Using Computer Vision to Study the Effects of BMI on Online Popularity and Weight-Based Homophily

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Abstract. Increasing prevalence of obesity has disconcerting implications for communities, for nations and, most importantly, for individuals in aspects ranging from quality of life, longevity and health, to social and financial prosperity. Therefore, researchers from a variety of backgrounds study obesity from all angles. In this paper, we use a state-of-the-art computer vision system to predict a person's body-mass index (BMI) from their social media profile picture and demonstrate the type of analyses this approach enables using data from two culturally diverse settings – the US and Qatar. Using large amounts of Instagram profile pictures, we show that (i) thinner profile pictures have more followers, and that (ii) there is weight-based network homophily in that users with a similar BMI tend to cluster together. To conclude, we also discuss the challenges and limitations related to inferring various user attributes from photos.

Keywords: Body-mass index · Computer vision · Social media

1 Introduction

Understanding social aspects surrounding obesity is of great interest to many stakeholders. However, studying the social context requires collecting data beyond the affected individual which can be challenging for standard approaches. At the same time, social media provide information on social context and are being increasingly used for studies in computational social sciences. Yet, these studies typically do not have access to an individual's weight information as this is rarely shared online. To tackle this challenge, [13] proposed a new system called Face-to-BMI to infer a person's BMI from their profile picture.

In this paper, we build an end-to-end data processing pipeline that first detects and localizes a user's face in their social media profile picture, and then, inputs the localized face region into the Face-to-BMI system to predict the user's BMI. We then apply this pipeline to hundreds of thousands of Instagram profile

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pictures to study population-level BMI from two angles. First, we investigate if there is a link between online popularity and weight status, showing a negative trend between BMI and the number of followers. Second, we investigate the existence of BMI-based homophily revealing that social connections on Instagram are linked to a smaller-than-expected difference in BMI values of the two connected users. All of these experiments are conducted in two diverse cultural contexts, the US and Qatar.

2 Related Work

Several studies have shown that being overweight can lead to a range of negative consequences in people's social interactions and health [5,15,19]. Some recent studies in the social sciences investigate how humans perceive health from profile pictures [7,12]. To scale the findings of these studies to larger populations, researchers have developed systems for predicting BMI from profile pictures using computational techniques [13,21,25].

As computer vision makes continuous advances, certain tasks are also fast becoming commodities with Google[1], Microsoft[2] and others offering cloud-based solutions. Among such tools, Face++[3] provides a service that, given a picture of a person, infers the position of the face and various demographic attributes of the person. Face++ has been successfully applied on social media profile pictures to study large-scale demographics [4] and the spread of happiness [2]. In our work, we use Face++ both to filter out non-faces and detect face bounding boxes, as well as to enrich our data with gender information.

Typically, existing studies on social media only analyze data from the Western world. Our work offers a cross-cultural perspective by juxtaposing results for the US with results from Qatar. In the context of Qatar, privacy plays a different role and Islamic religious values and cultural norms influence online behavior. An existing emphasis on gender roles has implications on the way social media users from different genders manage their online identities [3].

3 Social Media Profile Images

3.1 Data Collection

Our Instagram data comes from both the US and Qatar. The two data sets were obtained at different points in time following slightly different methodologies, though both were location-centric data collections.

[1] https://cloud.google.com/vision/.
[2] https://www.microsoft.com/cognitive-services/en-us/computer-vision-api.
[3] http://www.faceplusplus.com/api-overview/.

US Data. We started with a data set used in [16] that contained $\sim 21M$ Instagram posts, from $\sim 3.4M$ unique users across 316 US counties. For each unique user in this data set, we (i) identified the county that they resided in using the plurality or majority voting method over their Instagram posts, and (ii) crawled their Instagram profile pages to retrieve their *profile picture URL, follower count,* and *follow count.* After this, we were left with $\sim 2.7M$ unique users with all the corresponding retrieved information.

(a) Inferred-BMI<20 (b) Inferred-BMI>30

Fig. 1. Qualitative evaluation of the Face-to-BMI system on examples from our Instagram profile pictures data set, grouped by their predicted-BMI values. Black bars are added to respect user privacy in this paper, but they are not part of the input to the system.

Qatar Data. Following a two-step strategy, we first built a complete list of unique Instagram locations in Qatar. Then, for each retrieved location, we collected all the recent media data that were available via the Instagram Application Programming Interface (API) at the time of the collection. The resulting data set contained $\sim 1.7M$ Instagram posts from $\sim 137K$ unique users from $\sim 38K$ unique locations across Qatar. We assumed all of these users live in Qatar and crawled their Instagram profile pages to extract the same user information as for the US data.

3.2 Face-to-BMI System

The Face-to-BMI system operates in two stages [13]. First, the system employs a deep neural network model trained for face recognition to extract features from a face image. Then, the system uses an epsilon support vector regression model over these features to predict a BMI value for the given image. According to the paper, the Face-to-BMI system achieved a Pearson correlation $r = 0.65$ on the held-out test set, and performed on par with humans for distinguishing the more overweight person when presented with a pair of profile images. Since we do not have ground truth BMI values for the Instagram profile pictures analyzed in this study, we cannot quantitatively validate the performance of the Face-to-BMI system. However, Fig. 1 illustrates qualitatively the performance of the system on our data set of Instagram profile pictures.

3.3 Data Processing Pipeline

Combining the Instagram data and the Face-to-BMI system, the whole pipeline then works as follows. As a pre-filter to remove images without any face, the downloaded profile images are fed into OpenCV Face Detection[4] and only images with at least one detected face are kept. These images are then passed through the Face++ API[5] to not only further refine the detection of faces, but also return their position in the image, as well as the predicted gender of the person. For the BMI prediction, the profile pictures with exactly one detected face were retained. Eventually, the detected face using the bounding box from Face++ was cropped and fed into the Face-to-BMI system to get a BMI estimation.

For the US data set, we first filtered out counties with less than 3,000 unique users. We then sampled 3,000 unique profiles from each of the remaining 130 counties, totaling $390K$ users. After running our data processing pipeline for this sample, we obtained $\sim 149K$ individual visible faces with BMI estimations. For the Qatar data set, we simply ran the data processing pipeline for all the $\sim 137K$ user set, and obtained $\sim 48K$ users with BMI estimations.

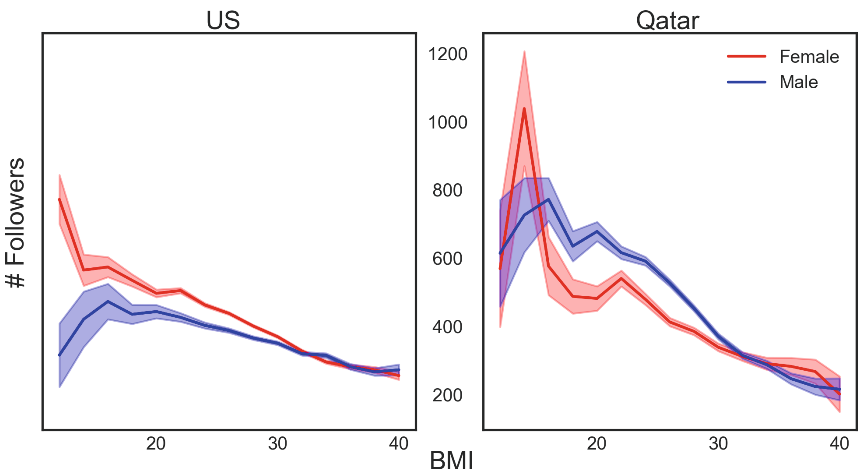

Fig. 2. Popularity vs. inferred-BMI, for both the US and Qatar. Each line curve represents the median number of followers for the set of users with a similar inferred-BMI value, broken down by gender. The shaded bands indicate the standard error bounds on the number of followers.

[4] https://opencv.org/.
[5] https://www.faceplusplus.com/face-detection/.

4 Experiments

4.1 BMI and Online Popularity

Previous work [24] had observed that Twitter users with a more obese-looking profile picture tend to have fewer followers. We tried to replicate their findings by analyzing the link between a person's inferred-BMI value and their number of Instagram followers. Figure 2 shows a consistent pattern, both for the US and Qatar, linking a higher inferred-BMI to a smaller followership. These plots also demonstrate a striking similarity to those presented in [22] for correlations between physical attractiveness and BMI.

Followership and online popularity are intrinsically linked to the online activity level as a user who never produces content is unlikely to attract a large audience. Hence the reason for the observed difference could simply lie in differences in activity levels. To both assess a potential mediation effect of the number of posts on the number of followers and to look more at the gender-specific link between BMI and number of followers, we conduct the following experiment: We measure the fitness of various linear models to our data each time using a different set of independent variables, i.e., (i) just the number of posts on Instagram, (ii) just the person's inferred-BMI, and (iii) both the number of posts and the inferred-BMI, to predict the number of followers (i.e., dependent variable). We compute the corresponding least squares linear model coefficients, p values, and adjusted-R^2. Users with more than 2,000 followers were ignored for this analysis as their large followership introduced model instability. Table 1 summarizes the results from the fitted models.

Table 1. Results for different linear model fits using (i) only the number of posts (β_1), (ii) only the inferred-BMI (β_2), and (iii) both, where β_0 indicates the model intercept. Results are broken down by country and by gender. All the corresponding p values are less than 10^{-10}.

	♀/♂	Model	β_0	β_1	β_2	adj. R^2
United States	Female	#posts (β_1)	318.2	.102	–	0.080
		BMI (β_2)	606.7	–	−8.26	0.026
		#posts & BMI	555.1	.103	−8.54	0.108
	Male	#posts (β_1)	295.9	.117	–	0.094
		BMI (β_2)	501.3	–	−5.28	0.011
		#posts & BMI	466.7	.119	−5.90	0.107
Qatar	Female	#posts (β_1)	361.2	.236	–	0.123
		BMI (β_2)	761.6	–	−11.25	0.013
		#posts & BMI	648.5	.234	−10.40	0.135
	Male	#posts (β_1)	426.4	.211	–	0.073
		BMI (β_2)	953.5	–	−16.63	0.027
		#posts & BMI	895.9	.212	−16.75	0.101

In all cases, the models were stable in that (i) the coefficients for the single variable case were close to the coefficients in the dual variable case, and (ii) the adjusted-R^2 roughly added up. Both of these indicate that the effect of the BMI on the size of the followership is *not* mediated by differences in the number of posts. Furthermore, looking at the value of the coefficients, we observe that the effect of BMI is stronger for women than for men in the US, whereas it is stronger for men than women in Qatar.

4.2 Social Network Analysis

The authors in [6] claim that obesity may spread through social networks as a "contagious" disease. However, others have questioned their results for methodological reasons [8].[6] Our data lacks the long-term temporal coverage to attempt to make such strong claims but online social networks can still be used to test the weaker hypothesis of weight-based homophily. For example, [1] observed that Twitter users tend to cluster based on their predicted obesity status.

To find evidence for BMI-based network assortativity, we start by constructing a social network for our data set. Both for the US and for Qatar, we create a bidirected edge between two users if the two users mutually commented on each others' pictures. As the Instagram API only provides the eight most recent comments left on a post, older comments could not be considered for the network construction.

After constructing the two social networks, one for the US and one for Qatar, we compared the average absolute BMI difference between two friends with what would be expected by random chance. This comparison was done by creating 10,000 permutations where the BMIs of the nodes were randomly shuffled among

Table 2. Significance test results for the absolute BMI difference in the US and Qatar social networks, broken down by gender.

	Category	Count	Empirical	Shuffled**	p
US	All	1,848	5.208	5.383	.006
	M-M	234	5.441	5.356	.671
	F-F	812	5.212	5.350	.084
	M-F	802	5.137	5.328	.029
Qatar	All	3,686	4.478	4.706	.000
	M-M	2,496	4.451	4.622	.001
	F-F	390	4.754	5.261	.001
	M-F	800	4.430	4.603	.028

* M – Male, F – Female.

** Mean of the distribution.

[6] See http://sociograph.blogspot.qa/2009/11/is-obesity-contagious-review-of-debate.html for an overview of the discussion around the said topic.

the edges. We then compared the observed, empirical difference with the distribution of the simulated, shuffled differences to obtain p values for testing the hypothesis that the average absolute BMI difference is not linked to the network structure. We perform this experiment for (i) all edges, (ii) same-gender edges and (iii) cross-gender edges. All the results are presented in Table 2.

We notice that in most cases the difference between the empirical and shuffled values is not large in absolute terms, though it is still statistically significant. Interestingly, for the US, there was more evidence for cross-gender BMI homophily than for within-gender BMI homophily. As friends might largely be chosen due to proximity, and as being in the same county already increases the probability of having a similar BMI, we also split the US friendship pairs into a within-county and an across-county set. The results were consistent in both cases though, due to the smaller number of instances, the statistical power was reduced.

5 Discussion

5.1 Algorithmic Bias

Our data processing pipeline relies on several technologies such as OpenCV Face Detection to detect faces, Face++ to refine the face detections and to predict the person's gender, and finally, Face-to-BMI tool to predict the person's BMI. Though each of these may introduce certain algorithmic biases[7], the authors of [13] found no evidence for bias in terms of race or gender. However, we could not test if there is any algorithmic bias affecting women with head cover as we did not have ground truth for this. Manual inspection of several cases did not reveal abnormal BMI predictions in these cases though.

5.2 Ethical Considerations

Before advances in computer vision, one could try to remain a "face in the crowd." Due to face recognition, that is becoming harder and our tool could be seen as contributing to this trend. For example, services such as FindFace[8] offer to find users on social media given just a picture of them. The not-so-thinly advertised use case is for finding contact details for attractive women. Similarly, there has been a growing body of work that successfully applies computer vision techniques on social media pictures to infer a person's personality [10,11,14,17]. Although most of these methods work "better than random guessing" at an aggregate level, they are highly unreliable at an individual level. Furthermore, even at the aggregate level, the observations should be taken with caution since the data sets collected from social media are not a uniform sample of the population. However, with proper weighting schemes [26], this concern can be reduced.

[7] https://www.theatlantic.com/technology/archive/2016/04/the-underlying-bias-of-facial-recognition-systems/476991/.

[8] https://findface.ru/.

5.3 Cultural Differences

Having collected data from both the US and Qatar allows us to look at cultural differences. For example, the fact that women in Qatar were less likely than their male counterparts to have a profile image with a face might be related to privacy concerns [3,23]. One observation from Fig. 2 worth investigating further in the future is the fact that for women in the US "the thinner the better" concerning the follower counts on Instagram, whereas for women in Qatar and for men in both the US and Qatar a very low BMI seems to also correspond to a lower number of followers.

6 Limitations

Our experiments are based on *observational data from social media*, enriched with outputs from computer vision technologies. Observational studies are limited concerning the causal claims they support. Findings need to be understood in the context of their limitations and we discuss some of these below.

The performance of the Face-to-BMI system is not perfect, despite being on par with humans for picking the more obese given a pair of profile pictures. However, our data processing pipeline for social media profile pictures can be used to detect relative trends at the *population* level unless the pipeline proves to be systematically biased. In other words, results of the form "the average BMI for group X is larger than for group Y" are far more robust than results of the form "this individual from group X has a higher BMI than this other individual from group Y". This distinction also applies to the BMI itself which is useful for studying population health but has shortcomings when used as a tool for individual health [9,18].

The fact that we detected BMI-based assortativity despite the noise in the BMI predictions strengthens our results. Given a noise-free inference mechanism we would expect the effect sizes to be larger than the ones currently observed. To exemplify this point, if we assume that the face-to-BMI measurement error is uncorrelated with its estimate, we can apply standard approaches for correcting for attenuation [20]. Such a correction leads to a roughly 50% increase in the adjusted-R^2 of the BMI-only models (see Table 1). However, as the underlying statistical assumptions do not hold in practice, it is not clear if the true increase in R^2 would be bigger or smaller in a noise-free setting.

Nevertheless, regarding BMI and online popularity, we may be observing a *reverse* causality. That is, as an Instagram user starts getting more followers, they in turn start paying more attention to their profile picture (e.g., post photoshopped selfie images that potentially look thinner and better). In our social network analysis, the observed homophily can be affected by unobserved confounding factors. For example, as an ethnic group, Asians tend to be less overweight. So if users choose their friends based on ethnicity, then this could induce BMI-based assortativity.

7 Conclusions

We built a data processing pipeline that enables analysis of social media profile pictures to study (i) the link between an Instagram profile picture's BMI and their number of followers, and (ii) the link between a person's BMI and that of their social connections. Both were studied in two culturally diverse contexts, the US and Qatar. In both countries we observed that (i) a lower inferred-BMI is linked to a larger number of followers, and that (ii) there is BMI-based network assortativity.

We hope this work will help advance understanding of the social aspects of obesity in an effort to reduce anti-social behavior such as fat shaming and increase population health.

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