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Information extraction from articles on the impacts of COVID-19 lockdowns on air quality

A thesis submitted in fulfillment of the requirements for the degree of
Bachelor of Science in Computer Science

BY

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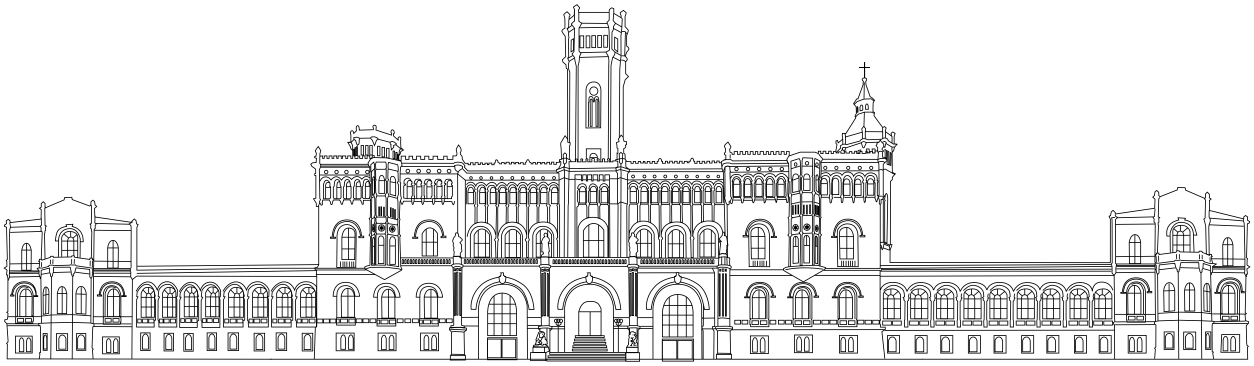

Declaration of Authorship

I, Quentin Münch, declare that this thesis titled, 'Information extraction from articles on the impact of COVID-19 lockdowns on air quality' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.

NAME

Signature: ______________________________

Date: ______________________________

"Mistakes are also important to me. I don't cross them out of my life, or memory. And I never blame others for them."

— Geralt of Rivia, book *Blood of Elves* (1994)

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Abstract

In response to the COVID-19 pandemic, cities worldwide imposed lockdowns to combat the spread of the virus. Governments ordered people to stay at home. Therefore, vehicle and industrial emissions changed drastically. Several researchers studied the impact of such lockdowns on air quality. The research centre Jülich accumulated various articles to gather all information. They manually searched each article and created a database containing the change in pollutants. Using the gathered data, they developed a website to illustrate their findings to the community. However, searching the articles by hand takes significant time and resources. Since, in the future, additional articles will be added to the database, developing models for automated extraction of such data can be beneficial. Here, we present a script utilising a rule-based matching approach to extract pollution data from articles automatically. Around 150 reviewed articles were split into 80% training and 20% test data. Using the training data, the model learns to detect various patterns in sentences and how to extract relevant information from them. After the training finishes, the program gets tested using the test data. It achieves a 22% recall and 43% precision value when executed. Compared to manual extraction, this result is significantly worse. A significant problem for the automated extraction present tables. They contain a plethora of data. However, extracting information from one does not work appropriately, let alone detecting a table. Nevertheless, by highlighting relevant text passages, the program offers a great starting point for manual extraction.
Keywords: Information Extraction, air quality, COVID-19, lockdown

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Acronyms

CO Carbon monoxide

COVID-19 Coronavirus disease 2019

FN False Negatives

FP False Positives

IE Information Extraction

IF Information Filtering

IR Information Retrieval

NH3 Ammonia

NMVOCS Nonmethane volatile organic compound

NO2 Nitrogen dioxide

O3 Ozone

PM Particulate matter

SO2 Sulfur dioxide

TN True Negatives

TP True Positives

Chapter 1

Introduction

The outbreak of the 2019 coronavirus disease (COVID-19) greatly impacted the entire world. Due to the virus being very contagious, social interactions had to be minimal. While the precise measures to reduce the virus spread differed from country to country, almost every part of the world introduced lockdowns. This prohibited people from going outside unless it was essential for their living. Companies had to let the employees work from home, so they did not need to leave the house. Clubs, bars and restaurants had to close down because of government orders and a lack of customers. Considering these points, it is apparent that people were not driving around as much as before the pandemic. Instead, they were staying at home, thus considerably reducing their transportation emissions.

Many scientists saw the unique opportunity to research how much of an impact such lockdowns have on air quality. While restrictions put daily life on hold, the streets of major cities were emptier than ever. Researchers published many articles regarding the change in air quality during these lockdowns. However, not all followed scientific methods and reviewing practices. In order to gather all the data in one place, the research centre Jülich accumulated every article about the change in air quality during lockdowns. The examined articles are all scientifically verified [5]. These articles contain a significant amount of data that must be processed manually. The research centre Jülich processed each article individually and collected the air quality data. They set up a website which presents the results in various charts.

However, the process of manually having to check each research article proves to be very inefficient. Therefore, models for automated information extraction of such air quality data points could provide a fitting solution. Since scientists are still researching the connection between lockdowns and air quality, these models would also be helpful for later database updates. Following the principles stated by Andersen

et al. (1992), this thesis deals with developing a rule-based information extraction model. For this, the definition of several distinct patterns is crucial. The program then searches the text for these patterns and stores each match. Afterwards, it extracts the information contained in the matches and makes them available for further use. The time spent skimming through the papers will be significantly reduced by automatically extracting the data.
On the contrary, the technology is error-prone. It is unlikely to find every single data point in the text. However, at the very least, it could provide a solid baseline for further examination.

1.1 Structure of the Thesis

In chapter one, the context of the study has been introduced. The research problem has been stated, and a possible solution has been presented. The value of such research was demonstrated while also showing its limitations.

Chapter two will outline the fundamental knowledge needed to understand the thesis concepts. This includes the basics of Information Extraction, important evaluation methods, and essential air pollutants.

In chapter three, the existing literature will be reviewed. Especially the different usages of rule-based and machine learning approaches will be discussed.

The two approaches to the problem will be explained in chapter four.

In chapter five, the implementation of the extraction program will be described.

In chapter six, the quality of the implementation will be assessed. For this, the evaluation and problems of the implementation will be presented.

In chapter seven, a conclusion will be drawn. The options for future work building up on this thesis will also be shown.

Chapter 2

Background

There are vast amounts of text data on the internet. There is so much of it that no human can ever read and understand everything. That is why we try to use the computer to help us guide through the data. For this, we mainly use the concepts of information extraction. To better understand the thesis's development, the following chapter introduces the main topics.

2.1 Information Extraction

There are several strategies for establishing order across texts, the most common being information retrieval (IR), information filtering (IF) and information extraction (IE) [4]. Information retrieval concerns itself with all the activities related to the organisation of, processing of, and access to, information of all forms and formats. It can also be seen as a document retrieval system since it is designed to retrieve information about the existence of documents relevant to a user query [3]. On the other hand, information filtering aims to remove irrelevant data from incoming streams of data items [7]. Information extraction is the automatic extraction of structured information such as entities or relations from unstructured sources [16].

In contrast to IR systems, IE systems must extract facts from the documents. We can use the extracted data for filling in databases, which are then available for various applications to process the data further [11]. Since information often spreads across multiple sentences, understanding natural language is fundamental to IE [6]. This concept can be a significant challenge because computers process information differently than humans. While human perception can easily create relations between entities, the computer has to process each word bit by bit. Usually, it forgets most of it a few words later. Hence it has difficulties finding relations between words.

However, technological advancement now makes it possible to reduce these problems' gravity.
Before the actual extraction occurs, it is often beneficial to employ various preprocessing techniques. These include splitting sentences into tokens (e.g. words, punctuation marks), recognizing the end of sentences, detecting word types, tracing back words to their original form or even correcting small spelling mistakes [11]. This preprocessing results in an enhanced performance during the extraction process. The program can concentrate on the main task by doing the hard work in advance. The document is now better structured and prepared for further analysis.

2.2 Evaluation methods

We use two metrics to measure data retrieval performance from a collection. Let $N_{correct}$ be the correctly extracted data, $N_{extracted}$ all extracted data and $N_{relevant}$ all relevant data. Then [6]

$$\text{precision} = N_{correct}/N_{extracted}$$
$$\text{recall} = N_{correct}/N_{relevant}$$

$N_{correct}$ is also known as true positives (TP). $N_{extracted}$ consists of TP and wrongly extracted data, called false positives (FP). $N_{relevant}$ includes TP and relevant data that the program overlooked, called false negatives (FN). Precision is a general metric to display the ratio of correctly and incorrectly retrieved data. At the same time, recall shows the percentage of how much of the relevant data the extraction found. There is also the possibility of combining these two measurements to create an "F score". Traditionally the F score is defined as

$$\text{F} = \frac{2 \cdot precision \cdot recall}{precision + recall}$$

However, there are also other possible specialisations of the F score that further emphasise precision or recall [6]. A higher score indicates a better performance of the extraction. Generally, we expect a program to reach a precision and recall value of 90%, especially in specialised domains [11].

For a successful evaluation, a good amount of data is essential. This data splits into two different areas called training and test data. The training data is the most critical and typically gets the most significant portion of the available data. As the name suggests, we use it for training the model. This data includes all previously collected information that has already been verified and found to be correct. Using this information, we can now train the model. By feeding past results to the program,

we aim to prime the model such that it identifies future results on its own. The larger the training data set is, the better this process becomes.
We use the remaining available data exclusively for testing. This data is necessary for the evaluation. To assess the quality of the model's extraction, we run the program on the test data. However, we do not use this data to modify the algorithm in any shape or form. We must compare the program's results with the already verified test data. For this, we use the previously mentioned precision and recall values.
A typical ratio between training and test data would be 80/20 or 70/30. Performing such a split provides ample training and testing data and ensures a well-rounded model.

2.3 Air pollutants

Since the articles for this project focus on the change in air quality during COVID-19 lockdowns, air pollutants play a significant role. Recognising the most critical pollutants is essential so we know what to look for in the text. The primary air pollutants are as follows:

1. nitrogen dioxide (NO2)
2. particulate matter (PM2.5, PM10)
3. ozone (O3)
4. carbon monoxide (CO)
5. sulfur dioxide (SO2)
6. ammonia (NH3)
7. nonmethane volatile organic compound (NMVOCS)

Chapter 3

Related Work

With the internet becoming more and more popular over the past decades, available information online increased rapidly. Consequently, the need for efficient algorithms to find data reliably and quickly increased. Thus, extracting information from texts has manifested itself as a critical research field. Scientists have already conducted much research on this topic proposing different approaches.

Andersen et al. (1992) examine a template-driven approach to extract facts from press releases automatically. They developed a program called JASPER (Journalist's Assistant for Preparing Earnings Reports) which scans company press releases from PR Newswire. After identifying relevant articles, it then automatically extracts a predetermined set of information. Afterwards, it transforms the collected data into an individual news story and sends it to a journalist for verification [1]. One can gain an edge over other companies by utilising such a program. They likely will be unable to match the extreme speed of outputting accurate news. Because a journalist has to approve the article beforehand, high quality is also guaranteed.
JASPER functions on a rule-based system. It checks if an information type has not been extracted yet and searches for the appropriate patterns in the sentence. On a match, it then extracts and interprets the information from that sentence. It takes JASPER, on average, about 25 seconds to process a relevant article while maintaining very high recall and precision values of around 80% [1].
The principles applied in this thesis are similar to the study conducted by Andersen et al. A significant difference is that we have to deal with larger amounts of data in general and more intricately presented information.

Due to the increasing amount of research on machine learning algorithms, tracking the progress has become difficult. Therefore, Kardas et al. (2020) developed an

automatic machine learning pipeline called AxCell to extract results from papers addressing machine learning topics. The goal is to extract tuples containing relevant information such as task, data set, metric name and value [10]. They approached this problem by defining subtasks in the AxCell pipeline. First, it needs to identify relevant tables, then it classifies each table cell and finally retrieves the resulting tuples.
For the training and evaluation of the AxCell pipeline, a considerable amount of data is necessary. Their primary input is the LaTeX source code of machine learning papers from arXiv.org [10]. In total, two data sets are essential for the training of this pipeline. They are starting with the previously mentioned arXiv papers as an unlabelled data set of over 100,000 machine learning papers. Since it consists of unlabelled data, they used it for self-supervised language model learning. The second training data set trains the pipeline on table cell classification. It contains 1994 tables with annotated table cells to learn. Following the training, they use a validation data set of over 200 annotated papers to adjust the pipeline's performance manually. Finally, they use a test data set of over 2000 annotated articles as an evaluation tool. When considering the extraction of tuples for entire records (task, data set, metric, score), it achieves good performance with precision and recall between 20-40%. However, if we leave out the score, the performance increases to 45-70%. This difference in efficiency is due to the model having difficulties accurately predicting the score's location in the tables. The remaining tuple (task, data set, metric) can also often be concluded from other results reported in the paper [10].
This research shows that a machine learning algorithm can provide solid results for a specified task when given enough data. It also lays out the difficulties such algorithms have to overcome.

The industry and academia are not united when choosing which approach to use. While recent academic research focuses mainly on machine learning, the commercial world prefers rule-based systems [2]. Chiticariu et al. (2013) display the reasons for such a separation and present solutions to reduce this gap. They believe that the disconnect arises from a difference in how the communities measure the costs and benefits of information extraction [2]. While academics evaluate their models using precision and recall on standard labelled data sets, it is not that simple for the industry. Some parts of a process might be more important to resolve than others. Thus, an easy metric may not be enough. When companies decide to change their requirements, rule-based systems are superior. They are easier to understand, alter, and maintain than a machine learning model requiring a complete retrain [2].
The paper states that another reason for the lack of rule-based research is the feeling

that there is a lack of research problems. However, in the eyes of Chiticario et al., this is not the case. Because the reviewed companies with a revenue of more than $100 million almost entirely rely on rule-based systems [2], their importance becomes clear. The article proposes the development of a standardised information extraction rule language in combination with a regulated data model. Following this could replicate the success of the SQL language in connecting data management research and practice [2].

Chapter 4

Approach

This chapter explains the problem at hand and the proposed solution.

4.1 Problem Statement

During the COVID-19 pandemic, many countries declared nationwide lockdowns. Governments ordered people to stay home, significantly reducing traffic and industrial emissions. To research how much air pollution changed during this time, researchers across the globe thoroughly inspected the air quality. They published their results as articles in several scientific journals. To make these results more accessible and visually appealing, the research centre Jülich aims to gather all the information in one place. They manually read each article, searching for information regarding pollution changes. Afterwards, they compress the information and display it on their website. An approach like that has its positives and negatives.
On the one hand, one can thoroughly search the entire document knowing that one probably did not miss anything. A human can easily understand and recognise relations in text, which enables the correct allocation of pollutant value pairs. On the other hand, it takes a lot of time and resources to search for information by hand. When the amount of articles increases daily, it is challenging to keep up. On top of that, the concentration decreases steadily after reading through the articles for a while. This fatigue can, in turn, lead to careless mistakes or not finding all vital information in the text.

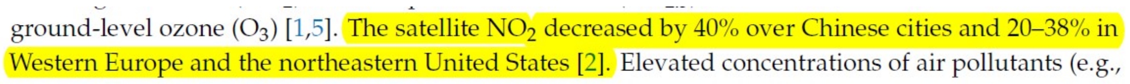
Since time is a valuable resource and errors are always undesired, getting the assistance of a computer may improve the situation. Computers are fast, efficient workers, albeit not particularly intelligent regarding understanding human concepts. They need precise instructions to exactly do what we need them to do. This simple knitted system that computers are based on also has its upsides. They are predictable. The computer will precisely do what we tell it if we write a program to execute a specific task. No conscience could influence its actions, nor will there be any lack of concentration. Thus a combination of the automatic extraction by a computer and the manual extraction by a human would provide an excellent trade-off between efficiency and effectiveness.

4.2 Proposed Solution

Generally, there are two viable solutions that we can explore. These are rule-based matching and machine learning. In information extraction, there is an important concept to keep in mind. The more data one has for training one's model, the better it will be at the extraction process. For our project, we have a training data set of 154 articles containing over 1000 points of data. These articles have already been manually searched by colleagues at the research centre Jülich. While 1000 data points might seem like a lot at first, it is not that much in reality. Consequently, the quality of our model will be lower than anticipated.

4.2.1 Rule-based Matching

First, we will look at rule-based matching, the most basic form of information extraction. It uses predefined rules to scan the text for patterns and extract information. For starters, we will have to investigate the articles themselves. Whenever the text contains any sign indicating a change in air quality, we need to analyse the sentence in question. We can then create patterns by analysing the kind of words that precede or follow the pollutant and the associated value. The created patterns now consist of words and numbers representing a sentence containing valuable information regarding air pollutants. Figure 4.1 shows an example sentence. Examining this sentence, we can deduce the first basic pattern. A pollutant (NO2) decreased by a certain amount (40%). We must let our program know that it should look for this pattern in the text. Each time a part of a sentence matches this pattern, the computer finds it and presents the contained information.



ground-level ozone (O_3) [1,5]. The satellite NO_2 decreased by 40% over Chinese cities and 20–38% in Western Europe and the northeastern United States [2]. Elevated concentrations of air pollutants (e.g.,

Figure 4.1: Example sentence containing a basic pattern

Unfortunately, having only this one pattern is not enough. There are various possibilities for describing a change in air pollution. Therefore it is necessary to look through more articles and thus define new patterns while further improving existing ones. In the end, there will be a wide range of patterns so that almost every possible expression is covered.

Although more data equals better results still applies here, it is not essential for the program's success. As long as one knows what one is looking for, one can think of different ways of communicating the information. That way, one can create patterns that one thinks might appear in a document, despite not having seen them. This approach enables training beyond actual training data. However, one must carefully evaluate such patterns to avoid many false positives. Since our training data was limited to 153 articles, we pursued this pattern recognition approach. In order to cover as many different sentences as possible, we created 59 distinct patterns in total. The program aims to look for these arrangements of words in the text.

4.2.2 Machine Learning

The second possible approach to an IE problem is machine learning. As the name suggests, the computer should learn on its own how to accomplish a task. On top of that, it should improve its execution each time it tries anew. For this purpose, the program needs a fitness function that assesses the result's quality. The program aims to maximise said function. Regarding information extraction, the fitness function could be the f score, i.e. a compound between precision and recall of the training data set.

There are two types of machine learning approaches, called supervised and unsupervised learning. For supervised learning, the program gets to use labelled data. These labels help the computer improve accuracy and speed up the training process. Usually, a human has been processing the data beforehand and labelled them accordingly. Unsupervised learning, on the other hand, does not use labelled data. It works on its own to determine the structure of the text. Hence, not having any sense of direction, there is a lot more training data needed. Otherwise, the results can end up considerably inaccurate. This problem is also the main drawback of machine learning. Models need enormous amounts of training data to produce satisfactory results. Comparing our 150 articles to the 100,000 articles used in Kardas et al. study, only about 150 articles for the training phase are undoubtedly insufficient. For this reason, we can not apply machine learning to our project and instead concentrate on the rule-based matching approach.

Chapter 5

Implementation

The implementation takes place in the *Extraction.py* file. For this project, we used the programming language python. *Extraction.py* represents the core of the project. It contains the code for the extraction of the values, as well as the highlighting of relevant text passages.
This chapter lays out the extraction script's structure and describes how it operates.

5.1 Modules

For this project, we must import several external modules.

pandas [13] Pandas is a valuable tool that provides data structures and data analysis tools. It shows its full potential when working with tables It can automatically convert a CSV file to a table in a pandas data frame. Conversely, it can also write a pandas data frame to a CSV file. Since the training data is in CSV format, using pandas for this project is an obvious choice.

spaCy [17] SpaCy is a natural language processing tool that offers various functionalities. It already has pre-trained pipelines for different languages, which enables it to predict linguistic attributes in context. Figure 5.1 shows an example dependency graph for a text passage that matched a pattern. It contains the distinct linguistic features the pipeline predicted. Using these features, we can enhance the ability to define concrete patterns to extract the desired information.

PyMuPDF [14] PyMuPDF is a python toolkit that can view and render different file formats. Since the articles for this project are PDF files, using a PDF

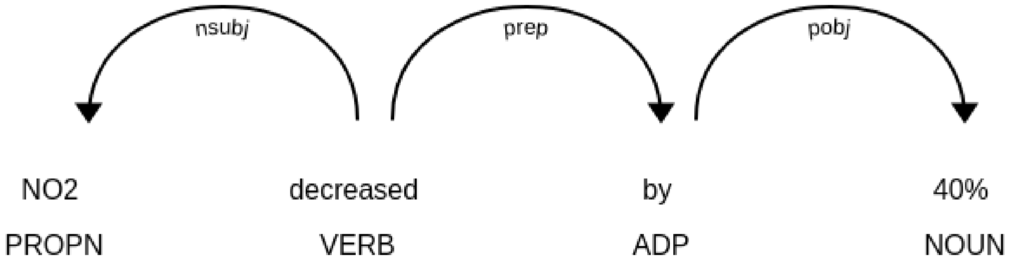
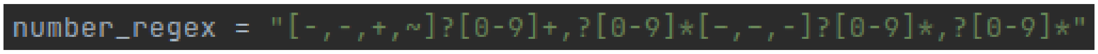


Figure 5.1: Example dependency graph for a matching pattern

reader is inevitable. PyMuPDF offers the best performance and highest quality results compared to other PDF modules for Python. On top of that, it allows highlighting text in a PDF file, which is helpful for manual evaluation.

re [**15**] This library contains regular expression matching operations. Since spaCy's pipeline predictions are sometimes not perfect, falling back to regular expressions is occasionally necessary. In figure 5.2, we can see the primary regular expression used throughout the project. It describes the different ways of expressing number values in the text.



```
number_regex = "[-,-,+,~]?[0-9]+,?[0-9]*[-,–,-]?[0-9]*,?[0-9]*"
```

Figure 5.2: Example regular expression for a number in the text

tabula [**19**] Tabula is a python module for reading tables from PDF files and converting them to a pandas data frame. Because the articles store a lot of the data in tables, having the ability to extract information from them is essential.

os [**12**] This module provides operating system-dependent functionalities. For our project, we use it to iterate over files in a directory.

BytesIO [**9**] BytesIO is part of the io module. It enables Python to deal with different types of input and output. We need it to store the parts of the PDF articles that need highlighting.

5.2 General Structure

The program is divided into different sections. We are starting with the definitions of different important variables. Noteworthy are the pollutants, trend words, and regular expressions that form a number. These three elements will appear in almost every declared pattern and are thus vital for the program's success.

There are five types of functions implemented. First comes the primary function *extract_text*. It contains the core logic of the program. Otherwise, there are different functions for extracting pollutants or values from a sentence, fixing pollutants' spellings, and the layout of pages. In the following, we will take a closer look at each of them.

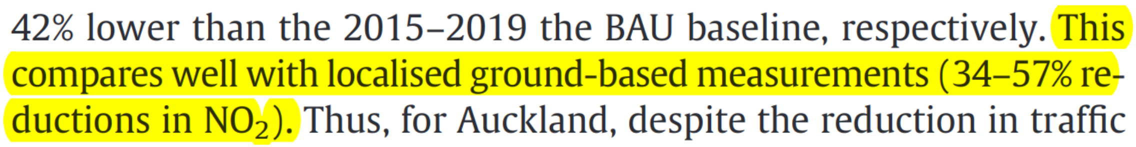
5.2.1 extract_text function

Algorithm 5.1 General structure of program

```
$nlp \leftarrow spacy.load(''en\_core\_web\_sm'')$            ▷ load nlp pipeline
$matcher \leftarrow Matcher(nlp.vocab)$            ▷ initialise the matcher's vocabulary
for $i = 0$ to $n$ do            ▷ define n patterns
    define pattern $i$
    add pattern to matcher
end for
for each article do
    for each page do
        if no DOI found yet then
            search for DOI on page
        end if
        $matches = matcher(page)$            ▷ run matcher on the current page
    end for
    $total\_data.append(article\_data)$            ▷ append extracted data to the total data
end for
export $total\_data$ to a csv file
```

This function is the heart of the project, as it contains the declaration of the various patterns and the matcher. Algorithm 5.1 shows the instructions procedure after the function's execution. It starts with initialising the NLP pipeline and the matcher. Since the articles are written in English, we must load the English language package. Other languages are undoubtedly available, too, if needed. When doing that, however, we would also have to adjust the patterns to the language.

Next are several patterns covering various occurrences of pollutant changes in texts. They then get added to the matcher. These rules each invoke an individual function, where the information gets extracted.
The program now looks at each article in the directory. Since PyMuPDF works on a page-by-page basis, each article page gets looked at individually. In order to identify the article and provide a better evaluation, the function first searches for the article's DOI. We can accomplish this initial extraction by looking at embedded links on the first page. If that delivers no results, we must search each line for anything resembling a DOI. Important to note is that when a line break splits a word, PyMuPDF does not automatically combine the parts back together. That is why we need the function *squish_page*, which converts all page content to a single line. As shown in Figure 5.3, the word "reductions" is split by a line break. Without the *squish_page* function, the program would recognise the word as two words, *re-* and *ductions*. This misreading could lead to the matcher not reacting to the pattern, although it technically matches.



42% lower than the 2015–2019 the BAU baseline, respectively. This
compares well with localised ground-based measurements (34–57% re-
ductions in NO_2). Thus, for Auckland, despite the reduction in traffic

Figure 5.3: Example word split by line break

Finally, we need to activate the matcher on the current page. That way, it will scan the specified page for any previously defined pattern and call their respective extraction function on a match. It will then add the resulting extracted data to the article's dictionary. After processing every page of the article, the program appends the collected article data to the total data list. This list contains every piece of extracted information and will get exported as *./extracted_data.csv* at the end.

5.2.2 squish_page function

This function is vital because PyMuPDF does not merge split words back together after a line break. Thus, we circumvent this issue by converting a page to a single line. In Algorithm 5.2, we can see the structure of the function. Initially, the program retrieves the content of the page. It checks for each line on the page whether a split occurred or not. If there is a split, the "-" gets removed. Otherwise, we need to

Algorithm 5.2 Format page to single line

```
$lines \leftarrow page.get\_text().splitlines()$        ▷ get content of the page as lines
$page\_text \leftarrow$ ""        ▷ initialise variable for the text
for line in lines do        ▷ iterate over each line
    $line \leftarrow line.strip()$        ▷ remove redundant spaces at beginning and end
    if line ends with "-" then
        $page\_text = page\_text + line[: -1]$        ▷ remove "-"
    else
        $page\_text = page\_text + line +$ " "        ▷ add space if no split
    end if
end for
return $page\_text$
```

insert a white space to separate the two words. When finished with the page, the function returns the text as a line.

5.2.3 get_pollutant function

There are two distinct functions to extracting the pollutants from a sentence. The first is called *get_pollutant*, which returns the first pollutant it finds in the text. The other function is called *get_all_pollutants*. Every pollutant in the sentence gets returned as a list, not just the first one. The matcher needs these functions when a match occurs. There it calls the respective function where the program then relates the pollutants to their values.

5.2.4 get_values function

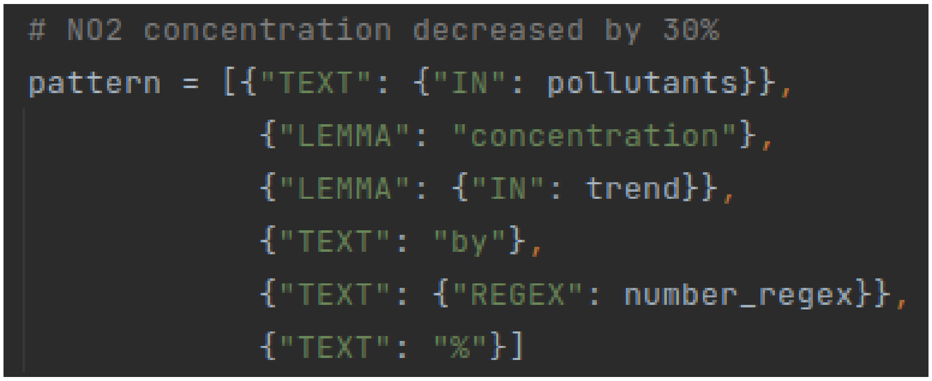
There are four different functions to extract values from a sentence. Similar to the pollutants, there is a *get_values* and a *get_all_values* function. This time, *get_values* extracts all numbers followed by a percentage sign and returns them as a list. *get_all_values*, however, extracts every number that occurs in the sentence, regardless of preceding and following characters. There is another function called *get_plus_minus_values* which specialises in numbers preceded by ±. The fourth function, *get_no_trend_values*, extracts values that already have a minus or plus sign in their name. Contrary to the previous three functions, this one only gets called once there is no trend word in the sentence. Therefore it needs to check the preceding character for the trend.

5.2.5 fix_pollutant function

This function, on the one hand, improves the structure and readability of the output and, on the other hand, simplifies the evaluation process. Since there are many different possibilities of spelling the pollutant, we need the *fix_pollutant* function. It checks the spelling of the current pollutant and returns it correctly spelt.

5.3 Patterns

Patterns are the foundation of this program. They provide the rules for what the matcher should look for in the document. Generally, one can say that the more patterns are defined, the better the result will be. SpaCy offers a rich tool set for describing patterns. Figure 5.4 shows a simple pattern definition. In this case, the text passage has to lead with a pollutant. The program stores every possible pollutant in the *pollutants* variable as a list. The pattern checks if the list contains the current word. If yes, it moves on to the next word. Using spaCy's linguistic features, we can look for the base form of a word. We can do this via the *lemma* keyword. It is also possible to make a word optional. Since not every pattern has to include ”concentration”, it could be a good idea to apply that here. Following is a trend word, e.g. *decrease* or *reduce*. The program also stores these in a predefined list. After the preposition ”by”, a number follows. We implement this using the regular expression shown earlier in figure 5.2. Finally, the pattern ends on a percentage sign.



```
# NO2 concentration decreased by 30%
pattern = [{"TEXT": {"IN": pollutants}},
            {"LEMMA": "concentration"},
            {"LEMMA": {"IN": trend}},
            {"TEXT": "by"},
            {"TEXT": {"REGEX": number_regex}},
            {"TEXT": "%"}]
```

Figure 5.4: Example pattern definition using spaCy

Using this pattern as a baseline, we can continuously define more patterns to cover many distinct constellations of words.

5.4 Matcher

Now that we defined the patterns, the matcher becomes effective. It takes the previously stated rules as input and starts searching the text. As soon as a sentence matches a known pattern, it calls the corresponding matcher function. There are 14 distinct matcher functions in total.

Algorithm 5.3 Basic matcher function

```
$span \leftarrow doc[start : end]$                ▷ get the excerpt that matched the pattern
$pol \leftarrow get\_pollutant(span)$                                    ▷ get the pollutant
$values \leftarrow get\_values(span)$                                      ▷ get the values
if pol not in $article\_data$ then            ▷ check if pollutant already has entries
    $article\_data[pol] = values$                ▷ if no → add data to dictionary
else
    for value in values do
        if value not in $article\_data[pol]$ then
            $article\_data[pol].append(value)$                ▷ if yes → append data
        end if
    end for
end if
$highlight\_match(span.sent.text)$                    ▷ highlight match in the text
```

Algorithm 5.3 shows the basic structure of a matcher function. Initially, we need to retrieve the text matching the pattern. We do this by getting the start and end index of the match and applying that to the document. With the help of the previously defined *get_pollutant(span)* and *get_values(span)* functions, we extract the pollutant and the values from the text. To store the extracted data, we utilise the associated *article_data* dictionary. It is essential to check whether the pollutant already has entries in the dictionary. If that is the case, we need to examine every value not to produce duplicates. Finally, we highlight the sentence containing the pattern.

There are various matcher functions that all have unique alterations. For some sentences, there might be no pollutant present in the excerpt. In this case, the *get_pollutant(span)* function would return an empty string. Therefore we implement the *no_pollutant_match* function. It calls the *get_all_pollutants(span)* function on the previous sentence instead of the current one and takes the last pollutant it found.
Another important matcher function is the *multi_matcher*. Sometimes a sentence contains a sequence of pollutants followed by a sequence of values. While the primary

matcher function can only handle one pollutant, the *multi_matcher* handles multiple at once. We do this by calling *get_all_pollutants(span)* and relating each pollutant to precisely one value. For this, checking that the number of retrieved pollutants equals the retrieved values is crucial. Otherwise, a mismatch can likely occur.
There are other matcher functions, e.g. when there is no trend word in the sentence, but most are combinations of the previously explained functions and work similarly. Additionally, there are matcher functions for extracting data from tables. Since the layout of the tables can differ, the implementation is challenging. Generally, we try to find the column or row that contains the values and relate that to a pollutant. Likewise, there is also a function that searches the captions of tables and highlights them if they seem interesting.

Chapter 6

Experimental Evaluation

Using the evaluation, we can assess the quality of the implementation. Then we can answer our research questions and discuss whether the project was successful or not. The research questions addressed by this thesis are: **RQ1)** Is the script able to output the same or better results compared to manual extraction? **RQ2)** Is using the script faster than using only manual extraction? **RQ3)** Is using the script more accurate than using only manual extraction? **RQ4)** Would using the script in combination with manual extraction benefit the outcome?

6.1 Evaluation Implementation

6.1.1 Modules

sys [18] Among other things, the sys module allows us to retrieve command line parameters. These parameters are important because they provide us with the tools to conduct different evaluations using different parameters dynamically.

6.1.2 General Structure

Three different evaluations are available for the primary function - one for test data, another for training data and the last for training and test data together. Additionally, these evaluations use several helper functions to assist with the assessment.

get_needed_pollutants function

This function iterates over every possible pollutant. The function appends the pollutant to a list if it exists in the extracted data. In the end, it returns the final list containing the pollutants in the extracted data. We need that to quickly and accurately access the columns of the extracted and training data.

get_total_data function

This function counts the entries in the training data. It checks every cell in the table and increases the count whenever there a number is inside. The total amount of entries is essential for the final recall calculation.

convert_to_list function

The extracted data is saved as a list in a pandas data frame during the extraction process. When reading in the file for the evaluation, pandas does not recognise the content as a list. It thinks the file contains strings. Since working with strings is always undesirable, we utilise the *convert_to_list* function. It converts every cell in the table to a list, so the data is easily accessible.

get_correctly_extracted function

This function is where the actual evaluation happens. Here we compare the extracted data to the training data. A precise comparison is possible by matching the DOIs in both data sets. Whenever a value in the extracted data matches the corresponding values in the training data, it increases a counter. After checking each extracted value, the function returns this counter.

calculate_score function

The final helper function calculates the precision and recall values using the previously retrieved information. It prints both values to the console, thus enabling a clear depiction of the evaluation result.

main function

The primary function combines all the helper functions. It has one input parameter, which is the desired training data. This parameter can either be the test data, the training data or all available data. It then converts the training and extracted data to a pandas data frame. Additionally, it renames the training data columns for easier referencing. Subsequently, the function calls all helper functions in the order mentioned above. After calling the last function, the evaluation process finishes.

6.2 Data Preparation

Before starting with the model training, we have to separate the training data. We decided to do an 80/20 split. Therefore we deducted 20% of the articles and used it solely as test data. Since the total number of articles is around 150, we selected 30 for testing. These articles do not contribute to the training phase, so we must keep them separate. The file containing the training data also splits into two files. The first one contains only test data, and the second one only training data. Additionally, we keep the initial training data file as a union of the other two. The data preparation is complete now that we have separated the articles and assembled the three files.

6.3 Evaluation Setup

To evaluate the script, we first need an output. For that, we need to know which evaluation we want to perform. Generally, the test data is the primary evaluation focus. As a consequence, it is essential that we only include the articles marked as test data in the extraction process. When that is verified, it is time to run the extraction. By executing the command `python Extraction.py`, the computer searches the articles and outputs the results to the *extracted_data.csv* file. Now that the extracted data and the training data are present, the evaluation can commence.

By comparing the set and actual values, we can assess the quality of the extraction. Since the evaluation focuses on the test data, we should run the command `python Evaluation.py test`. The script compares each entry of the extracted data with the test data and outputs the result to the console.
It is also possible to evaluate the entire data or only the training data. For this, we need only to use the desired articles again when running the extraction. Then we can run `python Evaluation.py training` or `python Evaluation.py` to evaluation the training or all data. It is now possible to answer the research questions using the gathered results.

6.4 Evaluation Results

Table 6.1 shows the results of the evaluation script. The test data compare well with the training data with a recall value of 22.36% and a precision of 43.32%. While the training data delivers slightly better outcomes (23.78% and 44.16%), the test data is still within two per cent. Interesting to note is that even though we trained the model using the training data, the precision and recall values are comparatively

	only test data	only training data	all data
recall	22.36%	23.78%	23.42%
precision	43.32%	44.16%	43.95%
F-score	29.50	30.91	30.56

Table 6.1: Evaluation results

low. This observation also answers the first research question. The automatically extracted results are worse than the manually extracted ones. This result was to be expected since humans can find text relations much easier than machines.

While achieving high precision is always the ambition, the focus for this project lies more within the recall. It is better to get more results for the IE task at hand because, unless we can achieve a 100% precision and recall value, manual supervision of the data is always needed. When manually searching the text, the highlighted parts quickly grab the reviewer's attention. This phenomenon can substantially speed up the process of finding relevant text passages. Knowing that the program highlights the majority of essential sections, the analyst can concentrate on those sections. Despite taking a few minutes to execute, it undoubtedly finishes faster than the manual extraction. Moreover, it is feasible to say that using the script can even increase the speed of the manual extraction. This result, therefore, answers research question number 2.

Regarding research question three, the program does not have great accuracy, with a precision of not even 50%. Albeit being of lesser concern for this project, it is evident that manual extraction yields more accurate results.

To answer the last research question, using the script has no significant downside. It might take a few minutes to set up and execute, but after all, it provides highlighted articles in combination with an easily editable extracted file. However, it is essential to remember that there will likely be values the program did not catch. Thus, we still need some manual effort for the extraction process.

In the end, the test data does not reach the desired 80 to 90% precision and recall. Considering there are several problems with the evaluation, as well as difficulties in the extraction, the result is still respectable regardless.

6.5 Problems

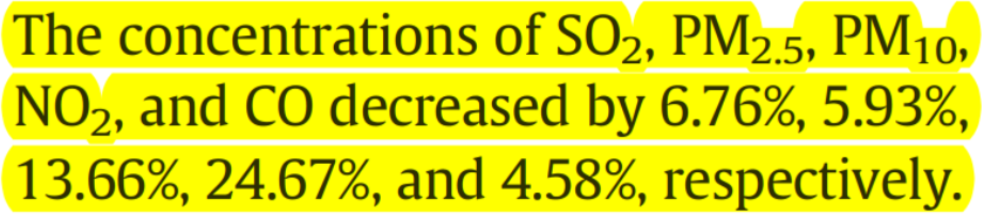
6.5.1 Extraction

As stated previously, the training data only reaches a recall value of around 24%. In theory, this should not be the case since the whole point of the training data is to train the model. If only about a quarter of the data is usable for training, the quality of the model drastically reduces. There are several valid reasons for such a poor performance.

First and foremost, working with PDF files is always a challenge. They are usually not meant to be processed again. Also, there is no general layout for PDF files, so almost every file has unique features. Since most articles use multi-column text, it amplifies this problem even further. Even using conversion tools such as GROBID [8] is not a viable alternative because there will always be some information loss. PyMuPDF is rather good at accessing the information in PDF files. However, a problem occurs since it processes documents on a page-by-page basis. If a pattern stretches over two pages, the matcher will never find it. Furthermore, cramming the entire document into a single line is not an option because the page number is necessary for highlighting.
Another problem with PyMuPDF is the lack of table recognition. A solution for this is using tabula. Tabula can recognise tables, but its automatic detection still has issues. The fact that each table has a different layout further intensifies this issue. There is no general extraction rule that we can apply here. This uncertainty presents a substantial issue. Tables contain immense amounts of data, and if there is no way of retrieving that information, much potential is lost. Similar to tables, some graphics include information. Graphics are even harder to process since one would need a tool for analysing images.

Another difficulty is that sometimes characters can be interpreted differently by PyMuPDF. Especially the - sign has many different characters used interchangeably, signifying the same. This confusion can lead to patterns not matching because it was another form of the same character.

Finally, some general difficulties are hard to fix. One needs a good balance when defining patterns. On the one hand, the pattern must be simple to match more than one sentence. However, on the other hand, it must also be precise not to output many false positives. Additionally, patterns might overlap and output incorrect results. Figure 6.1 shows an example of such an overlap. Two distinct patterns activate in this sentence. The first one matches *PM10, NO2, and CO decreased by 6.76%, 5.93%, 13.66%.* This match, however, yields invalid results since CO did not decrease by 13.66% but rather 4.58%. The second match finds all five pollutant number pairs and would be the only correct choice.



The concentrations of SO_2, $PM_{2.5}$, PM_{10}, NO_2, and CO decreased by 6.76%, 5.93%, 13.66%, 24.67%, and 4.58%, respectively.

Figure 6.1: Example overlap of patterns

6.5.2 Evaluation

Not only the extraction but also the evaluation faces challenges. The primary reason is the different methods of manually extracting and saving the data to the training data file. There are cases where the program extracted several (correct) values, but the training data only contained the averaged values for the comparison. The same concept also applies to manually rounded numbers in the training data.

Another problem for the evaluation is human error. Humans are prone to commit careless mistakes. Pollutants get mixed up, characters get interchanged, or cells get confused. By utilising the extraction script, we can minimise these errors. Therefore, the accuracy discussed in research question three would increase when combining automatic and manual extraction.

The final difficulty for the evaluation is that a DOI is necessary. If there is no DOI in the document or the extraction delivered a wrong DOI, we can not automatically evaluate the extracted information for that document. There are seven articles that either has no DOI or whose DOI does not get correctly extracted.

When taking all the problems mentioned above into account, the evaluation should, in theory, yield slightly better results. However, the change would arguably be less than a few percentage points.

Chapter 7

Conclusions and Future Work

Extracting information from the given COVID-19 lockdown articles proves to be complicated. In order to succeed, we need to overcome many challenges, from accurately working with PDF files to defining fitting patterns to correctly recognising tables and extracting their data. Those and a lot more problems arise. Eventually, the script created for the automated extraction does not provide ideal results. In fact, with not even a recall value of 25%, it can not stand on its own.
However, this is not to say that the program has no use. Because it highlights the sentence whenever it finds a match, it can facilitate the manual reviewing process. By directing the reviewer's attention to the marked sections, the need for extensive searching shrinks. Thus, enabling an overall faster extraction process. Furthermore, the script's output gets stored in a CSV file. This file can easily be accessed and edited if there are changes necessary.
Furthermore, the project revealed that we could commonly find the most critical information in the abstract or the results section. Following this, the manual reviewer should also shift its focus to these two chapters.

The main limitation of the program is the extraction of information from tables. The project will gain much value if the program can automatically recognise tables and then correctly transform them into machine-accessible data. Unfortunately, the used python module tabula does not deliver excellent results. However, tabula also has a standalone program where one can manually select tables in PDF files. The manual selection works very well, though it is not helpful for automated processes such as the work presented in this project. The poor performance of the table recognition also has to do with the countless different layouts of the tables. Each table has a unique layout, which in turn hinders not only the detection but also the extraction. Another limitation is the comparatively small amount of training data. With only

150 articles to work with, the model can not unleash its full potential. There is not enough information from which the model can learn. This situation also forces us to use a rule-based matching approach instead of machine learning. Having alternative options when carrying out a project is always desirable, which is not the case this time.

There are several opportunities for future work. Since working with PDF files is sometimes problematic, a different approach could be interesting. Because most articles are open access, HTML scraping might provide another solution. Following the approach of Kardas et al., working with the LaTeX source code of the articles may present another possibility. This method would also improve the recognition of tables because when using LaTeX, the tables are clearly defined. However, getting the source code of the articles could be challenging since it is not always available, and not everyone writes their papers using LaTeX.

At the moment, the program only extracts percentage values. Adding the detection of absolute values should be another future task. On top of that, additional improvements to the recognition of values are perpetually helpful.

In the future, more articles should be available regarding the change in air pollution during lockdowns. Therefore the training can be improved even further. Moreover, it might be possible to apply machine learning at some point. Using these new articles, one can further conduct a new study examining the helpfulness of the program. It would be interesting to see how much the manual extraction benefits from running the extraction script in advance.

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