Social Media Mining for Pharmacovigilance: challenges and opportunities

Case-control studies from Twitter???

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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/
[2]http://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/
[3]http://www.internetlive**stats**.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).

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Social Media Mining pipeline

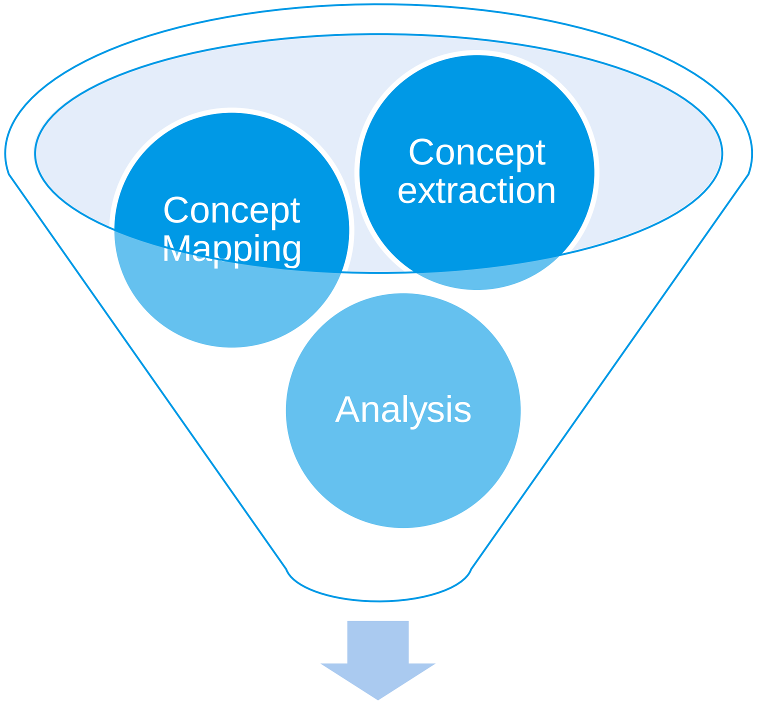
amazon

DailyStrength

Data collection

Annotation

Classification



Adverse event annotation example

Indication: mania (C0338831)

Indication: depression (C001157)

ADR: drowsiness (C0013144)

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

Other: diabetes

Indication: crying (C0010399)

ADR: emotional indifference (C0001726)

stops me from **crying** most of the time, **blocks most of my feelings**

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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]

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***$_{Indication}$.

1 Nikfarjam *et al.* Pharmacovigilance from social media.. cluster features. **JAMIA**. 2015.

Unsupervised learned clusters

Cluster	Topic	Examples of clustered words
c_1	Drug	abilify, adderall, ambien, ativan, aspirin, citalopram, effexor, paxil, …
c_2	Signs/Symptoms	hangover, headache, rash, hive, …
c_3	Signs/Symptoms	anxiety, depression, disorder, ocd, mania, stabilizer, …
c_4	Drug dosage	1000mg, 100mg, .10, 10mg, 600mg, 0.25, .05, ...
c_5	Treatment	anti-depressant, antidepressant, drug, med, medication, medicine, treat, …
c_6	Family member	brother, dad, daughter, father, husband, mom, mother, son, wife, …
c_7	Date	1992, 2011, 2012, 23rd, 8th, april, aug, august, december, …

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Classification task examples

- Adverse event mention classification[1]
- Drug abuse classification[2]
- Medication intake mention classification[3]
- Pregnancy announcement classification[4]

1 Sarker and Gonzalez. Portable automatic text classification. **J Biomed Inform.** 2015.
2 Sarker *et al.* Social media mining for toxicovigilance. **Drug Saf**. 2016.
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

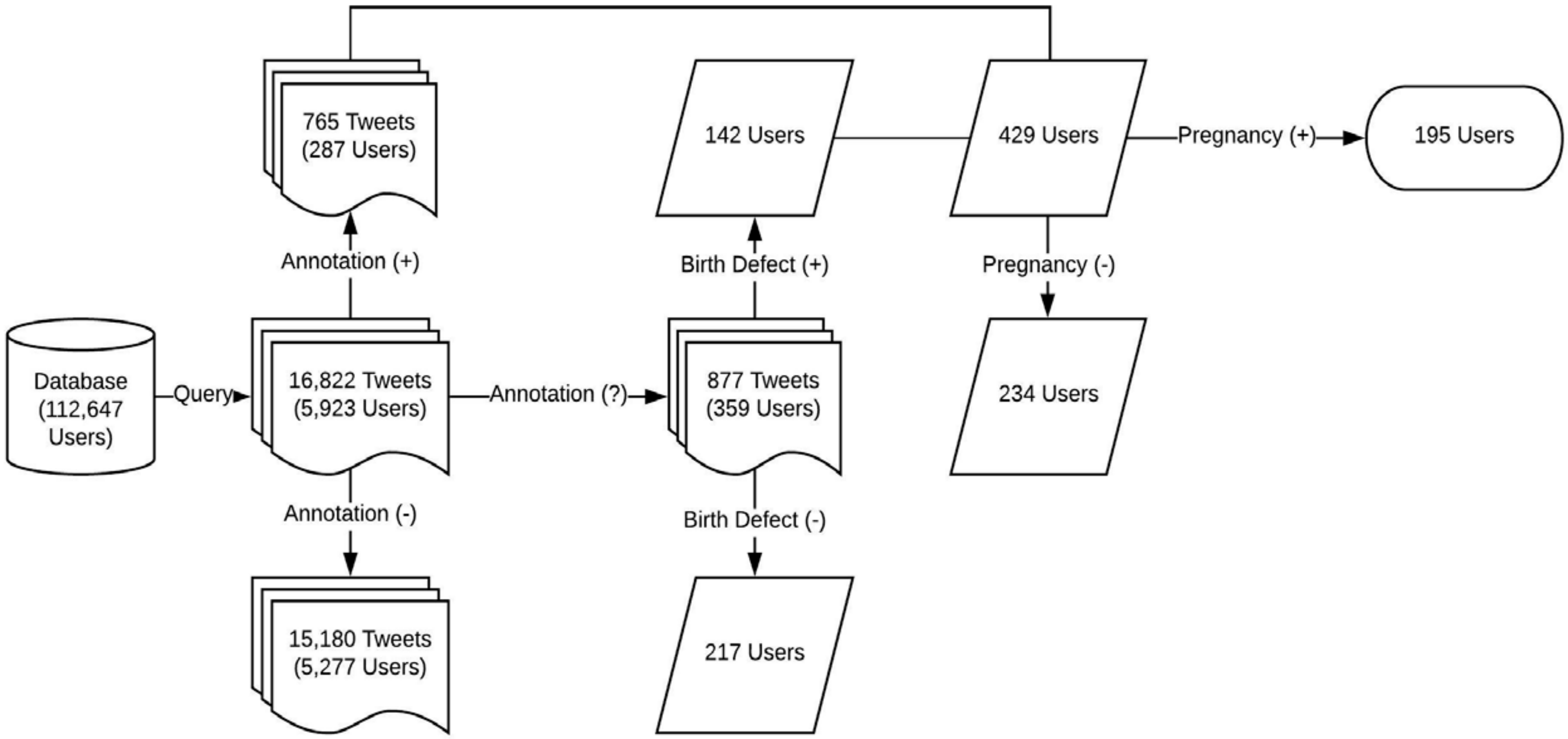
Case-control study with SM data?

- **Select cohort of pregnant women from SM[1]**
  - 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”

Finding cases – birth defects cohort



Birth defects data from Social Media

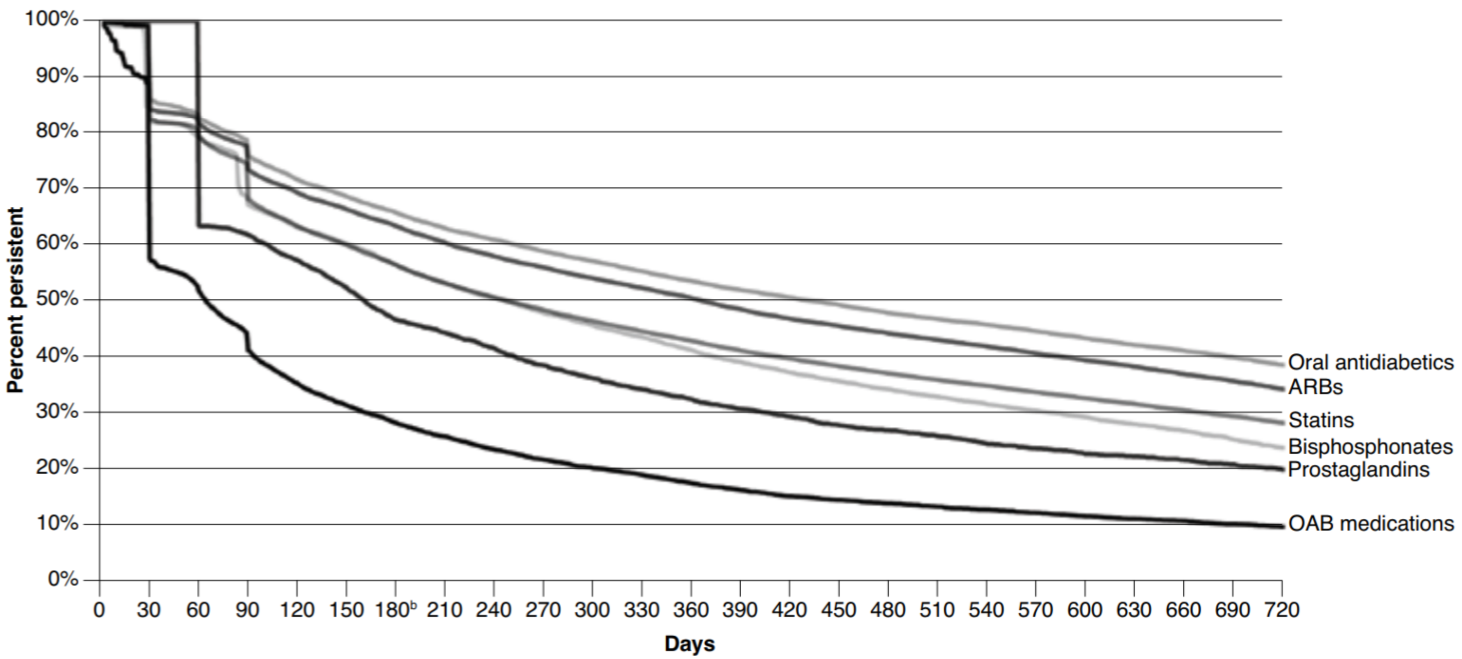
	Cases (n=197)	Controls (n=196)	OR or t-test [95% CI]	P-value
Age				
Median Age (IQR)	23 (20 to 28)	21 (19 to 23)	2 (1 to 3)	0.0001
Mean Age (range)	25 (17 to 42)	22 (16 to 37)	2.52 (1.38 to 3.66)	<0.0001
Women <30 years	80% (134/168)	91% (129/141)	0.37 (0.17 to 0.77)	0.004
Women <35 years	93% (156/168)	98% (138/141)	0.28 (0.05 to 1.08)	0.04
Missing data on age	14% (28/196)	28% (55/196)	0.43 (0.25 to 0.73)	0.0008
Race/Ethnicity				
Caucasian	73% (120/164)	55% (102/184)	2.19 (1.36 to 3.54)	chi^2 = 23.69, d.f. = 5 P < 0.001
Black	13% (22/164)	27% (51/184)	0.40 (0.22 to 0.72)	
Hispanic	9% (14/164)	12% (21/184)	0.72 (0.33 to 1.56)	
Asian	2% (4/164)	3% (5/184)	0.90 (0.17 to 4.24)	
Other (Islander, Native American/Indian, Multiracial/Mixed)	2% (4/164)	2% (5/184)	0.90 (0.17 to 4.24)	
Missing data on race	16% (32/196)	6% (12/196)	0.99 (1.44 to 6.58)	

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

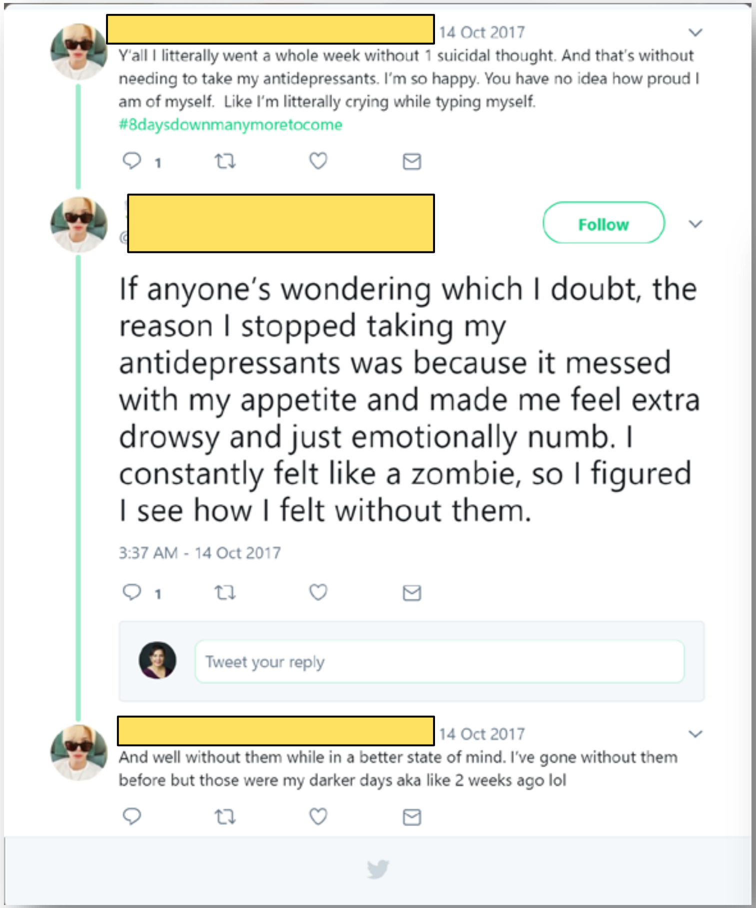
FIGURE 2 Time to Discontinuation[a] of 6 Chronic Therapy Classes, Allowing for 60-Day Treatment Gap

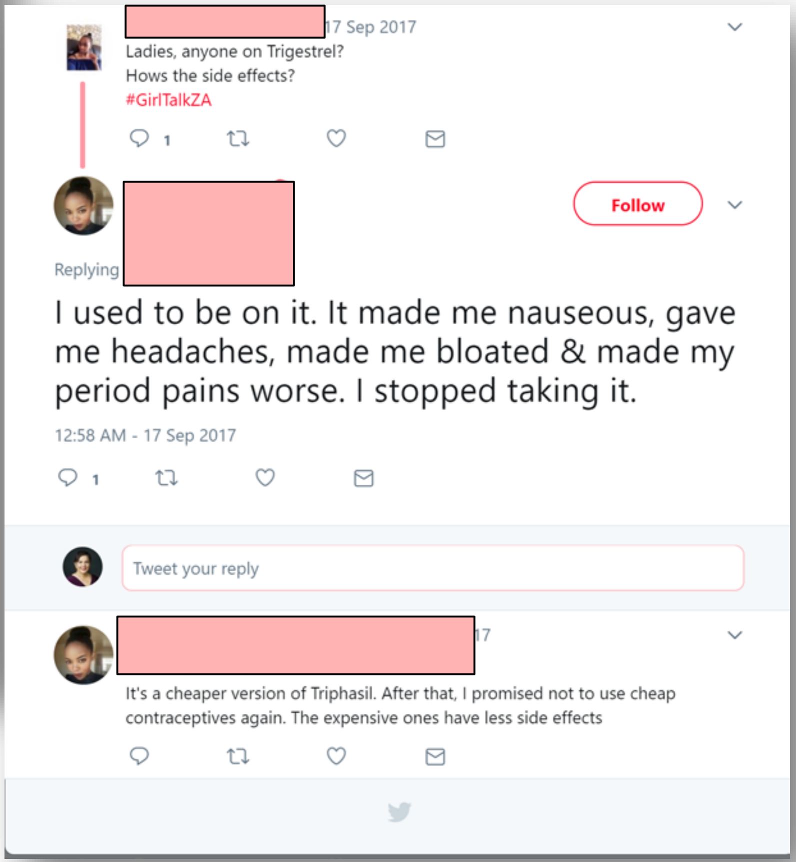


- prostaglandin analogs 47%
- statins 56%
- bisphosphonates 56%
- oral antidiabetics 66%
- angiotensin II receptor blocker 63%
- overactive bladder medications 28%

Comparing Adherence and Persistence Across 6 Chronic Medication Classes
Jason Yeaw, J Manag Care Spec Pharm, 2009 Nov;15(9):728-740.

“I stopped taking” & “made me”





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!

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