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SỌ̀RỌ̀: A Yorùbá Language Task Oriented Dialogue System

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Abstract
This paper presents Sọ̀rọ̀: a task-oriented dialogue system, developed utilising a rule-based technique. Sọ̀rọ̀ is fit for having a trade of four key sorts: greetings, small talk, basic number-crunching, and time/date. This dialogue framework has been fabricated following a linguistic investigation of the Yorùbá language and the rules defined from the analysis of publicly supported information. Sọ̀rọ̀'s conversational capacities are restricted to text-based trade and revolved only around a small domain of topics due to its limited vocabulary data sets. The framework involves three primary and auxiliary scripts each. The primary scripts are the bag-of-words, natural language understanding and natural language processing scripts while the auxiliary scripts are the task manager, the properties script, and the main script where dialogue sessions occur. This study developed rules that identify sentence types in utterances, split sentences into intent and entity, perform a list of tasks as identified in utterances and provide a response to this effect. This paper characterises rules that relate 66.7% accuracy the type of sentence contained within a sample utterance, with a precision of 94.7%. This study demonstrates the practicality of a Yorùbá language dialogue framework and simultaneously, design a dynamic dialogue system architecture likely to be improved upon with additional data.

Keywords: Chatbot, linguistic investigation, sọ̀rọ̀, task-oriented-dialogue, Yorùbá

1.0 INTRODUCTION

Humans, since the invention of computers, have been investigating how to make the most common way of connecting with these gadgets as consistent as could really be expected. When the primary computers were invented, their activity expected that the clients were exceptionally gifted in an interacting language to speak with the computers. Individuals' interactions with computers have become more simplified over time. In the twenty-first century, computing has evolved from a strictly professional perspective to a life skill. As a result, computers have become ubiquitous in all aspects of modern society.

The field of natural language processing (NLP) has existed nearly as long as the actual computer. Turing and Haugeland (1950) composed a paper named " *Computing* Machinery and Intelligence" which proposed what is currently known as the Turing test; a basis for deciding the intellectual prowess of a computer. It worked on the premise that the intellectual prowess of a processing framework could be tried by engaging with it behind closed doors. It is based on the ability to communicate with the system (Paliwal et al., 2020).

In the resulting years, NLP saw improvement made in machine translation (that is interpretation from one language to another) and somewhere between 1960 and 1964, Eliza was created by Joseph Weizenbaum to mimic a Rogerian psychotherapist. Her capacity to copy human discussion shook the software engineering world (Paliwal et al., 2020). A couple of comparable models came in the decade that followed including: MARGIE in 1975, SAM in 1978 and PAM in 1978 all of which utilised complex arrangements of manually written rules. By the 80s and 90s, improvement of additional strong calculations combined with a huge expansion in processing power brought about a transcendence of artificial intelligence (AI) in NLP (Schank

and Abelson, 2013). The presentation of statistical models, for example, Hidden Markov model for part-of-speech tagging changed the manner in which numerous NLP tasks are done even till today.
In 2011, the most successful general-purpose and task-oriented dialogue system, (or virtual assistant) was invented in the form of *Siri*® by Apple incorporation. A year later, Amazon and Google introduced their own virtual assistants: Alexa and Google Assistant respectively (Paliwal et al., 2020; Bhattad and Atkar, 2021). These three organisations have been setting the norm for what universally useful general-purpose task-oriented dialogue systems are supposed to be. Many autonomous dialogue frameworks and conversational specialists exist beyond these three. All are attempting to rethink the manners in which people communicate with the computers.

Conversational agents and dialogue systems, such as chatbots, personal assistants, and voice control interfaces, are becoming increasingly common in modern culture. Personal assistants on mobile devices, technical support over the phone lines, and online bots selling anything from fashion goods and cosmetics to legal advice and self-help therapy, among other things, are just a few examples (Serban *et al.*, 2017; Hasal *et al.*, 2021).

A chatbot is a computer software or AI agent that facilitates communication via aural or written means (Balint, 2017). These programs are frequently constructed to simulate how a person acts as a conversational mate. In software engineering literature by De Los Riscos and D'Haro (2021) as well as Klüwer (2011), it was presented that what many individuals refer to as chatbots are really portrayed as dialogue frameworks or conversational bots depending upon the use. These chatbots were perhaps the earliest issue to be endeavoured under AI made famous by the Turing Test. In this day and age, the most well-known occasions of chatbots are presumably virtual assistants in the likes of Siri®, Alexa, Cortana and Google Assistant, these frameworks use tremendous knowledge-base to give complex information based on simple queries. They convert free text input into something structured that can be converted to a query internally, and then a response generated from the query (Paliwal *et al.*, 2020). There are thousands of chatbot platforms currently available on registered account and Facebook messenger such as Wit.ai (Discover.bot, 2019), QnA Maker (Ndlovu, 2019), Motion.AI (Duraj, 2020), Converse.AI (Lucas, 2016), Botsify (Fox, 2020), IBM Watson (Porter, 2015) among others. All these platforms are sophisticated to the extent of streamlining the process of bot creation such that the developers need only define the entity and element to be extracted while the platforms do the extraction and inform the task manager. They also facilitate the process of developing conversational chatbots.
In AI parlance, a chatbot is an intelligent agent that abstracts the intellectual prowess of people. The characteristic ability to have a goal and autonomously sense, think and act as depicted in Fig. 1 is a vital quality of such frameworks.

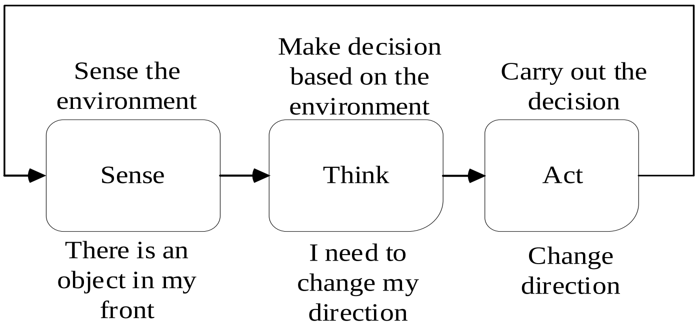

Figure 1: Illustration of intelligence in human

In the case of chatbots, the task of sensing is taken care of, since the input is directly entered by the user. For the thinking phase, however, the framework needs to understand the input and this is where natural language understanding becomes fundamental (Baez *et al.*, 2019).
A developing pattern and the inspiration that has brought about the requirement for this paper, is the monopolisation of English language in the sphere of chatbot creation. The English language is the most probable language that a chatbot speaks. At the time of writing this paper, Siri® offered nine distinct renditions of dialects, 22% of the dialects being English. This rate wouldn't be as troubling in the event that it was not so unrepresentative of this present reality. Out of the 7.8 billion individuals on the planet, just 380 million communicate in English as a first language (Simons and Fennig, 2018), which means generally 5%. In Nigeria, where English is the principal language, just 50% of the populace communicate in English (EF Education First, 2019). This stunning statistic proposes that around 80 million individuals in Nigeria are not being captured by the current chatbots consequently representing the need to construct dialogue models that put into consideration the Nigerian language.

Yorùbá is a tonal language spoken natively by about thirty million people in Nigeria and in the neighbouring countries of the Republic of Benin and Togo. The language has speakers in parts of Sierra Leone and its influence spreads as far as the Caribbean, parts of South America and Brazil. In Nigeria, Yorùbá speakers reside in the Southwest region in states such as Oyo, Ogun, Osun, Ondo, Ekiti, Lagos, Kogi and Kwara states. Yorùbá is a Kwa language, which belongs to the Yoruboid group under the Niger-Congo phylum (Adegbola *et al.*, 2011; Oluwatoyin, 2015). Yorùbá is one of the most widely spoken languages in Nigeria and its environs. It was one of the earliest languages to be put on google translate. In 2015, twitter added it to the languages it translated to. This, coupled with the relatively extensive amount of work that has been done on the language which makes it favourable to build a dialogue framework.
According to Oluwatoyin (2015), the words in Yorùbá language, are composed of rectilinearly chronological morphemes with each element being a meaningful morpheme. Yorùbá sentences can, therefore, be divided into the following order as shown in fig. 2.

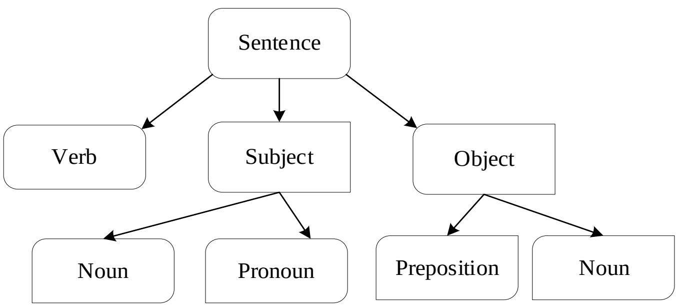

Figure 2: Word order tree in Yorùbá language (Oluwatoyin, 2015)

For the scope of this paper, the morphology of Yorùbá words and how it contributes to semantics within the language will be investigated. A language model will also be constructed upon which further statistical models can be employed to facilitate useful NLP tasks to be done. This work covers 6 of the 7 main sub sections of NLP which are morphology, lexical, syntactic, semantic, discourse and pragmatic. Phonology is being excluded since it deals with speech sounds and this paper deals primarily with text input and output.

1.2 Related Works

In the building of a task-oriented dialogue system, it was useful to analyse techniques used for query understanding and query intent detection. This can be achieved by means of natural language understanding (NLU) techniques built on the language model for Yorùbá as well as state-tracking and dialogue policy for dialogue management. It is worthy to note that while some approaches are based on well-defined rules of language, some techniques are data-driven. There are three major tasks being carried out within a dialogue system: NLU, dialogue management and natural language generation (NLG).

An NLU is a sub topic of NLP in AI that deals with machine reading comprehension. Essentially, NLU is considered as the segment of NLP that deals with a machine's ability to derive and represent meaning from natural language. NLU systems use a variety of methodologies, although many of them have similar components and architecture. Most systems employ lexicons for the language in question and use a parser as well as grammar rules to analyse sentence and derive internal representation from the sentence units. Some systems attempt to incorporate logical inference within their framework. This is usually achieved using a set of predicate logic assertions and then using logical deduction to arrive at conclusions (Covington, 1994).

Since NLP is a problem derived from linguistic research, it is apt to approach the solution in the four ways language understanding was formalised by the Stanford Computer Scientist, Professor Percy Liang. He presented the sub-sections as Distributional approach; Frame-based approach; Model-theoretical approach and Interactive learning (Liang, 2017).

1.2.1 Distributional Approach:

This method is also known as distributional semantics, and it entails large-scale statistical machine learning (ML) strategies. This method converts text into word vectors for mathematical analysis, allowing tasks like part-of-speech tagging, dependency parsing, and semantic relatedness to be performed. Dependency parsing (does this portion of a sentence alter another part of the sentence?) and semantic relatedness (do these various words have comparable meanings?). It gets its semantics from the interaction between words, not from the word itself. These NLP exercises are based on the connection between words rather than on comprehending the meaning of words. Distributional systems are broad, versatile, and scalable, and they may be used with a wide range of texts without the need for hand-engineered features (Liang, 2017; Yao, 2017).

1.2.2 Frame based Approach

A frame is a form of data structure that is used to describe a typical scenario. Sentences can be synthetically distinct while being semantically similar by definition. Identifying the frame in use and supplying the particular frame parameter are both part of the parsing process. The fundamental disadvantage of the frame technique is that it necessitates the construction of monitoring (Liang, 2017; Yao, 2017).

1.2.3 Model-theoretical approach

The foundations of this method are two language concepts: "model theory" and "compositionality." Model theory states that sentences refer to the world, as in grounded language, but compositionality states that the meanings of parts of a phrase may be combined to derive the overall meaning. Full world representation, complex semantics, and end-to-end processing are all advantages of a model-based approach, but the fundamental downside is that it necessitates hand-engineered features (Liang, 2017; Yao, 2017).

1.2.4 Interactive learning

This is the fourth method, which is based on a remark by Paul Grice, a British linguist who describes language as a game between a speaker and a listener. This, according to Liang, is a realistic strategy for addressing both the breadth and depth of language learning. As a result, he argues that rather than aiming to create stronger models, language comprehension efforts should be focused on building a better environment for computers to learn language interactively (Liang, 2017; Yao, 2017).

A dialogue manager (DM) is a component of a dialog system that is in charge of the conversation's state and flow. The DM is described as an "oversight module" that facilitates discussion with participant involvement (Williams, 1996). To do this, it must take user input via NLU and create system replies to the NLG on a concept level. The reaction it picks will be determined by the approach selected; this is yet another aspect of the DM's responsibilities. Strategies are concerned with maintaining the state of a conversation and the capacity to model the dialogue structure beyond a single statement (Martin and Jurafsky, 2009). The importance of dialogue management is defined by Larsson (2002). He claims that in order for Dialogue Systems to create flexible discussions with users, they must be implemented using "acceptable theories of dialogue modelling and dialogue management" Skantze (2007) believes that the tasks of the DM may be characterised into three groups:

i. **Contextual interpretation**—the ability to resolve ambiguous and referring phrases.
ii. **Domain knowledge management**—ability to reason about the domain and access information sources
iii. **Action selection**— the process of determining what to do next.

According to Andrey Zimovnov of the Higher School of Economics (HSE) National Research University, the DM has two primary responsibilities: state tracking and policy learner. The conversation manager, as a state tracker, is in charge of accessing an external database or knowledge base, tracking the evolving state of the discussion, and constructing the dialogue system's state estimation. In contrast, the Policy learner takes state estimation as input and chooses a conversation action (Coursera, 2018).

NLG is the process of generating natural language from a machine representation system, such as a knowledge base or a logical form. In our case, the DM system is referred to as the knowledge base. Language generation is in charge of providing a response to the user after each input/query/utterance. According to Reiter and Dale (2001), natural language production is a branch of AI and computational linguistics that focuses on computer systems that can generate understandable text in human languages. NLG systems use knowledge of language and its applications to automatically generate papers, reports, explanations, help messages, and other types of documents, typically starting with a non-linguistic representation of information. Traditional natural language creation strategies rely on hand-crafted templates and rules that necessitate knowledge of specific linguistic representations. Some of these techniques include rule-based (Mirkovic et al., 2011), corpus-based n-gram models (Oh and

Rudnicky, 2000), and a trainable generator (Stent et al., 2004). Techniques based on recurrent neural networks (RNNs) have recently shown promise in addressing NLG challenges.

RNN-based models have been used in NLG as a joint training model (Gardner et al., 2018; Tran and Nguyen, 2019; Wen et al., 2015) and an end-to-end training model (Wen et al., 2016). Annotated datasets for specific dialogue acts (DAs) are a common source of difficulty in such systems. The previous RNN-based models were also conditioned on a one-hot vector representation of the DA to ensure that the generated utterance accurately represented the intended meaning of the provided DA. Wen et al. (2015) used a heuristic gate to ensure that all slot-value pairs were captured correctly during generation. Following that, Wen et al. (2015) developed a semantically conditioned long short-term memory (SC-LSTM) generator that learned both the DA gating signal and the language model. To solve NLG tasks, encoder-decoder networks (Vinyals and Le, 2015; Wang et al., 2015), particularly attentional-based models (Mei et al., 2015; Milhorat et al., 2019; Wen et al., 2015), have recently been investigated.

Approaches based on the Attentional RNN Encoder-Decoder (Bahdanau et al., 2014) have also demonstrated improved performance on a variety of tasks, such as image captioning (Wang et al., 2015; Yang et al., 2016), and text summarisation (Nallapati et al., 2016; Rush et al., 2015). The approaches to building dialogue systems can be divided into two broad categories: handcrafted and machine learning.

Handcrafted

Handcrafted systems use rules and decisions that have been programmed mostly by a domain expert or developer of the system. The main benefit of implementing handcrafted rules is the simplicity with which they can be produced. Some of the studies in this area include the work by Burgan (2016) and Harms *et al.* (2018). The handcrafted methods highlighted in the literature include: the Finite state method, Information state, Rule-based, Frame-based, Plan-based and Agent-based.

Machine learning (ML)

Machine learning approaches are sometimes referred to as data-driven since they rely on vast datasets to generate conversation tactics. These systems are dynamic because they can frequently apply their learning algorithms while engaging with the user. However, they still need to go through a bootstrapping phase (e.g., reinforced learning) before they can communicate effectively. The following are some of the ML methods that have been used to pick conversation actions: Markovian models, Bayesian networks, and neural networks (Harms *et al.* 2018).

Following a thorough and critical review of the literature, it is clear that no chatbots in Yorùbá language exist. The purpose of this paper is to build a viable task-oriented dialogue system for the Yorùbá language, facilitating further research in the sector and capitalising on the already accomplished milestones. A dialogue system in Yorùbá will also redefine the way speakers of the language interact with computers and potentially pave the way for other relevant contributions. The potential beneficiaries from this work are the 30 million speakers of Yorùbá in Nigeria and around the world.

2.0 MATERIALS AND METHODS

2.1 Materials

Typically, in building chatbots, two major components are implemented: software and hardware. This study was implemented using Python on HP Laptop computer.

2.2 Methods

To fabricate a model that can satisfactorily deal with the Yorùbá language, a linguistic understanding of the language is vital. In this study, a methodology that combines both a data-driven component with a rule-based component was utilised. This is done by using collected data to inform the development of rules. In an absolutely data-driven approach, the model is flooded with data and permitted to respond to it, providing insight into future data. A purely rule-based approach requires far reaching understanding of how the Yorùbá language works. Attempting to initially secure this aptitude would take excessively lengthy. Hence, consolidating the two methodologies seem like the best other option. The methodology of this investigation is as displayed in Fig. 3

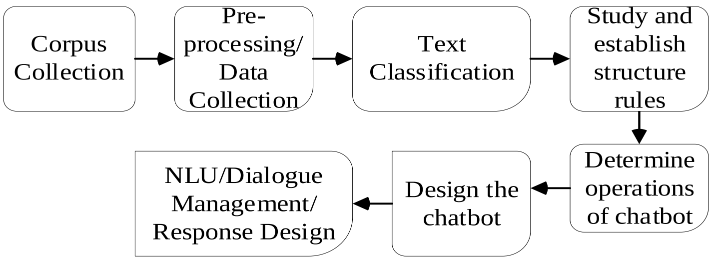

Figure 3: Flow diagram of the chatbot methodology

2.2.1 Yorùbá corpus collection

Text samples were required for the study of the Yorùbá language model. The text samples for this study were obtained online from Twitter users via Google forms, which were used to collect prompted sentence types.

2.2.2 Pre-processing/ Data cleaning

This task entailed preparing the text samples obtained for use in the study. The text corpus gathered in the manner described above was pre-processed to remove non-Yorùbá words and correct misspelled words. The corpus was also whitespace tokenised to aid in the analysis of each word and its context.

2.2.3 Text Classification

The goal of this step in the methodology process is to categorise or classify pieces of text. Text classification is a popular task in NLP because it is used in a variety of operations. In this study, text classification was accomplished through semantic tagging of the most frequently occurring words in the corpus. This functioned as part-of-speech tagging as well.

2.2.4 Study and establish structure rule

Based on the corpora and papers on the morphology of Yorùbá words, verb sorting, and sentence structure, researchers were able to determine which structural rules should be used in their investigation. In this case, the rule used word-lists / word-bags as sentence-type markers. Within word-bag, each utterance was cross-examined to determine whether the sentence was imperative, declarative, or interrogative. Then, depending on the type of sentence identified, operational rules are defined to split sentences into intent and entity.

2.2.5 Determine the operations of the chatbot

Before beginning any actual work on building the dialogue system, it was necessary to identify and highlight the purpose and operations of the dialogue system. Sọ̀rọ̀'s architecture was designed to be adaptable to a variety of operations. It performs the following operations: Respond to greetings (Ìkíni), small talk (Báwo ni, kíni orúkọ ẹ), tell the time and date, and answer basic math questions.

2.2.6 Design of Chatbot Architecture dialogue flow and Conversational approach

Sọ̀rọ̀'s architecture was designed in such a way that it engaged every utterance that could not be classified under any of the preliminary tasks as a search query. The conversation was supposed to start with time-sensitive greetings, then move on to the task at hand, and then engage in brief conversation. The remainder of the exchanges followed this pattern: Utterance split (into sentences) → sentence identification → sentence processing (split into intent and entity) → parse intent via task manager script → return result → response generation.

A Chatbot can be designed to give the aspired intellectual response to a natural language speech conversation. The input to this Chatbot is the text received from the user, while the output is the programmed response, which will be, for example, an application running or any other text or speech response (Abdul-Kader and Woods, 2015).

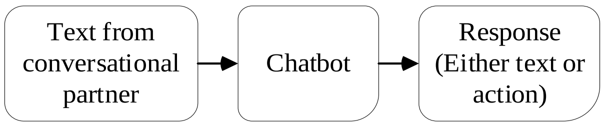

Figure 4: Chatbot interface between input and output (Abdul-Kader and Woods, 2015)

2.2.7 NLU Engineering, Dialogue Management and Response Design

Both Sọ̀rọ̀'s NLU and NLG scripts worked by utilising the bag-of-words scripts that served as Sọ̀rọ̀'s vocabulary. The rules responsible for understanding utterances and generating responses were housed in the NLU and NLG scripts. The dialogue was managed in three auxiliary scripts: task manager scripts, properties scripts, and the main script. When the NLU script identified an imperative sentence, the task manager script was called, and when the NLU script identified an interrogative sentence, the properties script was called. In both cases, the NLG receives the results and generates an appropriate response.

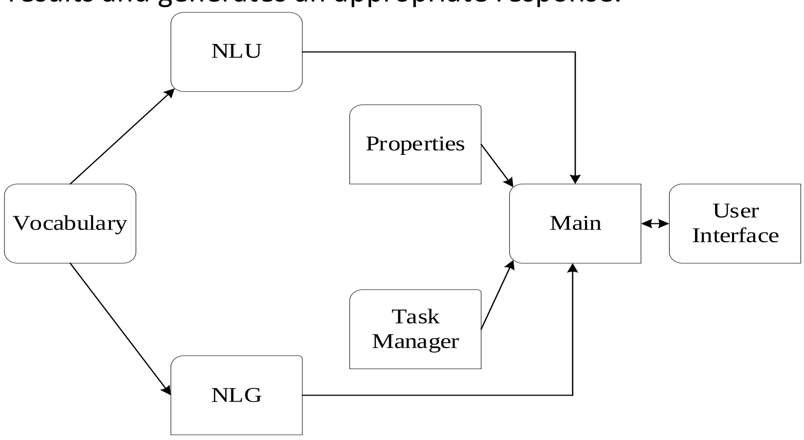

Figure 5: Architecture of Sòrò's scripts

3.0 RESULTS AND DISCUSSION

After the various twits were collected from Twitter and data cleaning was carried out on them, the sample of the cleaned data is shown in Table 1.

The rules implemented for the Sọ̀rọ̀ chatbot were used to design the architecture of the dialogue system. This architecture had two parts.

- Conversation Initiation.
- Tête-à-tête.

1.) **Conversation initiation:** consisted of a function that leveraged on established sentence concepts in the NLG script to commence an exchange between Sọ̀rọ̀ and the user. The exchanged was such that the NLU script did not do any processing because the responses were anticipated by Sọ̀rọ̀. In the case that a user's utterance did not fall in par with Sọ̀rọ̀'s expected response, the dialogue system broke out of the conversation initiation function and into a loop of NLU and NLG exchanges; the tête-à-tête. By the end of the conversation initiation function, Sọ̀rọ̀ would have completed 2 out of the 5 tasks it was aimed to equip her with performing: Greeting and small talk.

Table 1: A sample of cleaned Yorùbá corpus

English	Yorùbá
Good morning	Ẹ káàárọ̀
Good afternoon	Ẹ ká àsán
Good evening	Ẹ kú rọ̀lẹ́
	Ẹ ká alẹ́
Good night	O da aarọ
Goodbye	O da abọ
Welcome	Ẹ káàbọ̀
Hello	Báwo ni?
How are you?	Ṣe daadaa ni o wa? (*Are you good?*)
	Ṣe o wa dada? (*Are you ok?*)
	Bawo ni? (*How are things?*)
	Ṣálàáfíà ni? (*Is it peace?*)
Reply to 'How are you?'	Mo wa daadaa, o̩ se. Iwọ naa n kọ?
What's your name?	Kí ni orúkọ ẹ?
	Kí ni orúkọ yín?
	Kí lorúkọ ọ̀ ẹ?
	Kí lorúkọ yín?
My name is ...	Orúkọ mi ni …
	... ni orúkọ mi
I'm from ...	Mo wa lati ...
Pleased to meet you	Inu mi dun lati mọ ọ
What is the time?	Kini aago sọ
What is one plus two?	Kini okan ati meji je

2.) **Tête-à-tête:** In the tête-à-tête segment of the dialogue session, Sọ̀rọ̀ performs the three main dialogue system tasks: NLU, task manager and NLG. In language understanding it follows the flow as illustrated earlier:

Utterance split (into sentences) → sentence identification →sentence processing (split into intent and entity) → Parse intent through task manager script → return result → Response generation.

A cross section of a simple interaction with Sọ̀rọ̀ is shown in Table 2.

Table 2: A cross section of a simple interaction with Sọ̀rọ̀

```
========== RESTART: C:\Users\User\Documents\Soro-A-chatbot\main.py =
e kaaro
ko esi> e kaaro
bawo ni
ko esi> mo wa dada
ki le fe
so nkankan>kini ojo eni
ibere le bi

Monday 15 10 18
so nkankan>kini aago so
ibere le bi
akoko ti koja ago 7 pelu iseju 30
so nkankan>kini oruko e
ibere le bi
Oruko mi ni Soro
so nkankan>kini okan ati meje je
ibere le bi
8
so nkankan>
```

This research set out to utilise a rule-based method in the development of a dialogue system. To achieve this, a road map was drawn out. This road map substantially included some comprehensive research into the structure of the Yorùbá language (as comprehensively as was possible without taking a formal degree). The insight acquired from this research was compared with patterns identified in crowd-sourced Yorùbá sentences. This paper was then able to define rules that could identify with up to 66.7% accuracy the type of sentence contained within a sample utterance. The precision of this classification was as high as 94.7%. This result is positive as compared to the work by Haruna et al. (2020) who worked on Hausa intelligent chatbot system. Their result was presented in form of how people were able to differentiate if they were chatting with humans or computer. 90% of the students could not differentiate if they were chatting with humans or computer, while 78% experts could not do the same. The classification rules aided the development of rules that could split sentences depending on their type into intent and entity. The intent-entity extraction model is very important in NLU and Sọ̀rọ̀'s ability to achieve this even to a small degree spelt a huge potential for further studies to attain higher levels of success. The bulk of work done in this research work was in defining rules for the NLU engine of Sọ̀rọ̀ to achieve a decent level of success. This is not to imply that NLG is less significant or more difficult, although, it may be true. It is however a little trickier to express to any degree the efficiency of the NLG engine designed. The rules were less flexible because they had to be defined in specific contexts. There was also no metric to measure the success of the NLG outside its ability to generate the responses fed to it by the dialogue manager.

The chatbot was tested and the results obtained is shown in Table 3.

After the testing of the chatbot, Sọ̀rọ̀ was able to correctly classify 66.7% of the sentences in the test corpus used. It classified only 3.7% wrongly which means it had roughly a 94% precision. Moreso, 29.6% of the sentences in the test corpus were not classified to any of the sentence types.

Table 3: Challenges faced, and solutions proffered during this research

Challenges Faced	Initial Precision	Solution	Improved Precision
Missing words Imperative sentences	60.0%	Added words to script	89.0%
Proper noun use	-	Requires further research	-
Word position influence	40.0%	Rewrote structure rule for declarative sentences	66.7%

4.0 CONCLUSION

Based on the findings of this research work, the following conclusions can be drawn: Whilst it is possible to define a rule to correctly classify all the sentences of either the imperative or the declarative nature, any such rule would have a poor degree of precision. In defining rules for sentence classification, it is preferable to favour a higher level of precision as opposed to a higher level of accuracy. This idea is likened to the occurrence in machine learning where it might be sometimes favourable to minimise false positives as against maximising true positives. The Yorùbá language shares enough similarities with other languages that if a substantial amount of corpus can be gathered, a machine learning used for any other language would most probably achieve similar levels of success for Yorùbá. The Extraction of intent and entity differs depending on the type of sentence being classified. The declining usage of standard Yorùbá causes discrepancies in the data used in this study and further research would have to consider methods to reconcile these discrepancies to be able to maximise efficiency. Creating this Chatbot system would propel the Yorùbá language into the realm of artificial intelligence, and it would serve as a resource for future research and development.

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