Clinical Data Wrangling

Data Exploration with Burro

Aaron S Coyner, PhD

HIP 523

Acknowledgements

- Slides
  - Adapted from the Clinical Data Wrangling Workshop
  - Nicole Weiskopf, PhD
  - Ted Laderas, PhD
- Data
  - Adapted from the synthetic patient cohort used in BMI 569: Data Analytics

Learning Objectives

- **Understand** the purpose of Exploratory Data Analysis (EDA)
- **Learn** how to perform EDA using `burro`
- **Answer** questions about associations between variables

Overall Goal

- **Predict** 30-day hospital readmissions from our patients
  - **Explore** potential variables in the data to include in our model
    - **Understand** what each variable means
    - **Understand** interactions between variables
  - **Output** a list of potential variables to include in our model

Exploratory Data Analysis

What is it?

- Pioneered by John Turkey
- Detective work on your data
- An **attitude** toward data, not just techniques
- **“Find patterns, reveal structure, and make tentative model assessments.”**
  — John Behrens, *Principles and Procedures of Exploratory Data Analysis* (1997)

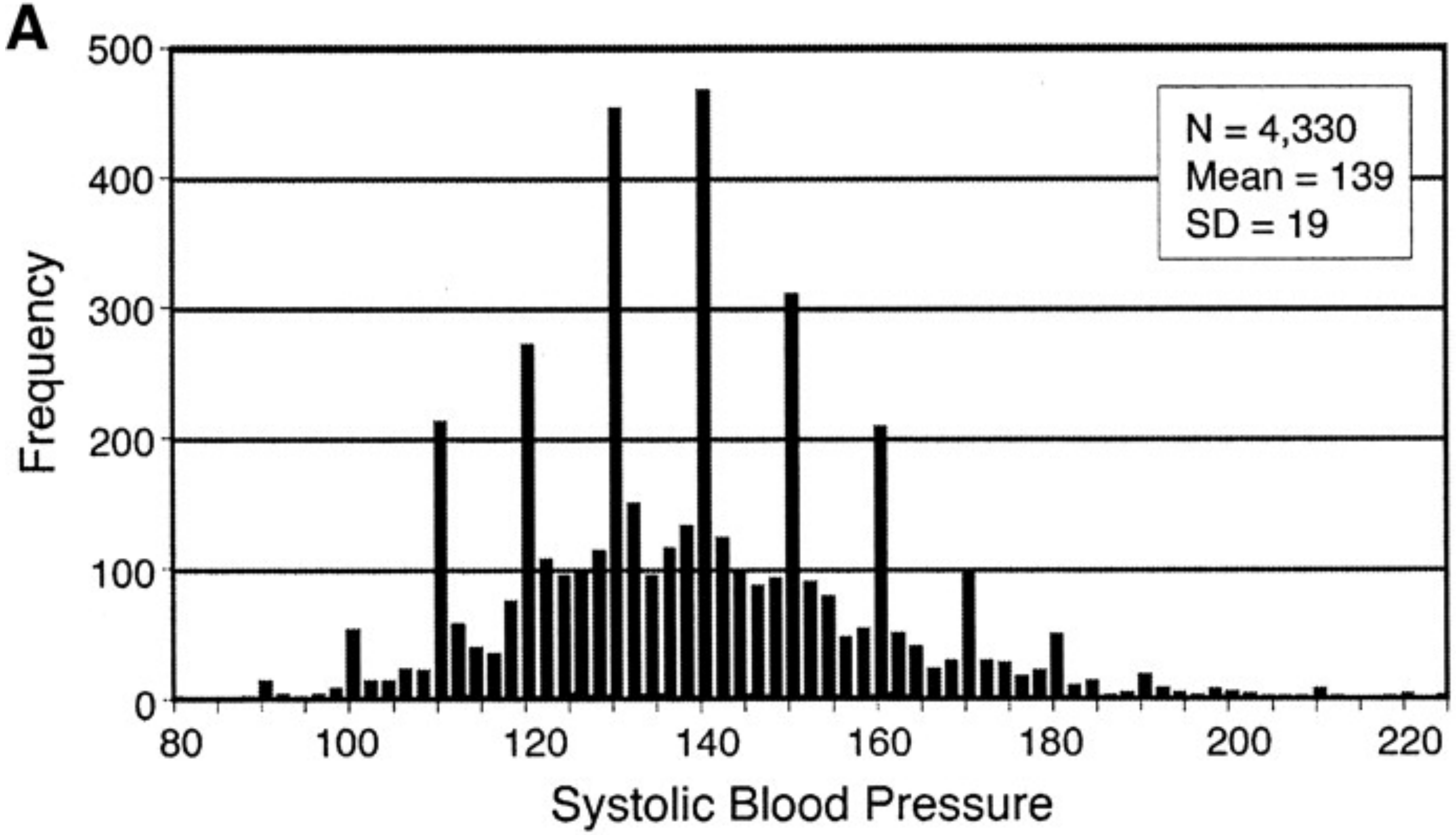
Exploratory Data Analysis

A Quote to Remember

- “Exploratory data analysis can never be the whole story,
  but nothing else can serve as the foundation stone.”
  — John Tukey, *Exploratory Data Analysis* (1977)

Exploratory Data Analysis

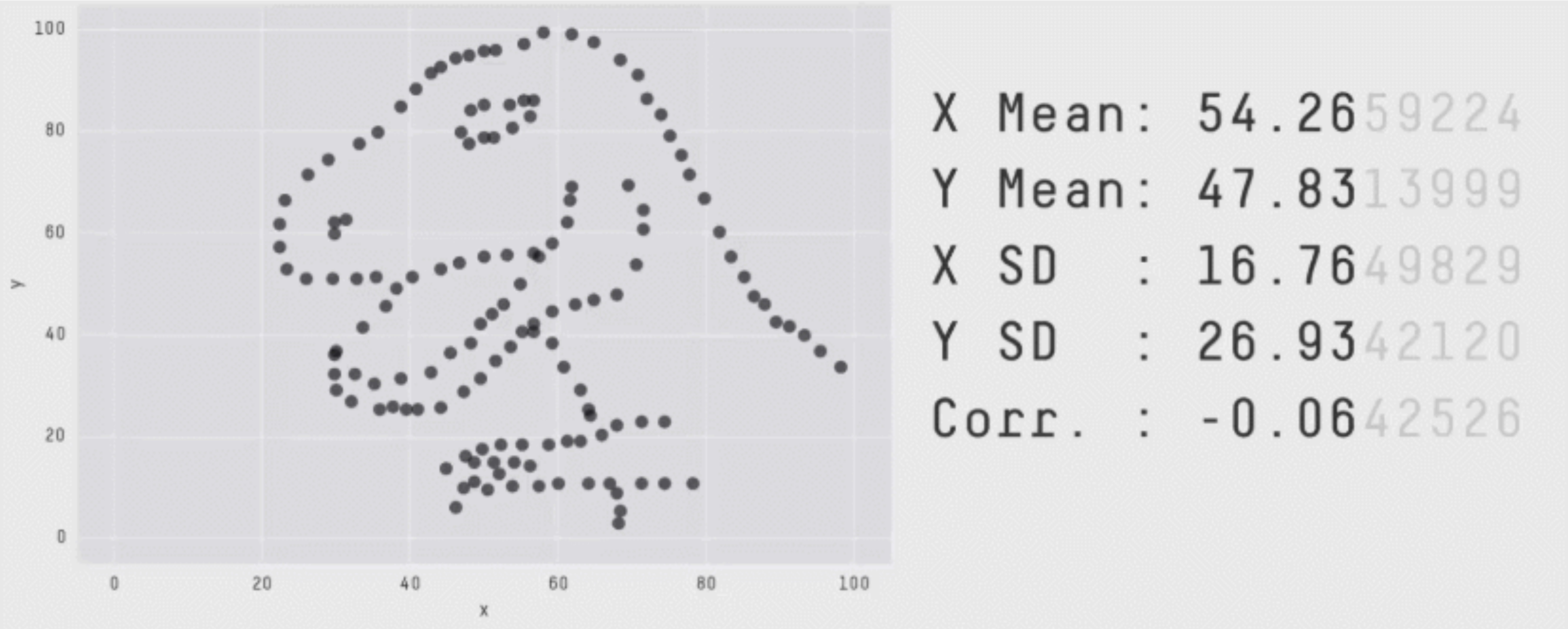
Why should we visualize our data?



Need to be aware of issues in the data!

Exploratory Data Analysis

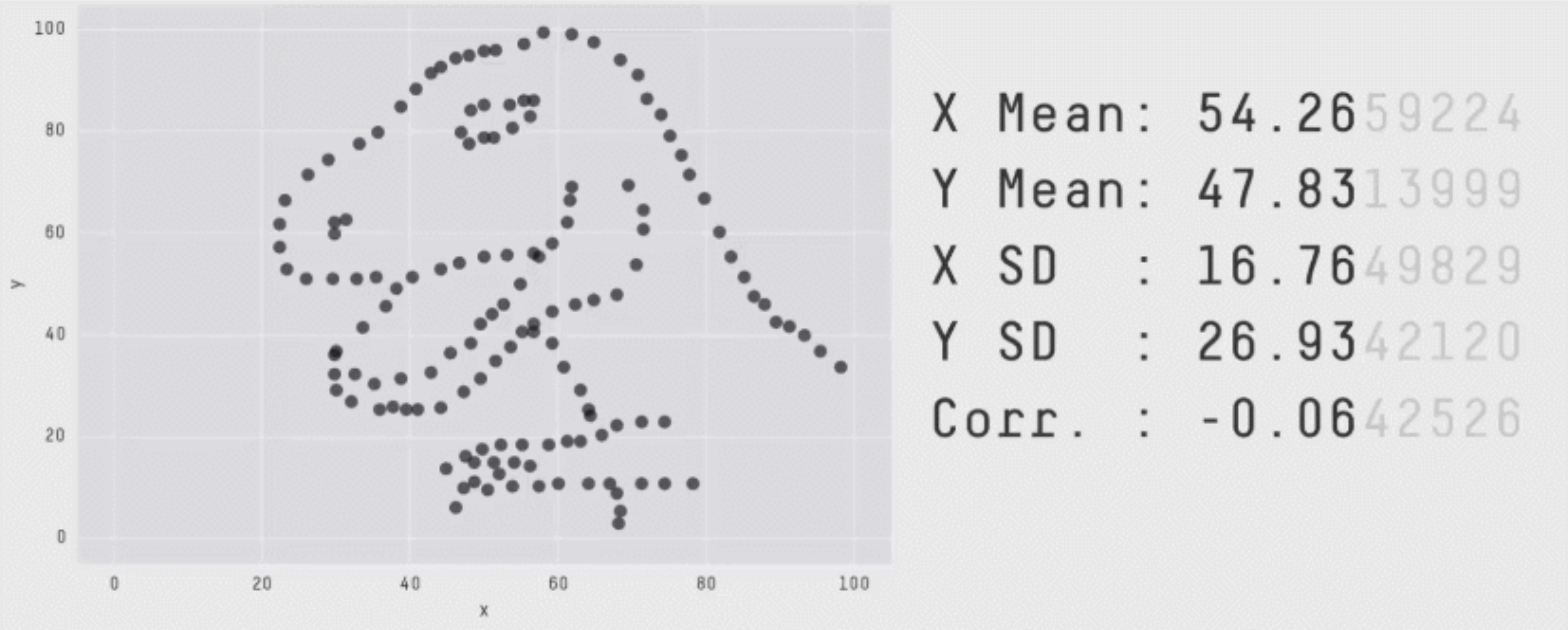
BEWARE: Datasaurus Dozen!



12 datasets. Same mean. Same standard deviation. Both dimensions.

Exploratory Data Analysis

BEWARE: Datasaurus Dozen!



```
X Mean: 54.2659224
Y Mean: 47.8313999
X SD  : 16.7649829
Y SD  : 26.9342120
Corr. : -0.0642526
```

12 datasets. Same mean. Same standard deviation. Both dimensions.

Visualization

Look first

- Visualization is a **gateway**
- **Understand** the issues
- Not going to focus on modeling and coding
    - **Build** your foundations and intuitions about your data
    - *Then* we can start getting technical

Burro

A Package for Data Exploration

- Created by Ted Laderas
- Useful for examining issues in your datasets
  - Missing data
  - Associations
  - Correlations
- If you are interested, it is freely-available here: http://laderast.github.io/burro

Workflow

Selecting Variables for Modeling

Workflow

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- Ultimately, need to make decisions about which variables we think may be useful for predicting 30-day readmissions

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- **Missingness**
    - Are there too many missing cases in our variable?

Workflow

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- **Usefulness**
    - Is there a correlation between the variable and our outcome?

Workflow

Selecting Variables for Modeling

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- **Association (multi-collinearity)**
    - How associated is our variable with other variables in the model? Should we choose one or the other?

Workflow

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- **Missingness**
  - Are there too many missing cases in our variable?
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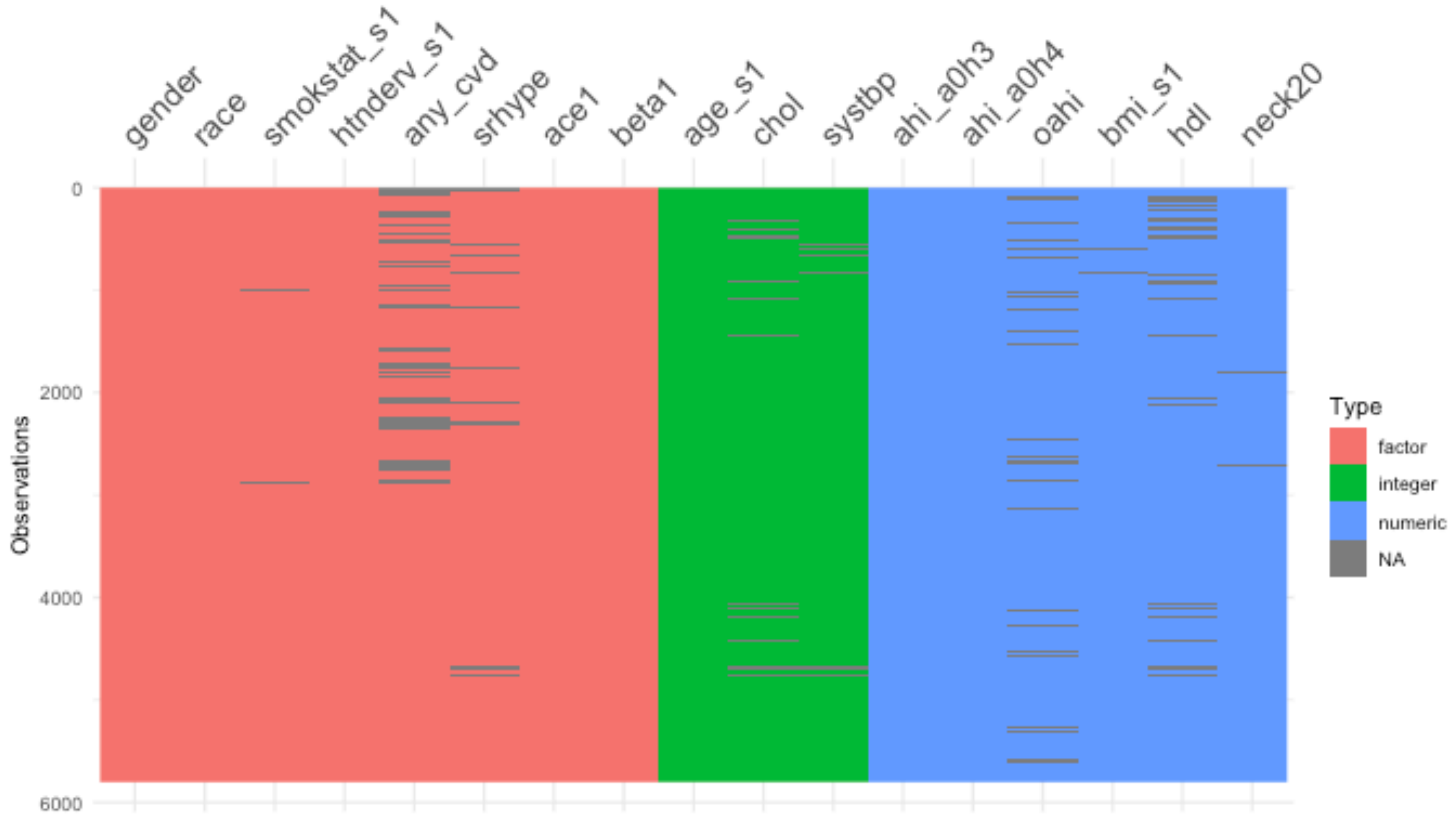
  - Is there a correlation between the variable and our outcome?
- **Association (multi-collinearity)**
  - How associated is our variable with other variables in the model? Should we choose one or the other?
- **Clinical**/domain-specific considerations
  - How were the data collected and does that affect our measurement?

Burro

https://bit.ly/hip_dw

The
Overview Panel



HIP523 Data
Data Overview
Categorical Data
Continuous Data
Visual Summary
Tabular Summary
Data Dictionary
patientid
readmit30
diabetes_complications
myocardial_complications
outcome
admit_source
age
length_of_stay
0
2000
4000
Observations
Type
character
date
factor
integer
logical
numeric

HIP523 Data
Data Overview
Categorical Data
Continuous Data
Visual Summary
Tabular Summary
Data Dictionary

Data summary

Name	my_data_table
Number of rows	5603
Number of columns	8
_______________________	
Column type frequency:	
character	1
factor	5
numeric	2
________________________	
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
patientid	0	1	1	5	0	5603	0

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
readmit30	1635	0.71	FALSE	2	0: 3411, 1: 557
diabetes_complications	755	0.87	FALSE	2	0: 4767, 1: 81
myocardial_complications	951	0.83	FALSE	2	0: 3474, 1: 1178
outcome	0	1.00	FALSE	3	Dis: 2787, SNF: 2238, Reh: 578
admit_source	0	1.00	FALSE	4	Eme: 2652, Cli: 1463, Tra: 1177, SNF: 311

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
age	755	0.87	35.18	6.00	21.29	30.09	35.13	40.04	53.9	▂▇▇▃▁
length_of_stay	0	1.00	7.97	10.41	2.00	3.00	5.00	9.00	298.0	▇▁▁▁▁

HIP523 Data
Data Overview
Categorical Data
Continuous Data
Visual Summary
Tabular Summary
Data Dictionary
Show 50 entries
Search:

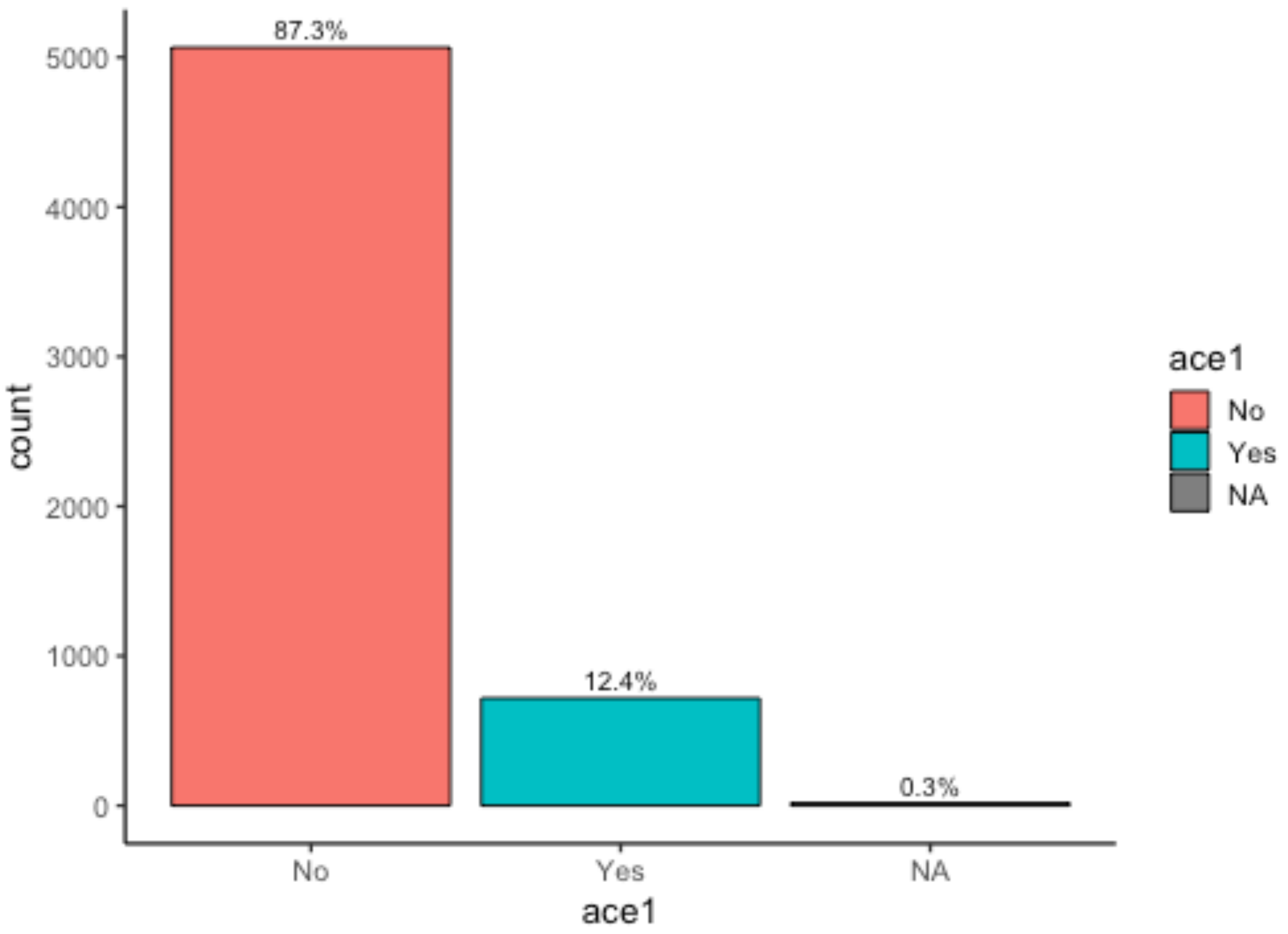
	ï..variable.name	description
1	age	Age of patient in years
2	patientid	Numeric ID
3	length_of_stay	length of stay in the hospital for previous admission in days
4	readmit30	1/0 value of whether the patient was readmitted to the hospital within 30 days
5	diabetes_complications	Whether the patient has complications related to diabetes. Calculated by using the Charleson Comorbidity Index on ICD9 codes
6	myocardial_complications	Whether the patient has complications related to myocardial infarctions. Calculated by using the Charleson Comorbidity Index on ICD9 codes
7	outcome	Where the patient ended up after admission
8	admit_source	Department where the patient was admitted

Questions

From the Overview Panel

- How big is the dataset?
- How many categorical variables (factors) are there?
- How many missing `readmit30` cases (coded as `NA`) are there?
- What is the mean age of the dataset?
    - Is it what you would expect?
- Link to `Burro`: https://bit.ly/hip_dw
- Link to the data: https://bit.ly/hip_sheet

The
Category Panel



HIP523 Data
Data Overview
Categorical Data
Continuous Data
Single Variable
Outcome View
Tabular

Select Categorical Variable

admit_source

47.3%
26.1%
21.0%
5.6%
2000
1000
0
count
Clinic
Emergency Room
SNF
Transfer
admit_source

```
readmit_data %>%
  mutate(gr = 1) %>%
  ggplot(aes_string(x = admit_source, fill = admit_source)) +
  geom_bar(aes(y = ..count..), color = "black") +
  viridis::scale_fill_viridis(discrete = TRUE, option = "magma") +
```

HIP523 Data
Data Overview
Categorical Data
Continuous Data
Single Variable
Outcome View
Tabular
5000
4000
3000
2000
1000
0
count
85%
1%
13%
0
1
NA
diabetes_complications

Select Categorical Variable

diabetes_complications

```
readmit_data %>%
  mutate(gr = 1) %>%
  ggplot(aes_string(x = diabetes_complications, fill = diabetes_complications)) +
  geom_bar(aes(y = ..count..), color = "black") +
  viridis::scale_fill_viridis(discrete = TRUE, option = "magma") +
```

HIP523 Data
Data Overview
Categorical Data
Continuous Data
Single Variable
Outcome View
Tabular

Select Variable: diabetes_complications

Select Outcome Variable: readmit30

readm
■ 1
□ 0
□ NA
1.00
0.75
0.50
0.25
0.00
count
0
1
diabetes_complications

HIP523 Data
Data Overview
Categorical Data
Continuous Data
Single Variable
Outcome View
Tabular

Select Variable

readmit30

Select Outcome Variable

diabetes_complications

diabet
■ 1
🟨 0
□ NA
count
1.00
0.75
0.50
0.25
0.00
0
1
readmit30

HIP523 Data
Data Overview
Categorical Data
Continuous Data
Single Variable
Outcome View
Tabular
n: 482
diabetes_complications: 1
readmit30: 2
readmit30
1
0
0
1
diabetes_complications

Select Crosstab Variable (x): readmit30

Select Crosstab Variable (y): diabetes_complications

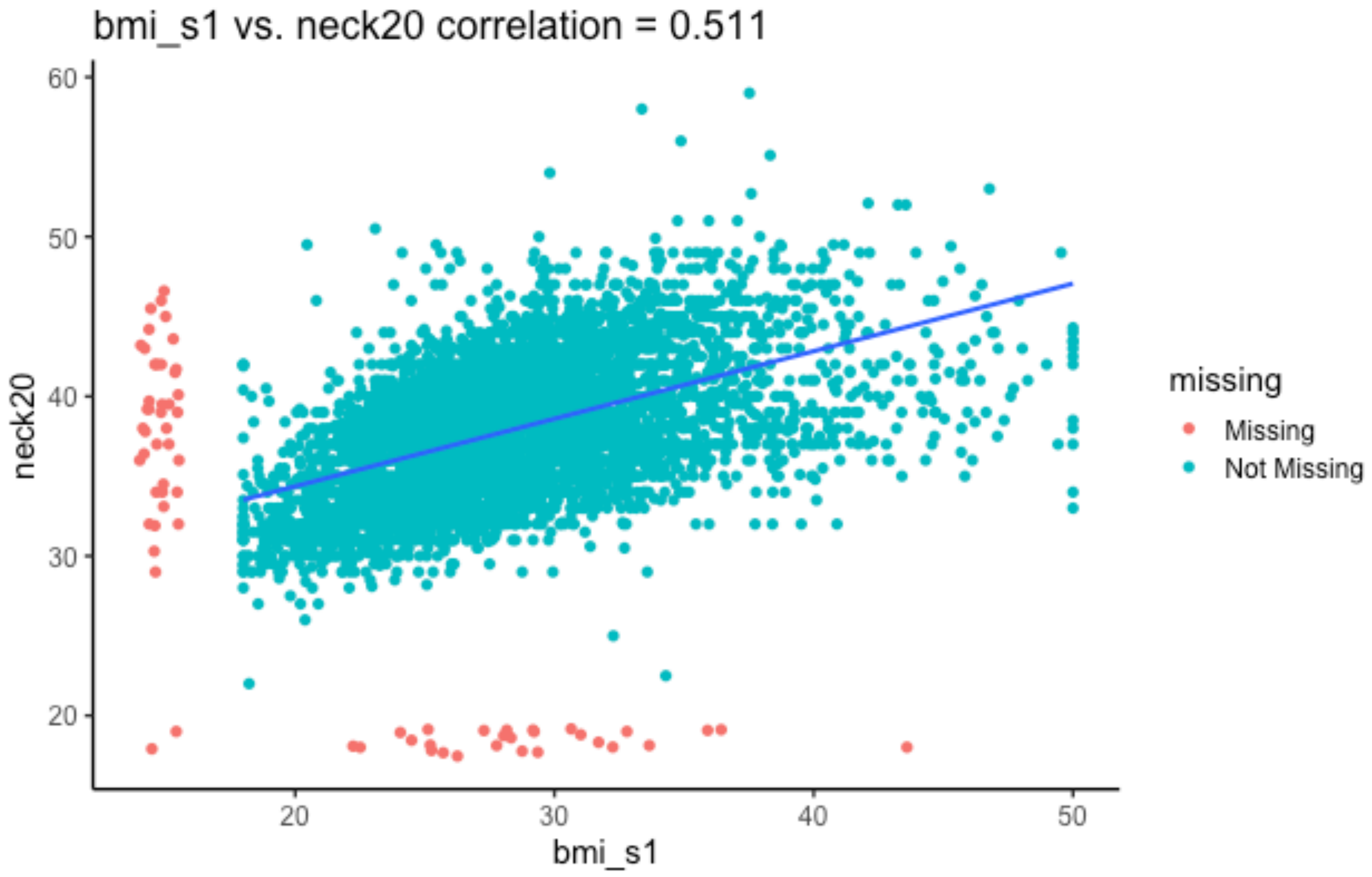
```
readmit_data %>%
  data.frame() %>%
  ggplot(aes_string(y = readmit30, x = diabetes_complications)) +
  geom_count() +
  theme(axis.text.x = element_text(angle = 90))
```

Questions

From the Category Panel

- How many categories are there for `outcome`?
- Are the proportions of `readmit30` balanced across `admit_source`?
- Are the proportions of missing data for `readmit30` balanced across `outcome` categories?
- Link to `Burro`: https://bit.ly/hip_dw
- Link to the data: https://bit.ly/hip_sheet

The
Continuous Panel



HIP523 Data
Data Overview
Categorical Data
Continuous Data
Histogram Explorer
Boxplot Explorer
Correlation Explorer
1
50
1
6
11
16
21
26
31
36
41
46
50
3000
2000
1000
0
count
0
100
200
300
length_of_stay

Select Numeric Variable

length_of_stay

Number of bins:

30

HIP523 Data
Data Overview
Categorical Data
Continuous Data
Histogram Explorer
Boxplot Explorer
Correlation Explorer
age
50
40
30
20
0
1
NA
myocardial_complications

Select Numeric Variable: age

Select Category Variable: myocardial_complications

HIP523 Data
Data Overview
Categorical Data
Continuous Data
Histogram Explorer
Boxplot Explorer
Correlation Explorer

Select Y Variable: age

Select Y Variable: length_of_stay

age vs. length_of_stay correlation = -0.0234

300
200
100
0
length_of_stay
20
30
40
50
age
missing
Missing
Not Missing

Questions

From the Continuous Panel

- What is the distribution of `age` in our patients?
- Is `age` evenly distributed across `readmit30`? If not, how is it distributed?
- Are `age` and `length_of_stay` correlated? Are you surprised?
- Should we include both `age` and `myocardial_complications` in our model?
- Link to `Burro`: https://bit.ly/hip_dw
- Link to the data: https://bit.ly/hip_sheet

Selecting Predictors

For Next Time

- **Missingness**
  - Which variables have missing data?
  - Is the missingness correlated for any two variables?
  - How could we deal with this?
- **Associations and Correlations**
  - Including interacting variables as predictors can affect their predictive power
  - For example, `age` and `myocardial_complications`
- **Select your predictor covariates of** `readmit30`
  - **We’re going build predictive models of the dataset using these predictors**

Wrap Up

- Data exploration can be fun “detective” work
- Be curious! Start with a question.
- Assess the impact of adding a covariate to a model:
  - Does the distribution look like other populations?
  - Is it associated with your outcome?
  - Is it associated with other variables?
  - Is the data missing in a suspicious way?