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IMPLEMENTATION OF A CHABOT FOR CUSTOMER RETENTION WITH CUSTOMER FEEDBACK SENTIMENT FOR BUSINESS TO CUSTOMER SUPPLY CHAIN (B2CSC) USING FUZZY SEARCH CLASSIFIER AND RULE-BASED APPROACH

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Abstract— This research focuses on the Business to Customer Model for Supply Chain (B2C SC) which covers that of a retailer offering electronic goods to consumers as well as customer retention and feedback sentiment in the B2C SC domain. Solving a customer retention problem for the customer to have faster demand requests and better responses to their queries and analyzing customer feedback to promote better services and product delivery is crucial. Sometimes, customer service representatives don't have immediate answers and they must transfer the customer to another person. That's how they serve multiple customers, and it is fair enough to take a long resolution time to resolve the customer service tickets. However, the problem identified in this research is customer retention with feedback sentiment. We studied research papers on customer retention using machine learning conversation agents and to the best of our knowledge, we couldn't find researches that solve both customer retention with feedback sentiment using fuzzy search classifier, rule-based approach, and Vadar Library. In this research, the B2C SCM covered the fulfillment of orders and the retailer has to manage stock levels in warehouses. When an item in stock falls below a certain threshold, the retailer restocks from the relevant manufacturer's inventory. The system business rules were created using Transact SQL Procedure and the fuzzy classifier function was written as a user-defined Function in Microsoft SQL Server 2019. C# written in Dynamic Link Library was used to call the procedure and fuzzy function methods from the Microsoft SQL Server and ASP.NET was used to design the user interface for the users of the system.

Key Words – B2C, Supply Chain, Customer Retention, Fuzzy Search Classifier, Vader Library

Introduction

Research has shown that there is an increase in the use of service technologies (Geoffrey, Kelvin, and Daniel, 2020) which has led to increased research attention due to problems in service marketing (Amin, et al., 2017, Coussement, Lessmann, and Vertraeten, 2017, Hou, Wu, and Du, 2017).

Customers have higher expectations in terms of service when they make a purchase, which is why, it is crucial to provide a better customer experience than a direct competitor (Vishakha, 2019).

Communicating with customers through live chat interfaces has become an increasingly popular means to provide real-time customer service in SC (Martin, Michael, and Alexander, 2020). The real-time nature of chat services has transformed customer service into two-way communication with significant effects on trust, satisfaction, and repurchase (Mero, 2018).

Over the last decade, chat services have become the preferred option to obtain customer support (Charlton, 2020). Due to the advancement in technology, human chat service agents are frequently replaced by conversational software agents (CAs) such as chatbots (Benlian, Adam, and Wessel, 2020), designed to communicate with human users utilizing natural language (Feine, Gnewuch, Morana, and Maedche, 2019).

Chatbots are generally dialog systems having various purposes like customer service, information acquisition, automated information retrieval, etc. (Sandeep and Vishakha, 2020).

Chatbots provide efficient and immediate responses as they are integrated with AI (Vishakha, 2019). They are easily accessible and adopted (Dirican, 2015). All bots have a common back-end system and process which helps them in responding to the customers (Achilles, 2021). Moreover, the SC Industry has also introduced chatbots for storing the data and streamlining the entire process (Feine, Gnewuch, Morana, and Maedche, 2019).

The chatbots are open domain and the closed domain chatbot (Ketakee and Tushar, 2017). In this research, we will be more concerned with the closed domain chatbot built for the business rules in the area of SC using Fuzzy Search and Rule-based algorithm which we cover the functions of the ordering of goods, canceled orders for the consumer, track goods in real-time and analyze customer feedback sentiment to the retailers, manufacturers, and administrators using the Vadar library.

This application development for this research uses the Business to Customer (B2C) Model (Carol, 2020), which covers that of a retailer offering electronic goods to consumers. To fulfill orders, the retailer has to manage stock levels in warehouses. When an item in stock falls below a certain threshold, the retailer restocks from the relevant manufacturer’s inventory.

Statement of the problem

The problem identified in this research is the customer retention and feedback sentiment problem in the SCM for electronics. Customer retention is the activities and actions companies and organizations take to reduce the number of customer defections (Molly, 2020). Solving a customer retention problem for the customer to have faster demand requests and better responses to their queries and analyzing customer feedback to better promote services and product delivery is crucial. Sometimes, customer service representatives don't have immediate answers and they must transfer the customer to another person. That's how they serve multiple customers, and it is fair enough to take a long resolution time to resolve the customer service tickets. However, this could disappoint customers. So, instead of disappointing them, we could handle these challenges by adding an intelligent chatbot. As a result, 24/7 customer support can enhance customer satisfaction. To save up the time that manual system processes take using the human customer agents, chatbots emerged on the scene as the trusted sidekick.

Existing works of literature

Abhishek, et al. (2017), introduced the task of Visual Dialog, which requires an AI agent to hold a meaningful dialog with humans in natural, conversational language about visual content. Specifically, given an image, a dialog history, and a question about the image, the agent has to ground the question in an image, infer context from history, and answer the question accurately. Their work serves as a general test of machine intelligence while being grounded in vision enough to allow objective evaluation of individual responses and benchmark progress.

Doherty (2018), implemented a web-based chatbot to assist with online banking, using tools that expose artificial intelligence methods such as natural language understanding. Allowing users to interact with the chatbot using natural language input and to train the chatbot using appropriate methods so it will be able to generate a response. The chatbot will allow users to view all their personal banking information from within the chatbot.

Xu et. al. (2018), introduced a new conversational system to automatically generate responses for users' requests on social media. Their system is integrated with state-of-the-art deep learning techniques and is trained by nearly 1M Twitter conversations between users and agents from over 60 brands.

Xiujun et. al. (2018), introduced one of the major drawbacks of modularized task-completion dialogue systems which showed that each module is trained individually, which presents several challenges. For example, downstream modules are affected by earlier modules, and the performance of the entire system is not robust to the accumulated errors.

Boris et. al. (2019), introduced conversational agents that are capable of handling more complex questions on contractual conditions, formalizing contract statements in a machine-readable way.

Kyoko (2019), introduced Chat-Bot-Kit, a web-based tool for text-based chats that was designed for research purposes in

computer-mediated communication (CMC). Their Chat-Bot-Kit enables them to carry out language studies on text-based real-time chats for research: The generated messages are structured with language performance data such as pause and speed of keyboard-handling and the movement of the mouse.
Amir et. al. (2019), Introduced work on retrieval-based chatbots, like most sequence pair matching tasks, can be divided into Cross-encoders that perform word matching over the pair, and Bi-encoders that encode the pair separately. The latter has better performance, however since candidate responses cannot be encoded online, it is also much slower. Lately, multi-layer transformer architectures pre-trained as language models have been used on a variety of natural language processing and information retrieval tasks.
Pragaash et. al. (2019), proposed a system that leverages customer/system interaction feedback signals to automate learning without any manual annotation. Users of these systems tend to modify a previous query in hopes of fixing an error in the previous turn to get the right results.
Bao, et al. (2021), introduced the effective training process of PLATO-2 via curriculum learning. There are two stages involved in the learning process. In the first stage, a coarse-grained generation model is trained to learn response generation under the simplified framework of one-to-one mapping. In the second stage, a fine-grained generative model augmented with latent variables and an evaluation model are further trained to generate diverse responses and to select the best response, respectively.
Oguntosin (2021), introduced a web-based chatbot called Hebron for the Covenant University Community Mall which is developed using Python and React.js as the programming languages and MySQL (Structured Query Language) server as the database to give a structure to the e-commerce datasets and Admin Portal process.
María et. al. (2021), described the chatbot journey and focused on its implementation within the digital marketing strategy in the first part of a company's sales funnel. Their main goal was to apply a chatbot via Facebook Messenger supported by the Many Chat platform to increase the number of leads, comparing the chatbot with the previous strategy used by the company to obtain contact information.

Literature Findings

Various Research papers have been studied for our research. We were able to understand what was done in previous research from 2017 to 2021 and based on the best of our knowledge, we couldn't find a research paper that solves both the customer retention problem with feedback sentiment which was identified as a problem to be solved in this research. We adopt a fuzzy search classifier and rule-based approach to make our chatbot intelligent for customer retention which we only cover ordering of goods, canceling of goods, and tracking of goods for the consumer in real-time. To solve the feedback sentiment from consumers to aid the retailer, manufacturer, and the Administrators of the system to understand the strength and weaknesses they need to work on, we adopt the Vadar library for sentiment analysis which classifies text into either positive or negative or neutral.

Rule-based Algorithm

Rule-based algorithms are series of defined rules. These rules are the basis for the type of problems for specific domain research. In this research, we are looking at making our conversation agent understand the set of rules for our business logic which is the ordering of goods, canceling of orders, tracking of orders, and customer feedback sentiment.

Fuzzy Search Classifier

Fuzzy Matching (also called Approximate String Matching) is a technique that helps identify two elements of text, strings, or entries that are approximately similar but are not the same (Varghese, 2020). In this research, we adopt the Fuzzy search classifier to train our chatbot to understand the best output for a given input by the user. In the fuzzy search classifier, we used the Cosine similarity approach

Cosine Similarity:

Cosine Similarity between two non-zero vectors is equal to the cosine of the angle between them. If we represent each string (name) by a vector, we can compare the strings by measuring the angle between their corresponding vector representations.

If the vectors are parallel (theta=0 and cos(theta)=1) then they are equal to each other, however, if they are orthogonal (theta=90 degrees and cos(theta)=0) they are dissimilar.

Let us understand the various steps involved in computing the cosine similarity check to produce the desired output to the user for this research. In this research, we created our conversation table that consists of thousands of conversations to suit the business rules for our system. To understand Cosine similarity efficiently, let us try to explain it using just two words which are Hello and Helo. This means, that the consumer may say or type helo, and then the fuzzy classifier will be responsible for comparing the words that match the user input and produce the desired output for the user. The procedures are:

- Split the names into their corresponding "n-gram" representations.
- Vectorize each n-gram by using an encoding technique. The most commonly used encoding techniques are Bag-of-words encoding or tf-idf encoding. In this research, we will use the Bag of words model.
- Compute the cosine similarity between the vectors between the words.

VADAR (Valence Aware Dictionary for Sentiment Reasoning) Library for Sentiment Analysis.

VADAR is a model used for text sentiment analysis that is sensitive to polarity (positive, negative, or neutral) and intensity (strength) of emotion. Vadar can be applied to unlabeled text data (Pio, 2020).

VADAR sentimental analysis relies on a dictionary that maps lexical features to emotion intensities known as sentiment scores (Pio, 2020). The sentiment score of a text can be obtained by summing up the intensity of each word in the text.

In our software development using Visual Studio 2019, we downloaded the VADAR Library from the NuGet Package and import the library to our software to solve the problem of consumer sentiment. With Vadar, we were able to get the consumer sentiment from our chatbot to show if it is positive, negative, or neutral to enable the retailer, manufacturer, or administrator to know where and how to improve on the B2C services and development.

Design and Architecture

The research methodology adopted in this research is the Design Science Research (DSR). It is seen as a research activity that builds new or invents, innovates artifacts for problems solving or improvement attainment such new innovative artifact creates a new reality, rather than the existing reality been explain or trying to make sense from it, it creates and evaluates IT artifact which is intended to solve some identified organizational problems. The Design Science Research Methodology is relatively a new approach in the field of Information Systems, and Computer Science because of its prominence rapid growth in the discipline (Alturki, 2011). Design science is an outcome-based information technology research methodology, which offers specific guidelines for evaluation and iteration within research projects.

Design science research focuses on the development and performance of (designed) artifacts with the explicit intention of improving the functional performance of the artifact. Design science research is typically applied to categories of artifacts including algorithms, human/computer interfaces, design methodologies (including process models), and languages. Its application is most notable in the Engineering and Computer Science disciplines, though is not restricted to these and can be found in many disciplines and fields (Kuechler B, 2008).

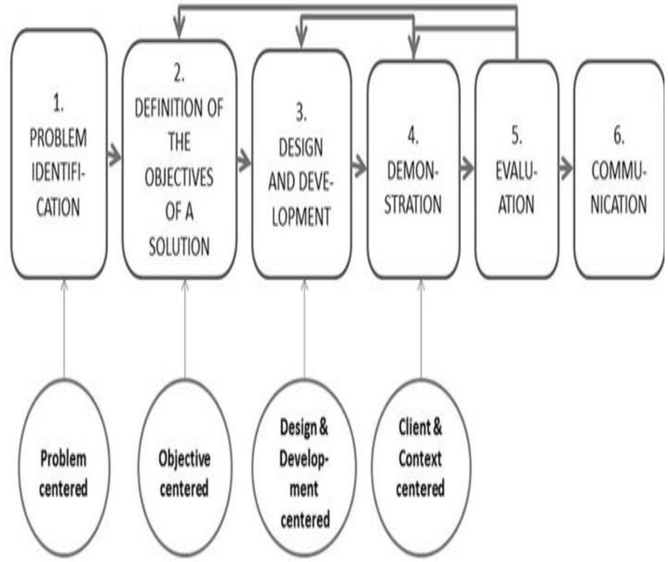

Figure 1: Design Science Research Methodology (Peffers, 2007)

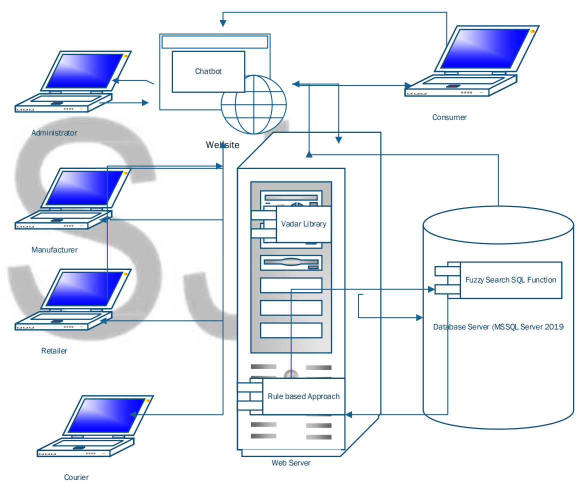

Figure 2. System Architecture

We adopted the Business to Customer (B2C) Model (Carol, 2020), which covers that of a retailer offering electronic goods to consumers. To fulfil orders, the retailer has to manage stock levels in warehouses. When an item in stock falls below a certain threshold, the retailer restocks from the relevant manufacturer's inventory. However, the architecture design showed five actors using the system which are the Administrator, Manufacturer, Retailer, Consumer and Courier. Each of the users are assigned roles and responsibility of the system. The system architecture shows how they request for information from the website, the website then takes their request to the webserver where the web server takes it to the database server. The database server then processes the request and returns a desired output to the user. From the diagram as shown in figure 1, we can see that the fuzzy search classifier function was built inside the database server, while the rule-based function was built using the C# dynamic link library. We created a web service for the rule-based algorithm and call the webservice to the Chatbot. The Consumer interacts with the chatbot to order, track and cancel product. The consumer can also leave sentiment feedback of the system. The sentiment is then analyzed using the Vadar library in the web server to classify sentences into either positive, negative or neutral. The result is then viewed on the dashboard for the Retailer, Manufacturer and Administrator to see and to know how to improve on their services.

Implementation and Results

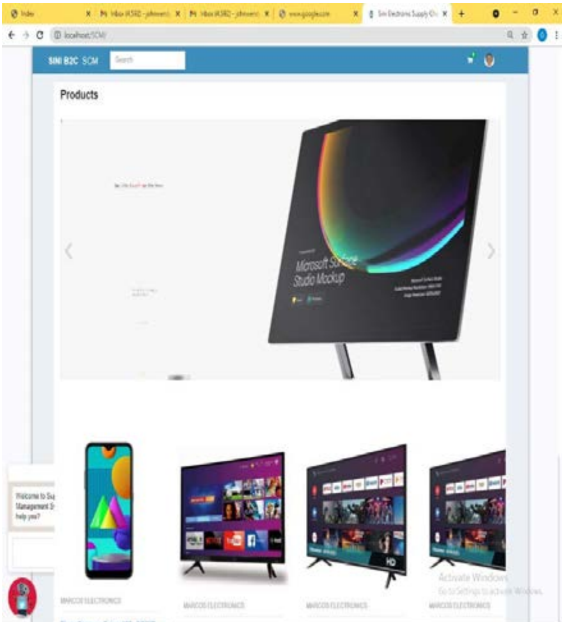

Figure 3: Index Page for the proposed system

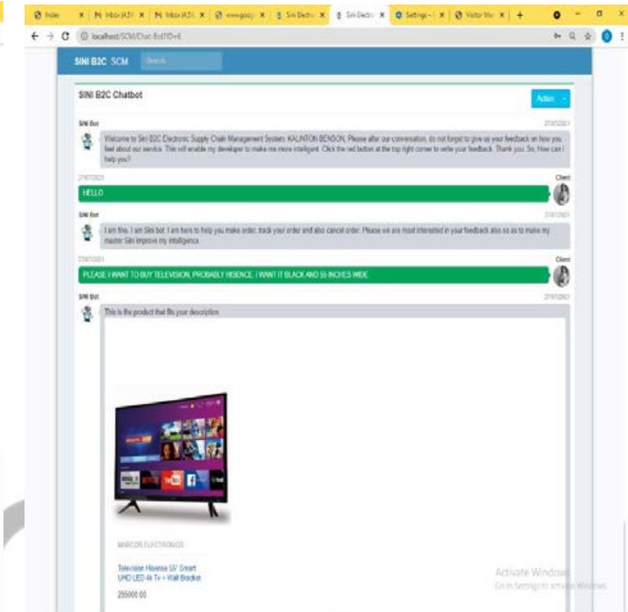

Figure 4: Chatbot Interface for the proposed system

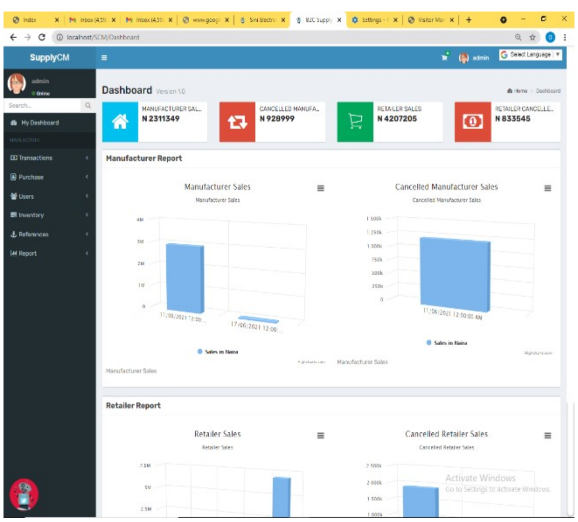

Figure 5: Dashboard Interface of the proposed system

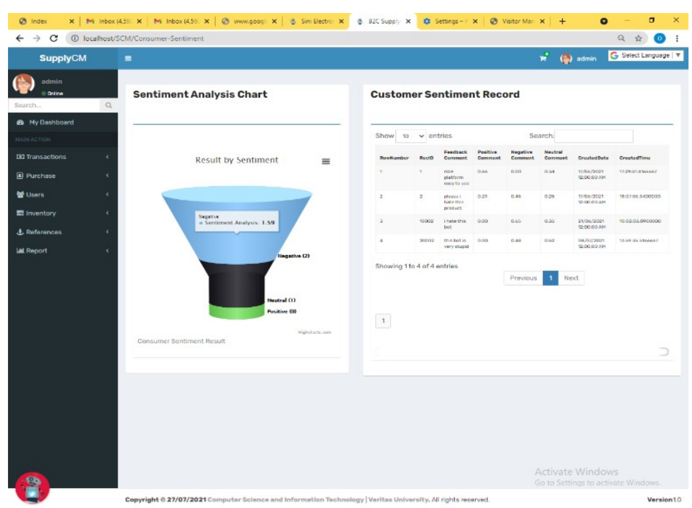

Figure 6: Sentiment Analysis Interface

Discussion

We have successfully studied the business to customer model for Supply chain management, analyzing different works of literature done on SCM. We identified the problem of customer retention with feedback sentiment. Based on the aforementioned problem. We designed and developed an intelligent Chabot using the Fuzzy Search Classifier and the Rule-based approach. We used the Vadar Library for our sentiment analysis of the consumer. The fuzzy search approached was written in transact SQL and stored as a function in MSSQL Server 2019. Rule-based algorithm and the Vadar Library were written in the C# dynamic link library and a web service was built for our Chabot using C# RESTFUL web service which we call to our Chabot to function effectively. We successfully built the user interface using the ASP.NET website and successfully deployed the system on our local server. The main advantage of our system is that the consumer can be flexible enough to express the kind of product he or she needs to order instead of just specifying names, categories, or types. In the future, we aim to investigate artificial neural networks, deep reinforcement learning, conventional neural network, and fuzzy semantic search to find out the best fit for the chatbot based on the B2C SCM domain to make it more scalable, intelligent, and efficient. Due to the poor search retrieval using fuzzy search when it comes to large data, we were able to optimize our code to perform effectively well with the aid of a rule-based approach.

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