November 2023

AUTOMATED AND PERSONALIZED OUTBOUND CONTACT CENTER CAMPAIGNS

Anil Kumar M L

Ottalingam T Satyanarayanan

AUTOMATED AND PERSONALIZED OUTBOUND CONTACT CENTER CAMPAIGNS

AUTHORS:
Anil Kumar M L
Ottalingam T Satyanarayanan

ABSTRACT

Techniques are presented herein that support, within a contact center, an automated solution that addresses two important scenarios – first, the case of a customer who abandons their call to a contact center and second, the case of a customer who remains unsatisfied with their last interaction with a contact center. Aspects of the presented techniques employ natural language processing (NLP)-based models and leverage call interaction records to determine if a caller was satisfied with their last contact center interaction. If the caller was not satisfied, then the caller may be contacted through a proactive outbound message or voice call. Further aspects of the presented techniques leverage a caller's previous interactions and business transactions to allow a contact center agent to better handle the customer. When applied, the presented techniques can contribute significantly to the ongoing challenge of a business retaining its customers.

DETAILED DESCRIPTION

As an initial matter, it is important to note that the term "call," as it is employed in the following narrative, may refer to one or more of any number of media channels (including voice, electronic mail, text (such as Short Message Service (SMS)-based) messaging, chat, facilities that are available through a social media platform, etc.) and is not limited to just, for example, a voice conversation during a telephone call.

A customer who reaches out for service through a contact center may abandon (e.g., drop) their call for various reasons. The narrative that follows focuses specifically on calls that are abandoned when the customer is interacting with a text- or speech-based virtual agent (VA) service that is powered by a natural language understanding (NLU)-based dialog management service (which henceforth may be referred herein to as a "bot").

When a customer call is handled through a VA service or a chat bot application as part of a self-service business flow, a set of existing and well-known natural language processing (NLP)-based artificial intelligence (AI) models may be applied to determine the sentiment and the emotional state of the customer during their interaction with the system. Such models may include, for example, a caller sentiment analysis model, a voice pitch analysis model, and an abusive language detection model.

For abandoned calls, various factors may be used to assess the overall sentiment of the customer, including (for voice-based calls) the language that was used by the customer and the pitch of the customer’s voice. Additionally, an analysis of a customer’s interaction (through, for example, an examination of a captured session transcript) may be used to determine whether a bot came anywhere close to determining the intent of the customer. Interaction analysis can also be used to determine the time and the number of iterations that it took for the bot to arrive at the correct intent. Obviously, the longer that it takes for the bot to determine the customer's intent the lower will be the satisfaction of the customer with the overall interaction, eventually leading to an abandoned call.

Within the context that was described above, a caller may abandon their call for any number of reasons, including the inability of a bot to understand the caller’s accent, inappropriate options that are suggested during the automated handling of a business flow, long self-service times due to repeated requests by a bot for information, an incorrect detection and resulting options that are provided by an AI model, an inability to reach the correct service options to solve the customer’s problem, and a poor interaction with a live agent.

As a consequence of any of the above-described reasons, a customer may become frustrated by the system and end their call as they are unable to make forward progress. Consequently, a customer who is, for example, looking to purchase a new product or service from their vendor is unable to do so and they may end up going to another vendor for their business.

With the increased adoption of AI models for self-service, encompassing features such as VAs and chat bots, an increasing number of customers may encounter poor experiences (such as described above) when dealing with non-human VAs. Therefore, it is critical for a business to identify such affected customers and follow up with them through a proactive outbound contact in order to realize a vastly improved customer service experience.

To address the above-described challenges, techniques are presented herein that take into account a number of factors (including missed intent, partial intent discovery, the time for intent discovery, and the emotional state of a customer) to craft a personalized outbound interaction that may be delivered to a customer through one or more media channels. Such a personal message may provide detailed insights into the potential reasons for the customer's abandonment of their last interaction. For example, if the customer was unable to obtain a price quote for an "economy plus" seat that is specifically reserved for mobility-impaired passengers in a particular airline flight segment, the intent discovery mechanism of the presented techniques (that, for example, may examine in detail the overall transcript of an interaction) may provide the required options to the customer in an outbound interaction. Additionally, depending upon a customer's sentiment the outbound message may also include discounts or promotions that are designed to bring a customer back to a business.

To further explain the presented techniques, it will be helpful to review the use cases that deal only with intent discovery and handling under the three phases during which a customer may abandon their call – during a self-service process, while waiting in a queue, or while interacting with a human agent.

For calls that are abandoned during a self-service process, the customer would have stated their intent at the beginning of their interaction with a self-service bot. The call may have been abandoned for any number of reasons including network issues, the inability of the bot to understand the caller's accent, a delay in routing the call to a human agent, or a misunderstanding concerning the intent itself. Note that a self-service interaction requires that the customer's intent be discovered in a near real-time fashion to ensure that the interaction remains meaningful. This requirement may lead to errors as only limited processing resources can be brought to bear in order to respond to the customer in a timely manner. If the call is abandoned and then later analyzed, more powerful models with more computing resources (such as, for example, a large language model (LLM)) may be used to discover the customer's intent with far better accuracy. This can then be used to craft a personalized outbound call to the customer with the relevant context.

A similar approach may be taken for calls that are abandoned while they reside in a queue. In such a case, the customer would have voluntarily consented to the placement of the call in a queue to await a human agent, with the intent either fully or partially discovered. The reasons for placing a call in a queue may include, for example, a bot being unable to service the customer request using its pre-programmed sources of information.

When a call is disconnected or dropped while the customer is interacting with a human agent, it may be due to network access issues. In this case, the intent of the customer is mostly known as the agent would have been progressing through a workflow to satisfy the customer request. Consequently, the contact center has a record of both the call context and the customer information, and it is a relatively straightforward matter to place an outbound interaction to the customer with the relevant context.

By gathering and analyzing the information that is associated with the type of interactions that were described above, as they occur throughout the day, a personalized automated outbound campaign may be constructed by a contact center's system to reach out to an affected customer in order to win back their business.

Figure 1, below, presents elements of the data flow and the decision logic that may reside within one system that is possible according to the presented techniques and which is reflective of the above discussion.

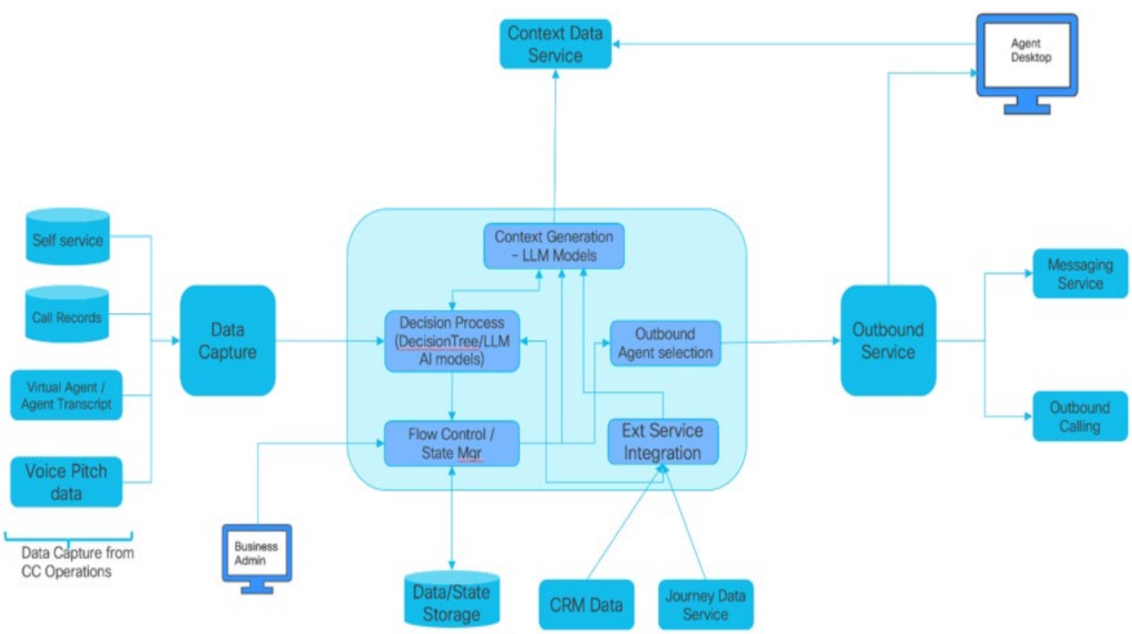

Figure 1: Exemplary Data Flow and Decision Logic

Within a system like the one that is depicted in Figure 1, above, an illustrative customer context is shown in Figure 2, below, that captures elements of a case where an outbound call to a customer was answered and the agent handling the call had complete insight into both the reason for the last customer interaction and any previous customer interactions.

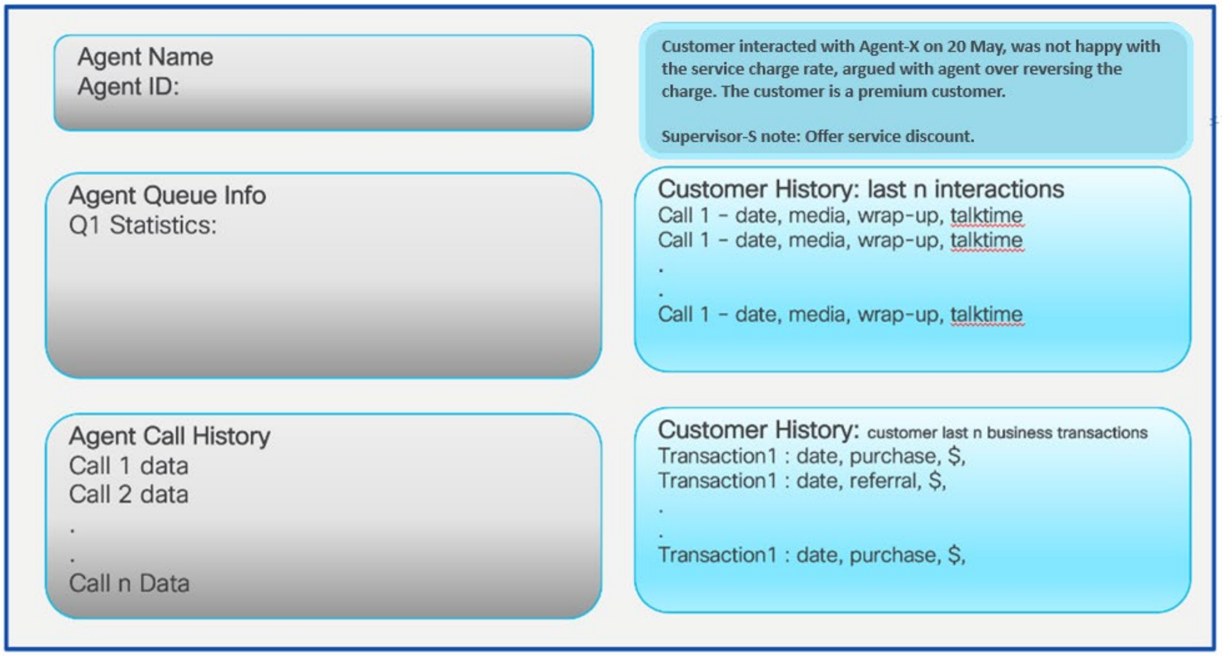

Figure 2: Illustrative Customer Context

In Figure 2, above, the contextual information that appears in the top right blue bubble may be generated using, for example, an LLM.

The presented techniques may be further understood through an examination of the circumstances under which a customer may drop their call due to frustration or anger during the above-described three phases (i.e., during a self-service process, while waiting in a queue, or while interacting with a human agent).

First, a customer may drop their call during a self-service process. Under this case, a customer’s anger or frustration, while interacting with an NLU-based bot, may express itself in two different ways – a raised pitch of the voice and a use of bad language. Existing models may be brought to bear to record the customer’s sentiment at the point that the call is disconnected by taking both factors (i.e., voice pitch and language) into account. Such an approach requires a weighted correlation between the model assessments with more weight (such as, for example, 75%) given to the detection of bad language as opposed to voice pitch detection. Such a sentiment may then be used by an agent during an outreach campaign to entice the customer not only with the correct information or solution but also with additional offers and discounts.

Second, a customer may drop their call while they are waiting in a queue. Similar to the above scenario, under this case a customer's frustration or anger factor can build as the customer waits longer in a queue. Therefore, the queue wait time is an additional factor that must be taken into account when computing an overall customer sentiment. This can be easily identified using customer call records that are generated within a contact center and against which a threshold value P (for some specific queue wait time) may be defined.

And third, a customer may drop their call while they are interacting with a human agent. Under this case, and in a fashion similar to the self-service scenario that was described above, the existing NLU-based models may be applied to record the customer's sentiment by taking into account the customer's voice and language.

For a particular customer, a customer sentiment (CS) value or score, as referenced above, may be developed using the following mathematical expressions:

```
CSS = (k1 * VoicePitchScore) + (k2 * BadLangScore)
EstimatedCSAT = 1 - CCC
```

In the above expressions, the term `CSS` is an estimated customer sentiment score, the value of which may range from zero (0) to one (1) with 1 representing the highest value; the term `k1` is a voice pitch weighting which may be set to 25%; the term `VoicePitchScore` is a previously-developed voice pitch score; the term `k2` is a bad language weighting which may be set to 75%; the term `BadLangScore` is a previously-developed bad language score; and the term `EstimatedCSAT` is an estimated customer satisfaction (CSAT) score.

Importantly, the closer the above CSS value is to 1 the more it expresses a customer's elevated frustration and/or anger level and, accordingly, the more that such a measure must be factored into the personalized outreach campaign for the customer. Further, as a customer's CSAT value is computed through the above expressions any value that is less than some specific threshold S may indicate the need for an outbound call. A system (such as the one that was shown in Figure 1, above) may dynamically adjust the value of such a threshold at regular intervals by collecting data on the ratio of personalized outbound calls to the total volume of inbound calls.

Under the presented techniques, data regarding a customer's journey may also be included in various of the instant calculations. Such data may contain the past history of the customer's interactions with a contact center, including the intent of a call, the number of times the customer had to call to satisfy a given intent, the customer's satisfaction record from post-call surveys, and the net promoter score (NPS) that is associated with the customer (i.e., the number of positive referrals that have resulted from the customer).

Within such a context, the survey scores for a particular customer may be developed through the following mathematical expression:

$$Average_{RCSAT} = \frac{1}{n}\sum_{i=1}^{n}\frac{CSATScore_i}{MaxCSATscore}$$

where the term $Average_{RCSAT}$ is the average CSAT value for the customer, the term n is the number of survey responses that were provided by the customer, the term $CSATScore_i$ is the ith recorded customer satisfaction score, and the term $MaxCSATScore$ is the maximum attainable customer satisfaction score.

Additionally, the monetary value that a customer has brought into a business during the last (e.g., X) number of years may be calculated as the sum of the customer's purchased products and services (or, in the case of a financial organization, the sum of the customer's deposits and investments) divided by the total revenue (or the total deposits and investments) of the business over the last X years. Such a measure may be referred to herein as a customer's "business worth" and may be expressed through the term $BusinessWorth$.

Leveraging the above-described calculations, and their resulting values and scores, under the presented techniques an overall customer value (CV) may be developed for a particular customer through the following mathematical expression:

$$CustomerValue = \theta_0 + \theta_1 * Average_{RCSAT} + \theta_2 * NPS + \theta_3 * BusinessWorth$$

where, in the above expression, the term $CustomerValue$ is the calculated CV; the term θ_0 can be defined as the base value when associated predictors are all zero [the value for this can be an implementation specific value that can be set for customers]; and the terms θ_1 through θ_3 are coefficients that are associated with, respectively, an average CSAT value for the customer (through the term $\texttt{Average}_{\texttt{RCSAT}}$), the customer's NPS value (through the term `NPS`), and the customer's business worth (through the term `BusinessWorth`).

A CV, as described above, may be estimated based on a set of training data. Initially, such training data may be computed manually (using a scale that ranges from 0 to 1, with a higher customer value indicating the importance or the premium nature of the customer to a business) and then augmented with actual data that is captured from within a contact center and compared with an estimated value. A threshold value T may be established to determine whether or not a customer is a premium customer. If a CV exceeds such a threshold, then the customer may be contacted to manage the customer's satisfaction problem with a contact center's services.

In addition to above-described computed values, the presented techniques support the collection of a number of other parameters including a call treatment code (a value indicating whether a call was serviced in the contact center (by an agent, by a VA, or by a self-service process) or whether the call was abandoned before servicing), a self-service indicator (a value indicating whether a call was completed in the self-service stages of a business' logic), and a call wait time (a value indicating the period of time a call waited in a queue before an agent serviced the call).

All of the above-described captured and estimated data points may be used by the presented techniques to determine whether a particular caller requires attention through an outbound message or an outbound interaction with an agent (with the agent having before them the extensive customer context). An exemplary decision tree that captures elements of the above-described logic and process flow is presented in Figure 3, below.

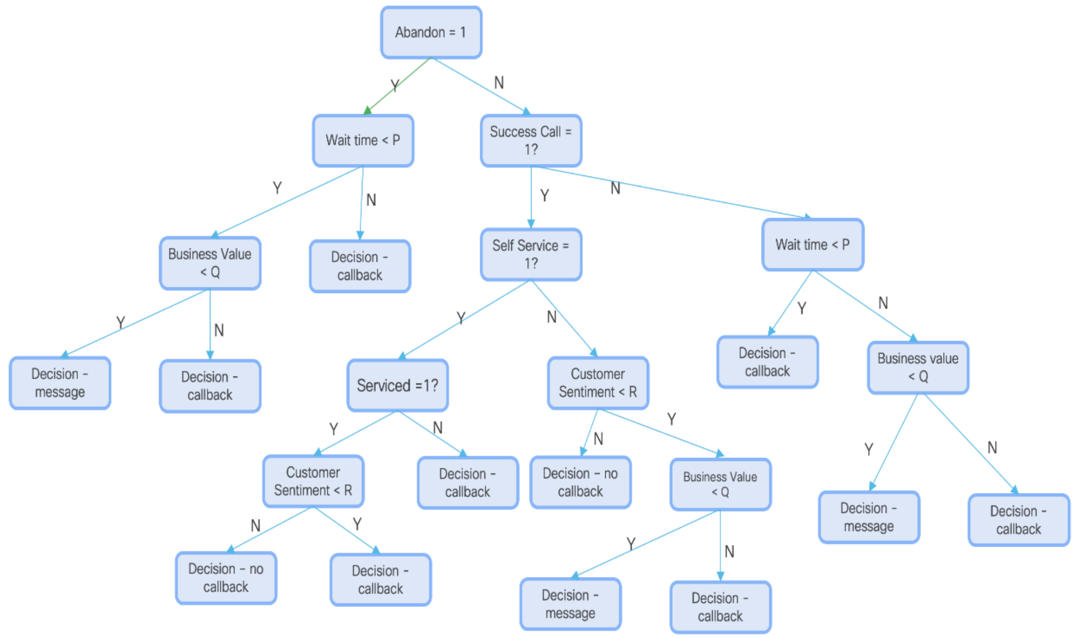

Figure 3: Exemplary Decision Tree

The output of a decision tree (such as the exemplary tree that is depicted in Figure 3, above) may be one of an outbound callback, an outbound personalized message, or no action. If a decision is taken to send an outbound message, a personalized message may be constructed that incorporates the captured and computed fields (as described above) and then sent to the customer. If a decision is taken to initiate an outbound voice call, a full context may be created (including the reason for the outbound call) before the interaction is initiated. Once the customer and agent are connected, the agent's desktop may be populated with the complete context so that the agent may handle the customer and solve the problem, thus improving the customer's satisfaction.

As described and illustrated in the preceding narrative, the presented techniques support the construction of personalized and targeted outbound campaigns based on various factors that are associated with inbound calls. Traditionally, outbound campaigns in contact centers have been used to run canned marketing or sales campaigns to lure new customers or to upsell existing customers, without taking into account any customer context. Such an approach typically results in very low conversion rates. The presented techniques leverage a contact center's outbound infrastructure to make targeted, personalized calls with the specific purpose of retaining existing customers and taking a customer's NPS to the next level.

It is important to note how the above-described approach, according to the presented techniques, differs from possible alternative approaches such as, for example, the dispatch to an affected customer of a simple post-call feedback survey. Typically, such a survey has less than a 10% chance of generating a response from the customer. Additionally, such a survey is meant only as a one-way communication channel with no expectation of any further interaction with the customer. In contrast, an outbound campaign is oriented towards having an interaction with the customer, and a contact center may go to great lengths to ensure that an agent is always available to service the customer in the case of successful contact establishment. The presented techniques, as described and illustrated above, support the automatic construction of a personalized outbound campaign that is based on abandoned calls and calls that are, from a customer's perspective, unsatisfactory.

In summary, techniques have been presented herein that support an automated solution that addresses two important scenarios – first, the case of a customer who abandons their call to a contact center and second, the case of a customer who remains unsatisfied with their last interaction with a contact center. Aspects of the presented techniques employ NLP-based models and leverage call interaction records to determine if a caller was satisfied with their last contact center interaction. If the caller was not satisfied, then the caller may be contacted through a proactive outbound message or voice call. Further aspects of the presented techniques leverage a caller's previous interactions and business transactions to allow a contact center agent to better handle the customer. When applied, the presented techniques can contribute significantly to the ongoing challenge of a business retaining its customers.