

R Notebook

Intro

In the wake of the Great Recession of 2009, there has been a good deal of focus on employment statistics, one of the most important metrics policymakers use to gauge the overall strength of the economy. In the United States, the government measures unemployment using the Current Population Survey (CPS), which collects demographic and employment information from a wide range of Americans each month. In this exercise, we will employ the topics reviewed in the lectures as well as a few new techniques using the September 2013 version of this rich, nationally representative dataset

Dataset used

(Compact version) **PeopleInHousehold**: The number of people in the interviewee's household. **Region**: The census region where the interviewee lives. **State**: The state where the interviewee lives. **MetroAreaCode**: A code that identifies the metropolitan area in which the interviewee lives (missing if the interviewee does not live in a metropolitan area). The mapping from codes to names of metropolitan areas is provided in the file `MetroAreaCodes.csv`. **Age**: The age, in years, of the interviewee. 80 represents people aged 80-84, and 85 represents people aged 85 and higher. **Married**: The marriage status of the interviewee. **Sex**: The sex of the interviewee. **Education**: The maximum level of education obtained by the interviewee. **Race**: The race of the interviewee. **Hispanic**: Whether the interviewee is of Hispanic ethnicity. **CountryOfBirthCode**: A code identifying the country of birth of the interviewee. The mapping from codes to names of countries is provided in the file `CountryCodes.csv`. **Citizenship**: The United States citizenship status of the interviewee. **EmploymentStatus**: The status of employment of the interviewee. **Industry**: The industry of employment of the interviewee (only available if they are employed).

1.1) Loading and Summarize the Dataset

```
library(readr)
library(skimr)

## Warning: package 'skimr' was built under R version 3.4.4

library(dplyr)

## Warning: package 'dplyr' was built under R version 3.4.4
##
## Attaching package: 'dplyr'
##
## The following objects are masked from 'package:stats':
##
##   filter, lag
##
## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

library(gridExtra)

##
## Attaching package: 'gridExtra'
```

```

## The following object is masked from 'package:dplyr':
##
##      combine
library(tidyverse)

## Warning: package 'tidyverse' was built under R version 3.4.2
## -- Attaching packages -----
## v ggplot2 3.1.0      v purrr  0.2.5
## v tibble  2.0.1      v stringr 1.3.1
## v tidyr   0.8.0      v forcats 0.3.0
## Warning: package 'ggplot2' was built under R version 3.4.4
## Warning: package 'tibble' was built under R version 3.4.4
## Warning: package 'tidyr' was built under R version 3.4.3
## Warning: package 'purrr' was built under R version 3.4.4
## Warning: package 'forcats' was built under R version 3.4.3
## -- Conflicts -----
## x gridExtra::combine() masks dplyr::combine()
## x dplyr::filter()      masks stats::filter()
## x dplyr::lag()         masks stats::lag()
CPS = read_csv("CPSData.csv")

## Parsed with column specification:
## cols(
##   PeopleInHousehold = col_integer(),
##   Region = col_character(),
##   State = col_character(),
##   MetroAreaCode = col_integer(),
##   Age = col_integer(),
##   Married = col_character(),
##   Sex = col_character(),
##   Education = col_character(),
##   Race = col_character(),
##   Hispanic = col_integer(),
##   CountryOfBirthCode = col_integer(),
##   Citizenship = col_character(),
##   EmploymentStatus = col_character(),
##   Industry = col_character()
## )
CPS %>% glimpse()

## Observations: 131,302
## Variables: 14
## $ PeopleInHousehold <int> 1, 3, 3, 3, 3, 3, 3, 2, 2, 2, 2, 1, 4, 4, 4...
## $ Region            <chr> "South", "South", "South", "South", "South"...
## $ State             <chr> "Alabama", "Alabama", "Alabama", "Alabama",...
## $ MetroAreaCode     <int> 26620, 13820, 13820, 13820, 26620, 26620, 2...
## $ Age               <int> 85, 21, 37, 18, 52, 24, 26, 71, 43, 52, 29,...
## $ Married           <chr> "Widowed", "Never Married", "Never Married"...
## $ Sex               <chr> "Female", "Male", "Female", "Male", "Female..."

```

```
## $ Education      <chr> "Associate degree", "High school", "High sc...
## $ Race            <chr> "White", "Black", "Black", "Black", "White"...
## $ Hispanic        <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ CountryOfBirthCode <int> 57, 57, 57, 57, 57, 57, 57, 57, 57, 57, 57, 57,...
## $ Citizenship      <chr> "Citizen, Native", "Citizen, Native", "Citi...
## $ EmploymentStatus <chr> "Retired", "Unemployed", "Disabled", "Not i...
## $ Industry         <chr> NA, "Professional and business services", N...
```

Most common industry of employment

```
CPS %>%
```

```
  count(Industry) %>%
```

```
  arrange(desc(n))
```

```
## Warning: package 'bindrcpp' was built under R version 3.4.4
```

```
## # A tibble: 15 x 2
```

	Industry	n
##	<chr>	<int>
##	1 <NA>	65060
##	2 Educational and health services	15017
##	3 Trade	8933
##	4 Professional and business services	7519
##	5 Manufacturing	6791
##	6 Leisure and hospitality	6364
##	7 Construction	4387
##	8 Financial	4347
##	9 Transportation and utilities	3260
##	10 Other services	3224
##	11 Public administration	3186
##	12 Information	1328
##	13 Agriculture, forestry, fishing, and hunting	1307
##	14 Mining	550
##	15 Armed forces	29

```
# or
```

```
sort(table(CPS$Industry), decreasing = T)
```

##	
##	Educational and health services
##	15017
##	Trade
##	8933
##	Professional and business services
##	7519
##	Manufacturing
##	6791
##	Leisure and hospitality
##	6364
##	Construction
##	4387
##	Financial
##	4347
##	Transportation and utilities
##	3260

```
##                Other services
##                3224
##      Public administration
##                3186
##                Information
##                1328
## Agriculture, forestry, fishing, and hunting
##                1307
##                Mining
##                550
##      Armed forces
##                29
```

Which state has the fewest interviewees?

```
sort(table(CPS$State))
```

```
##
##      New Mexico      Montana      Mississippi
##      1102           1214           1230
##      Alabama       West Virginia  Arkansas
##      1376           1409           1421
##      Louisiana      Idaho         Oklahoma
##      1450           1518           1523
##      Arizona        Alaska        Wyoming
##      1528           1590           1624
##      North Dakota   South Carolina Tennessee
##      1645           1658           1784
## District of Columbia Kentucky      Utah
##      1791           1841           1842
##      Nevada         Vermont        Kansas
##      1856           1890           1935
##      Oregon         Nebraska       Massachusetts
##      1943           1949           1987
##      South Dakota    Indiana        Hawaii
##      2000           2004           2099
##      Missouri       Rhode Island    Delaware
##      2145           2209           2214
##      Maine          Washington      Iowa
##      2263           2366           2528
##      New Jersey     North Carolina New Hampshire
##      2567           2619           2662
##      Wisconsin      Georgia        Connecticut
##      2686           2807           2836
##      Colorado       Virginia      Michigan
##      2925           2953           3063
##      Minnesota      Maryland      Ohio
##      3139           3200           3678
##      Illinois       Pennsylvania Florida
##      3912           3930           5149
##      New York       Texas         California
##      5595           7077           11570
```

```
# or
```

```
CPS %>% count(State) %>% arrange(n)
```

```
## # A tibble: 51 x 2
##   State      n
##   <chr>    <int>
## 1 New Mexico 1102
## 2 Montana    1214
## 3 Mississippi 1230
## 4 Alabama    1376
## 5 West Virginia 1409
## 6 Arkansas    1421
## 7 Louisiana    1450
## 8 Idaho        1518
## 9 Oklahoma     1523
## 10 Arizona     1528
## # ... with 41 more rows
```

What proportion of interviewees are citizens of the United States

```
table(CPS$Citizenship)
```

```
##
##      Citizen, Native Citizen, Naturalized      Non-Citizen
##      116639                7073                7590
```

```
CPS %>%
  group_by(Citizenship) %>%
  summarize(n = n()) %>%
  mutate(freq = n/ sum(n))
```

```
## # A tibble: 3 x 3
##   Citizenship      n  freq
##   <chr>        <int> <dbl>
## 1 Citizen, Native 116639 0.888
## 2 Citizen, Naturalized 7073 0.0539
## 3 Non-Citizen    7590 0.0578
```

```
# https://stackoverflow.com/questions/24576515/relative-frequencies-proportions-with-dplyr
0.88832615 + 0.05386818
```

```
## [1] 0.9421943
```

For which races are there at least 250 interviewees in the CPS dataset of Hispanic ethnicity?

```
CPS %>%
  count(Race, Hispanic)
```

```
## # A tibble: 12 x 3
##   Race      Hispanic      n
##   <chr>        <int> <int>
## 1 American Indian      0 1129
## 2 American Indian      1  304
## 3 Asian                0 6407
## 4 Asian                1  113
```

```
## 5 Black 0 13292
## 6 Black 1 621
## 7 Multiracial 0 2449
## 8 Multiracial 1 448
## 9 Pacific Islander 0 541
## 10 Pacific Islander 1 77
## 11 White 0 89190
## 12 White 1 16731
```

2.1) Evaluating Missing Values

Which variables have at least one interviewee with a missing (NA) value?

<https://stackoverflow.com/questions/8317231/elegant-way-to-report-missing-values-in-a-data-frame>

```
colSums(is.na(CPS))
```

```
## PeopleInHousehold      Region      State
##           0           0           0
##      MetroAreaCode      Age      Married
##           34238           0      25338
##           Sex      Education      Race
##           0      25338           0
##           Hispanic CountryOfBirthCode      Citizenship
##           0           0           0
##      EmploymentStatus      Industry
##           25789      65060
```

or

```
apply(is.na(CPS), 2, sum)
```

```
## PeopleInHousehold      Region      State
##           0           0           0
##      MetroAreaCode      Age      Married
##           34238           0      25338
##           Sex      Education      Race
##           0      25338           0
##           Hispanic CountryOfBirthCode      Citizenship
##           0           0           0
##      EmploymentStatus      Industry
##           25789      65060
```

```
table(CPS$Region, is.na(CPS$Married))
```

```
##
##           FALSE  TRUE
## Midwest  24609  6075
## Northeast 21432  4507
## South    33535  7967
## West     26388  6789
```

```
table(CPS$Sex, is.na(CPS$Married))
```

```
##
##           FALSE  TRUE
## Female  55264 12217
```

```
## Male 50700 13121
```

```
table(CPS$Age, is.na(CPS$Married))
```

```
##  
##      FALSE TRUE  
##  0         0 1283  
##  1         0 1559  
##  2         0 1574  
##  3         0 1693  
##  4         0 1695  
##  5         0 1795  
##  6         0 1721  
##  7         0 1681  
##  8         0 1729  
##  9         0 1748  
## 10         0 1750  
## 11         0 1721  
## 12         0 1797  
## 13         0 1802  
## 14         0 1790  
## 15 1795         0  
## 16 1751         0  
## 17 1764         0  
## 18 1596         0  
## 19 1517         0  
## 20 1398         0  
## 21 1525         0  
## 22 1536         0  
## 23 1638         0  
## 24 1627         0  
## 25 1604         0  
## 26 1643         0  
## 27 1657         0  
## 28 1736         0  
## 29 1645         0  
## 30 1854         0  
## 31 1762         0  
## 32 1790         0  
## 33 1804         0  
## 34 1653         0  
## 35 1716         0  
## 36 1663         0  
## 37 1531         0  
## 38 1530         0  
## 39 1542         0  
## 40 1571         0  
## 41 1673         0  
## 42 1711         0  
## 43 1819         0  
## 44 1764         0  
## 45 1749         0  
## 46 1665         0  
## 47 1647         0  
## 48 1791         0
```

```
## 49 1989 0
## 50 1966 0
## 51 1931 0
## 52 1935 0
## 53 1994 0
## 54 1912 0
## 55 1895 0
## 56 1935 0
## 57 1827 0
## 58 1874 0
## 59 1758 0
## 60 1746 0
## 61 1735 0
## 62 1595 0
## 63 1596 0
## 64 1519 0
## 65 1569 0
## 66 1577 0
## 67 1227 0
## 68 1130 0
## 69 1062 0
## 70 1195 0
## 71 1031 0
## 72 941 0
## 73 896 0
## 74 842 0
## 75 763 0
## 76 729 0
## 77 698 0
## 78 659 0
## 79 661 0
## 80 2664 0
## 85 2446 0
```

```
table(CPS$Citizenship, is.na(CPS$Married))
```

```
##
##                FALSE  TRUE
## Citizen, Native   91956 24683
## Citizen, Naturalized 6910  163
## Non-Citizen       7098   492
```

How many states had all interviewees living in a non-metropolitan area (aka they have a missing MetroAreaCode value)? For this question, treat the District of Columbia as a state (even though it is not technically a state).

Approach: find states that have 0 for False

How many states had all interviewees living in a metropolitan area? Again, treat the District of Columbia as a state. Approach: find states that have 0 for True

```
table(CPS$State, is.na(CPS$MetroAreaCode)) # FALSE= living in metropolitan area/ TRUE: not
```

```
##
##                FALSE  TRUE
## Alabama         1020   356
```


##	Alaska	0	1590
##	Arizona	1327	201
##	Arkansas	724	697
##	California	11333	237
##	Colorado	2545	380
##	Connecticut	2593	243
##	Delaware	1696	518
##	District of Columbia	1791	0
##	Florida	4947	202
##	Georgia	2250	557
##	Hawaii	1576	523
##	Idaho	761	757
##	Illinois	3473	439
##	Indiana	1420	584
##	Iowa	1297	1231
##	Kansas	1234	701
##	Kentucky	908	933
##	Louisiana	1216	234
##	Maine	909	1354
##	Maryland	2978	222
##	Massachusetts	1858	129
##	Michigan	2517	546
##	Minnesota	2150	989
##	Mississippi	376	854
##	Missouri	1440	705
##	Montana	199	1015
##	Nebraska	816	1133
##	Nevada	1609	247
##	New Hampshire	1148	1514
##	New Jersey	2567	0
##	New Mexico	832	270
##	New York	5144	451
##	North Carolina	1642	977
##	North Dakota	432	1213
##	Ohio	2754	924
##	Oklahoma	1024	499
##	Oregon	1519	424
##	Pennsylvania	3245	685
##	Rhode Island	2209	0
##	South Carolina	1139	519
##	South Dakota	595	1405
##	Tennessee	1149	635
##	Texas	6060	1017
##	Utah	1455	387
##	Vermont	657	1233
##	Virginia	2367	586
##	Washington	1937	429
##	West Virginia	344	1065
##	Wisconsin	1882	804
##	Wyoming	0	1624

Which region of the U.S. has the largest proportion of interviewees living in a non-metropolitan area?

```
table(CPS$Region, is.na(CPS$MetroAreaCode)) # FALSE= living in metropolitan area/ TRUE: not
##
##           FALSE  TRUE
## Midwest    20010 10674
## Northeast   20330  5609
## South       31631  9871
## West        25093  8084

# Proportion of interviewees living in a non-metropolitan area (True/Total)
10674 / (10674 + 20010) # Midwest

## [1] 0.3478686

5609 / (5609 + 20330) # Northeast

## [1] 0.2162381

9871 / (9871 + 31631) # South

## [1] 0.237844

8084 / (8084 + 25093) # West

## [1] 0.2436628

CPS %>%
  group_by(Citizenship) %>%
  summarize(n = n()) %>%
  mutate(freq = n/ sum(n))

## # A tibble: 3 x 3
##   Citizenship          n   freq
##   <chr>          <int> <dbl>
## 1 Citizen, Native    116639 0.888
## 2 Citizen, Naturalized  7073 0.0539
## 3 Non-Citizen        7590 0.0578
```

Which state has a proportion of interviewees living in a non-metropolitan area closest to 30%

(Use `tapply()` with the `mean` function to answer)

```
# FALSE= living in metropolitan area/ TRUE: not
sort(tapply(is.na(CPS$MetroAreaCode), CPS$State, mean), decreasing = TRUE) # summary, group, function

##           Alaska           Wyoming           Montana
##           1.00000000           1.00000000           0.83607908
##           West Virginia       North Dakota       South Dakota
##           0.75585522           0.73738602           0.70250000
##           Mississippi         Vermont           Maine
##           0.69430894           0.65238095           0.59832081
##           Nebraska           New Hampshire       Kentucky
##           0.58132376           0.56874530           0.50678979
##           Idaho           Arkansas           Iowa
##           0.49868248           0.49049965           0.48694620
##           North Carolina       Kansas           Tennessee
##           0.37304315           0.36227390           0.35594170
```

##	Missouri	Oklahoma	Minnesota
##	0.32867133	0.32764281	0.31506849
##	South Carolina	Wisconsin	Indiana
##	0.31302774	0.29932986	0.29141717
##	Alabama	Ohio	Hawaii
##	0.25872093	0.25122349	0.24916627
##	New Mexico	Delaware	Oregon
##	0.24500907	0.23396567	0.21821925
##	Utah	Virginia	Georgia
##	0.21009772	0.19844226	0.19843249
##	Washington	Michigan	Pennsylvania
##	0.18131868	0.17825661	0.17430025
##	Louisiana	Texas	Nevada
##	0.16137931	0.14370496	0.13308190
##	Arizona	Colorado	Illinois
##	0.13154450	0.12991453	0.11221881
##	Connecticut	New York	Maryland
##	0.08568406	0.08060769	0.06937500
##	Massachusetts	Florida	California
##	0.06492199	0.03923092	0.02048401
##	District of Columbia	New Jersey	Rhode Island
##	0.00000000	0.00000000	0.00000000

```
# Answer: Wisconsin
```

Which state has the largest proportion of non-metropolitan interviewees, ignoring states where all interviewees were non-metropolitan?

```
# Answer: Montana
```

3.1) Integrating Metropolitan Area Data

Codes like `MetroAreaCode` and `CountryOfBirthCode` are a compact way to encode factor variables with text as their possible values, and they are therefore quite common in survey datasets. In fact, all but one of the variables in this dataset were actually stored by a numeric code in the original CPS datafile.

When analyzing a variable stored by a numeric code, we will often want to convert it into the values the codes represent. To do this, we will use a dictionary, which maps the the code to the actual value of the variable. We have provided dictionaries `MetroAreaCodes.csv` and `CountryCodes.csv`, which respectively map `MetroAreaCode` and `CountryOfBirthCode` into their true values. Read these two dictionaries into data frames `MetroAreaMap` and `CountryMap`.

```
MetroAreaMap = read_csv("MetroAreaCodes.csv")
```

```
## Parsed with column specification:
## cols(
##   Code = col_character(),
##   MetroArea = col_character()
## )
```

```
MetroAreaMap %>% glimpse()
```

```
## Observations: 271
## Variables: 2
## $ Code      <chr> "00460", "03000", "03160", "03610", "03720", "06450"...
## $ MetroArea <chr> "Appleton-Oshkosh-Neenah, WI", "Grand Rapids-Muskego..."
```

```
CountryMap = read_csv("CountryCodes.csv")
```

```
## Parsed with column specification:
## cols(
##   Code = col_integer(),
##   Country = col_character()
## )
```

```
CountryMap %>% glimpse()
```

```
## Observations: 149
## Variables: 2
## $ Code      <int> 57, 66, 73, 78, 96, 100, 102, 103, 104, 105, 106, 108,...
## $ Country   <chr> "United States", "Guam", "Puerto Rico", "U. S. Virgin ...
```

To merge in the metropolitan areas, we want to connect the field `MetroAreaCode` from the CPS data frame with the field `Code` in `MetroAreaMap`. The following command merges the two data frames on these columns, overwriting the CPS data frame with the result:

```
CPS = merge(CPS, MetroAreaMap, by.x="MetroAreaCode", by.y="Code", all.x=TRUE)
```

The first two arguments determine the data frames to be merged (they are called “x” and “y”, respectively, in the subsequent parameters to the merge function). `by.x="MetroAreaCode"` means we’re matching on the `MetroAreaCode` variable from the “x” data frame (CPS), while `by.y="Code"` means we’re matching on the `Code` variable from the “y” data frame (`MetroAreaMap`). Finally, `all.x=TRUE` means we want to keep all rows from the “x” data frame (CPS), even if some of the rows’ `MetroAreaCode` doesn’t match any codes in `MetroAreaMap` (for those familiar with database terminology, this parameter makes the operation a left outer join instead of an inner join).

Review the new version of the CPS data frame with the `summary()` and `str()` functions. What is the name of the variable that was added to the data frame by the `merge()` operation?

```
CPS = merge(CPS, MetroAreaMap, by.x = "MetroAreaCode", by.y = "Code", all.x = TRUE)
```

```
summary(CPS)
```

```
## MetroAreaCode  PeopleInHousehold  Region      State
## Min.      :10420  Min.      : 1.000  Length:131302  Length:131302
## 1st Qu.:21780  1st Qu.: 2.000  Class :character  Class :character
## Median :34740  Median : 3.000  Mode  :character  Mode  :character
## Mean      :35075  Mean      : 3.284
## 3rd Qu.:41860  3rd Qu.: 4.000
## Max.      :79600  Max.      :15.000
## NA's      :34238
##      Age      Married      Sex      Education
## Min.      : 0.00  Length:131302  Length:131302  Length:131302
## 1st Qu.:19.00  Class :character  Class :character  Class :character
## Median :39.00  Mode  :character  Mode  :character  Mode  :character
## Mean      :38.83
## 3rd Qu.:57.00
## Max.      :85.00
##
##      Race      Hispanic  CountryOfBirthCode  Citizenship
## Length:131302  Min.      :0.0000  Min.      : 57.00  Length:131302
## Class :character  1st Qu.:0.0000  1st Qu.: 57.00  Class :character
## Mode  :character  Median :0.0000  Median : 57.00  Mode  :character
```

```
##           Mean    :0.1393    Mean    : 82.68
##           3rd Qu.:0.0000    3rd Qu.: 57.00
##           Max.    :1.0000    Max.    :555.00
##
## EmploymentStatus      Industry      MetroArea
## Length:131302      Length:131302      Length:131302
## Class :character      Class :character      Class :character
## Mode  :character      Mode  :character      Mode  :character
##
##
##
##
```

```
str(CPS)
```

```
## 'data.frame':    131302 obs. of  15 variables:
## $ MetroAreaCode      : int  10420 10420 10420 10420 10420 10420 10420 10420 10420 10420 ...
## $ PeopleInHousehold : int   4 4 2 4 1 3 4 4 2 3 ...
## $ Region             : chr  "Midwest" "Midwest" "Midwest" "Midwest" ...
## $ State              : chr  "Ohio" "Ohio" "Ohio" "Ohio" ...
## $ Age                : int   2 9 73 40 63 19 30 6 60 32 ...
## $ Married            : chr  NA NA "Married" "Married" ...
## $ Sex                : chr  "Male" "Male" "Female" "Female" ...
## $ Education          : chr  NA NA "Some college, no degree" "High school" ...
## $ Race               : chr  "White" "White" "White" "White" ...
## $ Hispanic           : int   0 0 0 0 0 0 0 1 0 0 ...
## $ CountryOfBirthCode: int   57 57 57 362 57 57 203 57 57 57 ...
## $ Citizenship        : chr  "Citizen, Native" "Citizen, Native" "Citizen, Native" "Citizen, Naturali
## $ EmploymentStatus  : chr  NA NA "Retired" "Not in Labor Force" ...
## $ Industry           : chr  NA NA NA NA ...
## $ MetroArea          : chr  "Akron, OH" "Akron, OH" "Akron, OH" "Akron, OH" ...
```

How many interviewees have a missing value for the new metropolitan area variable? Note that all of these interviewees would have been removed from the merged data frame if we did not include the `all.x=TRUE` parameter.

```
table(is.na(CPS$MetroArea)) # True = have missing values -> live in non-metro area
```

```
##
## FALSE TRUE
## 97064 34238
```

Which metropolitan area has the highest proportion of interviewees of Hispanic ethnicity? Hint: Use `tapply()` with `mean`, as in the previous subproblem. Calling `sort()` on the output of `tapply()` could also be helpful here.

```
sort(tapply(CPS$Hispanic,CPS$MetroArea, mean), decreasing = TRUE)
```

```
##           Laredo, TX
##           0.966292135
##           McAllen-Edinburg-Pharr, TX
##           0.948717949
##           Brownsville-Harlingen, TX
##           0.797468354
##           El Paso, TX
```

##	0.790983607
##	El Centro, CA
##	0.686868687
##	San Antonio, TX
##	0.644151565
##	Madera, CA
##	0.614035088
##	Corpus Christi, TX
##	0.606060606
##	Merced, CA
##	0.566037736
##	Salinas, CA
##	0.557692308
##	Las Cruces, NM
##	0.542056075
##	Tucson, AZ
##	0.506622517
##	Riverside-San Bernardino, CA
##	0.502325581
##	Bakersfield, CA
##	0.489795918
##	Miami-Fort Lauderdale-Miami Beach, FL
##	0.467824968
##	Victoria, TX
##	0.465517241
##	Santa Fe, NM
##	0.461538462
##	Los Angeles-Long Beach-Santa Ana, CA
##	0.460263286
##	Albuquerque, NM
##	0.441707718
##	Cape Coral-Fort Myers, FL
##	0.438356164
##	Visalia-Porterville, CA
##	0.438016529
##	Fresno, CA
##	0.409240924
##	Vineland-Millville-Bridgeton, NJ
##	0.407407407
##	Santa Barbara-Santa Maria-Goleta, CA
##	0.401515152
##	Killeen-Temple-Fort Hood, TX
##	0.386138614
##	Oxnard-Thousand Oaks-Ventura, CA
##	0.359550562
##	Houston-Baytown-Sugar Land, TX
##	0.359005458
##	Yakima, WA
##	0.357142857
##	Midland, TX
##	0.352941176
##	Modesto, CA
##	0.341772152
##	Danbury, CT

##	0.339285714
##	Waco, TX
##	0.329113924
##	Stockton, CA
##	0.321243523
##	San Jose-Sunnyvale-Santa Clara, CA
##	0.316417910
##	Austin-Round Rock, TX
##	0.310077519
##	Pueblo, CO
##	0.307692308
##	Longview, TX
##	0.292307692
##	Lubbock, TX
##	0.285714286
##	Dallas-Fort Worth-Arlington, TX
##	0.283950617
##	Poughkeepsie-Newburgh-Middletown, NY
##	0.273631841
##	San Diego-Carlsbad-San Marcos, CA
##	0.269018743
##	Sacramento-Arden-Arcade-Roseville, CA
##	0.263868066
##	Amarillo, TX
##	0.261363636
##	Phoenix-Mesa-Scottsdale, AZ
##	0.254376931
##	Las Vegas-Paradise, NV
##	0.251732102
##	Waterbury, CT
##	0.248407643
##	San Luis Obispo-Paso Robles, CA
##	0.246753247
##	Farmington, NM
##	0.234375000
##	Santa Rosa-Petaluma, CA
##	0.232558140
##	Denver-Aurora, CO
##	0.232047872
##	Napa, CA
##	0.229508197
##	New York-Northern New Jersey-Long Island, NY-NJ-PA
##	0.228508042
##	Beaumont-Port Author, TX
##	0.227642276
##	Springfield, MA-CT
##	0.219354839
##	Orlando, FL
##	0.213114754
##	Salem, OR
##	0.211764706
##	Reading, PA
##	0.211267606
##	Vallejo-Fairfield, CA

##	0.210526316
##	Columbus, GA-AL
##	0.203389831
##	San Francisco-Oakland-Fremont, CA
##	0.199855700
##	Reno-Sparks, NV
##	0.196774194
##	Naples-Marco Island, FL
##	0.182926829
##	Chicago-Naperville-Joliet, IN-IN-WI
##	0.167388167
##	Greeley, CO
##	0.160493827
##	Tampa-St. Petersburg-Clearwater, FL
##	0.159144893
##	Ocala, FL
##	0.157894737
##	Fayetteville, NC
##	0.155844156
##	Salt Lake City, UT
##	0.154910097
##	Santa-Cruz-Watsonville, CA
##	0.151515152
##	Fayetteville-Springdale-Rogers, AR-MO
##	0.148837209
##	Boulder, CO
##	0.146198830
##	Ogden-Clearfield, UT
##	0.144208038
##	Grand Rapids-Wyoming, MI
##	0.138157895
##	Scranton-Wilkes Barre, PA
##	0.136363636
##	Lakeland-Winter Haven, FL
##	0.134228188
##	Wichita, KS
##	0.133489461
##	Trenton-Ewing, NJ
##	0.131868132
##	Prescott, AZ
##	0.129629630
##	Jacksonville, NC
##	0.126984127
##	Green Bay, WI
##	0.125000000
##	Lawton, OK
##	0.123711340
##	Athens-Clark County, GA
##	0.123076923
##	Kansas City, MO-KS
##	0.121621622
##	Washington-Arlington-Alexandria, DC-VA-MD-WV
##	0.121378980
##	Fort Collins-Loveland, CO

##	0.121359223
##	Olympia, WA
##	0.121212121
##	Colorado Springs, CO
##	0.120967742
##	Raleigh-Cary, NC
##	0.119047619
##	Charlotte-Gastonia-Concord, NC-SC
##	0.117988395
##	Chico, CA
##	0.116666667
##	Kankakee-Bradley, IL
##	0.114942529
##	Tulsa, OK
##	0.114551084
##	Providence-Fall River-Warwick, MA-RI
##	0.114273205
##	Fort Walton Beach-Crestview-Destin, FL
##	0.112500000
##	Bridgeport-Stamford-Norwalk, CT
##	0.112328767
##	New Orleans-Metairie-Kenner, LA
##	0.111716621
##	Durham, NC
##	0.111111111
##	Waterloo-Cedar Falls, IA
##	0.108974359
##	Oklahoma City, OK
##	0.107615894
##	Hartford-West Hartford-East Hartford, CT
##	0.105084746
##	Norwich-New London, CT-RI
##	0.103448276
##	Lancaster, PA
##	0.102564103
##	Tuscaloosa, AL
##	0.102564103
##	Port St. Lucie-Fort Pierce, FL
##	0.100917431
##	Deltona-Daytona Beach-Ormond Beach, FL
##	0.100000000
##	Portland-Vancouver-Beaverton, OR-WA
##	0.094582185
##	Topeka, KS
##	0.093406593
##	Augusta-Richmond County, GA-SC
##	0.093167702
##	Boise City-Nampa, ID
##	0.093167702
##	Davenport-Moline-Rock Island, IA-IL
##	0.091666667
##	Jacksonville, FL
##	0.091603053
##	Leominster-Fitchburg-Gardner, MA

##	0.090909091
##	Atlantic City, NJ
##	0.090090090
##	Seattle-Tacoma-Bellevue, WA
##	0.088446215
##	Hickory-Morgantown-Lenoir, NC
##	0.087719298
##	Allentown-Bethlehem-Easton, PA-NJ
##	0.086826347
##	Fort Smith, AR-OK
##	0.085714286
##	Atlanta-Sandy Springs-Marietta, GA
##	0.085695876
##	Milwaukee-Waukesha-West Allis, WI
##	0.085434174
##	Medford, OR
##	0.085365854
##	Lansing-East Lansing, MI
##	0.084033613
##	Worcester, MA-CT
##	0.083333333
##	Baltimore-Towson, MD
##	0.082265678
##	Shreveport-Bossier City, LA
##	0.082191781
##	Syracuse, NY
##	0.080717489
##	Columbia, SC
##	0.079037801
##	Philadelphia-Camden-Wilmington, PA-NJ-DE
##	0.078458844
##	Chattanooga, TN-GA
##	0.077844311
##	Eugene-Springfield, OR
##	0.076530612
##	Canton-Massillon, OH
##	0.076271186
##	Vero Beach, FL
##	0.075949367
##	Greensboro-High Point, NC
##	0.075697211
##	Utica-Rome, NY
##	0.075000000
##	Des Moines, IA
##	0.073852295
##	New Haven, CT
##	0.073122530
##	Indianapolis, IN
##	0.071929825
##	Omaha-Council Bluffs, NE-IA
##	0.070010449
##	Tallahassee, FL
##	0.069767442
##	Boston-Cambridge-Quincy, MA-NH

##		0.069537909
##	Nashville-Davidson-Murfreesboro, TN	
##		0.069306931
##	Kingston, NY	
##		0.068965517
##	Panama City-Lynn Haven, FL	
##		0.067796610
##	Ocean City, NJ	
##		0.066666667
##	Provo-Orem, UT	
##		0.064724919
##	Anderson, IN	
##		0.064516129
##	Monroe, MI	
##		0.063492063
##	Peoria, IL	
##		0.062500000
##	Lafayette, LA	
##		0.060773481
##	Asheville, NC	
##		0.060344828
##	Cleveland-Elyria-Mentor, OH	
##		0.060205580
##	Honolulu, HI	
##		0.059644670
##	Myrtle Beach-Conway-North Myrtle Beach, SC	
##		0.058823529
##	Racine, WI	
##		0.058823529
##	Rochester, NY	
##		0.058631922
##	Bremerton-Silverdale, WA	
##		0.057471264
##	Dover, DE	
##		0.057017544
##	Winston-Salem, NC	
##		0.055118110
##	Birmingham-Hoover, AL	
##		0.053571429
##	Palm Bay-Melbourne-Titusville, FL	
##		0.053571429
##	Decatur, AL	
##		0.052083333
##	Minneapolis-St Paul-Bloomington, MN-WI	
##		0.052008239
##	Virginia Beach-Norfolk-Newport News, VA-NC	
##		0.050251256
##	South Bend-Mishawaka, IN-MI	
##		0.049382716
##	Anniston-Oxford, AL	
##		0.049180328
##	Valdosta, GA	
##		0.047619048
##	Sarasota-Bradenton-Venice, FL	

##	0.046875000
##	Albany, GA
##	0.044117647
##	Rockford, IL
##	0.043859649
##	Columbus, OH
##	0.043557169
##	Springfield, MO
##	0.043478261
##	Gainesville, FL
##	0.042857143
##	Richmond, VA
##	0.042857143
##	York-Hanover, PA
##	0.042735043
##	Columbia, MO
##	0.042553191
##	Sioux Falls, SD
##	0.042016807
##	Punta Gorda, FL
##	0.041666667
##	Binghamton, NY
##	0.041095890
##	Albany-Schenectady-Troy, NY
##	0.041044776
##	Lawrence, KS
##	0.040816327
##	Lexington-Fayette, KY
##	0.040404040
##	Cincinnati-Middletown, OH-KY-IN
##	0.040333797
##	Flint, MI
##	0.039215686
##	Michigan City-La Porte, IN
##	0.038961039
##	Louisville, KY-IN
##	0.038535645
##	Johnson City, TN
##	0.038461538
##	Baton Rouge, LA
##	0.038167939
##	Greenville, SC
##	0.037837838
##	Detroit-Warren-Livonia, MI
##	0.037666174
##	Little Rock-North Little Rock, AR
##	0.037128713
##	Fort Wayne, IN
##	0.036764706
##	Toledo, OH
##	0.034042553
##	Champaign-Urbana, IL
##	0.032786885
##	Youngstown-Warren-Boardman, OH

##	0.032679739
##	Kalamazoo-Portage, MI
##	0.031496063
##	Iowa City, IA
##	0.030534351
##	Rochester-Dover, NH-ME
##	0.030534351
##	St. Louis, MO-IL
##	0.030334728
##	Janesville, WI
##	0.030303030
##	Roanoke, VA
##	0.030303030
##	Billings, MT
##	0.030150754
##	Springfield, OH
##	0.029411765
##	Memphis, TN-MS-AR
##	0.028735632
##	Pensacola-Ferry Pass-Brent, FL
##	0.028037383
##	Lynchburg, VA
##	0.027397260
##	Saginaw-Saginaw Township North, MI
##	0.027027027
##	Coeur d'Alene, ID
##	0.025641026
##	Spokane, WA
##	0.025641026
##	Fargo, ND-MN
##	0.025462963
##	Lake Charles, LA
##	0.024691358
##	Madison, WI
##	0.024647887
##	Erie, PA
##	0.022988506
##	Harrisburg-Carlisle, PA
##	0.022988506
##	Muskegon-Norton Shores, MI
##	0.022222222
##	Bend, OR
##	0.021428571
##	Evansville, IN-KY
##	0.020202020
##	Spartanburg, SC
##	0.020202020
##	Niles-Benton Harbor, MI
##	0.019607843
##	La Crosse, WI
##	0.017543860
##	Buffalo-Niagara Falls, NY
##	0.017441860
##	Charleston-North Charleston, SC

##	0.017241379
##	Joplin, MO
##	0.016949153
##	Pittsburgh, PA
##	0.016393443
##	Duluth, MN-WI
##	0.015873016
##	Gulfport-Biloxi, MS
##	0.015384615
##	Cedar Rapids, IA
##	0.015306122
##	Kingsport-Bristol, TN-VA
##	0.014925373
##	Bangor, ME
##	0.014423077
##	Bellingham, WA
##	0.014285714
##	Springfield, IL
##	0.013157895
##	Akron, OH
##	0.012987013
##	Holland-Grand Haven, MI
##	0.012820513
##	Altoona, PA
##	0.012195122
##	St. Cloud, MN
##	0.012195122
##	Oshkosh-Neenah, WI
##	0.011764706
##	Portland-South Portland, ME
##	0.011412268
##	Wausau, WI
##	0.010416667
##	Montgomery, AL
##	0.009708738
##	Burlington-South Burlington, VT
##	0.009132420
##	Jackson, MS
##	0.009009009
##	Appleton,WI
##	0.008000000
##	Charleston, WV
##	0.007633588
##	Knoxville, TN
##	0.005952381
##	Monroe, LA
##	0.005586592
##	Dayton, OH
##	0.003731343
##	Anderson, SC
##	0.000000000
##	Ann Arbor, MI
##	0.000000000
##	Barnstable Town, MA

```
##                0.000000000
##      Bloomington-Normal IL
##                0.000000000
##      Bloomington, IN
##                0.000000000
##      Bowling Green, KY
##                0.000000000
##      Decatur, IL
##                0.000000000
##      Eau Claire, WI
##                0.000000000
##      Florence, AL
##                0.000000000
##      Hagerstown-Martinsburg, MD-WV
##                0.000000000
##      Harrisonburg, VA
##                0.000000000
##      Huntington-Ashland, WV-KY-OH
##                0.000000000
##      Huntsville, AL
##                0.000000000
##      Jackson, MI
##                0.000000000
##      Johnstown, PA
##                0.000000000
##      Macon, GA
##                0.000000000
##      Mobile, AL
##                0.000000000
##      Salisbury, MD
##                0.000000000
##      Savannah, GA
##                0.000000000
##      Warner Robins, GA
##                0.000000000
```

Determine the number of metropolitan areas in the United States from which at least 20% of interviewees are Asian.

```
sort(tapply(CPS$Race == "Asian", CPS$MetroArea, mean), decreasing = TRUE)
```

```
##                Honolulu, HI
##                0.501903553
##      San Francisco-Oakland-Fremont, CA
##                0.246753247
##      San Jose-Sunnyvale-Santa Clara, CA
##                0.241791045
##      Vallejo-Fairfield, CA
##                0.203007519
##      Fresno, CA
##                0.184818482
##      Warner Robins, GA
##                0.166666667
##      Stockton, CA
```

##	0.155440415
##	Atlantic City, NJ
##	0.144144144
##	Sacramento-Arden-Arcade-Roseville, CA
##	0.142428786
##	San Diego-Carlsbad-San Marcos, CA
##	0.142227122
##	Los Angeles-Long Beach-Santa Ana, CA
##	0.135056070
##	Olympia, WA
##	0.131313131
##	Salinas, CA
##	0.125000000
##	New York-Northern New Jersey-Long Island, NY-NJ-PA
##	0.104270660
##	Seattle-Tacoma-Bellevue, WA
##	0.099601594
##	Visalia-Porterville, CA
##	0.090909091
##	Green Bay, WI
##	0.088235294
##	La Crosse, WI
##	0.087719298
##	Ann Arbor, MI
##	0.082352941
##	Bakersfield, CA
##	0.081632653
##	Greensboro-High Point, NC
##	0.079681275
##	Las Vegas-Paradise, NV
##	0.078521940
##	Minneapolis-St Paul-Bloomington, MN-WI
##	0.076725026
##	Brownsville-Harlingen, TX
##	0.075949367
##	Bloomington-Normal IL
##	0.075000000
##	Oxnard-Thousand Oaks-Ventura, CA
##	0.074906367
##	Lake Charles, LA
##	0.074074074
##	Norwich-New London, CT-RI
##	0.073891626
##	Atlanta-Sandy Springs-Marietta, GA
##	0.072809278
##	Washington-Arlington-Alexandria, DC-VA-MD-WV
##	0.070624850
##	Portland-Vancouver-Beaverton, OR-WA
##	0.069788797
##	Hartford-West Hartford-East Hartford, CT
##	0.066666667
##	Cedar Rapids, IA
##	0.066326531
##	Rochester, NY

##	0.065146580
##	Columbia, MO
##	0.063829787
##	Dallas-Fort Worth-Arlington, TX
##	0.062801932
##	Danbury, CT
##	0.062500000
##	Riverside-San Bernardino, CA
##	0.062015504
##	Houston-Baytown-Sugar Land, TX
##	0.061249242
##	Boulder, CO
##	0.058479532
##	Chicago-Naperville-Joliet, IN-IN-WI
##	0.058441558
##	Reno-Sparks, NV
##	0.058064516
##	Baltimore-Towson, MD
##	0.057990560
##	Lancaster, PA
##	0.057692308
##	Nashville-Davidson-Murfreesboro, TN
##	0.057425743
##	Fort Smith, AR-OK
##	0.057142857
##	Merced, CA
##	0.056603774
##	Madison, WI
##	0.056338028
##	Peoria, IL
##	0.053571429
##	Iowa City, IA
##	0.053435115
##	Springfield, IL
##	0.052631579
##	Austin-Round Rock, TX
##	0.052325581
##	Buffalo-Niagara Falls, NY
##	0.052325581
##	Boston-Cambridge-Quincy, MA-NH
##	0.052041274
##	San Luis Obispo-Paso Robles, CA
##	0.051948052
##	Fayetteville-Springdale-Rogers, AR-MO
##	0.051162791
##	Orlando, FL
##	0.050819672
##	Raleigh-Cary, NC
##	0.050595238
##	Tulsa, OK
##	0.049535604
##	Anniston-Oxford, AL
##	0.049180328
##	Burlington-South Burlington, VT

##	0.048706240
##	Jacksonville, FL
##	0.048346056
##	Jacksonville, NC
##	0.047619048
##	Milwaukee-Waukesha-West Allis, WI
##	0.047619048
##	New Haven, CT
##	0.047430830
##	Trenton-Ewing, NJ
##	0.043956044
##	Detroit-Warren-Livonia, MI
##	0.043574594
##	Gainesville, FL
##	0.042857143
##	Portland-South Portland, ME
##	0.042796006
##	Decatur, AL
##	0.041666667
##	Albuquerque, NM
##	0.041050903
##	Syracuse, NY
##	0.040358744
##	Duluth, MN-WI
##	0.039682540
##	Tampa-St. Petersburg-Clearwater, FL
##	0.039192399
##	Providence-Fall River-Warwick, MA-RI
##	0.038966725
##	Bridgeport-Stamford-Norwalk, CT
##	0.038356164
##	Pittsburgh, PA
##	0.038251366
##	Phoenix-Mesa-Scottsdale, AZ
##	0.038105046
##	Des Moines, IA
##	0.037924152
##	Fort Walton Beach-Crestview-Destin, FL
##	0.037500000
##	Fort Wayne, IN
##	0.036764706
##	Richmond, VA
##	0.036734694
##	Huntington-Ashland, WV-KY-OH
##	0.036585366
##	Mobile, AL
##	0.036363636
##	Salt Lake City, UT
##	0.035961272
##	Palm Bay-Melbourne-Titusville, FL
##	0.035714286
##	Miami-Fort Lauderdale-Miami Beach, FL
##	0.035392535
##	Lexington-Fayette, KY

##	0.035353535
##	Hickory-Morgantown-Lenoir, NC
##	0.035087719
##	Oklahoma City, OK
##	0.034768212
##	Worcester, MA-CT
##	0.034722222
##	Kansas City, MO-KS
##	0.034303534
##	Cape Coral-Fort Myers, FL
##	0.034246575
##	Harrisonburg, VA
##	0.033333333
##	Philadelphia-Camden-Wilmington, PA-NJ-DE
##	0.032924694
##	Greenville, SC
##	0.032432432
##	Denver-Aurora, CO
##	0.031914894
##	Anderson, SC
##	0.031250000
##	Athens-Clark County, GA
##	0.030769231
##	Gulfport-Biloxi, MS
##	0.030769231
##	Wichita, KS
##	0.030444965
##	Akron, OH
##	0.030303030
##	Omaha-Council Bluffs, NE-IA
##	0.029258098
##	Montgomery, AL
##	0.029126214
##	Bellingham, WA
##	0.028571429
##	Fargo, ND-MN
##	0.027777778
##	Columbia, SC
##	0.027491409
##	Lakeland-Winter Haven, FL
##	0.026845638
##	Virginia Beach-Norfolk-Newport News, VA-NC
##	0.026800670
##	Rochester-Dover, NH-ME
##	0.026717557
##	Ogden-Clearfield, UT
##	0.026004728
##	Fayetteville, NC
##	0.025974026
##	Holland-Grand Haven, MI
##	0.025641026
##	Augusta-Richmond County, GA-SC
##	0.024844720
##	Indianapolis, IN

##	0.024561404
##	Naples-Marco Island, FL
##	0.024390244
##	Bangor, ME
##	0.024038462
##	Bremerton-Silverdale, WA
##	0.022988506
##	Baton Rouge, LA
##	0.022900763
##	Albany-Schenectady-Troy, NY
##	0.022388060
##	Little Rock-North Little Rock, AR
##	0.022277228
##	Cincinnati-Middletown, OH-KY-IN
##	0.022253129
##	Topeka, KS
##	0.021978022
##	Deltona-Daytona Beach-Ormond Beach, FL
##	0.021428571
##	Davenport-Moline-Rock Island, IA-IL
##	0.020833333
##	Eugene-Springfield, OR
##	0.020408163
##	El Centro, CA
##	0.020202020
##	Tucson, AZ
##	0.019867550
##	Savannah, GA
##	0.019801980
##	Flint, MI
##	0.019607843
##	Fort Collins-Loveland, CO
##	0.019417476
##	Spokane, WA
##	0.019230769
##	Las Cruces, NM
##	0.018691589
##	Pensacola-Ferry Pass-Brent, FL
##	0.018691589
##	Prescott, AZ
##	0.018518519
##	Columbus, OH
##	0.018148820
##	Memphis, TN-MS-AR
##	0.017241379
##	Panama City-Lynn Haven, FL
##	0.016949153
##	Champaign-Urbana, IL
##	0.016393443
##	Napa, CA
##	0.016393443
##	Colorado Springs, CO
##	0.016129032
##	Johnstown, PA

##	0.015873016
##	Kalamazoo-Portage, MI
##	0.015748031
##	Winston-Salem, NC
##	0.015748031
##	Sarasota-Bradenton-Venice, FL
##	0.015625000
##	Charlotte-Gastonia-Concord, NC-SC
##	0.015473888
##	Dover, DE
##	0.015350877
##	Corpus Christi, TX
##	0.015151515
##	Allentown-Bethlehem-Easton, PA-NJ
##	0.014970060
##	Ocala, FL
##	0.013157895
##	Youngstown-Warren-Boardman, OH
##	0.013071895
##	Provo-Orem, UT
##	0.012944984
##	Waterloo-Cedar Falls, IA
##	0.012820513
##	Birmingham-Hoover, AL
##	0.012755102
##	Springfield, MO
##	0.012422360
##	Greeley, CO
##	0.012345679
##	Medford, OR
##	0.012195122
##	Louisville, KY-IN
##	0.011560694
##	Harrisburg-Carlisle, PA
##	0.011494253
##	Kingston, NY
##	0.011494253
##	Boise City-Nampa, ID
##	0.010869565
##	Lawton, OK
##	0.010309278
##	Cleveland-Elyria-Mentor, OH
##	0.010279001
##	Lawrence, KS
##	0.010204082
##	Evansville, IN-KY
##	0.010101010
##	Sioux Falls, SD
##	0.010084034
##	Grand Rapids-Wyoming, MI
##	0.009868421
##	Yakima, WA
##	0.008928571
##	Coeur d'Alene, ID

##	0.008547009
##	York-Hanover, PA
##	0.008547009
##	Toledo, OH
##	0.008510638
##	Santa Rosa-Petaluma, CA
##	0.007751938
##	Santa Barbara-Santa Maria-Goleta, CA
##	0.007575758
##	Dayton, OH
##	0.007462687
##	Bend, OR
##	0.007142857
##	Modesto, CA
##	0.006329114
##	Chattanooga, TN-GA
##	0.005988024
##	Monroe, LA
##	0.005586592
##	Charleston-North Charleston, SC
##	0.004310345
##	San Antonio, TX
##	0.003294893
##	New Orleans-Metairie-Kenner, LA
##	0.002724796
##	St. Louis, MO-IL
##	0.002092050
##	Albany, GA
##	0.000000000
##	Altoona, PA
##	0.000000000
##	Amarillo, TX
##	0.000000000
##	Anderson, IN
##	0.000000000
##	Appleton,WI
##	0.000000000
##	Asheville, NC
##	0.000000000
##	Barnstable Town, MA
##	0.000000000
##	Beaumont-Port Author, TX
##	0.000000000
##	Billings, MT
##	0.000000000
##	Binghamton, NY
##	0.000000000
##	Bloomington, IN
##	0.000000000
##	Bowling Green, KY
##	0.000000000
##	Canton-Massillon, OH
##	0.000000000
##	Charleston, WV

##	0.000000000
##	Chico, CA
##	0.000000000
##	Columbus, GA-AL
##	0.000000000
##	Decatur, IL
##	0.000000000
##	Durham, NC
##	0.000000000
##	Eau Claire, WI
##	0.000000000
##	El Paso, TX
##	0.000000000
##	Erie, PA
##	0.000000000
##	Farmington, NM
##	0.000000000
##	Florence, AL
##	0.000000000
##	Hagerstown-Martinsburg, MD-WV
##	0.000000000
##	Huntsville, AL
##	0.000000000
##	Jackson, MI
##	0.000000000
##	Jackson, MS
##	0.000000000
##	Janesville, WI
##	0.000000000
##	Johnson City, TN
##	0.000000000
##	Joplin, MO
##	0.000000000
##	Kankakee-Bradley, IL
##	0.000000000
##	Killeen-Temple-Fort Hood, TX
##	0.000000000
##	Kingsport-Bristol, TN-VA
##	0.000000000
##	Knoxville, TN
##	0.000000000
##	Lafayette, LA
##	0.000000000
##	Lansing-East Lansing, MI
##	0.000000000
##	Laredo, TX
##	0.000000000
##	Leominster-Fitchburg-Gardner, MA
##	0.000000000
##	Longview, TX
##	0.000000000
##	Lubbock, TX
##	0.000000000
##	Lynchburg, VA

##	0.000000000
##	Macon, GA
##	0.000000000
##	Madera, CA
##	0.000000000
##	McAllen-Edinburg-Pharr, TX
##	0.000000000
##	Michigan City-La Porte, IN
##	0.000000000
##	Midland, TX
##	0.000000000
##	Monroe, MI
##	0.000000000
##	Muskegon-Norton Shores, MI
##	0.000000000
##	Myrtle Beach-Conway-North Myrtle Beach, SC
##	0.000000000
##	Niles-Benton Harbor, MI
##	0.000000000
##	Ocean City, NJ
##	0.000000000
##	Oshkosh-Neenah, WI
##	0.000000000
##	Port St. Lucie-Fort Pierce, FL
##	0.000000000
##	Poughkeepsie-Newburgh-Middletown, NY
##	0.000000000
##	Pueblo, CO
##	0.000000000
##	Punta Gorda, FL
##	0.000000000
##	Racine, WI
##	0.000000000
##	Reading, PA
##	0.000000000
##	Roanoke, VA
##	0.000000000
##	Rockford, IL
##	0.000000000
##	Saginaw-Saginaw Township North, MI
##	0.000000000
##	Salem, OR
##	0.000000000
##	Salisbury, MD
##	0.000000000
##	Santa Fe, NM
##	0.000000000
##	Santa-Cruz-Watsonville, CA
##	0.000000000
##	Scranton-Wilkes Barre, PA
##	0.000000000
##	Shreveport-Bossier City, LA
##	0.000000000
##	South Bend-Mishawaka, IN-MI


```
##              0.000000000
##      Spartanburg, SC
##              0.000000000
##      Springfield, MA-CT
##              0.000000000
##      Springfield, OH
##              0.000000000
##      St. Cloud, MN
##              0.000000000
##      Tallahassee, FL
##              0.000000000
##      Tuscaloosa, AL
##              0.000000000
##      Utica-Rome, NY
##              0.000000000
##      Valdosta, GA
##              0.000000000
##      Vero Beach, FL
##              0.000000000
##      Victoria, TX
##              0.000000000
##      Vineland-Millville-Bridgeton, NJ
##              0.000000000
##      Waco, TX
##              0.000000000
##      Waterbury, CT
##              0.000000000
##      Wausau, WI
##              0.000000000
```

```
# answer: 4
```

Determine which metropolitan area has the smallest proportion of interviewees who have received no high school diploma

```
sort(tapply(CPS$Education == "No high school diploma", CPS$MetroArea, mean, na.rm = T))
```

```
##              Iowa City, IA
##              0.02912621
##      Bowling Green, KY
##              0.03703704
##      Kalamazoo-Portage, MI
##              0.05050505
##      Champaign-Urbana, IL
##              0.05154639
##      Bremerton-Silverdale, WA
##              0.05405405
##      Lawrence, KS
##              0.05952381
##      Bloomington-Normal IL
##              0.06060606
##      Jacksonville, NC
##              0.06122449
##      Eau Claire, WI
```

##	0.06250000
##	Palm Bay-Melbourne-Titusville, FL
##	0.06666667
##	Salisbury, MD
##	0.06779661
##	Gainesville, FL
##	0.06896552
##	Fort Collins-Loveland, CO
##	0.06936416
##	Altoona, PA
##	0.07142857
##	Madison, WI
##	0.07423581
##	Tallahassee, FL
##	0.07500000
##	Fargo, ND-MN
##	0.07902736
##	Albany-Schenectady-Troy, NY
##	0.07929515
##	Ocean City, NJ
##	0.08000000
##	Lakeland-Winter Haven, FL
##	0.08130081
##	Billings, MT
##	0.08280255
##	Coeur d'Alene, ID
##	0.08333333
##	Burlington-South Burlington, VT
##	0.08394161
##	Akron, OH
##	0.08421053
##	Ann Arbor, MI
##	0.08695652
##	Asheville, NC
##	0.08695652
##	Pensacola-Ferry Pass-Brent, FL
##	0.08695652
##	Oshkosh-Neenah, WI
##	0.08823529
##	Rochester-Dover, NH-ME
##	0.08928571
##	Knoxville, TN
##	0.08965517
##	Pittsburgh, PA
##	0.09060403
##	Barnstable Town, MA
##	0.09090909
##	Bridgeport-Stamford-Norwalk, CT
##	0.09563758
##	Johnstown, PA
##	0.09615385
##	Austin-Round Rock, TX
##	0.09629630
##	La Crosse, WI

##	0.09677419
##	Boulder, CO
##	0.09701493
##	Charleston-North Charleston, SC
##	0.09890110
##	Fort Wayne, IN
##	0.09900990
##	Roanoke, VA
##	0.10169492
##	Prescott, AZ
##	0.10204082
##	Santa Rosa-Petaluma, CA
##	0.10280374
##	Evansville, IN-KY
##	0.10389610
##	Spokane, WA
##	0.10434783
##	Poughkeepsie-Newburgh-Middletown, NY
##	0.10559006
##	Tampa-St. Petersburg-Clearwater, FL
##	0.10579710
##	Grand Rapids-Wyoming, MI
##	0.10612245
##	Portland-South Portland, ME
##	0.10638298
##	Honolulu, HI
##	0.10739300
##	Michigan City-La Porte, IN
##	0.10769231
##	Eugene-Springfield, OR
##	0.11038961
##	Boston-Cambridge-Quincy, MA-NH
##	0.11080485
##	Bend, OR
##	0.11111111
##	Vero Beach, FL
##	0.11428571
##	Sarasota-Bradenton-Venice, FL
##	0.11464968
##	Fort Walton Beach-Crestview-Destin, FL
##	0.11475410
##	Flint, MI
##	0.11538462
##	Cedar Rapids, IA
##	0.11564626
##	Minneapolis-St Paul-Bloomington, MN-WI
##	0.11638204
##	Portland-Vancouver-Beaverton, OR-WA
##	0.11657143
##	Washington-Arlington-Alexandria, DC-VA-MD-WV
##	0.11683748
##	Mobile, AL
##	0.11702128
##	Scranton-Wilkes Barre, PA

##	0.11724138
##	Topeka, KS
##	0.11724138
##	Colorado Springs, CO
##	0.11764706
##	Olympia, WA
##	0.11764706
##	Reno-Sparks, NV
##	0.11764706
##	Appleton,WI
##	0.11827957
##	Santa Fe, NM
##	0.11904762
##	Virginia Beach-Norfolk-Newport News, VA-NC
##	0.11909651
##	Allentown-Bethlehem-Easton, PA-NJ
##	0.11929825
##	Rochester, NY
##	0.12132353
##	Seattle-Tacoma-Bellevue, WA
##	0.12168793
##	Kansas City, MO-KS
##	0.12172775
##	Napa, CA
##	0.12244898
##	Duluth, MN-WI
##	0.12264151
##	New Haven, CT
##	0.12354312
##	Canton-Massillon, OH
##	0.12371134
##	Fayetteville, NC
##	0.12500000
##	San Luis Obispo-Paso Robles, CA
##	0.12500000
##	Worcester, MA-CT
##	0.12605042
##	Philadelphia-Camden-Wilmington, PA-NJ-DE
##	0.12717253
##	Davenport-Moline-Rock Island, IA-IL
##	0.12727273
##	Waterloo-Cedar Falls, IA
##	0.12800000
##	Pueblo, CO
##	0.12844037
##	Baton Rouge, LA
##	0.12871287
##	Racine, WI
##	0.12903226
##	Des Moines, IA
##	0.12944162
##	Detroit-Warren-Livonia, MI
##	0.12964642
##	Omaha-Council Bluffs, NE-IA

##	0.12972973
##	Richmond, VA
##	0.12990196
##	Savannah, GA
##	0.13013699
##	Danbury, CT
##	0.13043478
##	Bloomington, IN
##	0.13095238
##	Valdosta, GA
##	0.13157895
##	Wausau, WI
##	0.13157895
##	Deltona-Daytona Beach-Ormond Beach, FL
##	0.13178295
##	Tulsa, OK
##	0.13178295
##	Harrisburg-Carlisle, PA
##	0.13286713
##	Las Vegas-Paradise, NV
##	0.13307985
##	Myrtle Beach-Conway-North Myrtle Beach, SC
##	0.13333333
##	Provo-Orem, UT
##	0.13366337
##	Anderson, IN
##	0.13461538
##	Chico, CA
##	0.13461538
##	St. Louis, MO-IL
##	0.13461538
##	Niles-Benton Harbor, MI
##	0.13513514
##	Ogden-Clearfield, UT
##	0.13571429
##	Baltimore-Towson, MD
##	0.13583333
##	Buffalo-Niagara Falls, NY
##	0.13684211
##	Milwaukee-Waukesha-West Allis, WI
##	0.13693694
##	Chicago-Naperville-Joliet, IN-IN-WI
##	0.13737734
##	Louisville, KY-IN
##	0.13785047
##	Lynchburg, VA
##	0.13793103
##	Peoria, IL
##	0.13829787
##	Sioux Falls, SD
##	0.13832200
##	Ocala, FL
##	0.13888889
##	Leominster-Fitchburg-Gardner, MA

##	0.14035088
##	Oklahoma City, OK
##	0.14137214
##	San Diego-Carlsbad-San Marcos, CA
##	0.14188267
##	Jacksonville, FL
##	0.14244186
##	Atlantic City, NJ
##	0.14285714
##	Holland-Grand Haven, MI
##	0.14285714
##	Medford, OR
##	0.14285714
##	Naples-Marco Island, FL
##	0.14285714
##	Punta Gorda, FL
##	0.14285714
##	Victoria, TX
##	0.14285714
##	Winston-Salem, NC
##	0.14285714
##	Salt Lake City, UT
##	0.14338235
##	Atlanta-Sandy Springs-Marietta, GA
##	0.14421553
##	Decatur, IL
##	0.14516129
##	Springfield, IL
##	0.14516129
##	Monroe, MI
##	0.14545455
##	Denver-Aurora, CO
##	0.14574558
##	Hartford-West Hartford-East Hartford, CT
##	0.14574899
##	Greeley, CO
##	0.14615385
##	San Francisco-Oakland-Fremont, CA
##	0.14651368
##	Boise City-Nampa, ID
##	0.14653465
##	Greenville, SC
##	0.14666667
##	Birmingham-Hoover, AL
##	0.14678899
##	Saginaw-Saginaw Township North, MI
##	0.14754098
##	Santa-Cruz-Watsonville, CA
##	0.14814815
##	Trenton-Ewing, NJ
##	0.14814815
##	Lexington-Fayette, KY
##	0.14838710
##	San Jose-Sunnyvale-Santa Clara, CA

```

##                                0.14922481
##                                Bellingham, WA
##                                0.15000000
##                                Norwich-New London, CT-RI
##                                0.15060241
##                                Lubbock, TX
##                                0.15094340
##                                Huntington-Ashland, WV-KY-OH
##                                0.15151515
##                                St. Cloud, MN
##                                0.15151515
##                                Jackson, MS
##                                0.15168539
##                                Dayton, OH
##                                0.15207373
##                                Chattanooga, TN-GA
##                                0.15217391
##                                Syracuse, NY
##                                0.15428571
## New York-Northern New Jersey-Long Island, NY-NJ-PA
##                                0.15573586
##                                Columbia, SC
##                                0.15600000
##                                Columbus, OH
##                                0.15617716
##                                Memphis, TN-MS-AR
##                                0.15714286
##                                Orlando, FL
##                                0.16108787
##                                Warner Robins, GA
##                                0.16216216
##                                Cleveland-Elyria-Mentor, OH
##                                0.16250000
##                                Columbia, MO
##                                0.16279070
##                                Durham, NC
##                                0.16326531
##                                Miami-Fort Lauderdale-Miami Beach, FL
##                                0.16356589
##                                Indianapolis, IN
##                                0.16371681
##                                Albuquerque, NM
##                                0.16424116
##                                Cape Coral-Fort Myers, FL
##                                0.16528926
##                                Amarillo, TX
##                                0.16666667
##                                Anniston-Oxford, AL
##                                0.16666667
##                                Athens-Clark County, GA
##                                0.16666667
##                                Binghamton, NY
##                                0.16666667
##                                Phoenix-Mesa-Scottsdale, AZ

```

##	0.16687737
##	Green Bay, WI
##	0.16831683
##	Bangor, ME
##	0.16860465
##	Providence-Fall River-Warwick, MA-RI
##	0.16915688
##	Muskegon-Norton Shores, MI
##	0.16923077
##	Tuscaloosa, AL
##	0.16949153
##	Rockford, IL
##	0.17021277
##	Las Cruces, NM
##	0.17283951
##	Gulfport-Biloxi, MS
##	0.17307692
##	Huntsville, AL
##	0.17391304
##	Utica-Rome, NY
##	0.17391304
##	Fort Smith, AR-OK
##	0.17441860
##	Charlotte-Gastonia-Concord, NC-SC
##	0.17444717
##	El Centro, CA
##	0.17567568
##	Erie, PA
##	0.17567568
##	Jackson, MI
##	0.17741935
##	Cincinnati-Middletown, OH-KY-IN
##	0.17773788
##	Springfield, MA-CT
##	0.17829457
##	Reading, PA
##	0.17857143
##	Vallejo-Fairfield, CA
##	0.17924528
##	Salem, OR
##	0.17985612
##	Nashville-Davidson-Murfreesboro, TN
##	0.18112245
##	Johnson City, TN
##	0.18181818
##	Wichita, KS
##	0.18181818
##	York-Hanover, PA
##	0.18181818
##	Janesville, WI
##	0.18292683
##	Lansing-East Lansing, MI
##	0.18348624
##	Greensboro-High Point, NC

##	0.18357488
##	Decatur, Al
##	0.18421053
##	Albany, GA
##	0.18604651
##	Augusta-Richmond County, GA-SC
##	0.18796992
##	Charleston, WV
##	0.18834081
##	Shreveport-Bossier City, LA
##	0.18918919
##	Raleigh-Cary, NC
##	0.18959108
##	Toledo, OH
##	0.18965517
##	Spartanburg, SC
##	0.18987342
##	Dallas-Fort Worth-Arlington, TX
##	0.19077135
##	Sacramento-Arden-Arcade-Roseville, CA
##	0.19136961
##	Santa Barbara-Santa Maria-Goleta, CA
##	0.19191919
##	Monroe, LA
##	0.19205298
##	Dover, DE
##	0.19220056
##	South Bend-Mishawaka, IN-MI
##	0.19354839
##	Fayetteville-Springdale-Rogers, AR-MO
##	0.19393939
##	Columbus, GA-AL
##	0.19607843
##	Kingston, NY
##	0.19696970
##	Port St. Lucie-Fort Pierce, FL
##	0.19767442
##	Waterbury, CT
##	0.19852941
##	Little Rock-North Little Rock, AR
##	0.19939577
##	Springfield, MO
##	0.20000000
##	Modesto, CA
##	0.20325203
##	Houston-Baytown-Sugar Land, TX
##	0.20439739
##	Oxnard-Thousand Oaks-Ventura, CA
##	0.20657277
##	Anderson, SC
##	0.20689655
##	Midland, TX
##	0.21052632
##	New Orleans-Metairie-Kenner, LA

##	0.21088435
##	Fresno, CA
##	0.21120690
##	Lake Charles, LA
##	0.21739130
##	Visalia-Porterville, CA
##	0.21782178
##	San Antonio, TX
##	0.22004357
##	Hagerstown-Martinsburg, MD-WV
##	0.22222222
##	Yakima, WA
##	0.22222222
##	Hickory-Morgantown-Lenoir, NC
##	0.22448980
##	Los Angeles-Long Beach-Santa Ana, CA
##	0.22882883
##	Panama City-Lynn Haven, FL
##	0.22916667
##	Harrisonburg, VA
##	0.23287671
##	Kankakee-Bradley, IL
##	0.23437500
##	Beaumont-Port Author, TX
##	0.23469388
##	Youngstown-Warren-Boardman, OH
##	0.23622047
##	Riverside-San Bernardino, CA
##	0.23780488
##	Farmington, NM
##	0.23913043
##	Killeen-Temple-Fort Hood, TX
##	0.24050633
##	Waco, TX
##	0.24074074
##	Montgomery, AL
##	0.24137931
##	Tucson, AZ
##	0.24603175
##	Lafayette, LA
##	0.24822695
##	Joplin, MO
##	0.25000000
##	Stockton, CA
##	0.25333333
##	Brownsville-Harlingen, TX
##	0.25396825
##	Lancaster, PA
##	0.26771654
##	Bakersfield, CA
##	0.27218935
##	Vineland-Millville-Bridgeton, NJ
##	0.27500000
##	Lawton, OK

```
##                0.28000000
##                Merced, CA
##                0.28358209
##                Corpus Christi, TX
##                0.29702970
##                El Paso, TX
##                0.30219780
##                Springfield, OH
##                0.31034483
##                Florence, AL
##                0.32075472
##                Madera, CA
##                0.33333333
##                Salinas, CA
##                0.34090909
##                Laredo, TX
##                0.34426230
##                Kingsport-Bristol, TN-VA
##                0.36363636
##                Longview, TX
##                0.38297872
##                McAllen-Edinburg-Pharr, TX
##                0.38297872
##                Macon, GA
##                0.40816327
```

4.1) Integrating Country of Birth Data

```
CPS = merge(CPS, CountryMap, by.x = "CountryOfBirthCode", by.y = "Code", all.x = TRUE )

CPS %>% glimpse()
```

```
## Observations: 131,302
## Variables: 16
## $ CountryOfBirthCode <int> 57, 57, 57, 57, 57, 57, 57, 57, 57, 57, 57, ...
## $ MetroAreaCode      <int> 10420, 71650, 10420, 10420, 10420, 10420, 1...
## $ PeopleInHousehold  <int> 2, 4, 5, 2, 2, 3, 1, 3, 4, 4, 1, 1, 1, 5, 4...
## $ Region             <chr> "Midwest", "Northeast", "Midwest", "Midwest...
## $ State              <chr> "Ohio", "New Hampshire", "Ohio", "Ohio", "O...
## $ Age                <int> 73, 5, 10, 30, 30, 0, 34, 32, 6, 9, 63, 25,...
## $ Married            <chr> "Married", NA, NA, "Married", "Married", NA...
## $ Sex                <chr> "Female", "Female", "Female", "Female", "Fe...
## $ Education          <chr> "Some college, no degree", NA, NA, "Associa...
## $ Race               <chr> "White", "White", "White", "White", "White"...
## $ Hispanic           <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0...
## $ Citizenship        <chr> "Citizen, Native", "Citizen, Native", "Citi...
## $ EmploymentStatus   <chr> "Retired", NA, NA, "Employed", "Employed", ...
## $ Industry           <chr> NA, NA, NA, "Trade", "Mining", NA, "Constru...
## $ MetroArea          <chr> "Akron, OH", "Boston-Cambridge-Quincy, MA-N...
## $ Country            <chr> "United States", "United States", "United S..."
```

How many interviewees have a missing value for the new country of birth variable?

```
table(is.na(CPS$Country))
```

```
##
## FALSE TRUE
## 131126 176
```

Among all interviewees born outside of North America, which country was the most common place of birth?

```
sort(table(CPS$Country), decreasing = TRUE) # Philippines
```

```
##
## United States Mexico
## 115063 3921
## Philippines India
## 839 770
## China Puerto Rico
## 581 518
## El Salvador Vietnam
## 477 458
## Germany Cuba
## 438 426
## Canada Korea
## 410 334
## Dominican Republic Guatemala
## 330 309
## Jamaica Columbia
## 217 206
## Honduras Japan
## 189 187
## England Russia
## 179 173
## Haiti Poland
## 167 162
## Brazil Italy
## 159 149
## Iran Ecuador
## 144 136
## Peru Africa, not specified
## 136 129
## Thailand United Kingdom
## 128 111
## Guyana Pakistan
## 109 109
## Ukraine Taiwan
## 104 102
## Laos Iraq
## 98 97
## Nigeria Elsewhere
## 85 81
## Ethiopia Ghana
## 80 76
## Nicaragua France
## 76 73
```

##	South Korea	Somalia
##	73	72
##	Egypt	Argentina
##	65	64
##	Hong Kong	Portugal
##	64	64
##	Bosnia & Herzegovina	Venezuela
##	61	61
##	Trinidad and Tobago	Israel
##	60	57
##	Greece	Kenya
##	56	55
##	Romania	Liberia
##	55	52
##	Cambodia	South Africa
##	49	48
##	Turkey	Lebanon
##	48	45
##	Myanmar (Burma)	Nepal
##	45	44
##	Panama	Australia
##	44	43
##	Bangladesh	Spain
##	42	41
##	Asia, not specified	Ireland
##	39	39
##	Chile	Jordan
##	37	36
##	Armenia	Cameroon
##	35	32
##	Syria	Guam
##	32	31
##	Bulgaria	Costa Rica
##	29	29
##	Saudi Arabia	Netherlands
##	29	28
##	Sweden	Afghanistan
##	28	26
##	Indonesia	Hungary
##	26	25
##	Belarus	Scotland
##	24	24
##	Yugoslavia	New Zealand
##	24	23
##	Switzerland	Yemen
##	23	23
##	Azores	USSR
##	22	22
##	Malaysia	Serbia
##	20	20
##	Europe, not specified	Uzbekistan
##	19	19
##	West Indies, not specified	Albania
##	19	18

##	Norway	Austria
##	18	17
##	Morocco	Sri Lanka
##	17	17
##	U. S. Virgin Islands	Uruguay
##	17	17
##	Cape Verde	Eritrea
##	15	15
##	Sierra Leone	Uganda
##	15	15
##	Antigua and Barbuda	Belgium
##	13	13
##	Bermuda	Bolivia
##	13	13
##	Grenada	Sudan
##	13	13
##	Croatia	Macedonia
##	12	12
##	Moldova	Czech Republic
##	12	11
##	Dominica	Paraguay
##	11	11
##	Bahamas	Finland
##	10	10
##	Kuwait	Lithuania
##	10	10
##	Algeria	Americas, not specified
##	9	9
##	Belize	Fiji
##	9	9
##	St. Vincent and the Grenadines	South America, not specified
##	9	7
##	St. Lucia	Barbados
##	7	6
##	Denmark	Latvia
##	6	6
##	Samoa	Senegal
##	6	6
##	Singapore	Slovakia
##	6	6
##	Tonga	Zimbabwe
##	6	6
##	Georgia	Azerbaijan
##	5	3
##	Czechoslovakia	St. Kitts--Nevis
##	3	3
##	Northern Ireland	Tanzania
##	2	2

What proportion of the interviewees from the “New York-Northern New Jersey-Long Island, NY-NJ-PA” metropolitan area have a country of birth that is not the United States? For this computation, don’t include people from this metropolitan area who have a missing country of birth.

```
tapply(CPS$Country != "United States", CPS$MetroArea == "New York-Northern New Jersey-Long Island, NY-NJ-PA",
      ##      FALSE      TRUE
      ## 0.1392772 0.3086603
      # In this case, the group is the interviewees in the Metro Area "NY-NJ-LI", the summary is the interviewees
```

Which metropolitan area has the largest number (note – not proportion) of interviewees with a country of birth in India? Hint – remember to include na.rm=TRUE if you are using tapply() to answer this question.

```
table(CPS$Country == "India")
```

```
##
## FALSE TRUE
## 130356 770
```

```
India =
  CPS %>%
  filter(Country == "India")
```

```
India %>%
  count(MetroArea) %>%
  arrange(desc(n))
```

```
## # A tibble: 84 x 2
##   MetroArea      n
##   <chr>      <int>
## 1 New York-Northern New Jersey-Long Island, NY-NJ-PA 96
## 2 <NA>      60
## 3 Washington-Arlington-Alexandria, DC-VA-MD-WV 50
## 4 Philadelphia-Camden-Wilmington, PA-NJ-DE 32
## 5 Chicago-Naperville-Joliet, IN-IN-WI 31
## 6 Detroit-Warren-Livonia, MI 30
## 7 Atlanta-Sandy Springs-Marietta, GA 27
## 8 San Francisco-Oakland-Fremont, CA 27
## 9 Hartford-West Hartford-East Hartford, CT 26
## 10 Minneapolis-St Paul-Bloomington, MN-WI 23
## # ... with 74 more rows
```

```
# Answer: New York-Northern New Jersey-Long Island, NY-NJ-PA
```

In Brazil?

```
Brazil =
  CPS %>%
  filter(Country == "Brazil")
```

```
Brazil %>%
  group_by(!is.na(MetroArea)) %>%
  count(MetroArea) %>%
  arrange(desc(n))
```

```
## # A tibble: 50 x 3
## # Groups:   !is.na(MetroArea) [2]
```

```
##      `!is.na(MetroArea)` MetroArea      n
##      <lg1>                <chr>      <int>
##  1 FALSE                  <NA>        20
##  2 TRUE                   Boston-Cambridge-Quincy, MA-NH      18
##  3 TRUE                   Miami-Fort Lauderdale-Miami Beach, FL  16
##  4 TRUE                   Los Angeles-Long Beach-Santa Ana, CA   9
##  5 TRUE                   Washington-Arlington-Alexandria, DC-VA-MD-WV  8
##  6 TRUE                   Bridgeport-Stamford-Norwalk, CT       7
##  7 TRUE                   New York-Northern New Jersey-Long Island, NY-- 7
##  8 TRUE                   San Francisco-Oakland-Fremont, CA      6
##  9 TRUE                   Danbury, CT        5
## 10 TRUE                   Davenport-Moline-Rock Island, IA-IL    4
## # ... with 40 more rows
```

```
# answer: Boston-Cambridge-Quincy, MA-NH
```

In Somalia

```
Somalia =
  CPS %>%
  filter(Country == "Somalia")
```

```
Somalia %>%
  count(MetroArea) %>%
  arrange(desc(n))
```

```
## # A tibble: 14 x 2
##   MetroArea      n
##   <chr>      <int>
## 1 Minneapolis-St Paul-Bloomington, MN-WI  17
## 2 <NA>        9
## 3 Phoenix-Mesa-Scottsdale, AZ           7
## 4 Seattle-Tacoma-Bellevue, WA           7
## 5 St. Cloud, MN                         7
## 6 Columbus, OH                         5
## 7 Fargo, ND-MN                         5
## 8 Burlington-South Burlington, VT       3
## 9 Portland-South Portland, ME           3
## 10 Portland-Vancouver-Beaverton, OR-WA   3
## 11 Houston-Baytown-Sugar Land, TX       2
## 12 Sioux Falls, SD                     2
## 13 Dayton, OH                          1
## 14 Richmond, VA                        1
```

```
# Answer: Minneapolis-St Paul-Bloomington, MN-WI
```