DEALING WITH MISSING DATA IN R

Performing and tracking imputation

Nicholas Tierney
Statistician

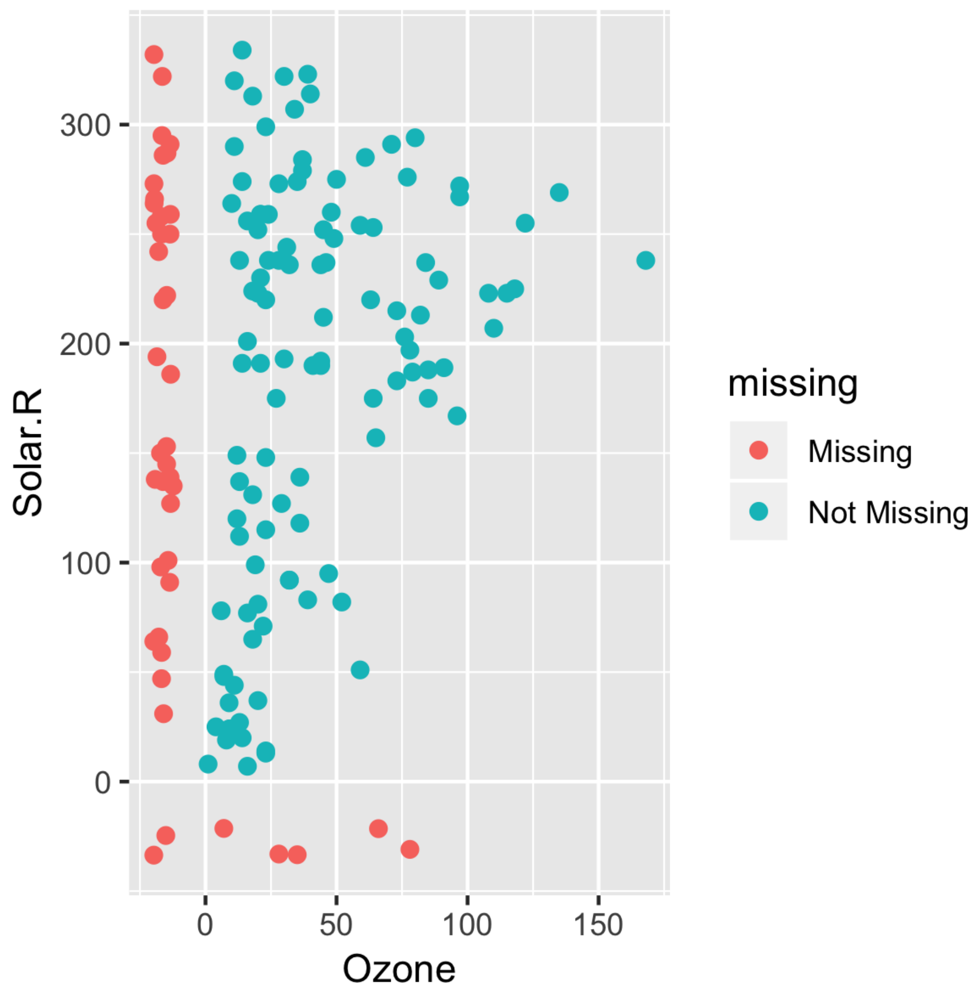
Lesson overview

Using imputations to understand data structure

Visualising + exploring imputed values

- Imputing data to explore missingness
- Track missing values
- Visualise imputed values against data

Using imputations to understand data structure




```
> impute_below(c(5,6,7,NA,9,10))
[1]  5.00000  6.00000  7.00000
[4]  4.40271  9.00000 10.00000
```

impute_below

- `impute_below_if()`:

```
impute_below_if(data, is.numeric)
```

- `impute_below_at()`:

```
impute_below_at(data, vars(var1,var2))
```

- `impute_below_all()`:

```
impute_below_all(data)
```

Tracking missing values

```
> df
# A tibble: 6 x 1
   var1
  <dbl>
1     5
2     6
3     7
4    NA
5     9
6    10
```

```
> bind_shadow(df)
# A tibble: 6 x 2
   var1 var1_NA
  <dbl> <fct>
1  5     !NA
2  6     !NA
3  7     !NA
4  NA     NA
5  9     !NA
6 10     !NA
```

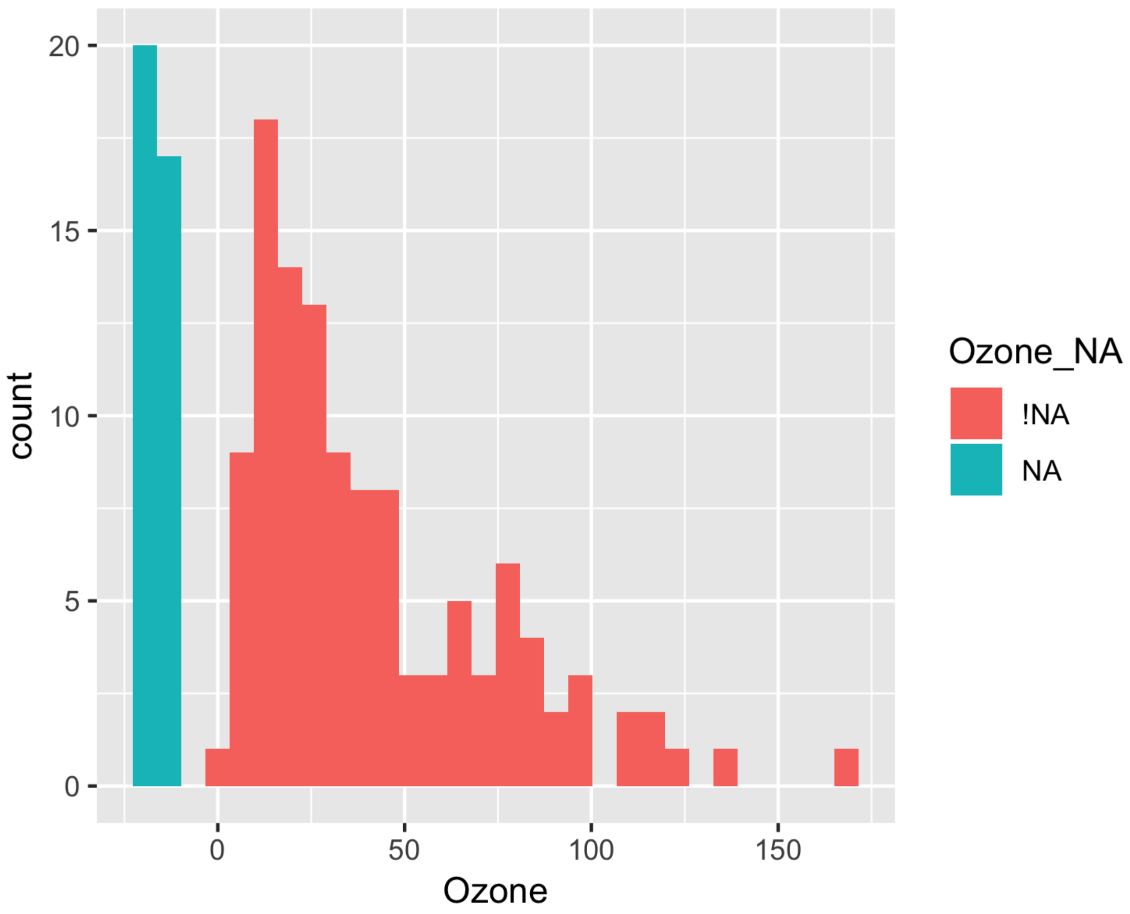
```
> impute_below_all(df)
# A tibble: 6 x 1
   var1
  <dbl>
1  5
2  6
3  7
4  4.40
5  9
6 10
```

```
> bind_shadow(df) %>%
impute_below_all()
# A tibble: 6 x 2
   var1 var1_NA
  <dbl> <fct>
1  5     !NA
2  6     !NA
3  7     !NA
4  4.40 NA
5  9     !NA
6 10     !NA
```

Visualise imputed values against data values using histograms

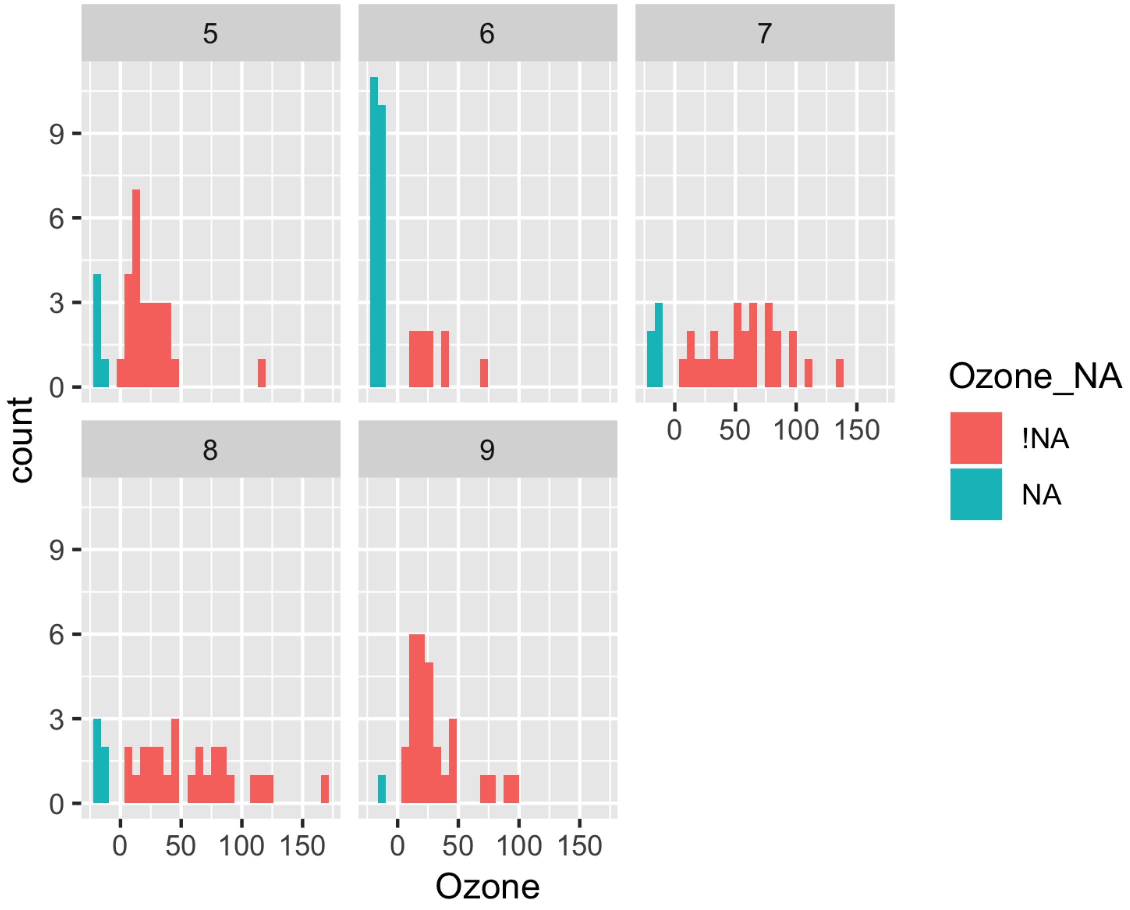
```
> aq_imp <- airquality %>%
   bind_shadow() %>%
   impute_below_all()

> ggplot(aq_imp,
         aes(x = Ozone,
             fill = Ozone_NA)) +
   geom_histogram()
```



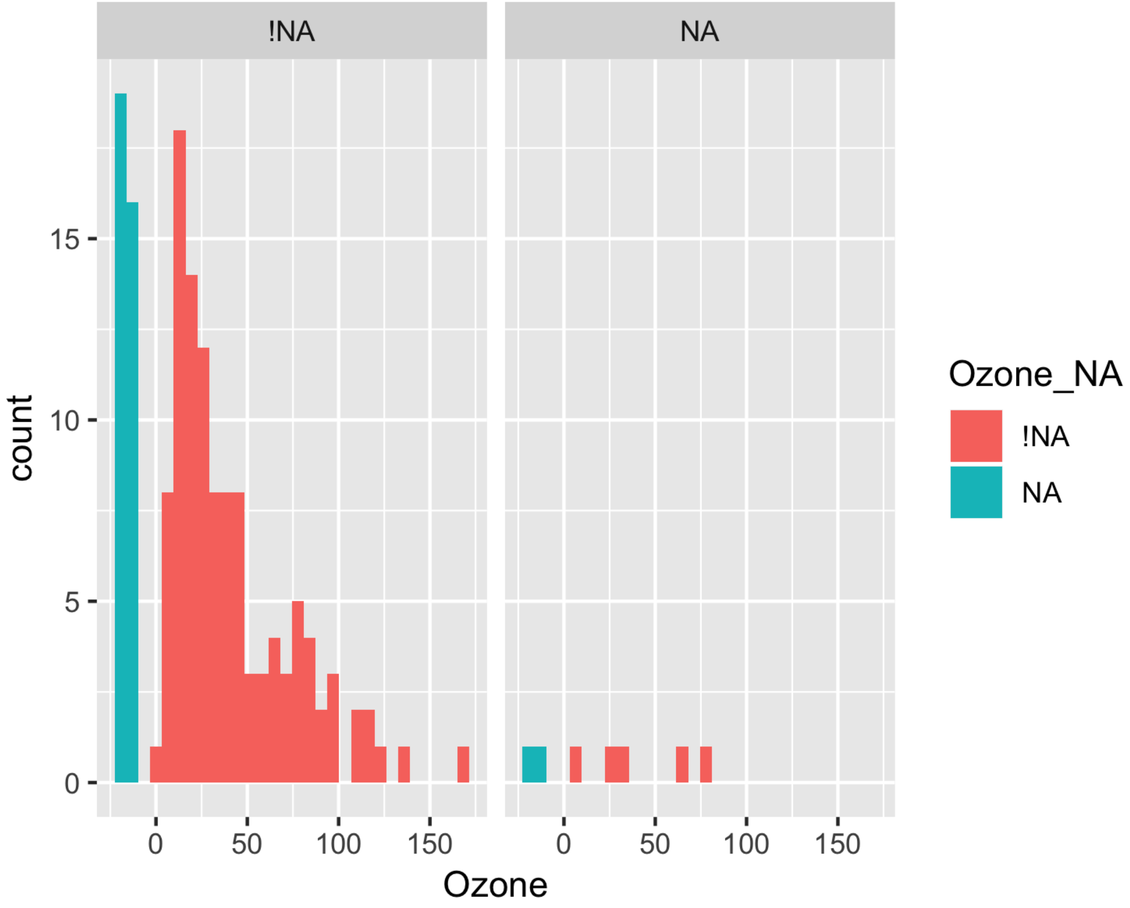
Visualize imputed values against data values using facets

```
ggplot(aq_imp,
       aes(x = Ozone,
           fill = Ozone_NA)) +
  geom_histogram() +
  facet_wrap(~Month)
```



Visualize imputed values using facets

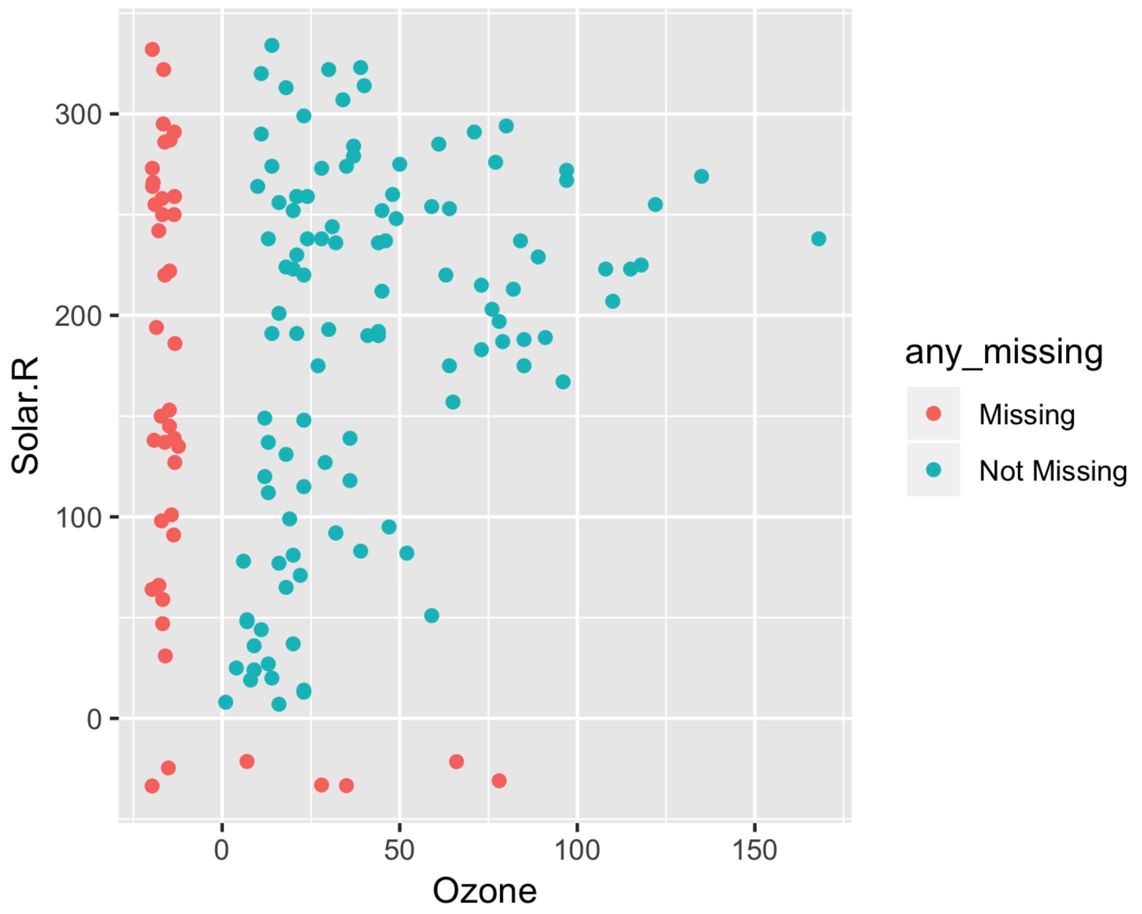
```
ggplot(aq_imp,
       aes(x = Ozone,
           fill = Ozone_NA)) +
  geom_histogram() +
  facet_wrap(~Solar.R_NA)
```



Visualize imputed values against data values using scatterplots

```
aq_imp <- airquality %>%
  bind_shadow() %>%
  add_label_missings() %>%
  impute_below_all()

ggplot(aq_imp,
       aes(x = Ozone,
           y = Solar.R,
           colour = any_missing)) +
  geom_point()
```



DEALING WITH MISSING DATA IN R

Let's practice!

DEALING WITH MISSING DATA IN R

What makes a good imputation

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Statistician

Lesson overview

- Understand good and bad imputations
- Evaluate missing values:
  - Mean, Scale, Spread
- Using visualisations
  - Boxplots
  - Scatterplots
  - Histograms
  - Many variables

Understanding the good by understanding the bad

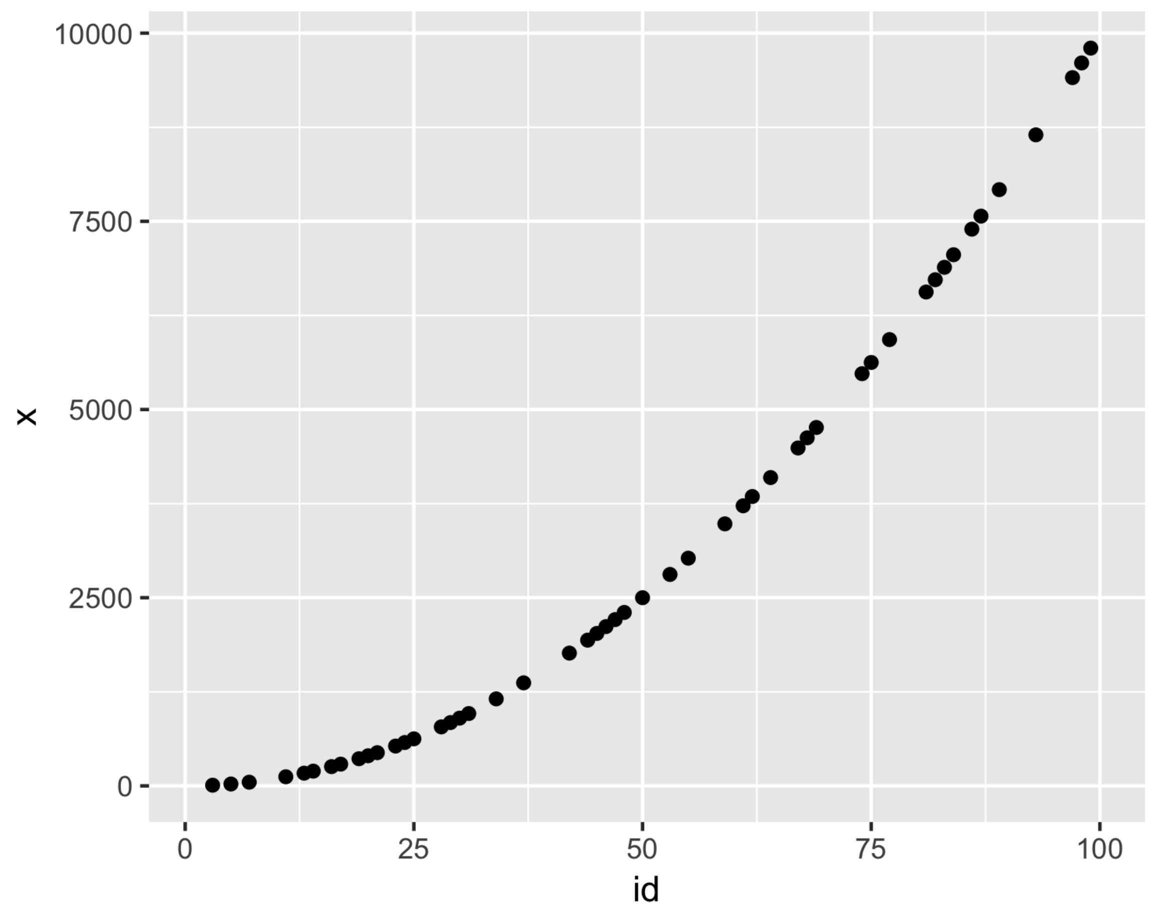
```
#> # A tibble: 6 x 1
#>         x
#>     <dbl>
#> 1       1
#> 2       4
#> 3       9
#> 4      16
#> 5      NA
#> 6      36
```

```
> mean(df$x, na.rm = TRUE)
[1] 13.2
```

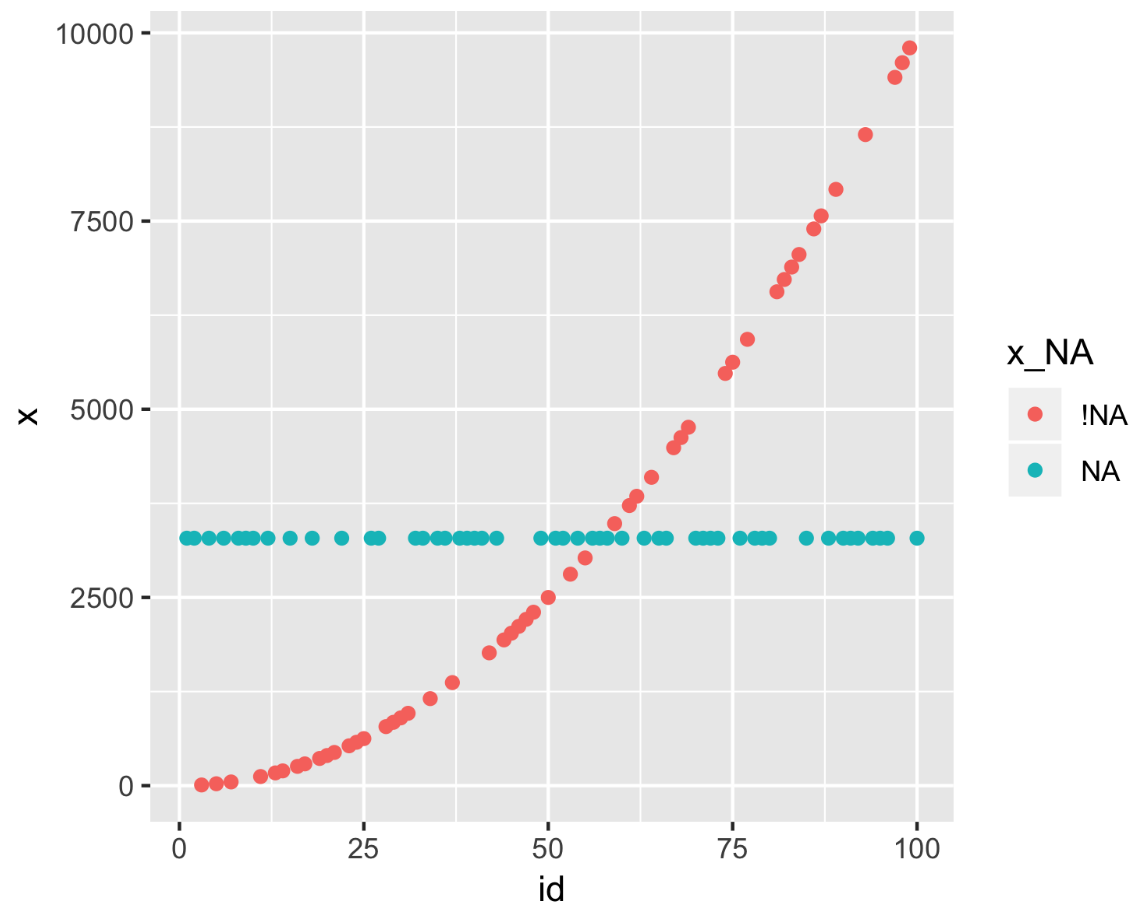
```
#> # A tibble: 6 x 1
#>         x
#>     <dbl>
#> 1    1
#> 2    4
#> 3    9
#> 4   16
#> 5   13.2
#> 6   36
```

Demonstrating mean imputation

Data with missing values



Data with mean imputations



Explore bad imputations: The mean

- `impute_mean(data$variable)`
- `impute_mean_if(data, is.numeric)`
- `impute_mean_at(data, vars(variable1, variable2))`
- `impute_mean_all(data)`

Tracking missing values

```
aq_impute_mean <- airquality %>%
  bind_shadow(only_miss = TRUE) %>%
  impute_mean_all() %>%
  add_label_shadow()

aq_impute_mean
```

```
# A tibble: 153 x 9
   Ozone Solar.R  Wind  Temp Month   Day Ozone_NA Solar.R_NA any_missing
   <dbl>   <dbl> <dbl> <dbl> <dbl> <dbl> <fct>    <fct>      <chr>
 1  41       190   7.4    67     5     1 !NA      !NA        Not Missing
 2  36       118   8      72     5     2 !NA      !NA        Not Missing
 3  12       149  12.6    74     5     3 !NA      !NA        Not Missing
 4  18       313  11.5    62     5     4 !NA      !NA        Not Missing
 5  42.1     186.  14.3    56     5     5 NA       NA         Missing
 6  28       186.  14.9    66     5     6 !NA      NA         Missing
```

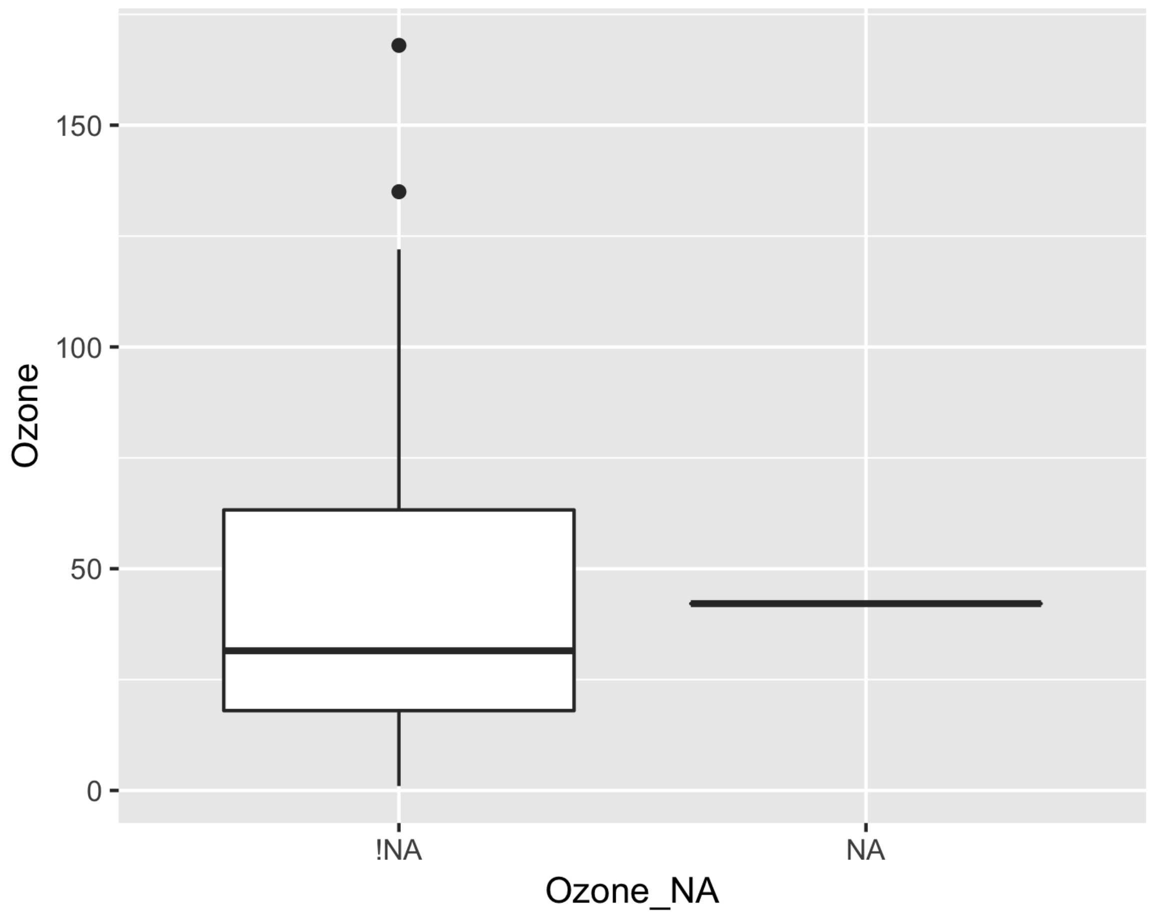
Exploring imputations using a boxplot

When evaluating imputations, explore changes / similarities in

- **The mean/median** (boxplot)
- The spread
- The scale

Visualizing imputations using the boxplot

```
ggplot(aq_impute_mean,
       aes(x = Ozone_NA,
           y = Ozone)) +
  geom_boxplot()
```

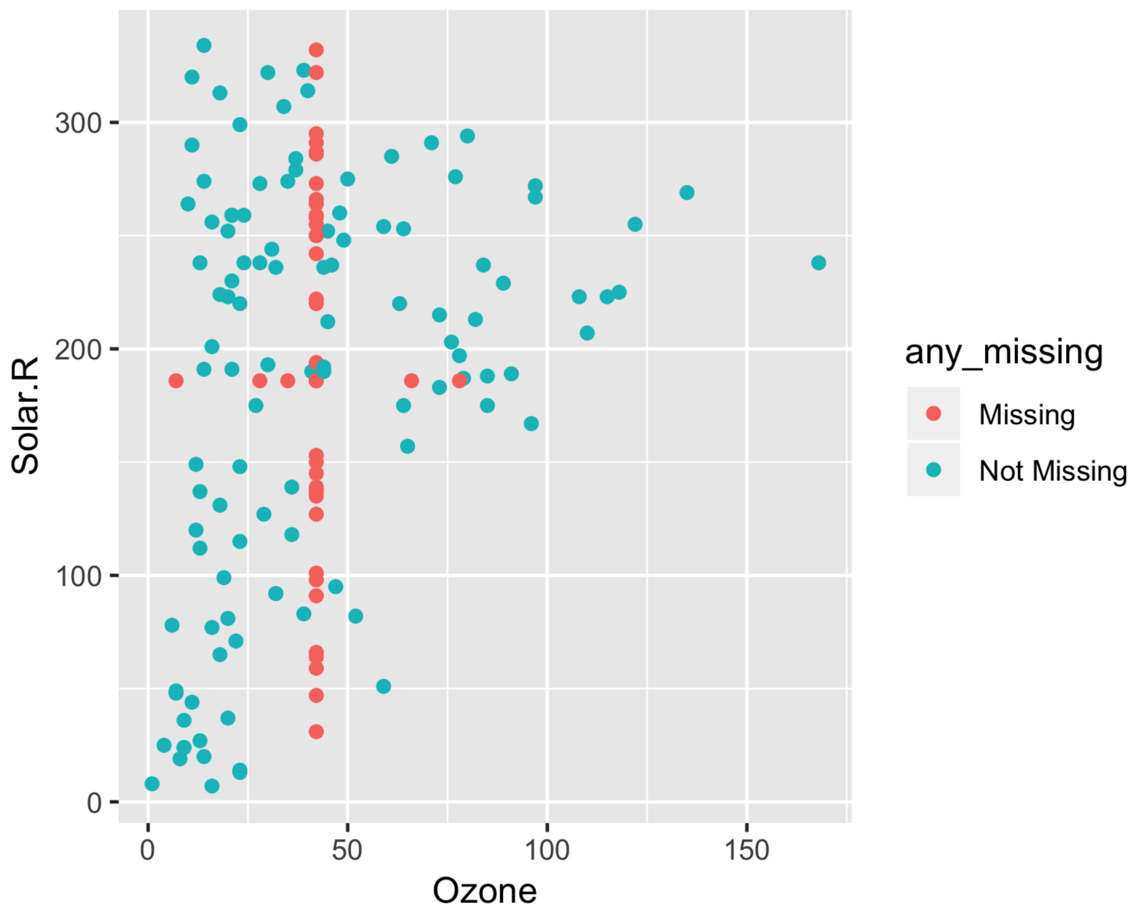


Explore bad imputations using a scatterplot

When evaluating imputations, explore changes/similarities in

- **The spread (scatterplot)**

```
ggplot(aq_impute_mean,
       aes(x = Ozone,
           y = Solar.R,
           colour = any_missing)) +
  geom_point()
```



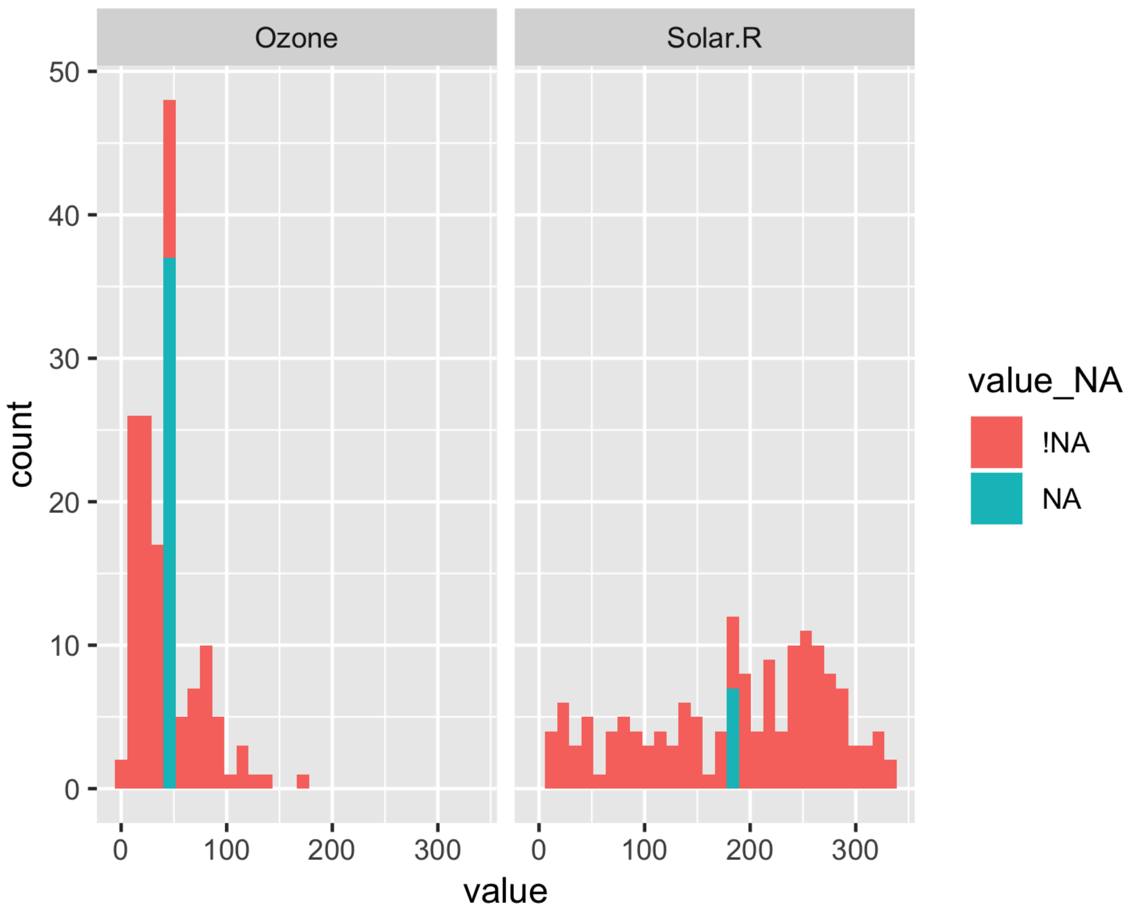
Exploring imputations for many variables

```
aq_imp <- airquality %>%
  bind_shadow() %>%
  impute_mean_all()

aq_imp_long <- shadow_long(aq_imp,
                           Ozone,
                           Solar.R)

aq_imp_long
```

```
# A tibble: 306 x 4
   variable value variable_NA value_NA
   <chr>    <dbl> <chr>       <chr>
 1 Ozone     41   Ozone_NA    !NA
 2 Ozone     36   Ozone_NA    !NA
 3 Ozone     12   Ozone_NA    !NA
 4 Ozone     18   Ozone_NA    !NA
 5 Ozone     42.1 Ozone_NA    NA
 6 Ozone     28   Ozone_NA    !NA
 7 Ozone     23   Ozone_NA    !NA
 8 Ozone     19   Ozone_NA    !NA
 9 Ozone      8   Ozone_NA    !NA
10 Ozone     42.1 Ozone_NA    NA
# ... with 296 more rows
```

Exploring imputations for many variables

```
ggplot(aq_imp_long,
       aes(x = value,
           fill = value_NA)) +
  geom_histogram() +
  facet_wrap(~variable)
```



DEALING WITH MISSING DATA IN R

Let's Practice!

DEALING WITH MISSING DATA IN R

Practicing imputing with different models

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Lesson Overview

- Imputation using the `simputation` package
- Use linear model to impute values with `impute_lm`
- Assess new imputations
- Build many imputation models
- Compare imputations across different models and variables

How imputing using a linear model works

```
> df
# A tibble: 5 x 3
      y    x1    x2
  <dbl> <dbl> <dbl>
1  2.67  2.43  3.27
2  3.87  3.55  1.45
3 NA     2.90  1.49
4  5.21  2.72  1.84
5 NA     4.29  1.15
```

```
df %>%
   bind_shadow(only_miss = TRUE) %>%
   add_label_shadow() %>%
   impute_lm(y ~ x1 + x2)
```

```
# A tibble: 5 x 7
      y    x1    x2 y_NA  any_missing
  <dbl> <dbl> <dbl> <fct> <chr>
1 2.67  2.43  3.27 !NA   Not Missing
2 3.87  3.55  1.45 !NA   Not Missing
3 5.54  2.90  1.49 NA    Missing
4 5.21  2.72  1.84 !NA   Not Missing
5 2.56  4.29  1.15 NA    Missing
```

Using impute_lm

```
aq_imp_lm <- airquality %>%
  bind_shadow() %>%
  add_label_shadow() %>%
  impute_lm(Solar.R ~ Wind + Temp + Month) %>%
  impute_lm(Ozone ~ Wind + Temp + Month)
```

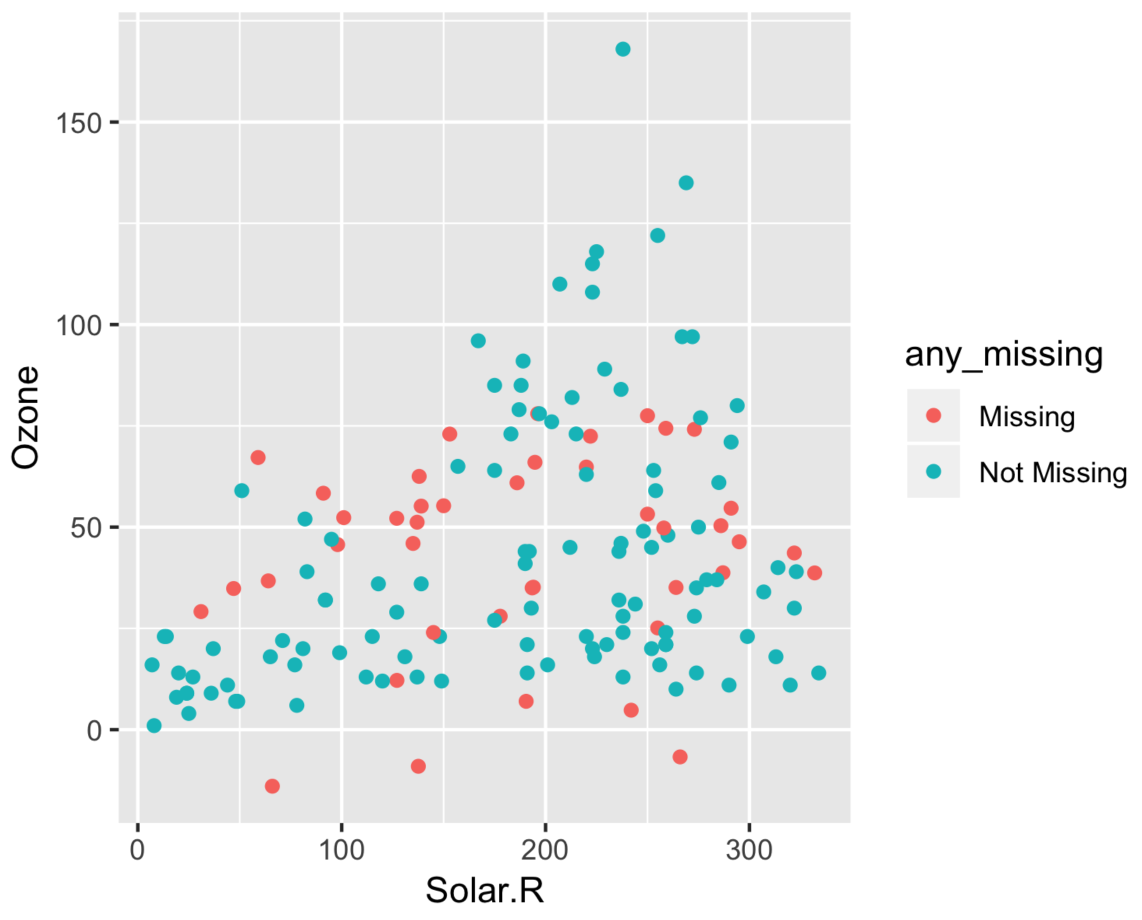
```
aq_imp_lm
```

```
# A tibble: 153 x 13
    Ozone Solar.R  Wind  Temp Month   Day Ozone_NA Solar.R_NA
 *  <dbl>   <dbl> <dbl> <int> <int> <int> <fct>    <fct>
 1  41       190    7.4    67     5     1 !NA      !NA
 2  36       118    8      72     5     2 !NA      !NA
 3  12       149   12.6    74     5     3 !NA      !NA
 4  18       313   11.5    62     5     4 !NA      !NA
 5  -9.04    138.  14.3    56     5     5 NA       NA
 6  28       178.  14.9    66     5     6 !NA      NA
# ... with 147 more rows, and 5 more variables: Wind_NA <fct>,
#   Temp_NA <fct>, Month_NA <fct>, Day_NA <fct>,
#   any_missing <chr>
```

Tracking missing values

```
aq_imp_lm <-
airquality %>%
  bind_shadow() %>%
  add_label_missings() %>%
  impute_lm(Solar.R ~ Wind + Temp +
            Month) %>%
  impute_lm(Ozone ~ Wind + Temp +
            Month)
```

```
ggplot(aq_imp_lm,
       aes(x = Solar.R,
           y = Ozone,
           colour = any_missing)) +
  geom_point()
```



Evaluating imputations: Evaluating and comparing imputations

```
aq_imp_small <- airquality %>%
  bind_shadow() %>%
  impute_lm(Ozone ~ Wind + Temp) %>%
  impute_lm(Solar.R ~ Wind + Temp) %>%
  add_label_shadow()

aq_imp_large <- airquality %>%
  bind_shadow() %>%
  impute_lm(Ozone ~ Wind + Temp + Month + Day) %>%
  impute_lm(Solar.R ~ Wind + Temp + Month + Day)  %>%
  add_label_shadow()
```

Evaluating imputations: Binding and visualising many models

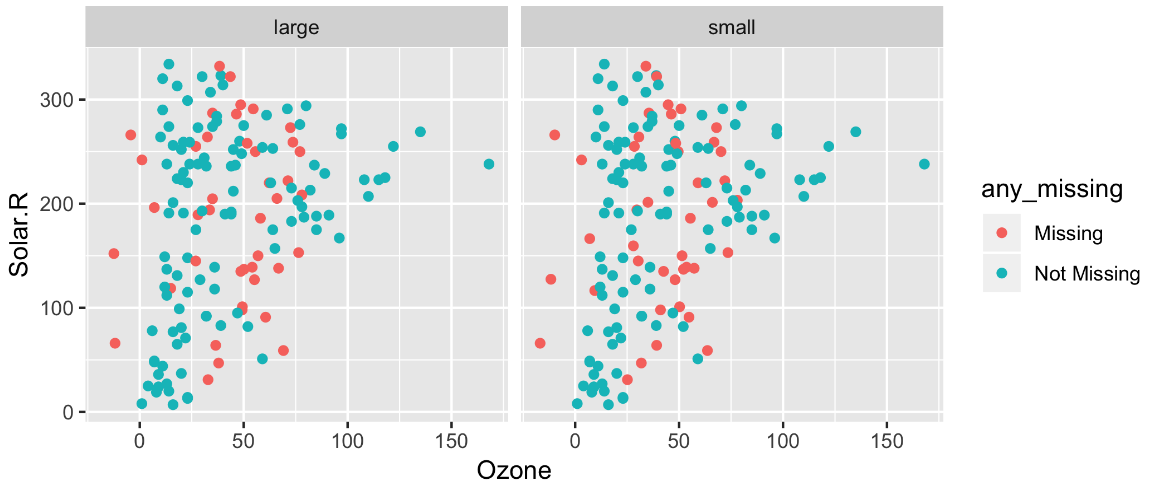
```
bound_models <-
bind_rows(small = aq_imp_small,
          large = aq_imp_large,
          .id = "imp_model")

bound_models
```

```
     imp_model     Ozone  Solar.R Wind Temp Month Day
  1:     small  41.00000 190.0000  7.4   67     5   1
  2:     small  36.00000 118.0000  8.0   72     5   2
  3:     small  12.00000 149.0000 12.6   74     5   3
  4:     small  18.00000 313.0000 11.5   62     5   4
  5:     small -11.67673 127.4317 14.3   56     5   5
 ---
302:     large  30.00000 193.0000  6.9   70     9  26
303:     large  26.92183 145.0000 13.2   77     9  27
304:     large  14.00000 191.0000 14.3   75     9  28
305:     large  18.00000 131.0000  8.0   76     9  29
306:     large  20.00000 223.0000 11.5   68     9  30
```

Evaluating imputations: exploring many imputations

```
ggplot(bound_models,
       aes(x = Ozone,
           y = Solar.R,
           colour = any_missing)) +
  geom_point() +
  facet_wrap(~imp_model)
```



Explore imputations in multiple variables and models

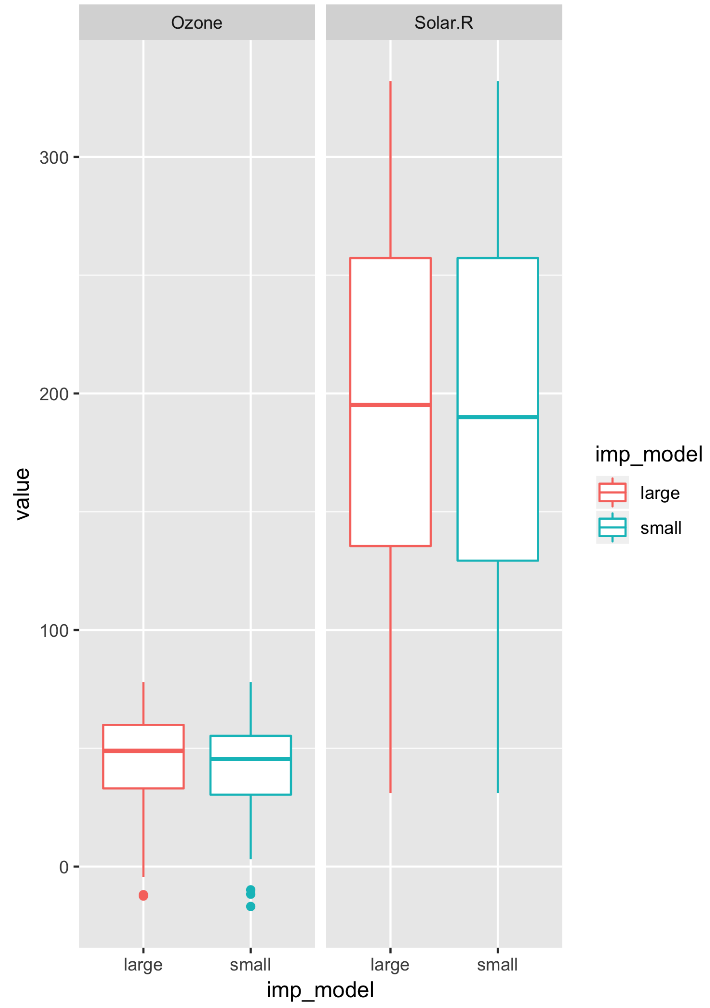
```
bound_models_gather <- bound_models %>%
  select(Ozone, Solar.R,
         any_missing, imp_model) %>%
  gather(key = "variable", value = "value",
         -any_missing, -imp_model)

bound_models_gather
```

```
     any_missing imp_model variable      value
  1: Not Missing     small    Ozone   41.00000
  2: Not Missing     small    Ozone   36.00000
  3: Not Missing     small    Ozone   12.00000
  4: Not Missing     small    Ozone   18.00000
  5:     Missing     small    Ozone  -11.67673
 ---
608: Not Missing     large  Solar.R  193.00000
609:     Missing     large  Solar.R  145.00000
610: Not Missing     large  Solar.R  191.00000
611: Not Missing     large  Solar.R  131.00000
612: Not Missing     large  Solar.R  223.00000
```

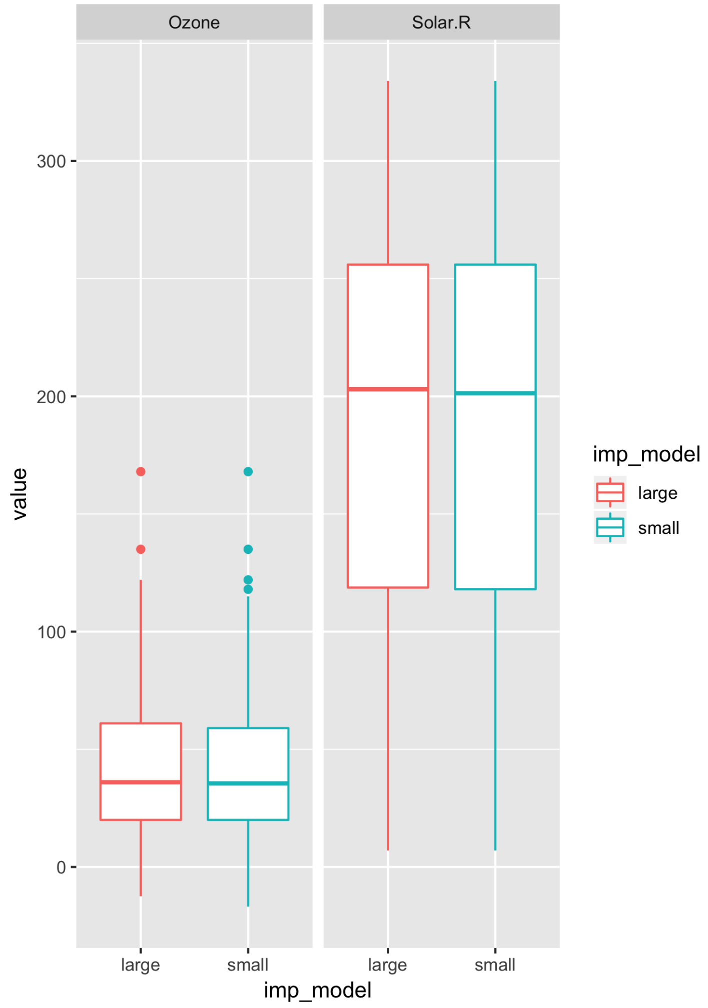
Explore imputations in multiple variables and models

```
ggplot(bound_models_gather,
       aes(x = imp_model,
           y = value)) +
  geom_boxplot() +
  facet_wrap(~key)
```



Explore imputations in multiple variables and models

```
bound_models_gather %>%
  filter(any_missing == "Missing") %>%
  ggplot(aes(x = imp_model,
             y = value)) +
  geom_boxplot() +
  facet_wrap(~key)
```



DEALING WITH MISSING DATA IN R

Let's practice!

DEALING WITH MISSING DATA IN R

Assessing inference from imputed data in a modelling context

Nicholas Tierney
Statistician

Exploring parameters of one model

```
lm(Temp ~ Ozone + Solar.R + Wind + Month + day, data = airquality)
```

1. Complete case analysis

2. Imputation using the imputed data from the last lesson

Combining the datasets together

```
#1.  Complete cases
aq_cc <-   airquality %>%
  na.omit() %>%
  bind_shadow() %>%
  add_label_shadow()
```

```
#2. Imputation using the imputed data from the last lesson
aq_imp_lm <- bind_shadow(airquality) %>%
  add_label_shadow() %>%
  impute_lm(Ozone ~ Temp + Wind + Month + Day) %>%
  impute_lm(Solar.R ~ Temp + Wind + Month + Day)
```

```
# 3. Bind the models together
bound_models <- bind_rows(cc = aq_cc,
                          imp_lm = aq_imp_lm,
                          .id = "imp_model")
```

Combining the datasets together

```
bound_models

imp_model Ozone Solar.R Wind Temp Month Day Ozone_NA Solar.R_NA any_missing
cc        41      190    7.4   67     5   1     !NA         !NA   Not Missing
cc        36      118    8.0   72     5   2     !NA         !NA   Not Missing
cc        12      149   12.6   74     5   3     !NA         !NA   Not Missing
cc        18      313   11.5   62     5   4     !NA         !NA   Not Missing
cc        23      299    8.6   65     5   7     !NA         !NA   Not Missing

imp_lm    30      193    6.9   70     9  26     !NA         !NA   Not Missing
imp_lm    NA      145   13.2   77     9  27      NA         !NA       Missing
imp_lm    14      191   14.3   75     9  28     !NA         !NA   Not Missing
imp_lm    18      131    8.0   76     9  29     !NA         !NA   Not Missing
imp_lm    20      223   11.5   68     9  30     !NA         !NA   Not Missing
```

Exploring the models

```
model_summary <- bound_models %>%
  group_by(imp_model) %>%
  nest() %>%
  mutate(mod = map(data,
                   ~lm(Temp ~ Ozone + Solar.R + Wind + Temp + Days + Month
                       data = .)),
         res = map(mod, residuals),
         pred = map(mod, predict),
         tidy = map(mod, broom::tidy))

model_summary
```

```
# A tibble: 2 x 6
  imp_model data                 mod      res          pred         tidy
  <chr>     <list>               <list>   <list>       <list>       <list>
1 cc        <tibble [111 × 13]> <S3: lm> <dbl [111]> <dbl [111]> <tibble [3 × 5]
2 imp_lm    <tibble [153 × 13]> <S3: lm> <dbl [153]> <dbl [153]> <tibble [3 × 5]
```

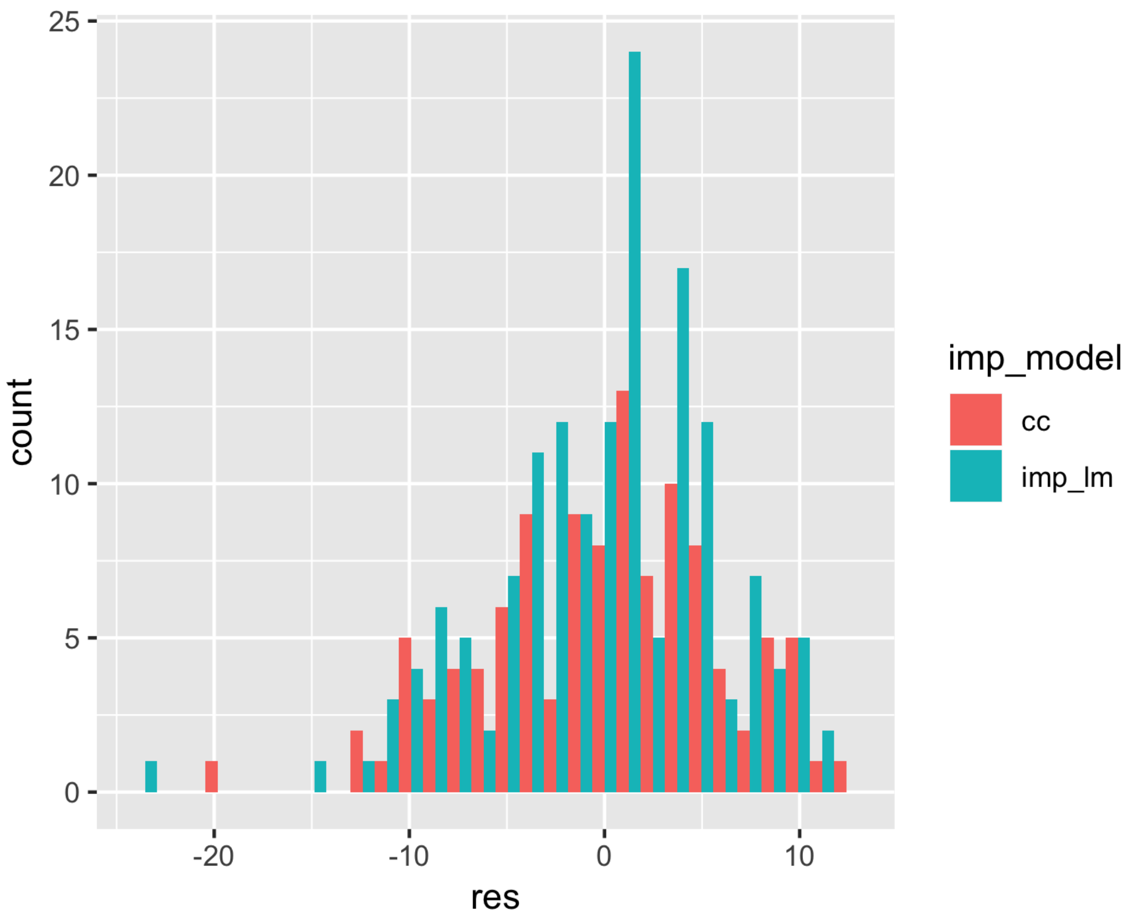
Exploring coefficients of multiple models

```
model_summary %>%
  select(imp_model,
         tidy) %>%
  unnest()
```

```
# A tibble: 6 x 6
  imp_model term        estimate std.error statistic  p.value
  <chr>     <chr>          <dbl>     <dbl>     <dbl>    <dbl>
1 cc        (Intercept) 68.5       1.53       44.8   1.31e-71
2 cc        Ozone        0.194     0.0210      9.26  2.22e-15
3 cc        Solar.R      0.00604   0.00766     0.789 4.32e- 1
4 imp_lm    (Intercept) 67.2       1.30       51.5   2.68e-97
5 imp_lm    Ozone        0.215     0.0180     12.0   1.40e-23
6 imp_lm    Solar.R      0.00787   0.00630     1.25  2.13e- 1
```

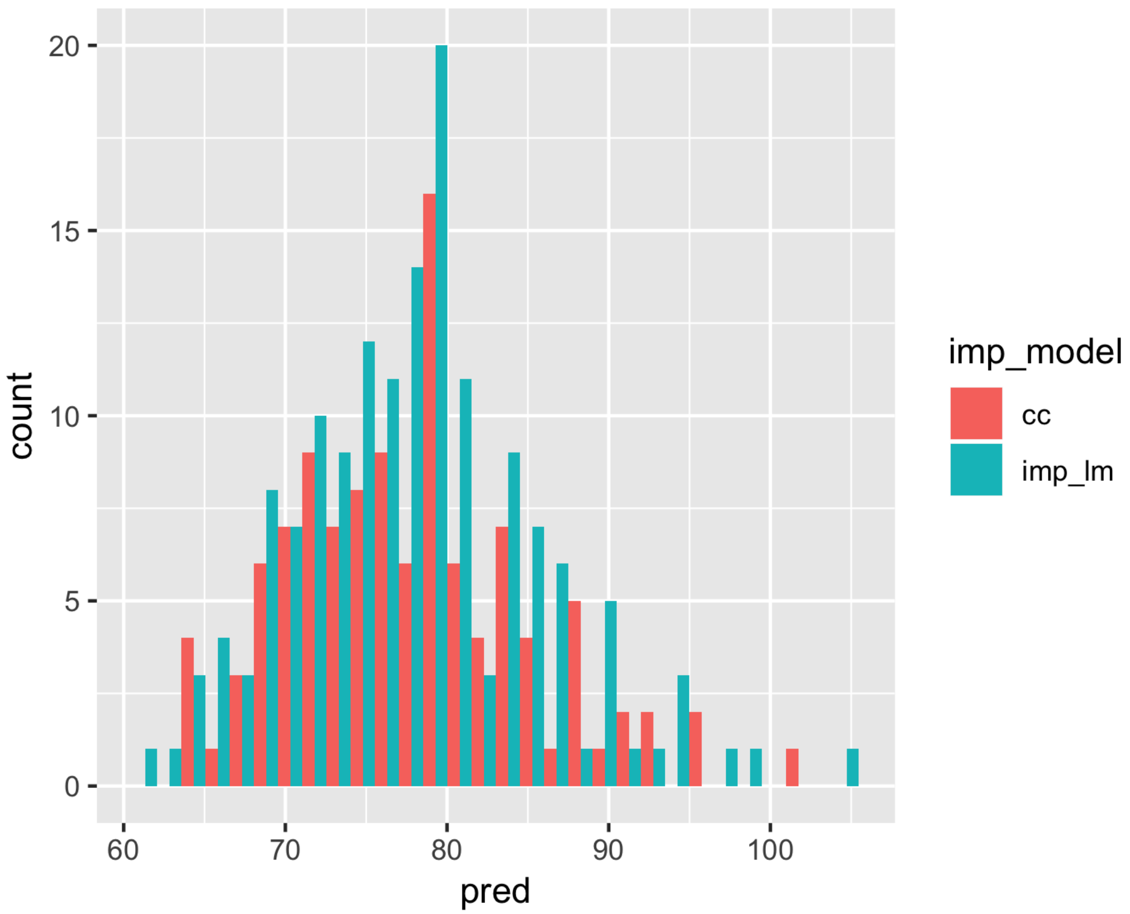
Exploring residuals of multiple models

```
model_summary %>%
  select(imp_model,
         res) %>%
  unnest() %>%
  ggplot(aes(x = res,
             fill = imp_model)) +
  geom_histogram(position = "dodge")
```



Exploring predictions of multiple models

```
model_summary %>%
  select(imp_model,
         pred) %>%
  unnest() %>%
  ggplot(aes(x = pred,
             fill = imp_model)) +
  geom_histogram(position = "dodge")
```



DEALING WITH MISSING DATA IN R

Let's practice!

DEALING WITH MISSING DATA IN R

Congratulations!

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Statistician

Chapter 1

What missing values are

Missing values are values that should have been recorded but were not.

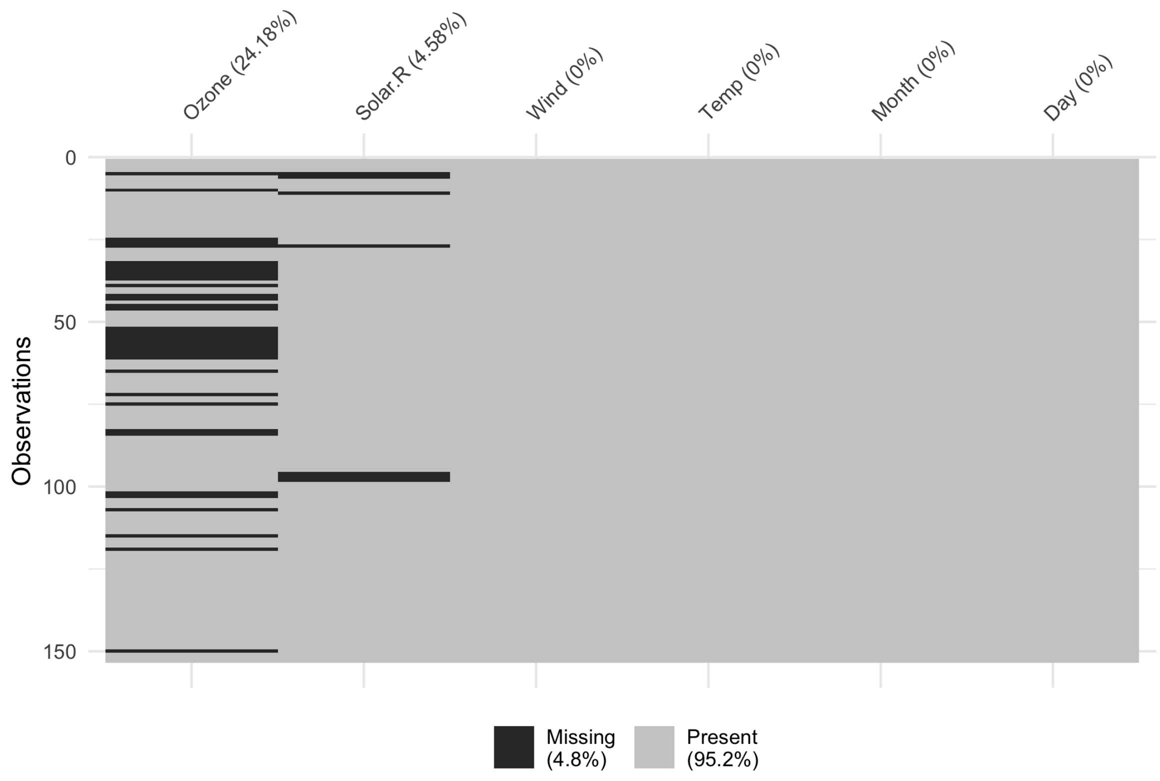
How to summarize missing values

```
miss_var_summary(airquality)
```

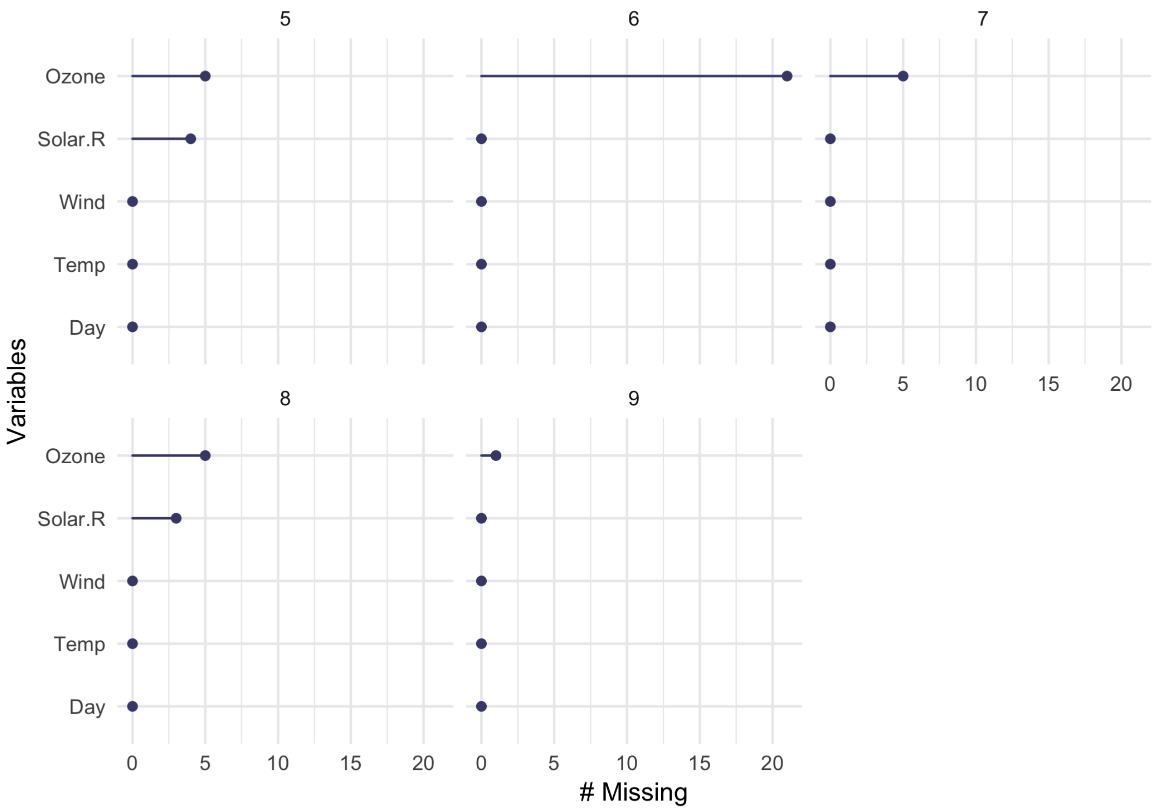
```
A tibble: 6 x 3
  variable n_miss pct_miss
  <chr>     <int>    <dbl>
1 Ozone        37    24.2
2 Solar.R       7     4.58
3 Wind          0     0
4 Temp          0     0
5 Month         0     0
6 Day           0     0
```

Chapter 1

```
vis_miss(airquality)
```




```
gg_miss_var(airquality, facet=Month)
```



Chapter 2

Find alternative missing values

```
miss_scan_count(data = pacman,
                search = list("N/A"))
```

Replace alternative missing values

```
replace_with_na(pacman,
                replace = list(
                  year = c("N/A"),
                  score = c("N/A")
                  )
                )
```

Implicit Missing values

```
frogger_tidy <- frogger %>%
  complete(time, name)
```

Missing Data Dependence

- MCAR
- MAR
- MNAR

Chapter 3

shadow matrix, nabular data

```
nabular(airquality)
```

```
#> # A tibble: 153 x 12
#>    Ozone Solar.R  Wind  Temp
#>    <int>   <int> <dbl> <int>
#>  1   41      190   7.4    67
#>  2   36      118   8      72
#>  3   12      149  12.6    74
#> # ... with 150 more rows, and 3
#> # more variables: Month <int>, Day
#> # Ozone_NA <fct>, Solar.R_NA <fct>,
#> # Wind_NA <fct>, Temp_NA <fct>,
#> # Month_NA <fct>, Day_NA <fct>
```

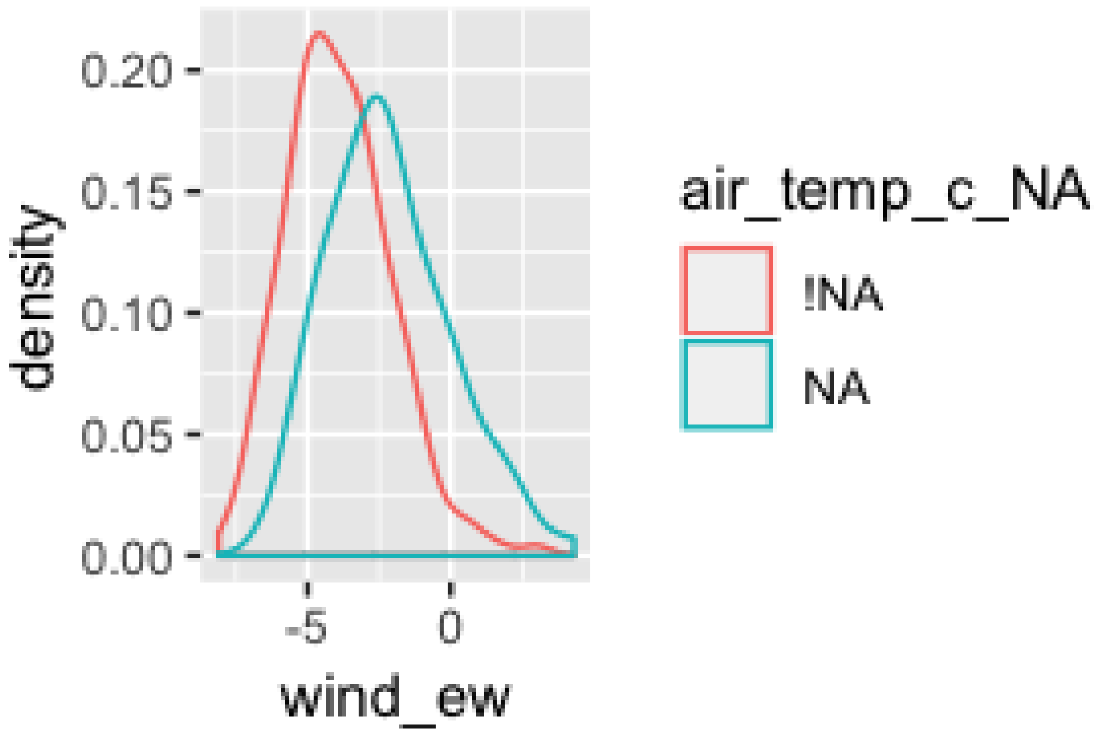
Explore missingness, link summaries to data values

```
oceanbuoys %>%
  bind_shadow() %>%
  group_by(humidity_NA) %>%
  summarise(
    wind_ew_mean = mean(wind_ew)
)
#> # A tibble: 2 x 2
#>   humidity_NA wind_ew_mean
#>   <fct>              <dbl>
#> 1 !NA                -3.78
#> 2 NA                 -3.30
```

Chapter 3

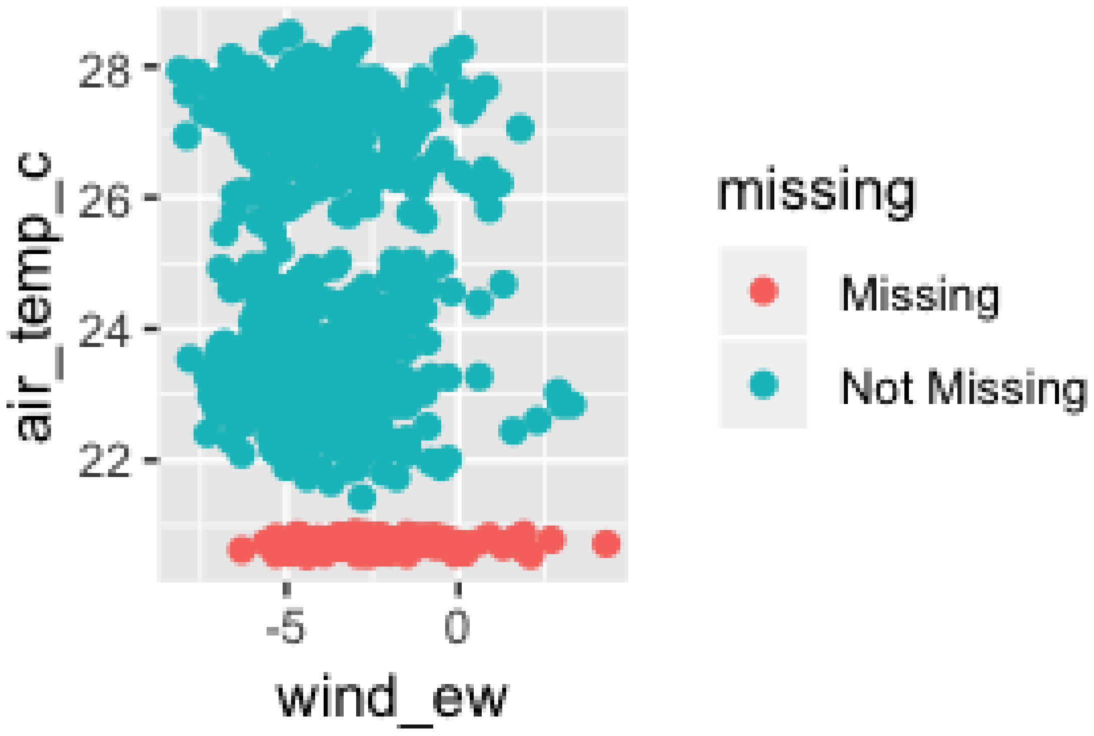
How values change with missingness.

```
nabular(oceanbuoys) %>%
  ggplot(aes(x = wind_ew,
             color = air_temp_c_NA)) +
  geom_density()
```



Visualise missings across 2 variables.

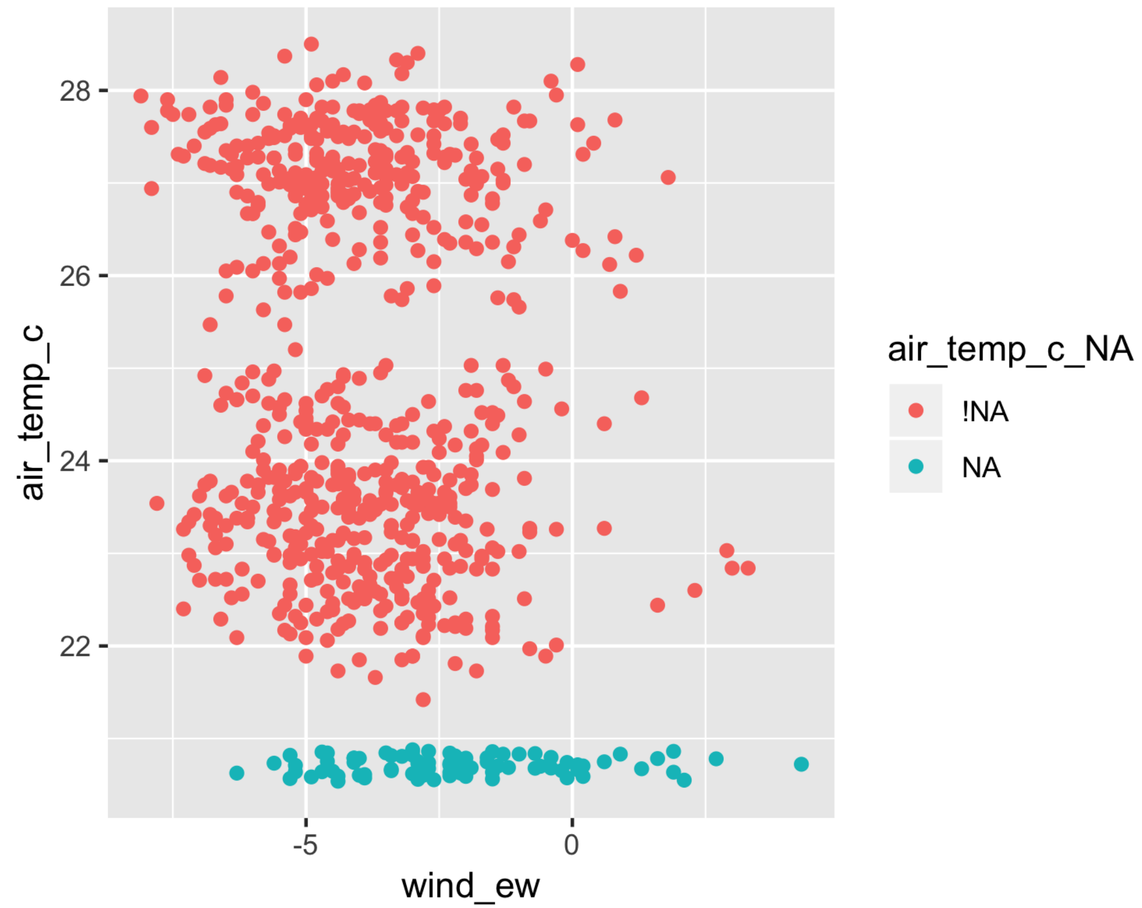
```
ggplot(oceanbuoys,
       aes(x = wind_ew,
           y = air_temp_c)) +
  geom_miss_point()
```



Chapter 4

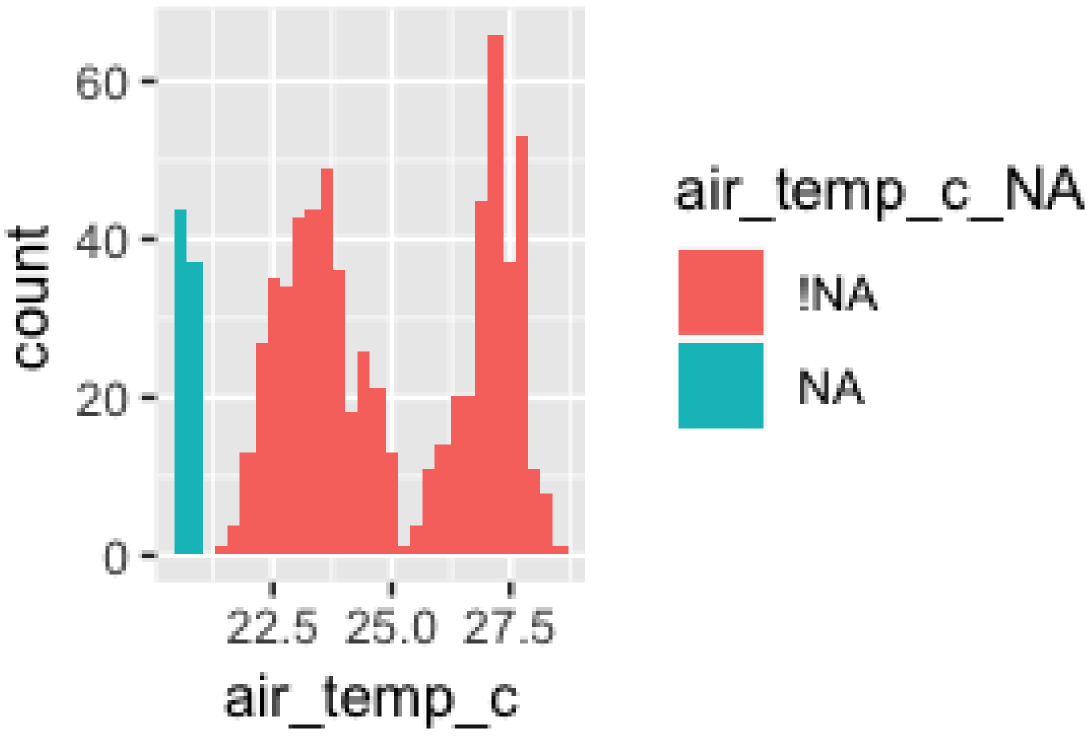
Good and bad imputations

```
naniar::impute_mean_all()
simputation::impute_lm()
```



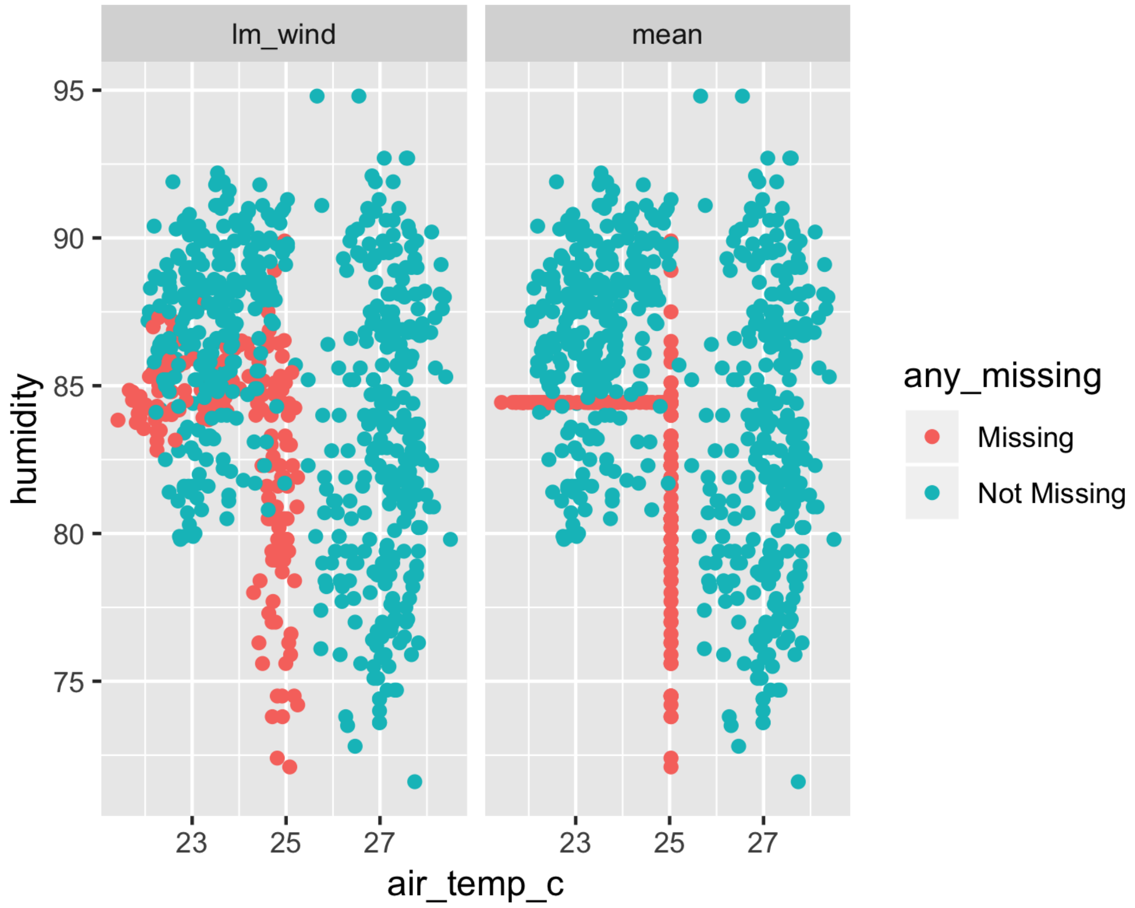
Compare imputed and original values

```
ggplot(ocean_imp_track,
       aes(x = air_temp_c,
           fill = air_temp_c_NA)) +
  geom_histogram()
```



Chapter 4

Using different imputation models



How imputation models affect subsequent inference

```
# A tibble: 12 x 6
   imp_model term   estimate
   <chr>      <chr>     <dbl>
 1 cc         (Int… -7.35e+2
 2 cc         air_…  8.64e-1
 3 cc         humi…  3.41e-2
 4 cc         year   3.69e-1
 5 imp_lm_w… (Int… -1.71e+3
 6 imp_lm_w… air_…  3.78e-1
 7 imp_lm_w… humi…  2.18e-2
 8 imp_lm_w… year   8.66e-1
 9 imp_lm_a… (Int… -6.97e+2
10 imp_lm_a… air_…  8.90e-1
11 imp_lm_a… humi…  1.27e-2
12 imp_lm_a… year   3.51e-1
# ... with 3 more variables:
#   std.error <dbl>,
#   statistic <dbl>,
#   p.value <dbl>
```

This is only the beginning!

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mice R package

Flexible Imputation of Missing Data

DEALING WITH MISSING DATA IN R

Thank you!