Data Driven Methods for Disease Forecasting

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October 27, 2014
1 Introduction
   • Motivation: Data driven epidemiology
   • Data driven Epidemiology: Problems
   • Main Goals

2 Methods
   • Data Sources
   • Custom User Keywords
   • Matrix Factorization using Nearest Neighborhood
   • Model level vs Data level fusion

3 Instability Analysis

4 Ablation Test

5 Conclusion
   • Extending to other sources: Opentable
   • Summary
Traditional Approaches: Computational Epidemiology

- Computational models (ode, etc.)
- Population level vs Network level
- Effectiveness depends on Good Surveillance data.
Traditional Approaches: Computational Epidemiology

- Computational models (ode, etc.)
- Population level vs Network level
- Effectiveness depends on Good Surveillance data.
- Surveillance often delayed
- Surveillance often updated over time
Epidemiology in data driven world

- Surrogate information can be found in social medium
- Physical indicators can also have causal effects on diseases.
- Can complement traditional surveillance
  - Provide real-time estimates
  - Provide robust estimates of already published data
Example Problems (see www.dac.cs.vt.edu)

- Predicting Hantavirus outbreaks from news articles*
- Chikungunya Spread detection
- Influenza like Illness (ILI) forecasting.

* Saurav Ghosh et al. “Forecasting Rare Disease Outbreaks with Spatio-temporal Topic Models”. In: NIPS 2013 workshop on Topic Models. 2013
Problem Overview

Near-horizon forecast of ILI case counts at country level*
Near-horizon forecast of ILI case counts at country level

- Predicting weekly Influenza-like-illness (ILI) case counts for 15 Latin American countries
- Investigating different open source data-streams as possible surrogate indicators of ILI

Main Goals

1. Real-time prospective study - most studies till this paper were retrospective.
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4. Accounting for uncertainties in the official surveillance estimates
5. Investigate importance of different sources - Ablation test
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Key Ingredients

- Better Data - extract information from external indicators.
- Better Models - handle non-linearity.
- Handle Real world noise
Overall Framework

Data Enrichment

Healthmap Data
71 MB Historical
1.5 MB per week

Twitter Data
500 GB Historical
10 GB per week

Weather Data
1 GB Historical
18 MB per week

Google Trends
600 MB Historical
8 MB per week

Google Flu Trends
4 MB Historical
100 KB per week

OpenTable Res Data
11 MB Historical
170 KB per week

Filtering for Flu Related Content

Time series Surrogates
Extraction

ILI Prediction

Healthmap Data
12 MB
Weather Data
50 MB
Twitter Data
7 GB

Healthmap Data
140 MB Historical
3 MB per week

Twitter Data
1 TB Historical
20 GB per week
Data Sources

- Non-physical indicators
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  1. Google Flu Trends - uses unpublished set of keywords
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- **Non-physical indicators**
  1. Google Flu Trends - uses unpublished set of keywords
  2. Custom User Keywords
    - 1. Google Search Trends
    - 2. Healthmap News Feed
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Data Sources

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- Physical indicators

- Misc. Indicators
  1. Opentable reservations
Google Flu Trends
Finding Custom user keyword dictionary

A multiple step process:

- Started with a seed set of keywords from experts.
  - Seed set contains words in Spanish, Portuguese, and English.
  - Example: *gripe* (flu in Spanish)
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- Pseudo-query expansion
  - Crawled top 20 web-sites for each seed word.
  - Crawled “expert” web-sites e.g. CDC.
  - Crawled few other hand-picked sites.
  - Top 500 frequently occurring words selected.
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  - Interesting words such as *ginger* and *Acemuk* found.
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- Final filtering: 114 words
Finding Custom user keyword dictionary (contd..)

Symptomatic words: “bronquitis”, “catarro”, “tos seca” (whooping cough)

Medicinal words: “acemuk”, “claritromicina” (clarithromycin)

Interesting words: ginger (“jengibre”), leave letter (“letra de deja”)
GFT vs other non-physical indicators using custom keyword set

Google Search Trends (GST)

Healthmap

Twitter
Physical Indicators

- Meteorological data for every lat-long, worldwide, every 8 hours
- Humidity, Temperature, Rainfall
- Analyzing grid cells covering PAHO sites.
System framework once again!!
Preliminaries

- To find predictive model $f$

$$f : \mathcal{P}_t = f (\mathcal{P}, \mathcal{X})$$

- Variable Setup

$$\mathcal{V}_t \equiv \langle P_{t-\beta-\alpha}, X_{t-\beta-\alpha}, P_{t+1-\beta-\alpha}, X_{t+1-\beta-\alpha}, \ldots, P_{t-\alpha}, X_{t-\alpha} \rangle$$

$$\mathcal{L}_t \equiv P_t$$

- Parameters
  - $\alpha$: the lookahead window length
  - $\beta$: the lookback window length
Matrix Factorization (MF)

- Can find latent factors in the dataset.
Matrix Factorization (MF)

- Can find latent factors in the dataset.
- Model

\[
\hat{M}_{i,j} = b_{i,j} + U_i^T F_j \\
b_{i,j} = \bar{M} + b_j
\]
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\]

- Fitting

\[
b_*, F, U = \arg\min \left( \sum_{i=1}^{m-1} \left( M_{i,n} - \hat{M}_{i,n} \right)^2 + \lambda_1 \left( \sum_{j=1}^{n} b_j^2 + \sum_{i=1}^{m-1} \| U_i \|^2 + \sum_{j=1}^{n} \| F_j \|^2 \right) \right)
\]
Nearest Neighbor model (NN)

- Impose non-linearity.
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- $\mathcal{N}(i) = \{ k : V_k \text{ is one of the top K nearest neighbors of } V_i \}$
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- \( \mathcal{N}(i) = \{ k : V_k \text{ is one of the top } K \text{ nearest neighbors of } V_i \} \)
- Fitting

\[
\hat{P}_{T'} = \left( \sum_{k \in \mathcal{N}(T')} \theta_k L_{k, T-\alpha} \right) / \sum_{k=1}^{K} \theta_k
\]  

(2)
Matrix Factorization using Nearest Neighborhood (MFN)

- Inspired from Koren et al.’s work* in Recommender systems.
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\[
\hat{M}_{i,j} = b_{i,j} + U_i^T F_j + F_j |N(i)|^{-\frac{1}{2}} \sum_{k \in N(i)} (M_{i,k} - b_{i,k}) x_k
\]  

(3)
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(3)

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b_*, F, U, x_* = \text{argmin} \left( \sum_{i=1}^{m-1} \left( M_{i,n} - \hat{M}_{i,n} \right)^2 + \lambda_2 \left( \sum_{j=1}^{n} b_j^2 + \sum_{i=1}^{m-1} ||U_i||^2 + \sum_{j=1}^{n} ||F_j||^2 + \sum_{k} ||x_k||^2 \right) \right)
\]  

(4)

Accuracy comparison

的质量指标

$$A = \frac{4}{N_p} \sum_{t=t_s}^{t_e} \left( 1 - \frac{|P_t - \hat{P}_t|}{\max(P_t, \hat{P}_t, 10)} \right)$$

(5)
Accuracy comparison

On average, MFN has better performance over MF and NN.

In Mexico, MF has the best accuracy - possibly because the 2013 ILI season in Mexico was late by a few weeks than in usual.

Table 1: Comparing forecasting accuracy of models using individual sources. Scores in this and other tables are normalized to [0,4] so that 4 is the most accurate.

<table>
<thead>
<tr>
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<th>Sources</th>
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Model level fusion

- Output from models combined based on historical accuracy.
Model level fusion

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- Model

\[
c\mathcal{M}_t = \begin{bmatrix}
1\hat{P}_t & \ldots & c\hat{P}_t & P_t
\end{bmatrix}
\]  

\hspace{1cm} (6)
Model level fusion

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- Model

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c \mathcal{M}_t = \begin{bmatrix} 1 \hat{P}_t & \cdots & c \hat{P}_t & P_t \end{bmatrix}
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c \hat{\mathcal{M}}_{i,j} = \mu_i + c b_j + c U_i^T c F_j + c F_j |c \mathcal{N}(i)|^{-\frac{1}{2}} \sum_{k \in c \mathcal{N}(i)} (c \mathcal{M}_{i,k} - \mu_i + c b_k) c x_k
\]
Data level fusion

- Feature vector is a tuple over all data set features.

\[ \mathbf{x}_t = \langle \mathcal{T}_t, \mathcal{W}_t \rangle \]

- Use MFN to fit the value
Accuracy comparison

Table 2: Comparison of prediction accuracy while combining all data sources and using MFN regression.

<table>
<thead>
<tr>
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</table>

- On average, model level fusion produces better accuracy than data level fusion.
- Interesting deviations like Chile and El Salvador indicates that a possible strategy could be a mix of data level and model fusion - however complexity of training will increase manifold.
Introduction

- Motivation: Data driven epidemiology
- Data driven Epidemiology: Problems
- Main Goals

Methods

- Data Sources
- Custom User Keywords
- Matrix Factorization using Nearest Neighborhood
- Model level vs Data level fusion

Instability Analysis

Ablation Test

Conclusion

- Extending to other sources: Opentable
- Summary
Uncertainty in official estimates

- Can take up to several months to stabilize.

- Average relative error of PAHO count values with respect to stable values. (a) Comparison between Argentina and Colombia (b) Comparison between different seasons for Argentina.
Correcting uncertainty

- Recognize high, low and mid-season months for countries.
- Variable setup

\[ \mathcal{P}_A^S = \{(1, P_i^{(1)}, \dot{P}_i, N_i^{(1)}), \ldots, (m, P_i^{(m)}, \dot{P}_i, N_i^{(m)}), \ldots\} \]

- Correction Model

\[ \hat{P}_i^{(m)} = a_0 + a_1 m + a_2 P_i^{(m)} + a_3 N_i^{(m)} \]  \hspace{1cm} (8)
Correcting uncertainty

- Recognize high, low and mid-season months for countries.
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$$P_A^S = \{(1, P_i^{(1)}, \dot{P}_i, N_i^{(1)}), \ldots, (m, P_i^{(m)}, \dot{P}_i, N_i^{(m)}), \ldots\}$$

- Correction Model

$$\hat{P}_i^{(m)} = a_0 + a_1 m + a_2 P_i^{(m)} + a_3 N_i^{(m)} \quad (8)$$
1 Introduction
   - Motivation: Data driven epidemiology
   - Data driven Epidemiology: Problems
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2 Methods
   - Data Sources
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   - Model level vs Data level fusion

3 Instability Analysis

4 Ablation Test

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   - Extending to other sources: Opentable
   - Summary
Investigating importance of each source: Ablation Test

Table 4: Discovering importance of sources in Model level fusion on MFN regressors by ablating one source at a time.

<table>
<thead>
<tr>
<th>Sources</th>
<th>AR</th>
<th>BO</th>
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<td>2.96</td>
</tr>
</tbody>
</table>

- Greater drop in accuracy $\Rightarrow$ Source more important
- Physical indicators are in general more important
- Still there is value in supplementing physical indicators with non-physical indicators.
Final look at real time predictions

- Weekly predictions sent out for 15 Latin American countries
- Predictions publicly available at http://embers.cs.vt.edu/embers/alerts/visualizer_isi
Conclusion:
How to extend to other sources

- Data about number of unreserved tables at restaurants in Mexico

Table 5: ILI case count prediction accuracy for Mexico using OpenTable data as a single source, and by combining it with all other sources using model level fusion on uncorrected ILI case count data.

<table>
<thead>
<tr>
<th>Method</th>
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<th>Dinner</th>
<th>Lunch &amp; Dinner</th>
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<td>Model Fusion</td>
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<td>2.87</td>
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</table>
Summary

- MFN performs better than MF, NN on average over individual sources for predicting ILI case counts.
- In average there is a small advantage in combining models over different sources than to combine data.
- Employing information about number of samples used and how far from the actual date the estimate is being updated by the reporting agency, we have been able to improve our overall accuracy by a quality score of 0.05.
- Generally physical indicators offer more advantage over non-physical indicators. However for some situations Healthmap and Twitter feed have been found to outperform physical indicators.
- Experiments with Opentable reservation data shows that there is some perceptible signal embedded w.r.t to ILI case counts.
Future Work

- Reconcile these phenomenological models with true epidemiological models.
- Explore inter-country characteristics of ILI profiles.
Acknowledgements

Supported by the Intelligence Advanced Research Projects Activity (IARPA) via Department of Interior National Business Center (DoI/NBC) contract number D12PC000337 and by the Defense Threat Reduction agency (DTRA) via the CNIMS Contract HDTRA1-11-D-0016-0001. The US Government is authorized to reproduce and distribute reprints of this work for Governmental purposes notwithstanding any copyright annotation thereon.

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Thanks!
Thanks!

Any questions?
References


Appendix: Physical Indicators Collection Framework

GDAS
ftp:ladsweb.nascom.nasa.gov/allData/5/GDAS_0ZF

Weather Processor
Extracts features from sample sites in GSR ILI countries

Time Series
Weather
ILI
Appendix: Accuracy of different methods for different countries

Figure 4: Accuracy of different methods for each country.