Amadioha: An Open Domain Question Answering Tool for Encouraging Citizen Participation in Developing Countries.

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Abstract

In Nigeria, a steady decline of voter participation over the last two decades reflects a larger challenge of low citizen participation. For citizens to participate, they must be adequately educated and engaged on critical institutions in the country. In this work, we introduce *Amadioha*, an open domain question answering (QA) tool designed to improve citizen engagement by answering natural language questions related to institutions in Nigeria. It is built using a two-stage process where relevant documents are identified using information retrieval techniques, and a neural network model is subsequently used to identify answers within documents. As part of the project, we also introduce a novel dataset - *NigeriaNews* - which contains 1.3 million articles written between 2009 and 2019, sourced from reputable Nigerian news websites. We hope the dataset will foster further research and NLP product development for the Nigerian community.

1 Introduction - Citizen Participation in Nigeria

In February 2019, Nigeria held her presidential election followed by governorship elections in each of the 36 states. However, voter participation was reported at approximately 37% - the lowest in the history of the country [1]. This follows a historically declining level of voter participation over the last two decades in the country and is representative of a larger challenge of low citizen participation. Citizen participation which advocates for the involvement of private individuals in the decision making process of a nation has been identified as a critical ingredient for a successful democracy. However, in order to participate, citizens must be adequately educated and engaged on the issues facing critical institutions (such as healthcare, governance, judiciary, security, and education) within the country. More importantly, this education needs to move beyond engagements during election cycles towards a sustainable and continuous model that can be used by various stakeholders such as educators, activists, policy makers and government agencies.

These reflections motivate the need for (technology) tools that enable citizen education. In this work, our approach is to design an interface that enables citizens "ask natural language questions",

* (webpage, alternative address)—*not* for acknowledging funding agencies.

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effectively enabling an inquiry based approach to education. With the rise of large repositories of potentially trusted text data (online news outlets, government websites etc) and with advances in natural language processing (NLP), it is now possible to build intelligent interfaces that can ingest these textual data and automatically generate answers to questions during an educational inquiry session.

2 Related Work

http://www.nancyotero.net/creature-machine-learning-for-human-learning.html

This work cuts across several research domains which have been reviewed - citizen participation, conversational agents and natural language processing, and educational tool design. There is currently no existing educational tool that aims to encourage citizen participation using conversational agents and natural language processing altogether. There are, however, pioneer tools in citizen engagement, AI conversational agents and Natural Language Processing. As such, the existing work in each of the research sub-domains of this project will be examined separately - Citizen Participation, AI conversational agents and Natural Language Processing (NLP), AI Conversational Agents and Education, and Educational Tool Design and Inquiry-based learning.

2.1 Technology Tools for Citizen Engagement

BudgiT:[2] This is a Nigerian civic organization that utilizes blended social advocacy and technology tools to intersect citizen engagement with institutional improvement, with a view to aiding societal change. It uses refined data mining to innovatively represent data and empower citizens to use the resulting information in demanding improved service delivery, with the primary goal of raising the standard of transparency, accountability and fiscal inclusion in the extractive industries, while also supporting government, media and civil society institutions. Tracka[3] is one of BudgiT's project-tracking tool. It allows Nigerians to upload pictures of developmental projects in their communities, with BudgIT's project officers aiding citizens offline to communicate with their elected representatives, and demand completion of the government projects in their neighbourhoods. FixOurOil.com[4] is a BudgiT initiative which aims to enhance citizen engagement, encourage stakeholder accountability, provide beneficial ownership, monitor oil and gas legislation and provide key data and analytics leading to reforms in the oil and gas industry in Nigeria. OpenAlliance Nigeria:[5] This is a group of civil society groups in Nigeria which seek to promote good governance in Nigeria. OpenAlliance Nigeria provides a platform which allows Civil Society Organizations to report and document their roles in government partnership processes.

2.2 Inquiry Based Learning

Edelson et al (1999)[6] outline five significant challenges to employing inquiry-based learning and present strategies for addressing them through the design of technology and curriculum. They also present a design history covering four generations of software and curriculum to show how these challenges arise in classrooms and how the design strategies respond to them. Healey (2005)[7] examines the strict spaces in which the connections between research and teaching are developed, while reasoning that some of the complexity and contested nature of the connections between research and teaching show variances in the way that the terms are preconceived. His work shows that students are likely to benefit more from research when they are also involved in research through various forms of active learning, such as inquiry-based learning. Kirschner et al (2006)[8] provide evidence for the superiority of guided instruction as explained in the context of their knowledge of human cognitive architecture, expert–novice variances, and cognitive load. According to them, evidence from empirical studies over the past half-century consistently show that minimally guided instruction is less effective and less efficient than instructional methods that place a strong emphasis on guidance of the student learning process. Spronken-Smith et al (2010)[9] examined the potential of inquiry-based learning to reinforce the teaching–research link by analysing three case studies, which are essentially structured, guided and open inquiry course modules.

2.3 AI for Improving Educational Experiences

Graesser et al (2001)[10] present a new generation of intelligent tutoring systems that hold mixed-initiative conversational dialogues with the learner. The tutoring systems present stimulating problems and questions to the learner, the learner types in answers in English, and a lengthy multiturn dialogue is presented as complete solutions or answers evolve. Kerlyl et al (2006)[11] discuss the development and capabilities of the Open Learner Modelling (which unites work in several areas - chatbots, natural language processing in an educational dimension, intelligent tutoring systems). Open Learner Modelling has been advanced to support student reflection on their learning, where the system's model of the user's knowledge is shown to the user, to encourage student reflection on their learning. Aleven et al (2003)[12] perform a selective review which (1) inspect theoretical perspectives on the position of on-demand help in Interactive Learning Environments (ILEs), (b) examines literature on the connection between help seeking and learning in ILEs, and (c) determines reasons for the lack of effective help use. Chatbot systems are not only built to mimic human conversation. Shawar et al (2007)[13] investigate other applications of chatbots. A range of chatbots with useful applications, including several based on the ALICE/AIML architecture, are presented in their work. Jia (2009)[14] present the system architecture, underlying technologies, and the educational application results of CSIEC (Computer Simulation in Educational Communication). CSIEC, with newly created functions for English instruction, focuses on supplying a virtual chatting partner (chatbot), which can chat in English with the English learners anytime and anywhere. Benotti et al (2014)[15] proposed a software platform called Chatbot which is built to promote engagement while teaching basic computer science concepts. They also carried out two experiments using Chatbot and Alice in: 1) an online nation-wide competition, and 2) an in-class 15-lesson pilot course in 2 high schools. The results show that retention and girl interest are higher with Chatbot than with Alice, indicating student engagement had occurred. Pereira (2016)[16] presents the design and implementation of a Telegram bot, @dawebot, a learning application for training students in any subject using multiple choice question quizzes. The bot is also evaluated in a 15 week long subject with 23 Computer Science students. This evaluation documents the students' opinion about this bot and the usage of bots in the eLearning area. According to Winkler et al (2018)[17] past research has shown that the efficacy of chatbots in education is complex and is dependent on a range of factors. The authors make two principal contributions: first, they structure and synthesize past research by using an input-process-output framework, and secondly, they utilize the framework to indicate research gaps for guiding future research in that area. Singh (2018)[18] shows that artificial intelligence and chatbots are influencing education and are providing benefits such as intelligent tutoring through chatbots; enhanced student engagement through communication platforms; smart feedback for improving learning; teaching assistance by monitoring students' learning and other aids; providing students with instant help; providing enhanced student support; and information management for educational institutions.

2.4 Natural Language Processing

Burstein (2009)[19] described two systems, e-rater® and Text Adaptor, are examined as illustrations of NLP-driven technology. They present nascent opportunities for natural language processing (NLP) researchers in the development of educational applications for writing, reading and content knowledge acquisition. Manning et al (2014)[20] describe the design and use of the Stanford CoreNLP toolkit, a core natural language processing analysis extensible pipeline toolkit, widely used in the NLP research community and in commercial and government circles in open source NLP technology. In their work, the advantages of the toolkit include a simple, approachable design, straightforward interfaces,and the inclusion of robust and good quality analysis components. Graesser et al (2014)[21] describe some intelligent tutoring systems where agents communicate with students in natural language while being aware of their cognitive and emotional states. These systems comprise tutorial dialogues, conversational trialogues in which two agents (a tutor and a "peer") communicate with a human student, and other conversational ensembles. Devlin et al (2018)[22] introduce BERT (Bidirectional Encoder Representations from Transformers). BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context (or text sequence) in all training layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create ultra-modern models for a wide range of tasks, such as question answering and language deduction. Gao et al (2019)[23] examine neural approaches to conversational AI that have been developed in the past few years. They classified conversational systems into three categories - (1) question answering agents, (2) task-oriented dialogue agents, and (3) chatbots.

For each category, they present an analysis of neural approaches, draw the linkage between these approaches and traditional approaches. Radford et al (2019)[24], in their work, introduce a Dialog Agent based on OpenAI GPT and GPT-2 Transformer language models. This tool uses a large-scale pre-trained language model, called OpenAI GPT or GPT-2, combined with a transfer learning adjustment technique. This dialog agent possesses a knowledge base which stores a few sentences describing who it is (persona) and a dialog history. When a new utterance is received from a user, the agent combines the content of this knowledge base with the newly received utterance to generate a reply.

In the domain of NLP, it is common to have specific datasets built to foster research in a given area or for a given domain. For example Google News/parliament news was useful for linguistic analysis of American history and biases, Pub Med Abstracts and MCMII datasets have enabled research on medical text data analysis [25] etc. However, there are no public repositories that have been designed and are actively maintained for understanding human interactions for developing countries. The Nigerian News corpus takes a first step in this direction.

3 Amadioha Tool Design

Our goal with Amadioha is to build an interactive tool that supports inquiry based learning [12] such that users can ask natural language questions related to institutions within Nigeria and receive fact based answers where possible. To this end, we assemble a novel dataset, and leverage this in building a QA interface.

3.1 Question Answering Model

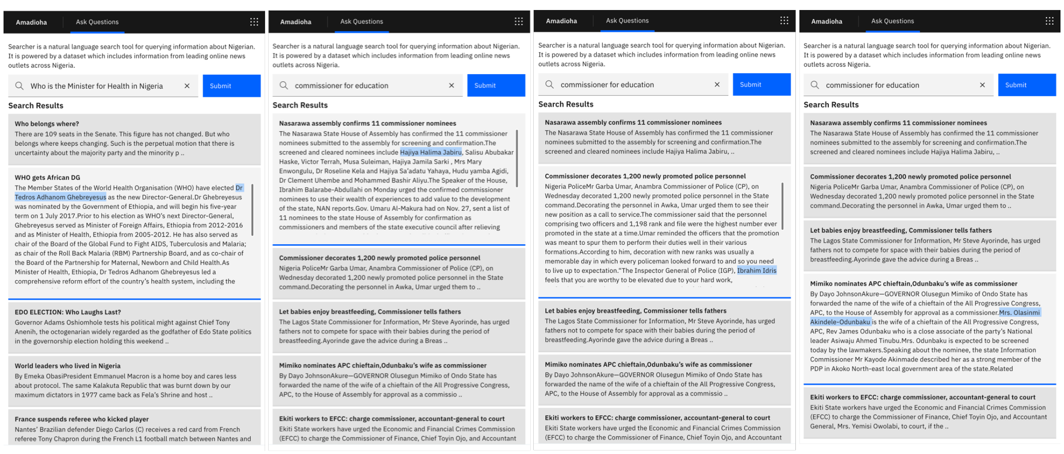

Figure 1: Screenshots from the Amadioha tool interface show a list of documents returned in response to natural language queries by users. Users can select each document and our QA Model can then identify what subset of the passage contains an answer to the question.

Similar to existing work in this area [26, 27], we use a two-stage approach. First we use traditional information retrieval solutions (Apache Solr) in extracting a subset of relevant documents from our corpus. Next, we use a BERT-based neural QA [22] model fine-tuned on the SQuAD datasets [28, 29] to extract subsets of each document that may contain answers to questions and display them to the user. Finally, we built a web application (see Figure 1, appendix) using the React Javascript library that allows users to enter their natural language question and perform a search. Their query is then processed by Apache Solr [30] which returns the top 5 most relevant articles; for each article, our BERT-based QA model returns a prediction on the sub string within the article that contains an answer to the question. Currently, qualitative results suggest that the current approach allows a user explore answer predictions for their questions.

3.2 Model Evaluation

We created a qualitative analysis benchmark.

4 Limitations

The current implementation of the Amadioha QA system is limited by its dependence on a neural QA model trained on the SQuAD dataset [28, 29]. While this dataset is also in English and provides a solid baseline [27], there may be subtle differences in how the English language is used and word association pattern in a Nigerian text corpus as opposed to Wikipedia on which SQuAD is designed. Furthermore, due to the size of our BERT-based QA model, inference time is significant (>5s on a CPU, 0.19s on a GPU). Future work will focus on exploring the construction of a QA dataset from our *NigeriaNews* corpus. This will enable us perform fine-tuning of our BERT-based QA model and support empirical evaluation (exact match and F1 score). Next, we will explore approaches for further refining the quality documents retrieved (e.g. using passage re-ranking with Bert [31]) quantizing the resulting model and possible offline integration into mobile apps. We will also implement gamification principles and social media integration to further increase interaction and engagement with our tool. We believe this effort demonstrates first steps on how NLP techniques can be applied to the critical problem of improving citizen participation especially for developing countries.

5 Conclusion

We find ...

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6 Appendix