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著者(和文)	由 菁怡
Author(English)	You Jingyi
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論 文 要 旨

THESIS SUMMARY

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学生氏名： Student's Name	由 菁怡 You Jingyi	審査員主査： Chief Examiner	奥村 学 教授

要旨（英文 800 語程度）
Thesis Summary（approx.800 English Words ）

A graph, in the context of computer science and mathematics, is a collection of objects that are interconnected. These objects are typically referred to as nodes, and the connections between them are known as edges. It is a universal language that depicts relationships, captures interactions, and visualizes complex systems. Graph-structured data are widely present in real life and in various fields, so methods utilizing graphs have significant effects in many application scenarios, such as text summarization, community detection, recommendation systems, and knowledge graphs. To demonstrate how graphs can be applied in these applications, we take an extractive summarization method as an example. Extractive summarization is the process of identifying and selecting key phrases or sentences from the original text to form a summary, while maintaining the original context and meaning. In extractive summarization, a graph can be used by representing sentences as nodes, connecting similar sentences with edges. Then, we can apply graph-based ranking algorithms, like PageRank, to identify the most important sentences to include in the summary.

Recently, incorporating temporal information into a variety of static tasks has shown great success, due to the ability to reflect evolving relationships and handle time-sensitive data. By leveraging temporal cues, the accuracy and interpretability of clustering results can be enhanced, while a concise and coherent timeline can be constructed, presenting a more logical and comprehensive representation of the events. However, previous studies have been conservative in tackling the challenge of simultaneously learning node representations with temporal information and performing downstream clustering tasks. When node representation learning and clustering tasks are treated separately, it becomes challenging to directly incorporate specific clustering objectives into the learning process. The learned node representations may not be optimized for the specific clustering task at hand, resulting in suboptimal clustering results. Besides, temporal information plays a crucial role in understanding the evolution and dynamics of the data. Without incorporating temporal context during node representation learning, the resulting representations may not effectively capture the time-dependent patterns and relationships. To the best of our knowledge, there is currently no method that can address the aforementioned challenges in both tasks through end-to-end learning.

Our first work concentrates on dynamic community detection (or graph clustering) in temporal networks, which has attracted much attention because it is promising for revealing the underlying mechanism of complex real-world systems. Current methods are criticized for the independence of graph representation learning and graph clustering, considerable noise during temporal information smoothing, and high time complexity. We propose a **R**obust **T**emporal **S**moothing **C**lustering method (RTSC), which involves joint graph representation learning and graph clustering, to solve these problems. RTSC can be formulated as a constrained multi-objective optimization problem. Specifically, three-order successive snapshots are first projected into the same subspace via graph embedding. We then use the embedding matrices to learn a common low-rank block-diagonal matrix that contains current clustering information and specific noise matrices with a sparse constraint to remove noise at each time step. To efficiently solve the challenging optimization problem, we also propose an optimization procedure based on the augmented Lagrangian multiplier (ALM) scheme. Experimental results on six artificial datasets and four real-world dynamic network datasets indicate that RTSC performs better than six state-of-the-art algorithms for dynamic clustering in temporal networks.

In the second research, we focus on addressing several challenges that plague the field of timeline summarization. Timeline summarization (TLS) is defined as a task for summarizing events in chronological order, which gives readers a comprehensive understanding of an evolutionary story. Previous studies on the timeline summarization (TLS) task ignored the information interaction between sentences and dates, and adopted pre-defined unlearnable representations for them. They also considered date selection and event detection as two independent tasks, which makes it impossible to integrate their advantages and obtain a globally optimal summary. In this paper, we present a *joint learning-based heterogeneous graph attention network for TLS* (HeterTLS), in which date selection and event detection are combined into a unified framework to improve the extraction accuracy and remove redundant sentences simultaneously. Our heterogeneous graph involves multiple types of nodes, the representations of which are iteratively learned across the heterogeneous graph attention layer. And we are the first to joint consider to combine the advantages into a unified framework to improve the accuracy and remove topic irrelative and redundant sentences. We evaluated our model on four datasets, and found that it significantly outperformed the current state-of-the-art baselines with regard to ROUGE scores and date selection metrics.