Associating Colours with Emotions Detected in Social Media Tweets

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Abstract. This project involves two major areas of work, the detection of emotions in text from Twitter posts (tweets), and the association of that emotion with colour. Emotion mining is the field of natural language processing which is concerned with the detection and classification. It is a subfield of semantic analysis which contains both emotion and opinion mining. Both tasks depend on an emotion model to classify detected emotions and to associate a colour depending on the location of the emotion in the model. This research paper demonstrates preliminary results from classification of tweets to assign emotion labels. Also designs are presented for a prototype web interface for displaying the assigned colour and emotion associated with tweets.

1 INTRODUCTION

The overall aim of this project was to develop a colour coding system for real-time tweets to be used for marketing, or audience research. This incorporates three individual project aims of collecting tweets as they are posted, analysing the text, and applying a coloured label.

The motivation is that tweets could be colour coded according to the emotional sentiment content, enabling people to rapidly visualise an overview of sentiments within tweets.

The hypothesis is that a program can be created to apply a colour label to social media posts based on its emotion.

To achieve this aim, the system will complete the following objectives:

1. Identify current approaches to NLP processing used in text-to-scene applications
2. Assess suitability of python programming with machine learning for tweet classification.
3. Research methods of displaying the emotions using colour through Twitter python API.
4. Investigate the associations between colour and emotion for labelling.
5. Develop prototype system to display tweets with the coloured emotion label.

2 BACKGROUND

As early as the 1950s development into NLP began with what Lehnert & Ringle (1982) calls the “era of machine learning” during which, techniques focused on the extraction of single words and interpreting them separately for translating texts between languages. However, this technique lacked the ability to correctly understand words which can have opposite meaning depending on the surrounding words and structure. An example would be the word “accident” which can be good (happy accident) or bad (damaging accident) (Cambria & White, 2014).

Recent approaches to NLP for sentiment analysis involves training large neural networks with large knowledge bases of vocabulary. One such method in this approach is called ‘skip-gram’ which passes each keyword to another neural network, which then predicts the words either side to produce a binary tree which can be analysed (Witten, Frank, Hall, & Pal, 2016).

Recent SemEval winning methods have shown that word embedding is shown to perform best for sentiment analysis. The topic was well explored in the Computational Linguistics community, with machine learning (Strapparava & Mihalcea 2008), using a Lexicon to associate colour (Volkova et al., 2012), crowdsourcing Word-Emotion associations (Mohammad & Turney, 2013), Word–Colour associations (Mohammad, 2011), and color of text emotions (Strapparava & Ozbal 2010).

3 TECHNOLOGY

Twitter is a social media platform that allows users to post 280-character posts called Tweets. Tweets can also contain a hashtag, which is a categorisation system that allows users to tweet about similar events, products, etc.

Machine learning algorithms for NLP can be developed in many languages; however, some languages will perform better and be easier to develop for than others. The most popular languages for machine learning and ‘deep learning’ are Python, R, and Java (Puget, 2016).

4 RELATED STUDIES

Machine learning has been used with various NLP techniques to enable them to be more accurate than the hard-coded alternatives. Techniques such as ‘bag-of-words’ which analyses each word separately without context can be used with machine learning (Cronin, Fabbri, Denny, Rosenbloom, & Jackson, 2017). Machine learning was used to perform emotion mining by Alm, Roth, & Sproat (2005) who used the emotion from text to change how words were spoken by a text-to-speech system.

NLP is only one aspect of the project, with the display of mood colours being the other. Mapping certain colours to moods will be different for each user so groups of colours will have to be assigned to each mood using the most common colours as a starting map (Moon, Kim, Lee, & Kim, 2013).

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5 NATURAL LANGUAGE PROCESSING

The first NLP systems attempted to parse text using ‘semantic information processing’ which uses keywords in sentences to trigger actions (Lehnert & Ringle, 1982). These applications worked on the principle that language is structured and that there are varying probabilities that a word may appear in a sentence. Early programs used a statistical model for a specific domain and apply these to calculate the probability of the next word. This approach is called n-grams where n is the number of probabilities required to specify a statistical model (Shannon, 1948). One such program was called SHRDLU, which was able to determine actions specified by a user using natural language (Winograd, 1972).

From this syntax based approach, research into NLP split into using semantic analysis and machine learning techniques (Cambria & White, 2014). Semantic analysis aims to recognise the semantic structure of a sentence to understand its meaning. “… in order to understand a sentence, it is necessary to know its syntactic pattern.” (Chomsky, 1957). This approach was popular in machine translation as the second language could be generated over the semantic structure of the original sentence (Schank, 2014).

Current approaches to NLP utilise neural networks for machine learning on top of adaptable knowledge bases. Current research into machine translation focuses on recurrent neural networks with enhanced ‘long short-term memory’ to better maintain information throughout a sentence (Hirschberg & Manning, 2015). This memory is achieved via backpropagation through time (BTT) algorithms which allow data to be propagated back through time and be remembered over multiple steps in the hidden layer of the network (Mikolov, Kombrink, Burget, Cernocky, & Khudanpur, 2011).

6 EMOTION MINING

Emotion mining is used to detect and understand, the emotions present in a passage of text. It is like opinion mining in that it is a form of sentiment analysis, however, opinion mining detects a person’s emotion towards another entity, rather than their internal mood. Current emotion mining techniques work on the sentence level, classifying emotion for each sentence, and use annotated data models to calculate the expressed emotion (Yadollahi, Shahraki, & Zaiane, 2017). Polarity determination is also important for emotion mining as it determines whether a sentence is expressing positive or negative emotions (Ravi & Ravi, 2015). This is useful when applied to naïve approaches which look for key emotion words instead of analysing the entire sentence. Keyword searching may interpret the sentence “I am not happy” as happy as it is the only emotion word. However, polarity determination would recognise the not before the keyword and reverse happy to sad.

Research into emotion mining has focused on text generated by users on social media or for marketing purposes which aims to detect the emotion of the writer. However, for this project, the aim was to classify the emotion that the writer aims to invoke in the user. Pizzi. et al, (2007) expands this and used NLP to present each character in a story with their own internal emotion to better capture the emotions between characters. This can be used to calculate the overall mood of the section with weights given main characters.

Alm, et al., (2005) also used narrative text as the basis for their research. Their application of emotion mining is used to enhance a text-to-speech system for reading fairy tales. Machine learning was also utilised to detect the valence of basic emotions to change the pitch and speed of the output speech.

7 MODELLING MOOD, EMOTION AND COLOUR

To detect emotions, they must first be categorised in a model so that it can be analysed against the text. An emotional model is a system which uses either category of emotions, such as ‘anger’, or emotional dimensions, such as valence and arousal (Burkhardt & Stegmann, 2009).

In a study to display the mood of music via coloured lighting, Moon, et al., (2013) used Thayer's emotion model to determine the emotion. The Thayer emotional model is a 2D grid of emotions plotted against arousal and tension (Thayer, 1990). Because this model doesn’t just use emotion adjectives, there is less ambiguity (Moon, Kim, Lee, & Kim, 2013).

From an emotion model, colours can be assigned to specific mood. Once an emotion has been determined, a system could generate a colour from a simple look-up table. However, the emotion a person associated with a colour can depend on many factors. Manav (2017) says that a person associates a colour with personal experience, memories, and cultural perceptions. Only cultural perceptions can be applied to a wide range of people and so multiple colour-emotion tables could be required. This could be made easier as, a study into emotion and colour preferences from Ou, et al., (2004) found that some emotions may be associated with the same colour across many countries.

8 IMPLEMENTATION

Following current approaches to NLP in literature, this project utilised machine learning techniques to perform emotion detection (Puget, 2016).

Tokenized Datasets

The first tokenized dataset contains tweets. Each tweet consists of a string, a category as string and an attribute label from the set {negative, neutral, positive}. The dataset was from Sentiment140 (2017) which is available online.

The second data used was from the Grimms’ tale dataset. Each sentence has been labelled for emotion and mood by two separate annotators. The dataset contains 8 labels: {N, A, D, F, H, SA, SU+, SU-}, which relate to emotional classes: neutral, angry, disgusted, fearful, happy, sad, positively surprised, negatively surprised. A second version of the dataset was created using only 2 labels: {Neutral, Emotional}. The dataset was formatted to combine 20 labelled Grimms’ tales into a single dataset, containing 2036 labelled sentences, only containing the emotion labels from the first annotator to improve consistency.

Method

The same method was applied to both datasets from tweets and Grimms combined dataset. This method was based on previous research by Kiritchenko et al. (2014) and the AffectiveTweets package for analyzing emotion and sentiment.

First a pre-processing filter was applied, converting the text string to Sparse Feature Vectors (SFV). The SFVs are calculated including word and character n-grams. This has been previously useful for filtering out infrequent features and setting the weighting approach. A support vector machine (SVM) was trained. For comparison, SVM training was completed twice for each dataset, once with SFV pre-processed data and once with raw data. Ten-fold cross validation was applied to assess the classification accuracy which has advantages over using a training/test data split.

Results

With the tweets dataset pre-processed into Sparse Feature Vectors (SFV), the trained SVM classified 74% of tweets correctly into one of the three labelled classes (Table. 1).
Without any pre-processing, SVM classification was not as successful, producing 36% correct classification.
The same method of pre-processing and SVM classification was applied to the Grimms' tales dataset. Sentences were correctly classified 66.6% of instances (Table. 2). When the dataset contains only two class labels {Neutral, Emotional} classification accuracy increased to 71%.

Correctly classified instances	37	74%
Incorrectly classified instances	13	26%

Table 1. Classification results: 74% correctly with the tweet data using pre-processed labelled data converted to Sparse Feature Vectors (SFV) and classified with a trained support vector machine (SVM).

1169	24	23	17	72	16	6	22	N
58	21	0	0	4	6	1	2	F
58	2	27	3	8	1	0	1	A
45	1	4	16	1	0	4	2	D
111	4	3	1	74	4	0	0	H
52	4	4	3	9	30	0	4	Sa
22	2	2	2	4	0	0	2	Su+
55	0	2	4	6	2	2	14	Su-
N	F	A	D	H	Sa	Su+	Su-	
Classified as								

Table 2. Confusion matrix - results correctly classifying 1351 (66%) from the 2036 sentence Grimms' tales dataset using a trained support vector machine (SVM).

Online web prototype design for tweets

Following on from this initial prototype of the tweet emotion classification methods, the next objective would be to display the tweets to the user along with a visual indication of its emotion. Designs were created for how this could be integrated into a web browser. In future work we plan to implement this feature for use in a web browser to display emotion for real-time tweets. The goal would be to use an individual web-page or use twitter itself via a web browser extension to add elements and styling. Figure 1. shows one of the proposed designs for a browser extension solution.

In the prototype, colours could be associated with the 8 emotional classes: N, A, D, F, H, SA, SU+, SU-}, which relate to emotional classes: neutral (N) - grey, angry (A) - red, disgusted (D) - green, fearful (F) - purple, happy (H) – yellow, sad (SA) - blue, positively surprised (SU+) - orange, negatively surprised (SU-) - turquoise.

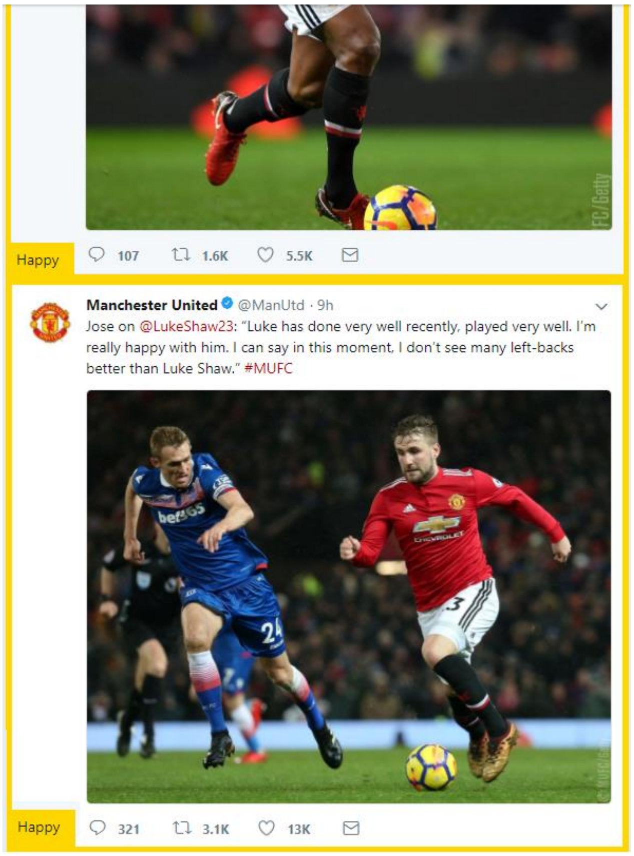

Figure 1. Emotion labels added to tweets inside the Twitter web browser.

9 CONCLUSIONS & FUTURE WORK

This paper builds on the existing work in emotion modelling. A proof-of-concept implementation was presented, which has been functionally tested and which will provide a test bed for further research into this area. We intend to perform a range of experiments to see how well this performs in various functions and to explore the advantages and disadvantages of several approaches for incorporating user satisfaction into the decision making.

Future work could include extending this to other platforms. A review into the current approaches to machine learning by Yadollahi, et al., (2017) finds that much of the research into emotion mining utilises machine learning with neural networks to classify the emotion of a complete sentence. On the topic of machine learning for emotion mining, Bantum, et al., (2017) says that its goal is to apply many features to detect and analyse text at the sentence level.

No single study found is the same as this project the most relevant sources for this project was Alm, et al., (2005) and Pizzi. et al, (2007) which aimed to detect emotion from a story first before completing their own output objective. Another notable study was Moon, et al., (2013) which displayed emotion via lights and so their work into matching colour and emotions was very important for the output task of the project.

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