NLP tasks, especially for low-resource languages. For our task, we added a fully-connected layer on top of the pre-trained XLM-R model. We fed the pre-trained model with vectors that represent the tokenised sentences, and subsequently, the pre-trained model fed the dense layer with its output, i.e., the context-aware embedding (length of 768) of the [CLS] token of each sentence. The number of nodes in the output layer is the same as the number of classes (eight). Figure 2 illustrates the architecture of the system. We fine-tuned the multilingual XLM-R first on the English SE+ and then we further fine-tuned it on the Greek ART and PALO.GR datasets, yielding two models: \(\text{X:ART}\) and \(\text{X:PALO}\) respectively. We also experimented with merged \(\text{ART}\) and \(\text{PALO.GR}\), yielding \(\text{X:ART+PALO}\). To assess the benefits of using an English dataset as a prior step, we fine-tuned XLM-R directly on \(\text{PALO.GR}\), without any fine-tuning on SE+, which yielded \(\text{X:NOPE}\). and we also tried zero-shot learning by training the model only on SE+, yielding to \(\text{X:ZERO}\).

GreekBERT was introduced by Koutsikakis et al. (2020) and it is a monolingual Transformer-based PLM for the modern Greek language. The architecture of the model is similar with XLM-R, as can be seen in Figure 2.\(^\text{12}\) We fine-tuned GreekBERT on \(\text{PALO.GR}\), which led to the BERT:PALO

\(^{10}\) AUPR captures the tradeoff between precision and recall for different thresholds.

\(^{11}\) We used TFIDF and default parameters of: https://scikit-learn.org/stable/.

\(^{12}\) We used: https://huggingface.co/.
We used as our evaluation set the high quality Appendix B (Table 9). This means that using an English dataset as a prior step, assisted in the detection of the subjective emotions. In specific, X:PALO was the best for positive and BERT:PALO for negative ones.

### Zero-shot classification

Considering its zero-shot learning, X:ZERO achieved considerably high scores in DISGUST and NONE (0.82 and 0.92 respectively), also scoring high in JOY. More generally for positive emotions, it scored only three units lower from the best performing X:PALO. X:ZERO also outperformed X:ART, which had the worst results. The low performance of X:ART indicates that retrieving data based on keywords may not be the right way to build a training dataset, when the evaluation dataset is sampled otherwise. On the other hand, combined with other datasets it can lead to improvements, as for example X:ART+PALO that outperforms both X:ART and X:PALO for the emotion classification task, and especially for subjective emotions.

### Emotion classification averaged across systems

Figure 3 presents the average (across systems) AUPRC score of all eight systems in emotion (in purple), sentiment (light green), subjectivity (dark green) classification.

Figure 3: Average AUPRC score of all eight systems in emotion (in purple), sentiment (light green), subjectivity (dark green) classification.

Table 4 presents the AUPRC per emotion and macro-average across all emotions (last column). The average across three restarts is shown per model. Experimental details for all our models are shared in Appendix B.

### 4.2 Experimental Results

We used as our evaluation set the high quality PALO.es dataset and we present the results in emotion, sentiment and subjectivity classification.

### Emotion classification

Table 4 presents the AUPRC (average across three restarts) of all eight models, per class and overall, for the task of emotion classification. The standard error of mean is also calculated and shared in Appendix B (Table 9). X:ART+PALO was the best overall, achieving the best performance in ANGER, FEAR, SADNESS and NONE. X:PALO followed closely, with best performance in ANTICIPATION, JOY, SURPRISE, TRUST and (shared) in NONE.

### Sentiment and subjectivity classification

Table 5 presents the AUPRC for the task of sentiment and subjectivity detection. X:ART+PALO, X:PALO and BERT:PALO perform equally high in subjectivity (0.98). These models were also top performing for the neutral sentiment and the objective class, along with the X:NOPE model, which did not use fine-tuning in English as a prior step. This means that using an English dataset as a prior fine-tuning step, assisted in the detection of the

Table: Emotion classification AUPRC per emotion and macro-average across all emotions (last column). The average across three restarts is shown per model.

| Emotion        | ANGER | ANTIC. | DISGUST | FEAR | JOY | SADNESS | SURPRISE | TRUST | NONE | AVG |
|----------------|-------|--------|---------|------|-----|---------|----------|-------|------|-----|
| X:ZERO         | 0.38  | 0.12   | 0.82    | 0.03 | 0.49| 0.10    | 0.07     | 0.18  | 0.92 | 0.35|
| X:ART          | 0.33  | 0.13   | 0.68    | 0.07 | 0.31| 0.07    | 0.05     | 0.10  | 0.89 | 0.29|
| X:ART+PALO     | 0.51  | 0.43   | 0.94    | 0.15 | 0.50| 0.19    | 0.06     | 0.25  | 0.99 | 0.45|
| X:PALO         | 0.46  | 0.50   | 0.93    | 0.09 | 0.54| 0.09    | 0.02     | 0.28  | 0.99 | 0.44|
| X:NOPE         | 0.43  | 0.19   | 0.90    | 0.03 | 0.48| 0.03    | 0.03     | 0.20  | 0.98 | 0.37|
| BERT:PALO      | 0.49  | 0.31   | 0.95    | 0.03 | 0.45| 0.03    | 0.03     | 0.24  | 0.98 | 0.39|
| RF:PALO        | 0.34  | 0.14   | 0.81    | 0.30 | 0.15| 0.03    | 0.03     | 0.10  | 0.93 | 0.28|

Table 5: AUPRC in sentiment and subjectivity classification, using our eight emotion classifiers (the average across three restarts is shown). The two macro average scores are shown on the right of each task.

| Sentiment | Subjectivity | | |
|-----------|--------------|-------------|-----------|-------------|-----------|-------------|-----------|
| neg | pos | neu | | subj | obj | AVG |
| X:ZERO | 0.84 | 0.40 | 0.93 | | 0.72 | 0.80 | 0.93 | 0.86 |
| X:ART | 0.69 | 0.18 | 0.90 | | 0.59 | 0.72 | 0.90 | 0.81 |
| X:ART+PALO | 0.95 | 0.41 | 0.99 | | 0.74 | 0.97 | 0.99 | 0.98 |
| X:PALO | 0.95 | 0.44 | 0.99 | | 0.79 | 0.96 | 0.99 | 0.98 |
| X:NOPE | 0.93 | 0.39 | 0.99 | | 0.77 | 0.95 | 0.99 | 0.97 |
| BERT:PALO | 0.96 | 0.39 | 0.99 | | 0.78 | 0.97 | 0.99 | 0.98 |
| RF:PALO | 0.84 | 0.17 | 0.95 | | 0.68 | 0.87 | 0.95 | 0.91 |
5 Detecting emotions in political speech

We mechanically annotated and studied the emotion in the textual records of the Greek Parliament. We focused on the DISGUST emotion, which is the emotion that our classifiers capture best (see Figure 3). We opted for detecting a single emotion, instead of sentiment or subjectivity, because the latter could be linked to multiple emotions and hence provide us with an inaccurate signal. For example, ‘fear’ and ‘anger’ are both negative, but the pessimistic view of the former differs from the optimistic view of the latter (Seyeditabari et al., 2018). Such subtle differences, however, should not be ignored in our socio-political study (Ahmad et al., 2020), where we: (a) explore the emotion evolution in political speech, (b) utilise its presence to compare Greek political parties, (c) explore the context of terms used to stigmatise people (Rose et al., 2007).

The Greek Parliament Corpus, which we used to undertake this study, comprises 1,280,918 speeches of Greek Parliament members from 1989 to 2020, which were split into 9,096,021 sentences (with average word length of 19) for the purposes of our research. Preliminary experiments with our top three emotion classifiers, X:PALO, BERT:PALO, X:ART+PALO, showed that the first performs best. Hence, we used X:PALO to perform the emotion/sentiment analysis that we discuss next.

Figure 4 illustrates the detected DISGUST emotion, monthly averaged, with the highest values (i.e., months) highlighted. A probability score was computed for each sentence of the Greek Parliament records, by employing the DISGUST emotion head of our X:PALO model (the model selection process is discussed in Appendix C). Then, we macro-averaged the computed scores per month. The highest DISGUST score was observed between 1991 and 1993 (i.e., September 1991, April 1992, April 1993, August 1993) in 2000 (i.e., January 2000, March 2000), in 2015 (i.e., November 2015, April 2015) and in 2019 (i.e., January 2019, May 2019). By investigating the main events of each of these months, we find that there is at least one event per month that could potentially rationalize these high scores (more information about the selected events and some examples of text may be found in Table 11 and Table 12 in Appendix C).

5.1 ‘Disgust’ evolution in political speech

By computing the average DISGUST score per party, we were able to compare all political parties, as depicted in Figure ?? . We observe that the score is relatively high for the top two rows, which correspond to the far right wing. The Democratic Social Movement and the Communist Party of Greece follow closely. On the lower end of the diagram are the Opposition and the Parliament. Opposition consists of one or more political parties that are opposed, primarily ideologically, to the government, party or group in political control of the country. Parliament is simply the coordinator of the speakers in the Parliament. Both these two are characterised by lack of any emotion, which can be explained by the template sentences that they use in their speeches. For example, the most common sentence of the Parliament is ‘Μάλιστα, μάλιστα’ (translated as: ‘Affirmative, affirmative’). Correspondingly, a common sentence of Opposition is the ‘Κατά πλειοψηφία’ (translated as: ‘By majority.’). However, the DISGUST of Opposition is higher than that of Parliament, most probably because the former also comprises sentences that could express DISGUST, such as: ‘Αίσχος, αίσχος’ (translated as: ‘Disgrace, disgrace’)

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13 https://doi.org/10.5281/zenodo.2587904
## Political Party Score

| Political Party                        | Score |
|---------------------------------------|-------|
| Golden Dawn                           | 33%   |
| Greek Solution                        | 28.6% |
| Democratic Social Movement            | 28.3% |
| Communist Party of Greece             | 26.4% |
| Alternative Ecologists                 | 25.2% |
| Political Spring                      | 24.6% |
| Independent (out of party)            | 24.5% |
| Independent Democratic MPs            | 23.8% |
| Center union                          | 23.5% |
| Democratic Alliance                   | 21.6% |
| Coalition of the Radical Left         | 21.5% |
| Coalition of the Left, of Movements and Ecology | 20.7% |
| European Realist Disobedience Front   | 20.7% |
| Independent Greeks                    | 20.6% |
| New Democracy                         | 19.6% |
| Patriotic Alliance                    | 19.2% |
| The River                             | 19%   |
| Polpular Unity                        | 19%   |
| Movement for Change                   | 18.5% |
| Panhellenic Socialist Movement         | 17.4% |
| Democratic Left                       | 17.2% |
| Democratic Renewal                    | 15.3% |
| Extra Parliamentary                   | 14%   |
| Popular Orthodox Rally                | 13.3% |
| Opposition                            | 6.3%  |
| Parliament                            | 0.3%  |

Table 6: Average DISGUST score per political party. The color intensity reflects the score.

### 5.3 Evolution of ‘disgust’ for target terms

Studying language evolution can reflect changes in the political and social sphere (Montariol et al., 2021), changes whose importance increases when they regard language used to stigmatise people. Rose et al. (2007) presented 250 labels used to stigmatise people with medical illness in school. In this work, we (a) explore the frequency of some of these terms in the parliamentary records, and (b) utilise emotion classification to investigate the evolution of the negative context they may appear in over time. Although static word embeddings (yet with multiple spaces) can be used to capture semantic shift and word usage change (Levy et al., 2015; Gonen et al., 2020), as well as contextual embeddings to detect global context shifts (Kellert and Zaman, 2022), we argue that emotional context shifts also apply and that emotion classifiers can unlock their use to the study of language evolution.

We employed the words ‘handicapped’ (ανάπηρος), ‘disability’ (ειδικές ανάγκες) and ‘crazy’ (τρελός), retrieving sentences comprising them from the Greek parliament corpus. We then sliced our corpus as in (Gonen et al., 2020), focusing on three periods: from 1989 to 2000, from 2001 to 2010, and from 2011 to 2020. From each decade we sampled 100 sentences, each of which was scored with X:PALO regarding the DISGUST emotion, in order to report the average DISGUST score per decade. These are words that describe specific conditions, hence we hypothesise that use in a negative emotional context indicates stigmatised use and we are looking for an increased score over time. Statistical significance of the differences is computed with bootstrapping.\(^\text{16}\)

**Control groups** were created with the words ‘bad’ and ‘good’, repeating the same study, as well as with words related to politics whose usage could also be linked to stigma. One group comprised ‘racism’ and ‘illegal immigrant’ while the other comprised the words ‘communism’, ‘capitalism’, ‘left’ and ‘right’. The support of all the selected words is shared in the Appendix (Table 6).\(^\text{17}\)

The results are shown in Figure 5. The words ‘handicapped’ and ‘disability’ show a statistically significant increase during the last decade. From our control groups, only the words ‘left’ and ‘illegal immigrant’ followed the same pattern.\(^\text{18}\)

### 6 Conclusion

This study presented three new datasets for emotion classification in Greek, which we release for public use. We benchmarked seven state of the art baselines that were based on machine, deep and transfer learning, and we showed that the performance for the emotion of ‘disgust’ was comparable...
to that of sentiment and subjectivity detection. By using a model to score sentences from the Greek Parliament records, we detected months where the ‘disgust’ emotion was generally high and we undertook a comparative analysis of the Greek political parties. Finally, we presented a way to use emotion classification in order to analyse the emotion evolution of a word’s context, providing proof that two words describing a medical condition, are increasingly used in a negative emotional context in the Parliament, which may be alarming and should be further analysed in the future.

References
Francisca Adoma Acheampong, Chen Wenyu, and Henry Nunoo-Mensah. 2020. Text-based emotion detection: Advances, challenges, and opportunities. Engineering Reports, 2(7):e12189.

Zishan Ahmad, Raghav Jindal, Asif Ekbal, and Pushpak Bhattacharyya. 2020. Borrow from rich cousin: transfer learning for emotion detection using cross lingual embedding. Expert Systems with Applications, 139:112851.

Georgios Alexandridis, Konstantinos Korovesis, Iraklis Varlamis, Panagiotti Tsantilas, and George Caridakis. 2021. Emotion detection on greek social media using bidirectional encoder representations from transformers. In 25th Pan-Hellenic Conference on Informatics, pages 28–32.

Vasileios Athanasiou and Manolis Maragoudakis. 2017. A novel, gradient boosting framework for sentiment analysis in languages where nlp resources are not plentiful: A case study for modern greek. Algorithms, 10:34.

Richard P. Bagozzi, Mahesh Gopinath, and Prashanth U. Nyer. 1999. The role of emotions in marketing. volume 27.

Scott Brave and Clifford Nass. 2002. Emotion in human–computer interaction. The Human–Computer Interaction Handbook: Fundamentals, Evolving Technologies and Emerging Applications.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Unsupervised cross-lingual representation learning at scale. arXiv preprint arXiv:1911.02116.

Avishek Das, Omar Sharif, Mohammed Moshiiel Hoque, and Iqbal H. Sarker. 2021. Emotion classification in a resource constrained language using transformer-based approach.

Dorottya Demszky, Dana Movshovitz-Attias, Jeong-woo Ko, Alan Cowen, Gaurav Nemade, and Sujith Ravi. 2020. Goemotions: A dataset of fine-grained emotions.

Shrey Desai, Cornelia Caragea, and Junyi Jessy Li. 2020. Detecting perceived emotions in hurricane disasters.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

J. L. Fleiss and J. Cohen. 1973. The equivalence of weighted kappa and the intraclass correlation coefficient as measures of reliability. In Educational and Psychological Measurement, page 613–619, New Orleans, Louisiana.

Bharat Gaind. 2019. Emotion detection and analysis on social media 1.

Hila Gonen, Ganesh Jawahar, Djamé Seddah, and Yoav Goldberg. 2020. Simple, interpretable and stable method for detecting words with usage change across corpora. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 538–555, Online. Association for Computational Linguistics.

Michael A. Hedderich, David Adelani, Dawei Zhu, Jesujoba Alabi, Udia Markus, and Dietrich Klakow. 2020. Transfer learning and distant supervision for multilingual transformer models: A study on african languages.

Md Yasin Kabir and Sanjay Madria. 2021. Emocov: Machine learning for emotion detection, analysis and visualization using covid-19 tweets. Online Social Networks and Media, 23:100135.

Neel Kant, Raul Puri, Nikolai Yakovenko, and Bryan Catanzaro. 2018. Practical text classification with large pre-trained language models.

Olga Kellert and Md Mahmud Uz Zaman. 2022. Using neural topic models to track context shifts of words: a case study of covid-related terms before and after the lockdown in april 2020. In Proceedings of the 3rd Workshop on Computational Approaches to Historical Language Change, pages 131–139.

John Koutsikakis, Ilias Chalkidis, Prodromos Malakasiotis, and Ion Androustopoulos. 2020. Greek-bert: The greeks visiting sesame street. 11th Hellenic Conference on Artificial Intelligence.

Maria Krommyda, Anastasios Rigos, Kostas Bouklas, and Angelos Amidis. 2020. Emotion detection in twitter posts: a rule-based algorithm for annotated data acquisition. In 2020 International Conference on Computational Science and Computational Intelligence (CSCI), pages 257–262. IEEE.

Pedamuthevi Kiran Kumar and Ishan Kumar. 2021. Emotion detection and sentiment analysis of text.
Anne Lauscher, Vinit Ravishankar, Ivan Vulić, and Goran Glavaš. 2020. From zero to hero: On the limitations of zero-shot cross-lingual transfer with multilingual transformers.

Omer Levy, Yoav Goldberg, and Ido Dagan. 2015. Improving distributional similarity with lessons learned from word embeddings. Transactions of the Association for Computational Linguistics, 3:211–225.

George Markopoulos, George Mikros, Anastasia Iliadi, and Michalis Linton. 2015. Sentiment analysis of hotel reviews in greek: A comparison of unigram features. 9:373–383.

Saif Mohammad, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. 2018. SemEval-2018 task 1: Affect in tweets. In Proceedings of The 12th International Workshop on Semantic Evaluation, pages 1–17, New Orleans, Louisiana. Association for Computational Linguistics.

Saif M Mohammad. 2016. Sentiment analysis: Detecting valence, emotions, and other affectual states from text. In Emotion measurement, pages 201–237. Elsevier.

Saif M Mohammad, Xiaodan Zhu, Svetlana Kiritchenko, and Joel Martin. 2015. Sentiment, emotion, purpose, and style in electoral tweets. Information Processing & Management, 51(4):480–499.

Syrille Montariol, Matej Martinc, Lidia Pivovarova, et al. 2021. Scalable and interpretable semantic change detection. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics Human Language Technologies. The Association for Computational Linguistics.

Laura Ana Maria Oberländer and Roman Klinger. 2018. An analysis of annotated corpora for emotion classification in text. In Proceedings of the 27th International Conference on Computational Linguistics, pages 2104–2119.

Elisavet Palogiannidi, Polychronis Koutsakis, E Losif, and Alexandros Potamianos. 2016. Affective lexicon creation for the greek language.

Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is multilingual bert?

Robert Plutchik. 1980. A general psychoevolutionary theory of emotion. In Theories of emotion.

Tharindu Ranasinghe and Marcos Zampieri. 2020. Multilingual offensive language identification with cross-lingual embeddings.

Diana Rose, Graham Thornicroft, Vanessa Pinfold, and Aliya Kassam. 2007. 250 labels used to stigmatise people with mental illness. BMC health services research, 7(1):1–7.

Sara Rosenthal, Noura Farra, and Preslav Nakov. 2017. SemEval-2017 task 4: Sentiment analysis in Twitter. In Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017), pages 502–518, Vancouver, Canada. Association for Computational Linguistics.

Kashfia Sailunaz, Manmeet Dhaliwal, Jon Rokne, and Reda Alhajj. 2018. Emotion detection from text and speech: a survey. Social Network Analysis and Mining, 8(1):1–26.

Armin Seyeditabari, Narges Tabari, and Wlodek Zadrozny. 2018. Emotion detection in text: a review. arXiv preprint arXiv:1806.00674.

Abrahalei Tela, Abraham Woubie, and Ville Hautamaki. 2020. Transferring monolingual model to low-resource language: The case of tigrinya.

Ashish Vaswani, Noam Shazeer, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. Advances in neural information processing systems, 32.

Appendix

A Annotation

The examples shown to the annotators of our dataset (PALO.ES and PALO.GR), addressing the question: Which of the following options best describes the emotional state of the tweeter?, are shown in Table 7.

The guidelines were updated with the note and the example of Table 8, for the final annotation of PALO.ES and PALO.GR parts.

B Experimental details

GreekBERT and XLM-R were trained for 30 epochs with early stopping, patience of 3 epochs, batch size 16, learning rate 1e-5 for XLM-R and 5e-5 for GreekBERT, monitoring the validation loss, maximum length of 109 for XLM-R and 85 for GreekBERT.

C Emotion detection in political speech

Model selection

We manually evaluated our 3 best performing emotion detectors, vis. X:PALO, BERT:PALO, X:ART+PALO, on a small dataset, consisting of sentences that were randomly sampled from the
anger (also includes annoyance, rage)  
<e> “En ti mpeto llaa thn ena kera pistiki tis Politeias. Tis Synodeugia ta skoletika ton me to tinon. Eide to kera katoa Synodeugia. Xara xara gia mna na mia mna tin na gia...” #SYRIZA #ΔΗΛΩΣΗ #AΠΟΚΛΕΙΣΤΙΚΟ!

anticipation (also includes interest, vigilance)  
<e> “Ελέγξε να καταγράψει να αναξίωσε ποιοτικά το νευρικά μας εμπόδιο έτοιμο στο νεουρικό.”

disgust (also includes dislike, distaste, loathing)  
<e> “Παλαια μα συνήλθα μακριά από FORTHNET γιατί από αυτό θα εικονιζόταν σε ένα νοσοκομείο.”

Tear (also includes apprehension, anxiety, terror)  
<e> “Φόβος πως της επόμενη χώρα της πανδημίας στη γύρω οικογένεια από ό,τι έπαιζε. Τι φθόνος τα πράγματα ήταν σχεδόν βίαια από την επανάσταση σε ένα νόσο ενός.”

joy (also includes serenity, ecstasy)  
<e> “Αυτή της χώρα μου θα γίνει λαϊκός πλάγιος ΕΠΙΠΕΔΟΥΣ το Νετφλιξ. Θα μπορούσε εγκατασταθεί σε Όλο και Ολο.”

sadness (also includes pensive, grief)  
<e> “Με λύπη μου σε αυτούς που αποκλείονται από την αποκατάσταση της μισρά και να περιμένετε μια βιομηχανία!!!”

surprise (also includes distraction, amazement)  
<e> “Προηγούμενα εφαρμογή Netflix διέσχισε την Σάββατο Κυριακό”

trust (also includes acceptance, liking, admiration)  
<e> “Τι άρέσει ημέρας σε ξένες; @cosmote Το κύριο τηλεφωνικό επικεφαλής Νετφλιξ από την κατακτήσεις της για τον Μεταξιούς έχετε τεχνική βλάβη ούτε άκρη θα βρείτε Σάββατο Κυριακό.”

#cyprus #cyta @anastasiades_cy #ΜΕΝΟΜΕΝΟΜΕΝΟ #StavAtHome

Table 7: The options and the corresponding examples from the guidelines during the annotation for the development of our dataset.

Table 11 presents events that potentially rationalise the highest DISGUST scores in the respective months. These are September of 1991, April of 1992, April of 1993, August of 1993, January of 2000, March of 2000, November of 2015, 21992, 2019, 222019.

Greeks Parliament Corpus. X:PALO was found to perform slightly better in this sample, hence it was preferred over X:ART+PALO (one unit higher in AUPRC in DISGUST; see Table 4) for this study.

Events potentially responsible for ‘disgust’

Table 11 presents events that potentially rationalise the highest DISGUST scores in the respective months. These are September of 1991, April of 1992, April of 1993, August of 1993, January of 2000, March of 2000, November of 2015.

Table 8: Note and example added to the annotation guidelines during the development of the PALO.ES dataset.

April of 2015, January of 2019, and May of 2019.

Emotional context shift

The support of the selected terms is shown in Figure 6, where we can see that the usage of half of them (i.e., ‘capitalism’, ‘left’, ‘right’, ‘racism’, ‘illegal immigrant’) is increased in the last decade.

The P-values of the target terms are shown in Table 13. Besides the two words that are being used to stigmatise people with medical illness (top three rows), we observe that the context of the terms LEFT and ILLEGAL IMMIGRANT is also being shifted towards a more negative emotional state.
| Emotion | anger | antic. | disgust | fear | joy | sadness | surprise | trust | none | AVG |
|---------|-------|--------|---------|------|-----|---------|---------|-------|------|-----|
| X: ZERO | 0.34 (0.01) | 0.13 (0.01) | 0.48 (0.04) | 0.07 (0.01) | 0.31 (0.04) | 0.09 (0.01) | 0.05 (0.01) | 0.10 (0.01) | 0.89 (0.04) | 0.39 |
| X: ART  | 0.31 (0.06) | 0.15 (0.00) | 0.53 (0.04) | 0.13 (0.01) | 0.19 (0.04) | 0.19 (0.04) | 0.06 (0.01) | 0.25 (0.01) | 0.99 (0.00) | 0.45 |
| X: ART+PALO | 0.48 (0.01) | 0.19 (0.01) | 0.90 (0.00) | 0.03 (0.01) | 0.48 (0.03) | 0.04 (0.01) | 0.03 (0.01) | 0.20 (0.01) | 0.98 (0.00) | 0.44 |
| X: NOPE | 0.43 (0.00) | 0.02 (0.01) | 0.39 (0.05) | 0.03 (0.02) | 0.45 (0.09) | 0.03 (0.01) | 0.03 (0.01) | 0.24 (0.00) | 0.98 (0.00) | 0.37 |
| BERT:PALO | 0.40 (0.02) | 0.01 (0.02) | 0.36 (0.05) | 0.05 (0.02) | 0.13 (0.02) | 0.12 (0.01) | 0.01 (0.01) | 0.10 (0.01) | 0.95 (0.06) | 0.38 |
| RF: PALO | 0.34 (0.01) | 0.14 (0.02) | 0.31 (0.01) | 0.05 (0.01) | 0.13 (0.02) | 0.02 (0.00) | 0.01 (0.01) | 0.10 (0.01) | 0.95 (0.06) | 0.38 |

Table 9: AUPRC (average across three repetitions) of emotion classifiers with the standard error of the mean (SEM) in the brackets.

| Sentiment | neg | pos | neu | AVG | Subjectivity | subj | obj | AVG |
|-----------|-----|-----|-----|-----|-------------|------|-----|-----|
| X: ZERO   | 0.84 (0.01) | 0.40 (0.02) | 0.93 (0.01) | 0.72 | 0.80 (0.02) | 0.93 (0.01) | 0.86 |
| X: ART    | 0.69 (0.03) | 0.18 (0.03) | 0.90 (0.01) | 0.59 | 0.72 (0.03) | 0.90 (0.01) | 0.81 |
| X: ART+PALO | 0.95 (0.00) | 0.41 (0.00) | 0.99 (0.00) | 0.78 | 0.97 (0.00) | 0.99 (0.00) | 0.98 |
| X: PALO   | 0.95 (0.00) | 0.43 (0.02) | 0.99 (0.00) | 0.79 | 0.96 (0.00) | 0.99 (0.00) | 0.98 |
| X: NOPE   | 0.93 (0.00) | 0.39 (0.02) | 0.99 (0.00) | 0.77 | 0.95 (0.01) | 0.99 (0.01) | 0.97 |
| BERT:PALO | 0.96 (0.00) | 0.39 (0.06) | 0.99 (0.00) | 0.78 | 0.97 (0.00) | 0.99 (0.00) | 0.98 |
| RF: PALO  | 0.84 (0.01) | 0.17 (0.01) | 0.95 (0.00) | 0.65 | 0.87 (0.01) | 0.95 (0.00) | 0.91 |

Table 10: AUPRC (average across three runs) of sentiment and subjectivity classifiers with the standard error of the mean (SEM) in the brackets.

| Date    | Event                                                                                                                                 |
|---------|----------------------------------------------------------------------------------------------------------------------------------------|
| 1991, Sep | Bill of the Minister of Education Vassilis Kontogiannopoulos brought reactions.                                                        |
| 1992, Apr | Meeting of political leaders; Macedonian issue.                                                                                         |
| 1993, Apr | FYROM officially becomes a member of the UN.                                                                                           |
| 1993, Aug | Quarrels leading to the fall of the government.                                                                                       |
| 2000, Jan | Finalization of the drachma exchange rate against the euro.                                                                           |
| 2000, Mar | Elections New Democracy succeeds Panhellenic Socialist Movement.                                                                      |
| 2015, Nov | The Greek Prime Minister visits the Turkish Prime Minister.                                                                           |
| 2015, Apr | The Greek Prime Minister visits the Russian Prime Minister.                                                                          |
| 2019, Jan | Macedonian Issue.                                                                                                                     |
| 2019, May | Loss in European elections leads to a call for early parliamentary elections.                                                        |

Table 11: The months with the higher values of DISGUST, potentially rationalised by the shown events.
Table 12: Parliamentary texts classified as DISGUST, selected from the 10 highest-scored months.
| Target Term    | P-value |
|---------------|---------|
| HANDICAPPED   | **0.027** |
| DISABILITY    | **0.026** |
| CRAZY         | 0.134   |
| COMMUNISM     | 0.328   |
| CAPITALISM    | 0.437   |
| LEFT          | **0.046** |
| RIGHT         | 0.404   |
| RACISM        | 0.227   |
| ILLEGAL IMMIGRANT | **0.019** |
| GOOD/BAD      | 0.209   |

Table 13: The target terms with their corresponding p-values. On the top are terms used to stigmatise people and lower are two control groups. In bold are values lower than 0.05.