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DEVELOPMENT OF CHATBOT-PSYCHOLOGIST: DATASET, ARCHITECTURE, DESIGN AND CHATBOT IN USE

Abstract. Virtual assistants are software applications that allow users to have conversations with the software in the same way as they would in real life. Creating functional conversational agents have been the most challenging aspect of working with AI ever since the field was first introduced. Virtual conversational agents' primary responsibility is to properly interpret natural communication and reply in an acceptable manner, in spite of the fact that they may do a range of activities. In the past, AI agents were created either via the use of handwritten rules and commands or by straightforward statistical approaches. End-to-end Automation has mostly supplanted these models because of its superior potential for learning new skills. The encoder-decoder deep learning approach is currently the method that has the greatest amount of interest for simulating conversations. The domain of linguistic understanding served as a source of motivation for the development of this concept. In this article, we present an overview of the findings from our study into the development of an immersive digital conversational agent that might potentially provide sufferers psychological aid. We used Rasa NLU approach, which is based on NLP practices, in order to construct and train the chatbot. The findings of the study indicated that providing appropriate replies to patients' questions and concerns during conversations had a prediction accuracy about 75 percent.

Keywords. Mental health, natural language processing, natural language understanding, artificial intelligence, machine learning.

Introduction.

Online human-computer conversation systems[s] using natural language processing techniques is what conversational agents are referred [1]. Alan Turing, who in 1950 posed the question «Can machines think?,» is generally credited as having been the first person to conceive of the chatbots. Conversational artificial intelligence technology has advanced significantly since Turing's work thanks to developments in NLP and artificial intelligence. In a similar vein, the use of chatbots has also risen, particularly since major messaging apps like Facebook, Telegram, Skype, WeChat have introduced their own chatbot systems.

In recent years, automated conversational agent have become more popular as a result of the many uses they provide. The success of conversational agetns may be attributed, in addition to their vast multitude of scenarios, to the fact that they are accessible, that they improve user satisfaction, their ability to handle a huge number of clients, as well as that they are highly cost efficient []. It has been noted that using conversational agents assists in decreasing the total expenses associated2 with running a business [3].

It is anticipated that conversational agents would cut the amount of work required at upper management levels by as much as 70 percent in the next few years. As a result of this, it is anticipated that businesses would spend high amount of money on the advancement of automated conversational agents [4]. Figure 1 demonstrates working structure of the virtual conversational agents or chatbots *[5]*.

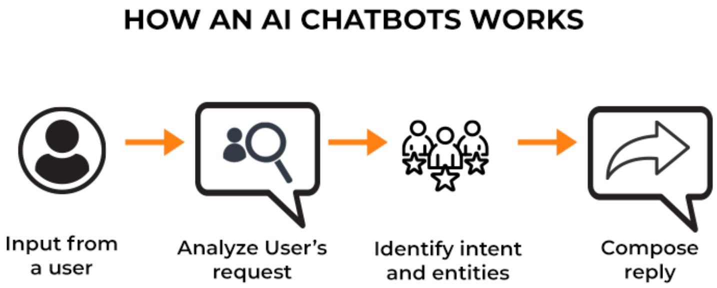

Figure 1 - Workflow of the proposed Model [8]

Although conversational agetnts are capable of imitating human interaction and providing users with entertainment, this is not their primary purpose. Programs including such academic achievement, knowledge representation, marketing, and electronic commerce may all benefit from their use [6]. The widespread adoption of automated online conversational agents may be attributed to the various benefits that they provide not only to consumers but also to engineers. The majority of solutions are platform-agnostic and make content immediately accessible to users without requiring any installs. Contact with the chatbots may be made via a patient's social network without the user having to leave the messenger app in which the chatbots reside [7]. This app also offers and ensures the user's identification. Additionally, financial solutions are included into the messenger service, where they may be used in a secure and dependable manner. Non active customers can be re-engaged via the usage of a message system. Machine learning may be included into ongoing group chats or shared like any other connection, and numerous chats can be conducted on in simultaneously with one another. The knowledge gained in the operation of one chatbots are readily transferable to the operation of other conversations, and the amount of data that is required is minimal. Some of the benefits for programmers include seamless connectivity, rapid and straightforward development cycles, an absence of version separation, and reduced design work for the interfaces [5].

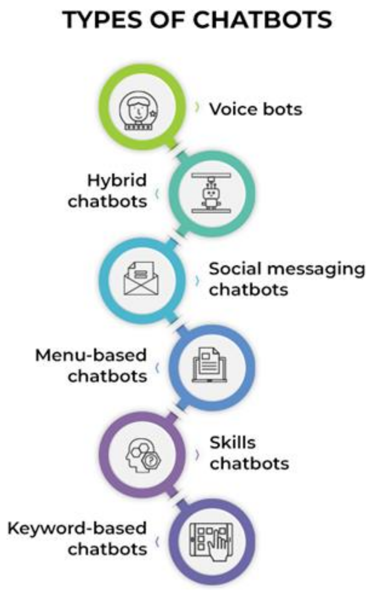

Figure 2 - Types of chatbots [8]

Figure 2 demonstrates types of chatbots depending on their goal of application. There are different types of chatbots voice chatbots, hybrid chatbots, social messaging chatbots, menu-based chatbots, skills chatbots, and keyword-based chatbots. The chatbot is able to carry out a variety of other duties, including the search for songs, photographs, information, calculators, and displays of weather forecasts and currency rates [9]. The majority of these functionalities are implemented on the web and may be accessed through an external application programming interface. The gender recognition, with the goal of rendering the chatbots responses more human-like, is the purpose of this study. The system that will examine and parse the text entered by the user in in order to automatically generate a response from the chatbot is being created [10]. The architecture of the text as well as the themes of communication are taken into consideration by this technique. The prefixed functions and the hashing will be used as the basis for the algorithm's operations. In addition, there will be a comparison done between the newly designed algorithm and the algorithms that already exist. This study will cover the process that was used to develop an interface for a Telegram chatbot, the primary purpose of which is to convert audio communications into text.

Related Works. It was in the year 1950 that Alan Turing posed the question, «Can machines think?» The challenge was recast by Turing as a «imitation game», in which a «interviewer» posed questions to both human and computer participants in an effort to determine which was which. When distinguishing between a person and a machine becomes impossible, we claim that the machine is capable of thought [12]. ELIZA, the first first chatbot, was invented by Joseph Weizenbaum at MIT in 1966. ELIZA is credited as coming the closest to mimicking human conversational behavior. In order to create acceptable replies, ELIZA would, when presented with an input phrase, first detect keywords and then patterns match that phrases vs a set of predetermined criteria [13]. NLP techniques are feature that may be given to computers. This skill enables the computer to communicate in human languages with other computers or machines, as well as with users communicating directly with the computer. Understanding natural language requires performing three types of analyses: parser, semantic analysis, and knowledge-based structural analysis [14]. The process of parser involves an investigation of the structural components of phrase syntax. During this stage of the process, the major grammatical relations are identified so that the sentences may be parsed into their respective subjects, predicates, and objects. Following the phase of understanding and interpretation, a meaningful representation of the texts is produced [15]. The understanding of the meaning of words and the structure of language, such as the transitivity of nouns and verbs, is used in the understanding and interpretation. In natural language processing, a phrase serves as the handling focus. It's possible that a sentence is designed to be interpreted as bigger phrases consist of more than individual terms. There is a difference in the kinds of structural relationships that exist between words and between sentences. The phrases and the clause are the two media syntactic elements that may be found in between the words and the sentences. A clause is a syntactic unit that comprises of two or more predicate components. Clauses may be independent or dependent. A particular topic, a predicate, an object, a complement, and an adverb make up the components of a predicate. The phrase is an example of a grammar that consists of two or more words but does not include any predicate components in its construction [16].

One reason for this is because the replies that chatbot applications provide are often predetermined, rather than situational, and they include information that is both useless and illogical. The conversation system is the fundamental component of the chatbot that is responsible for managing the answers. A conversation system is made up of three different modules: one for input, one for output, and one for control. These include a NLU module, a conversation module, and a response generation module. All of these works together to ensure that the system is able to communicate effectively. Dialog systems are often differentiated from one another based on the coherence and scalability of their dialog. On the one hand, dialog systems that consist of handmade domain-specific dialog rules make it possible for goal-oriented chats to have meaningful conversations on a particular subject (for example, ELIZA). The amount of work that chatbot designers put into the construction of conversation rules and the writing of rule-specific chatbot replies is the primary factor that determines the degree to which chatbot responses seem realistic [17]. On the contrary side, data-driven dialog managers are able to automatically construct chatbot replies by drawing on vast dialog corpora that already exist (for example, Xiaoice). They make it possible for a user's message to be probabilistically matched to instances within the training set. These methods are often used in the creation of chatbots that do not focus on achieving specific goals. The naturalness of the replies, though, is highly dependent on the quality of the training data, and data-driven techniques do not have the coherency and robustness necessary to account for this. In the past, rule-based conversation systems were the norm in the chatbot environment; now, data-driven conversation systems are quickly becoming the norm. The generation of high-quality chatbot replies and training data is a significant obstacle in the process of creating chatbots, and this obstacle exists regardless of the kind of dialog system being used.

Materials and methods.

When determining how a particular word or phrase should really be understood, the whole context is taken into consideration. This is done by using practical evaluation and conversation integrating in order to determine the final interpretation of the text's real meaning. The processes of text realisation and text preparation are used in human language production in order to provide responses that can be understood. On the contrary side, or stated other way, speech generation is the process that is accountable for the production of sentences and phrases that adhere to the rules of proper grammar. Understanding the intricate character of genuine human dialogue is one of the most fundamental challenges facing NLP today. Figure 3 demonstrates bot managing process.

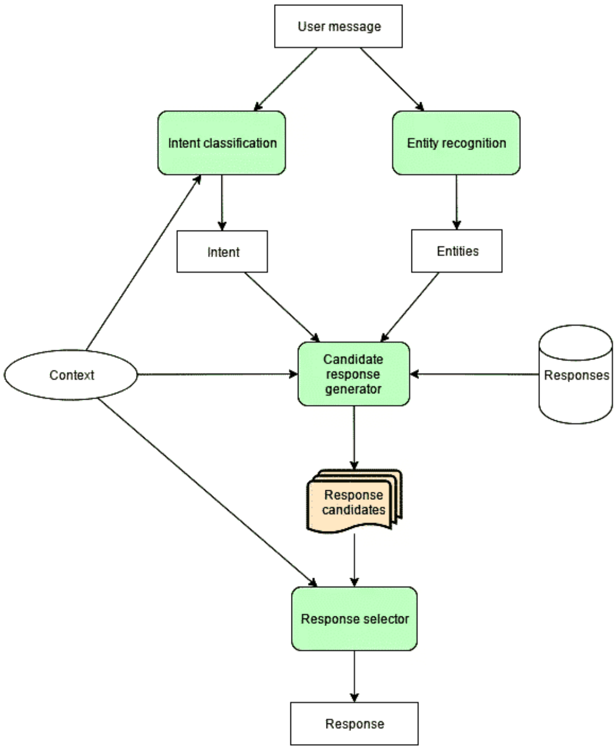

Figure 3 - Enterprise Bot Manager [9]

Results.

Dataset.

In addition to the modules that are responsible for processing user input, detecting intentions, and creating answers, a psychological chatbot needs specific diagnostic functions. These diagnostic functionalities should be included into the chatbot. As a result of this, we made use of a selection of well-established psychological examinations. These tests have a proven track record of being accurate and are highly recommended for use in screening processes. They are as follows:

1) Beck Depression Inventory (BDI).
2) 9-question Patient Health Questionnaire (PHQ-9).
3) Generalized Anxiety Disorder 7 (GAD-7).
3) Columbia Suicide Severity Rating Scale (C-SSRS).
4) Buss-Perry Aggression Questionnaire (BPAQ-24).
5) CRAFFT Screening Test.
6) Beck Hopelessness Scale (BHS).

For the purpose of accurately representing the reasoning behind surveys, the finite-state automaton is used. The user chooses one of the available questionnaires to fill out, and the transitions between states are responsible for carrying out the logic of the questionnaire and calculating the results.

Chatbot Design.

Data extraction, intention detection, and response searching are all possible uses for RASA NLU, which is fundamentally a natural language processing system. The conversational agent processing structure, which can be shown in Figure 4, was constructed with the assistance of Rasa. After receiving a message from the user, the Interpreter will convert the message into a dictionary. This dictionary includes not only the text itself but also any identifiable entities and intents associated with it. A tracker is a piece of technology that monitors the progression of the discussion and keeps track of whether or not the message was successfully sent. After the tracker status has been provided to the policy, we will go to the next phase and decide what to do. After the tracker has finished recording the action that was chosen, the answer is then sent to the user.

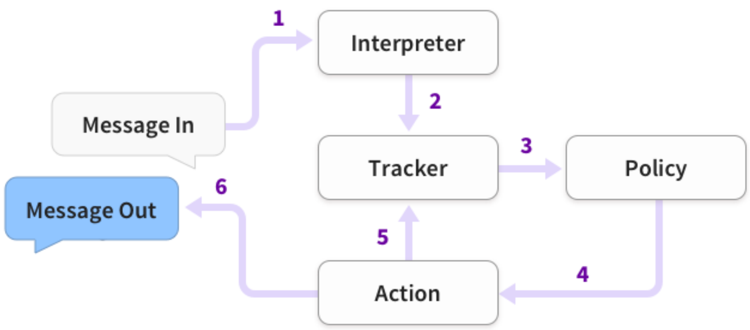

Figure 4 - Chatbot Processing Structure

Chatbot-Psychologist in Use.

There are two primary delivery options available via Rasa for distributing training sets. It's possible to build chatbots by leveraging NLP techniques, as well as intents that have been pre-trained and managed. All of these concepts are implemented in the architecture of the chatbot that can be seen in Figure 5. Within a chatbots, the collection of Intent and purpose serves as a reference that is always the same, is always defined, and is always stated.

Because of the pre-trained data, the categorization of the user's intentions will be utilized to determine whether each sentence of the text should be expressed as an embedding phrase or as an input vectors of the phrase. For the purpose of classifying user intentions, pre-filtered sets will be used. These sets might have been obtained from a number of different sources, such as FastText and Spacy, or even controlled intentions. Because there is a scarcity of openly accessible training data, the user of this approach will be required to generate the data sets from scratch in order to utilize it. The technique of determining an individual user's purpose based on an utterance made by that individual user is referred to as «intent classification».

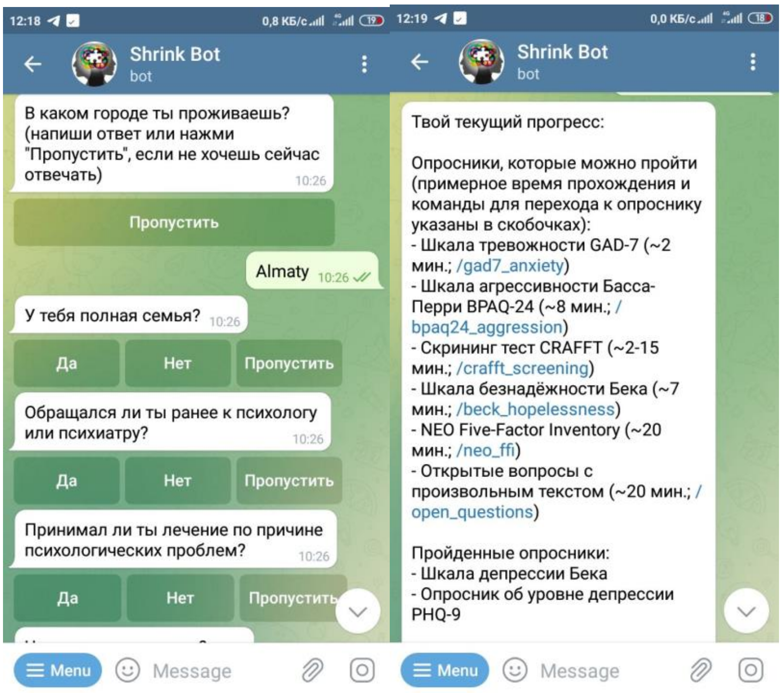

Figure 5 - Chatbot in Use

The actions that chatbots has to perform in order to operate properly are outlined in more detail in Figure 6. It begins by receiving the inputs, then analyzes it with a number of probable replies, assesses the degree of trust in each message, and then presents the customer with the response that has the greatest level of trust.

In order to extract named entities, the Rasa NLU has been used, and it has been shown that this approach is extremely trustworthy due to the fact that there are no mistakes in entity extraction for the whole of the phase when applying the appropriate training and test evidence. In the subsequent stage of our investigation, we are going to use natural language processing methods to investigate datasets similar to in order to locate signals that are associated with depression.

Discussion.

Conversational agents in mental healthcare settings has been made apparent by the fast pace of artificial intelligence and machine learning development. In terms of natural language computing, classification, enhanced computing, and round-the-clock support with data science, artificial intelligence beats people. Nevertheless, complexity, rational reasoning, and higher-level interactions cannot be replaced by a computer. Before conversational agents are widely used in the mental healthcare industry, there are additional complexity issues that need to be recognized, handled, and minimized.

Numerous of the variables covered in this chapter might be used to highlight the difficulty in overcoming doctors' hesitation and patients' slow acceptance. The opinions of 100 active practicing doctors were obtained in a cross-sectional web-based survey to learn more about conversational agents in mental health. Even though many positive features were mentioned, there were also plenty of issues. More than 70% of doctors think conversational agents can't deliver all the care that clients require, can't express people's emotions, can't provide in-depth treatment plans, and might be dangerous if people self-diagnose or don't completely understand their diagnostic. Fears about using conversational agents in mental health may gradually fade if their drawbacks are better recognized and addressed. This section concludes by examining the difficulties and concerns that patients, healthcare providers, and decision-makers must face.

The resilience of conversational agents to integrate and learn from massive medical datasets, combined with its capacity to engage with customers in a consistent way, is a contributing factor to the scale based of conversations in a wide range of healthcare systems. Conversational agents are likely going to be an important part of the ongoing development of cancer treatment given the present state of the industry and the obstacles that it faces. To be more precise, they offer promise in terms of solving the triple purpose of health care, which involves enhancing the quality of treatment, trying to better health of people, and decreasing the burden or expense of our current medical systems. Further than the treatment of cancer, there are a growing number of innovative applications for chatbots that may be found in the field of health care. During the last pandemic, conversational agents were already being used to disseminate information, make recommendations on action, and provide emotional comfort. This will allow for future advancement in the medical fields and understanding.

Conclusion.

In this article, we shared the findings from our early research into creating a digital chatbots for medical prupose in Kazakhstan. We also used many different NLU to train the conversational agents in treatment. Over 75% accuracy was shown in identifying patient reactions in the experiment. The data that has been made public suggests that chatbot applications may have an audiences in Kazakhstan. In the next stages, we intend to employ additional AI methods in an effort to enhance the outcomes we have so far achieved.

Machine Learning will become an essential tool for mental health practitioners in order to alleviate the burden of assessing new patients and classifying them into appropriate treatment plans. In addition to potentially helping more individuals in need, the application of AI in the treatment of mental illness difficulties might provide the prospect for continuing, tailored control over the problem.

The aforementioned chatbot has certain limitations in its Kazakh language support. This research aimed to assess the potential for creating a mobile chatbot fluent in Kazakh. It's clear from the findings that chatbots can have a basic discussion in Kazakh. To further enhance our outcome, we want to create chatbots that can detect and treat individuals who are exhibiting depressive symptoms.

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ЧАТ-БОТ ПСИХОЛОГЫНЫҢ ДАМУЫ: ДЕРЕКТЕР ЖИЫНТЫҒЫ, АРХИТЕКТУРА, ДИЗАЙН ЖӘНЕ ҚОЛДАНЫЛАТЫН ЧАТ-БОТ

Аңдатпа. Виртуалды көмекшілер-бұл пайдаланушыларға бағдарламалық жасақтамамен нақты өмірде сөйлесуге мүмкіндік беретін бағдарламалық жасақтама. Функционалды сөйлесу агенттерін құру бұл сала алғаш енгізілгеннен бері жасанды интеллектпен жұмыс істеудің ең күрделі аспектісі болды. Виртуалды сұхбаттасушылардың негізгі жауапкершілігі-табиғи қарым-қатынасты дұрыс түсіндіру және олар бірқатар әрекеттерді орындай алатынына қарамастан, қолайлы түрде жауап беру. Бұрын жасанды интеллект агенттері қолмен жазылған ережелер мен командалардың көмегімен немесе қарапайым статистикалық тәсілдердің көмегімен құрылды. Аяқтау автоматикасы негізінен бұл модельдерді жаңа дағдыларды үйрету үшін керемет әлеуетімен алмастырды. Терең оқыту әдісі декодерлік кодтаушы қазіргі уақытта сөйлесулерді модельдеуге үлкен қызығушылық тудыратын әдіс болып табылады. Лингвистикалық түсіну саласы осы тұжырымдаманы жасауға ынталандыру көзі болды. Бұл мақалада біз зардап шеккендерге психологиялық көмек көрсете алатын иммерсивті сандық сөйлесу агентін дамыту бойынша зерттеу нәтижелеріне шолу жасаймыз. Біз чат-ботты құру және оқыту үшін NLP тәжірибесіне негізделген Rasa nlu тәсілін қолдандық. Зерттеу нәтижелері көрсеткендей, әңгімелесу кезінде пациенттердің сұрақтары мен алаңдаушылығына тиісті жауаптар беру шамамен 75 пайызды болжау дәлдігіне ие болды.

Түйінді сөздер. Психикалық денсаулық, табиғи тілді өңдеу, табиғи тілді түсіну, жасанды интеллект, машиналық оқыту.

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РАЗРАБОТКА ЧАТ-БОТА-ПСИХОЛОГА: НАБОР ДАННЫХ, АРХИТЕКТУРА, ДИЗАЙН И ИСПОЛЬЗУЕМЫЙ ЧАТ-БОТ

Аннотация. Виртуальные помощники — это программные приложения, которые позволяют пользователям вести беседы с программным обеспечением так же, как они это делали бы в реальной жизни. Создание функциональных разговорных агентов было самым сложным аспектом работы с искусственным интеллектом с тех пор, как эта область была впервые представлена. Основная ответственность виртуальных собеседников заключается в том, чтобы правильно интерпретировать естественное общение и отвечать приемлемым образом несмотря на то, что они могут выполнять целый ряд действий. В прошлом агенты искусственного интеллекта создавались либо с помощью рукописных правил и команд, либо с помощью простых статистических подходов. Сквозная автоматизация в основном вытеснила эти модели из-за ее превосходного потенциала для обучения новым навыкам. Подход глубокого обучения кодировщик-декодер в настоящее время является методом, представляющим наибольший интерес для моделирования разговоров. Область лингвистического понимания послужила источником мотивации для разработки этой концепции. В этой статье мы представляем обзор результатов нашего исследования по разработке иммерсивного цифрового разговорного агента, который потенциально может оказать страдающим психологическую помощь. Мы использовали подход Rasa NLU, основанный на практиках НЛП, для создания и обучения чат-бота. Результаты исследования показали, что предоставление надлежащих ответов на вопросы и опасения пациентов во время бесед имело точность прогнозирования около 75 процентов.

Ключевые слова. Психическое здоровье, обработка естественного языка, понимание естественного языка, искусственный интеллект, машинное обучение.

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