5 Steps to Make Art Museums Tweet Influentially

Marco Furini*, Federica Mandreoli†, Riccardo Martoglia† and Manuela Montangero†
*Dipartimento di Comunicazione ed Economia,
Università di Modena e Reggio Emilia
42121 Reggio Emilia, Italy
Email: marco.furini@unimore.it
†Dipartimento di Scienze Fisiche, Informatiche e Matematiche
Università di Modena e Reggio Emilia
41125 Modena, Italy
Email: name.surname@unimore.it

***Abstract*—A growing number of museums has started using social networks as different forms of engagement that can act outside museum architectural bounds. Specifically, museum leaders are praising Twitter as a necessary tool to any online programming or presence in museums today. Nevertheless, using Twitter in a satisfactory way so to increase museums' influence is not an easy task and there has been a gap between its usage and the possibilities it represents. In this paper, we propose an easily understandable framework to analyze the key content factors in museum conversations, including novel formulas for the evaluation of tweets and Twitter accounts influence. We apply the framework to a dataset of 100,000 messages related to 26 museum accounts to understand which museum is more influential in writing tweets, and which features have more impact on the influence of a tweet. Finally, we propose 5 key steps that museums can perform in order to write more influential tweets.**

I. Introduction

Web 2.0 technologies have been creating new ways in the museum field to engage with visitors and enhance their museum experience. To this extent, the potential of these new channels is huge: the possibility to reach people world wide, to update and disseminate information in real time and especially at low costs. Therefore, a growing number of museums has started using social networks such as Twitter, Facebook, and Instagram as different forms of engagement that can act outside museum architectural bounds. Specifically, museum leaders are praising Twitter as a necessary tool to any online programming or presence in museums today [1]. Museum account curators on Twitter are called to write short messages mainly to inform people about upcoming events and exhibitions, to build community and audiences around their institutions, and to engage people to co-produce the narratives of the museum in ways which are (potentially) more radical and profound [2]. In this way, museums hope their influence grows amongst, between and around individuals and communities in this social media space, and, finally, attract new visitors. Nevertheless, this is not an easy task. Indeed, some researches showed that Twitter has not been always used in a satisfactory way, e.g., [2] showed that there was a gap between the usage of social media and the possibilities they represent and [1] concluded that museum visitors engagement trough Twitter was not effective yet. Therefore, it is evident the need of methods, tools and guidelines to help museums achieve the former goals (e.g., [3], [4]).

The final aim of this work is to help museums in tuning their tweet writing to have more influence on their readers. To this end, we analyze the key content factors that contribute to tweet influence on museum conversations. Specifically, the main contributions of this paper are the following:

- We propose an easily understandable and implementable framework made up of features characterizing tweets content and formulas for the evaluation of tweets and Twitter accounts influence.
- We apply the framework to a dataset of 26 Twitter museum accounts and 100,000 tweets to understand which museum is more influential in writing tweets, and which features have more impact on the influence of a tweet.
- We propose 5 key steps that museums can perform in order to write more influential tweets.

The remainder of this paper is organized as follows: Section II introduces the framework of our proposal, including tweet features and the tweet influence formula; Section III reports our experimental setting and results; Section IV gives an overview of related works and we draw conclusions in Section V.

II. Methods

In this section, we describe the conceptual framework of our proposal. The framework aims at evaluating tweets and Twitter accounts influence with respect to features characterizing tweets content.

In line with previous literature (e.g. [5], [6]), we consider the following content features for each tweet:

- *availability of supplementary information*, in particular we focus on the availability of *URLs* and *images* that are widely diffused in this specific context;
- the *topics* density, where we assume that the involved topics correspond to the hashtags mentioned in the text and we state that a tweet is dense of topics if the number of hashtags is greater than a given threshold, set to 5;
- *subjectivity*, where we want to examine if a tweet written in a more emotional, more personal, and more subjective voice can resonate stronger with the readers [6];

- the *length*, where we state that a tweet is long if the number of characters is greater than 100.

Our final aim is to suggest to museums strategic choices for tweet composition and increase their influence in the Twitter platform. Such suggestions focus on tweet content and, therefore, the performed analysis aims to understand the impact that such features have on the influence value. We are interested in a measure of influence that allows us to compare the influence of tweets relative to accounts with different contexts in the Twitter platform. Our measure of influence derives from the success that a tweet has among Twitter users because of its content. Such success is thus defined in terms of intentional and detectable actions made by users on messages, namely retweeting and placing favorites. We assume that a user places a favorite or retweets a message because (s)he found the message somehow interesting and that such actions are not accidental. Finally, the number of favorites and retweets can be derived from metadata while, for example, it is not possible to know if a user just read a message. However, such numbers can vary greatly not only because of the content of the message, but also because of the author context (e.g., the number of the author's followers on Twitter, etc.). For this reason, our measure is designed to make the final values as independent as possible from this context effect.

In the following, a *message* is either a tweet or a retweet, while a *tweet* is not a retweet. Given a message m, we will use the following notation:

- $Fv(m)$ is the number of *favorite* of m;
- $Fo(m)$ is the number of the *followers* of the author of m;
- $Fg(m)$ is the number of the *followings* (a.k.a. friends) of the author of m.

We first introduce the notion of tweet thread that groups together an original tweet and its propagation messages.

Definition 1 (Tweet Thread): Given a tweet T, the *thread* of tweet T is the set $\mathcal{T}(T) = \{T, rT_1, rT_2, \dots, rT_k\}$, where rT_i is either a retweet of T or a retweet of a retweet of T.

Tweet influence is then defined by considering all messages in its thread.

Definition 2 (Context-independent tweet Influence): Given a tweet T and its corresponding thread $\mathcal{T}(T)$, the tweet influence $\mathcal{I}(T)$ is given by

$$\mathcal{I}(T) = \frac{\sum_{m \in \mathcal{T}(T)} Fv(m)}{\sum_{m \in \mathcal{T}(T)} Fo(m)} \cdot \log \left(\sum_{m \in \mathcal{T}(T) \setminus \{T\}} Fg(m) \right). \quad (1)$$

The left hand side of the formula essentially aims to represent the ratio of people that read the original tweet, or one of its retweets, and appreciated it by placing a favorite. The number of people that read the original tweet is approximated through the number of followers. For instance, if we compare the influence of two tweets having the same number of favorites, one retweeted by a very famous museum that has a large number of followers and the other one retweeted by a small museum with less followers, then the second message is in principle more successful than the first one because it obtained the same performance but in a smaller context. The right hand side, instead, introduces an adjustment factor based on the "effort" spent by a user that retweeted a message. The main idea is that the more accounts a user follows the more tweets (s)he receives and should read before deciding whether to retweet or not, hence greater the "effort". The log function is used to smooth the total amount of followings.

Finally, to determine the influence of a Twitter account on a set of tweets, we compute the average of the tweets influences in the given set.

Definition 3 (Twitter account Influence): Given a set of tweets $\tau = \{T_1, T_2, \dots, T_n\}$, related to the same Twitter account A, the account influence is given by

$$\mathcal{AI}(A, \tau) = \frac{\sum_{i=1}^{n} \mathcal{I}(T_i)}{n}. \quad (2)$$

Observe that the influence measures are non negative numbers, the larger the number, the larger the influence.

In the following of this paper, we will compute the influence of museum Twitter accounts by using Equation (2), with τ being either the set of all tweets or a proper subset with specific features (e.g., containing an image or not).

As a final observation, we highlight that tweet and account influence values are easy to compute, to understand, and are exclusively based on the information provided by the Twitter API used to collect data.

III. Experimental Assessment

A. Dataset

We observed Twitter data for 45 days, collecting data related to well-known museums located around the world. In particular, we focus on conversations centered around 26 Twitter accounts: Guggenheim NY (3.35M followers), Metropolitan NY (3.68M), Tate Art galleries London (4.7M), MoMA NY (5.3M), Saatchi Gallery London (2.8M), Louvre Paris (1.25M), British Museum London (1.56M), Prado Madrid (1.18M), Van Gogh Amsterdam (1.33M), Getty Los Angeles (1.25M), National Gallery London (887K), Orsay Paris (610K), Centre Pompdou Paris (970K), MAXXI Rome (190K), Picasso Barcelona (65K), Philadelphia (247K), Art Institute Chicago (273K), National Gallery Washington (216K), Fine Arts Boston (332K), Romes Civic Museum (264K), Venice Museum (88K), MART Trento (64K), Uffizi Galleries Florence (20K), Egyptian Torino (22K), Diamanti Palace Ferrara (5K), and MUSE Trento (12K).

We grouped the museum Twitter accounts into three groups: large follower base museums (10 well-known museums with more than 1M followers), medium follower base museums (9 well-known museums with less than 1M followers), and Italian museums (8 well-known Italian museums). In total, the collected dataset is composed of 100,117 messages (73,255 for group 1, 20.323 for group 2, and 6,539 for group 3).

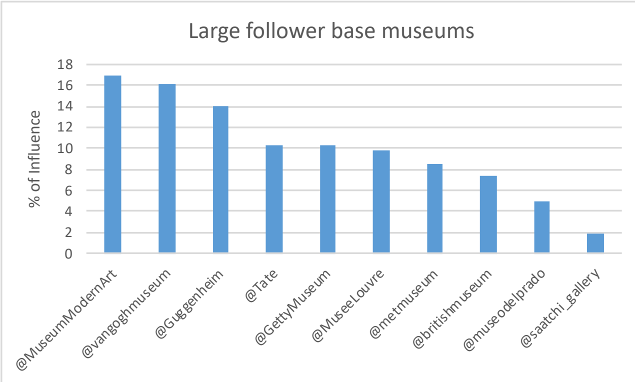

Fig. 1. Twitter account influence comparison for museums with large follower base.

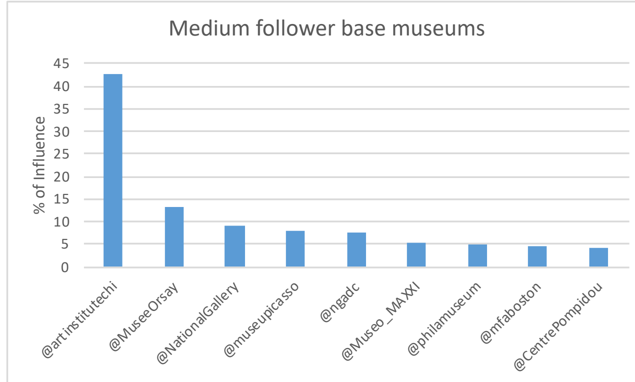

Fig. 2. Twitter account influence comparison for museums with medium follower base.

B. Tweeter account influence

To understand which museum is the most influential in writing tweets, we consider all the tweet threads related to official museum accounts. For each official museum account, we apply Equation (1) to each tweet thread and, according to Equation (2), we average the obtained results to get a measure of how influential the official museum account is. Then, we compare the obtained results with the ones of the other museums in the same group in order to understand which museum is the most influential in writing tweets.

Figure 1 compares the museums with large follower base with respect to their influential value. It can be noted that the three most influential museums are: Museum of Modern Art (16.8% of the overall influence of this group of museums are obtained by threads related to this museum), Van Gogh Museum (16.1%) and Guggenheim Museum in NY (13.9%). The less influential ones are: Saatchi Gallery (1.8%), Museo del Prado (4.9%) and British Museum (7.4%).

Figure 2 compares the museums with medium follower base with respect to their influential value. The three most influential museums are: Art Institute in Chicago (42.6%), Orsay Museum (13.2%) and National Gallery (9.2%). The less influential ones are: Centre Pompidou (4.1%), Museum of Fine Arts in Boston (4.6%) and Philadelphia Museum (5.1%).

Figure 3 compares the Italian museums with respect to their influential value. The three most influential museums are: Uffizi Galleries in Florence (17.9%), Musei in Comune Rome (16.2%) and MAXXI Museum (15.9%). The less influential ones are: Mart Museum (8.5%), Palazzo Diamanti (8.9%) and MUSE Museum (9.5%).

C. Tweets features

In this section we analyze the distribution of tweets with respect to the features introduced in Section II. In details, we investigate the set of tweets according to: presence or absence of *images* and *URLs*; *topic* density (more/less than 5 hashtags); *subjectivity*, where we used AFINN[1] to measure the sentiment conveyed by the tweet and we state that a tweet is subjective

[1] https://github.com/fnielsen/afinn

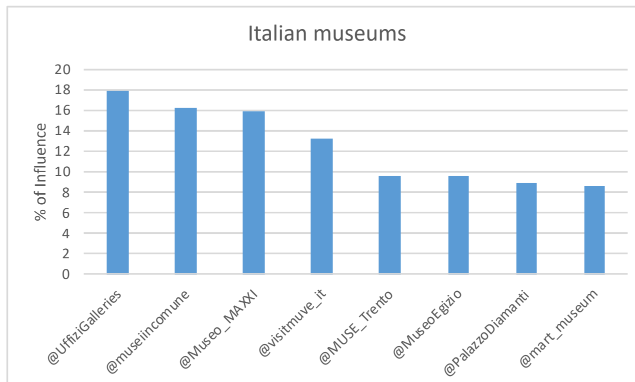

Fig. 3. Twitter account influence comparison for Italian museums.

if the AFINN value is not 0; *long* or *short* (resp. containing more/less than 100 characters).

Figure 4 describes the features of the tweets written by museums of the first group. It can be noted that an external URL is introduced in the majority of the tweets (e.g., 81% of the tweets written by Museo del Prado includes an external URL). Conversely, less than 50% of the tweets contains images (e.g., the highest value is the one achieved by Saatchi Galleries with 45.1%). The percentage of dense tweets is very limited (e.g., the highest value is the one of the Van Gogh Museum 22.1%). Similarly, also the percentage of subjective tweets is quite limited (e.g., the highest value is the one achieved by Saatchi Galleries with 43.3%, but all the other values range between 12 and 27%). Finally, the length of the tweets does not seem to characterize the message (almost half tweets are long and half tweets are short). On average, the majority of tweets generated by museums with large follower base do not contain images, are not dense and not subjective, whereas they contain external URLs. In particular, 37.1% of tweets has an image, 69.3% has an external URL, 15.1% is dense, 24.6% is subjective and 49.4% is long.

Figure 5 describes the features of the tweets generated by museums with medium follower base. On average, 45% of tweets has an image, 72.6% has an external URL, 12.1% is

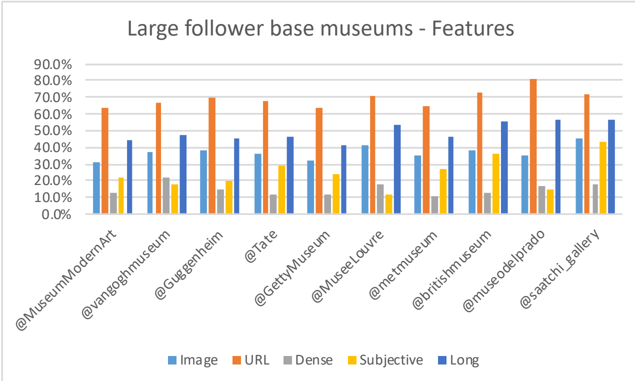

Fig. 4. Features of the tweets generated by museums with large follower base.

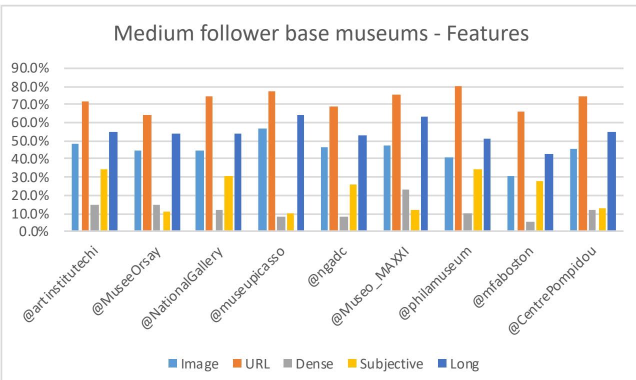

Fig. 5. Features of the tweets generated by museums with medium follower base.

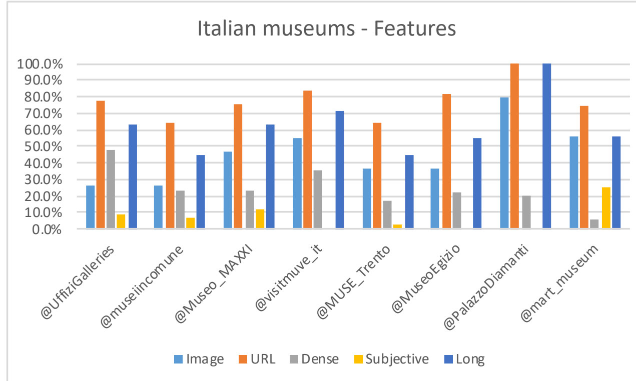

Fig. 6. Features of the tweets generated by Italian museums.

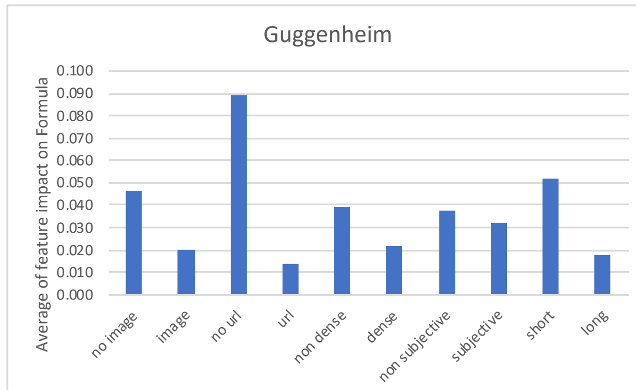

Fig. 7. How tweet features impact on tweet influence. The Guggenheim case.

dense, 22.3% is subjective and 54.6% is long.

Figure 6 describes the features of the tweets generated by Italian museums. On average, 45.4% of tweets has an image, 77.7% has an external URL, 24.5% is dense, 6.9% is subjective and 62.2% is long.

Notice that the behavior in the first and second group is very similar, while the group of Italian museums differs in the percentages of dense tweets (higher) and subjective ones (lower).

D. Features impact on account influence

To understand the impact that each feature has on the influential value given by Equation (1), we compute the average influence value that tweets with specific features have on the final value for each museum. This allows us to understand whether it is better to have/not have that specific feature when writing a tweet.

To clarify the idea, Figure 7 analyzes the tweets produced by the Guggenheim museum. It shows how the tweet features impact on the tweet influence as computed by Equation (1). This analysis is essential to understand whether the average influence of a tweet is given by specific features. For instance, with respect to images, tweets that do not contain images influence more than tweets than contain images; the same applies to whether or not to introduce an external URL within a tweet: tweets without URLs have much more influence on the traffic than tweets with URLs.

Table I provides the raw numbers of how every single feature impacts on the overall tweet influence. Cell values are obtained using Equation (2), where the set τ of tweets is composed only of the tweets having the specific feature stated in the table column. The Table provides a sort of quality guideline for every single feature. For instance, suppose you want to improve the performance of a museum of the first group (or suppose you have a museum that might be inserted into this group). When writing a tweet, you have to decide whether or not to insert an image. By looking at Table I, it can be noted that the museum that obtains the best results when using an image is the GettyMuseum (0,033 is the highest value), whereas the Museum of Modern Art is the museum that obtains the best results when writing tweets without images. Therefore, these museums can be seen as examples to look at when writing tweets with or without images. A similar way of thinking can be applied to all the features and to all the groups. For instance, in the second group, the museum that takes advantage of the sentiment when writing tweets is the Art Institute in Chicago (highest value in group 2 for the subjectivity feature).

TABLE I
FEATURES IMPACT ON TWEET INFLUENCE.

	no image	image	no url	url	non dense	dense	not subjective	subjective	short	long
@MuseumModernArt	**0.059**	0.011	**0.106**	0.009	0.049	0.013	**0.053**	0.012	**0.072**	0.010
@vangoghmuseum	0.051	**0.028**	0.083	0.022	**0.052**	0.007	0.049	0.013	0.059	0.023
@Guggenheim	0.046	0.020	0.089	0.014	0.039	**0.022**	0.038	**0.032**	0.052	0.018
@Tate	0.037	0.010	0.065	0.009	0.030	0.008	0.033	0.013	0.042	0.010
@GettyMuseum	0.024	0.033	0.030	**0.025**	0.029	0.010	0.025	**0.032**	0.027	**0.027**
@MuseeLouvre	0.025	0.027	0.032	0.023	0.027	0.021	0.027	0.014	0.027	0.024
@metmuseum	0.023	0.021	0.034	0.016	0.023	0.015	0.022	0.022	0.026	0.018
@britishmuseum	0.015	0.027	0.016	0.021	0.020	0.013	0.015	0.027	0.015	0.023
@museodelprado	0.013	0.013	0.015	0.013	0.014	0.007	0.014	0.010	0.015	0.012
@saatchi_gallery	0.005	0.005	0.006	0.004	0.005	0.005	0.006	0.004	0.005	0.005
@artinstitutechi	**0.035**	**0.091**	**0.062**	**0.062**	**0.071**	0.011	**0.031**	**0.122**	**0.040**	**0.080**
@MuseeOrsay	0.020	0.018	0.021	0.018	0.021	0.007	0.018	0.026	0.018	0.020
@NationalGallery	0.012	0.015	0.019	0.011	0.014	0.004	0.013	0.014	0.014	0.013
@museupicasso	0.007	0.015	0.012	0.012	0.010	**0.030**	0.010	0.026	0.008	0.014
@ngadc	0.011	0.010	0.017	0.008	0.010	0.020	0.010	0.012	0.012	0.010
@Museo_MAXXI	0.008	0.007	0.011	0.007	0.007	0.011	0.009	0.003	0.009	0.008
@philamuseum	0.007	0.008	0.015	0.006	0.008	0.002	0.006	0.010	0.008	0.007
@mfaboston	0.005	0.010	0.008	0.006	0.007	0.006	0.007	0.005	0.006	0.008
@CentrePompidou	0.007	0.005	0.010	0.005	0.006	0.007	0.006	0.005	0.007	0.005
@UffiziGalleries	0.008	**0.012**	**0.012**	**0.008**	**0.011**	0.006	**0.009**	0.006	0.010	**0.008**
@museiincomune	0.010	0.002	0.009	0.007	0.008	0.008	0.008	0.005	**0.011**	0.005
@Museo_MAXXI	0.008	0.007	0.011	0.007	0.007	**0.011**	**0.009**	0.003	0.009	**0.008**
@visitmuve_it	**0.011**	0.003	0.003	0.007	0.004	**0.011**	0.007	0.000	0.006	0.007
@MUSE_Trento	0.004	0.006	0.006	0.004	0.004	0.010	0.005	0.002	0.004	0.006
@MuseoEgizio	0.006	0.002	0.004	0.005	0.005	0.003	0.005	0.000	0.008	0.002
@PalazzoDiamanti	0.000	0.006	0.000	0.004	0.004	0.004	0.004	0.000	0.000	0.004
@mart_museum	0.005	0.004	0.000	0.006	0.004	0.002	0.003	**0.007**	0.005	0.004

E. Steps to be influential

The analysis provided in this paper allows museums to tune their tweet writing in order to have more influence in the Twitter platform. To clarify, let us suppose that museum XY wants to tune its tweet writing. To be influential, the following steps should be considered:

1) Map museum XY into one of the three groups;
2) Identify the museums that perform better within the selected group (Figures 1-3);
3) Analyze the tweet features of the selected group and of the museums that perform better within the selected group (Figures 4-6). Use this information to decide which metrics are worth using in your tweets;
4) When writing a tweet, analyze Table I to identify the museums that better use the considered features (i.e., "What is the museum that does not use the images to get the best results?", "What is the museum that uses the images to get the best results?", "What is the museum that does not use external URLs to get the best results?", etc.);
5) Analyze the composition of the tweets of the museums identified in the previous step to understand good practice (e.g., painting vs. photo, short URLs vs. extended URLs, sentiment words vs. emoticons, etc.).

IV. RELATED WORK

The ecology of communication of the cultural sector has been changing significantly thanks in large part to new media technology. Some papers already investigate this phenomenon. A first exploration conducted in 2011 in the museum sector in the UK and beyond is described in [2]. The main finding was that there was a gap between the possibilities presented by social media, and their use by many museums. The author argued that it was crucial that museums increase their understanding of the frames within which such activity is being encouraged and experienced. Subsequent research activities have been conducted in this direction. For instance, the paper [7] presents a theoretical framework for understanding the online strategies of museums use of Web and social media, their sources of online value (efficiency, novelty, lock-in, complementarities) and some measurements of Internet performance, such as the Alexa Internet ranking and the number of followers of museums in social media. The study was conducted on the 40 most physically visited museums and the most interesting finding was that there exists positive synergies for museums between the physical and online presence. [8] studies Danish archives and museums using Instagram for digital curating, outreach and communication. The conclusion shows that the relation between cultural heritage institution and user is not even. The media offer a room for involvement, even if it seems to be the institution not the audience that decides the arena in most cases. [9] provides a quantitative and qualitative study of the messages sent on Twitter during the MuseumWeek event. "MuseumWeek" is a communication event that was designed and planned by Twitter in 2014 together with various European museums to improve their visibility. The organization principle was simple: each day was dedicated to a theme, with specific hashtag, and users were encouraged to use the hashtag of the day as well as the generic hashtag #MuseumWeek. The outcomes show that the main goals of this promotional event were achieved. [3] introduces a set of Key Performance Indicators (KPIs) for quantitative estimation of Cultural Heritage Sensitivity as expressed by social network users. The approach is data driven: it analyzes terms and concepts belonging to Twitter users' messages and compares them to concepts from domain specific and general ontologies, such an analysis is then integrated with geo-referencing and temporal analysis.

In line with the papers above, this paper focusses on the cultural sector and, in particular, on museums. However, the goal of this work is completely different. It is not a coarse grain analysis of the use of social media but rather a fine grain analysis of the content factors that characterize tweets on museums and their impact on tweet influence.

Generally speaking, different approaches have been recently proposed in the literature to analyse and also predict tweet influence [10], [11], a.k.a. popularity. For instance, paper [12] focuses on news agencies accounts on Twitter and studies the propagation characteristics of news on Twitter as a backbone of a Twitter news popularity prediction model. In this study, they also found that the negative sentiment of news has some correlation with tweet popularity while the positive sentiment does not have such obvious correlation. The work in [5] is concerned with a popular microblogging website in China, Sina Weibo, and aims to discover content factors and contextual factors that affect the popularity of tweets. Four content-related factors are included in the study: topics, length, affective degree (number of emoticons and modal particles), and availability of supplementary information. While the considered context factors are users' degree of activeness, self-disclosure degree, experience, and authoritativeness. Popularity of tweets was measured by considering the width of tweets distribution and depth of deliberation on tweets, i.e.,the number of comments tweets received. They found that the two factors are equally important to predict the first popularity measure but content outperforms context when predicting the second popularity measure. In [13], authors aim to identify features for popularity prediction that are both effective and effortless, i.e., easy to obtain or compute. All the considered features were contextual. From the experimental assessment, it follows that a relative small set of features, in particular temporal features, can achieve comparable performance to all features. While all these papers focus on a notion of tweet popularity that is influenced by the popularity of the user that forward the tweet, our aim, instead, was to introduce a popularity measure that is not affected by context features. Moreover, the focus is on museums that, as to our knowledge, have never been studied in this context.

The impact of multimedia content on tweet popularity and life span is studied in [14] on Sina Weibo. Their preliminary study shows that multimedia tweets dominate pure text ones both because they are more popular and because survive longer. Finally, the paper [15] investigates whether the community sentiment energy of a topic is related to the spreading popularity of the topic. Experiments on two communities find the linear correlation between the community sentiment energy and the real spreading popularity of topics.

V. Conclusions

In this paper, we focused on the use of Twitter by art museums. Indeed, we proposed a novel framework designed to measure the influence that tweets and Twitter accounts may have within the Twitter platform. To evaluate our proposal, we considered conversations centered around 26 well-known museum Twitter accounts. The obtained results showed that it is possible to devise a 5-steps procedure able to help museums in writing tweets in order to be more influential within the Twitter scenario.

VI. Acknowledgments

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