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Optimizing the Influence of Temporal Dynamics, Network Topologies, and Semantics on Unsupervised NLP Algorithms

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Abstract- The purpose of this study was to generate an algorithm able to decipher bots in social media. Prior research shows that variables/parameters affect the detection of AI; however, none attempt to compile an algorithm accurate enough to be deployed into a real-world scenario. Data was collected through mixed methods, in which data was collected online and through questionnaires. Participants included individuals from all demographics, only restricted to demonstrate no bias. Initial results show a strong correlation with variables on the usage of AI. This means that a model which can effectively deduce the usage of AI is plausible. Therefore, the conclusion can be made that it is possible to find bots in social media; however, this is limited to 70% accuracy, given the available resources. Future research should be targeted towards making sure text can be deciphered with more accuracy.

Index Terms- Bot detection, algorithm development, social media, deciphering

I. INTRODUCTION

In our contemporary digital landscape, social media platforms like Twitter, Facebook, and TikTok have become integral aspects of our daily lives, critically influencing how we communicate and interact with those around us. However, lurking beneath the surface of these platforms lies a significant issue - the presence of bots. As highlighted by lecturers Line Henriksen and Cancan Wang (2023), their autoethnographic study found that “on Twitter, Facebook, or TikTok, one can find millions of bots liking, following, commenting, sometimes even posting their content and buying stuff on their own” (p.2). “According to the Pew Research Center, 23 percent of Americans said they had shared fake news, either knowingly or unknowingly” (“Disinformation and the public,” n.d). Despite the acknowledgment of the widespread existence of social media bots, the authenticity of the information shared through these platforms remains unquestioned. Our reliance on social media as a primary source of information is undeniable, and yet we often fail to adequately attribute the influence of bots on disseminating information.

Aligning with Henriksen and Wang’s observations, DM Cook (2014) concurs, pointing out that "social media metrics are sufficiently manipulated away from authentic discrete usage so that the trustworthiness of identity, narrative, and authority are constantly uncertain” (p.2). By naively placing our conscience in the hands of artificial intelligence, “elections, social causes, political agendas and new modes of online governance can now be influenced by a range of virtual entities that can cajole and redirect opinions without affirming identity or allegiance” (Cook, 2014, p.2). Gradually leading to the weaponization of social media, many implications emerge, including misinformation, selective targeting, and the fabrication of false narratives. A visualization of these consequences is presented in Figure 1.

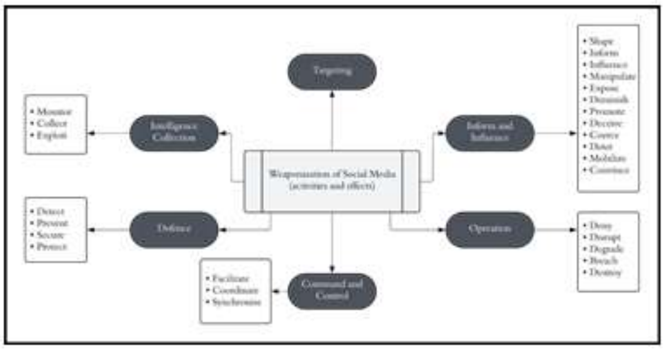

Fig.1. Each node in this mind map corresponds to a specific consequence of the weaponization of social media, containing various aspects of misinformation and harmful behavior.

Elaborating on the implications visualized by Sanda Svetoka in Figure 1, assistant professor Douglas Guilbeault (2018) comments that “Regulators and the public have called on social-media companies to address the global rise of online disinformation, emphasizing the detection and removal of particularly Russian hackers” (p.1). Therefore, it is imperative to take action towards identifying bots across social media platforms, as attempting to prevent their expansion is not plausible given the rapidly evolving nature of our digital landscape. To effectively prevent individuals from falling prey to misinformation and provide them with continual updates on whether text or information is human- produced, one solution is the implementation of machine learning algorithms. These algorithms, already being developed, can be further optimized by adjusting their parameters and topologies to provide users with the optimal guidance for using information on social media to their benefit.

II. LITERATURE REVIEW

1. Search Strategies

Sources were located in academic databases such as JSTOR and EBSCO and filtered for peer-reviewed papers to maintain credibility. Keywords utilized during the search were Bots, machine learning, and Social Media Misinformation.

2. Dynamics of Existing Bot Development

With the rapid spread of misinformation and adulteration of information in social media, professionals have called for creating various models to counter the lead cause, social media bots, each with their architecture, strengths, and weaknesses. The models being made are based on advanced frameworks such as machine learning and deep learning, all to detect and halt the spread of bot-driven misinformation. Regardless of the complexity and creativity of such a model, while attempting to address the issue of rapidly transforming bots in social media, challenges regarding the adaptability and limitation of these algorithms remain.

Design of Algorithm Architecture: The algorithms designed to counteract social media bots function in a structured and sequential manner. Initially, these models gather data (tweets) from various social media platforms, such as Twitter, for the sake of this study and take logs of user interactions, content dissemination, and network connections. These collected bytes serve as the parameters for the algorithm, and the collected data goes through preprocessing to ensure clarity. Key features of the text are then extracted from this preprocessed data, mainly consisting of behavioral patterns, linguistic cues, and network characteristics. These features now serve as the inputs for training the machine learning models, which are essentially tasked to differentiate between bot-generated and human-generated activity. Following this stage comes the evaluation/analysis stage, where the models are tested for their accuracy in accomplishing their tasks. This is done by assessing metrics such as accuracy and precision. Once validated, these models are deployed in real-world scenarios to potentially counter the proliferation of bots. However, in the evaluation stage, data analyst Chris Hays (2023) states that "existing bot detection tools show discrepancies in predictions, highlighting the need for improved sampling strategies" (p.2).

Emerging Trends in Bot Development: The trends in bot development highlight a heavy reliance on labeled features and structured ensemble modeling, ultimately presenting challenges in real-world implementation. Ashkan Dehgan's (2023) study on detecting bots in social networks concludes that the current "techniques are very powerful, but a supervised machine learning algorithm is only as good as the data used for training. Unfortunately, good quality datasets with the ground truth are rarely available" (p.3). This acknowledgment emphasizes the scarcity of high-quality labeled datasets that these algorithms are trained with, significantly impacting the efficacy of the supervised approach toward detecting bot behavior. Moreover, a trend that the study points out that they failed to account for was the struggle to keep pace with the ever-changing bot behavior (Dehgan et al., 2023). Thus, while the emerging advanced techniques such as feature fusion and supervised learning promise generalizability, trends such as the continually limited labeled data remain critical to address for advancing the efficacy of bot detection.

3. Shortcomings and Necessary Developments

Table 1: Qualitative Characteristics of Each Study's Respective Algorithms

Study	Supervised	Algorithm	Parameters
(Hays, 2023)	Yes	Machine Learning	Profile Information
(Aljabri, 2023)	Yes	Machine Learning – Random Forest	Verified Status
(Dehgan, 2023)	Yes	Natural Language Processing	User Profile
(Hayawi, 2023)	Yes	Machine Learning – Random Forest	Textual Context
(Heidari, 2022)	Yes	Machine Learning	User Profile

Table 1. Each row in this qualitative table describes each of the analyzed major studies, listing the topology/framework characteristics of each algorithm suggested for implementation.

As illustrated in Table 1, five major studies propose algorithms to counter the proliferation of bots in social media. Dehgan emphasized in his study that requiring labeled data is a limitation, urging its resolution. Analyzing all the existing proposed algorithms, it is evident that they all rely on supervised learning, a limitation that could be addressed using an unsupervised approach. Studies by Chris Hays, Malak Aljabri, and Khadim Hawayi (2023), all of whom are key figures in programming the predominant algorithm, indicate that their proposed models have lower accuracy rates, possibly due to small sample sizes or an inadequate understanding of the users' environment. This issue strikes the need for

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enhancive parameters to ensure the adaptability of the algorithms as the bots naturally evolve. The algorithms described in Table 1 mainly utilize machine learning models, such as Random Forest, but fail to consider the potential of NLP methods, which have been proven effective in text recognition. To a greater degree, researcher Maryam Heidari (2022) of George Mason University sums up the scholarly works, claiming that "we need different information about each user's account, such as users' features and network features, to differentiate a human account from a bot account." (p. 5). Leveraging the insights acknowledged from the limitations of previous models, I aim to contribute to this field by enhancing the bot-detecting algorithms through utilizing unsupervised NLP models while essentially targeting the goal of optimizing the influence of parameters such as temporal dynamics, network topologies, and semantics.

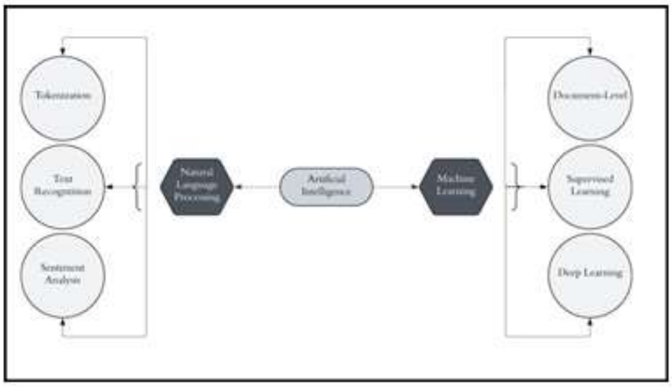

Fig.2. Each node in this mind map corresponds to a specific section of AI (NLP or ML), containing key attributes of their respective technique.

As visualized in Figure 2, most machine learning models use supervised models but also utilize deep learning. Whilst supervised models have proven to be less efficient, as shown in Figure 4, deep learning models are complex and provide an O(n^2) factor of efficiency, exponentially better than the O(n) a standard NLP method would provide. Previous models have incorporated one aspect or the other; therefore, using the limitations of these models published in 2023, I aim to develop an algorithm that utilizes text recognition (NLP), additional parameters, and mainly unsupervised, relevant data to optimize the performance of my model.

III. METHODS

1. Study Design

This study will explore and attempt to optimize the influence of various parameters on an unsupervised NLP algorithm. The ultimate goal is to help prevent the proliferation of bots in social media and implement an inbuilt algorithm to warn users of existing bots. This study is crucial and demands room to ensure replicability. With the spread of false information potentially endangering our consciousness and awareness, developing an effective algorithmic aid becomes imperative to provide individuals with the truth. Likewise to most researchers in this field, in this research study, the objective "is to detect Twitter bots based on diverse content-specific feature sets and explore the use of state-of-the-art machine learning classifiers" (Alarfaj, 2023, p.2). To pursue this objective, as illustrated in Figure 3, a three-part, mixed-methods study was conducted. This approach allows for a qualitative and quantitative analysis of the data collected from the users and the API's.

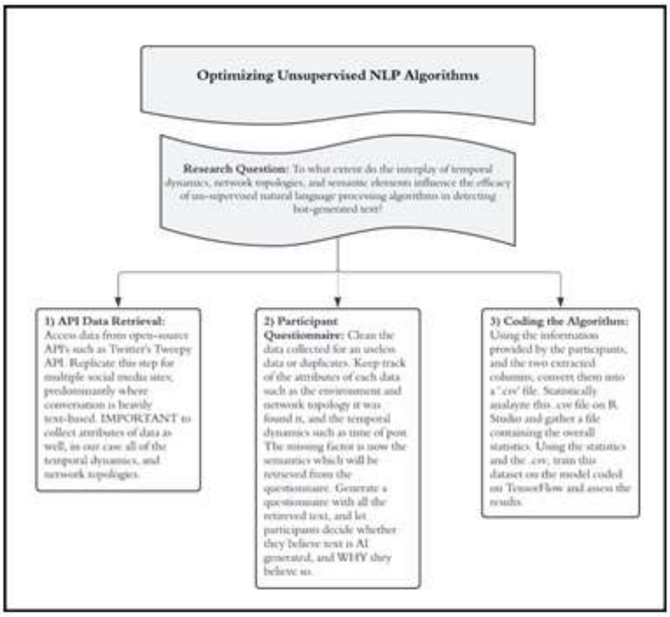

Fig.3 Each node in this mind map corresponds to a specific step in the methodology of my study, and each node contains a brief overview of the respective step.

2. Variables

The study incorporates various 'input' factors critical for determining the text's authenticity while awaiting the 'outcome' variables indicating whether the text was produced using the influence of AI bots. As outlined in the Literature Review, many independent variables were taken into account, such as the temporal dynamics (time & date), network topologies (type of website & average daily users), and semantics (syntax & diction). These independent variables were collectively input into a model, ultimately aiding in deciphering the text and quantifying the dependent variable, a binary statistical measure indicating whether the text was made in the presence of AI (yes or no).

3. Participants

One hundred participants contributed to my study by completing the required questionnaire. To ensure equal representation amongst all ages, the participants were equally split up into age groups: 25 participants under the age of 18,

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25 college students, 25 employed individuals, and 25 retirees. Participants were allowed to participate in this questionnaire through a flyer posted across various outreach platforms, enabling broad access to potential participants. Notably, the only prerequisite was that participants were fluent in English.

4. Research Instruments

To conduct this study, there were a few tools that were required, metaphorically and practically, and from the beginning to the end. As depicted in Figure 5, the first instrument we require is an open-source API of a social media site, one capable enough such that it can provide text and certain pertinent attributes such as temporal dynamics. Subsequently, the conversion of text into vectors is conducted through the GloVe method, as indicated by Figure 5. As written out in (1), (2), and (3), all of these equations, at a deeper level, attempt to standardize the text using the 'T' optimizer to convert text on the RHS to vectors on the LHS. The equations are part of a module called ELMo, and they aid in converting text to vectors. Lastly, critical software programs for data analysis and machine learning, R Studio, and TensorFlow, are employed. The vector data accumulated from the ELMo modules were input into R Studio to produce a statistical measure and used whilst training my model on TensorFlow.

$$p(x_1, ..., x_n) = T_{i=1}^{n} p(x_i | x_1, ..., x_{i-1}) \quad (1)$$

$$p(x_1, ..., x_n) = T_{i=1}^{n} p(x_i | x_{i+1}, ..., x_n) \quad (2)$$

Most importantly, the instruments that I will be using to conduct my study will all be tailored to unsupervised models, so the packages and methods I import will be related to this field. Figure 4 substantiates this choice, as it is evident the unsupervised workflow is more efficient and more replicable in a real-life scenario, not requiring manual labeled feature extraction.

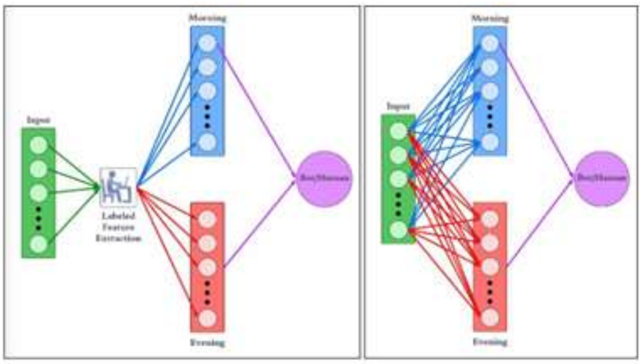

Fig.4 The section of the figure representing the supervised model (left) depicts how the method requires manual extractions of patterns/features in the data. The section of the figure representing the unsupervised model (right) depicts how the method uses inbuilt techniques to extract patterns/features of the data automatically.

3. Procedures

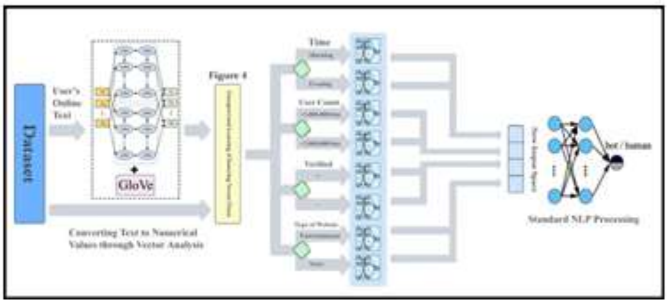

Fig.5 The workflow progresses from left to right, starting with a collected dataset on the left and advancing through the process of developing a model, concluding with an NLP algorithm on the right.

Figure 5 illustrates the detailed overview outlined in this 'Procedures' paragraph. Most studies to date are observational and, therefore, unable to disentangle the effects of confounding factors such as temporal dynamics, network topologies, or semantics of the community structure. Here, we describe a novel controlled experiment that we performed using a multitude of steps (Monsted, 2017). Beginning with the retrieval of data, I started my study with the collection of text from various social media APIs, Twitter's Tweepy, for example, to ensure the data collected was from both human-generated text and text that was confirmed to have been generated by bots. The collected data was randomly divided into two halves for further pre-processing. Employing the ELMo equations, the textual data was converted into vectors using R Studio. Subsequently, a questionnaire containing a subset of the data was administered to 100 diverse participants. Utilizing the vector data and the questionnaire responses, I input them into R Studio once again, retrieving crucial statistics on which variables perceptively had the most influence in determining social media bots. For the final step of the procedure, I coded an algorithm to cluster the variables themselves and split the data amongst various parameters, such as morning or evening for the time of day and entertainment or news for the type of website. Given the objective of generating an unsupervised model, I provided only one example of labeled data and coded the algorithm to sort through a lot of numbers to label them automatically. I also provided whether each text in the dataset was generated by AI or not, as this was crucial for training the algorithm to optimize the parameters with the correct outcome. At the culmination of this procedure, I developed an unsupervised deep learning NLP model that was capable of discerning whether the text was created by a bot/human, as depicted on the right-hand side of Figure 5.

IV. FINDINGS

Concluding the development of the model, it was imperative to extract findings and specific insights from this study. My methodology was executed through a very cautious approach: utilizing half of the APA-collected dataset for training the model and using the other half for testing. This separation was made to ensure evaluation integrity, akin to conducting a test without providing access to the answer key. During the testing of the model, text was input to the algorithm with various parameters, prompted to generate binary responses indicating whether the text was of AI or human origin. The visual representation of my findings is shown in Figure 6; the x-axis denotes each text sample (1-30) for each text type, human and AI text, and the y-axis depicts the disparity between the model's output and the truth as stated on the API. To construct these graphs, I assigned values for the truth: 0 for human-generated text and 1 for AI-generated. The model was then run approximately 2000 times for each dataset, and the responses were averaged for each text sample to mitigate any bias. The difference between the model output and the actual label (0 or 1) was computed for each input and visualized on the chart. As shown in Figure 6, my model comes with commendable accuracy in classifying whether the text is generated artificially [75.76% in identifying AI- generated text and 69.194% accuracy in discerning human- generated text]. On aggregate, these statistics highlight the model's proficiency in unsupervised learning, where it splits the text into its various attributes and detects the classification of text.

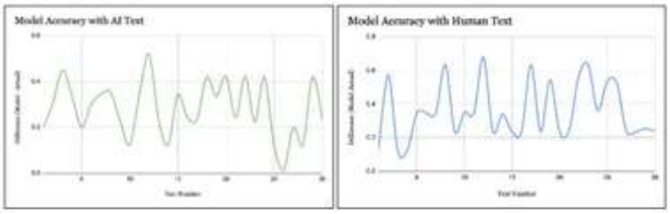

Fig.6 The model was tested multiple times for accuracy against AI-generated text (left) and human-generated text (right), both collected from an open-source API.

1. Performance of Algorithm

The algorithm's consistent performance, averaging over 70% accuracy over multiple tests, heavily underscores the reliability of a model, especially one that has not been around for years. This study reveals key insights into the performance and the ability to optimize such a model. As I tested my models across various attributes, such as the optimizer, the number of training and testing sessions, and several epochs, certain thresholds became more significant. Running more than 75 training sessions and testing the model had become a benchmark due to its performance logarithmically plateauing after these values. It was also evident that testing the model many times through testing sets just confined the confidence interval of results rather than fluctuating the accuracy. While these were the external and 'manual' findings that were relevant to the performance of the model, the true discoveries lay around the influence of various parameters. With the rapid enhancements of these social media bots surfacing online, the use of "more variables are required to potentially find a more sophisticated bot" (Efthimion et al., 2018, p.18). R Studio offers various numerical values on the impact of various parameters (guided) by the participant feedback from the questionnaire. Rather than directly adjusting the weights of each parameter before optimizing my model again, I played around with the weight of each parameter individually until I got an output that provided the most accuracy. As shown in Table 2, it was evident that for my model, given the specific weights I have given for each parameter, the 'Adam' optimizer had provided the most accuracy of around 76% given specific training sessions, testing sessions, and several epochs.

Table 2: Quantitative Values of Model Development Attributes

Type of Optimizer	Training Sessions	Testing Sessions	# of Epochs	Accuracy
Gradient Descendant	100	2000	25	55.67%
Adagrad	85	2000	20	61.93%
Adadelta	75	2000	15	64.23%
RMSProp	85	2000	20	59.64%
Adam	125	2000	15	75.76%

Table 2. Each row in this quantitative table describes each of the major optimizers used to train the model and the model's respective accuracy given various parameters such as training and testing sessions.

Overall, these findings, especially the ability to adjust the weightage of each parameter, are very significant, as this adds a new dimension to optimizing an algorithm. This lets algorithm designers implement the ability to automatically adjust the weights of each parameter, along with using the approximate values shown in Table 2 to effectively optimize their respective NLP algorithms.

V. ANALYSIS

After testing the developed model through training sets extracted from Tweepy's API, it was apparent that the model had achieved a significant level of accuracy. However, to comprehensively evaluate whether the study's overall goal of optimizing existing algorithms through various parameters was achieved, it is imperative to compare this model to the pre-existing publications. As shown in the following Figure 7, the accuracy of my model (over the average of each text sample) is plotted versus the preexisting models. To construct the graph found in Figure 7, I took modelAI-Text and modelHuman-Text and averaged their accuracy, 80% and

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90%, respectively, to plot 85% as the response accuracy for 'MyModel' on text sample #1. To compare the results of my model with those of the previous models, I utilized the same datasets to test the five pre-existing models as outlined in my 'Literature Review.' However, only two of the most accurate models were plotted in Figure 7.

Fig.7 The name of my model is highlighted in black to adhere to 'Privacy' guidelines. The progression of the line in 'blue' represents the accuracy of the model developed in this study across various text samples, and the progression of the 'orange' and 'green' lines represents the accuracy of pre-existing studies.

1. Observations and Understanding

As shown in Figure 6, 'MyModel,' the product of this study, exhibited an overall accuracy averaging 70-75%. As mentioned, to ensure clarity in the chart, I ran the 'testing' dataset through each of the pre-existing models but only plotted the two the most accurately. Given this, it becomes evident that 'MyModel' surpasses the average accuracy of the previous models by around 15-20%, implying significant improvements and successful algorithmic optimization through the variation of parameters. Other than just the initially striking patterns, it is evident through further analysis that 'MyModel' also demonstrated a smaller standard deviation, with results falling in the same approximate range, while the previous models exhibited a wide range of accuracy, including responses as low as 20%. These statistics underscore the efficacy of the unsupervised approach and the NLP integration. The unsupervised approach now has a testament as it significantly boosted accuracy, with testing time for 2000 rotations being less than a minute, supporting Dr. Deghan's assertion, as he stated that supervised learning, while powerful, is useless in the real-world scenario due to the manual intervention required to assort the data input to the algorithm (Deghan, 2023). While direct validation for the NLP integration is challenging, previous studies affirm and testify to its effectiveness in pattern detection within text. Notably, with the inclusion of various parameters such as temporal dynamics, network topologies, and semantics as part of the parameters in my model, it was evident that they had a crucial role in ensuring accurate results. Although the result may not be satisfactory (<95%), adjusting the weightage of the various parameters, as demonstrated in Table 2, proved beneficial in the algorithmic optimization, suggesting avenues for future research to be held in that direction to further enhance the accuracy of the algorithm. Ultimately, as elucidated by Professor Jun Wu, the primary objective of the algorithm is to achieve effective time series patterns based on compressing raw sequences from high- dimensionality vectors to low-dimensionality vectors (Wu et al., 2023). Ultimately, as depicted in Figure 5, this was achieved in this model, as more than 2000 cycles were executed within a minute, possible through leveraging the 'Glove' equations to convert text into numerical vectors.

VI. CONCLUSION

Throughout this academic study, many tasks were accomplished, many ideas were internalized, and many limitations and mistakes were comprehended. Concluding this academic venture aimed at optimizing algorithms for detecting artificially generated text, it is evident that the primary object has been achieved. While the extent of this success remains uncertain, this journey over the past 8 months has led to the product of 'MyModel,' an algorithm more efficient than its predecessors. Throughout this journey, I've gained invaluable insights into the complexities of algorithm development. From grappling with the limitations to delving into intricate details past my educational level, each step has been a unique learning experience. While 'MyModel' currently boasts a 75% accuracy rate, it falls short of the 100% accuracy users typically expect, as evident with tools such as 'Grammarly.' To bridge the remaining 25% margin of error and ensure 'MyModel' meets the real-world expectations, it is imperative to address the limitations and outline the possible future directions.

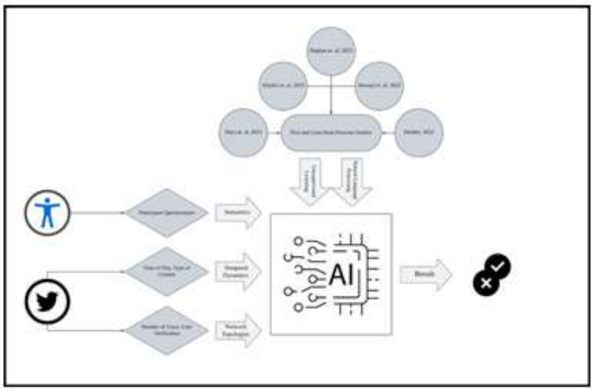

Fig.8 The workflow is a simplified representation of the methodology used to conduct the study. The circles on the top refer to the 'Literature Review,' the quadrilaterals on the left refer to the 'Questionnaire' process, and the circles on the right refer to the binary 'Findings.'

1. Limitations

Before delving into the limitations of my study, it is beneficial to recap the entire process by viewing Figure 8. As depicted in Figure 8, there are a couple of key steps that lead to the model deciphering whether text was artificially generated or not. Firstly, as explained in the 'Literature Review,' the framework of the model was deduced from the existing literature. Examining the gaps in the existing literature led to the hypothesis that using unsupervised learning and NLP would lead to a model with greater accuracy. After the framework of the model was agreed upon, the next step was deciding how the parameters of the model would be designated. Another hypothesis was that including multiple parameters would lead to greater accuracy, and therefore came the idea of 'optimizing the influence of temporal dynamics, network topologies, and semantics on unsupervised NLP algorithms'. To better categorize the data into the categories of temporal dynamics and network topologies, I made sure to collect data and their specific attributes, as mentioned in Figure 8, so that I would have a broad range of parameters. Given this behind-the-scenes process, the outcome would be a binary result whether the model perceived the text to be artificially generated or not. This process, given its complexities, has its downsides, and the first is my limited machine-learning experience. Every single author conducting research in this field has gotten, at the very least, an undergraduate exposure to machine learning, and given this lack of experience, 'MyModel' may not be as efficient or accurate. Moreover, budget-wise, I was restricted to using the free version of Tweepy's API and utilized datasets that were possibly not of the best quality in terms of diversity or authenticity. This was because the subscription version would have tallied me a couple of grand, which would be completely out of my budget. The last issue was a time issue, and this was due to the preliminary processes taking up so much time that post my data collection and model development, I had about three weeks to train my model, in which I was able to fit only 100 sessions. As stated by Dr. Li Shen and his college, around 100-200 training periods per model are suggested for maximum accuracy, once again proving to be a limitation in the development of 'MyModel' (Shen et al., 2023).

2. Future Directions

To address the stated limitations and pave the way for the eventual implementation of 'MyModel' on social media platforms, several steps can be taken. Firstly, steps I could take outside this restricted research environment would be to consult with students or professors with more expertise in the field of AI and let them point out potential improvements and areas for refinement. Moreover, it would be beneficial to secure sponsorships, especially in the field of research related to artificial intelligence, as this can alleviate the financial burden that is associated with acquiring various datasets from extraction sites such as Tweepy API. Looking ahead, dedicating focused extended periods during the summer for extensive training sessions could significantly boost the accuracy of this algorithm, as stated by Dr. Shen. Despite these technical 'future directions,' there are broader implications for the 'global' development of this model. The inception of this project stemmed from the trap of misinformation and partially due to the proliferation of social-media bots. This algorithm, with the ability to be deployed a couple of years from now after producing close to 100% accuracy, could benefit a lot of people, as they can be assured that the text they are reading is authentic. While it is not possible to guarantee the accuracy of the information, 'MyModel' can provide users with the confidence that the text is not artificially generated, thus promoting a healthy online environment.

3. Reflections

Through this research process, I've undergone significant personal and intellectual growth, and this paper serves as a testament to my learning. However, it's necessary to specifically articulate key take-aways. One crucial lesson learned from this journey is the importance of analyzing existing literature. While my childhood aspirations were centered on inventing entirely novel concepts, this research project has instilled in me the value of using the knowledge of others and building from their mistakes. I've come to an understanding that the true mastery of any field grows from learning the missteps and the limitations of the predecessors, the shortcomings of previous bot-detection algorithms in the case of this study. Learning from the insights and experiences of others is a superior form of guidance, warning to not face the same setbacks. Therefore, through embracing my newfound respect towards collaboration, I take this as a fundamental aspect of my approach to any future task.

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