

# Sentiment

Measuring and Analyzing Emotion in  
Customer and Agent Interactions



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## Introduction

Many years have passed since the advent of Big Data, and the analytics programs that gain insight into that data. Many iterations of analytics technology have evolved over those years. One of the most influential achievements of analytics technology is the ability to accurately measure human behavior, and human emotion. But with analytics of any flavor, it is incumbent on the people using the insights to understand the purpose of the measurements at their fingertips and to take action.

Read on to learn about sentiment analytics as the foundation of AI modeling for understanding customer and agent interactions, and how they influence customer satisfaction, loyalty, and experience. Whether it be agents, products, or processes, every part of the business needs to be aware of highs and lows to remain relevant and competitive. Beyond sentiment analysis, an even more dynamic future awaits through analytics of customer experience quality outside the contact center.

## What is Sentiment?

As it applies to customer service and contact centers, sentiment is generally referred to as a method of measuring emotion in customer and agent interactions. The reason behind this measurement is to analyze these customer and agent interactions to uncover areas of the business that need improvement, to monitor areas that are critical to customer loyalty and retention, and to monitor agent behaviors.

Using analytics and the Big Data already available through many sources and across many areas of the business, it is possible to create data sets from any number of channels such as phone calls, emails, chats, social media posts – any channel stored as voice or text in a database – and probe into these interactions for greater insights into where customer sentiment is low or high, and why.

Sentiment is a machine learning (AI) model trained to measure whether a customer interaction is positive, negative, or neutral, on a relational scale.



## How Does Sentiment Work?

To be truly effective for businesses, the sentiment measurement needs to be sophisticated enough to identify the relative emotion of agents and customers separately for more accurate results. First and foremost, language models are employed to identify positive and negative words and phrases, whether spoken or text based. The semantics of this are key, however, because positive phrases can offset negative ones. Likewise, words and phrases need to be scored carefully within the context in which they are spoken. Some words that may normally be used in a positive manner can also indicate sarcasm or frustration.



monthly bill  
no problem ridiculous  
last payment alternate number better deal  
new address so annoyed order number

A sample discovery word cloud identifies conversations with words and phrases such as “awesome” or “no problem,” but these statements can be positive or negative depending on the context of the conversation.

Beyond language modeling, other layers are added to further calibrate and tune sentiment scores for accuracy. For example, laughter detection can indicate a positive change in an otherwise negative conversation. Cross-talk (where the agent and customer talk over each other) might indicate confusion or frustration. Changes in pitch and tone, or speaking rate, can signal changing emotions during the interaction.

Interactions are scored as negative, positive or neutral on a relational scale. They are also scored as starting positive and moving to negative, or the other way around, for the purposes of identifying that category of interactions for root cause analysis. Both positive and negative interactions can have a number of contact reasons, whether it be something wrong with a process or product, or frustration with an agent. Interactions that begin positive and end negative can also have many reasons behind them, such as an agent’s confusion trying to help the customer or customers not liking what they are being told (e.g., in a collections or billing scenario).

On a more granular level, accuracy of sentiment scoring is further improved with different weights applied to each quartile of an interaction. Studies have shown that the latter portion of an interaction drives customers’ reported satisfaction more heavily than the former. A final scoring calibration is the length of an interaction. The longer the interaction, the more opportunities there are to drive a sentiment score. As such, it becomes important to normalize longer interactions with shorter ones so that they score within similar scale.

With all of these details covered, machine learning is then applied to more than half a million customer interactions and their resulting survey scores across industry verticals. With continued training and development, the result is a powerful AI sentiment model that accurately scores all interactions for further root-cause analysis. As false positives become fewer and fewer in the machine learning algorithm, accuracy and speed to insight improves.

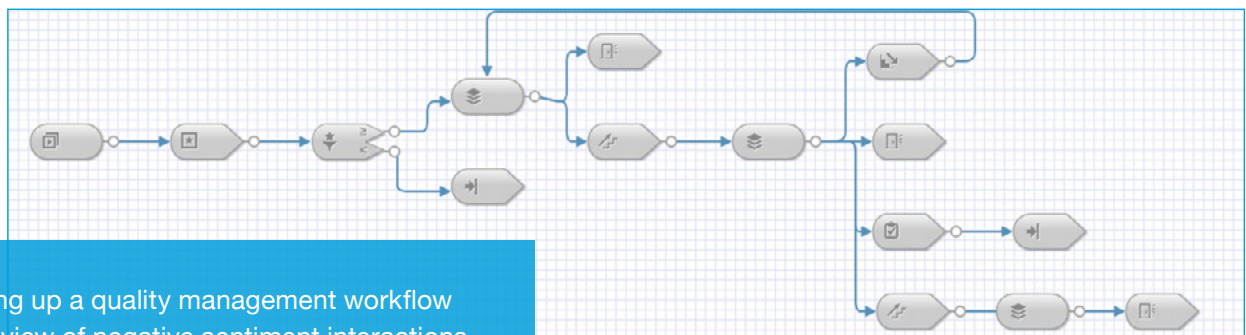
The capability scores every single interaction, but it is important to understand that the measurement is most successful in aggregate. While identifying one negative phone call is still worthy of note, it doesn’t help solve the larger picture of how negative calls are trending, and what topics are driving those negative calls. Understanding volume and trends is the real value behind sentiment analysis, and there are many uses for which it can deliver value. As such, one of the most powerful uses for sentiment is when it is combined with other analytics data, such as topics and queries, or when using metadata to filter specific agents or teams.

## How is Sentiment Used?

## QUALITY MANAGEMENT

A well-established use case for sentiment analysis today is with quality management. Using sentiment to score agent interactions removes the need for random sampling because the interactions are already scored. It also empowers quality programs to analyze 100% of interactions to get a true sense of trends and the reasons behind them. Negative sentiment calls don't necessarily mean that agent behavior needs improvement, so understanding where negative interactions occur in the contact center as well as who they are associated with presents the opportunity to uncover issues with products, processes, and with agent behaviors.

Instead of random sampling, a workflow can be set up for review of negative sentiment calls. These calls can be sent to different queues for further review based on any criteria. For example, if a new product line is seeing an upward trend in negative interactions, those interactions can be sent for review by the quality manager for that product line. If an agent's behavior caused a customer to get angry, that interaction can be sent to the agent's supervisor for review or to an evaluations queue.



Setting up a quality management workflow for review of negative sentiment interactions can be a powerful way to uncover issues with products, processes, or agent behaviors.

## AGENT ENABLEMENT AND COACHING

For agent quality and evaluations, sentiment is especially useful for ranking team members individually, ranking teams alongside other teams, or even showing site by site comparisons in sentiment. This method of scoring helps to reveal top performers and bottom performers, which is especially useful for understanding what behaviors make a top performer's sentiment so high as well as where a bottom performer might need coaching assistance. Understanding the behaviors that make a top performer successful helps supervisors and trainers create effective coaching packages that can be tailored to address low performers, and sentiment trend monitoring helps ensure that those training packages are effective.

## PRODUCT PERFORMANCE MONITORING

The power of sentiment scoring is that it works on any data set, from any viewpoint. A quick search in a data set for a product name can reveal a sentiment model that tips to the negative or positive at any given point in time. Queries and reports built around that product allow for better sentiment monitoring to see how customer satisfaction diminishes or grows as the product matures. Being able to deep-dive into the individual interactions can uncover product defects that need correction, customer confusion due to lack of documentation, or agent confusion about how to help the customer due to self-help gaps, to name a few.





## **SALES EFFECTIVENESS**

When an organization puts a sales initiative into place, tracking sales effectiveness and the sentiment around sales attempts can be very helpful for understanding where employees are struggling or doing well. Sales take on different flavors, as they can be net new sales, up-sell to existing customers, or cross-selling to customers with related products. Sentiment analysis surrounding the different types of sales attempts can further reveal which employees are strong or weak in these specific areas, and targeted coaching can be provided to improve overall revenue numbers. Outside of the employees, sentiment around the sales initiatives themselves can be indicators of whether the intention behind the initiatives are successful in operation, or need refinement.

## **PROCESS IMPROVEMENT ANALYSIS**

Just as agent behaviors can drive sentiment, so can broken processes. As explained previously, building quality workflows so that negative sentiment interactions can be evaluated often reveals situations where there are issues outside of the agents' or customers' control that are causing the poor experience. Broken processes can be problems that leave agents unable to help customers, business processes that cause unintended consequences, or even missing processes for unanticipated events.

For example, one retail product line had two models that were almost identical. The documentation for both models was the same, but their button configuration was slightly different. When people called in confused about how to use the product, the agents were reading the same documentation as the customers and were unable to understand why the troubleshooting wasn't working. Both agent and customer concluded that the product was defective.

But after they sent replacement models to these customers, the same customers called in again saying the replacement wasn't working either. It was a simple process problem of the documentation not specifying the difference between the two models, with unintended consequences. By analyzing the sentiment of interactions surrounding that product model, it became clear that there was an issue. But in this case, the product was not defective.

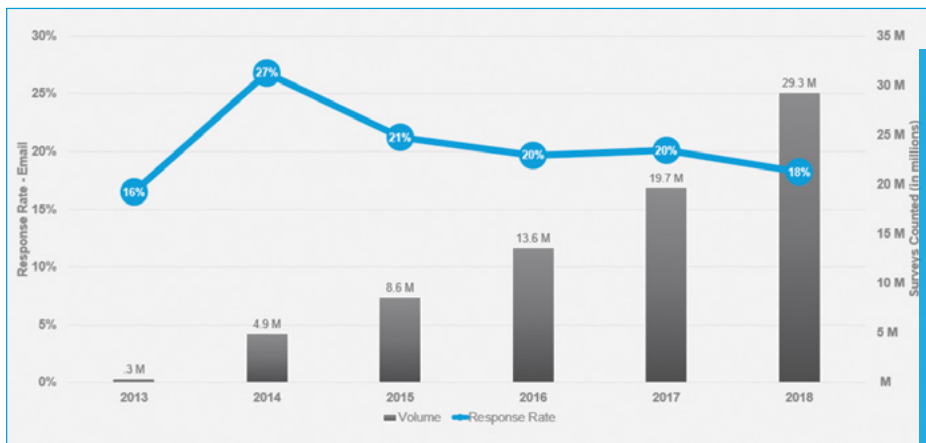
If businesses build workflow queues and staff individuals who can identify and fix broken processes such as this documentation and self-help problem, the improved efficiency will directly affect sentiment and overall customer satisfaction. Trend monitoring and reporting over time can help ensure the process improvements are successful.

## **ADAPTIVE SURVEY COLLECTION**

When it comes to Voice of the Customer, sentiment analysis is especially powerful because it scores every single interaction customers have with a business. Traditional survey collection is known to result in a dichotomy of very positive to very negative feedback, with very little data in between. Additionally, the major challenge of survey collection is that the data set is indicative of only a very small number of customers' experiences. At worst, some companies report a less than 10% response rate to their surveys.

An innovative way to refresh the usefulness of the VOC program is to build an adaptive survey system. For interactions that end negatively, the adaptive survey program could send a brief survey asking if that customer would like to be contacted back to resolve their issue. If a negative interaction occurs around a product mention, billing, account management, etc., surveys can be sent that address the specific issue so that the customer has an opportunity to further explain the problem.

On the other hand, if a positive sentiment interaction is detected, a survey could be sent asking if the customer is especially pleased with a product or experience and if they might provide a product review or a positive social-media mention. In this way, the survey collection is more likely to produce substantive feedback that can then be qualified and quantified with the larger analytics program.



A NICE benchmark report showing the explosion in the number of surveys sent each year, with declining response rates year over year. Sentiment analysis can provide indirect feedback to augment survey programs' visibility into customer experience.

## Taking Sentiment to the Next Level

As a machine learning, AI powered solution, sentiment analysis presents endless possibilities. It has been proven to be predictive of NPS (Net Promoter Score), and sentiment is often considered synonymous with the term, "Predictive NPS." As such, it can be a helpful method of understanding how to improve customer experience and drive sentiment further into the positive.

### JOURNEY EXCELLENCE SCORE

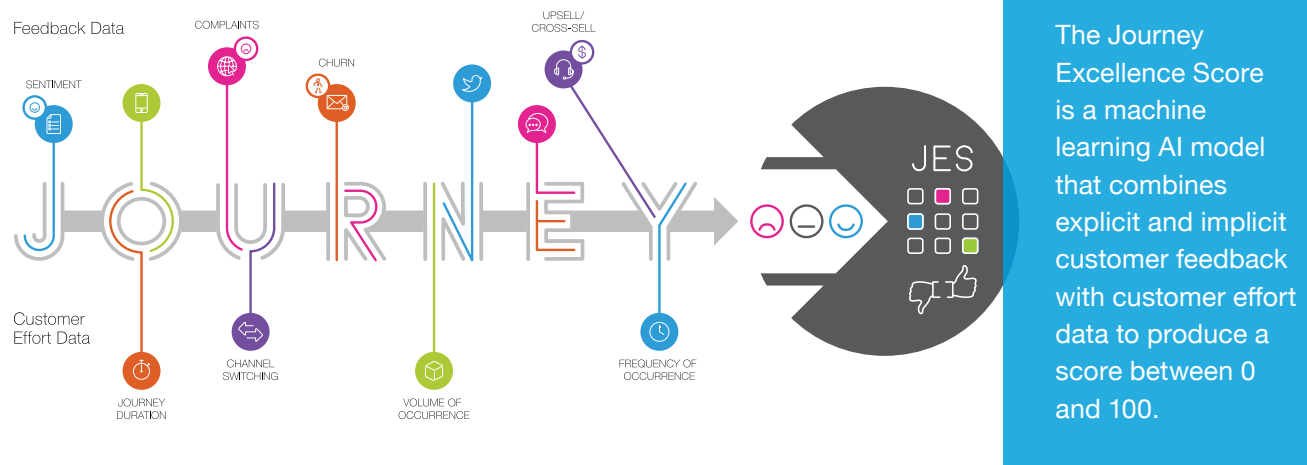
Improving customer experience doesn't just mean the customer's experience when interacting with agents. The customer's experience with a business involves touchpoints outside the contact center as well. Most customers have vastly more engagement with a company online than they do with an agent in the contact center, and picking up the phone is rarely the first interaction in the overarching customer journey. Experience with self-service channels such as the website or mobile applications, retail store visits, mailed promotions or account updates, or the time it takes for an order to be received, to name a few, can directly or indirectly affect how the customer views the business. Being able to accurately measure customer experience begins with pulling together data from all sources where a customer may have explicitly or implicitly provided feedback

along their journey with the business and putting it together in a timeline so that experiences as they move from touchpoint to touchpoint across channels can be better understood and analyzed. Contact center interactions are an invaluable source for measuring sentiment, but sometimes situations occur prior to the interaction that may affect the customer's sentiment when they do make direct contact.

The Journey Excellence Score (JES) is an amalgamation of many different methods of measuring customer experience quality, delivered as a score from 0 to 100. It uses many customer experiences indicators, including but not limited to the following:

- **Interactions** involving specific contact reasons like cancellations or complaints
- **Events** such as a closed sale, upgrade, or lost sale.
- **Survey responses**
- **Sentiment scores** on contact center interactions
- **Journey “effort,”** often expressed in terms of the number and duration of interactions

The Journey Excellence Score provides the next level of sentiment scoring, effectively offering businesses the ability to predict sentiment by finding customer journeys that need improvement. Just as sentiment is an AI machine learning model, so is JES. It is trained with a robust dataset prior to deployment, and its performance is maintained by retraining the model periodically to prevent data drift (this is typical maintenance for a machine learning model).



The resulting information is presented in a dashboard that presents overall Journey Excellence Score for the entire dataset in aggregate, also broken down into different business processes, contact reasons, or intent across multiple interactions. The model also recommends journey types for further investigation. To learn more about the Journey Excellence Score, download the [white paper](#).



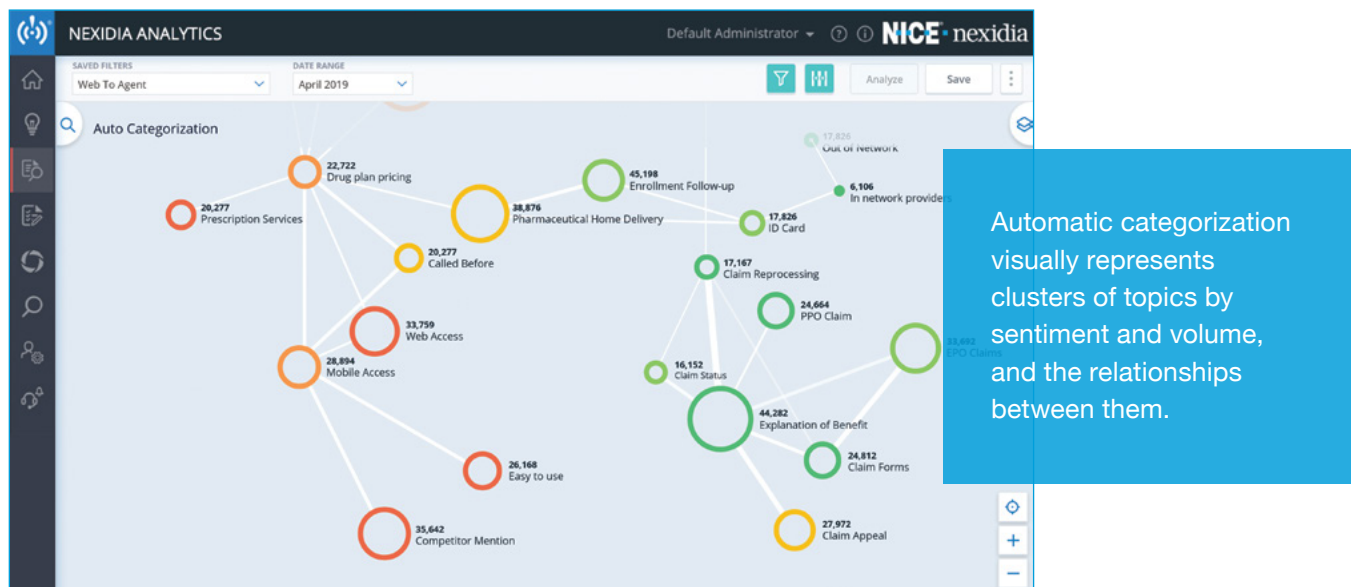
## AUTODISCOVERY

The role of sentiment in analysis continues to grow from a single reporting metric to a value that contributes to bigger picture metrics such as the Journey Excellence Score, or as in the AutoDiscovery module, a first class filter working alongside AI generated categories to slice into data models. AutoDiscovery consists of three main capabilities: Automatic Categorization, Anomaly Detection, and Query Coverage Analysis. These are designed to help reduce time to insight, reduce effort surfacing high volume or low sentiment categories, detection of anomalous activity in contact center trends, and better understanding of how well queries are covering priority conversations for the business.

As the name “AutoDiscovery” implies, these modules are most helpful in the discovery phase of analytics. Discovery is the phase when data is mined for insights that are not yet known, quantified, or qualified. These tools are designed to surface unknowns and quantify them automatically by mining the data without human supervision, so that work can be focused exactly where in the data further analysis is needed.

## AUTOMATIC CATEGORIZATION

The unsupervised machine learning model for Automatic Categorization uses customer data to automatically identify clusters of topics and relationships amongst the clusters within the interaction data. The clusters are visualized by size and color via metric filters such as sentiment, volume, interaction duration, trend anomalies, average handle time, volume and cross-talk providing for quick insight to the topics occurring in the data and associated attributes.



## QUERY COVERAGE ANALYSIS

Query Coverage Analysis maps existing manually curated structured queries amongst the topics discovered in automatic categorization, providing the analyst an easy mechanism for identifying topics that are not currently being quantified or tracked. This makes it easy to see where fast action might be taken to close knowledge gaps, while also providing a confidence level for topics already being monitored. In some cases, a query might provide coverage of a topic, but be missing additional information that indicates that the topic is not fully quantified – the visualization of this gap makes it possible to strengthen existing queries.

## ANOMALY DETECTION

It is conceptually intuitive to mine data for high volume topics that have unusual occurrence patterns. But what if there is a pocket of low volume conversations that have a high value to the business? Anomaly detection automatically identifies phrases and topics whose “arrival pattern” differs from its typical pattern. By automatically identifying these changes in trends, Anomaly Detection can help surface emerging topics whose volume is likely to grow due to a newly uncovered problem, as well as uncovering topics that might never otherwise be identified through day to day analysis of big data and high volumes of interactions.

## The Future of AI Analytics

Big Data is just getting bigger, and no human can handle the task of manually uncovering the valuable insights that have the power to change how organizations deliver on high customer expectations. Sentiment analytics represents one of the early AI models that delivers insights across a myriad of scenarios. Using its capabilities not just as a single metric but as a first class filter among other AI based metrics is just one use case for how predictive AI analytics is taking over analytics programs. Additionally, the need for data insights beyond just interactions data and into the full customer journey opens the door for predictive AI models such as the Journey Excellence Score.

Using supervised, semi-supervised, or unsupervised machine learning to mine Big Data for the purpose of improved customer experience, among many other benefits to businesses, is the natural progression for modern analytics programs. AI models simply need enough data to train them to be accurate enough to operate efficiently and accurately once deployed. Data sets can be used to build models that can predict customer churn, personality traits needed in contact center staffing, sales opportunities, behavioral insights, cross-functional insights, improved customer understanding, and on and on. The possibilities are endless.

To learn more about how AI is revolutionizing customer experience and contact center analytics, visit [www.nexidia.com](http://www.nexidia.com).



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