**Section 5:**

**Lexical Study of Emojis**

This chapter aims to evaluate relevance of parameters for inclusion in an emoji lexicon with respect to the most optimal outcomes for later use to detect sarcasm. The most prevalent methodologies in literature are largely unfit for this purpose as sentiment is derived from the corresponding text, however, incongruency in text and emoji sentiment is widely cited as a marker of sarcasm thus there are validity concerns with regards to any works which deploy this strategy.

Section 5.2.1

**Dataset selection**

*Basic Emotional Theory*

By the nature of the problem domain, there is a necessity for human-annotated data, where emojis are presented independent of any text which may influence classifications. The EmoTag1200 dataset contains information regarding volunteers’ association of emojis to basic emotions, based on the Plutchik model. The presentation of emojis without any textual prompts makes this dataset uniquely suitable for this task, and methodologies for its generation are robust; \*\*\* discuss further here\*\*\*

Section 5.2.2

*Dimensional Theory*

The dataset used in this section was the Emoji Sentiment Ranking dataset, containing rankings of the 751 most popular emojis annotated by 83 annotators as positive, negative, or neutral. Annotators were presented with the emoji alongside the text, however, were instructed to rank the emoji sentiment only. While bias associated with the textual component of the content cannot be totally ruled out in this case, no datasets presently exist which are created where emojis were annotated independently of text. Work will be conducted, validating findings using this dataset against the more robust dataset used to evaluate emojis using the basic emotional theory in section \*\*\* to ensure validity of conclusions drawn using this data.

**Basic Emotional Theory**

*Sentiment classification:*

**Dimensional Theory**

*Sentiment classification:*

The Emoji Sentiment Ranking Dataset contains information regarding the frequency to which emojis are classified as positive, negative, or neutral. These classifications can be represented by discrete values which consider logical ordering of categories of equal distance apart to facilitate quantitative analysis:

Using these values, a discrete probability distribution for sentiment label *c*, can be determined where an assumption that the sum of the three respective probability distributions is equal to one is made to normalise data due to varying ranking frequencies across the dataset:

Where *c* is the sentiment label, and the following abbreviations were used to denote negativity, neutrality, and positivity:

(Negativity)

(Neutrality)

(Positivity)

Due to the low occurrence of annotation (*N* ≥ 5 is true for the lower quartile) presented in the dataset, relative frequency is not an ideal metric for approximation of sentiment scores as will equal zero in events not observed in the data; such situations would result in bias due to the implication that certain events are impossible, whereas a low probability is more likely. For machine learning, contributes to overfitting as data is more sparse. Where non-zero probabilities are assigned to unseen events, some information about their potential occurrence is preserved and thus more robust patterns can be captured. Probability distributions were thus determined using a Laplace estimate:

Where *k* is the cardinality of the class, in this case |c| = 3. The assumption of uniform distribution for the estimator is true for the dataset in question. Finally, defining as the mean of the probability distributions, a sentiment score can be determined:

This approach aims to acknowledge the varying perceptions of emoji sentiment, dependent upon an individuals’ personal usage, while retaining ability to evaluate the sentiment with regards to the consensus classification. An overall sentiment score for sentiment using discrete categorisations often employs a majority decision methodology, however in this context an alternative methodology which acknowledges a high degree of subjectivity is preferable. The standard error of the mean is one such methodology which enables a more nuanced classification methodology:

The result of such a methodology enables the identification of a most probable classification and inclusion or exclusion of secondary potential classifications at a 95% confidence.

A diagram of emojis

Description automatically generated

***Figure X*** Sample of result of emoji sentiment classification using dimensional emotional theory. Coloured bars are proportional to *p+, p0* and *p-*. Markers (black) represent . Grey markers represent the limits of the 95% confidence intervals for the . Note weary face (left) has high confidence that a negative classifier is appropriate, however ghost (right) cannot necessarily be classified as positive with 95% confidence.