International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2015): 78.96 | Impact Factor (2015): 6.391

Analysis of Multi-Modality Contents in Data for Visualization of Events

Prajakta Sonone[1], Prof. A. V. Deorankar[2]

[1]P.G. Scholar, Department of Computer Science and Engineering, Government College of Engineering, Amravati, Maharashtra, India

[2]Associate Professor, Department of Information Technology, Government College of Engineering, Amravati, Maharashtra, India

Abstract: ***Any Social media documents or any document collected from internet contains multiple stories attached with it. Especially having images concerned with that story. Searching sorting and analyzing this huge amount of documents is quite tedious job for user. Because it is very time consuming to sort the documents containing particular story and clustering of such multiple events is time consuming job for analyzers. Modeling these events according to their year and type is useful for easily sort the information among the huge data. So the detailed analysis of multi-modality contents in the dataset, the methodologies for modeling visual representative topics and text oriented topics together is also presented in this paper. Multi-modality contents can model using the topic allocation model but studying semantic relationship between them is again the difficult job. So semantic relationship is also highlighted in the paper so as to model the information and images efficiently. One part is detect and scrutinize dense block of data which is worth inspecting, typically indicating fraud and sort them in the order of importance ("suspiciousness") is also described. In multimodal visualization with help of Graphical representation such as pie charts, Bar graphs the comparison between the various events can be easily done. The workflow is presented and finally conclusion is presented along with future work.***

Keywords: Dense data block, event, multimodal data, semantics, topic model, visualization

1. 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 large extent, it is very time consuming task to model this data as well as images associated with them. Semantic relationship always plays important role when it comes to text and visual data. It is very important thing which helps to learn the semantic features of each modality. And which must be taken into consideration while dealing with visualization and tracking of multi-modal data. Multi-modal data modeling and visualization are very popular terms for analyzing theses events. Social media sites like Twitter, Face book, Google news etc usually don't explored the datasets publicly so exact multi-modality 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. There is dense block of data having multimodal features in datasets. This multi-modal data is always worth inspecting. Dense block inspection is carried out with the help of some algorithms which are able to detect the suspicious and malicious behavior of data. For experimental results we have collected the stocks related information of various years in our datasets. Stock related company which provides the huge amount of information related to various products, their availability, comparison with other products, various advertise on their portal. So while analyzing, sorting the stocks, products, their availability, turnover with respect to previous years or taking the detailed summary of any stock related information is taken for mining so that we can get extracted information which is useful for customers. Reviews collection, reviews sorting is also important while purchasing the product. So to sort the products and their reviews is important part. These portals have many stories related with stocks products. Multi-modal topic model for visualization is efficient for modeling huge amount of information. The suspiciousness of the dense block having different numbers of modes is the aim of finding dense block. Behavioral factors are studied in deep because they can spread fake ads and can spread the spam.

So Many commercial products and approaches are attracted towards the behavior analysis of the problem so that this fraud containing information or any spam and advertising with URL hijacking can be detected. For this the use of adjacency matrix is becoming popular. While visualizing and summarizing the available data in the datasets various graphs are taken for analysis. The graphs are the graphical data of adjacency matrix. Detecting dense blocks in the adjacency matrix of graph data, and tensors of multimodal data has becoming popular. Very few or no method gives a exact and accurate way to detect the suspiciousness of dense blocks having different numbers of data modes and ranking that data is also difficult job according to people's choice. So we have presented the detailed analysis and workflow of the multimodality visualization along with semantic features study, which can be used for effective modeling and visualization.

2. Literature Review

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.

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.

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. Michele Merler in 2012 proposes a Semantic model vectors representation. In this work video event detection has been studied, which combines semantic model vectors and other static or dynamic visual descriptors by extracting the information from various frames in videos.

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. These patterns of fraud have been found to show up in eBay reviews, opinion spam, and false accounts. Many methods have focused on labelling individual users, such as by using belief propagation or TrustRank or Page-Rank-like scores. These methods label suspicious nodes/users, but do not return suspicious grouping behaviours themselves.

Later work found that adding additional modes of information aided in detecting suspicious behavior. CopyCatch found that suspicious patterns of Page Likes on Facebook correlated in time were good indicators of fraud. CatchSync proposed the synchronicity and normality features to summarize the distributions of followers in a two-dimensional feature space, and thus caught the synchronized behaviours of zombie followers. Jindal et al. analysed Amazon reviews, examining product, reviewer, rating, date, review title/body and feedbacks, to catch opinion spam.

3. Proposed Methods Workflow

3.1 Overview of Methodologies Used:

Following tasks are performed for visualizing and analyzing the results for modeling multi-modal contents.

In the overall evaluation of text and image data tracking, clustering, classification and visualization techniques the topic containing text data which is nothing but the collection of words are modeled with the visual representative topics i.e. image data. Using multi-modal modeling two types of data can be modeled efficiently. Latent Dirchlet allocation is applied for topic modeling. For parameter inference in the model, Dirchlet constant values for document at some epoch are taken as input parameters. A visual-representative topic, non-visual-representative topics and document-topic distributions is the output of inference of parameters in topic model. After that their prior values are initialized. Another task is to obtain the prior parameters of a topic in visual-representative topics at epoch. And obtaining the prior parameters of a topic in non-visual-representative topics at epoch, initialize topic assignment randomly for all word in document and finally the updating strategy is applied over data of each modality.

Following diagram shows the overall workflow and further objective of this visualization model is described in details.

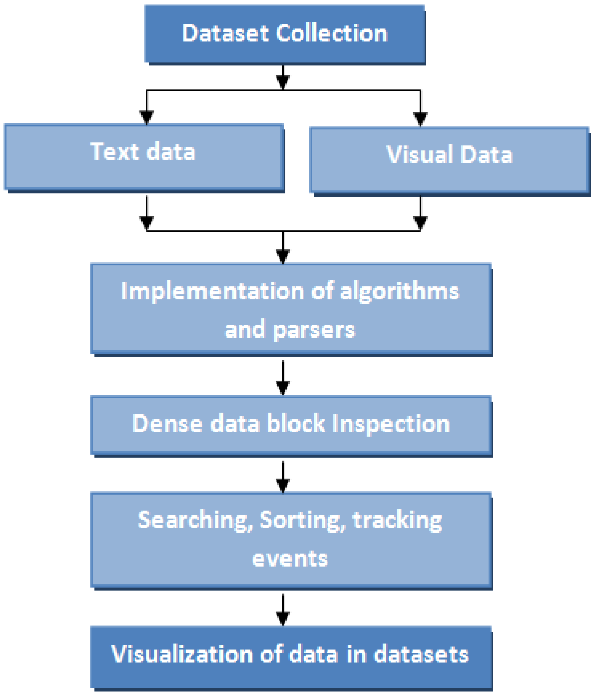

Figure 1: Workflow Diagram of proposed model

1. The multi-modal topic mining module is helpful for effectively model multi-modal event documents, which can learn the correlations between textual and visual modalities to separate the visual representative topics and non-visual-representative topics.

2. To analyse the data on the basis of parameters available in the dataset and visualize it.
3. Display, Search Sort the information.
4. To propose an algorithm to spot dense blocks that are worth inspecting, typically indicating fraud or some other noteworthy deviation from the usual, and sort them in the order of importance ("suspiciousness").
5. For Analysis of events of various years creating pie charts and graph charts for tracking those events.
6. In case of multi-modality of data text and images are mostly concerned. We have to model these two contents together.
7. Multi-modal topic model works very well for modelling these contents together. In case of Text data, dataset contains the information regarding each topic and images concerned with it. With the help of some algorithms and mathematical derivations Multi-modal data can be modelled.
8. After processing the model user need to import two datasets on the JSP page as meta-dataset and reviews-dataset. Both datasets will be internally processed.
9. On View Reviews page, you can search and sort the reviews, products, etc
10. On Search Page, you can write text by your own, or copy any review from the dataset file, and search it. It will give the images by mining according to the text searched. Also it gives corresponding textual result data.
11. Dense block detection module is suggested to detect malicious behaviour. Where data block is dense then that information is always remains worth for inspecting.
12. After studying the models mentioned in this paper, proposed model can efficiently model text and an image containing dense block which also comes under inspection.

4. Conclusions

In this paper, multimodal event topic model visualization and suspicious block inspection methods are depicted. It is suitable approach for visualizing any social media event or any document over the internet regarding to some specific topic. Analysis of Multi-modal event topic model has been used for event tracking and evolution. It is also used for generating effective summaries of those events over the time. Separating the visual representative topics and non-visual representative topics, this framework can model the correlations between textual and visual modalities. Some algorithms and multi-modal tensors can detect the dense data block for identifying suspicious behaviours in dataset. For future work Event summarization and event attribute mining in social media can be studied. In addition, we can explore whether the visualization and 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] 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.
[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] M. Jiang, P. Cui, and C. Faloutsos, "Suspicious Behavior Detection:Current Trends and Future Directions," in IEEE Intelligent Systems, no. 1, pp. 31–39, 2016.
[8] Meng Jiang, Alex Beutel, Peng Cui, Bryan Hooi, Shiqiang Yang Senior Member, IEEE, Christos Faloutsos,IEEE Trans. knowledge and Data Engineering, Manuscropt ID "Spotting Suspicious Behaviors in Multimodal Data: A General Metric and Algorithms".
[9] 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.
[10] X. Yang, T. Zhang, C. Xu, and M. Yang, "Boosted multifeature learning for cross-domain transfer," *TOMCCAP*, vol. 11, no. 3, pp. 35:1–35:18, 2015.
[11] S. Qian, T. Zhang, C. Xu, and M. S. Hossain, "Social event classification via boosted multimodal supervised latent Dirichlet allocation," *TOMCCAP*, vol. 11, no. 2, pp. 27:1–27:22, 2014.
[12] Y.-R. Lin, H. Sundaram, M. D. Choudhury, and A. Kelliher, "Discovering multirelational structure in social media streams," *TOMCCAP*, vol. 8, no. 1, p. 4, 2012.
[13] 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 *Proc. ICDM*, 2008, pp. 3–12.
[14] J. Makkonen, H. Ahonen-Myka, and M. Salmenkivi, "Simple semantics in topic detection and tracking," *Inform. Retrieval*, vol. 7, no. 3–4, pp. 347–368, 2004. L.
[15] Xie *et al.*, "Discovering meaningful multimedia patterns with audio-visual concepts and associated text," in *Proc. ICIP*, 2004, pp.
[16] Y.-R. Lin, H. Sundaram, M. D. Choudhury, and A. Kelliher, "Discovering multirelational structure in social media streams," *TOMCCAP*, vol. 8, no. 1, p. 4, 2012.
[17] L. Page, S. Brin, R. Motwani, and T. Winograd, "The pagerank citation ranking: Bringing order to the web," in 1999.
[18] J. Sun, H. Qu, D. Chakrabarti, and C. Faloutsos, "Neighborhood formation and anomaly detection in bipartite graphs," in IEEE ICDM, p. 8, 2005.

[19] Y Gong and X. Liu, “Generic text summarization using relevance measure and latent semantic analysis,” in *Proc. SIGIR*, 2001, pp. 19–25. H.-H. Mao, C.-J. Wu, E. E. Papalexakis, C. Faloutsos, K.-C. Lee, and T.-C. Kao, “Malspot: Multi2 malicious network behavior patterns analysis,” in PAKDD, pp. 1-14, 2014.
[20] A. Mukherjee, B. Liu, and N. Glance, “Spotting fake reviewer groups in consumer reviews,” in WWW, pp. 191-200, 2012.
[21] L. Akoglu, R. Chandy, and C. Faloutsos, “Opinion fraud detection in online reviews by network effects,” in ICWSM, 2013
[22] M. Jiang, P. Cui, A. Beutel, C. Faloutsos, and S. Yang, “Inferring strange behavior from connectivity pattern in social networks,” in PAKDD, pp. 126-138, 2014.
[23] J. Pei, D. Jiang, and A. Zhang, “On mining cross-graph quasicliques,” in ACM SIGKDD, pp. 228-238, 2005.
[24] A. Sun and S. S. Bhowmick, “Quantifying visual-representativeness of social image tags using image tag clarity,” in *Proc. Social Media Modeling Comput.*, 2011, pp. 3–23.
[25] S. Qian, T. Zhang, R. Hong, and C. Xu, “Cross-domain collaborative learning in social multimedia,” in *Proc. ACM MM*, 2015, pp. 99–108.
[26] 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.
[27] N. Shah, A. Beutel, B. Gallagher, and C. Faloutsos, “Spotting suspicious link behavior with fbox: An adversarial perspective,” in IEEE ICDM, pp. 959–964, 2014.
[28] A. Beutel, W. Xu, V. Guruswami, C. Palow, and C. Faloutsos, “Copycatch: stopping group attacks by spotting lockstep behavior in social networks,” in WWW, pp. 119-130, 2013.
[29] S. Pandit, D. H. Chau, S. Wang, and C. Faloutsos, “Netprobe: a fast and scalable system for fraud detection in online auction networks,” in WWW, pp. 201-210, 2007.
[30] K. Maruhashi, F. Guo, and C. Faloutsos, “Multiaspectforensics: Pattern mining on large-scale heterogeneous networks with tensor analysis,” in ASONAM, pp. 203-210, 2011.
[31] H.-H. Mao, C.-J. Wu, E. E. Papalexakis, C. Faloutsos, K.-C. Lee, and T.-C. Kao, “Malspot: Multi2 malicious network behavior patterns analysis,” in PAKDD, pp. 1-14, 2014.
[32] J. Pei, D. Jiang, and A. Zhang, “On mining cross-graph quasicliques,” in ACM SIGKDD, pp. 228-238, 2005.
[33] J. Chen and Y. Saad, “Dense subgraph extraction with application to community detection,” in IEEE TKDE, vol. 24, no. 7, pp. 1216-1230, 2012