Using network analysis of colleague relationships to find interesting new investment managers

Robin Penfold (@p0bs)

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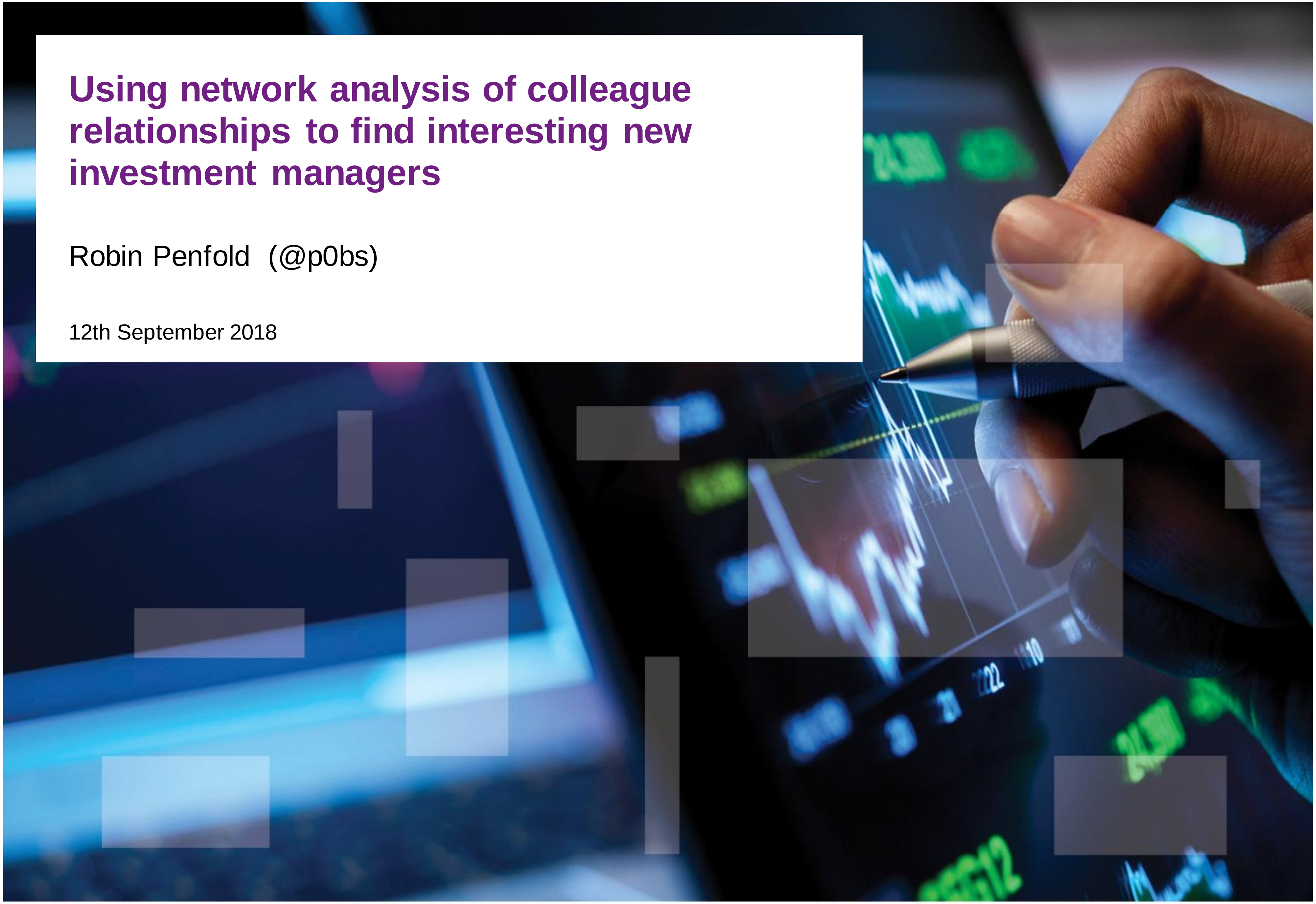

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Why study colleague relationships in investment managers?

- We provide investment services to large institutions, like pension funds
- For example, we recommend which investment managers our clients should use to invest their assets
  - We seek the minority of investment managers that are likely to do better than the market over time
- Our research team therefore interviews many investment managers. But how do we know who to interview?
- One way is to consider those individuals who had an excellent tutor at a previous firm

Bring on the data!

- Industry database of investment managers, showing where they have worked and when
- Dates and current firm are from a drop-down list; previous firms are in free text!
  - “ABC DEF Investment Mgmt, Hong Kong” … not “ABC DEF”
  - “XYZ private equity asset partners in Miami” … not “XYZ”

A computer once beat me at chess
but it was no match for me at kick-boxing

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Our clean data

- After much de-duplication, we had four columns:
  - newFirmID
  - individual_id
  - start_year
  - end_year

- We can then find the colleague pairings that worked at the same firm in the same year:

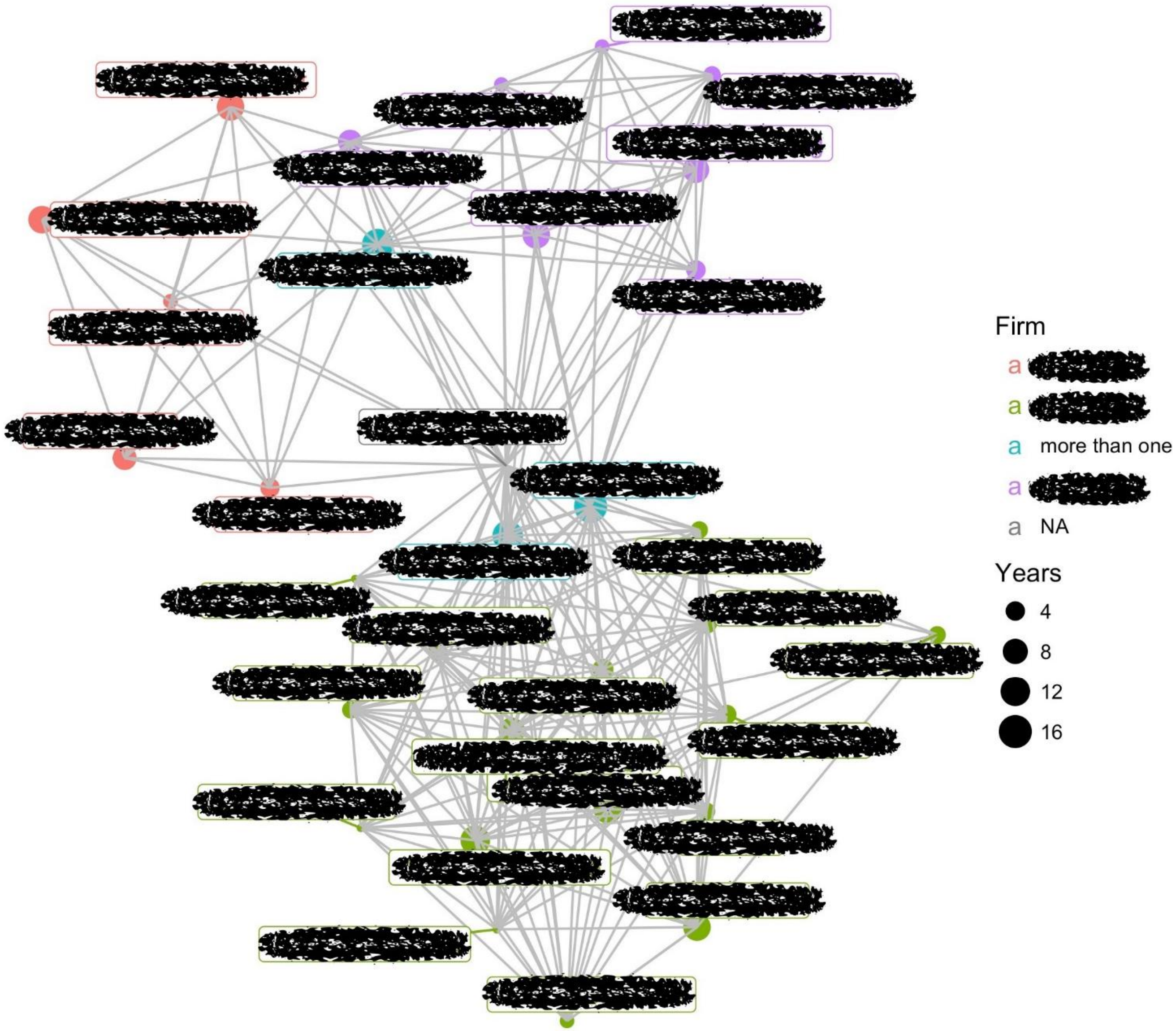
```
> glimpse(colleagues)
Observations: 592,122
Variables: 7
$ newFirmID <int> 9010724, 9009549, 9009549, 9009549, 9009549, 9009549, 9009549, 9009549, 9009549, 9013586, 9013586, 90 ...
$ V1        <int> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 3, ...
$ V2        <int> 386, 82497, 2223, 56608, 54621, 1405, 40317, 82463, 47783, 42924, 42926, 1999, 2001, 31619, 6268, 627 ...
$ years     <int> 2, 3, 2, 7, 8, 9, 9, 9, 4, 1, 1, 19, 18, 17, 15, 13, 13, 13, 11, 10, 10, 10, 9, 8, 7, 5, 4, 4, 8, 2,  ...
$ lastYr    <dbl> 1988, 1990, 1991, 1994, 1995, 1996, 1996, 1996, 1996, 1996, 1996, 2014, 2014, 2014, 2014, 2014, 2014, ...
$ FirmLite  <chr> "painewebber", "mitchell hutchins", "mitchell hutchins", "mitchell hutchins", "mitchell hutchins", "m ...
$ firmFREX  <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N ...
```

Building the network with tidygraph

```
# A tbl_graph: 12415 nodes and 592122 edges
#
# An undirected multigraph with 26 components
#
# Node Data: 12,415 x 1 (active)
  name
  <chr>
1 2
2 3
3 5
4 6
5 7
6 8
# ... with 1.241e+04 more rows
#
# Edge Data: 592,122 x 6
   from    to firmFREX years lastYr newFirmID
  <int> <int>    <dbl> <int>  <dbl>     <int>
1     1   166       NA     2   1988   9010724
2     1 10386       NA     3   1990   9009549
3     1   707       NA     2   1991   9009549
# ... with 5.921e+05 more rows
```

(Thank you, Thomas Lin Pedersen)

Current and former equity investment colleagues of [redacted]



Which individuals that we don't know have the best former colleagues?

Method 1: Database-like approach

- Find our average 'recommendation rating' across each individual's colleagues

```
tg5 <- tg4 %>%
  activate(nodes) %>%
  mutate(name = as.integer(name)) %>%
  mutate(id = row_number()) %>%
  left_join(EData11_latest, by = c("name" = "InvProID")) %>%
  rename(FirmIDlast = "newFirmID") %>%
  mutate(FirmIDlastFREX = ifelse(
    FirmIDlast %in% InputData1$newFirmID,
    InputData1$firmFREX[match(FirmIDlast, InputData1$newFirmID)],
    NA)) %>%
  mutate(FirmIDlastFREXgd = ifelse(FirmIDlastFREX < goodFREXpoint, FirmIDlast, NA)) %>%
  mutate(neighbours = local_members(order = 1)) %>%
  mutate(colleagueFREXav = map_local_dbl(
    order = 1,
    .f = function(neighborhood, ...) {
      mean(as_tibble(neighborhood, active = 'nodes')$FirmIDlastFREX, na.rm = TRUE)
    })) %>%
  mutate(colleagueFREXgd_distinct = map_local_int(
    order = 1,
    .f = function(neighborhood, ...) {
      length(unique(as_tibble(neighborhood, active = 'nodes')$FirmIDlastFREXgd, na.rm = TRUE))
    }))
```

- Generates a 'best place to look' table of firms and individuals that we don’t yet know

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Which individuals that we don't know have the best former colleagues?

Method 2: Pure network approach

- Find individuals that we don't know who are most ‘central’ between those we recommend

```
second_network <- tg5 %>%
  activate(nodes) %>%
  mutate(topFirm = FirmIDlastFREX <= topFirmBreakpoint) %>%
  filter(topFirm == TRUE | is.na(topFirm)) %>%
  mutate(wt_node = ifelse(is.na(topFirm), 1, topFirmWeight)) %>%
  activate(edges) %>%
  select(-goodFREXfrom, -goodFREXto, -FREX_average_from, -FREX_average_to) %>%
  mutate(wt_edge = .N()$wt_node[from] + .N()$wt_node[to]) %>%
  activate(nodes) %>%
  mutate(centr_score = centrality_betweenness(weights = wt_edge, directed = FALSE))
```

- Generates a 'best place to look' dataframe of firms and individuals

- Bringing all this together, we can prioritize who to meet first (and at which firms)

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