

Modeling Dynamic Multi-Topic Discussions in Online Forums

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Abstract

In this paper, we propose a novel framework for modeling dynamic multi-topic discussions in online forums. We first model the topic evolution process as a Markov chain, and then propose a novel topic model based on the Markov chain. We also propose a novel algorithm for topic inference based on the Markov chain. The experimental results show that our framework outperforms the existing methods in modeling dynamic multi-topic discussions in online forums.

Introduction

In recent years, online forums have become an important part of our daily life. People can express their opinions and ideas on various topics through online forums. However, the information in online forums is often noisy and unstructured. It is difficult for people to find the information they need from online forums. In this paper, we propose a novel framework for modeling dynamic multi-topic discussions in online forums. We first model the topic evolution process as a Markov chain, and then propose a novel topic model based on the Markov chain. We also propose a novel algorithm for topic inference based on the Markov chain. The experimental results show that our framework outperforms the existing methods in modeling dynamic multi-topic discussions in online forums.

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so far, the most popular topic model is the Latent Dirichlet Allocation (LDA) model. However, the LDA model is not suitable for modeling dynamic multi-topic discussions in online forums. In this paper, we propose a novel framework for modeling dynamic multi-topic discussions in online forums. We first model the topic evolution process as a Markov chain, and then propose a novel topic model based on the Markov chain. We also propose a novel algorithm for topic inference based on the Markov chain. The experimental results show that our framework outperforms the existing methods in modeling dynamic multi-topic discussions in online forums.

- 1. From the perspective of topic evolution, the topic model should be able to capture the dynamic changes of topics over time.
- 2. From the perspective of topic inference, the topic model should be able to infer the topic of each word in the document.
- 3. From the perspective of topic modeling, the topic model should be able to model the topic evolution process as a Markov chain.
- 4. From the perspective of topic inference, the topic model should be able to infer the topic of each word in the document.

Overview

In this paper, we propose a novel framework for modeling dynamic multi-topic discussions in online forums. We first model the topic evolution process as a Markov chain, and then propose a novel topic model based on the Markov chain. We also propose a novel algorithm for topic inference based on the Markov chain. The experimental results show that our framework outperforms the existing methods in modeling dynamic multi-topic discussions in online forums.

Intuitions

The intuition behind the model is that the information is flowing from early posters (users who post) to late posters. The model is based on the following assumptions:

- Thread Document:** A thread document $d \in D$ is a sequence of posts p_1, p_2, \dots, p_n where p_i is the i -th post in the thread.
- Reply Link:** A reply link l_{ij} is a directed edge from post p_i to post p_j where $i < j$.
- Peer-Influence:** The influence of a post p_i on a post p_j is determined by the number of reply links from p_i to p_j .
- Self-Preference:** The preference of a user u_i for a post p_i is determined by the user's activity on the platform.
- Participation Rank:** The participation rank of a user u_i is determined by the number of posts they have made.
- Topic-level Influential Network:** The influential network is a graph where nodes represent posts and edges represent reply links.
- User Preference:** The user preference vector $y = [y_1, \dots, y_n]^T$ represents the preference of each user for each post.
- Random Walks:** The model uses random walks to simulate the flow of information through the network.

Problem Formulation

The problem is to predict the number of replies for each post in a thread document.

Data Input

- Thread Document:** A sequence of posts p_1, p_2, \dots, p_n where p_i is the i -th post in the thread.
- Reply Link:** A directed edge from post p_i to post p_j where $i < j$.
- User Preference:** A vector $y = [y_1, \dots, y_n]^T$ representing the preference of each user for each post.
- Participation Rank:** A vector $r = [r_1, \dots, r_n]^T$ representing the participation rank of each user.
- Topic-level Influential Network:** A graph $G = (V, E)$ where V is the set of posts and E is the set of reply links.

The data output is the predicted number of replies for each post in the thread document.

Data Output

- Influential Network:** A graph $G = (V, E)$ where V is the set of posts and E is the set of reply links.
- Topic-level Influential Network:** A graph $G^z = (V^z, E^z)$ where V^z is the set of posts and E^z is the set of reply links.
- User Preference:** A vector $y = [y_1, \dots, y_n]^T$ representing the preference of each user for each post.
- Participation Rank:** A vector $r = [r_1, \dots, r_n]^T$ representing the participation rank of each user.

w_{ij} represents the strength of the relationship between user u_i and user u_j . It is calculated as the sum of the weights R_{ij}^d for all domains $d \in D$.

$$w_{ij} = \sum_{d \in D} R_{ij}^d$$

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$$S = D^{-1}W + (1 - \alpha)N$$

D is a matrix where D_{ii} is the degree of user u_i . W is a matrix where W_{ij} is the weight of the relationship between user u_i and user u_j . N is a matrix where N_{ij} is the weight of the relationship between user u_i and user u_j .

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$$y_i = \sum_{d \in D} C_i^d$$

q is a vector where q_i is the weight of the relationship between user u_i and user u_j .

$$q_i = y_i \sum_{i=1}^n y_i$$

p is a vector where p_i is the weight of the relationship between user u_i and user u_j .

$$p_{(t+1)} = S^T p_{(t)} + (1 - \alpha)q$$

$p_{(t)}$ is a vector where p_i is the weight of the relationship between user u_i and user u_j . It is calculated as the sum of the weights R_{ij}^d for all domains $d \in D$.

$p_{(t)}$ is a vector where p_i is the weight of the relationship between user u_i and user u_j . It is calculated as the sum of the weights R_{ij}^d for all domains $d \in D$.

$$p^* = S^T p^* + (1 - \alpha)q$$

p^* is a vector where p_i is the weight of the relationship between user u_i and user u_j .

$$p^* = (1 - \alpha)(I - S^T)^{-1}q$$

I is the identity matrix. S^T is the transpose of the matrix S . q is a vector where q_i is the weight of the relationship between user u_i and user u_j .

Topic-specific Topic Flow Model

w_{ij}^z represents the strength of the relationship between user u_i and user u_j for topic z . It is calculated as the sum of the weights R_{ij}^d for all domains $d \in D$.

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$$w_{ij}^z = \sum_{d \in D} P(z|d)R_{ij}^d$$

w_{ij}^z represents the strength of the relationship between user u_i and user u_j for topic z . It is calculated as the sum of the weights R_{ij}^d for all domains $d \in D$.

$$y_i^z = \sum_{d \in D} P(z|d)C_i^d$$

y_i^z is a vector where y_i^z is the weight of the relationship between user u_i and user u_j for topic z .

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Time-sensitive Topic-specific Topic Flow Model

w_{ij}^z represents the strength of the relationship between user u_i and user u_j for topic z at time t . It is calculated as the sum of the weights R_{ij}^d for all domains $d \in D$.

w_{ij}^z represents the strength of the relationship between user u_i and user u_j for topic z at time t . It is calculated as the sum of the weights R_{ij}^d for all domains $d \in D$.

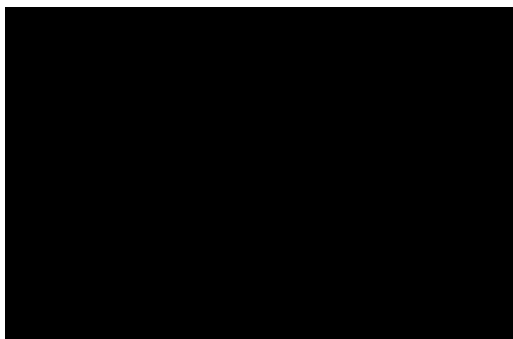
w_{ij}^z represents the strength of the relationship between user u_i and user u_j for topic z at time t . It is calculated as the sum of the weights R_{ij}^d for all domains $d \in D$.

$$w_{ij}^z = \sum_{d \in D} \exp(-\lambda \Delta t_d) P(z|d)R_{ij}^d$$

Eqn. 9

$$y_i^z = \sum_{d \in D} \exp(-\lambda \Delta t_d) P(z|d) C_i^d$$

...



Experimental Results

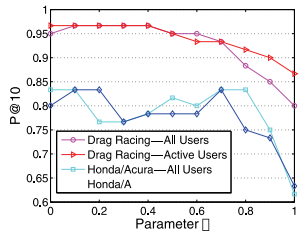
...

Timestamp	User Name	User ID	Replied	User Name
...
...

...

$\alpha = 0.01$

Tests	Tests	Dragon		Dragon A	
		Tests	Tests	Tests	Tests
A	no	-	4	-	44
	os	4	4	-	-
	B F	9	9	9	9
	F	0.960	0.960	0.9	0.9
	F	0.960	0.960	0.940	0.940
A	no	9	44	-	44
	os	94	9	-	-
	B F	-	9	-	-
	F	-	9	-	4
	F	0.643	0.736	0.576	0.652



Related Work

o r no pr o s s
ons r pro o n n
op s s ons n on n or s sp ro p r
sp o n or on o o r r o n s
o os r or r h s on

Online Forums

n s o on n or s o s on pp ons
s s q s on ns r s r s Con n
on s s r o Cro n 9 n n
r r s r ors n n s s n r n
o n s D n r nn r on B on n
B n s 9 s no r n r n
s 99 o s r s s r s s o s no o r s ors s p r r r r n