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THE ART OF LISTENING ON SOCIAL MEDIA PLATFORMS: HOW FIRMS FOLLOW USERS ON SOCIAL MEDIA FAN PAGES

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Research

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Abstract

Organizations seeking to improve user engagement continue to invest in fan pages on social media platforms anticipating that in a progressive global marketplace users will utilize these technologies, which will enhance organizational competitive advantages. With the steady growth of the number of users who followed firm fan pages it is not clear whom should firms listen to? Since fan page followers participate and contribute on fan pages in various ways, a one size fits all strategy to select users to follow them back may not work. To address these issues, we focus on firm fan pages on Twitter. Using tweets generated by active users on fan pages, this study examines firms' strategy of following back users on their fan pages. We examine users based on their activities, nature, and sentiments of their contents created and disseminated. We apply topic modeling and sentiment analysis to the tweets of two prominent airline fan pages in pacific region. We discuss the results obtained from a set of almost 21277 tweets of the 4735 active users. Our results show that automated categorization via LDA-based topic modeling and sentiment analysis of the users tweets can help firms select whom to follow back. We find that firms follow back their users based on a mix of users' activities, topic of content created or disseminated and sentiments of their contents. Results and managerial implications are discussed. The outcomes of this paper help businesses to invest wisely on their social media activities and specifically fan page management.

Keywords: User engagement, fan page, topic modelling, sentiment analysis.

1 Introduction

Firms' Fan pages on social media platforms has become an integral part of any firm's social media strategy and organisations seeking to improve user engagement in these environments. Online social networks have potential to affect organizational reputation, perception and opinions of the observers about the firm (Bampo, Ewing, Mather, Stewart, & Wallace, 2008). Online social networks have changed the dynamic of customer and firm interactions by empowering a high level of two-way discussion between the organization and its clienteles and by bringing new mechanisms for customers to cooperate amongst themselves (Larson & Watson, 2011). So by new technological forms of display, communication, recording and playback, firms achieve new ways of focusing as well as defocusing attention for listening, looking and concentrating on their clients (Crawford, 2009). Fan pages provide opportunity for firms to listen to their customers (followers of fan pages). However, user heterogeneity leads to different patterns of user engagement and this diversity between users could bring different listening disciplines for the firm. Further, with the steady growth of the number of users on the firm fan pages the firms will inevitably face the need to fine-grain the user categories to manage and lead fan page events.

Crawford (2009) argued that the concept of listening as metaphor could be used in a productive way to analyse the forms of online engagement and deeper consideration of online attention. Functioning listening process on fan pages in a highly responsive and attentive way requires firms to be vigilant with rapid and targeted feedbacks to the followers (Crawford, 2009). As the popularity of firm fan pages is growing with ever increasing number of followers, it is still not clear who are more valuable followers for firms or in other words, whom should a firm listen to? The concept of listening in online environment related to a dynamic process of online attention that is critical for networked engagement (Crawford, 2009). Further, we do not yet understand the dynamic ecosystem between firms' fan page strategies and user engagement. In this ecosystem every user moves between the states of listening and disclosing online. Firms can listen or understand their value customers by *following them back*[1] to be more proactive in this dynamic environment. While most of the firms tend to follow celebrity users such as well-known media personalities, politicians, industry gurus, for various reasons, but they also need to listen to and understand their own customers and followers who can provide valuable feedback regarding their services and market competition. Fan page followers are heterogeneous in their contribution (content creation, dissemination, feedback, etc.) and therefore, a one size fits all strategy to select users to follow back may not work and further, firms are also heterogeneous in how they select users to follow back on social media platforms.

To address these issues, we focus on firm fan pages on Twitter, which is a popular social media platform for fan pages. A twitter fan page allows firms to facilitate positive consumer–brand interactions by offering promotions and valuable information to increase customer engagement with these fan pages. Using 21277 fan page tweets generated by a pool of 4735 active users on fan pages of Air New Zealand (AirNZ) and Jetstar over a period of five years, this study aims to examine firms' strategy of following back users on fan pages. We examine users based on their activities, nature, and sentiments of content (created and disseminated) on fan pages. We employ topic-modelling approach to analyse content and machine learning algorithm to analyse the sentiments of tweets. We find that firms follow back their users based on a mix of users' activities, topic and sentiment of their content (created or disseminated). Results and managerial implications are discussed.

The rest of this paper is ordered as follows. Following the brief introduction, we present a review of the theory and literature to provide a good basis for this research. After that we discuss research methodology, data collection and data analysis employed in this study. Finally, we present the findings

[1] Following your own followers on Twitter is termed as "following back".

and discuss the implication of finding on theory and practice. The limitation of this study and concluding the identifying future avenues of research are also discussed.

2 Literature Review

In this section we provide a review of the theory and relevant literature. First we discus actor network theory and attribution theory to explain actors engagement in a network. After that we present some literature about learning process and explain how users can adjust their behaviour following firms' action on fan pages. Finally we argue that firms needs to understand user behaviour before they develop their strategy for firm fan pages..

2.1 Theory: Actor network theory

Social media are online spaces where users and firms connect, collaborate and share their content. Although the learning and sharing on social media platforms is flourishing, and it appears that the information exchange via social media is valuable for firms and users, there is little research into the processes and nature of such learning on firm fan pages. Following Couldry (2008), we use Actor Network Theory ('ANT') to explain the web of connections between users, firms, technologies and objects. As users connect or follow firms' fan pages, these fan pages acquire power through number of followers, extensiveness and stability of the connections routed through them. Such connections are contingent and emerge historically and play important roles in markets and society. ANT seems perfectly placed to explain the role(s) of media and communication technologies in contemporary societies, but the strengths and nature of ties between actors has not been explored very well. Social media users self-consciously consider what they might post to keep followers or readers entertained, which connections to curate, which to reject, and which to maintain in the most strategic ways. These "things" also significantly mediate and translate identity, for example, a highly favourite tweet may change users' updates and reputation within a specific hashtag, or peer group (e.g. McGaw, 2012; Pariser, 2011).

We posit that the level of user engagement and content generated or disseminated by users on fan pages will affect expectation of other users and their loyalty to the firm's product or services. In the context of fan page activity, users can learn from the human agents, technologies and objects simultaneously and adjust their behaviour in many ways. First, users learn from human agents on twitter when a firm posts a tweet or reply a tweet on fan page. In this instance user can comprehend about the company desires, directions and strategies by following firm's fan page activities. Second, users learn from technology by exploring the mechanisms (retweet, hashtags, favourite, etc.) that is embedded in that social media platform and observing other users. For instance users may learn to use and develop preferences for new or existing mechanism (e.g., using favourite mechanism more than retweet) in certain contexts and environments. We argue that users' adoption or reaction towards new or existing mechanisms could be considered as the social connection between user and technology. Third, users can learn from the objects as other users. When users see the comments from other users and interpret them in their own way, they can see and provide different perspective to the fan page community. So in this case, the topics and sentiments that other users employ in their posts would be affective on the user behaviour. In this research we argue that firm fan page managers need to understand this dynamics of user and firm interactions. Drawing from attribution theory, users make attributions to the events of the firm on social media and update their knowledge about other users. Comparing with other users (social comparison theory) users make inference about their participation and may change their level of engagement on firms fan pages. We argue that firms who endeavour to listen to the followers, need to understand followers' behaviour and their choices on firm's fan pages.

2.2 Social media and learning

Experience has different features. As Walls, Okumus, Wang, and Kwun (2011) discussed experiences are subject to the reactions, feelings, and situation of one who is involved in those products, services, and environments. They propose that customer experience is different from routine life and many components and situations can precipitate individual characteristics like emotional, physical, and cognitive responses to the situations. In other words environmental factors that shape customer experiences are individual characteristics, human interaction elements, physical experience elements, and situational factors(Walls et al., 2011). We contribute to this nascent literature by connecting user participation and user engagement. Followers of company on social media not only get used to tracking the updates and events of the company and participating, but also learn in the engagement process. Simultaneously, based on the feedback that users get from this environment, their perceptions and expectations of the other users and the company approach would increase and it gets harder to manage them. These variations reflect on their referring, writing, or liking behaviour. So the users' satisfaction on the firm fan page is a dynamic concept. The fundamental cause of the change in affection and cognition level can be the learning throughout the engagement process. They learn and evolve by participating and getting feedback repeatedly. In this setting, social participation accelerates learning through different mechanisms.

Customer-firm interaction enabled on social media platforms allow firms to identify new trends, connect with their customers and better understand their markets. Firms are not the only ones who benefit from these interactions, customers too get a chance to directly connect with the firms and also with other customers which wasn't possible earlier. Both firms and customers learn from these interactions and change their participation behaviour on social media platforms. Hence, understanding this interaction is critical for both firms and users. For firms, understanding user engagement strategies are critical for effective customer relationship management, which directly affect firm's revenue.

Considering studies that have been done in online social networking services, little attention has been paid to the impact of contributing to social media regarding the activities of users (Miller & Tucker, 2013) . User behaviour may change over time and it may affect their outlook of the products or services. In this research we assume that the engagement process itself and the feedback from the company, the affection of customers from each other's and user learning over time are the factors that change consumer engagement on firm fan pages. Following firms on social media, customers' experience through their participation. This experience may change the behavior of users over time.

The social network itself may be considered an actor or agent in the learning process, whether through filtering, tailoring or obscuring information (e.g. Pariser, 2011), through shaping the possible varieties and scope of interactions within these spaces (e.g. Jenkins 2012), or through setting official policy and informal or implicit etiquette of the space (e.g. Hine, 2000).

2.3 User Heterogeneity in Fan Pages

Extant literature has proposed four levels of customers' engagement value for firms- Customer knowledge value, customer influencer value, customer referral value and customer lifetime value. Marketers view social media platform as a facilitator for consumers to expose their behaviour (C. Leventhal et al., 2014) and argue that it is important to correctly detect and put effort on users who can be beneficial for the company.

Scholars argue that followers of fan pages are heterogeneous and can be categorized as passive or active. Passive members mostly hang around for benefits, and contribute little to the community (Burnett, 2000; Preece, Nonnecke, & Andrews, 2004), threfore, have been branded as "lurkers or free riders" (Preece et al., 2004). However, presence of lurkers brings some value for the community. An online community may be considered popular if it has a large number of lurkers because they increase website traffic statistics and upsurge "hits". However, lurkers do not necessarily lead to the success of an online community (Ridings, Gefen, & Arinze, 2006). In comparison with passive members, active members are engaged with the community by creating messages, disseminating information, and providing emotional support to others (Casaló, Flavián, & Guinalíu, 2007). Active users can also improve members' brand knowledge (Muniz Jr & O'guinn, 2001) and their existence is vital to online communities (Kozinets, 1999).

Based on user activity levels, Muntinga, Moorman, and Smit (2011) present three types of engagement on social media platforms which reflect positively valenced engagement behaviour as consuming (low level), contributing (medium level) and creating (highest level). Another recent study(Shahbaznezhad & Tripathi, 2015) investigating users activity on fan pages on twitter, grouped users based on their following (favourites and retweets) and creative(hashtags, tweets and comments) attitudes to examine their engagement on firm fan pages. They find that firms have different preferences when it comes to following back some of their fans. We argue that since users are heterogeneous in the behaviour, firms need to understand user behaviour to determine who should be followed back on firm fan pages.

3 Method

3.1 Topic Modeling

The themes in the documents can be extracted by qualitative approaches, such as content analysis, grounded theory approach or thematic analysis, and also by quantitative algorithmic text mining methods such as clustering, term frequency and topic modeling. In recent years, Topic modelling has become one of the most popular and automated methods for discovering the themes in the documents. Topic modeling algorithms are statistical methods to uncover latent topics that are inherent in the documents and help researchers to interpret documents with topic labels (Blei, 2012). Topic modelling techniques present semantically coherent and interpretable topics by calculating the most probable words for each topic. This approach do not require human intervention or prior labeling of documents, which allows an unbiased and repeatable analysis of documents (Vakulenko, Müller, & Brocke, 2014). Though there are few topic modeling approaches are available, this study exploits the Latent Dirichlet Allocation (LDA) (Blei, 2012; Blei, Ng, & Jordan, 2003) technique to identify the most relevant topics in each cluster of users on firm fan pages on social media platforms. LDA is known to information systems researchers and has been applied to analyse twitter data (e.g. Zhao et al., 2011). This method has been used for content analysis of academic papers (Sidorova, Evangelopoulos, Valacich, & Ramakrishnan, 2008), social media posts (Evangelopoulos & Visinescu, 2012), sustainability reports (Reuter, Vakulenko, vom Brocke, Debortoli, & Müller, 2014), vendor case studies (Herbst et al., 2014), and customer feedback (Coussement & Van den Poel, 2008). The goal of LDA is to infer hidden distributions, given the observed words per document (Blei et al., 2003). Topic modeling via LDA, or its predecessor Latent Semantic Analysis (LSA), is considered as a popular research method for the quantitative analysis of qualitative data (Vakulenko et al., 2014). LDA has many advantages over other topic modelling techniques (Uys, Du Preez, & Uys, 2008). For example, LDA treats each document as a "bag of words" considering some words as "stop words" which have no significance in classifying topics. By creating corpus of meaningful words and maintaining the reference directory of each word and also frequency of word occurrence, LDA model generates topics by associating words with one or more topics. The number of topics and the number of words associated with each topic is determined by researcher. So the researcher review each topic and then provide a descriptive label by judging the words related to each topic.

The R package "tm" and "RTextTools", which is available in R library, is used for creating corpus and corresponding matrix. Also "topicmodels" package is used for fitting topics (Hornik & Grün, 2011). Regarding our data set, LDA consider each tweet as a single document. As long as the number of tweets in each cluster is not the same and varies from 50 postings to 2100 postings and considering that we want to compare the topics of different clusters with each other's, so we decided to select 10 topics per each cluster (e.g.Uys et al., 2008). This number was the maximum number of topics and in some cases we couldn't even find 10 different topics based on the output of the LDA. Moreover, the 10 topics were highly discriminant and were easy to interpret. Subsequently, the words in each topic are thoroughly interpreted and the topics are labelled.

3.2 Sentiment Analysis

Opinion mining or sentiment analysis is a systematic approach for understanding author's opinions, emotions, evaluations, attitudes, and behaviour through a specific subject or its characteristics (Liu, 2012). Considering several general-purpose sentiment analysis algorithms have been developed, interpreting the context and domain specific sentiments still a big challenge (Liu, 2012). Since interaction of users as potential customers and companies on microblogging services like Twitter represents a unique context, we decided to use machine learning algorithms and distant supervision for classifying sentiment of messages (Go, Bhayani, & Huang, 2009). Apart from previous approaches such Jeffry Breen's approach[2] for sentiment analysis that they just require a list of negative and positive words to calculate sentiment valence, the Go et al. (2009)'s method consists of Twitter messages with emoticons, which are used as noisy labels. This method also employs Maximum Entropy classifier built from machine learning algorithms and it's different from previous methods that use a simpler keyword-based approach, which may have higher precision, but lower recall. The tweets are analysed using sentiment 140 package[3] in R. Algorithm classifies each tweet as positive, negative or neutral.

3.3 Data Collection

To address our research questions, we have collected customer-firm interactions happening on social media platforms. These are interactions between current or prospective customers and firm on official firm fan pages on social media platforms. To control the effect of the products or services on user engagement, we have selected the airline industry where the types of services are limited. Although social media platforms proliferated in last decade, we are particularly interested in the most popular microblogging platform-Twitter where the user can show any emotions or opinion to any subjects without any restrictions. In addition, these are famous enough that every user can access easily and create comment. Further, interactions on third party platform such as twitter are likely to be unbiased compared to the one hosted on firms' platform. Twitter type platforms increase transparency and openness that are considered critical for promoting democracy[4]. Further, the likelihood of managing and changing users' opinions on a twitter-type platforms would be considerably less than on the company's own website. Also, in data collection process controlling the same simplistic mechanisms for different companies would be easier.

Twitter was started in 2006 as a real-time information network[5] and now it is one of the most popular microblogging and social networking services. As a social networking microblog, Twitter has risen to be a prominent player in the SM arena[6]. Twitter can be also employed as a giant focus group where companies can listen into positive and negative comments about their product and services (Crawford, 2009). On Twitter, each user has an account that acts as individual microblogs by which they send "tweets" confined to 140 characters. Tweets are posted with different devices such as web, SMS, smart phone applications, synchronization to other blogs, and Facebook. Twitter users configure networks by contributing to other microblogs as followers, "following" accounts' Twitter activities. Therefore, we argue that users create a social network by "following" others, or allowing others to follow them. For example, a user can follow a firm's fan page and the firm often follow back some of their followers. In this case it can be shown to what extent a user would be important for the company. Users share fascinating and/or useful tweets by "retweeting" them for personal feeds, and, if interested, sharing a post initially posted by another user. Users similarly "save tweets for later", or specify worth of it by making a tweet a "favorite". Key codes used in the Twitter language are the "@" symbol which is applicable for replying to specific user accounts. The "#" or hashtag symbol designates a common reference and/or grouping of information (Jung, 2012).

This study examines how firms choose which of their followers to follow back. To make that decision, firms need to understand behavioural patterns of active followers of company Therefore we are interested in Twitter postings (including retweets, favourites, hashtags, comments, tweets) that is liked, disseminated or generated by active users of the two airlines in pacific region - Jetstar and AirNZ. We

[2] https://jeffreybreen.wordpress.com/2011/07/04/twitter-text-mining-r-slides/
[3] https://github.com/okugami79/sentiment140
[4] http://www.forbes.com/sites/sap/2013/04/25/how-twitter-and-facebook-are-changing-democracy/
[5] http://twitter.com/about
[6] http://techcrunch.com/2006/07/15/is-twttr-interesting/

have developed an agent to collect, store, pre-process, clean and transform the data. Using Twitter's APIs this automated agent captures all the customer-firm interactions happening on twitter fan page of these two airlines -.Air New Zealand and Jetstar. Air New Zealand is a full-service airline, and Jetstar is a budget airline. Since Air New Zealand and Jetstar have started their activity on Twitter from Jan 2009, we have only focussed on user activities from January 2009 to August 2014. These companies have a huge number of followers (275 K for AirNZ and 79.3 K for Jetstar), but as expected, only a fraction of these followers are active on firm fan pages on Twitter, therefore, we are only focussing on active followers (Shahbaznezhad & Tripathi, 2015). Followers are considered active if they have at least two status updates (posted tweets) and favourites and have created at least one firm related hashtag, retweet and post/comment since joining the Twitter. Based on this criterion, we find 4196 actives users/followers for Air New Zealand and 539 active users/followers for Jetstar. For these number of active users we could capture 19533 and 1744 tweets, hashtag, retweet, comments that are generated by active followers of Air New Zealand and Jetstar accordingly. In Figure 1, we report general stats about firms' followers and users that are followed back by the firm.

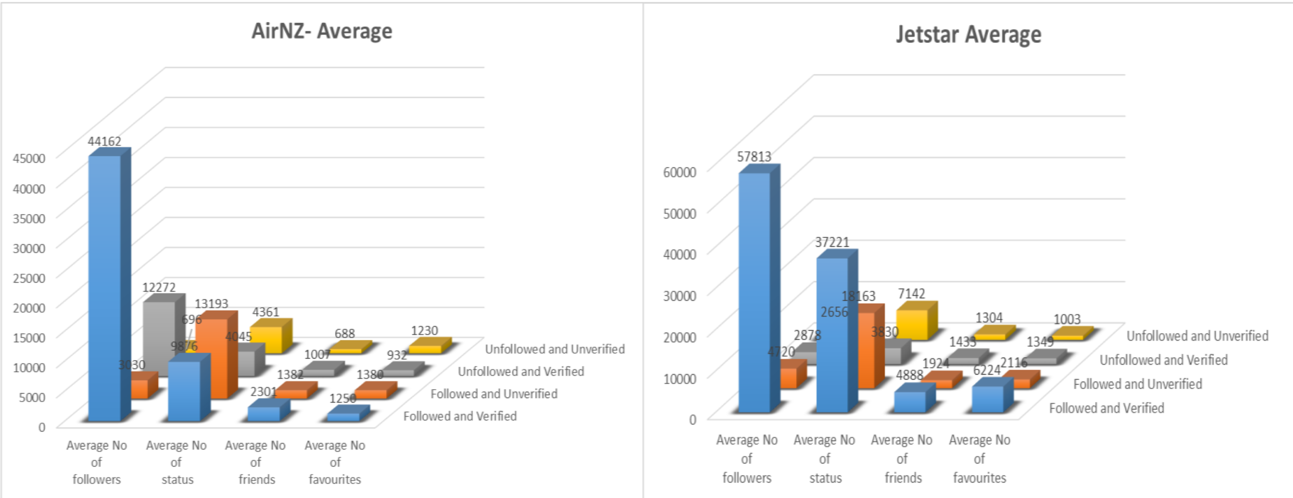

Figure 1. Followers' general stats

Figure 1 shows that firms tend to follow two main groups. First group verified users that their average number of followers is much higher of other ordinary or even other verified users and they might be celebrities or some companies that can be considered in the same industry. The second group are unverified users that the average number of status (posting) is quite high and they can be considered as opinion leaders. But as it expressed previously this argument is just based on the average and within each group there should be diversities in terms of user behaviour. Since a follower which is followed back by company considered important for this study, table 1 provide the basic statistics of the data that is stored in our dataset.

Company	Total number of active followers	Number of active followers who are followed back by company	Percentage of active followers who are followed back by company	Total number of postings in our dataset	Number of post generated by those who followed back	Percentage of the posts which is generated by each users whom are followed back by company
AIRNZ	4196	554	13.20%	19533	5216	26.7%
JETSTAR	539	26	4.82%	1744	94	5.3 %

Table 1. Data set general statistics

3.4 Social Media Data Analysis

Active followers employ different twitter mechanisms such as tweet, comments, hashtag, etc. to create and disseminate the content on fan pages with the firm and other users. For example, some users contribute by creating the new content whereas others may contribute by sharing and disseminating he existing content. A recent study (Shahbaznezhad & Tripathi, 2015) has clustered (see clusters in Table 2) the active followers of AirNZ and Jetstar based on their creative (tweet, hashtag and comments) and following (retweet and favourite) activities. They identified six different clusters for AirNZ and Jetstar and five of those clusters were similar between two companies. We build on that work and analyse the how followers' activities may affect firm's decision to follow them back. The results are reported in Table 2.

		Air New Zealand			Jetstar		
No.	Cluster	Proportion of each cluster among active followers	Percentage of active followers who are followed by AirNZ	Proportion of postings of active followers for each cluster	Proportion of each cluster among active followers	Percentage of active followers who are followed by Jetstar	Proportion of postings of active followers for each cluster
1	Quiet followers	58.3%	46%	24%	24.7%	12%	10%
2	Cheerleaders	0.2%	3%	10%	23.6%	31%	32%
3	Loyal fans	8.0%	0%	4%	5.2%	4%	20%
4	Super loyal fans	31.9%	0%	3%	1.5%	4%	12%
5	Peacocks	0.1%	15%	23%	41.6%	50%	24%
6A	Casual Writers	1.5%	35%	36%	-	-	-
6J	Casual Learner	-	-	-	3.5%	0%	2%
Sum/percentage		100%	100%	100%	100%	100%	100%
Sum/ number		4196	604	19533	539	26	1744

Table 2. Percentage of each cluster population/company followings/postings per each cluster of AIRNZ and Jetstar

Regarding table 2, it is clear that AirNZ prefers to follow Peacocks, Casual Writers and Quiet Followers. This is intuitive because, the users belonging to these clusters, account for more than 80% activities of all active followers of AirNZ. From these statistics, it is clear that AirNZ prefers to follow back very active users. For example, the number of active users clustered as peacocks and casual writers are very small (first column of Table 1) but they are highly active. Last three columns of the Table 2 show results for Jetstar. The argument that firms tend to follow active users (followers on fan page) is weaker for Jetstar because we observe that Jetstar is following users (followers on fan page) from across the board, a bit in a proportionate way. Therefore, one can argue that users' activities don't explain how Jetstar decides to follow back their active users on fan pages and we need further investigation.

Note that, AirNZ is not following back loyal fans and super loyal fans, though their activity is mostly dedicated for company fan page (Shahbaznezhad & Tripathi, 2015). We can conjecture that these active followers are likely be the company employees participating on fan page activities. Prior work (Miller and Tucker (2013) has found that firms' employees are one of the most active users of the firm's social media fan pages and their presence would help recruitment or retention of other users on fan pages.

Results in Table 2 only partially answer our question- how firms choose to follow back their fans? It is intuitive that firms tend to follow active fans but that is only a part of the whole narrative. For example, AirNZ follows Peacocks and Casual Writers which are highly active fans (see Table 2) but AirNZ also follows Quiet Followers who aren't that active compared to other clusters (see Table 2). Similarly, Jetstar follows back Peacocks and Cheerleaders who account for more than 50 percent of activity from active followers. But like AirNZ, Jetstar also follows back Quiet followers who aren't very active compared to other clusters. Further, AirNZ doesn't follow all the users (fans) in Peocock and Casual Writers cluster, which means, one can argue that all active fans are not equal, or in other words, firms only follow some of their active followers (fans), not all of them. To investigate a bit further why firms follow only some of their followers (fans), and how to choose whom to follow, we focus on the content created or disseminated by firms' followers.

To understand the value and relevance of the content created or disseminated by users, it may easier to track individual users over time and analyse the content. However, the majority of the active users tend to have less than four posts/tweets (Figure 2). Figure 2, reports the total count of postings and number of users in each category.

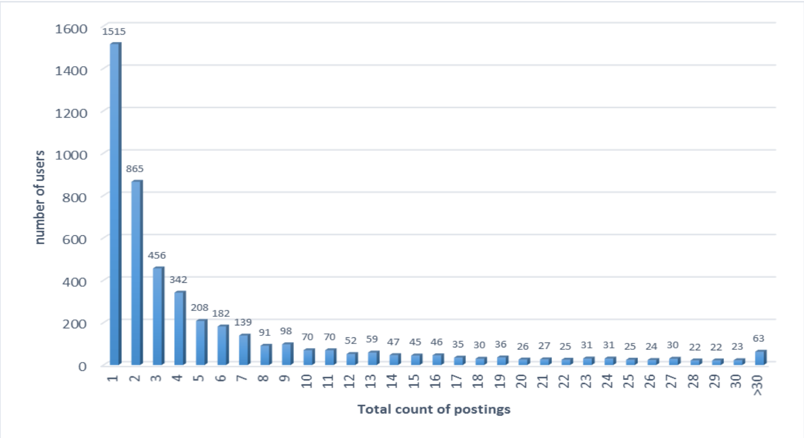

Figure 2. *Postings dissemination*

Since data is very sparse, we recommend content analysis at cluster level. We employed topic modelling algorithm for each clusters to examine the difference across clusters. By comparing these topics we want to explore the dissimilarities in the content created and disseminated by users from different clusters thereby affecting firms' decision of following back their fans. For almost half of the clusters, we further split the clusters based on the users who are followed back by the firm and ones who are not followed back by the firm. Table 3 lists the topics for each cluster. We also did the topic modeling for company postings to compare the topic of different clusters with company postings.

Airline	Followed or not followed by company	Cluster	Most specific Topics
AIRNZ	Followed	Quiet followers	Travel Cost - back to home - dollar/Airpoints/card- wishing to win- pack checking- NZT- safety video- hobbit- social media
		Peacocks	Koru lounge- queen- Dreamliner Boeing- flight time- App- safety video- Airpoints - NZT- AMP
		Casual writers	flight with Boeing - safety video- busy board- world pic- Airpoints- Praising words (awesome- love- amazing-treasure)
	Not followed	Quiet followers	All blacks- safety army- winning- hobbit- flight safety- AMP- Wellington/Queenstown
		Peacocks	Love video- queen- Dragon- Dreamliner Boeing- Great new look- Airnz share me- All Blacks
		Casual writers	Hobbit- safety video – aircraft safety- Taranaki/Queenstown- Airnzshareme(promotion)- love pic- praising words (awesome- amazing)
		Cheerleaders	Safety video- All blacks- Dreamliner Boeing- Queen- Social media- Auckland/Wellington/Los Anjeles- Koru Style- flight time
		Loyal fans	Great crew/great services- hiring/dream jobs- Social media/photo- hobbit video- first Boeing delivery-Queensland/Auckland/Wellington/home/land- All blacks- One news- Mount Maunganui – NZ Herald - Love proud thank

		Super loyal fans	Service info- holiday/flashback Friday-airline service- sunrise window seat- view Taranaki- Airnzsharеme- Airnzfairy - Auckland airport- Los Angeles- Wellington- island-southern world alps
		Company Postings	Hobbit- safety video- sorry for services- look to hear- pass detail to team- call/email-thanks for tweet- thanks for time- congrats for win- new address- rugby team will win
Jetstar	Followed	Quiet followers	Cheap- price- changing flight schedule- booking- travel board bags- claim about services and seating- staying in long queue- interaction with flight board- inflight interest- traveling to Houston as long journey
		Peacocks	Support kids- alert for ash movement in Bali- amazing deal- comfort booking- final hottest game for All Blacks (New Zealand rugby national team)- ideal for family- booking a custom date- Dreamliner rout- Some new flights destinations like Darwin - some amazing entertainment like AJ Hackett Bungy or New Zealand ski resort like Coronet Peak
		Cheerleaders	Baggage cracking- a new look of Jetstar airplane as birds-eye view- betting in Jetstar lottery- asking for checking fee- amazing rout and travel- Merlion statue in Singapore – appreciation for services
	Not Followed	Peacocks	Custom services- appreciation for changing flight- hot sale- airbus birthday- Dreamliner first Boeing – Booking- flyer/phone- hope to not working now for using the offer-appreciation for not charging- some destinations like gold coast, Sydney and Melbourne
		Quiet followers	Domestic airport issues- carrying baggage- charging more for Dreamliner- appreciation for services and crew- great deal- showing interest for booking flights- wasting time for checking- customize service for bags- cheap flight- amp compensation
		Cheerleaders	Delay time- praising services- free flight- love Dreamliner- bag checking- changing flight- new fee- Qantas airways- Virgin Australia- Sydney- Melbourne
		Casual learners	Anita resort as a new destination- Boeing beauty body- showing happiness about having experience about company- first Boeing has new smell- Gold coast- cyclone in Melbourne Australia- watching parcels- alert for volcano activity and ash in Bali- expect for cancelling and restoring- airport terminals and domestic maps
		Loyal Fans	Good news for fare- Qantas airways/Virgin Australia- promotion and win the voucher-long customs service- promoting Bali and Melbourne- booking process and time amendment, check-in
		Super loyal fans	Mostly promoting some destinations such as Melbourne, Sydney, Queenstown, Rockhampton, Fukuoka, Mackay, Brisbane, Hamilton island- Entertainment: Facebook, sports bet, - introducing new payment method as Polipay
		Company Postings	Sorry to hear-thanks for feedback- custom check delay- low fare- sale- book flights-great services-sorry can't change booking

Table 3. Clusters and topics

The topic modelling provides a different perspective on firms' choice of fans to follow back. AirNZ, which is a full service airline, appears to follow fans who are creating and disseminating a wide range of content, from services (current and upcoming routes and planes, rewards), safety (AirNZ famous safety video[7], Hobbit video[8]) to overall flying experience. This content appears more like product evaluation, which can help AirNZ to improve their services. Further, one can argue that AirNZ seems to follow fans whose content can attract and entice a wide range of prospective customers than a narrow niche within Australasia region. This reflects on firms' desire to expand their market through social media platforms. Since AirNZ's own promotional campaigns using safety video[9] and Hobbit vid-

[7] http://www.airnewzealand.co.nz/press-release-2015-airnz-men-in-black-safety-defenders-video

[8] http://www.airnewzealand.co.nz/press-release-2014-airnzs-epic-safety-video-the-most-popular-yet

[9] http://time.com/3995293/men-in-black-airnewzealand-in-flight-safety-video/

eo[10], are very successful, firm doesn't get much value by following fans only focusing on these promotional campaigns. It appears that firms consider users' activity and the content they post or share in deciding whether to follow back or not.

Contrary to AirNZ, Jetstar is a budget airline, and competes on prices. Jetstar seem to follow fans focusing on operational issues, such as prices, services and flight information. Since they aim to provide good services at lower prices, they prefer to hear about operational issues from their fans. Though Table 3 provides some insights about firms' choices of following back their fans, but it still doesn't provide a complete picture. For example, we observe clusters that may focus on similar content, but all of them are not followed back by the firm. To further investigate firms' choices of following back their fans, we perform a sentiment analysis of users' content. As we argued earlier, we do sentiment analysis at cluster level and report results in Tables 4.

Sentiment /cluster	Quiet Followers followed	Quiet Followers Not followed	Peacocks-Followed	Peacocks-Not followed	Casual writers-followed	Casual Writers-not followed	Loyal fans Not followed	Super loyal fans Not followed	Cheerleaders Not followed
AIRNZ									
Positive	61	438	131	435	174	806	136	127	292
Neutral	379	3241	980	2504	1037	4206	640	374	1467
Negative	32	127	88	82	59	180	3	4	62
Total number of postings in this Cluster	472	3806	1199	3021	1270	5192	779	505	1821
Positiveness	12.92%	8.20%	3.60%	11.70%	9.10%	12.10%	17.10%	24.40%	12.60%
Negativeness	6.78%	3.34%	7.34%	2.71%	4.65%	3.47%	0.39%	0.79%	3.40%
Total sentiment	6.14%	4.86%	-3.74%	8.99%	4.45%	8.63%	16.71%	23.61%	9.20%
Jetstar									
Positive	1	22	3	42	4	64	34	42	5
Neutral	7	127	16	304	26	389	279	169	19
Negative	3	21	4	47	4	66	37	Table	3
Total number of postings in this Cluster	11	170	23	393	34	519	350	217	27
Positiveness	9.1%	12.9%	13.0%	10.7%	11.8%	12.3%	9.7%	19.4%	18.5%
Negativeness	27.3%	12.4%	17.4%	12.0%	11.8%	12.7%	10.6%	2.8%	11.1%
Total sentiment	-18.2%	0.6%	-4.3%	-1.3%	0.0%	-0.4%	-0.9%	16.6%	7.4%

Table 4. Airnz and Jetstar different clusters sentiment

Table 5 reports the sentiments of the postings of both companies. Positiveness is the percentage of positive posts to the total number of posts and negativeness is the percentage of negative posts to the total number of posts. Total sentiment is the net of positive and negative posts. Sentiment analysis reveals that most of the posts are neutral instead of positive or negative (Table 5). This shows that, in general, fans are less likely to complain on social media platforms. This holds true for both AirNZ and Jetstar. Further, the sentiment analysis shows that firms tend to follow clusters with higher negative sentiments. This appears to be true for both AirNZ and Jetstar. For example, in Table 5, Quiet Followers who are followed by AirNZ, have a higher negative sentiment (6.78%) compared to Quiet Follow-

[10] http://www.nzherald.co.nz/business/news/article.cfm?c_id=3&objectid=11448216

ers who aren't followed back from AirNZ. This is an interesting finding that firms are using social media platforms to listen to customer complaints and negative experience to help them improve their offerings.
As we see from Table 3, Jetstar fans are focussed on operational issues instead of social media fancy topics. It is possible because these users couldn't see any special serendipity that is generated by the company on its fan page. Because of cheap and accessible services of Jetstar, users are likely to focus on operational issues. Table 5 shows that total negative and positive sentiment is higher for Jetstar compared to AirNZ. It appears that followers of Jetstar are more polarized than followers of AirNZ. We argue that this polarity is due to Jetstar's fan page management strategy. Jetstar is a budget airline, which tries to minimise the overhead costs and doesn't create much promotional and fancy videos that can provide serendipity for users compared to AirNZ. Therefore, users mostly concentrate on service or operational issues/problems. This might bring a high level of polarity because users often have different opinions (positive or negative) about the same service. AirNZ social media team provides lots of fancy social media content and users are less likely to have split opinion about that content, therefore less polarization.

SENTIMENT/CLUSTER	AIRNZ	JETSTAR
Positive	1143	1926
Neutral	9029	11515
Negative	731	1944
Total number of messages in this Cluster	10903	15385
Positiveness	10.48%	12.52%
Negativeness	6.70%	12.64%
Total sentiment	3.78%	-0.12%

Table 5. AirNZ and Jetstar postings sentiments

The total sentiment of the postings of AirNZ is more positive than the total sentiment of Jetstar. It is possible because Jetstar followers complain more on fan page and Jetstar says "sorry" (Table 3) more often than AirNZ, so, the sentiment analysis algorithm considers that as a negative sentiment.

4 Discussion and Conclusion

Fan pages on social media platforms are becoming an important part of firms' social media strategy. These fan pages also serve as a tool for customer relationship management. Firms are becoming strategic in how they manage their fan pages on social media platforms and decide whom to follow back among their fan page followers. In this study we investigated if users' activities, topic of the content and sentiments of their contents have any effect on firms' decision to follow them back. We used there different approaches to examine how firms select followers to follow them back. We discuss results obtained from three different methods- clustering users based on their activities, topic modelling and sentiment analysis of each cluster of users. We employed Latent Dirichlet Allocation (LDA) to analyse to the tweets of two airlines to identify recurrent topics in the collection. Our results demonstrate that by relying on new quantitative analytical methods to structure, analyse and manage the content, companies can get a better insight of the user behaviour in fan pages and consequently can codify an appropriate strategy. One of the limitation of this study is that dataset used is a snapshot of the user activities. Since users learn by participating on these fan pages, their behaviour changes over time. Therefore, a longitudinal data of user behaviour and activities would help understand the firms' strategies and evolving behaviour. We aim to continue data collection for active followers over a period of time. Also this study is performed for two airlines in Australasia region. Implementing the same method for more diverse industries and higher number of firms would strengthen the results. Our results show that firms don't follow all their active followers, nature of the content and sentiments of the contents also play significant role in selecting users who are followed back by the firms.

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