Topic Identification via Human Interpretation of Word Clouds: The Case of Instagram Hashtags

Stamatios Giannoulakis, Nicolas Tsapatsoulis

Topic identification via human interpretation of word clouds: The case of Instagram hashtags

Stamatios Giannoulakis[0000−0003−3020−3717] and Nicolas Tsapatsoulis

Department of Communication and Internet Studies
Cyprus University of Technology
30, Arch. Kyprianos str., CY-3036, Limassol, Cyprus
{s.giannoulakis,nicolas.tsapatsoulis}@cut.ac.cy

Abstract. Word clouds are a very useful tool for summarizing textual information. They can be used to illustrate the most frequent and important words of text documents or a set of text documents. In that respect they can also be used for topic visualisation. In this paper we present an experiment investigating how the crowd understands topics visualised via word clouds. In the experiment we use the topics mined from Instagram hashtags of a set of Instagram images corresponding to 30 different subjects. By subject we mean the research hashtag we use to gather pairs of Instagram images and hashtags. With the aid of an innovative topic modelling method, developed in a previous work, we constructed word clouds for the visualisation of each topic. Then we used a popular crowdsourcing platform (*Appen*) to let users identify the topic they believe each word cloud represents. The results show some interesting variations across subjects which are analysed and discussed in detail throughout the paper. Given that the topics were mined from Instagram hashtags, the current study provides useful insights regarding the appropriateness of hashstags as image annotation tags.

Keywords: Wordclouds · Topic modelling · Instagram hashtags · Image annotation · Visualisation.

1 Introduction

Word clouds are used to depict word frequencies derived from a text or a set of text documents. The size of each depicted word in the cloud depends on its frequency: words that occur often are shown larger than words with rare appearance while stopwords are removed. Thus, a Word cloud can be seen as a synopsis of the main themes contained in textual information [2, 11]. Word clouds became popular in practical situations and are commonly used for summarizing a set of reviews presented as free texts (i.e., "open questions").

In order to construct a classic word cloud it is necessary to calculate the word frequencies in a text or set of texts. However, word frequencies can be replaced by any other measure that reflects the importance of a word in a text document. In that respect word clouds can be used for the visualisation of topics derived from

a collection of texts. Topic models infer probability distributions from frequency statistics, which can reflect co-occurrence relationships of words [4]. Through topic modeling we can reveal the subject of a document or a set of documents and present in a summarized fashion what the document(a) is / are about. This is why topic modeling is, nowadays, a state-of-the-art technique to organize, understand and summarize large collections of textual information [1].

Let us now assume a set of Instagram photos grouped together via a common property such as the queried hashtag that was used to collect them. In the context of the current word we name the query hashtag as *subject*. Instagram photos are frequently accompanied by hashtags [3] that the photo owner and other Instagram users use to describe photos' content and, in several cases, their feelings, moments and reactions related with those photos. We can see, therefore, the hashtags of an Instagram image as a textual representation of it and in this way Instagram collections of images can be seen as textual documents and can be analysed via topic modelling techniques once textual preprocessing, such as word splitting is applied first. Since with topic modelling we can measure the most relevant terms of a topic we can assume that by applying topic modelling on the hashtags sets [19] we can derive a set of terms best describing the set of Instagram photos grouped together within a subject.

In this paper we investigate how the crowd understands the topics derived from the hashtag sets of Instagram photos that were grouped together by a common query hashtag which we call subject. The topics are illustrated as word clouds with the queried hashtags (subjects) hidden and the crowd is asked to guess the hidden hashtag providing their best four guesses. The aim of the current work is first to assess whether a word cloud presentation is appropriate for visualising hashtags sets and, second, to investigate any variations in interpreting word clouds corresponding to different subjects. We believe that through this meta-analysis we gain useful insights on whether words mined form Instagram hashtags [6] can be used for image tagging in a collective manner allowing for quick development training sets for Automatic Image Annotation [17, 18, 15].

2 Related Work

Word clouds is an informative data visualisation tool [16] primarily used to summarize textual information but it has been also applied for the analysis of social media data.

Jin [10] used Twitter data about Hurricane Maria to identify and understand the main communication patterns of the related thread. She approached that problem in quantitative manner by topic modeling and word clouds to capture topics related to Hurricane Maria, and then, to qualitatively explain the results.

Nogra analysed Instagram comments in order to locate words that are mentioned more frequently according to the media photo and visualised the results with word clouds [14]. The overall aim was to identify appropriate words to be associated with online product advertisements to better target possible customers.

In a study on how the Instagram is used to depict and portray breastfeeding, and how users share perspectives and information about that topic. Marcon *et al.* analysed 4089 images and 8331 corresponding comments posted with popular breastfeeding-related hashtags such as *#breastfeeding*, *#breastmilk*, *#breastisbest*, and *#normalizebreastfeeding*. They used word clouds to visualize the comment discussions in order to quickly identify the main discussion trends [12].

Vitale *et al.* [20] investigated how Igers ('instagrammers' which allow people who do not follow them to find their photos) represent themselves and their experience at museums in a textualised fashion. They analyzed the captions and hashtags of Igers' Instagram photos and presented the most frequent words used in word clouds for quick interpretation.

Mittal *et al.* [13] study some user interaction properties, such as hashtags and post time, along with photo properties such as photo features or applied image filters to understand users' engagements with Instagram posts. As a part of their analysis, they apply the Latent Dirichlet Allocation (LDA) algorithm in order to locate the most commonly used hashtags at a specific location. The most common hashtags per location are depicted as word clouds.

Kamil *et al.* [9] collected 1017 Instagram posts, tracked with the hashtag *#prayfornepal*, related to the Nepal earthquake in April 2015 to investigate how the people respond and express themselves emotionally for a disaster of such massive scale. By using posts' date, time, geolocation, image, post ID, username and ID, caption, and associated hashtags they categorized the posts into seven categories and they created the word clouds for each one of those categories using the captions and the hashtags to visually illustrate the main topic facets related with the disaster.

In order to study the reactions of Instagram users on an Indonesian action entitled GERMAS, aiming to promote healthy living community movement, Habibi *et al.* [8] collected posts related to hashtag *#germas*. They applied topic modeling on the captions of those posts and used word clouds to illustrate the resulting topics. For topic modelling the authors used the Latent Dirichlet Allocation (LDA) algorithm.

The previous discussion shows that while presentation of Instagram related textual data, such as captions, comments and hashtags, via word clouds is quite common, no meta analysis of the word clouds themselves has been conducted in anyone of those works. Word clouds have been mainly used for visualisation purposes but the appropriateness of this visualisation format was never assessed. Thus, in addition to the application perspective of our work, which emphasizes on mining terms from Instagram hashtags for image tagging, the crowd-based meta analysis of word clouds provides also useful insights about their appropriateness for topic visualisation. Some of the reported works applied topic modelling to summarize textual information using the classic LDA approach. Our topic modeling algorithm [19] is quite different and tailored to the specific case of Instagram posts. Photos and associated hashtags are modelled as a bipartite network and the importance of each hashtags is computed via its authority score obtained by applying the HITS algorithm [7].

3 Word clouds creation

As already mentioned the main purpose of the current work is to investigate and discuss the crowd-based interpretation of word clouds created from Instagram hashtags. A dataset of 1680 Instagram posts (photos along with their associated hashtags) was created by querying with 30 different hashtags (see Table 1) which in the context of the current work are called *subjects*.

All collected hashtags were undergone preprocessing so as to derive meaningful tokens (words in English). Instragram hashtags, are unstructured and ungrammatical, and it is important to use linguistic processing to (a) remove stophashtags [5], that is hashtags that are used to fool the search results of the Instagram platform, (b) split a composite hashtag to its consisting words (e.g. the hashtag '#spoilyourselfthisseason' should be split into four words: 'spoil', 'yourself', 'this', 'season'), (c) remove stopwords that are produced in the previous stage (e.g. the word 'this' in the previous example), (d) perform spelling checks to account for (usually intentionally) misspelled hashtags (e.g. '#headaband', '#headabandss' should be changed to '#headband'), and (e) perform lemmatization to merge words that share the same or similar meaning. Preprocessing was conducted with the help of Natural Language ToolKit (NLTK - https://www.nltk.org/), Wordnet[1] and personally developed code in Python.

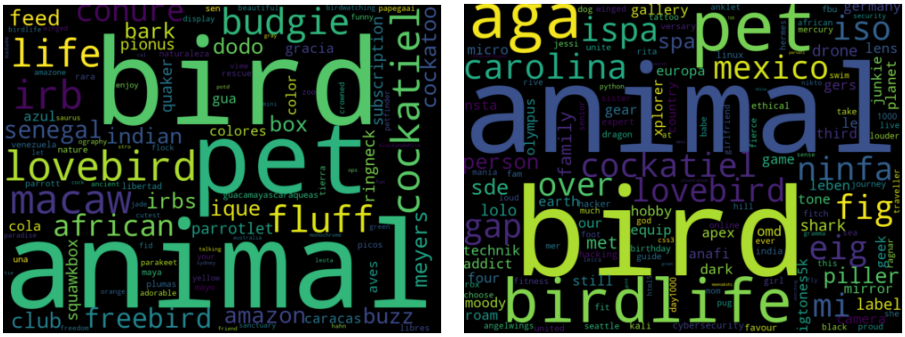


Fig. 1: Two different word clouds for the subject (queried hashtag) parrot

By finishing all preprocessing steps we ended up with a token set for each one of the 1680 Instagram photos. Instagram photos and the associated hashtag sets belonging to a common subject were grouped together and modeled as a bipartite network. Then, topic models were created for each one of the subjects following the approach described in [19]. A total of 46 different topic models were developed since for some subjects we had two or more topics. The importance of each token within a topic model was assessed by applying the HITS algorithm as described in [7]. For each one of the topics a word cloud was created. The

[1] https://wordnet.princeton.edu/

token corresponding to the associated subject (query hashtag) was excluded in order to examine whether the crowd would guess it correctly (see Section 4 for the details). Word clouds visualization (see an example in Figure 1) was done with the help of WordCloud[2] Python library.

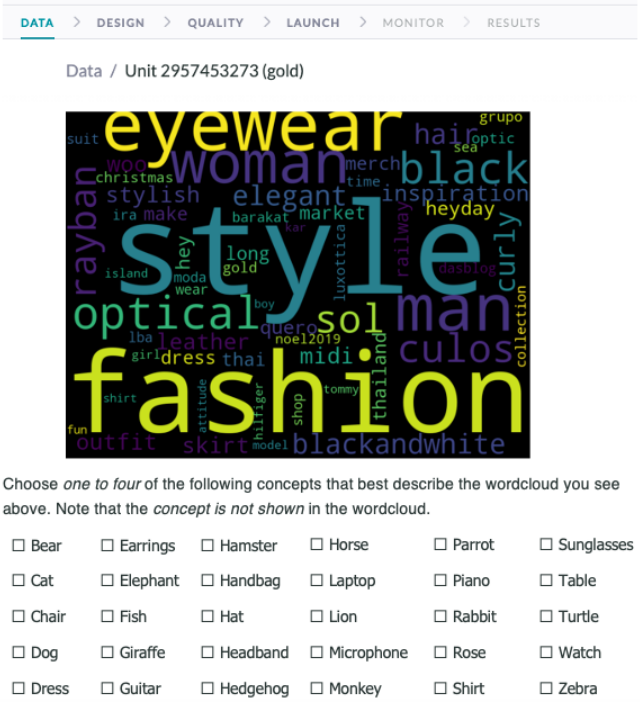


Fig. 2: The way the wordclouds were presented to the crowd through the Appen crowdsourcing platform

4 Crowd-based interpretation of word clouds

Crowd-based interpretation of word clouds was conducted with the aid of the *Appen* (https://appen.com/) crowdsourcing platform. The word clouds were presented to the participants as shown in Figure 2 and the participants were asked to select one to four of the subjects that best match the shown word cloud according to their interpretation. The participants were clearly informed that the token corresponding to the correct subject was not shown in the cloud.

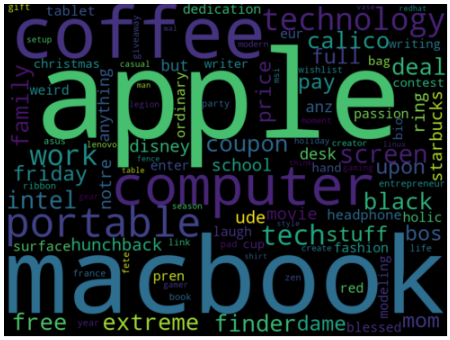
Every word cloud was judged by at least 30 annotators (contributors in Appen's terminology) while eight word clouds were also used as 'gold questions'

[2] https://amueller.github.io/word_cloud/

for quality assurance, i.e., identification of dishonest annotators and task difficulty assessment. The correct answer(s) for the gold clouds were provided to the crowdsourcing platform and all participants had to judge those clouds. However, gold clouds were presented to the contributors in random order and they could not know which of the clouds were the gold ones. A total of 165 contributors from more than 25 different countries participated in the experiment. The cost per judgement was set to \$0.01 and the task was completed in less than six hours.

(a) Word cloud for the subject 'fish'

(b) Crowd based interpretation of the 'fish' word cloud



(c) Word cloud for subject 'laptop'

(d) Crowd based interpretation of the 'fish' word cloud

Fig. 3: Word clouds and crowd-based interpretation for the subjects 'fish' and 'laptop'

The crowd interpretations of each one of the word clouds were also transformed as word clouds, i.e., meta word clouds, for illustration purposes. The importance of each token in a meta word cloud was based on the frequency of its selection by the contributors. Meta word clouds are presented in Figures 3b, 3d, 4b, 4d, 5b, 6b, 7b. The tokens in a meta word cloud can be seen as the topic model suggested by the crowd for the Instagram photos grouped under the

corresponding subject. For instance we could say that the topic model for the images grouped under the subject 'microphone' includes also the words 'guitar' and 'piano' and thus all three words can be used for tagging the corresponding photos even for creating training datasets for AIAI purposes [19].

Not all word clouds present the same difficulty in interpretation. Thus, in order to quantitatively estimate that difficulty per subject we used the typical accuracy metric, that is the percentage of correct subject identifications by the crowd. By correct identification we mean that a contributor had selected the right subject within her/his one to four choices (see Figure 2). We see for instance in Table 1 that the accuracy of the first guitar word cloud is 93%. This means that 93% of the contributors included the word 'guitar' in their interpretation for that word cloud, regardless the number (1 to 4) of contributor choices.

Table 1: Crowd-based topic identification accuracy.

Subject	Acc.(%)	Subject	Acc.(%)	Subject	Acc.(%)	Subject	Acc.(%)
Guitar	93	Dress	80	Cat	90	Chair	47
Guitar	87	Dress	60	Dog	87	Chair	43
Microphone	67	Shirt	53	Fish	100	Laptop	100
Microphone	57	Shirt	33	Fish	93	Laptop	80
Piano	70	Earrings	90	Hamster	7	Table	77
Piano	47	Handbag	93	Hamster	3	Table	73
		Hat	7	Parrot	90		
Bear	43	Hat	3	Parrot	87	Hedgehog	0
Elephant	37	Headband	30	Rabbit	77	Hedgehog	0
Giraffe	63	Headband	17	Turtle	21	Horse	87
Lion	60	Sunglasses	67	Turtle	20	Rose	63
Lion	67	Watch	87				
Monkey	33						
Zebra	57						

5 Results and discussion

The accuracy of interpretation for all word clouds is presented in Table 1. In order to better facilitate the discussion that follows the subjects (query hashtags) were divided into six categories: (a) **Music**: Guitar, Piano, Microphone (b) **Wild animals**: Bear, Elephant, Giraffe, Lion, Monkey, Zebra (c) **Fashion**: Dress, Earrings, Handbag, Hat, Headband, Shirt, Sunglasses (d) **Office**: Chair, Laptop, Table, (e) **Pets**: Cat, Dog, Fish, Hamster, Parrot, Rabbit, Turtle (f) **Miscellaneous**: Hedgehog, Horse, Rose.

We see in Table 1 that the interpretation accuracy varies within and across categories. As we explain later through specific examples, there are three main

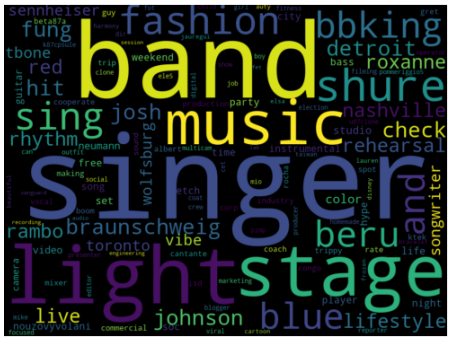
parameters which affect the difficulty of interpretation. The first one is the conceptual context for a specific term. It is very easy, for instance, to define a clear conceptual context for the term fish but very difficult to define clear conceptual contexts for terms such as hat and hedgehog. This difficulty is, obviously, reflected in the use of hashtags that accompany photos presenting those terms. As a result the corresponding word clouds do not provide the textual context and hints that allow the correct interpretation of word clouds. Thus, textual context and key tokens in the word clouds is the second parameter affecting the difficulty of interpretation. This is, obviously, a data related factor and its effect can be minimized by creating word clouds from a larger number of Instagram posts per subject (note that in our case we have used on average 56 Instagram posts per subject). The third parameter that affects interpretation, is the familiarity of people with the concepts. Concepts such as dog, cat and horse are far more familiar to everyday people than concepts such as hedgehog and hamster.

Overall, the word clouds corresponding to the subjects 'Laptop' and 'Fish' had the highest interpretation accuracy both reaching the absolute 100%. In the case of fish word cloud (see Figure 3a) the prominent presence of the tokens fisherman, aquarium created as strong and clear context and led the annotators to select the concept fish as their single selection. That resulted in a meta word cloud (see Figure 3b) consisting of a single word, the word fish. A similar case is seen in the case of the laptop word cloud (see Figure 3c). The prominent presence of tokens apple, macbook, computer and portable make it clear to the annotators that the right concept choice is laptop. We see in the corresponding meta word cloud that the a significant number of contributors chose the concept 'table' as well triggered mainly by the strong presence in the cloud of the token coffee (see Figure 3d).

In the following we present and discuss some representative / interesting examples for each one of the six categories mentioned above.

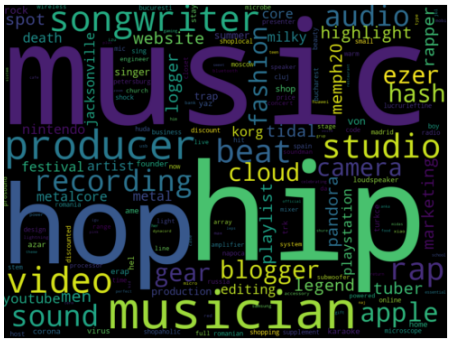
The word clouds in the Music category have very high scores of interpretation accuracy. Music related terms share a strong conceptual context which results in clear textual contexts in the Instagram hashtags. In Figure 4 we see two different word clouds for the subject 'microphone'. While the word clouds are quite different (see Figures 4b and 4c) the music-singing conceptual context is prominent. Tokens like band, singer, music, hop, hip and stage create a strong and clear textual content. Thus, the annotators chose all music-singing related terms, namely guitar, piano and microphone, as it can be seen in the corresponding meta word clouds (see Figures 4b, 4d).

The monkey word cloud (see Figure 5a) was in fact a confusing one. The most prominent tokens were art, animal and nature while some other terms such as artist, artwork, and work could also confuse the contributors (annotators). We see in the meta word cloud (Figure 5b), however, that the key tokens animal and nature combined with the term gorilla in the upper right corner of the word cloud led the contributors to make selections from the wild animal category including the correct subject (accuracy 33%).



(a) The first word cloud for 'microphone'

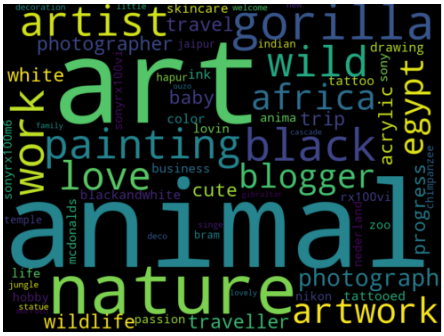
(b) Crowd based interpretation of the first 'microphone' word cloud



(c) The second word cloud for 'microphone'

(d) Crowd based interpretation of the second 'microphone' word cloud

Fig. 4: Two different word clouds and the corresponding crowd-based interpretations for the subject 'microphone'

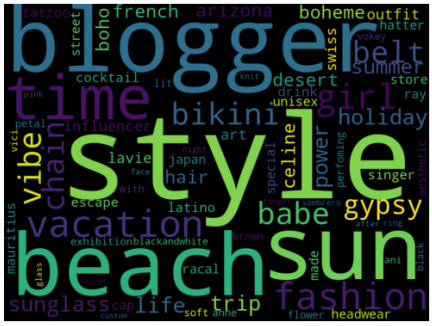


(a) Word cloud for the 'monkey' subject

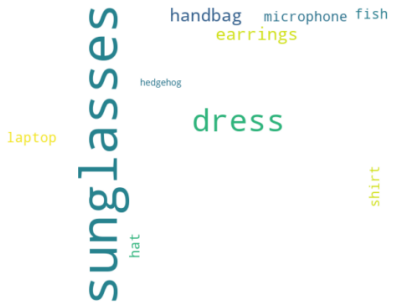
(b) Crowd based interpretation of the 'monkey' word cloud

Fig. 5: Word cloud and crowd-based interpretation for the subject 'monkey'

In the case of subject 'hat' (see word cloud in Figure 6) we have a situation where there are many different conceptual contexts. As a result, the hashtags appeared in different Instagram photos differ significantly and the resulting word cloud is confusing. We see that the most prominent tokens in the cloud are blogger, style, sun, and beach (obviously these are concepts shown in some of the Instagram photos grouped under the subject 'hat'). There is no doubt that the subject 'hat' fits well with those terms. However, the same terms fit well or even better to other subjects such as 'sunglasses' and dress which were the primary choices of the annotators (see Figure 6b).



(a) Word cloud for the 'hat' subject



(b) Crowd based interpretation of the 'hat' word cloud

Fig. 6: Word cloud and crowd-based interpretation for the subject 'hat'

The case of hedgehog is a classic example showing that the familiarity with a concept affects the difficulty in interpretation of the word cloud derived from Instagram hashtags. While in the word cloud (see Figure 7a) the words pygmy, pet and animal are by far the most important ones none of the participants selected the right subject. It appears that the contributors were non-familiar with the word pygmy. The African pygmy hedgehog is the species often used as pet. By examining the meta word cloud (see Figure 7b) we see that the contributors mixed up concepts related to pets with concepts related to wild animals.

6 Conclusion

Presentation of Instagram related textual data (or social media data in general), such as captions, comments and hashtags through word clouds for quick interpretation is quite common both in real-world applications and in the scientific community. In the current work we have presented a crowd-based meta analysis of word clouds created from Instagram hashtags. The main purpose was to identify appropriate tags for Instagram photos that share (and grouped together) a common hashtag (called subject in the current work). Through this

(a) Word cloud for the 'hedgehog' subject (b) Crowd based interpretation of the 'hedgehog' word cloud

Fig. 7: Word cloud and crowd-based interpretation for the subject 'hedgehog'

meta analysis we concluded that there is significant variation in the difficulty of interpretation of word clouds corresponding to different terms and we named three parameters affecting this interpretation: conceptual context, textual context and familiarity with concept. Terms having a clear conceptual context, for instance the terms 'fish', 'guitar', 'laptop', have an easily interpreted word cloud of Instagram hashtags as a clear conceptual context is reflected on a clear textual context. On the contrary, terms whose conceptual context can vary a lot, such as the term 'hat', result on a confusing word cloud of Instagram hashtags. The familiarity with a term is also an important reason affecting the ease of interpretation of its word cloud. For instance the word clouds corresponding to the concept 'hedgehog' were far more difficult to interpret than their counterparts for the concepts 'dog' and 'cat'.

The main conclusion is that we can mine information from Instagram hashtags for image tagging, and subsequently for developing training sets for Automatic Image Annotation (AIA) purposes, but not for every single concept / term. We are currently in the process to assess deep learning models, trained on Instagram photos corresponding to the 30 subjects included in the current study, in terms of image classification. The aim is to examine whether the difficulty in crowd-based word cloud interpretation is correlated with the effectiveness of the trained models.

References

1. Alami, N., Meknassi, M., En-nahnahi, N., El Adlouni, Y., Ammor, O.: Unsupervised neural networks for automatic Arabic text summarization using document clustering and topic modeling. Expert Systems with Applications, **172**, (2021).
2. Atenstaedt, R.: Word cloud analysis of the BJGP: 5 years on. British Journal of General Practice. **67**(658), pp. 231-232 (2017).
3. Daer, A., Hoffman, R., Goodman, S.: Rhetorical functions of hashtag forms across social media applications. Communication Design Quarterly. **3**, pp. 12-16 (2015).

4. Fu, X., Wang, T., Li, J., Yu C., Liu, W.: Improving Distributed Word Representation and Topic Model by Word-Topic Mixture Model. In: Durrant R. J., Kim K.-E.b (eds) Proceedings of the Asian Conference on Machine Learning, vol. 63, pp 190-205 (2016).
5. Giannoulakis, S., Tsapatsoulis, N.: Defining and identifying stophashtags in instagram. 2nd INNS Conference on Big Data. pp. 304-313. Springer Nature, Cham, Switzerland (2016).
6. Giannoulakis, S., Tspatsoulis, N.: Evaluating the descriptive power of Instagram hashtags. Journal of Innovation in Digital Ecosystems, **3**(2), pp. 114-129 (2016).
7. Giannoulakis, S., Tspatsoulis, N.: Filtering Instagram hashtags through crowdtagging and the HITS algorithm. IEEE Transactions on Computational Social Systems, **6**(3), pp. 592-603 (2019).
8. Habibi, M., Priadana, A., Saputra, A., Cahyo, P.: Topic Modelling of Germas Related Content on Instagram Using Latent Dirichlet Allocation (LDA). 2nd International Conference of Health, pp. 260-264. Atlantis Press (2020).
9. Kamil, P., Pratama, A., Hidayatulloh, A.: Did we really #prayfornepal? Instagram posts as a massive digital funeral in Nepal earthquake aftermath. AIP Conference Proceedings, **1730**, 090002-1-090002-10 (2016).
10. Jin, X.: Understanding Social-Mediated Disaster and Risk Communication with Topic Model. pp. 159-174. Springer Nature, Switzerland (2021).
11. Lohmann, s., Heimerl, F., Bopp, F., Burch, M., Ertl, T.: ConcentriCloud: Word Cloud Visualization for Multiple Text Documents. In: Banissi E. et al. (eds) Proceedings of the 19th International Conference on Information Visualisation, pp. 114-120. IEEE, Piscataway, NJ (2015).
12. Marcon, A., Bieber, M., Azad, M.: Protecting, promoting, and supporting breastfeeding on Instagram. Maternal & Child Nutrition, **15**(1), e12658 (2019).
13. Mittal, V., Kaul, A., Gupta, S., Arora, A.: Multivariate Features Based Instagram Post Analysis to Enrich User Experience. Procedia Computer Science, **122**, pp. 138-145 (2017).
14. Nogra, J.A.E.: Text Analysis on Instagram Comments to Better Target Users with Product Advertisements. International Journal of Advanced Trends in Computer Science and Engineering, **9**, pp. 175-181 (2020).
15. Ntalianis, K, Tsapatsoulis, N, Doulamis, A., Matsatsinis, N.: Automatic annotation of image databases based on implicit crowdsourcing, visual concept modeling and evolution. Multimedia Tools and Applications, **69**(2), pp.397-421 (2014).
16. Shahid, N., Ilyas, M., Alowibdi, J., Aljohani, N.: Word cloud segmentation for simplified exploration of trending topics on Twitter. IET Software. **11**, pp. 214-220 (2017).
17. Theodosiou, Z, Tsapatsoulis, N: Image Retrieval Using Keywords: The Machine Learning Perspective. Semantic Multimedia Analysis and Processing (Eds: E. Spyrou, D. Iakovides, P. Mylonas). CRC Press / Taylor & Francis, pp. 3-30 (2014).
18. Tsapatsoulis, N.: Web Image Indexing using WICE and a learning-free Language Model. 12th IFIP International Conference on Artificial Intelligence Applications and Innovations (AIAI 2016), pp. 131-140 (2016).
19. Tsapatsoulis, N.: Image retrieval via topic modelling of Instagram hashtags. 15th International Workshop on Semantic and Social Media Adaptation & Personalization, pp.1-6. IEEE, Piscataway, NJ (2020).
20. Vitale, P., Mancuso, A., Falco, M.: Museums' Tales: Visualizing Instagram Users' Experience. 14th International Conference on P2P, Parallel, Grid, Cloud and Internet Computing, pp. 234-245. Springer Nature, Switzerland (2020).