Towards an Enhanced Aspect-based Contradiction Detection Approach for Online Review Content

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Abstract. User generated content as such online reviews plays an important role in customer’s purchase decisions. Many works have focused on identifying satisfaction of the reviewer in social media through the study of sentiment analysis (SA) and opinion mining. The large amount of potential application and the increasing number of opinions expresses on the web results in researchers interest on sentiment analysis and opinion mining. However, due to the reviewer’s idiosyncrasy, reviewer may have different preferences and point of view for a particular subject which in this case hotel reviews. There is still limited research that focuses on this contradiction detection in the perspective of tourism online review especially in numerical contradiction. Therefore, the aim of this paper to investigate the type of contradiction in online review which mainly focusing on hotel online review, to provide useful material on process or methods for identifying contradiction which mainly on the review itself and to determine opportunities for relevant future research for online review contradiction detection. We also proposed a model to detect numerical contradiction in user generated content for tourism industry.

1. Introduction

The ease of producing numerous user generated content online has led to a significant impact on the quality of information which is accessible to users worldwide. Currently, tourism field have widely used the facilities in web services as their one of the main source to understand the consumer’s behaviours based on their reviews towards their products and services. The World Wide Web creates an important medium in information exchange between consumer and the producer[1]. These information between the consumer, industry suppliers which in this case hotels, attractions, intermediaries as such travel agencies, controllers such as governments and administrative bodies, as well as non-profit organizations plays an important role in travel sector revenue.

As stated by Xiang and partners [2], search engines, online travel booking websites and websites of marketing organization assist in information exchange between travelers. User generated content on the Internet has been particularly important in a travel sector[3]. At this age, user generated content such as online review has become a trend for every consumer when purchasing any services online. Consumer can simply write whatever they thought for a specific hotel or services that they purchased for other consumer to read. Take TripAdvisor.com for instance, is an example of a popular website that collects and published consumer reviews of hotels, restaurants and other travel-related services.
Primarily, online reviews could greatly improve consumers’ ability to evaluate products. That is why online reviews are an important source of information for customers booking accommodation and travel [4]. Even if they do not book their travel online, most customers will at least review Online Travel Agencies (OTAs) and review sites before making a booking decision. However, the differences among users’ preferences and perspective may lead to conflicting opinions about the target product, which could confuse a potential consumer when online reviews are one of the main sources of product information [5]. The increasing use of mobile devices for making travel bookings further enhances the importance of online reviews for travel decisions.

In order to observe the possible significance of this issue, we undertake a systematic literature analysis of the event. The paper reviews a number of papers in this field and presents the overview of identify contradiction in online review. The objectives of this paper are: (1) To investigate the type of contradiction in online reviews which mainly focusing on hotel online review, (2) To provide useful material on process or methods for identifying contradiction which mainly on the review itself, (3) To determine opportunities for relevant future research for online review contradiction detection.

This paper is structured as follows: Section 2 contains the contradiction issues in user generated content. In Section 3 contains the literature review on previous works regarding contradictory information in user generated content, and followed by Section 4 where we proposed a contradiction detection model on numerical mismatch. Lastly, Section 5 serves as the conclusion of this paper.

2. Contradictions in Online Review

The review strategy are based on the established methods of System Literature Review (SLR) guidelines for Software Engineering by [6] and Social Science [7]. Referring to the SLR guidelines, the systematic review is consists of 3 phases that includes planning the review, executing the review and formatting the report as shown in Figure 1.

The output of planning stage is review protocol which was structured on specifying research context, defining review protocol and structuring a research questions. This is then followed by the executing stage that performs search strategy and data extraction to categorize data items as the output. In reporting stage, the review will be documented in result and discussion.

| Planning | Executing | Reporting |
|----------|-----------|-----------|
| 1. Specify research context. | 1. Perform Search Strategy : | 1. Synthesize data in excel format |
| 2. Define review protocol. | a) Identify search terms. | 2. Document the Result |
| 3. Structure research questions. | b) Search in literature sources and perform search process. | |

**Figure 1. Systematic Review Phases**

2.1. Definition

Online review is basically an opinion, view, sentiment or judgment of a consumer towards a business, product or services that is post online as such a review site. A consumer’s review, is user-oriented, describing attributes in terms of usage situations, and measuring performance from a user’s
perspective[8]. Any individual can upload content online, in the form of images, audio or video for others to respond and comment, which forms the basis of Web 2.0. An online review is supposed to be helpful to other consumers as it plays a major role for travel purchase decisions.

The increasing use of mobile devices for making travel bookings further enhances the importance of online reviews for travel decisions. Customers trust reviews by other travellers more than they do official business communication, because they assume that the reviews are independent. Although some issues around fake reviews have reduced the trusts that consumers place in them, they still affect most travel decisions. However, the presence of conflicting or contradictions in online review, given a specific item or services, may have at least given negative effects on consumer and producer surplus.

There were several popular review sites that consumer can expose their innermost thoughts about a product. The first one would be Amazon.com. Amazon was one of the first online stores to allow consumers to post reviews of products in 1995, and it remains one of the most important resources for consumers looking to make informed purchase decisions.

Social media and consumer-generated content on the Internet continue to grow and impact the hospitality industry [9]. For Tourism and Hospitality domain, the most popular website is TripAdvisor.com [10]. It enables registered members to post reviews on hotels, restaurants, airlines, entertainment places to the site. We believe that online reviews play a vital role for consumer to purchase products as such in TripAdvisor. Therefore these online reviews should be precise when it comes to describing the important facts about a product, because other consumer wouldn’t want to be.

Online reviews were usually in a text manner where it is written by the reviewer in sentences or a paragraph or an essay. There is also reviewer who reviewed product by posting it using videos or audio but for the purpose of the study; we focus on Text Online Reviews. Most of the review data that were posted online are in unstructured form. An unstructured documents usually have title and the content that is not organized in any structured manner which it will not have any attributes. Therefore, in order to identify whether a text online review is contradict or not, we need to recognize what are the features of contradictions and based on what feature does a text online review contradicts to each other.

2.2. Preliminary Study: TripAdvisor.com
We examined the reviews made by consumers focusing in particular on hotel reviews on TripAdvisor.com. This positive review on My Hotel in Bukit Bintang, Malaysia shows some conflicting information on the location of the hotel and Puduraya Bus Station. From the excerpts that we’ve taken in TripAdvisor.com, we highlighted the contradicting information that is based on numerical contradiction between these consumer reviews. (Refer Table 1).

Based on Table 1 also, we have found that the type of attribute of a text that is needed to be examined is either qualitative or quantitative. For the distance aspect, the consumers describe as short and near of walking with various time stated in their review. According to the observation made this feature of contradiction were discussed by [11] in their study. They categorized this as numeric mismatch which there exist contradiction when two sentences that contains numeric (dates or time) information are not similar to each other.
3. Related Works

3.1. Contradiction Detection
Based on the studies that have been identified, the contradiction analysis area is relatively a growing
of research. There were no established common framework for describing and modeling the relevant
problems. Though, there were some studies have made few steps towards this direction.

The study that is related to contradiction detection on text started since 2008 where it is being
treated with recognizing textual entailment. Recognizing textual entailment (RTE) was introduced in
2005 has the objective of discovering whether some text (T) entails a hypothesis (H). In other words,
given two text fragments, it requires to recognize whether one text can be inferred from the other. This entailment defines a directional relationship between pairs of text expressions[12].

This two-way RTE task requires systems to label each entailment pair as either "entailed" or "not entailed", regardless of the hypothesis (H) is a "true" fact. As for example; T entails H or T does not entail H. However in 2008, a three-way RTE task which was introduced. The concept of contradiction is established. the three-way RTE task requires to label each entailment pairs as either "entailed", "contradicted" or "unknown". As for example; T entails H or H contradicts T or unknown between H and T.

RTE has been established and fostered by PASCAL Recognizing Textual Entailment Challenge (RTE) in 2005[13]. Whereby PASCAL produced RTE1, RTE2, RTE3 datasets. Followed by RTE4, RTE5, RTE6 and RTE7 corpora was produced by NIST. This challenge is at the heart of many Natural Language Processing (NLP) tasks which includes Information Retrieval, Information Extraction, Question Answering, Machine Translation and other tasks to explore the linguistic expression. PASCAL and NiST

Generally, RTE model which is based on [13] includes preprocessing, enrichment, graph generation, alignment and inference (Refer figure 3).

**Figure 3. General Architecture of Textual Entailment. Adapted from [13].**

Entailment pair needs to be pre-processed before launching a full-fledged analysis. Example of preprocessing annotators is part of speech tagging, dependency parsing, and some information extraction task like named entity recognition, reference resolution, semantic role labelling (SRL).

Enrichment is said to be differed with pre-processing by [13] as it involves either extraction or augmentation process of the output resulting from pre-processing. Extraction process is to abstract the annotation patterns by mapping them to its relation whereas augmentation is to enhancing the existing annotation by identifying implicit contents and changing it to explicit as new relation.

Graph generation is when the Text (T) and Hypothesis (H) are represented as graphs and being compared. Alignment step is basically the constituent or the output of analytics of T and H is being map. Alignment step is crucial in identifying the relevant portion of T and H which can simplify the inference step. Inference step is the part where decision on labelling the entailment pair. Number of approach has been introduced as for example discourse commitment extraction by [14], whereby implicit belief is extracted and decision-tree classifier is used to decide the entailment in inference step.

CD in text has also been treated with Sentiment Analysis (SA). SA is not a new direction of study; it has been a fundamental method for the task of detecting, extracting, and classifying opinions and sentiment which based on different topics that is expressed in textual input. SA is a part of area in text analytics and make use of techniques from natural language processing (NLP), information retrieval (IR), information extraction (IE) and artificial intelligence(AI). Generally, SA task includes (1) document selection (2) document processing; (3) document analysis (4) sentiment evaluation (Refer Figure 4).
At first step of sentiment analysis, the document will be selected and collected, based on the topic. Document processing generally involves information extraction (IE) techniques. Some of popular preprocessing technique is tokenization, stemming, parts of speech (POS) tagging, and feature extraction and representation. Tokenization is a technique in breaking down sentences into word, phrases or meaningful toks by removing punctuation marks. Stemming is the process to convey a word into its root form. To recognize the different part of speech in text, parts of speech (POS) tagging is performed.

Document analysis step is where the classification technique of the sentiment analysis is being performed. According to [16], sentiment classification techniques consist of machine learning approach, lexicon based approach and hybrid approach. The Machine Learning Approach (ML) performs the famous ML algorithms and uses linguistic features. The Lexicon-based Approach relies on a sentiment lexicon, a precompiled sentiment terms. It is divided into dictionary-based approach and corpus-based approach which use statistical or semantic methods to find sentiment polarity. The hybrid approach combines both approaches and is very common with sentiment lexicons playing a key role in the majority of methods. In sentiment evaluation, the models are being evaluated to calculate the accuracy.

Figure 5 shows additional contradiction analysis component is being added in SA. Study by [18] defines contradiction as sentiment diversity on document collections related to one or more topics and classify them based on time and the context. The author creates a novel contradiction measure based on mean value (\(\mu^2\)) that indicates the aggregated sentiment and sentiment variance (\(\sigma^2\)).

\[
C = \frac{nM_2 - M_1^2}{\vartheta n^2 + M_2^2} \cdot W \quad \ldots(1)
\]

Where,
\[\begin{align*}
 n & \quad \text{Cardinality of number of document} \\
 \vartheta & \neq 0 \\
 M_1 & \quad \text{mean value (\(\mu^2\))} \\
 M_2 & \quad \text{used to limit the level of contradiction when } \mu^2 \text{ is close to zero} \\
 \end{align*}\]
\[ M_2 = \sum_{i=1}^{n} S_i^2 \] - sentiment variance (\(\sigma^2\))

\[
W = \text{Weight function; } \left(1 + \exp\left(\frac{\bar{n} - n}{\beta}\right)\right)^{-1} \quad \ldots(2)
\]

\(\bar{n}\) = average number of topic document involved in the analysis;
\(\beta\) = scaling factor.

The sentiment \(S\) was defined as a real number in the range \([-1, 1]\) that indicates the polarity of the author’s opinion on Topic \(T\) expressed in a text. The aggregated sentiment \((\mu^2)\) was defined as the mean value over all individual sentiments assigned in that collection of documents \(D\) on topic \(T\). The contradiction on a given topic \(T\), between two groups of documents, \(D_1, D_2 \subset D\) is defined in function of the information conveyed about \(T\).

Based on these definitions, a three stages framework for contradiction detection was proposed. The first stage of the framework consists of identifying the topics for each sentence of the data. The second stage assigns a sentiment to each sentence-topic pair. Then, contradiction analysis is performed in the final step.

3.2. Contradiction Detection

Nonetheless, there were few features of contradiction that were put forth by previous research that is also can be examined (Refer Table 2). Based on our literature review, studies as such [14] put forth negation, antonymy and contrast. They define negations as directly or indirectly. Directly negations include (1) overt negative markers (e.g. don’t, won’t, can’t) (2) negative quantifiers (e.g. no, no one, nothing) and (3) negative adverbs (e.g. never). Indirectly negations is categorized as (1) verb or phrasal verb (e.g. deny, refuse) (2) prepositions (e.g. without, except) (3) weak quantifiers (e.g. few, any, some) and (4) traditional negative polarity (e.g. anymore). Harabagiu et al. also stated antonymy as a feature of incompatibilities. Antonymy is when a word is directly the opposite of one another, as such “long or short” and “big or small”. They detect antonymy by using WordNet lexicon that has more than 7000 antonymy relation. By analyzing sentences and phrases, they generate antonymy chains by using lexico-semantic chains. Contrast on the other hand is slightly differing from antonymy. Contrast is the course relation between separate phases or clauses within the same sentence. Contrast is detected when there is an occurrence of the word “but” or “although”.

[11] introduces features of contradiction that consist of seven types of features for example 1) Number, date and time features; which this include the presence of numeric mismatch as mention earlier; 2) Structural features; syntactic structure of sentences (alignment of subjects), (example based on the subject: “Milo defeated Atticus” or “Atticus defeated Milo”); 3) Polarity features; the presence of negative polarity text (example: “Not”); 4) Antonymy features; presence of aligned antonyms (example: “dark and bright”); 5) Modality feature; presence of predefined modality markers (example: “can”, “could”, “may”); 6) Factivity features; presence of factive construction (example: “forget”, “remember”, “know”); 7) Relational features; relations between sentences (example: “Corvus lives in Italy” and “Corvus would like to go to Italy”).

Ambiguity is one of the features stated by [19]. It is a state where different classes of words, and the relationships between word as such homonyms and polysemy may create ambiguity. An expression is ambiguous if more than one meaning can be assigned to it. However, since this study is based on contradiction, this feature might not be included in the study.

Therefore based on this discussion for research question one, it is safe to say that, there exist features of contradiction in text online review which based on tourism industry. This direction of this study is to focus on numeric mismatch contradiction detection where the aspect of the review will be analyzed to identify contradiction in online review.
Table 2. Features of Contradictions

| Features / Study           | [11] | [14] | [20] | [19] | [21] | [22] |
|---------------------------|------|------|------|------|------|------|
| Negation                  | /    | /    | /    | /    | /    | /    |
| Antonymy                  | /    | /    | /    | /    | /    | /    |
| Contrast                  | /    | /    | /    | /    | /    | /    |
| Number/Date/Time          | /    | /    | /    | /    | /    | /    |
| Structural                | /    | /    | /    | /    | /    | /    |
| Polarity                  | /    | /    | /    | /    | /    | /    |
| Modality                  | /    | /    | /    | /    | /    | /    |
| Factivity                 | /    | /    | /    | /    | /    | /    |
| Relational Features       | /    | /    | /    | /    | /    | /    |
| Ambiguity                 | /    | /    | /    | /    | /    | /    |

4. Proposed Model

Limitation in identifying contradiction in text online review that we would like to highlight is based in the numerical feature of the text. As in Table 2, we highlighted the essence of numerical mismatch in online review. We also found that most of the study focuses on the data pre-processing and analysis in order to identify contradiction.

We found that the numerical feature detection only being discussed by [11] in detailed. Study by [11] proposed that all numerical aspects such as date and time expression will be normalized and numbers are represented by range. The aligned numbers is then considered contradict if the numbers is incompatible between T and H and the words are referring to the same entity.

Therefore, in this section we would like to propose an enhanced aspect-based contradiction detection in text for numerical mismatch. Study by [11] investigates the alignment scores of the T and H, we would like to suggest other ways on targeting to the problem such as hybridizing the aspect-based sentiment analysis and textual entailment general component(graph generation). The proposed contradiction detection focuses more on data processing and feature selection to achieve higher accuracy.

![Figure 6: Proposed contradiction detection in text for numerical mismatch.](image-url)
5. Conclusion

This paper investigates the type of contradiction in online review which mainly focusing on hotel online review, to provide useful material on process or methods for identifying contradiction which mainly on the review itself and to determine opportunities for relevant future research for online review contradiction detection. A total of 35 primary studies were selected and analyzed. Results of this review show that there was only one method for contradiction detection particularly in numerical contradiction. This paper also highlighted the issue of numerical contradiction that exists in user generated content for tourism industry. Also, the paper proposed a model for detection of contradictory information in online review for tourism industry. Our future work will be to verify our model to improve the accuracy of contradiction detection in online review which includes the numerical component such as distance and time.

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