USING EMOTION EMBEDDINGS TO TRANSFER KNOWLEDGE BETWEEN EMOTIONS, LANGUAGES, AND ANNOTATION FORMATS

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ABSTRACT

The need for emotional inference from text continues to diversify as more and more disciplines integrate emotions into their theories and applications. These needs include inferring different emotion types, handling multiple languages, and different annotation formats. A shared model between different configurations would enable the sharing of knowledge and a decrease in training costs, and would simplify the process of deploying emotion recognition models in novel environments. In this work, we study how we can build a single model that can transition between these different configurations by leveraging multilingual models and Demux, a transformer-based model whose input includes the emotions of interest, enabling us to dynamically change the emotions predicted by the model. Demux also produces emotion embeddings, and performing operations on them allows us to transition to clusters of emotions by pooling the embeddings of each cluster. We show that Demux can simultaneously transfer knowledge in a zero-shot manner to a new language, to a novel annotation format and to unseen emotions. Code is available at https://github.com/gchochla/Demux-MEmo.\textsuperscript{1}

Index Terms— Multilingual emotion recognition, Zero-shot, Emotion clusters

1. INTRODUCTION

Human experience is permeated by emotions. They can guide our attention and influence our information consumption, beliefs, and our interactions \cite{10, 26}. Deep learning has enabled us to extract affective constructs from natural language \cite{7, 5}, allowing emotion recognition from text at scale \cite{13}. Nevertheless, the need for better performance across various metrics of interest still exists.

When inferring emotions from text, earlier approaches have utilized emotion lexicons \cite{21}. These struggle in more realistic settings, because, for example, they do not handle context, like negation. On the other hand, while modern efforts relying on deep learning achieve better performance \cite{7, 3}, these data-driven models have to contend with a multitude of biases, such as annotation biases in the data used to train the models.

The needs for emotional inference from text have also diversified. First, the domain of interest can vary greatly between applications, ranging from everyday dialogues \cite{17} to tweets \cite{19}. Secondly, it is desirable for the models to be able to handle multiple languages \cite{19}, such as when studying perceptions and reactions to international news stories. Finally, the emotions of interest can differ between applications, and perhaps even the annotation scheme might not be similar. For example, in this work, we analyzed tweets annotated for clusters of emotions, where emotions that co-occur frequently were grouped, in contrast to single emotions in other settings. Hence, transfer learning is hindered by the mismatch.

In this work, our main goal is to achieve transfer of emotion recognition between annotation formats, emotions and languages. Our experimental design examines this step-by-step. First, we leverage pretrained multilingual language models \cite{2, 9} to enable knowledge transfer between languages. We also use and extend Demux \cite{7}, a model that incorporates the labels in its input space to achieve the final classification. Emotions are then embedded in the same space as the language tokens. Emotion word embeddings can facilitate transfer between emotions, as shown in \cite{7}, so we study whether this can also be achieved in a zero-shot manner. Lastly, we examine how an extension of Demux to clusters can transfer knowledge between different annotation formats by directly performing operations on label embeddings \cite{18}. Our contributions include the following:

- We show that multilingual emotion recognition models can be competitive with or even outperform monolingual baselines, and that knowledge can be transferred to new languages.
- We demonstrate that Demux can inherently transfer knowledge to emotions it has not been trained with.
- We illustrate that operations on the contextual emotion embeddings of Demux can successfully achieve transfer to novel annotation formats in a zero-shot manner. To the best of our knowledge, we are the first to study this setting.
- We show that Demux can be critical for flexible emotion recognition in a dynamic environment with ever-changing inference needs, such as the addition and subtraction of emotion types, changes in language, and alterations in the annotation format, e.g., the clustering of different emotions.

2. RELATED WORK

2.1. Emotion Recognition

Earlier works utilized Bag-of-Words algorithms driven by emotion lexicons. For instance, LIWC \cite{21} is a lexicon that is widely used to perform word counting, while DDR \cite{12} extends lexicon-based methods from word counting to computing similarities between words. More recently, deep learning has enabled more accurate extraction of emotion signals from text. Initial efforts have treated the task as single-label, and use a threshold to transform into the desired multi-label output \cite{15}. LSTMs have been widely used for the task \cite{11, 3} e.g., for SemEval 2018 Task 1 \cite{19}, where some also

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used features from affective lexicons. More recently, Transformers [25] have dominated the field. Demux and MEMO [7], state of the art models in SemEval 2018 Task 1 E-c, prompt BERT-based [9] models in different ways, by including all emotions in the input or [MASK] tokens in language prompts, respectively. They also employ an intra-group correlation loss to further improve performance. Transformers have also been used with other architectures [27].

2.2. Multilingual Models & Emotion Recognition

Multilingual transformers attempt to model many languages simultaneously. Normalized sampling from each language is used so that low-resource languages are not severely hindered, which we also adopt. This is achieved, given $\alpha \in [0, 1]$, by transforming the frequency $p_l$ of each language as $p_l' \leftarrow p_l^\alpha$ and renormalizing to create the new sampling distribution [16]. Note that as $\alpha$ decreases, the distribution becomes more balanced, achieving parity at $\alpha = 0$.

BERT [9] and XLM [16] require preprocessing of languages that do not use spaces to delimit words. Both are trained on 100 languages on Wikipedia, and use $\alpha = 0.7, 0.5$ respectively. XLM also uses language embeddings, and incorporates Translation Language Modeling (TLM) as a pretraining technique, which requires parallel data. XLM-R [8] handles all languages without preprocessing. It decreases $\alpha$ to 0.3 and switches to the CommonCrawl dataset, which has a more balanced language distribution. It also disposes of language embeddings and TLM. XLM-T [2] extends XLM-R by finetuning it on tweets to perform multilingual sentiment analysis, as does XLM-EMO [4] for emotion recognition on four emotions.

2.3. Zero-shot Emotion Recognition

Very few works explicitly study zero-shot emotion recognition in text with transformer-based models [28, 22]. They do so by formulating the problem as a Natural Language Inference problem, i.e., by creating a different prompt per emotion of interest, and classifying whether each prompt follows from the input sequence (entailment) or not (contradiction). This requires running the model once per emotion, creating a bottleneck for classification. Most similar to ours are earlier approaches that used semantic similarity with emotion word embeddings to classify in a zero-shot manner [24].

3. METHODOLOGY

We present the technical details of interest for Demux and our simple extension for it to handle clusters of emotions. Let $E = \{e_i : i \in [n]\}$ be the set of emotions and $C = \{C_i : i \in [m]\}$ be some clustering of $E$ s.t. $n \geq m, \cup_{i \in [m]} C_i = [n]$ and $\cap_{i \in [m]} C_i = \emptyset$.

3.1. Demux

Let $x$ be an input text sequence. Demux constructs $x'$ as “$e_1, e_2, \ldots$ or $e_n$?” and use a LM $L$ with its corresponding tokenizer $T$:

$$\hat{x} = T(x', x) = ([CLS], t_{1,1}, \ldots, t_{1,N_1}, \ldots, t_{n,1}, \ldots, t_{n,N_n}, [SEP], x_1, \ldots, x_t),$$

where $x_i$ are the tokens from $x$, $t_{j,i}$ the $j$-th subtoken of $e_i$, and [SEP] and [CLS] are special tokens of $T$. $\hat{x}$ is propagated through $L$ to get $\hat{x} = L(\hat{x})$, where $\hat{x}$ contains one output embedding corresponding to each input token. We denote the output embedding corresponding to $t_{j,i}$ as $\hat{e}_{j,i} \in \mathbb{R}^d$, where $d$ is the feature dimension of $L$. Finally, Demux averages the embeddings of each emotion's subtokens, and predicts using a 2-layer neural network mapping embeddings to scalars, $NN : \mathbb{R}^d \rightarrow \mathbb{R}$, followed by sigmoid $\sigma$:

$$\forall i \in [n], \quad p(e_i | x) = \sigma(\mathbb{N}(\mathbf{NN}(\sum_{j=1}^{N_i} \hat{e}_{j,i} / N_i))).$$

Notice that the same NN is applied to all emotions. For emotion clusters, we modify $x'$ to contain all emotions from all clusters. After the forward pass through $L$, we instead aggregate across all emotions of a cluster instead of a single emotion and predict, for each cluster:

$$\forall i \in [m], \quad p(C_i | x) = \sigma(\mathbb{N}(\sum_{j \in C_i} \sum_{k=1}^{N_j} \hat{e}_{j,k} / N_j))).$$

Moreover, when using multilingual models, we keep all emotions in English to retain the same prompt, $x'$, across all languages.

3.2. Correlation-aware Regularization

To provide extra supervision to the model and enhance its correlation awareness between emotions, Demux includes a label-correlation regularization loss. This loss takes into account the ground-truth labels for each example in its formulation. Therefore, the emotions are split into two groups, the present and the absent emotions based on annotations $y$, $P$ and $N$ respectively. Intra-group relationships are regularized, meaning we only pick pairs of emotions when they are both in $P$ or both in $N$. The formulation is:

$$L_{\text{intra}}(y, \hat{y}) = \frac{1}{2} \left\{ \frac{1}{|\mathcal{P}|^2 - |\mathcal{P}|} \sum_{(i,j) \in \mathcal{P}^2} e^{\hat{y}_i + \hat{y}_j} + \frac{1}{|\mathcal{N}|^2 - |\mathcal{N}|} \sum_{(i,j) \in \mathcal{N}^2} e^{-\hat{y}_i - \hat{y}_j} \right\},$$

where $\hat{y}$ is the prediction of the model and subscripts indicate indexing. In this manner, we decrease the distance of pairs of emotions when they have the same gold labels. The denominators simply average the terms. The final loss is a convex combination of the classification and the regularization loss, dictated by hyperparameter $c$:

$$L = (1 - c)L_{\text{BCE}} + cL_{\text{intra}}.$$
We find that training and evaluating on all languages in SemEval E-c has either only slightly negative or strongly positive influence on accuracy for higher-resource languages. Our dev set results are presented in Table 2. It becomes immediately obvious that models trained on Twitter comfortably outperform their general-purpose alternatives (first and the second row, and third and final row). We also observe that using a dev set of multiple languages not only does not hurt performance, but actually achieves positive knowledge transfer for Spanish, achieving the best JS overall. The monolingual alternatives perform favorably in English and Arabic, with the increase in the former being relatively minor. Overall, since our ultimate goal is to transfer to French tweets, and given the competent or superior performance for Latin-based languages, we do adopt the multilingual model trained and evaluated on multilingual data for pretraining.

Transfer to New Languages In trying to establish how emotion recognition knowledge is transferred to new languages, we conducted experiments with one SemEval E-c language left out during training. Results are shown in Table 3. We notice a drop in performance, with all models performing roughly equivalently across all metrics on the new language notwithstanding original performance. In detail, all metrics drop by around 25% in Arabic, < 22% for Spanish, while the drop in English ranges from 18% to 32%. Nonetheless, emotion recognition in the new language occurs at a competent level, picking up clear signals despite the noise from the language switch, rendering multilingual emotion recognition models capable of being used with new languages.

4.4. Knowledge Transfer to New Emotions

We also assess Demux’s ability to perform zero-shot emotion recognition by excluding emotions from SemEval E-c, one at a time. We can predict unseen emotions since the final classifier maps embeddings to probabilities, agnostic to specific emotions. We choose anger, joy, pessimism, and trust to capture the change in accuracy across a wide spectrum of performance levels. In particular, joy and trust are the highest and lowest performing emotions, whereas anger and pessimism have relatively high and low scores, respectively. Results are presented in Table 4. We notice a decrease in performance. However, the model can still predict these unseen emotions, especially those with which the original model was competent at.

To remedy the decrease in performance, we experimented with freezing word embeddings in an effort to retain the relationships between emotions. We examine two alternatives, freezing the word embedding layer altogether, and freezing only the emotion word embeddings to probabilities, agnostic to specific emotions. We choose anger, joy, pessimism, and trust to capture the change in accuracy across a wide spectrum of performance levels. In particular, joy and trust are the highest and lowest performing emotions, whereas anger and pessimism have relatively high and low scores, respectively. Results are presented in Table 4. We find this decreases performance for the model, indicating it already captured relationships across emotions in its input.
Twitter-based or general-purpose models, monolingual or multilingual training, where the training set is comprised of one or a mixture of all languages. This speaks to the subjectivity of the annotations, allowing monolingual models to transfer knowledge to a new language.

Table 2. Comparing Jaccard scores in SemEval 2018 Task 1 E-c. The variables we consider are: monolingual or multilingual models, Twitter-based or general-purpose models, monolingual or multilingual training, where the training set is comprised of one or a mixture of all languages, and monolingual or multilingual evaluation, where the evaluation set is comprised of one or a mixture of all languages.

Table 3. Leave-one-language-out experiments.

Table 4. Zero-shot performance of unseen emotions.

Table 5. Performance in French election data when the models pretrain on SemEval E-c and/or finetune on the corresponding dataset.

5. CONCLUSION

In this work, we study how to transfer emotion recognition knowledge to different languages, different emotions, and different annotation formats. We find that multilingual models have the capacity to transfer that kind of knowledge sufficiently well. In order to transfer knowledge between emotions, we leverage Demux’s transferability between emotions through word-level associations. We see that the model also inherently performs zero-shot emotion recognition without the need for further changes. Finally, we modify Demux to perform aggregation operations on its label embeddings, and show this can transfer knowledge to novel annotation formats, such as clusters of emotions, even in conjunction with the presence of novel emotions and in a different language. We show that multilingual models pretrained on other languages perform favorably in the zero-shot setting to native models pretrained on machine translations.
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