National College of Ireland

Project Submission Sheet

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Programme:	MSc in Data Analytics	**Year:**	2024
Module:	Data Mining and Machine Learning 2		
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Submission Due Date:	17/02/2024		
Project Title:	DMML2 TABA		
Word Count:	3704		

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Date: 17/05/2024

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Case Study: Detection of LLM Generated Text

1. Exploratory Data Analysis / Data Cleaning

In recent years, the advancement of artificial intelligence (AI) technologies has given rise to the development of systems capable of human-like interactions. Among these innovations is language modelling, which serves to mimic human intelligence in computers (Larson, 2023). Large Language Models (LLMs) are the most important part of these systems, and they use AI algorithms to understand and generate text in very realistic ways.

As the name suggests, LLMs are powered by large networks with deep learning architectures and they generally operate by predicting the next word from a sequence of words. A large amount of textual data is used for training (Ruan et al., 2024), where the model learns textual structures such as the syntax and grammar, allowing them to generate the most appropriate and coherent text that matches the context of the sentence. However, because of the complex and advanced nature of the technology being used in LLMs, it has become a big challenge differentiating between AI-generated and human text. This distinction is important to ensure authenticity and avoid the spread of misinformation, especially when it comes to social media platforms. In this context, the process of exploratory data analysis to identify patterns in data serves as an initial step in understanding the composition of an LLM-generated text, and develop methods to accurately detect and classify such data.

Regardless of its source, data consists of information that can be used by a company or an individual. When data is collected, it might not be in the form required by the user due to its incoherence or inconsistent format etc. For this reason, it must be carefully managed before it is used (Biscontini, 2023). This management of data involves cleaning, correcting, and restructuring its content as deemed fit, resulting in an accurate representation of what the user demands of the data. In most cases, EDAs is merely removing missing values, checking outliers, refining the time or date format etc, however, when it comes to LLMs, because its capability is almost fully dependent on the large volumes of data it is trained on, more time must be spent on managing the data.

As mentioned before, LLMs use very complex technologies. In detecting text created by an LLM, the assumption is that the text might contain both human-written and AI-generated text. Because these models are trained on a significantly large set of textual data which includes multiple styles and even languages, it is designed to mirror the variability in human-texts. Though these models are proficient, subtle textual patterns that are not common in human-speech might be present. Detecting these inconsistencies can be hard, especially as these models incorporate NLP algorithms (Zhecheva, 2024), and so the use of software and programming languages such as Python is highly recommended due to its large number of functions and tools for language processing.

Based on the assumption that the text may be of mixed composition, identifying texts suspected to be LLM generated would be the first approach. Keyword searches is a reasonable choice for this but other automated methods can also do the job. In their research, Smith and Climer (2023) discussed the significance of handling missing data and other anomalies, and this is especially true for models that are entirely text-focused. Their use of Greedy algorithm, though successful, might be computationally extensive, but the preprocessing of text data can be mainly done using Python and its libraries. Techniques such as tokenization and stemming can be included and implemented in a defined function. In this function, the removal of special characters and stop words is recommended to ensure consistency across the text, which can then be applied to the data for normalization.

Data cleaning itself is not enough to detect LLM generated text, but addressing these inconsistencies lays the foundation for further exploratory analysis and makes the process of detection easier and more reliable than if there were noises in the text.

2. Dimensionality Reduction / Feature Selection

Exploratory analysis is also essential in understanding correlations between features. Since LLMs are trained on billions of text data, certain characteristics of the generated texts might not resemble obvious human language. For example, a study conducted on differentiating between human-written and LLM-generated texts found the former to be more expressive and less prone to grammar repetition (Prajapati et al. 2024). The study also made mention of the analysis of language patterns associated with LLM text, especially ChatGPT, which typically outputs longer texts than humans unless explicitly stated not to.

Dimensionality reduction techniques such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) can improve the efficiency of a model. The feature space of an LLM would be high, consisting of a wide range of language patterns. Consequently, LLM-generated text would have an extremely high dimensionality. However, not all extracted features would be relevant, so selecting a subset of relevant features becomes the priority. A reasonable approach would be extracting set of features characterized by a specific attribute. Narrowing the data to a lower-dimensional space allows for a better analysis, but care must be taken to preserve the necessary information (Bishnoi, Jaison and Wadhwa, 2024). Quantitative algorithms such as linear regression or neural networks are suited for numerical features, while qualitative algorithms such as random forest and naïve bayes can manage textual data (Keco, Obucic, and Poturak, 2024). If applied correctly, these algorithms assess the importance of each feature, considering specific textual traits and prioritizing the most informative text to be used for classification.

Regarding the dimensionality reduction techniques, significant texts can easily be identified. Reducing the feature space not only improves the training phase of the model but also guarantees its interpretability because only essential components would remain, improving the model's performance.

3. Feature Engineering / Feature Extraction

Feature extraction also helps in the selection phase in the context of text detection. As stated before, LLM-generated text possesses distinct characteristics, and extracting features such as semantic representations can distinguish human written text from AI ones (Thejas, 2024). Creating new features or transforming existing ones is an approach one can take, especially with techniques such as scaling or the encoding of variables.

The transformation of existing textual data involves evaluating the text length, syntax complexity, and other verbal relationships or patterns. By extracting features such as these, there is an increasing chance of detecting AI-generated text with even greater accuracy and reliability.

The feature extraction stage is important in this proposed methodology as it eases the complexity of further analysis. Interpretable representations of textual data gives transparency in the detection process, and with the encoding of features, the model can provide an accurate classification.

4. Choice of modelling techniques

In choosing the most appropriate modelling technique, factors such as computational efficiency, performance, and interpretability should be considered. Detection tools have been commonly used for this task but have not been entirely successful. As LLMs, such as ChatGPT, become increasingly complex, users can modify the input prompts in ways that forces the program to generate responses that resembles human speech. For example, one can ask ChatGPT to generate a response as if explaining to a child, or in a specific tone, or using a specific language (Weber-Wulff et al., 2023), making it difficult to assume if the generated response is indeed written by AI or not.

The architecture of LLMs also introduces ambiguity that complicates the detection process. Many language models can refine their language gradually based on user interaction, improving their ability to generate human-like speech and patterns. The variability in prompts speeds this process, as the generated outputs also range in tone and language. Consequently, establishing a criteria to detect LLM-generated text becomes a challenge (Tang, Chuang and Hu, 2024). This was echoed in Elkhatat, Elsaid and Almeer (2023)'s study which found that detection tools might also perform unfavourably depending on the language model whose data it is evaluating.

Detecting LLM-generated text requires predictive modelling. Compared to traditional detection tools, predictive modelling techniques have much better flexibility in capturing complex patterns. Due to the variability in LLM-generated texts, these techniques are capable of generalizing across a wide textual range. Ensemble methods use multiple algorithms to obtain better predictive performance. The way they work is by combining so-called "base learners" to produce a final output. Common ensemble techniques include Gradient Boosting, Adaptive Boosting (Adaboost) and Bagging. Advanced neural networks such as Generative Adversarial Network (GAN) are also dependable detective models (Majovsky et al., 2024). Their structure reduces the risk of overfitting, and some techniques also automatically select the most relevant features, improving the overall performance.

The predictive capabilities of textual data constitutes generative sequence of words. Recurrent neural networks (RNN) is a good choice for such analysis since they are well-suited for modelling sequential data (Karn, Knechtel and Sinanoglu, 2024). RNNs can handle sequential data regardless of its length and excel at capturing textual patters that occur in all positions within the sequence, which matches the manner at which LLM texts are generated. Random Forest models can also handle high-dimensional spaces but might not do well in capturing sequential data since they operate by aggregating multiple decision trees (Simon and Bankapur, 2024). Bidirectional Encoder Representations from Transformers (BERT) is another alternative model known for its complexity. Capable of capturing data in a comparable way to RNNs, BERT performs well in language processing tasks (Areeba et al., 2024). However, BERT is known to be very computationally extensive and may be difficult to employ for many tasks.

Based on the evaluation of relevant modelling techniques, RNN is the proposed methodology for detecting LLM-generated text. It offers a balance of flexibility and efficiency in its performance, capable of capturing complex patterns, making it a well suited model for detecting LLM-generated response.

5. Hyperparameter Optimization

Default hyperparameters may not always yield optimal model performance. Even though an algorithm shows satisfactory results or has very high accuracy, it can always be improved. Most classification tasks can be completed via data mining algorithms, and research has used support vector machines (SVM), naïve bayes, logistic regression, random forest etc for similar tasks, each with extremely high results. Optimizing hyperparameters improved the capabilities of these algorithms significantly. In a text processing task, Winarno, Wiranto and Harjito (2023) compared the performances of different machine learning algorithms before and after parameter-optimization. Two techniques were implemented: grid search and random search, to find the best hyperparameters. The result showed that the accuracy of the model, especially SVM, was improved from hyperparameter-optimization.

Besides grid search and random search, Bayesian optimization can also be a suitable alternative for hyperparameter optimization. When it comes to RNN, hyperparameters such as the batch size, epochs, learning rate etc are considered. Sahay, Pugalenthi, and Raghavan (2023) performed this operation in Google Colab, utilizing the Bayesian approach and tree structured Parzen Estimator (PZE). The Python library has tools for optimizing parameters - Optuna being commonly used. It recommends the necessary configurations by minimizing the errors and creating the most optimal hyperparameters.

The aim of hyperparameter optimization is to find the best mix of parameters that gives the highest model performance. The mentioned techniques each have their own capabilities, and depending on the data, might not be the most suitable. For example, grid search may not do well when it comes to complex data (Sayilar and Ceylan, 2023), however parameter tuning always guarantees better algorithmic performance. The efficiency of any algorithm, including neural networks, depends on the hyperparameters used. Exploring the hyperparameter space to find the best configuration becomes a priority when it comes to maximizing model performance. With hyperparameter tuning, the model's ability to capture textual patterns and detect LLM-generated text is enhanced, contributing to a more practical model with better computational efficiency and faster training times. From preprocessing the textual data, relevant features are extracted and encoded to a suitable format if needed. In the case of RNN, the model's architecture would be fine-tuned, adjusting the mentioned parameters as done in the literature also.

6. Model Evaluation

Common evaluation metrics for classification tasks include precision, recall, F1-score, accuracy, and AUC-ROC. An accurate assessment of the model's performance is necessary because appropriate model evaluation ensures the reliability of predictions and the model itself. These different metrics provide insights into many aspects of the model's predictive capability. For example, accuracy represents the ratio of correct predictions while recall is a measure of how a model correctly identifies true positives (S et al., 2023). Within the proposed methodology for detecting LLM-generated text, selecting evaluation metrics tailored to the task is the first step. These common classification metrics should be enough to provide a balanced assessment of the model.

Also, model evaluation covers the model's generalization capability, especially on unseen data. Biases should be addressed as they can introduce errors and affect the model's validity. Mitigation strategies exists for this cause, ensuring fairness during assessment. Cross-validation techniques provides more reliable estimates of the model's performance on unseen data. Criteria such as the evaluation threshold e.g. probability cut-off should be specified. The choice of thresholds can impact the balance between certain metrics, such as a high threshold increasing specificity. Detecting LLM-generated text with high precision is the aim of this proposal, therefore a higher threshold would be preferred.

7. Scalability Issues

When it comes to scalability, it is possible to encounter issues with large datasets. Traditional algorithms might not perform well due to the increasing number of large data being used by organizations. Frameworks such as Spark can be used to handle big data, and should be considered (Samudrala et al., 2023). One advantage of these frameworks is that they can analyse large volumes of data effectively without affecting the model's performance.

In the context of detecting LLM-generated text, the volume of textual data available is a major concern for scalability problems. Algorithms might struggle to process data, leading to inferior performance. Also, the computational power needed to train and evaluate these models increases, exceeding the capacity of traditional models. Apache Spark is also cost-effective and spreads its computing operation across different nodes (Cheedella, Fathimabi and Chinamuttevi, 2024), and this speeds of the analysis process significantly, mitigating these scalability issues. Different models perform differently based on the complexity of the evaluated data.

8. Ethical Implications

Among the main ethical issues surrounding AI content is the collection of data, analysis bias, and the mishandling of information. The impact on society is also a major concern (Nitu and Dascalu, 2024). Reducing the risk of generating malicious content via misuse is an ongoing discussion. On a wider scale, advanced tools like ChatGPT have been researched extensively when it comes to ethical use. ChatGPT is possibly the most commonly used AI platform, and is known for its versatility. Perhaps the most ethical concern surrounding its use is in education, specifically plagiarism. With access to it, students can solve very complex problems ranging from mathematical to coding, and this causes a lack of critical thinking. Consequently, students might become incompetent in their job as they lack creativity and the ability to solve problems on their own (Khan at al., 2023). Students might also not pay attention to the grammatical errors or standard of writing present in AI-generated outputs, because they believe AI to be as accurate as possible.

Beyond academic work, when implementing a model to detect these texts, it is important to recognize the implications associated with this technology. As stated earlier, LLMs, such as ChatGPT, can generate human-like text, raising concerns about potential misuse for disinformation. A balance between maintaining freedom of expression and mitigating any risks must be met. Some of these ethical considerations include transparency in the use of AI-generated text, protecting user privacy, and checking for algorithmic bias. Individuals using AI in different ways have the responsibility to maintain these principles, promoting integrity and accountability.

Paper Review: Modified Query Expansion Through Generative Adversarial Networks for Information Extraction in E-commerce

This evaluation report provides a critical review of the paper: “Modified Query Expansion Through Generative Adversarial Networks for Information Extraction in E-commerce”.

Structure & Title

The paper’s structure is laid out in a very organized way, and has all the key elements present, following a logical progression throughout from the abstract down to the conclusion. Each section is clearly titled, making the paper easy to navigate. The title itself is very informative, and describes the article in detail with reference to the aim (query expansion), model to be implemented (GAN), and the focused area of research (e-commerce).

Abstract

The abstract gives a good summary of the methodology used, as well as quantitatively highlighting the key findings. It mentions the specific methods used to carry out the experiment, giving readers a concise overview of the report. However, even though it reflects the content of the article, the abstract is poorly written from a grammatical point of view. It contains noticeable capitalization errors that could put off certain readers and make the report seem not compelling enough to read.

Introduction

The introduction goes beyond the recommended count of two paragraphs, but it gives enough context and background information to the research problem, including its general context within the field of e-commerce. It also gives an overview of the importance of the research, summarizing and challenging the general findings from other authors’ work, justifying the need for the experiment by identifying existing gaps. The last two paragraphs describe what the author hopes to achieve, and the potential contribution of their work. While it is a good introduction, it could be further improved by clearly identifying the research question, however it does cover the experimental design and gives a good description of the proposed solution.

Graphical Abstracts/Highlights

The paper does not have a lot of visual content that summarizes the findings of the article. However, the tables in the paper give a quantitative summary of the findings.

Methodology

In the experiment section of the paper, the author not only references the data source, but also explains its content. Ethical implications are considered, and the author implies fair use by removing any information that can be considered sensitive. The author has provided enough relevant information that users can emulate this data collection step in a straightforward way.

The proposed framework, which includes a sequence-to-sequence generator and an LSTM model, is capable of performing classification tasks, and generating expanded queries similar to input queries. The use of a real-world dataset makes the experiment practical, and the increase of 10% on model performance compared to baseline models validates the suitability of the design. Regarding the methodology, there is enough detail to provide a clear understanding of the approach. An informed reader might be able to replicate the study by merely following the methodology. However, because the paper does not give the actual dataset used or the code implemented, replicating the study might not be as straightforward especially for those with limited understanding of machine learning. The algorithm is vaguely described, but the steps are outlined in a meaningful way, from the collection of data to the evaluation metrics.

As the paper uses a novel approach by integrating GANs into the query expansion process, the author provides a good level of detail regarding its implementation especially for the generator and discriminator models. There is also a visual summary of the LSTM model which provides the number of layers and the overall structure, as well as the tuning of hyperparameters. Necessary details such as batch size, learning rate and number of epochs are also provided both for replication, and understanding the new proposed method.

Although no specific sampling method is mentioned, the use of a real-world dataset from an e-commerce platform and the use of real queries ensures the validity of the study. The type of data recorded is also clear such as: user queries, product names, and semantic similarity between sequences. For evaluation, the model’s accuracy is recorded as well as the language diversity of the expanded queries, the latter done by implementing a new metric. The software program is also described as well as the relevant libraries used to conduct the research.

Results

The result section gives an overview of the proposed model’s performance in comparison to baseline models specifically in terms of semantic similarity. It gives both a qualitative and quantitative summary of the findings in detail, clearly demonstrating the effectiveness of the proposed model. The use of a comparative analysis also makes the reading engaging, and gives a good justification and understanding of the framework. The use of visual aids such as tables and figures help capture the main findings concisely.

These findings are also laid out in a logical sequence, from discussing the framework and the evaluation metric, to explaining the experimental results and validating its use for other datasets. Each subsection builds upon the previous one, ensuring clarity and coherence.

Conclusion/Discussion

Based on the results from the experiment, the author's proposed framework shows promise. Given its novelty, the success of the model as indicated by quantitative results, has led the author to recommend its broader real-world use. While the paper acknowledges the limitations of alternative techniques, it also discusses the limitations present in the proposed model such as the challenges in generalizability, alternative training methodologies, and dataset characteristics. Its comparison to baseline models is a good indicator that it can be deployable, and future research can implement this new model with greater confidence in its performance. However, researches should carefully consider generalizability concerns, particularly in e-commerce. Although the paper neither explicitly supports nor contradicts previous theories, it builds upon existing research, thus contributing to existing the body of knowledge in the field.

Language

The language used in the paper is clear and appropriate. However, capitalization errors are present in many cases, especially in the abstract. Although no sections are entirely poorly written, certain sentences can also be improved grammatically, for clarity.

Previous Research

Though the article references previous works, its formatting is very inconsistent. For example, for in-text citations in the case of 4 or more authors, it uses both "et al" i.e. (Mikolov et al., 2013) and in other cases it lists the full names i.e. (Keskar, McCann, Varshney, Xiong, & Socher, 2019). As with all references, it should remain consistent and strictly adhered to, but the paper fails to meet this criteria.

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