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Sentiment Analysis and Opinion Mining: Current State of the Art and Review of Google and Yahoo Search Engines' Privacy Policies

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Abstract

Sentiment analysis is the review of written or verbal communications to determine some measure of emotion or feeling in the communication. Search engines are one of the most popular sites visited on the Internet generating hundreds of billions of hits per month worldwide. Obviously privacy policies related to these search sites are extremely important. Our study reviews the privacy policies of the two largest US based search engines, Google and Yahoo to determine the overall sentiment of their privacy policies. Significant individual findings and significant differences were found using several sentiment and opinion analysis methods.

Keywords: sentiment analysis, opinion mining, search engines, Google, content analysis, qualitative analysis

1. INTRODUCTION

The field of sentiment analysis and opinion mining is exploding. There is a virtual flood of qualitative data available from a wide variety of sources on the web that can be used to analyze the attitudes behind textual material. Millions of Twitter posts or tweets, millions of Facebook posts and billions of web pages and other documents can be reviewed to determine the opinions behind the words. This analysis can be extremely useful for both researchers and practitioners. Marketing professionals can monitor text communications to determine current attitudes towards their products. Politicians can analyze text communications to determine popularity and feelings toward their candidacy and their stands on issues. Researchers can likewise study text data to find differences, patterns, or trends in a wide variety of text, from policies to presentations, from documents to websites.

This manuscript presents an overall review of the current state of the art in sentiment and opinion analysis. It begins with a review of sentiment analysis including its definition, history, and a review of the literature. Following this is a review of current tool terms and dictionaries that are used in contemporary sentiment and opinion analysis tools. Finally, a detailed example of the use of these tools is presented comparing the sentiment of the privacy policies of two major search engines, Google and Yahoo. A statistical comparison is made of the sentiment results of these two documents and statistical conclusions are made with regard to their sentiment differences.

2. LITERATURE REVIEW

Sentiment analysis has been used extensively in current research. Applications have ranged from education to health care quality to mental health to student performance to customer feedback to politics to product reviews.

One of the most cited and major works dealing with Sentiment Analysis is Sentiment Analysis and Opinion Mining by Bing Liu (2012). In the first chapter he defines the domain. "Sentiment analysis, also called opinion mining, is the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes." Sentiment Analysis is the review of written or other forms of communication or qualitative data to determine a quantifiable and comparable measure of some form of feeling in the communication or data.

Pang and Lee (2008) suggest that one of the most studied areas of sentiment analysis is sentiment polarity and degree of positivity. A simple concept is to determine whether a particular communication is positive or negative. Eguchi and Lavrenko (2006) note this can be done for summarizing an overall document or retrieving selected sentiment text. "One of the first and still most used method of sentiment analysis is keyword analysis, where a text is reviewed word by word and compared against a dictionary. This dictionary has been previously prepared and will classify each word in its dictionary into a sentiment rating. As an example, good would have a high positive sentiment rating and bad would have a low sentiment rating. But this common analysis has some obvious flaws." Cambria, Schuller, Xia and Havasi (2013). They note two problems with keyword analysis. "Keyword spotting is weak in two areas: it can't reliably recognize affect-negated words, and it relies on surface features. "

Nasukawa and Yi (2003) studied 8 popular sentiment analysis implementations including LIWC and SentiNEt and found some wide variances of polarity between the different methods. This, therefore, suggests that there is not a clear answer when it comes to sentiment ratings and polarity and results should be verified with alternative methods and compared to each other to obtain agreement prior to making definitive conclusions.

Many studies have been performed on privacy policies of Internet sites. Jensen and Potts (2004) examined privacy policies as a decision making rule. Miyazaki and Krishnamurthy (2002) studied the relationship between privacy policies and consumer perception. There is considerable research as well on the inclusion of fair information practices into privacy policies.

There has also been much research on Google and other search engines privacy policies. Tene (2007) detailed legal issues associated with the Google search site. Piper (2005) warns of the data collection via use of the Google search engine. Zimmer (2008) examined search engine privacy threats.

After a comprehensive Google Scholar search, we could find no instances of sentiment analysis or opinion mining of privacy policies in the literature. With so much information and so much activity, analysis of the major search engines is a fertile area of research. Our review is to analyze privacy statements of the major search engines with regard to sentiment analysis.

3. METHODOLOGY

There are many sources and algorithms for sentiment analysis. But all sentiment analysis include some uncertainty since absolute sentiment analysis is not possible at this time. There are many reasons for this including negation, sarcasm, word combinations, and relative subjectivity. As a result it is useful to use multiple measures to confirm any sentiment analysis findings. This is the approach we have taken. In this way we can both demonstrate and explain different approaches as well as confirm our findings with several sources and algorithms.

There are a variety of tools that can be used for sentiment analysis. We will examine three major tools and show how they measure sentiment, compare results where, and perform a review of two the most popular search engines privacy policies, Google and Yahoo and analyze their sentiment with these tools. In addition, we will discuss an excel lookup function using a significantly larger dictionary than almost all current sentiment analysis engines. We have developed an excel VBA worksheet that analyzes documents using this greatly expanded dictionary and compare these results to traditional sentiment analysis tools. We will also perform statistical analysis t-test to determine if there is significant difference in specific sentiment dimensions in these two privacy policies. This will serve as a review and example of available sentiment analyses and how they can be utilized for qualitative document and communication analysis.

For our analysis, we utilize several online and commercial products as well as several new analyses we have developed using extensive new affective word dictionaries. Specifically we used: RIOT (Recursive Inspection of Text) SCAN software and AYLIEN software as well as two word analyses using DIC-LSA dictionary (Warriner, Kuperman, and Bryssbaert, 2013) and also norms of valence, arousal, and dominance for 13,915 English lemmas dictionary (Bestgen, Y., & Vincze, N., 2012). With these latter two analyses we are able to calculate significant differences between the two policies. This was because our self-developed algorithm had values for every word in the document and was thus able to allow calculation of means, standard deviations and perform t-tests on the data.

The Google and Yahoo search engine privacy policies (henceforth known as policies or privacy policies) were download from their respective sites and used to perform all analysis. RIOT SCAN is specific downloadable software that you to specify documents in text format and perform detailed content analysis on your documents. The software contains dozens of dictionaries and tables and returns 536 metrics using these dictionaries and other tools. (Boyd, 2014). Though most of these metrics do not measure sentiment, there are several where sentiment analysis is performed.

Three major sentiment calculations are performed by ANEW (Affective Norms for English Words), Harvard General Inquirer, and Lexicoder Sentiment Dictionary. ANEW is popular Sentiment dictionaries and was developed by Bradley and Lang in 1999. It includes three sentiment measures pleasure (or Valence), Arousal, and Dominance. Other dictionaries such as DIC-LSA have adopted this three measure sentiment categories. The categories are Affective Valence (happy to unhappy), Arousal (excited to calm) and Dominance (in-control to not in control). The scale is 1 to 9 with higher numbers indicating favorable affect (happy, excited, in-control). A text is parsed into individual words which are then mapped to a dictionary. The researchers who develop the dictionary performed surveys to determine relative affect score for each word. The ANEW dictionary includes only 1034 words however, and is thus limited in its generalizability.

The Harvard General Inquirer sentiment rating has two separate measures, one for positive words and another for negative words. The current version of the dictionary is extensive now including over 11,000 words (Guerini, Gatti, and Turchi, 2013). The measure calculated is the percentage of words that can be classified as positive or negative words in the entire document.

Young and Soroka (2012) developed their own freely available Lexicoder Sentiment Dictionary in 2012. It includes 4567 positive and negative words and was developed for analysis of news stories related to politics. One of the unique output measures from Lexicoder is a net positive and negative percentage. It reviews the text for positive and negative words but also for negated positives or negatives and then reverses these to their proper categories. As such, it is a unique addition to the problem of negated words.

A popular sentiment analysis tool is available from the software company AYLIEN. "AYLIEN Text API is a package of Natural Language Processing, Information Retrieval and Machine Learning tools for extracting meaning and insight from textual and visual content with ease." (AYLIEN, 2015) The AYLIEN API analyzes any text and returns a series of sentiment variables to "Detect sentiment of a document in terms of polarity (positive or negative) and subjectivity (subjective or objective)." (AYLIEN, 2016) We used the AYLIEN API plug-in free edition in conjunction with RapidMiner Studio to perform polarity and subjectivity analysis of our policies.

	DIC-LSA Norms
DICLSA_Arousal	cupboard, shelf, fold (low arousal), murderous, violent, coward (high arousal)
DICLSA_Dominan	suffer, loss, victim (low dominance), feat, talent, dedication (high dominance)
DICLSA_Valence	virus, murder, stressful (low/negative valence), enchanting, beauty, dancing (high/positive valence)
DICLSA_Concrete	tomato, spoon, bin (high concreteness), theoretical, imply, vagueness (low concreteness)

Table 1 DIC-LSA Norms

In addition to the external software, we also developed our own VBA enabled Excel spreadsheet in conjunction with two freely available sentiment dictionaries to independently determine sentiment in our policies. This approach also allowed us to determine statistical significance of the differences found between the policies. The two dictionaries used were DIC-LSA (Dictionary Latent Semantic Analysis) and WKB (Warriner, Kuperman, and Brysbaert). The DIC-LSA Norms with example words are presented below. The metrics are all averages of ratings based on the dictionaries. For Concreteness, higher scores = more concreteness, lower scores = more abstractness. WKB are similar to ANEW.

Metric	Software used	Measures
ANEW All Valence Mean	RIOT	Valence (Positive/Negative)
ANEW All Arousal Mean	RIOT	Arousal
ANEW All Dominance Mean	RIOT	Dominance
Harvard General Inquirer Positive	RIOT	Valence Positive
Harvard General Inquirer Negative	RIOT	Valence Negative
Lexicoder (LSD) Positive Final	RIOT	Valence Positive
Lexicoder (LSD) Positive Final	RIOT	Valence Negative
AYLIEN Polarity	RapidMiner and AYLIEN	Valence
DICLSA Valence	Authors and Dictionary	Valence
DICLSA Arousal	Authors and Dictionary	Arousal
DICLSA Dominance	Authors and Dictionary	Dominance
DICLSA Concreteness	Authors and Dictionary	Concreteness
WKB Valence	Authors and Dictionary	Valence
WKB Arousal	Authors and Dictionary	Arousal
WKB Dominance	Authors and Dictionary	Dominance

Table 2 Metrics Used

Overall, we used twelve separate measures used a variety of software to determine and confirm sentiment analysis of our policies. These twelve measures are summarized in table 2.

4. RESULTS

The results were processed using the software noted and for DICSLA and WKB using SPSS 23 for t-test of independent samples. The numerical results were obtained from analyzing the ratings from the respective metrics of each software product. Each word in the respective document is processed through the dictionary in each dictionary and assigned a scalar variable. These results are either averaged for items such as ANEW_All_Val or shown as percentages as in HARV_Positiv. The scales for RIOT SCAN are shown in table 3.

	Google	Yahoo	Scale
ANEW_All_Val	6.068	6.342	(1-negative to 9-positive)
ANEWAll_Arous	4.539	4.675	(1-calm to 9-excited)
ANEW_All_Dom	5.541	5.573	(1-controlld to 9-in-control)
HARV_Positiv	8.073	7.466	% of positive words
HARV_Negativ	1.790	1.333	% of negative words
LSD_Positive_Final	4.212	4.733	% positive and negated negative words
LSD_Negative_Final	1.088	0.866	% negative and negated positive words

Table 3 RIOT Scan

Recursive Inspection of Text results are presented in table 3. ANEW results show that both Google and Yahoo have positive sentiment scores reflecting generally favorable emotional tone such as happy and pleasant at a 6 on a 1-9 scale. Yahoo has a slightly more pleasant tone. Excitement for both Google and Yahoo are about neutral, neither excited nor calm. Yahoo has marginally more stimulated content. Finally, Dominance for both show somewhat controlled tone at 5.5 on a scale of 1-9. Yahoo is marginally more dominant.

Harvard results reflect a percentage of positive versus negative words. According to this measure, Both Google and Yahoo have much higher positive words than negative words. The gap is wider in this case for Google resulting in a higher net positive emotional rating for Google.

Finally, the LSD results adjust for the inclusion of negated positive words (e.g. not good) and include them in negative words and vice versa. The results still show that both policies have more positive words than negative and thus are strongly positive in tone. Here though, Yahoo shows a more net positive tone.

Google	**Yahoo**
polarity : positive,	polarity : positive,
subjectivity : unknown,	subjectivity : unknow n,
text : Welcome to the Google Privacy Policy When you use Google services, you trust us with your information. This Privacy Poli...,	text : Welcome to the Yahoo Privacy Center -- take a look around. You'll learn how Yahoo treats your personal information, alon...,
polarity_confidence : 0 .98328690807	polarity_confidence : 0.984126984
subjectivity_confidence : 0	subjectivity_confidenc e : 0

Table 4 AYLIEN results

The results of the RapidMiner with ALYLIEN plugin are presented in table 4. Here we have a black box comparison of polarity (positive or negative, Valence) judgment and a polarity confidence. Both Google and Yahoo are calculated to be positive documents and they both have very high polarity confidence which is the measure of certainty of the polarity determination of positive and negative. Yahoo polarity confidence is slightly higher. Neither policy provides enough information to determine subjectivity levels of the texts (subjective to objective).

Access the DIC-LSA and WKB dictionaries allowed us to perform a word by word analysis of each of our policies. This allowed us to perform statistical analysis of the differences between each policy with regard to the overall metrics calculated. The DIC-LSA Valence results are shown in table 5 and 6.

	GorY	N	Mean	Std. Deviation	Std. Error Mean
V	1.00	1966	5.8669	.53241	.01201
	2.00	902	5.8527	.54557	.01817

Table 5 DIC-LSA Valence (1=Google, 2=Yahoo)

		Levene's Test			
		F	Sig.	t	Sig. (2-tailed)
V	Equal variances assumed	1.382	.240	.658	.511
	Equal variances not assumed			.652	.514

Table 6 DIC-LSA Valence t test for variance

Both Google and Yahoo scored somewhat high in overall valence with scores of nearly 6 on a 9 point scale. The independent samples t-test reveals that the difference between the valences of each is not significant at $p < .05$ or $p < .10$. There is no significant difference in valence between Google and Yahoo privacy policies.

	GorY	N	Mean	Std. Deviation	Std. Error Mean
A	1.00	1966	5.1474	.20949	.00472
	2.00	902	5.1580	.18981	.00632

Table 7 DIC-LSA Arousal (1=Google, 2=Yahoo)

		Levene's Test			
		F	Sig.	t	Sig. (2-tailed)
A	Equal variances assumed	5.174	.023	-1.297	.195
	Equal variances not assumed			-1.345	.179

Table 8 DIC-LSA Arousal t test for variance

Both Google and Yahoo scored somewhat neutral in overall arousal with scores of nearly 5 on a 9 point scale. The independent samples t-test reveals that the difference between the arousal of each is not significant at p < .05 or p < .10. There is no significant difference in arousal between Google and Yahoo privacy policies.

	GorY	N	Mean	Std. Deviation	Std. Error Mean
D	1.00	1966	5.4118	.28251	.00637
	2.00	902	5.4054	.29376	.00978

Table 9 DIC-LSA Dominance (1=Google, 2=Yahoo)

		Levene's Test			
		F	Sig.	t	Sig. (2-tailed)
D	Equal variances assumed	.001	.982	.549	.583
	Equal variances not assumed			.541	.589

Table 10 DIC-LSA Dominance t test for variance

Both Google and Yahoo scored somewhat positive in overall dominance with scores of nearly 5.5 on a 9 point scale. The independent samples t-test reveals that the difference between the dominance of each is not significant at p < .05 or p < .10. There is no significant difference in dominance between Google and Yahoo privacy policies.

	GorY	N	Mean	Std. Deviation	Std. Error Mean
C	1.00	1966	4.0287	.35063	.00791
	2.00	902	4.0275	.32965	.01098

Table 11 DIC-LSA Concreteness (1=Google, 2=Yahoo)

A unique metric in the DIC-LSA dictionary is concreteness. Concreteness is a measure of whether the text is abstract or has definitive or concrete tone. Both Google and Yahoo scored somewhat abstract in overall concreteness with scores of nearly 5.5 on a 9 point scale. The independent samples t-test reveals that the difference between the concreteness of each is not significant at p < .05 or p < .10. There is no significant difference in concreteness between Google and Yahoo privacy policies.

		Levene's Test			
		F	Sig.	t	Sig. (2-tailed)
C	Equal variances assumed	1.663	.197	.090	.928
	Equal variances not assumed			.092	.927

Table 12 DIC-LSA Concreteness t test for variance

In our analysis of Google and Yahoo privacy policies using the WKB dictionary, we again had access to their dictionary and performed our own word by word analysis. The statistical analyses that resulted from this comparison are shown in this section.

In order to analyze whether there is a statistically significant difference between the mean Valence of Google's and Yahoo's privacy policies, an independent samples t-test is performed. The results are presented in table 13 and 14. The first item needing to be analyzed is Levene's Test for Equality of Means. Since the significance here is not p < .05, we can conclude that there is not a significance between the variances in the Google and Yahoo data. We therefore need to evaluate the t-test for Equality of Means with the "Equal Variances assumed" row. The t-test significance is p < .012. This result is that the difference between the means for Arousal are significant and Google has a significantly higher Valence sentiment than Yahoo. Google has a more positive sentiment than Google at 5.81 versus 5.68 on a 9 point scale.

	GoogYaho	N	Mean	Std. Deviation	Std. Error Mean
V	1.00	894	5.8071	.83748	.02801
	2.00	442	5.6849	.81957	.03898

Table 13 WKB Valence (1=Google, 2=Yahoo)

		Levene's Test			
		F	Sig.	t	Sig. (2-tailed)
V	Equal variances assumed	.920	.338	2.527	.012
	Equal variances not assumed			2.545	.011

Table 14 WKB Valence t test for variance

	GoogYaho	N	Mean	Std. Deviation	Std. Error Mean
A	1.00	894	3.6199	.75372	.02521
	2.00	442	3.9026	.96875	.04608

Table 15 WKB Arousal (1=Google, 2=Yahoo)

		Levene's Test			
		F	Sig.	t	Sig. (2-tailed)
A	Equal variances assumed	44.163	.000	-5.852	.000
	Equal variances not assumed			-5.383	.000

Table 16 WKB Arousal (1=Google, 2=Yahoo)

In order to analyze whether there is a statistically significant difference between the mean Arousal of Google's and Yahoo's privacy policies, an independent samples t-test is performed. The results are presented in table 1. The first item needing to be analyzed is Levene's Test for Equality of Means. Since the significance here is p < .001, we can conclude that there is a significance between the variances in the Google and yahoo data. We therefore need to evaluate the t-test for Equality of Means with the "Equal Variances not assumed" row. The t-test significance is p < .001. This result is that the difference between the means for Arousal are significant and there is a significant difference between Yahoo and Google in Arousal sentiment. Both are low in Arousal at 3.90 and 3.62 but Yahoo is significantly more aroused than Google.

	GoogYaho	N	Mean	Std. Deviation	Std. Error Mean
D	1.00	894	5.7700	.73987	.02474
	2.00	442	5.7578	.69715	.03316

Table 17 WKB Dominance (1=Google, 2=Yahoo)

		Levene's Test			
		F	Sig.	t	Sig. (2-tailed)
D	Equal variances assumed	2.465	.117	.290	.772
	Equal variances not assumed			.296	.767

Table 18 WKB Dominance t test for variance

In order to analyze whether there is a statistically significant difference between the mean Dominance of Google's and Yahoo's privacy policies, an independent samples t-test is performed. The results are presented in table 17 and 18. The first item needing to be analyzed is Levene's Test for Equality of Means. Since the significance here is p < .117, we cannot conclude that there is a significance between the variances in the Google and yahoo data. We therefore need to evaluate the t-test for Equality of Means with the "Equal Variances assumed" row. The t-test significance is p < .772. This result is that the difference between the means for Dominance are not significant and there is no significant difference between Yahoo and Google in Dominance sentiment. Both Google and Yahoo has a high In Control Sentiment at 5.77 and 5.7578.

5. DISCUSSION

The overall results of our sentiment analysis of the two major search engines privacy policy yielded interesting and mostly consistent results. These results are summarized in table 19 and shown in detail in Appendix A.

Overall, both policies have positive valence or sentiment. The six various analyses are fairly evenly split on which has higher positive sentiment though. The only metric shown to be statistically significant in valence was the WKB Valence which showed Google slightly higher and statistically significant. The overall consensus though appears to be that there is little difference in the positive valence but slightly more in Google. This first metric illustrates the variability that exists among the sentiment tools. The reason for this is that each use different dictionaries. They each have a different number of words in their dictionary and they all have done their own survey to determine sentiment ratings.

Metric	Measures	Results of Both
ANEW All Valence Mean	Valence (Positive/Negative)	Both somewhat positive
ANEW All Arousal Mean	Arousal	Both Neutral
ANEW All Dominance Mean	Dominance	Both somewhat in-control
Harvard General Inquirer Positive	Valence Positive	Both strongly positive
Harvard General Inquirer Negative	Valence Negative	Both low negative
Lexicoder (LSD) Positive Final	Valence Positive	Both positive
Lexicoder (LSD) Positive Final	Valence Negative	Both low negative
AYLIEN Polarity	Valence	Both Positive
DICLSA Valence	Valence	Both Somewhat positive
DICLSA Arousal	Arousal	Both Neutral
DICLSA Dominance	Dominance	Both somewhat in-control
DICLSA Concreteness	Concreteness	Both somewhat abstract
WKB Valence	Valence	Both somewhat positive
WKB Arousal	Arousal	Both somewhat less aroused
WKB Dominance	Dominance	Both somewhat in-control

Table 19 Summary of Results

The second metric calculated was the Arousal metric. ANEW, DICLSA, and WKB all calculated a level of excitement or arousal for the policies. In two analyses, both policies were found to be neutral in arousal. The WKB results showed slightly less arousal than neutral. In all three, Yahoo showed a higher arousal level and it was statistically significant in WKB. Thus, it can be said that both policies are neutral to less than neutral arousal and Yahoo is a bit more exciting.

ANEW, DICLSA and WKB also provided a measure of Dominance or feeling of being in control. Not surprisingly, both privacy policies which explicitly deal with control showed metrics above neutral and both showed "somewhat in-control". The three analyses are split between which had the higher control and none were statistically significant. We therefore conclude that there was no difference in level of dominance in the policies.

The final metric measured by DICLSA was concreteness. Surprisingly, both policies were less than neutral and both were somewhat abstract, not well defined or concrete. There was no statistical difference between the two policies based on concreteness. One possible reason the policies are abstract to leave room for the companies to have legal flexibility.

6. CONCLUSION

Overall this study has contributed to the literature in three ways, first it defines, presents and demonstrates six different methods of sentiment analysis. Researchers and practitioners can use this manuscript as a source, primer and guide for developing their own sentiment analysis of any communication. Second, the study illustrates the inexact but relatively consistent results that are generated by several sentiment analysis tools and dictionaries. Researchers and practitioners can reliably use any of the tools and obtain similar results regardless of the tools used. Note that there is some small variation that will be experienced. Finally, the study analyzes the privacy policies and sentiment and tone of the two largest search engines. The results show little differences in any of the sentiment measures between Google and Yahoo. Both are somewhat positive in sentiment, neutral in arousal, somewhat in control in dominance, and somewhat abstract documents. Researchers can use these findings to compare to other search engines policies or other privacy policies for other type sites to compare and contrast their sentiment characteristics. Search engines companies can use these findings to improve their overall sentiment if they choose. Potential changes in privacy policies for companies could be to make privacy policies, happier, less controlled, provide a change in arousal, and be more concrete.

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Appendix A

Metric	Measures	Results of Both	Higher rated	Significant
ANEW All Valence Mean	Valence (Positive/Negative)	Both somewhat positive	Yahoo	NA
ANEW All Arousal Mean	Arousal	Both Neutral	Yahoo	NA
ANEW All Dominance Mean	Dominance	Both somewhat in-control	Yahoo	NA
Harvard General Inquirer Positive	Valence Positive	Both strongly positive	Google	NA
Harvard General Inquirer Negative	Valence Negative	Both low negative	Yahoo(less negative)	NA
Lexicoder (LSD) Positive Final	Valence Positive	Both positive	Yahoo	NA
Lexicoder (LSD) Positive Final	Valence Negative	Both low negative	Yahoo (low negative)	NA
AYLIEN Polarity	Valence	Both Positive	Yahoo	NA
DICLSA Valence	Valence	Both Somewhat positive	Google	NO
DICLSA Arousal	Arousal	Both Neutral	Yahoo	NO
DICLSA Dominance	Dominance	Both somewhat in-control	Google	NO
DICLSA Concreteness	Concreteness	Both somewhat abstract	Google	NO
WKB Valence	Valence	Both somewhat positive	Google	YES
WKB Arousal	Arousal	Both somewhat less aroused	Yahoo	YES
WKB Dominance	Dominance	Both somewhat in-control	Google	NO

