Content and Community based Hybrid Tag Recommendation

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น.ส.อุมาพร ผดุงเกียรติวัฒนา

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อุมาพร ผดุงเกียรติวัฒนา : ระบบแนะนำแท็กแบบผสมโดยใช้เนื้อหาและชุมชนเป็นฐาน. (Content and Community based Hybrid Tag Recommendation) อ.ที่ปรึกษาหลัก : รศ. ดร.ศรันญา มณีโรจน์

ระบบแนะนำแฮชแท็กส่วนบุคคลคือระบบการแนะนำแฮชแท็กที่เกี่ยวข้อง ให้แก่ ไมโครบล็อก โดยมีความเฉพาะกับพฤติกรรมของผู้ใช้ แม้ว่าประสิทธิภาพของงานวิจัยก่อนหน้าจะได้รับการพัฒนา แต่งานดังกล่าวมีข้อจำกัดหลักสามประการ ประการแรก งานวิจัยก่อนหน้าเรียนรู้พฤติกรรมของผู้ใช้จากปฏิสัมพันธ์ระหว่างผู้ใช้และแฮชแท็กที่เกิดขึ้นโดยตรงเท่านั้น ส่งผลให้ไม่สามารถรองรับความหลากหลายของพฤติกรรมผู้ใช้ เช่น พฤติกรรมการปฏิสัมพันธ์ระหว่างผู้ใช้ และพฤติกรรมการเกิดร่วมระหว่างแฮชแท็ก นอกจากนี้งานวิจัยก่อนหน้าจำกัดความสัมพันธ์จากผู้ใช้ทางตรงเท่านั้น และไม่คำนึงความสัมพันธ์จากผู้ใช้ทางอ้อมซึ่งอยู่ภายใต้ชุมชนเดียวกัน ประการที่สอง งานวิจัยก่อนหน้าทำการปรับแต่งส่วนบุคคลในระดับไมโครบล็อก โดยไม่พิจารณามุมมองส่วนบุคคลที่ผู้ใช้มีต่อแต่ละคำในไมโครบล็อก ประการที่สาม งานวิจัยก่อนหน้าพิจารณาความสัมพันธ์ระหว่างแฮชแท็กในไมโครบล็อกเดียวกัน โดยยึดลำดับของแฮชแท็ก จากด้านซ้ายไปด้านขวา ส่งผลให้แฮชแท็กได้รับความสัมพันธ์จากด้านซ้ายเพียงอย่างเดียว และขาดความสัมพันธ์จากด้านขวา ด้วยเหตุนี้ ในงานวิจัยนี้ จึงเสนอระบบแนะนำแฮชแท็กส่วนบุคคล ที่ประยุกต์ใช้โครงข่ายประสาทเทียมแบบกราฟเพื่อเรียนรู้พฤติกรรมของผู้ใช้และคุณลักษณะของแฮชแท็กจากสามเครือข่าย ได้แก่ เครือข่ายการปฏิสัมพันธ์ระหว่างผู้ใช้และแฮชแท็ก เครือข่ายสังคมระหว่างผู้ใช้ และเครือข่ายการเกิดร่วมระหว่างแฮชแท็ก จากนั้นประยุกต์ใช้เบิร์ตเพื่อปรับแต่งส่วนบุคคลในระดับคำและสกัดความสัมพันธ์ของแฮชแท็กแบบไม่มีลำดับจากสองทิศทาง จากผลการวิจัยโดยใช้ชุดข้อมูลทวิตเตอร์พบว่างานวิจัยนี้สามารถเพิ่มประสิทธิภาพการแนะนำให้มีความแม่นยำมากขึ้นกว่างานวิจัยก่อนหน้า

สาขาวิชา	วิทยาการคอมพิวเตอร์และเทคโนโลยีสารสนเทศ	ลายมือชื่อนิสิต ....
ปีการศึกษา	2565	ลายมือชื่อ อ.ที่ปรึกษาหลัก ....

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Personalized hashtag recommendations can provide relevant hashtags for a microblog. Despite performance improvement, three challenges remain unexplored. First, previous works construct user and hashtag representations based on relations from themselves. We argue that users and hashtags are influenced not only by their own relations (i.e., first-order relations) but also by the relations of a distant user/hashtag that is indirectly connected in multiple communities (i.e., high-order relations). Second, prior works perform personalization at the microblog level while ignoring the user aspects presented for each word in the microblog. Third, past studies capture correlations among hashtags in the same microblog by considering their sequence. We argue that hashtag correlations are sequenceless since they can reorder without changing their relevance to the microblog. To overcome these three challenges, we propose a personalized hashtag recommendation that consists of three parts. First, we employ graph neural networks to derive user and hashtag representation from high-order multiple relations in three communities: (1) user-hashtag interaction; (2) user-user social; and (3) hashtag-hashtag co-occurrence. Second, for word-level personalization, we extend the bidirectional attention to take both word and user representation as input. Finally, for sequenceless hashtag correlations, we feed the hashtag representation into the bidirectional attention and train using mask modeling. Experiments on the Twitter dataset show that our proposed method outperforms the state-of-the-art on precision, recall, and F1-score.

Field of Study:	Computer Science and Information Technology	Student's Signature ....
Academic Year:	2022	Advisor's Signature ....

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Umaporn Padungkiatwattana

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CHAPTER I INTRODUCTION

A massive quantity of data is created nowadays from numerous sources, particularly microblogs on social media platforms (i.e., user postings containing brief chunks of text). Hashtags are labeled depending on their associated categories to organize such microblogs and boost accessibility. As a result, hashtag recommendations have been proposed to indicate appropriate hashtags for content, allowing users to choose related hashtags rather than manually entering them, hence boosting the quality of chosen hashtags.

Personalized hashtag recommendations successfully use user preferences to provide relevant hashtags for a microblog. Despite their improved performance, we reexamine them and contend that in terms of *interaction* and *influence*, they are not entirely comparable to current social media behavior. In terms of *interaction*, while users are more likely to contribute implicit relations, the majority of prior methods that model user representation mostly focused on the explicit relations from the user's historical posts. According to our research, there are three primary implicit relations that strongly reflect both user behaviors and hashtag attributes:

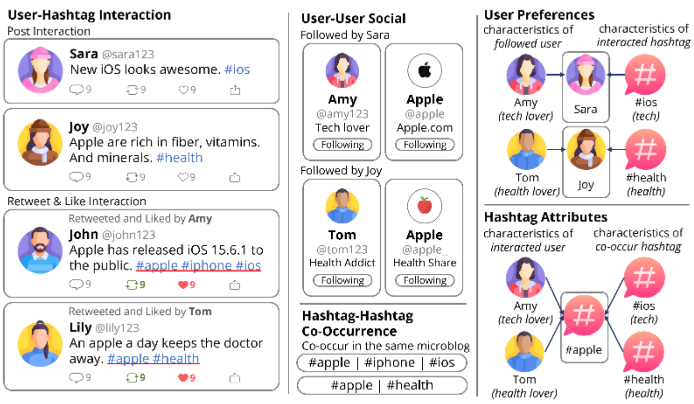


Figure 1. Multiple relations in social community

- **User-Hashtag Interaction**: A retweet or a like between a user and a hashtag on a microblog. The majority of earlier research primarily examined hashtags in microblogs that users themselves had posted. In actuality, users often retweet and interact with other microblogs that contain hashtags relevant to them. This implies that the hashtag characteristics, which are user preferences, might be reflected in the interacted hashtags. As seen in Figure 1, Amy demonstrates her interest in technology by retweeting or liking microblogs with the hashtags "#apple" and "#ios". Because relying just on a user's post interaction may result in the loss of certain important interests, we should take into account retweet and like interactions in order to extract active interests more accurately for user representation. Additionally, in earlier approaches, hashtag representation was generated solely from text data, which only contains word-semantic perspectives. In actuality, hashtags may signify different things to different people. There are several users who utilize "#apple," as seen in Figure 1. Different user groups can use the same hashtag (technology lovers and health lovers). Therefore, including user-hashtag interaction can contribute to more effective hashtag representation.

- **User-User Social**: An interaction between users and the individuals they follow. Users often follow persons who interest them. This shows that users and the individuals they follow have comparable interests, which may represent similar user characteristics. As seen in Figure 1, Joy follows the accounts linked to health, determining her interests in health, whereas Sara follows the accounts relating to technology, determining her interests in technology. The user representation can therefore be improved by taking into consideration the latent characteristics of the users' following people.
- **Hashtag-Hashtag Co-occurrence**: A collection of hashtags used regularly on the same microblogs. In reality, as Figure 1 demonstrates, users frequently add many hashtags to a single microblog, with some of them being omitted from the text due to character restrictions. For instance, the microblog posts "Apple has released iOS 15.6.1 to the Public." along with the regularly used hashtags "#apple," "#ios," and "#iphone." Only "#apple" and "#ios" display as words in the text; "#iphone" does not. The co-occurring hashtags might show comparable hashtag characteristics because they are in the same microblog with the same content. We may lose some hashtags that are pertinent and commonly tagged together but not present in the content if we simply take into account the little amount of content in the microblog. By integrating these relations, hashtag representation may be made more effective and the content restriction can be alleviated.

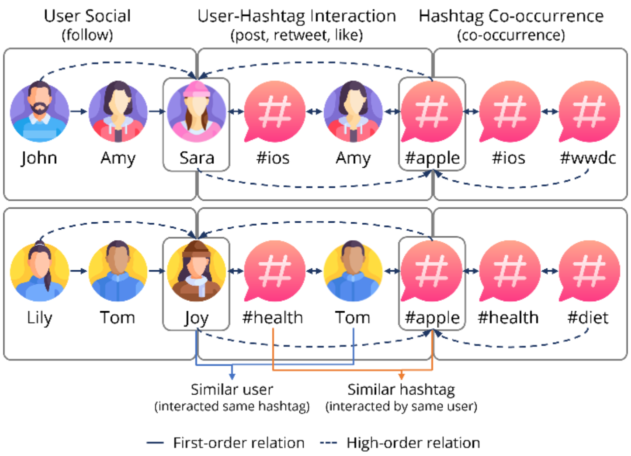


Figure 2. High-order multiple relations

In terms of *influence*, each user/hashtag is influenced by both first-order and higher-order relations (i.e., relations derived from a distant user/hashtag that is indirectly connected), whereas prior research only examined first-order relations (i.e., relations derived from a user/hashtag that is directly connected). Figure 2, for instance, shows the higher-order impacts in three networks. Due to their connection to the same "#ios," Sara and Amy are similar users. Even if Sara never used "#apple" or followed John, she could be impacted by both because they both connect with Amy, who has similar interests. Similarly, "#apple" and "#ios" are similar hashtags because they are interacted by Amy. Even "#apple" has never been used by Sara and tagged with "#wwdc", it might be influenced by them since both of them have interacted with "#ios", which shares similar attributes. Some techniques use graphs as a data structure in their analysis of social connections, although they are still dependent on statistical techniques (e.g., frequency or node degree), making them unable to capture higher-order relations. Thus, our *first challenge* is to extract high-order relations in user-user social, user-hashtag interaction, and hashtag-hashtag co-occurrence networks for the more fruitful user and hashtag representation.

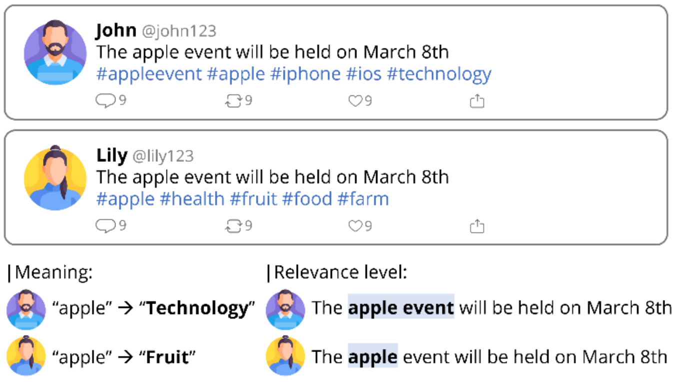


Figure 3. User's personalized aspects at the word level

In addition to the fruitful user and hashtag representation, the personalization strategy is crucial for personalized hashtag recommendation. Previous studies perform personalization at the microblog level [1-3]. In actuality, the meaning and degree of relevance at the word level may be personalized for the user. Figure 3 illustrates how John and Lily create microblogs with the same content, but they use totally different hashtags. When we look at the words used in the microblogs, we immediately recognize that the different meanings of the word "apple" are what cause the same microblog to have different hashtags (technology and fruit). Lily uses the word "apple" to describe fruit, but John uses the word to describe the technology. This strongly supports that users have personalized meanings for each word in the microblog. In addition to the personalized meanings, John and Lily have personalized relevance levels for each word in the microblog. John is highly relevant to both the word "apple" and "event" since they both occur in the hashtag "#appleevent", while Lily is highly relevant to the word "apple". This indicates that users have personalized relevance levels for each word in the microblog. To this end, our *second challenge* is to incorporate word-level personalization for more accurate performance.

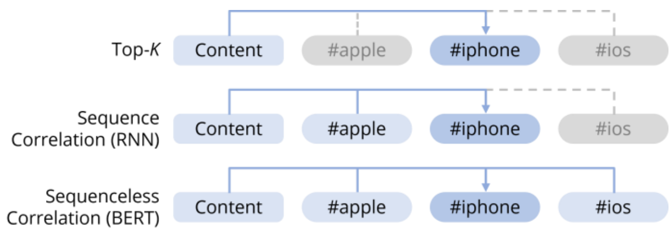


Figure 4. Sequenceless hashtag correlations

Additionally, the majority of earlier personalized methods recommend top-K hashtags, which have the strongest connections to the microblog. However, those suggested hashtags have no connection to one another because they were created independently [1-3]. In actuality, hashtags that are used on the same microblog are connected. To solve this issue, recent non-personalized techniques use recurrent neural networks (RNN) to extract hashtag correlations [4, 5]. However, those correlations are captured with regard to the order of hashtags. In this way, correlations are captured from the left side and affect when reordering the hashtags. Actually, hashtag connections lack any sense of order. Their order might be adjusted without affecting the microblog's overall significance. As shown in Figure 4, when collecting correlations for "#iphone", the sequenceless method enables the "#iphone" to collect correlations from both "#apple" and "#ios" because it captures relations from both the left and right sides, whereas the RNN-based method only collects correlations from "#apple" and loss correlations from "#ios" that are located on the right side. Thus, our *third challenge* is to fully collect hashtag correlations from the whole microblog without being constrained by the hashtag sequence.

To overcome the above three challenges, we propose a novel personalized hashtag recommendation called PAC-MAN. *First*, for modeling user and hashtag representation from high-order multiple relations, we introduce Multi-relational Attentive Network (MAN) which apply graph neural networks (GNN) [6] on three networks: (1) user-hashtag interaction; (2) user-user social; (3) hashtag-hashtag co-occurrence. In this way, the representations of user and hashtag fruitfully contain detailed characteristics based on the community. *Second*, for word-level personalization, we introduce Person-And-Content based BERT (PAC) extends BERT by inserting not only word representation but also the fruitful user representation derived from the MAN part. In this manner, each word is allowed to obtain personalized aspects from a specific user. Finally, for sequenceless hashtag correlations, the fruitful representations of hashtags from MAN that contain the community-based meanings are inputted into BERT to integrate with the semantic-based meanings, and a hashtag prediction task is then conducted for the recommendation.

CHAPTER II RELATED WORK

In this chapter, we briefly review the related hashtag recommendations, including non-personalized hashtag recommendations and personalized hashtag recommendations. Then, we describe the process of the graph neural networks. Last, we explain the process of the attention-based method.

2.1 Hashtag Recommendation

2.1.1 Non-Personalized Hashtag Recommendation

Most previous hashtag recommendations recommended relevant hashtags based on microblogging content similarity. The idea is that similar hashtags should be used for similar content. In recent years, neural networks have shown promising results in hashtag recommendation. Word2Vec is a neural network approach for creating word representations that is used in many hashtag recommendations. Hashtagger+ [7] recommends hashtags for news articles using a learning-to-rank model based on word2vec. However, word2vec does not take into account the sequence of words in the microblog. The recurrent neural network (RNN) approach is widely used in many works to handle the nature of sequential words. TCAN [8] gathers content attention from RNN and topic attention from LDA for the recommendations. However, RNNs have bottleneck problems that cause information loss in long sequences. Transformer [9], an attention-based technique, has recently been presented to overcome the problem in RNN and obtain state-of-the-art text processing outcomes. Some hashtag recommendations are enhanced by utilizing Transformer and its variants, such as BERT [10]. EmHash [11] employs BERT to construct a representation of microblogs for hashtag recommendation.

Apart from content modeling approaches, recommendation approaches are crucial for performance improvement. All of the methods described above independently recommend the top-K relevant hashtags while ignoring the correlations between them. Some recent methods construct the recommendation as a hashtag generation task using RNN, allowing correlations among hashtags to be captured. For instance, ITAG [4] uses a gated recurrent unit (GRU) to capture correlations among hashtags and combine them with sequential text for making recommendations. AMNN [5] utilizes GRU to capture correlations among hashtags and combine them with multimodal features for making recommendations.

However, the aforementioned methods lack personalization since they solely consider textual information and ignore user preferences. In reality, user content may be associated with various hashtags based on their preferences. In other words, even if the recommended hashtags are appropriate for the text, the user may not favor them. In contrast, we want to model user preferences based on community and combine them with textual content to provide personalized recommendations. In this manner, the recommended hashtags are more relevant to the preferences of a specific user. Furthermore, the RNN technique allows correlations in the aforementioned studies to be collected while taking their order into account. In other words, reordering the hashtag positions affects the correlations because they only include the left side. In actuality, correlations among hashtags are sequenceless and should be gathered bidirectionally from both the left and right sides. Unlike previous methods, we use BERT and provide hashtag prediction tasks utilizing the mask modeling technique to model hashtag correlations under sequenceless conditions. This removes the sequence limitations and allows hashtag correlations to be collected from both the left and right sides.

2.1.2 Personalized Hashtag Recommendation

Non-personalized hashtag recommendations lack personalization since they focus solely on content while disregarding the preferences of the user. In other words, hashtags that are recommended solely based on content semantics may not be relevant to user preferences. To increase personalization and performance, personalized hashtag recommendations that integrate content information and user preferences have been proposed. Most studies rely on previous posts by users to determine user preferences. Earlier works relied on similarity techniques. Hashtag-LDA [12] employs LDA to find related microblogs based on topic and recommends hashtags from those microblogs that are most similar to the user. Recently, several personalized hashtag recommendations have used neural network approaches to improve user representation. MACON [2] applies a memory network to extract user preferences from historical posts to construct user representation for recommendation in photo-sharing services.

Recently, graphs have been used as a data structure in studies to investigate social interactions. DeepTagRec [1] constructs user representation from user-hashtag interaction using the node2vec technique. CBHR [3] constructs a network of users based on their interactions and detects communities based on node degree. Then, for recommendation, it finds similar microblogs from similar users in the community.

The aforementioned studies combine user representation and microblog representation for recommendation, which makes personalization occur at the microblog level. In other words, before personalization occurs, all words in a microblog are compressed into a single vector to construct the microblog representation. In this way, each word cannot obtain personalized aspects of a specific user. Unlike prior studies, we extend BERT to input not only word representation but also user representation, enabling each word to obtain the personalized aspect of a specific user for personalization at the word level.

However, the above studies extract user preferences from only historical posts, while users express their preferences in several ways. Moreover, the above studies extract hashtag attributes based solely on semantic perspectives, whereas its attributes can be reflected from community perspectives. Furthermore, the above studies only take into account the relations from themselves (i.e., first-order relations), while users/hashtags are also influenced by similar users/hashtags in the community that are indirectly connected (i.e., high-order relations). Unlike the previous studies, we aim to employ the GNN technique to extract user preferences as well as hashtag attributes across three community types: (1) user-hashtag interaction; (2) user-user social; and (3) hashtag-hashtag co-occurrence, to enhance a more fruitful representation for the user and hashtag. The next section provides additional details on the GNN and BERT techniques.

2.2 Graph Neural Network

To learn node embeddings, early graph techniques use random walk statistics. In this manner, if nodes co-occur on short random walks in the graph, their embeddings are similar. However, the node attributes that have useful information are not taken into account by these statistical techniques. Recently, graph neural network (GNN) [6] techniques that combine neighborhood aggregation techniques with neural networks have been presented to address this issue. Unlike the statistics-based techniques, GNN builds node embedding by aggregating attributes from its neighboring nodes. Then, the aggregation is iterated to gather broader attributes from the higher-order nodes in the graph. After all iterations, the final embedding contains fruitful information based on graph connections.

Motivated by GNN, we employ the GNN technique to extract user preferences and hashtag attributes across three community types: (1) user-hashtag interaction; (2) user-user social; and (3) hashtag-hashtag co-occurrence. We construct user representations by gathering relations from the interaction community and the social community because users are central to both. Similarly, we build hashtag representations by combining relations from the interaction and co-occurrence communities, as hashtags are central to both. After that, higher-order relations are retrieved by iterative propagation of the fused representations. As a result, we have a more fruitful representation for users and hashtags that can satisfy high-order multiple relations.

2.3 Attention-based Method

Recently, the Transformer [9] proposes a multi-head attention-based technique to overcome the bottleneck problem in RNN and achieve state-of-the-art outcomes in text modeling. It divides attention into multiple heads, allowing each head to work in parallel at the same time. Multi-head attention enables the combination of information from multiple representation subspaces. The values from each head are weighted according to the relevance levels and then concatenated as output. Because of its effectiveness, the multi-head attention technique is used in several hashtag recommendations. For example, SANN [13] applies a multi-head attention technique to model representation for microblogs.

Many studies has been proposed in recent years to improve transformer performance. One of Transformer's variants, Bidirectional encoder representations from transformers (BERT) [10] proposes to gather information from both left and right contexts using a mask modeling technique for learning representation. Some hashtag recommendations utilize the BERT technique for performance improvement. EmHash [11] applies the BERT technique to construct a representation of microblogs for hashtag recommendation.

We develop the two-level attentive aggregation in GNN using the attention mechanism since it can weight input based on relevance levels. This two-level attentive aggregation can cope with dynamic relations by dynamically aggregating information from the neighborhood based on their relevance levels. Furthermore, inspired by BERT, we extend BERT to include both personal and textual features as BERT's input. Every user and word have the ability to dynamically gather information from the others in this way. As a result, each word obtains personalized aspects from users, making it personalized for them. Additionally, we use the mask modeling technique for training BERT to capture hashtag correlations under sequenceless. In this manner, the masked hashtags are predicted based on information from both the left and right sides, leading to more precise recommendations.

CHAPTER III PROPOSED METHOD

To achieve our three challenges, we proposed the personalized hashtag recommendation named PAC-MAN. The architecture of our proposed PAC-MAN is shown in Figure 5. According to the figure, to achieve our *first challenge* of modeling the fruitful user and hashtag representation from high-order multiple relations, we introduce the Multi-relational Attentive Network (MAN). The MAN method employs GNN on three community types: (1) user-hashtag interaction; (2) user-user social; and (3) hashtag-hashtag co-occurrence. With GNN, relations from higher orders in the community are extracted and used to construct fruitful user and hashtag representation. Second, to achieve our *second challenge* of word-level personalization, we introduce the Person-And-Content based BERT (PAC). The PAC method extends BERT by inputting not only representations of words in the microblog but also the fruitful representation of users from the MAN method. With BERT, each word is allowed to receive personalized aspects from users, making each word personalized for them. Finally, to achieve our *third challenge* of sequenceless hashtag correlations, the representation of hashtags that have community perspectives is inserted into the PAC method to fuse with their semantic perspectives, and the PAC method is trained under the concept of mask modeling and uses the same position embedding for all hashtags. With mask modeling and the same position embedding for all hashtags, the sequence of hashtags is removed, and correlations are captured without any sequence constraints.

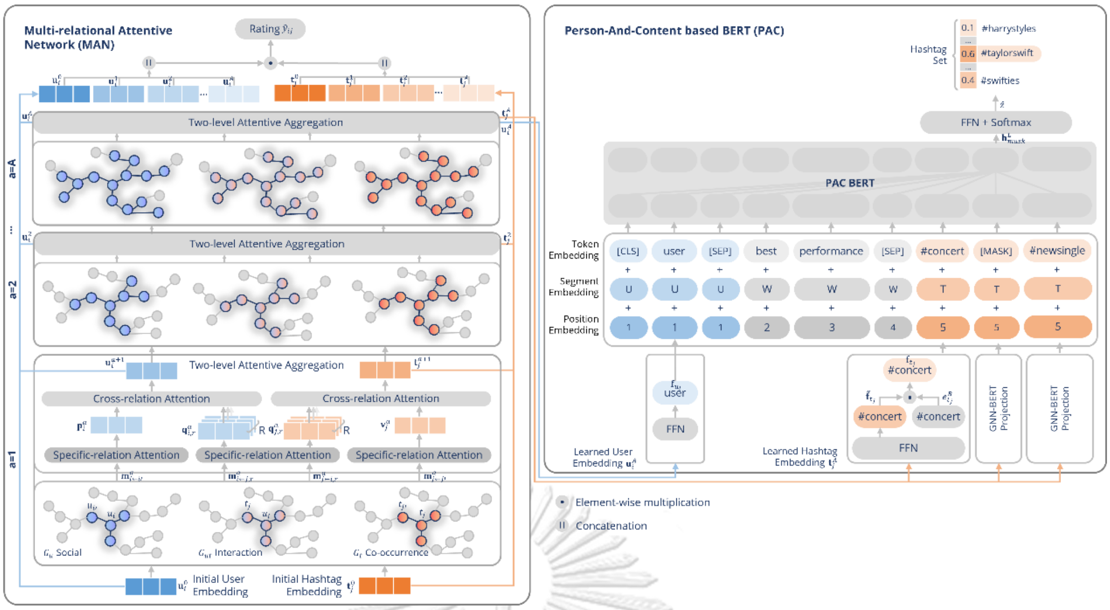


Figure 5. Model architecture

3.1 Problem Formulation and Definition

Given a user $u_i \in U$ and a microblog x_i that contains a sequence of words $w_n \in W$, $x_i = [w_1, \dots, w_N]$, where N is the maximum content length, the purpose of our proposed method is to predict the set of most suitable hashtags t_j. To represent users, we initialize user embedding $\mathbf{e}_{u_i}$ for every user u_i. The user embedding is stored in the user matrix $\mathbf{E}_U \in \mathbb{R}^{|U| \times d_G}$, where d_G is the dimension size of the GNN. To represent words, we initialize word embedding $\mathbf{e}_{w_n}$ for every word w_n. The word embedding is stored in the word matrix, where d_B is the dimension size of BERT. To represent hashtags, it has two types of embedding: GNN-based hashtag embedding $\mathbf{e}^G_{t_j}$, which is stored in the GNN-hashtag matrix $\mathbf{E}^G_T \in \mathbb{R}^{|T| \times d_G}$, and BERT-based hashtag embedding $\mathbf{e}^B_{t_j}$, which is stored in the BERT-hashtag matrix $\mathbf{E}^B_T \in \mathbb{R}^{|T| \times d_B}$.

We define three graphs to represent the connections in three community types: (1) user-hashtag interaction, (2) user-user social, and (3) hashtag-hashtag co-occurrence.

Definition 1: User-Hashtag Interaction Graph G_{ut}. We construct user-hashtag interaction graph $G_{ut} = (U, T, \mathcal{E}_{ut})$. The connections in the graph are represented by an interaction tensor $\mathcal{E}_{ut} \in \mathbb{R}^{|U| \times |T| \times R}$, where R is the number of interaction types (post, retweet, like). In the interaction matrix $\mathcal{E}^r_{u,t} \in \mathcal{E}_{ut}$, if the user u_i interacts with the hashtag t_j under type-r interaction, the value $e^r_{i,j} = 1$, otherwise $e^r_{i,j} = 0$. Moreover, we define $N^r_{u_i,t}$ as a neighbor set of a user u_i that contains all hashtags the user u_i interacts with via type-r interaction (i.e., $N^r_{u_i,t} = \{t_j; e^r_{i,j} = 1\}$).

And, we define N^r_{u,t_j} as a neighbor set of a hashtag t_j that contains all users who interact with the hashtag t_j via type-*r* interaction (i.e., $N^r_{u_i,t_j} = \{u_i; e^r_{i,j} = 1\}$).

Definition 2: User-User Social Graph G_u. We construct user-user social graph $G_u = (U, \mathcal{E}_u)$. The connections in the graph are represented by a social matrix $\mathcal{E}_u \in \mathbb{R}^{|U|\times|U|}$. In the social matrix $\mathcal{E}_u$, if the user u_i follows user $u_{i'}$, the value $e_{i,i'} = 1$, otherwise $e_{i,i'} = 0$. Moreover, we define N_{u_i} as a neighbor set of a user u_i that contains all users whom the user u_i follows (i.e., $N_{u_i} = \{u_i; e_{i,i'} = 1\}$).

Definition 3: Hashtag-Hashtag Co-Occurrence Graph G_t. We construct hashtag-hashtag co-occurrence graph $G_t = (T, \mathcal{E}_t)$. The connections in the graph are represented by a co-occurrence matrix $\mathcal{E}_t \in \mathbb{R}^{|T|\times|T|}$. In the co-occurrence matrix $\mathcal{E}_t$, if the hashtag t_j co-occurs with hashtag $t_{j'}$, the value $e_{j,j'} = 1$, otherwise $e_{j,j'} = 0$. Moreover, we define N_{t_j} as a neighbor set of a hashtag t_j that contains all hashtags that co-occur with the hashtag t_j (i.e., $N_{t_j} = \{t_j; e_{j,j'} = 1\}$).

3.2 Multi-relational Attentive Network (MAN)

To achieve our challenge of high-order multiple relation extraction for fruitful user and hashtag representation, we introduce the MAN method by applying GNN [6] to three community types: (1) user-hashtag interaction, (2) user-user social, and (3) hashtag-hashtag co-occurrence. GNN can extract relations from higher orders in the community and use them to learn more fruitful user and hashtag representation. In this section, we explain the aggregation approach for three community types: (1) user-hashtag interaction, (2) user-user social, and (3) hashtag-hashtag co-occurrence. Then, we describe the propagation approach of information in higher order, as well as the learning approach used to build fruitful user and hashtag representations. First of all, we introduce initial embedding and multi-head attentive aggregation, which are used in the method.

Initial Embedding: At GNN layer $a = 0$, user embedding $\mathbf{e}_{u_i}$ is set as the initial user embedding $\mathbf{u}_i^0$ and hashtag embedding $\mathbf{e}_{t_j}$ is set as the initial hashtag embedding $\mathbf{t}_j^0$, as shown in Equation (1) and Equation (2), respectively.

$$\mathbf{u}_i^0 = \mathbf{e}_{u_i} \tag{1}$$

$$\mathbf{t}_i^0 = \mathbf{e}^G_{t_j} \tag{2}$$

Multi-Head Attentive Aggregation MHA$(\cdot)$: Because a user and hashtag have a dynamic relevance level towards their neighbors, we apply an attention mechanism for our aggregation function in GNN. The function divides the dimension size d_G of the messages from neighbors into h_G heads. Each head processes in parallel and then concatenates again, as shown in Equation (3).

$$\mathbf{MHA}(\mathbf{Q},\mathbf{K},\mathbf{V}) = \left[head_1 \parallel \cdots \parallel head_{h_G}\right]\mathbf{W}^{O_G};$$
$$head_i = \mathbf{Attention}(\mathbf{Q}\mathbf{W}_i^{Q_G}, \mathbf{K}\mathbf{W}_i^{K_G}, \mathbf{V}\mathbf{W}_i^{V_G}) \tag{3}$$

where $\mathbf{W}^{O_G} \in \mathbb{R}^{d_G \times d_G}$, $\mathbf{W}_i^{Q_G} \in \mathbb{R}^{d_G \times d_G/h_G}$, $\mathbf{W}_i^{K_G} \in \mathbb{R}^{d_G \times d_G/h_G}$, $\mathbf{W}_i^{V_G} \in \mathbb{R}^{d_G \times d_G/h_G}$ are model parameters. The $\mathbf{Attention}(\cdot)$ function is the scaled dot-product attention function from [9]. The attention function applies the dot product operation between query $\mathbf{Q}$ and key $\mathbf{K}$, divides by $\sqrt{d_G/h_G}$, and passes it to the softmax function. The output is the attention score. The attention score is then used to weight the value $\mathbf{V}$, as shown in Equation (4).

$$\mathbf{Attention}(\mathbf{Q},\mathbf{K},\mathbf{V}) = softmax\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_G/h_G}}\right)\mathbf{V} \tag{4}$$

In this way, messages from neighbors are aggregated based on their relevance to the target user or target hashtag.

3.2.1 User-Hashtag Interaction Aggregation

We concatenate the hashtag embedding $\mathbf{t}_j^a$ from all interacted hashtags t_j of user u_i, $\forall t_j \in N_{u_i,t}^r$, to construct the type-$r$ interaction messages $\mathbf{m}_{i\leftarrow j,r}^a$, as shown in Equation (5). In the same way, we concatenate the user embedding $\mathbf{u}_i^a$ from all interacted users u_i of hashtag t_j, $\forall u_i \in N_{u,t_j}^r$, to construct the type-$r$ interaction messages $\mathbf{m}_{j\leftarrow i,r}^a$, as shown in Equation (6).

$$\mathbf{m}_{i\leftarrow j,r}^a = concat\left(\mathbf{t}_j^a\right);\ \forall t_j \in N_{u_i,t}^r \tag{5}$$
$$\mathbf{m}_{j\leftarrow i,r}^a = concat(\mathbf{u}_i^a);\ \forall u_i \in N_{u,t_j}^r \tag{6}$$

Then, the type-r interaction message $\mathbf{m}_{i\leftarrow j,r}^a$ from all interacted hashtags are aggregated based on its important levels to the user for constructing the interaction-based user embedding $\mathbf{q}_{i,r}^a$ by applying the multi-head attention mechanism $\mathbf{MHA}(\cdot)$, as shown in Equation (7). In the same way, the type-r interaction message $\mathbf{m}_{j\leftarrow i,r}^a$ from all interacted users are aggregated based on their important levels to the hashtag for constructing the interaction-based hashtag embedding $\mathbf{q}_{j,r}^a$ by applying the multi-head attention mechanism $\mathbf{MHA}(\cdot)$, as shown in Equation (8).

$$\mathbf{q}_{i,r}^a = \mathbf{MHA}(\mathbf{u}_i^a, \mathbf{m}_{i\leftarrow j,r}^a, \mathbf{m}_{i\leftarrow j,r}^a) \tag{7}$$
$$\mathbf{q}_{j,r}^a = \mathbf{MHA}(\mathbf{t}_j^a, \mathbf{m}_{j\leftarrow i,r}^a, \mathbf{m}_{j\leftarrow i,r}^a) \tag{8}$$

3.2.2 User-User Social Aggregation

We concatenate the user embedding $\mathbf{u}_{i'}^{a}$ from all following users $u_{i'}$ of user u_i, $\forall u_{i'} \in N_{u_i}$, to construct the social message $\mathbf{m}_{i\leftarrow i'}^{a}$, as shown in Equation (9).

$$\mathbf{m}_{i\leftarrow i'}^{a} = concat(\mathbf{u}_{i'}^{a});\ \forall u_{i'} \in N_{u_i} \quad (9)$$

Then, the social message $\mathbf{m}_{i\leftarrow i'}^{a}$ from all followed users are aggregated based on its important levels to the user for constructing the social-based user embedding $\mathbf{p}_i^{a}$ by applying the multi-head attention mechanism $\mathbf{MHA}(\cdot)$, as shown in Equation (10).

$$\mathbf{p}_i^{a} = \mathbf{MHA}(\mathbf{u}_i^{a}, \mathbf{m}_{i\leftarrow i'}^{a}, \mathbf{m}_{i\leftarrow i'}^{a}) \quad (10)$$

3.2.3 Hashtag-Hashtag Co-Occurrence Aggregation

We concatenate the hashtag embedding $\mathbf{t}_{j'}^{a}$ from all co-occurrent hashtags $t_{j'}$ of hashtag t_j, $\forall t_{j'} \in N_{t_j}$, to construct the co-occurrence message $\mathbf{m}_{j\leftarrow j'}^{a}$, as shown in Equation (11).

$$\mathbf{m}_{j\leftarrow j'}^{a} = concat\left(\mathbf{t}_{j'}^{a}\right);\ \forall t_{j'} \in N_{t_j} \quad (11)$$

Then, the co-occurrence message $\mathbf{m}_{j\leftarrow j'}^{a}$ from all co-occurrent hashtags are aggregated based on its important levels to the hashtag for constructing the co-occurrence based hashtag embedding $\mathbf{v}_j^{a}$ by applying the multi-head attention mechanism $\mathbf{MHA}(\cdot)$, as shown in Equation (12).

$$\mathbf{v}_j^{a} = \mathbf{MHA}(\mathbf{t}_j^{a}, \mathbf{m}_{j\leftarrow j'}^{a}, \mathbf{m}_{j\leftarrow j'}^{a}) \quad (12)$$

3.2.4 High-Order Propagation

To obtain the high-order relations, the recursive propagation is performed. We construct the multi-relation user embedding $\mathbf{c}_{u_i}^{a}$ by concatenating the social-based user embedding and the interaction-based user embedding, as shown in Equation (13). Similarly, we construct the multi-relation hashtag embedding $\mathbf{c}_{t_j}^{a}$ by concatenating the co-occurrence based hashtag embedding and the interaction-based hashtag embedding, as shown in Equation (14).

$$\mathbf{c}_{u_i}^{a} = concat(\mathbf{p}_i^{a}, \mathbf{q}_{i,r}^{a});\ \forall r \in R \quad (13)$$

$$\mathbf{c}_{t_j}^{a} = concat(\mathbf{v}_j^{a}, \mathbf{q}_{j,r}^{a});\ \forall r \in R \quad (14)$$

We aggregate all multi-relation user embedding $\mathbf{c}_{u_i}^{a}$ by applying multi-head attention mechanism $\mathbf{MHA}(\cdot)$ to construct the aggregated multi-relation user embedding for the next GNN layer a+1, $\tilde{\mathbf{u}}_i^{a+1}$, as shown in the Equation (15). In the same way, we aggregate all multi-relation hashtag embedding $\mathbf{c}_{t_j}^{a}$ by applying multi-head attention mechanism $\mathbf{MHA}(\cdot)$ to construct the aggregated multi-relation hashtag embedding for the next GNN layer a+1, $\tilde{\mathbf{t}}_j^{a+1}$, as shown in the Equation (16).

$$\tilde{\mathbf{u}}_i^{a+1} = \mathbf{MHA}(\mathbf{u}_i^{a}, \mathbf{c}_{u_i}^{a}, \mathbf{c}_{u_i}^{a}) \tag{15}$$

$$\tilde{\mathbf{t}}_j^{a+1} = \mathbf{MHA}(\mathbf{t}_j^{a}, \mathbf{c}_{t_j}^{a}, \mathbf{c}_{t_j}^{a}) \tag{16}$$

Then, the user embedding for the next GNN layer a+1, $\mathbf{u}_i^{a+1}$, and hashtag embedding for the next GNN layer a+1, $\mathbf{t}_j^{a+1}$, are updated as shown in Equation (17) and Equation (18), respectively.

$$\mathbf{u}_i^{a+1} = \sigma(\mathbf{u}_i^{a} + \tilde{\mathbf{u}}_i^{a+1}) \tag{17}$$

$$\mathbf{t}_j^{a+1} = \sigma(\mathbf{t}_j^{a} + \tilde{\mathbf{t}}_j^{a+1}) \tag{18}$$

3.2.5 Representation Learning

To modeling the user and hashtag representation, by following [14], we concatenate the user and hashtag embedding from all layer and apply an element-wise multiplication to obtain the rating vector $\mathbf{r}_{ij}$, as shown in Equation (19).

$$\mathbf{r}_{ij} = [\mathbf{u}_i^{0} \parallel \cdots \parallel \mathbf{u}_i^{A}] \odot [\mathbf{t}_j^{0} \parallel \cdots \parallel \mathbf{t}_j^{A}] \tag{19}$$

Then, to train the model for representation learning, we conduct the prediction task by feeding the rating vector into fully connected layer, as shown in Equation (20).

$$\hat{y}_{ij} = \alpha(\mathbf{W}^{R} \cdot \mathbf{r}_{ij} + \mathbf{b}^{R}) \tag{20}$$

where the rating score $\hat{y}_{ij}$ has two values: value 1 means the user interacted with the hashtag and value 0 means otherwise.

3.3 Person-And-Content based BERT (PAC)

To achieve our challenge of word-level personalization, we introduce the PAC method by extending BERT [10] to insert not only word representation but also fruitful user representation obtained from the MAN method. With BERT, each word can receive personalized aspects from users and be personalized for them. In this section, we revisit the BERT process and then describe how the PAC method works.

3.3.1 Review of BERT

The BERT process is based on multi-layer transformers [9]. In transformers, there are two sub-layers: a multi-head self attention sub-layer and a position-wise feed-forward network sub-layer. The output from two sub-layers is then inserted into transformer stacks until the L layer.

Multi-Head Self Attention: The function divides the dimension size d_B of the word representation into h_B heads. Each head processes in parallel and then concatenates again, as shown in Equation (21).

$$\mathbf{MH}(\mathbf{H}^l) = [head_1 \parallel \cdots \parallel head_{h_B}]\mathbf{W}^{O_B};$$
$$head_i = \mathbf{Attention}(\mathbf{H}^l\mathbf{W}_i^{Q_B}, \mathbf{H}^l\mathbf{W}_i^{K_B}, \mathbf{H}^l\mathbf{W}_i^{V_B}) \tag{21}$$

where $\mathbf{W}^{O_B} \in \mathbb{R}^{d_B \times d_B}$, $\mathbf{W}_i^{Q_B} \in \mathbb{R}^{d_B \times d_B/h_B}$, $\mathbf{W}_i^{K_B} \in \mathbb{R}^{d_B \times d_B/h_B}$, $\mathbf{W}_i^{V_G} \in \mathbb{R}^{d_B \times d_B/h_B}$ are model parameters. The $\mathbf{Attention}(\cdot)$ function is the scaled dot-product attention function. The attention function applies the dot product operation between query $\mathbf{Q}$ and key $\mathbf{K}$, divides by $\sqrt{d_G/h_G}$, and passes it to the softmax function. The output is the attention score. The attention score is then used to weight the value $\mathbf{V}$, as shown in Equation (22).

$$\mathbf{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = softmax(\frac{\mathbf{QK}^T}{\sqrt{d_B/h_B}})\mathbf{V} \tag{22}$$

Position-wise Feed-Forward Network: Two fully connected layers with GELU activation are then applied to the output from the multi-head self attention sub-layer $\mathbf{S}^l$ to strengthen the model with nonlinearity as shown in Equation (23).

$$\mathbf{FFN}(\mathbf{S}^l) = GELU(\mathbf{S}^l\mathbf{W}_1^F + \mathbf{b}_1)\mathbf{W}_2^F + \mathbf{b}_2 \tag{23}$$

where $\mathbf{W}_1^F \in \mathbb{R}^{d_B \times 4d_B}$, $\mathbf{W}_2^F \in \mathbb{R}^{d_B \times 4d_B}$, $\mathbf{b}_1 \in \mathbb{R}^{4d_B}$, $\mathbf{b}_2 \in \mathbb{R}^{4d_B}$ are trainable parameters.

Transformer Stacks: To improve the ability to learn more complex representations, the above two sub-layers are stacked as the transformer layer until the L layer. Residual connection and layer normalization $LN(\cdot)$ are used to accelerate more deep training on both the multi-head self-attention sub-layer $\mathbf{MH}(\cdot)$ and the point-wise feed-forward network sub-layer $\mathbf{FFN}(\cdot)$, as shown in Equation (24).

$$\mathbf{H}^{l+1} = \mathbf{Trm}(\mathbf{H}^l); \forall l = [1, L];$$

$$\mathbf{Trm}(\mathbf{H}^l) = LN\left(\mathbf{S}^l + \mathbf{FFN}(\mathbf{S}^l)\right); \qquad (24)$$
$$\mathbf{S}^l = LN(\mathbf{H}^l + \mathbf{MH}(\mathbf{H}^l))$$

As a result, the final representation $\mathbf{H}^L$ is obtained with information from both left and right sides.

3.3.2 Person-And-Content based BERT (PAC)

Once the MAN part training complete, we use the fruitful user and hashtag representation from the MAN part to insert into the PAC part. First of all, we project the user representation $\mathbf{u}_i^A$ and hashtag representation $\mathbf{t}_j^A$ from GNN subspace to BERT subspace by feeding into fully connected layer, as shown in Equation (25) and Equation (26), respectively.

$$\mathbf{f}_{u_i} = \sigma(\mathbf{W}_u^P \cdot \mathbf{u}_i^A + \mathbf{b}_u^P) \qquad (25)$$

$$\tilde{\mathbf{f}}_{t_j} = \sigma(\mathbf{W}_t^P \cdot \mathbf{t}_j^A + \mathbf{b}_t^P) \qquad (26)$$

We fuse the projected hashtag representation from the MAN part $\tilde{\mathbf{f}}_{t_j}$ that has the community perspectives with the hashtag representation from the pre-trained BERT $\mathbf{e}_{t_j}^B$ that has the semantic perspectives, as shown in Equation (27).

$$\tilde{\mathbf{f}}_{t_j} = \tilde{\mathbf{f}}_{t_j} \odot \mathbf{e}_{t_j}^B \qquad (27)$$

Then, by following BERT, the representation of user, word, and hashtag are sum with position embedding $\mathbf{e}_{pos}$ and segment embedding $\mathbf{e}_{seg}$. Since we aim to capture the sequenceless hashtag correlations, we use the position embedding of the hashtag element as the same number, instead of the ordering number as in the BERT original.

$$\mathbf{h}_{u_i}^0 = \mathbf{f}_{u_i} + \mathbf{e}_{pos_b} + \mathbf{e}_{seg_u}$$
$$\mathbf{h}_{w_n}^0 = \mathbf{e}_{w_n} + \mathbf{e}_{pos_b} + \mathbf{e}_{seg_w} \qquad (28)$$
$$\mathbf{h}_{t_j}^0 = \mathbf{f}_{t_j} + \mathbf{e}_{pos_b} + \mathbf{e}_{seg_t}$$

After that, all input representation of user, word, and hashtag are concatenated and feed into the BERT model, as shown in Equation (29) and Equation (30), respectively.

$$\mathbf{h}^0 = [\mathbf{h}_{u_i}^0 \parallel \mathbf{h}_{sep}^0 \parallel \mathbf{h}_{w_1}^0 \cdots \mathbf{h}_{w_n}^0 \parallel \mathbf{h}_{sep}^0 \parallel \mathbf{h}_{mask}^0] \qquad (29)$$

$$\mathbf{h}^L = \mathbf{BERT}(\mathbf{h}^0) \qquad (30)$$

3.4 Sequenceless Hashtag Correlations

To achieve our challenge of sequenceless hashtag correlations, we train the PAC method under the mask modeling concept. That is, we randomly masked the hashtag elements and try to predict masked hashtags by inputting to fully connected layer, as shown in Equation (31). In this way, correlations of hashtags from both left and right sides can be obtained under sequenceless.

$$\hat{z} = \alpha(\mathbf{W}^Z \cdot \mathbf{h}^L_{mask} + \mathbf{b}^Z) \quad (31)$$

3.5 Time Complexity

The time complexity of our proposed PAC-MAN consists of two parts. For Multi-relational Attentive Network (MAN), given the dimension size of GNN d_G, the computational cost for the aggregation process over $|N|$ users/hashtags in R interaction types is $\mathcal{O}(R|N|^2 d_G)$. Furthermore, the computational cost for the propagation process of all R interaction types is $\mathcal{O}(R^2 d_G)$. Hence, given U users and T hashtags, each GNN layer consumes $\mathcal{O}((U+T)(R|N|^2 + R^2)d_G)$. We perform A GNN layers, so the total cost for the MAN method is $\mathcal{O}(A(U+T)(R|N|^2 + R^2)d_G)$. For Person-And-Content based BERT (PAC), the computational cost is $\mathcal{O}(B^2 d_B)$, where B is the length of BERT input and d_B is the dimension size of BERT, respectively.

CHAPTER IV EVALUATION

In this chapter, we explain how we prepare datasets, how we set parameters for training our proposed method, what evaluation metrics we use for evaluation, what baselines we compare, and the result from our experiment.

4.1 Data Preparation

Table 1. Statistics of the dataset

Statistics	
Microblogs	324,016
Users	6,387
Hashtags	3,150
U-H Types	Post, Retweet, Like
U-U Types	Follow
H-H Types	Co-occurrence

We crawl the Twitter dataset by using Twitter API. Then, we perform data cleaning to create a high-quality dataset. The first step is to lowercase all text and hashtags. We remove emojis and URLs from the content. Then, all hashtags are lemmatized, which means that the same hashtags in various forms are converted into the same standard form (e.g., "#laptops" is lemmatized into "#laptop"). After the lemmatization, we remove the duplicate hashtags on the same microblog. Following that, we remove low-frequency hashtags because they are rarely used. Finally, microblogs with at least one hashtag are retained, but those with more than 10 hashtags are removed because they generally include advertisements. The dataset statistics are shown in Table 1.

4.2 Experimental Settings

We sort the historical microblogs of users by timestamp. Then we split the dataset into three parts. The first 80% of the dataset is for training, another 10% is for validation, and the last 10% is for testing. We need different experimental settings for the two core parts of our proposed PAC-MAN.

4.2.1 Settings for Multi-relational Attentive Network (MAN)

For training the MAN method, we build a triple set from the dataset that includes a user, a hashtag, and a label but excludes textual microblogs (i.e., [user, hashtag, label]). We collect all hashtags used by users and assign the label to 1. Following [14], we utilize negative sampling to decrease bias in training data by randomly picking unused hashtags and labeling them as 0. TensorFlow is used for implementation. A normal distribution is used to initialize all parameters. The GNN layer A is chosen from [0, 1, 2, 3]. The dimension size d_G varies from [16, 32, 64]. The number of heads in a multi-head attentive aggregation h_G is 2. We use Adam as the optimizer. The learning rate varies over [0.0001, 0.0005, 0.001, 0.005]. The L2 regularizer is optimized from [0.0001, 0.001]. The batch size is adjusted from [128, 256, 512].

4.2.2 Settings for Person-And-Content based BERT (PAC)

The PAC method is implemented in PyTorch using the Hugging Face library [15]. The pre-trained BERT named "bert-based-uncased" is used. The parameters in the PAC method are set to the same as in the original BERT [10]. The BERT layer L is 12. The dimension size d_B is 768. All hashtags are added to the BERT vocabulary as new tokens for hashtag embedding. Some hashtags can overlap with words. For example, the hashtag "#apple" can overlap with the word "apple". Those hashtags are initialized with the pre-trained weights of their overlap words from BERT. We initialize hashtags with a normal distribution for those that do not overlap any words. We use Adam as the optimizer. The learning rate is chosen from [0.0001, 0.0005, 0.001, 0.005] and the batch size is optimized over [128, 256, 512].

4.3 Metrics

We use three metrics which are precision@K, recall@K, F1-score@K to evaluate the experimental results.

4.3.1 Precision@K

Precision@K is the fraction of top-K recommended hashtags that are correctly related to the microblog, as shown in Equation (32),

$$P@K = \frac{|TK \cap GT|}{|TK|} \tag{32}$$

where TK is the top-K recommended hashtag set, GT is the ground-truth hashtag set, and $|TK| = K$.

4.3.2 Recall@K

Recall@K is the fraction of correct hashtags of the microblog found in the top-K recommendations, as shown in Equation (33).

$$R@K = \frac{|TK \cap GT|}{|GT|} \tag{33}$$

4.3.3 F1-Score@K

F1-score@K is the harmonic mean of precision@K and recall@K, as shown in Equation (34).

$$F1@K = 2 \cdot \frac{P@K \cdot R@K}{P@K + R@K} \tag{34}$$

4.4 Baselines

To measure the performance of our proposed PAC-MAN, we compare the experimental results of PAC-MAN with three state-of-the-art methods named ITAG, MACON, and DeepTagRec. To clearly see the difference between our proposed PAC-MAN and all baseline methods, we compare the characteristics of each method as illustrated in Table 2.

Table 2. Characteristics comparison of all compared methods

Topics	Charateristics	ITAG	MACON	DeepTagRec	PAC-MAN$_{w/o\ user}$	PAC-MAN$_{w/o\ com}$	PAC-MAN
Hashtag Correlation	Hashtag Correlation	✓	-	-	✓	✓	✓
	Sequenceless Hashtag Correlation	-	-	-	✓	✓	✓
Personalization	Microblog-Level Personalization	-	✓	✓	-	✓	✓
	Word-Level Personalization	-	-	-	-	✓	✓
User Representation	First-Order Single Relation	-	✓	✓	-	✓	✓
	High-Order Multiple Relation	-	-	-	-	-	✓
Hashtag Representation	Word-Semantic Relation	✓	✓	✓	✓	✓	✓
	High-Order Multiple Relation	-	-	-	-	-	✓

We describe the details of ITAG, MACON, and DeepTagRec as follows:

- **ITAG** [4]: The non-personalized hashtag recommendation that employs RNN to extract hashtag correlations with regard to the hashtag sequence.
- **MACON** [2]: The personalized hashtag recommendation that applies the neural network approach to construct the user representation from only the first-order user-hashtag interaction.
- **DeepTagRec** [1]: The traditional graph based personalized hashtag recommendation that applies the traditional graph approach to construct user representation from only the first-order user-hashtag interaction.

Moreover, we create two variants named PAC-MAN (w/o user) and PAC-MAN (w/o com) in order to measure the effectiveness of our three parts: sequenceless hashtag correlaitons, word-level personalization, and high-order multiple relations. We describe the details of each baseline as follows:

- **PAC-MAN (w/o user)**: To measure the effectiveness of sequenceless hashtag correlations, we modify PAC-MAN to work closely with ITAG. We remove the MAN part to ignore the community and remove the user representation from the PAC input to ignore the word-level personalization. That is, the hashtag representation is derived from only semantic perspectives.
- **PAC-MAN (w/o com)**: To measure the effectiveness of high-order multiple relations, we remove the MAN part. We derived the user representation from the first-order user-hashtag interaction instead. Since the MAN part is remove, the hashtag representation is derived from only semantic perspectives.

4.5 Experiment Result

All methods experiment on the same datasets to avoid bias. The experimental results of our proposed PAC-MAN, our variants (PAC-MAN (w/o user) and PAC-MAN (w/o com)), and baseline methods (ITAG, MACON, and DeepTagRec) in terms of P@K, R@K, and F1@K with K equal to $\{1, 3, 5, 7, 9\}$ on the Twitter dataset are shown in Table 3.

Table 3. Experimental results in terms of precision, recall, and F1-score

Metric		ITAG	MACON	DeepTagRec	PAC-MAN$_{w/o\ user}$	PAC-MAN$_{w/o\ com}$	PAC-MAN	Improv.
K=1	P@K	0.5410	0.5779	0.6016	0.5643	0.6261	**0.7208**	19.80%
	R@K	0.1654	0.2164	0.2413	0.1928	0.2570	**0.3374**	39.80%
	F1@K	0.2534	0.3149	0.3445	0.2873	0.3644	**0.4597**	33.43%
K=3	P@K	0.3972	0.4387	0.4488	0.4226	0.4977	**0.5791**	29.01%
	R@K	0.2827	0.3245	0.3464	0.3014	0.3768	**0.4485**	29.48%
	F1@K	0.3303	0.3731	0.3910	0.3519	0.4289	**0.5055**	29.27%
K=5	P@K	0.3428	0.3725	0.3943	0.3599	0.4214	**0.4966**	25.96%
	R@K	0.3671	0.3999	0.4141	0.3796	0.4430	**0.5319**	28.45%
	F1@K	0.3545	0.3857	0.4039	0.3695	0.4319	**0.5137**	27.16%
K=7	P@K	0.3052	0.3437	0.3710	0.3258	0.4036	**0.4988**	34.45%
	R@K	0.4645	0.4925	0.5178	0.4801	0.5385	**0.6016**	16.17%
	F1@K	0.3684	0.4049	0.4323	0.3882	0.4614	**0.5454**	26.17%
K=9	P@K	0.2523	0.2967	0.3252	0.2737	0.3715	**0.4549**	39.87%
	R@K	0.4745	0.5034	0.5304	0.4900	0.5499	**0.6405**	20.75%
	F1@K	0.3295	0.3733	0.4032	0.3512	0.4434	**0.5320**	31.93%

From the experimental results, it is shown that PAC-MAN prominently outperforms all compared methods over all metrics and K values, followed by DeepTagRec, MACON, and ITAG, respectively. When compared with the best compared methods DeepTagRec, with K equal to five different values, PAC-MAN achieves 19.80%-39.87%, 16.17%-39.80%, and 26.17%-33.43% absolute improvements in terms of precision, recall, and F1-score, respectively.

When comparing our variants, PAC-MAN outperforms the others in all metrics and K values, followed by PAC-MAN (w/o com) and PAC-MAN (w/o user). In terms of precision, recall, and F1-score, PAC-MAN outperforms PAC-MAN (w/o user) by 27.74%-66.21%, 25.30%-75.05%, and 39.02%-59.97%, and PAC-MAN (w/o com) by 15.12%-23.58%, 11.70%-31.30%, and 17.86%-26.14%, respectively.

When comparing baselines and our variants, PAC-MAN (w/o user) performs worse than MACON and DeepTagRec. However, in terms of precision, recall, and F1-score, PAC-MAN (w/o user) outperforms ITAG by 4.30%-8.47%, 3.26%-16.51%, and 4.22%-13.40%, respectively. PAC-MAN (w/o com) outperforms all three baselines. In terms of precision, recall, and F1-score, the improvement over the best baseline DeepTagRec, is 4.07%-14.23%, 3.67%-8.77%, and 5.78%-9.97%, respectively.

CHAPTER V DISCUSSION

In this chapter, we discuss the effects of sequenceless hashtag correlations, word-level personalization, high-order multiple relations, and parameter sensitivity.

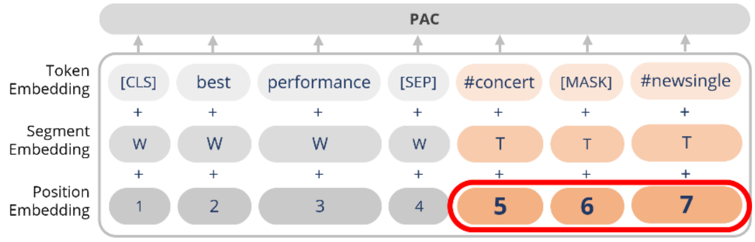
5.1 Sequenceless Hashtag Correlation

Table 3 shows that PAC-MAN (w/o user) outperforms ITAG across all K values and metrics. This supports our hypothesis that hashtag correlations are sequenceless. Using RNN to capture hashtag correlations forces ITAG to only capture correlations on the left side. As a result, each hashtag is highly dependent on the patterns of its left-side hashtags, regardless of the patterns of its right-side hashtags, which also influence the hashtag characteristics. Furthermore, the order of the hashtags is taken into account when capturing correlations with RNN. Characteristics from nearby hashtags are thus more emphasized, whereas characteristics from distant hashtags are degraded, resulting in distance bias. As a result, the characteristics of the hashtags are affected when they are reordered, causing ITAG to not perform well on the recommendation.

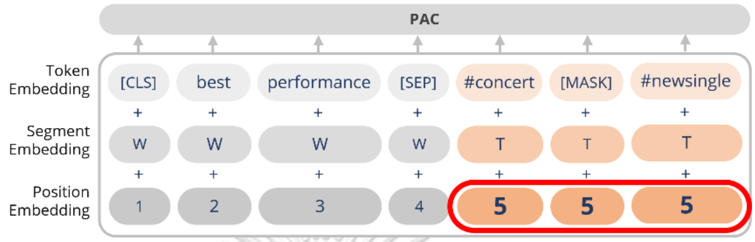
PAC-MAN (w/o user), unlike ITAG, captures correlations using BERT under mask modeling with the same position embedding for all hashtag elements. By training BERT with mask modeling, each hashtag can thoroughly extract correlations from its surrounding hashtags on both the left and right sides. By using the same position embedding for all hashtag elements, the order of hashtags is ignored, allowing hashtags to retain information in any order. As a result, PAC-MAN-U generates more accurate recommendations.

PAC-MAN (w/o user) outperforms ITAG due to the incorporation of two factors in hashtag correlations: bi-direction and sequenceless. To clearly illustrate the effect of sequenceless, we isolate these two factors by performing the following ablation study:

- ***w/ h pos***: Instead of utilizing the same position embedding for all hashtag elements, we alter PAC-MAN (w/o user) by using the BERT original sequence position embedding. Such that, hashtag correlations are captured in both directions in reference to hashtag sequence. Figure 6 depicts position embedding in *w/ h pos* and PAC-MAN (w/o user).



(a) Position embedding of hashtag element in w/ h pos.



(b) Position embedding of hashtag element in PAC-MAN (w/o user).

Figure 6. Position embedding at hashtag element of w/ h pos and PAC-MAN (w/o user)

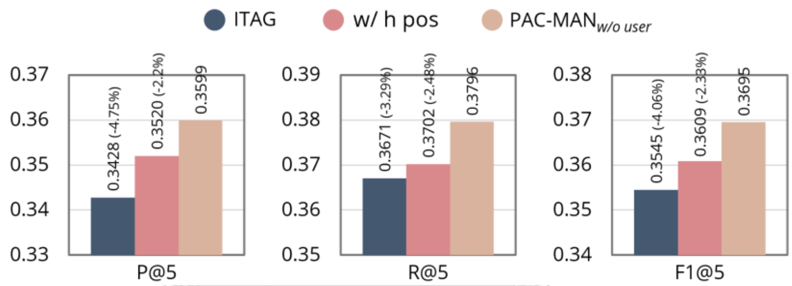
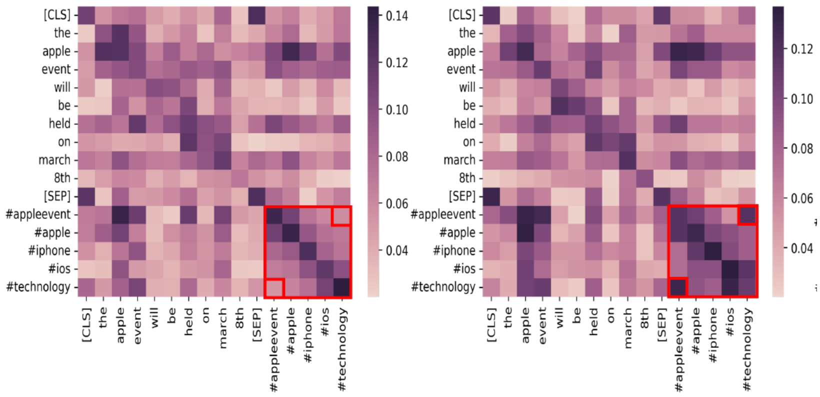


Figure 7. Results from ablation study of sequenceless hashtag correlation

Figure 7 illustrates the precision, recall, and F1-score results when K=5 for ITAG, *w/ h pos*, and PAC-MAN (w/o user). As can be seen, *w/ h pos* degrades the performance of PAC-MAN (w/o user) while outperforming ITAG throughout all metrics. In terms of precision, recall, and F1-score, *w/ h pos* reduces by 2.20%, 2.48%, and 2.33%, whereas ITAG reduces by 4.75%, 3.29%, and 4.06%, respectively, when compared to PAC-MAN (w/o user). These findings highlight the importance of sequencelessness in hashtag correlations. *w/ h pos* captures hashtag correlations in a bidirectional manner based on hashtag sequence. It overcomes the side constraint of ITAG's unidirectional hashtag correlations by incorporating bidirectional hashtag correlations from both the left and right sides, demonstrating an improvement over ITAG. However, it retains a distance bias since hashtag correlations from both sides are derived in reference to their sequence, resulting in a performance decrease when compared to PAC-MAN (w/o user).

PAC-MAN (w/o user), on the other hand, produces the greatest outcomes since it takes into account both factors. That is, training BERT via mask modeling enables a hashtag to comprehensively gather correlations from its surrounding hashtags on both the left and right sides without regard for side constraints. Furthermore, having the same position embedding for the hashtag elements improves a hashtag's ability to gather correlations from nearby and distant hashtags without distance bias. As a result, both bi-direction and sequenceless should be combined for complete sequenceless in hashtag correlations, which are critical for improving performance in hashtag recommendation.



(a) Attention weights from *w/ h pos*

(b) Attention weights from PAC-MAN$_{w/o\ user}$

Figure 8. Attention weights from w/ h pos and PAC-MAN (w/o user)

To identify relevant patterns of hashtag correlations in *w/ h pos* and PAC-MAN (w/o user), we used a heatmap to depict their attention weights, as shown in Figure 8. According to the figures, the attention weights among hashtags that are represented in the right bottom of the heatmap might reflect the correlations that each hashtag has with each other. The dark color indicates a high level of relevance, whereas the light color indicates a low level of relevance. *w/ h pos* appears to attend to nearby hashtags and gradually less attends to distant hashtags, whereas PAC-MAN (w/o user) has a greater ability to attend to relevant hashtags without any constraints. PAC-MAN (w/o user), for example, can discover correlations between "#appleevent" and "#technology", but *w/ h pos* cannot owing to the distance in the sequence between them.

5.2 Word-level Personalization

Table 3 shows that, when compared to non-personalization methods (ITAG and PAC-MAN (w/o user), PAC-MAN (w/o com) outperforms both ITAG and PAC-MAN (w/o user) in terms of overall K values and metrics. This guarantees that hashtag recommendations benefit from personalization. When only textual content is considered, like in ITAG and PAC-MAN (w/o user), the recommendation is based solely on content. Even though the recommendation is relevant to the content, it may not correspond to the user's preferences, resulting in an incorrect recommendation.

Table 3 illustrates that, when compared to the microblog-level personalization methods (MACON and DeepTagRec), PAC-MAN (w/o com) surpasses both MACON and DeepTagRec in terms of overall K values and metrics. This validates our hypothesis that users have personalized aspects at the level of not just microblogs but also each word inside them. MACON and DeepTagRec both conduct personalization at the microblog level. That is, word representations in the microblog are compressed into one vector to generate a microblog representation before personalization, thus words cannot receive personalized aspects from a particular user. Because of this, the same words have the same meaning even when used by users with diverse preferences and meanings. Because words can have several meanings, treating the same word with the same meaning for all users might lead to incorrect meanings that may not correspond to the user's preferences. Besides having the same meaning, neglecting word-level personalization results in the same words being weighted under the same relevance levels, despite receiving dynamic relevance levels from the users who used them. Because words can be extremely informative for some users but not for others, considering the same words with the same weight for all users can result in unrelated noise from irrelevant words and neglect important relations from relevant words. Hence, personalization at the microblog level overlooks the personalized aspects of users and words, resulting in the same words receiving the same meanings and being weighted with the same relevance levels. As a result, MACON and DeepTagRec may give personalization that does not match user preferences, resulting in inappropriate recommendations.

Personalization in PAC-MAN (w/o com), on the other hand, is more extensive than in MACON and DeepTagRec since it is conducted at the word level. It extends BERT by inputting not only word representation but also user representation. In this approach, user aspects and word semantics can incorporate each other. This enables each word to be personalized by a particular user. By inputting user and word representations in BERT, each word representation is merged with the user representation. This means that each word can receive user characteristics, personalizing the meanings of the words based on user preferences. Furthermore, because BERT is an attention-based method, incorporating user and word representations into BERT enables each word to be weighted based on dynamic relevance levels for a particular user. That is, words that are strongly relevant to the user are reinforced, whereas words that are less relevant to the user are diminished. Consequently, personalization at the word level, as performed in PAC-MAN (w/o com), enables words to gain personalized aspects from a specific user, resulting in personalized meanings and weighting based on the dynamic relevance levels between users and words, leading in a more accurate recommendation.

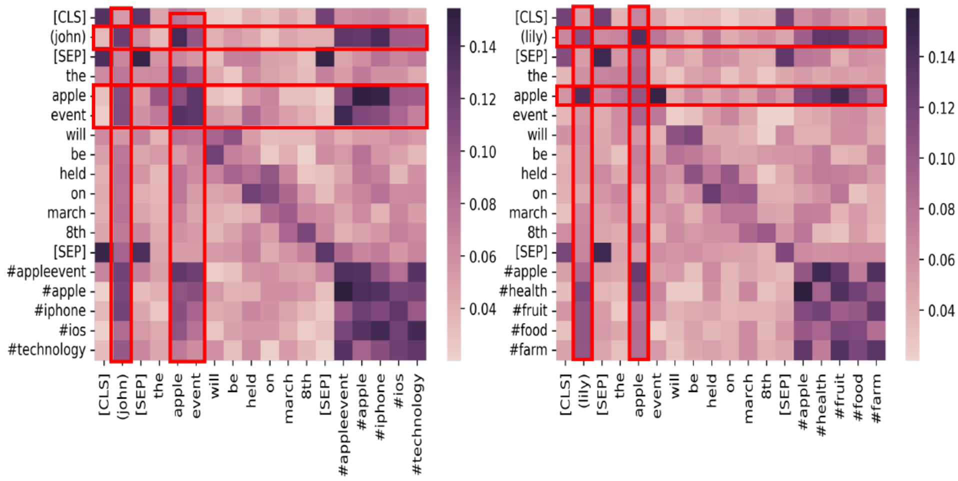


Figure 9. Attention weights from PAC-MAN (w/o com).

For better understanding, we input the same content ("The apple event will be held on March 8th") and different user representations (John and Lily) into the method. Then, we visualize the attention weights generated by the method by using a heatmap, as shown in Figure 9. These attention weights indicate the levels of relevance among users, words, and hashtags on the same microblog content for different users John and Lily. The dark color shows a high relevance level, while the light color shows a low relevance level. John and Lily have different preferences. John prefers technology, whereas Lily prefers health. From the figure, even if John and Lily have the same microblog content, PAC-MAN (w/o com) can detect the personalized meanings behind the content and can recommend hashtags to John and Lily that are appropriate for their preferences. Technology hashtags are recommended to John, who prefers technology, and health hashtags are recommended to Lily, who prefers health. In addition to personalized meanings, PAC-MAN (w/o com) can weight each word depending on John and Lily's dynamic relevance levels. Lily highly attends to just the word "apple", but John highly attends to both "apple" and "event". Thereby, word-level personalization allows each word to gain personalized aspects from a particular user, resulting in personalized meanings and weighting under dynamic relevance levels, leading to a more accurate recommendation.

5.3 High-Order Multiple Relation

As shown in Table 3, PAC-MAN surpasses PAC-MAN (w/o com), as well as MACON and DeepTagRec overall K values and metrics, proving our assumption that users and hashtags are influenced by not only first-order single relations, but also high-order multiple relations.

To model user representation, PAC-MAN (w/o com), MACON, and DeepTagRec exclusively leverage user-hashtag interaction, neglecting user-user social. As a result, the user representation is restricted to a single type of relation. In other words, only the characteristics of the user's interacted hashtags are used to derive user preferences for representing users. Aside from interacted hashtags, users on social media may show their preferences via a follow. Therefore, modeling user representation based solely on user-hashtag interaction yields only characteristics of interacted hashtags while ignoring characteristics of followed users, which also indicate significant user preferences. As a result, they lose some crucial preferences and receive inaccurate recommendations. Aside from user representation, hashtag representation in PAC-MAN (w/o com), MACON, and DeepTagRec relies mainly on the word-semantic perspective and neglects the meaning based on user perspective in the community. In reality, hashtags have meanings dependent on user perspectives. Different user groups in the community might use the same hashtag with different meanings. When hashtags are derived only from word-semantic viewpoints, recommendations may be different from how users in a community really use hashtags. Furthermore, PAC-MAN (w/o com), MACON, and DeepTagRec disregard hashtag co-occurrence. In fact, users frequently attach many hashtags to the same microblog, and some of them do not appear in the microblog's content due to character limits. We may lose some hashtags that are significant and commonly tagged together but are not included in the content if we simply consider the limited content in the microblog.

Additionally, PAC-MAN (w/o com), MACON, and DeepTagRec only take into account first-order relations. MACON and DeepTagRec use a neural network and a traditional graph technique to construct user representation from user-hashtag interaction, respectively. With the neural network technique, MACON can only extract first-order relations since higher connection networks and recursive propagations are not permitted in the structure of this technique. Even if the graph structure allows for the construction of higher connection networks, DeepTagRec still captures only first-order relations since this technique is dependent on graph statistics, which prevent recursive propagations for capturing high-order relations. In other words, user or hashtag nodes are similar when they commonly co-occur in the same random walk, without taking any user or hashtag characteristics into account in each node. As a result, both neural network and traditional graph techniques impose MACON, and DeepTagRec can only model first-order relations. In other words, they neglect interactions of similar users or hashtags that are indirectly connected at a higher level in the community and only take advantage of interactions of those users or hashtags themselves that are directly connected. Because users and hashtags in the same community have similar preferences, they are influenced by not only first-order but also higher-order relations. Therefore, considering just their own first-order relations and disregarding higher-order relations in the community results in a representation that contains only previous preferences and may fail for new preferences.

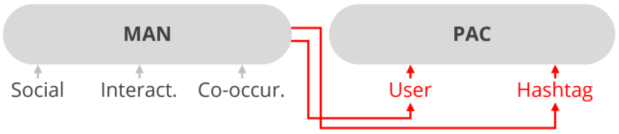
PAC-MAN, on the other hand, applies a graph neural networks technique to construct both user and hashtag representation from not only first-order but also higher-order relations in three community types: (1) user-hashtag interaction; (2) user-user social; and (3) hashtag-hashtag co-occurrence. These three community types provide fruitful characteristics to user and hashtag representations. For user representation, PAC-MAN derives user representation not just from user-hashtag interaction but also from user-user social. User-user social improves user representation, allowing it to be more fruitful in the characteristics of people that user follows. Because users prefer to follow people they are interested in, users and the people they follow could be considered similar users having similar characteristics. As a result of including user-user social, PAC-MAN can recommend hashtags that meet the preferences of people the user follows but does not in user-hashtag interaction. For hashtag representation, PAC-MAN considers hashtag meanings from both word-semantic and community perspectives. To acquire community-based meanings, PAC-MAN constructs hashtag representation from user-hashtag interaction and hashtag-hashtag co-occurrence. User-hashtag interaction enables representation of hashtag to gain characteristics about people who engage with the hashtag. Because the hashtag is interacted by users who are interested in the hashtag, the characteristics of these users can represent the various meanings used by various groups of people who are more likely to be involved in the hashtags. So, taking into account user-hashtag interaction enables PAC-MAN to recommend hashtags that correspond not just to the content but also to the actual usage of users in the community. In addition to user-hashtag interaction, hashtag-hashtag co-occurrence enables hashtag representation to acquire hashtag characteristics that co-occur within the same microblog. Because the co-occurring hashtags are on the same microblog with the same content, they may be considered similar hashtags containing similar characteristics. As a result of incorporating hashtag-hashtag co-occurrence, PAC-MAN can overcome the limitations of content. The relevant hashtags that are commonly tagged together but absent from the content can be recommended to users.

Additionally, PAC-MAN captures first-order and high-order connections among three different communities. Connections of higher order and recursion of propagation are permitted with the graph neural networks technique that enables high-order relations to be captured. Users and hashtags are impacted by relations of both first order and high order in the community because users and hashtags within the same community have similar interests. Taking into account high-order relations in three communities enables characteristics of relevant users and hashtags in the community that are indirectly connected to be provided to users and hashtags. By receiving broader preferences from the higher order in the community rather than depending just on their own historical preferences from the first order, user and hashtag representation becomes more fruitful. Because users and hashtags are influenced by the communities in which they participate, their growing tastes often line with the community's preferences. The ability to manage when new preferences emerge could be strengthened by modeling user and hashtag representation from larger community preferences, leading to more accurate recommendations.

Furthermore, we conduct ablation studies in three topics: (1) user and hashtag community; (2) community type; (3) user-hashtag community.

5.3.1 User and Hashtag Community

Our proposed PAC-MAN takes into account multiple relations at a higher order in the community of both users and hashtags. In order to construct a fruitful representation of both user and hashtag, the MAN component extracts multiple relations from the higher order in the community of user and hashtag. The PAC component then receives the fruitful user and hashtag representation from MAN and utilizes it to produce recommendations. Figure 10 shows an ablation study performed to evaluate the impact of user and hashtag communities when modeling user and hashtag representation. The following are the details of each ablation method:



PAC Input	User Repr.	Hashtag Repr.	
	MAN	MAN	BERT
PAC-MAN$_{w/o\ com}$	- *	-	✓
w/o u com	- *	✓	✓
w/o h com	✓	-	✓
PAC-MAN	✓	✓	✓

** Derive from first-order single relation (historical post) instead.*

Figure 10. Ablation study of user and hashtag community

- ***w/o u com***: To assess the impact of the user community, the user representation developed by MAN is excluded from the PAC input and replaced with the user representation modeled in past posts using only user-hashtag interaction at the first order.
- ***w/o h com***: To assess the impact of the hashtag community, the hashtag representation created by MAN is deleted from the PAC input. Without any consideration for community perspectives, hashtags are exclusively formed from semantic perspectives.

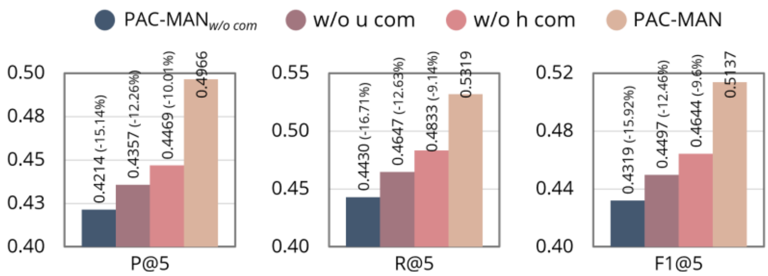
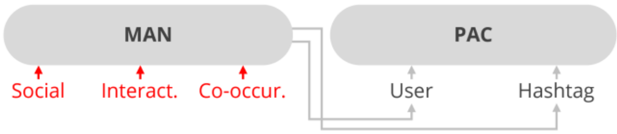


Figure 11. Results from ablation study of user and hashtag community

The precision, recall, and F1-score of PAC-MAN (w/o com), *w/o u com*, *w/o h com*, and PAC-MAN are illustrated in Figure 11. As can be seen, PAC-MAN achieved the best outcomes in all metrics when both the user and the hashtag community are included. These highlight the importance of the user and hashtag communities. In addition, performance suffers when some of the hashtag and user communities are excluded. The performance of *w/o u com*, which excludes the user community, falls more than that of *w/o h com*, which excludes the hashtag community, across all measures. This implies that communities have a bigger effect on users than hashtags. Besides, by excluding both the user and hashtag communities, PAC-MAN (w/o com) yields the lowest results in all metrics. This implies that the community has an impact on both the user and the hashtag. In other words, high-order relationships from various networks, as well as first-order relationships, have an impact on users and hashtags. Improving performance necessitates the representation of users and hashtags in relation to their community.

5.3.2 Community Type

In our approach, we include higher-order relationships in three communities: (1) user-hashtag interaction; (2) user-user social; and (3) hashtag-hashtag co-occurrence. Figure 12 shows the conduct of an ablation study to investigate the impact of each community type. The following are the details of each ablation method:



MAN Input	UU Social	UH Interaction			HH Co-occurrence
		Post	Retweet	Like	
w/o uu+hh	-	✓	✓	✓	-
w/o multi-uh	✓	✓	-	-	✓
w/o hh	✓	✓	✓	✓	-
w/o uu	-	✓	✓	✓	✓
PAC-MAN	✓	✓	✓	✓	✓

Figure 12. Ablation study of community type

- ***w/o uu+hh***: In order to investigate the impact of both user-user social and hashtag-hashtag co-occurrence, PAC-MAN is modified by excluding both from the MAN component. In other words, the MAN component only utilizes user-hashtag interaction to represent users and hashtags.
- ***w/o multi-uh***: In order to investigate the impact of multiple user-hashtag interactions, PAC-MAN was modified by deleting retweet and like interactions from the MAN component. In other words, only post interaction is utilized for user-hashtag interaction.

- ***w/o hh***: In order to investigate the impact of hashtag-hashtag co-occurrence, PAC-MAN is modified by excluding hashtag-hashtag co-occurrence from the MAN component. In other words, the MAN component only utilizes user-hashtag interaction and user-user social to represent users and hashtags.
- ***w/o uu***: In order to investigate the impact of user-user social, PAC-MAN is modified by excluding user-hashtag interaction and hashtag-hashtag co-occurrence from the MAN component. In other words, the MAN component only utilizes user-user social to represent users and hashtags.

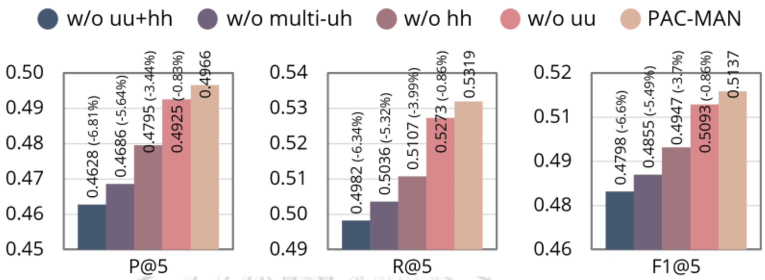
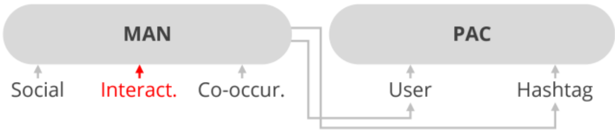


Figure 13. Results from ablation study of community type

Precision, recall, and F1-score results for *w/o uu+hh*, *w/o multi-uh*, *w/o hh*, *w/o uu*, and PAC-MAN are shown in Figure 13. As illustrated in the figure, PAC-MAN achieves the highest outcomes across all metrics by taking into account all three types of communities. This emphasizes the importance of the three types of communities. Furthermore, deleting certain of the community types has a negative impact on performance. The results are worse when hashtag-hashtag co-occurrence is excluded from *w/o hh* than when user-user social is excluded from *w/o uu*. Users and hashtags are therefore more impacted by hashtag-hashtag co-occurrence than by user-user social. One possible reason is that the hashtag set that is frequently used by the community is also utilized by the users. People who users follow have little impact on them. Moreover, *w/o multi-uh*, which utilizes single user-hashtag interactions, performs worse in all metrics than *w/o hh* and *w/o uu*. Users are more likely to retweet and like interactions than post interactions, implying that simply relying on post interactions is insufficient for accurately reflecting user preferences. Lastly, the method that receives the lowest performance is *w/o uu+hh*, which excludes both user-user social and hashtag-hashtag co-occurrence. This indicates the impact of user-hashtag interactions, as well as user-user social and hashtag-hashtag co-occurrence, on users and hashtags. Thus, the improved performance in PAC-MAN is due to the fruitful representation of user and hashtag that derives from user-hashtag interaction, user-user social, and hashtag-hashtag co-occurrence.

5.3.3 User-Hashtag Interaction

The PAC-MAN we propose comprises three user-hashtag interactions, which are post, retweet, and like. Figure 14 shows an ablation experiment that will be used to evaluate the impact of each interaction. The following are the details of each ablation method:



MAN Input	UU Social	UH Interaction			HH Co-occurrence
		Post	Retweet	Like	
w/o rt+like	✓	✓	-	-	✓
w/o rt	✓	✓	-	✓	✓
w/o like	✓	✓	✓	-	✓
PAC-MAN	✓	✓	✓	✓	✓

Figure 14. Ablation study of user-hashtag interaction

- ***w/o rt+like***: To investigate the impact of retweet and like interactions, these interactions are deleted from the PAC-MAN, leaving only the post interaction.
- ***w/o rt***: To investigate the impact of retweet interaction, retweet interaction is eliminated from the PAC-MAN, leaving just post and like interaction.
- ***w/o like***: To investigate the impact of like interaction, like interaction is eliminated from the PAC-MAN, leaving just post and retweet interaction.

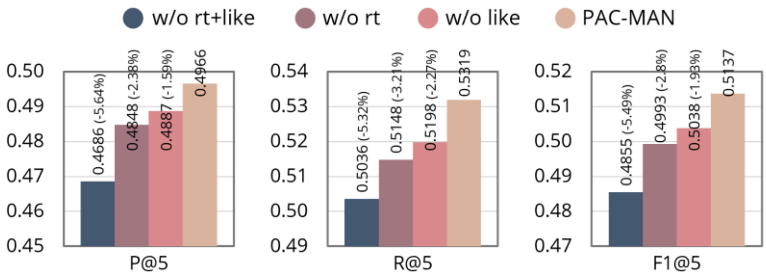


Figure 15. Results from ablation study of user-hashtag interaction

Precision, recall, and F1-score results for *w/o rt+like*, *w/o rt*, *w/o like*, and PAC-MAN are shown in Figure 15. From the figure, PAC-MAN delivers the greatest results across all metrics by taking into account all interactions of posts, retweets, and likes. This proves that multiple user-hashtag interactions are important. Furthermore, performance suffers when some interactions are deleted. As can be seen, *w/o rt*, which eliminates retweet interaction, yields worse outcomes in all metrics than *w/o like*, which eliminates like interaction. This implies that users prefer to use hashtags with which they have interacted via retweets over hashtags with which they have interacted via liking. One possible reason is that users can share microblogs on their own timelines by using the retweet function. Microblogs that people retweet are more attractive to them than those that they just like. Besides, the lowest outcomes across all measures are obtained by *w/o rt+like*, which eliminates both retweet and like interaction. This implies that user preferences are largely expressed in retweet and like interactions, and that both contribute to enhanced performance. As in our proposed PAC-MAN, we can extract active user interests along with hashtag attributes by integrating retweet and like interactions with post interactions. As a result, user and hashtag representation becomes more fruitful, leading to performance enhancement in hashtag recommendations.

5.4 Parameter Sensitivity

We investigate the sensitivity of three parameters in our proposed PAC-MAN: (1) the number of recommended hashtags K, (2) the GNN dimension d_G, and (3) the GNN layer A.

5.4.1 Number of Recommended Hashtags K

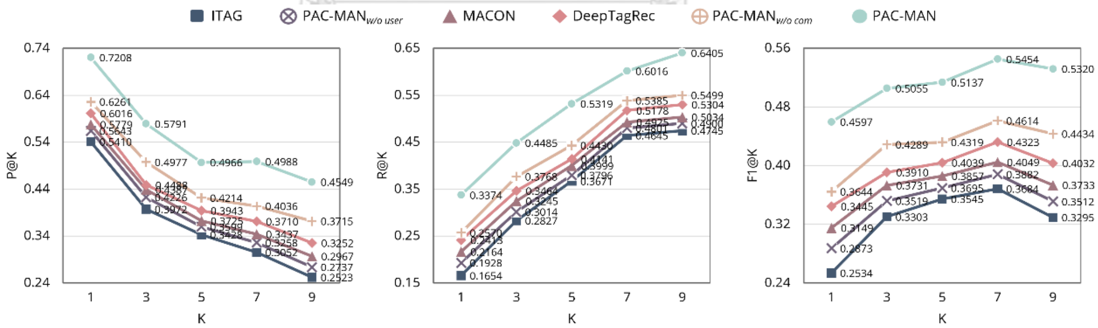


Figure 16. Results from different number of recommended hashtags K

The value of K is adjusted between 1, 3, 5, 7, and 9 to investigate the influence of the number of recommended hashtags. Figure 16 demonstrates that PAC-MAN outperforms all baselines across all metrics and K values. In terms of precision, PAC-MAN and other baselines perform best when K is 1 and rapidly degrade as K increases. When K increases from 1 to 7, the PAC-MAN and other baselines considerably improve in terms of recall and F1-score. When K is 7, F1-scores in PAC-MAN and baselines peak, and then begin to decline as K rises to 9. Other baselines start to become stable for recall outcomes, but PAC-MAN can slightly improve performance.

5.4.2 GNN Dimension d_G

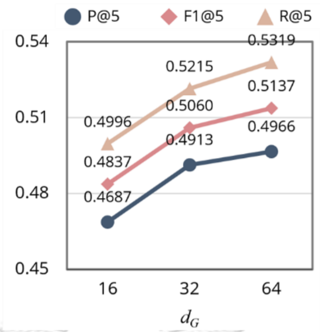


Figure 17. Results from different GNN dimension d_G

To explore the effect of the GNN dimension d_G, the values are varied to 16, 32, and 64. As shown in Figure 17, PACMAN has better performance with a larger dimension size in all precision, recall, and F1-score. When d_G increases from 16 to 32, the performance significantly improves. Then, it continuously improves and achieves the best performance when d_G is 64. This is because a larger dimension size may be beneficial to capture more latent characteristics of users and hashtags.

5.4.3 GNN Layer A

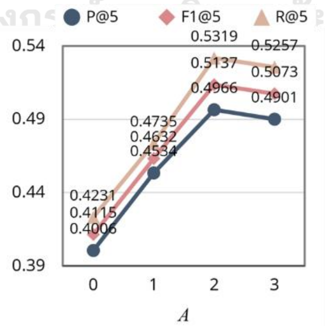


Figure 18. Results from different GNN layers A

To measure the effectiveness of the GNN layer A, the values are varied to 0, 1, 2, and 3. Figure 18 demonstrates that PACMAN performs better with a deeper GNN layer in terms of precision, recall, and F1-score metrics. Performance increases immediately when A is increased from 0 to 1, and it operates best when A is set to 2. When A becomes 3, the performance declines. This leads to the conclusion that two layers of higher-order relations are sufficient for modeling user and hashtag communities, and adding further layers may result in unnecessary neighbors that reduce efficiency.

CHAPTER VI CONCLUSION

In this thesis, we propose a novel personalized hashtag recommendation system, named PAC-MAN, that investigates high-order multiple relations to construct user and hashtag representation before combining with word representation to personalize at the word level and incorporating hashtag correlations under sequenceless for making recommendations. *First*, for the more fruitful user and hashtag representation, Multi-Relational Attentive Network (MAN) employs GNN to retrieve high-order multiple relations across three community types: (1) user-hashtag interaction, (2) user-user social, and (3) hashtag-hashtag co-occurrence. *Second*, for enabling each word to obtain personalized aspects from a specific user, Person-And-Content based BERT (PAC) extends BERT to input not only word representations but also user representation from the MAN method. *Finally*, the PAC method feeds the hashtag representations from the MAN method that include community perspectives into BERT so that they can be fused with their semantic perspectives, and then constructs a recommendation as a hashtag prediction using mask modeling to gather sequenceless correlations from both the left and right sides.

PAC-MAN outperforms various state-of-the-art baseline approaches in hashtag recommendations across precision, recall, and F1-score, according to experimental results using the Twitter dataset. In hashtag recommendations, the baselines contain three distinct ways: (1) non-personalized neural network based methods, (2) personalized neural network based methods, and (3) personalized traditional graph based methods. These experiments provide strong support for three of our claims: (1) constructing user and hashtag representation from high-order multiple relations across three community types (user-hashtag interaction, user-user social, and hashtag-hashtag co-occurrence); (2) accounting for personalization at the word level; and (3) extracting hashtag correlations under sequenceless. All of these strategies are useful for performance improvement in personalized hashtag recommendations.

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