**Prediction of Emotion Intensity in Text**

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| **1. Task description** The goal of this task is to predict the intensity level of a perceived emotion in a given textual input. Each input consists of a short target text and a corresponding target emotion (one of: joy, sadness, fear, anger, surprise). The model must predict a numerical intensity class (ordinal, ranging from 0 to 3) representing the strength of the perceived emotion, where:   * 0 denotes no emotion, * 1 denotes low intensity, * 2 denotes moderate intensity, * 3 denotes high intensity.   This is an ordinal regression/classification problem with emotion-specific conditioning. | This task addresses a growing need in NLP to go beyond binary or multi-class emotion detection by tackling the fine-grained quantification of emotional experience.  **3. Dataset**  The dataset consists of 2768 records with 7 attributes. Each record is uniquely identified by an 'id' attribute. Other attributes are the 'text' and the different emotions - 'fear','anger','joy','sadness' and 'surprise'.  The columns expressing the various emotions have values ranging from 0-3 expressing the intensity of each with respect to a particular text. The set of ordinal intensity classes : 0 - for no emotion , 1 - for a low degree of emotion, 2 - for a moderate degree of emotion, 3 - for a high degree of emotion. |
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| **2. Motivation**  Emotions in text play a crucial role in sentiment analysis, human-computer interaction, social media monitoring, and mental health applications. Traditional emotion recognition tasks focus on identifying the presence or absence of emotion, but often fail to quantify the intensity with which the emotion is expressed. Predicting emotional intensity enables more nuanced applications, such as detecting emotional distress on social platforms, prioritizing customer service queries based on emotional urgency, or enhancing empathetic responses in conversational AI. | . |
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| The different distribution level of each emotion corresponding to varying intensity shows how emotions manifest in our dataset. From the distribution we can infer that 'Anger' is the least expressed with almost 2500 texts with 0 intensity. And 'Fear' has the highest frequency with intensity 3. | A preliminary frequency count reveals imbalances among intensity classes and emotions. Here high-intensity emotions are under-represented, which could bias predictions. When plotting the sentiment balance distribution marking ‘joy’ and ‘surprise’ as positive emotions and the rest of them as negative, we can see that the peak of the histogram is on the left side of zero, indicating that most texts have stronger negative emotion intensities than positive ones. |
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| Emotions such as fear and surprise show a notably high positive correlation, suggesting that when one of these emotions is strongly expressed, the other is likely to be similarly intense. This aligns with their psychological proximity as both are considered negative, reactive states.  Similarly, sadness and fear are also moderately positively correlated, reflecting how these emotions often co-occur in contexts involving loss, threat, or distress. Emotions like joy typically exhibit a weak or even negative correlation with negative emotions such as anger, sadness, and fear. This is expected, as joy represents a fundamentally different emotional dimension compared to the others.  **4. Methodology**  *Text + Emotion*  *↓*  *Preprocessing (cleaning text, emotion embedding)*  *↓*  *Tokenization (BERT tokenizer with [CLS] text [SEP] emotion [SEP])*  *↓*  *Vectorized Input → BERT Model*  *↓*  *Classifier Head → Predict Intensity (0–3)*  *↓*  *Evaluate with F1-Score and additional metrics* | **5. Evaluation** Multiple evaluation metrics will be used to assess model performance.  *Mean Absolute Error (MAE)***:** Evaluates the average distance between predicted and actual intensity values, suitable for ordinal outcomes.  *Confusion Matrix*: Provides a visual understanding of model misclassifications, particularly in neighboring intensity levels.  *Class-wise F1-scores:*  To analyze model performance across different intensity levels (0 to 3) and identify where the model struggles (e.g., confusion between adjacent intensity levels like 2 and 3). |
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