

# REPORT: Group H

## I. Introduction

### i. Background

In the digital age, data is one of the most important assets for every business. As such, the care of this asset must be a primary concern. Data governance has become an important field to achieve a purposeful, responsible, legal and efficient treatment of data, in which control over such data is fundamental.<sup>1</sup>

A proper control of data throughout its lifecycle can result in saving and preventing costs and risks, both from an operational<sup>2</sup> and legal perspective. In this particular, the period of time data is retained by a business in the European Union (EU) is of utmost importance for the compliance with legal provisions such as the General Data Protection Regulation (GDPR), which establishes a limit to the storage of data that may allow the identification of individuals (personal data) for longer than is necessary, for the purposes for which the personal data are processed (storage limitation principle).<sup>3</sup> Likewise, the GDPR requires that personal data be adequate, relevant and limited to what is necessary in relation to the purposes for which they are processed (data minimisation principle).<sup>4</sup>

To comply with such principles, businesses may resort to the deletion of the data, however, some of that data may still be useful to perform other tasks and thus, recycling that data is a way to save costs by optimizing its potential.

### ii. Our project

Our project aims to provide organizations and individuals in the medical field with the ability to maximize the value of the data they collect and process, specifically in relation to their legal obligations related to personal data, by providing a tool for data anonymization powered by Artificial Intelligence (AI). With it, they will be able to “clean” their data by extracting those data points that might be used to identify a person from the rest of the data that could be further reused for other purposes. In addition, by having a better control and understanding of the time of retention of their data and its uses, they may also reduce their expenses regarding storage and archiving.<sup>5</sup>

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<sup>1</sup> Marijn Janssen and others, ‘Data Governance: Organizing Data for Trustworthy Artificial Intelligence’ (2020) 37 Government Information Quarterly 101493, 2.

<sup>2</sup> Vijay Khatri and Carol V Brown, ‘Designing Data Governance’ (2010) 53 Communications of the ACM 148, 151.

<sup>3</sup> European Parliament and Council Regulation (EU) 2016/679 of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation) (Text with EEA relevance) [2016] (‘GDPR’), art 5, (e).

<sup>4</sup> Ibid, (c).

<sup>5</sup> Khatri and Brown (n 2) 151.

With AI, we seek to support a better data governance design through more robust control and management of data. Our tool not only serves as an instrument for compliance with legal obligations in relation to personal data but also allows organizations and individuals obtain the maximum potential of the data they collect and process.<sup>6</sup>

## II. Previous Work

Developed in JavaScript, this tool anonymizes PDF documents by first detecting the personal data and then randomizing its characters and the typography and format of the data is preserved. However, the randomization of dates will still have an output of numbers but often the numbers would be absurd, for example: the year 9025. The tool takes the PDF document as an input and produces 2 possible output PDF-document in which:

- [illegible]

- No explanation behind the data anonymization.
- The regeneration of the PDF with randomized data using different typography (shape, font style, height, and weight) causes often problems


<sup>6</sup> Simson L Garfinkel, 'De-Identification of Personal Information' (National Institute of Standards and Technology 2015) NIST IR 8053 4 <<https://nvlpubs.nist.gov/nistpubs/ir/2015/NIST.IR.8053.pdf>> accessed 3 March 2024.

- It is very difficult to perform analytics with randomized data thus losing one of the main advantages of anonymizing data in the first place.

## ii. ArtLabss/open-data-anonymizer:

Unlike the previous tool, this one is not only limited to PDF files, it has also the option of both tabular data along with images and facial anonymization techniques. Written in Python, the tool relies on regular expressions to identify the personal data from a PDF document, it also uses techniques of Optical character recognition to mask the personal data after its identification.

The tool gives the option to decide which personal data could be masked, for example emails only. The data that is considered personal data is then masked later:

<ul style="list-style-type: none"> <li>• Names</li> <li>• Dates</li> <li>• Location</li> <li>• Job status</li> <li>• Companies Name</li> </ul>	
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## Limitations:

- Regular expressions will produce poor output of personal data if different example formats are introduced.
- No explanation behind the data anonymization.
- Only the Personal data on header and the introduction are masked, but the other sections are not masked.

## III. Activities and Outputs

### i. Data Construction

We used synthetic data for our study, generating a model of medical reports through ChatGPT-3.5, tailored to mimic those produced by healthcare professionals. Subsequently, we introduced variations in the personal data sections. We manually **created approximately 100 medical reports** to supply our natural language processor with diverse training examples.

## **ii. Medical reports**

We relied on a variety of personal medical reports, which contain a lot of information about a medical consultation; patient's history, examinations performed on the patient, the diagnosis or recommendations to be followed, etc. We focused our project on the following categories of personal data:

- **Person:** The **name** of the patient and the doctor concerned.
- **Geo-Political Entity (GPE):** The **location** of the patient's home and the hospital.
- **Date:** The **dates** of the patient's birth and of the medical consultation.
- **ID:** The patient's **ID number**.
- **Insurance:** The patient's **insurance number**.
- **Email:** The patient's **email address**.
- **Credit card:** The patient's **credit card number**.

## **iii. Legislation involved**

We based our data categorization on the definition of personal data provided by the GDPR, given that our tool is meant to be used initially in the EU.

Article 4 of the GDPR defines personal data as “Any information relating to an identified or identifiable natural person, who can be recognized directly or indirectly, particularly by reference to an identifier.”

According to such definition, each of the chosen categories contain personal data, as explained below:

- **Person:** Based on Article 4(1) of the GDPR, this information contains data that can be related to an identified or identifiable natural person, in this case directly by reference to a name. The name and surname of an individual are the most common identifiers.
- **Geo-Political Entity (GPE):** The GPE category includes information indirectly or directly linked to a person, notably through location data. The personal address of an individual constitutes information that can be used to directly identify an individual. The address of the hospital is an identifier that, when combined with other pieces of information, can be associated with a person.
- **Date:** The date of birth of a person and the date of a medical consultation contains data that, combined with other pieces of information, such as a name, will allow the individual to be identified.
- **ID:** The ID in the medical report contains information that can be related to an identified or identifiable natural person, in this case by reference to an identification number. An identification number is a unique identifier assigned to each patient to distinguish them within the healthcare system. This ID number serves as a reference point for accessing and managing an individual's medical information. Therefore, an identification number contains data that can be used to directly identify a person.

- **Insurance:** This specific information contains data that can be related to an identified or identifiable natural person (directly or indirectly). The insurance number of an individual is considered personal data due to its direct association with an individual's financial and health-related information. This number uniquely identifies an individual.
- **Email:** An email address is considered personal data because it directly relates to an individual by reference to an online identifier.
- **Credit Card:** A credit card is considered an identifier that expresses the economic identity of a natural person and that can be directly or indirectly related to an individual.

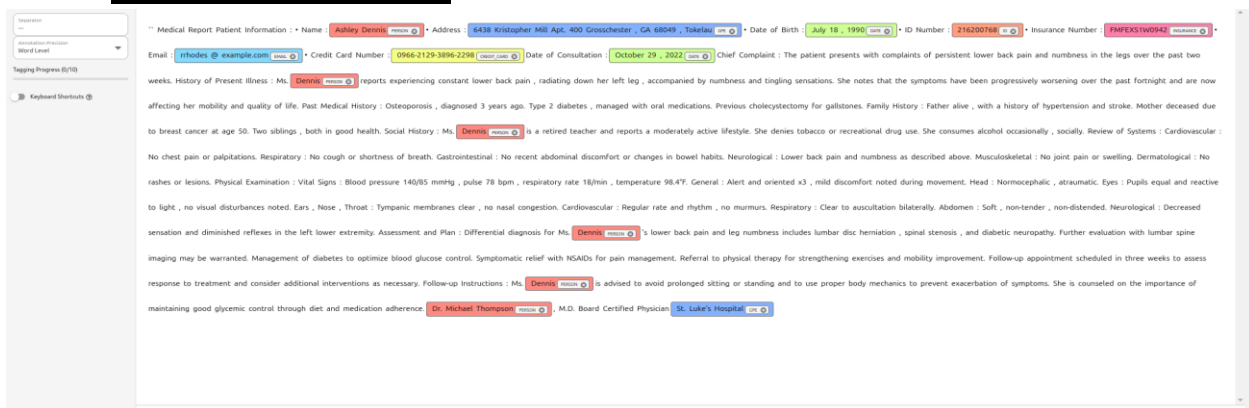
#### iv. Data Annotation

The process of data annotation was facilitated by utilizing the [Ner-annotator](#) website. Within this phase, seven distinct categories of personal data were identified and annotated within the documents, as shown in the image below.

1. Person (Name & Surname).
2. Geo-Political Entity (GPE).
3. Date (birth & Consultation dates).
4. ID.
5. Insurance number.
6. Emails.
7. Credit Cards.

The annotator operates by taking a text file as input and generating a JSON file as output. Following this, a minor preprocessing step is applied to the JSON file before it is utilized as input for the selected Natural Language Processor (NLP).

#### v. Artificial Intelligence



The model utilized for this task was SpaCy which is an open-source library for NLP in Python. It is designed to be efficient, fast and capable of handling large volumes of text. SpaCy provides tools and pre-trained models for various NLP tasks such as tokenization and named entity recognition (NER) which is what is needed for this project. The idea was mainly to create our

synthetic data, define our categories of personal data, and then fine-tune one of SpaCy NER models to detect the personal data within our documents.

Following the adjustment of the machine setup to utilize Graphics Processing Unit (GPU) resources instead of Central Processing Unit (CPU), a notable enhancement in training speed was observed, resulting in a threefold increase. This optimization led to an overall reduction in training time to just 5 minutes 54 seconds. The utilized machine boasted the following characteristics:

- Ram: 16gbs
- CPU: AMD Ryzen 7 6800H
- GPU: RTX 3050 TI

We have utilized the SpaCy model named “en\_core\_web\_trf” based on the positive results given compared to other models. The relevant parameters used during the fine-tuning were:

- Vectors: " en\_core\_web\_trf"
- batch\_size: 1000
- eval\_frequency: 200
- patience: 1600
- learn\_rate: 0.001
- Dropout: 0.1

In the following image, certain metrics are listed as shown below:

- Loss TOK2VEC & NER: The mean squared error (MSE) in the context of Tok2Vec & NER training.
- Score: Accuracy which is  $(TP+TN)/total\ Predictions$ .
- Ents\_f: Weight for the F1 score of entities.
- Ents\_p: Weight for the precision score of entities.
- Ents\_r: Weight for the recall score of entities.
- Ents\_per\_type: Weight for entity scores per type.

```

python -m spacy train config.cfg --output ./ --paths.train ./train.spacy --paths.dev ./train.spacy
Saving to output directory: .
Using CPU

===== Initializing pipeline =====
✓ Initialized pipeline

===== Training pipeline =====
Pipeline: ['tok2vec', 'ner']
Initial learn rate: 0.001
E   #   LOSS TOK2VEC   LOSS NER   ENTS_F   ENTS_P   ENTS_R   SCORE
---  ---  ---
0     0       0.00      38.33      0.00      0.00      0.00      0.00
152   200     14.18     780.33    100.00    100.00    100.00     1.00
352   400      0.00      0.00     100.00    100.00    100.00     1.00
552   600      0.00      0.00     100.00    100.00    100.00     1.00
752   800      0.00      0.00     100.00    100.00    100.00     1.00
952  1000      0.00      0.00     100.00    100.00    100.00     1.00
1152  1200      0.00      0.00     100.00    100.00    100.00     1.00
1352  1400      0.00      0.00     100.00    100.00    100.00     1.00
1552  1600      0.00      0.00     100.00    100.00    100.00     1.00
1752  1800      0.00      0.00     100.00    100.00    100.00     1.00
✓ Saved pipeline to output directory
model-last

```

-SpaCY Training Evaluation-

The picture shows different evaluation metrics and their values during each epoch, stopping at 1800 saving two models, best and last.

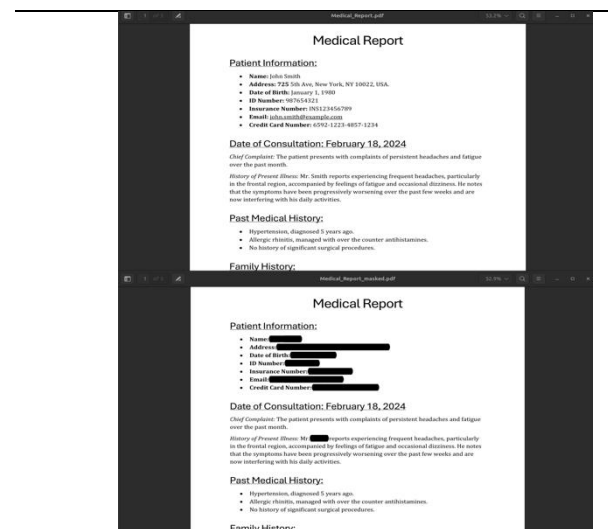
## vi. Output

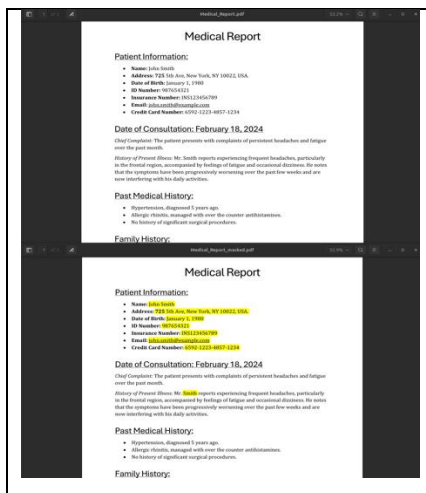
The AI system we developed can perform two distinct tasks: anonymization and personal data identification.

1. For anonymization, the system masks the detected data by overlaying a black box, effectively obscuring sensitive information.
2. In the case of personal data identification, the system **highlights** the detected personal data and provides explanations regarding why it was classified as such. This classification is reinforced by references to relevant articles of the GDPR, supported by additional clarifications as needed.

The Data Anonymizer employs a systematic procedure to execute the data masking process, which includes the following steps:

1. Utilizing the Python library pymuPDF to scan the PDF-document comprehensively.
2. Extracting all words present within the document, thereby obtaining the complete textual content.
3. Feeding the entirety of the text into the AI model, which generates annotations for each identified entity (Text section that is considered personal data).
4. Locating the extracted entities within the original PDF-document and subsequently applying masking techniques to conceal this sensitive information effectively.





The Data Highlighter employs a systematic procedure like the Data Anonymizer with slight modifications in the subsequent processes:

1. Steps 1 to 3 remain unchanged:
4. After annotation, the Data Highlighter locates the extracted entities within the original PDF-document.
5. Rather than masking, the Data Highlighter applies highlighting techniques to emphasize the identified entities. Simultaneously, each highlighted entity is accompanied by a specific GDPR explanation detailing why it was classified as personal data.

## IV. Discussion

### i. Feasibility

Our project offers a **simple, fast, and advantageous solution** for organizations obliged to comply with data minimization and storage limitation requirements outlined in the GDPR. Here's why:

- **Ease of Implementation:** The project leverages existing AI technologies, making it **adaptable to various organizational structures and technical setups**.
- **Minimal Disruption:** The system integrates seamlessly with existing workflows, requiring minimal changes to current data management processes.
- **Cost-Effectiveness:** Compared to traditional anonymization methods, this AI-powered approach offers **significant cost savings** in terms of time, resources, and manpower required.

**However, it's important to acknowledge the following considerations:**

- **Data Complexity:** The accuracy of the AI model might require adjustments based on the specific data formats, languages, and complexities encountered within an organization's data landscape.
- **Continuous Improvement:** As with any AI system, ongoing monitoring and refinement of the model might be necessary to maintain optimal performance and address evolving data privacy regulations.

**Overall, the project demonstrates a highly feasible and advantageous approach not only to data anonymization, but also to storage limitation offering organizations a simple and effective solution for achieving compliance while preserving valuable non-personal data.**

- **Reduces Data Retention Needs:** By identifying and masking personal data within files, our project allows organizations to **retain non-personal data** for further use even after fulfilling the initial purpose for collecting the data. This eliminates the need to delete the



entire file, adhering to the storage limitation principle while still allowing organizations to utilize valuable insights from the non-personal data.

- **Minimizes Data Subject Risk:** By removing or obscuring personal data, our project **reduces the amount of sensitive information** organizations need to store. This lowers the potential risk of data breaches and minimizes the impact on individuals if a breach occurs, aligning with the GDPR's objective of protecting data subjects.
- **Enables Secure Data Exchange:** Anonymized data allows for **safer and easier sharing** within the organization and potentially with external entities. This facilitates collaboration and knowledge sharing while minimizing privacy concerns associated with exchanging personal data.
- **Simplifies Data Management:** our project can help organizations **streamline their data management processes** by eliminating the need to determine which files require complete deletion due to personal data content. This reduces the administrative burden and simplifies compliance efforts.

## **ii. Practicality**

Building upon the project's foundation, several areas can benefit from further development to enhance its practicality:

- **Scalability and Performance:** Optimizing the system to handle large data volumes efficiently is crucial for broader organizational adoption.
- **User Interface and Training:** Developing intuitive contextual interfaces and comprehensive training materials will ensure user-friendliness and facilitate seamless integration into existing workflows.
- **Security Enhancements:** Implementing robust security measures throughout the anonymization process is essential to safeguard sensitive data and maintain user trust.

By addressing these practical considerations, we can further strengthen the project's real-world applicability and empower organizations to confidently leverage anonymized data for various purposes while adhering to data minimization and storage limitation principles. Continuous evaluation, improvement, and adaptation are key to ensuring the long-term success and widespread adoption of our solution.

## **V. Conclusion**

Through this report, we have presented an AI model capable of performing extremely useful tasks that allow better control over the data organizations and individuals collect and process in the medical field. By providing a useful and fast tool capable of identifying and anonymizing personal data, we expect that our work will serve as a practical detailed guideline to realize the same data minimization work in other specific contexts for individuals and organizations to have a tighter

control and management over their data, while facilitating the compliance with data protection legislation.

## **Future work**

As AI models are in continuous development and monitoring, we acknowledge the challenges we must address for a broader use of our tool in different data landscapes. Accordingly, we intend to improve our model by creating an effortless and practical interface for users, as well as enriching the data training sets for the model, to enhance its output capabilities so that it can be used in a more general data landscape.