Natural Language Processing Supporting Clinical Decision Support

Applications for Enhancing Clinical Decision Making
NIH Worksop; Bethesda, MD,
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Why bother about NLP?

Fast growing electronic clinical data

Rapid adoption of Electronic Health Records (EHR).
Increasing requirements for electronic documentation of healthcare.
Exponentially growing quantities of electronic investigation results information (imaging, genetic testing, etc.)

So what's the problem?

Mostly unstructured information, like **narrative text**, dictated and transcribed or typed in.
Most structured information coded with administrative and reimbursement-oriented terminologies.

Why bother about NLP?

What does the EHR contain?

- Documents
  - History and Physicals
  - Clinical notes, Consult notes
  - Operative reports
  - Surgical pathology reports
  - Progress notes, Letters
  - Orders
  - Discharge summaries
- Imaging / Radiology
- Prescriptions (pharmacy; CPOE)
- Laboratory results
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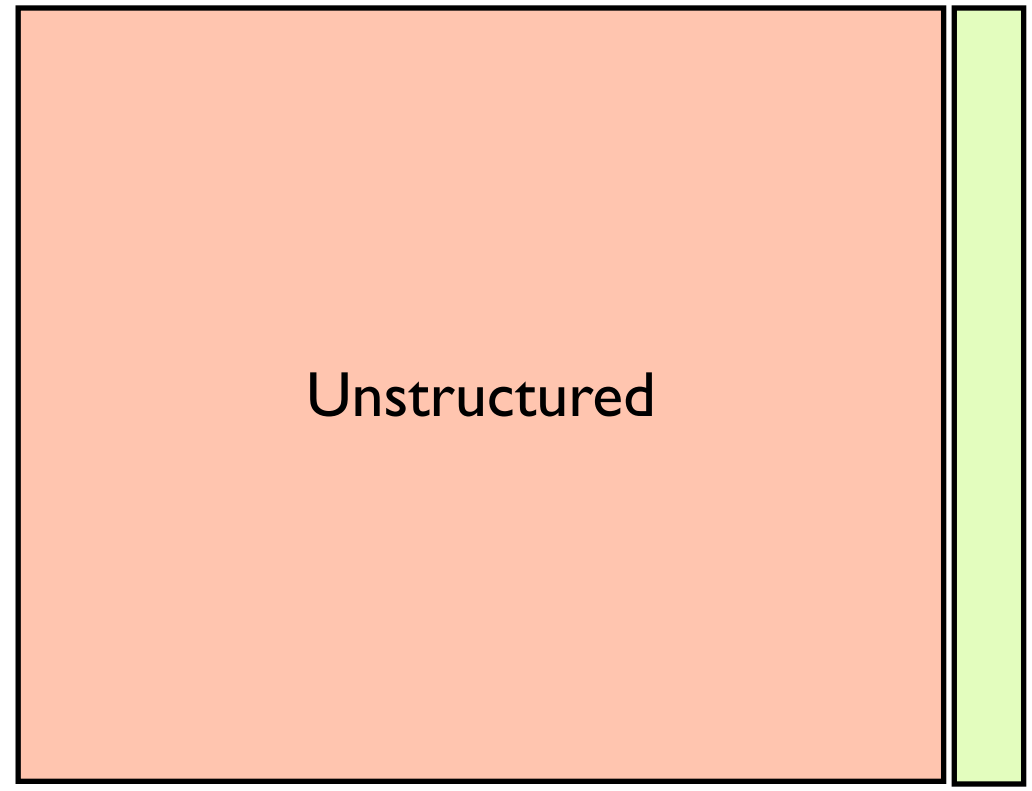

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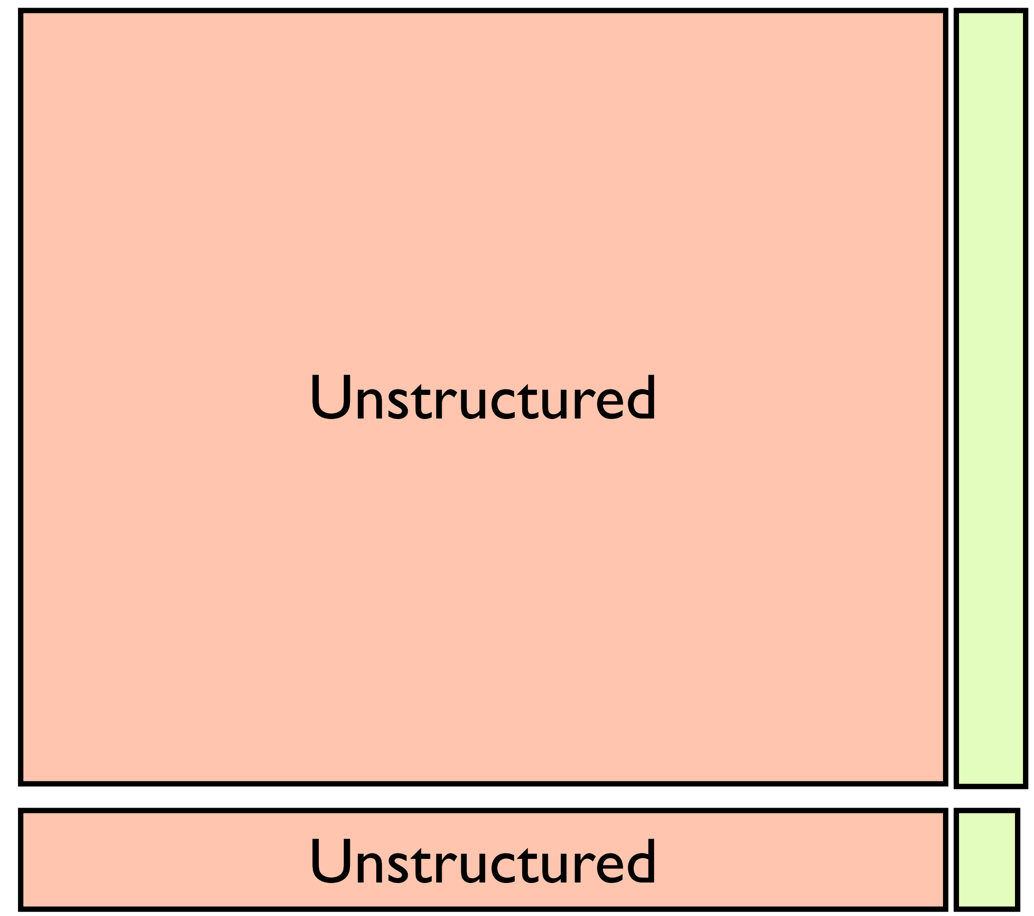

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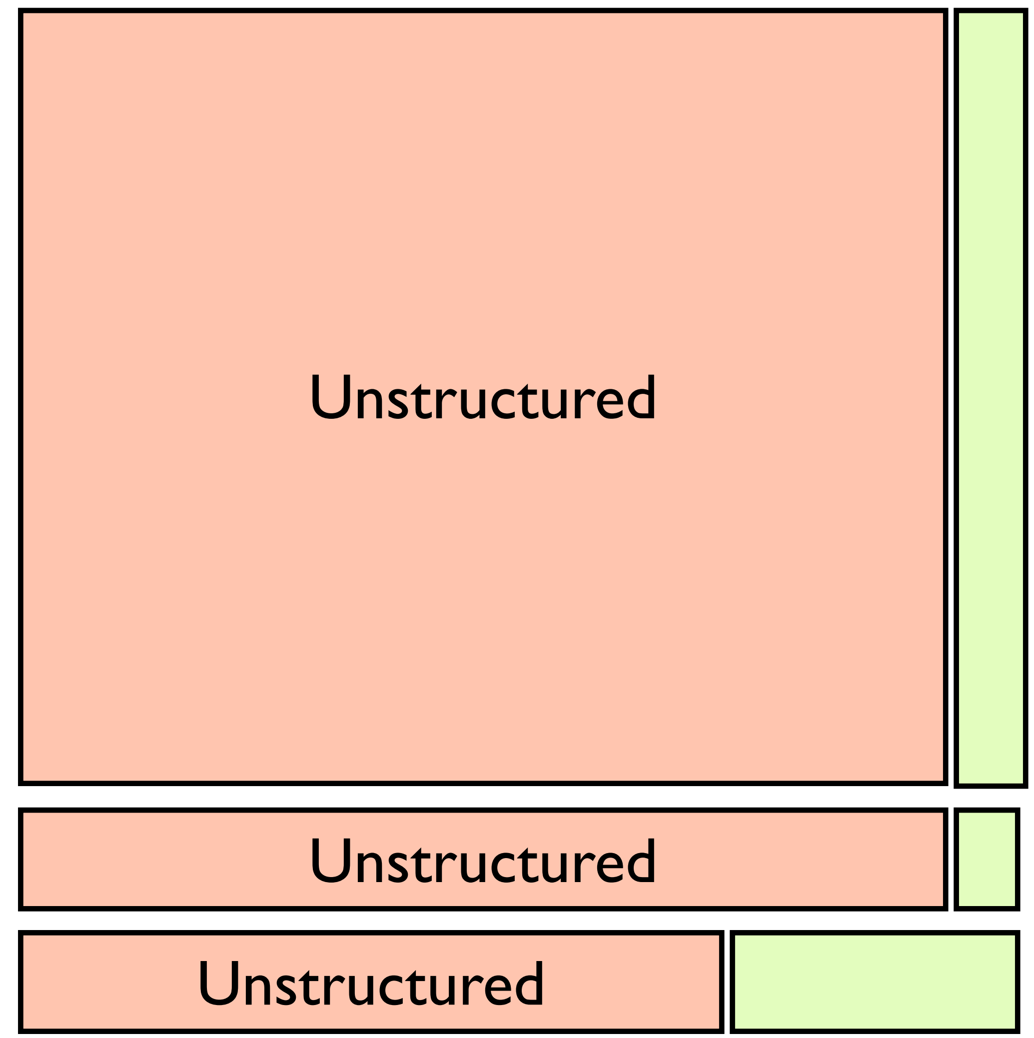

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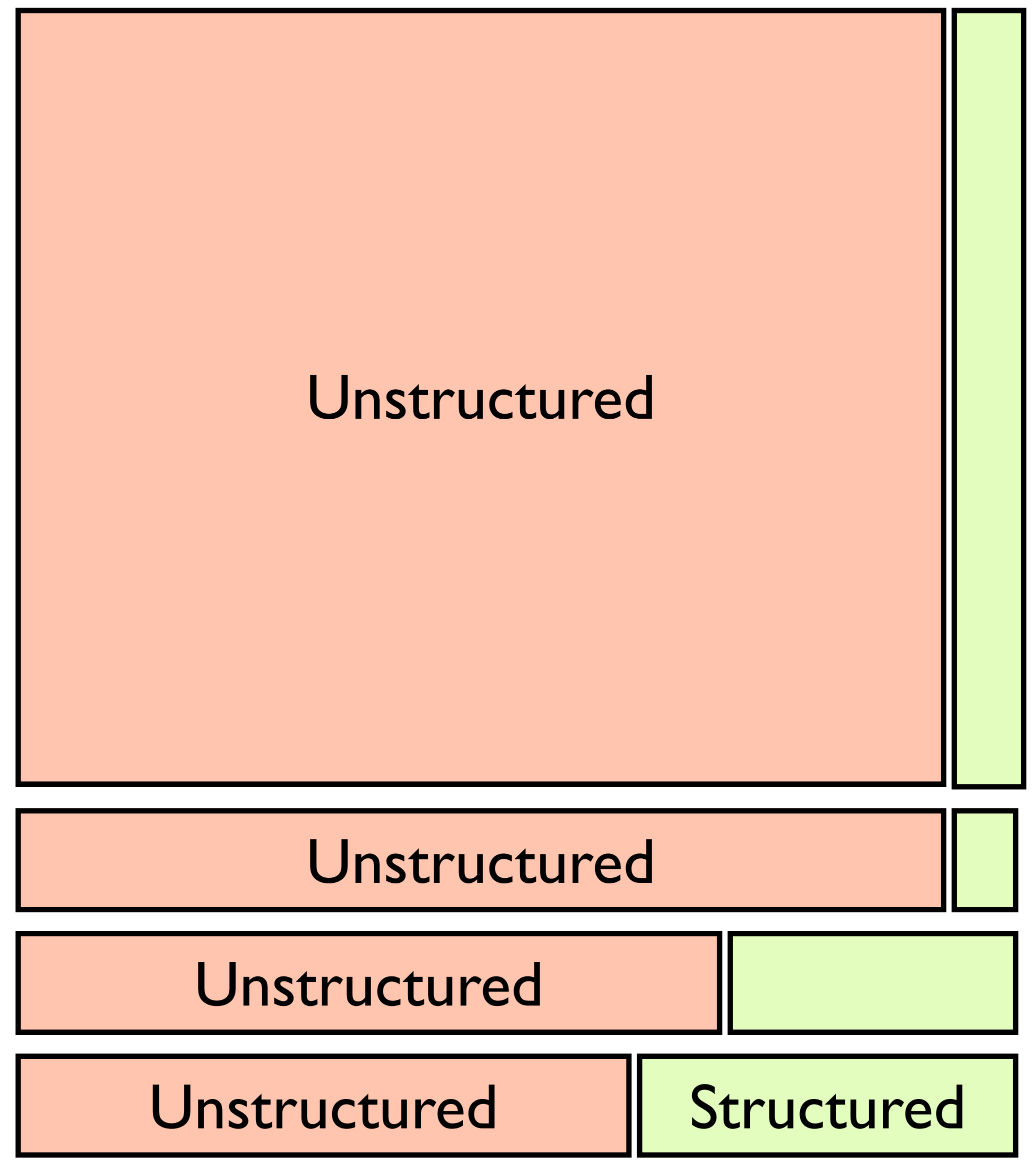

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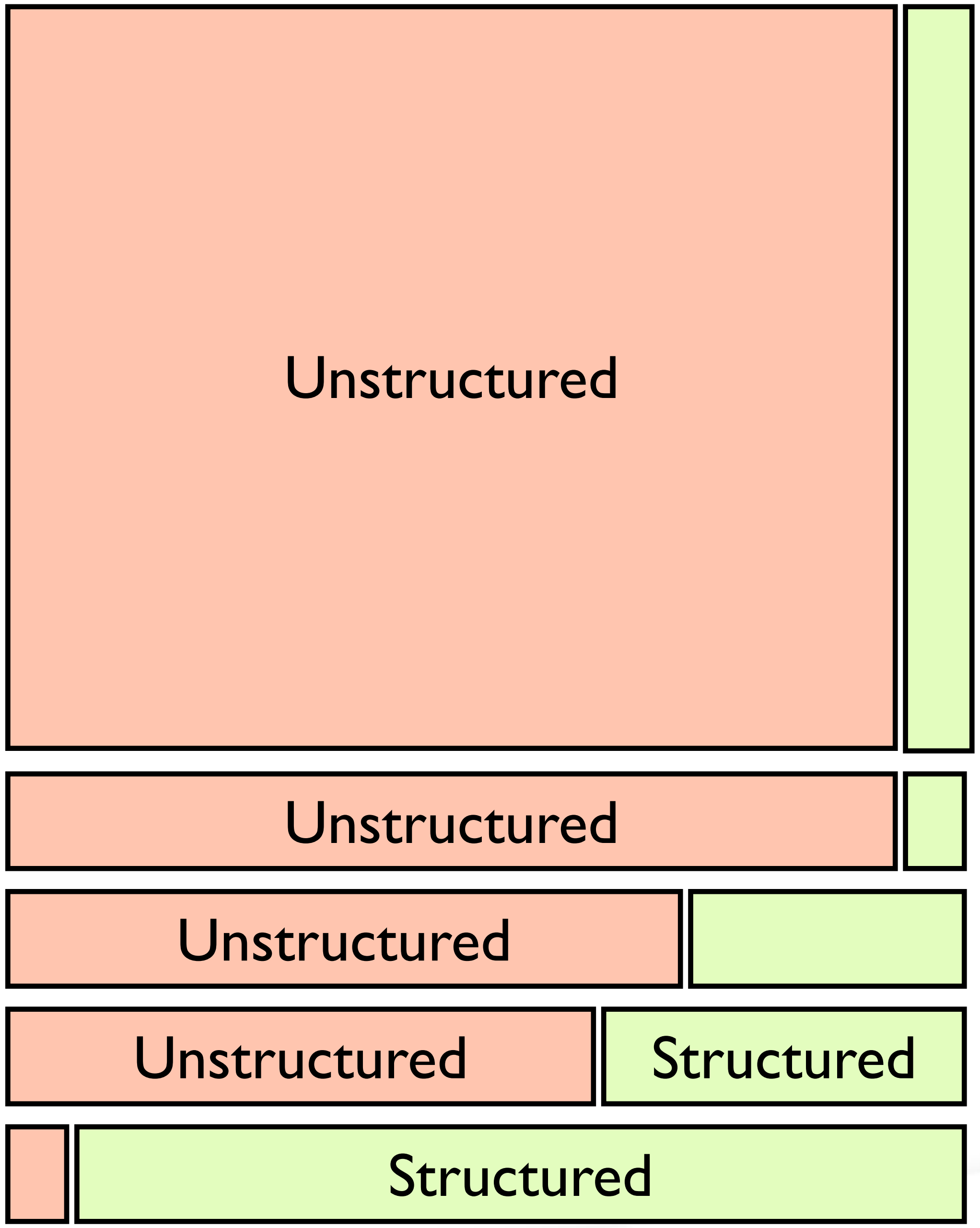

Why bother about NLP?

CDS information needs

Structured (i.e., using some data model) and **coded** (i.e., labeled with some standard terminology) clinical information

...but most EHR content is narrative text, unstructured, and is therefore inaccessible for CDS.

Detailed clinical information, at various levels of granularity

...but most terminologies used were created for mortality and morbidity public health statistics, and for reimbursement (i.e., ICD-9-CM, CPT-4), and don't allow for detailed, clinical care-oriented coding.

Why bother about NLP?

Possible solution to these problems

Natural Language Processing (NLP) can be used to automatically extract various types of clinical information from the EHR narrative text content

⇨ Clinical Information Extraction (IE)

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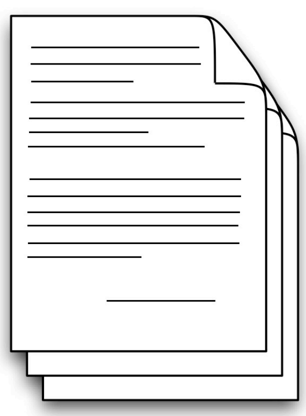

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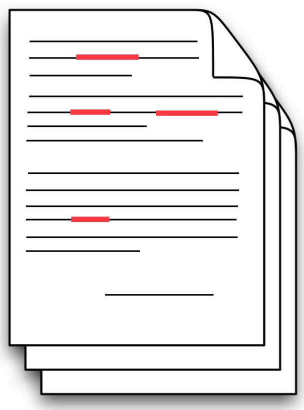

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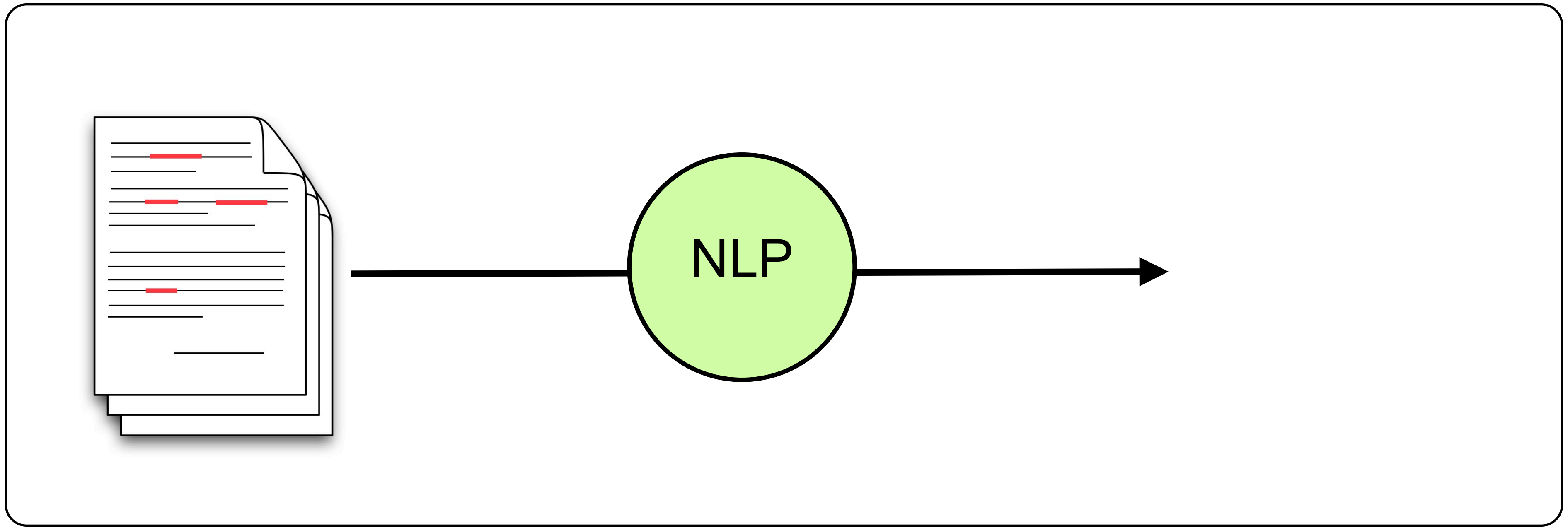

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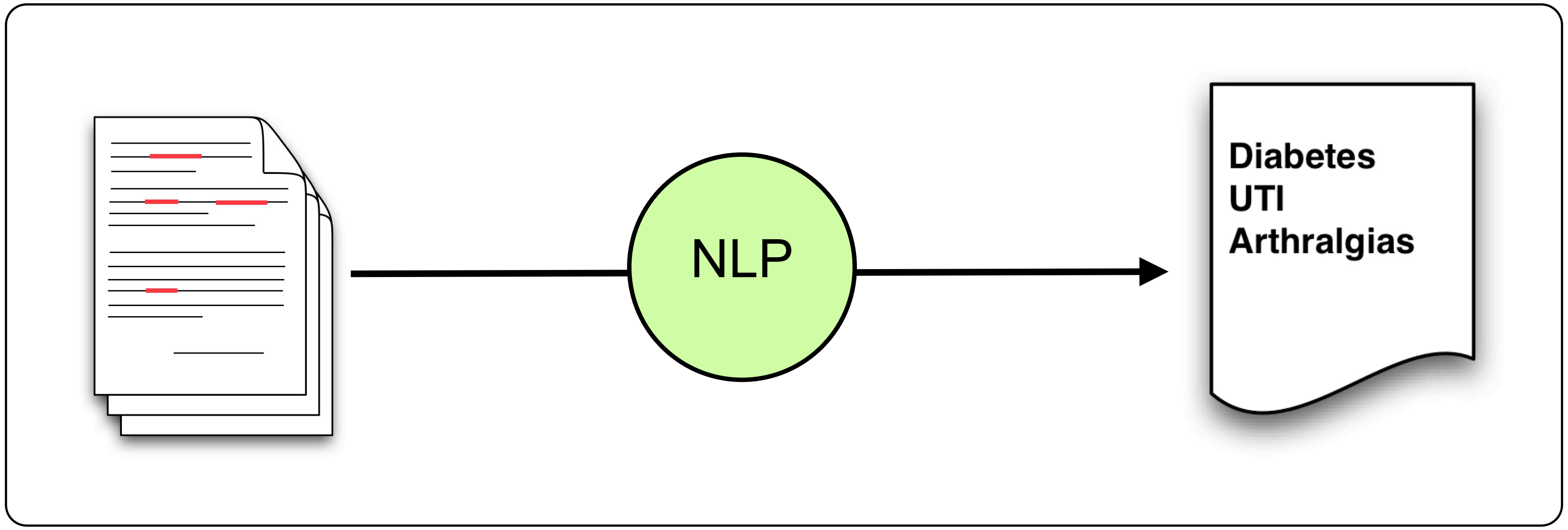

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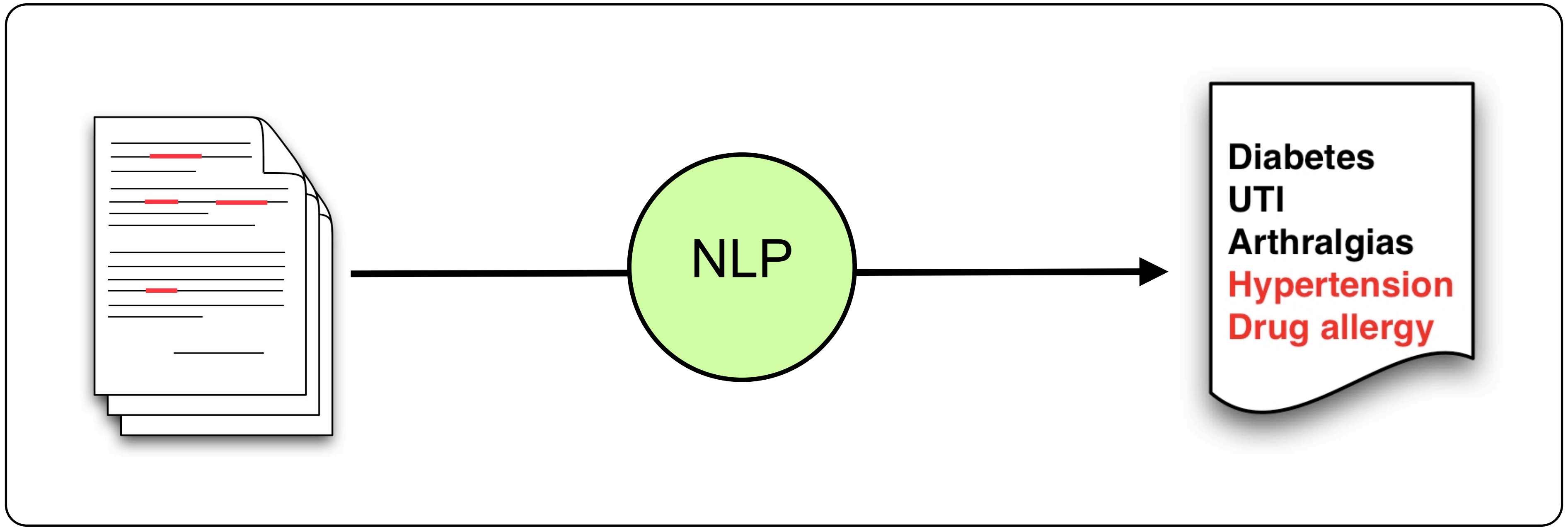

Why bother about NLP?

Clinical information extraction

Information Extraction (IE) involves extracting predefined types of information from text (e.g., people, diseases, symptoms, medication doses).

The development of IE applications in the biomedical domain has been far more advanced than in the clinical domain, mostly for two reasons:

- Extremely limited availability of clinical text because of patient confidentiality and privacy reasons.
- Characteristics of clinical text and related difficulties to analyze it.

The Automated Problem List

What was the problem?

An electronic problem list was already available at IHC, but

- it was often incomplete, inaccurate, not timely…not used!
- the problem list was becoming a central component of the EHR and was to be used by many applications (CPOE, documentation, knowledge access, etc.).

Clinical Information Extraction

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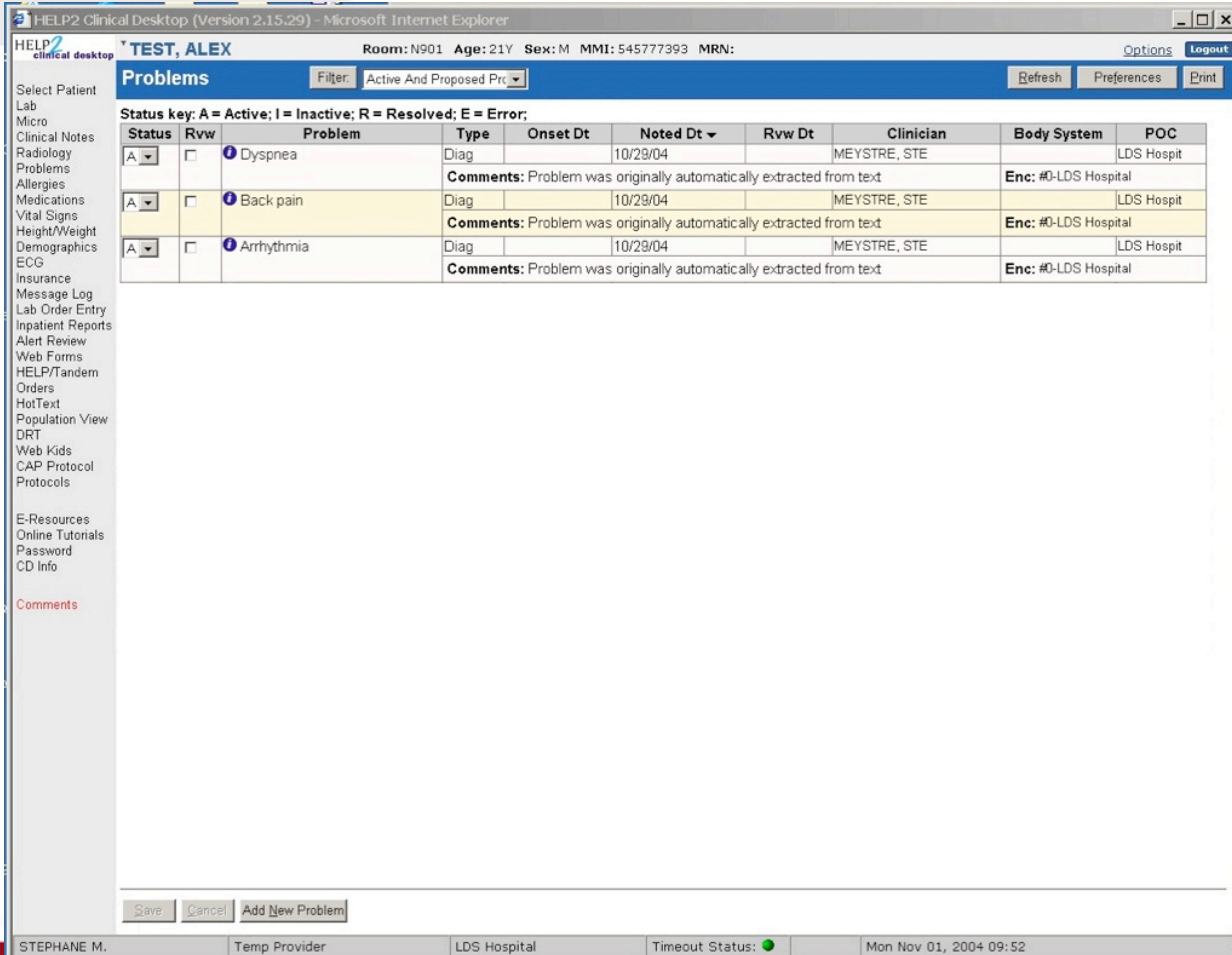
➪ Need for a problem list of good quality (complete, accurate, timely, and coded)

The Automated Problem List



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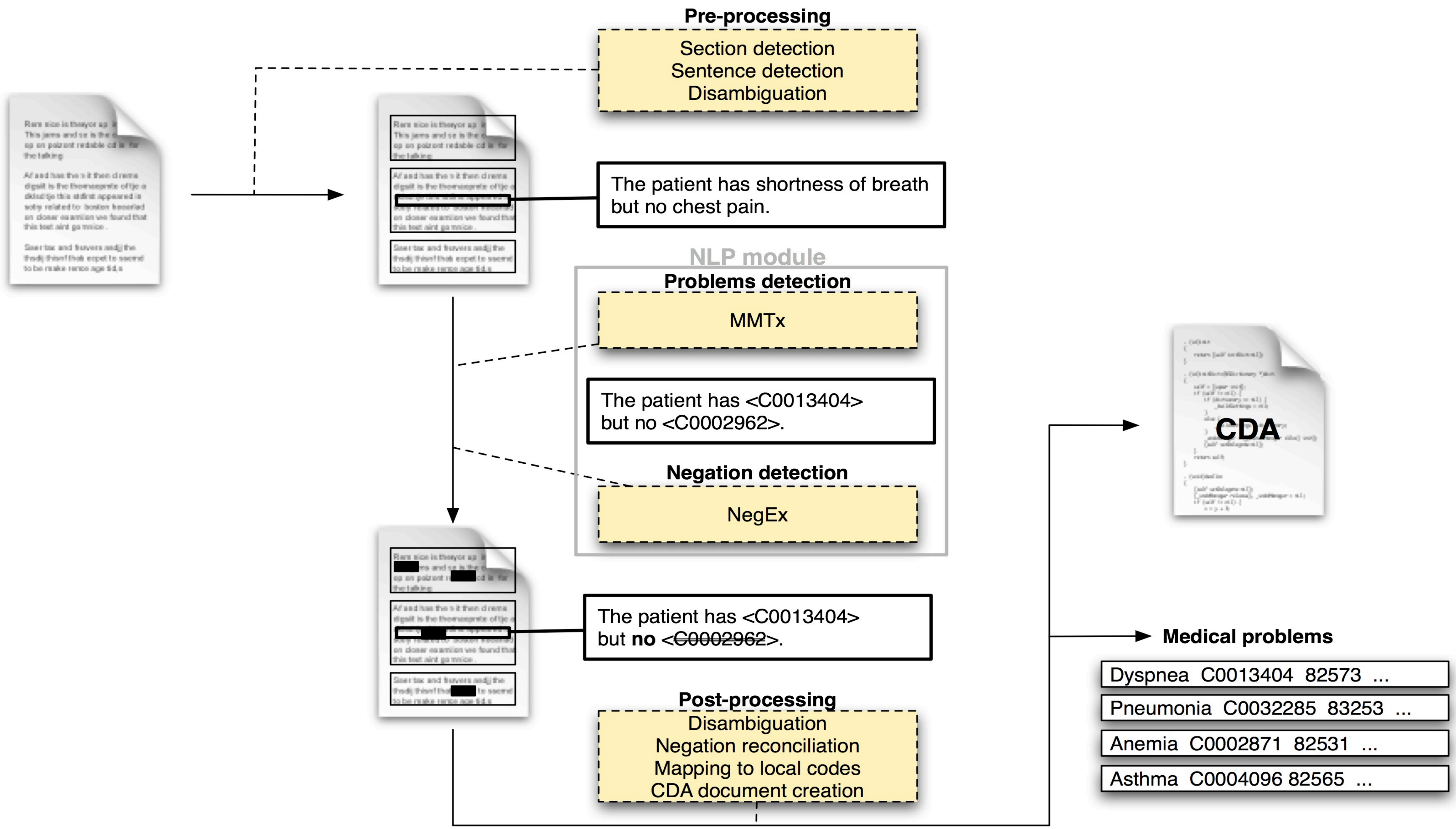
The Automated Problem List

Information Extraction application components



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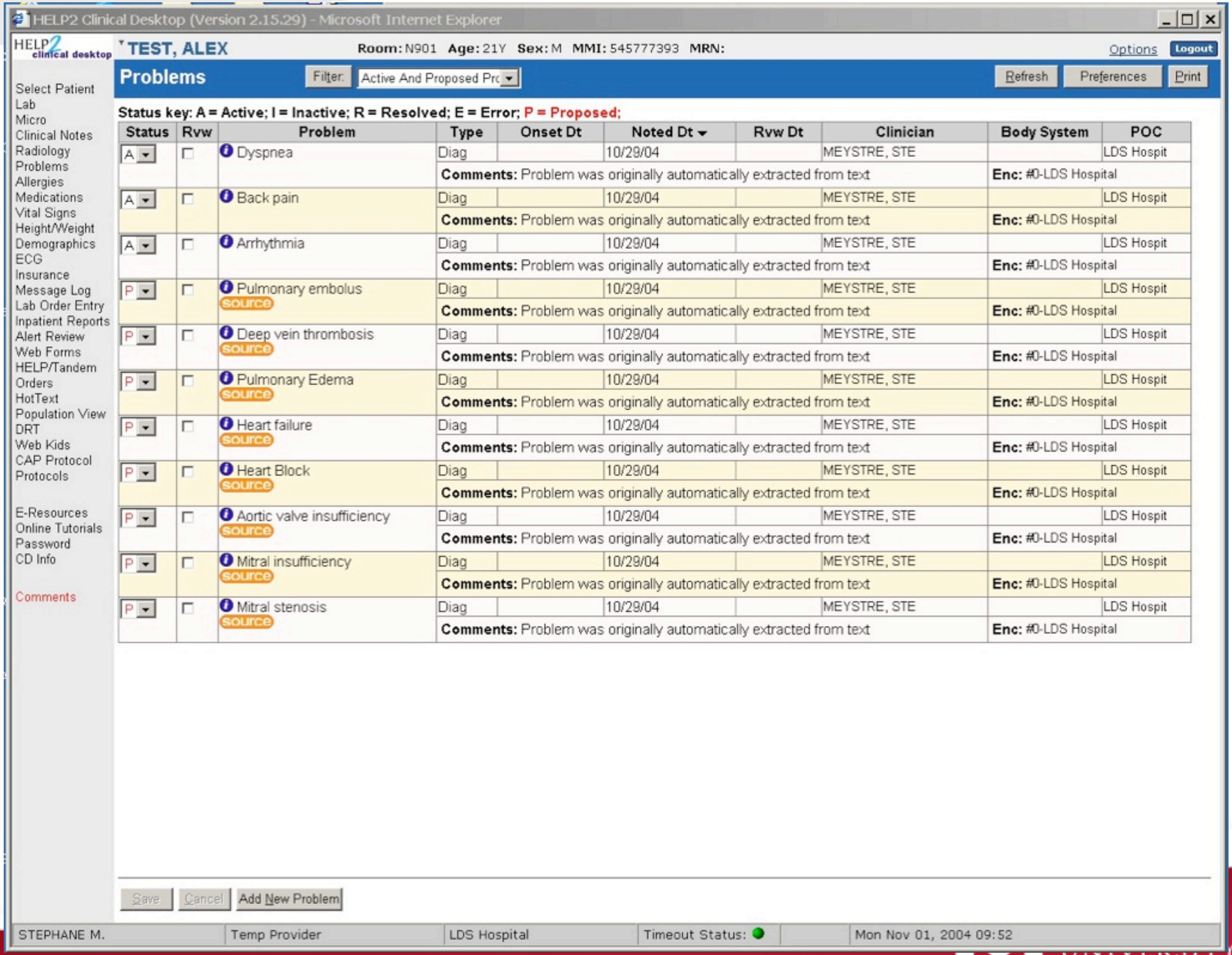

HELP2 Clinical Desktop (Version 2.15.29) - Microsoft Internet Explorer

HELP2 clinical desktop

TEST, ALEX   Room: N901 Age: 21Y Sex: M MMI: 545777393 MRN: Options Logout

Select Patient
Lab
Micro
Clinical Notes
Radiology
Problems
Allergies
Medications
Vital Signs
Height/Weight
Demographics
ECG
Insurance
Message Log
Lab Order Entry
Inpatient Reports
Alert Review
Web Forms
HELP/Tandem
Orders
HotText
Population View
DRT
Web Kids
CAP Protocol
Protocols

E-Resources
Online Tutorials
Password
CD Info

Comments

Problems Filter: Active And Proposed Prc Refresh Preferences Print

Status key: A = Active; I = Inactive; R = Resolved; E = Error; P = Proposed;

Status	Rvw	Problem	Type	Onset Dt	Noted Dt	Rvw Dt	Clinician	Body System	POC
A		Dyspnea	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
A		Back pain	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
A		Arrhythmia	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
P		Pulmonary embolus source	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
P		Deep vein thrombosis source	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
P		Pulmonary Edema source	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
P		Heart failure source	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
P		Heart Block source	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
P		Aortic valve insufficiency source	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
P		Mitral insufficiency source	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	
P		Mitral stenosis source	Diag		10/29/04		MEYSTRE, STE		LDS Hospit
			Comments: Problem was originally automatically extracted from text					**Enc:** #0-LDS Hospital	

Save Cancel Add New Problem

STEPHANE M. Temp Provider LDS Hospital Timeout Status: Mon Nov 01, 2004 09:52

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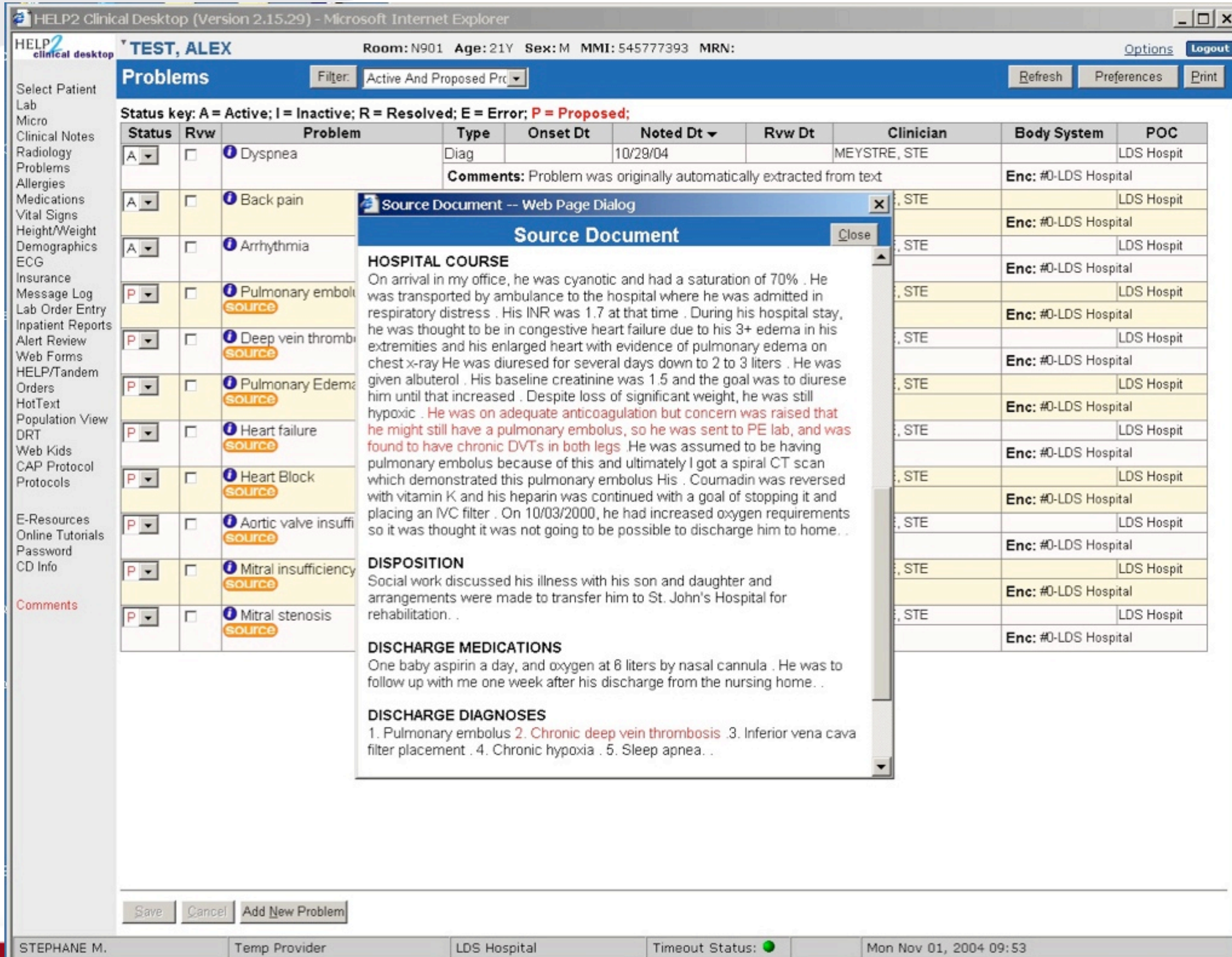

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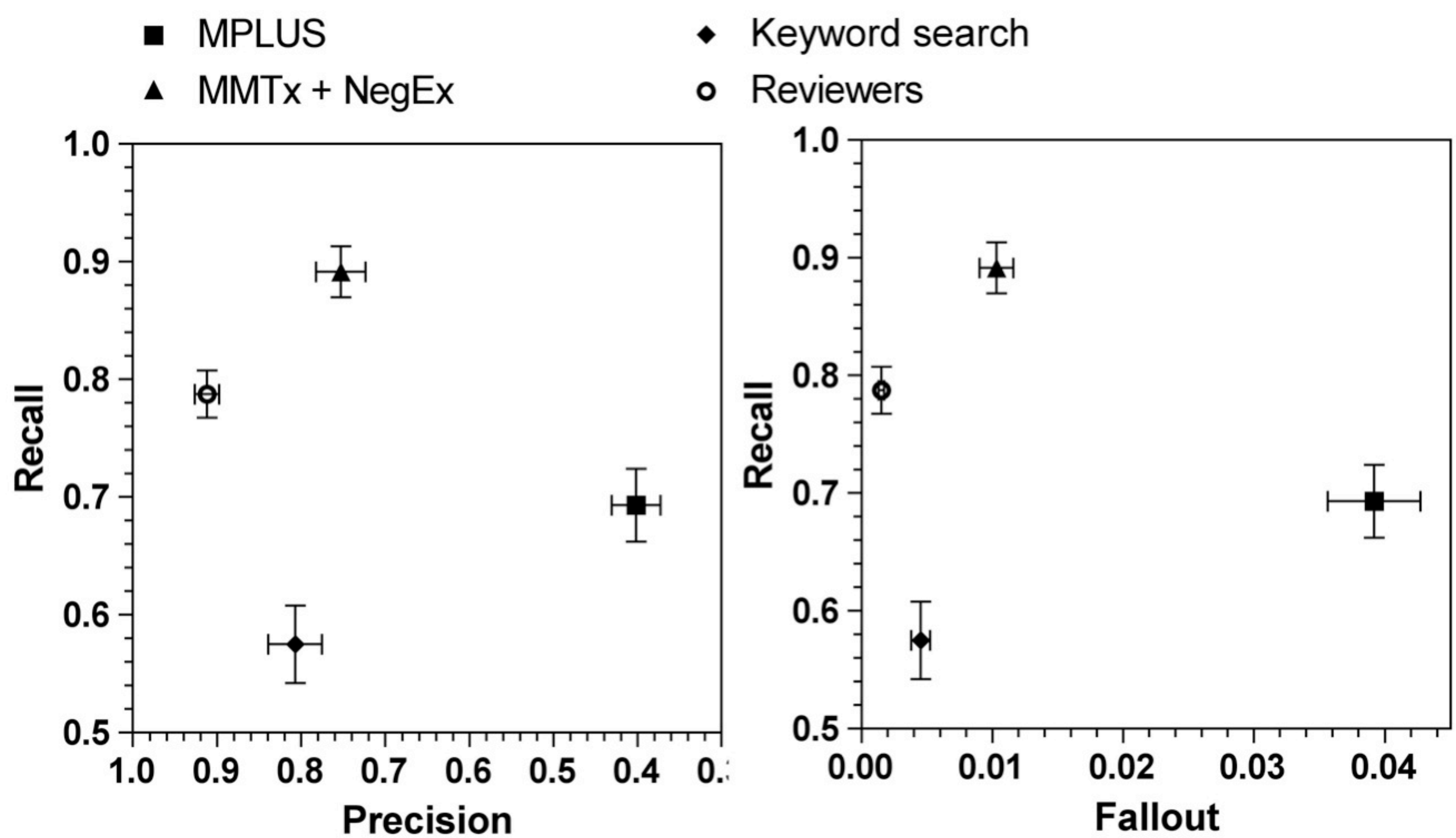
Information Extraction application versions comparison



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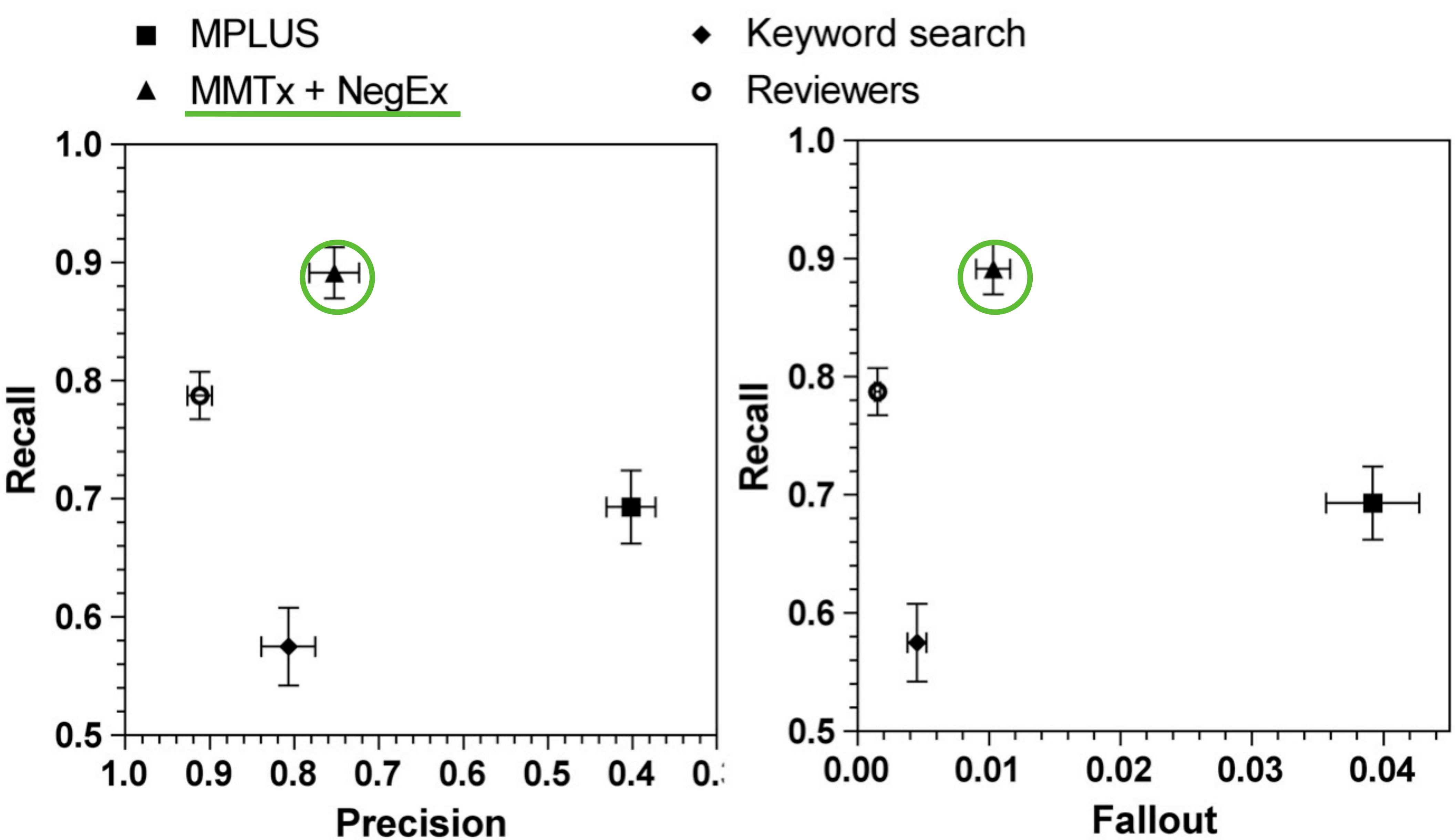

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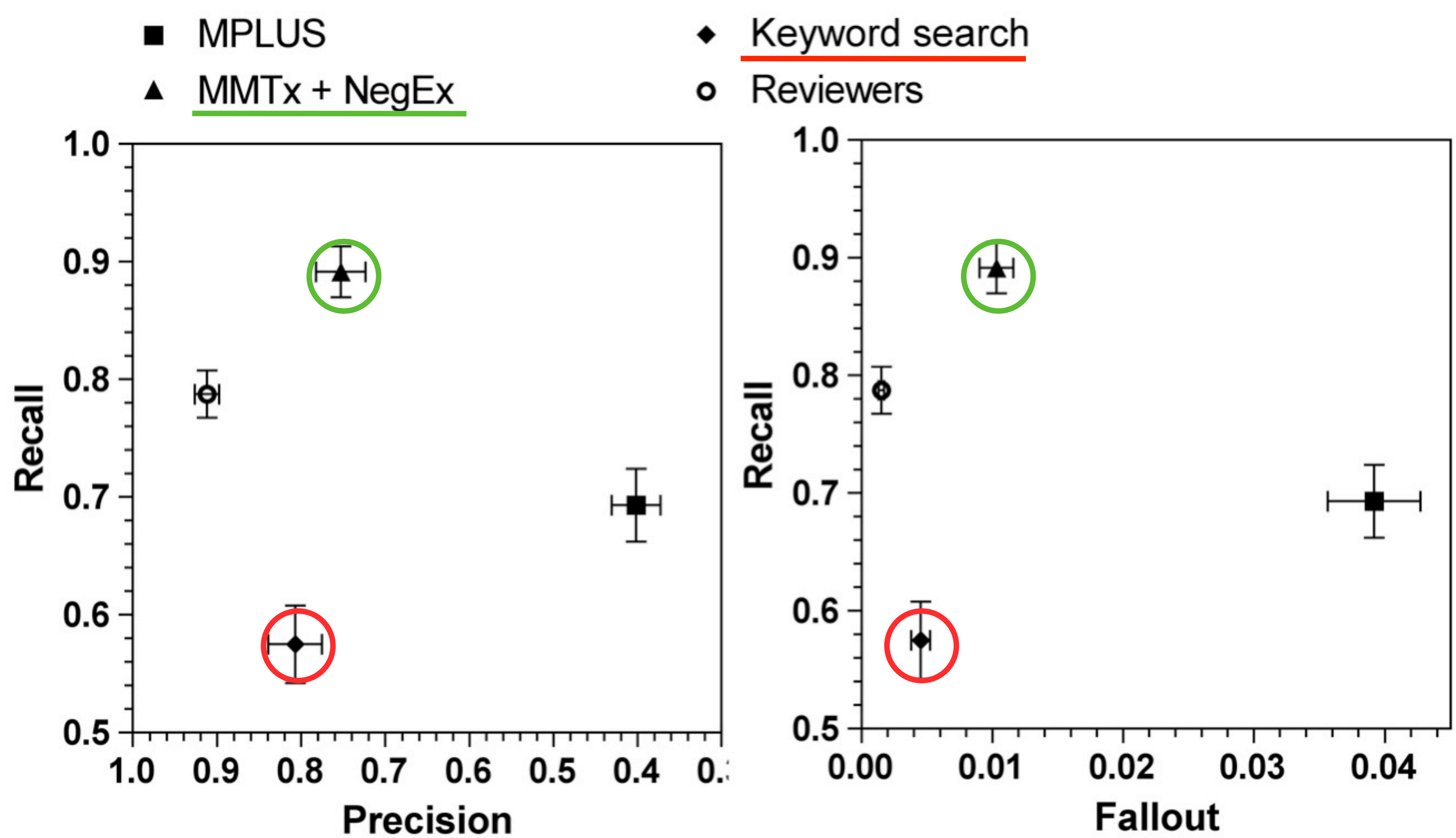

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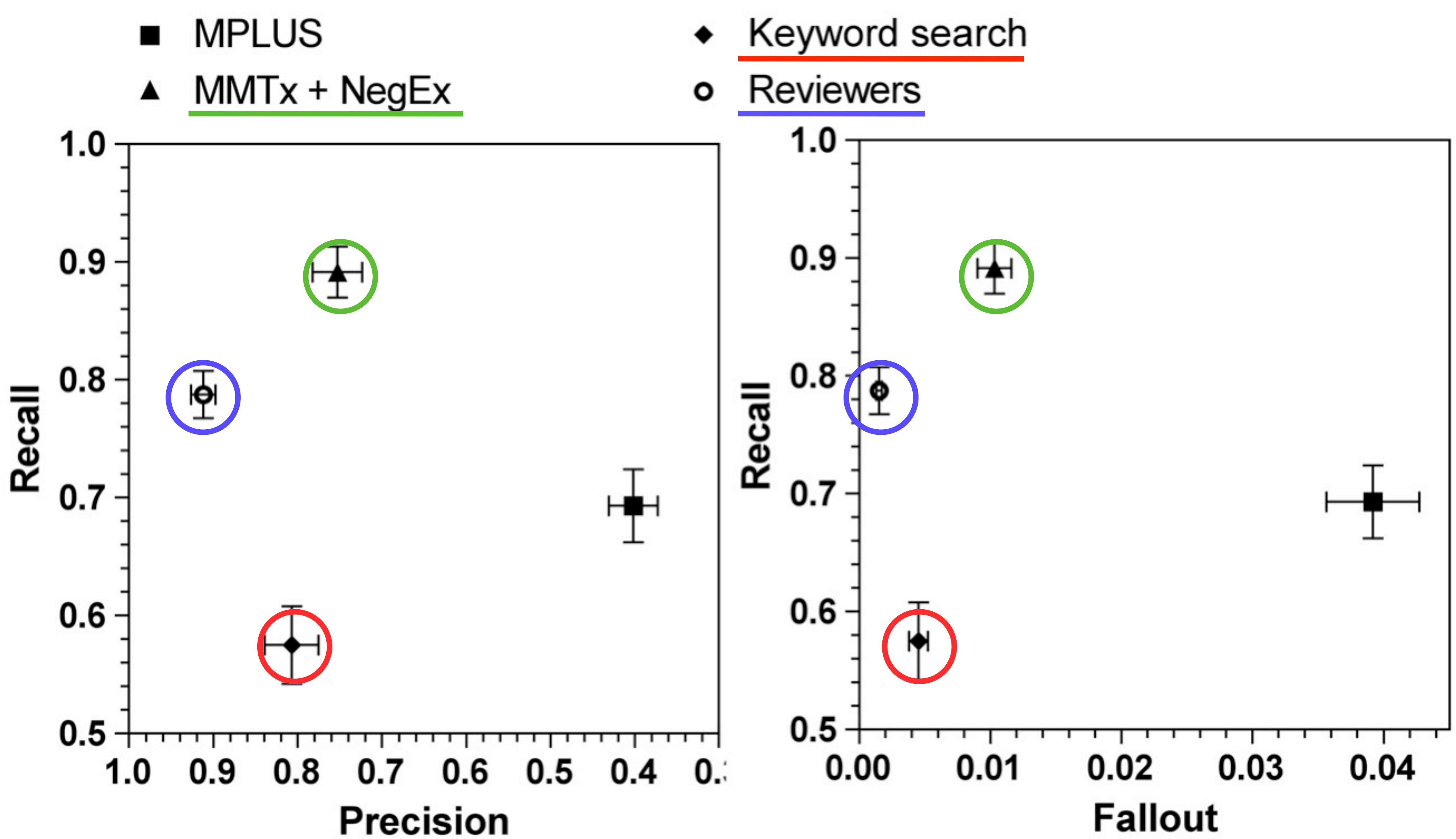

The Automated Problem List

Study population

- Adult inpatients in the ICU and the Cardiovascular Surgery unit (LDS Hospital, Salt Lake City, UT)
- **Control** group: physicians had access to the standard electronic problem list
- **Intervention** group: physicians had access to the APL (i.e. with *proposed* problems)

	All patients	ICU patients	CVS patients
Initial controls	76	44	32
RCT: Tests	88	54	34
RCT: Controls	83	51	32
TOTAL	247	149	98

The Automated Problem List

APL system RCT results

		Sensitivity	Specificity
All patients	Controls	0.102 (0.069-0.135)	0.998 (0.995-1)
	Tests	0.266 (0.192-0.34)	0.993 (0.988-0.999)
	Tests with proposed probs.	0.815 (0.771-0.859)	0.957 (0.947-0.966)
ICU patients	Controls	0.089 (0.049-0.129)	0.999 (0.998-1)
	Tests	0.41 (0.308-0.512)	0.989 (0.98-0.998)
	Tests with proposed probs.	0.774 (0.714-0.835)	0.963 (0.95-0.976)
CVS patients	Controls	0.123 (0.063-0.182)	0.995 (0.989-1)
	Tests	0.037 (0.013-0.063)	1
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Clinical Information Extraction

Textractor (for medications extraction)

Why extract medications?

- CPOE and e-Prescribing systems becoming widely available in the healthcare system.
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⇨ This is where automated medication information extraction could (and will) help!

Textractor (Medications Extraction)

2009 i2b2 Medication Extraction Challenge Task :

Identification of medications and related details in discharge summaries:

- Medication name (brand name, generic name, drug class)
- Dosage
- Route
- Frequency of the administration (incl. "as needed")
- Duration of the treatment
- Reason(s) for the prescription

Corpus

1249 discharge summaries, de-identified and re-identified with realistic surrogates, split in a training corpus (696 documents) and a testing corpus (553 documents).

Textractor

Application details

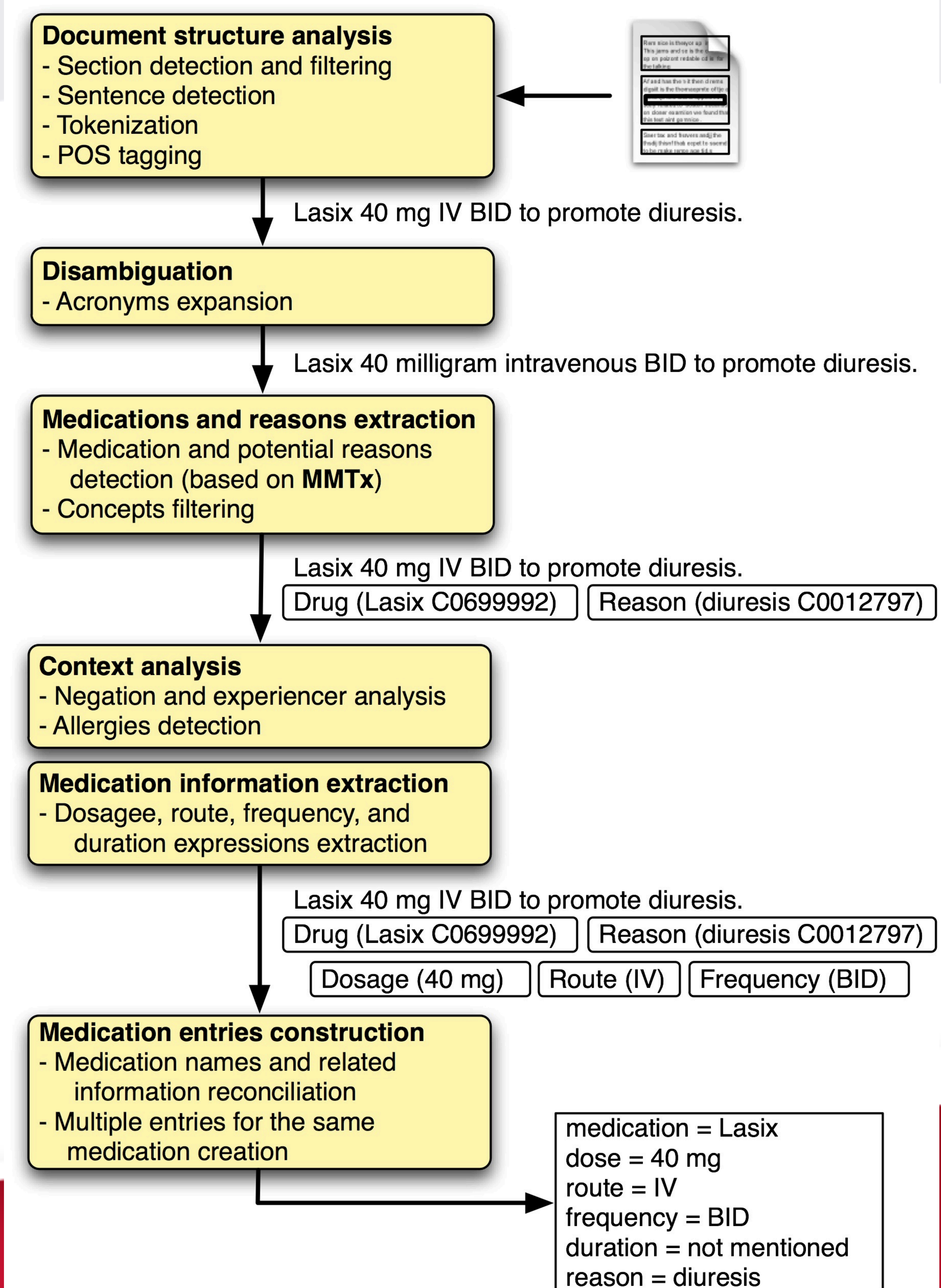
Built on UIMA, with functionalities developed as modules (TAEs), organized in a pipeline.

Several components based on OpenNLP tools, wrapped and retrained.

Uses MMTx (version 2.4.C), wrapped for UIMA in its first version. Dictionary lookup now based on Lucene.

Context analyzer based on the ConText algorithm, with improvements for this task.

Regular expressions used to extract dosage, route, etc.



Textractor (Medications Extraction)

2009 i2b2 Medication Extraction Challenge Evaluation :

Fields	Exact match			Inexact match		
	Recall	Precision	F_1-measure	Recall	Precision	F_1-measure
Medication	0.746	0.772	0.759	0.763	0.784	0.773
Dose	0.757	0.916	0.829	0.786	0.925	0.850
Route	0.817	0.920	0.865	0.803	0.926	0.860
Frequency	0.789	0.892	0.837	0.742	0.924	0.823
Duration	0.326	0.397	0.358	0.326	0.501	0.395
Reason	0.169	0.669	0.270	0.148	0.703	0.245
Overall	0.715	0.832	0.769	0.693	0.839	0.759

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Conclusions

For customers of automatically extracted clinical information, or CDS based on this information, trust can be based on several factors:

- Ensuring that there is a **human expert in the loop** for all clinical information generated by NLP and becoming part of the EHR.
- Allowing users to know the **origin of the extracted information** (and the methods used; and therefore use NLP methods that make it possible).

With trust in the NLP-generated information, even moderate performance is acceptable (moderate sensitivity, but sufficient PPV).