Let’s read in the data on African names and use
skimr to see what’s there.

```
african_names <- readr::read_csv("https://raw.githubusercontent.com/rfordatascience/tidytuesday/master/data/2020/2020-06-16/african_names.csv")
```

```
skimr::skim(african_names)
```

```
## ── Data Summary ────────────────────────
##                            Values
## Name                       african_names
## Number of rows             91490
## Number of columns          11
## _______________________
## Column type frequency:
##   character                6
##   numeric                  5
## ________________________
## Group variables            None
##
## ── Variable type: character ──────────────────────────────
──────────────────────
##   skim_variable  n_missing complete_rate   min   max empty n_unique
whitespace
## 1 name                   0             1     2    24     0    62330
0
## 2 gender             12878         0.859     3     5     0        4
0
## 3 ship_name              1          1.00     2    59     0      443
0
## 4 port_disembark         0             1     6    19     0        5
0
## 5 port_embark         1126         0.988     4    31     0       59
0
## 6 country_origin     79404         0.132     3    31     0      563
0
##
## ── Variable type: numeric ──────────────────────────────
────────────────────────
##   skim_variable n_missing complete_rate    mean       sd    p0    p25    p50
## 1 id                    0             1  62122.  51305.      1  22935. 45822.
## 2 voyage_id             0             1  17698.  82017.    557   2443   2871
## 3 age                1126         0.988    18.9     8.60   0.5     11     20
## 4 height             4820         0.947    58.6     6.84     0     54     60
## 5 year_arrival          0             1   1831.     9.52 1808   1826   1832
##        p75    p100 hist
## 1 101264. 199932 ▇▆▂▁▁
## 2    3601   500082 ▇▁▁▁▁
## 3      26       77 ▆▇▁▁▁
## 4      64       85 ▁▁▂▇▁
## 5    1837     1862 ▁▅▇▂▁
```

There is data missing in both the gender and age variables, two I am interested in.

This is a dataset of individual people who were liberated from slave ships. Where did the people in this dataset *leave* their ships?

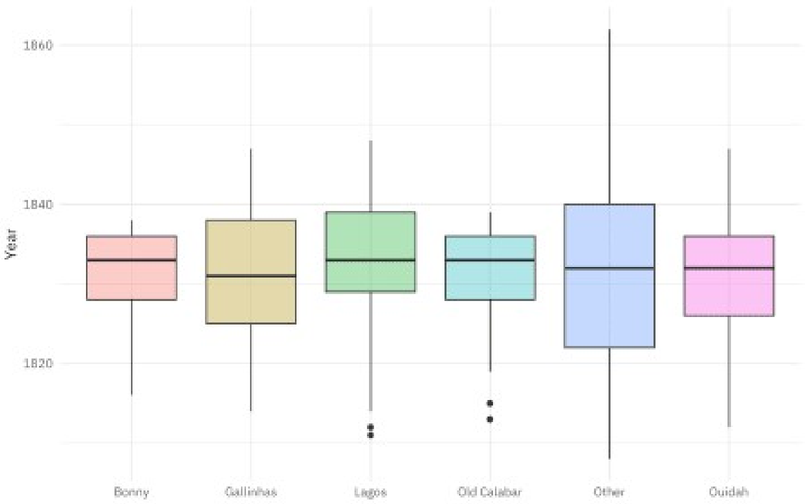
```
african_names %>%
  count(port_disembark, sort = TRUE) %>%
  kable()
```

port_disembark	n
Freetown	81009
Havana	10058
Bahamas unspecified	183
Kingston, Jamaica	144
St. Helena	96

Most of the freed captives in this database were liberated in either Freetown, Sierra Leone (so on the eastern side of the Atlantic) or Havana, Cuba (on the western side). Both cities had tribunals/courts to judge ships seized by anti-slaving patrols after European countries outlawed or restricted slavery.

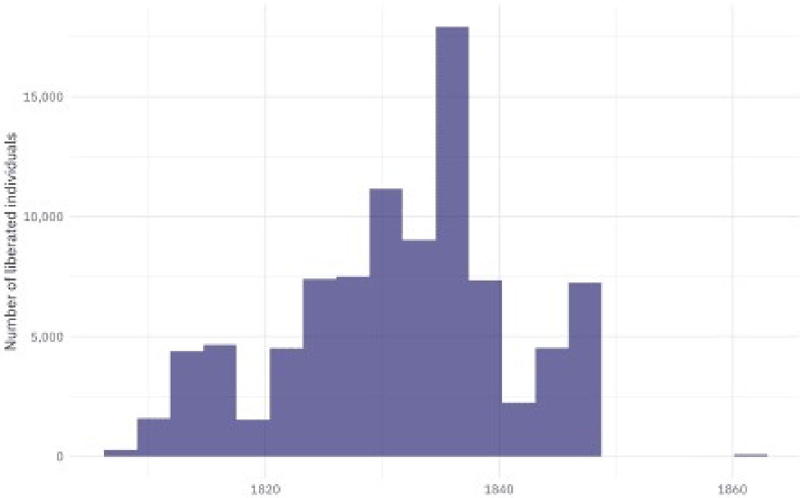
Where did these people start their forced journeys?

```
african_names %>%
  add_count(port_embark) %>%
  mutate(port_embark = case_when(
    n < 4000 ~ "Other",
    TRUE ~ port_embark
  )) %>%
  ggplot(aes(port_embark, year_arrival, fill = port_embark)) +
  geom_boxplot(alpha = 0.4, show.legend = FALSE) +
  labs(x = NULL, y = "Year")
```



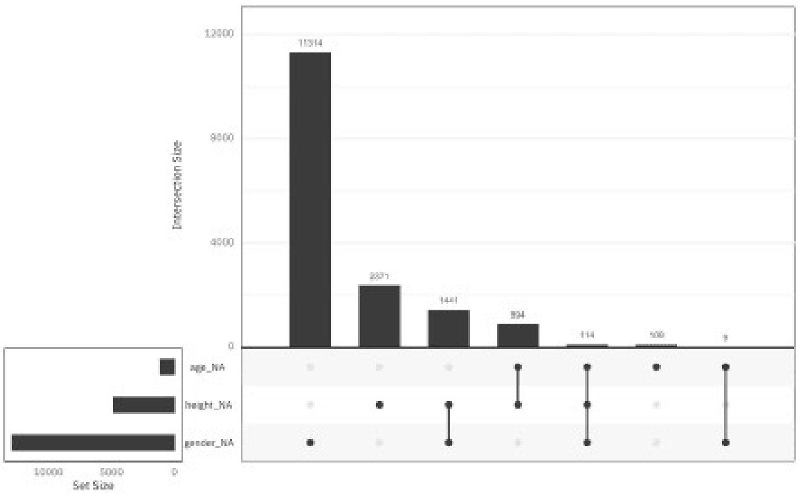
When is this data from?

```
african_names %>%
  ggplot(aes(year_arrival)) +
  geom_histogram(bins = 20, fill = "midnightblue", alpha = 0.7) +
  scale_y_continuous(labels = scales::comma_format()) +
  labs(
    y = "Number of liberated individuals",
    x = NULL
  )
```



What is the pattern of missing data?

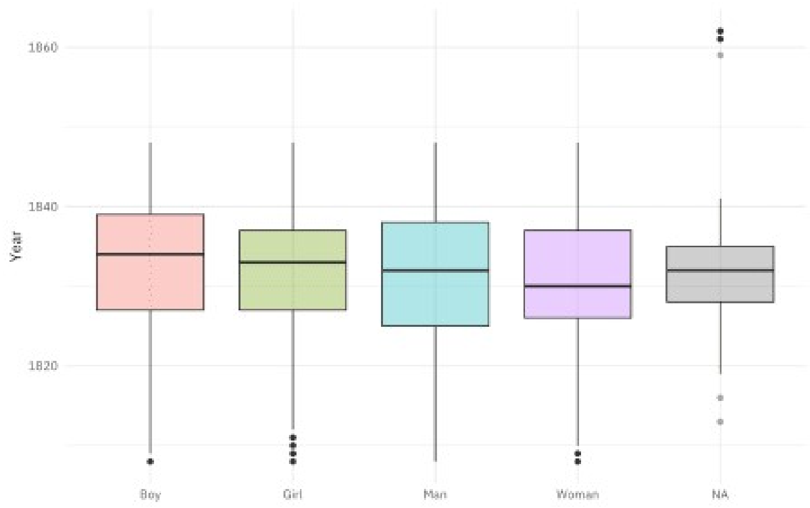
```
library(naniar)

african_names %>%
  select(gender, age, height, year_arrival) %>%
  gg_miss_upset()
```



Gender has the highest proportion of missing data, and there is not much data missing from the `age` column. Fortunately for our attempt to impute missing values, not many rows have all three of these missing.

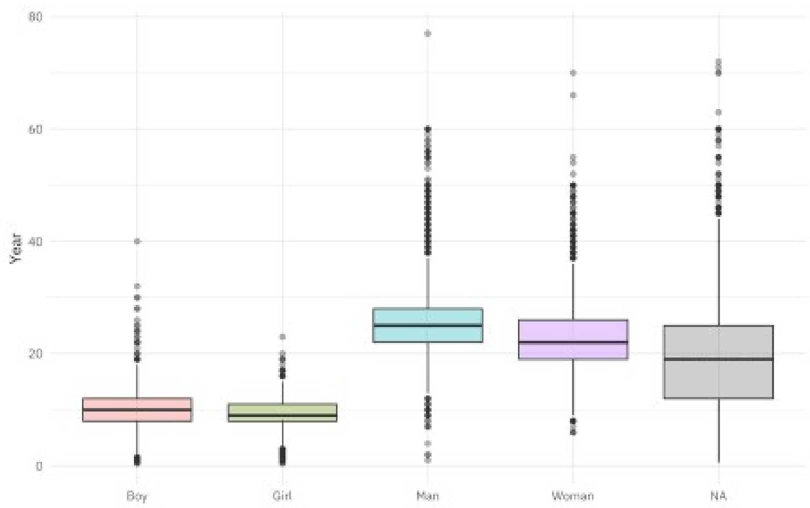
What is the relationship between gender and year of arrival?

```
african_names %>%
  ggplot(aes(gender, year_arrival, fill = gender)) +
  geom_boxplot(alpha = 0.4, show.legend = FALSE) +
  labs(x = NULL, y = "Year")
```



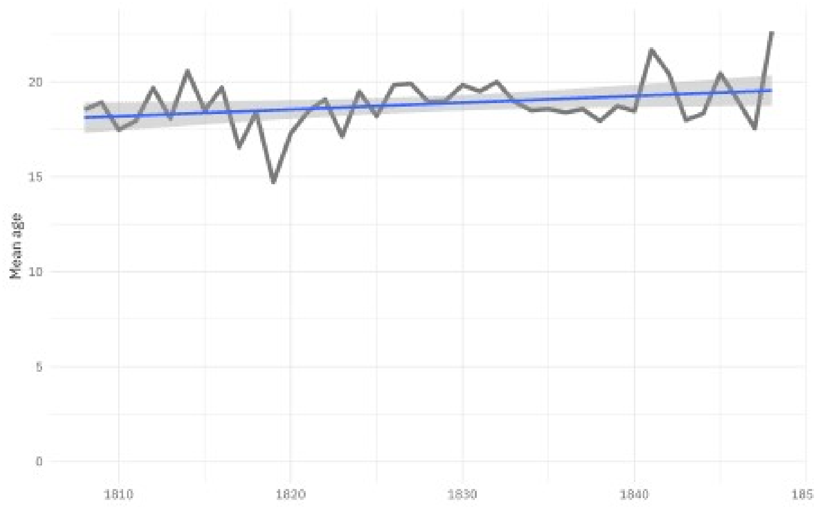
Gender was coded as both man/woman and boy/girl, but there is a fair amount of overlap in ages (children coded as “man”, for example).

```
african_names %>%
  ggplot(aes(gender, age, fill = gender)) +
  geom_boxplot(alpha = 0.4, show.legend = FALSE) +
  labs(x = NULL, y = "Year")
```



What is the relationship between age and year of arrival?

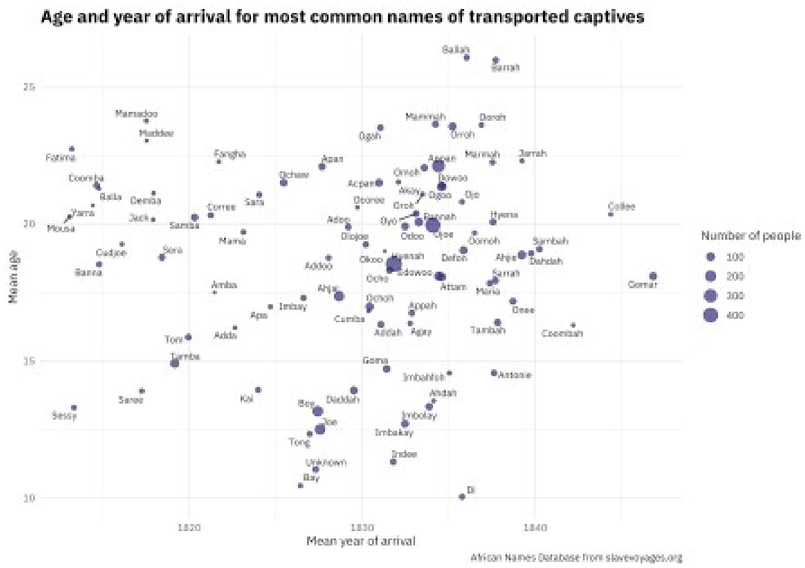
```
african_names %>%
  filter(year_arrival < 1850) %>%
  group_by(year_arrival) %>%
  summarise(age = mean(age, na.rm = TRUE)) %>%
  ggplot(aes(year_arrival, age)) +
  geom_line(alpha = 0.6, size = 1.5) +
  geom_smooth(method = "lm") +
  scale_y_continuous(limits = c(0, NA)) +
  labs(x = NULL, y = "Mean age")
```



Overall, the age is drifting up slightly, although the previous plot on boys/girls/men/women calls this into question. We can use modeling to explore this better.

One of the most unique and valuable characteristics of this dataset is the names. We can make a scatterplot to understand more about the distribution of ages and year of arrival.

```
library(ggrepel)

african_names %>%
  group_by(name) %>%
  summarise(
    n = n(),
    age = mean(age, na.rm = TRUE),
    year_arrival = mean(year_arrival, na.rm = TRUE)
  ) %>%
  ungroup() %>%
  arrange(-n) %>%
  filter(n > 30) %>%
  ggplot(aes(year_arrival, age)) +
  geom_text_repel(aes(label = name), size = 3, family = "IBMPlexSans") +
  geom_point(aes(size = n), color = "midnightblue", alpha = 0.7) +
  labs(
    x = "Mean year of arrival", y = "Mean age",
    size = "Number of people",
    title = "Age and year of arrival for most common names of transported
captives",
    caption = "African Names Database from slavevoyages.org"
  )
```



I’m looking forward to how else folks explore this #TidyTuesday dataset and share on [Twitter](https://twitter.com).

Impute missing data

Our modeling goal is to estimate whether some characteristics, say age and gender, of trafficked Africans changed during this time period. Some data is missing, so let’s try to impute gender and age, with the help of height. When we do imputation, we aren’t adding new information to our dataset, but we are using the patterns in our dataset so that we don’t have to throw away the data that have some variables missing.

First, let’s filter to only the data from before 1850 and recode the `gender` variable.

```
liberated_df <- african_names %>%
  filter(year_arrival < 1850) %>%
  mutate(gender = case_when(
    gender == "Boy" ~ "Man",
    gender == "Girl" ~ "Woman",
    TRUE ~ gender
  )) %>%
  mutate_if(is.character, factor)

liberated_df
```

```
## # A tibble: 91,394 x 11
##        id voyage_id name  gender   age height ship_name year_arrival
##
## 1      1      2314 Bora  Man       30    62.5 NS de Re…          1819
## 2      2      2315 Flam  Man       30    64   Fabiana            1819
## 3      3      2315 Dee   Man       28    65   Fabiana            1819
## 4      4      2315 Pao   Man       22    62.5 Fabiana            1819
## 5      5      2315 Mufa  Man       16    59   Fabiana            1819
## 6      6      2315 Latty Man       22    67.5 Fabiana            1819
## 7      7      2315 So    Man       20    62   Fabiana            1819
## 8      8      2315 Trua  Man       30    65.5 Fabiana            1819
## 9      9      2315 Tou   Man       18    61.5 Fabiana            1819
## 10    10      2315 Quaco Man       23    62   Fabiana            1819
## # … with 91,384 more rows, and 3 more variables: port_disembark ,
## #   port_embark , country_origin
```

Next, let’s impute the missing data using a recipe.

```
library(recipes)
```

```
impute_rec <- recipe(year_arrival ~ gender + age + height, data = liberated_df)
%>%
  step_meanimpute(height) %>%
  step_knnimpute(all_predictors())
```

Let's walk through the steps in this recipe.

- First, we must tell the `recipe()` what's going on with our model what data we are using (notice we did not split into training and testing, because of our specific modeling goals).
- Next, we impute the missing values for height with the mean value for height. Height has a low value of missingness, and we are only going to use it to impute age and gender, not for modeling.
- Next, we impute the missing values for age and gender using a nearest neighbors model with all three predictors.

Once we have the recipe defined, we can estimate the parameters needed to apply it using `prep()`. In this case, that means finding the mean for height (fast) and training the nearest neighbor model to find gender and age (not so fast). Then we can use `juice()` to get that imputed data back out. (If we wanted to apply the recipe to other data, like new data we hadn't seen before, we would use `bake()` instead.)

```
imputed <- prep(impute_rec) %>% juice()
```

How did the imputation turn out?

```
summary(liberated_df$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.50   11.00   20.00   18.89   26.00   77.00    1030
```

```
summary(imputed$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.50   11.00   19.00   18.77   26.00   77.00
```

```
summary(liberated_df$gender)
```

```
##   Man Woman  NA's
## 52723 25889 12782
```

```
summary(imputed$gender)
```

```
##   Man Woman
## 60992 30402
```

No more `NA` values, and the distributions look about the same. I like to keep in mind that the point of imputation like this is to be able to use the information we have in the dataset without throwing it away, which feels especially important when dealing with historical data on individuals who experienced enslavement.

Fit a model

The distribution of year of arrival was a bit wonky, so that is good to keep in mind when training a linear model.

```
fit_lm <- lm(year_arrival ~ gender + age, data = imputed)
```

We can check out the model results.

```
summary(fit_lm)
```

```
##
## Call:
```

```
## lm(formula = year_arrival ~ gender + age, data = imputed)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -23.7206  -5.3343   0.9842   5.6828  17.0903
##
## Coefficients:
##               Estimate Std. Error   t value Pr(>|t|)
## (Intercept)  1.832e+03  8.163e-02 22440.485  < 2e-16 ***
## genderWoman -3.014e-01  6.724e-02    -4.482 7.40e-06 ***
## age         -2.123e-02  3.665e-03    -5.793 6.95e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.476 on 91391 degrees of freedom
## Multiple R-squared:  0.0005149,     Adjusted R-squared:  0.000493
## F-statistic: 23.54 on 2 and 91391 DF,  p-value: 6.012e-11
```

```
tidy(fit_lm) %>%
  kable(digits = 3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	1831.869	0.082	22440.485	0
genderWoman	-0.301	0.067	-4.482	0
age	-0.021	0.004	-5.793	0

During the years (about 1810 to 1850) included here, as time passed, there were some gradual shifts in the population of who was found on (i.e. liberated from) these slave ships.