Developing a Scale to Visually Evaluate BMI from Twitter Profile Pictures

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Abstract:
Data from social media networks, and Twitter in particular, are a promising new source for research on the social determinants of behaviors related to obesity. Up to this point, a major limitation has been difficulty in obtaining objective measures of body mass index (BMI) from Twitter users. In this paper, we develop a scale for visual estimation of BMI from Twitter profile photos. The scale uses reference Twitter images with known BMI information and asks coders to place photos of users with unknown BMI in the BMI category that most closely matches the photos. We describe an experimentation plan for refining this scale and present preliminary results from pretesting.

Extended Abstract
Obesity is a large public health problem. Currently 35.7% adults (aged 20+ years) are obese (defined as a body mass index (BMI: weight [kg] / height [m]^2) ≥30) and 16.9% children and adolescents (aged 2–19 years) are obese (defined as a BMI ≥ 95th percentile adjusted for age and sex).[1] Even more alarming are the racial/ethnic disparities in obesity.[1,2] Levels of obesity are particularly high for Black Americans, specifically black women:[3] 58.5% of non-Hispanic black women are obese compared to 41.4% of Hispanic and 32.2% of non-Hispanic white women. Disparities exist even after adjusting for socioeconomic factors and health behaviors.[4-6] Reasons for these disparities remain unclear; often cultural explanations in attitudes toward obesity-related health behaviors and body type norms are offered as explanations.[6-8] However, burgeoning research has begun to suggest the importance of social networks in impacting obesity status, as well as other health conditions.[9-12] In addition, increasing attention has been given to the use of social networking platforms such as Facebook and Twitter to examine both social networks and health outcomes.[13,14]

Social media networks, such as Twitter and Facebook, offer an unprecedented opportunity to understand the role social networks play in obesity for a diverse group of individuals. In particular, social media data present a new perspective on data collection for social and behavioral scientists working on public health problems. Whereas surveys ask respondents to recall behaviors or health conditions retrospectively, social media data afford the opportunity to observe behaviors, reports of health, and human interaction in real-time and on a large scale.

Social media data are also distinct from data derived from surveys because they allow for the collection of reports of behaviors that are unsolicited and unprompted by a researcher. Such analyses may be particularly helpful in examining racial/ethnic minority populations who have different social norms and ideas about body size[7,8] and often use different terminologies to discuss their health conditions. For example, black women who may not consider themselves overweight/obese (despite having BMI≥25),[15] might not affirmatively indicate they are overweight/obese on a survey. The same women might, however, report that they are "thick" in Twitter posts/conversations.[16] In addition, unlike many surveys, Black Americans are overrepresented on Twitter.[17] This is important because many surveys do not contain sufficient information on African Americans, necessitating the use of oversampling or weighting adjustments.[18]

However, although such data offer new and interesting opportunities to better understand the social determinants of health, the majority of population health researchers have not yet made the most of these novel data sources. This is in part due to unavailability of demographic and health information for Twitter users. In particular, though some Twitter users report their BMI directly, the majority do not. One possible strategy for ascertaining BMI is through assessment of users' profile photos. However, there is currently no platform for systematically collecting BMI information from social media network users' profile images. The aim of this paper is to address this limitation by developing and validating a scale to code BMI from images posted on Twitter.

Methods

In this section we describe the process of developing the BMI scale, present our plan for refining the scale, and present results from pre-testing. Our BMI scale uses facial images of Twitter users with known BMI information as reference photos (refer to Figure 1). We then show third party coders a profile picture from our Twitter test sample and ask them to place the photo in the BMI category that most closely matches the reference photos on a gender-specific scale according to facial adiposity.[19] In practice, we use the Amazon Mechanical Turks (AMTs) as coders ([https://www.mturk.com/mturk/welcome)](https://www.mturk.com/mturk/welcome). See Figure 2 for an example task from pre-testing.

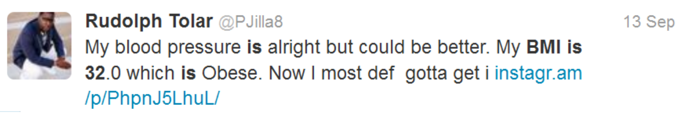

Figure 1. A Twitter user tweeting his BMI.

We will test multiple variations of the scale design to maximize the accuracy of the results. Experiments will evaluate the number of BMI categories, the presence of labels (weight classification categories), and the spacing between the reference images.[20-23] Each arm of the experiment will use a test set of images with known BMI information. To ensure that we attain the overall most reliable scale, we will use a factorial design.[24]

Preliminary Results

We tested a preliminary version of the scale with 100 users with known BMI information and asked AMTs to assign these test photos to one of eight BMI categories. We showed each test image to three AMTs. All three AMTs agreed on the weight category for 10% of photos, two of three AMTs agreed on the weight category for 68% of the photos, and no AMTs agreed on weight category for 22% of the photos. Using the majority vote of the three AMTs as the BMI classification, AMTs correctly identified the correct BMI category for 13% of test images. AMTs correctly identified the BMI within one category in 54% of test images and within two categories in 78%. We anticipate accuracy will increase as we further refine the scale using the experimental design noted above.

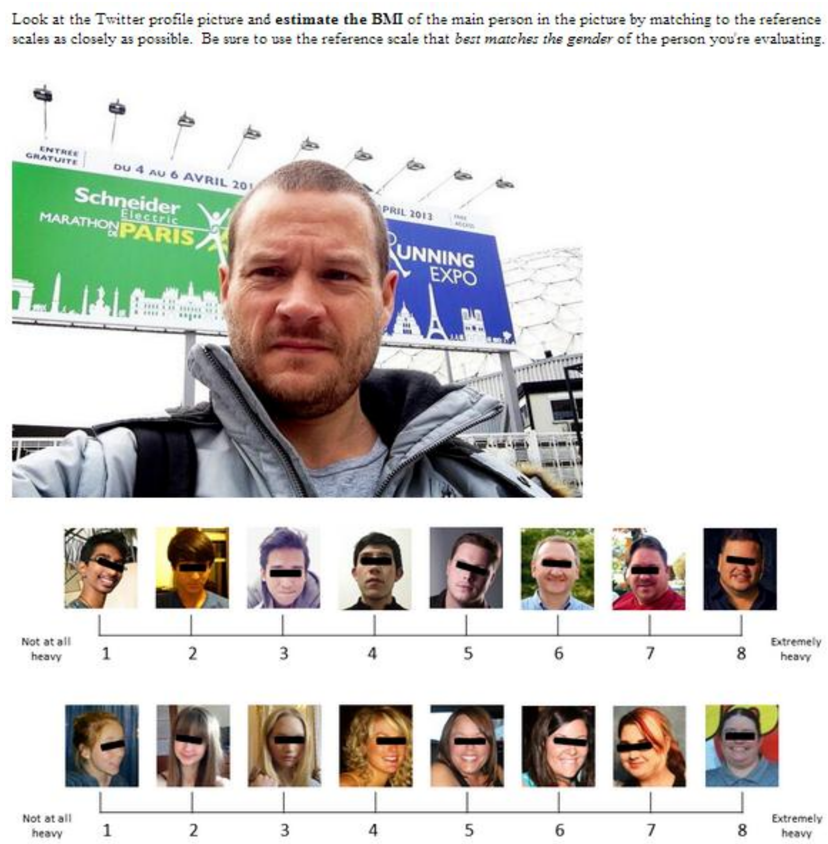

Figure 2. Example of task given to coder to estimate Twitter user's BMI

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