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COLOR KEYWORD SENTIMENTS IN GERMAN AND JAPANESE TWEETS

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Abstract. *Colors continue to influence societies and characterize cultural usage of them and their key terms. The influence and cultural impression of many colors have been documented by liberal arts and behavioral psychology to reflect sentiments of colors. Color keywords and the use of them in social media open a new dimension to understanding cultural use of color terms and their associated sentiment. This research analyzes social media posts (Twitter) using 11 color keywords in German and Japanese language and their respective sentiment.*
Keywords: Color analysis, Cultural analysis, Sentiment analysis, Twitter, Social media

1. **Introduction.** Color continues to be an important topic and the cultural identification plays many important roles in society. The cultural influence and different use of colors in these societies have been researched, mostly by affective engineering and social experiments in liberal arts or behavioral psychology such as Japanese color perceptions compared with that of Americans, color space representation in multilingual context, influences of color on cultures, and Korean color usage in culture, arts, costumes, games and graphics [1-4]. Many of comparative studies, including the ones mentioned before, suffer from limited data sets due to manual identification and analysis [5,6]. Another limitation is the hand selected data sets, e.g., in comparing Japanese and other Asian color preferences. Others are historical presentations of colors not being universal, dating back many thousands of years.

Red is the predominant focus of these types of researches as it is one of the more distinct colors and has clear cultural differentiation as well as meanings shared in many cultures, namely what can be understood as universal and what is not, and a cross cultural investigation in culturally diverse color categories dependent on languages [7,8]. A set of 11 colors (Table 1) can be considered a basic color set that is the most common in numerous cultures.

Colors also have been used to convey sentiments or gender based preference on Twitter [9]. Twitter is one of the most popular social networking sites based on 140 character text messages (Tweets). The social network itself is based on followers and friends, which also allows directed and undirected graph networks. Basic colors exist differently in cultures as shown in Russian language discrimination of the color term blue, color variability in languages, and culturally related use of color terms [7,10-12]. As colors play an important role in product design and marketing, shown by a cross-national study, cross-cultural review, and their impacts on marketing [13-15], viability for system implementation is deemed promising. Other fields such as Kansei engineering address emotional reactions to form, haptic, and coloring. The latter has been ported to textual indexing based on emotions [16] and can be understood to influence fashion, products, user interface,

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Table 1. German and Japanese basic color terms

German	Japanese	*English* (reference)
schwarz	黒	*black*
weiß	白	*white*
rot	赤	*red*
grün	緑	*green*
blau	青	*blue*
grau	灰色	*grey*
braun	茶色	*brown*
orange	橙、オレンジ	*orange*
gelb	黄色	*yellow*
violett	紫	*purple*
pink	ピンク	*pink*

representative photographs, and others. The emotional response of colors cannot easily be determined by hue alone, as Gao et al. have shown in a cross-cultural analysis of hue, brightness and saturation [17]. The research was conducted in eight languages: English, Cantonese, Taiwanese, Japanese, Thai, Swedish, Spanish and Italian. Their paper shows that saturation and brightness account for 82% of the variance in emotional reaction, whereas hue accounted for 7% of the total variance explained.

To be able to link emotional content to color keywords, Twitter text was categorized by their sentiment, language, and color term. Sentiment analysis of Tweets has been a focus a few years after the inception of Twitter in 2006. A peak is not yet in sight, with an epidemic-like increase since 2013. Twitter especially poses a challenge in the inherent limited-character-style of writing messages. Mozetič et al. have concluded in a 2016 paper that the quality of classification models depends heavily on the quality and size of training data compared with on the type of the model trained [19]. The analysis was performed in 13 languages and a data set of 1.6 million annotated tweets.

In this paper, 10,000 Tweets related to 11 color terms in two languages – German and Japanese – were gathered and analyzed, accounting for a total of 110,000 Tweets per language. The color keywords can be seen in Table 1.

Summarizing most of past research with regards to color keywords, analysis done by data mining is still in the early stages (a previous research was published by the author [18]). One of the major motivations for this current research is the intriguing insight of already established research on very small data point. Using information and communication technology (ICT), new insights with better nuance could be done. One of the first investigations was performed on color key terms in different languages with word co-occurrences and differences, and this research is to extend to a further dimension, that is, emotional differentiation or sentiment analysis in multi-cultural environment.

This paper is structured into the following sections. Section 2 (Data set and Methodology) provides background knowledge of the data from social network service Twitter and methodologies used to perform the analysis – with Sections 2.1, 2.2, 2.3, Data set acquisition and pre-processing, Analysis and results and Discussions, respectively – describe the data acquisition process, detailed analysis and a review of the results and drawn insights from it. Section 3 (Conclusions) summarizes and concludes the paper with some notes on future research directions.

2. **Data Set and Methodology.** The purpose of this research is to investigate the relation between the cultural (language) aspects of color terms on the social networking site Twitter, and the sentiment distribution of these Tweets.

Twitter was used as data source because of its widespread international presence – especially in Germany and Japan – and amount of textual data produced each day. Due to the popularity of the micro-blogging platform in these countries, fine-grained and targeted data mining is possible. In a previous study by the author, color terms and relevant word co-occurrences were investigated to research patterns and differences in cultural use of colors on the online social media service Twitter [19]. This study showed a different approach to analyzing usage of color to liberal arts and focused on text mining instead of pictorial investigation. A large data sample was analyzed and investigated with the use of t-test to emphasize differences in the feature variables of each color keyword. These findings prompted to look further into differences and spawned followup research such as this paper.

The study at hand extends this research in the aforementioned paragraph into sentiment analysis to add another dimension to understand, classify, and create knowledge of the use of colors in different languages and cultures. Sentiment is a fundamental dimension of communication and recently, the unique short messaged social medial platform Twitter has been the focus of attention for sentiment analysis. As colors are also a way of conveying emotions – may it be through product design, graphical user interface, hospital indoor architecture – sentiment analysis was added to investigate their connection with color keywords in Twitter messages.

2.1. **Data set acquisition and pre-processing.** A Python algorithm was written to access the Twitter API (Application Programming Interface) and to acquire raw Twitter Status Objects. The process is straight forward but requires a developer's account at the social media service Twitter and several data and time limitations apply when downloading the raw data[1]. Each Twitter Status Object represents a status update (Tweet) of an account with metadata attached, such as user information – including user ID, use name, date of account setup, mission statement, follower count, geo tag information, language settings, over ten individual design choices for the visual profile, time zone, and more – the Tweet ID, the actual Tweet content as UTF-8 text, location data – including profile location, name of country and city, location of the tweet, GPS coordinates (listed with decreasing likelihood the user has turned these features on) – and more metadata to track conversations such as the name, ID, and status of a connected Tweet ("in-reply-to" relation). The data per status object averages to roughly 5.5 kilobytes for tweets without extensive location data and close to 6.5 kilobytes for a tweet with more location information.

The Tweets were filtered by language and color keyword, respectively, resulting in 22 independent feature vectors. Each feature vector was then pre-processed, and the results stored to a text file containing JSON objects (JavaScript Object Notation[2]), the native file format of a Twitter Status Object. API access was implemented using the TwitterSearch package to facilitate filters such as language, and necessary keywords.

Tweets were filtered by language rather than by GPS (Global Positioning System) data. GPS data is not always enabled on the user account. Moreover, in cultural terms, language is assumed to be more prevalent than location.

The data acquisition process and filtering is visualized on the following page with Figure 1.

Extensive textual pre-processing was conducted by omitting retweets (simple forwarding of original Tweets), website links, and non-standard symbols often found in extravagant

[1]Twitter's API adheres to changing restrictions and limits. As of this research, the time limit for search was 10 days or a 10,000 data points limit, whichever hit first. For details, refer to https://developer.twitter.com.

[2]Refer to www.json.org for detailed implementation and usage.

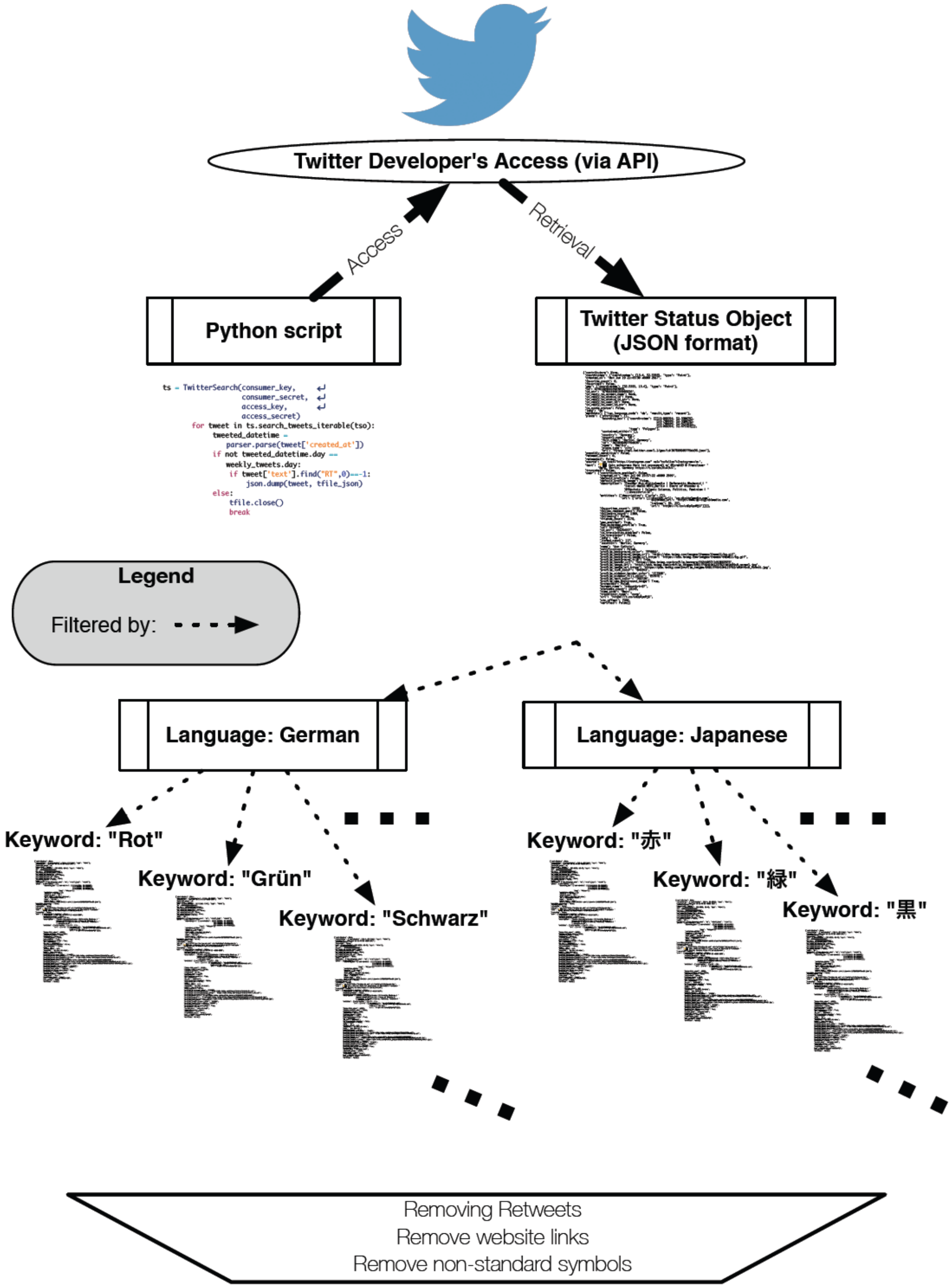

FIGURE 1. Data acquisition and filtering of twitter status objects

emoticons. Standard emoticons and Emojis (both pictorial and text based) remained in the data set to facilitate the automated sentiment determination.

2.2. **Analysis and results.** This research addresses the following questions.

1) Are color keywords used differently in cultural context?
2) Are emotions connected with color keywords in general?
3) Do these sentiments differ in cultural context (also for the same colors)?

The first question was analyzed in previous research and prompted for further investigation. Color key-terms show distinct differences in their cultural context. Word co-occurrences in particular showed expected overlapping in culturally similar languages and distinct differences across languages as well [18]. In addition – and addressing question two – this research attempts to model the overall sentiment of Tweets for any given color keyword. For the last questions, the latter findings are woven into previous research on cultural differences. In Section 2.3, some of the results are discussed more in-depth to show its relevance.

To address the emotional classification of social media content, sentiment analysis was considered. Sentiment analysis is well established technology that profits from large data sets. For this analysis, sentiment analysis was conducted by Wolfram Mathematica 11.1[3] integrated classification algorithms for social media postings. The packages of Mathematica are regarded as high quality and in combination with [19], the automated classification was performed on 10,000 Tweets for each color term in German and Japanese. Sentiments are – as crystallized since the beginning of the research – as a three-category set, namely "positive", "negative", and "neutral". Mathematica returns each classification with a probability factor to reflect the percentage in confidence of categorizing into a given sentiment. The author is considering using this additional information in future research to get a more nuanced insight.

Each set of Tweets gathered for a color term was split to perform cross validation. After performing the sentiment analysis for all color terms and their cross validation, the sum or square error was calculated for the cross-validated sets. For all 11 color terms, the sum of square error was $R^2 = 0.97$ for the German set and $R^2 = 0.95$ for Japanese set. The fluctuation is believed to reflect differences in time-periods and could be resolved by bootstrapping analysis.

Most peculiar were results for black and red, as the `Positive/Negative/Neutral` ratio was particularly distinct. Percentage distribution resulted for black in German Tweets `44/11/44`[4], and for Japanese Tweets `95/3/2`[4]. The messages for red in German resulted in `40/6/50`[4] whereas the Japanese Tweets were classified as `96/2/2`. The rest of the color terms were in the margin of error balanced and did not show any cultural distinction.

The results show that for a given set of social media posts and given color scheme, a sentiment indicator can lead to insight on color keyword usage. With high confidence level, most colors represented similar emotional background with the exception of the aforementioned. For further investigations with word associations and the apparent outliers are planned.

2.3. **Discussions.** As was shown in the results for color terms red and black, a sentiment influence can be quite impactful. This indicator also prompts for several directions to consider for future research. As certain emotions have already been established in liberal arts and successfully implemented in product designs, considering different cultures, the use of textual data to promote in different languages poses a different problem. By text mining color terms and determining positive/negative tendencies in different languages can help formulate engaging texts. For this, however, further research is needed to identify related keywords as presented by the author in another publication [18]. To associate positive sentiment Tweets with relevant keywords or content is one major focus.

Another focus is to conduct a long-term study to see temporal influences on sentiments in social media messages. Color terms might not only have language specific characteristics, but also change during the time of year.

[3]Sentiment analysis – or Sentiment Polarity, as described by Wolfram – was introduced in version 10 and provides automatic classification into three polarities.

[4]Numbers not adding up to 100% due to a few omitted intermediate/unclassified sentiment messages.

Lastly to consider are location based differences. Although the amount of data significantly dwindles when analyzing Tweets with location data, in combination with this research, intermediate findings and bootstrap analysis, the findings could give yet another insight in the difference of color term usage.

3. **Conclusions.** This research gives an insight in the use and the sentiment of color terms in German and Japanese social media messages of the platform Twitter. In particular the terms black and red resulted in a strong difference of sentiment distribution of positive, negative, and neutral messages.

This insight is considered to be used in further research into color keywords and building a comprehensive model of color term usage in different languages and possible new insights to gain from it.

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