Internal Talent Management Chatbot: find the right employee at the right time

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Abstract : In today's competitive world, organizations spend a lot of resources to hire and retain the best talents. This would allow them to offer better products and services and stay ahead the competition. Among other aspects, how well Talent Management is performed, can have an impact on company's success as well as on the employee's turnover. This paper introduces chatbot for internal Talent Management. The prototype shows how supervisors can find suitable employees within the organization. On other side employees can share their project experience, skills, language levels and much more with the chatbot. Dialogflow ES is used to create the chatbot and the Graph Database - Neo4j for storing and retrieving user information. The work discusses briefly the potentials and limitations with the proposed approach compared to traditional softwares. It targets researches and organizations to view new technics for Talent Management as well as the use of Graph Database for chatbots.

Keywords: *Talent Management, Chatbot, Dialogflow ES, Graph Database, Neo4j, NLP, NLU.*

I. Introduction

In order that organizations can stay competitive, they hire the best talents by being able to offer better products and services than the competition. For innovative products and services, how well Talent Management (TM) is done is crucial. TM is identification and retention of the appropriate talent [1]. Companies can't neglect this area, since it can have an impact on employees satisfaction, grievances [2] but also on the company's success. Supervisors need to have efficient tools by being able to find the right employee for the right task, position or project at the right time. Employees (peers) need to have also an access in order to collaborate or for knowledge exchange based on similar interests, skills etc.

Companies can build or buy TM Softwares to supervise employee's skills, recommend the proper training, find the right internal talent for a new project etc. The limitations that come with traditional softwares are time consuming to keep them up to date, maintenance, training for using the software.

Instead of using traditional softwares, organizations could use a Chatbot for internal TM. A chatbot uses Artificial Intelligence that simulates human conversations by allowing users to input questions and the chatbot will return meaningful answers [3]. The conversations could be through voice or text and backed by Natural Language Processing (NLP) and Natural Language Understanding (NLU) [4]. Chatbots have been used for education, customer service, games, health, productivity, sports, marketing, travel and much more [5].

The intention of this work is to prototype a closed domain chatbot for internal TM that would allow to search for internal employees based on specific skills as well as everyone within the company could add and update their skills, profile, certifications, project experience and much more. The chatbot could be used by supervisors as well as a peer to peer knowledge distribution e.g. finding someone quickly within other department for a task collaboration. Moreover the work will also briefly discuss the potentials and limitations of this approach compared to traditional softwares.

II. Brief history of chatbots

One of the first chatbot was ELIZA implemented by Weizenbaum around mid – 1960 that use pattern matching to respond to user's questions and should mimic the role as an psychologist [6]. An improved version named PARRY was developed in 1972 and in 1995 ALICE was developed and won the Loebner Prize. ALICE was developed using Artificial Intelligence Markup Language (AIML) [4].

Chatbots got more attention with lunching of personal assistants such as Apple Siri, Microsoft Cortana, Amazon Alexa, Google Assistant and IBM Watson [4]. Due to increase of chatbot capabilities, nowadays users can expect a classification of chatbots such as knowledge domain - , service provided -, goal - and response generation method – oriented chatbots [7].

III. Related work

In this work [8] authors propose a chatbot system of profiling of contenders based on company's needs. Beside that a brief review of chatbot in Human Resources (HR) is given. Nishad Nawaz and Anjali Mary Gomez [9] show the influence of chatbots on the recruitment process and how the candidates would be attracted through this technology. The study [10] represents the ramifications of chatbots for Human Resources Development and also emphasizes advantages and disadvantages of the AI in this domain.

On the implementation side Dialogflow has been used for multiple works: e.g. such as handling placement activities in college [11], as a movie recommendation [12], as a Natural Language Interface to Database [13], based on English conversation chatbot [14]. In the perspective of using Neo4j as a database platform for chatbots, [15] uses it for developing a chatbot dealing with cancer people. Patients can ask about symptoms, treatments etc. and the data are stored in the Neo4j.

IV. CHATBOT DESIGN

The implementation of the Talent Management Chatbot is separated in following main parts:

- Dialogflow configuration
- Neo4j configuration
- Orchestration
- Slack integration

A. Dialogflow configuration

The chatbot was developed using Dialogflow ES. Dialogflow it's a Natural Language Understanding (NLU) platform that helps easily to design and integrate chatbots as well as interactive voice response systems. The platform can take user inputs such as text or audio (e.g. phone or voice recordings) and respond with text or with synthetic speech [16].

Dialogflow ES was chosen mainly due to following reasons:

- Automatic language processing – no pre-processing steps are required as in [15] such as tokenization, converting to lowercase, punctuational removal, stop words removal
- Intuitive Use Interface
- User friendly integration to different channels Facebook, Website, Slack etc.

Beside Dialogflow ES developers could use common platforms such as IBM Watson Assistant [17], Microsoft Luis [18], Amazon Lex [19], Pandorabots [20], RASA [21].

In order that supervisors can ask questions, such as: "who can speak Spanish and has experience with Python" or "looking for someone who knows Data Mining", peers intents are required. Intents are user's intention for one conversation and by introducing more intents Dialogflow uses intent classification to match the best intent [22].

All intents in Dialogflow ES are structured based on peer and supervisor intents. Peers intents are for example: "I would like to add French and Spanish", "add Python", "add a new project". The chatbot can recognize that e.g. French and Spanish is a language and "Python" is a skill due to prior definition of entities. Entities shows how the data are extracted from user's intent [23].

B. Neo4j configuration

The database acts as the brain of the chatbot. It ensures that all peer intents can be manipulated accordingly. The chatbot uses a graph database from Neo4j to store and update user's data. Neo4j is a graph database that connects data as it's stored in form of nodes. It helps to perform complex connections and uses Cypher – a Graph Query Language [24].

Neo4j Graph Database has been used due to following main reasons:

- Data motel flexibility
- Complex queries
- Graph algorithms
- Nodes connection

Developers could have connect Dialogflow ES to other database technologies such as MySQL [25], Firebase [26], MongoDB [27].

Entities such as e.g. skills, languages, projects etc. have been saved as nodes (see Fig.1).

Fig 1: Data model in Neo4j

The main node is “Employee” and from there most of the relationships are created. Relationships are crucial when it comes data manipulation. When a supervisor asks e.g. “who speaks Spanish?”, Dialogflow identifies it as a “language” entity and Neo4j performs following query:

```
MATCH(e:Employee)-[s:SPEAKS]->(sp:Language{name:"Spanish"}) RETURN e,s,sp
```

When peers are trying e.g. to “Add Python”, “Python” will be identified by Dialogflow ES as a “Skill” entity and Neo4j will store it. However the chatbot will still ask the skill level that is saved in “Level” node and not as a property to the skill level. This will easily to query data by level through entire employee.

C. Orchestration

The last part is connecting the Dialogflow ES with Neo4j. Each time a supervisor is trying to find the suitable candidate, a connection between user’s intent and database query must be enabled. This is done through Neo4j driver.

D. Slack Integration

Slack, a business communication platform [28], has been chosen as the user’s interface interacting with the chatbot. However this chatbot could be integrated within a website, Hangouts, LINE, Telegram, Twilio [29] etc.

V. Results and Discussion

Peers can easily connect to the Slack messaging platform, because it’s being used for daily conversation. In order to look for a peer with specified skills or add any other information, there is no need to leave the messaging platform. The chatbot could be updated not only by peers, but also automatically, e.g. when specific training is done by an employee, the knowledge base is automatically updated.

In order that a supervisor can find a suitable candidate for a particular tasks, employees input are required. Figure 2 illustrates the result when a peer adds a new language and a new skill. Later on the user updates the language level (see Fig. 3). Figure 4 shows Neo4j’s nodes representation to the particular user after the update has been occurred.

Fig 3: User adds a new language and a new skill

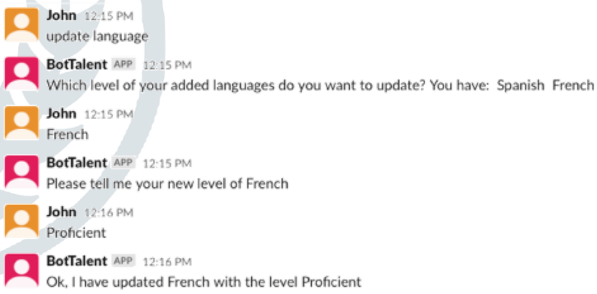

Fig 2: User updates the language level

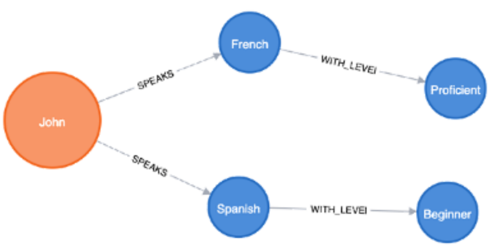

Fig 4: Database view after updating language level

After the employee would introduce their skills, projects experiences, certifications etc., supervisors would be able to find suitable candidate. Figure 5 shows an example when a supervisor searches for a candidate who speaks “French” , can provide project experience with a “Chatbot” and has some knowledge in “Python”. Figure 6 shows how the data are represented in Neo4j.

Fig 5: Supervisor query for project experience and skills

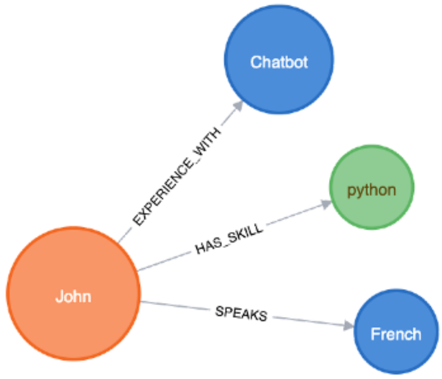

Fig 6: Database view when retrieving data

Applying a chatbot as an internal Talent Management tool allow individuals to quickly access and update any information intuitive. Individuals won't require to use multiple systems for any Talent Management tasks. Due to that employee's data can be updated within a chat, data can stay up to date and allows organizations to retain their top talents. There is an increased engagement between supervisors and employees. Employees would have a new experience using company's softwares.

From developing point of view it's important to mention, that it takes time to find all possible user's intents, especially when it comes to multiple follow-up questions. Developers might create a flexible conversation roadmap that is possible to scale anytime. Since within one process such as employee updates a skill, could raise different follow – up questions: "please tell me which other trainings I should attend?", "Which course is good for Chatbots"? etc. How well the database is structured, will define how efficient information retrieval will take place. If database would contain duplicates, this would lead to wrong answers by the chatbot. The integrity between entities and intents should follow a logical structure since e.g. "Python" could mean that is should be saved as a skill, certification or some project experience that implied this skill.

Limitations that comes with this approach is when e.g. the supervisor would get as a result a long lists of employees with e.g. multiple properties such as department name, age etc. This would be easier to show as a table. However in a chat window this might not be convenient, especially when some columns e.g. should be filtered. A solution for that could be that the chatbot generates a link that will open a window browser with that specific larger table. Other aspect is once's the chatbot provided an answer and if the user needs it's again, scrolling through the chat would be required. Alternatively the user would ask the same question again. Moreover at the beginning of chatbot lunching, it can occur that the system doesn't understand all questions asked by supervisors or employees. With enough testing time and continuously learning, the chatbot can become more powerful.

VI. Conclusion

This paper shows how a chatbot can be used for internal Talent Management. Peers could add languages, skills and the level accordingly, as well as certification, project experiences including performed tasks and much more. They can update any information previously given, such as level language etc. Peers are responsible to keep data up to date. On other side supervisors can search for employees that meets internal project requirements, e.g. employees that speak a specific language, had project experience and additionally provide certain skills.

Peers as well as supervisors could access the chatbot within Slack. So if Slack is already the main communication tool within the company, users don't have to leave the application in order to perform Talent Management actions. This could lead to increase of administrative process performance and companies might have more accurate state of employee's since new information can be updated easily. Actions for the TM can be performed in a different way, this might have an impact on employee's satisfaction using internal applications. Beside that users don't need to undergo different applications until they want to perform a simple action e.g. updating a skill. Developing a bot vs. traditional softwares could decrease developing costs, since there is no "User Interface" that always need to be modified when new functionalities are implemented, no training required and a faster go live of the application.

However it's important to mention the limitations that come with this approach such as showing larger amounts of information (text or tables) or finding past answers within the chat, as well as using the chatbot that wasn't in production for a longer time. At the same time possible numerous multiple follow up questions should be considered when developing the conversational flow. The database structure should provide scalability and ovoid duplicates for correct answers.

VII. Future Work

Talent Management Chatbot enables supervisors as well as their employees quickly to add any information as well as retrieve it. In order to improve the chatbot's capabilities following features might be relevant:

- Document Understanding – e.g. by uploading a certification, the bot will extract main properties and will require only user confirmation in order to save the data
- Page ranking – showing the best match to the supervisor , e.g. based on which criteria employees will be filtered

- Training recommendations – based on past projects, the chatbot could proactively suggest new trainings or as a reminder if someone gets beginner level for python, bot will actively suggest to increase the level
- Supervisors could generate reports containing data such as, headcount, skills per employee etc.

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