Assignment5_Collaboration

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Kaggle open call project

My handle on Kaggle

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Open competition of interest

I am interested in the Santander Product Recommendation competition. The goal of this competition is to predict whcih product their existing customers will use in the next month based on their past behavior and that of similar customers. To be more specific, given a 1.5 years of customers behavior data from Santander bank as a training data, we need to develop a machine learning model to predict what a customer will buy in addition to what they already had at the last month in the training data.

In order to join the competition and make a submission, I need to go to the Data page to understand and download the dataset. After data cleaning, I probably will conduct some starter/exploratory analysis, such as the distrubition of certain customer attributes (e.g., age, long term deposit etc) across time and some simple but obvious bi-variate correlation between the product choice and certain customer features. Then I probably will consider develop and (re)train a machine learning model majorly based on logistic regression before submitting the predicted test dataset (in .csv) on the submission page.

Explore a dataset on Kaggle —- Emerging Asia country remittance network

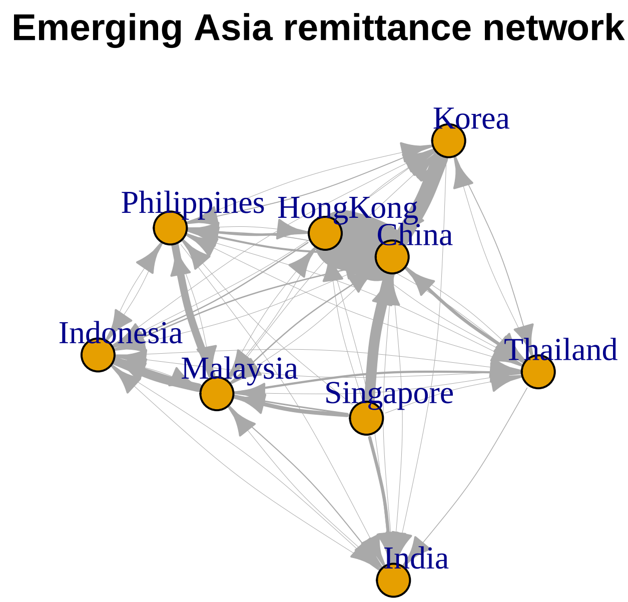
I will explore a bit of the bilateral-remittance dataset published by World Bank. I will focus on depicting the empirical network structure of this remittance relation through a descriptive network chart for Emerging Aisa economies. The thickness of the edge represents the amount of remittance. It shows that the remittance tie between China and Hong Kong is extremely strong (both to and from). Also, the remittance from Korea/Singapore to China is also noticable, while Thailand and india are relatively segregated from the remittance network from other countries. And Singapore seems to serve as a transmission hub between East Asia countries(centered around China) and SOuth East countries (Philippines, Malaysia and Indonesia).

A potential research question related to this database is to study the relationship between this remittance network with trade network of capital flow network among emerging Asia countries and to see whether we could use thes remittance flow data to construct a proxy for variables where high quality data is not available (like capital flow data). However, the current database doesn't publish time series of the bilateral remittance, we probably need to rely on the time dynamics of this network to construct the proxy.

```r
# load in the data
remit = as.data.frame(read.csv("./bilateral-remittance.csv"))
rownames(remit) = remit[,2]
remit[,c(1, 2)] = NULL
country_list = c("China", "India", "Philippines", "Indonesia", "Singapore", "Thailand",
                 "Korea", "Malaysia", "HongKong")
remit_ea = remit[country_list, country_list]
remit_ea$India = as.numeric(levels(remit_ea$India))[remit_ea$India]
```

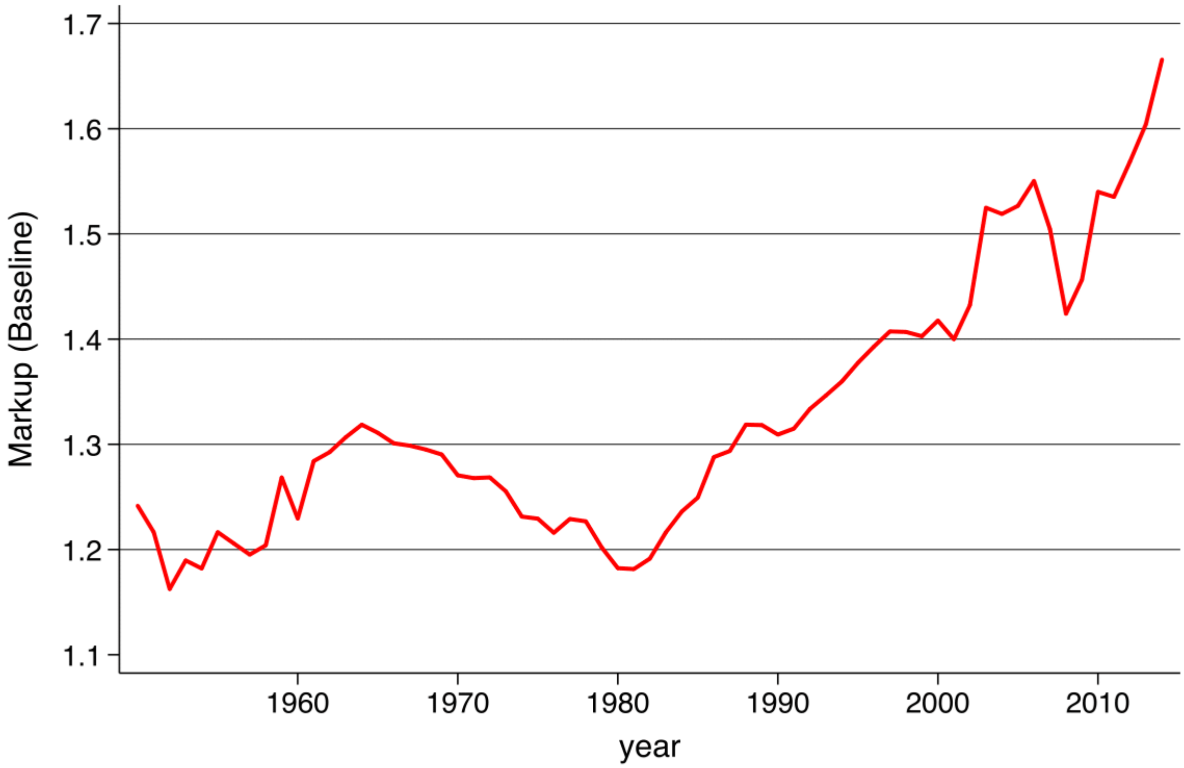
```
## Warning: NAs introduced by coercion
```

```r
#remit_ea[remit_ea == 0] = 1e-10
remit_ea = as.matrix(remit_ea)
#net=graph.adjacency(remit_ea,mode="directed",weighted=TRUE,diag=FALSE)



# Plotting the network graph
set.seed(231)
colourlist <-
  #palette(
  c(
    "#6a3d9a",
    "#1f78b4",
    "#b2df8a",
    "#33a02c",
    "#fb9a99",
    "#e31a1c",
    "#fdbf6f",
    "#ff7f00",
    "#cab2d6"
  )
g <- graph.adjacency(remit_ea, mode = "directed", weighted = T)

#E(g)$width <- E(g)$weight/4.5
E(g)$width <- E(g)$weight/500
E(g)$arrow.size <- .8
g$main <- "Emerging Asia remittance network"
plot(g, vertex.label.dist=2, edge.curved = 0.1)
```



Improving a journal article using human computational techniques

The study I am focusing on in this subsection is a recent NBER working paper "The Rise of Market Power and the Macroeconomic Implications" by Jan De Loecker and Jan Eeckhout. The main empirical findings documented in this study is that there has been a steady increasing trend in US companies' markup since 1980s from 1.18 to 1.67 in 2014. The paper is calculating the makrup using a production function approach from the supply side via comparing the ratio of cost of goods sold to total sales weighted by the output elasiticity of variable inputs. However, one piece that is missing from the study (authors also pointed out explicitly in the study) is an analysis on where this emerging markup origins from. Even though from the title of the paper, authors assume the rising markup is an indication of rising market power, I believe the origin of this surging markup needs more detailed analysis where we could utilize some human computational techniques.



Alternative homework: InfluezaNet

This study will focus on comparing and constrasting among InfluenzaNet, Google flu and traditional tracking system (physician-based reporting system) and discuss a bit on the potential caveats facing respective systems when there is a counterfactual flu outbreak.

Tracking system comparison

We will conduct the comparison from the following three aspects: source of data & data collection process, tracking design & associated costs and potential deficiency in the system.

Data sources & data collection process

The data recorded in the tradtional physician-based surveillance system relies on the incidence of provision of health care in primary health care practices, namely, only patients who uses the health care services will be recorded and reported in the system. While the InfluenzaNet will recruit participants from the general population after they completed an intake questionaire that includes certain demographic and lifestyle questions. After the registration, participants will receive a weekly newsletter, requesting a questionire to be filled regarding certain symptoms they might experience during the last week. They could also create account for other related personnels on their behalf, like parents for children etc. To motivate the patients, the organizer will provide the most up-to-date information on the current dynamic of Ifluenza-like-illness (ILI hereafter). Google, in 2008, proposed an innovative “Nowcasting” system of ILIs tracking system according to people’s google search on ILIs related information, based on the assumption that these searches have a close relation with whether the people who search them are potentailly sick.

In terms of coverage of data, we see an ascending scale from physician-based reporting to InfluenzaNet then to Google Flue tacking. Besides scale, there are also some distinct differences among the three of them. Physician-based reporting and Google flu data seem to have a "self-selecting" nature in them, in the sense that the primary sources of their data might have already been infected with the ILIs while InfluenzaNet is more like a random controlled trials that actually would exclude participants who have already been infected with ILIs from their database.

Also, a quite significant difference among them is that Google flu/physician-based system are using a "Revealed preference" data while InfluenzaNet is using a "Reported preference" data, i.e. data in Google flu and physician-based tracking system will directly observe people's behavior, not suffering from certain reporting/survey bias issue. (This in no sense means they are better, they actually have very severe issues of their own, as I will show later)

Tracking design & associated costs

Among these three surveillance systems, physician-based tracking system is the most straightforward — simply based on the counting of report filed by health care service practioners, though suffering from quite several caveats (we leave the discussion on this in the last subsection), the simplicity in the tracking design doesn't necessarily compromises the quality of the data, given it's reported by expertised professionals. InfluenzaNet's design has more random-control features in it compared to physician-based reporting —- The extensive set of information they collected in the intake questionaires, including demographic information, medical history and life-styles will help them to filter and weight the data in their construction of more aggregated indicator (e.g., regional/national attack rate). Google flu is actually using the following model:

$$logit(P) = \beta_0 + \beta_1 logit(Q) + \epsilon$$

where P is the physician-based reporting, and Q is one of the 50 million time series of Google common query with weekly frequency. Then they are using the historical data to train the model in order to select the queries/query that fitts the physician-based reporting the best and use these queries to "Nowcast" the trend of ILIs. In terms of cost, Google Flu trend definitely stands out in its cost efficieny given its data are generated at an almost zero variable/marginal cost per data entry while InfluenzaNet might incurr considerable amount of financial needs, like costs associated with participants recruitment, campaign costs (campaign that promotes the InfluenzaNet), educational purpose related costs and website/staff maintainance costs.

Potential errors

All three tracking system will suffer from non-negligible while different types of potential errors. The biggest potential risk associated with Physician-based reporting is in its coverage and selection bias — not everyone infected will pay a visit to health care provider. Actually, the fact that many of them wouldn't use health-care service will be highly correlated with the outbreak of the ILIs. Also, the accessibility of health care services is proved to be correlated with many demographic/economic.geographical variables, leading to the potential biased estimation of the dynamic of ILIs.

While one of InlfuenzaNet's primary design motivations is to remedy the deficiency in physician-based system We just mentioned, itself also suffers from certain selection bias in randomizing, for example, the younger and older population (two tails of population distribution) are significantly under-represented in their survey system. Given that these two groups of population are actually more vulnerable to ILIs based on their average immune system robustness, under-representation of them in the tracking system will significantly harness the accuracy of its estimates. Also, one challenge facing InfluenzaNet is that how to account for differential participants (e.g., participants might have differential involvment in the weekly survey, therefore how to weight responses with different response rate). All the potential biasedness issue associated with survey methods will apply to InfluenzaNet system.

After success in estimation accuracy for sometime, Google flu fails tragically at predicting the 2013 flu peak by missing it by 140%!. Some research shows a persistent pattern with Google Flu's performance: performing well for 2-3 years then failing significantly. A biggeset caveat lies in the overfitting of their algorithm to some seasonal terms totally unrelated to flu. Because flu outbreak may possesses very strong seasonal patterns, its coincidence with other highly-seasonal query doesn't necessarily predict its outbreak. Such type of machine learning model would require very frequent revision to avoid over-fitting issue. Aparts from all the discussion, we need to remind us that both InfluenzaNet and Google Flu will highly depend on the fact that data sources will have access to Internet.

A counterfacutal ILI outbreak scenario

After conparing the three tracking system above, let's now consider a counterfactual ILI outbreak scenario and analyze how each system will potentailly fail. In order to push these three systems to break, we firstly define certain characters of this counterfactual outbreak:

1) This counterfactual outbreak is starting from under-developed countries where internet access and physician services are very limited

2) This counterfactual outbreak is drastically different from historical ILIs pattern, in that the "dormant period" from infection to emergence of symptoms will be longer.

According to our first setup of these counterfactual outbreak, the lack of medical service access in these under-developed countries will severly harness the timeliness and reliability of the pyhsician-based reporting system. Though organizations like Doctor Without Borders would be able to partially alleviate the situations, it's certain possible that the population in these under-developed countries will be distributed in a macro-disaggregated but locally concentrated pattern, which will significantly dilute the "firing power" of these organizations, therefore the quality of pyhsician-based reporting system. Given the fact that Internet access is also poor in these counterfactual case, both InfluenzaNet and Google flu will not be able to help much. Let alone the fact that InfluenzaNet, especially, will depend on a well-established social infrastructures (e.g., government, network of NGOs) to operate efficiently.

Even if we assume Internet access is not a problem (e.g., Facebook's design of Internet in the air in India), our second setup in the counterfactual design might harness the effectiveness of Google flu tracking system. As we discussed above, Google flu's algorithm is significantly depending on the historical data where it's been trained. Given this counterfactual outbreak is drastically different from historical ILIs' patterns with a much longer dormant period, it's possible that when people began to search terms related to the symptoms, the infected population has alreday been much larger. The Nowcasting feature of Google flu might not be that "Now" anymore.

To conclude, no tracking system is perfect, and as our counterfactual case shows that under certain assumptions, all of them could potentially fail significantly. However, from physician-based reporting to InfluenzaNet to Google Flu shows a clear evolutionary trend in ILIs tracking system, with more integration of different databases and better designed algorithm, big data techniques will certainly be helpful in helping estimating and predicting the ILIs outbreaks in the future.