



PRAMS Data Analysis

(Asynchronous-Online)

PRAMS Data

About PRAMS

[PRAMS](#) is the Pregnancy Risk Assessment Monitoring System (PRAMS). According to the CDC's website for [About PRAMS](#):

i What is PRAMS?

PRAMS is the Pregnancy Risk Assessment Monitoring System. It is a joint surveillance project between state, territorial, or local health departments and CDC's Division of Reproductive Health. PRAMS was developed in 1987 to reduce infant morbidity and mortality by influencing maternal behaviors before, during, and immediately after live birth.

i What is the purpose of PRAMS?

The purpose of PRAMS is to find out why some infants are born healthy and others are not. The survey asks new mothers questions about their pregnancy and their new infant. The questions give us important information about the mother and the infant and help us learn more about the impacts of health and behaviors.

Getting the PRAMS Data

- You can request the [PRAMS Data](#) from the CDC.
- Once granted access, follow the instructions from the CDC to download the data and sign the data sharing agreement.
- For the purposes of the TIDAL R training session, we will be working with [PRAMS Phase 8 ARF \(Automated Research File\)](#) dataset.



PRAMS Documentation and Resources

- See the details on the [PRAMS Questionnaires](#).
 - Learn more about the [PRAMS Data Methodology](#) including details on how the samples are weighted.
 - **Download and Read** this helpful [paper on PRAMS design and methodology](#) (Shulman, D'Angelo, Harrison, Smith, and Warner, 2018).
 - There are also helpful tutorial videos on working with PRAMS data by [ASSOCIATION OF STATE AND TERRITORIAL HEALTH OFFICIALS \(ASTHO.org\)](#).
-



0. Pework - Before You Begin

Install R Packages

Before you begin, please go ahead and install (or make sure these are already installed) on your computer for these following packages - these are all on CRAN, so you can install them using the RStudio Menu Tools/Install Packages interface:

- [haven](#)
- [dplyr](#)
- [survey](#)

```
library(haven)
library(dplyr)
library(survey)
```

Create a NEW RStudio Project

BEFORE you begin any new analysis project, it is **ALWAYS** a good idea to begin with the NEW RStudio project.

Go to the RStudio menu “File/New Project” and create your new project (ideally in a NEW directory, but it is also ok to use an existing directory/folder on your computer).

This new directory (or folder) will be where all of your files will “live” for your current analysis project.

See the step-by-step instructions for [creating a new RStudio project](#) in [Module 1.3.2](#).



1. Get PRAMS Data and Select Subset for Analysis

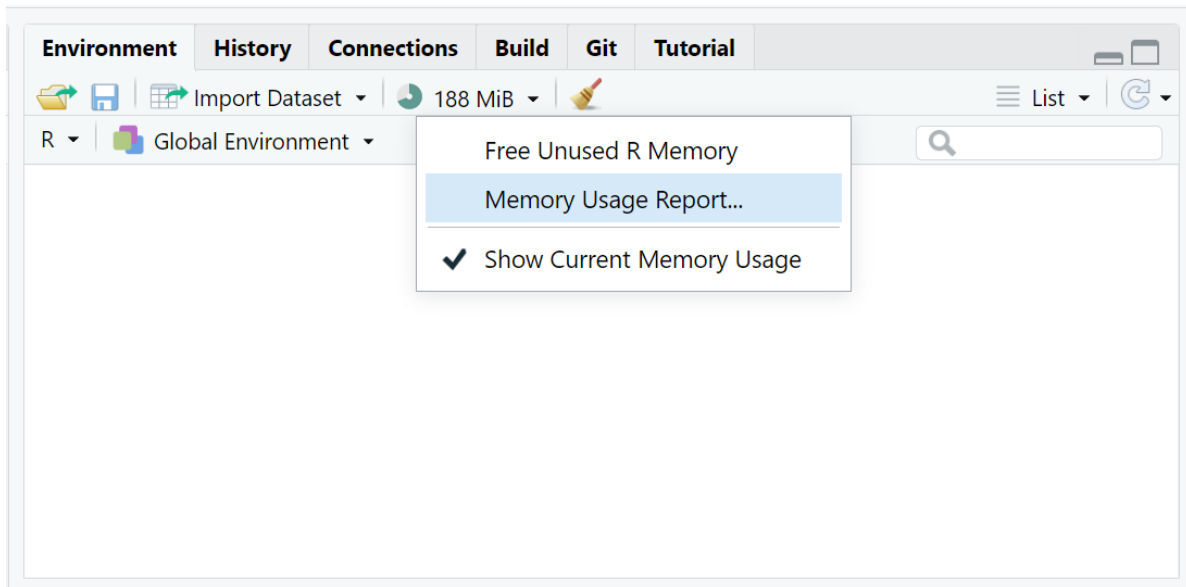
A. Read-in the PRAMS Phase 8 2016-2021 combined dataset

The PRAMS data provided by the CDC will be in SAS format (*.sas7bdat). We can read the native SAS file into R using the `haven` package and the `read_sas()` function.

⚠ Memory Warning

The size of the `phase8_arf_2016_2021.sas7bdat` dataset is a little over 1GB. So, make sure your computer has enough available memory to fully load this dataset. I will provide some more details below on how we can reduce the size of the dataset and improve the memory issues below.

You can check your available memory, by checking your “Global Environment” TAB (upper right window pane) click on the down arrow next to the icon with “XX MiB” just to the left of the little broom:



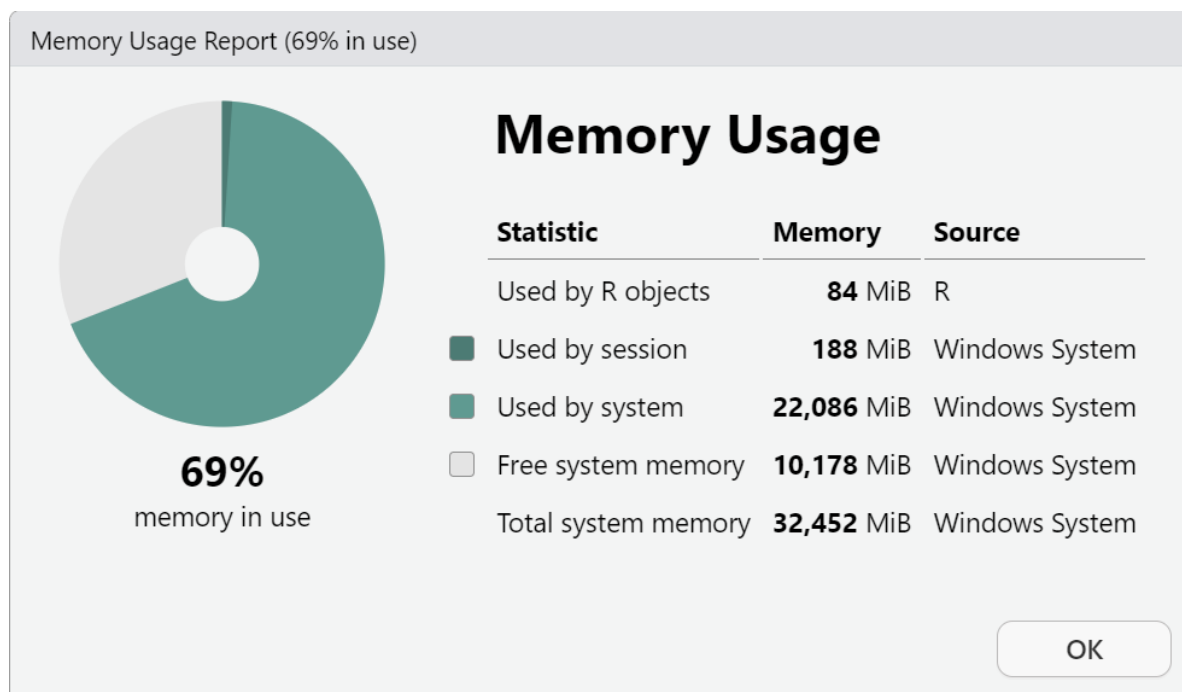
Click on the “Memory Usage Report” to see a detailed breakdown. This window will show:

- Memory used by R objects (in your “Global Environment”)
- Memory used on your computer by your current R Session
- Memory currently in use for everything currently running on your computer (all apps running - active and in background) - you can compare this to your “task manager” memory viewer.



- Free System Memory - when this gets low the “XX MiB” graphic will change color from green - to yellow - to orange - to red. Once you get to red, your R session will most likely crash since there is not enough memory to perform operations or run analyses.

This is a screen shot of my computer (yours will look different) BEFORE I load the PRAMS dataset.



Run the following R code to load the PRAMS Phase 8 dataset into your R Session and check the “Global Environment”.

```
library(haven)
prams <-
  read_sas("phase8_arf_2016_2021.sas7bdat")
```

Here is my memory AFTER loading the PRAMS dataset into my “Global Environment”.



EnvironmentHistoryConnectionsBuildGitTutorial

Import Dataset

1.06 GiB

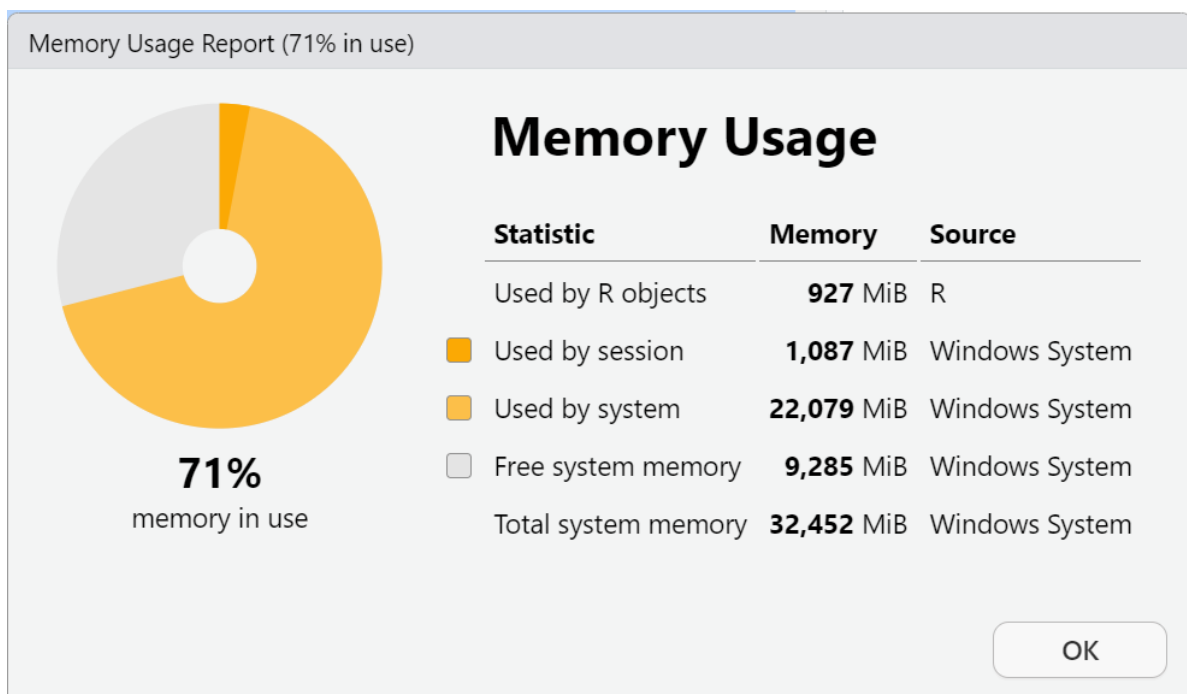
List

RGlobal Environment

Data

prams

221381 obs. of 484 variables



B. Save the data as a *.RData binary file for use in later analyses

One way to reduce the size of the PRAMS dataset is to save it as a native *.RData binary file format. So, let's save the PRAMS dataset in this format on your computer.



```
# save the whole dataset as *.RData format
save(prams,
      file = "prams.RData")
```

On my computer, here is a comparison of the size of these 2 files:

- `phase8_arf_2016_2021.sas7bdat` is 1,095,499,776 bytes (which is 1.02 GB)
- `prams.RData` is only 34,713,319 (which is only 0.0323 GB)

This is a file size reduction of 96.83%!!

Name	Date modified	Type	Size
mkh_getStarted.R	1/7/2025 2:16 PM	R File	8 KB
phase8_arf_2016_2021.sas7bdat	12/3/2024 4:01 PM	SAS Data Set	1,069,824 KB
prams.RData	1/13/2025 9:09 AM	R Workspace	33,900 KB
prams_2021.RData	1/13/2025 8:50 AM	R Workspace	5,377 KB
prams_mkh.R	12/3/2024 6:50 PM	R File	1 KB
PRAMS_mkh_notes.docx	12/6/2024 11:14 AM	Microsoft Word D...	596 KB
PRAMS-Phase-8-ARF-Codebook-H.pdf	12/3/2024 4:22 PM	Adobe Acrobat D...	170 KB

Now that we've reduced the file size of the dataset on your computer's hard drive (or cloud storage), let's also clear up the "Global Environment" back in your current RStudio computing session.

C. Clean up files to save memory

Now that we've saved the data, let's remove the PRAMS data object from the RStudio session.

- For now we can simply remove everything using the `rm(list=ls())`.
- However, if you have other objects you want to keep, you can specifically only remove the PRAMS dataset using `rm(prams)`.



```
# remove all objects from Global Environment
rm(list=ls())

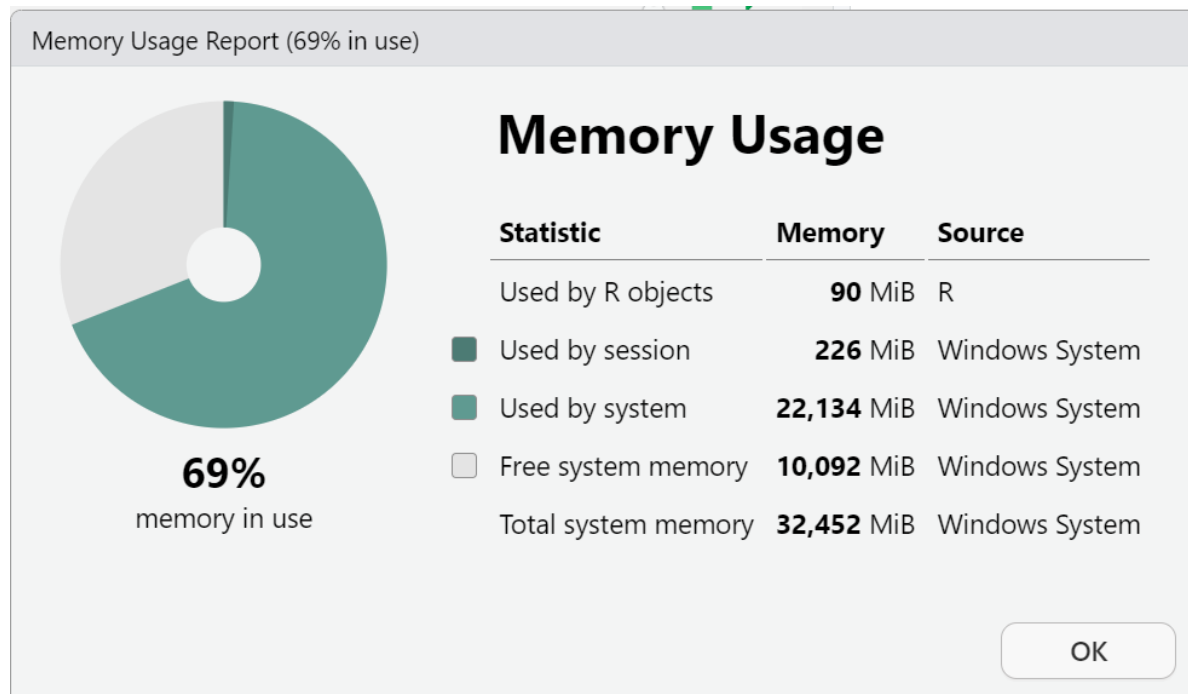
# confirm Global Environment is empty
# list all objects
ls()
```

```
character(0)
```

```
# and free any currently unused memory
gc()
```

```
      used (Mb) gc trigger      (Mb) max used (Mb)
Ncells 2133815 114.0   4192005  223.9   4192005  223.9
Vcells 3893029  29.8  153333518 1169.9 112138869 855.6
```

After we remove everything, let's look at the session memory again.

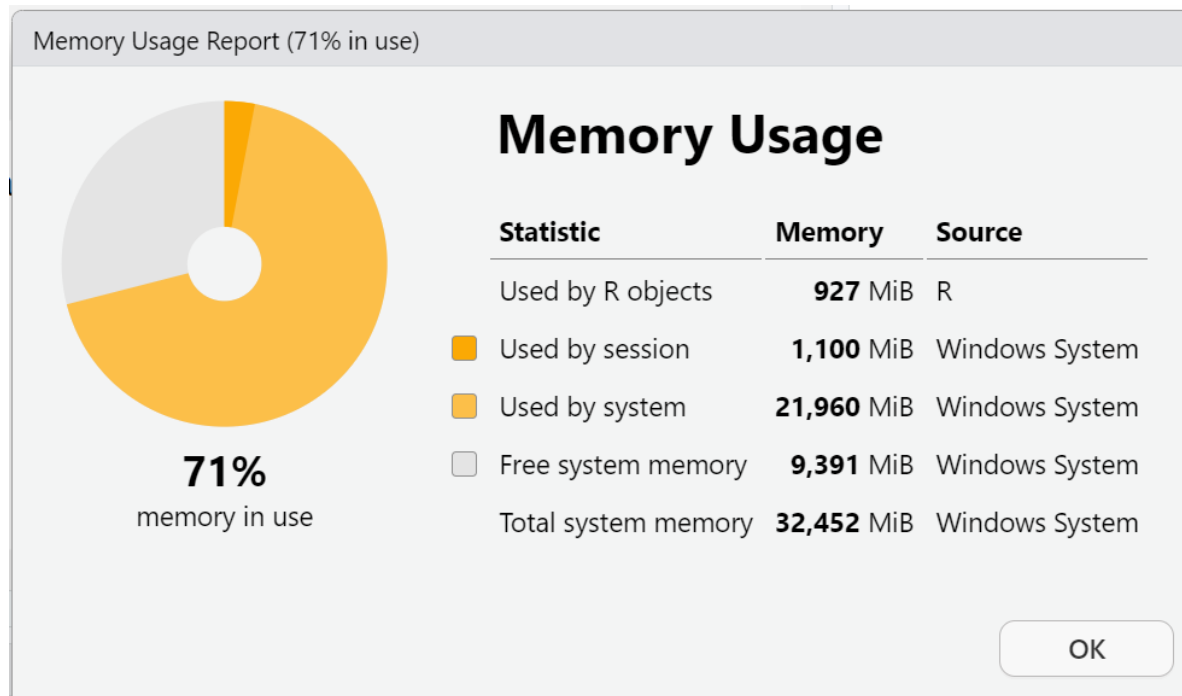


Now let's read the PRAMS data back in, but this time read in the `prams.RData` binary R data formatted file. We will use the built-in `load()` function.



```
# load back only the prams dataset  
load(file = "prams.RData")
```

Let's check the R session memory again:



I know this didn't make a large difference for the R session available memory, but by doing this process:

1. The PRAMS dataset now takes up less memory on your computer's file storage, and
2. The `load()` function for the `prams.RData` file should run faster when beginning your R computing session instead of having to use the `haven` package to read in the SAS formatted file everytime.

As a quick comparison on my computer (Windows 11), the time to read in the SAS formatted file was about 14 sec:

```
> system.time(  
+   prams <-  
+   read_sas("phase8_arf_2016_2021.sas7bdat")  
+ )  
   user  system elapsed  
13.44    0.47    13.96
```



And the time to read in the `prams.RData` file was only about 1.5 sec.

```
> system.time(  
+   load("prams.RData")  
+ )  
      user  system elapsed  
      1.45    0.08    1.54
```



2. Getting started with PRAMS Data

Breastfeeding summary - UNWEIGHTED data

Let's look at whether the mother ever breastfed her baby - this is variable `BF5EVER`, where 1 = "NO" and 2 = "YES".

[PRAMS Phase 8 Codebook](#)

```
# create a factor variable
# and add labels
prams$BF5EVER.f <- factor(
  prams$BF5EVER,
  levels = c(1, 2),
  labels = c("NO", "YES")
)
```

For the UNWEIGHTED data, let's get a simple table of breastfeeding by STATE (variable `STATE`) and YEAR (variable `NEST_YR`).

As we can see below, in 2017 for the state of GA, 919 women responded to this question:

- 919 women responded
 - 170 said NO
 - 749 said YES
- 36 were missing a response (indicated by `<NA>`)

```
prams %>%
  filter(NEST_YR == 2017) %>%
  with(., table(STATE, BF5EVER.f,
                useNA = "ifany"))
```

	BF5EVER.f		
STATE	NO	YES	<NA>
AK	71	927	47
AL	181	659	42
CO	73	1037	18
DE	126	728	37
GA	170	749	36
IA	136	867	30
IL	140	1048	36
KS	81	856	58



KY	139	536	27
LA	285	586	23
MA	115	1268	40
MD	97	928	35
ME	88	754	30
MI	290	1532	75
MO	166	908	37
MT	66	851	20
ND	102	472	17
NH	42	523	15
NJ	125	1102	31
NM	123	1038	19
NY	109	706	33
PA	164	1023	42
PR	81	928	23
RI	105	960	37
SD	150	946	35
UT	93	1305	49
VA	88	969	26
VT	54	780	14
WA	69	1138	31
WI	221	1051	74
WV	186	475	38
WY	49	438	16
YC	99	1125	69

This aligns with the [CDC PRAMS Indicators Report for GA in 2020](#) - scroll to the bottom to see the RAW count of 919 women who responded to “Ever Breastfed” in GA in 2017.

**Breastfeeding summary - WEIGHTED data**

In the [CDC PRAMS Indicators Report for GA in 2020](#) the columns that have the 95% CI (confidence intervals) for the percentages are the population weighted percentage estimates for the Stats of GA during that year.

To get the estimated percentage of women in the stats of GA who had “ever breastfed” in 2017, we need to use the `survey` package and apply the proper sample weighting to get these estimates.

```
library(survey)

# Let's look at just GA to start with
# use dplyr to filter out just GA
prams_ga <- prams %>%
  filter(STATE == "GA")

# create the survey design file for GA
prams_ga.svy <-
  svydesign(ids = ~0, strata = ~SUD_NEST,
            fpc = ~TOTCNT, weights = ~WTANAL,
            data = prams_ga)

# get a table of ever breastfed
# by YEAR
svyby(~BF5EVER.f, ~NEST_YR,
      design = prams_ga.svy,
      svytotal, na.rm=TRUE)
```

	NEST_YR	BF5EVER.fNO	BF5EVER.fYES	se.BF5EVER.fNO	se.BF5EVER.fYES
2017	2017	17639.96	101686.10	2045.415	2271.075
2018	2018	20187.62	98909.35	2151.496	2351.330
2019	2019	24099.04	95019.86	2273.415	2279.851
2020	2020	21827.55	94125.72	2209.745	2457.097
2021	2021	23724.68	93896.73	2266.811	2256.488

From this we can see that the population estimates for 2017 are:

- Breastfed ever = NO: 17639.96 +/- 2045.415
- Breastfed ever = YES: 101686.10 +/- 2271.075

This leads to a percentage of YES estimate of $101686.10 * 100 / (101686.10 + 17639.96) = 85.2170096\%$ which should match pretty closely to what is in the [CDC PRAMS Indicators Report for GA in 2020](#).



We can also get the percentage of overall breastfeeding YES for the USA for the 40 “states” (technically 38 states, Puerto Rico, and New York City) that were included in the PRAMS dataset in 2020 (see the last column in the CDC report), using the following R code. *Note: 2 “states” did not have data in 2020: Connecticut and Florida.*

```
# get overall for 2020 - all states
# make survey design file
prams.svy <-
  svydesign(ids = ~0, strata = ~SUD_NEST,
            fpc = ~TOTCNT, weights = ~WTANAL,
            data = prams)

svyby(~BF5EVER.f, ~NEST_YR,
      design = prams.svy,
      svytotal, na.rm=TRUE)
```

	NEST_YR	BF5EVER.fNO	BF5EVER.fYES	se.BF5EVER.fNO	se.BF5EVER.fYES
2016	2016	187666.4	1324171	4398.541	4798.836
2017	2017	208863.1	1497127	4762.339	5452.232
2018	2018	242991.5	1716913	5220.222	5979.598
2019	2019	236841.9	1680987	5404.761	6877.697
2020	2020	225560.3	1609464	4884.871	5540.240
2021	2021	212618.8	1521303	5196.234	6058.572

From this we can see that the population estimates for the “whole USA” for 2020 were:

- Breastfed ever = NO: 225560.3 +/- 4884.871
- Breastfed ever = YES: 1609464 +/- 5540.240

This leads to a percentage of YES estimate of $1609464 * 100 / (1609464 + 225560.3) = 87.7080483\%$ which is pretty close to what is in the [CDC PRAMS Indicators Report for GA in 2020](#) - with some numerical precision variation due to software algorithms.

Congratulations on getting started with the PRAMS Dataset



3. Data Wrangling with PRAMS

Data wrangling with the PRAMS data isn't much different from the methods already covered in [Module 1.3.2](#).

The code below shows an example of recoding the `VITAMIN` variable from PRAMS.

```
# create a factor variable
# and add labels
prams$VITAMIN.f <- factor(
  prams$VITAMIN,
  levels = c(1, 2, 3, 4),
  labels = c("1 = DIDNT TAKE VITAMIN",
             "2 = 1-3 TIMES/WEEK",
             "3 = 4-6 TIMES/WEEK",
             "4 = EVERY DAY/WEEK")
)

# create variable for anyone who
# took vitamins 4+ times a week
prams$VITAMIN_4plus <-
  ifelse(prams$VITAMIN > 2, 1, 0)

# add labels, make a factor
prams$VITAMIN_4plus.f <- factor(
  prams$VITAMIN_4plus,
  levels = c(0, 1),
  labels = c("3x/week or less",
             "4x/week or more")
)

# get stats for 2020 for GA
prams %>%
  filter(NEST_YR == 2020) %>%
  filter(STATE == "GA") %>%
  with(., table(STATE, VITAMIN_4plus.f,
                useNA = "ifany"))
```

	VITAMIN_4plus.f		
STATE	3x/week or less	4x/week or more	<NA>
GA	443	247	2



```
prams_ga <- prams %>%
  filter(STATE == "GA")

# create the survey design file for GA
prams_ga.svy <-
  svydesign(ids = ~0, strata = ~SUD_NEST,
            fpc = ~TOTCNT, weights = ~WTANAL,
            data = prams_ga)
```

Get table of weighted percentages for “Taking Multivitamin 4+/week” for GA by Year.

```
# get a table of vitamins 4+ times per week
# by YEAR
svyby(~VITAMIN_4plus.f, ~NEST_YR,
      design = prams_ga.svy,
      svytotal, na.rm=TRUE)
```

	NEST_YR	VITAMIN_4plus.f3x/week or less	VITAMIN_4plus.f4x/week or more
2017	2017	86492.91	37312.18
2018	2018	76796.28	43028.81
2019	2019	74523.87	46236.67
2020	2020	75313.80	42263.67
2021	2021	69861.41	48766.71
	se.VITAMIN_4plus.f3x/week or less	se.VITAMIN_4plus.f4x/week or more	
2017		2715.819	2653.349
2018		2817.611	2732.988
2019		2786.899	2666.692
2020		2779.229	2802.984
2021		2824.624	2693.566

The unweighted breakdown for GA in 2020

- NO Vitamins =< 3x/wk 443 64.2%
- YES Vitamins => 4x/wk 247 35.8%
- Total 690

Weighted Breakdown for GA in 2020

- NO Vitamins =< 3x/wk 75313.80 +/- 2779.229 (64.1%) []
- YES Vitamins => 4x/wk 42263.67 +/- 2802.984 (35.9%) [33.6%, 38.3%]
- Total 117,577.47



Get Proportions and 95% Confidence Intervals

```
prams_ga2000 <- prams %>%  
  filter(STATE == "GA") %>%  
  filter(NEST_YR == 2020)  
  
# create the survey design file for GA  
# for year 2020  
prams_ga2000.svy <-  
  svydesign(ids = ~0, strata = ~SUD_NEST,  
            fpc = ~TOTCNT, weights = ~WTANAL,  
            data = prams_ga2000)  
  
svytable(~VITAMIN_4plus,  
          prams_ga2000.svy)
```

```
VITAMIN_4plus  
      0      1  
75313.80 42263.67
```

```
svyciprop(~VITAMIN_4plus,  
           prams_ga2000.svy,  
           na.rm = T)
```

```
                2.5% 97.5%  
VITAMIN_4plus 0.359 0.315 0.407
```



Compare the results below to the EXCEL spreadsheet [Pregnancy Risk Assessment Monitoring System \(PRAMS\) MCH Indicators \(standard version\)](#) - see 2020 for GA - 1st set of indicators for Vitamins taken 4x a week or more.

The code below adds custom code for computing the confidence intervals with the survey-weighted dataset.

```
prams_ga2000 <- prams %>%
  filter(STATE == "GA") %>%
  filter(NEST_YR == 2020)

# create the survey design file for GA
# for year 2020
prams_ga2000.svy <-
  svydesign(ids = ~0, strata = ~SUD_NEST,
            fpc = ~TOTCNT, weights = ~WTANAL,
            data = prams_ga2000)

# get a table of vitamins 4+ times per week
# by YEAR
svyby(~VITAMIN_4plus.f, ~NEST_YR,
      design = prams_ga2000.svy,
      svytotal, na.rm=TRUE)
```

	NEST_YR	VITAMIN_4plus.f3x/week or less	VITAMIN_4plus.f4x/week or more
2020	2020	75313.8	42263.67
		se.VITAMIN_4plus.f3x/week or less	se.VITAMIN_4plus.f4x/week or more
2020		2779.229	2802.984

```
# add custom statistic for confidence intervals
confidence_intervals <- function(data, variable, by, ...) {

  ## extract the confidence intervals and multiply to get percentages
  props <- svyciprop(as.formula(paste0( "~" , variable)),
                    data, na.rm = TRUE)

  ## extract the confidence intervals
  as.numeric(confint(props) * 100) %>% ## make numeric and multiply for
  ↪ percentage
  round(., digits = 1) %>%             ## round to one digit
  c(.) %>%                             ## extract the numbers from matrix
  paste0(., collapse = "-")          ## combine to single character
}
```



Characteristic	Weighted total (N)	Weighted Count ^I	95%CI
VITAMIN_4plus	117,577	42,264 (36%)	31.5-40.7
Unknown		363	

^In (%)

```
library(gtsummary)
tbl_svysummary(
  data = prams_ga2000.svy,
  include = c(VITAMIN_4plus),
  statistic = list(everything() ~ c("{n} ({p}%)"))
) %>%
add_n() %>%
add_stat(fns = everything() ~ confidence_intervals) %>%
modify_header(
  list(
    n ~ "**Weighted total (N)**",
    stat_0 ~ "**Weighted Count**",
    add_stat_1 ~ "**95%CI**"
  )) %>%
as_gt() %>%
tab_options(latex.tbl.pos = "h")
```



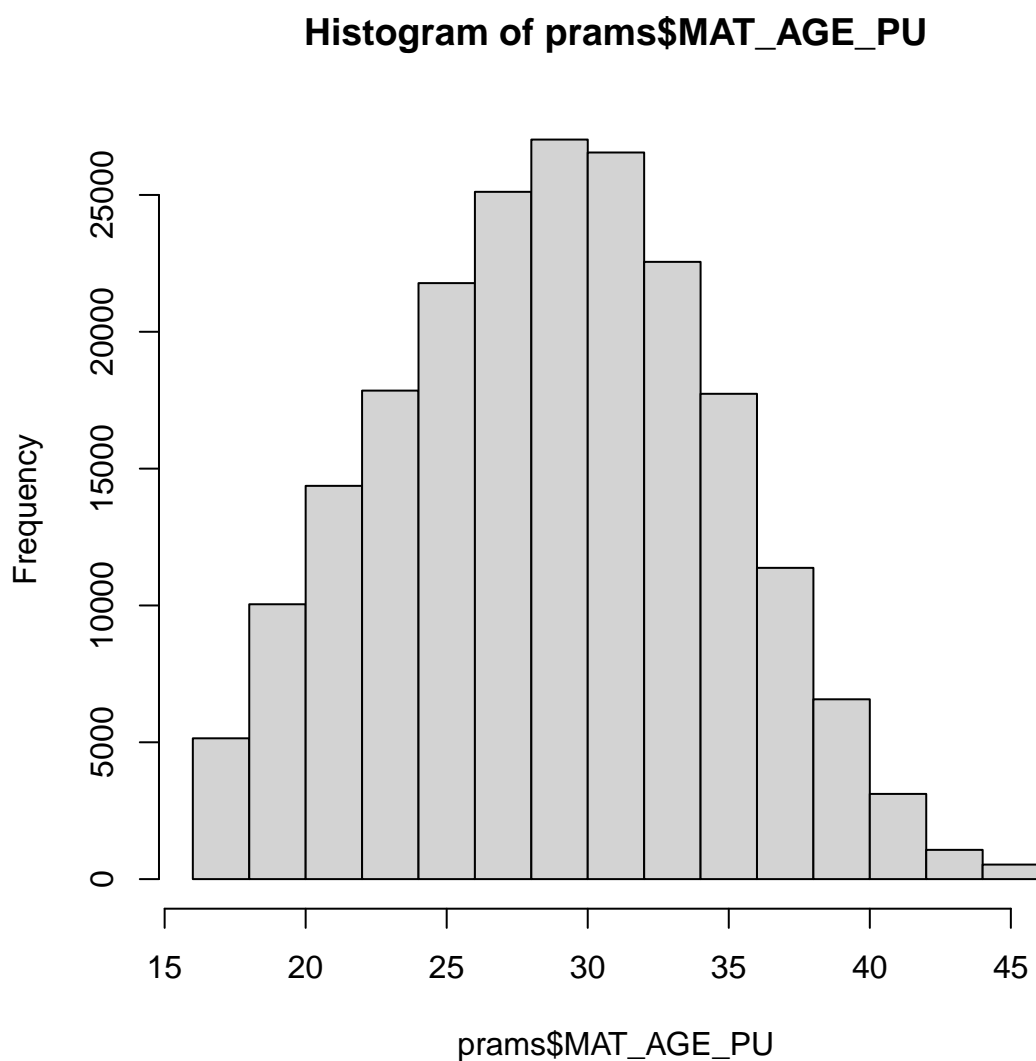
4. Visualizing PRAMS Data

Examples will be posted here for making graphs and figures with suggestions on handling very large datasets.

let's look at maternal age variable MAT_AGE_PU, see [PRAMS Codebook](#).

Histogram of Maternal Age - Unweighted

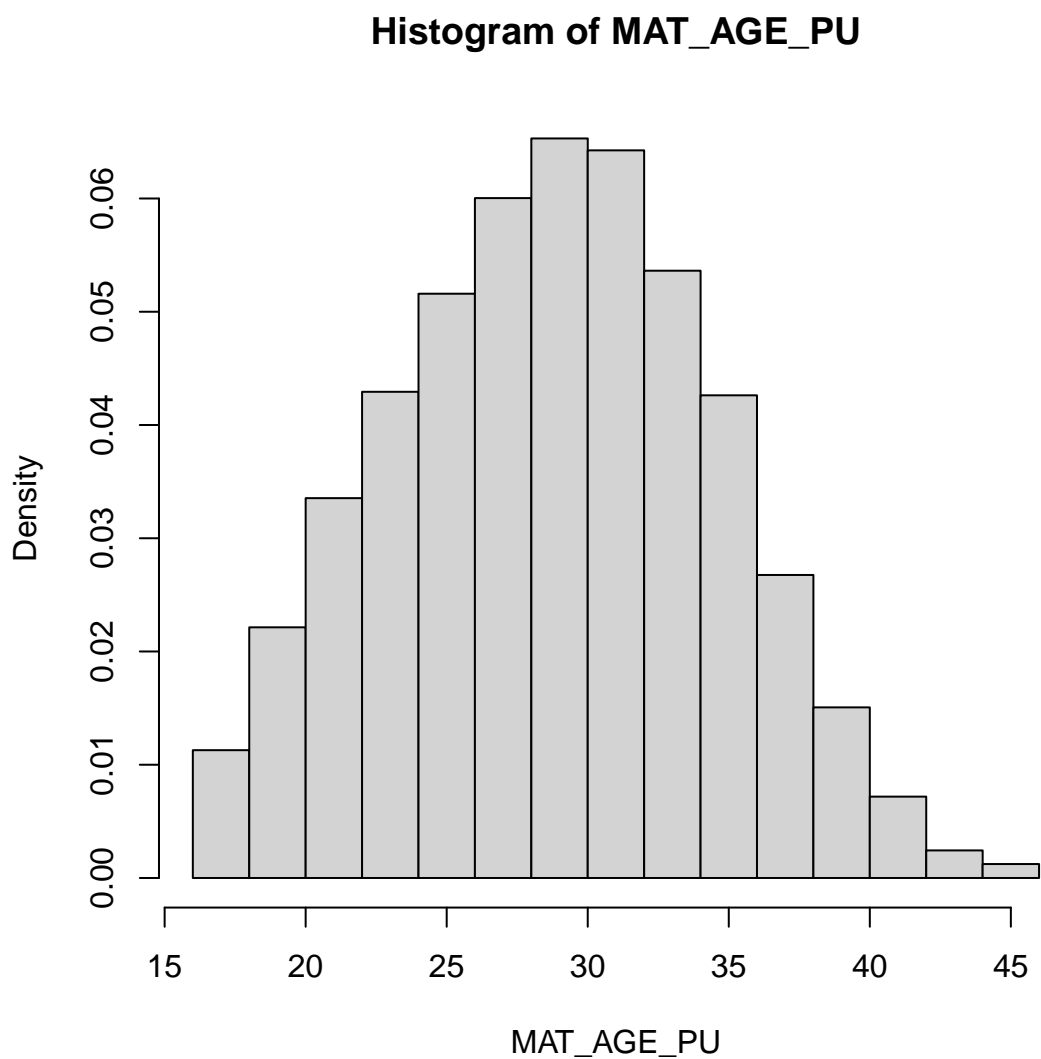
```
hist(prams$MAT_AGE_PU)
```





Histogram of Maternal Age - Complex Survey Weighted

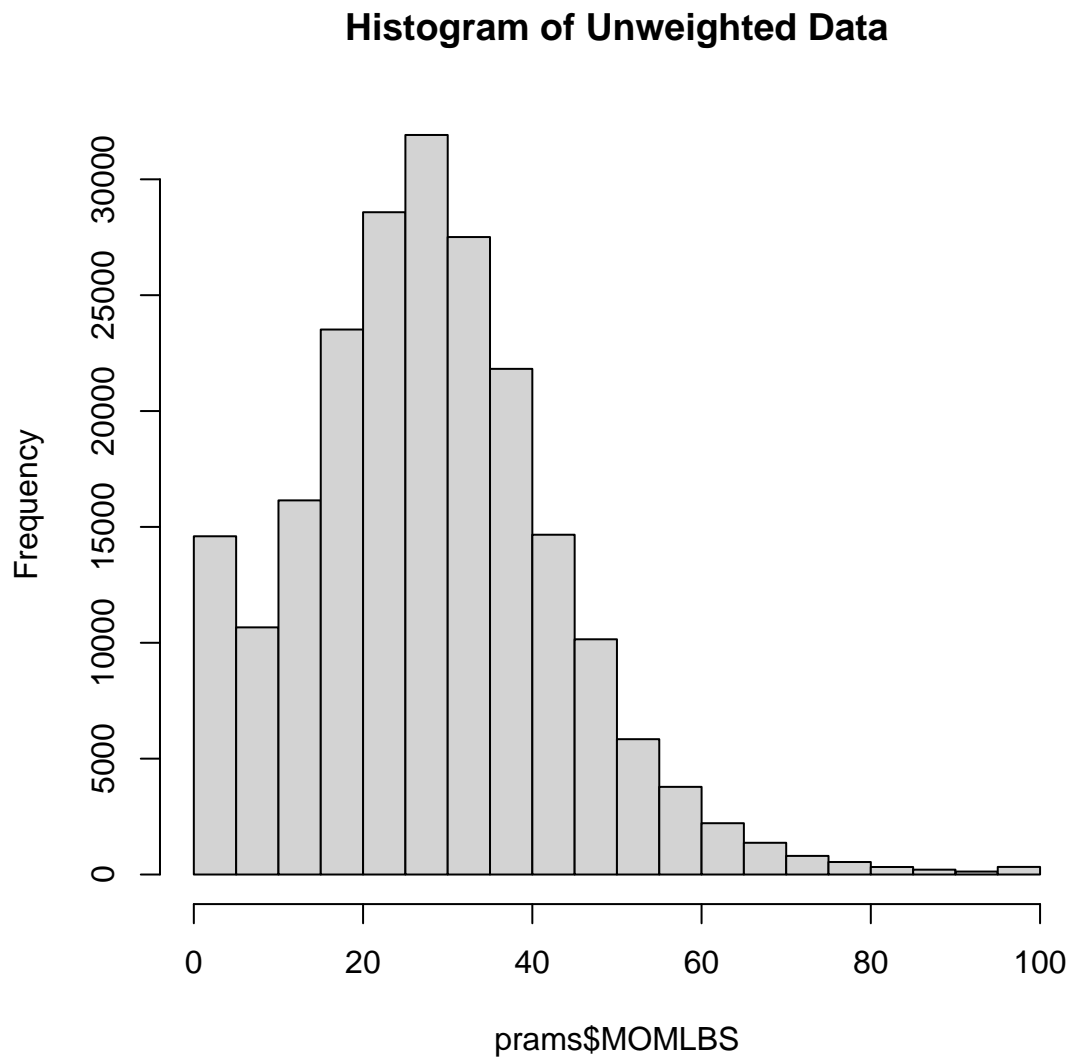
```
# use survey design data  
# get histogram using svyhist() function  
svyhist(formula = ~MAT_AGE_PU,  
        design = prams.svy)
```





Histogram of Maternal weight gain in lbs - Unweighted Data

```
# MOMLBS  
hist(prams$MOMLBS,  
      main = "Histogram of Unweighted Data")
```





Summary statistics of Unweighted Data

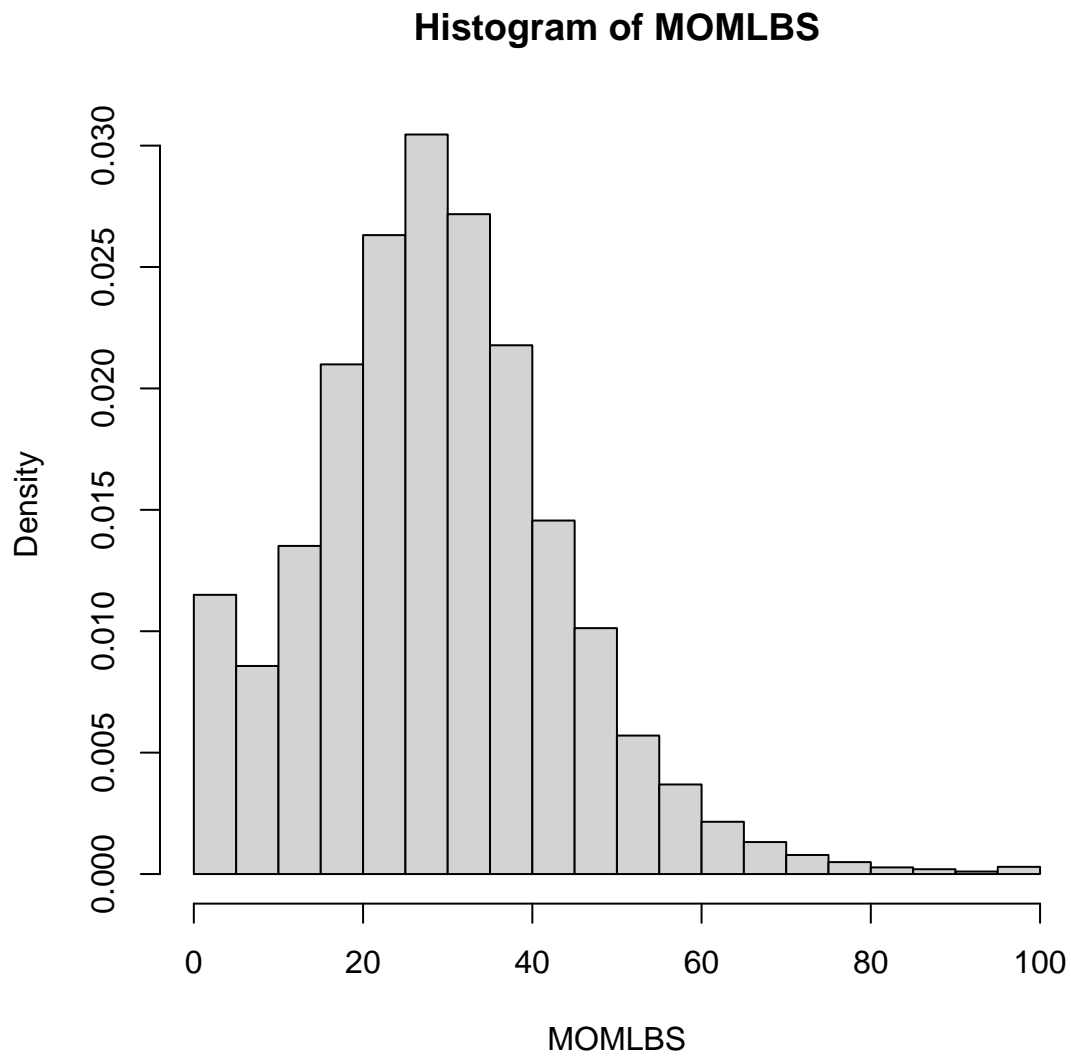
```
summary(prams$MOMLBS)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
0.00	19.00	28.00	28.48	37.00	97.00	6275



Histogram of Maternal weight gain in lbs - Complex Survey Weighted Data

```
svyhist(formula = ~MOMLBS,  
        design = prams.svy)
```

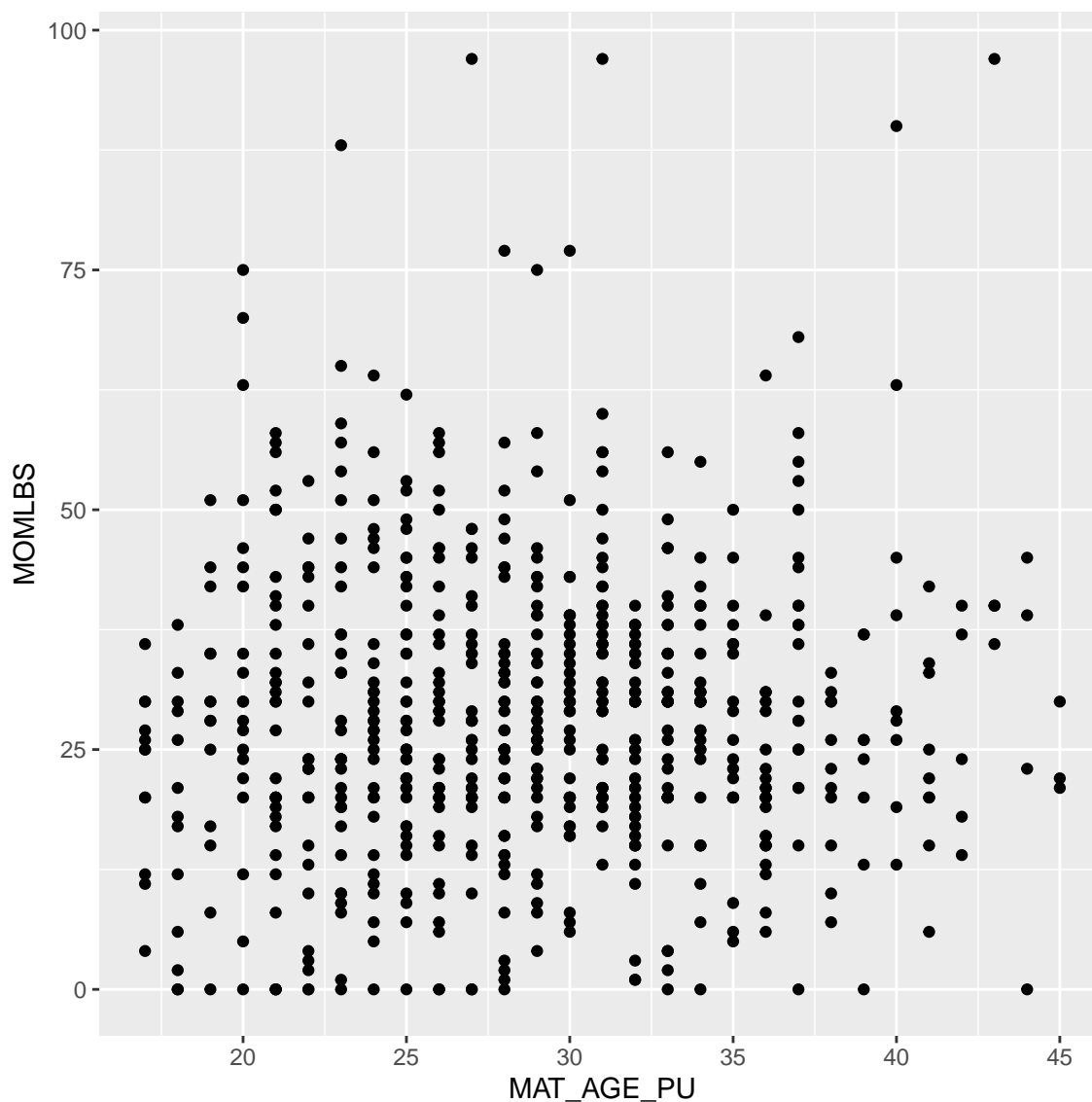




Scatterplot of Weight Gain by Age - Unweighted Data

Look at GA for 2020

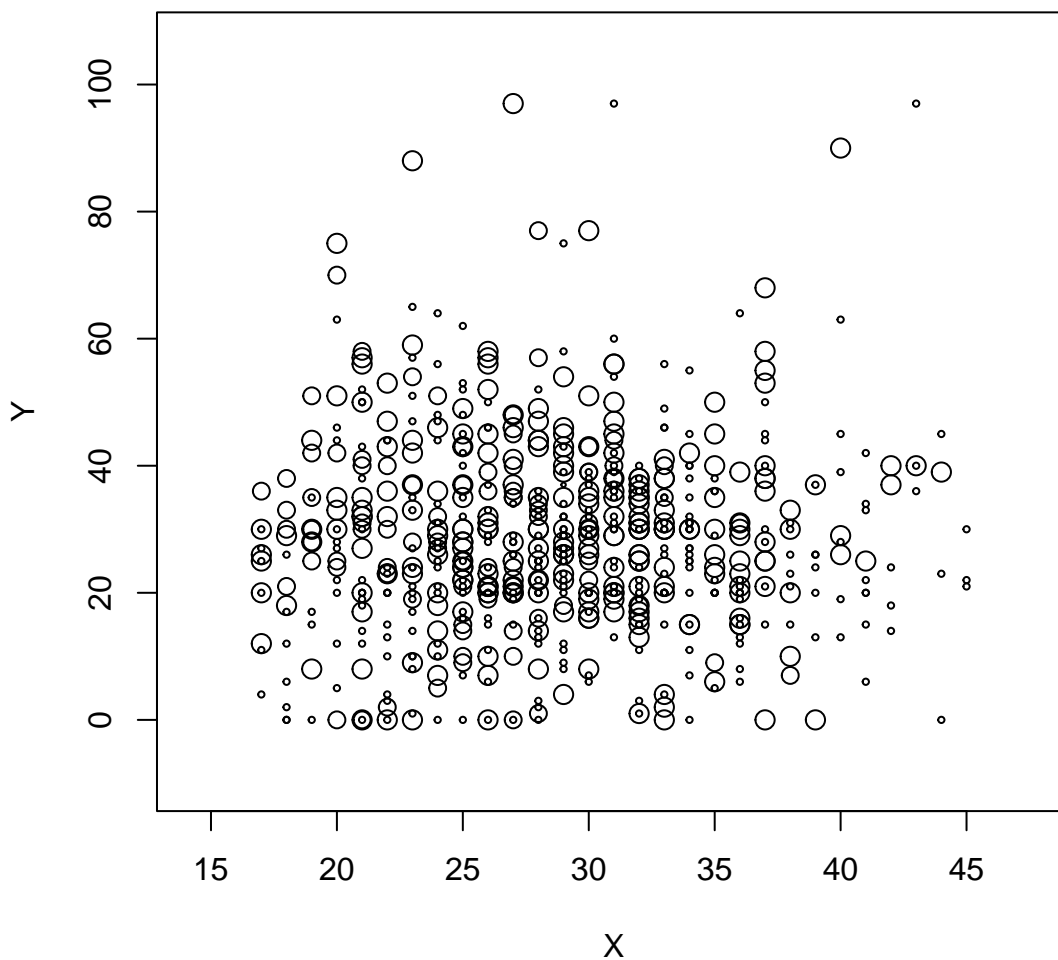
```
library(ggplot2)
ggplot(prams_ga2000, aes(x=MAT_AGE_PU, y=MOMLBS)) +
  geom_point()
```





Weighted plot - notice the varying sizes of the dots (bubbles)

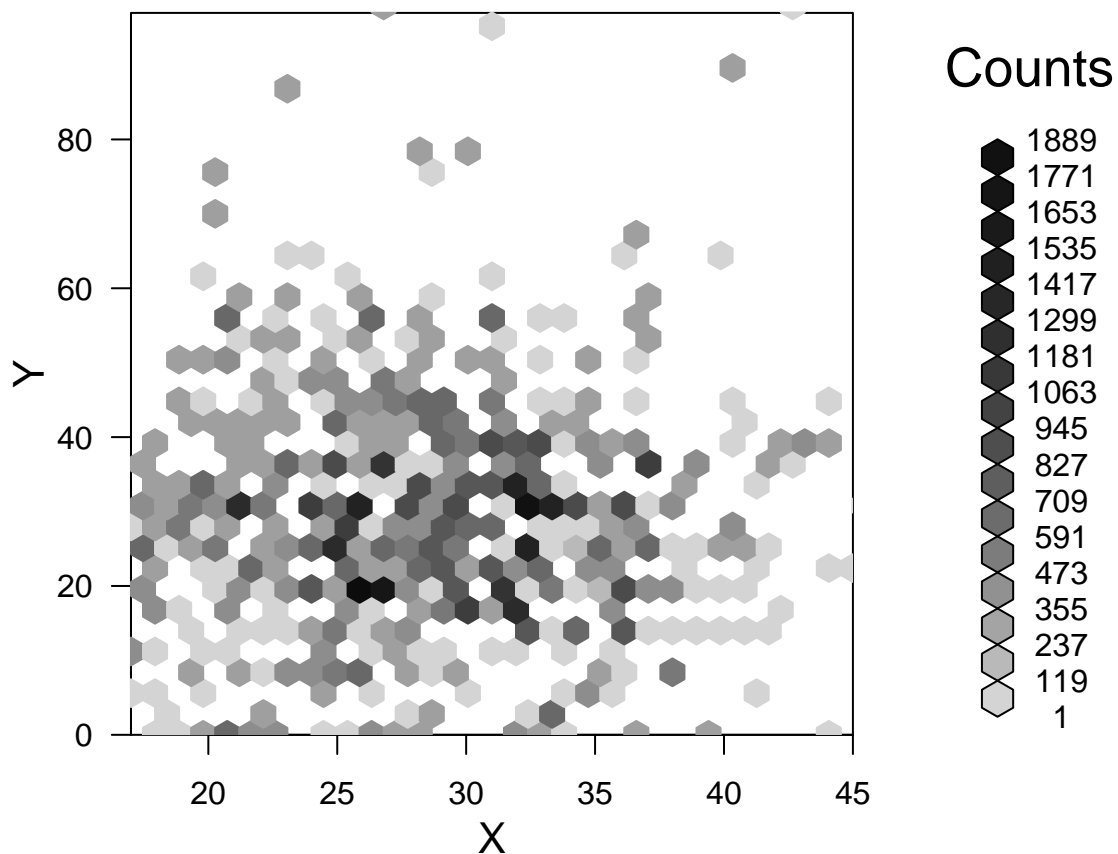
```
svyplot(MOMLBS~MAT_AGE_PU,  
        prams_ga2000.svy,  
        style = "bubble")
```





Another option - gray scale hex symbols - darker indicate higher counts, see `help(svyplot, package = "survey")`.

```
svyplot(MOMLBS~MAT_AGE_PU,  
        prams_ga2000.svy,  
        style = "grayhex")
```





5. Missing Data in PRAMS

Let's look at the missing data for the VITAMIN variable for GA in 2020.

```
prams_ga2000 <- prams %>%  
  filter(STATE == "GA") %>%  
  filter(NEST_YR == 2020)  
  
# amount of missing data for VITAMIN  
# unweighted  
#   1    2    3    4 <NA>  
# 390   53   33  214    2  
# 2/692 = 0.289%  
table(prams_ga2000$VITAMIN, useNA = "ifany")
```

```
   1    2    3    4 <NA>  
390   53   33  214    2
```

This is areallysmall amount - only 2 NAs - but this is much larger in the weighted sample.



Characteristic	Weighted total (N)	Weighted Count ¹	95%CI
VITAMIN_na	117,940	363 (0.3%)	0.1-1.8
¹ n (%)			

Create a missing value indicator variable for VITAMIN and look at the amounts in the weighted sample.

The amount is still small but the range in the weighted sample shown below is informative.

```
# add missing indicator for VITAMIN
prams_ga2000$VITAMIN_na <-
  as.numeric(is.na(prams_ga2000$VITAMIN))
sum(prams_ga2000$VITAMIN_na)
```

```
[1] 2
```

```
# create the survey design file for GA
# for year 2020
prams_ga2000.svy <-
  svydesign(ids = ~0, strata = ~SUD_NEST,
            fpc = ~TOTCNT, weights = ~WTANAL,
            data = prams_ga2000)

tbl_svysummary(
  data = prams_ga2000.svy,
  include = c(VITAMIN_na),
  statistic = list(everything() ~ c("{n} ({p}%)"))
) %>%
  add_n() %>%
  add_stat(fns = everything() ~ confidence_intervals) %>%
  modify_header(
    list(
      n ~ "**Weighted total (N)**",
      stat_0 ~ "**Weighted Count**",
      add_stat_1 ~ "**95%CI**"
    ) %>%
  as_gt() %>%
  tab_options(latex.tbl.pos = "h")
```



```
# weighted 0.3%, CI: 0.1 to 1.8%
```



6. PRAMS Statistical Tests and Models

Linear Regression Example

Association of age and weight gain using linear regression - Unweighted model

```
lm1 <- lm(MOMLBS ~ MAT_AGE_PU,  
          data = prams_ga2000)  
summary(lm1)
```

Call:

```
lm(formula = MOMLBS ~ MAT_AGE_PU, data = prams_ga2000)
```

Residuals:

Min	1Q	Median	3Q	Max
-29.566	-8.733	-1.089	8.161	68.722

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	26.23389	2.80325	9.358	<2e-16 ***
MAT_AGE_PU	0.07572	0.09545	0.793	0.428

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15.18 on 686 degrees of freedom

(4 observations deleted due to missingness)

Multiple R-squared: 0.0009166, Adjusted R-squared: -0.0005398

F-statistic: 0.6294 on 1 and 686 DF, p-value: 0.4279



Association of age and weight gain using linear regression - Weighted model

```
summary(svyglm(MOMLBS ~ MAT_AGE_PU,  
              design = prams_ga2000.svy))
```

Call:

```
svyglm(formula = MOMLBS ~ MAT_AGE_PU, design = prams_ga2000.svy)
```

Survey design:

```
svydesign(ids = ~0, strata = ~SUD_NEST, fpc = ~TOTCNT, weights = ~WTANAL,  
         data = prams_ga2000)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	30.210104	3.935380	7.677	5.65e-14 ***
MAT_AGE_PU	-0.005842	0.135304	-0.043	0.966

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 231.9695)

Number of Fisher Scoring iterations: 2



Contingency tables and Chi-square test - vitamin use by breastfeeding - Unweighted Data

```
table(prams_ga2000$VITAMIN_4plus.f,
      prams_ga2000$BF5EVER.f,
      useNA = "ifany")
```

```

      NO YES <NA>
3x/week or less  95 337  11
4x/week or more  18 225   4
<NA>              1   1   0
```

```
library(gmodels)
CrossTable(x = prams_ga2000$VITAMIN_4plus.f,
           y = prams_ga2000$BF5EVER.f,
           expected = TRUE,
           prop.r = FALSE,
           prop.c = TRUE,
           prop.t = FALSE,
           prop.chisq = FALSE,
           chisq = TRUE,
           format = "SPSS")
```

Cell Contents

```

|-----|
|              Count |
|      Expected Values |
|      Column Percent |
|-----|
```

Total Observations in Table: 675

	prams_ga2000\$BF5EVER.f		
prams_ga2000\$VITAMIN_4plus.f	NO	YES	Row Total
3x/week or less	95	337	432
	72.320	359.680	
	84.071%	59.964%	
4x/week or more	18	225	243
	40.680	202.320	
	15.929%	40.036%	



----- ----- ----- -----
Column Total 113 562 675
16.741% 83.259%
----- ----- ----- -----

Statistics for All Table Factors

Pearson's Chi-squared test

Chi^2 = 23.72972 d.f. = 1 p = 1.108573e-06

Pearson's Chi-squared test with Yates' continuity correction

Chi^2 = 22.69497 d.f. = 1 p = 1.898642e-06

Minimum expected frequency: 40.68



Contingency tables and Chi-square test - vitamin use by breastfeeding - Unweighted Data

```
svytable(~VITAMIN_4plus.f + BF5EVER.f,
         prams_ga2000.svy)
```

	BF5EVER.f	
VITAMIN_4plus.f	NO	YES
3x/week or less	18458.169	55008.856
4x/week or more	3334.398	38789.322

```
svychisq(~VITAMIN_4plus.f + BF5EVER.f,
         prams_ga2000.svy,
         statistic = "Chisq")
```

Pearson's X^2 : Rao & Scott adjustment

```
data:  svychisq(~VITAMIN_4plus.f + BF5EVER.f, prams_ga2000.svy, statistic =
"Chisq")
X-squared = 31.025, df = 1, p-value = 1.222e-05
```

Logistic Regression Example

Let's look at multi-vitamin use 4x/week by breastfeeding and maternal age.

Unweighted Logistic Regression Results

```
glm1 <-glm(VITAMIN_4plus ~ MAT_AGE_PU + BF5EVER.f,
           data = prams_ga2000,
           family = "binomial")
gtsummary::tbl_regression(glm1,
                          exponentiate = TRUE) %>%
  as_gt() %>%
  tab_options(latex.tbl.pos = "h")
```



Characteristic	OR ¹	95% CI ¹	p-value
Maternal age grouped BF5EVER.f	1.07	1.04, 1.11	<0.001
NO	—	—	
YES	2.82	1.67, 4.99	<0.001

¹OR = Odds Ratio, CI = Confidence Interval

Weighted Logistic Regression Results

```
wtglm1 <- svyglm(VITAMIN_4plus ~ MAT_AGE_PU + BF5EVER.f,
                 design = prams_ga2000.svy,
                 family=quasibinomial())
summary(wtglm1)
```

Call:

```
svyglm(formula = VITAMIN_4plus ~ MAT_AGE_PU + BF5EVER.f, design =
prams_ga2000.svy,
       family = quasibinomial())
```

Survey design:

```
svydesign(ids = ~0, strata = ~SUD_NEST, fpc = ~TOTCNT, weights = ~WTANAL,
         data = prams_ga2000)
```

Coefficients:

```
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.36672    0.60317  -5.582 3.46e-08 ***
MAT_AGE_PU   0.06250    0.01901   3.287 0.001064 **
BF5EVER.fYES 1.18775    0.33359   3.561 0.000396 ***
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for quasibinomial family taken to be 1.006803)

Number of Fisher Scoring iterations: 4

```
exp(coef(wtglm1))
```

```
(Intercept)    MAT_AGE_PU BF5EVER.fYES
    0.0345025    1.0644955    3.2797036
```



7. PRAMS Reproducible Research Report

Here is an example Rmarkdown analysis report provided as a template to “kick start” your research with the PRAMS dataset.

1. Download this Rmarkdown template [PRAMS Rmarkdown Report](#).
 2. Knit to HTML [PRAMS Report in HTML](#).
 3. Knit to DOC [PRAMS Report in DOCX](#).
 4. Knit to PDF (if you’ve installed `tinytex` package) [PRAMS Report in PDF](#).
 5. Knit with Parameters - Change the year from 2020 to 2018 and re-knit the document
-



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Other Helpful Resources

Other Helpful Resources