PREDICTIVE ANALYTICS USING NETWORKED DATA IN R

Motivation: Social networks and predictive analytics

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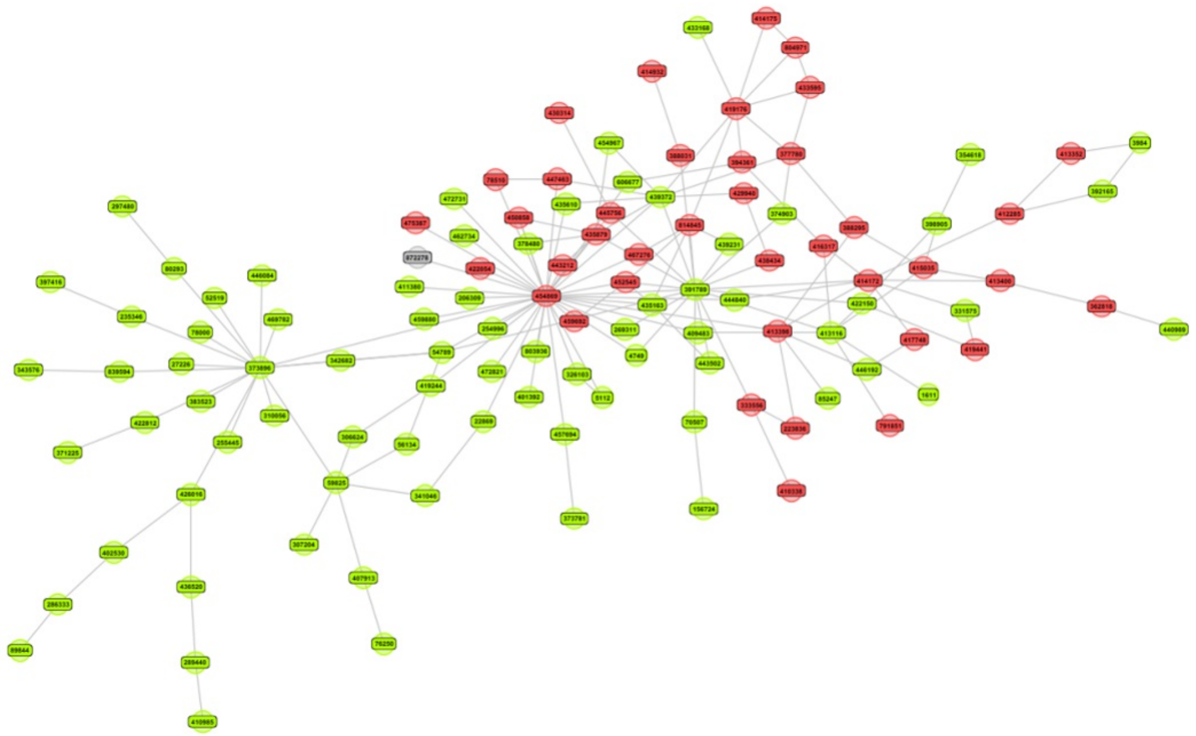
Applications

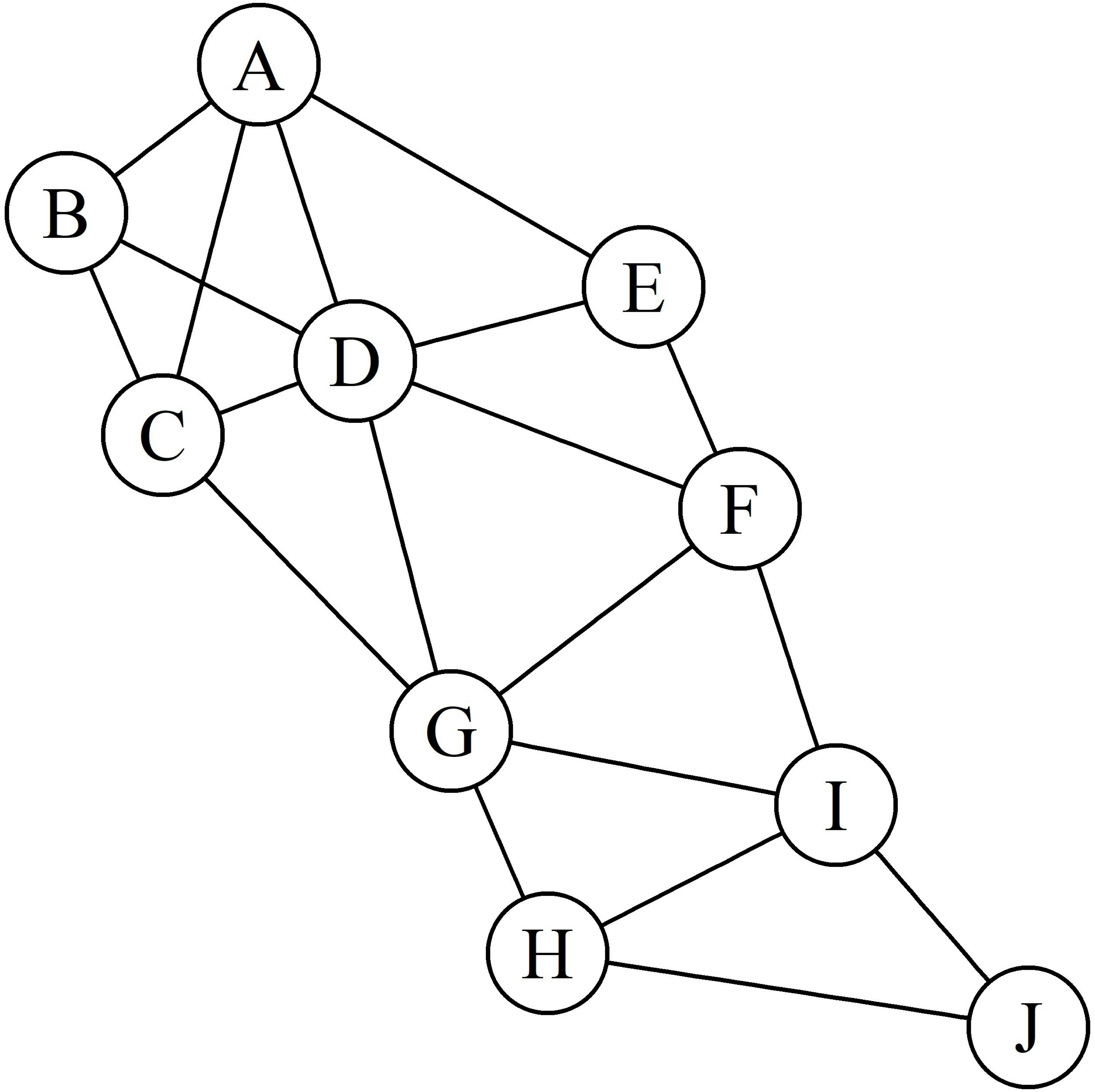
- Age
- Gender
- Fraud



- Churn
  - Customer defection
  - Companies predict who is most likely to churn using
    1. Machine learning techniques
    2. Social networks

Overview

- Labeled social networks
  - Construct and label networks
  - Network learning
- Homophily
  - Measure realational dependency
  - Heterophilicity and dyadicity
- Network featurization
  - Compute node features
- Predictive modeling with networks
  - Turn a network into a flat dataset
  - Predict churn among customers


A
B
E
D
C
F
G
I
H
J

Collaboration Network

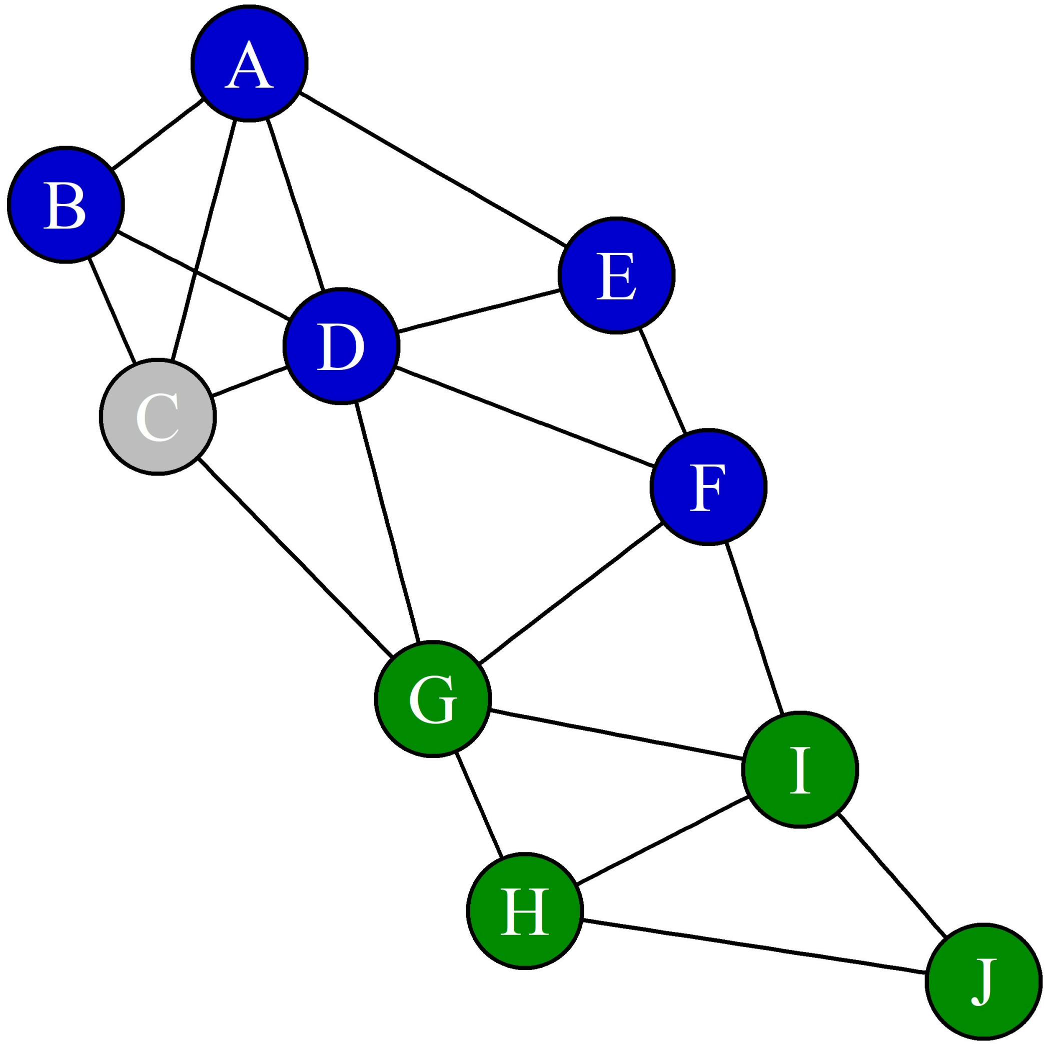
```
library(igraph);
DataScienceNetwork <- data.frame(
  from = c('A', 'A', 'A', 'A', 'B', 'B', 'C', 'C', 'D', 'D', 'D', 'E',
          'F', 'F', 'G', 'G', 'H', 'H', 'I'),
  to = c('B','C','D','E','C','D','D', 'G','E', 'F','G','F','G','I',
          'I','H','I','J','J'))
g <- graph_from_data_frame(DataScienceNetwork, directed = FALSE)
```

```
pos <- cbind(c(2, 1, 1.5, 2.5, 4, 4. 5, 3, 3.5, 5, 6),
             c(10.5, 9.5, 8, 8.5, 9, 7.5, 6, 4.5, 5.5, 4))
plot.igraph(g, edge.label = NA, edge.color = 'black', layout = pos,
            vertex.label = V(g)$name, vertex.color = 'white',
            vertex.label.color = 'black', vertex.size = 25)
```

Collaboration Network

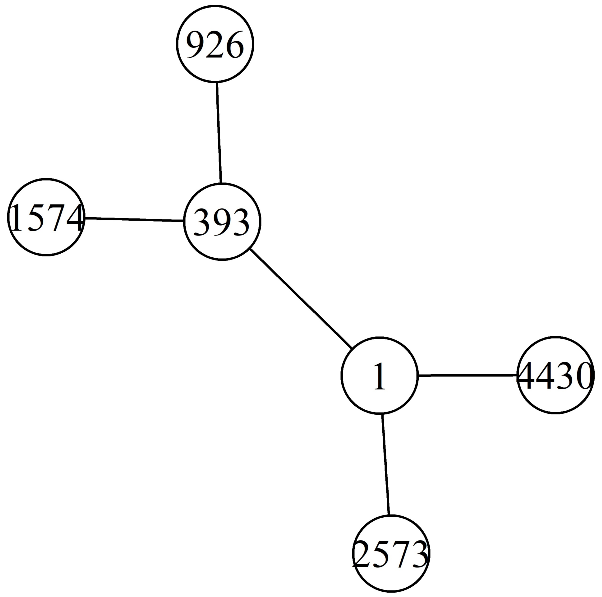
```
V(g)$technology <-
  c('R','R','?','R','R',
    'R','P','P','P','P')
V(g)$color <- V(g)$technology
```

```
V(g)$color <-
  gsub('R',"blue3", V(g)$color)
V(g)$color <-
  gsub('P',"green4", V(g)$color)
V(g)$color <-
  gsub('?',"gray", V(g)$color)
```



Churn Network

```
> edgeList
  from    to
1    1   393
2    1  2573
3    1  4430
4  393   926
5  393  1574
```



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Let's practice!

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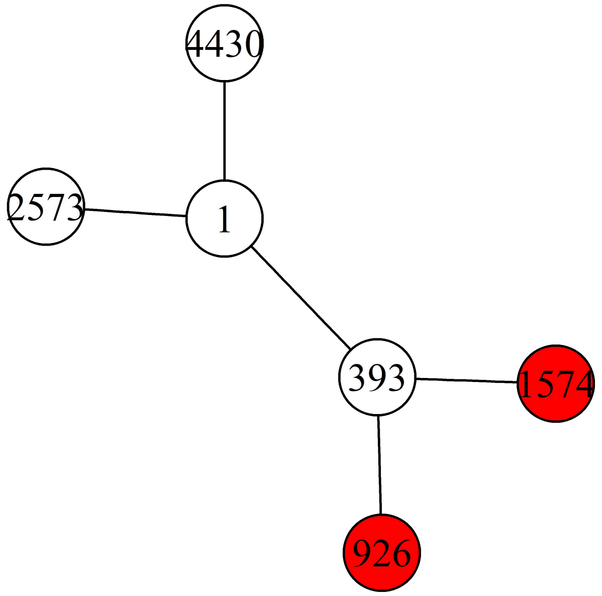
Labeled networks and network learning

María Óskarsdóttir, Ph.D.
Post-doctoral researcher

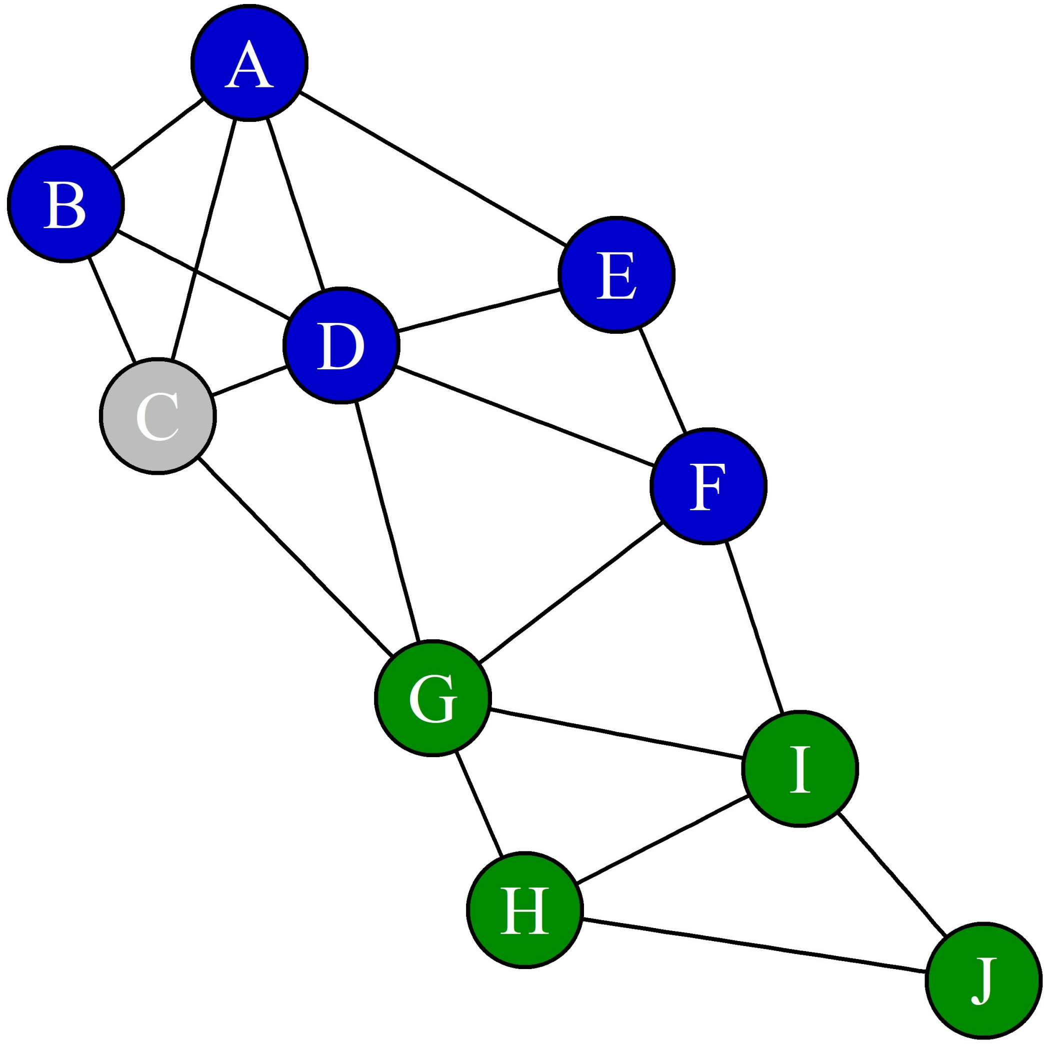
Churn prediction in social networks

```
> customers
    id churn
1    1     0
2  393     0
3 2573     0
4 4430     0
5  926     1
6 1574     1
```

```
> edgeList
  from    to
1    1   393
2    1  2573
3    1  4430
4  393   926
5  393  1574
```

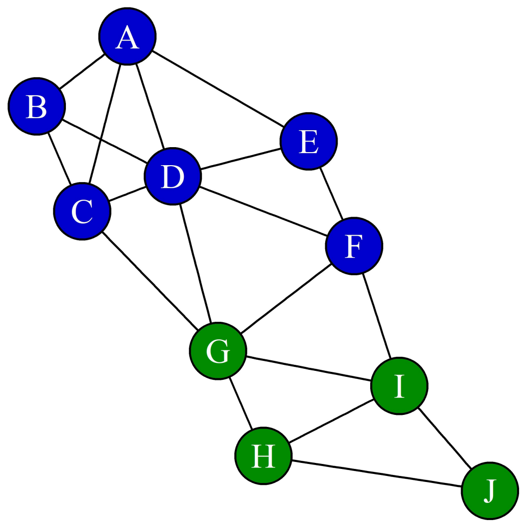


The Relational Neighbor Classifier



- Neighbors of **C**ecelia
  - A,B,D,G
- Neighbors of **C**ecelia that prefer R
  - A, B, D (75%)
- Neighbors of **C**ecelia that prefer Python
  - G (25%)
- **C**ecelia has a higher probability to prefer R

The Relational Neighbor Classifier




```
rNeighbors <- c(4,3,3,5,3,2,3,0,1,0)
pNeighbors <- c(0,0,1,1,0,2,2,3,3,2)

rRelationalNeighbor <- rNeighbors / (rNeighbors + pNeighbors)

rRelationalNeighbor
  1.00 1.00 0.75 0.86 1.00 0.50 0.60 0.00 0.00 0.00
```

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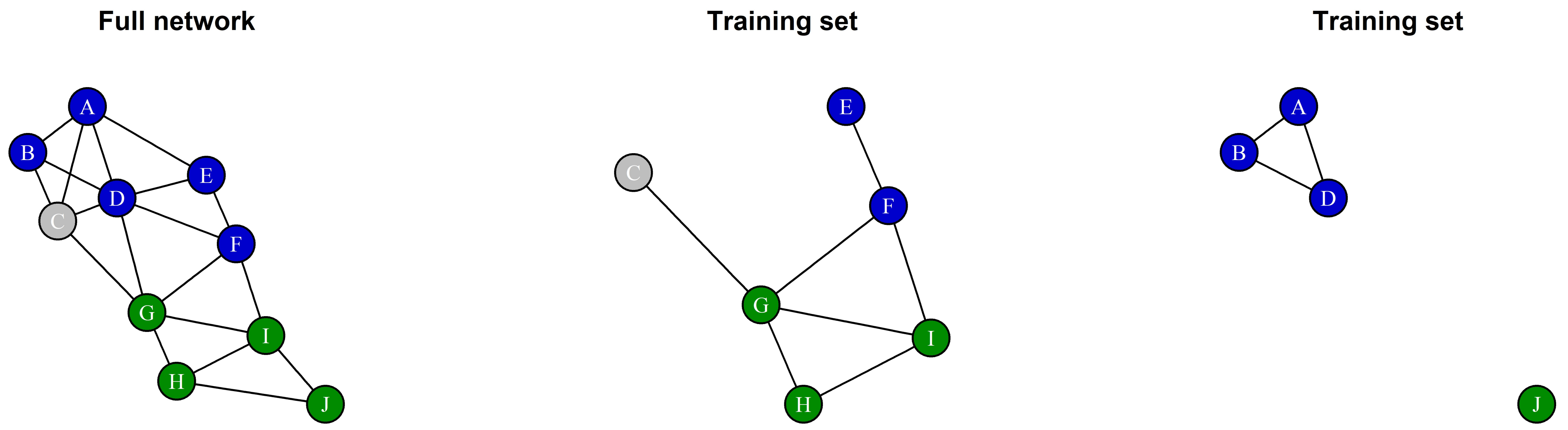
Challenges of network-based inference

María Óskarsdóttir, Ph.D.
Post-doctoral researcher

First Challenge

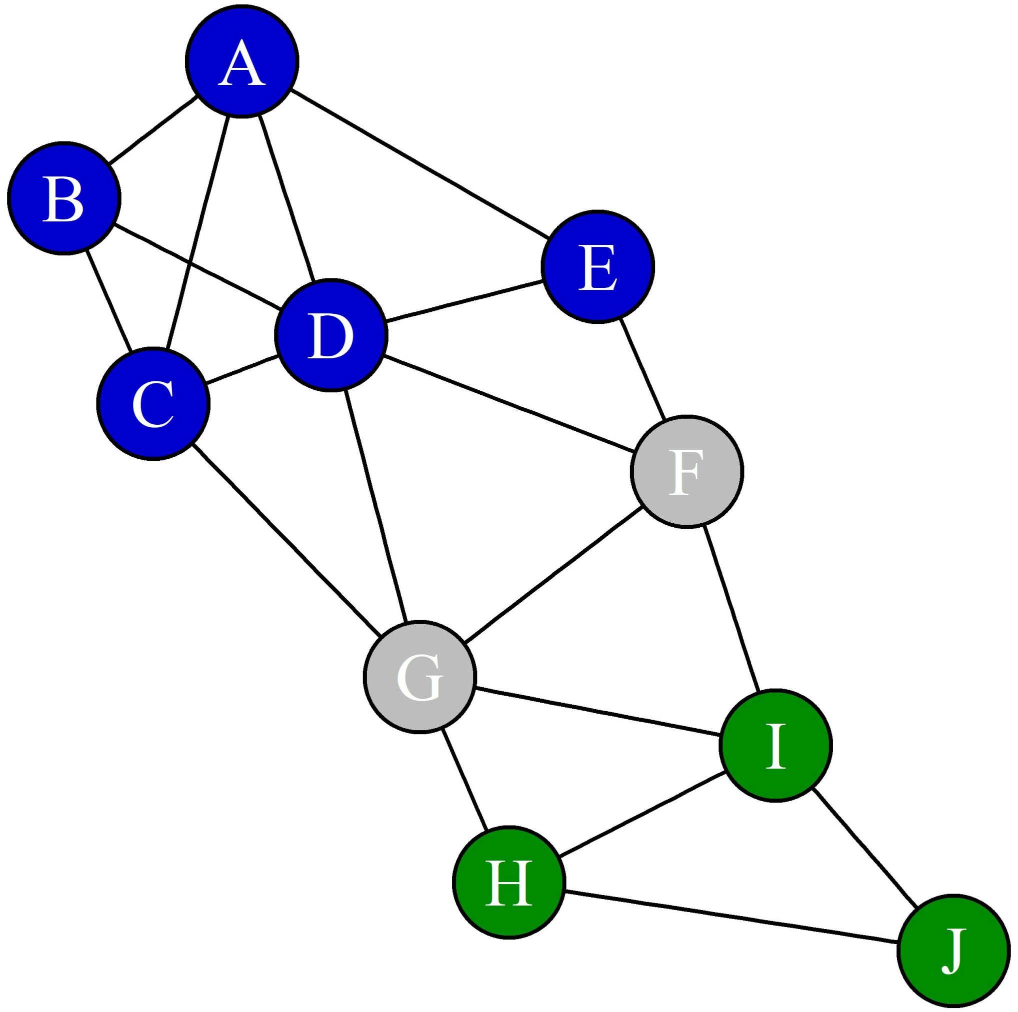
Splitting the data!

```
set.seed(1001)
sampleVertices <- sample(1:10, 6, replace=FALSE)
plot(induced_subgraph(g, V(g)[sampleVertices]))
plot(induced_subgraph(g, V(g)[-sampleVertices]))
```



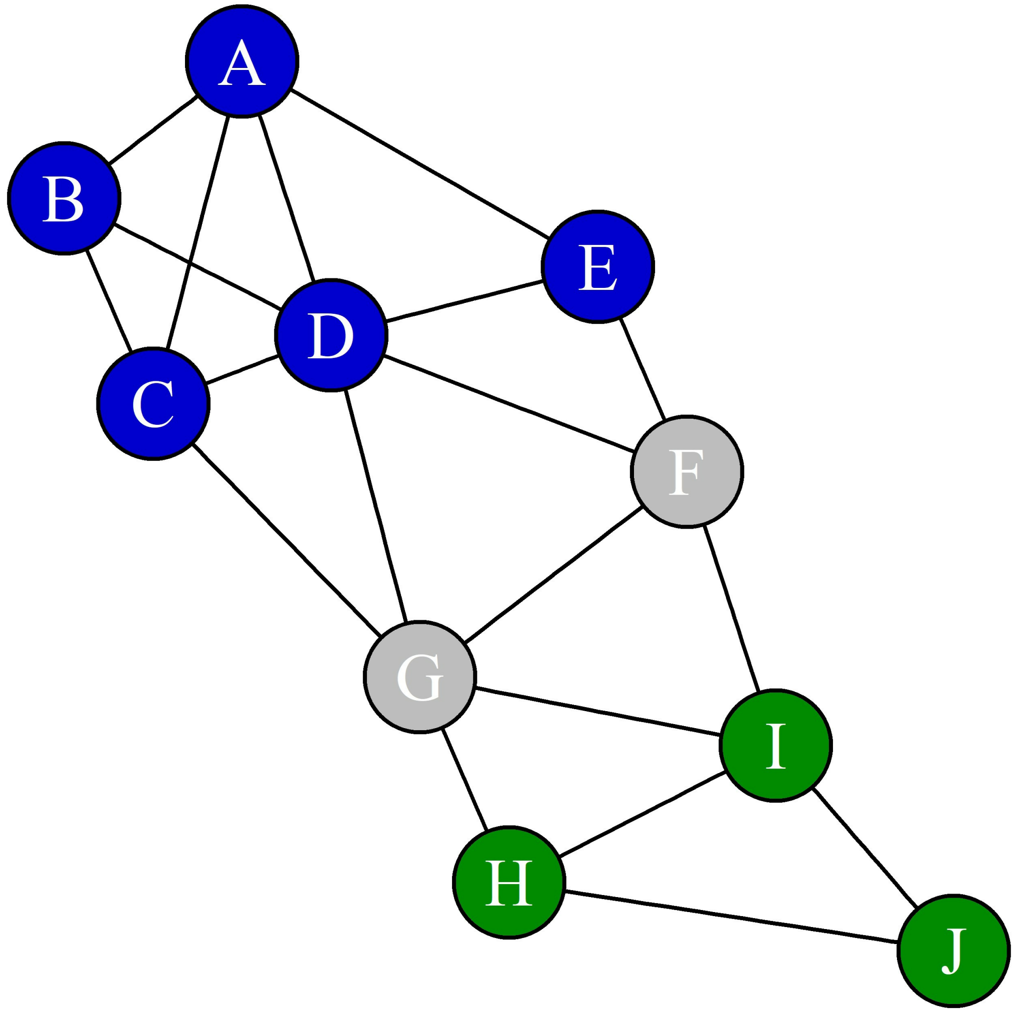
Second Challenge

The observations in the dataset are not independent and identically distributed (iid)

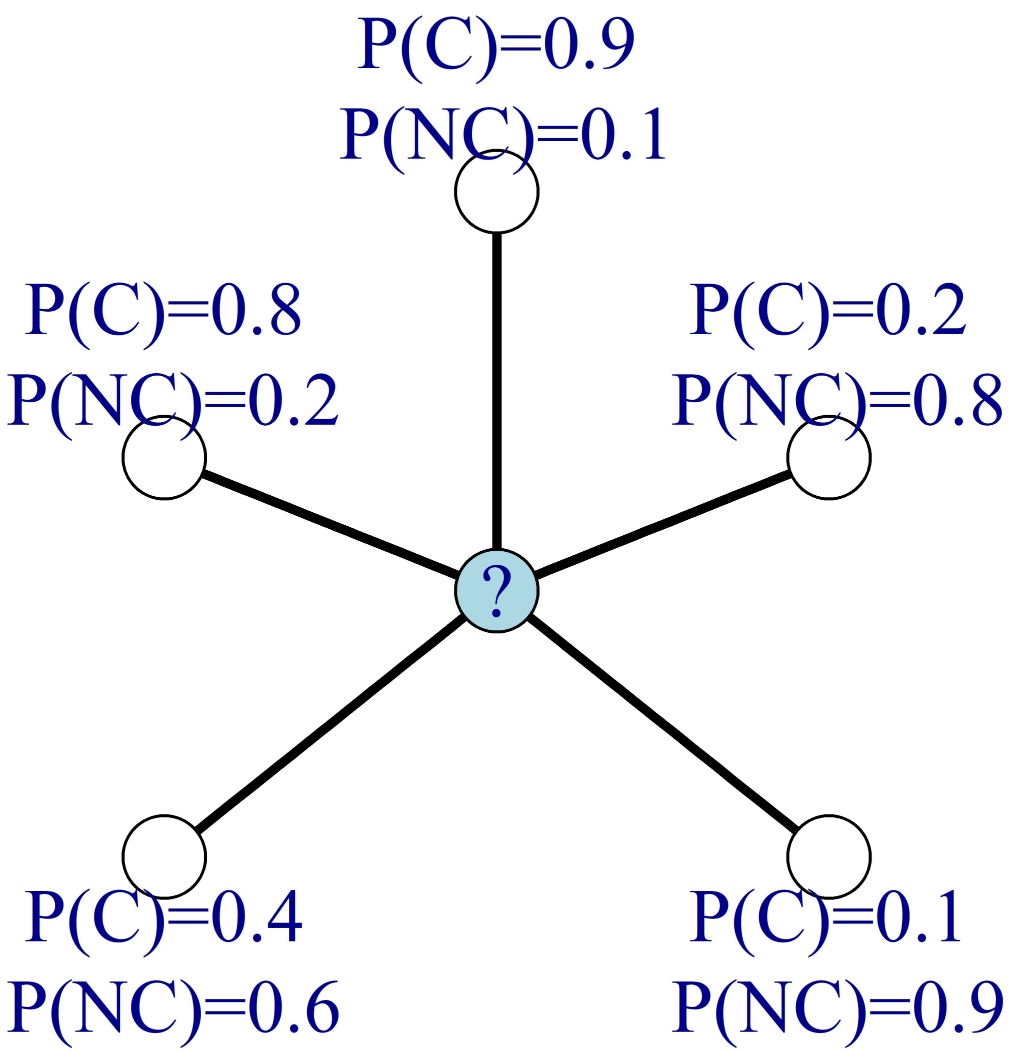


Third Challenge

Collective Inference!



Probabilistic relational neighbor classifier




```
# probability churn (C)
(0.9 + 0.2 + 0.1 + 0.4 + 0.8) / 5
[1] 0.48

# probability non-churn (NC)
(0.1 + 0.8 + 0.9 + 0.6 + 0.2) / 5
[1] 0.52
```

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