

Anonymisation and De-identification of Medical Documents Averbis GmbH, David Hübner

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De-identification: Scope

- **De-identification**: Removal of protected health information (PHI)
- In the EU, we currently lack an actionable definition of PHI, so we resort to the Health Insurance Portability and Accountability Act (HIPAA)



De-identification: Scenario



De-identification: Technical approach

- Use natural language processing (NLP) to identify PHI in clinical documents
- NLP models are trained on manually labeled datasets (>175.000 annotations)
- They can identify PHI information based on
 - **Context** ("Dear Mr ...")
 - World knowledge ("Berlin")
 - Layout (to some degree)
- Key technology: Usage of Transformer-based architectures, but fast enough to run on-premise (no LLMs)



De-identification: Key Results

- Recall > 98%: We can find 98-99% of all PHI
- Precision > 98%: If we mark a Token as PHI, it is correct to an accuracy of over 98%
- A dedicated Recall-optimized pipeline achieves an average of 99.3% Recall



De-identification: From annotations to de-identified documents

Once PHI was identified, we can modify the original documents.

Common strategies:

- Redaction: Replace PHI by XXX or by a tag, e.g. <date>
- Substitution: Substitute PHI with synthetic information
 - Advantages: Enhanced security It is unclear whether any remaining information was originally PHI
 - *Challenge*: Consistent replacements are difficult

De-identification = Anonymization? Not quite.

- Redaction/Substitution of PHI makes it much more difficult to identify the patients
- However, distinct medical diagnoses and contextual cues still may allow to identify the patient (see **k-anonymity**)
- To overcome this, we developed the **Snippet Workflow**

Snippet Workflow for retrieving anonymized texts

Goal: Workflow to retrieve texts that are **fully anonymized** but still valuable for ML model training







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