USING MACHINE LEARNING TO PREDICT EMOTION GENERATION AND EMOTION REGULATION

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INTRODUCTION

- The field of affective computing has focused on emotion generation, modeling the links between cognitive appraisal and emotion [1-4]
- However, emotion regulation has not been modeled using affective computing techniques
- Thus, using self-report ratings of appraisal, emotion, and emotion regulation regarding a specific situation, we trained and tested models of the relationships between not only appraisal and emotion, but also between emotion and the use of emotion regulation strategies

METHOD

Dataset

- 518 participants (72% female; M_{age} = 22.9 years) from three studies that involved the same survey of appraisal, emotion, and emotion regulation questionnaires
- Each study involved collecting self-report ratings related to a recent emotional situation
- Two of the studies were longitudinal and involved collecting multiple ratings – thus, 376 participants completed one survey and 142 participants completed 2-4 surveys (each about a different situation)
- Emotions were reported at different frequencies with determination, hope, and anxiety as the top reported emotions
- Emotion regulation strategies were also reported at different frequencies with perseverance, acceptance, and active coping as the top reported strategies

Emotion Generation Models

- Trained one-vs.-all binary classifiers via logistic regression and 10-fold cross validation to predict 10 emotions using 15 appraisal features
- Appraisal features: motivational relevance, motivational congruence, motivational incongruence, self-accountability, other-accountability, problem-focused coping potential, accommodative (emotion-focused) coping potential, future expectancy, goal attainment, the involvement of the unknown, urgency, expectation congruence, vastness, revealing a negative aspect of self, and revealing a positive aspect of self
- Emotion classes: anger, anxiety, challenge/determination, disgust, embarrassment, fear, guilt, hope, sadness, and shame

Emotion Regulation Models

- Again, we trained one-vs.-all binary classifiers via logistic regression and 10-fold cross-validation – this time, to predict the use of 8 emotion regulation strategies using the same emotion variables (10 emotion features)
- Our emotion features were the same emotions used in the emotion generation models
- Our regulation classes were: acceptance, active coping, perseverance, physical disengagement, reprioritization, rumination, suppression, and wishful thinking

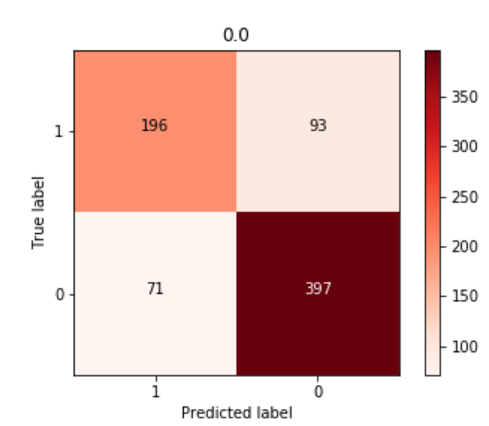
DISCUSSION

- Our models were able to classify positive emotions and certain emotion regulation strategies with high precision and sensitivity, perhaps because these emotions and strategies were most commonly reported in our dataset
- One limitation of our approach is that we used one-vs.-all classification with mostly negative emotions, which may be why our emotion generation models more accurately classified positive emotions
- Our emotion regulation models indicate how emotions tend to be naturally regulated in particular ways, namely via acceptance, active coping, perseverance, rumination, and wishful thinking
- We make a novel methodological contribution by using machine learning to classify emotion generation and emotion regulation
- Thus, we expand upon the processes modeled in the field of affective computing, demonstrating how emotion regulation strategies can be classified based on emotional experience

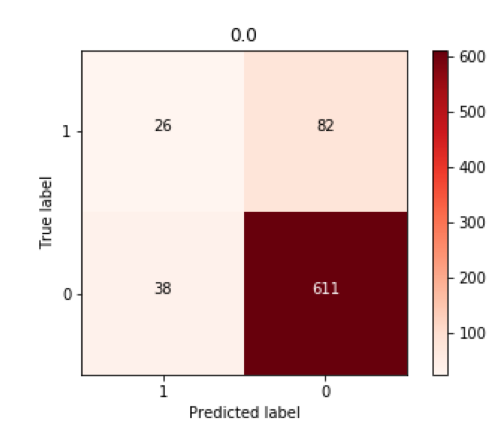
RESULTS: EMOTION GENERATION MODELS

- In separate models, appraisal features were used to predict each emotion – we present the results from each model using a F1 score and a confusion matrix
- The F1 score, which ranges from 0.00 to 1.00, is a measure of accuracy that considers both the model's precision and sensitivity
- For each confusion matrix, the x-axis indicates how the model labeled each situation (1=yes or 0=no as the emotion of interest) and the y-axis indicates the true label of the situation (1=yes or 0=no as the emotion of interest), with the color bar indicating how many situations were categorized into each quadrant of the confusion matrix

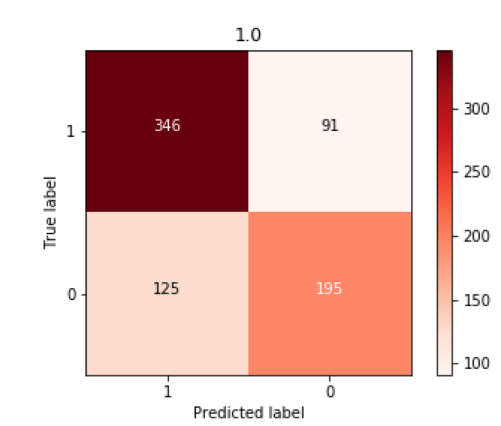
Anger
F1 score = .70



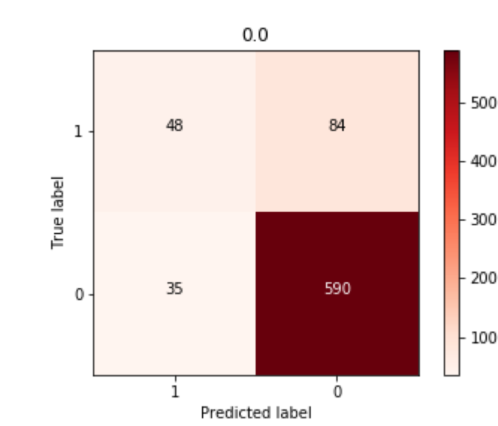
Disgust
F1 score = .28



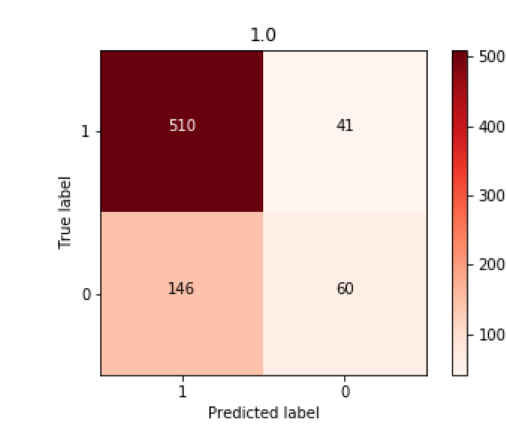
Anxiety
F1 score = .76



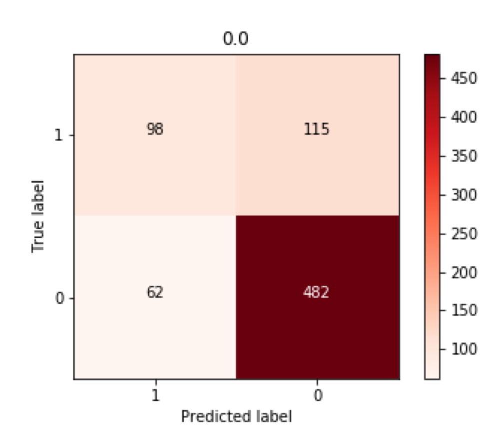
Embarrassment
F1 score = .45



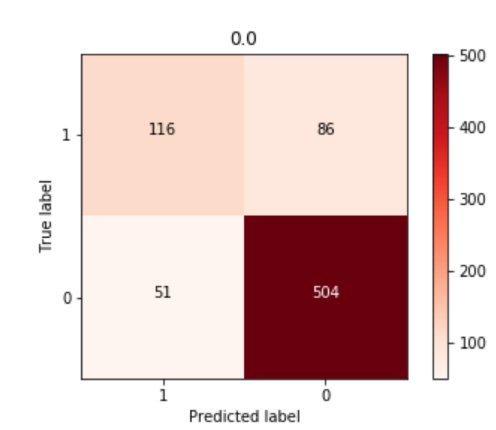
Determination
F1 score = .84



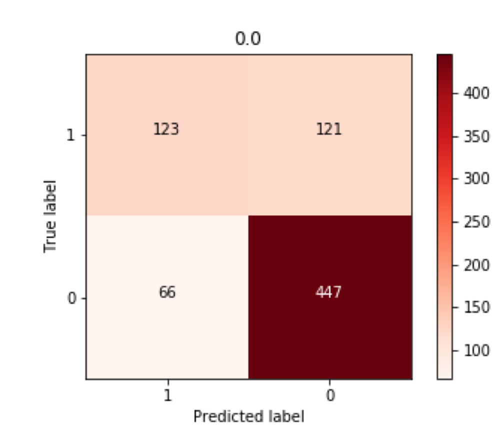
Guilt
F1 score = .53



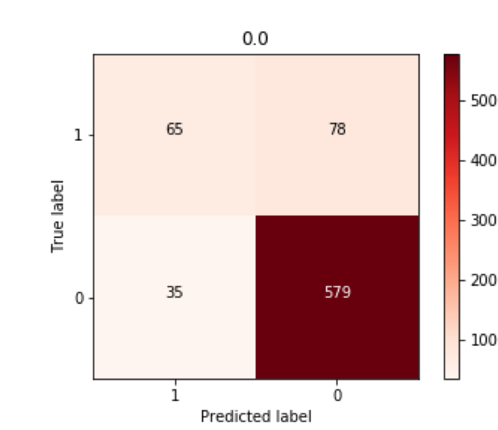
Sadness
F1 score = .62



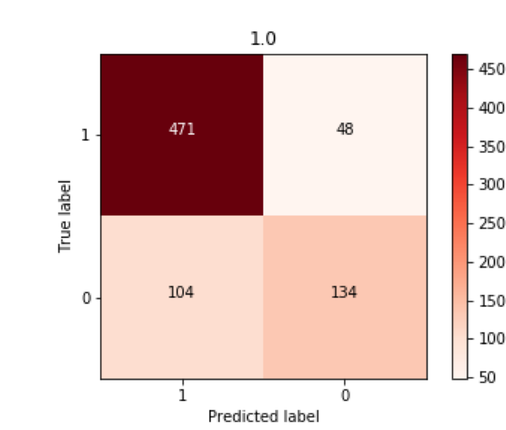
Fear
F1 score = .56



Shame
F1 score = .53



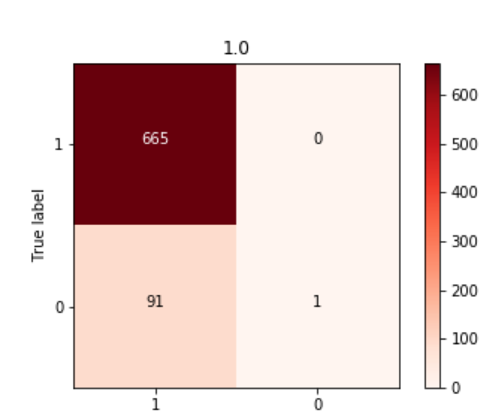
Hope
F1 score = .86



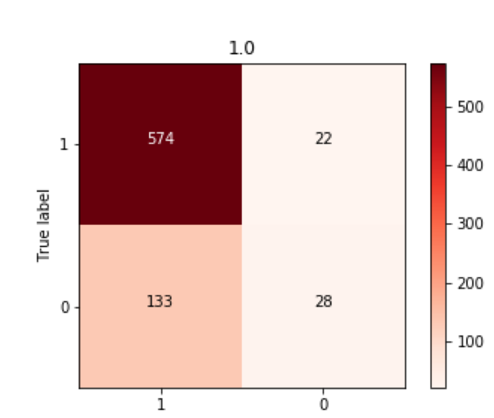
RESULTS: EMOTION REGULATION MODELS

- In separate models, emotion features were used to predict each emotion regulation strategy – again, we present the results from each model using a F1 score and a confusion matrix
- In general, our emotion regulation models were more accurate (mean F1 score = .75) at classification compared to our emotion generation models (mean F1 score = .61)

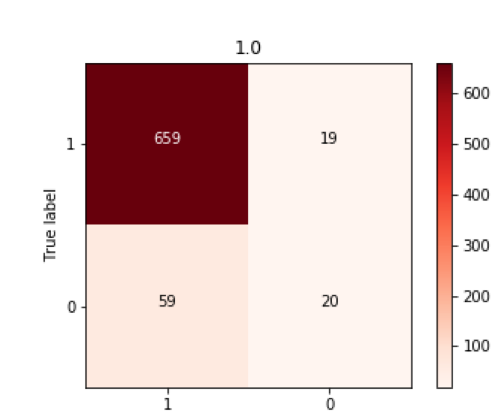
Acceptance
F1 score = .94



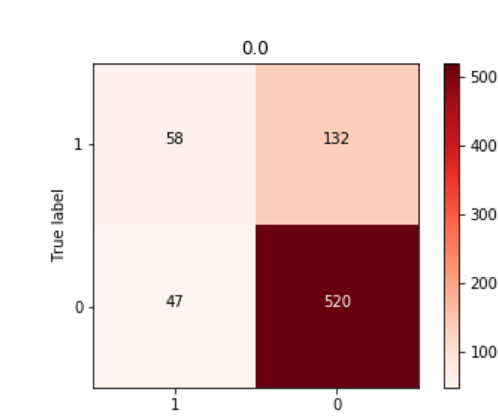
Active Coping
F1 score = .88



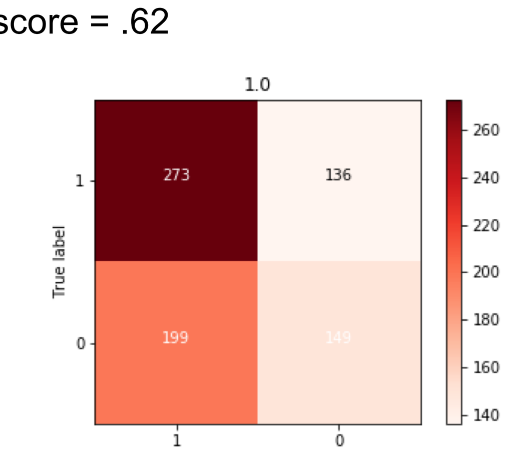
Perseverance
F1 score = .94



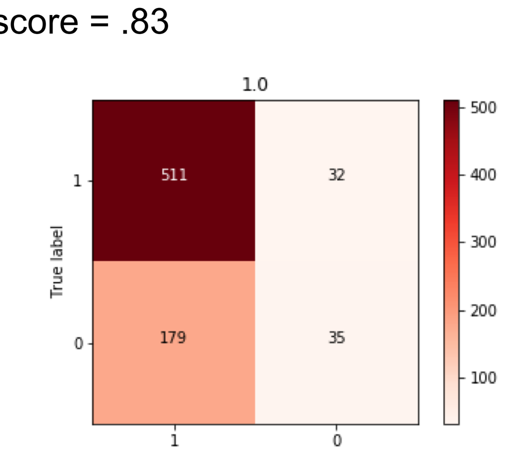
Physical Disengagement
F1 score = .38



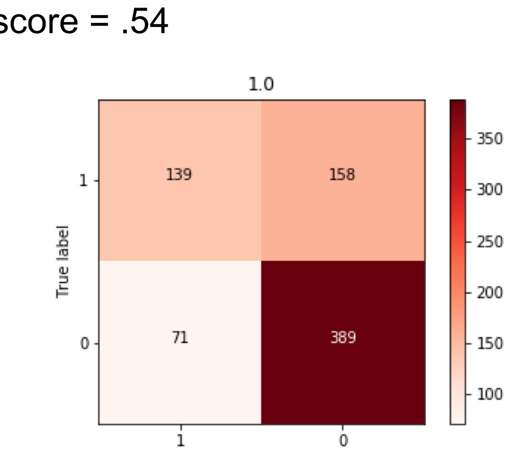
Reprioritization
F1 score = .62



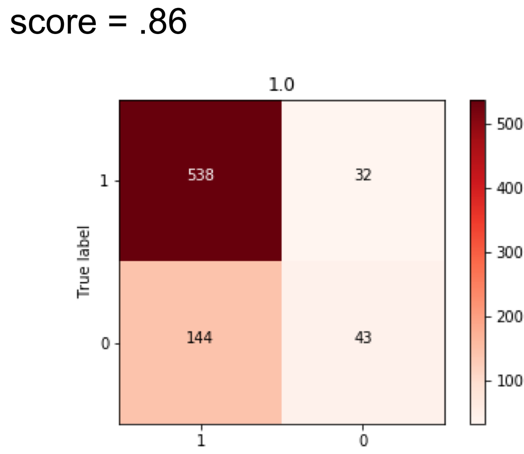
Rumination
F1 score = .83



Suppression
F1 score = .54



Wishful Thinking
F1 score = .86



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Presented at the 2018 Society for Affective Science conference