useR! 2006

Using R for Customer Analytics

A Practical Introduction to R for Business Analysts

by Jim Porzak

Loyalty Matrix

April 2006

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Outline

- Introduction:
  - What is "customer analytics" and why do we do it?
  - Specific Loyalty Matrix tools & biases.
  - Implications of working in a business environment.
- Part I - Getting Started: A Brief review of what needs to be done before serious analysis can start.
  - Sourcing business requirements.
  - Sourcing raw data.
  - Profiling raw data.
  - Data quality control & remediation.
  - Staging data for analysis.
- Part II - EDA and Basic Statistics: A Step-by-step look at basic customer data with three important variations of the usual business model.
  - The fundamentals: counts, amounts and intervals.
  - The geographical view.
  - Subscription businesses.
  - Hospitality businesses.
  - Big ticket businesses.
- Part III - Mining, Modeling, Segmentation & Prediction: An overview of some useful packages for advanced customer analytics.
  - Decision tree methods - rpart, tree, party and randomForest.
  - Survival methods - survival and friends
  - Clustering methods - mclust, flexclust.
  - Association methods - arules.
- Conclusion:
  - Review of applicable methods by type of client.
  - The customer analytics check list.

Note: For R setup details see first Appendix slide.

What is "Customer Analytics"?

Customer analytics exploit customer behavioral data to identify unique and actionable segments of the customer base. These segments may be used to increase targeting methods. Ultimately, customer analytics enable effective and efficient customer relationship management. The analytical techniques vary based on objective, industry and application, but may be divided into two main categories.

***Segmentation techniques** segment groups of the customer base that have similar spending and purchasing behavior. Such groups are used to enhance the predictive models as well as improve offer and channel targeting.*

***Predictive models** predict profitability or likelihood and timing of various events based on typical customer behavior and deviations from that behavior.*

-- Roman Lenzen, DM Review Magazine, June 2004

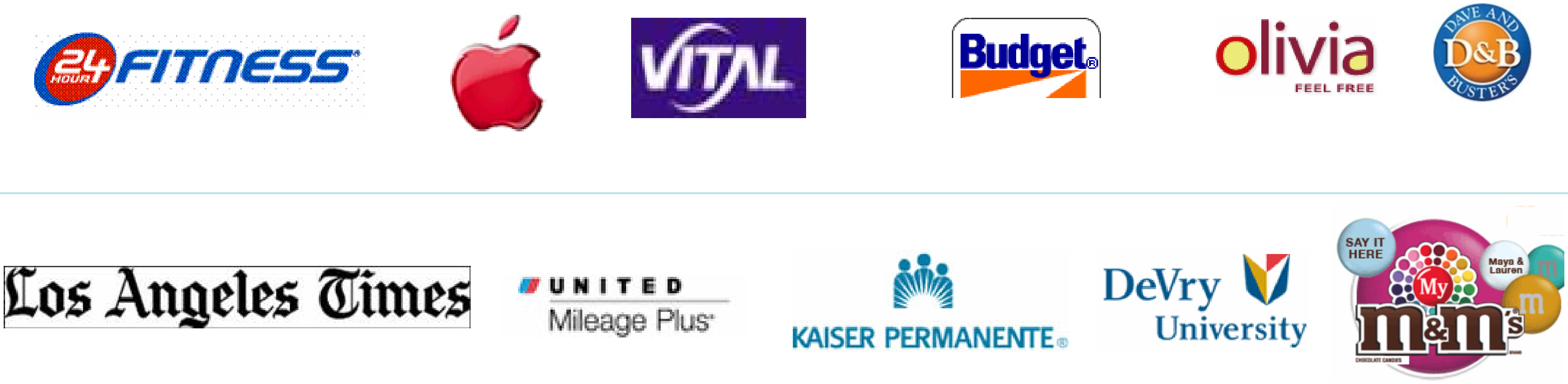
Why we do Customer Analytics.

If we understand our customers better, we can serve them better.

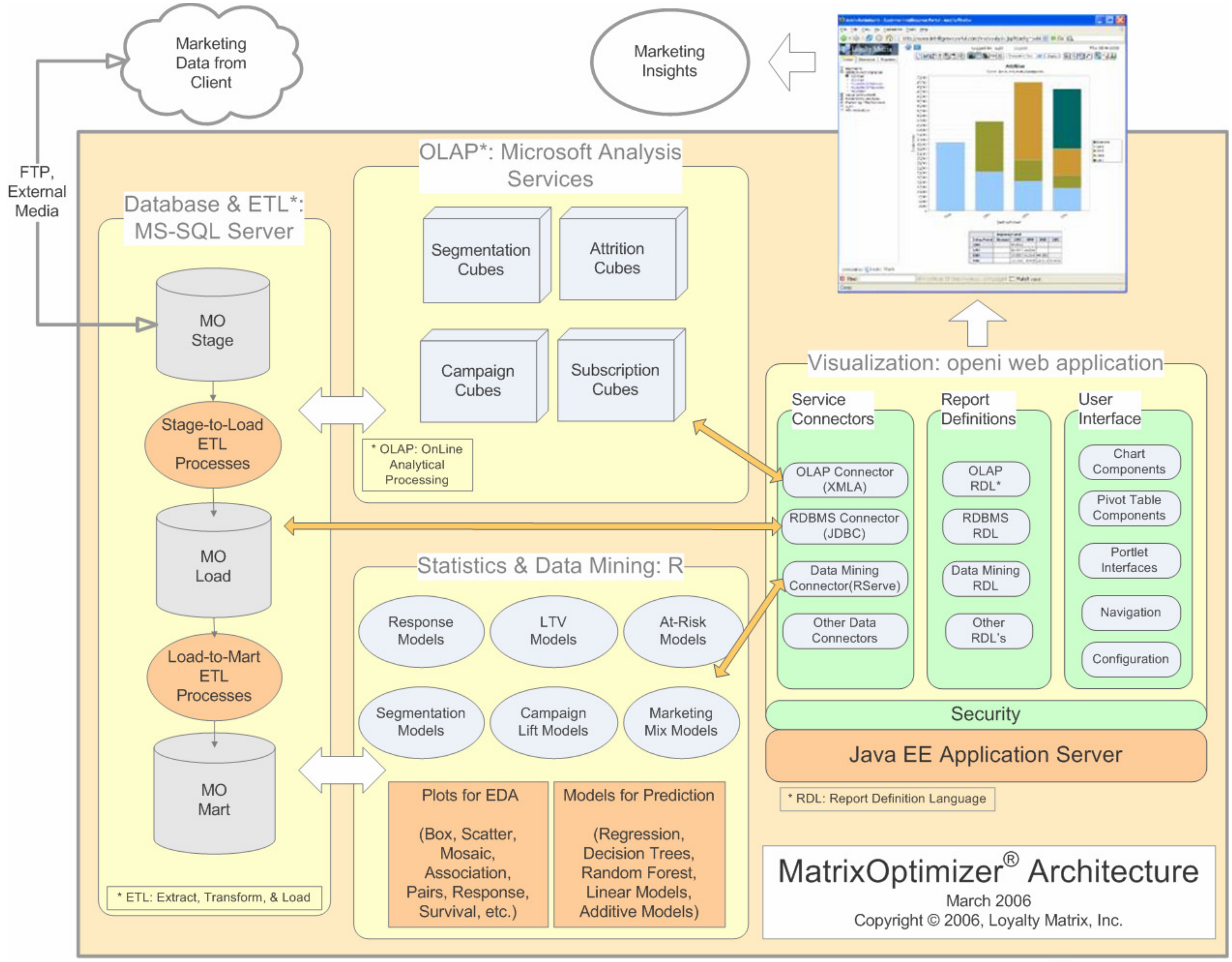
When we serve our customers better, they will help us be successful.

Background on Loyalty Matrix

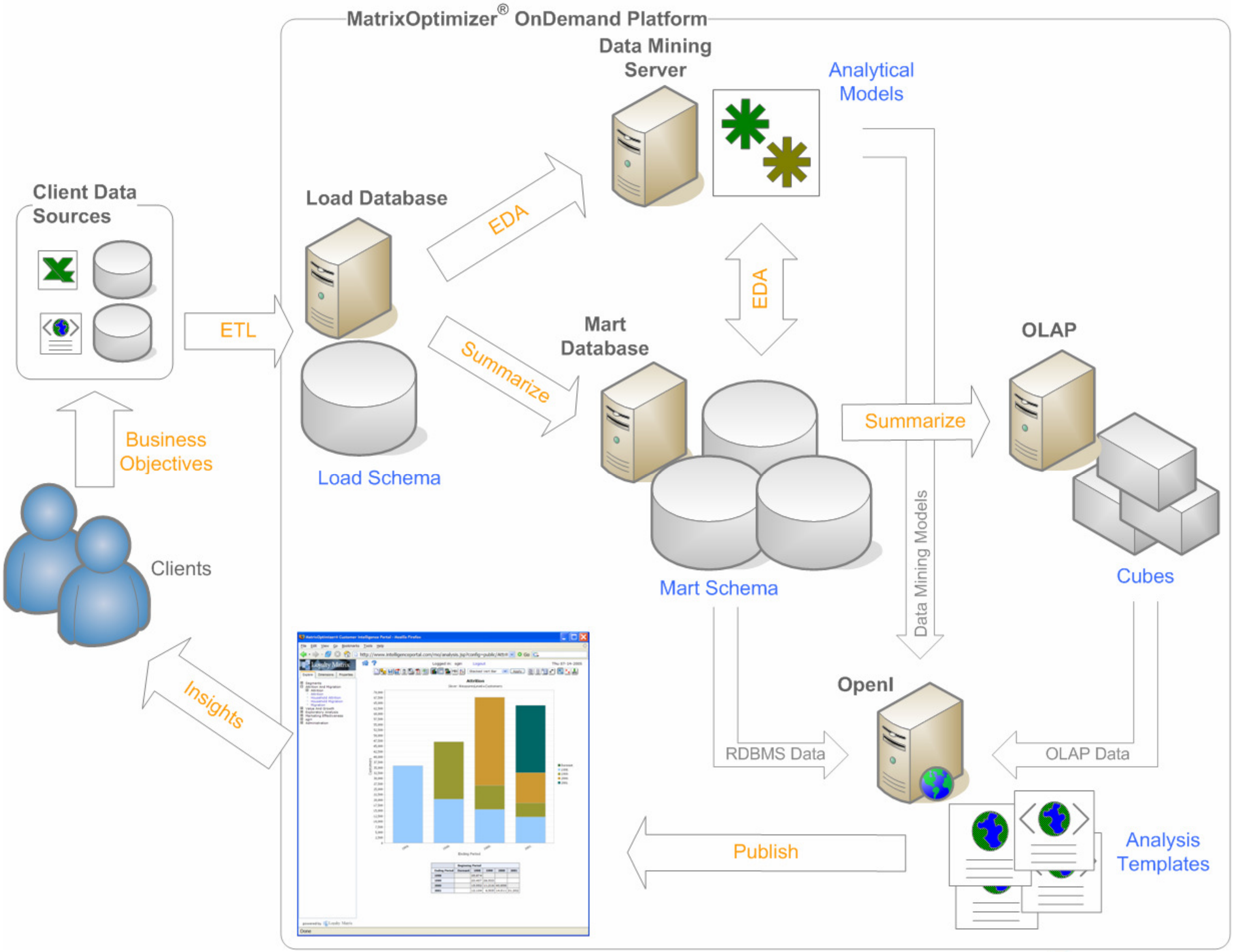
- Provide customer data analytics to optimize direct marketing resources
- OnDemand platform MatrixOptimizer® (version 3.2)
- Over 20 engagements with Fortune 500 clients
- Experienced team with diverse skills & backgrounds
- 15-person San Francisco firm with an offshore team in Nepal



MatrixOptimizer®: Architecture Overview


Marketing Data from Client
FTP, External Media
Marketing Insights
Database & ETL*: MS-SQL Server
MO Stage
Stage-to-Load ETL Processes
MO Load
Load-to-Mart ETL Processes
MO Mart
* ETL: Extract, Transform, & Load
OLAP*: Microsoft Analysis Services
Segmentation Cubes
Attrition Cubes
Campaign Cubes
Subscription Cubes
* OLAP: OnLine Analytical Processing
Statistics & Data Mining: R
Response Models
LTV Models
At-Risk Models
Segmentation Models
Campaign Lift Models
Marketing Mix Models
Plots for EDA
(Box, Scatter, Mosaic, Association, Pairs, Response, Survival, etc.)
Models for Prediction
(Regression, Decision Trees, Random Forest, Linear Models, Additive Models)
Visualization: openi web application
Service Connectors
OLAP Connector (XMLA)
RDBMS Connector (JDBC)
Data Mining Connector(RServe)
Other Data Connectors
Report Definitions
OLAP RDL*
RDBMS RDL
Data Mining RDL
Other RDL's
User Interface
Chart Components
Pivot Table Components
Portlet Interfaces
Navigation
Configuration
Security
Java EE Application Server
* RDL: Report Definition Language
MatrixOptimizer® Architecture
March 2006
Copyright © 2006, Loyalty Matrix, Inc.

MatrixOptimizer®: Environment Overview



MatrixOptimizer® OnDemand Platform

Client Data Sources

ETL

Load Database

Load Schema

EDA

Data Mining Server

Analytical Models

Summarize

Mart Database

EDA

Mart Schema

Summarize

OLAP

Cubes

Data Mining Models

OpenI

RDBMS Data

OLAP Data

Analysis Templates

Publish

Insights

Clients

Business Objectives

Implications of Business Environment

- It’s a Windows / Office world
- Focused Inquiries
- Large N
- Business Interpretation is Essential
- Rigor unexpected & unappreciated
  - Up to you to supply & enforce

Part I – Getting Started

A Brief review of what needs to be done before serious analysis can start.

- Sourcing business requirements.
- Sourcing raw data.
- Profiling raw data.
- Data quality control & remediation.
- Staging data for analysis.

Sourcing Business Requirements

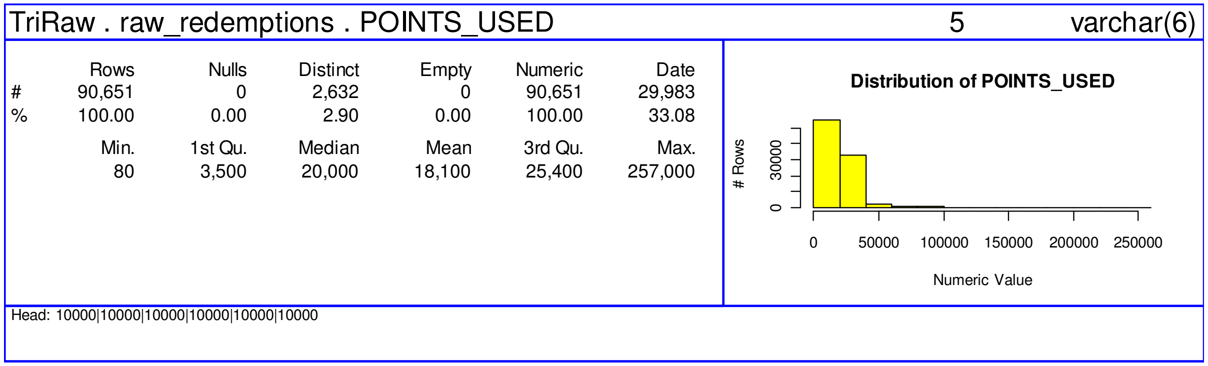
- Most Important Step!
- What are the real business issues?
  - Not what analyses to perform
  - Not immediate concerns of your individual client
  - The BIG business issue driving project
- How will success of project be measured?
  - Some Key Performance Indicators (KPI's)
  - Measure baseline values before starting
    - Ensure KPI's can be calculated
    - Get management signoff at onset
- Ensure everyone agrees on key requirements

Sourcing Raw Data

- Is data available to answer business questions?
  - Don’t believe the data structure diagram
- Translating between Marketing & IT
  - As an outsider, you are allowed stupid questions
- Get lowest level of detail
  - Not always feasible, but try for it
- BOFF set is typical
  - “Big ol’ Flat File”
- Avoid Excel as file transfer medium at all costs

Profiling Raw Data

- Profile staged raw data to check assumptions about data made when defining problem



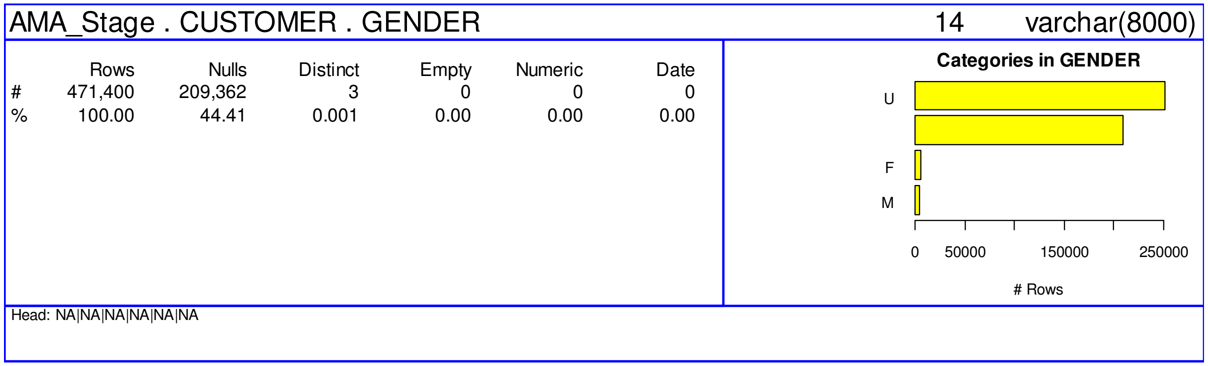
TriRaw . raw_redemptions . POINTS_USED 5 varchar(6)

	Rows	Nulls	Distinct	Empty	Numeric	Date
#	90,651	0	2,632	0	90,651	29,983
%	100.00	0.00	2.90	0.00	100.00	33.08

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
80	3,500	20,000	18,100	25,400	257,000

Distribution of POINTS_USED

Head: 10000|10000|10000|10000|10000|10000



AMA_Stage . CUSTOMER . GENDER 14 varchar(8000)

	Rows	Nulls	Distinct	Empty	Numeric	Date
#	471,400	209,362	3	0	0	0
%	100.00	44.41	0.001	0.00	0.00	0.00

Categories in GENDER

Head: NA|NA|NA|NA|NA|NA

Details in Friday's talk

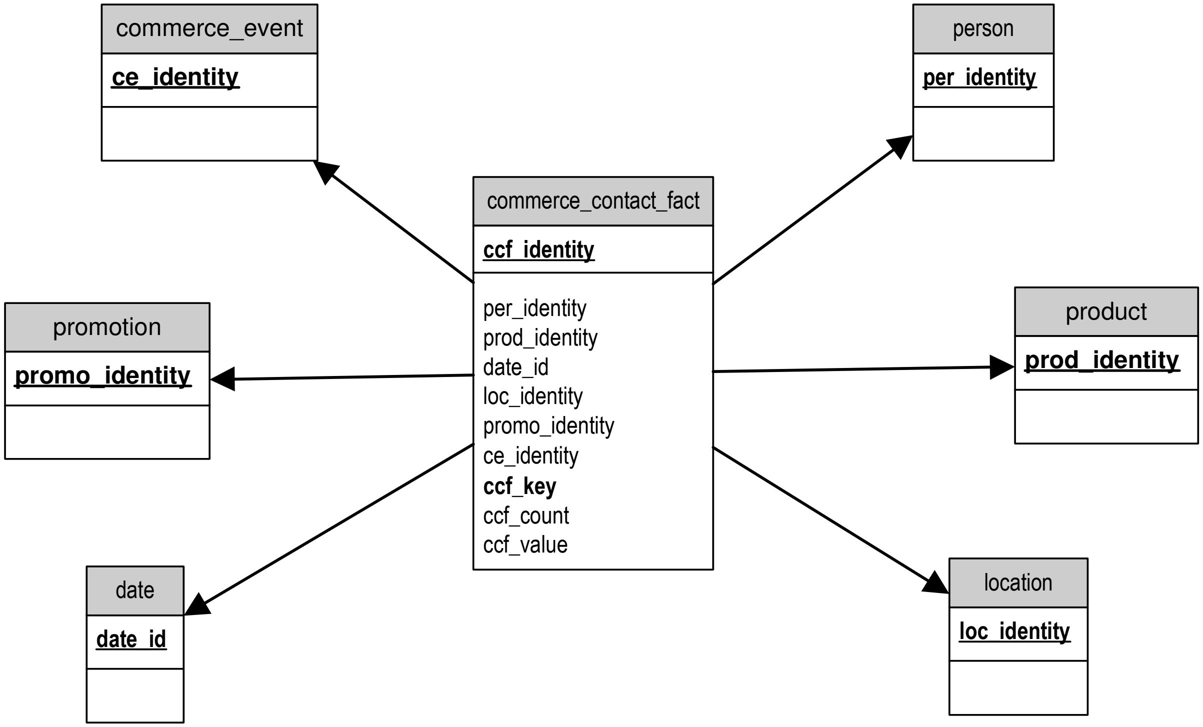
Loyalty Matrix

Quality Control & Remediation

- Watch out for
  - – The Cancellation Event
    - Opt-out Email
    - Canceling club membership
  - – Split Identities
    - Consolidating customer records to the individual & household
      - – Same Address, similar name, different business key
      - – Tracking Movers
  - – Magic Values
    - Especially Dates
- Outliers in amounts & counts probably real
  - – But need checking
- Limit data to problem(s) at hand

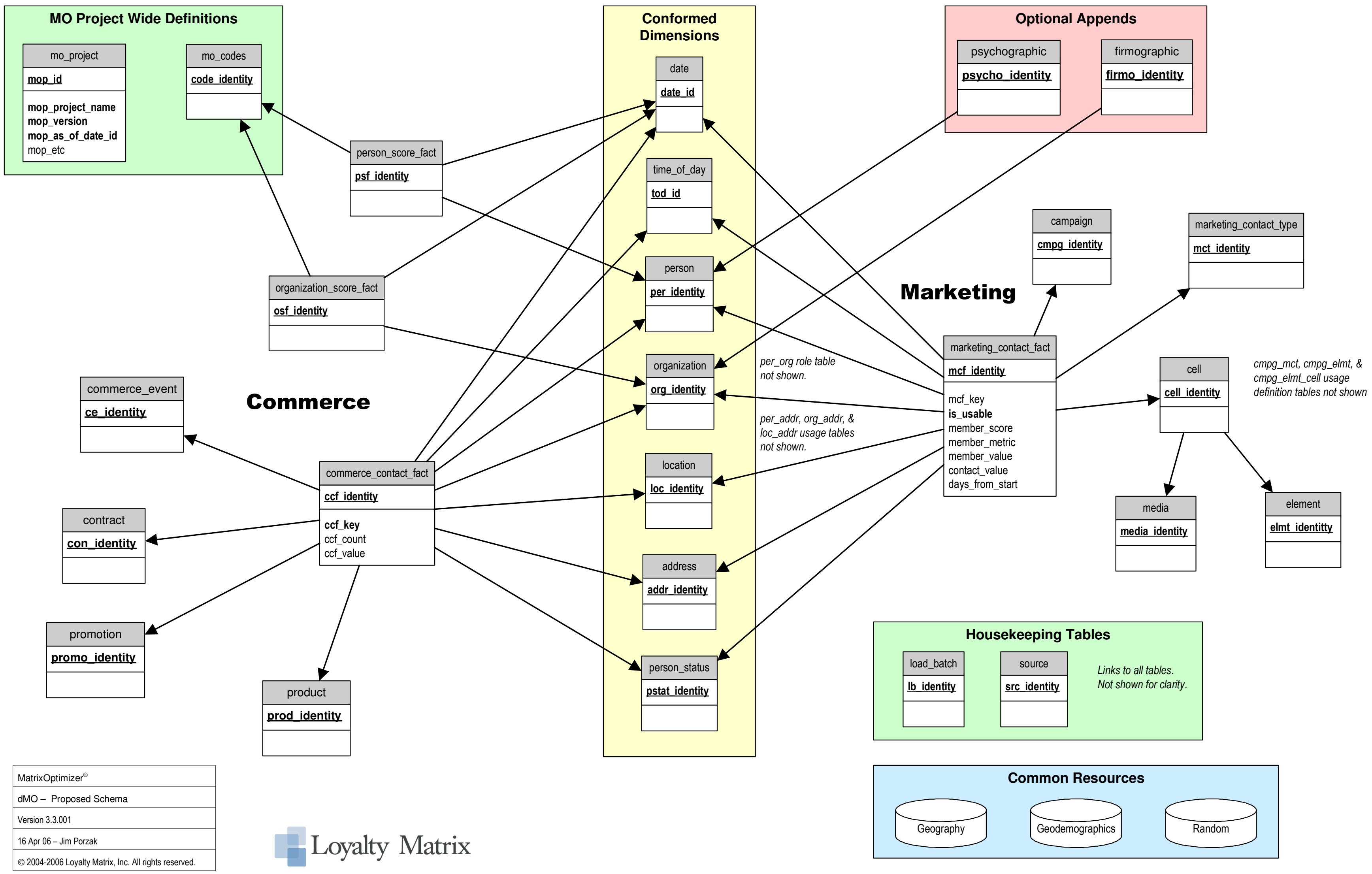
Staging Data for Analysis – Star Schema

- RDBMS Datamart using a Star Schema
  - See Ralph Kimball: http://www.kimballgroup.com
  - Holds "Analysis Ready" data



Loyalty Matrix

Our "MO" Schema's Two Main Modules



MO Project Wide Definitions

mo_project
mop_id
mop_project_name
mop_version
mop_as_of_date_id
mop_etc

mo_codes
code_identity

Conformed Dimensions

date
date_id

time_of_day
tod_id

person
per_identity

organization
org_identity

location
loc_identity

address
addr_identity

person_status
pstat_identity

Optional Appends

psychographic
psycho_identity

firmographic
firmo_identity

person_score_fact
psf_identity

organization_score_fact
osf_identity

Commerce

commerce_event
ce_identity

contract
con_identity

promotion
promo_identity

product
prod_identity

commerce_contact_fact
ccf_identity
ccf_key
ccf_count
ccf_value

Marketing

campaign
cmpg_identity

marketing_contact_type
mct_identity

marketing_contact_fact
mcf_identity
mcf_key
is_usable
member_score
member_metric
member_value
contact_value
days_from_start

cell
cell_identity

media
media_identity

element
elmt_identitty

per_org role table not shown.

per_addr, org_addr, & loc_addr usage tables not shown.

cmpg_mct, cmpg_elmt, & cmpg_elmt_cell usage definition tables not shown

Housekeeping Tables

load_batch
lb_identity

source
src_identity

Links to all tables. Not shown for clarity.

Common Resources

Geography

Geodemographics

Random

MatrixOptimizer®

dMO – Proposed Schema

Version 3.3.001

16 Apr 06 – Jim Porzak

Loyalty Matrix

Staging Data for Analysis – Moving to R

- Use RODBC to load directly from datamart

```
require(RODBC)
cODBC <- odbcConnect("KeyCustomers")                          # in Windows: odbcConnect("") works
myQuery <- readChar("../SQL/MyQuery.sql", nchars = 99999)     # use cat(myQuery) to view
MyDataFrame <- sqlQuery(cODBC, myQuery)
# Fix up datatypes, factors if necessary
MyDataFrame$DatePch <- as.Date(MyDataFrame$DatePch)
str(MyDataFrame)
head(MyDataFrame)
```

- Use SQL export & read.table
  - We'll use read.delim for tutorial (I like tab delimited)

```
KeyCustomers <- read.delim("Data/KeyCustomers.txt", row.names = "ActNum")
```

- Sampling large data sets
  - RANDOM table trick (two columns: integer identity & runif [0, 9999])

```
SELECT SUBT_ID, etc…
FROM NewSubscribers ns
  JOIN Random r
    ON r.identity_key = ns.SUBT_ID
   AND r.random <= 100  -- for 10% sample
```

Practical: First Data Set

- Manufacturer of parts & tools for construction trades
- Direct sales to key accounts
- Summary data set with:
  - Account ID
  - Standard Industrial Classification (SIC) code hierarchy
  - Sales metrics
    - Total $ for Year
    - # Invoices in Year
    - # Different Products in Year
  - Classified by "Potential Size" – created by sales team
    - Mega, Large, Medium, Small, Mini & Unknown
- Business Questions:
  - Does Potential Size classification work?
  - What are SIC differences

Practical: Getting Started (1 of 2)

- Check setup of R and our editing environment

```
R : Copyright 2006, The R Foundation for Statistical Computing
Version 2.3.0 (2006-04-24)
ISBN 3-900051-07-0

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> require(RWinEdt)
Loading required package: RWinEdt
[1] TRUE
>
```

Practical: Getting Started (2 of 2)

- Load our first customer dataset
  - *After looking at it with a text editor!*

```
> # CIwR_01_setup.R
> # Get started by loading, checkking & saving Key Customers data
>
> setwd("c:/Projects/CIwR/R")
> dir()
[1] "CodeArchive" "Data"        "Plots"
> dir("Data")
[1] "KeyCustomers.txt"
>
> KeyCustomers <- read.delim("Data/KeyCustomers.txt", row.names = "ActNum")
> str(KeyCustomers)
`data.frame':   48714 obs. of  10 variables:
 $ PotSize  : Factor w/ 6 levels "LARGE","MEDIUM",..: 5 1 2 2 4 4 4 4 2 2 ...
 $ Country  : Factor w/ 1 level "USA": 1 1 1 1 1 1 1 1 1 1 ...
 $ IsCore   : Factor w/ 1 level "Core": 1 1 1 1 1 1 1 1 1 1 ...
 $ SIC_Div  : Factor w/ 4 levels "Construction",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ SIC_Group: Factor w/ 11 levels "Building Construction General Contractors And Oper",..: 1 4 4 1 4 4 4
 $ SIC_Name : Factor w/ 43 levels "ARCH/ORNAMENTAL METAL",..: 16 11 9 16 40 9 19 18 9 18 ...
 $ PchPctYr : num  0.274 98.082 67.671  0.000  0.000 ...
 $ NumInvYr : int  2 60 10 1 1 1 4 1 7 1 ...
 $ NumProdYr: int  2 81 22 1 3 1 6 1 5 2 ...
 $ DlrsYr   : num    401 31021  6345   643   121 ...
> save(KeyCustomers, file = "KeyCustomers.rda")
> dir()
[1] "CodeArchive"      "Data"             "KeyCustomers.rda" "Plots"
```

Part II – EDA & Basic Statistics

EDA and Basic Statistics: A Step-by-step look at basic customer data with three important variations of the usual business model.

- The fundamentals:
  - Counts and amounts and intervals.
- The geographical view.
- Subscription businesses.
- Hospitality businesses.
- Big ticket businesses.

Practical: EDA of Key Customers (1)

- Retrieve saved data frame, take a close look

```
> load("KeyCustomers.rda")
> str(KeyCustomers)
`data.frame':           48714 obs. of  11 variables:
 $ PotSize  : Factor w/ 6 levels "LARGE","MEDIUM",..: 5 1 2 2 4 4 4 4 2 2 ...
 $ Country  : Factor w/ 1 level "USA": 1 1 1 1 1 1 1 1 1 1 ...
 $ IsCore   : Factor w/ 1 level "Core": 1 1 1 1 1 1 1 1 1 1 ...
 $ SIC_Div  : Factor w/ 4 levels "Construction",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ SIC_Group: Factor w/ 11 levels "Building Construction General Contractors And Oper",..: 1 4 4 1 4 4  ...
 $ SIC_Name : Factor w/ 43 levels "ARCH/ORNAMENTAL METAL",..: 16 11 9 16 40 9 19 18 9 18 ...
 $ PchPctYr : num   0.274 98.082 67.671  0.000  0.000 ...
 $ NumInvYr : int  2 60 10 1 1 1 4 1 7 1 ...
 $ NumProdYr: int  2 81 22 1 3 1 6 1 5 2 ...
 $ DlrsYr   : num    401 31021  6345   643   121 ...
 $ ZIP      : chr  "33063" "37643" "33569" "22151" ...
```

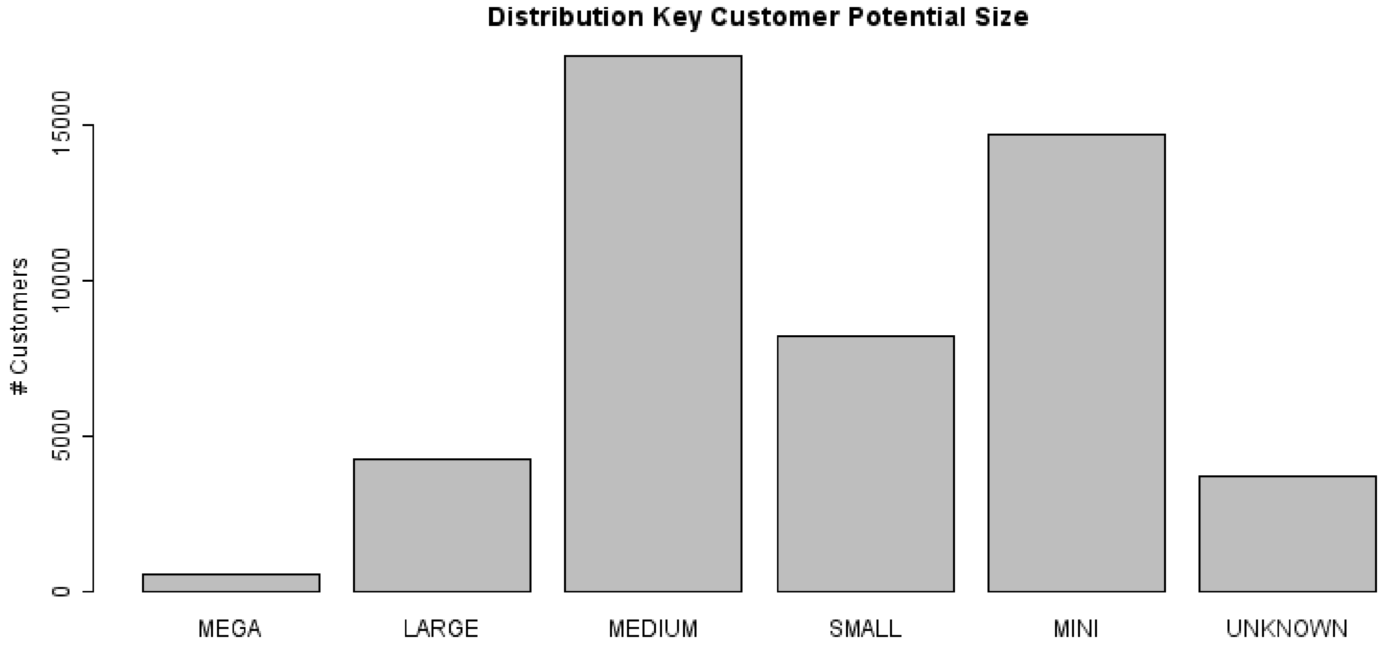
- Observe following & fix
  - PotSize should be ordered
  - Country & IsCore contribute no information

```
KeyCustomers$PotSize <- ordered(KeyCustomers$PotSize, levels = c("MEGA", "LARGE", "MEDIUM", "SMALL",
"MINI", "UNKNOWN"))
# Also, Country & IsCore are superfluous, remove them from analysis set
KeyCustomers <- subset(KeyCustomers, select = -c(Country, IsCore))
summary(KeyCustomers)
save(KeyCustomers, file = "KeyCustomers2.rda")    ## Save subseted data frame
```

Practical: EDA of Key Customers (2)

- Look at variables, starting with Potential Size

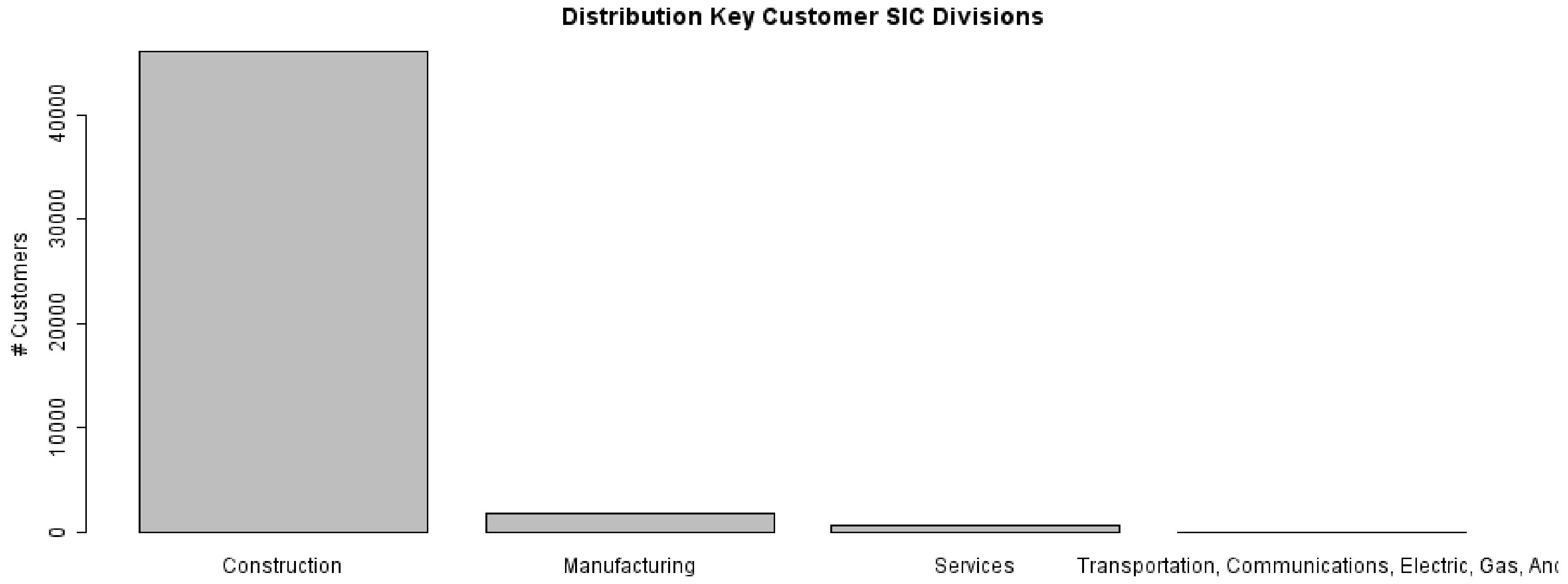
```
> attach(KeyCustomers)
> table(PotSize)
PotSize
   MEGA   LARGE  MEDIUM   SMALL    MINI UNKNOWN
    541    4288   17214    8227   14705    3739
> barplot(table(PotSize), ylab = "# Customers", main = "Distribution Key Customer Potential Size")
```



Practical: EDA of Key Customers (3)

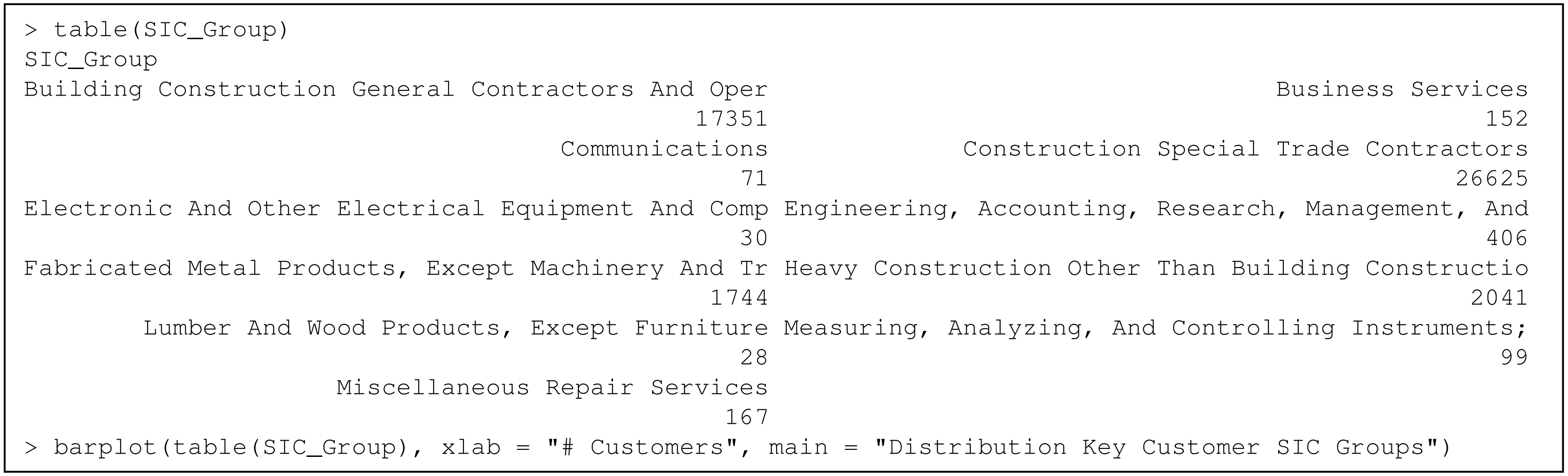
- Top level of SIC hierarchy shows focus of business

```
> table(SIC_Div)
SIC_Div
                    Construction                                           Manufacturing
                           46017                                                    1901
                        Services     Transportation, Communications, Electric, Gas, And
                             725                                                      71

> barplot(table(SIC_Div), ylab = "# Customers", main = "Distribution Key Customer SIC Divisions")
```

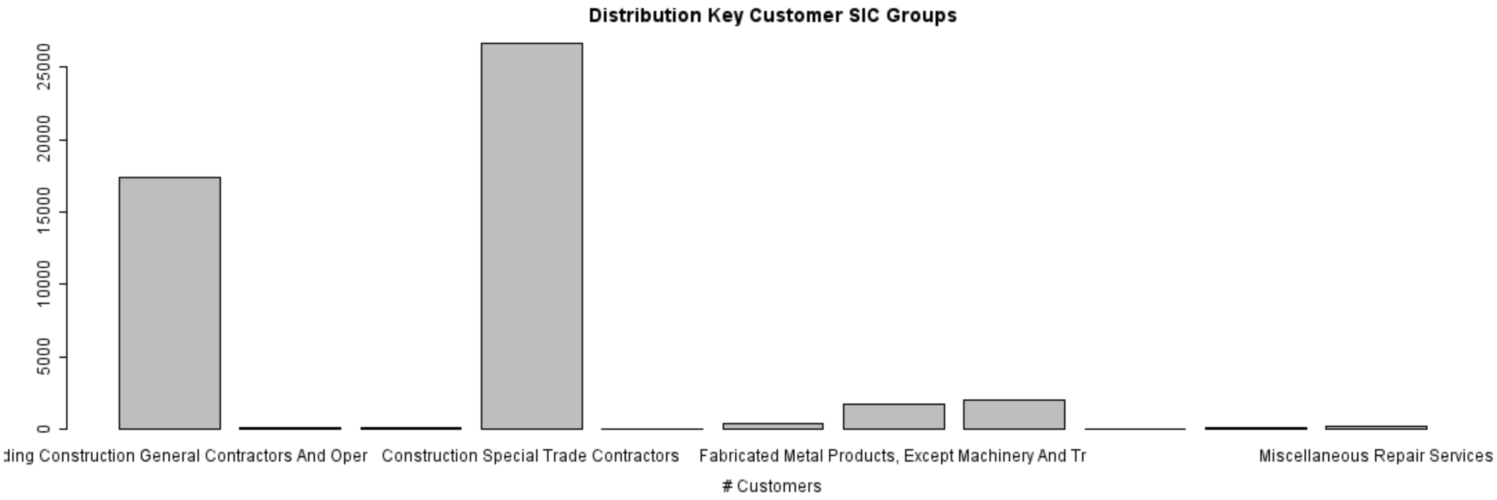


Practical: EDA of Key Customers (4)

- Second level of SIC hierarchy doesn't plot well



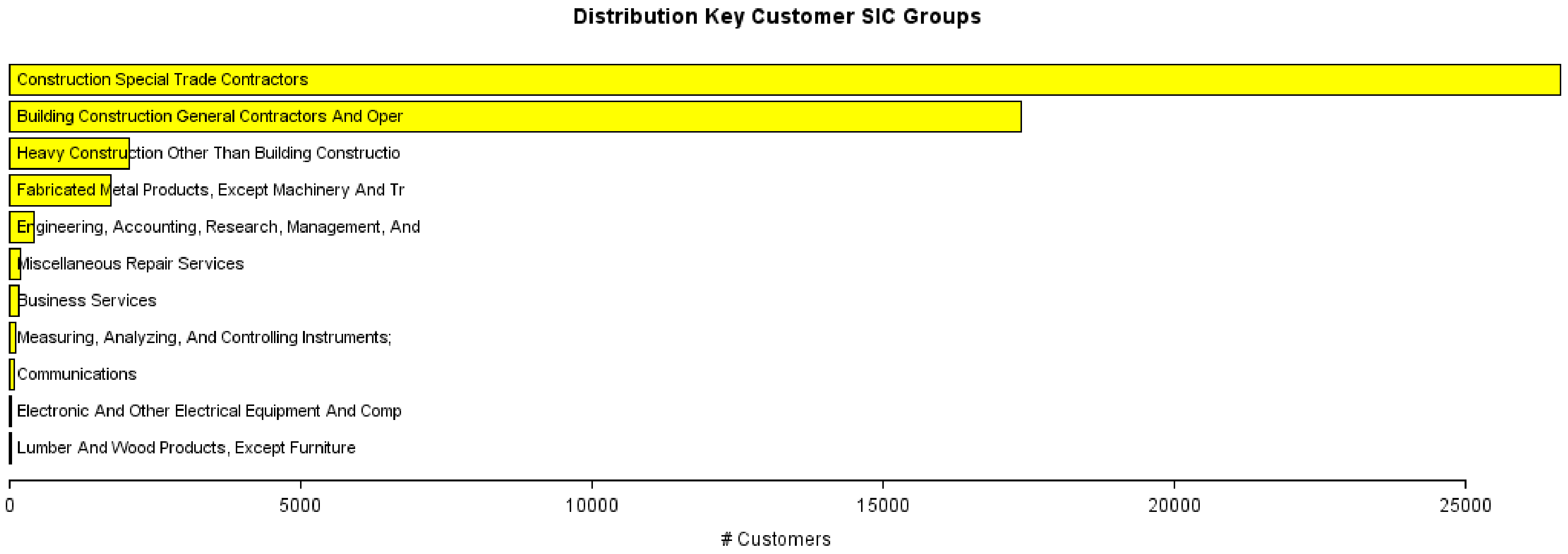
```
> table(SIC_Group)
SIC_Group
Building Construction General Contractors And Oper                                  Business Services
                                             17351                                                152
                                    Communications                Construction Special Trade Contractors
                                                71                                              26625
Electronic And Other Electrical Equipment And Comp Engineering, Accounting, Research, Management, And
                                                30                                                406
Fabricated Metal Products, Except Machinery And Tr Heavy Construction Other Than Building Constructio
                                              1744                                               2041
        Lumber And Wood Products, Except Furniture Measuring, Analyzing, And Controlling Instruments;
                                                28                                                 99
                     Miscellaneous Repair Services
                                               167
> barplot(table(SIC_Group), xlab = "# Customers", main = "Distribution Key Customer SIC Groups")
```



Practical: EDA of Key Customers (5)

- Let’s try horizontal bars
  - & then put labels in plot area

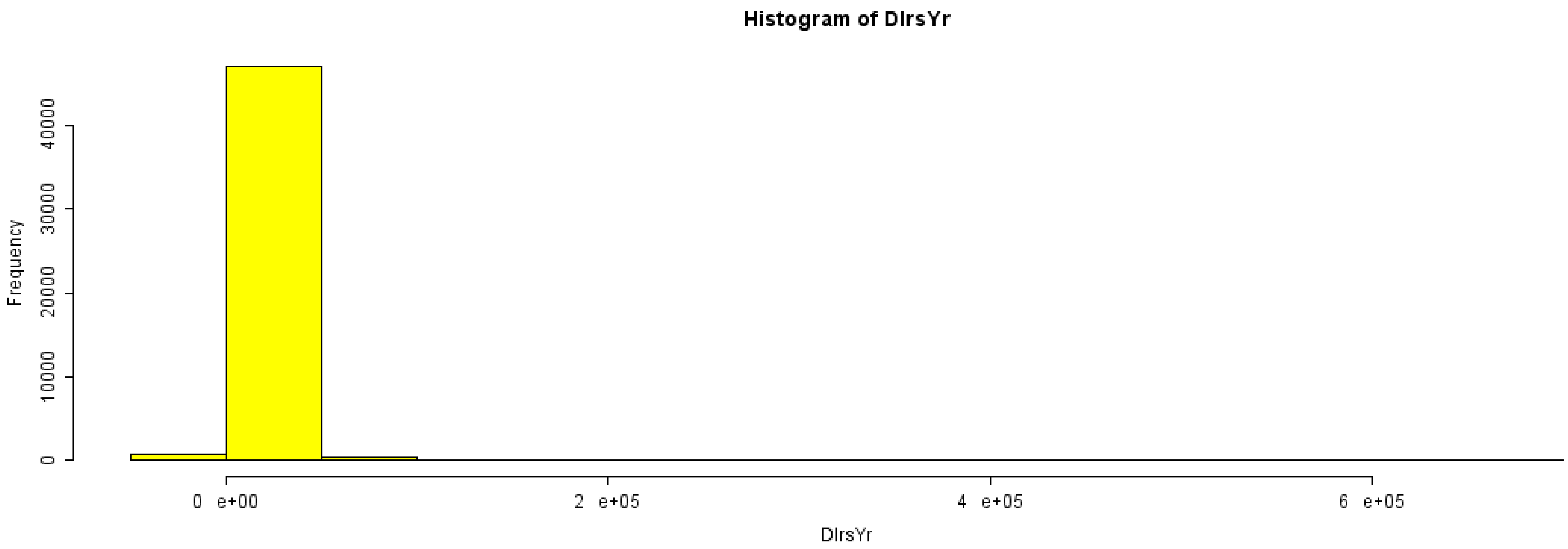
```
barplot(sort(table(SIC_Group)), horiz = TRUE, las = 1,
        xlab = "# Customers", main = "Distribution Key Customer SIC Groups")

bp <- barplot(sort(table(SIC_Group)), horiz = TRUE, las = 1,
              xlab = "# Customers", main = "Distribution Key Customer SIC Groups",
              col = "yellow", names.arg = "")
text(0, bp, dimnames(sort(table(SIC_Group)))[[1]], cex = 0.9, pos = 4)
```



Practical: EDA of Key Customers (6)

- On to continuous variables - $/Year first
  - Let R do all the work

```
> hist(DlrsYr, col = "yellow")
```



- A couple of interesting things
  - At least one huge customer
  - What's with "minus money"?

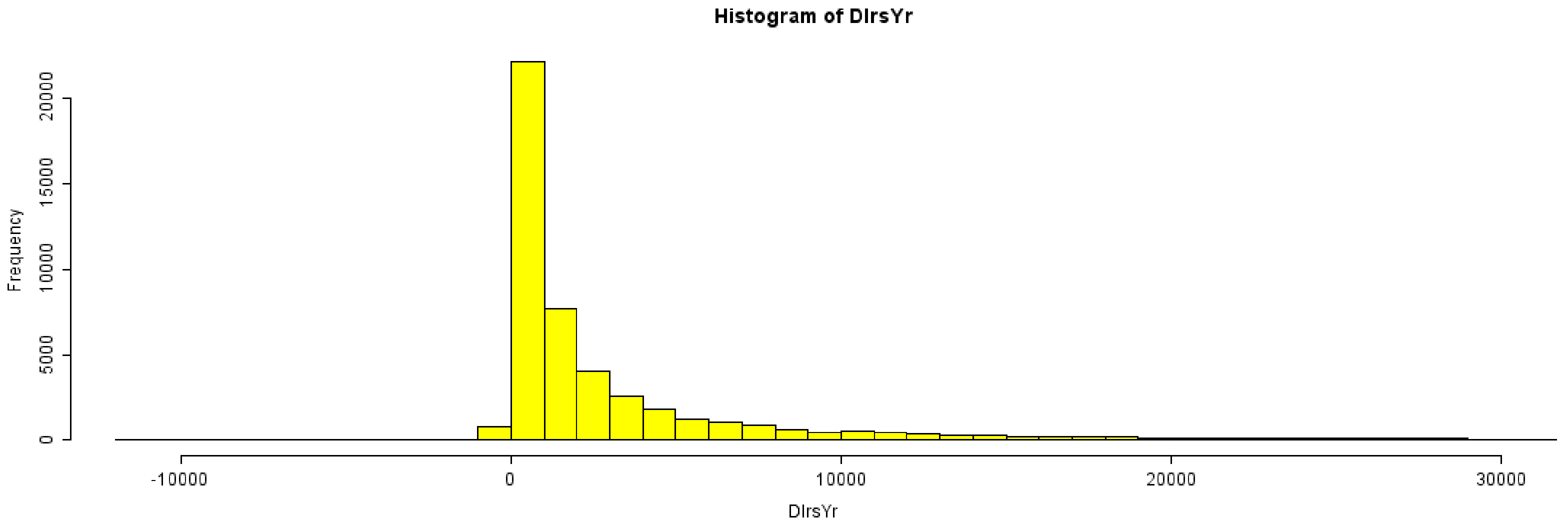
Practical: EDA of Key Customers (7)

- Let’s look at the numbers:

```
> summary(DlrsYr)                         ## look at the #'s
    Min.   1st Qu.    Median       Mean   3rd Qu.      Max.
-11670.0     334.2    1126.0     5000.0    3682.0 685200.0
```

- Zoom in on x-axis:

```
hist(DlrsYr, col = "yellow", breaks = 500,
      xlim = c(min(DlrsYr), 3e4))
```



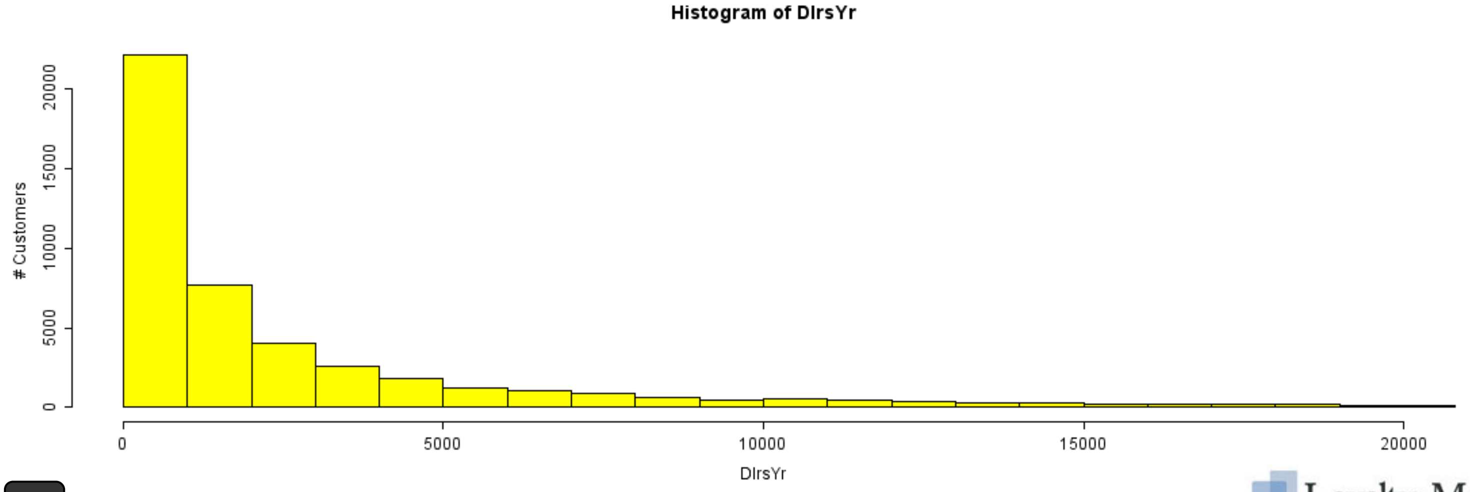
Practical: EDA of Key Customers (8)

- These are supposed to be “key” customers!
  - Remove those without at least $1/Yr , 1 invoice/Yr, &1 product/Yr

```
> detach(KeyCustomers)
> KeyCustomers <- subset(KeyCustomers, DlrsYr >= 1 & NumInvYr > 0 & NumProdYr > 0)
> comment(KeyCustomers) <- "Rev3: subset to just customers with positive Dlrs & Nums."
> str(KeyCustomers)
`data.frame':       47845 obs. of  9 variables:
 $ PotSize   : Ord.factor w/ 6 levels "MEGA"<"LARGE"<..: 4 2 3 3 5 5 5 5 3 3 ...
                        <...cut...>
 - attr(*, "comment")= chr "Rev3: subset to just customers with positive Dlrs & Nums."
> save(KeyCustomers, file = "KeyCustomers3.rda")
```

- Plot again. Label y-axis & zoom a bit more on x-axis:

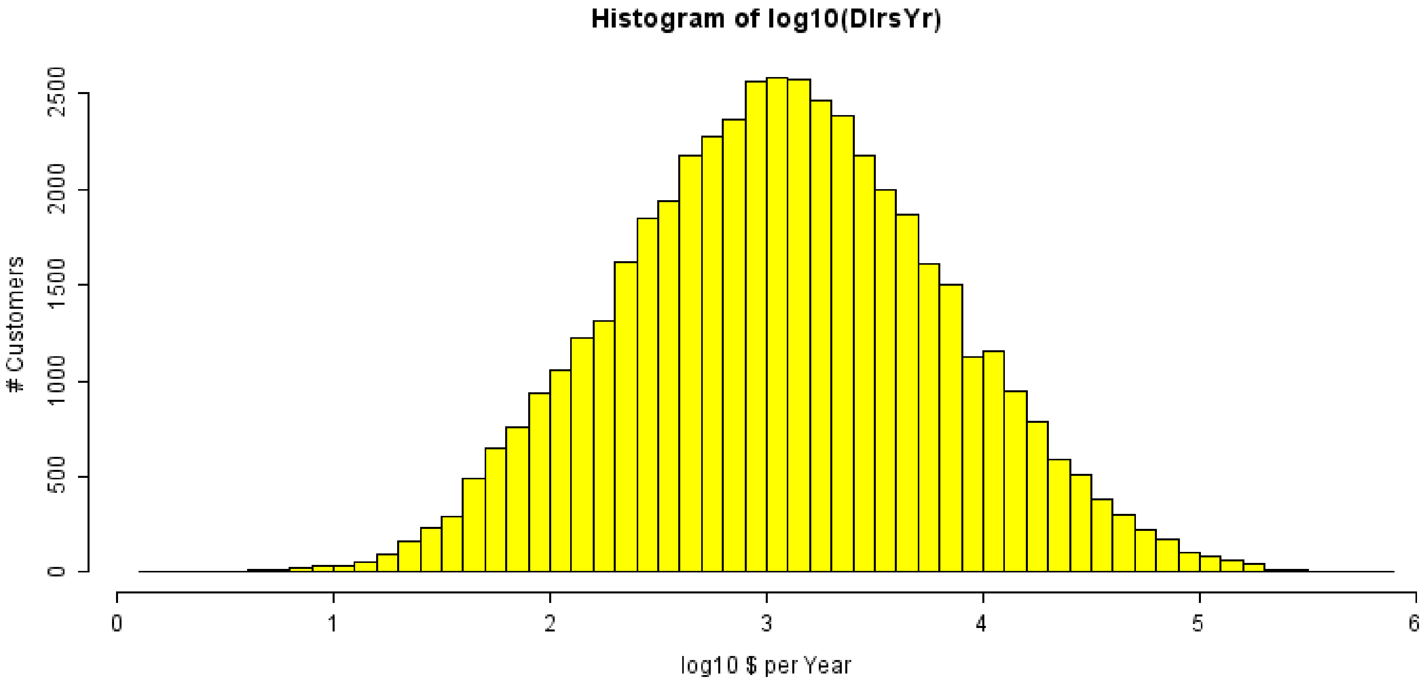
```
hist(DlrsYr, col = "yellow", breaks = 500, xlim = c(min(DlrsYr), 2e4),
     ylab = "# Customers")
```



Practical: EDA of Key Customers (9)

- Right! Log transform all right tailed stuff.
- Start with $ per Year:

```
hist(log10(DlrsYr), col = "yellow", ylab = "# Customers",
     xlab = "log10 $ per Year")
hist(log10(DlrsYr), breaks = 50, col = "yellow", ylab = "# Customers",
     xlab = "log10 $ per Year")
```



Practical: EDA of Key Customers (10)

- Let’s add log10 transforms to data frame & save:

```
log10_DlrsYr <- log10(DlrsYr)
log10_NumInvYr <- log10(NumInvYr)
log10_NumProdYr <- log10(NumProdYr)
detach(KeyCustomers)
KCComment <- paste("Rev4: adds log transfroms to data frame;",
comment(KeyCustomers))
KeyCustomers <- cbind(KeyCustomers, log10_DlrsYr, log10_NumInvYr,
log10_NumProdYr)
comment(KeyCustomers) <- KCComment
save(KeyCustomers, file = "KeyCustomers4.rda")
rm(log10_DlrsYr, log10_NumInvYr, log10_NumProdYr)
attach(KeyCustomers)
```

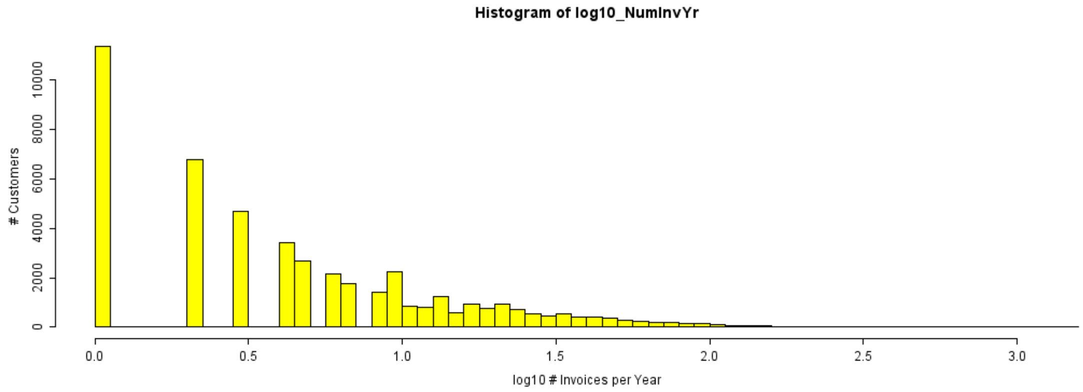
```
> str(KeyCustomers)
`data.frame':    47844 obs. of  12 variables:
 $ PotSize        : Ord.factor w/ 6 levels "MEGA"<"LARGE"<..: 4 2 3 3 3 ...
             <…cut…>
 $ log10_DlrsYr   : num  2.60 4.49 3.80 2.81 2.08 ...
 $ log10_NumInvYr : num  0.301 1.778 1.000 0.000 0.000 ...
 $ log10_NumProdYr: num  0.301 1.908 1.342 0.000 0.477 ...
 - attr(*, "comment")= chr "Rev4: adds log transfroms to data frame; Rev3:
subset to just customers with positive Dlrs & Nums."
```

```
save(KeyCustomers, file = "KeyCustomers4.rda")
```

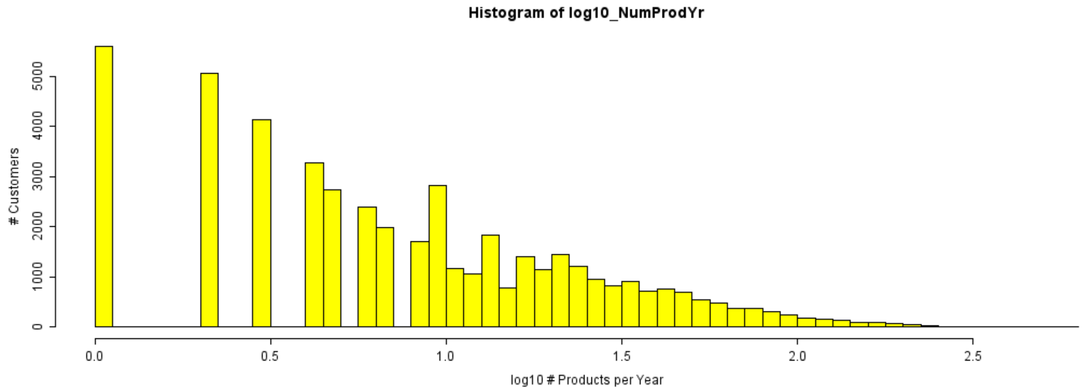
Practical: EDA of Key Customers (11)

- Remaining two log10 transformed variables:

  -
    ```
    hist(log10_NumInvYr, breaks = 50, col = "yellow", ylab = "# Customers",
    xlab = "log10 # Invoices per Year")
    ```



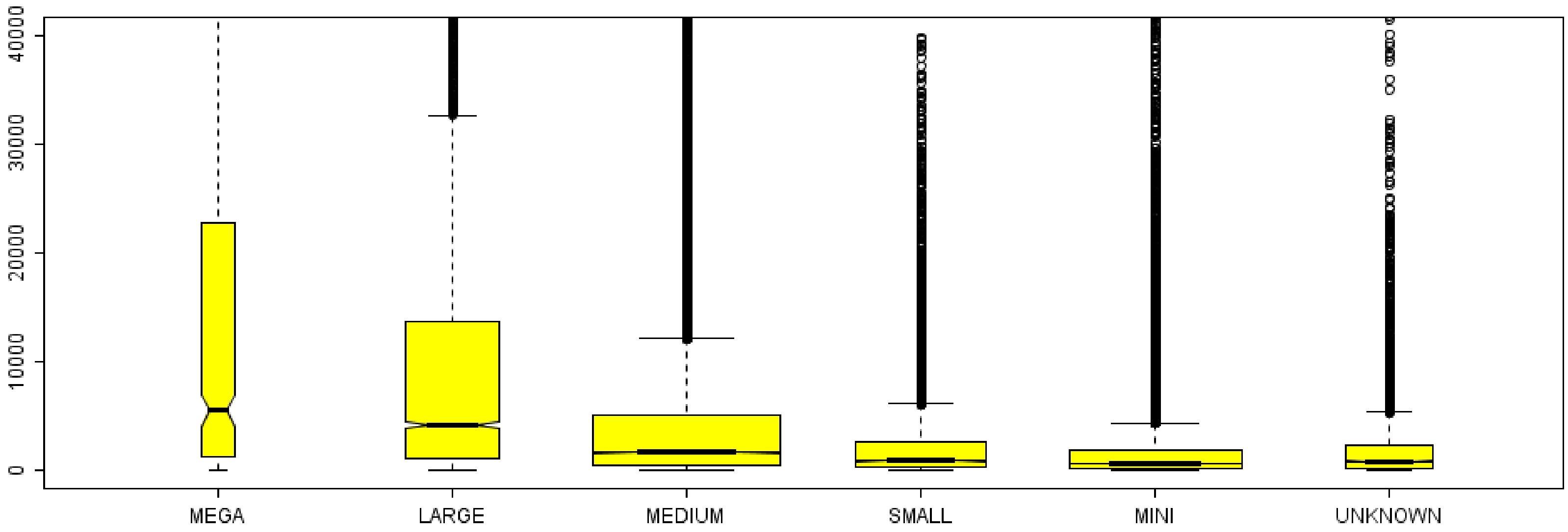
  -
    ```
    hist(log10_NumProdYr, breaks = 50, col = "yellow", ylab = "# Customers", xlab =
    "log10 # Products per Year")
    ```



Practical: EDA of Key Customers (12)

- Now let’s look at some interactions with PotSize
  - Use boxplot on DlrsYr by PotSize

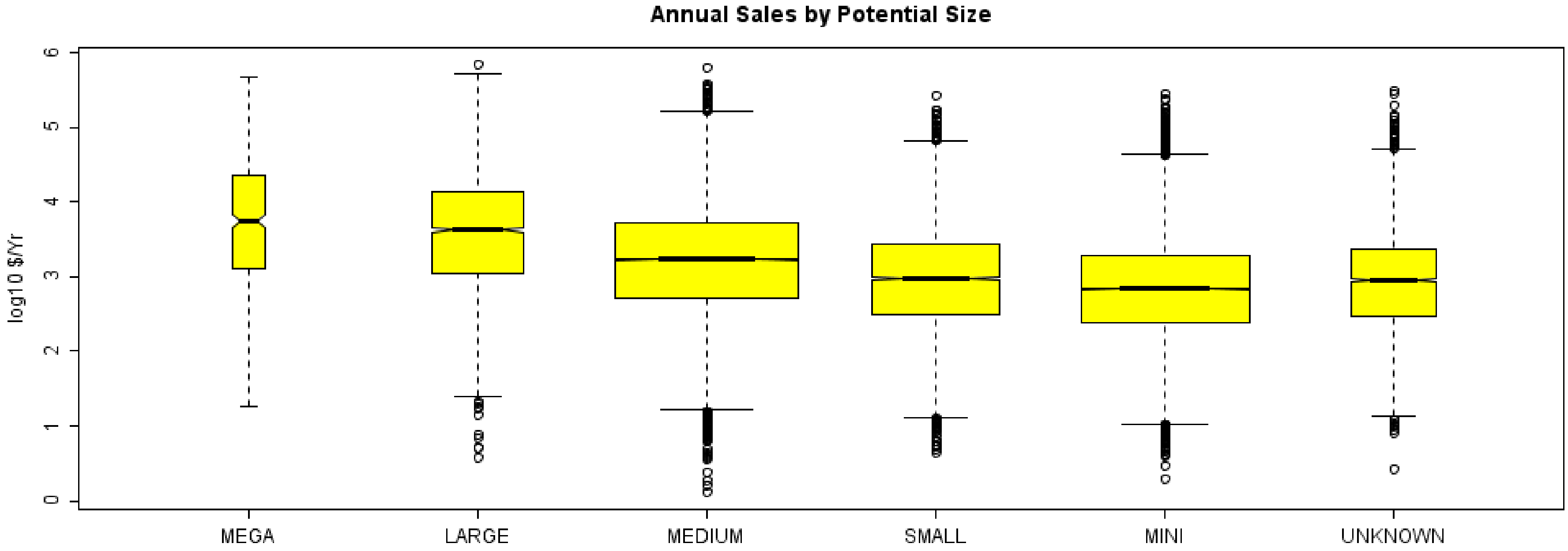
```
boxplot(DlrsYr ~ PotSize)
boxplot(DlrsYr ~ PotSize, ylim = c(0, 1e5))
boxplot(DlrsYr ~ PotSize, ylim = c(0, 4e4), notch = TRUE, varwidth = TRUE,
        col = "yellow")
```



Practical: EDA of Key Customers (13)

- Again calls out for log transform

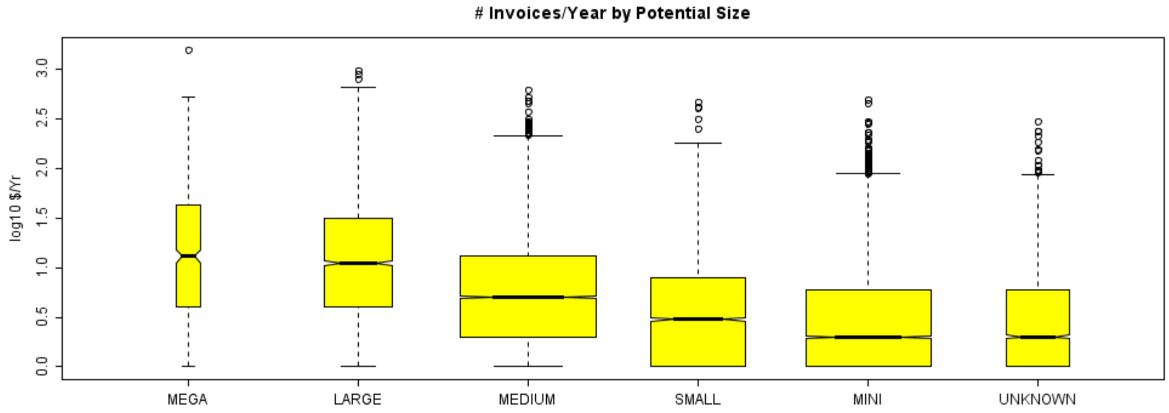
```
boxplot(log10_DlrsYr ~ PotSize, notch = TRUE, varwidth = TRUE, col = "yellow",
        ylab = "log10 $/Yr", main = "Annual Sales by Potential Size")
```



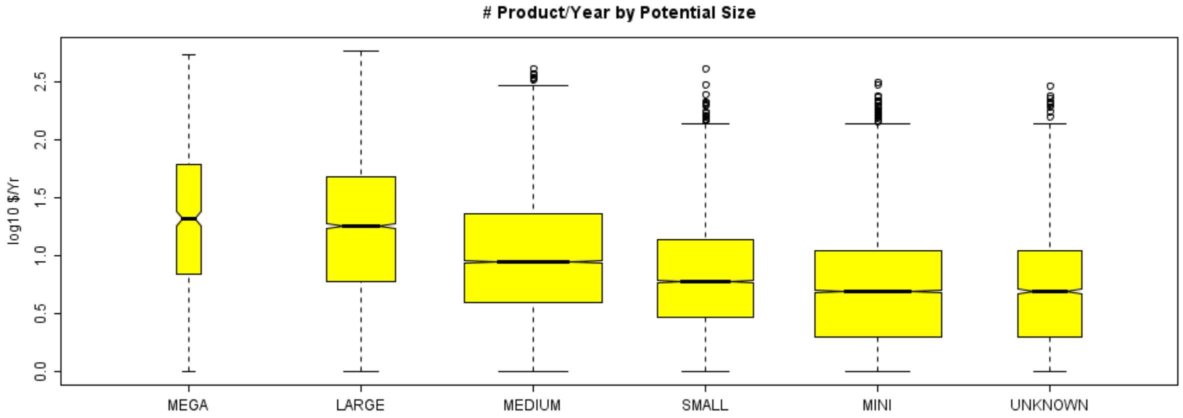
Practical: EDA of Key Customers (14)

- Boxplot the transforms of the two counts

```
boxplot(log10_NumInvYr ~ PotSize, notch = TRUE, varwidth = TRUE, col = "yellow",
        ylab = "log10 $/Yr", main = "# Invoices/Year by Potential Size")
```



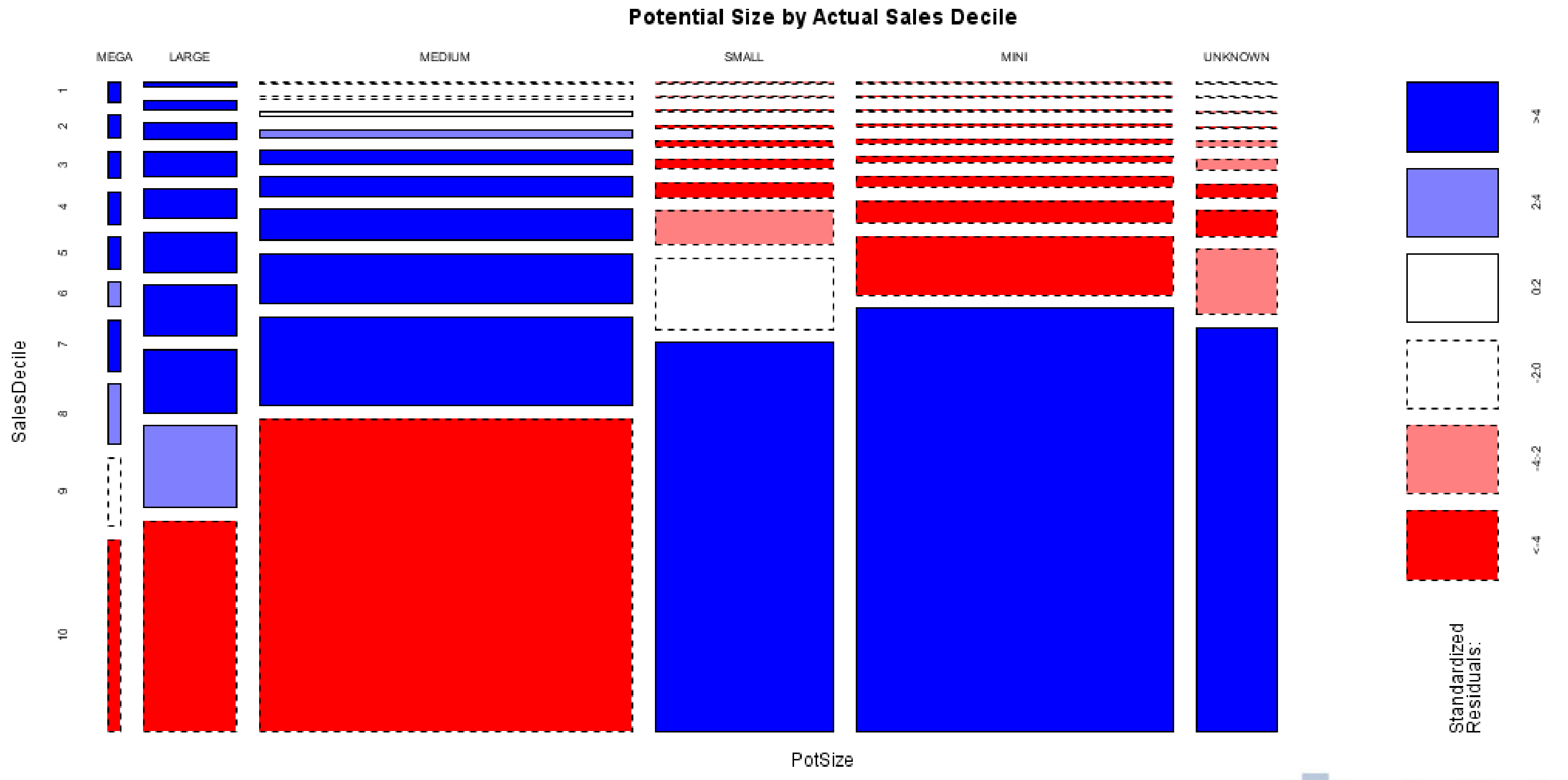
```
boxplot(log10_NumProdYr ~ PotSize, notch = TRUE, varwidth = TRUE, col = "yellow",
        ylab = "log10 $/Yr", main = "# Product/Year by Potential Size")
```



Practical: EDA of Key Customers (15)

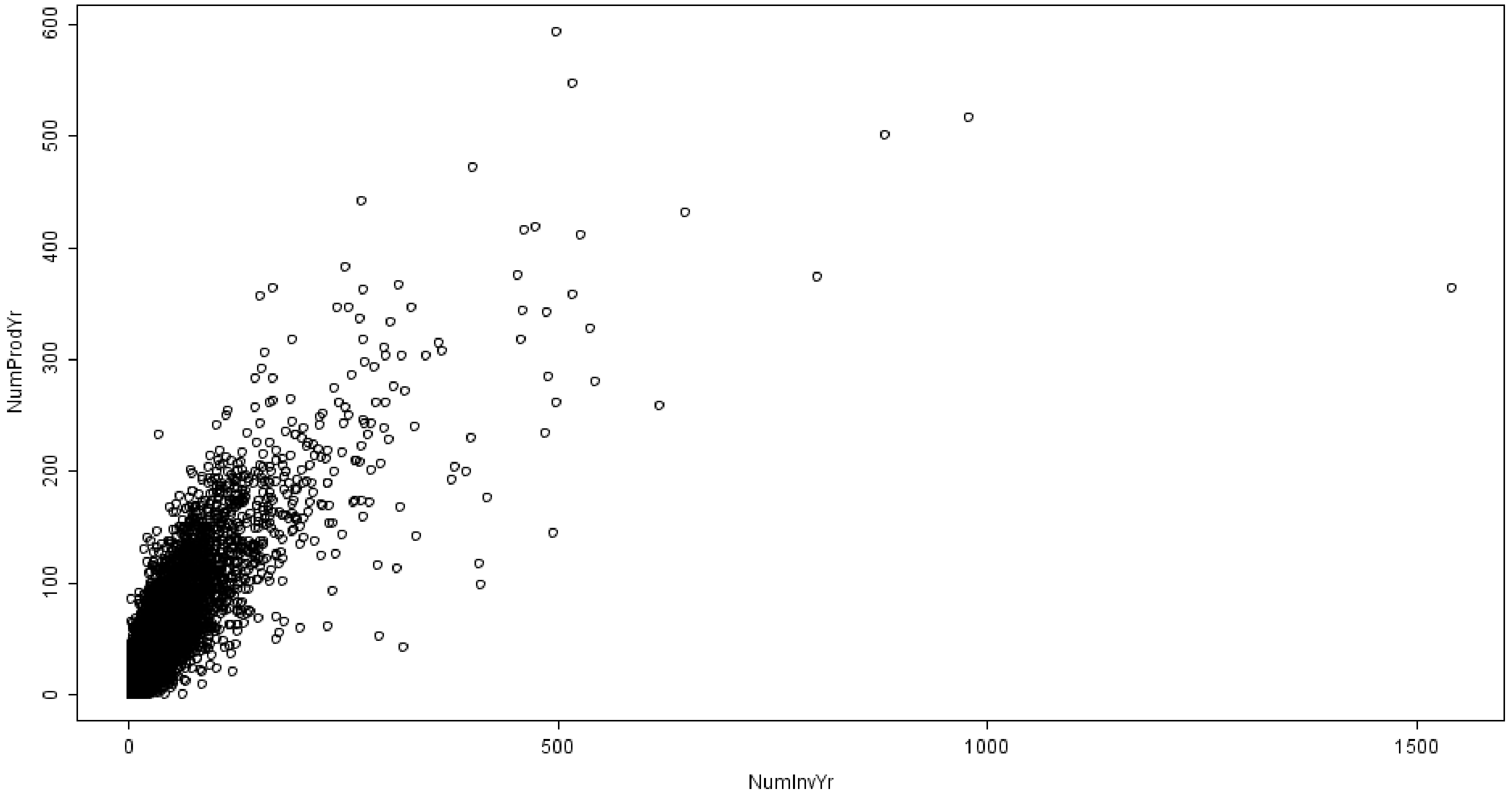
- Compute Sales Decile; check against PotSize

```
iRankCust <- order(DlrsYr, decreasing = TRUE)
SalesDecile[iRankCust] <- floor(10.0 * cumsum(DlrsYr[iRankCust]) / sum(DlrsYr)) + 1
aggregate(DlrsYr, list(SalesDecile = SalesDecile), sum)        ## a cross check
table(SalesDecile)                                             ## interesting counts
require(vcd)
mosaicplot(PotSize ~ SalesDecile, shade = TRUE,
           main = "Potential Size by Actual Sales Decile")
```



Practical: EDA of Key Customers (16)

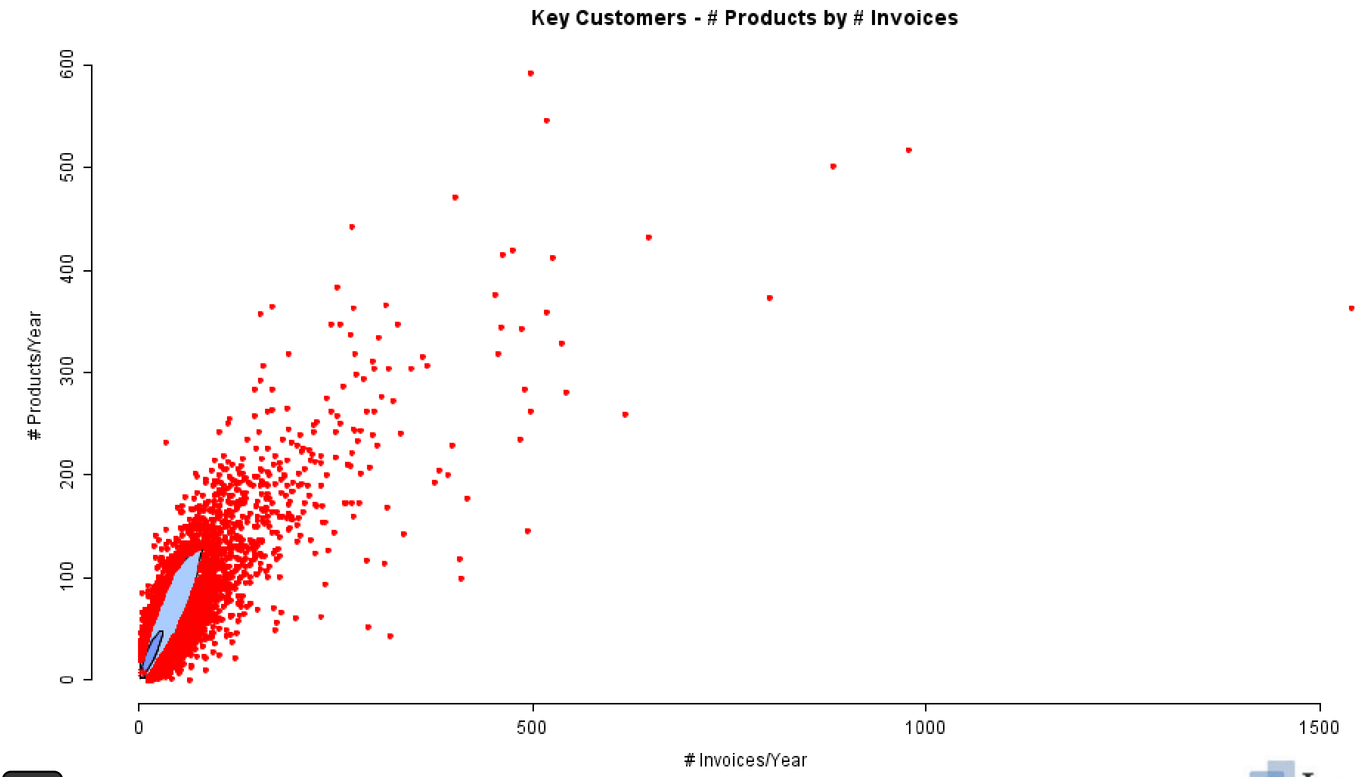
- Let's now look at # products by # invoices
  - Simple: `plot(NumInvYr, NumProdYr)`



Practical: EDA of Key Customers (17)

- We now have a better way – bagplot
  - *With much thanks to Peter Wolf & Uni Bielefeld!*

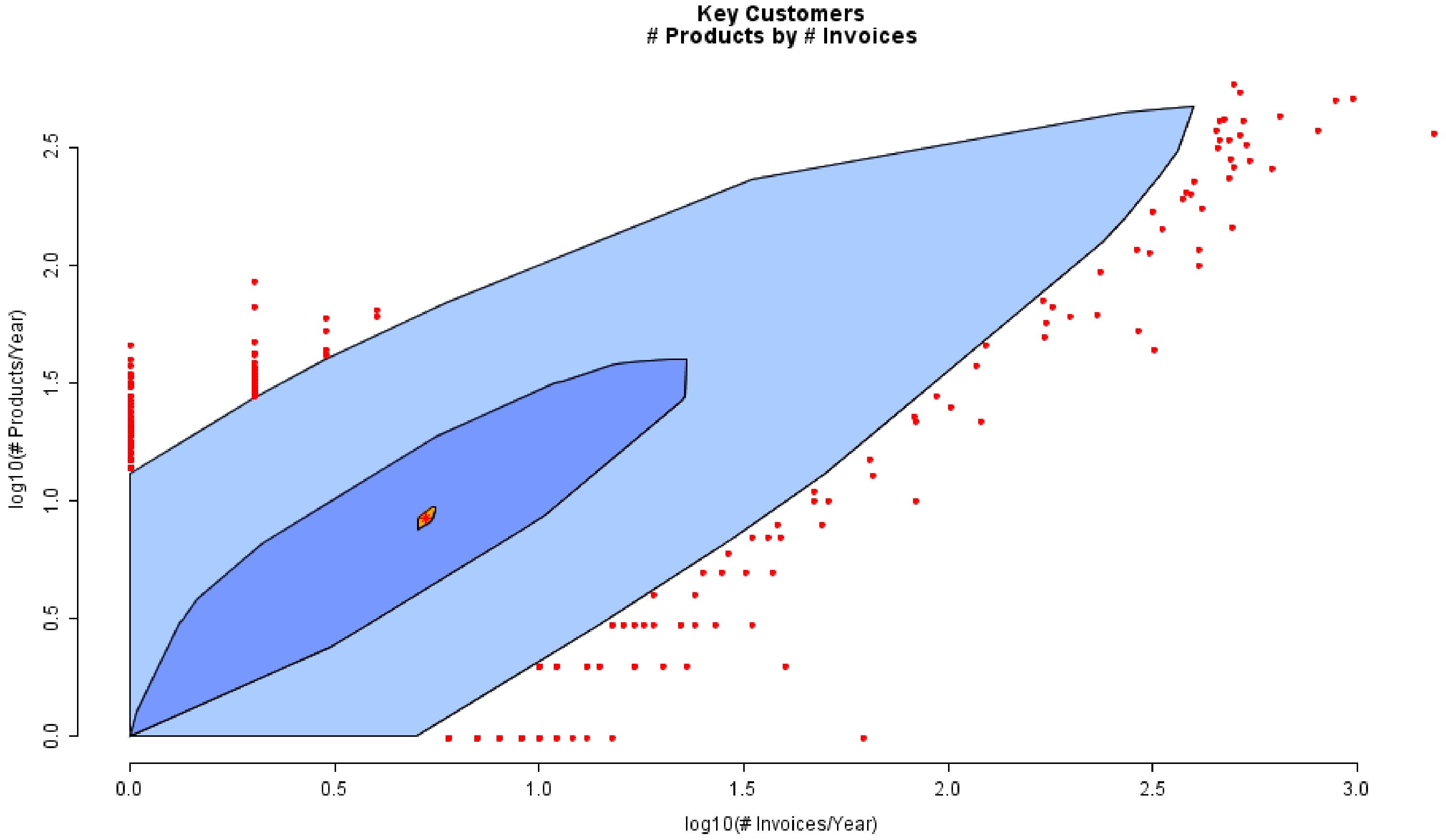
```
require(aplpack)
bagplot(NumInvYr, NumProdYr, show.looppoints = FALSE, show.bagpoints = FALSE,
        show.whiskers = FALSE, xlab = "# Invoices/Year", ylab = "# Products/Year",
        main = "Key Customers - # Products by # Invoices")
```



Practical: EDA of Key Customers (18)

- And, again use the log transforms

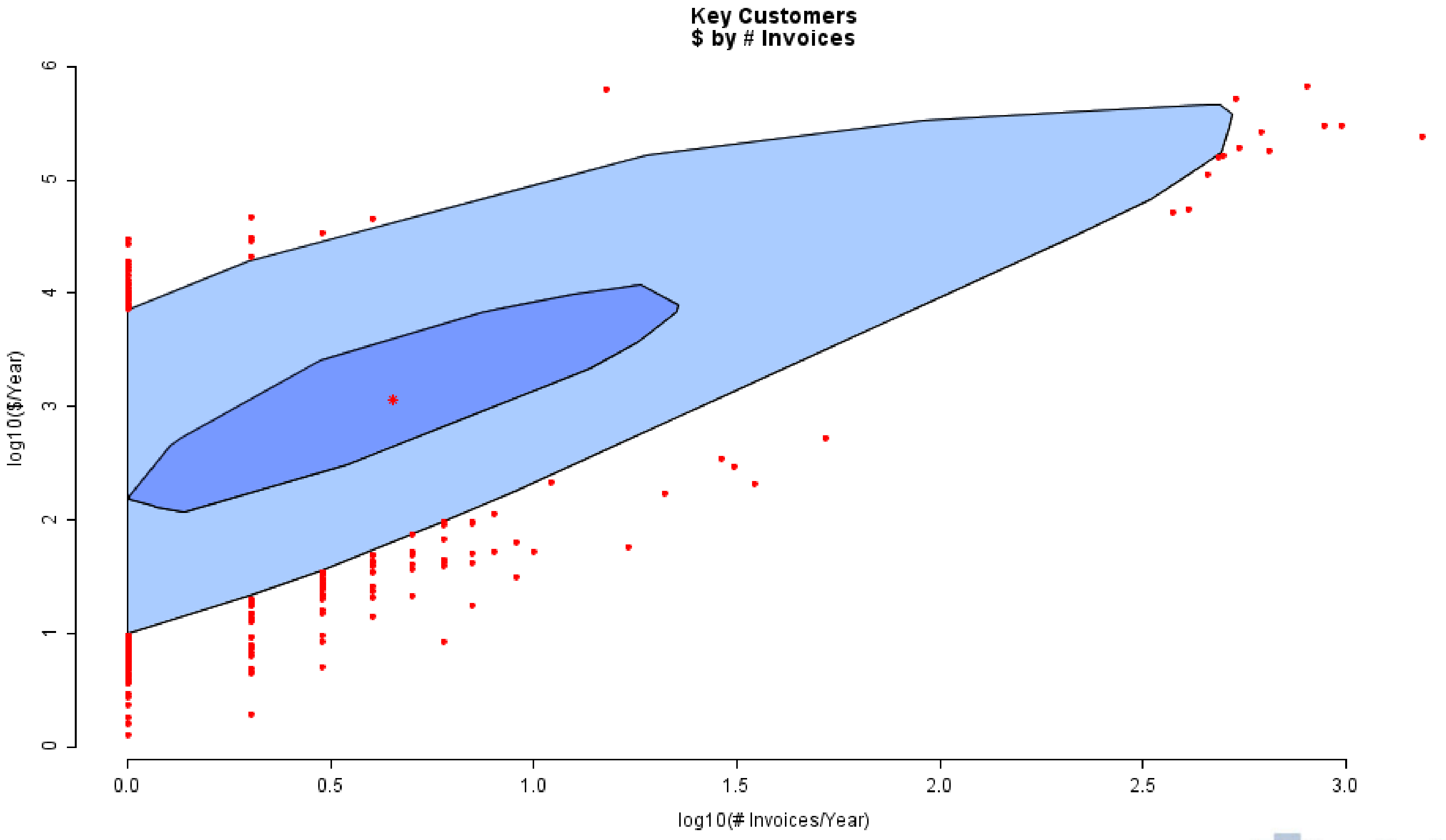
```
bagplot(log10_NumInvYr, log10_NumProdYr, show.looppoints = FALSE, show.bagpoints = FALSE,
        show.whiskers = FALSE, xlab = "log10(# Invoices/Year)",
        ylab = "log10(# Products/Year)", main = "Key Customers\n# Products by # Invoices")
```



Practical: EDA of Key Customers (19)

- Also Dollars by Number of Invoices

```
bagplot(log10_NumInvYr, log10_DlrsYr, show.looppoints = FALSE, show.bagpoints = FALSE,
        show.whiskers = FALSE, xlab = "log10(# Invoices/Year)",
        ylab = "log10($/Year)", main = "Key Customers\n$ by # Invoices")
```



Loyalty Matrix

Summary of Key Customers EDA

- Sales department still has a way to go with accounts identified as high “Potential Size “
- Potential fit between log transformed variables
- Pareto’s Rule still works:

```
> cumsum(table(SalesDecile))/length(SalesDecile)
      1       2       3       4       5       6       7       8       9      10 
0.00222 0.00709 0.01532 0.02803 0.04703 0.07568 0.11933 0.19204 0.33149 1.00000 
```

Part III – Mining, Modeling & Segmentation

Mining, Modeling, Segmentation & Prediction: An overview of some useful packages for advanced customer analytics.

- Decision tree methods - rpart, tree, party and randomForest.
- Survival methods - survival and friends
- Clustering methods - mclust, flexclust.
- Association methods - arules.

Random Forests

- Random Forest was developed by Leo Breiman of Cal Berkeley, one of the four developers of CART, and Adele Cutler now at Utah State University.
  - An extension of single decision tree methods like CART & CHAID.
  - Many trees are randomly grown to build the forest. All are used in the final result.
- Advantages
  - Accuracy comparable with modern machine learning methods. (SVMs, neural nets, Adaboost)
  - Built in cross-validation using "Out of Bag" data. (Prediction error estimate is a by product)
  - Large number candidate predictors are automatically selected. (Resistant to over training)
  - Continuous and/or categorical predicting & response variables. (Easy to set up.)
  - Can be run in unsupervised for cluster discovery. (Useful for market segmentation, etc.)
  - Free Prediction and Scoring engines run on PC's, Unix/Linux & Mac's. (R version)
- Versions
  - Original Fortran 77 source code freely available from Breiman & Cutler.
    http://www.math.usu.edu/~adele/forests/
  - R package, randomForest. An adaptation by Andy Liaw of Merck.
    http://cran.cnr.berkeley.edu/src/contrib/Descriptions/randomForest.html
  - Commercialization by Salford Systems.
    http://www.salford-systems.com/randomforests.php

Practical: Prediction with RF (1)

- Sample Data from a sports club
- Challenge – predict “at-risk” members based on membership usage data & simple demographics
- Training & Test data sets provided:
  - MemberTrainingSet.txt (1916 records)
  - MemberTestSet.txt (1901 records)
- Columns:
  - MembID (identifier)
  - Status = M or C
  - Gender
  - Age
  - MembDays
  - NumUses1st30d
  - NumUsesLast30d
  - TotalUses
  - FirstCkInDay
  - LastCkInDay
  - DaysSinceLastUse
  - TotalPaid
  - MonthlyAmt
  - MilesToClub
  - NumExtras1st30d
  - NumExtrasLast30d
  - TotalExtras
  - DaysSinceLastExtra

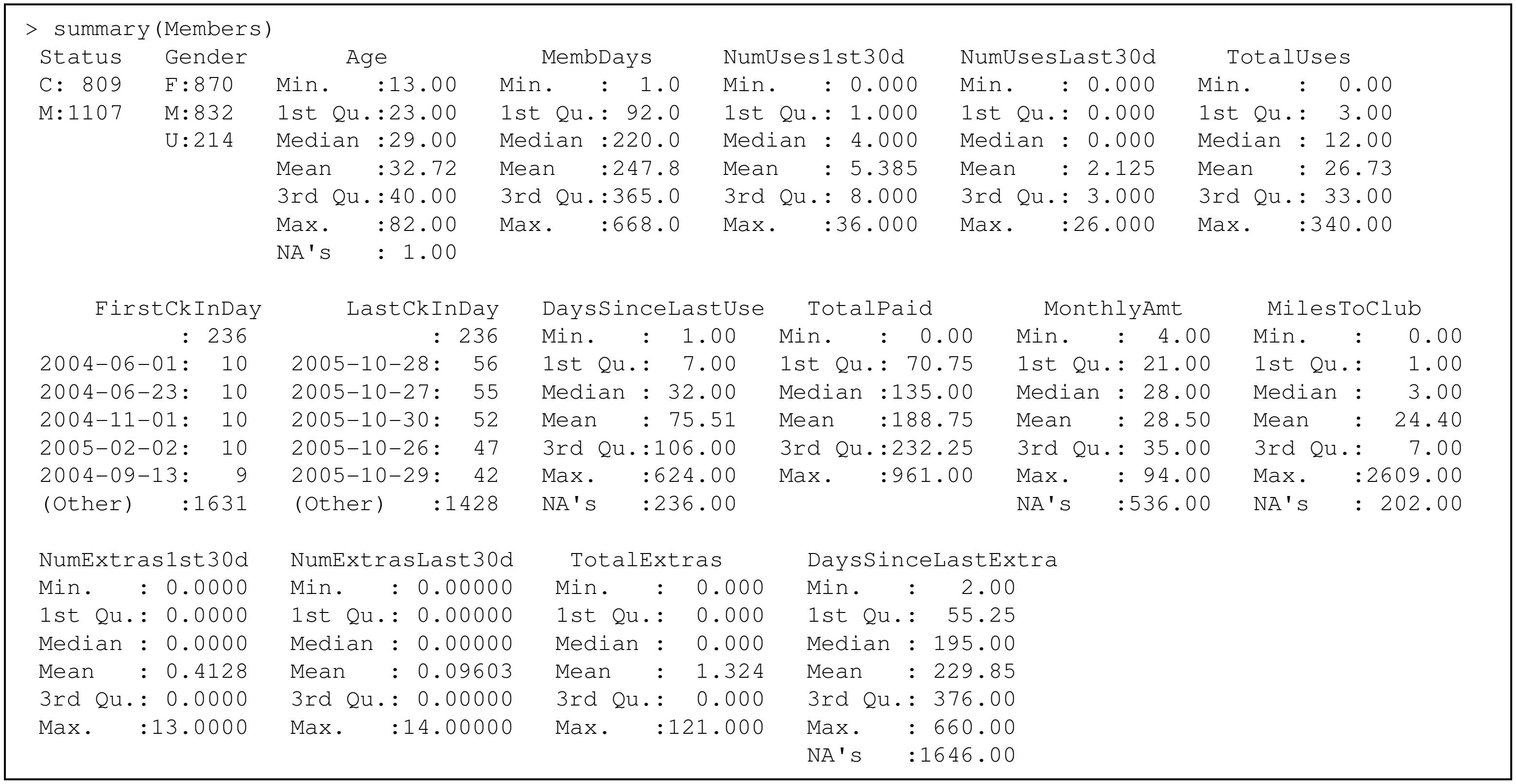
Practical: Prediction with RF (2)

- Getting Started – Load & understand training set

```
## CIwR_rf.R
require(randomForest)
setwd("c:/Projects/CIwR/R")
dir("Data")

Members <- read.delim("Data/MemberTrainingSet.txt", row.names = "MembID")
str(Members)
```

```
> str(Members)
`data.frame':   1916 obs. of  17 variables:
 $ Status          : Factor w/ 2 levels "C","M": 1 1 1 1 1 1 1 1 1 1 ...
 $ Gender          : Factor w/ 3 levels "F","M","U": 2 2 1 2 2 1 2 1 1 2 ...
 $ Age             : int  21 18 21 21 45 25 21 20 35 15 ...
 $ MembDays        : int  92 98 30 92 31 249 1 92 322 237 ...
 $ NumUses1st30d   : int  11 11 3 6 24 2 0 16 12 6 ...
 $ NumUsesLast30d  : int  6 6 3 1 24 0 0 4 0 0 ...
 $ TotalUses       : int  28 31 3 9 24 6 0 30 38 26 ...
 $ FirstCkInDay    : Factor w/ 556 levels "","2004-01-04",..: 132 264 140 157 507 151 1 124 234 319 ...
 $ LastCkInDay     : Factor w/ 489 levels "","2004-01-15",..: 134 242 83 145 414 111 1 121 280 356 ...
 $ DaysSinceLastUse : int  3 2 9 11 4 196 NA 12 138 65 ...
 $ TotalPaid       : int  149 136 100 129 75 134 138 149 582 168 ...
 $ MonthlyAmt      : int  NA 27 NA NA NA 31 30 NA NA 10 ...
 $ MilesToClub     : int  4 0 0 5 2593 4 5 4 NA 2 ...
 $ NumExtras1st30d : int  0 0 0 0 0 0 0 0 1 0 ...
 $ NumExtrasLast30d : int  0 0 0 0 0 0 0 0 0 0 ...
 $ TotalExtras     : int  0 0 0 0 0 0 0 0 6 0 ...
 $ DaysSinceLastExtra: int  NA NA NA NA NA NA NA NA 253 NA ...
```

Practical: Prediction with RF (3)



```
> summary(Members)
 Status     Gender        Age              MembDays        NumUses1st30d      NumUsesLast30d      TotalUses
 C: 809     F:870    Min.   :13.00    Min.    :  1.0    Min.    : 0.000    Min.    : 0.000    Min.    :  0.00
 M:1107     M:832    1st Qu.:23.00    1st Qu.: 92.0    1st Qu.: 1.000    1st Qu.: 0.000    1st Qu.:  3.00
            U:214    Median :29.00    Median :220.0    Median : 4.000    Median : 0.000    Median : 12.00
                     Mean   :32.72    Mean   :247.8    Mean   : 5.385    Mean   : 2.125    Mean   : 26.73
                     3rd Qu.:40.00    3rd Qu.:365.0    3rd Qu.: 8.000    3rd Qu.: 3.000    3rd Qu.: 33.00
                     Max.   :82.00    Max.   :668.0    Max.   :36.000    Max.   :26.000    Max.   :340.00
                     NA's   : 1.00

     FirstCkInDay        LastCkInDay     DaysSinceLastUse    TotalPaid          MonthlyAmt          MilesToClub
            : 236              : 236     Min.   :  1.00    Min.   :  0.00    Min.   :  4.00    Min.   :   0.00
 2004-06-01:  10    2005-10-28:  56     1st Qu.:  7.00    1st Qu.: 70.75    1st Qu.: 21.00    1st Qu.:   1.00
 2004-06-23:  10    2005-10-27:  55     Median : 32.00    Median :135.00    Median : 28.00    Median :   3.00
 2004-11-01:  10    2005-10-30:  52     Mean   : 75.51    Mean   :188.75    Mean   : 28.50    Mean   :  24.40
 2005-02-02:  10    2005-10-26:  47     3rd Qu.:106.00    3rd Qu.:232.25    3rd Qu.: 35.00    3rd Qu.:   7.00
 2004-09-13:   9    2005-10-29:  42     Max.   :624.00    Max.   :961.00    Max.   : 94.00    Max.   :2609.00
 (Other)   :1631    (Other)   :1428     NA's   :236.00                      NA's   :536.00    NA's   : 202.00

 NumExtras1st30d     NumExtrasLast30d      TotalExtras        DaysSinceLastExtra
 Min.   : 0.0000    Min.   : 0.00000    Min.   :  0.000    Min.   :   2.00
 1st Qu.: 0.0000    1st Qu.: 0.00000    1st Qu.:  0.000    1st Qu.:  55.25
 Median : 0.0000    Median : 0.00000    Median :  0.000    Median : 195.00
 Mean   : 0.4128    Mean   : 0.09603    Mean   :  1.324    Mean   : 229.85
 3rd Qu.: 0.0000    3rd Qu.: 0.00000    3rd Qu.:  0.000    3rd Qu.: 376.00
 Max.   :13.0000    Max.   :14.00000    Max.   :121.000    Max.   : 660.00
                                                           NA's   :1646.00
```

- Absolute Dates not useful (at least down to day level)
- RF does not like NA's!
  - Day's Since Last xxx is NA when no event, use large # days
  - Impute remaining NA's

Practical: Prediction with RF (4)

- Subset out the absolute dates:

  `Members <- subset(Members, select = -c(FirstCkInDay, LastCkInDay))`

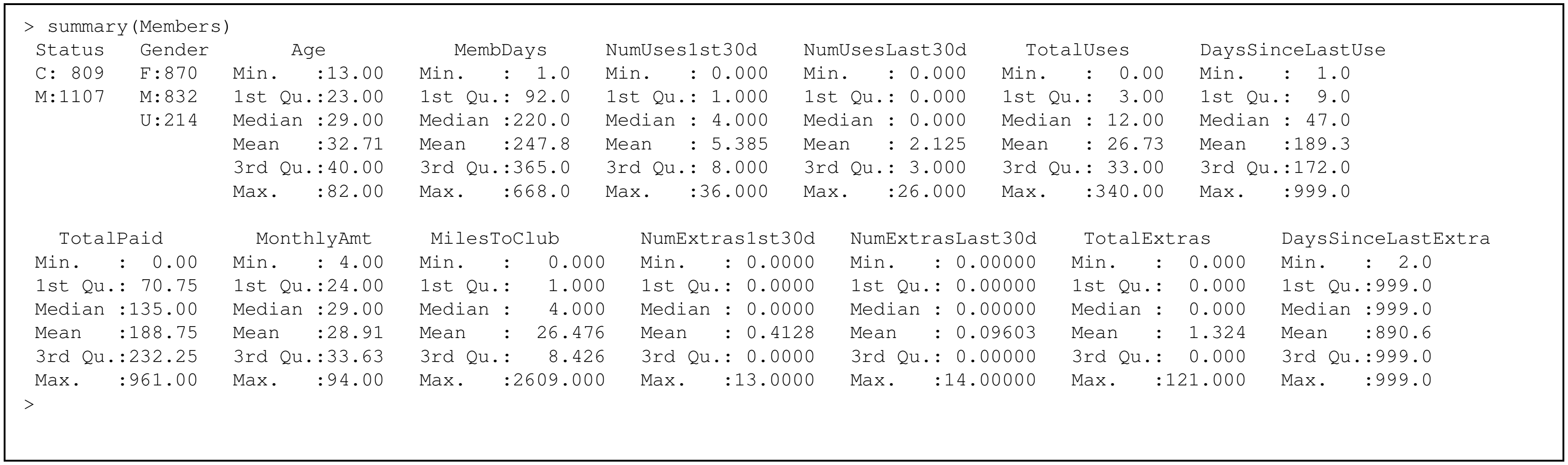
- Replace days since last NA's with 999:

  `Members$DaysSinceLastUse[is.na(Members$DaysSinceLastUse)] <- 999`

  `Members$DaysSinceLastExtra[is.na(Members$DaysSinceLastExtra)] <- 999`

- Impute remaining NA's with Random Forests' impute:

  `Members <- rfImpute(Status ~ ., data = Members)`



```
> summary(Members)
 Status   Gender      Age           MembDays     NumUses1st30d    NumUsesLast30d     TotalUses      DaysSinceLastUse
 C: 809   F:870    Min.   :13.00   Min.   :  1.0   Min.   : 0.000   Min.   : 0.000   Min.   :  0.00   Min.   :  1.0
 M:1107   M:832    1st Qu.:23.00   1st Qu.: 92.0   1st Qu.: 1.000   1st Qu.: 0.000   1st Qu.:  3.00   1st Qu.:  9.0
          U:214    Median :29.00   Median :220.0   Median : 4.000   Median : 0.000   Median : 12.00   Median : 47.0
                   Mean   :32.71   Mean   :247.8   Mean   : 5.385   Mean   : 2.125   Mean   : 26.73   Mean   :189.3
                   3rd Qu.:40.00   3rd Qu.:365.0   3rd Qu.: 8.000   3rd Qu.: 3.000   3rd Qu.: 33.00   3rd Qu.:172.0
                   Max.   :82.00   Max.   :668.0   Max.   :36.000   Max.   :26.000   Max.   :340.00   Max.   :999.0

   TotalPaid        MonthlyAmt     MilesToClub        NumExtras1st30d   NumExtrasLast30d    TotalExtras      DaysSinceLastExtra
 Min.   :  0.00   Min.   : 4.00   Min.   :    0.000   Min.   : 0.0000   Min.   : 0.00000   Min.   :  0.000   Min.   :  2.0
 1st Qu.: 70.75   1st Qu.:24.00   1st Qu.:    1.000   1st Qu.: 0.0000   1st Qu.: 0.00000   1st Qu.:  0.000   1st Qu.:999.0
 Median :135.00   Median :29.00   Median :    4.000   Median : 0.0000   Median : 0.00000   Median :  0.000   Median :999.0
 Mean   :188.75   Mean   :28.91   Mean   :   26.476   Mean   : 0.4128   Mean   : 0.09603   Mean   :  1.324   Mean   :890.6
 3rd Qu.:232.25   3rd Qu.:33.63   3rd Qu.:    8.426   3rd Qu.: 0.0000   3rd Qu.: 0.00000   3rd Qu.:  0.000   3rd Qu.:999.0
 Max.   :961.00   Max.   :94.00   Max.   :2609.000   Max.   :13.0000   Max.   :14.00000   Max.   :121.000   Max.   :999.0
>
```

Practical: Prediction with RF (5)

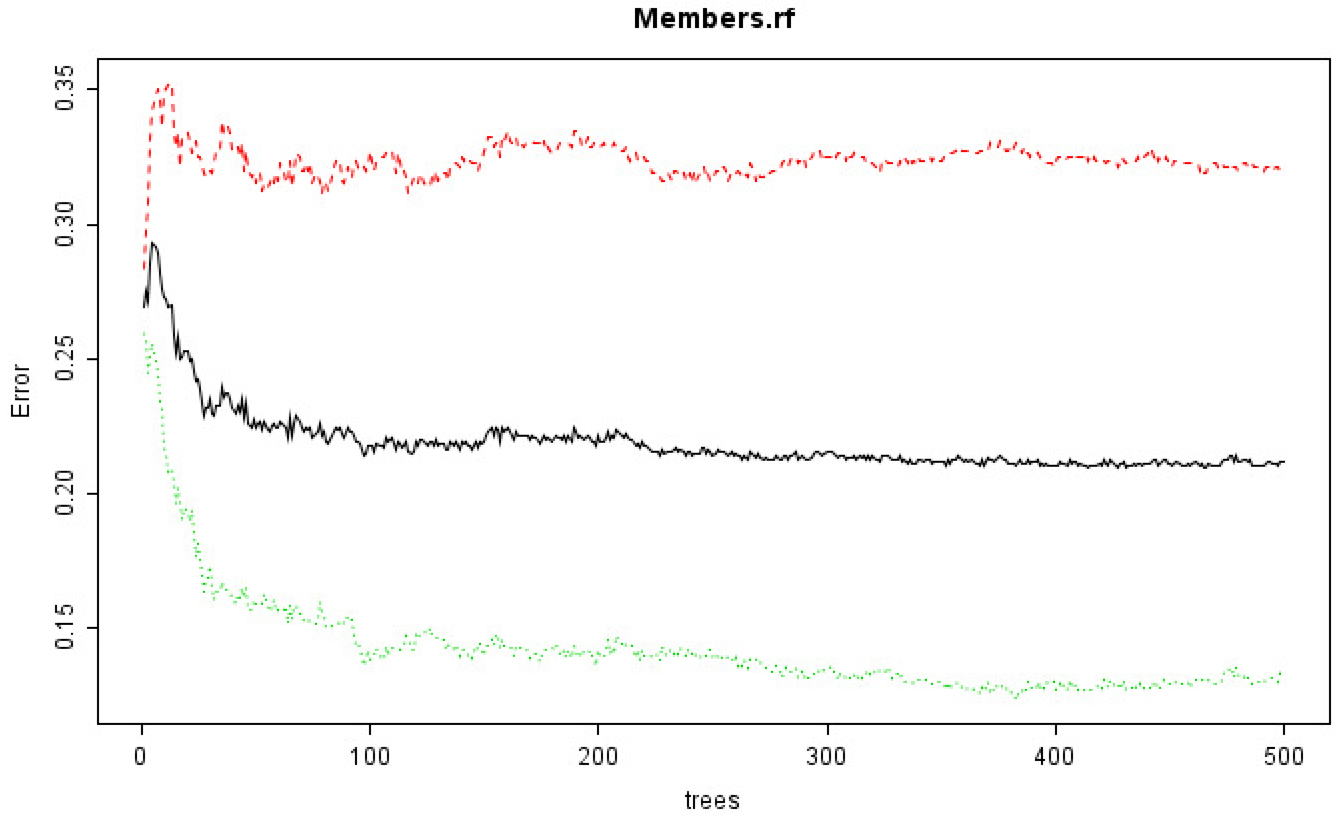
- Now we can build a forest!
  - ntree = 500 & mtry = 3 are defaults. Try tuning them.

```
> Members.rf <- randomForest(Members[-1], Members$Status, data = Members,
                mtry = 3, ntree = 500, importance = TRUE, proximity = TRUE)
> Members.rf
Call:
 randomForest(x = Members[-1], y = Members$Status, ntree = 500,
              mtry = 3, importance = TRUE, proximity = TRUE, data = Members)

               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 3

        OOB estimate of  error rate: 21.4%
Confusion matrix:
    C   M class.error
C 546 263   0.3250927
M 147 960   0.1327913
```

- Rather good results. Only ~20% overall error rate.
  - 33% false positive
  - 13% false negative

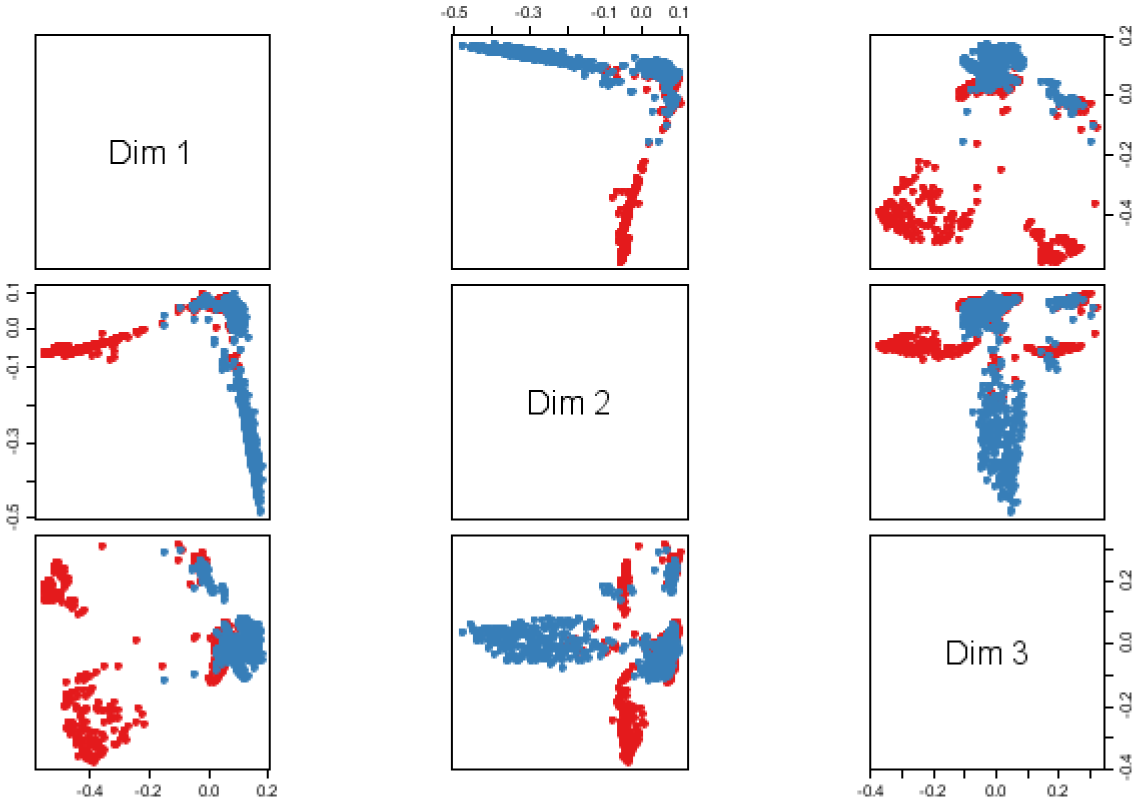
Practical: Prediction with RF (6)

- RF Diagnostics - OOB errors by # trees
  - `Plot(Members.rf)`



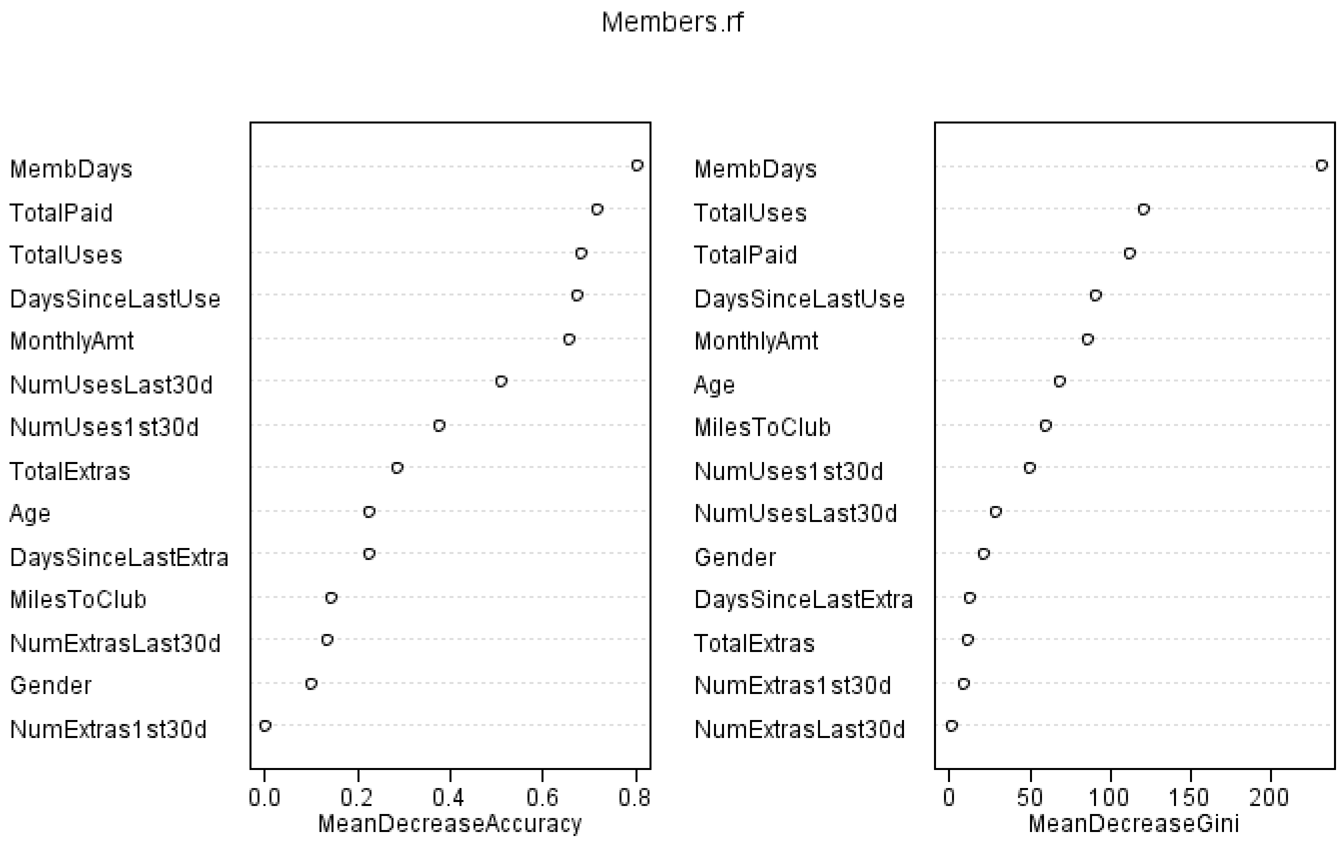
Practical: Prediction with RF (7)

- MDS Plot
  - `MDSplot(Members.rf, Members$Statue, k = 3)`



Practical: Prediction with RF (8)

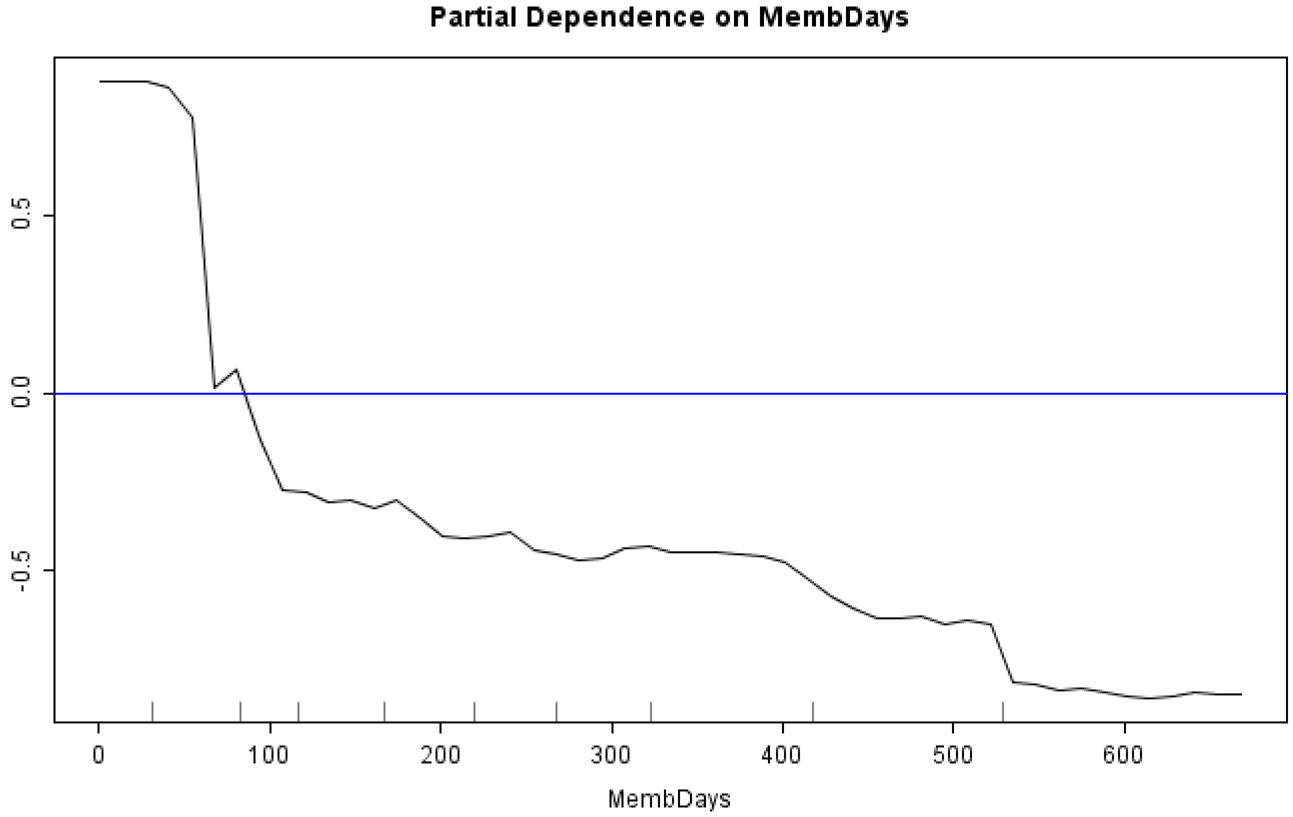
- RF Diagnostics – Variable Importance Plot
  - `varImpPlot(Members.rf)`



Loyalty Matrix

Practical: Prediction with RF (9)

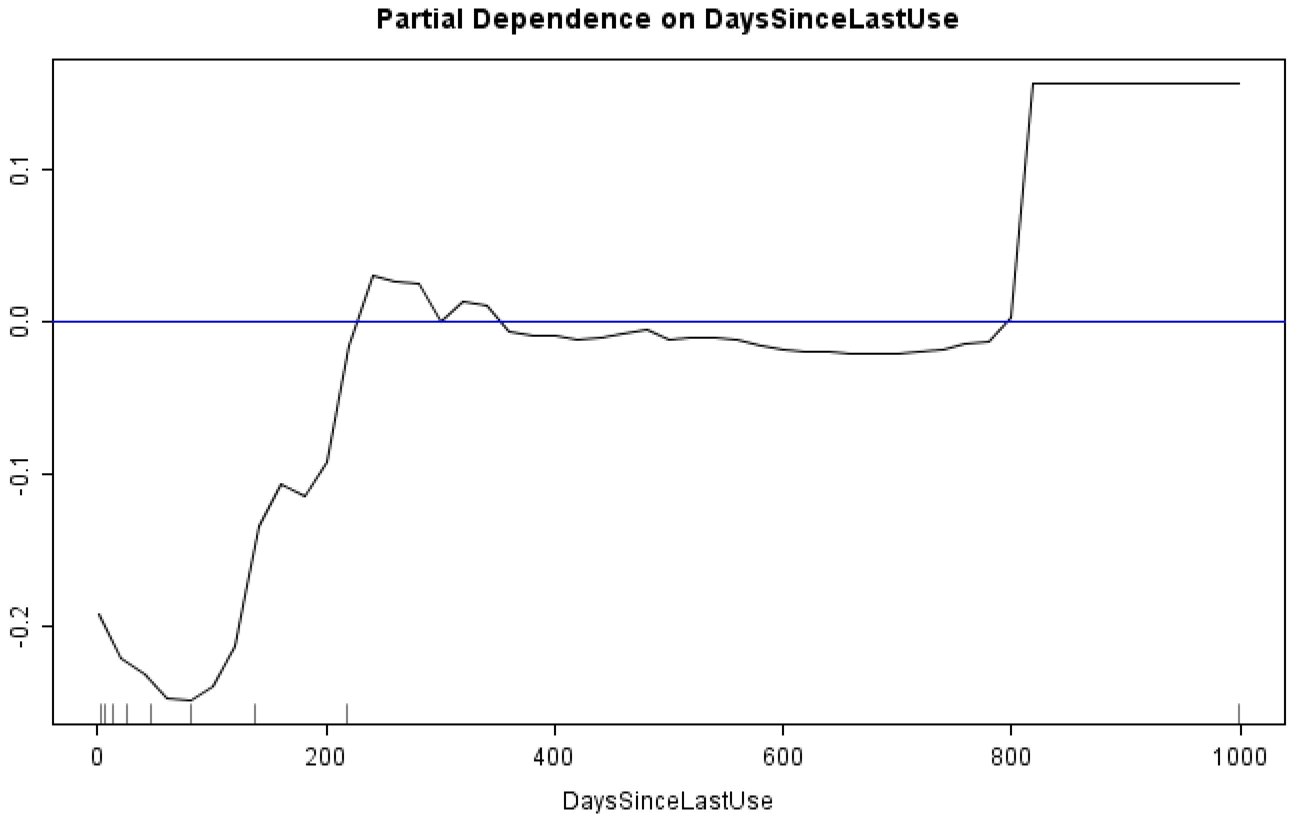
- RF Diagnostics – Partial Dependence 1
  - `partialPlot(Members.rf, Members[-1], MembDays)`
  - `abline(h=0, col = "blue")`



Loyalty Matrix

Practical: Prediction with RF (10)

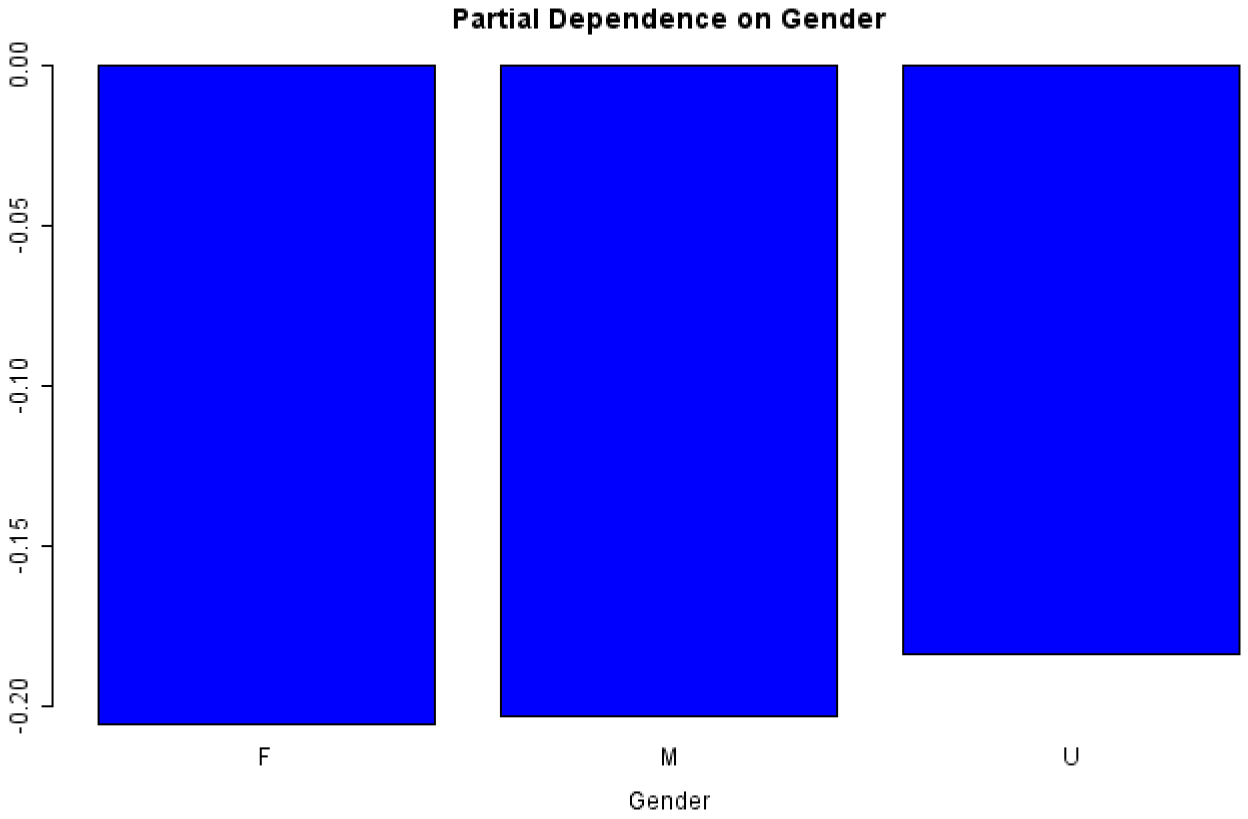
- RF Diagnostics – Partial Dependence 2
  - `partialPlot(Members.rf, Members[-1], DaysSinceLastUse)`
  - `abline(h=0, col = "blue")`



Loyalty Matrix

Practical: Prediction with RF (11)

- RF Diagnostics – Partial Dependence 3
  - `partialPlot(Members.rf, Members[-1], Age)`



Loyalty Matrix

Practical: Prediction with RF (9)

- RF Diagnostics – Prediction on Test Set
  - Need to do same variable selection & conditioning:

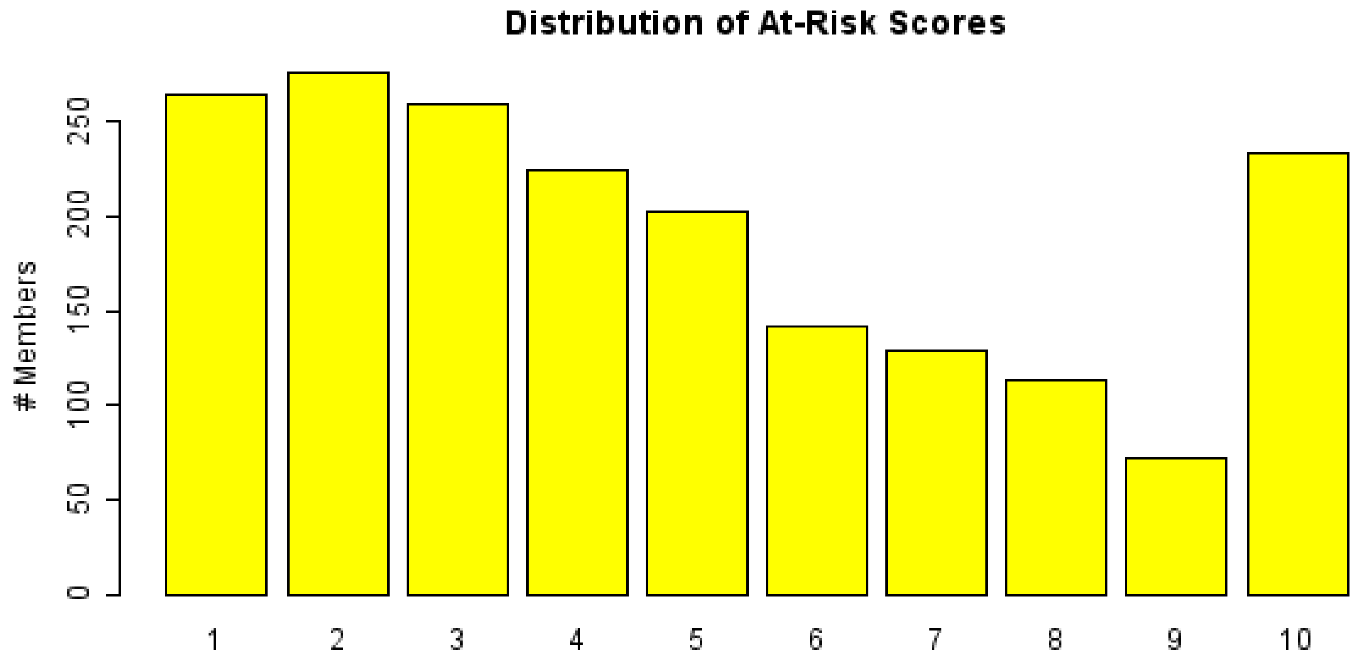
```
## Predictions on test set should be ~ OOB errrors
MembersTest <- read.delim("Data/MemberTestSet.txt", row.names = "MembID")
str(MembersTest)
summary(MembersTest)
MembersTest <- subset(MembersTest, select = -c(FirstCkInDay, LastCkInDay))
MembersTest$DaysSinceLastUse[is.na(MembersTest$DaysSinceLastUse)] <- 999
MembersTest$DaysSinceLastExtra[is.na(MembersTest$DaysSinceLastExtra)] <- 999
MembersTest <- rfImpute(Status ~ ., data = MembersTest)
save(MembersTest, file = "MemberTestSetImputed.rda")
MembersTest.pred <- predict(Members.rf, MembersTest[-1])
```

```
> ct <- table(MembersTest[[1]], MembersTest.pred)
> cbind(ct, class.error = c(ct[1,2]/sum(ct[1,]), ct[2,1]/sum(ct[2,])))
    C   M class.error
C 511 295   0.3660050
M 144 951   0.1315068

> (ct[1, 2] + ct[2, 1]) / length(MembersTest$Status)  ## Test Set Error
[1] 0.2309311
```

Practical: Prediction with RF (10)

- Need a score? Count the trees.

```
AtRiskScore <- floor(9.99999 * Members.rf$votes[, 1]) + 1
barplot(table(AtRiskScore), col = "yellow",
        ylab = "# Members", main = "Distribution of At-Risk Scores")
```



Random Forest Summary

- Has yielded practical results in number of cases
- Minimal tuning, no pruning required
- Black box, with interpretation
- Scoring fast & portable

Look at Examples

- Questions before we move on?

Questions? Comments?

- Email JPorzak@LoyaltyMatrix.com
- Call 415-296-1141
- Visit http://www.LoyaltyMatrix.com
- Come by at:
  580 Market Street, Suite 600
  San Francisco, CA 94104

APPENDIX

R Setup for Tutorial

This is the setup I will be using during the tutorial, you may, of course, change OS, editor, paths to match your own preferences.

- Windows XP SP1 on 2.5GHz P4 w/ 1G RAM.
- R Version 2.3.0
- RWinEdt & WinEdt V5.4 or JGR
- Following packages will be used
  - RWinEdt, aplpack, vcd, survival
- Directory Structure
  - R's working directory & source code: C:\Projects\CIwR\R
  - Tutorial data loaded in: C:\Projects\CIwR\R\Data
  - Plots will be stored in: C:\Projects\CIwR\R\Plots
- Other tools I like to use
  - TextPad: www.TextPad.com
  - DbVisualizer: http://www.dbvis.com/products/dbvis/

R Resources

- R & CRAN
- R Wiki
- Reference Cards