Ph.D. Dissertation Defense

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Degree:	Doctor of Philosophy
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Location:	Online (https://stevens.zoom.us/j/4075727484)
Title:	Three Essays on Graph-Based Deep Learning Models in Business Analytics
Chairperson:	Dr. Jingyi Sun, Information Systems & Analytics, School of Business
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Abstract

The matrix of today's world is fundamentally graph-based: from the interconnected web of supply chains to the intricacies of social networks, and from the sprawling expanse of online consumer behavior to the intertwined organizational collaborations. These graph structures encapsulate a wealth of patterns and insights waiting to be decoded. Although deep learning models have become crucial for managing the vast volumes of data that modern commerce produces, the potential of graph-based deep learning techniques remains largely untapped. A significant challenge is the opaqueness of these models that hampers informed decision-making, as stakeholders in the business realm grapple with the complexities of models they cannot elucidate. Consequently, there is a pressing need to architect explainable graph-based deep learning models to foster better, data-driven decisions.

To address the identified gaps, this dissertation explores three inherently connected avenues of graph-based deep learning techniques in the business analytics domain. In essay 1, we leverage graph structures to model interrelations among e-commerce products. We introduce a novel Graph Neural Network (GNN) that amalgamates both temporal data—historical sales of products—and spatial data—interrelations among products—for future sales prediction. Recognizing that product associations can either be transient or enduring, our model integrates both through the incorporation of static and dynamic attention mechanisms. This dual attention approach not only enables our model to surpass benchmark performance on a real-world dataset but also offers insights into how demand forecasts are made using the aggregated information from similar products.

In essay 2, we develop a theory-driven GNN model wherein information dissemination follows paths delineated by social network theory. We unveil the first-ever GNN that employs user stance as an edge feature. Recognizing that user stances can sculpt unique echo chambers, we delineate four theory-informed information propagation paths for the GNN to assimilate information. The model demonstrates commendable efficacy in proactively predicting misinformation dissemination in online communities. Moreover, the attention scores of each path quantify the varying influences of different echo chambers on the misinformation propagation trajectory.

In essay 3, we model the hierarchical graph structures inherent to online discussion threads. We focus particularly on bot approval processes on Wikipedia, characterized by dialogues between bot operators and the bot approval group, with the outcomes determining the bot's operational viability. While current literature has extensively scrutinized online bot detection and roles, the origination of bots remains a less treaded avenue. Our experiments with qualitative and quantitative evidence suggest that, when juxtaposed with models relying solely on plain text, the inclusion of discussion structure considerably enhances model efficacy when predicting approval outcomes.