State-of-Art of Health Natural Language Processing

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Overview

- Success stories
- State of the art: recent shared tasks
- Overview of methods
- Overview of applications

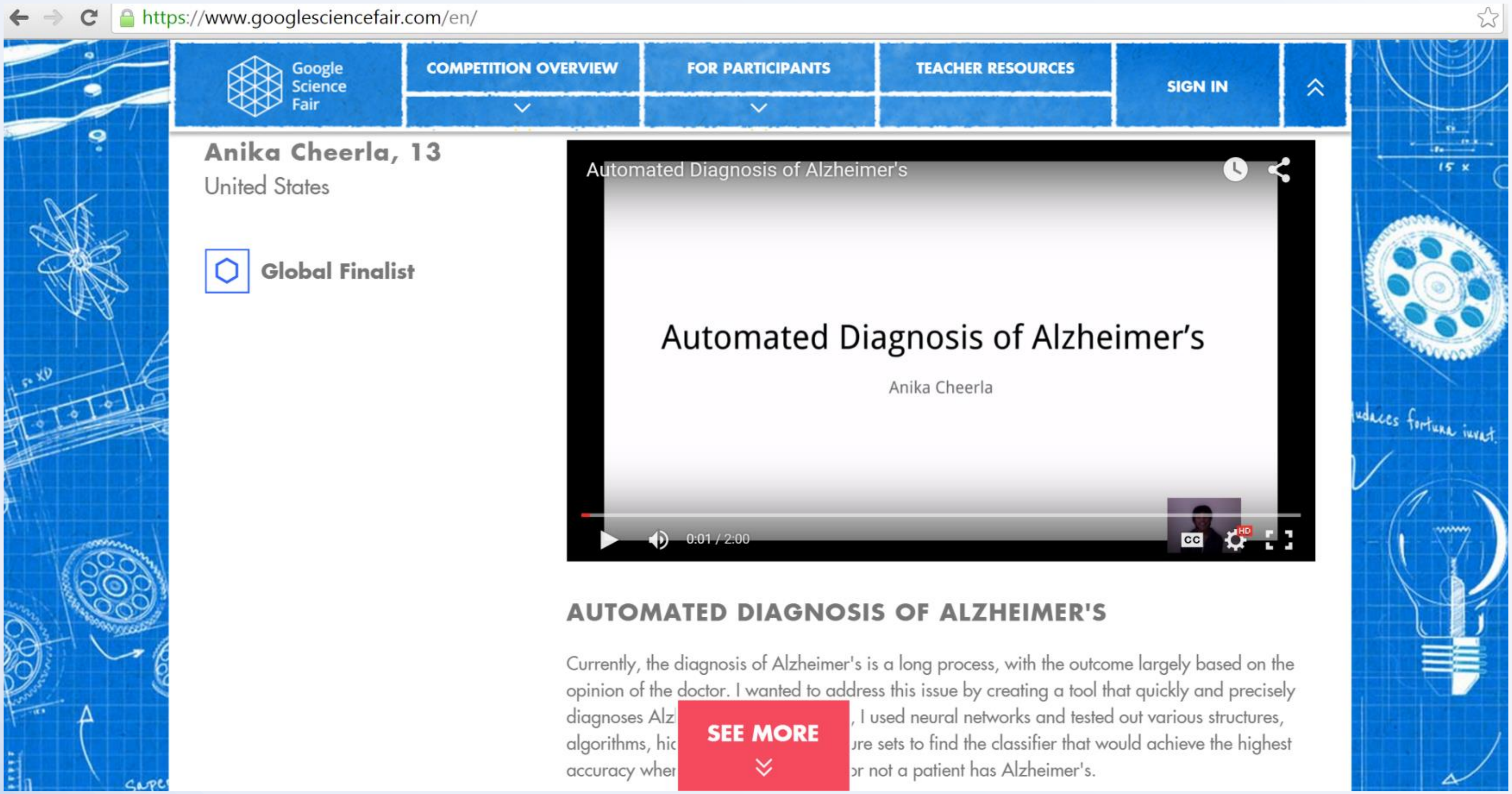
Clinical Narrative?

- Text written by the physicians at the point of care
- **Intense Thick Data**: overwhelmingly large amounts of text
- **Sparse**: for some concepts, sparsity problem
- **Missing but not at random (MNAR)**: language is MNAR
- **Ambiguity**: lexical, syntactic, semantic, discourse, and pragmatics
- Language is **heterogenous** and at **different levels of granularity**
- Language is **contextual**
- Language comes wi**th meta-data**

Success Stories

Scalable Phenotyping

- EMR as the source for finding large patient cohorts for PWAS/GWAS studies
- eMERGE, PGRN, PCORI
  - Goal is PPV above 0.9
  - Multiple diseases
  - eMERGE: understanding genetics of diseases
  - PGRN: understanding the pharmacogenetics of disease treatments
  - PCORI: empowering the patient as a driving force in research through phenotype/genetic contributions

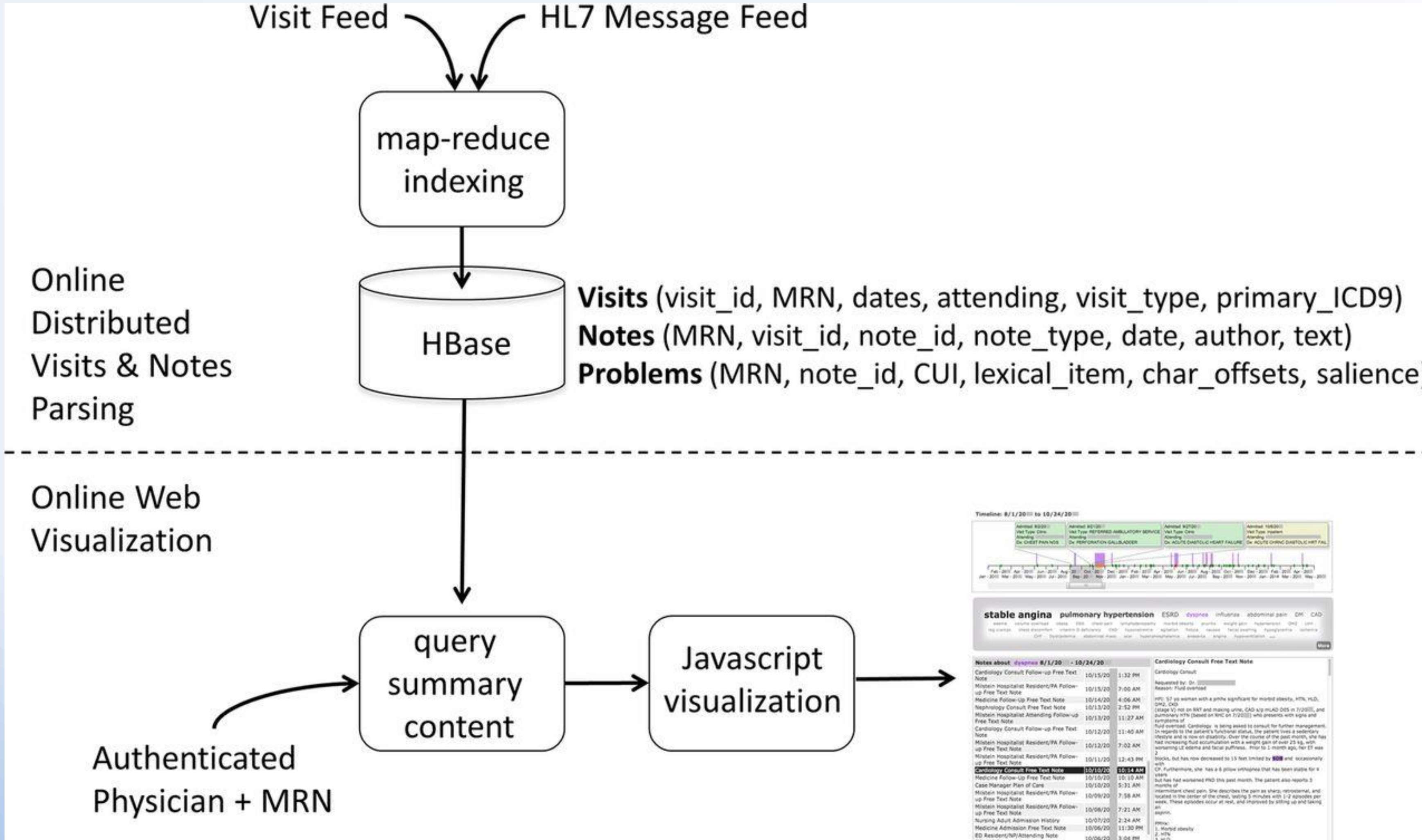

https://www.googlesciencefair.com/en/
Google Science Fair
COMPETITION OVERVIEW
FOR PARTICIPANTS
TEACHER RESOURCES
SIGN IN
Anika Cheerla, 13
United States
Global Finalist
Automated Diagnosis of Alzheimer's
Automated Diagnosis of Alzheimer's
Anika Cheerla
0:01 / 2:00
AUTOMATED DIAGNOSIS OF ALZHEIMER'S
Currently, the diagnosis of Alzheimer's is a long process, with the outcome largely based on the opinion of the doctor. I wanted to address this issue by creating a tool that quickly and precisely diagnoses Alz
, I used neural networks and tested out various structures,
algorithms, hi
ure sets to find the classifier that would achieve the highest
accuracy wher
or not a patient has Alzheimer's.
SEE MORE

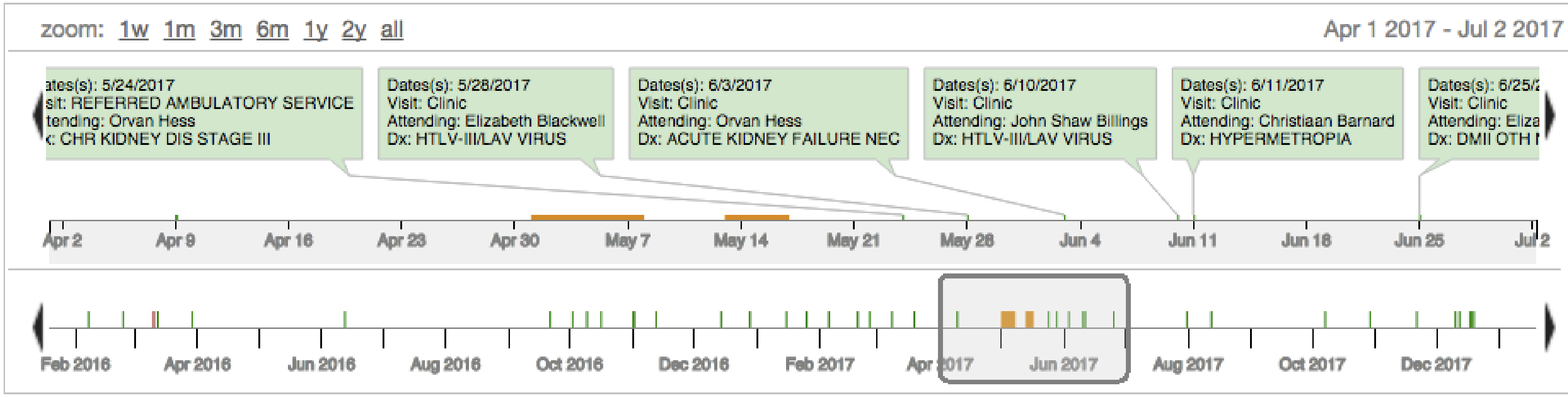
HARVEST

- Extracts content from a patient's longitudinal documentation
- Aggregates information from multiple care settings
- Visualizes content through a timeline of a patient's problem documentation and clinical encounters
- Distributed computing infrastructure
- Deployed at NewYork-Presbyterian hospital 1,000 users in 6 months (out of 10,000 users of NYP EHR)

Hirsch et al (2015) HARVEST, a longitudinal patient record summarizer. J Am Med Inform Assoc.

HARVEST

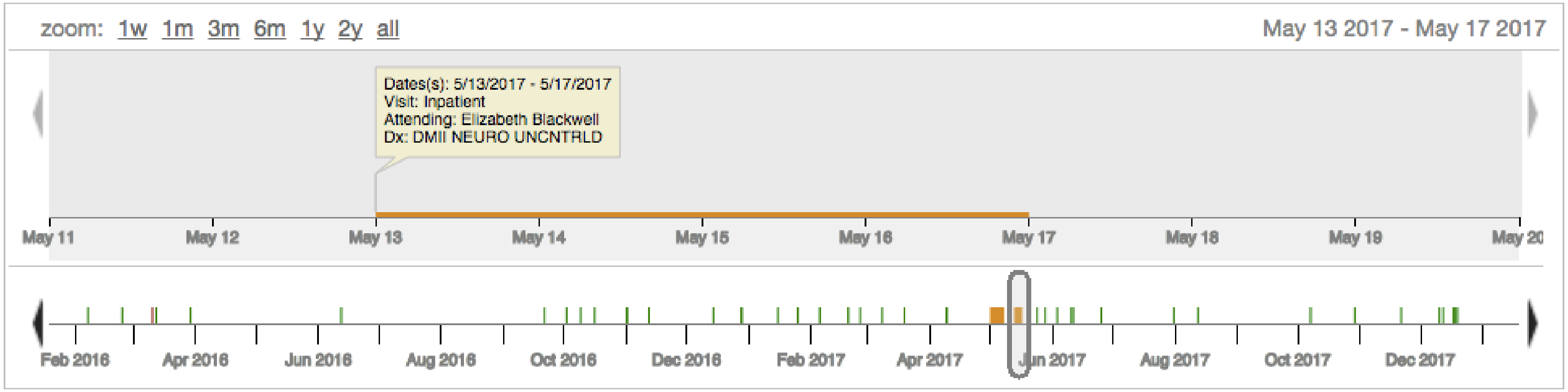

Visit Feed
HL7 Message Feed
map-reduce indexing
HBase
Online Distributed Visits & Notes Parsing
Visits (visit_id, MRN, dates, attending, visit_type, primary_ICD9)
Notes (MRN, visit_id, note_id, note_type, date, author, text)
Problems (MRN, note_id, CUI, lexical_item, char_offsets, salience)
Online Web Visualization
query summary content
Javascript visualization
Authenticated Physician + MRN
stable angina
pulmonary hypertension



HIV asthma DM cardiomyopathy hyperglycemia CHF DM2 COPD MGUS dry eyes gastroparesis vomiting nausea morbid obesity DCM anaphylaxis wheezes cough nausea/vomiting diabetic gastroparesis belching obese proteinuria ...

More

All notes 4/1/2017 - 7/2/2017	
Amb HP6 Adult Note	06/25/2017 7:25 AM
Amb Eye Clinic Note	06/11/2017 11:10 AM
Amb Eye IDT Note	06/11/2017 9:41 AM
Nephrology Consult Free Text Note	06/03/2017 2:15 PM
Amb HP6 Adult Note	05/28/2017 8:43 AM
Nephrology Consult Follow-up Free Text Note	05/17/2017 3:23 PM
Patient Discharge Instructions	05/17/2017 3:03 PM
Medicine Follow-Up Free Text Note	05/16/2017 11:33 AM
Nephrology Consult Free Text Note	05/16/2017 8:55 AM
Miscellaneous Nursing Note.	05/16/2017 5:00 AM
Medical Student Follow-up Free Text Note	05/16/2017 3:00 AM
NYP Discharge Summary Note	05/15/2017 4:07 PM
Medicine Follow-Up Free Text Note	05/15/2017 9:58 AM
Initial Nutrition Assessment	05/15/2017 9:22 AM
Medical Student Follow-up Free Text Note	05/15/2017 3:19 AM
Medicine Follow-Up Free Text Note	05/14/2017 6:30 AM
SW Initial Assessment - Adult	05/14/2017 6:12 AM
Miscellaneous Nursing Note.	05/14/2017 4:09 AM
Nursing Adult Admission History	05/13/2017 11:10 PM



HIV asthma vomiting gastroparesis DM DM2 belching nausea proteinuria CHF hyperglycemia dry eyes lightheadedness heartburn nausea/vomiting cardiomyopathy cholelithiasis MGUS reflux anaphylaxis obese AKI mallory weiss tear diabetic nephropathy acute cholecystitis bloating renal cyst COPD diabetic gastroparesis atelectasis hepatic steatosis hypertension ...

More

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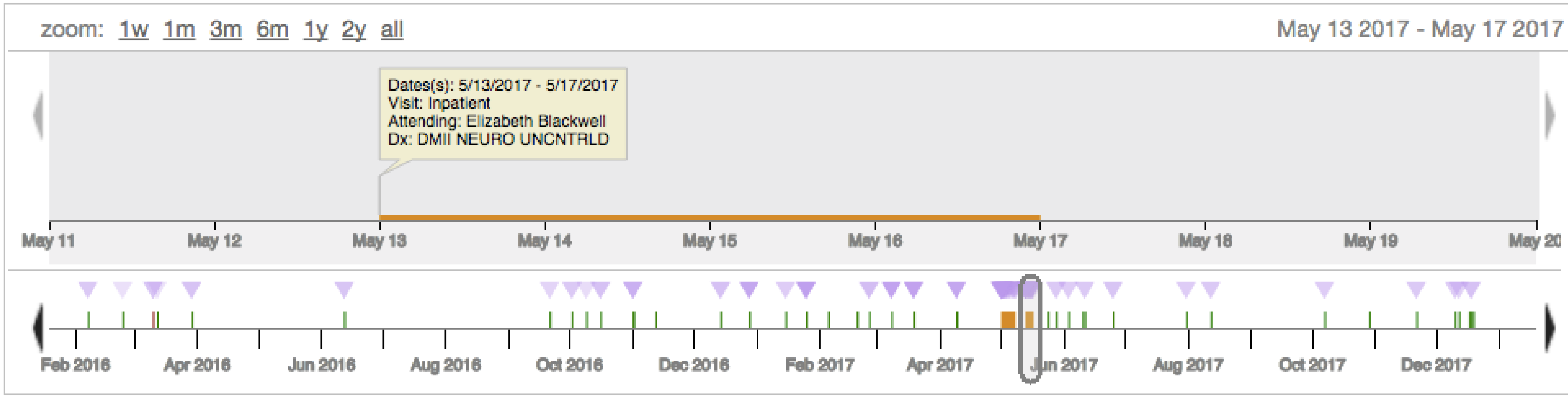
Nursing Adult Admission History	05/13/2017 11:10 PM
Medicine Admission Free Text Note	05/13/2017 10:23 PM
ED Disposition Note	05/13/2017 6:05 PM
Medical Student Admission Free Text Note	05/13/2017 6:11 AM
ED Attending Note (Milstein)	05/13/2017 6:07 AM



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More

Notes about HIV 5/13/2017 - 5/17/2017	
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ED Adult Pre-Assessment Note	05/13/2017 4:01 AM

Apache cTAKES: Sample Pipeline

The patient underwent a CT scan in April which did not reveal lesions in his liver.

Boundary Detection — … The patient underwent a CT scan in April which did not reveal lesions in his liver. …

Tokenization / Normalization / Part-of-speech Tagger

Tokenization	The	patient	underwent	a	CT	scan	in	April	which	did	not	reveal	lesions	in	his	liver	.
Normalization	-	-	undergo	-	-	-	-	-	-	do	-	-	lesion	-	-	-	
Part-of-speech Tagger	DT	NN	VBD	DT	NN	NN	IN	NNP	WDT	VBD	RB	VB	NNS	IN	PRP$	NN	.

Entity Recognition

CT scan	Lesion	Liver
Procedure	Disease / Disorder	Anatomy
UMLS ID: C0040405	UMLS ID: C0022198	UMLS ID: C0023884

Biomedical End-Use

Chunking

NP | VP | NP | PP | NP | VP | NP

Constituency Parsing

S | NP | DT | NN | VP … | …

Dependency Parsing

…

SRL

undergo.01 (A1.patient; A2.scan; AM-TEMP.in)
reveal.01 (A0.scan; R-A0.which; AM-NEG.not; A1.lesions; AM-LOC.in)

Entity Properties

CT scan	Lesion	Liver
Negated: no	Negated: yes	Negated: no
Subject: patient	Subject: patient	--

UMLS Relation

locationOf (lesions, liver)

Event, Temp. Expr.

CT scan | April | Reveal | Lesions

Temporal Relation

April *CONTAINS* CT scan | CT scan *CONTAINS* lesions

Coreference

identity (the patient, his)

Biomedical End-Use

cTAKES

The patient underwent a CT scan in April which did not reveal lesions in his liver.

Boundary Detection

...	The patient underwent a CT scan in April which did not reveal lesions in his liver.	...

Tokenization

	The	patient	underwent	a	CT	scan	in	April	which	did	not	reveal	lesions	in	his	liver	.	

Normalization

	-	-	undergo	-	-	-	-	-	-	do	-	-	lesion	-	-	-		

Part-of-speech Tagging

	DT	NN	VBD	DT	NN	NN	IN	NNP	WDT	VBD	RB	VB	NNS	IN	PRP$	NN	.	

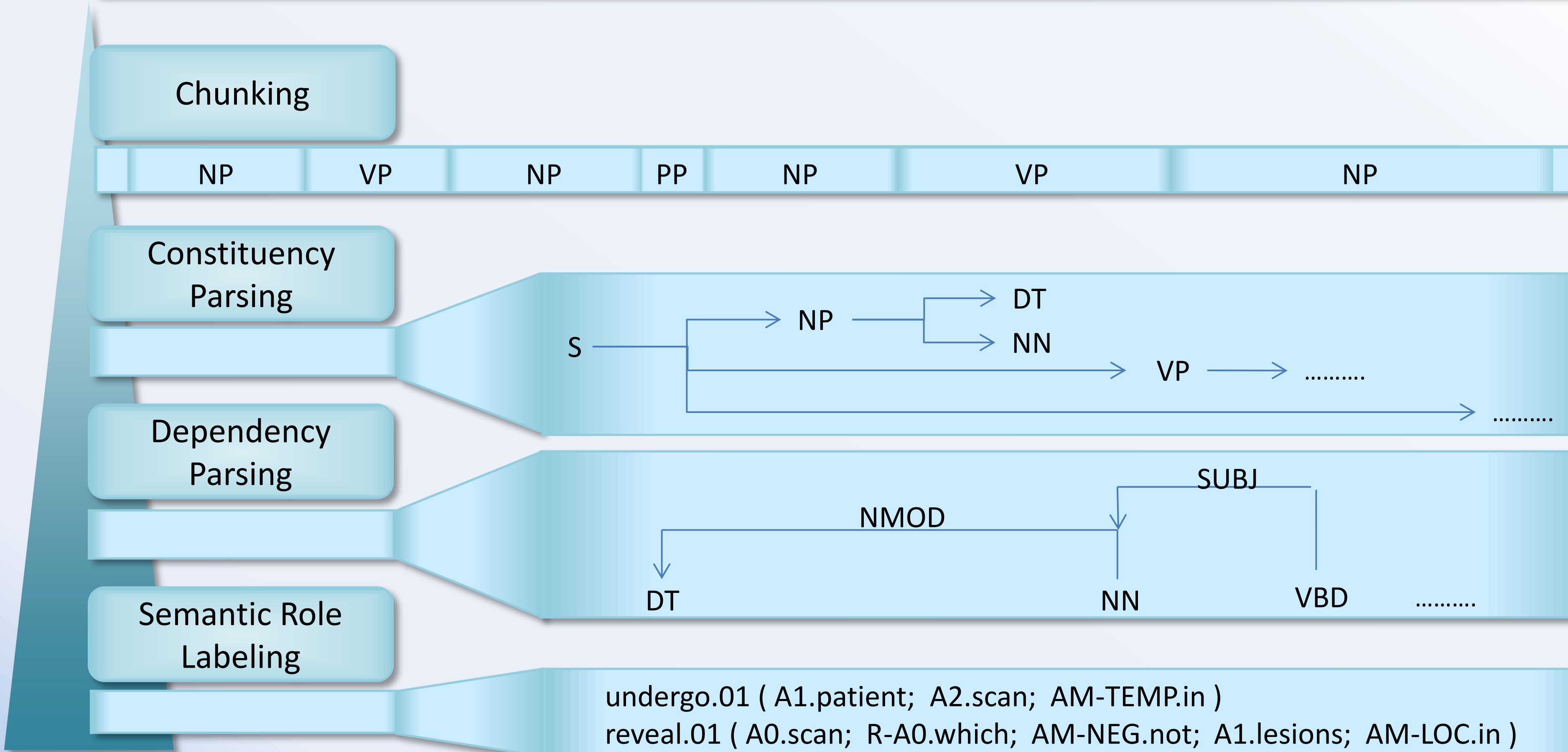
The patient underwent a CT scan in April which did not reveal lesions in his liver.

Boundary Detection	… The patient underwent a CT scan in April which did not reveal lesions in his liver. …																
Tokenization	The	patient	underwent	a	CT	scan	in	April	which	did	not	reveal	lesions	in	his	liver	.
Normalization	-	-	undergo	-	-	-	-	-	-	do	-	-	lesion	-	-	-	
Part-of-speech Tagger	DT	NN	VBD	DT	NN	NN	IN	NNP	WDT	VBD	RB	VB	NNS	IN	PRP$	NN	.

Entity Recognition	CT scan	Lesion	Liver
	Procedure	Disease / Disorder	Anatomy
	UMLS ID: C0040405	UMLS ID: C0022198	UMLS ID: C0023884

cTAKES can normalize to domain ontologies such as SNOMED-CT and RxNORM

The	patient	underwent	a	CT	scan	in	April	which	did	not	reveal	lesions	in	his	liver	.
DT	NN	VBD	DT	NN	NN	IN	NNP	WDT	VBD	RB	VB	NNS	IN	PRP$	NN	.



The patient underwent a CT scan in April which did not reveal lesions in his liver.

Chunking	NP VP NP PP NP VP NP
Constituency Parsing	S NP DT NN VP … …
Dependency Parsing	…
SRL	undergo.01 (A1.patient; A2.scan; AM-TEMP.in) reveal.01 (A0.scan; R-A0.which; AM-NEG.not; A1.lesions; AM-LOC.in)

Entity Properties	CT scan	Lesion	Liver
	Negated: no	Negated: yes	Negated: no
	Subject: patient	Subject: patient	--

UMLS Relation	*locationOf* (lesions, liver)

The patient underwent a CT scan in April which did not reveal lesions in his liver.

Events, Temporal Expressions

CT scan	April	Reveal	Lesions

Temporal Relations

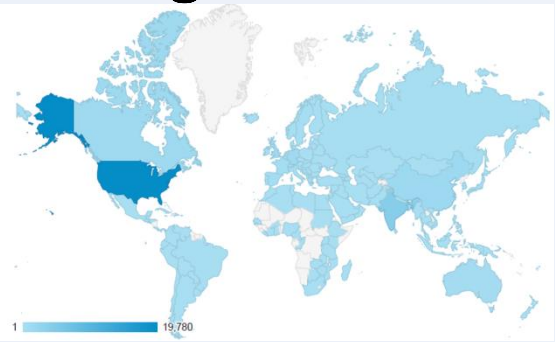
April *CONTAINS* CT scan	CT scan *CONTAINS* lesions

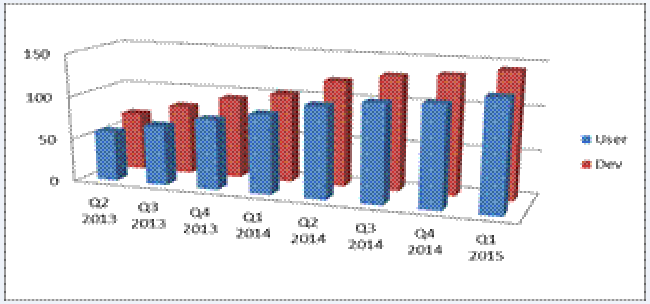
Coreferences

identity (the patient, his)

User Community

- cTAKES global community Mailing list subscribers (new)





- eMERGE, PGRN, i2b2, federal agencies
- NLP challenges (ShARe/CLEF and SemEval)
- Adaptation to other languages
- Oncology community
- Demo – ctakes.apache.org -> get started -> demos

Recent Shared Tasks

SemEval: Analysis of Clinical Text

- Analysis of clinical text (Shared Annotated Resources)
  - SemEval 2014 Task 7

    http://alt.qcri.org/semeval2014/task7/
  - SemEval 2015 Task 14

    http://alt.qcri.org/semeval2015/task14/

alt.qcri.org/semeval2015/task14/

Home | Task Description | Data and Tools | Results | Relevant Publications | Important Dates | FAQs

SemEval-2015 Task 14

SemEval-2015 Task 14: Analysis of Clinical Text

The purpose of this task is to enhance current research in natural language processing methods used in the clinical domain. The second aim of the task is to introduce clinical text processing to the broader NLP community. The task aims to combine supervised methods for text analysis with unsupervised approaches. More specifically, the task aims to combine supervised methods for entity/acronym/abbreviation recognition and mapping to UMLS CUIs (Concept Unique Identifiers) with access to larger clinical corpus for utilizing unsupervised techniques. It also comprises the task of identifying various attributes of the disorders and normalizing their values. We refer to this as the template filling task.

Contact Info

Organizers (in alphabetical order)

- Wendy W. Chapman, University of Utah
- Noemie Elhadad, Columbia University
- Suresh Manandhar, University of York, UK
- Sameer S. Pradhan, Harvard University
- Guergana K. Savova, Harvard University

Contact:

- Guergana.Savova@childrens.harvard.edu
- Noemie.Elhadad@columbia.edu

Other Info

Disease/Disorder (DD) Attribute Types	**Definitions from ShARe guidelines** A span of text that …	**Normalized Values**	**Cue word** span offset of lexical cue
Disorder CUI	indicates a disease/disorder	*null	span offset of lexical cue
Negation (NI)	*indicates a disease/disorder was negated*	*no, yes	span offset of lexical cue
Subject (SC)	*indicates who experienced the disease/disorder*	*patient, family_member, donor_family_member, donor_other, null, and other	span offset of lexical cue
Uncertainty Indicator (UI)	*indicates a measure of doubt into a statement about a disease/disorder*	*no, yes	span offset of lexical cue
Course Class (CC)	indicates progress or decline of a disease/disorder	*unmarked, changed, increased, decreased, improved, worsened, and resolved	span offset of lexical cue
Severity Class (SV)	indicates how severe a disease/disorder is	*unmarked, slight, moderate, and severe	span offset of lexical cue
Conditional Class (CO)	indicates conditional existence of disease/disorders under certain circumstances	true, *false	span offset of lexical cue
Generic Class (GC)	indicates a generic mention of a disease/disorder	true, *false	span offset of lexical cue
Body Location (BL)	represents an anatomical location of these UMLS semantic types: Anatomical structure; Body location or region; Body part; organ or organ component; Body space or junction; Body substance; Body system; Cell; Cell component; Embryonic structure; Fully formed anatomical structure; Tissue	*null	span offset of lexical cue

Default values indicated with *

Attributes Types	Example Sentence	Normalized Values	Cue word
Disorder CUI	The left atrium is moderately dilated	***C0344720*** (UMLS CUI)	**4-15, 31-37** (*left atrium…dilated*)
Negation Indicator (NI)	*Denies* numbness	*no, **yes**	***0-5** (Denies)*
Subject Class (SC)	*Son* has schizophrenia.	*patient, family_member, donor_family_member, donor_other, null, and other	***0-2** (Son)*
Uncertainty Indicator (UI)	*Evaluation of* MI.	*no, **yes**	***0-9** (Evaluation)*
Course Class (CC)	The cough *worsened* over the next two weeks.	*unmarked, changed, increased, decreased, improved, **worsened**, and resolved	***11-18***
Severity Class (SC)	He noted a *slight* bleeding.	*unmarked, **slight**, moderate, and severe	***12-17** (slight)*
Conditional Class (CO)	The patient should come back if any rash occurs.	**true**, *false	***30-31** (if)*
Generic Class (GC)	The patient was referred to the Lupus *Clinic*.	**true**, *false	***38-43** (Clinic)*
Body Location (BL)	Patient has *facial* rash.	***C0015450*** (UMLS CUI)	***12-17** (facial)*

Bold indicates the values for the example

Default values indicated with *

Dataset

- MIMIC corpus
  - Unlabeled part
  - Labeled part
    - Developed under the ShARe project
    - Layered syntactic and semantic annotations (in synch with general domain LDC and clinical domain UMLS)

	Train	Dev	Test
Notes	298	133	100
Words	182K	153K	109K

	Train	Dev
Disorder mentions	11,144	7,967
CUI=CUI-less	30%	24%
CUI	70%	76%
Unique CUIs	1,352	1,139
Negation = yes	19.6%	20.1%
Negation = no	80.4%	79.9%
Subject = patient	99.2%	98.4%
Subject = family_member	<1%	1.4%
Subject = other	<1%	<1%
Subject = donor_other	<1%	0%
Uncertainty = yes	8.9%	5.9%
Uncertainty = no	91.1%	94.1%
Course = changed	<1%	<1%
Course = resolved	<1%	<1%
Course = worsened	< 1%	<1%
Course = improved	< 1%	1%
Course = decreased	1.6%	<1%
Course = increased	2%	1.7%
Course = unmarked	94.1%	95.2%
Severity = slight	1.1%	<1%
Severity = severe	3.5%	2.6%
Severity = moderate	5.9%	2.3%
Severity = unmarked	89.49%	94.2%
Conditional = true	4.9%	6.2%
Conditional = false	95.1%	93.8%
Generic = true	<1%	1%
Generic = false	99.1	99%
Body Location = CUI	55.3%	44.7%
Body Location = null	44.4%	54.6%
Body Location = CUI-less	<1%	<1%
Unique BL CUIs	734	511

Task 2b

Team	run	F	A	F*A	WA	F*WA	BL	CUI	CND	COU	GEN	NEG	SEV	SUB	UNC
UTH-CCB	run 1	0.926	0.941	0.871	0.873	0.808	0.864	0.819	0.899	0.899	0.919	0.976	0.939	0.973	0.912
UTH-CCB	run 2	0.926	0.950	0.879	0.863	0.799	0.864	0.819	0.822	0.837	0.884	0.976	0.904	0.963	0.831
UTH-CCB	run 3	0.903	0.943	0.852	0.881	0.796	0.873	0.834	0.897	0.895	0.925	0.977	0.943	0.974	0.913
ezDI	run 1	0.915	0.935	0.856	0.868	0.795	0.826	0.858	0.816	0.866	0.921	0.978	0.812	0.911	0.857
UWM	run 2	0.893	0.852	0.761	0.798	0.713	0.532	0.858	0.839	0.794	0.845	0.932	0.907	0.929	0.838
CUAB	run 2	0.905	0.908	0.822	0.785	0.710	0.655	0.810	0.660	0.774	0.885	0.850	0.860	0.846	0.749
Bioinformatics-UA	run 2	0.853	0.884	0.754	0.814	0.695	0.691	0.866	0.697	0.856	0.889	0.807	0.877	0.819	0.800
Bioinformatics-UA	run 3	0.853	0.883	0.754	0.814	0.695	0.689	0.867	0.697	0.856	0.890	0.806	0.878	0.818	0.798
Bioinformatics-UA	run 1	0.843	0.883	0.745	0.813	0.686	0.692	0.864	0.697	0.857	0.887	0.807	0.878	0.811	0.799
TeamHCMUS	run 1	0.855	0.884	0.756	0.784	0.671	0.603	0.801	0.725	0.851	0.904	0.935	0.843	0.931	0.802
TeamHCMUS	run 2	0.855	0.884	0.756	0.784	0.671	0.603	0.801	0.725	0.851	0.904	0.935	0.843	0.931	0.802
TeamHCMUS	run 3	0.855	0.884	0.756	0.784	0.671	0.603	0.801	0.725	0.851	0.904	0.935	0.843	0.931	0.802
umlnlp2014	run 3	0.882	0.867	0.765	0.648	0.571	0.525	0.731	0.495	0.569	0.869	0.530	0.535	0.752	0.550
LIST-LUX	run 1	0.884	0.865	0.765	0.641	0.567	0.515	0.719	0.496	0.575	0.870	0.529	0.544	0.751	0.559
LIST-LUX	run 3	0.882	0.866	0.763	0.642	0.566	0.517	0.720	0.500	0.578	0.873	0.528	0.543	0.749	0.560
LIST-LUX	run 2	0.881	0.866	0.763	0.641	0.565	0.517	0.720	0.497	0.575	0.873	0.530	0.543	0.749	0.557
CUAB	run 1	0.839	0.873	0.732	0.669	0.561	0.523	0.784	0.490	0.564	0.855	0.543	0.522	0.736	0.539
umlnlp2014	run 2	0.820	0.864	0.708	0.641	0.526	0.511	0.732	0.482	0.547	0.882	0.516	0.521	0.761	0.544
umlnlp2014	run 1	0.820	0.864	0.708	0.640	0.525	0.511	0.730	0.482	0.547	0.882	0.516	0.521	0.761	0.544
UtahPOET	run 2	0.756	0.821	0.620	0.580	0.438	0.453	0.468	0.475	0.831	0.862	0.853	0.746	0.896	0.651
UtahPOET	run 3	0.756	0.821	0.620	0.580	0.438	0.453	0.468	0.475	0.831	0.862	0.853	0.746	0.896	0.651
UtahPOET	run 1	0.724	0.836	0.605	0.596	0.431	0.566	0.494	0.475	0.566	0.857	0.805	0.629	0.848	0.631
UWM	run 1	0.485	0.835	0.405	0.769	0.373	0.374	0.849	0.870	0.810	0.937	0.942	0.888	0.966	0.845

SemEval: Clinical TempEval

- Temporal relation extraction from clinical narrative
  - SemEval 2015 Clinical TempEval Task 6: http://alt.qcri.org/semeval2015/task6/
  - SemEval 2016

    http://alt.qcri.org/semeval2016/task12/
- Temporal Histories of Your Medical Events (THYME)
  - thyme.healthnlp.org

alt.qcri.org/semeval2015/task6/

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SemEval-2015 Task 6: Clinical TempEval

SemEval-2015 Task 6: Clinical TempEval

[Based on the Clinical TempEval draft proposal]

Clinical TempEval brings the temporal information extraction tasks of previous TempEvals to the clinical domain, using clinical notes and pathology reports for cancer patients from the Mayo Clinic. This follows recent interest in temporal information extraction for the clinical domain (e.g., the i2b2 2012 shared task) and broadens our understanding of the language of time beyond newswire-specific expressions. As in prior TempEvals, Clinical TempEval focuses on discrete, well-defined tasks which allow rapid, reliable and repeatable evaluation:

- TS: identifying the spans of time expressions
- ES: Identifying the spans of event expressions
- TA: identifying the attributes of time expressions
  - type=DATE, TIME, DURATION, QUANTIFIER, PREPOSTEXP or SET
  - value=TIMEX3 value string as defined by TimeML
- EA: identifying the attributes of event expressions

Contact Info

Organizers:
- Steven Bethard
- Leon Derczynski
- James Pustejovsky
- Marc Verhagen

Email:
clinical-tempeval@googlegroups.com

Other Info

Announcements
- 23 Dec 2014: Results are posted and test data annotations are available.
- 07 Nov 2014: Additional training data annotations are available.
- 30 Jul 2014: Training data annotations are available. Please file a data use agreement to access the source text.

- TS: identifying the spans of time expressions
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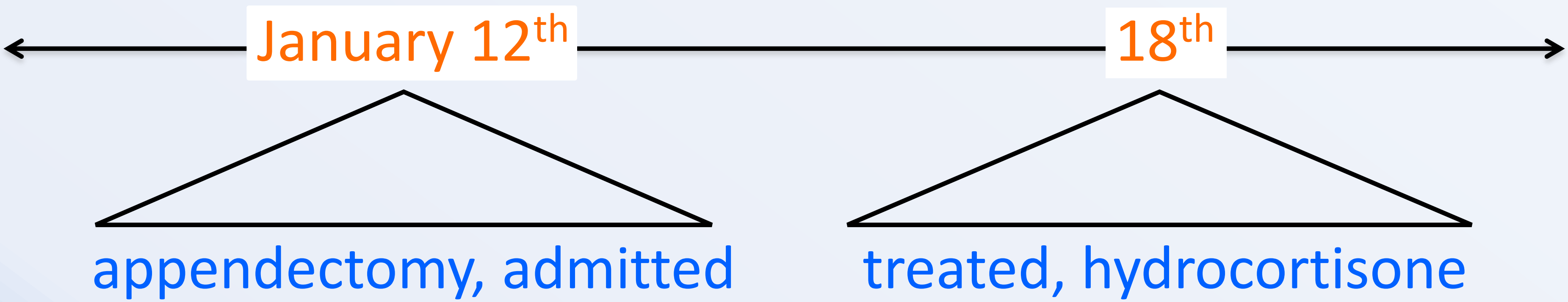
- TA: identifying the attributes of time expressions
  - type=DATE, TIME, DURATION, QUANTIFIER, PREPOSTEXP or SET
  - value=TIMEX3 value string as defined by TimeML
- EA: identifying the attributes of event expressions
  - type=N/A, ASPECTUAL or EVIDENTIAL
  - polarity=POS or NEG
  - degree=N/A, MOST or LITTLE
  - modality=ACTUAL, HEDGED, HYPOTHETICAL or GENERIC
- DR: identifying the relation between an event and the document creation time
  - docTimeRel=BEFORE, OVERLAP, BEFORE-OVERLAP or AFTER
- CR: identifying narrative container relations (CONTAINS a.k.a. INCLUDES)

Narrative Containers

"She was admitted for an appendectomy on January 12th. She had a rash after surgery, which we successfully treated with hydrocortisone on the 18th."

January 12th CONTAINS appendectomy, admitted

18th CONTAINS treated, hydrocortisone



If January 12th BEFORE 18th:

Appendectomy, admitted BEFORE treated, hydrocortisone

Dataset

- Developed under the THYME project (Temporal Histories of Your Medical Events; thyme.healthnlp.org)
  - Layered syntactic and semantic annotations (in synch with general domain LDC and clinical domain UMLS)

	Train	Dev
Documents	293	147
EVENTS	38890	20974
TIMEX3s	3833	2078
TLINKs with TYPE=CONTAINS	11176	6173

Results: TimeEx

Team	span			span + class			
	P	R	F1	P	R	F1	A
Baseline: memorize	0.743	0.372	0.496	0.723	0.362	0.483	0.974
BluLab: run 1-3	**0.797**	0.664	**0.725**	**0.778**	0.652	**0.709**	0.819
KPSCMI: run 1	0.272	0.782	0.404	0.223	0.642	0.331	0.948
KPSCMI: run 2	0.705	0.683	0.694	0.668	0.648	0.658	0.948
KPSCMI: run 3	0.693	0.706	0.699	0.657	0.669	0.663	0.973
UFPRSheffield-SVM: run 1	0.732	0.661	0.695	0.712	0.643	0.676	0.977
UFPRSheffield-SVM: run 2	0.741	0.655	0.695	0.723	0.640	0.679	0.950
UFPRSheffield-Hynx: run 1	0.479	0.747	0.584	0.455	0.709	0.555	0.952
UFPRSheffield-Hynx: run 2	0.494	0.770	0.602	0.470	0.733	0.573	0.951
UFPRSheffield-Hynx: run 3	0.311	0.794	0.447	0.296	0.756	0.425	0.951
UFPRSheffield-Hynx: run 4	0.311	**0.795**	0.447	0.296	**0.756**	0.425	0.952
UFPRSheffield-Hynx: run 5	0.411	**0.795**	0.542	0.391	**0.756**	0.516	**0.978**
Agreement: ann-ann	-	-	0.690	-	-	0.644	0.933
Agreement: adj-ann	-	-	0.774	-	-	0.747	0.965

Results: Events

Team	span			span + modality				span + degree			
	P	R	F1	P	R	F1	A	P	R	F1	A
Baseline: memorize	0.876	0.810	0.842	0.810	0.749	0.778	0.924	0.871	0.806	0.838	**0.995**
BluLab: run 1-3	**0.887**	**0.864**	**0.875**	**0.834**	**0.813**	**0.824**	**0.942**	**0.882**	**0.859**	**0.870**	0.994
Agreement: ann-ann	-	-	0.819	-	-	0.779	0.951	-	-	0.815	0.995
Agreement: adj-ann	-	-	0.880	-	-	0.855	0.972	-	-	0.877	0.997

Team	span + polarity				span + type			
	P	R	F1	A	P	R	F1	A
Baseline: memorize	0.800	0.740	0.769	0.913	**0.846**	0.783	0.813	**0.966**
BluLab: run 1-3	**0.868**	**0.846**	**0.857**	**0.979**	0.834	**0.812**	**0.823**	0.941
Agreement: ann-ann	-	-	0.798	0.974	-	-	0.773	0.944
Agreement: adj-ann	-	-	0.869	0.988	-	-	0.853	0.969

Results: DocTimeRel and CONTAINS

	To document time			Narrative containers					
				Without closure			With closure		
	P	R	F1	P	R	F1	P	R	F1
Phase 1: systems are given only the raw text									
Baseline: memorize	0.600	0.555	0.577	-	-	-	-	-	-
Baseline: closest	-	-	-	**0.368**	0.061	**0.104**	**0.400**	0.061	0.106
BluLab: run 1	**0.712**	**0.693**	**0.702**	0.085	0.080	0.082	0.100	0.099	0.100
BluLab: run 2	**0.712**	**0.693**	**0.702**	0.080	**0.142**	0.102	0.094	**0.179**	**0.123**
BluLab: run 3	**0.712**	**0.693**	**0.702**	0.084	0.086	0.085	0.090	0.103	0.096
Agreement: ann-ann	-	-	0.628	-	-	-	-	-	-
Agreement: adj-ann	-	-	0.761	-	-	-	-	-	-
Phase 2: systems are given manually annotated EVENTs and TIMEX3s									
Baseline: memorize	-	-	0.608	-	-	-	-	-	-
Baseline: closest	-	-	-	**0.514**	0.170	0.255	**0.554**	0.170	**0.260**
BluLab: run 1	-	-	**0.791**	0.100	0.104	0.102	0.117	0.128	0.123
BluLab: run 2	-	-	**0.791**	0.109	**0.210**	0.143	0.140	**0.254**	0.181
BluLab: run 3	-	-	**0.791**	0.119	0.137	0.128	0.150	0.155	0.153
Agreement: ann-ann	-	-	-	-	-	0.449	-	-	0.475
Agreement: adj-ann	-	-	-	-	-	0.655	-	-	0.672

Methods

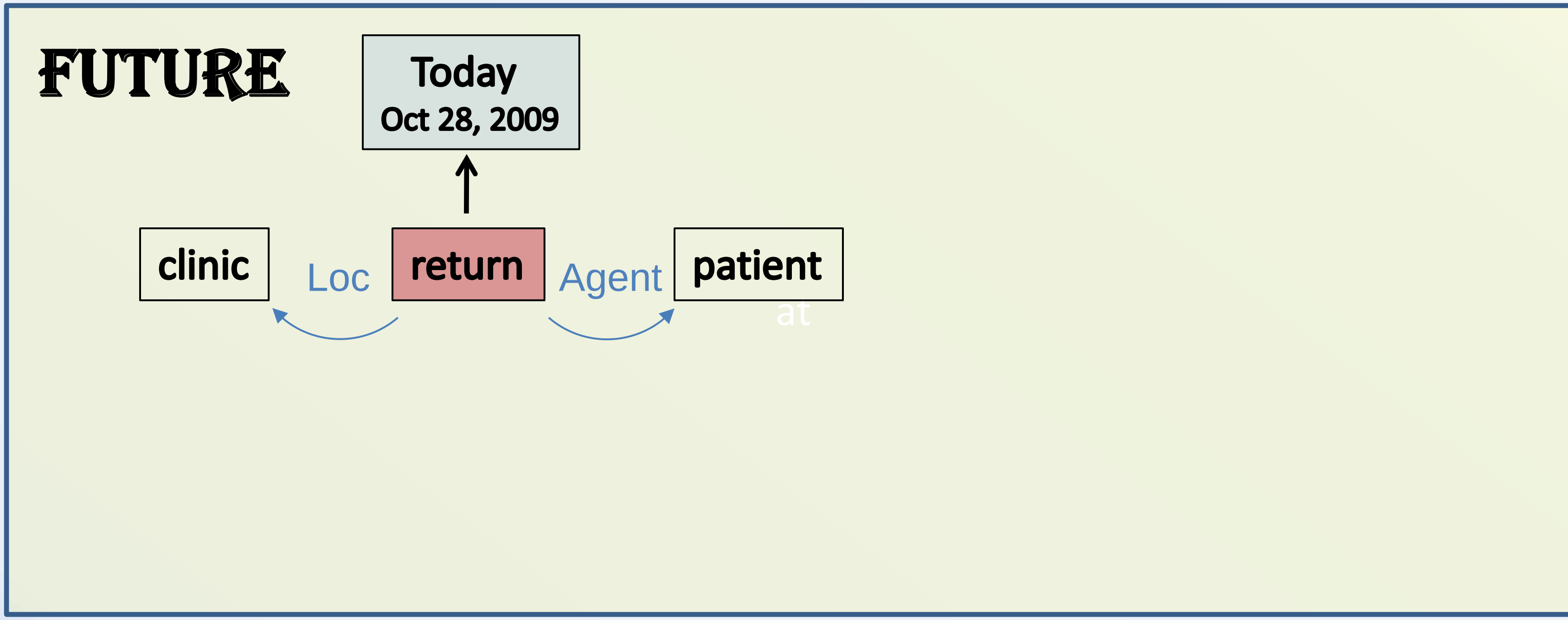
Overview

- In the last decade, clinical NLP has moved from boutique applications to general-purpose methods whose output can be applied to a wide array of use-cases
- Supervised
- Semi-supervised
- Unlabeled data
  - Word embeddings
- Trends
  - Complex NLP tasks
  - In many languages (not just English)
  - Active learning
  - Unlabeled data
  - Methods for low resource domains (LORELEI)
  - Thick data
  - Feature engineering

- Reproducibility through
  - Open source tools
  - Common datasets
  - Shared tasks

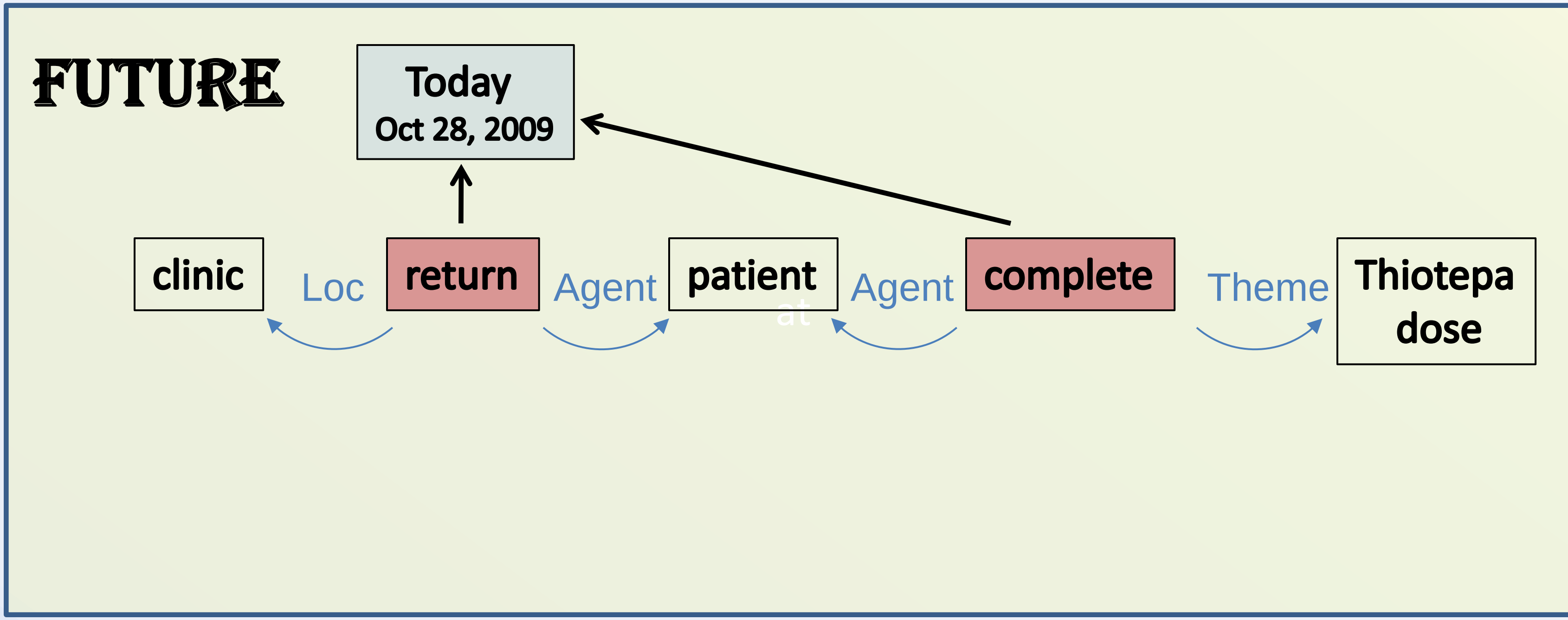
Integrating Time with Semantic Roles

The patient returns to the outpatient clinic today for follow-up



the patient will complete his thiotepa dose today , and he will return tomorrow for the last dose of his thiotepa .
His donor completed stem-cell collection yesterday

The patient returns to the outpatient clinic today for follow-up
the patient will complete his thiotepa dose today



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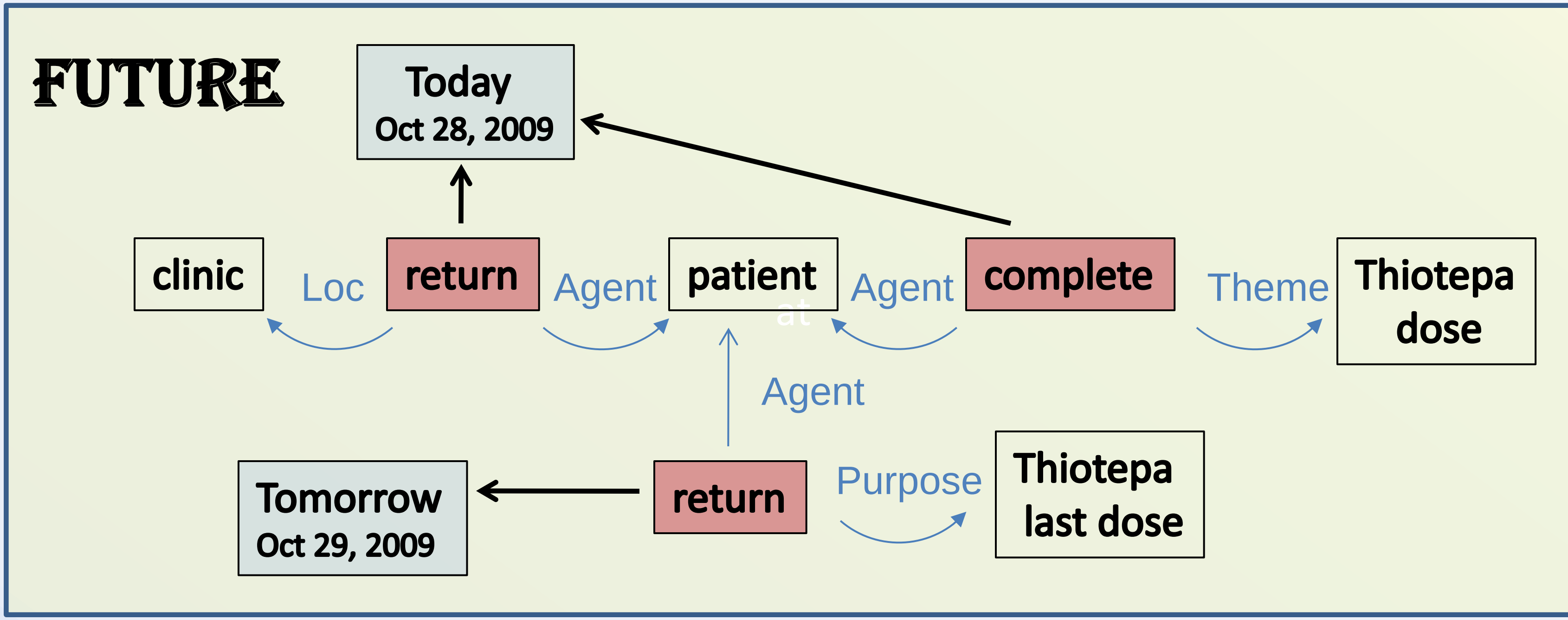
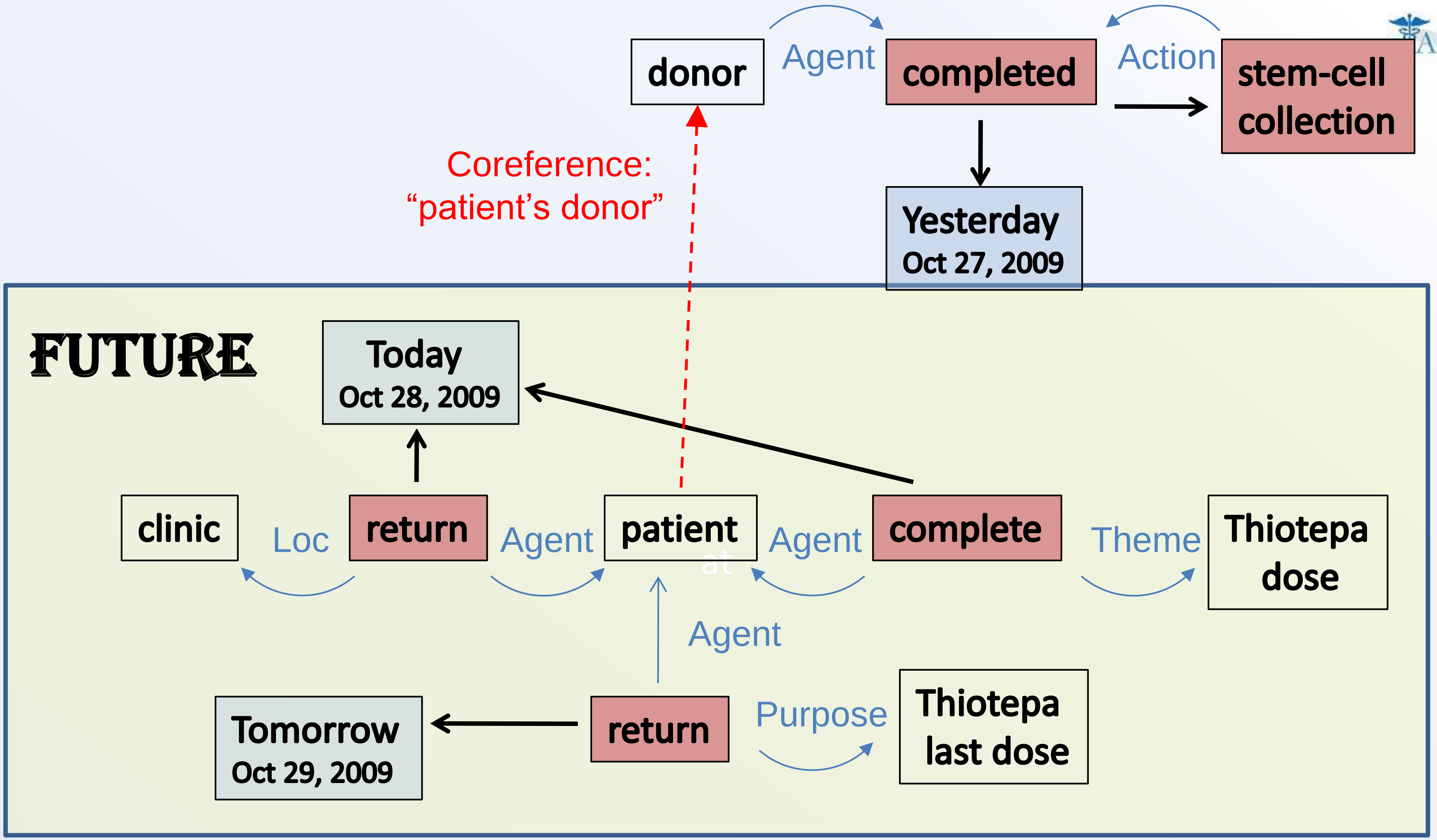


His donor completed stem-cell collection yesterday



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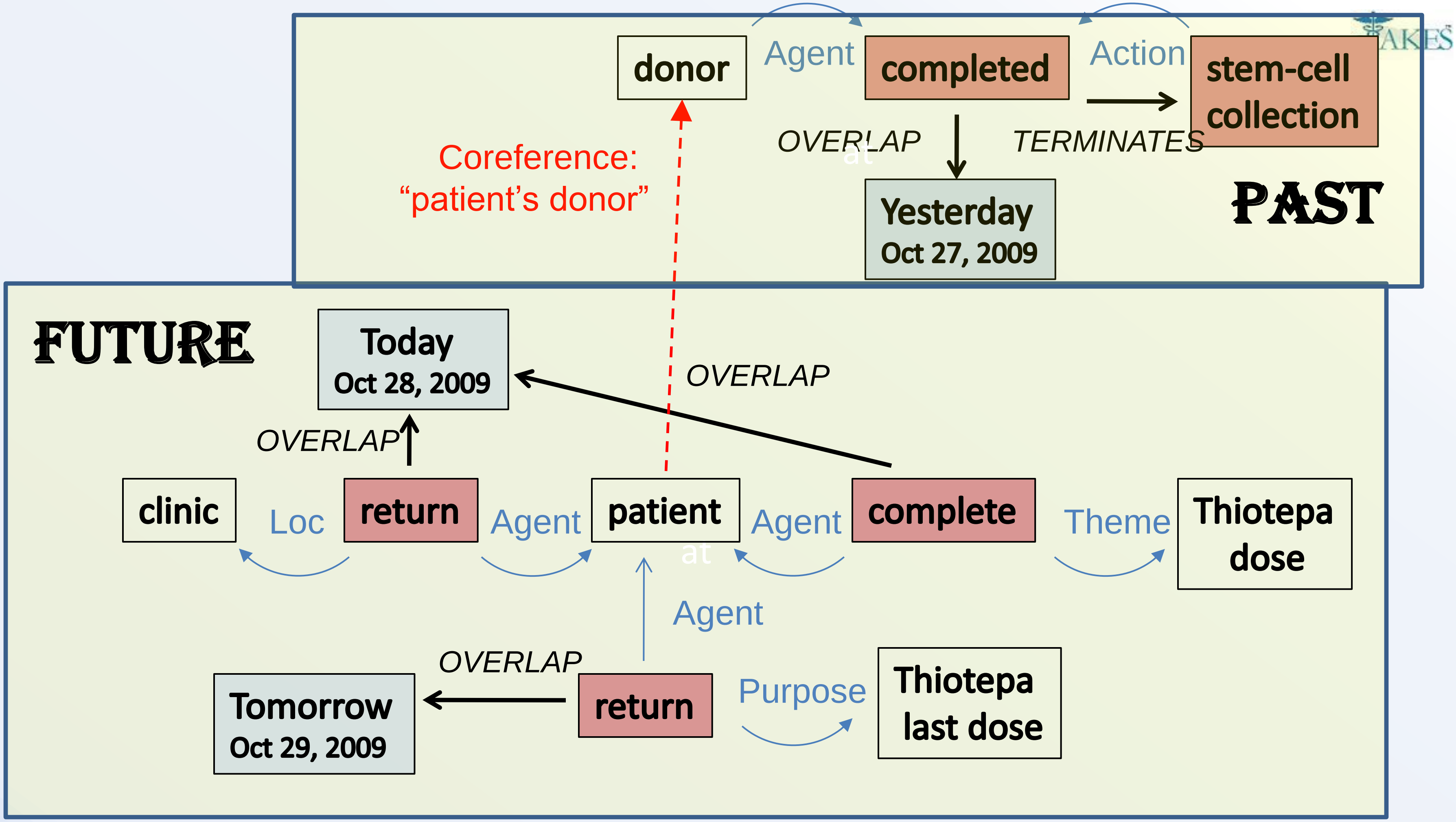

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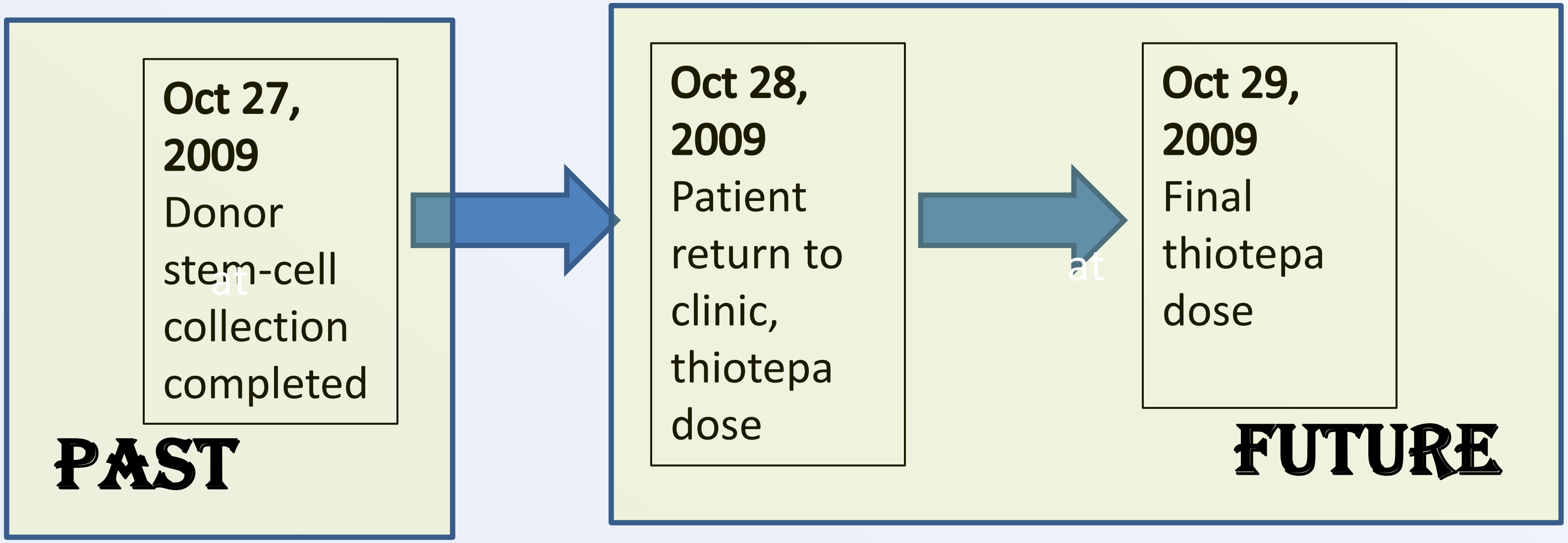

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the patient will complete his thiotepa dose today , and he will return tomorrow for the last dose of his thiotepa .

His donor completed stem-cell collection yesterday

cTAKES Component or Function	Score	Score Type
Sentence boundary [2]	0.949	Accuracy
Context sensitive tokenizer [2]	0.949	Accuracy
Part-of-speech tagging [2] [10]	0.936 – 0.943	Accuracy
Shallow parser [2]	0.952 ; 0.924	Accuracy ; F1
Entity recognition [2]	0.715 / 0.824	F1 [1]
Concept mapping (SNOMED CT and RxNORM) [2]	0.957 / 0.580	Accuracy [1]
Negation NegEx [11] [2]	0.943 / 0.939	Accuracy [1]
Uncertainty, modified NegEx [11] [2]	0.859 / 0.839	Accuracy [1]
Constituency parsing [12]	0.810	F1
Dependency parsing [10]	0.854 / 0.833	F1 [2]
Semantic role labeling [10]	0.881 / 0.799	F1 [3]
Coreference resolution, within-document [12]	0.352 ; 0.690 ; 0.486 ; 0.596	MUC ; B^3 ; CEAF ; BLANC
Relation discovery [13]	0.740-0.908 / 0.905-0.929	F1 [4]
Events (publication in preparation)	0.850	F1
Temporal expression identification [14]	0.750	F1
Temporal relations: event to note creation time [15]	0.834	F1
Temporal relations: on i2b2 challenge data [15]	0.695	F1

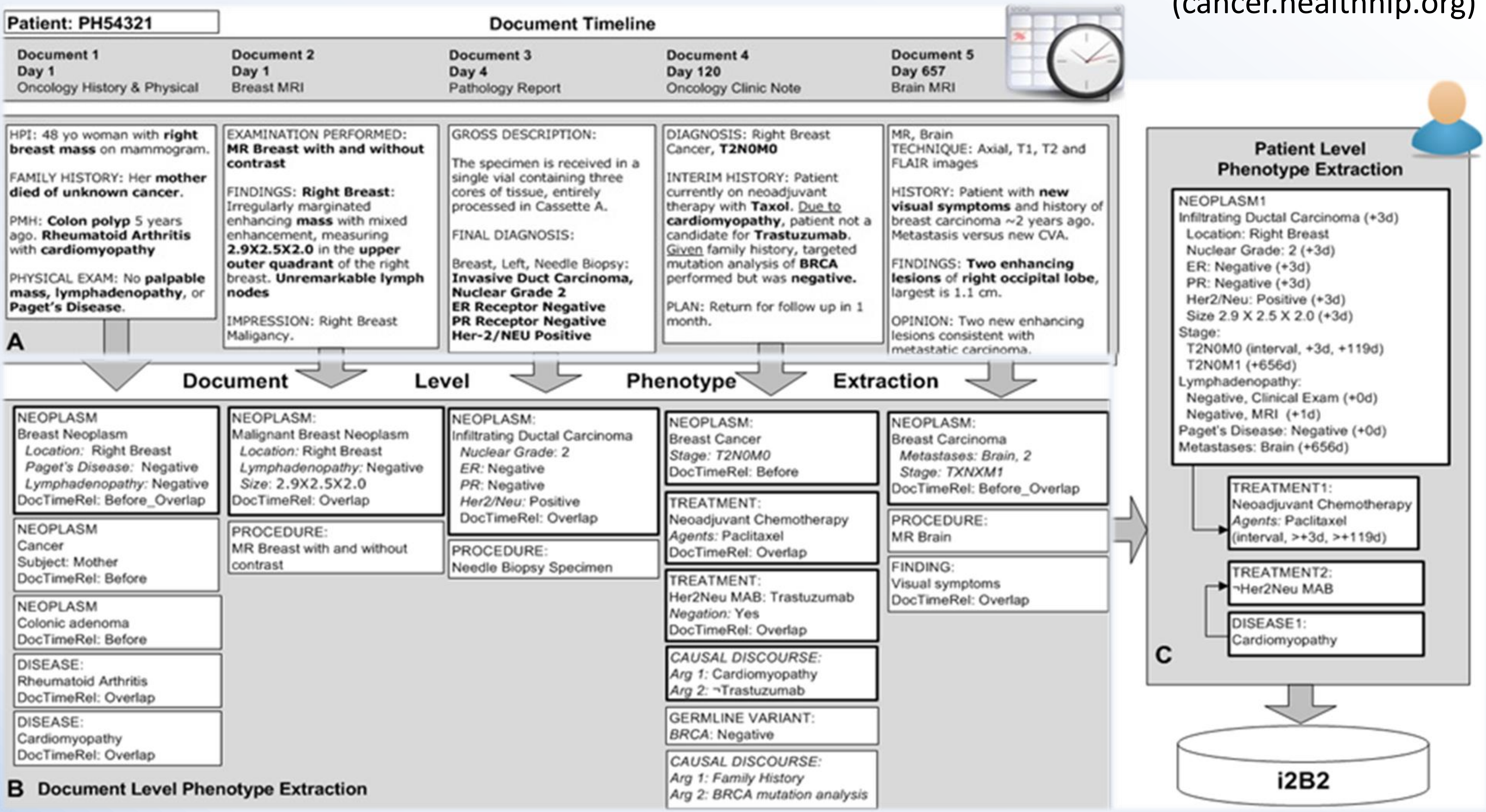
Applications to Biomedicine

Applications

- Patient cohort identification from the EMR – eMERGE, PGRN, i2b2
- Analysis of rare diseases – Phelan McDermit Syndrome
- Pharmacovigilance – adverse events
- Patient-facing applications – patient-interpretable clinical notes
- Point-of-care – summarization
- Question-answering
- Quality metrics
- Public Health

DeepPhe Project

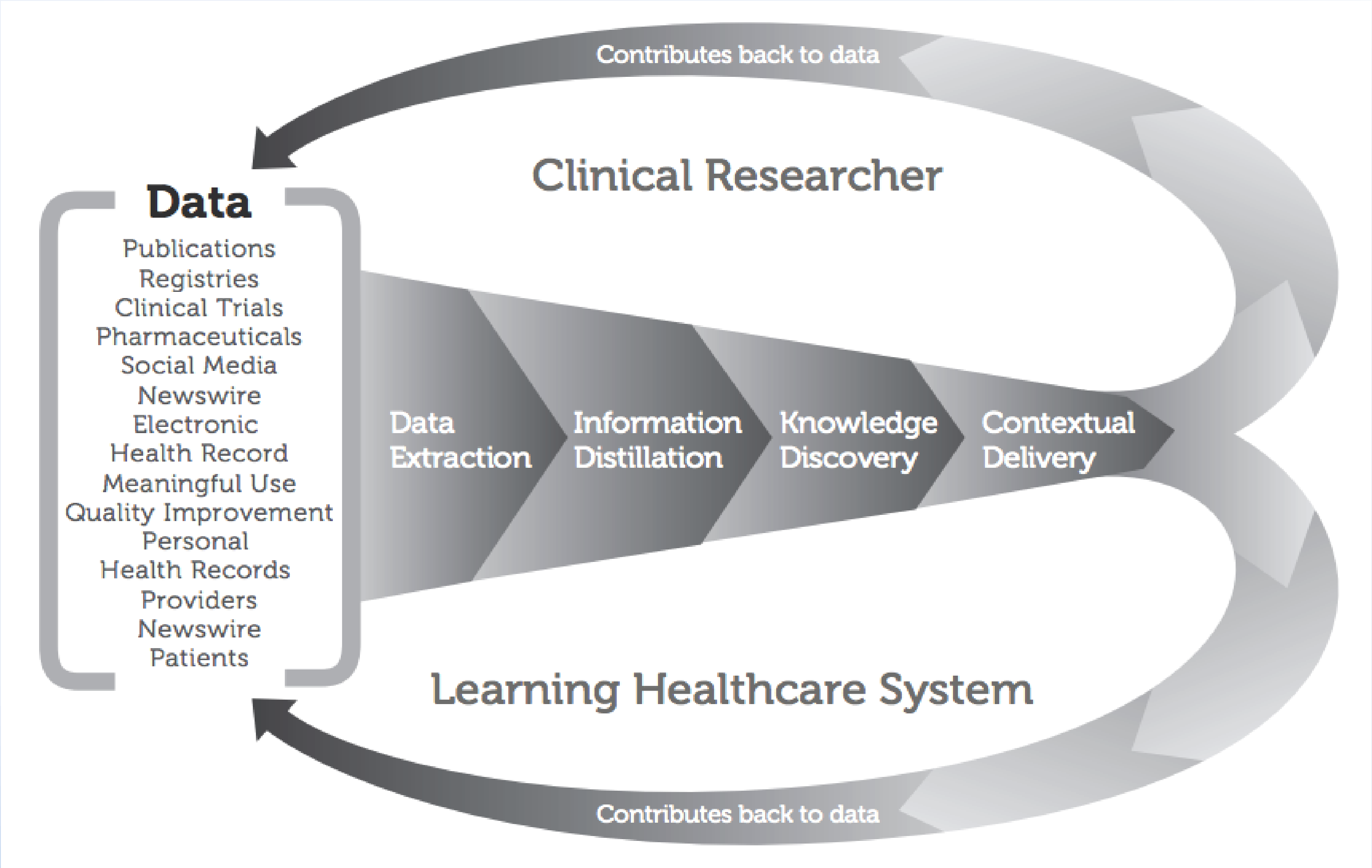
(cancer.healthnlp.org)



Funded by the National Cancer Institutes
within the Informatics Technology for Cancer Research (ITCR) Initiative

Informatics Technology for Cancer Research

Impact


Contributes back to data
Clinical Researcher
Data
Publications
Registries
Clinical Trials
Pharmaceuticals
Social Media
Newswire
Electronic
Health Record
Meaningful Use
Quality Improvement
Personal
Health Records
Providers
Newswire
Patients
Data Extraction
Information Distillation
Knowledge Discovery
Contextual Delivery
Learning Healthcare System
Contributes back to data

END