Lab 2: Data Tidying

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Overview

In this assignment you will work to tidy, clean, and analyze two different datasets, the first is a small dataset contained in a csv file called flightdelays.csv, and the second called MixedDrinkRecipes-Prep.csv.

The most important book chapters which cover the techniques you will practice here are R4DS Chapters 5 and 7. Also helpful are the `tidyr` vignette on pivoting and the ggplot help page on the geom_dotplot.

Submit your completed assignment on the course brightspace page by uploading your `.qmd` file and a compiled `pdf` or link to a compiled `html`, which you could host on your `github` or `rpubs` page as you wish.

Part 1: Airplane flight delays

Consider the following dataset:

		Los_Angeles	Phoenix	San_Diego	San_Francisco	Seattle
ALASKA	On_Time	497	221	212	503	1841
	Delayed	62	12	20	102	305
AM WEST	On_Time	694	4840	383	320	301
	Delayed	117	415	65	129	61

The above table describes arrival delays for two different airlines across several destinations. The numbers correspond the the number of flights that were in either the delayed category or the on time category.

Problems

Problem 1: Read the information from `flightdelays.csv` into R, and use `tidyr` and `dplyr` to convert this data into a tidy/tall format with names and complete data for all columns. Your final data frame should have `City`, `On_Time_Flights` and `Delayed_Flights` as columns (the exact names are up to you). In addition to `pivot_longer`, `pivot_wider` and `rename`, you might find the `tidyr` function `fill` helpful for completing this task efficiently. Although this is a small dataset that you could easily reshape by hand, you should solve this problem using tidyverse functions that do the work for you.

```
flightdelay = read_csv('flightdelays.csv')
```

```
# pivot longer
flightdelay1 <- flightdelay |> pivot_longer(cols = 'Los_Angeles':'Seattle', names_to = 'City

# rename df columns
flightdelay2 <- flightdelay1 |> rename('Airline'='...1', 'Status'='...2')

# Fill missing Airline values
flightdelay2 <- flightdelay2 %>%
  fill(Airline, .direction = "down")  # Fill downwards within each group

flightdelay2
```

```
# A tibble: 20 x 4
   Airline Status  City          N_of_flights
   <chr>   <chr>   <chr>                <dbl>
 1 ALASKA  On_Time Los_Angeles            497
 2 ALASKA  On_Time Phoenix                221
 3 ALASKA  On_Time San_Diego              212
 4 ALASKA  On_Time San_Francisco          503
 5 ALASKA  On_Time Seattle               1841
 6 ALASKA  Delayed Los_Angeles             62
 7 ALASKA  Delayed Phoenix                 12
 8 ALASKA  Delayed San_Diego               20
 9 ALASKA  Delayed San_Francisco          102
10 ALASKA  Delayed Seattle                305
11 AM WEST On_Time Los_Angeles            694
12 AM WEST On_Time Phoenix               4840
13 AM WEST On_Time San_Diego              383
14 AM WEST On_Time San_Francisco          320
```

```
15 AM WEST On_Time Seattle                301
16 AM WEST Delayed Los_Angeles            117
17 AM WEST Delayed Phoenix                415
18 AM WEST Delayed San_Diego               65
19 AM WEST Delayed San_Francisco          129
20 AM WEST Delayed Seattle                 61
```

```
flightdelay3 <- flightdelay2 |> pivot_wider(names_from = Status, values_from = N_of_flights,
# sum the duplicate values
 flightdelay3
```

```
# A tibble: 10 x 4
   Airline City          On_Time Delayed
   <chr>   <chr>           <dbl>   <dbl>
 1 ALASKA  Los_Angeles       497      62
 2 ALASKA  Phoenix           221      12
 3 ALASKA  San_Diego         212      20
 4 ALASKA  San_Francisco     503     102
 5 ALASKA  Seattle          1841     305
 6 AM WEST Los_Angeles       694     117
 7 AM WEST Phoenix          4840     415
 8 AM WEST San_Diego         383      65
 9 AM WEST San_Francisco     320     129
10 AM WEST Seattle           301      61
```

Problem 2: Take the data-frame that you tidied and cleaned in Problem 1 and create additional columns which contain the fraction of on-time and delayed flights at each airport. Then create a dot-plot using the `geom_dotplot` function (see the ggplot page for dotplot) to visualize the difference in flight delays between the two airlines at each city in the dataset. What conclusions can you draw from the dotplot?

Optional: If you want to make a fancier visualization consider adding text labels containing the airline names above the dots using `geom_text` and `position = position_nudge(...)` with appropriate arguments.

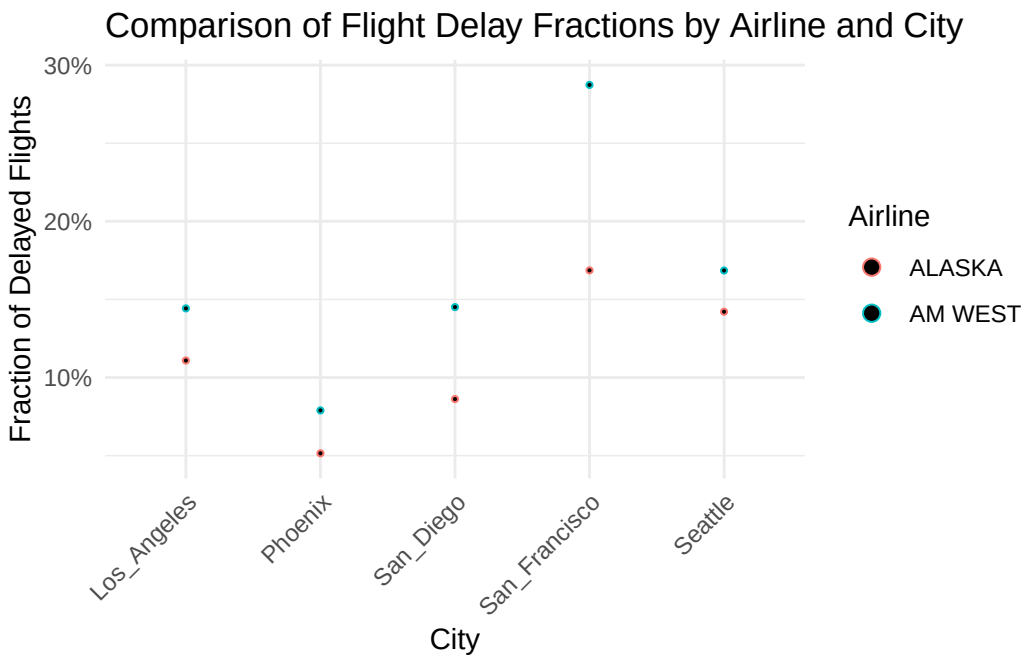
```
# Calculate fractions of on-time and delayed flights
flightdelay4 <- flightdelay3 %>%
  group_by(Airline, City) %>%
  mutate(fraction_on_time = On_Time / sum(On_Time, Delayed),
         fraction_delayed = Delayed / sum(On_Time, Delayed))

flightdelay4
```

```
# A tibble: 10 x 6
# Groups:   Airline, City [10]
   Airline City          On_Time Delayed fraction_on_time fraction_delayed
   <chr>   <chr>           <dbl>   <dbl>            <dbl>            <dbl>
 1 ALASKA  Los_Angeles       497      62            0.889           0.111
 2 ALASKA  Phoenix           221      12            0.948           0.0515
 3 ALASKA  San_Diego         212      20            0.914           0.0862
 4 ALASKA  San_Francisco     503     102            0.831           0.169
 5 ALASKA  Seattle          1841     305            0.858           0.142
 6 AM WEST Los_Angeles       694     117            0.856           0.144
 7 AM WEST Phoenix          4840     415            0.921           0.0790
 8 AM WEST San_Diego         383      65            0.855           0.145
 9 AM WEST San_Francisco     320     129            0.713           0.287
10 AM WEST Seattle           301      61            0.831           0.169
```

```
install.packages("ggrepel")  # Install if you haven't already
```

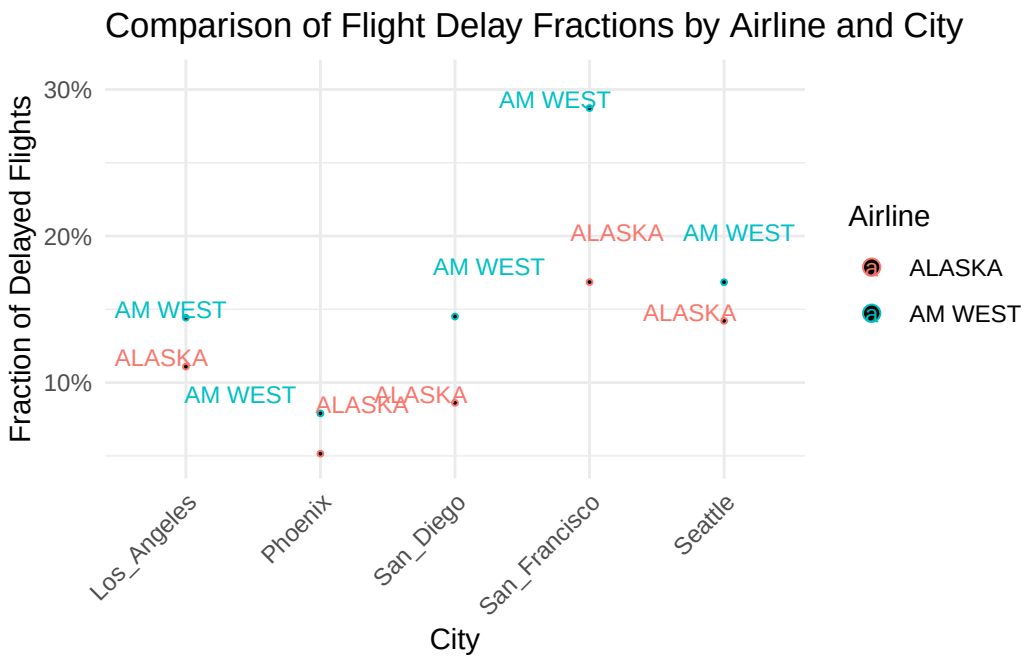
```
# Create the dot plot
ggplot(flightdelay4, aes(x = City, y = fraction_delayed, color = Airline)) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5) +
  scale_y_continuous(labels = scales::percent_format()) +  # Format y-axis as percentages
  labs(title = "Comparison of Flight Delay Fractions by Airline and City",
       x = "City", y = "Fraction of Delayed Flights") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) # Rotate x-axis labels for better
```

```
Bin width defaults to 1/30 of the range of the data. Pick better value with
`binwidth`.
```




```
# Optional: Add text labels for airlines (requires 'ggrepel' package)

library(ggrepel)

ggplot(flightdelay4, aes(x = City, y = fraction_delayed, color = Airline, label = Airline)) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5) +
  geom_text_repel(position = position_nudge(y = 0.02),  # Adjust nudge as needed
                  size = 3) +  # Adjust text size as needed
  scale_y_continuous(labels = scales::percent_format()) +
  labs(title = "Comparison of Flight Delay Fractions by Airline and City",
       x = "City", y = "Fraction of Delayed Flights") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
Bin width defaults to 1/30 of the range of the data. Pick better value with
`binwidth`.
```



Part 1 ***Discussion*** The fraction of delay flight increase with the size of the airport, Phoenix has the lowest ration while San Francisco hast the highest ratio of delayed flights. However one airline has lower performance that the other in both of the ariports.

Part 2: Mixed Drink Recipes

In the second part of this assignment we will be working with a dataset containing ingredients for different types of mixed drinks. This dataset is untidy and messy- it is in a wide data format and contains some inconsistencies that should be fixed.

Problems

Problem 3 Load the mixed drink recipe dataset into R from the file `MixedDrinkRecipes-prep.csv`, which you can download from my github page by clicking here. The variables `ingredient1` through `ingredient6` list the ingredients of the cocktail listed in the `name` column. Notice that there are many `NA` values in the ingredient columns, indicating that most cocktails have under 6 ingredients.

```
cocktail = read_csv('MixedDrinkRecipes-Prep.csv')
```

Tidy this dataset using `pivot_longer` to create a new data frame where each there is a row corresponding to each ingredient of all the cocktails, and an additional variable specifying the "rank" of that cocktail in the original recipe, i.e. it should look like this:

name	category	Ingredient_Rank	Ingredient
Gauguin	Cocktail Classics	1	Light Rum
Gauguin	Cocktail Classics	2	Passion Fruit Syrup
Gauguin	Cocktail Classics	3	Lemon Juice
Gauguin	Cocktail Classics	4	Lime Juice
Fort Lauderdale	Cocktail Classics	1	Light Rum

where the data-type of `Ingredient_Rank` is an integer. Hint: Use the `parse_number()` function in mutate after your initial pivot.

```
cocktail1 <- cocktail |> pivot_longer(cols = ingredient1:ingredient6, names_to = "Ingredient_

cocktail1
```

```
# A tibble: 3,934 x 4
   name            category              Ingredient_Rank Ingredient
   <chr>           <chr>                           <dbl> <chr>
 1 Gauguin         Cocktail Classics                   1 Light Rum
 2 Gauguin         Cocktail Classics                   2 Passion Fruit Syrup
 3 Gauguin         Cocktail Classics                   3 Lemon Juice
 4 Gauguin         Cocktail Classics                   4 Lime Juice
 5 Fort Lauderdale Cocktail Classics                   1 Light Rum
 6 Fort Lauderdale Cocktail Classics                   2 Sweet Vermouth
 7 Fort Lauderdale Cocktail Classics                   3 Juice of Orange
 8 Fort Lauderdale Cocktail Classics                   4 Juice of a Lime
 9 Apple Pie       Cordials and Liqueurs               1 Apple schnapps
10 Apple Pie       Cordials and Liqueurs               2 Cinnamon schnapps
# i 3,924 more rows
```

Problem 4: Some of the ingredients in the ingredient list have different names, but are nearly the same thing. An example include `Lemon Juice` versus `Juice of a lemon`. Make a list of the ingredients appearing in the ingredient list ranked by how commonly they occur along with the number of occurrences, and print the first 10 elements of the list here. Then check more ingredients (I suggest looking at more ingredients and even sorting them alphabetically using `arrange(asc(ingredient))`) and see if you can spot pairs of ingredients that are similar but have different names. Use `if_else`(click here for if_else) in combination with `mutate` to make it so that the pairs of ingredients you found have the same name. You don't have to

find all pairs, but find at least 5 pairs of ingredients to rename. Because the purpose of this renaming is to facilitate a hypothetical future analysis, you can choose your own criteria for similarity as long as it is somewhat justifiable.

```
# Count occurrences of each ingredient
ingredient_counts <- cocktail1 %>%
  group_by(Ingredient) %>%
  summarize(Count = n()) %>%
  arrange(desc(Count))

# Print the top 10 ingredients
print(head(ingredient_counts, 10))
```

```
# A tibble: 10 x 2
   Ingredient        Count
   <chr>             <int>
 1 Gin                 176
 2 Fresh lemon juice   138
 3 Simple Syrup        115
 4 Light Rum           114
 5 Vodka               114
 6 Dry Vermouth        107
 7 Fresh Lime Juice    107
 8 Triple Sec          107
 9 Powdered Sugar       90
10 Grenadine            85
```

```
# Sort ingredients alphabetically
sorted_ingredients <- cocktail1 %>%
  arrange(Ingredient) %>%
  distinct(Ingredient)

# Print the sorted ingredients (you'll need to visually inspect this output)
print(sorted_ingredients)
```

```
# A tibble: 673 x 1
   Ingredient
   <chr>
 1 100-proof Vodka
 2 151-Proof Rum
 3 17-year-old J. Wray and Nephew Ltd. Rum
```

```
 4 7-Up
 5 Absinthe
 6 Absinthe Substitute
 7 Absinthe or pastis
 8 Acai berry flavored vodka
 9 African rum
10 Agave nectar
# i 663 more rows
```

```
# Standardize ingredient names
cocktail2 <- cocktail1 %>%
  mutate(Ingredient = if_else(Ingredient == "Lemon Juice", "Juice of a Lemon",
                              if_else(Ingredient == "Lime Juice", "Juice of a Lime",
                                      if_else(Ingredient == "Almond milk", "Almond extract",
                                              if_else(Ingredient == "Orange Juice", "Juice o
                                                      if_else(Ingredient == "Absithe Substitu
                                                              Ingredient))))))

# Print first few rows to verify
print(head(cocktail2))
```

```
# A tibble: 6 x 4
  name            category          Ingredient_Rank Ingredient
  <chr>           <chr>                       <dbl> <chr>
1 Gauguin         Cocktail Classics               1 Light Rum
2 Gauguin         Cocktail Classics               2 Passion Fruit Syrup
3 Gauguin         Cocktail Classics               3 Juice of a Lemon
4 Gauguin         Cocktail Classics               4 Juice of a Lime
5 Fort Lauderdale Cocktail Classics               1 Light Rum
6 Fort Lauderdale Cocktail Classics               2 Sweet Vermouth
```

Notice that there are some ingredients that appear to be two or more ingredients strung together with commas. These would be candidates for more cleaning though this exercise doesn't ask you to fix them.

Problem 5: Some operations are easier to do on `wide` data rather than `tall` data. Find the 10 most common pairs of ingredients occurring in the top 2 ingredients in a recipe. It is much easier to do this with a `wide` dataset, so use `pivot_wider` to change the data so that each row contains all of the ingredients of a single cocktail, just like in the format of the original data-set. Then use `count` on the `1` and `2` rows to determine the most common pairs (see chapter 3 for a refresher on `count`).

Note: You may be interested to read about the **widyr** package here: widyr page. It is designed to solve problems like this one and uses internal pivot steps to accomplish it so that the final result is tidy. I'm actually unaware of any easy ways of solving problem 5 without pivoting to a wide dataset.

```
# Pivot the dataframe back to wide format
cocktail_wide <- cocktail2 %>%
  pivot_wider(id_cols = c(name, category),names_from = Ingredient_Rank,
              values_from = Ingredient)

# Count the most common pairs of ingredients in columns 1 and 2
top_ingredient_pairs <- cocktail_wide %>%
  count(`1`, `2`, sort = TRUE) %>%
  head(10)

# Print the top 10 pairs
print(top_ingredient_pairs)
```

```
# A tibble: 10 x 3
   `1`              `2`                  n
   <chr>            <chr>            <int>
 1 Juice of a Lemon Powdered Sugar      24
 2 Gin              Dry Vermouth        23
 3 Whole Egg        Powdered Sugar      13
 4 Light Rum        Fresh Lime Juice    12
 5 Gin              Triple Sec           9
 6 Bourbon whiskey  Fresh lemon juice    8
 7 Brandy           Sweet Vermouth       7
 8 Gin              Sweet Vermouth       7
 9 Light Rum        Pineapple Juice      7
10 Light Rum        Sweet Vermouth       7
```