FDA Workshop
NLP to Extract Information from Clinical Text

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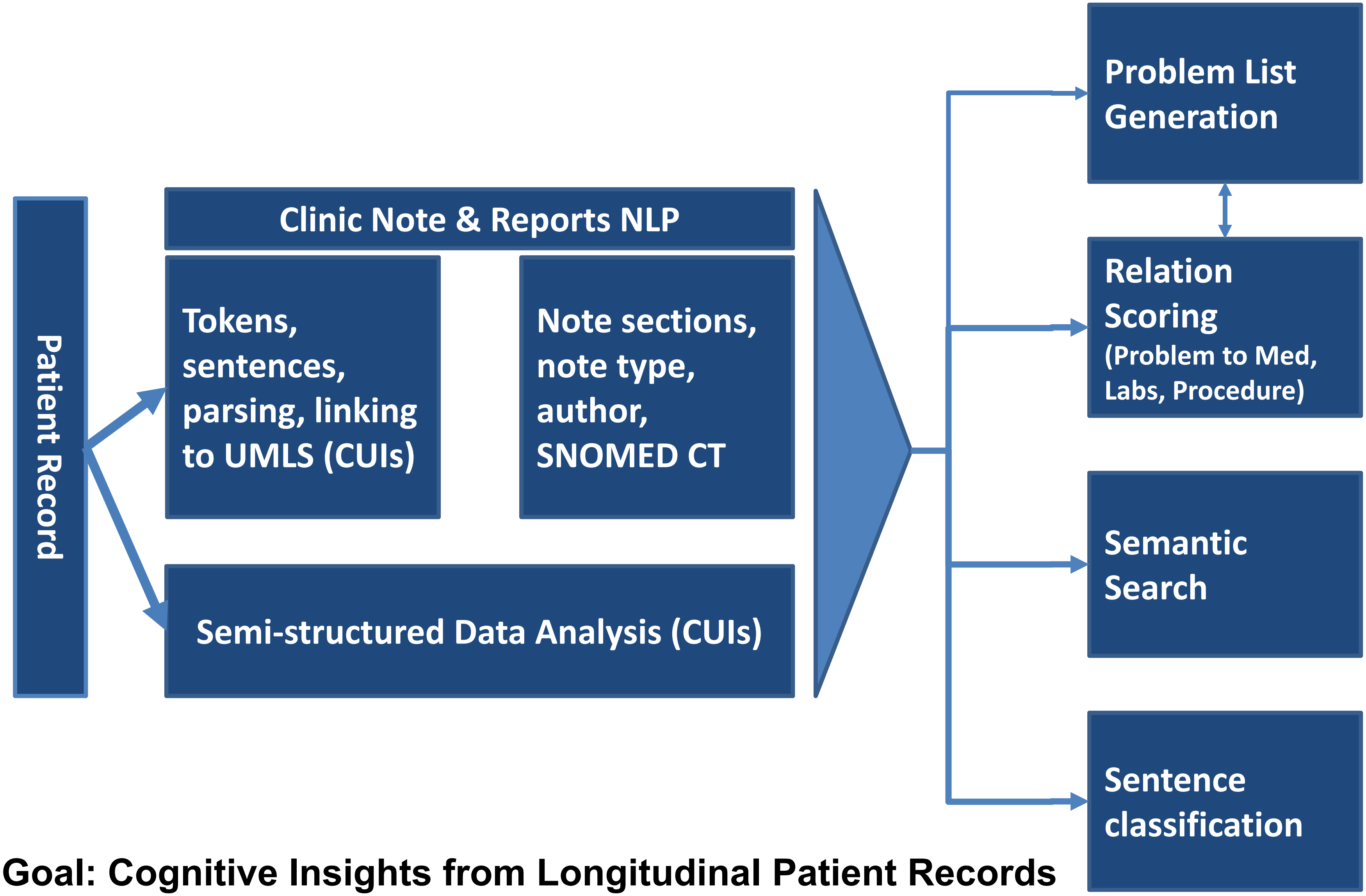
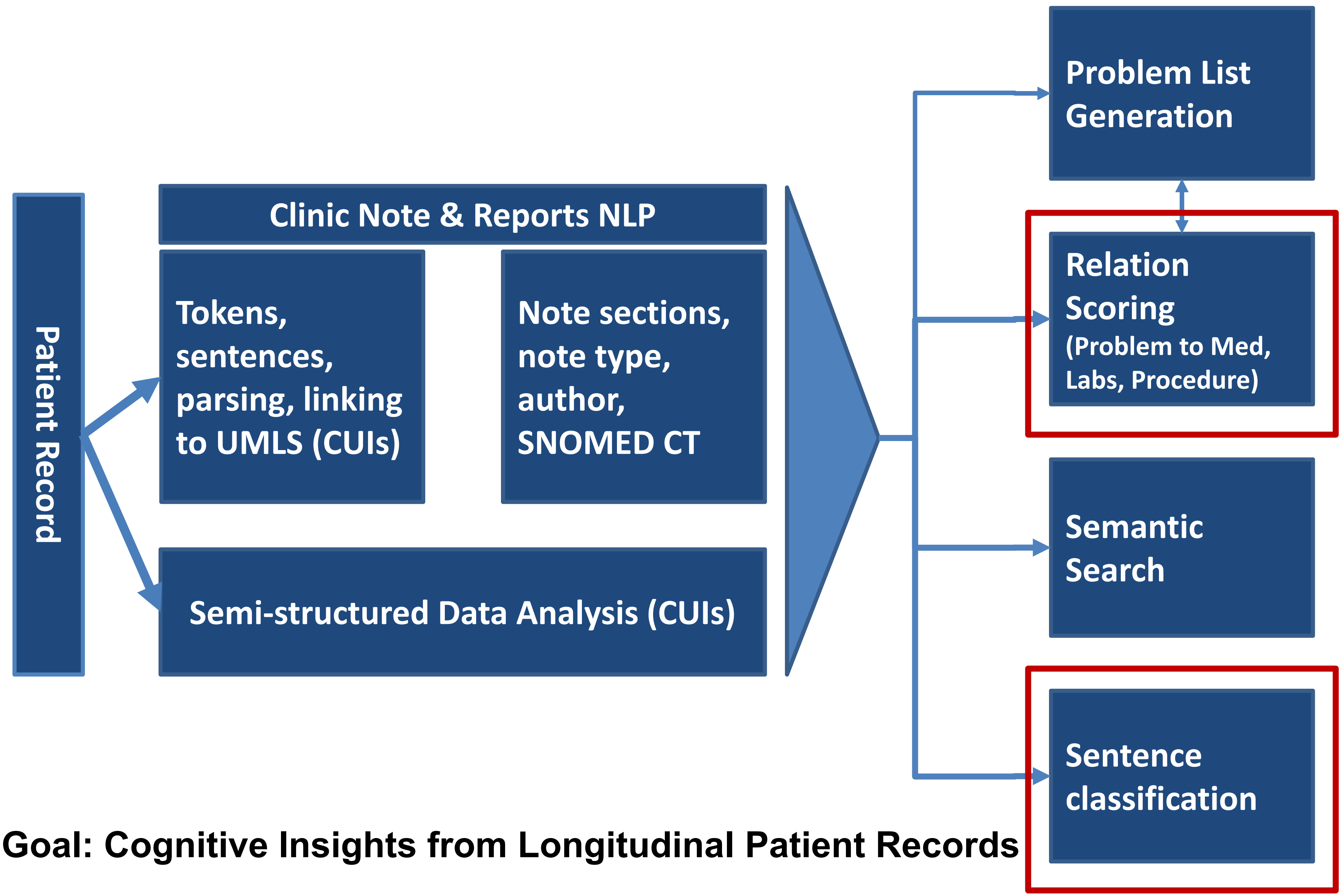
*This work is a part of the **IBM Watson EMRA** (Electronic Medical Records Analytics) project

Watson EMRA Research Initiative



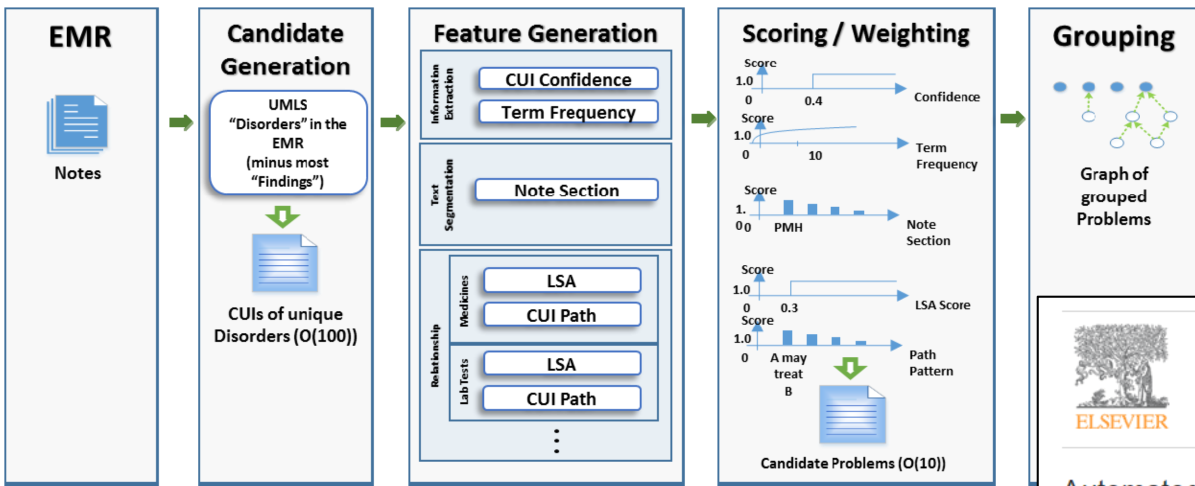
Goal: Cognitive Insights from Longitudinal Patient Records

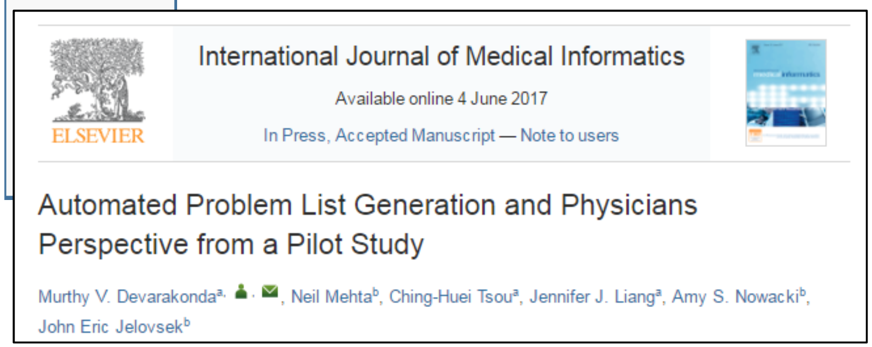
Watson EMRA Research Initiative



Goal: Cognitive Insights from Longitudinal Patient Records

Watson EMRA Problem List Generation





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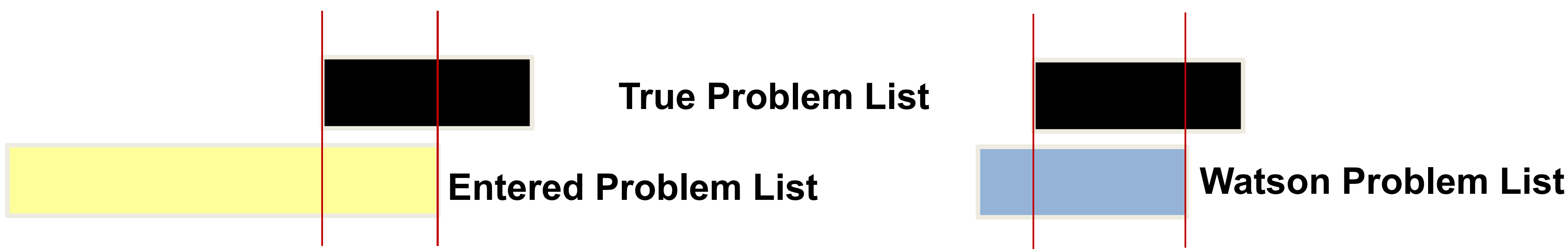
In Press, Accepted Manuscript — Note to users

Automated Problem List Generation and Physicians Perspective from a Pilot Study

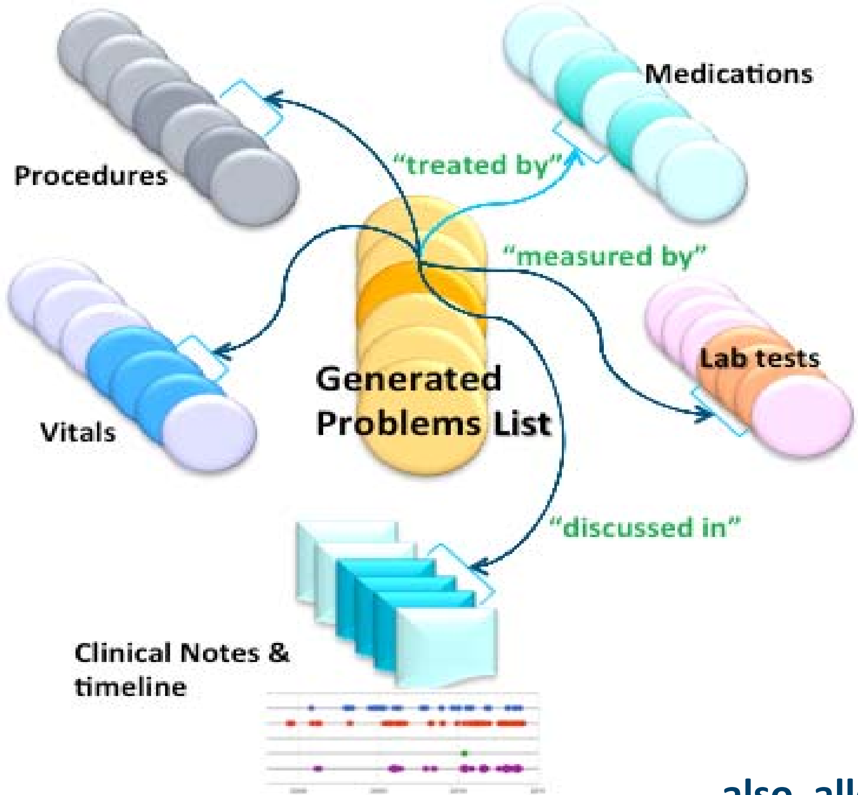
Murthy V. Devarakonda[a], Neil Mehta[b], Ching-Huei Tsou[a], Jennifer J. Liang[a], Amy S. Nowacki[b], John Eric Jelovsek[b]

<u>Entered Problem List Accuracy</u>
Recall (Sensitivity) = 0.55
Precision (Positive Predictive Value) = 0.28

<u>EMRA Problem List Accuracy:</u>
Recall (Sensitivity) = 0.70
Precision (Positive Predictive Rate) = 0.75



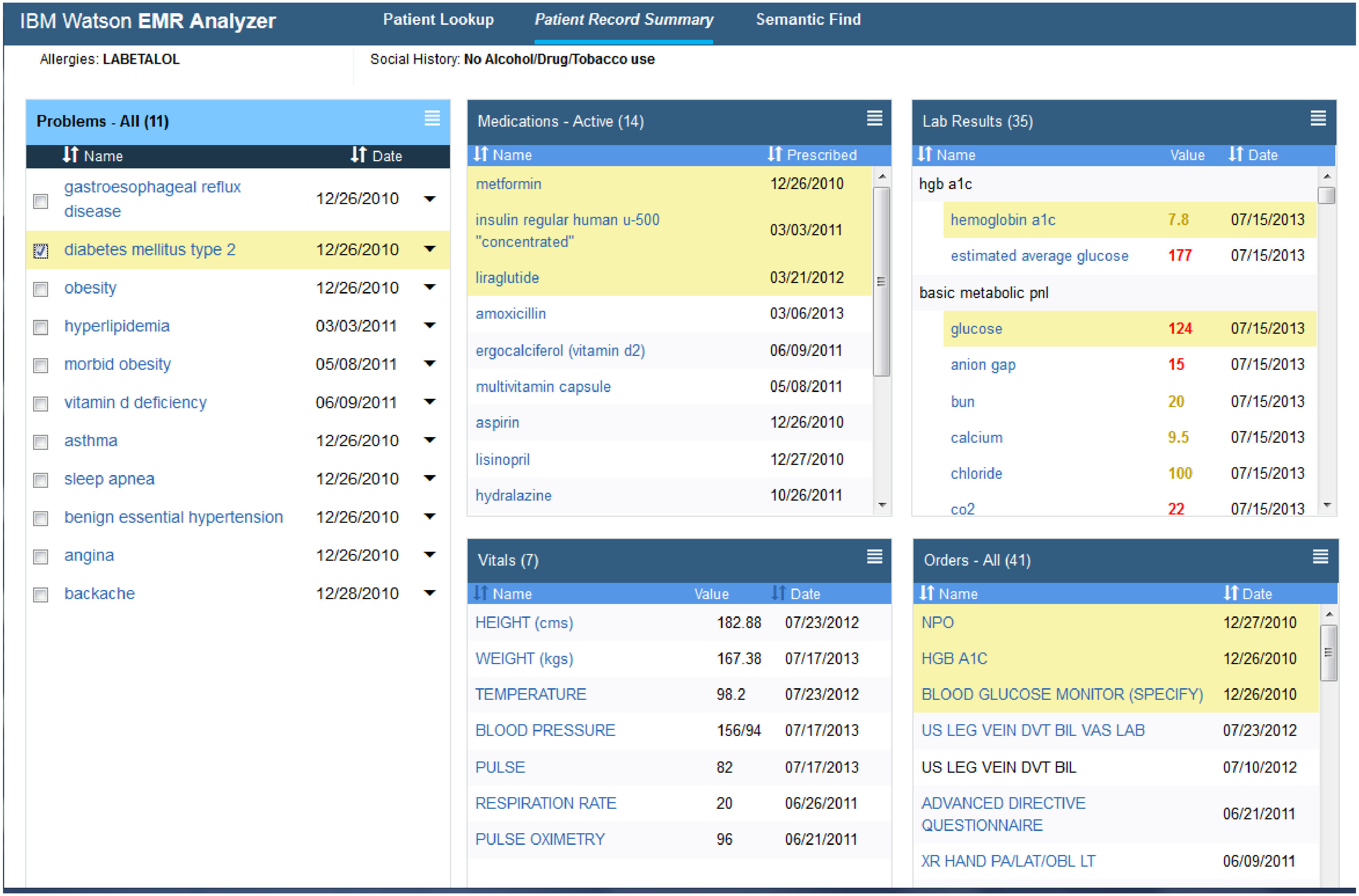
Problem-Oriented Patient Record Summary



- Uses generated problems list
- Relates medications, labs, procedures, and clinical notes to medical problems
- Organizes lists in a clinical order
- Enable one/two click access to raw data such as Notes, labs over a time line, medication history,…

…also, allergies, social history, and demography

Screen Shot: Research Prototype of Watson Patient Record Summary



IBM Watson **EMR Analyzer** | Patient Lookup | *Patient Record Summary* | Semantic Find

Allergies: **LABETALOL**

Social History: **No Alcohol/Drug/Tobacco use**

Problems - All (11)

Name	Date
gastroesophageal reflux disease	12/26/2010
diabetes mellitus type 2	12/26/2010
obesity	12/26/2010
hyperlipidemia	03/03/2011
morbid obesity	05/08/2011
vitamin d deficiency	06/09/2011
asthma	12/26/2010
sleep apnea	12/26/2010
benign essential hypertension	12/26/2010
angina	12/26/2010
backache	12/28/2010

Medications - Active (14)

Name	Prescribed
metformin	12/26/2010
insulin regular human u-500 "concentrated"	03/03/2011
liraglutide	03/21/2012
amoxicillin	03/06/2013
ergocalciferol (vitamin d2)	06/09/2011
multivitamin capsule	05/08/2011
aspirin	12/26/2010
lisinopril	12/27/2010
hydralazine	10/26/2011

Lab Results (35)

Name	Value	Date
hgb a1c		
hemoglobin a1c	7.8	07/15/2013
estimated average glucose	177	07/15/2013
basic metabolic pnl		
glucose	124	07/15/2013
anion gap	15	07/15/2013
bun	20	07/15/2013
calcium	9.5	07/15/2013
chloride	100	07/15/2013
co2	22	07/15/2013

Vitals (7)

Name	Value	Date
HEIGHT (cms)	182.88	07/23/2012
WEIGHT (kgs)	167.38	07/17/2013
TEMPERATURE	98.2	07/23/2012
BLOOD PRESSURE	156/94	07/17/2013
PULSE	82	07/17/2013
RESPIRATION RATE	20	06/26/2011
PULSE OXIMETRY	96	06/21/2011

Orders - All (41)

Name	Date
NPO	12/27/2010
HGB A1C	12/26/2010
BLOOD GLUCOSE MONITOR (SPECIFY)	12/26/2010
US LEG VEIN DVT BIL VAS LAB	07/23/2012
US LEG VEIN DVT BIL	07/10/2012
ADVANCED DIRECTIVE QUESTIONNAIRE	06/21/2011
XR HAND PA/LAT/OBL LT	06/09/2011

Indication or Reason to Use Extraction

2010 i2b2/VA challenge on concepts, assertions, and relations in clinical text

Özlem Uzuner,[1] Brett R South,[2,3,4] Shuying Shen,[2,3,4] Scott L DuVall[2,3] **JAMIA 2011**

Box 1 Relation annotated for the i2b2/VA challenge

1. Medical problem—treatment relations:
   a. Treatment improves medical problem (TrIP). Includes mention where the treatment improves or cures the problem, for example, *hypertension* was controlled on *hydrochlorothiazide*.
   b. Treatment worsens medical problem (TrWP). Includes mentions where the treatment is administered for the problem but does not cure the problem, does not improve the problem, or makes the problem worse, for example, the *tumor* was growing despite the available *chemotherapeutic regimen*.
   c. Treatment causes medical problem (TrCP). The implied

Limitations:
(1) Relations could be across sentences
(2) Needs aggregation from *instances* to *universal*

Relation classification				**F1 measure**
Roberts *et al*[23]	N	Supervised	N	0.737
deBruijn *et al*[25]	N	Semi-supervised	N	0.731

Generalized problem to medication relation

- Determine if a medication treats/prevents a problem? (not just in sentence)

  [*Lisinopril*, *HTN*] → ? (Ans: 0.78 out of 1.0 (strong association))
- Ensemble of methods:
  - Based on text books, papers, and dictionaries
    - Method 1: Using distributional semantics and UMLS (DRE)
    - Method 3: Using a small part of Watson question answering (SER)
  - Based on coded data in millions of patient records
    - Method 2: Using statistical measures mined (AD), e.g. Odds Ratio at diagnosis (M,D)

Method	Precision	Recall	F1	AUC
DRE	0.67	0.73	0.70	0.76
AD	0.75	0.54	0.63	0.63
SER	0.56	0.51	0.54	0.52
DRE + AD	0.78	0.69	0.73	0.79
DRE + AD +SER	**0.79**	**0.75**	**0.77**	**0.83**

Scoring Disease-Medication Associations using Advanced NLP, Machine Learning, and Multiple Content Sources

Bharath Dandala IBM Research
Murthy Devarakonda IBM Research
Mihaela Bornea IBM Research
Christopher Nielson US Dept. of Veterans Affairs

BioTxtM 2016

Does not find or analyze specific instances of reason/indication in a clinic note. That will come later…

Outcome and/or Adverse Events

Concept/framework research exists, but accurate and robust methods needed

Discovering Novel Adverse Drug Events Using Natural Language Processing and Mining of the Electronic Health Record

Carol Friedman

Active Computerized Pharmacovigilance Using Natural Language Processing, Statistics, and Electronic Health Records: A Feasibility Study

Xiaoyan Wang, MPhil, George Hripcsak, MD, MS, Marianthi Markatou, PhD, Carol Friedman, PhD

JAMIA 2009

Drug side effect extraction from clinical narratives of psychiatry and psychology patients

Sunghwan Sohn,[1] Jean-Pierre A Kocher,[1] Christopher G Chute,[1] Guergana K Savova[2]

Extraction of Adverse Drug Effects from Clinical Records

Eiji Aramaki[a], Yasuhide Miura[b], Masatsugu Tonoike[b], Tomoko Ohkuma[b], Hiroshi M

Adverse–E

M

Yasuhide Miura[a], Eiji Ar

Daigo Sugihara

Systematic Review: NLP performs better but still accuracy need to improve

BJCP British Journal of Clinical Pharmacology

2011

Using text-mining techniques in electronic patient records to identify ADRs from medicine use

Pernille Warren,[1,2,3] Ebba Holme Hansen,[1,2,3] Lars Juhl-Jensen[4] & Lise Aagaard[1,2,3]

From clinical narratives…

Pattern Mining for Extraction of mentions of Adverse Drug Reactions from User Comments

AMIA 2011

Azadeh Nikfarjam, MS[1], Graciela H. Gonzalez, PhD[1]

Pharmacovigilance on Twitter? Mining Tweets for Adverse Drug Reactions

Karen O'Connor[1], Pranoti Pimpalkhute[1], Azadeh Nikfarjam, MS[1], Rachel Ginn[1], Karen L Smith, PhD[2], Graciela Gonzalez, PhD[1]

International Conference on Smart Health

ICSH 2014: Smart Health pp 25-36

Identifying Adverse Drug Events from Health Social Media: A Case Study on Heart Disease Discussion Forums

Authors Authors and affiliations

Xiao Liu, Jing Liu, Hsinchun Chen

Identifying Plausible Adverse Drug Reactions Using Knowledge Extracted from the Literature

Ning Shang, MS[1], Hua Xu, PhD[1], Thomas C. Rindflesch, PhD[2], Trevor Cohen, MBChB, PhD[1]

From social media…

Adverse Events – Recent Work

- Two challenges are on the horizon

> Information Technology Laboratory
> Text Analysis Conference
> NIST National Institute of Standards and Technology
>
> **Adverse Drug Reaction Extraction from Drug Labels (ADR)**
> The purpose of this track is to test various natural language approaches for their information extraction performance on adverse drug reactions (ADR). Participants will be provided with mention-, relation-, and document-level annotations in order to extract structured ADR information from the Food and Drug Administration's (FDA) official pharmaceutical knowledge base

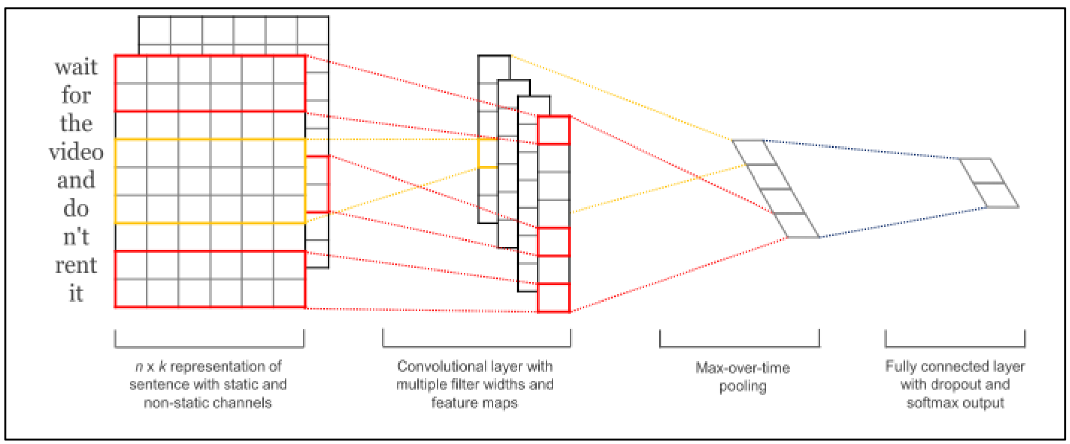
> NLP Challenges for Detecting Medication and Adverse Drug Events from Electronic Health Records (MADE1.0)
>
> hosted by University of Massachusetts Medical School

- Our approach
  - Classify sentences in a clinic note (is it asserting an ADR/ADE?) and then extract the ADR/ADE using the context
    - Can be applied to outcomes as well
  - A challenge is the definition and gold standard

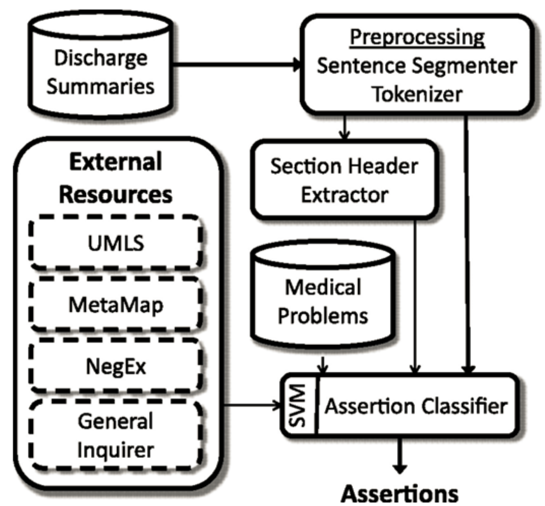
- "***Lisinopril*** *was discontinued and will start on Norvasc due to* ***hyperkalemia***" (Clearly ADR)
- "…discontinued his **amlodipine** due to **low BP** .." (is it ADR?)

Will sentence classification work?

- We adapted two methods to classify “sentences”
  - An SVM-based “assertion” framework
  - Deep learning, a convolution neural network (CNN)



Kim, Y., 2014. Convolutional neural networks for sentence classification. preprint arXiv:1408.5882.



A flexible framework for deriving assertions from electronic medical records

Kirk Roberts, Sanda M Harabagiu

J Am Med Inform Assoc (2011) 18 (5): 568-573.

Disease Status Sentences

- From Clinical Note text:
  - as a direct statement or as a discussion of the disease-related vitals/labs

```
401.9 HYPERTENSION NOS
Comment: not controlled today.
Plan: Increase Lisipnopril from 20 to 40 mg.  He is not on thiazide
Is also on metoprolol.
He will get a home machine and monitor BP and bring it in next time.
```

```
401.9 HYPERTENSION NOS
Comment: BP still running high 160/85.
Plan:increase metoprolol succinate XL from 25 to 50mg daily
```

Model / Features	**Training and Testing**	**Accuracy**	
		Sentence entails disease status?	**Controlled or not?**
Enhanced assertion framework (SVM) / features from text alone	10-fold cross validation using manual labels	**83%**	**77%**

Plan Sentences

OFFICE VISIT: February 27, 2014
Name: Mr.XXXX YYYY
PCP: CCCC, M.D

Active problems:
HTN
Hyperlipidemia
Smoking
...
...
ASSESSMENT:

1. HTN – started taking home BPs sporadically. Running 135-150/90-95. Admits to not taking his meds consistently. **Have reinforced the importance of controlling his BP due to the cumulative risks for CV events.** I explained how to use the feedback from his BP device to help reinforce the importance of his taking his med regularly. Patient agrees and says he will start taking his BPs regularly and taking his meds.
P: 1. **Check home BPs daily; report repeated BPs over 140/90**
2. **Reinforced importance of taking meds consistently**
3. **May increase meds if home BPs consistently elevated when he is taking his meds regularly**
4. **RTC 3 mo**

2. Smoking – talked to patient about the combination of smoking and HTN and his risk of MI, stroke. **Encouraged him to follow his wife's advice about joining the smoking cessation class. Enroll in smoking cessation class.**

3. Hyperlipidemia – will check LDL. Has been under control in the past.
Recommendations: 1. **Lipid panel**
2. **COMP METABOLIC PANEL.**

Method	Plan Sentences (Positive Class)			Positive & Negative Classes	
	Precision	Recall	F1	Micro F1	Macro F1
Baseline	0.868	0.230	0.364	0.472	0.600
SVM All Features	0.952	0.855	0.901	0.858	0.834
CNN non-static	0.953	0.884	0.917	0.880	0.849

Medication Disposition Sentences

"Add metoprolol 25 mg BID Tues, Thurs, Sat, Sun (days she doesn't have dialysis)"

→ positive, asserts disposition

"He is now going to gym regularly"

"Reported cough when she was on Lisinopril"

→ negative, no disposition

SVM model for sentence classification

Class	Precision	Recall	F-measure
No-Disposition	0.94	0.92	0.93
Disposition	0.79	0.85	0.82
Macro Average	0.87	0.88	0.87
Micro Average	0.9	0.9	0.9

Other Medication Related Tasks

- Confounder
  - Will require additional analysis
- Code validation
  - Our NLP stack maps medical concepts to SNOMED CT (CORE), ICD 9, ICD 10, LOINC, and RxNORM
- Clinical trials
  - IBM has an offering for Clinical Trial Mapping (matches form-based input to on-going clinical trials)

Acknowledgements

- Cleveland Clinic
  - For a multi-year research collaboration
  - De-identified patient records with IRB approval
- IBM Watson Researchers and Engineers, especially to the following, whose work is represented here:
  - Ching-Huei Tsou, Bharath Dandala, Jennifer Liang MD, John Prager, Partha Suryanarayanan, Sreeram Joopudi, Ananya Poddar, Diwakar Mahajan, Tong-Haing Fin, Michele Cestone, and Preethi Raghavan
- Paul Tang, MD (IBM)
  - For leadership and education in practice of medicine
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Summary

- Medications related information extraction from patient record text is clearly possible
- More research is needed for focused and advanced information extraction
- Inconsistencies exist between semi-structured (coded) data and text narratives in patient record
- Challenges/Risks: Availability of patient record data and gold standard