When writing about wine: how ratings impact reviews

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Abstract

This paper investigated whether the nature of the language in wine reviews differs by wine ratings. Reviews of 1-, 3- and 5-star wines were downloaded into text files, then analyzed for Word Count, Analytic, Clout, Authentic and Tone by using LIWC text analysis. ANOVAS was adopted to determine differences between reviews by ratings. There were significant differences between wines by star rating on Word Count, Analytic, and Tone, while there were no significant differences on Clout and Authenticity. This research was limited to South African wines, 1-, 3- and 5-star reviews. It was not possible to identify all individual reviewers. Also, price and availability were not considered. Research implications include using other textual analysis software to conduct inter-reviewer comparison of reviews with the same ratings by different influential wine writers, investigating price as a variable in rating and review, and authenticity as a factor in the context. Wine marketers can help wine makers gain a better understanding of what tastemakers prefer by analyzing wine reviews with automated text analysis software such as LIWC. A positive link between word count in a wine review, the degree of analysis and tone used with the ratings of wines by experts can be established.

KEYWORDS:
Wine reviews, wine ratings, wine marketing, automated text analysis, LIWC, content analysis

Introduction

Wine is an interesting consumer product for many reasons, among which is the fact that it is the most prolifically branded consumer good of all. There is an estimate of more than 15,000 brands of wine worldwide, with more than 7,000 brands sold in the USA alone (Veseth, 2013). The next most profusely branded product in most supermarkets is breakfast cereal, but the numbers pale in comparison to wine. Wine also exhibits by far the greatest price range for consumer goods. The most expensive breakfast cereal in a large American supermarket (perhaps some organic whole grain quinoa) might come in at around \$16 a pack, and the cheapest (perhaps a generic brand of oats) at around \$1.25 for the same size pack, for a price differential of just under 13–1. In Trader Joe's, a large US supermarket chain, consumers can shell out \$349 for the most expensive wine in the store, a Dom Perignon Vintage Rosé. Or, if their budget doesn't stretch that far, simply pay \$1.97 for a bottle of Charles Shaw Red, also known as ‘Two Buck Chuck’, for a price differential of around 197–1. The Dom is not even close to being the most expensive wine in the world, in a market where one can pay many thousands of dollars for a great Burgundy or Bordeaux.

Is it any wonder that so many wine consumers are confused, and that so much research (Dodd, Laverie, Wilcox, & Duhan, 2005; Ellis & Mattison Thompson, 2018; Vigar-Ellis, Pitt, & Caruana, 2015) on the objective knowledge of wine consumers shows that they generally score low on tests of actual wine knowledge?

Because so many wine consumers are confused about what to buy as they confront the dazzling array of offerings available to them, they develop heuristics to aid them in their purchase decision-making. Some, for example, find a brand they like, and stick to it. Others do the same with a grape and a region – for example, they find they like Australian shiraz, and stick with that. Others use the heuristics of price points, and purchase within those guidelines; for example, a UK consumer might reason that all red wines to go with a meal, priced at between seven- and fifteen pounds are a good buy. Others turn to the experts and rely on the reviews of wine writers. And this is of course another phenomenon that makes wine such an interesting product category: In the case of a consumer good with so much heterogeneity, and consumed by so many people all over the world, how can the perceptions and decisions of so many, be influenced by the opinions of so few?

As the late Chateau Margaux technical director Paul Pontallier said in 2006 (in Deighton, Pitt, Dessain, Beyersdorfer, & Sjöman, 2006, p. 8), ‘Twenty-five years ago, a decent wine press did not exist, except maybe in Britain. The merchants shaped expectations. But fifteen years ago, wine critics appeared and multiplied over the last years. Today, a few wine journalists dominate the industry.’ Some of the world's most influential wine writers include Jancis Robinson, of the *Financial Times,* James Suckling (formerly of *Wine Spectator*), and Robert Parker, of *Wine Advocate*. Of the latter it has been said, ‘Nobody sells wine like Robert Parker. If he turns around and says 2012 is the worst vintage I’ve tasted, nobody will buy it, but if he says it’s the best, everybody will (Edgecliffe-Johnson, 2012, para 10).’ Hay’s (2007) statistical analysis showed that Parker had a significant influence on Bordeaux wines, especially for the Médoc region. Almost one-third of the total variance in release price, and around 40 per cent of the increase in release price could be accounted for by Parker scores.

Influencers such as Parker, Robinson and Suckling tend to be global in their ambit, and taste, and critique and write about wines from all the world’s major wine producing regions. In addition, in some countries there are wine writers who concentrate solely on the wines produced in that particular country. For example, in Australia, Jeremy Oliver has produced the *Australian Wine Annual* every year since 1997. The best selling wine book in New Zealand for many years has been *New Zealand Wines: Michael Cooper’s Buyer’s Guide*, written by Michael Cooper and now in its 27th edition. John Platter started his annual book of reviews of South African wines, *Platter’s South African Wine Guide* in 1979 (locally referred to simply as ‘*Platter*’), and sold it in 1997, after which a team of wine writers wrote the reviews annually. The title of the guide remained unchanged, Platter is still the local ‘wine bible’, and Diner’s Club acquired it in 2013.

Exploring what reviews say

Food and allied product reviews serve as an interesting and insightful source of data for practitioners and scholars alike, providing insights above and beyond the kind of data that can be gathered by surveys, experiments, and qualitative research techniques such as focus groups and depth interviews. The advent of the internet has also increased the amount of review data available to researchers, and this has in turn led to the development of a wide range of computerized tools that facilitate automated text analysis (Humphreys & Jen-Hui Wang, 2017). Because the amount of textual data available to researchers, on social media and on review websites for example, has become so massive, researchers have turned to content analysis software in order to better analyze and interpret this data. In the food and wine arena specifically, recent examples include Cassar, Caruana, and Konietzny (2018) who analyze wine tour service firms' websites to better understand their positioning strategies, and Treen, Lord Ferguson, Pitt, and Vella (2018) who perform an emotion and sentiment analysis of wine websites.

In analyzing textual data, researchers have addressed a number of different questions and issues. For example, Vosoughi, Roy, and Aral (2018) analyzed more than four million Twitter feeds over an eleven-year period and discovered that fake news spread a lot more rapidly than the truth. In the finance discipline, Karapandza (2016) used text analysis of verbs in 10-K reports to show that firms that talk less about the future in these communications generate positive and abnormal returns. In tourism, Pitt, Opoku, Hultman, Abratt, and Spyropoulou (2007) used computerized text analysis of the tourism websites of African countries to measure the key dimensions of their brand personalities as articulated on their websites. This data was then used to position these brands in multidimensional space. Campbell, Pitt, Parent, and Berthon (2011) contrasted two different approaches to automated textual analysis in exploring how many hundreds of viewer responses to consumer-generated advertisements on YouTube could be interpreted.

In the domain of wine, researchers have also conducted projects to explore a range of issues by means of text analysis. These include work by Begalli, Codurri, and Gaeta (2009) on the wine and web marketing strategies of Italian wineries; Parsons and Thompson (2009) on the credibility of wine recommendations in social media; and, the effects of social media usage on wine buying intentions (Pucci, Casprini, Nosi, & Zanni, 2019).

Reviews by well-known wine experts as well as wine bloggers have provided text for analysis by researchers. In early work, Chaney (2000) content analyzed the text produced by journalists in specialist wine magazines and weekend newspapers but questioned the value of the information disseminated in the reviews. A study of the entire text contained in influential wine blogs, Beninger, Parent, Pitt, and Chan (2014) found that that these blogs all balance self-promotion with the content of their blogs, namely, wine and wine-related topics. The wine blogs, although evaluating wines in different ways, review not only the product attributes but also the experience surrounding wine and its consumption. More recently, Lord Ferguson, Ewing, Bigi, and Diba (2019) used the text contained in reviews produced by successful wine bloggers to cluster them into four distinct segments that could be targeted by wine marketers in different ways.

One of the features of most wine reviews, particularly those conducted by the well-known experts, is that they are inevitably accompanied by an overall evaluation in the form of points or stars. For example, Jancis Robinson uses a 20-point rating scale, and Robert Parker is famous amongst other things for introducing his 100-point scale. An issue less explored in empirical research is the extent to which the language used in the review relates directly to the number of points or stars awarded. The many questions that can be raised in this regard are for example: Can the words and language used by reviewers of wines be used to predict the scores they will award? When two different reviewers both award the same wine a perfect score (or an equally poor score, perhaps), how do the words and language that they use differ? How, and in what way, do the words and language of the same reviewer, or group of reviewers, differ depending on the number of points they award to a wine? The latter question is the one we seek to address in this paper.

We proceed as follows: First we outline the procedure used to collect data from a single source of wine reviews rated on a 5-star scale, for wines awarded 1-, 3- and 5 stars respectively. Then, we describe how this data was analyzed using a well-known automated text analysis software package in order to identify the text dimensions contained within each review. Next, we conduct a series of analysis of variance (ANOVA) procedures in order to determine the differences that may exist between reviews for the three categories of star ratings, before going on to discuss these results. We conclude by acknowledging the limitations of the research, the implications for wine marketers and managers and also for those in the broader food and beverage arena and identifying avenues for future research.

The dataset

The dataset used in this research consisted of the individual texts of 370 reviews of 5-star wines, and equal numbers of reviews of 3- and 1-star wines from the 2018 edition of *Platter's South African Wine Guide* downloaded from the source's website. In total, there were 370 wines awarded five stars in the 2018 edition, and in order to match this number, the reviews of 370 wines with three stars (an 'average' wine) and 1 star (a poor to fair wine) were also gathered, for a total number of reviews of 1,110. The Platter's Guide now uses a number of different wine reviewers to evaluate and review the wines featured, so it is not possible to identify which particular reviewer wrote a review and provided a score for a particular wine. Each review was scraped from the website and pasted into an individual text document.

Analyzing the reviews

The individual text documents were analyzed using an automated text analysis software program called LIWC (Linguistic Inquiry and Word Count) (see Pennebaker, Boyd, Jordan, & Blackburn, 2015). LIWC reads a given corpus of text and then counts the percentage of words that reflect different emotions, thinking styles, social concerns, and parts of speech. It then compares each word in the text against a set of dictionaries that contain words associated with psychologically relevant categories. The software then calculates the percentage of total words that match each of the dictionary categories.

LIWC makes it possible to analyze text using four summary variables that are algorithms constructed from various individual LIWC variables (such as personal pronouns, functional words and so forth) based on previous language research. These summary variables are scored as percentiles ranging from 0 to 100. Briefly, the summary variables are follows:

Analytical thinking (Analytic): captures the degree to which the words in text suggest formal, logical, and hierarchical thinking patterns. Low analytical thinking uses language that is more narrative, focuses on the present, and tends to be more personal, whereas highly analytical text suggests formal, logical, and hierarchical thinking Pennebaker, Chung, Frazee, Lavergne, and Beaver (2014).

Clout: writing that is high in 'clout' will emphasize relative social status, confidence, and leadership (Kacewicz, Pennebaker, Davis, Jeon, & Graesser, 2014).

Authenticity: Text that is authentic reveals honesty, and that the writer is likely more personal, humble, and vulnerable (Newman, Pennebaker, Berry, & Richards, 2003; Pennebaker, 2011).

Emotional tone (Tone): Tone is akin to the notion of sentiment (e.g. Turney, 2002) used in a lot of content analysis of social media textual data nowadays. Tone summarizes both the positive- and negative emotions expressed in a corpus of text into a single variable (Cohn, Mehl, & Pennebaker, 2004), so that the higher the number (above 50), the more positive the tone, and vice versa.

LIWC also conducts a word count, so that the amount of text used can be determined for a given document and compared across documents. The research questions that we sought to answer were whether there were differences in word count, analytic, clout, authentic and tone between the 1-, 3- and 5-star reviews for wines on the Platter's Guide. In order to test these differences, a series of analysis of variance (ANOVA) procedures was conducted, and the results of these are presented in the next section.

Data analysis and results

The result of the ANOVA for the differences between the star rating and their effect on word count in the reviews was significant at $p < .001$, as shown in Table 1, and star rating explains approximately 82% of the variance in word count. Word counts are significantly higher for 5-star ratings than for 3- and 1-star ratings, and the word counts of 3-star ratings are significantly higher than for 1-star ratings. Reviews for wines that received 5-star ratings were on average twice as long (at 40 words) than for 3-star wines, which were in turn roughly twice as long as 1-star wines.

Table 1. Analysis of variance table for word count by star rating.

Analysis of Variance Table for Word Count by Star Rating

Term	*SS*	*df*	*F*	*p*	$\eta_p 2$
Star Rating	173756.47	2	2534.48	< .001	0.82
Residuals	37946.38	1107			

Mean, Standard Deviation, and Sample Size for WC by Star Rating

Star Rating	*M*	*SD*	*n*
Five Star	40.09	7.43	370
Three Star	18.35	5.42	370
One Star	10.52	4.27	370

An ANOVA was then conducted to determine whether there were significant differences in the LIWC dimension of Analytic by Star Rating. The results of this procedure were significant at $p < .001$, indicating there were significant differences in Analytic among the levels of Star Rating, as shown in Table 2.

Table 2. Analysis of variance table for analytic by star rating.

Analysis of Variance Table for Analytic by Star Rating					
Term	*SS*	*df*	*F*	*p*	$\eta_p 2$
Star Rating	3228.10	2	15.82	< .001	0.03
Residuals	112913.69	1107			

Mean, Standard Deviation, and Sample Size for Analytic by Star Rating			
Combination	*M*	*SD*	*n*
Five Star	95.64	5.68	370
Three Star	93.90	9.98	370
One Star	91.49	13.20	370

Paired *t*-tests were conducted between each pair of measurements to further examine the differences among the variables. The mean of Analytic for 5-star reviews was significantly larger than for 1-star reviews (*M* = 91.49, *SD* = 13.20) and the mean of Analytic for 3-star reviews was also significantly larger than for 1-star reviews. However, the difference in means between 5- and 3-star reviews on the dimension of Analytic was not significant.

Following this, an ANOVA was conducted to determine whether there were significant differences in the dimension of Clout by Star Rating. The results of the ANOVA were not significant, as shown in Table 3.

Table 3. Analysis of variance table for clout by star rating.

Analysis of Variance Table for Clout by Star Rating					
Term	*SS*	*df*	*F*	*p*	$\eta_p 2$
Star Rating	337.65	2	0.62	.539	0.00
Residuals	301784.81	1107			

Mean, Standard Deviation, and Sample Size for Clout by Star Rating			
Combination	*M*	*SD*	*n*
Five Star	49.52	13.10	370
Three Star	48.35	16.79	370
One Star	48.34	19.08	370

Next, an ANOVA was conducted to determine whether there were significant differences in the dimension of Authentic by Star Rating. As shown in Table 4 below, the results of the ANOVA were not significant, indicating that the differences in Authentic among the levels of Star Rating were not significantly different.

Table 4. Analysis of variance table for authentic by star rating.

Analysis of Variance Table for Authentic by Star Rating					
Term	*SS*	*df*	*F*	*p*	$\eta_p 2$
StarRating	529.03	2	0.44	.644	0.00
Residuals	665768.51	1107			

Mean, Standard Deviation, and Sample Size for Authentic by Star Rating			
Combination	*M*	*SD*	*n*
Five Star	18.20	19.75	370
Three Star	16.86	24.81	370
One Star	18.42	28.26	370

Finally, an ANOVA was conducted to determine whether there were significant differences in Tone by Star Rating. The results are reported in Table 5 below. Perhaps not surprisingly, the results of the ANOVA were significant, indicating there were significant differences in Tone among the levels of Star Rating, and indicating that Star Rating explains approximately

16% of the variance in Tone. Tone for a 5-star wine was a very positive 85.91 on average, and 76.12 for a 3-star wine, while for 1-star wines, Tone was barely positive at only 52.16.

Table 5. Analysis of variance table for tone by star rating.

Mean, Standard Deviation, and Sample Size for Tone by Star Rating			
Combination	***M***	***SD***	***n***
Five Star	85.91	23.40	370
Three Star	76.12	33.86	370
One Star	52.16	37.29	370

Analysis of Variance Table for Tone by Star Rating					
Term	***SS***	***df***	***F***	***p***	$\eta_p 2$
Star_Rating	223112.66	2	108.50	< .001	0.16
Residuals	1.14×10^6	1107			

Discussion

The results of this study indicate that there are some differences between the text used in the reviews of wines, and that this can depend on the overall rating accorded the wine by a reviewer. In the wine reviews studied here, wine reviews differed in length, or word count, depending on the rating awarded the wine. The text of 5-star wine reviews was significantly longer than that used in the reviews of 3- and 1-star wines, and the reviews of 3-star wines were significantly longer than those for 1-star wines. In simple terms, the higher a reviewer rates a wine, the more they will tend to write about it. The reviews of both 5- and 3-star wines are also significantly more analytical than the reviews of 1-star wines. This is probably because when a reviewer really doesn't like a wine, the star awarded says it all, and they spend little time analyzing the wine itself. In the case of wines awarded 3- or 5 stars, reviewers use more words to write more formally, argue more logically and apply more hierarchical thinking.

There were no significant differences found in the Clout scores between the three wine rating categories, which means that there were no discernible differences in the relative social status, confidence, or leadership expressed by the reviewers. Similarly, there were no significant differences with regard to authenticity across the three wine rating categories, which suggests that the reviewers speak with equal honesty whether reviewing a low-, average- or highly rated wine. Finally, as would be expected, there are significant differences in the Tone expressed in reviews across the three different rating groups. While the Tone expressed in 5-star reviews is very high at 85.91, and high at 76.12 for 3-star wines, the Tone expressed in 1-star ratings is more or less neutral at only 52.16.

Limitations, managerial implications and avenues for future research

Limitations

There are limitations to the research presented here. First, the study was restricted to the *Platter's Guide*, and therefore by definition, South African wines only, and so we are unable to generalize findings to other wine regions of the world and other sources of ratings, even in South Africa. In addition, *Platter* uses a simple 5-star rating system, and so making results directly comparable to other systems that use more finely grained points might be challenging.

Second, because it was not possible to identify the individual reviewers in all cases who had written the reviews, we are not able to determine whether there were indeed differences between reviewers. For example, two different reviewers might each award 5 stars to the same wine but use very different words (and specifically, the 4 LIWC dimensions) in doing so.

Third, only a sample of the 1-, 3- and 5-star reviews was considered. So not all the wines in the 1- and 3- star rating categories were included in the analysis and there is a slight possibility that these may have been different. Furthermore, in order to make clear comparisons among poor/fair-, average- and excellent wine reviews categories, only 1-, 3- and 5-star wine reviews were analyzed. It is possible that by using samples of reviews from all the star categories, including 2 and 4, the results might have been more nuanced, or perhaps even have painted a different picture.

Finally, we did not consider issues such as price and availability: would a 5-star review for one wine costing three times more than a similar wine also receiving 5 stars, be different? Some of the 5-star wines would have only been available in small quantities to select clients through auctions or special events: would they have received different reviews to 5-star wines more widely available?

Managerial implications

A number of implications for those who manage and market wines are apparent from the findings reported here. First, wine marketers would be aware that there are consequences to wines with lower ratings. In many cases there may be a need to reduce prices and perhaps many of these wines are already selling at low prices, which exacerbates the situation. Consumers who rely on reviews will be less inclined to spend on wines that receive low ratings and poor reviews. Paradoxically the study also informs us that fewer words will be said about these wines in reviews, so it might not always be possible to determine exactly what it was about a particular wine that a reviewer did not like, and to be able to address the problem. By reading and understanding wine reviews wine producers and marketers can gain a better understanding of what tastemakers such as reviewers are looking for. Second, and more positively, 5-star reviews will give wine marketers even more to say about their offerings – they can use this in their own marketing materials, and also encourage wholesale customers such as wine merchants and fine restaurants to use this in their promotional materials and in wine lists.

Finally, wine marketers can use tools such as LIWC and the host of other automated textual analysis tools available, to gain a better understanding of what experts and enthusiasts alike are saying about their products. We used one source in this resource, namely the *Platter's Guide.* However, nowadays there is a host of other sources of textual data available in other guides both in print and online, in wine blogs, on wine websites, and on wine recommendation apps on smart devices. This rich data is relatively easy to gather and costs almost nothing in most cases. It can provide novel insights into how those who drink and think about wine feel about the vast array of offerings out there.

Future research

The work reported here suggests a number of avenues for further research in the future. First, while we were unable to identify and tie each reviewer's name to a particular review in this research, and thereby conduct inter-reviewer comparisons, this type of review is eminently possible if researchers were to use different sources of reviews for the same wine(s). As a simple example, fine French wines are reviewed by many different writers including Parker, Robinson and Suckling, and also others in the press and on blogs. While doing numerical comparisons of points scored, regardless of the writer's individual scoring system might be interesting, we contend that it would be even more insightful to compare their scores on dimensions of LIWC, such as those used in this study, or on the other dimensions of text used in text analysis software such as DICTION (e.g. Short & Palmer, 2008), or by using artificial intelligence analysis of text on platforms such as IBM's Watson (Pitt, Mulvey, & Kietzmann, 2019).

Second, and as mentioned, a limitation of the study reported here is that the prices of the wines being reviewed were not considered. Price is both an important and interesting variable, and worthy of further investigation. While one might easily suspect that there would be a linear relationship between price and the rating accorded (simply, more expensive wines would score more stars), there would be some inexpensive wines that would score high ratings, and similarly, expensive wines that would score low. So, the interesting differences to be explored here would be in the words used: Do expensive and inexpensive highly rated wines get reviewed in similar or different words? Do expensive and inexpensive lowly rated wines get reviewed in similar or different words?

A specific point that warrants further investigation is when a particular dimension of LIWC evidences a curvilinear, rather than linear result for a particular dimension. In the results reported here for example, on the dimension of authenticity, 1-star and 5-star wines both scored higher on this dimension than did 3-star wines in their reviews. We investigated this further in a regression procedure not reported in the paper and were still not able to refute the result. While the result was not significant in this case however, it might be worth investigating further in other, perhaps larger datasets. If it were found to be significant it might suggest that wine reviewers write with more authenticity, honesty and sincerity when they have stronger opinions, either positive or negative.

Conclusion

The study reported in this paper considered reviews of South African wines in the country's foremost wine guide, *Platter's Guide.* It compared the texts used in the reviews of equal large samples of wines awarded 1-, 3- and 5 stars, using the LIWC content analysis software tool on total word count, and the dimensions of Analytic, Clout, Authenticity and Tone. Wines that are awarded higher star ratings tend to be significantly longer and have reviews that show more Analytic and higher Tone. No significant differences were found in reviews between different star ratings on the dimensions of Clout and Authenticity.

The wine market presents a tough industry for producers to compete in with many thousands of brands vying for the consumer's attention. Most consumers are not very knowledgeable, and many rely on the reviews of expert tastemakers to guide them in the purchasing decision-making. The written reviews and scores awarded by these tastemakers provide valuable information not only to consumers, but also to wine marketers, and automated text analysis tools such as the one applied in this study offer these decision makers a valuable means of gaining greater insight into how the experts consider and think about their products. As the vast amounts of textual data available online continue to increase at a frenetic rate, these tools will become ever more valuable, and will warrant ongoing research into their use and effectiveness.

Disclosure statement

No potential conflict of interest was reported by the authors.

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