Intelligent Chatbot For Conducting Automated HR Interviews

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Abstract—Usually the last leg of any selection process is the Human Resources (HR) interview. Sometimes these are also mandated when someone is put up for promotion to gauge suitability for the position the candidate would assume. An increasingly large number of these generic interviews take place across industry and academia and basically between any candidate and potential employer, including Government.

We observe issues with the quality and associated costs, both direct and indirect, of such interviews caused by human nature and the inherent variability in the skill and experience of the interviewer. To name a few we observe that several times such interviews are not standardized, of poor quality and the content is variable and not addressed fully, presence of bias of the interviewer, non-scalability of the process due to bottlenecks caused by skilled human interviewer availability. We also note that the recruiting organizations may be exposed to liability due this defective and human oriented subjective process.

We note that Machine learning once applied successfully will constantly improve the process of the interview as more training data becomes available and feedback loops of current performance and outcomes versus past interview performance are closed by our Intelligent Chatbot System.

Index Terms—Analytics, Artificial Intelligence, Automation, Chatbot, Human Resources, Industrial Psychology, Interview, Interview Evaluation, Machine Learning, Text mining.

I. INTRODUCTION

A chatbot (a.k.a. talkbot, chatterbot, Bot, chatterbox, Artificial Conversational Entity) is a computer Program which conducts a conversation with a human subject via auditory or textual methods. Though the concept of a chatbot is quite old, we note that the messaging applications are far more mainstream now than they were a few years back. We note that in in the Second Quarter of the year 2015, the number of users of messaging applications have surpassed even those of Social Media! (2.5-3.0 Billion active users). Building a globally successful application, often means building for platforms that have a mass adoption and we note that text as a medium has suddenly become extremely acceptable to many users of technology and in fact it is the medium of choice for most users. We choose the Human Resources (HR) interview and not the technical interview for a few of reasons:

1 Issues observed occurring due to human subjectivity are persistent in nature (bias, subjectivity, opinion etc.) and have not been addressed via technology yet even though they were first studied in the year 1911[ref]!

2 We are motivated by the need for greater justice in the interview process.

3 It is generic in nature and once automated, it will be applicable across the spectrum of industry, government as well as academia. This is unlike the technical interview which would have a much narrower market size.

4 It is far more subjective and challenging to automate and hence an intellectually stimulating topic.

A. Enabling factors

1 Text mining algorithms are now in public domain and available for further enhancement, feature additions.

2 Several technologies like Speech to text, Data preprocessing algorithms and analytics reporting tools are now in Public domain (Open Source).

3 Cloud technology ensures Elastic Computing on demand thus enabling the taking on of large complex computing loads. This will be future work for this project as we expand the offering as a Software as a Service over public cloud.

B. Proposal

In this paper we propose a novel Intelligent Chatbot application, namely one that automates 4 aspects of the HR interview:

1 The interview Questions and recording of the candidate Answers via the Chatbot.

2 The conversion of the text transcript of the interview to data, its analysis against a standard set of responses.

3 Application of Text mining and Machine Learning Techniques to the interview transcript to convert the textual data to meaningful, quantifiable, and actionable information.

4 Presentation of the analytics report to the hiring manager to get a final decision from him/her.

II. REVIEW OF LITERATURE

Thombre et al. [1] 2018 note that bias is omnipresent in interviews and that the issue persists historically and to this day. In a 1982 Study [2] Arvey et al. note the low reliability in the past of personnel interviews and a weak correlation with job performance and lack of standardization as the same candidates presented to different hiring managers produced dramatically different results! Wagner [3] 1949 was impressed

with the structured methods of interviews rather that free-form or open-ended techniques and recommended that the interview may be useful in only 3 situations:

1 When rough screening in required. (Extremely large number of initial applicants)
2 When number of applicants is too small to warrant structured testing and other methods.
3 When certain traits required for the job at hand may be readily accessed by the interviewer.

Mayfield[4] 1964 agreed with Wagner and additionally noted that:

1 The material is not covered consistently in unstructured interviews
2 The same information may be weighed differently by different interviewers.
3 Structured interviews result in higher inter-rater reliability.
4 Tests seem to be better than interviews and test results may NOT be shared with interviewers who rate the applicant after the test.
5 Intelligence can be reliably judged by interviewers but other traits, which may be critical for the job, are not judged adequately!
6 Unfavourable information carries greater weight in the mind of the interviewer and is thus weighed in a biased manner.
7 Hiring Decisions are mentally made very early in unstructured interviews, typically within 4 minutes of the start interview, which may be completely unsuitable in most cases.
8 The attitude of the interviewer affects the interpretation of the interviewees responses.

In addition to the above information, Schmitt [5] 1976 further noted that:

1 Temporal placement of favourable and unfavourable information made a difference in the interview outcomes.
2 Interviewers had a mental Stereotype of an ideal employee and tended to size up interviewees against this Ideal Stereotype.
3 Reliability of the interview increased as interviewers received more information about the job description of the job to be performed by the applicant
4 He also noted that there exist individual differences in the decision process (e.g. some interviewers stressed on academic achievement, some on years of experience etc.) which result in inter-rater differences in evaluating candidates.
5 He also noted the significance of visual cues.
6 Additionally, he noted that attitudinal, racial and sexual similarity between the interviewer and interviewee result in skewing of results.
7 Schmitt also found that using a structured interview guide resulted in a more homogenous result

Arvey noted that Organizations should avoid interview questions which may differentially affect minority groups (race, age and handicapped groups amongst others), and female candidates vs male ones as this may attract liability. Arvey also noted, rather significantly, that attractive candidates are selected more often regardless of their sex. Landy[6] 1976, as well as several other researchers significantly noted that Panel interviews tended to be more fair and reliable that one-on-one interviews. Several other researchers noted that when college graduates were asked to conduct the interviews instead of experts, no great variation was seen in the result! Kalin and Rayco[7] 1978 noted that candidates with foreign accents received lower ratings for higher status jobs and vice versa! Imada and Hakell[8] 1977 noted that non-verbal communication had a reasonably significant impact on interviewer ratings and outcomes.

A. The case for Structured Interviews

In a 1993 study Marchese[9] and others made a meta-analysis of interview studies and noted 6 interview characteristics:

1 Number of interviewers
2 Length of interview
3 Gender of applicant pool
4 Blue/White collar jobs
5 Use of college students vs job applicants
6 Structure of the interview

And noted that Structure of the interview was the only characteristic which moderated the validity of the interview!

B. Impression Management

Impression Management is essentially a manipulative behaviour manifested in certain candidates in which they attempt to portray themselves in favourable light by engaging in certain behaviours. (e.g. Ingratiation, self-promotion, assertiveness, opinion conformity etc.) Stevens and Kristoff[10] 1995 noted that structured interviews reduced the effects of Impression Management tactics. Tullar[11] 1989, found that successful applicants tended to be more dominant, showed more equivalence, dominated more when the interviewer was submissive, and were more submissive when the interviewer was more dominant. When the interviewer structured, successful applicants structured less. This evidence suggests that successful applicants adapt to the interviewers communication style. Pingitore[12] and others in 1994 noted that applicant obesity was positively correlated with non-selection. Interviewer training is not always a solution as some training programs we effective whereas others were found to have no significant impact on the outcome! Harris[13] (1989) reported that interviewer ratings of applicants were higher when they were experiencing more positive mood states. Arvey also noted that the constructs such as:

1 Likeability,
2 Applicant work motivation,
3 Sociability,
4 Verbal fluency,
5 Job interests,
6 Career plans, and

7 Likes and dislikes.

Were typically measured in interviews. (Harris, 1999) [13] noted that additional constructs measured in the interview include

1 Cognitive ability,
2 Tacit knowledge,
3 Assessment centre dimensions,
4 Person-organization fit

C. Technology Mind-map

Please Refer figure[1] at the end of this paper.

III. PROPOSED SYSTEM ARCHITECTURE / SYSTEM OVERVIEW

We note three issues with the current process which we will address with the proposed system:

1 Personal Bias of the interviewer.
2 Accuracy and standardization of the recruitment process.
3 Time spent on the process by HRA as well as associated cost.

The proposed chatbot software addresses a specific segment of recruitment process to help HR Administrators in collecting and analyzing various personal and professional information from the job seekers/promotion candidates to estimate their:

1 Fitment in the company and provide a
2 Hiring decision as well as inputs for considering the
3 Compensation and benefits to be offered to the candidate.

A. Block Diagram

Please See Fig[2] at the end of this paper.

1 STT (Speech to text translation) engine is used to convert spoken speech to text which can be analyzed, after pre-processing by a machine learning/text mining algorithm.
2 Next we check and correct spelling and grammar
3 We remove stop words
4 Lemmatization to get to the root word.
5 Vectorization to convert the bag of words to vectors
6 Algorithm(s)
   a. Outputs Percent match with model answers kept in knowledge base
   b. Outputs hiring decision after taking the technical interview rating into account as well as the manual threshold for cutoff.
   c. Outputs compensation recommendation after taking the technical interview rating into account
7 Comprehensive Analytics report is presented to the hiring manager.

IV. LIMITATIONS

1 Certain type of bias can be eliminated whereas certain other types may not be eliminated by automation as automation relies on training data and there may be bias in the training data itself
2 Likeability, Sociability, verbal fluency, motivational factors and other subjective measures etc may not be effectively judged by the software/Machine

3 The machine may not eliminate the need for a short and final face-to-face human interview in our opinion.

V. CONCLUSION

We conclude that there has been a significant amount of research to investigate the role of bias in the interview process and it is noted that bias is omnipresent! Bias variables in no particular order include but are not limited to:

1. Age of candidate
2. Gender
3. Race
4. Accent of spoken language
5. Obesity
6. Disability of the candidate
7. Attractiveness of the candidate
8. Mood of the interviewer

Also, it is comforting to note that more variables are now being investigated than before in the interview process which may result in more comprehensive and standardized structured interviews in the future. Inconsistent coverage of the material can be eliminated by using automated software/machine. Reliability of the interview process can be increased as a single interviewer (machine) conducts ALL HR interviews. Standardization is easily achieved using the same computer model for various candidates. In our opinion, Manipulative behaviour such as impression management can be eliminated using bias-less and emotionless machines. Apart from intelligence, many other attributes which may be critical for a certain job function can be measured accurately by the machine. Unfavourable information and its weight, temporal placement of certain information in the interview, attitude of the interviewer and its subsequent effect on interview results etc. can all be eliminated or reasonably addressed by automation. The automated software can be made blind to factors such as race, gender, age, and physical disabilities of the candidate, amongst other things and focus on competence alone! Above point is a great case for avoiding liability for organizations! Panel interviews result in greater fairness and effectiveness. We note that this is consistent with the findings of ensemble learning in computer science literature.

VI. ACKNOWLEDGMENT

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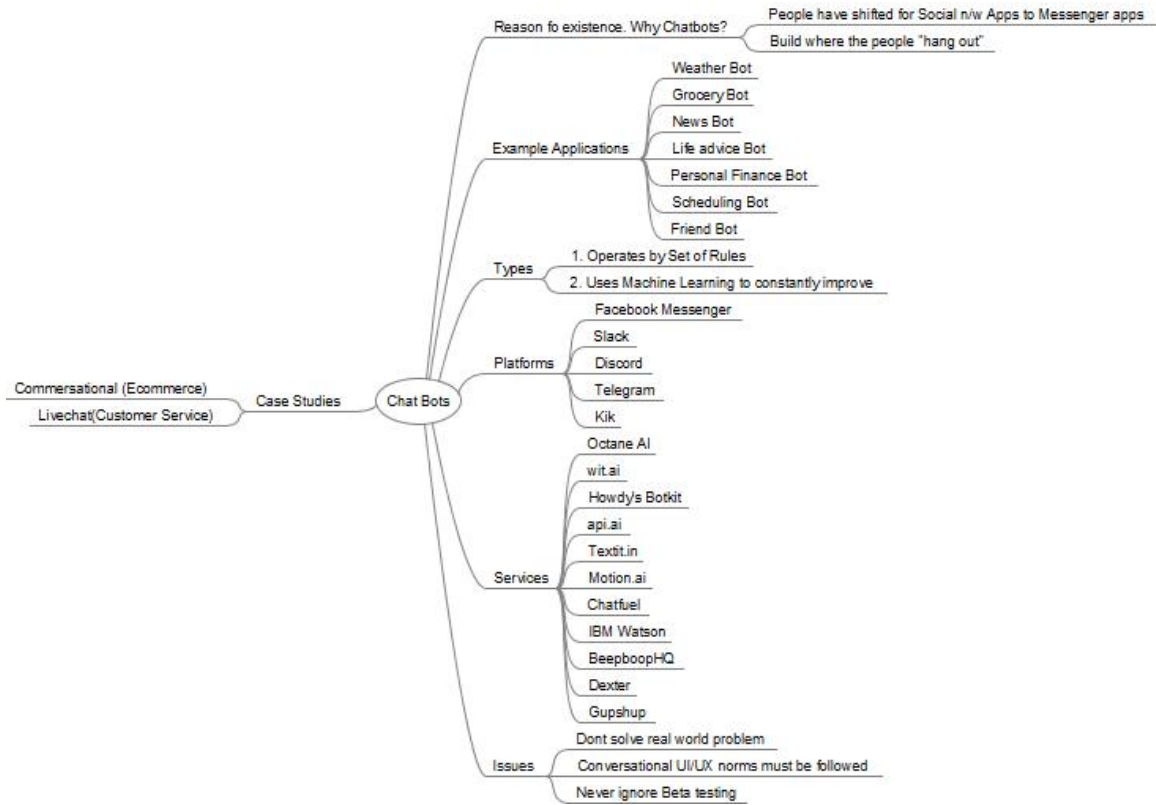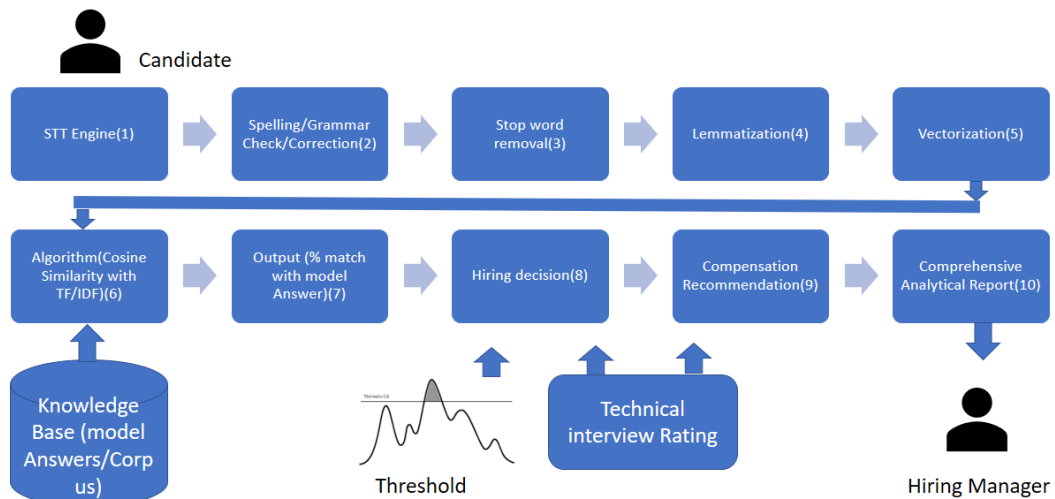
VII. Diagrams

Fig. 1. Mind-Map

Detailed System Architecture

Fig. 2. Block Diagram of Proposed System