multiBERT: A Classifier for Sponsored Social Media Content

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Keywords: Bert, Social Media, Influencer.

Abstract: Social media's rise has given birth to a new class of celebrities called influencers. People who have amassed a following on social media sites like Twitter, YouTube, and Instagram are known as influencers. These people have the ability to sway the beliefs and purchase choices of those who follow them. Consequently, companies have looked to collaborate with influencers in order to market their goods and services. But as sponsored content has grown in popularity, it has becoming harder to tell if a piece is an independent opinion of an influencer or was sponsored by a company. This study investigates the use of machine learning models to categorise influencer tweets as either sponsored or unsponsored. By utilising transformer language models, like BERT, we are able to discover relationships and patterns between a brand and an influencer. Machine learning algorithms may assist in determining if a tweet or Instagram post is a sponsored post or not by examining the context and content of influencer tweets and their Instagram post captions. To evaluate data from Instagram and Twitter together, this work presents a novel method that compares the models while accounting for performance criteria including accuracy, precision, recall, and F1 score.

1 INTRODUCTION

The social media sector has experienced significant growth, not only enabling individuals to communicate with one another, but also creating career prospects that were previously unimaginable. Social media has provided opportunities for content writers and influencers to gain recognition, popularity, and financial success. Additionally, it serves as a platform for online purchasing. One kind of social media marketing is Influencer Marketing, when an individual with expertise in a certain sector use their knowledge to promote the brand and products of others.

Many businesses these days make use of influencer marketing as part of their overall marketing strategy. When the influencer promotes the brand or it's products, the brand then compensates the influencer appropriately. Potential methods of marketing including product placement or evaluations, sponsored postings, or sponsored events. The influencer's objective is to enhance brand recognition among their followers and stimulate the purchase of the brand's items. The influencer marketing industry is seeing rapid expansion. Influencer marketing offers a distinct advantage for businesses by providing more precise targeting capabilities in comparison to traditional advertising tactics. Brands can engage in partnerships with influencers that specialise in targeting certain demographics that align well with their business objectives, therefore streamlining the process of reaching their desired audience. For example, a Sport or Health drink brand may form a partnership with a fitness influencer or an online fitness coach who possesses a significant following of other fitness enthusiasts. The followers of the influencer place their trust in the influencer and their recommendations, thus leading to an increase in the brand's sales figures.

With the growth of the industry, it has become essential to differentiate between genuine sponsored content and non-sponsored content. This is true from both the consumer's and the business's point of view. For the consumer, it is essential to be aware of and differentiate between whether the influencers they follow are posting organic content or whether that content is being paid for. Additionally, for the brand, this would provide the brand with a more comprehensive understanding of the shifting dynamics of influencers and assist them in quantifying the impact of such influencers.

The objective of this study is to utilise actual influencer data collected from Twitter and Instagram

Malvankar, K., Fallon, E., Connolly, P. and Flanagan, K.
multiBERT: A Classifier for Sponsored Social Media Content.
DOI: 10.5220/0012632400003690

In *Proceedings of the 26th International Conference on Enterprise Information Systems (ICEIS 2024) - Volume 1*, pages 706-713
ISBN: 978-989-758-692-7; ISSN: 2184-4992

to train BERT, along with a modified approach based on BERT, named multiBERT in order to effectively determine whether a tweet or Instagram post from an influencer is sponsored or not by the brand. The performance of these models will also be compared and evaluated based on evaluation metrics such as accuracy, precision, recall and F1 score.

2 RELATED WORK

Regarding work that involves data derived from Twitter and Instagram, multiple studies have been done to explore the potential of using this data, providing valuable insights into its applicability.

Yadav et al. proposed utilising a machine learning classifier to do sentiment analysis on Twitter. The researchers utilised the Kaggle dataset, which comprised phrases and keywords pertaining to a certain product. The writers intended to categorise types of positive and negative attitudes. During the pre-processing stage, the tweets' case was modified, appropriate spaces were inserted, unnecessary spaces were deleted. Making use of both unigrams and bigrams, the features for the model were retrieved. The process of lemmatization and removal of stop words was thereafter carried out. Their recommended technique was assessed for its efficacy using three prominent machine learning classifiers: Naive Bayes, Logistic Regression, and Support Vector Machine. (Yadav, Kudale, Rao, Gupta, & Shitole, 2021).

Twitter has shown to be beneficial in the realm of disaster management. Shah et al. (2018) conducted a comprehensive analysis of Twitter data to examine the Nepal Earthquake and identify several aspects related to the catastrophe. Using Twitter data acquired during the final week of April and the first week of May 2015, a total of 40,236 unprocessed tweets that appeared to be relevant to the Nepal earthquake were obtained. These messages were then pre-processed for analysis and subsequently analysed. This study demonstrates the utilisation of geolocation tag to identify hazardous areas and using visual analytics to analyse the dataset. The use of automated keyword identification led to the development of a disaster management module. This module is capable of identifying keywords associated with any particular catastrophe, enabling further investigation. The findings indicate that the disaster module used in the research may effectively operate on various hashtags without requiring manual parameter definition, as long as the dataset specific to the given situation is accessible. (Shah, Agarwal, Dubey, & Correia, 2018).

The results of recent research have shown that tweets may be used to make predictions about a wide range of significant events, such as elections and national revolutions as well as criminal activity. This is the primary concept, which states that the context, timing, and content of tweets can give insight into what will occur in the future. Whether local criminal activities can be predicted based on the tweets sent was the question that was addressed in a report that was published by the University of Virginia in November of 2014. According to the findings of the study, the inclusion of information from Twitter improves the accuracy of prediction for 19 out of 25 different types of criminal activity, and it does so considerably for a number of different surveillance scopes. (Gerber, 2014).

When it comes to twitter data, a lot of studies have been conducted, but most of them pertain to sentiment analysis regarding a particular topic. There exists a substantial gap in the research when it comes to influencers on Twitter.

In a study that was carried out by Briliani et al., the researchers looked for instances of hate speech that were found in the comments area of an Instagram post. Responses can be either good or negative, depending on the context. The use of hate speech is included in the negative comments on Instagram. Speech that promotes hatred is one of the most significant issues, and it is extremely hard for authorities to combat. In light of this, the K-Nearest Neighbour classification approach was utilised in this research project to develop a system that was capable of determining whether or not one was engaging in hate speech in the Instagram comment area. The results of this study have produced an accuracy of 98.13 percent, as well as precision, recall, and F1-score of 98 percent when employing K-Nearest Neighbour with K equal to three. (Briliani, Irawan, & Setianingsih, 2019).

Ekosputra et al. in their 2021 study made use of Supervised Machine Learning algorithms to detect fake accounts on Instagram. Logistic Regression, Bernoulli Naive Bayes, Random Forest, Support Vector Machine, and Artificial Neural Network (ANN) are the techniques that were utilised in the process of developing the supervised machine learning model. In this study, two tests were conducted. In the first test, the model is in its default state, which means that it does not have any parameters and no features are introduced. Furthermore, in order to enhance the precision of the experiment, new features and tuning factors were incorporated into the process in the second test. Logistic Regression and Random Forest, both of which have an accuracy of 0.93, are the models that perform better than other models based on the second experiment with additional variables and parameters thanks to their superior performance. (Ekosputra, Susanto, Haryanto, & Suhartono, 2021).

M. Singh presented an alternative method for identifying fraudulent accounts on Instagram in research done in 2023. One form of malicious behaviour on the Instagram platform is the creation and use of counterfeit accounts. This study employs a hybrid technique that takes into consideration both the content of the post and the photographs to identify phoney accounts on Instagram. The author assessed the presence of text spam using machine learning models such as Random Forest classification and identified picture spam using CNN models. The picture dataset was sourced from picture Spam Hunter, while the model was trained using a Kaggle dataset to categorise images based on their content. The suggested hybrid model has also undergone testing using the dataset obtained through web scraping from Instagram. The experimental classification results demonstrate that the suggested model achieves a classification accuracy of 97.1%. (Singh, 2023).

When it comes to BERT, there are a lot of studies that have been published.

M.T. Riaz et al. published a study in 2022 which introduced TM-BERT or twitter modified BERT for COVID 19 vaccination sentiment analysis. Within the scope of this research, a Twitter Modified BERT (TM-BERT) that is based on Transformer architecture is shown. Additionally, a new Covid-19 Vaccination Sentiment Analysis Task (CV-SAT) and a COVID-19 unsupervised pre-training dataset consisting of 70,000 tweets have been produced by this group. After being fine-tuned on CV-SAT, BERT attained an accuracy of 0.70 and 0.76, however TM-BERT achieved an accuracy of 0.89, which is a 19% and 13% improvement over BERT respectively. (Riaz, Shah Jahan, Khawaja, Shaukat, & Zeb, 2022).

The application of BERT for the detection of cyberbullying in the digital age is discussed by Yadav et al. in their article that was released in the year 2020. Using a novel pre-trained BERT model with a single linear neural network layer on top as a classifier, a new strategy is suggested to the identification of cyberbullying in social media platforms. This approach is an improvement over the results that have been obtained previously. During the training and evaluation process, the model is trained on two different social media datasets, one of which is very small in size, and the other of which is fairly large in size. (Yadav, Kumar, & Chauhan, 2020).

Software vulnerabilities pose a significant risk to the security of computer systems, and there has been a recent increase in the discovery and disclosure of these weaknesses. Ni et al. did a study in which they introduced a novel approach called BERT-CNN. This approach combines the specialised task layer of Bert with CNN to effectively collect crucial contextual information in the text. Initially, a BERT model is employed to analyse the vulnerability description and other data, such as Access Gained, Attack Origin, and Authentication Required, in order to provide the feature vectors. Subsequently, the feature vectors representing vulnerabilities together with their corresponding severity levels are fed into a Convolutional Neural Network (CNN), from which the CNN parameters are obtained. Subsequently, the fine-tuned Bert model and the trained CNN model are employed to predict the degree of severity associated with a vulnerability. This method has demonstrated superior performance compared to the current leading method, with an F1-score of 91.31%. (Ni, Zheng, Guo, Jin, & Li, 2022).

Guo et al. did a study in 2022 focusing on developing methods to detect false news. Current suggested methods for false news identification in centralised platforms do not consider the location of news announcements, but rather prioritise the analysis of news content. This study presents a distributed architecture for detecting false news based on regions. The framework is used inside a mobile crowdsensing (MCS) setting, where a group of workers are chosen to collect news depending on their availability in a particular location. The chosen workers disseminate the news to the closest edge node, where the local execution of pre-processing and detection of counterfeit news takes place. The detection technique used a pre-trained BERT model, which attained a 91% accuracy rate. (Guo, Lamaazi, & Mizouni, 2022).

Text categorization has consistently been a significant undertaking in the field of natural language processing. Text categorization has become extensively utilised in several domains such as emotion analysis, intention identification, and intelligent question answering in recent years. In a 2021 publication, Y. Cui et al. introduced a novel methodology. This study used the Bert model to produce word vectors. The text characteristics collected by a Convolutional Neural Network (CNN) were then combined to get more efficient features, enabling the completion of Chinese text classification. Experiments were performed using a publicly available dataset. Recent studies have demonstrated that the Bert+CNN model outperforms other text classification models in properly categorising Chinese text, mitigating overfitting, and exhibiting strong generalisation capabilities. (Cui & Huang, 2021).

A lot of studies have been conducted on the application of BERT and also on the data collected from social media sites such as Twitter and Instagram. However, there exists a significant gap in research when it comes to influencer behaviour on such sites. While there have been studies regarding the authenticity of accounts on such sites, detecting the authenticity of the content posted on such sites is also of equal importance.

3 METHODOLOGY

The general research methodology is outlined in figure 1. The data pre-processing step will be completed first. The data has been cleansed at this point. Once the data pre-processing step is completed, the next step is to determine the classification model that will be applied. To determine which model performs best, a classification evaluation will be done once each model has been trained. The methodology is visualized in Figure 1.

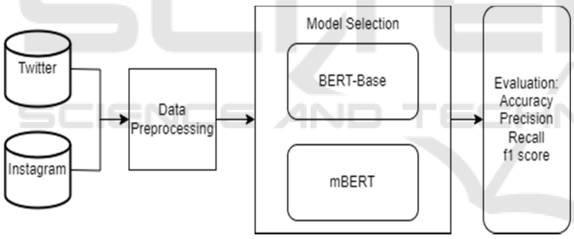

Figure 1: Methodology flow diagram.

3.1 Dataset

For the purpose of this study, real world user data was collected from Instagram and Twitter. The data was collected using the respective APIs provided by Twitter and Instagram. Twitter API allows us to extract either Tweets pertaining to a hashtag ("#") passed as keywords into the API or user information as data. All the tweets pertained to "#beauty" and "#gaming". The Instagram API allows us to extract post captions along with URL links to the photo itself. However, for the purpose of this study, only captions related to the hashtags mentioned above were collected. The data was divided into 4 datasets. Dataset 1 (D1) comprised of 1000 samples of Twitter data, Dataset 2 (D2) comprised of 80000 samples of Twitter Data, Dataset 3 (D3) comprised of 1000 samples of Instagram Data and Dataset 4 (D4) comprised of 80000 samples of Instagram data. 2 test sets were also created, Test set 1 (T1) comprised of 200 samples of Instagram and Twitter data and Test set 2 (T2) which comprised of 20000 samples of Instagram and Twitter data combined. The tweets/Instagram captions were manually annotated based on the "sponsored" and "Paid Partnership With" tags available in Twitter and Instagram respectively. The details of the datasets are detailed in Table I.

Table 1: Datasets.

Dataset	Sample size	Source
D1	1000	Twitter
D2	80000	Twitter
D3	1000	Instagram
D4	80000	Instagram
T1	200	Twitter + Instagram
T2	20000	Twitter + Instagram

As it can be observed in Table 1, the sample size for training was increased from 1000 samples to 80000 samples. This was done to measure the performance of the model when limited data is available and also when there is no limit on the data.

3.2 Data Preprocessing

The significance of the data pre-processing step lies in the fact that it has an impact on the efficiency of the future phases. Altering the syntax of tweets, removing information that is not essential from the text, and identifying any additional elements that are helpful are all included in this process. Python regular expressions were utilised in order to exclude special characters, emoji symbols, hashtags, and links from the text in order to accomplish the objectives of this study. It was decided not to remove the user handles and handles that were referenced in the tweets since doing so would be necessary in order to establish the relationships between influencers in the later phases of this experiment.

Preprocessing steps followed:

- Removal of hashtags
- Removal of links
- Removal of emoji
- Removal of special characters
- Removing extra spaces

3.3 Models

BERT (Bidirectional Encoder Representations from Transformers) is a publicly available machine learning framework designed for the purpose of natural language processing (NLP). BERT is specifically engineered to enhance computers' comprehension of the semantic nuances in ambiguous textual language by using the surrounding text to construct a comprehensive context. The BERT framework underwent pre-training using textual data sourced from Wikipedia and may thereafter be refined through the use of question-and-answer datasets. reference

BERT is a deep learning model that utilises Transformers. In this model, each output element is linked to every input element, and the weightings between them are dynamically computed depending on their relationship. This technique is referred to as attention in the field of natural language processing (NLP).

In the past, language models were limited to reading text input in a sequential manner, either from left to right or from right to left but were unable to do both simultaneously. BERT stands out due to its unique ability to do bidirectional reading simultaneously. The capacity to process information in both forward and backward directions, made possible by the use of Transformers, is referred to as bidirectionality.

BERT is trained bidirectionally, meaning it is trained on two distinct yet interconnected NLP tasks: Masked Language Modelling and Next Sentence Prediction.

The primary goal of Masked Language Model (MLM) training is to obfuscate a word within a phrase and thereafter enable the program to forecast the concealed word (masked) by leveraging the contextual cues of the hidden word. The goal of Next Sentence Prediction training is to enable the program to accurately determine whether two provided phrases exhibit a coherent, sequential link or whether their relationship is just arbitrary.

There are two primary variants of pre-trained BERT models, which differ based on the magnitude of their architectural design.

- The BERT-Base model consists of 12 layers, each with 768 hidden nodes and 12 attention heads. In all, it includes 110 million training parameters.
- The BERT-Large model consists of 24 layers, 1024 hidden nodes, 16 attention heads, and a total of 340 million training parameters.

The BERT-Base model was utilised for this project as it is relatively easier on the system as compared to BERT large model while keeping the architectural intricacies.

3.3.1 Proposed Model

To incorporate the use of multiple datasets in one model, an approach based on the BERT architecture is proposed. The architecture is outlined in Figure 2.

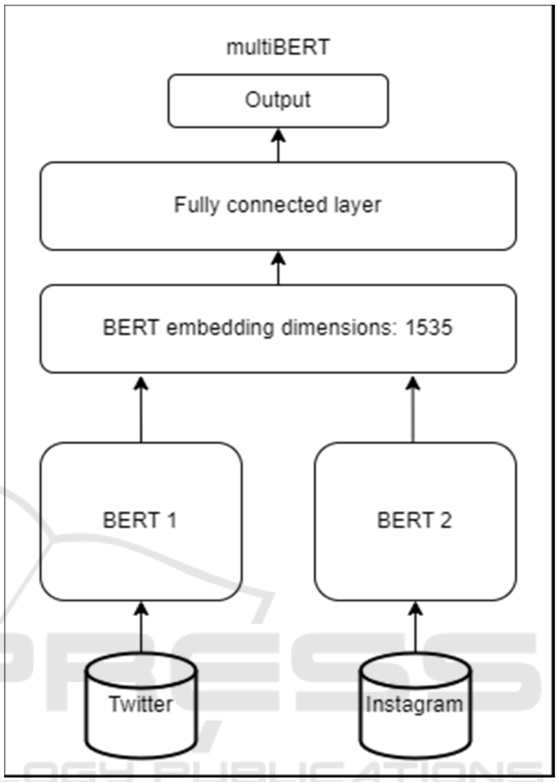

Figure 2: multiBERT.

Two BERT models, one to be trained on twitter data (BERT1) and one to be trained on Instagram data (BERT2), were paired together, with a fully connected layer and a 2-class linear layer on top.

To set the appropriate hyperparameters for tuning, a simple grid search strategy was utilized. The search space utilized was the search space recommended by the authors of BERT (Devlin, Chang, Lee, & Toutanova, 2019).

Parameter search space:

- Num_epochs: [2,3,4,5]
- Learning_rate: [2e-5, 3e-5, 5e-5]
- Batch_size: [16, 32]
- Weight_decay: [0, 0.1, 0.3]

A total of 72 trials were run, with each combination of the parameters for both BERT1 and BERT2. The best performing combination of parameters was selected for the model.

The hyper parameters set for BERT1 were:

- Epochs: 5
- Batch size: 16

- Learning rate: 3e-5
- Weight decay: 0.1

The hyper parameters set for BERT2 were:

- Epochs: 5
- Batch size: 16
- Learning rate: 2e-5
- Weight decay: 0.1

3.4 Experiments

A total of 6 experiments were conducted as part of this study. The BERT model was trained and tested separately on both Twitter and Instagram data to evaluate the results. The combined model was also trained and tested along with the BERT models. The first rounds of experiments were conducted with 1000 samples in the training set followed by the second round of experiments, where the training sets were populated with 80000 samples. The details of the experiments are given below:

- **Experiment 1:** $BERT_t$ trained on Twitter Data (1000 Samples)
- **Experiment 2:** $BERT_t$ trained on Twitter Data (1000 Samples)
- **Experiment 3:** $BERT_i$ trained on Instagram data (1000 Samples)
- **Experiment 4:** $BERT_i$ trained on Instagram Data (80000 Samples)
- **Experiment 5:** multiBERT (1000 Samples)
- **Experiment 6:** multiBERT (80000 Samples)

4 RESULTS

The objective of this study was to evaluate whether BERT-base and the proposed model multiBERT can be effectively used to classify user tweets and Instagram caption as sponsored or not sponsored. The results are detailed in Table 2.

Table 2 details the results of Experiment 1. While conducting training with 1000 samples, the model $BERT_t$ achieved an accuracy of 73.5%. The model had a precision score of 74.6% and a recall score of 73.5%, with the F1 score being 73.02.

Results observed for Experiment 2 are detailed in Table 2. While training with 80000 records on the twitter dataset, the model $BERT_t$ was able to achieve an accuracy of 79.5%, showing a 6% increase in performance due to additional training. The precision score of the model went up by 4.6% to achieve 79.2% precision and the recall score increased by 6%, to achieve a recall score of 79.5%. The model has a F1 score of 79.3%.

Table 2: Experimental Results.

Model	Accuracy	Precision	Recall	F1 Score
$BERT_t$ (1000 samples)	73.5%	74.6%	73.5%	73.02%
$BERT_t$ (80000 samples)	79.5%	79.2%	79.5%	79.3%
$BERT_i$ (1000 samples)	78.3%	78.9%	78.5%	78.7%
$BERT_i$ (80000 samples)	84%	85.05%	84%	84.5
multiBERT (1000 samples)	82%	83.1%	82%	82.5%
multiBERT (80000 samples)	89%	90.1%	89.3%	89.7%

Results observed for Experiment 3 are detailed in Table 2. While conducting training with 1000 samples, it is observed that $BERT_i$ achieves an accuracy of 78.3%. The model achieved a precision score of 78.9% and a recall score of 78.5%, with an F1 score of 78.7%. As compared to the BERT model trained on twitter data, the model trained on Instagram data is able to achieve a 6.5% increase in performance at the same task and same number of training samples.

Results observed from Experiment 4 are detailed in Table 2. While conducting training with 80000 samples, it is observed that in this experiment, the $BERT_i$ achieves an accuracy of 84%, showing an 4% increase in performance with additional training. The model achieved a precision score of 85.05% and a recall score of 84%, getting a F1 score of 84.5%. As seen with the previous experiment, even with additional training, the model trained on Instagram data with 80000 records achieves an accuracy improvement of 4.5% over the model trained on twitter data.

Results observed in Experiment 5 are detailed in Table 2. While training on 1000 samples, multiBERT was able to achieve an accuracy of 82% which is an 8.5% increase over the $BERT_t$ model trained on the same number of samples in Experiment 1 and a 2.1% increase over the $BERT_i$ model trained on the same number of samples in Experiment III. The model was also able to achieve a precision score of 83.1% and a recall score of 82%, with a F1 score of 82.5%

Results observed in Experiment 6 are detailed in Table 2. While training on 80000 samples, multiBERT was able to achieve an accuracy of 89% which is an 9.5% increase over the $BERT_t$ model trained on the same number of samples in Experiment 2 and a 5% increase over the $BERT_i$ model trained on the same number of samples in Experiment 4. The model was also able to achieve a precision score of 90.1% and a recall score of 89.3%, with a F1 score of 89.7%

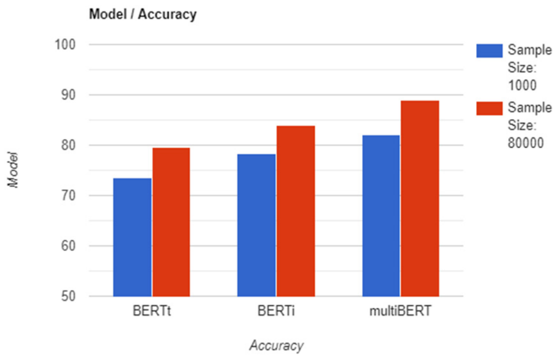

Figure 3: Training samples used & accuracy score of the models.

Figure 3 shows the results of all the experiments put together in terms of the accuracy of the models. It can be observed that the proposed model multiBERT achieves better performance while being trained on the same amount of data.

5 CONCLUSIONS AND FUTURE WORK

In this study, both BERT-Base as well as the proposed model, multiBERT were correctly able to classify Influencer posts as sponsored or not. With regards to performance, it was found that the new proposed model was the best in terms of accuracy, both with limited data as well as a large sample size. The multiBERT model achieved an accuracy of 82% when trained on 1000 samples, which is a 3.7% increase over the BERT-Base model trained on Instagram data ($BERT_i$) and an 8.5% increase over the BERT-Base model trained on Twitter ($BERT_t$). The performance increase is slightly more significant when the multiBERT model is trained on 80000 samples. The multiBERT model trained on 80000 samples achieved an accuracy of 89%, which is a 5% increase over the BERT-Base model trained on Instagram data and 9.5% increase over the model trained on Twitter data. An interesting observation here would be that the models trained with Instagram data outperformed the models trained with Twitter data consistently. When trained on 1000 samples, the $BERT_i$ achieved an accuracy of 78.3% which is an increase of 4.8% and when trained on 80000 samples, $BERT_i$ achieved an accuracy of 84% which was a 4.5% increase over the $BERT_t$ model. This inferior performance of the models trained on Twitter data may be attributed to the use of more slang words or the increased use of abbreviations as compared to Instagram.

Transformer models, like BERT, have previously been proven to be extremely effective and applicable in a wide range of machine learning applications. The findings of this study demonstrate that the proposed model, multiBERT, is capable of effectively categorizing tweets or Instagram posts as either sponsored or non-sponsored. Future work will focus on correlating influencer data with real world sales data using knowledge graphs. These graphs would effectively illustrate the evolving dynamics between influencers and ordinary users, in order to determine the effect that these influencers have on social media users and their behaviour and spread of online trends. Circana provides clients with data, industry insight, and advanced analytics to enhance their understanding of the retail sector. With access to propriety real world sales and POS data provided by Circana, future work will focus on implementing a system that can detect and quantify the effects of such influencers and the impact they can have on the purchase decisions of their followers by correlating influencer behaviour with real world sales data. Work will also focus on developing a system in tandem which would identify anomalous behaviour of the influencers on social media.

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