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# BOUTEF: Bolstering Our Understanding Through an Elaborated Fake News Corpus

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**Abstract.** This article presents BOUTEF, an original and comprehensive corpus of fake news. It encompasses content in Algerian and Tunisian dialects, Modern Standard Arabic (MSA), French, and English, featuring instances of code-switching between these languages. Moreover, for the Algerian and Tunisian dialects, we have preserved both Latin and Arabic scripts in the dataset. BOUTEF comprises over 3,600 fake news posts collected from various social media platforms spanning from 2010 to 2024. This corpus is developed as part of the TRADEF<sup>4</sup> project and is made available to the research community. Each fake news post in BOUTEF is associated with 16 attributes, providing rich contextual information. The data was gathered from Facebook, Twitter, YouTube, and TikTok, reflecting the diverse sources of misinformation. To enhance the depth of our analysis, we introduce a novel labeling scheme consisting of 40 categories. This scheme is developed through a thorough examination of the collected corpus, and we have also retained a tagging process inspired by Claire Wardle’s categorization. BOUTEF not only contributes to the understanding of fake news in multilingual contexts but also provides valuable resources for further research in this domain.

**Index Terms:** Fake news, Multilingual Context, Arabic dialect, Code-switching, Social Media misinformation, Labeling categories.

## 1 Introduction

The 4th Generation Warfare (4GW) is known as the information war involving non-necessarily military populations. It is conducted by national or transnational groups based on ideologies rooted in cultural beliefs, religious doctrines, economic or political interests, with the objective of sowing chaos in a targeted location in the world. In [10], the authors, some of whom were military personnel, explained in 1989 that fourth-generation warfare would be widespread and paradoxically undefined in the coming decades.

One of the points of attack in 4GW is the massive use of social media to manipulate minds. The objective is to prepare public opinion in a targeted location to accept a state of affairs and make it morally acceptable and politically correct. This can occur prior to the invasion of a country, approaching a presidential election, for provoking a collapse, increasing energy prices, or destabilizing politically fragile countries with democratic regimes, etc. The objective of this war is to alter reality, among other things, by often inundating the adversary’s population with false information, sometimes supported by so-called experts, rumors, fabricated or modified videos.

In the framework of the project TRADEF, we propose to address one form of disinformation: fake news. The idea is to rapidly detect the emergence of a fake, whether in textual, audio, or video form, on social networks and its propagation through the networks. Unlike Botsentinel<sup>5</sup>, which uses Twitter accounts to classify them as trustworthy or not by storing and monitoring them daily, the approach in TRADEF is completely different. The aim is to detect the emergence of a fake and track it over time. At any given moment, this potential rumor is analyzed and assigned a measure of trust by tracking it across social networks in the reference language as well as in other languages.

Our primary objective in this project is to gather and analyze a corpus of fake news. Specifically, we will focus on fake news circulating in Algerian and Tunisian social networks. In contrast to previous projects, our collected corpus not only includes the fake news itself but also the comments generated as a result of the spread of this misinformation. Our aim is to analyze people’s reactions to these disseminated falsehoods. The fake news articles have been categorized and associated with both major and minor themes. This approach allows us to identify the main areas where fake news creation is most prevalent. In future work, this will enable us to automatically extract fake news.

<sup>4</sup> <https://dgxy.link/tradef>

<sup>5</sup> <https://botsentinel.com/info/about>

This article gives a detailed overview of the collected corpus named BOUTEF (**B**olstering **O**ur Understanding **T**hrough an **E**laborated **F**ake news corpus), analyze its contents, and present preliminary findings regarding fake news generated in a few Maghrebi social networks.

## 2 Related Works

Creating a fake news dataset requires careful deliberation, encompassing factors like the topic, dataset’s scale, language, and whether metadata is included or excluded.

Regarding the subject matter, numerous datasets concentrate on specific topics, such as the 2016 US Elections [13], the COVID-19 crisis [11,5]. Others encompass broader themes like politics [20]. Some datasets are exceptionally comprehensive, covering a wide array of topics including politics, economy, investigation, health-care, sports, entertainment, and more [9,8]. The diversity of targeted topics is crucial because predictive models for fake news tend to perform poorly when applied to topics outside their domain [9].

Datasets predominantly revolve around the English language, as evidenced by numerous references [13,9,20]. However, several datasets exist in other languages, such as Arabic [2,1,16], Spanish [14], Portuguese [12,4], German [19], Brazilian Portuguese [6], Urdu [3], and more. In the course of this study, we will present a dataset structured around specific topics to delve into the fundamental mechanisms of false information related to Arabic dialects, with a particular emphasis on those prevalent in Algeria and Tunisia. Additionally, we encompass French, English, and Modern Standard Arabic, given their frequent usage on social media platforms in North Africa. This extension of our dataset is designed to cater to the demand for fake news identification in a multilingual and region-specific context.

The characteristics and document lengths within datasets require careful consideration. Several datasets predominantly comprise lengthy news articles [9,16]. In contrast, other datasets encompass shorter documents, including statements [20] and tweets [11,20].

In terms of dataset size, there is substantial variation. Some datasets are relatively small, containing fewer than a thousand documents, as seen in [13]. Conversely, larger datasets encompass several thousand documents, like those in [11] and [20]. On the other end of the spectrum, datasets like [9] consist of a vast number of documents, with 80,000 news articles, and [8], which includes 600,000 news articles from over 130 sources. However, it’s worth noting that these corpora often exhibit ambiguity in defining a fake news article. For instance, articles discussing fake news events are occasionally classified as fake news themselves. In our research, we will introduce a clear distinction among genuine fake news, comments related to fake news, and denials of fake news to enhance the precision and granularity of our analysis.

When it comes to labeling conventions, some datasets employ binary labels, distinguishing between fake and non-fake content, as shown in [11]. Conversely, several works adopt more nuanced sets of labels. For example, [13] employs labels like *False*, *Partial truth*, and *Opinion*. In contrast, [20] employs a scale with six degrees of veracity, while [8] uses eight labels, including *misleading*, *commotion*, *fake*, *selective*, *suspicious*, *true*, *myth*, and *satire*. Additionally, [15] categorizes fake news into three types: *Serious Fabrication*, *Large-Scale Hoaxes*, and *Humorous Fakes*. In our research, we will meticulously categorize fake news, going as far as differentiating between around forty distinct categories.

## 3 Building BOUTEF: An Innovative Fake News Corpus for Enhanced Research Opportunities

In the following, we will propose a new corpus collected from social networks. We curated BOUTEF by handpicking verified fake news from various social networks such as Facebook, Twitter, YouTube, TikTok, and certain internet newspapers known for spreading false information. In regards to the fake news extracted from social networks, we relied on specific Facebook pages known in Algeria, Tunisia, and the Middle East for reporting and cataloguing fake news<sup>6</sup>. To ensure the accuracy of each catalogued fake news, we cross-referenced it with multiple internet sources to confirm its authenticity before including it in BOUTEF. Within the gathered corpus, Figure 1 presents the distribution of fake news related to the two countries. In Table 1, we present the

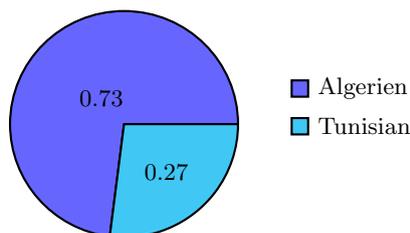


Fig. 1: Distribution of fake news pertaining to Algeria and Tunisia in BOUTEF

<sup>6</sup> Fake News DZ, Falso, Tunisia Check News

count of posts within this corpus containing over 62,000 words. This corpus is associated with one hundred images depicting fake content. Images serve as the initial impression that registers in an individual’s mind.

|                               |       |
|-------------------------------|-------|
| <b>Number of posts</b>        | 3668  |
| <b>Number of words</b>        | 62388 |
| <b>Number of unique words</b> | 23500 |
| <b>Number of images</b>       | 100   |

Table 1: Some figures on the BOUTEF corpus

In this article, we present an innovative fake news corpus crafted to provide a comprehensive dataset that can pave the way for novel research opportunities. Our primary objective is to simplify tracking and, more crucially, foster a deeper comprehension of the complexities surrounding fake news. For each fake news instance, we’ve compiled various data points, including publication dates, comments, source origins, follower counts, comment shares, geographical origins, posting users, and user gender. Most of the fake news items included images or videos, and we’ve preserved references to these multimedia elements. Additionally, we’ve introduced new data points to aid in categorizing fake news into different categories.

### 3.1 Multilingual Complexity: Analyzing Language Diversity in the BOUTEF Corpus

In BOUTEF corpus, we have 9 different languages and dialects: Modern Standard Arabic (MSA), French (FRE), English (ENG), Algerian dialect (ALGDIAL), ARABIZI (Algerian dialect written in Latin script), Tunisian dialect (TUNDIAL), Tunisian Arabizi (TARABIZI), MARABIZI (Modern Standard Arabic written in Arabizi) and Code-switching (SWITCHING) which corresponds to any combination of different languages. This makes BOUTEF corpus intriguing and challenging for further natural language processing. Table 2 presents statistics about languages in the corpus for the different kinds of posts. This table shows clearly that Modern Standard Arabic is the predominant language for spreading fake news. This is likely due to the intention of ensuring widespread comprehension within the Arab community for the dissemination of the fake message.

|                       | Fake       | Fake<br>Comments | Denial     | Total       |
|-----------------------|------------|------------------|------------|-------------|
| <b>MSA</b>            | 313        | 788              | 206        | 1307        |
| <b>ALGDIA</b>         | 24         | 786              | 1          | 811         |
| <b>TUNDIA</b>         | 0          | 382              | 0          | 382         |
| <b>CODE SWITCHING</b> | 7          | 308              | 6          | 321         |
| <b>ARABIZI</b>        | 0          | 110              | 0          | 110         |
| <b>TARABIZI</b>       | 0          | 61               | 0          | 61          |
| <b>ENG</b>            | 18         | 40               | 15         | 73          |
| <b>FRE</b>            | 90         | 419              | 91         | 600         |
| <b>MARABIZI</b>       | 0          | 1                | 0          | 1           |
| <b>TOTAL</b>          | <b>452</b> | <b>2895</b>      | <b>319</b> | <b>3666</b> |

Table 2: Quantitative information regarding the corpus and language distribution

### 3.2 Exploring Linguistic Variation in the BOUTEF Fake News Corpus

The corpus presents a very heterogeneous construction at the linguistic level insofar we observe a new form of discourse, completely different from standardized texts. In addition to the mix of languages presented in

Section 3.4, linguistic variation is apparent at several levels. At the syntactic and grammatical levels, fake news is triggered in most cases by a noun phrase in Arabic (e.g. رئيس المخابرات الجزائرية يموت سريراً), except in the case of direct fake news which addresses the death of celebrities, where the sentence contains a verb - indicating either death or injury - followed by the name of the celebrity (e.g. مات بوتفليقة). In a descriptive, expressive, and sometimes humorous style, sentences are generally declarative (affirmative or negative form), while the interrogative form is reserved for fake news comments. We also observe Emojis and interjections as essential component of fake news, sometimes expressing humor, irony, anger or concern. Anger is also conveyed using capital letters, particularly when the fake news is written in French or in Arabizi. On the semantic level, religious formulas and expressions are used to deny a fact, mock or correct the person who published the fake news.

At the sociolinguistic and pragmatic levels, fake news themes are classified according to the primary objective of the publication. These themes include politics, sports, economy, immigration and so on.

Undoubtedly, taking these variations into account can be complex and will require adaptations in natural language processing.

### 3.3 Classifying and Analyzing Fake News: A Granular Approach in the BOUTEF Corpus

First of all, we shared the collected posts into three different classes.

- **fake news**: falsified information relayed on social networks.
- **fake news comments**: the different reactions to the post which relayed the fake news.
- **fake news Denial**: a post or a comment that doesn't relay any falsified news, but debunks a fake news.

Next, we assigned multiple granularity labels to each post. These various levels of granularity help us map out the fake news landscape. Below, we provide details about these categories:

- **Major theme**: the explicit idea behind the fake news, directly or indirectly expressed.
- **Minor theme**: the implicit idea triggered by the major theme in the fake news, implied by contextual and situational facts.

In Table 3, we give an example of fake news collected from Facebook. This instance of misinformation falls into

|   |
|---|
| حريق يأتي على ٦٠ ألف نخلة بغابات المنبعا ولاية غرداية ويكبد الفلاحين خسائر فادحة  |
| A fire destroys 60,000 palm trees in the forests of El-Menea, Ghardaia province, causing significant losses to farmers. |

Table 3: Example of a fake

a category of fake news that distorts actual events by exaggerating them. In this particular post, the Major theme revolves around a *DISASTER*, with a secondary theme related to *FIGURES MANIPULATION*. While the fire did indeed occur, it resulted in the destruction of 1000 palm trees, not 60,000 as falsely claimed. The objective of this fake news is to spread fear and insinuate that the authorities were incapable of managing the fire.

Table 4 and 5 display respectively the predominant themes within the Algerian and Tunisian fake news found in the BOUTEF corpus. Notably, political-themed fake news are the most widespread in Algeria, ranking as the top theme among the forty categories. On the other hand, Tunisian fake news predominantly revolve around the war in Gaza and the country's economic situation. Globally, Fake news primarily revolve around the citizens' foremost concerns.

| MAJ THEME | Alg (%) |
|-----------|---------|
| Politics  | 21      |
| Sport     | 10      |
| Religion  | 7       |
| Spying    | 4       |
| Army      | 4       |
| Corona    | 4       |

Table 4: Ranking of Major Themes in Algerian Fake News

| MAJ THEME               | Tun (%) |
|-------------------------|---------|
| War                     | 17      |
| Economy                 | 13      |
| Politics                | 10      |
| Immigration             | 8       |
| Corona                  | 7       |
| Death of public figures | 5       |

Table 5: Ranking of Major Themes in Tunisian Fake News

### 3.4 Categorizing Fake News: An Analysis of Claire Wardle’s Framework in the BOUTEF Corpus

In addition to our major and minor themes, we decided to label also the posts by using the categories proposed by Claire Wardle [21]. While Major and Minor Themes aid in detecting potential fake news triggers, Claire Wardle’s seven categories, tailored to our dataset, establish a framework for interpreting fake news, comprehending its objectives, and assessing its impact on cognitive warfare. We have applied the following adapted categories from Wardle’s classification to label each fake news instance.

- Deny the existence (DE) of an event or something.
- Diverted information (DI) by using an image or a text from its real context.
- Exaggeration or extension (EE) of numbers or events beyond their actual scope.
- Satire or parody (SP), no intention to cause harm but has a potential to fool.
- Misleading content (MIC) misleading use of information to frame an issue or an individual.
- Manipulated content (MAC) involves making modifications to fool people.
- Fabricated content (FC), new content is 100% false, designed to deceive and do harm.

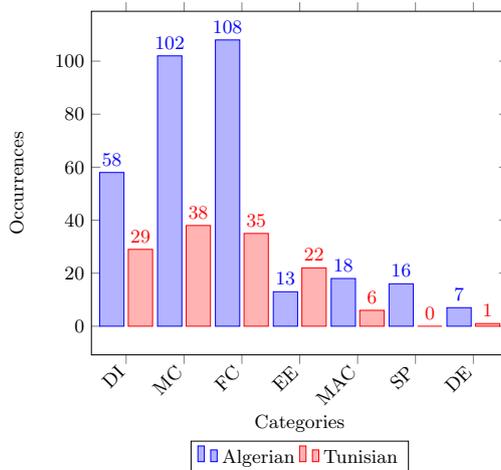


Fig. 2: Distribution of the fake news over the adapted Claire’s Wardle categories

Figure 2 illustrates the distribution of BOUTEF’s fake news using an adaptation of Wardle’s categorization. It is noteworthy that the most prevalent category for Algerian and Tunisian fake news is ”Misleading content with fabricated content,” and these categories are close to each other in terms of counts. In Table 6 offers a comparative analysis of the tagging systems used in various fake news datasets. It is worth noting that while many prior datasets employ a binary classification of fake or real, BOUTEF introduces a much finer-grained labeling scheme. This allows for a more nuanced analysis of the different facets of misinformation.

## 4 The Corpus Analysis

### 4.1 The Most Predominant Fake News in BOUTEF

In Tables 7 and 8, we provide an overview of the most prevalent instances of fake news found in two distinct sections of the BOUTEF corpus. It is worth noting that these tables offer insights into the major subjects that have gained prominence within the fake news landscape of these respective regions.

In the Algerian section of BOUTEF, we observe a recurring theme: the dissemination of false reports regarding the death of Bouteflika, when he was still alive. This subject has consistently held a prominent position

| Dataset             | Number | Labels                   | Fake Category  | Tags |
|---------------------|--------|--------------------------|--|------|
| FNC [18]            | 2      | Real, Fake               | NONE   | NONE |
| PolitiFact [7]      | 2      | Real, Fake               |  |      |
| FakeNewsNet [17]    | 2      | Real, Fake               |  |      |
| mahlous2021fake     | 2      | Real, Fake               |  |      |
| Breaking! [13]      | 3      |                          | False, Partial truth, Opinion  | NONE |
| rubin2015deception  | 3      |                          | Serious fabrication, Large-scale hoaxes, Humorous fakes  |      |
| LIAR [20]           | 6      |                          | degrees of veracity Pants-fire, False, Barely-true, half-true, mostly-true, true   |      |
| khalil2021detecting | 8      |                          | Misleading, Commotion, Fake, Selective, Suspicious, True, Myth, Satire   |      |
| BOUTEF              | 3      | Fake, FakeAnswer, Denial | Diverted information, Misleading content, Fabricated content, Exaggeration or extension, Manipulated content, Satire or parody, Deny the existence | 7    |

Table 6: Labels used for statements in each dataset (when a dataset has no specific name, it is identified by its principal author’s name)

| Algerian Fake Subject            | Rank |
|----------------------------------|------|
| Death of Bouteflika              | 1    |
| Hakimi Divorce                   | 2    |
| Death of Tebboune                | 3    |
| Neymar in Algerian football team | 4    |
| Russian Vaccin                   | 5    |

Table 7: The most frequent subjects in the Algerian part of BOUTEF

| Tunisian Fake Subject           | Rank |
|---------------------------------|------|
| Najib Belhadi Swimming record   | 1    |
| Declaration of War              | 2    |
| Seven hundred thousand migrants | 3    |
| Algerian juice banned           | 4    |

Table 8: The most frequent subjects in the Tunisian part of BOUTEF

in the realm of fake news within this segment. Additionally, other subjects such as Hakimi’s divorce, the alleged death of President Tebboune, Neymar’s purported involvement with the Algerian football team, and discussions surrounding the Russian vaccine have also garnered attention and feature prominently in this section. Shifting our focus to the Tunisian segment of BOUTEF, we confront another notable topic of fake news. In this domain, the most commonly occurring fake news subjects revolve around Najib Belhadi’s swimming record, followed by the conflict in Gaza, and notably, the attacks on sub-Saharan migrants. This underscores the significance of this issue within the Tunisian fake news sphere. Table 9 gives a comprehensive overview of the most frequently occurring words in the BOUTEF fake news corpus. It provides the word frequency count, reflecting the significance of specific terms within the corpus. Words with الله (God) and الجزائر (Algeria) topping the list. Indeed, in Muslim countries, when someone passes away, people turn to God to pray for his/her rest in peace. This illustrates how many fake news stories prompt individuals to seek divine assistance. The word ‘Algeria’ in French is prevalent, indicating that fake news and discussions often involve the use of the French language. The word فرنسا which means France is highly frequent, suggesting that fake news and debates concerning France are also common. The table also highlights words related to people’s passing and mentions of ‘Bouteflika,’ pointing to a substantial number of fake news stories about his death while he was still alive.

| Word                  | Freq | Word                           | Freq |
|-----------------------|------|--------------------------------|------|
| الله (God)            | 546  | الجزائر (Algeria)              | 219  |
| ربي (My God)          | 180  | مات (died)                     | 149  |
| تونس (Tunisia)        | 126  | يرحمو (may they rest in peace) | 125  |
| الخبر (The news)      | 118  | Algérie (Algeria)              | 110  |
| بوتفليقة (Bouteflika) | 93   | الصورة (The image)             | 91   |
| الجزائري (Algerian)   | 81   | فرنسا (France)                 | 79   |

Table 9: The most frequent words in BOUDEF

## 4.2 Comparative Analysis of Statement Length in BOUDEF Fake News Dataset

| Dataset             | Average length |
|---------------------|----------------|
| FNC [18]            | 773            |
| PolitiFact [7]      | 872            |
| FakeNewsNet [17]    | 521            |
| khalil2021detecting | 236            |
| mahlous2021fake     | 24             |
| LIAR [20]           | 18             |
| BOUDEF              | <b>12</b>      |

Table 10: Mean statement lengths for several corpora

Numerous datasets contain complete news articles categorized as fake or real, with varying degrees of veracity, while others focus on shorter documents like tweets. Our dataset falls into the latter category, as we manually selected individual statements from social media. Therefore, our primary focus is on very short documents, each typically containing a single statement. To provide a quantitative comparison with other works, we present in Table 10 a showcase of the average length of fake news articles in BOUDEF in contrast to other available datasets. On average, a fake news article in BOUDEF consists of 12 words. In contrast, comments and denials have average lengths of 7 and 225 words, respectively. This discrepancy is expected, as denials often require providing detailed information and evidence to refute the claims.

## 4.3 Exploring the Multilingual and Contextual Dimensions of the BOUDEF Fake News Corpus

Unlike many existing datasets, BOUDEF primarily focuses on fake news in Algerian and Tunisian dialects, along with Modern Standard Arabic (MSA), French, and English, often featuring instances of code-switching between these languages. This diversity reflects the linguistic complexity of social media discourse in North Africa. One of BOUDEF’s distinguishing features is its in-depth contextualization of fake news within their social context. This includes not only the fake news articles themselves but also the associated comments, denial posts, and a meticulous categorization system using major and minor thematic tags. These tags help dissect the nuanced aspects of each piece of misinformation. Each entry in the BOUDEF corpus comes with 16

attributes that shed light on the hidden processes involved in the creation and propagation of misinformation. These attributes cover various aspects, such as the major and minor themes, subject matter, image references, message content, message type, fake category, language, publication date, comments count, source site, number of followers, number of forwards, country of origin, gender of the user, and the username of the post’s author. Table 11 provides an illustrative example of how these attributes work together to enhance our understanding of fake news instances. In this example, please take note that the gender is denoted by *S*, indicating that we do not know the gender of the writer since it comes from a specific site.

| Features            | Value   |
|---------------------|---|
| Post                | وفاة ممرضة بمستشفى عبد الرحمان مامي بعد اصابتها بفيروس كورونا |
| Type Post           | Fake  |
| Subject             | Nurse Death   |
| Major Theme         | CORONA  |
| Minor Theme         | HEALTH  |
| Image Reference     | Nurse.png   |
| Fake Category       | Fabricated Content  |
| Language            | MSA   |
| Publication Date    | 10-05-2020  |
| Comments Count      | UND   |
| Site                | Facebook  |
| Number of Followers | 1,7 M   |
| Number of Forward   | UND   |
| Country             | Tunisia   |
| Gender              | S   |
| Post’s User         | Tunisscope  |

Table 11: Example of the structure of a post

#### 4.4 The Origin of News

Prior research in fake news detection primarily used fact-checking websites and established news sources. In contrast, our approach concentrated exclusively on social media posts, aiming to capture the inherent characteristics and dissemination patterns of fake news within these platforms. This unique data collection strategy distinguishes our dataset. Table 12 illustrates the sources used in different datasets, emphasizing our focus on social media-originated content for a more comprehensive analysis.

| Dataset     | News Source                                  |
|-------------|--|
| FNC         | nytimes.com<br>pewresearch.org               |
| PolitiFact  | snopes.com<br>politifact.com                 |
| FakeNewsNet | gossipcop.com<br>politifact.com              |
| Khalil      | more than 130 news sources                   |
| Mahlous     | Twitter                                      |
| LIAR        | politifact.com API                           |
| BOUTEF      | Facebook, Twitter<br>TikTok, Youtube, Others |

Table 12: Examples of news sources for the compared datasets

In Figures 3 and 4, we present the distribution of posts sourced from the social networks and web sites in our data collection. It is evident that the majority of the fake news in BOUTEF originates from Facebook, and this holds even more true for the Tunisian corpus. In the case of Algerian, a significant amount of misinformation is generated from various websites and newspapers. Twitter consistently serves as a prominent source of fake news within the Algerian segment of BOUTEF. When it comes to denials, the majority of them come from fact-checking platforms such as FALSO, DZ Fake News, AFP, etc.

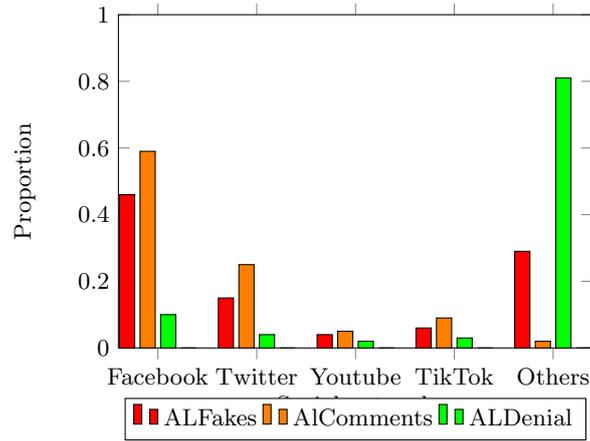


Fig. 3: Distribution of the sources of the Algerian misinformation

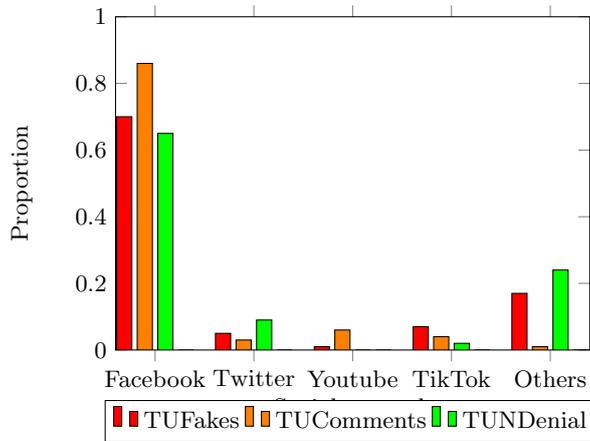


Fig. 4: Distribution of the sources of the Tunisian misinformation

#### 4.5 Does Gender Influence the Spread of Fake Information ?

We opted to retain the gender of the users associated with the propagation, commenting, or denial of each post (fake, fake comment, or denial). Table 13 presents this data categorized into four labels: Female, Male, Website, or Undefined.

| Gender | Fake | FakeComment | NoFake |
|--------|------|-------------|--------|
| Male   | 61   | 1230        | 9      |
| Female | 5    | 285         | 1      |
| Site   | 186  | 11          | 208    |
| UND    | 80   | 872         | 13     |

Table 13: Gender distribution of BOUTEF

We observe that the majority of fake news has been propagated by websites or pages with a significant number of followers, followed by men in the second position. It's important to highlight that women don't predominantly disseminate misinformation, although their commenting frequency may be lower than that of men. However, their contribution is still significant. The high number of "Undefined" gender labels can be attributed to various factors, including the widespread use of pseudonyms and names that make it impossible to determine gender.

#### 4.6 Temporal Distribution of Posts

In our investigation into the content of fake news, we consistently sought to determine whether certain years were more susceptible to fake news than others. In Figure 5, we have illustrated the distribution of fake news in both Algerian and Tunisian. We were particularly surprised to observe a peak in fake news activity in the Algerian segment of BOUTEF during the year 2020. This period coincided with the onset of the COVID-19 pandemic, during which a significant amount of misinformation proliferated due to the unprecedented nature of the situation. Both authorities and the public lacked precise information about the virus, and the lockdown measures also contributed to a heightened sense of boredom, leading individuals to seek out ways to entertain themselves or stay occupied.

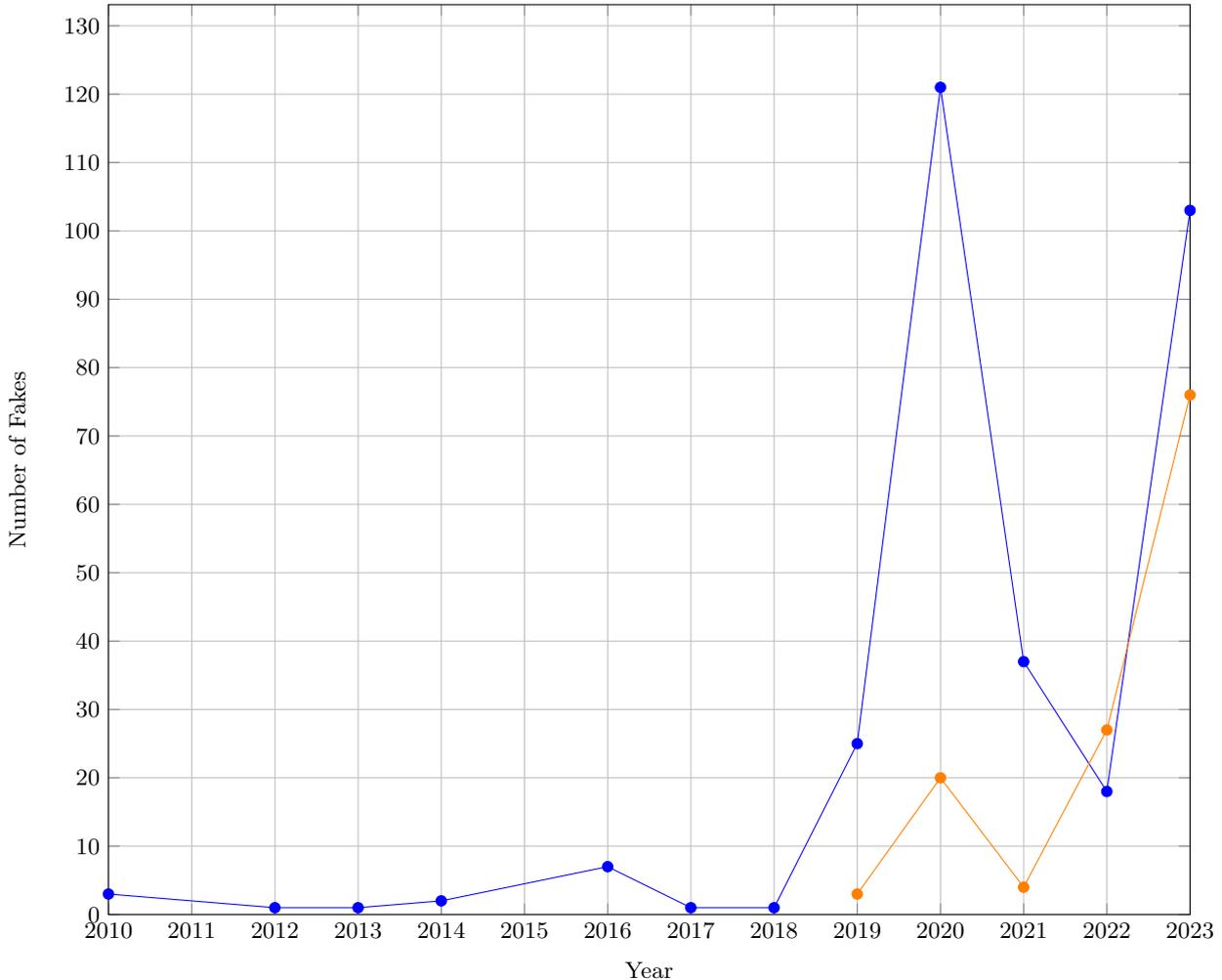


Fig. 5: Fakes distribution across the years

## 5 Conclusion

In this paper, we introduce BOUTEF, a fake news corpus. We will leverage this corpus for the early detection of fake news across various social networks, including Facebook, Twitter, YouTube, and TikTok. Furthermore, our goal is to monitor the evolution of fake news trends over time. BOUTEF not only collects fake news posts but also their associated comments, and whenever possible, we link each fake news item to a denial captured from a fact-checking platform. The primary focus of BOUTEF is on fake news originating from Algeria and Tunisia. We have enriched this corpus with extensive metadata, including the topic (spanning forty different categories), the purpose of the fake news (categorized into seven distinct categories), publication dates, comments, source origins, follower counts, comment shares, geographical origins, user information, and links to supporting videos. In the future, we intend to utilize BOUTEF to characterize fake news from social networks in terms of both static information (content and user profiles) and dynamic trends across various networks. Our ultimate aim is to identify fake news as early as possible, enabling swift responses from content providers and those targeted by fake news.

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