AN ANALYSIS ON PERFOMANCE EXHAUSTS USING CUSTOMER SENTIMENTS

Abstract

Customer sentiments were used to extract valuable insights about exhausts for companies.

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1. INTRODUCTION -

The automotive industry is constantly evolving, and every year, new technologies and trends emerge. One of the current emerging trends is the rising demand for high-performance exhaust systems. Such systems can considerably enhance the performance of vehicles by reducing back pressure and increasing exhaust flow. To cater to this demand, a performance exhaust industry has emerged, which focuses on making high-quality exhaust systems for vehicles, including cars and motorbikes. This industry comprises both aftermarket manufacturers and original equipment manufacturers (OEMs). Aftermarket manufacturers specialise in designing custom exhausts for specific vehicles, whereas OEMs make exhaust systems that are installed on vehicles during their production stage.

The performance exhaust industry is a dynamic and evolving segment of the automotive industry, spurred by the desire for high-performance vehicles and the pressing need to maintain a balance between performance and environmental sustainability. According to **(MarketsandMarkets, 2021),** the global market for automotive exhaust systems was valued at USD 74.5 Billion in 2021, and it is projected to grow at an annual growth rate of 5.41% during the period from 2022 to 2030, and could reach a value of USD 119.7 Billion.

The performance exhaust market has been the subject of numerous studies that have looked at everything from exhaust design and manufacture to performance assessment. For instance, **(Mohamed et al. 2019)** proved that performance exhaust systems can greatly improve vehicle performance by investigating the effect of an automobile silencer on vehicle performance using both experimental testing and ANSYS simulation software.Similarly, **(Deshmukh and Kolhe,2020)** found that the design of an exhaust system can significantly affect engine performance after investigating the effects using analytical and experimental methodologies.

Nevertheless, the performance exhaust market is not without its challenges, such as evolving emissions standards and environmental worries. The air quality and public health in metropolitan areas are greatly impacted by vehicle emissions, particularly nitrogen oxides (NOx) and particulate matter (PM), according to **(Kumar et al., 2016)**. Therefore, it is imperative to create exhaust systems that are kind to the environment, reduce emissions, and boost fuel efficiency while maintaining high levels of performance.

Although the performance exhaust market has been booming, there hasn't been a lot of research on consumer sentiment towards performance exhaust systems. But in recent years, interest in sentiment analysis has grown as a potentially useful tool. This method can be used to evaluate the tone of written material, such as news stories, social media posts, and reviews. It has gained popularity particularly in the field of marketing because it gives advertisers access to information on consumer preferences and sentiments, which can help them create more effective marketing campaigns.

The impact of online customer reviews on sales has been the subject of several studies, with varying findings. **(Huang and Benyoucef, 2015)** found that positive reviews have a stronger impact on purchase behaviour for less familiar products, while negative reviews have a stronger impact on more familiar products. **(Zhu and Zhang,2010)** discovered that online reviews have a significant impact on sales, especially for less popular products and those with high levels of uncertainty.**(Hu, Liu, and Zhang ,2008)** showed that reviews have a significant effect on sales, and sentiment analysis can be used to identify the most influential reviewers and the most important product features. **(Basile and Nissim, 2013)** also found that sentiment analysis can be useful for businesses in understanding consumer preferences and improving their products and services. Finally, **(Raza and Al-Hawasi, 2020)** conducted a sentiment analysis on Amazon product reviews using different machine learning algorithms and analysed the performance of these models. They found that the random forest model outperformed others in terms of accuracy, precision, and recall.

In this study, we will be conducting sentiment analysis on customer reviews of performance exhaust systems using Amazon review data. The objective of this study is to identify the sentiment of customers towards performance exhaust systems and to determine the factors that influence their sentiment. Reviews from a variety of customers, including auto enthusiasts, mechanics, and casual drivers, are included in the data collection. The text reviews offer details about the installation, sound quality, dependability, and overall performance of the performance exhaust system as well as the customers' experiences with it.

1.1. Data Set:

The data set used in this study is the Amazon review data collected by **(Ni, Li and McAuley,2018)** on all automotive parts and accessories. The data set contains customer reviews of various performance exhaust systems available on Amazon, along with the rating given by the customer and other relevant information such as the brand, product name, and price.

The data set includes reviews from a wide range of customers, including car enthusiasts, mechanics, and casual drivers. The reviews are in text format and provide insights into the customer's experience with the performance exhaust system, including its installation, sound quality, durability, and overall performance.

1.2. Research Question:

The main research questions addressed in this study are:

1. In predicting the sentiments of customer reviews, which machine learning model is the most accurate?
2. A detailed Sentiment analysis of the Top 5 most reviewed Performance exhausts.
3. Word pairs that are most frequently associated with positive and negative performance exhaust reviews using bigrams.

The following section will introduce the data in more detail and explain the steps taken to prepare, analyse and visualise the data.

2. DATA EXPLORATION AND PROCESSING:

The Amazon Automotive Review Dataset provided by **(Ni, Li and McAuley,2018)** consists of a vast range of data spanning two decades, from May 1996 to October 2018. This extensive dataset consists of two tables, each with unique information. The first table contained the review data and the second table had the meta data.

The 5-core version of the review data set was used which is a subset of the main data set. It contains 1,711,519 rows of data and 11 variables and each row pertains to one particular customer review. The following columns were of use in our study -

1. **Asin** - This is the unique product identifier which is in an alphanumeric format.
2. **ReviewText** - This column contains the text of all the reviews left by customers. This is the most important column used for sentiment analysis.
3. **Overall** - This column has all the ratings left by customers ranging from 1-5, with 1 being the worst and 5 being the best.

The remaining columns like “reviewerName” and ”summary” were filtered out as they had no relevance to our study.

The metadata table contains 932,000 rows with each row pertaining to a product. It holds information about the products, with columns containing product names, descriptions, image urls, categories, brands etc. From the metadata column, the rows containing performance exhausts were filtered out. This gave us a metadata set containing the information on all the performance exhausts sold on Amazon. The columns which were relevant for our analysis were filtered out as follows -

1. **Asin** - This is the same identifier used in the Review data set.
2. **Categories**- The category of the particular automotive product belongs to.
3. **Title** - This column contains the names of all the products.
4. **salesRank** - This column contains the rank information of each product.

In order to obtain a dataset that included both exhaust information as well as respective customer reviews, an inner join was performed on the two filtered dataset using the common column “Asin”. This resulted in a final dataset that was suitable for conducting our analyses and answering our research questions.

Further actions were taken to manipulate and clean data to make it suitable for machine learning and sentiment analysis. Firstly,Stop words were removed from the “reviewText” column. Stop words are the set of words that do not add to the sentiment that is conveyed in a body of text and can lead to inaccuracies during analysis. Examples of such words are “the, "is”, and "and”. Secondly, leading trails and special characters like commas, full stops, exclamations etc were also removed to make it uniform and grammatically sound.

In addition to text cleaning, a new variable called “sentiment” was added to teach the machine learning models how to classify the reviews. Reviews with an overall rating of 2 or below were classified as negative, ratings of 3 were classified neutral and 4 or above were classified as positive. A pipeline was utilised to perform this task.

Apache spark and Java were used in Google Colaboratory to perform all the tasks. Spark and Java are a powerful and efficient platform for data analysis. The libraries which were utilised were pyspark.ml, pyspark.sql for ML models, re and nltk for text processing and seaborn, matplotlib.pyplot, pandas, wordcloud and bigrams were used for visualisation.

3. DATA VISUALISATION AND INTERPRETATION:

This section will focus on all the results obtained after performing analytical processes. The final exhaust data set contained 135 unique products and 1860 rows of data.

Figure 1 shows the "overall" column's distribution which contains the ratings given by customers to all the exhausts.

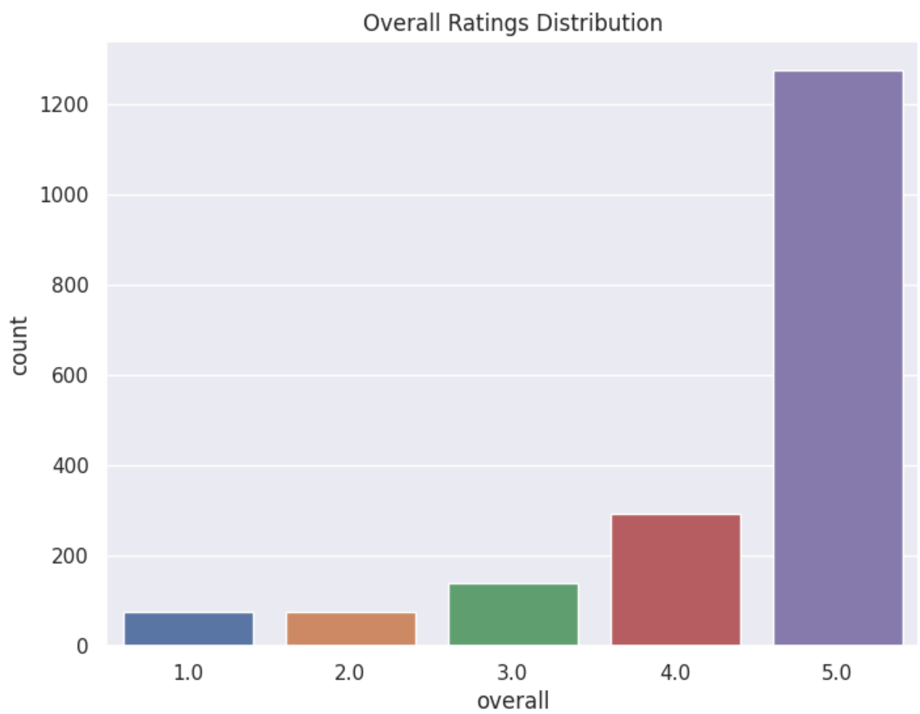

Figure 1- Overall Rating BarPlot

It is seen that the most frequent rating is 5 stars which has over 1200 occurrences. The frequency of 3 stars and below is significantly low in comparison, with all of them occurring less than 200 times each. The mean is 4.406 with a standard deviation of 1.061. The median and mode are both 5.

Now, before we take a look at the results from the machine learning models, let us begin by analysing the language used in the reviews by taking a look at the 30 most frequently occurring words in the "reviewText" column. This is depicted in Figure 2 below.

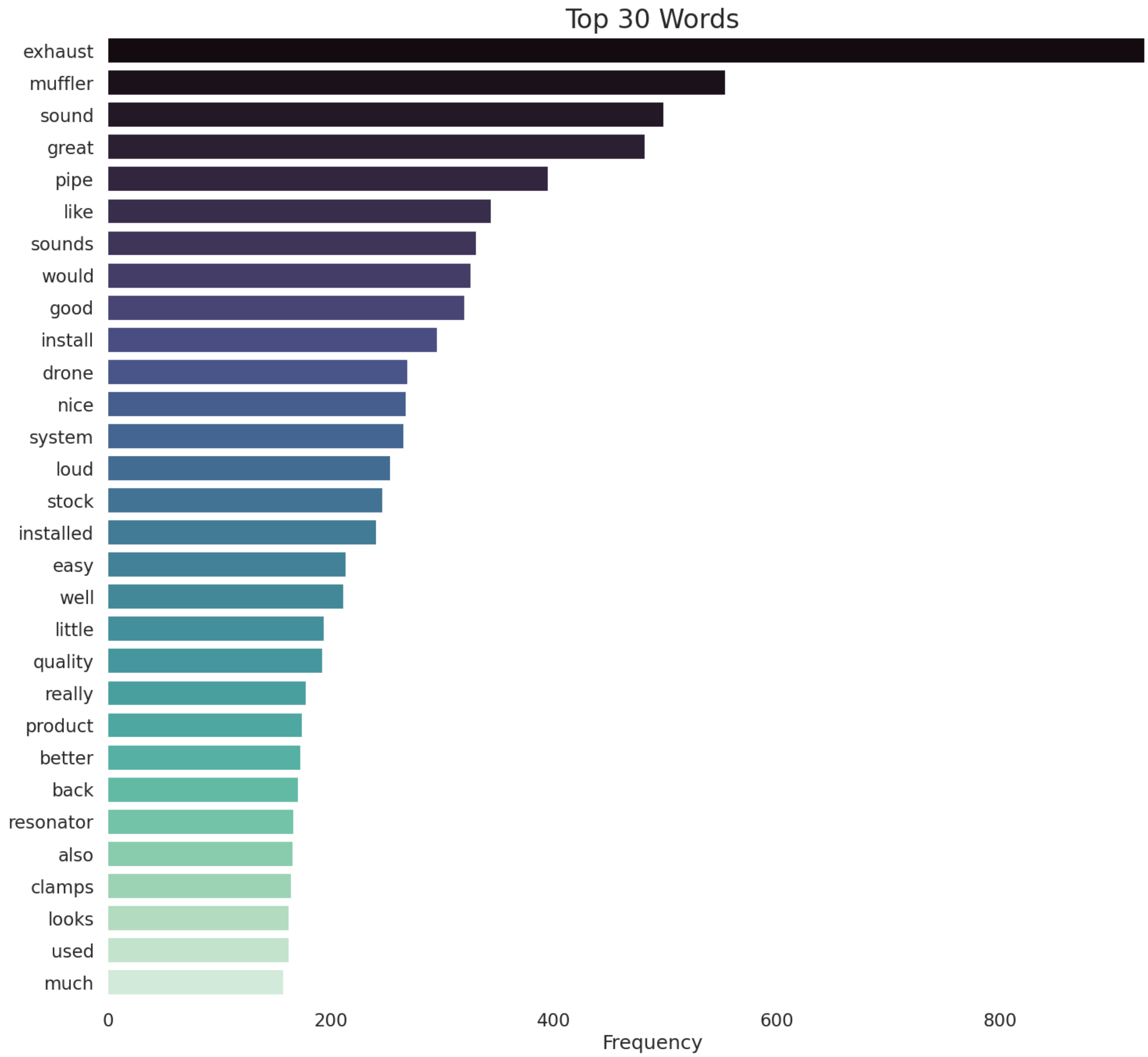

Figure 2- 30 most frequently occurring words

Evidently, the word “exhaust” is the most frequently occurring word. The second and third most occuring are “muffler” and “sound”. It is not surprising to see that the second and third most frequently occurring words are “muffler and “sound”. This can be attributed to the fact that the muffler is an essential part in controlling the noise level of exhausts. The high occurrence of the word “sound” can be explained by the fact that sound quality is one of the most commonly discussed things when it comes to reviewing an exhaust system.

Additionally, we can see many positive words like “great”, “good”, “nice” which goes in line with the majority of the reviews being positive. There are also words such as “like”, “easy”, “well” and “better” which could be perceived in a positive sense in certain contexts, but when paired with a negating word like “not”, these become negative sentiments. Therefore, the context needs to be considered.

3.1. Research Question 1 - Most accurate machine learning model for prediction:

3 different models were built using Feat, pipeline, LogisticRegression, RandomForestClassifier, CrossValidator, ParamGridBuilder and MulticlassClassificationEvaluator were utilised from the pyspark.ml Library.

Their details are listed below-

1. **Logistic Regression - Bag of word Approach:**
   The bag of word approach is a technique used in natural language processing to preprocess data where a text document is represented as a "bag" of its words by only keeping track of the frequency and not the grammar or word order.

2. **Logistic Regression - TF-IDF Approach:**
   The term TF-IDF stands for "Term Frequency-Inverse Document Frequency". This approach takes into account the frequency and rarity of a word in a document and the entire corpus respectively. This method was performed with and without parameter tuning and accuracies for each were recorded.

3. **RandomForest Approach:**
   This method is a supervised Ml algorithm used for classification. It builds multiple trees and combines several weak and uncorrelated trees to build a strong predictor. This approach can handle both classification and regression problems.

Table 1 details the input parameters,characteristics and accuracies of each model -

Model	Parameters	Accuracy
Bag-of-words	- Training/test set split: 70/30 - vocab size = 1000 - maxIter = 100	87.56%
TF-IDF	- Tuning with vocab size = 1000	85.82 %
TF-IDF with parameter tuning	- regParam [0.1,0.5,1,2,5] - 10-fold cross validation	89.3 %
RandomForest	- minDocFreq = [5,10] - numTrees = [20,40] - maxDepth = [5,4] - 10-fold cross validation.	88.30%

Table 1: ML Models: Input parameters & Accuracy

It is observed that all 4 models have reasonably good accuracies, with each of the scoring above 80%. The TF-IDF approach with parameter tuning has demonstrated the highest accuracy of 89.3% for the given dataset. To get a better understanding of the accuracies, a scatter plot is presented in Figure 3.

Therefore, We can conclude that the answer for research question 1 is the TF-IDF logistic regression model with parameter tuning.

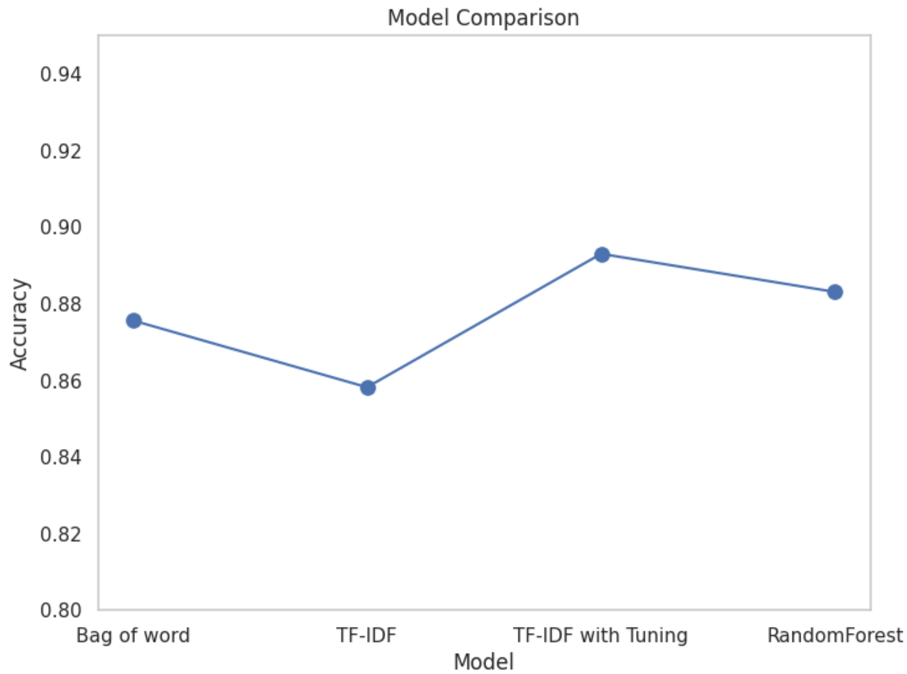

Figure 3: ML Model accuracies

3.2. Sentiment Analysis of Top reviewed exhausts:

After using VaderLexicon's SentimentIntensityAnalyser on the entire dataset, the Compound scores for each review was calculated. Figure 4 visalises these scores using a histogram.

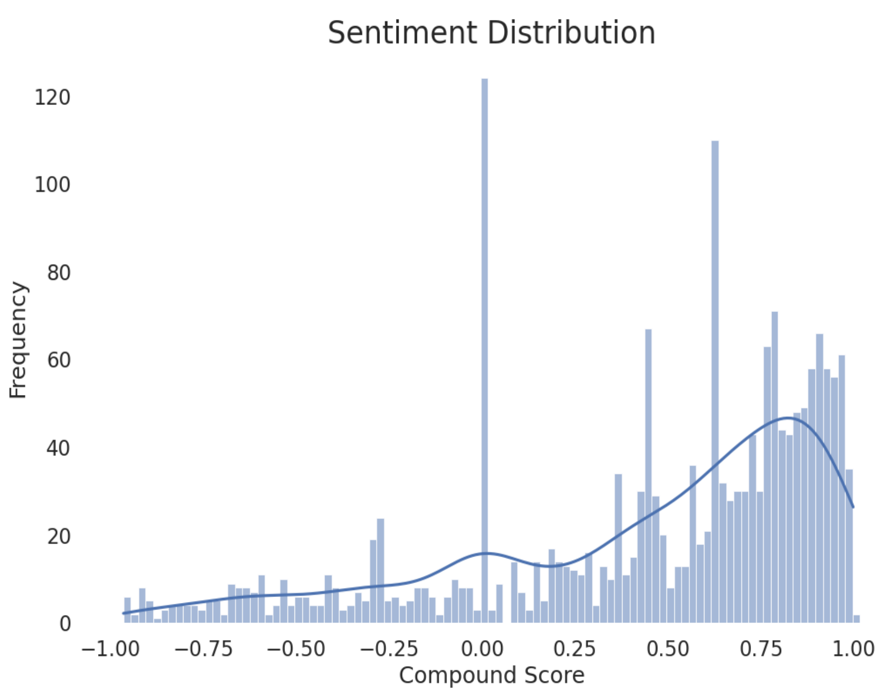

Figure 4: Compound Score Histogram

The X-axis of the histogram displays values ranging from -1 to 1, where -1 denotes the most negative score and 1 denotes the most positive score. As we can observe, the histogram is skewed to the left, indicating that the majority of the reviews have positive compound scores, which aligns with the trend of the overall ratings being heavily skewed towards 5 stars. It is noteworthy that over 120 reviews have a score of 0, and little over 100 reviews have a score of about 0.60 suggesting that a large number of ratings were in the range of 3 and 4 stars.

Subsequently, an analysis was conducted to identify the top 5 most reviewed exhausts and to determine their overall rating distributions. The results of this analysis are presented below for each of the identified products.

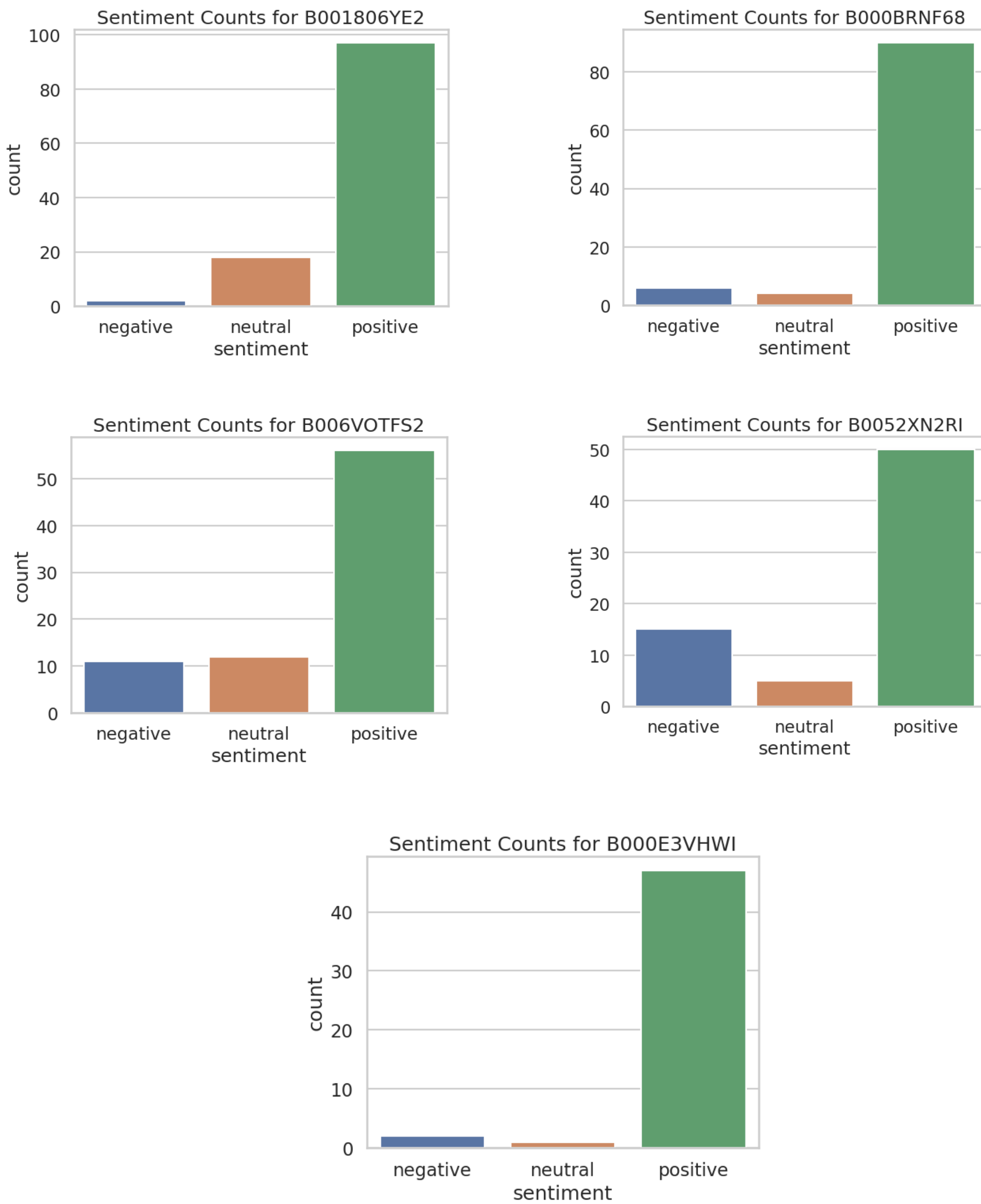

Figure 5: Sentiment Distribution For Top 5 reviewed exhausts

Top 5 Asin IDs along with product names:

1. B001806YE2 - Vibrant 1142 3" Ultra Quiet Resonator
2. B000BRNF68 - Design Engineering 010108 Exhaust Heat Wrap
3. B006VOTFS2 - Dynomax 39510 Super Turbo Muffler Cat-Back Dual System
4. B0052XN2RI - Dynomax 36474 Stainless Steel Universal Exhaust Tip
5. B000E3VHWI - Vibrant 1141 2.5" Ultra Quiet Resonator

These are all top brands in the exhaust industry. The analysis shows us that the majority of the ratings for all products are positive. However, the ASIN numbers "B006VOTFS2" and "B0052XN2RI" were found to have the highest frequency of negative sentiments among the 5 products.

Figure 6 depicts a word cloud which was generated to illustrate the frequently occurring words utilised in both positive and negative reviews for the aforementioned products.

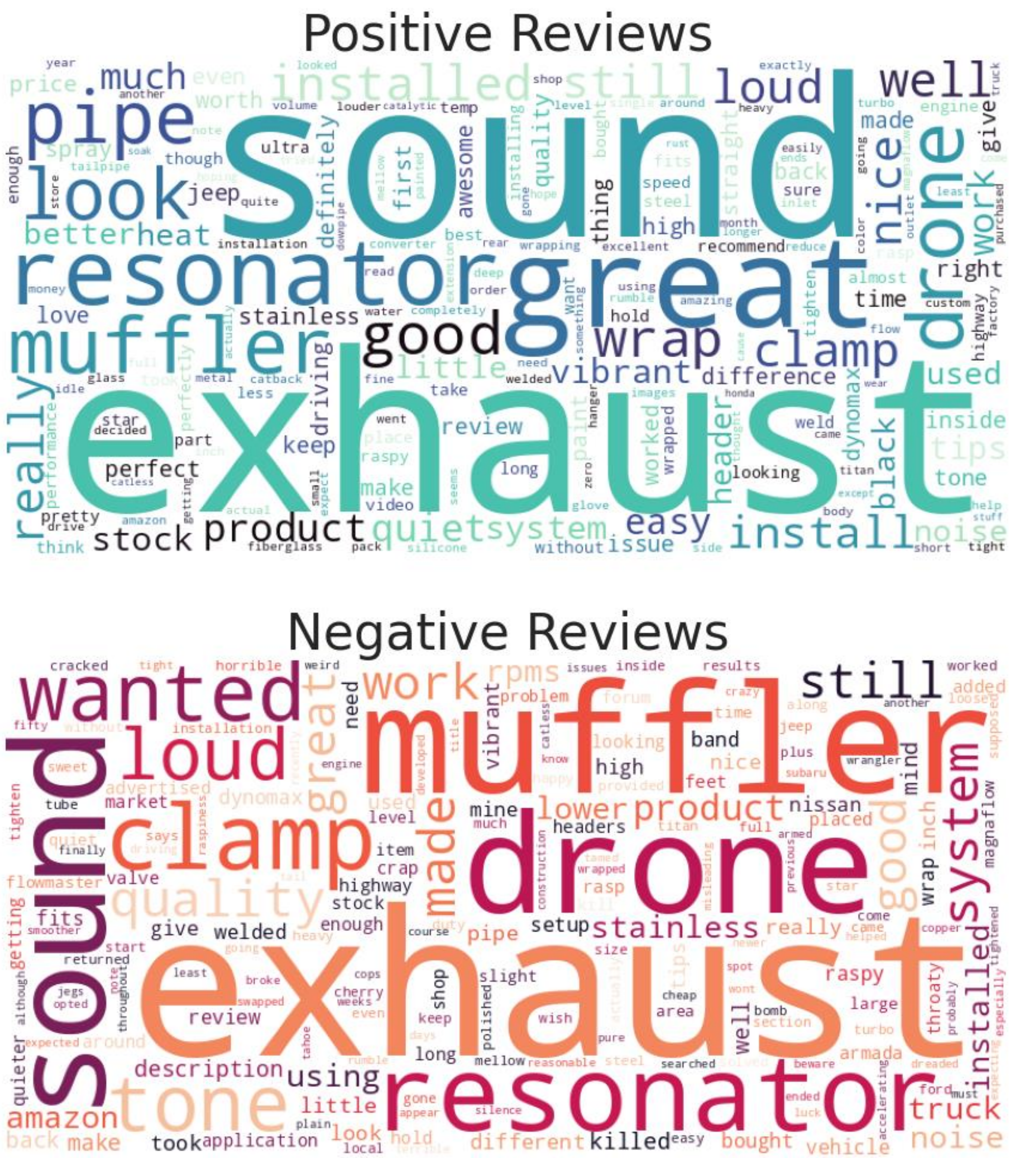

Figure 6: Word cloud for Positive and Negative reviews

The word cloud generated provides a visual representation of the most frequently used words in positive and negative reviews for the top 5 reviewed exhaust products. The most commonly occurring word across both clouds is "exhaust", which is often paired with words conveying positive or negative sentiment such as "good" or "bad", respectively. Additionally, the word "sound" appears frequently in both clouds, with positive reviews praising the sound of the exhausts and negative reviews criticising it. The positive cloud also contains words such as "well", "great", "good", and "nice", indicating positive sentiment in reviews. On the other hand, the negative cloud includes words such as "problem", "horrible", and "weird", suggesting negative reviews. However, the size of these negative words is relatively small in the cloud, indicating that they were used less frequently by customers.

Indeed, the analysis indicates that customers generally hold positive sentiments towards the exhaust products, as evident from the high overall ratings and positive word cloud. The top 5 most reviewed exhausts also have a majority of positive sentiments, further reinforcing this conclusion. This information can be valuable for companies to understand customer preferences and improve their products accordingly to meet customer needs and expectations.

3.3. Most common Word pair associations:

In the previous sections, we found that the most commonly occurring words in the positive and negative reviews did not provide us with information on the context in which they were being used. To gain a better understanding, we created a Bigram to visualize the most frequently occurring word pairs in the entire dataset, as shown in Figure 7.

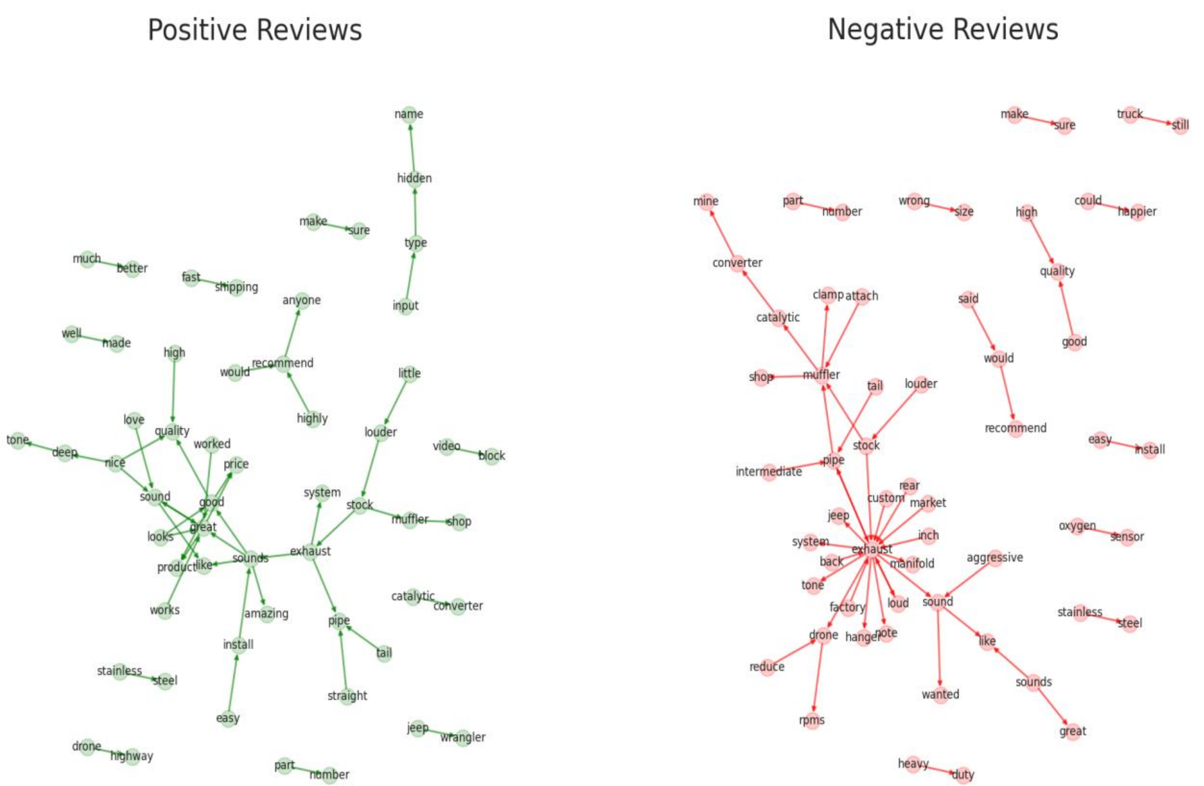

Figure 6: Bigram

The Positive Bigram showcases word associations that form complete sentences, such as "would highly recommend to anyone", "product works great", "amazing sound quality", and "works greats for the price", among others. The customers' positive feedback also contains expressions like "well made" and "much better," adding to the favourable sentiments towards the exhaust products. The frequent occurrence of such phrases suggests the customers' satisfaction with the exhaust products' quality and performance.

In terms of negative feedback, the identified bigrams provide useful insights into customer sentiments. Negative pairings such as "could be happier", "More aggressive sound wanted", "wrong size", "louder than the stock exhaust" and "could be happier" are indicative of customer dissatisfaction. Additionally, pairings such as "Exhaust loud" and "exhaust tone" suggest that customers were unhappy with the tone or decibel levels of the exhausts.

Overall, the observations drawn from these analyses, can be useful for exhaust manufacturers and highlight areas of improvement that they could focus on in order to meet customer expectations and improve customer satisfaction as well as marketing strategies.

4. CONCLUSION:

In conclusion, our investigation into customer feedback on exhaust systems offers useful suggestions for exhaust manufacturers looking to enhance their product line and marketing plans. The majority of reviews, which show customer satisfaction with exhaust systems, are favourable, according to our research. However, unfavourable reviews give manufacturers valuable insight into where they can make adjustments.

Three different ML models were used in our study to predict the sentiment of customer reviews. All three models—random forest, bag-of-words, and TF-IDF logistic regression—showed an adequate level of accuracy, each scoring above 80%. For the provided dataset, the TF-IDF logistic regression model with parameter tuning had the highest accuracy (89.3%).
The bigram analysis revealed more precise associations between words. In positive reviews, customers were impressed by the quality, performance, and sound of exhaust systems, whereas negative reviews concentrated on problems with sound quality and fitment.

Our analysis also revealed that the best-rated exhaust systems came from reputable companies with a long history of being on the market. This indicates that trusted brands have built consumer loyalty and trust by delivering consistent quality and results.
These insights can help manufacturers concentrate on enhancing fitment, sound quality, and handling customer complaints to raise customer satisfaction. Positive feedback can also be used to enhance marketing plans and enhance brand recognition. Our results highlight the significance of consumer input in product development and marketing plans.

In conclusion, our study of consumer opinions about automotive exhaust systems demonstrates the importance for manufacturers to pay attention to consumer input, pinpoint areas for improvement, and capitalise on positive reviews to improve their goods and marketing approaches.

5. REFERENCES:

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