Extracting adverse drug events from Twitter messages in real time using Naive Bayes classifier

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Adverse Event Reporting

Existing post-marketing adverse event surveillance systems suffer from under-reporting and data processing lags.

Clinical context:

- More than 80% of AEs are unreported

Significant under-reporting of AEs through official channels

Social media

Studies have suggested the potential of high-quality data generated by online social networks at low cost:

Kass-Hout TA, Alhinnawi H. Social media in public health. Brit Med Bull. 2013;108:5–24.

Knezevic MZ, Bivolarevic IC, Peric TS, Jankovic SM. Using Facebook to increase spontaneous reporting of adverse drug reactions. Drug Saf. 2011;34:351–2.

Edwards IR, Lindquist M. Social media and networks in pharmacovigilance: boon or bane? Drug Saf. 2011;34:267–71.

Social media

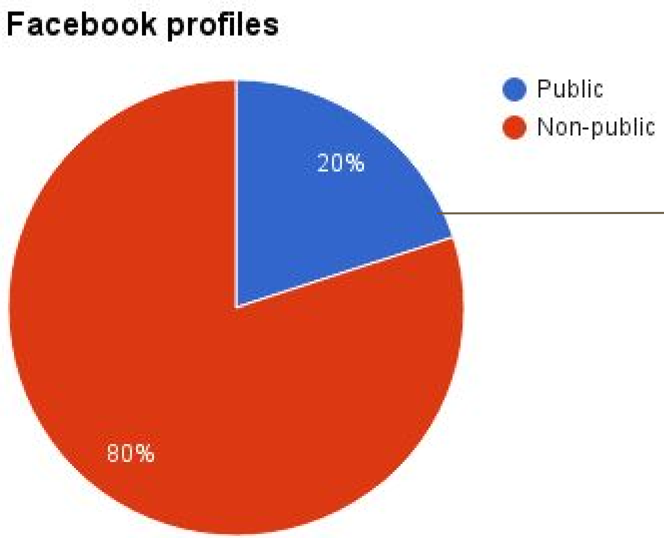
Approximately
- 20% of Facebook profiles

- 90% of Twitter feeds

are fully public

- a broad range of health-focused forums support public discussions

Social media



More than 200M users

Twitter

Twitter Usage Statistics

- Estimated Total Number of Twitter Registered Users: **1.3 billion**
- Estimated Total Number of Twitter Active Users: **313 million**
- More than 500 million tweets per day
- 29.2% of US social media users are Twitter users

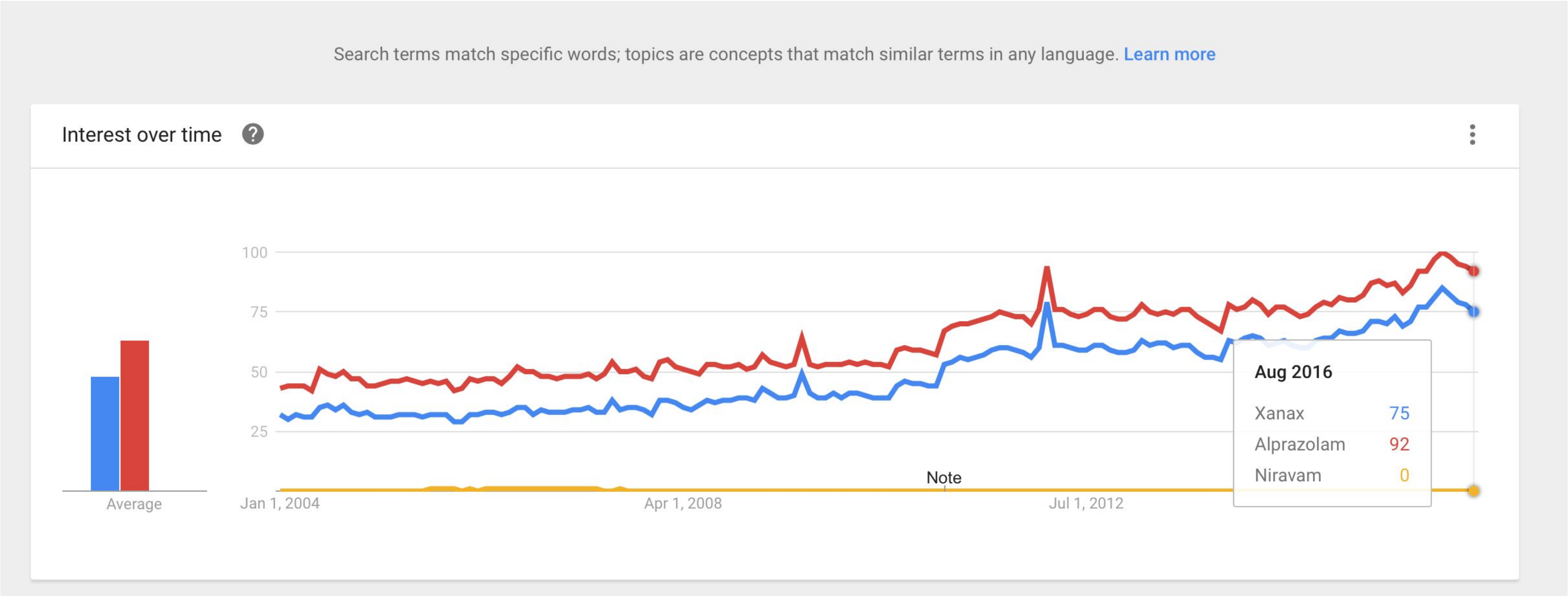
Twitter & Drug Adverse Events

Q:
Can we extract adverse events from users tweets?

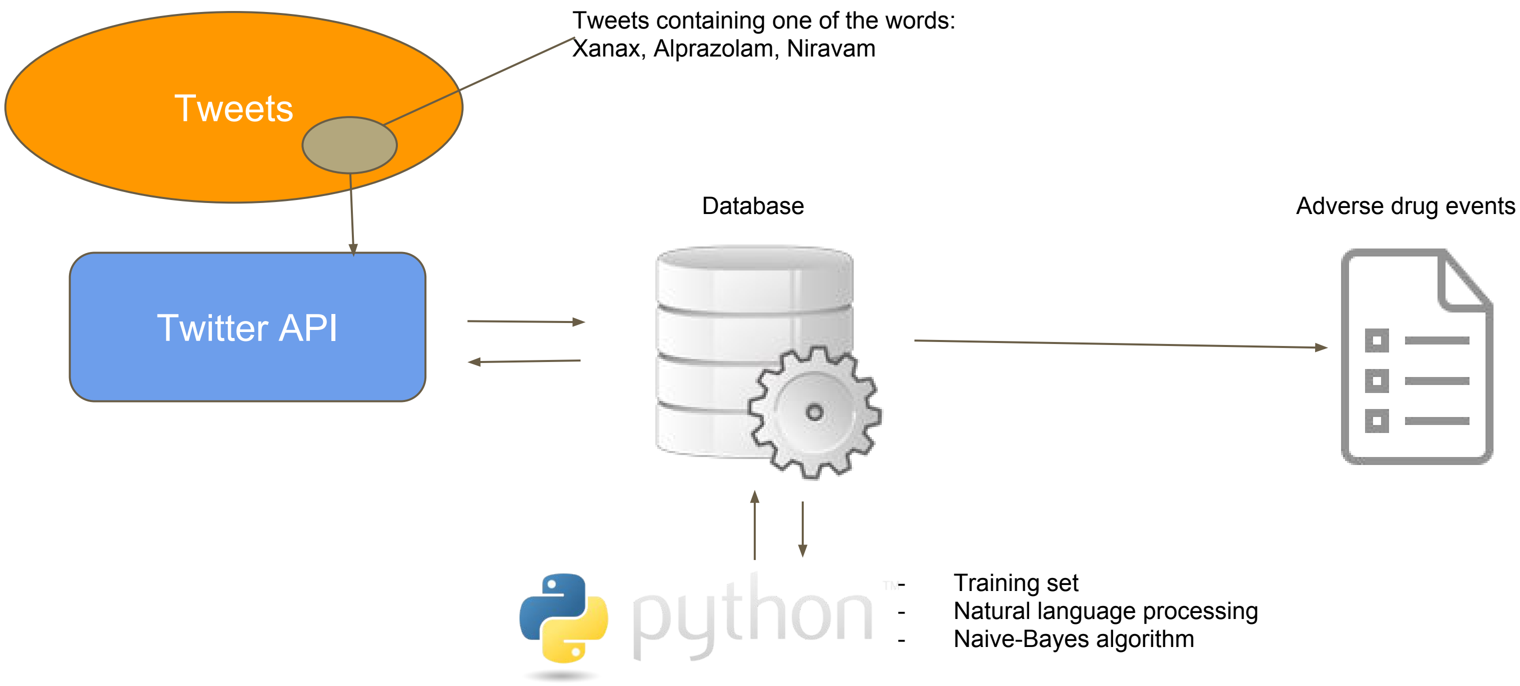
A:
Yes

We built a real-time system for Xanax

Xanax


Search terms match specific words; topics are concepts that match similar terms in any language. Learn more
Interest over time
100
75
50
25
Average
Jan 1, 2004
Apr 1, 2008
Jul 1, 2012
Note
Aug 2016
Xanax 75
Alprazolam 92
Niravam 0

Overview of the system

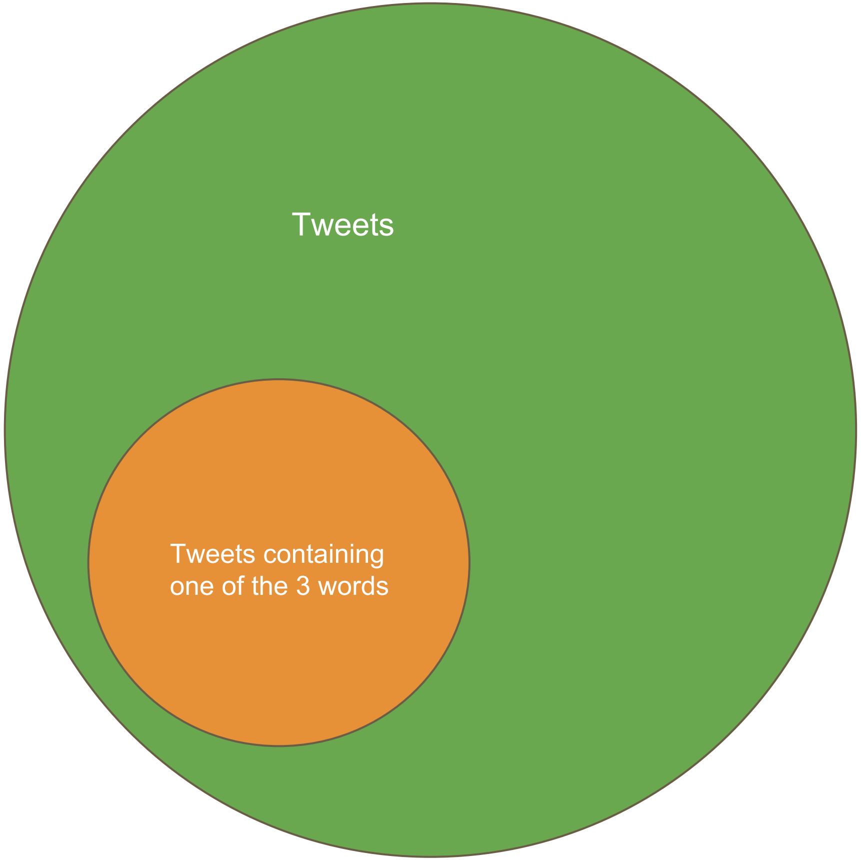


System in detail: Step 1

- Using the Twitter API, we search for tweets containing at least one of the words:

Xanax, Alprazolam, Niravam

- Re-tweets are excluded*
- Collected tweets are stored in our database

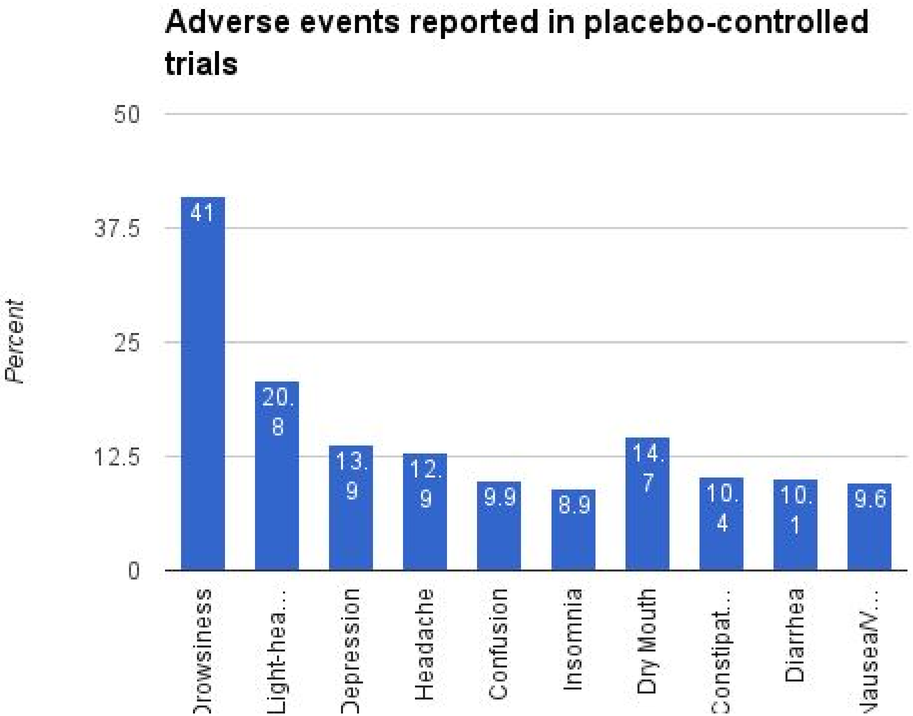


We'll come back to this later

System in detail: Step 2

Let's get the most frequent adverse events reported in placebo-controlled trials:

1. Drowsiness
2. Light-headedness
3. Depression
4. Headache
5. Confusion
6. Insomnia
7. Dry Mouth
8. Constipation
9. Diarrhea
10. Nausea/Vomiting



System in detail: Step 2

For each term we create a set of alternative names, including the original term. For example:

Drowsiness

A = {drowsiness, sleepiness, hypersomnia, somnolence, falling asleep}

Depression

C = {depression, misery, sadness, unhappiness, dejection, tearfulness,gloom,melancholy}

System in detail: Step 2

```
A -> Drowsiness = {drowsiness,sleepiness,hypersomnia,somnolence,falling asleep}
B -> Light-headedness = {headedness,dizzy,dizziness,vertigo, spinning}
C -> Depression = {depression, misery, sadness, unhappiness,dejection,tearfulness,gloom,melancholy}
D -> Headache = {headache,pain head,rebound headaches,medication overuse headaches,medicine overuse headaches}
E -> Confusion = {confusion,disorientation}
F -> Insomnia = {insomnia,sleep disorder,sleep issue,difficulty falling asleep,sleep hygiene}
G -> Dry Mouth ={dry mouth}
H -> Constipation={constipation,irregularity of bowels,lack of regular bowel movements}
I -> Diarrhea={diarrhea}
J -> Nausea/Vomiting = {nausea,vomiting}
```

System in detail: Step 3

- In machine learning, naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features.

- It is not a single algorithm for training such classifiers, but a family of algorithms based on a common principle: all naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable.

System in detail: Step 3

- For example, a fruit may be considered to be an apple if it is red, round, and about 10 cm in diameter.

- A Naive Bayes classifier considers each of these features to contribute independently to the probability that this fruit is an apple, regardless of any possible correlations between the color, roundness and diameter features.

System in detail: Step 3

We need a training set:

- We search our database for tweets containing words of terms alternative names, e.g. for insomnia:

“I have horrible insomnia what should I do tonight?
Keep in mind I'm 2 ambien and 2 Xanax deep and still jumpin”

- We insert this tweet on our training set:

```
train = [
        (u"I have horrible insomnia ..deep and still jumpin","F"),
```

System in detail: Step 3

- If the tweet is unrelated to the adverse event, we mark it as ‘neg’ (from *negative*), e.g.:

“I've literally had insomnia for the past two weeks somebody get me a Xanax”

```
train = [
    (u"I've literally had insomnia for the past two weeks somebody get me a Xanax","neg"),
```

- We stop once we insert 5-6 tweets for each category, and 5-6 negative training items

System in detail: Step 3

Example training set for category F

```
train = [
        (u"I have horrible insomnia ..deep and still jumpin","F"),
        (u"Xanax doesn't even help Insomnia","F"),
        (u"I pop Xanax and still have problems falling asleep","F"),
        (u"Plot twist: My Xanax cocktail has given Me existentialism insomnia. #solvingworldproblems","F"),
        (u"I've literally had insomnia for the past two weeks somebody get me a Xanax","neg"),
        (u"Thanks to my good friend Xanax I was able to get past my insomnia and sleep for 9 hours. Best feeling ever!","neg"),
        (u"People's Pharmacy: Pills aren't only way to address insomnia","neg"),
```

- Repeat this for each category
- Finally, our training set is ready
- The training set development is a <u>human supervised</u> action

System in detail: Step 4

- We classify each tweet, e.g.

```
(u'Meech back in bed...I didn\'t sleep that much after surgery when they had me on Xanax! #BB18 #BBAD', 123577, 'F', 0.94, 0.06)
```

where:

F -> the category that the tweet belongs

0.94 -> the probability for the tweet to belong to F

0.06 -> the probability for the tweet to be unrelated to an adverse event

System in detail: Step 4

- Compute accuracy of our training set

```
    ]

test = [
    (u"Benadryl has the opposite effect on me and makes me awake/ gives me panic attacks. It\'s Xanax and sleepy time tea for me", 'neg'),
    (u"This truly is the year of realizing things", 'neg'),
    (u"would rather deal with someone who is tripping on acid than with someone who was barred out on Xanax any fucking day", 'neg'),
    (u"I'm taking a Xanax, so I probably shouldn't be tweeting. The insomnia, the stress, and the headaches are really affecting me", 'F'),
    (u'when xanax, ambien, and nyquil have all failed to get you to sleep, what do you do?', 'F'),
    (u"2 Xanax bars 4 muscle relaxers and 6 Tylenol pm and still no sleep", 'F')
]
```

```
# Compute accuracy
print("Accuracy: {0}".format(cl.accuracy(test)))
Accuracy: 0.666666666
```

- Not bad, neither perfect
- We can improve our accuracy by developing a better training set

System in detail: Step 4

- We use Python & NLTK's bayesian classifier

- The Natural Language Toolkit, or more commonly NLTK, is a suite of libraries and programs for symbolic and statistical natural language processing (NLP) for English written in the Python programming language

- It’s fast, easy to implement and suitable for the ‘twitter language’

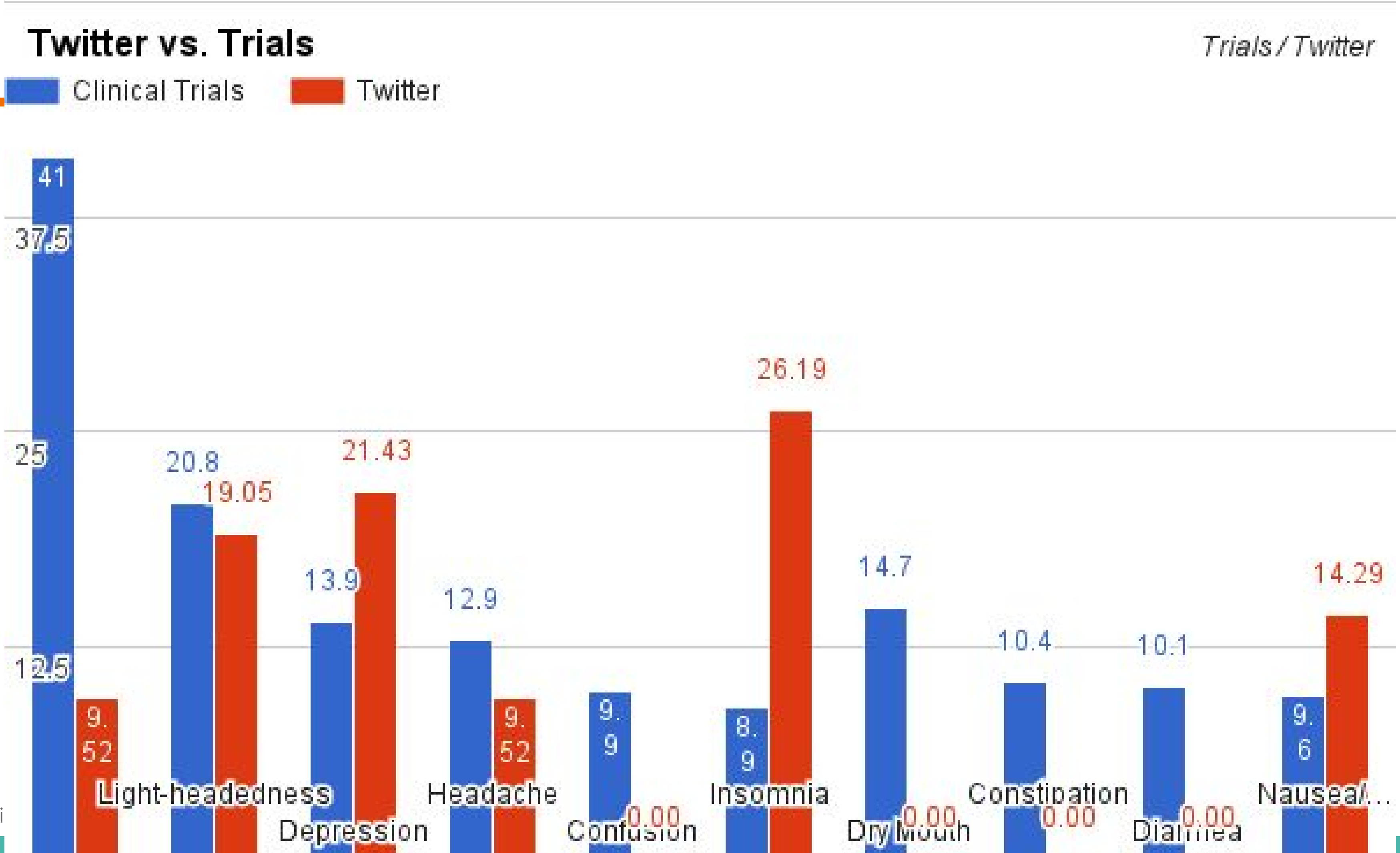
Testing & results

- More than **100K** tweets collected containing the words : Xanax, Alprazolam, Niravam
- From Jul.19.2016 to Aug.30.2016
- Tweets only in English language
- **37K** tweets analyzed (no re-tweets) using the system (and our developed training set)

Testing & results

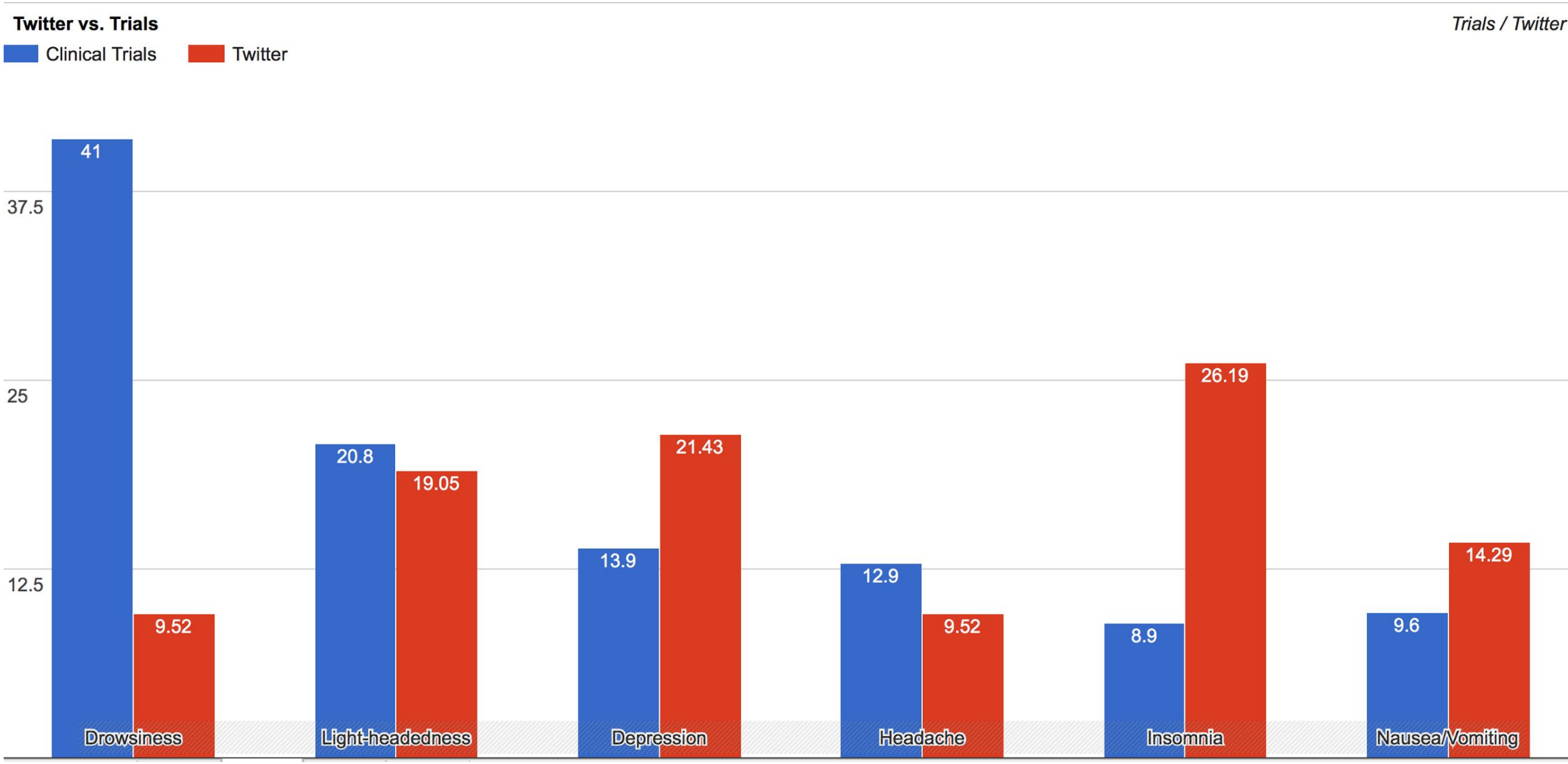
- **37K** tweets is a very-very small sample
- Frequencies comparing to most frequent adverse events reported in placebo-controlled trials

	Clinical Trials	Twitter
Drowsiness	41%	9.52%
Light-headedness	20.8%	19.05%
Depression	13.9%	21.43%
Headache	12.9%	9.52%
Confusion	9.9%	0.00%
Insomnia	8.9%	26.19%
Dry Mouth	14.7%	0.00%
Constipation	10.4%	0.00%
Diarrhea	10.1%	0.00%
Nausea/Vomiting	9.6%	14.29%



Twitter vs. Trials
Trials / Twitter
Clinical Trials
Twitter
41
37.5
25
12.5
20.8
19.05
13.9
21.43
12.9
9.52
9.52
9.9
0.00
8.9
26.19
14.7
0.00
10.4
0.00
10.1
0.00
9.6
14.29
Light-headedness
Depression
Headache
Confusion
Insomnia
Dry Mouth
Constipation
Diarrhea
Nausea/...

medici



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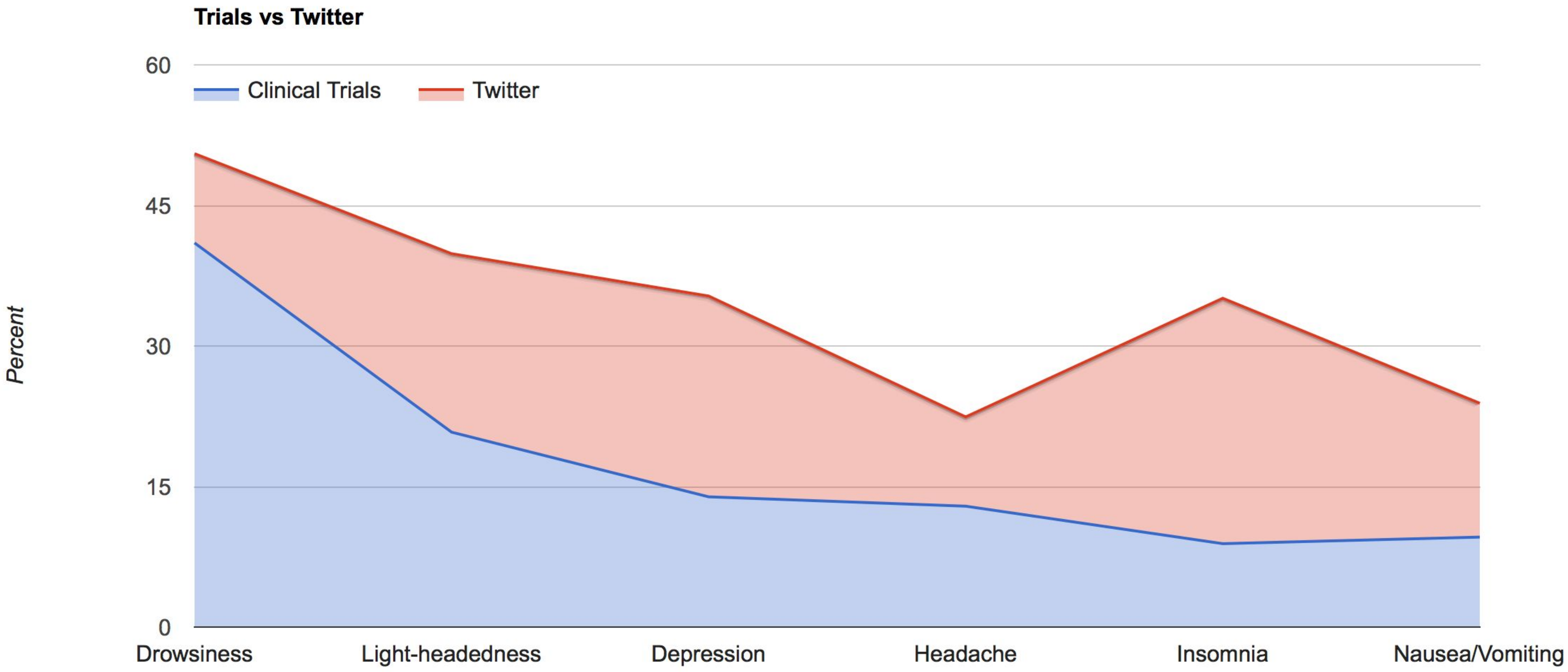
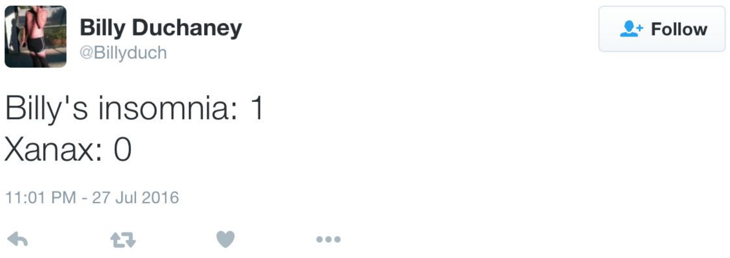
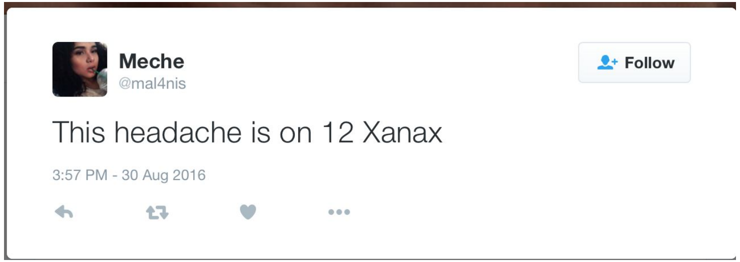

Trials vs Twitter
60
45
30
15
0
Clinical Trials
Twitter
Percent
Drowsiness
Light-headedness
Depression
Headache
Insomnia
Nausea/Vomiting

Some examples

- Tweet (related to an AE), impossible to spot with the specific training set

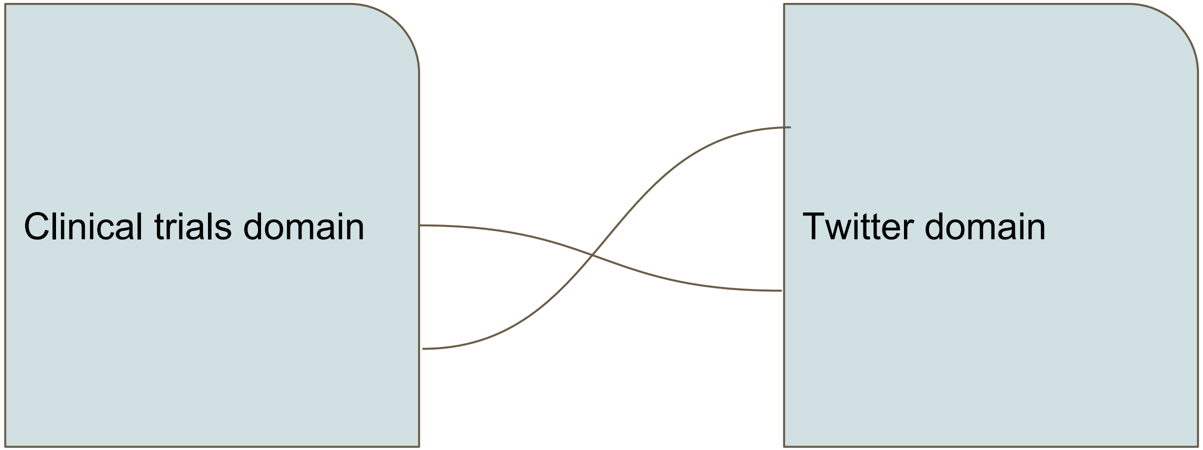


- And another tweet, related to an AE (headache) but obviously it's normal to have a headache after 12 pills



Conclusion

- A comparison between the frequencies of the AE in the messages and those reported in clinical trials, shows that although there are differences on the percentages (and, thus, the data cannot be considered as reliable), there is a pattern that indicates a possible correlation



Code & software will be released in my GitHub

under MIT license:

https://github.com/dspachos