Organizing Images from Social Media to Monitor Real-World Events

Paulo Cavalin, Flavio Figueiredo, Maíra de Bayser
IBM Research
International Business Machines (IBM)
Rio de Janeiro, RJ, Brazil
Email: pcavalin,flaviovdf,mgdebayser@br.ibm.com

Claudio Pinhanez
IBM Research
International Business Machines (IBM)
São Paulo, SP, Brazil
Email: csantosp@br.ibm.com

***Abstract*—Everyday, millions of images are posted in social media websites online. Given that in social media websites there are no guarantees of image precedence and quality, making sense of social media imagery presents itself as a challenging task. In this paper, we describe the architecture of a system developed to facilitate the analysis of social media imagery. Our system combines both low-level and high-level image analytics to organize the images into a reduced and semantically-linked set that can be explored by end-users. We evaluate our system on a large dataset of images posted during major social media events such as the 2014 World Cup Finals.**

***Keywords*-Social Media, Imagery Analytics, Visual Analysis**

I. Introduction

Social media networks (SMNs), such as Twitter, Facebook and Instagram, are broadly used worldwide. On these networks, people send millions of posts everyday. This huge amount of data allows researchers and companies to extract knowledge from the crowd, with the goal of understanding user behavior and public opinion, tracking the popularity of products and ideals, understanding how individuals communicate, studying the complex networks of social connections, and thus forth. Often, researchers and practitioners rely on analytics based on two types of data: graphs or texts [3], owing to the fact the SMNs have been originally created to connect individuals as to provide textual based communication.

Nevertheless, the adoption of SMNs allowing users to post multimedia content, images in particular, is also significant. Often, users post images to share personal moments or to expose their preferences, generally represented by images created with their own mobile devices, but also to express opinions either by means of their own creations or Internet memes[1]. Such a richfull source of data can provide other types of insights beyond what can be captured from texts and graphs. As a consequence, conducting analytics on images from social media is fundamental to leverage the capabilities of current SMNs analytics systems.

In the context of social media analytics, content summarisation regarding large-scale events is an important application for media, branding, and other domains. That is, on SMNs such as Twitter and the like, people tend to post a lot of content related to some event occurring in the real world, for instance sport games, TV shows, releases of new products, politics campaigns, and thus forth. Summarizing such content is important not only to understand public opinion, to check whether it corresponds to what is expected, but also to gather new insights that can be uncovered from the data. On one hand, doing such analytics on texts and/or user networks, can be successful to provide insights such as mention trends, opinion, and communities. Processing pictures or images, on the other hand, can go beyond those analyses, since one could monitor what is trendy but not mentioned in a post. Furthermore, one could search for visual similarity within the set, and find links to better understand the dataset as a whole.

That said, the main goal of this work is to present a system for social media imagery analytics. In other words, given a supposedly large set of social media images related to a real-world event – where the images in the set are likely to present duplicates, near-duplicates, and visual or semantic content similarity – the main goal of the system is to process the images and organize them in more manageable way. The end result is on providing users a set without redundant images and with a facilitated way to view the images that share common content. Afterwards, visualization interfaces can be built on top of this organized set, where the user can visualize, for instance, the most posted images, the most posted images in a timeline, groups of similar images, and thus forth.

The proposed system, which is better described in Section II, makes use of image processing algorithms, such as perceptual hashing, to deal with duplicates and near-duplicates, as well as a deep-learning-based representation to encode the images for similarity evaluation.In Section III, we present results of the application of the system on different datasets crawled from Twitter. We demonstrate that, compared with methods that rely only on metadata, the visual analysis of images can significantly reduce the set of images that an end user needs to deal with, making it a more manageable set. Also, regarding the similarity between images, we present a qualitative analysis to demonstrate examples where the similarity approach can successfully be used to group together images with similar visual or semantic content. Our results extend the analysis of social media images further than relying only on the most frequent images, as is usually done.

[1]An Internet meme is an activity, concept, catchphrase or piece of media which spreads, often as mimicry, from person to person via the Internet [21].

A. Image Analytics on Social Media

In this section, we provide an overview of the main challenges in designing a social imagery analytics system. It is worth mentioning image processing is a challenging task with social media images being no exception to this fact. However, social media images do present some inherent additional properties as we now discuss. Such properties may rise from characteristics of the social media application itself (e.g., posts have a natural time ordering), as well as the the fact that no guarantees on quality or precedence exist social media websites (e.g., any user can post any image online).

In Figure 1 we show some examples of these properties as we now discuss:

1) *Unconstraint in Quality*: images are posted without any quality guarantees (e.g., minimal resolution).
2) *Sequential in time*: social media websites annotate posts with timestamps. Thus, in these platforms we can keep track on tem temporal nature of images. This allows us to have a temporal overview of the social media imagery landscape;
3) *Repetitions*: images are reposted over time with none to minimal modifications, such as low-level modifications in image format, resolution, color, croppings; as well as with high-level modifications such as addition of texts;
4) *Different Images same Entity*: several different images can be created or generated but can be associated to the same entity or concept. For instance, the same person, place, or moment in time.

Fig. 1: a) Same image, different sizes and framings, text additions; b) same content, different angles and moments

After processing a set of social media images and dealing with the aforementioned issues, the user should then be able to get insights from the data. Two forms of achieving this is by means of a timeline view of the most posted images at given time intervals, as in Figure 2, or by exploring groups of similar images, as depicted in Figure 3.

It is important to mention that the aforementioned properties cannot be easily handled by image meta-data itself. For instance, whereas some repetitions (or duplications) can be tracked by considering the URL of the images, URLs cannot keep track of low-level modifications such as resolution modification. Also the detection of high-level modifications,

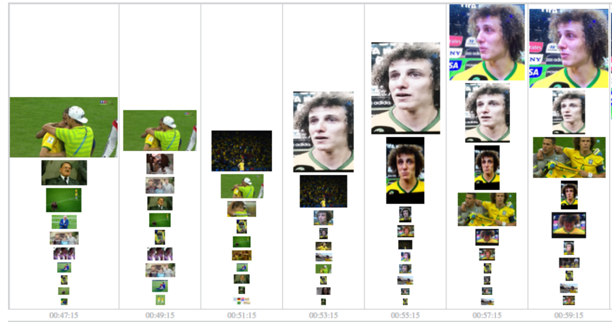

Fig. 2: A sample of a timeline visualization of social media imagery.

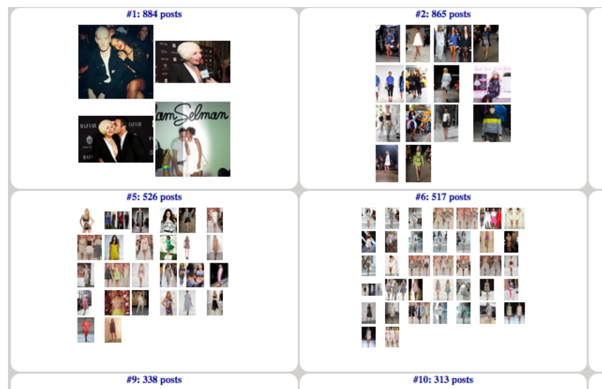

Fig. 3: A sample of semantically grouped visualization of social media imagery.

such as adding text, and keeping track of images related to the same entity over time are also challenges given the unconstrained large sets of social media images.

II. Social Imagery Analytics System

In this section, we present our proposed social imagery analytics system. The goal of our system is to process a large set of social media images and organize them in a way that helps data analysts to get insight from the images. The main modules of the system are depicted in Figure 4.

The initial input for the system consists of one or more social media sources (e.g., Twitter, Facebook, Instagram), and a set of rules (e.g., keywords, phrases or users). These rules are generally related to a given subject or events that are of interest to the domain expert. With these rules, social media posts are gathered through APIs and search engines. These posts consist of both data (e.g., a tweet and images) and metadata (e.g., timestamps).

For each post, the next module crawls the images linked the post. Our crawling module only considers posts with valid images, that is, those with working URLs.

The next step is indexing/de-duplication. The idea here is to help the analyst by presenting only unique images, preventing him/her to deal with redundant content. In order to find duplicate sets, we apply the perceptual hashing algorithm, where images are considered as duplicates when the hamming

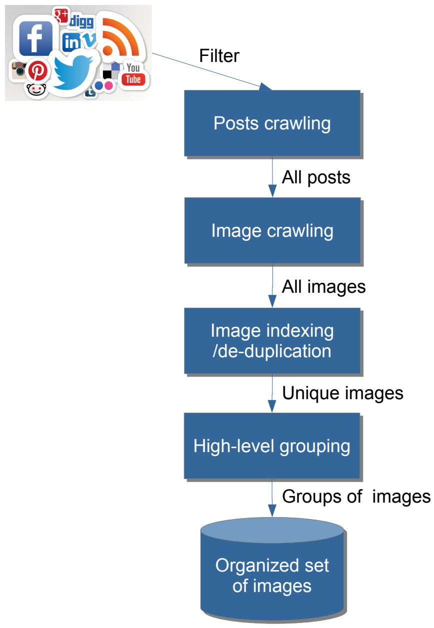

Fig. 4: System's main Workflow

distance between the binary hashing code is lower than 8, as suggested in [22]. The output of this module consists of a list of unique images, each one linked to the meta-data of their corresponding duplications.

In the high-level grouping module, the goal is to extract feature vectors that describe the visual semantic contents of the images, namely semantic feature vectors. Our goal with these vectors is to define groups of semantically similar images. That is, let s_i be the semantic feature vector of image i, and s_j the semantic vector of image j, where $i \neq j$, the semantic similarity $sim_{i,j}$ is defined as the euclidean similarity between s_i and s_j, or the inverse of the euclidean distance. In order to define the groups of images, a threshold θ is taken into account. That is, images i and j are assigned to the same group if $sim_{i,j} > \theta$. We make use of Softmax Neural Codes extracted from Imagenet to define these vectors. The details on how this module has been implemented are discussed in the next sub-section.

In the end, the output of the system is composed of a set of groups of images, supposedly with similar semantic content, where each group and each image is associated with the corresponding metadata such as frequency, posting time, etc.

Finding semantically similar images

The high-level grouping module has been implemented in the following way.

The semantic feature vector, which we refer to as Softmax Neural Codes (SNC), is based on a deep-learning approach, taking advantage of transfer learning [6] by means of reusing a previously-trained model. This feature set is defined as

TABLE I: Mean average precision (mAP) of different feature sets on the Holidays dataset. In bold it is highlighted the proposed feature set.

Feature set	mAP
Histogram	0.17
LBP	0.22
LPQ	0.28
HoG	0.06
NC	0.54
SNC	**0.58**

the output vector of the softmax layer (the last layer) of a convolutional neural network (CNN) [11] trained on the ImageNet dataset[2]. This dataset contains about 1.2 million images distributed into 1,000 classes organized according to the WordNet hierarchy. These classes represent semantic concepts, such as *rocket*, *wig*, *football helmet*, etc. Because of this, the softmax layer can be interpreted as a guide to the semantic concepts which are presented in an image. In this work, we consider the pre-trained implementation of the AlexNet model [10] available at the Caffe Deep-Learning framework[3].

As a proof of concept of our approach, we have validated the use of the aforementioned semantic vectors in the Holidays dataset [9]. Different from our social media images, the Holidays dataset provides for each individual input image (or query) a set of other related images (ground truth). This dataset is commonly used to evaluate multimedia information retrieval methods based on the mean Average Precision score (mAP) [9].

We compare our approach with traditional feature sets, that is: histogram, Local Binary Patterns (LBP) [17], Local Phase Quantization (LPQ) [18], and Histograms of Gradients (HoG) [4], as well as another a well-known deep learning based approach, namely Neural Codes (NC) [1]. This later method is based on exploring lower layers of the CNN. The baseline multimedia retrieval method considered herein basically consists of computing the euclidean similarity between the query image and the other images in the dataset, and ranking them from highest to lowest similarity value.

We present our results for the Holidays dataset in Table I. The results in the table clearly show that using the SNC is the best approach. Gains are of roughly 7.4% when compared to the second best result of using deep features, i.e. NC. Compared to the worst approach, HoG, results are roughly 10x better.

As stated, in social media imagery no ground-truth dataset currently exists. Nevertheless, given that Softmax Neural Codes present a simple and effective approach of finding semantically similar images, in our system we consider two images belonging to the same semantic set when their similarity in euclidean distance is over 0.8, i.e. $\theta = 0.8$.

[2]http://www.image-net.org/

[3]http://caffe.berkeleyvision.org/

III. Evaluation

In this section we present an evaluation of the proposed social imagery analytics system. For doing so, we consider four different datasets collected from Twitter, from the domains of Sports, Fashion, and Entertainment, related to widely viewed events such as the FIFA World Cup, the New York Fashion week, and the Academy Awards.

A. Datasets

The four datasets considered are composed of posts from Twitter, which have been collected either with the GNIP firehose service (the first two sets), or with Twitter Decahose. The firehose comprises 100% of the tweets posted, whereas the decahose corresponds to a 10% sample of the data. The post collection process basically consisted of defining a set of key-words related to the given event (e.g., BRAvGER for the World Cup match finals between Brazil and Germany). For every event, we also added temporal rules related to the event (e.g., the date of a World Cup match). Keywords and dates comprise the rules used to gather posts in our system.

The four datasets are the following:

1) **Soccer1 (S1)**: 7,786,049 posts related to the Brazil versus Germany game during the FIFA World 2014. This game became higly commented on social media when Germany beat Brazil by 7-1, which was an unexpected score. In this case, we have collected all posts in Portuguese that were related to the game from 8 July 2014, 9:41PM, until 9 July 2014, 1:29AM.
2) **Soccer2 (S2)**: this use case contains 5,067,668 posts in English from the FIFA World Cup 2014's final, the game at which Germany beat Argentina by an 1-0 score and won the competition. The posts related to the game were collected from 13 July 2014, 9:28PM, to 14 July 2014, 0:18AM.
3) **Fashion (F)**: this set involves posts related to the 2014 New York Fashion Week, which occurred from 4 September to 11 September 2014. A total of 118,914 of posts have been collected during those dates (from 04 September 0:00AM until 11 September 2014 0:00PM).
4) **Entertainment (E)**: this set is related to the 2015 Academy Awards ceremony, widely known as the Oscar, which is the most important event for the movie industry. A total of 734,395 posts have been captured between the 22 February of 2015, 00:00AM, until 23 February of 2015, 4:00 AM, covering both before, during and after the ceremony aired worldwide on TV.

In Table II, for each set, we present the total number of posts, as well as the number of posts containing images. We begin our analysis observing that the posts versus image posts ratio varies according to the event. In larger events such as S1 and S2, a smaller proportion of images is observed, i.e. 7.59% and 16.26%, respectively. In the smaller events, the proportion is close to one third, with 35.88% and 37.03%, for E and F, respectively. We believe that this variation might not be a result of the volume of posts itself, but it is likely related to the type of the event instead. Events S1 and S2 are related to sports games, where people generally cheer for one team or the other. These events result in a lot of reposts of images that they might find interesting or funny during the games.

TABLE II: Detailed numbers of the collect posts and images in each use case.

Dataset	#Posts	#Images	Proportion
S1	7,786,049	591,224	7.59%
S2	5,067,668	824,307	16.26%
F	118,914	44,040	37.03%
E	734,395	252,753	35.88%

The main evaluation of the system is related to how it can help to reduce the large set of a images, to a set with a more manageable size. It is worth mentioning that, on Twitter specifically, images are posted as link meta-data attached to the tweet. This is true even for newly uploaded images directly to Twitter, since the service will create a URL for each upload. In this sense, we evaluate the system by comparing the number of images or groups of images that result from the following approaches:

1) Total number of posts with images, regardless of being the same URL or duplicates. Such information is presented in Table II, and represent the initial set of images;
2) The total number of *unique* image URLs. Grouping images by the same URL is a naive deduplication approach, relying only on the metadata provided by the social media provider. This value represents the minimum set size that can be created without relying on analysing the contents of the images;
3) The total number of images after removing duplicates and near-duplicates. Here, we count the number of images after deduplication is conducting, by considering the content of the images. In this case, we can demonstrate how further the set of images can be reduced by analysing the content, but considering only nearly-to-identical visual similarity;
4) The total number of groups of semantically linked image clusters. The idea is to demonstrate what would be set of images, if they were semantically grouped by content.

In Figure 5 we present our results. From the figure, we can observe that a system for imagery analytics could be easily built by taking into account only the image URL posted and how many times each URLs was reposted. In this case, the original set of images can be reduced to 11% in the best case (S1), or to 44% percent in the worst case (F). By using a more advanced system, considering image deduplication, the same set can be reduced to somewhere between 5.5% or 30%, depending on the dataset. However, even in this best settings, the user has to analyze roughly 32,720 images, which is still a lot of data.

In the same figure we consider the results of our system, that takes into account deduplication and semantic groups. That is, by considering the semantic merging using visual similarity, the images in the S1 dataset can be reduced to 5,371 groups of similar images. This corresponds to 0.9% of the total of images posted, which is a much more reasonable set to deal with. Even in the worst case, the set is reduced to about 6%, which is still accounts for a significant reduction (compared to the original 30% without semantic groups).

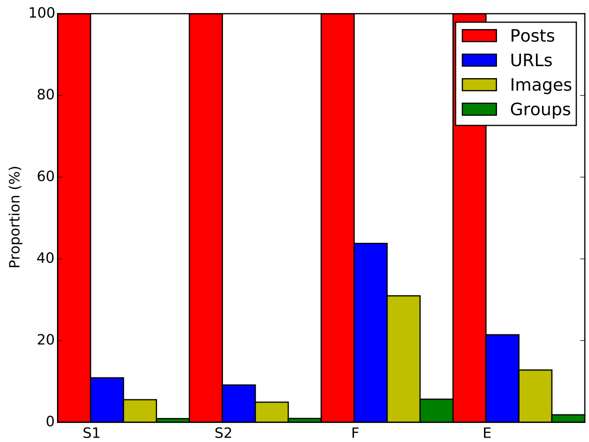

Fig. 5: Proportion of URLs, unique images and groups of images, compared with the total of posts related to images.

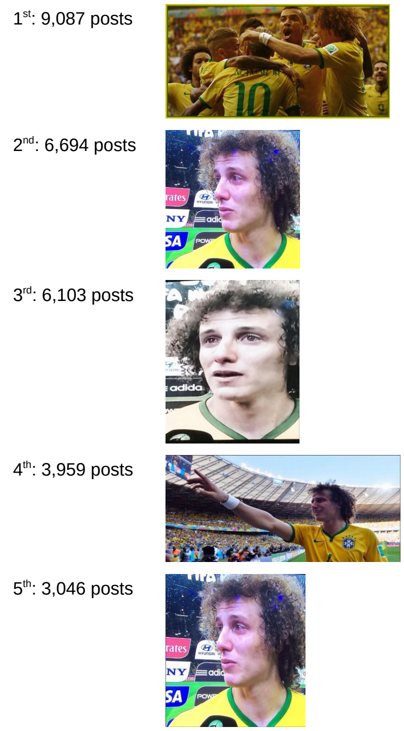

Fig. 6: Most posted links with images in the Soccer 1 use case, representing a total of 28,889 posts.

B. Use case analysis

In order to provide the reader a better idea of the potential of the proposed system, in this section we present some examples of a few use cases for a better understanding the impact of such a system on the analysis a large set of social media images.

By considering a use case based on the Soccer 1 dataset, in Figure 6 we present the top-5 most posted image URLs, without applying any kind of analysis in the contents of images. Just in this rank, we can observe not only that images 2, 3 and 4 present some degree of similarity, since the same person is in these picture, but also that images 2 and 5 are duplicates. These five images represent 28,889 posts, corresponding to 5% of the total of posts related to images in the event.

Compare now the previous results with the ones presented in Figure 7. This figure contains the top-5 most posted images, in this case after processing the content of the images to eliminate duplicates and near-duplicates. We can observe that only two images that appeared in the list in Figure 6 appear in this figure. Given the image duplication removal, the image that would be ranked 2nd in the top URLs is ranked 1st in the top images, since the number of posts of the various repetitions are combined. And the image that would be ranked 1st is only the 3rd most posted images in this case. This example highlights the importance of image analysis for a proper understanding of data. The number of posts covered by the top-5 images correspond to 46,408 posts, representing 8% of the total of images, which is an increase of 3 percentage points compared with the URL-based approach.

Then, in Figure 8, we present a ranking containing the top-5 most posted groups of images, considering the semantic similarity between all images as described in Section II. This figure shows that with such approach, a user can visualize more content at the same time, in a single view. For example, the group ranked 1st contains 12 images instead of single one, most of them with a high degree of visual similarity. In this case, not only a user can have a better view of the impact of given image in terms of number of posts, since the group aggregates closely-related images at different positions in the ranking of the most posted images, with ranking ranging from the 1st until the 1,372nd plance and with an average rank value of around 920, but also, this could be a way to measure the impact of an image in terms of the number of related content that the users have generated, i.e. the number of visually-similar (but not duplicated or near-duplicated) images found in the set. Another interesting aspect to mention is how this view allows to navigate in the data, as demonstrated by the 5th group. The meme ranked 4h in Figure 7 is linked to other memes that have not been very popular in terms of number of posts, but that can provide some interesting content to the user.

Another example of the potential of the semantic similarity approach is illustrated in Figure 9, were different pictures of Lady Gaga's[4] dress are presented. The most posted image is

[4]Lady Gaga is currently a very famous singer.

Fig. 7: Most post images in the Soccer 1 use case, representing a total of 46,408 posts.

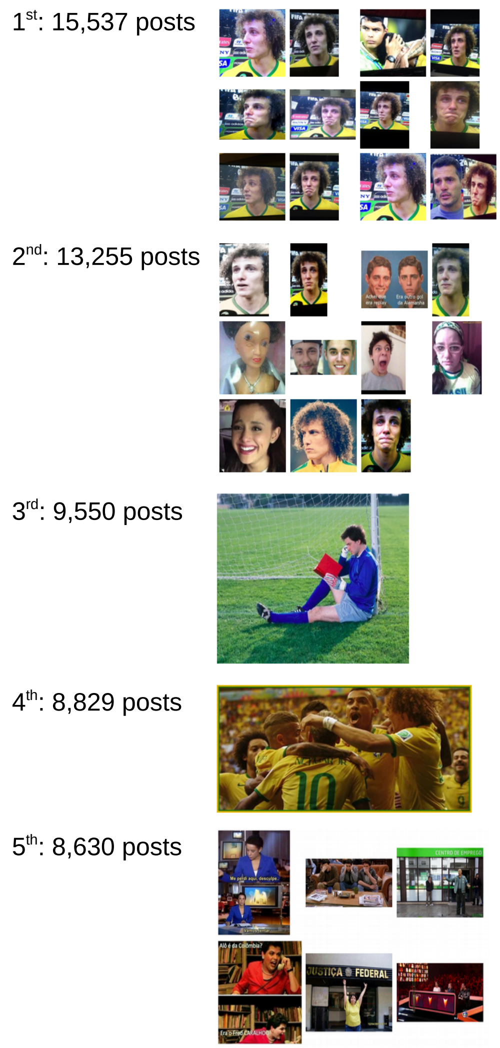

Fig. 8: Most post groups in the Soccer 1 use case, representing a total of 55,801 posts.

ranked 3rd in the list of most posted unique images, but the group of similar images shows that at least 12 other images are closely-related to that one. Note that the second most posted image in this grouped is ranked only 160th, and the average rank value is of about 956. Note that even the croquis of the dress appear in this group, demonstrating the accuracy of the proposed semantic features.

C. Discussion

From the results presented in this section, it is worth mentioning, first, that the quantitative analytics demonstrated that the proper processing of the content of the images may allow a significant reduction in the quantity of information that a user must deal with to understand the set. In some cases, such as the Soccer 1 set, the initial set of images can be reduced to only about 1% of the original size, which may help greatly the data analysis process.

The qualitative analysis demonstrated how the different approaches compared, highlighting the usefulness of our proposed system. Not only we demonstrate that image analytics is a much better approach that relying only on metadata such as image URLs, the computation of semantic similarity between images can be very helpful to point out content that may not be very popular, but that could be useful to extract insights from a dataset.

IV. Related work

The automatic analysis of social media is of great importance and has many applications, from steering of marketing campaigns to monitoring and understanding large events, among many others. The correct interpretation of the vast amount of data entailed represents many challenges, such as fast processing of enormous volume of information, correct classification of ambiguous content, fragmented information capturing a given topic, etc.

The analysis of images in social media leads the way to capture large amounts of information in a condensed manner. There has been a number of efforts in these areas to tackle the different aspects of this problem.

On the one hand, analytical and visual time series analysis for data mining have been extensively studied, in particular focusing on the different metrics for clustering (see [12], and

Fig. 9: Different images of Lady Gaga's dress, grouped by semantic similarity, from a total of 4,567 posts.

[13] for an extensive review) as well as for pattern recognition ([14], [7]). On [2], the authors focus on time series analysis of large volumes and real-time. These works focus solely on time series data.

Most work to date that analyze social media for topic detection and monitoring events, do so by extracting text content and metadata in some way or another, and either images are not used as in [15], or are mainly used to support the visualization of results. This is the case of [5], where the authors summarize social media in a tool for journalistic purposes, but no image analysis is done. In the same way, the authors of [20] propose a tool that processes text content in social media and append images (in a visual backchannel) as support to the visualization tool.

The authors of [19], focus on known topic detection techniques (e.g. Latent Dirichlet Allocation, or LDA) combined with graph theory methods to arrive at a global ranking of the best images that describe an event, but they do not approach the time dependence of topics and events.

The research focusing in image analysis for understanding events and topics in social media is particularly scarce. There has been work where image analysis is used, but not with the aim of describing an evolving topic in social media. This is the case for instance of [8] where images are analyzed to underscore the cultural differences in different places in the world.

Finally, the authors in [16] do tackle the problem of event summarization by analyzing images, but concentrate their effort in finding global rankings and selection only a subset of images.

V. Conclusions and Future Work

In this work we presented a system to organize and understand event-related images from social media. The system is able to process an input set of images at content-level, and organize them into a reduced set. This is done by removing duplicates and near-duplicate images, as well as connecting images with similar semantic content.

We have evaluated the system on four different social media datasets. Moreover, we discussed that the system can reduce significantly the quantity of information an end-user has to deal with to extract insight from a dataset of images. Furthermore, we have also demonstrated that the similarity links can sort out content that may not appear in the most popular images.

As future work, many directions can be followed. One is to enhance the way the final set of images is presented, by either improving the semantic similarity computation or by analyzing other methods to organize the set. Another interesting direction is to combine other social media analytics methods, for instance graph and text analytics, to better understand the data.

References

[1] A. Babenko, A. Slesarev, A. Chigorin, and V. Lempitsky. *Computer Vision – ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part I*, chapter Neural Codes for Image Retrieval, pages 584–599. Springer International Publishing, Cham, 2014.

[2] A. Biem, H. Feng, A. Riabov, and D. S. Turaga. Real-time analysis and management of big time-series data. *IBM Journal of Research and Development*, 57(3/4):8–1, 2013.

[3] P. Cavalin, M. Gatti, T. Moraes, F. Oliveira, C. Pinhanez, A. Rademaker, and R. de Paula. A scalable architecture for real-time analysis of microblogging data. *IBM Journal of R&D*, 59(2/3):16:1–16:10, March 2015.

[4] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, volume 1, pages 886–893 vol. 1, June 2005.

[5] N. Diakopoulos, M. Naaman, and F. Kivran-Swaine. Diamonds in the rough: Social media visual analytics for journalistic inquiry. In *Visual Analytics Science and Technology (VAST), 2010 IEEE Symposium on*, pages 115–122. IEEE, 2010.

[6] L. G. Hafemann, L. S. Oliveira, P. R. Cavalin, and R. Sabourin. Transfer learning between texture classification tasks using convolutional neural networks. In *Neural Networks (IJCNN), 2015 International Joint Conference on*, pages 1–7, July 2015.

[7] M. Hao, M. Marwah, H. Janetzko, R. Sharma, D. Keim, U. Dayal, D. Patnaik, and N. Ramakrishnan. Visualizing frequent patterns in large multivariate time series. In *IS&T/SPIE Electronic Imaging*, pages 78680J–78680J. International Society for Optics and Photonics, 2011.

[8] N. Hochman and R. Schwartz. Visualizing instagram: Tracing cultural visual rhythms. In *Proceedings of the Workshop on Social Media Visualization (SocMedVis) in conjunction with the Sixth International AAAI Conference on Weblogs and Social Media (ICWSM–12)*, pages 6–9, 2012.

[9] H. Jégou, M. Douze, and C. Schmid. Hamming embedding and weak geometric consistency for large scale image search. In A. Z. David Forsyth, Philip Torr, editor, *European Conference on Computer Vision*, volume I of *LNCS*, pages 304–317. Springer, oct 2008.

[10] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc., 2012.

[11] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. In *Proceedings of the IEEE*, pages 2278–2324, 1998.

[12] L. Li and B. A. Prakash. Time series clustering: Complex is simpler! In *Proceedings of the 28th International Conference on Machine Learning (ICML-11)*, pages 185–192, 2011.

[13] T. W. Liao. Clustering of time series dataa survey. *Pattern recognition*, 38(11):1857–1874, 2005.

[14] J. Lin, E. Keogh, and S. Lonardi. Visualizing and discovering non-trivial patterns in large time series databases. *Information visualization*, 4(2):61–82, 2005.

[15] A. Marcus, M. S. Bernstein, O. Badar, D. R. Karger, S. Madden, and R. C. Miller. Twitinfo: aggregating and visualizing microblogs for event exploration. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 227–236. ACM, 2011.

[16] P. J. McParlane, A. J. McMinn, and J. M. Jose. "picture the scene...";: Visually summarising social media events. In *Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management*, CIKM '14, pages 1459–1468, New York, NY, USA, 2014. ACM.

[17] T. Ojala, M. Pietikãinen, and T. Mãenpãã. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(7):971–987, 2002.

[18] V. Ojansivu and J. Heikkilä. Blunr insensitive texture classification using local phase quantization. In *Proceedings of the 3rd International Conference on Image and Signal Processing (ICISP '08)*, pages 236–243, 2008.

[19] M. Schinas, S. Papadopoulos, Y. Kompatsiaris, and P. A. Mitkas. Visual event summarization on social media using topic modelling and graph-based ranking algorithms. In *Proceedings of the 5th ACM on International Conference on Multimedia Retrieval*, pages 203–210. ACM, 2015.

[20] T. Schreck and D. Keim. Visual analysis of social media data. *Computer*, 46(5):68–75, 2013.

[21] K. Schubert. Bazaar goes bizarre. http://usatoday30.usatoday.com/tech/news/2003-07-28-ebay-weirdness_x.htm. Accessed: 2016-04-01.

[22] Z. Tang, X. Zhang, and S. Zhang. Robust perceptual image hashing based on ring partition and nmf. *IEEE Transactions on Knowledge and Data Engineering*, 26(3):711–724, 2014.