

Validating Belbin roles based on university students' Discord messages

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Abstract

Social media has found its way into education and together with team formation has started to play a big role in the life of students' university progress. In this paper, we discuss ways of validating Belbin roles by doing focused research on the direct effects of communication and verbal behavior in the social media environment of Discord, where the official University of Twente channels are hosted. Previous research has tried to generally analyze and give predictions about the influence of social media on the learning curve of students but was not concentrated on understanding the behavior of students within teams and directly linking it to Belbin roles which is crucial for forming teams. Furthermore, working with real-life data extracted from official university channels will give us an opportunity to propose a methodology and a pilot Belbin role automation tool to look further into the specifics of the problem. In addition, linking this to team roles and behavior concerns within the project teams will open the horizon for further research on how the performance of students within the teams is affected. We propose to create a preliminary tool and framework for validating Belbin roles through real-life social network data. Results show that it is possible to identify Belbin roles using natural language processing, but in order to maximize the accuracy, it is necessary to refine the set of words associated with every single personality trait.

Keywords

Belbin roles, Personality traits, Social networks, University students, Natural Language Processing

1 INTRODUCTION

Today it is common to see companies working with strategies based on teamwork, which is why universities have assigned these skills to their educational curricula.[2] A team that works can generate excellent results and a pleasant and productive work environment. However, it often happens that teams cannot work properly, generating problems and negative experiences among their team members[6]. Among the reasons why teams are ineffective relates to the tasks and responsibilities distribution, which lead teachers and

managers to use strategies based on forming teams with people that cover diverse team roles[7]. Belbin roles[3] is one of the most used sets of team roles, and it has been used to classify people according to their strengths and weaknesses in order to facilitate the distribution of responsibilities, and therefore, to increase team effectiveness[4].

The identification of Belbin roles requires that each member of the team complete a questionnaire predefined by the Belbin association[8]. This questionnaire proposes to the respondent a series of situations and a set of responses that are associated with personality characteristics, and which in turn are associated with a specific role. In a business context, it only takes time to collect data and interpret the results, and money to pay the cost of the questionnaire for each member of the team, a safe value for a long and stable career. However, in an academic context, team building usually happens at the beginning of each course, and teachers are unlikely to have the necessary information or resources to correctly identify the Belbin role of all students.

[4] found that Belbin's roles can be identified based on personality traits. These personality traits can be extracted from communication platforms and educational environments such as Canvas or Discord[9].

Combining these two ideas, it might theoretically be possible to identify students' Belbin roles automatically and at a low cost. Therefore, this study aims to explore the possibility of using written content in communication channels used in courses as a means of identifying personality characteristics, which can then be associated with Belbin roles. The results from previous research done on these topics will be useful for filtering and analyzing the data for our current study and setting general expectations for the final outcome. From what has been discussed, our goal can be divided into 3 separate parts:

- Goal 1:

Explore if it is possible to extract data that is representative of the personality traits from Discord and identify personality traits from the messages

- Goal 2:

Extract messages that show personality traits and use them to identify Belbin roles correctly. Link personality traits to Belbin roles.

- Goal 3:

TScIT 37, July 8, 2022, Enschede, The Netherlands

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Determine if it is possible to automate the process of identifying Belbin roles based on the messages extracted in order to reduce the cost of finding Belbin roles of subjects.

To this end, the following research questions have been proposed:

Research question: How can Belbin's roles be identified using the text messages that students write in the communication channels of a course?

Sub RQ1: How can we identify measurable personality traits from Discord messages?

Sub RQ2: How accurate is the prediction of Belbin roles based on natural language processing only?

2. BACKGROUND

Related work to this topic was found using Google Scholar, IEEE, findUT, and Sci-Hub using the keywords specified at the beginning of the document. The relevant results and findings of the chosen research will be discussed below.

2.1 Social media in education

The paper of Kumar Swain, R., & Pati, A. K. (2021) about the use of social networking sites and its repercussions on human psychology gives an overview of the behavioral effects associated with the activity of target users on social media platforms. [6] In this paper, it is shown that students who did multitasking between SNSs and assignments performed on average 20% worse, and in general, the use of SNS led to an addiction that leads to depression and anger. On the other hand, a lot of reports state there are no negative effects of usage of SNSs and many educational institutions use social media to maximize teaching efficiency [6]. Therefore, due to the contrast between findings, there is no clear winner between the two options. That is also why it is important to do further research on this specific topic.

Other research like Owusu-Acheaw, M., & Larson, A. G. (2015) and Liu, D., Kirschner, P. A., & Karpinski, A. C. (2017) on the use of social media and its impact on academic performance shows a conclusion of a negative effect of the use of social media due to extensive time waste. [10,11]

On the contrary, usage of social media in Saudi Arabia showed to have a positive effect if social media was not used extensively.[8] This means that it is not only important to analyze usage or no-usage but also take into consideration that the amount itself can play a huge role in the final conclusion. This means that the unbiasedness of the dataset for such a research is of key importance

The paper of Kaya, T., & Bicen, H. (2016) states an interesting conclusion from the analysis of Facebook and Instagram on educational activities by implying that these social networks have a huge potential in improving educational activities because they provide easy communication between students and teachers but it

also displays that the concentration of students is highly affected by the use of social media which can in turn negatively affect the learning development of students. Therefore, an important takeaway from this research paper is that setting a guided direction for the use of social media in the educational environment by adapting the psychologically and socially imposed norms can have a drastic positive impact on academic performance. [12]

2.2 Team development and Team roles

The second important prerequisite is studying team development and team roles. What are the team roles? What gives their true characteristic? What does previous research say about team roles, effectiveness, and the behavior of team members?

First of all, it is good to have knowledge about all nine roles described in Belbin's paper from 2004[3]. His research is at the core of the meaning of these roles and we will use the definitions defined throughout the study.

Furthermore, the paper of N Meslec, PL Curşeu 'Are balanced groups better?' [4] provides interesting tables and research on the effectiveness of Belbin roles. This study shows that it is important to only construct a sum of individual roles, but also look into group configurations. Hence, it is relevant for our research because the results show a positive correlation between Belbin roles, predictions, and team performance

In addition, the paper 'Team roles and team performance: Is there a link?' by Barbara Senior [21] provides a detailed overview in tables for the correlation of Belbin roles and team performance. In the table of 'Comparison of predicted team performance and actual team performance, we can see that team H and team E whose predicted and actual performance was the same had the in common not the balance but the match of their skills to the team roles. Therefore, seeing how to predict team roles based on skills displayed is relevant to improving and studying the correlation between team roles and team performance.

Furthermore, the paper of Ronald Batenburg, Wouter van Walbeek, and Wesley in der Maur titled 'Belbin role diversity and team performance: is there a relationship?' [20] gives an interesting look into the topic because the findings show that there is no correlation between role diversity and team performance but this is the case for individual results, it states that the situation is different when considering the research from a more team-oriented perspective and that potential indicators that show motivation and collaboration might lead to other results. Therefore, it is interesting to study groups and provide a tool for crafting profiles based on information bound to teams rather than looking at the performance of individuals.

3. METHODOLOGY

This research follows the CRISP Methodology procedure which consists of six steps – Business understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment.[15] The choice of this methodology was well-suited for this type of research

not only because it encourages best practices and is associated with data science projects but most importantly the fact that this methodology allows easier replication[14] which is important for this type of research that opens up the field of analyzing team progress through Belbin Role theory and social media data analysis.

For the study 20 student test subjects were examined. The data collected from them were treated in a confidential way in coordination with the guidelines defined by GDPR[22]. All of the participants in the study were treated anonymously.

3.1 Understanding Belbin Roles, Behavior, and Discord as social media

This part of the methodology in the scope of our research is associated with our first sub research question where we try to understand Belbin roles and their correlation with behavioral traits. Reading through previous research and analyzing the results of that research gives us information and clues about how we can approach the issue by analyzing the behavior through social media. The Belbin roles summary[3] provides a clear overview of the traits of every single Belbin Role. The other side of the matter was associated with how we can build this within technology to make use of it and update it throughout the whole system. This question led to the creation of a nested main Belbin role dictionary that contains all the Belbin roles as keys. Each of the Belbin roles is defined by another inner dictionary that contains the traits that are representative of that Belbin role and to each of these traits, there is a list of identifiers that act as signals showing that the subject being analyzed shows behavioral traits of that specific role. Adding all characteristics described by Belbin and previous research is a good foundation but the research showed that it was of great importance to lower the scope of these characteristics to find the ones that are truly measurable. This step was important to assure the building blocks of the research will be identifiable and analyzable in correspondence with the dataset available.

Aside from the Belbin Roles part, this part of the research also involves understanding Discord which is the social media environment for the study. Gaining access to discord channels and servers was a prerequisite for writing functions that lead to results that can be analyzed. Therefore, the first step was to make sure that all access was granted. It was important to have rights not only for general channels but also for team-specific ones because this is where the internal communication truly lies and this uncovers the true behavior of students.

3.1.1. Authorization

Aside from gaining channel rights, access to discord itself was required. The tool used for data analysis makes use of the requests python library. The authorization token was acquired by analyzing the header files of the package sent by typing in a message in a specific channel. 'Typings' response in the web development tools provides information about the channel id. The next step is crafting a URI that fetches the information about the channel based on the channel id.

3.2 Understanding the Discord Data

Understanding the underlying data can be divided into three parts:

3.2.1 Understanding the data format

The information from the access procedure explained above is retrieved in a JSON format that contains data including but not restricted to the id and name of the user that sent the message, the contents of the message, and the exact timeframe in which the message was sent, emojis used, tags. The important question here was, what specific values do we want to extract from this whole JSON dataset? What information is truly useful and manageable in the scope of this research? To answer the first question, we need to take a look at the potential value of the information. This is defined by quantity and quality where quantity shows how often this data type is available for the given data set and quality – what the impact on the research questions to be answered is. For the first reason, we can immediately exclude information like tags and reactions to the message because they are rarely found and even if analyzed properly the quantity is just not enough to produce an outcome. Similarly, paying specific attention to emojis out of the scope of just strings is not justified. From the quality side of the matter, for finding results ids can be excluded. Although useful for identifying other pieces of data, ids on their own carry no value towards producing an outcome. This leaves us with the content of the messages – the strings that show the exact messages and the timeframe of these messages.

3.2.2 Analyzing Discord channels data

In order to find relevant information and clues for the definition of the traits of the Belbin roles, direct analysis by hand was done. This boils down the data by removing channels that are either associated with teachers only or do not contain any messages at all. The relevant channels are then added to a file that is being read by the tool and every channel is accessed by its own channel id found in the typings header of that specific channel.

3.2.3 Constructing and analyzing Belbin roles identifiers

To find the signal words that build the traits dictionaries are used to build the Belbin roles reverse engineering procedure is applied. Firstly, the raw set of data is analyzed for clues. Secondly, a subset of the users' information on the three major Belbin roles was available from reliable university sources. Using this information, through looking through the dataset, analyzing the words associated with these names, and combining it with the knowledge of Belbin role theory the potential identifiers were pinpointed and used to populate the dictionaries. The steps taken followed the general framework of reverse engineering - information extraction, modeling, and reviewing.

3.3 Preparing the Discord data

3.3.1 Data Acquisition

All the data is retrieved by pulling and decomposing the JSON file for a specific channel id. The retrieval procedure is divided into retrieving names and retrieving information about the messages themselves. The former is associated with the retrieve_names function that issues a GET request to the specific channel provided and then stores the user ids and names of the students involved while filtering out deleted users and teachers. The latter issues a similar GET request but it is concerned with adding the contents of the specific message of the specific user to a separate dictionary and associating the timestamps of the messages of the user to the users themselves. This allows for ease of access to the data and more importantly maps the users to their own information which is used for the assessment of their roles.

3.3.2 Data Division

The big JSON chunk is divided into sub-dictionaries that each has its own task. This creates a separation of concerns and makes the tool more maintainable for future updates. The tool is made to use internal auxiliary space for all the internal data processing and computation and mapping that is independent of specific external APIs like Discord Bot. This assures that the tool is not only bound to one social media environment, in this case – Discord, but can easily be used as a foundation for increasing the scope to other social media platforms. Through this, the tool achieves higher reproducibility and scalability that gives ground for the creation of more complex and reliable libraries and frameworks for Belbin role automation which can be used for further research on team development and effectiveness analysis.

3.3.3 Natural Language Processing

The content of the JSON files that represent the text of the actual message is processed through word_tokenizer of the nltk library. The function read_and_parse_string(str) takes the whole message and removes all the stop words that do not hold any real information. After that the string is split into the words it consists of. This is needed to first separate strings that hold value from those that do not and secondly, to make every such string its own unit to be analyzed and fed into algorithms used for mapping this data to Belbin role traits and using the data to predict the Belbin role and visualize the outcome.

3.3.4 Timestamp formatting

The initially retrieved timestamps have a format that is difficult to use and not very manageable by the system. That is why the timestamps have been processed too. This is achieved by changing the predefined format to a format that is acceptable by the datetime library. To do this, the timestamps are stripped of letters and information that does not convey anything and does not match the requested format, and then the format is adjusted to the appropriate one. After that, the functionality of the system takes these

timestamps and converts them into seconds. After this conversion, the data is ready to be used in mathematical computation like getting the difference between messages and computing the average difference between messages.

3.4 Modelling the Data

3.4.1 The Data model

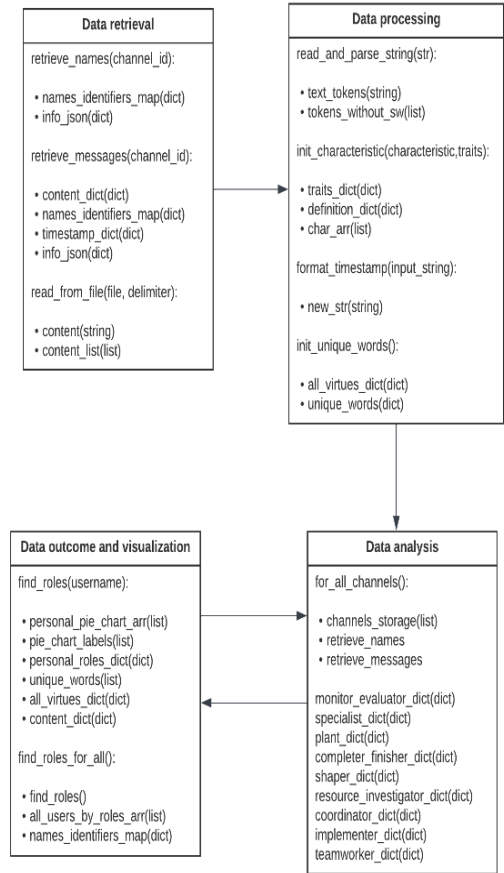


Fig 1.The data model describing the process and structures used.

The Belbin role predictions generated through the model showcased in figure 1 are computed on per user basis. The model consists of data retrieval where information from the JSON file like names and content plus information from local files is fetched, data processing where all the information is rendered, and data analysis where the information from the channels is analyzed and fed into the Belbin role signals and Data outcome and visualization where the outcome is determined and visualized for any user. The methodology of retrieval of processing was discussed in previous sections and the section on evaluation will discuss the feedback loop between data analysis and data outcome.

3.4.2 Data outcome and presentation

The outcome of the data represents how much of every role this specific user has in percentile format. This is achieved through

counting the number of matches between signal words and the actual words found in the content of the messages of the user plus additional tweaks and amounting supplementary potential identifiers like the average of the difference of times when the messages were sent. The final outcome is represented in a pie chart format that displays the Belbin profile of the student. An example of this can be found in appendix section C. The generation of these pie charts is done through "matplotlib", more specifically "matplotlib.pie" and "matplotlib.fig", and the data passed to format is found in the personal_roles_dict where every user is assigned all Belbin roles, and the amount that represents the consistency of each of the roles. In the end, additional formatting to the graphs is applied through "matplotlib" functions and function properties like explode(), Circle(), and tight_layout().

3.5 Evaluating the data and process

3.5.1 Evaluation procedure

The final stage before deployment is the evaluation part of the methodology. It is implemented in this research through iterating between data outcome and visualization and data analysis as displayed in figure 1. After the outcome is generated and displayed, it goes through the analysis procedure and is checked against validation data. After that, the information of the dictionaries is updated and re-rendered and the new outcome is displayed and re-evaluated.

3.5.2 Experimental results

The first experiment was to run the prediction on one single Belbin role. The choice of this role was the implementer because it is the most commonly found choice of computer science students. At that time the scope of each role was ambiguous because this was the first testing of the product. Every role contained a descriptive amount of traits that were defined based on research but not backed up by interaction with the actual dataset. While analyzing and re-evaluating it became apparent that some of the traits are either unmeasurable in the scope of the dataset or they are not relevant in the scope of the research because there is nothing to support them or they do not convey anything unique. For example, implementers have the trait of having practical common sense but it is difficult to accurately assess common sense without having information on a personal level for the target users. Therefore, the inner construction of the dictionaries built was refined and re-designed to match the characteristics of the dataset and the needs of the research. This led to boiling down the implementer to problem-solving skills, well-organized, reliable, and taking tasks that can be measured and analyzed.

The same procedure was applied to the rest of the roles. The scope for most of the definitions was reduced to three to four core and measurable traits. After having this complete, the second experiment was associated with composing an algorithm that would run on a per-user basis and assess all of the Belbin roles against the dataset with all the content for this user. The results were visualized as described in section 5.2.4.2. The outcome of this experiment was that there are words that can represent more than one trait, such words were found

for the specialist and implementer roles because they are both concerned with problem-solving skills and technical expertise. Therefore, the conclusion from this experiment was that not only the words need to be found, but also unique words for every role need to be identified. Then, the algorithm was adjusted such that the occurrence of unique words gets more value than the other words. This procedure led to smoothed and more focused output.

The last experiment was to run the algorithm with the aforementioned two adjustments and analyze the output against the dataset of Belbin roles of students. Since the first most dominant role was used to feed the dictionaries, the true assessment of the accuracy of the approach should be concerned with the second and third most dominant roles. The outcome of this will be covered in the results section.

4. RESULTS

Table 1 shows the overview of Belbin roles provided prior to the study. This is the data used for validation of the final results. For each of the 20 test subjects, the three dominant roles have been provided. Row Role 1 shows the most dominant one, row role 2 is the second most dominant, and row role 3 – the third most dominant.

The result of the research is in both a pie chart form that can be seen in figure 2 below and table output - table 2

| Test subject | Role 1 | Role 2 | Role 3 |
|--------------|--------------------|-----------------------|--------------------|
| 1 | Coordinator | Plant | Implementer |
| 2 | Implementer | Specialist | Plant |
| 3 | Plant | Implementer | Specialist |
| 4 | Completer-Finisher | Specialist | Shaper |
| 5 | Shaper | Specialist | Monitor-Evaluator |
| 6 | Plant | Completer-Finisher | Implementer |
| 7 | Specialist | Monitor-Evaluator | Plant |
| 8 | Plant | Coordinator | Implementer |
| 9 | Coordinator | Monitor-Evaluator | Teamworker |
| 10 | Shaper | Coordinator | Monitor-Evaluator |
| 11 | Specialist | Plant | Completer-Finisher |
| 12 | Monitor-Evaluator | Teamworker | Specialist |
| 13 | Specialist | Resource-Investigator | Implementer |
| 14 | Specialist | Shaper | Completer-Finisher |
| 15 | Specialist | Completer-Finisher | Shaper |
| 16 | Implementer | Plant | Specialist |
| 17 | Plant | Completer-Finisher | Teamworker |
| 18 | Coordinator | Shaper | Implementer |
| 19 | Shaper | Coordinator | Monitor-Evaluator |
| 20 | Implementer | Monitor-Evaluator | Coordinator |

Tab 1. Belbin roles data collected from test subjects

| Test subject | Role 1 | Role 2 | Role 3 |
|--------------|---------------------------|---------------------------|---------------------------|
| 1 | Coordinator - 25% | Plant -13% | Teamworker-12,5% |
| 2 | Implementer - 40% | Monitor-Evaluator - 20% | Plant - 10% |
| 3 | Plant - 33.3% | Implementer-17% | Specialist - 16.7% |
| 4 | Specialist - 42.9% | Completer-Finisher - 15% | Shaper - 14.3% |
| 5 | Specialist - 38.9% | Shaper-22.2% | Monitor-Evaluator - 11.1% |
| 6 | Plant - 26.2% | Specialist - 18.8% | Implementer-17.5% |
| 7 | Shaper - 37.5% | Plant - 25% | Monitor-Evaluator-12.5% |
| 8 | Plant - 22% | Implementer-20% | Shaper - 16% |
| 9 | Coordinator - 40% | Implementer - 33.3% | Plant - 16.7% |
| 10 | Specialist - 63.3% | Implementer - 12.4 % | Plant - 7.9% |
| 11 | Specialist - 26.5% | Shaper - 20.4% | Plant - 16.8% |
| 12 | Monitor-Evaluator - 20.8% | Specialist - 20% | Shaper - 18.8% |
| 13 | Implementer - 40% | Coordinator - 33% | Specialist - 22% |
| 14 | Specialist - 45.7% | Implementer-22.9% | Plant - 11.4% |
| 15 | Specialist - 36.3% | Teamworker-15% | Shaper - 13.3% |
| 16 | Specialist - 50% | Teamworker-25% | Shaper - 22% |
| 17 | Plant - 47.1% | Monitor-evaluator - 29.4% | Implementer-17.6% |
| 18 | Specialist - 31.8% | Coordinator-23.2% | Implementer-13.2% |
| 19 | Specialist - 29.5% | Shaper-22% | Implementer-21% |
| 20 | Implementer - 25% | Specialist-19.3% | Shaper-18.2% |

Tab 2. Final table outcome of the Belbin roles from the tool including their percentages

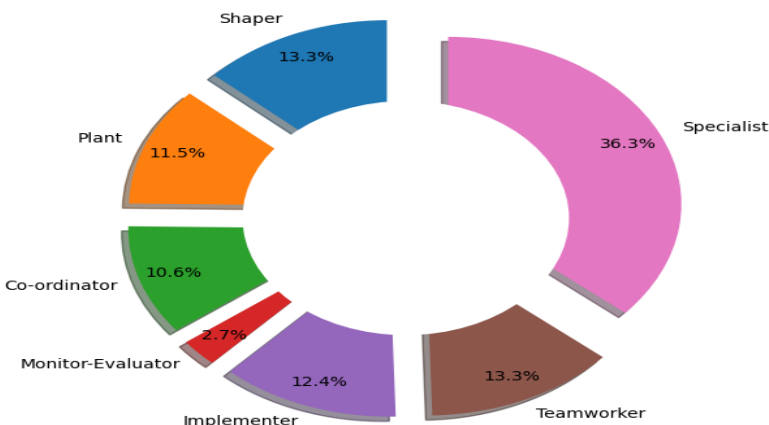


Fig 2. Final pie chart outcome example including all relevant Belbin roles up to all nine of them

As shown in figure 2 the tool provides an overview of roles more than the dominant three until covering all 9 Belbin roles.

The specific pie chart displayed in figure 2 is the profile outcome for test subject 15 and like all the others is directly generated from the find_roles(username) function. We can see an overview of all the roles that this person has shown signs of and their corresponding strength. This output is based on natural language processing. It provides a deeper analysis of every single test subject and showcases the accuracy of the result.

To view the broader aspect of this, we can have a look at the data from table 2 and compare it to table 1. Table 2 has the same structure and test subjects but it displays the output of the tool rather than the test subject data provided. The first row exhibits the role that the tool predicted to be most dominant, the second row the second most dominant, and the third row – the third most dominant. Each of the cells has been labeled according to the accuracy – green stands for correctly predicted, yellow stands for correctly identified but incorrectly allocated, and red for incorrectly identified. Thus, the correct predictions for the first role are 12/20, second role 2/20, and third role 7/20. Table 3(Appendix section A) gives an overview of the difference in sets of top roles predicted and roles provided where ‘top’ is defined as the roles corresponding to the bigger portions of the pie chart. If two roles have identical or very similar outcome percentages, then they are both considered in the final evaluation. Based on this, the tool shows to predict the set of roles accurately approximately 64% of the time using natural language processing only.

5. DISCUSSION

The answer to how we can identify measurable personality traits from Discord messages was hidden in the process itself and was achieved by looking through the dataset and mapping certain processed words to Belbin role definitions found in [3]. The more interesting aspect was finding out which one of the mapped personality traits is truly measurable. This means that every single one of them should have enough data to support them and it should be possible for it to be identified by words constructing the students’ text message exchanges. This led to building tight Belbin role dictionaries of three to four major personality traits that were quantifiable by the outcome. For example, the coordinator is associated with leadership, task division, and confidence because all of them have signaling words that point to these traits.

Based on the final results showcased in the section above, we can determine that the research provides a correct methodology for answering the question of how we can identify Belbin roles based on students’ text messages by following the procedure explained in the methodology section. However, the accuracy of correctly allocating the most dominant roles is low as can be seen in the outcome in table 2 and therefore the results show that the data from Discord using natural language processing alone is not sufficient to accurately predict and allocate Belbin roles. Nevertheless, provided that more

data is fed into the dictionaries and re-evaluated, the precision of correct allocation can be drastically improved.

There are two important remarks about the results. The first one is that the results from the first role can be biased because shared data has been used for both training and testing. The tool often recognizes the set of roles correctly but assigns them the incorrect slot. Furthermore, the difference in the outcome in percentages between the roles of the test subjects is often not that big or even equal so if the only difference is the slot, then one can argue that the tool is more accurate than it appears to be. Therefore, table 3 was introduced to give information about the total accuracy of correct identification of the tool.

Based on the information in Table 3, we see that the tool is not far from identifying the correct roles as the percentage of successfully identified roles is 64%. The data shows that the tool can identify the roles correctly in the majority of cases which serves as proof of correct methodology but the final outcome percentage is lower than the confidence bound and is therefore not enough to conclusively determine that natural language processing alone provides concretely reliable Belbin role identification automation.

5.1 Found Belbin roles dependencies

While researching, interesting findings about the personal characteristics of students became apparent. After analyzing and evaluating the messages, most of the students with common roles showcased very similar behavioral traits. The following findings were found:

Shapers tend to use more linking words and they are the ones that generally lead the conversations with representatives from the university side

Emojis produced interesting observations – face emojis, especially smiley faces were used by people with the roles that had the ‘introverted’ trait like the plant as opposed to the general expectation that people with a more extroverted mindset would use that

However, other emojis that represent values associated with a positive mindset like hope, prayer, and thumbs-up were found almost entirely in the dataset of people with more leadership and networking skills-oriented roles like shaper and coordinator.

Coordinators tend to address people directly. A higher occurrence of words representative of names of team members or teachers was found plus a higher frequency of words like check, question, and ask. Therefore, they are not afraid to question people and speak directly to them. Another interesting common behavioral characteristic found is that they are keen on sharing details about their look and more personal information on what they are wearing or how exactly they are feeling. This might seem normal in regular conversations, but for focused university teams, this is rather rarely found as the majority of students rarely shared any personal information but had messages mostly revolving strictly around the project and teamwork.

Furthermore, coordinators had more messages on average and had the confidence to openly say what is wrong or bad and what they do not like.

The main behavioral sign of a Specialist that the research showcased is the dense consistency of technical terms. Words that describe technologies like React, TypeScript, Java, and more architecture-oriented keywords and phrases like ‘XML’ and ‘HTTP request’ was found

Team workers show openly their support by using positive expressive sentences like ‘awesome!’, ‘great!’ and ‘keep up the good work !’

Completer-Finishers’ behavior led to the observation that the use of verbs in ‘-ing’ such as form ‘pushing’, and ‘committing’ is much more frequent than it is with other roles. Furthermore, the semantics of their sentences are often concerned with submission, committing, and file system management.

6. CONCLUSIONS

This research shows to propose a correct methodology for validating Belbin roles based on university students’ messages. However, the results were affected by limitations which lowered the final percentage outcome and hurt the accuracy of the tool. Therefore, further research can build upon the foundations discovered here by using larger portions of data from different sources to polish the outcome and improve the automation process.

6.1 Limitations

Firstly, the outcome of the program is bounded by the data accessible from the Discord channels. Some of the users that had content in Discord were either deleted or left the channel which made their information inaccessible to the study. Furthermore, the majority of students did not have a lot of messages in the channels which meant that the data was insufficient to consider them in the study or produce a correct outcome for their Belbin profiles.

Secondly, a limitation to the functionality of the software was associated with the reverse engineering procedure of finding identifiers. Some of the students used usernames that were not found in the database and therefore, their content could no longer be used for training purposes because their Belbin roles were unknown. This led to rendering good portions of data useless and lowering the amount of income in the data model, thus lowering the precision of the outcome.

Another limitation of the software is that the scope of the different Belbin roles dictionaries is not equalized. Some of the roles were associated with enough data to find a sufficient amount of identifiers like the Specialist role but others like the Resource-Investigator were not represented by enough students in the dataset and thus the data from them was used for feeding the dictionaries was not enough.

6.2 Further research

This research builds the ground and opens up the horizon for further research in Belbin role automation and analysis of teams using Belbin roles. The structure of the dictionaries and the methodology section can be used in other social media settings and applied to larger portions of data. The more data you have to provide to the dictionaries, the more dependencies you can study and the more accurate you can make the prediction. Therefore, this study can be proposed as a motivation for creating an open-source API or library based on machine learning recognition. Future researchers can extract larger amounts of data and re-create the process of feeding, evaluating, and refining the prediction using different social media platforms that can be used in education or even outside of the scope of education like WhatsApp, Facebook, Instagram, WeChat, and Telegram and make the containing dictionaries much more precise. In addition, future developers of the research can look into variables different from natural language processing. Interesting ideas for this include a deeper analysis of timestamps for determining activeness and reply speed, analysis of emojis used, and information cascading effects for example how the roles of friends of the subject affect the choice and behavior of that subject. All of them can make use of the methodology process defined in figure A and the tool's core because the study was made with reproducibility and scalability in mind.

REFERENCES

- [1] Tuckman, B. W., & Jensen, M. A. C. (1977). Stages of small-group development revisited. *Group & organization studies*, 2(4), 419-427. <https://doi.org/10.1177/105960117700200404>
- [2] Shapiro, M. J., Morey, J. C., Small, S. D., Langford, V., Kaylor, C. J., Jagminas, L., ... & Jay, G. D. (2004). Simulation-based teamwork training for emergency department staff: does it improve clinical team performance when added to an existing didactic teamwork curriculum?. *BMJ Quality & Safety*, 13(6), 417-421. <http://dx.doi.org/10.1136/qshc.2003.005447>
- [3] Belbin, M. (2004). Belbin team roles. *Book Belbin Team Roles*. https://www.sheffield.ac.uk/polopoly_fs/1.18832!/file/8-Horn-Team-roles-handout.pdf
- [4] Meslec, N., & Curşeu, P. L. (2015). Are balanced groups better? Belbin roles in collaborative learning groups. *Learning and Individual Differences*, 39, 81-88. <https://doi.org/10.1016/j.lindif.2015.03.020>
- [5] Easley, D., & Kleinberg, J. (2012). Networks, crowds, and markets. *Cambridge Books*. <https://www.cs.cornell.edu/home/kleinber/networks-book/>
- [6] Hsiung, C. M., Luo, L. F., & Chung, H. C. (2014). Early identification of ineffective cooperative learning teams. *Journal of Computer Assisted Learning*, 30(6), 534-545. <https://doi.org/10.1111/jcal.12062>
- [7] Senior, B. (1997). Team roles and team performance: is there 'really' a link?. *Journal of occupational and organizational psychology*, 70(3), 241-258.. <https://doi.org/10.1111/j.2044-8325.1997.tb00646.x>
- [8] Belbin Role association test <https://www.belbin.com/resources/free-belbin-test-looking-for-a-free-team-roles-test>
- [9] Woda, M., & Batogowski, J. (2020, June). Prediction of selected personality traits based on text messages from instant messenger. In *International Conference on Dependability and Complex Systems* (pp. 672-685). Springer, Cham. https://link.springer.com/chapter/10.1007/978-3-030-48256-5_66
- [10] Owusu-Acheaw, M., & Larson, A. G. (2015). Use of social media and its impact on academic performance of tertiary institution students: A study of students of Koforidua Polytechnic, Ghana. *Journal of Education and Practice*, 6(6), 94-101. <https://files.eric.ed.gov/fulltext/EJ1083595.pdf>
- [11] Liu, D., Kirschner, P. A., & Karpinski, A. C. (2017). A meta-analysis of the relationship of academic performance and Social Network Site use among adolescents and young adults. *Computers in human behavior*, 77, 148-157. <https://doi.org/10.1016/j.chb.2017.08.039>
- [12] Kaya, T., & Bicen, H. (2016). The effects of social media on students' behaviors; Facebook as a case study. *Computers in Human Behavior*, 59, 374-379. <https://doi.org/10.1016/j.chb.2016.02.036>
- [13] Abbas, J., Aman, J., Nurunnabi, M., & Bano, S. (2019). The impact of social media on learning behavior for sustainable education: Evidence of students from selected universities in Pakistan. *Sustainability*, 11(6), 1683. <https://doi.org/10.3390/su11061683>
- [14] Wirth, R., & Hipp, J. (2000, April). CRISP-DM: Towards a standard process model for data mining. In *Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining* (Vol. 1, pp. 29-39). <http://www.cs.unibo.it/~daniilo.montesi/CBD/Beatriz/10.1.1.198.5133.pdf>
- [15] Rivo, E., de la Fuente, J., Rivo, Á., García-Fontán, E., Cañizares, M. Á., & Gil, P. (2012). Cross-Industry Standard Process for data mining is applicable to the lung cancer surgery domain, improving decision making as well as knowledge and quality management. *Clinical and Translational Oncology*, 14(1), 73-79. <https://link.springer.com/article/10.1007/s12094-012-0764-8>
- [16] Batenburg, R., & van Walbeek, W. (2013). Belbin role diversity and team performance: is there a relationship?. *Journal of Management Development*. <https://www.emerald.com/insight/content/doi/10.1108/JMD-08-2011-0098/full/html?fullSc=1>
- [17] Biddle, B. J. (1979). *Role theory : expectations, identities, and behaviors*. Academic Press. <https://www.sciencedirect.com/book/9780120959501/role-theory>
- [18] Senior, B. (1997). Team roles and team performance: is there 'really' a link?. *Journal of occupational and organizational*

- psychology*, 70(3), 241-258.
https://bpspsychub.onlinelibrary.wiley.com/doi/abs/10.1111/j.2044-044-8325.1997.tb00646.x?casa_token=oPcNWSr0yRUAAAAA:g6vKWWsJxcXx51b2uirFwF6wSjaSrl1Hmu3lYE2TWUW-TwYZKxiOLYxd83wqU2C8ghBvgQydBFJLnvz
- [19] Kearney, E., Gebert, D., & Voelpel, S. C. (2009). When and how diversity benefits teams: The importance of team members' need for cognition. *Academy of Management journal*, 52(3), 581-598.
<https://journals.aom.org/doi/abs/10.5465/amj.2009.41331431>
- [20] Batenburg, R., & van Walbeek, W. (2013). Belbin role diversity and team performance: is there a relationship?. *Journal of Management Development*.
<https://www.emerald.com/insight/content/doi/10.1108/JMD-08-2011-0098/full/html?fullSc=1>
- [21] Senior, B. (1997). Team roles and team performance: is there 'really' a link?. *Journal of occupational and organizational psychology*, 70(3), 241-258.
<https://doi.org/10.1111/j.2044-8325.1997.tb00646.x>
- [22] 2019 General Data Protection Regulation <https://eur-lex.europa.eu/legal-content/NL/TXT/?uri=CELEX%3A32016R0679>

Appendix A

| Test subject | Roles provided | Top roles predicted | Roles not predicted | Roles predicted (in %) |
|--------------|--|--|--|------------------------|
| 1 | Coordinator,Plant, Implementer | Implementer, Monitor-Evaluator, Coordinator, Plant, Teamworker | - | 100% |
| 2 | Implementer,Specialist,Plant | Implementer, Monitor-Evaluator, Coordinator, Plant, Specialist, Completer-Finisher | - | 100% |
| 3 | Plant,Implementer,Specialist | Implementer, Monitor-Evaluator, Specialist, Plant | - | 100% |
| 4 | Completer-Finisher,Specialist,Shaper | Specialist, Shaper, Plant, Completer-Finisher | - | 100% |
| 5 | Shaper,Specialist,Monitor-Evaluator | Specialist, Shaper, Monitor-Evaluator | - | 100% |
| 6 | Plant,Completer-Finisher,Implementer | Plant, Specialist, Implementer, Monitor-Evaluator | Completer-Finisher | 66% |
| 7 | Specialist, Monitor-Evaluator, Plant | Shaper, Plant, Monitor-Evaluator, Teamworker, Specialist | - | 100% |
| 8 | Plant, Coordinator, Implementer | Plant, Shaper, Specialist, Implementer | Coordinator | 66% |
| 9 | Coordinator, Monitor-Evaluator, Teamworker | Coordinator, Implementer, Shaper, Plant | Monitor-Evaluator, Teamworker | 33% |
| 10 | Shaper, Coordinator, Monitor-Evaluator | Specialist, Implementer, Plant | Shaper, Coordinator, Monitor-Evaluator | 0% |
| 11 | Specialist, Plant, Completer-Finisher | Specialist, Shaper, Plant | Completer-Finisher | 66% |
| 12 | Monitor-Evaluator,Teamworker, Specialist | Specialist, Monitor-Evaluator, Shaper | Teamworker | 66% |
| 13 | Specialist, Resource-Investigator, Implementer | Implementer, Specialist, Coordinator | Resource-Investigator | 66% |
| 14 | Specialist, Shaper, Completer-Finisher | Specialist, Implementer, Plant | Shaper, Competer-Finisher | 33% |
| 15 | Specialist, Completer-Finisher, Shaper | Specialist, Teamworker, Shaper, Implementer | Completer-Finisher | 66% |
| 16 | Implementer, Plant, Specialist | Specialist, Teamworker, Shaper | Implementer | 66% |
| 17 | Plant, Completer-Finisher, Teamworker | Monitor-Evaluator, Plant, Implementer | Completer-Finisher, Teamworker | 33% |
| 18 | Coordinator, Shaper, Implementer | Specialist, Coordinator, Implementer | Coordinator | 66% |
| 19 | Shaper, Coordinator, Monitor-Evaluator | Specialist, Implementer, Shaper, Teamworker | Coordinator, Monitor-Evaluator | 33% |
| 20 | Implementer, Monitor-Evaluator, Coordinator | Implementer, Specialist, Shaper, Plant | Monitor-Evaluator, Coordinator | 33% |

Tab 3. Table showing the difference of Belbin role sets including top Belbin roles identified and prediction percentages.