Detecting Changed-Hands Online Review Accounts

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Abstract

A reputable social media or review account can be a good cover for spamming activities. It has become prevalent that spammers buy/sell such accounts openly on the Web. We call these sold/bought accounts the changed-hands (CH) accounts. They are hard to detect by existing spam detection algorithms as their spamming activities are under the disguise of clean histories. In this paper, we first propose the problem of detecting CH accounts, and then design an effective detection algorithm which exploits changes in content and writing styles of individual accounts, and a proposed novel feature selection method that works at a fine-grained level within each individual account. The proposed method not only determines if an account has changed hands, but also pinpoints the change point. Experimental results with online review accounts demonstrate the high effectiveness of our approach.

1 Introduction

Opinion spam has become a common type of spam in review sites such as Amazon and Yelp, as people continue to heavily rely on online reviews to make purchase decisions. Since the early work by Jindal and Liu [2008], detecting fake reviews and reviewers have drawn wide attention from both the research community and the industry. The problem has been investigated through different approaches, including those based on content or linguistic information [Ott et al., 2011; Li et al., 2014b], reviewer behaviors [Feng et al., 2012; Ye and Akoglu, 2015], temporal posting patterns [Xie et al., 2012] KC and Mukherjee, 2016, and relational analysis [Jiang et al., 2014; Rayana and Akoglu, 2015].

As a result of the advances in spam filtering techniques, spamming has become harder than before. For example, giving all-extreme ratings or posting many reviews in a short time frame can be easily caught. Driven by profits, opinion spammers resort to other strategies. One strategy is to offer to buy reputable accounts (those with a clean history) and use them to post spam reviews. Selling/buying accounts is also prevalent in other forms of social media. Karma farmers are such an example in the community website Reddit, who try to gain high karma (upvotes and reputation) quickly with new accounts so that their posts can show up in the front page, and then sell these seemingly reputable accounts to spammers.

In both of the above situations, accounts change hands at a certain time point and they unavoidably exhibit linguistic and writing style differences in the midst of their life span. It is hard for a spammer to align his writing style with the original account holder’s writing style for two reasons. First, there is no simple manual way to quantify another user’s writing style in every aspect. Second, since spammers have different objectives than legitimate users, e.g., promoting some products, their writing styles change naturally. To the best of our knowledge, such changes have not been studied before. This paper represents the first work on the topic.

In this paper, we propose this new problem of detecting changed-hands (CH) accounts from a content and writing style perspective. An algorithm, called CHAD (CH Accounts Detection), is proposed to identify if an account has changed hands and to estimate the time point of change if so. In case of a change, we assume there is only one change in an account’s life time because once there is a change, it should be detected before a second change happens. Existing spambber detection methods are not suitable for detecting such accounts, and cannot identify the change point for two reasons. (1) They assume there is a single user behind each account. (2) They examine the overall behavior of each account. For CH accounts, their spamming activities may not be obvious given a clean history. This work thus complements the existing review spam detection settings and algorithms.

Problem Definition: Given an account \( A = \{r_1, r_2, \ldots, r_n\} \) with reviews \( r_j \) sorted by their posting dates, CHAD determines whether a significant linguistic and/or writing style change has occurred starting from a particular review \( r_i \) (\( 1 < i < n \)). The algorithm returns \( i \) if yes, and returns none otherwise.

The problem has two unique challenges:

1. Inter-user differences: Different CH accounts exhibit different changes, because not every pair of users has the...
same differences in their writings. For example, in some CH accounts, the two users can be distinguished by the average length of the words they use. In some other CH accounts, the two users may be distinguished by the average sentence length but not by the average word length, because one uses long sentences while the other uses short ones, but both of them mainly use short words.

2. Intra-user variance: Every review is unique in some way, which results in a certain amount of difference and variance even when compared with other reviews of the same user. However, such differences do not indicate a real changing of hands between two users.

Given these two challenges, a desired detection method needs to perform detection at the account level and adjust itself to different individual accounts. In this paper, we propose an effective detection algorithm with a novel feature selection method, called pivot-level feature selection, to address these challenges. The key novelty of this feature selection method is that, due to the two challenges, it works at a fine-grained level within each individual account rather than the whole dataset as traditional feature selection methods do.

In summary, this paper makes the following contributions:
1. It proposes the new problem of detecting CH accounts, which have become prevalent in many social media sites, but have not been studied so far. This new problem complements the existing spammer detection settings.
2. It proposes a novel algorithm, CHAD, which leverages linguistic evidences and a novel new feature selection algorithm to identify if an account has changed hands during its lifetime and estimates the change point.
3. It evaluates CHAD on two datasets and show that the proposed approach is highly effective.

2 Related Work

Our work is related to opinion spam detection, tracking linguistic evolution and change point detection.

2.1 Opinion Spam Detection

Since the first work by Jindal and Liu [2008], a wide range of techniques have been proposed for detecting spam reviews [Li et al., 2011, Li et al., 2014a, Hai et al., 2016]. Individual spammers [Lim et al., 2010, Akoglu et al., 2013] and spammer groups [Mukherjee et al., 2012]. However, the use of CH accounts as a new instrument for spamming has not been studied thus far and no techniques are available for their detection.

Among existing techniques, detecting spammer accounts is most relevant to our problem. Lim et al. [2010] studied users’ rating behaviors; Akoglu et al. [2013] studied the relational collusion between reviewers and their target products; Mukherjee et al. [2013a] used a Bayesian approach to modeling the behavioral patterns of spammers and non-spammers. These approaches cannot detect CH accounts and pinpoint their change locations because they examine the overall behavioral patterns of each account. The spamming activities of CH accounts may go undetected given a clean history.

Sockpuppet detection [Hoseinia and Mukherjee, 2017] refers to the detection of a single author behind multiple accounts. These methods cannot be directly applied as they regard reviews from one account as written by a single author.

Our work is also related to using linguistic approaches to detecting spamming reviews [Ott et al., 2011, Ren et al., 2014] and loosely related to psycholinguistic deception detection [Newman et al., 2003, Perez-Rosas et al., 2015], as we also use a linguistic-based approach.

2.2 Linguistic Evolution & Change Point Detection

On tracking linguistic evolution across time, Juola [2003] quantified the rate of change in language across two time periods, and Lijffijt et al. [2012] studied lexical stability in a historical corpus. Our work is different because the above works compare language from two chosen time periods, while our goal is to estimate the change point from a sequence of documents. Tracking shifts in the meaning of words was studied in Mitra et al., 2014, Kulkarni et al., 2015. Our work does not study shifts of word meaning but “shifts in authorship.” However, authorship attribution and verification methods [Koppel and Schler, 2004, Sanderson and Guenter, 2006] cannot be applied as we don’t have any training data of the users. Change point detection is a core time series analysis problem [Taylor, 2000]. In our work, we adopt the single change point detection technique by Chen and Gupta [1999], as it aligns with our goal of detecting CH accounts.

3 Proposed CHAD Method

This section presents the proposed CHAD algorithm.

3.1 The Overall Algorithm

The main idea of CHAD is based on the observation that the reviews written by one user are similar among themselves but different from those written by a different user. The CHAD algorithm is outlined in Alg. 1 which works on one account at a time. Note that it needs a pre-selected feature set $F$ as input, which is a subset of all features $F$ (We will explain this shortly). We first introduce the five main steps, and then go into details of each step.

1. Generate similarity sequences (lines 2-9): For an input account $A$, this step builds a set of similarity sequences $S_i$ using features in $F$ for a pivot window of $K$ reviews starting from a review $r_i$. Each sequence $s_{ij} \in S_i$ is computed by comparing the similarity of reviews in the pivot window and reviews within a moving window of also size $K$ in the remaining reviews $\bar{A}$ using one ($f_j$) of the features in $F$ (line 7). For a CH account, we expect the similarities to be high when comparing reviews written by the same user, but low across two different users.

2. Eliminate noisy features (line 10)

3. Aggregate sequences (line 11): We aggregate the remaining sequences for each pivot window by averaging the sequences in the resulting $S_i$.

4. Change-point detection (line 12): We employ a statistical algorithm for change-point detection on each aggregated sequence $s_i$ to detect the change point.

5. Two-round voting (line 15-20): We perform two rounds of voting on the change-point detection results on the aggregated sequences of all pivot windows for an account to
As mentioned before, CHAD requires a pre-selected feature set $F$ as input. $F$ is selected globally by running Alg. 1 without line 10 (pivot-level feature selection) on all accounts of a development set for multiple iterations starting with all features level feature selection) on all accounts of a development set selected globally by running Alg. 1 without line 10 (pivot-window) for big feature evaluation (biggest performance gain in F1 score under the change-point for each removed feature is deleted from $F^{all}$; only the noisy sequence generated from the feature Adj&Adv. does not indicate real writing differences between two users. To solve these two problems, we propose to perform pivot-level feature selection (Alg. 2). The corresponding similarity sequence of each removed feature is deleted from $S_i$.

### 3.3 Pivot-Level Feature Selection

Now we describe the pivot-level-feature-select function in line 10 of Alg. 1. As we pointed out earlier, one of our key challenges is that the writing differences between a pair of users in one CH account may be different from those between other pairs in other CH accounts. Furthermore, each review is unique in some way which can result in a certain amount of difference when comparing similarity with other reviews using some features. Such differences however may not indicate real writing differences between two users. To solve these two problems, we propose to perform pivot-level feature selection (Alg. 2). The corresponding similarity sequence of each removed feature is deleted from $S_i$.

The pivot-level-feature-select function selects a subset of features from $S_i$ through correlation analysis, which is the same as selecting their corresponding features. It first averages all sequences in $S_i$ to construct a target sequence (line 1). It then computes Pearson’s correlation ($Pc$) for each sequence with the target and sorts the sequences based on correlation strength in descending order (line 3). Line 4 adds the sequences with the highest correlation to the set $E$. It then goes through the sorted sequence set $S_i'$ and tests if adding another sequence to $E$ would increase $E$’s average correlation to target (lines 5-13). If the correlation improves by the addition, we update $E$; otherwise exit and return $E$.

The intuition is that target is a representative sequence assuming only a few noisy sequences exist. Through correlation analysis, we identify the sequences that align with the target and discard those outlying ones that otherwise hinder the change point detection performance. Fig. 1 gives an example of several similarity sequences computed for a pivot window on a CH account in the Amazon dataset, where the actual change happens at review #119. For clarity, we only plot a subset of sequences generated using 4 features. Through correlation analysis, our Alg. 2 is able to effectively eliminate the noisy sequence generated from the feature Adj&Adv.

### 3.2 Features and Similarity Metrics

Now we list the set of all features $F^{all}$ used in the compute-sim-seq function (line 7) in Alg. 1. Features with * produce a single value for reviews in a given window and the rest use the Bag-of-Words (BoW) model. Single value features include average sentence length* and average token length*. BoW features include word unigrams, word bigrams, Part-of-Speech unigrams, Part-of-Speech bigrams, adjectives & adverbs, nouns, function words, and punctuations.

To measure the similarity between reviews in two review windows, we use cosine similarity for BoW features. We tried some other measures such as Jaccard similarity but they did not perform well. For single value features, we compute the similarity $sim$ using their absolute difference $diff$ and normalizing it to $[0,1]$:

\[
sim = 1/(1 + log(1 + diff))
\]  

(1)
3.4 Change Point Detection

As mentioned in the introduction, we assume there is at most one change point in each account. As such, we use the single point change detection algorithm by Chen and Gupta [1999], which uses the Schwarz Information Criterion (SIC) to search for the change point. Suppose $X_1, X_2, \ldots, X_n$ is a sequence of independent Gaussian random variables with means $\mu_1, \mu_2, \ldots, \mu_n$ and variances $\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2$, respectively. The method tests the hypothesis of whether there is a single change in both the mean and variance located at the unknown position $k$, $2 \leq k \leq n - 1$ as:

$$H_0: \mu_1 = \mu_2 = \cdots = \mu_n = \mu$$

and

$$H_1: \mu_1 = \cdots = \mu_k \neq \mu_{k+1} = \cdots = \mu_n$$

versus the alternative hypothesis

$$H_1: \mu_1 = \cdots = \mu_k \neq \mu_{k+1} = \cdots = \mu_n$$

where $\mu$ and $\sigma^2$ are unknown common parameters when there is no change. We thus have two models corresponding to the $H_0$ and $H_1$. The principle of minimum SIC is used to reject $H_0$. In particular, $H_0$ is not rejected if $\text{SIC}(n) \leq \text{SIC}(k)$, and rejected otherwise. $\text{SIC}(n')$ is defined as $-2\log L(\hat{\theta}) + p\log n'$, where $L(\hat{\theta})$ is the maximum likelihood function for each model, $p$ is the degrees of freedom in the model ($p = 2$ under $H_0$ and $p = 4$ under $H_1$), and $n'$ is the sample size.

3.5 Two-Round Voting

In Alg. 1 CHAD uses a two-round voting scheme (step 5) to determine if an account has changed hands and also to pinpoint the location of change (lines 15-20). In the first round (line 15), is-change-vote function determines if a change has occurred. Note that each element $c_i \in C$ returned by the change point detection algorithm is either a change point (i.e., a review) or none (indicating no change). This function simply counts the number of votes for each change point and none. If none has the highest number of votes, it returns none; otherwise it registers that a change has occurred and removes all the none elements from $C$ (line 17). It then moves on to the second round of voting to pinpoint the actual change location. Instead of directly voting based on elements in $C - \text{none}$, we perform smoothing on $C - \text{none}$ first (line 18). Let us look at an example. Given a set of votes in $C - \text{none}$ in the format of change-point:#-of-votes 10:8, 50:5, 51:7, 52:4, the point that gets the highest votes is 10. However, the actual change point is more likely to be around 51. In order to overcome this possible noise factor, we smooth the votes by adding some extra counts to near-by locations of every change point in $C - \text{none}$ to construct $C_{\text{smooth}}$. Specifically, we pick a smoothing factor $\lambda_S \in \mathbb{Z}_{>0}$ and for a change point $i$ with $v$ votes, we add $v/\lambda_S^\text{dist}$ extra votes to locations $i + \text{dist}$ and $i - \text{dist}$, where $\text{dist} = 1, 2, \ldots$. Finally, we perform the second round of voting on $C_{\text{smooth}}$ to determine the final change location.

4 Experiments

4.1 Datasets and Evaluation Metrics

Datasets: For experiments we constructed synthetic datasets for the following reasons: First, no publicly available labeled data exists for our problem; Second, identifying opinion spam manually has been shown to be very unreliable [Ott et al., 2011]. Lastly, although Mechanical Turkers have been used to write individual fake reviews [Ott et al., 2011], our case is much more complicated because of different sizes and the diversity of reviewed products for different accounts. In fact, synthetic data was used before, e.g., in sockpuppet detection [Qian and Liu, 2013]. In this work, we use two public review corpora to construct our data, one from Amazon [Jindal and Liu, 2008], which contains reviews for multiple product categories such as books, electronics, etc., and the other from Yelp [Mukherjee et al., 2013b], which contains only hotel reviews. The construction of CH accounts from each corpus is done as follows: We first randomly select two different original accounts with at least 10 reviews, $A_1 = \{r_{11}, r_{12}, \ldots, r_{1n}\}$ and $A_2 = \{r_{21}, r_{22}, \ldots, r_{2n}\}$, both sorted by their review posting dates, and then concatenate one account to the other, giving us $A_{\text{syn}} = \{r_{11}, r_{12}, \ldots, r_{1n}, r_{21}, r_{22}, \ldots, r_{2n}\}$, whose minimum size is 20. We in total constructed 350 CH accounts. Then we sample 350 original accounts with at least 20 reviews as non-CH (NCH) accounts that approximately match the mean and standard deviation of the sizes of the constructed CH accounts by following the 68-95-99.7 rule from statistics. This way of sampling (rather than random sampling) is important because it ensures that the NCH and CH accounts have similar number of reviews, which eliminates the bias due to joining two accounts in constructing CH accounts that can result in significantly more reviews for CH accounts than for NCH accounts. Thus for each dataset, we in total created 700 accounts. Statistics of the size of the accounts in both datasets are given in Table 1. In Sec. 4.5, we will show the results when the datasets are constructed in a different way.

Although it is possible that the original corpora already contain some CH accounts, we believe the chance of selecting existing CH accounts is very small because the original corpora are very large. Also, we believe it is reasonable to study accounts with more than 20 reviews because of our problem setting, i.e., an account changes hand after it has gained enough “reputation” or a long history.

We choose to use the Amazon and Yelp corpora for the following reason. The Amazon corpus has reviews of all kinds
of products. We use it to create the scenario where a spammer buys an account and uses it to review products that are potentially very different from those reviewed by the original user (although we do not enforce this when constructing the dataset). Moreover, products reviewed by a single user can also be quite diverse. In contrast, the Yelp corpus has only hotel reviews, which allows us to show whether our approach can detect CH accounts when the two users wrote reviews for the same type of entities (i.e., when the content change is not as drastic). As we will show, CHAD is able to perform well in both scenarios.

**Evaluation Schemes and Metrics:** We use two evaluation schemes, CH-accounts detection evaluation (eval\_cha) and change-point detection evaluation (eval\_cp), and report corresponding precision, recall, F1, and accuracy on both tasks. For eval\_cha, we only consider CH accounts but not the actual change locations. For eval\_cp, we go one step further to also evaluate the identified change locations. Since it is hard to identify the exact change point (the review) at which a change-of-hands has occurred, we define a window $x \pm y$ around the actual change point $x$ with window size $y$, and consider the predicted change point as accurate if it resides within the window. When a change point is detected for a non-CH account, it is considered an error. We study the performance by varying $y$ in Sec. 4.4.

All evaluation results are based on averaging the results of 5 runs on the constructed datasets. Each time we randomly sample 200 accounts from each dataset, 100 in each class, as the development set and use the rest 500 accounts as the test set. Statistical significance tests are also performed.

### Baselines

Since there is no previous work on detecting CH accounts, we propose the following baselines:

- **One Sequence (OS).** The simplest approach to detecting CH accounts is to construct a single sequence of feature values directly from a moving window of reviews of size $K$ (one similarity value per review window) of an account and use it to run a change point detection algorithm. The set of features we tried includes: average sentence length, average token length, ratio of nouns, ratio of adjectives and adverbs, ratio of function words, and ratio of punctuations and special characters. This baseline thus produces 6 results named with OS- as the prefix.

- **One Feature (OF).** This baseline is a variant of CHAD. It only uses one of the features from $F^{all}$ as input. Thus, lines 10-11 in Alg. 1 do not have any effect. Since $F^{all}$ contains 10 features, this baseline produces 10 different results, which are named with OF- as the prefix.

- **CHAD w/out Pivot-level Feature Selection (CHAD-PFS).** This baseline is another variant of CHAD. It does not perform pivot-level feature selection in Alg. 1. It employs the same procedure to pre-select a feature set and thus shares the same $F$ with CHAD.

- **CHAD w/out Pre-selecting F (CHAD-F).** This is a variant of CHAD that directly uses $F^{all}$ without pre-selecting feature set $F$ as input.

Note that we do not compare with existing spam filtering or sockpuppet detection methods as they all regard reviews from one account as written by a single author. Thus, none of them is able to detect stylistic changes within an account.

### Parameter Settings

For each run, we use the respective development set of each dataset to set parameters. For both datasets, $K = 5$ was chosen for the window size in constructing similarity sequences, and $\lambda_S = 2$ was chosen for vote smoothing. For change-point detection, we use the implementation in R changepoint package [Killick and Eckley, 2014], which outputs an estimated change point along with its confidence level. We set a confidence level threshold of $\theta_{\text{conf}} = 0.99$ based on the development set, and consider any detected change point with confidence level lower than $\theta_{\text{conf}}$ as no change (none). In parameter selection and in the main results reporting, we use $y = 5$ for eval\_cp, and later show the results by varying $y$.

We make the following remarks about these parameters. First, using a very small $K$ (e.g., 1 or 2) leads to bad performance due to the high variance in similarities between reviews. On the other hand, while using a large $K$ (e.g., 7 or 8) improves results for CH accounts detection (eval\_cha), the performance of change-point detection (eval\_cp) drops due to loss of granularity. Second, it is important to set the confidence level threshold $\theta_{\text{conf}}$ high to consider only the most confident detections—due to the fact that each review is unique in some way, and the constructed similarity sequences unavoidably fluctuate to a large extent.

### Main Results and Analysis

We present our main results on Amazon and Yelp datasets, respectively in Tables 2 and 3. For each dataset we only list the best-3 OS results, best-3 OF results, CHAD-PFS, CHAD-F and our proposed CHAD.

First, CHAD significantly outperforms all the baselines ($p < 0.03$) on both datasets. CHAD-F, which only performs pivot-level feature selection, and CHAD-PFS, which only performs global feature pre-selection are both worse.

Second, the best performing OS and OF baselines are consistent on both datasets. The results of OS baselines are quite poor, for which there are two possible explanations. First, they rely on computing a single value as feature, which may not be sufficient in capturing the differences between users in CH accounts. Second, they construct only one sequence, which is less reliable. Although OF baselines generally perform better, they are not reliable for the same reason.

Comparing the results on two datasets, we found that better results are generally achieved on Yelp dataset than on Amazon dataset. We believe the difference is mainly caused by the nature of the two datasets. Detecting CH accounts and their change locations are generally harder on Amazon dataset because it contains numerous categories of products. An Ama-

| Dataset       | Mean | Med. | Stdev | Min | Max |
|---------------|------|------|-------|-----|-----|
| Amazon\_NCH   | 60.0 | 40   | 37    | 20  | 170 |
| Amazon\_CH    | 53.6 | 41   | 33.2  | 20  | 231 |
| Yelp\_NCH     | 47.7 | 43   | 14.7  | 20  | 88  |
| Yelp\_CH      | 45.9 | 41   | 13.7  | 20  | 84  |

Table 1: Review Number Statistics.
zon reviewer is likely to post reviews on a variety of products, which creates big variance when computing similarities.

Lastly, we investigate the effect of window size $y$ (Sec. 4.1) under change-point evaluation $eval_{cp}$ by varying $y = 1, 3, 5, 7$. We report the results for CHAD-PFS, CHAD-F, and CHAD in Table 4. Only results for $eval_{cp}$ are listed as those for $eval_{cha}$ are not affected by $y$. Only average F1 scores are given. As we can see, CHAD significantly outperforms the rest methods ($p < 0.03$) regardless of $y$. And as expected, all results improve for increased values of $y$.

### 4.5 Experiments in Another Setting

For our main results above, we constructed two datasets in which the CH accounts and non-CH accounts have similar distributions in their sizes (numbers of reviews). In reality, this may not always be the case. CH accounts may in general contain more reviews because spammers may write a lot of fake reviews after purchasing the accounts. In order to test the performance of our method in such cases, we constructed two different datasets without matching the size distributions of CH and non-CH accounts. In particular, for both Amazon and Yelp corpora, we randomly sample 700 original contributions of CH and non-CH accounts. In particular, for both datasets, we randomly select 200 accounts in CH accounts. The reason we select at least 20 accounts in CH accounts is because we assume accounts change hands after a sufficiently long history. Statistics of the data is shown in Table 5. We only report F1 scores of two strong baselines (CHAD-PFS and CHAD-F), as well as our CHAD under both evaluation schemes (Table 6). As we can see, CHAD again performs the best in the new datasets. We also notice the CHAD performs better here than in the previous set of experiments (Table 2 and 3). The reason is that in the previous experiments setting, there are fewer reviews from the first user/reviewer in the CH accounts, which makes it harder for the algorithm to find reliable patterns.
5 Conclusion

This paper proposed the new problem setting of detecting changed-hands accounts which complements the existing spammer detection settings and problems. To the best of our knowledge, the problem has not been explored before. The problem presents some unique challenges due to the differences in intra-user and inter-user writing styles. We presented a novel detection algorithm to determine if an account has changed hands and the possible change point. Extensive experiments on two datasets constructed using Amazon and Yelp review data showed that our method outperforms a list of baselines significantly.

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