Interactive Applied Graph Chatbot with Semantic Recognition

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Abstract*— Companies and small medium businesses (UMKM) need to interact with customers to increase their customer retention rate. One of the ways is to use chatbot. Aside from being cost-effective, this method is also very effective and very easy for companies to use. To make an easy and effective chatbot requires a combination of two scientific fields, artificial intelligence and software engineering. This study has the following features. 1) Affective sentiment analysis, this feature is inspired by Russel's Circumplex Model. Adjective words will be mapped in a matrix with values based on the Russell Circumplex Model. This model will pay attention on the adjective words, polarity, and affection degree of a sentence. 2) Conjunction sentiment analysis, consider of free way of interaction nowdays, a sentiment analysis system need to determine the sentiment value in multilevel sentences. This multilevel sentence has one or more conjunctions. This conjunction sentiment system will break sentences based on conjunction. The fractional sentence will be processed by affective sentiment analysis. The system then considers the nature of the conjunction to determine the sentiment of the whole sentence. 3) Graph Chatbot, this feature is used to make it easy for companies to modify and generate their bots. This bot will interact with customers like humans, based on a graph chat map that has been created. Chatbot graphs were developed using javascript library Vue js to make it easier to manipulate the visual graph. The system produces satisfying accuracy. Graph chatbot can handle procedural conversations very well. The flow of conversation in accordance with the graph that has been defined. Graph chatbot has 100% accuracy and successfully responds to all user conversations. The sentiment method has 63% accuracy.

Keywords—retention rate, interactive graph chatbot , affective conjunction sentiment, circumplex model.

I. Introduction

Interaction is a social action that greatly impacts human life. Humans will interact based on what they will get from other humans [1]. Likewise a company, they will try to be always available to interact with their customers.

Figure 1 illustrates that interaction or communication between producers and companies users is one of the important things in a transaction so that producers can survive and develop [2]. Interaction is divided into two types, producer to companies user interaction and companies user to producer interaction. Interactions with companies users of various types. Interaction through suggestion boxes when companies users are around the company's area, direct interaction with company employees, interaction through social media, and interaction through customer service services.

Customer service by phone interaction is one of interaction types that often used by companies users because companies users do not need to visit the company building. Companies users are also greatly helped by the existence of customer service to get answers to companies user questions.

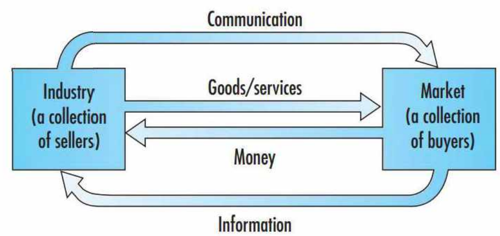

Fig. 1. Simple Marketing System

The better the customer service, the more new users use the company's services. the more new users, the more communication traffic on customer service. The customer service division's cost will be increasingly overwhelmed because they have to increase the number of employees to be placed as customer service operators. Even though company income increases, the expenditure also increases with the increase in the number of employees and resources for customer service equipment. In addition, customer service must serve 24 hours for the convenience of company users. This 24-hour service is a heavy burden for the company because there are a lot of resources that have to be spent such as additional electricity costs at night, additional security officers, food and beverage employees, and entertainment places for employees to not get bored at night.

This condition is very unproductive for a company. One of the seven ways to manage a company's productivity is to use the latest information technology [2]. With increasingly sophisticated information technology, companies only need to spend large funds at the beginning while the next only need to pay maintenance costs which is certainly far less cheaper than the cost of traditional customer service. There are several things that companies users want when interacting with customer service based on a survey conducted by Microsoft Dynamic 365 Global Customer Service in 5000 people spread from Brazil, Germany, Japan, the United Kingdom and the United States [3]. First, the companies user has a desire to be heard. As many as 90 percent of respondents want customer service to give comments or feedback about their experiences, but only 37 percent are given the opportunity [3]. Second, companies users expect to get services from anywhere and from any device. As many as 59 percent of respondents claimed to have to contact many parties before their questions were answered [3].

Figure 2 explains an indirect path so that sometimes there is incorrect communication on customer service. Lack of

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supervisory communication with frontliner customer service can cause unclear procedures for handling customer problems [4]. The human aspect is also the cause of inefficient communication that causes customer dissatisfaction [4]. In addition, the high costs of providing customer service (customer service) and 24-hour service that should not be done by humans. So, when switching to use information technology, companies will save costs and time [5] [6]. Information technology used to replace human roles in customer services is called chatbot. Chatbot is an automatic computing agent that has the main task of replying to conversations with humans [7].

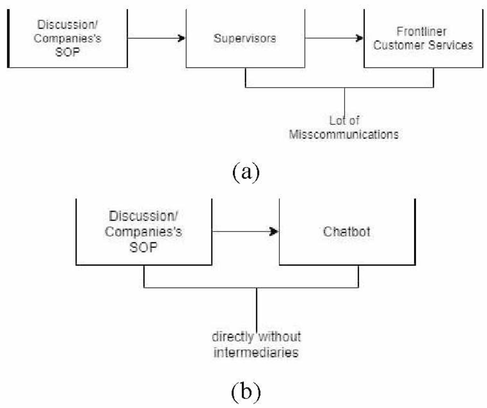

Fig. 2. Communication flow (a) Customer Service (b) Chatbot

Guan Mao et.al [8] aims to address the difficulties of giving an appropriate response to conversations in many contexts and they propose a method called the hierarchical aggregation network of multi-representation (HAMR). Panitan et.al [9] proposes and develops frequently asked question chatbots that will automatically reply to responses from e-commerce customers by using the Recurrent Neural Network (RNN) method with Long Short Term Memory (LSTM) to classify text. Ly Pichponreay et.al [10] focuses more on how to generate wider knowledge on chatbots by utilizing portable document format (pdf) electronic documents. Belfin et.al [11] aim to help cancer patients discuss the problem of their illness through graph chatbots. Yixuan Chai dan Guohua Liu [12] conduct research on free speech domains and also handle offensive speech responses using Reinforcement Learning Chatbot. Bingquan Liu et.al [13] aims to address the task of ranking personalized responses by including user profiles in the conversation model.

Our previous research also examined chatbot case [14]. Rico et al [14] try to solve the problem using knowledge based chatbot with context recognition. Rico et al [14] are trying to solve the problem in the Surabaya State Polytechnic New Student Admissions FAQ. The FAQ is a knowledge that can be used for chatbots. The FAQ can be used as basic knowledge for chatbots to have conversations with humans. For the basis of chatbot analysis, we use previous research on sentiment that has already been conducted. Kamal et al and Berlin et al [15] [16] have conducted research using rule-based sentiment methods. The rules on sentiment are based on part-of-speech patterns in Indonesian sentences. Kamal et al [15] used the ASEAN case study, while Berlin et al [16] used the Surabaya City Government case study. We improve the sentiment method from our previous sentiment research by adding conjunction rules and affective space models.

II. PROPOSED IDEA

This research proposes a new approach to create chatbots that can overcome procedural conversations using improved graph chatbot and semantic recognition. The chatbot graph referred in this study is a graph that combines graphs between text (the flow of conversation), and interactive application. The graph chatbot will be more responsive to user interactions. Graph chatbot also very easy to build with the interactive application. Interactive application visualize all the graph and provide editable graph for companies to improve their chatbot conversation. Interactive applications make it easy for companies or their manager to directly create their own chatbots without the need to program code manually. Graph Chatbot also has the ability to handle free conversations. Not to respond to the free conversation, but ignore it. Graph chatbot only serves conversations in accordance with what has been defined by the company. So, the conversation is only about company services. The company also needs to analyze all conversations between users and the chatbot conversation. Conversation analysis serves as additional data for decision making. For this reason, we use the sentiment analysis method to determine user impressions from chatbot conversations. Semantic recognition is used to recognize companies user languages. Semantic recognition contains three main features, text mining, affective sentiment and conjunction rule based sentiment method.

III. SYSTEM DESIGN

The system design covers the entire communication from end-users to back to end-users. There are two user roles namely admin and chatbot user. Admin users can view the dashboard to visualize the analysis of chatbot activity, enter knowledge for chatbots, manage flow dialogs for chatbots and manage word databases on chatbots. Chatbot users can interact with chatbot through two application platforms namely website and android.

Figure 3 shows the system design. In the system there are several main feature methods, namely, Affective Sentiment, Conjunction rule based methods, and Improved Graph Chatbot. Before discussing these main features. First we must discuss the process of cleaning text sent by the user in the text mining process.

Chatbot system need to translate human languages into computer languages first, before chatbot machines and humans can communicate. To be able to communicate with chatbots, input messages from users (queries) will be processed in several main methods. These methods are improved graph chatbot systems and sentiment analysis systems. Sentiment analysis consists of two affective space model methods and the conjunction rule method. Text mining is applied before all the main system started. Text mining is a method for cleaning text and stemming text. Clearing the text in question is to eliminate unnecessary words and delete unnecessary punctuation. Sentences that have been processed in text mining method will be sought its sentiment value using two methods, affective sentiment and conjunction sentiment.

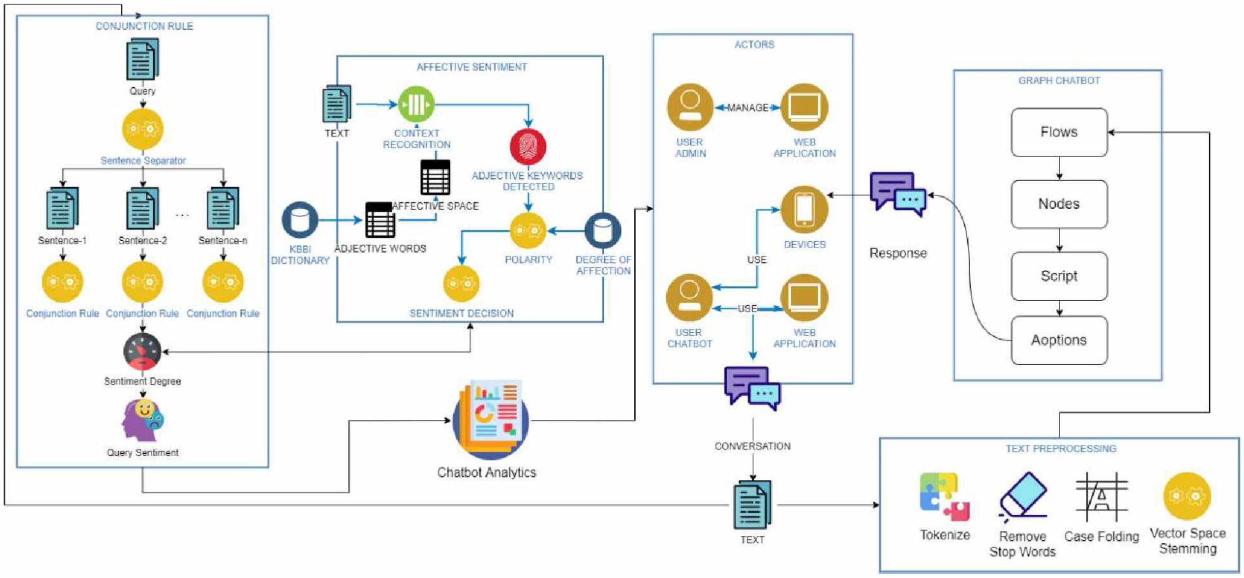

Fig. 3. System Design

During text mining, queries from users will be broken down based on conjunctions. Every sentence fragment is called a clause. Each clause will be searched for each sentiment value, then it will be processed in the conjunction method. Conjunction method serves to deduce the final sentiment of a query. If the query does not have a conjunction, the process stops at the affective space method. The query sentiment value is based on the results of the affective space method only.

Graph system is a chatbot method for handling procedural conversations. The purpose of procedural conversation is a conversation with steps that must be passed before the next conversation to reach a certain goal. Examples of wanting to buy goods, ranging from selecting goods, the number of goods, entering an address, entering a promo code, then you can checkout and items can be purchased. Sentiment analysis system functions as a model to recognize user emotions. User emotions are useful for companies to know whether a service is good or not. In addition, the company can find out the summary chatbot machine talks with all companies users who have used chatbots. The summary is in the form of language analysis such as sentiment analysis, services most talked about, services that are often problematic and others. Summary can help the company as a reference for decision making for the company's business going forward.

A. Admin Page

The admin page is created using javascript. JavaScript makes the website easier to manipulate. This convenience is able to support us to create more interactive websites. We need an interactive website so that users can easily manipulate graph chatbot models that we have made. We use javascript library to create a front end website called Vue js. Vue js was chosen because it is very light and very easy to develop. Many display and chart libraries that support the Vue js framework. Vue js are also very modular with component based components. There is a management state that is easy to use and also modular, called Vuex.

Figure 4 shows the life cycle of Vuex with back end and vue js [17]. When the Vue JS component, simply a small part of the Vue JS web page, requires data to be visualized, the component can retrieve directly to the state. State is data storage model on Vuex. According to best practice in vuex development, it is better to use the getters method provided by Vuex to retrieve data from state.

The data from state is retrieved from the back end API via Actions feature. Actions perform tasks like call APIs and handle asynchrous process. Actions can also perform or triggering the Mutations feature. Mutations can manipulate states, so that after actions retrieve sentiment data (for example) called by the Vue component, actions will call the API from the back end and send the return data from the back end to the mutations. Furthermore, mutations will update the state model where the sentiment data is stored. The state containing the sentiment data will be accessed by the Vue component via the getters method.

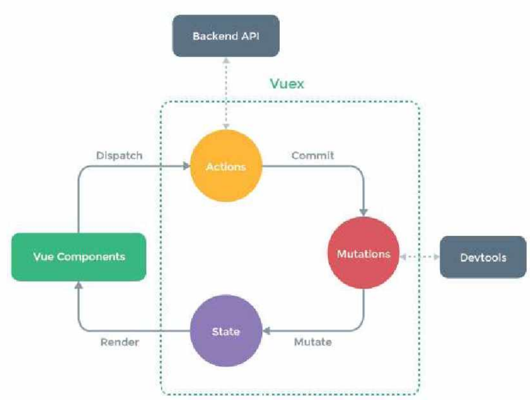

Fig. 4. Vuex Diagram

Figure 5 shows an example of the results utilizing Vue js and Vuex. Vue js and javascript are used to manipulate visuals so that they are easy to use by users. Whereas Vuex, has a role in regulating the flow of data to the website. Vuex will load and retrives graph flow data that user chooses. In Figure 5 the user selects the coba graph flow (try in english), then vuex will retrieve data from the state for the coba graph flow data. After trying to get the graph flow data, vue js will visualize the data as shown in Figure 5.

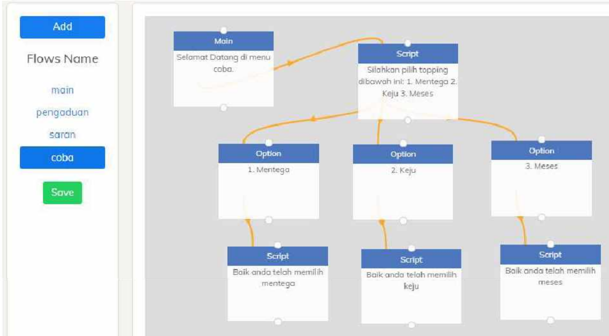

Fig. 5. Example of graph flow

B. Text Mining

Queries from chatbot users will be processed in text mining. Following is the basic process of the text mining process, selecting steps according to need [18].

1) *Select document scope*

   For text mining, text boundaries are easy to determine. For example, email or data calls will immediately be changed to one vector for each message. However, for longer documents the limit must be determined, whether directly using the whole document or dividing the document into several parts based on paragraphs or sentences.

2) *Case folding*

   The method for minimizing all letters in a query so that all letters are converted to lowercase letters. In a document that uses capital letters or the like sometimes it does not have in common, this can be due to writing errors.

3) *Tokenization*

   Break up text into collections of words or tokens. This process can have many types in doing the process, depending on the language to be analyzed. For Indonesian language, a tokenize is using white space and punctuation as parameters to break the text into tokens.

4) *Stopwords*

   Words that are considered not important. Stopwords deletion serves to clear text of words that are not important. It would be very useful in text mining to get rid of some words such as "which" and "with" which appear in almost every document with a large number.

5) *Punctuation*

   Examples of punctuation are commas, periods, exclamation points, question marks. Not all punctuation is deleted because it will affect the processing of the sentiment analysis system that requires comma and point to break sentences or phrases.

6) *Stemming Tagging*

   Stemming is the process for mapping and deciphering the form of a word into its basic word form or in other words the process of changing the word affixes into basic words.

The system will carry out the second tokenization process. The second tokenization is the process to break up the clean text based on conjunction. This text fragments are called clauses. Each clause will be extracted their sentiment value in the affective space model method. Then, the sentiment values of the affective method will be a parameter to calculate the sentiment value of the query sentence. The method for calculating the sentiment value of a query sentence is called the conjunction rule method. If the query sentence does not contain a conjunction, the sentiment value of the query sentence will be taken from the affective space model process. So, the conjunction rule is not applied.

C. Affective Sentiment

Figure 4 is Russell's Polar Coordinate model consisting of 28 adjectives [19]. These adjectives are happy, delighted, excited, astonished, aroused, tense, alarmed, angry, afraid, annoyed, distressed, frustrated, miserable, sad, gloomy, depressed, bored, droopy, tired, sleepy, calm, relaxed, satisfied, at ease, content, serene, glad, pleased. Horizontal axis is interpreted as the level of pleasure and displeasure. Vertical axis is interpreted as the level of excitement. So, Russel said each adjective has a value of pleasure (pleasure displeasure) and arousal (arousal) which is different from other adjectives.

Russell wrote the degree of these words into his paper, but there were 13 words that were not have the degree value. Angry, afraid, annoyed, distressed, frustrated, gloomy, depressed, bored, statisfied, at ease, content, glad, relaxed are 13 words that do not have the degree value. To get the horizontal axis (x) and vertical axis (y) values can be found using trigonometric comparisons. Because of the value of x, y or radius (r) is unknown, we measured the value of r manually to place the values of x and y more thoroughly. After getting the value of r, the value of x can be found using the trigonometric comparison cos with the formula 1.

$$\left(\cos\alpha = \frac{x}{r}\right) \tag{1}$$

The value of y can be searched using the trigonometric comparison sin with the formula 2.

$$\left(\sin\alpha = \frac{y}{r}\right) \tag{2}$$

Remember, the concept of emotions from Russell is mapped into two-dimensional semantic space, involving Pleasure (valence quality) whether the stimulus is pleasant (positive) or unpleasant (negative), and Arousal the degree of activation (high or low) [20].

R variable is a representation of the direct distance of the word point to the 0 axis that has been calculated manually. Whereas x and y variable represent valence and arousal. Moreover, these two affective dimensions have been considered as separate or orthogonal in the light of their low correlation[20][21]. The general presence of Valence and Arousal dimensions has been confirmed through comparative study with different cultural groups or language speakers[20][22]. To get the sentiment value of each word according to the quadrant of Russell, the conditions in formula 3.1 or 3.2 are used. If adjectives are in quadrants two or three then use the formula 3.2 equation because the word has negative sentiment. If adjectives are in quadrants one or four then use equation 3.1 because the word has positive sentiment.

$$d = x - y - 5 \tag{3.1}$$

$$d = x + y + 5 \tag{3.2}$$

The results of sentiment values will vary. Because of the sentiment value is between -1 to 1, then the sentiment value that has been obtained is normalized using minmax with a range of -1 to 1 on equation 4.

$$x' = \frac{(x - x_{min}) * (new_{max} - new_{min})}{(x_{max} - x_{min}) + new_{min}} \quad (4)$$

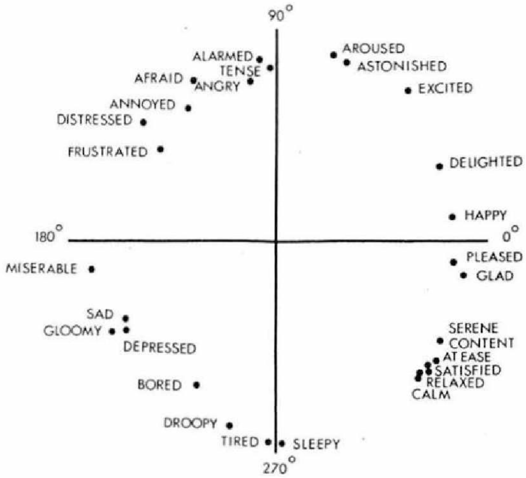

Fig. 6. Russel Cirumplex Model: Polar Coordinate

Table I shows the results of calculations to convert Russel's Polar Coordinate degrees into sentiment values. Sentiment values have a range of values between -1 to 1. The calculation results in the table have been normalized using min max in formula 4.

TABLE I. Converting Russel Model to Sentiment Value

adjectives	degree	r	y	x	sentimen
excited	48.6	4.4	3.3004	2.9097	1
astonished	69.8	4.25	3.9885	1.4675	0.930
aroused	73.8	4.3	4.1292	1.1996	0.9188
delighted	24.9	3.95	1.6630	3.5828	0.9112
happy	7.8	3.85	0.5225	3.8143	0.8275
pleased	353.2	3.8	-0.4499	3.7732	0.7341
glad	349.5	4.1	-0.7471	4.0313	0.7305
serene	328.6	4.15	-2.1621	3.5422	0.5552

1) *Affective Space*

TABLE II. Affective Space

Value	Happy	Delighted	At ease	Satisfied	Miserable	Alarmed	Frustated	Afraid
Janggal	0	0	0	0	0	0	0	-0.986
Senang	0.827	0	0	0	0	0	0	0
Ramah	0	0	0.504	0	0	0	0	0
Kecewa	0	0	0	0	-0.8	0	0	0
Kacau	0	0	0	0	0	0	-0.906	0

Table II shows affective space. Affective space is a matrix that maps adjectives with Russel's adjectives. This model indicates that an adjective has a difference in pleasure displeasure with other adjectives. Of the 663 adjectives, there are 78 words that have been mapped. There are many considerations such as synonyms, association of the word with 28 russel adjectives, and reference sources. These considerations made the mapping process take a long time and were only able to map 78 words when this research was written.

2) *Polarity of Sentiment*

There are several words that mark a polarity in a sentence. Tere are three types of polarity, namely positive, negative and random. Negative values can be seen from the word negation. In linguistic terms, negation is the name for the word denial. There are four word disclaimers in the Indonesian language, namely *tidak* (no), *bukan*(not), *belum*(not yet), and *jangan*(don't). Random or uncertain values can be seen from the words *mungkin*(maybe), *kirakira*(approximately), dan *kelihatannya*(apparently).

3) *Degree of Affection*

Degree of Affection can be seen from the examples of these words *sangat*(very), *lebih*(more), *paling*(most), *sekali*(once), *amat*(very), *kurang*(less), *agak*(somewhat). The word can express the increase or decrease in the degree quality of a sentence. The values given for the words are -0.5 and +0.5.

TABLE III. Degree of Affection

Degree Value	
+0.5	**-0.5**
sangat	*agak*
paling	*kurang*
sekali	*sedikit*
amat	*minim*
terlalu	

Table III shows the degree of affection for each affection word in Indonesian language.

4) *Degree of Sentiment*

Table IV shows the way to calculate the degree value of sentiment for each query is to pay attention to the adjectives in the query. There are already query example **on table IV, "Terimakasih bantuannya, saya senang.".** We match the adjectives with the affective space matrix. We take one line data with the same adjectives. The data has a value for each attribute, then added. The result of the addition is the sentiment value of the adjective. In table II word *senang* (happy) only have one value in attribute happy, so the sentiment of *senang* is 0.9456.

TABLE IV. Example 1

terimakasih	bantuan	saya	senang
+1	0	0	+0.827
Total	1,827		

Terimakasih word sentiment value is +1. After we know all of words sentiment value, we added all value. The result of that addition is 1,827. Now we will discuss about sentences that contain polarity and degree of affection.

Table V shows an example of this sentence "*Sangat tidak gembira dengan layanan ini*". Word *dengan* and *ini* not shown in table V because those words are stopwords. Those words are not important for the sentiment of the sentence.

TABLE V. Example 2

sangat	tidak	gembira	layan
+0.5	-1	0.9112	0
Total	1.3786 x (-1)	**-1.4112**	

D. Conjunction Rule

Queries with sentiment in each sentence will be processed in the conjunction rule method. The conjunction rule method has several rules for certain conjunctions to determine the sentiment of a sentence containing a conjunction. Before processing the conjunction rule, the query will be processed first on some of the rules above [16]. Conjunction itself has several types, namely coordinative conjunction and subordinative convergence. Based on the Indonesian Language Dictionary (KBBI) Coordinating conjunctions are conjunctions that combine words or clauses of equal or equal status. Whereas Subordinative conjunction is one type of conjunction that connects words or clauses that are not equal [23].

For conjunction rules, there are several rules in it. The provisional hypothesis is as follows [23].

1) Conflicting Coordinative Conjunction

If there is a conjunction such as tetapi(but), *tapi*(but), or *akan tetapi*(however), and the position of the conjunction is located in the middle of the sentence, then applied this rule.

if (konjungsi = CCC AND conj_position = middle) :
    sentiment = sentiment_clause1 +sentiment_clause2
if (sentiment <= 0) :
    sentiment = -1
else:
    sentiment = +1

2) Expectancy Subordinate Conjunction (ESC)

This type of subordinate conjunction consists of eight words. The eight kinds of forms of the word are *agar* (so that), *agar supaya*(so that), *biar*(let), *supaya*(so that), *hendaklah*(let), *mudah-mudahan*(hopefully), and *semoga* (hopefully). For this type of conjunction, program applied this rule.

if sentence pattern is [condition sentence+", +*ESC*+ expected condition sentence] *or* sentence pattern is [*ESC*+expected condition sentence]:
    if sentiment of expected condition sentence > 0
        sentiment = -1
    else: sentiment = +1
else sentiment = call_affective_space(sentence)

The position of the expectancy subordinate conjunctions lies in the middle of the sentence. If the sentence satisfies the condition, then the sentence sentiment value is determined by the sentiment of the condition sentence.

First example, "sudah 10 hari airnya masih keruh, mohon secepatnya diperbaiki, supaya air kembali bersih." in english mean "the water has been turbid for 10 days, please repair it as soon as possible, so that the water is clean again.".

The sentence structure consists of condition sentence, and expected condition sentence. The condition sentence in the complete sentence is "the water has been turbid for 10 days, please repair it as soon as possible". The expected condition sentence in the complete sentence is "so that the water returns clean". The complete sentence fulfills the rule. The rule is if there's expectancy subordinate conjunction in the middle or in the front of the sentence, than the sentiment value is determined by the expected condition sentence. The sentiment of expected sentence is positive because there is a clean word, but the overall sentiment of the example sentence is positive.

3) Conditional Subordinative Conjunction

There are twelve kinds of conjunctions of this type, in the form of words apabila(if), asal(provided that), asalkan(provided that), bila(if), bilamana(when), jika(if), jikalau(if), kalua(in case), manakala(when), sekiranya(if only), dalam mana(in where), dan tanpa(without).

if sentence pattern is [condition sentence+","+*if*+ conditional sentence]
    then sentiment = sentiment of condition sentence
if sentence pattern is [if+conditional sentence] or [if+ conditional sentence+","+then+condition sentence]
    then sentiment = sentiment of conditional sentence

E. Graph Chatbot

Chatbot graphs are very suitable for procedural conversations. Procedural conversation is a conversation that must go through several stages of conversation before reaching the goal. Chatbot graphs will have much higher accuracy when the chatbot user's character obey the conversation stages that must be passed. Chatbot consists of several flows. Flow is representation of a conversation goal. Flow consists of several nodes. Nodes are the stages and chatbot will give responses to users. Each node can be connected using a link. If between nodes are connected by a link, then it shows the next node path. Nodes and links can be dragged and dropped as needed. Drag and drop uses the javascript language that has been programmed in such a way.

Figure 7 is a display of the company's admin page for editing the chatbot graph. Admin can add and subtract flow. Admin can also add and subtract nodes in each flow. Admin can connect or break links between nodes. Nodes consist of several types namely, main, script, option, and flow. The main node is the beginning node flow. When entering or changing flow, the sentence on the main node is first spoken by the chatbot. The script node is the chatbot conversation reply node. This node only contains text. Script and main nodes are the simplest nodes among other nodes. Flow node is the trigger node to move to another flow. Node option is a node that allows handling conversations with certain conditions. For example, before the node option there is a script with a choice sentence in it.

This choice sentence contains numbers. Examples of choice sentences are "please select the following menu 1. Order 2. Complaint 3. Suggestion". Nodes that contain optional sentences must include the option node afterwards. The system will automatically detect options based on the number. If the number of options does not match the number of menus, the program can only detect the available options.

Conversation flow can be easily modified by the admin. Admin only needs to drag and drop the node. Every conversation with chatbot will be entered into the database. Data in the database will be analyzed using sentiment analysis.

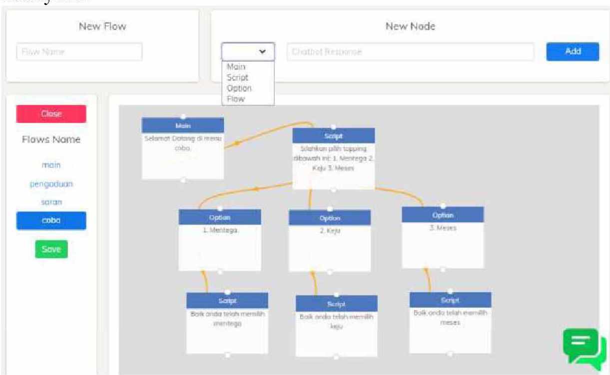

Fig. 7. Graph chatbot screenshot

IV. Experiment and Analysis

We developed the system method with experimental research methods. The experiment starts from the initial main systems, the sentiment analysis and then improved graph chatbot.

A. Sentiment Analysis

We have a sentences "*Air keluar sangat kecil sekali, padahal samping kanan dan kiri rumah airnya sangat lancar***"** means The water comes out very small, even though the right and left side of the house is very smooth. first, we will break the sentence down based on conjunctions. so there is phrase 1 " *Air keluar sangat kecil sekali* " and phrase 2 " *samping kanan dan kiri rumah airnya sangat lancar* ". Then, we calculate the sentiment value for both phrase using affective model.

TABLE VI. Phrase 1 Affective Sentiment

air	*keluar*	*sangat*	*kecil*	*sekali*
0	0	0	-1	0
Total	-1			

Table 3 shows that the sentiment of phrase 1 is -1. That's because there is *kecil* word in the sentiment dictionary worth -1.

TABLE VII. Phrase 2 Affective Sentiment

samping	*kanan*	*kiri*	*rumah*	*air*	*sangat*	*lancar*
0	0	0	0	0	0	0.7654
Total	0.7654					

Table 4 shows that the sentiment of phrase 2 is 0.7653. That's because there is *lancar* word in the affective space matrices worth 0.7654. Now, we will apply the conjunction rules. the example sentence has a "whereas" conjunction means it belongs to the type of conflicting coordinating conjunctions. With the conflicting coordinating conjunctions rule sentiment value -1 (negative) is obtained because clause one is -1 and clause two is 1. If one of the clauses is -1 then the sentiment value of the sentence is -1.

Experiment sentiment analysis data has 596 text data. A total of 390 data have conjunctions. A total of 206 data do not have conjunctions. Data are taken from twitter API. The 596 data are labeled manually according to human reasoning. We will conduct experiments using that data.

Table VIII shows the results of experimental sentiment analysis. In the first and second lines have results that are not in line with expectations because the accuracy still less than 80%. Though, the accuracy of the affective space model is less than the combined affective space model and conjunction which is indicate that the conjunction rule are successfully applied.

TABLE VIII. Sentiment analysis result

Experiment	Accuracy	Precision	Recall	F1-Score
Affective space	60.00%	73.17%	60.33%	65.19%
Affective space + conjunction	63.86%	74.19%	63.86%	67.99%

First, this happens because there are so many ambiguous sentences and lot of grammatical mistakes in the data such as too much abbreviation, wrong punctuation placement(hard to tokenize data), etc. Second, human reasoning classifies sentiments based on the object in question. As an example of experimental data discussing object A and B. The main object of experiment is object A. When there is a sentence supporting object A it will be labeled positive, but when there is a sentence denouncing object B then humans will give a positive label. In human psychology, if you denounce opponents is the same as supporting friends. We still have accuracy far below our previous research [15] [16] because our data are taken from general case studies. Not as specific as the studies of Kamat et al [15] and Berlian et al [16]. General case studies require extensive sentiment word dictionaries as well. At the moment we are still using 1371 words that have sentiment values labeled manually. The sentiment value will continue to be updated over the time.

B. Interactive Graph Chatbot

The graph chatbot test is done manually by 50 conversations. The flow of the conversation created in this experiment is a dummy conversation that always allow chatbot flows. This dummy conversation represents the character of chatbot users who always follow the chatbot conversation flow.

Figure 8 shows the conversation flow in the main flow. Main flow is the flow that will be run first when starting chatbot. The main node contains a welcome from chatbot. The next node is the script node that contains the selected sentence. Because it contains a choice sentence, then after the node script must add as many node options as the options mentioned in the node scipt.

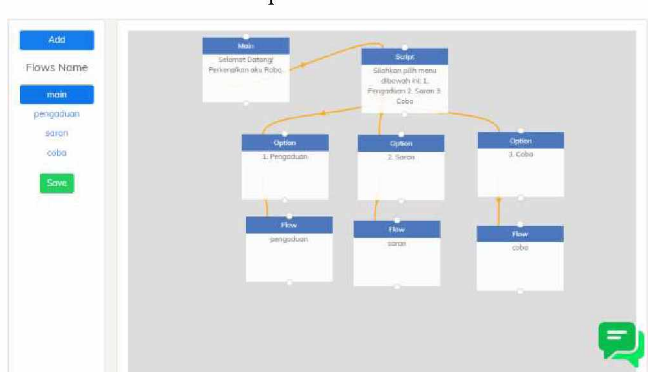

Fig. 8. Main flow graph chatbot

The green chat icon in the lower right corner is a button to open the simulator.

Figure 4 is the result of procedural chat produced by improved graph chatbot. After ordering, entity information such as time and name will be stored in a database. Users can immediately come to the place that has been ordered at the agreed time.

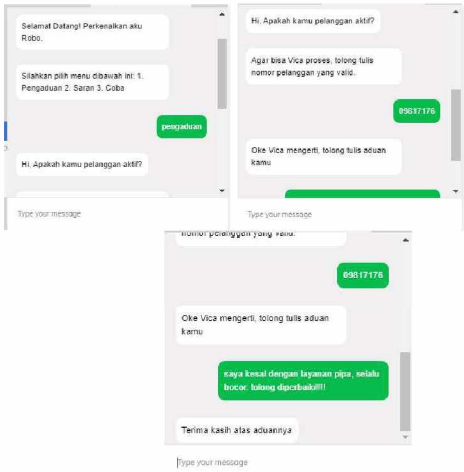

Fig. 9. Result of the chatbot

V. Conclusion

This research develops a chatbot generator application that is easy to modified by non-programmers. The main feature of chatbot is graph chatbot which can be easily modified manually. Graph chatbot allows answering all procedural conversations about company services. The company only needs to define sentences and flow on the website. The chatbot system is also able to analyze conversations using semantic recognition. Semantic recognition consists of two methods, namely the affective space model and the rule based conjunction. Each message from the user will be broken down based on conjunctions. The fraction is called a clause. Each clause will extract their sentiment values in the affective space model method. Then, the sentiment values of the affective method will be a parameter to calculate the sentiment values of the query sentence. The method for calculating the sentiment value of a query sentence is called the conjunction rule method. If the query sentence does not contain a conjunction, the sentiment value of the query sentence will be taken from the affective space model process. So, the conjunction rule is not applied. Graph chatbot allows to ignore the input of messages that do not fit into the conversation flow that has been defined by the admin. So the accuracy of the conversation is very high, which is 100% accurate for specific users character as mention in section III subsection E. This overfitting needs to be improved by implementing other methods. The method is to overcome chatbot ignorance by inputting messages that are not in accordance with the flow. Sentiment system has an accuracy of 63%. There're lot of grammatical and lexical dictionary that need to be improved in the program.

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