Accepted for publication in Knowledge and Information Systems

Analyzing Topics and Authors in Chat Logs for Crime Investigation

Abdur Rahman M. A. Basher and Benjamin C. M. Fung

Concordia Institute for Information Systems Engineering
Concordia University, Montreal QC, H3G 1M8, Canada

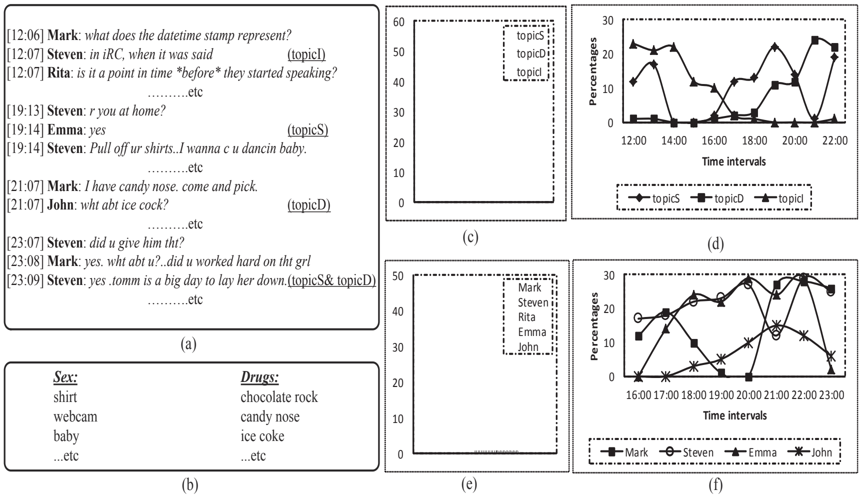
Abstract. Cybercriminals have been using the Internet to accomplish illegitimate activities and to execute catastrophic attacks. Computer Mediated Communication such as online chat provides an anonymous channel for predators to exploit victims. In order to prosecute criminals in a court of law, an investigator often needs to extract evidence from a large volume of chat messages. Most of the existing search tools are keyword-based, and the search terms are provided by an investigator. The quality of the retrieved results depends on the search terms provided. Due to the large volume of chat messages and the large number of participants in public chat rooms, the process is often time-consuming and error-prone. This paper presents a topic search model to analyze archives of chat logs for segregating crime-relevant logs from others. Specifically, we propose an extension of the Latent Dirichlet Allocation (LDA)-based model to extract topics, compute the contribution of authors in these topics, and study the transitions of these topics over time. In addition, we present a special model for characterizing authors-topics over time. This is crucial for investigation because it provides a view of the activity in which authors are involved in certain topics. Experiments on two real-life datasets suggest that the proposed approach can discover hidden criminal topics and the distribution of authors to these topics.

Keywords: Latent Dirichlet Allocation (LDA), topic modeling, Gibbs sampling, topic evolution, author-topics over time, cybercrime.

1. Introduction

Demand for Computer-Mediated Communication, such as online chat, instant messages, blogs, and tweets, is growing tremendously, and many software applications have been developed to serve this demand. Instant messaging seems to

Received Mar 01, 2012
Revised Nov 13, 2012
Accepted Jan 20, 2013



```
[12:06] Mark: what does the datetime stamp represent?
[12:07] Steven: in iRC, when it was said                (topicI)
[12:07] Rita: is it a point in time *before* they started speaking?
                    ..........etc
[19:13] Steven: r you at home?
[19:14] Emma: yes                                       (topicS)
[19:14] Steven: Pull off ur shirts..I wanna c u dancin baby.
                    ..........etc
[21:07] Mark: I have candy nose. come and pick.
[21:07] John: wht abt ice cock?                         (topicD)
                    ..........etc
[23:07] Steven: did u give him tht?
[23:08] Mark: yes. wht abt u?..did u worked hard on tht grl
[23:09] Steven: yes .tomm is a big day to lay her down.(topicS& topicD)
                    ..........etc
```

(a)

Sex:	***Drugs:***
shirt	chocolate rock
webcam	candy nose
baby	ice coke
...etc	...etc

(b)

(c)

(d)

(e)

(f)

Fig. 1. (a)- A detained chat log d. (b)- Criminal topics (Sex and Drugs) with their associated terms. (c)- Topics distribution in the chat log d. (d)- Topics over time in the chat log d. (e)- Authors distribution over topicD in the chat log d. (f)- Authors-Topics over time in the chat log d for topicS.

be preferred, especially chatting, because it provides one-to-one or one-to-many instant communication and can handle video and audio calls as well. However, the widespread use of communication applications increases both legitimate and illegitimate activities. Illegitimate activities include cyber bullying, cyber drug trafficking, child pornography, and cyber sexual harassment. Traditional crimes that are conducted through the Internet pose new challenges for law enforcement agencies to prevent, detect, investigate, and prosecute perpetrators. Unfortunately, the capability of current crime-investigation software tools does not fully meet the actual needs of real-life investigations.

In many cases an investigator seizes a suspect's computer that has an enormous amount of chat logs from, e.g., Windows Live Messenger or IRC chat rooms. The chat logs sometimes contain important information that is directly or indirectly related to the criminal activities under investigation. Figure 1(a) presents a general form of a chat log that contains information about criminal activities, such as Sex and Drugs.

The challenge is how to effectively and efficiently extract relevant information and evidence from a large volume of chat messages. In this paper, we propose a discovery method, in a context of chat log-topic and topic-author relations, to answer the following questions that are frequently raised by investigators:

Q 1. *How can an investigator determine which logs are crime-relevant? In identifying a crime-relevant log, what are the contributed topics in the log file? How have they evolved over time? Moreover, how can an investigator extract the crime-relevant topics from the identified crime-relevant log files?*

Q 2. *Who are the contributors to a topic in a given chat log? How can an investigator track the activity of authors in a log file?*

In general, we are concerned with generating Figures 1 (c), (d), (e), and (f) as results from our research questions. We would like to emphasize that the existing topics discovery methods [1][2][3][4] cannot be directly applied to address the problem illustrated in the context of crime investigation due to the differences in characteristics of chat messages from traditional, well-structured documents [5]:

- Chat is informal and its content is not well structured. Chat often contains spoken languages with a lot of grammatical and spelling mistakes.
- The contents (topics) in chat logs change frequently and implicitly over time as consequences of incoherence of message sequences.
- Messages on chat logs are often short, ranging from a few words to a few lines.
- Transliteration is often used and refers to writing, words, or letters in a language written in a different alphabet or script.
- Authors within these short messages use many deceptive techniques for covert communication. For example, they use emoticons to express human facial behavior that complements a text message. Moreover, the semantic of the words used within a chat log may be different from their apparent meaning; street terms are more frequently used in the context of illegitimate activities. For example, the word ‘snow’ used in drug trafficking means cocaine.

As a result, criminal-topics extraction from log files requires special handling, and the analytical techniques widely used for mining texts of literary and historic documents may not achieve the same accuracy when applied to online documents. Furthermore, these techniques do not collect information about authors composing criminal topics.

In this paper, we introduce a method for forensics investigators to precisely capture various characteristics of chat logs. Our study focuses on the first three aforementioned differences. Although some recent papers as [6] discusses the prediction of the future behavior of a large population after modeling the collective behavior from observed data using swarm intelligence during the training phase, our study focuses on the first three aforementioned differences and the last two differences will be addressed in our future work.

Our proposed method has four phases: searching crime-relevant logs, discovering crime-relevant topics from identified criminal logs, estimating the contribution of authors in the discovered topics, and representing transitions of the crime-relevant topics over time. We first identify whether or not a given chat log is crime-relevant based on the predefined criminal topics. Then we deploy a probabilistic topic model to extract the hidden semantic from the crime-relevant chat logs. Next, the authors’ contributions within the discovered topics are estimated. Finally, an evolution of topics under some specific time intervals is generated. In certain cases, investigators want to distinguish some authors from others within a period of time. This is achieved by including another phase to compute the bond relationship composed of authors-topics trends over time.

Contributions: The contributions of this paper can be summarized as follows: First, we present a *Criminal Topic* model to identify crime-relevant chat logs. Second, we propose two topic models, namely *LDA-Topics over Time (LDA-TOT)* and *Author-Topics over Time (A-TOT)*, to extract criminal topics, the distributions of authors with topics, temporal information in these topics, and author-topic relationships within a period of time. We also propose a distance measure to group authors according to their activity.

The rest of the paper is organized as follows: In Section 2 we discuss the related work. In Section 3 we formally define the problem. In Section 4 we describe the background information relevant to our proposed methodology. In Section 5 we present our proposed method. In Section 6 we evaluate the effectiveness, efficiency, and scalability of our proposed approach on real-life crime-related datasets. Finally, we conclude with discussion and present possible future research directions in Section 7.

2. Related Work

We summarize the state of the art in the literature of topics discovery and modeling. Blei et al. [1] proposed the *Latent Dirichlet Allocation* (*LDA*) model to extract topics and summarize a document corpus. The general idea of LDA is to generate a discrete distribution of words per topic and a discrete distribution over topics per document. Although LDA is expressive enough to reveal topics in a document, it does not provide a way of including labels in its learning procedure. Hence, LDA has been adapted in applications for topic labeling, as in [7][8][9][4]. Blei et al. [7] proposed *Supervised LDA* (*sLDA*), where a label is generated from the empirical topic mixture distribution of each document. Lacoste et al. [8] proposed *Discriminate variation on Latent Dirichlet Allocation (DiscLDA)*, where a document is related to a categorical variable or class label, and a topic mixture distribution is associated with each label. However, these models use single labeling to a document and do not provide multiple labels to each document. *Multi-Multinomial LDA* (*MM-LDA*) [9] assigns multiple labels for each document. Unfortunately, the topics learned by MM-LDA do not link directly with the label. Therefore, Ramage et al. [4] proposed the *Labeled-LDA* (*L-LDA*) model to directly associate the label set of each observed document with one topic.

Prior-LDA [10] introduces an approach to address the variations in label frequencies and the *Dependency-LDA* [10] extends the Prior-LDA to interpret the different dependencies between the labels.

Our way to solve topics labeling is by introducing a *Criminal Topic* model that includes predefined terms, with their distributions associated to each criminal topic. The discovered topics are labeled as crime-relevant whenever the distributions of these topics and topics from the Criminal Topic model are assumed to be relevant through some distance measurement.

Several extensions of LDA models have been proposed to identify authors and the proportion of each author in a document. For example, Rosen-Zvi et al. [2] introduced an *Author-Topic* (*AT*) model, a generative model for authors and their corresponding topic distributions. In their experiments, AT seems to outperform LDA when the test documents contain few observed words. Other works have been extended further to deduce the social networks between entities in different types of documents [11][3]. Chang et al. [11] presented a probabilistic topic model to describe the relationships between pairs of entities encoded in a collection of text documents. McCallum et al. [3] proposed a *Group-Topic (GT)* model to cluster entities into groups with relations between them. In their model, the discovery of groups is guided by the emerging topics and the discovery of topics is guided by emerging groups. In addition, the model is able to capture the language attributes being used within entities and this helps to assign group memberships. Their experimental results suggest that the inference of joint probability improves both the performance of both groups and topics discovery. Song et al. [12] proposed a method called *CommunityNet* to predict the behavior of authors in receiving and sending information by analyzing the contact and content of personal communications. In our approach, we modify the AT model to accommodate the evolution of topics discovered and the proportion of authors to these topics over time.

Studying the evolution of topics over time is valuable, because it reveals different characteristics of topics and their authors. Wang et al. [13] proposed the *Topics Over Time* (*TOT*) model, a non-Markov continuous time model of topical transitions. TOT models time-stamps by parameterizing a continuous beta distribution over time with each topic. They assume that the meaning of a particular topic can be relied upon as constant, but its occurrence and correlations change significantly over time. The *Continuous Time Dynamic Topic Model* (*cDTM*) [14] replaces the discrete state space model of the DTM [15] with its continuous form, called *Brownian motion.* The topics are modeled through a sequential collection of documents, where a topic is a pattern of word use that is expected to change over the course of the collection. Significantly, *cDTM* generalizes the *DTM* in that the only discretization it models is the resolution at which the time stamps of the documents are measured. AlSumait et al.[16] used an online version of the LDA model (*OLDA*), where topics are evolved through incremental updates for new data based on the current position. On the other hand, the *Sequential latent Dirichlet allocation (SeqLDA)* [17] captures the topic evolvements by detecting how topic distributions variate amongst segments, which can be a chapter, section, paragraph or sentence. This model applies the sequential structure of each document, which is the position of each segment, that the LDA model ignores. Although this model considers the document structure in the hierarchical modeling, it does not account the time intervals in the documents. To collect the distribution of topics over time, we employed an extended combination of three models (LDA, AT, and TOT) where discretization of time slots is used, since the time intervals in a chat log are relatively short, from a few minutes to a few hours.

The topic models discussed in most of the current literature are applied to structured documents, which are quite different from chat logs. As a result, it becomes very difficult to obtain an accurate model from logs. Hong et al. [5] focused on online messages, particularly Twitter. They conducted an empirical study of different strategies to aggregate tweets, based on the existing models. In contrast, our work focuses on four major aspects: criminal topics discovery, authors' proportions with respect to topics, evolution of topics with respect to time, and evolution of authors-topics over time.

3. Problem Definition

In this paper, we assume the user of our method is a crime investigator who has access to a collection of chat log documents and who would like to analyze the relationship between the topics discussed and the participating authors. We formally define an abstract representation of chat log documents, user-specified criminal topics, and some basic notions of topics and authors, followed by a problem statement.

Definition 1 (Chat log document). A *chat message* is a triplet $(a,\ \mu,\ \tau)$, representing a textual message μ written by author a at time τ. A *chat log document*, denoted by d, is a sequence of chat messages ordered by τ. ■

***Example* 1.** In Figure 1(a), *Mark* wrote the text message *"I have candy nose. come and pick."* at time *[21:07]*. This chat message is represented by a triplet *(Mark, "I have candy nose. come and pick.", [21:07])*. The chat log document is a sequence of chat messages ordered by time. ■

The following definition formally describes the notion of topic in a chat log document.

Definition 2 (Topics in chat log document). Let T be the universe of topics. Let D be a set of chat log documents. A chat log document $d \in D$ contains a set of topics $T_d \subseteq T$. A topic $t \in T_d$ is a probability distribution over a set of vocabularies V. Specifically, the probability distribution of a topic t is a collection of positive real numbers over V with sum equal to 1. ■

An investigator wants to identify the crime-relevant topics discussed in a chat log document and the authors participated in the discussion of the topics. Thus, the set of vocabularies V consists of $V_D \cup W_c$, where V_D is a set of distinct words in D and W_c is a set of crime-related words described in the following definition.

Definition 3 (Crime-relevant topic). Let $C \subseteq T$ be a set of investigator-specified criminal topics. A criminal topic $c \in C$ consists of a set of crime-related words W_c. Let $distance(t_1, t_2)$ be a function that describes the dissimilarity of two topics t_1 and t_2. A topic t is *relevant* to a criminal topic c if $distance(t, c) \leq \gamma$, where γ is a threshold specified by an investigator. ■

***Example* 2.** The chat log document d in Figure 1(a) contains three topics $T_d = \{topicI, topicS, topicD\}$. Figure 1(b) illustrates two investigator-specified criminal topics $C = \{Sex, Drugs\}$. Suppose $\gamma = 0.7$ and $distance(topicD, Drugs) = 0.56$. The *topicD*, discussed in d, is relevant to the criminal topic *Drugs* if $distance(topicD, Drugs) \leq \gamma$. The *distance* function will be defined in Section 6. ■

To identify relevant criminal information from a large collection of chat log documents, an investigator first has to identify the crime-relevant documents, and then the topics' distribution with respect to authors over time. The following definitions formally capture these notions.

Definition 4 (Crime-relevant document). A chat log document d is *crime-relevant* if d contains at least one crime-relevant topic such that $T_d \cap C = \{c_i \mid c_i \in C\}$, where T_d and C are defined in Definitions 2 and 3, respectively. ■

Definition 5 (Active topic). Let $[\tau_t^s, \tau_t^f]$ be a time interval of topic t discussed in a chat log document. The *active* level of t over the time interval $[\tau_t^s, \tau_t^f]$ is described by function $\mathcal{F}(t)_{\tau^s}^{\tau^f}$. ■

An investigator can define his/her own instantiation of function $\mathcal{F}$. One instantiation is given in Section 6.3.

Definition 6 (Active author). Let Λ_d be a set of authors participating in chat log document d. Let Λ_d^t be a set of authors participating in a topic t in d, where $\Lambda_d^t \subseteq \Lambda_d$. The *active* level of an author $a^t \in \Lambda_d^t$ is defined by $\mathcal{F}(a_d^t)_{\tau^s}^{\tau^f}$ provided t is active during $[\tau_t^s, \tau_t^f]$. ■

***Example* 3.** Figure 1(d) depicts the active levels of *topicI*, *topicS*, and *topicD* between *12:00* and *22:00*. For example, *topicD* is actively discussed between *20:00* and *22:00*, but is relatively inactive between *12:00* and *13:00*. Figure 1(f) defines the evolution (active level) of authors over the previous time intervals. ■

The problems studied in this paper are formally defined as follows:

Definition 7 (Authors-Criminal topics activity over time in a chat log). Given a collection of chat log documents D, a set of criminal topics C, and a relevance threshold γ, the problems are:

1. to identify all crime-relevant documents from D,
2. to identify all crime-relevant topics in each document $d \in D$ with respect to C and γ, and
3. to identify the active level of crime-relevant topics, and all their associated active authors over a given time interval $[\tau_t^s, \tau_t^f]$ for each identified crime-relevant document. ■

4. Background Information

Language modeling [18], a probability distribution over word sequences, provides a sound theoretical foundation to our research problem. The procedure first builds a probabilistic language model for both the chat log d and the crime-relevant topic c, then searches for the document d based on the probability of the model generating the c: $P(M_c|M_d)$, where M is a language model. Based on this knowledge, we propose a framework that searches the crime-relevant logs in collections of data. In this section, we briefly describe the statistical models LDA and AT and define the notations in Table 1.

4.1. Latent Dirichlet Allocation (LDA)

Latent Dirichlet Allocation (*LDA*) [1] is an unsupervised generative probabilistic model that discovers latent semantic topics in a corpus with large collections of discrete data, such as the words in a set of documents. It is based on a *"bag of words"* assumption, which treats each document as a frequency of word counts, ignoring the order of appearance. In the language of probability theory, this is an assumption of *"exchangeability"*: words are *independent* and *identically* distributed over the topics, and the topics are *infinitely* exchangeable throughout the document, based on some conditional parameters [1][16].

In LDA, a document can be viewed as a random mixture of hidden variables (i.e., topics) and observed data (i.e., words). Words in a document are generated from the hidden topics and are not linked to the documents directly, but are linked via latent variables (topics) that are responsible for using a particular word in the document drawn from a specific topic distribution that the document focuses on. The generative process can be described as follows:

1. For each document d, choose $|D|$ multinomials $\theta_d \sim$ Dirichlet prior α;

Table 1. Notations used in this paper

SYMBOL	DESCRIPTION
α	Dirichlet parameters for topics (Dirichlet prior)
$\bar{\alpha}$	Dirichlet parameters for authors (Dirichlet prior)
β	Topic-dependent Dirichlet parameters for word index (Dirichlet prior)
λ	Topic-dependent Dirichlet parameters for time slots (Dirichlet prior)
θ	Multinomial distribution of topics given the documents in the corpus
ϑ	Multinomial distribution of topics given the authors for the documents in the corpus
φ	Multinomial distribution of words to topics
η	Multinomial distribution of time intervals to topics for the documents in the corpus
D	Set of chat log documents
d_c	Crime-relevant document (chat log)
T	Universe of topics
c	a criminal topic
A	Number of authors
V	Set of distinct words in the vocabulary
W_c	Set of distinct crime-related words for c
N	Number of word tokens
Λ_d	Set of authors in document d

2. For each topic t, choose $|T|$ multinomials $\varphi_t \sim$ Dirichlet prior β;
3. For each word w_{di} per document d, in the corpus:
   - choose a topic $z_i \sim$ multinomial θ_d; $(P(z_i \mid \alpha))$
   - choose a word $w_i \sim$ multinomial φ_z; $(P(w_i \mid z_i, \beta))$

Since estimating θ and φ, which provides the proportions of topics in each document and the proportions of words to these topics, respectively, is intractable, different complex algorithms have been proposed, including *variational inference* [1], *expectation propagation* [19], and *Gibbs sampling* [20]. Gibbs sampling is a form of *Markov Chain Monte Carlo*, used for obtaining an approximate inference about parameters. In this model, the posterior distribution of topics over words are calculated as follows:

$$P(z_i = t \mid w_i = w, z_{-i}, w_{-i}, \alpha, \beta) \propto \frac{n_{w_{-i}} + \beta}{\sum_{v \in V} n_{w_{-i}t} + |V|\beta} \times \frac{n_{d_{-i},t} + \alpha}{\sum_{t \in T} n_{d_{-i},t} + |T|\alpha} \tag{1}$$

where $n_{w_{-i},t}$ is the vector count of the word w being assigned to the topic t, not including current word i. $n_{d_{-i},t}$ is the vector count of topic t being assigned to some words, not including the current word i, in a document d. After several iterations, specified by the user, the multinomial distribution of documents over topics θ and the multinomial distribution of topics over words φ are obtained from the posterior distribution of topics. The details for the Gibbs sampling and LDA can be found in [21][1], respectively.

4.2. Author-Topic (AT)

LDA discloses the underlying topics in the documents in a corpus. However, LDA does not identify authors of a document nor the association of authors to each topic in the topics of a document. As a result, Rosen-Zvi [2] proposed the *Author-Topic (AT)* model, an extension of LDA, that models the content of a document and the interests of authors. Each word in this model consists of two latent variables: an author and a topic. The generative process for this model follows:

1. For each author a, choose A multinomials $\vartheta_a \sim$ Dirichlet prior $\bar{\alpha}$;
2. For each topic t, choose $|T|$ multinomials $\varphi_t \sim$ Dirichlet prior β;
3. For each word w_{di} in each document d, in the corpus:
   - choose an author $x_i \sim$ uniform Λ_d; $(P(x_i \mid \Lambda_d))$
   - choose a topic $z_i \sim$ multinomial ϑ_a; $(P(z_i \mid x_i, \bar{\alpha}))$
   - choose a word $w_i \sim$ multinomial φ_z; $(P(w_i \mid z_i, \beta))$

Formally, the procedure for generating a document starts by choosing an author x, uniformly at random, from the set of authors Λ_d for each word w_i specific to the document d, and then a topic is sampled from the distribution of topics specific to that author x. Finally, the words are sampled from the distribution of topics over words [2]. This process is continued for all words in the document. However, it is important to note that there is no topic mixture for an individual document [5]. In other words, the multinomial distribution θ_d of topics, given documents, is not sampled in the AT model, unlike the LDA model.

An analogy to LDA, the Gibbs sampler for the posterior distribution of topics is:

$$P(z_i = t, x_i = a \mid w_i = w, z_{-i}, w_{-i}, x_{-i}, A_d, \bar{\alpha}, \beta) \propto \frac{n_{w_{-i}} + \beta}{\sum_{v \in V} n_{w_{-i},t} + |V|\beta} \times \frac{n_{x_{-i},t} + \bar{\alpha}}{\sum_{t \in T} n_{x_{-i},t} + |T|\bar{\alpha}} \tag{2}$$

where $n_{w_{-i},t}$ is the vector counts of the word w being assigned to the topic t, not including current word i, and $n_{x_{-i},t}$ is the vector count of words being assigned to topic t for author a to some words, not including the current word i. More details on the AT model are found in [2].

5. Proposed Approach

Probabilistic topic models, such as LDA and AT, model the hidden semantic structure of a document collection without prespecifying whether a document contains a specific topic or not. Therefore, we employ language modeling for both chat log d and criminal topic c, and then ask how different these two language models are from each other. The key point is to compute the probability of a language model M_c generating the document d and to determine the topics of interest in a given chat log. After that, we use two extended topic models to extract topics and discover the topics related to crime in d. The insight behind proposing the two models is to capture the topics' progressive information and to extract the authors' information as it evolves over time. We begin this section by describing some of the measurements used to process the search, and then we present our approach in detail.

5.1. Kullback-Leibler divergence

The general representation of the two language models, M_d and M_c, is in the form of distribution of words. In order to measure the dissimilarity between them, we employ the *Kullback-Leibler (KL) divergence.* In language models, KL is often used in clustering as a measure of (dis)similarity of some given language models. KL divergence is calculated as follows:

$$KL(M_c \parallel M_d) = \Sigma_{w \in V} P(w \mid M_c) \log \frac{P(w \mid M_c)}{P(w \mid M_d)} \tag{3}$$

where d and c are two probability distributions representing a chat log and a criminal topic, respectively. When using a code based on d, KL measures the expected number of additional bits required to code samples from c [16]. In other words, it measures how bad the probability distribution M_d is at modeling M_c. In this paper, we compute the average of KL($M_c \parallel M_d$) and KL($M_d \parallel M_c$).

5.2. Criminal Topic Model

n-grams are the most commonly used natural language model. It is a probabilistic model that takes the assumption that only the previous $n-1$ words, in a sequence, have any effect on the probabilities for the next word. In other word, the probability of a current word depends on the previous n-words. An n-gram model of size 1 is called a *unigram* model. In this model, the words for each document are drawn from a single multinomial distribution, independently. If we extend the unigram model by adding a discrete random topic c, the *mixture of unigrams* model is obtained [1]. We apply the mixture of unigrams model to explore a chat log and its relation to criminal activities. Throughout this paper we use *Criminal Topic (CT)* to refer to the mixture of unigrams model. Under this model, a single topic c generates N words. We assume that the topic c and the words w are observable in the CT model. The key point of developing this model is the assumption of exhibiting several criminal topics for any detained chat logs, and each of these topics is composed of its own distribution of words. Therefore, comparing the topics distributions in d with c indicates the relevance of d to crime.

The words are drawn from a single topic distribution:

$$P(w|c, \varphi) = \prod_{n=1}^{N} \varphi_{w_n,c} \tag{4}$$

where φ is the distribution of words under c. It describes the probability of each

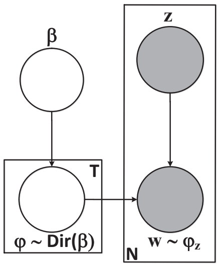


Fig. 2. The graphical model representation (plate notation) of Criminal Topic (CT) model

word w conditioned on c. φ_c is calculated as follows:

$$\varphi_c = \frac{n_{w_i,c} + \beta}{\sum_{n \in W_c} n_{w_i,c} + |W_c|\beta} \tag{5}$$

Using the CT model, in Figure 2, KL is applied to estimate the distance between d and c in order to distinguish crime-relevant logs from others. In addition, it is also applied to compute the distance between discovered criminal topics and c after the two extended models described in the next subsections have generated topics from d.

5.3. Mining for Crime-relevant Chat Logs, Topics, and Topics Over Time using LDA-TOT

Topic discovery is influenced not only by the occurrence of words and their frequencies, but also by the time stamp associated with each word in a chat log. The transition of topics over time in a given chat log can be estimated by introducing an observable variable t into the standard LDA model. Various models have been proposed to illustrate the transition of topics over time, such as the *TOT* model [13]. Nonetheless, we depict *LDA-Topics over Time (LDA-TOT)* model, in Figure 3, that identifies topics and their evolution over time.

The primary difference between this model and TOT is the use of discrete intervals of time instead of continuous time, as in TOT. Time intervals in a chat log are relatively short, ranging from a few minutes to a few hours. Therefore, we employ discrete time intervals in this model. Moreover, it is easy to include discretization of time, for learning and computation purposes, in order to generate the topics' distribution over time (η), rather than using continuous beta distribution. The generative process for LDA-TOT is described as follows:

1. For each document d, choose $|D|$ multinomials $\theta_d \sim$ Dirichlet prior α ;
2. For each topic t, choose $|T|$ multinomials $\varphi_t \sim$ Dirichlet prior β ;
3. For each word w_{di} in each document d, in the corpus:
   - choose a topic $z_i \sim$ multinomial θ_d; $(P(z_i \mid x_i, \alpha))$
   - choose a word $w_i \sim$ multinomial φ_z; $(P(w_i \mid z_i, \beta))$
   - choose a time interval $\tau_i \sim$ multinomial η_z; $(P(\tau_i \mid z_i, \lambda))$

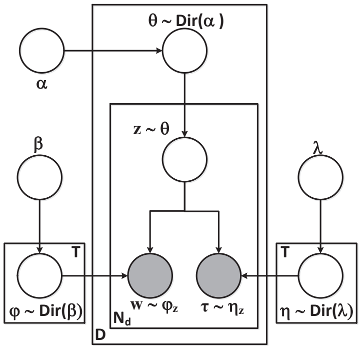


Fig. 3. The graphical model representation (plate notation) of LDA-Topics over Time (LDA-TOT) model

In the above procedure, the posterior distribution of topics depends on both word and time. We use Gibbs sampling to estimate the approximate inference, as done for both LDA and AT. We begin deriving with the joint distribution $P(w, \tau, z|\lambda, \alpha, \beta)$.

$$\begin{aligned} P(w,\tau,z|\lambda,\alpha,\beta) &= P(w|z,\beta)P(\tau|z,\lambda)P(z|\alpha) \\ &= \prod_{t\in T} \frac{\Gamma(\sum_{v\in V}\beta_v)}{\prod_{v\in V}\Gamma(\beta_v)} \frac{\prod_{v\in V}\Gamma(\beta_v + n_{v,t})}{\Gamma(\sum_{v\in V}\beta_v + n_{v,t})} \\ &\times \prod_{t\in T} \frac{\Gamma(\sum_{v\in V}\lambda_v)}{\prod_{v\in V}\Gamma(\lambda_v)} \frac{\prod_{v\in V}\Gamma(\lambda_v + n_{v,t})}{\Gamma(\sum_{v\in V}\lambda_v + n_{v,t})} \\ &\times \prod_{d\in D} \frac{\Gamma(\sum_{t\in T}\alpha_t)}{\prod_{t\in T}\Gamma(\alpha_t)} \frac{\prod_{t\in T}\Gamma(\alpha_t + n_{d,t})}{\Gamma(\sum_{t\in T}\alpha_t + n_{d,t})} \end{aligned} \tag{6}$$

Using the chain rule, we obtain the conditional distribution $P(z_i = t|w_i = w, z_{-i}, w_{-i}, \tau_{-i}, \lambda, \alpha, \beta)$:

$$\begin{gathered} P(z_i = t|w_i = w, z_{-i}, w_{-i}, \tau_{-i}, \lambda, \alpha, \beta) \propto \\ \frac{n_{w_{-i}} + \beta}{\sum_{v\in V} n_{w_{-i},t} + |V|\beta} \times \frac{n_{d_{-i},t} + \alpha}{\sum_{t\in T} n_{d_{-i},t} + |T|\alpha} \times \frac{n_{\tau_{-i}} + \lambda}{\sum_{v\in V} n_{\tau_{-i},t} + |V|\lambda} \end{gathered} \tag{7}$$

where $n_{w_{-i},t}$ and $n_{d_{-i},t}$ are the same as in the LDA model. $n_{\tau_{-i},t}$ is the vector counts of the word w being assigned to the topic t under time interval τ, not including current word i.

Now, we provide an algorithm to classify crime-relevant chat logs and to extract the underlying crime-relevant topics in these logs. We emphasize that this algorithm searches for a particular criminal topic in a chat log. An overview of the algorithm is shown in Algorithm 1. The process starts by employing the CT model to estimate φ for a single topic c (Line 2). This is the learning process for the CT model. It is common for a criminal topic c to contain a set of words W_c that might not be included in the pre-existing vocabulary set V_D. Therefore, we combine the words W_c in a criminal topic with the existing V_D words (Line 3).

It is important to emphasize that CT model is employed to collect the distribution of certain topics, such as sex and drugs. Although, the Twitter-LDA model [22] integrates background topic into the the model, we apply the CT model separately from the overall LDA-TOT and A-TOT models for computation purposes.

Next, the distance between a chat log d and the criminal topic c is calculated using KL divergence (Line 4), under the same vocabulary used for both c and d. At this point, the distribution of words φ for d is computed using the similar formula to the Equation 5. The results obtained from KL might or might not pass the user-specified threshold ϵ. In case the distance measurement KL is lower than or equal to ϵ (Line 5), the algorithm proceeds to the subsequent steps (Line 6-13); otherwise it terminates (Line 14). Then, LDA-TOT is applied to extract crime-relevant topics in a chat log, where all words in d are randomly assigned to topics (Line 6).

The iteration process starts by employing collapsed Gibbs sampling parameter estimation with number of loops to estimate the hidden topic structure of unseen chat logs (Line 8).

Next, the KL distance between each topic t and the provided c is computed (Line 9-11). Finally, when a topic t passes the threshold γ (Line 12) and the user's termination criteria ζ supports (Line 13), the algorithm terminates. The outputs are the three distributions (θ, φ, η); these are further analyzed in the experimental section (Section 6), using other evaluation measures to evaluate the performance of the proposed procedure.

Algorithm 1 Mining for crime-relevant chat logs, topics, and topics over time using LDA-TOT

```
 1: Input: $\alpha, \beta, \lambda, \epsilon, \gamma$
 2: $\varphi$=Calculate criminal topic-word distribution($|D|, \alpha, \beta, \lambda$)
 3: $V = V_D \bigcup W_c$
 4: $\Delta$=KL($d_i, c$)
 5: if $\Delta \leq \epsilon$ then
 6:     Initialize randomly for all words $w_i^N$ in a chat log $d$ to topics $z_t^{|T|}$
 7:     repeat
 8:         $[\theta_d, \varphi, \eta, z_t]$ = GibbsSampling($d, \tau_d, \alpha, \beta, \lambda$)
 9:         for $t$=1 to $|T|$ do
10:             $\sigma_t^{|T|}$=KL($\theta_{d,t}^{|T|}, c$)
11:         end for
12:         $L$ = GetLowest($\sigma_t^{|T|}$)
13:     until $\zeta$
14: end if
```

5.4. Mining for crime-relevant chat logs, topics, authors, and authors-topics over time using A-TOT

To answer the second research question, we introduce the *Author-Topics over Time (A-TOT)* model as in Figure 4. This model is an extension combined

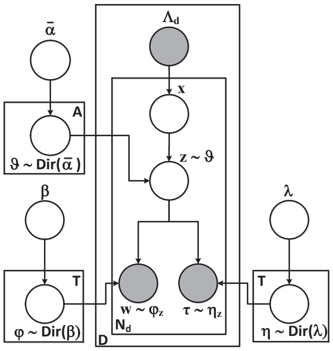


Fig. 4. The graphical model representation (plate notation) of Author-Topics over Time (A-TOT) model

from both models, AT and TOT. The aim of this unsupervised learning model is to achieve topics extraction, authors-topics distribution, and authors-topics distribution over time.

The generative process for A-TOT, which corresponds to the Gibbs sampling for estimating the parameters, is as follows:

1. For each author a, choose A multinomials $\vartheta_a \sim$ Dirichlet prior $\bar{\alpha}$;
2. For each topic t, choose $|T|$ multinomials $\varphi_t \sim$ Dirichlet prior β ;
3. For each word w_{di} in each document d, in the corpus:
   - choose an author $x_i \sim$ uniform Λ_d; $(P(x_i \mid \Lambda_d))$
   - choose a topic $z_i \sim$ multinomial ϑ_a; $(P(z_i \mid x_i, \bar{\alpha}))$
   - choose a word $w_i \sim$ multinomial φ_z; $(P(w_i \mid z_i, \beta))$
   - choose a time interval $\tau_i \sim$ multinomial η_z; $(P(\tau_i \mid z_i, \lambda))$

Formally, the set of authors Λ_d in a chat log d is observed. The procedure begins by choosing an author x, randomly at uniform, from the set of authors Λ_d. Afterward, the multinomial distribution ϑ_a, from the Dirichlet distribution $\bar{\alpha}$, is picked, and this distribution determines which topics are most likely to be assigned to the author x in a chat log d. Next, a single topic $z_i = t$ is sampled for each ith word (w_i) in d, from the multinomial distribution ϑ_a associated with the author x for that word. In general, we assume the ith word (w_i) in d is written by x for the topic $z_i = t$. Finally, in order to generate a word the model chooses a word w_i, from the vocabulary of V words, based on the multinomial distribution φ_z, and assigns a single time stamp τ_i from η_z to w_i. φ_z is generated from the Dirichlet distribution β for each topic t.

From the procedure, A-TOT depends on both word and time for generating topics. A topic in this model is sampled from the distribution of topics specific to author x, and the words are sampled from the distribution of words over topics. The distribution of words over topics $\sum_{v \in V} \varphi_{v,t} = 1$ is the same for both models, LDA-TOT and A-TOT. As for A-TOT, the distribution of topics over authors $\sum_{t \in T} \vartheta_{a,t} = 1$. Like LDA-TOT, η_z is a multinomial distribution for each word token w_i over time stamp τ_i, under a topic z.

The joint distribution $P(w, \tau, x, z|A, \lambda, \alpha, \beta)$ for A-TOT model is:

$$\begin{aligned} P(w, \tau, x, z|A, \lambda, \alpha, \beta) &= P(w|z, \beta)P(\tau|z, \lambda)P(z|\alpha)P(x|A) \\ &= \prod_{t \in T} \frac{\Gamma(\sum_{v \in V} \beta_v)}{\prod_{v \in V} \Gamma(\beta_v)} \frac{\prod_{v \in V} \Gamma(\beta_v + n_{v,t})}{\Gamma(\sum_{v \in V} \beta_v + n_{v,t})} \\ &\times \prod_{t \in T} \frac{\Gamma(\sum_{v \in V} \lambda_v)}{\prod_{v \in V} \Gamma(\lambda_v)} \frac{\prod_{v \in V} \Gamma(\lambda_v + n_{v,t})}{\Gamma(\sum_{v \in V} \lambda_v + n_{v,t})} \\ \times \prod_{d \in D} \frac{\Gamma(\sum_{t \in T} \alpha_t)}{\prod_{t \in T} \Gamma(\alpha_t)} & \frac{\prod_{t \in T} \Gamma(\alpha_t + n_{d,t})}{\Gamma(\sum_{t \in T} \alpha_t + n_{d,t})} \times \prod_{d \in D} \frac{1}{A_d^{N_d}} \end{aligned} \tag{8}$$

The conditional distribution $P(z_i = t, x_i = a \mid w_i = w, z_{-i}, w_{-i}, x_{-i}, \tau_{-i}, A, \lambda, \bar{\alpha}, \beta)$ uses the Gibbs sampling and is obtained using chain rule:

$$\begin{gathered} P(z_i = t, x_i = a \mid w_i = w, z_{-i}, w_{-i}, x_{-i}, \tau_{-i}, A_d, \lambda, \bar{\alpha}, \beta) \propto \\ \frac{n_{w_{-i}} + \beta}{\sum_{v \in V} n_{w_{-i},t} + |V|\beta} \times \frac{n_{x_{-i},t} + \bar{\alpha}}{\sum_{t \in T} n_{x_{-i},t} + |T|\bar{\alpha}} \times \frac{n_{\tau_{-i}} + \lambda}{\sum_{v \in V} n_{\tau_{-i},t} + |V|\lambda} \end{gathered} \tag{9}$$

where $n_{\tau_{-i},t}$ is number of the word w being assigned to the topic t under time interval τ, not including current word i.

The algorithm is similar to the previous one and it searches for the crime-relevant logs, extracts topics with authors, and collects the authors' distributions over time intervals within the discovered topics using A-TOT instead of LDA-TOT. The outputs are in the form of three distributions $(\vartheta, \varphi, \eta)$.

6. Empirical Study

In this section, we perform an empirical study on the two research questions addressed in Section 1 and provide the results with extensive details.

6.1. Data Preparation

The chat logs used in the experiment are obtained from a website called *perverted-justice.com* and *IRC* logs.

Perverted-Justice. This dataset consists of chat logs from various instant messages, e.g., Yahoo! and AOL, containing information about adults who seek online sexual conversations with others who are posing as children or underage teenagers (pseudo-victims). The dataset contains 250 log files and 500 authors [23]. We use only the time intervals associated with messages in these chat logs, without considering the exact date and time.

IRC. This dataset is collected from various IRC channels by running a mIRC application for about 10 days. The dataset contains 170 authors and 50 log files with a total of 4086 word tokens. There are 5 categories classified in multiple topics. Each message in the chat logs has a time stamp that is determined by the date and time intervals. As in the previous dataset, we use only the time intervals and ignore the date.

For both datasets, we first remove all links from the messages, stop words,

Table 2. Summary of the datasets

Dataset	Documents	Words	Unique Words
Perverted-Justice	250	27866	1455
IRC	50	4086	276

numbers, and non-English letters. The words are downcased and stemmed to their root source, using porter stemmer. However, words that rarely appear in a chat log are not removed, because the chat log differs from the structured documents and the words might be of value to the results. The results from the preprocessing step for both datasets consist of 620 authors and a total of 31952 word tokens. Some statistics of the two datasets after preprocessing are summarized in Table 2. The sizes of the two datasets are comparable to the size of datasets in real-life cases.

6.2. Evaluation Measures and Parameters Setting

To compute the correctness of the retrieved chat logs (d_c) by algorithms using LDA-TOT and A-TOT models, we calculate *Precision*, *Recall*, and *F-Measure*. The *Precision* of a model describes the number of the discovered chat logs d_c that are correct from overall retrieved logs that seem to be relevant; d_c is the crime-relevant chat log.

$$Precision = \frac{Number\ of\ true\ positives\ (truth\ d_c)}{Retrieved\ Documents} \tag{10}$$

The *Recall* of a model describes the number of the relevant (truth) chat logs d_c are successfully discovered by the model.

$$Recall = \frac{Number\ of\ true\ positives\ (truth\ d_c)}{Number\ of\ d_c\ are\ correct} \tag{11}$$

The *F-Measure* computes the weighted harmonic mean of precision and recall for a model.

$$F_\pi = (\pi^2 + 1) \cdot \frac{Precision \cdot Recall}{\pi^2 \cdot Precision + Recall} \tag{12}$$

where $\pi \in [0, \infty]$. In this paper, we use $\pi = 2$, which weighs recall higher than precision, and $\pi = 1$, which gives an equal weight for both measures, recall, and precision.

In addition to KL divergence, *Normalized Mutual Information (NMI)* is applied as a distance function. The NMI measures the contribution of the presence/absence of a term for making the correct classification decision on c. In our application, it measures the mutual dependence of t and the given c.

$$NMI(\Omega_t, C_c) = \frac{I(\Omega_t, C_c)}{(H(\Omega_t) + H(C_c))/2} \tag{13}$$

where $I(\Omega_t, C_c)$ refers to mutual information between the relevant topic Ω_t and a given criminal topic c. H stands for entropy [18]. *NMI* is always a number between 0 and 1, implying the two topics are independent or a complete match, respectively.

As for the other settings, we do not estimate the hyper parameters α, β, and

Table 3. Top 20 extracted crime-related words using CT

Word	Prob	Word	Prob
luv	0.0126	penis	0.0025
girl	0.0057	porn	0.0024
babi	0.0042	cum	0.0023
sweeti	0.0038	playin	0.0023
sex	0.0032	pretti	0.0021
suck	0.0031	cam	0.002
kiss	0.0031	pussi	0.0017
fuck	0.0029	naked	0.0015
watcha	0.0027	lick	0.0015
bed	0.0026	cock	0.0013

λ; instead, they are fixed at α=1, β=0.01, and λ=0.01, respectively. The number of topics T is also fixed at $|T|$=5 for both models.

The dataset *perverted-justice* contains explicit sex-related dialogue, which is considered to be a crime-relevant topic. To compute the φ distribution of topic c, where c is only sex related, we train the CT model with 200 chat logs from *perverted-justice*, and we keep 50 logs from *perverted-justice* and the other 50 from IRC for testing the outcomes from LDA-TOT and A-TOT. The objective of the test is to evaluate the effectiveness of using the proposed models to identify the crime-relevant, specifically the sex-related, chat logs. The chat logs are renamed $d_1, d_2, d_3, \ldots$ and authors are renamed $a_1, a_2, a_3, \ldots$ instead of using their true names due to privacy concerns.

We note that c could be any criminal topic and it is not fixed in its size. For the purpose of computing the likelihood of a language model M_c in generating the document d and to evaluate how different two probability distributions, c and d, are under different sizes of c, we use two sets of c, one containing 30 words and the other 50 words. In the experiments, we highlight different characteristics of the extracted topics and their transitions regarding the two sets of c. We also notice that some chat logs can be fully labeled as crime-relevant by providing only small set of terms in c.

The experiments are executed on a PC running Windows 7 (32-bit) with Intel 2.13GHz (2 CPUs) and 2GB memory. We run the application several times at a fixed number of 2000 iterations and record the outcomes each time in terms of KL$(t_{i,d}, c)$, NMI$(t_{i,d}, c)$, ϑ_a, and θ_d.

6.3. Scenario

In this subsection, we evaluate the effectiveness of our algorithms by performing an in-depth case study on the two aforementioned datasets to answer the two research questions. These two research questions elaborate on Definition 7, in Section 3. The resulting distributions $(\theta, \vartheta, \varphi, \eta)$ from LDA-TOT and A-TOT models are further analyzed to capture various characteristics of topics, authors, topics evolutions over time, and authors-topics over time intervals.

Q 1. How can an investigator determine which logs are crime-relevant? In identifying a crime-relevant log, what are the contributed topics in the log file? How have they evolved over time? Moreover, how can an investigator extract the crime-relevant topics from the identified crime-relevant log files?

Table 4. KL divergence between documents (d_1, d_2, d_3, d_4) and c when $|c|$=30 and $|c|$=50 using LDA-TOT and A-TOT

Documents	Size	KL(d_i, c)
d_1	$\|c\|$=30	2.9806
	$\|c\|$=50	3.0234
d_2	$\|c\|$=30	3.4087
	$\|c\|$=50	3.4684
d_3	$\|c\|$=30	3.0113
	$\|c\|$=50	3.0583
d_4	$\|c\|$=30	2.9729
	$\|c\|$=50	3.0220

Table 5. KL divergence and NMI between crime-relevant topics from documents (d_1, d_2, d_3, d_4) and c when $|c|$=30 and $|c|$=50 using LDA-TOT

Documents	Size	KL$(t_{i,d}, c)$	NMI$(t_{i,d}, c)$
d_1	$t_3(\|c\|$=30)	1.9664	0.0167
	$t_4(\|c\|$=50)	1.9760	0.0196
d_2	$t_3(\|c\|$=30)	1.2750	0.0206
	$t_0(\|c\|$=50)	1.3439	0.1725
d_3	$t_2(\|c\|$=30)	1.9358	0.3007
	$t_4(\|c\|$=50)	1.9290	0.0555
d_4	$t_2(\|c\|$=30)	1.6693	0.0039
	$t_1(\|c\|$=50)	1.6688	0.1033

To answer this question we apply the mining algorithm, using LDA-TOT to extract the crime-relevant topics, one chat log at a time. We select several logs randomly and record the similarities among these logs. Next, we adopt two expected cases, based on the results from KL(d, c) : 1- KL$(d, c) \leq \epsilon$ when d is crime-relevant. 2- KL$(d, c) > \epsilon$ when d is not crime-relevant.

For estimating the value of ϵ, we use the following equation:

$$\epsilon = \frac{\sum_{d \in D} KL(d, c)}{|D|} \times \varrho \tag{14}$$

The equation describes the average KL divergence between d and c of all the trained documents and the result is multiplied by ϱ. Supplementing ϱ, which is a user's threshold, in the equation adds some flexibility in controlling the average values and it avoids some extreme scores that might occur during the average computation process. For the γ value, we adopt the similar equation:

$$\gamma = \frac{\sum_{t \in T} KL(t, c)}{|T|} \times \varrho \tag{15}$$

From the training samples, we obtain the values ϵ=3.3109 and γ=2.0977, as an average over all the trained documents, for ϱ=0.5 and we use these settings for describing the two cases on 4 selected chat logs as below:

Case 1 (KL$(d, c) \leq \epsilon$)**:** From Definition 4, the document d is crime-relevant under this case. Based on the results from KL between d and c, as shown in Table 4, it is clear that 3 chat logs $\{d_1, d_3, d_4\}$ follow this case, and they are related to crime. We remind the reader again that topic c is sex related. LDA-

Table 6. Top 10 relevant words extracted for crime-relevant topics from documents (d_1, d_2, d_3, d_4) and their distribution over documents using LDA-TOT

d_1				d_2			
$\|c\|$=30		$\|c\|$=50		$\|c\|$=30		$\|c\|$=50	
t_3 (0.1666)	Prob	t_4 (0.1725)	Prob	t_3 (0.1550)	Prob	t_0 (0.1944)	Prob
girl	0.0463	guess	0.0655	dai	0.0194	wed	0.0259
feel	0.0301	good	0.0512	go	0.0194	know	0.0156
dad	0.0295	sweet	0.0209	talk	0.0161	earlier	0.0130
happi	0.0234	sleep	0.0166	sound	0.0065	thing	0.0104
stuff	0.0084	sex	0.0130	sad	0.0065	skidoo	0.0104
luv	0.0084	hot	0.0076	steal	0.0065	phone	0.0052
pantis	0.0080	young	0.0074	academi	0.0033	week	0.0052
plai	0.0071	bodi	0.0059	access	0.0033	color	0.0052
babi	0.0036	big	0.0052	channel	0.0033	pick	0.0052
dirti	0.0029	leg	0.0026	develop	0.0033	trust	0.0026

d_3				d_4			
$\|c\|$=30		$\|c\|$=50		$\|c\|$=30		$\|c\|$=50	
t_2 (0.1829)	Prob	t_4 (0.1742)	Prob	t_2(0.1622)	Prob	t_3 (0.1481)	Prob
preciou	0.0513	kiss	0.0203	pic	0.0406	sound	0.0223
wear	0.0434	babi	0.0168	eat	0.0180	eat	0.0194
luv	0.0433	time	0.0137	phone	0.0173	babi	0.0180
penis	0.0252	luv	0.0137	babi	0.0166	figur	0.0129
wear	0.0138	butt	0.0081	cloth	0.0113	sex	0.0115
kiss	0.0098	pic	0.0081	sex	0.0107	skirt	0.0115
sweet	0.0077	nite	0.0063	hot	0.0100	touch	0.0093
excit	0.0070	beauti	0.0059	ass	0.0093	hurt	0.0086
finger	0.0056	sweet	0.0044	naked	0.0087	shower	0.0072
lick	0.0026	lick	0.0029	cam	0.0087	masterb	0.0022

TOT generates 5 topics from each of these 3 chat logs, and the crime-relevant topics are shown in Table 6.

Not surprisingly, the top 10 relevant words, with high probabilities, provide sufficient information to classify these topics as crime-relevant, and the measurements from KL and NMI support our prospects as well. The θ_d^t distributions (between the round brackets) for these topics are above 0.2, which represents about one-fifth of the logs. This computation is far more essential because it distinguishes the crime-relevant chat logs from others, and the importance of θ_d is well demonstrated in case 2.

By observing KL(d, c) and KL$(t_{i,d}, c)$ from Tables 4 and 5, we notice that the results are not always monotonic. For example, KL(d_1, c)=2.981 and KL(d_3, c) =3.0113 when the size of $|c|$=30. However, KL(t_{2,d_3}, c)=1.9358 is more relevant to c than KL(t_{3,d_1}, c)=1.9664. In addition, NMI seems to behave different for both of these topics t_{3,d_1}=0.0167 and t_{2,d_3}=0.3007.

Probabilistic topic models, such as LDA-TOT, are based on the concept of generating topics randomly; each time it extracts topics with different probability distributions. Therefore, the results obtained from KL and NMI between discovered topics and c are not necessarily monotonic. Nevertheless, the algorithm discovers crime-relevant chat logs if they exist in a collection of data texts and it terminates if ζ is satisfied.

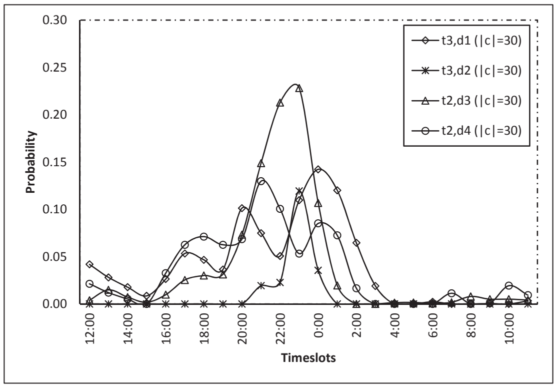


Fig. 5. Evolution of crime-relevant topics using LDA-TOT when $|c|$=30

Furthermore, the NMI of topic t_{0,d_4} should obtain better results because KL(d_4, c)=2.9729 clearly indicates that d_4 is more proximate to be classified as a crime-relevant log than the other chat logs shown in Table 4. After 4000 iterations, we found KL(t_{3,d_4}, c)=1.5944 and NMI of this topic is t_{3,d_4}=0.3564.

Case 2 (KL$(d, c) > \epsilon$)**:** This case occurs whenever a chat log does not satisfy the user-specified threshold ϵ. From Table 4, the only chat log that falls under this category is d_2. Obviously, t_{3,d_2} ($|c|$=30) for this chat log does not contain the expected words for it to be classified as crime-relevant.

We observe an interesting result from KL(t_{3,d_2}, c), and it satisfies the user-specified threshold γ. In general, KL measures the distance between the two models (t and c). This is achieved by comparing the probability of the shared words in both topics c and t_{3,d_2}. We do not consider fixed vocabulary in the comparison, rather we depend on the mutual words. Suppose the unique words for both $|c|$=30 and $|t_1|$=500. If the two models have joint words, with similar probability, then the KL distance for both models is similar. Consequently, the result from KL(t_{3,d_2}, c) fits with the threshold γ.

On the other hand, the $\theta_d^{t_1}$ distribution shows that approximately 0.1550 of d_2 is about criminal subjects. From KL(d_2, c), we conclude that the d_2 is not crime-relevant.

One might ask whether the condition KL$(t_{i,d}, c)$=0 applies for both cases. This might occur, but it does not necessarily mean that a topic is crime-relevant, and case 2 sheds some light on it. A topic t is considered to be crime-relevant whenever the two conditions hold: KL$(d, c) \leq \epsilon$ and KL$(t_{i,d}, c) \leq \gamma$.

When we alter the size of c by increasing the number of criminal terms to 50, the results from KL$(t_{i,d}, c)$ and NMI are improved, as observed in Table 5. The top 10 words in Table 6 include new crime-relevant terms that were not observed when $|c|$=30. This is not a coincidence, since the words used in c are drawn from the two datasets. In general, increasing the size of c gives better predictions about the distance between discovered topics and c.

In addition to topics extraction, the LDA-TOT is able to predict the time associated with each message in a chat log. Figure 5 includes the fluctuations of relevant topics from 4 chat logs when $|c| = 30$. The characteristics of the transitions can be classified through the transition function $F(t)_{\tau^s}^{\tau^f}$ as *active* and *not-active*. In many cases, the activity of topics is provided by investigators to

Table 7. Cosine similarities between each of the documents (d_1, d_2, d_3, d_4) and c for each words in V

	d_1	d_2	d_3	d_4
$sim(d_i, c)$	0.8403	0.5257	0.8267	0.7999

assist them in analyzing different rise and falls of topics. Therefore, we define the transition function as:

$$\digamma(t)_{\tau^s}^{\tau^f} = \begin{cases} \text{active} & \text{if } \sum_{\tau^s}^{\tau^f} p(t)^{\tau^s} \geq \text{user's threshold} \\ \text{not-active} & \text{if } \sum_{\tau^s}^{\tau^f} p(t)^{\tau^s} < \text{user's threshold} \end{cases}$$

$\sum_{\tau^s}^{\tau^f} p(t)^{\tau^s}$ sums the probability of a topic t during interval $[\tau_s, \tau_f]$. $\digamma(t)_{\tau^s}^{\tau^f}$ indicates the activity of t. We found the best results are obtained when an average of θ_d over the three highest topics is considered for estimating the user-specified threshold. For instance, when setting the user-specified threshold to 0.2143, as an average of θ_{d_1} over 3 topics, the topic t_{3,d_1} ($|c|$=30) is active during [22:00, 1:00] and not active elsewhere.

In general, the topics $t_{3,d_1}, t_{3,d_2}, t_{2,d_3}, t_{2,d_4}$ ($|c|$=30) are widely active during time intervals [15:00,3:30] when $p(t)_{\tau^s}^{\tau^f} \geq$0.2143, with a peak on [21:00,1:00]. Investigators collect information, within certain intervals, that indicates the activity of crime-relevant topics, thus providing the start point for the investigation process.

We conclude that a crime-relevant chat log d can be recognized through $KL(d, c)$, and the crime-relevant topics are determined by three factors: θ_d^t, $KL(d, c)$, and $KL(t_{i,d}, c)$. The characteristics of the relevant topics are studied through NMI, and the high probability of NMI means obtaining a better quality of discovered topics. In addition, the evolution of topics is demonstrated through the transition function $\digamma(t)_{\tau^s}^{\tau^f}$, in terms of active or not active, in the given time intervals associated with each message in logs.

To further demonstrate our process for segregating crime-relevant documents, we use the cosine similarity to measure document similarity:

$$sim(d_1, d_2) = \frac{\overrightarrow{q_{d_1}} \cdot \overrightarrow{q_{d_2}}}{|\overrightarrow{q_{d_1}}||\overrightarrow{q_{d_2}}|} \tag{16}$$

where $\overrightarrow{q_{d_1}} \cdot \overrightarrow{q_{d_2}}$ represents the standard vector dot product, described as $\sum_{v \in V}(q_{v,d_1}$ $q_{v,d_2})$, and the denominator represents the product of their *Euclidean lengths*, described as $\sqrt{\sum_{v \in V} q_{v,d_1}^2}$.

To compute vector q_c, we apply Equation 5 to determine the weighted value for each criminal term during the learning phase over V instead of W_c on the training samples. For q_{d_i}, we use the same Equation 5 to calculate the weighted value for each word in d_i over V dimensions. Table 7 quantifies the similarity scores between each of the 4 chat logs and c for each word in V. We observe that document d_2 differs from d_1, d_3, and d_4 in its similarity value. Furthermore, Table 8 shows the cosine similarities between pairs of the resulting V dimensional vectors for 4 chat logs. A cosine computation between documents d_1, d_3, and d_4

Table 8. Cosine similarities between pairs of the resulting V dimensional vectors for (d_1, d_2, d_3, d_4)

	d_1	d_2	d_3	d_4
$sim(d_i, d_1)$	1.0000	0.4358	0.6624	0.7586
$sim(d_i, d_2)$	0.4358	1.0000	0.4342	0.3760
$sim(d_i, d_3)$	0.6624	0.4342	1.0000	0.6373
$sim(d_i, d_4)$	0.7586	0.3760	0.6373	1.0000

Table 9. KL divergence and NMI between crime-relevant topics from documents (d_1, d_2, d_3, d_4) and c when $|c|$=30 and $|c|$=50 using A-TOT

Documents	Size	KL($t_{i,d}, c$)	NMI($t_{i,d}, c$)
d_1	$t_2(\|c\|=30)$	1.9558	0.0557
	$t_4(\|c\|=50)$	1.8599	0.0118
d_2	$t_0(\|c\|=30)$	1.2967	0.1698
	$t_1(\|c\|=50)$	1.2960	0.0095
d_3	$t_1(\|c\|=30)$	1.9538	0.1597
	$t_1(\|c\|=50)$	1.9820	0.3810
d_4	$t_4(\|c\|=30)$	1.6872	0.0560
	$t_0(\|c\|=50)$	1.7164	0.1407

shows that they are similar, but d_2 is different from other chat logs. If 0.75 is chosen to be the splitting point in classifying crime-related documents, we obtain similar conclusions with KL(d_2, c) value from Table 4. Since this value does not satisfy the user-specified threshold ϵ=3.3109,d_2 is not crime-relevant.

Q 2. Who are the contributors to a topic in a given chat log? How can an investigator track the activity of authors in a log file?

We divide this question into two parts. First, we determine the proportions of each author contributing in each of the extracted topics. Second, we explore the impacts of the authors throughout the time intervals on the extracted topics. This time, we employ the mining algorithm, using a A-TOT model to study the two parts of the question. The two users' threshold ϵ and γ are empirically set to 3.3109 and 2.0977, respectively.

A-TOT implementation is slightly different from the proposed one because we are concerned with collecting information related to θ_d and ϑ_a distributions. We apply the same 4 chat logs that explore the first research question. From each of these chat logs, A-TOT generates 5 topics with authors associated to each. The θ_d distribution for the crime-relevant topics, from the 4 chat logs, is displayed (between the round brackets) in Table 10. We observe similar results when comparing the distribution θ_d, from Tables 6 and 10, for both models, LDA-TOT and A-TOT. However, the comparison between A-TOT and LDA-TOT is not addressed in this paper.

The generated ϑ_a^t distribution using A-TOT is shown in Table 10. The top 3 authors with the highest probabilities for each of the crime-relevant topics in each of the 4 chat logs are displayed. For example, author a_1 in d_3 has a probability of 0.2000 for topic t_1, which outlines the contribution of a_1 out of all authors to the crime-relevant topic t_1 when $|c|$=30.

Though ϑ_a^t distribution assists investigators to identify the plausible authors in the crime-relevant topics, it does not provide the contributions and activity of

Table 10. Top 10 relevant words extracted for crime-relevant topics from documents (d_1, d_2, d_3, d_4), their distribution over documents, and their distribution over top 3 authors using A-TOT

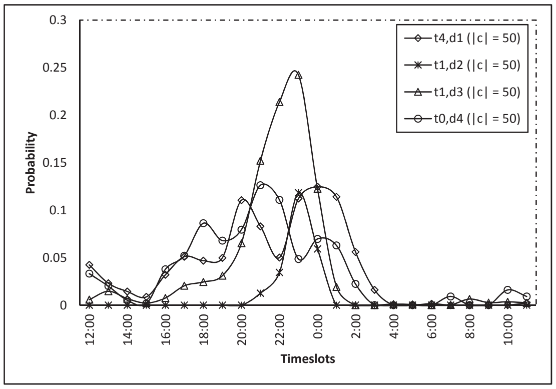
d_1				d_2			
$\vert c\vert=30$		$\vert c\vert=50$		$\vert c\vert=30$		$\vert c\vert=50$	
t_2 (0.2382)	Prob	t_4 (0.1648)	Prob	t_0 (0.2096)	Prob	t_1 (0.1790)	Prob
make	0.0487	talk	0.0280	wed	0.0299	wed	0.0312
link	0.0403	girl	0.0186	dai	0.0179	hour	0.0125
gui	0.0340	see	0.0107	earlier	0.0149	gnite	0.0094
nice	0.0258	nite	0.0092	care	0.0120	care	0.0063
show	0.0187	suck	0.0077	feel	0.0120	wonder	0.0063
butt	0.0175	cum	0.0069	old	0.0060	drive	0.0063
babi	0.0155	whatcha	0.0062	quit	0.0060	sound	0.0063
luv	0.0119	pic	0.0059	pc	0.0060	learn	0.0031
cum	0.0110	eat	0.0055	week	0.0060	convers	0.0031
figur	0.0098	bodi	0.0050	sound	0.0060	presum	0.0031
Authors	**Prob**	**Authors**	**Prob**	**Authors**	**Prob**	**Authors**	**Prob**
a_1	0.3117	a_1	0.1824	a_1	0.2257	a_5	0.2435
a_2	0.2365	a_2	0.1742	a_2	0.2188	a_4	0.2203
a_3	0.2361	a_4	0.1507	a_3	0.2075	a_7	0.2157

d_3				d_4			
$\vert c\vert=30$		$\vert c\vert=50$		$\vert c\vert=30$		$\vert c\vert=50$	
t_1 (0.1777)	Prob	t_1 (0.1930)	Prob	t_4 (0.1907)	Prob	t_0 (0.1941)	Prob
preciou	0.0740	think	0.1039	feel	0.0238	eat	0.0154
look	0.0527	luv	0.0558	suck	0.0168	phone	0.0149
wear	0.0259	tell	0.0543	kiss	0.0116	gf	0.0137
babi	0.0175	luv	0.0558	show	0.0110	show	0.0109
touch	0.0170	feel	0.0321	fuck	0.0052	luv	0.0109
hear	0.0103	butt	0.0166	watcha	0.0052	figur	0.0103
sweet	0.0101	suck	0.0162	porn	0.0052	peopl	0.0097
shower	0.0067	nite	0.0126	bra	0.0052	tit	0.0074
hand	0.0062	big	0.0115	stick	0.0046	cam	0.0074
eat	0.0062	show	0.0075	bike	0.0046	rite	0.0074
Authors	**Prob**	**Authors**	**Prob**	**Authors**	**Prob**	**Authors**	**Prob**
a_1	0.2000	a_3	0.2258	a_1	0.2355	a_1	0.2210
a_2	0.1998	a_4	0.2227	a_2	0.2020	a_2	0.2008
a_3	0.1613	a_1	0.2000	a_3	0.1835	a_3	0.1992

each author during specific time intervals within topics. From Definition 1, time τ_d is associated with both message μ_d and author a_d. Hence, for the second part of the question we keep tracking the times since the messages were composed. Following up, we characterize the contributions of authors during time interval $[\tau^s, \tau^f]$ by:

$$\digamma(a_d^t)_{\tau^s}^{\tau^f} = \begin{cases} \text{active} & \text{if } p(a_d^t)_{\tau^s}^{\tau^f} \geq \text{user's threshold, } \digamma(t)_{\tau^s}^{\tau^f} \text{ is active} \\ \text{not-active} & \text{otherwise} \end{cases}$$

An author is said to be *active* during the interval $[\tau^s, \tau^f]$ for topic t if the probability of an author participating in t, during that interval, exceeds the user-specified threshold, and $\digamma(t)_{\tau^s}^{\tau^f}$ is *active* within that period. The user-



[!t]

Fig. 6. Evolution of crime-relevant topics using A-TOT when $|c|$=50

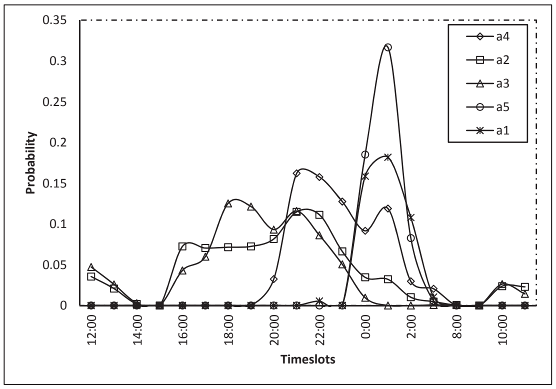


Fig. 7. Authors activity for crime-relevant topic t_{4,d_4} using A-TOT when $|c|$=50

specified threshold is calculated by taking an average of ϑ_a^t over authors for t. To compute $p(a_{i,d}^t)_{\tau^s}^{\tau^f}$, we first map the contribution of an author $a_{i,d}^t$, within $[\tau^s, \tau^f]$, using $P(a^{\tau^s}|t)=\frac{p(a^{\tau^s}|d^{\tau^s})\cdot p(t^{\tau^s}|d^{\tau^s})}{p(d^{\tau^s})}$ per time instance s. Next, we calculate $\sum_{\tau^s}^{\tau^f} P(a^{\tau^s}|t)$, as a total probability for author a^t during $[\tau^s, \tau^f]$.

The transitions of the crime-relevant topics when $|c|$=50 using A-TOT are shown in Figure 6. From this figure and the mapping function, we determine the activity of authors over time. For example, let us analyze the activity of authors in topic t_{4,d_4} during [16:00,19:00].

First, we determine the user-specified threshold, which is 0.1940 as an average of ϑ^{t_4}. Next, the mapping function is calculated for all authors. For simplicity, let us pick an author a_3 and time instance s=16:00. Then, we compute the mapping function, which is $P(a_{3,\tau^{16:00}}|t_4)$= 0.0584. Afterwards, the total probability of a_3 is estimated by computing $\sum_{\tau^{16:00}}^{\tau^{19:00}} P(a_{3,\tau^s}|t_4)$=0.2687. Consequently, we say the authors (a_2, a_3) for topic t_{4,d_1} are *active* for satisfying the two conditions when applying the transition function $\digamma(a_d^t)_{\tau^s}^{\tau^f}$, while the authors (a_1, a_4, a_5) are not.

Table 11. Precision, Recall, F_1, and F_2 using LDA-TOT and A-TOT

	Precision	Recall	F_1	F_2
$\|c\|$=30	0.8235	1	0.9032	0.9211
$\|c\|$=50	0.8642	1	0.9272	0.9409

Figure 7 summarizes the activity of authors for the crime-relevant topic t_{4,d_1}. It can be observed that the most active time for authors occurred during [0:00,7:00] and [15:00,23:00]. This helps the investigators to determine the initiator of a topic and to capture the plausible authors within intervals. If the given time period [15:00,19:00] is an important interval for an investigator, then the suspected authors are (a_2, a_3), since they are active during that phase of time, while (a_1, a_4, a_5) are not active.

Similarly to LDA-TOT, when we increase the size of c the probability of authors-topics are different in the context of crime-relevant topics. For example, from Table 10, the probability of author a_1 in t_{2,d_1} when $|c|$=30 is 0.3117, unlike 0.1824 when $|c|$=50. The NMI for the discovered crime-relevant topics, shown in Table 9, are improved and new words are obtained, as explored in Table 10. Hence, we determine that the NMI value of topics quantifies the best obtained results. Note, the criminal words used in c are collected from the two datasets.

We conclude that ϑ_a^t, which describes the authors-topics distribution, defines authors contributions in each topic. The characteristics of the authors during several intervals is studied through the transition function $\digamma(a_d^t)_{\tau^s}^{\tau^f}$. In addition, integrating the two distributions, ϑ_a and η_t, into the A-TOT model assists investigators in searching for authors-topics and topics over time, instead of relying on separate time-consuming computation.

For the purpose of estimating the precision and recall values regarding our mining algorithm, we compose randomly 100 chat logs as a combination of both aftermentioned datasets, perverted-justice and IRC, with minimum of 1500 word tokens per log file. In Table 11, we list the mode values of precision, recall, F_1, and F_2 measures for the two models previously described, LDA-TOT and A-TOT, after running the algorithm 10 times for 200 chat logs, 100 logs from the combination process and the other 100 are test logs that is described in Section 6.2. Both models found all the truth-relevant chat logs, achieving recall values of 1.0 for the two conditions ($|c|$=30 and $|c|$=50). For precision, there are 30 incorrect logs being retrieved for $|c|$=30 and 22 logs for $|c|$=50; therefore, the values are 0.8235 and 0.8642, respectively. The worst precision is 0.7910 and the best is 0.8485 for $|c|$=30 while running the algorithm 10 times. Similarly, for $|c|$=50, the worst precision is 0.8434 and the best is 0.8861.

The different precision values with the two different sizes of c can be explained through KL(d, c). Using fewer terms in c increases the KL(d, c) value, and thus decreases the precision; vice versa is also true. The calculated results seem to be subjective. This is because the datasets are not large enough, and we expect precision to be low whenever the size of terms provided in c is small in a huge collection of data.

Table 12. KL divergence and NMI between crime-relevant topics from documents (d_1, d_2, d_3, d_4) and c when $|c|$=30 and $|c|$=50 using LDA

Documents	Size	KL$(t_{i,d}, c)$	NMI$(t_{i,d}, c)$
d_1	$t_3(\lvert c\rvert$=30)	1.4080	0.0328
	$t_3(\lvert c\rvert$=50)	1.4214	0.0457
d_2	$t_2(\lvert c\rvert$=30)	1.2693	0.0589
	$t_0(\lvert c\rvert$=50)	1.2795	0.1037
d_3	$t_1(\lvert c\rvert$=30)	1.3101	0.0119
	$t_1(\lvert c\rvert$=50)	1.3257	0.0690
d_4	$t_1(\lvert c\rvert$=30)	1.3101	0.0119
	$t_2(\lvert c\rvert$=50)	1.3211	0.0249

Table 13. KL divergence and NMI between crime-relevant topics from documents (d_1, d_2, d_3, d_4) and c when $|c|$=30 and $|c|$=50 using AT

Documents	Size	KL$(t_{i,d}, c)$	NMI$(t_{i,d}, c)$
d_1	$t_1(\lvert c\rvert$=30)	1.7662	0.0339
	$t_1(\lvert c\rvert$=50)	1.9558	0.0518
d_2	$t_1(\lvert c\rvert$=30)	1.2874	0.0075
	$t_2(\lvert c\rvert$=50)	1.3173	0.0206
d_3	$t_0(\lvert c\rvert$=30)	1.9482	0.3730
	$t_3(\lvert c\rvert$=50)	1.9533	0.1249
d_4	$t_3(\lvert c\rvert$=30)	1.5904	0.2105
	$t_1(\lvert c\rvert$=50)	1.5638	0.0900

6.4. Comparison with LDA and AT models

In this section, we compare our models with LDA and AT. We apply the same algorithm with LDA and AT and the same settings of parameters ϵ=3.3109 and γ=2.0977 for ϱ=0.5. From Tables 13 and 12, we determine that d_2 is not crime-relevant, as with LDA-TOT and A-TOT, and d_1, d_3, and d_4 are crime-relevant. The topics' distributions, θ and ϑ, in d_1, d_2, d_3, and d_4 for LDA and AT are illustrated in Tables 14 and 15. Both models, LDA and AT, are able to discover crime words in the extracted topics and somehow similar to the results obtained using LDA-TOT and A-TOT in Tables 6 and 10. By manual checking, we observe that LDA-TOT and A-TOT models extract θ and ϑ in which is better than the topics discovered using LDA and AT. Furthermore, the authors' distribution over topics in A-TOT is much better comparing with AT. The reason is that words in chatlogs are associated with time-intervals and both models, LDA-TOT and A-TOT, embed this feature into the computation process unlike LDA and AT models. Although, LDA and AT discovers similar topics distribution, the LDA-TOT and A-TOT models are still very useful for two factors: one utilizing the topics over time and secondly employing the authors-topics over time.

In addition to the previous qualitative evaluating of our models, we estimate the power of LDA-TOT and A-TOT models by computing the perplexity of these models and comparing them with LDA and AT models. Perplexity is a standard measurement in document modeling that is used to measure the ability of a model to predict unseen data. Thus, the goal is to obtain high likelihood on a held-out test set. In other words, our objective is to evaluate the predictive power of the model in unseen data. A lower perplexity score indicates the higher

Table 14. Top 10 relevant words extracted for crime-relevant topics from documents (d_1, d_2, d_3, d_4) and their distribution over documents using LDA

d_1				d_2			
$\|c\|$=30		$\|c\|$=50		$\|c\|$=30		$\|c\|$=50	
t_3 (0.2038)	Prob	t_2 (0.2977)	Prob	t_2 (0.1703)	Prob	t_2 (0.1526)	Prob
rest	0.0178	believ	0.0149	think	0.0103	wed	0.0186
scream	0.0111	gross	0.0148	thank	0.0069	good	0.0130
wine	0.0089	nice	0.0138	wine	0.0069	dai	0.0112
butt	0.0089	feel	0.0135	grei	0.0069	earlier	0.0093
sweat	0.0067	fuck	0.0126	daughter	0.0035	minut	0.0093
nervou	0.0067	butt	0.0122	morn	0.0035	talk	0.0093
leg	0.0045	sound	0.0122	stomach	0.0035	feel	0.0075
pussi	0.0045	believ	0.0122	dinner	0.0035	nice	0.0075
crash	0.0045	whatcha	0.0114	internet	0.0035	care	0.0075
virgin	0.0045	gross	0.0102	appoint	0.0035	hour	0.0075

d_3				d_4			
$\|c\|$=30		$\|c\|$=50		$\|c\|$=30		$\|c\|$=50	
t_1 (0.2267)	Prob	t_1 (0.1975)	Prob	t_2(0.1927)	Prob	t_2 (0.1658)	Prob
miss	0.0627	see	0.0474	cool	0.0169	think	0.0222
feel	0.0475	time	0.0359	see	0.0162	cool	0.0176
butt	0.0358	luv	0.0310	luv	0.0156	see	0.0168
wear	0.0214	tell	0.0271	look	0.0149	luv	0.0162
cam	0.0209	look	0.0204	pic	0.0148	cum	0.0155
kiss	0.0182	miss	0.0196	cum	0.0138	girl	0.0153
concentr	0.0157	feel	0.0189	tell	0.0129	wear	0.0143
scroll	0.0144	butt	0.0176	girl	0.0116	nite	0.0134
christma	0.0131	kiss	0.0166	wear	0.0116	feel	0.0120
friend	0.0131	talk	0.0162	nite	0.0116	pussi	0.0120

the likelihood and a better generalization performance can be achieved. For AT and A-TOT, we do not explore the range of perplexity scores that these models assign to test sets from specific authors [2]. Formally, the perplexity for a set of test documents D_{test} is defined as

$$Perplexity(w) = exp\{-\frac{\sum_{d \in D_{test}} \log p(w_d)}{\sum_{d \in D_{test}} N_d}\} \tag{17}$$

We train LDA, AT, LDA-TOT and A-TOT models on a set of 200 logs from *perverted-justice* while holding 100 logs, 50 logs from *perverted-justice* and the other 50 from IRC, for computing and comparing the perplexity of the aftermentioned models. Figure 8 depicts the average runtime in minutes for LDA, AT, LDA-TOT and A-TOT models on the training samples. It clearly shows that the LDA and LDA-TOT outperform the AT and A-TOT models. Figure 9 shows the average perplexity results for multiple numbers of the topics varying from 3 to 25.

As can be seen, the A-TOT model achieves a significant improvement on the generalization performance in test set with respect to LDA, AT and LDA-TOT models. By utilizing authors and time-intervals into the A-TOT model, A-TOT has the lowest perplexity among the other models and over multiple

Table 15. Top 10 relevant words extracted for crime-relevant topics from documents (d_1, d_2, d_3, d_4), their distribution over documents, and their distribution over top 3 authors using AT

d_1				d_2			
$\|c\|$=30		$\|c\|$=50		$\|c\|$=30		$\|c\|$=50	
t_1 (0.2182)	Prob	t_2 (0.2380)	Prob	t_1 (0.1856)	Prob	t_2 (0.1550)	Prob
think	0.0195	friend	0.0262	feel	0.0124	wed	0.0226
eat	0.0176	nice	0.0258	night	0.0124	part	0.0129
wonderin	0.0176	fun	0.0210	physic	0.0062	feel	0.0129
place	0.0113	sweet	0.0114	miss	0.0052	morn	0.0097
badli	0.0113	watcha	0.0114	work	0.0045	pick	0.0065
tire	0.0113	skirt	0.0112	monei	0.0031	wine	0.0065
front	0.0094	luv	0.0098	start	0.0031	drive	0.0065
lookin	0.0076	sex	0.0096	final	0.0031	sunni	0.0033
rite	0.0069	kiss	0.0086	job	0.0031	place	0.0033
friend	0.0063	miss	0.0082	blow	0.0031	academi	0.0033
Authors	**Prob**	**Authors**	**Prob**	**Authors**	**Prob**	**Authors**	**Prob**
a_1	0.2887	a_3	0.2986	a_{10}	0.2838	a_3	0.2075
a_5	0.2738	a_5	0.2953	a_7	0.2157	a_6	0.2000
a_3	0.2694	a_4	0.2704	a_3	0.2075	a_7	0.1961

d_3				d_4			
$\|c\|$=30		$\|c\|$=50		$\|c\|$=30		$\|c\|$=50	
t_0 (0.1598)	Prob	t_3 (0.1745)	Prob	t_3 (0.1959)	Prob	t_1 (0.1969)	Prob
luv	0.1305	luv	0.0614	nite	0.0436	phone	0.0328
look	0.0582	miss	0.0580	peopl	0.0409	rub	0.0278
peni	0.0524	pretti	0.0443	sex	0.0334	whatcha	0.0265
wish	0.0233	sound	0.0390	keep	0.0306	brave	0.0215
cam	0.0214	stick	0.0363	bad	0.0204	boob	0.0152
babi	0.0193	night	0.0185	fingerin	0.0158	sex	0.0152
bad	0.0111	eat	0.0155	leg	0.0130	acoust	0.0126
kiss	0.0111	kiss	0.0127	shave	0.0130	masterb	0.0114
excit	0.0111	cum	0.0111	wrong	0.0130	chicken	0.0114
dream	0.0111	figur	0.0102	imag	0.0121	penis	0.0101
Authors	**Prob**	**Authors**	**Prob**	**Authors**	**Prob**	**Authors**	**Prob**
a_1	0.2000	a_1	0.2000	a_5	0.1445	a_5	0.1043
a_2	0.1873	a_3	0.1935	a_3	0.1132	a_3	0.0760
a_3	0.1613	a_2	0.1834	a_1	0.1123	a_1	0.0978

numbers of topics. That is, A-TOT is a better model by assigning higher likelihood to held-out documents than LDA, AT and LDA-TOT. Intuitively, all the four models have lower perplexity when $|T|$=5 and higher elsewhere. Furthermore, the perplexity escalates when $|T|$>5 for all of the models in Figure 9. This can be justified by manually analyzing the test datasets and we observe that the number of topics barely exceeds 5 to 6 topics and therefore; the perplexity is high and this is the reason behind choosing $|T|$=5 in our experiments.

It is possible to further lower the perplexity of LDA-TOT and A-TOT by computing the time-intervals in per word perplexity. But we do not conduct this direction because we focus on the illustrative part in our perplexity experiments and not necessarily conclusive. Finally, we note that the main focus for devel-

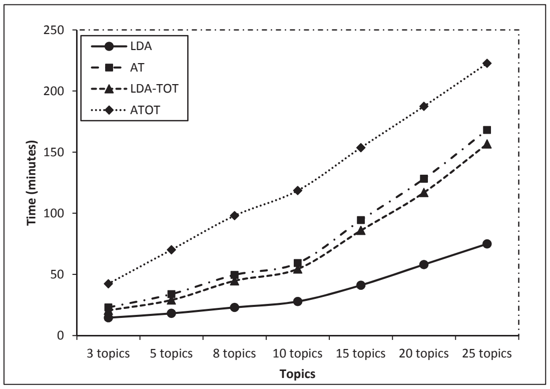


Fig. 8. Average time versions varying the number of topics for LDA, AT, LDA-TOT and A-TOT models on the training samples

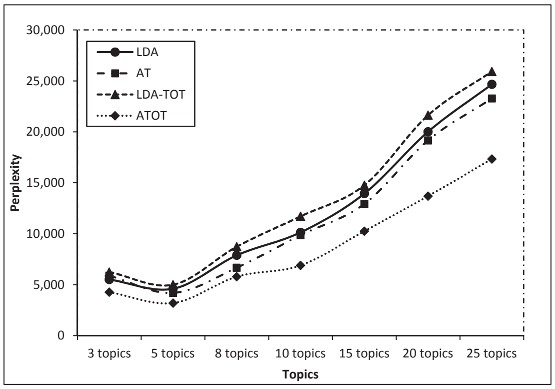


Fig. 9. Average perplexity for LDA, AT, LDA-TOT and A-TOT models

oping these two models is to reduce the computation and to capture temporal information, whether as topics over time, as LDA-TOT, or as authors-topics over time, as A-TOT, in addition to covering the first three differences in Section 1.

7. Conclusions and Lessons Learned

We propose an effective method to extract information from collections of documents. The collected information includes authors, topics, topics time-trends, and authors-topics over time. We sought to study chat logs, in different granularity, to identify and segregate crime-relevant logs and topics associated with these logs. Next, we studied the concept of evolution of topics over time in order to explore the temporal information in these topics. We went a step further by exploring the activity of authors within these topics, which represents the evolution of authors-topics over time. In an attempt to build our proposed method we developed two models, LDA-TOT and A-TOT, with multiple modality attributes influenced by three past models, LDA, AT, and TOT. As for evolution, we used discretization of time to capture different fluctuations of topics over discrete time stamps, instead of using continuous time as does the TOT model.

We conducted extensive empirical study of the proposed models by applying results on two real-life datasets, and we demonstrated that our approach can identify crime-relevant topics. Furthermore, based on topics expressed in a log and the activity of the authors, the system is capable of determining the most plausible authors.

Despite the advantages, probabilistic models, ours and in general, suffer from several shortcomings. We list the major limitations when applied to chat logs:

- **Document size.** Due to the short size of chat logs in general, it was hard to obtain the best mixture of topics θ_d and the authors-topics distribution ϑ_a when conducting experiments, and we applied the two algorithms for 10 times and captured the outcomes each times and the displayed results are randomly selected. Therefore, we deduce that the accuracy of the extracted topics depends on the size of the chat logs. Although several works, such as [5], deal with short text environments (microblogging), such as Twitter, none of them define a proper method for dealing with texts in chat logs.
- **Input processing.** In many cases, we observe that depending on the "bag of words" assumption might not infer a true topic in a chat log. For example, if a chat log is related to a drug topic and drug-related terms occur a few times, the model might generate topics not related to drugs. Additionally, none of these models care much about the words processing. These words might contain a lot of noise, ambiguity, and even imprecision.
- **Users' thresholds.** We used several thresholds in our experiments, such as the number of topics ($|T|$). Though Teh et al. [24] proposed a *Hierarchical Dirichlet Processes model* that automatically infers the number of topics among the documents, other thresholds as $\digamma(a_d^t)_{\tau^s}^{\tau^f}$, which lies outside the A-TOT model, are not automatically defined. Nonetheless, our choices are somewhat subjective, as there is no standard way to determine the optimal values.

These limitations motivate us to consider additional future research directions to address the limitations.

Finally, we would like to share our collaborative experience with the law enforcement sector. Criminal data are complex, often a combination of relational data, transaction data, and textual data. So far, our project focuses only on the textual data, but we notice that there is a pressing need for more crime data mining methods for heterogeneous types of data. Besides the technical issue, it is equally important to educate law enforcement management and frontline officers about the latest data mining technology. When management encounters a case that involves a large volume of digital data, the initial response is to allocate more team members to the case. In fact, alternative techniques are available that can significantly speed up the investigation process, such as the topic modeling technique presented in this paper.

Acknowledgements. The authors would like to thank the anonymous reviewers for their constructive comments that greatly helped improve this paper. The research is supported in part by research grants from Le Fonds québécois de la recherche sur la nature et les technologies (FQRNT) new researchers start-up program, Concordia ENCS seed funding program, and the National Cyber-Forensics and Training Alliance Canada (NCFTA Canada).

References

[1] D. M. Blei, A. Y. Ng, and M. I. Jordan, “Latent dirichlet allocation,” *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, 2003.

[2] M. Rosen-Zvi, T. Griffiths, M. Steyvers, and P. Smyth, “The author-topic model for authors and documents,” in *Proceedings of the 20th UAI*, 2004, pp. 487–494.

[3] X. Wang, N. Mohanty, and A. McCallum, “Group and topic discovery from relations and text,” in *Proceedings of the 3rd ACM LinkKDD*, 2005, pp. 28–35.

[4] D. Ramage, D. Hall, R. Nallapati, and C. D. Manning, “Labeled lda: a supervised topic model for credit attribution in multi-labeled corpora,” in *Proceedings of the 2009 EMNLP: Volume 1*, 2009, pp. 248–256.

[5] L. Hong and B. D. Davison, “Empirical study of topic modeling in twitter,” in *Proceedings of the 1st SOMA*, 2010, pp. 80–88.

[6] S. Banerjee and N. Agarwal, “Analyzing collective behavior from blogs using swarm intelligence,” *KAIS*, pp. 1–25, 2012.

[7] D. Blei and J. McAuliffe, “Supervised topic models,” in *Advances in Neural Information Processing Systems 20*, 2008, pp. 121–128.

[8] S. Lacoste-julien, F. Sha, and M. I. Jordan, “Disclda: Discriminative learning for dimensionality reduction and classification,” vol. 22. NIPS, 2008.

[9] D. Ramage, P. Heymann, C. D. Manning, and H. Garcia-Molina, “Clustering the tagged web,” in *Proceedings of the 2nd ACM WSDM*, 2009, pp. 54–63.

[10] T. Rubin, A. Chambers, P. Smyth, and M. Steyvers, “Statistical topic models for multi-label document classification,” *Machine Learning*, vol. 88, pp. 157–208, 2012.

[11] J. Chang, J. Boyd-Graber, and D. M. Blei, “Connections between the lines: augmenting social networks with text,” in *Proceedings of the 15th ACM SIGKDD*, 2009, pp. 169–178.

[12] X. Song, C.-Y. Lin, B. L. Tseng, and M.-T. Sun, “Modeling and predicting personal information dissemination behavior,” in *Proceedings of the 11th ACM SIGKDD*, 2005, pp. 479–488.

[13] X. Wang and A. McCallum, “Topics over time: a non-markov continuous-time model of topical trends,” in *Proceedings of the 12th ACM SIGKDD*, 2006, pp. 424–433.

[14] C. Wang, D. M. Blei, and D. Heckerman, “Continuous time dynamic topic models,” in *UAI’08*, 2008, pp. 579–586.

[15] D. M. Blei and J. D. Lafferty, “Dynamic topic models,” in *Proceedings of the 23rd ICML*, 2006, pp. 113–120.

[16] L. AlSumait, D. Barbará, and C. Domeniconi, “On-line lda: Adaptive topic models for mining text streams with applications to topic detection and tracking,” in *Proceedings of the 8th IEEE ICDM*, 2008, pp. 3–12.

[17] L. Du, W. Buntine, H. Jin, and C. Chen, “Sequential latent dirichlet allocation,” *KAIS*, vol. 31, pp. 475–503, 2012.

[18] C. D. Manning, P. Raghavan, and H. Schtze, *Introduction to Information Retrieval.* Cambridge University Press, 2008.

[19] T. Minka and J. Lafferty, “Expectation-propagation for the generative aspect model,” in *Proceedings of the 18th UAI*, 2002, pp. 352–359.

[20] T. L. Griffiths and M. Steyvers, “Finding scientific topics,” *Proceedings of the National Academy of Sciences*, vol. 101, pp. 5228–5235, 2004.

[21] G. Heinrich, “Parameter estimation for text analysis,” Tech. Rep., 2004.

[22] W. X. Zhao, J. Jiang, J. Weng, J. He, E.-P. Lim, H. Yan, and X. Li, “Comparing twitter and traditional media using topic models,” in *Proceedings of the 33rd ECIR.* Springer-Verlag, 2011, pp. 338–349.

[23] P. J. F. Inc., “Chat log conviction numbers.” [Online]. Available: http://www.ciise.concordia.ca/˜fung/pub/convictions.txt

[24] Y. W. Teh, M. I. Jordan, M. J. Beal, and D. M. Blei, “Sharing clusters among related groups: Hierarchical dirichlet processes,” in *Advances in NIPS*, 2005, pp. 1385–1392.

Author Biographies

Abdur Rahman M. A. Basher received a B.Sc. degree from King AbdulAziz University, Jeddah, Saudi Arabia, in 2008 and a M.A.Sc degree from Concordia University, Montreal, Canada, in 2011. Before pursuing his masters degree, he worked in the Center of Scientific Publishing as a professional software developer, Jeddah, Saudi Arabia from 2008 to 2009. His research interests include machine learning and pattern recognition, data mining, and bioinformatics.

Benjamin C. M. Fung is an Associate Professor at Concordia University in Montreal, and a research scientist of the National Cyber-Forensics and Training Alliance Canada. He received a Ph.D. degree in Computing Science from Simon Fraser University in 2007. He has over 60 refereed publications that span across the prestigious research forums of data mining, privacy protection, cyber forensics, web services, and building engineering. His data mining work in authorship analysis has been widely reported by media worldwide. Before pursuing his academic career, he worked at SAP Business Objects as a system software developer for four years. Dr. Fung is a licensed professional engineer in software engineering, and is currently affiliated with the Computer Security Lab in CIISE.

Correspondence and offprint requests to: Benjamin C. M. Fung, CIISE, Concordia University, Montreal, QC, H3G 1M8, Canada. Email: fung@ciise.concordia.ca