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MULTI-MODAL EVENT TOPIC MODEL FOR EVENT TRACKING

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ABSTRACT

In Social media documents or any document collected from Google contains certain events having long text. Due to variety of uploaded information over internet it is required to model them with appropriate images associated with story of particular event. Variety of text is considered to be different but the images are same for those events. Because may they have different textual information but the visual modalities are always same. Multimodal event topic model is proposed in this paper. Which can effectively model these events having so many images and text and find correlation between them. For evaluating the results we have prepared our own dataset which contains almost 5000 records related to stocks. For event tracking in case of multiple events, similarity computing identification method is used. For various documents rather multiple documents this method can be used to distribute topics in the document. For feature extraction Affinity Proportion Algorithm is suggested in this paper. For dataset parsing instead of XML parsing JSON parsing is used which can parse the entries for data efficiently. And in fast manner it can parse the dataset values. So Multi-modal topic model can effectively track the bunch of events over the time.

Keywords: CrossSpot, Event detection, Event tracking, multi-modal, Social media, Topic model.

I. INTRODUCTION

Social media sites or any documents from Google contains huge amount of data which can be classified as text data and visual data. Due to huge proportion, it is very difficult to model this data as well as images associated with them. Semantic relationship is also important factor which can be taken into consideration. So Multi-modal data modeling and visualization are very popular terms for analyzing theses events. Social media sites like flickr, face book, YouTube etc usually don't explored the datasets publicly so exact multimodality datasets are very difficult to find on internet, there are no free/public datasets available on internet. We have to do some extra work to get the dataset. In Multimodality, the relation between the textual information and the images is detected. We will be having the text information dataset with the images on the local machines, and the article will be mapped with the concerned image references. Any article contains any references available to the concerned images or not can be successfully detected using this model. Therefore, if we have to find the evolutionary trend of Rio Olympics then with help of this incremental framework we can find the evolutionary theme of the whole event in details. This event tracking mechanism is used to track the event happened in previous years. The events and their overall summary can be obtained with the help of event tracking mechanism.

II. LITERATURE SURVEY

A lot of work has been carried out in area of event tracking and topic detection. Among them most of the methods are based on single modality information or multi-modality information. However, these models studies visual and non-visual modalities in isolation to model the multimedia event data for social media analysis. Diakopolas et al. have proposed work for studying event visualization and social event analysis by using the twitter tweets related to particular event. Extracting information from large datasets and crawling the dataset information is included in this work for social event analysis. Topic modeling is gaining increasingly attention in different text mining communities. Latent Dirichlet Allocation (LDA) is becoming a standard tool in topic modeling. As a result, LDA has been extended in a variety of ways, and in particular for social networks and social media, a number of extensions to LDA have been proposed. Chang et al. proposed a novel probabilistic topic model to analyze text corpora and infer descriptions of the entities and of relationships between those entities on Wikipedia. McCallum et al. proposed a model to simultaneously discover groups among the entities and topics among the corresponding text. Zhang et al. introduced a model to incorporate LDA into a community detection process. Similar work can be found in and Related to this work, where we need to obtain topic mixture for both messages and authors, Rosen-Zvi et al. introduced an author-topic model, which can flexibly model authors corresponding topic distributions. In their experiments, they found that the model outperforms LDA when only small number of words are observed in the test documents. Ramage et al. extended LDA to a supervised form and studied its application in micro-blogging environment. Phan et al. studied the problem of modeling short text through LDA. However, their work mainly focused on how to apply it to Wikipedia and they did not provide any discussion on if there is other ways to train a same model. In web search, this line of research usually employs search engines directly. Sahami et al. introduced a kernel function based on search engine results. Yih et al. further extended the method by exploiting some machine learning techniques. and their Topic models that are widely used for the topic modelling includes Latent Dirchlet Allocation (LDA) and probabilistic Latent Semantic analysis. These topics are extended further by introducing Supervised Latent Dirchlet allocation (SLDA). Yang in 2015 proposes a novel cross domain feature learning framework based on stacked denoising auto-encoder. This algorithm helps to maximize correlations among various modalities and helps to extract semantic features at the same time. Al Sumait et al. propose online LDA method, which further extends Gibbs Sampling method, which derives topic-word distribution at next time slice. Hong et al. propose a topic model, which is time-dependent and can be used for considering multiple text sources. However, these models fail to properly model the multi-model data. Therefore, Corr-LDA was proposed to capture correlations between image and annotations. The mm-LDA can be used for multi-model information modelling which includes textual corpora and visual topics.

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III. MULTI-MODAL EVENT TOPIC MODEL

3.1 Architecture of Multi-Modal Event Topic Model

The multi-modal event topic model (mm-ETM) is suggested in this paper which is used for finding the correlations between visual and textual modalities. This model can also used to track and detect the events according to time when the event is happened. The dependency relationships between textual and visual modalities are different for different semantic concepts. The event may contain text as well as images corresponding to particular topic. Some topics are represented using textual information and some using visual descriptors. For modelling such text corpora and multimedia contents, the multi-model topic is well suited. The system architecture of multi-model event topic model is given in following figure.

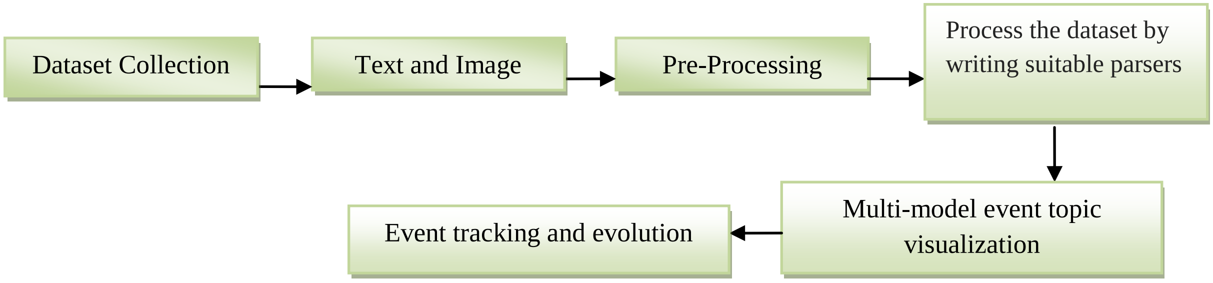

Fig 1.Workflow diagram for Multi-Modal Event Topic Model

3.2 Topic Assignments in Multi-Modal Event Topic Model:

According to the generative process of mmETM with visual words and textual words having document d can be described as follows.

- For Visual representative Topics, textual topic is denoted as Z^w and visual topics are denoted as Z^v. Here the Multinomial distribution over words is described using notation is, $\phi_w^s \sim Dir(\eta_w^s)$ and $\phi_v^s \sim Dir(\eta_v^s)$.
- For each document d , In case of Non- Visual representative Topics Z^w , the Multinomial distribution over words is described using notation is, $\phi_w^p \sim Dir(\eta_w^p)$.
- Binomial distribution of Visual representative Topics and Non- Visual representative can be written as $\pi_d \sim Beta(\gamma)$.
- Multinomial distribution over is Visual representative Topics $\Theta_d \sim Dir(\alpha)$,Multinomial distribution over is Non- Visual representative Topics $\Psi_d \sim Dir(\beta)$.
- For each word w_n in document d $X_{dn} \sim Binomial(\pi_d)$, For each visual word v_n individual topic assignment is $z_{dn}^v \sim mult(\theta)$

In the above assignments Z^w textual topic and visual topic is Z^v. Ψ_d and Θ_d are document-topic distributions. $\phi_w^s \phi_v^s$ are set of K-visual representative topic and H non-visual representative topic ϕ_w^p.

3.3 Event Tracking

With the help of incremental mmETM model learning, topic distributions related with each document can be obtained. Means For each document topic distribution can be done with this model over times. For tracking more than one event at a time similarity computing identification is applied. By using similarity computing

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identification method based on the learned mmETM model at epoch, multiple event documents can be classified into their corresponding events at epoch . In this way multiple events can be tracked over time.

3.4 SIMILARITY COMPUTING IDENTIFICATION

This method is used for tracking the events in the model. It can also be used in incremental mmETM model. One critical step in the item-based collaborative filtering algorithm is to compute the similarity between items and then to select the most similar items. The basic idea in similarity computation between two items *i* and *j* is to first isolate the users who have rated both of these items and then to apply a similarity computation technique to determine the similarity.

3.5 DATASET COLLECTION

As of now data sets are not available for processing multi-modal information we have collected events related stock company named as NASDAQ. Which have near about 5000 records of various stock related information. For processing this data set JSON parsing is used which have some advantages as compare to XML parsing as follows.

3.5.1 Advantages of JSON parsing With respect to XML parsing:

JSON is extended from JavaScript. JSON syntax is lighter than XML as JSON has serialized format of data having less redundancy. JSON does not contain start and end tags. JSON is light – weighted in compare to XML as it has serialized format and so faster also. JSON supports data type including integer and strings, JSON also supports array. It does not need any additional code for parsing. JSON syntax is lighter than XML as JSON has serialized format of data having less redundancy. JSON does not contain start and end tags. JSON is light – weighted in compare to XML as it has serialized format and so faster also. JSON is data oriented and can be mapped more easily.

3.6 Affinity Proportion Algorithm for feature Extraction:

In statistics and data mining, affinity propagation (AP) is a clustering algorithm based on the concept of "message passing" between data points. Unlike clustering algorithms such as *k*-means or *k*-medoids, affinity propagation does not require the number of clusters to be determined or estimated before running the algorithm. Similar to *k*-medoids, affinity propagation finds "exemplars", members of the input set that are representative of clusters. The inventors of affinity propagation showed it is better for certain computer vision and computational biology tasks, e.g. clustering of pictures of human faces and identifying regulated transcripts, than *k*-means, even when *k*-means was allowed many random restarts and initialized using PCA. A study comparing affinity propagation and Markov clustering on protein interaction graph partitioning found Markov clustering to work better for that problem. A semi-supervised variant has been proposed for text mining applications.

IV. CONCLUSIONS

In this paper, multimodal event topic model and suspicious block detection in multimodal datasets is proposed. It is suitable approach for social media event analysis. Multi-model event topic model have been used for event tracking and evolution it is also used for generating effective summaries of those events over the time. For separating the visual representative topics and non-visual representative topics this framework can model the correlations between textual and visual modalities. In addition, we can explore whether the tracking performance can be improved by using the different domains like Flickr, Youtube and Google News for dataset collection of social media event for its detailed analysis.

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