Apache Clinical Text Analysis and Knowledge Extraction System (cTAKES)

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- Industry
 - IBM UIMA grant
- Institutions contributing de-identified clinical notes
 - Mayo Clinic, Seattle Group Health Cooperative, MIMIC project (Beth Israel)

Outline

- Current Healthcare Challenges
- Apache cTAKES
- Technical details
- Demo





Patient January 16, 2006



Image courtesy of Piet C. de Groen



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Patient January 16, 2006



Image courtesy of Piet C. de Groen



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Questions

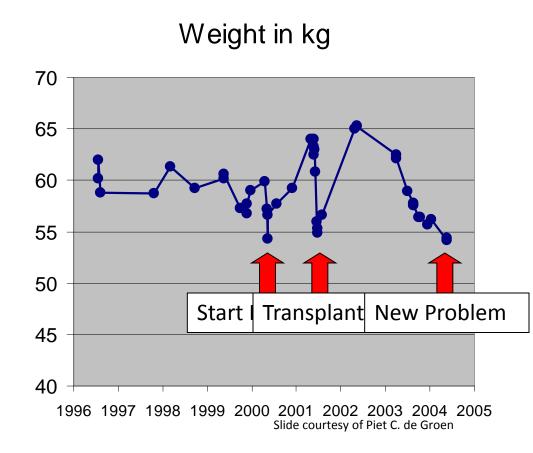
- What is exactly the patient's problem?
 - Are liver tests and weight loss due to Lipitor?
 - When did she use Lipitor?
 - What was the weight on what date?
- Impossible to review all notes!
 - Which notes are relevant to current symptoms?
 - Which have notes have weights and drug information?





EHR/Data Warehouse to the rescue!

- Structured Data
- Demographics
- ICD9 Codes
- Patient Vitals
 - weight



What happened to Cholesterol?

- She was on Lipitor, but:
 - When was it discontinued?
 - Did it do anything to her lipid levels?

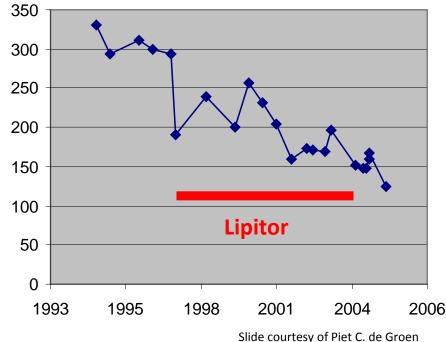
NLP to the rescue!

- Sort 33 identified Clinical Notes on date
- First note is from 1997
 - Lipitor is highlighted in the note
 - ...Dr. X recommended discontinuation of Pravachol and initiation of Lipitor ... have written a prescription for Lipitor ...
- Last note is from 2005
 - ... Lipitor was discontinued in 2004 ...
 - March 2004 note confirms discontinuation

Complete Picture

- Demographics
 - Paitent ID #
- Tests
 - Cholesterol exists
- Clinical Notes
 - "Lipitor"
- Result
 - 22 cholesterol levels

Cholesterol in mg/dL



– 243 notes: 33 mentioned "Lipitor"

NLP Areas of Research

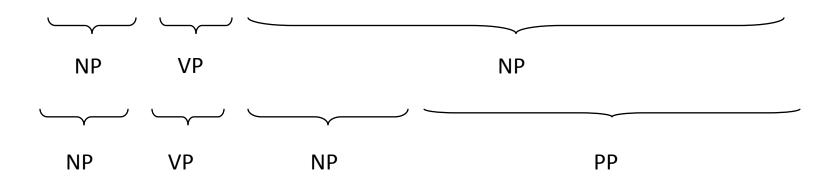
- Part of speech tagging
- Parsing constituency and dependency
- Predicate-argument structure (semantic role labeling)
- Named entity recognition
- Word sense disambiguation
- Relation discovery and classification
- Discourse parsing (text cohesiveness)
- Language generation
- Machine translation
- Summarization
- Creating datasets to be used for learning
 - a.k.a. computable gold annotations
 - Active learning





NLP: Example 1

I saw the man with the telescope. w1 w2 w3 w4 w5 w6 w7 pronoun verb article noun prep article noun







NLP: Example 2

I saw the man with the stethoscope. w1 w2 w3 w4 w5 w6 w7 pronoun verb article noun prep article noun







How do we get the semantics?



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The annotation guidelines will be made available at http://www.ohnlp.org_after_ manuscript publication. The clinical corpus created from Mavo Clinic notes is not released with cTAKES. For model-building purposes, that corpus was anonymized per Safe Harbor Health Insurance Portability and Accountability Act⁷⁶ guidelines. Technical details and discussions on technical topics related to cTAKES are posted on the Forums at http://www.ohnip. org.

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Mayo clinical Text Analysis and Knowledge Extraction System (cTAKES): architecture, component evaluation and applications

Guergana K Savova,¹ James J Masanz,¹ Philip V Ogren,² Jiaping Zheng,¹ Sunghwan Sohn,¹ Karin C Kipper-Schuler,¹ Christopher G Chute¹

ABSTRACT

We aim to build and evaluate an open-source natural language processing system for information extraction from electronic medical record clinical free-text. We describe and evaluate our system, the clinical Text Analysis and Knowledge Extraction System (cTAKES). released open-source at http://www.ohnlp.org. The cTAKES builds on existing open-source technologies-the Unstructured Information Management Architecture framework and OpenNLP natural language processing toolkit. Its components, specifically trained for the clinical domain, create rich linguistic and semantic annotations. Performance of individual components: sentence boundary detector accuracy=0.949; tokenizer accuracy=0.949; part-ofspeech tagger accuracy=0.936; shallow parser Fscore=0.924; named entity recognizer and system-level evaluation F-score=0.715 for exact and 0.824 for overlapping spans, and accuracy for concept mapping, negation, and status attributes for exact and overlapping spans of 0.957, 0.943, 0.859, and 0.580, 0.939, and 0.839, respectively. Overall performance is discussed against five applications. The cTAKES annotations are the foundation for methods and modules for higher-level semantic processing of clinical free-text.

INTRODUCTION

The electronic medical record (EMR) is a rich source of clinical information. It has been advocated that EMR adoption is a key to solving problems related to quality of care, clinical decision support, and reliable information flow among individuals and departments participating in patient care.¹ The abundance of unstructured textual data in the EMR NLP system designed to process and extract semantically viable information to support the heterogeneous clinical research domain and to be sufficiently scalable and robust to meet the rigors of a clinical research production environment. This paper describes and evaluates our system—the clinical Text Analysis and Knowledge Extraction System (cTAKES).

BACKGROUND

The clinical narrative has unique characteristics that differentiate it from scientific biomedical literature and the general domain, requiring a focused effort around methodologies within the clinical NLP field.² Columbia University's proprietary Medical Language Extraction and Encoding System (MedLEE)³ was designed to process radiology reports, later extended to other domains,4 and tested for transferability to another institution.5 MedLEE discovers clinical concepts along with a set of modifiers. Health Information Text Extraction (HITEx)6 7 is an open-source clinical NLP system from Brigham and Women's Hospital and Harvard Medical School incorporated within the Informatics for Integrating Biology and the Bedside (i2b2) toolset.8 IBM's BioTeKS9 and MedKAT10 were developed as biomedical-domain NLP systems. SymText and MPLUS11 12 have been applied to extract the interpretations of lung scans13 to detect pneumonia14 and central venous catheters mentions.15 Other tools developed primarily for processing biomedical scholarly articles include the National Library of Medicine MetaMap,16 providing mappings to the Unified Medical Language System (UMLS) Metathesaurus concepts,¹⁷¹⁸ those from the National Center for Text Mining (NaCTeM),19 JULIE lab,20 and





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Towards comprehensive syntactic and semantic annotations of the clinical narrative

Daniel Albright,¹ Arrick Lanfranchi,¹ Anwen Fredriksen,¹ William F Styler IV,¹ Colin Warner,² Jena D Hwang,¹ Jinho D Choi,³ Dmitriy Dligach,⁴ Rodney D Nielsen,^{1,5} James Martin,³ Wayne Ward,³ Martha Palmer,¹ Guergana K Savova⁴

ABSTRACT

Objective To create annotated clinical narratives with lavers of syntactic and semantic labels to facilitate advances in clinical natural language processing (NLP). To develop NLP algorithms and open source components. Methods Manual annotation of a clinical narrative corpus of 127 606 tokens following the Treebank schema for syntactic information, PropBank schema for predicate-argument structures, and the Unified Medical Language System (UMLS) schema for semantic information. NLP components were developed. Results The final corpus consists of 13 091 sentences containing 1772 distinct predicate lemmas. Of the 766 newly created PropBank frames, 74 are verbs. There are 28 539 named entity (NE) annotations spread over 15 UMLS semantic groups, one UMLS semantic type, and the Person semantic category. The most frequent annotations belong to the UMLS semantic groups of Procedures (15.71%), Disorders (14.74%), Concepts and Ideas (15.10%), Anatomy (12.80%), Chemicals and Drugs (7.49%), and the UMLS semantic type of Sign or Symptom (12.46%). Inter-annotator agreement results: Treebank (0.926), PropBank (0.891–0.931), NE (0.697–0.750). The part-of-speech tagger, constituency parser, dependency parser, and semantic role labeler are built from the corpus and released open source. A significant limitation uncovered by this project is the need for the NLP community to develop a widely agreed-upon schema for the annotation of clinical concepts and their relations.

Conclusions This project takes a foundational step towards bringing the field of clinical NLP up to par with NLP in the general domain. The corpus creation and NLP components provide a resource for research and application development that would have been previously impossible. other), the level of certainty associated with an event (confirmed, possible, negated) as well as textual mentions that point to the same event. We describe our efforts to combine annotation types developed for general domain syntactic and semantic parsing with medical-domain-specific annotations to create annotated documents accessible to a variety of methods of analysis including algorithm and component development. We evaluate the quality of our annotations by training supervised systems to perform the same annotations automatically. Our effort focuses on developing principled and generalizable enabling computational technologies and addresses the urgent need for annotated clinical narratives necessary to improve the accuracy of tools for extracting comprehensive clinical information.¹ These tools can in turn be used in clinical decision support systems, clinical research combining phenotype and genotype data, quality control, comparative effectiveness, and medication reconciliation to name a few biomedical applications.

In the past decade, the general natural language processing (NLP) community has made enormous strides in solving difficult tasks, such as identifying the predicate-argument structure of a sentence and associated semantic roles, temporal relations, and coreference which enable the abstraction of the meaning from its surface textual form. These developments have been spurred by the targeted enrichment of general annotated resources (such as the Penn Treebank (PTB)²) with increasingly complex layers of annotations, each building upon the previous one, the most recent layer being the discourse level.3 The emergence of other annotation standards (such as PropBank⁴ for the annotation of the sentence predicate-argument structure) has brought new progress in the annotation of semantic informa-





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About Getting Started



Welcome to Apache cTAKES

Apache clinical Text Analysis and Knowledge Extraction System (cTAKES) is an open-source natural language processing system for information extraction from electronic medical record clinical free-text. It processes clinical notes, identifying types of clinical named entities from various dictionaries including the Unified Medical Language System (UMLS) - medications, diseases/disorders, signs/symptoms, anatomical sites and procedures. Each named entity has attributes for the text span, the ontology mapping code, subject (patient, family member, etc.) and context (negated/not negated, conditional, generic, degree of certainty). Some of the attributes are expressed as relations, for example the location of a clinical condition (locationOf relation) or the severity of a clinical condition (degreeOf relation).

Apache cTAKES was built using the Apache UIMA Unstructured Information Management Architecture engineering framework and Apache OpenNLP natural language processing toolkit. Its components are specifically trained for the clinical domain out of diverse manually annotated datasets, and create rich linguistic and semantic annotations that can be utilized by clinical decision support systems and clinical research. cTAKES has been used in a variety of use cases in the domain of biomedicine such as phenotype discovery, translational science, pharmacogenomics and pharmacogenetics.

Apache cTAKES employs a number of rule-based and machine learning methods. Apache cTAKES components include:

 Sentence boundary detection 2. Tokenization (rule-based) Morphologic normalization 4. POS tagging Shallow parsing 6. Named Entity Recognition Dictionary mapping Semantic typing is based on these UMLS semantic types: diseases/disorders, signs/symptoms, anatomical sites, procedures, medications Assertion module 8. Dependency parser Constituency parser 10. Semantic Role Labeler Apache Software Foundation 11. Coreference resolver 12 Relation extractor 13. Drug Profile module 14. Smoking status classifier

> The goal of cTAKES is to be a world-class natural language processing system in the healthcare domain. cTAKES can be used in a great variety of retrievals and use cases. It is intended to be modular and expandable at the information model and method level. The cTAKES community is committed to best practices and R&D (research and development) by using cutting edge technologies and novel research. The idea is to quickly translate the best performing methods into cTAKES code.

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Recent Developments

- cTAKES
 - Top-level Apache Software Foundation project (as of March 22, 2013)
 - many new components for semantic processing
 - multi-institutional contributions (not an exhaustive list and in no particular order)
 - Boston Childrens Hospital
 - Mayo Clinic
 - University of Colorado
 - MITRE
 - MIT

...

- Seattle Group Health Cooperative
- University of California, San Diego





Apache cTAKES Usage



1.	United States	2,803	2.85	00:03:12	43.92%
2.	India	499	2.32	00:02:58	54.11%
3.	China	242	1.74	00:01:07	88.43%
4.	Germany	225	2.04	00:01:19	48.44%
5.	Canada	222	2.46	00:02:47	29.73%
6.	United Kingdom	111	2.10	00:01:39	78.38%
7.	South Korea	67	2.28	00:01:21	59.70%
8.	Japan	66	2.58	00:01:57	53.03%
9.	Taiwan	58	2.16	00:01:51	53.45%
10.	(not set)	58	1.74	00:00:42	96.55%
11.	France	48	1.81	00:01:03	70.83%
12.	Australia	45	2.40	00:04:24	73.33%
13.	Turkey	45	3.60	00:01:14	42.22%
14.	Italy	42	2.36	00:00:58	92.86%
15.	Spain	41	3.10	00:04:39	70.73%
16.	Brazil	39	2.26	00:02:17	94.87%
17.	Sweden	30	3.53	00:03:33	66.67%
18.	Russia	28	1.86	00:01:19	96.43%
19.	Switzerland	27	2.93	00:01:27	74.07%
20.	Greece	26	3.88	00:04:04	46.15%





Why ASF?

ASF provides necessary parts for a community driven project to succeed:

Infrastructure

- Compile Servers
- Jira Issues Tracking
- Mail Servers/Mailing Lists
- SVN/MVN Repositories
- Wiki

•Governance Framework

- Meritocracy
- Voting process
- Organization Structure
 (user | developer | committer | PMC member | PMC chair | ASF member)

http://www.apache.org/foundation/how-it-works.html







The Apache Way

- collaborative software development
- commercial-friendly standard license
- consistently high quality software
- respectful, honest, technical-based interaction
- faithful implementation of standards
- security as a mandatory feature
- keep things as public as possible

apache.org/foundation/how-it-works.html#management

Get Involved!

- You don't need to be a software developer to contribute to Apache cTAKES
 - provide feedback
 - write or update documentation
 - help new users
 - recommend the project to others
 - test the code and report bugs
 - fix bugs
 - give us feedback on required features
 - write and update the software
 - create artwork
 - anything you can see that needs doing
- All of these contributions help to keep a project active and strengthen the community.





Mailing Lists

Subscribe:

- •Development List: dev-subscribe@ctakes.apache.org
- •Commits List: commits-subscribe@ctakes.apache.org
- •Users List: user-subscribe@ctakes.apache.org





cTAKES: Components

- Sentence boundary detection (OpenNLP technology)
- Tokenization (rule-based)
- Morphologic normalization (NLM's LVG)
- POS tagging (OpenNLP technology)
- Shallow parsing (OpenNLP technology)
- Named Entity Recognition
 - Dictionary mapping (lookup algorithm)
 - Machine learning (MAWUI)
 - types: diseases/disorders, signs/symptoms, anatomical sites, procedures, medications
- Negation and context identification (NegEx)
- Dependency parser
- Constituency parser
- Dependency based Semantic Role Labeling
- Relation Extraction
- Coreference module
- Drug Profile module
- Smoking status classifier
- Clinical Element Model (CEM) normalization module



cTAKES Technical Details

- Open source
 - Apache Software Foundation project
 - Java 1.6 or higher
 - Dependency on UMLS which requires a UMLS license (free)
- Framework
 - Apache Unstructured Information Management Architecture (UIMA) engineering framework
- Methods
 - Natural Language Processing methods (NLP)
 - Based on standards and conventions to foster interoperability
- Application
 - High-throughput system





Toolkits used

- Don't reinvent the Wheel!
 - UIMA
 - UIMA-AS
 - OpenNLP
 - clearTK
 - uimaFIT

Component implementation, instantiation, definition, execution via Java code w/o xml descriptors.

Utils





Medication CEM template				
	associatedCode			
	Change_status			
	Conditional			
	Dosage			
	Duration			
	End_date			
	Form			
	Frequency			
	Generic			
	Negation_indicator			
	Route			
	Start date			
	Strength			
	Subject			
	Uncertainty_indicator 🦯 👘			

Procedure CEM template

associatedCode Body_laterality Body_location Body_side Conditional Device End_date Generic Method Negation_indicator Relative_temporal_context Start_date Subject Uncertainty_indicator

Sign/Symptom CEM template

Alleviating factor associatedCode Body laterality Body location Body side Conditional Course Duration. End time Exacerbating factor Generic Negation indicator Relative temporal context Severity Start time Subject Uncertainty indicator

Lab CEM template

Abnormal_interpretation associatedCode Conditional Delta_flag Estimated_flag Generic Lab_value Negation_indicator Ordinal_interpretation Reference_range_narrative Subject Uncertainty_indicator

Disease/Disorder CEM template

Alleviating factor Associated sign or symptom associatedCode Body laterality Body location Body side Conditional. Course Duration End time Exacerbating factor Generic Negation indicator Relative temporal context Severity Start time Subject Uncertainty indicator

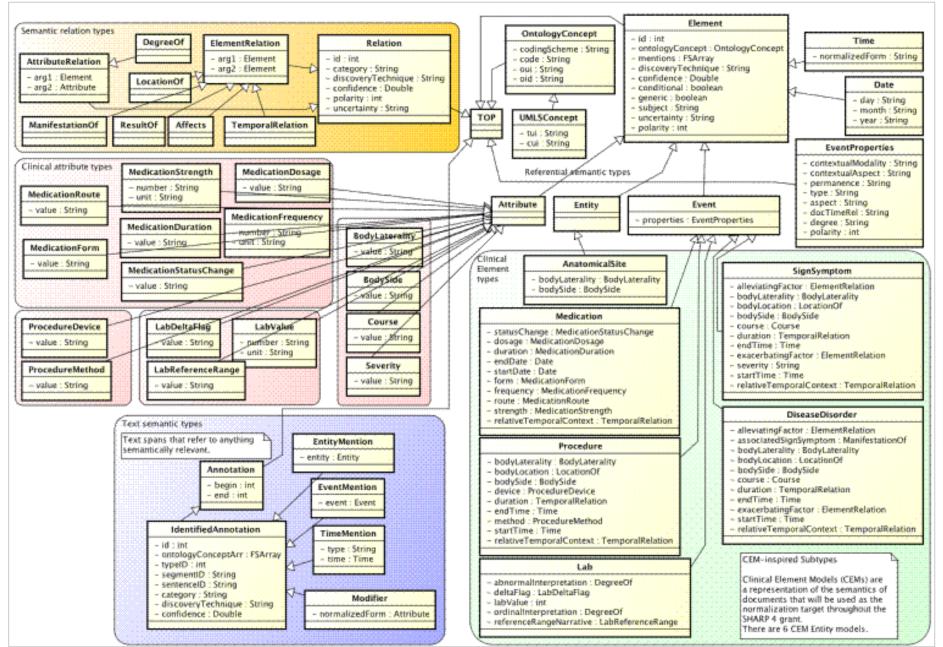
Anatomical Site CEM template

associatedCode Body_laterality Body_site Conditional Generic Negation_indicator Subject Uncertainty_indicator

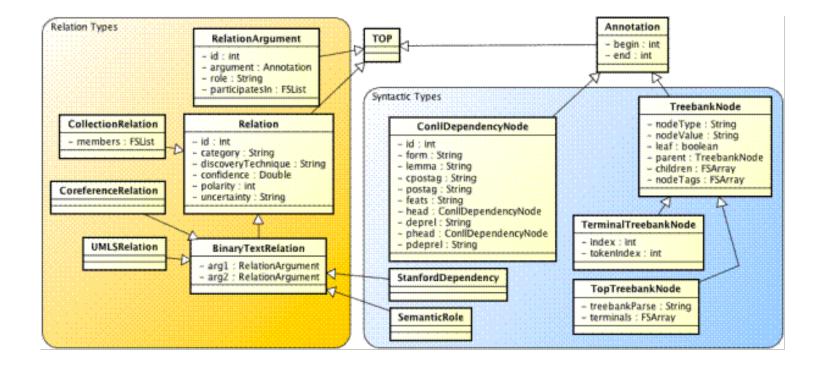




cTAKES Type System



Additional Spanned Types



UMLS, Named Entity Recognition



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UMLS Semantic Types, Groups and Relations

- UMLS (Unified Medical Language System) was developed to help with cross-linguistic translation of medical concepts
- Bodenreider and McCray (see Table 1 and Figure 3)

<u>http://semanticnetwork.nlm.nih.gov/SemGroups/Pap</u> <u>ers/2003-medinfo-atm.pdf</u>

 <u>http://clear.colorado.edu/compsem/documents/umls</u> <u>guidelines.pdf</u>





UMLS Example

 The patient underwent a radical tonsillectomy (with additional right neck dissection) for metastatic squamous cell carcinoma. He returns with a recent history of active bleeding from his oropharynx.

Example UMLS annotations:

Entities [patient]: Person [radical tonsillectomy (with additional right neck dissection)]: Procedure [radical tonsillectomy]: Procedure [additional right neck dissection]: Procedure [right neck]: Anatomy [metastatic squamous cell carcinoma]: Disorder [active bleeding from his oropharynx]: Disorder [active bleeding]: Disorder [active bleeding]: Disorder [oropharynx]: Anatomy





UMLS Terminology Services

- https://uts.nlm.nih.gov/home.html
 - Colorectal cancer
 - Ascending colon
 - MS
- Named entities
 - Mentions that belong to a particular semantic type (Ms. Smith Person; colorectal cancer Disease/Disorder; ascending colon anatomical site; joint pain sign/symptom)
 - Anything that can be referred to with a proper name





Named Entity Recognition

- Methods for discovering mentions of particular semantic types
 - Finding the spans of text that constitute the entity mention
 - Classifying the entities according to their semantic type
- Ambiguity in NER
 - -MS
 - Patient diagnosed with MS
 - Ms Smith was diagnosed with RA





Normalization of Named Entities

- Assigning an ontology code to varied surface forms
 - Patient diagnosed with RA (C0003873)
 - Patient diagnosed with *Rheumatoid Arthritis* (C0003873)
 - Patient diagnosed with *atrophic arthritis* (C0003873)





Attributes: Negation and Uncertainty

- Negation entity mention is negated
 - Patient denies *foot joint pain*.
 - foot joint pain, negated
 - C0458239, negated
- Uncertainty degree of uncertainty is associated with the entity mention
 - Results suggestive of *colorectal cancer*.
 - colorectal cancer, probable
 - C1527249, probable





Relation Extraction (UMLS)



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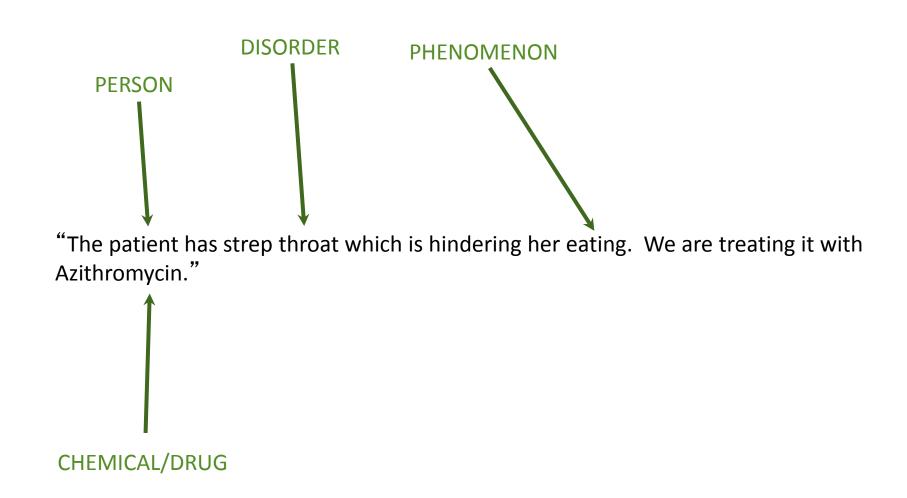


• Upcoming JAMIA manuscript

Dligach, Dmitriy; Bethard, Steven; Becker, Lee; Miller, Timothy; Savova, Guergana. (in press). Discovering body site and severity modifiers in clinical texts. Journal of the American Medical Informatics Association.

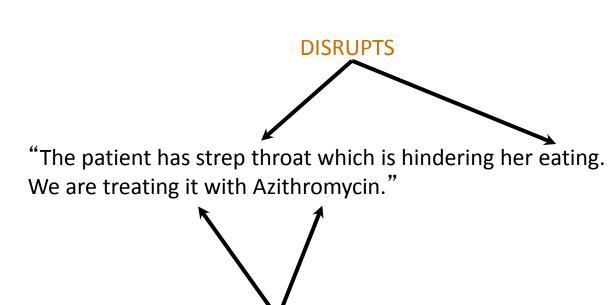












MANAGES/TREATS





UMLS Relations

- UMLS relations of interest:
 - LocationOf(anatomical site, disease/disorder)
 - LocationOf(anatomical site, sign/symptom)
 - DegreeOf(modifier, disease/disorder)
- Examples:
 - LUNGS: Equal AE bilaterally, no rales, no rhonchi.
 - LocationOf(lungs, rales)
 - LocationOf(lungs, rhonchi)
- DegreeOf relation
 - Severe headache
 - DegreeOf(severe, headache)





Modifiers

- DegreeOf
 - Modifiers
 - Entities
- Modifier discovery module
 - Implemented in cTAKES
 - BIO (Begin, Inside, Outside) representation
 - Word features
 - Algorithm: SVM
- Informal evaluation results





Relation Learning

- Statistical classifier
 - Input: a pair of entities
 - Output: relation / no relation label
- Training
 - Pair up all entity pairs
 - Assign a gold relation label (including NONE)
 - Downsample
 - Train an SVM model
- Testing
 - Pair up all entities in test set
 - Pass to the model
 - Assign label





Features

- Word features
 - Words of mentions
 - Context words
 - Distance
- Named entity features
 - Entity types
 - Entity context
- POS features
 - POS tags of entities
 - POS tags between entities

- Dependency features
 - Distance to common ancestor
 - Dependency path features
 - Governing/depedent word
- Chunking features
 - Head word of phrases between entities
 - Phrase head context
- Wikipedia features
 - Entity similarity
 - Article titles





Annotated Data

• SHARP

Total notes	Instances of LocationOf	Instances of DegreeOf
80	1852	308

- ShARe
 - Anatomical Sites and Disease/Disorders

Total notes	Instances of LocationOf	Instances of DegreeOf
130	2190	702





Evaluation

- Two-fold cross validation
- LibSVM
- Parameter search
 - Kernel (Linear/RBF)
 - SVM Cost parameter
 - RBF gamma parameter
 - Probability of keeping a negative example
- Evaluation on gold entities



Results

		F1 Score
	SHARP	ShARe
LocationOf relation	0.71	0.88
DegreeOf relation	0.93	0.94

- Best parameters
 - Linear kernel
 - Downsampling rate: 0.5
- Best features
 - Entity features
 - Word features





Upcoming

- Events
- Temporal Expression and their normalization
- Viz tool
- Question-answering (way in the future)

Applications in Biomedicine

- Translational science and clinical investigation
 - Patient cohort identification
 - Phenotype extraction
 - Linking patient's phenotype and genotype
 - eMERGE, PGRN, i2b2, SHARP
- Meaningful use of the EMR
- Comparative effectiveness
- Epidemiology
- Clinical practice





Processing Clinical Notes

A 43-year-old woman was diagnosed with type 23diabetes ld woman was diagnosed with type 2 diabetes mellitus by her family physician 3 months before this by her family physician 3 months before this presentation. Her initial blood glucose was 340 mg/df. Gbybunide initial blood glucose was 340 mg/dL. 2.5 mg once daily was prescribed. Since then, self-monitoring of once daily was prescribed. Since then, blood glucose (SMBG) showed blood glucose levels of 250+270ing of blood glucose (SMBG) showed blood mg/dL. She was referred to an endocrinologist for furtherels of 250-270 mg/dL. She was referred to an evaluation. endocrinologist for further evaluation.

On examination, she was normotensive and not acutely ill. Hershe was normotensive and not acutely body mass index (BMI) was 18.7 kg/m2 follor ill. Her body mass index (BMI) was 18.7 kg/m2 following weight loss. Her thyroid was symmetrically a recent 10 lb weight loss. Her thyroid was reflexes absent. Her blood glucose was 272 m symmetrically enlarged and ankle reflexes absent. Her hemoglobin Aic (HbAic) was 10.3%. A lipid plood glucose was 272 mg/dL, and her hemoglobin Aic cholesterol of 261 mg/dL, triglyceride level of 320 mg/ 10.3%. A lipid profile showed a total level of 48 mg/dL, and an LDL of 150 mg/dL. Thyroia Calles mg/dL, triglyceride level of 321 was normal. Urinanalysis showed trace ketones. dL, HDL level of 48 mg/dL, and an LDL of 150 mg/dL.

She adhered to a regular exercise program and vitamin regimen, Urinanalysis showed trace smoked 2 packs of cigarettes daily for the past 25 years, and limited her alcohol intake to 1 drink daily. Henenather's brother regular exercise program and vitamin was diabetic. regimen, smoked 2 packs of cigarettes daily for the

past 25 years, and limited her alcohol intake to 1 drink daily. Her mother's brother was diabetic.





Clinical Element Model

Disorder CEM text: code: subject: relative temporal context: negation indicator:	diabetes mellitus 73211009 family member not negated	
Tobacco Use CEM text: code: subject: relative temporal context: negation indicator:	smoking 365981007 patient 25 years not negated	She adhered to a regular exercise program and vitamin regimen, smoked 2 packs of cigarettes daily for the past 25 years Her mother's brother was diabetic.
Medication CEM text: code: subject: frequency: negation indicator: strength:	Glyburide 315989 patient once daily not negated 2.5 mg	
Disorder CEM text: code: subject: relative temporal context: negation indicator:	diabetes mellitus 73211009 patient 3 months ago not negated	A 43-year-old woman was diagnosed with type 2 diabetes mellitus by her family physician 3 months before this presentation. Her initial blood glucose was 340 mg/dL. Glyburide 2.5 mg once daily was prescribed.





Comparative Effectiveness

Disorder CEM text: code: subject: relative temporal context: negation indicator:	diabetes mellitus 73211009 patient 3 months ago not negated
Medication CEM text: code: subject: frequency: negation indicator: strength:	Glyburide 315989 patient once daily not negated 2.5 mg
Tobacco Use CEM text: code: subject: relative temporal context: negation indicator:	smoking 365981007 patient 25 years not negated
Disorder CEM text: code: subject: relative temporal context: negation indicator:	diabetes mellitus 73211009 family member not negated

Compare the effectiveness of different treatment strategies (e.g., modifying target levels for glucose, lipid, or blood pressure) in reducing cardiovascular complications in newly diagnosed adolescents and adults with type 2 diabetes.

Compare the effectiveness of traditional behavioral interventions versus economic incentives in motivating behavior changes (e.g., weight loss, smoking cessation, avoiding alcohol and substance abuse) in children and adults.



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Meaningful Use

Disorder CEM text: code: subject: relative temporal context: negation indicator:	diabetes mellitus 73211009 patient 3 months ago not negated
Medication CEM text: code: subject: frequency: negation indicator: strength:	Glyburide 315989 patient once daily not negated 2.5 mg
Tobacco Use CEM text: code: subject: relative temporal context: negation indicator:	smoking 365981007 patient 25 years not negated
Disorder CEM text: code: subject: relative temporal context: negation indicator:	diabetes mellitus 73211009 family member not negated

- Maintain problem list
- Maintain active med list
- Record smoking status
- Provide clinical summaries for each office visit
- Generate patient lists for specific conditions
- Submit syndromic surveillance data



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Clinical Practice

Disorder CEM text: code: subject: relative temporal context: negation indicator:	diabetes mellitus 73211009 patient 3 months ago not negated
Medication CEM text: code: subject: frequency: negation indicator: strength:	Glyburide 315989 patient once daily not negated 2.5 mg

• Provide problem list and meds from the visit





Example: Cohort Identification

- > 30MM records
- UIMA-AS
 - Scale out entire pipeline
 - Large Batch Processing
 - Dedicated Cluster(s) running LSF
 - > 96 concurrent pipelines
 - Custom start/stop scripts
- Future: UIMA-DUCC





Apache cTAKES Parallel Processing

- Background:
 - UIMA (2006)
 - UIMA-AS (2008)
 - Dedicated Cluster vs Grid Computing
- Future:
 - UIMA-DUCC (2013)
 (Distributed UIMA Cluster Computing)





What is UIMA (you – eee – muh)?

- Unstructured Information Management Architecture
- Open source scaleable and extensible platform
- Create, integrate and deploy unstructured information management solutions
- Many Open Source projects based on UIMA





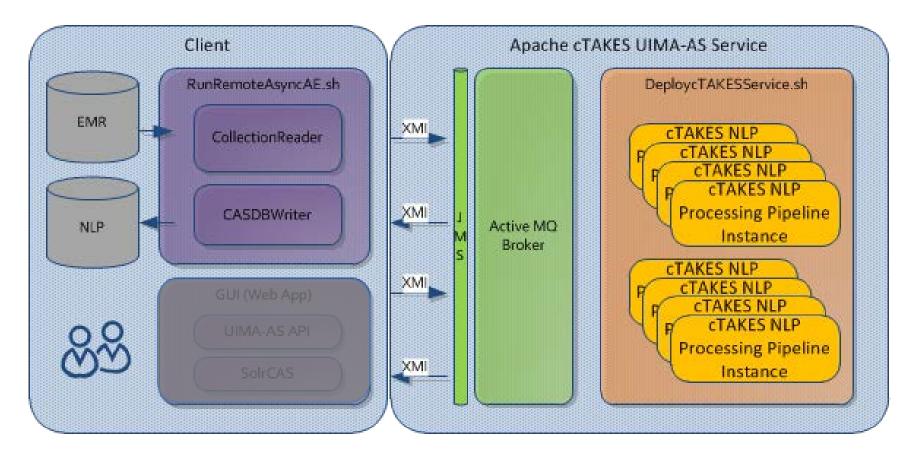
Why UIMA?

- Interoperability Many developers adopting UIMA
 - Easy to share and re-use resources
- Precisely controlled work flow
- Good scalability abilities
- Easy to utilize modules created by 3rd party developers
- Ongoing active development on new resources





Apache cTAKES UIMA-AS







Apache cTAKES Pipeline Deploy

- Define Pipeline (AggregatePlaintextUMLSProcessor.xml)
 - Collection Reader (CR)
 - Analysis Engine(s) (AE)
 - Cas Consumer (CC)
- Define Deploy Descriptor (DeployAggregatePlaintextUMLStoDb.xml)
 - BrokerURL
 - Input/Output Queue
- Start MQ Broker
- Deploy!





UIMA-AS Cluster Helper Scripts

set directories export ROOT DIR=/shared/chip nlp export UIMA HOME=\$ROOT DIR/app/uima-as/v2.4.0 export ACTIVEMQ HOME=\$ROOT DIR/app/activemq/apache-activemq-5.8.0 export CTAKES AS HOME=\$ROOT DIR/app/ctakes-as export CTAKES HOME=\$ROOT DIR/app/ctakes/apache-ctakes-3.1.0-incubating-SNAPSHOT export ACTIVEMQ OPTS MEMORY="-Xms1G -Xmx2G" # set ctakes-as defaults to be overridden per user export CTAKES AS QUEUE=org.apache.ctakes.service.pipeline.input.queue export CTAKES AS PORT=51515 export CTAKES AS WORK DIR=~ # Memory allocation for each Pipeline export UIMA JVM OPTS="-Xms256M -Xmx2G" # set up ctakes-as cluster configuration export CTAKES BROKER NODE=compute001 export CTAKES WORKER NODES="compute001 compute002 compute003 compute004" export CTAKES WORKER PIPES="1 2 3 4 5 6 7 8 9 10 11 12"

export CTAKES READER NODE=compute001

Use a pool with twice as many CAS Objects as there are Pipelines export CAS_COUNT=96

attempt setup of user-specific environment
. \$CTAKES AS HOME/setUserEnv.sh

final ctakes-as setup is based upon values either default or user export CTAKES_BROKER_URL=tcp://\$CTAKES_BROKER_NODE:\$CTAKES_AS_PORT export CTAKES_AS_LOG_DIR=\$CTAKES_AS_WORK_DIR/log export ACTIVEMQ_BASE=\$CTAKES_AS_WORK_DIR/activemq

Each user should have a ctakes-as/ directory and setProjectEnv.sh . \$CTAKES_AS_WORK_DIR/setProjectEnv.sh [ch150124@crit-hpc-head ctakes-as]\$





Dedicated Cluster(s) running LSF







Error Handling

• & Recovery

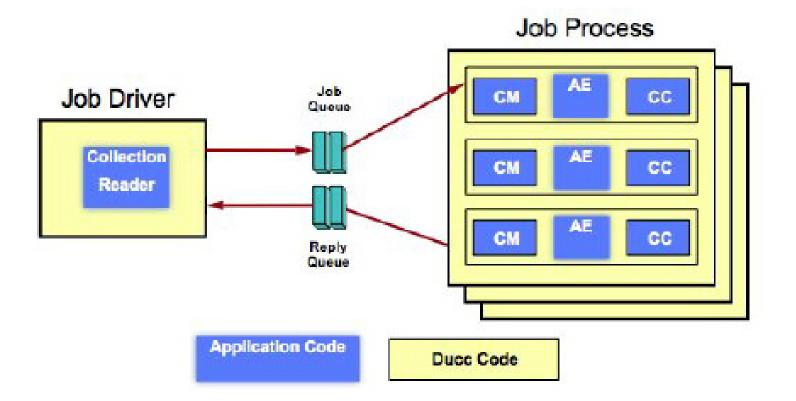


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Future: UIMA-DUCC

Jobs Reservations Services Surtem Services Surtem Refresh Manual Manual Manual Manual Manual Manual Manual Multice times 50.000 Manual Multice times 50.000 Manual Multice times 50.000 Manual Manual Manual Multice times 50.000 Manual Multice times 50.000 Multice times 50.0000 Multice times 50.0000 Multice times 50.0000 Multice times 50.0000 Multice times 50.0000 Multice times 50.00000 Multice times 50.0000 Multice times 50.0000		nlpdevlx2.chip.org:42133/system.machines.jsp ient ASF CMS Glossary
Machines List click column heading to sort	IMA-DUCC Machines ducc-mon 3.06.14 16:13:56 Distributed UIMA Cluster Computing Monitor V% Version: 0.8.0-beta Copyrights: © 2012-2013 The Apache Software Foundation and © 2012	Refresh Manual Automatic Manual Automatic
	click column heading to sort	Reserve(GB):size \$ Mem
Total 8 8 0 23 2 1 up 127.0.0.1 nlpdevlx2.chip.org 8 8 0 23 2 1		





Demo

000		ctakes-gui			112
🔹 🕨 🖾 📂 loca	lhost:9998			C Reader	
↔ 💭 🎹 Apple 🔻 eBay	y Yahoo! Ne	WS 🔻			+
TAPache cTAKES (Demo	o)	Logged on: admir	admin		Logout
Navigation 《	28 Process N	lotes 🗵			
Process Notes Proview Single Doc	Input Text				*
2 Create New Batch	Results				8
- 28 Results 🕀 🚱 Configuration	patient took 5	50mg of aspirin for pain for his shark bite.			
Advanced	Concept	Value	Begin	End	
H dministration	LookupWind	LookupWindowAnnotation sofa: _InitialView begin: 0 end: 7	0	7	
	NP	NP sofa: _InitialView begin: 0 end: 7 chunkType: "NP"	0	7	
	WordToken	WordToken sofa:initialView begin: 0 end: 7 tokenNumber: 0 normalizedForm: "patient" partOfSpeech: "NN" lemmaEn	-	7	
	VP	VP sofa: _InitialView begin: 8 end: 12 chunkType: "VP"	8	12	_
	WordToken	WordToken sofa:initialView begin: 8 end: 12 tokenNumber: 1 normalizedForm: "took" partOfSpeech: "VBD" lemmaEn	8	12	
	LookupWind	LookupWindowAnnotation sofa: _InitialView begin: 13 end: 56	13	56	
	NP	NP sofa: _InitialView begin: 13 end: 56 chunkType: "NP"	13	56	
	WordToken	WordToken sofa: _InitialView begin: 13 end: 17 tokenNumber: 2 normalizedForm: "50mg" partOfSpeech: "NNS" lemma	13	17	
	PP	PP sofa: _InitialView begin: 18 end: 20 chunkType: "PP"	18	20	
	WordToken	WordToken sofa: _InitialView begin: 18 end: 20 tokenNumber: 3 normalizedForm: "of" partOfSpeech: "IN" lemmaEntri	18	20	
	MedicationE	MedicationEventMention sofa: _InitialView begin: 21 end: 28 id: 0 ontologyConceptArr: FSArray typeID: 1 segmentID:	21	28	
	OntologyCo	OntologyConcept codingScheme: "RXNORM" code: "1191" oid: "1191#RXNORM" oui:	21	28	
		Powered by Apache cTAKES			





Demo

le Edit Run Tools Help		
nalysis Results		Text
uima.tcas.Annotation [73]	^	patient took 50mg of aspirin for severe pain in right knee.
 uima.tcas.DocumentAnnotation [1] 		
 org.apache.ctakes.typesystem.type.CopyDestAnnotation [0] 		
 org.apache.ctakes.typesystem.type.CopySrcAnnotation [0] 	=	
org.apache.ctakes.typesystem.type.syntax.BaseToken [12]		
🗣 org.apache.ctakes.typesystem.type.syntax.Chunk [9]		
 org.apache.ctakes.typesystem.type.syntax.ConllDependencyNode [13] 		
org.apache.ctakes.typesystem.type.syntax.TreebankNode [26]	-	
	•	
[3] = org.apache.ctakes.typesystem.type.textsem.Modifier		
[4] = org.apache.ctakes.typesystem.type.textsem.SignSymptomMention		
🗠 sofa = uima.cas.Sofa		
— <i>begin</i> = 40		
- end = 44		
- <i>id</i> = 0		
ontologyConceptArr = uima.cas.FSArray[5]		
- type/D = 3		
segment/D = <null></null>		
sentence/D = <null></null>		
discoveryTechnique = 1		
- confidence = 0.0		
- polarity = 0		
— uncertainty = 0		
- conditional = false		
generic = false		
- subject = <null></null>		
— historyOf = 0		
preferredText = <null></null>		
- event = <null></null>		
— alleviatingFactor = <null></null>		
— bodyLaterality = <null></null>		
bodySide = <null></null>		
bodyLocation = org.apache.ctakes.typesystem.type.relation.LocationOfTextRelation		
-id=0		
- category = "location_of"	=	
- discoveryTechnique = 0		
- confidence = 0.0		
polarity = 0		
- uncertainty = 0		
arg1 = org.apache.ctakes.typesystem.type.relation.RelationArgument		
•- arg2 = org.apache.ctakes.typesystem.type.relation.RelationArgument		
-id = 0		
argument = org.apache.ctakes.typesystem.type.textsem.AnatomicalSiteMention		
- role = "Related_to"		
participatesIn = <null></null>		
— course = <null></null>		
- duration = <null></null>		
— endTime = <null></null>		
exacerbatingFactor = <null></null>		
severity = org.apache.ctakes.typesystem.type.relation.DegreeOfTextRelation		
- startTime = <null></null>		
relativeTemporalContext = <null></null>		
[5] = org.apache.ctakes.typesystem.type.textsem.AnatomicalSiteMention		
 [6] = org.apache.ctakes.typesystem.type.textsem.Modifier [6] = org.apache.ctakes.typesystem.type.textsem.Modifier 		
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 [r] = orgraphicite.com/es/types/stern.type.textsern.Anatornicalonemention 		



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END



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Treebank Annotations



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Treebank Annotations

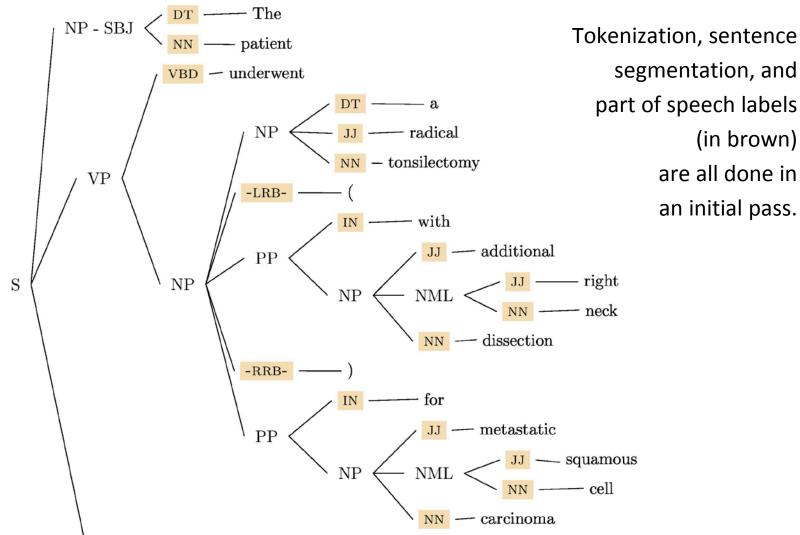
- Consist of part-of-speech tags, phrasal and function tags, and empty categories organized in a tree-like structure
- Adapted Penn's POS tagging guidelines, bracketing guidelines, and associated addenda
- Extended the guidelines to account for domain-specific characteristics

http://clear.colorado.edu/compsem/documents/treeba nk_guidelines.pdf





Treebank Review

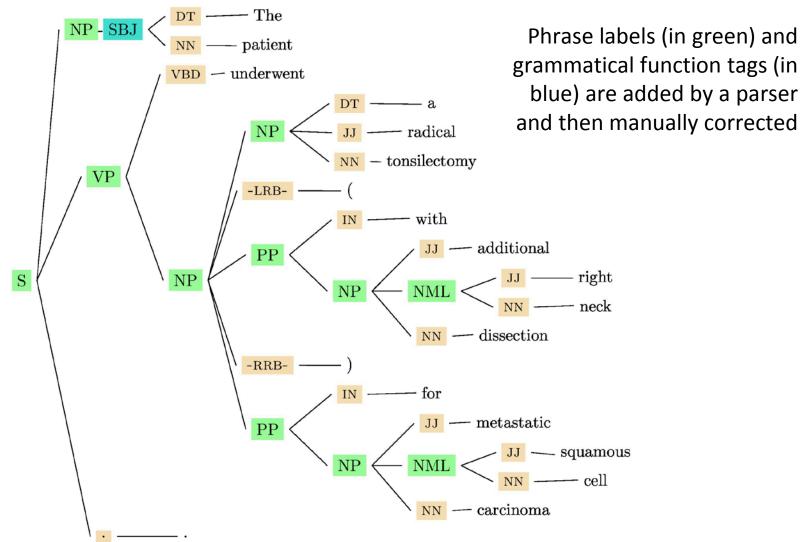


The patient underwent a radical tonsilectomy (with additional right neck dissection) for metastatic squamous cell carcinoma .





Treebank Review



The patient underwent a radical tonsilectomy (with additional right neck dissection) for metastatic squamous cell carcinoma .

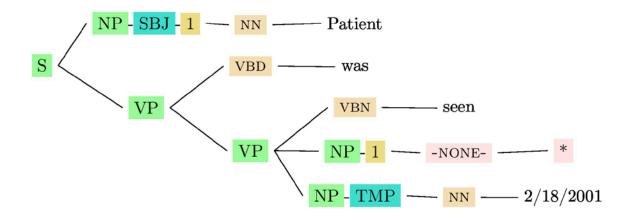




Treebank Review

In that second pass, new tokens are added for implicit and empty arguments (in red), and grammatically linked elements are indexed (in yellow)

Patient was seen 2/18/2001



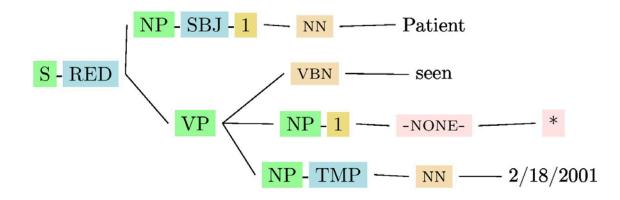




Clinical Additions – S-RED

Clinical language is highly reduced, and often elides copula ("to be"). -RED tag was introduced to mark clauses with elided copulas.

Patient (was) seen 2/18/2001



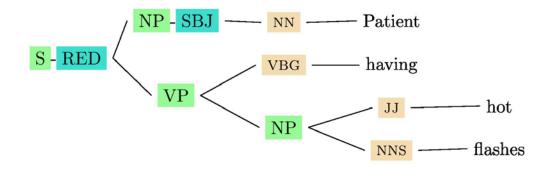




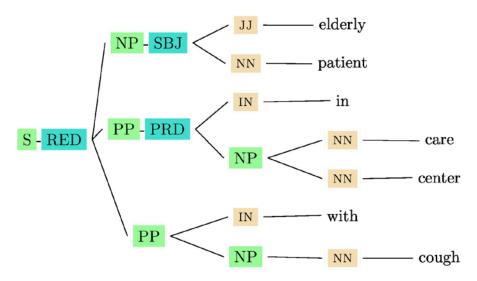
Clinical Additions – S-RED

Patient (is) having hot flashes

-RED tags are used for all elisions of the copula, including passive voice, progressive (top example) and equational clauses (bottom example).



Elderly patient (is) in care center with cough

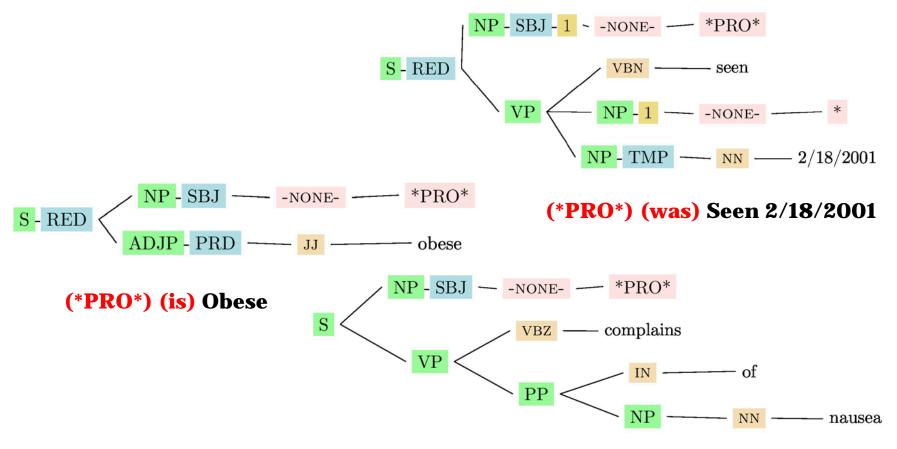






Clinical Additions – Null Arguments

Dropped subjects are very common in this data, and *PRO* tags are added to represent them.



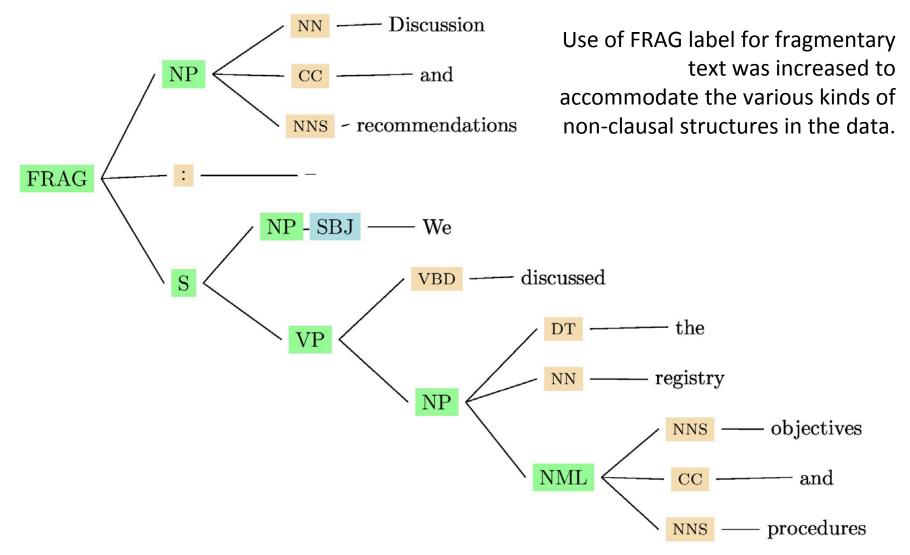
(*PRO*) Complains of nausea



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Clinical Additions – FRAG



Discussion and recommendations: We discussed the registry objectives and procedures.





Propbank Annotations



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What is Propbank?

- who did what to whom when where and how
- A database of syntactically parsed trees annotated with semantic role labels
- All arguments are annotated with semantic roles in relation to their predicate structure
- This provides training data that can identify predicate-argument structures for individual verbs.





Propbank Labels

- Labels do not change with predicate
- Meanings of core arguments 2-5 change with predicate
- Arg0 proto-agent for transitive verbs
- Arg1 proto-patient for transitive verbs
- Meanings of Adjunctive args do not change
- http://clear.colorado.edu/compsem/documents/propba nk_guidelines.pdf





Propbank Labels

- Arg0 = agent
- Arg1 = theme / patient
- Arg2 = benefactive / instrument/ attribute / end state
- Arg3 = start point / benefactive / attribute
- Arg4 = end point
- ArgM = modifier





Propbank Labels

ARG0(agent)	Adverbial	Manner		
ARG1(patient)	Cause	Modal		
ARG2	Direction	Negation		
ARG3	Discourse	Purpose		
ARG4	Extent	Temporal		
	Location	Predicatio		

emporal redication

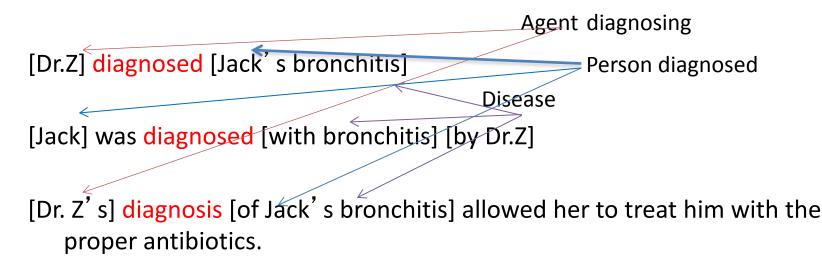






Why Propbank?

• Identifying a commonalities in predicateargument structures:







Stages of the Propank process

• Frame Creation

Predicate: undergo

undergo: Frames file for 'undergo' based on sentences in financial subcorpus.

Roleset id: undergo.01 , experience, undergo, vncls: , framnet: Undergoing

undergo.01: No Vncls. Comparison with 'go through'.

Roles:

Arg1: experiencer Arg2: experienced

Example: pretty typical

Periods before the advent of futures or program trading were often more volatile, usually when fundamental market conditions were undergoing change (1973-75, 1937-40, and 1928-33 for example).

Argl: fundamental market conditions Rel: undergoing Arg2: change



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Stages of Propbank

- Annotation
 - Data is double annotated
 - Annotators
 - 1. Determine and select the sense of the predicate
 - 2. Annotate the arguments for the selected predicate sense
- Adjudication
 - After data is annotated, it is passed to an adjudicator who resolves differences between the two annotators
 - This creates the *gold standard* corrected, finished training data





Annotation Example

gold 0:2-ARGM-TME 5:1-ARG1 6:0 rel 7:1-ARG2 9:1-ARGM-MNR greenim 0:2-ARGM-TME 5:1-ARG1 6:0 rel 7:1-ARG2 9:1-ARGM-MNR Roleset Information D: undergo.01 NP-TMP 0:2-ARGM-TMP 5:1-ARG1 6:0 rel 7:1-ARG2 9:1-ARGM-ADV TOP \$ NP-TMP 0:2-ARGM-TMP NP-TMP 0:2-ARGM-TMP NP-TMP 0:2-ARGM-TMP NP-TMP 0:2-ARGM-TMP NP-TMP 0:2-ARG1 CD 4 NP-TMP 0:2-1-ARG1 VP VBD underwent 6:0-rel NN resection \$ P P 9:1-ARGM-MNR IN by \$ NN resection \$ NP NNP S Drs. NNN protrutt NNNP S Drs. \$ NNN NP S Drs. \$ NNN NP S Drs. \$ NNN S Drs. \$ NNNP S Drs. \$ NNL \$ NNL \$ NNL \$ NNL \$ <	Prev	Next	2	undergo	under	go.01	
greenin 0:2-ARCM-TMP 5:1-ARC1 6:0-rel 7:1-ARC2 9:1-ARCM-TMR kast8504 0:2-ARCM-TMP 5:1-ARC1 6:0-rel 7:1-ARC2 9:1-ARCM-ADV TOP S NP-TMP 0:2-ARCM-TMP NP-TMP 0:2-ARCM-TMP NP-TMP 0:2-ARCM-TMP CD 4 CD 4 VP-TMP CD 2010 :				Roleset Information			
TOP Arg2 : experienced Image: NP-TMP 0:2-ARGM-TMP Image: Arg2 : experienced Image: NP-TMP 0:2-ARGM-TMP Image: Arg2 : experienced Image: NP-TMP 0:2-ARGM-TMP Image: Arg2 : experienced Image: NP-TMP 0:2-ARG1 Image: Arg2 : experienced Image: NP-TMP 0:2-ARG2 Image: Arg2 : experienced Image: NP 7:1-ARG2 Image: Arg2 : experienced <td< td=""><td colspan="3">greenlm 0:2-ARGM-TMP 5:1-ARG1 6:0-rel 7:1-ARG2 9:1-ARGM-MNR</td><td colspan="4">Name : experience, undergo</td></td<>	greenlm 0:2-ARGM-TMP 5:1-ARG1 6:0-rel 7:1-ARG2 9:1-ARGM-MNR			Name : experience, undergo			
PP 9:1-ARG2 IN resection PP 9:1-ARGM-MNR IN bv NNPS Drs. NML NML NML NML NML MML M-DIS (I) M-LVB (B)	TOP S NP-TMP 0:2-ARGM-TMP NNP August CD 4 NP-TMP CD 2010 : NP-SBI 5:1-ARG1 -NONE- *PRO* YP		Arg1 : experiencer Arg2 : experienced				
I surgical NN resection O 1 PP 9:1-ARGM-MNR IN bv NP NNPS Drs. NML NML NMP Orcutt NNP Orcutt NNP Orcutt				Argument View			
P NNPS Drs. ML M-ADJ (J) M-CAU (C) M-COM (8) M-DIS (I) M-DSP (S) M-GOL (G) M-LOC (L) M-LVB (B) M-MNR (M)	NN resection					2	
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	🕈 NML	cutt		M-DIS (I)	M-DSP (S)	M-GOL (G)	
	 • NML			M-LOC (L)	M-LVB (B)	M-MNR (M)	
NNP Charlie M-NEG (N) M-PRD (7) M-PRP (P)				M-NEG (N)	M-PRD (7)	M-PRP (P)	







JAMIA, 2013

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Towards comprehensive syntactic and semantic annotations of the clinical narrative

Daniel Albright,¹ Arrick Lanfranchi,¹ Anwen Fredriksen,¹ William F Styler IV,¹ Colin Warner,² Jena D Hwang,¹ Jinho D Choi,³ Dmitriy Dligach,⁴ Rodney D Nielsen,^{1,5} James Martin,³ Wayne Ward,³ Martha Palmer,¹ Guergana K Savova⁴

ABSTRACT

Objective To create annotated clinical narratives with lavers of syntactic and semantic labels to facilitate advances in clinical natural language processing (NLP). To develop NLP algorithms and open source components. Methods Manual annotation of a clinical narrative corpus of 127 606 tokens following the Treebank schema for syntactic information, PropBank schema for predicate-argument structures, and the Unified Medical Language System (UMLS) schema for semantic information. NLP components were developed. Results The final corpus consists of 13 091 sentences containing 1772 distinct predicate lemmas. Of the 766 newly created PropBank frames, 74 are verbs. There are 28 539 named entity (NE) annotations spread over 15 UMLS semantic groups, one UMLS semantic type, and the Person semantic category. The most frequent annotations belong to the UMLS semantic groups of Procedures (15.71%), Disorders (14.74%), Concepts and Ideas (15.10%), Anatomy (12.80%), Chemicals and Drugs (7.49%), and the UMLS semantic type of Sign or Symptom (12.46%). Inter-annotator agreement results: Treebank (0.926), PropBank (0.891–0.931), NE (0.697–0.750). The part-of-speech tagger, constituency parser, dependency parser, and semantic role labeler are built from the corpus and released open source. A significant limitation uncovered by this project is the need for the NLP community to develop a widely agreed-upon schema for the annotation of clinical concepts and their relations.

Conclusions This project takes a foundational step towards bringing the field of clinical NLP up to par with NLP in the general domain. The corpus creation and NLP components provide a resource for research and application development that would have been previously impossible. other), the level of certainty associated with an event (confirmed, possible, negated) as well as textual mentions that point to the same event. We describe our efforts to combine annotation types developed for general domain syntactic and semantic parsing with medical-domain-specific annotations to create annotated documents accessible to a variety of methods of analysis including algorithm and component development. We evaluate the quality of our annotations by training supervised systems to perform the same annotations automatically. Our effort focuses on developing principled and generalizable enabling computational technologies and addresses the urgent need for annotated clinical narratives necessary to improve the accuracy of tools for extracting comprehensive clinical information.¹ These tools can in turn be used in clinical decision support systems, clinical research combining phenotype and genotype data, quality control, comparative effectiveness, and medication reconciliation to name a few biomedical applications.

In the past decade, the general natural language processing (NLP) community has made enormous strides in solving difficult tasks, such as identifying the predicate-argument structure of a sentence and associated semantic roles, temporal relations, and coreference which enable the abstraction of the meaning from its surface textual form. These developments have been spurred by the targeted enrichment of general annotated resources (such as the Penn Treebank (PTB)²) with increasingly complex layers of annotations, each building upon the previous one, the most recent layer being the discourse level.3 The emergence of other annotation standards (such as PropBank⁴ for the annotation of the sentence predicate-argument structure) has brought new progress in the annotation of semantic informa-





Select Publications on cTAKES Methods



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- Albright, Daniel; Lanfranchi, Arrick; Fredriksen, Anwen; Styler, William; Warner, Collin; Hwang, Jena; Choi, Jinho; Dligach, Dmitriy; Nielsen, Rodney; Martin, James; Ward, Wayne; Palmer, Martha; Savova, Guergana. 2013. Towards syntactic and semantic annotations of the clinical narrative. Journal of the American Medical Informatics Association. 2013;0:1–9. doi:10.1136/amiajnl-2012-001317 <u>http://jamia.bmj.com/cgi/rapidpdf/amiajnl-2012-001317?ijkey=z3pXhpyBzC7S1wC&keytype=ref</u>
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- Jinho D. Choi, Martha Palmer, "Transition-based Semantic Role Labeling Using Predicate Argument Clustering", Proceedings of ACL workshop on Relational Models of Semantics (RELMS'11), 37-45, Portland, Oregon, 2011.
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Select Publications on cTAKES Applications



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