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Color and Psychological Functioning with LSTM: The Impact of Colors on Emotional Quotient

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Abstract

Artificial Intelligence (AI) has become a crucial component of every industry in today's globe. As the demand for computerized intelligence grows, emotional intelligence is perceived and employed by the machine, paving the door for an emerging novel study known as orange computing for humanistic care applications. Through this study, we hope to discover a link between color perception and human emotion, which will aid numerous industries in branding, advertisements, communications, human resource development, and, lastly, promoting societal mental wellness. We propose employing natural language processing, sentiment analysis, opinion mining, and different frequently used classifiers such as Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and Nave Bayes (NB) to work on this. In the future, this method might be used to a larger dataset to explore human behaviour and its distinctive reliance on colours on a broader scale, defining colour technology.

Keywords: Long Short-Term Memory (LSTM), Color Computing, Natural Language Processing (NLP), Machine Learning, Sentiment Analysis, Innovation,

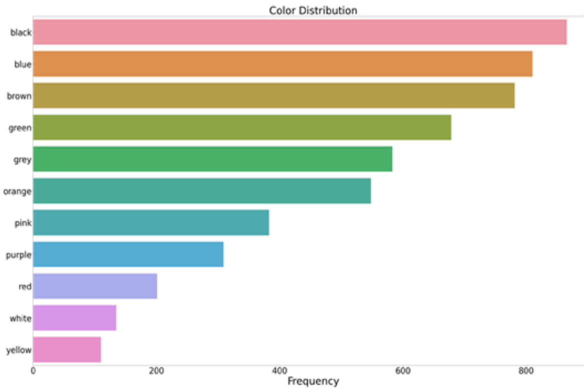
1. Introduction

Humans are unique among living things because they can reason, form ideas, and experience emotion. Understanding people necessitates gaining insight into the inner workings of the human brain, as well. Everything from the components responsible for movement and action to the parts that process sensory information and make decisions, and most crucially the part that feels. Emotions are the root cause of some of humanity's most convoluted experiences. Understanding human behaviour necessitates a thorough understanding of the function that emotions play in it. Every person has his own unique way of expressing their feelings and emotions. Emotions are not exclusive to the human species; animals of all kinds experience them as well. Anger, disgust, fear, sadness, anticipation, joy, surprise, and trust are the fundamental emotions. Other feelings include sadness, fear, and surprise. Emotions, which can at times feel confusing and overwhelming, benefit from this type of framework since it helps to bring clarity to them.

The complexity that surrounds feelings is only going to increase as a result of the fact that there are a variety of feelings that may be broadly categorized as either positive, negative, or neutral. This first categorization is utilized rather frequently whenever sentiment analysis, opinion mining, or any other type of Natural Language Processing (NLP) algorithm is being carried out. To provide a bit more context, states of mind such as joy, enthusiasm, and excitement are examples of what are categorized as positive emotions. Negative emotions include things like sadness, wrath, contempt, and fear, among others. Neutral emotions, on the other hand, are those that cannot be definitively categorized as either positive or negative. Examples of neutral feelings include boredom and distraction, among other things. This categorization is the foundational building block for comprehending human emotions (Boyatzis & Varghese, 1994) [14] and, by extension, human behaviour.

1.1 Colour Psychology

Colours have been known to be correlated to emotions in some form or the other. It is often said that red represents (Hill & Barton, 2005) [10] anger or even red represents love. Green is associated with optimism and similarly yellow is associated with happiness. Plutchik's wheel is a great diagrammatic representation of how some colours are associated with particular emotions. This representation forces one to think of a way that a defined correlation can be formed between colours and emotions and help in some applications.



Emotion is the gateway to the world of colour. The nature of colour theory can only be felt, seen, and understood by observing the world around us. This requires us to gaze through the world. "The way of expression is the way of delivering," which means that everyone is aware of the manner in which they behave and respond to their surroundings. This People are amazed when they learn how colour also works with human psychology since it brings forth a difference in each action that matches with colour theory. There are certain classifications in which colours and feelings are intertwined, and these two things have a very intimate relationship with one another. Warm colours, cool colours, happy colours, energising colours, sad colours, and calm colours will make up the categories that will be listed. These various classifications of colours each elicit a unique set of thoughts, sentiments, and experiences, all of which are dependent on the application of colour psychology (Elliot & Maier 2014) [1] in Fig. 1 represent the color distribution.

1.2 Orange Computing

Orange computing (Wang et al., 2013) [2] is frequently associated with altruistic actions and the general well-being of humans. In addition to this, it endeavors to bring about mental and bodily equilibrium. It cares about numerous areas of computing, such as the creation of programmes and systems that assist to the requirements of humans and make life a little bit simpler, in an effort to bring wellness into the realm of computer. In addition to this, it campaigns against harmful practices in the computing industry that are harmful to persons or their overall health. Because it contributes to a better understanding of human behaviour, orange computing includes both the analysis of feelings and the process of establishing a correlation between feelings and colours.

2. Literature Review

The scholarly interest in the development of colour theory can be traced back a very long time; the interlinking of emotions and colours (Strapparava & Ozbal, 2010) [3] can be traced back to the German poet and polymath Johann Wolfgang von Goethe. Color is perceived on virtually everything that we view in our day-to-day lives. A significant amount of study has been done to demonstrate the existence of an effective algorithm that can correlate human psychology with colour. However, the previously developed models for analysing human behaviour through the application of colour psychology have implemented unsupervised learning methodologies such as k-means. Clustering method that assumes spherical shapes of clusters (with a radius that is equal to the distance between the centroid and the farthest data point) and does not function very well when clusters are in diverse shapes. In addition to this, there is no built-in way to measure the degree of uncertainty present when there is overlap across clusters. For Example, the emotion that lies behind the colour red might be either happy or angry. The current classifiers make use of sentiment analysis to determine the polarity of the corpus as their foundation. They do not take into account the fact that colour, while it might be appealing, it can also be an offensive aspect, and it can be an essential factor. Therefore, in order to avoid offending someone or negatively impacting their mental health (Tariq et al., 2019) [4], it is essential to have a detailed understanding of which colour conjures up which feeling or associations (Hakan, 2008) [5]. There are certain common elements, or general patterns, that can be identified, which just explains how the interpretation of colours form a medium of visual communication and are also one of the factors which have caused advancement in the human race. Despite the fact that different species express their emotions in different ways, there are certain common elements, or general patterns, that can be identified (Bantum et al., 2017) [6]. Because the perception of colour is subjective for each individual, it is essential to have an understanding of the origin of colour in addition to the influence it has on people. A study based on colour that was conducted on both adults and children has showed how the response differs significantly from one age group to another. Hemphill and Boyatzis (Gao et al., 2007) [15], (Valdez & Mehrabian, 1994) [14] are the authors of this piece. Despite the fact that prior research (Hemphill, 1996) [9] investigated the connection between feelings and colours, more attention needs to be paid to the ways in which the human experience of colour changes according to language (Chomsky, 1957) [13] and culture. The concept of employing machine learning and natural language processing to educate models and construct emotional classifiers (Hakan, 2008 [5]; Bantum et al., 2017 [6]; Burkhardt & Stegmann, 2009 [11]) in order to examine the correlations between colour and emotion for the purpose of labeling has become rather widespread. Even though the majority of these models employed datasets from a specific place, it is still very necessary to construct datasets that are accessible worldwide. Therefore, in order to acquire a dataset that spans multiple cultures, our objective is to use data obtained through the Reddit API, which describes as "a global forum on which people can freely express their ideas."

3. Methodology

Reddit is a prominent site that is driven by its users and is divided into numerous communities known as subedits. Each sub reedit is devoted to the discussion of a specific topic. Users are able to provide unique content, links to other websites, and participate in discussions. This is not like any other web platform; rather than focusing on a single user, this one places a strong emphasis on the community. For the purpose of this project, we want to search Reedit for a variety of posts and compile all of those posts into a single dataset. Following that step, this dataset will be processed in order to construct a sentiment-emotion analyzer.

3.1 Emotion Mining

Emotion mining is a technique that may identify and make sense of the range of feelings expressed in a piece of written content. It is comparable to opinion mining in that it is a type of sentiment analysis; however, opinion mining determines a person's feeling in relation to another entity, as opposed to the person's internal state of mind. The most recent techniques for emotion mining are applied on the sentence level (Cambria & White, 2014) [12]. They categories feelings associated with each sentence and then utilize annotated data models to determine how those feelings were conveyed. Determining a sentence's polarity, or whether it is communicating positive or negative emotions, is an additional step that is necessary for emotion mining. When applied to naive approaches, such as those that search for key emotion words rather than analyzing the complete phrase, this can be effective. Because there is only one phrase that describes an emotion, keyword searching might read the sentence "I am not happy" as meaning "I am glad." On the other hand, polarity determination would take into account the not appearing before the keyword and turn happy into sad. Color preferences are intimately connected to the relationship that exists between colour and emotion. On the data set, data mining and opinion mining are carried out in order to first categories the data according to the feelings that they reflect and then get it ready for the process of generating a link between the feeling and the colour. Data mining is an extremely useful and powerful tool for NLP (Cambria & White, 2014) [12], and it contributes to the process of data collection in relation to the classifying requirements outlined in the algorithm. This, too, is going to be a significant stage in the overall process.

Various methods and algorithms have been deployed to analyze the ways in which humans express the various emotions experienced by them on a day-to-day basis in daily tasks such as conversations, deciding what to eat or what to watch, what colours they prefer, who they are talking to etc. Some of these algorithms are K means clustering, that form clusters of data that represent the same emotions. LSTM algorithms to create a model that analyses real time images and performs classification and has been proven to be more accurate and detailed. Another method is gradient boosted decision tree classifier that combines the two approaches and thus produces a decision tree classifier whose results have been enhanced using gradient boosting.

3.2 Algorithm Modeling

The detection of emotions in text also called as Emotion Analysis helps to determine and analyze the type of feeling associated with a text. This emotional Analysis on text comes under classification. We aim to use a LSTM + CNN based approach for building a robust classifier.

Support Vector Machines (SVMs) SVMs are a machine learning classification technique which uses a function called a kernel to map a space of data points in which the data is not linearly separable onto a new space in which it is, with allowances for erroneous classification.

Long short-term memory (LSTM) is a synthetic recurrent neural network (RNN) architecture employed in the sphere of deep learning. Unlike standard feed forward neural networks, LSTM has feedback connections. LSTM networks are well-suited to classifying, processing, and making predictions supported statistical data since there may be lags of unknown duration between important events in a very large statistic.

3.3 Data Preprocessing

We used the scraped dataset to train and validate our models. In total, these datasets contain texts labeled as either positive or negative in emotion and an assigned color to this text. We do pre-process on the text like converting to lowercase and removing punctuation. We have got all the strings in one huge string. The second data used was from the NRC Emotion lexicon or EmoLex. 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. Thus, we combine the two datasets to create a dataset with labeled emotions and colors.

The information is being exchanged, generated and data has been transferred in today's world at an exponential rate. The most common place where people freely express their opinion, exchange ideas is social media. Thus, for our course work we collect data from various social media websites. Thus, it's very crucial pre-process the data as it is collected from various different types of web sources and places. There are various challenges faced while collecting data like missing values, noisy data or inconsistent data values. Thus, to mitigate this, it is essential to convert the unstructured data in a structured form which can be done using data processing.

In order to do sentiment analysis on the text, we must first pre-process the data by identifying stop words, symbols, and the like, and then assess the subjectivity of the material. Only then can we move on to performing the actual analysis. Tokenization, Normalization, and Substitution are the fundamental processes involved in the preparation of a text.

Tokenization refers to the technique of chopping up lengthier texts into more manageable chunks that can be read more easily. The tokenization process can break down paragraphs into sentences, sentences into words, and words into their fundamental forms. These items are referred to as tokens. Tokenization is another name for lexical segmentation, while lexical analysis is still another. Tokens are synonyms for smaller words, whereas segmentation is typically believed to be more appropriate for longer phrases.

The process of translating text into a single canonical form is referred to as **normalization,** and it is part of the process of normalizing text. This includes changing all of the text to all uppercase, getting rid of punctuation, and changing numbers to words, among other things. In most cases, this is further broken down into two distinct subcategories: (1) stemming, and (2) lemmatization.

The process of stripping a word of its various prefixes, suffixes, infixes, and circumfixes in order to isolate its root, or stem, is referred to as stemming. Fig. 3. Describe the data transformation process

The lemmatization technique investigates the significance of the word and reconstructs its canonical form based on the lemma.

The other steps for text processing include:

- set all characters to lowercase
- remove numbers
- remove punctuation s
- strip white space (also generally part of tokenization)
- remove default stop words (general English stop words)

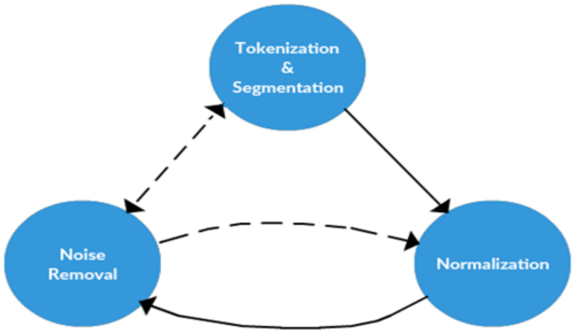


Figure 3: Data Transformation

3.4 Implementing Model

Identifying and labelling an individual's emotions is a challenging endeavour. A content-based classification problem, which may be solved with NLP and Deep Learning, underlies the process of emotion detection in written communication. In this case, in order to get a better grasp on how the mapping works, we can say something along the lines of "let E be the set of all the possible emotions, let R be the set of representatives, and let T be the set of representations of emotion-expressing texts." After that, we can define a relation as "r: R x T -> E."

We plan to use deep learning methods to perform this task of classification because these methods can capture the implicit semantic relations and have the added advantage of learning high-level features from low-level features. Although this task of classification can be performed using a variety of machine learning methods and

traditional lexicon-based methods, we intend to use deep learning methods.
In this particular piece of research, we have a tendency to employ a word 2vec model. This model takes the words and converts them into its own vector space. It then takes the features from this vector space because the model functions by grouping words that are similar. This is the most effective model, and its architecture is based on a neural network that is undergoing development. Words with similar meanings are clustered together, while words with different meanings are separated. Two models, the CBOW (Continuous Bag of Word) model and the Skip-grams model, might be examined in order to construct the word vector. One of these models is the Continuous Bag of Word model. It is possible to put the word2vec model into action by utilizing the genism package.
Using the dataset, our first step is to determine the three colours that appear in our database the most frequently. This will help us determine which colours have the most influence on people by revealing which ones are preferred. After running EDA on the dataset and visualizing the data, we have come to the conclusion that black, blue, and brown are the colours that are used the three times out of every hundred times. The word vectors are introduced into the model, which is made up of three CNNs and is then followed by the output layer. The output layer has a Sigmoid activation function and is a completely connected layer.
Word Vectors and CNN are just two examples of the many components that make up the architecture. The most important job that CNN and the max pooling layer have is to analyze words in order to learn relations and extract characteristics from them. After that, these features are transmitted to the layers that are related. A few examples of the different layers are the Embedding layer, the Convolutional layer, the Max Pooling layer, and the Fully Connected layer. Fig. 4 describes the process of embedding and sentiment score.

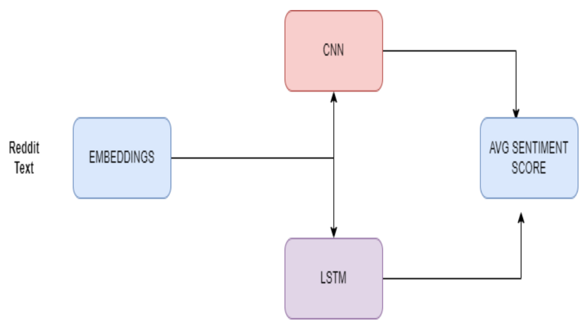


Figure 4: Sentiment score

Data from the NRC Emotion Lexicon, often known as EmoLex, was used for the purpose of this relationship. Two different labels, one for emotion and one for sentiment, have been applied to each word in this list. The dataset includes the following eight classes: neutral, furious, disgusted, afraid, pleased, and sad, as well as favourably surprised and negatively surprised.
We utilize an algorithm called "Clustering" to group the feelings according to their sentiment and colour. These can be utilized to put together a fundamental sinology concerning the colour, feeling, and word association. An emotion model allows for the categorization of colours according to specific states of mind. After identifying a feeling, a computer programme could next use a straightforward look-up table to assign a colour to represent that feeling.
The data is ONE-HOT-encoded first, and then the string is translated to numeric form so that it may be used. Every colour has a number, ranging from 0 to 9, that corresponds with it. For this purpose, a Label Encoder module derived from the sklearn library is utilized.

4. Results and Discussion

During the course of the trials, a wide variety of parameters, settings, and hyper-parameters were investigated and evaluated. Convolutional neural network (CNN) experiments used various size fitters, such as 4, 5, and 6, with 256-feature maps. These fitters were applied to the applied convolutional layer. An activation function is accomplished with the help of the ReLU function. In the past, the dropout for the recurrent layer was initially set to 0.5 in order to mitigate the issue of over fitting. A sigmoid function is used as the activation function in the LSTM, and there are 128 hidden states. During the course of the experiment, a total of 25 epochs will be employed. The scripts for the experiments were developed in Python and made use of the Tensor Flow framework.
The size of the training and test datasets is kept constant across all of the experiments, including those that employ distinct datasets and varying degrees of sentiment analysis. The size of the training set is equivalent to eighty percent of the entirety of the dataset, and the size of the test set is equivalent to twenty percent of the dataset. After the model has been trained with the help of the training set, the performance of the model is evaluated with the assistance of the test set. In each of the experiments, a total of 50 epochs were conducted. The accuracy results 0.81 obtained during the 25 epochs for the four datasets that made use of varying degrees of emotion. By highlighting

the best findings, it is possible to determine which of the three distinct utilized levels produced the most accurate results. Fig. 5 describe the cross validation and Fig. 6 describe the process of training data, test data through emotion classifier.

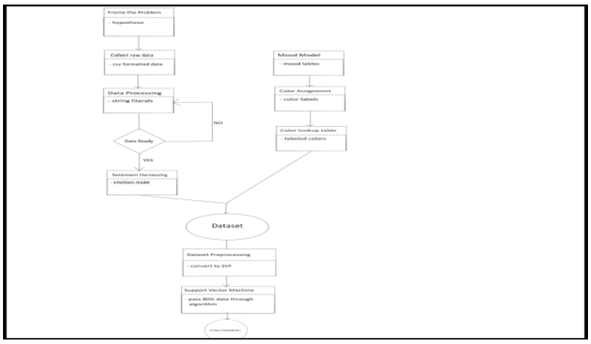


Figure 5: Cross validation

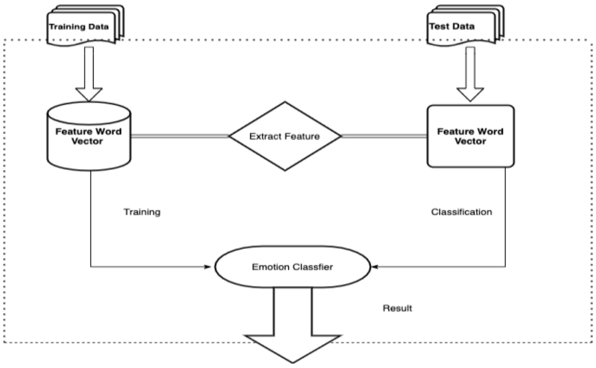


Figure 6: Training data, test data through emotion classifier

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