論文 / 著書情報
Article / Book Information

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学位種別(和文)	博士論文
Category(English)	Doctoral Thesis
種別(和文)	論文要旨
Type(English)	Summary

（博士課程）
Doctoral Program

論 文 要 旨

THESIS SUMMARY

系・コース： Department of, Graduate major in	情報工学 系 知能情報 コース	申請学位（専攻分野）： Academic Degree Requested	博士 （ 学術 ） Doctor of
学生氏名： Student's Name	JIN RUIDONG	審査員主査： Chief Examiner	村田 剛志

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

In this thesis, the author aims to develop advanced graph neural networks (GNNs) to learn entity representations within real-world graph-structured datasets. The developed GNNs aim to address predictive analytics on tasks in human behaviors and social trends activities. This thesis mainly focuses on three research questions: How to address prediction tasks on heterogeneous graphs? How to address prediction tasks on dynamic graphs? Finally, how to tailor GNNs for domain-specific prediction tasks. The author conducted three subworks to address the research questions and discussed the relationships within them.

The thesis begins in Chapter 1 with an introduction to the evolution of AI techniques in predictive analytics concerning human behavior and social trends. Subsequently, the author delves into GNNs and elucidate why they are recognized as one of the most essential and fastest-growing fields in deep learning, as well as one of the most powerful tools of analyzing real-world data. Chapter 2 provides a summary of preliminary topics that serves as the foundation for the work described in subsequent chapters.

In Chapter 3, the author explores a critical static scenario, namely emergency medical services (EMS) demand prediction. The author is the first to analyze EMS demand at the hospital-region level in a metropolis like Tokyo. The author analyzes the limitations of convolutional GNNs in bipartite graphs and propose a bipartite graph convolutional network (BiGCN), a novel approach adept at learning the node embeddings of binary entity groups by fully considering the structure characteristics of bipartite graphs. Based on the experimental observations, BiGCN significantly enhances the accuracy of EMS demand predictions, underscoring its efficiency in capturing nuanced patterns within static bipartite graph-structured datasets. BiGCN is not limited to the hospital-region bipartite graph in this paper but can potentially become a general model for accomplishing supervised learning tasks in non-specific bipartite graphs.

Expanding focus to dynamic scenarios, Chapter 4 delves into the challenges of learning in dynamic graphs. Recognizing the heightened difficulty of dynamic settings, the author proposes a temporal GNN framework tailored for discrete-time dynamic graphs (DTDGs), which consists of a timed sequence of graph snapshots. This novel approach addresses the limitations of prior research and presents its novelty in considering the latent influence of information diffusion in social networks while efficiently learning the representations of target entities, resulting in a substantial performance enhancement. The author assesses the efficiency of the proposed approach through experiments conducted on real-world social network datasets. Based on the experimental observations, the proposed approach consistently outperforms various baseline methods, showcasing its feasibility in real-world situations. This work tackles the crucial task of forecasting trajectories of public concerns and interests based on extensive real-world data, contributing valuable insights to the social trends.

Chapter 5 extends the dynamic GNN approach to continuous-time dynamic

graphs (CTDGs) by addressing the limitations of unknown information between consecutive graph snapshots within DTDG, which is likely to lead to potential inefficiencies in prediction results. By developing a novel temporal difference (TDGNN) model, the author can predict real-time graph events and efficiently learn node temporal embeddings within CTDGs. In addition, the author presents the first analysis and prediction of real-time donation income in live streaming services. It is a significant and innovative topic as live streaming has become one of the most popular entertainment way and work style nowadays. The author utilizes TDGNN model that learns temporal viewers' and streamers' representations and predicts real-time donation incomes. The author conducts experiments to demonstrate the effectiveness of the TDGNN model, which outperforms various baseline methods regarding both accuracy and timeliness.

Chapter 6 provides some discussions regarding the relationships within the three subworks introduced before. First, the author concludes the unified conceptions hidden in the design considerations of proposed GNN frameworks. Then, the author clarifies the coherency within the three subworks, which shows a linear progress from simpler and less general cases to the more challenging, complex, and general cases. In addition, the author exhibits the extensibility of the proposed GNNs by assessing them on other benchmark bipartite graphs and continuous-time dynamic graphs. The outstanding experimental results prove that the proposed GNN frameworks are feasible in various domains. Finally, the author clarifies the requirements of real-world human behaviors and social trends data that can be handled by proposed GNN methods.

In summary, the key contributions of this thesis lie in developing innovative GNN models that evolve from simple static homogeneous cases to intricate dynamic heterogeneous scenarios, providing practical solutions for various real-world situations. Each method is meticulously designed to tackle the unique challenges of different real-world situations. The proposed GNN models significantly enhance the understanding of complex relationships within evolving systems. This contribution reflects the commitment to advancing the field of GNNs, paving the way for more effective and versatile applications in predictive analytics for human behaviors and social trends.