GENDER IN TWITTER: STYLES, STANCES, AND SOCIAL NETWORKS

DAVID BAMMAN¹, JACOB EISENSTEIN², AND TYLER SCHNOEBELEN³

¹Language Technologies Institute, School of Computer Science, Carnegie Mellon University
²School of Interactive Computing, Georgia Institute of Technology
³Department of Linguistics, Stanford University

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1. INTRODUCTION

The increasing prevalence of online social media for informal communication has enabled large-scale statistical modeling of the connection between language style and social variables, such as gender, age, race, and geographical origin. Whether the goal of such research is to understand stylistic differences or to learn predictive models of “latent attributes,” there is often an implicit assumption that linguistic choices are associated with immutable and essential categories of people. Indeed, it is possible to demonstrate strong correlations between language and such categories, enabling predictive models that are disarmingly accurate. But this leads to an oversimplified and misleading picture of how language conveys personal identity.

In this paper, we present a study of the relationship between gender, style, and social network connections in social media text. We use a novel corpus of more than 14,000 individuals on the microblog site Twitter, and perform a computational analysis of the impact of gender on both their linguistic styles and their social networks. This study addresses two deficiencies in previous quantitative sociolinguistic analyses of gender.

First, previous quantitative work has focused on the words that distinguish women and men on a population level. This disregards strong theoretical arguments and qualitative evidence that gender can be enacted through a diversity of styles and stances. By clustering the authors in our dataset, we identify a range of different styles and topical interests. Many of these clusters have strong gender orientations, but their use of linguistic resources sometimes directly conflicts with the population-level language statistics. We find that linguistic tendencies that have previously been attributed to women or men as undifferentiated social groups often describe only a subset of individuals; there are strongly gendered styles that use language resources in ways that are odds with the overall population.

Second, previous corpus-based work has had little to say about individuals whose linguistic styles defy population-level gender patterns. To find these individuals, we build a classifier capable of determining the gender of microblog authors from their writing style, with an accuracy of 88%. We focus on the individuals that the classifier gets wrong, and examine their language in the context of their online social networks. We find a significant correlation between the use of mainstream gendered language—as represented by classifier confidence—and social network gender homophily (how much a social network is made up of same-sex individuals). Individuals whose gender is classified incorrectly have social networks that are much less homophilous than those of the individuals that the classifier gets right. While the average social network in our corpus displays significant homophily (63% of connections are same-gender), social network features provide no marginal improvement in the classifier performance. That is, social network gender homophily and the use of mainstream gendered linguistic features are closely linked, even after controlling for author gender, suggesting a root cause in the individual's relationship to mainstream gender norms and roles. We see these individuals not as statistical outliers, but as
people who coherently “doing” gender in a way that influences both their linguistic choices and their social behavior.

2. BACKGROUND: GENDER CATEGORIES AND LANGUAGE VARIATION

Gender is a pervasive topic in the history of sociolinguistics. Without attempting to do justice to this entire body of work, we summarize the findings that are most relevant to this paper. We begin with high-level linguistic distinctions that have been proposed to characterize language differences between genders: the first proposal contrasts accepted linguistic standards (prestige forms) from vernacular and taboo alternatives; the second proposal contrasts “informational” (content-based) language from “expressive” (contextual) language. Much of this work has emphasized drawing statistical correlations between gender and various word classes; the availability of large social media corpora has added new momentum to such quantitative approaches, while enabling the measurement of individual word frequencies. We review the results of this line of work, and examine its (often tacit) theoretical underpinnings. The quantitative methodology of corpus linguistics reaches its apogee in the instrumentalism of machine learning, which emphasizes predictive models that accurately infer gender from language alone. After summarizing this work, we step back to consider theoretical frameworks and empirical results which argue that gender can be enacted in many ways, depending on the situation, the speaker's stylistic choices, and the interactions between gender and other aspects of personal identity. We conclude the section by stating the main contributions of this paper, with respect to this prior literature.

2.1 The standard and the vernacular

The concepts of “standard” and “vernacular” language have been repeatedly recruited to explain and characterize gender differences in language (Cheshire, 2002; Coates & Cameron, 1989; Eckert & McConnell-Ginet, 1999; Holmes, 1997; Romaine, 2003). While there are a multiplicity of definitions for each term, standard language is often linked to the linguistic practices of upper-class or bourgeois speakers, while the vernacular is linked to the working class. It is usually argued that women's language is more standard than men. Based on this intuition, pre-variationist dialectology focused on non-mobile, older, rural male speakers, who were thought to preserve the purest regional (non-standard) forms (Chambers & Trudgill, 1980). When women were studied, the findings were said to confirm this commonsense intuition (Labov, 1966; Trudgill, 1974); the purported female preference for standard language was crucial for Trudgill (1983, p. 162), and the difference between genders was made into a principle of how languages change by Labov (1990).
Explanations for women's preference for standard forms often draw on the patterns of language stratification across class. Women's preference for standard or “prestige” forms is said to be about a need or a desire to acquire social capital. By contrast, many men pursue the “covert” prestige offered by non-standard variants, which index “toughness” or local authenticity (Trudgill, 1972). Deuchar (1989) argued that women do not use the standard to climb social ladders, but in order to avoid placing themselves in a precarious position: if the use of a non-standard variable were questioned, they could lose social capital. Inverting the scheme, Milroy et al. (1994) asked whether we should see women as creating norms rather than as following them. Each of these explanations involves some notion of “status consciousness,” although the theories differ as to who needs to be status conscious and why. But overall, the discourse on language and gender has moved away from seeing women using language in an attempt to claim an undeserved class status, in favor of seeing women's preference for standard language in terms of acquisition and deployment of symbolic capital (see also Holmes, 1997). These linguistic moves have causes and consequences not only at the level of socioeconomic class, but also in more intimate domains like the family.

2.2 Information and involvement

An orthogonal direction of gender-based variation relates to pragmatic characterizations such as “informativeness” and “involvement,” (Argamon, Koppel, Fine, & Shimon, 2003), which draw on earlier corpus-based contrasts of written and spoken genres (Biber, 1995; Chafe, 1982). The “involvement” dimension consists of linguistic resources that create interactions between speakers and their audiences; the “informational” dimension is focused on resources that communicate propositional content. The original work in this area focused on comparing frequencies of broad word classes, such as parts-of-speech. The paragon examples of involvement-related words are the first and second person pronouns, but present tense verbs and contractions are also counted (Biber, 1988, 2009; Tannen, 1982). The “informational” dimension groups together elements like prepositions and attributive adjectives, and is also thought to be indicated by higher word lengths. With respect to gender, word classes used preferentially by men are shown to be more informational, while female-associated word classes signal more involvement and interaction (Argamon et al., 2003; Herring & Paolillo, 2006; Schler, Koppel, Argamon, & Pennebaker, 2006).

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1 See, for example, Labov (1990), which attempted to account for how it is that women are more standard with stable variables but leaders of (some) changes-in-progress.

2 Alternatively, Chambers (1992, 1995) argued that gender differences in language stem from a biological difference in male and female brains making women more verbally dexterous than men (but for critiques of the data, see Fausto-Sterling, 1992).

3 Different parts of the social world allocate symbolic capital differently. Twitter is an interesting domain since it is used as a form of communication with friends and strangers, as a construction and marketing of self, in many cases.
A related distinction is contextuality: males are seen as preferring a “formal” and “explicit” style, while females prefer a style that is more deictic and contextual (Mukherjee & Liu, 2010; Nowson, Oberlander, & Gill, 2005). To quantify contextuality, Heylighen & Dewaele (2002) proposed an “F-measure”, 4 which compares the count of formal, non-deictic word classes (nouns, adjectives, prepositions, articles) with the count of deictic, “contextual” word classes (pronouns, verbs, adverbs, interjections). Heylighen & Dewaele argued that contextuality (and thus, the use of associated word classes) decreases when achieving an unambiguous understanding is more important or difficult—as in when interlocutors are separated by greater space, time, or background. The idea of distance is recruited to explain social factors—for example, it is increased when the speaker is male, introverted, and has more years of academic education.

Herring and Paolillo (2006) attempted to apply the informational/involvement word class features identified by Argamon et al. (2003) to a corpus of blog data. After controlling for the genre of the blog, they found no significant gender differences in the frequency of the word classes, though they did find gender differences in the selection of genres: women wrote more “diary” blogs and men wrote more “filter” blogs that link to content from elsewhere in the web. Moreover, the genres themselves did show a significant association with the gender-based features: the “diary” genre included more features thought to be predictive of women, and vice versa. But within each genre, male and female language use was not distinguishable according to the informational/involvement feature set proposed by Argamon et al. (2003).

Much of the quantitative research in this domain relied on predefined word classes, such as part-of-speech. Word classes are convenient because they yield larger and therefore more robust counts than individual words; a small corpus may offer only a handful of words that occur frequently enough to support statistical analysis. But any such grouping clearly limits the scope of quantitative results that can be obtained. For example, Heylighen and Dewaele took nouns as a group. Hammers, brooms, picnics, funerals, honesty, embarrassment, and freedom are all nouns, but no matter how one defines contextuality and explicitness, it seems difficult to argue that each of these nouns exhibits these properties to the same extent. A group-level effect may arise from a small subset of the group, so even statistically significant quantitative results must be interpreted with caution.

2.3 Predictive models
The arrival of large-scale social media data allows the investigation of gender differences in more informal texts, and offers corpora large enough to support the analysis of individual words. This has brought a wave of computational research on the automatic identification of “latent attributes” (Rao, Yarowsky, Shreevats, & Gupta, 2010) such as gender, age, and regional origin. This work comes from the computer science research tradition, and much of it is built around an instrumentalist validation paradigm that emphasizes making accurate predictions of attributes.

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4 Not to be confused with the statistical metric that combines recall and precision.
such as gender from words alone. In this methodology, the accuracy of the model then justifies a post hoc analysis to identify the words which are the most effective predictors. Finally, the researcher may draw high-level conclusions about the words which statistically characterize each gender. This reverses the direction of earlier corpus-based work in which high-level theoretical intuition is used to create word classes, and then statistical analysis compares their frequency by gender.

In one such study, Argamon, Koppel, Pennebaker, & Schler (2007) assemble 19,320 English blogs (681,288 posts, 140 million words); they build a predictive model of gender from the 1,000 words with the highest information gain, obtaining accuracy of 80.5%. For post hoc analysis, they apply two word categorizations: parts-of-speech (finding that men use more determiners and prepositions, while women use more personal pronouns, auxiliary verbs, and conjunctions) and an automatic categorization based on factor analysis. Some of the factors are content-based (politics and religion), while others are more stylistic. In general, the content-based factors are used more often by men, and the stylistic factors are used more by women—including a factor centered on swear words.

Rao et al. (2010) assembled a dataset of microblog posts by 1,000 people on the Twitter social media platform. They then built a predictive model that combined several million n-gram features with more traditional word and phrase classes. Their best model obtains an accuracy of 72.3%, slightly outperforming a model that used only the word class features. Post hoc analysis revealed that female authors were more likely to use emoticons, ellipses (...), expressive lengthening (nooo waaay), repeated exclamation marks, puzzled punctuation (combinations of ? and !), the abbreviation omg, and transcriptions of backchannels like ah, hmm, ugh, and grr. The only words that they reported strongly attaching to males were affirmations like yeah and yea. However, a crucial side note to these results is that the author pool was obtained by finding individuals with social network connections to unambiguously gendered entities: sororities, fraternities, and hygiene products. Assumptions about gender were thus built directly into the data acquisition methodology, which is destined to focus on individuals with very specific types of gendered identities.

Burger, Henderson, Kim, & Zarrella (2011) applied a different approach to build a corpus with gender metadata, by following links to Twitter from blogs in which gender was explicitly indicated in the profile (they also performed some manual quality assurance by reading the associated Twitter profiles). Analyzing more than 4 million tweets from 184,000 authors in many different languages (66.7% English), they obtained a predictive accuracy of 75.5% when using multiple tweets from each author, and 67.8% by using a single message per author. Remarkably, both of these were higher than the accuracy of human raters, who predicted gender at an accuracy of 65.7% from individual messages. The post hoc analysis yielded results that were broadly similar to those of Rao et al.: emoticons and expressive words like aha, ooo, haha, ay! were correlated with female authors, and there were few words correlated with males. The character sequences ht, http, htt, Googl, and Goog were among the most prominent male-associated features.
2.4 Beyond aggregation

From the accuracy of these predictive models, it is indisputable that there is a strong relationship between language and gender, and that this relationship is detectable at the level of individual words and n-grams. But to what extent do these predictive results license descriptive statements about the linguistic resources preferred by women and men? Herring and Paolillo (2006) have already shown us a case in which an apparent correlation between gender and word classes was in fact mediated by the confounding variable of genre; when genre was introduced into the model, the gender effects disappear. Had Herring and Paolillo simply aggregated all blog posts without regard to genre, they would have missed the mediating factor that provides the best explanation for their data.

As we have argued above, grouping words into classes (for example, nouns) is another form of aggregation that can produce misleading generalizations if the classes are not truly uniform with respect to the desired characterization (regarding, say, contextuality). But the quantitative analysis of language and gender requires other, more subtle forms of aggregation—not least, the grouping of individuals into the classes of “females” and “males.” As with word classes, such grouping is convenient; arguably, the quantitative analysis of gender and language would be impossible without it. But in examining the results of any such quantitative analysis, we must remember that this binary opposition of women and men constrains the set of possible conclusions.

To see this, consider how gender interacts with other aspects of personal identity (Eckert & McConnell-Ginet, 2003). The generalization that women are more standard fits the results of Wolfram (1969), who found that African American women in Detroit used fewer AAVE features than men, across socioeconomic levels. But Labov (2001) found that while upper middle class men used negative concord more than women, there was no real difference for lower middle class speakers; moreover, there was a reverse effect for lower working class speakers, where it was women who were the least standard. Examining the (DH) and (ING) phonological variables, Labov again found large differences for the upper middle class speakers, but no differences (or reverse differences) at lower ends of the socioeconomic spectrum. In Eckert’s (2005) study of school-oriented “jocks” and anti-school “burnouts”, the boys were less standard than girls in general, but the most non-standard language was employed by a group of “burned-out burnout” girls.

The complex role of gender in larger configurations of personal identity poses problems for quantitative analyses that aggregate individuals based on gender alone. Eckert (2008) and others have argued that the social meaning of linguistic variables depends critically on the social and linguistic context in which they are deployed. Rather than describing a variable like (ING) vs. (IN) as reflecting gender or class, Eckert (2008) argues that variables should be seen as reflecting a field of different meanings. In the case of ING/IN, years of research have shown that the variants have a range of associations: educated/uneducated, effortful/easygoing or lazy, articulate/inarticulate, pretentious/unpretentious, formal/relaxed. The indexical field of a linguistic re-
source is used to create various stances and personae, which are connected to categories like race and gender, as well as more local distinctions. This view has roots in Judith Butler's casting of gender as a stylized repetition of acts (1999, p. 179), creating a relationship between (at least) an individual, an audience, and a topic (Schnoebelen, 2012). For many scholars, this leads to anti-essentialist conclusions: gender and other social categories are performances, and these categories are performed differently in different situations (see also Coates, 1996; Hall, 1995).

Consider scholarship that does not insist upon a binary gender classification. Such work often sheds light on the ways in which the interaction between language and gender are mediated by situational contexts. For example, Rusty Barrett (1999) presents African American drag queens appropriating “white woman” speech in their performances, showing how styles and identities shift in very short spans of time. Marjorie Goodwin (1990) examines how boys and girls behave across a variety of activities, showing how sometimes they are building different types of gendered identities while in other activities they are using language the same way. Scott Kiesling (2004) shows how the term dude allows men to meet needs for “homosocial” solidarity and closeness, without challenging their heterosexuality. Each of these studies shows the richness of interactions between language, gender, and situational context.

Unlike such close, locally-based studies of the social construction of gender, we focus on quantitative analysis of large-scale social media data. Aggregation over thousands of individual situations—each with unique linguistic and social properties—seems fundamental to quantitative analysis. We hope that the development of more nuanced quantitative techniques will move corpus-based work to towards models in which utterances are not simply aggregated, but rather are treated as moments where individuals locate themselves within a larger backdrop. That is, identity categories are seen as “neither categorical nor fixed: we may act more or less middle-class, more or less female, and so on, depending on what we are doing and with whom” (Schiffrin, 1996, p. 199). We see quantitative and qualitative analysis as playing complementary roles. Qualitative analysis can point to phenomena that can be quantitatively pursued at much larger scale. At the same time, exploratory quantitative analysis can identify candidates for closer qualitative reading into the depth and subtlety of social meaning in context.

2.5 Our contributions
This paper examines the role of gender within a more holistic picture of personal identity. Building on a new dataset of 14,464 authors on the microblog site Twitter, we develop a bag-of-words predictive model which achieves 88.0% accuracy in gender prediction. We use this dataset and model as a platform to make three main research contributions:

1. We attempt a large-scale replication of previous work on the gender distribution of several word classes, and introduce new word classes specifically for corpora of computer-mediated communication.

2. We show that clustering authors by their lexical frequencies reveals a range of coherent styles and topical interests, many of which are strongly connected with
gender or other social variables. But while some of these styles replicate the population-level correlations between gender and various linguistic resources, others are in contradiction. This provides large-scale evidence for the existence of multiple gendered styles.

3. We examine the social network among authors in our dataset, and find that gender homophily correlates with the use of gendered language. Individuals with many same-gender friends tend to use language that is strongly associated with their gender (as measured by population-level statistics), and individuals with more balanced social networks tend not to. This provides evidence that the performance of popular gender norms in language is but one aspect of a coherent gendered persona that shapes an individual's social interactions.

3. Data

Our research is supported by a dataset of microblog posts from the social media service Twitter. This service allows its users to post 140-character messages. Each author's messages appear in the newsfeeds of individuals who have chosen to follow the author, though by default the messages are publicly available to anyone on the Internet. We choose Twitter among social media sources for several reasons. Twitter has relatively broad penetration across different ethnicities, genders, and income levels. The Pew Research Center (Smith, 2011) has repeatedly polled the demographics of Twitter; their findings show: nearly identical usage among women (15% of female internet users are on Twitter) and men (14%); high usage among non-Hispanic Blacks (28%); an even distribution across income and education levels; higher usage among young adults (26% for ages 18-29, 4% for ages 65+). Unlike Facebook, the majority of content on Twitter is explicitly public. Unlike blogs, Twitter data is encoded in a single format, facilitating large scale data collection.

Large numbers of messages (“tweets”) may be collected using Twitter's streaming API, which delivers a stream that is randomly sampled from the complete set of public messages on the service. We used this API to gather a corpus from Twitter over a period of six months, between January and June, 2011. Our goal was to collect text that is representative of American English speech, so we included only messages from authors located in the United States. Full-time non-English users were filtered out by requiring all authors to use at least 50 of the 1,000 most common words in the US sample overall (predominantly English terms).

Twitter is not comprised exclusively, or even predominantly, of individuals talking to each other: news media, corporations, celebrities and politicians also use it as a broadcast medium. Since we are especially interested in interactive language use, we further filtered our sample to only those

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5 Twitter authors may choose to make their messages private to their followers. Such messages are not available to us, and cannot appear in our dataset.
individuals who are actively engaging with their social network. Twitter contains an explicit social network in the links between individuals who have chosen to receive each other’s messages. However, a 2010 study found that only 22% of such links are reciprocal, and that their power-law distribution reveals a network in which a small number of “hubs” account for a high proportion of the total number of links (Kwak, Lee, Park, & Moon, 2010). Instead, we define a social network based on direct, mutual interactions. In Twitter, it is possible to direct a public message towards another user by prepending the @ symbol before the recipient's user name. We build an undirected network of these links. To ensure that the network is mutual and as close of a proxy to a real social network as possible, we form a link between two users only if we observe at least two mentions (one in each direction) separated by at least two weeks. This filters spam accounts, unrequited mentions (e.g., users attempting to attract the attention of celebrities), and mutual, but fleeting, interactions. For our analysis, we selected only those users with between four and 100 friends.

To assign gender to authors, we first estimated the distribution of gender over individual names using historical census information from the US Social Security Administration, taking the gender of a first name to be its majority count in the data. We only select users with first names that occur over 1,000 times in the census data (approximately 9,000 names), the most infrequent of which include “Cherylann,” “Kailin” and “Zeno.” One assumption with this strategy is that users tend to self-report their true name; while this may be true in the data overall, it certainly does not hold among all individual users. Our analysis therefore focuses on aggregate trends and not individual case studies. With all restrictions to name and the number of mutually corresponding friends and followers, the resulting dataset contains 14,464 authors and 9,212,118 tweets.

4. LEXICAL MARKERS OF GENDER
We begin with an analysis of the lexical markers of gender in our new microblog dataset. In this section, we take the standard computational approach of aggregating authors into male and female genders. We build a predictive model based on bag-of-words features, and then we identify the most salient lexical markers of each gender. The purpose here is to replicate prior work, and to set the stage for the remainder of the paper, in which we show how these standard analyses fail to capture important nuances of the relationship between language and gender.

4.1 Predicting gender from text
To quantify the strength of the relationship between gender and language in our data, we build a predictive model using a statistical classifier. We train the model on a portion of the data (the training set), and then evaluate its ability to predict the gender of the remainder of the data (the test set), where gender labels are hidden. We consider only lexical features—that is, the appearance of individual words. Some words are much stronger predictors than others, and the job of

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6 http://www.ssa.gov/oact/babynames/names.zip
the machine learning algorithm is to properly weight each word to maximize the predictive accuracy.

We apply the standard machine learning technique of logistic regression.\(^7\) The model estimates a column vector of weights \(\mathbf{w}\) to parameterize a conditional distribution over labels (gender) as 
\[
P(y | \mathbf{x}; \mathbf{w}) = \frac{1}{1 + \exp(-y \mathbf{w}' \mathbf{x})},
\]
where \(y\) is either -1 or 1, and \(\mathbf{x}\) represents a column vector of term frequencies. The weights are chosen to maximize the conditional likelihood \(P(y | \mathbf{x}; \mathbf{w})\) on a training set. To prevent overfitting of the training data, we use standard regularization, penalizing the squared Euclidean norm of the weight vector; this is equivalent to ridge regression in linear regression models. As features, we used a boolean indicator for the appearance of each of the most frequent 10,000 words in the dataset.

We evaluate the classifier using 10-fold cross-validation: the data is divided into ten folds, and ten tests are performed. In each fold, we train our model on 80\% of the data, tune the regularization parameter on 10\% (the development set), and evaluate the performance on the remaining held-out 10\%, calculating the overall accuracy as the average of all 10 tests. The accuracy in gender prediction by this method is 88.0\%. This is state of the art compared with gender prediction on similar datasets (e.g., Burger et al., 2011). The high accuracy of prediction shows that lexical features are indeed strongly predictive of gender, and justifies the use of a bag-of-words model.\(^8\) While it is possible that more expressive features might perform better still, bag-of-words features clearly capture a great deal of language's predictive power with regard to gender.

### 4.2 Identifying gender markers

The gender prediction analysis shows that the words in our social media corpus contain strong indicators of gender. Our next analysis is aimed at identifying the most salient markers, to get a sense of the linguistic profile that they reveal. This is inherently a task of division—how do we describe the ways men and women differ? Later we consider whether the phenomena identified by this contrast might be better explained by other categorizations of authors into coherent styles or personae.

We use a Bayesian approach to identify terms which are unusually frequent for one gender. Assume that each term has a corpus frequency \(f_i\), indicating the proportion of authors who use term \(i\). Now suppose that for gender \(j\), there are \(N_j\) authors, of whom \(k_{ij}\) use term \(i\). We ask whether the count \(k_{ij}\) is significantly larger than expected. When the answer is yes, the term is said to be associated with the gender \(j\) being examined.

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\(^7\) For an overview of statistical learning methods, see Hastie, Tibshirani & Friedman (2009).

\(^8\) “Bag-of-words” techniques ignore syntax and treat each individual word in a text as if it could be drawn at random out of a jumbled bag of all the words in the text. This is a standard approach in computational linguistics—it is obviously a weak model of language, but is nevertheless capable of achieving high levels of accuracy.
The standard statistical way to pose this question is to treat \( f_i \) and \( N_j \) as the parameters of a Binomial distribution, and to use the cumulative density of the distribution to evaluate the likelihood of seeing at least \( k_{ij} \) counts. We can call this likelihood \( p \), and report words for which \( p \) falls below some critical threshold.

However, the true corpus frequency \( f_i \) is not known; instead we observe corpus counts \( k_i \) and \( N \), representing the total count of word \( i \) and the total number of tokens in the corpus. We can make a point estimate of \( f_i \) from these counts if they are sufficiently large, but for rare words this estimate would have high unacceptably high variance. Instead, assuming a non-informative prior distribution over \( f_i \), the posterior distribution (conditioned on the observations \( k_i \) and \( N \)) is Beta with parameters \( k_i, N-k_i \). We can then describe the distribution of the gender-specific counts \( k_{ij} \) conditioned on the observations \( k_i, N \) and the total gender counts \( N_j \) by an integral over all possible \( f_i \). This integral defines the Beta-Binomial distribution (Gelman, Carlin, Stern, & Rubin, 2003), and has a closed-form solution. We evaluate the cumulative density function under the distribution, and mark a term as having a significant group association if \( \Pr(y \geq k_{ij} \mid N_j, k_i, N) < .05 \). Because we are making thousands of comparisons, we apply the Bonferroni correction (Dunn, 1961). Even with the correction, more than 500 terms are significantly associated with each gender; we limit our consideration to the 500 terms for each gender with the lowest \( p \)-values.

### 4.3 Comparison with previous findings

The past literature suggests that male markers will include articles, numbers, quantifiers, and technology words while female markers will include pronouns, emotion terms, more family terms, and blog or SMS-associated words like *lol* and *omg*.\(^9\) Previous research is more mixed about prepositions, swear words, and words of assent and negation. Table 1 compares these previous findings with the results obtained on our dataset.

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<thead>
<tr>
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<th>Previous literature</th>
<th>In our data</th>
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<td>Emotion terms</td>
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<td>Family terms</td>
<td>F</td>
<td>Mixed results</td>
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<td>CMC words (lol, omg)</td>
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<td>F</td>
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<td>Conjunctions</td>
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<td>F (weakly)</td>
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<td>Clitics</td>
<td>F</td>
<td>F (weakly)</td>
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<tr>
<td>Articles</td>
<td>M</td>
<td>Not significant</td>
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</tbody>
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\(^9\) See the literature review but we refer to Argamon, Koppel, Fine, & Shimoni, 2003; Argamon, Koppel, Pennebaker, & Schler, 2007; Burger, Henderson, Kim, & Zarrella, 2011; Koppel, Argamon, & Shimoni, 2002; Mukherjee & Liu, 2010; Nowson, Oberlander, & Gill, 2005; Rao, Yarowsky, Shreevats, & Gupta, 2010; Rayson, Leech, & Hodges, 1997; Schler, Koppel, Argamon, & Pennebaker, 2006.

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<tr>
<td>Quantifiers</td>
<td>M</td>
<td>Not significant</td>
</tr>
<tr>
<td>Technology words</td>
<td>M</td>
<td>M</td>
</tr>
<tr>
<td>Prepositions</td>
<td>Mixed results</td>
<td>F (weakly)</td>
</tr>
<tr>
<td>Swear words</td>
<td>Mixed results</td>
<td>M</td>
</tr>
<tr>
<td>Assent</td>
<td>Mixed results</td>
<td>Mixed results</td>
</tr>
<tr>
<td>Negation</td>
<td>Mixed results</td>
<td>Mixed results</td>
</tr>
<tr>
<td>Emoticons</td>
<td>Mixed results</td>
<td>F</td>
</tr>
<tr>
<td>Hesitation markers</td>
<td>Mixed results</td>
<td>F</td>
</tr>
</tbody>
</table>

**Table 1: Gender associations for various word categories in prior research and in our data.**

All of the pronouns detected by our Bayesian analysis as gender markers are associated with female authors: *yr, u, ur, she, she'll, her, hers, myself, herself.* Several of these terms are non-standard spellings, and might not have been detected had we employed a list of pronouns from standard English. Female markers include a relatively large number of emotion-related terms like *sad, love, glad, sick, proud, happy, scared, annoyed, excited, and jealous.* All of the emoticons that appear as gender markers are associated with female authors, including some that the prior literature found to be neutral or male: :-) :D and ;). Of the family terms that are gender markers, most are associated with female authors: *mom, mommy, moms, mom's, mama, sister, sisters, sis, daughter, aunt, auntie, grandma, kids, child, children, dad, husband, hubby, hubs.* However, *wife, wife's, bro, bruh, bros,* and *brotha* are all male markers. Computer mediated communication (CMC) terms like *lol* and *omg* appear as female markers, as do ellipses, expressive lengthening (e.g., *coooooool*), exclamation marks, question marks, and backchannel sounds like *ah, hmmm, ugh,* and *grr.*

Several of the male-associated terms are associated with either technology or sports—including several numeric “tokens” like *1-0,* which will often indicate the score of a sporting event. Swears and other taboo words are more often associated with male authors: *bullshit, damn, dick, fuck, fucking, hell, pussy, shit, shitty* are male markers; the anti-swear *darn* appears in the list as a female marker. This gendered distinction between strong swear words and mild swear words follows that seen by McEnry (2006) in the BNC. Thelwall's (2008) study of the social networking site MySpace produced more mixed results: among American young adults, men used more swears than women, but in Britain there was no gender difference.

Pure prepositions did not have strong gender associations in our data, although 2 (a male marker) is often used as a homophone for *too* and *to.* An abbreviated form of *with* appears in the female markers *w/a, w/the, w/my.* The only conjunction that appears in our list of significant gender

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10 It is not entirely clear whether one would want to include *bro, bruh, bros,* and *brotha* in a list of kinship terms. Approximations in the female markers might be *bestie, bff* and *bffs* ('best friend', 'best friend(s) forever').
markers is & associated with female authors. No auxiliary verbs display significant gender associations, except for the clitic in she’ll, also a female marker.\footnote{Tokenization was performed using an automated system designed explicitly for Twitter (O’Connor, Krieger, & Ahn, 2010). In some cases, the output of the tokenizer differs from previous standards: for example, the Penn Treebank Tokenizer, http://www.cis.upenn.edu/~treebank/tokenization.html would split she’ll into two tokens. However, standard tokenizers mishandle many frequent social media strings, such as emoticons. To our knowledge, there is no clear standard for how to treat strings such as w/\textit{my}.}

Acton’s (2011) analysis of speed dating speech finds that hesitation words are gendered, with \textit{uh}/\textit{er} appearing disproportionately in men’s speech and \textit{um} disproportionately in women’s speech. In our data, written terms like \textit{uh} and \textit{er} do not appear as significant male markers in our data. The related terms \textit{um} and \textit{umm} (along with ellipses of various lengths) are significantly associated with female authors. Words of assent and negation show mixed gender associations. \textit{Okay}, \textit{yes}, \textit{yess}, \textit{yesss}, \textit{yessss} are all female markers (as noted above, expressive lengthening also appears more frequently with women), though \textit{yessir} is a male marker. \textit{Nooo} and \textit{noooo} are female markers, but again, this may reflect the greater likelihood of women to use expressive lengthening; \textit{nah} and \textit{nobody} are male markers. \textit{Cannot} is a female marker, \textit{ain’t} is a male marker.

On the surface, these findings are generally in concert with previous research. Yet any systematization of these word-level gender differences into dimensions of standardness or expressiveness would face difficulties. The argument that female language is more expressive is supported by lengthenings like \textit{yesss} and \textit{nooo}, but swear words should also be seen as expressive, and they are generally preferred by men. The rejection of swear words by female authors may seem to indicate a greater tendency towards standard or prestige language, but this is contradicted by the CMC terms like \textit{omg} and \textit{lol}. These results point to the need for a more nuanced analysis, allowing for different types of expressiveness and multiple standards, and for multiple ways of expressing gendered identity.
4.4 Bundling predictive words into categories

The word classes defined in prior work failed to capture some of the most salient phenomena in our data, such as the tendency for men to use more proper nouns (apple’s, iphone, lebron) and for women to use non-standard spellings (vacay, yayyy, lol). We developed an alternative categorization, with the criterion that each word be unambiguously classifiable into a single category. We developed eight categories (shown below), and two of the paper's authors individually categorized each of the 10,000 most frequent terms in the corpus. The initial agreement was 90.0%; disagreements were resolved by discussion between all three authors.\(^\text{12}\)

- Named entities: proper nouns like apple’s, nba, steve, including abbreviations that refer to proper nouns, such as fb (Facebook)
- Taboo words: fuck, shit, homo
- Numbers: 2010, 3-0, 500
- Hashtags: Words that begin with the symbol #, a convention in Twitter that indicates a searchable keyword: #winning, #ff
- Punctuation: Individual punctuation marks: & , >, ?, *; does not include emoticons or multi-character strings like !!!
- Dictionary: words found in a standard dictionary and not listed as 'slang', 'vulgar', as proper nouns, or as acronyms, cute, quality, value, wish
- Other words that are pronounceable: nah, haha, lol; includes contractions written without apostrophes
- Other words that must be spelled out or described to be used in speech, including emoticons and abbreviations: omg, ;), api

The list constitutes a pipeline: each word is placed in the first matching category. For example, although #fb is a hashtag, and must be spelled out to be pronounced, it is treated as a “named entity” because that category is the highest on the list. Words that have homophones among several categories were judged by examining a set of random tweets, and the most frequent sense was used to determine the categorization. Thus while idol is a dictionary word, in a majority of uses it is a named entity (the television program American Idol) and is therefore coded as such.

Table 2 shows the counts of gender markers organized by category. Due to the large counts, all differences are statistically significant at p < 0.01. A few observations stand out: far more of the male markers are named entities, while far more of the female markers are non-standard words.

\(^{12}\)We were unable to classify three words because they were so evenly split among multiple uses: bg, oj, and homer. For example, in our Twitter data, homer refers to the cartoon character Homer Simpson as often as it refers to a home-run in baseball.
Thus it is possible to see support for the proposed high-level distinctions between female and male language: involved vs. informational, implicit vs. explicit, and contextual vs. formal. Nonetheless, we urge caution. "Involved" language is characterized by the engagement between the writer/speaker and the audience—this is why involvement is often measured by first and second person pronoun frequency (e.g., Argamon et al., 2007). Named entities describe concrete referents, and thus may be thought of as informational, rather than involved; on this view, they are not used to reveal the self or to engage with others. But many—if not most—of the named entities in our list refer to sports figures and teams, and are thus key components of identity and engagement for their fans.

<table>
<thead>
<tr>
<th></th>
<th>Female authors</th>
<th>Male authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Common words in a standard dictionary</td>
<td>74.2%</td>
<td>74.9%</td>
</tr>
<tr>
<td>Punctuation</td>
<td>14.6%</td>
<td>14.2%</td>
</tr>
<tr>
<td>Non-standard, unpronounceable words (e.g., :) , lmao)</td>
<td>4.28%</td>
<td>2.99%</td>
</tr>
<tr>
<td>Non-standard, pronounceable words (e.g., luv)</td>
<td>3.55%</td>
<td>3.35%</td>
</tr>
<tr>
<td>Named entities</td>
<td>1.94%</td>
<td>2.51%</td>
</tr>
<tr>
<td>Numbers</td>
<td>0.83%</td>
<td>0.99%</td>
</tr>
<tr>
<td>Taboo words</td>
<td>0.47%</td>
<td>0.69%</td>
</tr>
<tr>
<td>Hashtags</td>
<td>0.16%</td>
<td>0.18%</td>
</tr>
</tbody>
</table>

Table 2: Word category frequency by gender. All differences are statistically significant at $p < 0.01$.

Clearly, then, oppositions like involved vs. informational put us on delicate ground. But what of the deeper binary opposition at the core of this analysis—gender itself? In the next section, we undertake an alternative analysis which is driven by language differences without an initial categorization of authors into male and female bins.

5. Clusters of Authors

The previous section demonstrates the robustness of gender differences in social media language; these differences are so strong that a simple model using only individual words can predict the gender with 88% accuracy. This model makes no assumptions about how or why linguistic resources become predictive of each gender; it simply demonstrates a lower bound on the predictive power that those resources contain. However, the post hoc analysis—identifying lists of words that are most strongly associated with each gender—smuggles in an implicit endorsement of a direct alignment between linguistic resources and gender. This contradicts theoretical and empirical literature arguing that the relationship between language and gender can only be accurately characterized in terms of situated meanings, which construct gender through a variety of stances, styles, and personae (Eckert, 2005; Eckert & McConnell-Ginet, 2003; McConnell-Ginet, 2011; Ochs, 1992; Schiffrin, 1996).

Is it possible to build a quantitative model of the relationship between words and gender that is less reductionist? In this section, we revisit the lexical analysis with more delicate tools. Rather
than identifying relationships between words and genders directly, we identify clusters of authors who use similar lexical frequencies. We then evaluate the gender balance of those clusters. In principle, there is no requirement that the clusters have anything to do with gender; they might simply correspond to broad topics of interest, with no significant gender bias. But we find that most of the clusters are strongly skewed with respect to gender, again demonstrating the strong connection between gender and word frequencies. However, we find strong differences across clusters, even for pairs of clusters with similar gender distributions. This demonstrates that there are multiple linguistic styles which enact each gender. As we will see, the broad generalizations about word classes discussed in the previous sections hold for some author clusters, but are flouted by others.

5.1 Technical approach

Clustering is a statistical procedure for grouping instances with similar properties. In our case, we want to group authors who use similar words. We employ a probabilistic clustering algorithm, so that each cluster is associated with a probability distribution over text, and each author is placed in the cluster with the best probabilistic fit for their language. The maximum-likelihood solution is the clustering which assigns the greatest probability to all of the observed text.

We can approach the maximum-likelihood solution using the expectation-maximization (EM) algorithm (Dempster, Laird, & Rubin, 1977), which is procedurally similar to K-means clustering. Each Twitter author is assigned a distribution over clusters \( Q(z_n=k) \); each cluster has a distribution over word counts \( P(x; \beta_k) \) and a prior strength \( \theta_k \). By iterating between maximum-likelihood updates to these three quantities, we can arrive at a local optimum to the joint likelihood \( P(x, z; \beta, \theta) \). For simplicity of analysis, we perform a hard clustering—sometimes known as hard EM (Neal & Hinton 1998)—so that \( Q(z_n) \) is an indicator vector with a single non-zero element. Since the EM algorithm can find only a local maximum, we make 25 runs with randomly-generated initial values for \( Q(z_n) \), and select the iteration with the highest joint likelihood.

We apply this clustering algorithm to the social media corpus, setting the number of clusters \( K=20 \). The clusters are shown in Table 3, ordered from the highest to lowest proportion of female members (we show only clusters with at least 50 expected members). For each cluster, we show the 25 words with the highest log-odds ratio compared to the background distribution: \( \log P(\text{word} | \beta_k) - \log P(\text{word}) \). Our original dataset is 56% male, but in the clustering analysis we randomly subsample the male authors so that the gender proportions are equal.

---

13 The word distributions \( P(x; \beta_k) \) are defined by a log-linear parameterization of the multinomial distribution with a sparsity-inducing regularizer (Eisenstein, Ahmed, & Xing, 2011).
5.2 Analysis
The resulting clusters are shown in Table 3.\textsuperscript{14} Even though the clusters were built without any consideration for author gender, most have strong gender affiliations. Of the seventeen clusters shown, fourteen skew at least 60% female or male; for even the smallest reported cluster (C19, 198 authors), the chance probability of a gender skew of at least 60/40 is well below 1%. This shows that even a purely text-based division of authors yields categories that are strongly related to gender. However, the cluster-based analysis allows for multiple expressions of gender, which may reflect interactions between gender and age or race. For example, contrast the different kinds of females represented by C14 and C5, or the different kinds of males in C11 and C13; indeed, nearly every one of these clusters seems to tell a demographic story.

The highlighting in Table 3 shows reversals of gender trends. That is, it points out clusters whose behavior in a word class is the opposite of the pattern of that word class’s dominant gender. For example, women use unpronounceable words like emoticons and *lmao* at a rate of 4.28%, while men use it at a rate of 2.99%. The green cell in the “unPron” column shows a male-dominated cluster whose rate is significantly higher than 4.28% and the red cell shows a female-dominated clusters whose rate is significantly lower than 2.99%.

\textsuperscript{14} We omit three clusters with fewer than 100 authors.
<table>
<thead>
<tr>
<th>Skews...</th>
<th>size</th>
<th>%fem</th>
<th>dict</th>
<th>punc</th>
<th>unPron</th>
<th>Pron</th>
<th>NE</th>
<th>num</th>
<th>taboo</th>
<th>hash</th>
<th>TopWords</th>
</tr>
</thead>
<tbody>
<tr>
<td>c14</td>
<td>1.345</td>
<td>89.6%</td>
<td>75.58%</td>
<td>16.44%</td>
<td>3.27%</td>
<td>1.93%</td>
<td>1.66%</td>
<td>0.85%</td>
<td>0.14%</td>
<td>0.13%</td>
<td>hubs blogged bloggers giveaway @klout recipe fabric recipes blogging tweetup</td>
</tr>
<tr>
<td>c7</td>
<td>884</td>
<td>80.4%</td>
<td>73.99%</td>
<td>13.13%</td>
<td>5.27%</td>
<td>4.27%</td>
<td>1.99%</td>
<td>0.83%</td>
<td>0.37%</td>
<td>0.16%</td>
<td>kidd hubs xo =] xoxoxo muah xoxo darren scotty tyl authors pokemon hubs xd author arc xxx ^_^ bloggers d:</td>
</tr>
<tr>
<td>c6</td>
<td>661</td>
<td>80.0%</td>
<td>75.79%</td>
<td>16.35%</td>
<td>3.07%</td>
<td>2.15%</td>
<td>1.54%</td>
<td>0.70%</td>
<td>0.32%</td>
<td>0.09%</td>
<td>xo blessings :-) xoxoxo #music #love #socialmedia slash :)) xoxo</td>
</tr>
<tr>
<td>c16</td>
<td>200</td>
<td>78.0%</td>
<td>70.98%</td>
<td>14.98%</td>
<td>6.97%</td>
<td>3.45%</td>
<td>2.19%</td>
<td>0.90%</td>
<td>0.10%</td>
<td>0.43%</td>
<td>xxx :') xx tyga youu (: wbu thankyou heyy knowww</td>
</tr>
<tr>
<td>c8</td>
<td>318</td>
<td>72.3%</td>
<td>73.08%</td>
<td>9.09%</td>
<td>7.30%</td>
<td>7.06%</td>
<td>1.96%</td>
<td>0.80%</td>
<td>0.56%</td>
<td>0.15%</td>
<td></td>
</tr>
<tr>
<td>c5</td>
<td>539</td>
<td>71.1%</td>
<td>71.55%</td>
<td>14.64%</td>
<td>5.84%</td>
<td>4.29%</td>
<td>1.94%</td>
<td>0.82%</td>
<td>0.77%</td>
<td>0.16%</td>
<td>&amp;;&amp; hipster #idol #photo #lessambitiousmovies hipsters #americanidol #oscars totes #goldenglobes</td>
</tr>
<tr>
<td>c4</td>
<td>1.376</td>
<td>63.0%</td>
<td>77.09%</td>
<td>15.81%</td>
<td>1.84%</td>
<td>1.82%</td>
<td>2.02%</td>
<td>0.78%</td>
<td>0.52%</td>
<td>0.12%</td>
<td>wyd #oomf lmbo shyt bruh cuzzo #nowfollowing lls niggas finna</td>
</tr>
<tr>
<td>c9</td>
<td>458</td>
<td>60.0%</td>
<td>70.48%</td>
<td>10.49%</td>
<td>7.49%</td>
<td>7.70%</td>
<td>2.00%</td>
<td>0.89%</td>
<td>0.65%</td>
<td>0.30%</td>
<td>nods softly sighs smiles finn laughs // shrugs giggles kisses</td>
</tr>
<tr>
<td>c19</td>
<td>198</td>
<td>58.1%</td>
<td>70.25%</td>
<td>21.77%</td>
<td>3.72%</td>
<td>2.24%</td>
<td>1.28%</td>
<td>0.31%</td>
<td>0.36%</td>
<td>0.07%</td>
<td></td>
</tr>
<tr>
<td>c17</td>
<td>659</td>
<td>55.8%</td>
<td>72.30%</td>
<td>12.84%</td>
<td>4.78%</td>
<td>5.62%</td>
<td>1.82%</td>
<td>0.65%</td>
<td>1.69%</td>
<td>0.30%</td>
<td>lmfao niggas ctfu lmfaooo wyd lmaoo nigga #oomf lmaaoo lmfaoooo</td>
</tr>
<tr>
<td>c1</td>
<td>739</td>
<td>46.0%</td>
<td>75.38%</td>
<td>16.31%</td>
<td>3.15%</td>
<td>1.60%</td>
<td>2.25%</td>
<td>1.02%</td>
<td>0.11%</td>
<td>0.18%</td>
<td>qr /cc #socialmedia linkedin #photo seo webinar infographic klout</td>
</tr>
<tr>
<td>c15</td>
<td>963</td>
<td>34.7%</td>
<td>74.62%</td>
<td>15.40%</td>
<td>3.29%</td>
<td>2.42%</td>
<td>2.74%</td>
<td>1.05%</td>
<td>0.32%</td>
<td>0.17%</td>
<td>#photo /cc #fb (@ brewing #sxsw @getglue startup brewery @foursquare</td>
</tr>
<tr>
<td>c20</td>
<td>429</td>
<td>27.5%</td>
<td>75.38%</td>
<td>16.74%</td>
<td>2.09%</td>
<td>1.41%</td>
<td>3.10%</td>
<td>0.91%</td>
<td>0.23%</td>
<td>0.14%</td>
<td>gop dems senate unions conservative democrats liberal palin republican republicans</td>
</tr>
<tr>
<td>c11</td>
<td>432</td>
<td>26.2%</td>
<td>68.97%</td>
<td>8.32%</td>
<td>5.95%</td>
<td>11.16%</td>
<td>2.01%</td>
<td>0.88%</td>
<td>2.32%</td>
<td>0.38%</td>
<td>niggas wyd nigga finna shyt lls ctfu #oomf lmaoo lmaoo</td>
</tr>
<tr>
<td>c18</td>
<td>623</td>
<td>18.9%</td>
<td>77.46%</td>
<td>10.47%</td>
<td>2.75%</td>
<td>4.40%</td>
<td>2.84%</td>
<td>1.07%</td>
<td>0.82%</td>
<td>0.19%</td>
<td>@macmiller niggas flyers cena bosh pacers @wale bruh me @fucktyler</td>
</tr>
<tr>
<td>c10</td>
<td>1,865</td>
<td>14.6%</td>
<td>77.72%</td>
<td>16.17%</td>
<td>1.51%</td>
<td>1.27%</td>
<td>2.03%</td>
<td>0.89%</td>
<td>0.34%</td>
<td>0.06%</td>
<td>/cc api ios ui portal developer e3 apple's plugin developers</td>
</tr>
<tr>
<td>c13</td>
<td>761</td>
<td>10.6%</td>
<td>75.92%</td>
<td>15.12%</td>
<td>1.60%</td>
<td>1.67%</td>
<td>3.78%</td>
<td>1.44%</td>
<td>0.36%</td>
<td>0.10%</td>
<td>#nhl #bruins #mlb nhl #knicks qb @darrenrovell inning boozer jimmer</td>
</tr>
</tbody>
</table>

Table 3: Clusters, sorted by percentage of female authors, with frequencies of word classes and most distinctive words.
A key observation is that a number of the clusters directly contradict the findings about the relationship between gender and various word classes shown in Table 2. For example, at a population level we saw that women used significantly fewer dictionary words than men, and significantly more non-dictionary words (excluding named entities). Yet the most female-dominated cluster (C14, which is 90% composed of women) uses dictionary words at a significantly higher rate than men (75.6 to 74.9; the rate is 74.2 for women overall), and uses pronounceable non-dictionary words a significantly lower rate than men (1.93 to 3.35; the rate is 3.55 for women overall). An analysis of the top words associated with this cluster suggests that its members may be older (the top word, hubs, is typically used as a shortening for husband). Cluster C4 (63% women) displays similar tendencies, but also uses significantly fewer unpronounceable abbreviations (e.g., lol, omg, and emoticons) compared with men: 1.84 for the cluster, 2.99 for women overall, and 4.28 for men overall.

Among the male-dominated clusters, C11 is the clear outlier, bucking larger gender trends on dictionary words (69.0 vs. 74.2 for women and 74.9 for men overall), unpronounceable non-standard terms (5.95 to 4.28 for women, 2.99 for men overall), and pronounceable non-standard terms (11.2, by far the most of any cluster). This cluster captures features of African-American English: finna is a transcription of fixing to (just as the more standard gonna transcribes going to); the abbreviations lls and lmaoo have been previously shown to be more heavily used in messages from zip codes with high African-American populations (Eisenstein, Smith, & Xing, 2011). Interestingly, C9 also features several terms that appear to be associated with African-American English, but it displays a much lower rate of taboo terms than C11, and is composed of 60% women.

Taboo terms are generally preferred by men (0.69 to 0.47), but several male-associated clusters reverse this trend: C10, C13 C15, and C20 all use taboo terms at significantly lower rates than women overall. Of these clusters, C10 and C15 seems to suggest work-related messages from the technology and marketing spheres, where taboo language would be strongly inhibited. C13 and C18 are alternative sports-related clusters; C13 avoids taboo words and non-standard words in general, while C18 uses both at higher rates, while including the hip hop performers @macmiller, @wale and @fucktyler.

The word category whose gender association seems to generalize most reliably across all clusters is that of named entities. While there is variation in the rate at which named entities are mentioned, all of the male-associated clusters mention named entities at a higher rate than women overall, and all of the female-associated clusters mention them at a lower rate than men overall. The highest rate of named entities is found in C13, an 89% male cluster whose top words are almost exclusively composed of athletes and sports-related organizations. Similarly, C20 (72.5% male) focuses on politics, and C15 focuses on technology and marketing-related entities. While these clusters are skewed towards male authors, they still contain a sizable minority of women, and these women mention named entities at a rate comparable to the cluster as a whole—well above the average rate for men overall. Moreover, the tightly-focused subject matter of the words...
characterizing each of these clusters suggests that the topic of discourse plays a crucial role in mediating between gender and the frequent mention of named entities—just as Herring and Paolillo (2006) found genre to play a similar mediating role in blogs. In our data, men seem more likely to have and communicate about hobbies/careers that relate to large numbers of named entities, and this, rather than a generalized preference for “informativity” or “explicitness,” seems the most cogent explanation for the demonstrated male tendency to mention named entities more often.

Figure 1 shows the gender proportions of the social network ties of members of each cluster (the identification of social network ties is described in detail in the next section). Recall that authors are assigned to clusters based on using similar words; authors’ social networks come from the actual people they talk to (regardless of what clusters those people are part of). In general, the social network of an individual tracks the gender composition of the cluster they are a part of, but there are some notable outliers. C11 is 74% male, yet the social network ties of these authors are only 56% male. This is well below the linear fit, and below even its near neighbor C20, which has 72% male authors and 64% male social network ties. On the other side, C17 is 56% female, yet the social network ties are only 41% female; this is well above the proportion of male social network ties for its near neighbors C3 (57% female authors, 57% female ties) and C19 (58% female authors, 49% female ties). Interestingly, C11 and C17 share features of African American English, and the top words for C17 include the musicians Lil B and Chris Brown. This may suggest interesting differences in the social network structure among African American youth as compared with other groups, inviting further research.
5.3 Summary

In the large-scale quantitative analysis of gender, it is easy to forget that social categories are built out of individual interactions, and that the category of gender cannot be separated from other aspects of identity (see also Bourdieu, 1977; Giddens, 1984; Sewell, 1992). For example, there is a relationship between sports and gender—but is it the case that masculinity is the same for baseball fans and wrestling fans? While technology and sports clusters both skew disproportionately male, it seems unlikely that masculinity has the same meaning in each domain. These clusters suggest groups where gender may, in fact, be differently constructed. They offer sites for further investigation about how people “do” gender.

The cluster analysis reveals the danger in seemingly innocuous correlations between linguistic resources and high-level categories such as gender. If we start with the assumption that “female” and “male” are the relevant categories, then our analyses are incapable of revealing violations of this assumption. Such an approach may be adequate if the goal is simply to predict gender based on text. However, when we take the further step and begin to characterize the interaction between language and gender, it becomes a house of mirrors, which by design can only find evidence to support the underlying assumption of a binary gender opposition.
Finally, while most of the clusters are strongly gendered, none are 100% male or female. Consider authors who are part of clusters made up of 60% or more of people of the same gender. What can we say about the 1,242 men who are part of female-majority clusters, the 1,052 women who are part of male-majority clusters? These individuals may be seen as outliers or as statistical noise, because their language aligns more closely with the other gender. From the instrumentalist logic of machine learning, the best that can be said of these individuals is that they can serve as challenging cases to motivate more advanced classification algorithms. But rather than ask how we can improve our algorithms to divine the “true” gender of these so-called outliers, we might step back and ask what their linguistic choices say about their sense of gendered identity. These individuals are using language to do identity work, even as they construct identities that may be at odds with conventional notions of masculinity and femininity. And as we will see in the next section, far from being statistical noise, the language patterns of these individuals fit coherently into a larger picture of online social behavior.

6. GENDER HOMOPHILY IN SOCIAL MEDIA NETWORKS

Word counts and other corpus statistics are built out of situated, context-rich individual uses. In our microblog data, each tweet conveys a stance, which reflects the author, the topic, and the audience. Stances are constantly shifting as we talk to different people, about different things, and call up different selves to do the talking. While prior work has offered many insights on how language resources are assembled to create stances, new insights may come from the application of large-scale computational methods—if we can design methods that are flexible enough to model individual discourse situations.

As a first step in this direction, we compare the use of gendered language with the aggregate gender composition of the social networks of the individuals in our studied population. The theory of homophily—“birds of a feather flock together”—has been demonstrated to have broad application in a range of social phenomena (McPherson, Smith-Lovin, & Cook, 2001). Social media services like Facebook and Twitter make social networks explicit, and researchers have shown that it is possible to make disarmingly accurate predictions of a number of personal attributes based on the attributes of nearby individuals in the social network (e.g., Thelwall, 2009). The average social network in our dataset displays strong gender homophily: 63% of the connections are between same-gender individuals. But such aggregate social network analysis runs the same risk as correlations of word frequencies against author gender: by assuming that binary gender is the relevant category, we blind ourselves to the more nuanced ways in which notions of gender affect social and linguistic behavior.

We have seen that gender is correlated with various linguistic resources, and with social network composition (through homophily). If gender is truly a binary category, then individuals who do not employ a gender-typical linguistic style or who do not have homophilic social networks are statistical aberrations, outliers that are inevitable in any large population. But on this view, we
would not be licensed to imagine any correlation between language and social network composition, except for that which is carried by the gender category itself. In other words, women who use few female language markers should still have female-oriented social networks (and the same should hold for men). This would have consequences for predictive analysis: we would expect language and social network composition to be conditionally independent given gender, and thus, to disambiguate each other for gender prediction.

However, a more multifaceted model of gender would not be committed to viewing language and social behavior as conditionally independent. Sociolinguistic work on the relationship between language and social networks finds that individuals with a denser network of ties to their local geographical region make greater use of local speech variables (Bortoni-Ricardo, 1985; Gal, 1979; L. Milroy, 1980). We ask whether a similar phenomenon applies to gender: do individuals with a greater proportion of same-gender ties make greater use of gender-marked variables in social media? Such a finding would also have theoretical support on the level of individual interactions: both accommodation and audience design (Bell, 1984; Clark, 1996; Giles & Coupland, 1991) suggest that individuals will often modulate their language patterns to match those of their interlocutors. This literature argues for a theory of gender not as a binary category that is revealed by language; rather, gender can be indexed by various linguistic resources, but the decision about whether (and how) to use language to index gender depends on the situation and the audience.

To summarize, the binary model of gender is committed to viewing deviation from gender norms as a statistical aberration. It would therefore suggest that individuals who deviate from gender norms in language are not any less likely to have gender-homophilous social networks, and thus social network features can serve as a disambiguating cue for the prediction of gender. In contrast, multifaceted models of gender may view deviation from population-level gender patterns as part of coherent stance towards gender norms, and would thus expect correlation between the use of gendered language and the formation of gender-homophilous social network ties. Thus, conflicting theoretical accounts of the relationship between gender and language can be tied to measurable predictions about quantitative data.

6.1 Technical method

We construct an undirected social network from direct conversations in our data; the details are given in Section 3. Since the author genders can often be guessed from the first name, we can compute the gender composition of each network. We mark an individual’s local network as skewed if the gender composition would be highly unlikely to arise from a series of random draws with equal probability for each gender. Specifically, we compute the cumulative density function (CDF) of a binomial distribution \( P(y \geq l_n \mid M_n, \theta = 0.5) \), where \( M_n \) is the total number of friends of author \( n \), and \( l_n \) is the number of female (male) friends. If the cumulative density is greater than 0.95, then we regard the network as significantly gender-skewed.
6.2 Analysis
We find a strong correlation between the use of gendered language and the gender skew of social networks. The text-based gender classifier developed in Section 4.1 provides the most holistic account of the extent to which each author’s language use coheres with the population-level statistics for men and women. We correlate the output of the classifier with the gender network composition (Table 4), finding that the Pearson correlation is statistically significant for both women and men. The table shows 99% confidence intervals obtained from the Fisher transform; all confidence intervals are at most ±0.03. The more gendered an author’s language (in terms of population-level statistics), the more gendered their social network will be.

<table>
<thead>
<tr>
<th>Correlations</th>
<th>Female authors</th>
<th>Male authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>classifier vs. network composition</td>
<td>0.38 (.35 ≤ r ≤ .40)</td>
<td>0.33 (.30 ≤ r ≤ .36)</td>
</tr>
<tr>
<td>markers vs. network composition</td>
<td>0.34 (.31 ≤ r ≤ .37)</td>
<td>0.45 (.43 ≤ r ≤ .47)</td>
</tr>
</tbody>
</table>

Table 4: Pearson correlations between the gender composition of author social networks and the use of gendered language, as measured by the classifier and the proportion of gendered markers.

Figure 2 and Figure 3 present this information graphically, by binning the classifier confidence and plotting the gender composition for the authors in each bin. On average, the women in our dataset have social networks that are 58% female. However, for the decile of women whose language is most strongly marked as female by the classifier, the average network composition is 77% female. The decile of women whose language is least strongly marked as female have networks that are on average 40% female. Similarly, the average male in our dataset has a social network with is 67% male, but the extreme deciles of the social network gender distributions are 78% and 49% male respectively.
Figure 2: Male authors with male social networks are more confidently classified as male.

Figure 3: Female social networks translate into confident classification as females.

We obtain similar findings with the 1,000 lexical gender markers described in Section 4.2. For each author, we compute the total count of gender markers, and then compute the proportion that is accounted for by male markers. The female markers include more common words, so even for male authors, the average proportion of male markers is less than 50%. Individuals with more same-gender friends use a higher proportion of same-gender markers, and fewer other-gender
markers. Women with many male friends not only use more male markers than other women, they also use fewer female markers; the same holds for men.

In Figure 4 and Figure 5, we bin the authors by the proportion of their social network that is same-gender, and plot the proportion of same-gender markers. The decile of men with the most male-skewed networks use male and female markers at roughly equal rates (49% of markers are male), because the female markers include more common words. The men with the most female-skewed social networks use far more female lexical markers than male markers: only 26% of the markers they use are male. For women we find similar patterns: between 74% and 85% of the lexical markers that they use are female, increasing consistently with the proportion of women in the social network. Overall, these results paint a consistent picture, in which the use of gendered language resources parallels the gender composition of the social network.

![male authors](image)

*Figure 4: Male authors with more males in their social networks use more male markers.*
Finally, we ask whether the gender composition of an author's social network offers any new information about author gender, beyond the information carried by language (see Al Zamal, Liu, & Ruths, 2012 for a related analysis, using the text of individuals followed by the author). To measure this, we add features about the social network composition to the text-based gender classifier. The results are shown in Figure 6: classifier accuracy is on the x-axis, and the y-axis shows the effect of varying the maximum number of word tokens per author. In the limit of zero text, the accuracy with network features is 67% (corresponding to the degree of gender homophily), and the accuracy without network features is 56% (corresponding to the total proportion of authors in our dataset who are male). Network features offer some marginal information in settings where a limited amount of text is available, but their impact disappears when words are more abundant: given just 1,000 words per author, network features no longer offer any observable improvement in classification accuracy, even though the model hasn’t reached a ceiling—it is still misclassifying more than 15% of the population when given this amount of text.

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15 As described above, classification is performed using logistic regression with L2 regularization, tested in a tenfold cross-validation.
Figure 6: Gender prediction accuracy, plotted against the number of words seen per author. Social network information helps when there are few linguistic features, but in the limit it adds no new information.

If social ties and linguistic choices were both independently driven by the basic category of gender, then we would expect mutual disambiguation—the social network information should improve accuracy by correcting ambiguity in the linguistic signal. But given enough text to form an accurate picture of each author's linguistic choices, the social network features offer no further disambiguating power, because individuals who use linguistic resources from the other gender (or who do not use linguistic resources from their own gender) have consistently denser social network connections to the other gender. The gender information added by network features is largely redundant with the information in the text, and supports the interpretation that text and network composition are two views on gender as multifaceted and continuous, rather than binary and discrete.

6.3 Summary
In this section, we have examined the social and linguistic characteristics of individuals who do not follow population-level gender patterns. If gender is viewed as a binary opposition between essential categories, then these individuals can be understood only as statistical outliers. But as we have seen, they are not aberrations; rather, their behavior is part of a larger pattern in which social network ties and linguistic resources combine to create a coherent attitude towards the adoption of conventional gender norms. We examined the individuals for whom the classifier is least accurate, and found that they are the most likely to have non-homophilous social network ties. Next, we examined the individuals who have the greatest proportion of other-gender social ties, and find that they use more other-gender markers and fewer same-gender markers. Finally,
we show that the addition of social network information does not improve the gender classifier. This is because ambiguity in the use of linguistic resources is not the result of a statistical aberration, but rather, indicates individuals who have adopted a persona at odds with larger gender norms, and this persona shapes their social network connections just as it shapes their use of linguistic resources.

7. DISCUSSION

This paper presents three large-scale analyses of gender as a social variable in social media text. We begin with an approach that is rapidly becoming commonplace in computational social media analysis: we build a predictive model of the social variable, demonstrate that the model achieves high accuracy, and then perform a post hoc analysis of the predictive power of various linguistic features. In the case of gender, it is tempting to assemble results about lexical frequencies into larger narratives about very broad stylistic descriptors, such as a gendered preference for language that conveys “involvement” or “information.” By building our model from individual word counts, we avoid defining these broad descriptors from prior assumptions about which words or word classes are “contextual” or “explicit”—instead we let the data itself drive the analysis. But the same logic that leads us to question the identification of, say, all nouns as “informational” also leads us to revise our analysis of the social variable. A quantitative approach built around a binary gender opposition can only yield results which support and reproduce this underlying assumption. While the statistical relationships between word frequencies and gender categories are real, they are but one corner of a much larger space of possible results that might have been obtained had we started with a different set of assumptions.

Our subsequent analyses explore the possibilities inherent in alternative treatments of gender. By simply clustering authors into groups according to the words that they use, we obtain an alternative, more pluralistic perspective: most of the clusters demonstrate strong gender affiliations (despite the fact that gender was not built into the clustering model), but the multiplicity of male and female-associated clusters reveal that there are widely divergent linguistic enactments gender. Some clusters cohere with the population-level correlations between words and gender, but others directly contradict them. The diversity of female and male clusters suggests the interaction of gender with other social variables such as age, race, and class. This demonstrates the futility of quantitative analysis of individual social variables without at least controlling for the other constituents of personal identity. Traditional sociolinguistic research often addresses this by filtering the subject pool to include only a narrow band of demographic characteristics (for example, Labov’s emphasis on working-class urban white women in Philadelphia). But we see social me-
dia data and machine learning as presenting an opportunity for more holistic models that account for many aspects of personal identity simultaneously.\(^\text{16}\)

Finally, we relate the use of gendered language to the gender orientation of each author's social network on the social media site. Even though these social networks demonstrate strong gender homophily, the gender orientation of social network connections tracks the use of mainstream gendered markers in language: individuals who use language that is not strongly marked by mainstream gender features also have social networks that are non-homophilous, and so the social network features offers no marginal improvement to gender classification. This would be difficult to explain on a binary model of gender, but coheres well with a multifaceted model. Future work may explore the relationship of these results to audience design and accommodation theories of the influence of the social network on language use in specific sociolinguistic contexts.

The search for categories such as “male” and “female” is an attempt to reduce complexity variability into something manageable. But categories are never simply descriptive—they are normative statements that draw lines around who is included and excluded (Butler, 1999). Computational and quantitative models have often treated gender as a stable binary opposition, and in so doing, have perpetuated a discourse that treasures differences over similarities and reinforces the ideology of the status quo. Non-binary models of gender are hardly theoretical innovations. What our analysis adds is a demonstration, in large-scale quantitative terms, that reductionist models of gender are not only retrograde, but also descriptively inadequate.

Abandoning essentialism does not force us to abandon the idea that gender can be studied through quantitative methods. Rather, we see the convergence of machine learning and large social datasets as offering exciting new opportunities ways to investigate how gender is constructed, and how this construction is manifested in different situational contexts. Research in statistical machine learning has yielded a bountiful harvest of flexible modeling techniques that minimize the need for simplistic categorical assumptions and allow the data to speak for itself. These models permit exploratory analysis that reveals patterns and associations that might have been rendered invisible by less flexible hypothesis-driven analysis.

We are especially interested in quantitative models of how social variables like gender are constructed and reproduced in large numbers of individual interactions. In this paper, cluster analysis has demonstrated the existence of multiple gendered styles, stances, and personae; we hope that a more nuanced model might allow statistical reasoning on the level of individual micro-interactions, thus yielding new insights about the various settings and contexts in which gender is manifested in and constructed by language.

\(^{16}\) Notice that the ways race and age entered into the results suggest that characteristics be considered as “intersections” rather than “additions”—that is, as third wave feminists suggest, being an African American woman is more than “African American + woman”.
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REFERENCES


