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Optimization of Agent-User Matching Process Using A Machine Learning Algorithms

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***Abstract* – Contemporary dynamic market conditions are characterized by high levels of competition. Businesses are forced to make continuous changes in order to maintain a high level of customer's satisfaction. Contact centers are part of the global economy and a key channel for communication with customers. Access to the contact centers is realized through several channels (telephone, e-mail, fax, web forms, etc.), but the primary method is still a phone call. Most call centers use Interactive Voice Response (IVR) to route users with a particular problem for directing the user to an agent with appropriate capabilities (Skill-based routing – SBR). This type of contact center operation can have a negative impact on the quality considering customer's experience, due to the complexity and length of the process, which often results in directing calls to the inadequate agent and describing the problem multiple times to reach the right agent. This paper aims at applying machine learning methods based on prior experience with matching customers and agents in order to reduce time and target agents with adequate problem-solving abilities.**

***Keywords* – call center, agent, customer, skill-based routing, machine learning.**

1. Introduction

Modern companies use faster and more efficient decision-making systems that give them a competitive edge.

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These new systems are more complex, faster, and generate significantly more data. The basis of successful business in each company is the focus on customer service, based on quality and timely customer service.

A modern contact center is a central place for implementing the company's business strategy and external communication with the customer [1]. New advances in telecommunication technologies are revolutionizing the way users approach contact centers. In this context, in recent years, there has been an increasing interest in new software products. Today, contact centers represent jobs in which staff communicate with customers through available multimedia communication channels such as telephone, email, fax, letter, web, online live chat and social networks. Contact centers are equipped with intelligent tools that provide integrated data and knowledge tailored to the needs of users [2]. According to the nature of communication, we can distinguish two types of modern contact centers: incoming and outgoing contact centers [3]. Incoming calls are most often used to provide information to callers, with the aim of solving problems and increasing the quality of service. Outgoing calls, on the other hand, have the purpose of proactively communicating with customers or prospective clients with the aim of increasing sales, billing, or collecting new information.

In this paper, we consider the incoming contact center of a telecommunications provider with a telephone call service. Telecommunications companies are facing fierce competition in their industry and planning strategies to build long-term customer relationships. Users are becoming more sophisticated and sensitive to pricing due to the increased transparency, which requires a change in customer orientation [4]. It is more important for the provider to develop stable relationships in order to avoid losing customers than attracting new customers. If a customer's support solves the problem, the customer creates a positive image of the company and remains loyal to the service.

Failure to do so within the desired expectation causes a loss of user's trust which can lead to changing the service provider.

Therefore, developing customer's support and boosting customer's satisfaction is a very important approach to managing a telecommunications company. The end-user expects accurate and contextual service in real-time, on any device they use [5].

2. Literature Review

Call routing is a policy of assigning individual calls to agents [6]. First papers written for call center address homogeneous servers, in which all agents were doing the same job, that is, processed the same type of calls. This kind of routing is a problem for two reasons: training new agents can be time-consuming, since they need to have a wide range of practical knowledge before they are able to assist the users, and service time increases while productivity decreases when agents manage calls from different users with different kind of problems.

With the development of technology and the emergence of advanced IVRs, skill-based routing has become standard in all contact centers, with the exception of some smaller ones. IVRs are interactive voice response systems, also known as voice dialogue systems, voice user interfaces or voice applications. The IVR system is the front end of the call center. It is a computer system that allows users to interact with a company without the help of human agents [7]. IVR allowed agents to be divided into groups according to their skills. Incoming calls are routed based on the user entry in the IVR system. The primary reason for this type of routing which is called SBR (skill-based routing), is the desire to differentiate users and assign different priorities. Skill-based routing complicates most aspects of call center management. Specifically, decision-based matrices based on instructions such as "press 1 for sale, press 2 for technical support..." are de facto standard for "intelligent" customer service systems and often cause users to get frustrated before they reach an actual human voice, i.e. agent [8]. In the last decade, there has been a greater development of mobile and Self Service Technologies (SST). The authors in [9] found that the process of providing information technology support services does not have such a positive impact as traditional "human contact" in terms of perceived overall customer's satisfaction.

3. Motivation

In [10], the author assessed the impact of user-centered technology. The effectiveness of interaction within the contact center was studied, and the effectiveness of the system in resolving queries and complaints was analyzed. The complexity of the system was explored, instructions and menu options presented to users were clear and concise as well. This survey shows that 38.2% of respondents disagree that using IVR software is easy. 34.5% of respondents disagree that self-service options are fast and easy to use. Users want to make the call with as little, and as simple instructions as possible. Over-reliance on self-service technology to the point of eliminating human contact can have a negative impact on the company, so it is imperative to strike a balance.

In order to practically demonstrate the complexity of the IVR systems of different telecommunications companies, we conducted a short survey on three randomly chosen operators (marked as *X*, *Y*, and *Z* company) with a relatively large number of users (see table 1). We have come to the conclusion that the minimum number of levels in the IVR system is three. Tested IVRs took approximately 32,67 seconds of waiting time for listening to the whole massage in order to make a decision on what option to choose. However, even after selecting the appropriate option, the user is again placed in a new queue if all agents of the selected type are occupied.

The main objective of our paper is to simplify the guidance of users through the IVR contact center system and to speed up the process of reaching an agent who will have the skills to solve a user problem. The author in [11] states that, according to a report from a major European telecommunications provider, on average, a user talks to more than three different agents to solve his problem. The reason for this can be precisely the IVR system, because often the user does not wait until the end of the instructions, but presses the first number he hears and thus ends up with the wrong agent, who cannot solve his problem and has to be forwarded to another agent.

The Quality of Service (QoS) model with an emphasis on contact centers used by authors in [12] consists of seven dimensions: reliability, empathy, customer familiarity, customer focus, the cost of user waiting, user-friendly IVR unit and accessibility. According to the authors [13], in addition to these parameters, service time (communication with the agent) is added, as well as handling users by qualified agents and the handling by a single agent (transferring calls between multiple agents is not a suitable solution). In this paper, the authors identified the Key Performance Indicators (KPIs), which play a vital role in maintaining the quality of service and customer satisfaction, using the Big data method. They point out that personalized menus and IVR options affect these indicators by 95%.

Table 1. IVR systems of different telecommunications companies

Operator	IVR message	IVR delay	IVR levels
X	Telecommunication operator *X*. Customer support. This conversation can be recorded to improve service quality. Press 1 to report the interference Press 2 to activate the service and for service information Press 3 to change the language For the other kind of problems, please hold, the first free agent will contact you.	28 sec	4
Y	Welcome to *Y*'s contact center. For billing problems, press 1. For problems regarding your digital cable, internet, and landline telephony, press 2 To become a customer of one of our retail services, press 3 If you are a business user or you want to become one, press 4 If you are a user of our special tv service or want to become one, press 5 For more information about our company and our current services, press 6 If you have a pulse dial phone, please holt and wait for our first available operator to process your call. Thank you for your patience.	48 sec	6
Z	Welcome to *Z*'s customer support. To improve the quality of our services, this conversation may be recorded. For information on our products and services, please choose 2 For billing information, please choose 3 For technical support, please choose 4	22 sec	3

4. Simulation Settings

The basic idea behind a simulation is addressing a contact center with different types of calls, managed by different groups of agents (with different skill sets). Each group has a different number of agents with different types of knowledge and skills.

When making a phone call to a contact center, the user hears a message from IVR: "Dear customer, this is the contact center of Company XYZ. Please describe your problem briefly." Advanced IVR converts human speech to text. The call is then routed based on the content of the sentence that the user used to describe the problem.

Figure 1 shows the call routing scenario. It represents the flow of the reporting problem via telephone from the user, through IVR to Machine Learning Aided ACD (Automatic Call Distributor), which assigns the call to available agents with the appropriate skills. We used the Natural Language Processing (NLP) approach in which machine learning algorithms are applied to text and language. The aim is to identify patterns in human speech and to draw conclusions about the content of spoken words.

We have assumed that the user speech is automatically converted using the speech-to-text technique. We have not considered the approach and the concrete solution (specific software and hardware) that will convert users' speech into text, nor its performance. For the purpose of proving our thesis, we assumed that this part was done without errors. Our simulation sample consists of 328 records of actual user calls from a telecommunications company call center. Based on the call history, there is information on which agent has processed the call. All agents are grouped into three groups according to the type of problem they are specialized in:

1. Agents in group 1 - General information
2. Agents in group 2 - Technical issues
3. Agents in group 3 - Financial issues

The main goal is to apply a machine learning algorithm that independently recognizes a problem based on the processing of a user's speech, and automatically associates it with some of the agents in the group best fitted to solve that type of problem.

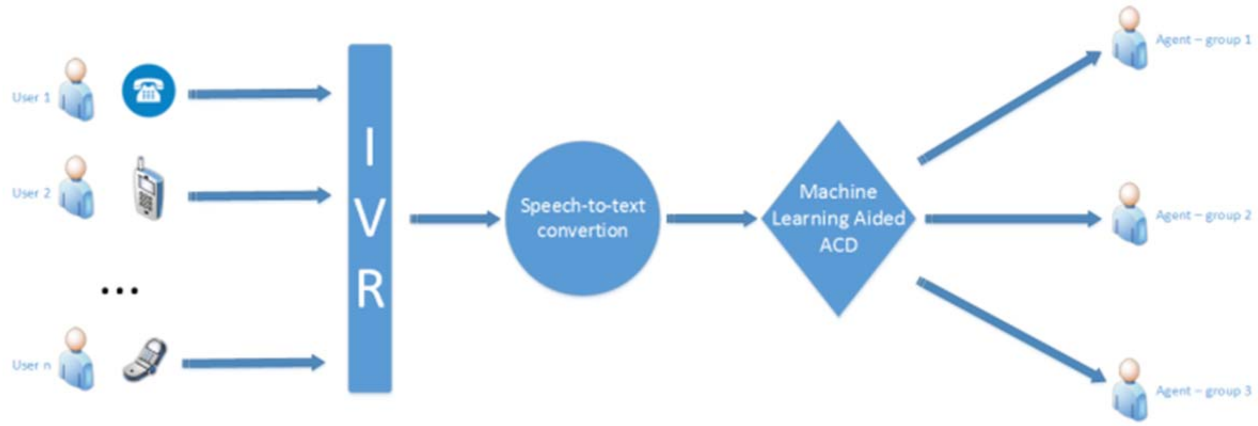

Figure 1. Call flow scenario

All data is divided into a training set for training the algorithm, made out of 80% of the mentioned 328 records, and a test set with 20% of records for analyzing the success of matching calls with agents. The code is implemented in *Python* programming language.

The *Bag of Words* model was used for preprocessing the text before fitting the machine learning classification algorithm. In data preprocessing, the text was prepared and "cleaned" for machine learning applications using the *re* and *NLTK* libraries. At this stage, the basic intention is to reduce the complexity of the date and simplify it for effective application of the classification algorithm. Everything but letters was dropped from the text (numbers, punctuation, etc.), all words were changed to lowercase, words that are irrelevant for matching the right agent (articles, prepositions, etc.) were excluded, words having the same root were treated as one word (eg restart, restarting, restarted were treated as the same word).

After the text was filtered, a Bag of Words model was created in the form of a sparse matrix. Matrix rows are represented by individual calls, and columns are single words that appear in all user calls. The formed matrix for all words represents the matrix of independent variables, while the vector in which the information about the matched group of agents is stored in the vector of the dependent variables. Each individual cell in the matrix represents a number that shows how many times a word is mentioned in a single call.

The machine learning algorithm will correlate the number of occurrences of individual words in a user's call to the outcome, that is, the group of agents to which it was matched. He will then be able to independently classify on samples for which he is not aware of the outcome in advance, i.e. to the test data. set.

When creating the Bag of Words model, for simplification purposes, the max_features parameter was set to 500, to further filter the data and use only the most relevant words. The words that appear only once or twice in all 328 records used will certainly not play a significant role in predicting the outcome, that is, the dependent variable.

5. Analyses of Results

Four machine learning algorithms for the classification problem were applied to the same set of preprocessed data, namely: Naive Bayes, Decision Tree, Random Forest, and Support Vector Machine (SVM). As the training set and test set were split at 80%:20% ratio, out of a total of 328 records, 262 were used in the training phase, and 66 records were used in testing the model accuracy. After applying each of these algorithms to the created Bag of Words model, we also created confusion matrices so that we could analyze the performance of the algorithms, and calculate and compare the accuracy of the methods used. The resulting matrices are shown in Table 2.

Table 2. Confusion Matrices: (a) Naive Bayes, (b) Decision Tree, (c) Random Forrest, (d) SVM

↓Users/ Agents→	Group solving problem type 1	Group solving problem type 2	Group solving problem type 3
With problem type 1	19	2	9
With problem type 2	3	16	4
With problem type 3	2	1	10

(a)

↓Users/Agents→	Group solving problem type 1	Group solving problem type 2	Group solving problem type 3
With problem type 1	25	4	1
With problem type 2	3	20	0
With problem type 3	1	1	11

(b)

↓Users/Agents→	Group solving problem type 1	Group solving problem type 2	Group solving problem type 3
With problem type 1	27	3	0
With problem type 2	2	21	0
With problem type 3	1	1	11

(c)

↓Users/Agents→	Group solving problem type 1	Group solving problem type 2	Group solving problem type 3
With problem type 1	25	4	1
With problem type 2	2	20	0
With problem type 3	3	0	11

(d)

Correct predictions are shown on the diagonal of the matrix, while the fields below and above the diagonal are incorrect predictions. Thus, if a user with the problem type *N* is matched to an agent who is qualified to solve type *N* problems, the prediction is considered successful. In all other combinations, the algorithm made a mistake.

To evaluate the precision of the algorithms, the following equation was used:

$$A(\%) = \frac{P_t}{P_f} \cdot 100\% \qquad (1),$$

in which A is accuracy, P_t is the number of true predictions, P_f is the number of false predictions.

The analysis showed that the best results were achieved using the Random Forrest method, which, of 66 records tested, correctly matched 59 users with the appropriate agent, giving the accuracy of 89,39%. Remaining three methods, Decision Tree and SVM achieved an accuracy of 84,84%, while the Naive Bayes method achieved an accuracy of 68,18%.

High percentage of correct predictions indicates that the application of methods for classifying based on machine learning to the maching process of users and agents certainly has the potential to be applied in call centers. It should be noted that the sample on which we conducted our testing is relatively small. It is clear that a larger set of data would create stronger correlations between the words of user's speech and the assigned agent type, and the percentage of correct predictions would certainly be significantly higher.

6. Conclusion

The approach used in our paper simplifies the way users report problems in many ways. First of all, we avoided situations in which users had to simultaneously listen to IVR recorded voice and enter instructions via the phone keyboard.

This process can be quite painstaking, especially when using a mobile phone. In that case, the user has to lower the device in his hand, activate the cell phone keypad during a call, and then choose the desired option by pressing the appropriate number. To make matters worse, this process is repeated multiple times (as many times as the IVR has levels). It is not negligible that the users are of different ages and education, and often have low IT literacy, and these conditions require a troublesome effort for them.

Our approach reduces the time spent in the system for problem reporting. Using machine learning methods shortens IVR system message duration, avoids usage of keyboard and process of choosing the desired call center options, as well as it eliminates the need for multiple routing levels. Another benefit of our approach is to reduce the possibility of making the wrong choice and pairing of users with inadequate agents. Automatic pairing overall has the potential to provide a more efficient user-agent matching process.

On the other hand, the authors of this paper have assumed that recognizing the user's speech in the speech-to-text conversion is error-free, that is perfect. This is certainly not possible in practical implementation. In a future study, the authors will try to take this parameter into consideration by using the real data output from speech-to-text software. Correspondingly, the authors assumed that there are three groups of agents classified according to the three types of problems they are capable of solving. It is important to check the accuracy of the methods used in cases where we have a different (greater) number of agent groups. It would also be desirable to investigate the performance of other classification methods such as CART or Maximum Entropy.

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