

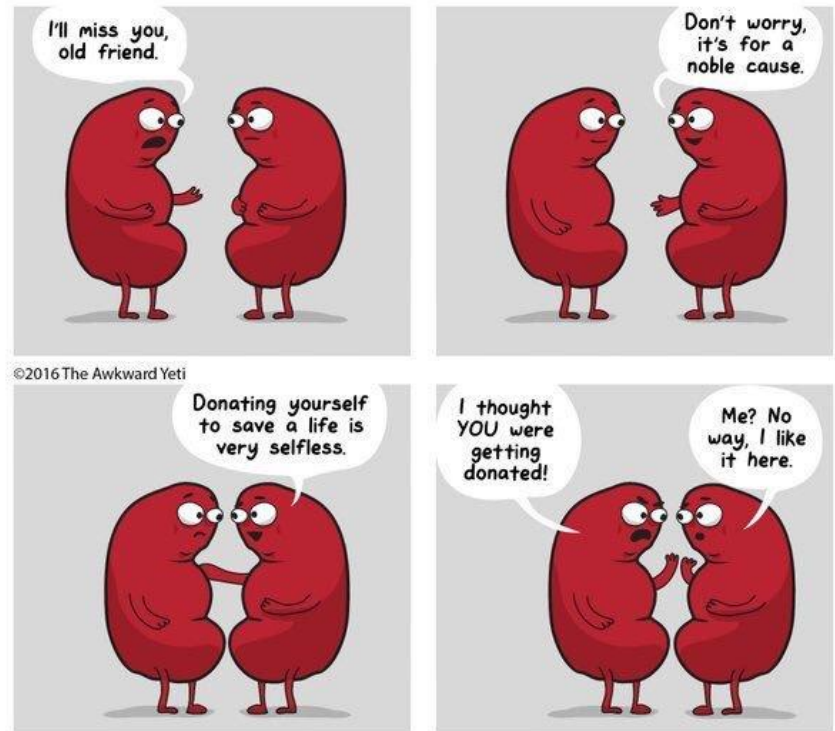
Detecting Named Entities and Relations in German Clinical Reports

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- Background
- Clinical Data
- Annotations
- Methods
- Experiments
- Results
- Conclusion
- (small Demo)



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Background

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Supported by:



Federal Ministry
for Economic Affairs
and Energy

on the basis of a decision
by the German Bundestag



AOK Nordost –
Die Gesundheitskasse



Techniker
Krankenkasse
Gesund in der Zukunft



Medical Software Solutions

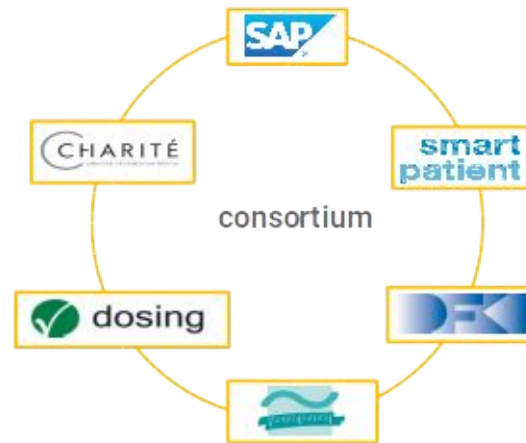


People and Ideas for Innovation in Healthcare

stakeholder

MACSS:

Medical Allround-Care Service Solution



BOSCH + SOHN
GERMANY



stakeholder

Background

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need for an interconnected treatment for chronically ill patients with modern communication technology



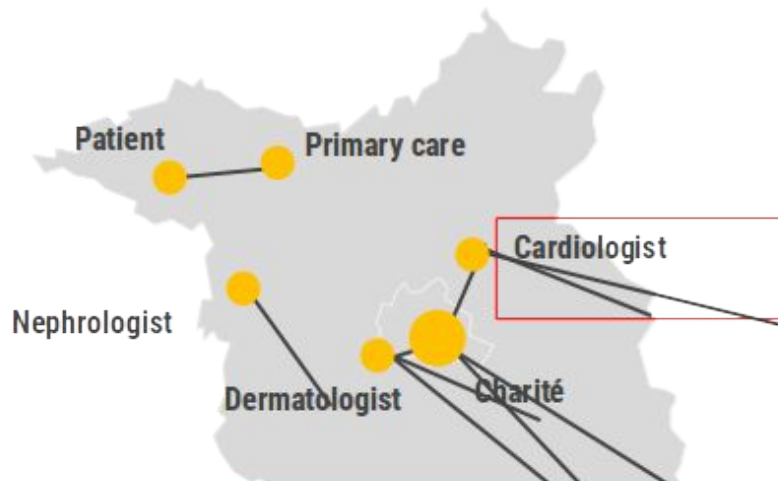
"Since I am quite busy with Romy I would love to have a system, which reminds me to take the drugs, to measure blood pressure, and provides an easy way to make a new appointment."

Marleen, 30 years

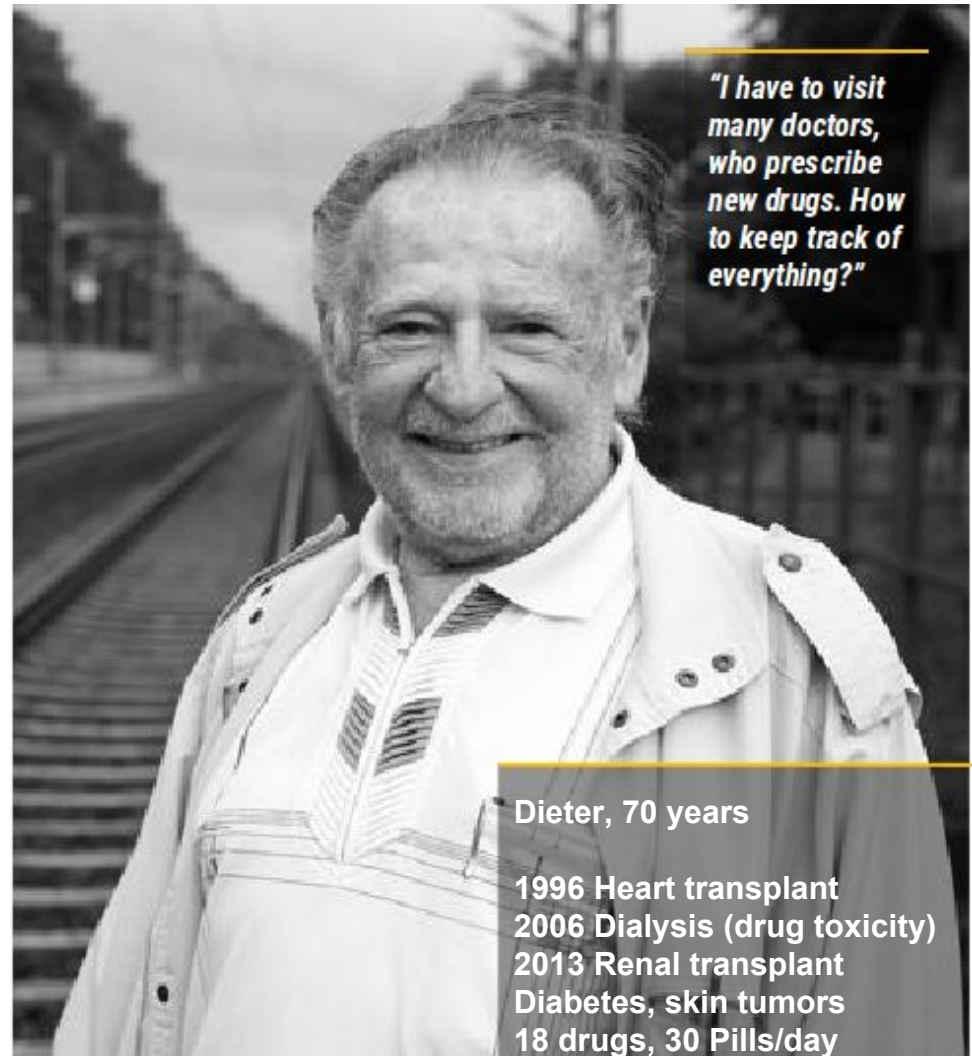
3. renal transplant,
hypertension,
8 outpatient visits/year
7 drugs, 13 pills/day
cost: 12.013 € /year

Background

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Need for a real-time and bidirectional communication **within a single platform** for optimized drug dosing and close surveillance of chronically ill patients



"I have to visit many doctors, who prescribe new drugs. How to keep track of everything?"

Dieter, 70 years

1996 Heart transplant
2006 Dialysis (drug toxicity)
2013 Renal transplant
Diabetes, skin tumors
18 drugs, 30 Pills/day

Background

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My data: The patient decides:

The patient carries his data. Aggregation of data only within the data trust center at Charité.

Drug chart
diary

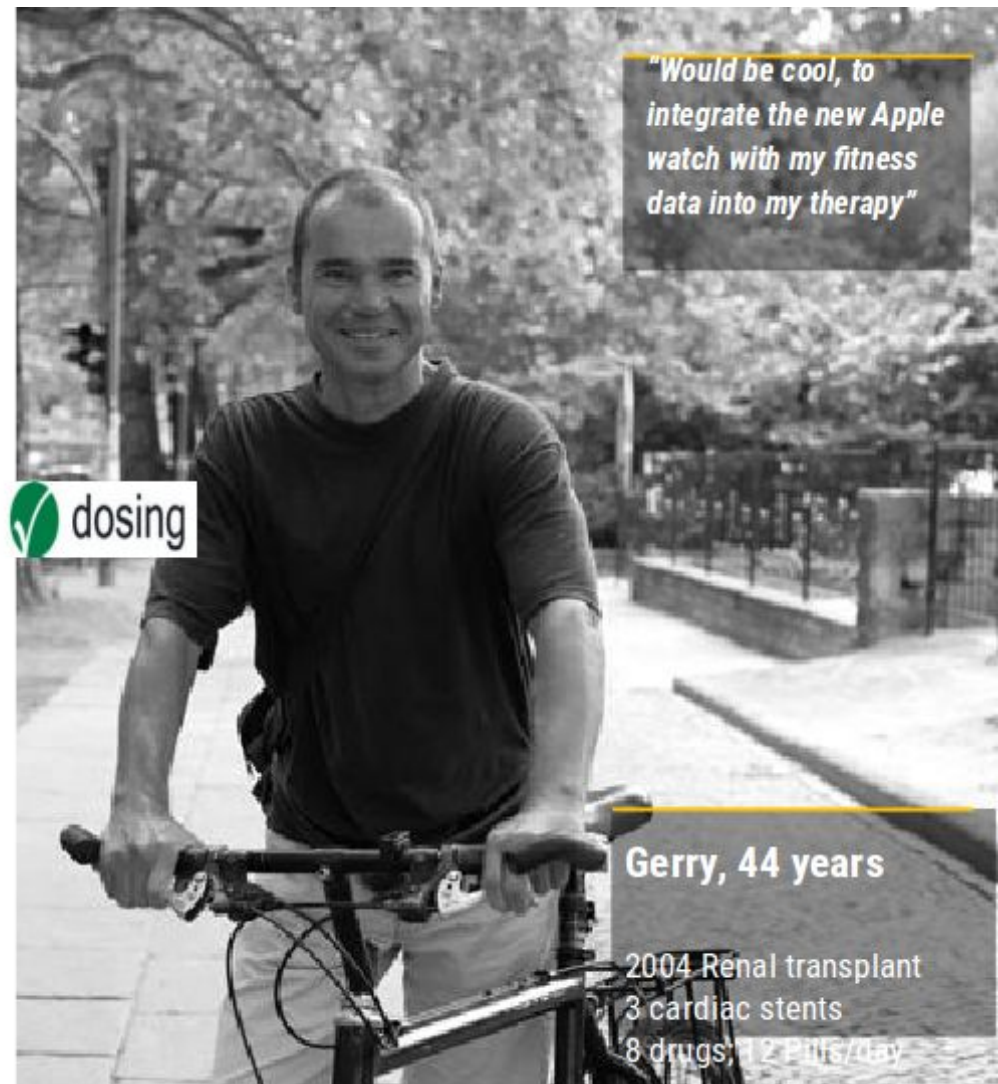
Tagebuch und Erinnerung
für Ihre Gesundheit.

smart
patient

Messenger
Drug check



weight, activity, blood
pressure...



*"Would be cool, to
integrate the new Apple
watch with my fitness
data into my therapy"*

Gerry, 44 years

2004 Renal transplant
3 cardiac stents
8 drugs; 12 Pills/day

Overview

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- **Focus:** Nephrology reports - clinical notes
- **Goal:** Support physicians to access information
- **Problems:**
 - Availability & accessibility of data
 - Domain dependence
 - Less resources for German
- **This paper presents:**
 - Preliminary NER & RE results on German nephrology reports
 - Ongoing work

Clinical Data

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- Clinical Notes (dt. Verlaufsnotizen)
 - Short notes written during a visit
 - Often just a few sentence
- Discharge Summaries (dt. Arztbriefe)
 - Written during stay in hospital
 - Semi-structured
 - Much longer than clinical notes
- Characteristics Clinical Data:
 - Information density
 - Technical language
 - Abbreviations, Negations, Uncertainty

Clinical Data

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	Discharge Summaries	Clinical Notes
#documents available	118	1607
#words (total)	89691	68480
#sentences (total)	16068	11871
avg. words per document (std. deviation)	760.09 (208.62)	42.61 (35.74)

Examples: Clinical Notes

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Gutes Befinden. Keine Fieber, kein Infekt, keine Beschwerden bei Miktion. Keine Stuhlgangprobleme. Unklarer papillöser Hautbefund. Abklärung durch Dermatologie empfohlen. Soll ggf. vor Ort in der Kur geschehen.

MCP abgesetzt. Bei leicht erhöhten Blutdruckwerten Metrolopol in der Dosis erhöhten, ggf. weitere Dosissteigerung. Leberwerte weiter gestiegen. CyA reduziert. Montag Abklärung der Lebersituation.

Good condition. No fever, no infection, no micturition disturbances. No problems with defaecation. Unclear papillose structures on the skin. Dermatological examination recommended. Should be made during course of treatment, if necessary.

Discontinuation of MCP. Increase in Metrolopol dosage, the blood pressure being slightly increased, further dosage increases, if necessary. Further increased liver levels. Ciclosporin reduced. Examination of the liver on Monday.

Annotations

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Label	Explanation
Body_Part	Body parts; organs
Med_Con	Medical_Condition: symptom, diagnosis and observation
Process	Body's own biological processes
Health_State	Positive, wanted finding; contrary to <i>Med_Con</i>
Treatment	Therapeutic procedures, treatments
Medication	Drugs, medicine
Med_Spec	Medical_Specification: closer definition; describing lexemes, often adjectives
Local_Spec	Local_Specification: anatomical descriptions of position and direction

Annotations

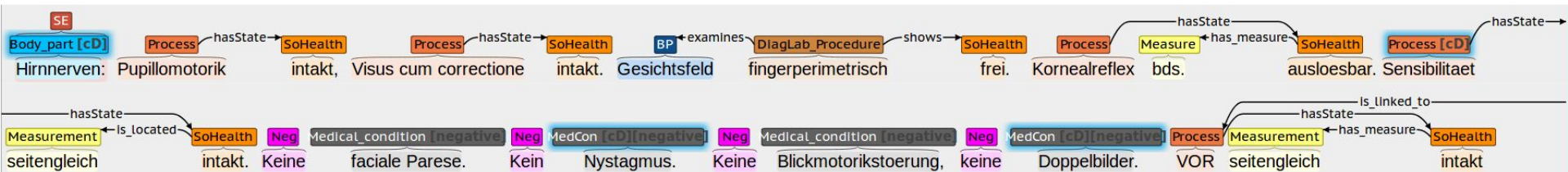
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Label	Explanation
hasState	describes the state of health (positive and negative) of different entities (e.g. <i>Process</i> , <i>Med_Con</i> , <i>Body_Part</i>)
involves	describes a relation between <i>Treatment</i> and <i>Medication</i> : e.g. to use or to discontinue a medication
has_measure	links a <i>Measurement</i> to a corresponding concept
is_located	links a positional information (<i>Body-part</i> , <i>Local_spec</i>) to concepts such as <i>Med_con</i> or <i>Process</i>
is_specified	links <i>Medical_Spec</i> to a corresponding concept (e.g. <i>Med_Con</i> , <i>Process</i>)

Annotated Data

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■ Example Annotations



Methods

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- Using existing methods to explore reliability
 - Named Entity Recognition:
 - Conditional Random Field (CRF)
 - based on Jiang et al., (2008)
 - Bidirectional LSTM (CharNER NN)
 - implementation of Kuru et al., (2016)
 - Relation Extraction
 - Support Vector Machine (SVM)
 - impl. of Giuliano et al., (2006)
 - Convolutional Neural Network (CNN)
 - Nguyen and Grishman (2015)

Experiment

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- Pre-Processing
 - Sentence Splitting, Tokenization
 - POS Tagging (Hellrich et al. 2015)
 - Snowball Stemmer
- Setup
 - 626 clinical notes used for training & testing
 - Only 267 documents contain relations
 - Considering only a subset of concepts and relations for the experiments
 - Cross validation

Results

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■ Results: Concept Recognition

Label	Freq.	CRF			CharNER NN		
		Prec	Rec	F1	Prec	Rec	F1
Medical_Condition	2453	95.17	75.16	83.98	89.12	82.15	84.93
Treatment	1680	85.79	69.63	76.81	80.46	76.37	78.33
State_of_Health	1451	86.68	76.35	81.18	83.55	80.80	82.14
Medication	1214	92.28	68.56	78.55	90.37	82.39	86.17
Process	1145	90.53	60.56	72.57	84.74	66.29	74.02
Body_part	840	96.96	65.23	77.90	89.15	68.78	77.53
Medical_Specification	764	78.76	48.82	60.20	65.32	53.04	58.21
Local_Specification	189	95.83	31.94	45.87	81.84	49.77	61.05

Results

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■ Results: Relation Extraction

Label	Freq.	SVM			CNN		
		Prec	Rec	F1	Prec	Rec	F1
hasState	388	86.86	86.86	86.86	81.96	88.10	84.64
involves	370	88.96	78.38	83.33	81.51	90.42	85.58
has_measure	427	80.25	88.52	84.19	81.47	76.61	78.97
is_located	162	46.96	85.80	60.70	65.14	64.12	63.48
is_specified	112	94.85	82.14	88.04	76.34	83.83	79.89

Conclusion & Future Work

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- First promising results:
 - Training dataset small
 - Classifier not optimized
- Future Work:
 - Building applications on top of NER and RE
 - Summarization
 - Cohort Group generation
 - Reduction of re-hospitalization

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Thank you.