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Student Number	Student Name	Nature of Contribution	Percentage contribution
19300379	Adhishwar Singh Mittal	- Ambassador – Communicated with other groups - Research for text analysis and natural language processing mechanisms - Methodology design, hypothesis testing, model evaluation and explanation - Wrote the data collection and preparation, methodology, results and conclusion in the report - Managed team deliverables through online documentation platforms and meetings	20%
19300369	Piyush Saxena	- Accountant – Kept track of time devoted and associated contributions of each member of the group to the group project - Literature review and research - Validated SHAP values using individual predictions - Model improvement through algorithm selection - Wrote abstract, limitation, future work in the report - Formatting of essay	20%
19300366	Srijan Roy	- Chair – Arranged and chaired meetings and group/lecturer communications; produced meeting agendas - Literature review and research - Designed rarity score metric for feature matrix - Wrote prior work in the report	20%
19310363	Sujit Jadhav	- Recorder – Produced minutes of group meetings and maintained its record - Literature review and research - Design of POS count vectors for Feature matrix - Explained model predictability with respect to POS tags - Helped with report formatting	20%
19304373	Vishal Kumar	- Verifier – Verified weekly responsibilities of other group members - Literature Review and Research - Feature matrix design for text complexity features - Contributed in literature review in the report writing - Report layout in Latex using standard article guidelines	20%

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We have also completed the Online Tutorial on avoiding plagiarism 'Ready, Steady, Write', located at http://tcd-ie.libguides.com/plagiarism/ready-steady-write

We declare that this assignment, together with any supporting artefact is offered for assessment as our original and unaided work, except in so far as any advice and/or assistance from any other named person in preparing it and any reference material used are duly and appropriately acknowledged. We declare that the percentage contribution by each member as stated above has been agreed by all members of the group, and reflects the actual contribution of the group members.

Signed:

Group-6 MOM https://tinyurl.com/u6f52y3

GitHub repository https://github.com/amittal-tcd/TCD-work/blob/master/Text%20Analytics

Exploring Differences in Language Usage in Customer Reviews on Weekends vs Weekdays

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Abstract

It is often seen on online platforms that customers have different behaviours with respect to browsing, shopping or spending at different points of time. For an online food ordering service, customers are more active during dinner as compared to breakfast, or more active on weekends than weekdays. Similarly, for online merchandise stores, customers are more active during festive seasons. This makes us think, can their behaviour while writing reviews on these platforms also vary? And hence, the research question, can we identify patterns of language usage across different time cycles? In this paper we attempt to find differences in language usage in amazon reviews on weekends vs weekdays. We study the frequency of words and complexity of language to explain the correlation between review texts and the day on which the review was posted being a weekday or a weekend[1].

Keywords: amazon reviews, timecycle, language usage, Tree SHAP, count vectors, parts of speech, ZipF score, feature extraction, text complexity, point-biserial, Kruskal-Wallis

1 Introduction

The ecommerce industry has grown substantially in the past few years with multiple platforms coming up across different geographical regions and for a wide variety of products. Apart from the comfort of buying products with just a few clicks, the transparency and availability of content is also an important reason for the rapid growth of the industry. One such source of content is the review posted by fellow customers which provides a great unbiased source of content which does not aim to advertise the product but to show the true image as perceived by other buyers.

Studies [Maslowska et al. , 2017], [Von Helversen et al. , 2018], [Jia , 2018], [Lin et al. , 2012], [Yu et al. , 2017] have been carried out to find and explain factors that influence a user into buying a particular product. The cost competitiveness is the key factor which is followed by other reasons such as fast deliveries, product customisation, marketing strategies etc. Studies show that reviews of the products are considered as one of the most effective factors in influencing a customer's decision. Sentiment analysis of user reviews and validating them with their ratings is a widely pursued research topic [Hang , 2015], [Jia , 2018], [Lei et al. , 2016], [Yu et al. , 2017], [Park , 2018]. This paper focuses on understanding the language usage patterns in the review texts which can be useful to understand user behavior thereby providing insights for marketing campaigns and similar business strategies. The user information available to online platforms may be

[1] https://github.com/amittal-tcd/TCD-work/blob/master/Text%20Analytics

limited. We know the user's demographics, spending capacities, product interests etc. The texts written by the users can act as a secondary source of information which users do not provide while signing up, or through their browsing or spending patterns. This motivates us to find a pattern between the information provided by the user in review texts and the time cycle which is a novel research topic as no similar studies have been formally recorded in the past.

The further part of the research paper is divided into following sections. Section 2 discusses related work, section 3 and 4 present data collection and processing which consists of features extraction using tokenization, complexity parameters and count vectors. Section 5 and 6 present the analysis methodology evaluations which consist of correlation study, hypothesis testing, predictive model creation and model evaluations. Section 7, 8 and 9 discuss the limitations, conclusions and future work for the underlying methodology.

2 Prior Work

The E-commerce industry has seen various research works in order to understand user behavior with respect to spending and browsing in to target business strategies. Research by [Maslowska et al. , 2017] shows that valence, volume and price factor are co-related. Work by [Von Helversen et al. , 2018] compares buying habits of young people to that of older people.The study by [Jia , 2018] suggests correlating ratings with reviews quantitatively. The accuracy of a recommender system can be improved using the Rating prediction method (RPS) suggested by [Lin et al. , 2012] which is a sentiment-based algorithm. [El-Said , 2020] analysed the impact caused by online reviews with the intention to book hotels. [Park , 2018] helped in automatically predicting how helpful the reviews are. The key similarity in a lot of these works is the use of user reviews.

Various studies have been conducted to study language usage for text classification and analysis outside the e-commerce domain which are utilised in this paper to understand the complex relationship between text and time cycles. Study carried out by [Das and Rakesh , 2014] on Movie Reviews used a feature matrix created by counts of POS taggings in unigrams, bigrams and POS tagged bigrams as training features. In the research work done by [Hachey and Grover , 2005] on summarization of legal judgement, the author adopted the method of point-biserial correlation for evaluation of their ranking methods. While in another experiment by [Preoundefinediuc-Pietro et al. , 2016], also used the similar technique for prediction of the attributes like gender, age and occupational class. The results are significant in both the above experiments. The point-biserial coefficient is given as

$$r_{pb} = \frac{M_0 - M_1}{S_y}\sqrt{\frac{n_0}{n}\frac{n_1}{n}}$$

where M_0 = the mean of the data from group 0, M_1 = the mean of the data from group 1, S_y = the standard deviation of the continuous data, n_0 = the number of items in group 0, n_1 = the number of items in group 1, n = the number of items in both groups together (aka the total rows in the data set)

Kruskal-Wallis test, a non-parametric correlation, was used by [Beltrami et al. , 2018] in their experiments to prove the correlation between the subject groups and education level. In his work, [Kruskal and Wallis , 1952] used the same method to establish their Hypothesis on Artificial Intelligence Assistants.

$$H = \frac{N-1}{N}\sum_{i=1}^{C}\frac{n_i[\overline{R}_i - \frac{1}{2}(N+1)]^2}{(N^2-1)/12}$$

n_i is the number of observations in group
$\overline{R}_i$ is the mean of the n_i ranks in the ith sample.
$(N+1)/2$ is the mean and $(N^2-1)/12$ is the variance of the uniform distribution over the first N integers.

Zipf scale word frequency estimator, introduced by [Van Heuven et al. , 2014], is a variation of word frequency counter where it returns the output into logarithmic scale i.e. count in log10 of the occurrence of a particular word per billion words for easy understandability. These works direct our design of the feature matrix which is used for training the predictive model. One such model is LightGBM [Ke et al. , 2017], a gradient boosting framework designed by Microsoft that uses tree based learning algorithms. It is designed to be distributed and has advantages such as faster training speed, higher efficiency, lower memory usage, better accuracy, support of parallel and GPU learning, capability of handling large-scale data etc. [Chen et al. , 2020] proposed a method for recognition of paper citations in which both Bert and LightGBM are trained using pairwise methods. Its authors won first place in the Citation Intent Recognition competition (WSDM Cup 2020 track1). [Bejuk et al. , 2018] presented a LightGBM approach to rank comments according to relevance to a given question and to rank already existing questions according to relevance to a given question.

Complex predictive models cannot be explained in the same way as parametric models such as logistic regressions. [Shapley , 1953] introduced a cooperative game theoretic approach which was later incorporated to explain a prediction made by ensemble models by [Lundberg et al. , 2018]. The approach explains the expected value of prediction probability in a classification model. SHAP (SHapley Additive exPlanations) [Lundberg et al. , 2018] is a method to explain individual predictions. It is based on the game theoretically optimal Shapley Values. SHAP specifies the explanation as:

$$g(z') = \phi_0 + \sum_{j=1}^{M} \phi_j z'_j$$

where g is the explanation model, $z' \in \{0,1\}^M$ is the coalition vector, M is the maximum coalition size and $\phi_j \in R$ is the feature attribution for a feature j i.e. the shapley values. Coalition vectors are called simplified features. [Lundberg et al. , 2018] also proposed TreeSHAP, a variant of SHAP for tree-based machine learning models such as decision trees, random forests and gradient boosted trees.

3 Data Collection

For this, an Amazon Reviews data set is used. Table 1 shows a subset snapshot of the data used for this research and Table 2 gives description of the features.

primaryCategories	reviews.rating	reviews.text	reviews.title	reviews.date
Health & Beauty	3	I order 3 of them and one of the item is bad q...	... 3 of them and one of the item is bad quali...	2017-03-02T00:00:00.000Z
Health & Beauty	4	Bulk is always the less expensive way to go fo...	... always the less expensive way to go for pr...	2016-08-31T00:00:00.000Z
Health & Beauty	5	Well they are not Duracell but for the price i...	... are not Duracell but for the price i am ha...	2016-12-06T00:00:00.000Z
Health & Beauty	5	Seem to work as well as name brand batteries a...	... as well as name brand batteries at a much ...	2016-03-28T00:00:00.000Z
Health & Beauty	5	These batteries are very long lasting the pric...	... batteries are very long lasting the price ...	2017-04-22T00:00:00.000Z

Table 1: Snapshot of dataset

The complete description of the data can be found at - Consumer Reviews of Amazon Products.

4 Dataset Preparation and Pre-Processing

Required fields from the amazon reviews data are selected and pre-processed. Non-english words, special characters and words containing numbers are removed. Review text is broken into unigrams. Count vectors are created using unigrams and parts of speech tags. Complexity features - sentence count, ZipFScore [Speer et al. , 2018] are created. The review timestamp is used to extract day or week and flagged as weekend or weekday. Finally, the data is split in a 70-30 ratio for the purpose of cross validation.

Feature	Datatype	Description
primaryCategories	Categorical,nominal	category of reviewed product
reviews.rating	Numerical, discrete	Rating corresponding to user review
reviews.text	Text field	Contains text from the customer review
reviews.title	Text field	Contains title of the review decided by the customer
reviews.date	DateTime	Timestamp when the review was posted

Table 2: Data description

5 Methodology

The continuous predictor fields are checked for correlation with the binary target variable using Point-Biserial [Tate , 1954] correlation and Kruscal-Wallis [Kruskal and Wallis , 1952] test. A gradient boosting model is trained using the LightGBM API [Ke et al. , 2017] from microsoft. To assess the statistical significance, a permutation test by [Venkatraman , 2000] is performed. The null hypothesis is - "The text features cannot predict if a text was written on weekend or weekday." Actual labels of the test data are randomly shuffled and accuracy is calculated. Histogram of the accuracies is plotted and compared with model accuracy. ROC and confusion matrix for the model are inspected. AUC is calculated and cross-validated over test data. Finally we explain the model prediction using SHAP values [Lundberg et al. , 2018]. Features are ranked by contributions in predictions and top features are individually analysed for decision rules.

6 Results and Evaluation

6.1 Feature correlations

Point-Biserial correlation metric [Tate , 1954] and [Kruskal and Wallis , 1952] show the correlation between predictor fields and target fields. Table 3 shows the Point-Biserial correlations for top 10 fields by absolute correlation coefficient with p-values less than 0.05. The percentage difference shows significant change in usage of words denoted by predictor field name. The complete table can be referred from our Github repository[2].

Predcitor Field	Point-Biserial Correlation	Point-Biserial p.value	Mean Value on Weekday	Mean Value on Weekend	Percentage Differnece in Mean
outside	-0.03	0.0000001	0.0019	0.0065	-70%
lose	-0.03	0.0000003	0.0005	0.0033	-84%
card	-0.03	0.0000015	0.0083	0.0164	-50%
unless	-0.03	0.0000020	0.0014	0.0049	-71%
boost	-0.03	0.0000038	0.0000	0.0012	-100%
ready	-0.03	0.0000079	0.0019	0.0058	-66%
attractive	-0.03	0.0000125	0.0002	0.0019	-88%
everybody	-0.03	0.0000189	0.0000	0.0010	-100%
unlimited	-0.03	0.0000265	0.0015	0.0047	-68%
straight	-0.03	0.0000292	0.0004	0.0023	-82%

Table 3: Point-Biserial correlations for top 10 fields

Table 4 shows the results of Kruskal-Wallis test. It can be seen that there are only two features - JJ i.e. number of adjectives and IN i.e. number of prepositions which are correlated with target having p-value

[2]https://tinyurl.com/Correlations-xlsx

less than 0.05. Both features have a 5% difference in mean on weekend vs weekday. It may be a function of shorter texts on weekday vs weekend and needs more exploring.

Predcitor Field	Kruskal Statistic	Kruskal Statistic p.value	Mean Value on Weekday	Mean Value on Weekend	Percentage Differnece in Mean
JJ	9.86	0.0016937	1.4887	1.5705	-5%
IN	7.13	0.0075985	1.8455	1.9436	-5%

Table 4: Kruskal-Wallis test results

6.2 Hypothesis Test Results

The permutation test, with 10,000 permutations of shuffled test labels, yields the histogram of prediction accuracies as shown in Figure 1. The red line denotes actual model accuracy which is 100 percentile of the permutation distribution giving us a p-value significantly lower than 0.05 and hence, negating the null hypothesis. This proves that the model can predict whether an Amazon review text was written on a weekend or weekday.

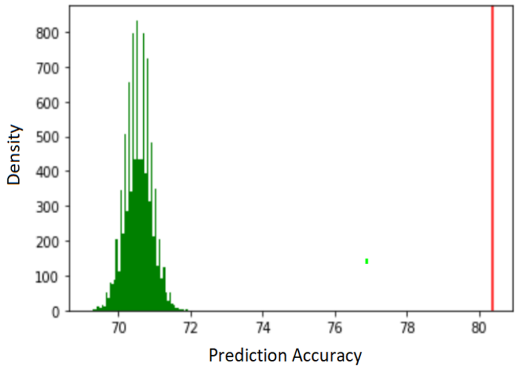


Figure 1: Histogram of prediction accuracies from permutations of shuffled test labels

6.3 Model Evaluation

The model is evaluated through cross-validation on 30% test data. Figure 2 shows the ROC and confusion matrix for the model. For the test data, AUC is ∼0.72, precision is 0.81 and recall is 0.965.

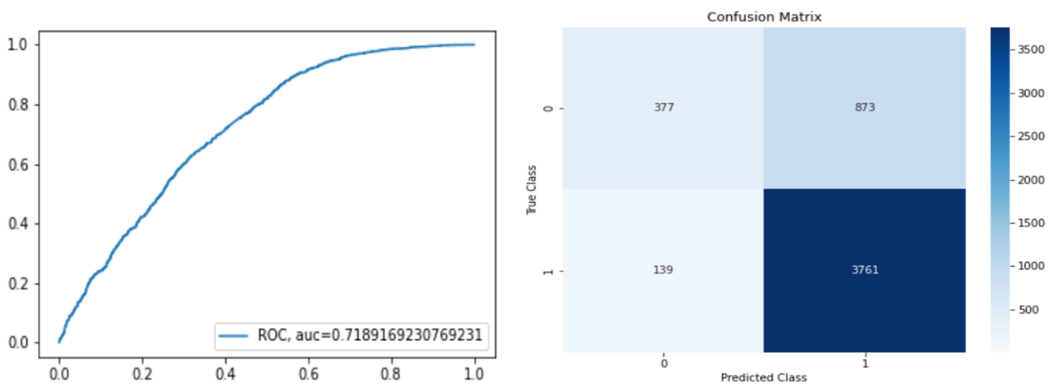
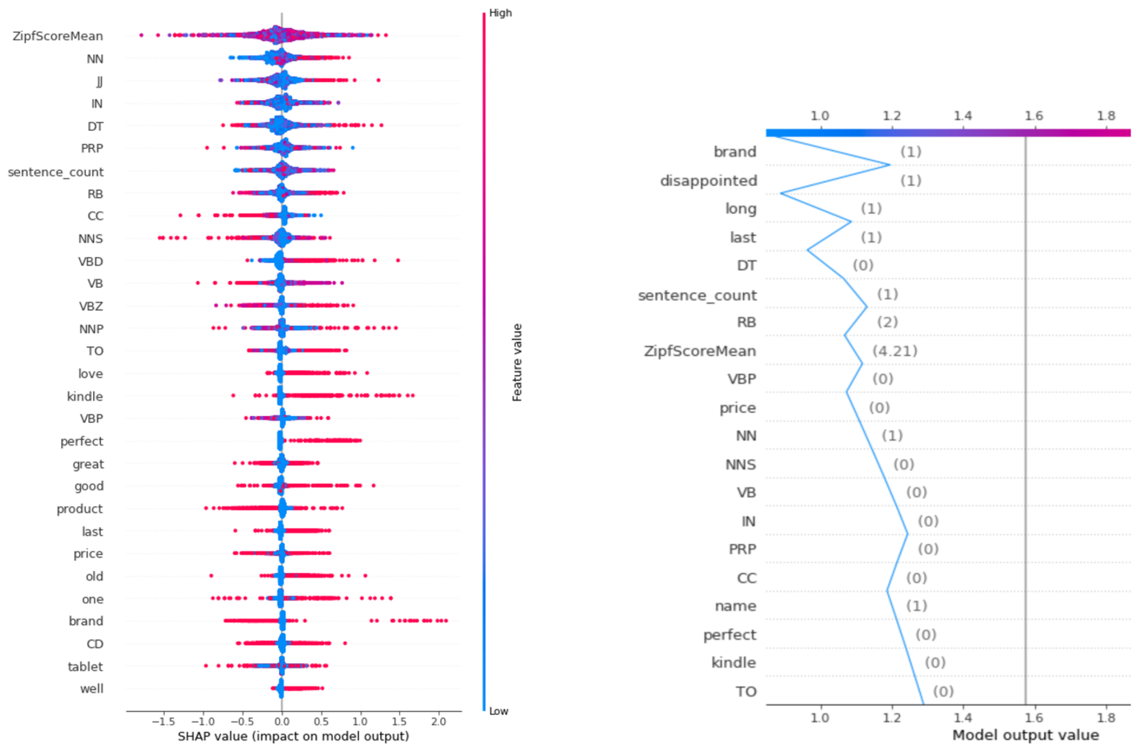


Figure 2: ROC and Confusion Matrix

6.4 Model Explanation

The difference between base value and output prediction value of whether a review was written on a weekend or a weekday is explained using SHAP values collected from Gradient Boosting [Ke et al. , 2017] model. The SHAP summary in Figure 3a shows top 20 features on the y-axis and impact on the x-axis denoted by SHAP values. The features shown in capital letter are POS[3] tags. The red color presents any positive force by SHAP values to push base value to output value whereas the blue color is the negative impact. Each dot shows one instance in the test data used for cross-validation of model performance. It can be seen that when the word "love" has higher counts in a text, there is a higher probability of the text being written on a weekday than on a weekend. Similarly, higher frequencies of the words "perfect" and "kindle" suggest that the reviews have been written on a weekday. A more detailed summary is available at our Github repository[4].

SHAP results are confirmed through individual predictions using force and decision plots. The decision plot in Figure 3b and the force plot in Figure 4 show SHAP values for a randomly chosen instance in the validation data. It can be seen that "ZipFScore" and "sentence_count" have negative SHAP forces on the prediction value which imply a negative correlation as depicted by the summary plot. Maximum force is applied by the count of the words "brand" and "disappointed" in the text. The former has a negative force while the latter has a positive force.



(a) (b)

Figure 3: (a) SHAP summary of top 20 features & (b) SHAP summary decision plot for each individual prediction

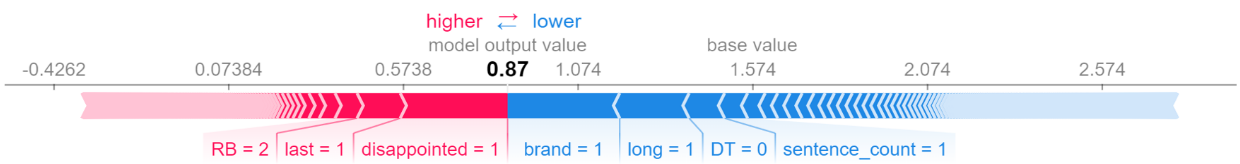


Figure 4: Force plot showing the force of each individual feature

[3] https://tinyurl.com/tag-20descriptions-xlsx
[4] https://tinyurl.com/Summary-20100-20Features-png

6.5 Proposed Decision Rules / Lexicon

A set of decision rules can be proposed with the help of SHAP values. The rules are divided in 2 parts -

A. Features which imply higher probability of weekend - ZipfScoreMean, PRP (Personal pronoun), sentence_count, CC (coordinating conjunction), NNS (noun plural), VBD (verb past tense), great, product, brand, tablet, PRP (possessive pronoun), VBG (verb gerund), VBN (verb past participle), long, fire, version, battery, case, like, turn, happy, wife.

B. Words which imply higher probability of weekday - NN (noun, singular), JJ (adjective), DT (determiner), RB (adverb), VBD (verb past tense), VBZ (verb, present tense, 3rd person singular), NNP (proper noun, singular), TO (infinite marker), love, kindle, VBP (verb, present tense not 3rd person singular), perfect, good, last, old, one, CD (cardinal digit), well, use, MD (modal), parental, think, really, works, even, lot, watch, always, value, far, son, though, much.

The lists given above only show the top 50 features. A complete list can be created using the detailed summary plot[5].

6.6 Feature Importances

The importance of the features can be seen through the model feature importances as shown in Figure 5. The value is an estimate of overall model predictions as given by the LightGBM API.

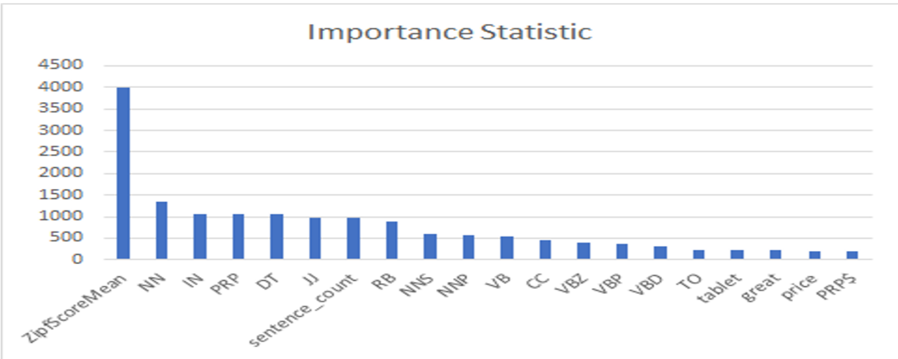


Figure 5: Feature Importances

It can be seen that the same features such as ZipfScoremean, POS count vectors and sentence count along with prominent unigrams are on the top. Complete list of importances can be seen at our Github repository[6].

6.7 Applications

The aforementioned words can direct key business strategies. For example, the word "wife" occurs more on weekdays which may be an indication about a certain cohort of users, husbands in this context, making purchases for their wifes online. Campaigns for products such as merchandise aimed at couples can be advertised more rigorously during weekdays for targeting the campaigns better for lower cost of marketing without any loss of sales or maybe even an increase in the sale.

Signs of more positive words can be seen on weekends. For example, the word "happy" in the text suggests that the review text was written on a weekend. There is a probability that people as a whole write happier reviews over the weekends. If this hypothesis can be confirmed, campaigns can be targeted such as "Could you answer these questions ?" which amazon often does to provide more content over the products in the form of verified buyer reviews over the weekend instead of weekdays so that buyers have more reason to buy products from the more positive reviews.

[5] https://tinyurl.com/Summary-20100-20Features-png
[6] https://tinyurl.com/Results-LGBMImportances-JPG

7 Limitations

The analysis is specific to the amazon reviews data and may not hold true universally for all reviews across all platforms. It is an inherent limitation of SHAP values that feature interactions are ignored. Therefore, the decision rules must be used with caution. The analysis may simply be a function of different cohorts of users posting reviews on amazon on weekday vs weekend. To look at changes in a single person's writing style, multiple reviews from the same user must be referred.

8 Conclusion

We demonstrated how review text from a user can be used to find out if the text was written on a weekend or a weekday. Complexity of text, rarity of words and word count vectors are found having significant correlations with time cycle. The predictions were broken down by feature contributions and boosting tree explanations to analyse which features or words have prominent differences in values on weekday vs weekend. A significant model performance with a precision of 0.81 and recall of 0.96 is achieved. AUC for the model is 0.72. A set of decision rules to predict time cycle is also proposed. We observed significant changes in language usage with respect to word frequencies, use or parts of speech, rarity of words and text complexity on weekdays as compared to weekends. These language usage differences can direct market strategies by providing extra information about the customers

9 Future Work

We can compare the prediction contribution of different features using similar concepts like SHAP such as LIME [Tulio et al. , 2016] which creates a locally interpretable model to justify the model predictions as a whole. Other variants of the local context modellers can be used such as SP-LIME. Also, we can clearly see the dependence of the features as a lot of the words occur together in the english language. So, using a simple factor analysis or principal component analysis, we can look at the dependence of words and reduce the data for predictions as well. This will further point us to a clearer lexicon of key words and their impacts as a broader spectrum of predictability explanation of the boosting algorithm.

References

Bejuk, B., Brajdic, K. and Luksic, D. , 2018, 'Solving community question answering ranking problem using lightgbm', pp. 21–25.

Beltrami, D., Gagliardi, G., Rossini Favretti, R., Ghidoni, E., Tamburini, F. and Calzà, L. , 2018, 'Speech analysis by natural language processing techniques: A possible tool for very early detection of cognitive decline?', *Frontiers in Aging Neuroscience* **10**.

Chen, W., Liu, S., Bao, W. and Jiang, H. , 2020, 'An effective approach for citation intent recognition based on bert and lightgbm', *wsdm* .

Das, O. and Rakesh, C. , 2014, 'Sentiment analysis of movie reviews using pos tags and term frequencies', *International Journal of Computer Applications* **96**, 36–41.

El-Said, O. A. , 2020, 'Impact of online reviews on hotel booking intention: The moderating role of brand image, star category, and price', *Tourism Management Perspectives* **33**, 100604.

Hachey, B. and Grover, C. , 2005, 'Sentence extraction for legal text summarisation', *IJCAI International Joint Conference on Artificial Intelligence* pp. 1686–1687.

Hang, S. , 2015, 'How products are evaluated? evaluation in customer review texts', *Language Resources and Evaluation* **50**, 475–495.

Jia, S. S. , 2018, 'Behind the ratings: Text mining of restaurant customers' online reviews', *International Journal of Market Research* **60**, 561–572.
URL: *http://journals.sagepub.com/doi/abs/10.1177/1470785317752048*

Ke, G., Meng, Q., Finley, T., Wang, T. and Chen, W. , 2017, 'Lightgbm: A highly efficient gradient boosting decision tree', *NIPS* .

Kruskal, W. H. and Wallis, W. A. , 1952, 'Use of ranks in one-criterion variance analysis', *Journal of the American Statistical Association* **47**, 583–621.

Lei, X., Qian, X. and Zhao, G. , 2016, 'Rating prediction based on social sentiment from textual reviews', *IEEE Transactions on Multimedia* **18**, 1910–1921.

Lin, Y., Zhang, J., Wang, X. and Zhou, A. , 2012, 'An information theoretic approach to sentiment polarity classification', *Proceedings of the 2nd Joint WICOW/AIRWeb Workshop on Web Quality - WebQuality '12* .

Lundberg, S., Erion, G. and Lee, S.-I. , 2018, 'Consistent individualized feature attribution for tree ensembles'.

Maslowska, E., Malthouse, E. C. and Viswanathan, V. , 2017, 'Do customer reviews drive purchase decisions? the moderating roles of review exposure and price', *Decision Support Systems* **98**, 1–9.

Park, Y.-J. , 2018, 'Predicting the helpfulness of online customer reviews across different product types', *Sustainability* **10**, 1735.

Preoundefinediuc-Pietro, D., Xu, W. and Ungar, L. , 2016, 'Discovering user attribute stylistic differences via paraphrasing', *AAAI Press* p. 3030–3037.

Shapley, L. , 1953, 'A value for n-person games. annals of mathematics studies', pp. No. 28, 307–317.

Speer, R., Chin, J., Lin, A., Jewett, S. and Nathan, L. , 2018, 'Luminosoinsight/wordfreq: v2.2'.
URL: *https://zenodo.org/record/1443582#.XpTHJMhKguU*

Tate, R. F. , 1954, 'Correlation between a discrete and a continuous variable. point-biserial correlation', *The Annals of Mathematical Statistics* **25**, 603–607.

Tulio, M., Singh, S. and Guestrin, C. , 2016, '"why should i trust you?": Explaining the predictions of any classifier', *arXiv* **1602.04938**, 97–101.

Van Heuven, W. J. B., Mandera, P., Keuleers, E. and Brysbaert, M. , 2014, 'Subtlex-uk: A new and improved word frequency database for british english', *Quarterly Journal of Experimental Psychology* **67**, 1176–1190.

Venkatraman, E. S. , 2000, 'A permutation test to compare receiver operating characteristic curves', *Biometrics* **56**, 1134–1138.

Von Helversen, B., Abramczuk, K., Kopeć, W. and Nielek, R. , 2018, 'Influence of consumer reviews on online purchasing decisions in older and younger adults', *Decision Support Systems* **113**, 1–10.
URL: *https://www.sciencedirect.com/science/article/pii/S0167923618300861*

Yu, J., Zha, Z.-J., Wang, M. and Chua, T.-S. , 2017, 'Product aspect ranking based on online customer reviews', *International Journal of Modern Trends in Engineering & Research* **4**, 124–129.