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Smart Meeting Assistant: An Extractive Text Summarizer

Apoorva Dharadhar[1], Shreya Mangade[2], Samir Kapure[3], Geetha Chillarge[4]
[1, 2, 3]UG Student, [4]Assistant Professor, Department of Computer Engineering, Marathwada Mitra Mandal's College of Engineering Pune, India

Abstract: Be it any institution or organization, meetings are conducted on a daily basis. There is a possibility that a person may attend more than one meeting in a day. People try to note down important points as the meeting proceeds. It may happen that the person in the meeting misses out on some important points in a hurry of taking notes. The smart meeting assistant will give a simpler way to review what happened during the meeting. It will be possible for people to get an overview of the important points discussed during the meeting by just reading the summary generated by the assistant. The participants of the meeting can worry less about taking notes for later and focus more on what is more important, like building client relationships, brainstorming ideas or taking business decisions. Automatic text summarization is an interesting field of NLP but is also very challenging. The Smart Meeting Assistant is implemented by using Google Speech to Text API and is developed in Python. Summary is generated with the help of an extractive unsupervised machine learning algorithm called TextRank.
Keywords: Google Speech to Text API, Python, Automatic Text Summarization Technique, Natural Language Processing, Unsupervised Machine Learning Algorithm, TextRank.

I. INTRODUCTION

The Smart Meeting Assistant is implemented using Google Speech to Text API and is used for converting the audio recording of the meeting into text. While the audio is converted into text, speaker diarization takes place. Speaker diarization is the process in which the mapping of speaker to speech takes place. After the transcript is ready, it is sent for further summarization. There are two types of text summarization, extractive text summarization and abstractive text summarization. The extractive text summarization method relies on extracting important sentences from the text.

Whereas, in abstractive text summarization advanced Natural Language Processing techniques are used to generate an entirely new summary. So, some parts of the summary may not appear in the text. Abstractive text summarization can be implemented using supervised machine learning algorithms, where the model can be trained on human generated summary. In this project we have implemented an unsupervised machine learning algorithm called TextRank. TextRank is inspired from PageRank. In PageRank, the webpages are ranked and to rank these pages a score is computed called as PageRank score. This score is nothing but the probability of a user visiting that page.

II. LITERATURE SURVEY

There are many approaches to text summarization. We mainly focused on extractive text summarization. Narenda Andhale and L.A Bawoor [1] in their paper presented a comprehensive survey of both the approaches in text summarization. In [2] the relationship between text mining and text summarization is considered. A review of some of the text summarization techniques and evaluation methods is proposed.

Oguzhan Tas and Farzad Kiyani in [3] have given a comparative study of various text summarization techniques. In [4] Kaiz Merchant and Yash Pande have proposed an automatic text summarization system that generates short and useful summaries and they have used a natural language processing technique called latent semantic analysis(LSA) to capture the concepts within the same document. Jaya Kapoor and Kailas K. Devadkar in [5] have presented a clustering approach for automatic text summarization. In [6] an extractive text summarization technique based on sentence ranking is presented. [7] presents an enhanced TextRank approach for content summarization of conversation in the context of virtual meetings. [8] demonstrates that the performance of TextRank is competitive with that of some of the best summarization systems that are available today. In [9], a graph based text summarization method has been described which captures the aboutness of a text document. In [10], Dazhi Yang and Allan N. Zhang, moving from words to semantics, the task of automatic text summarization of research papers is discussed. In [11], a comparative study of TextRank and iTextRank is made.

III. PROPOSED SYSTEM

Smart Meeting Assistant comprises mainly of three phases::

A. Speech to Text conversion.
B. Extractive Text Summarization.
C. Generating the document containing summary

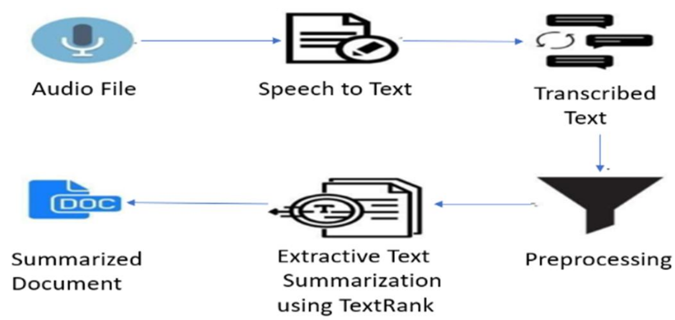


Fig. 1 System Architecture

IV. MODULES INVOLVED

A. Speech to Text

The audio file is to be given as input. It is necessary for the audio file to have .wav extension. The frame rate of the channel is determined and stored. The channel of the audio file is checked. If it is a stereo file then it is converted into a mono file. Google Speech to Text API is used for conversion of speech to text. With Google Speech to Text API it is possible for developers to convert voice information to text by applying powerful neural network models in an easy to use application programming interface. This API can recognize over 180 different languages. However, we have limited the scope of our project to just English language. There are two methods by which audio file transcription can be done. One is synchronous speech recognition and the other is asynchronous speech recognition. There is a limitation on the number of minutes of the audio file that can be transcribed in synchronous speech recognition method. Therefore, we have chosen the asynchronous speech recognition method in our project. Asynchronous speech recognition requires the audio data in a single channel format so that the necessary transformation of audio file into mono channel from stereo channel can be done using a python library “ pydub”. It is also necessary for the frame rate of the audio file to be specified and the audio file to be in .wav format. Speaker diarization is basically used for identifying the speaker. Speaker identification and tagging is necessary as the summary generated will have the important sentences along with the speaker which will give a clearer overview of the meeting to the reader. There is also a provision made in the project which will collect all the sentences mapped to a particular speaker and group them together under the respective tag which will help in generating a much more effective summary. Highly ranked sentences or the sentences of greater importance are selected as a summary. This process of collecting all the sentences spoken by the speaker together, will help in increasing the algorithm’s performance.

B. Extractive text Summarization

TextRank algorithm is used for text summarization. As TextRank is inspired from the PageRank algorithm, there are some similarities between PageRank and TextRank. The following are some of the similarities-

1) Sentences are used in place of webpages.
2) The similarity between the sentences is used as an equivalent to webpage transition probability.
3) The similarity scores are stored in a square matrix.

Initially, the sentences from the text taken as input are split. Then in the next step, we find vector representation (word embedding) for each and every sentence. Word embedding is basically vector representation of words. It is one of the most popular representations of document vocabulary. Word embedding is capable of capturing the context of the word in the document along with semantic and syntactic similarity with other words. After vector representation of the sentences, similarity between these sentence vectors is calculated and stored in a matrix. Cosine similarity between the pair of sentences is computed. This similarity matrix is then converted into a graph.

The nodes of the graph represent the sentences and edges between these nodes represent the similarity score between these sentences. On this graph, we apply the PageRank algorithm to determine the ranking of the sentences. Adjacency matrix is prepared on the basis of this graph. With the help of the formula that is used for calculating probability of each and every node, a probability matrix is constructed. Finally, the scores of each and every sentence are calculated and only highly scored sentences are selected in the summary. The size of the summary is controllable. The document file containing the summary is saved at the location previously specified.

V. EXAMPLE OF MEETING SUMMARY

A. Meeting Transcript

speaker_01: So the purpose of the interview today is so we can find out a little bit more about you in order to decide who to appoint. We have prepared some questions and all the panel members will be asking questions as we go through. There's no trick questions in this they're all about you so you should be able to answer them. And clearly we will be assessing against elements on the person specification. And at the end of the interview, I will give me an opportunity to ask us questions. That's great very quick,

No problem. Okay, well the first question is from me so can you explain to me what first attracted you to this post.

Okay. You mentioned the skills that you've acquired in your previous role, could you explain to me what skills that you think you'd be able to transfer into this role. Sounds great. Thank you. And I think that's the end of our questions now. As promised, do you have any questions for us. Well, yes as outlined in the person specification and the, the role requires five days in any seven for work. So obviously that does include some weekends. What we want to do is absolutely agree those days with the successful candidates.

Yeah, no problem at all. We understand that can be very difficult. Well thanks so much for coming in.

speaker_02: I'm good.

Well I've been in the same role for about three years, and alas I've been there for quite a lot of skills. Yeah, and I love to put these to produce.

And yes, I've got an occasional colorization of skills, and I've also assisted in organizing stock orders. And I've also helped out when organizing the casual stuff writers. Touch very much

Yes, I have a sane GCSE English, and also as part of my own BBQ, I have to complete written assignments. And my current role I have interaction with customers on a daily basis. So I understand the need for good communication, and also for treating people the way that I would like to be treated. Because.

Yes. Would I be required to work a weekend.

Okay, that's great.

speaker_03: good communication skills are an integral part of this role, as is completing paperwork and various bits of constituent job. Can you demonstrate your written and verbal communication skills.

B. Output

speaker_01: You mentioned the skills that you've acquired in your previous role, could you explain to me what skills that you think you'd be able to transfer into this role.Sounds great. Well, yes as outlined in the person specification and the, the role requires five days in any seven for work. Yeah, no problem at all.

speaker_02: I'm good.Well I've been in the same role for about three years, and alas I've been there for quite a lot of skills. And yes, I've got an occasional colorization of skills, and I've also assisted in organizing stock orders.

speaker_03: good communication skills are an integral part of this role, as is completing paperwork and various bits of constituent job.

VI. ACCURACY MEASUREMENT

The machine generated summary and human generated summary must be similar. The machine generated summary must include all the important points that the human generated summary will contain.

VII. FUTURE WORK AND SCALABILITY

A. With more data, developing an abstractive text summary which can be operated with factual data, that is implementing a supervised machine learning approach.

B. Scaling the project to enable video conferencing and capturing the video as well as identifying the speakers with visuals.

C. Making the meeting assistant multi-lingual.

D. Developing an Android App of our project

VIII. CONCLUSION AND FUTURE WORK

The proposed system effectively summarizes the meetings and thus reduces the human efforts of taking notes of important points being discussed during the meeting, thereby, helping the participants to focus more on the actual meeting. We further wish to extend our application by adding the functionality of recording the meetings and keeping a record of previous meetings. We are also planning to develop an android application of the same.

REFERENCES

[1] R. Sagayam, A survey of text mining: Retrieval, extraction and indexing techniques, International Journal of Computational Engineering Research, vol. 2, no. 5, 2012.

[2] N. Padhye, D. Mishra, R. Panigrahi et al., “The survey of data mining applications and feature scope,” arXiv preprint arXiv:1211.5723, 2012.

[3] W. Fan, L. Wallace, S. Rich, and Z. Zhang, “Tapping the power of text mining,” Communications of the ACM, vol. 49, no. 9,pp. 76–82, 2006.

[4] S. M. Weiss, N. Indurkhya, T. Zhang, and F. Damerau, Text mining:predictive methods for analyzing unstructured information. Springer Science and Business Media, 2010.

[5] S.-H. Liao, P.-H. Chu, and P.-Y. Hsiao, “Data mining techniques and applications–a decade review from 2000 to 2011,” Expert Systems with Applications, vol. 39, no. 12, pp. 11 303–11 311, 2012.

[6] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473, 2014.

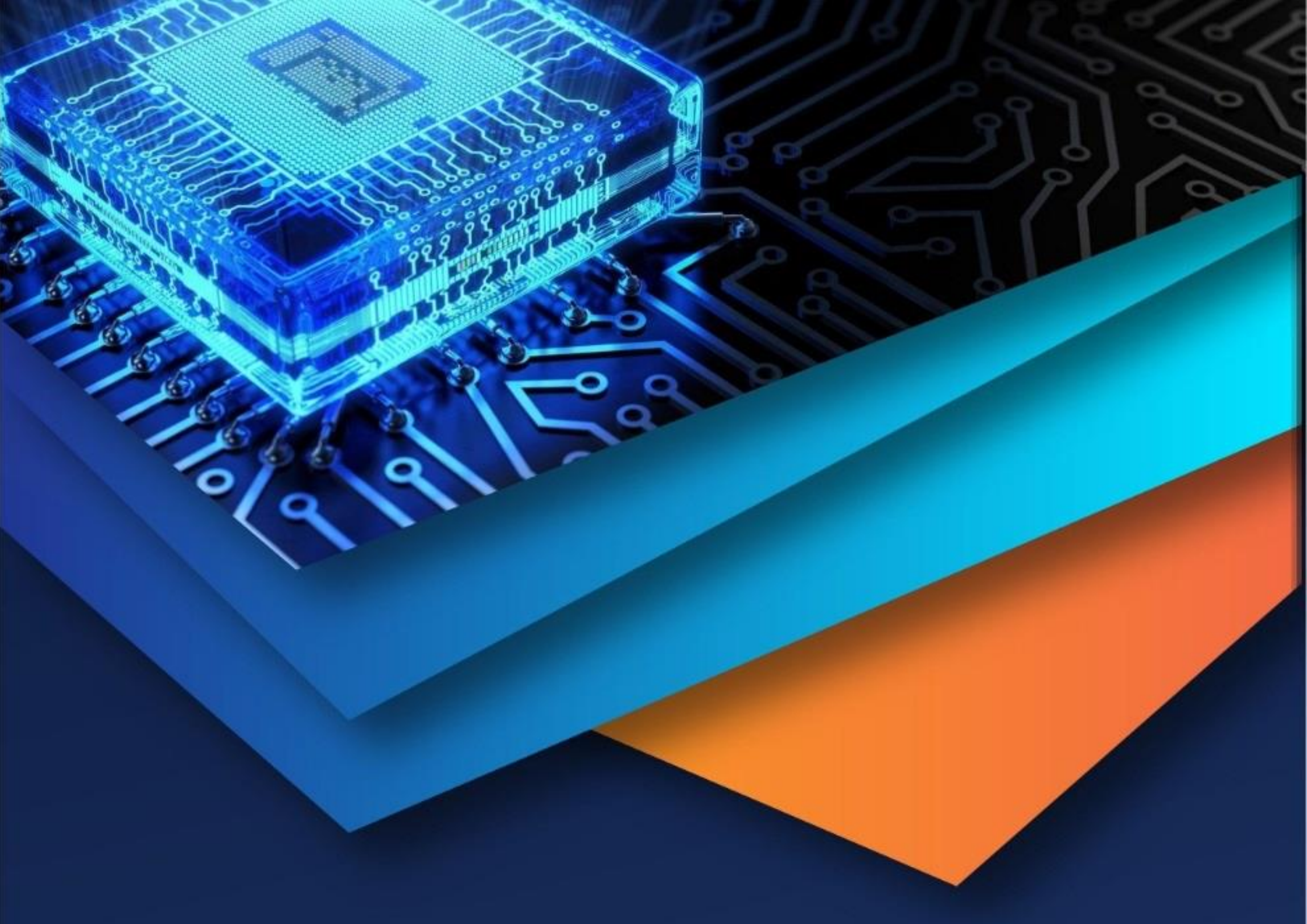
[7] Ramesh Nallapati, Bowen Zhou, Caglar Gulcehre, Bing Xiang, et al. Abstractive text summarization using sequence-to-sequence rnns and beyond. arXiv preprint arXiv:1602.06023, 2016.

[8] Romain Paulus, Caiming Xiong, and Richard Socher. A deep reinforced model for abstractive summarization. arXiv preprint arXiv:1705.04304, 2017.

[9] Alexander M Rush, Sumit Chopra, and Jason Weston. A neural attention model for abstractive sentence summarization. arXiv preprint arXiv:1509.00685, 2015.

[10] Abigail See, Peter J Liu, and Christopher D Manning. Get to the point: Summarization with pointer generator networks. arXiv preprint arXiv:1704.04368, 2017.

[11] Zhaopeng Tu, Zhengdong Lu, Yang Liu, Xiaohua Liu, and Hang Li. Modeling coverage for neural machine translation. arXiv preprint arXiv:1601.04811, 2016.



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