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ABSTRACT
Fact-checking is a staple of journalists’ work. As more and more important data is available in electronic format, computational fact-checking, leveraging digital data sources, has been gaining interest from the journalists as well as the computer science community. A particular class of interesting data sources are statistics, that is, numerical data compiled mostly by governments, administrations, and international organizations.

We propose to demonstrate StatCheck, a fact-checking system specialized in the French media arena. StatCheck builds upon a prior pipeline [CMT17, CMT18, DCM19] for fact-checking statistical claims against the INSEE national statistic institute’s data and reports. In collaboration with factchecking journalists from France Info (Radio France), we have revisited and improved this pipelined, and enlarged its database by an order of magnitude by adding all Eurostat statistics. StatCheck also includes two novel statistic claim extraction modules, generalizing and improving over [DCM19]. Based on the journalists’ feedback, we built a new user interface, suiting better their needs. We will showcase StatCheck on a variety of scenarios, where statistical claims made in social media are checked against our statistic data.

1 INTRODUCTION
Professional journalism work has always involved verifying information with the help of trusted sources. In recent years, the proliferation of media in which public figures make statements, including traditional media available online, as well as social media, has lead to an explosion in the amount of content that may need to be verified in order to distinguish accurate from inaccurate, and even potentially dangerous, information.

Computational fact-checking is a growing and multidisciplinary field [CLL*18, NCH*21] which has lead to the creation of meeting venues such as the Conference for Truth and Trust Online1. The main tasks of a fact-checking system are: identifying the claims made in an input document, finding the relevant evidence from a reference dataset, and optionally producing an automated verdict or if not, letting an end user decide on the truthfulness of the claim. Recent systems proposed in this area include [HZA*17, KSPT20, PMYW18]. In a recent survey [SP21], the authors compare the performance of four statistical fact-checking systems [CWCT20, HNMT20, JTY*19, KSPT20]. A statistical claim is defined as any textual claim that can be verified over a trustworthy database by performing a mathematical expression on the database cell value [SP21]. The four systems take in input a claim and a table, and should output the truth value of the claim.

We propose to demonstrate StatCheck, a fact-checking system specialized in the French media arena. Differently from the above-mentioned systems, StatCheck also includes a claim detection step, while assuming that an end user will decide if a claim is true or not based on the evidence retrieved. Another specificity is our focus on checking statistical claims, with the help of large public statistic databases (specifically, INSEE and Eurostat); the nature and organization of these databases raises specific challenges when searching for the statistic most appropriate to check a given claim.

2 STATISTIC DATA ACQUISITION AND STORAGE
INSEE publishes each statistic report as an HTML page that links to statistic tables, which may be in Excel (the most frequent case) or in HTML. The tables are not relational. On one hand, they have human-understandable header cells not only for each column (as is the case for a relational table), but also for each line. From this perspective, a statistic file resembles more a multidimensional aggregate query result. On the other hand, many tables feature hierarchical (nested) headers: for instance, a header cell corresponding to "Paris (75)" may appear as a child of another header cell corresponding to "Île-de-France". To capture such structure, the data is modeled as an RDF graph, as illustrated in Figure 2; each cell becomes an RDF URI, connected to its closest line header (blue arrows), and closest column header (red arrows). The black arrows are triples relating column header cells to their parent header cell.

While revisiting the platform, we re-crawled the INSEE Web site up to May 2022, leading to 60,902 Excel files and 58,849 HTML files. We then extract statistic tables from those files and convert them into RDF graphs, accounting for 7,362,538,629 RDF triples, including 22,366,376 row or column header cells. To store this large amount of data, we use JENA TDB2; loading the complete set of INSEE published statistics took around 29 hours. Subsequently, we incrementally re-crawl the Web site each night to retrieve and ingest the possible studies published every day.

1https://truthandtrustonline.com/
2https://jena.apache.org/documentation/tdb2/
3.1 Dataset Indexing and Search

For each dataset, we call metadata of d its title together with any comment published by INSEE next to the dataset. Further, the statistical tables within d have row headers and column headers which may be INSEE internal codes, not directly readable by non-experts. In such cases, d also includes (in a separate sheet) the natural language descriptions of the dimensions involved in all these headers. These are also part of the dataset’s metadata.

We split the metadata of d into a set of tokens T = {t1, . . . , tN}. For each token t, we identify, based on a Word2Vec model3, the 50 tokens t’ closest semantically to t. Next, for each appearance of a token t in a location l within d, our term-location index ITL stores: (i) the index entry (t, d, l) corresponding to the token actually found in d; and (ii) 50 entries of the form (t’, d, l, dist), corresponding to the 50 closest tokens to t. These extra entries enable answering queries on terms close to (but disjoint from) the dataset content. For instance, when t is “Enseignement”, t’ could be “Ecole”, “Enseignant”, “Elève”, etc. To determine the datasets pertinent for the query Q, we look up the query keywords in ITL; a dataset containing at least one keyword is potentially interesting.

To rank datasets, a relevance score was introduced in [CMT18], based on word distances between the query keywords and the datasets’ metadata, and also reflecting the locations where the keywords were found for each dataset. To this custom score, we have added the classic BM25 [RZ09] computed over all the datasets’ metadata, and are currently experimenting with the two.

3.1.1 Improving the INSEE pipeline. We brought several improvements over [CMT18]. First, we collected and processed metadata during data acquisition (as opposed to retrieving it from Fuseki after loading). Tokening and lemmatization, based on Spacy, were sped up by accumulating all the metadata of a table in a single string for which we call Spacy only once per dataset.

Next, we improved the understanding and interpretation of geographical query terms. Users may query for a city, department, such as “Essonne”, or region, while statistic data may be available at different levels of aggregation, e.g., a dataset may be about “Ile-de-France” (the region). The system needs to be aware of the relationship between the two, in order to also consider returning data about the region. To that purpose, we used a list4 containing

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3We used the model frWac_non_lem_no_postag_no_phrase_200_skip_cut100.bin from https://faucconnier.github.io

4https://www.data.gouv.fr/fr/datasets/regions-departements-villes-et-villages-de-france-et-doute-mes/
the names of all cities, departments and regions of France (35,984 names in all). To quickly identify them in user queries, we used an implementation\(^5\) of the FlashText algorithm [Sin17], capable of finding, in a document of size \(N\), one of \(M\) fixed keywords, in \(O(N)\) time complexity. This is much faster than the typical \(O(NM)\) cost of regular expression pattern matching, a sizable advantage for us. The optimizations introduced above allow us to reduce the overall INSEE loading and indexing from 39 hours to about 3h.

### 3.1.2 Eurostat indexing pipeline

As detailed in Section 2, Eurostat datasets (i) have a simpler tabular structure, (ii) together, are much larger than the INSEE corpus, leading to metadata 100x larger, and (iii) contain a significant number of very large files (hundreds of millions of rows). This discourages row- or cell-level indexing of the Eurostat metadata, as the index would be much too large.

Instead, we decide to use Eurostat statistical concept codes as a basis for indexing, as follows. Let \(c\) be a Eurostat concept, e.g., ED1, appearing in dataset \(d\) at a location \(l \in \mathcal{L}\). We insert in a concept-dataset index \(I_{c}\) the entry \((c, d, l)\). For instance, if \(c\) appears in 1 million row headers in \(d\), only one entry with \(l = RH\) is generated.

Next, let \(d_c\) be the natural-language description that Eurostat associates to \(c\), e.g., “Enseignement primaire” for ED1. Let \(T = \{t_1, t_2, \ldots, t_N\}\) be the tokens in \(d_c\), and for \(1 \leq i \leq N\), let \(t_i^j\), for \(1 \leq j \leq 50\), be the closest tokens to \(t_i\). For each \(t_i \in T\), we look up all the \((c, d, l)\) pairs in \(I_{c}\), and insert in the term-dataset index \(I_T\), a \((t_i, d, l)\) entry. Next, for every \(t_i^j\) similar to \(t_i\), we insert in \(I_T\) an entry \((t_i^j, d, l, dist, t_i)\), where \(dist\) is the distance between \(t_i\) and \(t_i^j\). \(I_{c}\) and \(I_T\) are stored in Redis; \(I_{c}\) only serves to accelerate the construction of \(I_T\), which was prohibitively slow without it. Indexing the complete Eurostat data in this way took around 4 minutes.

When a query \(\{k_1, \ldots, k_m\}\) is asked, we search \(I_T\) for entries of the form \((k_i, d, l)\) or \((k_i, d, l, dist, k_j^i)\). Any dataset having an entry for at least one \(k_i\) is potentially interesting; then, we score them either using either BM25 or the score introduced in [CMT18].

### 3.2 Data Cell Indexing and Search

From the 20 highest-scores datasets, we try to extract results at the cell, row, or column level. Given the query \(\{k_1, \ldots, k_m\}\), the index \(I_{c}\) (INSEE) or \(I_T\) (Eurostat) returns, for each \(1 \leq i \leq m\), a set of entries, each containing: a keyword \(k_i\) or a close term \(k_i^j\), a dataset \(d\), and a location \(l\). Let \(d\) be one of the most interesting datasets, and \(I(d)\) be the set of all index entries for this query and \(d\).

If \(I(d)\) only features title \((T)\) or comment \((C)\) locations, then \(d\) is pertinent as a whole, and no cell search is needed.

On the contrary, if \(I(d)\) has some entries with \(l = RH\), say, for keyword \(k_1\) (or a close term \(k_1^j\)), and other entries with \(l = CH\), say, for \(k_2\) (or some \(k_2^j\)), then at the intersection of the row whose header matches \(k_1\), with the column whose header matched \(k_2\), is a cell that appears to be a very fine-granularity answer to \(Q\).

- If \(d\) is an INSEE dataset, \(I(d)\) specifies exactly which rows and columns are concerned. Then, the cell is identified by asking a SPARQL query [CMT18], evaluated by Fuseki.
- On the contrary, if \(d\) is an Eurostat dataset, \(I(d)\) only specifies that "some row (column) headers match". Identifying the relevant cells require more effort, as we explain below.

### Identifying the right columns

An Eurostat file has at most a few dozen columns. To find the column referred to by an \(I(d)\) entry whose key is \(k\), we read the first (header) line of \(d\), and identify the column(s) whose header contains \(k\). This step is very fast, because we only read the beginning of the file.

### Identifying the right rows

This requires an extra index to be efficient even on files with millions of rows. Specifically, when indexing the data, we also create a row location index \(I_R\) which, for every row header entry \((k, d, RH) \in I_T\), stores \((k, d, R_{k,d})\), where \(R_{k,d}\) is the list of the indexes of data rows in \(d\) which contain \(k\) in their header. For efficiency, \(I_R\) is saved directly as a file on disk, and supports direct access by \(k\) and \(d\), following the Adaptive Positional Map of [ABB*15].

### Cell extraction

Once the right rows and column indexes are known, we read the relevant rows from \(d\), and carve out of them the relevant data cell(s). With the help of a line cache library\(^6\), this process is quite efficient.

Overall, on INSEE datasets, using Fuseki, data cell search takes 35ms up to 2.86s. On Eurostat, using \(I_R\), we record 4.76\(\mu\)s up to 2.66s. The lower bound is higher for INSEE because we have to pass SPARQL queries across a connection to the Fuseki server.

### 4 CLAIM DETECTION

A claim is a statement to be validated, that is we aim to establish if it is true of false. The validation is achieved by finding related statements, called evidence, which back up or disprove the claim.

In our work, the claims are detected in an input text, while the evidence is retrieved from a set of trusted sources, our reference datasets. Our platform detects claims from text stored in .txt, .odt, .docx or .pdf files, and from the Twitter and Facebook posts of public figures. For posts, our platform retrieves regularly the most recent updates of a predefined group of users.

#### 4.1 Statistical Claim Detection

In [DCMT19], the authors introduced a statistical claim detection method that given an input set of statistical entities (e.g. chômage, coefficient budgétaire) and a sentence, it retrieves all the statistical statements of the form \((\text{statistical entity}, \text{numerical value and unit}, \text{date})\) present in the sentence. The statistical statement, if present, represents the statistical claim to be verified. The statistical entities and units are retrieved using exact string matching, while the date is extracted using HeidelTime [SG10], a time expression parser. If no date is found by the parser, the posting timestamp is used. More context about the claim to be verified is found using a Named Entity Recognition (NER) model, which returns organizations and locations. We note, however, that the organization and location are optional, while a statistical statement is not complete without one of its three elements. The initial statistical entity list is constructed from the reference datasets by taking groups of tokens from the headers of tables, we refer to [DCMT19] for more details.

We improved the method presented in [DCMT19] to optimize both speed and quality of extractions. We refer to the two methods as OriginalStatClaim [DCMT19] and StatClaim. We first performed a more careful match between the tokens of a sentence and our input statistical entities. Using the syntactic tree of the sentence and a lemmatizer, statistical entities are matched on using their

\(^5\)https://github.com/vi3k6i5/flashtext

\(^6\)https://docs.python.org/fr/3/library/linecache.html
Figure 3: Screen captures of our tool. Top: sample candidate data cells with the corresponding header row (blue) and header column (red); bottom: tweet analysis interface.

lemma, and are extended to contain the entire nominal group of the matched token. Numerical values are associated with units using both lemma matching from our set of units and a syntactic analysis. Units can be a noun following a numerical value, or a nominal group containing one or more units. (e.g. “millions d’euros”). As in the original approach, if we retrieve a statistical statement of the form \(\langle\text{statistical entity, numerical value and unit, date}\rangle\), we have found a claim to verify. In the default setting of our algorithm, a claim should contain all the three elements. In addition, we filter claims coming from sentences in which the verb is in the future tense or in the first person. We have incorporated feedback from the journalists and we allow through our interface a relaxation of the approach: the numerical value can be missing, and the filtering on the verbs can be removed.

4.2 Check-worthy Claim Detection

To complement the statistical claim detection model, we developed a model that is not conditioned on a set of initial statistical entities. The model classifies a sentence as check-worthy or not, where check-worthiness is defined as sentences containing factual claims that the general public will be interested in learning about their veracity [AHLT20]. We leveraged the ClaimBuster dataset [AHLT20], an English dataset containing check-worthy claims from the U.S. Presidential debates, to train a cross-lingual language model, XLM-R [CKG*19], which is able to perform zero-shot classification on French sentences after having been trained on English data.

The ClaimBuster dataset

ClaimBuster is a crowd-sourced dataset where the sentences from the 15 U.S. presidential elections debates from 1960 to 2016 have been annotated. The labels are Non-Factual Sentences (NFS), Unimportant Factual Sentences (UFS) or Check-Worthy Factual Sentences (CFS). The dataset contains 23K sentences, and a subset of higher quality of 11K sentences was produced by the authors for training models on classification tasks. In this smaller dataset, the NFS and UFS labels are grouped together as negative labels, and the CFS labels are considered positive. We chose this higher quality dataset to fine-tune the XLM-R model.

4.3 Integration and Evaluation of the Claim Detection Models

We evaluate the claim detection models, (OriginalStatClaim [DCMT19], StatClaim and CheckWorthyClaim), on a set of 1595 tweets. Each tweet was labeled with two classes: “Verifiable numerical claim” (True if the tweet contains at least one numerical and verifiable claim”) and “INSEE statistical claim” (True if the tweet contains at
least one numerical, statistical claim verifiable against the INSEE dataset). We chose these two labels as the first one gives us an indication of the tweets that can be verified if we had an unlimited access to resources, while the second class identifies the tweets verifiable in the setting in which we have access to only one resource. To construct our set, we gathered 1595 random tweets from our scraped dataset. Then, we automatically detected if a tweet contained a numerical value, if not, the tweet was labeled as negative for both classes. After that first step, we manually labeled the remaining 101 tweets. Two annotators labeled each tweet, and the gold standard was chosen as True if both annotators agreed. For the class “verifiable numerical claim”, we obtained a Kappa inter-Annotator Agreement score of 0.917 (almost perfect agreement) and 59 tweets were labeled as positive. For the class “INSEE statistical claim” we obtained an inter-annotator Agreement score of 0.807 (substantial agreement) and 16 tweets were labeled as positive.

Evaluation procedure For StatClaim and OriginalStatClaim, a tweet is considered positive if the model returns a check-worthy score > 0.9. We report the results in Table 2 and Table 3. StatClaim performs better than the original at detecting INSEE verifiable claims, and CheckWorthyClaim vastly outperforms both models on the detection of numerical claims, as they are a subset of check-worthy sentences that the model was trained to detect.

Default claim detection strategy. By default, StatCheck uses StatClaim for statistical claim detection. However, given the good performance of CheckWorthyClaim on numerical claims, we allow users to switch to it, even if we might not be able to verify them against the reference datasets.

5 DEMONSTRATION SCENARIOS

Our system is developed in Python and deployed on a Unix server. Its GUI is accessible via a Web server; Figure 3 shows two screen captures. Demonstration attendees will be able to:

• Ask queries in the statistic search interface, and inspect the results, at the level of cell, line, or column, together with their metadata from the original statistic site (INSEE or Eurostat);
• Visualize incoming social media messages (as they arrive in real-time and are stored and analyzed by our platform), in order to see (i) the statistical mentions and (ii) claims deemed potentially check-worthy, identified in these messages, as illustrated in Figure 3. Note that the system also proposes candidate search queries for the statistic search interface.

• Users will be able to select various options (restrict to numerical claims or not, include statements about the future or not, include first-person texts or not, etc.) and see their impact on the claim extraction output.

• Write their own text and/or suggest other content to be processed by our analysis pipeline (Section 4).

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