Well-Being Depends on Social Comparison: Hierarchical Models of Twitter Language Suggest That Richer Neighbors Make You Less Happy

Salvatore Giorgi,[1] Sharath Chandra Guntuku, [1] Johannes C. Eichstaedt, [2] Claire Pajot, [2] H. Andrew Schwartz, [3] Lyle H. Ungar [1]

[1] University of Pennsylvania
[2] Stanford University
[3] Stony Brook University
{sgiorgi@sas, sharathg@cis, ungar@cis}.upenn.edu, johannes.stanford@gmail.com, cpajot@stanford.edu, has@cs.stonybrook.edu

Abstract

Psychological research has shown that subjective well-being is sensitive to social comparison effects; individuals report decreased happiness when their neighbors earn more than they do. In this work, we use Twitter language to estimate the well-being of users, and model both individual and neighborhood income using hierarchical modeling across counties in the United States (US). We show that language-based estimates from a sample of 5.8 million Twitter users replicate results obtained from large-scale well-being surveys — relatively richer neighbors leads to lower well-being, even when controlling for absolute income. Furthermore, predicting individual-level happiness using hierarchical models (i.e., individuals within their communities) out-predicts standard baselines. We also explore language associated with relative income differences and find that individuals with lower income than their community tend to swear (f*ck, sh*t, b*tch), express anger (pissed, bullsh*t, wtf), hesitation (don't, anymore, idk, confused) and acts of social deviance (weed, blunt, drunk). These results suggest that social comparison robustly affects reported well-being, and that Twitter language analyses can be used to both measure these effects and shed light on their underlying psychological dynamics.

Introduction

In the 1970s, the economist Richard Easterlin formulated the "Easterlin Paradox" about the relationship between well-being and income (Easterlin 1974)This paradox states that an individual's income and self-reported happiness are positively correlated within a given country, but as countries become richer over time, happiness does not increase. Easterlin's interpretation was that *relative* income, as opposed to *absolute* income, matters for happiness. On the other hand, studies have shown that absolute differences in income matter more, especially at lower income brackets. For example, Kahneman and Deaton showed relationships between income and well-being vary depending on the measure: both emotional well-being (e.g., happiness) and life evaluation (e.g., life satisfaction) increase with income, but happiness does not continue to increase beyond a certain income threshold (Kahneman and Deaton 2010). This distinction between the "relative" vs. "absolute" importance of income on happiness is contested, with studies supporting both interpretations (Veenhoven 1991; Diener et al. 1993; Clark and Oswald 1996; McBride 2001; Blanchflower and Oswald 2004; Ferrer-i Carbonell 2005; Firebaugh and Schroeder 2009; Layard, Mayraz, and Nickell 2010; Kaiser and Vendrik 2019).

To gain further insight into the relationship between relative income and happiness, Luttmer explored various mechanisms mediating the relationship between neighbors' earnings and happiness, alongside a robust set of controls (Luttmer 2005). He showed that individuals who socialize more with their neighbors, as opposed to friends who are not their neighbors, are more likely to suffer from decreased happiness due to social comparison effects that represent psychological utilities rooted in relative consumption (over and above levels of absolute consumption).

In this paper, we examine how relationships between an individual's income and their community's income affect their happiness as measured through language on social media, using data from a large sample of US county mapped Twitter users ($N = 5,894,644$). We use Hierarchical Linear Models (HLM), which allows us to model variance at both the individual level and within and across communities. Modeling this variance increases predictive accuracy (measured using cross-validation) over standard methods. This hierarchical modeling also allows us to look at signed differences in effect sizes between the individual and community level, allowing us to see the linguistic correlates of relative income differences (e.g., poorer individuals who live in richer areas vs richer individuals living in poorer areas).

Related Work Using publicly available Twitter data to study community level factors has become common, with studies in many fields: health and mortality (Culotta 2014a,b; Paul and Dredze 2011; Eichstaedt et al. 2015; Abebe et al. 2020), politics (Miranda Filho, Almeida, and Pappa 2015), and substance use (Curtis et al. 2018; Sarker et al. 2019; Anwar et al. 2020; Giorgi et al. 2020). Similarly, spatial variations in Twitter based estimates of well-being have been studied at multiple resolutions, including states (Mitchell et al. 2013), counties (Culotta 2014a), and cities (Quercia, Seaghdha, and Crowcroft 2012). Schwartz et al. (2013a) assessed county level life satisfaction and showed that increased life satisfaction corresponds to increased mentions of words relating to exercise, spiritual meaning and good jobs. Jaidka et al. (2020) systematically examined word-level and data driven approaches for estimating well-being in US counties, showing that regional and socio-economic variation in language use results inconsistent lexical based well-being estimates. However, few community level Twitter studies look at the bi-directional relationships between individuals and communities, as is done in the current study. When this relationship is examined, it is typically focused on leveraging people to create reliable estimates at the community level (Culotta 2014a; Giorgi et al. 2018; Jaidka et al. 2020). To our knowledge, this is the first study to directly model the role of *community* attributes on an *individual's* social media language.

Most modern machine learning techniques, including deep learning, assume i.i.d. observations. In practice, this is often not attainable, especially in situations where one has nested or hierarchical data (e.g., words within sentences, sentences within documents, and documents across users). HLMs allow for non-i.i.d. data and model both random effects (i.e., a random sample of a categorical predictor) and hierarchical effects (i.e., predictors at multiple levels within hierarchy) (Garson 2013). In this study, HLMs allow us to properly model individuals within their communities, while also modeling variation across observations at both the community and individual level. Furthermore, to our knowledge, this is the first study to use HLMs to model social media language variation across people within communities.

Contributions Our contributions are as follows: (1) we show that individuals of any given income who live in communities with higher income are less happy *as measured through language on social media* (2) we show that hierarchical modeling of individuals and their communities outpredicts standard baselines for predicting a person's happiness; and (3) we qualitatively examine community effects on individuals' well-being through social media language.

Data

Our data set consists of individual level Twitter data and census data from their communities (US counties). Both types of data are described below.

Individuals: Twitter Data For individual Twitter data we use the County Tweet Lexical Bank (Giorgi et al. 2018), an open source data set consisting of over 6 million Twitter accounts mapped to US counties through either latitude / longitude coordinates in tweets or self-reported location in their user profile field (Schwartz et al. 2013a).

Communities: Census Data For US counties we used 5 year estimates of log median income and percentage of the population with a Bachelor's degree from the 2015 US Census American Communities Sample (ACS).

We limited our analysis to Twitter accounts for which we had at least 30 posts and US counties which contained at least 100 such Twitter accounts. Our final sample size consisted of 1,784 US counties and 5,894,644 Twitter users.

Well-being and Socio-Demographic Estimates

For each user in Twitter data set described above, we estimated happiness, income, age, gender, and education from tweet language. The happiness model is novel to this paper; details on the income, age, gender, and education models, all of which were previously published, are summarized here to orient the reader.

Happiness. A sample of 2,676 participants were recruited from the Qualtrics survey platform and answered a series of well-being questions and shared their Facebook status updates. Each participant posted at least 500 words across their statuses and responded to the following item: "The following questions ask about how you felt yesterday on a scale from 0 to 10. Zero means you did not experience Happiness 'at all' yesterday while 10 means you experienced Happiness 'all of the time' yesterday.". We then built a predictive model using a set of 2,000 Latent Dirichlet Allocation (LDA) topics with a Ridge regression ($\alpha = 10,000$) and PCA for dimensionality reduction (Schwartz et al. 2013b; Eichstaedt et al. 2015). Using 10-fold cross validation, the models produced an accuracy (Pearson r) of 0.21. This model was built using the data set described in Jaidka et al. (2020).

Income. Income was estimated using the model built in Matz et al. (2019). They collected a sample of 2,623 participants from Qualtrics in 2015. Each participant reported their annual income and shared their Facebook status updates. For each participant, they extracted 1-3grams and topic loadings for a set of 2,000 LDA topics. Each 1-3gram was encoded both as a relative frequency of use and a binary 0/1 indicating if the 1-3grams was ever user. Using 10-fold cross validation with a Ridge regression the authors obtained an accuracy of Pearson r = .41.

Age / Gender. We applied an age and gender predictive lexica (Sap et al. 2014). This lexica was built over a set of annotated users from Twitter, Facebook, and blogs and predicted age with a Pearson r = 0.86 and and binary gender with an accuracy = 0.90. The model produced real values for both age and gender. We encoded the gender value to 1 for "female" and 0 otherwise, and thresholded age predictions to between 13 and 80. See Sap et al. for full details (2014).

Education. We applied an education estimation model which was built over a sample of 4,062 users, recruited from Qualtrics, who reported education level and shared Facebook status data (Giorgi et al. 2019). For each user the authors extracted 1-3grams and loadings for a set of 2,000 LDA topics and used a linear-svc for a multi-class classifier (0: less than high school diploma, 1: high school diploma or Associate's degree 2: Bachelor's degree or higher). This model obtained an accuracy of .62 and an F1 score of .53 using 10-fold cross validation. We then used this model to predict class probabilities for each user in our Twitter data set and collapsed the first two classes into a single class, so as to match our census variable (percentage of the population with a Bachelor's degree). This resulted in two final education classes, encoded as 0 or 1 based on their probabilities: (0) less than a Bachelor's degree and (1) Bachelor's degree or higher. See Giorgi et al. (2019) for more details on this estimation model.

Ethics Statement Social media based assessments of well-being and socio-demographics raise a number of ethical questions, including privacy issues. Additionally, biases in training data as well as the impact of misclassifications should be considered when using such language based assessments. As such, this study was reviewed by an academic institutional review board and found to be exempt, non-human subjects data. All data used in this study are publicly available. For additional privacy protection, **no** intermediate information derived within the approach (i.e., individual-level socio-demographic and well-being estimates) will be made public. While imperfect, we believe that these socio-demographics estimates allow researchers to study such constructs at scale in a non-obtrusive manner. Furthermore, such measurements have been used in past studies to help gain insight to other forms of bias, such as racial bias in hate speech detection (Sap et al. 2019).

Methods

Hierarchical Linear Models

We use a two-level hierarchical linear model with level-1 being the individual and level-2 the county (Woltman et al. 2012). These models estimate three types of parameters: (1) fixed effects, parameters that do not vary across groups (or, in our case, US counties); (2) random level-1 coefficients which vary across groups; and (3) covariance and variance components. This third parameter set includes variances of both level-1 and level-2 error terms and the covariance between level-2 error terms (i.e., intercept and slope parameters at the second level).

HLMs are well suited for analyzing nested data because they take both level-1 and level-2 regressions into account. The following issues occur when using standard regression techniques with nested data: (1) shared variance, both within- and between-group, is no longer accounted for; (2) the independence assumption on observations (in standard Ordinary Least Squares) is violated; and (3) honest statistical tests rely only on level-1 sample sizes (Gill 2003). In addition to modeling nested data, HLMs can also handle small sample sizes and missing data (Woltman et al. 2012).

Metrics For both individual and community level independent variables we report t values and standardized coefficients β. Additionally, for each model, we present two goodness-of-fit metrics: marginal R^2 and conditional R^2 (Nakagawa and Schielzeth 2013). The marginal R^2 represents the variance explained by the fixed factors and is calculated as follows:

$$R_m^2 = \frac{\sigma_f^2}{\sigma_f^2 + \sum_{l=1}\sigma_l^2 + \sigma_e^2 + \sigma_d^2}, \tag{1}$$

where σ_f^2 is the variance of the fixed effects, σ_l^2 is the variance for each level l (individual and community), σ_e^2 is the additive dispersion and σ_d^2 is the distribution specific variance. The conditional R^2 represents the variance explained by the entire model (i.e., both fixed and random factors) and is calculated as follows:

$$R_c^2 = \frac{\sigma_f^2 + \sum_{l=1}\sigma_l^2}{\sigma_f^2 + \sum_{l=1}\sigma_l^2 + \sigma_e^2 + \sigma_d^2}. \tag{2}$$

While these metrics are standard within hierarchical modeling literature, the specifics are beyond the scope of this short paper, and we hope the interested reader will explore.

Experimental Setup

To examine relationships between an individual's income and happiness relative to their community, we perform three tasks: (1) using Twitter language, we replicate previous questionnaire based results showing that one's neighbors income predicts ones happiness; (2) we use HLMs to model individual and community features in order to predict happiness of held-out people; and (3) we explore language associated with relative differences in individual and community income using an open vocabulary approach (i.e., we do not rely on a priori assumptions about the relationship between language, happiness, and income).

Task 1 We first show that higher community income, relative to individual level income, predicts lower levels of happiness. We built models to predict happiness using three sets of independent variables: (1) individual income, (2) community level income, and (3) both individual income and community income. We also build models using estimated age, gender, and education (at the individual level) as well as community education (percent Bachelor's degree) to show that the effects are robust to socio-demographic confounds.

Model fit is reported via two pseudo-R^2 metrics: R_m^2 (marginal R^2) and R_c^2 (conditional R^2) (Nakagawa and Schielzeth 2013). Here R_m^2 represents the variance explained by the fixed factors while R_c^2 represents the variance explained by the entire model (i.e., both fixed and random factors). While these metrics are standard within hierarchical modeling literature, the specifics are beyond the scope of this short paper. We also report t values and standardized coefficients (β).

Task 2 Next, we use 10-fold cross validation to predict individual level happiness from both individual and community features. Here we compare a hierarchical model to a standard (non-nested) linear regression, using individual income, age, gender, and education, as well as county level median income and education (percent Bachelor's degree) as our independent variables. The 10-fold split is randomly chosen so that all individuals mapped to a given US county are completely contained within a single fold. The same fold splits are used in both the HLMs and linear regressions. Additionally, since we are using a small number of independent variables (at most six) we do not use any regularlization or feature selection in our modeling.

Task 3 Finally, we explore relationships between social media language and income. Here, we use a similar setup as Task 1 (i.e., individual income and community income as independent variables) but change our dependent variable. Instead of happiness as our dependent variable, we use individual level-language features. To do this, we extract unigrams from each Twitter user in our sample and use the relative frequency of each unigram to derive topic loadings for each user. Our topics consists of a set of 2,000 LDA clusters derived from a large set of Facebook data; see Schwartz et al. (2013b) for more details on the LDA topics. In the end, for each Twitter user in our data set we have exactly 2,000 topic loadings, which are used as dependent variables in our modeling. For each topic, we build a single HLM which includes both individual and community income (as our independent variables) and the topic loading (as our dependent variable). This allows us to examine language patterns driven by sign differences in the individual and community income coefficients (i.e., language predicted by relative differences in income). To address the large number of comparisons we use a Benjamin–Hochberg FDR correction (Benjamini and Hochberg 1995), only report topics which have both significant individual and community income coefficients and set a minimum absolute effect size on both level coefficients ($|\beta| > 0.25$ and $|\beta| > 0.005$ for individual and community, respectively).

Results

Task 1 Table 1 shows the results of predicting an individual's happiness from their income as well as their community's income. We evaluate three models: (1) individual income (i_I), (2) community level income (i_C) and (3) both individual income and community level income (i_I + i_C). Models (1) and (2) show that *increased* income, at either the individual or community level, predicts happiness — increased income is associated with higher happiness. Model (3) shows that *lower* community level income predicts higher happiness when controlling for individual level income. We note the the sign flip in the community level income coefficient when modeling both individual and community income.

Task 2 Figure 1 shows the results of our 10-fold cross validation. Both models include income, age, gender, and education as individual predictors, as well as US county median income (logged) and education as group level predictors. Here we see that modeling happiness with both individual and community level predictors within a hierarchical model (Pearson r = 0.55) out-predicts standard regression techniques (Pearson r = 0.52). Using a paired t test on each model's errors, we see a significant difference ($t = 146.4$, $p < 0.001$) between the two models.

Task 3 Finally, Figure 2 shows the results from our open vocabulary analysis. We show six topics as word clouds each of which are associated with a negative individual income coefficient and a positive community income coefficient – that is, coefficients signs which would predict *lower* happiness in Task 1. A full list of significant topics is presented in the appendix. We see topics related to swearing, younger language (homework, school and sucks; omfg, soooo and freakin), anger (hate, effin, and grr), and alcohol/drug use (weed, blunt, drunk).

Figure 1: Predicting individual happiness with 10 fold cross validation, using flat and hierarchical models (reported Pearson r). Each model includes individual income, age, gender, and education as well as community level income and education. * significant differences between models ($p < .001$).

Conclusion

In this study, we investigated the role of community-level income when predicting an individual's well-being from their own income, providing a novel evaluation of the "Easterlin Paradox". We showed that while community-level income had a positive association with individual well-being (suggesting people are generally happier in more afluent areas), the association reversed once accounting for an individual's income, suggesting a hierarchical relative effect: individuals' well-being is lower if they are less afluent than their neighbors. This provides new evidence for a previously suggested "relative" theory of well-being (Luttmer 2005): social comparison effects decrease an individual's happiness.

We also showed that using hierarchical modeling to predict an individual's happiness was more accurate than standard regression techniques. Finally, we explored language patterns related to social comparison effects, and found that people who earn less than their neighbors are more prone to swearing, anger and excitement, even when controlling for their absolute income level. These findings suggest that counties of residence can approximate the psychologically salient context of local comparison, and that county-aggregated Twitter language can capture these phenomena.

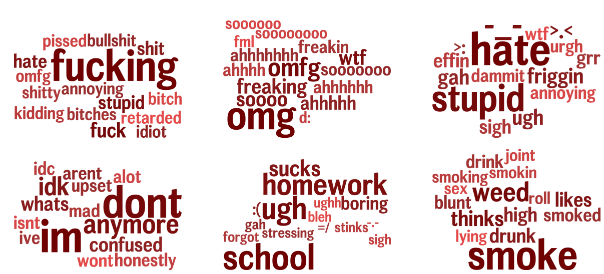

Figure 2: Topics predicted by a negative individual income coefficient and a positive community income coefficient.

Model	R_c^2	R_m^2	Individual Income		Community Income	
			β	t	β	t
i_I	.333	.310	.587	229	-	-
i_C	.035	.002	-	-	.047	11.7
i_I + i_C	.333	.310	.587	229	-.013	-4.67
i_I + a_I + g_I	.372	.352	.374	169	-	-
i_I + a_I + g_I + e_I	.376	.355	.369	160	-	-
i_I + a_I + g_I + i_C	.371	.351	.374	169	-.018	-6.62
i_I + a_I + g_I + e_I + i_C	.374	.354	.368	160	-.020	-7.96
i_I + a_I + g_I + e_I + i_C + e_C	.375	.354	.368	160	-.026	-7.70

Table 1: Predicting estimates of happiness. Models include individual income i_I and/or community income i_C. Note the change in sign on the community income coefficient when both i_I and i_C are present. All models significant at $p < .05$ after Benjamini Hochberg FDR correction.

Additionally, we show that hierarchical models can be used for both explanatory (Tasks 1 and 3) and predictive value (Task 2).

Further studies could examine social comparison effects on happiness through other socio-demographics such as age, gender, race, education, or religious affiliation, as well as other measures of subjective well-being (e.g., satisfaction with life, purpose, and sadness). We also hope that other applications in NLP or Computational Social Science may leverage hierarchical modeling, as social media posts are nested within people, sentences within posts, and words within sentences.

Limitations One limitation in this study is that we use categorical language-based estimates for age, gender, income, and education. While collecting this data by self-report might be more accurate, it is often difficult and expensive for large samples. Additionally, our language-based estimates are all built from the same language sample, which could introduce shared method variance (i.e., variance attributed to the estimation method rather than the construct's relationships). While one can imagine ways around this, for example, estimating from different time periods or separate social media platforms, collecting such data across geography at this scale is difficult and expensive.

Furthermore, the predictive accuracy of the happiness model (Pearson r = 0.21) was the lowest of all of the estimators used in this paper. Other studies which have estimated psychological constructs from text have found larger accuracies. For example, Park et al. (2015) estimated Big 5 personality traits from social media, resulting in a range of Pearson r values from of 0.39 (Neuroticism) to 0.46 (Openness to experience). We note that constructs such as personality are psychological traits (i.e., behaviors or characteristics that are stable across time and situations) as opposed to states (i.e., situational behaviors or characteristics). The happiness measure used here asks how one felt *yesterday* and is thus a trait. Both the traits in Park et al. (2015) and the state here (happiness experienced yesterday) are estimated from a person's entire history of social media posts. Thus, a single day's happiness is measured across a time span that may cover years. Using such spans of text data may make the task of predicting state-like constructs more difficult, resulting in lower accuracies.

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