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Identification of Psychological Harassment via Digital Communication Media

Manorama Singh[1*], Abhay Kumar[2]

[1*]Dept. of CSE, J.B. Institute of Engineering and Technology, Hyderabad, India
[2]Dept. of CSE, J.B. Institute of Engineering and Technology, Hyderabad, India

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Abstract: Although the Internet has transformed the way our world operates, it has also served as a venue for cyberbullying, a serious form of misbehavior among youth. With many of today's youth experiencing acts of cyberbullying [2], a growing body of literature has begun to document the prevalence, predictors, and outcomes of this behavior, but the literature is highly fragmented and lacks theoretical focus. Therefore, our purpose in the present article [1] is to provide a critical review of the existing cyberbullying research. This systematic review and meta-analysis [6][7] offers a synthesis of the relationship between cyber-victimization and educational outcomes of adolescents aged 12 to 17, including 25 effect sizes from 12 studies drawn from a variety of disciplines. The general aggression model is proposed as a useful theoretical framework from which to understand this phenomenon. Additionally, results from a meta-analytic review are presented to highlight the size of the relationships between cyberbullying and traditional bullying, as well as relationships between cyberbullying and other meaningful behavioral and psychological variables. A series of random-effects meta-analyses [12] using robust variance estimation revealed associations between cyber-victimization [4] and higher class presence problems (r = .20) and academic achievement problems (r = .14). Results did not differ by provided definition, publication status, reporting time frame, gender, race/ethnicity, or average age. Implications for future research are discussed within context of theoretical, critical, and applied discussions.

Keywords: cyber-victimization, victimization, meta-analysis, adolescents, academic achievement, school attendance, Cyberbullying Detection, Text Mining, Representation Learning

I. INTRODUCTION

As more people turn to the Internet for school, work, and social use, so too do more people turn to the Internet to take out their frustrations and aggression. One form of cyber aggression [9] has been gaining the attention of both researchers and the public in recent years: Cyberbullying is typically defined as aggression that is intentionally and repeatedly carried out in an electronic context (e.g., e-mail, blogs, instant messages, text messages) against a person who cannot easily defend him or herself (Kowalski, Limber, & Agatston, 2012; Patchin & Hinduja, 2012). Many researchers have noted that cyberbullying is occurring at widespread [13] rates among youth and adults, with some studies showing nearly 75% of school-age children [4] (Juvonen & Gross, 2008; Katzer, Fetchenhauer, & Belschak, 2009) experiencing this form of aggression at least once in the last year. The experience of cyberbullying has been linked with a host of negative outcomes for both individuals and organizations (e.g., schools), including anxiety, depression, substance abuse, difficulty sleeping, increased physical symptoms, decreased performance in school, absentee is mend truancy, dropping out of school, and murder or suicide (Beran& Li, 2005;Mitchell, Ybarra, & Finkelhor, 2007;Privitera &Campbell, 2009;Ybarra, Diener-West, & Leaf, 2007).Our purpose in the current article is threefold[11]: (a) to provide a narrative review of the extant research on cyberbullying among youth, including a look into the prevalence and antecedents of this behavior and associated outcomes [14][15]; (b) to synthesize the relationships among cyberbullying, cyber victimization, and meaningful behavioral and psychological variables with meta-analytic techniques; and (c) to critique the existing research, noting areas where findings conflict and gaps remain, thereby allowing us to provide future researchers with directions where additional attention is needed.

II. BACKGROUNG

Cyberbullying as mentioned earlier, most researchers agree that cyberbullying involves the use of electronic communication technologies to bully others. However, as will be seen, assessments of the prevalence of cyberbullying have proven difficult because there is a lack of consensus regarding the more specific parameters by which cyberbullying should be defined (Olweus, 2013;P. K. Smith, delBarrio, & Tokunaga, 2012;Ybarra, Boyd, Korchmaros, & Oppenheim, 2012). Table 1 presents an expansive although not exhaustive list of research in the field and

reports on both the assessment methods and prevalence rates of cyberbullying across varying samples.2As noted in the table, although there are common across operational definitions, they differ in terms of specificity versus generality. Whereas some simply define cyberbullying as bullying that occurs via the Internet or mobile phones, others are more specific in terms of the taxonomy of technology, with clear implications for measurement, as discussed later.

III. OTHER TECHNIQUES FOR CYBERBULLYING DETECTION

Cyberbullying versus Traditional Bullying: A logical question to ask when investigating cyberbullying is the degree to which our knowledge of traditional bullying carries over to this newer mode of bullying. Cyberbullying shares with traditional bullying three primary features: It is an act of aggression; it occurs among individuals among whom there is a power imbalance; and the behavior is often repeated [15][16] (Hunter, Boyle, &Warden, 2007; Kowalski, Limber, & Agatston, 2012; Olweus, 1993, 2013;P. K. Smith, del Barrio, & Tokunaga, 2012). The aggressive nature of cyberbullying is discussed later in this article, although few would question that cyberbullying is an aggressive action. As with traditional bullying, the power imbalance with cyberbullying can take any of a number of forms [13]: physical, social, relational, or psychological (Dooley, Pyz˙alski, & Cross, 2009; Monks & Smith, 2006; Olweus, 2013;Pyzalski, 2011). Of importance, the fact that one person is more technologically savvy than another can create a power imbalance. Furthermore, the anonymity inherent in many cyberbullying situations may create a sense of powerlessness on the part of the victim (Dooley et al., 2009; Vandebosch & Van Cleemput, 2008).

Measurement of Cyberbullying

Some have noted that the cyberbullying research domain has a measurement problem. Part of the reason for the added attention to the issue of measurement is the wide-ranging prevalence rates for the occurrence of cyberbullying, as noted above. Beyond their differences in sample characteristics (e.g., age, gender, country of origin), studies also differ on a number of important factors with regard to measurement, and these differences may influence prevalence rates and relationships among measured variables. Some of these factors include the nature of the items utilized in the cyberbullying measure, whether a definition of bullying is provided, and whether traditional bullying is also measured (David-Ferdon & Hertz, 2007;Kowalski, Limber, & Agatston, 2012). Each of these factors is described below.

Literature Search: Four methods were used to search for relevant studies. First, we performed searches of 14 databases: Academic Search Complete, Business Source Complete, Communication & Mass Media Complete, Criminal Justice Abstracts, Education Research Complete, Family Studies Abstracts, Health Source: Nursing/Academic Edition, Human Resources Abstracts, MEDLINE, PsycARTICLES, PsycINFO, SocINDEX, Social Sciences Full Text, Pro-Quest Dissertations and Theses Full-text, and Web of Science [4][5]. The search terms included variants of online behavior (cyberor Internet or net or web or online or chat or electronic), and variations on perpetration or victimization (harass or bully or victim or perpetrate). We also used the following limiters to exclude any studies dealing with stalking or sexual victimization (NOT sex, NOT stalk). Additionally, in a separate search, we added terms for various outcomes of interest (depress or esteem or anoxic or lonel or satis or stress or somatic or symptomor health). Second, we searched the reference lists of existing reviews of cyberbullying. Third, we searched the in-press or online first sections of the following journals: Aggressive Behavior[13]; British Journal of Developmental Psychology; Computers in Human Behavior; Cyber psychology, Behavior, and Social Networking; Developmental Psychology; European Journal of Developmental Psychology; Journal of Adolescence; Journal of Adolescent Health; Journal of School Psychology; Journal of School Violence; Journal of Youth and Adolescence; New Media & Society; School Psychology International; School Psychology Quarterly; School Psychology Review. Fourth and finally, we contacted active researchers for unpublished studies or conference presentations. We identified a total of 1,365 studies in the initial search.

IV. PROPOSED TECHNIQUES

SEMANTIC ENHANCEMENT FOR MSDA: The advantage of corrupting the original input in mSDA can be explained by feature co-occurrence statistics [2]. The co-occurrence information is able to derive a robust feature representation under an unsupervised learning framework, and this also motivates other state-of-the-art text feature learning methods such as Latent Semantic Analysis and topic models. As discussed above a denoising autoencoder is trained to reconstruct these removed features values from the rest uncorrupted ones. Thus, the learned mapping matrix W is able to capture correlation between these removed features and other features. It is shown that the learned representation is robust and can be regarded as a high level concept feature since the correlation information is invariant to domain-specific vocabularies. We next describe how to extend mSDA for cyberbullying detection. The major modifications include semantic droupout noise and sparse mapping constraints.

SEMANTIC- ENHANCED MARGINALIZED STACKED DENOISING AUTO-ENCODER

We first introduce notations used in our paper. Let D = $\{w_1........w_d\}$ be the dictionary covering all the words existing in the text corpus. We represent each message using a BoW vector x €R^d. Then, the whole corpus can be denoted as a matrix: X = [x1;:: : ; xn] € R^{d*n}, where n is the number of available posts. We next briefly review the marginalized stacked denoising auto-encoder and present our proposed Semantic enhanced Marginalized Stacked Denoising Auto-Encoder.

MARGINALIZED STACKED DENOISING AUTO-ENCODER

Chen et.al proposed a modified version of Stacked Denoising Auto-encoder that employs a linear instead of a nonlinear projection so as to obtain a closed-form solution. The basic idea behind denoising auto-encoder[2] is to reconstruct the original input from a corrupted one ~x1; : : : ; ~xn with the goal of obtaining robust representation. Marginalized Denoising Auto-encoder [2][3]: In this model, denoising auto-encoder attempts to reconstruct original data using the corrupted data via a linear projection. The projection matrix can be learned as:

$$\mathbf{W} = \underset{\mathbf{W}}{\operatorname{argmin}} \frac{1}{2n} \sum_{i=1}^{n} \|\mathbf{x}_i - \mathbf{W}\tilde{\mathbf{x}}_i\|^2 \qquad (1)$$

where $\mathbf{W} \in \mathbb{R}^{d\times d}$. For simplicity, we can write Eq. (1) in matrix form as:

$$\mathbf{W} = \underset{\mathbf{W}}{\operatorname{argmin}} \frac{1}{2n} tr\left[(\mathbf{X} - \mathbf{W}\tilde{\mathbf{X}})^{\mathrm{T}}(\mathbf{X} - \mathbf{W}\tilde{\mathbf{X}})\right] \qquad (2)$$

where ~X = [~x1; : : : ; ~xn] is the corrupted version of X. It is easily shown that Eq. (2) is an ordinary least square problem having a closed-form solution.

V. COMPARISON OF TECHNIQUES

We used meta-analysis to examine data from 131 studies on cyberbullying. This meta-analysis is the first of its kind to quantitatively synthesize the growing body of research on cyberbullying, to highlight the magnitude of the relations between predictors and outcomes of CB and CV, and to identify the conditions under which these relationships might differ. The studies included in the meta-analysis represented a wide array of approaches to the study of cyberbullying, both in terms of sample characteristics (e.g., sample size, country of origin, breakdown of gender in each sample) and of measurement features (e.g., reporting time frame, number of items in the measure, inclusion of a bullying definition, whether traditional bullying [4] was also measured). Our proposed Semantic-enhanced Marginalized Stacked Denoising Autoencoder is able to learn robust features from Bow [3] representation in an efficient and effective way. These robust features are learned by reconstructing original input from corrupted (i.e., missing) ones. The new feature space can improve the performance of cyberbullying detection even with a small labeled training corpus. Semantic information is incorporated into the reconstruction process via the designing of semantic dropout noises and imposing sparsity constraints on mapping matrix. In our framework, high-quality semantic information, i.e., bullying words, can be extracted automatically through word embeddings.

Finally, these specialized modifications make the new feature space more discriminative and this, in turn, facilitates bullying detection.

VI. CONCLUSION

Throughout this article, we have made numerous references to areas of research that are in need of additional investigation. The list is long, but this is not surprising, given the relatively recent emergence of the phenomenon under investigation. Below we propose additional directions for future research, beyond those directions already mentioned, and organize them within the context of the GAM as dealing with either person factors or situation factors to help broaden the application of the GAM to the cyberbullying research domain. We also provide future research directions dealing with study design features. This paper addresses the text-based cyberbullying detection problem, where robust and discriminative representations of messages are critical for an effective detection system. By designing semantic dropout noise and enforcing sparsity, we have developed semantic-enhanced marginalized denoising autoencoder as a specialized representation learning model for cyberbullying detection. In addition, word embeddings have been used to automatically expand and refine bullying word lists that are initialized by domain knowledge. The performance of our approaches has been experimentally verified through two cyberbullying corpora from social Medias: Twitter and MySpace. As a next step we are planning to further improve the robustness of the learned representation by considering word order in messages.

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