TrueView: Harnessing the Power of Multiple Review Sites

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ABSTRACT
Online reviews on products and services can be very useful for customers, but they need to be protected from manipulation. So far, most studies have focused on analyzing online reviews from a single hosting site. How could one leverage information from multiple review hosting sites? This is the key question in our work. In response, we develop a systematic methodology to merge, compare, and evaluate reviews from multiple hosting sites. We focus on hotel reviews and use more than 15 million reviews from more than 3.5 million users spanning three prominent travel sites. Our work consists of three thrusts: (a) we develop novel features capable of identifying cross-site discrepancies effectively, (b) we conduct arguably the first extensive study of cross-site variations using real data, and develop a hotel identity-matching method with 95% accuracy, (c) we introduce the TrueView score, as a proof of concept that cross-site analysis can better inform the end user. Our results show that: (1) we detect 7 times more suspicious hotels by using multiple sites compared to using the three sites in isolation, and (2) we find that 20% of all hotels appearing in all three sites seem to have low trustworthiness score.

Our work is an early effort that explores the advantages and the challenges in using multiple reviewing sites towards more informed decision making.

Categories and Subject Descriptors: H.3.3 [Information Search & Retrieval]: Relevance feedback; Search process; Search process; Information filtering.

Keywords: Opinion Spam; Multi-Site Features; Review Mining; Anomaly Detection; Hotels; Trust

1. INTRODUCTION
How do you use online reviews before booking a hotel, especially if the hotel appears on multiple review sites? This is the overarching question that motivates this work. On the one hand, online reviews provide an unprecedented mechanism for customers to inform potential customers. On the other hand, reviews can suffer from: (a) relevance, as the needs and expectations of customers varies, and (b) fraudulent behavior, from “biased” users or the product providers themselves. As a result, it is not easy for customers to interpret and use such reviews. One often relies either on the overall rating or laboriously goes through many reviews to identify relevance and trustworthiness.

How can we leverage reviews from multiple review sites to make more informed decisions and detect fraud? The use of multiple review sites is the key differentiating factor for our work. 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 ubiquity. 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. Specifically, we intend to expand our work to restaurants in the near future.

Most previous work so far has focused on analyzing a single review site, and typically, focus on temporal [7], textual [13], behavioral [16], distributional [8] and graphical features.
As our key contribution, we develop a systematic methodology to analyze, compare, and synthesize reviews from multiple review sites. The key novelty of our work lies in its focus on multiple review sites. Another key contribution is a systematic method to match hotel identities across different 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 a 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 spanning five years for each site.

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 review in one site using cross-site features leveraging information from the other sites. We find that using cross-site features nearly double 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 on different sites, which is a non-trivial problem to automate. Our study provides several interesting observations:

1. Our identity-matching method matches hotels with 93% accuracy 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, 9.3% from Hotels.com and TripAdvisor.com, exhibit significantly different rating characteristics, which is usually 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: (a) temporal, contextual, and behavioral features from each site, and (b) cross-site features across the sites. By applying TrueView, we find that 20% of all hotels appearing in all three sites seem to have 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.
2.2 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 for good results.

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 10,500 between Hotels.com and TripAdvisor.com. Booking.com is a much newer site, and we hypothesize that is the reason for its reduced coverage.

3. 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. [9]: 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.

In the reminder of the paper, we will use HDC for Hotels.com, TA for TripAdvisor.com and BDC for Booking.com.

3.1 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.

3.1.1 Spatial Inconsistency

We 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.

3.1.2 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 25 businesses on January 22, 2006, which are located across 15 states. Additionally, 21 of these reviews are “first time reviews”, 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.

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### Table 1: Simple Statistics of the three datasets collected from three prominent travel websites.

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

3.1.3 **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 [6]. 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.

3.2 **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.

#### 3.2.1 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 ratings. Typically such behavior is prevalent in the early years of the inception of a hotel in the hosting site. Figure 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.
and 1-star ratings but a small number of 4-, 3-, and 2-star
cally, a “J” shaped distribution has a large number of 5-star
distribution has a strong tie to the spamming hotels. Typi-
assume perfect correlation.

If the overlap is too small, we naively
day from two sites. We use only the overlapping time dura-
coefficient between the time series of number of ratings per
spotting misbehavior. We calculate Pearson's correlation
a lack of correlation across sites is a significant indicator for
come to evaluating hotels. The hotel might have received
eral reasons, each of which are worth considering when it
summer of 2012.

An example of oscillating ratings is shown in Figure 2. We see that eight out of ten 1 star ratings were followed immediately by 5 star ratings.

3.2.2 Temporal Correlation

Temporal correlation between number of ratings of a ho-
tel in different sites is a valuable indicator of consistent cus-
tomer satisfaction. Commonly, a hotel should have very sim-
ilar behavior across sites in terms of number of ratings. For
example, any hotel in Myrtle Beach, SC shows a high num-
ber of ratings per day in summer, decreasing in the winter.
Since the number of occupants at hotels in Myrtle Beach, SC [2] decreases from 80% in the summer to 30% in the winter, this pattern makes sense; the number of ratings per day follows the average occupants of the hotel and such be-
avior is consistent across sites. In Figure 4, 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 peak/density in HDC, especially in
summer of 2012.

Such discrepancy in temporal behavior can exist for se-
veral 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 Pearson's correlation
coefficient between the time series of number of ratings per
day from two sites. We use only the overlapping time dura-
tion for calculation. If the overlap is too small, we naively
assume perfect correlation.

3.2.3 Rating Distributions

In [8], authors have suggested that the shape of rating distribution has a strong tie to the spamming hotels. Typi-
cally, 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
ting groups has been artificially inflated by spam reviews.
Whereas in [8] they had to compare distributions between
hotels, we take a multi-site approach to validate the con-
sistency of distributions across sites for individual hotels.
To find this value we calculate the Pearson’s correlation co-
efficient between the rating distributions of a hotel across
different sites, represented by two vectors of counts of inte-
ger ratings. We also directly compare the distributions of
the ratings by using the one-sided p-value from the Mann
Whitney U Test as a feature.

Figure 4 shows the correlation coefficients of the distribu-
tions 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, 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. Around 5% of the hotels in GA show
negative correlation, which is much greater than that (1%)
in CA and NV.

3.3 Review-Centric Features

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

3.3.1 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 typing. We find an abundance of empty
reviews in HDC and BDC, with 20% and 25% empty re-
views, 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 ex-
ample, 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 over-

Figure 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 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.
all 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 is visible through the website. Such behavior of hiding consumer reviews has been reported several times in [1] 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. Sometimes multiple features together describe a suspicious hotel. In Figure 3, we show a hotel having three suspicious behavior captured by three of our features.

3.3.2 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, suggests that the hotel is soliciting many spam reviews.

3.4 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, which we use to calculate a TrueView score, we calculate 52 cross-site features for the hotels that exist in multiple sites. These cross-site features are combination 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 supporting page [3].

4. 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 which ones 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.

4.1 Outlier Scores

Once all the features are available, we take three approaches to rank the hotels with outlier scores. We use global density-based score, a local outlier factor, and a hierarchical cluster-based score. We describe each technique in this section.

4.1.1 Global Density-based Score

We calculate how different a hotel is from the centroid of hotels in the feature space. 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 in many features with the mode, which makes its reviews 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.

4.1.2 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.

\[ lrd_k(x) = \frac{1}{\sum_{y \in N_k(x)} ||x - y||} \]

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

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

4.1.3 Hierarchical Cluster-based Score

Both of the density-based methods above use k-neighbors 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. The method evaluates pairs of clusters based on the minimum distance between any pair of points that form the two clusters and 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.

4.2 TrueView Scores

The three above approaches produce three different outlier scores. A big challenge is that the scores are not at the same scale. Before combining individual scores, we need to regularize and normalize the outlier scores. We take the approach of [11][19] to normalize the outlier scores from each of
the above approaches using logarithmic inversion and gaussian scaling.

Let a hotel be $x$ and the outlier score of $x$ is $S(x)$. We do a log transform $z = -\log S(x)/S_{max}$ for each hotel $x$ and scale it using a gaussian distribution to produce a probability $P(x)$ of the hotel $x$ being an outlier. Such a probability score is useful because it is bounded within $[0,1]$ and can easily be converted to a trustworthiness score by a simple linear inversion.

$$P(x) = \max(0, erf(\frac{x-\mu}{\sqrt{2} \sigma}))$$
$$TV(x) = 1 - P(x)$$

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 Experiments section 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.

5. EXPERIMENTS

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 [3]. We also have additional materials such as presentation slides, csv sheets of raw numbers, and more experiments.

5.1 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 values for subsequent experiments.

In the global density-based method, we have $\epsilon$ and $k$ as parameters. We fix $k = 10$ and vary $\epsilon$ and record the percent of the dataset labeled as outlier. In the local outlier factor method, we have the neighborhood size $k$ as the parameter. In the hierarchical method we use the cutoff value as the parameter and record the percentage of the dataset labeled as outlier. Figure 5 shows the behavior of 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.

5.2 Feature Importance

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

5.2.1 Spectral Feature Selection

We use the method in [23] 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 6, 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.

Figure 6: Feature importance percent score for 142 features. Cross-site features are more important than single-site features.

5.2.2 Distance from Mode

In this approach, we consider the outliers produced by the 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 cross-site features that become important for more than half of the outliers. In Figure 7, we show the results for other feature categories as described in section 3.

5.3 Validation

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

5.3.1 Sanity Check on Synthetic Frauds

![Figure 5](image-url) (left) Percentage of outliers detected in the density-based method as we vary $\epsilon$. (right) The same as we vary neighborhood size $k$ in LOF method.
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.

5.3.2 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 calculate 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 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.

![Figure 7: Relative importance of review-reviewer- and hotel-centric features based on the distance from the centroid.](image)

![Figure 8: (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.](image)

<table>
<thead>
<tr>
<th>Feature</th>
<th>LOP</th>
<th>Mode Density</th>
<th>Linkage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cross-site</td>
<td>3.93E-07</td>
<td>1.63E-08</td>
<td>4.60E-11</td>
</tr>
<tr>
<td>Single-site</td>
<td>1.63E-06</td>
<td>8.04E-15</td>
<td>1.08E-12</td>
</tr>
<tr>
<td>Booking.com</td>
<td>1.49E-05</td>
<td>0.419</td>
<td>0.019</td>
</tr>
<tr>
<td>Hotels.com</td>
<td>0.308</td>
<td>4.41E-04</td>
<td>0.038</td>
</tr>
<tr>
<td>TripAdvisor.com</td>
<td>0.379</td>
<td>0.052</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Table 2: p-values of Wilcoxon rank-sum test. Bold faced values mean that there is a significant difference between the top and bottom 40.

6. CASE STUDIES

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

![Figure 9: Empirical cumulative distribution function of TrueView scores.](image)

**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 again when 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.

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...
<table>
<thead>
<tr>
<th>Hotel</th>
<th>HDC Stars</th>
<th>T1-HDC</th>
<th>TA Stars</th>
<th>TV1-TA</th>
<th>TV2</th>
<th>TrueView</th>
<th>Trustworthy?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Super 8 Terre Haute</td>
<td>3.30</td>
<td>1.0</td>
<td>3.00</td>
<td>0.235</td>
<td>0.734</td>
<td>1.0</td>
<td>✓</td>
</tr>
<tr>
<td>Excalibur Hotel and Casino</td>
<td>3.60</td>
<td>0.846</td>
<td>3.50</td>
<td>0.850</td>
<td>0.951</td>
<td>0.761</td>
<td>✓</td>
</tr>
<tr>
<td>Comfort Suites Newark</td>
<td>3.80</td>
<td>0.688</td>
<td>3.00</td>
<td>0.705</td>
<td>0.773</td>
<td>1.0</td>
<td>✓</td>
</tr>
<tr>
<td>Paradise Resort, Myrtle Beach</td>
<td>4.20</td>
<td>1.0</td>
<td>4.00</td>
<td>0.573</td>
<td>0.699</td>
<td>1.0</td>
<td>✓</td>
</tr>
<tr>
<td>Bluewater Resort, Myrtle Beach</td>
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<td>1.0</td>
<td>3.00</td>
<td>0.735</td>
<td>0.790</td>
<td>0.462</td>
<td>X</td>
</tr>
<tr>
<td>Comfort Inn &amp; Suites, Statesboro</td>
<td>3.60</td>
<td>1.0</td>
<td>3.60</td>
<td>0.783</td>
<td>0.669</td>
<td>0.264</td>
<td>X</td>
</tr>
</tbody>
</table>

Table 3: TrueView scores for suspicious hotels. (Stars is the average overall rating)

There has been work on joining multiple criteria from single sources to better detect fraud [21]. Various types of fraud have been identified in the literature: groups of fraudsters [16][15], unusual behavioral footprints [14], unusual distributional footprints [8], unexpected rules [10] and unusual rating behaviors [12].

Existing works deal with diverse set of review data in both supervised and unsupervised manners. In [5] 15,094 apps are ranked based on network effects. In [21] 45 hotels are ranked based on an unsupervised hedge algorithm. In [8] 4000 hotels located in 21 big cities are analyzed to identify distributional anomalies. In [9] reviews on 700,000 products for a month are analyzed using review-, reviewer-, and product-centric features. In [18], 7,345 car repair shops are crawled to collect 270,121 reviews and the data of their users spanning three prominent travel sites. We find that there are significant variations in reviews, and we find evidence of review manipulation.

8. CONCLUSION

The goal of our work is to show the significant benefits we can have by combining reviews from multiple review sites. As our key contribution, we develop a systematic methodology to cross-compare, and synthesize reviews from multiple review sites. The novelty of our approach relies on 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.
9. FUNDING STATEMENT
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10. REFERENCES