# Information diffusion analysis in online social networks based on deep representation learning

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# English Summary

With the emergence of online social networks (OSNs), the way people create and share information has changed, which becomes faster and broader than traditional social media. Understanding how information (both good and harmful) spreads through OSNs, as well as what elements drive the success of information diffusion, has significant implications for a wide range of real-world applications. In this thesis, we conduct research to analysis the diffusion of information in OSNs via using deep representation learning. Specifically, we aim to develop deep learning-based models to solve two specific tasks, i.e., information cascades modeling and rumor detection.

Our contributions are as follows:

We propose recurrent cascades convolutional network (CasCN) in Chapter 4, a graph-based neural model for macro-level information cascade prediction. CasCN utilizes a combination of graph convolutional network and recurrent neural network to predict the incremental size of a cascade by extracting structural-temporal features from a sequence of timestamp-based subgraphs. CasCN also introduces CasLaplacian for directed graphs, which overcomes the limitations of previous graph neural networks when dealing with directed graphs. The experimental results conducted on two real-world datasets, show that CasCN is well-suited for modeling structural-temporal features from cascades.

We propose multi-scale cascades model (MUCas) in Chapter 5, which aims at capturing multi-scale features for macro-level information cascade prediction. MUCas utilizes a multi-scale graph capsule network and an influence attention to learn and fuse the multi-scale information (i.e., dynamic-scale, direction-scale, position-scale, and high-order-scale) to form a unique cascade representation. MUCas also improves the sampling methods in CasCN by sampling subgraphs based on time intervals rather than timestamps. We conduct experiments on real-world datasets and demonstrate that MUCas is particularly effective at extracting features on cascades from different scales, and multi-scale features are vital for improving prediction accuracy.

We propose macroscopic and microscopic-aware rumor detection model (MMRD) in Chapter 6, a diffusion-based rumor detection model that detects rumors by only

exploring different levels of diffusion patterns. MMRD leverages graph neural networks to learn the macroscopic diffusion of rumor propagation and capture microscopic diffusion patterns using bidirectional recurrent neural networks while taking into account the user-time series. MMRD also leverages knowledge distillation technique to create a more informative student model and further improve the model performance. MMRD is evaluated on the well-known Twitter data sets and could obtain good detection results in the early stage of rumor spreading.

We propose participant-level rumor detection model (PLRD) and multi-view learning with attention for rumor detection model (UMLARD) in Chapter 7. Both PLRD and UMLARD are designed at user-level. PLRD exploits various fine-grained user features from the diffusion threads, i.e., the users' social homophily, influence, susceptibility, temporal features, and then uses these features to determine whether the information is true or false. PLRD also introduces a variational autoencoder (VAE) to handle the uncertainty which exists in the feature learning phase. UMLARD extends PLRD and solves one burning limitation left by PLRD, i.e., input features entangled with learned high-level features, by using three view-specific embedding methods with distinct inputs. UMLARD also innovatively proposes a capsule-based attention layer to replace the original attention mechanism in PLRD, which is more effective in both performance and time cost. Both PLRD and UMARD outperform other non-user-level models, which demonstrates that developing models at the user level indeed improves detection performance.