Detecting Cringe: Analysis of a Complex Social Signal

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1 ABSTRACT

The use of the word cringe to describe uncomfortable, awkward, and even embarrassing phenomena has become increasingly popular in Western society. Currently, there is limited research around the facial expression that is induced by modern cringe definitions, making it hard to distinguish from neighboring expressions. We address this by differentiating action units induced from cringe-worthy scenarios to other nearby social signals, such as pain and disgust. We collected dynamic samples of facial expressions as a result of cringe, pain, and disgust and trained a Support Vector Machine using this data. Results indicated that cringe could not be successfully distinguished from pain, but showed some promise against disgust. Consequently, this experiment contributes a dataset of cringe reactions and its confusion levels between pain and disgust expressions.

2 INTRODUCTION

Although cringe is traditionally known as an obvious physical reaction of recoiling in embarrassment or disgust, the modern-day meaning has evolved to describe an array of awkward, uncomfortable, and socially painful observations. The use of cringe as an adjective became popular with the introduction of cringe comedy, which is a form of comedy where experiences of amusement and embarrassment are combined. The popularity of cringe also increased due to mass content-sharing and resulting memes on the Internet. With the rise of social media and content platforms, more people are sharing cringe-worthy moments and more users are online to view these posts.

Cringe, also known as vicarious embarrassment, is most probably attributed to social ties with the people and environment one interacts with [3]. The second-hand embarrassment, social pain, or disgust one feels when observing another person's social integrity under threat could result in expressions of cringe. Knowing this, feeling cringe is considered an empathic emotion, as the observer perceives the target's situation and feels the emotion they believe the target is feeling. Current studies focus on the experience of vicarious embarrassment rather than the facial expression that accompanies it. For instance, Mayer et al. [2] associate cringe with physiological responses, such as "... increased heart rate, blood pressure, and change in skin conductance, as well as pupil dilation, blushing, and an increase in neural activation in brain regions associated with high arousal". The study done by Müller-Pinzler et al. describes the vicarious experience to be "associated with neural activation of the anterior cingulate cortex (ACC), the anterior insula (AI) and, if induced strong enough, higher-order somatosensory cortex areas". This study also claims the neural experience of vicarious embarrassment is linked to the neural experience of vicarious physical and social pain. Consequently, a facial expression depicting pain makes sense when one reacts to a situation that is painful to watch.

According to Patrick Wöhrle [4], "merely refers to a physical reaction that is open to interpretation and whose actual triggers remain obscure". Therefore, the different directions of attribution result in a plethora of ways for how people express cringe. The main problem this paper is attempting to address is classifying cringe based on its various expressions. For example, when one feels vicarious embarrassment, they may display a facial expression closely related to disgust or when one feels vicarious social pain, they may display a facial expression closely depicting the expression of physical pain. The goal of the project is to be able to detect expressions that are a result of cringe situations from expressions that are a result of actual pain or actual disgust.

3 APPROACH

The data was collected from a variety of sources including websites such as Giphy and YouTube. The samples from these websites were manually clipped, annotated and processed. Another source for our samples is a dataset developed by Heer, Yan and Lim [1] containing negative affect smiles, which are typically present in a cringe expression. Examples of the respective social signals are depicted in Figure 1. Next, during pre-processing, we only considered frames that were processed successfully according to OpenFace, and those with 80% or higher confidence. This sanitization step was to ensure low quality samples that may tamper with the quality of our model's final predictions were excluded.

After cleaning the data, we used Principal Component Analysis (PCA) to reduce the dimensionality of the components. The components were reduced to just two principal components per sample, for visualization purposes. Following this, we clustered our data using the Gaussian Mixture Model (GMM) with two main clusters. GMM was chosen as a visualization tool, since it is a soft clustering model with similarity percentages per sample quantifying their likeliness to belong to either group. We chose the data to be clustered into two main groups, since the scope of our project is concerned

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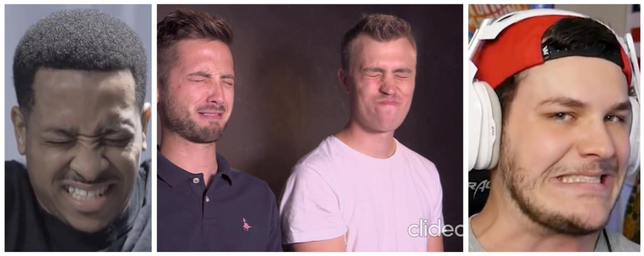

Figure 1: A set of facial expressions depicting pain, disgust, and cringe.

with separating cringe from pain or from disgust at a specific instance. When comparing all three of the emotions together, we opted for 3 clusters.

Finally, we processed the data samples using Support Vector Machine (SVM) with 5-fold cross validation which helped us maximize the usage of our collected data. We specifically chose to analyze AU intensities instead of AU presence, since a majority of the features are common between expressions of pain, disgust and cringe. The distinguishing factor is the intensities of these common expressions, which appeared more intense in reactions of pain or disgust, as opposed to cringe.To aid in the processing of our data, we used a variety of libraries such as Pandas, scikit-learn, NumPy, Matplotlib and Seaborn. Our models were mainly derived from scikit-learn and we used Matplotlib for plotting our graphs.

4 EXPERIMENTS AND RESULTS

Our main goal was to build and test a model to successfully distinguish dynamic samples of cringe expressions from samples depicting pain and disgust. Our hypothesis for the project is that we cannot distinguish cringe from pain and disgust, as we are limited to using just facial expressions. Furthermore, our hypothesis included that for successfully distinguishing cringe from similar emotions, it was necessary to have more context of the situation and data across different cultures.

After preprocessing and cleaning the data, we conducted three different analyses. The first two analyses focused on comparing cringe directly against disgust and directly against pain, respectively. For the final comparison, all three social signals were compared to one another. For each comparison, we visualized which action units with intensities above 2.0 were occurring in each social signal. We found that AU6 (cheek raiser), AU07 (eyelid tightener), AU10 (upper-lip raiser), AU12 (lip corner puller), AU14 (dimpler) were the most commonly occurring AUs with high intensities between the three social signals. This is displayed in Figure 2.

We then applied PCA to this data and reduced it to two dimensions. This helped us retain the trends and patterns in the data while simplifying it from its original complex form. After reducing it to two dimensions, the data had an explained variance of 25%. Our next step was to select the number of components and covariance of our Gaussian Mixture Model (GMM) and then use it for cluster visualization as shown in Figure 3. The visual made it clear that there was no clear clustering distinction between the three social signals.

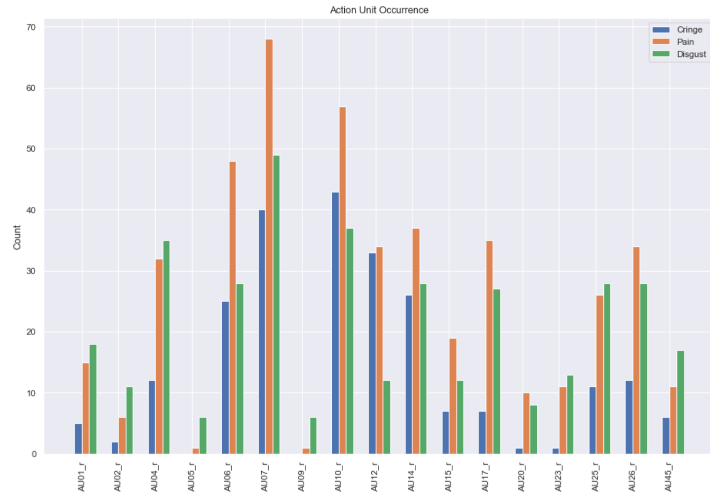

Figure 2: AU occurrences with intensities > 2.0.

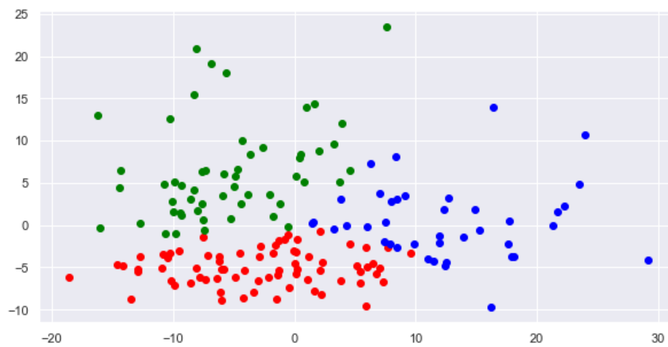

Figure 3: AU occurrences with intensities > 2.0.

Our final step was to perform 5-fold cross validation using Support Vector Machine (SVM) to calculate the average accuracy, precision, recall and F1 scores. Cross-validation was used to prevent overfitting, given the relatively small dataset. Running 10 epochs on the test dataset, the average accuracy and f1 scores are shown in figure 4. Based on the results, the closest neighbor to cringe is the social signal representing pain expressions. A more visual representation of the results is shown in the confusion matrix in figure 5.

Scores	Cringe vs Pain	Cringe vs Disgust	Cringe vs Pain vs Disgust
Accuracy	0.6176470588235294	0.7666666666666667	0.50000
Recall	0.6462450592885376	0.7850678733031675	0.49414434197042895
Precision	0.6284722222222222	0.7916666666666666	0.49847222222222226
F1 score	0.6091954022988506	0.7664071190211346	0.49006209599429945

Figure 4: Performance scores for each respective analysis

5 DISCUSSION

Our processing yielded the following observations. Firstly, looking at the accuracy, recall, precision and F1 scores when comparing

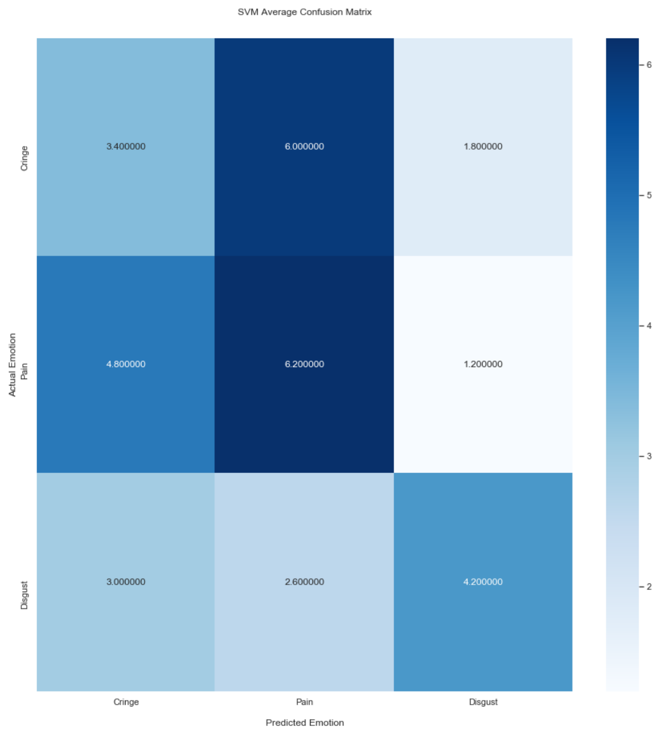

Figure 5: Confusion matrix for SVM test.

cringe versus disgust, we can notice slightly higher averages across all four metrics when compared with the averages for cringe versus pain. This signifies the fact that disgust is an emotion that is more easily distinguishable from cringe as opposed to an emotion like pain. This may partly be due to the fact that cringe reactions are generally intertwined with some pain responses, which may be social or mental. The empathic feeling of second-hand embarrassment, as mentioned previously, is a feeling that is synonymous to pain, since it involves reciprocating the emotions that a subject may be experiencing in the form of social anxiety, uneasiness or embarrassment itself. Disgust on the other hand, is often triggered due to a variety of physical triggers such as taste, touch, sound etc. Although there are instances of physical triggers triggering a cringe reaction among subjects, they are rare.

Another observation to mention is the fact that facial expressions of disgust and cringe are also easily distinguishable by humans whereas expressions of pain and cringe may be hard to distinguish without sufficient context and multimodal information. Our metrics for the comparison of all three emotions together showcases the arbitrariness involved in separating and classifying the samples according to their respective emotions. The multitude of facial features common across all three expressions, coupled with the lack of background information of the events resulting in the reactionary expression within our data samples, is one of the major causes we attribute the low accuracy of our model to. The low averages across both sets of comparisons also indicate that cringe, pain and disgust classification is extremely difficult. With contextual input, multimodal data such as body language, social data and cultural data being crucial for classification, our model has reproduced the expected performance and low accuracy. Therefore, future research could have a better chance of developing a more accurate model if the alternative methods of expressions of these emotions and the previously mentioned affecting factors were accounted for.

6 CONCLUSION

This paper shows the complexity for detecting cringe compared to other emotions similar to it, namely pain and disgust.Despite various similarities in the facial expressions for each of these three social signals and the activation of similar Action Units (AU's), detecting a secondary emotion, such as cringe cannot be successfully done using just facial expressions. Thus, aligning with our hypothesis for the project stating that in order to successfully identify cringe using algorithms, more situational context and cultural data alongside facial expressions is required for more accurate results.

7 APPENDIX

7.1 Contribution by Group Members

Data Collection:
Ravjot, Vishaal, and Jasim

Project Code:
Ravjot

Poster:
Ravjot, Vishaal, and Jasim

Report:
Abstract, Introduction, reviewing and editing: Ravjot
Approach and Discussion: Vishaal
Experiments Results and Conclusion: Jasim

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