THE UNIVERSITY OF CHICAGO

Thesis Proposal

How Are Negative Reviews Useful? Assessing the Values of Negative Reviews on Amazon.com

By

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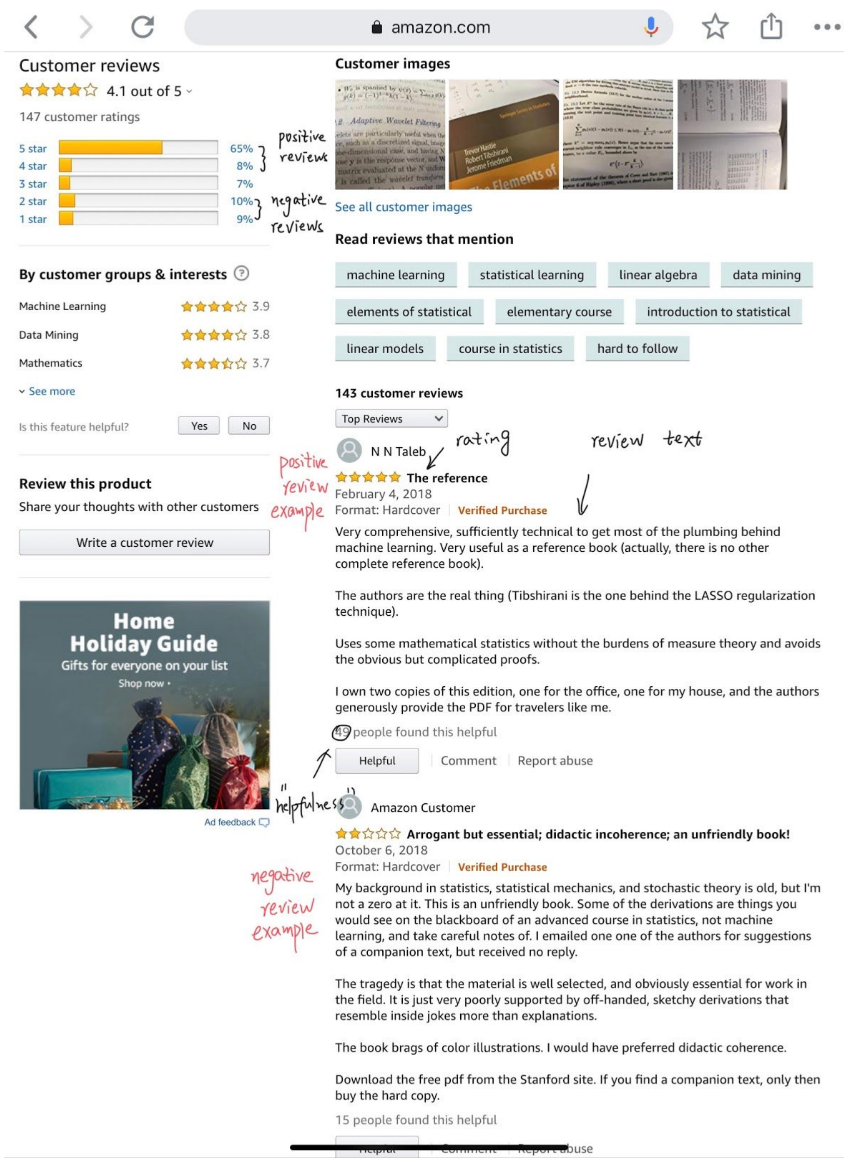
This research seeks to understand how are negative reviews helpful for customers when shopping online. My hypothesis is that negative reviews cover a wider range of topics than positive reviews. Using review data from Amazon, I want to find evidence that customers look for more detailed users' experience to help decisions when reading negative online reviews, compared with positive reviews. I quantify the helpfulness of the reviews by the votes they received from all viewers (see Graph1 for reference). Using natural language processing techniques, I will generate features from the content of the reviews that are potentially helpful for customers, such as sentiments, latent topics, length, etc. Then I will divide the reviews of a given product into two groups: negative or positive reviews. For each group, I will estimate the relative importance of these features in predicting the helpfulness by machine learning (random forest and penalized regression). The results would illustrate what features in negative reviews are comparatively more predictive for the perceived helpfulness.



Graph 1: Screenshot taken on 11/15/19 of Customers Review Page for the book: The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition

I will provide a new perspective on understanding how and why people reading reviews while shopping online. Customer reviews, written by the customers who previously purchased or used the products, are playing a vital role in our daily decision making. You might think the reviews are just helpful additional resources, but you may not be aware of what drives you to read the negative reviews and how you process the information differently. As more and more people believe the positive reviews are more likely to be fake or written with incentives, negative reviews become more trustworthy. If you want to buy an iPhone 8, you already trust Apple as a reliable brand and read reviews to figure out how others use the new features. However, positive reviews might not add much new information to your prior knowledge. Instead, negative reviews could show you some worse case scenarios that other customers have experienced.

I contribute to the literature on customer reviews by discovering the distinctness of negative reviews and how it could help companies understand customers' decision process. Traditionally, researchers would conduct surveys, focus groups, or lab experiments to study people's attitudes and choices. However, many papers have illustrated that reviews tell a lot about the reviewers. Timoshenko and Hauser (2019) show that user-generated content (including reviews, images, etc) could efficiently identify customers' needs by using machine learning. The text data has been popular in business and economics research as new features for the models (Gentzkow et al., 2019 and Berger et al., 2019).

The method of this thesis is inspired by the literature on studying the characteristics of the helpful reviews. When reading a review, customers would evaluate the 'helpfulness' by reading the text of the reviews and vote by putting 'thumbs up' if they find a certain piece is useful. Thus, the helpfulness is measured by the ratio of people who vote for helpfulness against the total number of votes (Singh et al., 2017). Mudambi and Schuff (2010) used the regression model and found review extremity, review depth, and product type affect the review helpfulness. Textual features such as polarity, subjectivity, entropy, and reading ease are generated and proven to help predict the helpfulness by ensembles learning techniques (Singh et al., 2017). The helpfulness is also a good approximation of the popularity (amount of people who read the piece). I plan to incorporate different useful linguistic and semantic features explored in previous research into our model by text mining and feature engineering. As these features are visible for customers, the customers would vote if the output of the features function reaches a certain threshold. Thus, I argue that the important features will be highly correlated with the helpfulness as the customers process the information. Moreover, machine learning will be powerful to approximate the feature functions in the customers' minds.

The main data will be the reviews and product metadata on Amazon. The dataset is scraped by several computer science researchers at the University of California, San Diego and made available for the public (Ni et al., 2019). The raw review data is 34 GB with around 233 million reviews for various products in almost 30 categories. Moreover, the reviews are in the range of May 1996 to October 2018. For each review, it has the reviewer's name, ratings, text, summary, attached image URL, and helpfulness votes. For each product, the data provides detailed information on its characteristics, such as color, price, package type, descriptions, technical details, similar products, image features, categories information, sales rank, etc. As most of the existing literature only explore reviews in a short period for very few products, the data I am going to explore will enable me to compare the helpfulness of negative reviews across product categories, such as books, electronics, groceries, etc.

The major methods will potentially draw from techniques in machine learning and content analysis. In particular, I plan to use the sentiment analysis and topic modeling that could generate more information from the review text. The machine learning techniques that are most appropriate for estimating the weights, in this case, are potentially penalized regression and random forest. However, I will try other new methods that perform better than the purposed ones during the thesis writing period.

There are three main future steps for addressing the research question. Firstly, I will conceptualize customer's perceived helpfulness for reviews as the function of multiple feature variables generated from the reviews that play a role during the process, such as text length, topics, sentiment, grammatical mistakes, readability scores, ratings, etc. Secondly, I will apply machine learning techniques (such as random forest and penalized regression) to estimate the relative feature importance of predicting the helpfulness for two groups: negative and positive reviews. Thirdly, I will compare these features importance between the two groups.

References

Anderson, E. T., & Simester, D. I. (2014). Reviews without a purchase: Low ratings, loyal customers, and deception. *Journal of Marketing Research*, *51*(3), 249–269.

Ansari, A., Li, Y., & Zhang, J. Z. (2018). Probabilistic Topic Model for Hybrid Recommender Systems: A Stochastic Variational Bayesian Approach. *Marketing Science*, *37*(6), 987–1008. https://doi.org/10.1287/mksc.2018.1113

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the Pricing Power of Product Features by Mining Consumer Reviews. *Management Science*, *57*(8), 1485–1509. https://doi.org/10.1287/mnsc.1110.1370

Baek, H., Ahn, J., & Choi, Y. (2012). Helpfulness of online consumer reviews: Readers' objectives and review cues. *International Journal of Electronic Commerce*, *17*(2), 99–126.

Bajari, P., Nekipelov, D., Ryan, S. P., & Yang, M. (2015). Machine Learning Methods for Demand Estimation. *American Economic Review*, *105*(5), 481–485. https://doi.org/10.1257/aer.p20151021

Balducci, B., & Marinova, D. (2018). Unstructured Data in Marketing. *Journal of the Academy of Marketing Science*, *46*, 557–590. https://doi.org/(2018) 46:557–590 https://doi.org/10.1007/s11747-018-0581-x

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2019). Uniting the Tribes: Using Text for Marketing Insight. *Journal of Marketing*, 0022242919873106. https://doi.org/10.1177/0022242919873106

Berger, J., & Milkman, K. L. (2012). What Makes Online Content Viral? *Journal of Marketing Research*, *49*(2), 192–205. https://doi.org/10.1509/jmr.10.0353

Berger, J., Sorensen, A. T., & Rasmussen, S. J. (2010). Positive Effects of Negative Publicity: When Negative Reviews Increase Sales. *Marketing Science*, *29*(5), 815–827. https://doi.org/10.1287/mksc.1090.0557

Büschken, J., & Allenby, G. M. (2016). Sentence-Based Text Analysis for Customer Reviews. *Marketing Science*, *35*(6), 953–975.

Cao, Q., Duan, W., & Gan, Q. (2011). Exploring determinants of voting for the “helpfulness” of online user reviews: A text mining approach. *Decision Support Systems*, *50*(2), 511–521. https://doi.org/10.1016/j.dss.2010.11.009

Chen, P.-Y., Dhanasobhon, S., & Smith, M. D. (2008). *All Reviews are Not Created Equal: The Disaggregate Impact of Reviews and Reviewers at Amazon.Com* (SSRN Scholarly Paper No. ID 918083). Retrieved from Social Science Research Network website: https://papers.ssrn.com/abstract=918083

Chen, Y., & Xie, J. (2008). Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix. *Management Science*, *54*(3), 477–491. https://doi.org/10.1287/mnsc.1070.0810

Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, *43*(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Chintagunta, P. K., Erdem, T., & Wedel, M. (2006). Structural Modeling in Marketing: Review and Assessment. *Marketing Science*, *25*(6), 604–616.

Chintagunta, P. K., & Nair, harikesh S. (2011). Structural Workshop Paper—Discrete-Choice Models of Consumer Demand in Marketing. *Marketing Science*, *30*(6), 977–996.

Dai, W., Jin, G. Z., Lee, J., & Luca, M. (2012). Aggregation of Consumer Ratings: An Application to Yelp.com. *NBER Working Paper*, *No. 18567*.

Eslami, S. P., Ghasemaghaei, M., & Hassanein, K. (2018). Which online reviews do consumers find most helpful? A multi-method investigation. *Decision Support Systems*, *113*, 32–42.

Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the Relationship Between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets. *Information Systems Research*, *19*(3), 291–313. https://doi.org/10.1287/isre.1080.0193

Gentzkow, M., Kelly, B. T., & Taddy, M. (2019). Text as Data. *Journal of Economic Literature*, *forthcoming*.

Geron, A. (2017). *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems* (Vols. 1–1st). O'Reilly Media, Inc.

Ghose, A., & Ipeirotis, P. G. (2011). Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics. *IEEE Transactions on Knowledge and Data Engineering*, *23*(10), 1498–1512. https://doi.org/10.1109/TKDE.2010.188

Ghose, A., Ipeirotis, P. G., & Li, B. (2012). Designing Ranking Systems for Hotels on Travel Search Engines by Mining User-Generated and Crowdsourced Content. *Marketing Science*, *31*(3), 493–520. https://doi.org/10.1287/mksc.1110.0700

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (2nd ed.). Springer.

Hutto, C. J., & Gilbert, E. (2014, June). *VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text*. Presented at the Eighth International Conference on Weblogs and Social Media (ICWSM-14), Ann Arbor, MI.

Kannan, P. K., & Li, H. "Alice." (2017). Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing*, *34*(1), 22–45. https://doi.org/10.1016/j.ijresmar.2016.11.006

King, R. A., Racherla, P., & Bush, V. D. (2014). What We Know and Don't Know About Online Word-of-Mouth: A Review and Synthesis of the Literature. *Journal of Interactive Marketing*, *28*(3), 167–183. https://doi.org/10.1016/j.intmar.2014.02.001

Lee, T. Y., & Bradlow, E. T. (2011). Automated Marketing Research Using Online Customer Reviews. *Journal of Marketing Research*, *48*(5), 881–894. https://doi.org/10.1509/jmkr.48.5.881

Liu, X., Lee, D. (DK), & Srinivasan, K. (2017). *Large-Scale Cross-Category Analysis of Consumer Review Content and Sales Conversion Leveraging Deep Learning*. Retrieved from https://papers.ssrn.com/abstract=2848528

Liu, X., Singh, P. V., & Srinivasan, K. (2016). A Structured Analysis of Unstructured Big Data by Leveraging Cloud Computing. *Marketing Science*, *35*(3), 363–388. https://doi.org/10.1287/mksc.2015.0972

Luca, M. (2011). Reviews, Reputation, and Revenue: The Case of Yelp.com. *Harvard Business School Working Paper*, *No. 12-016*.

Ludwig, S., de Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than Words: The Influence of Affective Content and Linguistic Style Matches in Online Reviews on Conversion Rates. *Journal of Marketing*, *77*(1), 87–103. https://doi.org/10.1509/jm.11.0560

McAuley, J., & Leskovec, J. (2013). Hidden Factors and Hidden Topics: Understanding Rating Dimensions with Review Text. *Proceedings of the 7th ACM Conference on Recommender Systems*, 165–172. https://doi.org/10.1145/2507157.2507163

McAuley, J., Leskovec, J., & Jurafsky, D. (2012). Learning Attitudes and Attributes from Multi-aspect Reviews. *2012 IEEE 12th International Conference on Data Mining*, 1020–1025. https://doi.org/10.1109/ICDM.2012.110

Moe, W. W., & Schweidel, D. A. (2011). Online Product Opinions: Incidence, Evaluation, and Evolution. *Marketing Science*, *31*(3), 372–386. https://doi.org/10.1287/mksc.1110.0662

Moe, W. W., & Schweidel, D. A. (2017). Opportunities for Innovation in Social Media Analytics. *Journal of Product Innovation Management*, *34*(5), 697–702. https://doi.org/10.1111/jpim.12405

Moe, W. W., Schweidel, D. A., & Trusov, M. (2011). What Influences Customers' Online Comments. *MIT Sloan Management Review; Cambridge*, *53*(1), 14–16.

Moore, S. G. (2015). Attitude Predictability and Helpfulness in Online Reviews: The Role of Explained Actions and Reactions. *Journal of Consumer Research*, *42*(1), 30–44. https://doi.org/10.1093/jcr/ucv003

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful review? A study of customer reviews on Amazon. com. *MIS Quarterly*, *34*(1), 185–200.

Mullainathan, S., & Spiess, J. (2017). Machine Learning: An Applied Econometric Approach. *Journal of Economic Perspectives*, *31*(2), 87–106. https://doi.org/10.1257/jep.31.2.87

Ni, J., Li, J., & McAuley, J. (n.d.). *Justifying Recommendations using Distantly-Labeled Reviews and Fine-Grained Aspects*. 10.

Ni, J., Lipton, Z. C., Vikram, S., & McAuley, J. (2017). Estimating Reactions and Recommending Products with Generative Models of Reviews. *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 783–791. Retrieved from https://www.aclweb.org/anthology/I17-1079

Ni, J., & McAuley, J. (2018). Personalized Review Generation By Expanding Phrases and Attending on Aspect-Aware Representations. *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, 706–711. https://doi.org/10.18653/v1/P18-2112

Pan, Y., & Zhang, J. Q. (2011). Born Unequal: A Study of the Helpfulness of User-Generated Product Reviews. *Journal of Retailing*, *87*(4), 598–612. https://doi.org/10.1016/j.jretai.2011.05.002

Reisenbichler, M., & Reutterer, T. (2019). Topic modeling in marketing: Recent advances and research opportunities. *Journal of Business Economics*, *89*(3), 327–356. https://doi.org/10.1007/s11573-018-0915-7

Sen, S., & Lerman, D. (2007). Why are you telling me this? An examination into negative consumer reviews on the Web. *Journal of Interactive Marketing*, *21*(4), 76–94. https://doi.org/10.1002/dir.20090

Singh, J. P., Irani, S., Rana, N. P., Dwivedi, Y. K., Saumya, S., & Roy, P. K. (2017). Predicting the “helpfulness” of online consumer reviews. *Journal of Business Research*, *70*, 346–355.

Taddy, M. (2019). *Business Data Science: Combining Machine Learning and Economics to Optimize, Automate, and Accelerate Business Decisions* (1 edition). New York: McGraw-Hill Education.

Timoshenko, A., & Hauser, J. R. (2019). Identifying Customer Needs from user-Generated Content. *Marketing Science*, *38*(1), 1–20. https://doi.org/10.1287/mksc.2018.1123

van Laer, T., Edson Escalas, J., Ludwig, S., & van den Hende, E. A. (2019). What Happens in Vegas Stays on TripAdvisor? A Theory and Technique to Understand Narrativity in Consumer Reviews. *Journal of Consumer Research*, *46*(2), 267–285. https://doi.org/10.1093/jcr/ucy067

Varian, H. R. (2014). Big Data: New Tricks for Econometrics. *Journal of Economic Perspectives*, *28*(2), 3–28. https://doi.org/10.1257/jep.28.2.3

Varian, H. R. (2016). Causal inference in economics and marketing. *Proceedings of the National Academy of Sciences*, *113*(27), 7310–7315. https://doi.org/10.1073/pnas.1510479113

Wan, M., Misra, R., Nakashole, N., & McAuley, J. (2019). Fine-Grained Spoiler Detection from Large-Scale Review Corpora. *ArXiv:1905.13416 [Cs]*. Retrieved from http://arxiv.org/abs/1905.13416

Wang, Y., Wang, J., & Yao, T. (2019). What makes a helpful online review? A meta-analysis of review characteristics. *Electronic Commerce Research*, *19*(2), 257–284. https://doi.org/10.1007/s10660-018-9310-2

Weathers, D., Swain, S. D., & Grover, V. (2015). Can online product reviews be more helpful? Examining characteristics of information content by product type. *Decision Support Systems*, *79*, 12–23. https://doi.org/10.1016/j.dss.2015.07.009

Wedel, M., & Kannan, P. K. (2016). Marketing Analytics for Data-Rich Environments. *Journal of Marketing*, *80*(6), 97–121. https://doi.org/10.1509/jm.15.0413

Yin, D., Bond, S. D., & Zhang, H. (2014). Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews. *MIS Quarterly*, *38*, 539–560. https://doi.org/10.25300/misq/2014/38.2.10

Zhang, Y., & Lin, Z. (2018). Predicting the helpfulness of online product reviews: A multilingual approach. *Electronic Commerce Research and Applications*, *27*, 1–10.

Zhao, Y., Yang, S., Narayan, V., & Zhao, Y. (2012). Modeling Consumer Learning from Online Product Reviews. *Marketing Science*, *32*(1), 153–169. https://doi.org/10.1287/mksc.1120.0755

Zhu, F., & Zhang, X. (Michael). (2010). Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. *Journal of Marketing*, *74*(2), 133–148. https://doi.org/10.1509/jm.74.2.133