Ukrainian Language Chatbot for Sentiment Analysis and User Interests Recognition based on Data Mining

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Abstract

Real-time sentiment analysis allows to monitor social networks and process negative comments before the situation worsens, gives an opportunity to gather customer response to the marketing campaigns or product launches and get an overview of how customers react to the product or prevent negative ones events determining the mood of people (posts on social networks, videos on YouTube, Twitch or live). The development of this system aims at testing the capabilities of the natural language processing system in the recognition of the Ukrainian language.

Keywords

Ukrainian language, Chatbot, sentiment analysis, Ukrainian text, Data Mining

1. Introduction

As computer technology goes beyond its artificial limitations, organizations are looking for new ways to reap the benefits. The sharp increase in computing speeds and capabilities has led to new, highly intelligent software systems, some of which are ready to replace or increase human services based natural language processing (NLP) technology and Ukrainian dictionary [1-6]. The objective of our research is to build an algorithm for recognizing emotions behind user text messages written in Ukrainian based on linguistic analysis technology [7-18]. It is connected with the rapid growth of NLP which is based on the development of smart chatbots being available to transform the world of customer service and more [19-24]. NLP is about understanding the interaction between computers and machines through language [25-31]. To understand natural language, computers must listen to, process, and analyze human text and speech. Understanding natural language is especially difficult for machines when it comes to thoughts, especially when people use sarcasm and irony [32]. However, sentiment analysis can identify subtle nuances of emotions and thoughts and identify whether they are positive or negative [33-38]. The developed system can facilitate further work with the Ukrainian segment of users in social networks and in general on the Internet how it development for other languages [39-44]. Moreover, it can be used to determine the negative attitude of the society to recent events by specifying target audience by product mentions in posts, analyze the reaction of users to the release or update of certain technical means or the political situation in the country or comments on HEI's website for information image analysing etc. based on Data Mining [45-52]. In its turn, these studies contribute to the development of NLP in the field of Ukrainian languages based on results of publications [53-64].

2. Related Works

In this section we provide a thorough analysis of analogue systems which are available on the market.

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The first one under discussion is *Daylio* programme. Its main advantages include the following points. The application has a special calendar that allows its users to record the mood by date and add notes (possibly about the events that affected it). It means that the application is effective in subsequent trips to a psychologist to prescribe treatment or analysis of the client. What is more, it supports interface localization in 28 languages (including Ukrainian). Its main drawback is that users can simply enter their mood manually without having support for virtual assistants or language recognition.

The next one considered is the *MoodKit* system. Among its benefits we should mention that it is an intuitive and easy-to-use application which is based on a well-studied therapy model and designed for people struggling with anxiety, stress and depression. Also, the advantage of this application is that it offers tips for dealing with a bad mood. One of its main disadvantages is that only English language is supported there. Besides, the *MoodKit* application is limited to iOS users and there is no free version of it. The user can enter his mood manually, not having support for virtual assistants and language recognition. The application has not yet gained enough users, so there is no rating for it in the App Store.

The last application we discuss is *Worry Watch* programme. While acknowledging its positive features, we note that the application works close to a personal diary and allows to record worries by date and set reminders after the event that caused the worries has passed. Thus, it helps to trace the analytics on how many of the experiences were correct. Its users' rating is rather high. What comes to the negative effect of the programme, we should specify that it supports for 16 languages, but not including Ukrainian. What is more, *Worry Watch* is only available for iOS users in a paid version. And as it is with the mentioned above programmes, users can enter their mood manually without having support for virtual assistants and language recognition.

3. Materials and Methods

We have chosen *Dialogflow ES* to develop this system. Dialogflow Customer Experience (Dialogflow CX) was recently launched by Google. It provides a new way of designing agents considering the approach of the state machine to the design of agents. Such an approach gives a clear and sharp conversation control combined with a better end-user experience and workflow. The older version of Dialogflow, Dialogflow ES, short for Dialogflow Essentials, is still supported, but Dialogflow CX should allow higher-complexity chatbots to build more seamlessly with a visual editor and not to require developers to write complex code.

Table 1
Differences between two versions

Category	Agent ES	Agent CX
Interaction with the user console	Mostly text forms	Visual graphs showing conversation paths and text forms for configurations
Reusable	Intentions are combined with performance, events, and feedback that are difficult to reuse	Intentions are simplified and designed specifically for multiple use
Max project agents	1	100
Recommended agent size	Medium-sized agents	Agents of large sizes
Recommended complexity of the agent	Agents of medium complexity	Agents of high complexity

Another possible option which fits our needs is *Cognigy* programme. It is a corporate software platform that helps automate artificial intelligence on the conversational level. Thus, there are three services provided. They are *Dialogflow ES*, *Dialogflow CX* and *Cognigy*. Since *Cognigy* only works on a subscription basis for their services, we also exclude this service.

Among the two remaining services, it would be better to choose the version that has a built-in flow editor, but, unfortunately, at the moment *Dialogflow CX* does not support integration and limits the possibilities for processes not built in English. Therefore, the construction of this system is chosen to work with *Dialogflow ES* and integrate this system with a free flow editor. The designed system has three constituents: user, dialogflow, and system. They are shown in Fig.1.

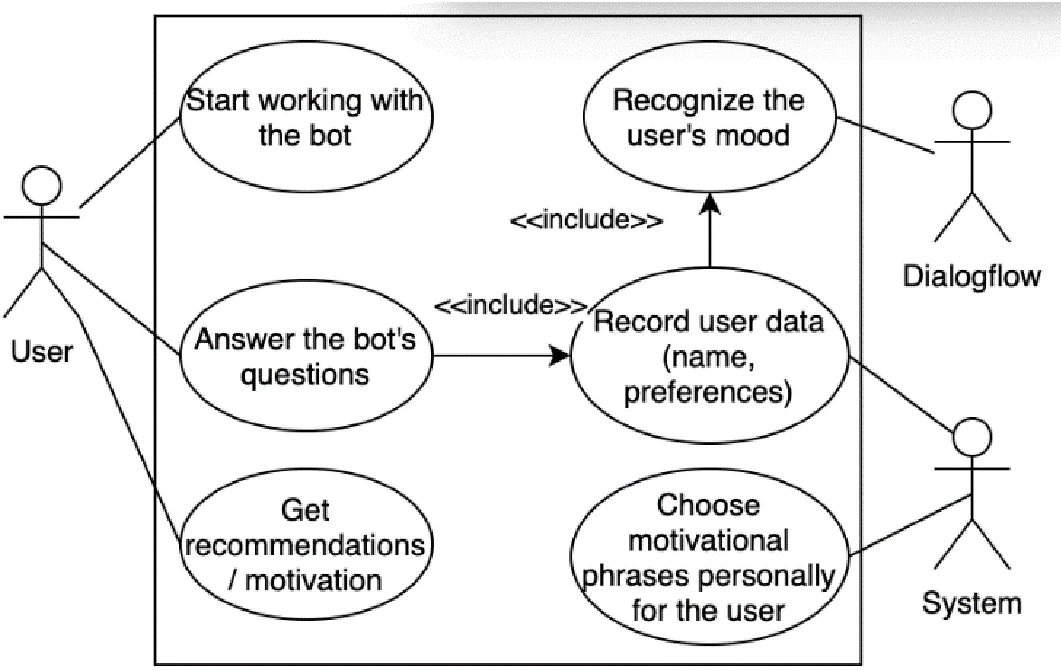

Figure 1: A user diagram

The actions the user can do include the following: start working with the bot, answer the bot's questions, get a recommendation / motivation. *Dialogflow* recognizes the user's mood after the user answers the bot's questions. What comes to the system functions, they record user data (name, preferences) and select personal phrases for the user. After the user answers the bot's questions, the system records the user's data (name, preferences) and *Dialogflow* programme identifies the user's mood.

With the help of a cooperation diagram, you can describe the full context of interactions as a kind of time "slice" of a set of objects interacting with each other to perform a specific task or business goal of the software system. This diagram shows 3 objects: system, user, dialogflow (Fig. 2). They are connected by the following connections:

1. The user initiates work with the bot
2. The system asks questions to the user
3. The user answers the bot's questions
4. The system processes user data
5. The system sends responses to *Dialogflow* recognition
6. *Dialogflow* defines intent and entities
7. The system formulates a motivational response to the user
8. The system sends a response to the user

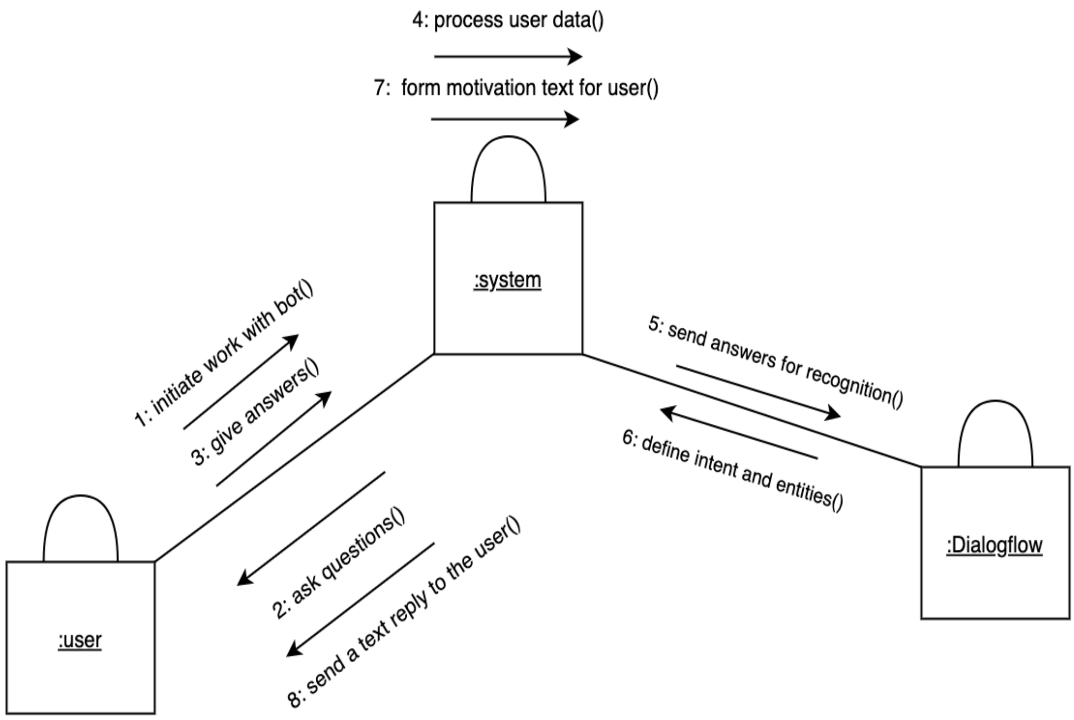

Figure 2: Cooperation diagram

4. Experiments

We develop and add training phrases to intents (Fig. 3-4).

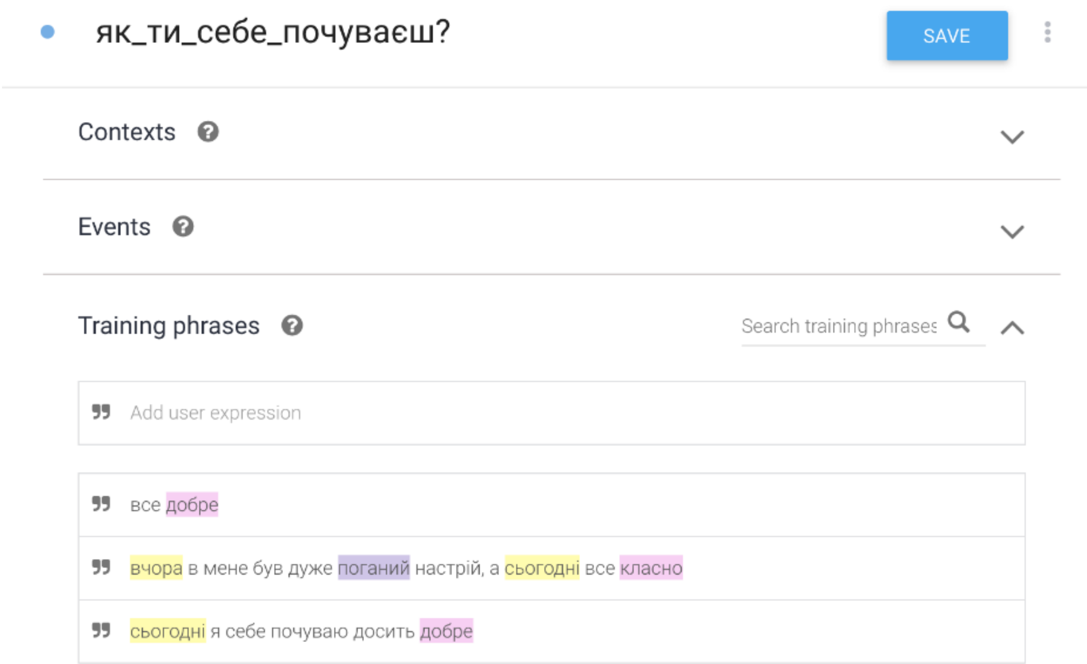

Figure 3: Forming an intent

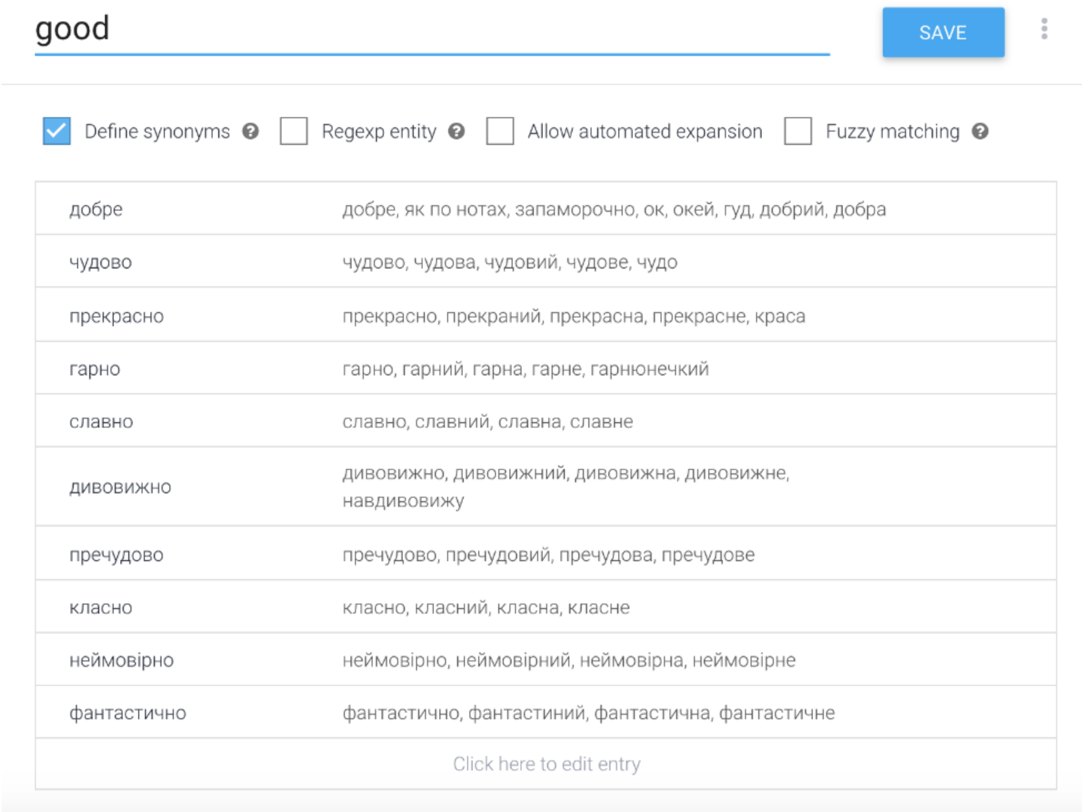

Figure 4: List of emotionally positive words: good domain

In Figure 3, you can see that some words are highlighted in the training phrases. It shows that these entities carry extra emotional or informational meaning. For this purpose, entities with positive and negative shades of meaning are placed in one domain. With the aim of further dialogue analysis and gathering some analytics, they will be placed in different entities. First, all emotionally positive words are put into *good* domain. The domain name is written in English, as *Dialogflow* platform only recognises the characters A-Z, a-z, 0-9 for giving a name. And Fig. 4 includes a list of emotionally positive words of *good* domain.

5. Results

To demonstrate how it works we will show here the results of the Test case #1. The description of the task requires to ensure that the *Dialogflow* recognizes a positive answer to the question "How are you today?" The *Dialogflow* console will be used to conduct a testing.

Instructions: to perform this test, one needs to log in to the *Dialogflow* console and type in the answer "good" in the input field.

1. Steps:
2. Log in to the *Dialogflow* console
3. Select the input field on the right
4. Type in “good”
5. Get the result

Expected Result: after recognizing the word “good”, *Dialogflow* should identify:

1. One of the three text answers:
   a. Thank you for trusting me! Did you have the opportunity to meet friends?
   b. I'm very interested, let’s continue)) In fact, to meet your loved ones helps a lot to relieve a daily stress. Have you had such an opportunity recently?

c. I'm here to talk to you about it. Did you have a chance to meet your family or friends last week?

2. Source contexts
3. A “good” domain

Case status. As based on the case results, we should admit that the expected output is achieved. The test results are presented in Fig. 5. In this test case, a positive answer to the question “How are you today?” is successfully recognized by the *Dialogflow* programme. The identification of the required intent and domain is completed.

Output. To reset the system, select the Reset Context option in the *Dialogflow* console.

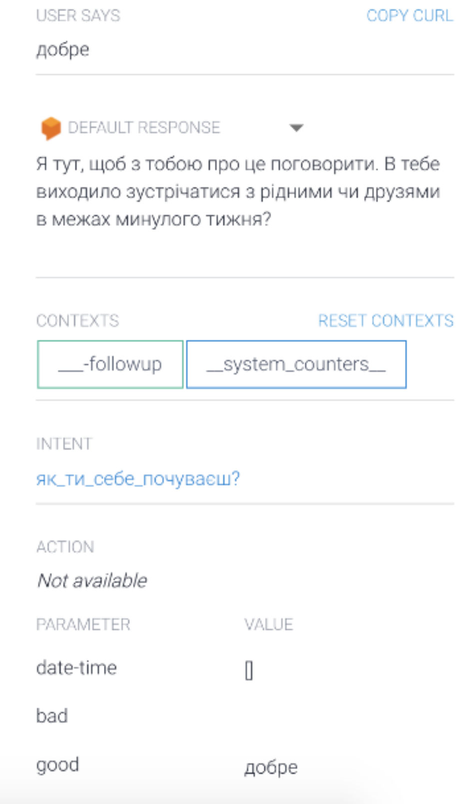

Figure 5: Successful completion of Test case #1

The next test we have conducted is the Test case #2. The description of the task requires to ensure that the Dialogflow recognizes a negative answer to the question “How are you today?” The Dialogflow console will be used to perform the testing.

Instructions: to perform this test, one need to log in to the *Dialogflow* console and write “bad” in the input field.

1. Steps:
2. Log in to the Dialogflow console
3. Select the input field on the right
4. Type in “bad”
5. Get the result

Expected Result: After recognizing the word “good”, *Dialogflow* should determine:

1. One of three text answers:
    a. Thank you for trusting me! Did you have the opportunity to meet friends?
    b. I'm very interested, let’s continue)) In fact, to meet your loved ones helps a lot to relieve a daily stress. Have you had such an opportunity recently?

c. I'm here to talk to you about it. Did you have a chance to meet your family or friends last week?

2. Source contexts
3. A “good” domain

Case status. Considering the case results, we may confirm that the expected output is gained. The test results are presented in Fig. 6. In this test case, a negative answer to the question “How are you today?” is successfully recognized by the *Dialogflow* programme. The identification of the required intent and domain is completed.

Output. To reset the system, select the Reset Context option in the *Dialogflow* console.

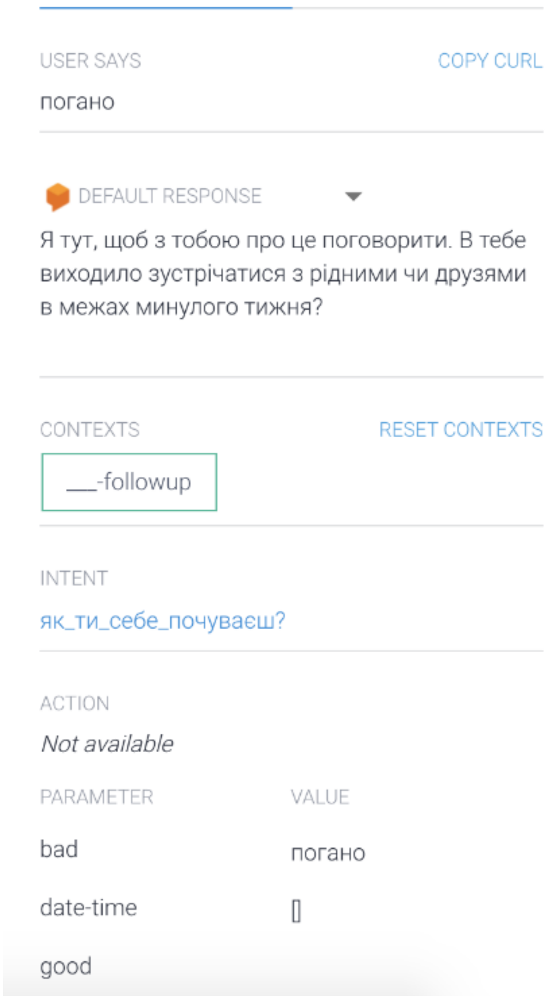

Figure 6:Successful completion of Test case #2

To check whether the *Dialogflow* programme identifies a complex positive answer to the question “How are you today?”, the Test case #3 is conducted. The necessary condition is that the training phrases are not included in the list. The *Dialogflow* console will be used to perform the testing.

Instructions: to perform the test, one needs to log in the *Dialogflow* console and give an answer “Actually, I feel great today” in the input field.

Steps:

1. Log in the *Dialogflow* console
2. Select the input field on the right
3. Enter text “Actually, I feel great today.”
4. Get the result

Expected result: after recognizing the sentence “Actually, I feel great today” *Dialogflow* should determine:

1. One of three text answers:
    a. Thank you for trusting me! Did you have the opportunity to meet friends?
    b. I'm very interested, let's continue)) In fact, to meet your loved ones helps a lot to relieve a daily stress. Have you had such an opportunity recently?
    c. I'm here to talk to you about it. Did you have a chance to meet your family or friends last week?
2. Source contexts
3. A "good" domain
4. System domain with date.

Case status. The case corresponds to the expected result. The test results are presented in Fig. 7. In this test case, a positive answer to the question "How are you today?" is successfully recognized by the *Dialogflow* programme with the identification of the required intent and domain.
Output. To reset the system, select the Reset Context option in the *Dialogflow* console.

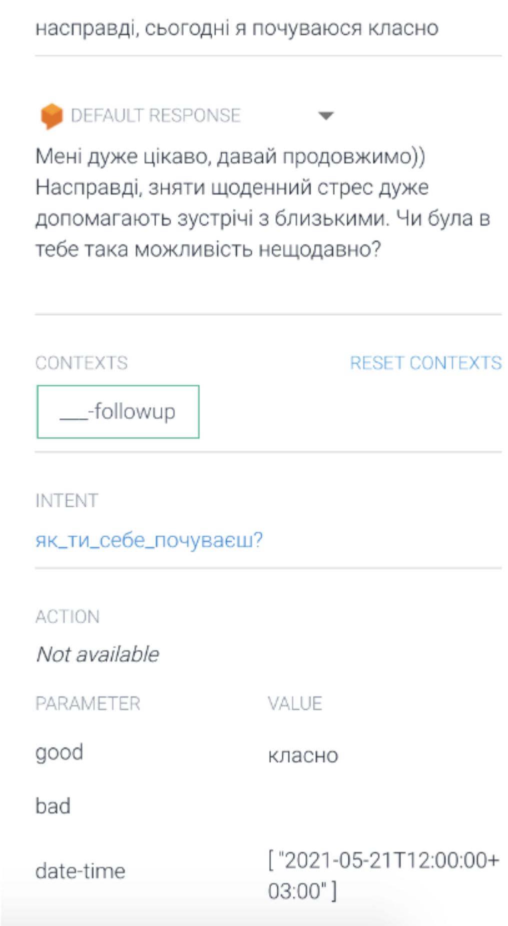

Figure 7:Successful completion of Test case #3

6. Discussion

To review the ratio of the number of recognized phrases to the number of unrecognized phrases among the total number of phrases used in testing, a diagram is developed (*see* Fig. 8). The total number is 70 phrases, 54 out of them are successfully recognized, and 16 belong to the Default Fallback Intent.

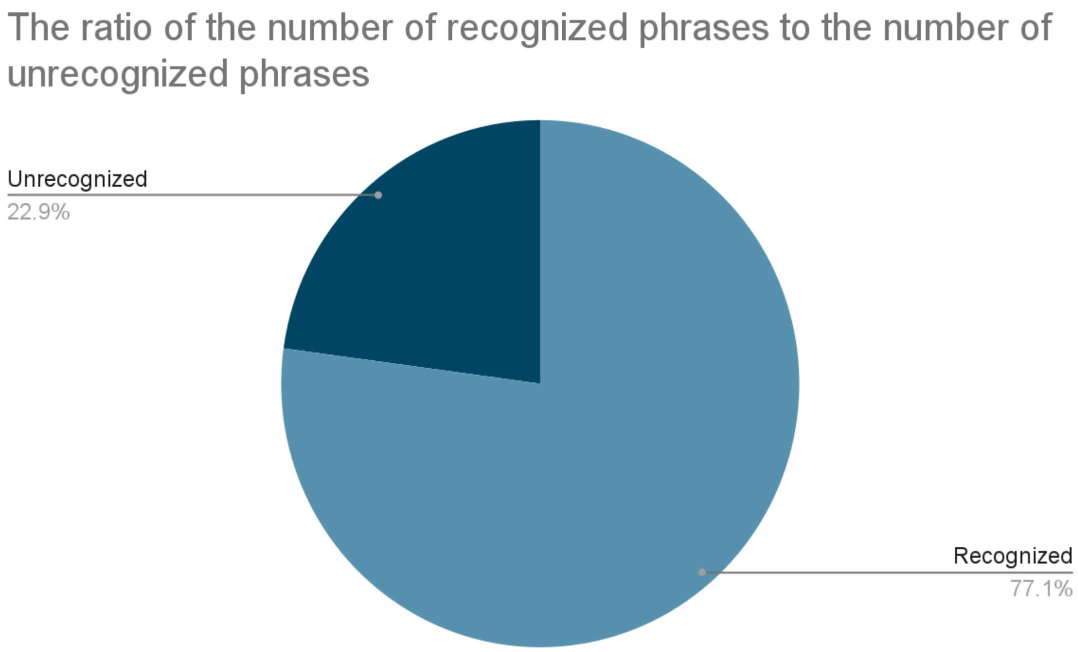

Figure 8: Ratio of recognized phrases to unrecognized phrases

On the pie chart it is shown that more than 77% of the entire sample of 70 phrases is successfully recognized. Such statistics indicate that the agent has been trained successfully.

Our next step is to consider the number of training phrases which contain keywords – entities to improve recognition. Of the sample of 70 phrases, only 26 phrases include entities (*see* Fig. 9).

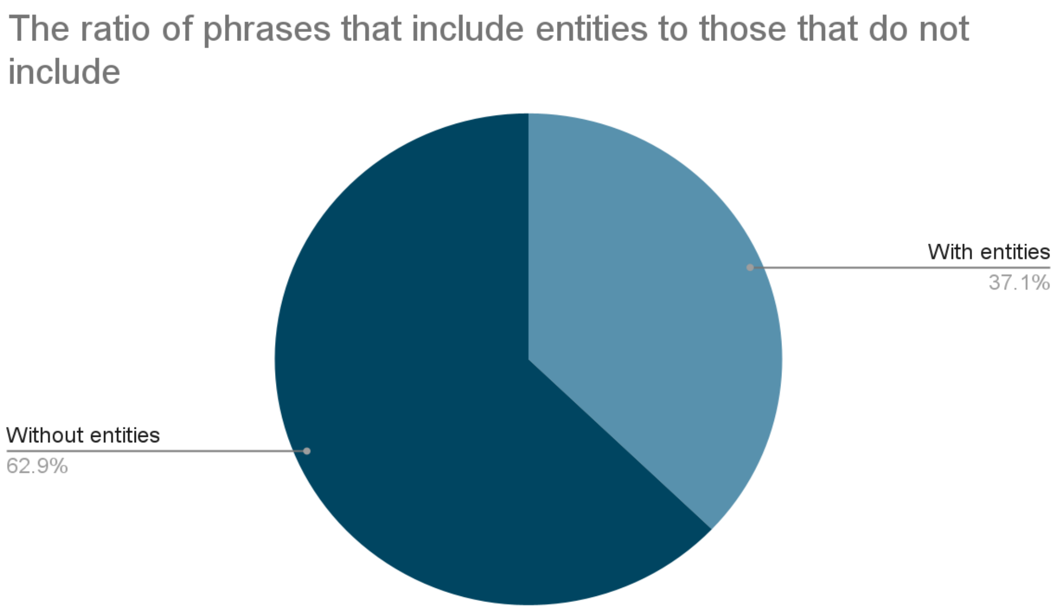

Figure 9: Ratio of phrases that include entities to those without it

Taking into account the ration in Fig. 9, we may conclude that the agent is well trained to recognize the context of phrases even if they do not include predefined entities. It is proved by the fact that the number of 62.9% of recognized phrases has been successfully identified without keywords.

In Fig. 10, it is shown a bar chart with the number of training phrases differentiated according to the level and their recognizability.

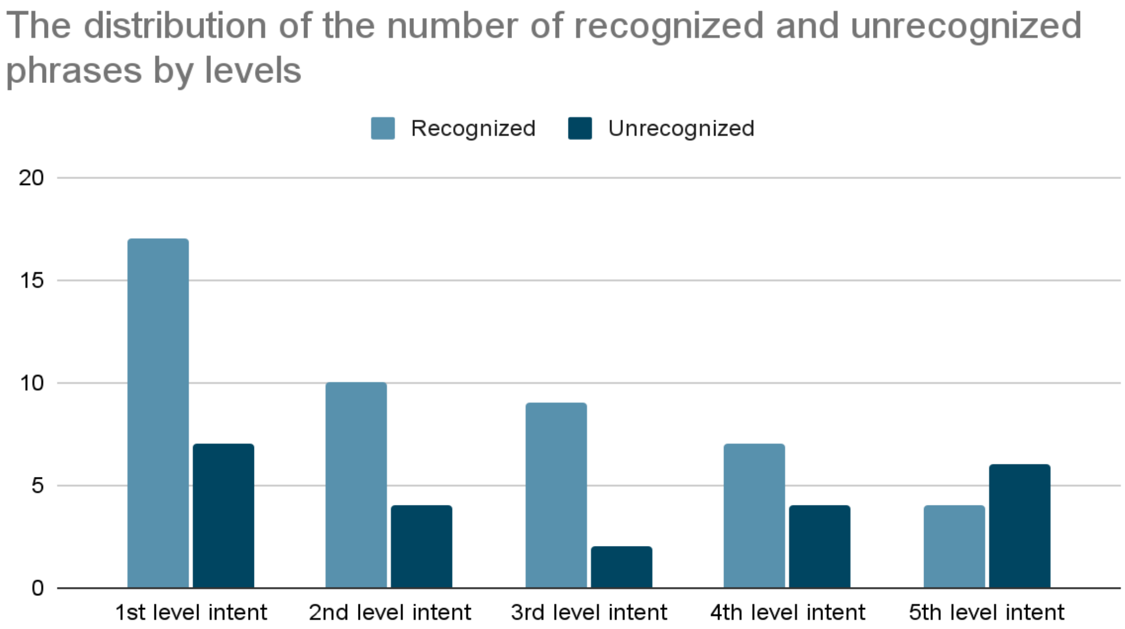

Figure 10: Training phrases differentiated according to the level and their recognizability

The results derived in the diagram indicate that the 1st level intent is called the most times, and the 5th level intent is the least one. In addition, we can conclude that among all the intents, the best recognized is the intent of the 3rd level, and the lowest – of the 5th level. It means that further research and investigation of training phrases should be conducted.

7. Conclusions

To conclude, we would like to state that the development of NLP is experiencing its rapid progress and its application in various areas of science contributes to the general technology-oriented approach. In our research, its application resulted in developing of 32 custom intents, 2 system intents, 2 custom entities, one system domain, and 300+ training phrases as based on *Dialogflow* programme. Besides that, 16 intents are set as the end of the conversation. Because of the complexity of the Slavic word formation system it is a challenging task to use NLP systems in this field. In practice, it means that the recognition of the Ukrainian language by NLP systems is highly complicated due to its extensive system of inflections. Further research in this area would be a valuable contribution both to the development of NLP and Ukrainian language software advances in technology.

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