## Welcome to the Sentinel Innovation and Methods Seminar Series

#### The webinar will begin momentarily

Please visit <u>www.sentinelinitiative.org</u> for recordings of past sessions and details on upcoming webinars.

Note: closed-captioning for today's webinar will be available on the recording posted at the link above.



## Ontology-driven weak supervision for clinical entity classification in electronic health records

Nigam Shah



#### A patient timeline view of the data



Stanford MEDICINE Stanford Health Care and School of Medicine

### Converting patient timelines to datasets





← Features →

Decisions to make:

- About source and choice of features, including text
- About handling of time
- About defining an electronic phenotype
- About building a cohort



#### Text is <u>one source</u> to use [be careful how deep you go!]





#### Core concepts

- Processing of Text vs. Natural Language Processing
- Handling of knowledge graphs
- Ascertaining whether the patient had an "event" or not (and when)
  - We can choose to do this task just using a textual document
  - We can do this task as a classification problem, where text-extracted content is just one element on a patient timeline.



### Handling of text – two world-views

Dr. Nigam Shah examined a patient with osteoarthritis. The patient is a female CEO of an internet company on page mill road, with several buildings requiring her to walk between offices. Patient complains that pain worsens on walking. [\*\*\* name \*\*\*] examined a patient with osteoarthritis. The patient is a female CEO of an internet company on page mill road, with several buildings requiring her to walk between offices. Patient complains that pain worsens on walking. Redacting "PHI"

osteoarthritis.	patient
female	patient
pain worsens wal	walk Patient complains Lking.

Keeping "medical terms"



Simple text processing



LePendu et al, Pharmacovigilance using clinical notes. Clin Pharmacol Ther. 2013 Jun;93(6):547-55. doi: 10.1038/clpt.2013.47

#### Trade-off: simple or advanced [text-processing]



# Weak supervision

#### The State of Clinical Concept Extraction in 2020

- Largely rule-based + manual feature engineering
- Many clinical entity types do not have expert labeled training sets available
- For existing labeled datasets we're locked into their annotation choices
- PHI / Privacy considerations when sharing labeled data

**Fu et al. 2020** *Journal of Biomedical Informatics.* "Clinical concept extraction: A methodology review"





not many hand-labeled datasets



but many ontologies!

### Ontology-based Labeling

#### **Semantic Labeling** Term mapped to entity type probability

aortic stenosis -> [0.0, 1.0] present -> [1.0, 0.0] aortic -> [1.0, 0.0]

#### Synonym Labeling

Use entire document context to tag **synonymous** entities

{aortic stenosis, AS}  $\rightarrow$  [0.0, 1.0] {mitral regurgitation, MR}  $\rightarrow$  [0.0, 1.0] AORTIC VALVE: Mildly thickened aortic valve leaflets (3). No AS. MITRAL VALVE: Normal mitral valve leaflets with trivial MR.

CONCLUSIONS

The aortic valve leaflets (3) are mildly thickened but aortic stenosis is not present. Trace aortic regurgitation may be present. The mitral valve appears structurally normal with trivial mitral regurgitation.

Ontologies —> Type and Synonymy Information

## Weakly Supervised: Ontologies + Task Rules

	+Tas	+Task-specific rules				Hand-labeled	
Task	LFs	MV	LM	WS	FS	SOTA	
Chemical	+9	81.1	$89.2 \pm 0.2^{+}$	91.1 ± 0.1*	92.4 ± 0.2	93.5 <sup>24</sup>	
Disease	+6	76.4	$79.8 \pm 0.3^{+}$	79.9 ± 0.2	84.5 ± 0.2	87.2 <sup>24</sup>	
Disorder	+11	71.2	$75.0 \pm 0.2^{+}$	76.3 ± 0.1*	79.6 ± 0.3	80.1 <sup>65</sup>	
Drug	+11	82.2	$85.8 \pm 0.4^{+}$	88.3 ± 0.3*	$93.2 \pm 0.3$	91.4 <sup>66</sup>	
Negation	17	92.5	$93.0 \pm 0.0^{+}$	92.7 ± 0.6*	96.1 ± 0.2	~	
DocTimeRel	27	67.8	$69.2 \pm 0.0^{+}$	72.9 ± 0.5*	86.2 ± 0.1	83.4 <sup>67</sup>	

NER performance within 4.1% F1 of models trained with hand-labeled data



**Stanford** Fries et al, Ontology-driven weak supervision for clinical entity classification in electronic health records. Nat Commun. 2021 Apr 1;12(1):2017. doi: 10.1038/s41467-021-22328-4.

#### Continuous Symptom Monitoring for COVID-19

Could we use presenting symptoms to prioritize who should be tested for COVID-19?



Emergency Department

*Daily feed of all notes + timestamped edit deltas* 



Use first 30 minutes of note edits

Virus	AUROC
Adenovirus	0.68 (0.60–0.76)
Influenza virus A	0.73 (0.68–0.77)
Metapneumovirus	0.64 (0.57–0.71)
Parainfluenza virus	0.60 (0.53–0.68)
RSV	0.77 (0.73–0.80)
Rhinovirus	0.62 (0.58–0.66)
SARS-CoV-2	0.64 (0.49–0.79)

Limited ability to discriminate respiratory viruses from symptoms alone (Callahan et al. 2020)

Weakly supervised symptom tagger +2.3 F1 points over baseline

#### **Enabled Symptom Data Sharing**

Bill & MelindaCMU Delphi Group'sGates FoundationCOVIDCAST



#### Medical device surveillance with EHRs



Callahan and Fries et al, npj Digital Medicine volume 2, Article number: 94 (2019)



#### Extracting Structured Information from Notes





Goal: Automatically supplement joint implant registry information

### Implant Outcomes as Relation Extraction





## Example labeling function

#### A. CLINICAL NOTE + MARKUP



#### Output from text-processor

#### **B.** LABELING FUNCTION DEFINITIONS



```
def LF4_negated(c):
v = NegEx.is_negated(c)
return FALSE if v else ABSTAIN
```

FALSE: -1 ABSTAIN: 0 TRUE: 1

Labeling function

CATEGORY	# INSTANCES	PRECISION	RECALL	F1	+/- F1
Revision	63	75.5	58.7	66.1	+16.2%
Component Wear	48	72.9	72.9	72.9	+38.6%
Mechanical Failure	25	91.7	44.0	59.5	+40.3%
Particle Disease	65	97.1	52.3	68.0	+496.5%
Radiographic Abnormality	17	60.0	25.3	44.4	-18.5%
Infection	58	90.7	84.5	87.5	+54.0%
Implant-Complications	276	82.7	62.3	71.1	+53.2%
Pain-Anatomy	236	80.2	82.6	81.4	+12.7%



**6**X More complication events than with coded data alone

# Closing thoughts



#### Acknowledgements and Contact Information

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