AI-Driven Clinical Documentation with MedKnowts

David Sontag, Luke Murray, Monica Agrawal (MIT) & Steven Horng (BIDMC)

HL7 working group II February 28, 2022
Who we are

Monica Agrawal
PhD Student, ML

Luke Murray
PhD Student, HCI

David Karger
Professor, HCI

David Sontag
Assoc. Professor, ML

Steven Horng, MD
Emergency Med. @ BIDMC

Divya Gopinath
MEng Student, ML

Sharon Jiang
UROP ’21 / MEng ’22

Nicholas Kurtzman, MD
Emergency Med. @ BIDMC

Irbaz Riaz, MD
Oncologist @ Mayo Clinic and DFCI
Electronic health records are used nearly everywhere in the United States. EHR usage increased from ~20% in 2004 to ~90% in 2017.

[Menachemi et al., 2011; Moy et al., 2021; Siegler et al., 2015; Ahmed et al., 2011; Rule et al., 2015]
What medical problems does this patient have?

Chief complaint: chest pain
69 y/o man W/o ...
- On insulin?
- Back issues?
- Does this patient have cancer?
- Does this patient have heart problems?
- Are they being anticoagulated? If so with what? Is it in range?
- What is their heart history? Last cath/stress/echo
- On insulin?
- Back issues?
- Does this patient have cancer?
- Does this patient have heart problems?
- Are they being anticoagulated? If so with what? Is it in range?
- What is their heart history? Last cath/stress/echo

- On insulin
- Chronic back pain
- Colorectal cancer, in remission
- 3 vessel coronary artery disease
- Anticoagulated, but may have been stopped due to frequent falls
- Are they still being anticoagulated? If so with what? Is it in range?
- What is their heart history? Last cath/stress/echo

- On warfarin, is INR in range?
• Are they still being anticoagulated? If so with what? Is it in range?
• What is their heart history? Last cath/stress/echo

• INR is only 1
• They are not taking warfarin!
- What is their heart history? Last cath/stress/echo

<table>
<thead>
<tr>
<th>Date</th>
<th>Type</th>
<th>Study/Procedure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Imaging</td>
<td>CHEST (PA)</td>
</tr>
<tr>
<td></td>
<td>Cardiovascular</td>
<td>ECG</td>
</tr>
<tr>
<td></td>
<td>Imaging</td>
<td>CHEST (PA)</td>
</tr>
<tr>
<td></td>
<td>Imaging</td>
<td>CLAVICLE L</td>
</tr>
<tr>
<td></td>
<td>Imaging</td>
<td>C-SPINE, TF</td>
</tr>
<tr>
<td></td>
<td>Imaging</td>
<td>CHEST (POF)</td>
</tr>
<tr>
<td></td>
<td>Cardiovascular</td>
<td>ECG</td>
</tr>
<tr>
<td></td>
<td>Cardiovascular</td>
<td>ECG</td>
</tr>
</tbody>
</table>
chief complaint: chest pain

69 y/o man w/o dm, htn, hld, CABGx3, colon CA s/p colectomy in remission, mechanical MVR non-compliant on coumadin with last INR 1.0 here c/o chest pain. Last cath 1 yr ago with residual 90% stenosis in LAD that was too high risk for intervention.

- Why were they too high risk?
- How does today EKG compare to prior?
- What about the cancer history?
- What is their risk for a pulmonary embolism that can also cause chest pain?
Summary of provider challenges with clinical notes

● Data is organized by how it was generated, not by how it will be used
● Information is fragmented across several systems, leaving it to the user to integrate this information
  
  Patient summaries, for example, are manually curated, which means they are rarely up to date

● Workflows consist of many repetitive tasks, but highly specific to a user:
  ○ Find information on __
  ○ Keep track of __
  ○ Communicate __ to another provider
Patients also need clinical notes

Frequency and Types of Patient-Reported Errors in Electronic Health Record Ambulatory Care Notes

Sigall K. Bell, MD; Tom Delbanco, MD; Joann G. Elmore, MD, MPH; et al


- Sent survey to 150k patients across 80 centers, 30k responded
- 1/5 of patients found errors
- 40% described them as serious errors
Patients also need clinical notes

**Frequency and Types of Patient-Reported Errors in Electronic Health Record Ambulatory Care Notes**

Sigall K. Bell, MD1,2; Tom Delbanco, MD1,2; Joann G. Elmore, MD, MPH3; et al

New Prescriptions: How Well Do Patients Remember Important Information?

Dr. Darjung M. Tarn, MD, PhD and Dr. Susan A. Flocke, PhD

- Approximately 1/3 forgot important information
- Other estimates 40%+ of medical information is immediately forgotten

- Sent survey to 150k patients across 80 centers, 30k responded
- 1/5 of patients found errors
- 40% described them as serious errors
Patients also need clinical notes

**Frequency and Types of Patient-Reported Errors in Electronic Health Record Ambulatory Care Notes**

Sigall K. Bell, MD1,2; Tom Delbanco, MD1,2; Joann G. Elmore, MD, MPH3; et al

- Sent survey to 150k patients across 80 centers, 30k responded
- 1/5 of patients found errors
- 40% described them as serious errors

---

**New Prescriptions: How Well Do Patients Remember Important Information?**

Dr. Darjung M. Tarn, MD, PhD and Dr. Susan A. Flocke, PhD

- Approximately 1/3 forgot important information
- Other estimates 40%+ of medical information is immediately forgotten

---

**Readability of discharge summaries: with what level of information are we dismissing our patients?**

- Only about a quarter could adequately understand their surgical summary
- 65% didn’t have reading level
21st Century Cures Act makes clinical notes immediately available to patients, online

There is huge opportunity to make notes more useful for patients
Researchers need structured data from clinical notes.
Researchers need structured data from clinical notes

- **Disease Status**

- **Interventions**

- **Symptoms**

- **Confounders** Cirrhosis, CHF
In summary, the current state of clinical notes affects:

1. **Clinicians**, who have difficulty finding and synthesizing information,

2. **Patients**, who need help with follow-up and cannot understand medical jargon,

3. **Research**, that requires structured data, and

4. **AI algorithms**, that need to be contextually integrated into the clinical workflow.
Synoptic reporting is being increasingly adopted in some fields (radiology and pathology) but infeasible in most others.

Accession: AAAA0000  
Procedure: radical prostatectomy  
Histologic type: acinar adenocarcinoma  
Grade group: 2  
Margins: uninvolved by invasive carcinoma  
Number of lymph nodes involved: 0  
Number of lymph nodes examined: 3  
Pathologic stage classification (AJCC 8th edition): Primary tumor: pT2

(Synthetic note written by Madhur Nayan)
Goal

Our goal is to improve EHRs for all parties involved

Aim 1: Make clean documentation seamless

Aim 2: Unify interfaces for data retrieval and data entry

Aim 3: Serve as an anchor to deploy other ML models
What we propose...

Make documentation cleaner and easier via ML

Use cleaner data collected to build better ML models.

Gopinath et al., MLHC 2020; Murray et al., UIST 2021
A demo
Part 1: DATA ENTRY:

Making clean documentation seamless

“Fast, Structured Clinical Documentation via Contextual Autocomplete”
<table>
<thead>
<tr>
<th>ED Document</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Triage Assessment</td>
<td>Short note describing patient’s status (free-text), <strong>vitals</strong> (blood pressure, temp, pulse ox, heart rate, respiratory rate)</td>
<td>patient complains of chest pain s/p fall. has trouble breathing</td>
</tr>
<tr>
<td>2 Chief Complaint</td>
<td>One-phrase summary describing reason for visit (structured)</td>
<td>CHEST PAIN</td>
</tr>
<tr>
<td>3 Nurse Notes</td>
<td>RN comments describing patient and care throughout visit (free-text)</td>
<td>36 y/o female with CP, no prior cardiac history</td>
</tr>
<tr>
<td>4 Doctor Notes</td>
<td>More thorough MD comments about patient including <strong>history</strong>, <strong>current status</strong>, <strong>diagnosis</strong>, and <strong>treatment</strong> (free-text)</td>
<td>36 y/o F p/w CP s/p fall, no prior cardiac history, family history of ...</td>
</tr>
<tr>
<td>5 Discharge Summary</td>
<td>Official note filed in medical record that <strong>summarizes visit</strong>, usually updated from MD comments (free-text)</td>
<td>Patient is a healthy 36 year-old woman who came in complaining of...</td>
</tr>
<tr>
<td>ED Document</td>
<td>Description</td>
<td>Example</td>
</tr>
<tr>
<td>----------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------</td>
</tr>
<tr>
<td>1 Triage Assessment</td>
<td>Short note describing patient’s status (free-text), <strong>vitals</strong> (blood pressure, temp, pulse ox, heart rate, respiratory rate)</td>
<td>patient complains of chest pain s/p fall. has trouble breathing</td>
</tr>
<tr>
<td>2 Chief Complaint</td>
<td><strong>One-phrase</strong> summary describing reason for visit (structured)</td>
<td>CHEST PAIN</td>
</tr>
<tr>
<td>3 Nurse Notes</td>
<td><strong>RN comments</strong> describing patient and care throughout visit (free-text)</td>
<td>36 y/o female with CP, no prior cardiac history</td>
</tr>
<tr>
<td>4 Doctor Notes</td>
<td>More <strong>thorough MD comments</strong> about patient including <strong>history, current status, diagnosis, and treatment</strong> (free-text)</td>
<td>36 y/o F p/w CP s/p fall, no prior cardiac history, family history of ...</td>
</tr>
<tr>
<td>5 Discharge Summary</td>
<td><strong>Official note</strong> filed in medical record that summarizes visit, usually updated from MD comments (free-text)</td>
<td>Patient is a healthy 36 year-old woman who came in complaining of...</td>
</tr>
</tbody>
</table>
With **contextual autocomplete**, we capture clinical concepts at the point-of-care via learned suggestions.

56 y/o with t2dm and afib on Coumadin. Complaining of n/v and chest pain. Coughing hills.

1. Create semi-structured notes as *they are written* (focusing on ED notes).

2. *Decrease documentation burden* for clinicians, who now type less.

3. Normalize concepts to clinical ontologies (UMLS, LOINC).
Some design considerations:

- The note is a live document and changes over time.
Some design considerations:

- The note is a live document and changes over time.
- Stringent computation & security considerations.
Some design considerations::

- The note is a live document and changes over time.
- Stringent computation & security considerations.
- Context-specific domain knowledge/vocabulary that needs to be integrated and modified over time.
Some design considerations:

- The note is a **live document** and changes over time.
- Stringent **computation & security** considerations.
- **Context-specific domain knowledge**/vocabulary that needs to be integrated and modified over time.
- Our tool should be **opt-in**— doctors can type as before with no breaks to their workflow, and avoid our system in case of errors.
Some design considerations:

- The note is a live document and changes over time.
- Stringent computation & security considerations.
- Context-specific domain knowledge/vocabulary that needs to be integrated and modified over time.
- Our tool should be opt-in—doctors can type as before with no breaks to their workflow, and avoid our system in case of errors.
- It’s not just plaintext—we want to create a prospective corpus of cleanly labelled clinical data which can be normalized to medical ontologies.
There are six types of clinical concepts currently supported. They are color-coded in the tool:

<table>
<thead>
<tr>
<th>CONDITION</th>
<th>SYMPTOM</th>
<th>MEDICATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAB</td>
<td>VITAL SIGN</td>
<td>PROCEDURE</td>
</tr>
</tbody>
</table>

Each concept has a list of approved synonyms that can be tagged, so you can use acronyms and abbreviations as you would in a normal note (like htn):

Patient has a history htn and afib (on Coumadin to treat). She is concerned about possible prediabetes -- GLUCOSE is slightly elevated (GLUCOSE 92 (7/5/16)). She presents with fever and wheezing but no chills -- O2Sat 98 (5/7/10) seems normal.
Clinical concepts are automatically linked to clinical ontologies.
Quantitative information such as **lab and vital values** can be documented inline:

```
/gluco
<table>
<thead>
<tr>
<th>Dx</th>
<th>Dx</th>
</tr>
</thead>
<tbody>
<tr>
<td>glucose intolerance</td>
<td>glucose-6-phosphate dehydrogenase</td>
</tr>
<tr>
<td>borderline diabetes</td>
<td>deficiency</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th>Visit</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLUCOSE</td>
<td>Result Count: 1</td>
</tr>
<tr>
<td>BLOOD CHEMISTRY</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th>6 Month</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLUCOSE</td>
<td>Result Count: 6</td>
</tr>
<tr>
<td>URINE HEMATOLOGY</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th>1 Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLUCOSE</td>
<td>Result Count: 8</td>
</tr>
<tr>
<td>ASCITES CHEMISTRY</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GLUCOSE</td>
<td></td>
</tr>
<tr>
<td>CSF CHEMISTRY</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GLUCOSE</td>
<td></td>
</tr>
<tr>
<td>JOINT FLUID CHEMISTRY</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GLUCOSE</td>
<td></td>
</tr>
<tr>
<td>OTHER BODY FLUID CHEMISTRY</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GLUCOSE</td>
<td></td>
</tr>
<tr>
<td>PLEURAL CHEMISTRY</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GLUCOSE</td>
<td></td>
</tr>
<tr>
<td>STOOL CHEMISTRY</td>
<td></td>
</tr>
</tbody>
</table>

GLUCOSE (91-108) avg: 97.17 std: 7.03
Quantitative information such as **lab and vital values** can be documented inline:

Both individual and **aggregate** values are supported with reasonable defaults.

GLUCOSE (91-108) avg: 97.17 std: 7.03
Sources of information in contextual autocomplete:

Use available information from a given patient to predict concepts that will be documented in a clinical note.

- Prior notes (EHR)
- Triage assessment
- Chief complaint
- Doctor’s Notes (our focus)
Language Model

1. Use local context to predict when to autocomplete and what concept type is needed.
Language Model

1. Use **local context** only to predict **when** to autocomplete and **what concept type** is needed.

2. Use **past data** (triage note, medical history) to **rank suggested terms** to autocomplete for each concept type.

- SOB
- Chest Pain
- Syncope
We dramatically reduced the keystroke burden of data entry in a live setting.

(see also Greenbaum, Jernite, Halpern, Calder, Nathanson, Sontag, Horng. *International Journal of Medical Informatics*, 2019)
Auto-fill text based on recognized clinical concepts reduces redundant data entry.
Post recognitions provide automatic intelligent highlighting when autocomplete isn’t used.
Semantic meaning is recognized and preserved

Shoulder Pain
Clinical Term

Left Anterior Shoulder Pain
Clinical Term with Modifier

No Left Anterior Shoulder Pain
Clinical Term with Modifier and Negation Phrase
DATA RETRIEVAL
EHRs silo information by type instead of organizing it around problems.

[Luff et al., 1996;]
Doctors have to manually synthesize data into data driven narratives.

[Mamykina et al., 2012]
Why should I tag concept?

When concepts are tagged, cards with relevant information are immediately displayed in the sidebar.
### History of Presenting Illness

**76 y/o M**

### Past Medical History

### Medications

### Review of Symptoms

### Physical Exam

### ECG

### Radiology

### Procedures

### Medical Decision Making
Why should I tag concept?

Concepts can be hovered to view information directly in the documentation interface.
Anatomy of a Card

Name

Relevant Labs

cardiac testing

Relevant Notes
We designed MedKnowts in a year-long iterative prototyping process with a clinician and a clinician’s scribes across 1185 patients.

We evaluated MedKnowts in a month-long deployment with four scribes across 234 patients.