Proceedings of the Ninth International AAAI Conference on Web and Social Media

Linguistic Bias in Collaboratively Produced Biographies: Crowdsourcing Social Stereotypes?

Jahna Otterbacher
Graduate Program in Social Information Systems
Open University of Cyprus
jahna.otterbacher@ouc.ac.cy

Abstract

Language is the primary medium through which stereotypes are conveyed. Even when we avoid using derogatory language, there are many subtle ways in which stereotypes are created and reinforced, and they often go unnoticed. Linguistic bias, the systematic asymmetry in language patterns as a function of the social group of the persons described, may play a key role. We ground our study in the social psychology literature on linguistic biases, and consider two ways in which biases might manifest: through the use of more abstract versus concrete language, and subjective words. We analyze biographies of African American and Caucasian actors at the Internet Movie Database (IMDb), hypothesizing that language patterns vary as a function of race and gender. We find that both attributes are correlated to the use of abstract, subjective language. Theory predicts that we describe people and scenes that are expected, as well as positive aspects of our in-group members, with more abstract language. Indeed, white actors are described with more abstract, subjective language at IMDb, as compared to other social groups. Abstract language is powerful because it implies stability over time; studies have shown that people have better impressions of others described in abstract terms. Therefore, the widespread prevalence of linguistic biases in social media stands to reinforce social stereotypes. Further work should consider the technical and social characteristics of the collaborative writing process that lead to an increase or decrease in linguistic biases.

Introduction

The rise of social media has provided us a variety of means to offer cognitive surplus in the creation and sharing of knowledge that can benefit everyone (Shirkey 2011). From collaborative efforts such as Wikipedia, to systems that aggregate individual contributions (e.g., consumer-contributed reviews), the common goal is to document collective wisdom about a growing number of subjects. With information-centric social media among the most popular on the Web (e.g., Amazon.com ranked sixth and Wikipedia.org ranked seventh among Websites worldwide by Alexa at the time of writing[1]), it is clear that what gets published in such systems is of growing importance in society. The information shared represents "what is known" or "what we believe to be true" at the collective level, at a given point in time.

The collaboratively produced biography is a genre of social media text receiving increasing attention. Such biographies can be found at general-purpose, open-edit knowledge production and sharing sites (e.g., Wikipedia[2]), as well as at special-interest community sites (e.g., the Internet Movie Database (IMDb)[3] or Music Wiki[4]). In these systems, users create and edit biographies. The accuracy, completeness and clarity of the information provided often reach a high level, given the participation of sufficient numbers of contributors (Kittur and Kraut 2008). In fact, the introduction of incorrect information is often corrected within a matter of hours[5]. However, it is not only information that is inaccurate or misleading that should concern us, but also the subtle communication patterns that create or reinforce *social stereotypes*.

Quality and Bias in Collaborative Biographies

It is not surprising that the *quality* of collaboratively produced biographies of famous people has been the focus of previous research. For those still living, one's digital biographies convey his or her reputation, and the consequences this reputation can have one's life experiences are obvious. For the deceased, crowdsourced digital biographies serve as a collective memory (Pentzold 2009) of the person, her lifetime accomplishments and how she was as a character. Flekova and colleagues (Flekova, Ferschke, and Gurevych 2014) reported that over one-fifth of Wikipedia articles describes people, most of whom are still living. They call for the development of automated methods to ensure that biographies are of a high quality, given their vulnerability to corruption and vandalism. Developing machine learning techniques guided by human judgments on quality, they scored articles on four dimensions: completeness, writing quality, trustworthiness and, most relevant to our work, objectivity. Interestingly, they found that textual features

[1]http://www.alexa.com/topsites
[2]http://wikipedia.org
[3]http://www.imdb.com
[4]http://music.wikia.com/wiki/Music_Wiki
[5]http://alex.halavais.net/the-isuzu-experiment

(rather than Wikipedia-based features such as links or article age), including the use of words carrying sentiment, were the best predictors of biography subjectivity/objectivity. This demonstrates that the manner in which we describe others conveys information not only about the subject described, but also about ourselves as information sources.

In a similar vein, others have described *biases* in collaboratively produced knowledge resources. Wikipedia again receives the lion's share of attention, with previous work examining whether the user base is really diverse (i.e., participation biases) and how information is documented (i.e., content biases). As mentioned, with a sufficiently numerous and diverse group of participants, collaboratively produced texts reach a high level of quality. However, in online communities, a particular user demographic, men, often dominates. At Wikipedia, men hold the majority both in terms of active users and edits, with many suggesting that Wikipedia essentially conveys a man's view of the world[6] (Lam et al. 2011; Antin et al. 2011; Forte et al. 2012). While it is difficult to assess how participation bias impacts the content created, it surely results in undesirable consequences, such as imbalances in the topics discussed and documented, and the development of community norms that women and minority social groups find intimidating (Herring 2003; Hemphill and Otterbacher 2012).

With respect to content biases at Wikipedia, across language versions, there is significant variation with respect to which topics are covered, thus reflecting cultural differences (Hecht and Gergle 2010). Callahan and Herring found significant differences in famous persons' biographies, both as a function of the Wikipedia community (Polish vs. English) and the nationality of the person being described (Polish vs. American scientists) (Callahan and Herring 2011). Via content analysis, they discovered that more personal details were described for Americans, and that descriptions were more positive toward Americans as compared to the Polish scientists. In general, English language biographies were more positive in tone than those documented in Polish. Like any technology, Wikipedia is not values-free; what is covered there reflects the interests, culture, and social standing of the people who use it (Pfeil, Zaphiris, and Ang 2006; Royal and Kapila 2009).

Like the researchers cited here, we share a concern for the quality of collaboratively produced knowledge resources, and in particular, for biographies of persons both living and deceased. However, our work departs from previous research in important ways. We offer the first study of *linguistic biases* in social media descriptions of people. As will be explained, linguistic biases are not attributed to cultural differences, nor to any conscious attempt to alter the content created. They are believed to have cognitive origins, although as we will see, they have very social consequences.

Another point of departure is that we study biographies at the Internet Movie Database. IMDb is arguably a less formal knowledge source as compared to Wikipedia. It is not an encyclopedia, but rather, a database, aiming to be the "world's most popular and authoritative source for movie, TV and celebrity content."[7] It has no Neutral Point of View policy, does not feature a talk page, where users discuss their views and opinions on a page's content and style, nor can one see which user edited what. Nonetheless, true to its mission, IMDb is currently ranked 49th in the world in terms of traffic, and 25th in the U.S.,[8] typically appearing in the first hits from a search engine, given a famous actor's name. Motivated by theories of linguistic bias, we consider the language in biographies of famous African American and Caucasian actors and actresses, comparing the extent to which patterns vary based on the subject's race and gender.

The Language of Biographies: Subtle Stereotypes?

Psychologists and communication scientists have become increasingly convinced that the manner in which we use language plays a key role in the transmission and maintenance of social stereotypes (Maass 1999; von Hippel, Sekaquaptewa, and Vargas 1997). Even when we avoid using derogatory language (e.g., racial slurs, sexist terms), our linguistic biases may still give away the stereotypes that influence us. We use Beukeboom's definition of linguistic bias (Beukeboom 2013):

> **A systematic asymmetry in the way that one uses language, as a function of the social group of the person(s) being described**.

We consider two patterns that may reveal underlying social expectations: the use of abstract versus concrete language, and the use of subjective words (e.g., nice, bad, beautiful, ugly). Consider the following three statements:

1. Morgan Freeman played in *The Shawshank Redemption*.
2. Morgan Freeman was amazing in *Shawshank Redemption*.
3. Morgan Freeman is an amazing actor.

The first statement is the most concrete and objective of the three: it is restricted to a particular context, and is devoid of subjective words. In contrast, the third sentence is the most abstract of the three, as it makes a general statement about Freeman (i.e., is not restricted to the context of a single film) and contains a subjective adjective ("amazing"). The question at hand is the extent to which we observe differences in the use of abstract and subjective language, as a function of the social groups of the actors.

Research Questions

Due to the growing number of media that enable us to collaboratively produce biographies, an important question is whether subtle linguistic biases make their way into these influential and popular texts. Linguistic biases have been explored extensively by social psychologists, although in small-scale, experimental contexts. However, we are unaware of previous studies that have attempted to understand

[6] http://www.nytimes.com/roomfordebate/2011/02/02/where-are-the-women-in-wikipedia

[7] http://www.imdb.com/pressroom/?ref_=ft_pr

[8] http://www.alexa.com/siteinfo/imdb.com

		Description	Example
More Abstract	**Adjectives**	Describes a characteristic or feature of a person.	Morgan Freeman is an amazing actor.
	State verb	Describes an enduring cognitive or emotional state with no clear beginning or end.	Morgan Freeman amazes his audiences.
	Interpretive action verb	Refers to various actions with clear beginning and end.	Morgan Freeman was amazing in *The Shawshank Redemption*.
	Descriptive action verb	Refers to a single, specific action with a clear beginning and end.	Morgan Freeman played in *The Shawshank Redemption*.

Figure 1: The Linguistic Category Model.

whether and how linguistic biases might manifest themselves in social media texts. Therefore, as a starting point, we aim to answer the following research questions:

RQ1: Which types of linguistic biases could manifest in a textual biography of a famous person?
RQ2: Is there evidence of linguistic bias based on the gender of the person being described?
RQ3: Is there evidence of linguistic bias based on the race of the person described?

Linguistic Biases

We describe two linguistic biases discussed by social psychologists and communication scientists: the *Linguistic Expectancy Bias* (LEB) and the *Linguistic Intergroup Bias* (LIB). These biases manifest through two characteristics of the language used to describe someone: the specificity of the description, and the use of words that reveal sentiment toward the target individual. Therefore, we begin with an overview of Semin and Fiedler's Linguistic Category Model (LCM) (Semin and Fiedler 1988).

Linguistic Category Model

Both the LEB and the LIB build upon the Linguistic Category Model. LCM proposes a shift in the methodological approach to the analysis of language, from the individual to the social, emphasizing that "to understand social behavior one has to develop a handle on language as a tool that carries communication and makes social interaction possible," ((Coenen, Hedebouw, and Semin 2006), p. 4).

LCM specifies four categories of predicates with respect to the level of abstraction in a description of a person, as depicted in Figure 1. As illustrated, the most concrete description is that involving a descriptive action verb; it describes an observed event with no interpretation. In contrast, the most abstract is that involving an adjective; here, the description generalizes across any scenario or event. In between the two extremes, we have the use of a state verb, which describes an ongoing state of affairs, as well as the use of an interpretive action verb, in which what is being described is attributed only to a specific event or action.

As will be described, systematic differences in the level of abstractness of the language used to describe people, is used to detect LEB and LIB. The underpinnings of these biases are cognitive in nature, as familiar and/or stereotypical scenes are easier to process (Winkielman et al. 2006). However, the consequences are of a social nature and are quite serious, especially if they prove to be as pervasive in social media as they are in interpersonal interactions.

Abstract language is powerful because it implies stability over time, as well as generalizability across situations. It has been shown that recipients of messages are impacted by biases; they interpret abstract descriptions as enduring qualities of the target person, and concrete descriptions as being transient (Wigboldus, Spears, and Semin 2000). Thus, it is believed that linguistic biases contribute to the maintenance and transmission of stereotypes, as information encoded in an abstract manner is more resistant to disconfirmation.

Linguistic Expectancy Bias

LEB describes the tendency to describe other people and situations that are expectancy consistent (e.g., stereotype-congruent individuals) in a more abstract, interpretive way. Abstract descriptions of a target individual provide more information about their perceived traits and characteristics, and less about a particular situation they are in or action they have taken. Studies have shown that when a target individual violates our expectations, we are likely to focus on more tangible, concrete details in our descriptions of him or her (Maass et al. 1989; Wigboldus, Spears, and Semin 2005). In contrast, stereotype-congruent people and behaviors are likely to be described more abstractly, using language that makes reference to their general disposition and traits. Although the LEB is pervasive in human communication, it has only been studied in the laboratory, with very few exceptions (e.g., (Hunt 2011)).

Linguistic Intergroup Bias

The key thesis of LIB is that we use language in a manner that renders the disconfirmation of preexisting ideas we hold about social groups very difficult (Maass et al. 1989). For members of our in-group, we tend to describe positive actions and attributes using more abstract language, and their undesirable behaviors and attributes more concretely. Conversely, when an out-group individual does or is something desirable, we tend to describe him or her with more concrete language, whereas her undesirable attributes are encoded more abstractly. LIB builds on LEB, since we expect our in-group members to have desireable attributes and/or to exhibit desireable behaviors, whereas positive characteristics of out-group members may be unexpected.

Linguistic biases are not only driven by cognitive and motivational underpinnings, they are also influenced by social and communicative context (Maass et al. 1989). Specifically, the LIB is more likely to occur when messages are designed to serve a clear communicative purpose. In other words, LIB may serve as a device that signals to others both our status with respect to an in-/out-group, as well as our expec-

	Expectancy-congruent (LEB) In-group (LIB)	Expectancy-incongruent (LEB) Out-group (LIB)
Familiar/ Desirable Actions and Traits	More abstract	More concrete
	More adjectives More subjective words	Fewer adjectives Fewer subjective words
Unfamiliar/ Undesirable Actions and Traits	More concrete	More abstract
	Fewer adjectives Fewer subjective words	More adjectives More subjective words

Figure 2: Linguistic Features Predicted by LEB and LIB.

tations for their behaviors. When communicative purpose is removed from the situation (i.e., when people cannot construct an image of their audience), LIB is less likely to occur.

Detecting Linguistic Bias in Social Media

Figure 2 summarizes the linguistic properties of textual biographies predicted by theory, as a function of the social relationship between biographers (i.e., IMDb participants) and the actors being described. As mentioned, IMDb is a less formal collaborative system as compared to Wikipedia, as it lacks many of the social features that build in reputation and accountability. These properties make it an interesting case for our study. Because linguistic biases are mitigated by the communicative context, we might expect collaborative biographies created in a more anonymous communication environment, such as IMDb, to suffer less from linguistic bias, where the social identity of the biography's subject is the primary trigger for LIB and LEB.

Previous studies of linguistic bias have involved manually annotating textual descriptions of people by LCM categories (Semin and Fiedler 1988). While the LCM is clearly a complicated model to fully automate, we currently take the first steps toward this process. This will allow us to study a sufficient number of IMDb biographies in order to compare them across race and gender.

The LCM Manual notes that the textual segments we should annotate and how we should apply LCM depends on the research questions to be addressed (p. 8). Two clear observations emerge from our review of the literature. The first is that *adjectives* play a key role in conveying abstract information about people, and they can be distinguished from verbs in a straightforward manner (p. 6). Furthermore, linguists have long considered the possibility that part-of-speech (POS) is intricately linked to underlying cognitive functions (Brown 1957). Thus, the use of more adjectives over verbs likely affects how communicators view a situation or person.

The second observation is that subjective words of all POS play a key role in more abstract descriptions. Subjective language injects the author's sentiment and/or inferences about the target person, into the description. Since our work is inspired by the claim that language biases play a role in the creation and maintainence of stereotypes, it is worth noting that many seminal works on stereotypes (e.g., (Devine and Elliot 1995)) ask participants to describe the core attributes of a social group of interest using subjective adjectives. Based on these insights, we consider the following textual features of biographies:

1. The use of adjectives versus verbs.
2. The use of subjective words of any POS.
3. The use of subjective adjectives.

We measure the above properties in various ways, and using appropriate statistical models, compare their use in IMDb biographies across actor race and gender. Significant differences across social groups will be a strong indication of linguistic bias.

	Men	Women	Total
African American	72	38	110
Caucasian	91	94	185
Total	163	132	295

Table 1: IMDb biographies by race and gender.

Data

Given that IMDb is based in the United States, we defined lists of top Hollywood actors. To this end, we used Wikipedia to identify names of prominent African American and Caucasian American actors and actresses.[9][10][11][12] We then obtained the most recent dump of the IMDb biographies dataset.[13] Table 1 summarizes the number of biographies from our list of prominent actors and actresses, by social group, that were available at IMDb.

Preprocessing

From the 295 biographies we created three datasets: 1) the full text biographies, 2) the first five sentences of the biographies and 3) the opening sentence of each biography. The five-sentence dataset was used to emulate the "teaser" a reader sees at an actor's page at IMDb, before clicking to see the entire biography. The first-sentence dataset was created with the intuition that it sets the general topic and tone of the text. Table 2 provides examples of the first sentences in four biographies, along with the proportion of words that are adjectives, and the proportion of words that are subjective. Subjective words are in bold letters.

Texts were labeled for part-of-speech using the CLAWS tagger (Garside and Smith 1997). The Version 5 tagset was

[9] http://en.wikipedia.org/wiki/List_of_African-American_actors

[10] http://en.wikipedia.org/wiki/AFI's_100_Years...100_Stars

[11] http://en.wikipedia.org/wiki/List_of_Best_Actor_winners_by_age

[12] http://en.wikipedia.org/wiki/List_of_Best_Actress_winners_by_age

[13] ftp://ftp.fu-berlin.de/pub/misc/movies/database/

Actor	First sentence	Prop. Adjs	Prop. Subj.
Paul Newman	Screen legend, **superstar**, and the man with the most **famous** blue eyes in movie history, Paul Leonard Newman was born in January 1925, in Cleveland, Ohio, the second son of Theresa (Fetsko) and Arthur Sigmund Newman.	3/36	2/36
John Amos	A native of New Jersey and son of a mechanic, African-American John Amos has relied on his **imposing** build, eruptive nature and **strong, forceful** looks to obtain acting jobs, and a **serious desire** for **better** roles to earn a **satisfying** place in the annals of film and TV.	8/48	7/48
Amy Adams	Amy Lou Adams was born in Italy, to American parents Kathryn (Hicken) and Richard Kent Adams, while her father was a U.S. serviceman.	1/23	0/23
Margaret Avery	**Slender, attractive** actress Margaret Avery, **spellbinding** in her role of Shug in Steven Spielberg's The Color Purple (1985), is certainly no "one-hit wonder."	3/23	3/23

Table 2: First sentence for each of four sample biographies.

used,[14] which has been used to tag the British National Corpus (BNC). On written texts in the BNC, CLAWS achieved an overall error of 1.14%.[15] With respect to the identification of adjectives, which play a key role in abstract descriptions of people, the error rate was 1.35%. We identified all adjectives, nouns or verbs, of any subcategory. We considered all three subcategories of adjectives (unmarked, comparative and superlative), all four subcategories of nouns (those neutral for number, singular, plural and proper nouns), and all 25 subcategories of verbs (all tenses, aspects and modalities).

After the POS tagging, we used the *Subjectivity Lexicon* (Wilson, Wiebe, and Hoffman 2005) to identify words in the biographies that convey sentiment. The Lexicon lists over 8,000 English words, each of which is associated with a type (strongly or weakly subjective), its POS, and its prior polarity. Words with weak subjectivity convey sentiment in certain, but not all, contexts. In contrast, strongly subjective words most always convey sentiment. A word's prior polarity refers to whether it evokes positive or negative sentiment, regardless of context. Examples of subjective adjectives, nouns and verbs, are shown in Table 3.

[14]http://ucrel.lancs.ac.uk/claws5tags.html

[15]http://ucrel.lancs.ac.uk/bnc2/bnc2error.htm

	Strong	Weak
Positive	Happy, Smile, Smile	Light, Dream, Dream
Negative	Ugly, Frown, Frown	Fat, Death, Attack

Table 3: Example subjective adjectives, nouns and verbs.

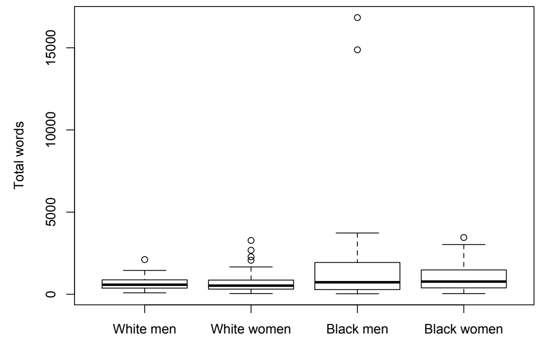

Figure 3: Distribution of biography length by social group.

Descriptive Statistics

Since IMDb offers no information on the number or identity of user edits, the only available measure of effort made to document an actor's life and career is biography length. Figure 3 depicts the distribution of biography length, by racial/gender group. As expected, the distribution is skewed to the right, with several outliers. The Kruskal-Wallis rank sum test (McKnight and Najab 2010), the non-parametric equivalent of ANOVA, detects no significance differences between the four groups, although biography length among African Americans varies more than within the groups of Caucasian Americans. For instance, the longest biography is that of Michael Jackson (16,836 words), and the shortest (30 words) describes Rusty Cundie. In the datasets of opening sentences (first five, first), the median number of words is 108 and 24, respectively. As illustrated in Figure 4, the opening sentences of biographies describing white men tend to be longer, as compared to the other groups.

Analysis

As mentioned, the LCM Manual emphasizes the differentiation of predicates involving adjectives versus verbs. Our automated analysis involves POS tagging and not full syntactic parsing. Nonetheless, if we observe salient differences between social groups with respect to the proportion of words used in biographies that are adjectives versus verbs, this would be a very good indication that the target individuals' characteristics correlate to biographers' tendencies to describe *how they are* (i.e., greater use of adjectives) versus *what they have done* (i.e., greater use of verbs). Likewise, frequent use of subjective or evaluative words would indicate a tendency to abstract away from concrete observations concerning the target individual.

	Full text		First five sent.		First sent.	
	Adjs.	Verbs	Adjs.	Verbs	Adjs.	Verbs
White men	**0.06884**	**0.1166**	0.06481	0.1170	0.06061	**0.09091**
Black men	0.05746	0.1202	**0.05430**	0.1214	0.0403	0.1258
White women	0.05916	0.1222	0.06232	0.1288	0.0417	0.1237
Black women	0.05960	0.1205	0.06287	0.1186	0.05573	**0.1000**
Chi-square	22.017	7.8794	7.7814	4.0869	4.0529	13.651
p-value	<0.001	<0.05	<0.100	0.2522	0.2558	<0.01

Table 4: Median proportion of words that are adjectives vs. verbs.

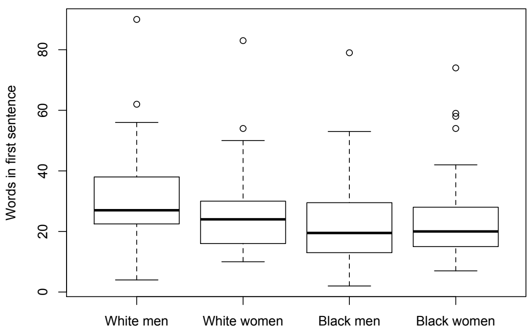

Figure 4: Distribution of words in first sentence.

	Full texts	First five	First sent.
White men	**0.03854**	0.02597	0.02000
Black men	0.03401	0.03262	0
White women	0.03589	0.02405	0
Black women	0.03229	0.02692	0
Chi-square	12.1318	3.6413	7.8169
p-value	<0.01	0.3029	<0.05

Table 5: Median prop. of subjective words (any POS).

	Full texts	First five	First sent.
White men	**0.1154**	0.006061	0
Black men	0.08686	0	0
White women	0.1026	0	0
Black women	0.08718	0.02692	0
Chi-square	12.8312	3.4274	8.1113
p-value	<0.01	0.3303	<0.05

Table 6: Median prop. of adjs that are **strongly** subjective.

Table 4 shows the proportion of adjectives and verbs used in the three datasets, broken out by the four social groups. We again use Kruskal-Wallis to test these differences. Post-hoc pairwise Wilcoxon rank sum tests using the Bonferroni correction confirm that on full texts, only the white men differ from the other groups. (In Tables 4 through 6, a bolded score indicates a group that differs from all others with $p < 0.01$). On the first five sentences of biographies, again, the post-hoc tests reveal that black men are described with fewer adjectives as compared to other groups. In the opening sentences of biographies, white men and black women are described with fewer verbs as compared to the other groups. In short, we begin to observe a pattern here: white actors tend to be described in a more abstract manner, with relatively greater use of adjectives and fewer verbs.

Table 5 displays the median proportion of words (any POS) that are strongly or weakly subjective. In full texts, white men are again shown to be described more abstractly, with a greater proportion of subjective words, as compared to the three other groups. In opening sentences, white men are described more abstractly than are black men or white women, but the post-hoc test reveals no difference between white men and black women.

As shown in Table 6, in the full texts, there are significant differences with respect to the proportion of adjectives used in a biography that are strongly subjective (i.e., carry sentiment regardless of context). The post-hoc test reveals that white men are described with more strongly subjective adjectives as compared to African Americans of both genders. In the opening sentences of biographies, the post-hoc test again reveals that white men and black women are described with more strongly subjective adjectives as compared to black men or white women.

Because the proportion of words conveying abstract information becomes quite small when we consider the first sentence(s) of a biography, we also modeled these characteristics as discrete variables. In particular, Table 7 details the proportion of texts in which there is at least one subjective adjective, along with the Chi-square test of independence (Diaconis and Efron 1985). This binary variable makes it easier to compare across the four groups and confirms the findings thus far: white men are described in a more abstract, subjective manner as compared to others.

Finally, we use logistic regression to model the log odds of a biography containing a subjective adjective, based on the race and gender of the target individual (i.e., actor). More specifically, we fit a logit model as follows:

$$\ln \frac{Pr(y_i = 1)}{Pr(y_i = 0)} = \beta_0 + \beta_1 * Race_i + \beta_2 * Gender_i + \beta_3 * RG_i$$

where β_0 is the intercept, and the response, y_i , takes the value of 0 if the text is contains little abstract language (i.e., contains no subjective adjective) and 1 if the text is rela-

	Full texts	First five	First sent.
White men	0.945	0.5274	0.2418
Black men	0.750	0.361	0.1111
White women	0.904	0.394	0.0957
Black women	0.816	0.395	0.1579
Chi-square	219.6	39.02	186.92
p-value	<0.0001	<0.0001	<0.0001

Table 7: Prop. of texts with at least one **strongly** subjective adj.

	Full texts	First five	First sent.
Intercept	2.845****	0.1100	-1.1431****
Race	-1.7463***	-0.6805**	-0.9364**
Gender	-.5995	-0.5421*	-0.1024***
RG	0.9889	0.6852	1.5078**
****$p < 0.001$, ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$			
Class.error	0.1128	0.2479	0.1285

Table 8: Logit models to predict the presence/absence of abstract language.

White men	*Black men*	*White women*	*Black women*
greatest	**talented**	**greatest**	**talented**
talented	sly	unorthodox	**stunning**
handsome	outrageous	tragic	**profound**
spectacular	**handsome**	**talented**	**precious**
sly	**eloquent**	**striking**	**gifted**
shrewd	demeaning	**poetic**	**elegant**
renowned	**confident**	**exuberant**	**captivating**
notable	**charming**	**elegant**	**attractive**
nervous	**charismatic**	**distinguished**	
mean	boisterous	**delightful**	
little	**better**	**best-known**	
great		**astonishing**	
gifted			
flexible			
famed			
enduring			
brash			
best-known			
beautiful			
acclaimed			

Table 9: Subjective adjectives in first sentence.

tively more abstract (i.e., contains at least one strongly subjective adjective). Race is a binary variable where 1 indicates African American; likewise, Gender is 1 for actresses and 0 for actors. We also include an interaction term.

Table 8 shows the estimated model for each of the three datasets along with the p-value for the appropriate test of significance for each coefficient. In addition, the last row of the table shows the results of a 10-fold cross validation experiment, implemented in R (Starkweather 2011), in which we used each actor's respective race and gender to predict whether or not his or her IMDb biography contained a subjective adjective. As observed, all models perform better than random (i.e., a classification error of 0.50); since this is the first study of linguistic bias in social media texts, we are unaware of any other baseline to which we might compare the model's performance.

Across all three datasets, there is a significant main effect for race on the use of subjective adjectives, with African Americans' biographies being less likely to contain abstract language. For the datasets consisting of the biographies' first sentence(s), there is also a significant effect on gender: women are less likely to be described in abstract terms. Finally, we observe that for the opening sentences dataset, that describing an African American woman in the biography boosts the likelihood of using abstract language, as the interaction term is statistically significant.

Finally, we have a qualitative look at the most frequently used subjective adjectives describing each of the four social groups, in their respective IMDb biographies. Since we have seen that there is a good deal of variance with respect to the length of IMDb biographies, with white actors having longer biographies as compared to the other groups, we compare the words used to describe the target individuals in the first sentences of their biographies. In addition, the opening sentence is arguably the most important in that it sets the tone for the rest of the text. It is clearly and prominently displayed at the actor's IMDb page, and is always present in the teaser for the biography.

Table 9 displays all subjective adjectives found in the first sentences of the biographies, in order by frequency of use, separated by group. Words carrying positive sentiment are in bold. We can make several observations here. First, as expected, we find the most subjective adjectives in the opening sentences describing white men. This is also the most diverse list; we find a total of 15 positive and five negative words. In contrast, in the first sentences of biographies of African American actresses, we find no subjective adjectives carrying negative sentiment.

We can also observe how IMDb biographers use subjective adjectives in the opening sentences. These words are used to describe a person's appearance (e.g., "handsome," "stunning"), disposition ("shrewd," "charismatic") and professional abilities ("talented," "flexible"). Finally, it appears to be the case that biographers use negative adjectives primarily in the opening sentences of male actors. In general, these qualitative observations support the findings of the quantitative analyses: the race and gender of the biography subject correlate to the extent to which IMDb biographers' use abstract and evaluative language in their descriptions.

Discussion

There is a growing literature surrounding the language of social media. Some scholars have documented the linguistic style of particular media, in order to better understand how users exploit and expand their communication affordances (e.g., (Hu, Talamadupula, and Kambhampati 2013)) or when and why people might change their linguistic style (Danescu-Niculescu-Mizil et al. 2013; Michael and Otterbacher 2014). In contrast, others have studied the correlation between participants' linguistic patterns and their offline demographics and identities (e.g., (Pennacchiotti and Popescu 2011; Fink, Kopecky, and Morawski 2012; Park et al. 2013).

Both areas of research attempt to learn from the variations in language patterns to better understand people and their interactions via social media. However, previous work has not considered the possibility of linguistic biases in social platforms.

We framed and motivated our study of linguistic biases in social media in terms of the Linguistic Category Model, and the two most frequently studied biases, the Linguistic Expectancy Bias and the Linguistic Intergroup Bias. This body of research has already demonstrated that linguistic biases are commonplace in face-to-face interactions. In addition, they have demonstrated the effect that such biases have on how message recipients interpret the information conveyed. In short, linguistic bias tends to be very subtle, goes unnoticed much of the time, and yet it plays a salient role in the persistence of social stereotypes in society.

In our analyses, white men actors were consistently described with more abstract, interpretive language as compared to African American actors, and actresses of both races. Without a doubt, IMDb readers would notice the use of blatantly offensive or derogatory language in the biographies of actors and actresses. However, they may not consciously pick up on the subtle differences in the level of abstractness in the language used in the biographies. Because abstract descriptions of people tend to be much more powerful as compared to concrete descriptions, there is cause for concern. When presented with abstract descriptions, message recipients perceive the information conveyed as being more stable over time (Wigboldus, Spears, and Semin 2005). In fact, in experimental settings, counter-stereotypical people can be made more likeable, being evaluated more positively by study participants, when they are described in a more abstract manner (Rubin, Paolini, and Crisp 2013).

We believe that the LEB and/or the LIB could take place at IMDb. LEB might occur when an IMDb participant attempts to describe an actor or actress, who somehow violates her expectations. When something or someone is unexpected, LEB predicts that the biographer would tend to focus on more concrete descriptions, avoiding the use of more abstract language that is subjective or inferential. Again, the reasons put forward thus far in the research indicate that the basis for this bias is cognitive (Karpinski and von Hippel 1996): unexpected information, which does not align with our existing prototypes, is more difficult for us to process.

For instance, a participant might not expect that an African American woman, Oprah Winfrey, who grew up in an underprivileged environment, could grow up to become one of the most famous, wealthy women in America. Winfrey's IMDb biography begins with the following, quite concrete statements:

> Born Orpah Gail Winfrey in Kosciusko, Mississippi, United States. Orpah was born to mother, former maid Vernita Lee, and father, war veteran Vermon Winfrey.

We can contrast the above to the opening lines of the biography of Arnold Schwarzenegger, a white male actor who also had a humble upbringing. As can be seen, the language used is more abstract, characterizing Schwarzenegger in a more generalizable way:

> With an almost unpronounceable surname and a thick Austrian accent, who would have ever believed that a brash, quick talking bodybuilder from a small European village would become one of Hollywood's biggest stars, marry into the prestigious Kennedy family, amass a fortune via shrewd investments and one day be the Governor of California!?

The LIB might occur because of the relationship between the IMDb participant and the target individual (i.e., the in-group or out-group status with respect to social attributes such as race and gender). If participation at IMDb is indeed male-dominated, as suggested by previous studies (e.g., (Hemphill and Otterbacher 2012)), then our results are expected. In other words, LIB predicts that white men biographers, the majority, are more likely to describe the achievements of white men actors in an abstract manner, and those of other social groups in a more concrete manner. In this way, they imply that their own group behaves in a positive way, and that achievement by other social groups are not usual (i.e., are not broadly generalizable) (Guerin 1994).

Limitations

Our study's findings should be interpreted in light of its main limitation, which it shares with all observational studies of social media behavior: we report correlations but not causal relationships between the variables studied. More specifically, we were not able to control for confounding variables that might affect an IMDb biographer's attitudes toward the actors and actresses in our dataset, as well as his or her writing style. Factors such as one's age, ethnicity, or gender are very likely to affect the manner in which he or she writes (Labov 1990).

At IMDb, participation in the creation and editing of biographies is anonymous. In addition, the biographies are a collaborative effort. Only in a controlled experimental setting, where we could manipulate the social identities of the biographers and the target individuals, could we venture to say whether LIB, LEB or some other factor is the cause of the systematic differences in linguistic patterns that we have documented.

Nonetheless, the present work takes a very important first step toward developing methods to detect linguistic biases in social media descriptions of people. We have motivated the need for such studies, demonstrating how linguistic biases might manifest themselves through the use of abstract, subjective language. Finally, we have provided initial evidence that linguistic biases are, as expected, prevalent in social media just as they are in our offline interactions.

Conclusions

The current study laid the groundwork for a deeper analysis of linguistic biases in social media. Just as mass media researchers have cautioned that the presence of linguistic biases in messages can prime dominant stereotypes (e.g., in crime-related news and the variations in the descriptions of perpetrators as a function of race (Gorham 2006)), we would argue for further studies that gauge the extent to which LIB and LEB permeate our descriptions of people via social media, and with which consequences.

Studying linguistic biases in social media communication, as compared to offline interactions, adds a additional layer of complexity to these phenomena. We would not be at all surprised to observe differences in the types of biases, as well as in the frequency of their occurances, were we to compare similar content and tasks (e.g., collaborative production of biographies of famous people) across social media platforms (e.g., Wikipedia vs. IMDb). Because the communicative context appears to mitigate the occurance of bias (especially in the case of LIB (Maass et al. 1989)), future research must consider the role of factors such as: the specific communication affordances provided by a given platform, its participant base, and the social norms surrounding its use (e.g., the degree to which participants tend to self-disclose, whether or not participants maintain more friendly or formal relationships). In short, both the technical features and social cues surrounding the collaborative writing process likely correlate to the type of linguistic biases we observe in descriptions of people, as well as how often they occur. Only by achieving a better understanding of the relationships between such factors can we gauge whether or not the crowdsourcing of knowledge production also leads to the crowdsourcing of social stereotypes.

References

Antin, J.; Yee, R.; Cheshire, C.; and Nov, O. 2011. Gender differences in wikipedia editing. In *Proceedings of the 7th International Symposium on Wikis and Open Collaboration*, WikiSym '11, 11–14. New York, NY, USA: ACM.

Beukeboom, C. 2013. Mechanisms of Linguistic Bias: How Words Reflect and Maintain Stereotypic Expectations. In Laszlo, J.; Forgas, J.; and Vincze, O., eds., *Social Cognition and Communication*. New York, NY: Psychology Press. 313–330.

Brown, R. 1957. Linguistic Determinism and the Part of Speech. *The Journal of Abnormal and Social Psychology* 55(1):1–5.

Callahan, E., and Herring, S. 2011. Cultural Bias in Wikipedia Content on Famous Persons. *Journal of the American Sopciety of Information Science and Technology* 62(10):1899–1915.

Coenen, L.; Hedebouw, L.; and Semin, G. 2006. Measuring Language Abstraction: The Linguistic Category Model Manual. Technical report, Free University Amsterdam, Amsterdam, The Netherlands.

Danescu-Niculescu-Mizil, C.; West, R.; Jurafsky, D.; Leskovec, J.; and Potts, C. 2013. No Country for Old Members: User Lifecycle and Linguistic Change in Online Communities. In *Proceedings of the 22nd International Conference on World Wide Web*, 307–318.

Devine, P., and Elliot, A. 1995. Are Racial Stereotypes Really Fading? The Princeton Trilogy Revisited. *Personality and Social Psychology Bulletin* 21(11):1139–1150.

Diaconis, P., and Efron, B. 1985. Testing for Independence in a Two-way Table: New Interpretations of the Chi-square Statistic. *The Annals of Statistics* 845–874.

Fink, C.; Kopecky, J.; and Morawski, M. 2012. Inferring Gender from the Content of Tweets: A Region Specific Example. In *Proceedings of the 6th International AAAI Conference on Weblogs and Social Media*.

Flekova, L.; Ferschke, O.; and Gurevych, I. 2014. What makes a good biography?: Multidimensional quality analysis based on wikipedia article feedback data. In *Proceedings of the 23rd International Conference on World Wide Web*, WWW '14, 855–866. New York, NY, USA: ACM.

Forte, A.; Antin, J.; Bardzell, S.; Honeywell, L.; Riedl, J.; and Stierch, S. 2012. Some of all human knowledge: Gender and participation in peer production. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work Companion*, CSCW '12, 33–36. New York, NY, USA: ACM.

Garside, R., and Smith, N. 1997. A Hybrid Grammatical Tagger: CLAWS4. In Garside, R.; Leech, G.; and McEnergy, A., eds., *Corpus Annotation: Linguistic Information from Computer Text Corpora*. London: Longman. 102–121.

Gorham, B. 2006. News Media's Relationship with Stereotyping: The Linguistic Intergroup Bias in Response to Crime News. *Journal of Communication* 56:289–308.

Guerin, B. 1994. Gender Bias in the Abstractness of Verbs and Adjectives. *The Journal of Social Psychology* 134(4):421–428.

Hecht, B., and Gergle, D. 2010. The tower of babel meets web 2.0: User-generated content and its applications in a multilingual context. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '10, 291–300. New York, NY, USA: ACM.

Hemphill, L., and Otterbacher, J. 2012. Learning the Lingo?: Gender, Prestige and Linguistic Adaptation in Review Communities. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, 305–314.

Herring, S. 2003. Gender and Power in Online Communities. In Holmes, J., and Meyeroff, M., eds., *The Handbook of Language and Gender*. Oxford: Blackwell. 202–228.

Hu, Y.; Talamadupula, K.; and Kambhampati, S. 2013. Dude, srsly?: The Surprisingly Formal Nature of Twitter's Language. In *Proceedings of the 7th International AAAI Conference on Weblogs and Social Media*.

Hunt, A. 2011. *The Linguistic Expectancy Bias and the American Mass Media*. Ph.D. Dissertation, Temple University, Philadelphia, PA.

Karpinski, A., and von Hippel, W. 1996. The Role of Linguistic Intergroup Bias in Expectancy Maintenance. *Social Cognition* 14:141–163.

Kittur, A., and Kraut, R. E. 2008. Harnessing the wisdom of crowds in wikipedia: Quality through coordination. In *Proceedings of the 2008 ACM Conference on Computer Supported Cooperative Work*, CSCW '08, 37–46. New York, NY, USA: ACM.

Labov, W. 1990. The Intersection of Sex and Social Class in the Course of Linguistic Change. *Language Variation and Change* 2(2):205–254.

Lam, S. T. K.; Uduwage, A.; Dong, Z.; Sen, S.; Musicant, D. R.; Terveen, L.; and Riedl, J. 2011. Wp:clubhouse?: An exploration of wikipedia's gender imbalance. In *Proceedings of the 7th International Symposium on Wikis and Open Collaboration*, WikiSym '11, 1–10. New York, NY, USA: ACM.

Maass, A.; Salvi, D.; Arcuri, L.; and Semin, G. 1989. Language Use in Intergroup Context: The Linguistic Intergroup

Bias. *Journal of Personality and Social Psychology* 57(6):981–993.

Maass, A. 1999. Linguistic Intergroup Bias: Stereotype Perpetuation through Language. In Zanna, M., ed., *Advanced in Experimental Social Psychology*. San Diego, CA: Academic Press. 79–121.

McKnight, P., and Najab, J. 2010. Kruskal-Wallis Test. *Corsini Encyclopedia of Psychology*.

Michael, L., and Otterbacher, J. 2014. Write Like I Write: Herding in the Language of Online Reviews. In *Proceedings of the International AAAI Conference on Weblogs and Social Media*.

Park, J.; Barash, V.; Fink, C.; and Cha, M. 2013. Emoticon Style: Interpreting Differences in Emoticons Across Cultures. In *Proceedings of the 7th International AAAI Conference on Weblogs and Social Media*.

Pennacchiotti, M., and Popescu, A.-M. 2011. A Machine Learning Approach to Twitter User Classification. In *Proceedings of the 5th International AAAI Conference on Weblogs and Social Media*.

Pentzold, C. 2009. Fixing the Floating Gap: The Online Encyclopedia Wikipedia as a Global Memory Place. *Memory Studies* 2(2):255–272.

Pfeil, U.; Zaphiris, P.; and Ang, C. 2006. Cultural Differences in Collaborative Authoring of Wikipedia. *Journal of Computer-Mediated Communication* 12:88–113.

Royal, C., and Kapila, D. 2009. What's on Wikipedia, and What's Not? *Social Science Computer Review* 27(1):138–148.

Rubin, M.; Paolini, S.; and Crisp, R. 2013. Linguistic Description Moderates the Evaluations of Counterstereotypical People. *Social Psychology* 14:289–298.

Semin, G., and Fiedler, K. 1988. The Cognitive Functions of Linguistic Categories in Describing Persons: Social Cognition and Language. *Journal of Personality and Social Psychology* 54:558–568.

Shirkey, C. 2011. *Cognitive Surplus: How Technology Makes Consumers into Collaborators*. New York: Penguin Books.

Starkweather, J. 2011. Cross-validation Techniques in R: A Brief Overview of some Methods, Packages and Function for Assessing Prediction Models. *Benchmarks Online*. Accessed: 2015-01-23.

von Hippel, W.; Sekaquaptewa, D.; and Vargas, P. 1997. The Linguistic Intergroup Bias as an Implicit Indicator of Prejudice. *Journal of Experimental Social Psychology* 33:490–509.

Wigboldus, D.; Spears, R.; and Semin, G. 2000. How do We Communicate Stereotypes? Linguistic Biases and Inferential Consequences. *Journal of Personality and Social Psychology* 78:5–18.

Wigboldus, D.; Spears, R.; and Semin, G. 2005. When do We Communicate Stereotypes? Influence of the Social Context on the Linguistic Expectancy Bias. *Group Processes & Intergroup Relations* 8(3):215–230.

Wilson, T.; Wiebe, J.; and Hoffman, P. 2005. Recognizing Contextual Polarity in Phrase-level Sentiment Analysis. In *Proceedings of the ACL HLT / EMNLP*.

Winkielman, P.; Halberstadt, J.; Fazendeiro, T.; and Catty, S. 2006. Prototypes are Attractive because they are Easy on the Mind. *Psychological Science* 17(9):799–806.