Customer Segmentation with R

Deep dive into flexclust

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useR! 2015
Aalborg, Denmark
July 1, 2015

Outline

1. Why and how to segment?
2. Segmenting “binary choice” surveys.
3. flexclust deep dive.
4. Solving issues of numbering and stability.
5. Picking the “best” number of clusters.
6. Wrap-up.

Appendix has real-world examples, references, and links to learn more.

Customer Segmentation Themes

Strategic	How Used?	Tactical
General	Level?	Detailed
Long	Time Constant?	Short
Simple	Implementation?	Complex
1x Huge	Impact (if correct)?	Σ(Small)

How to Segment?

"We've broken your list into eighty-four subgroups. Our work here is done."

Many Segmentation Methods!

Today’s Focus: Binary choice surveys

- Simplest of surveys to design & take.
- Cluster analysis is a great tool to understand how respondents fall into natural segments
- Methods also apply to any binary choice behavioral data sets.

For examples of other segmentation methods see archives at DS4CI.org.

Today's Example Data Set

The *volunteers* data set from the flexclust package.

1415 Australian volunteers responded to the survey which had 19 preference check boxes for motivations to volunteer. The question could look like:

Q5. Please check all motivations that apply to you:

- ❑meet.people
- ❑no.one.else
- ❑example
- ❑socialise
- ❑help.others
- ❑give.back
- ❑career
- ❑lonely
- ❑active
- ❑community
- ❑cause
- ❑faith
- ❑services
- ❑children
- ❑good.job
- ❑benefited
- ❑network
- ❑recognition
- ❑mind.off

Segmenting Binary Choice Data

- “Pick all that apply” type question.
  - Not picking is not the opposite of picking an attribute.
    - (item checked) <> NOT (item unchecked)
- *Totally unsupervised*. We only specify the number of clusters we want.
- Two *necessary criteria* for a “good” solution:
  1. The cluster solution is stable

     ~ Repeatable with different random starts
  2. The segments make sense to the business

     - Believable story AND is actionable AND has anticipated impact.

Tool we use: flexclust by Fritz Leisch

- Allows different distance measures
  - In particular, the Jaccard distance which is suited for binary survey data or optional properties lists.
  - 1 is a “yes” to the question - it is significant.
  - 0 is a “does not apply” – not opposite of “yes”
- Predict(kcca_object, newdata) to segment new customers.
- Additionally flexclust has very good diagnostic and visualization tools. As an R package, it leverages the rest of the R ecosystem.

Simple flexclust Run (1 of 2)

Set up input to flexclust:

```
library(flexclust)
data("volunteers")
vol_ch <- volunteers[-(1:2)]
vol.mat <- as.matrix(vol_ch)
```

Set up the parameters:

```
fc_cont <- new("flexclustControl") ## holds "hyperparameters"
fc_cont@tolerance <- 0.1
fc_cont@iter.max <- 30
fc_cont@verbose <- 1     ## verbose > 0 will show iterations
fc_family <- "ejaccard" ## Jaccard distance w/ centroid means
```

Invoke kcca(): “k-centroid cluster analysis”

```
fc_seed <- 577 ## Why we use this seed will become clear below
num_clusters <- 3 ## Simple example – only three clusters
set.seed(fc_seed)
vol.cl <- kcca(vol.mat, k = num_clusters, save.data = TRUE,
               control = fc_cont, family = kccaFamily(fc_family))
```

Simple flexclust Run (2 of 2)

First few iterations:

```
## 1 Changes / Distsum : 1415 / 951.9513
## 2 Changes / Distsum : 138 / 997.9507
## 3 Changes / Distsum : 39 / 998.6126
```

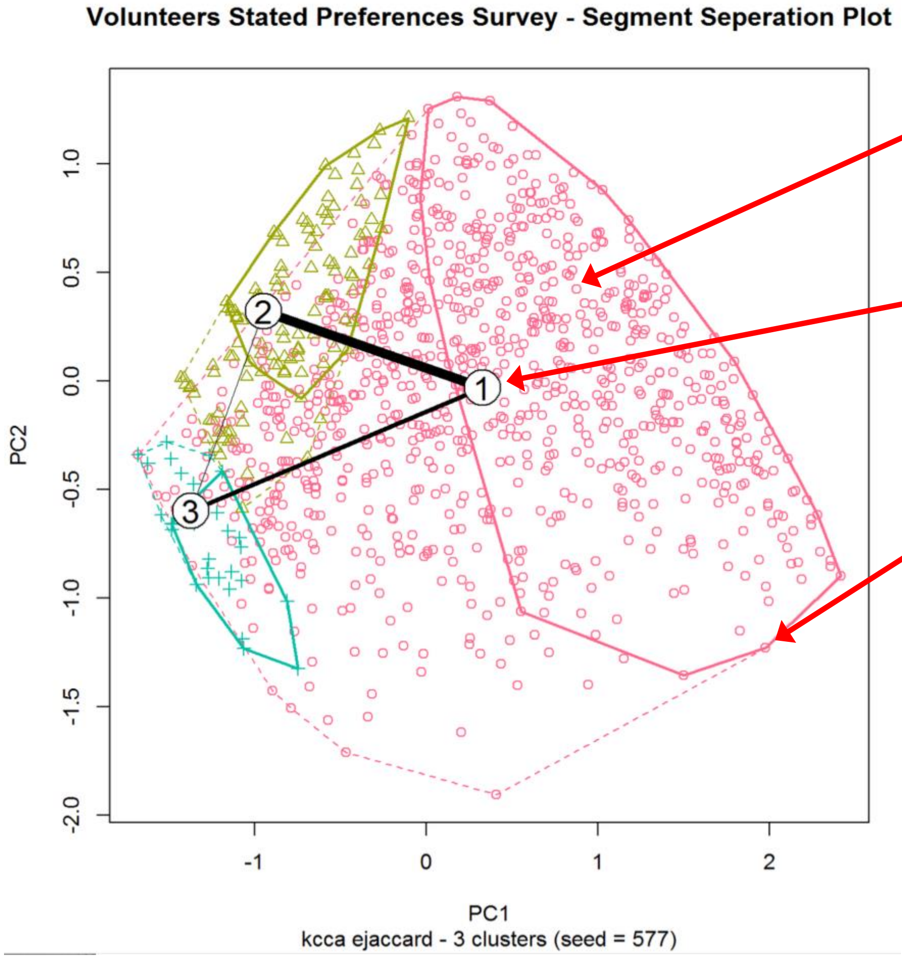
• • •

Results:

```
summary(vol.cl)
## kcca object of family 'ejaccard'
## call:
## kcca(x = vol.mat, k = num_clusters, family = kccaFamily(fc_family),
##     control = fc_cont, save.data = TRUE)
##
## cluster info:
##   size   av_dist  max_dist separation
## 1 1078 0.6663440 1.0000000  0.6455246
## 2  258 0.7388715 1.0000000  0.6568168
## 3   79 0.8962851 0.9569892  0.8284482
##
## no convergence after 30 iterations
## sum of within cluster distances: 979.7542
```

Segment Separation Plot

```
vol.pca <- prcomp(vol.mat) ## plot on first two principal components
plot(vol.cl, data = vol.mat, project = vol.pca, main = . . .)
```



Each respondent plotted against the first two principal components of data. Color is cluster assignment.

Centroid of each cluster. A thin line to other centroid indicates better separation (in real problem space)

Solid line encloses 50% of respondents in cluster; dotted 95%.

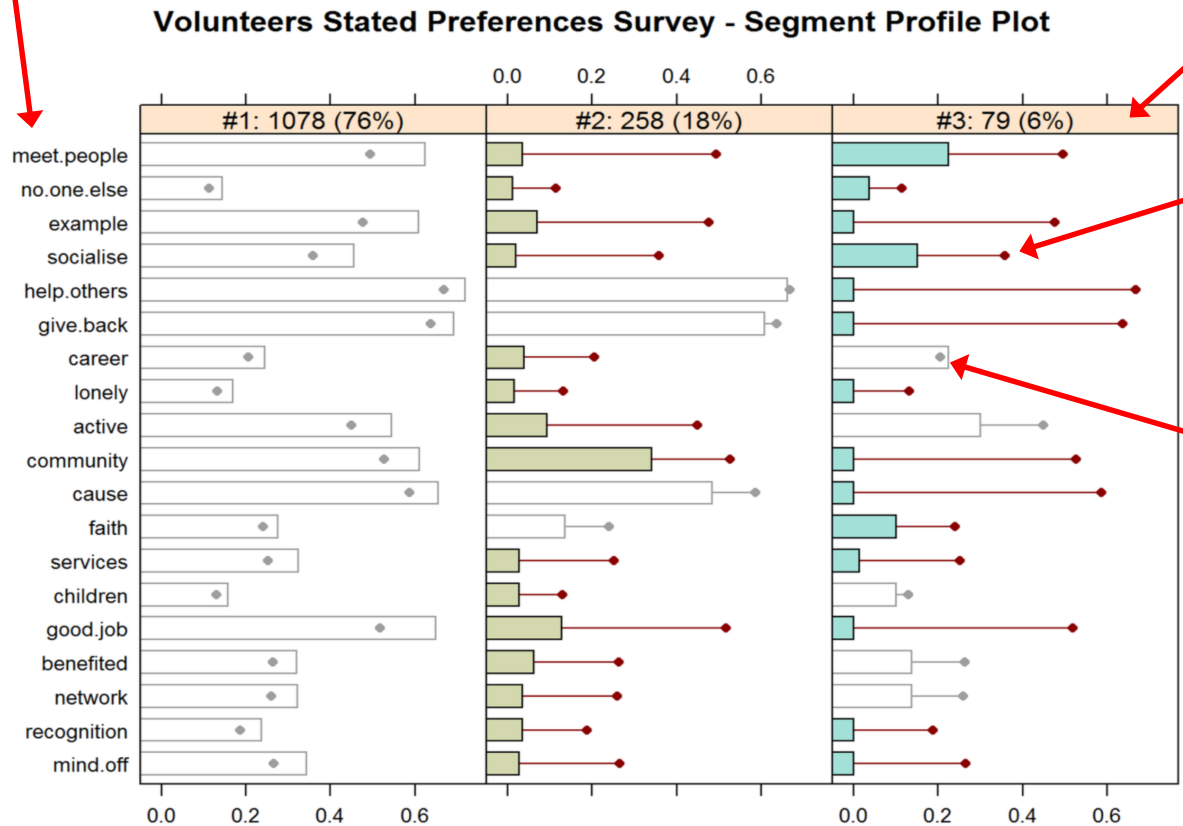
Purpose: Help business partners visualize clusters and how respondents fall within cluster boundaries. IOW, are clusters “real”?

Also known as “neighborhood plot.”

Segment Profile Plot

```
barchart(vol.cl, strip.prefix = "#", shade = TRUE,
         layout = c(vol.cl@k, 1), main = . . .)
```

Tick-box labels



Header: segment #, Count, & % total

Bar: proportion of response in cluster.
Red line/dot: overall proportion

Greyed out when response not important to differentiate from other clusters.
BUT, can still be an important characteristic of cluster

Purpose: Help business partners translate clusters into segment stories.
IOW, describe the clusters in business friendly terms.

So far: we've used standard flexclust techniques.

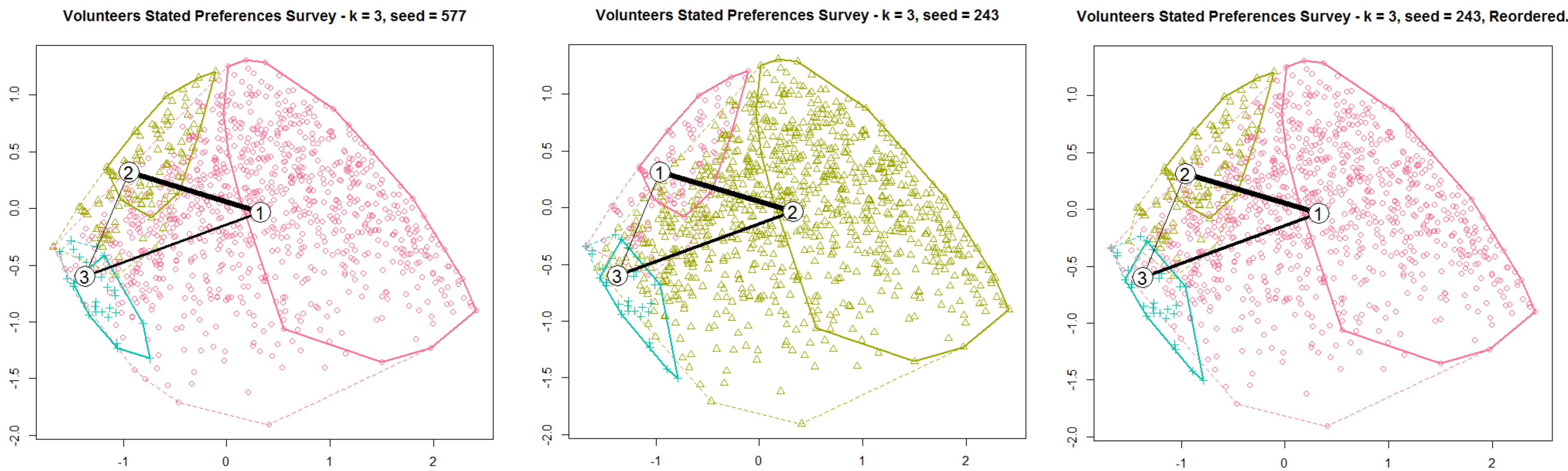
See appendix for references and links.

Now, we'll address three practical issues:

1. Different starting seeds will number ~ equal clusters differently. *The numbering problem.*
2. Different starting seeds will result in quite different clusters. *The stability problem.*
3. There is no automatic way to pick optimum k. *The "best" k problem.*

The Numbering Problem

Two different seeds have nearly equal solutions, but are labeled differently:



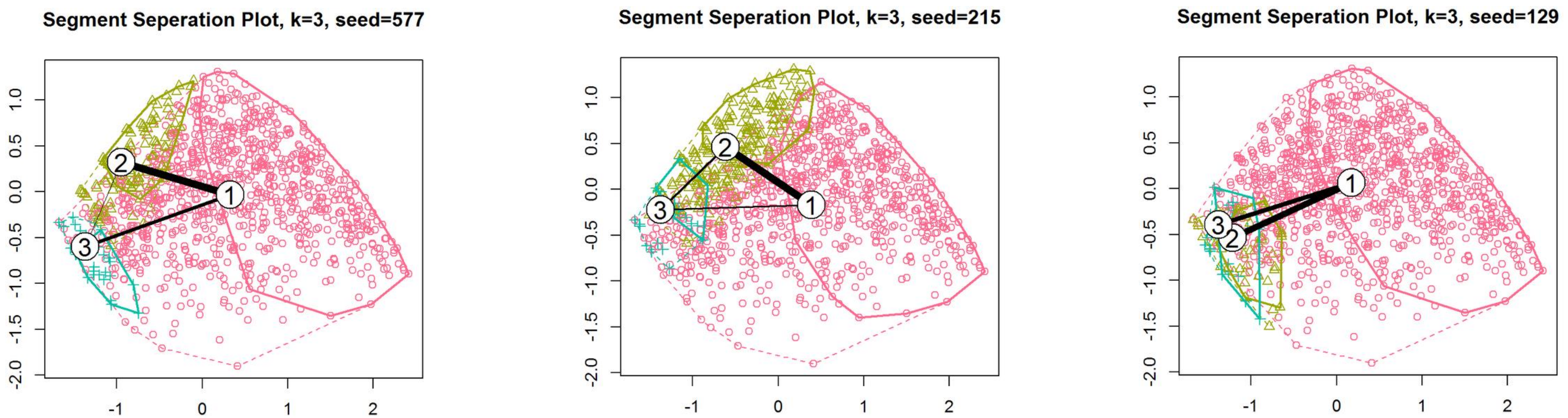
fc_reorder {CustSegs}

Reorder clusters in a kcca object.

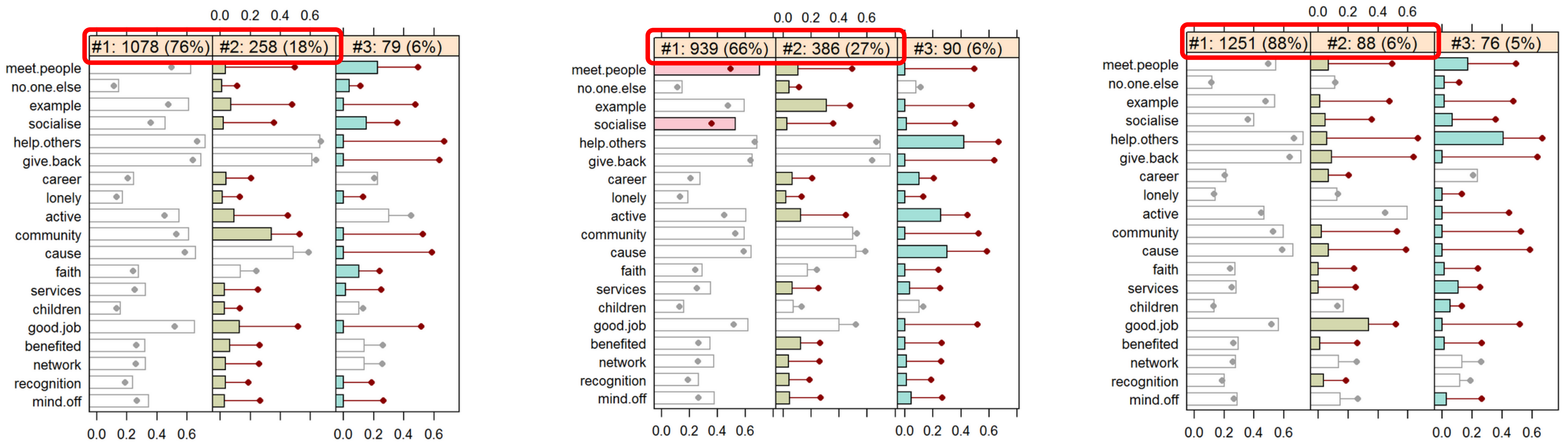
Usage: `fc_reorder(x, orderby = "decending size")`

The Stability Problem

Three different seeds have quite different solutions:



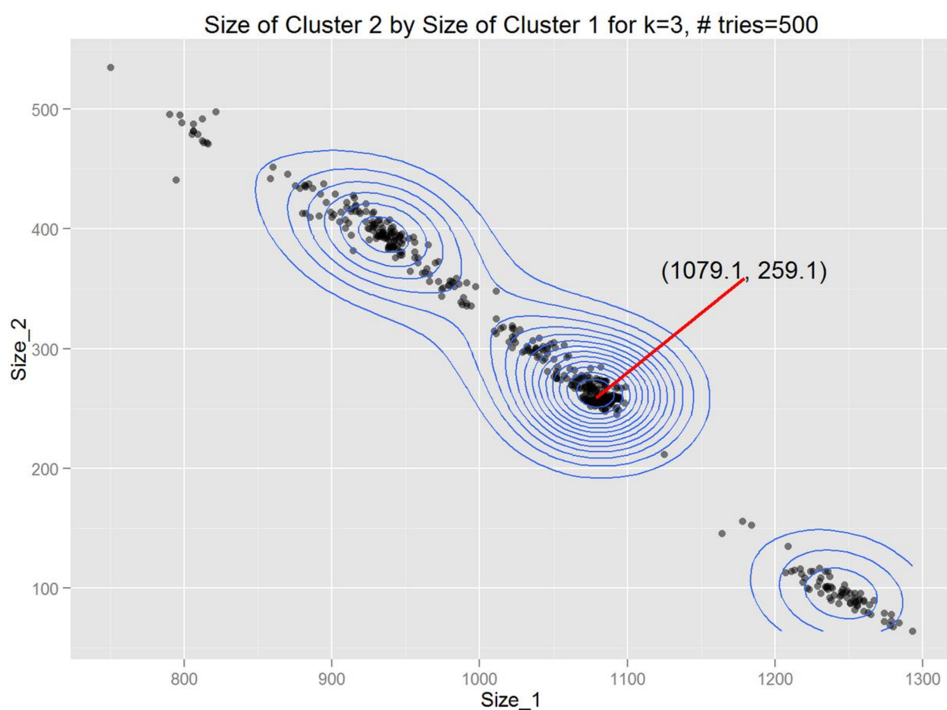
We need a simple way to classify each solution – just use sizes of two biggest clusters:

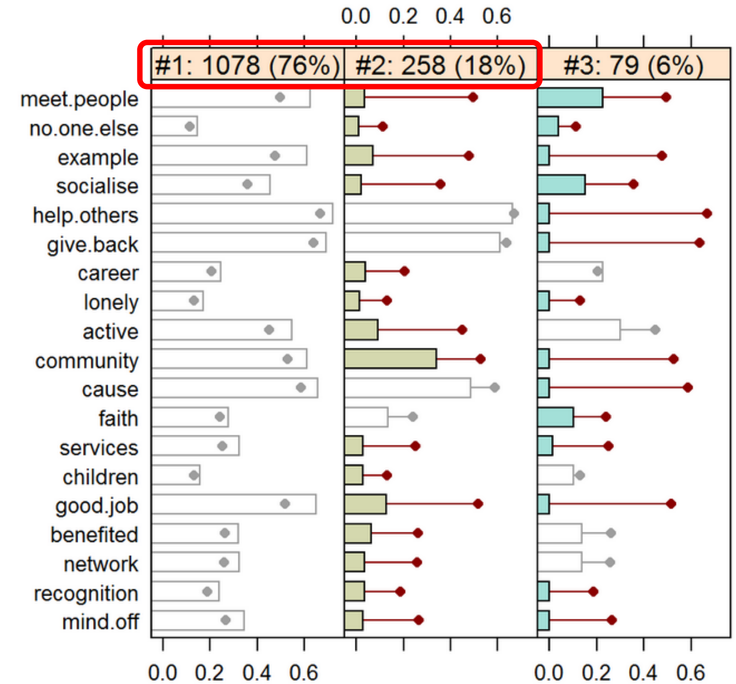


Simple Method to Explore Stability

- For a given k, run a few hundred solutions (incrementing seed each time):
  - Re-order clusters in descending size order
  - Save: k, seed, cluster #, & count
- Call Size_1 the count for 1st cluster;
  Size_2 the count for 2nd cluster.
- Scatter plot w/ 2D density curves: Size_2 x Size_1
- Solve for peak location

Stability Plot of kcca Solutions for k=3





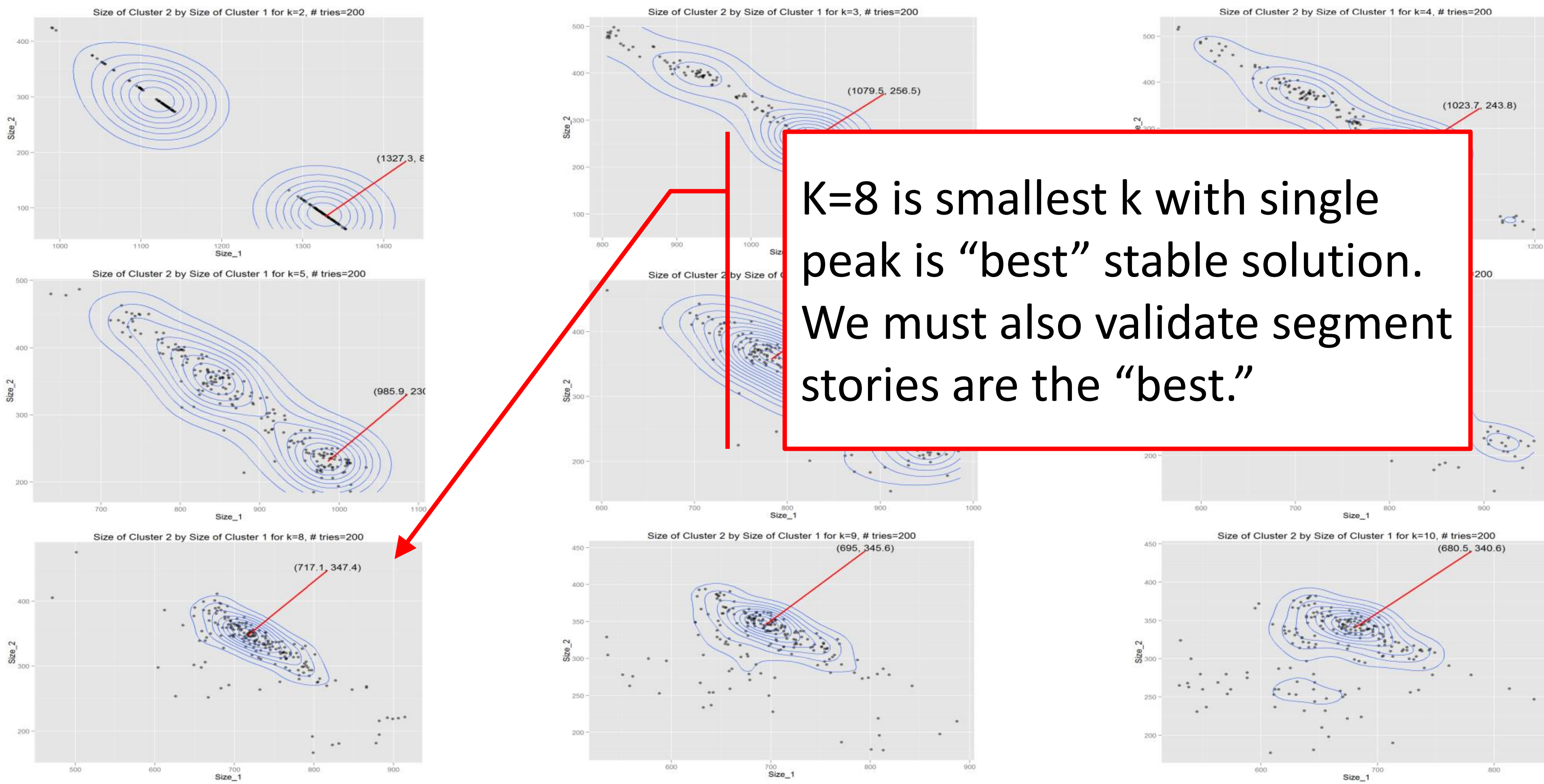
fc_rclust {CustSegs}

Generate a List of Random kcca Objects.

Usage: `fc_rclust(x, k, fc_cont, nrep = 100, fc_family, verbose = FALSE, FUN = kcca, seed = 1234, plotme = TRUE)`

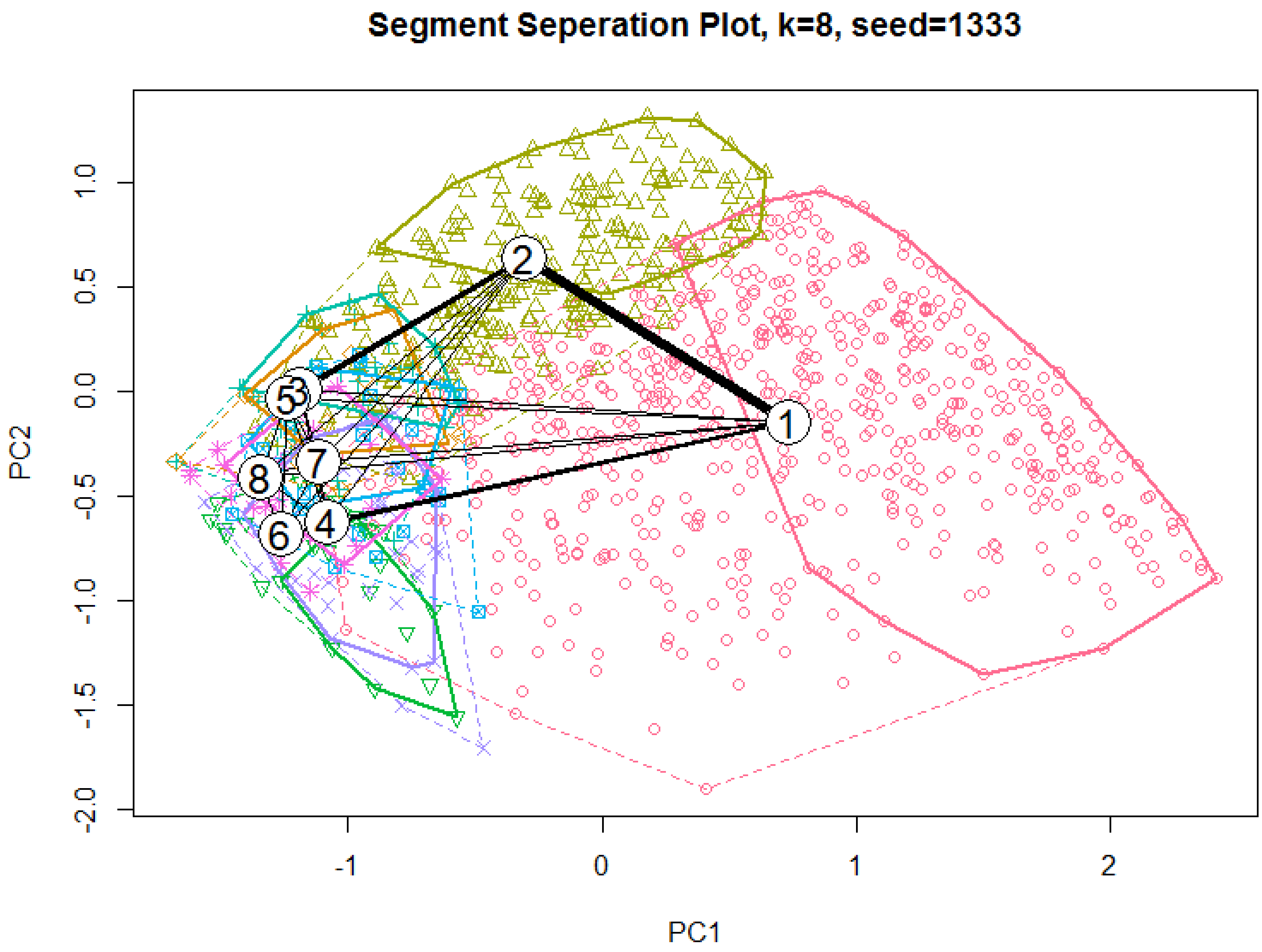
The “Best” k Problem

Generate stability plots for k = 2, 3, …, 10:



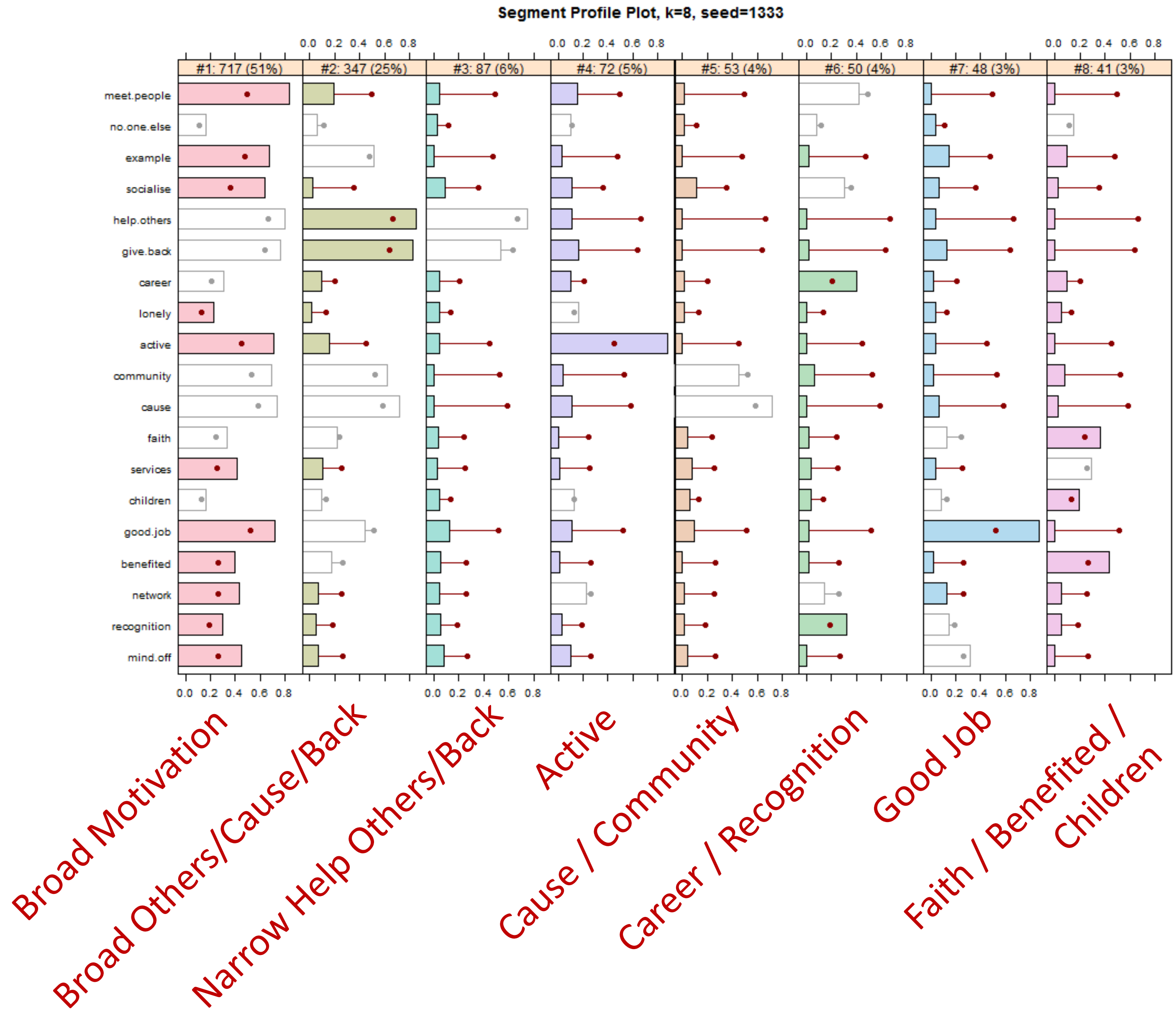
K=8 is smallest k with single peak is “best” stable solution. We must also validate segment stories are the “best.”

Segment Separation for “best” k = 8 (seed = 1333)



Profile Plot for "best" k = 8 (seed = 1333)

One Segment Story (k = 8,seed = 1333)



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What We Covered

- Customer segmentation background.
- Deep dive into using flexclust on “binary choice” type data
  - Example kcca() run
  - The numbering problem.
  - The stability problem
  - Provisional rule-of-thumb that “best” k is min(k, for single peak contours)
- Next Steps
  - Get typical respondent(s) closest to each centroid.
  - Respondent flow plot between segments.
- Jim@DS4CI.org

Questions? Comments?

Now is the time!

APPENDIX

References

Flexclust details – start here:

Leisch, F. A Toolbox for K-Centroids Cluster Analysis. Computational Statistics and Data Analysis, 51 (2), 526-544, 2006.

Leisch, F. Package ‘flexclust’, CRAN, 2013

Leisch, F. Neighborhood graphs, stripes and shadow plots for cluster visualization. Statistics and Computing, 20 (4), 457-469, 2010.

Application to marketing – start here:

Dolnicar, S. A review of data-driven market segmentation in tourism, Faculty of Commerce - Papers(2002)

Dolnicar, S., Leisch, F. Winter Tourist Segments in Austria - Identifying Stable Vacation Styles for Target Marketing Action, Faculty of Commerce - Papers (2003)

Dolnicar, S., Leisch, F. Using graphical statistics to better understand market segmentation solutions. International Journal of Market Research (2013)

For all of Sara and Fritz’s work see:

http://works.bepress.com/sdolnicar/doctype.html#other

Learning More

- Jim's CustSegs package development at https://github.com/ds4ci/CustSegs
- Tenure based segmentation & subscription survival
  - Subscription Survival for Fun & Profit: https://ds4ci.files.wordpress.com/2013/05/paw_sf2012_subscriptionsurvivalforfunandprofit.pdf
- RFM based segmentation
  - Workshop at N Cal DMA lunch group https://ds4ci.files.wordpress.com/2015/03/rfmb_dmanc_200905201.pdf
  - Using R for Customer Segmentation workshop at useR! 2008 Dortmund https://ds4ci.files.wordpress.com/2013/09/user08_jimp_custseg_revnov08.pdf
    - Also has sample data set & flexclust example
- Customer Classification
  - See above useR! 2008 workshop for details on flexclust
- Jim's Archives www.ds4ci.org/archives
- Contact: Jim@DS4CI.org

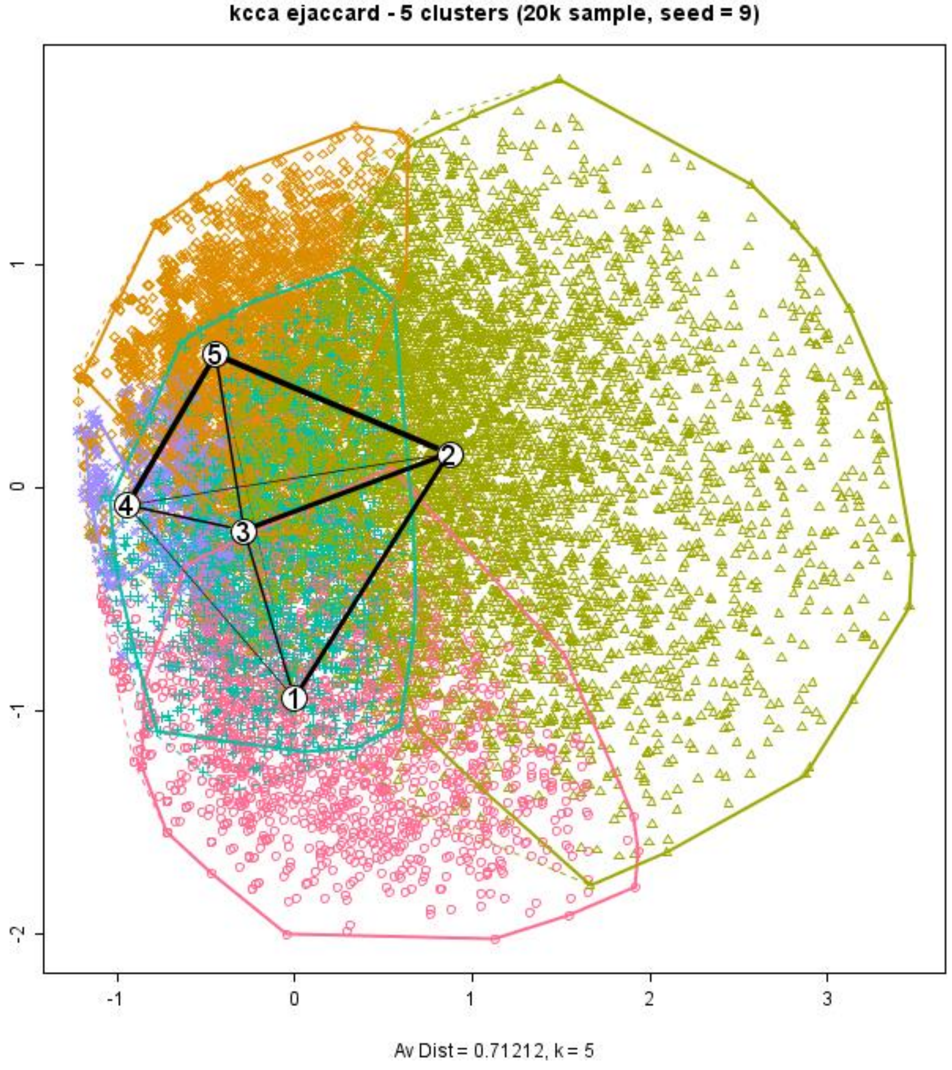
A couple of real world examples

Example 1 – Survey Responses

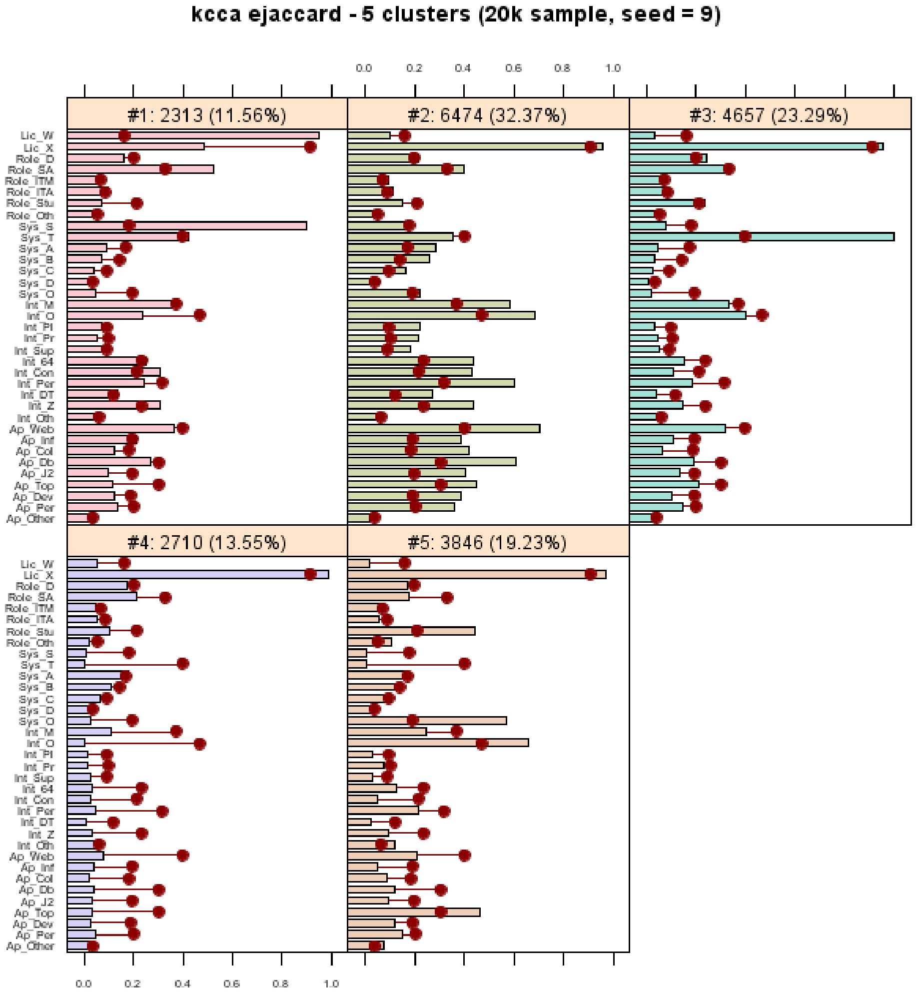
- 20k respondents to technical product use survey
- 35 check boxes or radio buttons
  - None are required, coded as binary responses
- Goal: come up with “a few” segments which can be used to segment new respondents for follow up sales actions.
- 5-cluster solution: OS loyalists, Other brand responders, Other brand non-responders, Students
- See https://ds4ci.files.wordpress.com/2013/05/paw_09-sun-microsystems-case-study.pdf

Example 1 - The 5-cluster solution

The 20k subjects plotted over the first two principal components:



The 5 clusters showing distribution of responses to each question:



Example 2 – Business Attributes

- ~1k respondents to "nature of your business" survey
- 62 check boxes or radio buttons
  - In six topics
  - Some are required
  - Coded as binary responses
- Goal: come up with "a few" segments to characterize the fundamental nature of the on-line business.
- 6-cluster solution: Enterprise, Freemium, Marketplace, Ads/Leadgen, Ecommerce, SAAS.

Example 2 – the 6-cluster solution