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Online media content trustworthiness and influence: an introductory survey.

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Abstract:- *The increasing popularity of social media articles and microblogging systems is changing the way online information is producer. Twitter and YouTube. Twitter is a micro-blogging service, which has gained popularity as a major news source and information dissemination agent over last few years. Users on Twitter, create their public / private profile and post messages (also referred as tweets or statuses) via the profile. Users are both content publishers and content consumers. Since information is produced and shared by common users, who usually have a limited domain knowledge, and due to an exponential growth of the available information, assessing online content trustworthiness is vital. Several works in the state of the art approach this issue and propose different models to estimate online content trustworthiness, content relevance and user influence. In this paper we investigate the most relevant research worksin this domain, highlighting their common characteristics and peculiaritiesin terms of content source type, trust-related content features, trust evaluation methods and performance assessment techniques. The tweets are considered main source of information for this study.The maximum length of the tweet can be 140 characters. Each post on Twitter is characterized by two main components: the tweet (content and associated metadata) and the user (source) who posted the tweet. Studies have explored and highlighted the role of Twitter as a news media and a platform to gauge public sentiments.*

Keywords : *trustworthiness, relevance, influence, Social media.*

Introduction

With the rise of new technologies in the field of the internet and social media, the popularity and importance of numerous social media platforms have risen to new levels, as more people spend more time online and companies follow their potential customers because of its ease of use, speed and reach. Social media is fast changing the public discourse in society and setting trends and agendas in topics that range from the environment and politics to technology and the entertainment industry. One such social media platform that has seen an explosive rise in popularity is Twitter.

Approximately 1 billion tweets are generated by Twitter users every five days. With theincreasing popularity of social media, user-generated content [26] (i.e., content created by users and publicly available on the Web) is reaching an un-precedence mass. Users often rely on their own knowledge, intuition and analytic capabilities to assess content relevance and trust. However, this becomes unfeasible with the current massive consumption of user-generated content: large volumes of low-quality, non-significant information are produced every day, and valuable content drowns in the large ocean of irrelevant content with little probability of being found by users.

The overload of user-generated content makes hard to identifyrelevant content and to extract trustworthy and high qualityinformation. Assessing trust [24], content relevance [16] and user influence [11] is a criticalissue in everyday social activities, where it is vital to alter non-authoritativelow quality and non-verified content to provide users with trusted informationand content produced by experts.As a motivating example, Motutu and Liu [33] report the "\Restless LegSyndrome" case: in 2008, when looking for information about the syndrome on Google, a wrong (and possibly dangerous) treatment promoted by the web-site WikiHow[1]was returned as top-result. This could obviously characterize a serious risk for patients; nevertheless, its rank wrongly suggested it could be trusted as verified and high quality information.

A misevaluation of user-generated content, can affect are: disasterAssessing, online media content trustworthiness, relevance and influencemanagement during emergencies [(e.g., via false rumors on social networks during emergencies),environmental monitoring [18] detection of news [25] (e.g., via the diffusion of wrong news over the network). Consequently, it is vital to identify an automatic contenttrust estimation procedure which helps users in discarding unworthy informationand focusing on significant content. Three ingredients are necessary to performtrust estimation: i) the evaluation of content relevance [15]; ii) the identificationof influential users and experts [9], which are often focused on a specific topic,and produce mostly valuable content; iii) the evaluation of the level of trust [26]one can put on the content and people producing it. These ingredients are usuallyobtained by applying knowledge extraction algorithms and building appropriatetrust models on user-generated content.

In recent years, several works in this field have emerged. In particular, severalsubfields significantly overlap between one another .Online content qualityand relevance estimation [22], user reputation estimation [13] and influencer'sdetection. All take part in assessing the quality of information one can findon the Web. This survey overviews the main state-of-the-art methods used inthe automatic estimation of content quality, based on either content characteristics (i.e., content trustworthiness, relevance and credibility) or user characteristics (i.e., user trustworthiness and influence), which are strongly intertwined. High quality content often derives from highly experienced and influential users

Specifically, while other survey works go deeper in the details of trust estimation methods and applications, we deem our work merges togetherconcepts from all the listed sub-fields and holds a practical relevance for practitioners and researchers who approach these themes for the first time.

The rest of this document is structured as follows: Section 2 introduces theconcepts of trust, content relevance and user influence; Section 3 lists content anduser profile features used as ingredients to assess content/user trustworthiness; Section 4 discusses methods to aggregate those features and provide additional trust score; Section 5 surveys the different approaches for performance assessment andoutput validation. Finally, Section 6 concludes the work with final considerations And possible future directions in this field.

2 Trust, content relevance and user influence

In this section we introduce the definitions of trust, content relevance and influence, and list the research questions associated with these themes discussed inthe state of the art.[30]Assessing online media content trustworthiness, relevance and influence

2.1 Definitions

The concept of trust has been largely studied in the literature, bothfrom a sociological [21] and philosophical [6] point of view. However, with theadvent of social media [32, 17], studies on trust have recently shifted towardsthe construction of a trustworthiness model for digital content .Cvetkovich [31] define trust as a tool that reduces social complexity: users thattrust other users believe in their opinions, without making rational judgments. Sztompka [32] defines trust as \the gambling of the belief of other people's possiblefuture behavior".The concept of relevance (or pertinence) is crucial in the ability of an information retrieval system to find relevant content. Many research worksstudy the definition of relevance and its subjectivity in terms of system-oriented relevance, user relevance judgment [14], situation relevance etc. Content relevance and popularity [10, 19] are often connected: topic-related highquality content becomes often viral. Social influence is defined as the power exerted by a minority ofpeople, called opinion leaders, who act as intermediaries between the societyand the mass media [33]. An opinion leader is a subject which is very informedabout a topic, well-connected with other people in the society and well-respected.The concepts of trust, content relevance and social influence are stronglyintertwined: i) influential users (i.e., opinion leaders) are often experts in aspecific field; ii) domain experts produce trustworthy content; iii) trustworthy,

Topic-related content has high relevance to the selected field. Moreover, popularity plays its role too: viral content is transmitted through the network in thesame way a disease spreads among the population, and the more influential arethe users sharing it, the larger is its popularity.

In this work we talk indistinctly about trust, relevance and influence, sincethey all represent quality measures for the object in question (i.e., either usersor content). For the ease of the reader, henceforth, trust refers also to otherdiscussed qualities, namely relevance and influence.

2.2 Research questions

A model of trust is defined as a function that extracts a set of features from acontent object and aggregates them into a trustworthiness index. The construction of such model raises three research questions:

1. Which features better define the concept of trust and content quality?
2. How do we aggregate such features into a trustworthiness index?
3. How do we assess the quality of the trustworthiness index?

In the next sections these questions are addressed separately.

3 Trust model: features selection

In this section we describe features frequently used in the literature to assess thetrustworthiness of Web content.

3.1 Source-based features

User-generated content is retrieved from a Web publishing source. Thus, thefeatures one can extract from content to assess its quality depend on what can beextracted from the Web source. Although each source has its own characteristicsand differences.We can classify them into two main categories:

Article-based sources focus on the content itself, published in the form ofarticles. Content is usually long, and sometimes authors are encouraged toreview, edit, rate and discuss it, thus creating high quality, multi-authoredinformation. The author of the content may be thus unknown. Examples ofthese kind of sources are blogs, online encyclopedias (e.g., Wikipedia2) andquestion-answering communities (e.g., stackoverflow). Several works applytrust estimation techniques on these sources (e.g., [1, 3]).

Social media promote users as content authors: common people producecontent which could become viral in short time. Users' authority becomes akey factor in the evaluation of content trustworthiness: non-expert authorsoften generate low quality, unreliable content. Examples of these kind ofsources include Facebook, Twitter and LinkedIn. Several works applytrust estimation techniques on these sources: some examples can be foundin [9].Trust assessment studies performed on article-based sources tend to use content-based features (e.g., article length), since often the author is unknown, whileworks are performed on social media focus both on author properties (e.g., number of connection with others) and content characteristics.

3.2 Content and author-based features

Moturu and Liu [33] propose a classification of features which takes inspirationfrom what people use to assess the trustworthiness of a person or a contentin the real world. To evaluate user and content trustworthiness, we base ouranalysis on users past actions (i.e., reputation), user/content present status (i.e., performance) and user/content perceived qualities (i.e., appearance). In thefollowing, we describe each category separately. For a more complete overviewsee [7].

Reputation User reputation suggests how much one should trust their content [32]. The reputation depends on which actions users perform on social media, such as:content creation or consumption, answers to others' content, interactions with others, and social networking.

Reputation can be furthersplit in the following feature categories:

Connectedness. The more a user is connected with others, the higher is hisreputation in the network. Connectedness features are related to connectionsbetween users, and comprise simple features such as author registration status [33], number of followers/friends [4], number of accounts in different social media [29]. Furthermore, more complex features can be defined inthis context, such as author centrality in graph of co-author network ,social connectedness [33], number of reading lists the author is listed in ,H-index and IP-influence (i.e., influence vs. passivity) . The identification of highly connected people is vital in case the objective is to spreadcontent virally. Actions on the content. The more acknowledged is the content one produces,the higher is his reputation on the network. Features in this category includethe quantity/frequency of contributions to articles [33, 29], the amount ofcontent sharing on social media [3], the number of upvotes/likes [29],the number of answers to others' content [29], the number of retweets andretweeting rate [29] and the Klout influence score [29].

3.3 Performance

User performance describes the behavior of that user and hisactions [33], and can be used to estimate his trustworthiness. On the otherhand, content performance can be determined from user's actions towards it andfrom the interest it generates. Performance-related features vary significantlydepending on which social media platform we consider in our analysis. Example of such features include:

Number of content edits, Direct actions on the content (e.g., number of responses/comments to a blogpost [2] and retweets [29]).

Characteristics of content update procedures (e.g., edit longevity [50], median time between edits, median edit length, and proportion of reverted edits [33]).

References to content by external sources (e.g., number of internal links [45,2], incoming links [2], references by other posts [2], weighted reference score [45],Publication date and place [29], variance on received ratings [29]).

Appearance External characteristics that represent the individual's appearance, personality, status and identity can be used to assess his trustworthiness.Similarly, the characteristics of content, such as style, size and structure, areuseful in judging its quality. The most used features of this category include: Measure of the author reliability based on the structure of the content (e.g.,length of blog posts, number of sections and paragraphs [33]). Language style (e.g., punctuation and typos [8], syntactic and semantic complexity and grammatical quality [3], frequency of terms belonging to a specific category [51], keywords in a tweet [8]). Originality of the content (e.g., presence of reused content [29], patterns ofcontent replication over the network [8].

4. Trust model: features aggregation

In Section 3 we present various feature categories used to assess the trustworthiness of online media content and users. Those features are transformed ina trust/quality index (usually scalar) through trustworthiness estimation algorithms.

Although it is common to find naive feature aggregation methods [29],the literature proposes a variety of more complex methods used to compute the final trust score. The categorization of such methods is not trivial, due to a fuzzyseparation between feature definition and feature aggregation methods.Statistical approaches. It is common for features to be aggregated throughcluster rank scores [45, 29, 12] or maximum feature values [2]. Several worksuse more refined approaches, such as cumulative distribution-based ranking, K-nearest neighbors and Naive-Bayes classification [8], regressiontrees [4], mixture models [5], Gaussian Mixture Model and Gaussian ranking .

Graph-based algorithms. Social connections play an important role in assessing the level of trust of a user and his content: the more connected isthe user, the more others are interested in what he produces. Thus, several algorithms use

graph-based methods, e.g., PageRank [27] and its variants [28], HITS [35], impact of a user on the social connections graph entropy, graph centrality measures
[27], in degree vs. out degreeand other custom metrics based on information exchange over graphs [8]. In some cases, trust is computed based on characteristics of a specific content source, e.g., number of followers vs. friends in the Twittergraph [28].Feature correlation. Several works do not define an aggregation method, andsimply study the correlation between features. Correlation between user influence and content relevance. Some works useinfluencer's retrieval techniques to identify influential users from a social network, and then navigate through the content they produce to collect the most relevant one.Generally, the lack of uniformity in the proposed evaluation metrics and the heavy dependence on the type of content source (see Section 3.1) make it difficult to compare such metrics and state which one is most suited for a specific context.We believe that a further standardization of features would encourage the development of more sophisticated aggregation methods, e.g., based on supervisedmachine learning regressions and classifiers, as already proposed by Agichtein etal. [3] and by Castillo et al. [7].

5 Trust model: evaluation techniques

In this section we describe the experimental evaluation techniques that are usedto assess the performance of the proposed trustworthiness estimation methods.We state that the discussed research fields suffer from the absence of standardizedrequirements for the expected output. Thus, it is often difficult for the authorsto compare their methods with respect to other state-of-the-art approaches.

5.1 Datasets

Due to the high variance of the type of data one can retrieve from each contentsource type, there exists a large collection of datasets in the state of the art,rarely made publicly available.
Custom datasets. Almost all works create their own dataset by crawling datafrom the selected content publishing platforms. Several works (e.g., [7] base their analysis on Twitter, for several reasons:

i) high volume ofpublicly available user-generated content;
ii) presence of both textual andmultimedia data;
iii) access to public user profiles and their connectionswith other users
iv) Easy storage of content (for further analysis) due tothe limited length of posts.

However, sometimes also article based platformsare taken into account (e.g., Wikipedia in Qin et al. Or question-answerplatforms in Agichtein et al. [3]).
Use of standard datasets. Sometimes, more standard datasets are used, e.g.,the Enron Email Database analyzed by Shetty and Adibi or the WikiProject History in which articles have been assigned class labels according to the Wikipedia Editorial Teams quality grading scheme.
Building a gold standard. To assess the performance of a trust computationtechnique, it is often necessary to build a gold standard (or ground truth),i.e., a set of manually annotated data in which annotators are asked to statewhether the content can be trusted, and labels are supposed to be error-free. In several contexts, labeling content is usually performed by a groupof people (either part of an internal crowd or workers in some crowdsourcing platform [20]), which manually annotate content. Then, the outputof the proposed algorithm is compared with the ground truth, to assess the precision and recall of the retrieved set of trusted content/users [33].
However, trustworthiness, content quality and relevance are highly subjective characteristics, and thus the ground truth one builds is based on eachannotator's perception of what being trustworthy means, which makes itbiased and not reliable.

5.2 Performance assessment

Trust and influence metrics are all different and sometimes difficult to compare. Several works, thus, evaluate their performance with respectto similar algorithms applied to the same content sources. For this reason, therange of the metrics considered in this document is wide.
https://www.cs.cmu.edu/~./enron/
https://en.wikipedia.org/wiki/Wikipedia:WikiProject_History
Manual validation. Many works tend to evaluate and discuss the resultsthrough manual inspection, where an internal crowd [9, 27] oranonymous users via user studies [23, 28, 12] assess the quality of the retrieved set of users/content.
Classification performance. In some works, the authors manage to cast thetrust evaluation problem as a classification problem, in which users are classified as influential/non-influential and content is labeled as trusted/non-trusted. These works are likely to present standard classification performance
Metrics: precision, TP-rate, FP-rate, accuracy [7] and ROC curves [3].
Evaluation of rankings. In other cases, the output of the algorithm is a rankedlist of authoritative content/users, and thus ranking correlation indexes (i.e., Pearson correlation or generalized Kendall-Tau metrics) are used toassess the performance of the proposed algorithm. In the same perspective, NDCG [30] (originally designed to test the ability of a document retrievalquery to rank documents by relevance) is used to evaluate quality, trustworthiness and influence estimations, both in article-based content sources [33] and microblogging platforms.

Comparison with known rankings. Some works compare the output rankingof content/user with some rankings one can found on the Web, e.g., Digg [2],Google Trend and CNN Headlines [37]. Characteristics of users. In some cases, one takes into account some characteristics of the involved users (e.g., activity [64] or validation of profile onTwitter [5]) to assess the performance of the algorithm. A high-performanceresult, in this sense, is the one maximizing the overlap between the set ofactive (validated) users and the users retrieved by the proposed algorithm.Custom metrics. Finally, some works build their own performance metrics, since in such cases it is difficult to compare the proposed algorithm with theones available in the state of the art.

6 Conclusions and open challenges

In this survey we presented an overview of major recent works in the field ofautomatic estimation of trustworthiness, relevance and influence of online content. As discussed, trust estimation is important in Web search, and can beperformed by capturing multiple signals deriving from both user profiles andcontent characteristics: authoritative (or influential) users produce mainly highquality content, and high quality content is largely trusted on the network ofusers. We thus reviewed several algorithms, listing their common characteristicsand peculiarities in terms of content type, trust evaluation features and algorithms and performance assessment metrics.

We believe that these recent research topics are of great interest and practicalimportance in several domains such as automatic content retrieval and analysis,viral marketing, trend analysis, sales prediction and personal security. Nevertheless, in our opinion, there is enough space and need for future works that aim atbuilding a concrete base of gold standards common to all discussed topics, andsolidly integrating the proposed techniques to merge the efforts and convergetowards a unified approach for user trust and content relevance estimation.Current research works by the authors include methods for multi-platformand multimedia collective intelligence extraction from user-generated content,e.g., to perform trend analysis on the preference of Twitter users and to estimate environmental characteristics such as the presence of snow on mountains.Extracting relevant information from user-generated content implies: i) the identification of the influential users; ii) the estimation of content relevance; iii) theestimation of content trustworthiness. We believe that a strong cooperation ofmethods operating on multiple platforms and multiple content types (e.g., text, images, videos) is fundamental to define new standards this field lacks of.

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