Improving Disease Outbreak Forecasting Models for efficient targeting of Public Health Resources

CPRsouth 2017
Yangon, Myanmar
Sep 01st, 2017

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This work was carried out with the aid of a grant from the International Development Research Centre, Canada and the Department for International Development UK.
A multi-disciplinary, multi-stakeholder collaborative effort

- Tripartite collaboration with Epidemiology Unit of the Ministry of Health, University of Moratuwa, and LIRNEasia
  - Epidemiology Unit provides expertise on epidemiology/entomology as well as case data (Key Collaborators: Dr. Hasitha Tissera, Dr. Azhar Ghouse)
  - University of Moratuwa provides expertise on computational modeling (Key Collaborator: Dr. Shehan Perera)
  - LIRNEasia provides CDR data as well as research expertise

- Research is funded by IDRC, Canada and the Senate Research Committee of University of Moratuwa
Dengue - A global menace & the rising trend in Sri Lanka

● WHO estimates 50-100 million infections globally every year
  ○ Endemic in over 100 countries (including Sri Lanka)

● Main vectors: Aedes aegypti and Aedes albopictus (Monath, 1994)
  ○ Aedes mosquitoes have a limited spatial range (Muir & Kay, 1998)
  ○ Human mobility plays a critical role in introducing dengue across regions (Stoddard et. al, 2009; Wesolowski et. al 2015)

● 2017 saw the worst ever dengue epidemic in Sri Lanka
  ○ 125,387 cases reported up to August
  ○ Over 200 deaths
  ○ ~ 29k cases in 2015
  ○ ~ 55k in 2016, a record at the time
  ○ Official reported statistics from Epidemiology Unit - Ministry of Health (2017)

● Need better predictions for efficient prevention & control
What can we do with better predictions?

- Developing countries have limited resources to effectively prevent or control an outbreak
  - With our predictive models, we can predict where the next outbreak will most likely occur

Limited Public Health Sector Resources: In Sri Lanka, during an outbreak, security forces are called in to help with dengue prevention and control due to resource shortages - Source: http://www.army.lk/files_eng/Centraldengue_1.jpg
What are the policy questions we are trying to answer?

- Can we use Call Detail Records (CDR) to derive human mobility models & apply for disease outbreak predictions?
- Can disease outbreak forecasts be used for
  a. allocating public health sector resources efficiently?
  b. formulating epidemic disease policy?
- Can we extend this work to predict other infectious disease outbreaks as well?
  - The severe dengue epidemic in 2017 would not have benefited much from forecasting beforehand
  - What if we get hit by a different infectious disease like Zika or Chikungunya?
Methodology: Forecasting models using big data & machine learning

- Different human mobility models derived from CDRs
  - Tried a probabilistic model, a trip based model & a risk based model
  - We wanted to know which mobility model predicts best
- Evaluated multiple machine learning methods as well
  - Literature did not point towards a conclusive single technique
  - Evaluated Support Vector Regression, Neural Networks, XGBoost and Random Forests
  - Predict dengue incidence 2 weeks ahead
  - Lot of feature engineering and tuning in between data collection & prediction
- All models were run with/without mobility as an input
- Used evolutionary algorithms to improve feature selection
- RMSE and $R^2$ to measure model performance

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}
\]

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}
\]
How can we use big data to infer human movement patterns?

- Mobile Network Big Data (MNBD) can provide detailed information on human mobility patterns

- Structure of a Call Detail Record

<table>
<thead>
<tr>
<th>Calling Party Number</th>
<th>Called Party Number</th>
<th>Caller Cell ID</th>
<th>Call Time</th>
<th>Call Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>A24BC1571X</td>
<td>B321SG141X</td>
<td>3134</td>
<td>13-04-2013 17:42:14</td>
<td>00:03:35</td>
</tr>
</tbody>
</table>

- Records of all calls made and received by a person created mainly for the purposes of billing
- The Cell ID in turn has a lat-lon position associated with it

- We used CDR data for more than one year in 2012-2014
  - Covers under 10 million SIMs
  - Nearly 1.5 billion records
Other data sources for the forecasting models

- Weekly dengue cases for a Medical Officer of Health (MOH) division (2012 to 2014)
- Temperature & rainfall data (22 stations)
  - From NOAA Integrated Surface Data (ISD)
  - Projected to weekly average estimate for an MOH
- Mean Normalized Difference Vegetation index (NDVI)
  - Using MODIS satellite data from NASA
  - Done by a colleague at U. of Moratuwa

Right: Mean Vegetation Index for given MOH
CDR based human mobility models improve predictive performance

- Verified correlation of each input vs dengue incidence
  - Mobility has very high correlation - Second most highly correlated after past dengue cases

- In preliminary evaluations, mobility improved model performance consistently, even if marginal in some cases

<table>
<thead>
<tr>
<th>Model (Before GA Optimization)</th>
<th>R² Without Mobility</th>
<th>R² With Mobility</th>
<th>RMSE Without Mobility</th>
<th>RMSE With Mobility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forests</td>
<td>0.628</td>
<td>0.639</td>
<td>6.907</td>
<td>6.812</td>
</tr>
<tr>
<td>Neural Networks</td>
<td>0.063</td>
<td>0.335</td>
<td>10.966</td>
<td>9.239</td>
</tr>
<tr>
<td>XGBoost</td>
<td>0.630</td>
<td>0.640</td>
<td>6.892</td>
<td>6.794</td>
</tr>
<tr>
<td>Support Vector Regression (SVR)</td>
<td>0.680</td>
<td><strong>0.704</strong></td>
<td>6.408</td>
<td><strong>6.170</strong></td>
</tr>
</tbody>
</table>
Prediction curve matches trend, good prediction accuracy

<table>
<thead>
<tr>
<th>Machine Learning Technique</th>
<th>Overall RMSE</th>
<th>Overall $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forests</td>
<td>8.258</td>
<td>0.926</td>
</tr>
<tr>
<td>Neural Networks</td>
<td>12.154</td>
<td>0.839</td>
</tr>
<tr>
<td>XGBoost</td>
<td>7.852</td>
<td>0.933</td>
</tr>
<tr>
<td>SVR</td>
<td>8.618</td>
<td>0.919</td>
</tr>
</tbody>
</table>

Final predictions done for 20 MOH divisions
- Used genetic algorithms to improve results further
- XGBoost showed best results

Prediction for MC-Colombo for year 2014
Can repurpose our models with minimum modifications

- Dengue case data is used as a response variable for these models, while past case data is provided as an input for the model.
- For vector-borne infectious diseases like zika or chikungunya, we simply need to replace dengue data with other disease data and retrain with minimal effort.
  - Zika, chikungunya are transmitted by the same aedes mosquitoes with very similar characteristics.
- For other infectious diseases, we would have to modify some aspects of the methodology.
  - Different time lags for input features due to different incubation periods of the diseases.
  - Risk scores assigned in the mobility model would change.
Policy findings & recommendations

- CDR is a rich source of data to model human mobility for disease outbreak prediction
  - CDR might have issues of representativity compared to one time surveys, but still highly useful (Consider high resolution photo vs. low resolution video)
  - Even in regions where the disease is endemic, human mobility is critical for dengue propagation
  - Mobility models should be consumed by the Ministry of Health for formulating public policy on infectious diseases

- Use the disease outbreak forecasts to
  - allocate public health sector resources efficiently
  - formulate epidemic disease policies
Policy findings & recommendations: Cntd.

● Repurpose these models to predict other infectious disease outbreaks
  ○ Sri Lanka is an island which has a single point of entry for most international travellers
  ○ Easier to track and predict outbreaks if an entirely new infectious disease is introduced to the country

● Negotiate data access from mobile operators with the assistance of government organisations to establish a sustainable model to continuously predict outbreaks
Next steps: Risk maps & predictive classification models

- Our work focuses on regression models that attempt to predict the exact number of dengue cases.
- But in order to improve public service delivery, we need risk maps.
- To generate risk maps, we need classification models.
- Next step: Identify risk bands and give our predictions as a risk classification for an MOH division.
  - Simply need to retrain the machine learning models to do classification instead of regression.
  - With risk classification, our models should be able to classify with higher confidence.
  - Easier to visualize and communicate.
  - Easier for public health sector officials to act upon such an output.
References


Thank you