

# Case Study: Modelling the Impact of Social Influence on Individual's' Vaccination Decision Making

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## **Human Behaviour Concerning the Spread of infectious diseases.**

Societies have been confronted with infectious diseases throughout history. In medieval times european countries experienced the most deadly disease outbreak in history, the bubonic plague coined Black Death. More recently, wide scale epidemics such as the outbreak of Ebola in West Africa resulted in significant morbidity and mortality throughout these areas. Human behaviour is intrinsically linked to the outbreak of diseases. For example, during the Black Death, accounts from Boccaccio recorded individuals isolating themselves as a quarantine attempt. Outbreaks of SARS in 2003 saw people adopt face masks and change their modes of transport. Because individual behaviour fundamentally affects the spread and impact of infectious diseases there is a desire to model complex human behaviour in a disease epidemic scenario. Computational Modelling provides a solution to model the social systems in disease epidemics and analyse how human behaviour can affect disease spread and transmission.

## **Anti Vaccine Movements and Behaviour**

An important prevention method for disease epidemics is vaccination. The opposition to vaccination has been prevalent since the first enforcements of compulsory vaccinations. In 1881 the Dutch Association to Oppose Compulsory Vaccination was formed in response to compulsory vaccination of school children. At the same time many parents faced prosecution in england for failing to comply with compulsory vaccination of small pox in infants. Recently the medical community has become increasingly concerned with the growth in anti vaccination ideology. While some diseases have been successfully eradicated through vaccination such as smallpox in 1980, resistance to the uptake of some vaccinations have resulted in such low levels of immunity within communities that outbreaks have been possible, such as the recent outbreaks in measles and whooping cough. Reasons for anti vaccination views vary, some are motivated by religion and while others see vaccination as a violation of human liberty.

As the decision to vaccinate is primarily a complex human behaviour in a disease epidemic scenario efforts to apply computational model to this behaviour can be useful in evaluating the impact of anti vaccination views on the spread and affect of infectious diseases.

The following sections present my modified model of an existing model (S. Xia, J. Liu, 2013) for assessing the impact of individual decisions to vaccinate on disease spread including communal stance on vaccination as a social pressure that affects individuals decisions. The model provides a solution combining game theory analysis and social impact theory (SIT) in agents of a social network graph. The implementation can be found at <https://github.com/wizzfizz94/vaccination-impact-model> .

## Modelling Individual's Decisions to Vaccinate

In this model the individual's decision is modelled off game theory analysis. This approach uses formalised logic to evaluate an individual's decision dependant on its environment. In this case the individual's environment is described by the social associations with other individuals. The evaluation attempts to achieve some goal. In this case the goal is minimizing the cost associated with vaccination.

Faced with an infectious disease an individual's decision to vaccinate is dependent on many factors. Firstly human decisions are somewhat based in rational conclusions. Thus an individual is likely to access both the cost of being vaccinated  $c_{vac}$  and the cost of not vaccinating  $c_{inf}$  during an epidemic. The cost of being vaccinated can be attributed to any side-effects, expenses or distress the individual associates with being vaccinated and is assumed constant. Similarly  $c_{inf}$  relates to all detrimental effects to the individual on being infected. In rational evaluation the individual also calculates their perceived risk of infection  $\hat{\lambda}_i$ . This is dependant on their observations of the decisions of social relations to vaccinate and can be calculated for an individual  $i$  as;

$$\hat{\lambda}_i = \hat{\beta} \frac{N_i^{non}}{(N_i^{non} + N_i^{vac})}$$

Where  $N_i^{non}$  and  $N_i^{vac}$  are the number of social relations that have decided not to vaccinate and the number that have decided to vaccinate respectfully. Note also that  $\hat{\beta}$  denotes the perceived infection rate. In this model an individual's decisions  $\sigma_i$  can be 1 or -1 where is equivalent to deciding to vaccinate or not vaccinate respectfully. The cost of a decision based only on rationale  $\tilde{\sigma}_i$  can be calculated as;

$$C_i(\tilde{\sigma}_i) = (1 + \tilde{\sigma}_i)r + (1 - \tilde{\sigma}_i)\hat{\lambda}_i$$

Where  $r = c_{vac}/c_{inf}$  is the cost ratio of vaccination. Given that individuals attempt to minimise cost an individual's rational decision follows these rules;

$$\tilde{\sigma}_i = \begin{cases} +1, & \text{if } r < \hat{\lambda}_i \\ -1, & \text{if } r > \hat{\lambda}_i \\ \text{unchanged,} & \text{if } r = \hat{\lambda}_i \end{cases}$$

This process is iteratively evaluated for each individual in the population until the decision choices have stabilized and there is no incentive for decision change. Once this is achieved individual's decisions are subjected to social pressures. This idea is modeled off the concept of SIT which in general states that an individual's behaviour is influenced by the social structure of their environment. In this case behavior refers to the individual's decisions on vaccination and social influences for an individual are evaluated by considering the decisions of their social acquaintances and the degree of influence of these social relations given by  $w_{ij}$  for the relationship between two individuals  $i$  and  $j$ . This takes into that account that certain relations will have a greater effect on an individual's choice than others. For example your mother's decision is more likely to influence you than say your work colleague (hopefully) and thus should be included in the model. Social pressures to vaccinate  $l_i^{vac}$  and to not vaccinate  $l_i^{non}$  for an individual  $i$  can be evaluated as;

$$l_i^{vac} = (N_i^{vac})^{1/2} \sum_{j \in N_i^{vac}} w_{ij}^2$$

$$l_i^{non} = (N_i^{non})^{1/2} \sum_{j \in N_i^{non}} w_{ij}^2$$

The resultant social pressure  $\Delta l_i$  is the normalized difference between the two pressures given by:

$$\Delta l_i = \frac{l_i^{vac} - l_i^{non}}{l_i^{vac} + l_i^{non}}$$

The decision of the individual based purely on social pressure  $\hat{\sigma}_i$  is then found following the rule;

$$\hat{\sigma}_i = \begin{cases} +1, & \text{at probability } P(\Delta l_i) \\ -1, & \text{at probability } 1 - P(\Delta l_i) \end{cases}$$

Where  $P(\Delta l_i)$  is calculated using the the Fermi function;

$$P(\Delta l_i) = \frac{1}{1 + \exp(-\alpha \Delta l_i)}$$

Note the constant  $\alpha$ . This affects the ease for an individual's decision to change. Finally an individual's final decision is decided with the rule;

$$\sigma_i = \begin{cases} \tilde{\sigma}_i, & \text{at probability } 1 - p \\ \hat{\sigma}_i, & \text{at probability } p \end{cases}$$

Where  $p$  defines how inclined an individual is to follow social pressures. The higher the  $p$  value the more socially influenced the individual is. My model provides an improvement by modelling social influence  $p$  and weights of individual relations with a binomial distribution. This allows the variation of behaviour of individuals in response to social pressures and variation of relationship influences to be taken into account.

## Modelling the Impact of Vaccination Decisions

Impact of vaccination decisions are measured in two ways. Firstly vaccination coverage describes the proportion of the population immunized from the disease through vaccination. This provides a measure of vulnerability of a population to disease epidemics and a measure of how detrimental this epidemics would be. We are also interested in observing how vaccine coverage effects infection rates over the epidemic. In simulating epidemic impact dynamically a standard SIR model can be used. This partitions the population into three categories Susceptible (S), Infected (I) and Recovered (R). The overall population is given by the sum of these  $N = S + I + R$ . For each iteration changes to these populations can be described using the following differential equations;

$$\frac{dS}{dt} = -\lambda S$$

$$\frac{dI}{dt} = \lambda S - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

Each iteration  $\lambda S$  people become infected.  $\lambda$  denotes the risk of infection for susceptible individuals and is proportional to the infected population size and the disease transmission rate. This is given by the equation below.

$$\lambda = \beta \frac{I}{N}$$

$\gamma$  describes the recovery rate for infected individuals while  $\beta$  defines the transmission rate of the disease. Recovered individuals are assumed to be immunized to the disease through

exposure and transition to the R population at amount  $\gamma I$  per iteration.  $\beta$  can be found by the following expression, where  $R_0$  defines the threshold for disease transmission.

$$\beta = R_0 \gamma$$

For my experiments the recovery rate  $\gamma$  and  $R_0$  were kept constant at 0.312 and 1.6 respectively, as these properties are dependant on the diseases biological characteristics. Vaccination coverage  $0_{vac}$  is given by the following, Where  $N_{vac}$  is the proportion of the population vaccinated;

$$0_{vac} = \frac{N_{vac}}{N}$$

Using the above model we can derive the risk of infection and determine the rate of changes in SIR populations. This is useful as it allows grasp at what rate and degree the epidemic will spread through the population.

## Modelling the Social Network

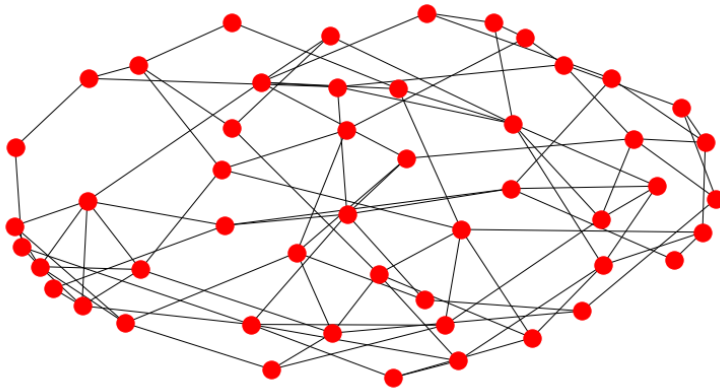
The social relations described above are modelled by a graph between individuals. The graph represents the social network of the population. Weights are assigned to the edges which define the degree of influence of a social relation. For simplicity it assumed the influence between individuals sharing a relationship is equal, this allows the graph to be non-directed.

The study (S. Xia, J. Liu, 2013) fails to describe the type of graph used to form the social network. Because of this i looked at a variety of graph structures used for modelling social networks.

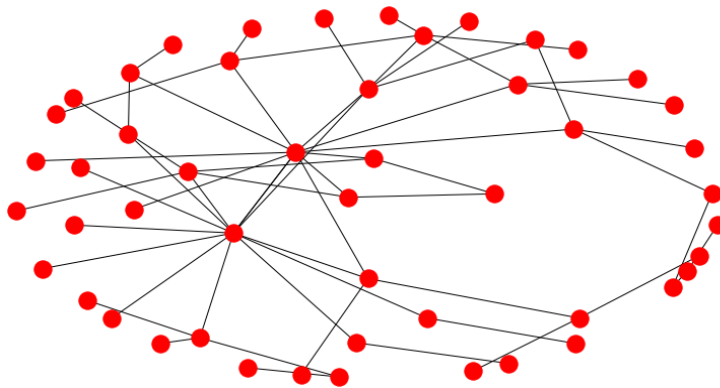
Much research has been done into social networks in which three recurring properties have been observed. Firstly social networks have what is know as “small world” properties. This shows that apparently distant individuals in a social networks are actually related via short chains between intermediate associations. The chain lengths are what is known as “degrees of separation” in social networks. Secondly social networks show properties of clustering. Mathematically this means that the probability of two individuals being associated increases when they both are associated with more of the same individuals in the network. Lastly social networks usually display the property of a skewed degree distribution in their nodes. The degree of a node being the number of edges connected to it. An example representing this situation in a global social network would be the vast number of relations a politician would have compared to say a farmer.

With these properties in mind various algorithms have been developed to generate random graphs that support these characteristics. These random graphs are useful in computational modeling involving social networks at they allow realistic social environments to be replicated, increasing the validity of model results. In my experiments i modified the experiments to use three different random graph generators for social networks. These were Watts–Strogatz,

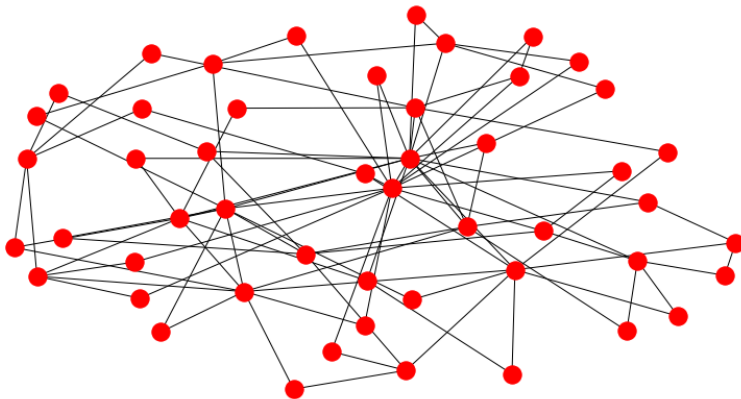
scale free and random graph generators. Examples of each ones resultant graphs can be seen in Figures 1, 2 and 3 respectively.



*Figure 1. Watts–Strogatz Graph*



*Figure 2. Scale Free Graph*



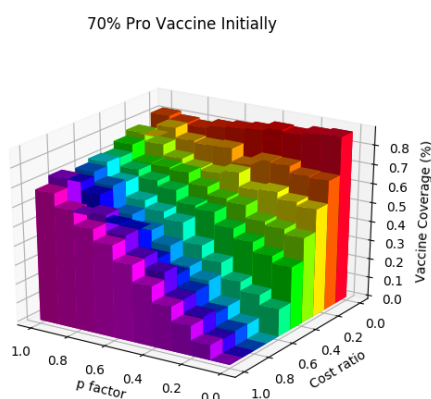
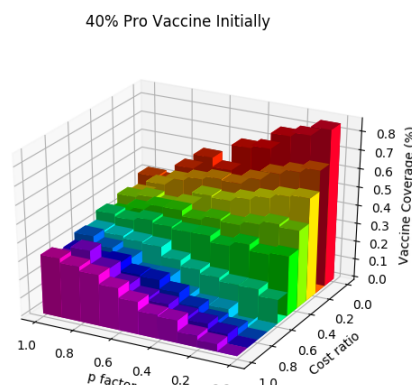
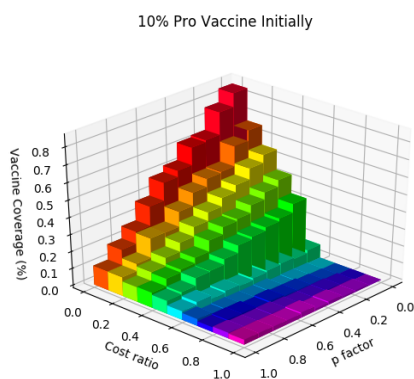
*Figure 3. Barabasi Albert Graph*

The Watts–Strogatz Graph is one of the first to be used to model social networking. Its effectively models characteristics of clustering, note the clustered node areas seen in Figure 1. It also effectively produces degrees of separation, note the top left corner of the figure showing a single chain linking two large portions of the graph. However it fails to introduce skewed degree distributions, note the fairly even degrees of the nodes in the graph. In contrast the Scale Free Graph has skewed degree distribution, and high clustering. Note the clusters forming off individual nodes in Figure 2. Figure 3. shows the Barabasi Albert Graph.

This graph produces effective degree distribution but lacks clustering characteristics. Both Scale Free and Barabasi Albert graphs produce chains of separation as seen above. Because Scale Free graphs maintain all the desired properties of social networks they are the cutting edge of social network modelling. However the correct graph is also dependant on the social environment we are modelling. Modelling of close knit social communities, such as an organization or school environment, have more uniform degree distributions. In these cases Watts–Strogatz and Barabasi Albert graphs could produce more accurate model results for these environments. Since these experiments will consider a small population (less than a thousand) the chosen graph was Watts–Strogatz as this reduced degree distribution skew and still maintained clustering characteristics.

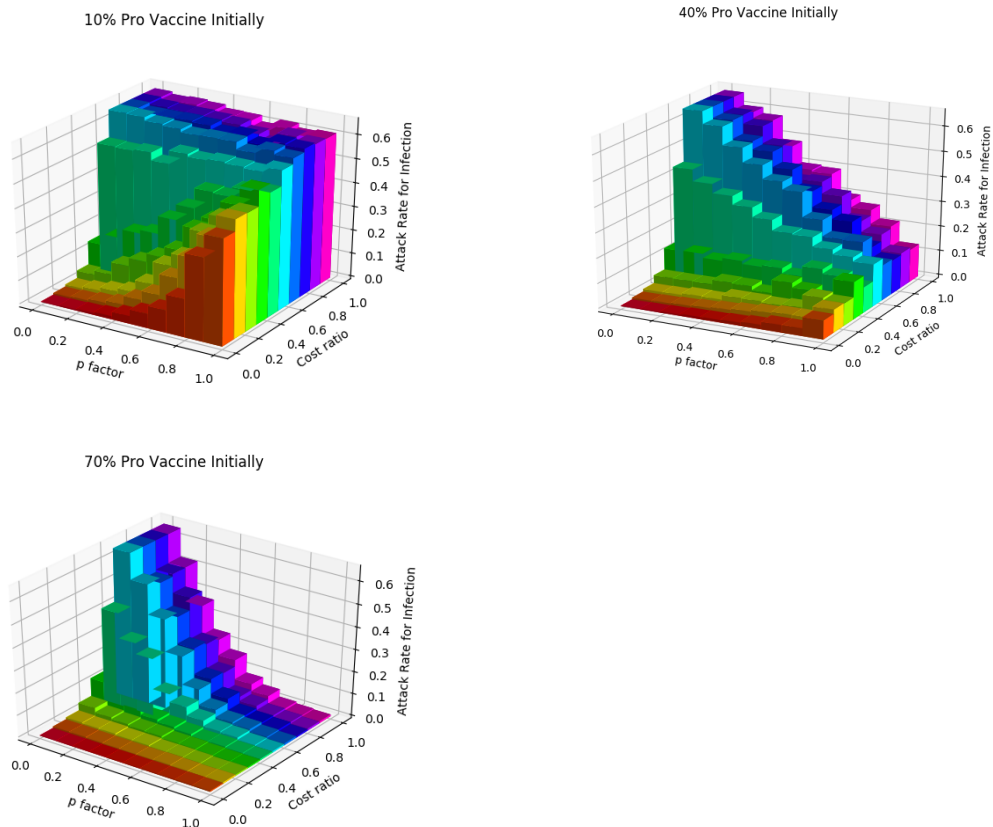
## Experiments and Results

Following the original experiment, tests were done to measure the effect of social influences on vaccine coverage and infection rates during the epidemic. Figures 4 to 6 show how vaccination coverage varies at different cost ratios and social influence levels for different initial vaccine approval levels. We see that at 10% initial vaccine approval vaccine coverage is high only when both the cost of infection is great and social influence is low. As initial vaccine approval rises to 40% and 70% the overall vaccination coverage improves. This can be accredited to pro vaccine decisions in the social network have an influence on swaying anti vaccine individuals. Similarly we see as social influence increases at higher initial vaccination approval rates vaccine coverage increases.



Figures 4, 5 and 6 going clockwise.

For measuring impact on infection rates the above SIR model is applied, again at varying cost ratios and social influence levels. Figures 7 to 9 show the effect of attack rates for infection. This is the number of individuals infected by the disease over the epidemic as a percentage of the population. We see with 10% initial pro vaccination (Figure 7) the infection rate is very high. Only when individuals aren't swayed by influences (i.e.  $P$  is close to zero) do we see a low attack rate. As the initial pro vaccine percentage increases in Figures 8 and 9 we see social influence having a reducing effect on attack levels, as more individuals are swayed by community opinion to be pro vaccine. In Figure 9 we see that attack rates are only high when the cost of vaccinating is high and the influence from social pressures are low.



Figures 7, 8 and 9 going clockwise

## References

A. B. Downey, *Think complexity*: Beijing: OReilly, 2012.

"Anti-vaccinationists past and present," *Bmj*, vol. 325, no. 7361, 2002.

"Anti-vaccination movements and their interpretations." [Online]. Available: [http://www.bing.com/cr?IG=D352F1FDCD1748EAB96E571529EC9704&CID=130ECFD0A7276D7E1589C55EA6216CD8&rd=1&h=EC1hUZLDI0euN3d8dVyW0R0cX\\_w4b119kBxGULI85U&v=1&r=http%3a%2f%2fwww.sciencedirect.com%2fscience%2farticle%2fprii%2fS0277953605003047&p=DevEx,5063.1](http://www.bing.com/cr?IG=D352F1FDCD1748EAB96E571529EC9704&CID=130ECFD0A7276D7E1589C55EA6216CD8&rd=1&h=EC1hUZLDI0euN3d8dVyW0R0cX_w4b119kBxGULI85U&v=1&r=http%3a%2f%2fwww.sciencedirect.com%2fscience%2farticle%2fprii%2fS0277953605003047&p=DevEx,5063.1). [Accessed: 26-May-2017].



"Immunization coverage," World Health Organization. [Online]. Available: <http://www.who.int/mediacentre/factsheets/fs378/en/>. [Accessed: 26-May-2017].

"Impact of anti-vaccine movements on pertussis control: the ..." [Online]. Available: [http://www.bing.com/cr?IG=D1555D7BAA5B46A8A68AD8445AF6251B&CID=3FF6C850CCBD614A09C7C2DECDBB60C2&rd=1&h=jhlF7NzYyUgQdUS3LLp\\_6LjcFCYQJ5Wj4Yg7lqGRchU&v=1&r=htt%3a%2f%2fwww.sciencedirect.com%2fscience%2farticle%2fpii%2fS0140673697043341&p=DevEx,5063.1](http://www.bing.com/cr?IG=D1555D7BAA5B46A8A68AD8445AF6251B&CID=3FF6C850CCBD614A09C7C2DECDBB60C2&rd=1&h=jhlF7NzYyUgQdUS3LLp_6LjcFCYQJ5Wj4Yg7lqGRchU&v=1&r=htt%3a%2f%2fwww.sciencedirect.com%2fscience%2farticle%2fpii%2fS0140673697043341&p=DevEx,5063.1). [Accessed: 26-May-2017].

I. Staff, "Game Theory," Investopedia, 15-Apr-2016. [Online]. Available: <http://www.investopedia.com/terms/g/gametheory.asp>. [Accessed: 26-May-2017].

"Modeling the Effects of Vaccination and Treatment on ..." [Online]. Available: <https://www.bing.com/cr?IG=CFBC0C3A389C456D888478E4782193BA&CID=11597B24A0A06CE83F5671AAA1A66D92&rd=1&h=wWRwQDSwFMehRNAqMxB3lHja9Br743UkkzgigjrXpZM&v=1&r=https%3a%2f%2fink.springer.com%2farticle%2f10.1208%2fs12248-011-9284-7&p=DevEx,5061.1>. [Accessed: 26-May-2017].

"The History Of Vaccines And Immunization: Familiar ..." [Online]. Available: <http://www.bing.com/cr?IG=9D986BF3C00D470A9BF08A2816FA999E&CID=04DB65D412006E5D384A6F5A13066F3F&rd=1&h=Rk-gbTxD1zttwx2IaQgPsj1a-300X5jQwaLiVA3JJTk&v=1&r=htt%3a%2f%2fcontent.healthaffairs.org%2fcontent%2f24%2f3%2f611.full&p=DevEx,5065.1>. [Accessed: 26-May-2017].

"The SIR Model for Spread of Disease - The Differential Equation Model," The SIR Model for Spread of Disease - The Differential Equation Model | Mathematical Association of America. [Online]. Available: <http://www.maa.org/press/periodicals/loci/joma/the-sir-model-for-spread-of-disease-the-differential-equation-model>. [Accessed: 26-May-2017].

S. Funk, M. Salathé, and V. A. A. Jansen, "Modelling the influence of human behaviour on the spread of infectious diseases: a review," *Journal of The Royal Society Interface*, 26-May-2010. [Online]. Available: <http://rsif.royalsocietypublishing.org/content/early/2010/05/25/rsif.2010.0142.short>. [Accessed: 26-May-2017].

S. Xia and J. Liu, "A Computational Approach to Characterizing the Impact of Social Influence on Individuals' Vaccination Decision Making," *PLoS ONE*, vol. 8, no. 4, Sep. 2013.