

Gauging Public Opinion: Polling to Machine Learning

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Abstract

To make informed decisions, policymakers need to understand what the public thinks about various issues. There are a number of ways to gather public opinion, which have developed over time through the advancements in technology. Given the importance of accurately representing peoples' opinions, it is necessary to constantly improve the methods which determine the general public's opinion. This paper argues that machine learning is a disruptive technology; it also argues that given the entwinement of the development of socially disruptive technologies and public opinion throughout history, machine learning is likely to be used in the gathering and interpretation of public opinion

Introduction

The knowledge, and influence, of public opinion holds massive power in contemporary society, from extensive influence coverage, such as country elections and policy creation, to the much smaller scale product popularity and creator influencing. People always want to know what others are thinking, which is one of the reasons why public opinion sites such as Twitter have risen to such popularity. However, how public opinion is acquired is different over different topics and has changed over time. Currently, political polls are used to gauge public opinion on the candidates up for election (Kennedy, 2020), by advocacies and the public express their views to lawmakers to attempt to influence policies made (ICPA, 2014), and by shoppers to gauge others' opinions on products through language and ratings given in product reviews (Yang et al., 2016). Given the improvements made to technology in recent years and the constant development of acquiring information on public opinion, the next step to gauging people's views may be through disruptive technology, and as such, we should learn about these technologies, from potential risks to possible benefits, in order to better prepare for their potential future use.

In this paper, I will analyze how people gather information on the public, including the history of some of the most important indicators of public opinion and how they change with newly developed disruptive technologies. This will include a discussion on how modern information gathering can be

flawed. Next, I will examine how interested groups can use the information on public opinion to attempt to sway outcomes. I will then discuss machine learning as a disruptive technology, how it has been used to gather information on public opinion, and how it can be used for more in-depth research on the public (Arif & Dulhare, 2017).

Public Opinion and Polling

The history of gathering people's opinions is filled with developments tied to disruptive technologies. As such it is important to review how the methods for gathering and interpreting data have changed over time. This section will discuss the history of public opinion in relation to polling and politics to reveal how information gathering and interpreting technology has developed over time.

Public opinion is intertwined in the nature of democratic politics, with people voting for who they believe will be most likely to implement changes to a country that will align with their beliefs. As such, it has become necessary for politicians to know what the public wants and who they are likely to vote for, so they can adjust their plans and campaign accordingly. The use of public polling to predict election results is an old idea that was first introduced, in an unsophisticated manner, in July of 1824. A Pennsylvanian newspaper reported on a survey conducted by *American Watchman* and *Delaware Advertiser* in which they asked the voters among their readers their opinions on an upcoming election, and based on the results, they found that 70% of respondents intended to vote for Andrew Jackson (Tankard, 1972). As it turned out, he won the popular vote by a small margin but was not elected by the house of representatives. This poll led to other publications running their own polls, though these were generally inaccurate because they were not scientific by design. They relied on having readers of the publications send back a printed-out form, meaning there was not much design behind the demographics of who got the surveys (Rhodes, 2018).

Polling started out very primitively, with a lot of room for improvement. One of the first major developments in polling was developed by George Gallup, who is now one of the most famous pollers in the history of American polling. Gallup had a faith in numbers and statistics that drove his eventual

development of political polling (Rothman, 2016). Most modern polls are derived from the same method that Gallup designed and first implemented in 1932, which is based on randomly sampling a statistically average group of people to attempt to extrapolate the public's general opinion. This method is not 100% accurate as that is not possible without accurately polling every voter; however, it is more advanced than previous techniques (Rhodes, 2018).

Gallup polls are not only the main driving force behind public political opinions but they are often used when important policies are debated. For instance, advocacies for and against gun control run polls to gauge what the public wants in regards to new policies being created (Turner, 2021) and when education is being discussed, polls are used to determine what the public is worried about and try to remedy it (Billingham & Kimelberg, 2016). In addition, polls can be utilized as an effective tool to help ascertain how well an advocacy is doing (ADVOC8, 2018).

Jeroen Hopster is a PhD in Philosophy holder who is a postdoctoral researcher in the Ethics of Socially Disruptive Technologies (J. K. G. Hopster, n.d.) who defines socially disruptive technologies as “technologies that have [some of the core values of being] deep, important, ethically salient and wide-ranging impacts, that occur rapidly, provoke uncertainty and cannot be easily reversed (Hopster, 2021)”. In his framework, this means that a technology should affect deeply held beliefs/social norms essential in their impact on society, have a morally significant impact, and be disruptive strongly in, or both in and out of, their domain. They should also inflict changes to society quickly, be sudden and difficult to anticipate, and not easily reversed to be considered socially disruptive. A socially disruptive technology does not have to fit into every category, but the more it aligns with the core values, the more socially disruptive it can be considered.

The Gallup method of polling is a socially disruptive technology whose impacts are still currently in use to this day. Gallup polls changed polling and opinion gathering at the base level, leading to a change in how politics has worked in the United States and how polling has worked around the globe. His methods created deep and important changes in society. Not only this, but this method is still in effect today and has been integrated into almost all contemporary polls. To discard this method completely

would be to set back public opinion gathering and would dismantle the many systems which need information on public opinion, meaning it is difficult to reverse.

Internet-based polling is one of the newer information technologies put into practice. The main methods of collecting poll information before internet-based polling was through telephone interviews over landline or cell phone. Using Roper Center, a public opinion archive specializing in data from public opinion surveys, I collected four randomly chosen gun control polls using older phone interviews and newer web-based survey techniques. The average sample size of four gun control polls using the older methods was 1114 (CNN, 2019; Marquette Law School, 2021; Quinnipiac University Polling Institute 2021a, 2021b), while the average sample size of four gun control polls using web-based surveys was 76716 (Fox News/Associated Press 2018, 2020; IQSS, Harvard/MIT 2014, 2016), which displays the severe difference in audience reach between these two methods. Despite the advantages of sample size, there are many fewer web surveys than phone polls, though I believe that will change, given the rise of internet popularity over the past two decades.

Public Opinion and User Reviews

A second huge field of public opinion is in reviews given by customers, whether on products or services. Whereas political polling, whether electoral or policy-wise, can be done on the internet and through phone calls and physical mediums such as newspaper or mail responses, public opinion via customer reviews only really took off during the age of the internet. Online reviews first started appearing in 1999 and mainly occurred in seller sites like eBay, though soon after that, there emerged three major contenders, Epinions, RateItAll, and Deja. These companies generated reviews of products and entertainment and were eventually sold to more prominent companies (Jones, 2018).

In 2001, Yellow Pages added a review feature to their online business directory, letting people review companies and inform others of their experiences at local businesses (Laughton, 2021). This was the beginning of an information age that generated consumerism born of public opinion. Several large companies added review features to their websites within the next two decades, allowing reviews and

interactions to inform the public. In recent years, almost any website will have reviews of products, with some taking it a step further and introducing targeted advertisements based on viewership. Three prominent examples of public opinion being used by big companies are Google, Facebook, and Amazon. Google introduces public opinion directly to the user, as whenever someone searches for something, they are presented with a barrage of reviews, ratings, and things that others liked. Facebook has been known to host many company pages and advertise them based on popularity, though more recently, this has been changed to paid advertisements. Amazon is one of the biggest proponents of public opinion through reviews, as each product likely has a host of text reviews from buyers alongside a star rating out of five based on the average of buyer ratings (Sprague, 2019).

Ratings and reviews increase sales and market performance. They have been the focus of research studies trying to discover the effects and relationships between reviews, including volume and rating, and buyer confidence (Yang et al., 2016). People tend to trust public opinion and go with the crowd, and interest may be sparked by well-written reviews, which means that sellers want well-written, positive reviews for their products (Fera, n.d.).

In this case, the disruptive technology is internet-based product reviews. Before the introduction of this technology, people had to rely on two main sources to determine the quality of a product or service. People would use personal relationships to determine quality or turn to customer review magazines like Consumer Reports, which provide original reviews for a range of consumer products every month (The Editors of Encyclopaedia Britannica, 2009). Internet-based product reviews capitalize on the vast information spread allowed by internet connectivity to provide in-depth customer feedback to other customers and vendors. It is socially disruptive because buying habits have changed fundamentally and permanently, given the influx of reviewer information (Sprague, 2019). This change has led to significant societal changes, from consumer opinion-based advertising to moral questions about data collection on customer preferences.

Flaws in Politics and Polling

It is unlikely that polling will ever be 100% accurate due to its nature being based on the extrapolation of data. This is one of the major flaws of polling because when the polls are wrong, as Kennedy points out, the trust in those polls is heavily wounded unnecessarily. However, more often than not, an incorrect prediction is often due to an error in prediction, as election polls not only have to measure public opinion but also predict which people are going to vote and for who (Kennedy, 2018). Electoral polls are quite hard to interpret, even given a truly representative dataset, as many variables play a part in election results, such as how voter location plays a role in how states will vote in the electoral college.

Another issue with polling is that politics can become too focused on polls. A common critique that sways both ways is that politicians are poll-driven or not poll-driven enough (Rhodes, 2018). The problem, at this point, is one whose results are and will be forever purely theory, as polling is here to stay. However, it does bring up important matters, such as whether poll-driven politicians tend to lie more to gain support based on poll results? Does a politician's appeal to public opinion lead to changes in line with what people want? Does the main focus on polling lead to good results while campaigning? These are important questions; however, they are not within the scope of this paper.

One of the biggest flaws of polling, especially related to public opinion on policies, is that the pollers can heavily influence the poll. Advocacies for both sides of a policy are aware of this and use it to attempt to convince lawmakers that the public favors their side. This can be seen specifically in Texas, where the Texas State Rifle Association's (TSRA) legislative director published a paper pointing out biases in other groups' polls and discussed how opinion polling is ineffective for public policy (Turner, 2021). Not only this, but polls can be designed in such a way as not only to skew results but frame issues in a way to provide misleading information with leading questions. This means that human influence on polls can lead to misrepresentation of public opinion and the harmful spread of misinformation.

Flaws in Product Reviews

Product reviews are a good source of information about the public consensus about a product due to the nature of the text review, with associated number rating. People can understand the reasoning behind a rating given an explanation of expectations and reality. However, this text-based format can lead to issues because the products and services in question are often subjectively rated. Incorrect focus and differing opinions can lead to clashing information. Not only this, but product reviews can lead to negative review attacks, or products can be overwhelmed by bought fake reviews that inflate its rating falsely, both of which are more likely given anonymous reviews (Jones, 2018). Companies can be inundated with negative reviews to attempt to reduce the likelihood of someone buying from them. Whether a desire to destroy for fun or to redirect traffic, malice from people is something that public opinion from product reviews suffers from.

How Public Opinion Information is Used

Despite the limitations mentioned, public opinion is still a central part of contemporary society. For example, public opinion is frequently used to inform the general public about the current consensus. However, the fact that people tend to hop on the bandwagon has led people to question whether public opinion information leads to a self-fulfilling prophecy situation. As a result, there have been many studies on the effects of reporting public opinion, with varying results, from a study that found that public opinion expressed through polls can affect individual opinions to an extent (Rothschild & Malhotra, 2014), to one which found that no feedback loops exist due to knowledge of others answers (Arnesen et al., 2017).

Public opinion information can be used in many different ways. From advocacies trying to gauge the demographics that are interested in their policies to companies trying to devise new products that are likely to get people buying. Given the negative effects that can be caused by various models of gathering information on the public, an argument could be made that it is a bad idea to continue collecting public opinion. However, given that it seems like polling and gathering public opinion is here to stay, I propose machine learning models as a way to help take out some of the possible negative issues associated with collecting public opinion.

Machine Learning for Public Opinion

With interpersonal communication and extrapolation methods developing over time, so have the techniques used to gather public opinion information developed. Political polling started as postcards and newspaper responses, and while those still may be in use, it has moved on to phone calls and online surveys. It seems that the method of actually ascertaining peoples' opinions has not changed throughout this. It is a set of questions created by humans to understand complex beliefs about public issues or, in the case of product reviews, a text box of unfettered human writing. Given that some of the problems associated with gathering information about public opinion are based on human error, whether intentional or not, introducing a more objective determination would reduce the corresponding human error.

Machine learning is a subfield of artificial intelligence that deals with the design and development of algorithms that can learn from and make predictions about data similarly to humans. (IBM Cloud Education, 2020). In machine learning, there are supervised models, which take labeled training datasets and try to make a model that predicts outputs accurately based on an input in a similar fashion to the training dataset, and unsupervised models, which take in data without labels and try to build a model that clusters data, which can be used to find hidden patterns.

Machine learning has yet to gain much traction in everyday uses, though researchers have been applying it to certain areas of data mining for public opinion. For instance, one team utilized supervised learning while testing with different learning methods to gather information about the sentiments of public tweets and found that using a Maximum Entropy Improved Iterative Scaling Classifier (MaxEnt-IIS), they were able to get an 81.6% prediction accuracy, which could be further improved using negation techniques (Arif & Dulhare, 2017). Another team used One-Hot-Encoding, or true or false labeling, to separate out groups of pro-vaccine and anti-vaccine groups based on twitter posts to gauge the likely patterns and demographics of each group (Hallberg et al., 2021). These examples show that using machine learning to determine public opinion in a variety of manners has been done before and is viable.

OpenAI is a company based in California on the cutting edge of AI systems. One of their most recent developments, GPT-3, is a large-scale language processing machine learning model that is the current most powerful model. It has an order of magnitude more parameters than the next biggest language model. It has the ability to comprehend intentions, understand questions, and draw conclusions (Lowe & Leike, 2022). With the development of large-scale models such as this one, the possibilities for gathering information on the public are nearly limitless. For example, people could write their written language opinions on current political policies and have this large-scale machine learning model interpret the sentiment behind it or gather key ideas shared across the public's opinions. You could collect tweets and sort them by intent on a topic and location. Product reviews could be sorted into the most impactful, with language pertinent vocabulary highlighted to present the best information to new customers. The ability to process language is hard for machine learning models, given that languages can be so complex. Still, given the advancements made by OpenAI, newer and better models are in development to deal with language processing. This field is one of the most promising for the development of machine learning-based opinion polling.

Given pure data, machine learning forms mathematical conclusions based on possible groupings. However, there are many forms of biases in datasets that can affect machine learning models. Supervised learning is more likely to be susceptible to biases present in data, as the labeling done on the original dataset is labeled by humans, and is likely to contain biases that will directly be learned by the machine learning model. This is called historical bias, where generated data is based on some flaw or bias. Unsupervised models can also be vulnerable to biased data; for instance, if during training the model is given selective datasets that have been filtered already, they are likely to build clustering models that have the filter as a bias. This is more often than not a representation bias, in which datasets built for a model are poorly representative of the group the model will serve (Cook, n.d.). The creation of biased machine learning models has recently become a topic of public discussion. Biases are restrictive on smaller scale models trained to perform one specific task, as the training data is likely biased. This does not detract machine learning as an option for public opinion gathering though, as data sets can go through multiple

rounds of statistical averaging and pruning before making it to the training model. Not only this but larger-scale models, such as GPT-3, are trained on enormous datasets to learn language comprehension, which, depending on where the data was gathered, can help mitigate biases.

Machine learning is a massively disruptive technology, not solely in the field of public opinion. While defining a framework, Jeroen Hopster himself said that machine learning, as a field, has a strong case to fit into the previously mentioned core categories of disruptive technologies (Hopster, 2021). In the case of public opinion, machine learning also has the potential to be a socially disruptive technology. Machine learning can potentially change the steadily held standard of human created and judged polling which may create some unforeseen moral dilemmas. It is clear that it is disruptive outside of the domain of public opinion, and if it does gain traction in this field, I believe that it will become the new standard, becoming not easily reversible.

The previous inspection of the history of public opinion technologies revealed how socially disruptive technologies have driven the development of public information gathering and interpretation. This historical trend is the reason why I believe that if machine learning gains more traction as a socially disruptive technology, it will become integrated into the gathering and interpretation of public opinion given its many possible uses.

Counterargument

One counterargument to machine learning becoming part of judging public opinion is that the information that such technology could gain on people would present a moral challenge. Currently, Google is experimenting and using machine learning to help with personalized ads, and their algorithms are extremely good at predicting demographics given your search history (Dischler, 2018). This itself is morally questionable, and many people find it invasive, so a large-scale machine learning model predicting public opinion may cross a moral line for many people. In terms of public opinion through product reviews, mitigating the moral quandary becomes a bit tougher. Given that there are already

restrictions on cookies being used to track people, I believe that a similar situation can be applied to machine learning models. If you restrict machine learning only to be used as a measure of comments on products instead of a tool used to derive private information from individual customers, you eliminate many moral issues.

In this case, machine learning is very much like polling as a whole. Polling is a tool, one that is useful in many situations and can be misused in many ways. However, while it does seem to be here to stay, given the public's dependence on it, it is not a principle (Dionne & Mann, 2003). The tool's misuse is limited by the nature of the public's suspicion of the tool in general. Machine learning is in a similar boat. It is here as a tool, and it is here to stay, so the public should remain wary as ever of peoples' attempts to misuse tools.

Conclusion

By studying the history of gathering public information and how technical innovations disrupted and developed the techniques used to collect data, we can trace public opinion technology throughout the ages. Machine learning as a whole is a socially disruptive technology in the domain of society. Though it faces moral challenges of being an invasive judge of people's opinions, I believe that restrictions, such as only using specified machine learning models to judge opinions on relevant topics or using large-scale models to evaluate the public as a whole, not individual people, would help alleviate some of the moral quandaries that may appear from this on the political side. If one thing prevents the adoption of machine learning, it is likely to be the moral issues given people's desire for privacy. However, this paper has shown that it is likely to become the next socially disruptive technology in the line of developments made to the domain of ascertaining public opinion by applying a Socially Disruptive Technology framework. History has shown that disruptive technologies drive the development of public opinion gathering and interpreting, and now machine learning is likely to be a deep, important, ethically salient, and not easily reversed change to public opinion technology.

References

- ADVOC8. (2018, November 27). How to Use Polling for Effective Advocacy. <https://www.advoc8.co/blog/how-to-use-polling-for-effective-advocacy>
- Arif, F., & Dulhare, U. N. (2017). A Machine Learning Based Approach for Opinion Mining on Social Network Data. *Computer Communication, Networking and Internet Security*, 5, 135–147. https://doi.org/10.1007/978-981-10-3226-4_13
- Arnesen, S., Johannesson, M. P., Linde, J., & Dahlberg, S. (2017). Do Polls Influence Opinions? Investigating Poll Feedback Loops Using the Novel Dynamic Response Feedback Experimental Procedure. *Social Science Computer Review*, 36(6), 735–743. <https://doi.org/10.1177/0894439317731721>
- Billingham, C. M., & Kimelberg, S. M. (2016). Opinion polling and the measurement of Americans' attitudes regarding education. *Journal of Education Policy*, 31(5), 526–548. <https://doi.org/10.1080/02680939.2015.1135255>
- CNN. (2019). CNN Texas Poll (Version 1) [Dataset]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research.
- Cook, A. (n.d.). Identifying Bias in AI. Kaggle. <https://www.kaggle.com/code/alexisbcook/identifying-bias-in-ai/tutorial>
- Dionne, E. J., & Mann, T. E. (2003, June 1). Polling & Public Opinion: The good, the bad, and the ugly. Brookings. <https://www.brookings.edu/articles/polling-public-opinion-the-good-the-bad-and-the-ugly/>
- Dischler, J. (2018, July 10). Putting machine learning into the hands of every advertiser. Google Ads Help. <https://support.google.com/google-ads/answer/9065075?hl=en>
- The Editors of Encyclopaedia Britannica. (2009, November 12). Consumer Reports | American magazine. Encyclopaedia Britannica. <https://www.britannica.com/topic/Consumer-Reports>
- Fera. (n.d.). How Product Reviews Influence Shoppers. <https://www.fera.ai/blog/posts/product-reviews-influence-shoppers>
- Fox News/Associated Press (AP-Votecast). (2018). Associated Press-NORC Center for Public Affairs Research Poll: AP VoteCast 2018 (Version 5) [Dataset]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research. doi:10.25940/ROPER-31116384
- Fox News/Associated Press (AP-Votecast). (2020). Associated Press-NORC Center for Public Affairs Research Poll: AP VoteCast 2020 Democratic Primaries (Version 3) [Dataset]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research. doi:10.25940/ROPER-31117747

- Hallberg, A. G., Cortes, E. G., & Barone, D. A. C. (2021). An analysis of Twitter users opinions on vaccines using Machine Learning techniques. 2021 IEEE 33rd International Conference on Tools with Artificial Intelligence (ICTAI), 1311–1315.
<https://doi.org/10.1109/ictai52525.2021.00207>
- Hopster, J. K. G. (n.d.). J.K.G. Hopster (Jeroen). University of Twente.
<https://people.utwente.nl/j.k.g.hopster>
- Hopster, J. (2021). What are socially disruptive technologies? *Technology in Society*, 67.
<https://doi.org/10.1016/j.techsoc.2021.101750>
- IBM Cloud Education. (2020, July 15). Machine Learning. IBM.
<https://www.ibm.com/cloud/learn/machine-learning>
- ICPA. (2014). 2.1 Defining policy advocacy. International Centre for Policy Advocation: Making Research Evidence Matter.
<https://advocacyguide.icpolicyadvocacy.org/21-defining-policy-advocacy>
- IQSS, Harvard/MIT. (2014). 2014 Cooperative Congressional Election Survey (CCES) (Version 5) [Dataset]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research.
doi:10.25940/ROPER-31116790
- IQSS, Harvard/MIT. (2016). 2016 Cooperative Congressional Election Survey (CCES) (Version 3) [Dataset]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research.
doi:10.25940/ROPER-31116791
- Jones, M. (2018, April 4). It's All About Trust: A Brief History of Online Reviews. WebPunch.
<https://webpunch.com/a-brief-history-of-online-reviews/>
- Kennedy, C. (2018, May 14). Can we still trust polls? Pew Research Center.
<https://www.pewresearch.org/fact-tank/2018/05/14/can-we-still-trust-polls/>
- Kennedy, C. (2020, August 5). Key things to know about election polling in the United States. Pew Research Center.
<https://www.pewresearch.org/fact-tank/2020/08/05/key-things-to-know-about-election-polling-in-the-united-states/>
- Laughton, R. (2021, September 7). A History of Online Reviews. ReviewInc.
<https://reviewinc.com/2021/09/07/a-history-of-online-reviews/>
- Lowe, R., & Leike, J. (2022, January 27). Aligning Language Models to Follow Instructions. OpenAI. <https://openai.com/blog/instruction-following/>
- Marquette Law School. (2021). Marquette Law School National Poll (Version 1) [Dataset]. Cornell

University, Ithaca, NY: Roper Center for Public Opinion Research.

Quinnipiac University Polling Institute. (2021, September 27). Quinnipiac University Texas Poll (Version 1) [Dataset]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research.

Quinnipiac University Polling Institute. (2021, December 6). Quinnipiac University Texas Poll (Version 1) [Dataset]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research.

Rhodes, C. (2018, December 24). A brief history of opinion polls. Museum of Australian Democracy at Old Parliament House.

<https://www.moadoph.gov.au/blog/a-brief-history-of-opinion-polls/#>

Rothman, L. (2016, November 17). How One Man Used Opinion Polling to Change American Politics. Time. <https://time.com/4568359/george-gallup-polling-history/>

Rothschild, D., & Malhotra, N. (2014). Are public opinion polls self-fulfilling prophecies? Research & Politics, 1(2). <https://doi.org/10.1177/2053168014547667>

Sprague, D. (2019, December 20). The History and Evolution of Online Reviews. Shopper Approved. <https://5stars.shopperapproved.com/the-history-and-evolution-of-online-reviews/>

Tankard, J. W. (1972). Public Opinion Polling by Newspapers in the Presidential Election Campaign of 1824. *Journalism Quarterly*, 49(2), 361–365. <https://doi.org/10.1177/107769907204900219>

Turner, A. (2021). Lies, Damn Lies, and Polls: How gun control manipulates public opinion surveys. <https://tsrapac.com/wp-content/uploads/2021/10/Andis-Answers-Polls.pdf>

Yang, J., Sarathy, R., & Lee, J. (2016). The effect of product review balance and volume on online Shoppers' risk perception and purchase intention. *Decision Support Systems*, 89, 66–76. <https://doi.org/10.1016/j.dss.2016.06.009>