TFW, DamnGina, Juvie, and Hotsie-Totsie: On the Linguistic and Social Aspects of Internet Slang

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ABSTRACT
Slang is ubiquitous on the Internet. The emergence of new social contexts like micro-blogs, question-answering forums, and social networks has enabled slang and non-standard expressions to abound on the web. Despite this, slang has been traditionally viewed as a form of non-standard language – a form of language that is not the focus of linguistic analysis and has largely been neglected.

In this work, we use UrbanDictionary to conduct the first large scale linguistic analysis of slang and its social aspects on the Internet to yield insights into this variety of language that is increasingly used all over the world online. First, we begin by computationally analyzing the phonological, morphological and syntactic properties of slang in general. We then study linguistic patterns in four specific categories of slang namely alphabetisms, blends, clippings, and reduplicatives. Our analysis reveals that slang demonstrates extra-grammatical rules of phonological and morphological formation that markedly distinguish it from the standard form shedding insight into its generative patterns. Second, we follow up by analyzing the social aspects of slang where we study subject restriction and stereotyping in slang usage. Analyzing tens of thousands of such slang words reveals that the majority of slang on the Internet belongs to two major categories: sex and drugs. Further analysis reveals that not only does slang demonstrate prevalent gender and religious stereotypes but also an increased bias where even names of persons are associated with higher sexual prejudice than one might encounter in the standard form.

In summary, our work suggests that slang exhibits linguistic properties and lexical innovation that strikingly distinguish it from the standard variety. Moreover, we note that not only is slang usage not immune to prevalent social biases and prejudices but also reflects such biases and stereotypes more intensely than the standard variety.

KEYWORDS
Natural Language Processing, Social Media Analysis, Computational Social Science

1 INTRODUCTION
The Internet is global, diverse, and dynamic, all of which are reflected in its language. One aspect of this diversity and dynamism is the abundance of slang and non-standard varieties – an aspect which has traditionally received little linguistic attention. In fact Labov [27] argues that all articles focusing on slang should be assigned to an “extra-linguistic darkness”. According to Eble [16], while the development of socio-linguistics has legitimized the study of slang, slang does not naturally fit into the controlled framework of socio-linguistics where correlations between social factors like age, gender and ethnicity with language use are studied, and is better explained through the lens of social connections (like personal kinship). In other words, slang is firmly grounded in social connections and contexts enabling “group identity”. However, the evolution of Internet and social media has radically transformed these social contexts [11, 16]. First, slang is no longer restricted to oral communication but is now widely prevalent on the Internet in written form. Second, the notion of a group associated with slang now extends to a network that is increasingly global where members are not necessarily associated by friendship or face-to-face interactions but are participants in new and evolving social contexts like forums and micro-blogs [11, 16]. Consequently, Eble [16] claims “slang is now world-wide the vocabulary of choice of young people (who compose the majority of inhabitants of the earth) and reflects their tastes in music, art, clothing and leisure time pursuits” and further argues that its study has fallen behind since it is not an integral part of socio-linguistics.

Here, we address this gap and conduct the first large scale computational analysis of slang on the Internet using UrbanDictionary, addressing both linguistic as well as social aspects.

First, we characterize linguistic patterns dominant in the formation of slang and provide supporting evidence of its distinctiveness from the standard variety not only supporting claims made by Mattiello [30] but also revealing new insights into the phonological, morphological and syntactic patterns evident in slang through a large scale quantitative analysis. Figure 1 illustrates some of these patterns. hmu is an ALPHABETISM, more specifically an INITIALISM...
for hit me up. BLENDS are formed by mixing parts of existing words. For example, loltastic is a blend of lol and fantastic. Other examples include words like netizen, infotainment, frenemy, and bootylicious. While BLENDS are formed by the mixture of two or more words, CLIPPINGS are formed by shortening the original word. stache is an example since it is a shortened form of mustache. Finally, REDUPLICATIVES, also called echo words consist of word pairs, where the first word is phonetically similar to the second word. Examples are teenie-weenie, artsy-fartsy, boo-boo, chick-flick. While these patterns are not exhaustive, they suggest that slang exhibits rich and varied linguistic formation patterns. We therefore, conduct an in-depth investigation into the phonological, morphological and syntactic properties of slang words and contrast them with the standard form yielding insights into the linguistic mechanisms at play in slang formation (see Section 3).

Second, we analyze the social aspects associated with slang. In-line with Eble [16] who claims “One of the greatest challenges to scholarship in slang is to fit slang into the current conversations going on in sociolinguistics about such topics as identity, power, community formation, stereotyping, discrimination and the like”, we investigate two social aspects of slang: (a) Subject Restriction – Slang is strongly associated with certain subjects like SEX, DRUGS or FOOD. We study this aspect by proposing a model to classify slang words into set of 10 pre-defined categories to reveal dominant subjects (b) Stereotyping – We analyze and quantify biases and stereotypes evident in slang usage and show evidence of gender stereotypes, sexual and religious prejudices – prejudices that are much more extreme in slang than those observed in the standard form (see Section 4).

In a nutshell therefore, our contributions are:

1. **Linguistic Aspects of Slang**: We analyze the phonological, morphological and syntactical properties of slang and contrast them with those found in the standard form revealing insights into patterns governing slang formation.
2. **Social Aspects of Slang**: We analyze two social aspects associated with slang: (a) Subject Restriction and (b) Stereotypes and prejudices reflected in slang usage online.

Altogether, our results shed light on both the linguistic and social aspects governing slang formation and usage on the Internet.

## 2 DATASETS

**Slang Data Set.** In discussions of slang, one controversial issue has always been its definition. Mattiello [30] notes that there are multiple views to characterize slang. One dominant view (a sociological view) adopted by [17, 36] is that it primarily enables one to identify with a specific group/cohort. Others like [38] adopt a more stylistic view and are of the opinion that slang should be categorized according to attitudes that vary from “the casual to the vulgar”. Still others emphasize the novelty of slang and characterize slang as a variety of language that is inclined towards lexical innovation [15, 34, 43]. In our work, we adopt a broad definition of slang which includes non-standard expressions (words) and emphasizes both the sociological viewpoint as well as the viewpoint of lexical innovation and novelty. We constructed a large data set of slang, by scraping the popular online slang dictionary UrbanDictionary as of July 2017. For each word, we obtain the top 10 definitions (when available) as well as their example usage and vote counts. We remove very rare words and short-lived trends by considering only instances with at-least 100 votes (weeding out rare/noisy slang like jeff’ cohoon which has no votes or short-lived trends such as Naimbia which was added after President Trump mistook it for a country). This yields a dataset of 128, 807 words and 328, 170 definitions spanning the time period 1999 – 2017 leaning towards relatively long-lived slang words rather than short-lived fads/phenomena. We note that even though Urban Dictionary was created in 1999, the majority of the words entries are introduced after 2005 which interestingly coincides with evolution of social media like Facebook and Twitter. Finally, we observed that the fraction of single word slang is slightly higher than 50%, suggesting that a significant fraction of slang consists of multiple words or phrases in contrast with standard English where almost all dictionary entries are exclusively single words or two-word phrases.

**Standard English (SE).** To contrast slang with the more standard usage of English, we consider a list of 67, 713 words released by the Dictionary Challenge [24] which consists of words and their definitions obtained from electronic resources like Webster’s, WordNet, The Collaborative International Dictionary of English and Wiktionary and pre-dominantly contains words in standard usage (including technical jargon, scientific terms etc).

## 3 LINGUISTIC ASPECTS OF SLANG

Having described our datasets, we now proceed to analyze several linguistic aspects of slang words and contrast them with those in Standard English (SE).

### 3.1 Phonology

Mattiello [29] suggests that slang incorporates broad phonological phenomena like echoisms, mis-pronunciations and assimilation. However little is known about specific phonological patterns/properties of slang where lexical innovation is so rampant. What are the phonological properties of slang and how do they differ from those of words in Standard English?

To analyze phonological properties, we obtain the phoneme representation of each word using G2PSeq2Seq [46], a neural pre-trained model for the task of grapheme (letter) to phoneme conversion trained on the CMU Pronouncing Dictionary. To illustrate, the phoneme representation for woody is W UH D IY. Each phoneme is also associated with one of the 8 articulation manners shown in Table 1.

**Are certain phonemes over-represented in slang?** To answer this question, we estimate the distribution over phonemes for words in our data-sets and rank the phonemes in descending order of their odds ratio (between slang and Standard English). Figure 2 shows the top 5 phonemes in slang that are over-represented. In particular, note the presence of phonemes like W, G and Z which are used less frequently in Standard English. Examples of slang that uses these phonemes are zazzed, zucker, pizzle, fonzie, woodie, faggot suggesting evidence of phonological variation between slang and Standard English.

\[1\] These words are also called portmanteaus.
Does slang differ in manners of articulation? Figure 3 shows the distribution of articulation manners obtained for the first and final phonemes in both slang and Standard English (SE). First, consider the distribution in the first phoneme (Figures 3a and 3b). We observe the following: (a) In slang, Fricatives as the first phoneme are more common than Vowels. We explain this by noting that several slang words use phonemes like Z in words like zucker, jizz etc.

Observations: First, note the much higher mass assigned to non-standard prefixes in Standard English account for 10% of the total mass where as the top 25 prefixes in Standard English account for 15% suggesting a rich and more varied word formation in slang. Second, note the much higher mass assigned to non-standard pre-fixes in slang like nigger, fuck, irish, man, black, ass, shit, white, cock and sex. Similar observations are noted in the case of morphological suffixes as well by noting the presence that many formations of slang have been largely ignored since they are far displaced from the regular word formation patterns and thus extra-grammatical, with only a small focus on standard word formation rules in slang [17]. Consequently, [30] claims that studying the expressive morphological characteristics of slang can shed light not only on the creative process of language formation, grammar formation but also provide insight into its semantics and sociological impact.

In line with this viewpoint, we now analyze the morphological patterns of slang. Our analysis yields insight into the morphological patterns evident in formation of different classes of slang like blends, clippings and reduplicatives.

3.2 Morphology

While morphological patterns and derivations are widely studied for standard forms of English [2, 4, 32, 41], Mattiello [30] observes

| Manner    | Phonemes               |
|-----------|------------------------|
| Stop      | B, D, G, K, P, T       |
| Fricative | DH, F, S, SH, TH, V, Z, ZH |
| Vowel     | AA, AE, AH, AO, AW, AY, EH, ER, EY, IH, IY, OW, OY, UH, UW |
| Nasal     | M, N, NG               |
| Liquid    | L, R                   |
| Affricate | CH, JH                 |
| Aspirate  | HH                     |
| Semivowel | W, Y                   |

Table 1: Manners of Articulation for phonemes as per CMUdict.

Figure 2: 5 most over-represented phonemes in slang. Note the over-representation of W, G, Z, UW and CH in slang. We explain this by noting several slang words use phonemes like Z in words like zucker, jizz etc.

Figure 3: Articulation Manners in slang and Standard English (SE). Observe significant differences for the first and final phoneme in slang when contrasted with the standard form. For example, Fricatives are more common than Vowels as the first phoneme in slang. Similarly Affricates as the first phoneme are more common in slang than in Standard English (for example: chemtard, chadzing).
of non-standard suffixes like school, man, out, girl, sex, fuck, head and ass.

**Conclusion:** Our large scale computational analysis is consistent with the observations made by [31] who notes that morphology in slang exhibits extra-grammatical rules which are not observed in word formation in standard English. Moreover, we quantitatively estimate the likelihoods of these patterns (both prefixes and suffixes) characterizing the heavy tail nature of such patterns in slang.

### 3.2.2 Slang Classes

Having analyzed morphological patterns of slang broadly, we now turn our attention to 4 specific categories of slang identified by Mattiello [31] that “exhibit underlying preferences for some underlying morphological patterns”. We describe these classes briefly and then thoroughly analyze morphological patterns for each of these classes revealing insights into their generative process.

- **Alphabetisms** are shortenings of a multi-word sequence (for eg. hmu from hit me up or TV from tranvestite). Alphabetisms can be sub-categorized into two types based on their pronunciation although the distinction may not always be clear: (a) **Acronyms** are pronounced by using the regular reading rules (for eg. dink) (b) **Initialisms** are pronounced letter by letter (for eg. BLT). While it may appear that construction of alphabetisms is very predictable, it is not necessarily the case. For example, as Mattiello [31] notes, University of the Arts London could be abbreviated as UAL or U0TAL.

- **Blends** are formed by merging parts of existing words. For example, sextini is formed by merging parts of sex and martini. Mattiello [31] observes that even though blends are ubiquitous in slang, they do not exhibit strict rules of formation but instead only show affinities for some patterns which we characterize quantitatively.

- **Clippings** are obtained by shortening a lexeme into a small number of syllables. For eg. fave is a clipping of favorite and gym is a clipping of gymnasium. Clippings can be further classified into 3 major classes depending on the portion that is being clipped: (a) **Back clipping** where the beginning of the word (lexeme) is retained (like nigg from nigger) (b) a **Fore clipping**, where the end of a word is retained (like roach from cockroach) and (c) A compound clipping (slowmo) is a clipping of a compound word (slow motion).

- **Reduplicatives** (also called echo-words or flip-flop words) are word pairs obtained by either repeating a word (boo boo) or by alternating certain vowels or consonants so that they are phonologically similar (teenie weenie).

Finally while [31] provides a manually compiled list of 1580 words belonging to each of the 4 different classes mentioned, it is important to note that these categories are not exhaustive and several slang words do not fall into any of these categories (for eg. edging).

**Morphological patterns of Slang Classes.** Here, we analyze common word patterns in (a) Blends (b) Clippings and (c) Reduplicatives, using the above gold standard dataset of 1580 words.

- **Blends** Figure 4a shows the top 5 suffixes in blends compiled by [12, 31]. Note the dominant presence of suffixes like lish, licious, tainment which yield a large number...
of blends like Hinglish, bootlicious, fergilicious, sextainment, and infotainment supporting [31] quantitatively that blends have affinities to certain suffixes.

- Clippings Figure 5b shows the fraction of each clipping type. Most clippings are Back clippings while Fore clippings are relatively rare.

- Reduplicatives Figure 6 shows preferred patterns of reduplicative formation. First, observe that reduplicatives are pre-dominantly formed by one of the following processes: (a) Duplication (DUP) like boo-boo (b) Exchanging a vowel (EX_VOW) like flip-flop and (c) Exchanging a consonant (EX_CONS) like bitsy-witsy while a small fraction of reduplicatives are formed by (d) Prefixing schm, shm (SHM) like moodle-schmoodle and (e) other patterns (UNK). Second, vowel and consonant substitutions reveal dominant preferences. i is more likely to be substituted with a and o among other letters (Figure 6b). h is much more likely to be substituted by b and p whereas t is much more likely to be substituted by w (Figures 6c and 6d). Examples are bling-blang, shick-shack, flip-flop, hurly-burly, teenie-weenie.

Conclusion In summary, our analysis reveals varied patterns of formation of blends, clippings and reduplicatives.

3.2.3 Detection of Slang Classes. Having obtained insights into linguistic patterns governing four different slang categories, we demonstrate the utility of these insights in developing a predictive model to classify slang into one of these 4 proposed categories. We evaluate our model quantitatively on a small gold-standard test set as well and apply our learned model to infer labels for a large list of words from UrbanDictionary to construct a much larger data-set to aid future qualitative and quantitative analysis.

Gold standard Dataset. We once again use the data-set of 1580 words by [31] as the gold standard data set for learning a classification model to classify slang into one of these 4 proposed categories. We create a gold standard training and test data set by a random split using 10% of the data as the test set.

Learning the model. We consider a simple Logistic Regression classifier and experiment with two sets of features:

- Character N-gram features of (length:1-5) where feature size is restricted to 200.

- Morphemes: We consider morpheme-grams (1-5) as features and restrict our feature size to 200. Given, the small amount of training data, we expect the morpheme feature set to be much sparser than the character n-gram features and therefore expect a model learned using these features to perform worse than using character n-grams.

Finally, as a baseline we consider a random model which randomly draws predictions from the training data label distribution.

Quantitative Evaluation on Gold Standard Test Set. Table 2 shows the performance of the various models on the gold standard test set. Observe that both the morpheme and the character n-gram models substantially outperform the baseline random classifier. Furthermore the model using character-n-gram features significantly outperforms the morpheme based model. This is primarily because the morpheme based feature representation is too sparse for robust estimation of the decision boundary given the small amount of annotated training data. We believe that the morpheme features will be most effective when the amount of training data is much larger, to reduce the feature sparsity of general morpheme features. Finally, Figure 7a shows a confusion matrix for the character-n-gram based model when evaluated on the gold standard test set. It is evident that the classifier does well on ALPHABETISMS, CLIPPINGS and REDUPLICATIVES but is relatively worse at identifying BLENDS. We hypothesize this is because BLENDS are much more linguistically complex than other classes like ALPHABETISMS where distinctive features are much more easier to detect.

In order to gain insight into the model that we learned using character n-grams, we examine the feature weights learned by the classifier. For ALPHABETISMS, we find distinctive features which involve periods, upper-case letters and other symbols like &, / etc. For blends we observe strings that make up blends like ny, sh etc. Similarly for CLIPPINGS we observe distinctive suffixes like ly-, ity, tie while for REDUPLICATIVES we see patterns like -, ween, win, um as well (used in words like teenie-weenie and bum bum) suggesting that our model effectively picks up on linguistic cues to effectively distinguish between the classes.

Inducing labels on the Urban Dictionary Data. As mentioned in Section 3.2.2, slang does not exhaustively fall into the four categories we considered. Consequently, naively applying our learned model on UrbanDictionary data where slang can additionally belong to multiple “unknown” classes would result in poor performance (since several words which belong to none of the 4 categories would be incorrectly assigned to one of these known categories). Observe that this is essentially the problem of open set recognition studied quite rigorously in computer vision [25, 39, 40, 42], where several methods to address this problem are available. In our work, we consider one such approach that augments the trained model with a posterior probability estimator and a decision threshold to also optionally reject an instance. Specifically, the approach consists of the following steps (see Algorithm 1). Given C, the set of known classes, and a closed set model H that outputs Pr(y|X), a probability distribution over C given a feature vector X, we want to make predictions using H on a data set D where instances could potentially belong to a unknown set of “UNKNOWN” classes in addition to C. To do this, for each instance we compute a score signifying the confidence of H in its prediction and reject the instance if this confidence is below a manually chosen threshold δ. This

![Table 2: Performance of different models on Gold Standard Test set. Note that using character n-grams demonstrates the best performance.](image)

5 Other models like SVM’s also yielded similar performance.

6 Hyper-parameter tuning was done using cross validation.

We leave other complicated approaches which might boost performance on this task using W-SVM as future work.
Algorithm 1 PredictWithReject (C, H, D, δ, F)

Input: C: Set of known classes, H: Classifier for closed set C, D: Dataset of instances from an open set. Each instance needs to be assigned a label in C or REJECTED if it belongs to none of the classes in C. δ: Reject threshold. F: Score type: NEGATIVE ENTROPY or MAXPROB.

Output: Predicted Label Assignments for each instance in D where each label l ∈ C ∪ REJECTED.

1: SCOREFUNC ← F [Initialize the scoring function to either compute the negative entropy or the maximum value of the output probability distribution.]
2: for e ∈ D do
3: Compute p the output probability distribution over C.
4: \textbf{SCORE}(w) ← \textbf{SCOREFUNC}(w)
5: \textbf{LABELS}(w) ← \textbf{arg max}_{c∈C} p
6: if \textbf{SCORE}(w) ≤ δ then
7: \textbf{LABELS}(w) ← \textbf{REJECTED} [Failed threshold so reject]
8: end if
9: end for
10: return \textbf{LABELS}

(a) Confusion Matrix - Gold (b) Confusion Matrix - 600BUD
Figure 7: Performance of our model on character n-gram model on the gold and 600BUD test sets in closed class setting. Note good performance on all classes. (ALP: Alphabetisms BLE: Blends CLI: Clippings and REDUP: Reduplicatives).

score could be (a) the maximum probability over the known classes or (b) the negative entropy of the output probability distribution.

Table 3 shows some of the top words detected by our model for each category on UrbanDictionary data. Our method effectively identifies instances of each class while also rejecting instances not belonging to four classes. We identify slang like E.V.I.L and S.P.E.W as Alphabetisms and detect Blends like IrealItalian:Irish+Italian or Obamerica:Obama+America. Similarly, our model is able to detect Clippings like Stevie (Steven), Bishie (bishounen) and Reduplicatives like hooty–hoo.

We also evaluate our model quantitatively in a closed class setting on a balanced manually created test sample of the UrbanDictionary data-set of 600 words (600BUD) over which we obtained a weighted F1-score of 86% (see Figure 7b for the confusion matrix on 600BUD). Finally, we evaluated our model in the open class setting using cross-class validation [42] which yields a mean weighted F1 score of 66.43 implying that our model generalizes reasonably well to this open set recognition setting as well.

3.3 Syntax

How do the syntactic roles in which slang words are used differ from those in Standard English? We investigate this by analyzing the part of speech (POS) roles of slang. We obtain the POS tags for slang words by using a pre-trained part of speech tagger7 on the example usages of slang. We also obtained the POS tags of words in Standard English by querying Dictionary.com. We observed that slang contains a much higher proportion of Nouns (~ 72%). In contrast, the fraction of Nouns in Standard English was ~ 50%. Further analysis reveals that about 28% of slang are used as Proper Nouns. We explain this by noting that even names of people can be used as slang (with a creatively assigned connotation, as we will see in Section 4) which is quite rare in the standard form. Examples of such words include Trumance, Angry Bill Cosby, Erik Erikson, Annabelle, Ria, Debby etc.

4 SOCIAL ASPECTS OF SLANG USAGE

According to the sociological viewpoint of defining slang [30], slang is associated with several sociological properties with perhaps the most widely accepted one being group restriction. In addition to this, slang also exhibits properties like debasement, humor, obscenity, and subject-restriction to name a few. While several scholars have studied the social aspects of slang they have been largely qualitative [14] or restricted to a very specific group [7], a quantitative large scale analysis of social aspects of Internet slang has not been addressed to the best of our knowledge. Here, we consider two such aspects: (a) Subject restriction: Slang can be associated with a particular subject. Examples of such slang are crack, junkie, acid, crystal, all related to the subject of drugs. Similarly, slang words abound in obscenity with a plethora of terms related to sex. (b) Stereotypes and Prejudices: We investigate the question of whether slang like the standard form reflects prevalent gender and religious biases/prejudices.

\[7\] We use TextBlob for inferring POS tags.
4.1 Subject Restriction in Internet Slang

UrbanDictionary categorizes slang words into one of 10 categories when possible, namely: **SEX** (eg. bathing, spear), **DRUGS** (eg. weeded, blower), **MUSIC** (eg. bridestep, tweenwave), **NAME** (eg. bat, hannah-montana), **COLLEGE** (eg. architorture), **SPORTS** (huck, poned), **INTERNET** (eg. typeractive, eracism), **RELIGION** (eg. kyke, joo2), **FOOD** (eg. grubbins, scrum) and **WORK** (eg. pixel-counting, vandy). It is to be noted that these categories are not exhaustive and once again form an open-set (there are are many slang words that belong to multiple "unknown" classes in addition to the 10 known classes). Figure 8a shows the fraction of each category using this gold standard labeled data. Observe that the top 2 categories are **SEX** and **DRUGS** suggesting the dominance of these topics in slang.

Given a small number of gold standard annotated data from UrbanDictionary, we seek to infer labels for the much larger un-annotated data-set noting that the labels are not exhaustive. As before, we learn a classifier on the supervised labeled data and extend it to handle open-set recognition using Algorithm 1.

4.1.1 Learning Slang Embeddings. To capture semantics of slang words, we learn embeddings of slang words by capturing distributional cues based on their usage in examples. To illustrate, one example usage of thizz is "thizz is NOT pure exacty.....thizz is a bunch of shitty drugs ( meth, heroin, exacty, coke, and acid if your lucky...) all mixed up and put into a pill press", which suggests that thizz is a slang that is related to **DRUGS**. We learn Skipgram [35] word embeddings of dimension $d = 100$ using negative sampling.

4.1.2 Learning the Categorization Model. Using the slang embeddings learned as features, we learn a K-nearest neighbor classifier $^8$ on the gold standard annotated dataset (we set $k=5$). To quantitatively evaluate the performance of our learned model, we manually created a labeled test set of 200 words. Our model obtained a weighted F1-score of 63.22% on this test set. In contrast, predicting a label according to the training data label distribution yields an F1-score of 13.45%. We further observed that our classifier does the best on words belonging to **SEX**, **DRUGS**, **INTERNET**, and **MUSIC** and **SEX** which are more prominent and performs quite poorly on **FOOD** and **RELIGION** which occur infrequently in slang.

Finally, we extend our model to the "open-set" recognition setting by augmenting the learned classifier with a probability threshold, using Algorithm 1 and apply our model on an additional 11000 (11K) unlabeled slang words. Table 4 shows the top words identified by our learned model for 5 categories as exemplars. Specifically, note that words like pipe, shots, herb, roll, cigs are correctly classified by our model as being related to **DRUGS**. More generally, observe that most of the words in each category are representative of their corresponding class, suggesting that our learned model is able to effectively pick up on contextual usage of the word to learn its categorization. Finally using the labels inferred by our model on these 11000 words and including the gold standard dataset we created a larger dataset. We estimated the mean proportion of each subject (at different rejection thresholds) on this larger dataset which clearly suggests that **SEX** and **DRUGS** are dominant topics in slang (see Figure 8b) consistent with our previous observation.

| Category | Word               |
|---------|--------------------|
| SEX     | fine ass, bum hole, penis, foreskin, entrails, tooth, finger, hard dick, facial hair |
| DRUGS   | pipe, shots, herb, dwayne, dead presidents, nuggs, bomb, roll, cubba, cigs |
| COLLEGE | med school, quiz, league, good boy, math, dropout, derbie, preppy, herd |
| FOOD    | pepperoni, chocolate chip, ice cream, tortilla, cake, chili, hot dog, gluten |

Table 4: Examples of Top words in 4 of the 10 categories detected by model with Algorithm 1 along with examples of words correctly rejected. Note how words like pipe, shots and herb are correctly categorized as belonging to **DRUGS** while sexual terms like entrails are correctly identified as belonging to **SEX**.

4.2 Stereotypes in Internet Slang

Recent research has shown that word embeddings learned on data (where language is standard) typically from Wikipedia and even the more formal Google News reveals gender biases and reinforces existing gender stereotypes [6, 8, 47]. Inline with these observations we investigate this in slang through the lens of slang embeddings.

Does slang reflect gender stereotypes? While traditional gender stereotypes with respect to occupations are prevalent in News and even on Wikipedia, one might posit that since the user demographics of UrbanDictionary is skewed towards younger age groups where 18 – 24 and 25 – 34 are significantly overrepresented $^9$, prevalent occupational stereotypes with respect to gender might be weaker than what one might observe in general language.

To answer this question, we follow the method outlined by [6] to quantify gender bias and stereotypes using their pre-defined humanly validated list of occupations. We applied their method to quantify direct bias (DirectBias$_d$) [6] on the slang embeddings. Ideally, if there is no gender bias, this would be 0.0. However, we notice a significant DirectBias$_d$ = 0.09 for slang embeddings (corresponding value for GoogleNews was 0.08 [6]). This suggests that slang also reflects traditional gender stereotypes at a level comparable to other standard language used in News. Finally, Figure 9 shows the extreme 5 occupations based on their projections

$^8$Other classifiers like SVM yield comparable results.

$^9$Data from Amazon Alexa.
Does slang exhibit sexual prejudice? Noting the significant proportion of sexual terms in slang, it is natural to ask the question Does slang exhibit sexual prejudices when referring to males/females?

To answer this question, we first observe that several person names are also added as slang entries (for example, female names like neelam, sangeeta, ganga, ria, annabelle and male names like vance, reuben). First, we obtain a pre-compiled list of words (not an exhaustive one) primarily associated with sexual prejudice namely slut, whore, shrew, bitch, faggot, sexy, fuck, fucked, nude, porn, cocksucker. Given a word w, we define its sexual prejudice score as the mean cosine similarity of the word embedding for w and each of the words in the above set. Specifically, we define: \[SEXPRE(w) = \frac{\sum_{c \in |L|} \text{Cosine}(w,c)}{|L|}\]. We then obtained a list of ~ 5000 slang words which are names of persons, inferred their gender (male or female) using a pre-trained model and computed their sexual prejudice score using slang embeddings. As a baseline, we also computed the corresponding sexual prejudice scores for the same set of names using the pre-trained GoogleNews word embeddings. Figure 10 shows the mean sexual prejudice score for males and females in both Slang and Google News. Observe that in both Google News and Slang, both male and female names are associated with sexual prejudices. Furthermore, sexual prejudices associated with female names is (statistically significantly) higher than male names in both sources. More interestingly, we observe that sexual prejudice associated with people names is significantly higher in Slang than in a more standard and formal domain like News. Some examples of female names which reflect such sexual prejudices in slang from UrbanDictionary which would be very unlikely in formal domains like News are (a) ria: hey tht chic is such a ria’, u’hey look...its ria!, and (b) debby: That girl is such a debby, the guys are always checking her out.

Conclusion: Similar to standard language and even formal news, slang is not immune to gender biases and stereotypes.

Does slang show religious prejudices? We now investigate the prevalence of religious prejudices in slang. First, we define two lists: (a) Religious terms a list of religious terms spanning multiple religions. These include words like sikh, muslim, islam, jews, christian, agnostic, atheist, agnostic, buddhist. (b) Prejudice terms which reflect prejudices. Examples of such words include terrorist, evil, sexy, suave and good. These lists are in no-way exhaustive but representative. Given a religious term r and a prejudice term p we compute a prejudice score for \((r,p)\) defined as the cosine similarity of \(r\) with \(p\). We standardize these scores over all religious terms for a given prejudice p. Figure 11 shows the standardized scores obtained for each of the religious terms for several prejudice terms. Note how for prejudices terrorist, and illegal, religious terms Islam, muslim, and christian have the highest scores where as buddhist and jewish have the most negative scores (see Figures 11a, 11b). Furthermore observe that for positive traits good, sexy (Figures 11c, 11d), buddhist, jewish are associated with very high positive scores while islam, agnostic, muslim are associated with extreme negative scores thus reinforcing existing stereotypes. Finally we observed the mean prejudice score over all \((r,p)\) pairs in slang was significantly greater than Google News (0.34 vs 0.16 pval<0.0001) suggesting that such prejudices manifest more extremely in slang.

Conclusion: We show that slang usage reveals prevalent religious stereotypes suggesting that slang like standard language is subject to the same biases and stereotypes prevalent in standard language.

5 RELATED WORK

Socio-variational Linguistics A large body of work studies linguistic aspects of language and its correlation with social factors like age, gender, ethnicity, and geography[3, 18–20, 28, 33, 44]. Most
of these works either study the standard form of English (in written or online social media) and do not focus primarily on slang. Mencken [33] outlines variation between American English and British English and Labov [28] studied language variation in time and geography, and outlined principles of language change. In the age of social media, Eisenstein et al. [18, 19, 20] study lexical variation in social media, propose models to detect geographic lexical variation in social media and study its diffusion across regions. Bamman et al. [3] then follow-up by studying gender identity and lexical variation in social media.

There has been little work on the linguistic and social aspects of slang with the exception being the work of Mencken [34] who studies the origin and nature of American Slang. Consequently, few dictionaries documenting slang have been compiled before the evolution of Internet and social media [9, 21]. Recently, Mattiello [30] notes and provides qualitative evidence for the extragrammatical morphological properties of slang while some works attempt to explicitly incorporate slang to improve tasks in natural language processing (like sentiment detection) especially for social media like Twitter [1, 13, 26, 37].

The works that are closest to ours are that of Dhuliawala et al. [13], Mattiello [29, 30]. Dhuliawala et al. [13] use Reddit and URbandictionary to build a lexical resource called SlangNet that captures slang semantics. Mattiello [29, 30] notes the pervasiveness of slang on the Internet, outlines the extra-grammatical nature of slang morphology and compiles a dataset of 1580 slang words. Differing from all of these works, we distinguish ourselves by explicitly focusing and analyzing slang on both aspects: linguistic and social at a large scale. We not only provide supporting quantitative evidence for observations made by Mattiello [30] but additionally conduct the first phonological, morphological and syntactical analysis of tens of thousands of slang words – revealing new linguistic insights into diverse patterns of slang generation.

**Fairness in Machine Learning** There has been a surge of research into quantifying bias and analyzing fairness of machine learning models including word embeddings [5, 6, 10, 22, 23, 48]. Among these, the most relevant works are by [5, 6] who analyze and quantify the gender bias prevalent in pre-trained word embedding models like Google News word embeddings. They also propose methods to debias such word embeddings. Our work builds on their approach where we not only quantify such bias in slang, but also reveal the presence of additional sexual and religious prejudices.

6 CONCLUSION

In this work, we conducted the first large scale analysis of slang on the Internet on both aspects: linguistic and social. Our linguistic analysis of slang, which included phonological, morphological and syntactical analysis reveals that slang exhibits linguistic properties markedly different from the standard variety. Furthermore our analysis reveals insights into generative mechanisms of four different classes of slang: ALPHABETISMS, BLENDS, CLIPPINGS and REDUPLICATIONS. We also propose a model to classify slang words into these categories yet effectively reject words which do not belong to any of these four known classes.

We also analyzed social aspects of slang pertaining to subject restriction and stereotyping. Our analysis revealed two dominant subjects of slang: SEX and DRUGS. Additionally, we showed that slang like its standard variety exhibits a non-trivial gender bias. More interestingly, our analysis reveals that both male and female names are disproportionately sexualized in slang. In general, we noted that slang is not immune to prevalent sexual and religious prejudices and in fact manifests such prejudices to a greater degree.

Our work also suggests several directions for future research. First, our analysis is restricted to slang in UrbanDictionary which mostly reflects slang usage on the Internet and as used by youth. It would be interesting to analyze slang in alternate settings like forums, micro-blogs, printed media, audio/video content as well as specific demographic groups (like senior citizens etc). Second, our insights can enable development of generative models for slang and its diffusion in social media. Thirdly, the methods outlined in our work can enable a study of slang in the multi-lingual and cross-cultural setting where slang usage and its social aspects can be quite culture specific.

Finally, we conclude by noting that our work has implications to the larger fields of Internet Linguistics and natural language processing which is increasingly being applied to non-standard language varieties so prevalent in social media.

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