SUPERCARS FANS ON TWITTER

What are They Talking About?

Group 6

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Introduction

This project experimented with a dataset related to the Supercar events, which included live tweets and live television viewership ratings. There are two main goals of this Machine Learning (ML) project. First, to investigate the different topics remarks, and sentiments that happen during Supercar events by exploring electronic word-of-mouth (e-WOM) live tweets data. e-WOM is defined as "the exchange of consumption experiences among consumers" (Borgida & Nisbett, 1977, cited in Choi, 2020). Secondly, this project aims to examine the impact of the Second Screen Phenomenon by exploring the impact of live tweets on TV viewership data. Three main ML techniques are used to inspect these two goals: topic modelling, sentiment analysis, and regression analysis.

Problem Definition

The context of this project is the Supercar Championship. There is now a growing trend among Fans of The Supercar Championship to embrace the second screen phenomenon. The second screen phenomenon refers to the simultaneous consumption of two different devices that are used to express opinions and share relevant information (de Meulenaere, Bleumers, & van de Broeck, 2015) online while watching the Supercar Championship broadcasts. This project investigates Supercars fans' online behaviour through Twitter data and its impact on TV viewership. The questions that are explored for this project are listed below:

- Q1: What is the most popular topic for each event?
- Q2: Is there any correlation between sentiment score and popularity of each game?
- Q3: How do eWOM communications impact TV rating and online engagements
 - Q3(1): How do eWOM communications impact TV viewers in different locations?
 - Q3(2): How do eWOM communications impact online engagements on different race weekends?

Other potential questions can be answered by the dataset, such as how the variation in sentiment influences TV viewership, whether there are any events when Supercar's fans are most engaged,

and others. However, due to time limitations, it was decided that it was best to explore the four main questions listed above.

Q1: What is the most popular topic for each event?

It is practical to start by investigating the overall Topic Modeling result. Some preprocessing is required. In addition to the English vocabulary stop words, some words in raw materials may not help determine the topics. For instance, the website keywords like "HTTP" and the Twitter keywords like "t" and "rt" do not make any sense in any sentences. Besides, some common words do not refer to a specific topic but appear quite frequently, like "v8sc" and "v8supercars". After that, further analysis requires lowering the characters, tokenizing the texts, and lemmatizing the tokens.

It is then proper to apply the Latent Dirichlet Allocation (Figure 1) on all the tokens and select the top topics. Locations appear quite frequently, also the competitions and racers' names. This model includes all texts, i.e., tweet texts from all 14 events.

	Overall Topic Heatmap													
Topic 1	sydnrma	racing	morning	herald	rain	syd	amp	melbourne	tasbranded	idr				
	8.1	7.3	3.2	1.4	0.8	0.3	0.2	0.2	0.2	0.1				
Topic 2	tonight 13.2	movie 12.0												
Topic 3	jamiewhincup	race	syd	baronvonclutch	new	redbullracingau	safety	car	racing	herald				
	7.4	6.2	5.8	3.9	3.5	3.4	3.2	3.2	2.9	2.7				
Topic 4	idr	bag	free	bahan	fashion	tasmurah	tasbranded	rain	untuk	ransel				
	8.7	7.7	5.6	4.6	4.1	4.0	3.9	3.8	3.6	3.5				
Topic 5	winston	realestate	listing	realtor	check	tour	free	join	kjffbmf	creative				
	26.9	13.2	11.8	5.6	5.4	4.3	3.6	3.6	3.6	3.6				
Topic 6	australia	job	salem	winston	itjob	alert	view	new	tasmurah	racing				
	12.9	10.0	5.5	5.4	4.1	4.1	4.1	0.3	0.2	0.1				
Topic 7	dog	amp	team	check	day	marcosambrose	winston	melbourne	race	stereosonic				
	5.2	5.1	3.5	2.4	2.2	2.2	1.0	0.2	0.2	0.2				
Topic 8	vkohliadmirer	thatviratadorer	deepthisgt	kohlateral	imzakali	yuganticool	imvkohli	fashion	tonight	job				
	3.4	3.4	3.4	3.4	3.4	3.4	3.4	0.2	0.2	0.2				
Topic 9	smclaughlin	marcosambrose	love	listing	realestate	kjffbmf	join	creative	new	free				
	7.8	6.8	4.8	0.2	0.2	0.1	0.1	0.1	0.1	0.1				
Topic 10	stereosonic	amp	day	melbourne	amazing	showtekmusic	doin	sonnywilsonnl	round	vassy				
	49.7	48.9	40.0	25.2	23.3	22.7	21.4	21.4	21.4	16.1				
	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10				

Figure 1

The topic mapping could help identify the inter-topic distance based on the LDA model. As is shown in the figure, there are no significant intersections between any pairs of topics given two principal components as scalers. The mapping also shows the word frequency in a subset compared to the entire set. For example, topic nine (Figure 2) included 10.3% of tokens overall. The word

"Morris," i.e., Paul Morris the racer, appears most frequently. In addition, almost all the appearance of the word "Morris" goes to this topic.

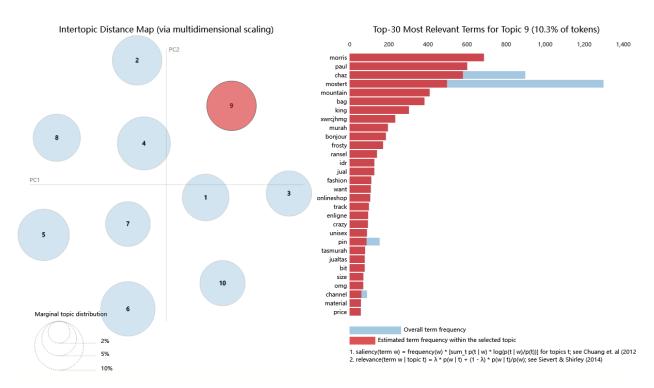


Figure 2

After that, a word cloud (Figure 3) helps visualize the word frequencies. There are several kinds of words that look similar. It is then natural to categorize these frequent words into groups. For example, there are names of racers, like "Paul Morris"; words that are closely related to some specific events, like "mountains"; and some words and phrases that are closely related to racing, like "race," "final lap," and "safety car."



Figure 3

Now that the question is about the topics for each event, further research requires dividing the raw materials into 14 subsets according to their corresponding events and repeating the previous process on each set. The results include the top ten topics for each event and their mapping.

After that, the results with the top ten topics in each event, see Appendix Figure 1, indicate some preliminary findings on these topics. For instance, there are some common topics shared between events. Each of these events has at least one topic that a racer's name appears most frequently. Some unique topics appear only in specific events. Most importantly, there is a topic similarity among these events. For example, when a racer's name appears in a topic, it is highly likely to be one of the most frequent words on this topic.

Recommendation

Based on the findings above, we have come up with two recommendations. First, the promotion campaigns in the future shall focus on racers since racers are the most popular amongst all components in each topic. Also, it seems that customized promotions can be helpful for each event based on unique topics since the tweets of these events do not always focus on the same point.

Q2: Is there any correlation between sentiment score and popularity of each game?

In this section, we measure each game's popularity by the number of tweets and viewers during each game. Additionally, we also investigated supporters' sentiments. Since viewers may support different teams and racers, it was hypothesized that they might have different sentiments about the same result.

Simply averaging the sentiment scores of different viewers would give a result close to zero, ignoring the intensity of different viewer sentiments. Therefore, the absolute value is considered a more accurate evaluation of the overall sentiment intensity of the audience.

First, we will use the sentiment analyzer to analyze the sentiment score of each tweet. The compound score ranges from -1 to 1, where -1 is entirely negative, 0 is neutral, and 1 is entirely positive. The absolute value, on the other hand, regardless of positive or negative, only measures the intensity of the sentiment.

Considering that the popularity of each game varies greatly, for example, event 11 was very popular. Over 13,000 tweets had over 9,000 tweets during event 11, and the 70,000+ viewers also accounted for a significant proportion of the 200,000+ viewers. So, we implemented a pivot table like function in python to group all the tweets by event and calculate the total number of tweets during each game, the average of the two Sentiment Scores, and the total number of viewers for each game. Finally, the two data frames are merged to facilitate the extraction of variables later.

Finally, the correlation function is used to find the correlation index (Figure 4) of the different variables.

	number_of_tweet	number_of_tv_viewer	senti_ab_mean	senti_mean
number_of_tweet	1.000000	0.968909	0.721953	0.280913
number_of_tv_viewer	0.968909	1.000000	0.786485	0.404227
senti_ab_mean	0.721953	0.786485	1.000000	0.584623
senti_mean	0.280913	0.404227	0.584623	1.000000

Figure 4

As the table shows, the number of tv viewers showed a high positive correlation with the number of tweets. Sentiment score also shows a positive correlation with these two variables.

The absolute value of the sentiment score, on the other hand, has a higher correlation than the sentiment score itself, somehow indicating that putting aside the positive and negative aspects of emotions, people show stronger emotions in the popular games.

Hence, we can reach a conclusion that, during the more popular event, people get into higher engagement and contribute to higher sentiment scores (evaluated by absolute value).

Recommendation

The primary revenue of a sporting event comes from broadcasting rights, sponsorship and tickets, and Supercar is known to generate revenue from sponsorship, tickets, and media rights. Therefore, we focus on increasing its TV rating by raising the Sentiment Score or, in other words, e-WOM to raise the price of media rights and sponsorship to increase revenue (Cadario, 2015).

Our recommendations are provided below:

- Evaluation in advance could be done to predict which event could be a big hit. They can seize the opportunity to enhance their brand image and commercial value and use their marketing resources more effectively.
- Before the event, which is predicted to be a big hit, prepare more event-relevant official content for social media in advance to improve users' engagement to make the event series a hot topic on social media to improve tv ratings for following events.
- Run a profitable marketing campaign on social media during the popular event. For example, social media challenges that might go viral and reach a wider audience. This can be used as an opportunity to attract high-quality sponsors and raise advertising income.

Q3: How do eWOM communications impact TV viewers and online engagements?

Recent developments have shifted audiences into active media consumption participants (Segijn, et al., 2020). As a result, audiences integrate an additional second screen to engage in social conversations and access real-time information to enhance their experience. Twitter is one of the platforms that is often used for this purpose (Voorveld, van Noort, Muntinga and Bronner, 2018, as cited in Segijn, et al., 2020).

In this section, we aim to delve into the effect of these live tweets on TV ratings in various cities in Australia: Sydney, Brisbane, Melbourne, Adelaide, Tasmania, and Perth. This variable was transformed into dummy variables with Adelaide as the base case. Furthermore, this project also investigates how eWOM communication influences online engagement (i.e., total likes, comments, and retweets) on other race weekends. This variable was also transformed into dummy variables where weekday 5 is set as the base case.

The dataset contains information from a merged dataset that combines live tweets data and TV rating data during each Supercar event throughout the year.

Q3(1): How does eWOM communications impact TV viewers in different locations?

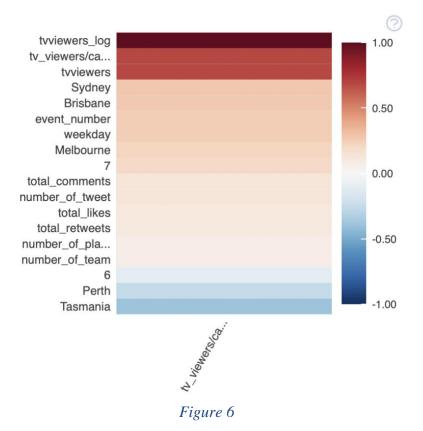
In this section, the goal is to identify whether different locations (i.e., Australian cities) influence the impact of eWOM communications for TV viewers. The table (Figure 5) below summarizes the independent variables in relation to each city. Each city is represented somewhat equally, except for Tasmania.

		city	tvviewers	number_of_player	number_of_team	total_retweets	total_likes	total_comments
	city							
4	Adelaide	469	16263	385.0	56.0	1159.0	2043.0	409.0
E	Brisbane	467	47413	388.0	56.0	1157.0	2027.0	406.0
M	elbourne	471	46599	386.0	56.0	1159.0	2049.0	409.0
	Perth	476	14083	387.0	56.0	1177.0	2079.0	411.0
	Sydney	473	53420	387.0	56.0	1166.0	2050.0	412.0
Т	asmania	375	7470	353.0	52.0	920.0	1847.0	381.0

Figure 5

Furthermore, the cities that are included in the model (i.e., Adelaide, Brisbane, Melbourne, Perth, Sydney, and Tasmania) have different population sizes. As such, to control for this, we introduce a new variable that is tv_viewers/capita, which comes from the division of total tv viewers divided by the total population of each city in 2014 from the Australian Bureau of Statistics (Australian Bureau of Statistics [ABS], 2016) to match the Twitter data period.

In exploring the effects of e-WOM communications in different cities, first, a Pearson correlation matrix (Figure 6) was generated to see the relationship between the variables in the merged dataset and the target variable: log-transformed TV viewers/capita.



The matrix indicates that e-WOM in Sydney, Brisbane, and Melbourne are positively correlated with viewership while those in Perth and Tasmania are negatively correlated. The OLS regression model is written as:

```
Log(TV\ Viewers/Capita) = -13.02 + 0.01\ Number\ of\ Tweet\ -0.05\ Number\ of\ Players + 1.12 Brisbane + 0.98\ Melbourne - 0.22\ Perth + 1.14 Sydney - 0.78\ Tasmania + 0.06\ Number\ of\ Comments
```

Based on the result, we can interpret that eWOM communications in Brisbane, Melbourne, and Sydney are more likely to generate TV viewership than Adelaide. On the other hand, eWOM communications in Perth and Tasmania are more likely to reduce TV viewership compared to Adelaide.

Shifting the focus to e-WOM communications variables, it seems that tweets that contain mention of players negatively impact tv viewership. But, engaging tweets, those with comments, have 6% more odds of increasing tv viewership compared to those with no words. Other measures of

engagement for e-WOM which are *total_likes* and *total_retweets* are not significant for the regression model with p-values 0.243 and 0.072 respectively.

The OLS regression model output (Figure 7) is provided below:

OLS Regression Results											
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	L	s/capita_log OLS east Squares 26 May 2022 12:06:15 2732 2719 nonrobus	0.401 0.399 165.7 5.40e-293 -3608.0 7240. 7311.								
	coef	std err	t	P> t	[0.025	0.975]					
const number_of_tweet number_of_player number_of_team Brisbane Melbourne Perth Sydney Tasmania total_likes total_comments	-13.0258 0.0144 -0.0603 0.0127 1.1172 0.9799 -0.2242 1.1313 -0.7659 0.0031 -0.0098 0.0554	0.046 0.003 0.014 0.037 0.059 0.059 0.059 0.063 0.003 0.005 0.015	-280.913 4.900 -4.196 0.347 18.804 16.528 -3.791 19.102 -12.159 1.167 -1.798 3.822	0.000 0.000 0.000 0.729 0.000 0.000 0.000 0.000 0.243 0.072 0.000	-13.117 0.009 -0.088 -0.059 1.001 0.864 -0.340 1.015 -0.889 -0.002 -0.020 0.027	-12.935 0.020 -0.032 0.085 1.234 1.096 -0.108 1.247 -0.642 0.008 0.001 0.084					
Omnibus: Prob(Omnibus): Skew: Kurtosis:		3129.348 0.000 -5.615 73.992	Durbin-Wats Jarque-Bera Prob(JB): Cond. No.		587838	.668 .507 0.00 133.					

Figure 7

Recommendation

In light of this, we came up with some recommendations:

Maintain engagement with Supercars fans by replying/commenting on their tweets. E-WOM communications are often used to express opinions and share relevant information (de Meulenaere, Bleumers, & van de Broeck, 2015). By replying to fans' tweets from the

Supercars official account, Supercar can leverage the persuasive and informative effects (Bae & Hye-Jin, 2020) of e-WOM communications to increase TV viewership. For example, by replying to the fans' tweets, Supercar can persuade fans to watch the next event's live broadcast when they posted a tweet that shows disappointment that their team was losing in the previous event.

• Seeing that Perth and Tasmania have a negative correlation to TV viewership, we recommend that Supercar place more attention on broadcasts in those areas. They can also increase fans' participation by promoting the supercar e-series, the virtual racing competition to offer different types of content for the fans (Colter, 2020).

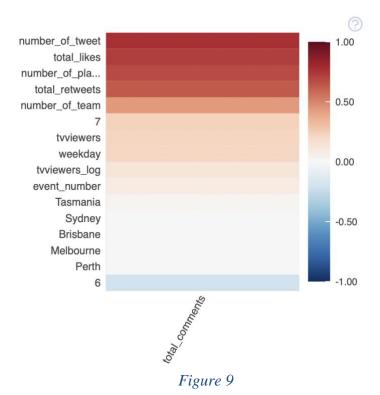
Q3(2): How does eWOM communications impact online engagements on different race weekends?

In this section, total comments were chosen as the online engagement variable due to two reasons. Firstly, upon regressing the independent variables to tv viewership, the number of comments was a significant variable. As we wanted to maintain the connection between tv viewership and e-WOM communications, total comments were chosen as the target variable. Secondly, from our experiment, we found that using total comments as the dependent variable, the regression model had a higher R-Squared score (Figure 8).

Variable	R-Squared Score
total_likes	0.533
total_retweets	0.535
total_comments	0.657

Figure 8

In exploring the effects of eWOM communications to online engagements on different race weekends, Pearson correlation matrix (Figure 9) was generated to see the relationship between the variables in the merged dataset and the target variable: *total_comments*.



The matrix indicates that tweets that contain mention of players are positively correlated with total comments, but tweets that contain mention of the team have a negative correlation on total comments. This might be because fans are more attached to players rather than teams, and as such,

The OLS regression model is written as:

tweets that contain teams do not interest them as much.

```
Total\ Comments = -0.48 + 0.07\ Number\ of\ Tweets + 0.16\ Number\ of\ Players - 0.32\ Number\ of\ Teams + 0.21\ weekday\ 6 + 0.28\ weekday\ 7 + 0.02\ Total\ Retweets + 0.05\ Total\ Likes
```

Based on this, it seems that tweets on weekday 6 and 7, on average, are associated with an increase in total comments compared to weekday 5. Holding all the other variables constant, tweets in

weekday 7 are associated with a 28% increase, on average, for total comments. Furthermore, tweets in weekday 6 are associated with a 21% increase, on average, for total comments.

The OLS regression output (Figure 10) is provided below:

OLS Regression Results

Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Leas Thu, 26	_comments	R-squared: Adj. R-squar F-statistic: Prob (F-stat Log-Likeliho AIC: BIC:	tistic):	0.657 0.656 745.2 0.00 -4367.2 8750. 8798.		
	coef	std err	t	P> t	[0.025	0	
const number_of_tweet number_of_player number_of_team 6 7 total_retweets total_likes	-0.4828 0.0689 0.1560 -0.3177 0.2081 0.2813 0.0160 0.0528	0.091 0.004 0.019 0.048 0.095 0.096 0.007 0.003	-5.300 18.673 8.269 -6.601 2.196 2.942 2.223 15.627	0.000 0.000 0.000 0.000 0.028 0.003 0.026 0.000	-0.661 0.062 0.119 -0.412 0.022 0.094 0.002 0.046	-(((((
Omnibus: Prob(Omnibus): Skew: Kurtosis:		1088.164 0.000 1.592 12.428	Durbin-Watso Jarque-Bera Prob(JB): Cond. No.	2.154 11267.234 0.00 142.			

Figure 10

Recommendation

Based on this result, we recommend that Supercars focus on two things on their Twitter account.

- Post live updates on the official account that mention players to promote online engagements.
- Facilitate online discussion on weekdays 6 and 7 to enhance the fans' sense of belonging with the event (Kasavana et al., 2020, Torres, 2017, as cited in Kharouf, et al., 2020).

These two strategies are advised so that Supercar official account can generate higher online engagement by creating posts with content that might interest Supercars' fans more, that is, tweets that mention players such as Paul Morris or Jamie Whincup. By leveraging their support for their favourite racers, fans are more likely to participate in online discussions. As such, Supercars' can maintain consumer engagement with the championship and build "long-term, sustainable customer relationships" (Noh, et al., 2020).

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Appendix

Figure 1: Topic Heatmaps for Each Event

dec	Topic Heatmap for Event 1							Topic Heatmap for Event 2					fol to found							
Topic 1 - clay 25.9	15.5	weekend 10.6	soundwavefest 9.4	8.7	going 8.6	8.5				Topic	photo 4.3	0.8	0.2	pin 0.2	male 0.2	font 0.2	branded 0.2	fish 0.2	0.2	female 0.2 lens 0.2
Topic 2 - race 46.2	22.3	16.3	15.5	14.4	walsh 12.6	podium 12.0	polestar 9.9	polestarrace 9.9		Topic	6.1					nice 3.5	mickyo 3.2	saturday 2.8	for 1.5	0.2
Topic 3 amp 25.7	brunomars 18.1	10.6	naked 8.8		great m	oonshinejunglet 7.0	our cabaret 6.1	5.7	lola 5.4	Topic	winston 10.8	4.3			Iap 2.2 sebiecus	heading 1.6	need 1.6	miss 0.2	ciaa 0.2	taking 0.2
Topic 4 love 16.0		yeah 5.5	smclaughlin 5.3	seeing 4.6	grmotorsport 2.4	weekend 1.8	redbullracingau 1.6	1.0	1.0	Topic	race 9.1	just 7.0	smclaughlin 6.4	volvo 5.7	whincup 5.6	day 5.0	4.2	year 4.1	great 3.9	3.7
Topic 5 - today 16.9	amazing 16.2									Topic	great 0.2	unisex 0.2								lens 0.2
Topic 6 13.5	13.0	idr 10.9	10.9	jamiewhincup 10.4	qualifying 10.0	official 9.2	dog 8.7	final 8.6	material 7.7	Topic	start 5.7		1.6	fan 1.3	Just 0.2	need 0.2	amp 0.2	photo 0.2	import 0.2	australian 0.2
Topic 7 Minston 61.9	52.3	que 37.7	hay 27.6	por 26.7	llora 26.6	paredes 25.8	rayado 25.8	muerte 25.8	lloran 25.8	Topic	19.1	bonjour 17.0	branded 10.6	unisex 8.6	ransel 8.6	female 8.6	enligne 8.6	male 8.6	anlineshop 8.6	tonight 5.0
Topic 8 26.4	murah 16.9									Topic	year 0.2	branded 0.2	tonight 0.2	jelly 0.2	0.2	import 0.2	ciaa 0.2	alterbridge 0.2	themes 0.2	male 0.2
Topic 9 mclaughlin 19.5	del 16.2									Topic	lens 7.0	eye 5.7	murah 4.9	dompet 4.9	font 3.6	amp 3.6	jual 3.6	jelly 3.6	themes 3.6	fish 3.6
Topic 10 art 9.8	photo 9.5	cat 9.0	aigner 8.9	man 8.8	free 8.4	concert 8.1	best 7.4	harga 7.3	108 7.0 Word 10	Tapic 1	Ciaa 22.5	amp 15.4	winston 12.7	miss 12.7	congrats 11.4	powergirisno 11.3	oakes 11.3	crown 11.3	vanity 11.3	heading 11.3
Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Ward 9	Word 10		Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
				Topic Heatma	ap for Event 3											ap for Event 4				
Topic 1 - Winton 29.6	10.0		amp 7.9						team 4.2 cuenta 0.2	Topic	***	bio 21.0	cek 21.0	minat 21.0	jualtas 21.0	murah 18.1	winston 15.1	tasbagus 14.7	jualantasmurah 14.7	fashion 12.0
Tepic 2 2.8	winston 0.2	todo 0.2	vallenilla 0.2	supuesto 0.2	agresi 0.2	veusnoticias 0.2	testigo 0.2	edmomsiklz 0.2		Topic	groovinthemoo 11.4	10.3								5.7
Topic 3 12.7						colour 10.9				Topic	branded 35.8	pin 33.5	harga 30.6	saudara 30.6	kandung 30.6	lokasi 30.6	alambatam 30.6			aca 30.6
Topic 4 today 7.3	great 6.4	road 4.9	melbourne 4.1	2.6	mercedes 1.8	sepaket 0.2	taswanita 0.2	docmart 0.2	totebag 0.2	Topic	ibm 23.6	fun 17.1	race 14.9	jinxaxelstar 14.5	mic 14.5	nightlife 14.5	vriowzły 13.6	bandatsunset 12.4		teamdir 8.4
Topic 5 wireston 81.1	vallenilla 30.4	cuenta 29.5	testigo 29.5	agresi 29.5	todo 29.5	supuesto 29.5	edmornslklz 25.2	veusnoticias 22.0		Topic	australia 16.8									thing 6.2
Topic 6 ransel 18.0	bonjour 15.6	bag 14.6	male 9.0	unisex 7.9						Topic	hypetour 20.0	ready 16.7	justicecrew 15.9	entertainment 12.2	centre 12.2			ouzhig 9.7		tasmurah 6.0
Tepic 7 - totebag 37.2	taswanita 37.2	sepaket 36.4	sepatu 33.1	docmart 31.4						Topic	sepaket 12.3	taswanita 12.3	totebag 12.3	docmart 12.0			sepatuwanita 6.9	cool 5.0	anzacday 4.5	3.6
Topic 8 cumberbatci 6.2										Topic	johnirpearce 17.7	hypetour i 16.4	officialjalwaetford 13.3	let 13.3	selfie 13.3	crazy 13.3	zfoy 12.5	22.5		ijasonbright 7.2
Topakc 9 - info 6.6								5.0 branded 2.5		Topic	bag 17.6	bonjour 14.7								ransel 7.3
Topic 10 ozcomiccon 30.6	benedictcumberb 15.6	atchrumberbatch 7.3	furla 6.0	sherlocksbees 5.9	photo 5.9	hermes 5.2	import 3.3	branded 2.5	best 2.4	Topic 10	dog 24.2	maika 18.2	17.2	14.9	lost 14.4	amp 13.6	sms 11.7	handmade 11.4	park 9.9	adelaidedogs 9.7
Word 1	Ward 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Wand 9	World 10		World 1	World 2	Word 3	Word 4	World 5	World 6	Word 7	Word II	Word 9	Word 10
				Topic Heatma	ap for Event 5										Topic Heatma	p for Event 6				
Tepic 1 winston 33.7	lave 4.2									Topic	\$150 4.7		little 13	love 0.2	winston 0.2	lens 0.2	magnetic 0.1	traumatic 0.1	eye 0.1	dompet 0.1
Topic 2 dog 6.4										Topic :	win 7.9		whatsoninad 6.0	family 5.3	5.3	5.3	just 4.0			3.4
Topic 8 Hdr 5.4	marchinmay 4.8					great 0.2				Topic	bag 61		order 1.9	bandung 1.5	dog 1.5	lost 0.2	pin 0.2	ready 0.1	lewis 0.1	milestone 0.1
Topic 4 bog 12.1	branded 3.5									Topic	14.3									ready 3.2
Topic 5 - perth 21.1	smclaughlin 7.5						adifoodcentral 0.2			Topic	winston 31.1	good 14.9	lost 14.8	money 14.3		vipsaccess 4.0	marthasvineyar 4.2			hotel 3.2 practice 0.1
Topic 6 food 8.8										Topic	today 14.2	holden 13.0	race 6.4					weather 0.1		practice 0.1
Topic 7 . Rish 5.5										Topic	lens 12.5	amp 7.6	dompet 7.6	murah 7.5	pin 7.5		info 6.3			themes 6.3
Topic 8 day 6.2										Topic	8mp 0.2	love 0.2	retweet 0.2		528 0.1	indonesia 0.1	whatsoninad 0.1	good 0.1	win 0.3	tweet 0.1
Tepic 9 - 3afood 6.5	food 4.2									Topic	peter 6.7									mortin 4.0
Topic 10 para 4,8	murah 0.3									Topic 1	australia 6.6									kamera 3.4
Word 1	Ward 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Ward 9	Word 10		Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
				Topic Heatma	ap for Event 7										Topic Heatma	ap for Event 8				
Rok 1 olamide 14.5	phyno 13.2	better 8.8	naijablogger 8.4	trendsetter 8.4	language 7.3	indigenous 7.3	19p 7.3			Topic	winston 0.2									asylum 0.2
Topic 2 - guy 5.7	nextontem 5.1	dir 5.1		sell 0.9					0.2 architecture 0.2	Topic	sdcc 0.2									missing 0.2
Topic 3 - adlarchigran 12.2	sachapter 12.2	saaawards 12.2	southaustralia 12.1	holden 10.1	architecture 9.8	racing 9.0	edlukac 8.5	fielders 6.4	carrera 6.1	Topic	ipswich 4.3									corp 0.2
Topic 4 vrinston 20.1	amp 8.6	happy 3.2	ramadhan 0.3							Topic	photo 2.7									winston 0.2
Topic 5 happy 1.8										Topic	great 7.7									kid 0.2
Tepic 6 - central 9.1	market 9.1	ramadhan 9.1	travel 7.2	southaustralia 7.2	ttot 7.2	sale 6.4				Topic	away 0.2						sarahinthesen 0.2			photo 0.2
Topic 7 race 8.7	guy 1.4									Topic	missing 6.7	run 6.0								kid 5.7
Topic 8 - sell 7.3	jual 7.0	hellokitty 5.9	carireseller 5.9	cariproduk 5.9	model 5.9	just 5.6	better 0.8			Topic	male 9.2	time 8.6	corp 3.8	run 0.4	sarahinthesen 0.2	photo 0.2	abb 0.2	missing 0.2	seeker 0.2	thank 0.2
Topac 9 - avec 11.0	nelles 10.9	rooogerrr 10.9	vomir 10.9	চ্ছ 10.9	est 10.9	rixyejl 10.9	vais 10.9	lunettes 10.9	anny 10.2	Topic	winston 24.2									missing 0.2 ipswich 0.2
Topic 10 bag 17.5	bonjour 14.4	onlineshop 10.3	ransel 9.6	female 9.6	branded 8.1	enligne 7.3	unisex 7.3	male 7.3	model 0.3	Topic 1	missing 0.2									
Word 1	Ward 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Ward 9	Word 10		Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
				Topic Heatma	p for Event 9										Topic Heatma	p for Event 10				
Topic 1 lens 16.3	amp 14.8	dompet 10.1					magnetic 8.3			Topic	love 8.8							https 0.2	lost 0.3	bag 0.1
Торис 2 - bag 59.3	bandung 31.9	murah 30.7	price 30.1	size 29.6	material 29.6	brown 29.6	jual 29.6	colour 28.6	jakarta 28.6	Topic	whincup 10.3									check 0.9
Topic 3 bog		onlineshop 7.7								Topic :	job 5.5									thegreens 3.5
Topic 4 tasmania 7.0		0.7		bandung 0.5						Topic	day 11.1	ambrose 9.4	good 9.0	return 8.4		race 5.4				great 0.2
Topic 5 check 10.6									fantasy 5.8	Topic	nowplaying 34.4	mntqa 34.4	k)dz 34.4		tupelo 23.2	boston 18.2		holdsworth 0.2		lee 0.2
Topic 6 Rens 0.3			magnetic 0.2					themes 0.2		Topic	ransel 17.4	bag 14.4	bonjour 12.4	jualtas 9.0	fashionbag 8.4	bags 8.4	replikatas 8.4			unisex 6.3
Topic 7 - adelaidemad 11.8			arthunterofsa 11.8	radelaide 11.8	aneale 11.0	urbanart 10.2	isjot a 5.0			Topic	volturi 6.0									met 0.2
Tepic 8 - free 5.0					bandung 0.3					Topic	winston 18.8									big 0.2
Topic 9 veinston 11.9	Face 5.8									Topic	olshop 4.7									0.2
Topic 10 dothan 0.2	free 0.2	hvgrhi 0.2	sde 0.2	nowplaying 0.2	winner 0.2	check 0.2		branded 0.2		Topic 1	amp 14.4	dompet 8.6	like 8.4		beam 4.7		great 3.9			just 2.7
Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Ward 9	Word 10		World 1	Word 2	Word 3	Word 4	Word 5	World 6	Word 7	Word 8	Word 9	Word 10
					p for Event 11										Topic Heatma	p for Event 12				
Topic 1 amp 376.3	just 313.0	nissan 257.8	today 242.4	racing 215.2						Topic	10.9	stones 12.3	start 11.0	tonight 9.5						claire 4.9 s-ish 5.2
Topic 2 - 180 283.7	won 190.9									Topic :	атр 24.2	brenttodenan 10.6	new 8.9	parking 6.1	central 6.1	structure 6.0	metbourne 5.6	housing 5.2	building 5.2	5-ish 5.2
Topic 3 Face 580.9	best 213.3	great 210.8	sport 193.1	seen 140.3	finish 123.6	love 115.9				Topic	street 19.4	barber 16.5	lansbury 16.5	dir 16.5	musica 16.5	prince 16.5	demon 16.5	george 16.5	angela 16.5	nextontcm 16.5
Topac 4 morris 595.9	chez 560.7	paul 520.6	mostert 470.2 537 135.3	mountain 355.5	king 262.3	xwrcjhmg 204.1				Topic	tonight 32.0	just 31.1	storm 27.4	amp 19.4	rollingstones 16.6	lightning 15.3	ronniewood 14.7	0ig 14.2	ready 13.9	backstage 13.0
Topic 5 - fuel 321.3	whincup 223.9									Topic	southaustralia 13.6	9.5	congratulation 9.6			great 8.5		coxplate 7.0		aidan 6.8
Topic 6 chazmozzie 393.7	australia 362.9	fpr 344.4	win 158.5							Topic	stone 19.5	goodwood 19.3	rollingstones 17.6	matey 16.6	area 16.6	storm 15.7	halp 15.7	placid 25.7	rolling 14.4	mikey 13.8
Topic 7 - WOW 284.7	frosty 150.6									Topic	winston 15.3	win 12-1	today 11.9	ryanmoore 11.5	photo 11.3	coxplate 9.6	markgatt 8.5	7.6	aobrienfansite s 7.6	nooneevalleycc 7.6
Tente 8 home 107.2		brilliant 80.6	thanks 78.2	happy 60.9	fashion 56.0	didn 43.4	taswanita 42.5	murah 40.2	lokal 39.1	Topic I	coxplate 28.9				famouspony 22.4	ownerbreeder 19.6	winner 16.7	enjoys 16.6	del 12.7	goracing 11.3
Topic 9 Car 450.1	§nish 330.4	amazing 261.6	race 222.4	van 173.4	999 169.8					Topic	12.9	sunset 11.8					nathanjgodwin 6.8	lightningstrikes 6.0		whincup 5.8
Topic 10 ehincup 678.6	mostert 625.0	win 441.5	ford 423.6	lowndes 400.6	lap 382.3	jamie 252.0	winterbottom 237.7	fnal 234.1	chaz 212.9	Topic 1		theadelaideoval	bag 9.3	situbondo 8.1	idr 8.1	genteng 8.1	banyuwangi 8.1	modemoisell 8.1		bwi 8.1
Word 1	Word 2	Word 3	Word 4	Word 5	World 6	Word 7	Word 8	Ward 9	Word 10		Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
				Topic Heatma	p for Event 13										Topic Heatma	p for Event 14				
Topic 1 winston 0.5	pic 0.4	discovertasmar 0.3	nia tassie 0.3 reokstate 1.2	amp 0.3	eye 0.3 check 0.4	murah 0.3	tasmania 0.3	magnetic 0.3	jelly 0.3	Topic	sydnrma 8.1		morning 3.2	herald 1.4	rain 0.8	syd 0.3 director 11.3	amp 0.2	melbourne 0.2	tasbranded 0.2	idr 0.1 afraid 11.3
Topic 2 love 5.1				amp 0.3 job 0.7						Topic	tonight 13.2	movie 12.0				director 11.3		nextontem 11.3		afraid 11.3
Topic 3 winston 20.0	realestate 12.0	listing 8.6	job 6.2			murah 0.3 eye 0.3 themes 0.3		magnetic 0.3 info 0.3 dompet 0.3		Topic	jamiewhincup 7,4									herald 2.7
Topic 4 fashion 2.6		lens 0.3	tasmania 0.3							Topic	idr 8.7								racing 2.9 untuk 3.6 kjffbmf 3.6	ransel 3.5
Topic 5 check 3.5	winston 0.6			realestate 0.5						Topic	winston 26.9	realestate 13.2	Esting 11.8							creative
Topic 6 - amp 5.6	winston 2.4				realestate 0.4					Topic	australia 12.9									racing 0.1
Topic 7 - amp 0.5	tasmania 0.4		magnetic 0.4			dompet 0.4				Topic	dog 5.2							melbourne 0.2		racing 0.1 stereosonic 0.2
Topic 8 lens 11.4	fish 5.9	magnetic 5.8	jusal 5.8	themes 5.8	font 5.8	dompet 5.8	eye 5.8	info 5.8	jelly 5.8	Topic	vkohladmirer 3.4									job 0.2
Topic 9 - tassie 6.6	bag 6.6	discovertasmar 5.0				fashion 0.3	fish 0.3	amp 0.3	info 0.3	Topic	smclaughlin 7.8			listing 0.2	realestate 0.2					free 0.1
Topic 10 vrinston 0.3										Tapic 1	stereosonic 49.7	amp 48.9	day 40.0	melbourne 25.2	amazing 23.3	showtekmusic 22.7	doin 21.4	sonnywilsonnl 21.4	round 21.4	V8559 16.1
Word 1	Ward 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Ward 9	Word 10		Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Ward 8	Word 9	Word 10