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Spam, Fraud, and Bots: Improving the Integrity of Online Social Media Data

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by

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DISSERTATION

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Dedication

This dissertation is dedicated to my husband Jayson Grace,
my dogs Nala and Archimedes, and my parents.

Acknowledgments

There are many people who have helped me these past six years.

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I will never be able to fully express the level of gratitude that I feel for my mother, Maya Gokhale, and the support she has given me throughout this degree. She is the first person I call when Jayson or I have any kind of issue, and she always puts her full effort into helping us. Whether it was when I called her crying my first semester because I didn't understand what a method was in Java or when I was pushing to meet the last paper deadline of my PhD, she has always been there, confident in my abilities and ready with the dose of reality that I needed, along with the knowledge for how to solve the problem at hand. Thank you Mom, for all that you do.

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Abstract

Online data contains a wealth of information, but as with most user-generated content, it is full of noise, fraud, and automated behavior. The prevalence of "junk" and fraudulent text affects users, businesses, and researchers alike. To make matters worse, there is a lack of ground truth data for these types of text, and the appearance of the text is constantly changing as fraudsters adapt to pressures from hosting sites. **The goal of my dissertation is therefore to extract high-quality content from and identify fraudulent and automated behavior in large, complex social media datasets in the absence of ground truth data.** Specifically, in my dissertation I design a collection of data inspection, filtering, fusion, mining, and exploration algorithms to: automate data cleaning to produce usable data for mining algorithms, quantify the trustworthiness of business behavior in online e-commerce sites, and efficiently identify automated accounts in large and constantly changing social networks. The main components of this work include: noise removal, data fusion, multi-source feature generation, network exploration, and anomaly detection.

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Chapter 1

Introduction

We are currently in the age of information overload. The Internet has moved from static pages to those containing dynamic user-generated content. This gives us increased interactivity and information, but also has a downside: in the online sphere, we are deluged by junk. The rate of data creation is high, but the quality of the data is low. In a world where people can post whatever they want on virtually every web page they interact with, the result is noisy, messy, illegible, unintelligible, and at times spamming and fraudulent data. Whether through negligence or desire for monetary gain, it is hard to understand, much less trust, much of what you see online.

This lack of trust affects users, businesses, and researchers alike. Users who do not know any better receive misinformation that can affect their understanding of current events, their purchasing decisions, and their perception of the world at large. Businesses mining these data can at worst get a false view of their clientele if the data are fraudulent and at best waste time and resources trying to sift through these noisy, messy data [1][7][14]. Researchers who are trying to learn broad principles about social networks and user behavior face similar issues, both obtaining spurious results based on fraudulent behavior and spending large amounts of time cleaning the data to make it usable for their algorithms. This cleaning and sifting process is repeated over and over by different groups,

which is wasteful to an extreme degree. This problem is a severe one, and as the number of users and the amount of content they generate grow, finding quality and trustworthy content in the midst of noise becomes increasingly difficult. Furthermore, in addition to the volume and low quality of data, there often exists no ground truth with which to validate findings.

For my PhD dissertation, I designed a collection of data inspection, filtering, fusion, and mining techniques to identify and remove low quality and fraudulent content from online data. The main components of this work include: noise removal, data fusion, multi-source feature generation, network exploration, and anomaly detection. All data collected and code written for this work have been made available to the research community at large.

There are many types of online data that can take advantage of the analysis techniques that are presented in this dissertation. For the case studies in my dissertation, I focus on online review and Twitter data. These types of data contains rich text, complex user networks, and are highly longitudinal, allowing for time series analysis as well. Furthermore, unlike social media sites like Facebook, with strong privacy controls, it is relatively easy to collect a review system in its entirety, and Twitter has an API specifically designed for data collection. Furthermore, the inclusion of financial motivations for reviews and tweets, including fake reviews or check-ins to encourage patronage as well as the use of referral codes to receive monetary rewards, increases the likelihood of spamming and fraudulent behavior, making these the perfect online data sources on which to test my fraud-detection algorithms.

1.1 Noise removal

Broadly, data contamination can be viewed in two categories: noise and deliberate misrepresentation. Both of these are a hindrance to extracting value and meaning. To identify and

remove noise, we create ClearView, which is an automated data cleaning pipeline. This work is published in the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining [47] . In this work, we examine a large corpus of reviews from TripAdvisor.com[10] and the Google Play Marketplace[4]. We identify three specific types of noise in these datasets that need to be filtered out: syntactic noise (character- and word-level), semantic noise (sentence-level), and rating noise (review-level). Each type of noise presents a unique challenge.

For syntactic noise, filtering out reviews that are genuinely useless while keeping ones that are misspelled but legible is a difficult balance. The appearance of non-printable characters, the high percentage of nonsense words, and a high percentage of words from our blacklist dictionary are indicators of syntactic noise in text.

For semantic noise, we use the confidence scores produced by the Stanford Core-NLP parser[37] to identify severely malformed reviews. This approach is generalizable to any form of English text.

In fusing text and form data, disagreement between the sentiment of the review and the rating attached to the review may appear, which we denote as rating noise. To identify rating noise, we iteratively train a sentiment classifier, producing an extremely over-fitted classifier that can identify reviews whose rating does not match the sentiment of their text. This is a novel approach that we developed, and it is a way to validate labels whose precision is in doubt.

1.2 Behavioral profiling applied to fraud detection

In addition to noise, the identification and removal of fraudulent material is necessary to ensure online data integrity. Online review websites are riddled with fraudulent reviews, but the lack of ground truth makes it impossible to simply create a classifier to identify these reviews on a review-by-review basis. To solve this problem, we create TrueView, a

metric for the "trustworthiness" of a given entity's review behavior. This work, as applied to hotel reviews, was published in the 24th International World Wide Web Conference in 2015[48], and the method was officially patented in 2016[42].

Our approach to detecting fraud leverages the fusion of multiple sources to create cross-site features. Using cross-site features leads to a more thorough and comprehensive behavior profile of the entity being reviewed, leading to better support for anomaly detection. When combining data from multiple sources, disambiguating attribute values in common is a challenging problem. We developed a novel method to match hotels using latitude and longitude, with which we annotated the large hotel dataset using Google's Geocoding API, and a text comparison measure similar to length-normalized edit distance. This technique is generalizable to any data fusion task where the entities have a name and a location.

Lastly, we generated a new metric, TrueView, that identifies entities that have unusual behavior profiles both within and across sites. This score was based on an ensemble of anomaly detection algorithms, which allowed us to find entities that were anomalous in different ways. We included a global density-based measure, a local density-based measure, and a global distance-based measure. We also develop methods to validate our findings in the absence of absolute ground truth.

1.3 Efficient Adaptive Exploration of the Twitter Bot Network

In addition to businesses themselves generating fraudulent content directly, they also can create automated accounts on social media, called 'bots,' to push out sponsored or spamming content. More than a billion people use online social networks, and the presence of bots compromises the empowerment of these online social communities. An estimated 8.5% of Twitter accounts are bots [62] and the number of bots is growing at a higher rate

than the rate at which Twitter removes them. Furthermore, due to suspension pressure, Twitter bots are constantly changing their behavior to evade detection, which renders traditional supervised methods ineffective.

To address this problem, we create BotWalk, a near-real time unsupervised adaptive Twitter exploration framework. This work is arguably the first to employ an unsupervised approach to intelligently explore the Twitter network and identify bots exhibiting novel behavior, and will be published at the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining.

Key contributions of this work are the implementation of an adaptive approach to feature selection and the utilization of domain knowledge to intelligently partition the feature space, which leads to up to a 30% increase in precision. We perform experiments to evaluate the performance of an ensemble of outlier detection algorithms, achieving an precision of 90%. We also perform three levels of iterative exploration and show that we are able to identify bots that exhibit different behavior than the seed users at a higher detection rate than existing methods.

1.4 Roadmap

This dissertation proceeds as follows: Chapter 2 describes techniques to remove noise from online review data (ASONAM 2016), Chapter 3 discusses data fusion, feature extraction, and anomaly detection in online review data (WWW 2015), Chapter 4 discusses network exploration and adaptive bot detection in a huge and rapidly changing network (ASONAM 2017), and Chapter 5 concludes the work.

Chapter 2

ClearView: Cleaning Noisy and Spamming Reviews

2.1 Introduction

Online reviews form a unique source of unbiased information about products and services for consumers, manufacturers, distributors, and sellers. Online reviews have been analyzed and mined for over a decade to extract useful knowledge such as opportunities to improve services [14] and business planning [7]. Hosting sites have also evolved to collect various forms of information from mass consumers, such as star ratings, review text, and helpfulness ratings.

Online reviews are typically noisy and contain many types of abnormalities. In Figure 2.1, we show a set of noisy reviews that contain no informative content. The top row shows a set of un-intelligible reviews where meaningless sequences of English characters are posted as legitimate reviews in the Google Play Marketplace. It also shows a review in Russian, which, while valid content, is not meaningful to English-speaking audiences. The second row shows repeated text, inconsistently rated reviews in which the sentiment

in the text is the opposite of the rating, and a review containing promotional content and non-Unicode characters masquerading as standard English characters.

Noisy reviews appear in almost every kind of hosting system, including tourism, e-commerce[10], real-estate[15], and mobile apps[4]. Surprisingly, there is no formal cleaning process for online reviews that can be generically applied before presenting them to consumers or mining them for knowledge discovery. The absence of clean reviews may lead to *flawed* marketing strategies[1] and *lack of trust* in customers[48].

In this chapter, we discuss various types of abnormalities that exist in different review sites and develop filtering techniques to clean them. Our methods use natural language processing (NLP) parsers and classifiers targeting three kinds of noise. To evaluate the efficacy of our cleaning process, we conduct a user study and find that our pipeline improves the quality of the dataset by up to 3.4 times. We also examine the distributions of features that have been shown to identify abnormal and fraudulent behavior in online review hosting sites[48]. We show that our cleaning technique standardizes these feature distributions and improves the quality of the reviews for knowledge discovery processes.

2.2 Background

Online reviews for products and services are written by consumers with the intention of helping people make informed decisions when making a purchase. Natural variations in reviews occur because of the diverse backgrounds of the writers. However, fake reviews, incentivized reviews, and revengeful reviews introduce unique anomalous variations.

We identify three major types of variations that appear in almost all review datasets. We describe the categories below.

Syntactic Noise Reviewers often make syntactic errors. For example, misspelled words, nonsense words, and slang are commonly used in the review space. Another example

Figure 2.1: (top row) Unintelligible reviews. (second row) Repeated text, spamming content, and non-English reviews (third row) Positive rating with negative text (bottom row) Negative rating with positive text

is using non-standard characters to write English words, with the intention of defeating content-based filtering (see Section 2.4).

Semantic Noise Reviewers often write incorrect sentences that are not intelligible. Such reviews can be the result of automated text completion during typing, or can simply be due to the negligence of the reviewer.

Rating Noise Sometimes the review text consists of well-formed, meaningful sentences, but the star-rating accompanying the text does not match the text sentiment. Such reviews are confusing for the reader and not trustworthy. Furthermore, using the rating as a feature or label in a data mining algorithm for reviews with this type of noise would lead to erroneous results.

We develop detection and filtering techniques for each type of noise.

2.3 Related Work

Current research on online reviews can broadly be classified based on methodology and application. Researchers have developed topic discovery [46] and sentiment classification [56] methods from review text. Connecting users, products and reviews in an information network is another promising method to analyze reviews [18]. Researchers have applied these methods for fraud detection [50] and recommending products [46].

Current text-cleaning pipelines tend to be limited and interactive [39]. They are designed to prepare text for use in single algorithm specified by a data analyst, rather than for general use. Existing data cleaning pipelines are created in an iterative [34] rather than fully automated way. Thus, our method is arguably the first attempt to automatically filter and normalize noisy and useless reviews.

2.4 Syntactic Cleaning

We perform two types of syntactic cleaning: character-level cleaning and word-level cleaning.

Character-level cleaning When examining samples of Google Play reviews, we find many reviews that contain non-Unicode characters masquerading as normal text. We believe that this is done in an attempt to evade keyword filters which are used to detect spammers. For example, in the reviews for the app Key Ring: Cards Coupon & Sales, a user left the review shown in Figure 2.1, bottom right. Although it looks normal in the Google Play site, when the text is processed by the LaTeX compiler it reads: "`Cool ! Also try "WILD WLL" - Mon Online!  Downld "Wild Wllt" Right Now!`

`Do not forget to ntr  nus d:  1050157`." This is because the review contains many words that are hiding non-Unicode characters. These are words that a filter may be looking for because they indicate a spamming behavior: *money, wallet, code, bonus, enter,* and *app*. This user has left 11 other reviews with this same signature. We catch such reviews by checking if the characters in the review are printable, which is defined as digits, letters, punctuation, and whitespace. If the percentage of such non-printable characters (including non-English characters) is above a tunable threshold, we view the review as not informative and filter out the review. Using a strict threshold value removes a large number of syntactically unusable reviews.

Word-level cleaning At the word level, we check for black-listed keywords, abnormal repetitions, and meaningless words. There are only a few valid reasons to have a long sequence of alpha-numerals in a review. Reviewers may identify the price, model, and feature of a product in their review to describe their experience. However, such alpha numerals are also a sign of abusive reviews. For example, personal ID or code for referral rewards and promotions are advertised via reviews, e.g. `Please enter my code 8zl12j to help us both get rewards!` We filter such reviews by identifying the percentage of words that are in a set of black-listed keywords we compiled. This black-list contains words that most often represent abusive behavior, for example, `promo-code`, `invitation code`, and `HTTP`, among many others.

We also check for abnormal repetition of a word or phrase. Some reviewers just copy and paste words such as `good`, `great`, and `nice` many times. Such reviews contain very little information compared to the length of the review.

Another type of useless review we see is reviews comprised mainly of nonsense words. There are many ways meaningless words are written. Sometimes authors use English letters to write another language, which, while obviously containing meaning, is not informative for English-only reader or a natural-language processing algorithm. Authors also invent spellings, such as the use of `nyc` to represent the word `nice`, the use of `gr8`

to represent the word `great`, and so on. Reviews that primarily consist of such words contain little-to-no usable information about the product, especially from a text analysis perspective. Using the *Enchant* library from Python, we identify the percentage of words in the sentence that are in its large corpus of English words. Since reviews often contain misspelled words or colloquial words not in this corpus, we set a threshold for our filter: if less than a threshold of the words in a review are in this corpus, then the review is filtered out. This threshold is a tunable parameter that can be set depending on the end usage of the text: sentiment classification needs a high threshold, compared to robust clustering which requires a lower threshold. We find that the Google Play dataset contains a much greater percentage of reviews with syntactic errors than the TripAdvisor dataset. A threshold of 90% correctness works well for TripAdvisor reviews, but is much too strict for Google Play reviews. We find that a threshold of 50% is more appropriate for these. Table 2.1 shows the results from this part of the pipeline.

	Full Dataset	Non-Printable Percent	Misspelled Percent	Final Count
TripAdvisor, 90% threshold	3,167,036	0.32%	24.4%	2,292,761
Google Play, 90% threshold	21,112,036	26.85%	69.99%	653,866
Google Play, 50% threshold	21,112,036	26.85%	22.15%	10,754,606

Table 2.1: Results of syntax filtering process.

2.5 Semantic Cleaning

To identify nonsensical reviews, we analyze the semantic structure of the sentences in a review. We use the Stanford CoreNLP Parser[37] to label words with part-of-speech tags and to parse sentences into tree structures. We use the confidence score of the parser as a

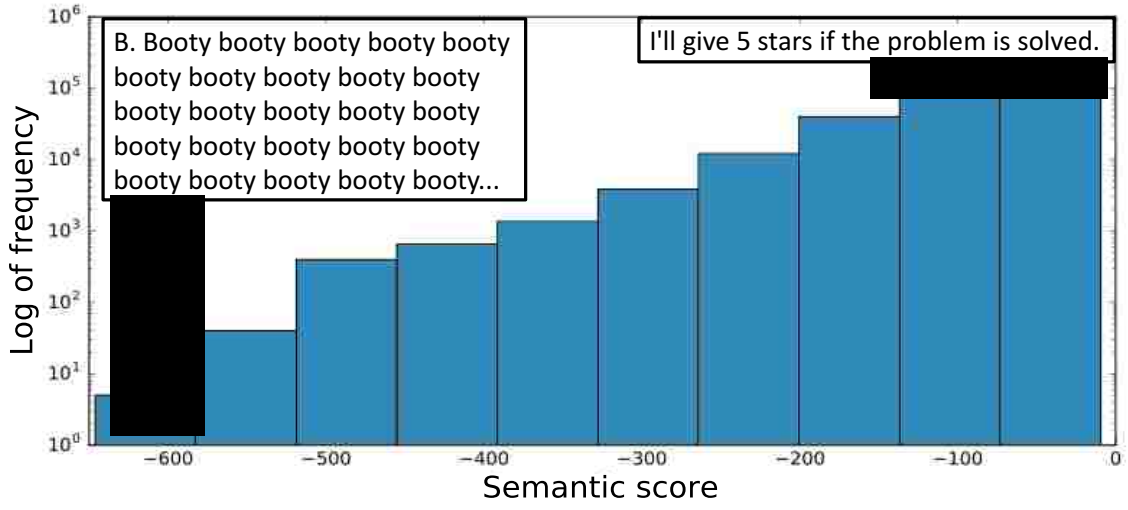


Figure 2.2: The distribution of semantic scores.

measure of the semantic correctness of a sentence. The lower the score, the less likely that the sentence is valid. For example, for the first review in Figure 2.1, the second sentence contains mostly valid words but does not make any sense: "`From me our toward u eyes on me owned yourself to him but needed not known seems burl.`" The tree generated for this sentence is: From/IN me/PRP our/PRP toward/IN u/NN eyes/NNS on/IN me/PRP owned/VBN yourself/PRP to/TO him/PRP but/CC needed /VBN not/RB known/VBN seems/VBZ burl/JJ ./. and the score is -174.3. If we compare this with a sentence found in many reviews: "I highly recommend it.", we get a much higher score of -33.9 because the tree is forms is highly probable: I/PRP highly/RB recommend/VBP it/PRP ./. In Figure 2.2, we show the distribution of scores of the sentences of all reviews. Note the log scale in the y-axis.

2.6 Rating Cleaning

The second row of Figure 2.1 shows reviews in which the sentiment of the text does not match the rating.

We develop a method to clean such reviews by using an ensemble of sentiment classifiers. We use the sentiment classifiers to iteratively label the sentiment of the reviews to obtain the maximal agreement with the user-given ratings. When a writer and the classifiers agree on the sentiment, the review is more likely to be high quality. However, when they mismatch, it can be either writer error or classifier error. For cleaning purposes, precision is more important than recall rate. Hence, we remain strict on absolute consensus.

2.6.1 Classifiers

The first classifier, Stanford's Sentiment Classifier in the CoreNLP suite [44][61], is widely acknowledged to be a top-performing sentiment classifier. This recursive neural tensor net classifier stores sentences in a parsed tree format, rather than the typical bag-of-words approach. This allows the classifier to take the sentence structure into account when classifying sentiment. While this approach is thorough, it is also quite slow, requiring weeks to train and classify our full datasets.

The second classifier we use is based on [52]. This classifier is a simple Naive Bayes classifier that is smart enough to handle both negation and double negation, and adds a negated form of the word to the opposing class's word bank (e.g. if "good" occurs in a review with a positive label, it adds "not_good" to the negative class). This algorithm also uses bigrams and trigrams in addition to unigrams to further improve performance. Lastly, low-occurring words are pruned at the end of every training round.

We added in the capability for 5-class classification and iterative training to both of these classifiers, as well as input and output pipelines including customizable performance

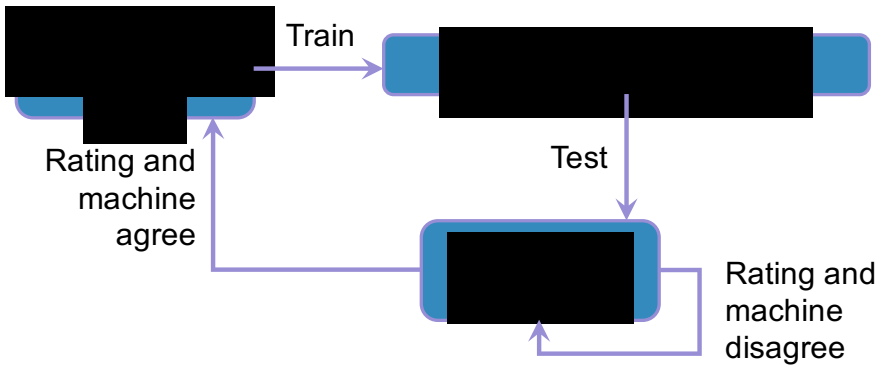


Figure 2.3: Starting with the Sentiment tree bank we will append training data where human and the classifier agree and continue until convergence. Arrows represent flow of review data.

visualizations. Note that both of the classifiers rate individual sentences; we aggregate the ratings to calculate one score for a review that may contain many sentences based on the sentence scores normalized by the sentence lengths.

2.6.2 Iterative Training

The process starts with a classifier trained on the Standard Tree Bank[60]. This tree bank contains more than 11,000 sentences from movie reviews on RottenTomatoes.com. 215,000 individual phrases of these sentences were manually labeled from "Very Negative" to "Very Positive." We train a classifier on these data and then generate sentiment labels for our reviews using this classifier. We then form a training set of reviews whose sentiment scores match the user-given ratings. Reviews whose sentiment scores do not match their ratings form the new test set. To improve the classifier, we then train the current classifier using the new training set and evaluate its performance on the new test set. We continue this process iteratively, adding matched reviews to the training set at every iteration. When the process converges, we have an extremely *overfitted* sentiment classifier that has almost memorized the noisy set, excluding the reviews remaining in the test

set. The leftover test set is more likely to contain erroneous cases, as even an overfitted classifier has failed to classify its members correctly.

We overfit two classifiers using the above process and filter out any reviews that have a single disagreement between the sentiment labels and the user-given rating.

2.7 Experimental Analysis

2.7.1 Data Description

Two datasets were used for the experiments described in this section. The first dataset consists of reviews from TripAdvisor.com. We collected all the reviews and associated information for almost all of the US hotels on this site. For the second dataset, we collected reviews and their associated information from nearly all of the applications in the Google Play Store. A summary of the whole dataset is given in Table 2.2.

	TripAdvisor.com	Google Play Store
Number of reviews	11,275,833	50,358,932
Number of Hotels or Apps	52,696	1,057,497
Number of users	1,462,460	23,575,301
Average number of reviews	213.98	47.62
Average rating	3.35	3.80
Date range	09-30-2009 - 05-17-2014	06-2014 - 07-2014

Table 2.2: Summary of the datasets.

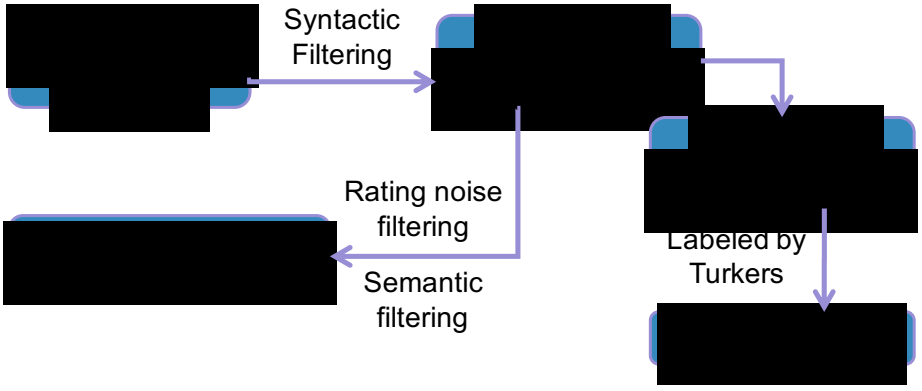


Figure 2.4: Overall experimental design.

2.7.2 User Study

We run these datasets through the ClearView pipeline and filter out 874,275 malformed reviews from the TripAdvisor dataset and 10,357,430 from the Google Play dataset. We then perform semantic filtering and rating validation for a randomly selected subset of 60,000 reviews from each of our filtered datasets.

We also randomly select 10,000 reviews from each subset to evaluate in our user study. For this study, we use the Amazon Mechanical Turk Marketplace to have readers evaluate the sentiment of 10,000 reviews from each dataset. We require three different Turkers to score each review and average these scores. The annotators can pick a score from 1-5, just like the ratings on review websites, and we provide text examples for each rating classification to standardize the scoring process.

2.7.3 Rating Noise Filtering Results

This user study allows us to both validate the performance of the sentiment classifier and the filtering process as whole. Figure 2.5 shows the convergence of the sentiment classifiers over 20 training rounds for the TripAdvisor dataset. Note that the Naive Bayes

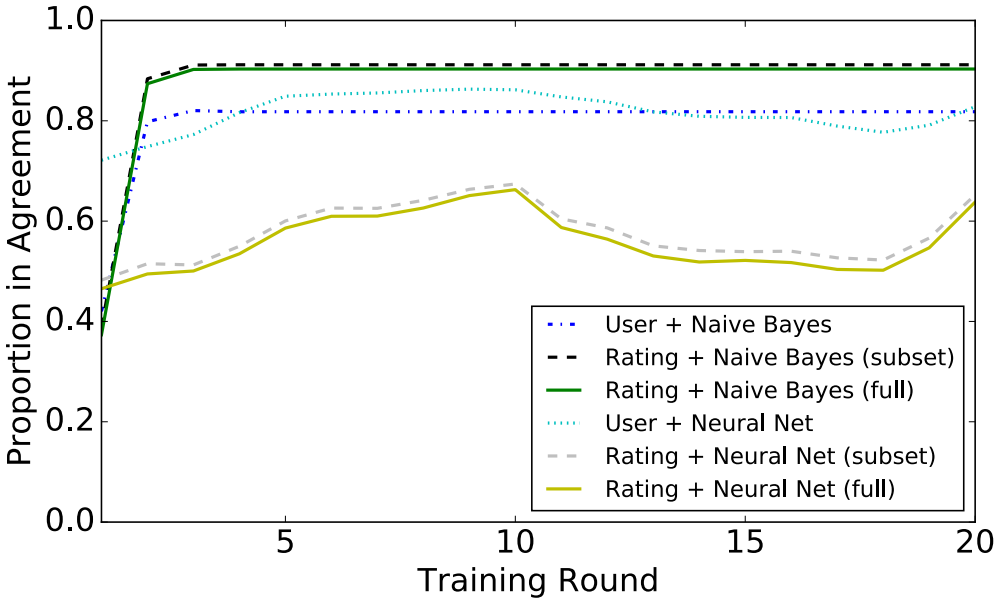


Figure 2.5: Iterative training results for TripAdvisor

classifier starts out with lower precision but surpasses the performance of the neural net classifier after a few training iterations. Furthermore, the entire 20 rounds ran in a few minutes for this Naive Bayes classifier, as opposed to days for the neural net. We find that Google Play reviews are much more difficult to properly classify. They contain many more colloquialisms than the TripAdvisor reviews and have less consistent structure. Table 2.3 shows some examples of rating noise identified using this filtering process. We find that many of these examples have to do with some kind of app update or change in the entity being reviewed. Thus, this method could potentially be utilized by app developers to find reviews describing update issues. This would help them to more quickly assist with remediation of the issue and could lead to an increase in customer satisfaction.

Review	Writer	Turker	NLP
I cant log in...i try to update the game but i still cant log in. please fix this bug.	5	1	1.67
beautiful view of the lake and really enjoyed sitting on our private balcony. free wifi and no problems...	1	4	4.19
Loving it. Not too long ago i mention to the developers that the game was crashing out on my galaxy note 2 it seems like they fixed it so now i'm playing the game again thank you.	3	4.33	5
Back to a 5 star status. Plus a cookie for devs who care about their product. my s5 went back to the store for fixing and during this process they performed a factory reset. i don't have the issue anymore and can't replicate the previous issue either so i am back to a happy customer!	1	4	5
Try star girl. You guys won't get disappointed trust me has beautiful clothes. you can join in contest once you reach level 5. i've been playing celebrity story trust me i'm at level 7 there's not even a contest. try out star girl.	2	4	5
I cant log in. One month ago i can log in and play. but now it says authentication failed. i try to update the game but i still cant log in. please fix this bug.	5	1.67	1
I cant play the game. Is anybody know how to fix it and i will appriciate it if somebody could let me know how to fix it thank you for the attention and maybe you need space for the game in internal storage.	3	1.67	1
Latest update keeps crashing. This is annoying especially when im trying to make use of the mobile coupon and the app keeps crashing when i want to make payment. this causes multiple payments deducted from my account but not captured on the system.	3	1.67	1
Game hanging. Remove the halloween update. the game is hanging a lot. and the bike is going in slow motion.	5	2	1
Crashes without reason. I've gotten a new phone yesterday and immediately installed this. today it's begun to crash multiple times even though i've closed all other apps. it'd be nice if you fixed this. otherwise a very good game. i love the animations!	4	2	1

Table 2.3: Sample of reviews identified as inconsistent through iterative sentiment classification.

2.7.4 Results of Overall Pipeline

	Full Dataset	Percent Filtered	Agreement Before Filtering	Agreement After Filtering
TripAdvisor	3,167,036	30%	17.7%	59.9%
Google Play	21,112,036	70%	18.7%	36.9%

Table 2.4: Results of the ClearView pipeline for the TripAdvisor and Google Play datasets.

Table 2.4 shows the results of the ClearView filtering pipeline as a whole. We use the agreement between the rating of the review and the averaged sentiment score from the user study as a measure of the quality of the review. If a review is nonsensical, then it is unlikely that the Turkers' sentiment score would agree with the review's rating. Therefore an increase in 'agreement' signifies an increase in quality of the dataset. TripAdvisor agreement increases from 17.7% to 59.9%, which is an over three times increase. Furthermore, only 30% of the reviews were filtered, which is a reasonable level. Google Play agreement increases from 18.7% to 36.9%, which is a two times increase. Considering the highly noisy nature of app reviews, this represents a significant improvement. However, 70% of the dataset had to be filtered out to achieve this improvement. This suggests that for text typed on mobile phones, filtering individual sentences on a review level may be more effective than filtering whole reviews.

Figures 2.6, 2.7, and 2.8 show feature distributions before and after filtering. These features were shown in [48] to be effective in characterizing anomalous hotels on three different online review websites. In all three subfigures, filtering either reduces the skewness of the distribution or removes an abnormal bump, even though there was no specific filtering done on title/ review length or rating.

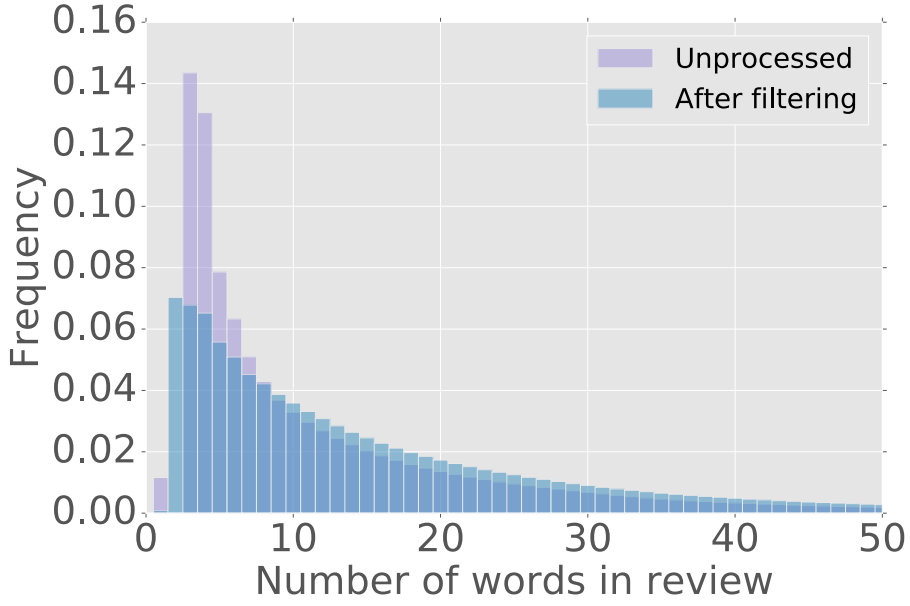


Figure 2.6: Distribution of the number of words in Google Play reviews before and after filtering.

2.7.5 Sensitivity and Scalability

Sensitivity In the ClearView pipeline we have several thresholds that can be set depending on the needs of the user. The percentage of non-printable characters, blacklisted words, and misspelled words, as well as the minimum semantic score, can all be set separately, allowing for customization of this pipeline depending on the desired end-use of the data.

Scalability The Stanford sentiment classifier is unusable for the large set of reviews we consider. For example, our training data consisted of a collection of 1.75GB for the TripAdvisor dataset and 6.62GB for the Google Play dataset. Processing such data using a single classification process would take on the order of days.

To calibrate the runtime of a single iteration, we run the entire workload on a single "fat" server with 2TB memory, 120 hyperthreaded Xeon E7-4870 1.2GHz cores. Both input and output files were accessed in tmpfs[59], making all file I/O in-memory. We use

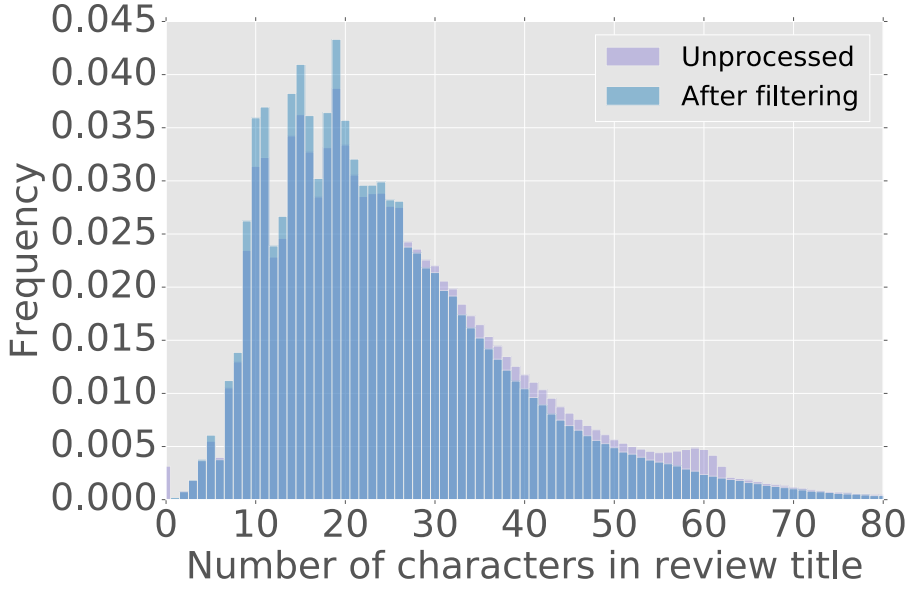


Figure 2.7: Distribution of the number of characters in TripAdvisor titles before and after filtering.

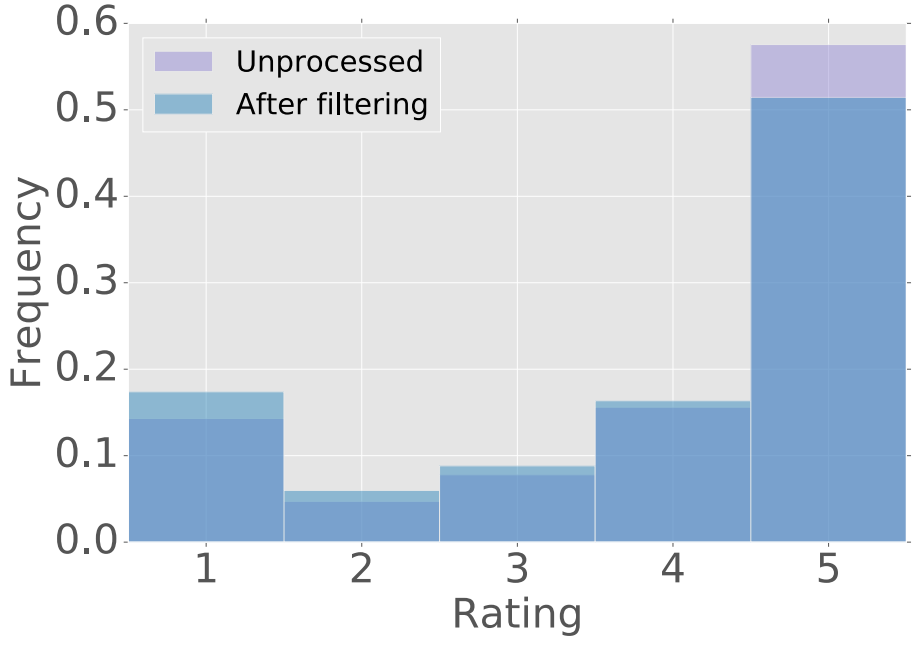


Figure 2.8: Rating distributions of Google Play reviews before and after filtering

a taskbag model in which a pool of compute server processes (i.e. workers) iteratively fetches and executes work from the taskbag. The workers invoke the Stanford NLP sentiment classifier with preset parameters and input/output file names tagged with the id of the fetched task. The whole job is self load-balancing and the task dispatch algorithm was written in 200 lines of *Go* code. One iteration to classify the review set with this highly optimized setup takes 30 hours, showing that implementation on a single laptop is clearly infeasible for this classifier.

2.8 Conclusion

In this chapter, we presented ClearView, an automated data cleaning pipeline. We discussed various types of abnormalities that exist in different review sites and developed filtering techniques to identify and remove them. We evaluated the performance of our pipeline through an in-depth user study and found that our pipeline improves the quality of the dataset by up to 3.4 times. We also examined the distributions of significant features and found that our cleaning technique standardized these feature distributions. These evaluations show that ClearView is an effective first step in the cleaning of review data in preparation for a variety of data mining algorithms.

Chapter 3

TrueView: Ranking Hotels Based on Trustworthiness

3.1 Introduction

Online reviews on products and services can be very useful for customers, affecting many aspects of our day-to-day life (where to eat, what to buy, what to watch, where to travel). These reviews provide an unprecedented mechanism for current customers to share information with potential customers. However, review hosting sites can suffer from fraudulent behavior, generated by "biased" users or the product providers themselves. So far, most studies have focused on analyzing online reviews from a single hosting site. The key question of this chapter is: how could one leverage information from multiple review hosting sites to detect fraud?

Currently, the existence of multiple review sites can add to the confusion of the user. Each of these sites may give a different view of a hotel, and it can be difficult for the consumer to know whom to trust. We focus on reviews of hotels for reasons we discuss below, and we frame the problem as follows: we are given several review sites that review

a set of partially overlapping hotels. The reviews typically include a score, user comments, time of review and possibly a user-id. The required output is a trustworthiness score for the reviews of a hotel that take into consideration the reviews from each site. We use the term **suspicious hotel** to refer to hotels whose reviews seem to have been manipulated, e.g. padded with fake reviews. Note that we only focus on trustworthiness and not the relevance of reviews for a particular user, e.g. whether a hotel is a pet-friendly, which is an important but distinct problem.

We focus on hotel reviews for a combination of reasons. First, the hospitality industry exhibits relative stability and consistency. Proximity to the beach does not change, unlike product properties which quickly lose their attractiveness, let alone that the products themselves may be replaced altogether by newer models. Second, hotel properties provide some structure and ubiquitousness. Hotels are consistently evaluated on a relatively limited number of factors (cleanliness, service, location, noise, comfort) as opposed to say electronic goods which can vary significantly depending on the interests and intent of the user (e.g. think digital cameras, or TVs). Our work could easily be expanded to reviews of other "well-defined and persistent" services, such as restaurants. Thus, our overall framework and fundamental functions are a great starting point for expanding our work to other commercial sectors, even if some sector-specific adjustments are required.

Most previous work so far has focused on analyzing a single review site, and typically, focus on temporal [29], textual [63], behavioral [51], distributional [30] and graphical features [18] to detect fraudulent reviews. In section 3.2, we discuss the existing work in more detail.

As our key contribution, we develop a systematic methodology to analyze, compare, and synthesize reviews from multiple review sites. First, we introduce and evaluate features that capture cross-site discrepancies effectively. Second, we conduct arguably the first extensive study of cross-site discrepancies using real data. Third, we provide the **TrueView score**, a non-trivial synthesis of multi-site reviews, that assesses the trustworthiness of a group of reviews. We provide TrueView as a proof of concept that cross-site

analysis can significantly improve the information that the user sees. In our study, we use more than 15M reviews from more than 3.5M users spanning three prominent travel sites, TripAdvisor, Hotels.com, Booking.com.

We highlight our contributions and key results below.

a. A systematic approach to cross-site review evaluation using behavioral features. We propose a comprehensive methodology for comparing and synthesizing reviews from different sites. We use 142 features that go beyond simple rating analysis to consider a set of behavioral and contextual features including review-centric, reviewer-centric, and hotel-centric features. Our features capture temporal, spatial, behavioral, and graph-based characteristics, which provides a multi-faceted view of the reviewing process of a hotel. A key feature of the work is that we evaluate the trustworthiness of the overall hotel in one site using **cross-site features** leveraging information from the other sites. We find that using cross-site features significantly increases the number of suspicious hotels that we find in our experiments.

b. An extensive study of cross-site review differences. We apply our approach to our 15M reviews spanning three sites. As a necessary step, we develop an automated method to match hotel identities across different sites, which is a non-trivial problem. Our study provides several interesting observations:

1. Our identity-matching method matches hotels with 93% precision which we validate manually. This method could be of independent interest even outside the scope of this work.

2. There are big differences in the overall score of a hotel across different sites. We find that 10.4% of common hotels from Booking.com and TripAdvisor.com and 9.3% from Hotels.com and TripAdvisor.com, exhibit significantly different rating characteristics, which is often a sign of suspicious behavior.

3. Using multiple sites can help us detect 7 times more suspicious hotels than the union

of suspicious hotels found for each site in isolation.

c. Developing a cross-site scoring system: TrueView. We develop the TrueView score as a proof-of-concept that leveraging multiple sites can be very informative and change our assessment of the hotels significantly. TrueView is a sophisticated score, combining: (a) temporal, contextual, and behavioral features from each site, and (b) cross-site features across the sites. By applying our algorithm, we find that 20% of all hotels appearing in all three sites have a low trustworthiness score (TrueView score less than 0.75). Although there may be better ways to combine cross-site reviews, we argue that TrueView already demonstrates the potential of such an approach.

Our work in perspective. Our work is arguably the first effort that focuses on the synthesis of reviews from different sites. Our goal is to raise the awareness of the opportunity and the challenges related to this problem. At the same time, our approach provides a foundation for follow up studies in the following directions: (a) detection of fraudulent behaviors, (b) assessing the trustworthiness of review sites, since some may have policies that enable misbehavior, and (c) creating effective review aggregation solutions. Ultimately, the collective wisdom of the users is valuable and empowering, and we would like to protect this from fraudulent behaviors.

3.2 Related Work

Existing works focus on identifying fraud reviews and reviewers, while we focus on businesses such as hotels that promote fraudulent reviews. Existing work can be categorized based on the methodologies they adopt to detect frauds. Fraud detection using Graphical/Network structure is studied in [18][21][67] where authors exploit network effects and clique structures among reviewers and products to identify fraud. Text-based detection of fraud is studied to spot a fake review without having the context of the reviewer and reviewed product in [54][35][63]. Temporal patterns, such as bursts, have been identified

as fraudulent behavior of businesses [69][29].

There has been work on joining multiple criteria from single sources to better detect fraud [68]. Various types of fraud have been identified in the literature: groups of fraudsters [51][50], unusual behavioral footprints [49], unusual distributional footprints [30], unexpected rules [36] and unusual rating behaviors [40].

Existing works deal with a diverse set of review data in both supervised and unsupervised manners. In [18], 15,094 apps are ranked based on network effects. In [68], 45 hotels are ranked based on an unsupervised hedge algorithm. In [30], 4000 hotels located in 21 big cities are analyzed to identify distributional anomalies. In [35], reviews on 700,000 products for a month are analyzed using review-, reviewer-, and product-centric features. In [57], 7,345 car repair shops are crawled to collect 270,121 reviews and the data of their 195,417 reviewers.

Our work considers 15 million reviews for over 10 years from three websites and thus considers significantly more data than existing works do. None of the existing work considers reviews from multiple sites to understand fraudulent behavior. Our work is fundamentally different from most existing work, since our focus is on evaluating hotels/businesses instead of reviews.

The closest commercial competitor of TrueView is the TrustYou score [11], which calculates a trustworthiness score for a hotel based on the reviews about that hotel from multiple sites. TrustYou is fundamentally different in that it scores the goodness of the hotel itself based mainly on semantic text analysis, while TrueView scores the trustworthiness of the hotel based on a wide range of features.

3.3 Location Disambiguation

We crawled TripAdvisor.com, Hotels.com, and Booking.com. We collected all the reviews for almost all of the hotels in these sites. For each review, we collected its text, reviewer-name, date-time and rating. For each hotel, we collected its name, address, and overall average rating and any overall sub-category ratings (cleanliness, etc.). A summary of the whole dataset is given in Table 3.1.

These three websites have a lot of hotels in common and thus, provide rich cross-site information about those hotels. We focus on the location disambiguation problem across these three websites.

3.3.1 Challenges

The most significant challenge in location disambiguation is that hotel names are not unique. Therefore, a full name and address is needed to uniquely identify a hotel. Unfortunately, addresses are also not standard across websites, and the differences between sites are seemingly random. Differences can be as simple as *Street* versus *St.* versus *St* or as complex as *Hotel Atlântico Búzios Convention & Resort - Estrada da Usina, s/n, Humaita, Búzios, CEP 28950-000* and *Hotel Atlantico Buzios Convention and Resort, strada da Usina 294Morro do Humait, Buzios, RJ, 28950-000, Brazil*. For international addresses, words can be in different orders, names can be formatted differently, country names can be excluded, and numbers can be morphed. Addresses can even use waypoints as reference, such as *1000 Yang Gao Road N Pudong Near Pilot Free Trade Zone Gate 3*, which are not standard across websites. Even US addresses, which one might assume follow a standard format, are not immune. For example: *Hilton New Orleans Riverside, Two Poydras Street, New Orleans Central Business District, New Orleans, LA 70130* and *Hilton New Orleans Riverside, 2 Poydras St, New Orleans, LA 70130, United States*. We can look at these two addresses and tell that they are describing the same hotel, but their

differences are non-trivial: the use of 'Two' versus 2 and the inclusion of 'New Orleans Central Business District'. Another domestic example: *Mauna Kea Beach Hotel, 62-100 Mauna Kea Beach Drive, Waikoloa, HI 96743* and *Mauna Kea Beach Hotel, 62-100 Mauna Kea Beach Dr, Kamuela, HI, 96743 United States*. These two addresses have every field in common but one: one city is listed as Waikoloa and the other as Kamuela. How much weight should be given to each field? Due to the variety of differences possible, this is a difficult problem to automate.

3.3.2 Disambiguation techniques

We use a combination of hotel name analysis and geodesic distance to disambiguate hotels. Geodesic distance ensures that the addresses are located in the same place, despite differences in formatting, and name comparison makes sure the hotels' names are similar enough to likely refer to the same business.

Hotel name comparison To compare two hotel names, we devise a similarity measure comparing the number of letters they have in common. The similarity measure we use is the length of the set intersection of the hotel names divided by the length of the longer name. This measure is faster to compute than edit distance and succeeds in the face of small spelling differences or omitted words. This measure on its own has very high precision but low recall, so when combined with geodesic distance we are able to loosen this matching requirement.

Geodesic distance To compare the physical location of the hotels, we employ geocoding. Using the Google Geocoding API, we translate hotel addresses into latitude and longitude coordinates for all of our hotels. This API works well with strangely formatted addresses, both domestic and international. We use a cluster of computers to speed up the coordinate generation process as there is a limit on the number of requests per day. We then calculate the geodesic distance between two sets of latitude and longitudes. To do this we first convert latitude and longitude to spherical coordinates in radians, compute the arc length, then multiply this by the radius of earth in miles to get the distance in miles between the

two addresses.

Combining measures: By combining geodesic distance with a distance measure of the hotel names, we are able to have efficient, high-precision matching. To find the ideal distance maximum and similarity minimum, we explored the parameter space for distances from 90 miles to 0 miles and similarities from .1 to .9. By sampling 30 hotels at each parameter combination and manually checking matching fidelity, we found a local maximum in precision at a geodesic distance max of 1 mile and a name similarity minimum of 0.66. Since we want high-quality matching results, we err on the side of caution with our matching constraints.

Results of disambiguation Using these constraints, we find 13,100 total matches. 848 hotels were matched across all three sites, 1007 between Booking.com and Hotels.com, 655 between Booking.com and TripAdvisor.com, and 10,590 between Hotels.com and TripAdvisor.com. Booking.com is a much newer site, and we hypothesize that is the reason for its reduced coverage.

	Booking.com	Hotels.com	TripAdvisor.com
Number of reviews	11,275,833	9,050,133	3,167,035
Number of hotels	52,696	155,763	51,395
Number of unique usernames	1,462,460	1,020,054	1,426,252
Average number of reviews	213.98	74.3	68.71
Average rating	3.35	3.07	3.99
Percent empty reviews	24.4%	19.6%	0.0039%
Date range	09-30-2009 - 05-17-2014	02/01/2006 - 06-01-2014	02/28/2001 - 09/08/2013
Geographic range	International	International	United States

Table 3.1: Simple Statistics of the three datasets collected from three prominent travel websites.

3.4 Novel Feature Set

Hotels show various inconsistencies within and across hosting sites. In this section, we present several such inconsistencies that are not discussed previously in the literature and derive relevant features for our trustworthiness scoring. We categorize our features in a similar way to Jindal et al. [35]: reviewer-centric features, review-centric features and hotel-centric features. Features are either generated using one site or multiple sites after the hotels are joined based on location. All the single-site features are combined to put them in the context of multiple sites.

A note worth mentioning is that the location information of these hotels provide an unprecedented opportunity to validate goodness of the reviewers and reviews. All of our novel features described below show promising capabilities in identifying suspicious behavior, and most of the time it is possible to spot such behavior for our novel location disambiguation and merging.

For the rest of this chapter, we will use HDC for Hotels.com, TA for TripAdvisor.com and BDC for Booking.com.

3.4.1 Reviewer-Centric Features

We identify three new scenarios involving inconsistent and unlikely reviews and capture these scenarios through reviewer-centric features. Since it is not possible to disambiguate users across sites, all of the reviewer-centric features are based on individual sites.

Spatial Inconsistency

We first focus on identifying reviewing behaviors that are spatially inconsistent. We find a user named “AmishBoy” who reviewed 34 hotels in Amish Country located in Lancaster, PA over 5 years. Lancaster County spans only 984 square miles, meaning that many of

the hotels this user reviewed are right next door to each other. He gave 32 out of these 34 hotels 4 or 5 star ratings, which means he was pleased with his stay. Why then would he continually switch to new hotels? Even if he is simply visiting the area for business or pleasure every couple of months, his pattern of continually switching to new hotels is suspicious. Whether innocent or not, the reviews of this user should be discounted on the grounds that he does not represent a 'typical' traveler visiting this area.

We create a feature that identifies if a user has such a bias to a specific location and accumulate the contributions of such reviewers to every hotel. This feature is first calculated as the maximum count of the number of reviews a reviewer made in a given zip-code. If this value is greater than a threshold, typically 5, the reviewer is marked as a suspicious user. To propagate the feature up to the hotel level, we then sum the number of reviews each hotel has that came from suspicious users. If a hotel has many reviewers who have such spatial preference, it strongly suggests potential review manipulation by the hotel.

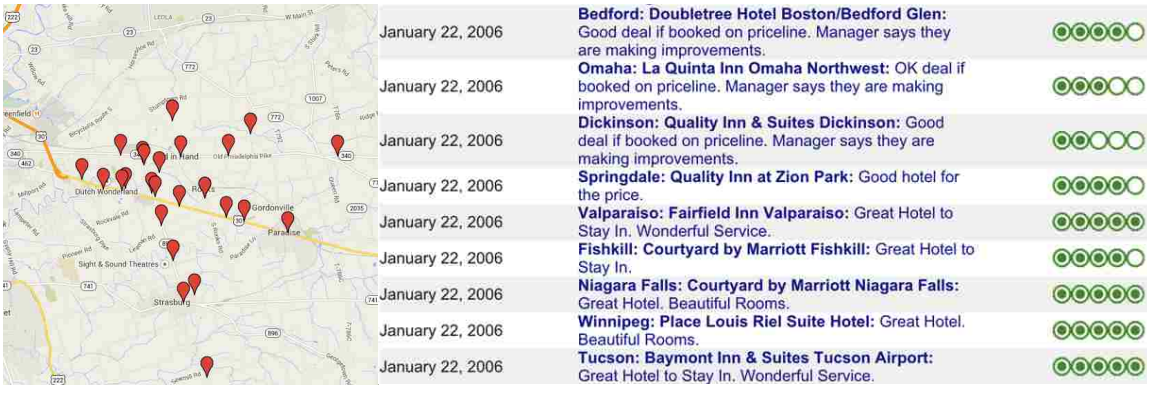


Figure 3.1: (left) Locations of the hotels the user AmishBoy reviewed around Lancaster, PA in TA (right) A snapshot of the reviews tonyk81 wrote in TA. He left a total of 29 reviews January 22, 2006 for businesses located across 15 states.

Temporal Inconsistency

Another type of suspicious behavior of a reviewer is writing many reviews on the same day. Typically a traveler may review a set of businesses after he comes back from a trip.

However, the frequency of such trips and the spatial distribution of the businesses can provide valuable insights. For example, a user named "tonyk81" reviewed 29 businesses on January 22, 2006, which are located across 15 states. Additionally, 21 of these reviews are "first time reviews" for the respective hotels. The reviews describe visit dates starting from May, 2005 till January, 2006 and *all* of the reviews have the words *great* and *good* in the titles. Furthermore, many sentences in the review titles and text are repeated verbatim, for example "Cleanliness seems to be a high priority at this hotel and the rooms are in like new condition." and "This hotel lives up to Marriotts high standards of quality." The user has only reviewed 3 hotels in the last eight years after this burst, all on the same day in 2007. Putting these pieces of evidence together, it is clear that tonyk81 is likely a spam account.

Singleton bursts have been identified as potential indicator of manipulating hotels in [69]. The above example suggests non-singleton bursts can show evidence of spamming users as well. If a hotel has a large number of such reviewers, it likely has manipulated its reviews. To calculate this feature, we find the maximum number of reviews a reviewer left in a given day. If this is greater than a threshold, typically 3, that user is marked as suspicious. We then propagate up to the hotel level as described above, by summing the number of reviews each hotel has that came from suspicious users.

Graphical Inconsistency

Bipartite cliques in user-store graphs can identify groups of users that boost a set of stores by doing a number of small transactions in the form of positive reviews [21]. Inspired by this, we create a feature to capture information about the cliques a reviewer participates in. We restrict ourselves only to cliques of size two and search for the maximum number of hotels a user has reviewed in common with any other user. We find several cases where such a clique points to an abnormal pattern in reviews. One such case we identify is two users who have reviewed over 95% of the hotels in common on nearly the same dates,

usually off by one day. Upon researching the reviewers further we discovered that they are married! While a valid reason for such behavior, this shows that our method for finding anomalous behavior by identifying bipartite cliques is successful. Another example is two users from Germany, who have reviewed 117 of the same restaurants, hotels, or landmarks all over the world in the past 5 years out of 189 and 186, respectively. Furthermore, they each are 'first to review' (meaning they were one of the first five reviewers of that location in their native language) for 136 and 144 locations. They also have surprising synchronicity in both the review dates and stay dates for the hotels they have in common. These facts indicate that these may be two accounts may be held by the same person, which is the behavior of a paid spammer.

3.4.2 Hotel-Centric Features

Hotel-centric features are relatively more successful in identifying outliers (see Experiments). As before, we have three types of inconsistencies for hotels.

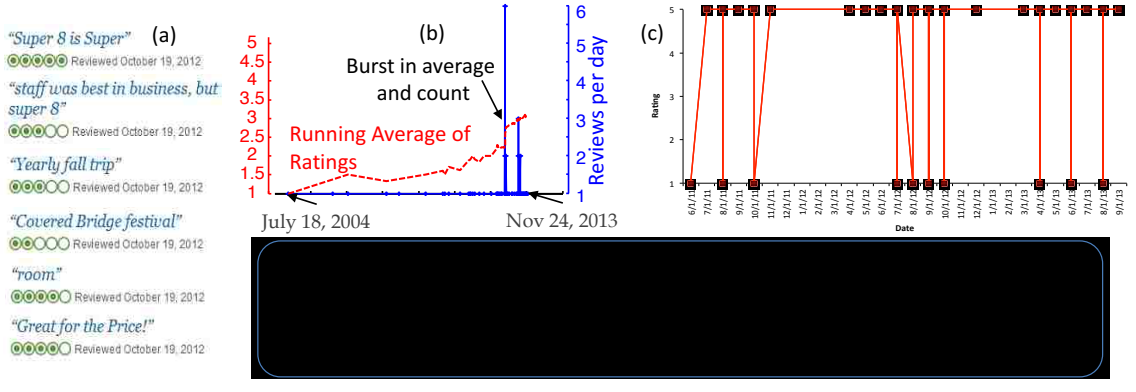


Figure 3.2: (a) Six reviews for Super 8 hotel in Indiana in the same day (October 19, 2012), all positive, and five of them are singleton reviews where the authors have not reviewed again in TA. (b) The number of reviews per day for a this hotel jumps to 6 on that day which was sufficient to give the hotel a 0.5 star boost in the average rating showing in red. (c) Immediate 5-star ratings after 1-star ratings are frequent in some hotels such as Cherry Lane Motor Inn in Amish Country. (d) Examples of two successive opposite reviews on the same day from two reviewers.

Temporal Bursts and Oscillations

Bursts of positive reviews for a hotel specifically aimed to increase the average rating is well identified in the literature. We find several such cases where there are bursts of singleton reviews with an increase in the average rating. Typically such behavior is prevalent in the early years of the inception of a hotel in the hosting site. Figure 3.2 shows an example of such a burst. Bursts were calculated by taking the difference between maximum number of reviews in a day and average number of reviews in a day for each hotel.

In addition to bursts, we show cases of oscillation in ratings that are targeted to keep a high rating at the top of the "new-to-old" sorted list. We created two features to characterize oscillation: the number of times a 5 star review was immediately followed by a 1 star review for each hotel, and the number of times a 1 star review was immediately followed by a 5 star review for each hotel. These summed feature values capture the level of oscillation of ratings for a given hotel.

An example of oscillating ratings is shown in Figure 3.2. We see that eight out of ten 1 star ratings were followed immediately by 5 star ratings.

Temporal Correlation

The correlation between the number of ratings a hotel receives over time on different sites is a valuable indicator of consistent customer satisfaction. Commonly, a hotel should have very similar behavior across sites in terms of number of ratings. For example, since the number of occupants at hotels in Myrtle Beach, SC [6] decreases from 80% in the summer to 30% in the winter, any hotel in Myrtle Beach, SC should show a high number of ratings per day in summer, decreasing in the winter, as the number of ratings per day follows the average occupants of the hotel. In Figure 3.3, we show hotels and their number of ratings per day in HDC and TA. We see the top two hotels have summer peaks in both of the sites. However, Bluewater Resort has dense summer ratings in TA but no significant

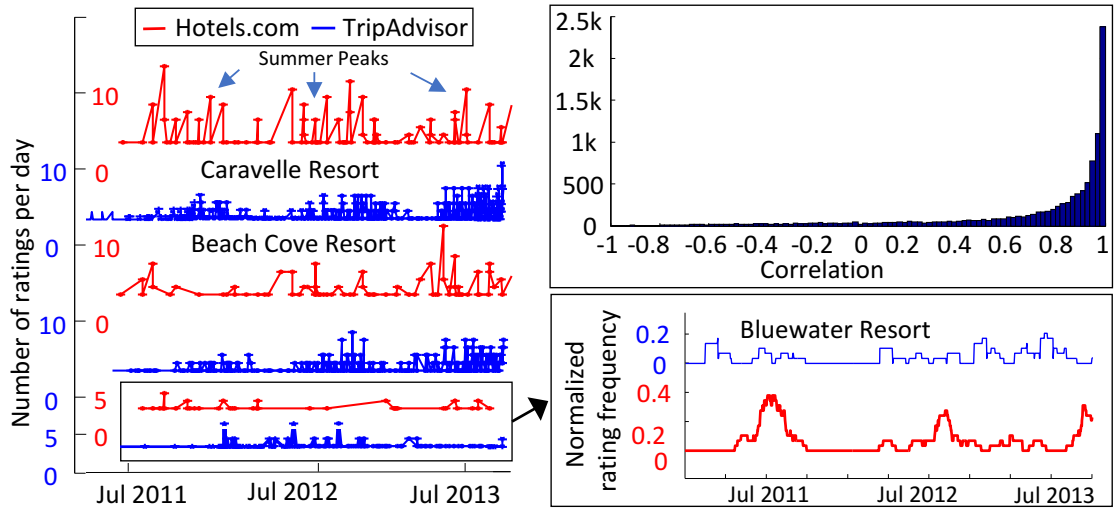


Figure 3.3: (left) The time series of number of ratings per day for three hotels in Myrtle Beach, SC. The top two hotels show summer peaks in both TA and HDC. The bottom hotel does not show any summer effect in HDC. (top right) Distribution of correlation between ratings of hotels in TA and HDC.

peak/density in HDC, especially in summer of 2012.

Such a discrepancy in temporal behavior can exist for several reasons, each of which are worth considering when it comes to evaluating hotels. The hotel might have received more poor ratings in the summer which were omitted by the hosting site, or the hotel could have sponsored some winter reviews. There can be extreme cases such as the hotel was closed for construction, but irrespective of the real reason, a lack of correlation across sites is a significant indicator for spotting misbehavior. We calculate the Pearson's correlation coefficient between the time series of number of ratings per day from two sites. We use only the overlapping time duration for calculation. If the overlap is too small, we naively assume perfect correlation. The distribution of these correlations is shown in Figure 3.3 as well.

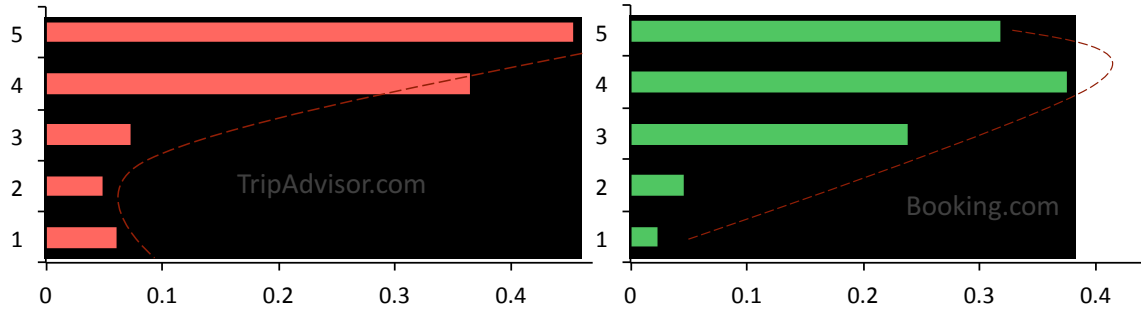


Figure 3.4: Distribution of ratings for the same hotel in two websites showing negative correlation.

Rating Distributions

In [30], authors have suggested that the shape of rating distribution has a strong tie to the spamming hotels. Typically, a "J" shaped distribution has a large number of 5-star and 1-star ratings but a small number of 4-, 3-, and 2-star ratings. Such a distribution may occur if users review only when they are extremely happy or disappointed. However, it is suspicious to have nearly equal numbers of people who hated and loved a hotel. This suggests that one of those rating groups has been artificially inflated by spam reviews. Whereas in [30] they had to compare distributions between hotels, we take a multi-site approach to validate the consistency of distributions across sites for individual hotels. To find this value we calculate the Pearson's correlation coefficient between the rating distributions of a hotel across different sites, represented by two vectors of counts of integer ratings. We also directly compare the distributions of the real-valued ratings by using the one-sided p-value from the Mann Whitney U Test as a feature.

Figure 3.4 shows the correlation coefficients of the distributions between HDC and TA. We take a threshold of -0.9 and locate all the hotels that show less than -0.9 correlation. As shown in Figure 3.5, we find an interesting co-location pattern for negatively correlated hotels around Atlanta, GA which is more densely populated with such hotels than any major urban area or popular vacation spot, such as Las Vegas, NV or Los Angeles, CA.

Figure 3.5: Negatively correlated hotels are more abundant in the vicinity of Atlanta, GA and almost non-existent in Las Vegas, NV area where both the cities have more than three hundred hotels.

Around 5% of the hotels in GA show negative correlation, which is much greater than that (1%) in CA and NV.

3.4.3 Review-Centric Features

Review-centric features are based on review text and titles. We do not use any natural language processing techniques to spot a spam review by only text, but rather focus on structural properties of reviews.

Empty Reviews

Reviewers often write empty reviews with no title and no comment. The incentive for such reviews is that they can be submitted without any typing. We find an abundance of empty reviews in HDC and BDC, with 20% and 25% empty reviews, respectively, while TA has only 3% empty reviews. In addition to these reviews being potentially suspicious,

we find that hosting sites treat these reviews differently. For example, in HDC, empty reviews were visible during the time when we collected the data; however, HDC now hides the empty reviews, while keeping counts of them in their overall review tallies. For example, Excalibur Hotel and Casino in Las Vegas, NV has 2500 empty reviews out of 13,144 reviews in HDC, but none of them are visible through the website. Such behavior of hiding consumer reviews has been reported several times in [3], and clearly such an omission is not fair to consumers.

There exist some hotels that have a significantly greater proportion of empty reviews than average. For example, Comfort Suites Newark in New Jersey has 86 empty reviews out of 193 reviews which is more than 44% of the reviews. We find 66 hotels that have only empty reviews in HDC. BDC has a similar-sized body of empty reviews.

Matching Reviews

Inspired by tonyk81's matching review text described above, we create a feature that captures the proportion of sentences any pair of reviews from the same reviewer share to the total number of reviews that reviewer made. While repeating the occasional phrase is to be expected, having reviews that share the majority of the sentences, or are completely identical, is not. We calculate this score by comparing pairwise all reviews made by a given user. We keep a count of the number of sentences these reviews share, and then divide this value by the total number of reviews a reviewer wrote. We then attach this score to each review a reviewer left. For each hotel we aggregate this score for all of its reviews to characterize the lack of uniqueness of its review set. A hotel with many reviewers who use the same sentences repeatedly is likely soliciting spam reviews.

3.4.4 Cross-Site Feature Preparation

We generate 90 features including the novel features described in the previous section for each hotel in each site. In addition to these single-site features we calculate 52 cross-site features for the hotels that exist in multiple sites. These cross-site features are combinations of similar single-site features from many sites. Cross-site features can identify discrepancies that a hotel has between a pair of sites, for example, a difference in the percentages of empty reviews.

We combine the single-site features in three different ways. First, we take ratios for scalar values, such as number of reviews. Some of the scalars are only meaningful relatively, such as number of 5-star ratings. We use relative frequencies when taking the ratio of these scalar features. Second, we take correlation coefficients for sequences, such as numbers of high to low ratings. And third, we take the p-value of the Mann-Whitney U test for distributions, such as the distributions of review lengths in words.

The next step is to normalize these features to make them reasonably close to standard normal distribution. The intention is to treat each feature as independent and identically distributed. Some of the features require a log transformation to be converted to standard normal because of their exponential fall out, for example, counts of rating scores, counts of empty reviews, and text similarity scores. After log transformations, we normalize each feature by Z-score. For a complete list of features and their values for all of the hotels please visit the TrueView page [9].

3.5 Trustworthiness Score

Our work is fundamentally different from existing works. We do not wish to evaluate if a review is fake or untruthful as most existing works do. We believe it is very difficult to achieve high *recall* in identifying review fraud, mostly because of the dynamics of the

fraudsters and the lack of labeled data. Even if we assume hypothetically that we can achieve high recall and prevent fake reviews from being shown to the readers, the hotels and sites that promote fraudsters are not penalized and site users are not notified of which hotels are trying to lie to their customers.

We believe that a better approach to this problem is to evaluate hotels and sites to find ones that promote untruthful reviews, and to produce a trustworthiness score to present to the user. We think such scores are more beneficial to the review readers as they can use these scores in their ultimate judgment.

3.5.1 Outlier Scores

Once all the features are generated, we use an ensemble of anomaly detection algorithms to generate the TrueView score. This ensemble consists of a global density-based score, local outlier factor, and a hierarchical cluster-based score. Using these algorithms in ensemble allows for different types of normal and anomalous behavior. We describe each technique in this section.

Global Density-based Score

To calculate this score, we need to find *how different a hotel is from the centroid of hotels in the feature space.* To do this, we take the mode of each feature and form a hypothetical hotel which lies in the center of a large "normal" cluster. We use the simple intuition that most hotels are playing fair and only a small fraction of hotels are generating fake and untruthful reviews. If a hotel is largely dissimilar to the mode/centroid hotel, the hotel might disagree with the mode in many features, which makes its behavior less trustworthy.

We use the concept of density connectedness to form a large cluster of points (i.e. hotels) carrying the mode. A point is a *core point* if it has k or more points within ϵ distance in the Euclidean space. Two points are density-connected if there is a sequence

of core points from one to another where every point is within ϵ-neighborhood of the previous point. Thus, any point that is not in the core cluster is an outlier and the degree of outlying is proportional to the distance from the nearest core point. This method is inspired from the original density based clustering algorithm, DBSCAN. This method has a unique advantage that the core cluster can be of any shape and based on the two parameters (i.e. ϵ and k) we can control the size of the core cluster and thus, the size of the outlying cluster.

Local Outlier Factor (LOF)

The global method assumes that all normal hotels form a core cluster. However, there can be alternative structures with numerous small clusters of normal hotels with varying densities in the feature space. We use local outlier factor to score outliers. Local outlier factor uses the notion of k-distance ($dist_k(x)$) which is defined as the distance to the k-th nearest neighbor of a point. Local reachability distance (lrd_k) of x is the average of the reachability distances from x's neighbors to x. Here $N_k(x)$ is the set of k-nearest neighbors of x.

$$lrd_k(x) = \frac{||N_k(x)||}{\sum_{y \in N_k(x)} \max(dist_k(y), dist(x,y))}$$

The LOF of a point x is the average of the ratios of the *local reachability* of x and its k-nearest neighbors. LOF can capture several normal clusters of arbitrary densities that makes it robust for any data domain. Formally, LOF is defined as below

$$LOF_k(x) = \frac{\sum_{y \in N_k(x)} \frac{lrd_k(y)}{lrd_k(x)}}{||N_k(x)||}$$

Hierarchical Cluster-based Score

Both of the density-based methods above use k-neighborhoods to estimate densities or connectivities. Our third approach differs from that and uses a hierarchical clustering approach. We cluster the data hierarchically using the *single linkage* method. The single

linkage method starts with singleton clusters and evaluates pairs of clusters based on the *minimum distance* between any pair of points that form the two clusters. It then merges the closest two clusters at every step. This simple bottom-up strategy can produce a dendrogram over the points without any input parameters.

Once the complete hierarchy is built, a set of clusters can be obtained by cutting the hierarchy at a cutoff level. Here again, we assume there is a global normal cluster that contains most hotels and any hotel not in this cluster is an outlier. Under this assumption, we can tune the cutoff level to get a certain percentage of points in the set of outliers.

3.5.2 TrueView Scores

One of the major challenges of creating a method based on an ensemble of anomaly detection algorithms is that it requires the combination of multiple scores that are not on the same scale. There are several different methods that can be used to combine these scores, depending on the potential application. Some methods focus on unifying rankings, while others focus on normalizing and combining scores [58]. For our application, having one unified score is preferable to having an overall ranking, thus we seek to normalize and combine these four scores. Our method is as follows, based on [38][58].

Let a hotel be x and the outlier score of x is $S(x)$. We first do a log transform $z = -\log S(x)/S_{max}$ for each hotel x to obtain a trustworthiness score, and then we scale it using a Gaussian distribution to produce a probability $P(x)$ of the hotel x being trustworthy. Such a probability score is useful because it is bounded within [0,1].

$$TV(x) = \max(0, erf(\tfrac{z-\mu_z}{\sqrt{2}\sigma_z}))$$

Here, $TV(x)$ is the **TrueView** score. The TrueView score describes the probability of a hotel's reviews being truthful and is unitless. As described above, we can now produce TrueView scores from any feature set of these hotels. We define two intermediate scores

that can be created as well as the overall TrueView score. First, **TV1** is produced only using features from *one* site. Second, **TV2** is produced using an union of features from *all* sites. Third, the **TrueView** score is produced using the union of all single-site features and the cross-site features from all three sites. Each outlier detection algorithm produces its own scores, and we average them to get the overall **TrueView** score. We provide empirical evidence in Section 3.6 that **TrueView** identifies successfully identifies outliers.

There are two weaknesses of the above approaches. First, the score of a hotel can change if other hotels connect it to the core cluster. Second, there can be hotels which are unusually good labeled as untrustworthy. These cases are pathological and become rare with more reviews per hotel.

3.6 Experimental Analysis

We start with our reproducibility statement: all of the experiments in this section are exactly reproducible with the code and data provided in the supporting page [9]. We also have additional materials such as presentation slides, the complete feature set, and more experiments.

3.6.1 Parameter Sensitivity

The three algorithms we use for outlier detection have a set of parameters to tune. Based on the values of these parameters, we can have different sized sets of outliers. We experiment to test the sensitivities of these parameters and select appropriate values for subsequent experiments.

In the global density-based method, we have ϵ and k as parameters. We fix $k = 10$ and vary ϵ and record the percentage of the dataset labeled as outliers. In LOF, we have the neighborhood size k as the sole tunable parameter. In the hierarchical method we use the

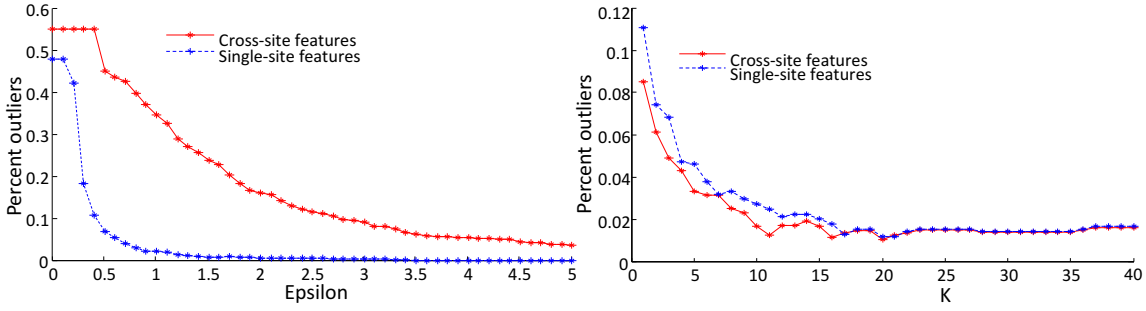


Figure 3.6: (left) Percentage of outliers detected in the density-based method as we vary ϵ. (right) The same as we vary neighborhood size k in the LOF method.

cutoff value as the parameter and record the percentage of the dataset labeled as outliers. Figure 3.6 shows the behavior of the mode-distance and LOF methods. We select the parameters such that we can rank order 30% of the hotels using all three methods. This number is an arbitrary choice and can be different in other systems.

3.6.2 Feature Importance

We evaluate feature importance in the calculation of the TrueView score. We use two different and independent approaches to evaluate the features.

Spectral Feature Selection

We use the method in [71] to evaluate the importance of our 142 features. The method identifies redundancy in the feature values and properly demotes dependent features. The result is shown in Figure 3.7, where more than 100 features show very uniform importance scores, which supports the validity of our feature set. In addition, we categorize the features into cross-site and single-site classes. We see that the most important features are cross-site features, showing the importance of multiple-site data for evaluating hotels. Note that the feature selection algorithm does not take into account the ultimate usage of

these features in the algorithm, which is outlier detection in this work, but rather their intrinsic informativeness.

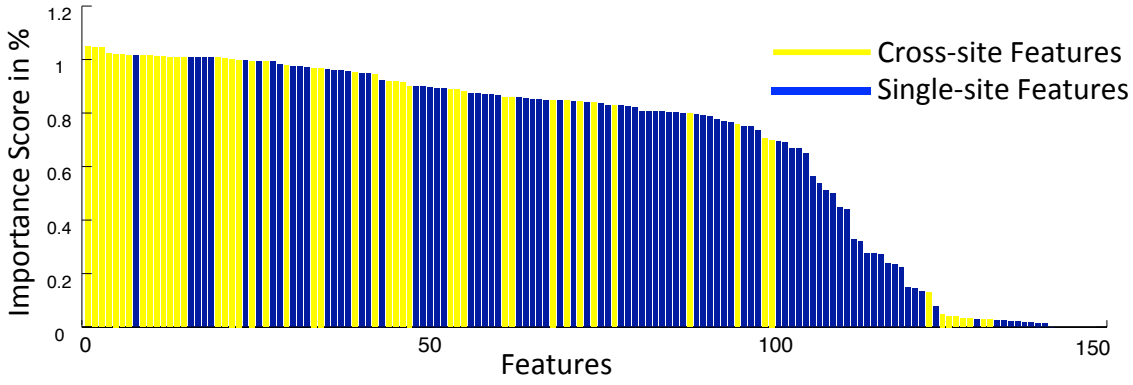


Figure 3.7: Feature importance percent scores for our 142 features. Cross-site features are more overall important than single-site features.

Distance from Mode

In this section, we consider the outliers produced by our global density-based approach. We pick the most different feature of an outlier with respect to the mode of that feature as the representative for that outlier. We see a massive shift in importance of our cross-site features, especially the star rating-based ones, that are important for more than half of the outliers. In Figure 3.8, we show the results for other feature categories as described in Section 3.4.

3.6.3 Validation

Since the algorithm for computing TrueView score is unsupervised, and we do not have labeled data that identifies fraudulent hotels, we cannot directly validate with ground truth information. We therefore take two alternate approaches to validate the soundness of our method.

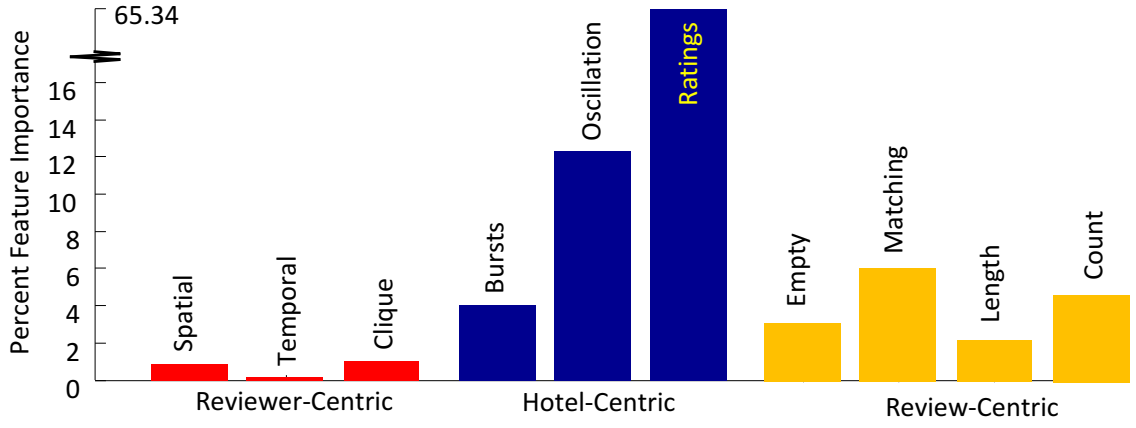


Figure 3.8: Relative importance of review-,reviewer- and hotel-centric features based on the distance from the centroid.

Sanity Check on Synthetic Frauds

First we generate a synthetic set of outlying hotels to validate that our global density-based approach correctly identifies outliers. To create these outliers, we copy the center point representing the mode of all features and mutate random feature values, randomly setting them to either the ninety-fifth or the fifth percentile. We then calculate their TrueView score based on the global density-based method described above. This experiment is repeated 100 times. We find the distributions of TrueView scores are heavily skewed towards zero, showing that on the whole, they were given very low TrueView scores. Thus our algorithm passes this sanity check, classifying 100% of our synthetic data as outliers and giving them correspondingly low TrueView scores.

Evaluation of Extreme Features

Second, we validate that the hotels with low TrueView scores show a significant difference in the number of extreme feature values from the hotels with high TrueView scores. To evaluate this we find the number of features that are below the fifth percentile or above

the ninety-fifth percentile for each hotel. We use the Wilcoxon rank-sum test to determine whether the 40 most trustworthy hotels significantly differ in the number of extreme features from the 40 least trustworthy accounts. A p-value of < 0.05 rejects the null hypothesis, and asserts that the two populations are distinct. Table 3.2 lists the p-values for each outlier algorithm and each feature subset. The cross-site and combined single-site feature sets show statistically significant results for every algorithm, meaning that these feature sets are effective in differentiating outliers. It also means that hotels given high TrueView scores are indeed trustworthy, as most of them have only a few extreme features.

	LOF	Mode Density	Linkage
Cross-site	**3.93E-07**	**1.63E-08**	**4.60E-11**
Single-site	**1.63E-06**	**8.04E-15**	**1.08E-12**
Booking.com	**1.49E-05**	0.419	**0.019**
Hotels.com	0.308	**4.41E-04**	**0.038**
TripAdvisor.com	0.379	0.052	**0.002**

Table 3.2: p-values of Wilcoxon rank-sum test. Bold faced values mean that there is a significant difference between the top and bottom 40.

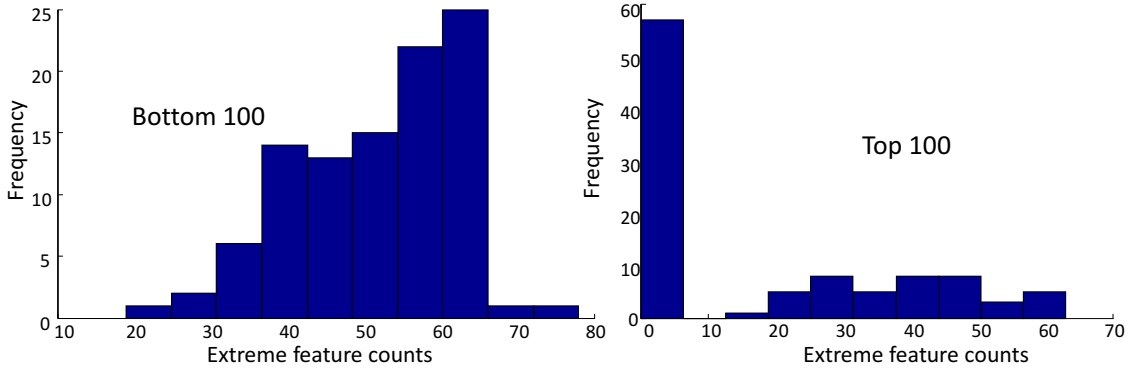


Figure 3.9: (left) Distribution of the number of extreme features (95th percentile) in the bottom 100 hotels in TrueView ordering (right) Distribution of the same in the top 100 hotels in TrueView ordering. Distributions are significantly different.

3.7 Case Studies

We want to provide some initial ideas on how the TrueView score could be used in practice. We identify two possibilities: (a) enabling the site owner to detect misbehaving hotels, and (b) by the end user.

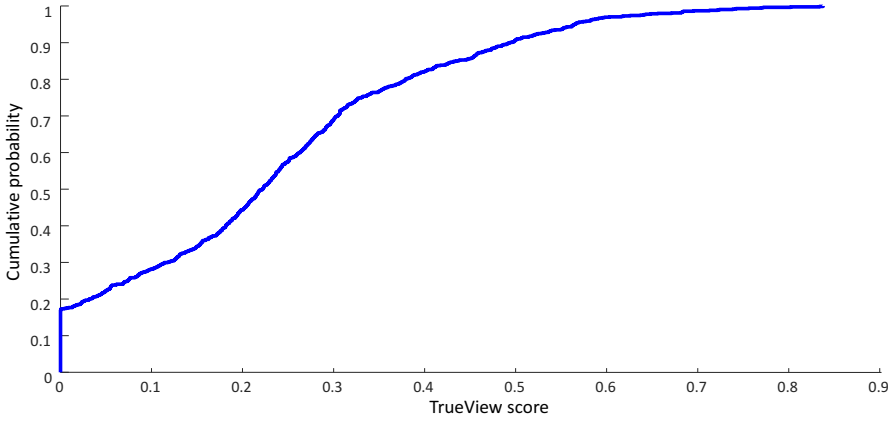


Figure 3.10: Empirical cumulative distribution function of TrueView scores.

A. TrueView for the site administrator. The usage here is fairly straightforward as a way to identify misbehaving hotels. The administrator can apply TrueView on the data from his own site alone, in which case TrueView resolves to TV1. Assuming cross-site cooperation, the administrator could use data from other sites.

B. TrueView for the end user. The TrueView score could help the user select hotels that are more likely to have non-altered scores. In other words, the user can be more confident that a rating of say 3.5 stars is the true reflection of unbiased customers. TrueView could be used when only a single site is available, but its power lies in its ability to combine reviews from multiple sites.

We see two basic ways the TrueView could be used. (a) as a way to re-rank hotels, by altering the the rate of the hotels, and (b) as a filtering mechanism, in which hotels with unreliable TrueView score are not even shown to the user.

Hotel	HDC Rating	T1-HDC	TA Stars	TV1-TA	TV2	**TrueView**	**Trust-worthy?**
Super 8 Terre Haut	3.30	0.0	3.00	0.765	0.266	**0.0**	**X**
Excalibur Hotel and Casino	3.60	0.154	3.50	0.150	0.049	**0.239**	**X**
Comfort Suites Newark	3.80	0.312	3.00	0.295	0.227	**0.0**	**X**
Paradise Resort, Myrtle Beach	4.20	0.0	4.00	0.427	0.301	**0.0**	**X**
Bluewater Resort, Myrtle Beach	2.90	0.0	3.00	0.265	0.210	**0.538**	**X**
Comfort Inn & Suites, Statesboro	3.60	0.0	3.60	0.217	0.331	**0.736**	✓

Table 3.3: TrueView scores for suspicious hotels.

a. Weighted rating using TrueView. There are many ways that to modify the rating of a hotel based on the trustworthiness score. The full input is the rating from each site, the number of reviews per site, the trustworthiness of each site (TV1), and the TrueView across all sites. One approach would be to take the average rating and multiply it by the trustworthiness score, but this method's simplicity is not a proof of effectiveness without extensive study.

b. Filtering using TrueView. In this method, we need only to find the cut-off threshold of trustworthiness **TV-thres** which forms the cut-off point for hotels with a score less than the threshold. The filtering threshold needs to balance the ability to remove suspicious hotels with its false positive rate, which would reduce the overall choice for the end user. This is the fundamental trade-off that needs to be considered. We present some initial thoughts on how we could develop a threshold like this.

Disclaimer: The discussion below is not intended to be indicative of and not a conclusive and thorough determination of a filtering method. For that, a more extensive analysis is needed to derive a conclusive statement. In addition, the user-facing service and even the user herself can have significant impact on how "strict" the filtering process should be.

Calibration: Known suspicious hotels. First, we show the distribution of hotels having a TrueView score less than a threshold in Figure 3.10. Obviously, we cannot just mark the bottom 25% as being untrustworthy. However, we can evaluate how well our scoring process works for a known set of misbehaving hotels. If we filter out the bottom 25%, we need a threshold of 0.7. We present results for 6 suspicious hotels that were identified

Figure 3.11: Dissimilar distribution of ratings, temporal bursts in number of ratings per day and frequent empty reviews are just a few of the suspicious features that characterize this hotel.

in Section 3.4 in Table 3.3. Figure 3.11 shows an example of the suspicious features that characterize these hotels.

We see a threshold of 0.7 would give us 83% precision. In other words, filtering out hotels with a score of less than 0.7 would ensure that 5/6 known malicious hotels are filtered, while reducing the overall choice of hotels by 25%. For the sake of this case study, one can argue that 0.7 could be a reasonable threshold. In a real deployment, this

needs to be based on a much large labeled dataset.

Case study: Finding hotels in Amish Country. We choose the top 20 hotels in Amish Country, Lancaster County, PA from Hotels.com and TripAdvisor. We choose hotels in Amish Country because during our initial investigation many potentially suspicious hotels were present. Amish Country is a small area with many competing hotels trying to access a similar market, so the competition is fierce. We calculate the TrueView scores for those that are part of our matched dataset. The results of this study are show in Table 3.4. We find that all of these hotels have scores below our threshold of 0.7. We validate these results we manually assess these hotels and find that they all do show suspicious behavior.

Hotel	HDC Rating	TV1-HDC	TV2	**TrueView**	**Trustworthy?**
After Eight Bed & Breakfast	4.80	0.139	0.182	**0.233**	**X**
Comfort Suites Amish Country	4.70	0.063	0.642	**0.392**	**X**
Bird In Hand Village Inn & Suites	4.60	0.039	0.0	**0.092**	**X**
Amish Country Motel	4.60	0.0	0.285	**0.501**	**X**
Country Inn & Suites By Carlson Lancaster	4.60	0.0	0.325	**0.522**	**X**
Strasburg Village Inn	4.50	0.376	0.218	**0.0**	**X**
Hawthorn Suites by Wyndham Lancaster	4.10	0.329	0.406	**0.442**	**X**
Sleep Inn & Suites Ronks	4.10	0.437	0.264	**0.224**	**X**

Table 3.4: TrueView scores for hotels from Hotels.com.

3.8 Conclusion

The goal of our work is to show the significant benefits we can gain by combining reviews from multiple review sites. As a key contribution, we develop a systematic methodology to collect, match, and analyze hotels from multiple review sites. The novelty of our approach relies one the introduction and assessment of 142 features that capture single-site and cross-site discrepancies effectively. Our approach culminates with the introduction of the TrueView score, in three different variants, as a proof-of-concept that the synthesis of multi-site reviews can provide important and usable information to the end user. We conduct arguably the first extensive study of cross-site discrepancies using real data from 15M reviews from more than 3.5M users spanning three prominent travel sites. We find that there are significant variations in reviews, and we find evidence of review manipulation.

Chapter 4

BotWalk: Efficient Adaptive Exploration of Twitter Bot Networks

4.1 Introduction

More than a billion people use online social networks for information dissemination, entertainment, and social interaction. Unfortunately, these platforms are exploited by abusive automated accounts, also known as bots, for financial or political gain. The presence of these bots is a constantly growing problem that compromises the empowerment of online social communities. Automated accounts easily allow botmasters to spam inappropriate content [5], participate in sponsored activities [31], and make money by selling accounts with human followers [65]. An estimated 8.5% of Twitter accounts are bots [62] and the bots are growing at a higher rate than the rate at which Twitter suspends them.

The identification and suspension of bots is a challenging problem for several reasons: these social networks are massive – Twitter alone is estimated to contain over 300 million users and billions of edges. Furthermore, the amortized cost of creating a bot[1] is much

[1]Cost of creating a bot is equivalent to a mouse click by a human to solve re-captcha.

less than that of detecting a bot, and the cost of suspending a user incorrectly is much higher. Lastly, the bot-masters creating these automated accounts are constantly evolving the bots' behavior to attempt to evade detection. This is the typical 'Red Queen' effect, well known in biology and cybersecurity, in which "It takes all the running you can do, to keep in the same place"[45]. As Twitter's detection methods evolve, so do the botmasters'. To win this arms race, or to even keep up, a bot detection method must have the following characteristics:

- Very high *detection rate*, ideally higher than the rate at which automated accounts can be created, which would guarantee eradication of bots.
- *Scalable*, the method is robust in the face of increasing social network size.
- *Adaptive*, which means it retains the above two properties when bot-masters evolve. Simply training on labeled data that matches the current state is not enough, for as the bots' behaviors change, static classifiers will quickly become obsolete. This indicates that *unsupervised* solutions that detect novel, anomalous behavior are likely to be more effective in this quickly evolving environment.
- Completely *automated*, so that it can keep up with the rate of bot-master activity.

In this chapter, we propose a bot detection technique using Twitter's restricted API access for online updates that is adaptive, scalable and has the highest detection rate of current methods. Our BotWalk algorithm uses an adaptive search strategy to maximize detection rate in a rapidly changing social network. In the Twitter network, BotWalk can identify up to 6000 bots per day and adapt to detect novel bot behaviors automatically.

Problem Formulation: The high-level goal of this work is to efficiently explore the evolving Twitter network and identify bots manifesting continually changing behavioral patterns.

Contributions:

- Creation of BotWalk, a near-real time adaptive anomaly detection framework with 90% precision in detecting bot behavior in Twitter data

- Implementation of an adaptive approach to feature selection, necessitated by the limited amount of data accessible in real-time and the rapidly changing Twitter environment
- Utilization of domain knowledge to intelligently partition the feature space, leading to up to a 30% increase in precision
- Assembly of a comprehensive Twitter dataset, collected over the course of formulating this work, and made available to the public [8]

4.2 Related Work

Twitter bot detection has received significant interest in the literature. Most current approaches focus on supervised, non-adaptive methods [32][28][16]. Unfortunately, a supervised approach has several shortcomings. The classification is only as good as the labeled data, which is often biased or outdated. Supervised algorithms can be useful when trying to classify a given user as a bot, but what if the goal is identification of new bots? And what if these bots are constantly exhibiting new behavioral patterns? It is in these cases that supervised algorithms fall short.

In [64], the authors present an approach to semi-automatically label users as bots by identifying several features that can discriminate between obvious bots and human users. For each feature, the threshold value has to be manually set, and these values can vary depending on the candidate bot set, which reduces the automated aspect of the work. Other feature-based approaches use only a few linguistic attributes and test on a small number of manually-labeled accounts [25], or only temporal features in a supervised [55] or unsupervised way by identifying highly-correlated activity streams [22]. The latter approach has high recall and a low false positive rate, but is very easy to evade since it is just based on one feature. One study extracted a large number of features [26], but they used them in a supervised fashion. We compare their detection rate to BotWalk's in Section 4.6.3.

Our work is unique because it is an unsupervised exploratory method that is able to adaptively identify novel bot behavior using a variety of features which capture different dimensions of behavioral profiles. By using an unsupervised method seeded from known bots, rather than simply training a classifier on labeled data, BotWalk is able to discover new, unknown behavioral patterns.

4.3 Framework

Bot detection in a rapidly changing social network with limited external visibility is a challenging computational problem. As with malware, bot masters continually modify bot characteristics including communication patterns, content, and connectivity. Additionally, Twitter's query interface restrictions place significant limitations on the amount of new data that can be collected relative to the amount being generated.

Figure 4.1 shows our approach, which combines known data, domain expertise, and unsupervised anomaly detection. As described in Algorithm 1, we begin by selecting a seed bots (see Section 4.6.2) and a set of random users. This random set can consist of both normal users and bots, as it is not labeled. However, since estimates say that at most 8.5% of Twitter users are bots [62], a random sample should on average adhere to this constraint. The anomaly detection algorithm considers the random user set as containing the 'normal' group.

For each Twitter user from the seed bot one-hop follower neighborhood and the random user set, metadata such as timeline and user account information is collected (Lines 6 – 10). Features of the seed bot neighborhood and random user sets are then assembled from these raw data (Lines 11 – 13). Feature selection and assembly is a major contribution of this work, and is discussed in Section 4.4.

Finally, the ensemble anomaly detection algorithm is applied, resulting in identification of bots and normal users. Elements from these sets are used to update the seed bot and

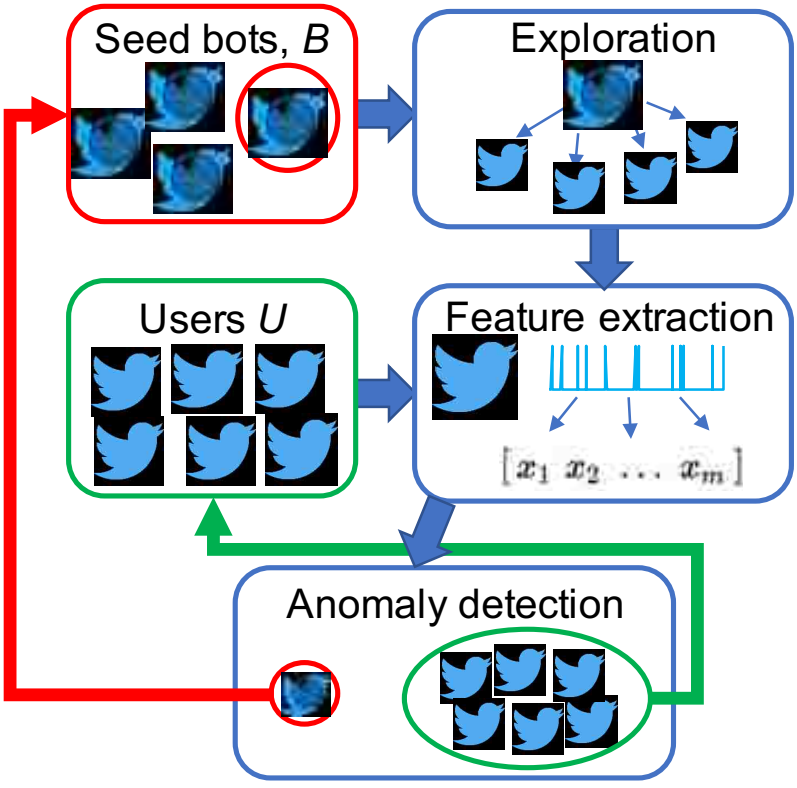


Figure 4.1: Overall framework of our bot identification algorithm

random user sets respectively (Lines 14 – 16). The anomaly detection algorithms and our partitioning approach to ensemble anomaly detection is the topic of Section 4.5.

Our exploration method combines depth-first and breadth-first exploration. Depth-first exploration constrains the search space but limits the scope, so if a human node is reached it can be difficult to return to a bot node. Breadth-first exploration maximizes the likelihood of reaching other bots at each step, since it is collecting all the followers of the current anomalous node, but the scale quickly explodes (for example, some Twitter users have tens of thousands of followers). Our method allows us to maximize the likelihood of identifying bots by collecting and analyzing the followers of the current seed bot, while still constraining the search space by continuously repeating the exploration process starting from individual random anomalous users. This has the added benefit of making our approach scalable by construction; by using a limited, carefully-chosen stream selected

Algorithm 1 `NetworkExploration`

Input: Set of seed bots $\mathcal{B}$, Set of random users $\mathcal{U}$;
while $explore$ = $True$ **do**
  b = pop random element from $\mathcal{B}$;
  $\mathbf{F_{user}}$ = feature matrix of $\mathcal{U}$;
  $N(b)$ = follower neighborhood of b;
  for neighbor c in $N(b)$ **do**
    // Metadata via the Twitter REST API
    $I_M(c) =$ `get_profile_info(c);`
    // Timeline info: 200 most recent tweets
    $I_T(c) =$ `get_timeline_info(c);`
    // Extract metadata-, content-, network-, and
    // temporal-based features (Secs. 4.4.1-4.4.4)
    $\mathbf{F_N}(c) =$ `create_feat_vector`$(I_M(c), I_T(c))$;
  $(\mathcal{B}_{out}, \mathcal{U}_{out}) =$ `UnsupervisedOutlierDet(` $[\mathbf{F_{user}}, \mathbf{F_N}]$`);` // (Secs. 4.4.1)
  $\mathcal{B}.update(\mathcal{B}_{out})$;
  $\mathcal{U}.update(\mathcal{U}_{out})$;

from this huge, constantly-changing network, this method is robust in the presence of increasing network size.

4.4 Feature Selection and Data Collection

To generate a comprehensive behavior profile for a given user, we compile a large collection of features which capture different aspects of a user's behavior. Each feature (e.g., temporal bursts) alone has been shown to be effective for identifying bots in a *supervised* setting (note that we target unsupervised settings). However, bots are a diverse group and can have many different behavioral patterns. Just looking for bots with spamming content,

	Metadata	Content	Network	Temporal	Total
Before/ After Feature Selection	9,035/ 127	23/ 22	5/ 5	14/ 14	9,077/ 168

Table 4.1: Description of feature set before and after feature selection is performed.

for example, could ignore bots that are trying to farm followers. By combining a large collection of features indicative of different aspects of behavior, we reduce bias and expand the quantity and types of bots that we can identify.

Currently there is considerable interest in the machine learning community in using latent features or learned representations, rather than engineered features. While this has been shown to be effective in some cases (such as classification and link prediction), it requires a huge learning space. Online bot behavior changes rapidly due to suspension pressure [45]. With severely rate-limited data acquisition, massive data updates are not feasible and impede latent feature generation, as the dataset quickly becomes stale. Additionally, in the case of identifying bots and potentially suspending users, there needs to be a level of interpretability in the results. By using features that can be understood, rather than latent features, we address this need.

Our features can be divided into four categories: metadata-, content-, temporal-, and network-based. We will describe a subset of members of each category, as well as the intuition behind them. A full listing of the features from each category is available on the BotWalk page [8].

4.4.1 Metadata-based features

Features that characterize a user's profile shed light on the level of effort a user put in when generating it. We would expect a bot to have this process automated, so there may be parts missing or repeated [66]. Bots may also want to provide less information because what they are claiming is false, e.g., if the account claims the user is from California but all of its

tweets are coming from China, it would not want the geo-enabled setting to be turned on. Conversely, real users often like these types of features because they provide intelligent shortcuts when entering content. Other attributes like age of the account and whether the username was auto-generated can provide valuable information about the likelihood that an account is a bot. In addition to these features, we also look at whether an account is protected or verified, neither of which a bot account is likely to be, the total number of tweets and number of followers, both of which are likely to be higher in a bot account that has managed to persist on Twitter, and several other metadata-related features.

4.4.2 Content-based features

Automated accounts are created for a specific purpose. Whether it is to gain followers for marketing campaigns, disseminate information, spam sponsored content, or collect data on other users, there is a goal in mind for each account. There are many features in the content of the tweets themselves that capture this goal-oriented behavior. Features quantifying items like hashtags, URLs, and domains, both on a tweet and user level, have been shown to be effective in identifying bots [25][17]. Identifying repetition in these entities is also informative. For example, a bot trying to direct followers to a certain site will want to include that site's URL in as many tweets as possible. Perhaps they try to use different URL shorteners to camouflage this effort, so looking for repeated domains in the extended URL is also helpful [19]. For hashtags, URLs, and domains, we look at both the average number of entity per tweet as well as the average number of tweets with that entity. We also quantify the number of duplicate hashtags, URLs, and domains. Another informative feature is the normalized retweet count. Creating original content is costly for automated accounts, so retweeting is an easy way to add a life-like feel to a profile without having to generate this content [33]. Additional features we examine include the maximum, minimum, mean, and standard deviation of the Jaccard similarity of inter-tweet bags-of-words, the number of special characters, and tweet lengths.

4.4.3 Temporal-based features

Analyzing the time series of tweets is a powerful way to distinguish between bots and humans; indeed, whole papers have been written on bot identification based solely on temporal characteristics [55][22][23]. Because there are limits to how rapidly and how often a human being can tweet, quantification of burstiness, defined as $\frac{\sigma-\mu}{\sigma+\mu}$ [55], the average number of tweets per day, and the duration of the longest tweet session without a 10 minute break are informative features. Statistics describing the minimum, maximum, mean, standard deviation, and entropy of the inter-arrival time of consecutive tweets help to identify bots whose goal is to get as much content out as quickly as possible, or whose activity is on a programmed schedule. Other features we use to identify scheduled behavior are the p-values of the χ^2 test applied to the second-of-minute, minute-of-hour, and hour-of-day distributions, which evaluates whether tweets are drawn uniformly across these distributions.

4.4.4 Network-based features

Network-based features can be very helpful in characterizing Twitter user behavior. Research has shown that bots that persist in the Twitter network tend to amass a large number of followers [27] and friends. Figure 4.2 shows the connections between a set of previously-labeled bots.

There are a variety of connections that can join nodes, including follow, friends, and mention connections. We take an ego-based approach to these relationships, quantifying the out-degree of the user's follow network, the out-degree of the user's friend network, and the out-degree of the user's mention network. These help to summarize the user's connectivity to others in a variety of ways.

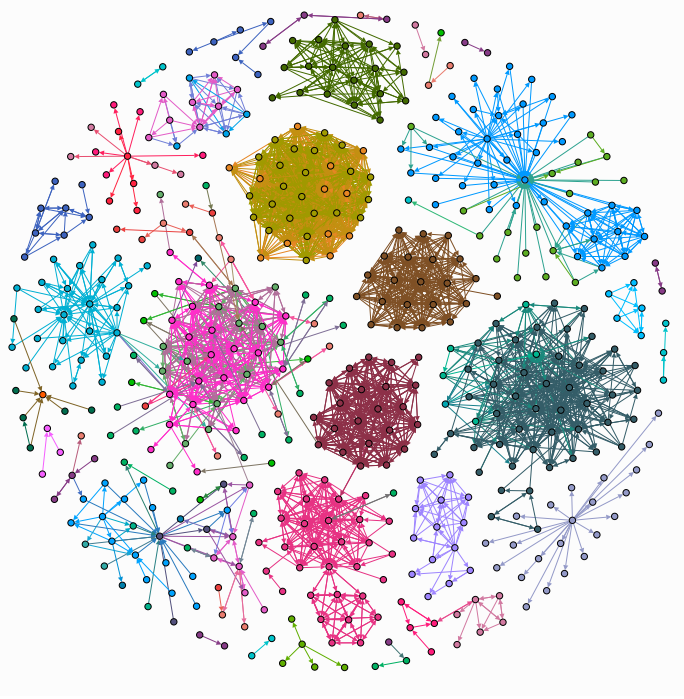


Figure 4.2: Follower relationships between Twitter bots. Node colors represent highly-correlated activity stream clusters (see Section 4.6.2). Note the highly-connected nature of many of the bots.

Number of Nodes	Number of Edges	Number of complete out-edge sets	Number of 48hr streams collected
362,000	226 Million	110,800	75,000

Table 4.2: Statistics of our publicly-available dataset

4.4.5 Feature selection and normalization

After encoding categorical features using one-hot encoding we have over 9000 features. It is likely that not all of these feature are informative, so we choose to remove features that have the same value in 99.9% of samples, which reduces the feature space to 130 features. We then use the L2 norm to independently normalize each sample. For the partitioned outlier detection method, described in Section 4.5.3, we perform feature selection and feature normalization on each subset separately.

4.4.6 Publicly-available dataset

Through the course of this research, we collected and analyzed a large body of Twitter data, which we are releasing for public use on the BotWalk page [8]. This dataset was collected using the Twitter API and the Tweepy Python library [12]. We collected 5 types of information: friendship relationships, follower sets, activity streams, timelines (which includes a user's 200 most recent tweets), and user metadata. We store the bot and follower metadata in a PostgreSQL database (exported to CSV files for public release) and the user stream and timeline data in JSON files. Table 4.2 contains basic statistics of this dataset.

4.5 Ensemble Anomaly Detection

In order to adaptively identify bots with ever-changing behavior, we employ an unsupervised anomaly detection approach. Anomaly detection has been shown to be successful in identifying samples with previously-unseen or fraudulent behavior [43][48] , so it is appropriate for this application. We employ true unsupervised anomaly detection in our method, which learns from the structure of the data itself with no outside guidance or labels.

To capture a variety of types of anomalous behavior, we use an ensemble of anomaly detection algorithms, which was shown to be effective in Chapter 3. In general, anomaly detection algorithms can be classified into four broad categories: density-based; distance-based; angle-based; and, more recently, isolation-based. For this work we use on from each of these categories. We choose to use Local Outlier Factor (LOF) as our baseline for comparison, since it is well-known, commonly used, and shown to be effective on a wide variety of data [20][48]. We find that this ensembling method improves precision by 5% when compared to LOF alone.

Algorithm 2 `UnsupervisedOutlierDet`

Input: Feature Matrix $\mathbf{F}$
for column $\mathbf{c}$ in $\mathbf{F}$ **do**
  $\sigma^2_{\mathbf{c}} = \frac{\sum_{i=1}^{N}(\mathbf{c}-\mu)^2}{N}$;
  if $\sigma^2_{\mathbf{c}} < 0.001$ **then**
    Remove $\mathbf{c}$ from $\mathbf{F}$;
for row $\mathbf{r}$ in $\mathbf{F}$ **do**
  $\mathbf{x} = \frac{\mathbf{r}}{\sqrt{r_1^2+...+r_i^2+...+r_n^2}}$; // Normalize row
  Normalized LOF score, $s_{LOF} = Eq4.8(Eq4.2(\mathbf{x}))$;
  Normalized distance score, $s_D = Eq4.8(Eq4.4(\mathbf{x}))$;
  Normalized cos distance score, $s_C = Eq4.8(Eq4.5(\mathbf{x}))$;
  Normalized IF score, $s_{IF} = Eq4.8(Eq4.6(\mathbf{x}))$;
  $s_r = \frac{s_{LOF}+s_D+s_C+s_{IF}}{4}$;
Return: Scores $\mathbf{S}$;

4.5.1 Anomaly Detection Algorithms

Local Outlier Factor

Local Outlier Factor (LOF) was described in detail in Section 3.5.1. We repeat the definitions here for clarity and readability. LOF uses the notion of k-distance ($dist_k(x)$), which is defined as the distance to the k-th nearest neighbor of a point. Local reachability distance (lrd_k) of x is the average of the reachability distances from x's neighbors to x. Here $N_k(x)$ is the set of k-nearest neighbors of x.

$$lrd_k(x) = \frac{||N_k(x)||}{\sum_{y \in N_k(x)} \max(dist_k(y), dist(x,y))} \tag{4.1}$$

The LOF of a point x is the average of the ratios of the *local reachability* of x and its k-nearest neighbors. LOF can capture several normal clusters of arbitrary densities, which

makes it robust for any data domain. Formally, LOF is defined as below:

$$LOF_k(x) = \frac{\sum_{y \in N_k(x)} \frac{lrd_k(y)}{lrd_k(x)}}{||N_k(x)||} \tag{4.2}$$

Distance- and Angle-Based Methods

In addition to a density-based measure, we use distance- and angle-based measures. We first generate an ideal 'normal' node by calculating the median of each feature (because we have many categorical features, we use the median, rather than the mode, which was used in Section 3.5.1).

$$\mathbf{c} = median(\mathbf{col}) \; \forall \; \mathbf{col} \; in \; \mathbf{F} \tag{4.3}$$

We then find the Euclidean distance between every user $\mathbf{x}$ and this ideal individual $\mathbf{c}$, giving us a distance-based outlier score.

$$DBD(\mathbf{x}) = \sqrt{(x_1 - c_1)^2 + ... + (x_n - c_n)^2} \tag{4.4}$$

To calculate an angle-based outlier score, we use the same center node but calculate the cosine distance between the two nodes.

$$ABD(\mathbf{x}) = \frac{\mathbf{x} \cdot \mathbf{c}}{||\mathbf{x}|| \; ||\mathbf{c}||} \tag{4.5}$$

Isolation-based Method

Lastly, we use an Isolation Forest algorithm [41]. Rather than constructing an idea of normality and identifying instances that differ from that, this algorithm instead isolates outliers from normal samples. Given our feature matrix $\mathbf{F}$, this algorithm recursively splits the rows of $\mathbf{F}$ by randomly selecting a column $\mathbf{c}$ and a split value s, where $min(\mathbf{c}) <= s <= max(\mathbf{c})$. This recursive splitting forms a tree structure, and an Isolation Forest contains k such trees. The anomaly score is then defined based on the path length $h(\mathbf{x})$, which is the number of edges a sample traverses before terminating in an external node.

Specifically, the anomaly score for a sample $\mathbf{x}$ from a size n dataset is defined by the equation:

$$s(\mathbf{x}, n) = 2^{-\frac{E(h(\mathbf{x}))}{c(n)}} \tag{4.6}$$

where $E(h(\mathbf{x}))$ is the average of $h(\mathbf{x})$ from a collection of isolation trees, and $c(n)$ is the average path length of an unsuccessful search in a Binary Search Tree, which is defined as

$$c(n) = 2H(n-1) - (2(n-1)/n) \tag{4.7}$$

Intuitively, if a sample has very anomalous feature values, it is going to be easily split from the remaining samples and thus will have, on average, a much shorter path length than a normal sample. Thus, when $E(h(\mathbf{x}))$ is close to 0, $s(\mathbf{x}, n)$ is close to 1, indicating it is very likely an anomalous sample. When $E(h(\mathbf{x}))$ is close to n, $s(\mathbf{x}, n)$ is close to 0, indicating it is a normal sample.

4.5.2 Combining different anomaly detection scores

As discussed in Section 3.5.2, each of the above methods produces a different type of score: Equation 4.2 returns a local reachability score, Equation 4.4 returns a distance, Equation 4.5 returns a cosine distance, and Equation 4.6 returns a score based on an averaged path length. Before combining these scores, we need to regularize and normalize them. We take the approach used in Chapter 3 from [38][58], which employs Gaussian scaling to normalize each outlier score separately before combining them into a single score.

Let a user be $\mathbf{x}$ and the outlier score of $\mathbf{x}$ is $s(\mathbf{x})$. We scale each $s(\mathbf{x})$ using a Gaussian distribution to produce a probability $p(\mathbf{x})$ between 0 and 1 of the user $\mathbf{x}$ being an outlier.

$$p(\mathbf{x}) = \max(0, erf(\frac{s(\mathbf{x}) - \mu_s}{\sqrt{2}\sigma_s})) \tag{4.8}$$

We then can average these probabilities to produce one outlier score per user.

4.5.3 Applying domain knowledge to improve performance

In addition to the interpretability of the bot labels produced by this method, another advantage to using observed features is that we can employ domain knowledge of the feature space to improve performance. As described in Section 4.4, we have four feature categories: metadata-, content-, temporal-, and network-based. These feature subsets describe different aspects of a user's online behavior and have different feature spaces and scales. For example, the majority of the metadata features are categorical, e.g., language and time zone, and thus explode into a large feature space when using one-hot encoding. This could potentially overwhelm other features, leading to results biased towards metadata anomalies. Based on this observation, we choose to *partition* the feature space into these four subdomains and apply feature selection, sample normalization, and anomaly detection *separately* in each feature sub-space. We then combine these scores using the method described in the previous section. We perform this partitioned anomaly detection both with the ensemble of outlier detection algorithms and local outlier factor, as a baseline. Our experimental results show that this separation increases the precision of LOF by 30% and the ensemble method by 25%, achieving an precision of 90% for both methods.

4.6 Experimental Analysis

4.6.1 Real-time data collection

Section 4.3 described the high-level exploration algorithm. We now go into the details of the actual execution. All code from these experiments is available on GitHub [2].

To expand from a seed user using the Twitter REST API [13], we first collect the follower set of this user, limited to the 5000 most recent followers to constrain the search space. (These followers are also less likely to be suspended since they have performed a recent activity, so in this way we avoid wasting queries.) We then collect the *timeline*,

which is the 200 most recent tweets by the user, and the *user_information*, which is the metadata associated with this account, for every follower in this set. We can collect 180 timelines every 15 minutes and metadata for 90,000 users every 15 minutes (queries must be performed sequentially, not concurrently). Once we have collected these data, we extract our comprehensive set of features and perform anomaly detection.

4.6.2 Experimental Design

We design our experiments to assess the following items:

- Is our algorithm effective at identifying bots?
- As we explore and replace the seed bots, do we continue to find high-quality results?
- Are we able to identify bots with novel behavior as we explore?

For our experiments, we first randomly select 15 non-suspended bots from our labeled dataset. This dataset contains $\sim 700,000$ labeled bot accounts identified by DeBot [22], which finds users with highly-correlated activity streams. Debot has a mathematically proven false positive rate of very close to zero [23], so we can have high confidence in the precision of these labels. Note that these users represent a specific subset of bot behavior, as they are so-called 'dumb' bots, with an obvious behavioral giveaway. We start with these users as seed bots, and then gradually adapt to identify bots with different behavior patterns.

We explore from these seed bots using the four outlier detection methods described in Section 4.5: LOF and partitioned LOF as our baselines, the ensemble of four anomaly detection algorithms (density-, distance-, angle-, and isolation-based), and this ensemble partitioned across the feature space. We run one round of exploration per seed bot, yielding a total of 15 rounds explored per method, which we call *Level 1 exploration*. We then randomly select 15 followers from our most accurate method with the highest average pairwise percent agreement, *partitioned ensemble*, and perform one round of exploration

for each of these 15 seed bots (again using the partitioned ensemble method), which we call *Level 2 exploration*. We repeat this process one more time, and call this *Level 3 Exploration*. The purpose of these multi-level experiments is twofold: to examine how the identity of the seed bot affects precision and to understand how the behavior of the identified bots changes as we explore.

4.6.3 Validation

We use four measures to evaluate our results: manual validation, examination of the distribution of feature values in the 90th or 10th percentile, differences in the distributions of specific feature values as modeled by the maximum likelihood estimated of the empirical data, and a comparison with the leading supervised method[26] and the leading unsupervised method[23].

User Study

In fraud identification research, one challenge is that the ground truth is, in reality, unknowable. Only the user or botmaster herself truly knows if a given account is a bot. User studies are thus typically performed to manually validate the results of the algorithm. While human labeling can of course contain bias, it is still the standard way to label bot accounts. We base our experimental design on methods from the literature [16][70] to reduce bias as much as possible.

We first conduct a manual examination of a random sample of 20 anomalous users from each of the six experiments to evaluate precision. The procedure for this examination is as follows: we first train our three annotators by showing them 100 different labeled bot accounts of different types. Next, we have them label each account with 'bot', 'human', or 'unknown'. We take the majority vote for each account as its label and calculate the average pairwise percent agreement, which is where the agreements of all possible

Experiment Type	Number of BotWalk-identified bots	Precision	Annotator Agreement
LOF	3984	60%	67%
Ensemble	3928	65%	80%
Partitioned LOF	3633	90%	87%
Level 1 Exploration (Partitioned Ensemble)	4040	90%	90%
Level 2 Exploration	2215	85%	83%
Level 3 Exploration	3302	75%	87%

Table 4.3: Results from the user study for the four anomaly detection methods and the three levels of exploration.

pairs are calculated and averaged. Table 4.3 shows the results, along with the number of anomalous users identified by BotWalk in each experiment. We estimate that starting from the initial 15 seed bots, over the three rounds of exploration we identify 7,995 new bots, which is over 500 times more than the initial seed bot set size. This estimate is calculated by multiplying the number of BotWalk-identified bots found by the calculated precision for each round and summing them. By scaling these values we avoid over-estimating this number.

Column 3 in Table 4.3 shows that even humans do not always agree on what a bot looks like. However, apart from unpartitioned LOF, which also has low precision, indicating it is not an effective method in this context, all of our experiments have average pairwise percent agreement values of 80% or higher, which is described as an acceptable level of agreement in the literature [53]. Without partitioning, using an ensemble of anomaly detection algorithms improves the precision by 5%. However, when partitioning is included, both LOF and the ensemble have 90% precision. This means that the human annotators agree with 90% of the bot classifications given by our partitioned anomaly detection algorithms. While partitioned LOF and the partitioned ensemble had the same precision in this experiment, the ensemble had higher average pairwise percent agreement than partitioned LOF. Furthermore, understanding that bot behavior continually changes, having an ensemble of techniques may still provide better anomaly detection for future evolving

behaviors.

When examining the results for exploration, we can see that as we explore further, the precision stays fairly high. Level 3 Exploration contains the followers of followers of followers of our labeled bots, so the fact that we are still able to identify a high percentage of bots shows that our exploration method is effective. The slight dip in precision suggests that adding some guidance into the system when selecting the seed bots could be helpful. Perhaps choosing a small number of the *most* anomalous followers and only adding those into the seed bank, rather than a random set selected from all fairly anomalous users, could improve performance. Investigations into these types of enhancements are left to potential future work.

Extreme feature values

To profile the anomalous users identified by BotWalk, we identify how many features each potential bot has that are in the 10th or 90th percentile when compared to a feature vector of 17,000 random users. We limit this evaluation to integer- and floating point-valued features. We then plot the distribution of these values for all of our Level 1 Exploration experiments in Figure 4.3. We also include the percentiles for these random users for reference. We can see that our identified anomalies have high numbers of 'extreme' features, which shows that our algorithm is successfully identifying anomalous users. Since we know that the features in our comprehensive feature set are effective at identifying bots, these results validate that we are indeed identifying bots in our exploration.

Figure 4.4 is a zoomed-in version comparing these distributions for the different anomaly detection methods. We can see that the partitioned versions of the outlier detection algorithms are more effective at identifying highly anomalous users than those applied to the feature space as a whole.

To examine how multiple iterations of the exploration process affect the type of anomalous users we are identifying, we compare the extreme feature values for the anomalies

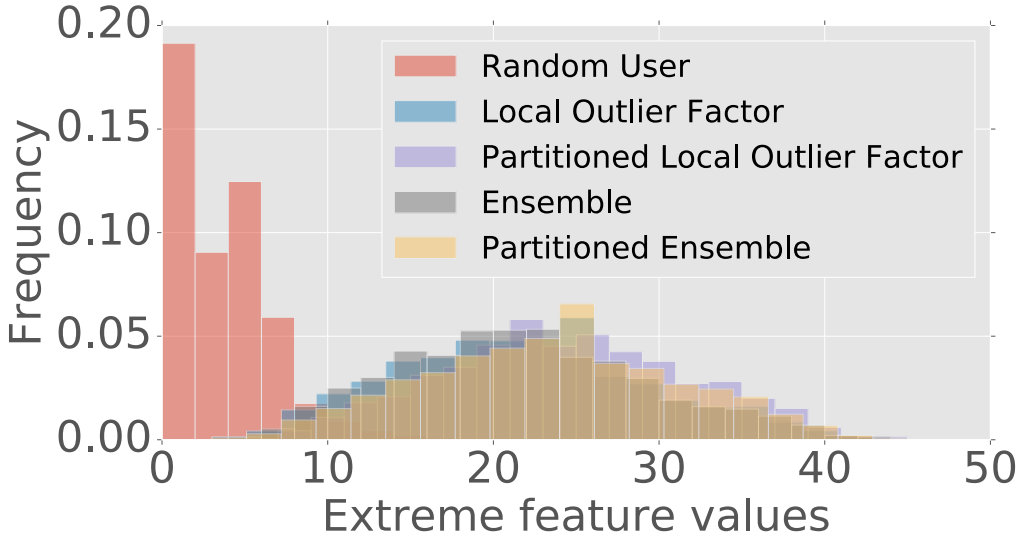


Figure 4.3: Distribution of number of extreme features for 17,000 randomly-selected users versus BotWalk-detected outliers. BotWalk-detected anomalous users have many more 'extreme' feature values when compared to random users.

found from Level 1, Level 2, and Level 3 Explorations. Figure 4.5 shows the results of this analysis. We can see that the anomalous users' behavior changes after the first round of exploration, and then remains constant. This makes sense, since for our first round we use Debot-labeled bots as our seed bots, which tend to exhibit very obvious 'dumb' bot behavior, whereas for the following rounds we use randomly-selected anomalous followers as our seed bots.

Examination of feature distributions

We next wanted to explore the differences in behavior between random users, Debot-labeled bots, and the bots discovered in our three levels of exploration. To perform this comparison, we took a random sample of 10,000 of the previously-labeled bots, 10,000 random users, and the bots identified in each level of exploration and modeled their distributions using the maximum likelihood estimation of the empirical data for the above-

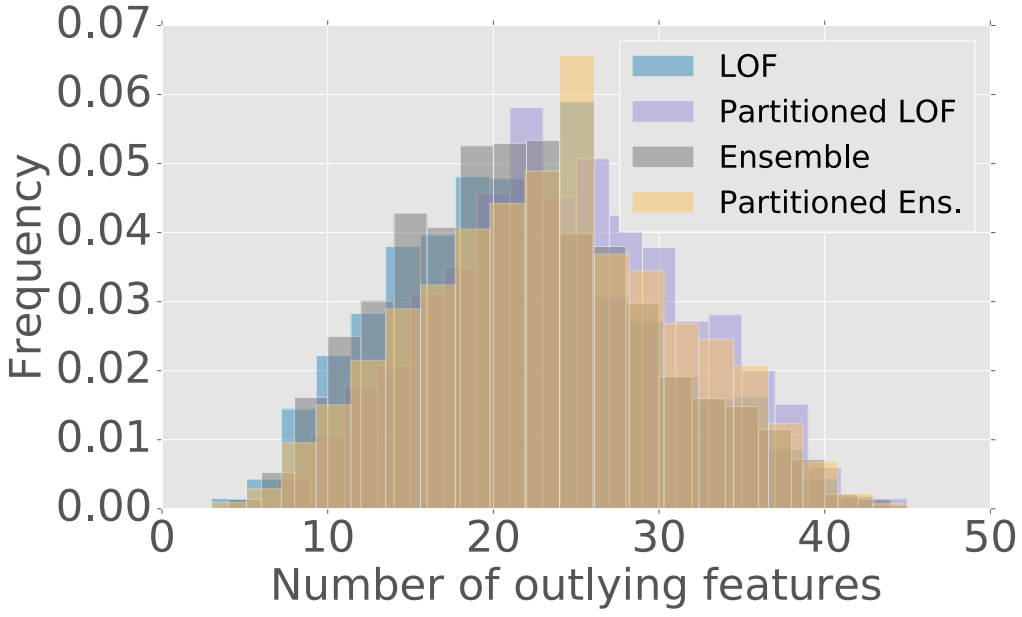


Figure 4.4: Zoomed in view of the distribution of the number of extreme features for outliers detected in the 4 experiments. Partitioned anomaly detection methods identify outliers with more 'extreme' feature values.

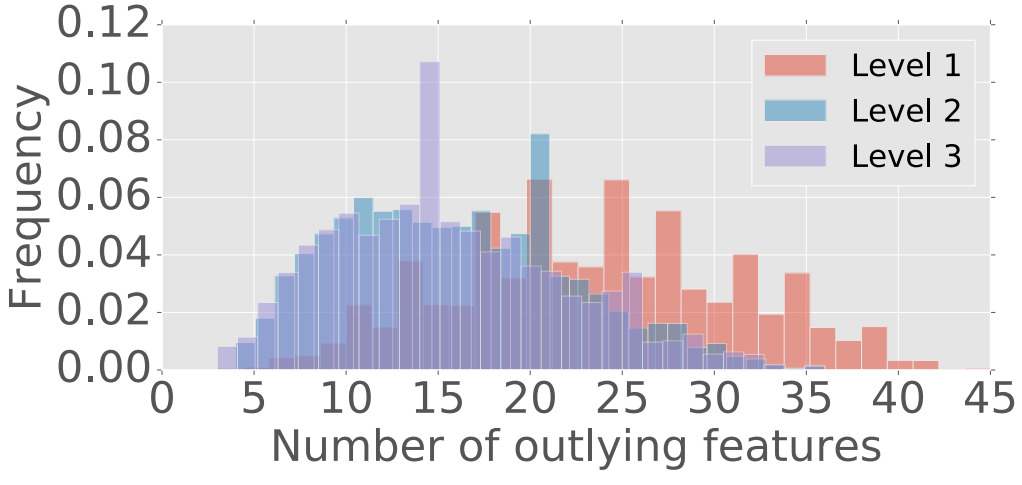
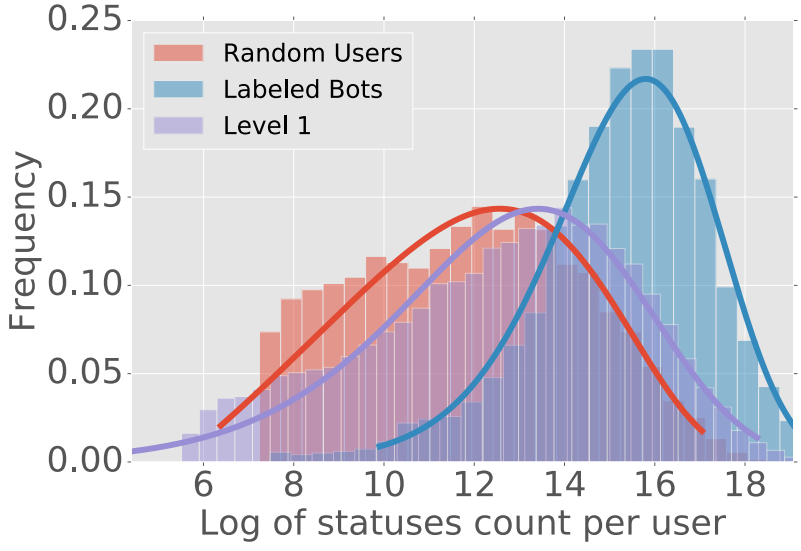
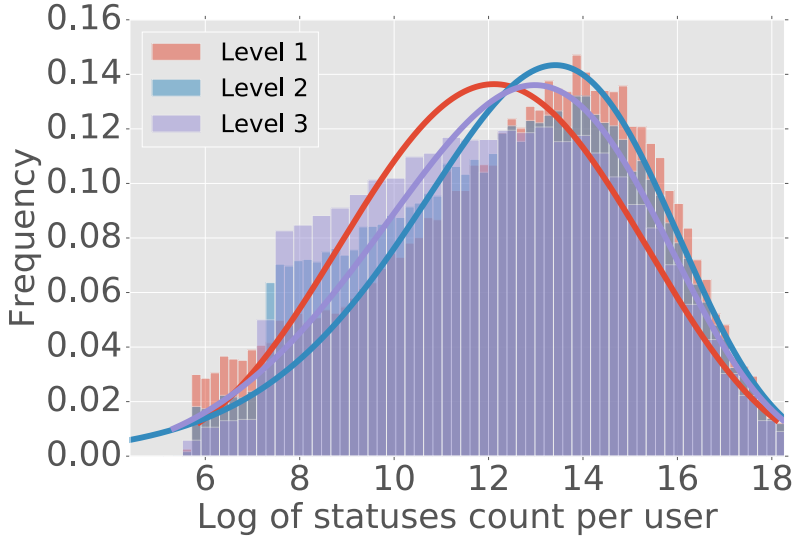


Figure 4.5: Comparison of of the distribution of the number of extreme features for exploration Levels 1, 2, and 3. Level 1 anomalies have a different extreme feature distribution compared to Level 2 and Level 3 anomalies, which are very similar.

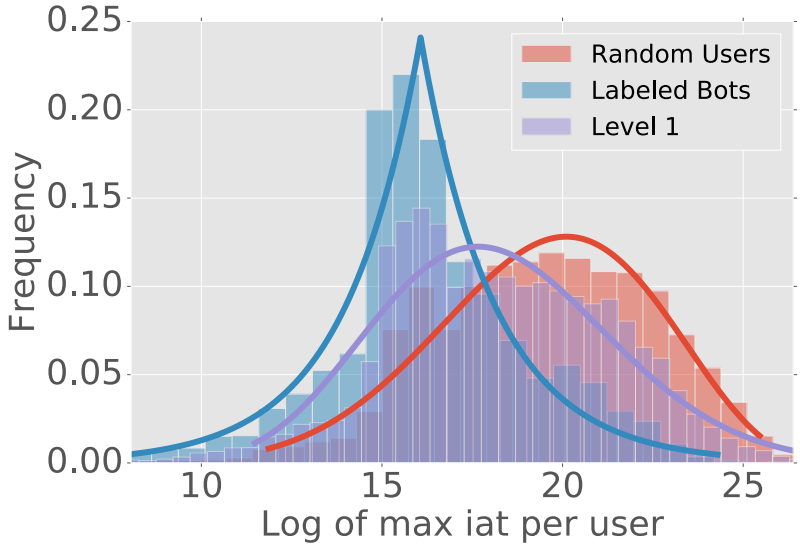


(a) Random users are modeled by the exponentiated norm distribution, previously-labeled bots by the lognorm distribution, and bots identified in Level 1 exploration by the Beta distribution.

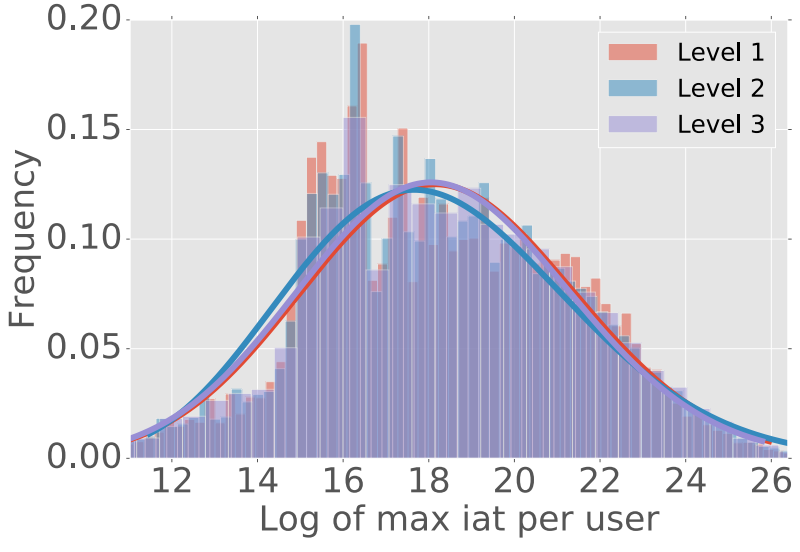


(b) Bots identified in Level 2 exploration are modeled by the power-lognorm distribution, while those from Level 3 exploration are modeled by the exponentiated Weibull distribution.

Figure 4.6: Distributions of number of tweets per user.

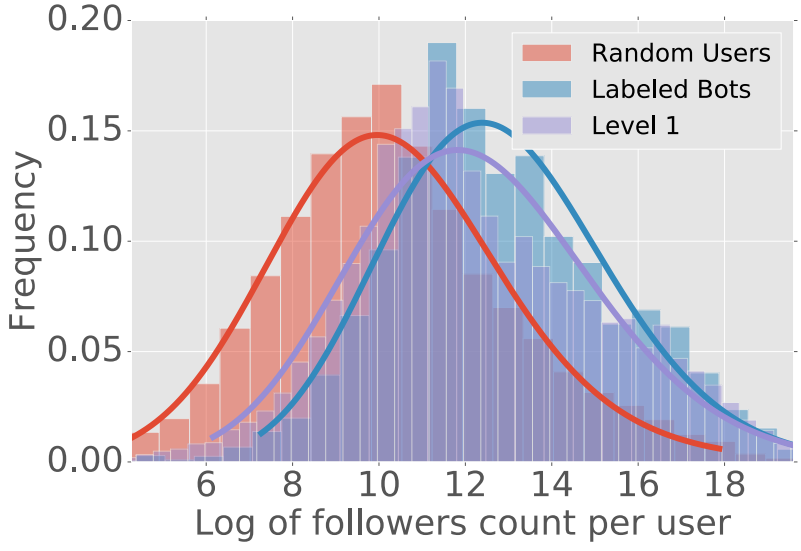


(a) Random users are modeled by the Beta distribution, previously-labeled bots by the log-Laplace distribution, and bots identified in Level 1 exploration by the Beta prime distribution.

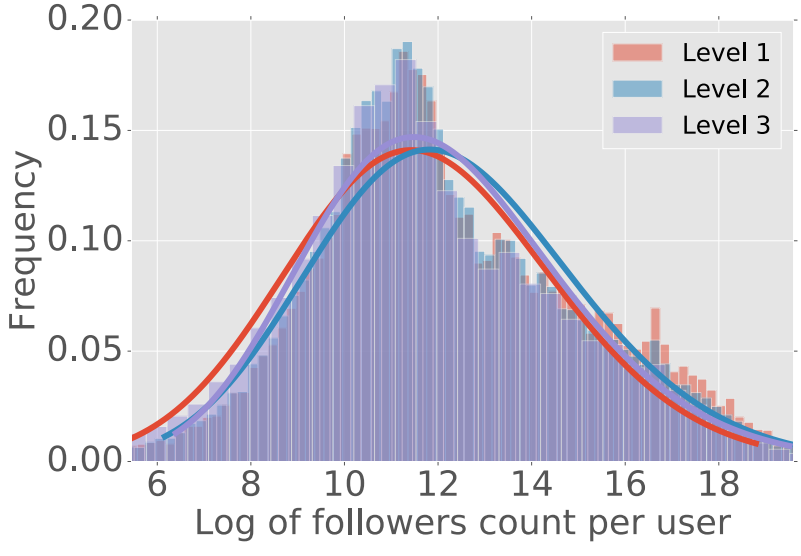


(b) Bots identified in Level 2 exploration are modeled by the power-lognorm distribution and those from Level 3 exploration by the Beta prime distribution.

Figure 4.7: Distribution of the maximum inter-arrival time per user.



(a) Random users are modeled by the exponentiated power distribution, while both previously-labeled bots and bots identified in Level 1 exploration 1 are modeled by the exponentiated Weibull distribution.



(b) Bots identified in Levels 1, 2, and 3 exploration are all modeled by the exponentiated Weibull distribution.

Figure 4.8: Distributions of out-degree of the ego network per user.

described features. We find that BotWalk-discovered bots have significantly different behavior than both Debot-labeled bots and random users for many of our features. Fur-

	Random User	Debot Bots	Level 1 Bots	Level 2 Bots	Level 3 Bots
Random User	100%	22.2 %	22.2%	16.7%	8.33%
Debot Bots	–	100%	33.3%	8.33%	8.33%
Level 1 Bots	–	–	100%	40.9%	38.6%
Level 2 Bots	–	–	–	100%	59.1%
Level 3 Bots	–	–	–	–	100%

Table 4.4: Percentage of features that have matching distributions

thermore, we find that as we explore we are identifying bots that are exhibiting novel behaviors.

Table 4.4 shows the percentage of features that have matching MLE distributions for each pair of user sets. A subset of these distributions is shown in Figures 4.6, 4.7, and 4.8. These results show that BotWalk bots behave differently than both random users and Debot-labeled bots. Furthermore, bots identified in Level 3 exploration are the most dissimilar. This shows that we are continuously identifying bots with novel behavior as we explore.

Comparison with known methods

We compare BotWalk with the most promising unsupervised algorithm, Debot [22][23], and the most popular supervised Twitter bot detection algorithm, BotOrNot [26]. We first evaluate what percentage of our anomalous users these methods are able to detect as bots. Note that we are examining the relative support of these methods, not comparing performance, since this is a one-sided comparison. Table 4.5 shows the results of this study. We see that Debot only identifies between 8.6 and 21% of our anomalous users, which shows that BotWalk-identified bots are exhibiting novel behavior which is different from the Debot-labeled seed bots. We find BotOrNot shows between 49-60% detection of our bots.

Experiment	Debot Detection	BotOrNot Detection
LOF	21%	49%
Ensemble	21%	51%
Partitioned LOF	17%	64%
Level 1 Exploration (Partitioned Ensemble)	19%	60%
Level 2 Exploration	11%	56%
Level 3 Exploration	8.6%	49%

Table 4.5: Detection levels of new bots by known methods

We next compare the bot-detection rate of these three methods. This rate necessarily depends on the rate limitations imposed by Twitter for all three methods. Assuming that these restrictions are in place, our algorithm has a much higher bot detection rate than these two leading methods. Since supervised algorithms need to be given specific accounts to test, the number of bots found depends on the query rate of the algorithm and the prevalence of bots in Twitter. Using BotOrNot as an example, which has a query rate of 180 requests per 15 minutes, 17,280 users could be tested per day. Since the current estimate of bots in Twitter is 8.5%, this method would yield on average 1,469 bots per day. Debot needs time to collect and analyze users' data, so it is limited as well: Debot's average detection rate is estimated to be 1,619 bots per day [24]. Our method easily beats both of these, identifying on average 6,000 bots per day. Furthermore, our algorithm is infinitely linearly scalable: the only shared resource is the two seeds banks, and everything else can be independent. Therefore, with additional parallel machines and additional API keys, BotWalk's detection rate could be even higher.

4.7 Conclusion

This chapter introduces BotWalk, arguably the first near-real time unsupervised Twitter network exploration algorithm that adaptively identifies bots exhibiting novel behavior. Key contributions of this work are the implementation of an adaptive approach to feature

selection and the utilization of domain knowledge to intelligently partition the feature space, which leads to up to a 30% increase in precision. We perform experiments to evaluate the performance of an ensemble of outlier detection algorithms, achieving an precision of 90%. We also perform three levels of iterative exploration and show that we are able to identify bots that exhibit different behavior than the seed users at a higher detection rate than existing methods.

Chapter 5

Conclusion

The goal of this body of work was to design a collection of data inspection, filtering, fusion, and mining techniques to identify and remove low quality and fraudulent content from online data. This is a challenging problem in part because of the changing behavior of fraudsters and the lack of ground truth available. These challenges necessitate the creation of adaptive, unsupervised methods, which is what this work focuses on. The main components of this dissertation include: noise removal, data fusion, multi-source feature generation, network exploration, and anomaly detection. All data collected and code written for this work have been made available to the research community at large.

To identify and remove noise in online data, we created ClearView, which is an automated data cleaning pipeline. We discussed various types of abnormalities that exist in different review sites and developed filtering techniques to identify and remove them. We evaluated the performance of our pipeline through an in-depth user study and found that our pipeline improves the quality of the dataset by up to 3.4 times.

To identify and remove fraud, we created TrueView, a metric for the "trustworthiness" of a given entity's review behavior based on multi-source information. The goal of this work was to show the significant benefits that we can gain by combining reviews from multiple review sites. As a key contribution, we developed a systematic methodology to

collect, match, and analyze hotels from multiple review sites. The novelty of our approach relied one the introduction and assessment of 142 features that capture single-site and cross-site discrepancies effectively. Our approach culminated with the introduction of the TrueView score, in three different variants, as a proof-of-concept that the synthesis of multi-site reviews can provide important and usable information to the end user. We conducted arguably the first extensive study of cross-site discrepancies using real data from 15M reviews from more than 3.5M users spanning three prominent travel sites. We found that there are significant variations in reviews, and we found evidence of review manipulation.

To identify and remove automated accounts, we created BotWalk, arguably the first near-real time unsupervised Twitter network exploration algorithm that adaptively identifies bots exhibiting novel behavior. Key contributions of this work are the implementation of an adaptive approach to feature selection and the utilization of domain knowledge to intelligently partition the feature space, which led to up to a 30% increase in precision. We performed experiments to evaluate the performance of an ensemble of outlier detection algorithms, achieving an precision of 90%. We also performed three levels of iterative exploration and showed that we were able to identify bots that exhibit different behavior than the seed users at a higher detection rate than existing methods.

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