Social Media Mining for Pharmacovigilance: challenges and opportunities

Case-control studies from Twitter???

Health Language Processing Lab – Penn IBI
Graciela Gonzalez-Hernandez, PhD
email: gragon@pennmedicine.upenn.edu

Funded by NLM/NIH Grant 5R01LM011176
ASCPT 2018 #Science Session – Orlando, Florida
Social media as an “online health report”? 

- 26% of internet users actively discuss health information. Of that group … \(^1\)
  - 30% changed behavior as a result
  - 42% discussed current medical conditions

- “Extrapolating” this to Twitter… \(^2,3\)
  - Given 317 million active monthly users (Q3 2015): about 24 million would change their health behavior
  - Given 350,000 tweets/minute: about 38,220 tweets / minute about their current medical conditions

\(^1\)http://www.pewinternet.org/fact-sheets/health-fact-sheet/
\(^3\)http://www.internetlivestats.com/twitter-statistics/
SM data for pharmacovigilance studies

- **Patient reporting brings different perspective** (34 studies): more detail, info on severity and impact of ADRs in daily life. (PMID 27558545).

- **Abundant adverse event reports in SM** (29 studies): a higher frequency of adverse events are found in SM, particularly for ‘mild’ adverse events. (PMID 26271492).
Social Media Mining pipeline

Data collection

Annotation

Classification

Concept extraction

Concept Mapping

Analysis

Amazon

Daily Strength

Twitter

Perelman School of Medicine
University of Pennsylvania
Adverse event annotation example

Works to calm mania or depression but zonks me and scares me about diabetes issues reported.

Indication: mania (C0338831)
Indication: depression (C001157)
ADR: drowsiness (C0013144)
Other: diabetes
Indication: crying (C0010399)
ADR: emotional indifference (C0001726)

stops me from crying most of the time, blocks most of my feelings
Concept extraction: finding adverse events

- Given a set of postings, need to find a specific concepts automatically
- An algorithm is trained to find (extract) mentions of AEs and other concepts
- Our approach: conditional random fields and deep learning clusters to capture descriptive expressions beyond what lexicon-based approaches could\(^1\)

\(1\) Nikfarjam et al. Pharmacovigilance from social media. cluster features. JAMIA. 2015.

b) I felt awful, it made my stomach hurt\(_{ADR}\) with bad heartburn\(_{ADR}\) too, horrid taste in my mouth\(_{ADR}\) tho it does tend to clear up the infection\(_{Indication}\).
## Unsupervised learned clusters

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Topic</th>
<th>Examples of clustered words</th>
</tr>
</thead>
<tbody>
<tr>
<td>c₁</td>
<td>Drug</td>
<td>abilify, adderall, ambien, ativan, aspirin, citalopram, effexor, paxil, …</td>
</tr>
<tr>
<td>c₂</td>
<td>Signs/Symptoms</td>
<td>hangover, headache, rash, hive, …</td>
</tr>
<tr>
<td>c₃</td>
<td>Signs/Symptoms</td>
<td>anxiety, depression, disorder, ocd, mania, stabilizer, …</td>
</tr>
<tr>
<td>c₄</td>
<td>Drug dosage</td>
<td>1000mg, 100mg, .10, 10mg, 600mg, 0.25, .05, …</td>
</tr>
<tr>
<td>c₅</td>
<td>Treatment</td>
<td>anti-depressant, antidepressant, drug, med, medication, medicine, treat, …</td>
</tr>
<tr>
<td>c₆</td>
<td>Family member</td>
<td>brother, dad, daughter, father, husband, mom, mother, son, wife, …</td>
</tr>
<tr>
<td>c₇</td>
<td>Date</td>
<td>1992, 2011, 2012, 23rd, 8th, april, aug, august, december, …</td>
</tr>
</tbody>
</table>
Classification task examples

- Adverse event mention classification\(^1\)
- Drug abuse classification\(^2\)
- Medication intake mention classification\(^3\)
- Pregnancy announcement classification\(^4\)

---

3 Klein *et al.* Detecting Personal Medication Intake in Twitter. ACL *BioNLP Workshop 2017*
4 Sarker *et al* Discovering cohorts of pregnant women. *J Med Internet Res.* 2018
Case-control study with SM data?

- Select cohort of pregnant women from SM¹
  - About 120 thousand, 700 million tweets
- Within that, find cases of interest
  - “Women who gave birth to a child with a birth defect and whose public tweets include tweets during pregnancy”
- Annotate (100% of the data found)
- Find matching (control) subjects
  - “Women pregnant around the same time, for whom there is no evidence that their child was born with a birth defect”

1. Sarker et al Discovering cohorts of pregnant women .. J Med Internet Res. 2018
From Twitter, “I am 12 weeks pregnant”

Today, I am officially 12 weeks pregnant! Here’s my first personal blog post in two years... instagram.com/p/BgoHF_-le8C/

I am 12.5 weeks pregnant and suffering terrible morning sickness all day - any recommendations on what I could take to settle it? I've tried everything :( #help

I have a feeling I am 12 weeks pregnant because of how bloated my belly is, I can’t wait to get a blood test to find out what’s going on, I was supposed to have an ultrasound but didn’t have it yet this month 🤖

Fast forward to this year and now here I am sitting down watching this video currently 12 weeks pregnant. Thanks for helping me smile Mark :) you have the most beautiful heart and never change you big goof :)

my son is 15 months and my wife is 12 weeks pregnant. when I am home it's funny dealing with his high energy and tantrums

'Janet Mbugua Reveals She Is Expecting Baby Number Two classic105.com/i-am-12-weeks...
Finding cases – birth defects cohort

Database (112,647 Users)

- Query
  - 16,822 Tweets (5,923 Users)
    - Annotation (-)
    - 15,180 Tweets (5,277 Users)
      - Annotation (-)
      - 217 Users

- Annotation (+)
  - 765 Tweets (287 Users)
    - 142 Users
      - Birth Defect (+)
    - 429 Users
      - Pregnancy (+) → 195 Users
      - Pregnancy (-) → 234 Users
# Birth defects data from Social Media

<table>
<thead>
<tr>
<th></th>
<th>Cases (n=197)</th>
<th>Controls (n=196)</th>
<th>OR or t-test [95% CI]</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median Age (IQR)</td>
<td>23 (20 to 28)</td>
<td>21 (19 to 23)</td>
<td>2 (1 to 3)</td>
<td>0.0001</td>
</tr>
<tr>
<td>Mean Age (range)</td>
<td>25 (17 to 42)</td>
<td>22 (16 to 37)</td>
<td>2.52 (1.38 to 3.66)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Women &lt;30 years</td>
<td>80% (134/168)</td>
<td>91% (129/141)</td>
<td>0.37 (0.17 to 0.77)</td>
<td>0.004</td>
</tr>
<tr>
<td>Women &lt;35 years</td>
<td>93% (156/168)</td>
<td>98% (138/141)</td>
<td>0.28 (0.05 to 1.08)</td>
<td>0.04</td>
</tr>
<tr>
<td>Missing data on age</td>
<td>14% (28/196)</td>
<td>28% (55/196)</td>
<td>0.43 (0.25 to 0.73)</td>
<td>0.0008</td>
</tr>
<tr>
<td><strong>Race/Ethnicity</strong></td>
<td></td>
<td></td>
<td>chi² = 23.69, d.f. = 5, P &lt; 0.0001</td>
<td></td>
</tr>
<tr>
<td>Caucasian</td>
<td>73% (120/164)</td>
<td>55% (102/184)</td>
<td>2.19 (1.36 to 3.54)</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>13% (22/164)</td>
<td>27% (51/184)</td>
<td>0.40 (0.22 to 0.72)</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>9% (14/164)</td>
<td>12% (21/184)</td>
<td>0.72 (0.33 to 1.56)</td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>2% (4/164)</td>
<td>3% (5/184)</td>
<td>0.90 (0.17 to 4.24)</td>
<td></td>
</tr>
<tr>
<td>Other (Islander, Native American/Indian, Multiracial/Mixed)</td>
<td>2% (4/164)</td>
<td>2% (5/184)</td>
<td>0.90 (0.17 to 4.24)</td>
<td></td>
</tr>
<tr>
<td>Missing data on race</td>
<td>16% (32/196)</td>
<td>6% (12/196)</td>
<td>0.99 (1.44 to 6.58)</td>
<td></td>
</tr>
</tbody>
</table>
Adherence/persistence studies from SM

- Social media may be particularly useful for identifying sources of intolerability that lead to non-adherence/non-persistence
- These are often not reported by physicians or patients through standard means because are considered “mild”, “not serious” or are unexpected
- Significant problem, given that, on average:
  - 30% of treated patients have a beneficial response
  - 30% do not respond
  - 10% have only side effects
  - 35%-70% are non-adherent / non-persistent, often due to side-effects or perceived/real non-response
6-month persistence rate

- prostaglandin analogs 47%
- statins 56%
- bisphosphonates 56%
- oral antidiabetics 66%
- angiotensin II receptor blocker 63%
- overactive bladder medications 28%
“I stopped taking” & “made me”

If anyone’s wondering which I doubt, the reason I stopped taking my antidepressants was because it messed with my appetite and made me feel extra drowsy and just emotionally numb. I constantly felt like a zombie, so I figured I see how I felt without them.

I used to be on it. It made me nauseous, gave me headaches, made me bloated & made my period pains worse. I stopped taking it.

It’s a cheaper version of Triphasil. After that, I promised not to use cheap contraceptives again. The expensive ones have less side effects.
Social media data: challenges

- **Incompleteness:**
  - Not all health conditions may be revealed
  - Complete data about individual cases may be difficult to obtain: taking drug X, but dosage, frequency, length of treatment, may be missing
  - Participants from the cohort may dropout at higher rates

- **Accessibility:**
  - Data from social media is not easily collected: API limitations
  - Not easily processed once collected: challenging to process using automatic methods
  - Data collection methods may have to be changed frequently over time

- **Authenticity:**
  - Bots – a large portion of social media is generated by bots, making it harder to mine reliable data
  - *Automatic* processing of postings is often misleading: for example postings mentioning a drug might not necessarily mean intake.
Thank you!

gragon@pennmedicine.upenn.edu

Twitter: @gracielagon

HLP lab (datasets and software available): https://healthlanguageprocessing.org