

# A Survey on Multi-Model Event Topic Modelling for Social Media Event Analysis

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**ABSTRACT:** With the evolution of internet, there has been tremendous amount of growth in various social media sites. Large amount of information contents is available for users on internet. Large amount of events are happening all over the world. Therefore, managing these massive amounts of event is a tedious job. Monitoring, organizing, searching and browsing such events are difficult and time-consuming task. Social media contains the huge repository of rich event content information. So, a Multi-Model Event Topic Model is suggested in this paper for managing these events and keep track over newly updated events on social media. Social media events also contains the large amount of images with text data. This model is useful for effectively modelling the visual representative topics and non-visual representative topics. It also finds the correlations between textual and visual modalities.

**KEYWORDS:** Social media, topic model, multi-modality, Event tracking, event detection.

## I. INTRODUCTION

With the rapid growth of internet, more social media sites have evolved. The social media sites like Facebook, YouTube, Flickr, Google News contains large amount of information like images, videos and texts. This information content can be considered as multi-model data. The events happening over the world contains huge repository of multi-modality events. The social events happening around the world also contains rich multimedia contents, which are huge in proportion and very bulky for handling and monitoring. Users can upload these multimedia contents. The contents uploaded by the user can be associated with specific topic. One news may contain various posts, various tweets, and various images related to that particular news. Therefore, it is difficult task for the users to manually cluster them and identify the whole details about the particular topic which contains multiple posts related with it. When Users search for the specific event on Google News or Flickr using the search engines by entering well-defined queries, they could get lots of information related to the event topic. But it is difficult for them to find the evolutionary trends of that social media event. It would be great job, if we could find the evolutionary trend for that event and visualize the theme pattern over the time.

Recently, many research interests have attracted towards the mining and monitoring social media events. This includes social event tracking, social event detection and evolution. However, in existing systems, much work have focus over the textual features or image but at individual level. Means in isolation either the textual or images have been studied in details. However, in unified way there has been very limited work for studying textual as well as multimedia contents together. Multi-model feature fusion is important for carrying the social event analysis. Multiple features like tags, location, time or visual features plays important role for analysing social media events. However, the little efforts have been carried out for studying the importance of these features. Previous methods focuses on study related to textual and visual features in joint manner but ignoring the semantic relationships between these features. So keeping in mind, semantic relationships between various features also plays important role in social event analysis and tracking.

For dealing with these issues, many topic models have been proposed to explore the social media analysis. For example, Corr-LDA and mm-LDA are proposed for capturing the topic level relations between annotations and images. Corr-LDA and mm-LDA assume one-to-one relations between the topics of each modality. These approaches are restricted for using short words. Using existing topic models such as Corr-LDA and mm-LDA, one can only obtain the visual representative topic. Non-visual representative topics are neglected in these models. It also neglects textual information in social media events modelling.

In this paper the detailed survey related with social event analysis is shown which contains different models for detection, summarization, tracking and extracting social media events. Multi-model event topic model can model visual representative topics and non-visual representative topics together. It can learn the correlations between visual and textual cues. Semantic relationships between different modalities can be successfully learn with the help of this model efficiently. Therefore, if we have to analyse 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.

## II. LITERATURE SURVEY

### A. SOCIAL EVENT DETECTION AND TRACKING:

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.

- i. Diakopoulos et al. have propose 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.
- ii. Makkonen et al. propose the model for extracting meaningful semantics such as names, tags, time references Based on a single clustering partition. A similarity metric have been proposed for these events.
- iii. Hierarchical Hidden Markov model has been proposed by Xie et al. over the low-level audio-visual features for discovering the location and time based i.e. spatio-temporal patterns. For finding the clusters of text, the Latent Semantic Analysis is used.
- iv. Non-negative Matrix Factorization framework was proposed by Lin et al. by using multi-relational structures for modelling the image stream data including images and short tags form social media events.
- v. Zhang and Xu propose a CO-PMHT model to track event using cross domain knowledge and obtain their summary over time from social media events.
- vi. Michele Merler in 2012 propose a Semantic model vectors representation. In this work video event detection have been studied, which combines semantic model vectors and other static or dynamic visual descriptors by extracting the information from various frames in videos.

### B. EVENT SUMMARIZATION:

In the area of event summarization, multi-document event summarization leads to solve the problem regarding overloaded information over the internet with respect to social media events.

Gong and Liu propose generic text summarization method that creates text summaries by ranking and extracting sentences from the original document.

Zhou et al. propose two-layer summarization framework for summarizing multiple disaster related documents.

### C. SOCIAL EVENT ANALYSIS:

Social event analysis based on sentiment analysis and sentiment classification has derived much attention. Timo Reuter in 2012 proposes a system that is able to perform pattern classification of a social media streams. Hu et al. explained whether social relations could help sentiment analysis with the help of social approach to deal with noisy type of data and short texts for classification based on sentiments.

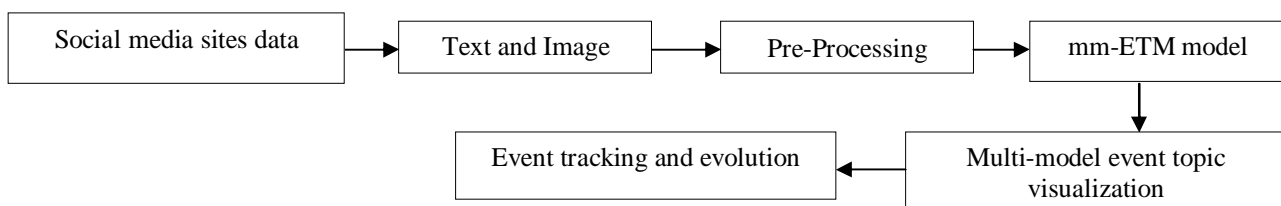
**D.TOPIC MODEL:**

Topic models that are widely used for the topic modelling includes Latent Dirichlet Allocation (LDA) and probabilistic Latent Semantic analysis. These topics are extended further by introducing Supervised Latent Dirichlet allocation (SLDA).

- i. Yang in 2015 propose 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.
- ii. Al Sumait et al. propose online LDA method, which further extends Gibbs Sampling method, which derives topic-word distribution at next time slice.
- iii. Hong et al. propose atopic model, which is time-dependent and can be used for considering multiple text sources. However, these models fail to properly model the multi-modal data. Therefore, Corr-LDA was proposed to capture correlations between image and annotations.
- iv. The mm-LDA is proposed for social relation mining. The mm-LDA can be used for multi-modal information modelling which includes textual corpora and visual topics.
- v. Putthividhya et al. propose a topic-regression multi-modal Latent Dirichlet Allocation (LDA) Model. The model mm-LDA is the extension of the special words with background (SWB) model. The multi-modal event topic model is advanced level model. Which is applied for the social event detection and tracking.
- vi. Blei and Lafferty Propose the dynamic model that makes the use of state space models based on the natural parameters.

**III. SYSTEM OVERVIEW**

The multi-modal event topic model (mm-ETM) is suggested in this paper is much suited for modelling multi-modal social event documents for event tracking and evolution analysis. The dependency relationships between textual and visual modalities are different for different semantic concepts. The event may contain long text and large amount of corresponding images. Some topics are represented using textual information and some using visual descriptors. For modelling such text corpora and multimedia contents, the multi-modal topic is well suited. The system overview of multi-modal event topic model is given in following figure.



**Figure 1. Workflow diagram for Multi-Model Event Topic Model**

The time ordered data is collected from social media sites like Facebook, YouTube, Flickr, Google News. Extracted information is processed depending on type of data like text and images. For feature extraction of images, the image is divided into multiple regions using rectangular grids with 3-level spatial pyramids. After collecting various features like histogram, texture, color moment, LBP, GIST features, the Affinity Proportion Algorithm is applied on the images for constructing the visual codebook.

**IV. CONCLUSION**

In this paper, a novel approach is suggested for social media event analysis. Multi-model event topic model have been used for event tracking and evolution framework to obtain the evolutionary trends of social media events. It also helps in 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. Incremental updating strategies will be used in this method. For future work Event summarization and event attribute mining in social media can be studied. 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.

**REFERENCES**

- [1] Shengsheng Qian, Tianzhu Zhang, Changsheng Xu, and Jie Shao, "Multi-modal event topic model For social event analysis" *IEEE transactions on multimedia*, vol. 18, no. 2, february 2016
- [2] M. Merler, B. Huang, L. Xie, G. Hua, and A. Natsev, "Semantic model vectors for complex video event recognition," *IEEE Trans. Multimedia*, vol. 14, no. 1, pp. 88–101, Feb. 2012.
- [3] T. Zhang and C. Xu, "Cross-domain multi-event tracking via CO-PMHT," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 10, no. 4, pp. 31:1–31:19, 2014.
- [4] X. Yang, T. Zhang, C. Xu, and M. S. Hossain, "Automatic visual concept learning for social event understanding," *IEEE Trans. Multimedia*, vol. 17, no. 3, pp. 346–358, Mar. 2015. N.
- [5] Diakopoulos, M. Naaman, and F. Kivran-Swaine, "Diamonds in the rough: Social media visual analytics for journalistic inquiry," in *Proc. IEEE Symp. Vis. Analytics Sci. Technol.*, Oct. 2010, pp. 115–122.
- [6] X. Wu, C.-W. Ngo, and A. G. Hauptmann, "Multimodal news story clustering with pairwise visual near-duplicate constraint," *IEEE Trans. Multimedia*, vol. 10, no. 2, pp. 188–199, Feb. 2008.
- [7] I. Kalamaras, A. Drosou, and D. Tzovaras, "Multi-objective optimization for multimodal visualization," *IEEE Trans. Multimedia*, vol. 16, no. 5, pp. 1460–1472, Aug. 2014.
- [8] W. Liu, T. Mei, and Y. Zhang, "Instant mobile video search with layered audio-video indexing and progressive transmission," *IEEE Trans. Multimedia*, vol. 16, no. 8, pp. 2242–2255, Dec. 2014.
- [9] C. Kang, S. Xiang, S. Liao, C. Xu, and C. Pan, "Learning consistent feature representation for cross-modal multimedia retrieval," *IEEE Trans. Multimedia*, vol. 17, no. 3, pp. 370–381, Mar. 2015.
- [10] S. Qian, T. Zhang, R. Hong, and C. Xu, "Cross-domain collaborative learning in social multimedia," in *Proc. ACM MM*, 2015, pp. 99–108.
- [11] T. Reuter and P. Cimiano, "Event-based classification of social media streams," in *Proc. ICMR*, 2012, pp. 22:1–22:8. S. Singh, A. Gupta, and A. A. Efros, "Unsupervised discovery of midlevel discriminative patches," in *Proc. ECCV*, 2012, pp. 73–86.
- [12] T. Zhang, C. Xu, G. Zhu, S. Liu, and H. Lu, "A generic framework for video annotation via semi-supervised learning," *IEEE Trans. Multimedia*, vol. 14, no. 4, pp. 1206–1219, Aug. 2012.
- [12] X. Yang, T. Zhang, and C. Xu, "Cross-domain feature learning in multimedia," *IEEE Trans. Multimedia*, vol. 17, no. 1, pp. 64–78, Jan. 2015.