Optimizing Customer-Agent Interactions with Natural Language Processing and Machine Learning

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***Abstract* - Efficient and successful customer service is an integral aspect of all businesses. In 2017, U.S. businesses lost $75 billion through poor customer service, where customers encountered unhelpful staff or spent too much time on unresolved issues. Customer experience management software companies analyze call center customer-agent transcriptions using methods such as sentiment analysis and topic modeling to improve their clients' customer service. However, these approaches are not optimized to account for the sequential nature of these customer-agent interactions. For example, while it is important to know how many customers cancel a service, businesses also need to understand how agents respond to a cancellation request and how certain actions may lead to a positive or negative outcome. To analyze the progression of conversations and understand actions that maximize positive outcomes, our research represents each contact center dialogue as a Markov decision process (MDP). For each conversation, we annotated whether the problem was resolved and whether the outcome was good or bad from a business perspective. We employed natural language processing (NLP) to extract the customer states and agent actions from call transcriptions. Our results identify and visualize the most frequent transcription sequences from successful conversations and estimate the expected probability of an outcome when an agent takes an action given a certain customer state. Such an approach may be used to develop programs to train agents for improved customer service in call centers.**

Index Terms - customer experience, Markov decision process, natural language processing

INTRODUCTION

Customer service is a method of direct communication between businesses and their customers. However, its value may be diminished through suboptimal call efficiency, exchanges, and customer satisfaction between customers and agents. Microsoft's 2017 State of Global Customer Service Report finds that 22% of people contacting customer service had to repeat information [1]. Substandard customer service may waste customers' time, decrease a company's reputation, and incur higher company costs. In addition, putting customers on hold or passing the call to another department may lead to lower customer satisfaction or unresolved issues. Just one bad experience with a company may lead customers to leave the brand [2].

Customers contact customer service departments when they cannot solve a problem on their own, and businesses spend $1.3 trillion on 265 billion customer service calls every year [3]. Each call includes various costs such as labor, hardware and software, electricity, maintenance, and system architecture. Businesses preempt answering straightforward calls by creating detailed online documentation, offering chatbots, or responding to calls using Interactive Voice Response (IVR). IVR systems prompt users to choose options from a menu, essentially "serving themselves" [4]. Businesses may save significantly by reducing call duration and redirecting customers to cheaper self-service platforms.

Natural language processing (NLP) is a computational technique that breaks down human language into components, analyzes their relationships, and explores how they combine to form meaning [5]. NLP may be used to analyze call transcriptions, classify conversation topics, and identify customer sentiment. NLP is increasing in popularity as a method to help companies make better decisions and provide improved customer service.

Despite streamlining customer service and reducing phone costs by utilizing NLP and offering online services, the process of resolving complex customer issues through phone calls can still be improved. We will identify conversations resulting in ideal outcomes for the business and customer to analyze how agents can direct conversation flow such that there is a higher probability that the call concludes positively. In the context of call centers, we prefer fast and effective problem resolutions in order to minimize costs.

PROJECT SCOPE AND DESIGN OBJECTIVES

The work aims to deepen understanding of client's customer service interactions. We conceptualize these interactions into three phases: listen, analyze, and act depicted in Figure I. The underlying software framework gathers customer feedback by recording interactions and transcribing them with a commercial speech-to-text tool. The platform stores and ingests these transcriptions, enriching them with topic modeling and sentiment, effort, and intent analysis.

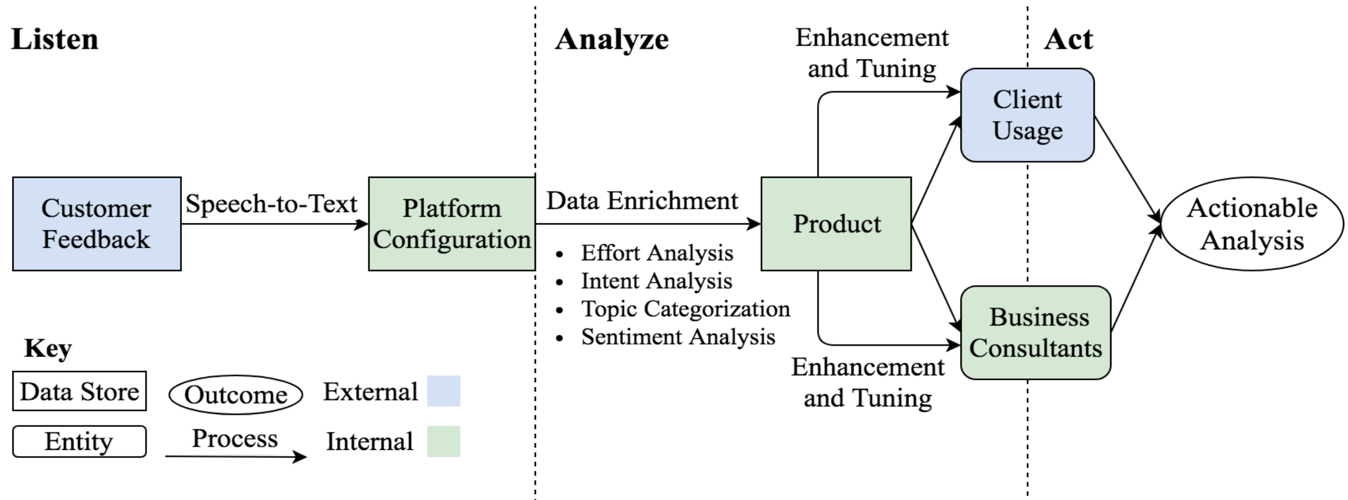

FIGURE I
CUSTOMER SERVICE FEEDBACK DATAFLOW

The platform has over 140 preset categorization templates used for topic modeling; however, users may build custom models to suit their needs. The current implementations are primarily rule-based models rather than machine learning models. These capabilities allow clients to gain insight into call motivation and evaluate customers' opinions or emotions regarding the call. Business clients and consultants can manipulate the data by adding attributes and creating visualizations. Consultants develop recommendations and actionable changes from key findings. Our project scope entails providing additional enhancements to these data enrichments. The platform's current capabilities capture overall trends and infer the context and motivation of customers in the data. However, the platform does not analyze the sequential structure of calls. Sequences are important in customer service calls because the outcome of a call depends on the events leading up to it. Agents can take specific steps to produce optimal sentiment and solve customers' problems. Sequential patterns, when captured properly, may increase model performance [6]. We hypothesize that modeling conversation sequences will provide businesses with coachable insights that may be used to improve customer satisfaction.

The overall objective of the sequential conversation model is to optimize outcomes of two-party, customer-agent interactions using sequential modeling. This objective is divided into two sub-objectives: optimizing agent training processes and inferring call motivation. We characterize performance in terms of customer satisfaction, customer churn, agent effort, and issue resolution.

RELATED WORK

Although textual and audio data mining of call center data have been researched, sequential analysis of call transcriptions has not been widely explored. Paprzycki et al. [7] studied the performance of call center representatives, assessing aspects such as quality or time management, by using a combination of statistical analysis, neural networks, and decision trees. Deslauriers et al. [8] developed continuous-time Markov chain models to optimize call center queuing processes to reduce hold time. These studies specifically focus on staffing rather than evaluating agent strategies used to guide conversation flow and outcomes.

Sequential models have many applications but few of these appear to focus on business intelligence. Puterman discussed the common application of sequential decision models for inventory management, maintenance problems, telecommunication systems, ecology, and game strategies [9]. The model has a general application for modeling decision-making where outcomes are partially random and controlled. Therefore, sequential models are effective for depicting problems and objectively comparing agent strategies. Levin, Pieraccini, and Eckhert developed a stochastic MDP for a learning dialogue system for an Air Travel Information System [10]. Although the model could determine optimal strategies, the model was applied to a man-machine dialogue system, in contrast to our human-human setting which has higher variability.

Prior NLP research has used NLP methods such as topic modeling or sentiment analysis to analyze conversations. Businesses use speech analytics to study customer needs and analyze speech-to-text conversation data to identify methods for improving conversations. Guo, Liang, and Deng used distributed computing to develop topic models for call centers [11], and Priyadarshana et al. measured sentiment intensity of sentences in call center conversations [12]. Although these NLP techniques produce high-level insights, they are insufficient for turn-by-turn training process improvement.

MODEL FORMULATION

A Markov decision process (MDP) provides a mathematical framework for modeling sequential decision problems in which an agent has some control over the outcome as the system progresses through time [13]. MDPs are useful for optimization problems solved using reinforcement learning and have been applied to dialogue systems to evaluate different strategies. An MDP is formally represented by a four-tuple (S, A, P_a, R_a), and it can be applied to identify optimal agent strategies [14].

S is the state space, where $s \in S$ is the current state. States are used to describe outcomes using all relevant information. In the context of this paper, the states pertain to the customer state.

A is the action space, and $a \in A$ is the action taken based on the current state. These actions are represented as agent actions and result in customer state changes.

$P_a(s)$ is the probability that action a in state s at time t will lead to state s' at time $t+1$.

$R_a(s)$ is the immediate reward or cost of action a from transitioning from state s to state s'. For actions taken before the final customer state, the intermediate reward incurs a unit cost per conversation turn to discourage lengthy calls. The final reward is defined by a reward or cost associated with the final outcome. In this problem, the objective is to maximize the cumulative reward.

The solution for an MDP is depicted through a policy, $\pi(s)$. The optimal policy $\pi^*(s)$ depends on the current state, intermediate rewards, final rewards, and transition probability. The utility $U(s)$, or true value, of a state is defined by the Equation (1), or the Bellman equation:

(1)

where γ is the discount factor that controls the importance of future rewards. In this case, future rewards are nearly equal to current reward, so the discount factor was set to 0.001. Value Iteration, a popular algorithm used to solve for the optimal policy, relies on this equation by maximizing the utility or cumulative reward at each state. The method starts with arbitrary value for the utility in the initial state. The algorithm repeatedly updates each side of the equation until they converge.

DATA

I. Data Source

The data used in this research were provided by the research sponsor, a leading customer experience management company. Multiple datasets spanned various industries, including telecommunications and streaming services. The raw data are a collection of voice transcriptions from contact center calls. Each conversation is divided into utterances, conversation turns in a dialogue, which are further analyzed into individual words. Attributes associated with each word include timestamps and confidence levels. Confidence levels are a measure of how sure the system is that the word transcribed matches the word spoken. It ranges from zero to one, with one indicating 100% confidence that the transcription is correct. The confidence level is often less than one and indicates the possibility of error, leading to inaccuracies or discrepancy in the data.

II. Preliminary Data Analysis

Data from a mattress and bedding products manufacturing company was chosen for preliminary analysis. The data was rearranged as a readable comma-separated value (CSV) file to be uploaded to the sponsor's platform. Once uploaded, analyses were performed to determine descriptive statistics.

The sponsor categorizes data using rule-based models, which sort data into non-mutually exclusive and relevant topics. The platform includes templates using the classification models specific to different industries. Various templates were applied, including *Actions Taken*, *Call Reasons*, *Contact Center Experience*, and *Retail* models. The *Actions Taken* model analyzes the call center agent's responses to customers. The agent executed actions like Thanked and Assisted, which occurred in 93.6% and 82.4% of the conversations, respectively. The *Call Reasons* model analyzes the purpose of the customer calling the call center. Out of 11,582 conversations, over 5,000 calls were due to issues regarding corporate policy, which involved product returns, warranty, and credit cards. The *Experience* model was also applied, and examines the environmental factors in determining the experience of the agent or customer. This model explores six categories: *On Hold, Agent Clarity, Interactive Voice Response (IVR), Post Call, Call Clarity,* and *Call Completion*. *On Hold* is a measure of the frequency of holds mentioned in the transcript, not the number of holds themselves. *Agent Clarity* and *Call Clarity* both relate to how coherent and intelligible the conversation was for either the agent or the customer. Surveys, feedback, and any follow-up after a conversation are categorized under *Post Call*. Lastly, *Call Completion* measures whether the call was initiated, followed-through, and then completed. Out of the six topics, On Hold occurred approximately 18% of the time, the most frequent out of all other topics. Lastly, the Retail model was applied, which analyzes various topics such as policy, product safety, and services. The topic relating to policy occurred the most frequently, with 31% of conversations falling under that category.

Analysis of effort, an attribute existing on the sponsor's platform, indicated that more than 70% of the conversations were categorized as *Hard* effort. In contrast, *Easy* effort comprised only 23.9% of the conversations. Effort measures how difficult the customer perceived the problem resolution to be. Analysis by Gartner indicated that 96% of customers became disloyal after a high-effort service interaction [15].

Our preliminary analyses provided insight into the problem as well as details that need to be taken into consideration. The results of the analyses ultimately led to the application of the MDP in modeling the conversations.

IV. Approach

To model the conversation sequence, we decomposed each conversation into turns, each of which is a single contribution from a member of the dialogue. Each turn represents either the agent's or the customer's utterance. We chose a random selection of 125 conversations to create an initial MDP. These conversations were annotated for turn type and outcomes. The customer and agent turn types would become the MDP's states and actions, respectively.

Conversation turns were separated into states and actions and concluded in an outcome. Call transcriptions did not include information from the IVR, making the motivations of the call and customer state unclear. As a result, we drew inferences from the narrative of the conversation to estimate customer states. *Intent Detection*, a predefined model in the platform's interface, served as a proxy and represented 17 customer states to categorize customer behavior. The platform uses *Intent Detection* to categorize expressions or behaviors a customer is displaying and provides insight into their intent. *Actions Taken*, another classification model in the platform's interface, represents 41 possible types of agent actions. The model analyzes the agent's responses to customers and can be used for coaching. Compared to the other classification models, these were the most appropriate for labeling customer state and agent action. In addition to the tags from the platform-enriched data, we included Null and Listening actions for the agent. When an agent spoke, but was not categorized by the model, a Null Action was applied. Listening occurs when the customer is speaking and the agent has no categorized action.

To extract platform-enriched data, we uploaded text data to the platform's API where it was processed by proprietary NLP algorithms, then returned with additional attributes and categorizations. From these categorizations, we calculated transition probabilities between states and actions for the MDP formulation. For each action, we created a stochastic matrix to describe the transition probabilities.

Then, we defined outcomes for each call center interaction. Two team members annotated the same set of conversations to cross-check and resolve conflicts. Outcomes involved two dimensions: Problem Resolution and Company Perspective. Problem Resolution determined whether or not the agent solved a customer request. Company Perspective captured whether the outcome was a good (e.g. subscription continuation) or bad (e.g. subscription cancellation) result for the business. Outcomes were sorted into four categories: Resolved/Good, Unresolved/Good, Resolved/Bad, and Unresolved/Bad. In the MDP, these outcomes were final customer states. Due to transcription quality, annotations could also be classified as unclear. The optimal outcome is Resolved/Good. Figure II displays the distribution of outcomes.

An example of a resolved and bad outcome is when a customer may call to request aid in a warranty claim. Although the agent is successful in fulfilling the request, companies lose money from warranty claims. Ideally, the best agent strategies shift conversation sequences towards the optimal outcome. Equation (2) ranks the preferences for outcomes:

(2)

	Problem Resolved		
Company Perspective	Resolved & Good 28.0%	Unresolved & Good 2.4%	Unclear & Good 0.0%
	Resolved & Bad 33.6%	Unresolved & Bad 12.8%	Unclear & Bad 4.0%
	Resolved & Unclear 4.8%	Unresolved & Unclear 1.6%	Unclear & Unclear 12.8%

FIGURE II
OUTCOME DISTRIBUTION

Many customer issues produce negative results for the business such as product returns or shipping problems. However, agents may still promote positive customer experiences with effective problem solving. Therefore, we considered Problem Resolution to be more important than Company Perspective. Tables I and II list the possible states and actions for the given dataset.

TABLE I
POSSIBLE CUSTOMER STATES

Intermediate		Final
Yes	Generic Praise	Resolved/Good
Hello/bye	No Comment	Resolved/Bad
Don't know	Apathetic	Unresolved/Good
Requests	Suggestions	Unresolved/Bad
Thanks	Cry for Help	
Null State	Churn	
Apology		

TABLE II
POSSIBLE AGENT ACTIONS

Actions		
Thanked	Price Matched	Repaired
Listening	Verified Info	Scheduled Delivery
Assisted	Resolved	Disclosure
Null action	Sent Info	Not Recommended
Requests	Generic Praise	Troubleshooted
Suggested	Transferred	Modified Delivery
Sold	Apology	Educated
Apologized	Provided Order Info	Provided Account Info
Hello/bye	Called Back	Provided Store Info
Yes	Upgraded	Issued Reward
Escalated	Modified Order	Dispatched
Don't know	Provided Product Info	Canceled Appointment
Modified Account	Generic Negative	Closed Case
Researched	Placed on Hold	Mini-miranda
Emailed	No comment	Canceled Order
Disconnected	Apathetic	

To align with our MDP framework, we set an incremental cost to represent the intermediate rewards and converted qualitative outcomes into scalar values to represent the final rewards. Since companies seek to minimize call duration to reduce cost, minimize customer effort, and improve customer loyalty, we specified a cost of -1 for each turn in the dialogue. Of the 125 conversations, 19 did not have data for speaker changes and were not considered. We based the scalar conversions on the descriptive statistics of the number of turns in each conversation. The summary is depicted in Figure III.

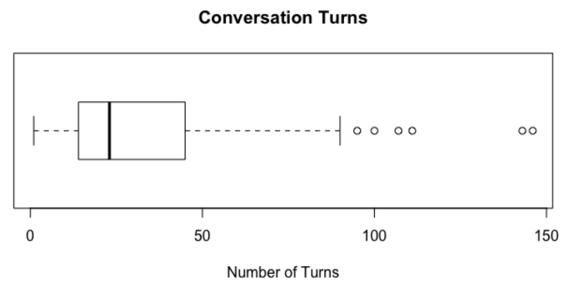

FIGURE III
CONVERSATION TURNS BOXPLOT

Since 90% of the conversations had fewer than 72 turns, we set the final rewards according to Table III, so the preferred outcomes would yield positive cumulative rewards.

TABLE III
REWARD

Reward	State/Outcome
-1	*Intermediate Customer State*
75	*Resolved/Good*
50	*Resolved/Bad*
25	*Unresolved/Good*
-25	*Unresolved/Bad*

MODEL RESULTS

I. Results

We estimated the optimal policy within our MDP using the Artificial Intelligence: A Modern Approach (AIMA) Python MDP module. The parameters for the MDP included the transitions matrices and reward matrices. The module applies several algorithms and functions to solve the MDP by maximizing the utility function *U(s)*. Compared to the other functions, Value Iteration was the most appropriate for the problem type because the method evaluates the policy at each action rather than evaluating a selection of fixed policies. Similarly, agents will be more effective by personalizing their assistance at each customer state than by following a set script.

The optimal policy, which identifies the action that maximizes the expected reward from a given state, is shown in Table V. The two most common best policies are Scheduled Delivery and Thanked both of which the MDP solution recommends at three distinct states. Referring to statements that include different forms of the words assessment, schedule, service, and delivery, Scheduled Delivery is the best agent action given generic customer states like Yes, Hello/Bye, and Thanks. This action is relatively unique, and only occurs 1, 2, and 4 times, respectively. The action Thanked is best when the customer is in a state of apology, generic praise, or suggestions. These actions occur in situations where a customer would likely perceive thankfulness as respectful and polite. In a situation where a customer is identified for risk of Churn or the customer is making Requests, the best action for the agent is Listening. Rather than immediately providing offers or solutions, the agent could prioritize hearing a customer and their problems first.

During the annotation of conversations, we noticed a trend where the agent and customer exchanged formalities and niceties at the end of a conversation regardless of the type of outcome. Thus, it is important to distinguish the difference between correlation and causation when inferring the relationship between agent actions, customer states, and call outcomes. For example, while Thanked is associated with positive outcomes, they may not cause outcomes.

TABLE V
OPTIMAL CUSTOMER STATE AND ACTION POLICY

Customer State	Best Policy
Yes	Scheduled Delivery
Hello/bye	Scheduled Delivery
Don't know	Price Matched
Requests	Listening
Thanks	Scheduled Delivery
Null State	Resolved
Apology	Thanked
Generic Praise	Thanked
Generic Negative	Yes
No Comment	Hello/Bye
Apathetic	Modified Account Info
Suggestions	Thanked
Cry for Help	Requests
Churn	Listening

II. Limitations

As stated earlier, the given conversation transcriptions contained confidence levels specifying the probability that the word transcribed is correct. Confidence levels were often less than one, indicating that transcribed words may not be 100% correct. In addition, transcriptions contained numerous inaccuracies involving sentences with missing words, extra words, misspellings, and incorrect grammar. Additionally, the lack of existing capabilities on the sponsor's platform contributed to technical limitations. The sponsor's platform was built for topic modeling, not sequential processing. We manipulated the dataflow so that sequential analysis could take place, which may contribute to some bias and flaws in the results. The sequence of steps taken by the agent was heavily dependent on call motivation. Due to varying levels of problem complexities, the MDP algorithm could easily be skewed towards simpler problems.

Furthermore, there was no precedence on which the research could refer to, as sequential processing in a call center setting has not been widely researched. Related work involved parts of this research and not this paper's topic as a whole. The absence of precedence made it difficult to devise a solution or verify its validity.

III. Future Work

Possible future work on this topic would be to generalize the model for applications in different client industries. Since the outcome measured in the MDP model was based specifically on the mattress industry, the results from this model may be unsuitable for other businesses. The model would have to be reapplied to another dataset to find the optimal policy for another industry. The annotation process was performed manually and may be automated in future works. The general model would enable more data to be processed and analyzed, contributing to more accurate results as the model adapts.

As speech-to-text transcription techniques and other natural language processing tools improve, we hypothesize a Markov decision process will identify training opportunities so that companies can better serve their customers in real-time.

CONCLUSION

Historically, call center transcriptions had been analyzed using topic modeling and visualization in aggregate. However, topic modeling does not capture the sequential nature of conversations. The interaction between call center agents and customers has an important impact on the outcome. This research applies an approach for sequential analysis of call transcriptions to enhance customer experience and reduce operating costs by finding the optimal policy for agent actions. The Markov decision process was used to model the sequential path of the decision-making process and analyze conversations. The optimal policy, or sequence of interactions, was found using the MDP algorithm.

The optimal policy yields the highest possible reward with the lowest possible cost. This sequence of interactions can be used by corporations to improve agent training, thereby providing a better experience for their customers.

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