This is the extended journal paper version of our IEE ICHI 2020 paper ‘Information Extraction Models for German Clinical Text’. Since then this version is still under review ...

RESEARCH

A Medical Information Extraction Workbench to Process German Clinical Text

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Abstract

Background: In the information extraction and natural language processing domain, accessible datasets are crucial to reproduce and compare results. Publicly available implementations and tools can serve as benchmark and facilitate the development of more complex applications. However, in the context of clinical text processing the number of accessible datasets is scarce – and so is the number of existing tools. One of the main reasons is the sensitivity of the data. This problem is even more evident for non-English languages.

Approach: In order to address this situation, we introduce a workbench: a collection of German clinical text processing models. The models are trained on a de-identified corpus of German nephrology reports.

Result: The presented models provide promising results on in-domain data. Moreover, we show that our models can be also successfully applied to other biomedical text in German. Our workbench is made publicly available so it can be used out of the box, as a benchmark or transferred to related problems.

Keywords: Clinical Text Processing; Information Extraction; Part-of-Speech Tagging; NLP Workbench

Background

The year is 2022 AD. The research community relies entirely on neural and computationally intensive methods using large datasets and pre-trained language models, which push the current development rapidly forward. Well, not entirely. One small domain still struggles with more fundamental problems: lack of existing datasets, corpora or pre-trained models; hurdles with legal aspects; and outdated computer infrastructure with limited user rights – just to name a few. The domain is called clinical text processing. This applies particularly for non-English clinical text processing.

In the English speaking world, however, various tools can be applied to process clinical text, such as cTAKES [1] or MetaMap [2]. Most of those tools focus on named entity recognition, partly combined with concept normalization and disambiguation. Moreover, some tools target a very particular topic or domain, such as pharmacovigilance (MedLEE [3]), detection of medications (MedEx [4]) or temporal information (MedTime [5]). A more detailed overview can be found in Wang et al. [6].

Regarding the availability of annotated clinical text in English, various challenges have been conducted in the last years. Challenges that share data and experiences on the same problem. The i2b2 NLP challenge (now n2c2) for instance addresses a large variety of different tasks, such as medication detection [7] or identification of heart disease risk factors [8]. Also other shared tasks such as CLEF eHealth or SemEval have been carried out already various times on clinical text (e.g. [9, 10, 11, 12]). In more recent years, those challenges also targeted non-English clinical texts. The CLEF eHealth challenge 2018 (Task 1 [13]), for instance, focused on the mapping of ICD codes to death certificates in French, Hungarian, and Italian, or NEGES at IberLEF targets negation detection from Spanish clinical reports [14]. A good overview about non-English clinical text processing in general is provided in Névél et al. [15].

For the German language, the situation looks worse in comparison to French or Spanish. In 2019 a CLEF
eHealth challenge for German text had been carried out, in which ICD-10 codes were mapped to health-related, non-technical summaries of experiments [16]. However, this data concerned animals, not humans. Besides, not much other data has been published. An overview of the current situation is presented in Borchert et al. [17]. The paper lists 13 different German text corpora with a clinical/biomedical context, but only three are freely available. First, GGPonc [17] a dataset of clinical practice guidelines, second TLC [18], posts of a patient forum with annotated laymen expressions, and finally JSynCC [19] a dataset of German case reports extracted from medical literature. In the case of JSynCC, authors actually provide a software to extract the relevant text passages from digital medical books, instead of providing the data itself — due to legal reasons.

Concerning existing tools and pre-trained methods to process German clinical text, the situation is similar to the availability of text data. Most prominent is JPOS [20], a tokenizer and part of speech tagger trained on clinical text. The authors published the tool, as they were not allowed to publish the underlying FRAMED corpus [21] itself. In addition to that, two NegEx [22] versions for German exist [23] [24], as well as a dependency tree parser [25], an abbreviation expansion [26] and a tool to pseudonymize protected health information (PHI) in German clinical text [27].

In very recent times, some additional resources highly related to this work have been published, as the field is developing quickly in recent years. BRONCO [28], is an annotated dataset of German discharge summaries of the oncology domain - the first clinical text dataset in German which has been published. The data is de-identified and sentences of all 200 documents were shuffled to lower the risk of any re-identification. Along with the data, the authors also make the baseline models available on request. GERNERMED [29] is a German medicalner model, which is trained on translated data from n2c2 2018 [30]. And finally, German MedBERT [31], a BERT model, optimized for German clinical text, has been published on Hugging Face [32], targeting ICD10 code mapping.

In order to further support the development of resources to process German clinical text, this work describes an annotated dataset of German nephrology reports. It contains fine-grained annotations of concepts, relations, attributes, as well as part-of-speech (POS) labels and dependency trees. Unfortunately, we are unable to share the dataset at this point due to unsolved data protection concerns. Thus, instead of publishing the dataset, we release the machine learning models which we trained on the de-identified data[1].

While the BRONCO models mainly target diagnosis, treatment, medications, as well as factuality, our work includes a larger variety of different named entities, which might be useful for other use cases. Moreover, our workbench also includes relation detection and a POS tagger. Similarly this applies to GERNERMED, which mainly targets medications, as well as its dosage, duration, frequency etc. Note, as this work was developed for over various years, we still rely on classical word embeddings, rather than testing the efficiency of German MedBERT for our scenario.

**German Nephrology Corpus**

The corpus consists of German documents of the nephrology division at Charité – Universitätsmedizin Berlin. All documents have been de-identified by removing protected health information (PHI) defined by HIPPA (Health Insurance Portability and Accountability Act), using deID [33]. Next, the documents were enriched with semantic annotations as described in the following.

We considered two different document types for our annotations, clinical notes and discharge summaries (or discharge letters). Both document types report on kidney transplanted patients who underwent long-term treatment, are written by medical professionals and address medical professionals. **Discharge summaries** (“Arztbriefe”) serve as a summary of a patient’s hospital stay, expressed as letters sent to the patient’s GP, and cover history, diagnostic and therapeutic procedures. Since discharge letters are relatively long, they often provide additional structural elements such as headings, enumerations, etc. **Clinical notes** (“Verlaufsnotizen”) summarize the results from a single consultation in the outpatient department, which results in rather short texts. In contrast to discharge letters, their content, form, and function are not subject to professional and structural standards, as they are used only for internal communication and largely depend on the doctor’s writing style.

**Characteristics of Clinical Language**

A characteristic of the (German) clinical language is the large proportion of technical terms, which mostly have their origin in Latin or Greek, and underlie specific morphological rules. Moreover, clinical language provides a characteristic and individual use of syntax, for example, a notation style that excludes function words (e.g., articles, auxiliary verbs) and might include non-standard term variants. As documents might be written in a hurry, sentences can include typos, can be

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[1] The workbench can be found here: [http://biomedical.dfki.de](http://biomedical.dfki.de) and [https://github.com/DFKI-NLP/mEx-Docker-Deployment](https://github.com/DFKI-NLP/mEx-Docker-Deployment).
Table 1 Overview of all concepts

| Concept                          | Description                                                                 | Translated examples               |
|----------------------------------|-----------------------------------------------------------------------------|-----------------------------------|
| Central                          | Signs, symptoms, diagnoses, diseases, findings                             | Aphasia, cachectic                |
| Diagnostic Lab Procedure         | Procedures (diagnostic or laboratory) that serve the clinical examination of the patient’s state | measure, CT angiography, sonography |
| Treatment                        | All variants of clinical interventions aiming at improving the health state  | blood pressure management, transplantation |
| Medication                       | Names of medications, their active substances                             | Prograf, Sandimmun                |
| Biological Chemistry             | Biochemical substances that play a role in human organism                 | creatinine, ANA, HbA1c            |
| Process                          | Endogenous processes and functions in human organism                       | peristaltic sounds, defecation    |
| Person                           | Mentions of people                                                          | gynecologist, GP                  |
| Body Part                        | Parts of the human body                                                    | renal, lung                       |
| Body Fluid                       | Fluid and excretions of the human body                                      | urine, sputum, blood              |
| Medical Device                   | Artificial or biological system that supports or replaces a failed function of human organism | kidney allograft, TEP, shunt      |
| Biological Parameter             | Functions, features and characteristics of the human body                  | nutritional status, blood count, body weight |
| Specifying                       | Clinically specifying elements                                              | chronic, symptomatic              |
| Local Specification              | Locally specifying elements                                                | perirenal, right                  |
| Time Information                 | Temporally specifying elements                                             | today in the morning, 2014, on 11.01.2018 |
| Dosing                           | Dosing instructions for medications                                        | 1 sachet daily, 1 in the morning - 1 in the afternoon - none at night, 5 mg daily |
| Measurement                      | Measurements and evaluations of functions, findings, states                | sonorous, active, distinct        |
| State of Health                  | The (aimed) health state or the ongoing improvement                       | properly adjusted, satisfactory, stable |

Table 2 Overview of all relations

| Relation | Description                                                                 |
|----------|-----------------------------------------------------------------------------|
| Has_state| Argument1 is described as being pathologic (Medical.Condition) or as being healthy (State_of_Health) |
| Has_dosing| A Medication or a Treatment is linked to a Dosing instruction               |
| Has_time_info| Argument1 is described by a Time_information                                  |
| Has_measure| Argument1 is described by a Measurement                                      |
| Is_located| Argument1 is described locally by Local_specification or Body_part          |
| Is_specified| Argument1 is described by Medical_specification                             |

This short expression does not use a verb - something like “to show” is presumably meant in this context. This information is however significant as it forms the relation between the examination process (Sono, “Sonogram”) and the (negated) finding (Stau, “congestion”). As the verb and therefore the relation is only implicitly expressed, a basic understanding of the subject is presupposed for the correct manual annotation.

(1) Im Sono kein Stau.
Sonogram [shows] no congestion.
Furthermore, many abbreviations are used in both document types. These abbreviations are often standardized, and their expansion and meaning are well documented. Conversely, the expansion of abbreviations can be complicated by the fact that abbreviations are often ambiguous. For example the German web dictionary *Beckers Abkürzungslexikon Medizinischer Begriffe* [34] for medical-related abbreviations lists 61 possible expansions for *KS* (for instance *Kaltschweißigkeit, Klopfschall, Kaiserschnitt, Kaufmann-Schema*) with additional subcategories of varieties. Only a sufficient context can help to disambiguate an abbreviation. However, as the clinical language tends to a compact and reduced language, such a disambiguating context is not always given. Another characteristic of clinical documents is the large number of negations and vague descriptions, particularly in context of symptoms and findings.

**Semantic Annotations**

Our semantic annotation schema is intended to cover the most relevant textual information in the corpus, and developed during the annotation process [35]. The schema has been developed from scratch, together with linguists, computer scientists, and physicians and focuses on the pathological health state (medical condition) of the patient as well as his or her treatments and diagnostic and laboratory examinations. The schema targets mainly the recognition of that information and everything which is connected to it. It is individually adapted to the demands of the German nephrology domain and applies for both discharge summaries and clinical notes. In order to gather this meaning, the schema is constructed of concepts, binary relations, and concept attributes which are introduced in the following.

**Concepts:** The concept schema can be divided into three groups: **central**, **relating**, and **specifying**. **Central** concepts describe – from our perspective – the most crucial information about a patient. It concerns the pathological health state of the patient as well as his or her treatments and diagnostic and laboratory examinations. **Relating** concepts describe other relevant information within the documents. By connecting them via relations (see below) to mostly central concepts, those information help to gather relevant information of the documents. **Specifying** concepts provide more detailed information to the other concepts, such as dosing, local or time information. An overview of the concept schema is provided in Table 1 and includes a short definition and examples.

**Relations:** Our relation schema describes a binary semantic relation between two concepts. It intends to connect the annotated concepts within the document with each other and to give the single concepts a stronger meaning. On a high level, relations can be divided into two groups, **describing** and **medical** relations. **Describing** relations connect two concepts with each other, of which one argument adds more information to the other one, such as the dosing of a medication, the pathological state of something, or a further specification. Usually one argument is a **specifying** concept. **Medical** relations instead describe more complex situations related to the examination and treatment of a patient.

Table 2 presents the set of relations including a short description. In most cases the relations are defined in a broader sense. While one argument is usually defined to be bound to one or two particular concept types, the other argument often has more freedom and can be bound to various concept types.

**Attributes:** Attributes are used for the further specification of an annotated concept. While a concept covers the term’s lexical information, the selected attribute value refers to extra-lexical/contextual information. Such information relates to **temporal information** or information about the **level of truth**. See Table 3 for the annotation schema of attributes.

The time information attribute *DocTime* helps to structure the described temporal course of the document. By applying one of its values, an entity can...
be highlighted as has happened in the past or as being planned in or predicted for the future. In most cases, a surrounding TIME_INFORMATION-concept triggers the attribute selection. If possible, both concepts are additionally linked by the relation HAS_TIME_INFO. This means that in many cases, this information is expressed twice: First by concept and second by attribute value.

The attribute LevelOfTruth highlights information that indicates vagueness, possibility, and negated expressions. Generally, both document types comprise plenty of expressions of assumptions. It is necessary to differentiate between a statement expressing certainty and an assumption, for example.

Corpus Generation
The annotation was carried out by three students (2 linguists, 1 medical student). The medical student in particular contributed to the understanding of the medical terminology. The task itself was conducted by using the Brat annotator tool [36] within several annotation cycles. This method led to various adaptations and updates of the annotation schema.

Table 4 Analysis of annotated documents

|                     | Discharge Summaries | Clinical Notes |
|---------------------|---------------------|----------------|
| # docs              | 61                  | 1300           |
| # words             | 57,219              | 54,206         |
| # sentences         | 6,213               | 6,618          |
| avg. words (std)    | 928 (246.33)        | 54 (45.43)     |

Table 4 provides an overview of the annotated dataset. Overall 1300 clinical notes and 61 discharge summaries have been annotated. Most documents were examined at least twice by two different annotators. However, between the two linguists, which annotated more than 80% of the data (53.3%, 30.9%), there exists a larger number of overlapping documents in comparison to the medical student (11% between linguists, 8% and 2% between the linguists and the medical student; only a small portion of documents was annotated by all three annotators, namely 1 discharge summary and 20 clinical notes).

The table shows the number of different annotated documents, the overall number of words in all documents, the overall number of sentences and the average words per document, including standard deviation (in brackets). Discharge summaries contain a larger average number of words per document compared to the clinical notes\[2\]. However, the standard deviation of the average word number per document shows that both document types have a large variation in text length. Some clinical notes contain only a few words.

Similarly as in Hripcsak and Rothschild [37] we calculate the inter-annotator-agreement (IAA) using the pairwise average F-score (micro) on character level. This results in an avg. F-Score across all annotators of 0.761 for the concepts and 0.636 for relations. Particularly the score of the relations does not seem to be very high. However, two aspects need to be taken into consideration: a consistent relation annotation strongly depends on the fact if the underlying concepts are annotated correctly beforehand, and secondly, the IAA between the two linguists, who annotated more than 80% of the data, have got a much stronger overlap, namely 0.822 for concepts and 0.697 for relations.

Challenges & Limitations
In order to meet the complexity of the German clinical language, we created a detailed and extensive annotation schema. We faced multiple challenges during the annotation process, due to the complexity of the language and the schema. These challenges had a substantial impact on the consistency of the annotations across the annotations (IAA), therefore decisions about the approach had to be made. The most relevant ones will be presented in the following.

Fine-Grained Annotation: The German language includes a large number of compound words. As compounds consist of two (or more) meaningful units that are linked via an inherent linguistic relation, the annotation of that relation seems possible. This can lead to subword annotations on multiple levels. Notably this applies to medical technical terms.

![Figure 1 Annotation Granularity](image-url)

Figure 1 shows an example of annotating on different levels. It shows the compound *Niereninsuffizienz* (“renal insufficiency”) whose two elements refer to the concepts BODY_PART and MEDICAL_CONDITION. The word itself also refers to a MEDICAL_CONDITION. The specifying adjective *terminale* (“terminal”) should be considered as an attached part of the technical term. Thus the preferred annotation here is *Terminale Niereninsuffizienz* as MEDICAL_CONDITION. Alternatively, *terminale* is annotated as MEDICAL_SPECIFICATION, Nie-
reninsuffizienz as MEDICAL_CONDITION and both are connected via the relation IS_SPECIFIED. The process of subword annotation goes beyond the scope of this corpus, therefore we opt for the annotation of larger spans. However, the possibility of both alternatives decreases the consistency in the annotation.

**Ambiguity:** The relations in our annotation schema are rather broadly defined. This means that one relation can be used to link several different argument pairs. For example, the relation shows with the concept MEDICAL_CONDITION as the second argument can make use of two different first arguments: Firstly it links to DIAGLAB_PROCEDURE. In such a case, the result or the finding of a diagnostic procedure is expressed. Alternatively it links to BIOLOGICAL_PARAMETER. Then the relation expresses that a specific parameter indicates a pathological condition.

In some contexts, the connection between the two entities can be expressed equally by two different relations. This is mainly the case for the link between the two concepts MEDICAL_CONDITION and BODY_PART. See Figure 2: The sentence describes the location of a symptom. This finding can either be described by using a IS_LOCATED-relation (Figure 2, first line) or by defining the health state of a body part as being pathological (HAS_STATE-relation, Figure 2, second line). Both are, according to our schema, correct and express the intended semantic relation equally. In order to achieve a consistent annotation, we opt for the first version as the MEDICAL_CONDITION-information seems more central here.

### Additional Datasets

While the previous section introduced the main corpus in detail, this part presents additional relevant data sources, namely Nephro_Gold, the Hamburg Dependencies Dataset, as well as a biomedical text corpus in German.

**Nephro_Gold: A syntactic dataset**

In addition to the semantic clinical corpus, also a small clinical syntactic dataset has been created in previous work [38] [25]. We refer to this corpus as Nephro_Gold.

The dataset also consists of clinical notes and discharge summaries, is rather small (44 clinical notes and 11 discharge summaries) and is a subset of the dataset described above. It includes part-of-speech (POS) annotations using the Stuttgart-Tübingen Tagset (STTS) [39] and dependency trees using the Universal Dependencies (UD) tagset [40].

### Hamburg Dependency Treebank

The Hamburg Dependency Treebank (HDT) [41] is a large dataset of more than 261,000 German sentences, and includes POS labels and syntactical annotations. The annotation scheme of HDT is also based on the Stuttgart-Tübingen Tag Set for morphological and POS annotation and a set of 35 dependency labels for dependency annotation. The corpus is freely available for scientific purposes. In this work, the dataset will be used for the POS tagger.

### BTC - A Biomedical Text Collection in German

Many modern NLP (natural language processing) methods use word embeddings as input. However, it turns out that embeddings specialized on the given domain often outperform embeddings trained only on general text. Although embeddings with a focus on the biomedical domain have been published, there are no embeddings specialized on German clinical text [3]. Moreover, as mentioned above, clinical text contains a large number of technical terms, which do not frequently occur in general news text or Wikipedia. This might result in many out-of-vocabulary words if we train a system using standard pre-trained embeddings.

For this reason, we collected German text data from multiple sources in order to train our own custom embeddings. Table 5 and Table 6 provide an overview about the different sources used. We scraped data from multiple webpages with a focus on biomedical topics, as well as forums. In addition to that we also used text from different medical books. In the following we will refer to our biomedical text collection as **BTC**.

### Methods and Setup

This section provides an overview of the technical aspects of our work. We briefly present the relevant methods and explain how we use or modify them for our experiments. As we mainly rely on existing implementations, the technical components will be presented relatively short.

[3]Note, after submission of the manuscript, the situation has slightly changed. See related work for more information.
Table 5 Overview of different biomedical text sources in German to create a new biomedical text collection

| Size   | Source Description                                    |
|--------|-------------------------------------------------------|
| 7.5 GB | Med1 Forum [42] German forum for clinical topics and information exchange |
| 91.8 MB| Deutsches Medizin Forum [43] German forum for clinical topics and information exchange |
| 28.6 MB| Spiegel Online [44] German news webpage, articles downloaded from the health section |
| 10.7 MB| Aerzte-Blatt [45] Official news publication of the German Medical Association |
| 10 MB  | NetDoktor [46] German online health portal for medical information from experts to patients |
| 7.1 MB | Onmeda [47] German online health portal, content extracted from the symptoms and diseases |
| 3.6 MB | German PubMed Abstracts [48] Archive of biomedical and life sciences journal literature |
| 1.9 MB | eDocTrainer [49] German collection of clinical case studies from all specialist disciplines |
| 16.5 MB| Medical Books Content from various medical books, see Table 6 |

Table 6 Overview of medical books

| Name                                      | Author                                      |
|-------------------------------------------|---------------------------------------------|
| Chirurgie: Mit integriertem Fallquiz - 40 Fälle nach neuer AO. Springer-Verlag, 2009 [50] | Siewert, Stein |
| Neurologie. Springer-Verlag, 2006 [51]    | Poeck, Hacke |
| Urologie. Springer-Verlag, 2014 [52]      | Hautmann, Gschwend |
| Basiswissen Augenheilkunde. Springer-Verlag, 2016 [53] | Walter, Plange |
| Hals-Nasen-Ohren-Heilkunde. Springer-Verlag, 2012 [54] | Lenarz, Boenninghaus |
| Notfallmedizin. Springer-Verlag, 2016 [55] | Ziegenfuß |
| Basiswissen Dermatologie. Springer-Verlag, 2017 [56] | Goebeler, Hamm |
| Basiswissen Psychiatrie und Psychotherapie. Springer-Verlag, 2011 [57] | Arolt, Reimer, Dilling |

Custom Word Embeddings with fastText

All methods used in this work rely on variant types of word, character, and document embeddings. For reasons of simplicity and compatibility with our NLP pipeline, fastText [58] was the method of choice. fastText is a lightweight library that offers pre-trained text classifiers. Moreover, it provides various multilingual word vectors that can be fine-tuned on new unlabeled data to obtain a better domain-specific characterization of our clinical data. In this work we used fastText to fine-tune our own embeddings using BTC and the German Nephrology corpus. We refer to this representation as ‘custom embeddings’. A total of 5 epochs were needed using CBOW for the generation of the new embeddings. In addition, we used the default German fastText embeddings, which we refer to as ‘default’.

Clinical Text processing with Flair

Large parts of our work relied on Flair [59], a state of the art NLP framework, which provides various functionalities, for instance, named entity recognition (NER) and part-of-speech-tagging (POS). Furthermore, its codebase, developed upon PyTorch, allows easy and efficient modifications to realize new tasks.

For this work, we partially relied on contextual string embeddings (FlairEmbeddings) [59] and pooled contextualized embeddings (Pool) [60]. Flair embeddings are a type of word embeddings, which merge the best attributes of three embeddings (Word embeddings, Character-level features, Contextualized word embeddings). Those embeddings represent words as a sequence of characters and are contextualized by their surrounding text, making the same words have a different type of embedding depending on its context. Flair also offers the opportunity to fine-tune this kind of embeddings on unlabeled datasets for a specific domain. Pool embeddings resolve the problem of representing rare occurrences of words that might carry more than one meaning in a given text. A pooling operation is applied to all contextualized instances of a word to generate a global word representation that encodes all the gathered features into a new one.

Part-of-speech Tagging: For the POS tagging we used a BiLSTM-CRF implementation of Flair. Overall we explored different setups with different embeddings and their combination. As the Nephro_Gold dataset is rather small, we also ran experiments with a training and development dataset extended by Hamburg Dependency Treebank.

Concept Detection: For the concept detection we again relied on a BiLSTM-CRF model implemented in Flair. Similar to POS tagging, we examined a range of different embeddings and their combination.

Relation Extraction

For relation extraction, we re-implemented a CNN-based relation classifier, as proposed by Nguyen and Grishman (2015) [61]. We used word- and positional embeddings to represent the meaning and relative position of each token. Short sentences and reduced language might provide insufficient context. Thus, we also added embeddings to provide the model with concept information about the two relation arguments.
Table 7: Part-of-Speech Tagging: Average accuracy with standard deviation (in brackets) over 5-fold cross validation

|                     | Def. Word | Custom Word | Def. Flair | Custom Flair | Def. Word+Flair | Cust. Word+Flair |
|---------------------|-----------|-------------|------------|--------------|-----------------|-----------------|
| only Nephro Gold    | 65.53 (0.66) | 77.65 (0.95) | 81.41 (0.75) | 80.80 (0.47) | 81.54 (0.69)    | 81.84 (1.37)    |
| Nephro Gold & HDT   | 97.07 (0.02) | 97.29 (0.02) | 98.47 (0.01) | 98.37 (0.01) | 98.57 (0.02)    | 97.96 (0.01)    |

Model Size: 1.3 GB 4.7 GB 248.7 MB 248.7 MB 1.6 GB 5.0 GB

Table 8: Concept Detection: Average micro F1 score with standard deviation (in brackets) over 5-fold cross validation

|                     | Strict Prec. | Strict Rec. | Strict F1 | Lenient Prec. | Lenient Rec. | Lenient F1 |
|---------------------|--------------|-------------|-----------|---------------|--------------|------------|
| Default Word Embeddings | 1.3 GB | 61.20 | 57.11 | 58.97 (0.44) | 72.4 | 67.4 | 69.6 (0.54) |
| Custom Word Embeddings | 4.7 GB | 73.82 | 71.19 | 72.47 (0.61) | 83.2 | 79.4 | 81.4 (0.54) |
| Default Flair Embeddings | 248.6 MB | 74.82 | 73.85 | 74.33 (0.30) | 83.0 | 81.75 | 82.25 (0.50) |
| Custom Flair Embeddings | 248.6 MB | 75.36 | 75.45 | 75.40 (0.46) | 83.75 | 83.25 | 83.25 (0.50) |
| Default Word + Def Flair Embeddings | 1.6 GB | 73.20 | 72.65 | 72.92 (1.17) | 81.8 | 80.8 | 81.6 (0.54) |
| Custom Word + Custom Flair Embeddings | 5.0 GB | 75.45 | 75.09 | 75.26 (0.56) | 84.2 | 83.4 | 83.8 (0.83) |
| Cust. Word+Cust. Flair+Cust. Pool Embeddings | 5.9 GB | 76.12 | 75.94 | 76.02 (0.64) | 84.8 | 84.2 | 84.4 (0.54) |

Experiments

In the following, we present our results in evaluating the models introduced in the previous section. To merge the overlapping documents, we prioritized the number of documents each student annotated (more documents, higher priority) to achieve a better consistency across the dataset. Then, we used JCoRe [20] for tokenization and sentence splitting, and removed annotations crossing sentence boundaries. We also removed nested annotations and retained only the longest span. In cases where tokens were assigned multiple concept annotations, we favored the one with the higher occurrence.

We used accuracy to report results for POS tagging, and precision, recall, and micro-averaged F1 score for concept detection and relation extraction. The concept detection was evaluated by using strict and lenient matching. Strict matching considers a predicted concept to be a true positive only if its offsets exactly match the ground truth, whereas for lenient matching it is sufficient for tags to overlap, similarly as defined in Henry et al. [30].

We evaluated all models using a 5-fold cross validation with a training, development, and test split of 75/10/15. The reported results only include part-of-speech tagging, concept detection, and relation extraction, because dependency tree parsing and attribute (negation) detection results were partly already presented in previous work and tools made available (see Kara et al. [25] and Cotik et al. [24]).

Part-of-speech Tagging

Table 7 presents the results of part-of-speech tagging. The upper line shows the performance of the POS tagger using only Nephro_Gold, and the line below the model including the extended training and development dataset using HDT. In addition we can see the performance of the standard word and Flair embeddings, also in combination, as well as the performance of the custom embeddings. The size of each model is presented in line at the bottom.

The table shows that combining Nephro_Gold with the much larger HDT data, all different setups show a strong increase of accuracy. The table also shows that custom word embeddings always outperform the default word embeddings, although the performance gain is much smaller in case of including HDT. Moreover, Flair embeddings show in all cases a boost over their word embedding equivalent. Interestingly default Flair embeddings outperform the (fine-tuned) custom Flair embeddings. Finally we can see that the combination of word and Flair embeddings tend to outperform their single equivalent - not in case of using HDT data and custom setup. However, the best setup can be achieved with HDT and both, default word and Flair embeddings.

The presented results indicate the custom embeddings are not necessary for the POS use case. In addition to that, regarding the model size, the default Flair embedding using HDT is our favored setup, as the performance is only 0.1 below the best performing system, but the model is much smaller.

Concept Detection

The results of the concept detection are presented in Table 8 and show the average F1 micro scores using a cross validation with the different setups. The evaluation was carried out using strict and lenient matching as described above.

The results show that in all cases the lenient score achieves a better performance, which is no surprise as we leave more flexibility. Moreover, we can see that the custom word embeddings outperform the default fastText embeddings. The Flair embeddings on the other
Table 9 Relation Extraction: Average micro F1 score with standard deviation (in brackets) over 5-fold cross validation

| Model Size                      | Prec. | Rec. | F1    | IAA   |
|---------------------------------|-------|------|-------|-------|
| Def. Word Embeddings + Relative Offsets [61] | 2.9 GB 63.0 | 74.0 | 68.0 (0.008) |
| Custom Word Embeddings + Relative Offsets | 4.7 GB 61.0 | 76.0 | 68.0 (0.007) |
| Def. Word + Concept Embeddings + Relative Offsets | 2.9 GB 80.0 | 87.0 | 83.0 (0.01) |
| Custom Word + Concept Embeddings + Relative Offsets | 4.7 GB 79.0 | 89.0 | 84.0 (0.003) |

Table 10 Fine-grained lenient score of (first run) concepts using custom Flair embeddings model, according to precision, recall and F1, sorted by frequency (#). Results are presented in comparison to IAA (micro avg. F1).

| Concept Name          | Prec. | Recall | F1    | #      | IAA    |
|-----------------------|-------|--------|-------|--------|--------|
| Medical condition     | 88.0  | 92.0   | 90.0  | 8953   | 87.39  |
| Measurement           | 77.0  | 83.0   | 80.0  | 5429   | 62.13  |
| Body part             | 82.0  | 85.0   | 83.0  | 3410   | 74.20  |
| Treatment             | 81.0  | 82.0   | 82.0  | 4379   | 79.24  |
| DiagLab Procedure     | 87.0  | 65.0   | 75.0  | 3209   | 66.54  |
| State of health       | 94.0  | 87.0   | 90.0  | 4025   | 83.32  |
| Process               | 86.0  | 67.0   | 76.0  | 2716   | 79.41  |
| Medication            | 89.0  | 90.0   | 90.0  | 3169   | 93.83  |
| Time information      | 89.0  | 73.0   | 80.0  | 3103   | 46.75  |
| Local specification   | 84.0  | 79.0   | 82.0  | 1716   | 63.83  |
| Biological chemistry  | 60.0  | 94.0   | 73.0  | 1363   | 71.13  |
| Biological parameter  | 68.0  | 66.0   | 67.0  | 966    | 60.22  |
| Dosing                | 93.0  | 85.0   | 88.0  | 1203   | 74.78  |
| Person                | 91.0  | 97.0   | 94.0  | 1265   | 85.26  |
| Medical specification | 40.0  | 31.0   | 35.0  | 1192   | 65.87  |
| Medical device        | 74.0  | 55.0   | 63.0  | 370    | 89.98  |
| Body Fluid            | 91.0  | 78.0   | 84.0  | 164    | 70.09  |

Table 11 Fine-grained score (first run) of relations using “custom word + concept embedding + relative offset” model, according to precision, recall and F1, sorted by frequency (#). Results are presented in comparison to IAA (micro avg. F1).

| Relation Name          | Prec. | Recall | F1    | #      | IAA    |
|------------------------|-------|--------|-------|--------|--------|
| Micro F1-Score         | 0.77  | 0.92   | 0.84  |        |        |
| Macro F1-Score         | 0.74  | 0.91   | 0.82  |        |        |
| rel-has-measure        | 0.77  | 0.95   | 0.85  | 3810   | 62.15  |
| rel-has-state          | 0.83  | 0.92   | 0.87  | 2880   | 76.58  |
| rel-has-time-info      | 0.76  | 0.93   | 0.83  | 2302   | 41.24  |
| rel-is-located         | 0.75  | 0.84   | 0.79  | 2160   | 56.38  |
| rel-involves           | 0.86  | 0.95   | 0.90  | 2015   | 85.79  |
| rel-shows              | 0.50  | 0.77   | 0.61  | 1192   | 65.87  |
| rel-has-dosing         | 0.85  | 0.97   | 0.90  | 1156   | 84.97  |
| rel-is-specified       | 0.78  | 0.99   | 0.87  | 628    | 39.19  |
| rel-examines           | 0.60  | 0.89   | 0.72  | 381    | 57.70  |

Hand outperforms the specialized custom embeddings, and at the same time, the size of the model is below 250 MB, while the pure word embedding approaches are always above at least one GB. The overall best performing model uses a combination of word, Flair and Pool embeddings, unfortunately resulting in a model with the largest size of nearly 6GB.

Table 10 shows the results of the custom Flair embeddings model on concept level. The table also shows the overall (including training and development) frequency of each concept in the dataset. As we can see, the distribution of the concepts is very unbalanced. Often multi-class approaches have problems dealing with unbalanced data. In our case the classifier can deal relatively well with the situation. Note, we also trained single classifiers for each concept, which led to marginal improvements in most cases. On the other hand this approach is not feasible for a real use-case, as each model needs to be loaded into the working memory, for only a slight overall improvement.

Moreover, Table 8 presents the micro avg. F1 IAA scores of the annotators. In most cases the IAA is below the score of the classifier, only in some cases, such as Medication, the IAA score is above. In the case of Medical Specification for instance the IAA is very low. This supports our hypothesis that concept information is beneficial to relation extraction from clinical text, as the context lacks important linguistic information.

Table 10 shows the detailed results (first run) of the default word + concept embeddings + relative offsets model, including the overall frequency of the different relations. Similarly to the concepts, the distribution of the relations is unbalanced. However, all relations can be detected very well, often with an F1 above 0.8.

Moreover, Table 11 presents the micro avg. F1 IAA scores of the annotators. Similarly as in Table 8, the IAA tends to be below the results of the machine learning model. Notably, while the performance of the relation is-specified achieves quite good results with an F1 score of 87, the IAA is only about 39. It is likely that the disagreements between the annotators regarding Medical-Specification have a strong influence on that. Conversely, more than 50% of the data was annotated by one particular annotator. This might have a strong influence on the overall annotations, and the model...
was probably able to learn this annotation style very well, which is reflected in the performance of that relation.

Medical Text Processing Workbench
Given the previous experiments we select the best models according to score and model size. Generally we prefer a small sized model with a score slightly below the best performing system. Moreover, as the evaluation was carried out within a 5-fold cross validation, resulting in five different models, we always pick the first model for the workbench. Overall the following models will be used: POS Tagger (Default Flair, run 1), concept detection (Custom Flair, run 1) and relation extraction (Default Word+Concept+Relative Offset, run 1).

The description of the workbench, to run the models out of the box, can be found on http://biomedical.dfki.de. The models themselves can be downloaded here: https://github.com/DFKI-NLP/mEx-Docker-Deployment. Note, in order to use the models, a user agreement must be signed first.

Testing Concept Detection on additional Datasets
The experiments above have been conducted on clinical text of the nephrology domain. All documents have been written within one hospital. Due to the restricted topic and due to the limited number of authors writing those reports, the data might be very homogeneous. Therefore models trained on this data might be not suitable to be tested on other biomedical/clinical texts in German.

In order to explore this, we carried out a small proof of concept. To do so, we tested our concept detection on two additional biomedical text datasets in German, namely (a) GGPONC [17], a dataset of clinical practice guidelines and (b) a set of posts published in a German health forum, taken from the TLC corpus [18]. In both cases we applied the model to 600 sentences of each dataset. The automatically generated labels were then corrected (if needed) by the main annotator of our nephrology corpus. Please note, we wanted to find out if our concept detection can work in general also on different text, given our annotation schema. So the annotator examined the given labels, but was not too strict about each single label.

Regarding micro F-Score, the IAA between classifier and annotator was 0.851 on GGPONC and 0.868 on the TLC forum data. These values are surprisingly good, also in comparison to the original concept detection results on the nephrology dataset. The fact that correcting a dataset instead of starting an annotation from scratch, might have an influence, as well as accepting ‘suggested labels’ which would have been not annotated in other cases. Overall the outcomes serve as a proof of concept, rather than a solid evaluation. However, the results indicate that our models might be a good first choice to process biomedical text in German. Data can be shared upon request.

Discussion and Analysis
We carried out experiments with different setups on three different tasks using clinical text in German. In most cases, we observed customized word embeddings to provide better results compared to their default counterpart. This performance gain, however, comes at the expense of increased model size, particularly for POS tagging and concept detection. Moreover, within the first two experiments we could see that the models using only Flair embeddings perform quite well and tend to have a smaller model size. The results show that character embedding-based approaches seem to perform well on clinical text. A reason for that might be the characteristics of some words (medication names often contain letters like ‘x’ and ‘y’ [62]) and possibly the features of the Greek and Latin origin of words (e.g. words ending with ‘-itis’ or ‘-asis’ might refer to a disease).

For applying and running such text processing models on the fly in clinical care, smaller models might be favoured, in order to be not too dependent on computational power and working memory. This means that the simple Flair embedding models would probably be the better choice for a real clinical use case. In case of relation extraction instead, we relied on an implementation which does not integrate Flair or character embeddings. Therefore the favoured models still have a size of 2.9 GB. It would make sense to switch to an efficient model which results in a smaller model size.

Moreover, we analyzed the predictions of the model. Generally, the clinical data of our corpus is heterogeneous. Even though a large range of health related problems can be described in the documents, they are all of the nephrology domain and always of the same department. Therefore, we frequently observed similar text patterns for sentences, mentioning similar medical problems, treatments or medications. Regarding POS tagging, the fact that the dataset is relatively small, and contains similar sentences (or often a similar sentence structure) might have been the reason for the good results.

The concept detection certainly also benefited from frequently re-occurring concepts. On the other hand the same words could be annotated differently, depending on context, but also depending on the annotator. This particularly made the strict matching more challenging. Analyzing the falsely predicted concepts, various cases could be found where the classifier attached
a label, which was not necessarily wrong. Interestingly our concept detection showed very promising results, when applied to two different biomedical datasets in German.

### Conclusion

In this work, we described an annotated corpus of German nephrology reports and further created a collection of German biomedical text to train customized word embeddings for clinical text. Based on this data in combination with existing methods and tools, we created and evaluated a set of German clinical text processing models: a part-of-speech tagger, a concept detector, and a relation extractor. To provide resources for the clinical text processing community, we combined the best performing models into a medical information extraction workbench, which we made publicly available for free use.

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### Abbreviations

NLP - Natural Language Processing; NER - Named Entity Recognition; RE - Relation Extraction; POS - Part-of-Speech Tagging; HDT - Hamburg Dependency Treebank; IAA - Inter-Annotator Agreement;

### Availability of data and materials

The description of the mEx workbench can be found on [http://biomedical.dfki.de](http://biomedical.dfki.de). The mEx models themselves can be downloaded on [https://github.com/DFKI-NLP/mEx-Docker-Deployment](https://github.com/DFKI-NLP/mEx-Docker-Deployment).

### Ethics approval and consent to participate

N/A

### Competing interests

The authors declare that they have no competing interests.

### Consent for publication

N/A

### Authors’ contributions

All co-authors are justifiably credited with authorship, according to the authorship criteria. In detail: RR- coordination, planning, development of annotation schema, writing, analysis; LR - development of annotation schema, annotations, evaluation, writing corpus section; AA - technical development, writing technical section; OM - critical revision of manuscript; OM - annotations, writing corpus section; MM - annotations, writing corpus section; CA - technical development, writing technical section; DS - technical support, data preparation; FH - development of annotation schema; MN - discussions, editing, revision of the manuscript; WD - discussions, editing, revision of the manuscript; KB - planning, critical revision of manuscript. All authors read and approved the final manuscript.

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