

Annotating Temporal Relations to Determine the Onset of Psychosis Symptoms

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Introduction: clinical use-case

- For patients with schizophrenia, longer durations of untreated psychosis (DUP) are associated with worse intervention outcomes
- In electronic health records (EHRs), information on symptom and treatment onset is often documented in the form of free text

Date: 2010-03-01

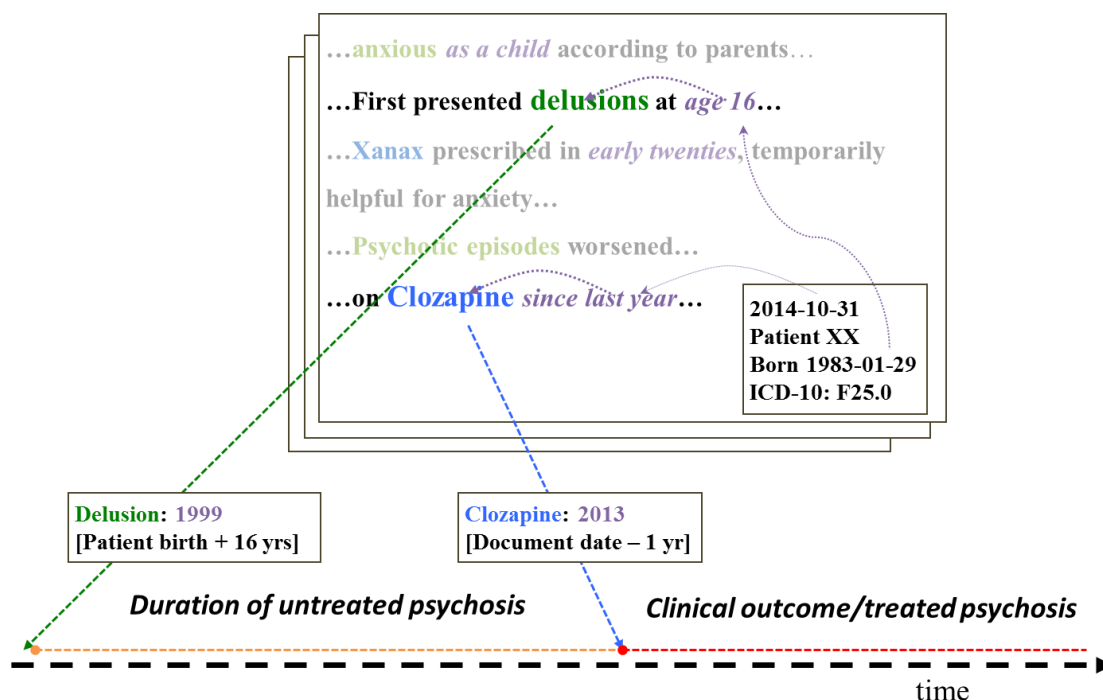
The patient reported she has been hearing voices since the age of 14...

First assessed on 07/10/2009, started treatment in November...

MeDESTO project: Measuring Duration of Untreated Psychosis by Extraction of Symptom and Treatment Onset from mental health records using language technology.

Swedish Research Council (2015-00359), Marie Skłodowska Curie Actions, Cofund, Project INCA 600398.

Introduction: information extraction



Entities in the texts

- Time expressions
- Events, i.e. symptoms
- Temporal relations

Our goal: Identification of temporal links (TLINKs) related to symptom onset

Image courtesy of Dr. Sumithra Velupillai, King's College London



Background

Natural Language Processing (NLP) in the clinical domain: few corpora developed for temporal information extraction

2012 i2b2

- Intensive care unit
- 310 discharge summaries
- 8 TLINK types between entity pairs (before, overlap, ...)

2012 i2b2 NLP Challenge

THYME corpus

- Oncology
- 1,254 records
- TLINKs to document creation time and narrative containers

2015, 2016, 2017 Clinical TempEval

- Sun W, Rumshisky A, Uzuner O. Annotating temporal information in clinical narratives. *Journal of biomedical informatics*. 2013;46:S5–S12.
- Styler IV WF, Bethard S, Finan S, et al. Temporal annotation in the clinical domain. *Transactions of the Association for Computational Linguistics*. 2014;2:143.

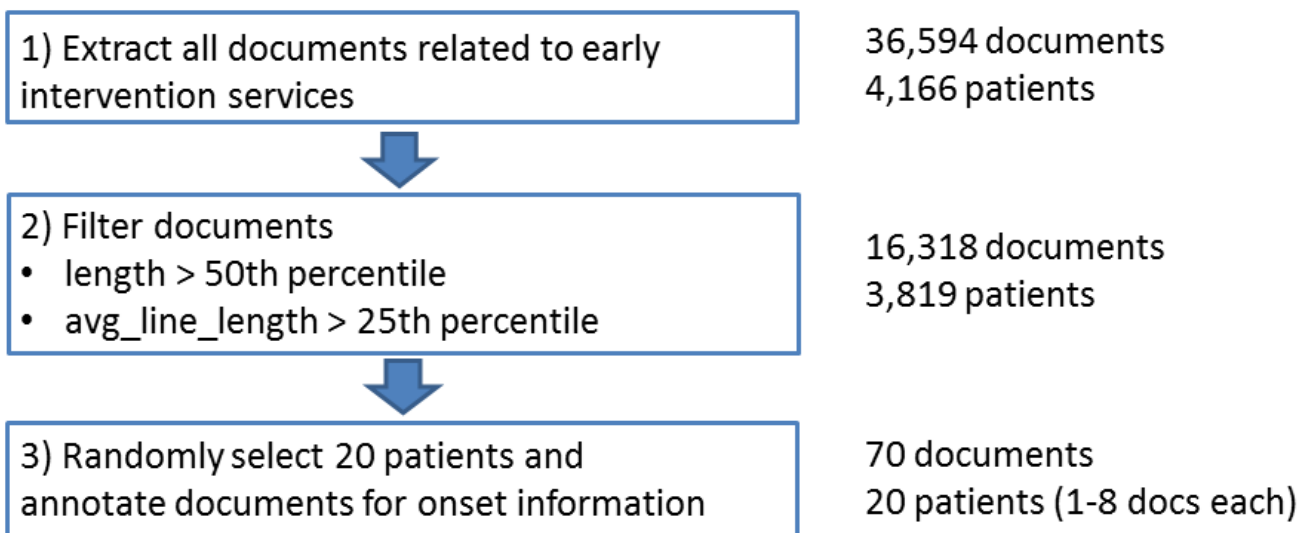
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Aims of the study

1. We propose a methodology for selecting the most relevant documents for the considered use-case
2. We develop a manual annotation process to temporally anchor all the relevant symptoms, thus enabling the extraction of symptom onset and other information of interest
3. We propose a preliminary NLP system to assess the utility of the created corpus

Dataset: corpus extraction

Mental health records from CRIS: early intervention services



- Perera G, Broadbent M, Callard F, et al. Cohort profile of the South London and Maudsley NHS Foundation Trust Biomedical Research Centre (SLaM BRC) Case Register: current status and recent enhancement of an Electronic Mental Health Record-derived data resource. *BMJ Open*. 2016;6(3):e008721.

Dataset: filtering steps

- 70 documents double-annotated for symptom onset information

“Difficulties were noted for the first time when the patient was 7 years old, as he was displaying aggressive behaviour”

- Documents analyzed in terms of clinical and temporal content, automatically identifying symptoms (keyword list) and time expressions
- Final set of documents to be used for annotation

- Angel X Chang and Christopher D Manning. Sutime: A library for recognizing and normalizing time expressions. LREC 2012.
- Jackson R, Patel R, Velupillai S, et al. Knowledge discovery for Deep Pheno-typing serious mental illness from Electronic Mental Health records. F1000Res. 2018;7:210.
- Viani N, Yin L, Kam J, et al. Time Expressions in Mental Health Records for Symptom Onset Extraction. Proceedings of Louhi 2018.

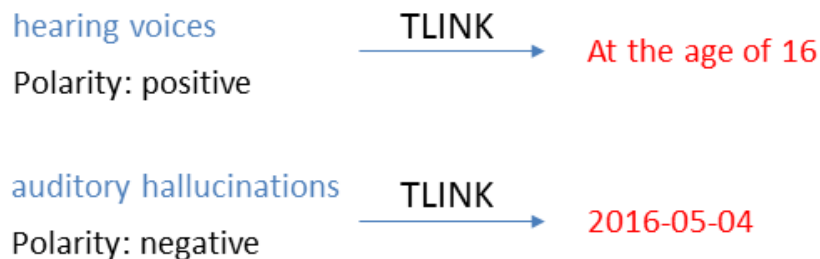
Temporal relation annotation

Documents pre-annotated with 26 symptoms and time expressions

Date of Birth: 1990-05-03

Visit Date: 2016-05-04

*“The patient started **hearing voices** at the age of 16. On mental state examination, today, **auditory hallucinations** could **not** be elicited.”*



- Each symptom linked to a time expression in the text (if possible)
- Each symptom assigned a polarity value (positive, negative)
- Three annotators, each document double annotated



Automated information extraction

Dataset split into training, development, test sets

Temporal relation module

- Rule-based system: section names (“clinical history”, “mse”), anchor dates (admission, discharge, clinic date)
- 10 rules

E.g., if section = “mental state examination on admission” → link to ADM_DATE

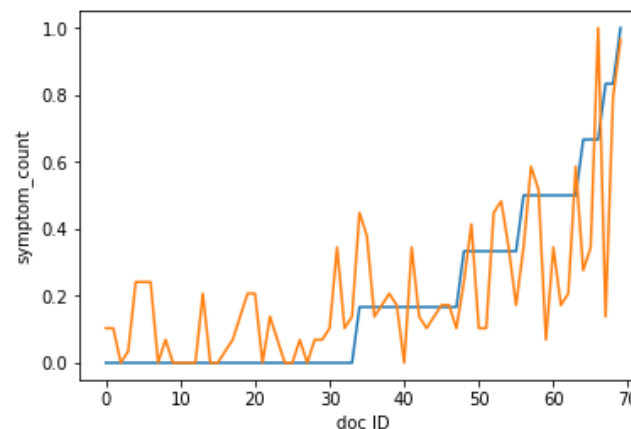
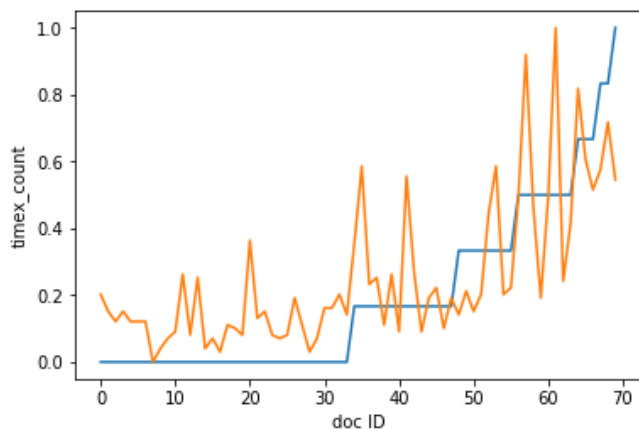
Polarity module

- Rule-based ConText algorithm, 11 modifiers (“no”, “denies”, ...)

• Chapman BE, Lee S, Kang HP, Chapman WW. Document-level classification of CT pulmonary angiography reports based on an extension of the ConText algorithm. J Biomed Inform. 2011; 44 (5): 728–737.

Results: Corpus selection

Documents with many clinical/temporal elements are more likely to contain information on symptom onset



Initial corpus filtered with additional criteria:
 $Symptom_count > 0$ and $Timex_count > 5$



9,779 documents
3,433 patients

Results: Corpus annotation

- **239** randomly selected patients (24 batches)
- **645** documents (2.7 per patient)

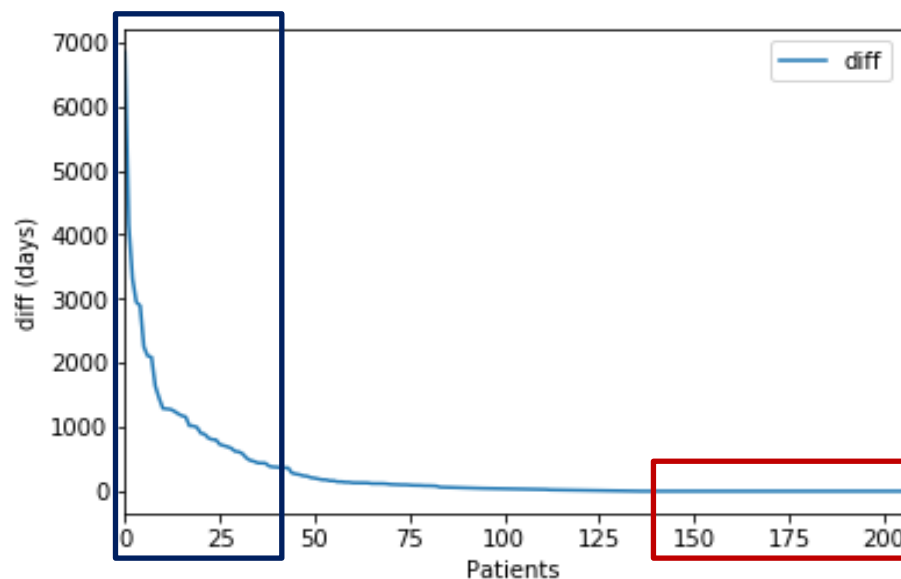
Item	IAA (average)	IAA (range/batch)
TLINK	0.73	0.60 - 0.84
Polarity	0.95	0.81 - 1

2,590 symptoms: *hallucinations, delusions, delusional, paranoia, thought disorder, ...*

Item	Value	Total
TLINK	Yes	1,661 (64.1%)
	No	929 (35.9%)
Polarity	Pos	1,900 (73.4%)
	Neg	690 (26.6%)

Results: TLINK analysis per patient

For each patient: difference (*diff*) between max and min “positive” symptom dates (206 patients)



41 patients with
diff > 1 year

71 patients with
diff = 0 days

Results: NLP development

Accuracy of NLP modules

Item	Model	Train	Dev
TLINK	baseline	0.47	0.54
	Rule-based	0.67	0.58
Polarity	baseline	0.76	0.72
	ConText	0.93	0.95

More work on TLINK module needed

Polarity is well captured by rules



Discussion (1)

- First temporally-annotated corpus that was developed for a specific clinical use-case besides clinical timeline reconstruction
- Dataset selection is a crucial step

Novelty of TLINK annotation task

- Temporal links between entities that are not close to each other
- Only one type of temporal link

Discussion (2)

- Long-term goal: extracting information on a patient-level
- Analysis of 41 patients with a *diff* value > 1 year

17	Clear onset date	<i>He has been suffering from psychosis since he was 10 years old when he started experiencing hallucinations</i>
15	Close to onset date	Other text would be more specific
9	Not an onset date	E.g., Error in written date

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Ongoing work and future directions (1)

- **Corpus selection:** Extend annotation work on a new set of documents (first referrals)
- **Keyword extension:** Search for textual variants of symptoms

Future directions

- **NLP development:** Refine rule-based approach and explore supervised extraction methods → Apply on large patient cohort

Ongoing work and future directions (2)

Automatic keywords extension

- Word embedding models: capture similarity among words (unsupervised)
- First experiments: full early intervention services dataset (~36K documents)
- Future studies: look at additional CRIS documents and other clinical corpora

most_similar('hallucinations')

word (bigram)	similarity
auditory_hallucinations	0.905801773
hallucination	0.878103852
visual_hallucinations	0.847281337
auditory_hallucination	0.845688939
perceptual_abnormalities	0.830208898
perceptual_disturbances	0.829540431
abnormal_perceptions	0.799558282
hallucinatory_phenomena	0.790262461
hallucinatory_experiences	0.789078951
auditory	0.785478473
psychotic_phenomena	0.783942819
passivity_phenomena	0.779936433
command_hallucinations	0.768690705
somatic_hallucinations	0.758699775
tactile_hallucinations	0.757349372



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Thank you!

Questions?