# transforming_data_dplyr

Teodor Chakarov

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## Contents



# Tutorium in R

## Exercise: Transforming data with dplyr - Number 4

### By: Teodor Chakarov 12141198

## Transforming data with dplyr

```
library("dplyr")
```

```
##
## 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("ggplot2")

counties <- readRDS("counties.rds")

glimpse(counties)
```

```
## Rows: 3,138
## Columns: 40
## $ census_id          <chr> "1001", "1003", "1005", "1007", "1009", "1011", "10~
## $ state              <chr> "Alabama", "Alabama", "Alabama", "Alabama", "Alabam~
## $ county             <chr> "Autauga", "Baldwin", "Barbour", "Bibb", "Blount", ~
## $ region             <chr> "South", "South", "South", "South", "South", "South~
## $ metro              <chr> "Metro", "Metro", "Nonmetro", "Metro", "Metro", "No~
## $ population         <dbl> 55221, 195121, 26932, 22604, 57710, 10678, 20354, 1~
```

```
## $ men                <dbl> 26745, 95314, 14497, 12073, 28512, 5660, 9502, 5627~
## $ women              <dbl> 28476, 99807, 12435, 10531, 29198, 5018, 10852, 603~
## $ hispanic           <dbl> 2.6, 4.5, 4.6, 2.2, 8.6, 4.4, 1.2, 3.5, 0.4, 1.5, 7~
## $ white              <dbl> 75.8, 83.1, 46.2, 74.5, 87.9, 22.2, 53.3, 73.0, 57.~
## $ black              <dbl> 18.5, 9.5, 46.7, 21.4, 1.5, 70.7, 43.8, 20.3, 40.3,~
## $ native             <dbl> 0.4, 0.6, 0.2, 0.4, 0.3, 1.2, 0.1, 0.2, 0.2, 0.6, 0~
## $ asian              <dbl> 1.0, 0.7, 0.4, 0.1, 0.1, 0.2, 0.4, 0.9, 0.8, 0.3, 0~
## $ pacific            <dbl> 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0~
## $ citizens           <dbl> 40725, 147695, 20714, 17495, 42345, 8057, 15581, 88~
## $ income             <dbl> 51281, 50254, 32964, 38678, 45813, 31938, 32229, 41~
## $ income_err         <dbl> 2391, 1263, 2973, 3995, 3141, 5884, 1793, 925, 2949~
## $ income_per_cap     <dbl> 24974, 27317, 16824, 18431, 20532, 17580, 18390, 21~
## $ income_per_cap_err <dbl> 1080, 711, 798, 1618, 708, 2055, 714, 489, 1366, 15~
## $ poverty            <dbl> 12.9, 13.4, 26.7, 16.8, 16.7, 24.6, 25.4, 20.5, 21.~
## $ child_poverty      <dbl> 18.6, 19.2, 45.3, 27.9, 27.2, 38.4, 39.2, 31.6, 37.~
## $ professional       <dbl> 33.2, 33.1, 26.8, 21.5, 28.5, 18.8, 27.5, 27.3, 23.~
## $ service            <dbl> 17.0, 17.7, 16.1, 17.9, 14.1, 15.0, 16.6, 17.7, 14.~
## $ office             <dbl> 24.2, 27.1, 23.1, 17.8, 23.9, 19.7, 21.9, 24.2, 26.~
## $ construction       <dbl> 8.6, 10.8, 10.8, 19.0, 13.5, 20.1, 10.3, 10.5, 11.5~
## $ production         <dbl> 17.1, 11.2, 23.1, 23.7, 19.9, 26.4, 23.7, 20.4, 24.~
## $ drive              <dbl> 87.5, 84.7, 83.8, 83.2, 84.9, 74.9, 84.5, 85.3, 85.~
## $ carpool            <dbl> 8.8, 8.8, 10.9, 13.5, 11.2, 14.9, 12.4, 9.4, 11.9, ~
## $ transit            <dbl> 0.1, 0.1, 0.4, 0.5, 0.4, 0.7, 0.0, 0.2, 0.2, 0.2, 0~
## $ walk               <dbl> 0.5, 1.0, 1.8, 0.6, 0.9, 5.0, 0.8, 1.2, 0.3, 0.6, 1~
## $ other_transp       <dbl> 1.3, 1.4, 1.5, 1.5, 0.4, 1.7, 0.6, 1.2, 0.4, 0.7, 1~
## $ work_at_home       <dbl> 1.8, 3.9, 1.6, 0.7, 2.3, 2.8, 1.7, 2.7, 2.1, 2.5, 1~
## $ mean_commute       <dbl> 26.5, 26.4, 24.1, 28.8, 34.9, 27.5, 24.6, 24.1, 25.~
## $ employed           <dbl> 23986, 85953, 8597, 8294, 22189, 3865, 7813, 47401,~
## $ private_work       <dbl> 73.6, 81.5, 71.8, 76.8, 82.0, 79.5, 77.4, 74.1, 85.~
## $ public_work        <dbl> 20.9, 12.3, 20.8, 16.1, 13.5, 15.1, 16.2, 20.8, 12.~
## $ self_employed      <dbl> 5.5, 5.8, 7.3, 6.7, 4.2, 5.4, 6.2, 5.0, 2.8, 7.9, 4~
## $ family_work        <dbl> 0.0, 0.4, 0.1, 0.4, 0.4, 0.0, 0.2, 0.1, 0.0, 0.5, 0~
## $ unemployment       <dbl> 7.6, 7.5, 17.6, 8.3, 7.7, 18.0, 10.9, 12.3, 8.9, 7.~
## $ land_area          <dbl> 594.44, 1589.78, 884.88, 622.58, 644.78, 622.81, 77~
```

Selecting columns to show

```r
counties %>%
  # Select the columns
  select("state", "county", "population", "poverty")
```

```
## # A tibble: 3,138 x 4
##    state   county   population poverty
##    <chr>   <chr>         <dbl>   <dbl>
##  1 Alabama Autauga       55221    12.9
##  2 Alabama Baldwin      195121    13.4
##  3 Alabama Barbour       26932    26.7
##  4 Alabama Bibb          22604    16.8
##  5 Alabama Blount        57710    16.7
##  6 Alabama Bullock       10678    24.6
##  7 Alabama Butler        20354    25.4
##  8 Alabama Calhoun      116648    20.5
##  9 Alabama Chambers      34079    21.6
## 10 Alabama Cherokee      26008    19.2
## # ... with 3,128 more rows
```

Arrange the data by descending order

```r
counties_selected <- counties %>%
  select(state, county, population, private_work, public_work, self_employed)

counties_selected %>%
  # Add a verb to sort in descending order of public_work
  arrange(desc(public_work))
```

```
## # A tibble: 3,138 x 6
##    state        county         population private_work public_work self_employed
##    <chr>        <chr>               <dbl>        <dbl>       <dbl>         <dbl>
##  1 Hawaii       Kalawao                85         25          64.1          10.9
##  2 Alaska       Yukon-Koyukuk~       5644         33.3        61.7           5.1
##  3 Wisconsin    Menominee            4451         36.8        59.1           3.7
##  4 North Dakota Sioux                4380         32.9        56.8          10.2
##  5 South Dakota Todd                 9942         34.4        55             9.8
##  6 Alaska       Lake and Peni~       1474         42.2        51.6           6.1
##  7 California   Lassen              32645         42.6        50.5           6.8
##  8 South Dakota Buffalo              2038         48.4        49.5           1.8
##  9 South Dakota Dewey                5579         34.9        49.2          14.7
## 10 Texas        Kenedy                565         51.9        48.1           0
## # ... with 3,128 more rows
```

Filter column

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

counties_selected %>%
  # Filter for counties with a population above 1000000
  filter(population > 1000000)
```

```
## # A tibble: 41 x 3
##    state      county         population
##    <chr>      <chr>               <dbl>
##  1 Arizona    Maricopa          4018143
##  2 California Alameda           1584983
##  3 California Contra Costa      1096068
##  4 California Los Angeles      10038388
##  5 California Orange            3116069
##  6 California Riverside         2298032
##  7 California Sacramento        1465832
##  8 California San Bernardino    2094769
##  9 California San Diego         3223096
## 10 California Santa Clara       1868149
## # ... with 31 more rows
```

```r
counties_selected %>%
  # Filter for counties with a population above 1000000
  filter(state == "California",
         population > 1000000)
```

```
## # A tibble: 9 x 3
##   state      county         population
##   <chr>      <chr>               <dbl>
## 1 California Alameda           1584983
```

```
## 2 California Contra Costa      1096068
## 3 California Los Angeles      10038388
## 4 California Orange            3116069
## 5 California Riverside         2298032
## 6 California Sacramento        1465832
## 7 California San Bernardino    2094769
## 8 California San Diego         3223096
## 9 California Santa Clara       1868149
```

```
counties_selected <- counties %>%
  select(state, county, population, private_work, public_work, self_employed)

counties_selected %>%
  # Filter for Texas and more than 10000 people
  filter(state == "Texas", population > 10000) %>%
  # Sort in descending order of private_work
  arrange(desc(private_work))
```

```
## # A tibble: 169 x 6
##    state county  population private_work public_work self_employed
##    <chr> <chr>        <dbl>        <dbl>       <dbl>         <dbl>
##  1 Texas Gregg       123178         84.7         9.8           5.4
##  2 Texas Collin      862215         84.1        10             5.8
##  3 Texas Dallas     2485003         83.9         9.5           6.4
##  4 Texas Harris     4356362         83.4        10.1           6.3
##  5 Texas Andrews      16775         83.1         9.6           6.8
##  6 Texas Tarrant    1914526         83.1        11.4           5.4
##  7 Texas Titus        32553         82.5        10             7.4
##  8 Texas Denton      731851         82.2        11.9           5.7
##  9 Texas Ector       149557         82          11.2           6.7
## 10 Texas Moore        22281         82          11.7           5.9
## # ... with 159 more rows
```

Create new column in the dataframe

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

counties_selected %>%
  mutate(public_workers = public_work * population / 100) %>%
  # Sort in descending order of the public_workers column
  arrange(desc(public_workers))
```

```
## # A tibble: 3,138 x 5
##    state      county         population public_work public_workers
##    <chr>      <chr>               <dbl>       <dbl>          <dbl>
##  1 California Los Angeles      10038388        11.5       1154415.
##  2 Illinois   Cook              5236393        11.5        602185.
##  3 California San Diego         3223096        14.8        477018.
##  4 Arizona    Maricopa          4018143        11.7        470123.
##  5 Texas      Harris            4356362        10.1        439993.
##  6 New York   Kings             2595259        14.4        373717.
##  7 California San Bernardino    2094769        16.7        349826.
##  8 California Riverside         2298032        14.9        342407.
##  9 California Sacramento        1465832        21.8        319551.
## 10 California Orange            3116069        10.2        317839.
```

```
## # ... with 3,128 more rows
```

```r
counties_selected <- counties %>%
  # Select the columns state, county, population, men, and women
  select(state, county, population, men, women)

counties_selected %>%
  # Calculate proportion_women as the fraction of the population made up of women
  mutate(proportion_women = women/population)
```

```
## # A tibble: 3,138 x 6
##    state   county   population   men women proportion_women
##    <chr>   <chr>         <dbl> <dbl> <dbl>            <dbl>
##  1 Alabama Autauga       55221 26745 28476            0.516
##  2 Alabama Baldwin      195121 95314 99807            0.512
##  3 Alabama Barbour       26932 14497 12435            0.462
##  4 Alabama Bibb          22604 12073 10531            0.466
##  5 Alabama Blount        57710 28512 29198            0.506
##  6 Alabama Bullock       10678  5660  5018            0.470
##  7 Alabama Butler        20354  9502 10852            0.533
##  8 Alabama Calhoun      116648 56274 60374            0.518
##  9 Alabama Chambers      34079 16258 17821            0.523
## 10 Alabama Cherokee      26008 12975 13033            0.501
## # ... with 3,128 more rows
```

```r
counties %>%
  # Select the five columns
  select(state, county, population, men, women) %>%
  # Add the proportion_men variable
  mutate(proportion_men = men/population) %>%
  # Filter for population of at least 10,000
  filter(population >= 10000) %>%
  # Arrange proportion of men in descending order
  arrange(desc(proportion_men))
```

```
## # A tibble: 2,437 x 6
##    state      county         population   men women proportion_men
##    <chr>      <chr>               <dbl> <dbl> <dbl>          <dbl>
##  1 Virginia   Sussex              11864  8130  3734          0.685
##  2 California Lassen              32645 21818 10827          0.668
##  3 Georgia    Chattahoochee       11914  7940  3974          0.666
##  4 Louisiana  West Feliciana      15415 10228  5187          0.664
##  5 Florida    Union               15191  9830  5361          0.647
##  6 Texas      Jones               19978 12652  7326          0.633
##  7 Missouri   DeKalb              12782  8080  4702          0.632
##  8 Texas      Madison             13838  8648  5190          0.625
##  9 Virginia   Greensville         11760  7303  4457          0.621
## 10 Texas      Anderson            57915 35469 22446          0.612
## # ... with 2,427 more rows
```

### Data Aggregation

```r
# Use count to find the number of counties in each region
counties_selected <- counties %>%
  select(county, region, state, population, citizens)
```

```
counties_selected %>%
  count(region, sort = TRUE)
```

```
## # A tibble: 4 x 2
##   region            n
##   <chr>         <int>
## 1 South          1420
## 2 North Central  1054
## 3 West            447
## 4 Northeast       217
```

```
# Find number of counties per state, weighted by citizens, sorted in descending order
counties_selected %>%
  count(state, wt = citizens, sort = TRUE)
```

```
## # A tibble: 50 x 2
##    state                 n
##    <chr>             <dbl>
##  1 California     24280349
##  2 Texas          16864864
##  3 Florida        13933052
##  4 New York       13531404
##  5 Pennsylvania    9710416
##  6 Illinois        8979999
##  7 Ohio            8709050
##  8 Michigan        7380136
##  9 North Carolina  7107998
## 10 Georgia         6978660
## # ... with 40 more rows
```

```
counties_selected <- counties %>%
  select(county, region, state, population, walk)

counties_selected %>%
  # Add population_walk containing the total number of people who walk to work
  mutate(population_walk = population * walk / 100) %>%
  # Count weighted by the new column, sort in descending order
  count(state, wt = population_walk, sort = TRUE)
```

```
## # A tibble: 50 x 2
##    state                n
##    <chr>            <dbl>
##  1 New York      1237938.
##  2 California    1017964.
##  3 Pennsylvania   505397.
##  4 Texas          430783.
##  5 Illinois       400346.
##  6 Massachusetts  316765.
##  7 Florida        284723.
##  8 New Jersey     273047.
##  9 Ohio           266911.
## 10 Washington     239764.
## # ... with 40 more rows
```

Creating new columns with min, max, mean

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


counties_selected %>%
  # Summarize to find minimum population, maximum unemployment, and average income
  summarize(min_population = min(population),
            max_unemployment = max(unemployment),
            average_income = mean(income))
```

```
## # A tibble: 1 x 3
##   min_population max_unemployment average_income
##            <dbl>            <dbl>          <dbl>
## 1             85             29.4         46832.
```

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


counties_selected %>%
  group_by(state) %>%
  summarize(total_area = sum(land_area),
            total_population = sum(population)) %>%
  # Add a density column
  mutate(density = total_population / total_area) %>%
  # Sort by density in descending order
  arrange(desc(density))
```

```
## # A tibble: 50 x 4
##    state         total_area total_population density
##    <chr>              <dbl>            <dbl>   <dbl>
##  1 New Jersey         7354.          8904413   1211.
##  2 Rhode Island       1034.          1053661   1019.
##  3 Massachusetts      7800.          6705586    860.
##  4 Connecticut        4842.          3593222    742.
##  5 Maryland           9707.          5930538    611.
##  6 Delaware           1949.           926454    475.
##  7 New York          47126.         19673174    417.
##  8 Florida           53625.         19645772    366.
##  9 Pennsylvania      44743.         12779559    286.
## 10 Ohio              40861.         11575977    283.
## # ... with 40 more rows
```

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

counties_selected %>%
  # Group and summarize to find the total population
  group_by(region, state) %>%
  summarize(total_pop = sum(population)) %>%
  # Calculate the average_pop and median_pop columns
  summarise(average_pop = mean(total_pop), median_pop = median(total_pop))
```

```
## `summarise()` has grouped output by 'region'. You can override using the
## `.groups` argument.
```

```
## # A tibble: 4 x 3
##   region        average_pop median_pop
##   <chr>               <dbl>      <dbl>
## 1 North Central    5627687.    5580644
## 2 Northeast        6221058.    3593222
## 3 South            7370486     4804098
## 4 West             5722755.    2798636
```

Top n values

```r
counties_selected <- counties %>%
  select(region, state, county, metro, population, walk)


counties_selected %>%
  # Group by region
  group_by(region) %>%
  # Find the greatest number of citizens who walk to work
  top_n(1, walk)
```

```
## # A tibble: 4 x 6
## # Groups:   region [4]
##   region        state        county                 metro    population  walk
##   <chr>         <chr>        <chr>                  <chr>         <dbl> <dbl>
## 1 West          Alaska       Aleutians East Borough Nonmetro       3304  71.2
## 2 Northeast     New York     New York               Metro       1629507  20.7
## 3 North Central North Dakota McIntosh               Nonmetro       2759  17.5
## 4 South         Virginia     Lexington city         Nonmetro       7071  31.7
```

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


counties_selected %>%
  group_by(region, state) %>%
  # Calculate average income
  summarise(average_income = mean(income)) %>%
  # Find the highest income state in each region
  top_n(1, average_income)
```

```
## `summarise()` has grouped output by 'region'. You can override using the
## `.groups` argument.
```

```
## # A tibble: 4 x 3
## # Groups:   region [4]
##   region        state        average_income
##   <chr>         <chr>                 <dbl>
## 1 North Central North Dakota         55575.
## 2 Northeast     New Jersey           73014.
## 3 South         Maryland             69200.
## 4 West          Alaska               65125.
```

```r
counties_selected <- counties %>%
  select(state, metro, population)


counties_selected %>%
```

```r
  # Find the total population for each combination of state and metro
  group_by(state, metro) %>%
  summarize(total_pop = sum(population)) %>%
  # Extract the most populated row for each state
  top_n(1, total_pop) %>%
  # Count the states with more people in Metro or Nonmetro areas
  ungroup() %>%
  count(metro)
```

```
## `summarise()` has grouped output by 'state'. You can override using the
## `.groups` argument.
```

```
## # A tibble: 2 x 2
##   metro        n
##   <chr>    <int>
## 1 Metro       44
## 2 Nonmetro     6
```

### Advanced Selecting methods

```r
# Glimpse the counties table
glimpse(counties)
```

```
## Rows: 3,138
## Columns: 40
## $ census_id          <chr> "1001", "1003", "1005", "1007", "1009", "1011", "10~
## $ state              <chr> "Alabama", "Alabama", "Alabama", "Alabama", "Alabam~
## $ county             <chr> "Autauga", "Baldwin", "Barbour", "Bibb", "Blount", ~
## $ region             <chr> "South", "South", "South", "South", "South", "South~
## $ metro              <chr> "Metro", "Metro", "Nonmetro", "Metro", "Metro", "No~
## $ population         <dbl> 55221, 195121, 26932, 22604, 57710, 10678, 20354, 1~
## $ men                <dbl> 26745, 95314, 14497, 12073, 28512, 5660, 9502, 5627~
## $ women              <dbl> 28476, 99807, 12435, 10531, 29198, 5018, 10852, 603~
## $ hispanic           <dbl> 2.6, 4.5, 4.6, 2.2, 8.6, 4.4, 1.2, 3.5, 0.4, 1.5, 7~
## $ white              <dbl> 75.8, 83.1, 46.2, 74.5, 87.9, 22.2, 53.3, 73.0, 57.~
## $ black              <dbl> 18.5, 9.5, 46.7, 21.4, 1.5, 70.7, 43.8, 20.3, 40.3,~
## $ native             <dbl> 0.4, 0.6, 0.2, 0.4, 0.3, 1.2, 0.1, 0.2, 0.2, 0.6, 0~
## $ asian              <dbl> 1.0, 0.7, 0.4, 0.1, 0.1, 0.2, 0.4, 0.9, 0.8, 0.3, 0~
## $ pacific            <dbl> 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0~
## $ citizens           <dbl> 40725, 147695, 20714, 17495, 42345, 8057, 15581, 88~
## $ income             <dbl> 51281, 50254, 32964, 38678, 45813, 31938, 32229, 41~
## $ income_err         <dbl> 2391, 1263, 2973, 3995, 3141, 5884, 1793, 925, 2949~
## $ income_per_cap     <dbl> 24974, 27317, 16824, 18431, 20532, 17580, 18390, 21~
## $ income_per_cap_err <dbl> 1080, 711, 798, 1618, 708, 2055, 714, 489, 1366, 15~
## $ poverty            <dbl> 12.9, 13.4, 26.7, 16.8, 16.7, 24.6, 25.4, 20.5, 21.~
## $ child_poverty      <dbl> 18.6, 19.2, 45.3, 27.9, 27.2, 38.4, 39.2, 31.6, 37.~
## $ professional       <dbl> 33.2, 33.1, 26.8, 21.5, 28.5, 18.8, 27.5, 27.3, 23.~
## $ service            <dbl> 17.0, 17.7, 16.1, 17.9, 14.1, 15.0, 16.6, 17.7, 14.~
## $ office             <dbl> 24.2, 27.1, 23.1, 17.8, 23.9, 19.7, 21.9, 24.2, 26.~
## $ construction       <dbl> 8.6, 10.8, 10.8, 19.0, 13.5, 20.1, 10.3, 10.5, 11.5~
## $ production         <dbl> 17.1, 11.2, 23.1, 23.7, 19.9, 26.4, 23.7, 20.4, 24.~
## $ drive              <dbl> 87.5, 84.7, 83.8, 83.2, 84.9, 74.9, 84.5, 85.3, 85.~
## $ carpool            <dbl> 8.8, 8.8, 10.9, 13.5, 11.2, 14.9, 12.4, 9.4, 11.9, ~
## $ transit            <dbl> 0.1, 0.1, 0.4, 0.5, 0.4, 0.7, 0.0, 0.2, 0.2, 0.2, 0~
```

```
## $ walk                <dbl> 0.5, 1.0, 1.8, 0.6, 0.9, 5.0, 0.8, 1.2, 0.3, 0.6, 1~
## $ other_transp        <dbl> 1.3, 1.4, 1.5, 1.5, 0.4, 1.7, 0.6, 1.2, 0.4, 0.7, 1~
## $ work_at_home        <dbl> 1.8, 3.9, 1.6, 0.7, 2.3, 2.8, 1.7, 2.7, 2.1, 2.5, 1~
## $ mean_commute        <dbl> 26.5, 26.4, 24.1, 28.8, 34.9, 27.5, 24.6, 24.1, 25.~
## $ employed            <dbl> 23986, 85953, 8597, 8294, 22189, 3865, 7813, 47401,~
## $ private_work        <dbl> 73.6, 81.5, 71.8, 76.8, 82.0, 79.5, 77.4, 74.1, 85.~
## $ public_work         <dbl> 20.9, 12.3, 20.8, 16.1, 13.5, 15.1, 16.2, 20.8, 12.~
## $ self_employed       <dbl> 5.5, 5.8, 7.3, 6.7, 4.2, 5.4, 6.2, 5.0, 2.8, 7.9, 4~
## $ family_work         <dbl> 0.0, 0.4, 0.1, 0.4, 0.4, 0.0, 0.2, 0.1, 0.0, 0.5, 0~
## $ unemployment        <dbl> 7.6, 7.5, 17.6, 8.3, 7.7, 18.0, 10.9, 12.3, 8.9, 7.~
## $ land_area           <dbl> 594.44, 1589.78, 884.88, 622.58, 644.78, 622.81, 77~
```

```r
counties %>%
  # Select state, county, population, and industry-related columns
  select(state, county, population, professional:production) %>%
  # Arrange service in descending order
  arrange(desc(service))
```

```
## # A tibble: 3,138 x 8
##    state   county population professional service office construction production
##    <chr>   <chr>       <dbl>        <dbl>   <dbl>  <dbl>        <dbl>      <dbl>
##  1 Missis~ Tunica      10477         23.9    36.6   21.5          3.5       14.5
##  2 Texas   Kinney       3577         30      36.5   11.6         20.5        1.3
##  3 Texas   Kenedy        565         24.9    34.1   20.5         20.5        0
##  4 New Yo~ Bronx     1428357         24.3    33.3   24.2          7.1       11
##  5 Texas   Brooks       7221         19.6    32.4   25.3         11.1       11.5
##  6 Colora~ Fremo~      46809         26.6    32.2   22.8         10.7        7.6
##  7 Texas   Culbe~       2296         20.1    32.2   24.2         15.7        7.8
##  8 Califo~ Del N~      27788         33.9    31.5   18.8          8.9        6.8
##  9 Minnes~ Mahno~       5496         26.8    31.5   18.7         13.1        9.9
## 10 Virgin~ Lanca~      11129         30.3    31.2   22.8          8.1        7.6
## # ... with 3,128 more rows
```

```r
counties %>%
  # Select the state, county, population, and those ending with "work"
  select(state, county, population, ends_with("work")) %>%
  # Filter for counties that have at least 50% of people engaged in public work
  filter(public_work >= 50)
```

```
## # A tibble: 7 x 6
##   state        county            population private_work public_work family_work
##   <chr>        <chr>                  <dbl>        <dbl>       <dbl>       <dbl>
## 1 Alaska       Lake and Peninsu~       1474         42.2        51.6         0.2
## 2 Alaska       Yukon-Koyukuk Ce~       5644         33.3        61.7         0
## 3 California   Lassen                 32645         42.6        50.5         0.1
## 4 Hawaii       Kalawao                   85         25          64.1         0
## 5 North Dakota Sioux                   4380         32.9        56.8         0.1
## 6 South Dakota Todd                    9942         34.4        55           0.8
## 7 Wisconsin    Menominee               4451         36.8        59.1         0.4
```

Rename a column

```r
# Rename the n column to num_counties
counties %>%
  count(state) %>%
  rename(num_counties = n)
```

```
## # A tibble: 50 x 2
##    state       num_counties
##    <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
```

```r
# Select state, county, and poverty as poverty_rate
counties %>%
  select(state, county, poverty_rate = poverty)
```

```
## # A tibble: 3,138 x 3
##    state   county   poverty_rate
##    <chr>   <chr>           <dbl>
##  1 Alabama Autauga          12.9
##  2 Alabama Baldwin          13.4
##  3 Alabama Barbour          26.7
##  4 Alabama Bibb             16.8
##  5 Alabama Blount           16.7
##  6 Alabama Bullock          24.6
##  7 Alabama Butler           25.4
##  8 Alabama Calhoun          20.5
##  9 Alabama Chambers         21.6
## 10 Alabama Cherokee         19.2
## # ... with 3,128 more rows
```

```
                  Keeps only specified variables      Keep other variables
```

Can't change values SELECT RENAME

Can change Values TRANSMUTE MUTATE

```r
counties %>%
  # Keep the state, county, and populations columns, and add a density column
  transmute(state, county, population, density = population / land_area) %>%
  # Filter for counties with a population greater than one million
  filter(population > 1000000) %>%
  # Sort density in ascending order
  arrange(density)
```

```
## # A tibble: 41 x 4
##    state      county         population density
##    <chr>      <chr>               <dbl>   <dbl>
##  1 California San Bernardino    2094769    104.
##  2 Nevada     Clark             2035572    258.
##  3 California Riverside         2298032    319.
##  4 Arizona    Maricopa          4018143    437.
##  5 Florida    Palm Beach        1378806    700.
##  6 California San Diego         3223096    766.
```

```
##  7 Washington King              2045756    967.
##  8 Texas      Travis            1121645   1133.
##  9 Florida    Hillsborough      1302884   1277.
## 10 Florida    Orange            1229039   1360.
## # ... with 31 more rows
```

Select vs rename vs mutate vs transmute:

```r
# Change the name of the unemployment column
counties %>%
  rename(unemployment_rate = unemployment)
```

```
## # A tibble: 3,138 x 40
##    census_id state   county   region metro population   men women hispanic white
##    <chr>     <chr>   <chr>    <chr>  <chr>      <dbl> <dbl> <dbl>    <dbl> <dbl>
##  1 1001      Alabama Autauga  South  Metro      55221 26745 28476      2.6  75.8
##  2 1003      Alabama Baldwin  South  Metro     195121 95314 99807      4.5  83.1
##  3 1005      Alabama Barbour  South  Nonm~      26932 14497 12435      4.6  46.2
##  4 1007      Alabama Bibb     South  Metro      22604 12073 10531      2.2  74.5
##  5 1009      Alabama Blount   South  Metro      57710 28512 29198      8.6  87.9
##  6 1011      Alabama Bullock  South  Nonm~      10678  5660  5018      4.4  22.2
##  7 1013      Alabama Butler   South  Nonm~      20354  9502 10852      1.2  53.3
##  8 1015      Alabama Calhoun  South  Metro     116648 56274 60374      3.5  73
##  9 1017      Alabama Chambers South  Nonm~      34079 16258 17821      0.4  57.3
## 10 1019      Alabama Cherokee South  Nonm~      26008 12975 13033      1.5  91.7
## # ... with 3,128 more rows, and 30 more variables: black <dbl>, native <dbl>,
## #   asian <dbl>, pacific <dbl>, citizens <dbl>, income <dbl>, income_err <dbl>,
## #   income_per_cap <dbl>, income_per_cap_err <dbl>, poverty <dbl>,
## #   child_poverty <dbl>, professional <dbl>, service <dbl>, office <dbl>,
## #   construction <dbl>, production <dbl>, drive <dbl>, carpool <dbl>,
## #   transit <dbl>, walk <dbl>, other_transp <dbl>, work_at_home <dbl>,
## #   mean_commute <dbl>, employed <dbl>, private_work <dbl>, ...
```

```r
# Keep the state and county columns, and the columns containing poverty
counties %>%
  select(state, county, contains("poverty"))
```

```
## # A tibble: 3,138 x 4
##    state   county   poverty child_poverty
##    <chr>   <chr>      <dbl>         <dbl>
##  1 Alabama Autauga     12.9          18.6
##  2 Alabama Baldwin     13.4          19.2
##  3 Alabama Barbour     26.7          45.3
##  4 Alabama Bibb        16.8          27.9
##  5 Alabama Blount      16.7          27.2
##  6 Alabama Bullock     24.6          38.4
##  7 Alabama Butler      25.4          39.2
##  8 Alabama Calhoun     20.5          31.6
##  9 Alabama Chambers    21.6          37.2
## 10 Alabama Cherokee    19.2          30.1
## # ... with 3,128 more rows
```

```r
# Calculate the fraction_women column without dropping the other columns
counties %>%
  mutate(fraction_women = women / population)
```

```
## # A tibble: 3,138 x 41
```

```
##    census_id state   county   region metro population   men women hispanic white
##    <chr>     <chr>   <chr>    <chr>  <chr>      <dbl> <dbl> <dbl>    <dbl> <dbl>
##  1 1001      Alabama Autauga  South  Metro      55221 26745 28476      2.6  75.8
##  2 1003      Alabama Baldwin  South  Metro     195121 95314 99807      4.5  83.1
##  3 1005      Alabama Barbour  South  Nonm~      26932 14497 12435      4.6  46.2
##  4 1007      Alabama Bibb     South  Metro      22604 12073 10531      2.2  74.5
##  5 1009      Alabama Blount   South  Metro      57710 28512 29198      8.6  87.9
##  6 1011      Alabama Bullock  South  Nonm~      10678  5660  5018      4.4  22.2
##  7 1013      Alabama Butler   South  Nonm~      20354  9502 10852      1.2  53.3
##  8 1015      Alabama Calhoun  South  Metro     116648 56274 60374      3.5  73
##  9 1017      Alabama Chambers South  Nonm~      34079 16258 17821      0.4  57.3
## 10 1019      Alabama Cherokee South  Nonm~      26008 12975 13033      1.5  91.7
## # ... with 3,128 more rows, and 31 more variables: black <dbl>, native <dbl>,
## #   asian <dbl>, pacific <dbl>, citizens <dbl>, income <dbl>, income_err <dbl>,
## #   income_per_cap <dbl>, income_per_cap_err <dbl>, poverty <dbl>,
## #   child_poverty <dbl>, professional <dbl>, service <dbl>, office <dbl>,
## #   construction <dbl>, production <dbl>, drive <dbl>, carpool <dbl>,
## #   transit <dbl>, walk <dbl>, other_transp <dbl>, work_at_home <dbl>,
## #   mean_commute <dbl>, employed <dbl>, private_work <dbl>, ...
```

```r
# Keep only the state, county, and employment_rate columns
counties %>%
  transmute(state, county, employment_rate = employed / population)
```

```
## # A tibble: 3,138 x 3
##    state   county   employment_rate
##    <chr>   <chr>              <dbl>
##  1 Alabama Autauga            0.434
##  2 Alabama Baldwin            0.441
##  3 Alabama Barbour            0.319
##  4 Alabama Bibb               0.367
##  5 Alabama Blount             0.384
##  6 Alabama Bullock            0.362
##  7 Alabama Butler             0.384
##  8 Alabama Calhoun            0.406
##  9 Alabama Chambers           0.402
## 10 Alabama Cherokee           0.390
## # ... with 3,128 more rows
```

### Babynames dataset

```r
babynames <- readRDS("babynames.rds")
glimpse(babynames)
```

```
## Rows: 332,595
## Columns: 3
## $ year   <dbl> 1880, 1880, 1880, 1880, 1880, 1880, 1880, 1880, 1880, 1880, 188~
## $ name   <chr> "Aaron", "Ab", "Abbie", "Abbott", "Abby", "Abe", "Abel", "Abiga~
## $ number <int> 102, 5, 71, 5, 6, 50, 9, 12, 27, 81, 21, 652, 24, 23, 104, 14, ~
```

```r
babynames %>%
  # Filter for the year 1990
  filter(year == 1990) %>%
  # Sort the number column in descending order
  arrange(desc(number))
```

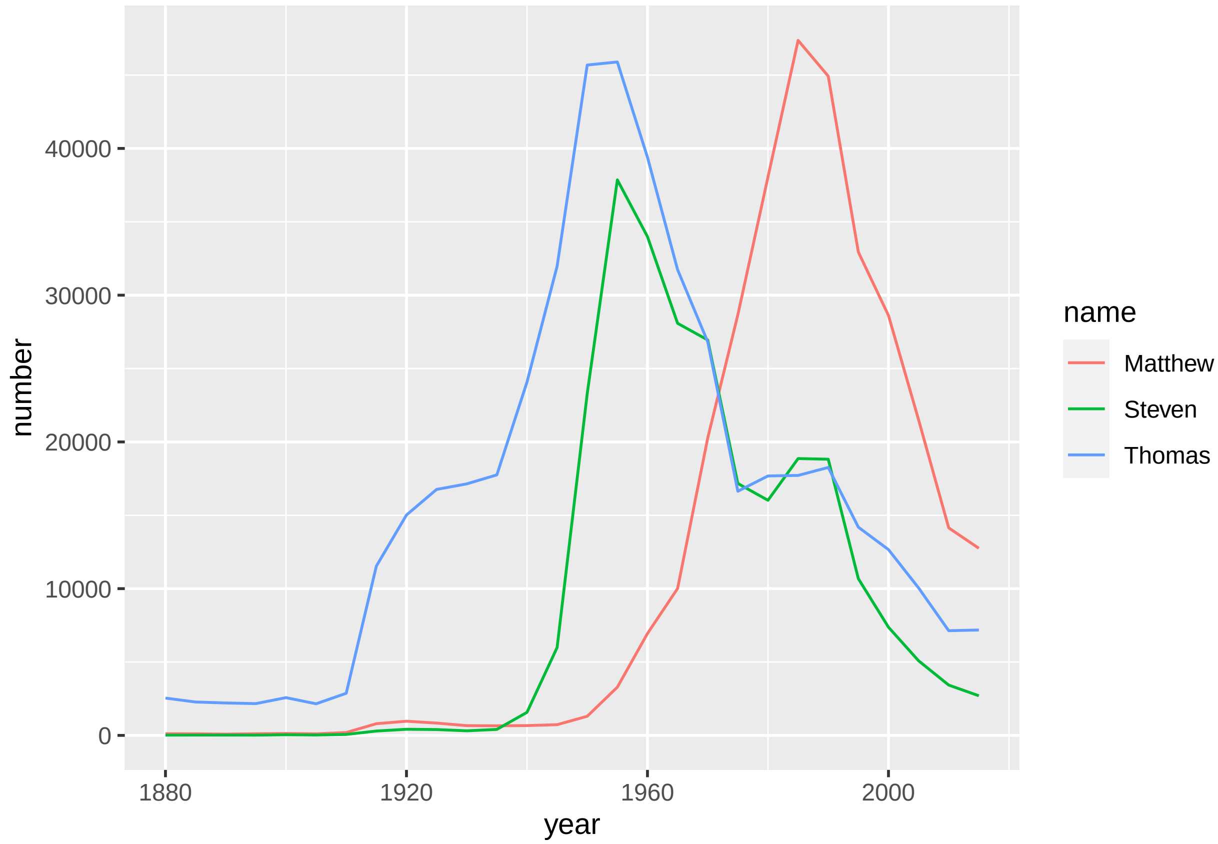
```
## # A tibble: 21,223 x 3
##     year name        number
##    <dbl> <chr>        <int>
##  1  1990 Michael      65560
##  2  1990 Christopher  52520
##  3  1990 Jessica      46615
##  4  1990 Ashley       45797
##  5  1990 Matthew      44925
##  6  1990 Joshua       43382
##  7  1990 Brittany     36650
##  8  1990 Amanda       34504
##  9  1990 Daniel       33963
## 10  1990 David        33862
## # ... with 21,213 more rows
```

```r
babynames %>%
  group_by(year) %>%
  top_n(1, number)
```

```
## # A tibble: 28 x 3
## # Groups:   year [28]
##     year name  number
##    <dbl> <chr>  <int>
##  1  1880 John    9701
##  2  1885 Mary    9166
##  3  1890 Mary   12113
##  4  1895 Mary   13493
##  5  1900 Mary   16781
##  6  1905 Mary   16135
##  7  1910 Mary   22947
##  8  1915 Mary   58346
##  9  1920 Mary   71175
## 10  1925 Mary   70857
## # ... with 18 more rows
```

Ggplot visualization

```r
# Filter for the names Steven, Thomas, and Matthew
selected_names <- babynames %>%
  filter(name %in% c("Steven", "Thomas", "Matthew"))

# Plot the names using a different color for each name
ggplot(selected_names, aes(x = year, y = number, color = name)) +
  geom_line()
```



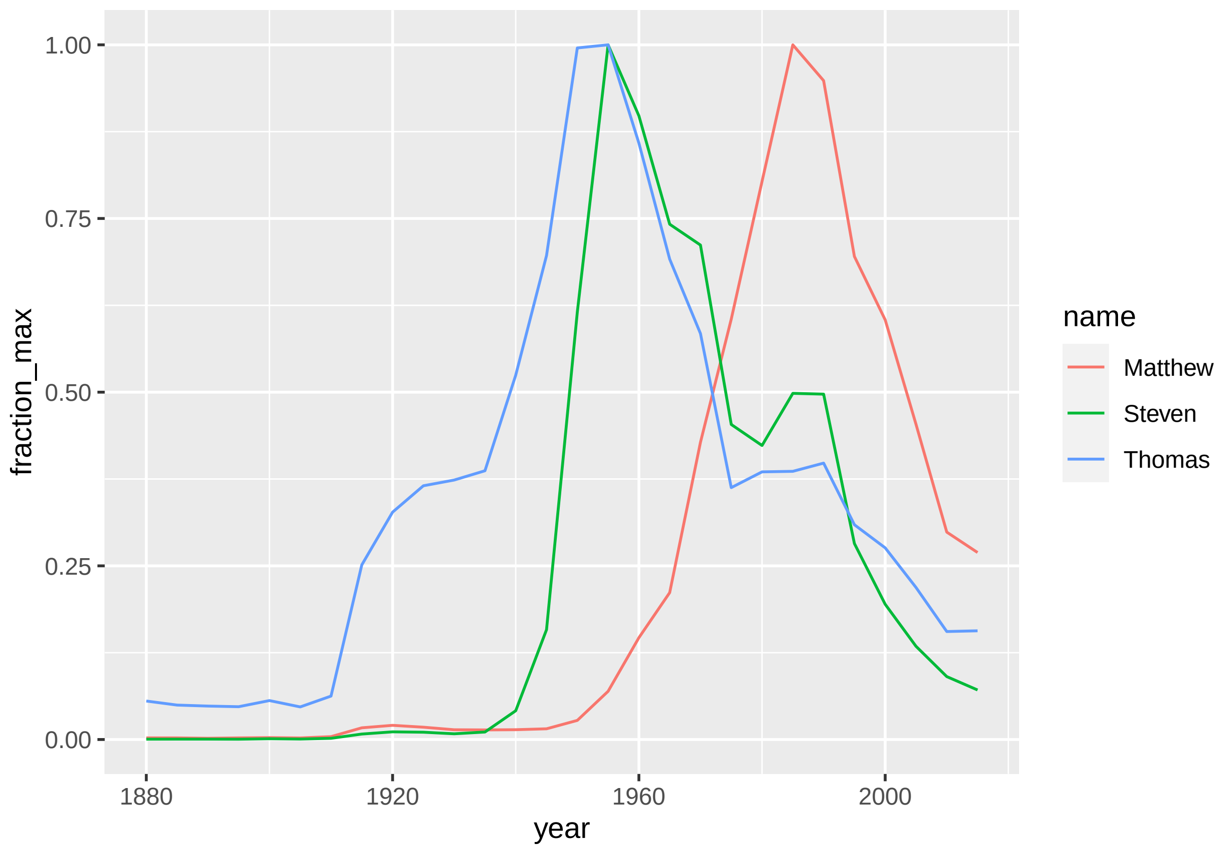

```r
# Calculate the fraction of people born each year with the same name
babynames %>%
  group_by(year) %>%
  mutate(year_total = sum(number)) %>%
  ungroup() %>%
  mutate(fraction = number / year_total) %>%
  # Find the year each name is most common
  group_by(name) %>%
  top_n(1, fraction)
```

```
## # A tibble: 48,040 x 5
## # Groups:   name [48,040]
##     year name      number year_total  fraction
##    <dbl> <chr>      <int>      <int>     <dbl>
##  1  1880 Abbott         5     201478 0.0000248
##  2  1880 Abe           50     201478 0.000248
##  3  1880 Abner         27     201478 0.000134
##  4  1880 Adelbert      28     201478 0.000139
##  5  1880 Adella        26     201478 0.000129
##  6  1880 Adolf          6     201478 0.0000298
##  7  1880 Adolph        93     201478 0.000462
##  8  1880 Agustus        5     201478 0.0000248
##  9  1880 Albert      1493     201478 0.00741
## 10  1880 Albertina      7     201478 0.0000347
## # ... with 48,030 more rows
```

```r
babynames %>%
  # Add columns name_total and name_max for each name
  group_by(name) %>%
  mutate(name_total = sum(number),
         name_max = max(number)) %>%

  # Ungroup the table
  ungroup() %>%
  # Add the fraction_max column containing the number by the name maximum
  mutate(fraction_max = number / name_max)
```

```
## # A tibble: 332,595 x 6
##     year name    number name_total name_max fraction_max
##    <dbl> <chr>    <int>      <int>    <int>        <dbl>
##  1  1880 Aaron      102     114739    14635     0.00697
##  2  1880 Ab           5         77       31     0.161
##  3  1880 Abbie       71       4330      445     0.160
##  4  1880 Abbott       5        217       51     0.0980
##  5  1880 Abby         6      11272     1753     0.00342
##  6  1880 Abe         50       1832      271     0.185
##  7  1880 Abel         9      10565     3245     0.00277
##  8  1880 Abigail     12      72600    15762     0.000761
##  9  1880 Abner       27       1552      199     0.136
## 10  1880 Abraham     81      17882     2449     0.0331
## # ... with 332,585 more rows
```

```r
names_normalized <- babynames %>%
                     group_by(name) %>%
                     mutate(name_total = sum(number),
                            name_max = max(number)) %>%
                     ungroup() %>%
                     mutate(fraction_max = number / name_max)

# Filter for the names Steven, Thomas, and Matthew
names_filtered <- names_normalized %>%
  filter(name %in% c("Steven", "Thomas", "Matthew"))

# Visualize these names over time
ggplot(names_filtered, aes(x = year, y = fraction_max, color = name)) +
  geom_line()
```




Using fractions

```
babynames_fraction <- babynames %>%
                      group_by(year) %>%
                      mutate(year_total = sum(number)) %>%
                      ungroup() %>%
                      mutate(fraction = number / year_total)

babynames_fraction %>%
  # Arrange the data in order of name, then year
  arrange(name, year) %>%
  # Group the data by name
  group_by(name) %>%
  # Add a ratio column that contains the ratio between each year
  mutate(ratio = fraction / lag(fraction))
```

```
## # A tibble: 332,595 x 6
## # Groups:   name [48,040]
##      year name    number year_total   fraction  ratio
##     <dbl> <chr>    <int>      <int>      <dbl>  <dbl>
##  1  2010 Aaban         9    3672066 0.00000245 NA
##  2  2015 Aaban        15    3648781 0.00000411  1.68
##  3  1995 Aadam         6    3652750 0.00000164 NA
##  4  2000 Aadam         6    3767293 0.00000159  0.970
##  5  2005 Aadam         6    3828460 0.00000157  0.984
##  6  2010 Aadam         7    3672066 0.00000191  1.22
##  7  2015 Aadam        22    3648781 0.00000603  3.16
```

```
## 8  2010 Aadan       11    3672066 0.00000300 NA
## 9  2015 Aadan       10    3648781 0.00000274  0.915
## 10 2000 Aadarsh      5    3767293 0.00000133 NA
## # ... with 332,585 more rows
```

```
babynames_ratios_filtered <- babynames_fraction %>%
                     arrange(name, year) %>%
                     group_by(name) %>%
                     mutate(ratio = fraction / lag(fraction)) %>%
                     filter(fraction >= 0.00001)

babynames_ratios_filtered %>%
  # Extract the largest ratio from each name
  top_n(1, ratio) %>%
  # Sort the ratio column in descending order
  arrange(desc(ratio)) %>%
  # Filter for fractions greater than or equal to 0.001
  filter(fraction >= 0.001)
```

```
## # A tibble: 291 x 6
## # Groups:   name [291]
##     year name    number year_total fraction ratio
##    <dbl> <chr>    <int>      <int>    <dbl> <dbl>
##  1  1960 Tammy    14365    4152075  0.00346  70.1
##  2  2005 Nevaeh    4610    3828460  0.00120  45.8
##  3  1940 Brenda    5460    2301630  0.00237  37.5
##  4  1885 Grover     774     240822  0.00321  36.0
##  5  1945 Cheryl    8170    2652029  0.00308  24.9
##  6  1955 Lori      4980    4012691  0.00124  23.2
##  7  2010 Khloe     5411    3672066  0.00147  23.2
##  8  1950 Debra     6189    3502592  0.00177  22.6
##  9  2010 Bentley   4001    3672066  0.00109  22.4
## 10  1935 Marlene   4840    2088487  0.00232  16.8
## # ... with 281 more rows
```