

# EARL 2015

EFFECTIVE APPLICATIONS OF THE R LANGUAGE

LONDON 14 - 16 SEPTEMBER

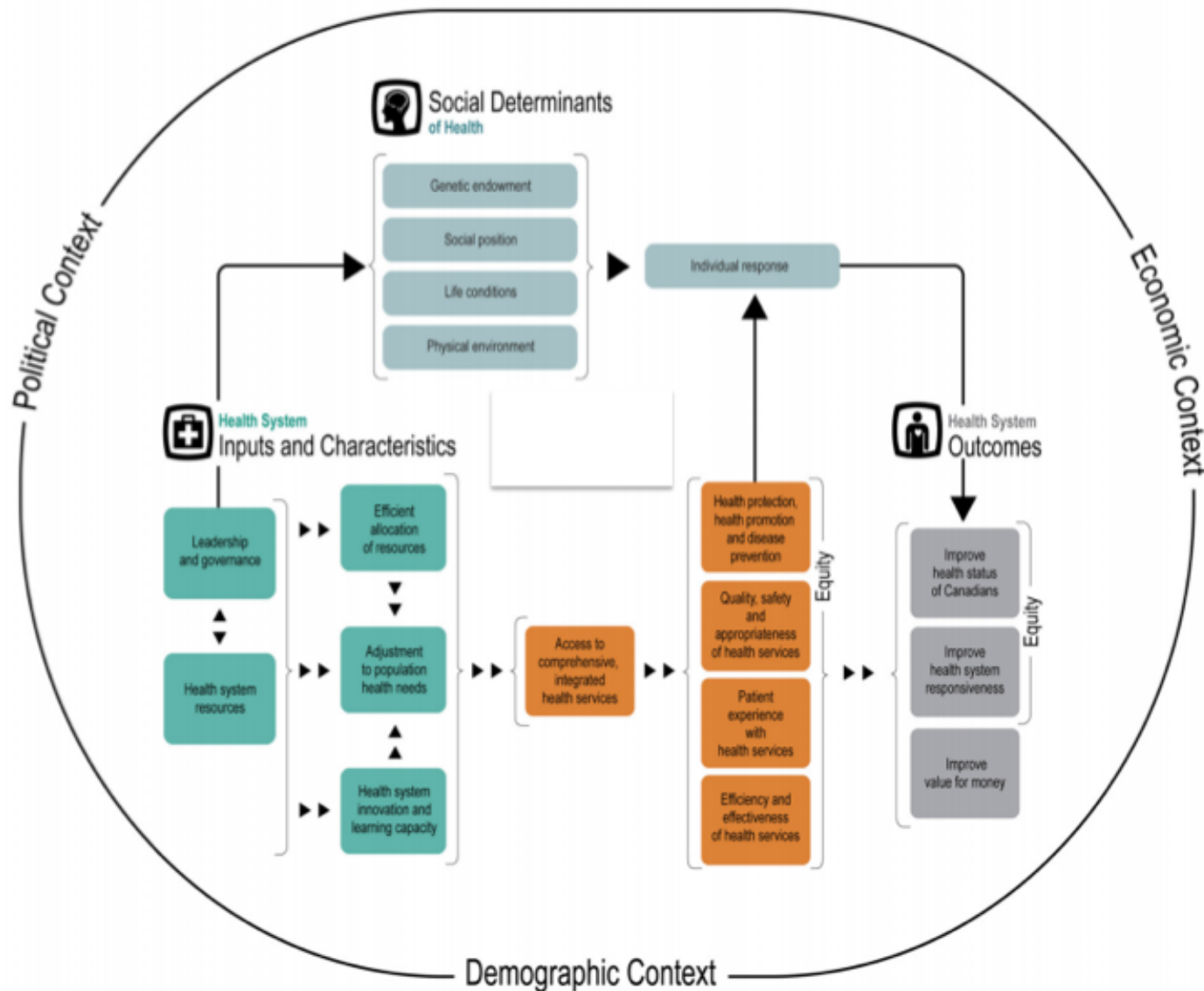


## **Building Interactive Visualizations with Shiny to Explore Data from Social and Health Care in UK**

Armando Vieira

# Summary

- The challenge
- The inputs and the outputs
- The predictive model
- Visualizations with Shiny and Google Motion Charts
- A random walk on graphs and causality



# The Inputs

## Social – Economics

- ✓ Demographics
- ✓ Economic Deprivation
- ✓ Obesity rates / Sports habits

## Health

- ✓ Readmissions
- ✓ Ashma & Diabetes prevalence
- ✓ Cardiovascular diseases

## Surveys

- ✓ ASCOF satisfaction
- ✓ Waiting times & service at PCT

## Costs

- ✓ Annual Budget
- ✓ Costs per 1000 patients (PCT)

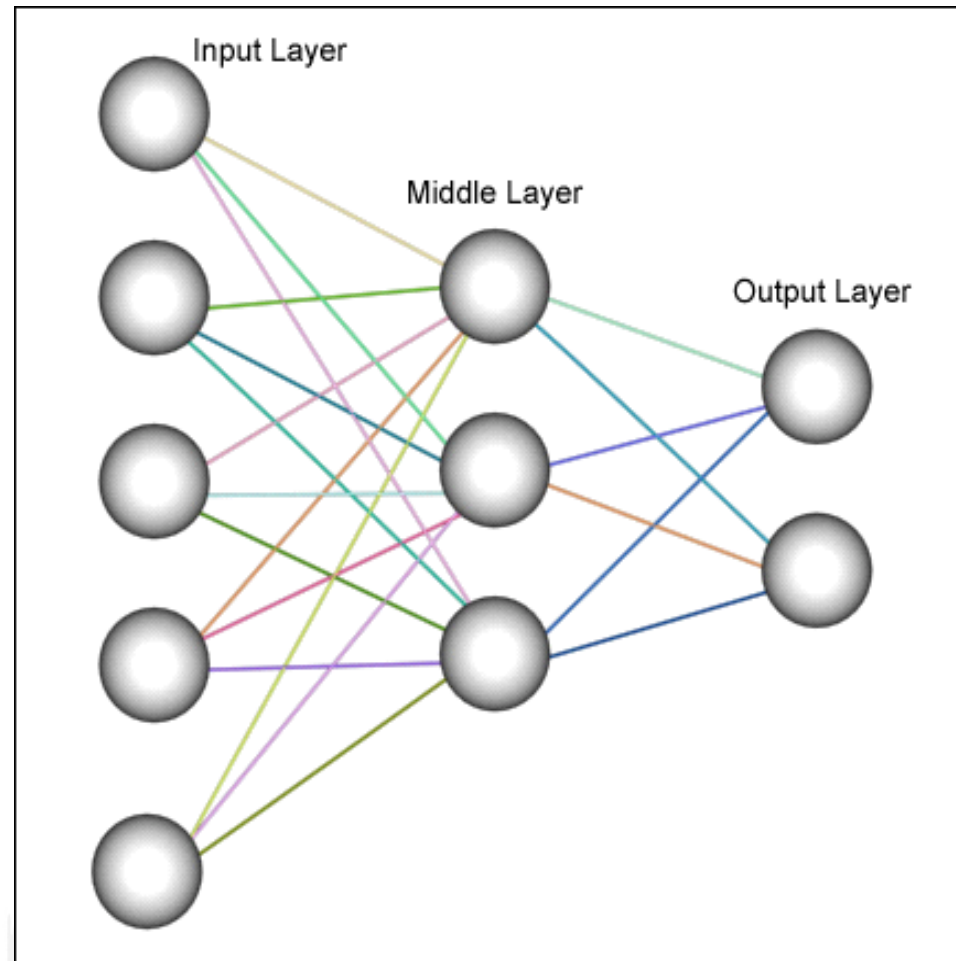
# The Outputs

**Health Score =**  
Life Expectancy . (1-Infant Mortality) . Satisfaction PCT Survey

**Stress Score =**  
Growth Elder Pop . Growth Pop . Waiting Times PCT survey

# Predictive model

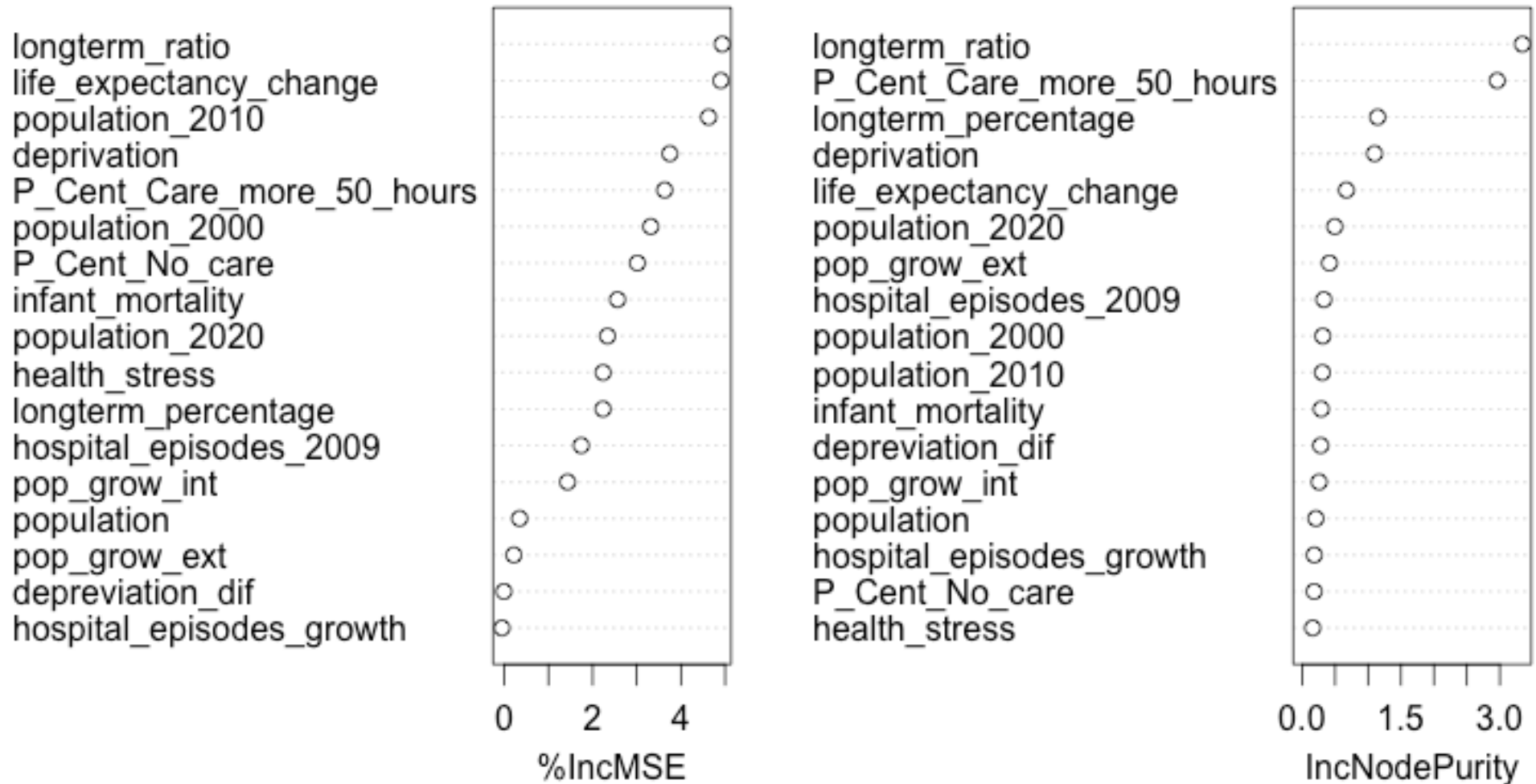
- % no care unpaid
- % > 50 hours unpaid
- Deprivation index
- Deprivation  $\Delta$
- Hospital episodes
- Hospital episodes  $\Delta$
- Infant mortal
- Life Expectancy  $\Delta$
- Long term illness
- Population
- Population internal
- Population external
- Population >65
- Population >65  $\Delta$
- Readmission score
- Sports
- Obesity
- Diabetes



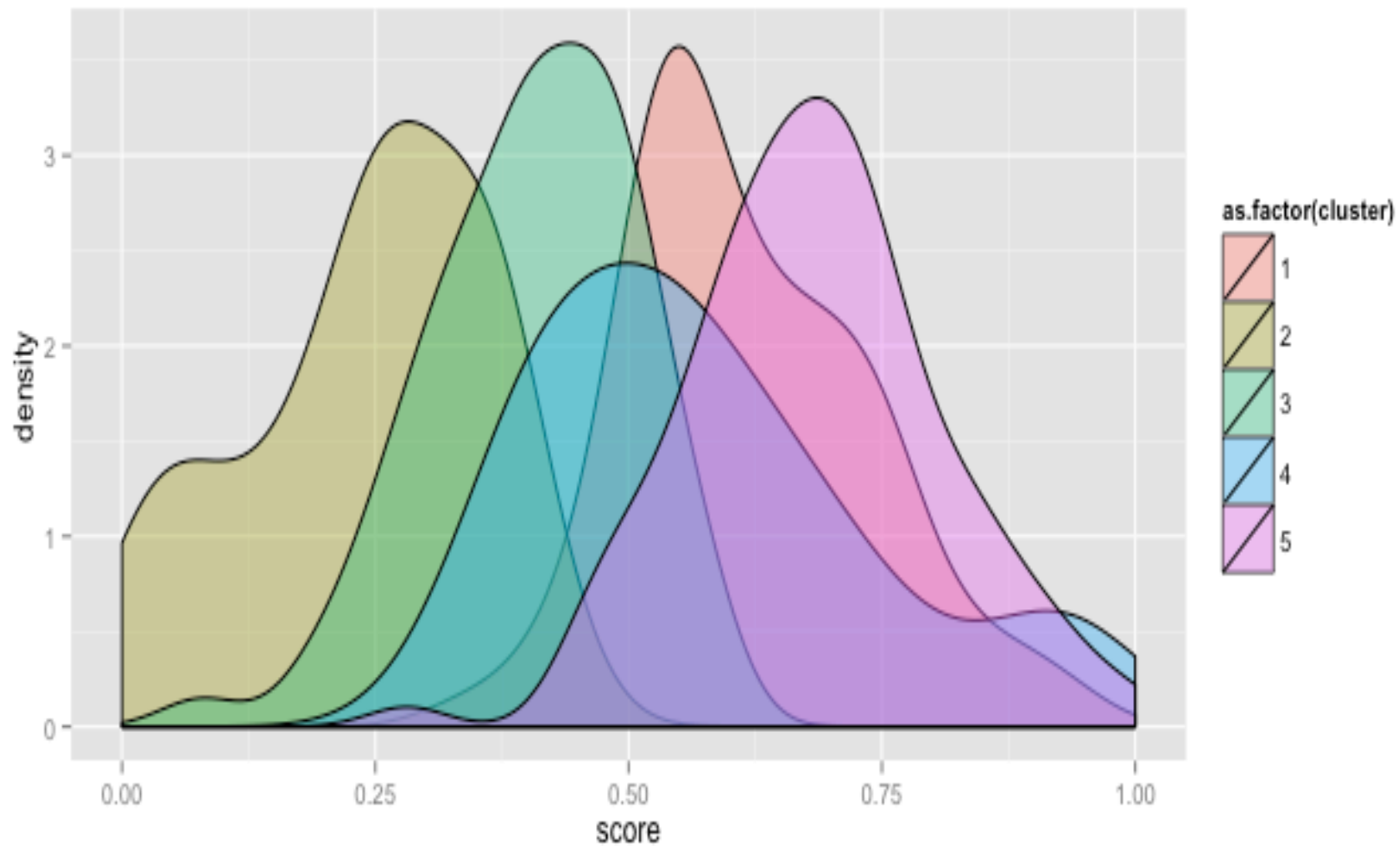
• **Health Score**

• **Stress Score**

## Importance in Health Score







# Online demos

1. Google Motion Charts
2. Shiny + Leaflet maps



# Two districts, two stories

## Chiltern

- ✓ Higher Health Score
- ✓ Stable population
- ✓ Healthiest
- ✓ High satisfaction score

## Liverpool

- ✓ Low Health Score
- ✓ Highest Hospital Episodes
- ✓ Economical deprived
- ✓ High percentage unpaid social care

# Conclusions I

The **Health Score** is:

- ✓ Higher for less deprived areas
- ✓ Lower for long term illness

Not related to:

- ✓ Health stress
- ✓ Infant mortality rate
- ✓ % of older population
- ✓ Population size

# Conclusions II

The **Stress Score** is:

- ✓ Higher for richer districts
- ✓ Higher for regions with large % of population > 65

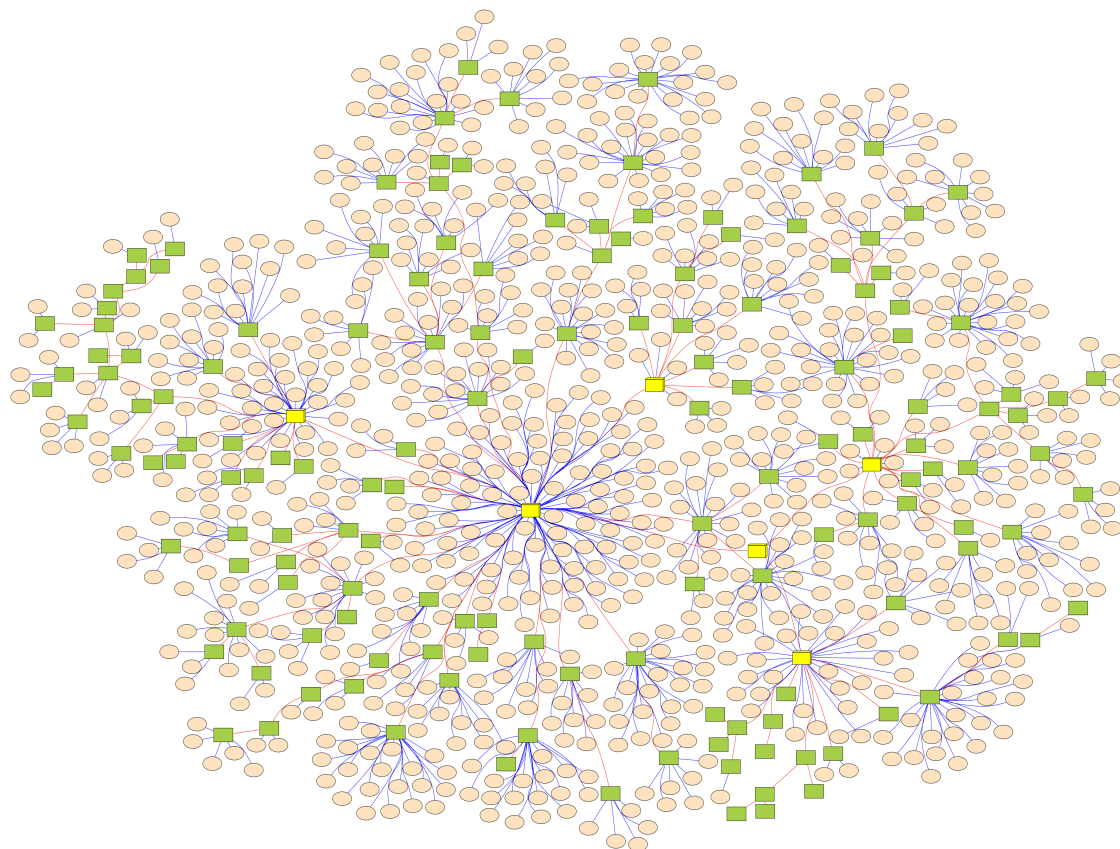
Not related to:

- ✓ % Long term illness
- ✓ Long term disability rate

# Why R?

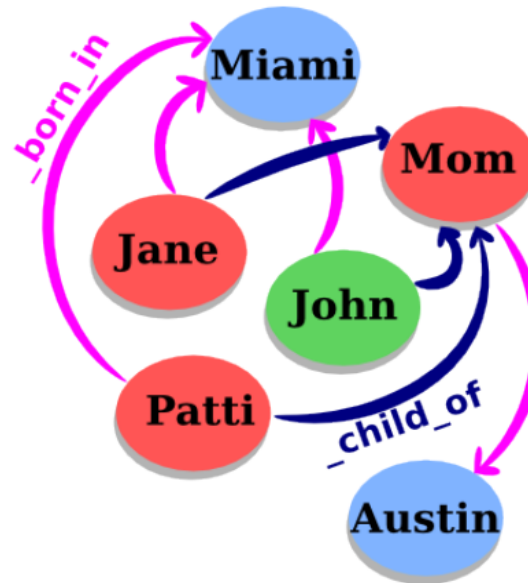
**With R and Shiny we can easily deploy interactive visualizations dashboards for powerful data exploration**

# A random walk on graphs and causality



## Multi-relational data

- Data is structured as a graph
- Each **node** = an **entity**
- Each **edge** = a **relation/fact**
- A **relation** = (*sub, rel, obj*):
  - *sub* = *subject*,
  - *rel* = *relation type*,
  - *obj* = *object*.
- Nodes w/o features.



# Example

"Who influenced J.K. Rowling?"

J. K. Rowling \_influenced\_by



G. K. Chesterton

J. R. R. Tolkien

C. S. Lewis

Lloyd Alexander

Terry Pratchett

Roald Dahl

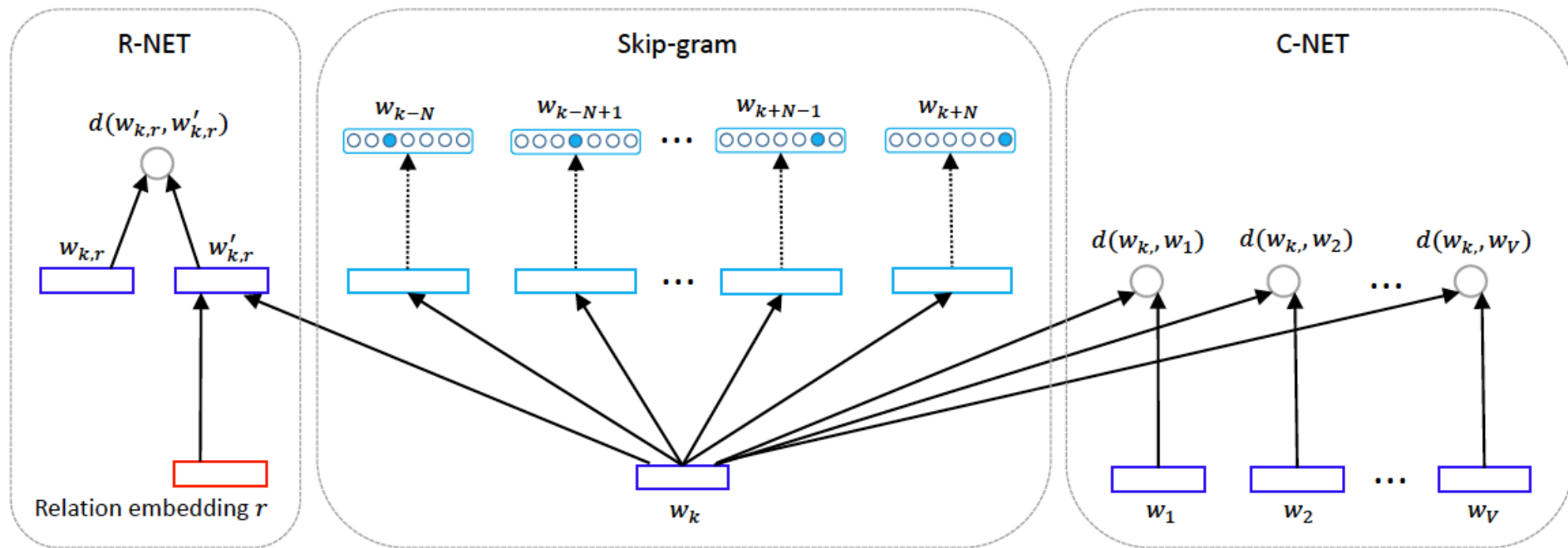
Jorge Luis Borges

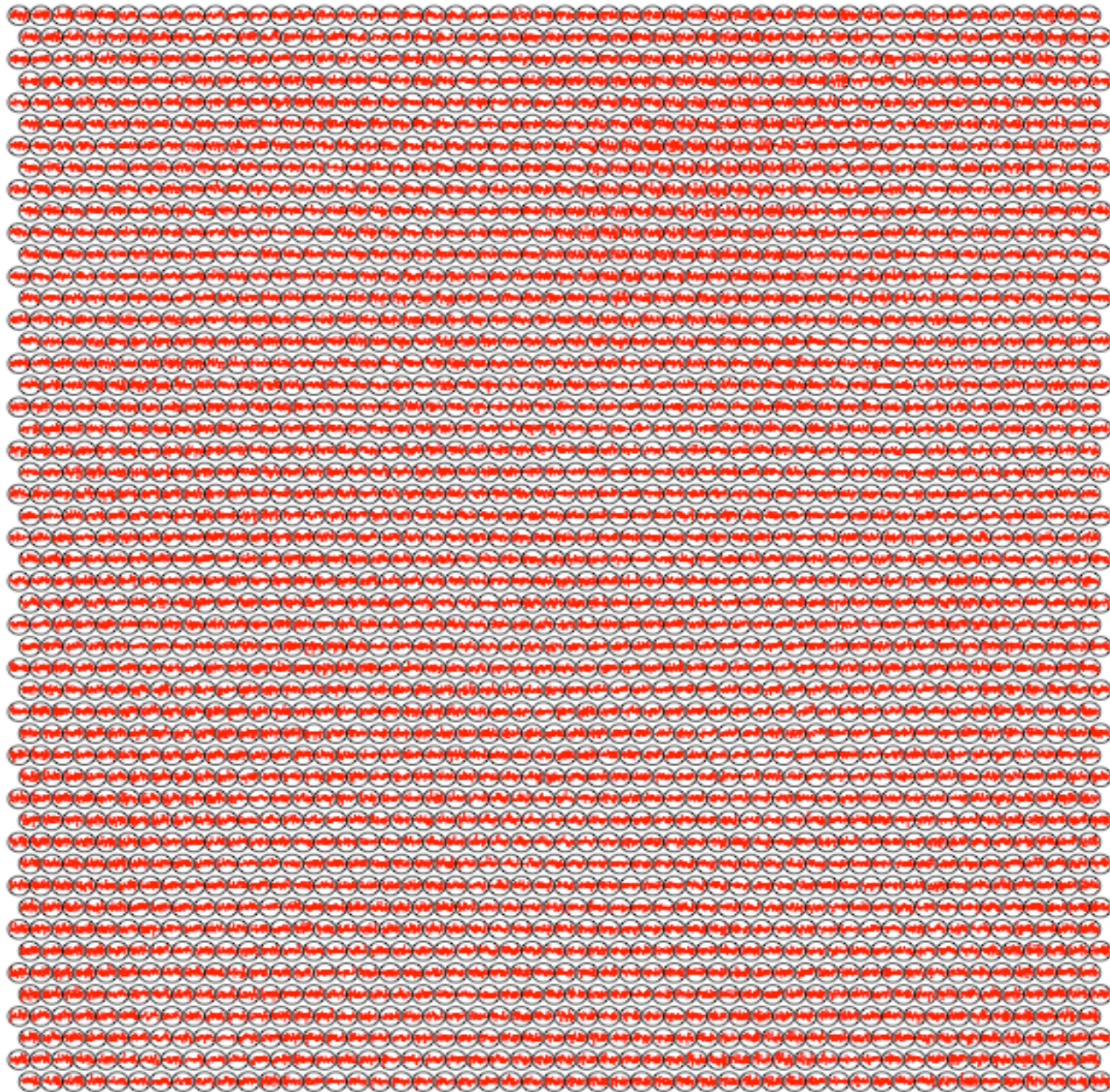
Stephen King

Ian Fleming

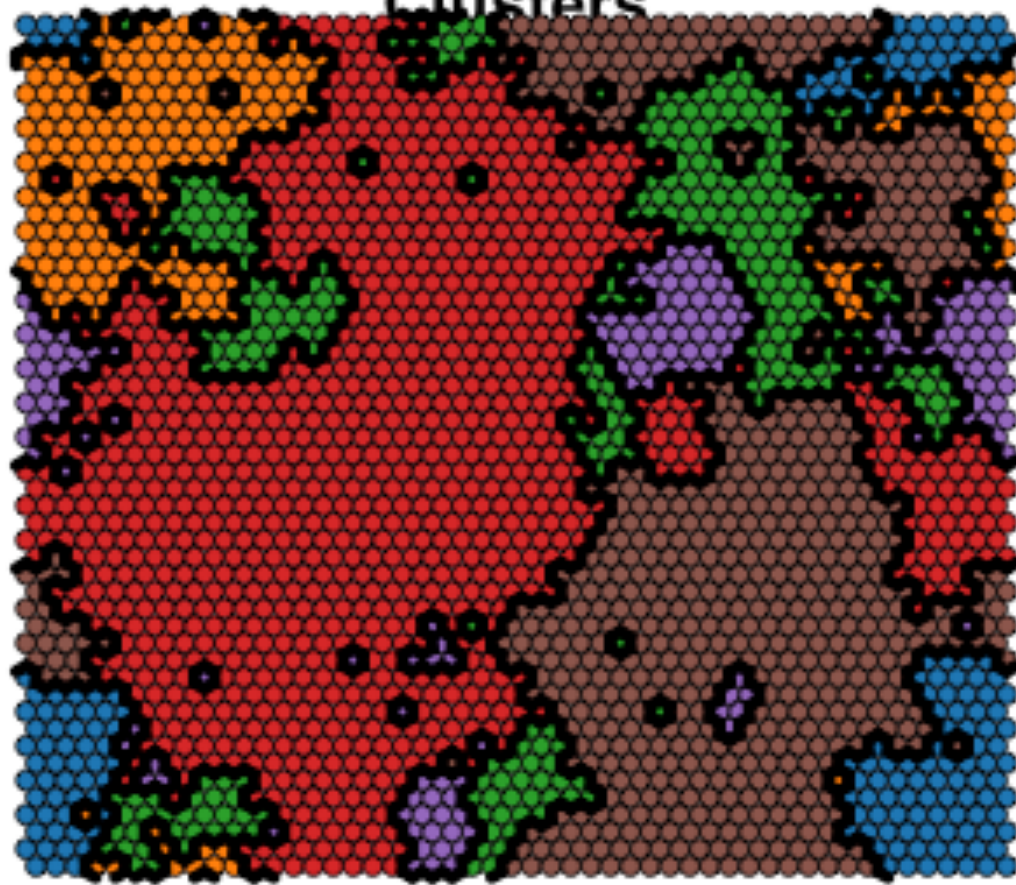
Green=Train Blue=Test Black=Unknown

# Learning embeddings



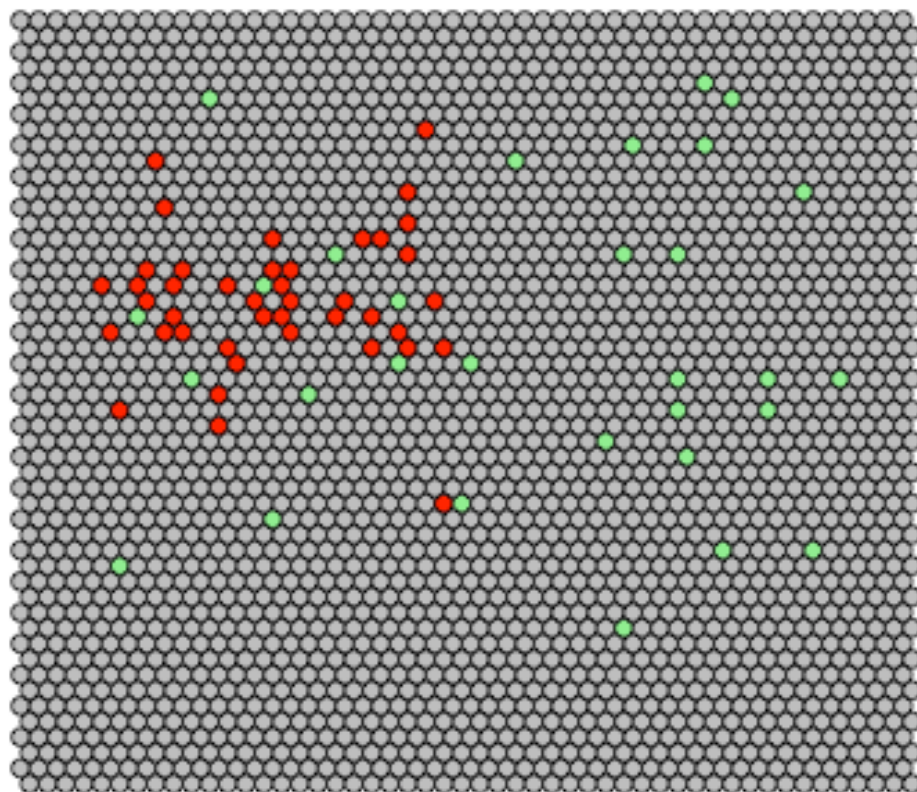


## CLUSTERS

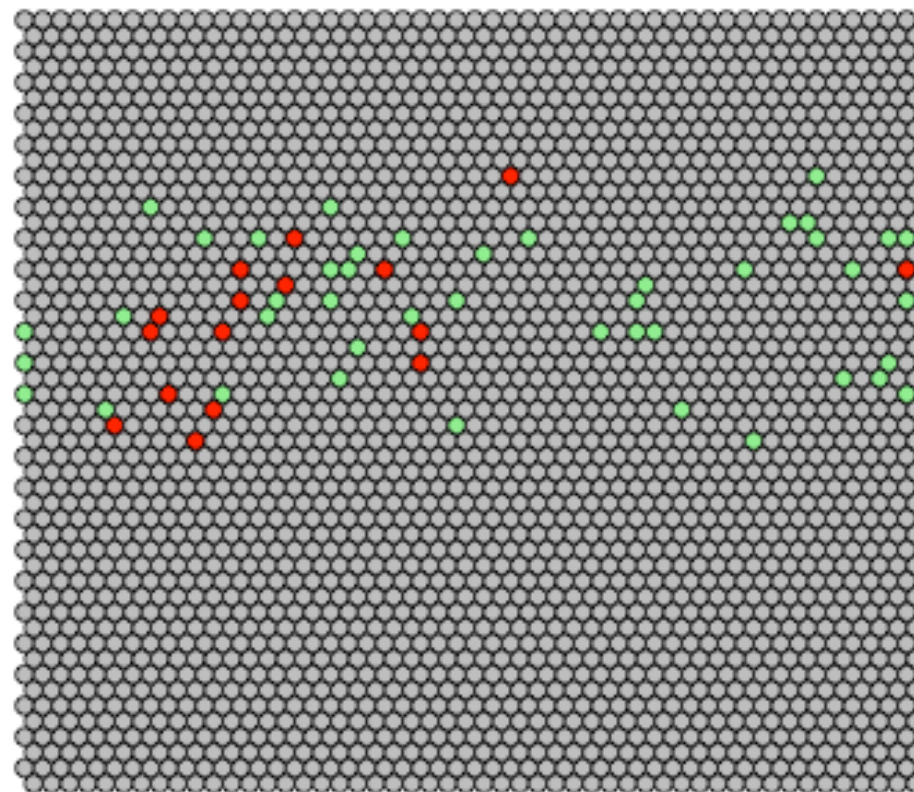


# Each disease has an unique fingerprint

Lung cancer



Ovary cancer



# Causality?

- “More police in precincts with higher crime; does that mean that police cause crime?”
  - Policy decision: should we add more police to a given district?
- “Lots of people die in hospitals, are hospitals bad for your health?”
  - Policy decision: should I go to hospital for treatment?
- “Advertise more in December, sell more in December.” But what is the causal impact of ad spending on sales?
  - Policy decision: how much should I spend on advertising?

# counterfactuals, confounding variables

- “If I go to hospital will be better off than I would have been if I didn’t go?”
- Sales = f(advertising) + other stuff
  - Xmas a confounding variable

# Beware of inferences

- The problem with doing inferences on data originated from unknown processes is related to the (implicit) assumption that the system and interactions of variables are in equilibrium.

# How much we should be worried?

- Economics
  - Experiment to determine policy change for population
  - Impact of treatment on population
  - Selection bias – are random samples really random?
- Business
  - Impact on advertisers who choose to use new feature or service
  - Impact of treatment on those who choose to be treated
  - Not necessarily worried about selection bias (but may be worried about early adopter bias)