Discovering Undisclosed Paid Partnership on Social Media via Aspect-Attentive Sponsored Post Learning

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ABSTRACT

The transparency issue of sponsorship disclosure in advertising posts has become a significant problem in influencer marketing. Although influencers are urged to comply with the regulations governing sponsorship disclosure, a considerable number of influencers fail to disclose sponsorship properly in paid advertisements. In this paper, we propose a learning-to-rank based model, *Sponsored Post Detector (SPoD)*, to detect undisclosed sponsorship of social media posts by learning various aspects of the posts such as text, image, and the social relationship among influencers and brands. More precisely, we exploit image objects and contextualized information to obtain the representations of the posts and also utilize Graph Convolutional Networks (GCNs) on a network which consists of influencers, brands, and posts with embed social media attributes. We further optimize the model by conducting manifold regularization based on temporal information and mentioned brands in posts. The extensive studies and experiments are conducted on sampled real-world Instagram datasets containing 1,601,074 posts, which mention 26,910 brands, published over 6 years by 38,113 influencers. Our experimental results demonstrate that SPoD significantly outperforms the existing baseline methods in discovering sponsored posts on social media.

CCS CONCEPTS

• Information systems → Data mining; Social networks; • Applied computing → Marketing.

KEYWORDS

Influencer marketing; Sponsorship detection; Aspect attention; Graph convolutional networks; Multimodal learning

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@sugarbearhair has
keeping my hair popping for 6 months
now, just take theses cute vitamins
and let your hair do the talking.♥
#sugarbearhair

Figure 1: An example of paid media that fails to disclose sponsorship. Despite the influencer advertises a product and mentions a certain brand name, no sponsorship is disclosed.

1 INTRODUCTION

Influencer marketing has been gaining significant attention from marketers as an essential advertising method recently [23]. As the rapid growth of the influencer marketing industry results in numerous paid advertisements in social media, the transparency issue of advertising posts has been raised. According to the regulations from the Federal Trade Commission (FTC) [9], the Advertising Standards Authority (ASA) [3], and the Organisation for Economic Co-operation and Development (OECD) [13], influencers are required to conspicuously disclose sponsorship when they publish paid advertisements. That is, mentioning brand names and the relationship between a mentioned brand and an influencer in paid advertisements, thereby having transparency in advertising posts. However, a noticeable number of influencers fail to disclose paid partnerships with brands in their advertising posts, either because they are not aware of the regulations [2] or because they are concerned about lowering the effectiveness of the advertisement [12]. Surprisingly, the recent survey [2] reveals that only 52% of influencers and 60% of marketers have a good understanding of the regulation. This implies that the lack of legal knowledge and education for social media users can lead to social issues amid the rapid growth of social media. Figure 1 shows an example of a paid media where the influencer advertises the product of the brand in the absence of mentioning sponsorship.

The sponsored posts without disclosing the sponsorship may cause the following problem. Audiences will be increasingly skeptical toward the influencers' posts, and hence influencers lose the trust. Influencer marketing can only become effective when people think that influencers are trusted sources of information [21]. Furthermore, the lack of transparency in the advertising posts can negatively impact brand image [12]. For the steady growth of the influencer marketing industry with proper advertising practice, the FTC has monitored and warned a few famous celebrities in social media who violated the endorsement regulations¹. However, it is impractical to monitor the millions of influencers on social media.

¹<https://www.ftc.gov/news-events/press-releases/2017/04/ftc-staff-reminds-influencers-brands-clearly-disclose>

Although influencer marketing has gained noticeable attention recently, only a limited number of studies focused on sponsorship disclosure in influencer marketing. Some previous works examine the effect of the presence of sponsorship in social media [12, 31, 37] and suggest that disclosing sponsorship helps audiences to identify the post as an advertisement but lowers purchase intention. Moreover, Wojdyski et al. [35] attempt to measure the sponsorship transparency of paid advertisement by considering audiences' perceptions. While the previous works discuss the importance of detecting undisclosed sponsorship of social media posts, no study has proposed a method yet. Additionally, the previous works solely rely on a small number of survey results, thereby lacking evaluation with a large dataset.

In this paper, we propose a learning-to-rank based model, *Sponsored Post Detector (SPoD)*, that can detect sponsorship of social media posts. Our model incorporates three different aspects (i.e., modalities) on social media including graph, text, and image to represent the social media posts. We first employ the Graph Convolutional Networks (GCNs) [20] to leverage the characteristics of posts and the social relationship among influencers and brands. To adopt GCNs, we construct a heterogeneous network that connects influencers, posts, and brands. Besides the graph features, we also generate image and text features of each post to further describe the characteristics of the posts. Particularly, we use the pre-trained Inception-V3 model to obtain the image object features which have 1,000 categories [32] and utilize BERT [10] to create contextualized features of social media post captions. Moreover, we apply attention [34] over the three sets of features to estimate the importance of each aspect of social media posts, thereby utilizing more important aspects to detect hidden sponsorship. In addition to the attentive post features, we conduct a manifold regularization method to optimize the model performance. More specifically, we propose to exploit posting time and mentioned brands from social media posts for temporal regularization. For example, we place more weight on posts created at similar times and mentioning the same brand, that is, posts that likely belong to the same marketing campaign. With the proposed temporal regularization, our model takes the attentive post features as input to rank given social media posts by their sponsorship scores.

We summarize our contributions as follows:

- To the best of our knowledge, this is the first attempt to rank social media posts by their sponsorship scores. We believe that our proposed SPoD can be beneficial for marketers and government organizations to find brands and influencers in violation of endorsement guides [3, 9, 13], thereby protecting consumers. Besides, social media platforms can utilize SPoD to help users recognize the sponsorship disclosing regulation. As SPoD exploits the prevalent social media features, our model can be practically adopted to any social media.
- We propose a novel learning-to-rank model, SPoD, that incorporates with texts, images, and relationships among influencers and brands. Moreover, we estimate the importance of the different modalities by using attention to acquire decent post representation. Besides, we employ the redundancy between the posts and their published times to learn temporal sponsored relationships.

We conduct extensive experiments on a real-world dataset collected from Instagram which is known as the most popular social media for influencer marketing [23]. Our extensive experimental results demonstrate that SPoD improves performance by 54.3% in detecting undisclosed sponsorship compared to the best baseline method.

- Our analysis further reveals that the text features significantly improve the ranking performance. We find that contextualized features improve SPoD by 53.8%. We also observe that SPoD properly ranks the posts which are in various caption lengths. Particularly, SPoD obtains 216% improvement over the state-of-the-art text baseline method with very short caption posts by taking advantage of the graphical structural information.
- To make our research reproducible and benefit the whole research field, we release the proposed model and the benchmark dataset². Specifically, the dataset consists of 38,113 influencers and their 1,601,074 posts which mention 26,910 brand names.

2 PROBLEM STATEMENT

In this section, we formally define the goal of this paper. Suppose we have a set of posts $P = \{p_n\}_{n=1}^{|P|}$ published by a set of users $U = \{u_m\}_{m=1}^{|U|}$. Each post can be represented as $p_n = (t_n, a_n, b_n, l_n)$ where t_n , a_n , b_n , and l_n denote text, image(s), mentioned brand(s), and posting time of the post, respectively. Note that a post mentions at least one brand where the brand is in the set of brands $B = \{b_k\}_{k=1}^{|B|}$. Given text and images of a post, we extract text features and image features, $X^T \in \mathbb{R}^{n \times f}$ and $X^I \in \mathbb{R}^{m \times g}$, respectively, where f and g are the numbers of features. Moreover, we have graph features, $X^G \in \mathbb{R}^{n \times h}$, where h is the number of features. The graph features can be generated from a heterogeneous network $\mathcal{G} = (E, V)$ where the vertices $V = (U, P, B)$ are composed of users, posts, and brands, respectively. Given a set of posts P , we aim to rank the posts by learning the distinctive features of sponsored posts so that sponsored posts with the absence of sponsorship disclosure can be discovered.

3 METHODOLOGY

3.1 Framework Overview

Here we briefly give an overview of our proposed framework, SPoD, as shown in Figure 2. To leverage multimodal inputs of social media posts, we utilize three encoders, including graph encoder, text encoder, and image encoder. The graph encoder takes the heterogeneous network that includes users, posts, and brands as an input. Moreover, each node in the graph has a set of features as contextual representations to indicate the entity characteristics. Based on the heterogeneous structures of different entities and their features, graph convolutional networks (GCNs) are applied to derive appropriate node representations. In addition to GCN-encoded features, the text and image of each post are encoded by a contextualized text encoder and an image encoder, respectively. We then apply attention [34] over the three sets of features to estimate their importance and generate the post representations. The sponsorship scores of candidate posts are then computed based on all of the corresponding features and ranked for discovering sponsored posts.

²https://github.com/ksb2043/WSDM21_Sponsored-Post-Detector-SPoD

Figure 2: The overall framework of the SPoD. The aspect-attentive heterogeneous post encoder generates post representations. The estimated sponsorship scores are optimized by conducting temporal regularization for detecting sponsored posts.

Finally, we optimize the sponsorship scores by conducting temporal regularization based on posting time and mentioned brands from the input post set.

3.2 Aspect-Attentive Heterogeneous Post Encoder

To acquire decent representations of posts, we utilize three encoders including the graph, text, and image encoders to capture knowledge from different aspects, and apply aspect-attention over the three sets of features as shown in Figure 3.

3.2.1 Graph Encoder. To model posts with the graphical structure, we first construct a heterogeneous network and then apply graph convolutional networks (GCNs) [20] to derive GCN-encoded features for each candidate post.

Heterogeneous Network Construction. To construct a heterogeneous network, we consider three different entities including posts, users (i.e., influencers), and brands mentioned in posts. Note that the constructed heterogeneous network in our framework can be flexibly expanded with any additional relevant entities. The edges in the heterogeneous network indicate the interactions between entities behind nodes. The node of each post is linked to the node of the author user. If a brand is mentioned in a post, the post node has an edge to the brand node. Note that since more than one brand can be mentioned in a post, a post node can have multiple edges to brand nodes. More specifically, the edges of the network are represented by a sparse matrix $A \in \mathbb{R}^{N \times N}$, where $A_{ij} = 1$ if the i -th and j -th nodes are connected; otherwise, $A_{ij} = 0$.

Node Features. Each node in the network has a set of features while all of the features can be represented as

$$Z = [Z^P; Z^U; Z^B] \in \mathbb{R}^{N \times d},$$

where Z^P , Z^U , and Z^B are the features of nodes for posts, influencers, and mentioned brands, respectively; N and d are the number

Figure 3: The illustration of the post encoder using heterogeneous information.

of all nodes in the network and the number of features for each node, respectively. The detailed features in this paper are defined in Section 3.2.5.

Graph Convolutional Networks To leverage the knowledge of structural information, we propose to apply GCNs to encode node representations with both node features and network structures. First, the adjacency matrix A is transformed into a normalized adjacency matrix $\hat{A}$ as follows:

$$\hat{A} = D^{-\frac{1}{2}} A D^{-\frac{1}{2}},$$

where D is the diagonal matrix of node degrees. GCNs can then be operated based on the normalized adjacency matrix $\hat{A}$ and the feature matrix Z .

To model complicated network structures, we consider multi-layer GCNs by propagating information through different layers. Formally, the outputs of the i -th layer in GCNs, $H^{(i)} \in \mathbb{R}^{N \times k}$, can be computed as follows:

$$H^{(i)} = \sigma(\hat{A} H^{(i-1)} W^{(i-1)}),$$

where k is the number of hidden dimensions in GCNs; $H^{(i-1)}$ is the outputs of the previous layer; $W^{(i-1)}$ is a matrix of layer-specific trainable weights; $\sigma(\cdot)$ is a nonlinear activation function. Note that $H^{(0)} = Z$ as the base case. Finally, the GCN-encoded representations X can be computed by concatenating the outputs of different layers as follows: $X^G = [H^{(1)}, H^{(2)}, \dots, H^{(L)}]$, where L is the number of layers in GCNs.

3.2.2 Text Encoder. To model contextualized knowledge from text in posts, we encode the text t_n in a given post p_n . Instead of learning from scratch, we apply the pre-trained state-of-the-art neural language model, BERT [10]. Note that any potential language model can be applied to the text encoder. Given the text in a post t_n , a length j sequence of words $c = [c_1, c_2, \dots, c_j]$, BERT adds an initial token [CLS] to alleviate the positional bias in input embedding $c' = [[\text{CLS}], c'_1, c'_2, \dots, c'_j]$. The input word sequences of n posts, $\mathbb{Q}^{(j'+1) \times n}$, then goes to the transformer F_T with o layers. We generate the output of the o -th transformer $F_T(F_T^{o-1}) = D^o = [d_{[\text{CLS}]}, d_1^o, d_2^o, \dots, d_j^o]$ as the representation

of each word in the word sequences. Finally, we only adopt the $d_{[CLS]}^o$ to form the text representation X^T .

3.2.3 Image Encoder. In addition to the graph and text, we use images attached in the posts since images are known as one of the most important factors in effectively advertising products in social media marketing [24]. For example, the influencer in Figure 1 holds the product in the image for advertising purposes. We apply the pre-trained Inception-V3 model trained with one-million images in 1,000 object categories [32] to avoid training images from scratch. Particularly, the image encoder takes input images from a post and generates a feature vector with g dimensions where each dimension represents the probability that the image contains the corresponding object. That is a list of s_n images from a post p_n , $a_n = [a_{n1}, a_{n2}, \dots, a_{ns}]$. We use the maximum value for each dimension while aggregating the feature vectors as follows: $F_I(a_n) = \max\text{-pool}(\{a_{ni} \mid 1 \leq i \leq s_n\})$, where the function $\max\text{-pool}(\cdot)$ remains the maximum value for each dimension over the feature vectors of s_n images. Finally, the image representation X^I contains the image object vectors from n posts.

3.2.4 Aspect-Attention. To estimate the importance of features from different aspects, including the heterogeneous graph, texts, and images, we apply the attention mechanism over the three sets of features. We first apply a fully-connected hidden layer to each set of features to have the same dimension of the features as:

$$V^G = \mathcal{F}_G(X^G), V^T = \mathcal{F}_T(X^T), V^I = \mathcal{F}_I(X^I),$$

where $\mathcal{F}_G(\cdot)$, $\mathcal{F}_T(\cdot)$, and $\mathcal{F}_I(\cdot)$ are fully-connected layers for the graph, text, and image features, respectively. The sets of features from different modalities can be represented as:

$$V = [V^G, V^T, V^I].$$

The importance α_i of feature V_i can be estimated as:

$$\alpha_i = \frac{\exp(r_i \cdot r^c)}{\sum_j \exp(r_j \cdot r^c)},$$

where $r_i = \tanh(\mathcal{F}(V_i))$ is the hidden representation of the feature V_i ; $\mathcal{F}(\cdot)$ is a fully-connected layer; $\tanh(\cdot)$ is the activation function; r^c is the context vector for importance estimation. The estimated score α_i is multiplied with corresponding features V_i to get weighted values, and the representation of the post can be derived by taking all the weighted values of the graph, text, and image features as follows:

$$X = \sum_i \alpha_i \cdot V_i.$$

3.2.5 Node Features in GCNs. To represent characteristics of nodes in the network, we incorporate four types of node features, including node type, influencer, post, and brand as shown in Table 1. Note that our proposed framework is not limited to these features, therefore, any potential feature can be additionally applied to the model.

- **Node type features.** To indicate one of the three types of nodes, including post, influencer, and brand, we apply the one-hot coded node type feature in this category.

Table 1: Node features that represent characteristics of each type of node in GCNs.

Category	Feature	Description
Node	Node Type	Node type in the heterogeneous network.
Influencer	Keywords	The normalized frequency of keywords.
	Followers	Number of followers.
	Followees	Number of followees.
	Posts	Number of published posts.
Posts	Influencer Category	Major interest of the influencer.
	Likes	Number of likes in a post.
	Comments	Number of comments in a post.
	Hashtags	Number of hashtags(#) in a post.
	Usertags	Number of usertags(@) in a post.
	Caption Length	Length of text in a post.
	Images	Number of images in a post.
Brand	Posting Day	The day a post was published.
	Followers	Number of followers.
	Followees	Number of followees.
	Posts	Number of published posts.
	Brand Category	Business type of the brand.

- **Influencer features.** We exploit the normalized frequency of keywords to capture textual patterns of influencers. We select the frequently used keywords based on their Chi-square values. Note that we use the top 100 keywords in this study. We also use the number of followers, followees, and published posts features that represent the reputation of influencers [18]. Moreover, we exploit the major interest of the influencers such as Food and Interior [19].
- **Post features.** To represent post characteristics, we exploit the features which are widely used in any social media. We first obtain the numbers of likes and comments in a post which can represent the popularity of the given post. Since it is well known that people tend to avoid advertising [8, 17], such post popularity features can help provide a distinguishable representation of sponsored posts. We also employ the numbers of hashtags and usertags that are particularly used for disclosing names of brands, products, or marketing campaigns in paid advertisements [37]. Additionally, we use the number of images in a post while most social media accept multiple images in a post, and the day a post was published (e.g., Sunday, Monday) since publishing time affects the popularity of advertising posts in social media [26].
- **Brand features.** To characterize the brand nodes, we have the business type of the brands³. Additionally, we use the number of followers, followees, and published posts to measure brand awareness [37].

3.3 Sponsorship Estimation and Ranking

To estimate the sponsorship score of a post, all of the GCN-encoded features, text features, and image features can be useful because many aspects of the post are considered.

For a post i , all of the features are concatenated as the ultimate representation X_i . The predicted sponsorship score $\hat{y}_i$ of the post i can then be generated by a linear unit with a fully-connected hidden layer as follows:

$$\hat{y}_i = \mathcal{F}_p(\sigma(\mathcal{F}_h(X_i))),$$

³<https://business.instagram.com/>

where $\mathcal{F}_h(\cdot)$ and $\mathcal{F}_p(\cdot)$ are two fully-connected hidden layers; $\sigma(\cdot)$ is a nonlinear activation function. Therefore, the candidate posts can be ranked by the predicted sponsorship scores.

3.4 List-wise Learning to Rank

Since our goal is to rank posts by their likelihood scores to be sponsored posts, it is intuitive to apply learning to rank approaches to deal with the problem. More specifically, in this paper, we modify the ListMLE [36], which is list-wise learning to rank approach that can benefit overall ranking performance.

Suppose that X is the set of features for posts to be ranked; Y is the output space of permutations of the posts; P_{XY} is an unknown but fixed joint probability distribution of X and Y . If a ranking function can be represented by $\hat{y} : X \rightarrow Y$, the expected loss $R(\hat{y})$ to be optimized can be derived as follows:

$$R(\hat{y}) = \int_{X \times Y} L(\hat{y}(X_i), y) dP(X_i, y),$$

where $y \in Y$ is a permutation; $X_i \in X$; $L(\hat{y}(X_i), y)$ is the 0-1 loss between the ranked result $\hat{y}(X_i)$ and the position in the permutation y such that

$$L(\hat{y}(X_i), y) = \begin{cases} 1 & , \text{ if } \hat{y}(X_i) \neq y \\ 0 & , \text{ if } \hat{y}(X_i) = y \end{cases}$$

To make the training process more efficient, candidate lists with n labeled posts are sampled from the whole training space in each iteration. Given independently and identically distributed samples in a candidate list $S = \{(X_i, y_i)\}_{i=1}^n \sim P_{XY}$, we minimize the empirical loss R_S as follows:

$$R_S(\hat{y}) = \frac{1}{n} \sum_{i=1}^n L(\hat{y}(X_i), y_i),$$

where y_i is the ground truth permutation.

3.5 Temporal Regularization

Timing is important for publishing posts in influencer marketing [26], so the redundancy between different posts with similar published times can be leveraged to improve the performance for sponsorship estimation. In addition, brands usually hire a number of influencers for a marketing campaign at a time. For example, the posts that are published at a similar time and mention the same brand name are more likely to be sponsored posts. In this paper, therefore, we conduct manifold regularization [16] by using the redundancy between the posts and their published times. Formally, the regularization loss $Q(\hat{y})$ can be defined as:

$$Q(\hat{y}) = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n (|\hat{y}_i - \hat{y}_j| \times \frac{w_b(i, j)}{\max(|l_i - l_j|, 1)}),$$

$$w_b(i, j) = \begin{cases} 1 & , \text{ if } b_i = b_j \\ 10^{-1} & , \text{ if } b_i \neq b_j \end{cases},$$

where $\hat{y}_i$ and $\hat{y}_j$ are the estimated sponsorship scores of the posts p_i and p_j mentioning the brands b_i and b_j at time l_i and l_j ; $w_b(i, j)$ indicates the brand-based regularization weight. Note that the posting time difference, $|l_i - l_j|$, is measured in days. Finally, the ultimate

objective for discovering sponsorship L can be a combination of two loss functions as;

$$L(\hat{y}) = R_S(\hat{y}) + w_l \cdot Q(\hat{y}),$$

where w_l is the weight for manifold regularization.

4 EXPERIMENTS

4.1 Experimental Dataset

4.1.1 Dataset Construction. To evaluate our proposed model, our dataset samples influencer posts from Instagram, which is the most popular social media platform for influencer marketing [23]. Note that we implement the data collection method in [19] and comply with the Instagram policy⁴. To find posts that mention brand names, we first collect a set of brands on Instagram by searching branded content, i.e., sponsored posts. Note that Instagram provides the branded content tool for influencers to disclose sponsorship by showing a partnered brand name on the top of a post⁵. From the searched sponsored posts, we obtain 26,910 brand names. Next, we find brand mentioning posts that contain at least one brand name by searching user tags in the corresponding caption. To reduce noises in the dataset, we filter out a post if it is published by a user with less than 1,000 followers which is a generally required number of followers to be considered as an influencer⁶. Finally, we collect 1,601,074 brand mentioning posts that are published from 2013 to 2019 by 38,113 influencers. Note that the number of posts is exponentially grown over time; the average follower count of the influencers is 127,279.

4.1.2 Sponsorship Labeling. Since our goal is to find sponsored posts that do not disclose paid partnerships, we first classify the posts in the dataset into two classes, including ‘Sponsored’ and ‘Unknown’. We label the posts as ‘Sponsored’ if the posts explicitly disclose sponsored relationships by using certain keywords. More specifically, a given post is labeled as ‘Sponsored’ if the post either uses the branded content tool from Instagram or has one of the following hashtags, #ad, #sponsored, and #paidAD, which are widely used hashtags for sponsorship disclosure in influencer marketing [12, 37]. The remaining posts that are not identified as sponsored posts are labeled as ‘Unknown’. That is, the ‘Unknown’ posts may contain non-sponsored and sponsored posts with no sponsorship disclosure. We label all posts in the dataset and finally have 221,710 ‘Sponsored’ posts and 1,379,364 ‘Unknown’ posts which account for 13.8% and 86.2%, respectively. After labeling the posts, we remove all of the sponsorship-related keywords and hashtags from the posts to prevent information leakage in the experiments. Therefore, our model can detect sponsored posts without relying on such keywords. To evaluate the performance of detecting sponsored posts from the ‘Unknown’ posts, we further manually investigate the unknown posts. The details of manual labeling procedure are described in Section 4.4.2.

4.1.3 Heterogeneous Network. We build the heterogeneous network by using the 1,601,074 posts which include 2,273,578 brand

⁴<https://help.instagram.com/325135857663734>

⁵<https://business.instagram.com/a/brandedcontentexpansion>

⁶<https://www.digitalmarketing.org/blog/how-many-followers-do-you-need-to-be-an-influencer>

mentions. As a result, the network has 38,113 influencer nodes, 26,910 brand nodes, and 1,601,074 post nodes with 3,874,652 edges.

4.2 Experimental Settings

To measure the performance of the proposed SPoD, we treat the task as a one-class ranking problem and assign a relevance score for each post so that posts with higher scores are more likely to be sponsored posts. That is, the posts labeled as ‘Sponsored’ have relevance 1 while the ‘Unknown’ posts have the relevance 0. As SPoD ranks the candidate posts by their sponsorship scores, the relevances are used to evaluate the rank quality. More specifically, we use mean average precision (MAP), mean reciprocal rank (MRR), and average precision (AP) as our evaluation metrics.

We use TensorFlow [1] to implement our model. We split the dataset into three partitions for training, validation, and testing with a ratio of 7:1:2 by randomly selecting the posts. Therefore, the ratios of sponsored posts and unknown posts on three partitions are the same. Additionally, we ensure that the same influencers are not included across the training, validation, and testing sets to avoid information leakage from learning relationships between influencers and brands (e.g., a certain influencer repetitively advertises a certain brand). We tune the parameters with the validation set and set a single hidden layer with 128 hidden nodes. The learning rate and the dropout probability are set as 10^{-3} and 0.5, respectively. We set the regularization weight, w_l , as 10^{-4} .

4.3 Comparative Baseline Methods

We compare the performance of the proposed model with the baseline methods in three different categories, including *Ranking*, *Graph*, and *Text*.

Ranking Baselines. As our model applies the learning-to-rank approach, we apply the identical feature sets of the proposed model for the ranking baselines, therefore, we can evaluate the model capability for the ranking task of the proposed model. We deploy three ranking baseline methods as follows: *ListNet* (LN) [6] is a list-wise learning-to-rank algorithm that exploits gradient descent on neural networks to optimize a list wise loss function. *MART* [14] is a pair-wise learning-to-rank algorithm that uses gradient boosted decision trees for prediction tasks. *LambdaMART* (LM) [5] directly optimize rank cost functions by using gradient boosted regression trees based on *MART*.

Graph Embedding Baselines. The baseline methods in this category only exploit the graphical structure without other information. We deploy the LINE [33] and the GCN [20] as two graph baseline methods. The baselines use the heterogeneous network as input features and disregard the text and image features.

Text Modeling Baselines. In addition to the ranking and the graph baselines, we also have two text baseline methods since influencers usually reveal paid partnerships using text. As the baselines, we deploy two state-of-the-art language models, Embeddings from Language Models (ELMo) [28] and Bidirectional Encoder Representations from Transformers (BERT) [10].

4.4 Experimental Results

In this section, we evaluate the performance of our proposed SPoD compared to the baseline methods with the following two steps: (i)

Table 2: Performance comparison with the baseline methods. SPoD significantly outperforms all types of baseline methods. The temporal regularization and aspect-attentive components improve the ranking performance.

Method	MAP	MRR	AP@k			
			10	100	1000	10000
LN [6]	0.250	0.500	0.714	0.643	0.487	0.380
LM [5]	0.269	1.000	0.867	0.451	0.461	0.395
MART [14]	0.290	1.000	0.507	0.398	0.432	0.421
LINE [33]	0.317	1.000	0.894	0.701	0.587	0.473
GCN [20]	0.370	1.000	0.935	0.744	0.709	0.566
ELMo [28]	0.352	1.000	0.926	0.751	0.714	0.608
BERT [10]	0.376	1.000	0.947	0.788	0.755	0.653
SPoD w/o regularization	0.558	1.000	1.000	0.967	0.956	0.902
SPoD w/o aspect-attention	0.573	1.000	1.000	0.973	0.960	0.913
SPoD	0.592	1.000	1.000	0.994	0.984	0.941

We first examine the sponsored post ranking performance without taking into account sponsored posts in the unknown posts. (ii) We then investigate highly ranked unknown posts to evaluate the performance of detecting hidden sponsored posts in the unknown posts.

4.4.1 Sponsored Posts Ranking Performance. Table 2 shows the performance of the proposed SPoD and the baseline methods. We find that ranking baselines show poor ranking performance compared to the graph and the text baselines. Despite the graph and the text baselines only exploit the network features and the contextualized text features, respectively, these baselines outperform the ranking baselines which use all the proposed features. This is because the text features can be easily over-fitted over the complicated structures in ranking baseline methods. In other words, the ranking baselines fail to leverage the contextualized features. We also find that, in the graph and the text baselines, GCN and BERT have better rank quality than LINE and ELMo, respectively, which are adopted to our proposed post encoder.

Finally, our proposed model, SPoD, significantly outperforms all of the other baseline methods. More specifically, SPoD obtains a 57.45% improvement in mean average precision over BERT. Unlike ranking baselines, SPoD separates text and image features from GCN features and then applies attention over the features, thus effectively utilizing more important post features for ranking. Furthermore, SPoD shows a more robust ranking performance than other baselines. Note that average precision at 10,000 of SPoD is 0.941 while the performance other baseline methods tend to decrease if the ranked list size increases. Figure 4 shows precision at retrieval rates of SPoD and the other baseline methods. While the precision of the baseline methods significantly drops as the retrieval rates increase, SPoD shows highly robust performance. That is, SPoD has high ranking accuracy even while finding a large number of sponsored posts. Furthermore, we perform an ablation study by removing the temporal regularization and the aspect-attention. As shown in Table 2, SPoD loses a 5.74% and 3.21% rank performances in the measure of MAP without using the proposed regularization and the aspect-attention, respectively. This suggests that the proposed regularization that exploits the redundancy between the posts and their published times plays an important role in discovering sponsorship of social media posts. This also reveals

Figure 4: Precision at retrieval rates of the proposed model and the baseline methods. SPoD shows efficient and robust ranking performance compared to the baseline methods.

Table 3: Precision results on the top-ranked unknown posts. SPoD outperforms other baseline methods in detecting undisclosed sponsorship of the unknown posts.

Precision@k	10	50	100	150	200
GCN [20]	0.600	0.540	0.420	0.380	0.355
BERT [10]	0.800	0.820	0.750	0.673	0.580
SPoD w/o regularization	1.000	0.960	0.910	0.873	0.810
SPoD w/o aspect-attention	1.000	1.000	0.950	0.920	0.860
SPoD	1.000	1.000	0.990	0.967	0.920

that the aspect-attention effectively generates post representations by finding more important features.

4.4.2 Detecting Unlabeled Sponsored Posts. Since the goal of SPoD is to detect sponsored posts which do not clearly disclose sponsored relationship with brands, we evaluate the performance of detecting such sponsored posts by investigating the ranking results from Section 4.4.1. To this end, we first extract a set of highly ranked unknown posts and then examine their images and captions to manually label the posts. To ensure the quality of our labeling procedure, two authors of this paper have carefully read and understood the FTC’s endorsement regulation, then investigated the top 200 unknown posts from each ranking result of SPoD, SPoD without regularization, BERT, and GCN. More specifically, we decide an unknown post as a sponsored post when an influencer exclusively promotes a certain product or service by expressing appreciation for sponsorship indirectly in text and holding the product to show brands in images. Cohen’s kappa coefficient of our labels is 0.784 which suggests that our labeling result is highly reliable [25]. Note that there are only 9 disagreements out of the 200 posts. We consider an unknown post as a sponsored post only if both labelers agree.

Table 3 shows the precision of detecting sponsored posts from the unknown posts. The result demonstrates that SPoD is very effective in discovering the sponsored posts with the absence of sponsorship disclosure compared to the baseline methods. Note that SPoD gains 58.6% and 159.2% improvements in precision scores at 200 over BERT and GCN, respectively by achieving 0.920 precision score. This implies that the proposed post representations are remarkably useful to identify sponsorship of social media posts even if the paid partnership is not explicitly disclosed. On the other hand, using only graph structural or contextualized information may fail to detect such posts. We also find that SPoD loses 11.96% and 6.52%

Figure 5: Examples of successfully detected sponsored posts with absence of sponsorship disclosure, and highly ranked non-sponsored posts.

performance in the precision at 200 without using the temporal regularization and the aspect-attention, respectively. This suggests that proposed temporal regularization significantly improves the performance of detecting undisclosed sponsorship by detecting advertising posts in the same marketing campaigns. This also reveals that the aspect-attention is useful to obtain more important knowledge from different aspects of social media posts.

Figure 5 showcases the example posts that are in the top 200 of the rank result of SPoD. The posts in Figure 5(a) and 5(b) are the sponsored posts with absence of sponsorship disclosure. In the sponsored posts, the influencers tend to describe details of the products by sharing their experience and recommending the products in the captions. In addition to the text, we observe the evidence of sponsorship in the image as they hold the products for advertising. However, the sign of sponsorship disclosure is not found from the text and hashtags. On the other hand, Figure 5(c) and 5(d) show the non-sponsored posts that are in high-rank positions. These posts may have been highly ranked due to an object in the images (e.g., products), contextual similarity, and social relation between influencers and brands.

4.5 Analysis and Discussions

In this section, we first study the effectiveness of the proposed model with different feature sets to understand the impact of features to discover sponsored posts. We then evaluate the performance of SPoD with the sets of posts that have different caption lengths.

4.5.1 Feature Importance. To understand the importance of each feature set in the proposed SPoD for detecting sponsored posts, we evaluate the rank performance over different feature sets. Figure 6(a) shows the performance loss of MAP scores of the models trained with the features excluding one particular node feature against the full model as the leave-one-out analysis. We find that the post features have a larger loss value than other node features since sponsored posts have distinct characteristics from non-sponsored posts [37]. Figure 6(a) also shows that the node type features have a large loss value. This suggests that social relations between influencers and brands that are indirectly learned from node types provide valuable information to detect sponsorship of posts.

Figure 6: The post node features and the text features play an important role in detecting sponsorship of posts. SPoD significantly improves the performance in the short post set.

Figure 6(b) shows the average precision scores of the proposed SPoD over (i) only image features, (ii) only GCN features, (iii) only text features, (iv) GCN and image features, (v) image and text features, (vi) GCN and text features, and (vii) All features. The result reveals that the text features significantly improve the performance while the image features contribute to the slight improvement. Note that SPoD loses 27.86%, 12.55%, and 6.47% performance in MAP when it excludes text, GCN, and image features, respectively. This suggests that the contextualized information from captions is very useful for discovering sponsored posts. Due to the nature of paid advertisements, influencers try to recommend the products, convey detailed information of products, and to make a good impression on the brand in the text [35]. This consequently makes the paid advertisements to have distinct contextualized features from non-sponsored posts. The image features, on the other hand, have fewer benefits in discovering sponsored posts compared to the other features. Unlike the text features, which naturally show similar characteristics due to the commonality of language, images can be generated in various ways by different users, thereby making it difficult to rank the posts.

4.5.2 Caption Length of Posts. Since we find that textual information plays an important role in determining whether given social media posts are sponsored, we investigate the performance of the proposed model over different sets of posts with various caption lengths. We split the test dataset into three subsets, including short, medium, and long posts, which have less than 250 (34.5%) and 500 (31.9%), and more than 500 (33.6%) characters in a caption, respectively. Note that we use the same training set for the post sets with different caption lengths thus our model can be used for posts with various caption lengths to detect sponsorship. Figure 6(c) shows the performance of SPoD and two baseline methods over the post sets in different caption lengths. By comparing the performance of MART and BERT, we observe that BERT obtains noticeable improvement in medium and long length posts. This reveals that the contextualized information greatly help detect paid partnership in the posts. However, because of the same reason, BERT fails to improve the performance on the short posts due to insufficient contextualized information from captions. As shown in Figure 6(c), the proposed SPoD outperforms the baseline methods over all the post sets in various caption lengths. Particularly, SPoD remarkably improves the performance in the short post set. This implies that SPoD effectively leverages the knowledge of both graph structures and the various features to detect the sponsorship of social media

posts. For example, a sponsored post with a very short caption can be detected by our model by understanding the social relations and characteristics of adjacent influencers and brands.

5 RELATED WORK

Sponsorship Disclosure in Influencer Marketing. As influencer marketing has become a popular advertising method in recent years [4, 19, 21], several previous studies show the effect of disclosing sponsorship. Evans et al. [12] find that sponsorship disclosure helps audiences recognize paid partnerships but lowers purchase intention. Stubb and Colliander [31] find that impartiality disclosure, e.g., adding “This is not sponsored post”, helps generate high influencer credibility. Moreover, Evans et al. [11] investigate the effects of sponsorship text disclosure and sponsor pre-roll video advertising on YouTube. They find that the sponsor pre-roll advertising help audiences to understand sponsorship transparency. Yang et al. [37] reveal that distinct characteristics of sponsored posts, e.g., less number of usertags, longer caption than non-sponsored posts, that help exclusive promotion in advertising posts. Wojdyski et al. [35] present a metric to measure sponsorship transparency based on consumers’ perceptions. However, this study only uses a very small number of sample posts and automated method has not been proposed.

Multimodal Deep Learning. Multimodal deep learning [27] is the method that can effectively generate the joint representations of different modalities by leveraging multiple sources of inputs. Since different modalities usually carry different information, combining various types of information can improve performance in learning tasks. The effectiveness of multimodal learning has led other researchers to exploit multi modalities, such as speaker identification [29], social media user profiling [19], visual question answering [22], sentiment prediction [7], depression detection [30], and speech recognition [15]. Despite the excellent performance of multimodal learning and the popularity of influencer marketing, no previous studies have yet adopted multimodal learning to discover sponsored posts.

6 CONCLUSIONS

In this paper, we propose a learning-to-rank model for discovering undisclosed sponsorship on social media. Our proposed model, SPoD, employs the aspect-attentive heterogeneous post encoder that incorporates graph, text, and image features to estimate their importance for representing the characteristics of social media

posts, and then optimizes the ranking performance by using the regularization based on posting time and mentioned brands. As our proposed model effectively discover undisclosed sponsorship on social media, we strongly believe that SPoD can be deployed as follows: Companies and marketers can utilize SPoD to avoid influencers who frequently hide sponsorship in their advertising social media posts so they can collaborate with highly transparent influencers. SPoD also can be used by social media platforms to alert social media users to be conscious of undisclosed sponsorship, thereby helping them recognize the regulations on advertising posts. As a consequence, SPoD can help resolve the undisclosed sponsorship issue in influencer marketing by making influencers and brands comply with the regulations.

As future work, we intend to conduct the following studies: First, we plan to apply the proposed model to other datasets from various social media platforms as companies have started collaborating with influencers in video-based social media, including YouTube, and TikTok. In addition, we will further collect data from Instagram to include regular posts since the current dataset only contains brand mentioning posts. Next, our proposed SPoD is designed to be a ranking model to discover a set of untransparent influencers and their advertising posts with high confidence. We aim at improving the proposed model by changing it from a ranking model to a binary classifier so that the model can decide the sponsorship of a given post rather than making a ranked list of posts.

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