Weight of Statistical Evidence

Detection and Correction of Publication Bias

Servan Grüninger

Supervisor: Prof. Dr. Stephan Morgenthaler (EPFL)

External expert: Prof. Dr. Reinhard Furrer (University of Zurich)

Master's Programme in Computational Science and Engineering

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Outline

Publication Bias—The Bane of Scientific Publishing

Many studies land in the file drawer (Image: Geckoboard)

The Woozle Effect

Pooh and Piglet tracking down the elusive Woozle (Image: Ernest H. Shepard)

Influenza Surveillance in the USA

Virology: total & influenza respiratory specimens per week

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Strengths:

- reliable
- comparably fast (ca. 1-2 weeks)
- virological "ground truth"
- severe cases covered

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Weaknesses:

- only tip of the iceberg
- comparably slow (ca. 1-2 weeks)
- weak cases are missed

Twitter as complementary information source

Virology: total & influenza respiratory specimens per week

-> **ILI patients:** % of total per week & state

Mortality: influenza related deaths

Hospitalisation: influenza related hospitalisations

-> **Geographic spread of influenza:** within each state

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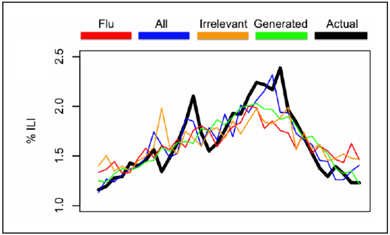
Flu surveillance via twitter: two approaches

correlate aggregated tweets with aggregated CDC data



Bodnar and Salathé [2013]

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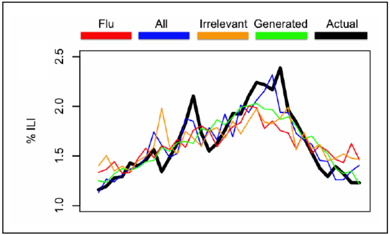

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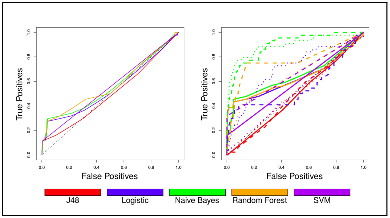
correlate individual tweets with disease state of individuals



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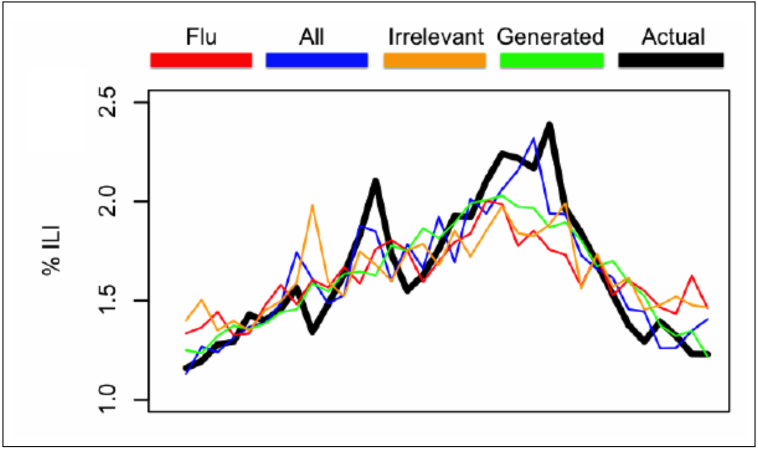
Use aggregate data to detect the flu



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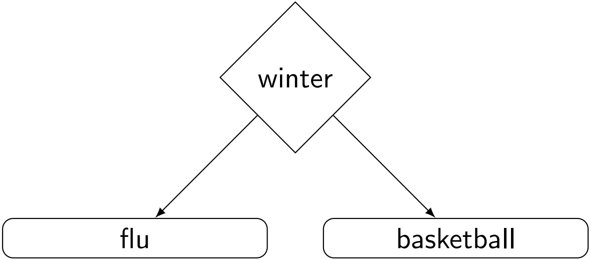
Weaknesses:

- prone to overfitting
- random data performed as good as tweets with flu related tweets
- temporal & spatial division of data influence model

The dangers of confounders



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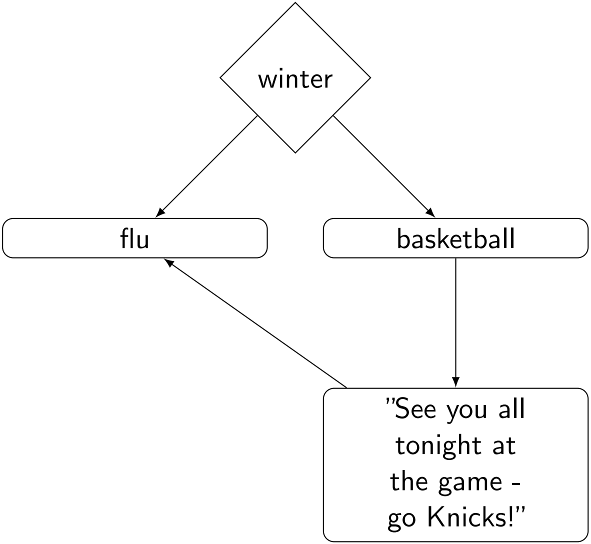
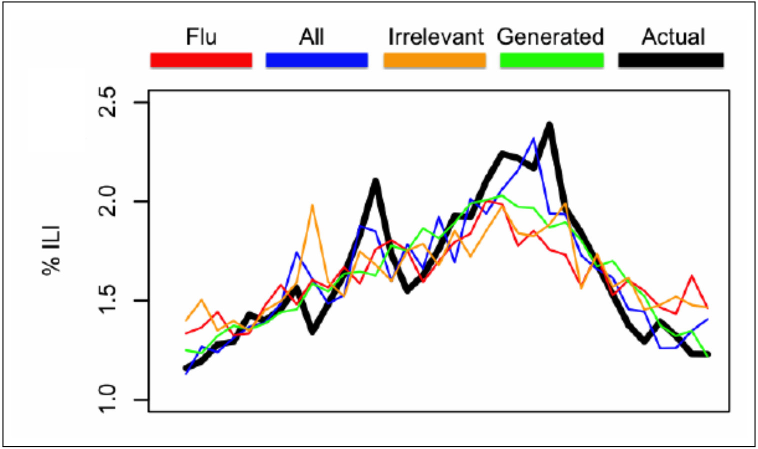


The cautionary tale of Google Flu Trends

Overfitting: The bane of machine learning



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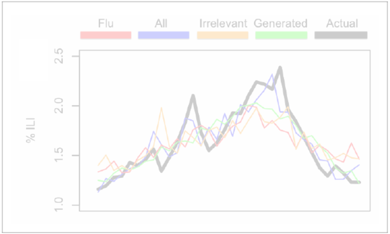

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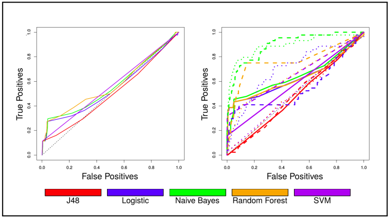

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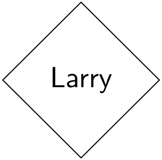
Use individual-level data to detect the flu



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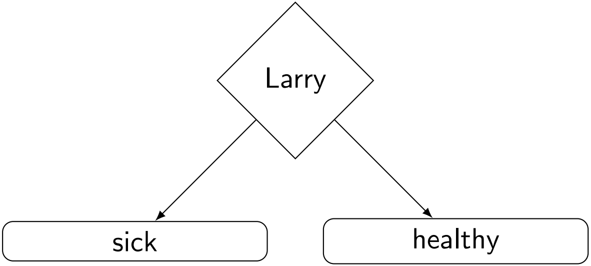

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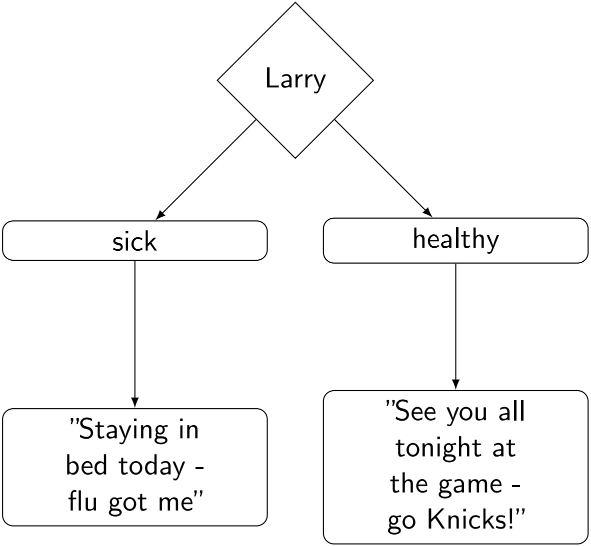

On the ground validation of online diagnosis with Twitter and medical records [Bodnar et al., 2014]

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On the ground validation of online diagnosis with Twitter and medical records [Bodnar et al., 2014]

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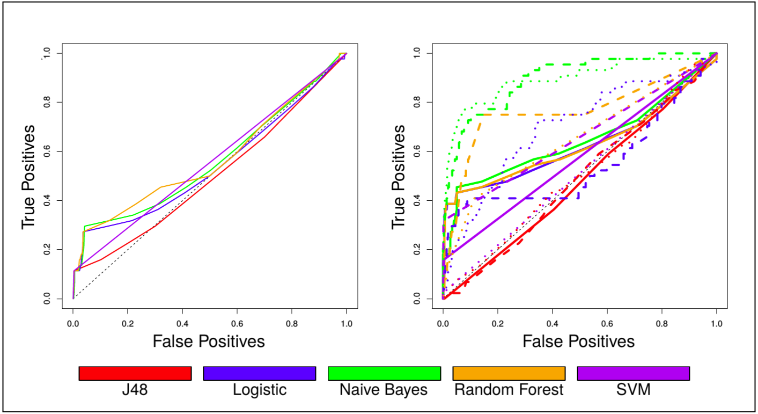
- ranked list of 12'393 most common keywords
- rank established by different machine learning methods

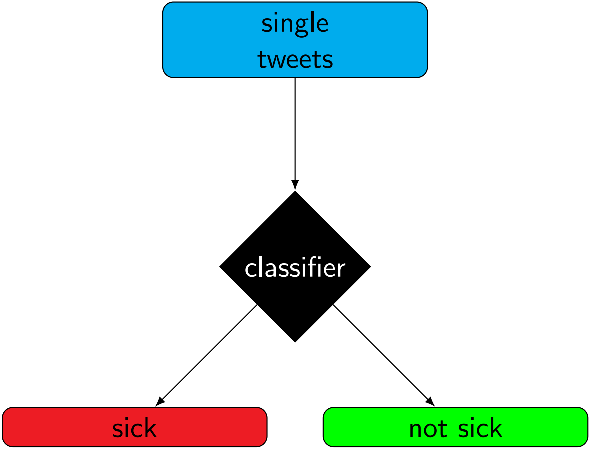


Bodnar et al. [2014]

The classifier model

- naive Bayes classifier: $p(C_k \mid \mathbf{x}) = \frac{p(C_k)\ p(\mathbf{x}|C_k)}{p(\mathbf{x})}$
- 100 most predictive keywords
- accuracy: 89.72%, AUC: 0.8544

Tweet classification: workflow



Strengths and weaknesses of the Twitter classifier

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Weaknesses:

- small data set (-> low external validity?)
  - 104 individuals w/ influenza, 122 individuals w/o influenza
  - only 1609 tweets from 35 users in "sick" category
- low temporal resolution (one month time window)
- ethical concerns (anonymity might be compromised)

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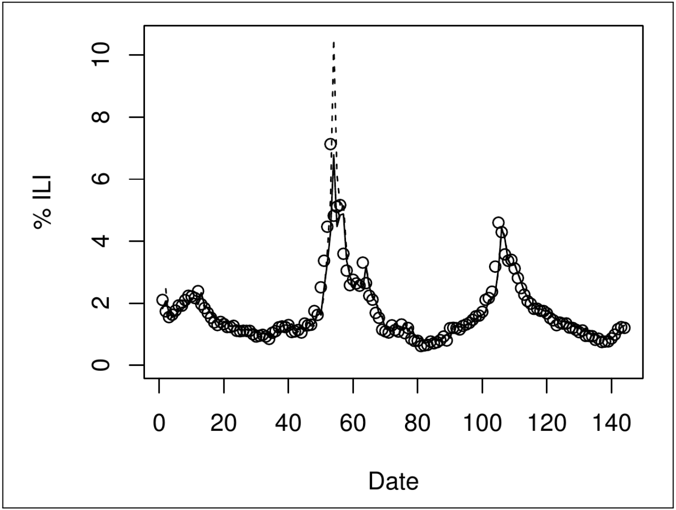
A first proof of principle



Bodnar [2015]

An adventure in reproducibility

http://blog.revolutionanalytics.com/2014/10/introducing-rrt.html

To replicate or to reproduce?

Reproducibility according to Goodman et al. [2016]:

- methods reproducibility
- results reproducibility (replicability)
- inferential reproducibility

The three main goals:

- Assess the validity of the Twitter classifier for large data sets (results and inferential reproducibility)
- Reproduce key findings from Bodnar [2015] (methods reproducibility)
- Ensure the methods reproducibility of this thesis

The Twitter Data Set

The nature of the data beast

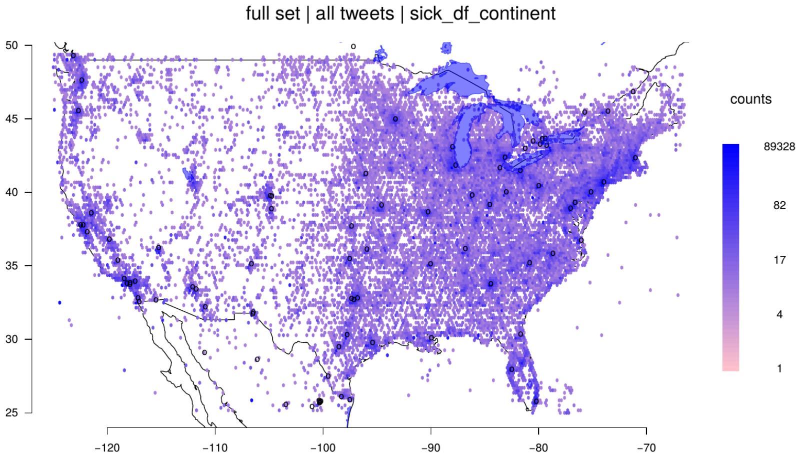
- `all_tweets`: the whole set of rated tweets (2'847'039'672 tweets)
- `one_hundred`: the rated tweets of those users who sent at least 100 tweets (42'611'004 tweets)
- `sick_users`: the rated tweets of all those users who sent at least one sick tweet (4'131'650 tweets)

The nature of the data beast

```
##           userID longitude latitude       time sick state
## [1,] 1000007198 -86.34844 39.63168 1424580963    0    30
## [2,] 1000007198 -86.34844 39.63168 1424580963    0    30
## [3,] 1000009051 -87.63464 24.39631 1409880397    0    56
## [4,] 1000009051 -87.63464 24.39631 1409880397    0    56
## [5,] 1000010509 -90.14008 29.86666 1394405061    0    36
## [6,] 1000010509 -90.13791 29.88957 1411750890    0    36
```

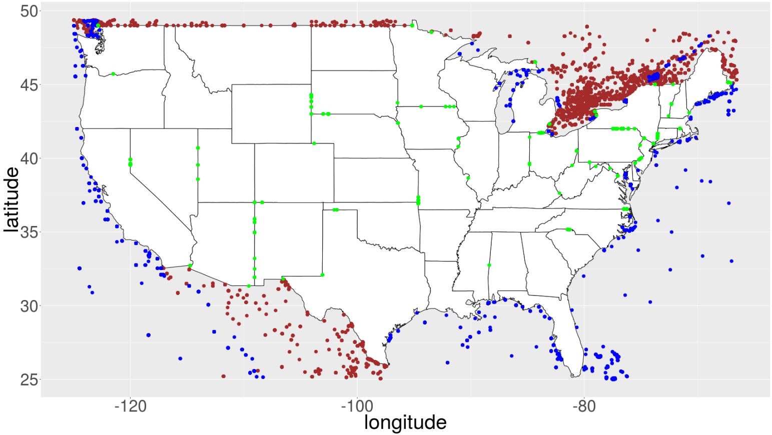
```
         used (Mb) gc trigger  (Mb) max used  (Mb)
Ncells 409223 21.9     847687  45.3   641597  34.3
Vcells 828218  6.4   23885155 182.3 23324386 178.0
```

The sick_users data set - full



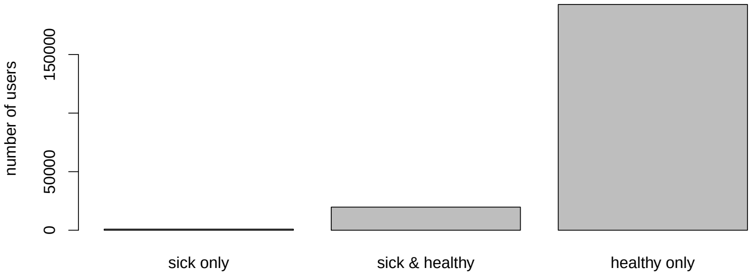
4'131'650 tweets from 222'446 users before pre-processing

sick_users: pruned tweets

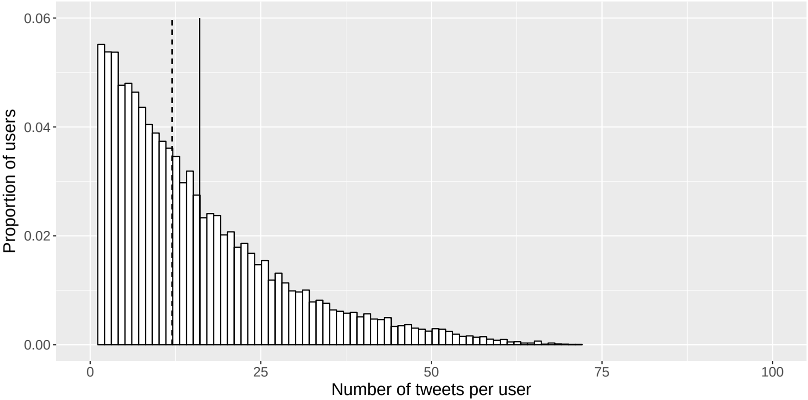


3'696'989 tweets from 213'426 users after pre-processing

`sick_users`: only few sick people in the data set

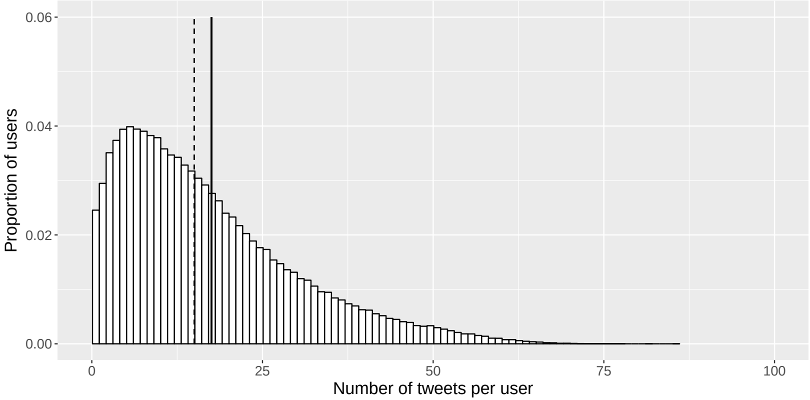


`sick_users`: differences between sick and healthy



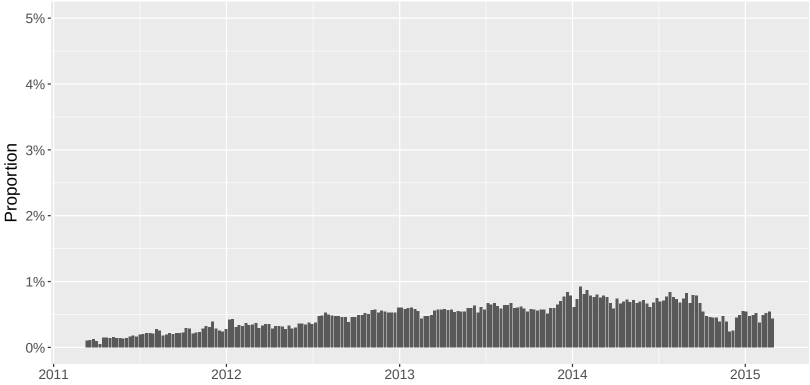
Mean = 16.01 (solid line); median = 12 (dashed line)

sick_users: differences between sick and healthy



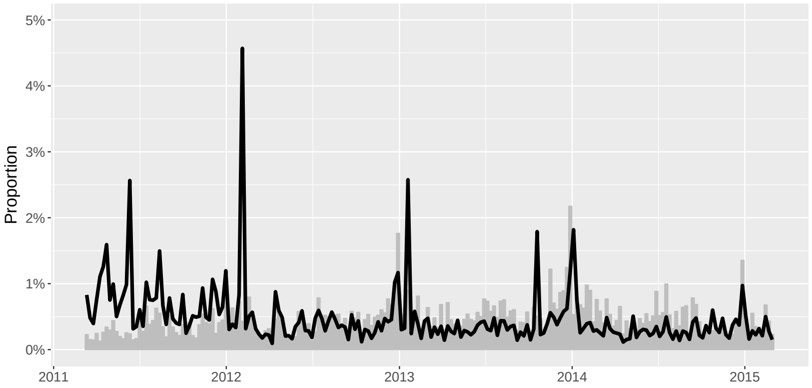
Mean = 17.53 (solid line); median = 15 (dashed line)

The `all_tweets` data set



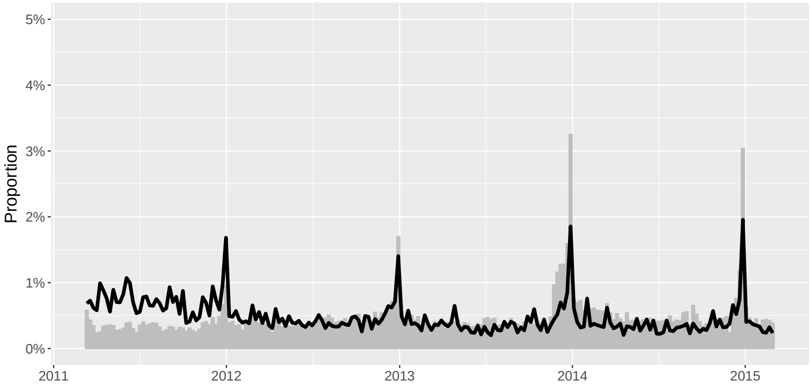
2’847’039’672 tweets sent by 16’015’981 users before pruning;
2’764’210’962 tweets and 15’229’049 users after pruning

all_tweets: sick tweets over time

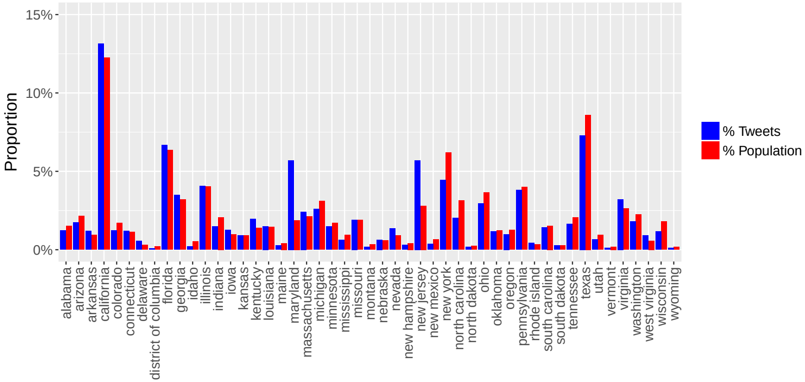


1’189’809 sick tweets from max. 27’052 users

all_tweets: sick users over time



all_tweets: total users over space



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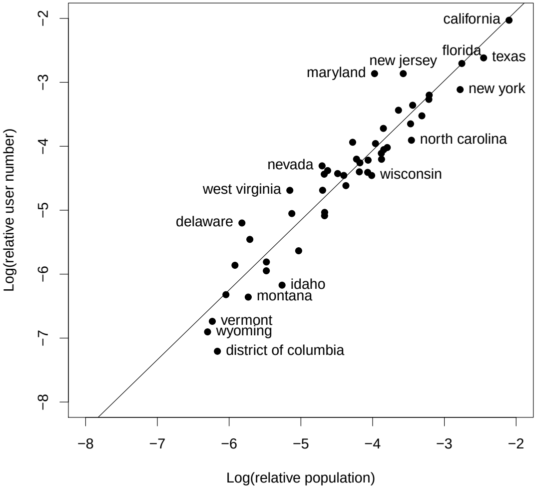

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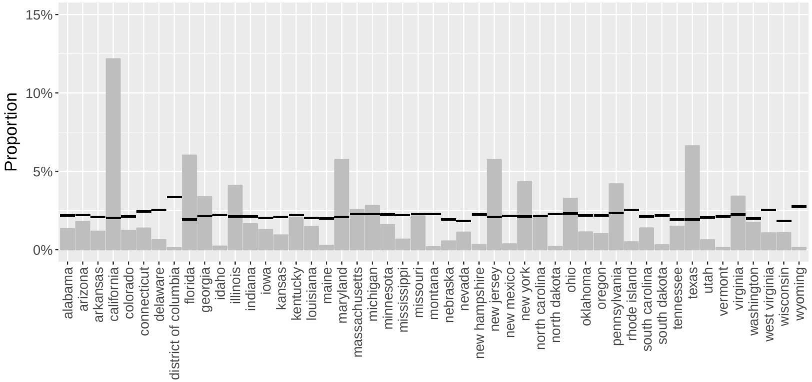

Competing For Gold

CDC ILI rates: the gold standard

Influenza-like illnesses are defined as:

- fever (body temperature of 37.8°C or greater) AND

CDC ILI rates: the gold standard

Influenza-like illnesses are defined as:

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- cough and/or sore throat AND

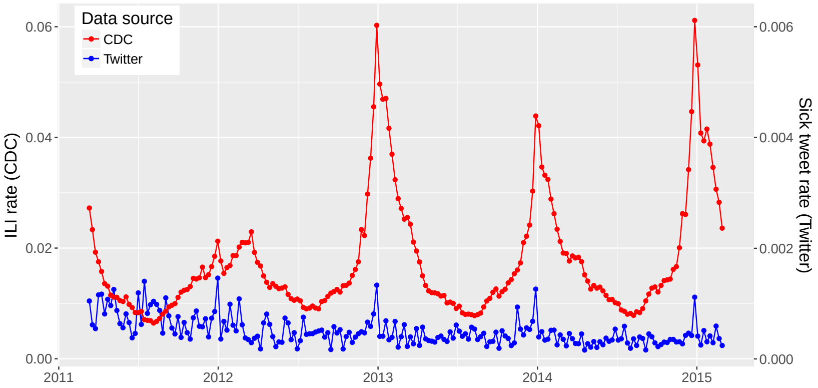
CDC ILI rates: the gold standard

Influenza-like illnesses are defined as:

- fever (body temperature of 37.8°C or greater) AND
- cough and/or sore throat AND
- no other known cause

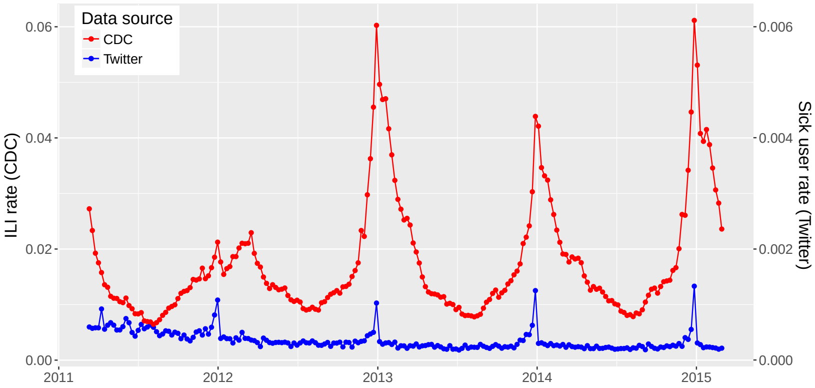
ILI rates are defined as the percentage of patients who visit ILINet sentinal clinics and show ILI symptoms.

CDC vs. Twitter: tweet-based



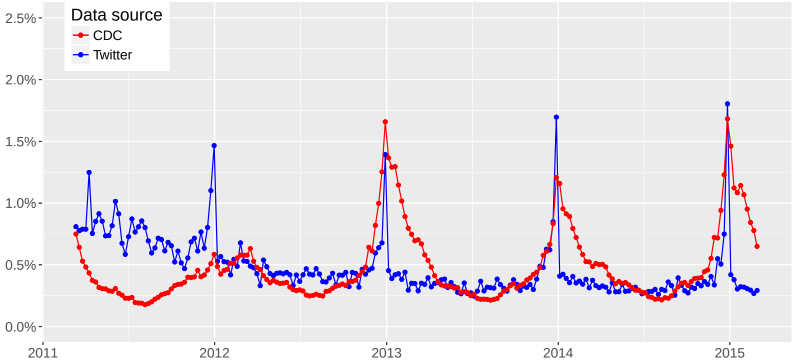
CDC ILI rates compared with Twitter sick tweet rate

CDC vs. Twitter: user-based

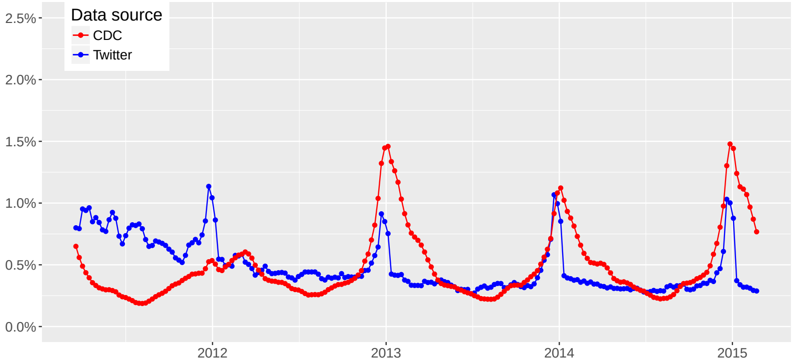


CDC ILI rates compared with Twitter sick user rates

CDC vs. Twitter: normalised and user-based



CDC vs. Twitter: normalised, user-based, and smoothed



CDC flu activity levels

0 insufficient data

1 below baseline

2 less than 1 SD above baseline

3 less than 2 SD above baseline

...

9 less than 8 SD above baseline

10 more than 8 SD above baseline

CDC flu activity levels - Baseline Calculation

CDC calculation

$$\text{baseline} = \frac{1}{n}\sum_{i=1}^{n} x_i + 2s$$

x_i = percentage of ILI patients among in week i;

n = # of non-influenza weeks in previous three season

s = sample standard deviation

CDC flu activity levels - Baseline Calculation

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$n = \#$ of non-influenza weeks in previous three season

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adopted for Twitter data set

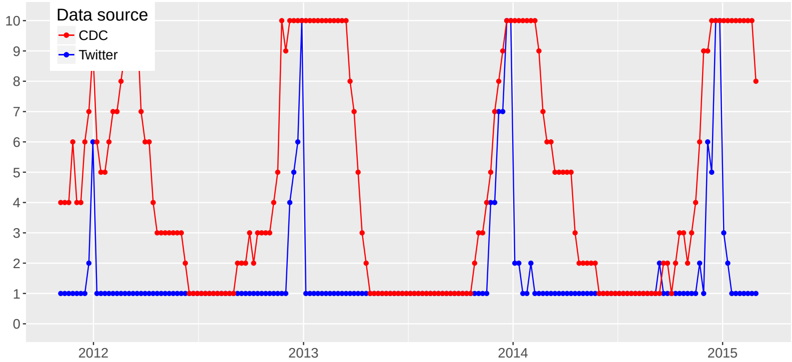
baseline $= \frac{1}{n} \sum_{i=1}^{n} x_i + 2s$

$x_i =$ number of tweets labelled "sick" in week i;

$n = \#$ of non-influenza weeks in previous summer (Jun, Jul, Aug & Sep)

$s =$ sample standard deviation

CDC vs. Twitter: based on activity levels



CDC ILI activity levels: spatiotemporal activity

Twitter flu activity levels: spatiotemporal activity

CDC vs. Twitter: spatiotemporal comparison

Exercises in Reproducibility

Reproducing key figures from Bodnar [2015]

- SIR model parameters β and γ

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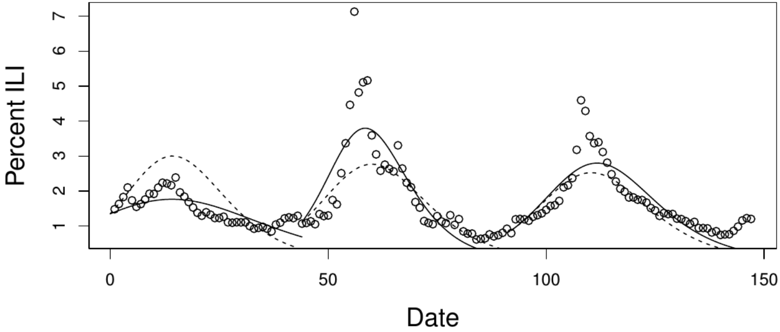
- SIR model parameters β and γ
- SIR model figure

Reproducing key figures from Bodnar [2015]

- SIR model parameters β and γ
- SIR model figure
- full Twitter model figure

SIR model in Bodnar [2015]



SIR model based on yearly (solid) and combined (dashed) parameters

SIR model theory

- $\frac{dS}{dt} = -SI\beta$

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- $\frac{dS}{dt} = -SI\beta$
- $\frac{dI}{dt} = -SI\beta - I\gamma$
- $\frac{dR}{dt} = I\gamma$

β and γ are estimated by minimising the residual sum of squares:

$$\mathsf{RSS} = \sum_t (I_{\gamma,\beta}(t) - I_{\mathsf{CDC}}(t))$$

SIR model: data basis for calculation

- `cdcoffset`
- `full_base`
- `full_autocor`
- `full_autocor2`
- `full_both`
- `full_both2`

Optimisation done with a simple grid-search algorithm.

National best-fit parameters from the CDC (white) and Twitter data (grey)

Year	γ	β	RSS
2011-2012 (Bod)	0.4	0.44	0.00041
	0.37	0.41	0.00036

National best-fit parameters from the CDC (white) and Twitter data (grey)

Year	γ	β	RSS
2011-2012 (Bod)	0.4	0.44	0.00041
	0.37	0.41	0.00036
2011-2012 (Gru)	0.17	0.17	0.00010
	0.12	0.12	0.00013

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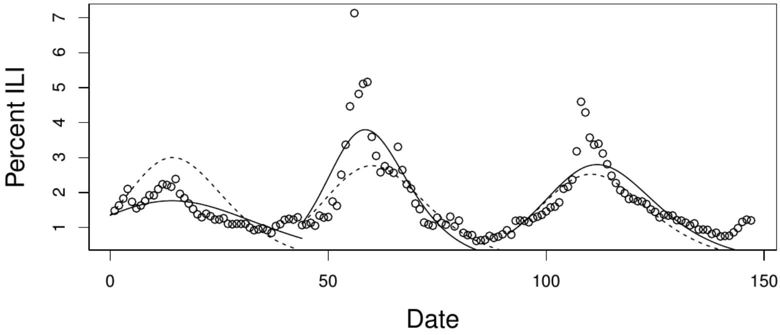

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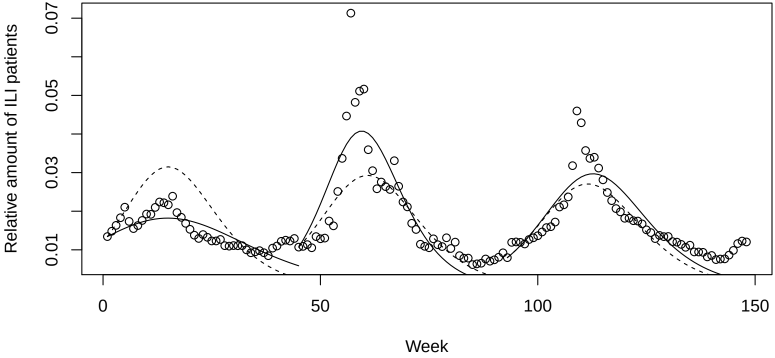
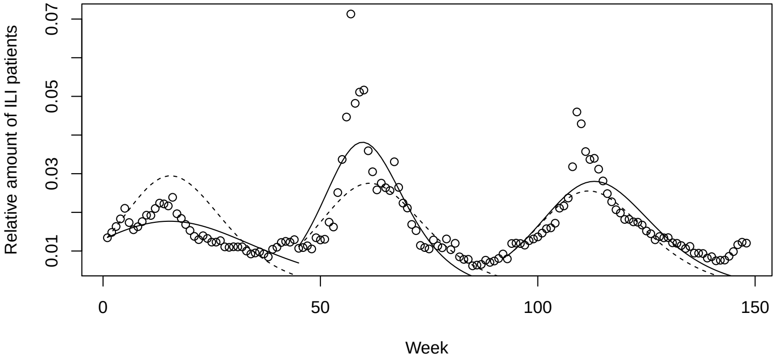
SIR model: based on `cdcoffset`

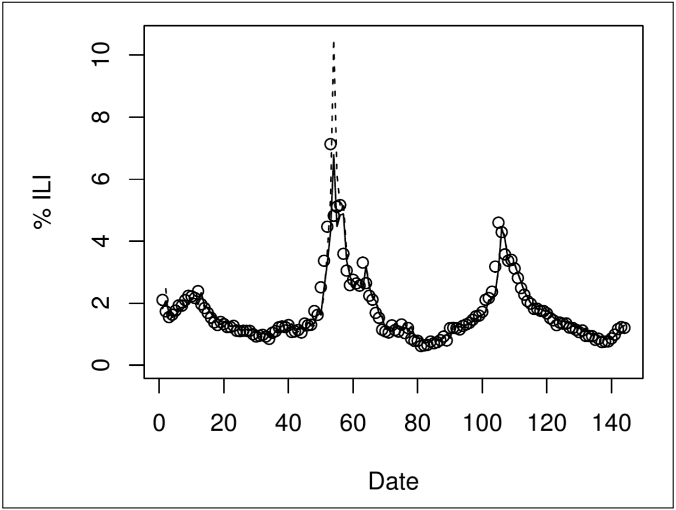


SIR model: based on `full_both2`



Full model consisting of AR(2) model based on CDC data and Twitter base model

Full Twitter model from Bodnar [2015]

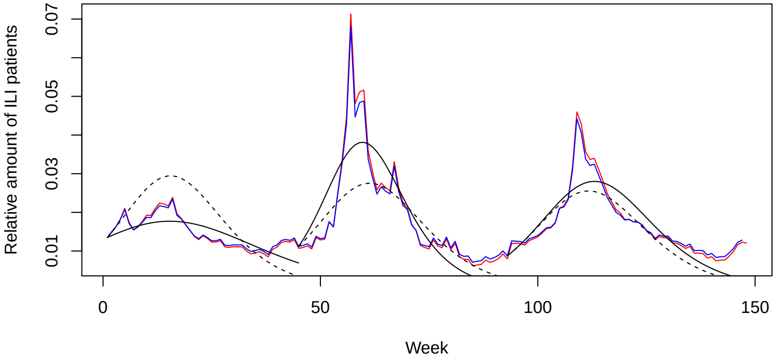


Bodnar [2015]

Full Twitter model from Bodnar [2015]

$$I_{\mathsf{full}}(t+1) = a \cdot I_{\mathsf{CDC}}(t-1) + b \cdot I_{\mathsf{CDC}}(t) + c \cdot I_{\mathsf{Twitter}}(t) + d.$$

Full Twitter model from Bodnar [2015]



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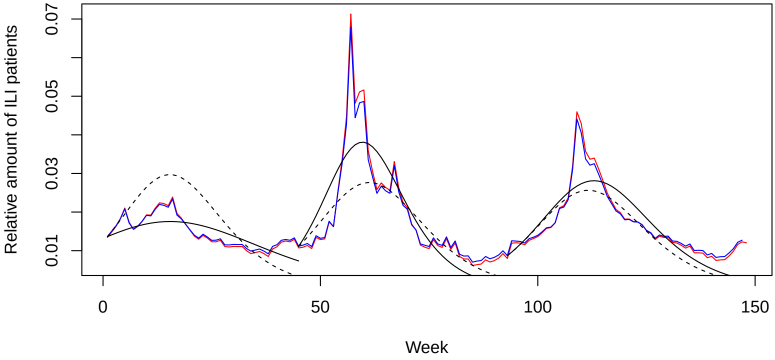
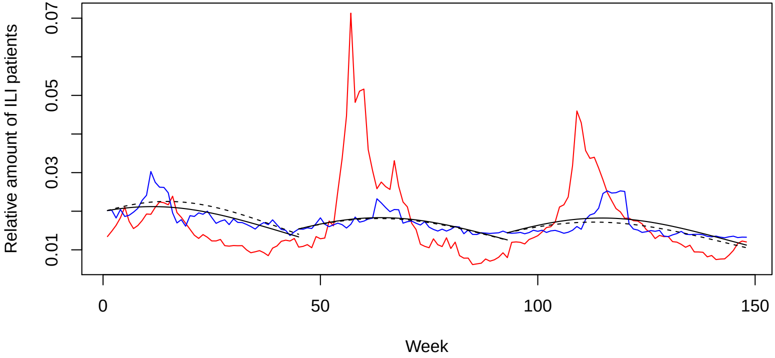
CDC AR(2) model



Model consisting of AR(2) model based on CDC data

Twitter base model



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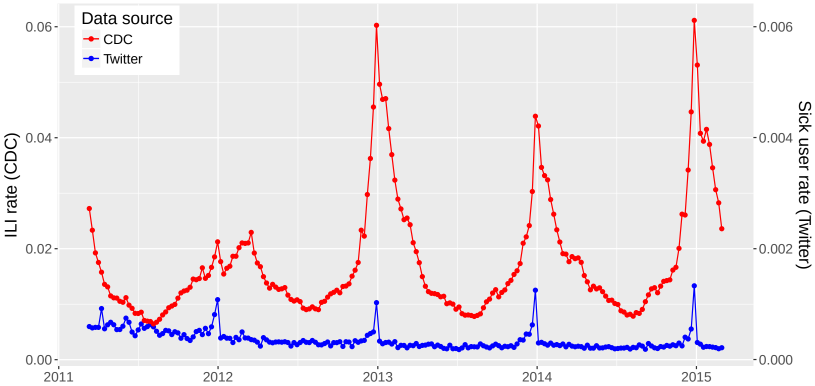

CDC ILI rates compared with Twitter sick user rates

Discussion

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With regard to:

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Most likely explanation: Data set used by Bodnar [2015] was pruned, filtered, or otherwise transformed.

Support for "Transformation hypothesis"

- stark discrepancies with regard to basic parameters of the two dat sets (e.g. mean tweets sent, total number of users, relative distribution of sick users)

Differences in data sets

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# users	15'560'328	15'229'049	raw

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median tweet rate	10 tw/pp	32.53 tw/pp	per week
# total users in 2011	45'086	175'382	processed

Support for "Transformation hypothesis"

- stark discrepancies with regard to basic parameters of the two dat sets (e.g. mean tweets sent, total number of users, relative distribution of sick users)
- sick rates in Bodnar [2015] were 10-times larger than in my set
- `sick_user` subset

Discrepancies between Grüninger [2017] and Bodnar [2015]

With regard to:

- methods reproducibility: figures & tables not reproducible
- results reproducibility: Classifier results did not fit CDC rates
- inferential reproducibility: Classifer detects flu peaks, but is only of complementary use

Another explanation: Data set used by Bodnar [2015] was the same, but there were crucial gaps and/or fundamental errors in reporting.

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- large, unwieldy data-set, analysed by novice data scientist
- no access to complete code and processed data base used by Bodnar [2015]

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- analysed & aggregated data in various ways (spatial, temporal) and with various methods
- key statistics of aggregated data resemble real-world Twitter statistics more closely
- Because the literature and Bodnar [2015] say so

Recommendations

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- Assessing validity of analysis of Grüninger [2017]
- re-establishing functionality of Twitter classifier
- testing classifier with representative subset of Twitter users

Stop.

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