SCALABLE DATA PROCESSING IN R

The Bigmemory Suite of Packages

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So far ..

- Import
- Subset
- Assign values to big.matrix objects

Associated Packages

TABLES AND SUMMARIES

- biganalytics
- bigtabulate

Associated Packages

LINEAR ALGEBRA

- bigalgebra

Associated Packages

FIT MODELS

- bigpca
- bigFastLM
- biglasso
- bigrf

The FHFA's Mortgage Data Set

- Mortgages that were held or securitized by both Federal National Mortgage Association (Fannie Mae) and Federal Home Loan Mortgage Corporation (Freddie Mac) from 2009-2015
- FHFA Mortgage data is available online here
- We will focus on a random subset of 70000 loans

A first example: using bigtabulate with bigmemory

```
> library(bigtabulate)

# How many samples do we have per year?
> bigtable(mort, "year")
 2008  2009  2010  2011  2012  2013  2014  2015
 8468 11101  8836  7996 10935 10216  5714  6734

# Create nested tables
> bigtable(mort, c("msa", "year"))
  2008 2009 2010 2011 2012 2013 2014 2015
0 1064 1343  998  851 1066 1005  504  564
1 7404 9758 7838 7145 9869 9211 5210 6170
```

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Let's practice!

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Split-Apply-Combine

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Split-Apply-Combine

- Split: split()
- Apply: Map()
- Combine: Reduce()

Partition using split()

The split() function partitions data

- First argument is a vector or data.frame to split
- Second argument is a factor or integer whose values define the paritions

Partition using split()

```
> # Get the rows corresponding to each of the years in the mortgage data
> year_splits <- split(1:nrow(mort), mort[,"year"])

# year_splits is a list
> class(year_splits)
[1] "list"

> # The years that we've split over
> names(year_splits)
[1] "2008" "2009" "2010" "2011" "2012" "2013" "2014" "2015"

> # The first few rows corresponding to the year 2010
> year_splits[["2010"]][1:10]
 [1]  1  6  7 10 21 23 24 27 29 38
```

Compute using Map()

The Map() function processes the partitions

- First argument is the function to apply to each parition
- Second argument is the partitions

Compute using Map()

```
> col_missing_count <- function(mort) {
+   apply(mort, 2, function(x) sum(x == 9))
+ }
>
> # For each of the years count the number of missing values for all columns
> missing_by_year <- Map(
+   function(x) col_missing_count(mort[x, ]),
+   year_splits)
>
> missing_by_year[["2008"]]
           enterprise         record_number                   msa
                    0                    12                     0
# ...
```

Combine using Reduce()

The Reduce() function combines the results for all partitions

- First argument is the function to combine with
- Second argument is the partitioned data

Combine using Reduce()

```
> # Calculate the total missing values by column
> Reduce(`+`, missing_by_year)
          enterprise         record_number                   msa
                   0                    64                     0
# ...
>
> # Label the rownames with the year
> mby <- Reduce(rbind, missing_by_year)
> row.names(mby) <- names(year_splits)
> mby[1:3, 1:3]
     enterprise record_number msa
2008          0            12   0
2009          0             8   0
2010          0            10   0
```

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Visulize your results using Tidyverse

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Missingness by Year

```
> library(ggplot2)
> library(tidyr)
> library(dplyr)

> mort %>%
+     bigtable(c("borrower_gender", "year")) %>%
+     as.data.frame()
```

Missingness by Year

```
> library(ggplot2)
> library(tidyr)
> library(dplyr)

> mort %>%
+     bigtable(c("borrower_gender", "year")) %>%
+     as.data.frame() %>%
+     mutate(Category = c("Male", "Female", "Not Provided",
+                         "Not Applicable", "Missing"))
```

Missingness by Year

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> mort %>%
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+     gather(Year, Count, -Category)
```

Missingness by Year

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> library(ggplot2)
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> mort %>%
+     bigtable(c("borrower_gender", "year")) %>%
+     as.data.frame %>%
+     mutate(Category = c("Male", "Female", "Not Provided",
+                         "Not Applicable", "Missing")) %>%
+     gather(Year, Count, -Category) %>%
+     ggplot(aes(x = Year, y = Count, group = Category, color = Category)) +
+     geom_line()
```

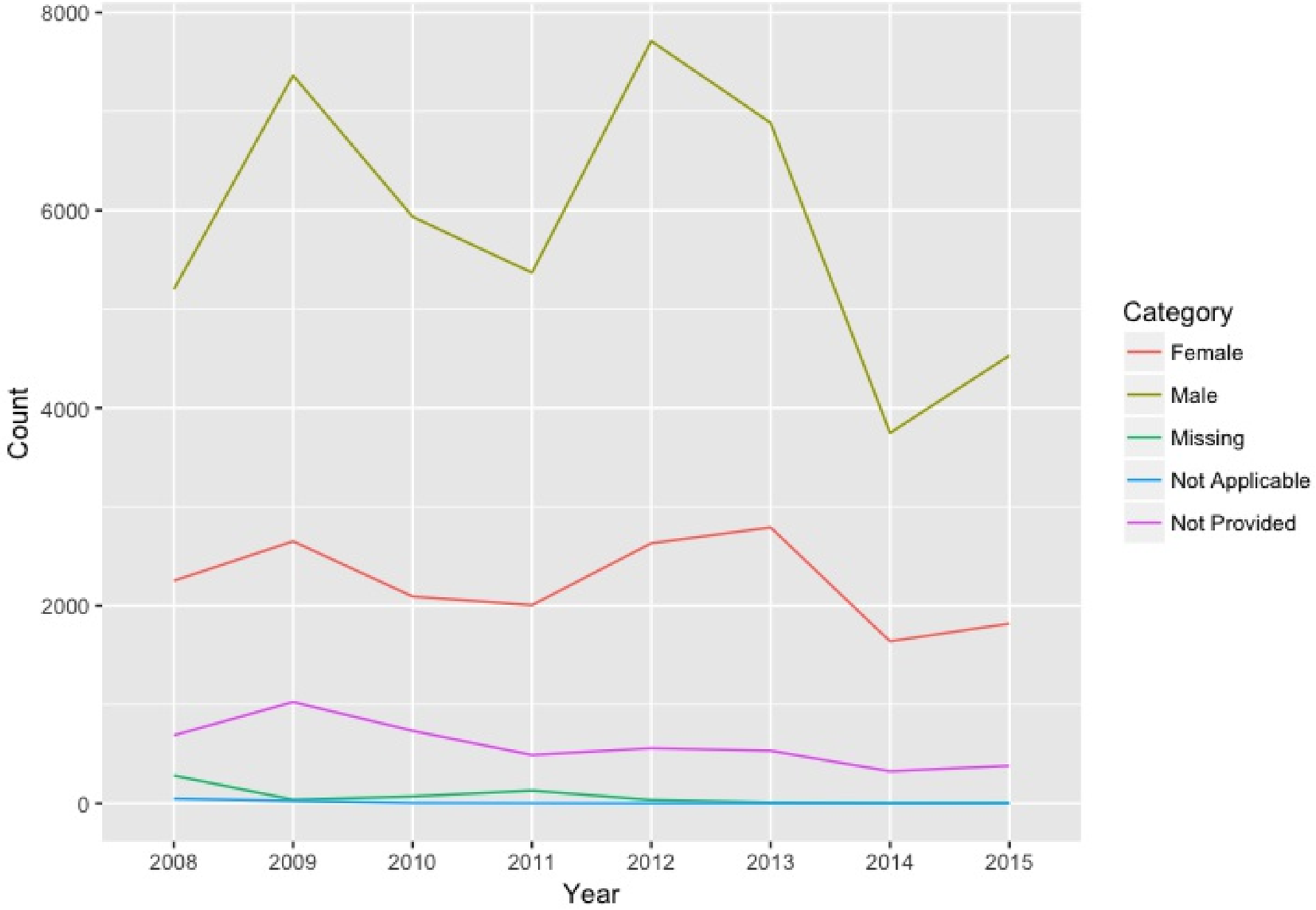
8000
6000
4000
2000
0
Count
2008
2009
2010
2011
2012
2013
2014
2015
Year
Category
Female
Male
Missing
Not Applicable
Not Provided

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Limitations of bigmemory

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Where can you use bigmemory?

- You can use bigmemory when your data are
  - matrices
  - dense
  - numeric
- Underlying data structures are compatible with low-level linear algebra libraries for fast model fitting
- If you have different column types, you could try the ff package

Understanding disk access

A big.matrix is a data structure designed for random access

Disadvantages of random access

- Can't add rows or columns to an existing big.matrix object
- You need to have enough disk space to hold the entire matrix in one big block

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