

# Detection of Cyberbullying Incidents on the Instagram Social Network

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## Abstract

Cyberbullying is a growing problem affecting more than half of all American teens. The main goal of this paper is to investigate fundamentally new approaches to understand and automatically detect incidents of cyberbullying over images in Instagram, a media-based mobile social network. To this end, we have collected a sample Instagram data set consisting of images and their associated comments, and designed a labeling study for cyberbullying as well as image content using human labelers at the crowd-sourced Crowdfunder Web site. An analysis of the labeled data is then presented, including a study of correlations between different features and cyberbullying as well as cyberaggression. Using the labeled data, we further design and evaluate the accuracy of a classifier to automatically detect incidents of cyberbullying.

## Introduction

As online social networks (OSNs) have grown in popularity, instances of cyberbullying in OSNs have become an increasing concern. In fact more than half of American teens have been the victims of cyberbullying (National Crime Prevention Council 2011). Although cyberbullying may not cause any physical damage initially, it has potentially devastating psychological effects like depression, low self-esteem, suicide ideation, and even suicide (Hinduja and Patchin 2010; E. Menesini 2009). Incidents of cyberbullying with extreme consequences such as suicide are now routinely reported in the popular press. For example, Phoebe Prince, a 15-year-old high school girl, committed suicide after being cyberbullied by negative comments in the Facebook social network (Goldman 2010). Hannah Smith, a 14-year-old, hanged herself after negative comments were posted on her Ask.fm page, a popular social network among teenagers (Smith-Spark 2013). Cyberbullying is such a serious problem that nine suicides have been linked with cyberbullying on the Ask.fm Web site alone (Broderick 2013). Although cyberbullying is not the direct cause of these suicides, cyberbullying was viewed as a contributing factor in the death of these teenagers (Cyberbullying Research Center 2013).

Given the gravity of the consequences cyberbullying has on its victims and its rapid spread among middle and high school students, there is an immediate and pressing need for research to understand how cyberbullying occurs in OSNs today, so that effective techniques can be developed to accurately detect cyberbullying. A recent survey on cyberbullying (Ditch the Label Anti Bullying Charity 2013) has listed the top five networks where the highest percentage of users have reported experiencing cyberbullying, namely Facebook, Twitter, YouTube, Ask.fm, and Instagram. Instagram is of particular interest as it is a media-based mobile social network, which allows users to post and comment on images. Cyberbullying in Instagram can happen in different ways, including posting a humiliating image of someone else by perhaps editing the image, posting mean or hateful comments, aggressive captions or hashtags, or creating fake profiles pretending to be someone else (Silva et al. 2013). Figure 1 illustrates an example of an attack in Instagram in which offensive hashtags and hateful comments were posted to humiliate the profile owner.

Cyberbullying has been defined as intentionally aggressive behavior that is *repeatedly carried out* in an online context against a person *who cannot easily defend him or herself* (Kowalski et al. 2012; Patchin and Hinduja 2012). It is important to this definition of cyberbullying that both the frequency of negativity and the imbalance of power between the victim and perpetrator be taken into account. In contrast, cyberaggression is a more general type of behavior that is broadly defined as using digital media to intentionally harm another person (Kowalski et al. 2012).

Prior works that investigated cyberbullying (Ptaszynski et al. 2010),(Dadvar et al. 2012),(K. Reynolds and Edwards 2011),(Dinakar et al. 2012),(H. Sanchez 2012),(Kontostathis et al. 2013), (Xu et al. 2012),(Nahar et al. 2014),(Nahar, Li, and Pang 2013),(Dinakar, Reichart, and Lieberman 2011),(Nahar et al. 2012) are more accurately described as research on cyberaggression, since these works do not take into account both the frequency of negativity and the imbalance of power. These works have largely applied a text analysis approach to online comments, since this approach results in higher precision and lower false positives than simpler list-based matching of negative words (Sood, Antin, and Churchill 2012). Other work analyzed negativity in Ask.fm (Hosseinmardi et al. 2014a) and Instagram comments (Hos-

seinmardi et al. 2014b), but did not label the data at all.

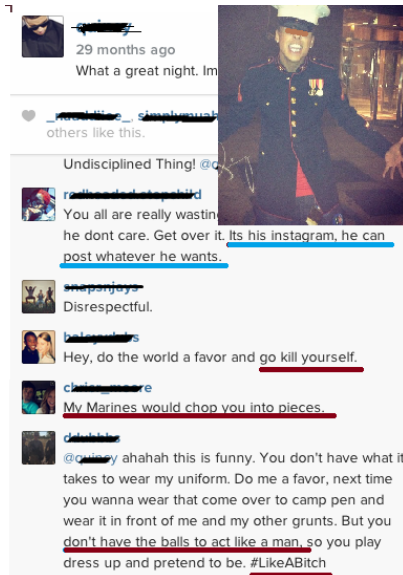


Figure 1: An example of comments posted on Instagram. To give more room for the text, we have moved the associated image to overlay some of the text.

Additional research investigated aspects of the Instagram social network, but not in the context of cyberbullying. For example, (Weilenmann, Hillman, and Jungselius 2013) explored users' photo sharing experience in a museum. (Silva et al. 2013) considered the temporal photo sharing behavior of Instagram users. (Y. Hu 2014) categorized Instagram images into eight popular image categories and the Instagram users into five types in terms of their posted images. By investigating user practices in Instagram, (Araujo et al. 2014) concluded that users tend to be more active during weekends and at the end of the day. They also found out that users are more likely to like and comment on the medias that are already popular, thereby inducing the rich get richer phenomenon.

In this paper, we make the following contributions:

- We provide a clear distinction between cyberbullying and general cyberaggression. Cyberbullying is one type of cyberaggression, and most of the earlier research in this area has focused on identifying cyberaggression, which is relatively easier than identifying cyberbullying.
- We investigate cyberbullying behavior in Instagram by labeling collected Instagram images and their associated discussion comments according to both the more restrictive definition of cyberbullying and the more general definition of cyberaggression.
- We present an analysis of the labeled images and comments, including the relationships of cyberbullying and cyberaggression to a variety of features, such as number of associated comments, N-grams, followed-by and following behavior of the posting users, liking behavior, frequency of comments, and labeled image content.

- We design and evaluate multi-modal classifiers to detect cyberbullying based on the labeled data, measuring accuracy across different feature sets including text, images, and meta data.

## Data Collection

Using a snowball sampling method, we have identified 41K Instagram user ids. 61% of these Instagram ids have public profiles, which is about 25K public profiles. These 25K public user profiles comprise our complete set of typical Instagram users data. For each public Instagram user, the collected profile data includes the media objects/images that the user has posted and their last 150 associated comments, user id of each user followed by this user, user id of each user who follows this user, and user id of each user who commented on or liked the media objects shared by the user. We consider each media object/image and its associated comments as a *media session*. For this set of 25K users, 697K media sessions were collected.

In order to make the labeling of cyberbullying more manageable, we sought to label a smaller subset of these media sessions. We focused on those media sessions that have a high percentage of negativity in their associated comments, since we reasoned that this should give us a higher likelihood of identifying cyberbullying once the data was properly labeled. We used the same approach as in the previous works (Hosseinmardi et al. 2014a; 2014b) for tagging a comments as a negative or not, by looking for profanity words coming from a dictionary obtain form (NoSwearing.com ; von Ahn's Research Group 2014). Specifically, we select images using the following two criteria:

- the media has at least 15 comments, and
- more than 40% of the comments by users other than the profile owner have at least one negative word.

Using these criteria, we were able to reduce the number of media sessions to a more tractable group of about 1, 203. When we returned to Instagram to collect images associated to the comments of selected media's for labeling, only 998 were still available, for the rest either the media session was deleted or the profile was made private or deleted. The reason for putting lower bound on the number of comments (minimum 15 comments) is to ensure that there are enough comments to adequately assess the frequency or repetition of negativity, which is an important part of the cyberbullying definition. The average number of comments per image is 59.6, and we decided to analyze all images with number of comments at least a quarter of this average number. For these 998 media sessions, the average number of comments associated with a media is about 64.3.

Figure 2 shows the distribution of the number of comments for our selected smaller subset of media sessions compared with the number of comments for the complete set of media sessions. We observe that the fraction of images with number of comments between 15 and 50 is higher in the selected data set than that in the complete set. However, the distribution is similar when the number of comments is greater than 50. This shows that media sessions with rel-

atively higher negativity tend to be confined to moderate number of comments.

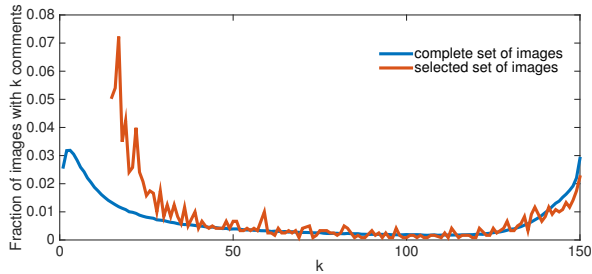


Figure 2: Comparison of the distribution of the number of comments per collected Instagram media session. Blue is for the complete set of media sessions, and red is for the selected subset of 998 media sessions with more than 15 comments and high degree of negativity.

Figure 3 illustrates the CCDF of the number of followed by and follows for users in both the complete and selected set of media sessions. We see that the number of follows for users in the complete and selected sets exhibit the same pattern. However, the distribution for selected users ends at around 7,500, while the distribution for all users goes to almost  $10^7$ . On the other hand, distributions of the number of followed by users are different for selected users and all users. The number of followed by users is higher for the selected users, but this distribution ends at around  $4.16 \times 10^6$ , while the distribution for all users goes all the way up to  $10^8$ . Looking at the data more closely, we found that a large number of images posted by the selected users set correspond to popular personalities or events, e.g., a lot of these users are singers, celebrities, tattoo artists, or simply users who are popular within a local area. These users draw a lot of attention. Because of their popularity, they have a relatively larger number of followers, and tend to attract a significant number of negative comments in the form of criticism from other users.

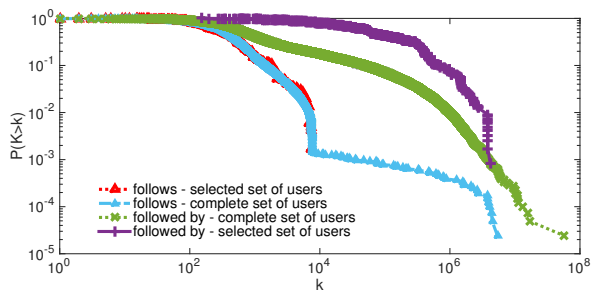


Figure 3: CCDF of the number of followed by and follows for users in the complete set and highly negative subset of media sessions.

## Cyberbullying Labeling

In this section, we explain the design and methodology for our survey labeling the selected set of media sessions. Our first challenge is choosing appropriate definitions of terms, which will then be used in ground truth labeling. Based on the literature, a major early choice that we have made is to distinguish between cyberaggression and cyberbullying. Cyberaggression is broadly defined as using digital media to intentionally harm another person (Kowalski et al. 2012). Examples include negative content and words such as profanity, slang and abbreviations that would be used in negative posts such as hate, fight, wtf. Cyberbullying is one form of cyberaggression that is more restrictively defined as intentional aggression that is repeatedly carried out in an electronic context against a person who cannot easily defend him or herself (Kowalski et al. 2012; Patchin and Hinduja 2012). Thus, cyberbullying consists of three main features: (1) an act of aggression online; (2) an imbalance of power between the individuals involved; and (3) it is repeated over time (Hunter, Boyle, and Warden 2007; Kowalski et al. 2012; Olweus 1993; 2013; Smith, del Barrio, and Tokunaga 2012). The power imbalance can take on a variety of forms including physical, social, relational or psychological (Dooly, Pyżalski, and Cross 2009; Monks and Smith 2006; Olweus 2013; Pyżalski 2010), such as a user being more technologically savvy than another (Kowalski et al. 2014), a group of users targeting one user, or a popular user targeting a less popular one (Limber, Kowalski, and Agatston 2008). Repetition of cyberbullying can occur over time or by forwarding/sharing a negative comment or photo with multiple individuals (Limber, Kowalski, and Agatston 2008).

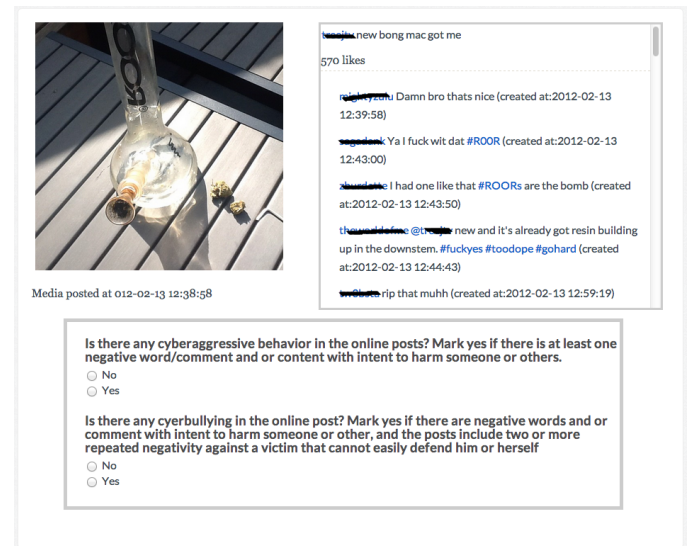


Figure 4: An example of the labeling survey, which shows an image and its corresponding comments, and the survey questions.

In Instagram, each media session consists of a media posted by the profile owner and the corresponding comments for the media object. The goal in this paper is to investigate cyberaggression and cyberbullying in this multi-modal (tex-

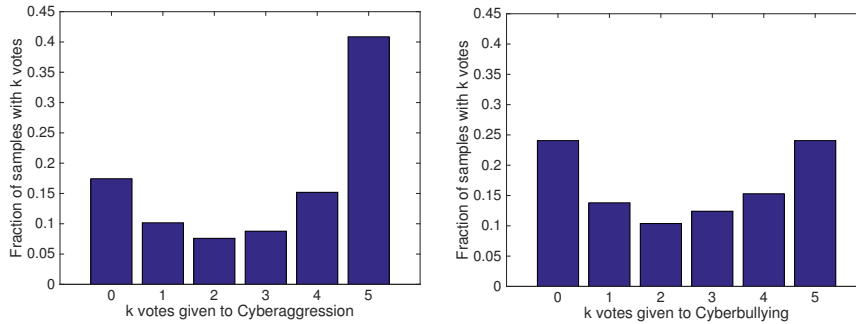


Figure 5: Fraction of media sessions that have been voted  $k$  times as cyberaggression (left) or cyberbullying (right).

tual comments and media objects) context. Therefore, the design of our survey needed to incorporate both the image and the associated text comments when asking the human labeler whether the media session was an instance of cyberbullying or cyberaggression. Figure 4 illustrates an example of our design for the labeling survey. On the left is the image, and on the right is a scrollable interface to help the labeler see all of the comments associated with this image. With the help of an expert, we decided to ask the labelers two questions, namely whether the media session constituted cyberaggression or not, and whether the media session constituted cyberbullying or not. During the instructional phase prior to labeling, labelers were given the aforementioned definitions of cyberaggression and cyberbullying along with related examples. Each media session was labeled by five contributors.

To monitor the quality of labeling, potential contributors were given the answers to a set of examples, and then were subjected to a pre-filtering step in which they were asked to answer a set of similar quiz questions. Contributors needed to answer correctly a minimum number of quiz questions to qualify as a labeler for our survey. Also during the job, random test questions were asked to monitor the quality of the labeling during the job. A minimum threshold amount of time was also set to filter out contributors who rushed through the labeling without spending a sufficient minimum duration to ensure the quality of the labeling.

We were also interested in image contents of media sessions that had been targeted with a high proportion of negative comments. If the type or category of an image could be identified, then this may prove to be a useful feature in classification of cyberbullying. We first sampled some of the images in the selected subset to determine a suitable set of representative categories or types to be used in the labeling. For example, some of the dominant categories were the presence of a human in the image, as well as animals, text, clothes, tattoos, sports and celebrities. We then conducted a second survey focused only on the image content, and asked labelers to identify which of the aforementioned categories were present in the image. Multiple categories could be selected for a given image.

## Analysis and Characterization of Labeled Cyberbullying

We submitted our survey with 998 media sessions (images and their associated comments) to CrowdFlower, a crowd sourcing website, each labeled by five different contributors. Figure 5 illustrates the distribution of the labeled answers among the five labelers for each of the two questions on cyberbullying and cyberaggression. The higher the number of votes for a given label, the more confidence that we have that a given media session constitutes cyberaggression or cyberbullying, where five votes constitutes unanimous agreement. The left chart in Figure 5 shows the percentage of samples that have been labeled as cyberaggression  $k$  times, and the right chart shows the percentage of samples that have been labeled as cyberbullying  $k$  times.

We notice that for cyberaggression, most of the probability mass is around media sessions labeled as cyberaggression by all five contributors. This is not surprising since all the samples have at least 40% negative comments. However, we observe that around 17% of the media sessions have not been labeled as cyberaggression at all by any of the five contributors. This suggests that only employing a high percentage of negativity threshold of 40% to detect cyberaggression can still produce many false alarms.

For cyberbullying labeling (right chart in Figure 5), we notice that about 24% of the media sessions have not been labeled as cyberbullying by any of the five contributors, even though these samples were originally selected for their high negativity. Further, we observe that about 48% of the media sessions have two or fewer votes. If we apply a majority vote criterion to deciding whether a given session was cyberbullying or not among the five labelers, then nearly half of the sessions would be defined as not cyberbullying, despite their high percentage negativity. *Therefore, a key finding of our labeling is that a large fraction of Instagram media sessions with a high percentage of negative words would **not** be deemed as cyberbullying.* The implication is that classifier design for cyberbullying here cannot solely rely on the percentage of negativity among the words in the image-based discussion, since this would produce many false positives, but instead must consider other features to improve accuracy.

*Another key observation is that the labelers are mostly in agreement about what behavior constitutes cyberbully-*

correlation	likes	media	followed by	following
cyberbullying	0.069	0.04	0.17	-0.02
cyberaggression	0.04	0.07	0.14	-0.00

Table 1: Correlation between number of votes for cyberbullying /cyberaggression and image/user meta data

ing and what does not in Instagram media sessions. That is, most of the labelers agree either that a media session is cyberbullying (about 40% of sessions have either four or all five votes for cyberbullying) or that it is not (about 38% of sessions have either zero or one vote). Only about 22% of media sessions have two to three votes, so there is some disagreement in a small fraction of cases about whether the session is cyberbullying or not.

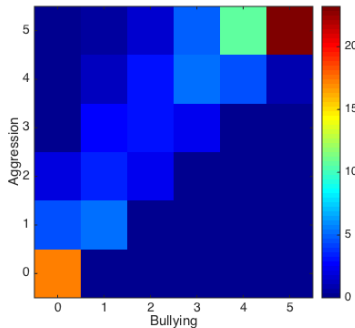


Figure 6: Two-dimensional distribution of media sessions as a function of the number of votes given for cyberaggression versus the number of votes given for cyberbullying, assuming five labelers.

In order to understand the relationship between labeled cyberaggression and labeled cyberbullying media sessions, we plotted in Figure 6 a two-dimensional heat map that shows the distribution of media sessions as a function of the number of votes each media session received for cyberaggression and cyberbullying. We observe that a significant fraction of the sessions exhibit strong agreement in terms of both receiving high numbers of votes for both cyberbullying and cyberaggressions, or both receiving low numbers of votes, i.e. the session is neither cyberbullying nor cyberaggression. This is shown by the high energy in the upper right and lower left along the diagonal. In addition, it is promising that the area below the diagonal is essentially zero, meaning no sessions have received more votes for cyberbullying than cyberaggression. This conforms with the definition that cyberbullying is a subset of cyberaggression.

We see that the remaining significant energy in the distribution appears in the area above the diagonal. Media sessions in this area exhibit the property that if they receive  $N_1$  cyberbullying labels, then they receive  $N_2 \geq N_1$  cyberaggression labels. This area corresponds to cases where there is cyberaggression but not cyberbullying. In particular, if we look at the cases where there is some disagreement as to whether a session is cyberbullying or not ( $N_1 = 2$  or 3 votes for cyberbullying), we see that there is significant support

that these sessions exhibit cyberaggression (there is significant energy for  $N_2$  values of four and five votes for cyberaggression). In fact, the dominant value for cyberaggression when  $N_1 = 2$  is  $N_2 = 4$ , and similarly the dominant value for cyberaggression for  $N_1 = 3$  is  $N_2 = 4$  or 5. As a result, our analysis is able to quantify that there is substantial support for identifying Instagram media sessions that exhibit cyberaggression but not cyberbullying.

Next, we would like to examine the correlation between the strength of labeled cyberbullying/cyberaggression and a variety of other factors. We define the strength of cyberbullying as the number of votes received for labeling a media session as cyberbullying, and similarly for cyberaggression. Table 1 shows the correlation between the strength of cyberbullying/cyberaggression and media properties such as the number of likes, as well as meta data about the profile owner of the shared media object, such as the number of followings, followed-by's, and total shared media. We observe that there is a correlation of 0.17 with the number of followed-by's while there is no significant correlation with the number of likes, total shared media, and followings. We also found that cyberaggression exhibits similar but slightly weaker correlations to the same factors.

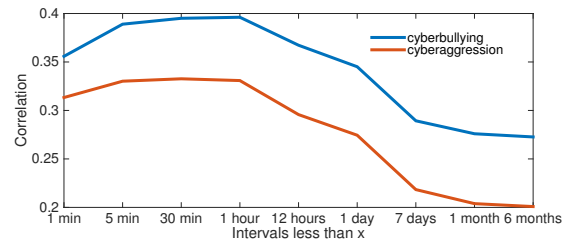


Figure 7: Temporal correlation analysis.

Our analysis further explores Pearson's correlation by considering temporal factors. We would like to understand how the human labelers incorporated the definition of cyberbullying, which includes the temporal notion of repetition of negativity over time, into their labeling. Given time stamps on every collected comment, we compute the interval or interarrival time between a comment and the next comment. We then counted the number of comment interarrival times in a media session less than some threshold value. Figure 7 describes our results, namely that there is a strong correlation of about 0.4 between the strength of support for cyberbullying and media sessions in which there are frequent postings within 1 hour of each other. Further, we find that as we expand the allowable duration between comments, that is comments are allowed to be further apart in time, then the correlation weakens considerably between more widely

separated comments and support for labeling this session as cyberbullying. We also considered cyberbullying’s correlation with other temporal factors such as the median, mean and variance, i.e. jitter, of the comment interarrival times but found little correlation. Cyberaggression temporal correlations follow a similar pattern.

*To summarize, we have found that there are strong correlations between the strength of support for labeled cyberbullying and the number of text comments as well as the temporal property of the number of comments that are posted within one hour of one another in an Instagram media session.*

### Image Labeling Analysis

In this subsection, we would like to understand the relationship between image content and cyberbullying in a media session. Towards this end, we display the distribution results of our second survey on labeling image content in Figures 8 and 9. First, we observe that among the media sessions with the highest negativity, the most common labels for the image content in these media sessions are Person/People, Text, Sports, and perhaps Tattoo, for most values of support for cyberbullying. Second, there is some skew in distributions for certain labels such as Person/People, Tattoo and Sports, as the amount of support for cyberbullying varies. For example, for images labeled as containing a Tattoo, we see a strong skew towards lower values of cyberbullying. Such a skew may be helpful in classifier design, since whenever a tattoo is present, there appears to be little support that there is cyberbullying occurring, while whenever there is strong support for cyberbullying, images with tattoos are more scarce. For Person/People, we see a skew in the opposite direction towards more cyberbullying support, and similarly for Sports. Similar behavior is exhibited for cyberaggression as well.

Since labeling of image content into more than one category was permitted, then we are further interested to see the distribution of multi-label images. Figure 10 shows the fraction of other categories assigned to a Person/People labeled image. For example, Figure 10 shows that more than 60% of images labeled with Person/People were exclusively labeled as such, but about 15% of such images were also labeled with the Text label. Very few images were labeled with three labels.

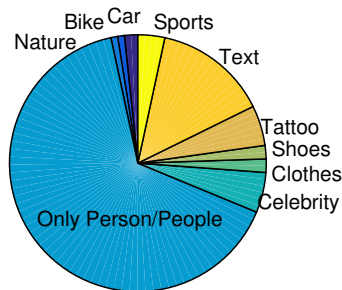


Figure 10: Fraction of other categories assigned to an image given that the image has been labeled as Person/People.

### Classifier Design and Evaluation

To design and train the classifier, we chose to apply a majority vote criterion on the labeled data to determine whether a media session was cyberbullying or not. Further, CrowdFlower provides us with a degree of trust for each labeler based on the percentage of correctly answered quiz and test questions during the labeling session. This trust value is incorporated by CrowdFlower into a weighted version of the majority voting method called a “confidence level”. We decided to employ this weighted trust-based majority voting metric as the basis for our classifier design. Media sessions whose weighted trust-based metric was equal to or greater than 60% were deemed to be strong enough support for cyberbullying. Actually, 90% of the original pure majority-vote based media sessions wound up in this higher-confidence cyberbullying-labeled group. For this higher-confidence data set, 52% in total belonged to the “bullying” group while 48% were not deemed to be bullying. This provides a base case from which to compare our classifier since we can simply apply a detector based on the 40% negativity threshold and achieve 0.52 accuracy for cyberbullying detection.

Two types of features were evaluated, namely those features obtained from the content of comments, and those features obtained from shared media objects and the profile owner. For the text features, first we applied a pre-processing step to remove characters such as “!”, “¿”, etc. and stop words such as “and”, “or”, “for”, etc. Features extracted from text include unigram, bigram, 3-gram, number of comments for the image, and number of posts within interval less than one hour. Features extracted from user and media information (named as meta data) includes the number of followed-by’s, follows, likes, and shared medias and features extracted from image content includes image categories.

Table 2 illustrates the best performance results among different examined classifiers (all numbers are average over 10-fold cross validation results). In the first row using low dimensional feature space of meta data and a simple Naïve Bayes Classifier we jumped to accuracy 0.71 from baseline 0.52. Next we observed that adding image categories increased the accuracy to 0.72, with a high recall 0.78.

In another experiment, only the text features unigram and 3-gram gave us the best accuracy using linear Support Vector Machine (SVM) Classifier. However, the dimension of unigrams and 3-gram features is very high, so next row shows the accuracy after applying Singular Value Decomposition (SVD) on text features. We observed keeping only the first 200 components, we can get the same accuracy.

In the next step we added meta data and image categories to the text features. To get the best accuracy, we first standardized these set of features, applied kernel PCA (Principle Component Analysis) and kept the first 20 components. Then we concatenate this set of reduced dimension features with the reduced dimension features obtained from text. Applying linear SVM classifier, the accuracy jumped to 0.87 with both high precision and recall.

*In summary, by employing multi-modal features obtained from text, meta data and images as input into a linear SVM classifier, the accuracy of cyberbullying detection was mean-*

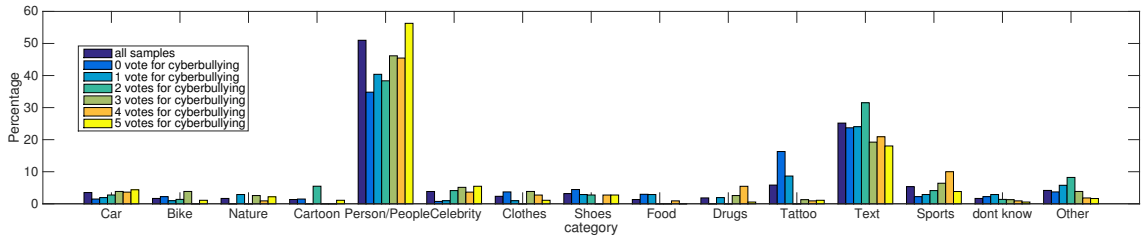


Figure 8: Distribution of image categories given the media sessions have been voted for k times for cyberbullying. As some images belong to more than one category, the bars will sum up to more than one.

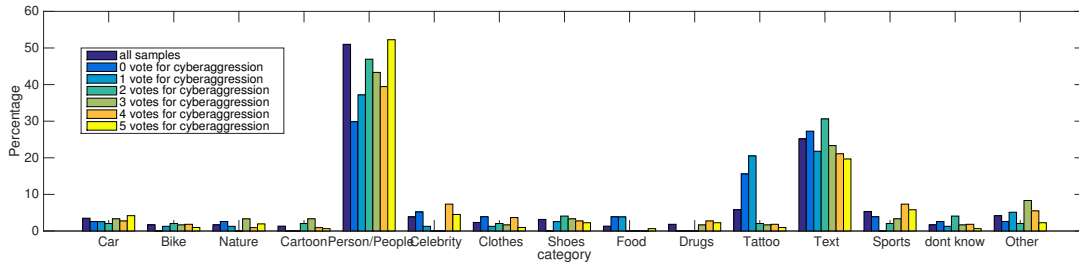


Figure 9: Distribution of image categories given the media sessions have been voted for k times for cyberaggression.

ingly improved by 0.35 to a total of 0.87 compared to a base case of 0.52. Simple meta data features gain accuracy 0.71, but to increase recall, more complex features are needed.

### Discussion and Future Work

One theme for future work is to improve the performance of our classifier by adding more input features, such as new image features, temporal behavior of commenting, mobile sensor data, etc. A limitation of our current classifier is that it is designed only for highly negative media sessions. A more general classifier that can apply to all media sessions is needed. This will also require us to enlarge our labeled data set substantially. Incorporating image features needs to be automated by applying image recognition algorithms. We plan to explore this research direction as well. We have applied a majority vote definition in designing our classifier. Another definition to consider is when at least one labeler has declared that he/she thinks this media session constitutes cyberbullying. New classifiers will have to be designed for this definition.

We also plan to consider designing classifiers for cyberaggression in addition to cyberbullying, and to investigate those media sessions that represent the former but not the latter behavior.

Another theme for future work is to obtain greater detail from the labeling surveys. Our experience was that streamlining the survey improved the response rate, quality and speed. However, we desire more detailed labeling, such as for different roles in cyberbullying – identifying and differentiating the role of a victim’s defender, who may also spew

negativity, from a victim’s bully or bullies.

### Conclusions

We believe this paper makes the following major contributions: an appropriate definition of cyberbullying that incorporates both frequency of negativity and imbalance power is applied in large-scale labeling, and is differentiated from cyberaggression; cyberbullying is studied in the context of a media-based social network, incorporating both images and comments in the labeling; a detailed analysis of the distribution results of the labeling of cyberbullying incidents is presented, including a correlation analysis of cyberbullying with other factors derived from images, text comments, and social network meta data; multi-modal classification results are presented that incorporate a variety of features to identify cyberbullying incidents.

The major findings of this paper comprise the following results. First, a key finding of our labeling is that about 48% of Instagram media sessions were not deemed as cyberbullying using a majority vote criterion among five labelers, even though these were among the media sessions with the highest percentage of profanity words, i.e. a significant fraction of negative content does not constitute acts of online cyberbullying. Second, labelers are mostly in agreement about what behavior constitutes cyberbullying and what does not in Instagram media sessions. Third, our analysis identified that there is significant class of Instagram media sessions that exhibits cyberaggression but not cyberbullying. Fourth, there are strong correlations between the strength of support for labeled cyberbullying and the number of text comments as well as the temporal property of the number

Features	Classifier	Accuracy	Precision	Recall
Meta data	Naïve Bayes	0.71	0.75	0.66
Meta data, image categories	Naïve Bayes	0.74	0.74	0.78
Unigram, 3-gram	linearSVM	0.85	0.88	0.84
SVD + Unigram, 3-gram	linearSVM	0.85	0.84	0.88
SVD +(Unigram, 3-gram), kernelPCA+(meta data, image categories)	linearSVM	0.87	0.88	0.87

Table 2: Cyberbullying detection’s classifier performance

of comments that are posted within one hour of one another in an Instagram media session. Fifth, we demonstrate that a Linear SVM classifier can significantly improve the accuracy of identifying cyberbullying to 87% by incorporating multi-modal features from text, images, and meta data for the media session.

## References

- Araujo, C. S.; Correa, L. P. D.; da Silva, A. P. C.; Prates, R. O.; and Jr, W. M. 2014. It is not just a picture: Revealing some user practices in instagram. In *Web Congress (LA-WEB), 2014 9th Latin American*, 19 – 23. IEEE.
- Broderick, R. 2013. 9 teenage suicides in the last year were linked to cyber-bullying on social network ask.fm. <http://www.buzzfeed.com/ryanhatetesthis/a-ninth-teenager-since-last-september-has-committed-suicide>. [Online;accessed 14-January-2014].
- Cyberbullying Research Center. 2013. Cyberbullying Research Center. <http://cyberbullying.us>. [Online; accessed September, 2013].
- Dadvar, M.; de Jong, F. M. G.; Ordelman, R. J. F.; and Trietschnigg, R. B. 2012. Improved cyberbullying detection using gender information. In *Proceedings of the Twelfth Dutch-Belgian Information Retrieval Workshop (DIR 2012), Ghent, Belgium*, 23–25. Ghent: University of Ghent.
- Dinakar, K.; Jones, B.; Havasi, C.; Lieberman, H.; and Picard, R. 2012. Common sense reasoning for detection, prevention, and mitigation of cyberbullying. *ACM Trans. Interact. Intell. Syst.* 2(3):18:1–18:30.
- Dinakar, K.; Reichart, R.; and Lieberman, H. 2011. Modeling the detection of textual cyberbullying. In *The Social Mobile Web*.
- Ditch the Label Anti Bullying Charity. 2013. The annual cyberbullying survey 2013. <http://www.ditchthelabel.org/annual-cyber-bullying-survey-cyber-bullying-statistics/>.
- Dooley, J. J.; Pyzalski, J.; and Cross, D. 2009. Cyberbullying versus face-to-face bullying. *Zeitschrift für Psychologie/Journal of Psychology* 217(4):182–188.
- E. Menesini, A. N. 2009. Cyberbullying definition and measurement. some critical considerations. *Journal of Psychology* 217(4):320–323.
- Goldman, R. 2010. Teens indicted after allegedly taunting girl who hanged herself, bbc news. <http://abcnews.go.com/Technology/TheLaw/teens-charged-bullying-mass-girl-kill/story?id=10231357>. [Online; accessed 14-January-2014].
- H. Sanchez, S. K. 2012. Twitter bullying detection. NSDI’12, 15–15. Berkeley, CA, USA: USENIX Association.
- Hinduja, S., and Patchin, J. W. 2010. Cyberbullying research summary, cyberbullying and suicide.
- Hosseinmardi, H.; Ghasemianlangroodi, A.; Han, R.; Lv, Q.; and Mishra, S. 2014a. Towards understanding cyberbullying behavior in a semi-anonymous social network. In *Advances in Social Networks Analysis and Mining (ASONAM 2014)*, 244 – 252.
- Hosseinmardi, H.; Rafiq, R. I.; Li, S.; Yang, Z.; Lv, Q.; Han, R.; and Mishra, S. 2014b. A comparison of common users across instagram and ask. fm to better understand cyberbullying. In *Big Data and Cloud Computing (BdCloud), 2014 IEEE Fourth International Conference on*, 355–362. IEEE.
- Hunter, S. C.; Boyle, J. M.; and Warden, D. 2007. Perceptions and correlates of peer-victimization and bullying. *British Journal of Educational Psychology* 77(4):797–810.
- K. Reynolds, A. K., and Edwards, L. 2011. Using machine learning to detect cyberbullying. *Machine Learning and Applications, Fourth International Conference on* 2:241–244.
- Kontostathis, A.; Reynolds, K.; Garron, A.; and Edwards, L. 2013. Detecting cyberbullying: query terms and techniques. In *Proceedings of the 5th Annual ACM Web Science Conference*, 195–204. ACM.
- Kowalski, R. M.; Limber, S.; Limber, S. P.; and Agatston, P. W. 2012. *Cyberbullying: Bullying in the digital age*. John Wiley & Sons.
- Kowalski, R. M.; Giumetti, G. W.; Schroeder, A. N.; and Lattanner, M. R. 2014. Bullying in the digital age: A critical review and meta-analysis of cyberbullying research among youth.
- Limber, S. P.; Kowalski, R. M.; and Agatston, P. A. 2008. *Cyber bullying: A curriculum for grades 6-12*. Center City, MN: Hazelden.
- Monks, C. P., and Smith, P. K. 2006. Definitions of bullying: Age differences in understanding of the term, and the role of experience. *British Journal of Developmental Psychology* 24(4):801–821.
- Nahar, V.; Unankard, S.; Li, X.; and Pang, C. 2012. Sentiment analysis for effective detection of cyber bullying. In *Web Technologies and Applications*. Springer. 767–774.



- Nahar, V.; Unankard, S.; Li, X.; and Pang, C. 2014. Semi-supervised learning for cyberbullying detection in social networks. In *Databases Theory and Applications*, LNCS'12, 160–171.
- Nahar, V.; Li, X.; and Pang, C. 2013. An effective approach for cyberbullying detection. In *Communications in Information Science and Management Engineering*, CISME'13.
- National Crime Prevention Council. 2011. National Crime Prevention Council. <http://en.wikipedia.org/wiki/Cyberbullying>. [Online; accessed 6-July-2011]. NoSwearing.com.
- Olweus, D. 1993. *Bullying at school: What we know and what we can do*. Blackwell.
- Olweus, D. 2013. School bullying: Development and some important challenges. *Annual review of clinical psychology* 9:751–780.
- Patchin, J. W., and Hinduja, S. 2012. An update and synthesis of the research. *Cyberbullying prevention and response: Expert perspectives* 13.
- Ptaszynski, M.; Dybala, P.; Matsuba, T.; Masui, F.; Rzepka, R.; Araki, K.; and Momouchi, Y. 2010. In the service of online order tackling cyberbullying with machine learning and affect analysis.
- Pyżalski, J. 2010. Electronic aggression among adolescents: An old house with. *Youth culture and net culture: Online social practices* 278.
- Silva, T. H.; de Melo, P. O. S. V.; Almeida, J. M.; Salles, J.; and Loureiro, A. A. F. 2013. A picture of Instagram is worth more than a thousand words: Workload characterization and application. In *DCOSS*, 123–132. IEEE.
- Smith, P. K.; del Barrio, C.; and Tokunaga, R. 2012. In book: *Principles of Cyberbullying Research. Definitions, measures and methodology, Chapter: Definitions of Bullying and Cyberbullying: How Useful Are the Terms?* Routledge.
- Smith-Spark, L. 2013. Hanna smith suicide fuels calls for action on ask.fm cyberbullying, cnn. <http://www.cnn.com/2013/08/07/world/europe/uk-social-media-bullying/>. [Online; accessed 14-January-2014].
- Sood, S.; Antin, J.; and Churchill, E. 2012. Profanity use in online communities. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1481–1490. ACM.
- von Ahn's Research Group, L. 2014. Negative words list form, luis von ahn's research group.
- Weilenmann, A.; Hillman, T.; and Jungselius, B. 2013. Instagram at the museum: Communicating the museum experience through social photo sharing. In *Proc. of the SIGCHI Conf. on Human Factors in Computing Systems*, CHI '13, 1843–1852.
- Xu, J.-M.; Jun, K.-S.; Zhu, X.; and Bellmore, A. 2012. Learning from bullying traces in social media. In *Proceedings of the 2012 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 656–666. Association for Computational Linguistics.
- Y. Hu, L. Manikonda, S. K. 2014. What we instagram: A first analysis of instagram photo content and user types. In Proc. of the 8th International AAI Conference on Weblogs and Social Media (ICWSM'14).