A large-scale TV video and metadata database for French political content analysis and fact-checking

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ABSTRACT

In this paper, we introduce a large-scale multimodal publicly available dataset[1] for the French political content analysis and fact-checking. This dataset consists of more than 1, 200 fact-checked claims that have been scraped from a fact-checking service with associated metadata. For the video counterpart, the dataset contains nearly 6, 730 TV programs, having a total duration of 6, 540 hours, with metadata. These programs have been collected during the 2022 French presidential election with a dedicated workstation.

KEYWORDS

multimedia verification; fact-checking; evaluation and benchmarking; large-scale dataset; TV workstation

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1 INTRODUCTION

Recent years have seen the proliferation of fake news, misinformation and disinformation online due to the advent of internet and social networks. It especially becomes a major and urgent concern when it touches the political sphere; concern that has to be addressed to improve the democratic accountability and the political discourse. Hence, several fact-checking initiatives and organisations have emerged to validate the veracity of claims that are easily spread online, but also on traditional media such as newspapers and television. Nevertheless, keeping up with the deluge of information that has to be verified appears to be impossible and finding effective and large-scale solutions to assist human fact-checkers becomes a necessity. This has shed light on the potential of *automated fact-checking* technologies that can assist human fact-checkers.

Automated fact-checking is an umbrella expression in academic research that encompasses several sub-tasks such as identifying check-worthy claims, verifying claims, identifying rumors and satire, or *fauxtography*, among others [1]. Thorough surveys on current automated fact-checking technologies can be found in [1][2], [2], or [3]. Figure 1 illustrates a classic fact-checking pipeline: first, one has to find claims that are worth fact-checking from various sources. Second, it appears relevant to verify if the selected claim has already been fact-checked previously. Third, one has to gather relevant evidence to help understanding the context and the veracity of the claim. Finally, one has to decide either the claim is wrong, mostly wrong, imprecise, mostly true or true. Note that several graduation scales can be considered in the latter step.

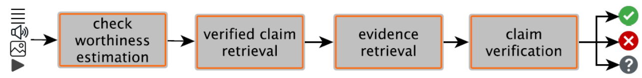

Figure 1: Classic fact-checking pipeline (illustration from [2])

Most of the efforts on asserting the veracity of information in the last decade have focused on textual content, either scraped from blogs and social media or obtained with video/radio transcripts, thanks to techniques from the Natural Language Processing (NLP) field. However, political information mainly appears in television (TV) broadcasts, such TV shows (interviews or debates) or breaking news. This fact leads to the need to leverage methods that can analyse multimedia content (image, audio, video) in order to perform *multimedia automated fact-checking*. To do so, relevant and large multimedia datasets related to fact-checking are required, to be used either for training machine learning methods or for evaluating the contributions that are proposed by the research community.

Table 1 presents a brief summary of fact-checked datasets in the literature. The datasets [8, 9, 11] have been obtained through the scraping of text information from websites and/or blogs without video analysis. Only the datasets [4, 7, 10, 24] have been constituted from videos. The videos that have been used are TV political debates and shows obtained alongside their transcriptions. A little amount of videos is used with a total duration of some tens hours at best. Furthermore, except the ClaimBuster dataset [4, 6], all the datasets are in English. There is no French dataset and a clear lack of datasets addressing simultaneously the scalability and multimodality.

To address this problem, we propose in this paper a new multimedia dataset for the analysis of political content and fact-checking. Figure 2 presents the organization of our dataset and how it can be used for the analysis of political content and fact-checking. It is composed of two sub-datasets. The first sub-dataset is detailed in Section 2. It provides claims that have been fact-checked and extracted from an online source, namely *Factoscope*[3]. It delivers

[1]See the FC page taking part of the STVD collection: http://mathieu.delalandre.free.fr/projects/stvd/

[2]https://github.com/neemakot/Fact-Checking-Survey

[3]https://rattrapages-actu.epjt.fr/factoscope

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https://doi.org/10.1145/nnnnnnn.nnnnnnn

Datasets / systems	Sources	Claims	Videos
Politifact (2014) [8]	Web blogs	106	No
ClaimRank (2017) [10]	US presidential debates	880	4 with transcripts
Tathya (2017) [7]	US presidential debates	967	18 with transcripts
LIAR (2017) [9]	Politifact	12, 836	No
FEVER (2018) [11]	Wikipedia	185, 445	No
ClaimBuster (2020) [4]	US presidential debates	1, 673	33 with transcripts
Full Fact (2020) [24]	UK political TV shows	1, 570	14 with annotations

Table 1: Datasets for political discourses fact-checking

text information and keywords to characterize the claims and news topics. The second sub-dataset, described in Section 3, provides TV audio/video files with program metadata. Transcripts can be obtained from the audio data with Speech-to-Text methods [31] and combined with NLP techniques to detect specific events related to political content (e.g. to recognize political actors with names entities [12, 13], to detect misinformation with keywords [14, 15] or for the discourse analysis [17]). The video data, related to the detected events, could be then processed for face recognition [32]. In terms of applications, the dataset could be leveraged for several scenarios currently being studied by researchers: to detect and identify claims for fact-checking [5, 16], to drive visual analytics of news videos [30], or to analyse the correlation between the social media and TV [18, 19].

Compared to the state-of-the-art datasets presented in Table 1, the proposed dataset presents several key properties:

- the dataset contains audio, video and metadata files allowing the multimodal analysis of political content as well as the detection and identification of claims for fact-checking,
- it is the largest dataset of the literature with 1, 200 fact-checked claims (collected during 5 years, related to 200 political figures) and 6, 730 news and political TV programs (having a duration of 6, 540 hours),
- the dataset offers high quality data with fact-checked claims by professional media and well-formatted TV video/audio files with metadata captured by a workstation,
- it is the second French dataset that has been published in the literature and the single one covering a French presidential election (2022),
- the dataset is public available[1] for the research community.

2 FACTOSCOPE

Factoscope is an initiative that has begun at the end of 2016, to address the political discourse claim fact-checking during the debates of the 2017 French presidential elections. Within the context of studies in a national School of Journalism, the members of the project have fact-checked several political claims themselves, but have also aggregated and highlighted claims that have been fact-checked by others professional media. Following the success of this initiative, the program has been funded for a 5-year span, with the support of Le Monde, one of the largest French daily newspaper. Currently, Factoscope is one of the member of the *Objectifs desINFOx*[4], a project led by AFP[5] (Agence France-Presse) and backed by Google, that will run until the end of June 2022, along with 20 others media, in order to fight against fake news, misinformation

[4]https://factuel.afp.com/objectif-desinfox-2022
[5]https://www.afp.com/en

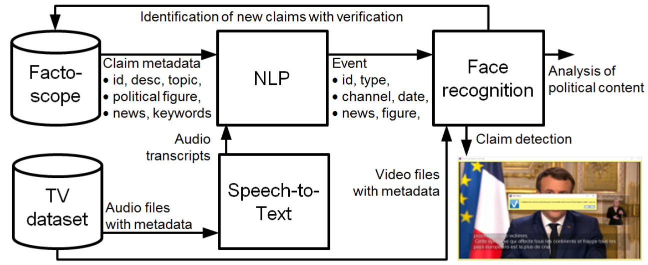

Figure 2: Dataset organization and use for political content analysis and fact-checking

and disinformation during the last presidential elections held in France in April 2022.

In the Factoscope website, each claim corresponds to a given article in a web page. Each article presents several features of the claim: its author and a picture of the author's face, the claim itself, the level of veracity of the claim, a contextual description of the claim, and links that have been used to perform the fact-checking. Since the claims are incrementally added as articles in a website powered by a content management system software, namely WordPress, a first step to curate the dataset has been to scrap the Factoscope website, and store these informations in a structured scheme. The BeautifulSoup[6] and spaCy[7] Python libraries have been used for the scraping part and the keyword extraction, respectively.

The scraping of the Factoscope website led us to create a dataset of more than 1, 200 fact-checked claims. Figure 3 presents the XML schema definition of the dataset. These claims deal with 12 various topics (*e.g.* education, environment, justice, health, security, etc.) that have been stated by more than 200 political figures during the last 5 years. Three levels of veracity are considered in the Factoscope fact-checking service: the 1, 200 claims that have been fact-checked are composed of 55% false claims, 25% of imprecise claims and 20% true claims. Sources to check the veracity of the claims are either original or extracted from well-known national fact-checkers, such as *Les Decodeurs* (le Monde)[8], *Le Vrai du faux* (France Info)[9] or *Factuel* (l'AFP)[10].

Early NLP analysis have been conducted on this dataset using Unitex/Gramlab [33], an open source [11], cross-platform, multilingual, lexicon- and grammar-based corpus processing suite. Focusing on the description attribute of each claim, we consider a corpus of 241, 202 words (with 17, 998 unique words), that contains 23, 886 named entities (mostly persons, organisations, roles, places and dates).

3 VIDEO CAPTURE ON TV WORKSTATION

The scraping of the Factoscope platform ensures to collect metadata and claims for the analysis and fact-checking of French political information. We then need to collect video candidates for the multimedia counterpart. As discussed in Section 1, political news are

[6]https://www.crummy.com/software/BeautifulSoup/
[7]https://spacy.io/
[8]https://www.lemonde.fr/les-decodeurs/
[9]https://www.francetvinfo.fr/replay-magazine/franceinfo/vrai-ou-fake-l-emission/
[10]https://factuel.afp.com/
[11]https://unitexgramlab.org/

```xml
<?xml version="1.0" encoding="UTF-8"?>
<xs:schema xmlns:xs='http://www.w3.org/2001/XMLSchema">
 <xs:simpleType name="valuelist">
  <xs:list itemType="xs:string"/>
 </xs:simpleType>
 <xs:element name="News">
  <xs:complexType>
   <xs:sequence>
    <xs:element name="id" type="xs:string"/>
    <xs:element name="urlFacto" type="xs:string"/>
    <xs:element name="author" type="xs:string"/>
    <xs:element name="date" type="xs:date"/>
    <xs:element name="title" type="xs:string"/>
    <xs:element name="veracity" type="xs:string"/>
    <xs:element name="description" type="xs:string"/>
    <xs:element name="keywords" type="xs:valuelist"/>
    <xs:element name="sources" type="xs:valuelist"/>
   </xs:sequence>
  </xs:complexType>
 </xs:element>
</xs:schema>
```

Figure 3: XML schema of the fact-checked claim dataset

mainly showed on television media [23]. Hence, one needs to deal with the real-time and scalability constraints as the TV is broadcasted continuously on multiple channels. These aspects have been rarely addressed in the literature, since most of the existing systems process from small TV video databases as shown in Table 1.

Since a large amount of TV candidates' videos has to be captured, a dedicated platform for the scalable capture of TV programs [25] is required. In our work, we have used the TV workstation depicted in [20]. This workstation has been mainly used for the task of real-time video processing [20–22]. We detail here how we have adapted it for the video capture of political TV programs. The next section details the TV workstation having a particular focus on the video capture and storage requirements. Then, we present the protocol that has been used to collect the candidate videos. Finally, a user selection of TV programs is introduced.

3.1 The TV Workstation

Figure 4 presents the TV workstation. It processes in three main steps detailed thereafter.

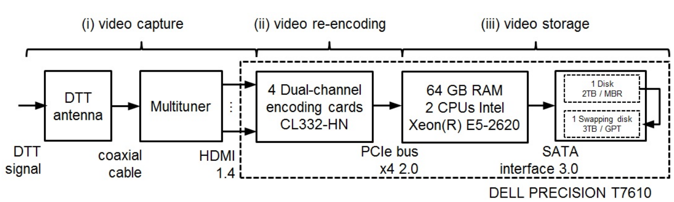

Figure 4: The TV workstation

(i) Video capture: the TV is broadcasted over different networks including the IPTV, the SaT and DTT signals[12]. The IPTV and SaT could suffer from disconnections. This is a critical point for a video capture processing continuously. To solve this problem, the capture in the workstation is driven from the French DTT signal. The french DTT delivers 30 TV channels at a 25 FPS rate and a Full HD resolution within the SECAM[13] standard. However, for normalization with the NTSC standard[13] and web videos it is common to capture at 30 FPS. The DTT signal is processed with a multiple tuner to demodulate the video streams corresponding to the channels. The video streams are delivered with HDMI using the MPEG format.

(ii) Video re-encoding: for the needs of storage and video quality, a re-encoding has to be applied. This is processed with a computer DELL PRECISION T7610. For a stable and real-time processing, the computer embeds Avermedia CL332–HN video cards [26]. These cards process the video streams at the hardware level for the control of the FPS, color-space conversion, downscaling, H.264 re-encoding and transfer to the main memory. Each card is able to process up to 2 channels at the Full HD resolution and with a 30 FPS rate. The cards are plugged to the PCIe bus within the computer using a *gen* 2.0 protocol with ×4 lanes. The computer embeds four cards able to process 8 channels.

(iii) Video storage: the video capture and re-encoding could deliver continuously 8 video streams at the Full-HD resolution. These streams have to be stored as video files (e.g. MPEG, AVI) raising processing constraints. Indeed, the CL332–HN cards are equipped with buit-in H.264 hardware encoders. However, an additional processing is still required at the computer level for the file formatting and disk transfer. The processing time depends then of the formatting process and the number of video streams.

For the hard real-time and scalability, a CPU processing is recommended [26, 27]. For a better support, we have set the DELL computer as a dual-core architecture. It was equipped with two Intel Xeon(R) CPUs E5 − 2620 2GHz able to execute 24 threads[14]. With this configuration, the workstation can record continuously the 8 video streams up to the SD resolution at a mean CPU rate Table 2. This process is performed with asynchronous audio/video. Better performances can be obtained with stronger CPUs[15] able to handle highest resolutions with synchronous audio/video [26].

Resolution		Audio/ Video	CPU rate	Video Mbps	TB/ month	Audio Kbps	GB/ month
HD	1280 × 720		85 %	3	7.23	256	621
SD	720 × 576	asyn	60 %	1.6	3.89	160	384
Low	320 × 240		35 %	0.56	1.36	128	308

(asyn)chronous

Table 2: T7610 performance for video storage

The video and audio files are stored in a hard disk of the workstation. This disk is set with a Master Boot Record (MBR) partitioning allowing a maximum size of 2 terabyte (TB). This partitioning is compatible with the drivers of the CL332–HN cards [26]. The storage of the 8 video streams could require a huge memory depending on the video/audio resolution and bitrates. The French DTT delivers the videos with a Variable Bit Rate (VBR) having a mean rate of 5 Mbps for the full HD resolution. We have adapted this bitrate for the lowest resolutions (see Table 2) based on the recommendations

[12] Internet Protocol, Satellite and Digital Terrestrial Television

[13] Sequential Colour with Memory, National Television System Committee

[14] Having an Average CPU Mark of 5, 285 cpubenchmark.net.

[15] The Workstation will shift to a Dell 5820 computer with an Intel Xeon W-2295 CPU (Average CPU Mark of 31, 595 cpubenchmark.net).

for the CL332−HN cards [26]. With the default parameters (8 channels, 24h a day, 30 days), the video storage requires several TB a month for the SD and HD resolutions. For the audio, the French DTT applies an Advanced Audio Coding (AAC) within a range of 128-256 Kbps. This needs some hundreds of GB a month as mentioned in Table 2. To support the storage, a swapping disk is used in the workstation. This disk is set with a GUID Partition Table (GPT) partitioning having a maximum size of 3 TB compatible with the firmware of the DELL computer. A swapping of 0.5 TB of data is nightly automatically triggered between the disks when the MBR disk reaches 1.75 TB.

3.2 Protocol for capture

We present in this section the capture protocol that has been used to collect the candidate videos for content analysis and fact-checking of French political information. This protocol is summarized in Table 3. To build-up our dataset, we have targeted the 2022 French presidential election. We have set the workstation to capture 8 French public channels for a period of 3 months. We have selected the main channels related to news and political content[16] among the 30 available in the French DTT. The capture campaign has been triggered the 1^{st} of February up to the 1^{st} of May 2022[17]. We have bounded the capture to 20 hours per day (from 6AM day$_i$ to 2AM day$_{i+1}$) and channel as little TV programs are scheduled during the night. Our dataset covers a total amount of 14, 400 hours.

Campaign			File			Total size	
Months	**Daily**	**Total**	**Type**	**Res**	**Kbps**	**Files**	**TB**
3 01/02 to 01/05	8×20h	14, 400h	Video	320×240	560	720	3.40
			Audio	Na	160	720	0.96
						1,440	**4.36**

Table 3: Protocol for capture

For storage optimization, we have set the video resolution to 320×240 for the capture with a parameter of 560 Kbps. This resolution has been set similar to [22, 25] and presented as the best trade-off between the memory cost and video degradation. Suitable for most of the computer vision tasks such as the face and human activity recognition [28, 29], it also fits with the workstation storage capacity of 5 TB and the campaign requirements of 3.4 TB. Finally, this resolution ensures a stable capture with a low CPU rate. We have fixed the audio coding rate at 160 Kbps for a good quality requiring one additional TB for storage. Our dataset contains 1,440 daily video/audio files for a total size 4.36 TB[18].

3.3 Selection of TV programs

The proposed protocol to capture the candidate videos ensures to collect daily video/audio files from the main French public channels related to the news and political content. However, some of these candidates still contain general TV broadcasts, such as TV shows, movies or entertainment programs. Hence, an additional filtering step need to be performed to build-up the final dataset. To deal with this issue, we have driven a user selection of programs based on TV metadata that can be obtained from Electronic Program Guides (EPGs), such as start and end times, channel, title, description, etc. We have developed a web bot to gather the French TV metadata from the web service[19]. The crawling was launched every day to guaranty up-to-date data.

Since, thousands of TV programs could be scheduled every months and appear in the metadata, the user selection is a challenging task. However, a large amount of these TV programs are repeated every day and week [25]. These repeated programs can be detected and grouped automatically to support the selection. For the detection, we have used the method [22] that leverages NLP techniques and hashing to generate a unique hashcode for every repeated program.

Table 4 details our program selection. We have obtained nearly seventeen thousand of crawled TV programs corresponding to more than one thousand of unique hashcodes. These programs have a total duration of around 9, 920 hours over the 14, 400 hours of captured videos. The gap is due to the hidden programs (e.g. advertising, short and night programs not appearing in the metadata, etc.). We have then selected a subset of 150 hashcodes corresponding the programs with news and political content. This selection groups around 6, 730 TV programs for a total duration of 4, 295 hours.

One last problem remains, indeed TV suffers from latency [25] implying a shift in the time obtained in the metadata. To deal with this issue, we have used the approach of [22]. The French TV latency is modeled as a gaussian distribution such as $\mathbf{L} \in [\mathbf{L}_{\min}, \mathbf{L}_{\max}]$ with $\mathbf{L}_{\min} < \mathbf{0}, \mathbf{L}_{\max} > \mathbf{0}$ and $|\mathbf{L}_{\min}| + \mathbf{L}_{\max} \simeq \mathbf{20}$ minutes. We have used the $\mathbf{L}_{\min}, \mathbf{L}_{\max}$ values to correct the start $\mathbf{t_0}$ and end $\mathbf{t_1}$ times of TV programs such as $\mathbf{t_0^-} = \mathbf{t_0} - |\mathbf{L}_{\min}|$ and $\mathbf{t_1^+} = \mathbf{t_1} + \mathbf{L}_{\max}$. This increases the total duration to a near 6, 540 hours for the extracted programs. Our final dataset has the following configuration: $\simeq$ 6, 730 TV programs representing 6, 540 hours and stored as 13, 460 audio/video files for a total size of 1.98 TB[20].

	Crawled programs	Selected programs	Extracted programs
TV Programs	17, 290	6, 730	
Hashcodes	1225	150	
Duration	9, 920h /14, 400h 68.9%	4, 295h /14, 400h 29.8%	6, 540h /14, 400h 45.4%

1^{st} of February to 1^{st} of May 2022

Table 4: Selection of TV programs with metadata

4 CONCLUSION AND PERSPECTIVES

In this paper, we have introduced a large-scale multimodal publicly available dataset for the French political content analysis and fact-checking. We believe that this dataset can stimulate further research and can be leveraged for automated multimedia AI fact-checking studies, but also other types of post-analytic studies (e.g. allotted speaking, time measurement, visual analytics, social TV, etc.). This dataset will also help us in our ongoing efforts to develop efficient and scalable multimodal automated fact-checking services (such as speaker identification, visual and audio keyword spotting, fusion-based matching techniques for claim detection and identification).

[16] **1.** TF1 | **2.** France 2 | **3.** France 3 | **7.** Arte | **13.** La Chaîne parlementaire | **15.** BFM TV | **16.** CNews | **27.** France Info
[17] 11 days after the presidential election debate of 20^{th} of April.
[18] Due to technical constraints (system update, networking, failures) $\simeq$ 70 files are missing resulting in a capture rate of 95%.
[19] https://xmltv.ch/
[20] Due to the technical constraints[18], $\simeq$ 670 files are missing.

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