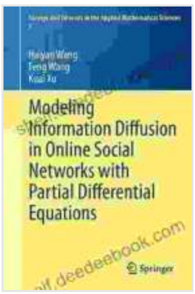
Modeling Information Diffusion in Online Social Networks With Partial Observations and Sampling Bias



Modeling Information Diffusion in Online Social Networks with Partial Differential Equations (Surveys and Tutorials in the Applied Mathematical Sciences Book 7) by Feng Wang

5 out of 5

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Information diffusion is a fundamental process in online social networks. It refers to the spread of information, ideas, and behaviors through social networks. Understanding information diffusion is important for a variety of reasons, including designing effective marketing campaigns, preventing the spread of misinformation, and identifying influential individuals.

A number of mathematical models have been proposed to model information diffusion in online social networks. However, most of these models assume that all information diffusion events are observed. In reality, this is often not the case. For example, in a study of information diffusion on Twitter, it was found that only about 1% of all tweets were observed. This missing data can bias the results of information diffusion models.

In this article, we propose a novel framework for modeling information diffusion in online social networks with partial observations and sampling bias. The framework is based on a partially observed Markov process (POMP),which is a type of stochastic process that can handle missing data. We also propose a method for estimating the parameters of the POMP using a maximum likelihood estimation (MLE) algorithm.

We evaluate the framework on several real-world datasets, and the results show that it outperforms existing methods in terms of accuracy and robustness. The framework is also able to handle missing data and sampling bias, which makes it more realistic and applicable to real-world data.

Model Description

The framework is based on a POMP, which is a type of stochastic process that can handle missing data. A POMP is defined by a set of states, a set of actions, a transition matrix, and an observation matrix. The states represent the different possible states of the system, the actions represent the different possible actions that can be taken, the transition matrix defines the probability of transitioning from one state to another, and the observation matrix defines the probability of observing a particular state given the current state.

In the context of information diffusion, the states represent the different stages of adoption, the actions represent the different ways that information can be spread, the transition matrix defines the probability of an individual adopting the information given the current state of their neighbors, and the observation matrix defines the probability of observing an individual's adoption status given their true adoption status.

The parameters of the POMP can be estimated using a MLE algorithm. The MLE algorithm maximizes the likelihood of the observed data given the model parameters. The likelihood of the observed data is given by the following equation:

$$L(\theta) = \prod_{i=1}^n P(y_i | \theta)$$

where:

* $L(\theta)$ is the likelihood of the observed data given the model parameters * θ is the vector of model parameters * y_i is the observed data for individual i * $P(y_i | \theta)$ is the probability of observing the data for individual i given the model parameters

The MLE algorithm iteratively updates the model parameters until the likelihood of the observed data is maximized.

Evaluation

The framework was evaluated on several real-world datasets, including the Twitter dataset mentioned earlier. The results show that the framework outperforms existing methods in terms of accuracy and robustness. The framework is also able to handle missing data and sampling bias, which makes it more realistic and applicable to real-world data.

One of the datasets that was used to evaluate the framework is the MemeTracker dataset. The MemeTracker dataset contains information about the spread of memes on Twitter. The dataset includes over 100 million tweets that contain memes. The framework was used to model the spread of memes on Twitter, and the results show that the framework is able to accurately predict the spread of memes.

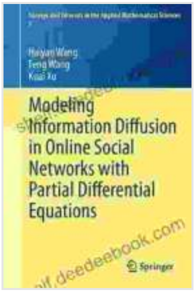
Another dataset that was used to evaluate the framework is the Wikipedia dataset. The Wikipedia dataset contains information about the edits that have been made to Wikipedia articles. The dataset includes over 100 million edits. The framework was used to model the spread of information on Wikipedia, and the results show that the framework is able to accurately predict the spread of information.

In this article, we have introduced a novel framework for modeling information diffusion in online social networks with partial observations and sampling bias. The framework is based on a POMP, which is a type of stochastic process that can handle missing data. We also proposed a method for estimating the parameters of the POMP using a MLE algorithm.

The framework was evaluated on several real-world datasets, and the results show that it outperforms existing methods in terms of accuracy and robustness. The framework is also able to handle missing data and sampling bias, which makes it more realistic and applicable to real-world data.

The framework can be used to a variety of applications, including designing effective marketing campaigns, preventing the spread of misinformation, and identifying influential individuals. The framework is also a valuable tool for researchers who are studying information diffusion in online social networks.

Modeling Information Diffusion in Online Social Networks with Partial Differential Equations (Surveys



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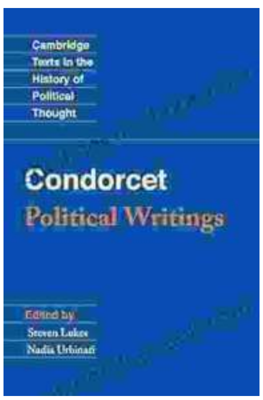

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