Voice of Customer

ANALYTICS

An *Express Analytics e-book* written by data analysts: Saurav Dosi, Utkarsh Prakash, Swapnik Jagarlapudi and compiled by Vinay Dabhade

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Everything You Wanted To Know About "Voice of Customer" Analytics

Introduction

In today's consumer-centric world, it is a challenge to meet the expectations of every customer. The term 'Voice of the Customer' was first used in a marketing paper with the same title by A. Griffin (UoC) and J. R. Hauser (MIT). They defined 'Voice of the Customer' as a 'product development technique that produces a detailed set of customer needs and wants, which are organized into a hierarchical structure'.

The paper said VoC had four aspects:

- Customer needs
- A hierarchical structure
- Priorities
- Customer perceptions of performance

Voice of Customer Analytics (VoCA) utilizes data science and analytics tools in order to gather relevant information from unstructured data such as reviews data and data collected from social media websites.

A VoCA suite may include tools such as:

*Sentiment analysis

*Fake review identification

*Topic identification

*Net promoter score

*Named entity recognition

All these can then be made part of a dashboard, making it convenient to run the analysis and check these metrics.

Let's say you are the manager of a restaurant in a particularly busy part of the city, where there's a lot of competition. You have so many things to take care of - hiring, training new staff, planning budgets, promotion, setting targets and so on.

Over time, you notice a drop in the number of customers, and a subsequent reduction in profits. On the surface, everything seems to be running smoothly - the staff is doing its best, you have encountered no hitch in your marketing, and no, there have been no health code violations. At the same time, it's impractical to check each and every social media comment in order to ascertain where the issue is, but you check and even reply to a few reviews from time to time but it does not seem to be enough.

Ignoring the social media comments obviously is no solution since this would mean that a large amount of "useful" information is being simply binned. This is where Voice of Customer Analytics (VoCA) comes in: to make sense of aggregated data and provide condensed information gleaned from this data.

Importance Of VoCA

As we illustrated in our introductory example, Voice of the Customer can provide a treasure trove of information. Understanding it and taking action based on that understanding leads to customer satisfaction as well as an increase in revenue. A study by Gartner has shown that collecting feedback from customers can increase the success rate of cross-selling and upselling by 15-20%. Also, companies that have a VoC program spend 25% less on customer retention than companies that don't. (Many well-known companies such as Apple and Amazon have a dedicated VoCA program.)

A study by The Aberdeen Group has shown that companies that engage in a VoCA program - not just collecting VoC data but also actively taking measures and responding to this feedback get:

- up to 43.2% new customers
- 25% increase in cross-selling and up-selling
- a 15% increase in average profit margin per customer each year

The same study showed a 36.8% increase in positive mentions on social media and a 17.6% increase in Net Promoter Score. Incidentally, companies that had a VoCA program but never completely engaged with it, however, registered less percentages on the same aspects.

Thus, a VoCA program can benefit the company in many ways and, in today's world, is a necessity for any company offering services. Not to mention that a business can achieve these benefits without much additional cost.

Tools Used For VoCA

Now that we have a basic understanding of what Voice of the Customer is all about, and the importance of Voice of Customer Analytics, let us look at some of the tools used for it.

Various tools, both statistical and machine learning, or even deep learning-based, exist if you want to deploy VoCA. We will not look at all of them here but instead focus only on some of the more interesting and effective ones.

Sentiment Analysis

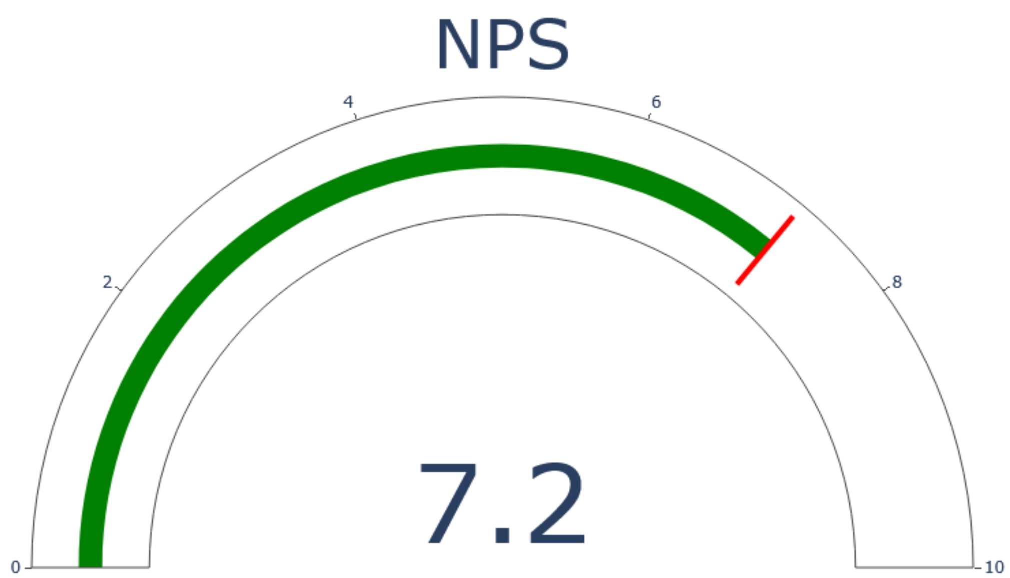
Sentiment analysis is the use of text analysis techniques such as natural language processing (NLP), to identify, extract and quantify the sentiment expressed by a piece of text. Sentiment expressed is one of the most basic aspects of the Voice of the Customer, and an instrumental attribute of VoC data. It serves as a base to a lot of the other modules that are used in VoCA. Data from various sources, such as social media reviews, reviews from aggregators, etc., can be combined to form a comprehensive customer sentiment profile for a given company. A lot of information can be derived on the basis of this analysis.

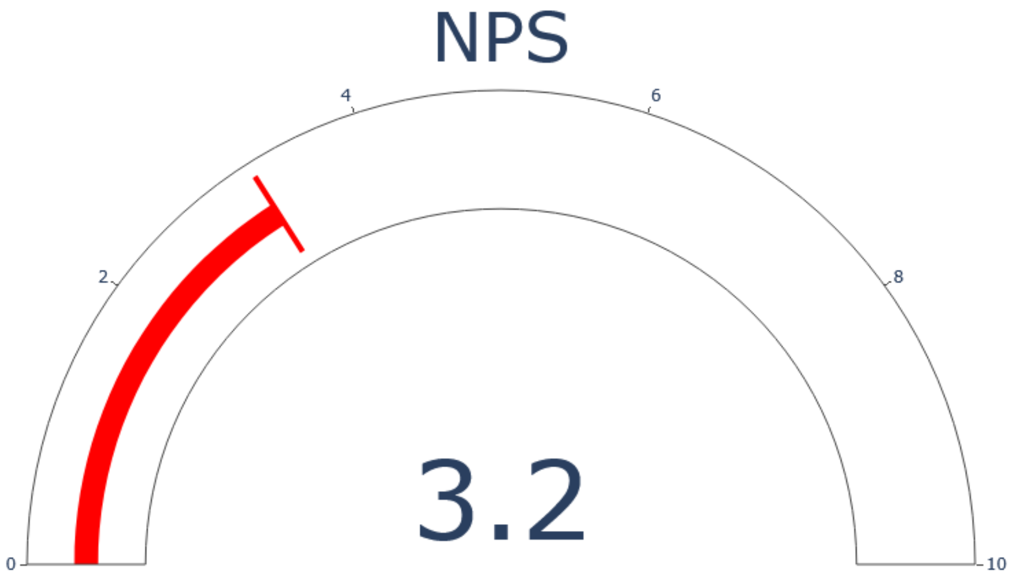
We will deep-dive into the details about how sentiment analysis works and its applications in the latter half of this e-book.

Net Promoter Score

Simply defined, Net Promoter Score (NPS) is the percentage of customers (called “promoters”) that is likely to recommend a product or service to others minus the percentage of customers (called “detractors”) who give a low rating or are unlikely to recommend the product or service. ‘Passives’, who generally give an ‘average’ rating, do not enter this calculation. A higher rating indicates better customer satisfaction and a greater likelihood of existing customers recommending the product, but may not necessarily indicate customer loyalty, which is why it should not be used as the sole measure of calculating customer satisfaction.

Sentiment analysis can be used to find out the percentages used to calculate the NPS. It is possible to use a more fine-grained and complex approach to calculating NPS, by using NLP to filter in reviews which specifically mention whether the customer would recommend the product or not. NPS can be represented as a score on a scale, for example, from 0-10 or -100 to 100.





The above is an example of an NPS scale from 0-10

Topic Modelling And Keyword Extraction

Topic modelling refers to the automated discovery and extraction of the topic which occurs in a given text, where 'topic' is defined as an abstract set of words, phrases and sentences that are related to something specific. Statistical methods may be used to extract the topic, but NLP-based methods are also effective.

Keyword extraction refers to the extraction of keywords, i.e., the words which convey an essence of the content of a given text. This is different from topic modelling in that the topic is something that a given set of words is related to, whereas keywords are, essentially, words which convey the summary of a given text, in a very loose sense.

We shall discuss both Topic Modelling and Keyword Extraction in-depth later in this e-book.

Named Entity Recognition

Named Entity Recognition refers to the extraction of 'named entities' from a given text. Named entities comprise parameters such as names of people, organizations, locations, products, quantities, etc. Generally, NLP-based methods are used for NER.

NER can be used for a variety of purposes, and in combination with sentiment analysis can provide useful insights. For example, by extracting mentions of locations in review text, a business can categorize reviews by location, which can allow a relevant branch to deal with issues. Apart from that, negative reviews which mention a competing organization can also provide some insight into what customers are dissatisfied with, and what they can do to improve their service.

In the next section, we will look at sentiment analysis and its applications in detail, along with a brief introduction to how to detect fake reviews.

Sentiment Analysis

Introduction

Every day we browse through a lot of content on social media platforms like Instagram, Twitter and Facebook. We come across updates about our friends and the people we follow. All these services appear to be absolutely free, right? We can post images and videos, comment on our friends' posts, start a new thread. We have our lives surrounded by Google. There is no one single day where we do not use Google Search or any of the other products of Google.

But as free as all of these services seem to appear, they are not. As someone once said: there's no such thing as a free lunch. All the major technological giants earn by showing us relevant advertisements based on the free use of our personal data that we expose in our posts on the social networks or by our browsing habits. Have you never noticed that when you search for a product on Google, you will start to see advertisements related to that same product on YouTube or a webpage that displays Google ads?

The same is true for the e-commerce sites like Amazon, e-Bay, Flipkart, etc. All these brands are competing with each other with their highly efficient and effective business models. Their intelligent technology is getting smarter every day with the blazing progress in the bubbling field of artificial intelligence (AI) and machine learning (ML). However, an essential part that drives their businesses is their users.

How often do you get a pop-up about how the call quality was when you exit a Google Meet or a WhatsApp call? Does Amazon send you mails to write a review after you have purchased one of their products? Why do they care so much about feedback? Well, the answer is such feedback helps them enormously to improve their technology and user experience. Amazon customers look at reviews before making a purchase which is why Amazon strives to keep the review section as real and transparent as possible.

These days not only ratings but the actual reviews also matter a lot. A rating might not be the exact reflection of what the review says. Yelp and Google My Business - frequently abbreviated as GMB - both are of immense importance to industries like restaurant, grocery, and other food related services. You need human-like consciousness to be able to intelligently understand these reviews. In today's world, data can be said to be the most valuable currency. When you are living in such a big data millennium, you cannot afford to have actual humans working. This is why we need AI built models to analyze all sorts of data. It is immensely important for any e-commerce business in the 21st century to primarily focus on data related customer's feedback and their experience about the service they consume. This information is useful for the brand to improve on their mistakes and make their fortes even more appealing to their consumers.

Why Do We Need Sentiment Analysis?

Any statement or a piece of text can be said to have a sentiment or an emotion attached to it. For example, “I had a nice day today!” expresses a positive emotion whereas, “I didn’t like today’s dinner!” expresses a negative one. Similarly, in an e-commerce scenario, when you purchase a product online, if you are happy with the product, you will post a positive review and may even recommend the product to others as well. However, if you receive a faulty piece, you may criticize the product. It is crucially important for the brand as well as the e-commerce platform to keep track of sentiment of the reviews to stay posted on the brand’s overall image or something that we call, “Net Promoter Score” (NPS). This sort of analysis is needed for brands to improve where they lack, and to understand the trend in terms of what their customers like or dislike about the product? By making use of such analysis they can not only improve on their shortcomings but also make their strong points stronger. This is why sentiment analysis is of paramount importance nowadays.

It is easy for us humans to classify whether these sentences or reviews are positive or negative, emotion-wise. However, in today’s world of big data, as valuable as it is, the data inflow is huge. Humans are unable to process this data. For it, we require technology. But how does one make a computer do the same job? This is where the whole natural language processing comes in.

Sentimental Analysis Of Social Media Posts

Now, to further underline what sentimental analysis means and how it can be helpful, we will use an example to actually build a sentiment analysis model for the reviews that customers post on social media platforms like GMB, Yelp, Twitter, Facebook, etc. Like we said earlier, these reviews are a good indicator of the customer's experience about the service or the product that they've purchased.

For this exercise, we used NLP-based approach to get some useful insights out of such reviews. We wanted to build a sentiment analysis model to extract the appropriate sentiment either positive or negative, from the reviews.

Data Set

The data we used to make our NLP model had reviews from various social media platforms. We decided to have three classes to classify the sentiment of the review: "Positive", "Negative", and an additional third class called "Neutral". A neutral class is crucial and many times, highly challenging which is why most products go for just the two other classes. This is the class where most people tend to talk both positively as well as negatively about the service, i.e., a mixed bag review.

Neutral reviews can also be those where the customer's sentiment is just okay, and he/she does not have a complaint nor a compliment. We would definitely not want to classify these into the positive or negative class, which is why we created the "Neutral" class. About 80% of the data was kept for training and the rest for development and testing purposes. We performed pre-processing on the data such that the model is trained accurately without any exceptional cases or outliers.

Actual Implementation

We then went on to train our supervised state-of-the-art deep learning-based model which was structured using LSTM architecture. While predicting the sentiment class, it not only considered words that expressed emotions: e.g. good, bad or okay but also took into account the context in which these words were used in a sentence. E.g.: "I loved the restaurant, the food was very good!" expresses a positive sentiment, but "I did not like this cafe, the coffee was not that good." expresses a negative sentiment even though it has the word "good" in it.

Sample examples for each class:

Positive Review:

"Clean store with employees always stocking items on shelves. Friendly staff that want to be helpful."

Negative Review:

"Horrible service to a police officer who was waiting for her food while other customers were helped."

Neutral Review:

“I only got cheese cake to go but was happy with it. I've eaten there in the past and it was just ok.”

We then customized and fine-tuned the model to yield the best possible results for the data set that we used for training. Hence, the predictions obtained were quite accurate.

Additional Features And Customization

Fine Grained Sentiment or Sentiment Score

After additional research, we were able to come up with a premium feature of having a fine grained sentiment score for every review. Having done so, our model not only could predict a three class label but also could assign a sentiment score ranging from 0 to 10. (A score which ranges from 0 to 3.5 is to be considered as negative. A score from 3.5 to 6.5 is neutral, and anything greater than 6.5 is positive.)

In our experiment, as we traverse from 0 to 10, the emotion of the text changes from negative to positive. Such a continuous score can then be moreover labelled with many classes as per the client’s requirement instead of being restricted to just 2 or 3 classes.

Review: “Terrible service and food very, very, very, very, very, very expensive...It’s crazy. And ridiculous”

Sentiment Score Prediction: 0.8, Class: Negative

Review: “Good but pricey. The food is good, but not outstanding. Portions are large though so that is a plus.” (change this review)

Sentiment Score Prediction: 6.5, Class: Neutral

Review: “Food was good, nachos weren't the best but the service and rest of the food was absolutely amazing.”

Sentiment Score Prediction: 9, Class: Positive

Emoji Support

In today’s world of social media and online texting, emojis have become important as a form of expression of emotions. Making use of emojis not only makes the text more expressive but also conveys the message with the right intent. This is why, many times while posting reviews, customers add emojis to express more emotively about their experience. There are many cases where people choose just emojis over text. We would not want to miss out on these cases as a considerable amount (~10-15% confirm) of the reviews nowadays contain emojis. Our model takes care of these edge cases with our additional feature called emoji support.

For example:

Review: “Food😍😍😍 Service😅😅😅 Waiting”

Sentiment Score Prediction: 5.9, Class: Neutral

Multilingual Support

Our model can also predict fairly accurate results for Spanish language reviews.

For example:

“Me encanta esa tienda. Siempre encuentro lo que busco a un excelente descuento”

Translation: “I love that store. I always find what I am looking for at an excellent discount”

Prediction by the model: Positive

“Muy sucia esta tienda no tenían las especiales que pucieron no volveré a esta tienda”

Translation: “Very dirty this store did not have the specials that puced I will not return to this store”

Prediction by the model: Negative

This feature of our model can also be extended to many other languages like Russian, Japanese, Chinese and Hindi. This particular additional provision to our sentiment analysis model ensured we did not miss out on those other language reviews which may not be as large in number as those in English. We can also have a translation model for such reviews so that the customer’s opinion is heard universally by the brand. The same feature can be concatenated to have a smart response model which will respond to these multilingual reviews targeting the specifics.

Evaluation

Quantitative Evaluation: We achieved an accuracy of above 95% while testing the final version of our model. We used an already labelled dataset having labels, “positive” and “negative”. As our model predicts sentiment in the format of a score, that score can be interpreted in as many classes as one wants.

Qualitative Evaluation: For manual inspection and to check how the model performed on any random unseen review from a completely different distribution, we picked up some of the authentic reviews from Yelp.com, looked through them and compared with the ratings.

For example:

Review: “Had my first experience at TCB. We ordered a 10 piece chicken special. It was okay. I wasn't blown away by it but the taste was passable. It wasn't too salty, it's far less salty than FKC. Some of the thigh pieces were incredibly small. The chicken skin was nice a crispy, the meat however was a little bit dry. Some were and some weren't. Some tasted like it was in the fryer too long. Overall, not a bad chicken, I wouldn't mind trying it again, but this time I'm going for spicy!”

Sentiment Score Prediction: 6.6, Class: Neutral

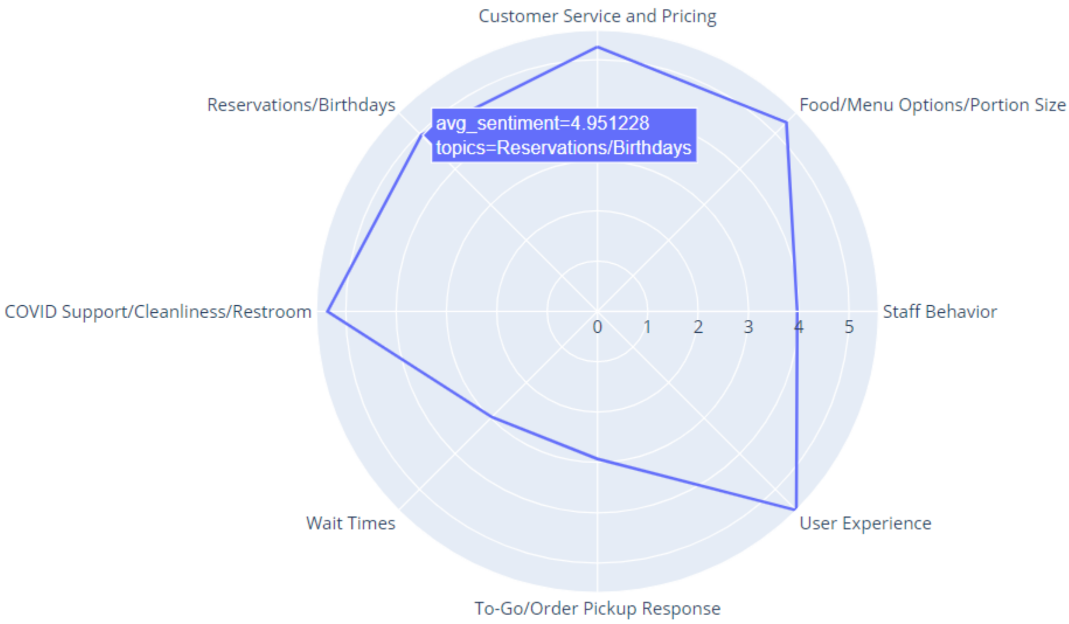
Review: “I just received my usual order of Chicken Marsala and it is downright disgusting. The chicken tastes straight up like someone dumped a bottle of vinegar on it. Completely inedible. It's so awful I'm wondering if the delivery guy peed on the food. Also, the sauce had dripped out all over the bag. I wish the containers were secured better. After delivery fees and tip, this was an expensive non-dinner. Now I need to figure out where to order another dinner from. Please talk to your kitchen staff. Something is terribly wrong. I won't be ordering from here again.”

Sentiment Score Prediction: 0.1, Class: Negative

Such a review analysis yields insights not only about the customer’s overall feedback but also about the actions that the brand should be taking to improve their brand image or NPS (Net Promoter Score).

Sentiment analysis is just the beginning of the journey of the VoCA facility. Merging the results of the sentiment analysis with topics and keywords modelling, and NER (Named Entity Recognition), a VoCA dashboard can be built with some fascinating data visualizations as follows:

Radar Chart



The image above shows a Radar Chart of topic-wise average sentiment score distribution. On the angular axes we have various topics of the reviews and on the radial axis a scale ranging from 0 to 10 which represents the average sentiment score of the reviews for that topic.

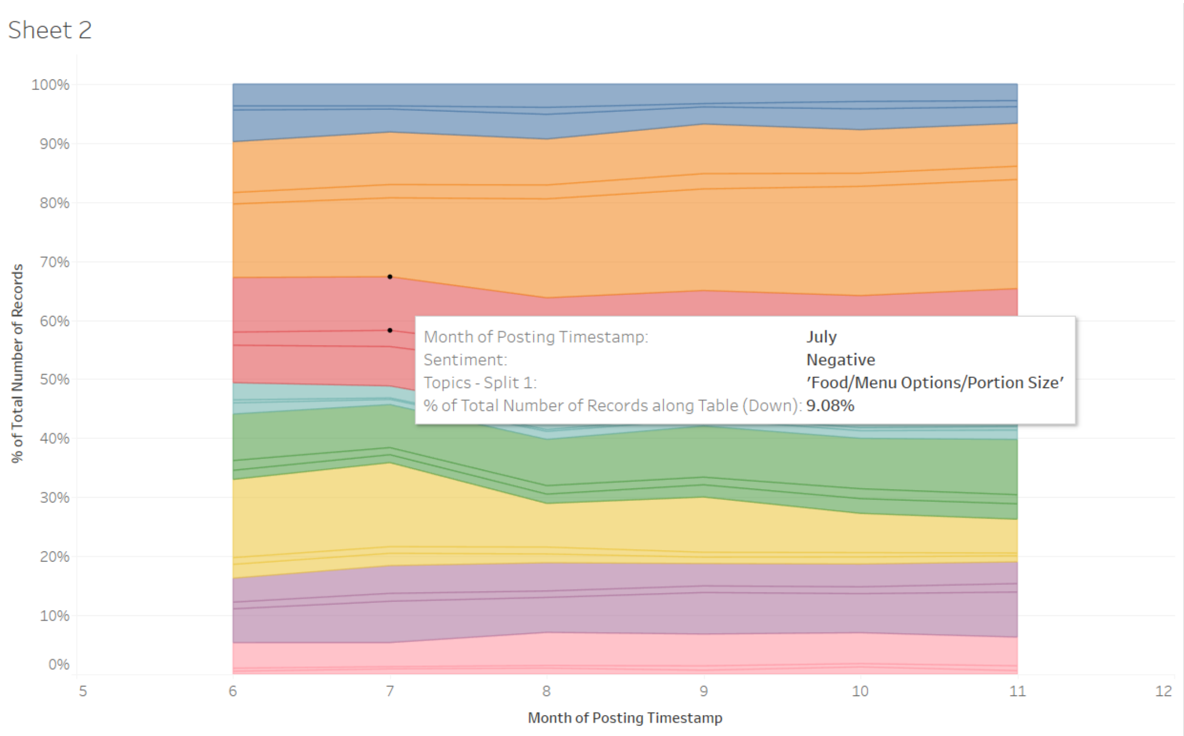
For the highlighted topic, COVID Support/Cleanliness, we got an aggregated sentiment score of 5.28, which implies that people were neither positive nor negative about this topic. By easily hovering on the radar plot, one can get the additional details required for designing the next plan of action. The primary utility of this visualization is that the monitoring team can get a quick bird's eye view of the sentiment distribution across various topics and can take appropriate actions to ameliorate the customer feedback.

Area Chart

Another eye-catching visualization we can have is an Area Chart of the percentage distribution of the reviews based on topics and sentiment varying with time. The two useful insights to be drawn from this chart are:

Total number of reviews posted by customers mentioning each of the topics across time

Sentiment distribution of these topic-wise segregated reviews across time



For the highlighted segment from the chart, we get to know about the percentage of negative reviews (9.08% of the total reviews) in the month of July for the topic, "Food/Menu Options/Portion Size". This plot is of immense importance for monitoring the sentiment for each topic across time and to check whether specific actions taken by the brand in order to improve the customer experience related to a particular topic increase the percentage of positive reviews or not.

Analyzing data effectively is the secret of technological giants like Google and Amazon to successful business. This largely comprises analyzing the customer's opinions and their emotions about their experience with a particular service. In today's data driven world, we cannot afford to have human resources analyzing uncountable instances of records. We need machines to do this job for us and that is exactly why we need a powerful tool like sentiment analysis to efficiently extract the exact emotion expressed by each customer.

Fake Reviews Detection - A Brief Introduction

How often do you purchase from Amazon? Don't you take a look at the reviews to verify the authenticity of the product in order to avoid having regrets after the purchase? That is exactly what every buyer thinks of while ordering a product from such e-commerce sites. Before buying people often tend to read the positive as well as the critical reviews and look at their rating-wise distribution so that they know how genuine the product is. This is why genuine reviews are of paramount importance to the competing brands as they reflect the quality of their product and attract more customers if and only if most of the reviews are positive. No wonder why all the brands would struggle for positive reviews, however, ideally a brand should take note of the critiques and work on them to improve the brand image. But not all the companies choose the same route.

In today's time, it is reasonably easy to generate text using NLP models. But this technology is also misused like posting fake reviews. Many brands today, to take on the competition, are attempting to rig the marketplace either by posting critical reviews about their competitor brands or by paying random people to write positive reviews about their own products. Such tactics takes a toll on the genuine brands that are struggling hard to make their brand a success in the market.

Amazon reportedly addresses the problem of fake reviews by having a "verified purchase" tag for each of the genuinely purchased product reviews so that nobody can post a review without purchasing the product. However, this sort of flagging does not tackle issues of fake reviews on social media platforms like Facebook. The social networks in today's time can make a huge impact on your business' growth as more the accounts your business reaches, the more will be the brand growth. Another way of tackling this issue is to knock the crooked brands out of the marketplace by reporting their product as fake and letting the e-commerce organization know about the unlawful actions of the brand and generally legal actions are taken against the dubious brand. However, since these actions work the best in the aftermath of noticing the issue and by then the truthful brands would have lost a lot of money and traction, we would want a preventive measure and by that we mean that we intend to build a Fake Reviews Detection algorithm which will flag the crooked reviews based on various data features and take appropriate legal actions against such users as well as the brands.

In the next part, we discuss topic modelling and keyword extraction in a Voice of Customer Analytics context, along with their applications.

Voice of Customer Analytics - Topic Modelling And Keyword Extraction

Introduction

Let’s suppose your company is constantly receiving negative reviews from customers. You as a manager of your company would like to know what are the areas in which your customers are constantly complaining. Even if your company is getting positive feedback from customers, you may want to know the areas in which your company is not performing well in order to improve in those areas. With just the sentiment of reviews, you will have to manually go through all the reviews to identify pain points or areas of improvement. That can be quite cumbersome and tiring. This is where topic modelling of the reviews comes to your rescue.

Topic modelling is an NLP technique which helps us to automatically discover and extract topics from a given text, where ‘topic’ can be defined as an abstract set of words, phrases and sentences that are related to something specific. Topic modelling is an unsupervised technique. This means that the model itself can identify topics in the text based on the patterns, without having to pre-define the exact topics you want.

Let’s consider an example of a review for a restaurant chain.

“I had the grilled salmon with broccoli, Cesar Salad and calamari as an appetizer. My wife had Chicken Madera with asparagus and mashed potatoes. The salmon was delicious, the broccoli was a little hard but was ok though, but the Cesar Salad tasted funny so I didn't finish it. Overall good meal.”

So what does the above review talk about? Is it just the food, or is it about cleanliness or customer service? The model will discover this review to be related to food by recognizing the sequences of words, "grilled salmon-broccoli-Cesar salad-calamari-appetizer-Madera-"… and so on.

So far so good. You have recognized the associated sentiment with the review and also identified the high-level categories to which the review belongs. As the next step you would like to know which particular food item is trending or popular among the customers. Moreover, you may also like to know how people reviewed the taste, presentation, quantity served or price of that food item. For example, in the above review the customer found the salmon to be delicious whereas the broccoli was a little hard and the customer was also not satisfied with the taste of Cesar Salad. In order to be able to do such a fine grained analysis of reviews/feedback we have keywords extraction.

Keywords extraction/detection or analysis is a technique under NLP to automatically extract the most frequent words and expressions from a piece of content.

Coming up next: how we at Express Analytics have leveraged the state-of-the-art machine learning techniques to build models for topic modelling and keywords extraction.

How Express Analytics Uses ML To Extract Keywords

Dataset

The dataset we used for this experiment consists of reviews from various social media platforms such as Google My Business (GMB), Yelp, Foursquare, etc. Businesses can also add to these reviews from more conventional sources such as those collected from surveys, telephonic calls, emails, feedback forms, etc.

Pre-processing

As done in this experiment, EA, too, employs multiple NLP processes for processing. The pre-processing of data plays an important role in determining the quality and robustness of any machine learning model. In order to extract more coherent topics we used only those reviews which had the number of words greater than the average number of words in the reviews. For your business, we also recommend using at least 1000 such long reviews for the model to be able to capture semantically similar words associated with a topic.

The next step in pre-processing involves removal of “stopwords” and “cleaning” the data by removing unnecessary characters and punctuation marks as they usually don’t add any useful information to the sentence.

Words like “eat”, “eating”, “eaten” etc. although different, come from the same root word i.e., “eat”. If we treat these words differently in our model, we would be unnecessarily increasing the dimension of the input vector to the model. This is where lemmatization and stemming of words come into picture. Stemming is a crude heuristic process that chops off the ends of words in the hope of achieving the root form of a word. Lemmatization is an NLP technique which uses a pre-built vocabulary to find the base or dictionary form of a word known as lemma. For example, the word “corpora” can be converted to its root form “corpus” using lemmatization. Now after all these steps of pre-processing each review is represented as a high-dimensional vector.

Model

We use Non-Negative Matrix Factorisation (NMF) for topic modelling. NMF decomposes (or factorizes) high-dimensional vectors into a lower-dimensional representation. These lower-dimensional vectors are non-negative, which also means their coefficients are non-negative. This means that NMF assumes that each review is a combination of topics and therefore tries to express each review as a weighted sum of lower dimensional vectors (topics) where weights are non-negative. The number of topics is a hyper-parameter which is provided as input to the model and is refined after looking at the quality of the topics obtained after training the model.

The problem with low dimensional vectors is that they are not human interpretable. So, once we have the low dimensional vectors, we extract the top words (generally 30 words) associated with that vector to understand to which human-interpretable topic does the vector correspond to. For example, let's say we obtain top words related to a topic as "chicken", "pasta", "shrimp", "sauce", "dish", "salad", "good taste" etc. It is clear that the topic is related to food. Now, the dominant topic for a review is the one associated with the highest weight.

For example, consider the review

"I had a similar issue to another reviewer. They don't apply their Covid-19 policies fairly to everyone. We were asked constantly to move, in and out of the restaurant, while others stood in large groups inside. They seem enforce strictly on some and ignore others. Frustrating experience. To top it off, the food was subpar for such a high price. Bland, tasteless. Horrible time."

Now, for a 5-topic NMF model the results for the above review will be:

0.0174*Covid Support + 0.0099*Food + 0.0098*Customer Service + 0.0013*User Experience + 0*Reservations

Since the weight for the COVID Support topic is the highest we label that the dominant topic in the review is "COVID Support" which is indeed the case. The second most dominant topic in the review is "Food" as we can see from the review. Moreover, we can see as the review has nothing to do with the reservations or bookings hence the weight associated with it is also zero.

Now, we discuss our implementation of keywords extraction. For the purposes of our experiment the keywords we considered were not only single words (unigrams) but also sequences of two words (bigrams) and three words (trigrams). This was done because sometimes a single word cannot capture the essence of the sentence. For example, the bigram "bad taste" conveys much more information than the individual words "bad" and "taste". Similarly, the trigram "poor customer service" gives more insight than the unigrams "poor", "customer" and "service". We, then, created a bag of or vocabulary of the most frequently occurring unigrams, bigrams and trigrams in the whole corpus of reviews. Then, for the review, we tried to establish whether these frequent words (or sequence of words) occurred in the review or not. In this way we were able to extract the most important keywords from the review.

For example, consider the review

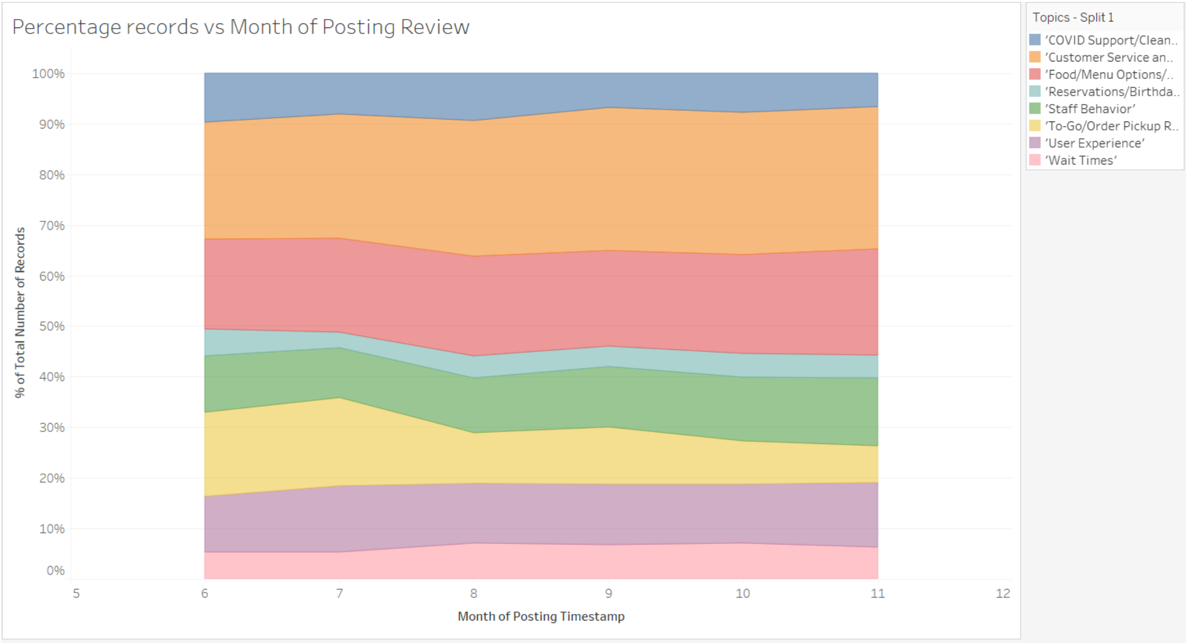
"Just had lunch with the family and totally enjoyed it!!! The restaurant was clean and seating was socially distanced as it should be. The waitress was friendly and knowledgeable. When we got our food it was plentiful and delicious…so much so we brought dessert home!!! Definitely recommend!!!"

The extracted keywords for the above review are 'definitely recommend', 'restaurant clean', 'socially distance' and 'waitress friendly'.

Use Cases

Smart response: You can have pre-defined templates for each of the topics and use them to smartly respond to the reviews based on the dominant topic predicted by the model in the review.

Trends in the topics: You can visualize the trending topics in the market with the help of an area chart for a restaurant chain as shown below. By identifying the key areas in the market, you can improve your services in that particular domain.



As we can see from the above area chart, during the month of July more reviews were associated with the 'To-Go/Order Pickup Response' topic.

This made sense as during July although lockdowns were relaxed, people were still hesitant to eat in a restaurant and hence opted for order pickup. This is a strong indication for any restaurant chain to improve their order pickup services by allocating more staff to handle increased volumes of phone calls, smoothen out the process of order collection etc.

Analysis of newly launched product/store: You can analyze the feedback of a newly launched product/store with the help of the sentiment score, topic and keywords extracted.

In conclusion: Voice of Customer can be a very important method for a business to understand how happy or upset its customers are, and the channels where they are expressing these sentiments. Companies that deploy VoCA spend 25% less on customer retention than companies that don't. So if you want to join them, get in touch with us at Express Analytics to know more about our Voice of Customer Analytics tools, and how to make them a part of your business. Just fill up this simple form.

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TEXAS CHICKEN & BURGERS - 49 Photos & 49 Reviews - Burgers - 120-20 Queens Blvd, Kew Gardens, Kew Gardens, NY - Restaurant Reviews - Phone Number - Menu (yelp.com)

Top 10 Best Cheap Birthday Dinner in San Francisco, CA - Last Updated March 2021 - Yelp

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