NLP Innovations – what does the healthcare industry see as knowledge gap in the NLP research

Moderator:

Hongfang Liu, Mayo Clinic

Panelists:

Eric Brown, IBM Watson
Richard Wolniewicz, 3M Health Information Systems
Brian Hazlehurst, Kaiser Permanente Northwest Center for Health Research
Scott DuVall, VA Salk Lake City VAMC
Ruth Reeves, VA Tennessee Valley VAMC
Dialogues in a clinical setting

• From researchers:
  – Great, you can do NLP, right? I want to retrieve the number of patients newly diagnosis of diabetes with GI symptoms. I need that number for my submission next week.

• From quality improvement analysts:
  – NSQIP – 30-day re-admission? Can you help me obtain the number of re-admissions from EMR? VA did that.

• From clinicians:
  – Documentation support and computer-assisted coding
  – Clinical decision support
  – Outcomes.

• From leaders:
  – We have established partnerships with XXX, YYY and ZZZ companies to solve the above problems.
**NLP use case: Heart Failure**

<table>
<thead>
<tr>
<th>Problem List</th>
<th>Clinical Note</th>
<th>Echocardiography Notes</th>
<th>Medications</th>
<th>Current Visit Information</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heart Failure</td>
<td>Diagnosis</td>
<td>Ejection fraction</td>
<td>ACE Inhibitors</td>
<td>h/o MI Medications</td>
<td>CPK</td>
</tr>
<tr>
<td>Edema</td>
<td>Current History</td>
<td></td>
<td>Digoxin B-Blockers</td>
<td>smoker</td>
<td>TnI</td>
</tr>
<tr>
<td>Arrhythmia</td>
<td>Quality of Life</td>
<td></td>
<td></td>
<td></td>
<td>S. Potassium</td>
</tr>
</tbody>
</table>

- **Quality reporting**
  - e.g. how many HF admissions

- **Decision support**
  - e.g. put diagnosis on problem list and provide educational material to HF patients

- **Clinical Research**
  - e.g. identify HF cohort for survey
IBM Watson NLP in Healthcare

Eric Brown, PhD
IBM Watson Group
Yorktown Heights, NY
Physician’s Workflow

Visit Preparation

- Get an overview of the patient
  - What are the patient’s active problems?
  - What are possible concerns that need to be addressed?

History and Physical

- Review the patient’s history
  - Chief compliant or reason for the visit?
  - Past medical history?
  - Current medications?
  - Most recent lab results?

Assessment

- Determine diagnostic workup
  - Explore diagnostic tests and screening / diagnostic guidelines
  - Apply knowledge to make diagnosis

Plan

- Determine treatment plan
  - Explore treatment options and possible management guidelines

EMR

Medical Knowledge

Population and Similarity Analytics

Performance Metrics Evaluation, Research, Cohort Analysis
food would “get stuck” when she was swallowing
swallowing difficulty...
...food gets held-up...

Causation
...can cause food to move slowly in the esophagus.

Terminology

Magnitude

Fever
Temperature

Fever after acute symptoms subside...

Chronology

Negation
productive cough after nonproductive cough
nonproductive cough

Domain

Location

Abdomen Pain exacerbated by exercise

Terminology

pneumaturia
bubbles in the urine

Causation

Abdomen Pain
Urination Pain
Dysuria

Chronology

sudden onset of chills
cold
chills

Chronology

Normal QRS Pattern
Abnormal QRS Complex
Delta-Wave
PR Interval

Terminology
coryza

Terminology

Kidney Pain
Lower Back Pain

Abdomen Pain
Flank Pain

Domain

Fever Temperature
High

Abdomen Pain

Flank Pain

Location

Fever

Temperature
High

Abdomen Pain

Flank Pain

Location

Fever Temperature
High

Abdomen Pain

Flank Pain

Location

Fever Temperature
High

Abdomen Pain

Flank Pain

Location
A 58-year-old woman presented to her primary care physician after several days of dizziness, anorexia, dry mouth, increased thirst, and frequent urination. She had also had a fever and reported that food would "get stuck" when she was swallowing. She reported no pain in her abdomen, back, or flank and no cough, shortness of breath, diarrhea, or dysuria. Her history was notable for cutaneous lupus, hyperlipidemia, osteoporosis, frequent urinary tract infections, three uncomplicated cesarean sections, a left oophorectomy for a benign cyst, and primary hypothyroidism, which had been diagnosed a year earlier. Her medications were levothyroxine, hydroxychloroquine, pravastatin, and alendronate. She lived with her husband and had three healthy adult children. She had a 20-pack-year history of smoking but had quit 3 weeks before presentation. She reported no alcohol or drug abuse and no exposure to tuberculosis. Her family history included oral and bladder cancer in her mother, Graves' disease in two sisters, hemochromatosis in one sister, and idiopathic thrombocytopenic purpura in one sister.
Co-Reference

Anaphora
Aortic stenosis. With aortic stenosis, the murmur is systolic, beginning after S1 and ending at or before aortic valve closure. It's harsh and grating, medium-pitched, and crescendo-decrescendo.

No Co-referent term
The clinical presentation of the patient with constriction resembles that of the individual with tamponade except for normal pulse pressure and lack of pulsus paradoxus in constriction. Inspiratory increase in jugular venous pressure (Kussmaul's sign) is occasionally seen.

Discourse Segmentation (Confusors)

Collagenous colitis and lymphocytic colitis are distinguished by the presence or absence of a thickened subepithelial collagen layer. The cause of microscopic colitis syndrome is uncertain.
• UMLS (Unified Medical Language System) from NLM
  – ~100 sources, sort of merged
  – ~3M unique concept identifiers (not unique concepts), organized in a type hierarchy
    • activities, anatomy, chemicals/drugs, devices, disorders, genetics, organisms, physiology, procedures, ...
  – ~350 relation types; ~30M unique relation instances
    • diagnoses, treats, finding_site_of, has_causative_agent, contraindicates, ...

• Sample Uses of UMLS
  – Type Coercion: does a candidate answer match the type the question is seeking
  – Candidate generation
  – Term matching
  – Clinical factor identification
  – Relation generation in inference graph
Domain Model – key entities and relationships

- anatomy = anst, bdsy, blor, bpor, bsoj
- social_history = bhvr, dora, ocac
- demographics = geoa, popg
- microbe = arch, bact, fngs, virs
- disease = patf, anab, inpo
- gene = gngm

- demographics, social, genetic
- anatomy
- test
- clinical attribute
- bio-function
- treatment
- substance

- test = diap, lbpr
- finding = fndg
- substance = sbst
- bio_function = biof
- treatment = topp, phsu, clnd, medd, orch
- clinical_attribute = clna, bacs, orch, bcsu

- disease
- causeOf
- riskFactorOf
- locationOf
- mechanismOf
- diagnoses
- affects
- hasingredient
- measures
- manifestationOf

- treats, prevents
- treats
Individual EMR = plain text + semi-structured data

EMR (up to 50MBs per patient)

- Encounter (Clinical) Notes
- Medications
- Lab Results
Note-00020.xmi

HPI: **AGE in 50s** yr old man here for 

**h**ypothyroid, **d**iabetes mellitus,
c/o feeling **s**uggish, otherwise well. Able to perform rather strenuous physical activities.

TTE done.

Eye exam done - reportedly fine.

Medication: SYNTHROID 150mcg TABLET Take one (1) tablet daily.

Physical Exam:

Gen: alert, oriented, **NAD, obese**

HEENT: atraumatic, normocephalic, PERL, EOMI, **clear**, **conjunctiva pink**, 

**fundus crisp**, **TM’s clear**, **nares normal**, moist mucous membranes,

**opharynx clear** without 

**syphema** or **exudate**.

Neck: supple, no LAD, no carotid bruits, no **JVD**, **GIUTER**.

CV: S1, S2 regular, 3/6 SEM at **NAME[ZZZ]** SB

Resp: Clear to auscultation bilaterally, anterior and posterior, no **wheezes**, **rales** or **whist**

Abd: +BS, soft, nontender. **OBESE**, no **hepatosplenomegaly**

Ext: no **cyanosis**, no **rubbing**, no edema. **warm**

Pulses: **radial 2/2**, **brachial 2/2**, **axillary 2/2**, **femoral 2/2**

Skin: no **rashes**

Neuro: **focal**

244.9 **HYPOTHYROIDISM NOS**

Note: pt is subtherapeutic on synthyroid, will increase to 175 mcg. Follow up TSH in 3 months.

Plan: SYNTHROID 175mcg TABLET

250.0 **DIABETES MELLITUS UNCOMP**

Note: Newly diagnosed **DM type 2**. Will start glucophage.

Plan: Glucophage 500mg po bid

746.89 VSD

Note: TTE - preliminary results show: normal LV/RV function, mild RVH, small residual VSD with left to right flow, RVOT with subvalvular and valvular **PS**, **trivial TR**, **trivial** **NAME[YYY]**.

XXX has not seen peds cards since 1996. Although well should f/u.

Ptl am: **CONSULT TO CARDIOLOGY** f/u with **NAME[VWW]** [peds cards]

272.4 **HYPERLIPIDEMIA** **INITIALS**

Not e: LDL 109, should start statin, but pt wants to try diet and exercise. Will f/u in 3 months and re check lipid profile.

Plan: Lipid profile in 3 months.

**NAME[VWW][UUU]**, MD

Examined patient and confirmed key findings on history and examination and **NAME[SSS]** M. as noted by Dr. **NAME[TTT][UUU]** above and added by me [MY COMMENTS].

Summary of my findings and impressions are as follows:

**DM** - is well controlled with diet alone. He has been losing **weight** and has lost about 15-20 lb over the last 2 years per the patient. by our EMR he
**Problem-Oriented Patient Record Summary**

**Goals**
- Generate medical problems list automatically
- Relate medications, labs, procedures, and clinical notes to medical problems
- Organize lists in a clinical order
- Enable one/two click access to raw data such as Notes, labs over a timeline, medication history,…

...also, allergies, social history, and demography
• Medical problem list is a patient’s diagnosed diseases and significant not-yet diagnosed symptoms that require care and management
• Maintaining an accurate PL is challenge because it requires:
  – Broad and high level of medical expertise
  – Significant time
• Our assessment of entered problem list based on a gold standard indicates the challenge:

<table>
<thead>
<tr>
<th>Entered Problem List Accuracy</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Recall (Sensitivity)</td>
<td>0.55</td>
</tr>
<tr>
<td>Precision (Positive Predictive Value)</td>
<td>0.28</td>
</tr>
</tbody>
</table>
**EMRA Problem List Generation**

**Candidate Generation**
- UMLS "Disorders" in the EMR (minus most "Findings")
- CUIs of unique Disorders (O(100))

**Feature Generation**
- CUI Confidence
- Term Frequency
- Note Section
- CUI Path
- LSA
- CUI Path

**Scoring / Weighting**
- Score
- CUI Confidence
- Term Frequency
- Note Section
- LSA Score
- Path Pattern

**Grouping**
- Graph of grouped Problems

**Entered Problem List Accuracy**
- Recall (Sensitivity) = 0.55
- Precision (Positive Predictive Value) = 0.28

**EMRA Problem List Accuracy:**
- Recall (Sensitivity) = 0.84
- Precision (Positive Predictive Rate) = 0.53
Physician opens the EMR and sees a summary of the record...

- Automatically generated problems grouped by clinical relevance
- Medications grouped by clinical relevance
- Automatically categorized encounters
A closer look at the left side of the screenshot...

### Problems

<table>
<thead>
<tr>
<th>Name</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>metabolic syndrome x</td>
<td>10/12/2004</td>
</tr>
<tr>
<td>diabetes mellitus</td>
<td>12/04/2002</td>
</tr>
<tr>
<td>dyslipidemias</td>
<td>01/29/2003</td>
</tr>
<tr>
<td>obesity</td>
<td>01/29/2003</td>
</tr>
<tr>
<td>microalbuminuria</td>
<td>10/12/2004</td>
</tr>
<tr>
<td>hypothyroidism</td>
<td>12/04/2002</td>
</tr>
<tr>
<td>thyroid diseases</td>
<td>05/11/2005</td>
</tr>
<tr>
<td>sleep apnea syndromes</td>
<td>07/31/2012</td>
</tr>
<tr>
<td>allergic rhinitis (disorder)</td>
<td>07/31/2012</td>
</tr>
</tbody>
</table>

### Medications

<table>
<thead>
<tr>
<th>Name</th>
<th>Prescribed</th>
</tr>
</thead>
<tbody>
<tr>
<td>lisinopril</td>
<td>01/29/2013</td>
</tr>
<tr>
<td>glipizide</td>
<td>07/25/2007</td>
</tr>
<tr>
<td>metformin</td>
<td>06/29/2004</td>
</tr>
<tr>
<td>freestyle lancets</td>
<td>05/11/2005</td>
</tr>
<tr>
<td>freestyle system kit</td>
<td>06/11/2005</td>
</tr>
<tr>
<td>lipase-protease-amylase</td>
<td>02/17/2010</td>
</tr>
<tr>
<td>lactated ringers iv</td>
<td>05/22/2010</td>
</tr>
<tr>
<td>cyclobenzaprine</td>
<td>10/30/2010</td>
</tr>
<tr>
<td>fluocinonide</td>
<td>04/12/2013</td>
</tr>
<tr>
<td>clindamycin</td>
<td>10/30/2013</td>
</tr>
<tr>
<td>valacyclovir</td>
<td>07/28/2011</td>
</tr>
</tbody>
</table>

### Procedures

<table>
<thead>
<tr>
<th>Name</th>
<th>Order Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>CERVICAL AP/LAT + CBL/A21</td>
<td>06/27/1997</td>
</tr>
<tr>
<td>CHEST PA / LATERAL</td>
<td>11/10/1999</td>
</tr>
<tr>
<td>CHEST PA AND LATERAL</td>
<td>03/12/2003</td>
</tr>
<tr>
<td>COLONOSCOPY W/BX</td>
<td>02/17/2006</td>
</tr>
<tr>
<td>COLONOSCOPY, GI</td>
<td>03/22/2006</td>
</tr>
<tr>
<td>COMPLETE ECG</td>
<td>02/16/2011</td>
</tr>
<tr>
<td>CT ORBITS WWO CONTRAST</td>
<td>08/13/2013</td>
</tr>
<tr>
<td>DILATED FUNDUS EXAM</td>
<td>01/14/2014</td>
</tr>
<tr>
<td>DOPPLER ECHO</td>
<td>12/04/2002</td>
</tr>
<tr>
<td>HEART,COMPLETE</td>
<td></td>
</tr>
<tr>
<td>ECG COMPLETE W</td>
<td>01/18/2011</td>
</tr>
</tbody>
</table>

### Laboratory Test Values

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>albumin/creat rd ur</td>
<td></td>
<td></td>
</tr>
<tr>
<td>creatinine, ur random (ucr)</td>
<td>16.4</td>
<td>08/02/2013</td>
</tr>
<tr>
<td>albumin random urine</td>
<td></td>
<td></td>
</tr>
<tr>
<td>albumin, urine random</td>
<td>11.0</td>
<td>08/02/2013</td>
</tr>
<tr>
<td>basic metabolic pni</td>
<td></td>
<td></td>
</tr>
<tr>
<td>chloride</td>
<td>98</td>
<td>08/02/2013</td>
</tr>
<tr>
<td>glucose</td>
<td>151</td>
<td>08/02/2013</td>
</tr>
<tr>
<td>bun</td>
<td>17</td>
<td>08/02/2013</td>
</tr>
<tr>
<td>anion gap</td>
<td>11</td>
<td>08/02/2013</td>
</tr>
<tr>
<td>calcium</td>
<td>10.0</td>
<td>08/02/2013</td>
</tr>
<tr>
<td>co2</td>
<td>28</td>
<td>08/02/2013</td>
</tr>
<tr>
<td>creatinine</td>
<td>0.79</td>
<td>08/02/2013</td>
</tr>
</tbody>
</table>
A closer look at the right side of the screenshot…

Clinical Encounter Instance Timeline

Wed Oct/30/2013
One note...

Primary Care
Emergency Medicine
Specialties
Nursing
Other

Vitals

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLOOD PRESSURE</td>
<td>95/68</td>
<td>06/06/2013</td>
</tr>
<tr>
<td>HEIGHT (cms)</td>
<td>172</td>
<td>07/26/2011</td>
</tr>
<tr>
<td>PULSE</td>
<td>89</td>
<td>06/06/2013</td>
</tr>
<tr>
<td>PULSE OXIMETRY</td>
<td>97</td>
<td>02/16/2011</td>
</tr>
<tr>
<td>TEMPERATURE</td>
<td>97.7</td>
<td>06/20/2013</td>
</tr>
<tr>
<td>WEIGHT (kgs)</td>
<td>81.33</td>
<td>06/06/2013</td>
</tr>
</tbody>
</table>

Social History

<table>
<thead>
<tr>
<th>Alcohol</th>
<th>Drug</th>
<th>Tobacco</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not recorded</td>
<td>Not recorded</td>
<td>Not recorded</td>
<td>12:04/2011</td>
</tr>
<tr>
<td>Not recorded</td>
<td>Not recorded</td>
<td>Not recorded</td>
<td>12:04/2011</td>
</tr>
</tbody>
</table>

Allergies

<table>
<thead>
<tr>
<th>Name</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Erythromycin</td>
<td>10/17/2000</td>
</tr>
</tbody>
</table>
As the Physician selects Diabetes Mellitus, screen changes to show related active medications, labs, related Notes, ...

Labs show elevated glucose and A1C among the others...

When a problem is selected related labs, meds, notes are shown

Current and related meds are highlighted

Relevant labs are highlighted

Labs show elevated glucose and A1C among the others...
THANK YOU
NLP Research & Application

Richard Wolniewicz, Division Scientist, Health Information Systems Division
September, 2015
1: NLP Adds Value Within a Clinical Workflow

• Application Value Generally Delivered by:
  1. **Eliminating a human workflow** entirely, or
  2. **Increasing human productivity or effectiveness** in a workflow

• **Eliminating Human Workflow**
  ▪ **Confidence model** is essential

• **Increasing Human Effectiveness**
  ▪ Workflow-specific
  ▪ **Explicability** of NLP recommendations
  ▪ Reduction in **noise** (false positives) – is F-measure a good score?
2: \( N \geq 100,000 \)

- Real-world **Data** is **Big**
  - Does the result which held at 1,000 samples hold at 1,000,000 samples?
  - Does the algorithm add computational complexity? If so, is it worth it?
- Real-world **Targets** are **Big**
  - There are >100,000 ICD-10 codes. Does an approach which works for 100 codes really work on 100,000?
  - Do precision and recall fool us?
3: Protected Health Information

- PHI is Fundamental to Clinical NLP Research
- Volumes (and thus Risk Exposures) are Large
- Partitioning is Often Difficult
  - Not all algorithms are the same … open research question
- Algorithm Intermediate Results
  - E.g. are word embeddings PHI?
Top Ten features of text in electronic health records

Brian Hazlehurst, PhD
Kaiser Permanente
Center for Health Research
10. Physicians write cryptically

- Incomplete sentences
- Lack of grammar
- Shortened words and abbreviations
- Brief statements
- Sparse, ideosyncratic, or no use of punctuation

Fam Hx: Fa-aodm, pgf colon ca, mgm bone marrow ca
Clinical practice generates documentation variation

9. Documentation events in the EHR are created for many purposes
   administrative, billing, legal, patient care

8. There are many different providers that touch the patient, each with their own protocols for care and documentation
   Specialties, trainees, professional/legal divisions of labor
Clinical discourse is special

7. Traditions exist for writing notes and documenting care (e.g., SOAP structure for progress notes)
   – However, many EHR implementations don’t promote such structure to the writer

6. Concepts discussed are complex (e.g., disease, differential diagnosis, intentions for action by multiple parties with distinct roles)
   – Requires deep and situated knowledge to understand correctly
The EHR is a data aggregator (garbage collector?)

5. Patient is often seen by multiple institutions each with their own EHR implementation
   – Just because note writing has a “place” in the workflow of one does not mean these data are easily imported into the database of the other (the same is true across specialties within an institution)

4. Many practices are simply importing paper-based text (e.g., faxes, scans, legal and form letters) into the EHR
   – Creates a great historical “dossier” of contact with the patient, but a messy clinical record
EHR software generates documentation noise

3. Unused, partially-used, inconsistently-used templates for text entry

2. UI “features” allow point-click addition of content into notes (e.g., adding current medications list to the progress note)

1. Vendors are trying to keep all customers happy, allowing for near-infinite customizations to accelerate/simplify data entry
NLP Research Knowledge Gap

Scott L. DuVall

Sep 9 2015
Acknowledgements

• Resources and Facilities
  – Veterans Affairs Salt Lake City Health Care System
  – Department of Epidemiology, University of Utah

• Funding Support
  – VA Informatics and Computing Infrastructure VA HSR RES 13-457

• Financial Relationships
  – Federal funding from Centers for Disease Control and Prevention, Department of Defense, Department of Veterans Affairs, Intermountain Healthcare, National Heart, Lung, and Blood Institute, National Institute on Alcohol Abuse and Alcoholism, National Institute of Arthritis and Musculoskeletal and Skin Diseases, National Institute of General Medical Sciences, National Institute of Standards and Technology, National Library of Medicine, National Science Foundation, and Patient Centered Outcomes Research Institute
Acknowledgements

- Jonathan Nebeker
- Olga Patterson
- Patrick Alba
- Lalinda De Silva
- Ryan Cornia
- Brad Adams
- Tom Ginter
- VINCI team
The patient indicates that his symptoms have improved significantly, but not as much as he expected. He is still sleeping a lot (about 12 hours per day) and finds it hard to concentrate on looking for work. He denies suicidal ideation. His PHQ-9 score is 16 today.

The patient has a history of binge eating episodes. He is an emotional eater and often feels out of control, but continues to eat after job search disappointments. He often binges at night and has done this 3-4 times per week for the past several years.
Summary findings for bone mineral density (BMD) are as follows:

- L1-L4 BMD (g/cm²) = 1.397 ± 0.010
- L1-L4 T-score = Young Adult 113
- M = 1.3

Bone mineral density as determined from the left total femur is 0.610 grams per centimeter squared with a T-score of -3.1.

The spine T-score was -2.9 and BMD was 0.322 grams/cm squared.
AP spine T-score is now -2.4 and BMD is 0.843.

Left hip 0.724 g/cm², T-score -1.8. L1-L4 T-score -2.5, femur total -2.1.
Summary findings for bone mineral density (BMD) are as follows:

L1-L4 BMD (g/cm²) 1.397 +/- 0.010
L1-L4 % Young Adult 113% T = 1.3

Bone mineral density as determined from the left total femur is 0.610 grams per centimeter squared with a T score of -3.1.

the AP spine T-score was -2.9 and BMD was 0.922 grams/cm squared. AP spine T-score is now -2.4 and BMD is 0.843

left hip .724 g/cm², T -1.8. L1-4 T score -2.5, femur total -2.1
CC F/U Depression

The patient indicates that his symptoms have improved significantly, but not as much as he expected. He is still sleeping a lot (about 12 hours per day) and finds it hard to concentrate on looking for work. He denies suicidal ideation. His PHQ-9 score is 16 today.

The patient has a history of binge eating episodes. He is an emotional eater and often feels out of control, but continues to eat after job search disappointments. He often binges at night.
Specialization in early development and translation

Framework for rapid deployment and processing

Support of “shotgun” and “rifle” approaches – rapid, modular development
Questions?

Scott.Duvall@va.gov
Which Gap?

Natural Language Processing in HealthCare
GAP: Shareable Data for Reproducible Results
Evaluation metrics that are good for measuring the performance of information extraction tasks don’t necessarily extend to evaluating the contribution of NLP to healthcare related tasks.

NLP used for a hypothesis generating task needs to be measured differently from NLP used to discover incidental findings, yet differently again for NLP to identify changes in tumor size over time.

**GAP: Evaluations that Meet the Information Need**
The data model doesn’t necessarily speak to the information model.
The IT cost of classifying clinical information by financial claims data

Cohort definitions based on ICD codes often have to be revalidated against clinical narrative text or external human review.
• Event models for typing subparts of trend data
  - Populate event classes and subclasses with regular ol’ information extraction & mapping
  - Define semantic & temporal constraints on uniting subparts of clinical events; distinguishing these from unrelated events and their sub-events

• Semantics of Change & Transition States By Clinical Domain
  - Align clinical event model to temporal model
  - Calibrate probabilities of temporal relations between events

Automated Healthcare Inferencing
Temporal Reasoning in Support of Clinical Inferencing

- Knowledge of temporal relation between events
  - Necessary but not sufficient for causal hypotheses
  - Temporally ordered clusters of symptom events can predict disease progression
- Probabilistic engine for temporal relation assignment
  - Built and under evaluation in Post Traumatic Stress Disorder domain
  - Re-use of infrastructure for tracking pulmonary nodule changes
Statistically generated models that underwrite NLP systems are unlikely to be any more useful than butterfly collections for the next use-case down the line, without integration into other existent models and regular upkeep.
THANKS!