Alaska: Intelligent Email Assistant

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Abstract

Emails have become a part of our daily lives either for business communication or for personal use. Users can send emails to multiple individuals, making it easier to communicate information to large groups of people. Sending emails are not only a fast, cheap and efficient way to communicate but also provide an effective way to transmit electronic data, schedule meetings and set priority-based tasks to complete etc. Common voice assisted software's such as Amazon's Alexa, Apple's Siri and Google's Assistant have the ability to answer questions like "What is the weather like today?" and do tasks such as "Set my alarm for 9:00am". However, we have not yet seen the ease of sending emails through the aforementioned voice-activated assistants. In this paper, we design a product called 'Alaska' that will primarily take raw speech from a user and convert it to a structured email which can be further tweaked for minor changes and then sent to the recipient. The intelligent assistant makes use of pattern matching, text classification and question answering to interact with what the user says to the system. The system in response either carries out the instruction or asks a following question to clarify what it has been asked of.

Keywords: Intelligent Systems, Email Assistant, Speech Recognition
Github: github.com/umar1997/Alaska_Email_Assistantt

1. Introduction

In the last few decades, technology enhancements have revolutionized the way of communicating effectively. The Internet has played a vital role in communication, making it easily accessible for everyone worldwide [1]. Email is the most formal and professional way to communicate reliably and share confidential information.

Drafting an email or providing instant responses is usually not feasible for most people with their busy schedules. Providing convenience and saving time are the two important characteristics of any Artificial Intelligence (AI) based system [2]. The AI-based systems exploit Natural Language Processing and Speech Recognition to interact and understand human voice and language by extracting meaningful features such as keywords and expressions [3].

State-of-the-art voice assistants such as Amazon's Alexa, Google's Assistant, Apple's Siri are more general-purpose assistants which manage to carry out multiple tasks which are clearly shown in Table 1. The aforementioned products are extraordinarily efficient in recognizing a users voice, answering their queries and performing general-purpose tasks as simple as setting the alarm on your mobile device [4]. However, they all lack in providing more task-specific functionalities i.e., sending an email to one or many recipients with the main text of the email body via voice instruction. Thus, our product's intention is to create an AI-based task-specific tool that offers more features and flexibility to users by allowing them to send an email via speech. Our main objective is to develop a product that can securely, time-efficiently and effectively send emails with a performance as good as those of state-of-the-art voice-assistants.

Most of the existing voice-based email systems are designed using rule-based or pattern matching algorithms [5, 6]. The proposed system, on the other hand makes use of advanced deep learning methods such as text classification and question answering along with effective use of state-of-the-art speech recognition models to recognize what has been said more precisely. The QA system within our product pipeline intelligently maps and fetches the most relevant excerpts from the speech input.

We aim to create a more interactive, versatile, flexible tool for the ease of the user. Our proposed product collects raw speech from the user and through a Speech-to-Text model convert the user's speech into text. This unstructured textual representation of voice can contain noise or other information for an assistant to help distinguish various components of the email. The classifier module classifies the unstructured text into either a 'Email' or a 'Command'. Based on the class predicted the text is passed onto

Features	Siri	Cortana	Alexa	Google Assistant
Play music	✓	✗	✓	✓
Set alarm	✓	✓	✓	✓
Search the web	✓	✓	✓	✓
Make calls	✓	✓	✓	✗
Look up directions	✓	✗	✗	✓
Read emails	✓	✓	✓	✗
Send emails	✗	✗	✗	✗

Table 1. Comparision of Existing Voice Assistants.

the QA system or text classification model. Finally, after the email is properly extracted into it's various components, the text is post-processed and cleaned for formality and is ready to send to the recipient. Details on the entire pipeline are further discussed in detail in Section 4

The proposed approach consists of following contributions.

1. Designing and building a model with a novel architecture using state-of-the-art models to send emails via speech.
2. Creating a Web-platform and deploying it which hosts the service for people to test the product on a daily-basis for intelligent email assistance.
3. Fine-tuning spanBERT [7] QA model to extract and provides relevant answers to fundamental questions regarding the layout and content of the email
4. Creating a QA dataset for the problem we wish to solve from an existing email dataset.
5. Binary and Multi-Text classification which allows to differentiate between general commands given to the system from email text.

2. Related Work

2.1. Conversational Question Answering

Conversational question answering (CQA) is a sub-domain of QA systems. Traditional QA systems engage with the user in a single-turn: *user ask, system respond* setting, which is counter intuitive to how most real-world conversations take place. CQA provides a more natural, multi-turn *system ask, user respond* setting, where the user interacts with the system repeatedly and the system asks various follow-up questions to clarify the user's needs. CQA systems are broadly categorized into two categories: sequential knowledge-base question-answering (KB-QA) systems and conversational machine reading comprehension (CMRC) systems [8].

Sequential KB-QA systems are an extension to KB-QA systems, they iteratively query a structured KB such as Freebase [9], DBpedia [10], NELL [11], Wikidata [1], etc to model complex sequential question answering. Dynamic Neural Semantic Parsing DynSP [12] tackles the problem of sequential QA by formulating a weakly supervised reward-guided approach. The model is trained on SequentialQA, a dataset collected from decomposing WikiTableQuestions[2] entries into simpler sequential questions. Additionally, the authors develop a semantic parse language to map natural language into a logical form. However, DynSP fails when required to parse complex questions, especially utterances which exhibit ellipse phenomenon and need coreference resolution.

Dialog-to-Action (D2A) [13] solves the previous problem by deriving the logical form of utterances dynamically based on the current question q_i and the previous questions $q_{1:i-1}$. The task of generating a logical form is considered action generation. Consequently, the model runs into the problems of error propagation and unsupported actions, where error from previous actions is propagated to subsequent actions and examples where the model fails to derive the correct logical form. Multi-task Semantic Parsing (MaSP) [14] solves the coreference and error propagation problem by introducing a pointer-based semantic parsing model that jointly learns entity detection. The model leverages contextual information for entity type prediction and coreference resolution, which subsequently alleviates error propagation.

CMRC was introduced by [15] as an advancement over traditional MRC models which lack the conversational aspect. CMRC models include the following key functions: history selection and history modeling, encoding the given and context into embeddings, reasoning via a neural model to arrive at an answer vector, decoding the answer vector to natural language representation. Concretely, given a context, the question-answer pairs as history, and the current question Q_i, the model predicts the correct answer A_i.

Contextualized attentention based deep network (SDNet) [16], open retireval conversational question answering (ORConvQA) [17], and bi-directionational attention flow (BIDAF++) [18] are CMRC models that include history in current utterance by prepending to it the latest K rounds of conversational history turns. SDNet [16] uses both self-attention and inter-attention to extract relevant context from text passages. BiDAF++ [18] predicts the correct answer span by utilizing a layer with bi-directional attention flow followed by a biLSTM layer. ORConvQA [17] is a transformer-based end-to-end system that consists of passage retriever, passage ranker, and passage reader modules. However, these models do not account for topic return or topic shift. History Answer Modeling (HAM) [19] performs history selection based on relevancy using a weight-

[1]https://www.wikidata.org/wiki/Wikidata:Main Page
[2]https://github.com/ppasupat/WikiTableQuestions

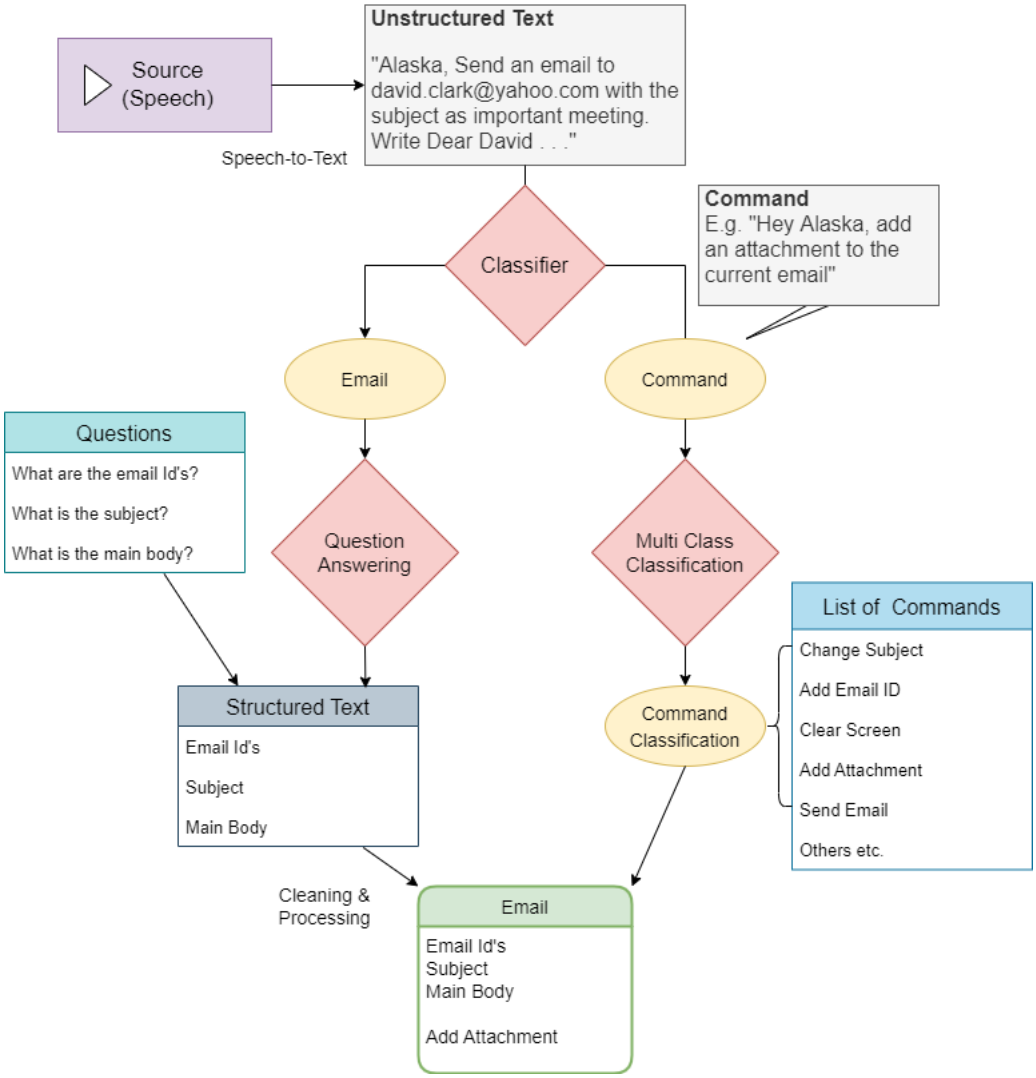

Figure 1. Alaska's architecture.

ing process.

2.2. SpanBERT

SpanBERT [7] is a modification of BERT [20] designed to predict spans of text. SpanBERT modifies BERT [20] in several ways: first, it changes the masked language model (MLM) objective to mask spans of words instead of individual tokens. Given a sequence X, the model samples a set of spans Y such that Y is 15% of X. Second, they introduce the span boundary objective (SBO). SBO predicts a span of text given the tokens at the boundary of the span. Formally, each token x_i in a span is represented using the output encodings of the two boundary tokens x_{s-1} and x_{e+1}, as well as the positional encodings of the token x_i, p_{i-s+1}. Third, they discard BERT's [20] next-sentence-prediction since the model processes a single segment of text during the training step instead of processing two. This approach removes noise from the MLM and ensures that the model can exploit longer full-length context. The SpanBERT [7] model significantly outperforms the existing baseline on question answering tasks, coreference resolution tasks and relation extraction tasks.

2.3. Digital Voice Assistants

In recent years digital voice assistants have gained prominence due to increasingly sophisticated technology incorporated in hand-held devices. They are also a popular choice for users who prefer to use voice commands to operate their phones. Siri [3], the digital assistant found on apple phones performs various tasks on behalf of the user, such as setting an alarm, reminding the user of specific tasks and

[3] https://www.apple.com/siri/

answer	context	question	email_addresses	subject	body
{'answer_start': [75], 'text': ['catherine34@g...	Alaska create an email with subject high speed...	What are the email addresses?	catherine34@gmail.com	high speed internet access	1 login pallen pw ke9davis i don t think these...
{'answer_start': [36], 'text': ['high speed in...	Alaska create an email with subject high speed...	What is the email subject?	catherine34@gmail.com	high speed internet access	1 login pallen pw ke9davis i don t think these...
{'answer_start': [127], 'text': ['1 login pall...	Alaska create an email with subject high speed...	What is the email content?	catherine34@gmail.com	high speed internet access	1 login pallen pw ke9davis i don t think these...
{'answer_start': [28], 'text': ['munozmichael@...	Hi Alaska write an email to munozmichael@yahoo...	What are the email addresses?	munozmichael@yahoo.com	original sept check closing	brenda please use the second check as my octob...
{'answer_start': [64], 'text': ['original sept...	Hi Alaska write an email to munozmichael@yahoo...	What is the email subject?	munozmichael@yahoo.com	original sept check closing	brenda please use the second check as my octob...

Figure 2. Prepared data for Span Bert QA Model

Hey Alaska send an email to david.clarke@yahoo.com with the subject as meeting tomorrow at nine. In the email say dear david hope you are doing well I am keeping the meeting for tomorrow's project alignment and proposal submission at nine am. Looking forward to seeing you there best regards Mark.
1. Who are the email recipients? 2. What is the subject for the email? 3. What is the main body?

Table 2. An example of an unstructured email voiced out by a user and the questions that our QA model will ask to structure the email

web searching etc. While Siri, in theory, can open, read and send emails. It does so with less precision, often not distinguishing the correct recipient or incorrectly formatting the email. Moreover, it still requires manual intervention from the user which is not always convenient. Other voice assistants such as Microsoft's Cortana [4], Amazon's Alexa [5], and Google's Assistant[6] suffer from similar problems when dealing with email.

3. Data Exploration and Processing

Enron Email Dataset: For our product we will use the Enron email dataset [7]. The Enron email corpus contains approximately 500,000 emails generated by employees of the Enron Corporation. This dataset was collected and prepared by the CALO Project(A Cognitive Assistant that Learns and Organizes). It contains data from about 150 users, mostly senior management of Enron, organized into folders. This data was originally made public, and posted to the web, by the Federal Energy Regulatory Commission after its investigation of Enron's collapse. Figure 3 shows a snapshot of the email data available.

We primarily used the Enron data to fine-tune our spanBERT [7] model to accurately answer which spans in the unstructured email refer to the recipients, subject and main body. This model was first trained by Hugging Face and then later fine-tuned on SQuADv1.0 [21]. For this dataset to run with the given model we had to do alot of data preparation and cleaning to get in the preferred format. Looking at the data in Figure 3 we will only be requiring the fields 'To', 'Subject' and 'Content'. To generate random email addresses we used python's Faker library [8] for the recipients for an email and to sign off with various names so that the model doesn't overfit on the limited users that sent or received emails from Enron Corporation. Furthermore, within all the fields there was a need to clean the data. For e.g. the content's include tags like 'Forwarded to ——' and 'Replied by ——' and the recipients were not in proper format as can be seen from the Figure 3. Finally, after cleaning all data fields there was a need to augment them to examples of voice instructions so that they properly match what is said by a user when they ask a digital assistant to send an email. These examples will be taken from survey from individuals who will record how they would voice an instruction to send an email. Thus, the email addresses, subject and body are inserted into a list of templates of natural lan-

[4]https://www.microsoft.com/en-us/cortana
[5]https://www.alexa.com/
[6]https://assistant.google.com/
[7]https://www.cs.cmu.edu/ ./enron/
[8]https://faker.readthedocs.io/en/master/

Message-ID	Date	From	To	Subject	CC	BCC	Content
<30866805.	7/13/2001 19:47	frozenset({	frozenset({	RTO Orders - Grid South, SE Trans,			The Southeast RTO orders ar
<26879196.	7/12/2001 11:36	frozenset({	frozenset({	More UC/CSU Info			---------- Forwarded
<15339082.	7/10/2001 0:47	frozenset({	frozenset({	California Update 07.09.01			The Bond Legislation The Der
<5265469.1	7/6/2001 20:45	frozenset({	frozenset({	Davis & Company -- incompetence			FYI ---------- Forward
<13706905.	7/6/2001 20:44	frozenset({	frozenset({	Link to DWR contract info			FYI ---------- Forward
<20784115.	6/22/2001 1:04	frozenset({	frozenset({	CPUC Proposed Decision Modifyin			In the same Decision that the
<16989362.	6/21/2001 21:29	frozenset({	frozenset({	CPUC Decis	Harry Kingerski <Harry		The following points highlight

Figure 3. Enron email dataset snapshot.

guages commanding a digital assistant to send an email. We then added the relevant fields into the randomly chosen templates and mark the fields starting and ending indices with it's respective question. So that for the question "What are the email addresses?" we will get the starting and ending indices of the emails respectively. This is then done for the other two questions and is added to the question answering dataset we feed to our Span Bert model. A snapshot of the data prepared and cleaned can be seen in Figure 2

4. Methods

To model our digital assistant product, we have designed an architecture which can be seen in Figure 1. The aim of the product is to assist individuals to send emails via speech along with other features that email sending has to offer. The input to the model or the source is raw speech from the user which is converted into text using a Speech-to-Text converter. The Speech-to-Text model used for this product is Google Cloud's Speech-to-Text [9] model. The Google Cloud's Speech-to-Text model achieves state-of-the-art accuracy on standard datasets as it makes use of extremely advanced deep learning neural network algorithms for automatic speech recognition (ASR). Using Google Cloud's Speech-to-Text model we convert the raw speech from the user and convert it into unstructured text data. This text data from here needs to be first cleaned and then passed onto the next phase of the pipeline where the cleaned unstructured is converted to structured text primarily comprising of 3 main components: email recipients, subject and main text body. Currently, the unstructured data includes trigger words like 'Hey Alaska' or has other words that user says while voicing out his email for e.g. 'Send an email to . . .' etc. The cleaning of data before sending to the binary classifier is mainly removing noise from the Speech-to-Text output and using regex.

After cleaning our Speech-to-Text output we send the unstructured text to a binary classifier which classifies whether the text is the actual email or just some command given to our product to carry out a task such as adding an attachment. For this we train binary classifier whose input is an unstructured text and output are two classes 'Email' and 'Command'. The class 'Email' refers to text that includes content such as email recipients, subject and the main body, whereas 'Command' refers to a text that includes a command that needs to be carried out such as adding an attachment or removing a recipient etc. To classify both texts we use a small hand-made dataset for the commands and used a small sample from our original email dataset for the emails. To classify both we used Scikit-Learn's [10] TF-IDF implementation to get features for the data and then use a Random Forrest classifier to train and test the model and use it within our architecture. In the scenario where the unstructured text is classified as an 'Email' from the user, it is then passed to our fine-tuned QA model which asks 3 fundamental questions from our unstructured text shown in Table 2. Here we borrow the idea of span-prediction whose concept originated from QA for machine reading comprehension (MRC). This specific type of QA model attempts to extract the correct answer of a given question from a single span within the given text. In our case, we fine-tune the SpanBERT [7] model on our emails dataset such that it extracts the answers of our 3 questions from the unstructured dataset to provide us with a structured format of the email the user wishes to send.

However, just before we send the email, there is a need to clean and process our structured data. Here we will use pattern matching to structure the email into a proper format. For example, if we instruct the Google Cloud's Speech-to-Text model via speech to "Send an email to david.clark@yahoo.com", the expected output would be "david dot clark at the rate yahoo dot com". Another example would be that the unstructured text coming in will give the main body of the email a passage-type look, we would have to begin a new line after the salutation and add a new line right before the users signature. There are other numerous examples of pattern matching that will be needed to ensure a satisfying and enjoyable user experience.

In the scenario where the binary classifier predicts the output text as a 'Command' sent to the product such as 'Hey Alaska, add an attachment to the current email'. This command is then passed onto a multi-class classification model which aims to predict the command text into pre-defined

[9] https://cloud.google.com/speech-to-text

[10] https://scikit-learn.org/stable/

commands whose command classes can be seen in Table 3. The model takes the words of the commands and converts them into pre-trained GloVe word embeddings. The embeddings for each word in the command are then added and normalized and their sentence embedding is calculated. The sentence embedding is compared with the command class key words and the cosine similarity is taken between the two. The class that outputs the highest similarity is chosen as the command and the command is propagated to the platform which conducts the corresponding action. Suppose the classifier predicts the 'Add Attachment' command from the unstructured text, this instruction will be then sent to the platform to carry out that task by opening the attachment prompt. Finally, when the user has constructed his entire email and wishes to send it he can instruct trigger the 'Send Email' command to do so.

Commands
Add Signature
Add Email Recipient
Clear Email
Send Email
Add Attachment

Table 3. List of Classes of Commands

5. Results and Discussion

There are four main models in our application, namely:

1. Google's Speech-to-Text which is a state-of-the-art library used to transcribe acoustic speech data. The speech-to-text API usually processes audio faster than real-time. Statistical studies conducted as of 2021 show that Google's STT API's accuracy is about 79%, much higher than competitors in this area such as Microsoft and Amazon [22].

2. A binary random forest classifier that classifies unstructured data into two classes: email or command. We compared it to a support vector classifier, multinomial Naive Bayes, as well as logistic regression. We found that the random forest classifier gave the best results. As of right now the accuracy of this model is estimated to be 100%.

3. Pre-trained SpanBert [11] which we fine-tune on the Enron email dataset. We chose SpanBert as it has shown empirically better results than Bert. The F1 and exact match scores of this model are highlighted in table 4

While we use SpanBert to enhance the accuracy of our question answering model, the questions used to extract the relevant parts are always the same. If the user does not follow the specified rules when sending the email, the question answering model may fail. Our audio recording functionality at this time is specific to Mozilla Firefox. For reasons that we don't currently understand it produces unexpected behaviour with other browsers. This needs to be investigated in the future. Furthermore, the data we used to fine-tune our model was specific to a company, the model would have produced much better results if we had obtained a more general purpose dataset. However, to the best of our knowledge such email dataset does not exist currently. Finally, the app requires to integrate more functionalities that are out-of-scope for our project but will help make it more user friendly and on par with the state-of-the-art voice assistants. For example, the user should be able to operate the app entirely based on voice commands, the email should be auto-formatted without user assistance and the app should automatically infer the subject from the email content without the user saying "Hey Alaska send an email to ... with the subject ...".

F1	Exact Match
85.13	76.74

Table 4. SpanBert Evaluation Scores

6. Conclusion

In this paper, we attempt to find a solution to sending an email via speech. Many giant companies have created digital assistants for the ease of the user which help them on a daily basis. However, non of these renowned digital assistants have worked on sending emails via speech. The task of sending emails is also one that an individual performs everyday at his work place. To create ease for the user we have designed a novel architecture which takes the raw speech of the user and converts it into a proper structured email. Our main contributions include building and designing a model with novel architecture to send an email via voice. We further created a platform for the product where we can test sending emails via speech. Lastly, we created a question answering dataset for these emails from existing email datasets. The model and the product use state-of-the-art components within the architecture which helps with the improved performance of the digital assistant. To achieve the structuring of the email our fine-tuned QA model gets a EM and F1 score of 76.74 and 85.13 respectively on our custom dataset. Future works include improving the Speech-to-text for our specific problem of voicing emails to the system, improving the extraction of the e3 components of the email text and finally adding more functionality to the final product.

[11] github.com/huggingface/notebooks/blob/main/examples/

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