VICTORIA UNIVERSITY OF WELLINGTON
Te Whare Wananga o te Upoko o te Ika a Maui

A Sentiment Analysis of TripAdvisor Report: The Case of Small Towns in New Zealand

A research report presented to the

School of Information Management

Victoria University of Wellington

In partial fulfilment of the requirements for the course on

Research Project

(INFO 510)

By

Tianfu Yuan

Supervised by Dr Markus Luczak-Roesch & Dr Allan Sylvester

25th June 2018

A Sentiment Analysis of *TripAdvisor* Report: The Case of Small Towns in New Zealand

Abstract

User-generated content is a research hotspot in the context of web 2.0. The emergence of social networks and community-based websites have changed the way people use the Internet. It makes people no longer limited to reading the information provided by professional channels, but to creating personal profiles, generating personalized content, or sharing photos, videos, blogs, etc. This kind of information constitutes the current online user-generated content. With the continuous development of the tourism industry, the number of online travel platforms has also been increased. The development of online travel review website has shifted from providing aggregate hotel information to the acquisition of high-quality travel content. This paper examines lexicon-based sentiment analysis, investigating the polarity of different categorization in order to find motional status of online reviews on *TripAdvisor*. The latent Dirichlet allocation (LDA) topic modelling method is applied to gather similar topics that help us define an alternative categorization beside the default settings. In addition, to the best of our knowledge, only a few studies to apply both sentiment analysis and topic modelling methods in online review study field. Therefore, the results show the significant view about the differences between various categorizations on *TripAdvisor*, and also additional categories to identify review content. Similar to other research studies, limitations have also been found during our study.

Keywords: sentiment analysis, lexicon-based, opinion mining, data mining, latent Dirichlet allocation, TripAdvisor

Code and data link [GitHub]: all codes and datasets used in this research can be find at following link https://github.com/yuan901202/info510_tripadvisor

Acknowledgements

The successful completion of this research project is unable to complete without acknowledging the great people who made it possible and who provide helpful guidance and encouragement to achieve the goals.

This academic research proudly supported by Dr Markus Luczak-Roesch and Dr Allan Sylvester. I also would thank Professor Pak Yoong who provided insight and expertise that greatly assisted this research. It would not have been possible without support from my supervisor Dr Markus Luczak-Roesch, who provided me with his extraordinary academic and research skills support to this research. I would also like to show our gratitude to the School of Information Management at Victoria University of Wellington for sharing their pearls of wisdom with us during this research.

I am grateful to all of those with whom I had a pleasure to work with this and other related research projects. I would also thank the members of my family, whose love and guidance are with me in whatever I pursue.

Table of Contents

Abbreviation explanation:

GDP – Gross Domestic Product

LDA – Latent Dirichlet Allocation

HMM – Hidden Markov Model

eWOM – Electronic Word of Mouth

CRM – Customer Relationship Management

PPMCC – Pearson product-moment correlation coefficient

POI – Points of interest

POS – Parts of speech

CSV – Comma separated values

URL – Uniform Resource Locator

HTML – Hypertext Markup Language

1. Introduction

Web 2.0 era is coming since we noticed the number of Web 2.0 websites rapidly growing in recent years. Online users no longer just explore content from an online website, they also generate online information without time and geographical constraints. In addition, information aggregation helps information to accumulate on the Internet. The well-known example is *TripAdvisor*, which is the world's largest travel website, enabling traveller plan a trip and share their knowledge. According to *TripAdvisor*, they currently have around 70 million registered users with 630 million reviews and opinions posted on the website. There is a total of around 7.5 million hotels, restaurants and attractions listed on their website across about 136,000 destinations around the world (https://tripadvisor.mediaroom.com/us-about-us).

Online reviews, a form of online user-generated content have been widely distributed across the Internet. It has become the most important resource for consumers and business managers. Consumers' decisions regarding the purchase of products or services is often based on these online reviews or feedback. Furthermore, business managers performing actions also rely on what consumers say about their products or services. Valdivia, Luzón and Herrera (2017) showed that when a consumer wants to buy products from an unknown merchant, they usually will make a decision based on other consumers' feedback or reviews. Duan, Cao, Yu and Levy (2013) mentioned that online user-generated content has become an information sharing tool for people who like to interact with others. Moreover, people heavily rely on how other people evaluate these products or services. On the other hand, local businesses are aware this valuable information is important, so they collect and evaluate it in order to improve their performance and understand consumer behaviour.

1.1 Introduction to the Research Project

Sentiment analysis is also known as opinion mining, sentiment mining, or subjectivity analysis. According to the *Oxford Dictionary*, sentiment analysis refers to "the process of computationally identifying and categorizing opinions expressed in a piece of text, especially in order to determine whether the writer's attitude towards a particular topic, products, etc. is positive, negative, or neutral" (https://en.oxforddictionaries.com/definition/sentiment_analysis). Pang and Lee (2008) stated that sentiment analysis and opinion mining became a world popular research problem in 2001. The reason is because of the rapid development and popularisation of the Internet and the rise of the review-based websites. The fundamental technology for sentiment analysis is classification and the process involves two tasks – training and classifying. The training process is to train datasets and identify model parameters. In addition, the classifying process is used to examine documents, whether positive or negative. The author also indicated that 32% of consumers use an online rating system to evaluate products or services, and 30% actually post a review on an online review website in the USA.

The process of sentiment analysis includes analysing, processing, summarising and inferring subjective texts with emotional terms, such as analysing tourists' attitudes to local hotels, restaurants and attractions in New Zealand in this research. We used lexicon-based sentiment analysis to study tourist sentiment expressed in online reviews on website. The first step is to determine whether a word is positive or negative, and subjective or objective. This step mainly depends on the types of sentiment dictionary. Several English dictionaries could be used, for example, SentiWordNet (http://sentiwordnet.isti.cnr.it/), Bing Liu and Minqing Hu Sentiment Lexicon (https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#lexicon), SenticNet (http://sentic.net/), MPQA Subjectivity Lexicon (http://mpqa.cs.pitt.edu/#subj_lexicon), etc. Devika, Sunitha and Ganesh (2016) stated that lexicon-based sentiment analysis is used to summarise the polarities of single words or phrases based on the sentiment dictionary. The disadvantage of using this unsupervised learning method is the sentiment dictionary usually requires a rich linguistic data. However, different areas have different emotional words, for example, the words "blue screen" do not appear in the emotional dictionary, but these words express dissatisfaction with electronic devices like mobile phones or laptops. Therefore, it is necessary to construct a targeted sentiment dictionary based on specific fields. We will talk about this later in limitations and implications. In the third step, emotional mining was upgraded to opinion mining. This step requires finding the product's attributes from the comments. This requires that on the basis of sentiment analysis, the attributes of the product should be excavated first, and then the emotions of the corresponding attributes should be analysed.

1.2 Problem Statement

According to a recent government report, tourism has become the largest export industry in New Zealand, and it contributed 5.9% of GDP (or $14.7 billion) in 2017 (http://www.mbie.govt.nz/info-services/sectors-industries/tourism/key-tourism-statistics). The report declared that the purpose of international and domestic visits is mainly for holidays and vacations. Especially, nearly 52.8% of international tourist is for holiday purposes. According to a recent statistical factsheet, the decrease of population in small towns will affect local infrastructure development, but the question is does it also affect the tourism industry? (http://archive.stats.govt.nz/browse_for_stats/population/census_counts/2013CensusUsuallyResidentPopulationCounts_HOTP2013Census/Commentary.aspx). Thus, we want to know what tourists think about their travelling experience in New Zealand. In this case, we are interested to find out tourists' travelling experience in small towns.

We took the following review example from a *TripAdvisor* page to show what sentiment analysis looks like, and this review was done by a user called "simonsch" from the United Kingdom who reviewed Motel Russell in Russell in the North Island (https://www.tripadvisor.co.nz/ShowUserReviews-g255679-d611614-r556822589-Motel_Russell-Russell_Bay_of_Islands_Northland_Region_North_Island.html):

*"**Good**-sized room with **lovely comfortable** bed. Lots of **hot** water and **good** shower/bathroom. All very **clean**. Kitchenette had everything you **need**. Wifi was patchy on occasion which was **frustrating**. Owner was really **friendly** and **helpful** making **sure** we had everything we needed. **Good** location with short stroll into Russell for restaurants, **bars**, shops, beach and ferries. Pool and garden looked **great** but **sadly** we didn't have the weather to be able to use them. Laundry facilities **excellent**. Would **definitely recommend** staying here."*

First, the program will remove all noise data from this piece of text. Then, we use the sentiment dictionary to process the text and classify the words with different polarity (see Table 1, red words are positive and green words are negative). Finally, we identify the polarity of the text based on the polarity words classified. In this case, the polarity of the text has been identified as a positive review.

Words	**Subjectivity**	**Polarity**
Good	Weak subjectivity	
Lovely	Strong subjectivity	
Comfortable	Weak subjectivity	
Hot	Weak subjectivity	
Clean	Weak subjectivity	

Need	Weak subjectivity	Positive
Friendly	Strong subjectivity	
Helpful	Weak subjectivity	
Sure	Strong subjectivity	
Bars	Weak subjectivity	
Great	Strong subjectivity	
Excellent	Strong subjectivity	
Definitely	Weak subjectivity	
Recommend	Strong subjectivity	
Frustrating	Strong subjectivity	Negative
Sadly	Strong subjectivity	

Table 1: Example of polarity classification for a *TripAdvisor* online review

One of the challenges doing online review sentiment analysis is online reviews are normally in an informal format, and there are often have grammatical and misspelling errors. This is leads to critical errors and affects the accuracy of sentiment analysis results. Thus, we need to pre-process the review data to eliminate any errors and useless symbols. Since we already know the polarity of reviews, then we want to know what reviewers talking about for this specific point of interest (POI). We certainly do not want to go through every online page to look at what these reviews talk about. As a result, we applied the latent Dirichlet allocation (LDA) method to classify tourist reviews on certain topics. Then, we also applied sentiment analysis to these topics in order to find out what tourists thinking about these points of interests. Thus, we can find the topics that are most discussed by tourists. Finally, we found an alternative categorisation to help us define the various topics based on the LDA method.

1.3 Research Goal and Question

When exploring the tourist reviews on *TripAdvisor*, I was guided by one main research question:

What are the sentiments people express in reviews on *TripAdvisor* about small towns in New Zealand? This research question breaks down into four sub-questions:

(1) Are there differences in the sentiment in reviews about different locations (North Island vs. South Island)?

(2) Are there differences in the sentiment in reviews about different categories (hotels, attractions, and restaurants)?
(3) Do we find an alternative categorisation by using topic modelling?
(4) Are there differences about reviews in different topics?

This paper is organised into the following five sections. Section 2 will give a literature review about the methods of sentiment analysis and topic modelling. Section 3 examines two methods we used in this research – lexicon-based sentiment analysis and latent Dirichlet allocation. Section 4 will describe the results and findings after we processed the data, and answer the research questions. Section 5 will discuss any existing research problems with our research, and explain new understanding related to our research questions. Sections 6, 7 and 8 will examine why this research is important, and any limitations that should be avoided in the future studies.

2. Literature Review

This literature review section will discuss some common sentiment analysis approaches and general issues when utilising sentiment analysis with social websites, such as *TripAdvisor*, *Twitter*, etc. The main goal of sentiment analysis is "to extract the global sentiment based on the subjectivity and the linguistic characteristics of the words within an unstructured text" (García, Gaines and Linaza, 2012, p. 35). So why is sentiment analysis important to analysing online social media? Social media is the most common tool that people use every day, and it is a good source of information. This information can provide insights into marketing strategy and consumer service. We can benefit from information by using the right sentiment analysis approach. Table 2 summarises some recent research using different sentiment analysis approaches to investigate how online reviews could influence people making a decision.

Authors	**Data Size & Source**	**Location**	**Language**	**Method**
García, A., Gaines, S., & Linaza, M. T. (2012)	1,000 restaurant reviews; 994 hotel reviews	Spain	Spanish	

	(*TripAdvisor*)			Lexicon-based approach
Gräbner, D., Zanker, M., Fliedl, G., & Fuchs, M. (2012)	80,000 hotel reviews (*TripAdvisor*)	New York	English	
Cataldi, M., Ballatore, A., Tiddi, I., & Aufaure, M. A. (2013)	259,000 hotel reviews (*TripAdvisor*)	London, Beijing, Shanghai, Montreal, New Delhi, Dubai, New York, Chicago, San Francisco, Las Vegas		
Jurek, A., Mulvenna, M. D., & Bi, Y. (2015)	25,000 movie reviews (IMDB)	Varies		
Tian, X., He, W., Tao, R., & Akula, V. (2016)	11,042 hotel reviews (*TripAdvisor*)	Beijing, Shanghai, Guangzhou, Shenzhen		
Bucur, C. (2015)	3,000 hotel reviews (*TripAdvisor*)	Rome		
Bjørkelund, E., Burnett, T. H., & Nørvåg, K. (2012)	50,1081 hotel reviews (*TripAdvisor*); 293879 hotel reviews (*Booking*)	London, New York, Athens, Paris, Dubai		Machine learning approach
Duan, W., Cao, Q., Yu, Y., & Levy, S. (2013)	70,103 hotel reviews (*TripAdvisor*)	Washington D.C.		

Farhadloo, M., & Rolland, E. (2013)	2,405 park reviews (*TripAdvisor*)	California, USA		
Raut, V. B., & Londhe, D. D. (2014)	1,000 hotel reviews (*TripAdvisor*)	Undefined		
Collomb, A., Costea, C., Joyeux, D., Hasan, O., & Brunie, L. (2014)	1,000 movie reviews; 1,000 airline reviews; 2,600 hotel reviews (Amazon & Epinion)	Varies		Lexicon-based and machine learning approach
Putri, I. R., & Kusumaningrum, R. (2017)	100 reviews (*TripAdvisor*)	Indonesia		Latent Dirichlet allocation (LDA)
Calheiros, A. C., Moro, S., & Rita, P. (2017)	52 hotel reviews (*TripAdvisor*)	Areias do Seixo hotel in Portuguese		Machine learning approach and latent Dirichlet allocation
Wu, W., Gao, B., Yang, H., & Sun, H. (2017)	217,518 hotel reviews (*TripAdvisor*)	Las Vegas		Word2Vec
Smyth, P. C. B., Wu, G., & Greene, D. (2010)	30,000 Irish hotel reviews; 50,000 Las Vegas hotel reviews (*TripAdvisor*)	Irish, Las Vegas		Rating comparison

Table 2: Summary of main characteristics of reviewed articles

We will briefly talk about three approaches in sentiment analysis – the lexicon-based approach, machine learning approach, and rule-based approach. We will also talk about latent Dirichlet allocation (LDA), the method we use to understand what a review is talking about at an abstract level. Then, we will review other research related to *TripAdvisor*.

2.1 Sentiment Analysis

In the field of information science, sentiment analysis refers to the use of technology such as natural language processing or machine learning to directly analyse subjective attitudes, emotions, and opinions about text. Figure 1 classifies sentiment analysis into two different approaches – the lexicon-based approach and machine learning based approach. This paper used lexicon-based sentiment analysis with a dictionary approach. The lexicon-based approach is mainly to formulate a series of emotional lexicons and rules, in order to calculate the emotional value, and finally to use the emotional value as the text's emotional tendency basis. However, Collomb, Costea, Joyeux, Hasan and Brunie (2014) stated that the difficulty in using lexicon-based sentiment analysis for simple text sentiment classification is that is does not have enough emotional words. However, the reviews we analyse contain strong emotional words, which allows us to use a lexicon-based method.

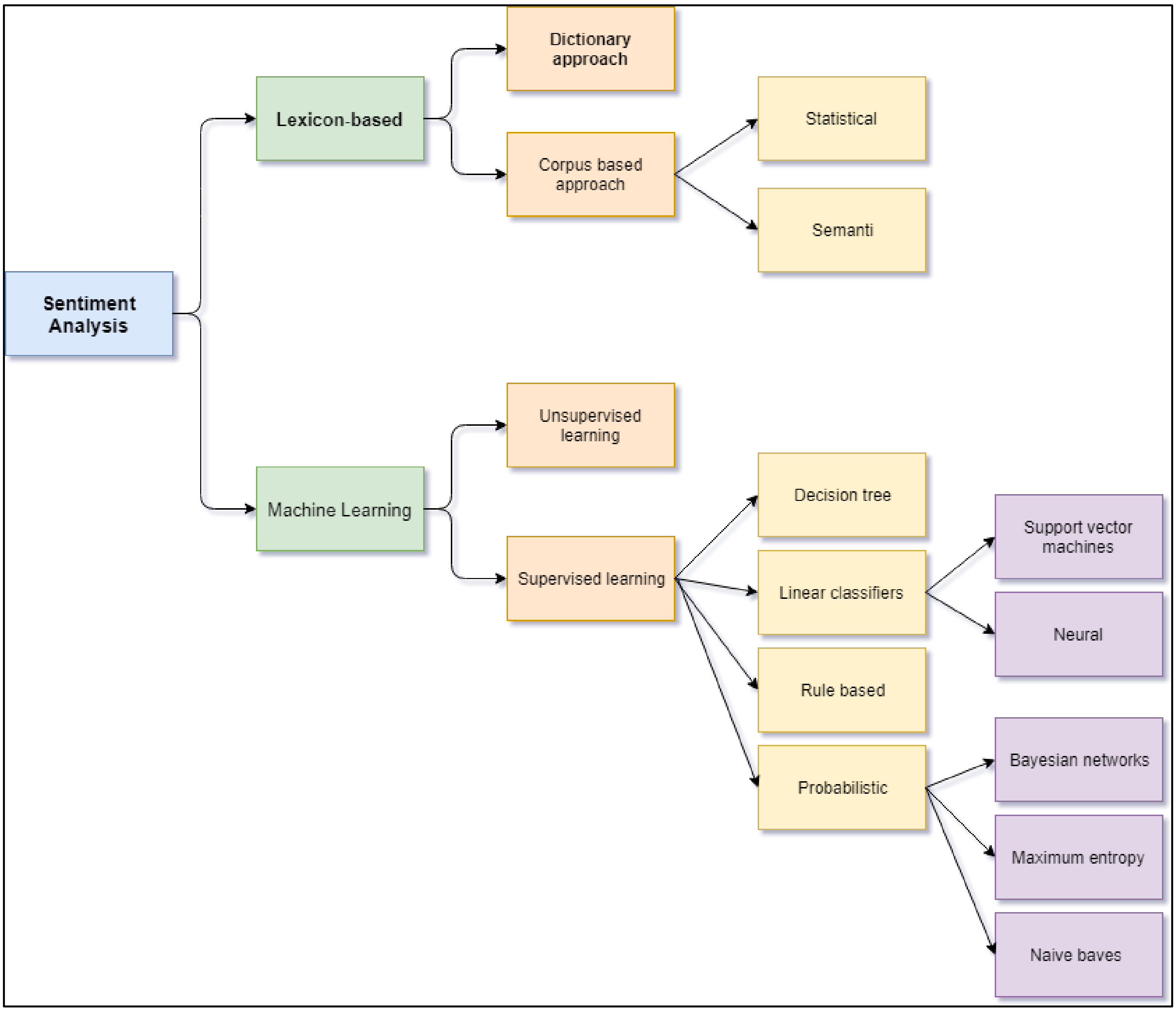

Figure 1: Sentiment analysis techniques (Kiprono and Abade, 2016, p. 42)

2.1.1 Lexicon-based Sentiment Analysis

The lexicon-based sentiment analysis originates from text analysis based on grammar rules (Amiri, Scerri and Khodashahi, 2015). The method is relatively simple, and it mainly depends on what sentiment dictionary used. In the study of sentiment analysis, the text should be pre-processed, like removing stop words. In the process of sentiment analysis of English text, stop words refer to filtering out some words that are frequently used but have no practical meaning. The purpose is to reduce the feature selection dimension, reduce the amount of calculations, and improve the efficiency of the analysis results. The stop words normally include articles, prepositions, numerals, interjections, etc. For example, “a/an”, “the” and “of/off” are the common stop words used in English text. García, Gaines and Linaza (2012) use a lexical database to study how Spanish user reviews on *TripAdvisor* could impact the tourism domain based on a lexicon-based sentiment analysis approach. And they stated that negative sentiment is hard to detect in the text compared to positive sentiment because negative sentiments are usually expressed in some ironic words or sentences. In addition, they stated that user reviews or feedbacks play a significant role during the decision-making process. Lexicon-based sentiment analysis is processed by “adjective followed or preceded by adverb is detected as opinion word or phrase” (Modak and Mondal, 2014, p. 284). The authors introduced three levels of sentiment analysis, including the lexicon level, sentence level and document level. Lexicon level is the easiest classification to detect sentiment. Sentence level is a relatively simple classification if a direct sentiment lexicon is found in a sentence. Document level is the hardest classification, because it considers a whole document as a single unit. Vohra and Teraiya (2013) also stated that a lexicon-based approach belongs to an unsupervised technique, and classification is done by giving a sentiment score evaluated by comparing a word in a lexicon dictionary. Thus, the system determines the polarity word is positive, negative, or neutral. In the end, if the document has more positive words, then the document is positive, otherwise it is negative. There are two different methods to construct a sentiment lexicon dictionary: corpus-based approach and dictionary-based approach. Feldman (2013) stated that the lexicon is the most important part of lexicon-based sentiment analysis. There are three different approaches to gathering sentiment lexicon – manually edit lexicon data, dictionary-based resources, and corpus-based approaches. In our research, we use the dictionary-based lexicon, but the disadvantage is the lexicon is “domain independent and hence does not capture the specific peculiarities of any specific domain” (Feldman, 2013, p. 86).

2.1.2 Machine Learning Sentiment Analysis

The method of machine learning is more accurate compared with the lexicon-based approach, because dictionary matching could cause larger errors due to the richness of semantic expression. Whether it is a subjective and objective classification or positive and negative polarity classification, machine learning can complete the required tasks. It does not need to dig into the terms, sentences and grammar like the lexicon-based approach, as the machine learning approach directly calculates the emotional words in the text and obtains their scores of emotional tendencies. The idea of the machine learning method is to select a part of the text to express positive and negative emotions, respectively. And then, use the machine learning method to train the text in order to obtain an emotion classifier. The final classification is to give the text a category of 0 or 1, or a probability value. For example, we could say ‘the positive probability of this text is 90%, and the negative probability is 10%’.

Vohra and Teraiya (2013) indicated that the differences between a machine learning based approach and a lexicon-based approach is that using a lexicon-based approach could help researchers examine the features of unstructured text data, but it heavily relies on sentiment dictionary. If a new word appears on the web, and there is no definition of this word, it cannot be measured by this method. On the other hand, a machine learning approach could overcome the effects of unknown words and turn it into a structured text to analyse. On the other hand, a recent study shows the benefit of using machine learning sentiment analysis as it can generate useful information from massive data, and obtain high accuracy classification, in order to help people to quickly understand user-generated content rather than read the whole document (Raut and Londhe, 2014).

Daiyan, Tiwari, Kumar and Alam (2015) indicated that current sentiment classification could not identify what reviewers like or dislike about the product if they only assign the review document to positive or negative polarity. A reviewer may like the most of product and not like a small part of the defects, but they give the positive feedback. The author also suggests some researches could also apply Hidden Markov Models (HMM) to perform object recognition in order to identify object features. The author mentioned that the major focus of machine learning sentiment analysis is using a statistical method to extract useful information from a mass of data. There have been various applications based on machine learning sentiment analysis, such as online search engines, credit card fraud detection, medical analysis and diagnosis, etc.

2.1.3 Rule-based Sentiment Analysis

Rule-based sentiment analysis is an unsupervised machine learning method. This method uses rule learning to extract product features. Yang and Shih (2012) stated that use rule-based sentiment analysis can automatically extract product features from a specific product reviews. And they declared that product feature is defined as a characteristic of product or service can help attract potential buyers, and also it used to develop a product marketing strategy. Normally, researchers will combine both machine learning and rule-based approaches to performing sentiment analysis in order to increase the accuracy and performance of calculation results. Khan, Baharudin and Khan (2011) introduced a rule-based sentiment analysis approach to study online consumer reviews on *TripAdvisor*. The method is to calculate a polarity scale to assign every review as positive, negative, or neutral. The results show the performance of sentence-level sentiment classification is better than word level.

2.1.4 Applications of Sentiment Analysis

There is an urgent need for computational approaches to assist users in processing emotional content with the explosive growth of commentary on the Internet. In the following, we will give a general introduction to the current landscape of applications of sentiment analysis. Table 3 lists seven common application scenarios:

Application Scenario	**Description**
Product reviews analysis (Fang & Zhan, 2015)	Using sentiment analysis could help a business to understand the user's satisfaction with the product, and then develop a suitable marketing strategy.
Commentary on a movie or TV show	This could help the producer to understand how users feel about the programme, and then develop a good story and suitable on-air time.
Public opinion analysis (Jiang, Lin & Qiang, 2015)	Government departments can understand citizens' sentimental statements towards hot events, and results could help the government in formulating relevant policies.
Character's sentiment analysis (Groh & Hauffa, 2011)	This can help people to analyse someone's personality through emotional changes.
Relationship analysis (Groh & Hauffa, 2011)	This can help us to understand the relationship between two people through the emotions expressed by their mutual reviews.
Comparative analysis of products	For example, analysing and comparing the reviews of various car brands can help businesses understand the difference between these products in the user's mind, and can also help users to choose the right car.
Predictive analysis of an event (Montesinos, Rodríguez, Orchard & Eyheramendy, 2015)	Using such information we could predict a certain event's results by analysing users'

	public comments, like movie box office, Oscar winners, and politicians' results.

Table 3: Example of sentiment analysis applications

Many applications can use sentiment analysis to improve business performance. Taboada, Brooke, Tofiloski, Voll and Stede (2011) introduced that there are several applications of use for lexicon-based sentiment analysis. First, monitoring social media. For example, the impact of negative comments on a certain brand could help an organisation's leaders to understand the influence of the brand. Secondly, improve or reshape a public relationship. For instance, sentiment analysis can help explore hotspots in sales and trends in the industry. Establishing and maintaining a cooperative relationship is clearly an effective public relationship management strategy. Finally, policy analysis. Analysing the comments on social media can help people to understand the public opinions about policies. One recent research of the University of Munich shows that the information on Twitter can reflect the voter's political inclinations. Researchers focused on the German federal election in 2009, and they found that Twitter's information can predict the results of the election, and the accuracy is higher than the traditional public opinion research results (Tumasjan, Sprenger, Sandner and Welpe, 2011). A recent study shows that tourists' sentiment analysis is important to local tourism industry development. Practitioners can benefit from this huge dataset to improve their performance. Online reviews can also help the international or local traveller to make a decision about choosing a right travel destination (Gao, Hao and Fu, 2015). On the other hand, Van Looy (2016) argues that an organisation who has a higher review rating and more positive reviews will have a higher number of sales or other business-related actions (like newsletter subscriptions and loyalty membership signing up). Compared with the 1990s when online social media was not widely known and used, people decide buying products or services after seeking advice from friends or people they know. Or consumer check in an officially released guide (like *The Michelin Guide*, https://guide.michelin.com/). In general, people choose to purchase something from a place that has relatively high credibility and reliability. The study also found that people were willing to pay for or buy products from 5-stars rating stores rather than 4-stars or even lower rating stores. Positive reviews also bring positive sales and higher competition. However, people should be aware of unethical behaviour. For example, some organisations might create fake reviews by themselves or hire someone to post a positive review on the online website. Or even worse, they might pay money to bloggers and ask them to remove negative reviews. The author also suggests consumers consider the identity of a reviewer and the purpose of consuming when they look at the online review. Especially, some extremely positive and negative reviews need to be take an extra care of, as these reviews might be misleading about the final judgement of the product. Ravi and Ravi (2015) stated that online reviews could also refer to electronic Word of Mouth (eWOM), which helps consumers share their point of views. Using sentiment analysis could help people or organisation to formulate marketing strategies, like market intelligence analysis, consumer satisfaction surveys, and film market revenue forecasts, etc. The study shows strong evidence that another consumer's personal opinion could influence buying decisions.

In addition, Farhadloo and Rolland (2013) presented a new method to improve the accuracy of sentiment score based on applying aspect-based sentiment analysis to *TripAdvisor*. The author introduced some sentiment analysis applications that could be used for both individuals and organisations, such as the market recommendation system, the automatic question-answer system and the online review search engine.

2.2 Topic Modelling

Topic modelling is like the central idea expressed in an article, a paragraph, or a sentence. A specific word frequency distribution underlies this approach to describe the subject from a point of statistical model viewpoint. The latent Dirichlet allocation (LDA) is an unsupervised machine learning technique that can be used to identify hidden subject information in a large-scale document collection or corpus. It uses a bag of words method, which treats each document as a word frequency vector. The LDA topic model is a multi-level probability generation model, which is a method for modelling the topic information of the text data.

2.2.1 Latent Dirichlet Allocation (LDA)

The consumer chooses the right product or service is based on positive reviews on the online platform. In contrast, product sellers or service providers are relying on negative feedback that they received. However, the different consumers gives different features with a different priority (Cataldi, Ballatore, Tiddi and Aufaure, 2013). For example, one consumer rated value as the most important feature when booking a hotel and service as less important. But, other consumers may rate sleep quality as the most important and value as less important. Thus, different feature priorities might influence a positive or negative rating. According to the online marketing tool *comScore*, around 81% of consumers did at least one piece of online research about a product or service that they wanted to buy, and around 87% of consumers think an online review is helpful and useful to make the final decision. Around 30% of consumers posted a review about a product or service after they bought it (https://www.comscore.com/Insights/Press-Releases/2007/11/Online-Consumer-Reviews-Impact-Offline-Purchasing-Behavior). As a result, using the latent Dirichlet allocation (LDA) approach could help researchers to detect and organise different "topics" within a large amount of online reviews data (Cataldi, Ballatore, Tiddi and Aufaure, 2013).

Calheiros, Moro and Rita (2017) stated that hotel owners should focus on solving challenging problems and find a way to improve hotel quality continuously. And also, data mining technology could help managers find hidden patterns in review data, and then convert this useful information into a solution to the problem. The authors also mentioned that applying sentiment classification could also help managers to explore their service characteristics, thus it can help deploy a consumer relationship management (CRM) strategy. The research applied LDA modelling to find gaps in hospitality management. It also helps group reviews on different topics according to their probability of chosen words in a review. The challenges of using a topic modelling method are the results are based on the techniques used to create topics. And also, the reviews cannot judge by single words, and they might have different meanings according to the remaining content. A recent article stated that the tourism industry is growing faster in recent years, and also has become one of the important foreign exchange sectors around the world. An online survey, a way to collect data about consumer thoughts, is not accountable as reliable cause participants remain unknown for privacy concerns. On the other hand, online reviews are considered as a suitable data to address consumer satisfaction and impression problems. The author indicated that using LDA is a proper way of processing a large dataset because the parameter is assigned with a random variable (Putri and Kusumaningrum, 2017).

2.2.2 Applications of Topic Modelling

(1) Scientific Research

In the field of scientific research, most of the evolutionary analysis attempts to analyse the research and development paths and hot spots of the subject areas are from journal articles, conference papers and other scientific reports (Jelodar, Wang, Yuan and Feng, 2017).

(2) News Area

At present, research in the field of journalism involves the tracking of news topics in a certain field, such as public opinion monitoring, media public opinion analysis and user feedback analysis. The raw data is from a wide range of sources, including traditional news media, self-organised media and news channel. This analysis generally faces the difficulties of a large amount of data, high update frequency and non-standard structure problems (Ma, Yuan, Wan, Qian, Zhang and Ye, 2016).

2.3 Previous Researches on TripAdvisor

There are several types of research that also use *TripAdvisor* as a study object, including sentiment analysis, structural equation modelling and degree of correlation. We will describe the three types of research based on the following reviewed articles:

Research 1 – Apply four sentiment analysis methods to study TripAdvisor in Spain

Valdivia, Luzón and Herrera's (2017) recent research used four different sentiment analysis methods (SentiStrength, Bing, Syuzhet, and CoreNLP) to study sentiment classification. The study uses three well-known places in Spain as an example to investigate the differences between these four methods. The authors applied four different methods to classify the hotel reviews scraped from *TripAdvisor*, and distinguish the percentage of polarity (negative, neutral and positive) between these four methods. The results show that positive user reviews make up a significant part of user ratings. However, different sentiment analysis methods have different polarity distributions compared to user ratings. They observed online users likely to put negative reviews on a positive user rating. This research study is similar to our research, but we use different sentiment analysis method.

Research 2 – The credibility and influence of online reviews on TripAdvisor

Hospitality and tourism businesses' recent focus has been on investigating how user-generated content could impact their business development, and now they have integrated an online review website into their business website. The importance of user-generated content has been raised to a high position now. Ayeh, Au and Law (2013) argued that the credibility of the online source has a huge impact on the decision-making process, and it also influences behavioural intention. On the other hand, the study found that there might have been other factors that could impact the final decision-making, but the credibility is built from two different dimensions – trustworthiness, and expertise. Trustworthiness is described as the confidence degree of a source, and expertise has been described as the knowledge expressed within the source. As a result, the study uses the component-based structural equation modelling to investigate the credibility of *TripAdvisor*. The result shows useful online reviews will impact tourists' travel planning, but the study needs to further investigate the relationship between additional factors and user-generated content. This research help us to develop a future research plan, which use sentiment analysis to investigate the relationship between tourists and local infrastructures development. For example, does tourist will affect the number of public toilet in a scenic area?

Research 3 – The relationship between TripAdvisor online reviews and hotel performance

Hotel owners could see consumer satisfaction with the hotel's services, rooms and facilities on the online review website. Some consumers share the wonderful experience in the hotel, but some post negative feedback and even complaints about the hotel. Replying to this feedback is an easy step, especially for positive feedbacks. How about negative feedback? The hotel does not have to reply to all the online reviews. Even responding to all feedbacks could reflect the hotel's high-quality consumer service, but it is impossible to follow up and manage all the feedback. Because the online information is quickly spreading around the Internet, it might be already forwarded to other sites before that is realised. Tuominen's study focuses on investigating the relationship between the number of reviews received online and hotel performance. The study applied the Pearson product-moment correlation coefficient (PPMCC) to examine the relationship between online reviews and hotel performance. The results show the number of reviews can help increase hotel occupancy, and also positive reviews could increase the chance of hotel recommendation (Tuominen, 2011). On the other hand, Smyth, Wu and Greene (2010) stated that hotel owners are very sensitive to online reviews, especially as they pay more attention to negative reviews. The study compared and contrasted the hotel rating stars to examine the relationship between hotel improvements and online reviews on *TripAdvisor*. However, the authors also indicated that fraudulent reviews are the major problems in an online reviews website, and it will influence the research results. This research will help our future research to investigate the relationship between online reviews and local products (or services), to find out whether the online reviews will improve the quality of products (or services) or not.

3. Methodology

This study is based on a quantitative research method. We transformed review data scraped from *TripAdvisor* into a usable format for sentiment analysis and natural language processing. We should be mention that *TripAdvisor* will have different number of reviews based on different domain. For example, the same hotel reviews on TripAdvisor New Zealand and TripAdvisor Australia will have different number of online reviews. In this case the review data we used is collected from TripAdvisor New Zealand (https://www.tripadvisor.co.nz/). Two methods were applied to this study - lexicon-based sentiment analysis and latent Dirichlet allocation (LDA). We use the lexicon-based sentiment analysis method to measure subjectivity and opinion in the review data (RQ 1&2) and use the latent Dirichlet allocation (LDA) method to observe and explain similar topics in the review data (RQ 3&4).

3.1 Research Method

We use a lexicon-based sentiment analysis method in this research. The analysis tool we used for sentiment analysis in programming language R is built by Timothy P. Jurka (https://github.com/timjurka/sentiment). The program contains two parts: subjectivity classification and emotion classification. The subjectivity dictionary contains 6,518 words based on the MPQA Subjectivity Lexicon (see Table 4). It also classifies 1,542 words into six basic human emotional labels: anger, disgust, fear, joy, sadness and surprise (see Table 5).

Word	**Condition**	**Polarity**
abandoned	weaksubj	negative
abandonment	weaksubj	negative
abandon	weaksubj	negative
abase	strongsubj	negative
abasement	strongsubj	negative

Table 4: Example of subjectivity dictionary

Word	**Emotion**
abhor	anger
abhorr	anger
abhorr	disgust

admir	surprise
adorably	joy

Table 5: Example of emotion dictionary

3.2 Research Data

Firstly, we extracted a list of small town names through the Statistics New Zealand government website, where the total population of a town is less than or equal to 1,000 peoples around New Zealand (including islands). The data we used is based on the 2013 census usually resident population (http://archive.stats.govt.nz/Census/2013-census/data-tables/population-dwelling-tables.aspx#). The biggest of the "small" towns in the North Island is called Tapapa in the Waikato region with a population of 999, but it does not have any hotels, attractions or restaurants. The smallest of the "small" towns in the North Island are two islands in the Auckland region – Little Barrier Island and Rikitu Island, where they do not have any POIs (points of interests). On the other hand, the biggest of the "small" towns in the South Island is called Parnassus in the Canterbury region with a population of 939, and the smallest is called Rabbit Island in the Tasman region with a population of three (and the same as other places these towns do not have any POIs) (see Table 6). Then, we based it on these names to search whether there were any POIs listed on *TripAdvisor* (https://www.tripadvisor.co.nz/). In the third step, we manually collected every URLs associated with each POI and saved it to CSV files. Finally, we use a self-designed Python program to perform a review data scraping function based on the *Scrapy* framework (https://scrapy.org/).

	Number of Small Towns	**Total Population (Based on 2013 Census Data)**	**Average Population per Town**	**Population of Biggest Town**	**Population of Smallest Town**
North Island	254	127,683	502	999 (Tapapa)	3 (Little Barrier Island, Rikitu Island)
South Island	160	67,974	424	939 (Parnassus)	3 (Rabbit Island)

Total	414	195,657	472	---	---

Table 6: Summary of small towns in New Zealand

We only scraped reviews from the first review until the reviews wrote on 5th May 2018. After scraped review data from *TripAdvisor*, we total got 158,282 individual reviews across 2,248 different points of interests. The largest amount of review data is from the accommodation section with a total of 47,313 reviews across 607 sites. The average review length is 80 words across the whole review data (see Table 7). Tourists would like to talk more about holiday rentals rather than other types of POIs.

POIs		**North Island**	**South Island**	**Total**
Accommodations	**# of Places**	188	419	607
	# of Reviews	8,978	38,335	47,313
	Average review length	97	94	95
Holiday Rentals (Vacation Rentals)	**# of Places**	216	34	250
	# of Reviews	387	110	494
	Average review length	99	85	96
Things to Do (Attractions)	**# of Places**	293	377	670
	# of Reviews	13,328	33,630	46,958
	Average review length	78	86	84
Restaurants	**# of Places**	429	292	721
	# of Reviews	27,765	34,752	62,517
	Average review length	69	62	65
Total	**# of Places**	1,297	1,651	2,248
	# of Reviews	50,455	106,827	157,282
	Average review length	76	81	80

Table 7: Summary of four POIs in small towns within New Zealand

3.3 Data Analysis and Research Process

In our research, we used the programming language R to perform sentiment analysis. Before we launched the program, two packages needed to be manually downloaded and installed from the R project website to the R Studio software: sentiment v0.2 package (https://cran.r-project.org/src/contrib/Archive/sentiment/) and Rstem v0.4-1 package (https://cran.r-project.org/src/contrib/Archive/Rstem/). The process of data analysis was divided into two different parts – emotion classification, and Bayesian classifiers for positivity and negativity. The emotion classification helps us to analyse review content and classify different types of emotion, and these emotion categories have been widely used to describe basic human facial expressions: anger, disgust, fear, joy, sadness, and surprise. In addition, we added "unknown" type to identify any emotions that could not be identified. Before applying sentiment analysis, we pre-processed the data as necessary, including text cleaning, removing whitespace, and removing stop-words. Medhat, Hassan and Korashy (2014) declared that there are some important text features when doing sentiment classification problems, such as terms frequency, parts of speech (POS), sentiment words and phrases, and negations. The text content should remove any stop-words and stemming words before applying sentiment analysis. Our research removed stop-words from review content before natural language processing in order to avoid distracting and non-informative results.

This study generally contains three phases to investigate sentiment expressed in the review data: data mining, sentiment analysis, and topic modelling. Figure 2 shows that the research process of performing sentiment analysis and topic modelling. Firstly, use a Python-based computer program to scrape review data from an individual review page on *TripAdvisor*. Based on the default *TripAdvisor* categorisation, there are four different categorisations associated with each place – attractions ("things to do"), hotels, restaurants, and vacation rentals ("holiday homes"). Then, we stored these review data into a CSV file for the future analysis. Finally, we performed sentiment analysis and topic modelling methods to analyse the review data.

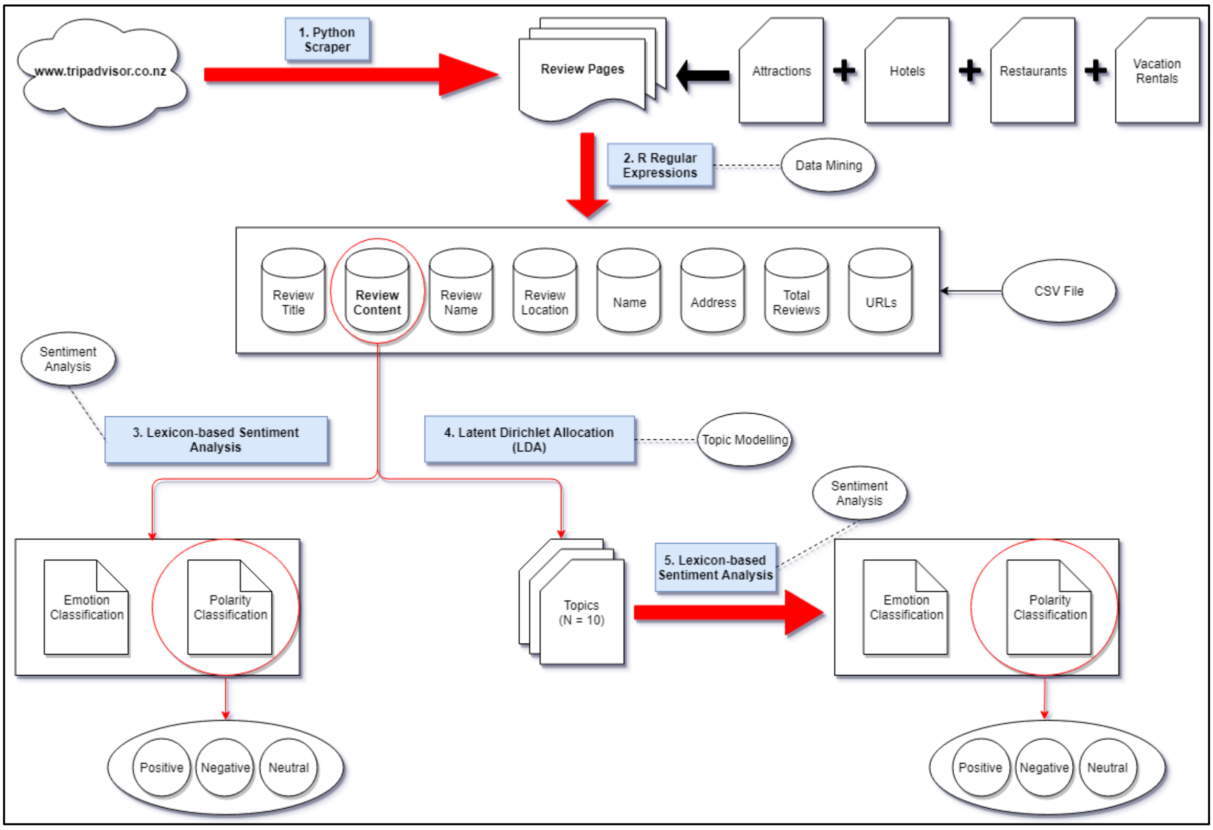

Figure 2: Data process and research method

4. Results and Findings

4.1 Tourists' sentiments for the North Island is similar to the South Island in New Zealand

We did not analyse rental vacation reviews because the amount of rental vacation review data is very small, and it is not suitable for doing sentiment analysis (check Table 7). The results show 75.80% of the tourists feel happy ("joy") when they are travelling around the North Island, compared to 75.01% in the South Island. In addition, other emotions (like "anger", "disgust", "fear", and "sadness") results in the main part of negative feeling, but this is only taking a small amount of review polarity. And also, 75.26% of the tourists feel happy about their travel experience in New Zealand overall (see Figure 3 and Appendices A, B).

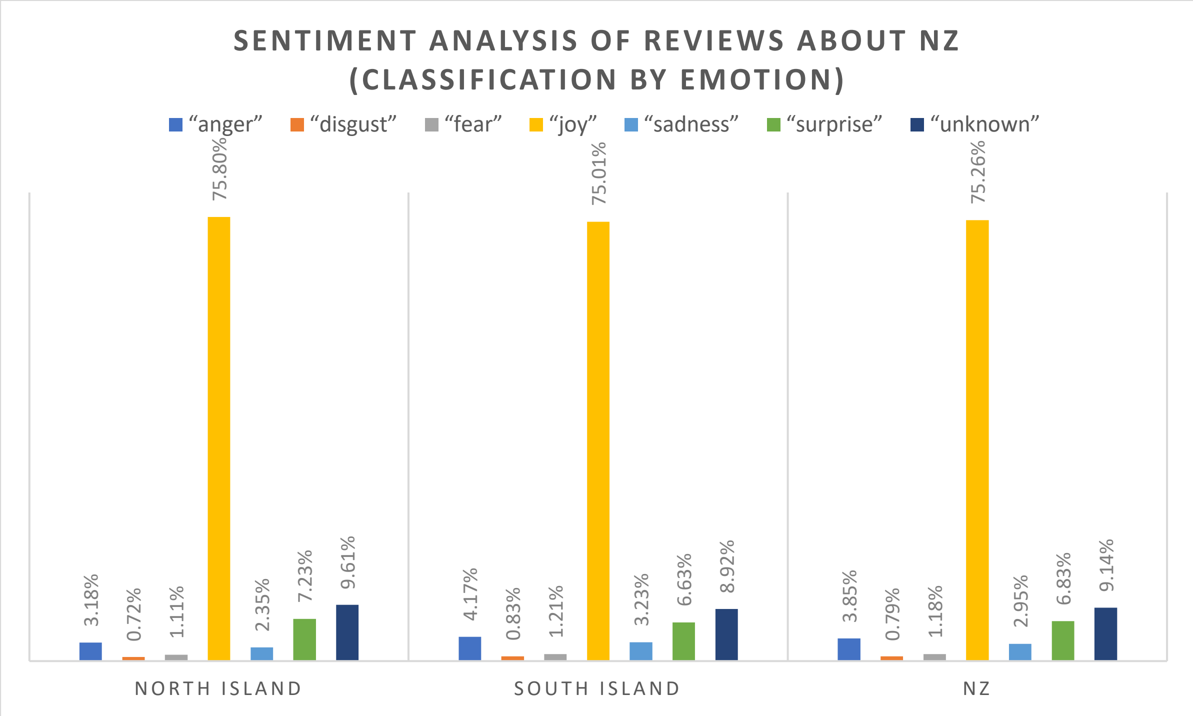

Figure 3: Sentiment analysis of reviews about NZ (classification by emotion)

On the other hand, the polarity is an orientation of how emotion is expressed in the text. The results can be positive, negative or neutral. Figure 4 shows that the North Island received 73.17% of positive reviews, and 18.47% of negative reviews about the travelling experience. For the South Island, 69.69% of tourists think they have a good travelling experience, but nearly 20.42% of tourists were not satisfied. Overall, the national wide travelling experience received a positive feedback, which occupies 70.80% of total reviews. The positive polarity between North Island and South Island is only 3.48% different, and negative polarity only 1.95% different.

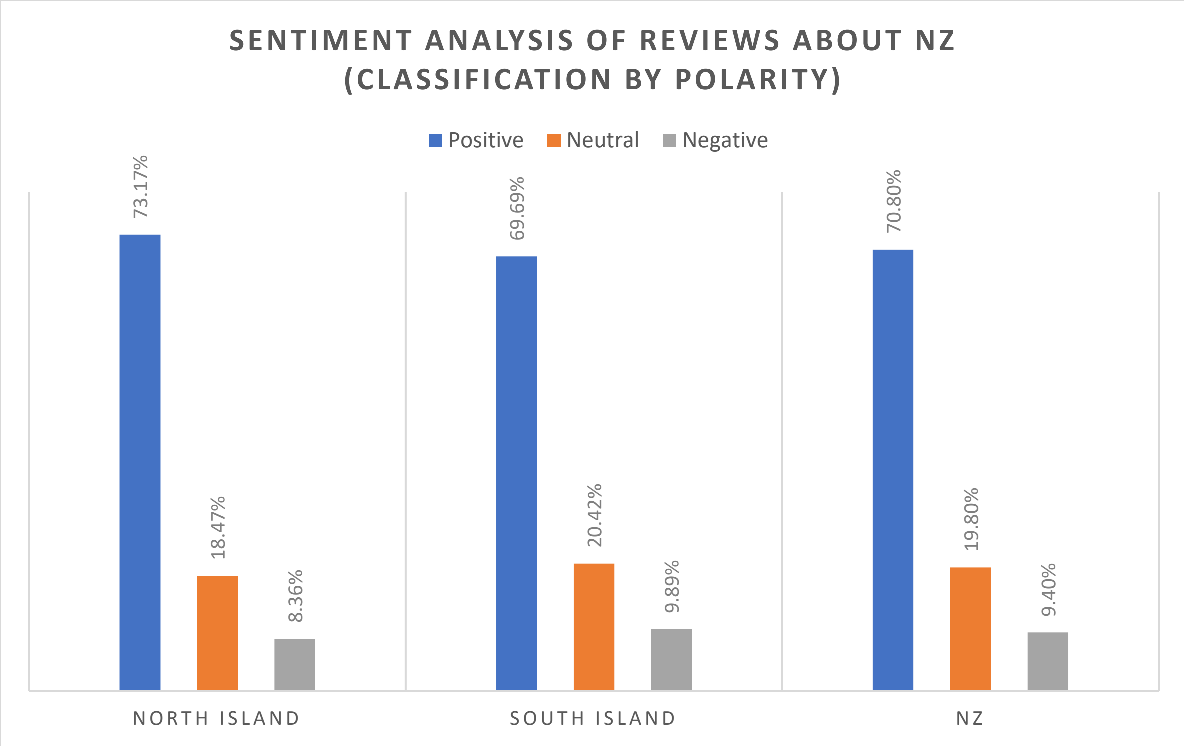

Figure 4: Sentiment analysis of reviews about NZ (classification by polarity)

4.2 Tourists are most satisfied with the hotels, followed by attractions and restaurants

Figure 5 shows tourists feel happy with the hotel service in the North Island (80.63% of tourists) and South Island (79.19% of tourists). The majority of tourists do feel good about attraction sites, 70.80% of the tourist feel happy in the North Island, and 68.79% in the South Island. However, if a high percentage of people does not feel happy it does not mean there is also have a high percentage of receiving negative feedback.

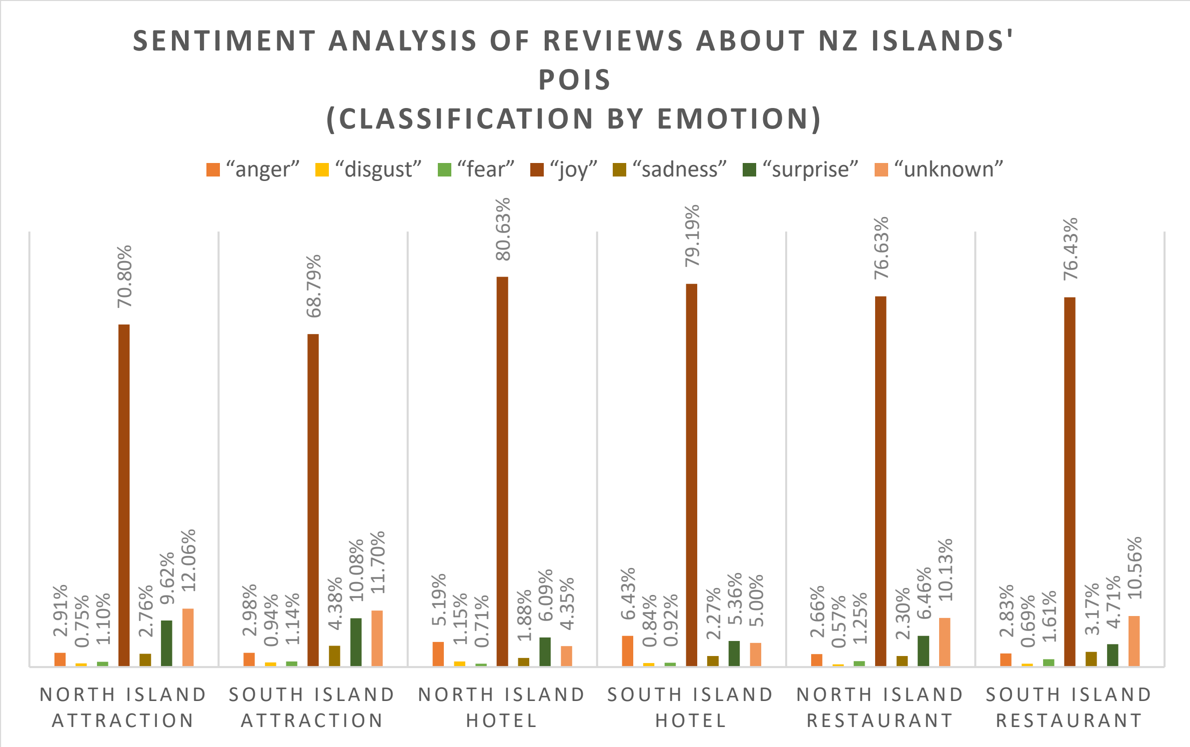

Figure 5: Sentiment analysis of reviews about NZ islands' POIs (classification by emotion)

Figure 6 shows around 76.14% of tourists give positive feedback about attraction site in the North Island, which is the highest percentage of positive sentiment polarity compared with other POIs. Restaurants in the South Island received around 67.67% of positive feedback, which is the lowest percentage of positive sentiment polarity. Most of the people were unsatisfied with attraction sites in the South Island (22.75%).

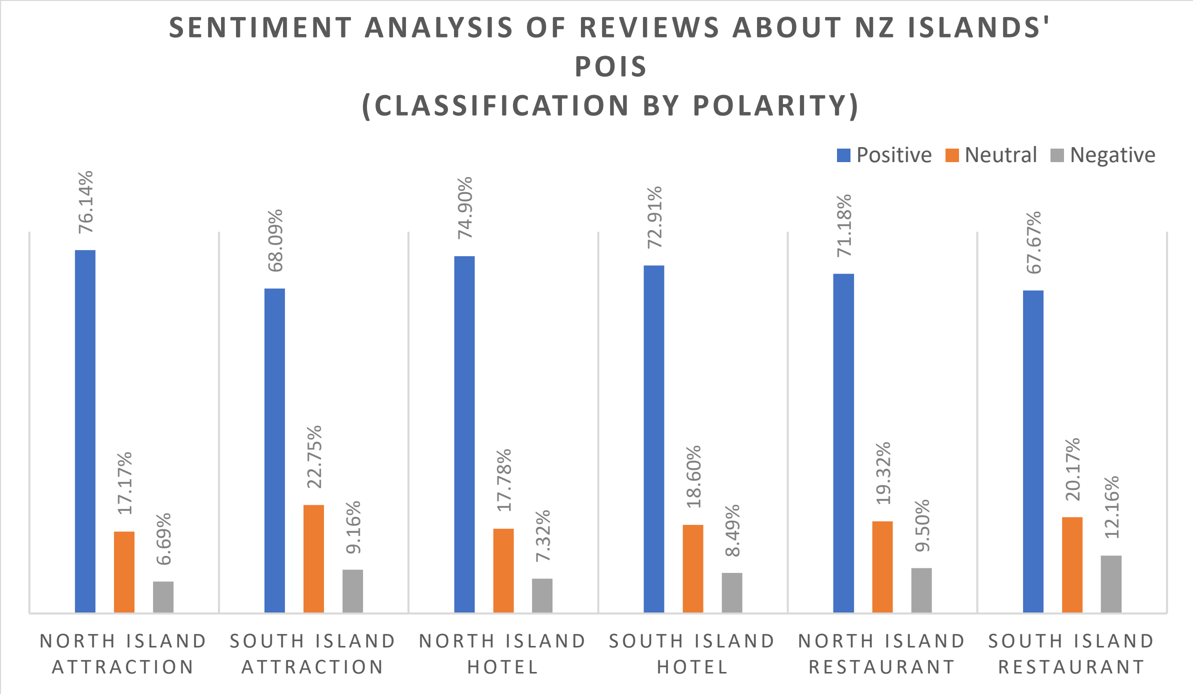

Figure 6: Sentiment analysis of reviews about NZ islands' POIs (classification by polarity)

Next, we move to nation-wide where 79.46% of tourist feel happy about hotel service in New Zealand, compared with 69.36% for attractions and 76.52% for restaurants (see Figure 7).

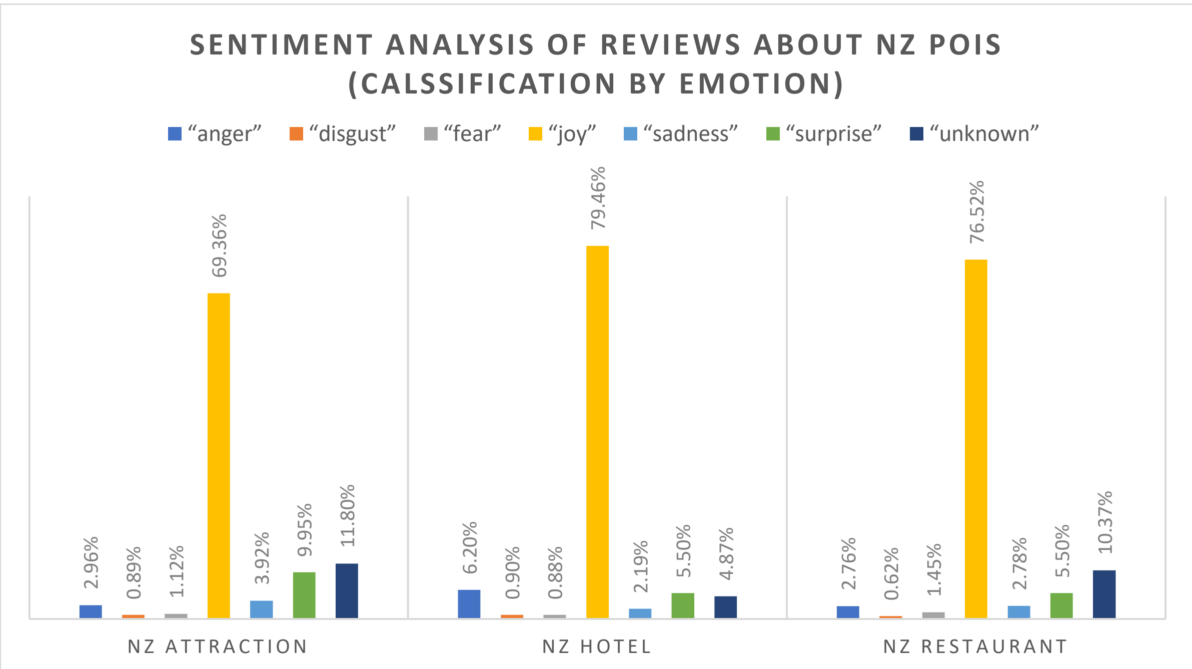

Figure 7: Sentiment analysis of reviews about NZ POIs (classification by emotion)

Figure 8 shows that hotel service received 73.92% of the positive feedback, compared with 70.38% for attractions and 69.23% for restaurants. In addition, the most unsatisfying point of interest (POI) is attraction sites across the country.

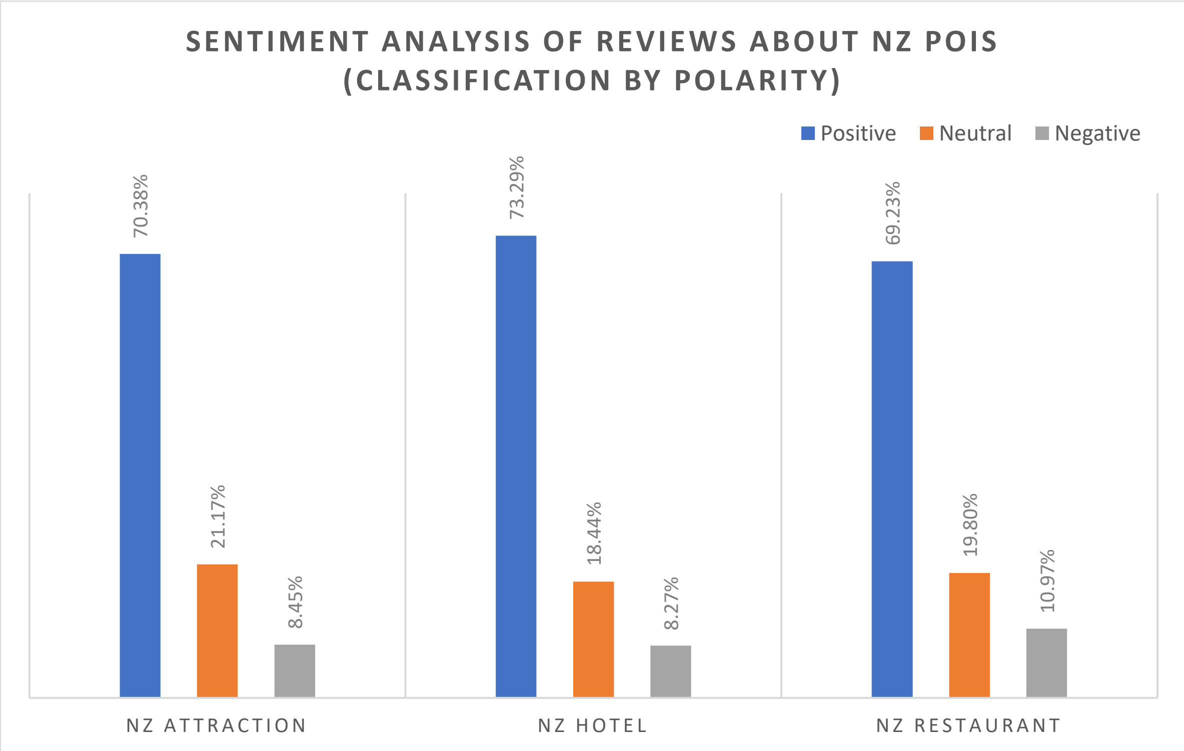

Figure 8: Sentiment analysis of reviews about NZ POIs (classification by polarity)

4.3 Keywords (top k-terms) - an alternative way to express the impression

The keywords or top k-terms are an alternative way to express the impression in different topics. After we have done sentiment analysis for each of the points of interest in New Zealand, we also applied the LDA method to these categorised review documents. Figure 9 describes how we used the LDA method to identify the various topics discussed in reviews. In this research, we categorised these reviews into twelve different categorizations, and then we divided the categorisations into ten different topics. Each topic contains the top eight words mentioned in the topic, and some topics shared the same keywords. The sequence of words is matters - from the first to last word is means the most mentioned word to the least mentioned word.

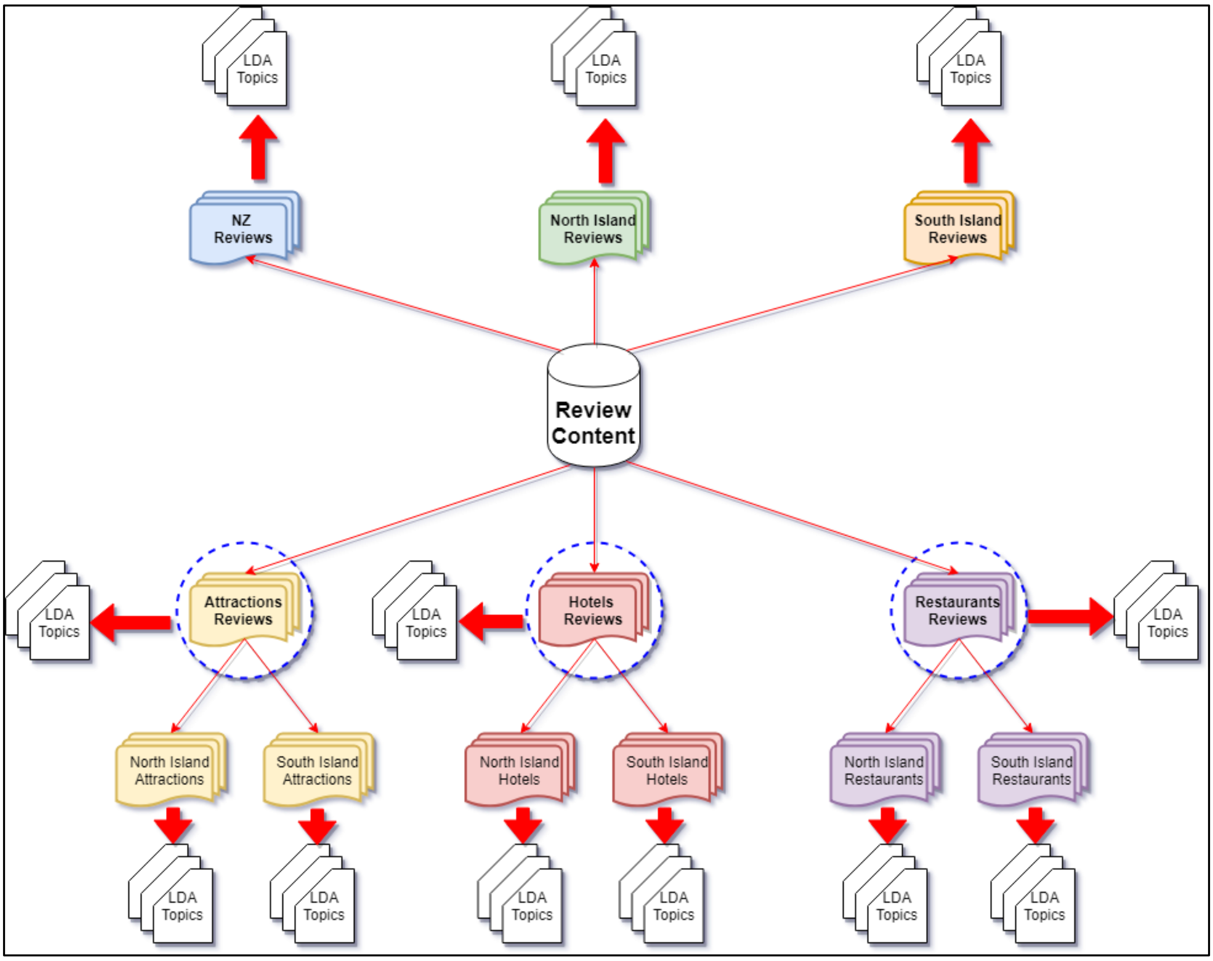

Figure 9: Applying the LDA method to twelve different categorisations

Figure 10 shows the whole online reviews has been classified into ten topics, but we also summarised each topic with two words. The order of words in each topic represents the number of occurrences of this word in the topic. We sum up with two words based on the description of these eight words. We will pay special attention to the appearance of nouns in topic. For example, eight words mentioned in topic 1, includes "service, made, lovely, beautiful, view, lunch, lile, and highly". "Line" is a noun English word for fish. These words describes a restaurant specialising in fish cuisine. Similar to topic 1, topic 2 to topic 10 describe different priorities of topic, and some topics share the same word. For example, the word "lovely" has appeared in six different topics.

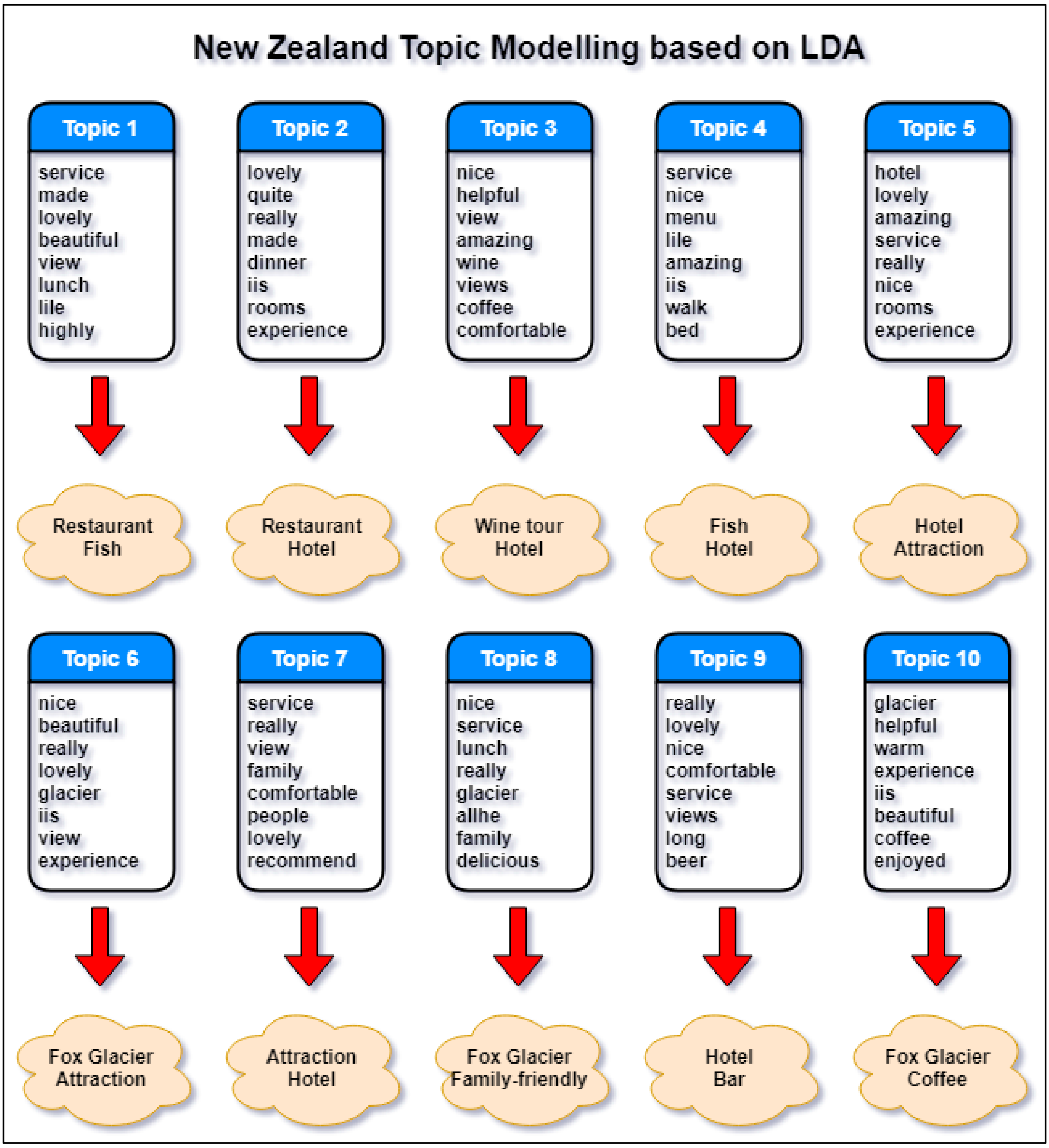

Figure 10: Categorisation 1 – New Zealand Topic Modelling based on LDA

We applied the LDA method to twelve different categorisations and each one contains ten different topics, and each topic contains eight frequency words. We summarised each topic with two of the most suitable words to describe the topic (see Figure 11-21).

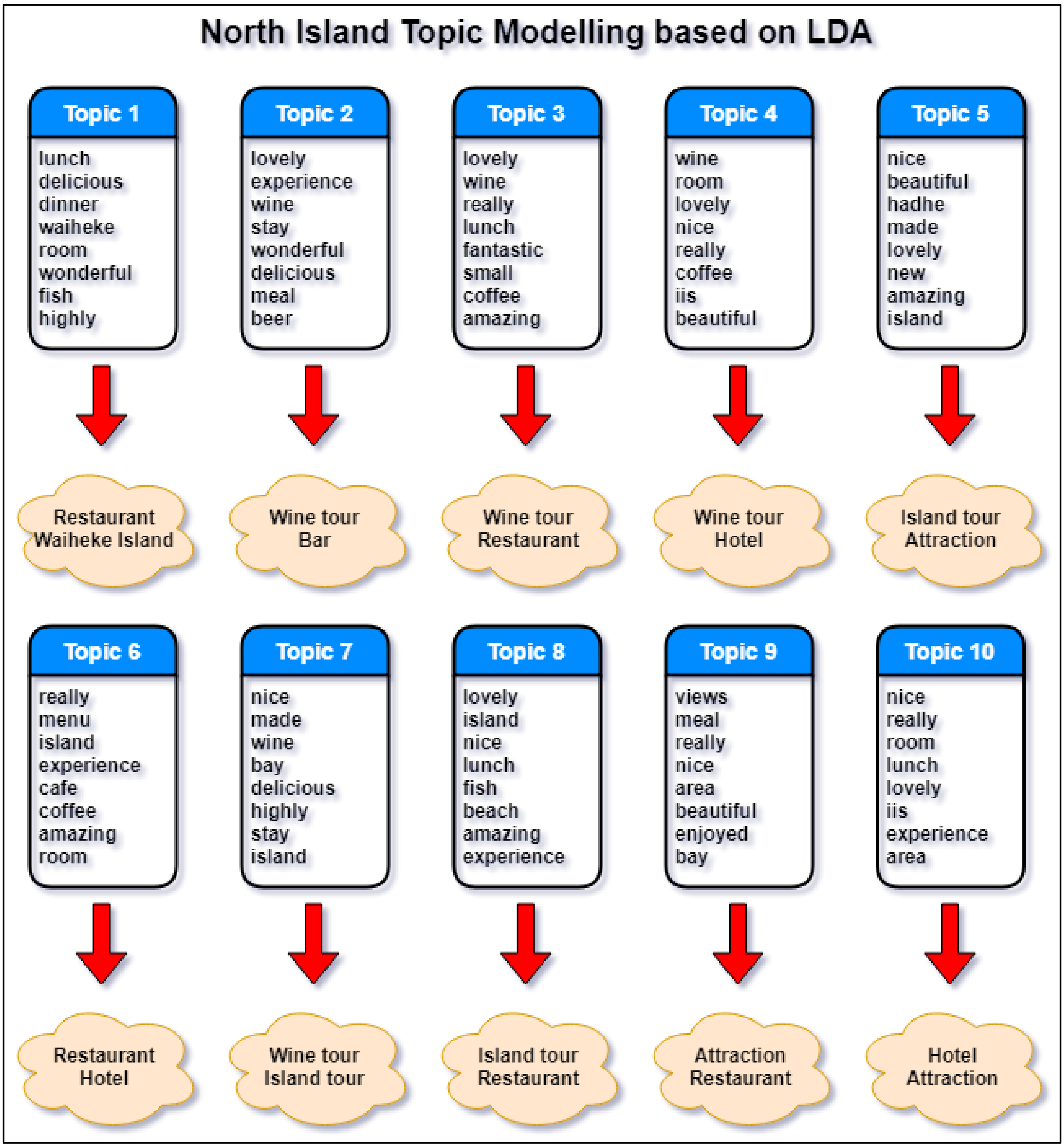

Figure 11: Categorisation 2 – North Island Topic Modelling based on LDA

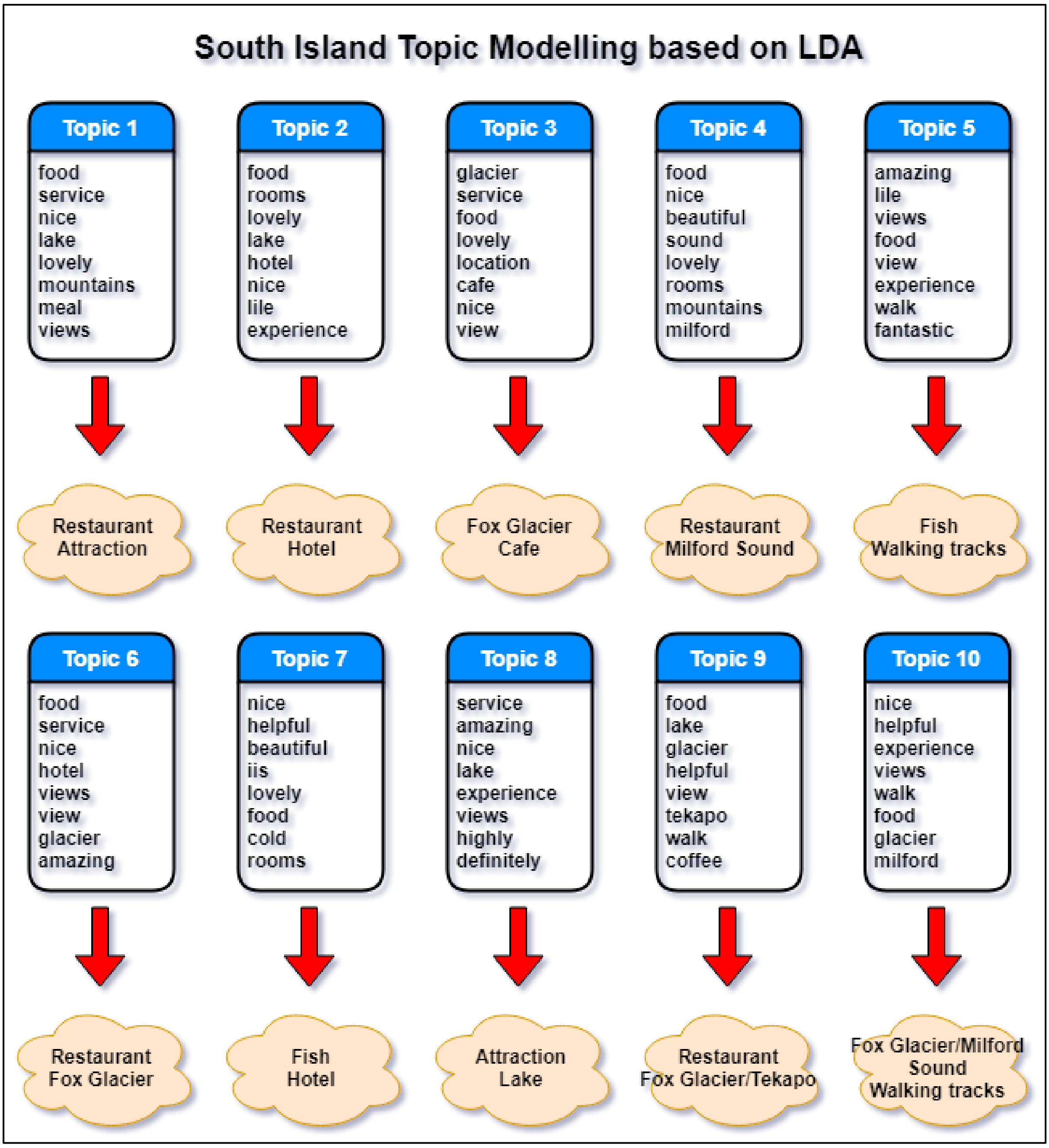

Figure 12: Categorisation 3 – South Island Topic Modelling based on LDA

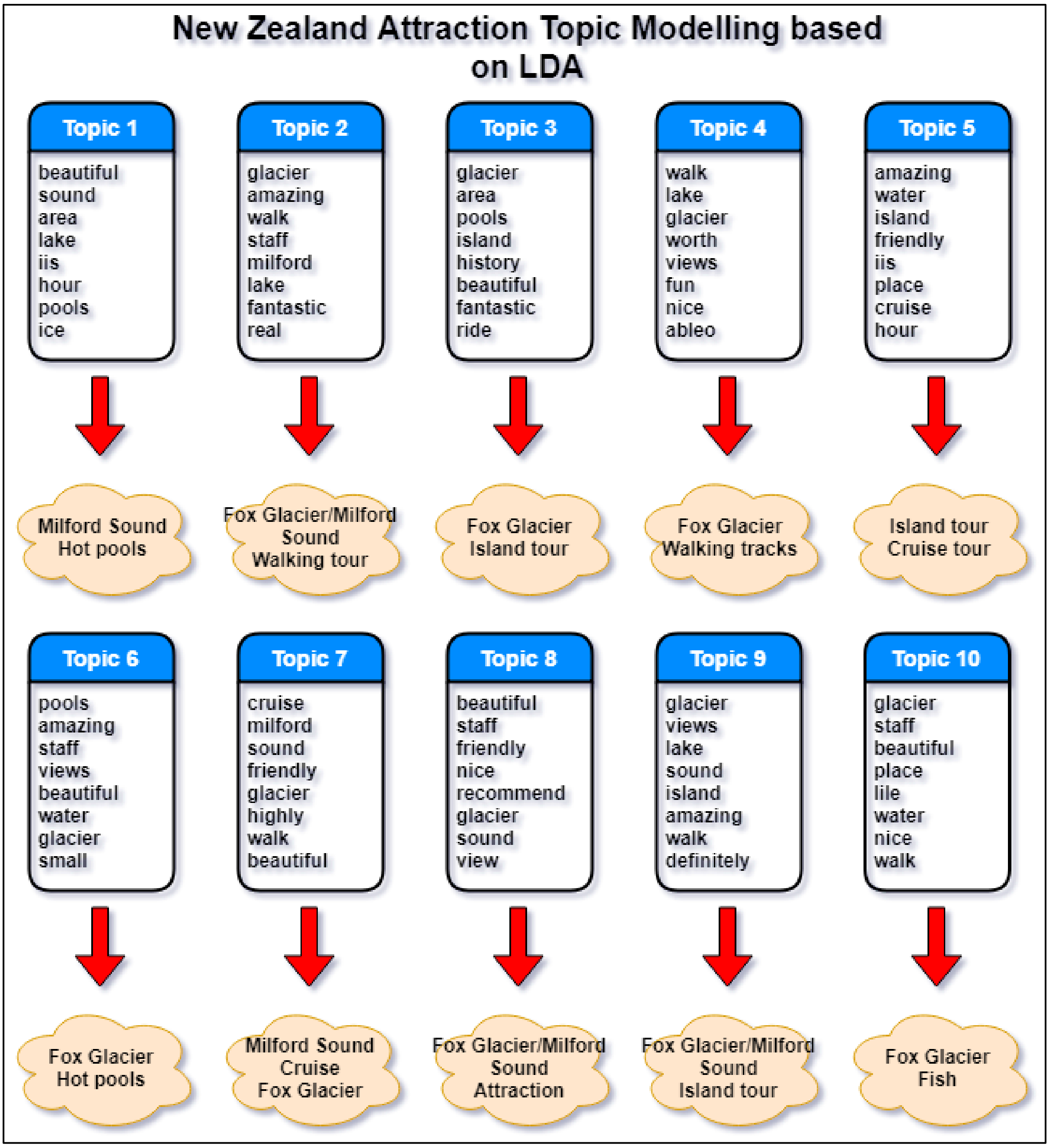

Figure 13: Categorisation 4 – New Zealand Attraction Topic Modelling based on LDA

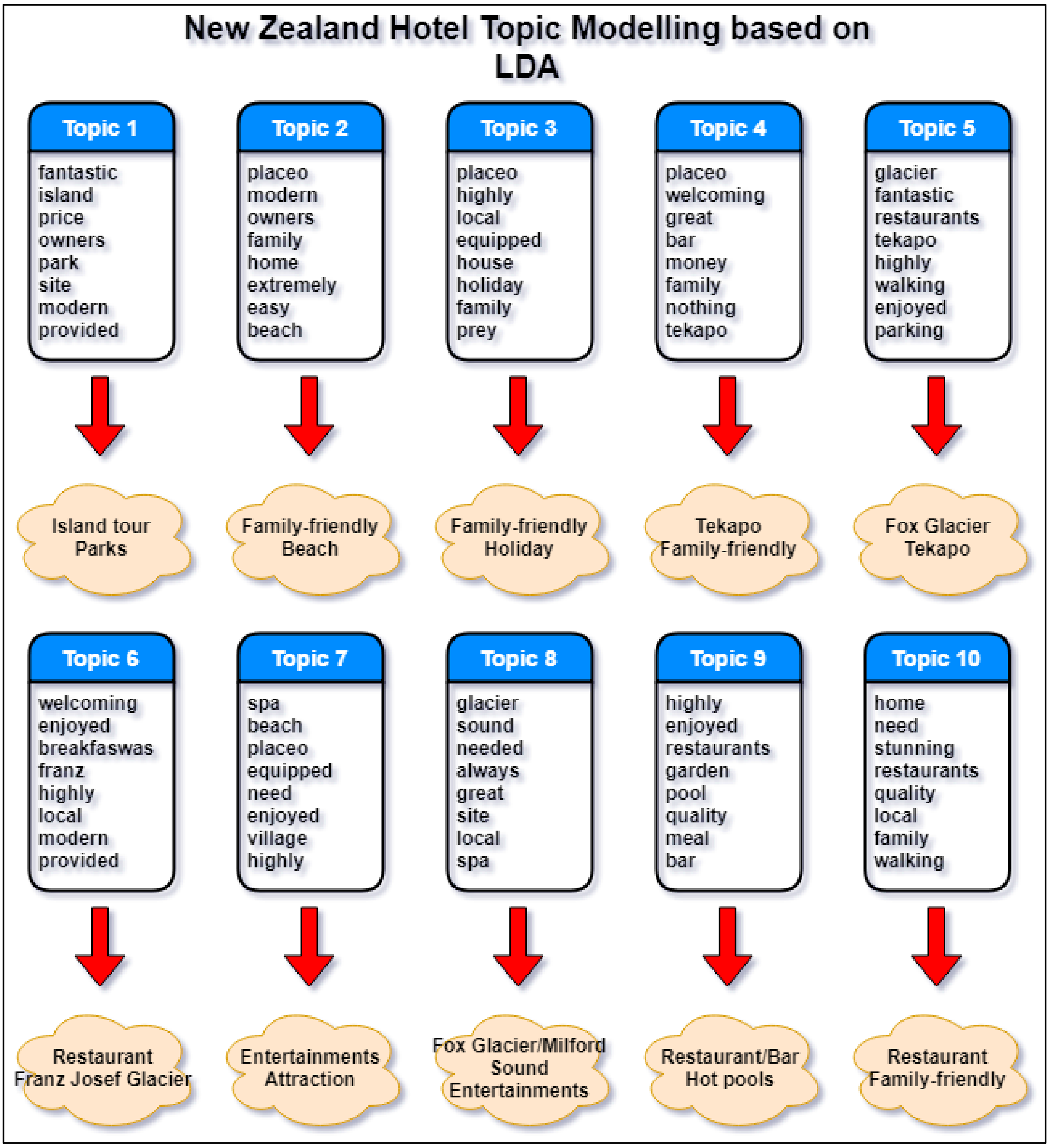

Figure 14: Categorisation 5 – New Zealand Hotel Topic Modelling based on LDA

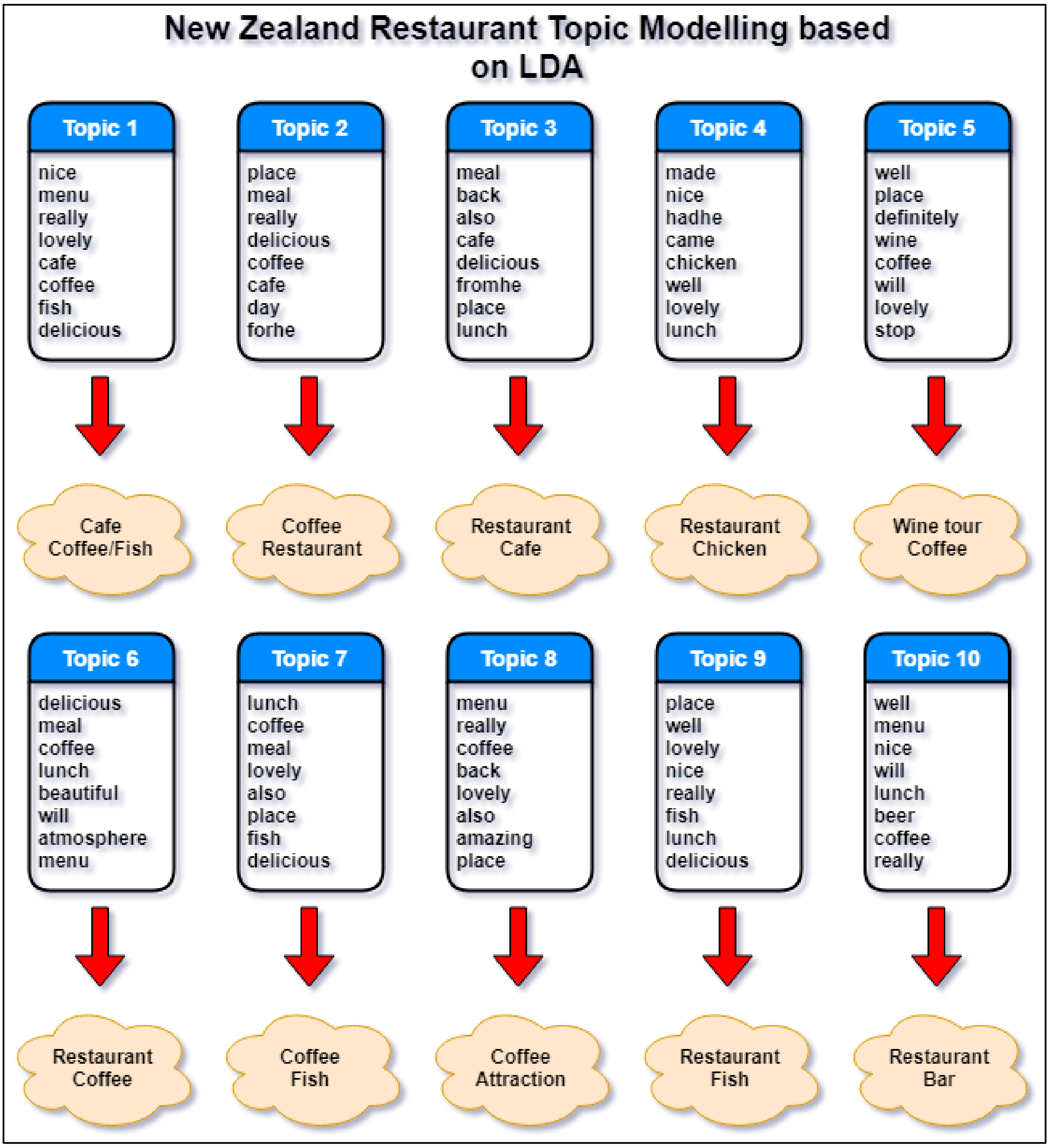

Figure 15: Categorisation 6 – New Zealand Restaurant Topic Modelling based on LDA

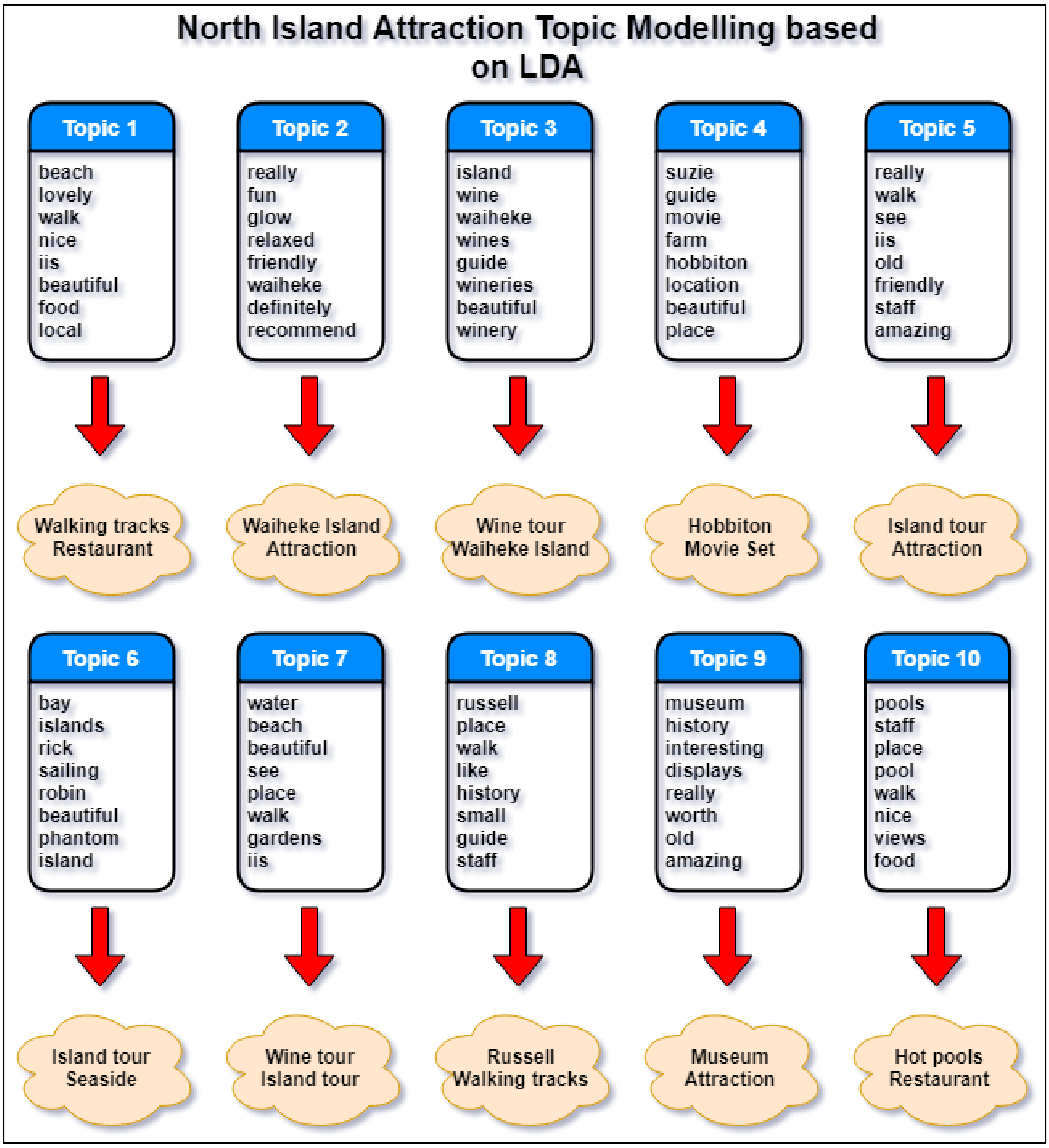

Figure 16: Categorisation 7 – North Island Attraction Topic Modelling based on LDA

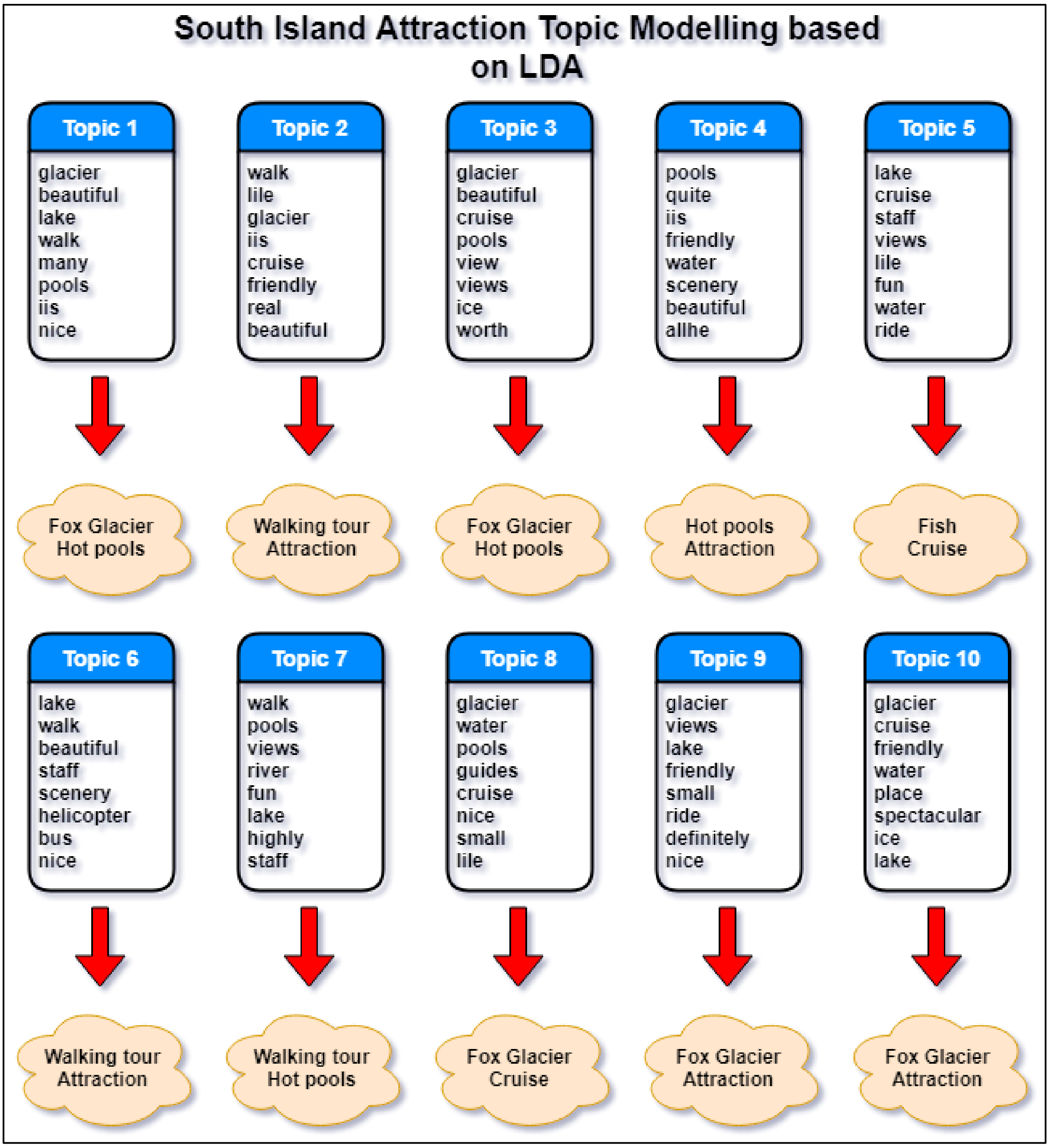

Figure 17: Categorisation 8 – South Island Attraction Topic Modelling based on LDA

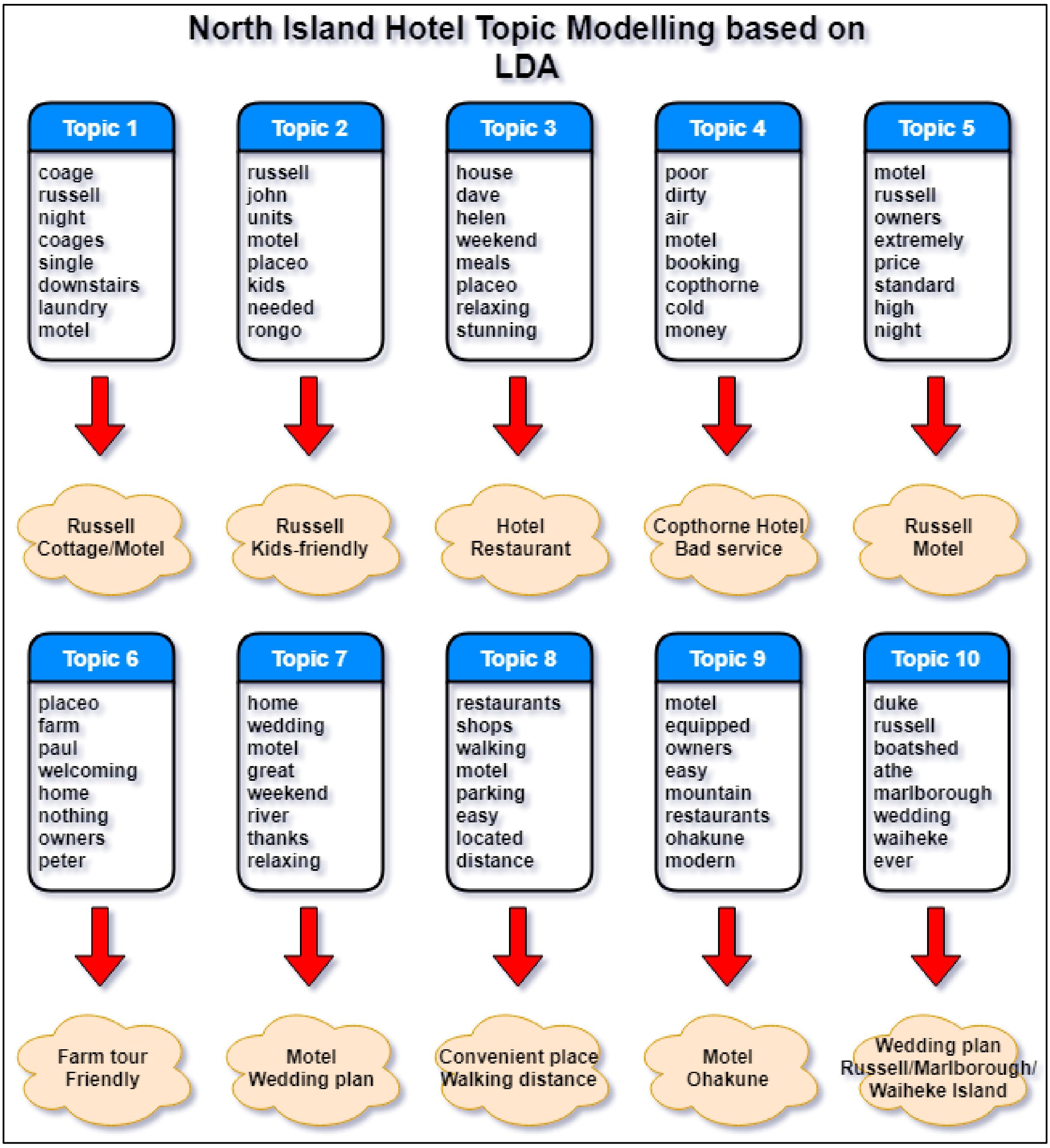

Figure 18: Categorisation 9 – North Island Hotel Topic Modelling based on LDA

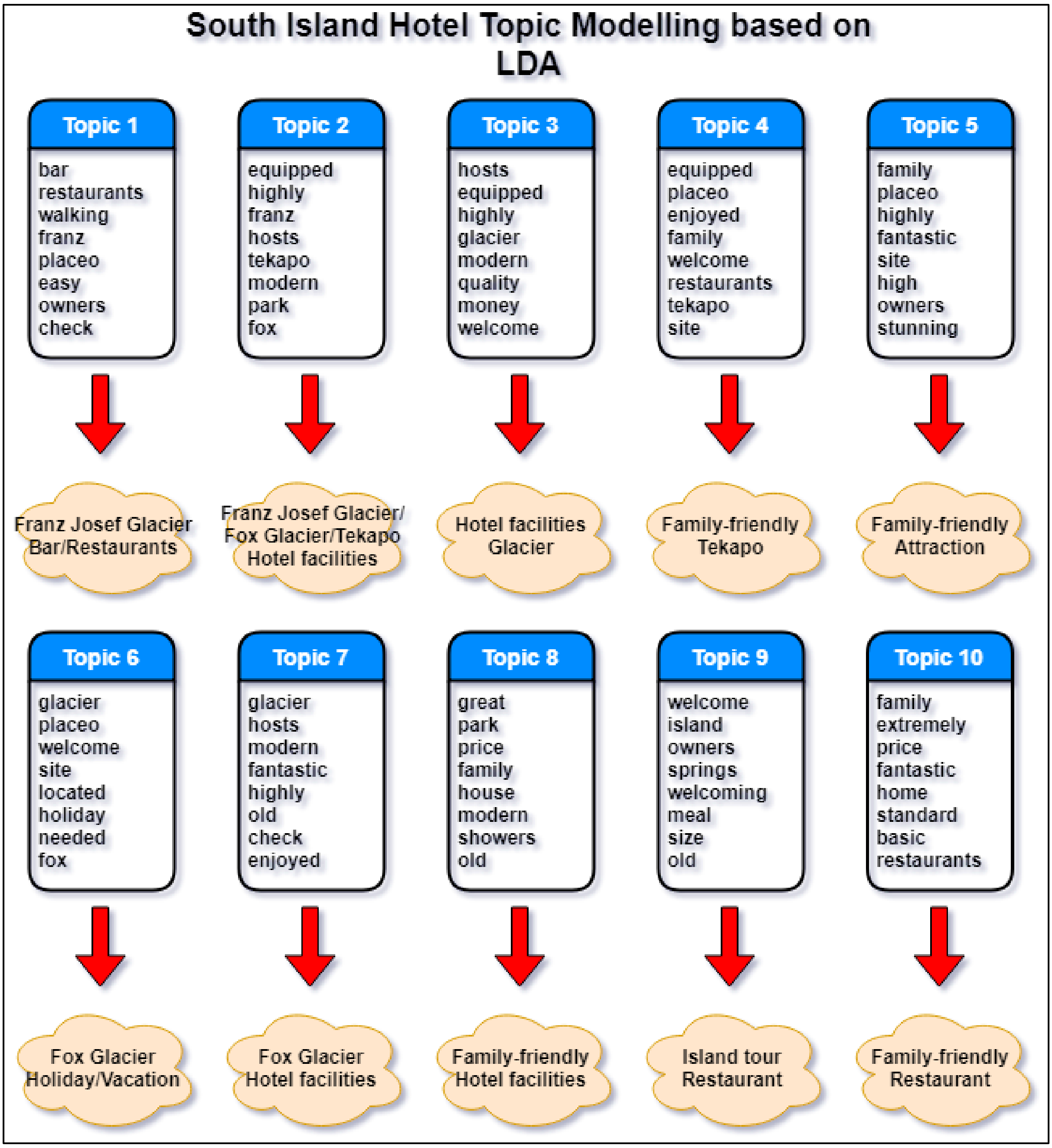

Figure 19: Categorisation 10 – South Island Hotel Topic Modelling based on LDA

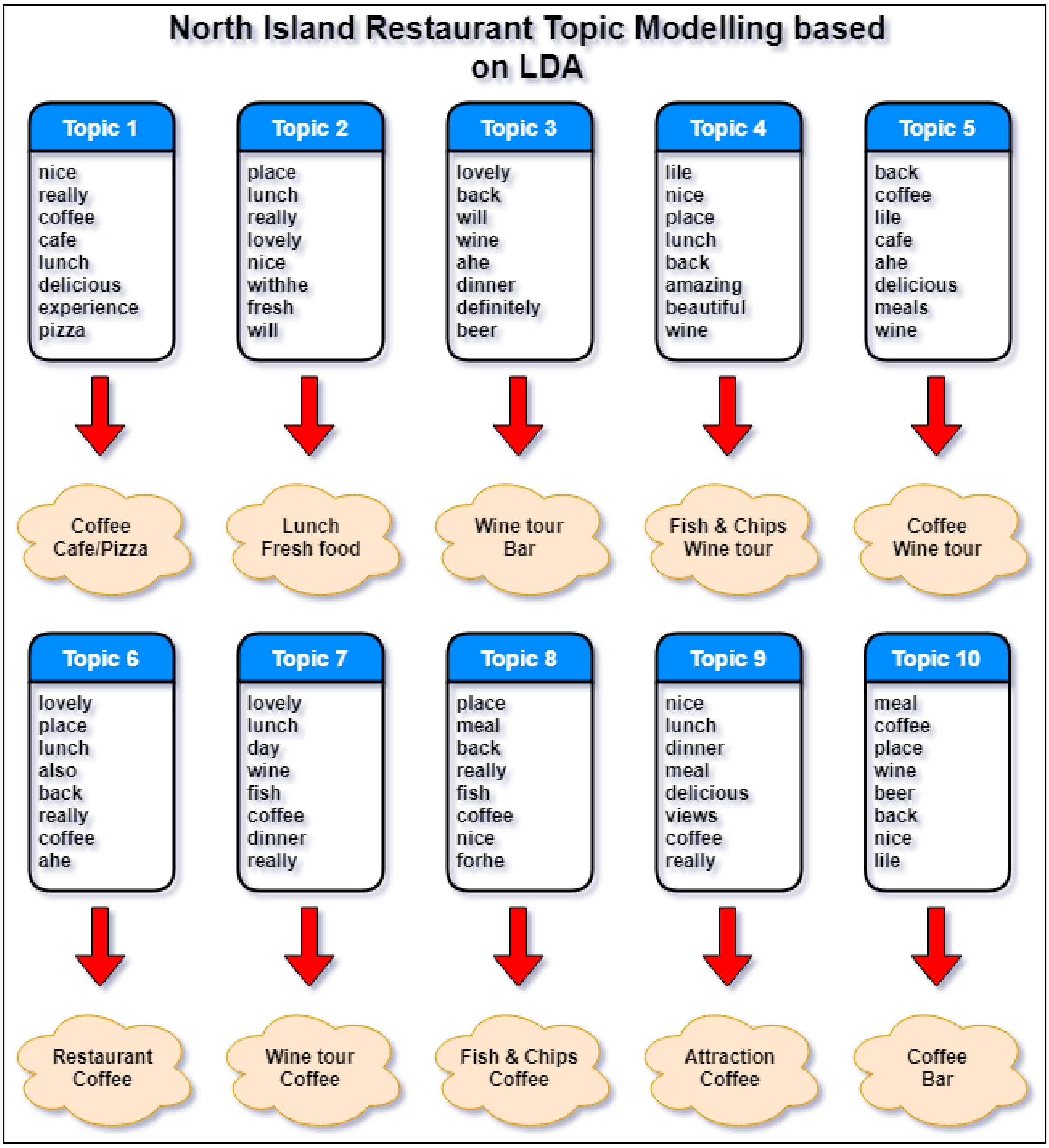

Figure 20: Categorisation 11 – North Island Restaurant Topic Modelling based on LDA

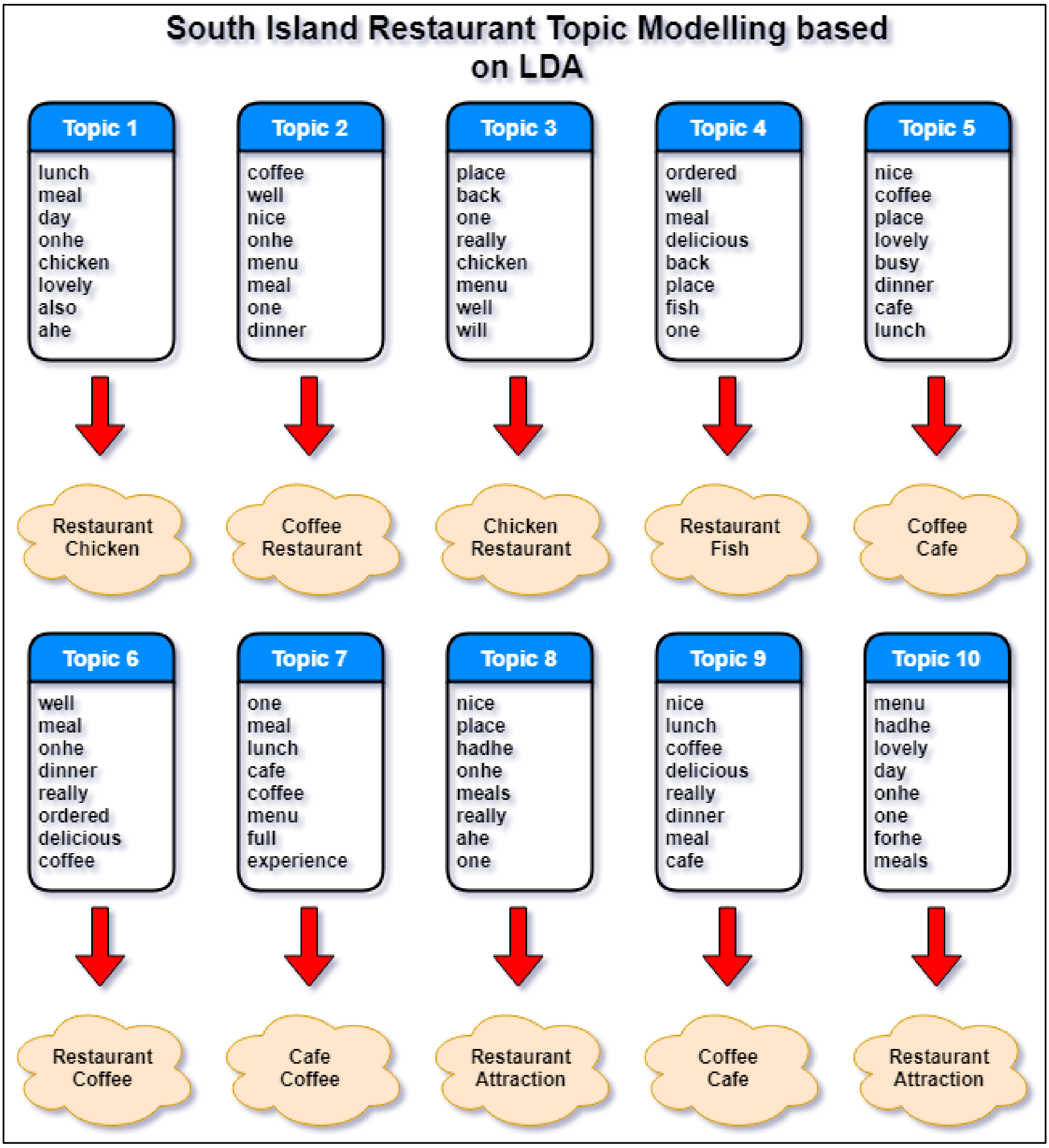

Figure 21: Categorisation 12 – South Island Restaurant Topic Modelling based on LDA

4.4 Different POIs in New Zealand received different sentiment results

We also applied sentiment analysis to each topic after we did topic modelling. Figure 22 shows that the results of sentiment analysis about different regions. Topic 7 has the highest number of positive reviews in the North Island review categorisation, and topic 1 has the highest positive number in the South Island. In addition, topic 3 in the New Zealand review categorisation has the highest number of positive reviews.

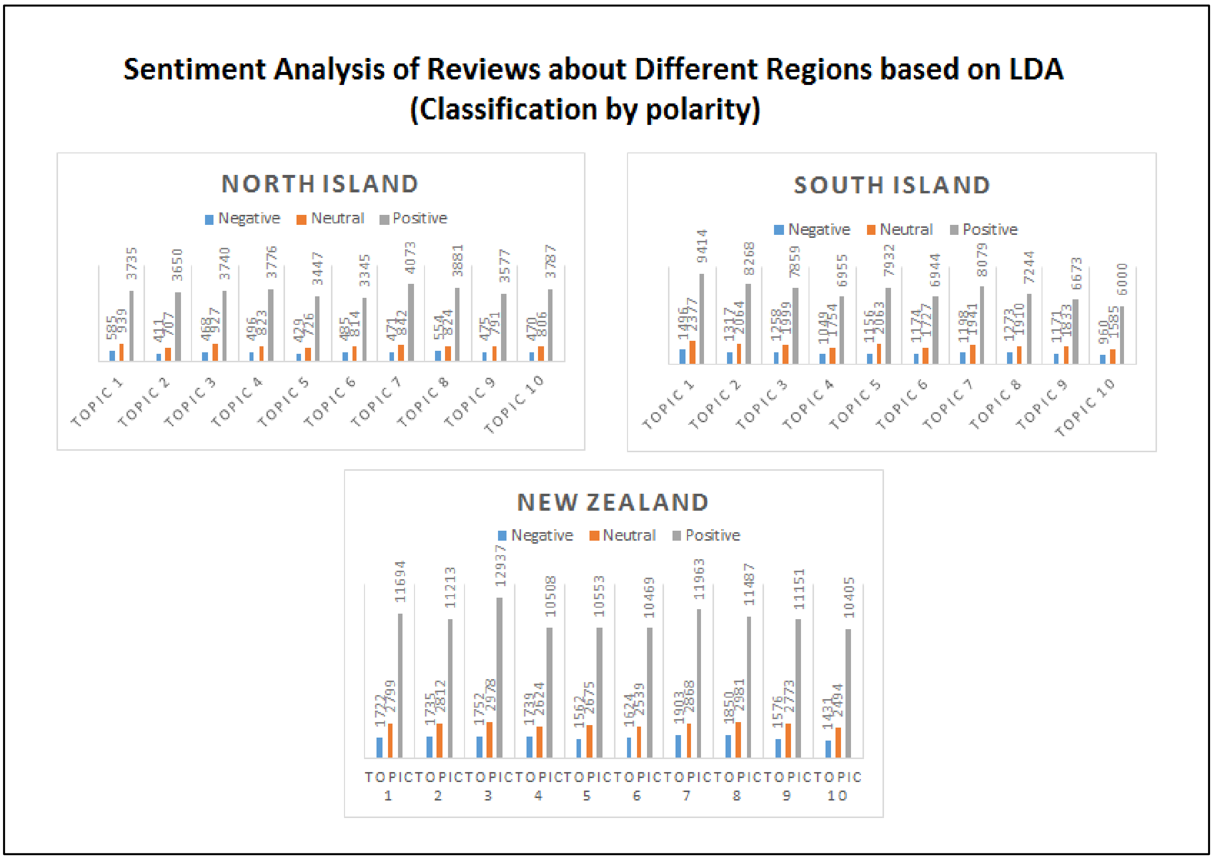

Figure 22: Sentiment analysis of reviews about different regions based on LDA (classification by polarity)

Table 8 gives the details about what the topic with the highest number of positive reviews is talking about. When tourists mentioned about New Zealand, these words will normally be associated with a picture of this country, like “nice, helpful, view, amazing, wine, views, coffee, and comfortable”. When talking about attractions, “cruise, milford, sound friendly, glacier, highly, walk, and beautiful” will come into mind. “spa, beach, place, equipped, need, enjoyed, village, and highly” are the words when talking about hotel service in New Zealand. Finally, “well, menu, nice, will, lunch, beer, coffee, and really” are the words when tourists describes restaurants in New Zealand.

Regions	Topic	Frequent Words
New Zealand	Topic 3	nice, helpful, view, amazing, wine, views, coffee, comfortable
North Island	Topic 7	nice, made, wine, bay, delicious, highly, stay, island
South Island	Topic 1	food, service, nice, lake, lovely, mountains, meal, views

Table 8: Most mentioned topics about different regions in NZ

In addition, we also applied sentiment analysis to different POIs in New Zealand (see Figure 23). Topic 7 received the highest number of positive reviews about New Zealand attractions. Topic 7 and topic 10 have the highest positive reviews numbers for New Zealand hotels and restaurants, respectively.

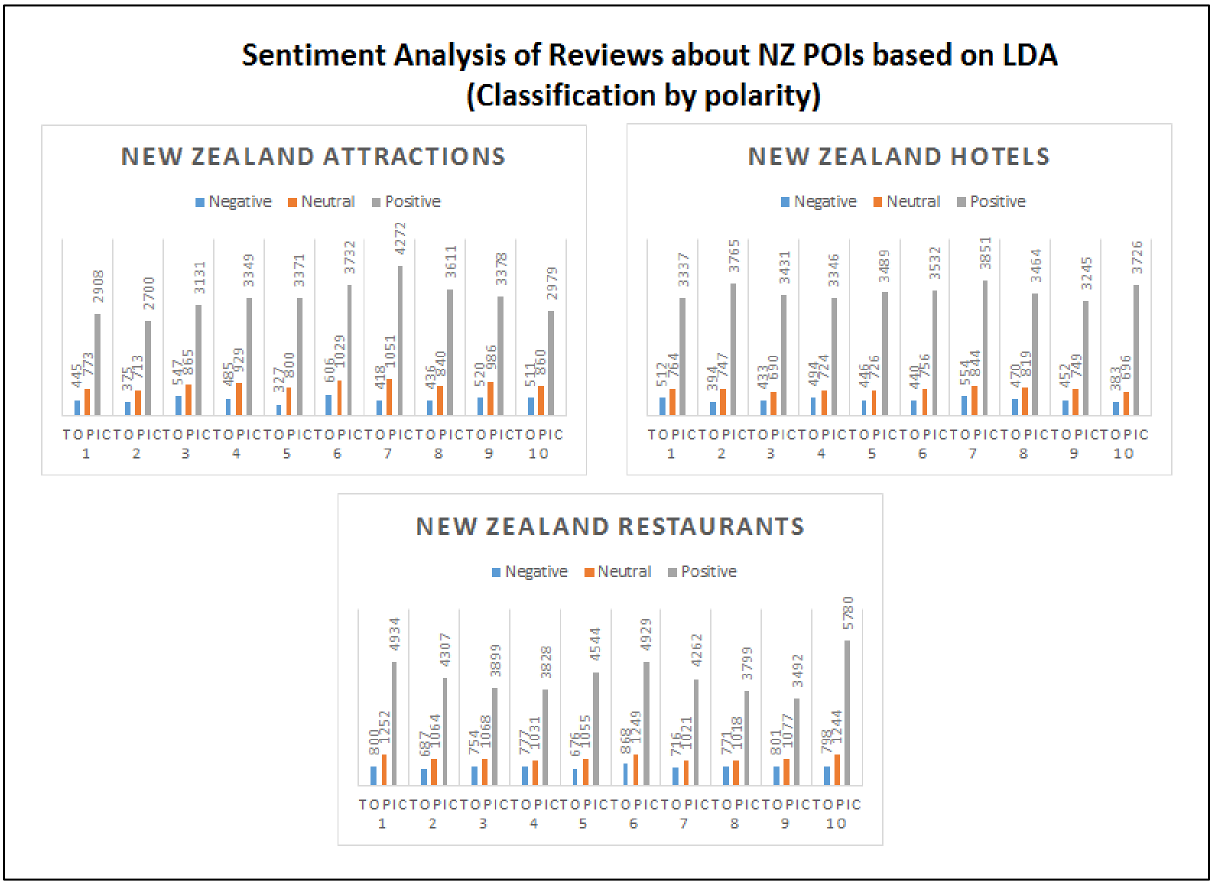

Figure 23: Sentiment analysis of reviews about NZ POIs based on LDA (classification by polarity)

Table 9 describes the most mentioned topic about POIs in New Zealand. The location name is mentioned in the topic, which means this location is a very popular place and attracts many tourists.

POIs	Topic	Frequent Words
New Zealand Attractions	Topic 7	cruise, milford, sound, friendly, glacier, highly, walk, beautiful
New Zealand Hotels	Topic 7	spa, beach, placeo, equipped, need, enjoyed, village, highly
New Zealand Restaurants	Topic 10	well, menu, nice, will, lunch, beer, coffee, really

Table 9: Most mentioned topics about POIs in NZ

More specifically, we were interested in the difference between the North Island and South Island's POIs. Figure 24 shows that different topics received a different number of positive reviews with different topics.

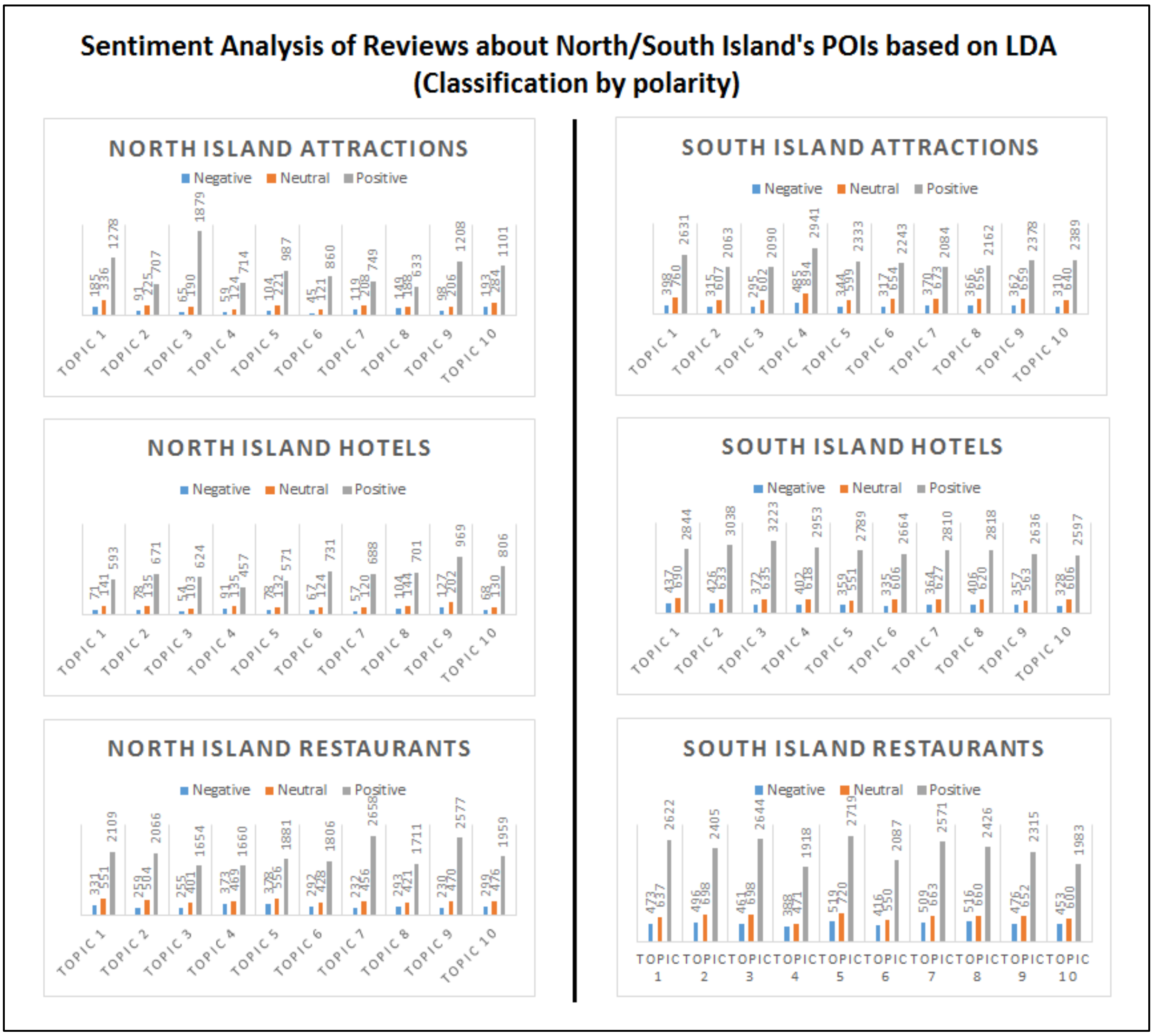

Figure 24: Sentiment analysis of reviews about North/South Island's POIs based on LDA (classification by polarity)

Table 10 summarises the most mentioned topic about North Island and South Island's POIs in New Zealand.

POIs	Topic	Frequent Words
North Island Attractions	Topic 3	island, wine, waiheke, wines, guide, wineries, beautiful, winery
South Island Attractions	Topic 4	pools, quite, friendly, water, scenery, beautiful
North Island Hotels	Topic 9	highly, enjoyed, restaurants, garden, pool, quality, meal, bar
South Island Hotels	Topic 3	hosts, equipped, highly, glacier, modern, quality, money, welcome
North Island Restaurants	Topic 7	lovely, lunch, day, wine, fish, coffee, dinner, really
South Island Restaurants	Topic 5	nice, coffee, place, lovely, busy, dinner, café, lunch

Table 10: Most mentioned topics about North/South Island POIs in NZ

5. Discussion

Tourists' feelings for the point of interests on the North Island is similar to the South Island in New Zealand, relatively small different have been found tourist give positive reviews for the North Island is slightly higher than the South Island. But the results could be due to the amount of POIs in the South Island being higher than in the North Island (see Figures 3 and 4). And it might be that most of the tourists are going to South Island, so it leads to the results of receiving more negative feedback about POIs in the South Island. According to recent news reported by local media, the top 10 traveller's destinations are Queenstown, Whitianga, Blenheim, Wanaka, Waiheke Island, Tauranga, Kaikoura, Invercargill, Te Anau, and Whakatane (https://www.stuff.co.nz/travel/destinations/nz/90713542/tripadvisor-names-best-holiday-destinations-in-new-zealand-and-the-world). Six of these ten destinations are located in the South Island. There is a fact about how people make a decision, as Gräbner, Zanker, Fliedl and Fuchs (2012) stated that around 73% to 87% of consumers will be affected in the decision of purchasing products when exploring online reviews. In other words, one place getting a high amount of reviews means that the popularity of this site.

When we book a hotel, we usually sort the hotel list by review ratings. However, these ratings only express the information about how these hotel present an overall expression. Bucur (2015) indicated that although the rating number or star did not present enough information, a simple rating system still can tell the traveller basic information about polarity classification. However, there are some review problems, like reviews are difficult to read compared with a simple rating star. The consumer needs to read the whole review content to find out if it is positive or negative. Different people looking for a different aspects of reviews, for example, backpackers are looking for a cheap and safe place to stay, but high-end business people are looking for a place with good services. On the other hand, hotel owners or managers are looking for constructive reviews that could help improve their business performance. The main challenge is to extract useful information from *TripAdvisor* due to the format of online reviews having an unstructured dataset. Tourists feels happy about their hotel service. This might be because the hotel service and infrastructure are well-developed by the local government and hotel owners. Gascón et al. (2016) stated there are two kinds of social networks – personal and professional networks. Personal networks are the social networks only for individuals sharing personal information with other users. But professional networks are the social networks for a particular topic, and they are both open to personal networks and other professional networks. *TripAdvisor* is one of this kind of professional networks that provides travel information to travellers, and also provides feedback to the management of organisations. Therefore, organisations create a virtual social space to let users share their experiences with others on their products or services. Hotel owners could gain experience from consumer feedback to make improvements in their hotel facilities. But for attraction sites, these are related to government decisions with regulations and policies, so the improvement of attractions could not immediately be changed. Tian, He, Tao and Akula (2016) also indicated that online user-generated content or electronic Word-of-mouth (eWOM) contains a large amount of consumer information with detailed feedbacks and helpful recommendations from experienced consumers or travel experiencers. Analysing and using this information is one of the most efficient ways to understand how consumers thinking about one specific product or service. Especially in the hotel industry, the study shows there is a very high percentage of people choosing their hotel who relying on online reviews. As a result, that information is also highly important to hotel managers to perform immediate actions to reduce the impact of negative reviews. And also, they could validate their action as useful or not to compare the review results.

The positive reviews make up a large part of review documents, and negative reviews are less significant in sentiment reviews (see Figures 4, 6 and 8). Salehan and Kim (2016) stated that online consumer reviews (OCRs) play an important role in products and services recommendation systems. Because reviews are based on real people in real use situations, unlike the product description it shows ideal usage scenarios. The authors indicated that people are more likely to read positive reviews than negative reviews, and the research found neutral reviews are more helpful. When positive and neutral reviews occupy a large percentage in a review page, the content of positive reviews will significantly influence other consumers' decisions. Moreover, Bjørkelund, Burnett and Nørvåg (2012) stated that travel websites have become an important online tool to help people make a decision. Hotels, especially, contains several consumer-based services that might influence consumer sentiment. On the other hand, the dynamic changing sentiment could also influence overall sentiment at any time, such as weather, outside noise, nearby facilities, etc. But the information is valuable for hotel owners to improve their hotel service quality.

The information on review websites is valuable to practitioners and researchers. Figures 11-22 gives the perfect example to show how people categorise online reviews based on the frequent words mentioned in the review content. The function can be added as a function under the menu of *TripAdvisor*. For example, a default hotel menu on *TripAdvisor* can add a sub-menu called "Family-friendly" (see Figure 15). The section of "Family-friendly" can list every hotel that is family-friendly across the country. On the other hand, we could categorise online reviews with different categorisations based on the LDA method. For instance, we can categorise these restaurants in the South Island with different specialty dishes, like fish, chicken, and coffee (see Figure 22). This gives an opportunity to help the practitioner to improve their business, and also helps tourists or travellers to quickly find the information that they want to. Lai and To (2015) stated that social media is the most important tool to perform information management, and it is the best platform to share information and build trust with the community. Unlike traditional market research (like interviews, focus groups and surveys), social media gives an opportunity to help researchers to gain information naturally, in other words, the data collection process is not affected by outside influences. By systematically studying user-generated content, researchers could understand how online users participate in business, which it provides valuable information. To the best of my knowledge, our research uses the largest amount of reviews data to study sentiment analysis in *TripAdvisor*.

The method of LDA helps us to distinguish between the different topics talked about in a certain place. For example, when we talk about the restaurant, we will mention food. Nanli, Ping, Weiguo and Meng (2012) indicated that human language contains have two types of information: “object information about facts and critical information with the human subjective sentiment” (Nanli, Ping, Weiguo and Meng, 2012, p. 572). In sentiment analysis we want to explore the hidden information that exists in such critical information, which includes two topics: distinguish between subjective and objective information, and classify subjective information. Thus, we use LDA to find an alternative categorisation to examine the POIs in New Zealand.

However, using online information is tricky and it could result in critical issues. Fake reviews, especially, it could change the whole point of views about one specific area. Nasukawa and Yi (2003) stated that monitoring online information might be involved in a critical issue, because this online information could influence general public opinion, and fake negative reviews may also cause an undesirable influence on organisations. On the other hand, the key issue of sentiment analysis is how to identify sentiments expressed within the mass of information.

6. Conclusion

This article summarises the research progress of sentiment analysis based on full investigation and in-depth analysis. We focus on several key issues in sentiment analysis, including the extraction of sentiment information, the classification of emotional information, and the retrieval of sentiment information. Sentiment analysis is a new research direction, and there are many areas that need to improve in the future studies. The method of latent Dirichlet allocation (LDA) gives us an opportunity for the automatic discovery of topics in the document set (distribution). We combined both methods to find out what tourists are saying or feeling about specific locations or services. We used the LDA model to extract representative statements to examine how to find an alternative way to describe the content and enable us to summarise tourists’ opinions. The LDA topic model is a multi-level probability generation model, which is a method for modelling the topic information of the text data.Through the observation of the experimental data, we found that the method still needed to improve and the accuracy of the algorithm should also be further improved. In addition, future research also needs to consider using other related methods with a proximity search function to more accurately determine the co-occurrence relationship between two words.

Some of the reviews are written by famous bloggers or professional experiencers, who are well-known and have a high reputation in the industry. When these peoples post an online review about a certain place, it will be recognised by other peoples and potential consumers. This has led to people being more willing to go to these places if they received a lot of positive reviews. Forman, Ghose and Wiesenfeld (2008) made a very interesting point about how the reviewer's identity disclosure could influence the product sales. The study shows that if an online review contains positive information as well as the reviewer's identity been known, it can help increase online product sales. And, reviewers with shared geographical location information could also help increase sales. The results show that if the reviewer's identity has been known or disclosed by themselves, the review content has less impact on the consumer buying decision. The online consumers are more likely to purchase a known product or the product's review contains known reviewers.

The principle of the *TripAdvisor* scraper we designed was to extract information from an HTML pages. The stable HTML page and clear structure will help us to extract useful information. However, the HTML structure of different *TripAdvisor* webpages is different, and it uses different HTML tags to define content. As a result, we need to adjust our Python program to make sure the crawler is working properly. Liu (2012) stated that monitoring a review website is hard, and the extract is remained difficulty challenge to researchers. In our case, *TripAdvisor* is preventing the user to scrap content from them, and different websites have different HTML structures, where the structure is changed periodically. The purpose of doing this is because *TripAdvisor* does not want people to crawl the web content. The author also stated that the most important part of sentiment analysis is sentiment words or opinion words. However, several issues were found when implementing lexicon-based sentiment analysis. Firstly, there have been different meanings with positive or negative words used in different situations. Secondly, a sentence includes sentiment words but does not express any sentiment. This usually comes with a question, or fact sentence in a review. Thirdly, in ironical sentences it is hard to detect whether the sentences are positive or negative, or even if it does not tell anything. Finally, a sentence without any sentiment words might express opinions. The author introduced three types of fake reviews: fake reviews, reviews about brand only and non-reviews. The most reliable method to detect fake reviews is manually reading these reviews, because nowadays spammers usually carefully write a fake review and make it like any other normal reviews.

7. Implications

In summary, the study of text sentiment analysis is still in its infancy and has achieved some research results. However, it also requires the collaborative research of multidisciplinary knowledge and solves many theoretical problems. Text sentiment analysis research is essentially an application direction of natural language processing. Natural language processing has accumulated a great deal of valuable and in-depth research results through years of research. Obviously, these research results also have significance in guiding and having application value for the analysis of sentiment orientation. However, judging from the current research situation, the research results of natural language processing have not yet been applied extensively and aptly in the analysis of text sentiment tendency. Therefore, the research finds a relationship between inheritance tendency analysis and traditional natural language processing. Making full use of the research results of natural language processing can enable more language technologies to be used in the analysis of affective tendencies and improve the research level of the technology. On the other hand, it also shows the results of natural language processing as important in specific applications. In sentiment analysis, it is often necessary to use various language tools and resources, such as various sentiment lexicons, defamed lexicons and evaluation information databases, as well as various training and testing corpus for various purposes. This shows that these resources are an indispensable part of the research. They can provide valuable knowledge and information for analytical research, and statistical data for various fields of application for research. However, the language tools, lexicons and experimental corpus summarised in this article do not have uniform specifications. Basically, they all use their own lexicons and linguistic materials to conduct their own research. The research results are difficult to compare with each other. At the same time, we have found that the various dictionaries, dictionaries and reference books used in daily life contain a lot of language knowledge and information. In the course of compilation, these tools consume a lot of manpower and time to ensure the accuracy of relevant information. The example sentences provided are also very normative and accurate. However, these tools have not been taken seriously in the research work. Therefore, how to effectively use existing language tools and related resources, how to standardise and quickly construct language tools and related resources, and make it widely adopted in research is a focus of further research. This research is important for future study about how infrastructure development in New Zealand as it provides a fundamental base to investigate tourism's impact on local government.

8. Limitations and Suggestions for Future Research

This study only uses *TripAdvisor* as a review resource to investigate how tourists expresses their sentiment reviews. This research could also collect data from other popular travel websites, like Booking (www.booking.com), Expedia (www.expedia.co.nz), Kayak (www.kayak.com), etc. These websites are more professional than *TripAdvisor* in some aspects. And it could provide more reliable and accurate tourist reviews.

Secondly, we could also study different types of tourists expressing their sentiments in the tourism industry. The study could be based on tourist choice of transport and accommodation to investigate the difference between five tourist types (coach tourist, backpacker, camper, free independent traveller and home visitor).

Thirdly, when we deal with sentiment analysis we should also be aware of different meanings of the word, sarcasm words, and a sentence describing facts but without any sentiment words. Additionally, computers, unlike humans, have a trouble deal with sarcastic words or sentences, and it will decrease the accuracy of sentiment analysis results. Modak and Mondal (2014) stated subjectivity detection is one of the common problems within the sentiment analysis, which is to identify sarcastic reviews. Some positive words have been identified in the content, but the real impact of this review is negative. On the other hand, detecting comparative opinion is a very hard subject, because this kind of reviews actually does not represent either a positive or negative argument. Moreover, Kennedy (2012) indicated that research should be concerned about the accuracy of analysis results and quality of data when doing sentiment analysis. One difficulty in understand the meaning of human language is letting the computer to understand irony, sarcasm, humour, and even abbreviation words or sentences in the review text. The author also argued that review websites like *TripAdvisor* pretend to provide a valuable information to consumers (like reviews and travel guides), but the truth is *TripAdvisor* gives the corporate clients' rights to access that information and use them to improve their business. Valdivia, Luzón and Herrera (2017) indicated that humans can use contextual understanding to determine the message is positive or negative, but the computer only can determine the polarity of words. And also, some consumers write negative reviews but with positive user ratings. Daiyan, Tiwari, Kumar and Alam (2015) stated that review spam is one of the issues that exists online. Unlike website spam and e-mail spam, review spam needs different technologies to identify and detect, for example, using the Shingles method to detect spam message. Liu and Zhang (2012) indicated that positive opinions could significantly change the reputation or beneficial results for private users and organisations. The fake reviews or bogus opinions sometimes happened in this situation, and it plays an important role in opinion spam detection. The authors also stated that spammers can post fake reviews online as an individual spammer or group spammer. We should pay attention to group spammers, because this kind of spammers working as a group targets a specific organisation, and they are very damaging to the online community. Group spammers normally are hired by competitors in order to destroy or damage other's reputation and provide misleading information to potential consumers. On the other hand, we should also be aware of some negative reviews with positive content (see Figure 25).

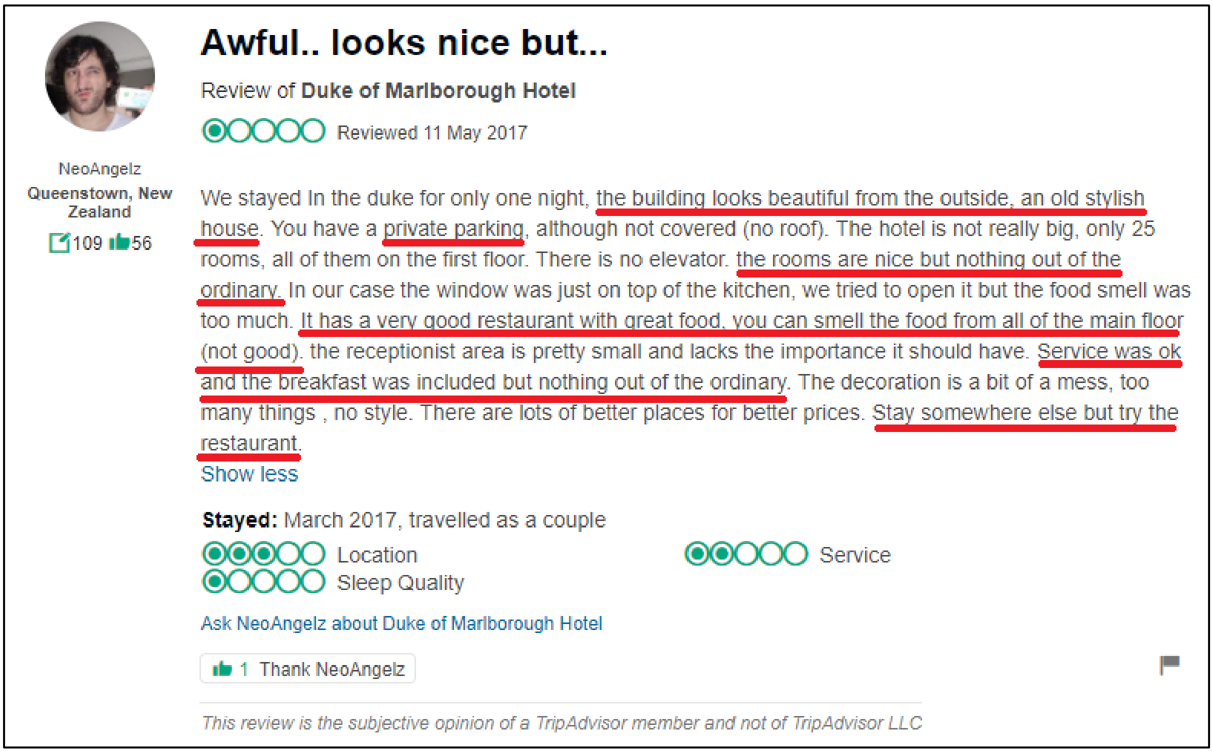

Figure 25: Example of a negative review in *TripAdvisor* (Source: https://www.tripadvisor.co.nz/ShowUserReviews-g255679-d293056-r483366032-Duke_of_Marlborough_Hotel-Russell_Bay_of_Islands_Northland_Region_North_Island.html)

In addition, this study is only to study English reviews in *TripAdvisor*, but we know many tourists are from non-English speaking countries. We should also collect other online reviews written by other languages, and then do the same sentiment process with English. We could also compare and contrast the differences between English and other languages. However, when we apply sentiment analysis to other languages, we should consider that cultural diversity and language expression is different from English. For example, there are exists many Chinese reviews on *TripAdvisor*, but the problem of doing Chinese sentiment analysis is Chinese emotional dictionary resources are insufficient. Jurek, Mulvenna and Bi (2015) conducted a study to show how to adapt a lexicon-based approach into a different language. The author stated that there are two problems when applying sentiment analysis to other languages: (1) the grammatical conjugation, inflection and gender difference between English and other languages, as one English word could have different forms in other languages; and (2) take care with words with ambiguity, and make sure English words have been appropriately translated into other languages.

Furthermore, some reviews do not have a username or register a location or both, because the early version of *TripAdvisor* did not require users to register an account to post online reviews. Further researches should consider only using validated reviews, where the review information is completed. And also, it could help us to identify fake reviews. Validated geo-location data could also help us to identify what kind of people to go to travelling in the North Island and South Island? Salehan and Kim (2016) mentioned that product sellers or service providers try to make fake positive reviews on an online review website, and make negative reviews about their competitors. Especially, private enterprises are more likely to post fake reviews compared to chain brand enterprises. The study also found if a hotel is close to other hotels, this hotel has a high chance of posting fake negative reviews. They stated that in order to find fake reviews on *TripAdvisor* it is important to compare with another booking website (like Expedia.com) because *Expedia* only allows people who actually booked a hotel to post a review.

Moreover, this study only compares the differences between islands and points of interest in small towns. Further study could also compare the differences between small towns and big towns in New Zealand. Thus, the study should not be limited to small towns, and we could also collect online reviews in big towns.

Additionally, different TripAdvisor websites will have different number of online reviews about the same hotel or other point of interests. Figure 26 shows the Rydges Wellington hotel total have 2,068 reviews on Chinese version TripAdvisor. However, TripAdvisor New Zealand site have 2,107 reviews about the same hotel (see Figure 27). These two screenshot took at the same time. In order to avoid such problem in the future study, we should only use the local version of TripAdvisor.

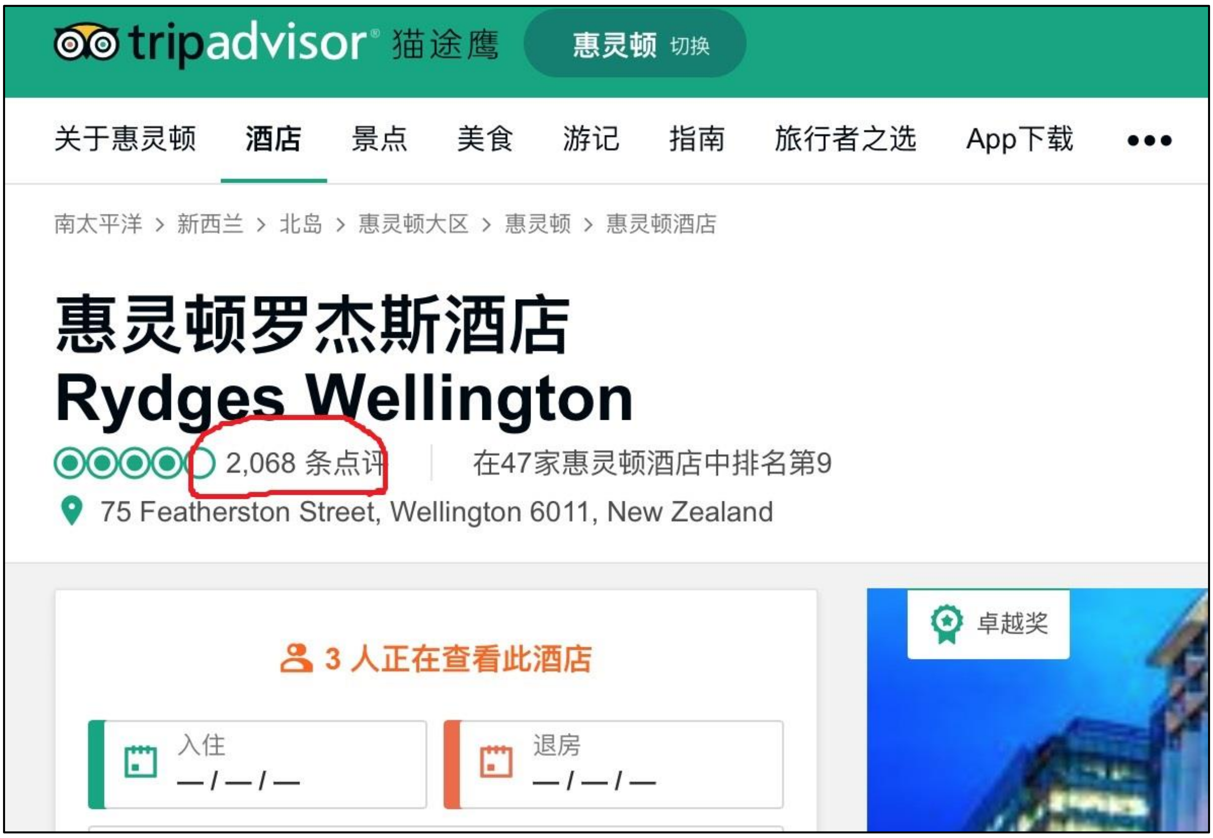

Figure 26: Rydges Wellington hotel on TripAdvisor China (Source: https://www.tripadvisor.cn/Hotel_Review-g255115-d631799-Reviews-Rydges_Wellington-Wellington_Greater_Wellington_North_Island.html)

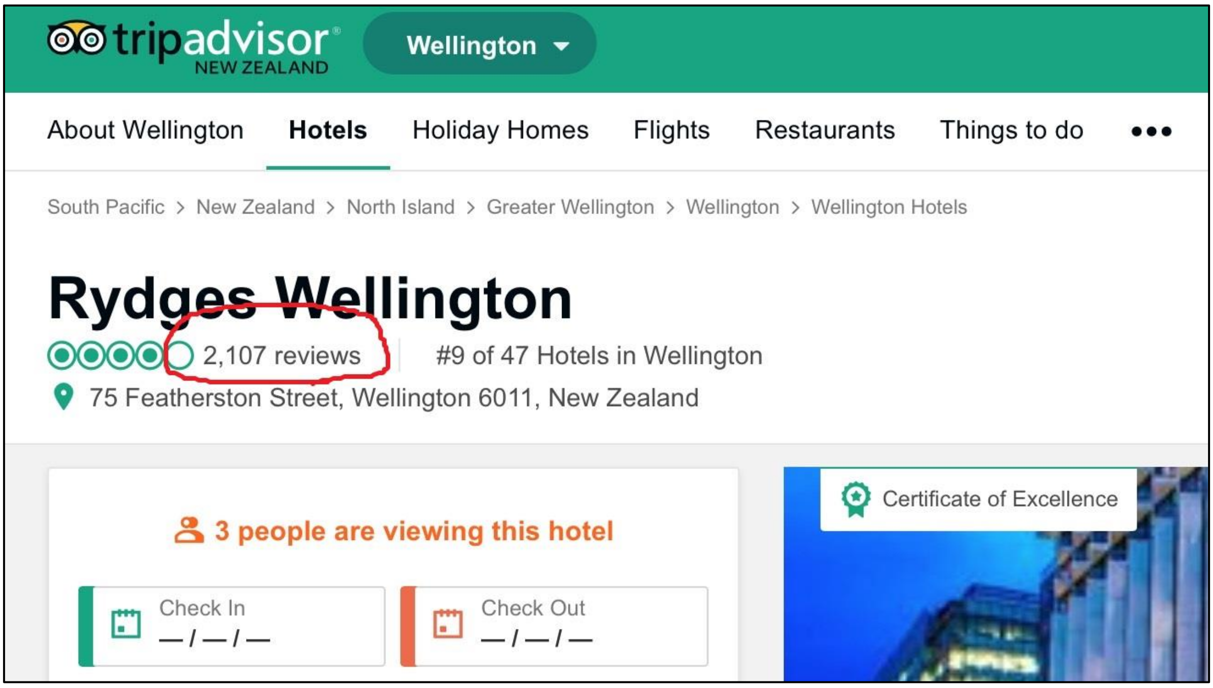

Figure 27: Rydges Wellington hotel on TripAdvisor New Zealand (Source: https://www.tripadvisor.co.nz/Hotel_Review-g255115-d631799-Reviews-Rydges_Wellington-Wellington_Greater_Wellington_North_Island.html)

Finally, this study could use different sentiment analysis methods to investigate sentiment expression in *TripAdvisor*. Wu, Gao, Yang and Sun (2017) who used the word2Vec method to study *TripAdvisor*. The study shows more featured categories mentioned in the user reviews, and the user more likely was not satisfied by the hotel. There is a significant difference in consumer concern for different featured categories in luxury hotels and budget hotels. Consumers are more concerned about the service with luxury hotels, but cleanliness with budget hotels. The study also confirmed that online reviews will affect products or services sales and consumer buying decisions. On the other hand, the study was mainly through questionnaires or the collection of numerical scores and did not analyse the true ideas of the consumer from user-generated content. However, this study will help hotel managers to obtain the highest overall satisfaction with the lowest cost of investment. The hotel should focus on facilities and services in order to leave a good first impression for customers. This study could also help hotel managers to develop a long-term development strategy for their hotel.

References

Amiri, F., Scerri, S., & Khodashahi, M. (2015). Lexicon-based sentiment analysis for Persian Text. Paper presented at the meeting of International Conference Recent Advances in Natural Language Processing (pp. 9-16). Hisssa, Bulgaria. doi: 10.13140/RG.2.1.2537.8327

Ayeh, J. K., Au, N., & Law, R. (2013). "Do we believe in TripAdvisor?" Examining credibility perceptions and online travelers' attitude toward using user-generated content. *Journal of Travel Research, 52*(4), 437-452. doi: 10.1177/0047287512475217

Bjørkelund, E., Burnett, T. H., & Nørvåg, K. (2012). *A Study of Opinion Mining and Visualization of Hotel Reviews.* Paper presented at the 14th International Conference on Information Integration and Web-based Applications & Services (pp. 229-238). ACM.

Bucur, C. (2015). Using Opinion Mining Techniques in Tourism. *Procedia Economics and Finance, 23*(2015), 1666-1673. doi: 10.1016/S2212-5671(15)00471-2

Calheiros, A. C., Moro, S., & Rita, P. (2017). Sentiment Classification of Consumer-Generated Online Reviews Using Topic Modeling. *Journal of Hospitality Marketing & Management*, *26*(7), 675-693. doi: 10.1080/19368623.2017.1310075

Cataldi, M., Ballatore, A., Tiddi, I., & Aufaure, M. A. (2013). Good location, terrible food: detecting feature sentiment in user-generated reviews. *Social Network Analysis and Mining*, *3*(4), 1149-1163. doi: 10.1007/s13278-013-0119-7

Collomb, A., Costea, C., Joyeux, D., Hasan, O., & Brunie, L. (2014). *A study and comparison of sentiment analysis methods for reputation evaluation.* Rapport de recherche RR-LIRIS-2014-002.

ComScore. (2007). Online Consumer-Generated Reviews Have Significant Impact on Offline Purchase Behavior. Retrieved from https://www.comscore.com/Insights/Press-Releases/2007/11/Online-Consumer-Reviews-Impact-Offline-Purchasing-Behavior

Daiyan, M., Tiwari, D. S., Kumar, M., & Alam, M. A. (2015). A Literature Review on Opinion Mining and Sentiment Analysis. *International Journal of Emerging Technology and Advanced Engineering*, *5*(4), 262-280. doi: 10.1108/IntR-04-2016-0086

Devika, M. D., Sunitha, C., & Ganesh, A. (2016). Sentiment analysis: A comparative study on different approaches. *Procedia Computer Science, 87*(2016), 44-49. doi: 10.1016/j.procs.2016.05.124

Duan, W., Cao, Q., Yu, Y., & Levy, S. (2013). *Mining online user-generated content: using sentiment analysis technique to study hotel service quality.* Paper presented at the 2013 46th Hawaii International Conference on System Sciences (HICSS), (pp. 3119-3128). IEEE. doi: 10.1109/HICSS.2013.400

Farhadloo, M., & Rolland, E. (2013). *Multi-class Sentiment Analysis with Clustering and Score Representation.* Paper presented at the 2013 IEEE 13th International Conference on Data Mining Workshops (ICDMW), (pp. 904-912). TX, USA. doi: 10.1109/ICDMW.2013.63

Fang, X., & Zhan, J. (2015). Sentiment analysis using product review data. *Journal of Big Data, 2*(1), 5. doi: 10.1186/s40537-015-0015-2

Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the ACM, 56*(4), 82-89. doi: 10.1145/2436256.2436274

Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research, 19*(3), 291-313. doi: 10.1287/isre.1080.0193

Gao, S., Hao, J., & Fu, Y. (2015). *The Application and Comparison of Web Services for Sentiment Analysis in Tourism.* Paper presented at the meeting of 2015 12th Service Systems and Service Management (ICSSSM). (pp. 1-6). Guangzhou, China. doi: 10.1109/ICSSSM.2015.7170341

García, A., Gaines, S., & Linaza, M. T. (2012). A lexicon based sentiment analysis retrieval system for tourism domain. *E-Review of Tourism Research (eRTR), 10*(2), 35-38.

Gascón, J., Bernal, P., Román, E., González, M., Giménez, G., Aragón, Ó., Roé, L., López, E., Rodríguez, J., Morales, C., & Crespo, J. (2016). *Sentiment analysis as a qualitative methodology to analyze social media: study case of tourism.* Paper presented at the meeting of the 2016 Congresso Ibero-Americano em Investigação Qualitativa.

Gräbner, D., Zanker, M., Fliedl, G., & Fuchs, M. (2012). *Classification of customer reviews based on sentiment analysis.* Paper presented at the meeting of the Information and Communication Technologies in Tourism 2012. doi: 10.1007/978-3-7091-1142-0_4

Groh, G., & Hauffa, J. (2011). *Characterizing Social Relations via NLP-Based Sentiment Analysis.* Paper presented at the meeting of the Fifth International AAAI Conference on Weblogs and Social Media, Barcelona, Spain.

Jelodar, H., Wang, Y., Yuan, C., & Feng, X. (2017). *Latent Dirichlet Allocation (LDA) and Topic modeling: models, applications, a survey.*

Jiang, H., Lin, P., & Qiang, M. (2015). Public-opinion sentiment analysis for large hydro projects. *Journal of Construction Engineering and Management, 142*(2), 05015013. doi: 10.1061/(ASCE)CO.1943-7862.0001039

Jurek, A., Mulvenna, M. D., & Bi, Y. (2015). Improved lexicon-based sentiment analysis for social media analytics. *Security Informatics, 4*(1), 9-21. doi: 10.1186/s13388-015-0024-x

Kennedy, H. (2012). Perspectives on Sentiment Analysis. *Journal of Broadcasting & Electronic Media, 56*(4), 435-450. doi: 10.1080/08838151.2012.732141

Khan, A., Baharudin, B., & Khan, K. (2011). *Sentiment Classification from Online Customer Reviews Using Lexical Contextual Sentence Structure.* Paper presented at the 2011 International Conference on Software Engineering and Computer Systems (pp. 317-331). Springer, Berlin, Heidelberg. doi: 10.1007/978-3-642-22170-5_28

Kiprono, K.W., & Abade, E.O. (2016). Comparative Twitter Sentiment Analysis Based on Linear and Probabilistic Models. *International Journal on Data Science and Technology, 2*(4), 41-45. doi: 10.11648/j.ijdst.20160204.11

Lai, L. S., & To, W. M. (2015). Content analysis of social media: a grounded theory approach. *Journal of Electronic Commerce Research, 16*(2), 138-152.

Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis lectures on human language technologies, 5*(1), 1-167. doi: 10.2200/S00416ED1V01Y201204HLT016

Liu, B., & Zhang, L. (2012). *A survey of opinion mining and sentiment analysis.* Mining Text Data (pp. 415-463). Springer-Verlag New York. doi: 10.1007/978-1-4614-3223-4_13

Ma, B., Yuan, H., Wan, Y., Qian, Y., Zhang, N., & Ye, Q. (2016). *PUBLIC OPINION ANALYSIS BASED ON PROBABILISTIC TOPIC MODELING AND DEEP LEARNING. PUBLIC OPINION.* Paper presented at the meeting of the 2016 Pacific Asia Conference on Information Systems (PACIS), Chiayi, Taiwan.

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal, 5*(4), 1093-1113. doi: 10.1016/j.asej.2014.04.011

Modak, S., & Mondal, A. C. (2014). A study on sentiment analysis. *International Journal of Advanced Research in Computer Science & Technology (IJARCST), 2*(2), 284-288.

Montesinos, L., Rodríguez, S. J. P., Orchard, M., & Eyheramendy, S. (2015). *Sentiment analysis and prediction of events in TWITTER.* Paper presented at the meeting of the 2015 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON), Santiago, Chile. doi: 10.1109/Chilecon.2015.7404680

Nanli, Z., Ping, Z., Weiguo, L., & Meng, C. (2012). *Sentiment analysis: A literature review.* Paper presented at the meeting of the 2012 International Symposium in Management of Technology (ISMOT), Hangzhou, China. doi: 10.1109/ISMOT.2012.6679538

Nasukawa, T., & Yi, J. (2003). *Sentiment analysis: Capturing favorability using natural language processing.* Paper presented at the meeting of the 2nd international conference on Knowledge capture, New York, USA. ACM. doi: 10.1145/945645.945658

Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends® in Information Retrieval, 2*(1–2), 1-135. doi: 10.1561/1500000011

Putri, I. R., & Kusumaningrum, R. (2017). Latent Dirichlet Allocation (LDA) for Sentiment Analysis toward Tourism Review in Indonesia. *Journal of Physics: Conference Series, 801*(1). doi: 10.1088/1742-6596/801/1/012073

Raut, V. B., & Londhe, D. D. (2014). *Opinion Mining and Summarization of Hotel Reviews.* Paper presented at the meeting of 2014 Computational Intelligence and Communication Networks (CICN). (pp. 556-559). Washington DC, USA. doi: 10.1109/CICN.2014.126

Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: tasks, approaches and applications. *Knowledge-Based Systems, 89*(2015), 14-46. doi: 10.1016/j.knosys.2015.06.015

Salehan, M., & Kim, D. J. (2016). Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. *Decision Support Systems, 81*(2016), 30-40. doi: 10.1016/j.dss.2015.10.006

Smyth, P. C. B., Wu, G., & Greene, D. (2010). *Does TripAdvisor makes hotels better?* (Technical Report UCD-CSI-2010-06). Derek Greene School of Computer Science & Informatics, University College Dublin Belfield.

Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational linguistics, 37*(2), 267-307. doi: 10.1162/COLI_a_00049

Tian, X., He, W., Tao, R., & Akula, V. (2016). *Mining Online Hotel Reviews: A Case Study from Hotels in China.* Paper presented at the meeting of the 2016 Twenty-second Americas Conference on Information Systems. San Diego, USA.

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2011). Election forecasts with Twitter: How 140 characters reflect the political landscape. *Social science computer review, 29*(4), 402-418. doi: 10.1177/0894439310386557

Tuominen, P. (2011). *The influence of TripAdvisor consumer-generated travel reviews on hotel performance.* University of Hertfordshire Business School Working Paper.

Valdivia, A., Luzón, M. V., & Herrera, F. (2017). Sentiment analysis in TripAdvisor. *IEEE Intelligent Systems, 32*(4), 72-77. doi: 10.1109/MIS.2017.3121555

Van Looy, A. (2016). Sentiment Analysis and Opinion Mining (Business Intelligence 1). Social Media Management - Technologies and Strategies for Creating Business Value (pp. 133-147). Springer, Cham. doi: 10.1007/978-3-319-21990-5_7

Vohra, S. M., & Teraiya, J. B. (2013). A comparative study of sentiment analysis techniques. *Journal of Information, Knowledge and Research in Computer Engineering, 2*(2), 313-317.

Wu, W., Gao, B., Yang, H., & Sun, H. (2017). The Impacts of Reviews on Hotel Satisfaction: A Sentiment Analysis Method. *Data Analysis and Knowledge Discovery, 1*(3), 62-71. doi: 10.11925/infotech.2096-3467.2017.03.08

Yang, C. S., & Shih, H. P. (2012). A Rule-Based Approach for Effective Sentiment Analysis. Paper presented at the meeting of the Pacific Asia Conference on Information Systems (PACIS) (p. 181), Hochiminh City, Vietnam.

Appendix

Appendices A - Sentiment analysis of reviews about North Island and South Island POIs on TripAdvisor (Classification by emotion)

Emotion	North Island Attraction	South Island Attraction	North Island Hotel	South Island Hotel	North Island Restaurant	South Island Restaurant
"anger"	388 (2.91%)	1,001 (2.98%)	466 (5.19%)	2,465 (6.43%)	739 (2.66%)	984 (2.83%)
"disgust"	100 (0.75%)	316 (0.94%)	103 (1.15%)	321 (0.84%)	158 (0.57%)	239 (0.69%)
"fear"	146 (1.10%)	382 (1.14%)	64 (0.71%)	353 (0.92%)	347 (1.25%)	561 (1.61%)
"joy"	9,435 (70.80%)	23,125 (68.79%)	7,233 (80.63%)	30,360 (79.19%)	21,269 (76.63%)	26,554 (76.43%)
"sadness"	368 (2.76%)	1,474 (4.38%)	169 (1.88%)	869 (2.72%)	638 (2.30%)	1,102 (3.17%)
"surprise"	1,282 (9.62%)	3,389 (10.08%)	546 (6.09%)	2,055 (5.36%)	1,792 (6.46%)	1,635 (4.71%)
"unknown"	1,607 (12.06%)	3,932 (11.70%)	390 (4.35%)	1,915 (5.00%)	2,811 (10.13%)	3,670 (10.56%)
Total	13,326	33,619	8,971	38,338	27,754	34,745

Appendices B – Sentiment analysis of reviews about North Island and South Island POIs on TripAdvisor (Classification by polarity)

Polarity	North Island Attraction	South Island Attraction	North Island Hotel	South Island Hotel	North Island Restaurant	South Island Restaurant
Positive	10,147 (76.14%)	22,892 (68.09%)	6,719 (74.90%)	27,953 (72.91%)	19,755 (71.18%)	23,513 (67.67%)
Neutral	2,288 (17.17%)	7,650 (22.75%)	1,595 (17.78%)	7,129 (18.60%)	5,363 (19.32%)	7,008 (20.17%)
Negative	891 (6.69%)	3,077 (9.16%)	657 (7.32%)	3,256 (8.49%)	2,636 (9.50%)	4,224 (12.16%)

Total	13,326	33,619	8,971	38,338	27,754	34,745

Appendices C - Sentiment analysis of reviews about New Zealand POIs on TripAdvisor (Classification by emotion)

Emotion	NZ Attraction	NZ Hotel	NZ Restaurant	North Island	South Island	NZ
"anger"	1,389 (2.96%)	2,931 (6.20%)	1,723 (2.76%)	1,593 (3.18%)	4,450 (4.17%)	6,043 (3.85%)
"disgust"	416 (0.89%)	424 (0.90%)	397 (0.62%)	361 (0.72%)	876 (0.83%)	1,237 (0.79%)
"fear"	528 (1.12%)	417 (0.88%)	908 (1.45%)	557 (1.11%)	1,296 (1.21%)	1,853 (1.18%)
"joy"	32,561 (69.36%)	37,593 (79.46%)	47,823 (76.52%)	37,938 (75.80%)	80,039 (75.01%)	117,978 (75.26%)
"sadness"	1,842 (3.92%)	1,038 (2.19%)	1,740 (2.78%)	1,175 (2.35%)	3,445 (3.23%)	4,620 (2.95%)
"surprise"	4,671 (9.95%)	2,601 (5.50%)	3,427 (5.50%)	3,620 (7.23%)	7,079 (6.63%)	10,699 (6.83%)
"unknown"	5,539 (11.80%)	2,306 (4.87%)	6,482 (10.37%)	4,809 (9.61%)	9,519 (8.92%)	14,328 (9.14%)
Total	46,946	47,310	62,500	50,053	106,704	156,758

Appendices D – Sentiment analysis of reviews about New Zealand POIs on TripAdvisor (Classification by polarity)

Polarity	NZ Attraction	NZ Hotel	NZ Restaurant	North Island	South Island	NZ
Positive	33,040 (70.38%)	34,673 (73.29%)	43,268 (69.23%)	36,623 (73.17%)	74,359 (69.69%)	110,983 (70.80%)
Neutral	9,938 (21.17%)	8,724 (18.44%)	12,372 (19.80%)	9,246 (18.47%)	21,788 (20.42%)	31,034 (19.80%)
Negative	3,968 (8.45%)	3,913 (8.27%)	6,860 (10.97%)	4,184 (8.36%)	10,557 (9.89%)	14,741 (9.40%)
Total	46,946	47,310	62,500	50,053	106,704	156,758