**Identifying Situational, Individual, and Demographic Determinants of Social Anxiety Using
a Naive Bayesian Classification Algorithm**

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Abstract

Social situations may play a role in the conceptualization and treatment of social anxiety disorder. However, situational variance is rarely examined and has not yet been directly compared to dispositional or demographic variance. We used situation-sampling methodology and naive Bayesian classification to determine the predictive power of situational features compared to individual and demographic variables. In Study 1, a sub-sample of 309 undergraduate students responded to random subsets of 680 situations to train a machine-learning algorithm that predicted whether a participant would endorse situational social anxiety. The predictions were then tested on the remaining participants in order to generate accuracy estimates. Situational variance alone improved accuracy by 21.39% (from 50%) whereas the addition of individual variance (+3.8%) and demographic information (-1.11%), did not add to the predictive accuracy. Situational features were rank-ordered by their likelihood ratios, and were grammatically edited to reflect the top, middle, and bottom features. In Study 2, a community sample of 211 people responded to these new situations and endorsement rate was compared to predictive accuracy estimations. We found consistent accuracy for high and middle social anxiety-provoking situations indicating that situational features may be particularly relevant when treating clients with higher levels of anxiety.

Keywords: Social anxiety; situation; text classification; fear hierarchy

Introduction

According to the Diagnostic and Statistics Manual of Mental Disorders, Fifth Edition (DSM-5; American Psychiatric Association, 2013) Social Anxiety Disorder (SAD) is characterized by disproportional anxiety in social or evaluative situations that cause clinically significant impairment in important areas of functioning. The long-term impairment and psychiatric comorbidity of SAD has been demonstrated with increased social isolation (Beidel, Turner, & Morris, 1999) and substance abuse (Clark & Sayette, 1993) in people suffering from the disorder. Most concerning, Compton et al. (2014) noted that in a sample of 488 youth aged seven to 17, a SAD diagnosis moderated the effects of an evidence-based treatment for youth anxiety and was related to poorer response to treatment. Therefore, careful examination of SAD, including subtypes, is needed.

Previous versions of the DSM have asked clinicians to specify the “generalization subtype” (American Psychiatric Association, 1987; 2000) and the most recent revision instructs clinicians to indicate if the SAD occurs in “Performance only” situations. The DSM-5 defines “Performance only” as applying to situations that are impairing to a person in their professional life, and notes the example of public speaking or giving a presentation. Studies related to the classification of SAD subtypes have historically found evidence for the utility of the DSM-5 “Performance only” specifier (Hofmann & Roth, 1996; Holt, Heimberg, Hope, & Liebowitz, 1992; Kessler, Stein, & Berglund, 1998; Turner, Beidel, & Townsley, 1992). For example, Turner, Beidel, and Townsley (1992) found evidence for generalized and specific SAD subtypes in 89 outpatient adult patients being treated for anxiety disorders. They defined the generalized subtype as patients who “feared parties (social gatherings), initiating conversations, or maintaining conversations,” and the specific subtype as patients who “feared only circumscribed

situations, such as giving speeches, speaking in meetings, eating or writing in public, or using public restrooms” (pg. 327; Turner et al., 1992). Holt et al. (1992) conceptually classified SAD into four categories of formal speaking/interaction, informal speaking/interaction, observation by others, and assertion, and found that most of their sample of 91 adults were likely to fall within the formal speaking/interaction classification. These findings were similar to results examining SAD subtypes in the National Comorbidity Survey (Kessler et al., 1998), which noted that the largest class within their normative sample of 8,098 adults was related to speaking fears.

Although the conclusions of these studies implicate several SAD domains, there have been few studies that have examined the situational variance in the expression of SAD (Buss, Davidson, Kalin, & Goldsmith, 2004; Dam-baggen, Van Heck, & Kraaimaat, 1992; Turner, Beidel, & Larkin, 1986). That is, what are the underlying contextual factors that may influence the severity and expression of symptoms in SAD? For example, Turner et al. (1986) demonstrated in a sample of 17 adults with and 69 without SAD that the *type* of social interaction as well as with *whom* a person was interacting were two important situational dimensions that activated different levels of physiological arousal and anxious thoughts. Specifically, they found increased heart-rate, systolic blood pressure, and negative cognitions among all participants when performing a speech task as compared to a having a social interaction—but not when that social interaction was with a member of the opposite sex (Turner et al., 1986). Additionally, Buss et al. (2004) found that in a sample of 80 youth, the presentation of social anxiety could be reliably differentiated based on physiological responses to situational factors, such as being in the presence of a stranger. As the situation’s intensity increased, so did youth’s physiological responses across low, medium, and high situations. The situation in which youth started displaying heightened arousal revealed differences in their coping strategies, which

subsequently predicted fear regulation behavior (Buss et al., 2004). Likewise, Dam-baggen et al. (1992) noted situational differences in behavioral responses to initiating a conversation with a stranger and refusing a request. Their study revealed more variation within behavioral responses when compared to physiological responses to these situations. Following a model proposed by Mischel & Shoda (1995), their analysis found greater consistency of behaviors when explained by interactions of *both* situational and dispositional factors rather than either alone.

Over and above situational factors predicting the degree to which social anxiety-related physiology and behavior is expressed, situational variation becomes even more important when providing psychosocial treatment for adults and youth with SAD. Reviews of large-scale treatment investigations have suggested that exposure therapy is both efficacious and effective in treating SAD in both individual (for reviews, please see Chambless & Ollendick, 2001 and Chorpita & Daleiden, 2009) and group (Hope, Heimberg, & Bruch, 1995) treatment settings. Much like the definition of SAD, exposure therapy is based off an individual's response to a variety of contextual cues across social situations. As a first step in exposure therapy, a client is instructed to build an idiographic fear hierarchy that details the circumstances which this person feels fear or anxiety (Barlow, 2014; Kendall, 1994). The typical fear hierarchy procedure has the client (a) construct a list of anxiety-provoking situations, (b) rank the situations in order of most anxiety-provoking to least anxiety provoking, and (c) assign numerical fear ratings to each situation. This fear hierarchy is then used to guide exposure therapy and allows the client to choose situations with relatively lower fear ratings to practice until habituation occurs (Barlow, 2014; Kendall, 1994; Hope et al., 1995). Examining the context of SAD fears with clients is also important as our understanding of the underlying mechanisms of exposure therapy changes. For example, habituation, or the reduction of fear ratings, has long been the accepted outcome of

successful exposure treatment (Barlow, 2014; Kendall, 1994; Hope et al., 1995). However, recent literature in exposure therapy have noted that both within- and between-session habituation was not associated with treatment outcome (Baker et al., 2010), and the variability of anxiety and feared stimuli are important considerations for successful fear extinction (Culver, Vervliet, & Craske, 2015; Kircanski et al., 2012).

One potential barrier to successful exposure treatment is the reliance on clients to independently generate context-specific items for their fear hierarchy. This can be even more problematic in SAD clients who have a long history of avoidance that have may have exacerbated these ongoing symptoms (Harned, 2008), or have limited insight or motivation with which to engage the therapeutic process (Becker, Zayfert, & Anderson, 2004). In these cases, it is common for the therapist and/or caregiver to join in the brainstorming process in order to aid in fear hierarchy construction. Indeed, when examining well-established treatment manuals for treating youth anxiety (Chorpita & Weisz, 2009; Kendall, 1994), common strategies for establishing the fear hierarchy includes using a combination of youth-specific situational data from previous assessments and guiding the youth through imaginal exercises to identify feared situations (Ollendick & Cerny, 1981).

In addition to situational and contextual factors, research has suggested that client demographic variables also impact the expression of SAD symptoms. Key demographic variables, such as sex, age, and socioeconomic status, are known to explain a large degree of variance in psychopathology (e.g., Wadsworth & Achenbach, 2005). Prior findings have demonstrated a higher prevalence rate of SAD for females as compared to males (Essau, Conradt, & Petermann, 1999; Kessler et al., 2006; Wittchen, Stein, & Kessler, 1999) and that this is often influenced by other sociodemographic variables such as income level, family

composition, and comorbidity (Kessler et al., 2006; Ollendick, Ost, Reuterskiold, & Costa, 2010; Southam-Gerow, Weisz, & Kendall, 2003). Other studies have also highlighted the importance of race and ethnic identity in anxiety symptom expression in normative samples (Asnaani et al., 2015; Krieg & Xu, 2015; Okamura et al., in press). Related to the current study, Asnaani et al. (2015) found evidence for performance/public speaking, social interaction, and observational SAD domains across African American, Latino, and non-Latino White non-clinical adults. However, this study, like others, focused on explaining variance by grouping SAD into factors rather than focusing on the variance associated with unique situations.

Current Study

The exploration of the context of fears associated with SAD has been long since been identified as a gap in the literature (Turner, Beidel, & Larkin, 1986) that has yet to be fully understood (Asnaani et al., 2015). Previous studies have examined these contextual factors from a top-down approach, attempting to determine meaningful SAD clusters within a sample. To our knowledge, there have been no studies examining the prevalence of situational anxiety within a normative sample. Understanding the saliency of situational factors as well as the roles they play are important to the accurate assessment and treatment of SAD. Specifically, clinicians may benefit by identifying concepts or themes present in situations that many people find to be social anxiety-provoking in order to facilitate generation of fear hierarchy items. Furthermore, given that demographic variables such as sex and ethnicity also appear to impact the expression of SAD symptoms. It may be beneficial to see the additive benefit of these demographic features when combined with situational features in order to best predict a social anxiety response.

The current study uses a supervised machine learning algorithm to identify key features associated with increased fear response in social anxiety-provoking situations. Machine learning

can be contrasted to a traditional statistical approach as ‘bottom-up’ vs. ‘top-down.’ Compared to traditional statistical tests that focus on model construction to best explain a given phenomenon, machine learning focuses on building robust predictions through carefully assigning weights to a variety of data features and continuing to nuance these weights by iterating through the data until the algorithm is most accurate (Raschka, 2015). Machine learning has revolutionized computer science and has been used in a wide variety of technical applications (Bryant, Katz, & Lazowska, 2008). In clinical psychology and psychiatry, machine learning has only just begun to be implemented, but has already proved useful in predicting the development of Posttraumatic Stress Disorder (Galatzer-Levy, Karstoft, Statnikov, & Shalev, 2014), evaluating responsiveness to Cognitive Behavior Therapy (Connor, Symons, Feeney, Young, & Wiles, 2007), analyzing the content of suicide notes (Pestian, Nasrallah, Matykiewicz, Bennett, & Leenaars, 2010), and even experimental procedures related to helping clinicians make real-time decisions during sessions (Kelly et al., 2012).

In contrast with traditional statistical theory and applications, machine learning algorithms emphasize the accuracy of prediction and replication using all available data rather than investigating a set of theoretically meaningful variables for model support and parsimony. Likewise, rather than limiting the data’s appropriateness by how well it fits statistical model assumptions, machine learning algorithms rarely impose model constraints or rules, making it therefore robust against violations in traditional model assumptions (Srivastava, 2015). Given the fruitful application and increased implementation of machine learning algorithms, it is hoped that the current study provides more support for this type of methodology in psychological research.

The specific aims of this two-part study was to (a) identify a list of situational features that can be used as themes to explore when constructing a fear hierarchy with clients, (b)

compare the relative predictive power of situational features to demographic features, and (c) examine variance in situational features across sex and ethnicity.

Study 1

The purpose of Study 1 was to examine the presence of social anxiety in a set of situations based on the (a) situation alone, (b) situation and person (i.e., ID), and (c) situation, person, and demographic (sex/ethnicity) variables. This study was conducted in two parts. First, feared situations were generated by a small sample of participants (see ‘Situation Generation’ below). Second, these situations were rated by a new set of participants. Details regarding our second set of participants are presented in ‘Participants’ below.

Method

Situation Generation. A total of 1,058 social anxiety-provoking situations were developed by a group of sixty undergraduate students ($M = 17.63$ items per person) who were recruited previously from the same subject pool and matched the current study’s sample on demographic characteristics (e.g., 65% female, 20.89 years old, 50% Asian American; see ‘Participants section’). Specifically, they responded to the following prompt: “Please create brief, specific situations where someone would feel socially anxious. Please list as many of these situations as possible until you cannot think of anymore.” The term “socially anxious” was not defined for participants in order maximize the number of responses given. In order to provide a clear description of the situations generated, all situations were rewritten into a standardized grammar format and spelling and grammatical errors were corrected (e.g., “When you acidently take someone elses coffee” became “Accidently taking someone else’s coffee.”).

After this initial step, we continued to clean the data by removing duplicate situations. Then, we removed situations related to specific geographic locations (e.g., Ala Moana Beach

Park), which may have conveyed unintended meanings to participants. Next, we removed situations related to (a) sex (e.g., “Wearing a bikini at the beach”), (b) specific ethnic groups (e.g., “Being the only Asian in the store”), (c) tautological statements (e.g., “Being afraid around others”), (d) non-evaluation (e.g., “Being the only one on campus at night”), and (e) situations that made no grammatical sense. A total of 680 (64.27%) statements remained.

Participants. Three-hundred and nine undergraduate students were recruited from University of Hawai‘i as a part of a subject pool that completed this study in exchange for course credit. Data were collected as a part of a larger study that examined cultural influence on psychopathology among Asian American and European American undergraduates. This group of participants was comprised of 66.34% women ($n = 205$) and had a mean age of 20.54 ($SD = 4.11$). One hundred sixty-two (52.42%) students identified as European American and 149 (48.22%) identified as Asian American. Among the Asian American sample, 12.50% indicated that both they and their parents were born outside the U.S. (1st generation), 30.63% indicated that they were born within the U.S. while their parents were born outside (2nd generation), 56.88% indicated that both they their parents were born in the U.S. (3rd generation). All European American participants were born within the U.S. These two groups represent the largest ethnic groups on the University of Hawai‘i campus.

Procedures. To avoid overburdening participants and in accordance of the situation sampling method proposed by (Kitayama, Markus, Matsumoto, & Norasakkunkit, 1997), we randomly selected a unique set of 30 situations for each participant and presented them with the prompt: “Would you feel anxious if this situation happened to you?” Responses were coded in binary as 1 for Yes and 0 for No. Generally, binary scales are not recommended for measurement because of restricting the response range, loss of statistical power, and loss of useful information

(Chang, 1994). However, due to our machine learning algorithm's preference for fewer response categories as well as the increased ability to readily interpret our results (e.g., Theeramunkong & Lertnattee, 2002), we opted to use binary data for this study. Each situation was presented an average of 14.00 times ($SD = 4.94$; Range: 4 - 39), and participants were not presented a situation twice. This resulted in a total of 7,631 observations.

Analytic Strategy. Our analysis relies heavily on text classification (Raschka, 2014), a sub-branch of the field of machine learning and is divided into two parts: data preparation and data classification.

Data Preparation. The situations' standardized text, participant's unique identifier (ID), binary demographic variables for ethnicity (1 = Asian American), sex (1 = female), social anxiety ratings for each situation (1 = anxiety-provoking) were processed and cleaned with the *Natural Language Toolkit* (nltk; Bird, Klein, & Loper, 2009) and *Beautiful Soup* (bs4; Richardson, 2015) libraries implemented in python v3.5. First, the text was separated from the binary data and all capital letters and punctuation were removed. A parser then went through each situation entry and tokenized individual words (i.e., separated them into distinct objects using the spaces between them). Next, we examined each entry for "stop words." Stop words are words in the English language that carry little meaning outside the grammatical function they provide. These include articles, prepositions, pronouns, as well as helping verbs (for a full list of *nltk* stop words please see Bird et al., 2009). We removed stop words so that the situation "having many people talk to you at one time" became "many, people, talk, on, tim." Finally, reducing each word to the stem word further standardize the remaining words. In this way, "strange," "stranger," and "strangers" all became "strang;" and "talk," "talks," "talked," and "talking" all became "talk." This worked to both reduce the number of dimensions that the

algorithm would have to separate as well as worked to combine conceptually and semantically similar words into one feature. In total, we had 557 remaining word parts.

Next, these word parts were converted into a dictionary where situations were coded “True” if they contained a word and “None” if they did not contain the word. For example, if a statement had the word “critical” the “crit” word part in the dictionary was coded as “True.” This process was repeated for all word parts, participant ID, and demographic variables, so that the predictor dataset was comprised of a set of dictionaries corresponding to each feature. The social anxiety outcome variable remained in numeric format. Finally, we concluded data preparation by randomly dividing the 7,631 cases into a training ($n = 5,341$) data set and test ($n = 2,290$) dataset, following the ratio recommendations from Raschka (2015) of 70% training and 30% test.

Naïve Bayes Classification. Supervised machine learning typically starts with a set of predictor features whose weight is set to an equal arbitrary value. In each subsequent evaluation, the weights associated with a particular feature shift by a certain degree. This continues for multiple iterations across the same set of training data until the weights have been fully optimized, reflecting the aggregated influence of the feature it represents. The method by which weights are updated, the learning rate, and the number of iterations required for optimization all vary widely among specific classification algorithms (please see Figure 1; Raschka, 2014; 2015). After model training, the next step typically involves using the learned weight of each feature to classify a set of test data including both features and outcomes. We can calculate and compare the accuracy of the model for both the training and test data from the results of both of these procedures. A much higher accuracy for the training data as compared to the test data is often indicative of model over-specification—a frequent concern within supervised machine learning. In model over-specification the model learns to classify features in a way that is too specific to

the training data and do not generalize to the test data (Raschka, 2015). After accuracy rates are obtained, the two data sets can be recombined and reentered as training data to allow the classifier to learn from the entire dataset. From this point, key predictive features as well as their relative weights are extracted.

In order to train our machine learning algorithm to correctly classify binary fear ratings via situational, person, and demographic features, we used a Naïve Bayes Classification algorithm (NB Classifier; Friedman, 1997; McCallum & Nigam, 1998; Raschka, 2014). True to the Bayesian Method, the NB Classifier begins by calculating the prior probability of each potential outcome value (in our case 0 = no anxiety or 1 = anxiety). The prior probability is simply derived by the rates of each outcome value and is combined with the contribution of each feature, and the weights are subsequently adjusted for its contribution to the correct classification into each outcome value. As a result, each feature is assigned a likelihood ratio. For instance, if the word part “run” (run, runs, running) is in 12% of situations classified as 1 and 6% of situations classified as 0, the likelihood ratio is $12 \div 6$ or 2.0. This likelihood is combined with other features that compete to push the decision towards one outcome or another. If this combination of probabilities results in a value over 0.50 for either category, that particular category is selected and compared to the actual outcome for feedback (Bird et al., 2009).

Using this algorithm, we tested three models. Model 1 classified anxiety response using only features from the situation text. In this way the first model examined situational variance alone without examining any person or sample characteristics. Model 2 added person data, specifically participant ID, to Model 1. This provided information on who scored each situation and allowed us to examine the impact of individual differences. Model 3 added participant-level demographic data: sex and ethnicity to Model 2. For each model we examined the accuracy as

well as the degree of model over-specification before recombining the data and retraining the NB Classifier to generate a list of important features as identified by a likelihood ratio greater than 2.

Results and Discussion

Model 1. We examined the ability of situations alone to predict anxiety response scores in our sample. Our NB Classifier was trained to account for 557 situational features across 5,341 observations in our training data. The trained algorithm then classified the test data by evaluating the situational features with the previously identified weights and generating the most likely value (1 or 0) that represents the situation overall. For the training data, 76.80% of the situations were correctly classified. In contrast, only 71.39% of the test situations were correctly classified (see Table 1). While both values out-performed the 50% probability that would be associated with random assignment ($\Delta = 26.80$ and 21.39 , respectively), the difference of 5.41% in the training data's accuracy is potentially indicative of over-specification. When we recombined the training and test datasets to the total 7,631 observations and retrained the NB classifier, the accuracy increased to 76.07% and influential word parts were extracted (see Appendix A for full list of word parts and likelihood ratios).

Model 2. In our second model, we added a dictionary of 309 person features (Participant IDs) to our initial set of 557 situational features for a total of 866 predictor features. Our NB Classifier was trained to account for these features across 5,341 observations in our training data. The trained algorithm then classified the test data by evaluating the situational features with the previously identified weights and generating the most likely value (1 or 0) that represents the situation overall. For the training data, 82.51% of the situations were correctly classified. In contrast, only 75.19% of the test situations were correctly classified (see Table 1). Again, both accuracy values out-performed the 50% probability that would be associated with random

assignment ($\Delta = 32.51$ and 25.19 , respectively), as well as Model 1's accuracy rates ($\Delta = 5.71$ and 3.80 , respectively). Additionally, the difference of 7.32% in training to test accuracy is indicative of increased over-specification as compared to Model 1. After recombining and retraining the NB Classifier, we examined the top 50 informative features (likelihood ratios ranged between 4.3 and 36.3) and found that 52% ($n = 26$) of them were participant IDs rather than situational features.

Model 3. Finally, we added a dictionary of two features (sex and ethnicity) to the 309 person features (Participant IDs) and 557 situational features for a total of 868 predictor features in this dataset. Upon training and testing our NB Classifier we generated estimates for classification accuracy as in previous models. For the training data, 81.68% of the situations were correctly classified. In contrast, only 74.08% of the test situations were correctly classified (see Table 1). Again, both accuracy values out-performed the 50% probability that would be associated with random assignment ($\Delta = 31.68$ and 24.08 , respectively), as well as Model 1's accuracy rates ($\Delta = 4.88$ and 2.69 , respectively). However, Model 3 slightly underperformed Model 2 ($\Delta = -0.83$ and -1.11 , respectively). Additionally, the difference of 7.60% in training to test accuracy is indicative of increased over-specification as compared to both Model 1 and Model 2. After recombining and retraining the NB Classifier, we examined all features and their respective likelihood ratios and found that both sex and ethnicity had a likelihood ratio of 1.2 , which is relatively weaker than the situational and person features examined in Model 1 and Model 2. Furthermore, since likelihood ratios have a minimum value of 1.0 , it is fair to say that in this analysis the influence of sex and ethnicity is objectively weak. The likelihood ratio 1.2 indicates that being a woman or Asian American increases the likeliness of endorsing feeling

socially anxious in any given situation by 20% as compared to being a man or European American, respectively.

Despite weak main effects of sex and ethnicity as predictors of feeling socially anxious in a given situation, these demographic variables may interact with situational features to predict social anxiety response. That is, a given situational feature may be more salient and more likely to contribute to one endorsing feeling anxious among a certain demographic rather than another. To explore this potential interaction, our sample was split into four groups: Asian American women (AAW; $n = 104$), Asian American men (AAM; $n = 42$), European American women (EAW; $n = 106$), and European American men (EAM; $n = 56$), and the top 50 informative features were compared. In the AAW group, 2,568 observations were divided into 70% ($n = 1,797$) training dataset and a 30% ($n = 771$) test dataset, and Model 1 was trained and tested. In the AAM group, 1,360 observations were divided into 70% ($n = 952$) training dataset and a 30% ($n = 408$) test dataset, and Model 1 was trained and tested. Likewise, in the WW group, 2,659 observations were divided into 70% ($n = 1,861$) training dataset and a 30% ($n = 798$) test dataset, and Model 1 was trained and tested. Finally, in the WM group, 1,044 observations were divided into 70% ($n = 730$) training dataset and a 30% ($n = 314$) test dataset, and Model 1 was trained and tested. Training data and test data accuracies for each group were 74.73% and 63.94% for AAW, 82.45% and 73.77% for AAM, 79.58% and 75.81% for EAW, and 83.97% and 73.57% for EAM. Neither the reduced accuracy or greater indication of over-specification were directly related to the number of observations available with which to train the NB Classifier ($r = -.36, -.47$, respectively; $p > .05$).

Word parts, related phrases, and likelihood ratios for all four groups are presented in Tables two and three. Very few of the situational features had significant overlap among sex and

ethnic groups. Furthermore, the word parts found within the top 50 important features among all four groups had very different likelihood ratios. For example, while “appear” (appearance, noticed for your appearance) was ranked within the top 50 in all four groups, the likelihood ratio was 3.9 for AAW, 4.8 for AAM, 10.9 for EAW, and 13.1 for EAM. The degree of variance in the likelihood ratio provides empirical evidence for a group by situational feature word interaction. Qualitatively, it appears that the words most salient to AAW revolved around the theme of reputation and interpersonal conflict. For AAM, it was the theme of embarrassment or humiliation. EAW’s most salient situational features had to do with being criticized for their appearance or being observed, and EAM endorsed situations related to competition and specific unassociated groups of people (judges, unsocial people, religious people, etc.) as most social anxiety provoking.

Study 2

The purpose of Study 2 was to validate Model 1 (situation-only algorithm) derived in the first study with actual data in a community sample. We generated a total of nine new situations using word roots from the top third ($n = 3$), middle third ($n = 3$), and bottom third ($n = 3$) of the distribution of likelihood ratios (see Appendix A). In order to validate our model, the percent of the 211 individuals in the new sample that endorsed anxiety was compared to the likelihood generated by Model 1 of our machine-learning algorithm.

Methods

Participants. 211 participants (45.97% female) were recruited from Amazon’s Mechanical Turk website. Mechanical Turk (MTurk) is an online labor market that has recently become popular among social scientists as a source to gather convenient and representative survey data for a relatively small fee. Scientific investigations of MTurk have found that these

data are just as reliable and valid, and oftentimes more representative of the general public than student samples (Buhrmester, Kwang, & Gosling, 2011; Paolacci & Chandler, 2014). The current sample was limited to the United States and participants were paid \$0.23 (equivalent to approx. \$7.00 per hour) for completing our short questionnaire.

Of the 211 participants, all but four endorsed being native English speakers, 45.97% were female, and 76.30% endorsed being employed full-time. Participants had an average age of 34.71 ($SD = 11.21$), 15.14 ($SD = 1.82$) years of education, and 38.33 ($SD = 10.10$) work hours per week. Our current sample was comprised of more ethnic groups than in Study 1 (European American: 74.41%, Asian American: 5.21%, African American: 4.74%, Hispanic American: 3.79%, Pacific Islanders: 3.32%, South Asian: 1.90%, Native American: 0.95%, and Biracial/Other: 5.68%).

Procedures. In order to validate our machine-learning algorithm derived in Study 1, the first and second author generated a set of nine new situations using the situational features identified by the NB algorithm. Three of our situations used features from the top third of the likelihood ratio distribution ($LR > 3.1$), the middle third ($LR = 2.6 - 3.1$), and the bottom third ($LR < 2.6$). The top situations were “Appearing stupid in front of others,” “Having your friend shout and act goofy next to you in public,” and “Hearing someone accuse you of doing something illegal.” The middle situations were “Being around unsocial people,” “Talking loudly in a public place,” and “Being unable to do what my elders could.” Finally, the bottom situations were “Voicing your opinion about whether or not to prank your friend,” “Having to look after many people,” and “Being late to a party.” Given the diversity of topics covered in these situations, we did not expect the three situations from each level to cluster together. As predicted, the Cronbach’s α values were small for each (top = .52; middle = .42; bottom = .51), indicating

that individual situations within each level are largely independent from one another. Participants responded to the prompt “Would you feel anxious if this situation happened to you?” (yes = 1, no = 0) after reading each situation presented in a random order.

Results and Discussion

We first evaluated all nine situations with our machine-learning algorithm from Model 1. In this evaluation, each situation was analyzed for learned features and assigned a probability that a given participant would endorse feeling socially anxious based on situational features alone. As can be seen in Table 4, top situations were given probabilities in the range of 74.80% - 96.18% ($M = 86.50\%$), middle situations were given probabilities in the range of 45.45% - 56.75% ($M = 52.07\%$), and bottom situations were given probabilities in the range of 17.28% - 22.02% ($M = 19.40\%$). As expected, the likelihood ratio used to generate each situation and the predicted probability of endorsement were highly correlated ($r = .67, p < .05$).

For each of the nine situations, we summed the endorsements and divided by the total number of observations (Average Likelihood Ratio in Table 4). We then compared the resulting percentage to the predicted probability value and calculated the difference and overall accuracy from these two numbers. As can be seen in Table 4, among top ranked situations, the overall difference between predicted endorsement and actual endorsement was 17.52% (range = 7.01% - 33.62%), which resulted in an overall accuracy of 81.12% (range = 65.03% - 92.07%). The accuracy value outperformed the predicted accuracy of 71.39% by over 10%, indicating that this algorithm is especially effective when predicting high valence situations. Among middle ranked situations, the overall difference between predicted endorsement and actual endorsement was 17.01% (range = 5.21% - 27.56%), which resulted in an overall accuracy of 73.42% (range = 62.25% - 90.36%). This was right in the range of expected accuracy, validating the model among

middle-ranked valence situations. Among bottom ranked situations, the overall difference between predicted endorsement and actual endorsement was 21.67% (range = 6.23% - 31.53%), which resulted in an overall accuracy of 51.71% (range = 38.78% - 75.23%). The accuracy value underperformed the predicted accuracy of 71.39% by over 20%, indicating that this algorithm is not best at predicting low valence situations. It is possible that more low valence—or non-anxiety situations—would be required to better train the NB model in a way that would increase sensitivity in the lower range of this distribution. Among these nine situations, accuracy was 68.75%, which was only slightly lower than the 71.39% anticipated accuracy. In this way, we garnered support that our NB model is valid and generalizable to new situations and a community sample.

General Discussion

Our study sought to identify a set of features that could be used to predict an anxiety response in social settings in order to address a long-standing gap in the literature that overlooked the importance of situational variance for SAD. We used a set of 680 freely generated situations and a naive Bayesian text classification algorithm to generate situational features that predicted anxiety responses in a large group of undergraduate students. Our results indicated that the majority of the predictive power in feeling anxious was within situational features as compared to person-related features (participant ID) or demographic features (sex, ethnicity). In this model, participant ID took into account all of the variability associated with being a unique individual within our sample. This includes trait level of social anxiety, interpersonal learning history, attention biases towards threat, threshold of sympathetic arousal, etc. Nonetheless, it was situational features rather than these person-related traits that explained

the most of the variance. These findings highlight the importance of situational factors in SAD—even when compared to well-known demographic and person-related variation.

Additionally, our Naïve Bayesian classifier was validated by generating new situations that would be considered to evoke “high,” “medium,” and “low” anxiety by incorporating features from the top, middle, and bottom third likelihood ratios from Study 1. We were also able to test the prediction accuracy among a sample of community members. All in all, our classifier demonstrated a good degree of accuracy for these new situations in both the high and medium category. We found less support for the lower anxiety category, which was likely due to the limited sample and exclusion of non-evaluative situations in the training sample.

Implications for Clinicians

This study was the first to our knowledge to develop situational variance across undergraduate college students and a community sample. While not exhaustive, Appendix A provides a list of salient situations in which people might experience social anxiety. It may be useful for therapists to reference this list when building fear hierarchies with clients who may have difficulty identifying situations, which increase their anxiety. For example, the word part “doorway” exists toward the top of the list with a likelihood ratio of 5.80. The physical location of a doorway could be explored with socially anxious clients to see what type of situation involving being at a doorway evokes an anxiety response for them. Possibilities include (a) having someone hold open the door for you when you are a long way off, (b) facing off someone passing the opposite way determining who passes through the door first, (c) arriving at a door at the same time as someone else and neither of you taking initiative to pass through first, (d) meeting an authority figure in a constricted area like a doorway, and many more. Appendix A may also be useful in generating situations that occur less frequently and cause a higher intensity

fear response. Recent research examining inhibitory learning and exposure therapy suggests that creating corrective learning experiences may be most helpful to clients when they are created in exaggerated situations that elicit a high degree of anxiety (Craske, Kircanski, Zelikowsky, Mystkowski, Chowdhury et al., 2008; Craske, Treanor, Conway, Zbozinek, & Vervliet, 2014). In this sense, exposure therapy may be enhanced by creating somewhat artificial situations and our list may be one way of eliciting these types of situations from clients.

Furthermore, situational anxiety responses tended to vary for Asian Americans, European Americans, men, and women. Research has implied that sex and ethnicity may influence the expression of anxiety symptoms (Essau, Conradt, & Petermann, 1999; Kessler et al., 2006; Krieg & Xu, 2015; Okamura et al., in press; Wittchen, Stein, & Kessler, 1999). However, it is unclear if these differences are truly related to demographic variables versus cultural construal of these various situations. Therefore, care should be taken when using Tables 2 and 3 with clients to generate fear hierarchy items. What may be more beneficial to therapists is understanding the common themes as presented in our results section related to Asian American and European American men and women. While these may not replicate within a clinical sample, it may be important to understand variation in situational themes across these groups in order to establish culturally-normative fear and anxiety for proper SAD diagnosis.

Implications for Researchers

This study serves as another call for clinical researchers to incorporate situational factors in SAD investigations. Particularly, there may be aspects outside of “objective” situational features (e.g., what was there, who was present), such as individual interpretation or construal of the situation (e.g., Sherman, Nave, & Funder, 2010), that influences the expression of SAD symptoms and impairment. Social Psychology literature embraces the idea of person- and

situation-related influence on behavioral responses (Kammrath, Mendoza-Denton, & Mischel, 2005; Mendoza-Denton, Ayduk, Mischel, Shoda, & Testa, 2001; Mischel & Shoda, 1995; Shoda, Mischel, & Wright, 1994). These studies have demonstrated that behavior is best understood with an “If... Then...” framework that embraces both situational and dispositional conditions. In this way, individual differences in situation construal may be more relevant for clinical researchers in order to understand and predict socially anxious behavior.

Furthermore, the results of our study have implications for understanding the structure of SAD. Although the performance-only specifier was designed to help delineate social anxiety that was constricted to a commonly-experienced social situation with specific features from a more severe, generalized fear of social evaluation, our findings revealed that among a non-clinical population the situational features that received the most endorsements of social anxiety were not necessarily related to social performance, but instead related more to social interactions. Future studies may wish to examine the content of feared situations among groups of individuals meeting criteria for the performance-only or generalized subtypes of SAD in an open-ended manner to better identify the degree of generalizability and overlap between the two subtypes.

At the same time, individual interpretation of situational stimuli may not be the only useful interaction effect to examine. While not the main purpose of the current study, our results also provide some evidence for differences in emotional response of certain situational features among groups of Asian Americans, European Americans, men, and women. It is possible that there may be shared cultural meaning associated with certain types of situational stimuli (e.g., Mendoza-Denton & Mischel, 2007) over and above idiographic situation interpretation and construal. Perhaps differences in SAD among sex (Xu et al., 2012) and ethnic groups (Krieg &

Xu, 2015; Okamura et al., in press) would be better explained upon gaining an understanding of these shared meanings in situational construal in anxiety provoking settings.

Another important contribution of the study was introducing the uncommonly used but powerful methodology of text classification and machine learning. In contrast to other attempts to describe social anxiety-provoking situational characteristics using researcher-generated situations or qualitatively-derived situational themes, our study was the first to use entirely participant-generated items, responses, and situational features with very little interference from our research team. This resulted in novel information about what particular text features are relevant to participants' experience of social anxiety. At the same time, there were several limitations with this particular approach in that it is not always clear how a certain situational feature or word part is directly related to the particular construct under investigation. Researchers and other experts simply know more about the construct of interest than general participants. A closer alignment with lay definitions of our construct likely represents both the cost and the benefit of this type of text classification implementation. We recommend using both researcher-generated themes and participant-generated situational information in tandem to better understand the situational variance in constructs such as social anxiety.

Limitations and Future Directions

Although our investigation had strengths related to novel methodology and multiple samples, there were also a few limitations. First, despite our efforts to explain the degree to which anxiety would be endorsed in a given situation, our classification algorithm did not gain optimal accuracy, scoring a maximum of 75.19% (or 25.19% above a random guess of 50%). Being unable to explain a higher degree of variance is indicative that there are still other factors that are not accounted for within situational features, dispositional differences, or demographic

information. One such possibility is cognitive style—patterns of thinking about the situations in which individuals find themselves (e.g., Yang et al., 2014). Perhaps future studies could include one's cognitive style or explanation style as a predictor to increase classification accuracy.

Second, even though our results identify salient, highly predictive situational features that lead to a social anxiety response, the nature of this type of analysis prohibits us from deriving the reasons why these situational features evoke these responses. In order to address this theory-related question, future investigations may benefit from using a mixed-method design, incorporating qualitative focus groups where participants explain the cognitive and affective response that they would have within that type of situation.

Finally, when deriving our situational features, we cleaned our data so that the resulting unit would be a single word stem. However, because certain word combinations vary in frequency, it is also likely that two or three-word groups (i.e., bigrams or trigrams) could result in a different level of feature saliency or an entire new meaning altogether. A potential expansion of the current study would be to investigate the influence of word combinations to see if classification accuracy increases. Through these efforts we may be able to develop a richer discussion of social anxiety and its situational determinants.

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Table 1.*Accuracy and Over-Specification Indication among Models*

Name	Training		Test		Over-specification	
	<i>Accuracy</i>	<i>Change</i>	<i>Accuracy</i>	<i>Change</i>	<i>Value</i>	<i>Change</i>
Model 0: Random Assignment	50%	~~	50%	~~	0%	~~
Model 1: Situational Variance	76.80%	26.80%	71.39%	21.39%	5.41%	5.41%
Model 2: Person Variance	82.51%	5.71%	75.19%	3.80%	7.32%	1.91%
Model 3: Demographic Variance	81.68%	-0.83%	74.08%	-1.11%	7.60%	0.28%

Table 2.

Top 50 Important Situational Features for Asian American Women and Men

Asian American Women			Asian American Men		
Word Part	Example Phrases	Likelihood Ratio	Word Part	Example Phrases	Likelihood Ratio
<i>explain</i>	explaining why	8.6	<i>spil</i>	spilling food	8.6
<i>illeg</i>	illegally parking	8.6	<i>zip</i>	zipper is down	8.6
<i>brut</i>	brutally honest	7.1	<i>follow</i>	being followed; nobody follow	8
<i>zip</i>	zipper is down	7.1	<i>send</i>	sending an email	4.8
<i>harsh</i>	harsh	7.1	<i>mat</i>	roommates; classmates	4.8
<i>reput</i>	affect your reputation	6.1	<i>entir</i>	entire class	4.8
<i>wond</i>	wondering how it will affect	6.1	<i>nobody</i>	nobody follow	4.8
	doesn't take it well; doesn't want to talk;				
<i>wel</i>	doesn't know; doesn't understand	5.5	<i>control</i>	cannot control	4.8
<i>back</i>	behind your back	5.5	<i>salesm</i>	salesman	4.8
<i>ready</i>	getting ready	5.5	<i>appear</i>	noticed for your appearance	4.8
	complicated vocabulary; receiving				
	compliments; competing for affection;				
<i>com</i>	failed to complete something	5.5	<i>cloth</i>	clothes	4.8
<i>sign</i>	romantic signals	5.5	<i>sery</i>	serious problem	4.8
<i>behind</i>	behind your back	5.5	<i>rip</i>	pants had ripped	4.8
<i>rum</i>	hearing rumors	5.5	<i>laugh</i>	laughs at you	4.8
<i>spirit</i>	mean-spiritedly	5.5	<i>shout</i>	shouted out	4.8
<i>snid</i>	snide comments	5.5	<i>stor</i>	store	4.8
<i>misread</i>	misreading	5.5	<i>body</i>	body	4.8
<i>smirk</i>	smirking	5.5	<i>miss</i>	missing calls	4.8
<i>tour</i>	going on a tour	5.5	<i>item</i>	embarrassing item	4.8
<i>spil</i>	spilling food	5	<i>worry</i>	worried about failing others	4.8
<i>introduc</i>	introducing yourself	4.4	<i>hard</i>	worked hard	4.8

Asian American Women			Asian American Men		
Word Part	Example Phrases	Likelihood Ratio	Word Part	Example Phrases	Likelihood Ratio
<i>hand</i>	shake hands	3.9	<i>movy</i>	movie theater	4.8
<i>seen</i>	being seen	3.9	<i>appoint</i>	appointment; disappointment	4.8
<i>without</i>	without hurting them; without knowing	3.9	<i>larg</i>	large group	3.9
<i>ful</i>	full of people	3.9	<i>trip</i>	tripping	3.7
<i>appear</i>	noticed for your appearance	3.9	<i>bad</i>	someone say something bad	3.7
<i>salespers</i>				bring up the situation; situation you	
<i>on</i>	salesperson	3.9	<i>situ</i>	cannot control; uninformed of a situation	3.7
<i>exchang</i>	exchanging phone numbers	3.9	<i>agr</i>	not agreeing	3.7
<i>lawy</i>	lawyer	3.9	<i>everyon</i>	everyone	3.5
<i>immodest</i>	being immodest	3.9	<i>fir</i>	first time	3.4
<i>permit</i>	permission	3.9	<i>email</i>	sending an email	3.4
<i>phys</i>	physically attractive	3.9	<i>alon</i>	alone with	3.4
<i>movy</i>	movie theater	3.9	<i>shop</i>	barber shop	3.3
<i>din</i>	dining	3.7	<i>told</i>	being told	3.1
<i>admit</i>	admitting a fault	3.5	<i>cashy</i>	cashier	2.9
<i>uninform</i>	uninformed of a situation	3.3	<i>lunch</i>	having lunch	2.9
<i>two</i>	two empty places	3.3	<i>review</i>	performance reviewed	2.9
<i>afraid</i>	afraid of hurting	3.3	<i>environ</i>	new environment	2.9
<i>empty</i>	two empty places	3.3	<i>assocy</i>	sales associate	2.9
<i>crush</i>	crush	3.3	<i>ful</i>	full of people	2.9
	forgetting someone's name; my name				
<i>nam</i>	shouted; being called names	3.1	<i>count</i>	counter argue	2.9
<i>hi</i>	say hi	3	<i>uns</i>	being unsure	2.9
<i>wheth</i>	whether	3	<i>admir</i>	admire	2.9
<i>next</i>	next to me; next to a stranger	3	<i>spirit</i>	mean-spiritedly	2.9
<i>stal</i>	bathroom stall	3	<i>fun</i>	being made fun of	2.9

Asian American Women			Asian American Men		
Word Part	Example Phrases	Likelihood Ratio	Word Part	Example Phrases	Likelihood Ratio
<i>mistak</i>	mistakes pointed out	3	<i>problem</i>	serious problem	2.9
<i>uns</i>	being unsure	2.9	<i>amount</i>	wrong amount of money	2.9
<i>pra</i>	pranked	2.9	<i>oppon</i>	opponent	2.9
<i>profess</i>	professor	2.8	<i>cowork</i>	coworker	2.9
<i>affect</i>	affect your reputation	2.5	<i>tabl</i>	table	2.9

Table 3.

Top 50 Important Situational Features for European American Women and Men

European American Women			European American Men		
Word Part	Example Phrases	Likelihood Ratio	Word Part	Example Phrases	Likelihood Ratio
<i>explain</i>	explaining why	13.3	<i>appear</i>	noticed for your appearance	13.1
<i>appear</i>	noticed for your appearance	10.9	<i>panel</i>	judge's panel	13.1
	bring up the situation; situation you cannot control; uninformed of a situation	10.9	<i>compet</i>	competing	9.3
<i>situ</i>	without hurting them; without knowing	8.5	<i>cle</i>	cleaning up after	9.3
<i>without</i>	heard you gossiping	8.5	<i>amount</i>	wrong amount of money	9.3
<i>gossip</i>	next to me; next to a stranger	8.5	<i>room</i>	bathroom; classroom, roomates	7.8
<i>next</i>	being immodest	8.5	<i>fut</i>	future	5.6
<i>immodest</i>	sending an email	6.1	<i>car</i>	car	5.6
<i>send</i>	flaws pointed out	6.1	<i>quiet</i>	quiet classroom	5.6
<i>flaw</i>	training someone	6.1	<i>rid</i>	ride	5.6
<i>train</i>	bring up an issue	6.1	<i>random</i>	random people	5.6
<i>issu</i>	mouth open	6.1	<i>us</i>	use	5.6
<i>mou</i>	material	6.1	<i>put</i>	put down; put on big screen	5.6
<i>mat</i>	entire class	6.1	<i>unsoc</i>	unsocial people	5.6
<i>entir</i>	wrong amount of money	6.1	<i>coff</i>	coffee shop	5.6
<i>amount</i>	movie theater	6.1	<i>issu</i>	bring up an issue	5.6
<i>movy</i>	lost something	5.7	<i>lab</i>	labmate; lab project	5.6
<i>lost</i>	schoolwork	5.1	<i>cloth</i>	clothes	5.6
<i>schoolwork</i>	counter argue	5.1	<i>crazy</i>	crazy religious people	5.6
<i>count</i>	rather	5.1	<i>wary</i>	being wary	5.6
<i>rath</i>					

European American Women			European American Men		
Word Part	Example Phrases	Likelihood Ratio	Word Part	Example Phrases	Likelihood Ratio
<i>oppon</i>	opponent	5.1	<i>caus</i>	causing an inconvenience; promote their cause	5.6
<i>review</i>	performance reviewed	4.7	<i>tough</i>	tough day	5.6
<i>ready</i>	getting ready	4.4	<i>mut</i>	mutual friends	5.6
<i>stal</i>	bathroom stall	4.4	<i>togeth</i>	together	5.6
<i>crush</i>	crush	4.2	<i>eld</i>	elders	5.6
<i>hi</i>	whether to say hi	3.6	<i>growl</i>	stomach growl	5.6
<i>wel</i>	doesn't take it well; doesn't want to talk; doesn't know; doesn't understand	3.6	<i>religy</i>	religious people	5.6
<i>barb</i>	barber shop	3.6	<i>afraid</i>	afraid of hurting	5.6
<i>environ</i>	new environment	3.6	<i>drop</i>	dropping	5.6
<i>away</i>	take away your phone	3.6	<i>whol</i>	whole school	5.6
<i>lov</i>	love interest; loved ones	3.6	<i>lawy</i>	lawyer	5.6
<i>cloth</i>	clothes	3.6	<i>think</i>	think; thinks highly	5.6
<i>guest</i>	guest in your home	3.6	<i>obvy</i>	obvious	5.6
<i>sensit</i>	something sensitive; sensitive topic	3.6	<i>immodest</i>	being immodest	5.6
<i>unaw</i>	unaware	3.6	<i>email</i>	sending an email	5.6
<i>afraid</i>	afraid of hurting	3.6	<i>cowork</i>	coworkers	5.6
<i>form</i>	perform; performance	3.6	<i>grasp</i>	grasp a concept	5.6
<i>market</i>	farmer's market	3.6	<i>affect</i>	affect your reputation	5.6
<i>lawy</i>	lawyer	3.6	<i>judg</i>	judge's panel	5.6
<i>email</i>	sending an email	3.6	<i>anyon</i>	anyone	5.6
<i>cowork</i>	coworkers	3.6	<i>job</i>	job	4.6
<i>permit</i>	permission	3.6	<i>top</i>	topic; sensitive topic	4
<i>elev</i>	elevator	3.6	<i>charg</i>	being in charge; taking charge	4
<i>boo</i>	being boo-ed	3.6	<i>two</i>	two empty places	4
<i>concert</i>	concert	3.6	<i>approach</i>	approaching; approached	4

European American Women			European American Men		
Word Part	Example Phrases	Likelihood Ratio	Word Part	Example Phrases	Likelihood Ratio
<i>unsoc</i>	unsocial people	3.6	<i>day</i>	first day	4
<i>task</i>	many tasks	3.6	<i>empty</i>	two empty places	4
<i>embarras</i>	embarrassing item	3.6	<i>nee</i>	need help	4
<i>accompl</i>	not accomplishing	3.6	<i>elev</i>	elevator	4
<i>fin</i>	finish soon	3.6	<i>fail</i>	failed to complete; failing	3.9

Table 4.

Study 2 Validation Results

Situation	Average Likelihood Ratio	Predicted Probability of Endorsement	Percent of Sample that Endorsed Social Anxiety	Difference	Percent Accuracy
Appearing stupid in front of others	9.5	74.80%	86.72%	+11.92%	86.25%
Having your friend shout and act goofy next to you in public	4.0	96.18%	62.55%	-33.62%	65.03%
Hearing someone accuse you of doing something illegal	13.3	88.53%	81.51%	-7.01%	92.07%
<i>Top Average:</i>	8.93	86.50%	76.93%	17.52%	81.12%
Being around unsocial people	2.7	54.03%	48.82%	-5.21%	90.36%
Talking loudly in a public place	3.5	45.43%	72.98%	+27.56%	62.25%
Being unable to do what my elders could	2.6	56.75%	38.39%	-18.26%	67.65%
<i>Middle Average:</i>	2.93	52.07%	53.40%	17.01%	73.42%
Voicing your opinion about whether or not to prank your friend	2.1	18.89%	25.11%	+6.23%	75.23%
Having to look after many people	2.2	22.02%	53.55%	+31.53%	41.12%
Being late to a party	2.3	17.28%	44.55%	+27.27%	38.78%
<i>Bottom Average:</i>	2.20	19.40%	41.07%	21.67%	51.71%

Figure 1. *Conceptual Diagram of Supervised Machine Learning.*

Note. Reprinted from “Giving Computers the Ability to Learn from Data” by S. Rascha, 2015, *Python Machine Learning*, 3. Copyright 2015 by Packt Publishing Ltd.

Appendix A

Comprehensive List of Important Situational Features and Likelihood Ratios

Word Part	Example Phrases	Likelihood Ratio
<i>illeg</i>	illegally parking	13.3
<i>crim</i>	crime scene	12.9
<i>appear</i>	noticed for your appearance	9.5
<i>freez</i>	freezing up when talking	6.5
<i>unwit</i>	unwittingly drawing attention	6.3
<i>doorway</i>	doorway	5.8
<i>bump</i>	bumping	5.8
<i>cry</i>	crying in public	5.7
<i>harsh</i>	harsh and brutally honest	5.5
<i>sensit</i>	something sensitive; sensitive topic	5.1
<i>wel</i>	doesn't take it well	5.1
<i>lost</i>	lost something	5.1
<i>accompl</i>	not accomplishing something on time	4.9
<i>without</i>	without hurting them; without knowing	4.8
<i>shout</i>	shouted out	4.5
<i>smirk</i>	smirking and making snide comments	4.3
<i>amount</i>	wrong amount of money	4.3
<i>com</i>	complicated vocabulary; receiving compliments; competing for affection; failed to complete something	4.3
<i>snid</i>	snide comments	4.3
<i>control</i>	cannot control; controlling something	3.8
<i>train</i>	training someone	3.5
<i>tal</i>	being talked about; do not have talent; many people talk; talk bad about you; talk/ing to; stuttering while talking	3.5
<i>immodest</i>	being immodest	3.5
<i>rum</i>	hearing rumors	3.5
<i>wond</i>	wondering how it will affect	3.5
<i>behind</i>	behind your back	3.5
<i>reput</i>	affect your reputation	3.5
<i>offens</i>	minor offense	3.5
<i>movy</i>	movie theater	3.5

<i>goofy</i>	acting goofy	3.5
<i>explain</i>	explaining why	3.1
<i>off</i>	office; police officers	3.1
<i>form</i>	being uninformed; performance	3.0
<i>troubl</i>	being in trouble	3.0
<i>barb</i>	barber shop	3.0
<i>stomach</i>	stomach growl	3.0
<i>send</i>	sending an email	3.0
<i>quiet</i>	quiet classroom	3.0
<i>mat</i>	roommates; classmates	3.0
<i>entir</i>	entire class	3.0
<i>growl</i>	stomach growl	3.0
<i>spirit</i>	mean-spiritedly	3.0
<i>uns</i>	being unsure	2.9
<i>spil</i>	spilling food	2.9
<i>doubt</i>	doubt your leadership	2.9
<i>zip</i>	zipper is down	2.8
<i>stal</i>	bathroom stall	2.8
<i>doesn</i>	doesn't take it well; doesn't want to talk; doesn't know; doesn't understand	2.8
<i>nam</i>	forgetting someone's name; my name shouted; being called names	2.8
<i>exchang</i>	exchanging phone numbers	2.7
<i>stud</i>	students	2.7
<i>unsoc</i>	unsocial people	2.7
<i>adv</i>	asking for advice	2.7
<i>complet</i>	failed to complete	2.7
<i>numb</i>	exchanging phone numbers	2.7
<i>chang</i>	being short changed	2.7
<i>empty</i>	empty places at the table	2.7
<i>affect</i>	affect your reputation	2.6
<i>email</i>	emailing your professor	2.6
<i>uninform</i>	being uninformed	2.6
<i>concert</i>	going to a concert	2.6
<i>gossip</i>	gossiping about them	2.6
<i>heard</i>	heard you gossiping	2.6

<i>wheth</i>	whether to say hi	2.6
<i>food</i>	spilling food	2.5
<i>cannot</i>	cannot control	2.4
<i>cloth</i>	clothes	2.4
<i>grasp</i>	grasp a concept	2.4
<i>eld</i>	elders	2.4
<i>ready</i>	getting ready	2.4
<i>bring</i>	bring up and issue	2.4
<i>lat</i>	late to work; too late to do anything	2.3
<i>intellig</i>	intelligent classmates; more intelligent	2.3
<i>ment</i>	mental illness; being mentioned	2.3
<i>afraid</i>	afraid of hurting	2.3
<i>next</i>	next to me; next to a stranger	2.3
<i>cowork</i>	coworkers	2.3
<i>loc</i>	local paper	2.3
<i>fail</i>	failed to complete; failing	2.2
<i>market</i>	farmer's market	2.2
<i>pul</i>	being pulled aside; pulled over	2.2
<i>lawy</i>	lawyer	2.2
<i>gramm</i>	didn't use correct grammar	2.2
<i>cal</i>	being called; calling out; calling someone	2.2
<i>many</i>	given many tasks; many people	2.2
<i>elev</i>	elevator	2.1
<i>voic</i>	voicing your opinion	2.1
<i>pra</i>	pranked	2.1
<i>cle</i>	cleaning up after	2.1
<i>tabl</i>	table	2.1
<i>situ</i>	bring up the situation; situation you cannot control; uninformed of a situation	2.0
<i>compet</i>	competing	2.0