WORKING HOLIDAY IN AUSTRALIA: A SOCIAL-DATA BASED STUDY ON THE CORRELATION BETWEEN PARTICIPANTS' PERCEPTION AND PARTICIPATION CHANGE

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ABSTRACT

The main purpose of the study is to understand the relationship between people's perception and participation regarding a future event. The analysis was performed to investigate whether the participation in Australian working holiday program changes due to the change in the perception of the people of Korea. In the research, we utilized time series statistical data and a set of sentiment data collected from a social platform. We used the number of Korean people who entered and exited Australia during the last 10 years and sentiment data from two social blogs, called cafes: 'I Love Australia' and 'Hoggoksung', having registered members of 150,500 and 110,127, respectively. The total numbers of posts were 169,827 and 196,217, respectively. In was found that the change in perception has strong impacts on the number of people participating in the program. We also found that the sentiment data-based prediction is much more effective than the simple numerical data-based prediction.

Keywords: *Big Data, Working Holiday, perception, Sentiment analysis, Australia.*

1. INTRODUCTION

The rapid growth of Information Technology (IT), including cloud computing, Internet of Things (IoT), artificial intelligence (AI) is changing every aspect of life and industry. The modern world is witnessing a massive explosion of diverse datasets referred to as 'big data' [1]. Unlike the traditional 'small' data, big data typically includes masses of unstructured data that needs critical analysis to get insights or useful information from the data [2]. Nowadays, many sophisticated techniques are introduced and used to analyze these big data for classification, prediction, and description of events more accurately and timely [3]. The recent breakthrough in the improvement of hardware performance allows the researchers to overcome the 'time factor' which has been one of the biggest obstacles to big data analysis. For example, improvement of the Graphics Processing Unit (GPU) allows the massively parallel processing of data. Therefore, the time required for analysis and processing big data has been reduced from days to minutes [4]. This development of capability in processing and analyzing big data made the machine learning technology practically applicable to many problems [3].

Men have an endless fascination for future, thus to this day, have devoted enormous efforts to predict future events. Undeniably, the development of the modern data analysis system has boosted our ability to do that. But the level of accuracy is yet to be improved, making it a vibrant and thriving area of research. In order to increase the accuracy of prediction based on available data, researchers, and practitioners of different sectors have started using 'Big Data' in recent years due to its volume, velocity, and contemporariness. The extraordinary development in processing 'Big Data' and extracting results using machine calculations through the 'machine learning' allows us to predict future events and interpret it as human insight. However, it took an enormous 'trial and error' for the development of the analytical technology; and still now various examples of new analysis are coming out [3,5].

The main purpose of the study is to understand the relationship between people's perception and participation to a future event. The analysis was performed to investigate whether the participation in Australian working holiday program changes due to the change in the perception of the people of Korea, one of the major participant countries. In the present research, we utilized time series statistical data and a set of sentiment data collected from a social platform. In contrast to previous studies where mostly one kind of dataset was used [6, 7], we used the arrival and departure records of Koreans who entered Australia for spending their working holiday there. Based on the data we predicted the number of future working holiday travelers in Australia. In addition, we collected data from two Korean famous social blogs in 'Naver Café' relating to Australia namely 'I love Australia' and 'Hoggoksung'. We used the keyword 'Working Holiday' and 'Wohol' in web crawler for sentiment analysis. By performing sentiment analysis, we examined whether the social data-based prediction provides more effective results than the simple numerical data-based prediction.

2. LITERATURE REVIEW

Prediction of tourism demand has critical economic consequences [8, 9], it enables tourist authorities and decision makers in the hospitality industries to formulate strategic planning [10, 11], therefore, tourism industries must forecast tourism demand accurately. While tourism demand is usually measured by tourist arrivals at a given destination, followed by tourist expenditure [12], no single model can provide the best tourism forecasts for any of the countries in the short, medium and long-run [13].

In search of accuracy, prediction models, single-equation or combined [10] are still continuously being proposed which range from time-series models to econometric models to modern artificial intelligence techniques [11, 14, 15]. For example, Hassani et al. used Singular Spectrum Analysis (SSA) for forecasting US tourist arrivals whereas Pai et al. proposed a combined FCM+LLS-SVRGA model and studied six other forecasting models in order to demonstrate its superiority over all [11, 16]. Furthermore, using monthly tourists' arrival data from the Australia Bureau of Statistics (ABS), Ma et al. forecasted Chinese tourists' arrival to Australia through time-series analysis with Autoregressive-integrated Moving Average (ARIMA) models [10].

Complementary to these, Lin et al. forecasted inbound visitors to Taiwan using three generally adopted forecasting models- conventional ARIMA, Artificial Neural Networks (ANNs) and Multivariate Adaptive Regression Splines (MARS) [17]. Lin et al. showed that on several bases ARIMA outperformed the other two as opposed to Cho who confirmed the superiority of ANN models through the empirical evidence against ARIMA and exponential smoothing models [17-20]. In Addition, Nor et al. studied the comparative performance of the neural network and two classical time series forecasting methods to prove its reliability in forecasting price data [21].

On the other hand, Linares et al. employed sentiment analysis to predict the influx of tourist to Peru utilizing Twitter data [22]. Text sentiment analysis based on the data from social network sites such as Twitter, Facebook, Online forums, and blogs has been extensively studied on different perspectives [23] due to their evident representativeness. Chong et al. for instance, conducted sentiment analysis of online reviews to predict product sales [24]. Therefore, we posit people sentiment of a certain region toward a destination is more precise and accurate predictor of future tourists than the time series data alone.

Regarding Artificial neural network (ANN), it is beneficial in time series forecasting due to its data-driven approach which can be trained up to chart past values of a time series [21]. We argue that because of the nature of the data, tourism demand, where human-made changes are not possible, ANN is less likely to accurately forecast tourist traffic to a destination. We rather propose to consider a fusion analysis combining both sentiment data and numeric time series data for more accurate tourism demand prediction.

In this study, we acquire Korean tourist (holding employment visa) arrival to and departure from Australia data from the ABS website in consistent with Ma et al. to predict the number of working holidaymakers arrival in Australia. As per Department of Immigration and Border Protection, International Visitor Survey, December 2016, working holiday maker comprises 14% of total youth travelers, aggregating 321,000 travelers every year [25]. Each working holidaymaker spends almost one third higher than a general youth traveler making it one of Australia's significant tourist segments. Specifically, working holiday

maker's expenditure is $10000 per trip while a general youth traveler spends $7700 during their stay in Australia which implies substantial contributions to the tourism and hospitality industry of the country.

The main purpose of Working Holiday Maker (WHM) visa program, as mentioned in the Working Holiday Maker Visa Program Report, June 2016, is to foster closer ties and cultural exchange between Australia and partner countries. Initiating in 1975, the program has been expanded to incorporate more countries which subsequently has increased the number of working holiday travelers over the years [26]. Considering the importance of working holidaymakers, a number of studies funded by the Australian government have been carried out on this particular group of travelers alone [27]. Therefore, studying working holiday travelers' pattern to accurately predict future working holiday maker's arrival in Australia is undoubtedly important and vibrant.

3. DATA COLLECTION AND PREPROCESSING

The 'Python' programming language was used to process the data for our study; 'Python' is an interpreted language which is different from 'Java, or 'C'. However, it was selected because of its suitability to use the visualization and analytical tool. In addition, it can verify the result of source code execution immediately in the development environment. Here, the 'Pandas module data frame' was used for data processing and then data were visualized by using 'Matplotlib and Plotly'. The algorithms and sentiment analysis that were used in this study have been discussed in detail in the next chapter.

3.1 Numerical data

The numerical data that is the entry and exit records of Koreans participating in Working Holiday program in Australia was collected from the Overseas Arrivals and Departures (OAD) database of Australian Bureau of Statistics (ABS) [28]. The OAD database is essentially a combination of historical OAD data and information about travelers for the relevant reference months from the Department of Immigration and Border Protection's (DIBP) traveler processing system. The data presented in the Excel file format includes the entrance and departure information of foreign nationals staying in Australia for different periods of time, and the

data can be customized using filters such as country of citizenship, age, gender as well as the predominant reasons for travel. In this study, only the data about the number of Koreans who visited Australia for the purpose of employment were used for analysis.

Here, we downloaded 10 files from July 2007 to June 2017 using Pandas Data Frame, a powerful data processing module in python and integrated them into one file for handling convenience. Table 1 shows the entries and exits of first five months of the selected time frame which includes resident departure as well as visitor arrival in Australia both for long-term and short-term.

Table 1: Monthly Sum of Movement by Category of Traveler

Time	Long-term resident departure	Long-term visitor arrival	Short-term resident departure	Short-term visitor arrival
2007-07-31	5	69	15	579
2007-08-31	7	68	0	670
2007-09-30	8	88	0	426
2007-10-31	20	103	30	535
2007-11-30	8	68	15	502

3.2 Social Data

The data for our sentiment analysis was collected from two social blog called cafés operated by Naver, one of Korea's leading web portals. In brief, 'Café' is a virtual space where various people come together to share their opinions, views, and experiences on a particular topic or person. The members of NaverCafé can express their feelings freely because most of the users are Koreans, and their anonymity is ensured through their nicknames. Therefore, the data found in Naver Cafes are the expression of authentic emotions of the users and the crawled data about Australia could be used without any filtering. The two cafes used for data collection were 'I Love Australia' and 'Hoggoksung', having registered members of 150,500 and 110,127, respectively; while, the total numbers of posts were 169,827 and 196,217, respectively. Among the total posts, around 8,000 articles were extracted by 'Working holiday' keyword search, and then the analysis was performed using the extracted data set. An example of the articles posted in 'NaverCafé' is shown in Figure 1.

Figure 1. Sample Article Posted In Naver Café

Search keywords are required for extracting the information using web crawler. Here, we used two keywords ('Working Holiday' and 'Wohol') for extracting the information from the 'I Love Australia' and 'Hoggoksung' Naver Cafes. Unlike the 'Naver blog', 'Naver café' does not display all of the results on one page; instead, it returns to the title of the posts through keyword search as a hyperlink. Therefore, after storing the addresses of the first link in the python list, the code for crawling the addresses of the posts stored in the list was repeated one by one using the loop, and thus collecting our required data. For analysis purpose the title, content, and date of the respective posts were extracted as .txt files and constructed the document in list form using the text. The top five data that have undergone these preprocessing steps are shown in Figure 2.
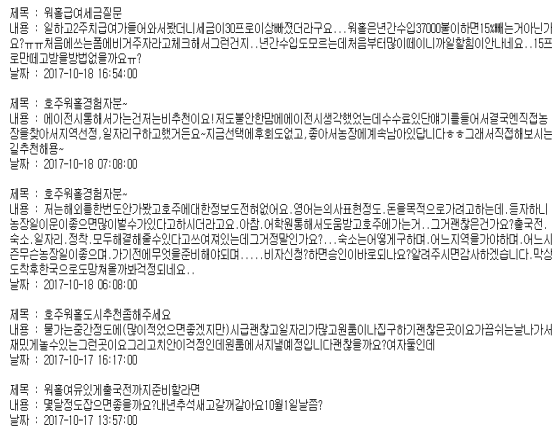

Figure 2. Top Five Pre-Processed Data (Posts) Crawled And Documented From The Café.

4. NUMERICAL DATA ANALYSIS

The numerical data used for the analysis was the number of Korean people who entered and exited Australia during the last 10 years using the employment visa as described above, and there were a total of 121 months from July 2007 to June 2017.

Based on these data we used two machine learning algorithms in order to predict the number of people who will potentially leave for working holiday program in Australia in the future. At first, we have visualized the numerical data after the preprocessing steps for easier analysis. As shown in Figure 3, the basic numerical data without an empirical test are used for basic visualization and prediction. X-axis shows the year and y-axis shows the number of arrived and departed Korean traveler. Different colored lines indicate short-term and long-term categorized entries and exits over the determined time period.
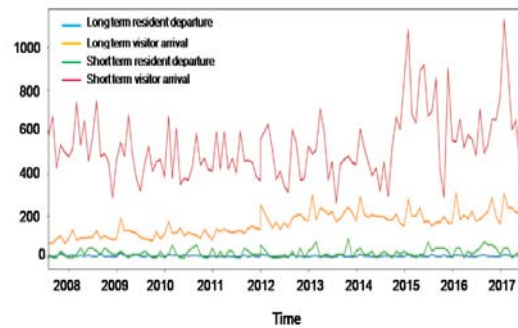

Figure 3. Overseas Arrival And Departure Data From July 2007 To June 2017.

4.1 Algorithm for Prediction

Machine learning is a type of artificial intelligence that allows a computer to learn and predict based on a given algorithm. There are myriads of learning algorithms, and the usage of which depend on the type of data set desired to be analyzed. For example, we analyzed and predicted the time series data by selecting algorithms of artificial neural network model namely Multilayer Perceptron and Stacked Circular Neural Network; the details description of the algorithm is as follows:

4.1.1 Multilayer Perceptron

The multilayer perceptron (MLP) is a class of feedforward artificial neural network. An MLP consists of at least three layers of nodes. Except for the input nodes, each node is a neuron that uses a

nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation training [29]. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable [30]. Multilayer perceptron is sometimes colloquially referred to as "vanilla" neural networks, especially when they have a single hidden layer [31]. In this algorithm the predicted values are calculated by substituting learning data into functions arbitrarily set by the user. The functions have weights (w) as the variable to be assigned, that is, the number of learning data to be input.

A function that calculates the product of input values and weights is called a net input function, while, a function that compares the result of a net input function with a specific threshold for prediction and provides the calculated predicted value is called an active function. If the predicted value is different from the test data by using these two functions, weights are adjusted and the final value is presented as a predicted value. In a single layer perceptron, as shown in Figure 4, the function part that responsible for these calculations is called a node or neuron, and is located in the middle layer of the algorithm. Therefore, it forms an artificial neural network that computes the result using one or more nodes, and helps to comprehend the phenomena in a better way [32].
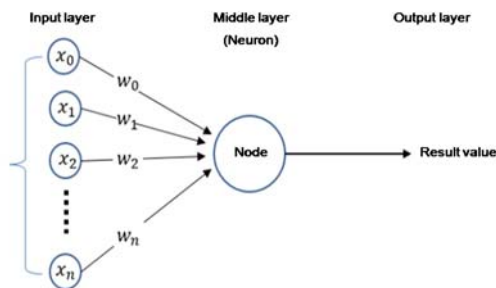

Figure-4: Single Layer Perceptron

In case of single layer perceptron algorithm, where the input layer and the output layer exist only as a single layer perceptron, it is possible to learn about the AND operation, but it is impossible to properly learn about nonlinear data. Hence, the MLP algorithm has been developed to compensate this disadvantage of single layer perceptron algorithm. This algorithm allows for in-depth learning by having several hidden layers and calculating several output values of the output layer. Thus, this is also classified as a deep learning algorithm [33].

4.1.2 Stacked Circular Neural Network

Stacked Neural Networks model is a model of the application of the Recurrent Neural Network (RNN), and basically follows the operation of the circular neural network model. Unlike feed forward neural networks, RNNs can use their internal memory to process arbitrary sequences of inputs. This makes them applicable to tasks such as unsegmented and connected handwriting recognition [34] speech recognition [35]. Therefore, RNN becomes an excellent performance model for solving natural language processing problems. In addition, we also used Long Short-Term Memory (LSTM) algorithm which is the most widely used algorithm in RNN. LSTM prevents back propagated errors from vanishing and exploding [36]. Like the basic RNN, it affects the output value through hidden variables. However, before computing the hidden variables, we have to determine whether to keep it in memory when moving to the next step [37].

The stacked circular neural network model used in this paper is composed of stacked layers of state-preserving circular neural network models. In this case, the layer at the upper part of the stack improves the performance by influencing the input of the existing layer. In other words, it is possible to obtain better prediction results because it constructs another iterative model with the input of repetitive model as new input. This algorithm is also a deep learning algorithm.

4.2 Visualization And Forecasting

Figure 5 shows the number of outbound travelers from Australia for the period between July 2007 and June 2017 along with the prediction for the last two years. The prediction is done using the 'multilayer Perceptron' model (Fig. 5a) and the 'Stacked Circular Neural Network Model' (Fig 5b). The time (Year) and the number of outbound travelers normalized from 0 to 1 are presented in the x-axis and y-axis, respectively.

a line chart shows the prediction of resident departure from 2015 to 2017 applying Multilayer Perceptron model whereas, **b** line chart demonstrates the same prediction employing Stacked Circular Neural Network model. Different groups of travelers are indicated by different colored lines.
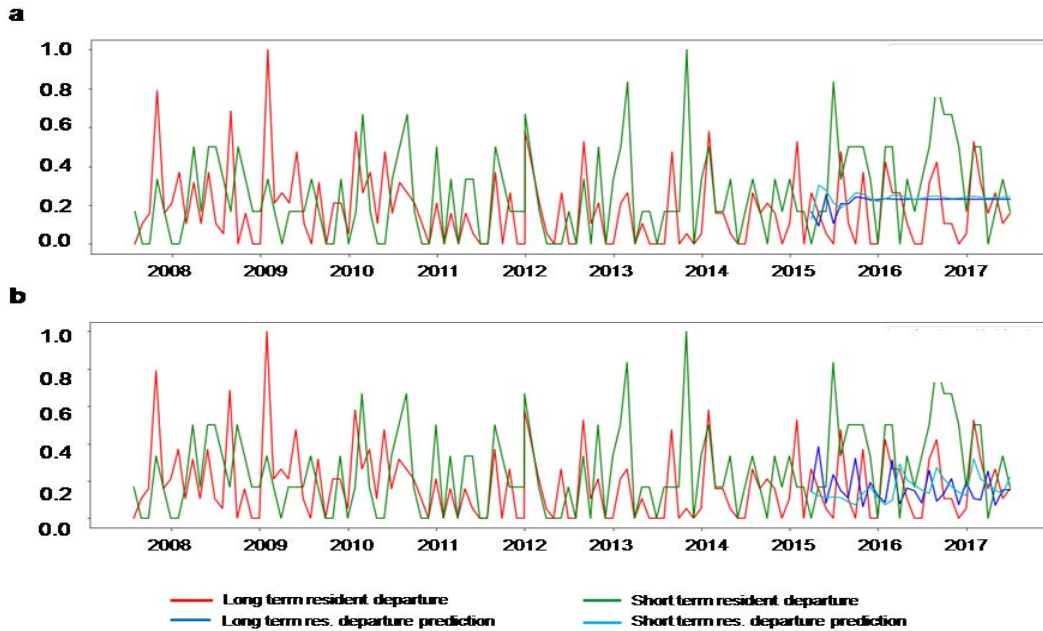
Figure 5. Numbers Of Past And Predicted Outbound Travelers From Australia.

As shown in Figure 5, there is almost no significant change in the outbound traveler's movement, even though the line graphs show a recurring trend. This data indicates that there will be no big change in the number of departing residents within the predicted time-frame. However, this prediction is not reliable because the predicted graphs do not show many similarities with the existing dataset.
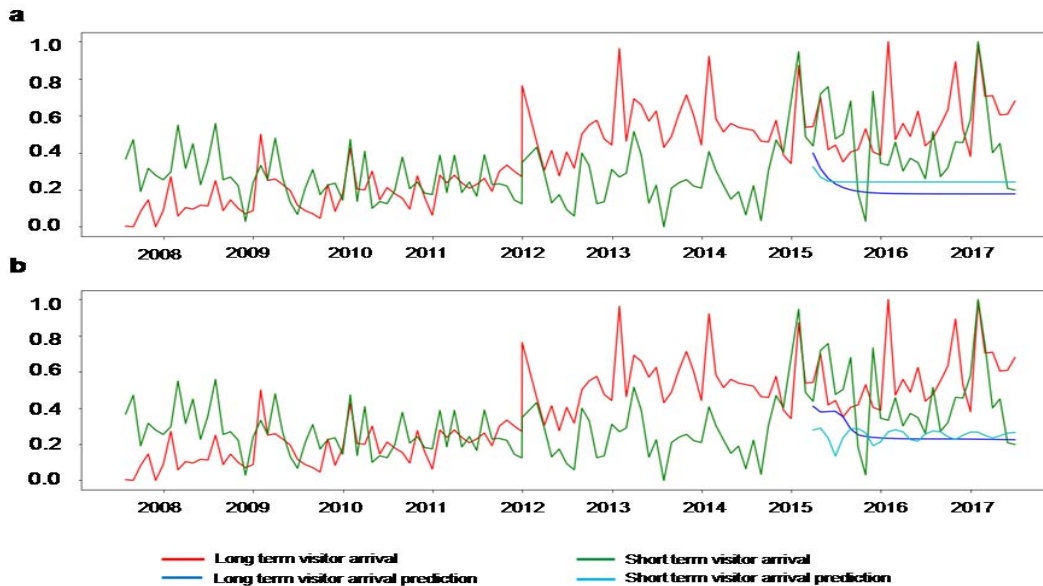

Figure 6. Number Of Past And Predicted Inbound Travelers Into Australia.

Similarly, the Figure-6 depicts the number of past and predicted future inbound travelers, in other words, the number of people who arrived in Australia for employment. The graphs show

predictions using multilayer perceptron model (Fig. 6a) as well as the predictions using Stacked Neural Network model (Fig. 6b). The time and the number of arrivals normalized in between 0 to 1 are presented in the x-axis and y-axis, respectively. **a** line graph represents the prediction of inbound travelers from 2015 to 2017 using multilayer perceptron model while **b** line graph shows the same prediction applying stacked circular neural network model. Different colored lines indicate different groups of traveler.

As shown in Figure-6, overall, the total number of travelers is decreasing. This data indicates that the number of inbound passengers will reduce within the predicted time-frame. However, this prediction is also unreliable, because the predicted graphs did not have many similarities with the existing dataset. Therefore, it could be concluded that it is quite impossible to make an accurate prediction of the arrival and departure status of the travelers by using the simple graphs (Fig.5 and Fig.6).

5. SENTIMENT DATA ANALYSIS

5.1 Analytical Tools

The sentiment analysis was performed using Google API. The Google API contains a dictionary that could define the positive and negative emotions with accuracy. There are three types of analysis (sentiment analysis, entity analysis, and parsing) that are usually performed using Google's natural language processing API service. Among them, the sentiment analysis was used for the present study, which is mainly based on Google's positive and negative word dictionary, and the result is extracted as a score and a magnitude. The algorithm used for analyzing sentiment is quite simple. Briefly, a word from the beginning of a sentence to the end was designated as a document, while the positive or negative words included in the document were examined to be given a score. However, it takes quite a while to implement these dictionaries, so we selected the Google natural language API application for quick analysis. Usually, the cafe's posts contain the emotions of the individual cafe users; therefore, we did not calculate the average of the cafe's weight. Instead, sentiment results were calculated by selecting only score among score and magnitude which are the results of sentiment analysis.

5.2 Analysis of Sentiment Data

As shown in Figure 7, the results of the sentiment analysis of the two cafés have been presented in a monthly order. This helps to make an easy comparison of the monthly sentiment data generated from the two cafes. Here, the mean of the existed data of each month has been shown, but the weight was not calculated during the calculation of the mean. The x value represents the time, and the y value represents the sentiment scores which are expressed in between -1 to 1.
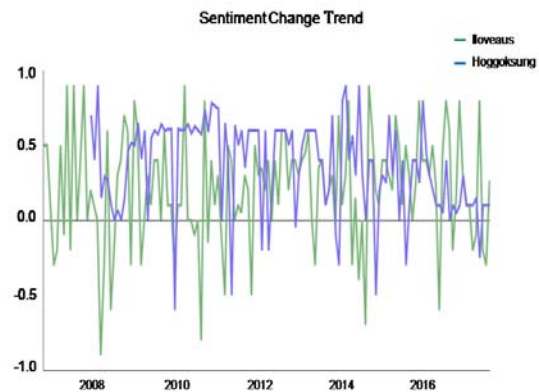

Figure 7. Sentiment Change Trend Of The Two Cafés ('I Love Australia' And 'Hoggoksung') In Between 2007 And 2017.

As shown in the graph, there are parts with strong negativity and strong affirmation, and most of which are found at similar times (Fig.7). These differences in prediction using the data from two cafes might be related to the variation of their establishment time along with the differences in their past posts. More specifically, the 'I Love Australia' cafe has a longer history and more information, while 'Hoggoksung' café has comparatively shorter history and less information about working holiday program in Australia. And this makes the variation in the prediction of future events. At the peak of the graph, there is no significant difference in the scores of people's sentiments. However, there are parts having little changes with the time difference, this could be the difference of the speed of the information that is spread to both sites. Also, the parts that did not overlap with each other were little in the past, this might be judged within the error range due to the atmosphere difference when the cafe was created initially, and thus the sentiment data could be integrated.

6. FINAL RESULTS AND DISCUSSION

Finally, the mean scores of the two cafes were put together based on the assumption that the sentiment data of the two cafes have the same weight.
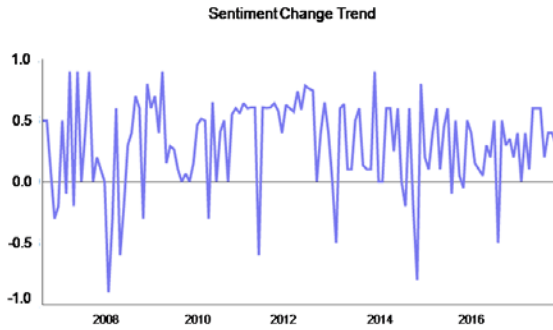

Figure 8: The Integrated Result Of Sentiment Analysis Data Of Two Cafes.

Figure 8 depicts the sentiment data that has taken place before the analysis, and integration process. The x-axis represents times, and the y-axis represents the sentiment scores normalized in between -1 to 1. In addition, the issues that occurred in Australia during this study time-frame were also investigated (some of which are listed in Table 2) to understand the low or high integration. Using this analysis it is possible to confirm the sudden increase and the sudden drop of emotion, and the reliability of the sentiment data can be verified.

Table-2: Sample Of Issues Happened In Australia During This Study Period

Negative Issues		
2012-12	Sharp Decline	Asians do not inquire assaults
2014-09	Sharp Decline	Terrorist Attack in August and September
2016-06	Negative	Terrorism Issues: April 1 case, May 2 case, June 1 case
Positive Issues		
2015-01	Upsurge	Australia Asian Cup, exchange rates plummeted (approx. 950-840 won)
2015-11	Increase	Recorded the lowest exchange rate in October (800.61 won)

A diagrammatic depiction of the effects of sample issues selected during the range of the observed time period has been shown in Figure 9. The sharp effects are red circled.
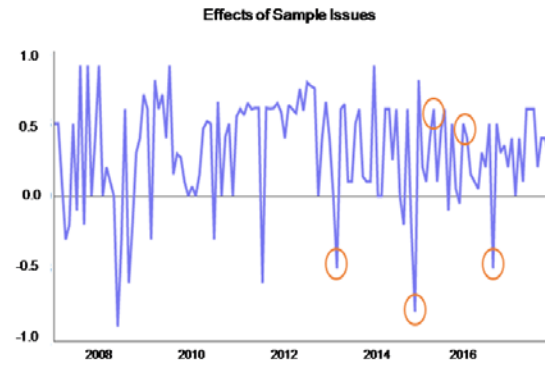

Figure 9: Depiction of Effects of Sample Issues During The Observed Time Period.

At last, a comparison was made between the results of numerical data and the sentiment data (Fig. 10) to see if there is any correlation exists between them. Since we normalized from -1 to 1, it could be compared easily to understand the sentiment score to the number of arrivals. The time and sentiment scores normalized in between -1 to 1 are presented in the x-axis and y-axis, respectively, while the number of arrivals and the sentiment analysis result of added cafés are directed by different colored lines.
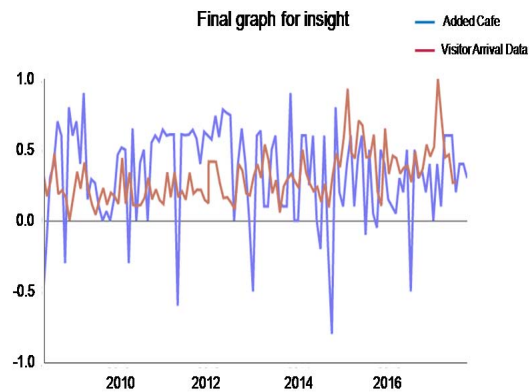

Figure 10. Comparative Scenario Between 'Actual Arrival Record' And 'Sentiment Analysis Result'.

As shown in Figure 10, except for the part where the sentiment score does not change much at the beginning, the sentiment data and the numerical data are almost similar in many parts. Although the changes of the two lines are not exactly the same, overall the numerical data increases as the sentiment data increases, and also the numerical data decreases as the sentiment data decreases,

given the speed at which information about Australian issues spread to the people, therefore, it

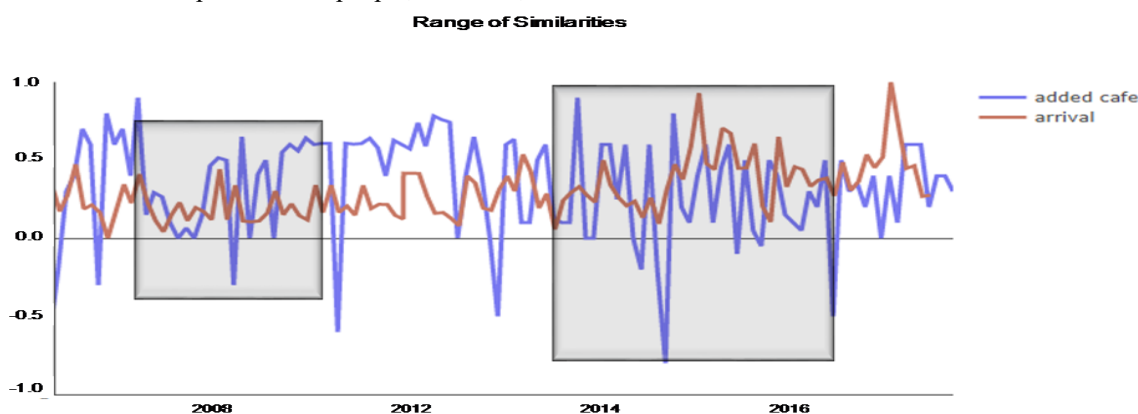is highly reliable. In particular, both lines show a

Figure 11. A Special Range Of Similarities Between Two Graphs

very similar trend of changes from around 2015 to the present. And Figure 11 confirms that the researchers have marked on points that they find are particularly similar. Therefore, it could be concluded that the perception of the public about the working holiday could be a better prediction than simple numerical data based prediction.

It should be noted that we have questioned the fact that there exists a point where the direction of the slope of two graph lines coincides with a point which deviates little by little. This is considered to be an error according to the propagation speed of information. Specifically, it is the difference between the time of information spread between people and the point of time when people actually leave for working holiday. It is possible that the information on the 'NaverCafé' is out of date because these researchers did not conduct sentiment analysis on all posts related to Australia. In addition, numerical graphs can be pushed backward than sentiment graphs at many points when people leave for Working Holiday based on previously reported information.

However, according to this analysis, it can be confirmed that it is more accurate to grasp the feelings of the public about the working holiday to predict the number of future travelers than the prediction using only the change of the simple numerical data as a variable.

7.   NOVELTY OF THE STUDY

This research has clear distinction from the extant simple predictive models which learn only from existing numerical values. The novelty it

offers is twofold. First, the study emphasizes and empirically proves that community perception is more reliable predictor of future events. Second, it does not stop just by looking at the feelings of the person who wrote the post on a social platform, but also analyzes the impact of the post on other people who read the post. Taking the working holiday in Australia into consideration, we studied the impact by using the emotions that post writers of the time period felt on average.

8.   CONCLUSION

In conclusion, this sort of analysis is very well applied when performing classification and clustering work but it has limitations in applying on human-made changes such as stock price using only numerical data. Therefore, we attempted to combine numerical data analysis and sentiment analysis to find better analytical methods with higher reliability and accuracy. Accordingly, it has been found that this fusion analysis using sentiment data is very much effective, and the effectiveness of the analysis is determined based on whether the sentiment analysis data of the Naver Cafe post and the numerical data of the number of immigrants show a similar trend of changes. Although the number of outbound passengers did not change with positive or negative sentiment scores, the results itself proved that the study is successful as it shows the same degree of change in both types of analysis (sentiment data analysis and numerical data analysis).

The limitations of this study includes not having more detailed data on the number of

immigrants, as well as not creating our own special positive and negative language dictionary for this particular dataset analysis due to the time limitation. In the future research, data on arrival and departure of Australia's working holiday participants as well as other reasons for travel such as business, convention/conference could be incorporated in the analysis. Finally, this analysis technique could be considered as an important addition to the 'Big Data' analysis technology, and it could be used for predicting the tendency of people's participation to an upcoming event based on the 'past history of people's perception'.

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