NLP For Health (HLP) Monthly Gathering

February 22, 2018
Program & Speaker List

♦ Welcome/Introduction – Graciela Gonzalez-Hernandez, PhD – Associate Professor, Division of Informatics, Department of Biostatistics, Epidemiology and Informatics. gragon@upenn.edu
Tweet @UPennHLP #HLPMeeeting

♦ Presentation
  Gary Weissman, MD, MSHP – Clinical Associate of Medicine, PSOM

♦ Short Presentations
  1. Graciela Gonzalez-Hernandez, PhD – Associate Professor, HLP Lab, DBEI
  2. Davy Weissenbacher – Research Associate, HLP Lab, DBEI
  3. Karen O’Connor – Staff Scientist, HLP Lab, DBEI

♦ Presentation
  Graciela Gonzalez-Hernandez, PhD – Associate Professor, HLP Lab, DBEI

♦ Open Discussion
Clinical decision-support opportunities and challenges in mining text of clinical encounter notes

Gary Weissman, MD, MSHP
Pulmonary, Allergy, and Critical Care
February 22, 2018

@garyweissman
gary.weissman@uphs.upenn.edu
Clinical encounter note

- Generated every time a clinician interacts with a patient (H&P, progress, consult, transfer, accept, discharge)
- Multidisciplinary: physician, nurse, social worker, respiratory therapist, physical therapist, pharmacist
- Multi-location: inpatient, outpatient, in-person home visit, telephone
- Semi-structured: "CC", "HPI", "Subjective", "Labs", "Meds", "Assessment and Plan"
Multiple sources of information and entry modes

• "Mrs. Smith reports feeling worsening shortness of breath today”

• "I don't think Mrs. Smith is going to get any better”

• "Radiology Report: The CXR revealed no pneumothorax, effusion, or alveolar infiltrate"
Why bother?

• Case identification

• Severity adjustment

• Prognostication

• Proactive population health surveillance and management

• Quality evaluation
Why bother?

• Case identification
• Severity adjustment
• Prognostication
• Proactive population health screening and management

Text of clinical encounter notes contains rich information not otherwise captured in administrative claims data or structured data fields in the EHR.
Hospital Readmission and Social Risk Factors Identified from Physician Notes

Amol S. Navathe, Feiran Zhong, Victor J. Lei, Frank Y. Chang, Margarita Sordo, Maxim Topaz, Shamkant B. Navathe, Roberto A. Rocha, and Li Zhou

Home Health Care: Nurse–Physician Communication, Patient Severity, and Hospital Readmission


Mining 100 million notes to find homelessness and adverse childhood experiences: 2 case studies of rare and severe social determinants of health in electronic health records

Cosmin A Bejan, John Angiolillo, Douglas Conway, Robertson Nash, Jana K Shirey-Rice, Loren Lipworth, Robert M Cronin, Jill Pulley, Sunil Kripalani, Shari Barkin, Kevin B Johnson, and Joshua C Denny
Prognostic information in inpatient notes of patients with critical illness?

• MIMIC-III
• 25,947 hospital admissions
  – Age > 18
  – Hospital LOS > 2 days
  – No limitations on life-sustaining therapy
  – At least one documented clinical note
• Outcome: died or ICU LOS >= 7 days
  – 5,504 (21.2%)
• Prediction at 48 hours of hospital admission

Weissman et al. Inclusion of Unstructured Clinical Text Improves Early Prediction of Death or Prolonged ICU Stay, Accepted at Critical Care Medicine, 2018.
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Weissman et al. Inclusion of Unstructured Clinical Text Improves Early Prediction of Death or Prolonged ICU Stay, Accepted at Critical Care Medicine, 2018.
What about sentiment?

Table 1: Adjusted odds ratio estimate for the proportion of daily positive sentiment for each sentiment method based on mixed-effects logistic regression model to assess concurrent validity; and distribution of daily sentiment.

<table>
<thead>
<tr>
<th>Sentiment method</th>
<th>Odds Ratio (95% CI)</th>
<th>p value</th>
<th>Median (IQR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opinion</td>
<td>0.25 (0.07 - 0.89)</td>
<td>0.033</td>
<td>0.50 (0.39 - 0.62)</td>
</tr>
<tr>
<td>EmoLex</td>
<td>1.89 (0.41 - 8.69)</td>
<td>0.412</td>
<td>0.60 (0.53 - 0.69)</td>
</tr>
<tr>
<td>AFINN</td>
<td>0.65 (0.23 - 1.87)</td>
<td>0.428</td>
<td>0.56 (0.44 - 0.68)</td>
</tr>
<tr>
<td>Pattern</td>
<td>0.09 (0.04 - 0.17)</td>
<td>&lt;0.001</td>
<td>0.63 (0.53 - 0.74)</td>
</tr>
<tr>
<td>sentimentr</td>
<td>0.37 (0.25 - 0.63)</td>
<td>&lt;0.001</td>
<td>0.71 (0.35 - 0.96)</td>
</tr>
</tbody>
</table>
Table 2: The most common terms from the Opinion lexicon found in the clinical text sample and their polarity.

<table>
<thead>
<tr>
<th>Term</th>
<th>Polarity</th>
<th>Appearances (n)</th>
<th>Representative context</th>
</tr>
</thead>
<tbody>
<tr>
<td>pain</td>
<td>negative</td>
<td>658,808</td>
<td>‘Pt reports back pain’, ‘Continue to monitor pain’</td>
</tr>
<tr>
<td>patient</td>
<td>positive</td>
<td>588,213</td>
<td>‘Encouraged patient to take his medicine’, ‘I saw and examined the patient’</td>
</tr>
<tr>
<td>stable</td>
<td>positive</td>
<td>411,028</td>
<td>‘stable frontal infarct’, ‘remains hemodynamically stable’</td>
</tr>
<tr>
<td>right</td>
<td>positive</td>
<td>383,482</td>
<td>‘only moving right arm’, ‘elevation of the right hemidiaphragm’</td>
</tr>
<tr>
<td>clear</td>
<td>positive</td>
<td>368,261</td>
<td>‘w/o clear evidence of infiltrates’, ‘Nutrition: clear liquids, advance diet’</td>
</tr>
<tr>
<td>well</td>
<td>positive</td>
<td>365,899</td>
<td>‘get radiation as well as this decision’, ‘sitting well, no resp distress’</td>
</tr>
<tr>
<td>support</td>
<td>positive</td>
<td>325,814</td>
<td>‘s/p arrest requiring ventilatory support’, ‘Emotional support given to patient &amp; family’</td>
</tr>
<tr>
<td>soft</td>
<td>positive</td>
<td>290,426</td>
<td>‘abdomen soft slightly distended’, ‘possibility of soft tissue pus collection’</td>
</tr>
<tr>
<td>failure</td>
<td>negative</td>
<td>268,838</td>
<td>‘PNA with hypercarbic respiratory failure’, ‘R-sided heart failure leading to hepatopedral flow’</td>
</tr>
<tr>
<td>bs</td>
<td>negative</td>
<td>259,638</td>
<td>‘PULM: decreased bs on left’, ‘soft distended with hypoactive bs’</td>
</tr>
</tbody>
</table>

Lexical coverage by hospital admission for each sentiment method

## Pitfalls in sentiment use

<table>
<thead>
<tr>
<th>Object</th>
<th>Aspect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient</td>
<td>Prognosis</td>
</tr>
<tr>
<td></td>
<td>Tumor</td>
</tr>
<tr>
<td></td>
<td>Affect</td>
</tr>
<tr>
<td></td>
<td>Pain</td>
</tr>
<tr>
<td></td>
<td>Personality</td>
</tr>
<tr>
<td></td>
<td>Compliance</td>
</tr>
<tr>
<td>Consulting services</td>
<td>Helpfulness</td>
</tr>
<tr>
<td>Hemodialysis machine</td>
<td>Flow through circuit</td>
</tr>
<tr>
<td>Central venous catheter</td>
<td>Lumen patency</td>
</tr>
<tr>
<td>Spouse</td>
<td>Cooperativeness</td>
</tr>
<tr>
<td>Pills</td>
<td>Size</td>
</tr>
</tbody>
</table>
Human-machine feedback trap in two stories

Day 1
Ms. Smith has a poor prognosis due to her comorbidities and severity of presentation.

Day 2
After reviewing the highly advanced, super-deep-learning decision-support tool which predicts a very poor prognosis for Ms. Smith, we have decided not to pursue aggressive curative therapy.

Day 3
Ms. Smith died peacefully with her family at the bedside this afternoon.
Human-machine feedback trap in two stories

Day 1
Ms. Smith has a poor prognosis due to her comorbidities and severity of presentation.

Day 2
After reviewing the highly advanced, super-deep-learning decision-support tool which predicts a very poor prognosis for Ms. Smith, we have decided not to pursue aggressive curative therapy.

Day 3
Ms. Smith died peacefully with her family at the bedside this afternoon.

Day 1
Ms. Smith has a poor prognosis due to her comorbidities and severity of presentation, but her supportive family remains hopeful and engaged at the bedside.

Day 2
After reviewing the highly advanced, super-deep-learning decision-support tool which predicts a cautious prognosis for Ms. Smith, we have decided to continue aggressive curative therapy for now.

Day 3
Ms. Smith continues to remain stable.
Ongoing work

• Identify actionable risk phenotypes among community-dwelling patients with chronic lung diseases to support deployment of resources to reduce the risk of low-value and preference-discordant hospitalizations

• Development of a word embedding model trained on de-identified clinical narrative text to support future projects and reproducibility
Take home points

• Rich information in text of clinical encounters

• Complex sentiment relations of object, aspect, time, source, objective vs subjective

• Domain-specific tools needed for clinical narrative text

• Practical and ethical framework needed before bedside deployment
Collaborators

• Scott Halpern
• Rebecca Hubbard
• Lyle Ungar
• Blanca Himes
• Casey Greene
• Michael Harhay
• Kate Courtright
• Janae Heath
• Jessica Dine
HLP Lab Current Collaborative Initiatives

Graciela Gonzalez-Hernandez @gracielagon

HLP Reading Group: 2nd Thursdays, same place/time, bring your own lunch. Blockley Hall 418, 12-1:30 - March 8, led by Davy W.

Upcoming proposals, still need domain experts as collaborators:
R01 Maternal Health – leveraging SM for health studies during pregnancy.
   Need: MD case leaders that develop/deploy specific case studies
R01 Pediatric Epilepsy – differential diagnosis using NLP + EHR / EEG data
R21 Cognitive Decline Language Models (written descriptive language).

Workshop
SMM4H @ EMNLP, shared task n

Open Writing:
A review paper on state-of-the-art predictive approaches that use unstructured EHR data.
a H1N1 virus was isolated in 2009 from a child hospitalized in Nanjing.

Organism = H1N1
Host = Homo Sapiens
Country = “China, Nanjing”
Building a Corpus

- Define Task/Data Collection
- Develop Guidelines
- Preliminary Annotation

Annotate Subset → Evaluate & Discuss

Revise Guidelines

Gold Standard ← Adjudication ← Calculate Agreement ← Full Annotation

Challenges with Social Media data:
- Sparse
- Noisy
- Context
- Colloquialisms/slang

Labeled Data

Training & Testing Machine Learning Models

Karen O’Connor, MS
Staff Scientist

Health Language Processing Lab (https://healthlanguageprocessing.org)
Department of Biostatistics, Epidemiology, and Informatics
karoc@pennmedicine.upenn.edu
Text Mining (and Machine Learning) for Precision Medicine

Graciela Gonzalez-Hernandez @gracielagon
Precision Medicine

An emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment, and lifestyle for each person.

Challenges to Precision Medicine

- Disparities: precision medicine efforts do not encompass all populations
- Disconnected findings: relevant variants found, but function/impact is a mystery.
- Data bias: emphasis on genomic aspects, “environmental and lifestyle” overlooked
  - Patient medical records (EMRs)
  - Patient surveys and self-reported comments from individual patients
  - Published literature
  - Clinical trials
  - Research data in public collections
  - Self-reports (social media, health forums)
Extracting social determinants from existing data sources such as EHRs

Used with the approval of Brittany Hollister, Ph.D, Social and Behavioral Research Branch, NHGRI.
Pregnancy Data from Social Media

- **Collect tweets announcing pregnancy**
  - Based on 18+ specific search queries
  - Example query: “iam * weeks/months pregnant”
- **Classification / annotation = cohort to study**
  - Medication use in pregnancy (about 100K)

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Sarker A et al. Discovering Cohorts of Pregnant Women From Social Media for Safety Surveillance and Analysis. PMID: 29084707
Research directions

- Predictive systems from **unstructured** EHR data.
- Differential diagnosis / disease progression modeling
- Genotype-phenotype association methods.
- Extraction, validation, discovery of disease-gene or gene-drug associations
- Text mining for pharmacogenomics
- Exploiting integrated datasets for hypothesis generation
- Social media for linking lifestyle and environmental factors
- Automatic extraction and integration of literature data for population-specific meta-analysis (systematic reviews)
- Drug effectiveness prediction at the general, population, or individual level
- Human computer interaction / visualization of extracted data
VisAGE: Integrating External Knowledge into Electronic Medical Record Visualization, by Huang et al.

- Presents a method that visualizes electronic medical records (EMRs) in a low dimensional space.

Annotating Gene Sets by Mining Large Literature Collections with Protein Networks, Wang et al.

- Proposes a natural language processing system that infers common functions for a gene set via the automated mining of scientific literature for relevant phrases.

GeneDive: A Gene Interaction Search and Visualization Tool to Facilitate Precision Medicine, Previde et al.

- Proposes a web-based tool that performs information retrieval, filtering and visualization for large volumes of interaction data.

Improving Precision in Concept Normalization, Boguslav et al.

- Proposes a strategy for improving precision in medical text concept normalization

https://psb.stanford.edu/psb-online/proceedings/psb18/
Thank you for coming!

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HLP lab:
https://healthlanguageprocessing.org