

The count verb

DATA MANIPULATION WITH DPLYR



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Count

```
counties %>%  
  count()
```

```
# A tibble: 1 x 1  
      n  
  <int>  
1  3138
```

Count variable

```
counties %>%  
  count(state)
```

```
# A tibble: 50 x 2  
  state      n  
  <chr>    <int>  
1 Alabama    67  
2 Alaska    28  
3 Arizona    15  
4 Arkansas   75  
5 California 58  
6 Colorado   64  
7 Connecticut 8  
8 Delaware   3  
9 Florida    67  
10 Georgia   159  
# ... with 40 more rows
```

Count and sort

```
counties %>%  
  count(state, sort = TRUE)
```

```
# A tibble: 50 x 2  
  state          n  
  <chr>        <int>  
1 Texas         253  
2 Georgia       159  
3 Virginia      133  
4 Kentucky      120  
5 Missouri      115  
6 Kansas        105  
7 Illinois      102  
8 North Carolina 100  
9 Iowa          99  
10 Tennessee    95  
# ... with 40 more rows
```

Count population

```
counties %>%  
  select(state, county, population)
```

```
# A tibble: 3,138 x 3  
  state    county    population  
  <chr>   <chr>         <dbl>  
1 Alabama Autauga         55221  
2 Alabama Baldwin      195121  
3 Alabama Barbour       26932  
4 Alabama Bibb           22604  
5 Alabama Blount        57710  
6 Alabama Bullock       10678  
7 Alabama Butler        20354  
8 Alabama Calhoun      116648  
9 Alabama Chambers      34079  
10 Alabama Cherokee     26008  
# ... with 3,128 more rows
```

Add weight

```
counties %>%  
  count(state, wt = population, sort = TRUE)
```

```
# A tibble: 50 x 2  
  state          n  
  <chr>         <dbl>  
1 California  38421464  
2 Texas       26538497  
3 New York    19673174  
4 Florida     19645772  
5 Illinois    12873761  
6 Pennsylvania 12779559  
7 Ohio        11575977  
8 Georgia     10006693  
9 Michigan     9900571  
10 North Carolina 9845333  
# ... with 40 more rows
```

Let's practice!

DATA MANIPULATION WITH DPLYR

The group_by, summarize, and ungroup verbs

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Summarize

```
counties %>%  
  summarize(total_population = sum(population))
```

```
# A tibble: 1 x 1  
  total_population  
      <dbl>  
1      315845353
```

Aggregate and summarize

```
counties %>%  
  summarize(total_population = sum(population),  
            average_unemployment = mean(unemployment))
```

```
# A tibble: 1 x 2  
  total_population average_unemployment  
      <dbl>          <dbl>  
1    315845353          7.80
```

Summary functions

- `sum()`
- `mean()`
- `median()`
- `min()`
- `max()`
- `n()`

Aggregate within groups

```
counties %>%
  group_by(state) %>%
  summarize(total_pop = sum(population),
            average_unemployment = mean(unemployment))
```

```
# A tibble: 50 x 3
  state      total_pop average_unemployment
  <chr>      <dbl>          <dbl>
1 Alabama   4830620         758.
2 Alaska    725461          257.
3 Arizona   6641928         180.
4 Arkansas  2958208         674.
5 California 38421464         626.
6 Colorado  5278906         477.
7 Connecticut 3593222          65.3
8 Delaware  926454           23.8
9 Florida   19645772         696.
10 Georgia  10006693        1586.
# ... with 40 more rows
```

Sorting summaries

```
counties %>%
  group_by(state) %>%
  summarize(total_pop = sum(population),
            average_unemployment = mean(unemployment)) %>%
  arrange(desc(average_unemployment))
```

```
# A tibble: 50 x 3
  state      total_pop average_unemployment
  <chr>      <dbl>         <dbl>
1 Mississippi 2988081         12.0
2 Arizona     6641928         12.0
3 South Carolina 4777576         11.3
4 Alabama     4830620         11.3
5 California  38421464         10.8
6 Nevada      2798636         10.5
7 North Carolina 9845333         10.5
8 Florida     19645772         10.4
9 Georgia     10006693          9.97
10 Michigan    9900571          9.96
# ... with 40 more rows
```

Metro column

```
counties %>%  
  select(state, metro, county, population)
```

```
# A tibble: 3,138 x 4  
  state metro county population  
  <chr> <chr> <chr> <dbl>  
1 Alabama Metro Autauga 55221  
2 Alabama Metro Baldwin 195121  
3 Alabama Nonmetro Barbour 26932  
4 Alabama Metro Bibb 22604  
5 Alabama Metro Blount 57710  
6 Alabama Nonmetro Bullock 10678  
7 Alabama Nonmetro Butler 20354  
8 Alabama Metro Calhoun 116648  
9 Alabama Nonmetro Chambers 34079  
10 Alabama Nonmetro Cherokee 26008  
# ... with 3,128 more rows
```

Grouping on multiple columns

```
counties %>%  
  group_by(state, metro) %>%  
  summarize(total_pop = sum(population))
```

```
# A tibble: 97 x 3  
# Groups:   state [50]  
  state      metro  total_pop  
  <chr>    <chr>    <dbl>  
1 Alabama Metro    3671377  
2 Alabama Nonmetro 1159243  
3 Alaska  Metro    494990  
4 Alaska  Nonmetro 230471  
5 Arizona Metro    6295145  
6 Arizona Nonmetro 346783  
7 Arkansas Metro    1806867  
8 Arkansas Nonmetro 1151341  
9 California Metro    37587429  
10 California Nonmetro 834035  
# ... with 87 more rows
```

Ungroup

```
counties %>%  
  group_by(state, metro) %>%  
  summarize(total_pop = sum(population)) %>%  
  ungroup()
```

```
# A tibble: 97 x 3  
  state      metro      total_pop  
  <chr>     <chr>     <dbl>  
1 Alabama  Metro      3671377  
2 Alabama  Nonmetro   1159243  
3 Alaska   Metro       494990  
4 Alaska   Nonmetro    230471  
5 Arizona  Metro      6295145  
6 Arizona  Nonmetro    346783  
7 Arkansas Metro     1806867  
8 Arkansas Nonmetro   1151341  
9 California Metro    37587429  
10 California Nonmetro    834035  
# ... with 87 more rows
```


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The slice_min and slice_max verbs

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slice_max()

- Returns the **largest** observations in each group

```
counties_selected <- counties %>%  
  select(state, county, population, unemployment, income)
```

```
counties_selected %>%  
  group_by(state) %>%  
  slice_max(population, n = 1)
```

slice_max() output

```
# A tibble: 50 x 5
# Groups:   state [50]
  state      county      population unemployment  income
  <chr>     <chr>          <dbl>          <dbl>    <dbl>
1 Alabama  Jefferson      659026          9.1    45610
2 Alaska   Anchorage Municipality 299107          6.7    78326
3 Arizona  Maricopa      4018143         7.7    54229
4 Arkansas Pulaski       390463          7.5    46140
5 California Los Angeles 10038388        10     56196
6 Colorado EL Paso       655024          8.4    58206
7 Connecticut Fairfield    939983          9     84233
8 Delaware New Castle   549643          7.4    65476
9 Florida  Miami-Dade  2639042         10     43129
10 Georgia  Fulton     983903          9.9    57207
# ... with 40 more rows
```

slice_min()

- Returns the **smallest** observations in each group

```
counties_selected %>%  
  group_by(state) %>%  
  slice_min(unemployment, n = 1)
```

slice_min() output

```
# A tibble: 51 × 5
# Groups:   state [50]
  state      county      population unemployment  income
  <chr>     <chr>          <dbl>         <dbl>    <dbl>
1 Alabama  Shelby          203530         5.5    70187
2 Alaska   Aleutians West Census Area  5684         2.1    84306
3 Arizona  Maricopa        4018143        7.7    54229
4 Arkansas Benton          238198         4.2    56239
5 California Marin          258349         5.7    93257
6 Colorado Jackson          1335          1.5    46014
7 Connecticut Middlesex      165165         6     79893
8 Delaware New Castle     549643         7.4    65476
9 Florida  Monroe          75901          6     57290
10 Georgia  Bacon           11222         4.4    37162
# ... with 41 more rows
```

Number of observations

```
counties_selected %>%  
  group_by(state) %>%  
  slice_max(unemployment, n = 3)
```

```
# A tibble: 153 × 5  
# Groups:   state [50]  
  state      county      population unemployment  income  
  <chr>    <chr>          <dbl>         <dbl>    <dbl>  
1 Alabama Conecuh      12865          22.6    24900  
2 Alabama Wilcox       11235          20.8    23750  
3 Alabama Monroe      22217          20.7    27257  
4 Alaska  Northwest Arctic Borough    7732          21.9    63648  
5 Alaska  Yukon-Koyukuk Census Area   5644          18.2    38491  
6 Alaska  Bethel Census Area      17776          17.6    51012  
7 Arizona Navajo      107656          19.8    35921  
8 Arizona Apache       72124          18.2    31757  
9 Arizona Graham      37407          14.1    45964  
10 Arkansas Phillips    20391          18.1    26844  
# ... with 143 more rows
```

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