Multi-domain Clinical Natural Language Processing with MedCAT: the Medical Concept Annotation Toolkit

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Abstract

Electronic health records (EHR) contain large volumes of unstructured text, requiring the application of Information Extraction (IE) technologies to enable clinical analysis. We present the open source Medical Concept Annotation Toolkit (MedCAT) that provides: a) a novel self-supervised machine learning algorithm for extracting concepts using any concept vocabulary including UMLS/SNOMED-CT; b) a feature-rich annotation interface for customising and training IE models; and c) integrations to the broader CogStack ecosystem for vendor-agnostic health system deployment. We show improved performance in extracting UMLS concepts from open datasets (F1:0.448-0.738 vs 0.429-0.650). Further real-world validation demonstrates SNOMED-CT extraction at 3 large London hospitals with self-supervised training over ~8.8B words from ~17M clinical records and further fine-tuning with 6K clinician annotated examples. We show strong transferability (F1>0.94) between hospitals, datasets and concept types indicating cross-domain EHR-agnostic utility for accelerated clinical and research use cases.

Keywords: Electronic Health Record Information Extraction, Clinical Natural Language Processing, Clinical Concept Embeddings, Clinical Ontology Embeddings

1. Introduction

Electronic Health Records (EHR) are large repositories of clinical and operational data that have a variety of use cases from population health, clinical decision support, risk factor stratification and clinical research. However, health record systems store large portions of clinical information in unstructured format or proprietary structured

formats, resulting in data that is hard to manipulate, extract and analyse. There is a need for a platform to accurately extract information from freeform health text in a scalable manner that is agnostic to underlying health informatics architectures.

We present the Medical Concept Annotation Toolkit (MedCAT): an open-source Named Entity Recognition + Linking (NER+L) and contextualization library, an annotation tool and online learning training interface, and integration service for broader CogStack[1] ecosystem integration for easy deployment into health systems. The

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MedCAT library can learn to extract concepts (e.g. disease, symptoms, medications) from free-text and link them to any biomedical ontology such as SNOMED-CT[2] and UMLS[3]. MedCATtrainer[4], the annotation tool, enables clinicians to inspect, improve and customize the extracted concepts via a web interface built for training MedCAT information extraction pipelines. This work outlines the technical contributions of MedCAT and compares the effectiveness of these technologies with existing biomedical NER+L tools. We further present real clinical usage of our work in the analysis of multiple EHRs across various NHS hospital sites including running the system over 20 years of collected data pre-dating even the usage of modern EHRs at one site. MedCAT has been deployed and contributed to clinical research findings in multiple NHS trusts throughout England[5, 6].

1.1. Problem Definition

Recently NER models based on Deep Learning (DL), notably Transformers[7] and Long-Short Term Memory Networks[8] have achieved considerable improvements in accuracy[9]. However, both approaches require explicit supervised training. In the case of biomedical concept extraction, there is little publicly available labelled data due to the personal and sensitive nature of the text. Building such a corpus can be onerous and expensive due to the need for direct EHR access and domain expert annotators. In addition, medical vocabularies can contain millions of different named entities with overlaps (see Fig. 1). Extracted entities will also often require further classification to ensure they are contextually relevant; for example extracted concepts may need to be ignored if they occurred in the past or are negated. We denote this further classification as meta-annotation or a 'contextualisation' of a recognised entity. Overall, using data-intensive methods such as DL can be extremely challenging in real clinical

This work is positioned to improve on current tools such as the Open Biomedical Annotator (OBA) service[10] that have been used in tools such as DeepPatient[11] and ConvAE[12] to structure and infer clinically meaningful outputs from EHRs. MedCAT allows for continual improvement of annotated concepts through a novel self-supervised machine learning algorithm, customisation of concept vocabularies, and downstream contextualisation of extracted concepts. All of

which are either partially or not addressed by current tools

1.2. NER+L in a Biomedical Context

Due to the limited availability of training data in biomedical NER+L, existing tools often employ a dictionary-based approach. This involves the usage of a vocabulary of all possible terms of interest and the associated linked concept as specified in the clinical database e.g. UMLS or SNOMED-CT. This approach allows the detection of concepts without providing manual annotations. However, it poses several challenges that occur frequently in EHR text. These include: spelling mistakes, form variability (e.g. kidney failure vs failure of kidneys), recognition and disambiguation (e.g. does 'hr' refer to the concept for 'hour' or 'heart rate' or neither).

1.3. Existing Biomedical NER+L Tools

We compare prior NER+L tools for biomedical documents that are capable of handling extremely large concept databases (completely and not a small sub-MetaMap[13] was developed to map biomedical text to the UMLS Metathesaurus. MetaMap cannot handle spelling mistakes and has limited capabilities to handle ambiguous concepts. It offers an opaque additional 'Word-Sense-Disambiguation' system that attempts to disambiguate candidate concepts that consequently slows extraction. Bio-YODIE[14] improves upon the speed of extraction compared to MetaMap and includes improved disambiguation capabilities, but requires an annotated corpus or supervised training. SemEHR[15] builds upon Bio-YODIE to somewhat address these shortcomings by applying manual rules to the output of Bio-YODIE to improve the results. Manual rules can be labour-intensive, brittle and time-consuming, but they can produce good results[16]. cTAKES[17], builds on existing open-source technologies—the Unstructured Information Management Architecture[18] framework and OpenNLP[19] the natural language processing toolkit. The core cTAKES library does not handle any of the previously mentioned challenges without additional plugins. ScispaCy[20] is a practical biomedical/scientific text processing tool, which heavily leverages the spaCy² library.

²https://github.com/explosion/spaCy

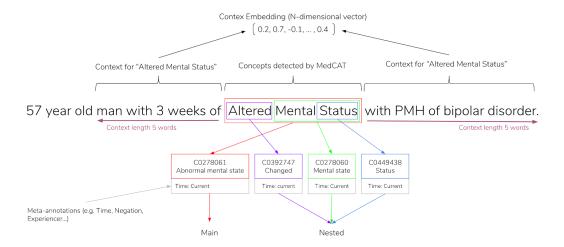


Figure 1: A fictitious example of biomedical NER+L with nested entities and further 'meta-annotations'; a further classification or 'context' applied to an already extracted concept e.g. 'time current' indicates extracted concepts are mentioned in a temporally present context. This context may also be referred to as an attribute of a recognised entity. Each one of the detected boxes (nested) has multiple candidates in the Unified Medical Language System (UMLS). The goal is to detect the entity and annotate it with the most appropriate concept ID, e.g. for the span Status, we have at least three candidates in UMLS, namely C0449438, C1444752, C1546481.

In contrast to other tools mentioned, ScispaCy is primarily a supervised model for NER with limited linking capabilities. CLAMP[21] is a comprehensive clinical NLP software that enables recognition and automatic encoding of clinical information in narrative patient reports. Similar to ScispaCy it is a supervised approach and not directly comparable to other tools mentioned here. MetaMap, BioYODIE, SemEHR, cTakes and ScispaCy only support extraction of UMLS concepts. BioPortal[22] offers a web hosted annotation API for 880 distinct ontologies. This is important for use cases that are not well supported by only the UMLS concept vocabulary[23] or are better suited to alternative terminologies[24]. However, transmitting sensitive hospital data to an externally hosted annotation web API may be prohibited under data protection legislation[25]. The BioPortal annotator is a 'fixed' algorithm so does not allow customisation or improvements through machine learning or support of non-english language corpora[26].

CLAMP, and in a limited capacity cTakes and SemEHR, support further contextualisation of extracted concepts. MetaMap, BioYODIE and scispaCy treat this as a downstream task although it is often required before extracted concepts can be used in clinical research. Med-

CAT addresses these shortcomings of prior tools allowing for flexibly clinician driven definition of concept contextualisation, supporting modern information extraction requirements for biomedical text.

2. Methods

MedCAT presents a set of decoupled technologies for developing IE pipelines for varied health informatics use cases. Fig. 2 shows a typical MedCAT workflow within a wider typical CogStack deployment. CogStack queries selectively extract relevant documents from the EHR including the structured and unstructured (freetext) notes. With MedCAT we firstly agree with clinical partners the relevant terms within a clinical terminology(1) and train MedCAT self-supervised(2). We load the model into the MedCATtrainer annotation tool(3) alongside a random sample of the extracted EHR documents(4). Clinical domain experts validate and improve the model using supervised online learning(5). Metrics demonstrate the quality of a fine-tuned MedCAT model(6) and once desired performance is reached the fine-tuned model is exported(7) and run upon the wider free-text EHR dataset(8,9), facilitating downstream clinical research through the newly structured data(10).

This section presents the MedCAT platform technologies, its method for learning to extract and contextualise biomedical concepts through self-supervised and supervised learning. Integrations with the broader CogStack ecosystem are presented alongside source code³. Finally, we present our experimental methodology for assessing MedCAT in real clinical scenarios.

2.1. The MedCAT Core Library

We now outline the technical details of the NER+L algorithm, the self-supervised and supervised training procedures and methods for flexibly contextualising linked entities.

2.1.1. Vocabulary and Concept Database

MedCAT NER+L relies on two core components:

- Vocabulary (VCB): the list of all possible words that can appear in the documents to be annotated. It is primarily used for the spell checking features of the algorithm. We have compiled our own VCB by scraping Wikipedia and enriching it with words from UMLS. Only the Wikipedia VCB is made public, but the full VCB can be built with scripts provided in the MedCAT repository (https://github.com/CogStack/MedCAT). The scripts require access to the UMLS Metathesaurus (https://www.nlm.nih.gov/research/umls).
- Concept Database (CDB): a table representing a biomedical concept dictionary (e.g. UMLS, SNOMED-CT). Each new concept added to the CDB is represented by an ID and Name. A concept ID can be referred to through multiple names with identical conceptual meanings such as heart failure, myocardial failure, weak heart and cardiac failure.

2.1.2. The NER+L Algorithm

With a prepared CDB and VCB, we perform a first pass NER+L pipeline then run a trainable disambiguation algorithm. The initial NER+L pipeline starts with cleaning and spell-checking the input text. We employ a fast and

lightweight spell checker (http://www.norvig.com/spell-correct.html) that uses word frequency and edit distance between misspelled and correct words to fix mistakes. We use the following rules:

- A word is spelled against the VCB, but corrected only against the CDB.
- The spelling is never corrected in the case of abbreviations.
- An increase in the word length corresponds to an increase in character correction allowance.

Next, the document is tokenized and lemmatized to ensure a broader coverage of all the different forms of a concept name. We used SciSpaCy[20], a tool tuned for these tasks in the biomedical domain. Finally, to detect entity candidates we use a dictionary-based approach with a moving expanding window:

- 1. Given a document d_1
- 2. Set window_length = 1 and word_position = 0
- 3. There are three possible cases:
 - (a) The text in the current window is a concept in our CDB (the concept dictionary), mark it and go to 4. Note that MedCAT can ignore token order, but only for up-to two tokens (stopwords are not counted in the two token limit).
 - (b) The text is a substring of a longer concept name, if so go to 4.
 - (c) Otherwise reset window_length to 1, increase word_position by 1 and repeat step 3
- 4. Expand the window size by 1 and repeat 3.

Steps 3 and 4 help us solve the problem of overlapping entities shown in Fig. 1.

2.2. Self-Supervised Training Procedure

For concept recognition and disambiguation, we use context similarity. Initially, we find and annotate mentions of concepts that are unambiguous, (e.g. step 3. a. in the previous expanding window algorithm) then we learn the context of marked text spans. For new documents,

³https://cogstack.atlassian.net/wiki/spaces/COGDOC/pages/733380653/Natural+Language+Processing

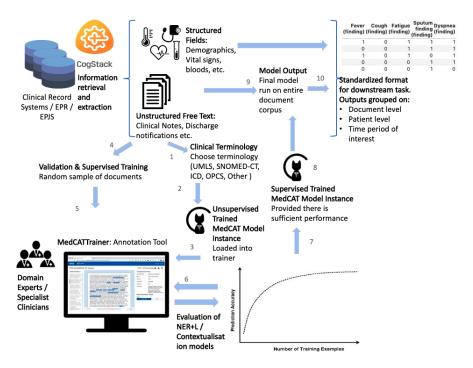


Figure 2: An example MedCAT workflow using the MedCAT core library and MedCATtrainer technologies to support clinical research.

when a concept candidate is detected and is ambiguous its context is compared to the currently learned one, if the similarity is above a threshold the candidate is annotated and linked. The similarity between the context embeddings also serves as a confidence score of the annotation and can be later used for filtering and further analysis. The self-supervised training procedure is defined as follows:

- 1. Given a corpus of biomedical documents and a CDB.
- For each concept in the CDB ignore all names that are not unique (ambiguous) or that are known abbreviations.
- Iterate over the documents and annotate all of the concepts using the approach described earlier. The filtering applied in the previous steps guarantee the entity can be annotated.
- 4. For each annotated entity calculate the context embedding V_{cntx} .
- 5. Update the concept embedding $V_{concept}$ with the context embedding V_{cntx} .

The self-supervised training relies upon one of the names assigned to each concept to be unique in the CDB. The unique name is a reference point for training to learn concept context, so when an ambiguous name appears (a name that is used for more than one concept in the CDB) it can be disambiguated. For example, the UMLS concept id:C0024117 has the unique name Chronic Obstructive Airway Disease. This name is unique in UMLS. If we find a text span with this name we can use the surrounding text of this span for training, because it uniquely links to C0024117. $\sim 95\%$ of the concepts in UMLS have at least one unique name.

The context of a concept is represented by vector embeddings. Given a document d_1 where C_x is a detected concept candidate (Equation. 1) we calculate the context embedding. This is a vector representation of the context for that concept candidate (Equation. 2). That includes a pre-set (s) number of words to the left and right of the concept candidate words. Importantly, the concept candidate words are also included in context embedding calculation as the model is assisted by knowing what words the

surrounding context words relate to.

$$d_1 = w_1 \ w_2 \ \cdots \ \widetilde{w_k \ w_{k+1}} \ \cdots \ w_n \tag{1}$$

Where:

 d_1 - An example of a document

 $w_{1..n}$ - Words in the document, or to be more specific tokens

 C_x - The detected concept candidate that matches the words w_k and w_{k+1}

$$V_{cntx} = \frac{1}{2s} \left[\sum_{i=1}^{s} V_{w_{k-i}} + \sum_{i=1}^{s} V_{w_{k+1+i}} \right]$$
 (2)

Where:

 V_{cntx} - Calculated context embedding

 V_{w_k} - Word embedding

s - Words from left and right that are included in the context of a detected concept candidate. Typically, s is set to 9 for *long* context and 2 for *short* context.

To calculate context embeddings we use the word embedding method Word2Vec[27]. Contextualised embedding approaches such as BERT[28] were also tested alongside fastText[29] and GloVe[30]. Results presented in Section 3.1 show the BERT embeddings (the Med-CAT U/MI/B configuration) perform worse on average compared to the simpler Word2Vec embeddings. Fast-Text and GloVe perform similarly to Word2Vec, therefore our default implementation uses Word2Vec for ease of implementation. We trained 300 dimensional Word2Vec embeddings using the entire MIMIC-III[31] dataset of 53,423 admissions.

Once a correct annotation is found (a word uniquely links to a CDB name), a context embedding V_{cntx} is calculated, and the corresponding $V_{concept}$ is updated using the following formula:

$$sim = max(0, \frac{V_{concept}}{\|V_{concept}\|} \cdot \frac{V_{cntx}}{\|V_{cntx}\|})$$
 (3)

$$lr = \frac{1}{C_{concent}}$$

$$V_{concept} = V_{concept} + lr \cdot (1 - sim) \cdot V_{cntx}$$

Where:

 $C_{concept}$ - Number of times this concept appeared during training

sim - Similarity between $V_{concept}$ and V_{cntx}

lr - Learning rate

The update rule is based on the Word2Vec model and aims to make the concept embedding $V_{concept}$ similar to the context in which the concept was presently found V_{cntx} . The scaling which is achieved via the cosine similarity is used to favour new contexts in which a concept appears over contexts that frequently appeared in the past.

To prevent the context embedding for each concept being dominated by most frequent words, we used negative sampling as defined in [27]. Whenever we update the $V_{concept}$ with V_{cntx} we also generate a negative context by randomly choosing K words from the vocabulary consisting of all words in our dataset. Here K is equal to 2s i.e. twice the window size for the context (s is the context size from one side of the detected concept, meaning in the positive cycle we will have s words from the left and s words from the right). The probability of choosing each word and the update function for vector embeddings is defined as:

$$P(w_i) = \frac{f(w_i)^{3/4}}{\sum_{i}^{n} f(w_i)^{3/4}}$$
 (6)

$$f(w_i) = \frac{C_{w_i}}{\sum_{j}^{n} C_{w_j}} \tag{7}$$

$$V_{ncntx} = \frac{1}{K} \sum_{i}^{K} V_{w_i}$$
 (8)

$$sim = max(0, \frac{V_{concept}}{\|V_{concept}\|} \cdot \frac{V_{ncntx}}{\|V_{ncntx}\|})$$
(9)

$$V_{concept} = V_{concept} - lr \cdot sim \cdot V_{ncntx}$$
 (10)

Where:

n - Size of the vocabulary

 $P(w_i)$ - Probability of choosing the word w_i

K - Number of randomly chosen words for the negative context

 V_{ncntx} - Negative context

2.2.1. Supervised Training Procedure

The supervised training process is similar to the selfsupervised process but given the correct concept for the extracted term we update the $V_{concept}$ using the calculated V_{ctx} as defined in Eq. 3-10. This no longer relies upon the self-supervised constraint that at least one name in the set of possible names for a concept is unique as the correct term is provided by human annotators.

2.2.2. Contextualisation of Identified and Linked Concepts: Meta-Annotations

Once a span of text is recognised and linked to a concept, further contextualisation or meta-annotation is often required. For example, a simple task of identifying all patients with a fever can entail classifying the located fever text spans that are current mentions (e.g. the patient reports a fever vs the patient reported a fever but ...), are positive mentions (e.g. patient has a high fever vs patient has no sign of fever), are actual mentions (e.g. patient is feverish vs monitoring needed if fever reappears), or are experienced by the patient (e.g. pts family all had high fevers). We treat each of these contextualization tasks as distinct binary or multiclass classification tasks Meta-annotations are equivalent to 'attributes' in cTakes parlance.

The MedCAT library provides a 'MetaCAT' component that wraps a Bidirectional-Long-Short-Term-Memory (Bi-LSTM) model trainable directly from Med-CATtrainer project exports. Bi-LSTM models have consistently demonstrated strong performance in biomedical text classification task[32, 33, 34] and our own recent work[35] demonstrated a Bi-LSTM based model outperforms all other assessed approaches, including Transformer models. MetaCAT models replace the specific concept of interest for example 'diabetes mellitus' with a generic parent term of the concept '[concept]'. The forward / backward pass of the model then learns a concept agnostic context representation of the concept allowing MetaCAT models to be used across concepts as observed in our results (Section. 3.3.3). The MetaCAT API follows standard neural network training methods but are abstracted away from end users whilst still maintaining enough visibility for users to understand when MetaCAT models have been trained effectively. Each training epoch displays training and test set loss and metrics such as precision, recall and F1. An open-source tutorial showcasing the MetaCAT features are available as part of the series of wider MedCAT tutorials⁴. Once trained, MetaCAT models can be exported and reused for further usage outside of initial classification tasks similarly to the MedCAT NER+L models.

2.3. MedCATTrainer: Annotation Tool

MedCATtrainer allows domain experts to inspect, modify and improve a configured MedCAT NER+L model. The tool either actively trains the underlying model after each reviewed document (facilitating live model improvements as feedback is provided by human users) or simply collects and validates concepts extracted by a static MedCAT model. The active learning is done on a concept level and MedCATtrainer will automatically mark some concepts as correct/incorrect and ask for user input for others where it is not confident enough. Version 0.1[4] presented a proof-of-concept annotation tool that has been rewritten and tightly integrated with the Med-CAT library, whilst providing a wealth of new features supporting clinical informatics workflows. We also provide extensive documentation ⁵ and pre-built containers ⁶ updated with each new release facilitating easy setup by informatics teams.

2.4. Datasets and Experimental Setup

2.4.1. Named Entity Recognition and Linking Open Datasets

MedCAT concept recognition and linking was validated on the following publicly datasets:

1. MedMentions[36] - consists of 4,392 titles and abstracts randomly selected from papers released on PubMed in 2016 in the biomedical field, published in the English language, and with both a Title and Abstract. The text was manually annotated for UMLS concepts resulting in 352,496 mentions. We calculate that ~ 40% of concepts in MedMentions require disambiguation, suggesting a detected span of text can be linked to multiple UMLS concepts if only the span of text is considered.

 $^{^4} https://colab.research.google.com/drive/1zzV3XzFJ9ihhCJ680DaQV2QZ5XnHa06X$

⁵https://github.com/CogStack/MedCATtrainer/blob/master/README.md

⁶https://hub.docker.com/r/cogstacksystems/medcat-tr

- ShARe/CLEF 2014 Task 2[37] we used the development set containing 300 documents of 4 types discharge summaries, radiology, electrocardiograms, and echocardiograms. We've used the UMLS annotations and ignored the attribute annotations.
- MIMIC-III[31] consists of ~ 58,000 de-identified EHRs from critical care patients collected between 2001-2012. MIMIC-III includes demographic, vital sign, and laboratory test data alongside unstructured free-text notes.

We attempted to use the SemEval 2019 shared task for the evaluation of the NER+L task⁷, but dataset access is currently under review for all requests to i2b2.

2.4.2. Clinical Use Case Datasets

Our further experiments used real world EHR data from the following UK NHS hospital Trusts:

- King's College Hospital Foundation Trust (KCH) Dataset:
 - 300 free text inpatient notes for Covid-19 positive patients, 121 Epilepsy clinic letters 2018-2019, 100 Cardiac Clinic letters, 200 echocardiographic reports, 100 CT pulmonary angiograms, 700 10k character chunks of clinical notes of patients with Diabetes Mellitus/ Gastroenteritis/ Inflammatory bowel disease/ Crohn's disease/ Ulcerative colitis for supervised training.
 - ~ 17M documents with ~ 8.8B tokens (entire KCH electronic health record from 1999 to 2020 consisting documents from 'multi-era', multi-vendor electronic health records (including iSoft iCM, EMIS Symphony and AllScripts) and multiple geographically-distributed hospital sites (Kings College Hospital, Princess Royal University Hospital and Orpington Hospital) were processed for self-supervised training.
- South London and Maudsley Foundation Trust (SLaM): 2200 free text notes for patients with a primary or secondary diagnosis of severe mental illness

- between 2007 and 2018 with each document reviewed for only a specific physical health comorbidity that may or may not appear in the note.
- University College London Hospitals Foundation Trust (UCLH) Covid-19 Datasets: 300 Free text clinical notes for Covid-19 positive or suspected patients from Jan - Apr 2020 from single-vendor electronic health record (Epic).

We used two large biomedical concept databases and prepared them as described in our source-code repository⁸, the databases are:

- UMLS 2018AB: 3.82 million concepts and 14 million unique concept names from 207 source vocabularies
- SNOMED CT UK edition: >659K concepts. The UK SNOMED CT clinical extension 20200401 and UK Drug Extension 20200325 with ICD-10 and OPCS-4 mappings.

2.4.3. Named Entity Recognition and Linking Experimental Setup

We use MedMentions[36], ShARe/CLEF[37] and MIMIC-III[31] datasets in our experiments. We denote the 'MedMentions' dataset (i.e. all concepts) and 'MedMentions Disorders Only' (i.e. only concepts grouped under the Disorder group as shown in[38]). We train MedCAT self-supervised on MIMIC-III configured with the UMLS database. We denote the version using Word2Vec embeddings as 'MedCAT' and the one using Bio_ClinicalBERT[39] embeddings as 'MedCAT BERT'.

An annotation by MedCAT is considered correct only if the exact text value was found and the annotation was linked to the correct concept in the CDB. We contrast our performance with the performance of tools presented in Section. 1.3. Appendix C provides self-supervised training configuration details.

2.4.4. Clinical Use Case NER+L Experimental Setup

For our clinical use cases we extracted SNOMED-CT terms, the official terminology across primary and sec-

⁷https://competitions.codalab.org/competitions/1935

 $^{^{8}} https://github.com/CogStack/MedCAT\#building-concept-databases-from-scratch$

ondary care for the UK National Health Health service, as this was preferred by our clinical teams over UMLS.

Fig. 3 shows our process of model training and distribution to partner hospital Trusts. Initially, we built our untrained MedCAT model using the SNOMED-CT concept vocabulary (M1), we then trained it self-supervised on the MIMIC-III dataset (M2). Next, the entire KCH EPR (17M documents with 8.8B tokens) is used for self-supervised training (M3). We collect annotations with clinician experts at KCH and train supervised (M4). We share this model with each partner hospital site where further self-supervised training (M5, M7) and specific supervised training with their respective annotation datasets (M6, M8).

Site-specific models (M3, M5, M7) are loaded into deployed instances of MedCATtrainer and configured with annotation projects to collect SNOMED-CT annotations for a range of site specific disorders, findings, symptoms, procedures and medications that our clinical teams are interested in for further research (i.e. already published work on Covid-19[5,6]). These included chronic (i.e. diabetes mellitus, ischaemic heart disease, heart failure) and acute (cerebrovascular accident, transient ischemic attack) disorders. For comparison between sites we find 14 common extracted concept groups (Appendix A) and calculate F1 scores for each concept group and reporting average, standard deviation (SD), and interquartile-range (IOR).

We shared fine-tuned MedCAT models between KCH and 2 NHS partner Trusts UCLH and SLaM. This was a collaborative effort with each hospital team only having access to their respective hospital EHR / CogStack instance. Each site collected annotated data using MedCAT-trainer, tested the original base model, a self-supervised only trained model and a final supervised trained model with the MedCATtrainer collected annotations.

2.4.5. Clinical Use Case Contextualisation Model Experimental Setup

From ongoing and published work[5, 6] we configured and collected meta-annotation training examples and trained a variety of contextualisation models per site as defined in Table. 1.

Our experiments test the effectiveness of our meta annotation modelling approach to flexibly learn contextual

Site	Task	Values	
KCH	Presence	Affirmed / Negated /	
		Hypothetical	
	Experiencer	Patient / Family /	
		Other	
	Temporality	Past / Present / Future	
UCLH	Negation	Yes / No	
	Experiencer	Yes / No	
	Problem Tempo-	Past Medical Issue /	
	rality	Current Problem	
	Certainty	Confirmed / Sus-	
		pected	
	Irrelevant	Yes / No	
SLaM	Status	Patient / Other / NA	
	Diagnosis	Yes / No	

Table 1: Meta Annotation Tasks Defined Per Site, KCH = King's College Hospital NHS Foundation Trust, UCLH = University College London Hospitals NHS Foundation Trust, SLaM = South London and Maudsley NHS Foundation Trust

cues by assessing cross-disorder and cross-site transferability (Section. 3.3.3. To assess cross-disorder transferability of each of the 11 disorder groups (as specified in Appendix A) we use the SLaM collected 'Diagnosis' dataset that consists of 100 annotations for each disorder group. We stratify our train/test sets by disorder, placing all examples for one disorder group in the test set and use the remaining disorder examples as a train set. We run this procedure 11 times so that each disorder group is tested once. We average all scores of each fold and report results.

To demonstrate cross-site transferability we derive an equivalent meta-annotation dataset from the 'Presence' (KCH) and 'Status' (SLaM) datasets as they are semantically equivalent despite having different possible annotation values. We merge 'Presence' annotations from Affirmed/Hypothetical/False to Affirmed/Other to match classes available in SLaM. We then train and test new meta annotation models between sites and datasets report average results.

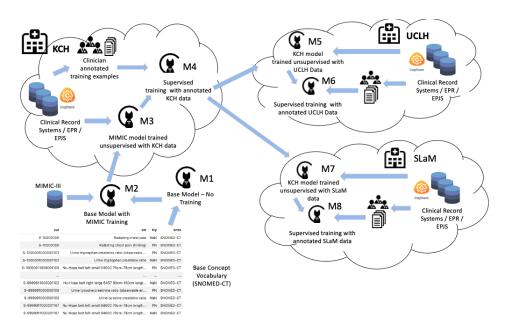


Figure 3: Model provenance for NER+L clinical use case results between datasets and sites. M1-8, showing the MedCAT model instances, the data and method of training and base model used across all sites.

3. Results

We firstly present our concept recognition and linking results, comparing performance across previously described tools in Section. 1.3 using the UMLS concept database and openly available datasets presented in Section. 2.4 We then present a qualitative analysis of learnt concept embeddings demonstrating the captured semantics of MedCAT concepts. Finally, we show real world clinical usage of the deployed platform to extract, link and contextualise SNOMED-CT concepts across multiple NHS hospital trusts in the UK.

3.1. Entity Extraction and Linking

Table 2 presents our results for self-supervised training of MedCAT and NER+L performance compared with prior tools using openly available datasets. Metrics for all the tools were calculated consistently. Bold indicates best performance. For each manual annotation we check whether it was detected and linked to the correct Unified Medical Language System (UMLS) concept. The metrics are precision (P), recall (R) and the harmonic mean of precision and recall (F1). MedCAT mod-

els were configured with UMLS concepts and trained (self-supervised) on MIMIC-III: the base version (Med-CAT) uses Word2Vec embeddings (trained on MIMIC-III), while (MedCAT BERT) uses static word embeddings from Bio_ClinicalBERT[39]. For the BERT version of MedCAT we do not use the full BERT model to calculate context representations, but only the pre-trained static word embeddings.

Our results show MedCAT improves performance compared to all prior tools across all tested metrics (excluding precision when compared to ScispaCy/CLAMP - which are supervised models). We observe that the best performance across all tools is achieved on the ShARe/CLEF dataset. However, MedCAT still improves F1 performance by 9 percentage points over the next best system. We note the simpler Word2Vec embedding (base MedCAT) on average performs better than the more expressive Bio_ClinicalBERT (BERT) embeddings. We provide a further breakdown of the range of performances by MedCAT across MedMentions and ShARe/CLEF split by UMLS semantic type in Table. 3.

Model \Dataset	Me	dMentic	tions MedMentions (Disorders Only)			nly) ShARe/CLEF			
	P	R	F1	P	R	F1	P	R	F1
SemEHR	0.252	0.165	0.200	0.295	0.499	0.371	0.680	0.623	0.650
Bio-YODIE	0.316	0.143	0.197	0.445	0.366	0.402	0.700	0.607	0.650
cTAKES	0.284	0.129	0.178	0.313	0.375	0.342	0.567	0.640	0.601
MetaMap	0.305	0.465	0.368	0.358	0.460	0.403	0.755	0.540	0.630
ScispaCy*	0.451	0.408	0.429	0.487	0.443	0.464	0.711	0.463	0.561
CLAMP*	0.324	0.067	0.110	0.533	0.236	0.327	0.772	0.447	0.566
MedCAT BERT	0.386	0.475	0.426	0.459	0.513	0.485	0.788	0.678	0.729
MedCAT	0.406	0.500	0.448	0.470	0.523	0.495	0.796	0.688	0.738
$+\delta$ (MedCAT-Best)	-0.045	0.035	0.019	-0.063	0.024	0.031	0.041	0.048	0.088

Table 2: Comparison of NER+L tools for the extraction of UMLS concepts. *The results for ScispaCy/CLAMP are not directly comparable to other tools as they are supervised models.

Comentie Tyne	Dataset	Me	dMenti	ions	ShA	ARe/CI	LEF
Semantic Type	Dataset	P	R	F1	P	R	F1
T047	Disease or Syndrome	0.59	0.59	0.59	0.87	0.75	0.80
T121	Therapeutic or Preventive Procedure	0.52	0.52	0.52	N	O DAT	Ά
T061	Pharmacologic Substance	0.49	0.38	0.43	N	O DAT	Ά
T184	Sign or Symptom	0.58	0.70	0.64	0.86	0.75	0.80
T048	Mental or Behavioral Dysfunction	0.63	0.55	0.58	0.71	0.63	0.66

 $Table \ 3: \ MedCAT \ performance \ for \ different \ UMLS \ semantic \ types \ on \ MedMentions \ and \ ShARe/CLEF$

3.2. Qualitative Analysis

For concept disambiguation the MedCAT core library learns vector embeddings from the contexts in which a concept appears. This is similar to prior work[40], although we also present a novel self-supervised training algorithm, annotation system and wider workflow. Using our learnt concept embeddings we perform a qualitative analysis by inspecting concept similarities, with the expectation that similar concepts have similar embeddings. Table. 4 shows the learnt context embeddings capture medical knowledge including relations between diseases, medications and symptoms. We train MedCAT self-supervised over MIMIC-III[31] using the entirety of UMLS, 3.82 Million concepts from 207 separate vocabularies. Training configuration details are provided in Appendix C.

3.3. Clinical Use Cases across Multiple Hospitals

The MedCAT platform was used in a number of clinical use cases providing evidence for its applicability to answer relevant, data intensive research questions. For example, we extracted relevant comorbid health conditions in individuals with severe mental illness and patients hospitalized after Covid-19 infection[5, 6, 41]. These use cases analysed data sources from 2 acute secondary/tertiary care services at King's College Hospital (KCH), University College London Hospitals (UCLH) and mental health care services South London and Maudsley (SLaM) NHS Foundation Trusts in London, UK.

The following results focus on providing an aggregate view of MedCAT performance over real NER+L clinical use-cases, meta-annotation or context classification tasks and model transferability across clinical domains (physical health vs mental health), EHR systems and concepts.

3.3.1. Entity Extraction and Linking

Table. 5 shows our results for NER+L across hospital sites, model and training configurations as described in Section 2.4.2 Our KCH annotations were collected across a range of clinicians, clinical research questions and therefore MedCATtrainer projects. This unfortunately led to a lack of resourcing to enable double annotations and calculation of inter-annotator-agreement (IIA) scores. SLaM annotations were collected by clinician

/ non-clinician pairs with average inter-annotator agreement (IIA) at 0.88, disagreements were discarded before results were calculated to ensure a gold-standard. UCLH IIA was at 0.85 between two medical students with annotation disagreements arbitrated by an experienced clinician providing the final gold-standard dataset. For our KCH results we use all annotations collected across various MedCATtrainer projects within our 14 concept groups as described in Section. 2.4.4 Both KCH and UCLH annotations contained occurrences of all 14 concept groups, SLaM annotated notes did not contain any occurrences of Dyspnea (SCTID:267036007), Pulmonary embolism (SCTID:59282003) and Chest pain (SCTID:29857009).

3.3.2. Entity Extraction and Linking Model Transferability

Table. 5 demonstrates the improved NER+L performance that arises from using domain specific data first self-supervised in MIMIC-III, then KCH. We observe further improvements with clinician expertise with supervised training using the KCH data. With model sharing to UCLH we observe a 0.044 average drop in F1 performance compared to KCH. Further self-supervised training directly on UCLH data offers minimal average performance gains but does reduce the F1 SD and IQR suggesting there is less variability in performance across concepts. Supervised training on a small (499) annotations from UCLH delivers comparable performance to our KCH trained model. For our experiments at SLaM we see average F1 performance drop initially by 0.062 using the KCH model directly on SLaM data. SLaM is a large mental health service provider where EHRs are markedly different to acute care hospitals KCH and UCLH. Interestingly, successive self-supervised (M7) and supervised training (M8) show benefits across all measures with final performance largely similar to final KCH performance.

Importantly, this suggests performance is transferred to the different hospital sites and initially only drops by ~ 0.04 . With self-supervised training and further supervised training we are able to reach KCH performance with $\sim 7 \times$ fewer manually collected examples at UCLH or $\sim 2 \times$ fewer examples at SLaM.

3.3.3. Contextualisation Model Performance

Contextualisation of extracted and linked concepts is, by design, bespoke per project. Due to this, reporting and

Disease → Medication	Disease → Procedure	Symptom → Medication
Hypertensive disease	Neoplastic Process	Fever
Metoprolol 50 MG	Chemotherapy	Levofloxacin
Metoprolol 25 MG	Radiosurgery	Vancomycin
Valsartan 320 MG	FOLFOX Regimen	Vancomycin 750 MG
Nadolol 20 MG	Chemotherapy Regimen	Azithromycin
Atenolol 100 MG	Preoperative Therapy	Levofloxacin 750 MG
Enalapril 10 MG	Anticancer therapy	Dexamethasone
Oral form diltiazem	Parotidectomy	Lorazepam
nimodipine 30 MG	Resection of ileum	Acetaminophen

Table 4: Qualitative Analysis of Learnt Concept Embeddings. UMLS concepts that have highest cosine similarity between learnt vector embeddings of concepts in **bold**. The first row defines the chosen concept and the target concept type. We have randomly chosen the most frequent concepts and presented the 8 most similar concepts for each target concept type. For example, Neoplastic Process (C0006826) and the following rows show the top 8 most similar Procedure concepts.

Model	Training Configuration	Hospital Test Site	# Annotated Examples	F1 μ	F1 SD±	F1 IQR
M1	Base - No Training	KCH	3,358	0.638	0.297	0.333
M2	Base + Self-Supervised MIMIC-III	KCH	3,358	0.840	0.109	0.150
M3	Base + Self-Supervised KCH	KCH	3,358	0.889	0.078	0.103
M4	KCH Self-Supervised + KCH Supervised	KCH	3,358	0.947	0.044	0.051
M4	KCH Self-Supervised + KCH Supervised	UCLH	499	0.903	0.103	0.112
M5	KCH Self-Supervised + KCH Supervised	UCLH	499	0.905	0.079	0.034
	+ UCLH Self-Supervised					
M6	KCH Self-Supervised + KCH Supervised	UCLH	499	0.926	0.060	0.086
	+ UCLH Self-Supervised + UCLH Super-					
	vised					
M4	KCH Self-Supervised + KCH Supervised	SLaM	1,425	0.885	0.095	0.088
M7	KCH Self-Supervised + KCH Supervised	SLaM	1,425	0.907	0.047	0.082
	+ SLaM Self-Supervised					
M8	KCH Self-Supervised + KCH Supervised	SLaM	1,425	0.945	0.029	0.025
	+ SLaM Self-Supervised + SLaM Super-					
	vised					

Table 5: NER+L Results Across Hospitals. MedCAT NER+L performance for common disorder concepts defined in Appendix A by clinical teams. Annotations for supervised learning are used as test sets for models M1, M2, M3, M5, M7. Average performance on a 10 fold cross-validation with a held out test set is reported for models M4, M6, M8. KCH: Kings College Hospital; UCLH: University College Hospital; SLaM: South London and The Maudsley NHS Foundation Trusts.

comparing results across studies / sites is difficult as the definitions of tasks and concepts collected are different and therefore output trained models are bespoke. Table. 6a shows aggregate performance at each site, and Table. 6b-6c show further experiments for cross-site and cross-concept model transferability.

We achieve strong weighted (0.892-0.977) / macro (0.841-0.860) F1 performance across all tasks and sites, with breakdown of each metric per site/task available in Appendix D. We report average macro and weighted F1 score demonstrating the variation in performance due to unbalanced datasets across most tasks.

For cross-concept transferability, Table. 6b shows a decrease in performance when stratifying by concept. However, we still observe a relatively high 0.82-0.85 score suggesting the model is capable of learning disorder independent representations that distinguish the classification boundary for the 'Diagnosis' task, not just the disorder specific contexts.

Our cross-site transferability results, Table 6c, suggest the 'Status' context model that is trained on cross site (i.e. KCH) data then fine-tuned on site specific data (i.e. SLaM) performs better (+ 0. 0.08 Macro / + 0.09 Weighted F1) compared with training on only the SLaM site specific training only (i.e. comparing row 3 and 4).

4. Discussion

4.1. Named Entity Recognition and Linking

Our evaluation of MedCAT's NER+L method using self-supervised training was bench-marked against existing tools that are able to work with large biomedical databases and are not use-case specific. Our datasets and methods are publicly available making the experiments transparent, replicable, and extendable. With the Med-Mentions dataset, using only self-supervised learning, our results in 3.1, demonstrate an improvement on the prior tools for both disorder detection (F1=0.495 vs 0.464) and general concept detection (F1=0.448 vs. 0.429). We observe all tools perform best with the ShARe/CLEF dataset. We suggest this broadly due to the lack of ambiguity and the more clinical setting allowing alternative systems to also perform reasonably well.

We now discuss the result between our BERT and regular (Word2Vec) configured MedCAT models. Generally

BERT, a deep neural embedding model, performs well for a range of downstream tasks[28] better than older approaches such as Word2Vec, i.e. a shallow neural embedding. We believe this due to our use of pre-trained static BERT embeddings that: 1) are not specifically trained to produce similar values for words appearing in a similar context, 2) Sub-word tokenization might be problematic if the tokenizer was trained on a non-medical dataset (no matter whether it was fine-tuned later on MIMIC-III, pubmed or similar).

The general concept detection task with MedMentions is difficult due to: the larger number of entities to be extracted, the rarity of certain concepts and the often highly context dependent nature of some occurrences. Recent work[42] highlights examples of ambiguous texts within the MedMentions dataset such as 'probe' with 7 possible labels ('medical device', 'indicator reagent or diagnostic aid' etc.) Further work[40] also showed a deep learning approach (BioBERT+) that achieved F1=0.56. When MedCAT is provided with the same supervised training data we achieve F1=0.71. We find our improved performance is due to the long tail of entities in MedMentions that lack sufficient training data for methods such BioBERT to perform well.

Our qualitative inspection of the learnt concept embeddings, 3.2 indicate learnt semantics of the target medical domain. This result mirrors similar findings reported in fields such as materials science[43]. Recent work has suggested an approach to quantity the effectiveness of learnt embeddings[38] in representing the source ontology. However, this relies on concept relationships to be curated before assessment requiring clinical guidance that may be subjective in the clinical domain. We leave a full quantitative assessment of the learnt embeddings to future work for this reason.

As more concepts are extracted the likelihood of concepts requiring disambiguation increases, particularly in biomedical text[44]. Estimating the number of training samples for successful disambiguation is difficult but based on our experiments we need at least 30 occurrences of a concept in the free text to perform disambiguation. We provide more details in Appendix B.

Finally, we note that there are no limitations algorithmically for MedCAT to support languages other than our tested language, English. As MedCAT uses a concept dictionary/vocab for NER+L, if there are existing re-

Table 6: Contextualisation Model Results

Site	Task	# Annotated examples	Macro F1	Weighted F1
KCH	Presence	37,310	0.846	0.929
	Temporality	18,670	0.803	0.943
	Experiencer	18,670	0.867	0.959
SLaM	Patient Diagnosis	1,152	0.904	0.913
	Status	1,152	0.775	0.812
UCLH	Negation	4,400	0.836	0.970
	Experiencer	4,400	0.940	0.996
	Problem Temporality	4,350	0.848	0.970
	Certainty	4,160	0.836	0.970
	Irrelevant	4,390	0.835	0.969

(a) Site Specific Contextualisation Model Performance. Weighted / Macro average F1 Meta annotation model performance custom defined and trained per site - detailed definitions are provided in Appendix D. Task definitions are uniquely defined at each site, e.g. Experiencer at KCH considers the values patient / family / other whereas Experiencer at UCLH only considers the value patient / other. Status at SLaM considers the values affirmed / other and Certainty at UCLH considers the values confirmed / suspected. We include all concepts of interest as defined under clinician guidance at each site, therefore site-to-site comparison in performance cannot be made.

Site	Task	Train / Test Split	Macro F1	Weighted F1
SLaM	Diagnosis	Concept Stratified	0.82	0.85
SLaM	Diagnosis	Random	0.90	0.91

(b) Cross Site Transferability Performance. 11 fold concept stratified CV vs randomized CV for SLaM 'Diagnosis' contextualisation task performance. The 11 concepts were selected from NER+L experiment concepts available at SLaM (Supplementary Table 1). The 'Diagnosis' task at SLaM was used as this was our most balanced dataset between all tasks and concepts collected.

Site	Trained on	# Annotated Examples	Macro F1	Weighted F1
KCH	KCH	37,310	0.89	0.93
SLaM	KCH	37,310	0.71	0.91
SLaM	SLaM	1,152	0.77	0.87
SLaM	KCH + SLaM	38,462	0.85	0.96

⁽c) Cross-site transferability of the MetaCAT model for Presence (at KCH) / Status (at SLaM converted to values of Affirmed/Other) - as that was the only task that existed across sites. Results show 10 fold CV where applicable - e.g. row 2 is direct testing of the KCH model on SLaM data, so no training is performed on the SLaM side.

sources (e.g. SNOMED-CT has already been translated into Spanish, Dutch, Swedish and Danish) they can be used directly for these languages with likely similar results. Alternatively, users could build their own custom concept dictionary (CDB) for their language of choice. Meta-annotation or contextualisation models also do not have language specific features, i.e. English, and would also likely perform well as they only rely on bi-directional context from supervised examples to make predictions.

4.2. Clinical Use Cases

MedCAT models and annotated training data have been implemented to be easily shared and reused, facilitating a federated learning approach to model improvement and specialisation with models brought to sensitive data silos. Our results in Section. 3.3 demonstrate that we are able directly apply models trained at one hospital site (KCH) to multiple other sites, and clinical domains (physical vs mental health datasets) with only a small drop in average F1 (0.044 at UCLH, 0.062 at SLaM), and after small amount of additional site specific training, we observe comparable performance (-0.021 at UCLH, -0.002 at SLaM).

We also highlight that separate teams were able to deploy, extract and analyse real clinical data using the tools as is by following provided examples, documentation and integrations with the wider CogStack ecosystem. Academic engineering projects are often built to support a single research project, however MedCAT and the CogStack ecosystem are scalable fit-for-purpose locally-tunable solutions for teams to derive value from their data instead of being stalled by poor quality code or lack of documentation. This means the model is broadly useful with top-up tuning also available for specific scenarios, domains and hospitals.

Each hospital site and clinical team freely defined the set of contextualisation tasks and associated values for each task. On aggregate our results show performance is consistently strong across all sites and tasks (Macro F1: 0.841-0.860, Weighted F1: 0.892-0.977). With many of the tasks the annotated datasets are highly unbalanced. For example, the 'Presence' task at KCH, disorders are often only mentioned in the EHR if they are affirmed (e.g. "...pmhx: TIA..."), and only rarely are hypothetical (e.g. "...patient had possible TIA...") or negated terms (e.g. "...no sign of TIA...") encountered. This explains

the differences in performance when reporting macro vs weighted average F1 score. We would expect generalization performance to lie between these reported metrics.

4.3. Limitations

MedCAT is able to employ a self-supervised training method as the initial pass of the algorithm uses a given unique name to learn and improve an initial concept embedding. However, if the input vocabulary linked to the concepts inadequately specifies possible names or the given names of a concept rarely appear in the text then improvements can only occur during standard supervised learning. The main limitation of our approach is that it greatly depends on the quality of the concept database. Large biomedical concept databases (e.g. UMLS) however have a well specified vocabulary offering many synonyms, acronyms and differing forms of a given concept.

A limitation of our concept embedding approach is if different concepts appear in similar contexts disambiguation and linking to the correct concept can be difficult. For example, 'OD' can link to 'overdose' or 'once daily', both referring to medications with very different implications. We have rarely seen this problem during real-world corpus. Our approach can also struggle if concepts appear in many varying contexts that are rarely seen or annotated for. With each new context updating the underlying concept embedding this may decrease performance of the embedding.

Supervised learning requires training data to be consistently labelled. This is a problem in the clinical domain that consists of specialised language that can be open to interpretation. We recommend using detailed annotation guidelines that enumerate ambiguous scenarios for annotators.

4.4. Future Work

MedCAT uses a vocabulary based approach to detect entity candidates. Future work could investigate the expansion of such an approach with a supervised learning model like BERT[28]. The supervised learning model would then be used for detection of entity candidates that have enough training data and to overcome the challenge of detecting new unseen forms of concept names. The vocabulary based approach would cover cases with insufficient annotated training data or concepts that have few

different names (forms). The linking process for both approaches would remain the same self-supervised.

Our self-supervised training over the ~20 year KCH EHR, as described in Section. 2.4, took over two weeks to complete. Future work could improve the training speed by parallelizing this process since concepts in a CDB are mostly independent of one another. Further work could address effective model sharing, allowing subsequent users/sites to benefit from prior work, where only model validation and fine-tuning is required instead of training from scratch.

Finally, ongoing work aims to extend the MedCAT library to address relation identification and extraction. For example, linking the extracted drug dosage / frequency with the associated drug concept, or identifying relations between administered procedures and following clinical events.

5. Conclusions

This paper presents MedCAT a multi-domain clinical natural language processing toolkit within a wider ecosystem of open-source technologies namely CogStack.

The biomedical community is unique in that considerable efforts have produced comprehensive concept databases such as UMLS and SNOMED-CT amongst many others. MedCAT flexibly leverages these efforts in the extraction of relevant data from a corpus of biomedical documents (e.g. EHRs). Each concept can have one or more equivalent names, such as abbreviations or synonyms. Many of these names are ambiguous between concepts. The MedCAT library is based upon a simple idea: at least one of the names for each concept is unique and given a large enough corpus that name will be used in a number of contexts. As the context is learned from the unique name, when an ambiguous name is later detected, its context is compared to the learnt context, allowing us to find the correct concept to link. By comparing the context similarity we can also calculate confidence scores for a provided linked concept.

With MedCAT we have built an effective, high performance IE algorithm demonstrating improved performance over prior solutions on open access datasets. We have commoditised the development, deployment and implementation of IE pipelines with supporting technologies

MedCATtrainer / MedCATservice supporting the transfer, validation, re-use and fine-tuning of MedCAT models across sites, clinical domains and concept vocabularies. MedCAT deployments are enabled by extensive documentation, examples, APIs and supporting real world clinical use cases outlined in prior published work.

Overall, MedCAT is built to enable clinical research and potential improvements of care delivery by leveraging data in existing clinical text. Currently, MedCAT is deployed in a number of hospitals in the UK in silo or as part of the wider CogStack ecosystem, with wide-ranging use cases to inform clinical decisions with real-time alerting, patient stratification, clinical trial recruitment and clinical coding. The large volume of medical information that is captured solely in free text is now accessible using state-of-the-art healthcare specific NLP.

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Data Availability

Data for reproduction of experiments for the assessment for the core NER+L in comparison with are available from prior work (MedMentions, ShARe/CLEF 2014 Task 2, MIMIC-III). Due to the confidential nature of free-text data, we are unable to make patient-level data available. Interested readers should contact the authors to discuss feasibility of access of de-identified aggregate data consistent with legal permissions.

Code Availability

All code for running the experiments, the toolkit and integration with wider CogStack deployments are available here:

 $\label{eq:medCAT:https://github.com/CogStack/MedCAT} MedCAT: https://github.com/CogStack/MedCAT$

MedCAT Tutorials/Example Code: https://github.com/CogStack/MedCAT/tree/master/tutorial

MedCATtrainer: https://github.com/CogStack/MedCATtrainer

MedCATtrainer Examples: https://github.com/CogStack/MedCATtrainer/tree/master/docs

MedCATservice: https://github.com/CogStack/
MedCATservice

CogStack: https://github.com/CogStack/CogS
tack-Pipeline

Declaration of Interests

JTHT received research support and funding from InnovateUK, Bristol-Myers-Squibb, iRhythm Technologies, and holds shares ¡£5,000 in Glaxo Smithkline and Biogen.

Data Access Ethics

NER+L experiments use freely available open-access datasets accessible by data owners. **SNOMED-CT** and UMLS licences were obtained by all users at all hospital sites. Site specific ethics is listed below. KCH: This project operated under London South East Research Ethics Committee approval (reference 18/LO/2048) granted to the King's Electronic Records Research Interface (KERRI); specific work on research on natural language processing for clinical coding was reviewed with expert patient input on the KERRI committee with Caldicott Guardian oversight. Direct access to patient-level data is not possible due to risk of reidentification, but aggregated de-identified data may be available subject to legal permissions. UCLH: UCLH is deploying CogStack within its records management infrastructure and is growing its capacity to annotate its clinical records as part of wider work for routine curation. The work at UCLH described here is a service evaluation

that represents MedCAT's annotation of the records. Access to the medical records will not be possible given their confidential nature. SLaM: This project was approved by the CRIS Oversight Committee which is responsible for ensuring all research applications comply with ethical and legal guidelines. The CRIS system enables access to anonymised electronic patient records for secondary analysis from SLaM and has full ethical approvals. CRIS was developed with extensive involvement from service users and adheres to strict governance frameworks managed by service users. It has passed a robust ethics approval process acutely attentive to the use of patient data. Specifically, this system was approved as a dataset for secondary data analysis on this basis by Oxfordshire Research Ethics Committee C (08/H06060/71). The data is de-identified and used in a data-secure format and all patients have the choice to opt-out of their anonymized data being used. Approval for data access can only be provided from the CRIS Oversight Committee at SLaM.

Author Contributions

ZK, TS, JT, RD, AS, AF conceived the study design ZK, TS, AS, LR, KN performed data processing and software development

ZK, TS, JT, AS, AM, LZ, ADS performed data validation

RD, JT, RS, ZI, AR, DB, ZI, RB, MPR, ADS, AM performed critical review

TS, ZK, AS, LR, ZI, RB, DB, AM, RD wrote the manuscript

Appendices

Appendix A. SNOMED-CT Groupings

Each group was defined with expert clinical guidance. S-267036007 - Dyspnea (finding), S-59282003 - Pulmonary embolism, (disorder) S-29857009 - Chest pain (finding) do not appear in the SLaM annotations for supervised training.

Table A.1: SNOMED-CT concept level groupings for clinical use cases

Container Concept	Concepts			
	S-44054006 - Diabetes mellitus type 2 (disorder)			
	S-46635009 - Diabetes mellitus type 1 (disorder)			
S-73211009 - Diabetes mellitus(disorder)	S-422088007 - Disorder of nervous system co-occurrent and due to di-			
	abetes mellitus (disorder)			
	S-25093002 - Disorder of eye co-occurrent and due to diabetes mellitus			
	(disorder)			
	S-73211009 - Diabetes mellitus (disorder)			
	S-128404006 - Right heart failure (disorder)			
	S-48447003 - Chronic heart failure (disorder)			
C 04114007 II (6'1 (1' 1)	S-56675007 - Acute heart failure (disorder)			
S-84114007 -Heart failure (disorder)	S-85232009 - Left heart failure (disorder)			
	S-42343007 - Congestive heart failure (disorder)			
	S-84114007 - Heart failure (disorder)			
	S-413439005 - Acute ischemic heart disease (disorder)			
G 414545000 T 1 1 1 1	S-413838009 - Chronic ischemic heart disease (disorder)			
S-414545008 - Ischemic heart disease (disorder)	S-194828000 - Angina (disorder)			
disease (disorder)	S-22298006 - Myocardial infarction (disorder)			
	S-414545008 - Ischemic heart disease (disorder)			
	S-31992008 - Secondary hypertension (disorder)			
C 20241002 Hymantomaiya digandan	S-48146000 - Diastolic hypertension (disorder)			
S-38341003 - Hypertensive disorder,	S-56218007 - Systolic hypertension (disorder)			
systemic arterial (disorder)	S-59621000 - Essential hypertension (disorder)			
	S-38341003 - Hypertensive disorder systemic arterial (disorder)			
0.10645005 01 1 1 1 1	S-195951007 - Acute exacerbation of chronic obstructive airways dis-			
S-13645005 - Chronic obstructive lung disease (disorder)	ease (disorder)			
iung disease (disorder)	S-87433001 - Pulmonary emphysema (disorder)			
	S-13645005 - Chronic obstructive lung disease (disorder)			
S-195967001 - Asthma (disorder)	S-195967001 - Asthma (disorder)			
S-709044004 - Chronic kidney	S-723190009 - Chronic renal insufficiency (disorder)			
disease (disorder)	S-709044004 - Chronic kidney disease (disorder)			
,	S-25133001 - Completed stroke (disorder)			
	S-371040005 - Thrombotic stroke (disorder)			
	S-371041009 - Embolic stroke (disorder)			
S-230690007 - Cerebrovascular	S-413102000 - Infarction of basal ganglia (disorder)			
accident (disorder)	S-422504002 - Ischemic stroke (disorder)			
	S-723082006 - Silent cerebral infarct (disorder)			
	S-1078001000000105 - Haemorrhagic stroke (disorder)			
	S-230690007 - Cerebrovascular accident (disorder)			
S-266257000 - Transient ischemic attack	S-266257000 - Transient ischemic attack (disorder)			
(disorder)				
(, , , , , , , , , , , , , , , , , , ,	S-352818000 - Tonic-clonic epilepsy (disorder)			

S-84757009 - Epilepsy (disorder)

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Container Concept	Concepts			
	S-19598007 - Generalized epilepsy (disorder)			
	S-230456007 - Status epilepticus (disorder)			
	S-509341000000107 - Petit-mal epilepsy (disorder)			
	S-84757009 - Epilepsy (disorder)			
S-49436004 - Atrial fibrillation (disorder)	S-49436004 - Atrial fibrillation (disorder)			
S-267036007 - Dyspnea (finding)	S-267036007 - Dyspnea (finding)			
S-59282003 - Pulmonary embolism (disor-	S-59282003 - Pulmonary embolism (disorder)			
der)				
S-29857009 - Chest pain (finding)	S-29857009 - Chest pain (finding)			

Number of examples per concept	F1 on Test
1	0.74
5	0.81
10	0.82
30	0.86

Table B.2: Relation between the number of training examples and performance of MedCAT concept disambiguation.

Appendix B. Estimating Example Counts for Sufficient F1 Score

To test the required number of examples to achieve a high enough F1 score, we created a mini-dataset from MedMentions. It contains two concepts: C0018810 (Heart Rate) and C2985465 (Hazard Ratio). Both concepts have a unique name and the ambiguous abbreviation HR that can link to either one. We chose these two concepts, as the abbreviation HR is the most frequent ambiguous concept in MedMentions, given the requirement that it must be ambiguous. Our dataset consists of:

- 60 training examples (30 per concept). In each example the full name of the concept was used, see below MedMentions Text Extracts.
- 174 test examples, each document contains the ambiguous abbreviation HR, see below MedMentions Text Extracts.

We have tested the performance for different sizes of the training set: 1, 5, 10 and 30. If we set the training set size to e.g. 5, we split the full training set into 6 parts (in total the training set has 30 examples per concept), each containing 5 examples per concept. Then we check the performance for each part and report the average over the 6 parts, see Table B.2.

Appendix C. Self-Supervised Training Configuration

Appendix C.1. Self-Supervised Training Configuration

MedCAT was configured for self-supervised training across experiments presented in Section. 2.1 as follows:

- Misspelled words were fixed only when 1 change away from the correct word for words under 6 characters, and 2 changes away for words above 6 characters.
- For each concept we calculate long and short embeddings and take the average of both. The long embedding takes into account s = 9 words from left and right (as shown in Equation 2). The short embedding takes into account s = 2 words from left and right. The exact numbers for s were calculated by testing the performance of all possible combinations for s in the range [0, 10].
- The context similarity threshold used for recognition is 0.3 unless otherwise specified. This means for a given concept candidate, or sequence of words, to be recognised and linked to the given concept the concept similarity provided by Equation 2 would be greater than 0.3.

Appendix C.2. Qualitative Analysis Training Configuration

We train MedCAT self-supervised over MIMIC-III using the entirety of UMLS, 3.82 Million concepts from 207 separate vocabularies. We use 2.4M clinical notes (nursing notes, notes by clinicians, discharge reports etc.) on a small one-core server taking approximately 30 hours to complete.

Appendix D. Contextualisation Task Results Per Site

Appendix D.1. Contextualisation Results Breakdown for KCH

Aggregate results for each defined meta-annotation at KCH. Performance is aggregated over all extracted concepts listed in Appendix A. We defined the following meta-annotation tasks:

- Presence: is the concept affirmed, negated or hypothetical, values: [Affirmed, Negated, Hypothetical]
- Experiencer: is the concept experienced by the patient or other, values: [Patient / Family / Other]
- Temporality: is the concept in the past, present or future, values: [Past, Recent, Future]

Levels of fibrin degradation products (FDP), D-dimer, fibrinogen, the ratio of FDP to fibrinogen, the ratio of D-dimer to fibrinogen, systolic blood pressure, **heart rate**, the Glasgow Coma Scale, pH, base excess, hemoglobin and lactate levels, the pattern of pelvic injury, and injury severity score were measured at hospital admission, and compared between the two groups.

NEAC was assessed by a validated food frequency questionnaire collected at baseline. We categorized the distribution of NEAC into sex - specific quartiles and used multivariable adjusted Cox proportional hazards regression models to estimate **hazard ratios** with 95% confidence intervals (95% CI).

In the overall population radical nephrectomy was not associated with an increased risk of other cause mortality on multivariable analysis compared to nephron sparing surgery (**HR** 0.91, 95% CI 0.6-1.38, p = 0.6).

Figure B.4: MedMentions Text Extracts: Three samples from the dataset used to test the amount of training samples needed for disambiguation to work. First example is a training case for the concept C0018810, second for C2985465 and third is used to test the disambiguation performance.

Table D.3: Meta Annotation Results at KCH

CLS	F	P	R	Support Test (10% of total)
Hypothetical	0.756	0.797	0.72	360
Negated	0.865	0.878	0.852	440
Affirmed	0.955	0.961	0.951	2930
Macro	0.86	0.875	0.846	3731
Weighted	0.927	0.927	0.929	3731

(a) Presence average 10 fold CV 90/10 ratio

CLS	F1	P	R	Support Test (10% of total)
Family	0.801	0.865	0.751	13
Other	0.823	0.838	0.809	205
Patient	0.977	0.975	0.98	1649
macro	0.867	0.893	0.847	1867
weighted	0.959	0.959	0.959	1867

(b) Experiencer average 10 fold CV 90/10 ratio

CLS	F	P	R	Support Test (10% of total)
Recent	0.969	0.964	0.94	1655
Past	0.771	0.807	0.74	162
Future	0.667	0.706	0.74	50
macro	0.803	0.825	0.783	1867
weighted	0.943	0.943	0.945	1867

⁽c) Temporality average 10 fold CV 90/10 ratio

Appendix D.2. Meta Annotation Results Breakdown for SLaM

Aggregate results for each defined meta-annotation at SLaM. Performance is aggregated over all extracted concepts listed in Appendix A. We defined the following meta-annotation tasks:

- Status: is the concept affirmed to be affecting the patient or not, values: [Patient / Other / NA]
- Diagnosis: is the concept a diagnosis related to the patient, or not, values: [Yes, No]

Appendix D.3. Meta Annotation Results Breakdown for UCLH

Aggregate results for each defined meta-annotation at UCLH. Performance is aggregated over all extracted concepts listed in Appendix A. We defined the following meta-annotation tasks:

- Negation: is the concept negated or not, values: [Yes / No]
- Experiencer: is the concept experienced by the patient or not, values: [Patient, Other]
- Problem Temporality: is the concept referring to a historical mention, values [Past Medical Issue, Current Problem]

Table D.4: Meta Annotation Results at SLaM

CLS	F	P	R	Support Test (10% of total)
NA	0.873	0.869	0.878	43
Other	0.544	0.663	0.475	7
Affirmed	0.908	0.893	0.924	60
Macro	0.775	0.812	0.757	109
Weighted	0.873	0.874	0.873	109

(a) Status average 10 fold CV 90/10 ratio

				Support Test
CLS	F	P	R	(10% of total)
Yes	0.931	0.935	0.926	68
No	0.872	0.889	0.880	39
Macro	0.904	0.908	0.905	109
Weighted	0.913	0.912	0.913	109

(b) Diagnosis average 10 fold CV 90/10 ratio

- Certainty: is the concept confirmed to be present, values: [Confirmed, Suspected]
- Irrelevant: is the concept relevant, values: [Yes, No]

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Table D.5: Meta Annotation Results at UCLH

CLS	F	P	R	Support Test (10% of total)
Yes	0.896	0.895	0.900	46
No	0.688	0.767	0.631	394
Macro	0.836	0.767	0.631	440
Weighted	0.970	0.969	0.971	440

(a) Negation: average 10 fold CV 90/10 ratio						
CLS	F	P	R	Support Test (10% of total)		
Other	0.681	0.883	0.65	3		
Patient	0.998	0.997	0.999	437		
Macro	0.940	0.940	0.825	440		
Weighted	0.996	0.996	0.996	440		

(b) Experiencer: average 10 fold CV 90/10 ratio

F	P	R	Support Test (10% of total)
0.710	0.758	0.676	23
0.985	0.981	0.988	412
0.848	0.870	0.832	435
0.970	0.969	0.971	435
	0.710 0.985 0.848	0.710 0.758 0.985 0.981 0.848 0.870	F P R 0.710 0.758 0.676 0.985 0.981 0.988 0.848 0.870 0.832 0.970 0.969 0.971

(c) Problem Temporality: average 10 fold CV 90/10 ratio

CLS	F	P	R	Support Test (10% of total)
Confirmed	0.985	0.980	0.989	395
Suspected	0.688	0.767	0.631	21
Macro	0.836	0.874	0.810	416
Weighted	0.970	0.970	0.971	416

(d) Certainty: average 10 fold CV 90/10 ratio

CLS	F	P	R	Support Test (10% of total)
Yes	0.685	0.846	0.579	24
No	0.986	0.976	0.994	415
Macro	0.835	0.911	0.787	439
Weighted	0.969	0.970	0.972	439

(e) Irrelevant: average 10 fold CV 90/10 ratio

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