

# COVID-19 Data Science Analysis

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Mentors: Dr. Niema Moshiri & Dr. Youwen Ouyang

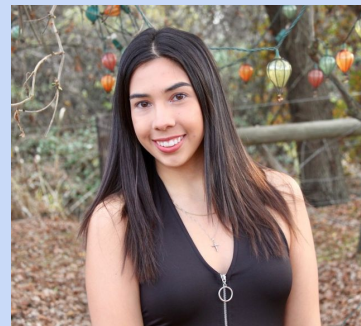
UCSD DBMI Summer Internship 2020  
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# About Us



**Mhealyssah (Mhea) Bustria**

A Computer Science undergraduate at CSUSM. She is always happy to give back to her community, and she is especially-interested in advancing the fields of education and health.



**Anjelina Velazquez**

Currently a fourth year Computer Science student at CSUSM. Enjoys keeping busy by always learning new concepts and ideas. She is always encouraging others to do the same.

# Outline

## BACKGROUND

- Motivation
- Our Project
- Methods

## RESULTS

- Reading patient data
- Analyzing the dataset

## CONCLUSIONS

- Lessons learned
- Next steps

# Background - Motivation

To combat the **COVID-19 pandemic**, researchers need to make inferences from data collected from patients.

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To combat the **COVID-19 pandemic**, researchers need to make inferences from data collected from patients.

**Are these inferences generalizable?**

Researchers need to account for...

**potential errors and inaccuracies**  
that are present in the data collected due to manual input

**potential confounding factors,**  
such as biases in patient sampling

# Background - Our project

Collection of over 75,000 SARS-CoV-2  
Patient Records

## **Manually-entered data**

Errors,  
inconsistencies, and  
missing data  
affects  
the data science  
analysis process.

## **Large dataset**

What do the patient  
records in our dataset  
look like?

What are some  
potential confounding  
factors?

# Research Goals

## **Reading patient data**

Demonstrate how  
manually-entered data  
affects  
data science analysis.

## **Analysis and visualization**

Show how  
demographic information varies  
in our large sample.



# Methods

This research was supported by the NLM training grant T15LM011271, the NSF RAPID grant NSF-2028040, and the GCP Research Credits Program.



## **Obtaining the dataset**

Global initiative on sharing all influenza data (GISAID)

- Extracted records were stored in a gzipped JSON file

# Methods



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## Data reading and analysis

Python

- Identify **what information can be found** in the records
- Decide **what information to use** for analysis and visualization

# Methods



## Obtaining the dataset

Global initiative on sharing all influenza data (GISAID)

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## Data reading and analysis

Python

- Identify **what information can be found** in the records
- Decide **what information to use** for analysis and visualization



## Data visualization

**matplotlib** Python library

- pie charts

**seaborn** Python library (based on matplotlib)

- bar plots
- count plots
- violin plots

# RESULTS

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## Reading Patient Data

# Results - Reading patient data

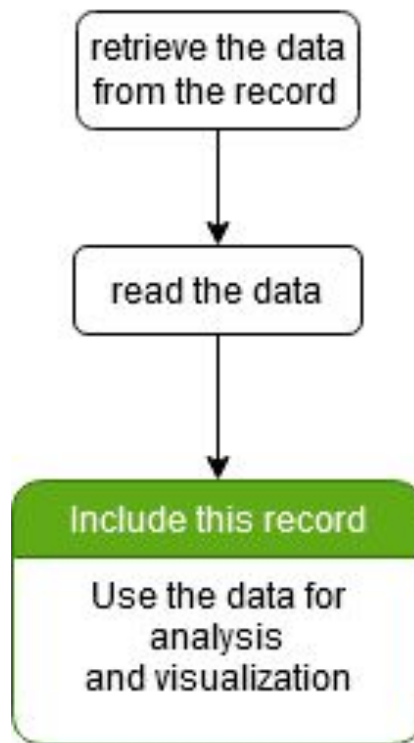
How were our analysis and visualization processes affected by manual data-entry practices?

How did we modify our data-reading strategies to account for unusable data?

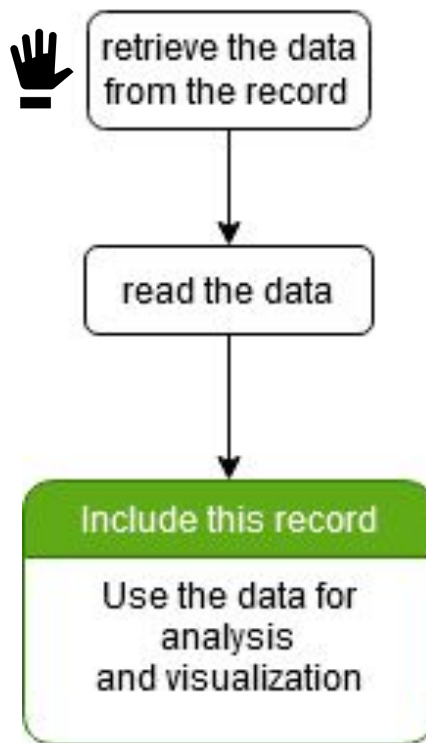
- data correction
- data exclusion

What are potential solutions to address the issues caused by manual data entry?

# Original strategy for reading the data

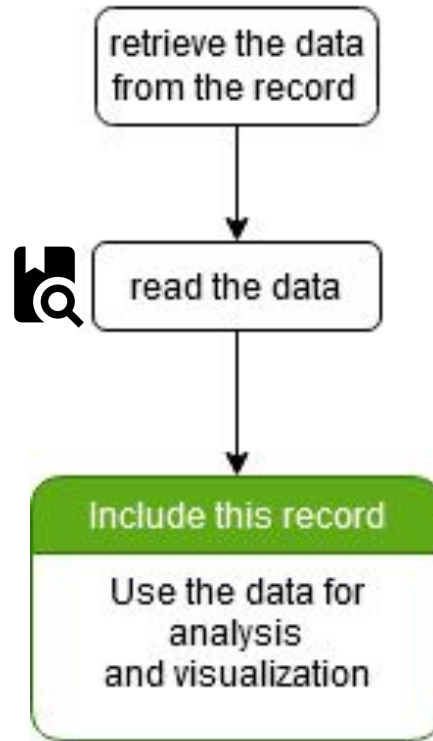


# Original strategy for reading the data

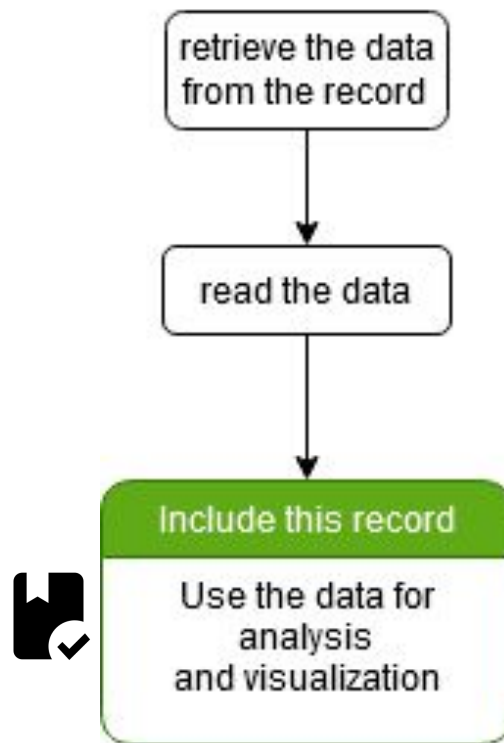




# Original strategy for reading the data



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# Types of missing / unknown / invalid data

## Type 1

Data for the  
attribute-of-interest was  
**not provided.**

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Data for the  
attribute-of-interest was  
provided, but was  
entered as some  
variation of  
**"unknown" or "not  
applicable"**.

# Types of missing / unknown / invalid data

## Type 1

Data for the attribute-of-interest was **not provided**.

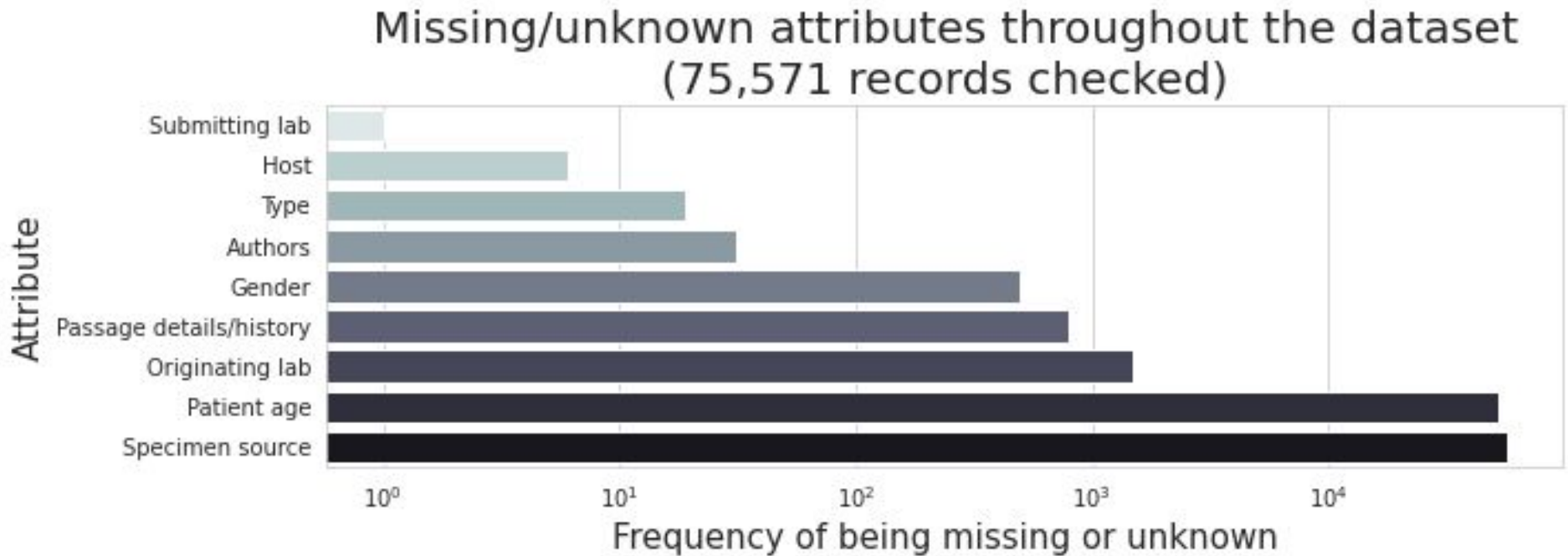
## Type 2

Data for the attribute-of-interest was provided, but was entered as some variation of **"unknown" or "not applicable"**.

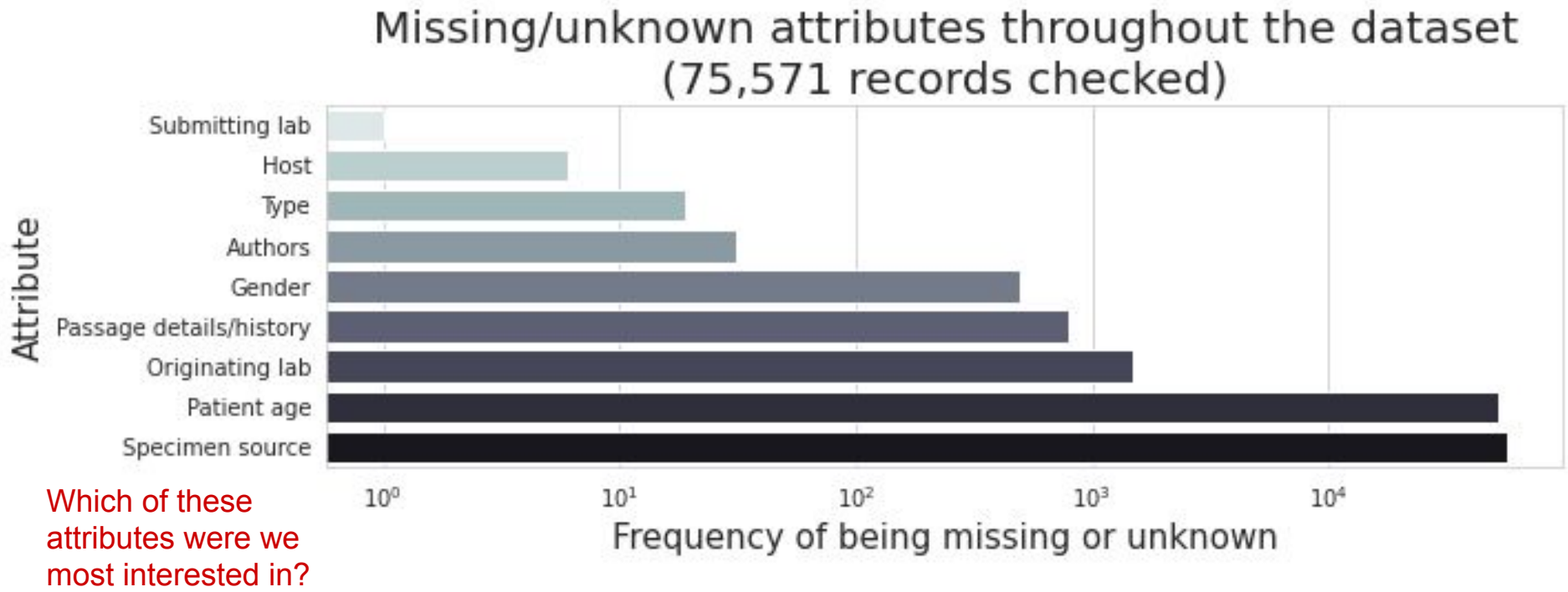
## Type 3

Data for the attribute-of-interest contained an error such as **formatting inconsistencies or misspellings**.

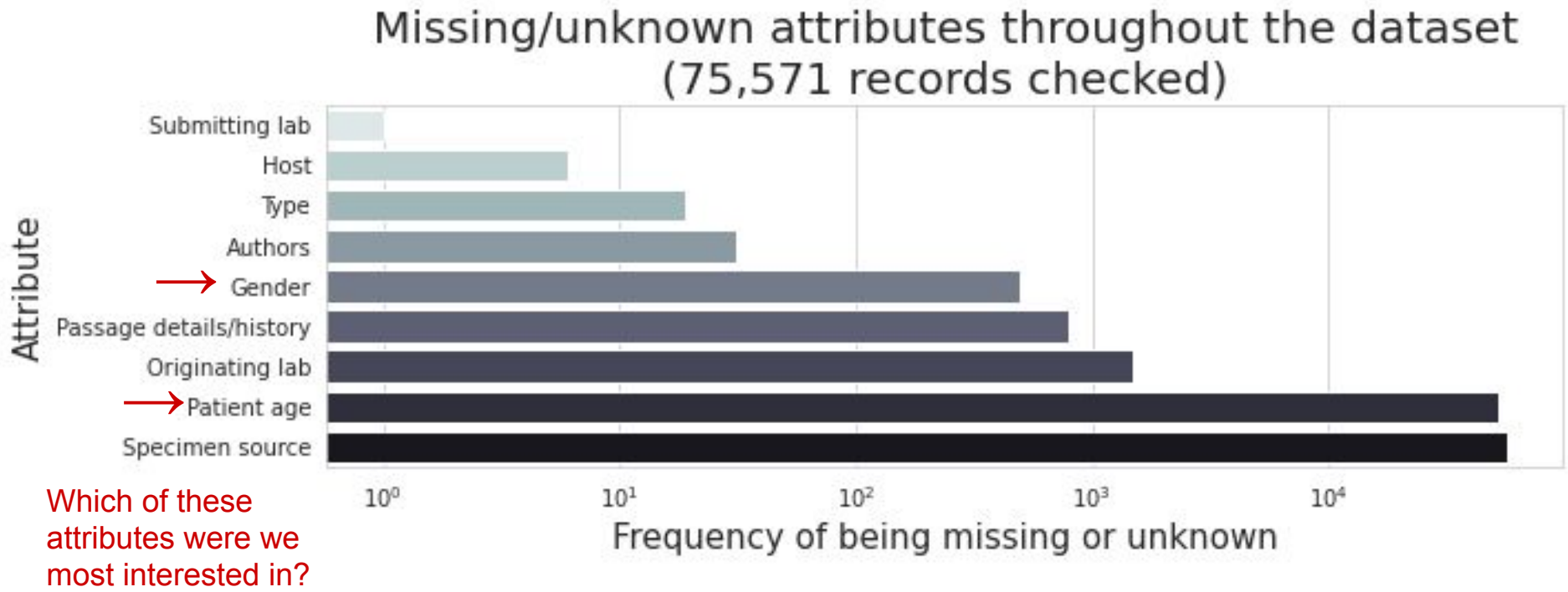
# 👤? How often was attribute data missing or invalid/unknown?



# 🧑? How often was attribute data missing or invalid/unknown?



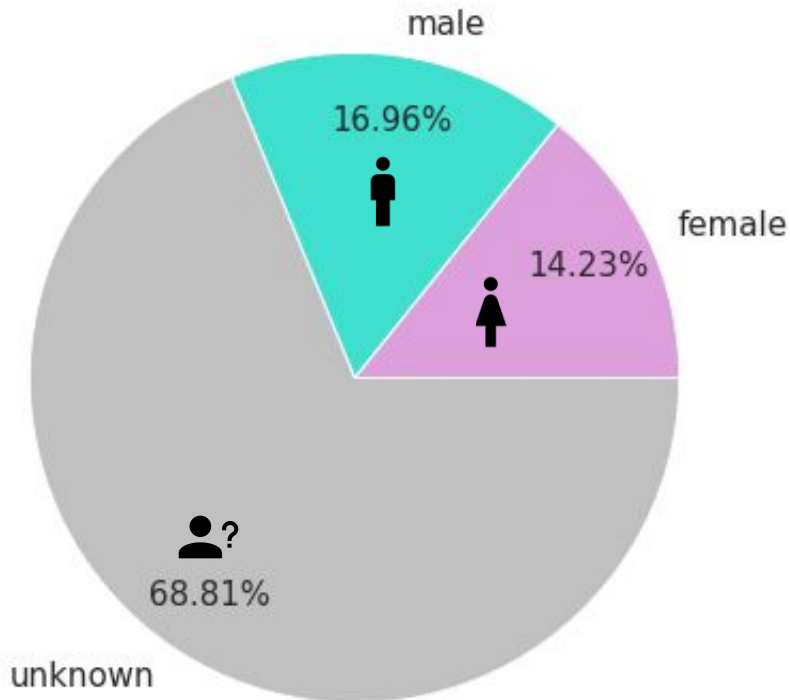
# 🧑? How often was attribute data missing or invalid/unknown?





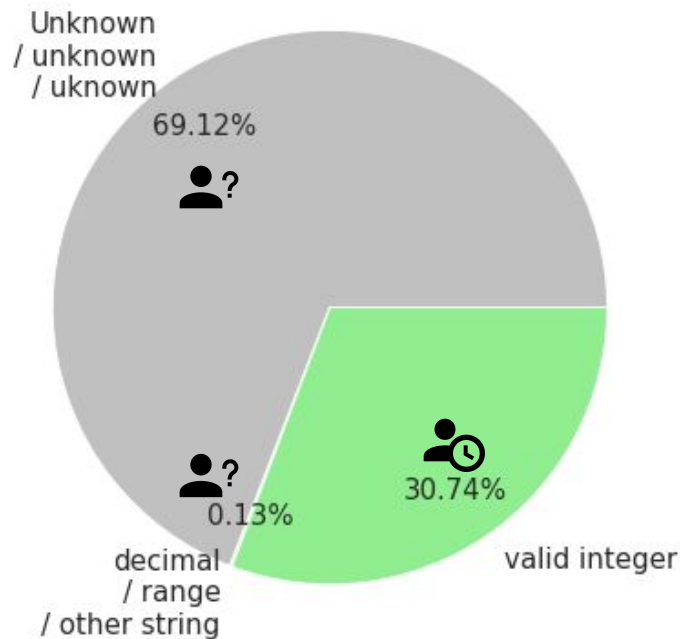
# 🧑🧒 How often did we encounter unknown gender data?

Amounts of known and unknown gender data from 75,571 records

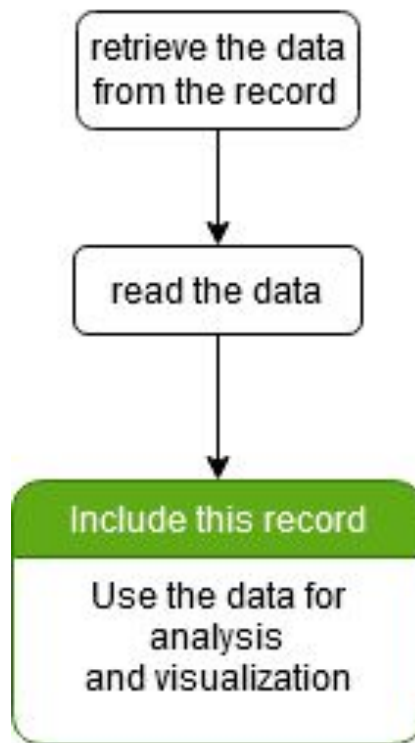


# How often did we encounter unknown or unusable age data?

Formats of age data of  
75,571 COVID-19 patient records

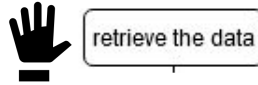


# Original strategy for reading the data



Throughout the study,  
how did we  
revise our strategies  
to handle the issues  
involved with  
manually-entered data?

# Handling manually-entered data

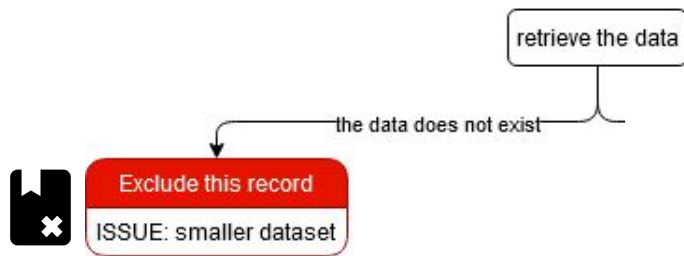


# Handling manually-entered data

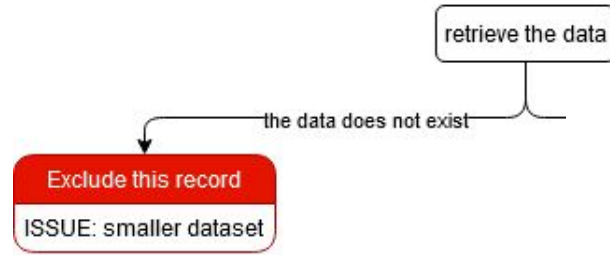
retrieve the data

the data may or may not  
be missing

# Handling manually-entered data

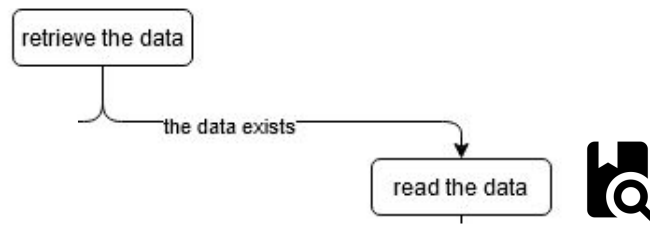


# Handling manually-entered data - example of data exclusion



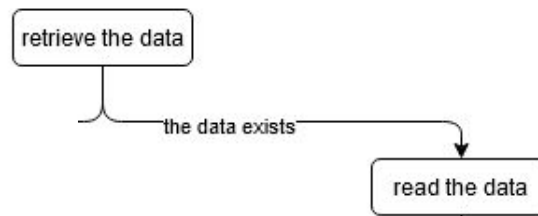
If age is an attribute of interest but there is no age provided in that record → **data exclusion**

# Handling manually-entered data



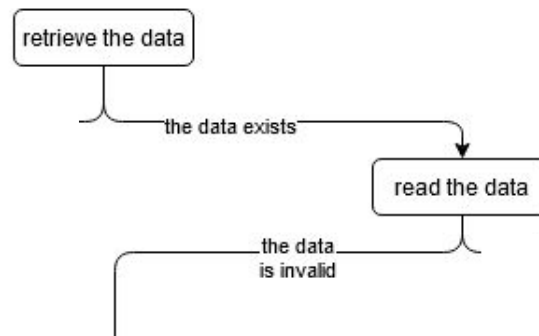


# Handling manually-entered data



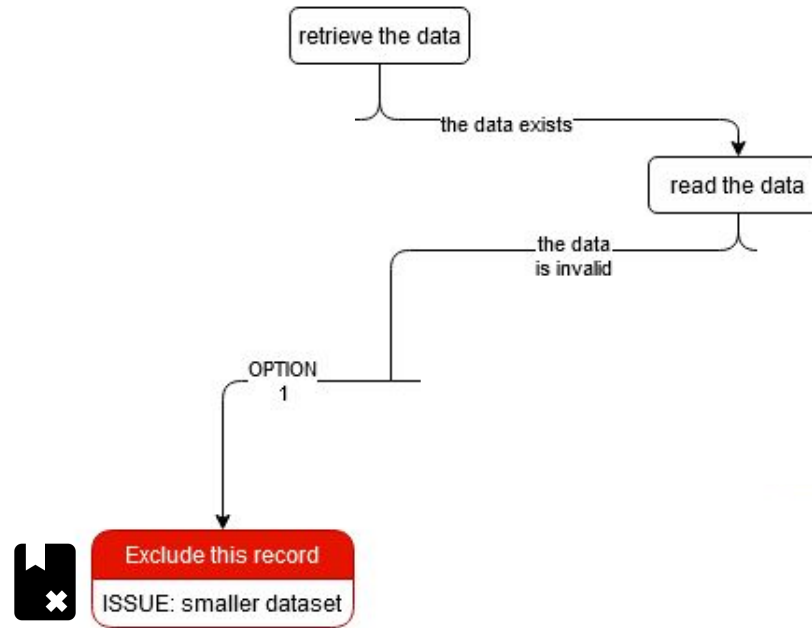
a data-entry error  
may or may not  
be discovered

# Handling manually-entered data

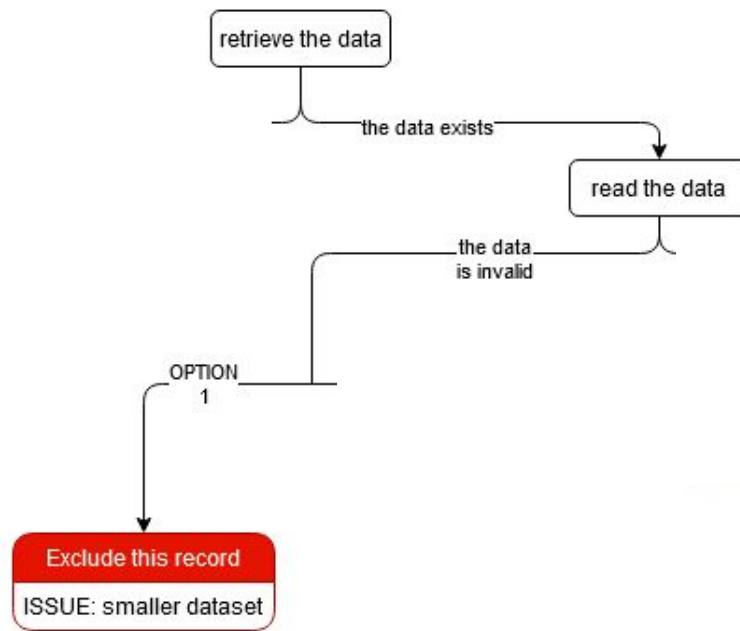


OPTIONS:  
data-exclusion  
or  
data-correction

# Handling manually-entered data

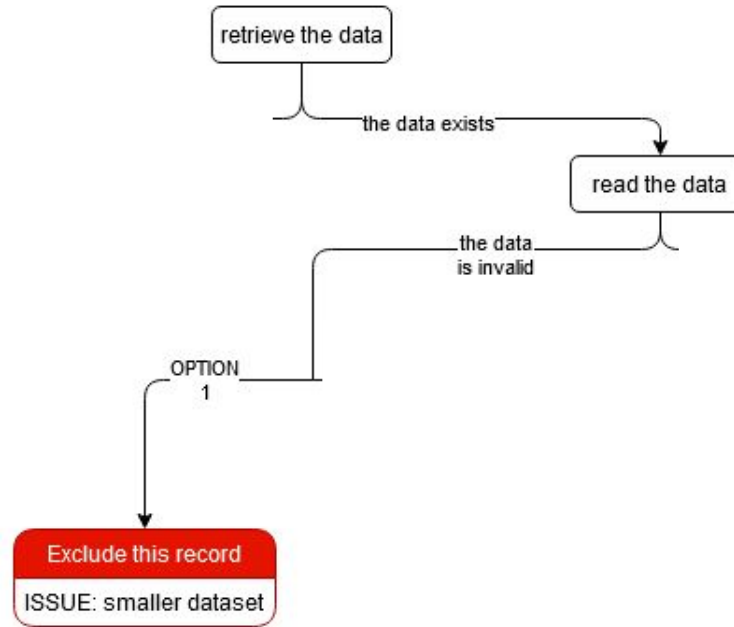


# Handling manually-entered data - example of data exclusion



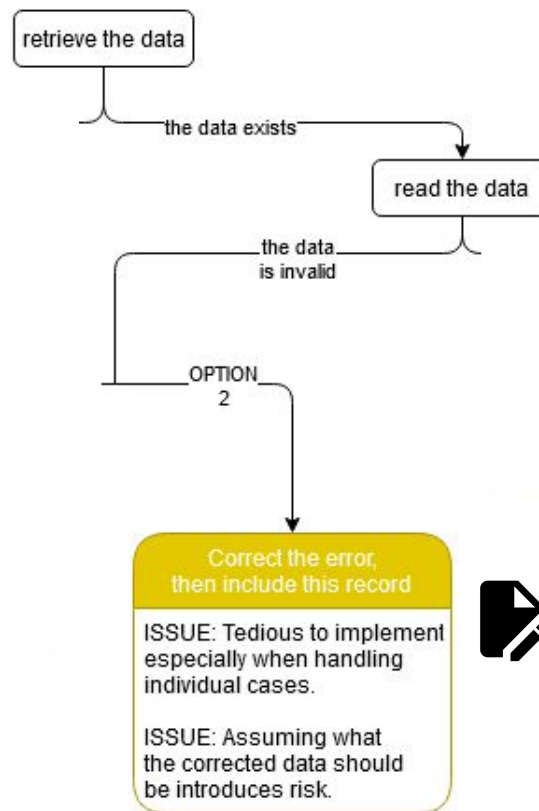
**"North America  
/ USA / LA"**  
could refer to Los Angeles or  
Louisiana. It is not specified  
whether the third piece is the  
state or the city.  
**ambiguous → exclude**

# Handling manually-entered data - example of data exclusion

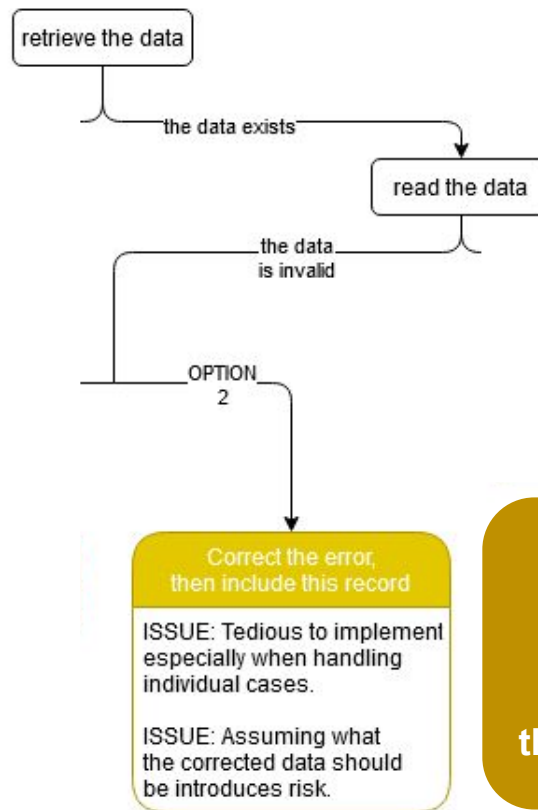


Age data is present in the record, but a value such as "unknown" or "not applicable" was provided.  
→ **exclude**

# Handling manually-entered data

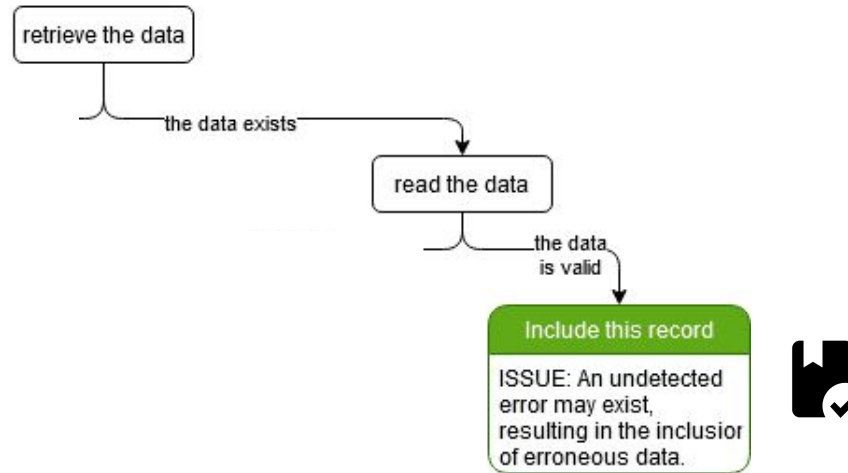


# Handling manually-entered data - example of data correction



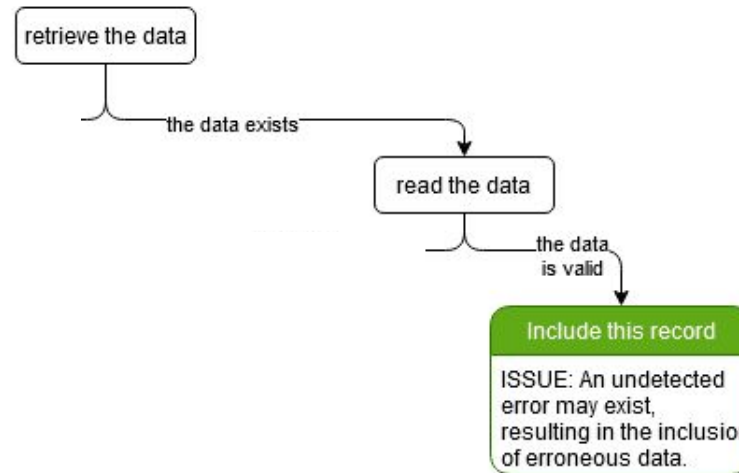
Location is provided as  
**"Oceania / Australia / NSW"**  
→ assume **"NSW"** means  
**"New South Wales"**, correct  
the value and include the data

# Handling manually-entered data





# Handling manually-entered data - example of data inclusion

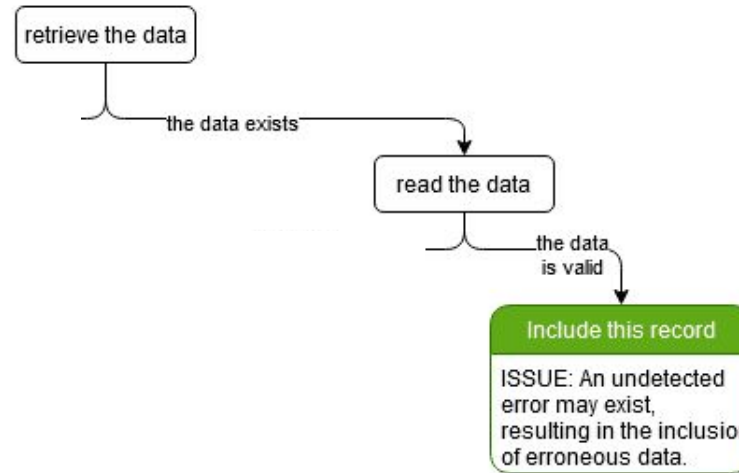


## "Asia / China / Wuhan"

Wuhan gets categorized as a state in China, but is really a city in Hubei, China.

→ **incorrect data was included due to unclear formatting**

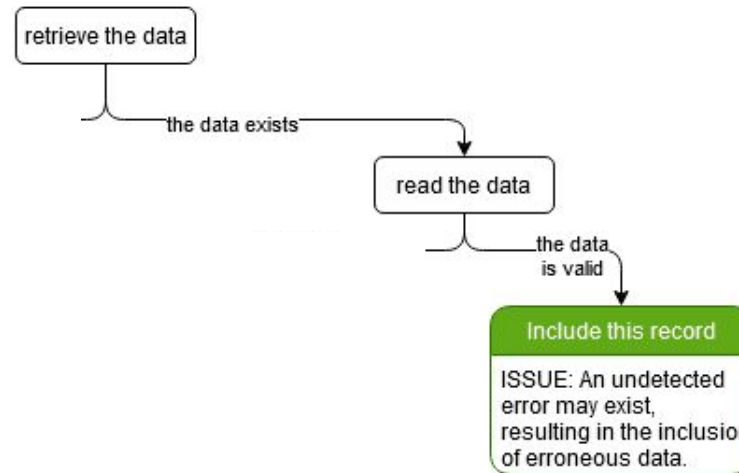
# Handling manually-entered data - example of data inclusion



**"Washington DC" and "District of Columbia" are stored as two separate categories.**

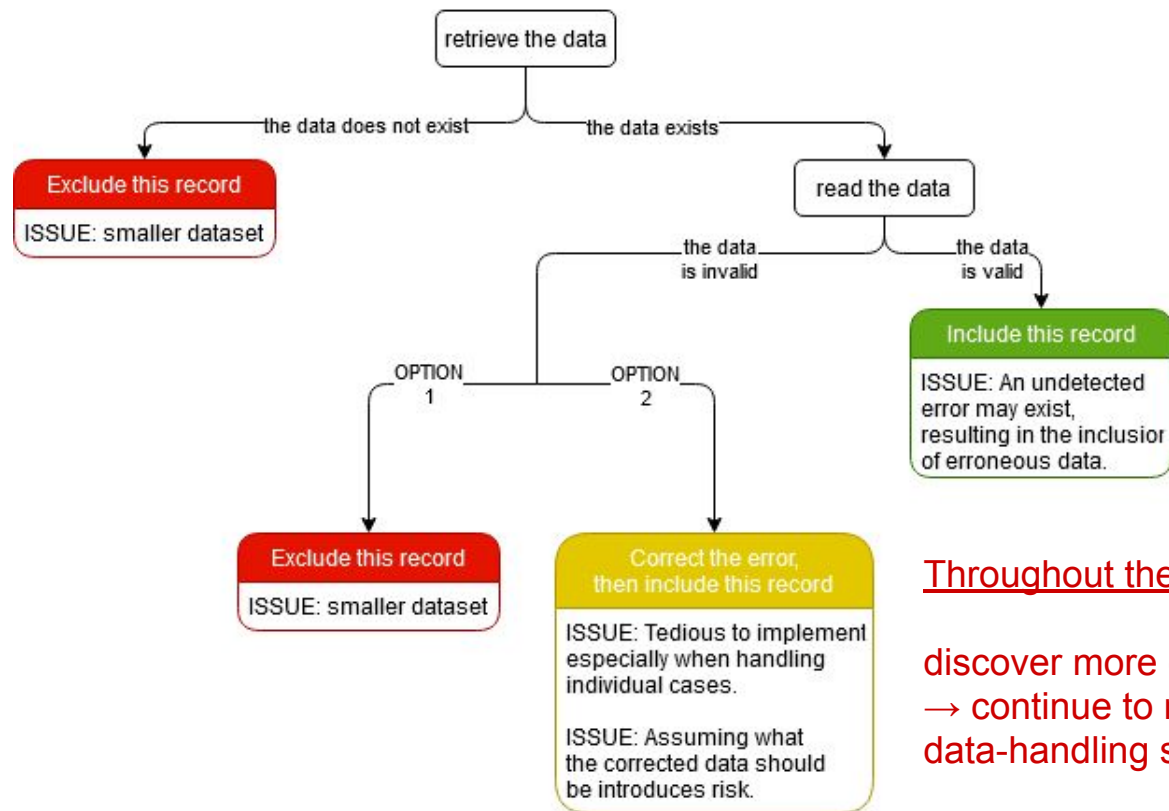
**→ dataset becomes misleading due to inconsistent naming conventions**

# Handling manually-entered data - example of data inclusion



**"Oceania / Australia /  
New South Wales / Sydney"**  
Sydney gets categorized into both  
"Australia" and "Wales".  
→ **incorrect data was included due to  
the categorization methods used**

# Handling manually-entered data



Throughout the study

discover more error cases  
→ continue to modify the  
data-handling strategies

# Potential solutions for improving data-entry practices

## **Improving Manual Data Entry**

- The use of dropdown menus instead of allowing the user to input information
- Adding Data Validation will ensure that all information being added is formatted correctly

## **Automated Data Capture instead of Manual Data Entry.**

Benefits of automation:

- Significantly reduces errors
- Improved efficiency and cleaner data

# RESULTS

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## Analyzing the dataset

# Results - Analyzing the dataset

What did our collection of 75,571 patient records look like?

Attributes that we looked at



## Location

Where the data was submitted from

- Continent
- Country
- State



## Gender

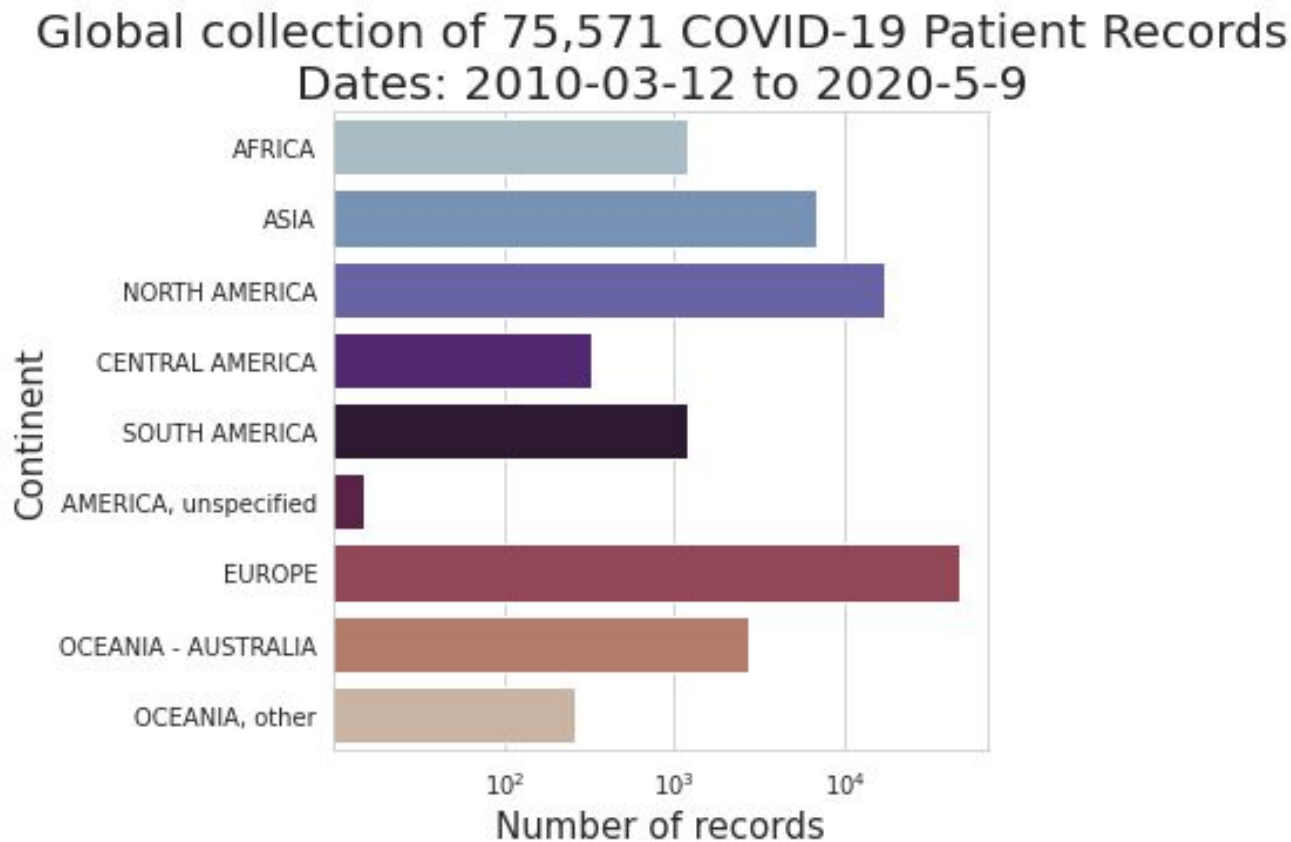
→ The gender data that was provided



## Age

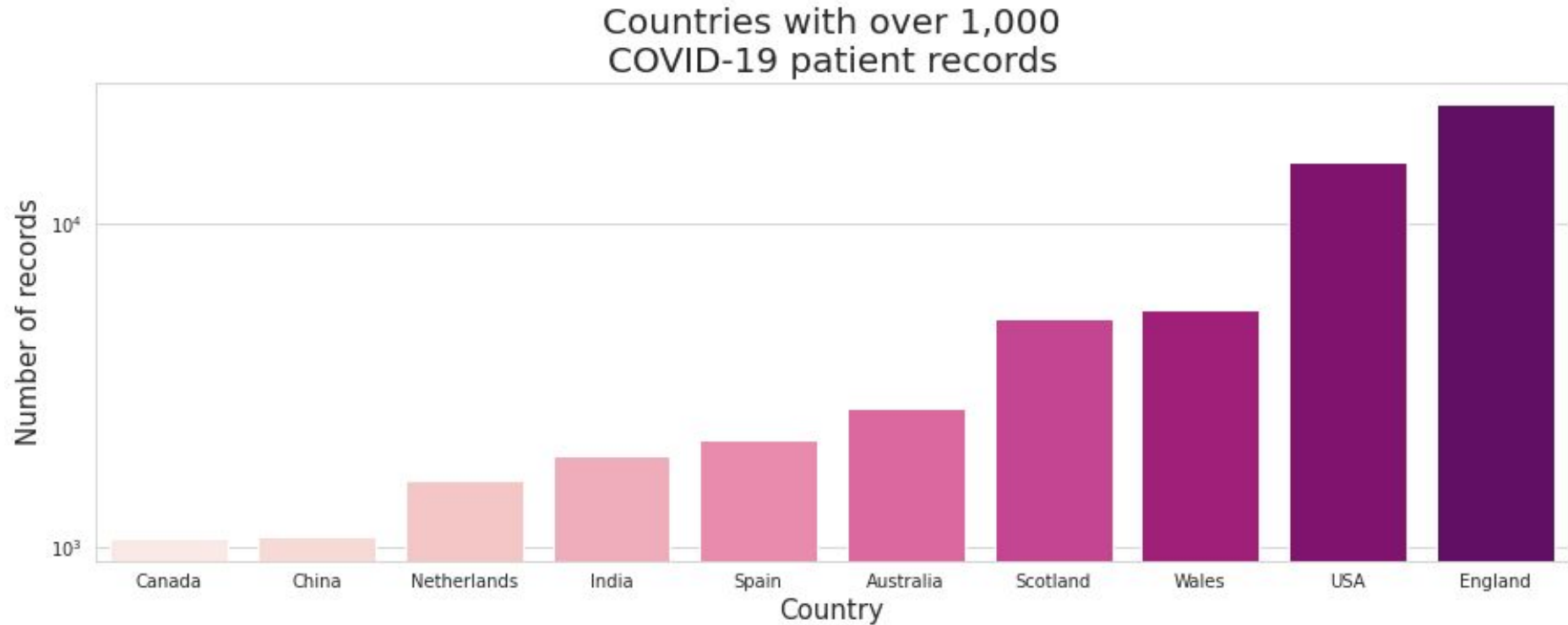
→ The age in years of the patient

# 📍 What continents were the records submitted from?



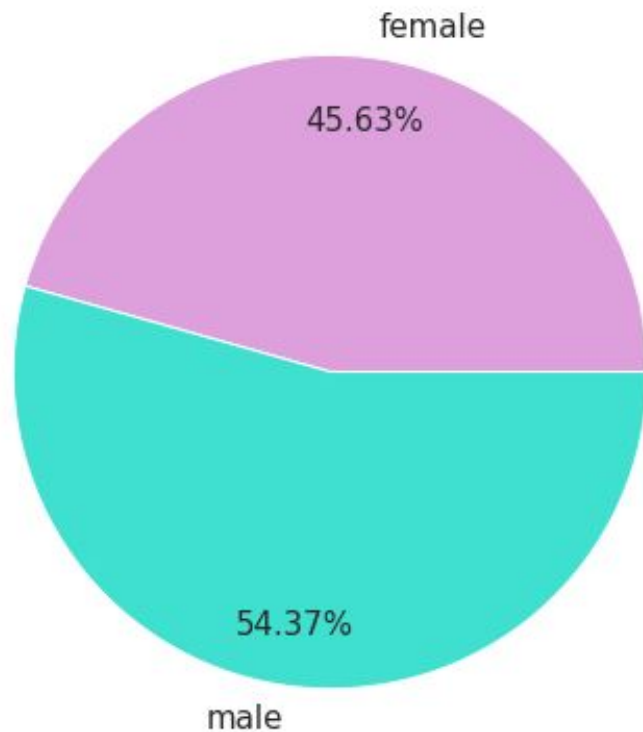


# 📍 Which countries have submitted over 1,000 records?



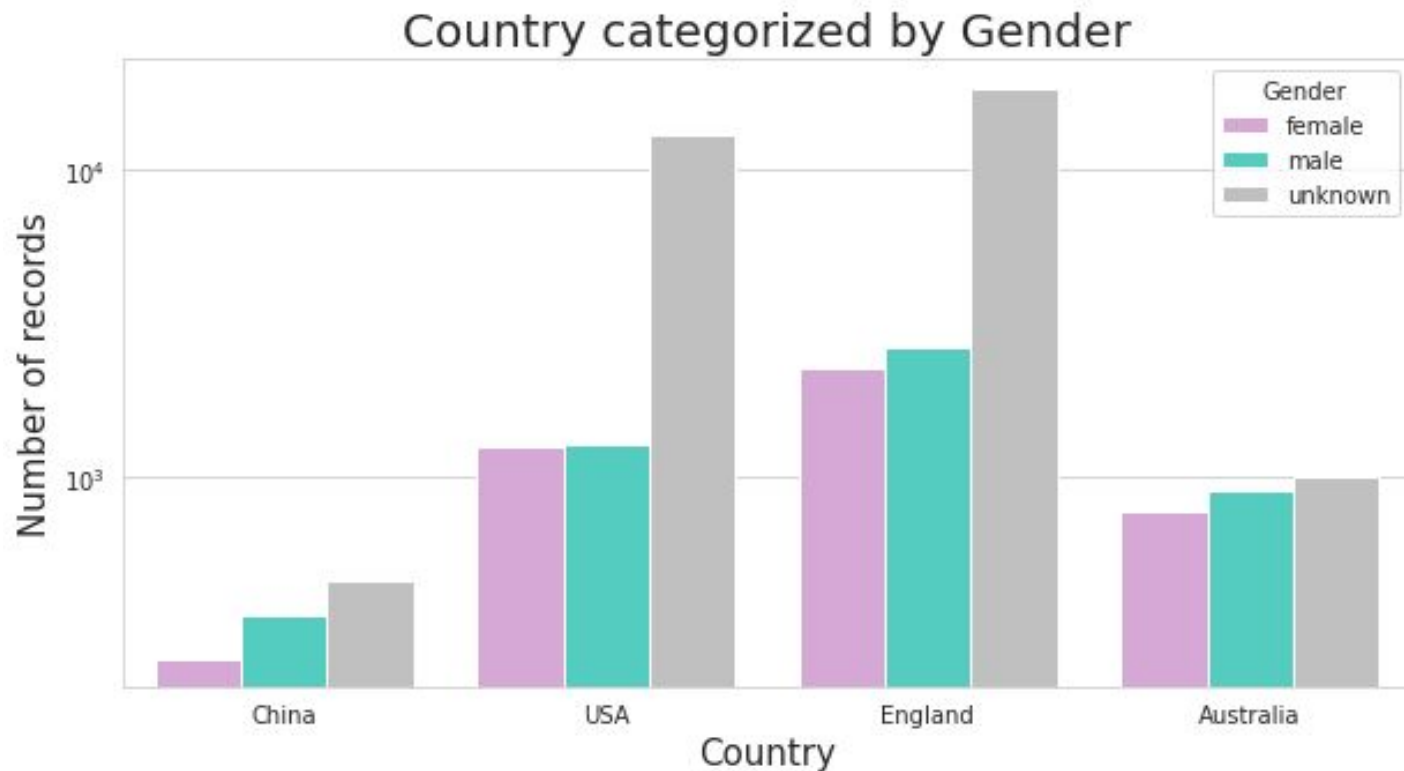
# 👤 What genders were found in the dataset?

Gender data found in 23,572  
out of 75,571 records (31.19%)



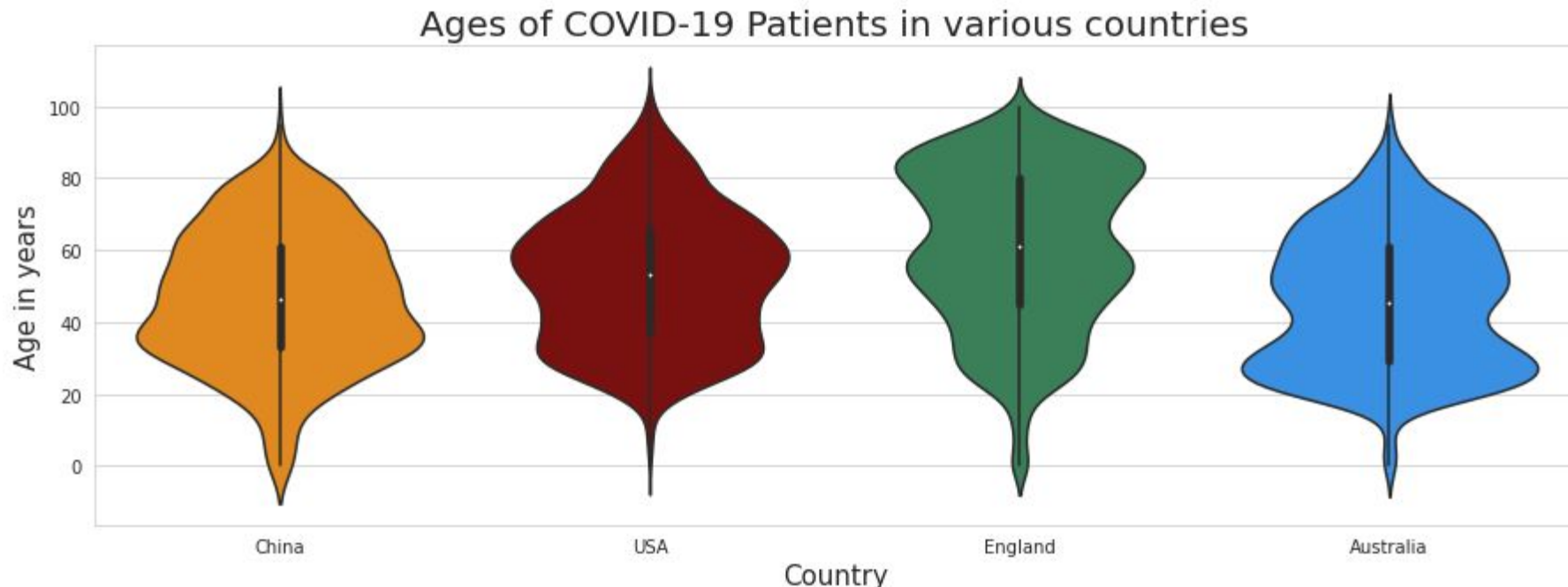


# What was the gender data in various countries?



Out of the 42,615 patient records from these countries,  
55.0% held either female or male gender data.

# 📍🕒 What was the age data in various countries?

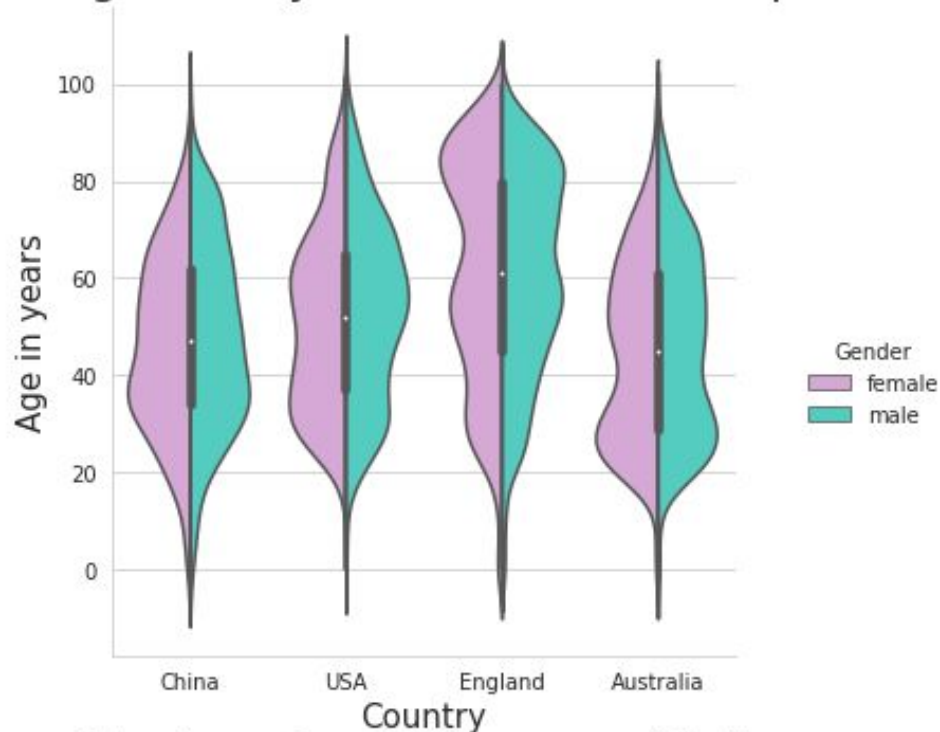


Note: Age data was obtained by  
9,689 out of 42,830 records in these countries (22.62%)



# What were the combinations of age and gender?

Age categorized by Gender of COVID-19 patients

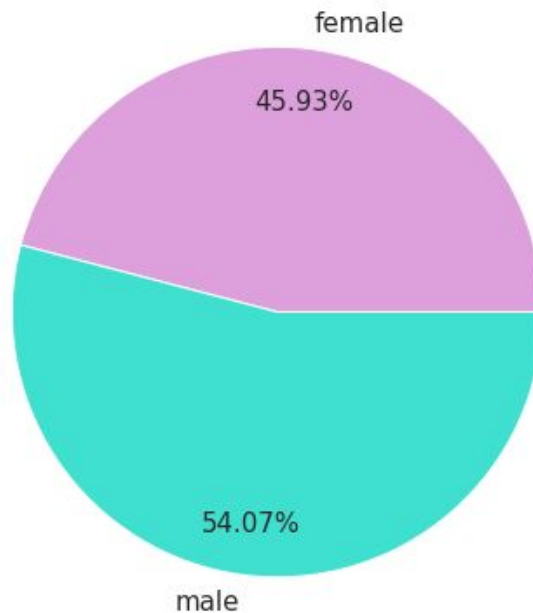


Note: Age and gender data was provided by 9,457 out of 42,830 records in these countries (22.08%)

# What genders were found in California?

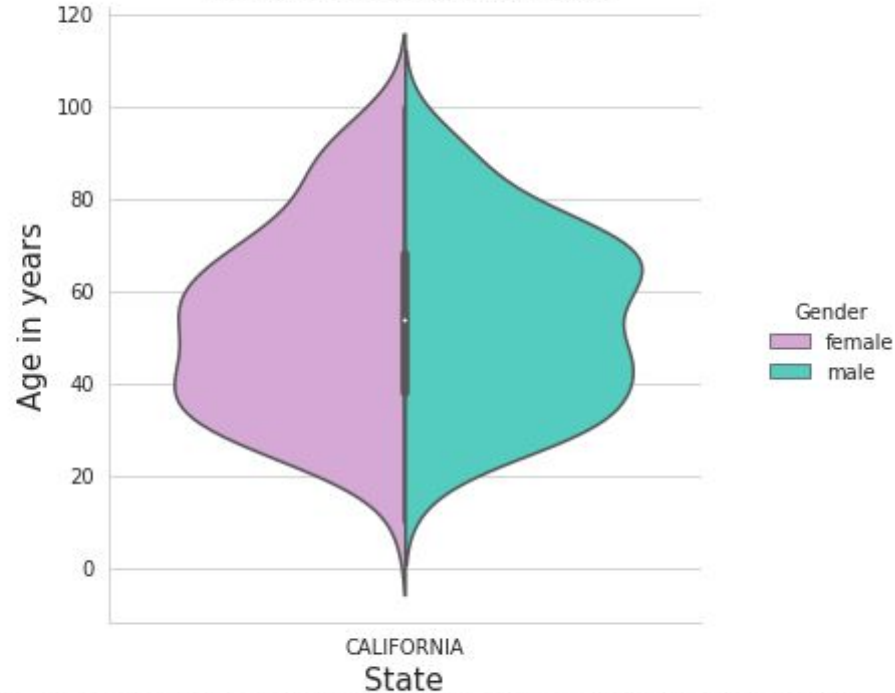
Genders of Patients in CALIFORNIA, USA

Note: Gender data was provided by  
246 out of 2,176 records  
in CALIFORNIA, USA (11.31%)



# What ages and genders were found in California?

Age categorized by Gender of COVID-19 patients  
in CALIFORNIA, USA



Note: Age and gender provided by 246 out of 2,176 records  
in CALIFORNIA, USA (11.31%)

# Lessons Learned - Biomedical Research

## **Reading patient data**

Data analysis is affected by the data-entry methods that were used to create the data.

Confounding errors such as the lack of correct data entry can cause misinterpretation.

## **Analysis and visualization**

In order to generalize inferences about a sample of patients, the differences in the patients should be accounted for instead of treating each patient as if they are the same person.



# Lessons Learned - Data Science

## **Reading patient data**

Loading and reading a collection of data from a file.

Identifying what information should be included in analysis and visualization.

## **Analysis and visualization**

Choosing the appropriate visualization types to show trends in data.

Using tools to generate the visualizations.

# Next Steps

## **Improve data-handling strategies in our code**

Current focus:  
error-handling for  
location data

Example: Use  
pre-defined lists of all  
states in a country to  
prevent  
misrepresentation

Improve  
**efficiency**,  
**readability**, and  
**reusability**  
of our code  
so that our methods  
can be used to assist  
with the study other  
datasets

Advocate  
for  
**improvement in  
data-entry  
practices**

# Acknowledgements

## **DBMI Summer 2020 Internship Program Leaders**

Nancy Herbst

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Dr. Lucila Ohno-Machado

Elizabeth Santillanez

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Dr. Niema Moshiri | Dr. Youwen Ouyang

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NSF-2028040

Google Cloud Platform (GCP) Research Credits Program

# Thank you for your time!

Any questions are welcome.

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