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1. OVERVIEW

The tremendous value of Big Data has been noticed of late also by the media, and the term "data journalism" has been coined to refer to journalistic work inspired by digital data sources. A particularly popular and active area of data journalism is concerned with fact-checking. The term was born in the journalist community and referred the process of verifying and ensuring the accuracy of published media content; since 2012, however, it has increasingly focused on the analysis of politics, economy, science, and news content shared in any form, but first and foremost on the Web (social and otherwise). These trends have been noticed by computer scientists working in the industry and academia. Thus, a very lively area of digital content management research has taken up these problems and works to propose foundations (models), algorithms, and implement them through concrete tools.

Our proposed tutorial: (i) Outlines the current state of affairs in the area of digital (or computational) fact-checking in newsrooms, by journalists, NGO workers, scientists and IT companies; (ii). Shows which areas of digital content management research, in particular those relying on the Web, can be leveraged to help fact-checking, and gives a comprehensive survey of efforts in this area; (iii) Highlights ongoing trends, unsolved problems, and areas where we envision future scientific and practical advances.

We believe the audience is likely to get many ideas for applications and research. It is timely in that the amount of ideas and research works involved is currently quite significant, and non-computer scientists (journalists mostly) are eager to be involved in designing and using novel tools for their work. We believe a missing piece of the puzzle to make it happen, is a dissemination effort on the needs on one hand and the available and future scientific tools on the other hand. This tutorial is an attempt to provide such a dissemination effort.

2. AUDIENCE

We believe the tutorial would be of interest to all conference attendees, especially to researchers and students working in one of the related areas. More broadly, from a societal perspective, there is a lot to gain by making data management scientists aware of the many concrete problems faced by fact checking journalists, activists and the general public, as they attempt to rely on data in order to separate the truth from misinformation. Many have already started doing so, e.g. [36, 37, 38]; we hope our tutorial may motivate more in the VLDB community to follow.

3. TUTORIAL STRUCTURE AND ORGANIZATION

In Section 3.1, we provide a short history of journalistic fact-checking and presents its most recent and visible actors, from the media and/or NGO communities. Section 3.2 discusses the scientific content management areas which bring useful tools for computational fact-checking, then Section 3.3 presents the organization of the proposed tutorial.

3.1 Data journalism and fact-checking: an overview

While data of some form is a natural ingredient of all reporting, the increasing volumes and complexity of digital data lead to a qualitative jump, where technical skills, and in particular data science skills, are stringently needed in journalistic work.

A particularly popular and active area of data journalism is concerned with fact-checking. The term was born in the journalist community; it referred to the task of identifying and checking factual claims present in media content, which dedicated newsroom personnel would then check for factual accuracy. The goal of such checking was to avoid misinformation, to protect the journal reputation and avoid legal actions. Starting around 2012, first in the United States (FactCheck.org[1]), then in Europe, and soon after in all areas of the world, journalists have started to take advantage of modern technologies for processing content, such as text, video, structured and unstructured data, in order to automate, at least partially, the knowledge finding, reasoning, and analysis tasks which had been previously performed
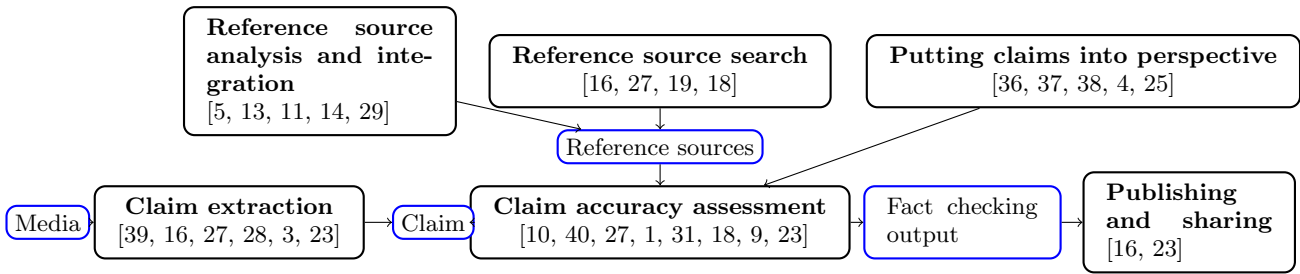
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[1] http://factcheck.org

Figure 1: Fact checking tasks, ingredients, and relevant works: an overview.

completely by humans. Over time, the focus of fact-checking shifted from verifying claims made by media outlets, toward the claims made by politicians and other public figures. This trend coincided with the parallel (but distinct) evolution toward asking Government Open Data, that is: the idea that governing bodies should share with the public precise information describing their functioning, so that the people have means to assess the quality of their elected representation. Government Open Data became quickly available, in large volumes, e.g. through `data.gov` in the US, `data.gov.uk` in the UK, `data.gouv.fr` in France etc.; journalists turned out to be the missing link between the newly available data and comprehension by the public. Data journalism thus found one of its most useful incarnations in fact-checking based on digital content and tools; there are natural connections with investigative journalism, which also needs to identify, analyze and exploit complex databases. This has been illustrated most visibly in recent years by the Panama Papers[2] and Paradise Papers[3], investigations into tax evasion across the world. Beyond journalists, concerned citizens, NGOs such as FactCheck.org, and scientists such as those running `climatefeedback.org` also joined the discussion; this has enlarged the scope of journalistic fact-checking, beyond politics, to issues related to health (medical scandals), the environment (pollution through dangerous pesticides, or the controversy over climate change, studied in particular by ClimateFeedback mentioned above) and many others. Another parallel development is the massive production of fake news and influence steering through bot-generated content. While (typically false) propaganda information is not novel, the Web and the social media, amplified by the so-called "echo chamber" and "filter bubble" effects, have taken its scale to a higher order of magnitude; fake news production is quasi industrial[4])

These aspects being noticed by computer scientists who, as citizens, are also eager to contribute to the way modern society works. An active research area has taken up these problems and works to propose foundations (models), algorithms, and implement them through concrete tools. The efforts have been many but scattered. Google, in particular, has recognized the usefulness and importance of fact-checking efforts, by making an effort to index and show them next to links returned by the users[5].

3.2 Related scientific areas

While a fully automatic approach to fact-checking is beyond reach (and probably not even desirable), several areas of data science contribute useful concepts and tools:

Data management, in the sense of persisting data and querying it: journalists need it both for the claims made (typically publicly through the Web) and for the reference data sources which they can use in their verification (such as reference statistic datasets published by government agencies). Yet, our interactions with journalists and fact-checkers highlight that establishing repositories of persistent data is not an obvious thing for them, especially that they may want to store data files, but also links, establish interconnections, annotate the data etc. We will briefly review the kind of data sources they have to deal with, and existing techniques which data management (and in particular Web data management) may have to offer.

Data integration allows exploiting together datasets of different origins and often independently produced. This plays a central role in analyses like the Panama and Paradise paper[6]. We will review the data integration architectures [15] (mostly focusing on data warehouses, mediators, data spaces [17] and data lakes [21]) and comment on their applicability to fact-checking scenarios we encountered. Still in a data integration scenario, a very relevant task is the selection of the best information sources to answer a specific query (in the classic scenarios) [7, 32], or to check a specific claim (in a modern fact-checking scenario) [23]. In a related field, truth discovery attempts to quantity the veracity of data when collected and merged from many, possible disagreeing, sources [12, 13].

Text analysis and information extraction, in particular through automated classification and learning, is gaining momentum as a way to cope with the huge number of documents published in social or mainstream media. In the context of the web, these techniques allow to go from unstructured or poorly structured text, to structured knowledge bases which lend themselves more easily to fact-checking answers. Text analysis can also be used to detect trends in news, to extract the source of claims [24, 35, 34] or to recognize rumors [6]. There has also been some attempts to create end-to-end fact validation systems collecting and monitoring facts, from online data, and looking for evidences to input claims [27, 22]. News analysis has established itself as a research topic on its own, covering news clustering over time, causality detection between news events or credibility analysis.

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[2]`https://panamapapers.icij.org/`
[3]`https://www.icij.org/investigations/`
`paradise-papers/`
[4]See e.g., `http://cnnmon.ie/2GqfWX8`
[5]`https://developers.google.com/search/docs/`
`data-types/factcheck`

[6]`http://bit.ly/2Drp4aJ`

Natural Language Processing has many related subfields: textual entailment is the task of comparing two portions of text and deciding whether the information contained in the first one can be implied from the second [10, 31]; stance detection aims at determining from a text whether it is in favor of a given target or against it [2]; entity linking consists in connecting an entity mention that has been identified in a text to one of the known entities in a knowledge base [30, 33].

Data and graph mining methods applied to structured and regular data enable the analysis of (static and streamed) information coming from the media; related work focus on very specific types of queries (e.g. checking that criminality rate has decreased during the mandate of M. X's as a mayor [22, 36]) or on tracking exceptional events [4]. The context in which an information item is produced may hold valuable hints toward the trustworthiness of that information. Existing research on social network analytics may help identify communities of fake news producers, identify rumor spreaders, etc.

Machine learning is frequently leveraged to help classify published content according to their topic, to their likely trustworthiness or to their ""checkworthiness" [6, 20, 23]. Journalists in particular strongly appreciate automated help to narrow the documents on which they should focus their verification effort. Fake news detection is now a very active fieldmobilizing a growing numbers of researchers, and is now the focus of international challenges[7],[8].

Temporal and spatial aspects of the above: the news arena is by definition one of perpetual movement, and many areas of reality follow the same pattern; time is a natural dimension of all human activity. Facts can be true during a period of time and then become false. Also, many hoaxes are spread periodically, and many "news" can be false just because the fact they relate happened years ago.

Image and video processing and classification: pictures and videos are a very common way to disseminate fake news, either by lying about their provenance or date or creation, or by doctoring their content. *audio, image and video processing* have been very dynamic on this subject, notably through the field of multimedia forensics, leading to verification systems and services such as RevEye, Tineye or InVID; however, their techniques are very specific and we will not be able to cover them in a 3-hour tutorial.

3.3 General tutorial organization

We propose to give the tutorial in **three hours**.

It will be organized and structured following a set of stages involved in fact-checking work; these stages are outlined in Figure 1, which we borrow from [26]. Tasks involved in fact checking are shown in black boxes, together with their inputs and outputs (shown in blue); main relevant works from the literature appear in their respective tasks.

The central task is to assess the accuracy of a claim accuracy, based on reference sources; this takes as input the claim, and outputs a fact check result or analysis. The claim may have to be extracted from a text source, made available through some media, such as newspapers, social media, political or government communication etc. Reference source search may be needed to identify the reference sources most suited in order to check a given claim. An active area of fact checking work is concerned with putting claims into perspective by analyzing how claim validity is impacted by a slight change in the claim statement. Finally, content management techniques are also called upon to facilitate publishing and sharing fact checking outputs.

Each stage will be the topic of a dedicated section of the tutorial, where we highlight the challenges, outline solutions in the area, and point to remaining open problems.

4. PRIOR PRESENTATIONS

An earlier version of this tutorial by the same authors was submitted in November 2017 to the Web Conference (formerly WWW), and will be presented in April 2017 in Lyon, France [26]. In collaboration with co-authors Sylvie Cazalens and Philippe Lamarre, the authors have subsequently published an article to appear in the "Journalism, misinformation and fact-checking" track of WWW 2018 [8], on which this proposal is based.

The core goals and most of the tutorial material will be the same between WWW and VLDB 2018, as both will correspond to the 70+ references we surveyed in [8]. However, the area is developing at a rapid pace and we plan to update our material for the VLDB presentation to reflect the latest advances. Moreover, we believe the overlap between the WWW and VLDB conference communities, while not empty, is not large either, given that data management works have significantly receded at WWW in recent years.

We are not aware of another tutorial on journalistic fact checking from a computer science perspective. The field is related to, yet distinct from, areas such as information extraction, knowledge base construction and querying, and social network analysis, to name a few. We consider our analysis of fact checking as a content management problem to be new and original, and we are eager to present the many opportunity for research raised by data journalism and journalistic fact-checking, to the VLDB community.

5. ORGANIZERS

Sylvie Cazalens[9], INSA Lyon & LIRIS - Université de Lyon, France.
Associate professor at INSA Lyon, LIRIS Lab since 2013 within the Database research group, her main research interests are on data integration and semantic interoperability.

Julien Leblay[10] is a Research Scientist at the National Institute of Advanced Industrial Science and Technology (AIST) in Tokyo, Japan.
As part of the Artificial Intelligence Research Center, his research interests cover data management and query processing in general, with a particular focus on applications to Web data, i.e., data typical found on web services and Open Data. From October 2013 to February 2015, Julien was a postdoctoral research assistant at the University of Oxford under the supervision of Michael Benedikt, where his work covered query optimization under constraints and access restrictions. He obtained his Ph.D. in Computer Science from the Université Paris-Sud and Inria, France, under the supervision of François Goasdoué and Ioana Manolescu. Prior to

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[7]`http://www.fakenewschallenge.org/`
[8]`https://herox.com/factcheck`

[9]`http://www.sylvie-cazalens.fr/`, sylvie.cazalens@insa-lyon.fr
[10]`https://staff.aist.go.jp/julien.leblay/`, julien.leblay@aist.go.jp

his academic career, he worked in industry for several years as a software engineer and consultant on topics ranging from machine translation to data integration.

Ioana Manolescu[11] is a senior researcher at Inria Saclay and Ecole Polytechnique. She is the lead of the CEDAR IN-RIA team focusing on rich data analytics at cloud scale. She is a member of the PVLDB Endowment Board of Trustees, of the ACM SIGMOD Jim Gray PhD dissertation committee, and an associate editor for PVLDB. Recently, she has been the program chair of SSDBBM 2016, and co-chair of ICDE 2018. She has co-authored more than 130 articles in international journals and conferences, and contributed to several books. Her main research interests include data models and algorithms for fact-checking, performance optimizations for semistructured data and the Semantic Web, and distributed architectures for complex large data.

Philippe Lamarre[12], INSA Lyon & LIRIS - Université de Lyon, France

Philippe Lamarre is full professor at INSA Lyon since 2011. He leads the Database group of the LIRIS laboratory. He received his PhD in Computer Science from the University Paul Sabatier of Toulouse in 1992. After a post-doc at Stanford University he became associate professor in Nantes University, LINA. His work is centered on data and knowledge base management in open distributed systems with special interest in query evaluation and autonomy of participants.

Xavier Tannier[13] is a professor at Sorbonne Université and researcher at the LIMICS lab bsince 2017. He was associate professor at University Paris-Sud and researcher at LIMSI-CNRS from 2007 to 2017. His main field of research lies in natural language processing and text mining in large collections of documents.

Fact-checking work and collaboration history J. Leblay and I. Manolescu have been among the first researchers considering fact-checking Web content from a data and knowledge management perspective, publishing a demonstration paper called "Fact-checking and analzing the Web" in the ACM SIGMOD conference in 2013 [19]. The demonstration was subsequently shown at the Computation+Journalism conference held in New York, in October 2014. X. Tannier has many years of experience on conducting text analysis and NLP projects together with major media actors, notably AFP (Agence France Presse). More generally, he has also worked extensively on event extraction from journalistic content, text classification etc.

Subsequently, the authors working in France started in 2016 a national research project called ContentCheck[14] dedicated to content management models, algorithms and tools for journalistic fact-checking, in collaboration with Les Décodeurs[15], a data journalism and fact-checking team of 12, part of Le Monde, France's leading national newspaper. The present tutorial proposal is issued of ContentCheck joint research, to which J. Leblay also contributes since 2017. Inria and JSPS (Japan Society for the Promotion of Science) support this

collaboration through a joint international associate team, WebClaimExplain.

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