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Proceedings of the 5th European Conference on Social Media

Limerick Institute of Technology Ireland

21 - 22 June 2018

Edited by
Prof. Vincent Cunnane and Dr Niall Corcoran

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A Sentiment Analysis on Miley Cyrus' Instagram Accounts

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Abstract: *Introduction.* Do haters' or admires' comments "Come in Like a Wrecking Ball"? In order to answer this question, a sentiment analysis of comments in Miley Cyrus' Instagram accounts was performed. The social media-sharing service Instagram gained popularity in the recent years. Every registered user is able to comment on the uploaded media and express one's sentiment about it. Especially celebrities seem to attract attention from mostly anonymous haters and admires. This investigation focuses on cyber hate and cyber love on a polarizing celebrity – Miley Cyrus. She gained fame as a teenage girl in the TV show Hannah Montana in 2006. She wanted to change her image and earned negative response for her performance at the MTV Video Music Awards in 2013 and her music clip of the song "Wrecking Ball". Does a polarizing celebrity like Miley Cyrus get positive or negative response on social media for her behavior? Additional research includes a time series on the sentiment towards Miley Cyrus' posts. Are there differences between the sentiments expressed on the official Miley Cyrus account and fan-based accounts? *Methods.* To discover what amount of sentiments (negative, positive, neutral) prevail in the comment section of a well-known celebrity and whether there is more negative or positive feedback, a dictionary-based sentiment analysis on more than 660,000 filtered comments of media concerning to Miley Cyrus has been performed. First the data has been collected through the Instagram API from the official as well as fan-based Miley Cyrus accounts. Afterwards the comments were preprocessed by a python script. The comments have been translated, words without any impact have been replaced with a general term (e.g. usernames or links), and comments with no sense (e.g. "first"), advertisements, as well as chain mails have been deleted. Finally, the sentiment of each comment has been computed. *Results.* The official Instagram account of Miley Cyrus has the least positive comments and is more susceptible for negative comments. Miley Cyrus gets more positive than negative feedback for her critical behavior; and the sentiment value decreases over time as she acts less polarizing and more unappealing.

Keywords: Sentiment Analysis, Social Media, Big Data, Instagram, User Comments, Miley Cyrus

1. Introduction

1.1 What this investigation is about

The multimedia sharing service Instagram grew and excelled in popularity since its launch as a free mobile application in the beginning of October 2010 (Hu, Manikonda and Kambhampati, 2014). In almost six years, Instagram got over 500 million users of which over 300 million use the app on a daily basis (Instagram Blog, 2016). Pictures and videos from the users' daily lives are shared, commented and liked by followers and other users. Some people, organizations and companies build their own fan base and start to grow a network (Alshawaf and Wen, 2015). Instagram is also used by many celebrities who mostly have a high number of followers (Djafarova and Rushworth, 2017). People are able to react on the uploaded media by writing a comment, liking a picture or video and following other users.

Celebrities may trigger positive or negative sentiments in members of the audience. Sometimes, the audience members report on their sentiments in social media via posts or comments (Hosseinmardi et al., 2015). Nowadays, the image-sharing service Instagram plays an important role in the social media landscape. As all comments on Instagram are text-based, we are able to identify, extract and analyze occurring negativity and positivity as well as neutral comments of users by a natural language-based sentiment analysis (Kaushik and Mishra, 2014).

This investigation is about the sentiment toward a polarizing celebrity – Miley Cyrus (Lam, Graling and Wheeler, 2013) in the comment section of Instagram concerning her own and various fan-based user accounts (Figure 1). Miley Cyrus, who was born on November 23, 1992 as a daughter of the country singer Billy Ray Cyrus, gained fame in 2006 through the popular teen show "Hannah Montana" (Kennedy, 2017). She wanted to change her image (Kennedy, 2014) and earned criticism for her performance with Robin Thicke at the MTV Video Music Awards in 2013 and her music clip of the song "Wrecking Ball" (Hann, 2013). Miley Cyrus seems to be seen as a ‘good girl’ as well as a ‘bad girl’ (Vares and Jackson, 2015) and has influence on her audience, especially on young girls (Jackson, Goddard and Cossens, 2016).

Figure 1: Prototypical Instagram post on Miley Cyrus’ official account including users’ comments

Why did we perform this study? Besides “nice” information for Miley Cyrus’ fan base as a by-product, we tried to get insights in the information behavior of celebrities’ fans on social media. We wanted to know how the majority of the audience of a celebrity’s social media account behaves. There is a discussion about celebrity harassment in terms of cyberbullying, online insulting and threatening (Whittaker and Kowalski, 2015). Does a polarizing celebrity like Miley Cyrus get positive or negative response on social media for her behavior? Do haters’ or admires’ comments “Come in Like a Wrecking Ball”? Our study is scientifically located in social media research; however, there are close relations to information science (especially informetrics; Stock and Weber, 2006) and to celebrity studies. To our knowledge, this is the first study which systematically combines celebrity studies and informetrics with social media research. Furthermore, the applied research methods and processes should serve as a base for further studies on the sentiments of Instagram posts and comments.

To determine the polarity of emotions towards a celebrity like Miley Cyrus on Instagram, a sentiment analysis was conducted in order to answer the following research questions:

- *RQ1***:** Does some kind of hate or negativity exist in the comment section of celebrities? If so, to what extent are the comments negative?
- *RQ2:* Is the official account of a polarizing celebrity more prone to negative or positive sentiments than fan-based accounts?
- *RQ3:* Do certain events and scandals in a celebrity’s life influence the overall sentiment on these accounts?
- *RQ4:* Is there a trend towards a specific sentiment over time?

First, comments from Instagram media of Miley Cyrus’ official account as well as fan-based accounts were collected. Additionally, the user ID and the media ID were saved to track the source they belong to. Moreover, the collected comments had to be preprocessed, e.g. filtering bots and deleting spam. Finally, a dictionary-based sentiment analysis was performed (Figure 2).

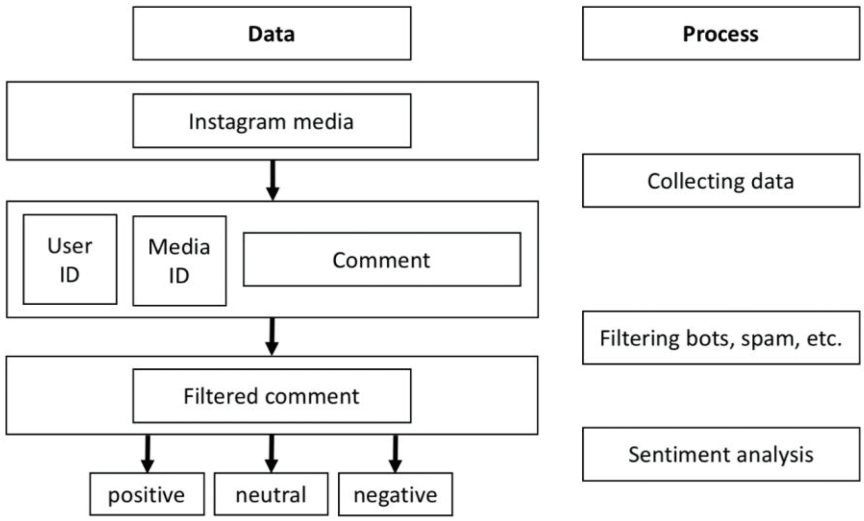

Figure 2: Research process

1.2 Related Work

The method of sentiment analysis can be differentiated in two main strategies: lexicon based and machine learning based technique. Before the analysis of an unknown dataset the machine learning based algorithm has to be trained by a training data set. For the lexicon based approach, the sum of the polarities for each word or phrase is the polarity of the document (Kaushik and Mishra, 2014). Khan, Atique and Thakare (2015) combine the methods of lexicon as well as machine learning based methods to improve precision and get a high recall. Kaushik and Mishra (2014) found a lexicon based approach for sentiment analysis that works fast. And, finally, Nielsen (2011) evaluated a word list for sentiment analysis in microblogs.

There are already several studies about sentiment analysis on Twitter posts (e.g. Pak and Paroubek, 2010; Kaushik and Mishra, 2014; Khan, Atique and Thakare, 2015) and product reviews (e.g. Dave, Lawrence and Pennock, 2003; Cui, Mittal and Datar, 2006; Mukherjee and Bhattacharyya, 2012). Boychuk, Sukharev, Voloshin and Karbovskii (2016) examined if the uploaded media and comments about soccer games on social media are more negative when there is violence during a soccer match. Therefore, they analyzed the emotion of Instagram photos and videos as well as comments of posts. Unlike to our approach, they worked with a machine learning based technique for the comments. Hosseinmardi et al. (2015) detected cyber hate on Instagram using a snowball method. They collected data from pictures and videos of 25,000 public Instagram accounts, including the comments of posts. Each post was manually checked for cyberbullying or cyber-aggressive behavior and labeled accordingly. As result, they found that users who get bullied in social media gain less likes for the posted media but more frequent comments.

2. Methods

Sentiment analysis in social media (Pozzi et al., 2017) is different from “classical” sentiment analysis of newspaper articles, for instance. Here, we have text and we have additionally emojis. A sentiment analysis in Instagram is virtually new scientific territory. We were only able to identify very few approaches of sentiment analysis of Instagram hashtags (Nam, Lee and Shin, 2015) and Instagram texts (Ranaweera and Rajapakse, 2016). We conducted for the first time a lexicon based sentiment analysis of Instagram post’s comments with a very large data base. First the required data (comments) have been collected and preprocessed. Afterwards, the sentiment analysis could be performed on over 660,000 comments.

2.1 Data Collection

The data were collected from the beginning of May 2016 until the beginning of June 2016 via the official Instagram API. It took place before the new Instagram API principles were realized (Instagram Platform Changelog, 2017). As a result of the Instagram API’s security measure, it was only possible to obtain the first 150 comments of each picture or video. The data was gathered from several Instagram accounts that upload media of Miley Cyrus. Four of the accounts (@mileycyrusrc, @mileyoffical, @mileybitch and @mileydoll) had a small number of posts (from 39 to about 250 posts). The remaining ones were @mileycyruspictures with approximately 5,000 posts and 70,000 followers and @mileysofficial with about 2,000 posts and an amount of 73,000 followers. Although these accounts have posted more media, @mileydoll (947,000 followers) and @mileyofficial (292,000 followers) have a higher number of followers. The official Miley Cyrus account (@mileycyrus) consisted of over 5,500 posts and had 52 million followers. Since the official account was the largest data source, not all comments of every picture and video could be retrieved. Only media dating from June 2014 to June 2016 were gathered from the official Miley Cyrus account. The data of the smaller accounts were collected from the time of their creation mostly in 2012 to June 2016. All comments were saved into a database with the ID of the picture or video, as well as the ID of the account and the timestamp. The database consisted of approximately one million records after the data extraction.

2.2 Preprocessing

Before analyzing the collected data, they had to be preprocessed by a python script. Spam such as chain mails, advertisements or comments with limited content like “first” (user expressing one is the first to comment on the picture or video) got deleted. Usernames and links in the comments were reduced to a more general term, namely “USERNAME” and “LINK”, without having an impact on the sentiment. Also, the language of the comments was checked and automatically translated to English. Replacing abbreviations with their actual term was not required in this investigation due to repeating characters having emotionality themselves. After eliminating useless comments and cleaning the data, the sentiment analysis was performed on approximately 660,000 remaining records.

2.3 Sentiment analysis

In our study, the sentiment analysis is used to identify, extract and analyze the opinions and feelings of the comments written under media relating to a celebrity. The following approach detects the sentiment strength (positive, neutral and negative) within an interval of -5 to +5 (from negative until positive). Sentiment strength of 0 is considered as a neutral sentiment. Using SentiStrength (Thelwall et al., 2010) as a model, the Python based sentiment analysis program consists of an emoticon list, an emotion lexicon, a negation lexicon, a lexicon for booster words like “very” or “totally” as well as a lexicon for phrases.

AFINN is a list of English words rated for valence with an integer between -5 and +5. Finn Årup Nielsen (2011) labeled the words manually in 2009 to 2011 for sentiment analysis on microblogs. An adapted version of AFINN-111 is used as the emotion lexicon in this sentiment analysis. Two words, “like” and “lie”, need a special treatment, because the lexicon itself cannot deal with ambiguity problems. As a solution, the Natural Language Toolkit (http://www.nltk.org/) for Python programs is used. With a POS-Tagger, the right part-of-speech is recognized, which leads to more correct sentiment word values. The sentiment analysis program operates different steps and assigns the final sentiment. Each comment gets a sentiment for the written text as well as one for the emoticons – those were combined to the final sentiment of the comment.

First, the comment gets tokenized into sentences and next the sentences into words. To calculate the text sentiment, each word gets a sentiment value from the emotion lexicon. Words in quotation marks are considered as quotes and assessed as neutral because they often do not reflect the users' emotionality. Phrases that are present in the phrase lexicon get the sentiment value of that particular phrase. If the words of the phrase appear in the emotion lexicon as well, only the phrase value is important for the final comment sentiment. Also, the other lexicons were checked for negotiations (which can change the sentiment of a word from positive to negative, e.g. “not very happy”) and booster words like “very”. All those sentiment values add up to the final text sentiment of a comment. Because emoticons show a facial impression and therefore an emotion, it is important to include them into an emoticon lexicon. Further included are a few emojis that do not show a face but also express an emotion, for example a heart. The final sentiment is then calculated with all resulting values. Besides the text and emoticon sentiment values, there are also some other aspects considered in the final sentiment like repeated punctuations, repeated characters, number of emoticons and whole sentences or words in uppercase, all of them expressing emotion. After the sentiment analysis, each final sentiment of a comment is normalized to an interval of -5 to 5 (Equation 1).

$$Normalized\ value\ = \frac{(5*sentiment)}{max(|sentiment|)} \qquad (1)$$

3. Results

The amount of analyzed comments in the sentiment analysis is N = 662,883. In total, 46% (306,648) of them are neutral, 39% (258,320) are positive and 15% (97,914) are negative. Most of the analyzed comments (89.18%) belong to the official Miley Cyrus account (@mileycyrus). The remaining 10.82% points are spread to fan-based accounts. Total 5.85% of comments are collected from the Instagram account @mileycyruspictures. Each of the other unofficial accounts holds under 2.5% of the comments. Emoticons occur in 23.88% (158,288) of the total comments, whereas 76.12% (504,595) are without. Uppercase letters occurred in 4%, repeated characters as well as booster words in 5%, and repeated punctuations in 6% of the comments.

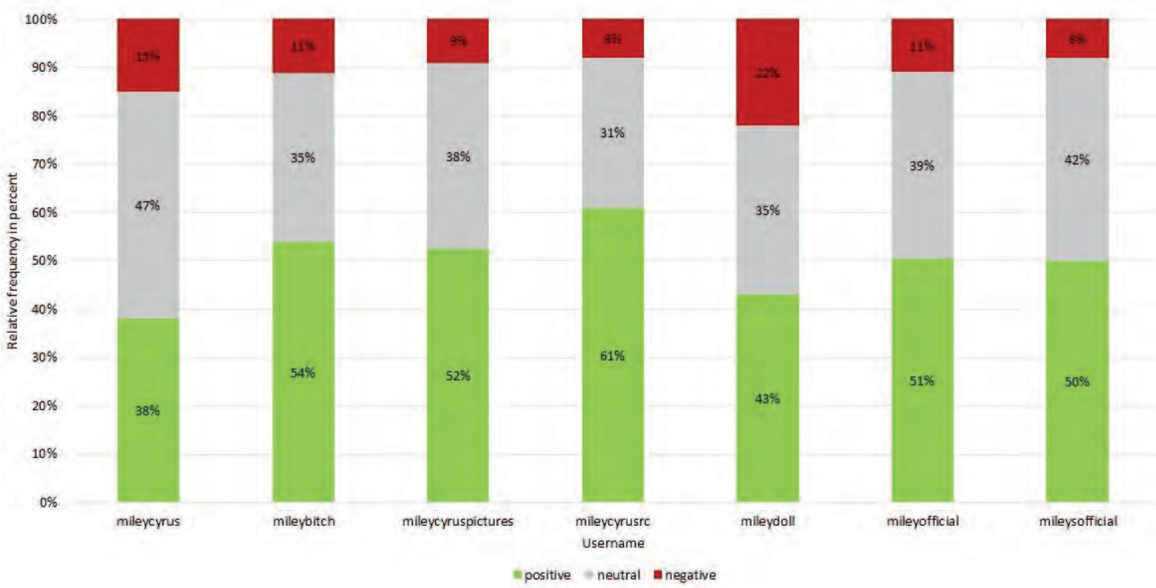

Figure 3: Relative frequency of negative, positive, and neutral comments for the analyzed accounts

As shown in Figure 3, from all comments of the official account (@mileycyrus) 38% are positive, 47% are neutral, and 15% are negative. One of the fan-based accounts (@mileybitch) has 11% negative, 35% neutral, and 54% positive comments. There are 9% negative, 38% neutral and 52% positive comments collected from the unofficial account named "mileycyruspictures". The most positive comments, with 61%, were collected from the account named "mileycyrusrc"; it has 31% neutral and only 8% negative comments. The account "mileydoll" had the most negative comments with 22%, 43% positive comments, and 35% neutral comments. Another fan based account, called "mileyoffical", has 51% positive comments, 39% neutral comments, and 11% negative comments. The last examined account (@mileysoffical) has 50% positive, 42% neutral as well as 8% negative comments. Overall, every account has more positive or neutral than negative comments. The neutral amount of comments is always smaller than the positive one except for the official Miley Cyrus account (@mileycyrus), which has more neutral than positive comments and the least positive comments (38%).

The average sentiment over time displays numerous positive and negative deflections (Figure 4). Over the entire time frame, the sentiment drops indicating that the comments are getting less positive over time. In August 2013, Miley Cyrus performed with Robin Thicke at the MTV Video Music Awards. Her controversial outfit and behavior received negative reviews (Mail Online, 2013). Miley's polarizing song and No. 1 hit "Wrecking Ball" and the corresponding video, published on the 9th of September in 2013 (MileyCyrusVEVO, 2013), brought a lot of attention as well. Especially the video got relatively negative reviews. The diagram shows that the sentiment on Miley Cyrus decreases during that time. Despite that, the average value of the sentiment is still positive. The following increase leads to a positive peak; this might indicate the success of her fourth studio album "Bangerz" that got released in the beginning of October 2013 (RcaRecords, 2013). The album got several, but mainly positive, reviews from critics (World History Project, 2013).

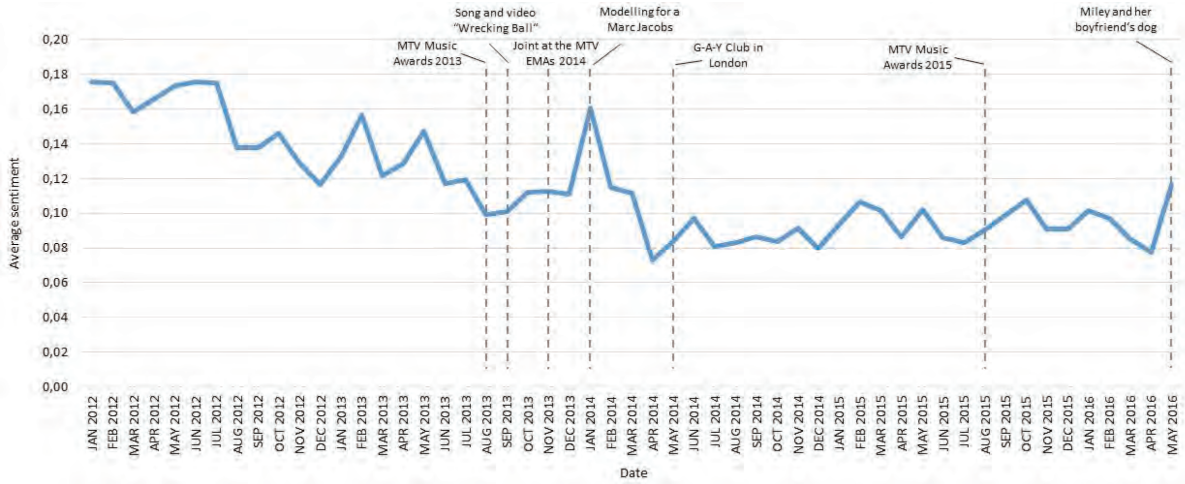

Figure 4: Time series of the average sentiment for all accounts by and on Miley Cyrus

The sentiment drops only a bit after November 2013 and then rises until January 2014 which contradicts with the scandal of Miley lighting a joint at the MTV Europe Music Awards (EMAs) in the same year. However, in January 2014 Miley Cyrus got positive publicity for modelling in a Marc Jacobs campaign for his Spring/Summer collection (Vogue, 2014). In May 2014 Miley took a ride on a huge phallus in the G-A-Y Club in London. She got a lot of bad publicity for her action (Albers Ben Chamo, 2014). Again, she received negative criticism for her behavior and her revealing outfit at the MTV Music Awards in August 2015 (ProSieben.de, 2016). Both actions also resulted in a drop of the sentiment after the positive feedback for the modelling campaign. In May 2016, the sentiment rises again after Miley Cyrus posted a picture of herself with her Ex-Boyfriend's dog which implied that they are dating again (Mail Online, 2017; Miley Cyrus Instagram, 2016).

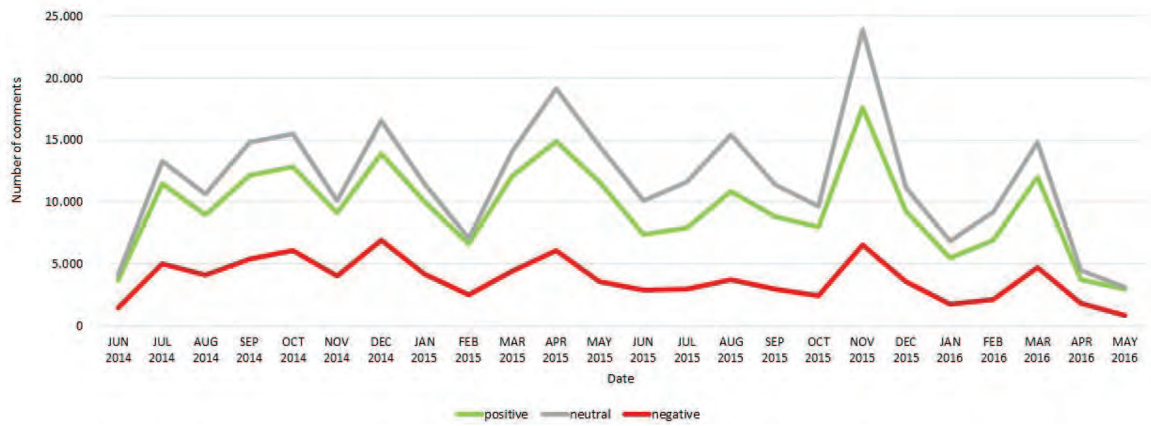

Figure 5: Number of comments with sentiment over time

Figure 5 displays the number of comments over time by neutral, positive and negative sentiment. The number of analyzed comments rises in June 2014, only because the comments from the official Miley Cyrus account were collected from June 2014 to June 2016. It features much more media than the fan-based accounts. The amount of neutral comments is always higher than the positive or the negative ones; also the number of negative comments is always lower than the number of positive ones. The distance between negative and positive comments gets bigger at the deflections.

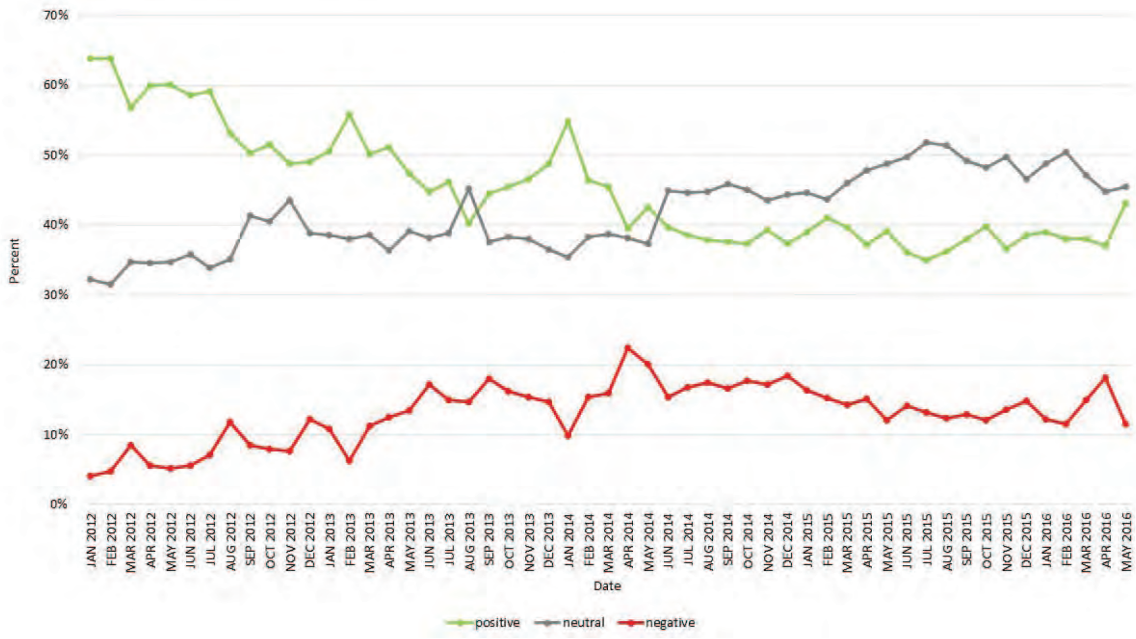

Figure 6: Sentiment of comments on Miley Cyrus over time in percent

In Figure 6 we can see that the relative frequencies of positive, negative and neutral comments. The sentiment's percentage shows that positive comments (green) decrease while negative (red) and neutral comments (blue) increase. In January 2012 there are around 63% positive, 5% negative, and 32% neutral comments. At this time, the positive comments are at their highest percentage. In August 2012 the lines show about 53% positive, 12% negative, and 35% neutral comments. One year later, in August 2013, we can detect 40% positive, 15% negative, and 45% neutral comments. In April 2014 the percentage of negative comments is at the highest point with around 22%. The neutral comments are at around 38% and the positive ones at 40%. In June 2014 the percentage of neutral comments gets higher than the percentage of positive comments. At this time, the comments from the official Miley account were collected. Coming to July 2015, with the highest peak of the neutral comments, they are at around 52 percent. The positive comments have a lowest point in July 2015, with 35%, and the negative ones are at 13%. In April 2016, the positive comments are at 38%, the negative ones are at 18%, and the neutral ones are at 44%.

4. Discussion

This investigation displays if there is negative response to uploaded images and videos on the social media account from a polarizing celebrity and, additionally, from fan-based accounts. Furthermore, the differences between the official account of Miley Cyrus as well as fan-based accounts are shown. Finally, the sentiment regarding to certain events was detected. Our study also discovered a huge amount of spam as well as chain mails in the comment section of a celebrity's uploaded media. Conclusively, the large fan base of a celebrity attracts many spammers.

The text-based sentiment analysis on data of different social media services has become an interesting and comprehensive research subject. There are already several studies about sentiment analysis, but none about a sentiment analysis on the reaction of a celebrity's audience. Our study should serve as a model and example for using the described dictionary based method for sentiment analysis, especially for Instagram comments. However, the used method can be applied to other text-based data as well.

4.1.1 RQ1: Does some kind of hate or negativity exist in the comment section of celebrities? If so, to what extent are the comments negative?

The overall sentiment is always slightly positive. Although the negative and hate comments are not predominating in the comment section of Instagram pictures related to Miley Cyrus, some negativity was found. Around 15% from over 660,000 comments was detected as negative, what makes an amount of nearly 100,000 negative comments.

4.1.2 RQ2: Is the official account of a polarizing celebrity more prone to negative or positive sentiment than fan-based accounts?

The official Miley Cyrus account (@mileycyrus) has the least positive and the most neutral comments. There is also only one of the six unofficial accounts having more negative comments than the official Miley account. Overall, fan-based accounts get more positive feedback for the pictures and less hate than the proofed Miley account. Haters seem to turn their negative comments directly against Miley Cyrus.

4.1.3 RQ3: Do certain events and scandals in a celebrity's life influence the overall sentiment on these accounts?

There are several events that are decisive factors for the rise of the number of comments, as well as for the downs of the negative decreases and the peaks of positive increases (e.g. release of a new album). Furthermore, modelling campaigns as well as relationship-based pictures attracted the attention of users to comment on the media of Miley Cyrus. Pictures with attention-gaining events are getting even more comments.

4.1.4 RQ4: Is there a trend towards a specific sentiment over time?

When the audience is going to comment more on the media, the users are posting more positive and neutral comments than negative comments. The negative line does not have such swings than the ones from the positive and neutral comments. The average sentiment over time has many ups and downs – but generally decreases in the reported time span.

The method of using sentiment analysis has some limitations. Because of the automated method for filtering spam and bots, there might be some of the spam comments left. Moreover, ironic sentences and comments including sarcasm may not be recognized by the script. Another difficulty appears at the misspelling of words. And even when translating one language into another, there could be some mistranslated words. Another limitation is bound to the Instagram APIs conditions. One is only able to collect the latest 150 comments of a medium. Maybe, there will be more positive or even negative feedback in the first comments of the media from the official account, which had more than 3,000 comments under most pictures and videos. Further research may include a comparison between emoticon sentiment and text sentiment of each comment as well as research of comments towards further celebrities. Also, a comparison about the sentiment of comments from different social media services would be interesting. Conclusively, the sentiment analysis of Miley Cyrus' Instagram posts displays that hater comments do not "come in like a wrecking ball" and are obviously outnumbered.

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