## VERICLIG: Extraction and Verification of Clinical Guidelines via Syntactic and Semantic Annotation

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#### Outline

- 1 Problem
- 2 Syntactic and Semantic Annotation
- 3 Concluding Remarks
- 4 References



#### Problem - CIG Extraction

#### We want to extract process representations from clinical guidelines

- 1 basic tool in hospitals and clinics [Got12]
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■ We need computer interpretable guidelines (CIGs) representing therapies as

- activities (e.g., surgery)
- 2 resources (e.g., a drug)
- 3 actors (e.g., patients, doctors, nurses)
- 4 control flows (e.g., conditional, sequential, parallel)
- 5 several formalisms: BPMN, Asbru, Glare, Proforma (PROTOCURE EU Project)



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QUE: Use (clinical) NLP annotation to extract CIGs?



#### Process Extraction - Diabetes 2 NCCN

1.5.1.2 Emphasise advice on healthy balanced eating that is applicable to the general population when providing advice to people with type 2 diabetes.

1.5.1.3 Continue with metformin if blood glucose control remains inadequate and another oral glucose-lowering medication is added.

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- $\Rightarrow$  Apply business process extraction techniques [FMP11]



## Process Extraction - Diabetes 2 NCCN

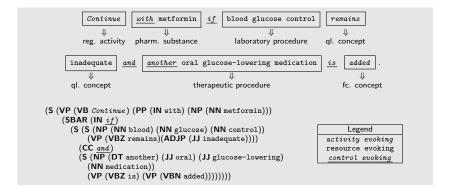
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- ▷ Data scarse to train state-of-the-art supervised annotators !
- $\Rightarrow$  Apply business process extraction techniques [FMP11]
- $\Rightarrow$  Distinguish
  - control-flow words (= discourse relations)
  - 2 activity, resources and actor words (= content words)

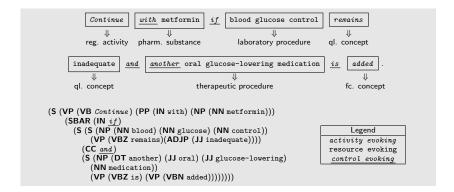


## NLP Annotation - Combining Resources





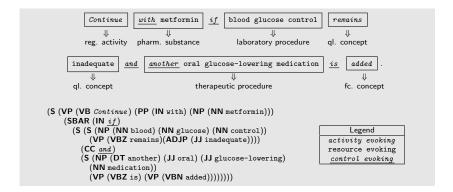
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 $\Rightarrow$  MetaMap & UMLS [AL10] finds activities, resources and actors



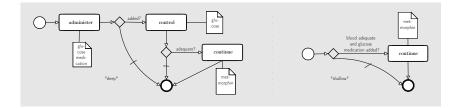
## NLP Annotation - Combining Resources



- $\Rightarrow\,$  MetaMap & UMLS [AL10] finds activities, resources and actors
- $\Rightarrow$  Stanford parser [dMMM06] finds discourse relations



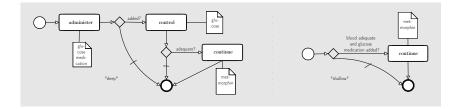
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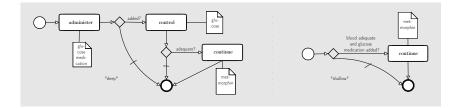
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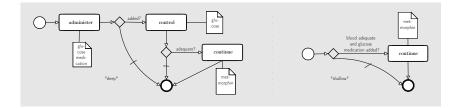
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  - 2 no clear evaluation methodology !



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- Limitations of rule-based CIG extraction
  - no clear clinical meaning for control-flow evoking words !
  - 2 no clear evaluation methodology !
- $\Rightarrow$  Surface-level clinical language peculiarities deceptive



#### Linguistic Patterns - PEWs and NEGs

- $\Rightarrow$  We checked control-flow evoking words (PEWs)
  - conjunctions and prepositions INs (subordinating prepositions, e.g., "if") CCs (coordinating conjunctions, e.g., "and", "or") CCs (subordinating conjunctions, e.g., "then")
  - adverbs: RBs (base adverbs, e.g., "after") RBRs (comparative adverbs, e.g., "later") RBTs (superlative adverbs, e.g., "latest") RNs (nominalized adverbs, e.g., ) RPs (adverbial particles, e.g., )
- $\Rightarrow$  We also checked negative rules (NEGs)
  - "" "not", of category \* (i.e., negation); "nobody", "none" and "nothing", of category PN, the negative determiner "no" of category AT
  - 2 negated modal verbs of category MD\* (e.g., "cannot", "will not").



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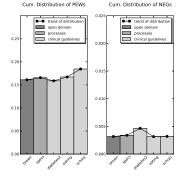
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QUE: Distribution uniform across domains or correlated to clinical domain?



#### PEWs and NEGs - Uniform & Uncorrelated

Distrib.	$\chi^2$ -ind.	$p \ (< 0.001 \ sig.)$	df.	t-one way	$\mu_0$	$p \ (< 0.01 \ {\rm sig.})$	df.
PEWs	9.39	0.009	2	1.02	0.20	0.36	4
PEWs NEGs	1.96	0.375	2	1.02 1.02	0.03	0.36	4



(Corpus)	(# Words)	(Domain)
Brown	1,391708	Open
Business	3,824	Business
Diabetes 2 guid.	7,109	Clinical
Eating dis. guid.	5,078	Clinical
Schizophr. guid.	5,367	Clinical



#### Current Work Plan

- Refine control-flow extraction methodologies
- Develop a methodology to evaluate process-mining rules vis-à-vis supervised techniques
- Use existing annotated corpora (e.g., SemRep) to understand how to disambiguate MetaMap/UMLS
  - 1 activity annotations
  - 2 resource annotations
  - 3 actor annotations
- Design ways to merge/integrate/link annotated datasets to experiment with supervised annotators



## Thank you :-)



#### References

Alan R. Aronson and François-Michel Lang. And overview of MetaMap: Historical perspective and recent advances. J. of the American Medical Informatics Association, 17(3):229–236, 2010.

A. Bottrighi, F. Chesani, M. Montali, and P. Terenziani. Conformance checking of executed clinical guidelines in presence of basic medical knowledge.

In Proc. of the 2011 Business Process Management Work., 2012.

Marie-Catherine de Marneffe, Bill MacCartney, and Christopher D. Manning. Generating typed dependency parses from phrase structure parses. In *Proc. of the 5th Int. Conf. on Language Resources and Evaluation (LREC 20006)*, 2006.

Fabian Friederich, Jan Mendling, and Frank Puhlmann. Process model generation from natural language text. In Proc. of the 23rd Int. Conf. on Advanced Information Systems Engineering (CAISE 2011), 2011.



Gregory Goth. Analyzing medical data.

Comm. of the ACM, 55(6):13-15, 2012.

