Network Diffusion of Innovations in R: Introducing **netdiffuseR**



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Acknowledgements



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netdiffuseR has benefited from input provided by participants of the Center for Applied Network Analysis (CANA), and the Computational Social Science Lab (CSSL) at the University of Southern California.

netdiffuseR's original code was developed by **Thomas Valente**, improved by **Stephanie Dyal** and **Timothy Hayes**, and extended by **George Vega Yon**.

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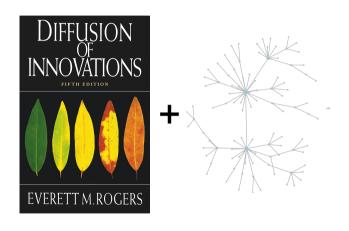




Network Diffusion of Innovations

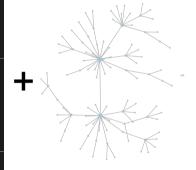


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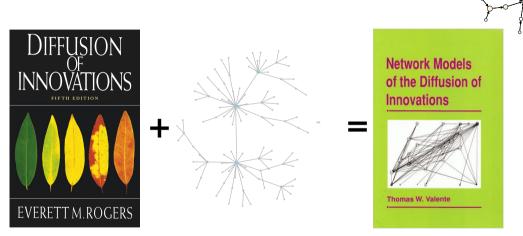








Network Diffusion of Innovations



So what is Network Diffusion of Innovations anyway?

Network Diffusion of Innovations



• Tries to explain how new ideas and practices (innovations) spread within and between communities.



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- More complex than $contagion \implies$ a single tie is no longer enough for an innovation to spread across a social system.
- We think of this in terms of adoption thresholds and social exposure.

Network Diffusion of Innovations



The basic idea

• Network thresholds (Valente, 1995), τ , are defined as the required proportion or number of neighbors that leads you to adopt a particular behavior (innovation), a=1. In (very) general terms

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Where E_i is i's exposure to the innovation and **X** is the adjacency matrix (the network).

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So now, what is **netdiffuseR**?



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netdiffuseR is an R package that

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- Can handle big graphs, more than 4 billion elements adjacency matrix (PR for RcppArmadillo),
- Already on CRAN (2 iterations) with 700 downloads since its first version, Feb 2016,
- A lot of features to make it easy to read network (dynamic) data, making it a nice companion of other net packages.



netdiffuseR distributes classical diffusion of innovations datasets:

| | Medical Innovation | Brazilian Farmers | Korean Family Planning |
|---------------------|---------------------------|--------------------------|-------------------------|
| Country | USA | Brazil | Korea |
| N Respondents | 125 Doctors | 692 Farmers | 1,047 Women |
| N Communities | 4 | 11 | 25 |
| Innovation | Tetracycline | Hybrid Corn Seed | Family Planning |
| Time for Diffusion | 18 Months | 20 Years | 11 Years |
| Year Data Collected | 1955-1956 | 1966 | 1973 |
| Ave. Time to 0.50 | 6 | 16 | 7 |
| Highest Saturation | 0.89 | 0.98 | 0.83 |
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Very nice... But it's better to show it with examples!

The basics: Reading data



```
library(netdiffuseR)
print(head(fakesurveyDyn))
##
     id toa group net1 net2 net3 age gender
      1 1991
                     NΑ
                               NΑ
                                   30
      2 1990
                               NA 35
                    NA 2 NA 31
      3 1991
                           5 NA 30
      4 1990
                                3
                                   40
      5 1991
## 6
     1 1991
##
                                                   note time
## 1
                             First wave: No nominations 1990
## 2
                              First wave: Nothing weird 1990
## 3
                     First wave: Only nominates in net2 1990
## 4 First wave: Nominates someone who wasn't interview 1990
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                          4 3
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                                  40
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                  First wave: Only nominates outsiders 1990
```

We can use the survey_to_diffnet function!

The basics: Reading data



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```
mydiffnet <- survey_to_diffnet(</pre>
 fakesurvevDvn.
 idvar = "id".
                                 # Id of each vertex
 netvars = c("net1", "net2", "net3"), # Net nominations (e.g. 'name 3 closest friends')
 toavar = "toa".
                                     # Time of Adoption
                                     # Group (e.g. neighbor, village, etc.)
 groupvar = "group",
 timevar = "time"
                                      # Timestamp
# Print method
mydiffnet
## Dynamic network of class -diffnet-
## # of nodes : 9 (101, 102, 103, 104, 105, 201, 202, 205, ...)
   # of time periods : 2 (1990 - 1991)
   Type
         : directed
## Final prevalence : 1.00
   Static attributes : -
## Dynamic attributes : group, net1, net2, net3, age, gender, note, time (8)
```

This is a diffnet object.



diffnet are

Lists that contains (among other things):

- A list of dgCMatrix objects (sparse matrices),
- A set of data.frames with vertex attributes,
- An integer vector with times of adoption



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Common methods

Other special functions

```
exposure (threshold) Basic net-diff stats
infection, susceptibility Some friends from epi
  struct_equiv Burt's (1987) structural equivalence
  struct_test We'll see this later...
```



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So, what can we do with diffnet objects?

Nice objects with a lot of methods

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Visualizing Diffusion: plot_diffnet



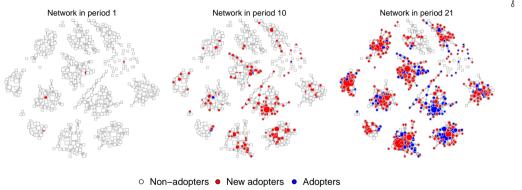
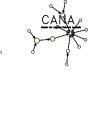


Figure: Diffusion of Hybrid Corn Seed (Brazilian Farmers) - 11 communities/20 years.

Visualizing Diffusion: plot_diffnet2



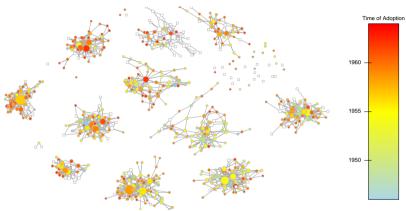


Figure: Diffusion of Hybrid Corn Seed (Brazilian Farmers) - 11 communities/20 years.

Visualizing Diffusion: plot_infectsuscept

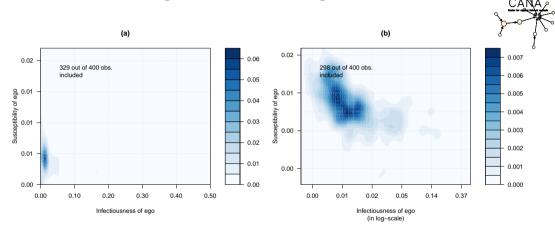


Figure: Joint distribution of Infectiousness and Susceptibility in a random bernoulli diffusion network: (b) shows (a) with log-scale.

Visualizing Diffusion: plot_threshold (a classic)



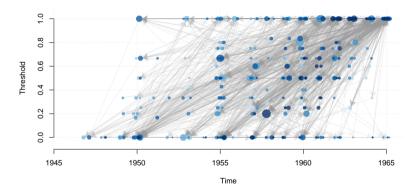


Figure: Adoption thresholds and times of adoption for the Brazilian Farmers: Colors and shapes represent villages. Size is scaled accordingly to each vertex degree.

Visualizing Diffusion: classify_adopters (also a classic)

Very High Thresh

0.29

2.58

2.96

34.19

14.04 8.40 0.57

5.64

1.34

1.53 0.00 0.00

11.65 5.54

5.06 6.21

Farly Adopters

Farly Majority

Late Majority

Laggards

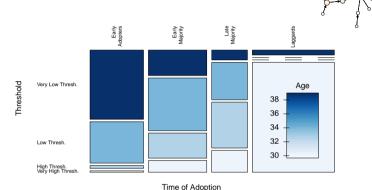


Figure: Adopters classification in the Korean Family data: From the mosaic we can see that in general low threshold levels and early adoption seems to be positively correlated with age.



What about **netdiffuseR** being big??

Visualizing Diffusion: plot_diffnet2 w/ big graph



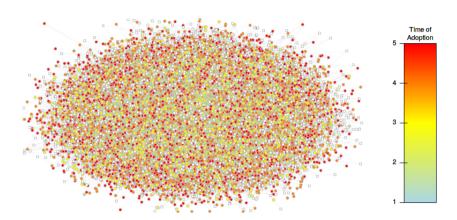


Figure: Random scale-free diffusion network: With 5e4 vertices, diffusion started at the central nodes.

Visualizing Diffusion: plot_diffnet2 + diffmap w/ big graph

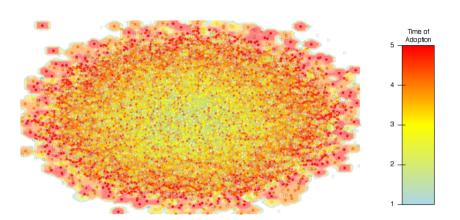


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Visualizing Diffusion: plot_diffnet2 + diffmap w/ big graph

But...be careful with this!

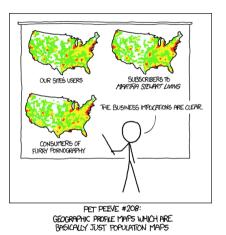


Figure: The heatmaps pitfall (source xkcd.com/1138)

Simulating Diffusion Process: rdiffnet



Simulations are a big thing in **netdiffuseR**. The rdiffnet function features:

```
set.seed(887)
mydn <- rdiffnet(
    n=1e3, t=5, # Number of vertices and time points
    seed.nodes = "random", # Set of initial adopters
    seed.p.adopt = .15, # Proportion of initial adopters
    seed.graph = "small-world", # Baseline graph
    rgraph.args = list(p=4), # Arguments for the rgraph call
    rewire.args = list(algorithm="swap", p=5), # Rewiring args after time 1
    threshold.dist = function(x) runif(1, .4, .8), # Distribution of thresholds
    exposure.args = list(normalized=TRUE) # Args for computing exposures
)</pre>
```

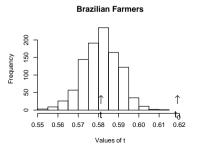
Statistical inference: struct_test

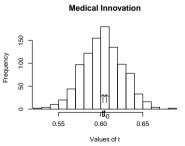
CANA

 $H_0: \mathcal{G} \perp \text{Time of Adoption (random time of adoption)}$

 $H_a: \mathcal{G} \not\perp \text{Time of Adoption (not random time of adoption)}$

| | Korean Family | Brazilian Farmers | Medical Innovation |
|-----------------------------------|---------------|-------------------|--------------------|
| p-val | 0.1440 | 0.0000 | 0.8440 |
| Obs. Avg. threshold t_0 | 0.6199 | 0.6191 | 0.6067 |
| Sim Avg. threshold \overline{t} | 0.6107 | 0.5813 | 0.6026 |







So, to conclude, netdiffuseR

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 - · Health behavior diffusion (tobacco, drinking, etc.),
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 - Country-level spill over effects (FCTC)
 - ... social contagion (human or not) in general.¹

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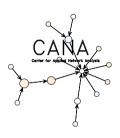


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- Is on active development, so stay tuned for more to come!

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Thank you!





More info

https://github.com/USCCANA/netdiffuseR

http://cana.usc.edu

contact

vegayon@usc.edu @gvegayon



Sesssion Info

| version | R version 3.3.1 (2016-06-21) | | |
|----------|------------------------------|--|--|
| system | x86_64, darwin15.5.0 | | |
| ui | unknown | | |
| language | (EN) | | |
| collate | en_US.UTF-8 | | |
| tz | America/Los_Angeles | | |
| date | 2016-06-29 | | |
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