SNOMED CT Web Series

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Experiences from automating hospital-wide SNOMED-CT extraction

October 19, 2022 | 14:00 UTC
Contents

- Complexity of Hospital Data
- What is Clinical Natural Language Processing (NLP)?
- Clinical NLP Workflows
- Project Examples
Background to a typical NHS Hospital

Electronic patient records (EPR)

- Big Data problem -> Volume, Variety, Velocity, and Veracity
- Developed primarily for direct patient care
- Majority of clinical information is within clinical narratives (unstructured data)
- Domain specialist knowledge is required
Queryable dataset
Unstructured, heterogeneous sources data

Clinical Record systems
Intensive care unit
Neurology
Cardiology

Hospital

CogStack

Rasterization
e.g. doc → png and pdf

Unstructured Data

Reliable Batch Process

Structured Data

Harmonization
binary doc → xhtml
Image → OCR→ xhtml

ElasticSearch Index

Filesvever

Centralized Medical records
Data Lake Availability

Unstructured, heterogeneous sources data

Queryable dataset

https://github.com/CogStack
CogStack

- Near real-time EPR data
- Allows users to query EPR using key words
- Each row represents one document
- `body_analysed` holds the content of the document
Dear Dr,

This patient attended the Emergency Department on

Triage Assessment: Witnessed tonic-clonic seizure by a cab driver 7 min / nil injuries post or incontinence LAs OBS: R16
sats 99%con air F96reg bp108/72 BM6.6 T35.6 PEARL GCS 14 PMHx3

Seen By: Doctor,

Investigations:
- Full Blood Count
- Renal/Liver/Urea

Working Diagnosis: Convulsions, epileptic / Epilepsy, unspecified

Referrals: No referrals recorded

Outcome: Discharged

Comments for GP:

If you have any queries, please contact us.

Yours sincerely,

The ED Team
What’s the Challenge?

Electronic patient record

Clinic letter Extract example

Dear Mr. TGF:

Mr. XY is a client of our Epilepsy clinic. He suffers from juvenile myoclonic epilepsy and was medically screened by you as a driver.

Your assessment of a diagnosis of jme has resulted in XY being denied the job and we need to point out the following:

DHX:
- allergic to chlorquine
- oxCarbaZePine 1200 mg
- keppra 1500 mg BID

• Records clinically valuable information.
• Unstructured – no data standardization requirements
• Difficult to extract information

Q) Does the patient have an Epilepsy diagnosis?
What’s the Challenge?

Electronic patient record

Clinic letter Extract example

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Q) Does the patient have an Epilepsy diagnosis?

- “Epilepsy” Keyword search is not ideal
Research Web Series

What’s the Challenge? – Accurate extraction from Text

Electronic patient record

London Hospital NHS Foundation Trust

Clinic letter Extract example

Dear Mr. TGF:

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oxiCarbaZEpine 1200 mg
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• Unstructured – no data standardization requirements
• Difficult to extract information

Q) Does the patient have an Epilepsy diagnosis?

• Ideally you would want a context dependent extraction of all Epilepsy-related terms.
• Possible to extract manually but huge amount of work!!!
What’s the challenge?

- Unstructured text (no data standardization requirements)
  - Misspellings -> The patient had a _siexure_.
  - Acronyms -> The pt experienced a tc sz in ed.
  - Synonyms -> The pt experienced a _grand mal seizure_ in ed
  - Incomplete -> BIBA 1840, PMHx Epilepsy, ?seizure
  - Ambiguous -> The patient had a _fit_.

- Must be labelled and annotated for “machine interpretable” analytics. i.e., tabulated or structured
Introduction to Natural Language Processing

**NLP** – how computers process and analyze natural language/free text information.

**Rule-based** – approach based on linguistic structures that imitates the human way

<table>
<thead>
<tr>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quick to write and fast to run</td>
<td>Can be challenging to identify all rules for a use case</td>
</tr>
<tr>
<td>High precision</td>
<td>Rules can become very complex and contradicting</td>
</tr>
</tbody>
</table>

**Machine-learning based** “Understand” language without being explicitly programmed but learns through examples

<table>
<thead>
<tr>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Easy to Scale</td>
<td>Requires lots of training data</td>
</tr>
<tr>
<td>“Learnability” without being explicitly programmed</td>
<td>Potentially difficult to debug</td>
</tr>
</tbody>
</table>
Named-Entity Recognition

- NLP task which aims to identifies key information in a text

- Open-source Ecosystem:
What is MedCAT?

MedCAT - MEDical Concept Annotation Toolkit

• A simple entity extraction and linking tool
• Free and Open-Source
• Disambiguates unique concepts based on context
• Leverages SNOMED CT concept standardization and hierarchies

Aim/Purpose:

• To automate and standardize the accurate extraction of clinically valuable information from unstructured text documents

Web app Demo

Try it out yourself!

Paper: https://doi.org/10.1016/j.artmed.2021.102083
Github: https://github.com/CogStack/MedCAT
MedCAT Demonstration

Try Out Model

Type text here

Try it out yourself!
MedCAT components

Vocabulary (Vocab) — The vocabulary is used for spell checking and word embeddings. It is made so that it can use any type of word embeddings (from Word2Vec to BERT). If your dataset is from a very specific domain, it is usually recommended that you create your embeddings. `vocab.py`

Concept Database (CDB) — The concept database contains all the concepts of interest for a specific case. In medical applications, large databases SNOMED are standard, which are then filtered down to the required concepts. MedCAT is made to work with any kind of concept database no matter how big/small. cdb.py to create a cdb this is found in the cdb_maker.py cdb is saved as .dat file

  → Config — This is stored within the cdb.config. It contains a variety of configurations. From filters, NER, linking, preprocessing, logging etc. `config.py`

  → SpaCy model — Used primarily and solely for preprocessing. Specifically used for tokenization. Although this model itself has other features, many of these features are disabled by default in the config. Model is specified here: `cat.cdb.config.general['spacy_model'] = 'en_core_web_md'`

Primarily used in preprocessing.tokenizers.py
## Visualization of Concept Embeddings

**Assumption:** If words appear in a similar context, we can assume that they represent similar ideas (describe similar concepts or have a similar meaning).

<table>
<thead>
<tr>
<th>Disease -&gt; Medication</th>
<th>Disease -&gt; Procedure</th>
<th>Symptom -&gt; Medication</th>
<th>Symptom -&gt; Everything</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypertensive disease</td>
<td>Cancer</td>
<td>Fever</td>
<td>Hemorrhage</td>
</tr>
<tr>
<td>Metoprolol 50 MG</td>
<td>Chemotherapy</td>
<td>Levofoxacin</td>
<td>Intracranial Hemorrhages</td>
</tr>
<tr>
<td>Metoprolol 25 MG</td>
<td>Radiosurgery</td>
<td>Vancomycin</td>
<td>Cerebellar hemorrhage</td>
</tr>
<tr>
<td>Valsartan 320 MG</td>
<td>FOLFOX Regimen</td>
<td>Vancomycin 750 MG</td>
<td>Postoperative Hemorrhage</td>
</tr>
<tr>
<td>Nadolol 20 MG</td>
<td>Chemotherapy Regimen</td>
<td>Azithromycin</td>
<td>Retroperitoneal Hemorrhage</td>
</tr>
<tr>
<td>Atenolol 100 MG</td>
<td>Preoperative Therapy</td>
<td>Levofoxacin 750 MG</td>
<td>Amyloid angiopathy</td>
</tr>
<tr>
<td>Enalapril 10 MG</td>
<td>Anticancer therapy</td>
<td>Dexamethasone</td>
<td>Internal bleeding</td>
</tr>
<tr>
<td>Oral form diltiazem</td>
<td>Parotidectomy</td>
<td>Lorazepam</td>
<td>Hematoma, Subdural, Chronic</td>
</tr>
<tr>
<td>nimODipine 30 MG</td>
<td>Resection of ileum</td>
<td>Acetaminophen</td>
<td>Intraparenchymal</td>
</tr>
</tbody>
</table>

**Learned vector representations (AKA concept embeddings) of SNOMED Concepts**

\[
e_{\text{Kidney Failure}} - e_{\text{Kidney}} + e_{\text{Heart}} = e_{\text{Heart Failure}}
\]

\[
e_{\text{Metoprolol 25MG}} - e_{\text{Hypertensive Disease}} + e_{\text{Epilepsy}} = e_{\text{Trileptal}}
\]

[Link: 50 nearest disorder concepts]
**Workflow: Identify and Retrieve**

**Step 1:** Define your Cohort and retrieve your dataset.

![CogStack](image)

(Data Lake)

---

**Structured data - CogStack**

<table>
<thead>
<tr>
<th>Doc ID</th>
<th>Hospital number</th>
<th>Episode</th>
<th>AGE</th>
<th>Gender</th>
<th>Department</th>
<th>Client_visit_type</th>
<th>DATE</th>
<th>etc..</th>
</tr>
</thead>
<tbody>
<tr>
<td>100001</td>
<td>Patient 1</td>
<td>KCH1</td>
<td>42</td>
<td>M</td>
<td>A&amp;E</td>
<td>Inpatient</td>
<td>12/03/2020</td>
<td>...</td>
</tr>
<tr>
<td>100002</td>
<td>Patient 1</td>
<td>KCH1</td>
<td>42</td>
<td>M</td>
<td>ICU</td>
<td>Inpatient</td>
<td>15/03/2020</td>
<td>...</td>
</tr>
<tr>
<td>100003</td>
<td>Patient 1</td>
<td>KCH2</td>
<td>45</td>
<td>M</td>
<td>Epilepsy</td>
<td>Outpatient</td>
<td>12/09/2020</td>
<td>...</td>
</tr>
<tr>
<td>100004</td>
<td>Patient 2</td>
<td>KCH3</td>
<td>23</td>
<td>F</td>
<td>Infectious disease</td>
<td>Inpatient</td>
<td>12/03/2019</td>
<td>...</td>
</tr>
<tr>
<td>100005</td>
<td>Patient 3</td>
<td>PRUH4</td>
<td>56</td>
<td>M</td>
<td>Cardiac</td>
<td>Outpatient</td>
<td>17/02/1994</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
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Structured data
Workflow: Identify and Retrieve

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Clinic letter Extract example

Dear Mr. TGF:

Mr. XY is a client of our Epilepsy clinic. He suffers from juvenile myoclonic epilepsy and was medically screened by you as a driver.

Your assessment of a diagnosis of jme has resulted in XY being denied the job and we need to point out the following:

DHX:
allergic to chlorquine
oxiCarbAZEpine 1200 mg
keppra 1500 mg BID

Hospital Document ID : 100003

Structured document metadata

Unstructured textual information
MedCATtrainer

- SNOMED Annotation tool
- Filter for specific concepts
- Simple point and click interface.
- Domain expert labelling
- Supervised training (teach the model how to extract snomed concepts from unstructured text)

Step 2: Validate and train
Missing annotations

free. Her non epileptic seizures\{Epileptic seizure, SCTID:313307000\} are...

If the concept of interest doesn’t exist:
• Possible to define your own concepts and add a custom SCTID.
Example: \textit{Malignant Middle Cerebral Artery infarction (disorder)}
• Which can then be later proposed to be incorporated into SNOMED CT
Meta-annotations: Capturing the contextual information

“The patient has not been started on antiepileptic medication.”
Annotation: {Anticonvulsant (substance),
Subject/Experiencer: Patient,
Presence: False,
Temporality: Recent}

Definitions:
Subject/Experiencer: Is the concept tagged mentioned present?

Presence: Is the concept present to the Subject/Experiencer?

Temporality: When did the concept/event occur?

• Options are customizable depending on use case
### Step 3: Run your model and annotate your dataset

Dear Mr. TGF:

Mr. XY is a [client S-32551000000105 - CLIENT (PERSON)] - T-15300 - PERSON - 1.0 of our [Epilepsy S-84757009 - EPILEPSY (DISORDER)] - T-02100 - DISORDER - 0.69. He suffers from [myoclonic epilepsy S-6204001 - JUVENILE MYOCLOMNIC EPILEPSY (DISORDER)] - T-02100 - DISORDER - 1.0 and was medically [screened S-20135006 - SCREENING PROCEDURE (PROCEDURE)] - T-10000 - PROCEDURE - 0.33 by you as a [driver S-236320001 - VEHICLE DRIVER (OCCUPATION)] - T-15200 - OCCUPATION - 1.0. Your assessment of a [diagnosis S-4394001 - DIAGNOSIS (OBSERVABLE ENTITY)] - T-05000 - OBSERVABLE ENTITY - 0.5 of [jme S-6204001 - JUVENILE MYOCLOMNIC EPILEPSY (DISORDER)] - T-02100 - DISORDER - 1.0 has resulted in [S-79409006 - RESULTING IN (ATTRIBUTE)] - T-14310 - ATTRIBUTE - 1.0 XY being denied S-441869009 - DENIED (QUALIFIER VALUE) - T-11000 - QUALIFIER VALUE - 1.0 the job [S-14679004 - OCCUPATION (OCCUPATION)] - T-15200 - OCCUPATION - 1.0 and

we need [S-410525008 - NEEDED (QUALIFIER VALUE)] - T-11000 - QUALIFIER VALUE - 0.8 to point [S-3212210000000103 - POINT (QUALIFIER VALUE)] - T-11000 - QUALIFIER VALUE - 1.0 out the following [S-255260001 - FOLLOWING (ATTRIBUTE)] - T-14310 - ATTRIBUTE - 0.57:

**DHX:**

| Allergic S-609328004 - ALLERGIC DISPOSITION (DISORDER) | T-02100 - DISORDER - 1.0 to chlorozine S-373468005 - CHLOROQUINE (SUBSTANCE) - T-19000 - SUBSTANCE - 0.69 |
| oxCarbaZEpine S-387025007 - OXCARBAZEPINE (SUBSTANCE) | T-19000 - SUBSTANCE - 0.85 1200 mg S-258684004 - MILLIGRAM |
| keppra S-9452601000010103 - KEPPRA (PRODUCT) - T-07000 - PRODUCT - 0.54 1500 mg S-258684004 - MILLIGRAM |
| - T-11000 - QUALIFIER VALUE - 0.52 BID S-229799001 - TWICE A DAY (QUALIFIER VALUE) - T-11000 - QUALIFIER VALUE - 1.0 |
“The patient does not suffered with epilepsy”

"annotations": [{"id": 1,
  "user": "admin",
  "sctid": "84757009",
  "name": "Epilepsy (disorder)",
  "source_value": "epilepsy",
  "start": 35, "end": 44,
  "validated": true,
  "correct": true,
  "deleted": false,
  "alternative": false,
  "terminated": false,
  "last_modified": "2021-08-25 17:23:41.557191+00:00",
  "manually_created": false,
  "acc": 0.69,
  "meta_anss": [{"Experimcer": Patient},
    {"Presence": False},
    {"Time": Recent}]}
}
**Workflow: Concept Extraction**

**MedCAT annotations**

**Clinic letter Extract example**

Dear Mr. TOF:

Mr. XY is a client S-3215100000000193 - CLIENT (PERSON) - T-15300 - PERSON - 1.0 of our Epilepsy S-64757000 - EPILEPSY (DISORDER) - T-02100 - DISORDER - 1.0. He suffers from juvenile myoclonic epilepsy S-6204001 - JUVENILE MYOCYCLONE EPILEPSY (DISORDER) - T-02100 - DISORDER - 1.0 and was medically screened S-3913006 - SCREENING PROCEDURE (PROCEDURE) - T-10000 - PROCEDURE - 0.33 by you as a driver S-236310003 - VEHICLE DRIVER (OCCUPATION) - T-15200 - OCCUPATION - 1.0. Your assessment of a diagnosis S-43849001 - DIAGNOSIS (OBSERVABLE ENTITY) - T-05000 - OBSERVABLE ENTITY - 0.5 of me S-6204001 - JUVENILE MYOCYCLONE EPILEPSY (DISORDER) - T-02100 - DISORDER - 1.0 has resulted in S-79495006 - RESULTING IN (ATTRIBUTE) - T-14370 - ATTRIBUTE - 1.0. XY being denied S-61868009 - DENIED (QUALIFIER VALUE) - T-11000 - QUALIFIER VALUE - 1.0. The patient S-16879004 - OCCUPATION (OCCUPATION) - T-15200 - OCCUPATION - 1.0 and we need S-3212100000000193 - NEED (QUALIFIER VALUE) - T-11000 - QUALIFIER VALUE - 0.8 to point S-3212100000000193 - POINT (QUALIFIER VALUE) - T-11000 - QUALIFIER VALUE - 1.0 out the following S-255020001 - FOLLOWINGS (ATTRIBUTE) - T-14310 - ATTRIBUTE - 0.57:

Chx:
- allergic S-65932004 - ALLERGIC DISPOSITION (DISORDER) - T-02100 - DISORDER - 1.0 to chlorquine S-37348005 - CHLOROQUINE (SUBSTANCE) - T-10000 - SUBSTANCE - 0.69
- Carb: S-387020007 - DECABAZEPINE (SUBSTANCE) - T-10000 - SUBSTANCE - 0.85 1200 mg S-25508004 - MILLIGRAM (QUALIFIER VALUE) - T-11000 - QUALIFIER VALUE - 0.52
- keppra S-9426201000000153 - KEPPRA (PRODUCT) - T-07000 - PRODUCT - 0.56 1500 mg S-25508004 - MILLIGRAM (QUALIFIER VALUE) - T-11000 - QUALIFIER VALUE - 0.52

Each grey box represents a model predict with meta-data in bold.

**Unstructured data - MedCAT**

<table>
<thead>
<tr>
<th>Epilepsy</th>
<th>Cardiac failure</th>
<th>Kidney failure</th>
<th>Covid-19</th>
<th>etc...</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Select Parent Concepts of interest

Groups a count of all child concepts encountered under the selected parent SCTID via the “is a” relationship

**SNOMED or Map to ICD-10**

Infer Structure

Filter
Workflow: Aggregate and Process

**Step 4:** Final validation and continue downstream analytics

Clinical information is presented in a structured, tabular format.

<table>
<thead>
<tr>
<th>Structured data - CogStack</th>
<th>Unstructured data - MedCAT</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Doc ID</strong></td>
<td><strong>Hospital number</strong></td>
</tr>
<tr>
<td>100001</td>
<td>Patient 1</td>
</tr>
<tr>
<td>100002</td>
<td>Patient 1</td>
</tr>
<tr>
<td>100003</td>
<td>Patient 1</td>
</tr>
<tr>
<td>100004</td>
<td>Patient 2</td>
</tr>
<tr>
<td>100005</td>
<td>Patient 3</td>
</tr>
</tbody>
</table>
Research Web Series

MedCAT - Automated extraction pipeline

1. Retrieve
2. Train
3. Extraction
4. Aggregate/process

Concept-based Validation Phase 1

Entire Pipeline Validation Phase 2

Inferred structure from free text documents

<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Document ID</th>
<th>Epilepsy</th>
<th>Rash</th>
</tr>
</thead>
<tbody>
<tr>
<td>pt_1</td>
<td>123</td>
<td>30</td>
<td>23</td>
</tr>
<tr>
<td>pt_1</td>
<td>124</td>
<td>36</td>
<td>0</td>
</tr>
<tr>
<td>pt_2</td>
<td>678</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>pt_3</td>
<td>500</td>
<td>0</td>
<td>34</td>
</tr>
<tr>
<td>pt_3</td>
<td>501</td>
<td>0</td>
<td>24</td>
</tr>
<tr>
<td>pt_4</td>
<td>809</td>
<td>26</td>
<td>0</td>
</tr>
<tr>
<td>pt_5</td>
<td>901</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

- Patient documents
- Trained MedCAT model annotation
- Validation & Supervised Training
- Inferred structure from free text documents

Medical record

- SCTID: 847570009 - Epilepsy
- Pt_1 known as Epilepsy
- Focal epilepsy
- Locational-related epilepsy
- Eruption of skin
- Rash
- Current Medication: Keppra
- Family History: father has Epilepsy and ASD.
Hospital-wide NLP summarising health data of 1 million patients over a decade

Top 10 most prevalent disorders

Proportions of semantic type and MetaTasks

Feedback Potential to SNOMED

1) Enables clinical domain experts with little to no knowledge of SNOMED CT to engage, explore and annotate SNOMED CT concepts in unstructured/free text.

2) Addition of commonly used synonyms for SNOMED concepts.

3) Identify relevant missing SNOMED CT concepts and propose new concepts required for real-world use cases. e.g. Malignant Middle Cerebral Artery infarction (disorder)
Further reading

- HFMA “Using artificial intelligence to unlock health records” Case Study
- World Economic Forum “Digital diagnosis: Why teaching computers to read medical records could help against COVID-19”
- Research Papers Publications – CogStack

Get Involved:

Join our growing community of deployment sites.
Discussion Board: https://discourse.cogstack.org/

Get in touch to discuss your use case:
contact@cogstack.org

Source-code:
https://github.com/CogStack
Transferring of Models

- MedCAT and COGSTACK are EPR vendor agnostic.
- MedCAT Model performance generalizes well to other hospitals.
- Models can simply be fine-tuned to different hospitals.

https://doi.org/10.1016/j.artmed.2021.102083
**Bean et al. 2020** -> ACE-inhibitors and Angiotensin-2 Receptor Blockers are not associated with severe SARS-COVID19

- Prevalence of diseases per group in pts with covid-19 (diagram right)

**Carr et al., 2021** -> Evaluation and improvement of the National Early Warning Score (NEWS2) for COVID-19: a multi-hospital study

- National early warning Score (NEWS2) -> Determines the degree of illness of a patient and prompts critical care intervention

**Nayagam et al., 2021** -> Persistent cholestasis in survivors of SARS-CoV-2
Further reading

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