Do Individuals Smile More in Diverse Social Company? Studying Smiles and Diversity Via Social Media Photos

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ABSTRACT

Photographs are one of the most fundamental ways for human beings to capture their social experiences and smiling is one of the most common actions associated with photo-taking. Photos, thus provide a unique opportunity to study the phenomena of mixing of different people and also the smiles expressed by individuals in these social settings. In this work, we study whether a social media-based computational framework can be employed to obtain smile and diversity scores at very fine, individual relationship resolution, and study their associations. We analyze two data sets from different social networks, Twitter and Instagram, over different time periods. Primarily looking at photographs, using computer vision APIs, we capture the diversity of social interactions in terms of age, gender, and race of those present, and smile levels. Analysis of both data sets suggest similar and significant findings: (a) people, in general, tend to smile more in the presence of others; and (b) people tend to smile more in a more diverse company. The results can help scale, test, and validate multiple theories related to affect and diversity in sociology, psychology, biology, and urban planning, and inform future mechanisms for encouraging people to smile more often in everyday settings.

KEYWORDS

Smile; diversity; happiness; faces; photos; images; Twitter; Instagram; social media

1 INTRODUCTION

Photographs are one of the most fundamental ways for human beings to capture their social experiences and smiling is one of the most common actions associated with photo-taking. Photos, thus provide a unique opportunity to study the social phenomena of mixing of different people and also the smiles expressed by individuals in these social settings. The associated concepts of smiles (or technically, the *displayed affect*) and diversity of people interacting have been studied in multiple disciplines and have several implications for human lives. For instance, intensity of a person's smile has been connected with longevity [4], and the diversity of social interactions has been connected with innovation, commerce, and well-being of the individuals [50].

While smiles have been studied quite actively in the computer science literature (multimedia, computer vision, and affective computing), there is little computational research focusing on the presence of others to study smiles in multi-person settings. On the other hand, there is significant social science literature that has studied the difference in the frequency and intensity of smiles of people of different race and gender and its influence on how people smile in diverse social interaction settings [43, 52]. However, such literature in social sciences either focuses on self-reported measures of smiles (e.g., recalling the number of times one smiled during a day) or requires controlled in-lab settings. This limits the sample sizes available, the duration of observation possible, and is fraught with multiple social and cognitive biases [29].

Advancing the understanding of the related phenomena of smiles (and well-being in general), and diversity of social interactions requires the development of methodologies that can scale effectively to millions of individuals, do not require human time and attention, and can capture the temporal dynamics of such phenomena. Building such methodologies can support the advancement of the related theories in relevant disciplines (e.g., psychology, sociology, physiology, biology) and also yield actionable insights on how to make people smile more and potentially live healthier, happier lives.

However, there is as yet very little work at the intersection of multimedia computing and social sciences that can support the study of the two important phenomena of smiling and diversity in social interactions. One important reason for this gap is that the related work often happens within the confines of the respective communities of practice (e.g., sociology and computer science), and working across domains to study these questions is considered risky. Answering such a question requires a single work to tackle both methodological and epistemological research questions. That is, the epistemological research questions cannot be answered unless a newer methodology is defined and implemented.

In this Brave New Ideas track paper we define a newer multimedia based methodology and then use that to answer an epistemological research questions connecting smiles and diversity of interactions. We define a social media-based computational framework that uses Computer Vision based APIs to quantify diversity of social interactions as well as the frequency and intensity of smiles expressed by the participants involved. This approach, for the first time, could allow social scientists, urban planners, and social computing researchers to study the interconnections between levels of smiles of individuals *in situ*, as they engage in diverse social interactions. Next, we collect and analyze data using this methodology to ask related epistemological questions connecting diversity and smile scores at very fine, individual relationships, resolution.

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Hence, in this work we ask the following research questions:

- **RQ1:** How can the visual content on social media (photos) be used to study the interconnections between diversity and smiles?
- **RQ2:** What are the effects of presence of others on the smile levels of the individuals in photos?
- **RQ3:** What are the effects of diversity of social interactions in terms of age, race, and gender on the smile levels of individuals in photos?

We use two popular social media sites, Twitter and Instagram, to explore the answers to the above research questions. Primarily looking at visual data (photographs), using computer vision APIs, we capture the diversity of social interactions and smile levels. Diversity is computed as a function of age, gender and race of those engaged in interpersonal social interactions in their social media posts and the smile scores are based on their expressed affects in the social media posts.

To the best of our knowledge, smiles in correspondence to diversity of social interactions have been investigated and measured using a computational mechanism for the first time in this work. More broadly, this Brave New Idea work motivates a case for utilizing multimedia based computational frameworks to study human social processes at scale. It opens the doors to further rigorous social (multi-)media data exploration in understanding the impacts of diversity and smiles, emotions, and empathy on other societal outcomes that are important factors in studies pursued by social scientists around the world. We hope that eventually, such a line of research can serve in recognizing the constituents to diverse and happier societies.

The rest of the paper is organized as follows. First we discuss the related work. Followed by that, we state and explain the new methodology introduced in the work along with the data corpus used and describe the tools, statistical methods and computer vision APIs used to analyze the data. We then interpret and conclude our results with a discussion.

2 RELATED WORK

2.1 Understanding Smiles and Affect

Understanding smiles has been an important sub-field in both computer science and the social sciences. Social sciences have considered smiles as a type of "affect display" i.e. a subject's externally displayed affect. The display can be by facial, vocal, or gestural means [68]. Similarly, in computer science, *affective computing* as a field focuses on different types of affects displayed by human beings [51].

Affect, in psychology, is defined as the experience of feeling or emotion [37]. Affect is a key part of the process of an organism's interaction with stimuli and sometimes used interchangeably with affect display. Affect display is also a critical facet of communication in the social domain. Interpersonal communication is influenced by displayed affect and there are various theories on affective reactions to stimuli to include conscious and non-conscious reaction as well as positive or negative affect. Social science research also often studies smiles in a broader umbrella of research on affects, emotions, mood, happiness, and subjective well-being. While each one of these concepts is nuanced in its own right, these aspects are often inter-related and studied together [48]. In this work, however, we maintain our focus on smiles, which are a specific type of affect display.

While other muscles can simulate a smile, only a peculiar movement of the zygomatic major and the orbicularis oculi produce a genuine expression of positive emotion. Psychologists call this the "Duchenne smile" and many consider it the sole indicator of true enjoyment [41]. There has also been significant recent research in affective computing focusing on face detection, smile detection, differentiating between genuine ("Duchenne smile") and posed smiles, and quantifying the intensity of smiling [18]. There is hence a wide variety of computational tools now available to automatically detect smiles, quantify their intensity and determine their genuineness. We use one such computer vision API in this work [1].

2.2 Understanding Diversity of Social Interactions

Diversity is an important socio-economic construct that has associations with multiple aspects of human life including commerce, innovation, well-being, criminal justice, civic responsibilities and health among others [36, 50]. Not surprisingly, it has been the objective of understanding in many sociology and psychology studies. Traditionally, though, diversity has been defined as a function of the number of people of different age, gender, ethnicity etc. living in the same neighborhood as observed through long-term data (e.g., census) [46]. Consistent with our recent related work in this area, we focus on the diversity in interpersonal relationships of a person. Hence, the focus is not on the residential address of the person, but rather with whom one spends their personal interaction time [63]. Previous work has shown that photos are important in social relationships. The content of photos show who is part of a group and telling stories about photos helps nurture relationships [67]. Hence, here we assume that people sharing the same "frame" in a single photo have some kind of interconnection among themselves.

2.3 Smile and Affect Analysis in Social Media

While the notions of emotions, sentiment, affect, and well-being are frequently studied in computational social science literature, most of such work still focuses on text analysis of the user content (e.g. [10, 15, 39]) or self-reported measures (e.g. Positive And Negative Affect Sampling (PANAS) [62, 66]) of the person's affect.

While there have been large number of studies that observe smiles using computational mechanisms (e.g., [33, 71]) the use of social media images for automatically inferring smiles and affect is relatively less common. However, recent efforts like that of Abdullah et al. have argued a case to use social media to measure affect using images [3]. Specifically, they introduce the methodology of Smile Index which is used to computationally measure societal happiness. Similarly, Dhall et al., study the "collective emotion" portrayed by a group of people in social media photographs [17]. We consider such efforts as inspirations, and this work moves the literature forward by connecting diversity of interactions with the levels of smiles portrayed by the participants.

2.4 Diversity Measures and Social Media

While there have been multiple efforts aimed at understanding diversity in its broadest sense using social media, most such efforts have focused either on self-reported, and hence manual, costly, estimates of individual demographics or utilized (sophisticated) text processing techniques to automatically infer user demographics descriptors (e.g., age, race, gender). The literature largely ignores a treasure trove of demographics explanatory data - photographs.

For instance, Adnan et al. examined the text of one million geo-tagged tweets in the Greater London area and constructs a map representing the city's ethnic groups [6]. By making use of Twitter usernames of the extracted tweets and the Onolytics methodology [2], Adnan et al. classify different societal groups through their idiosyncratic naming conventions. Similarly, Arnaboldi et al. used Twitter text to understand multicultural diversity via language detection in Milan [7]. Lastly, a recent effort by Santani and Gatica-Perez utilizes the bilingual communication (in text) to study diversity in Swiss Foursquare users [54].

However, the use of photographs which innately capture the aspects of age, race, and gender of the participants have been rarely used for diversity studies. An exception being a related effort by our group [63] that tries to utilize social media photographs to quantify diversity in different parts of New York city. Note though, that [63] focuses on geo-spatial diversity measured at zip-code level, while this work focuses on social interactions, their diversity, and the smiles captures within a single photograph i.e. a single social setting.

2.5 Interconnections between Smile and Diversity of Social Interactions

Multiple researchers have argued a case for studying smiles together with the associated social interactions. For instance, Hess argues that "[i]t is difficult to conceive of social interactions in which no emotions are expressed by any of the interaction partners" [35]. Similarly, Fridlund considers smiles to have a central role in social signaling [27].

The literature connecting smile and diversity comes from two major themes. First focuses on the difference in smiles, or more generally well-being, across different age and gender groups. For instance, Yang et al. identify the differences in reported happiness levels across age, race, and gender boundaries [70]. Similarly, Bruni et al., suggest that African American households are more likely to report a lower well-being scored as compared to other races [12]. We explicitly model this aspect of difference in smiles based on different demographics of the participants in this work. However, we consider this as an aspect that we need to control for, before being able to focus on the effects of *co-presence* of people of different demographics within the same photo-frame or personal space.

The second stream of research focuses on difference in smiles portrayed by individuals of different races or gender in specific settings. Such experiments are often conducted in controlled settings (e.g. a staged interview involving same-race and different-race dyads). The general finding across these studies has been that women tend to smile more than men, and minority races tend to smile less in the presence of majority races [19, 43]. However, these experiments focus on specific controlled settings and typically do not use computational mechanisms. This constrains the number of samples available in such studies and the cost for conducting such experiments. Hence, this work aims to push the boundaries further in this direction with this work.

We also note explicitly, that human affect and smiles are a complex phenomena, which can be influenced by multiple internal, external, cognitive, biological, and social factors. Further, there are multiple processes involved in emotional functioning, including verbal, facial, and behavioral expressiveness; emotional experiences and awareness; the ability to recognize or interpret emotions in others; physiological arousal; and the capability to regulate emotional expressions. Further, many of these aspects are known to vary across personality, social, cultural, and situational variables. Hence, we do not expect the diversity of interactions to be able to explain all or even most of the variation in the smile scores. Rather, we aim to study whether such social interactions have *any* effect on smile scores? Whether it is significant? And what is the directionality? Just like gender has been reported to have small but significant effect on an individual's propensity to smile, we want to test if the immediate social company that one is engaged with has a significant effect on a person's smile score.

3 METRICS

Having smiles and diversity as the key concepts in this work, we opt for a fine-grained photo-level interpretation of both measures. We consider smile score to be the target (dependent) variable and model it based on a combination interaction diversity and demographic variables. In this section, we discuss how we quantify each of these aspects.

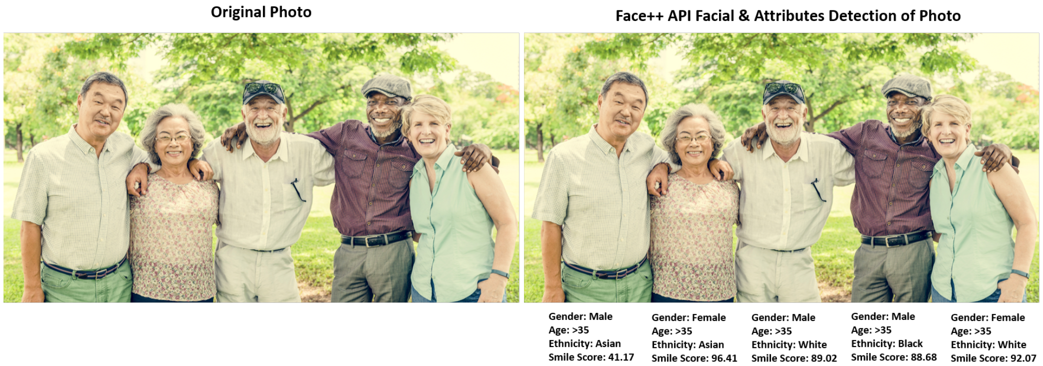
3.1 Dependent Variable- *Smile Score*

We obtain this smile score for individual images by submitting the image metadata URL to the Face++ API, a publicly available API produced by Face++ Cognitive Services [1]. The output gives an estimated smile score of each of the individuals in the image. The API detects smiles using computer vision techniques. Using the location of upper and lower lip contours and few other counters, a smile score based upon mouth contraction is calculated for each individual. This score is a number between 0, representing the lowest intensity of the smile (i.e. no smile), to 100, representing the highest intensity of the smile. Given, our focus on understanding the role played by interaction diversity on all the involved participants, we compute the average of all the smile scores in the given photograph (see Figure 1 for an example) to quantify the overall level of smile in a photographed experience.

3.2 Interaction Diversity Metrics

This work focuses on quantifying the diversity of interactions as they take place in one's immediate personal space. In this sense, it is very different from the more commonly used interpretations of diversity i.e. based on census count of the people living in a neighborhood.

The diversity methodology in this work is adapted from our previous related work [63]. It is based on a widely accepted metric called Shannon Entropy, also known as Shannon's Diversity Index [55]. The method was identified by Claude Shannon who used it initially to quantify entropy in strings of text. Later, it gained popularity in the studies of diversity in the United States. The



Our Interpretation of Results

Variable	Value
# of Males	3
# of Females	2
# of Whites	2
# of Blacks	1
# of Asians	2
<18 Age	0
>18 and <35 Age	0
>35 Age	5
Avg. Smile Score	81.47

Figure 1: Example of facial and attribute detection from the Face++ API and our interpretation of the API results. (Image not from the data set for privacy reasons. Sample image from Shutterstock.)

metric is calculated as follows:

$$SE = -\sum_{i=1}^{R} p_i \cdot ln(p_i) \tag{1}$$

where p_i is the proportion of individuals belonging to the i^{th} demographic description (e.g. male) in the data set of interest and R is the number of distinct 'bins' (e.g. male and female) considered.

We compute three measures of Shannon Entropy for each image based on different representation of the bins, i: gender (male and female), age ($<$ 18; 18-35; $>$ 35), and race (White, Black, and Asian). The three particular races were chosen based on the American Community Survey (ACS) demographics, which assert that White, Black and Asian are the three major racial groups in New York City, from where the data was collected for this study.

3.3 Demographics of Participants

Prior studies have suggested that smiles (frequency and intensity) may be different for different demographic groups. For example, women tend to smile more often than men [43]. Similarly, smile may be a function of the number of people present in an image [53]. Hence, we consider a number of additional variables in this work including the number of faces in the image, number of people of different gender (male/female), different race (White/Black/Asian), and different age groups. We explain these variables in more detail in the next section.

4 APPROACH

Figure 2 contains a summary of the approach employed in this work starting with data collection and ending with statistical analysis. We start with data collection and filtration. Next, we obtain variables of interest for each image using computer vision APIs and validate the variables. From there, we implement the methodology and statistically analyze the data.

4.1 Data Corpus

To apply our methodology, we collect a sample of data from two popular social media sites. We use Instagram, a primarily visual sharing platform with 32% of Internet users [58], and Twitter, a majorly text oriented platform with 24% of Internet users [58], as part of our study. With 35% more engagement with the addition of an image in a tweet, highest among the available tweet features, and the increasing use of visual content on its platform, Twitter also contains a large number of visual images that are shared [64]. The commonality between the two sites, with respect to our study, lies in the ability to create personal accounts and easily share life moments with followers via personal photos.

4.1.1 Data Collection. Two data sets spanning two weeks each were collected over different time periods. The Instagram data was sampled via Instagram's public API in April 2016 for the New York City area. We selected this area for its high penetration of social media usage and wanted to limit our sample to a single metropolitan area to reduce the variation in cultural norms surrounding smiles and diversity of social interaction. This sample consisted of photos and corresponding metadata related to the image. After 14 days of repeated collection of the most recent photos from the New York City precincts, our data set consisted of 34,382 unique images.

Similarly, the Twitter data was sampled via Twitter's Stream API in November 2016 for the New York City area. This sample consisted of tweet information, including images, if any. After 2 weeks of constant streaming, the Twitter data set consisted of 391,315 tweets. Tweets containing the media (image) feature were extracted resulting in a sample of 33,781 unique tweets.

4.1.2 Data Filtering. We intend to study the associations between diversity of interactions and smile in terms of "everyday life". However, being a common tourist attraction, tourists encompassing the New York City area can bias the results under the assumption that travellers tend to smile more in their photos. In order to keep the sample strictly in bounds of New York City residents, we use an approach similar to one proposed by Fischer [25]. Upon assessing recent media from the users in our data sets, if 50% of the media was determined to being outside of New York City, as determined by geo-located data, we label the user as a tourist. Further, since we are interested in studying smiles from facial data, we utilize Face++ Cognitive Services' publicly available Face++ API for facial recognition. As noted in a previous work [69] and stated by Face++ Cognitive Services [1], the Face++ API has a high accuracy in facial detection. The accuracy of face detection by this API has also been

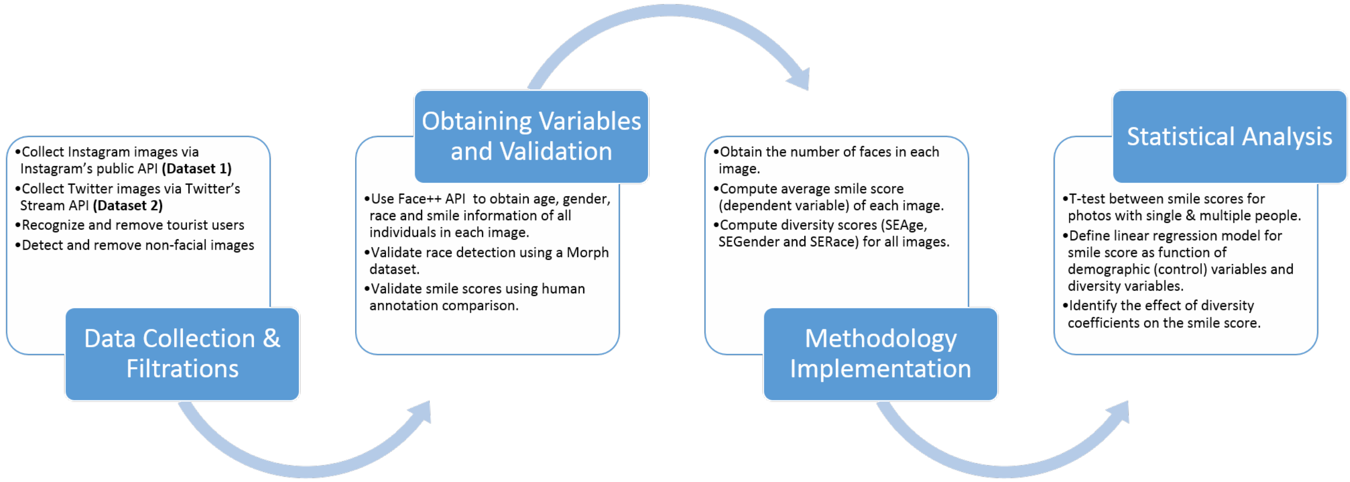


Figure 2: A summary of the work flow and approach pursued in this work.

validated in a previous work by Bakhshi et al [8]. From our subsets, approximately 8,067 (23% of all images) for Instagram and 7,142 (21% of all images) for Twitter comprised of facial images.

4.2 Variables, Validation, and Implementation

4.2.1 Computing Diversity and Smile Scores. In order to compute diversity based on our methodology described in Section 3, we required variables for the three measures of diversity: gender (male and female), age (< 18; 18-35; > 35), and race (White, Black, and Asian). The face detection, as mentioned in Section 4.1.2, gender, age, and race of each individual in the photograph is acquired from the Face++ API. Figure 1 displays an example of facial and attribute detection from the Face++ API and shows our interpretation of the API results. A formal description of each variable is noted below:

Number of Faces: Count of the number of faces detected by the API.

Number of Male (resp. Female) Faces: Count of the number of Male (resp. Female) faces detected by the API. It can be any whole number between 0 and the number of faces.

Number of <18 years (resp. >18 and <35 years; >35 years) old people: Count of the number of faces in the photo below 18 years of age (resp. >18 and <35 years; and >35 years) as identified by the API.

Number of White (resp. Black, Asian) Faces: Count of the number of White (resp. Black, Asian) faces in the photo as identified by the API.

The Face++ API output, as represented by the variables, has been validated for high accuracy in age and gender classification in previous studies by Wang et al. [69] and Bakhshi et al. [8]. However, since race classification has not been validated, we validate using a standardized (MORPH) data set as explained in Section 4.2.2.

With the variables, we compute three metrics of diversity, namely **SEGender**, **SEAge**, and **SERace**, for each photograph in the filtered data sets. Similarly, we use smile scores also provided by the Face++ API. In order to validate the smile score, we analyze inter-rate agreement as further explained in Section 4.2.3.

4.2.2 Validation of Race Classification. We follow a race validation approach as earlier described in [63]. We use a pre-labeled standardized MORPH database that has been used in a previous study to validate race classification for facial analysis of social media images [69]. The database consists of 55,000 unique images of over 13,000 entities that are all labeled for race . We use a compilation of 1,154 randomly chosen individuals, out of which 500 are racially Black, 500 are racially white and the remainder (all available) 154 are racially Asian, and validate race classification for New York's three major racial groups. The mean average precision (MAP) is 92.98%. Similar to what has been reported in a prior work [69], this race classification accuracy is considered fairly high and thus useful for the current analysis.

4.2.3 Validation of Smile Scores. To validate the accuracy of the computer vision technique offered by the Face++ API to detect and capture smile scores, we compare the results of the smile scores estimated by the API with those of two human labelers (two of the co-authors). We took a subset (randomly selected 50) of the images with one face only and obtained labels for those images for a smile score to the nearest decile (i.e. between 0 and 10) from the two annotators. The smile score was determined based on the intensity of smiling using the same criteria as used by the Face++ API.

We compare the scores assigned by the API with those of the two human annotators. We found a Pearson's correlation score of 0.92 between the API and Annotator1 and 0.86 between API and Annotator2. Lastly, we found a correlation score of 0.91 between the two annotators. This suggests that the similarity between API and human annotators is high and roughly comparable to that between two human annotators. We consider to be preliminary evidence on the suitability of using the automatically generated smile scores for the remaining data set.

5 RESULTS

In this section, we revisit our research questions mentioned in Section 1 and state our findings.

RQ1 asks how visual content on social media can be used to study the interconnections between diversity and smiles. The newly introduced application of the diversity metric combined with smile score terminology can be used to understand the interrelationship between diversity and smiles via social media posts. Further the feasibility of conducting this case study and the interpretability of the obtained results (explained further soon), suggest that the proposed methodology is a reasonable way to study the interconnections between smile and social interactions at scale. While making no claims on optimality, we consider the presented methodology to be one reasonable way to quantify and study the interconnections between smiles and interaction diversity at scale.

5.1 Does company influence smile score?

RQ2 focuses on the effect of the co-presence of multiple people on the smile levels of the people present in the photograph.

To answer this question, we split the data in each data set (Instagram and Twitter) into two groups based on the number of faces present in the image. Focusing on the Instagram data set, a comparison of the means for the smile scores for the two data groups is shown in Table 1. As can be seen the mean value for the smile score was 52.80 for the group with multiple faces and 33.75 for the group with a single image. A corresponding T-test between the two groups yielded a t-test statistic of 26.06; and a mean difference of 19.05 (95% confidence interval 17.61, 20.48), which was significant at the level $p < 0.001$, thus suggesting that there was indeed a significant difference between the group with multiple faces than the one without.

Table 1: Difference between average smile scores for photos with a single person and multiple people for Instagram data set

People in Photo		N	Mean	Std. Dev.	Std. Error
AvgSmile	Multiple	3157	52.80	28.83	0.51
	Single	4035	33.75	33.09	0.52

We repeated the same process with the Twitter data set and the results are presented in Table 2. As can be seen the mean value for the smile score was 53.70 for the group with multiple faces and 33.07 for the group with a single image. The t-test statistic was t=31.34; mean difference =20.63 (95% confidence interval 19.34, 21.92), which was significant at the level $p < 0.001$, thus, again suggesting that there was indeed a significant difference between the group with multiple faces and the one without.

Table 2: Difference between average smile scores for photos with a single person and multiple people for Twitter data set

People in Photo		N	Mean	Std. Dev.	Std. Error
AvgSmile	Multiple	3688	53.70	27.04	0.45
	Single	4380	33.07	32.10	0.49

Hence, we find very similar results across the two data sets and they both suggest that people do tend to smile more (frequency and/or intensity) in the presence of others.

5.2 Does diverse company influence smile score?

RQ3 questions the effects of diversity of social interactions on the smile levels of individuals. Based upon the analysis of both Instagram and Twitter data sets, our findings elucidate similar findings, suggesting that individuals tend to smile more in more diverse social interaction settings. The study is also indicative of all three diversity coefficients, age, gender, and race, being persistent across distinct social media platforms.

We follow the approach commonly used to identify the significance of certain factors in studying social phenomena [22, 23]. Specifically, we first define an OLS (Ordinary Least Square) linear regression model for the dependent variable (smile score) as a function of only the control variables. The control variables considered in the current analysis are the number of faces, number of male faces, number of female faces, number of White faces, number of Black faces, number of Asian faces, number of people below 18 years old, number of people 18-35 old, and number of people above 35 years old.

Next, we define a second OLS regression model with the control variables and the independent variables of interest (social interaction diversity). The significance of the regression coefficients indicates whether the independent variables of interest significantly affect the dependent variable after controlling for the effect of the other variables. The standardized coefficients provide a clue to the directionality of such an association and the difference in the adjusted R^2 value of the two models quantifies the additional explanatory power attributable to the independent variables.

5.2.1 *Instagram data set.*

The results of the two regression models using the Instagram data set are shown in Table 3. Model 1 includes all the demographic variables controlled for as listed above. While some of the features were automatically discarded by the OLS model due to multi-collinearity (e.g., number of female faces, given that the number of males was already included in the model) the remaining features were all found to be significant. Together these features account for 11.5% of the variance in the smile scores of the people captured in the pictures.

Next, we consider Model 2, which includes the additional variables that capture the diversity of the social interactions. After controlling for the effects of the demographic variables, we find that all the three interaction diversity terms (in terms of age, gender, and race) are significantly and positively associated with smile scores. Further, including them into the model allows for the model to explain 15% of the variance in smile scores, thus suggesting a modest but significant increase. Note that while this overall model has modest explanatory power, it is comparable to the results typically found in studying human behavior [22, 23, 63]. Indeed smiles and their intensity levels are complex human phenomena depending on the nuances of the person, the location, the mental state, the physiological state, and the situation. Given that we know nothing about the biology and the internal mental state of the person, we consider the finding that observing the demography based social setting in which one is present can explain 15% of the variance in smile scores as interesting in its own right. More importantly, the positive and significant associations found between the diversity of social interaction and smile scores are interesting from an epistemological perspective.

Table 3: Results of a multiple linear regression with SEAge, SEGender and SERace as the independent variables for the Instagram data set

	Model 1		Model 2	
	Std. Coeff. Beta	Sig.	Std. Coeff. Beta	Sig.
(Constant)	n/a	0.000	n/a	0.000
Gender: Male	-.356	.000	-.357	.000
Race:Black	-.051	.000	-.079	.000
Race:Asian	-.086	.000	-.107	.000
Age: Below 18	.089	.000	.036	.003
Age: 18 to 35	.354	.000	.287	.000
Age: Above 35	.299	.000	.216	.000
Diversity:Gender			.131	.000
Diversity:Race			.068	.000
Diversity:Age			.106	.000
R2	0.116		.151	
Adjusted R2	0.115		.150	
F	175.588	p<0.001	159.486	p<0.001
N	8,067		8,067	

5.2.2 Twitter data set. We follow a very similar procedure to analyze the effects of social interaction diversity on the levels of smiles in the Twitter based image data set. We first create a model using the control variables and then add the independent variables of interest.

As can be seen in Table 4, we find that all the demographic variables (except the number of people identified as Black in the photo) are significant. Such a model is able to explain 10.6% of the variance observed in smile levels. Model 2, which includes the social interaction variables shows that all the three coefficients for social interaction are positive and significant. The resulting model can explain 13.6% of the variance in the observed smile levels.

6 DISCUSSION

We notice that the results of the analysis are quite similar in terms of directionality and effect sizes for the two data sets. This consistency lends credence to the observations made. In particular, we use these results to interpret and discuss RQ2 and RQ3.

6.1 Social Company and Smile Scores

The results across the two data sets consistently suggest that people tend to smile more in the presence of others. This does not come as a surprise as smiling is often considered a biological social signaling mechanism [27, 56].

Besides being on outward expression of felt joy, it is often also used as a signal to let others know that one does not intend any harm [44]. In fact, in this sense, it transcends human relationships, and smiling behavior is observed in multiple other animal species too [53, 56]. For instance, Provine suggests that smiling is over four times likely to occur in social settings than in solitary situations [53]. Further, there is a notion of contagion in smiles [52, 53] and smile by one member of a group may lead to other people in the group smiling, thus increasing the overall smile score.

Table 4: Results of a multiple linear regression with SEAge, SEGender and SERace as the independent variables for the Twitter data set

	Model 1		Model 2	
	Std. Coeff. Beta	Sig.	Std. Coeff. Beta	Sig.
(Constant)	n/a	0.000	n/a	0.000
Gender: Male	-.314	.000	-.326	.000
Race:Black	.002	.844	-.028	.030
Race:Asian	-.057	.000	-.092	.000
Age: Below 18	.041	.001	-.012	.323
Age: 18 to 35	.284	.000	.224	.000
Age: Above 35	.324	.000	.253	.000
Diversity:Gender			.097	.000
Diversity:Race			.082	.000
Diversity:Age			.111	.000
R2	0.107		.136	
Adjusted R2	0.106		.136	
F	143.105	p<0.001	126.279	p<0.001
N	7,191		7,191	

However, such prior work (e.g., [52, 53]) was based on self-reports or manual observations. While [53] was based on self-report by 72 participants for a week, [52] was based on in-lab manual observation of 128 subjects. The proposed social media based approach, on the other hand, could be applied to newer settings involving millions of participants over long periods of time thus allowing future research in this direction to validate results at scale, over time, and render explicit some of the nuances including the effects of repeated exposures to to smiles and laughter, to different people, the attributes of people involved, the effects of indoor and outdoor environments, the surrounding situation, and so on.

6.2 Diverse Social Company and Smile Scores

We find that even after controlling for the demographic composition of the people present in the photographs, more diverse photos tend to also include higher levels of smile scores. This additional smile score however, tends to be quite modest, which is again not very surprising.

We consider two models in this work. First model focuses on the demographics of those present in the photographs. Note that this model merely focuses on the *presence of people of different groups rather than their co-presence.* This is an important differentiator between this work and previous efforts connecting happiness and emotional states with demographic variables. In fact, there is prior work that argues that that behavioral differentiation of the sexes is minimal when children are observed or tested individually. Sex differences emerge primarily in social situations, and their nature varies with the gender composition of dyads and groups [45]. We extend such an argument to consider the differences in a particular type of expressed affect - smile, based on gender, age, and race composition of dyads and groups.

6.2.1 Demography and Smile Scores. While, the phenomena of smiles is rarely studied at scale with demographic descriptors (most current studies are in-lab and deal with at most 100 people), we do find broad level consistencies between the results obtained for smiles and those which study subjective well-being and happiness of individuals of different demographic groups and the corresponding gaps. In general, sociological analyses have established the importance of social positioning to the distribution of happiness. The stratification hypothesis states that a higher rank along any evaluated dimension should produce greater happiness [14]. Empirical evidence also supports this hypothesis and suggests that happiness is moderately stratified by sex and strongly stratified by race and socioeconomic status.

We find a negative coefficient for the number of males in a photograph and this corroborates with previous empirical research that has reported that women are, on average, happier and more content than men, with or without controls for variables in which women are underprivileged [20, 60]. In a meta-analysis of sex differences in smiling based on 448 effect sizes derived from 162 research reports, LaFrance et al. have reported that women tend to smile more often [43].

We find the coefficients for the minority racial groups (Blacks and Asians) to also be negative (or non-significant). This is consistent with with the stratification hypothesis, and corroborates with prior empirical evidence studying the difference in subjective well-being of Black and White residents in the USA [38, 70].

Lastly, we notice that the coefficients corresponding to age groups are positive but with higher values for the higher age groups in the Twitter data set and the highest values for the 18-35 age group in the Instagram data set. Prior research has suggested a higher subjective well-being score with age even after controlling for different life stages and their implications [70]. This is in sync with the observations in the Twitter data set. The fact that we see the highest coefficient for the 18-35 age group in the Instagram data set could be a function of either the difference between smiles and subjective well-being as phenomena or the difference in the way the two different social media platforms considered (Twitter and Instagram) are used by the populace. We leave a further, detailed analysis of this aspect as part of our future work.

6.2.2 Social Interaction Diversity and Smile Scores. According to prior work, some critical aspects of context that affect emotional expressiveness are the characteristics of the participants in the interaction and the nature of their relationship, including their level of familiarity and intimacy, their power and status with respect to each other, and their gender [11]. For example, both men and women express more frequent and intense emotions to people they know intimately and to whom they feel closer [9].

Multiple prior studies have reported that individuals tend to self-sort based on gender homophily in day-to-day settings and the same holds true for social media [13]. We thus, interpret that social settings that involve different genders are more likely to involve salience - either in terms of the occasion (e.g., a celebration) or the relationship (e.g., significant other). This may explain the higher smile scores observed for such photographs. This is also consistent with prior literature that has reported significant differences in smiling and social behavior across same-sex and different-sex dyads [16, 40].

The positive coefficient found for racial diversity in interactions is at odds with prior literature on similar aspects. Recognition of different group memberships in the interaction has been reported to arouse "intergroup anxiety" [65]. Part of this anxiety may be due to uncertainty about how to behave in this intergroup context, and part may be a function of feelings of real or perceived threat.

In addition to anxiety, intergroup interactions can arouse a number of different motivations. For members of majority groups, for instance, intergroup interactions can arouse dominance orientations or the desire to appear nonprejudiced [28, 61]. For members of minority groups, the desire to detect and potentially compensate for anticipated discrimination by majority-group interaction partners may be activated [47, 59]. In general, these positions suggest that majority-group members would be likely to display nonverbal behaviors associated with lower levels of liking or attraction and with higher levels of social dominance or power [19]. While smiles are one specific type of non-verbal behavior, the results observed in our study suggest an opposite direction of effect.

One possible interpretation is that the diversity in terms of race could be a result of more mixed groups interacting, sharing diverse ideas, and engaging in more positive outlook towards life. The rationale of the observed effect could also be in the reverse direction, and perhaps those with more positive outlooks are more comfortable seeking out and spending time with people of different races. There could be multiple reasons for this observed difference between current and prior work, including the difference in the precise phenomena observed (general non-verbal behavior vs. smile score), the experiment conditions (e.g., formal lab settings vs. casual "in the wild" settings), and the sampled populations. While our current methodology does not allow us to establish causal rationale, we consider this finding to be interesting and one that motivates multiple research questions. Examples of such future research questions include studying the homophily in facial expressions, differentiating between different reasons for smiling [31], and understanding the "mimicing" i.e. following another person's behavior in smiles .

Lastly, we also observe positive coefficients for the age-based diversity in both the data sets. This could be interpreted as intergenerational groups (often families) smiling more often and more prominently. Given the wide brackets considered in this study, diversity in terms of age is most likely to occur with inter-generational photos that are also more likely to involve family ties. This corroborates past research which has connected family and the corresponding "strong ties" with higher emotional well-being [21, 32].

6.3 Limitations, Implications, and Future Work

While one of the goals of this work is to study smile behavior "in the wild", we note that many of the smiles in social media settings may be "posed" and base our reasoning on the idea that despite being posed, smile intensity, as measured by lip and mouth contractions, has demonstrated positive, sustaining effects in life satisfaction, marriage stability and lifespan [4, 30, 34, 49, 57], reflecting on long-term happiness. However, acknowledging the idea of posed smiles as a possible limitation of the current work, we place our focus more towards the variations observed due to the social interaction diversity assuming all other factors to be consistent across the compared groups. We also acknowledge that the population captured via social media data may not be representative of the overall US (or global) population. To reduce the effect of cultural norms, we focus on one metropolitan area New York City and only focus on its residents (not tourists) for this work.

We note that the demographic descriptors utilized in this work are limited. For example, we consider gender as a binary descriptor and focus only on the three most common races in New York City. We also acknowledge that many of the demographic descriptors are often best captured by self-identification. However, the current approach matches the self-identified demographic descriptors for a large proportion (> 90%) of the people in standardized data sets. Hence, it serves as a useful proof of concept to test and validate the ideas. In future work, with the availability of detectors for a wider gamut of descriptors, we, and other researchers, might be able to capture and support more nuanced versions of demographic descriptors.

We also acknowledge the modest effect sizes observed in this work. However, the sizes are typical of what can be expected in understanding human behavior and even tiny variations (e.g., one tenth of percentage of mood change on Facebook as observed in a recent study) can have significant effects over the population as a whole [24, 42]. Adoption rates of Instagram and Twitter, the consideration of only public, geotagged photos, and the privacy implications of photos used, are some other factors that need to be considered. With these limitations in mind, we present our methodology as a way of augmenting (rather than replacing) traditional (e.g., self-reporting and lab studies) methods for studying smiles, diversity, and well-being.

At the same time, this is one of the first attempts to leverage social media photos to not only study personal interaction diversity but also understand its associations with the affect (smile) portrayed. With refinements, the proposed approach could allow the experiments in multiple related field like sociology, psychology, communications and urban planning to be scaled up at significantly lower costs and generate an understanding of phenomena as they occur in everyday "in-the-wild" settings rather than controlled lab settings.

In particular, multiple of these research questions lie at the intersection of computational and social approaches and underscore the unique role that the multimedia research community can play in shaping the understanding of human behavior across disciplines and across application contexts. For example, automatic understanding of the scene or situation (e.g. indoor, outdoor, office, beach) in which the smiles are observed could allow for nuanced understanding of the situational factors affecting smiles. Similarly, automated video analysis could open doors to understanding the temporal process of smiling as well as understanding the social dynamics surrounding smiling. For instance, how often is a smile spontaneous vs. a "mimiced" response to those around the person? Delving further, one could study the effects of race and gender in this mimicing process, and so on. Understanding the effects of mixing of people of different backgrounds in physical and online spaces could also inform the emerging literature on "filter bubbles" and bias in the digital era [26]. Further, knowing such factors could have implications for related efforts in quality of life, sentiment mining, and in future yield prescriptive guidelines to support therapeutic applications involving laughter and smiles [5]. In effect, we posit that this "Brave New" approach for studying smiles and diverse social interactions could lead to multiple epistemological insights and also yield prescriptive guidelines towards supporting healthier, happier societies.

7 CONCLUSION

This paper defines a computational approach to study smiles at scale using social media photographs. Specifically, it studies the interconnections between the presence of multiple people and the smiles of the people in the photographs. The results indicate that people, on average, tend to smile more (frequency and/or intensity) when they are not alone. Further, while there is a noticeable difference in the smile scores of people with different gender and race, even after controlling for their effects, there is a significant effect of the diversity of those present in the photos and the average smile score. While the effects of gender, and age diversity are along expected lines, contrary to the prior results, our results show a positive association between smile and race diversity. With further validation, the proposed approach could be used to understand societal phenomena, and answer multiple questions related to diversity, smiles, happiness, and well-being across cities and countries. Essentially, the described computational approach using social media photos can be used to create data-driven insights into human phenomena, which could be instrumental in supporting, diverse, healthier, and happier societies.

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