Storytelling with data

01 | analytics communication challenges; example case study; workflow, a common approach with R or Python libraries

Scott Spencer | Columbia University

welcome, course overview

Meeting your professor

Education

Doctorate
Jurisprudence
Honors in research and writing
Focus — analysis

Master of Science
Sports Management
Focus — data science analytics
Won, SABR analytics competition

Bachelor of Science
Chemical Engineering
Focus — numerical methods, statistical process control

Scott Spencer

Columbia University

Faculty, Lecturer, Alumnus

Consultant, Data Scientist

Professional sports
Example — Major League Baseball research and development for player performance & manager decision-making

Data for good
Example — Bayesian, generative modeling effects of climate change on perceived expectations of property values

Innovation
Example — whether invented attributes of an edible oil previously existed or was made or sold by competitor

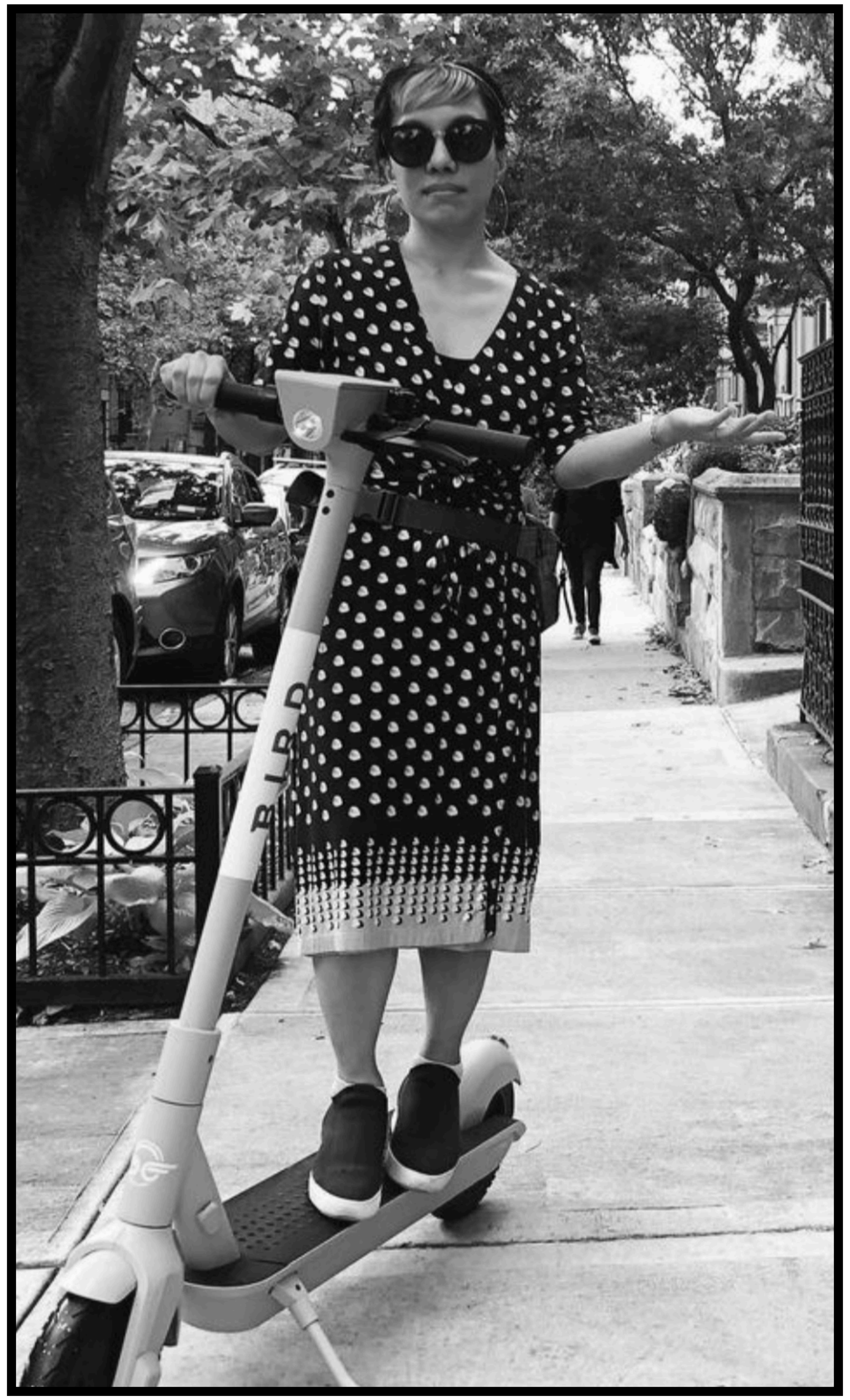
Teaching and Research

Developing generative models
Building Bayesian, generative models to enable decision-making in complex fields such as sports performance.

Communicating uncertainty
Writing monograph on quantitative persuasion amid uncertainty. Developing R packages to tie human perception to graphical representation of data.

Contributing open-source software
Contribute to interfaces to Stan, a probabilistic programming language.

Meeting your Associate



Education

Doctorate
Education

Master of Science
Media Studies

Bachelor of Fine Arts
Design

Background & Interests

Born: *Suwon, Korea*

Languages: *English, Korean, Japanese*

Hobbies: *Founder of the NYC Ramen Enthusiasts, Kickboxing, Travel*

Laura Scherling

Columbia University

Director, Associate Faculty SPS & TC
laurascherling.info
Instagram: laura.skierling

Industry Experience

Founder
GreenspaceNYC

Senior Interactive Designer
Marketing @ The New School

Designer & Developer
Marketing @ Housing Works

Designer & Developer
Motion Graphics, Advertising @ Guava Studios

Notable clients
HBO, NHL, Ogilvy, Stanford Medicine, Sesame Workshop, EWG, PBS, Barnes & Noble

Research & Publications

Areas of research
Management, Marketing Analytics, Ed Tech and Higher Ed Analytics, Information Design, Visual Design, Digital Transformation, Sustainability

Publications
Ethics in Design (Bloomsbury, 2020); Digital Transformation in Design (under review, Bloomsbury 2022, expected)

Research publications for:
Brooking Metro, Design Observer, Urban Activist, Design and Culture, Spark Journal, Interiors: Design/Architecture/Culture, Futures Worth Preserving Cultural Constructions of Nostalgia and Sustainability

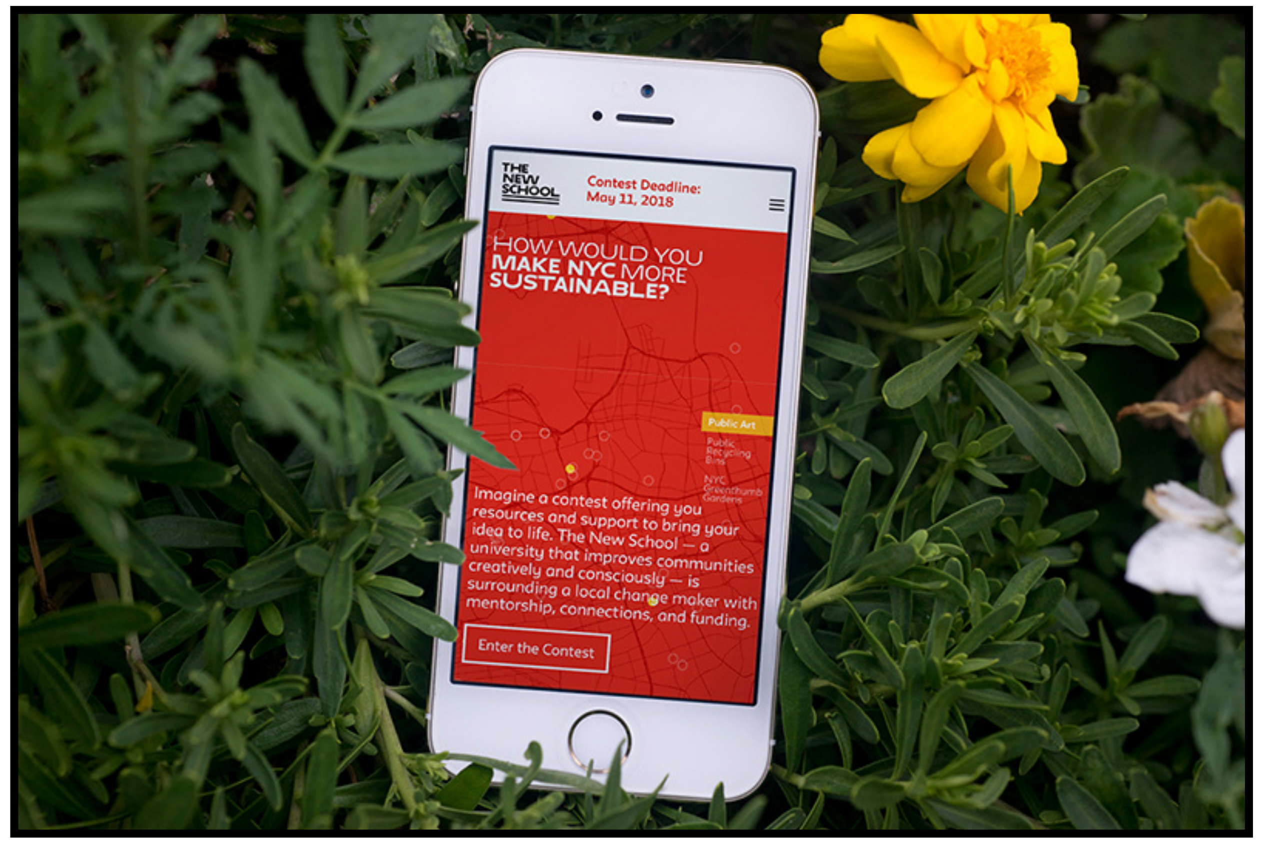
Laura Scherling, tools used in example projects

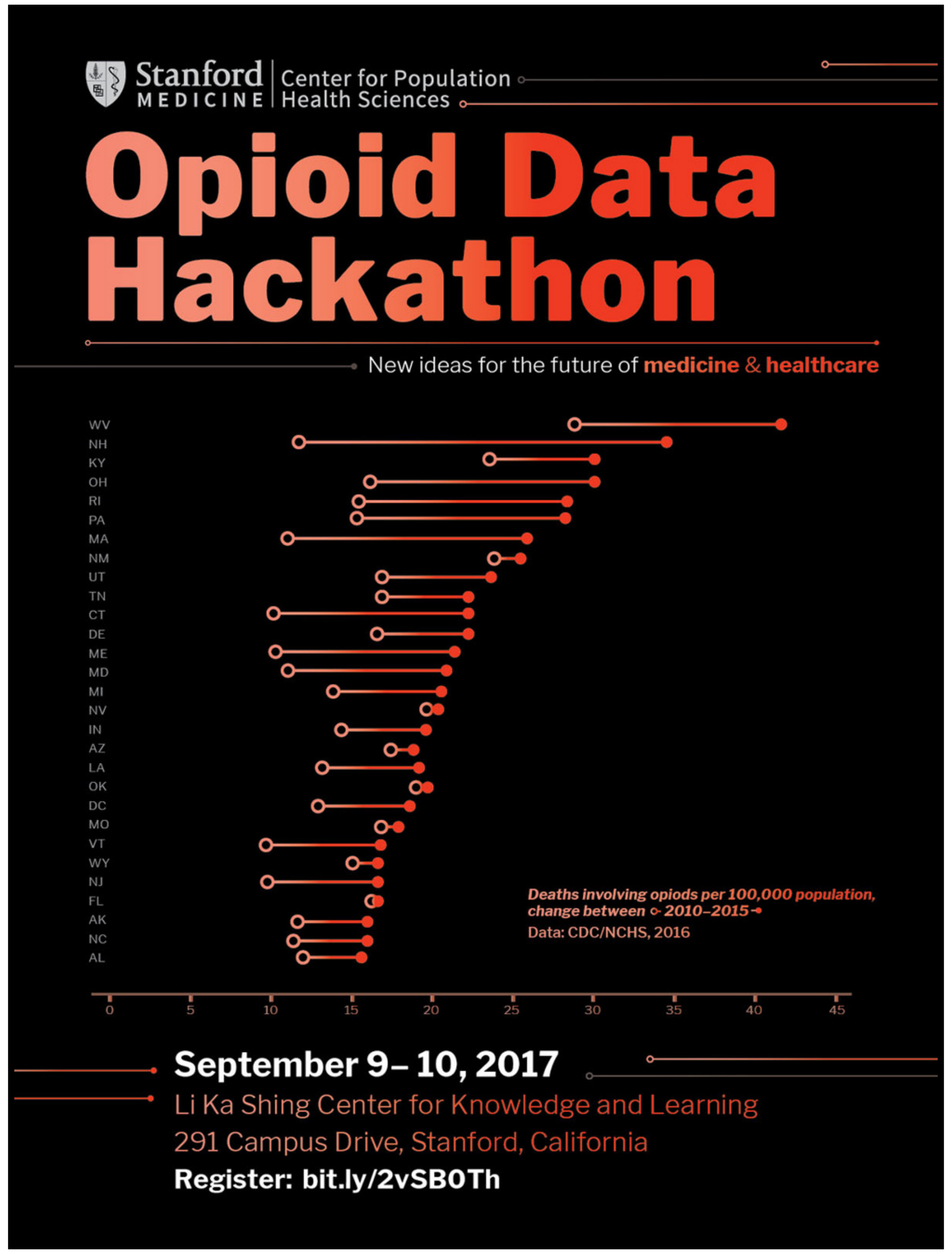
javascript

python

Excel

In Design





Illustrator

Media in small and large scale for mapping and infographics projects

photography

weekly, in-person discussion

Class meets Mondays 6:10-8PM
Riverside Church, Assembly Hall

office hours

Professor Scott Spencer
Click to schedule appointment

Associate Laura Scherling
Click to schedule appointment

In **groups of six**, appoint **one speaker to summarize**:

tools you (all) have used for data visualization,

previous **education** majors,

relevant (work) **experience**, and

hobbies.

Do this as quickly as possible. Several groups will have the opportunity to share out in **one minute elevator pitches**.

analytics communication challenges and course overview

challenges, **communication gaps**

communication gap

business ← **who $\stackrel{?}{=}$** → **data analytics**

data translator

challenges, bridging the gaps with data translators, qualities needed

project management

data wrangling

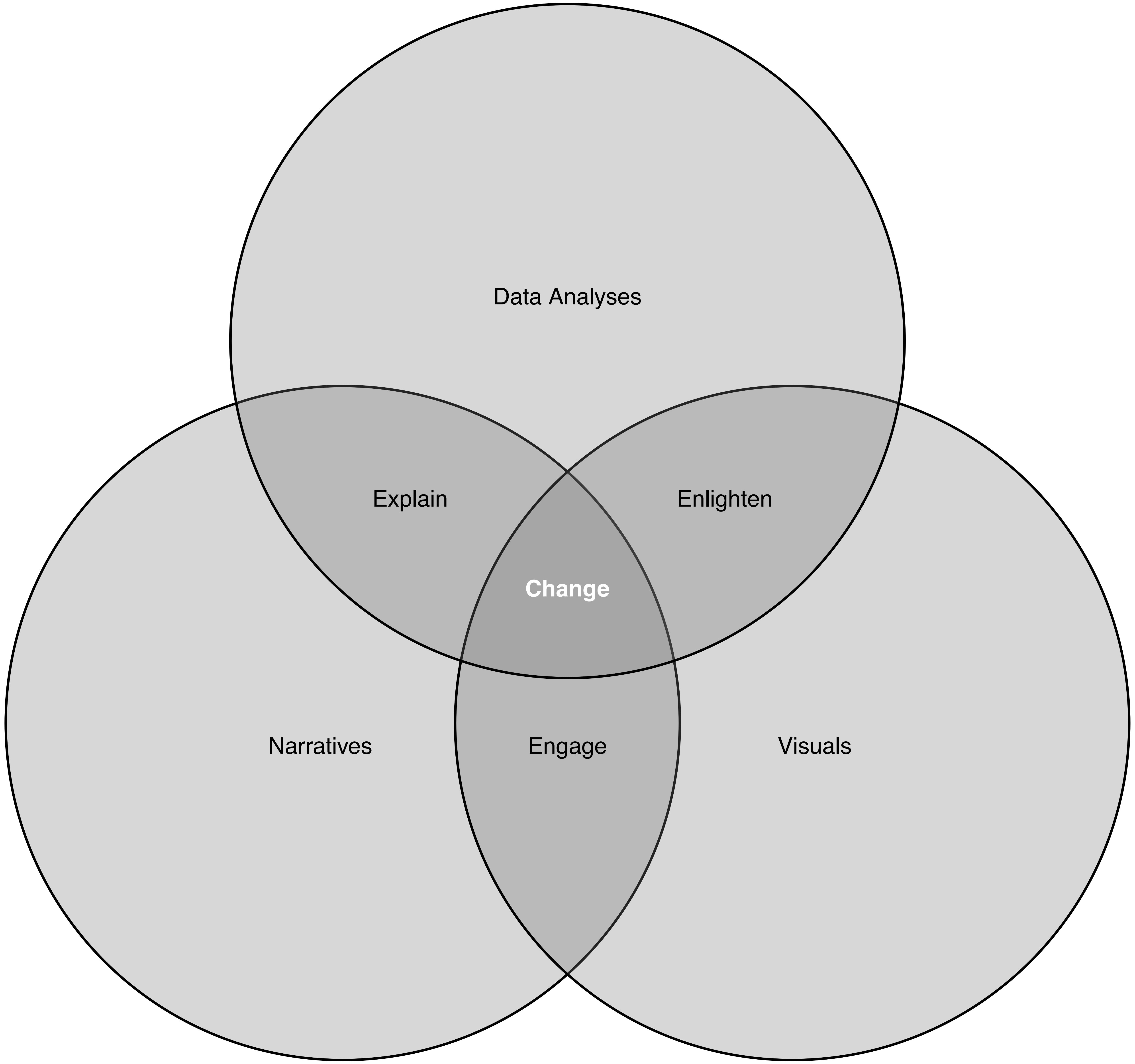
data analysis

subject expertise

design

storytelling

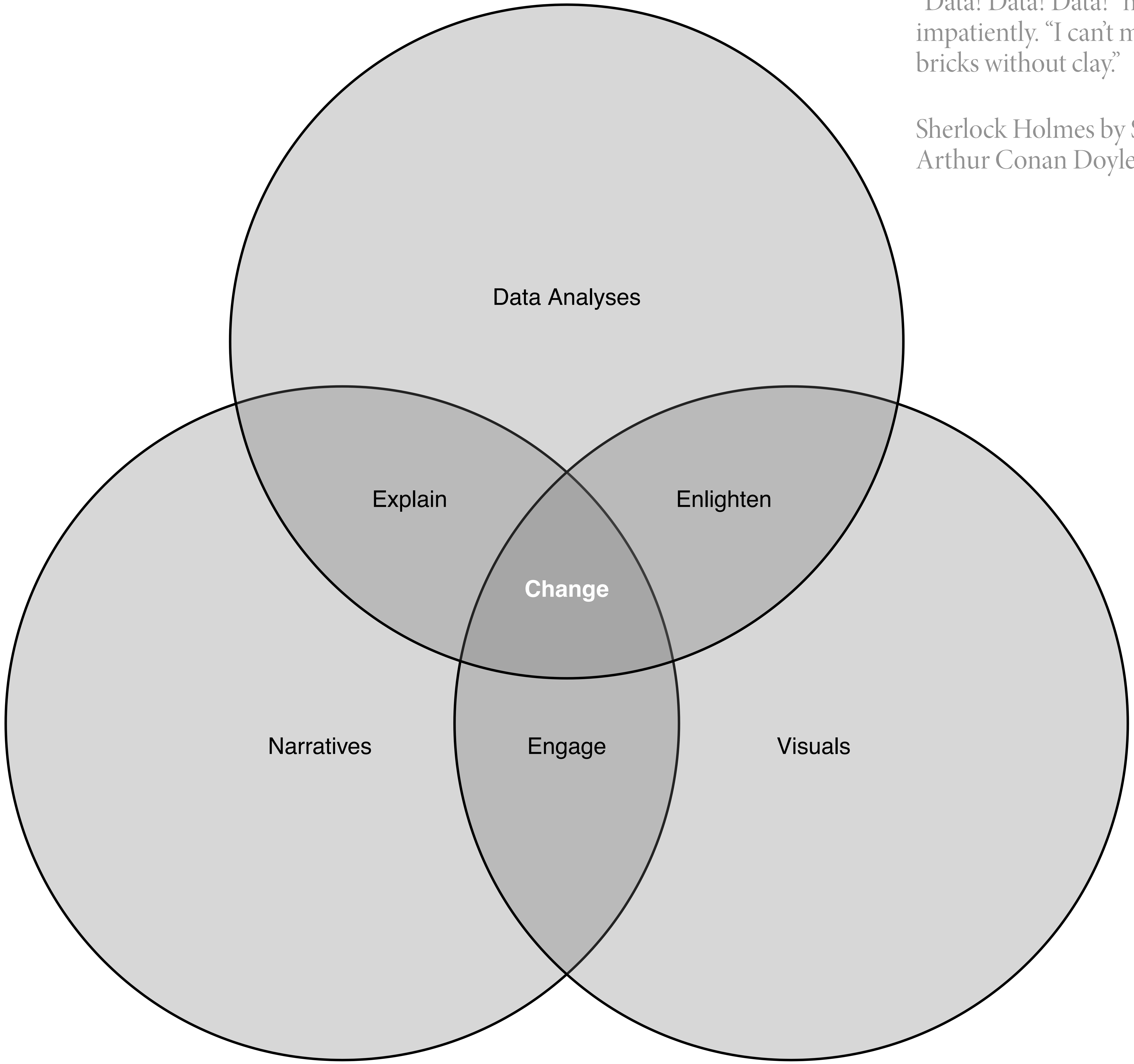
course overview, **learn to drive change using data visuals and narrative**



course overview, **learn to drive change using data visuals and narrative**

“Data! Data! Data!” he cried impatiently. “I can’t make bricks without clay.”

Sherlock Holmes by Sir Arthur Conan Doyle, *author*



No one ever made a decision because of a number. They need a story.

Daniel Kahneman, *psychologist, behavioral economist, and author*

The greatest value of a picture is when it forces us to notice what we never expected to see.

John W Tukey, *mathematician*

course overview, **course deliverables and structure**

Individual Work

For learning data visualization
and written narrative techniques

Group work

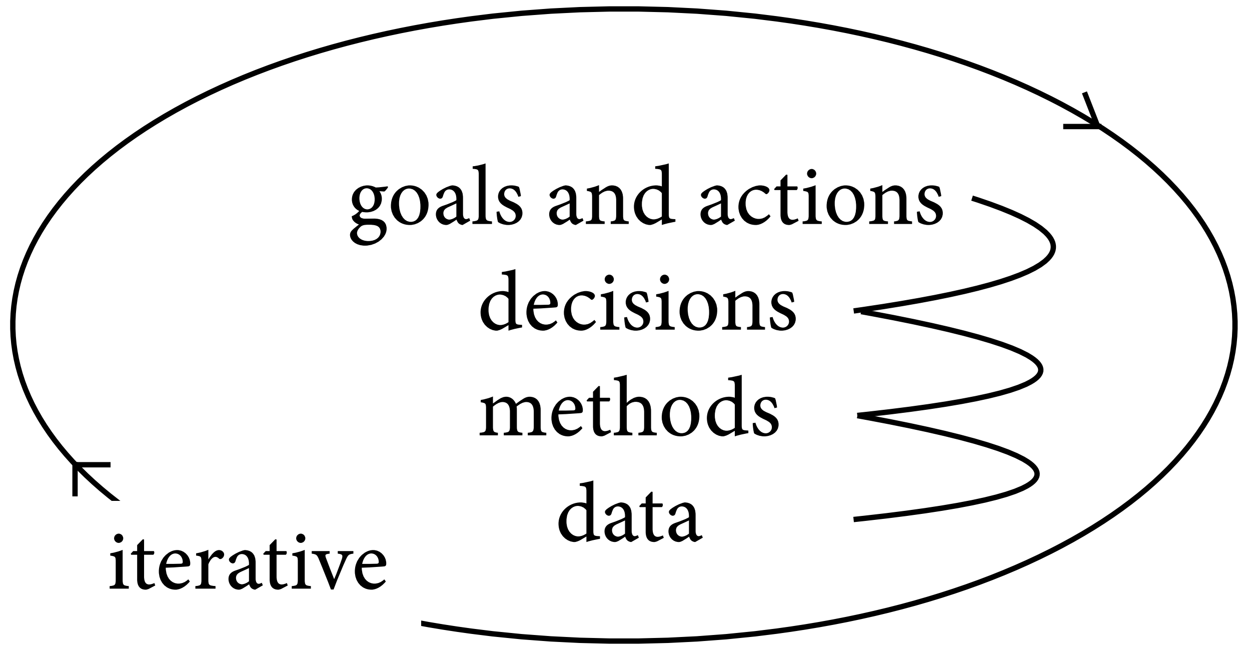
For building graphics and narrative
into interactive communications

Sept 30	Oct 14	Oct 28	Nov 18	Nov 18	Dec 11	Dec 13
Homework 1 graphics	Homework 2 graphics	Homework 3 writing	Homework 4 graphics	Proposal	Interactive Communication	Multimodal communication
10%	10%	10%	10%	15%	20%	15%
Participation 10%						

introducing an example case study

 let's begin a project (indeed, *any* data analytics project) with questions

process



initial questions

What **problem** is to be solved?

Is the problem **important**?

Could an answer have **impact**?

Do **data** have a role in **solving the problem**?

Are the right **data available**?

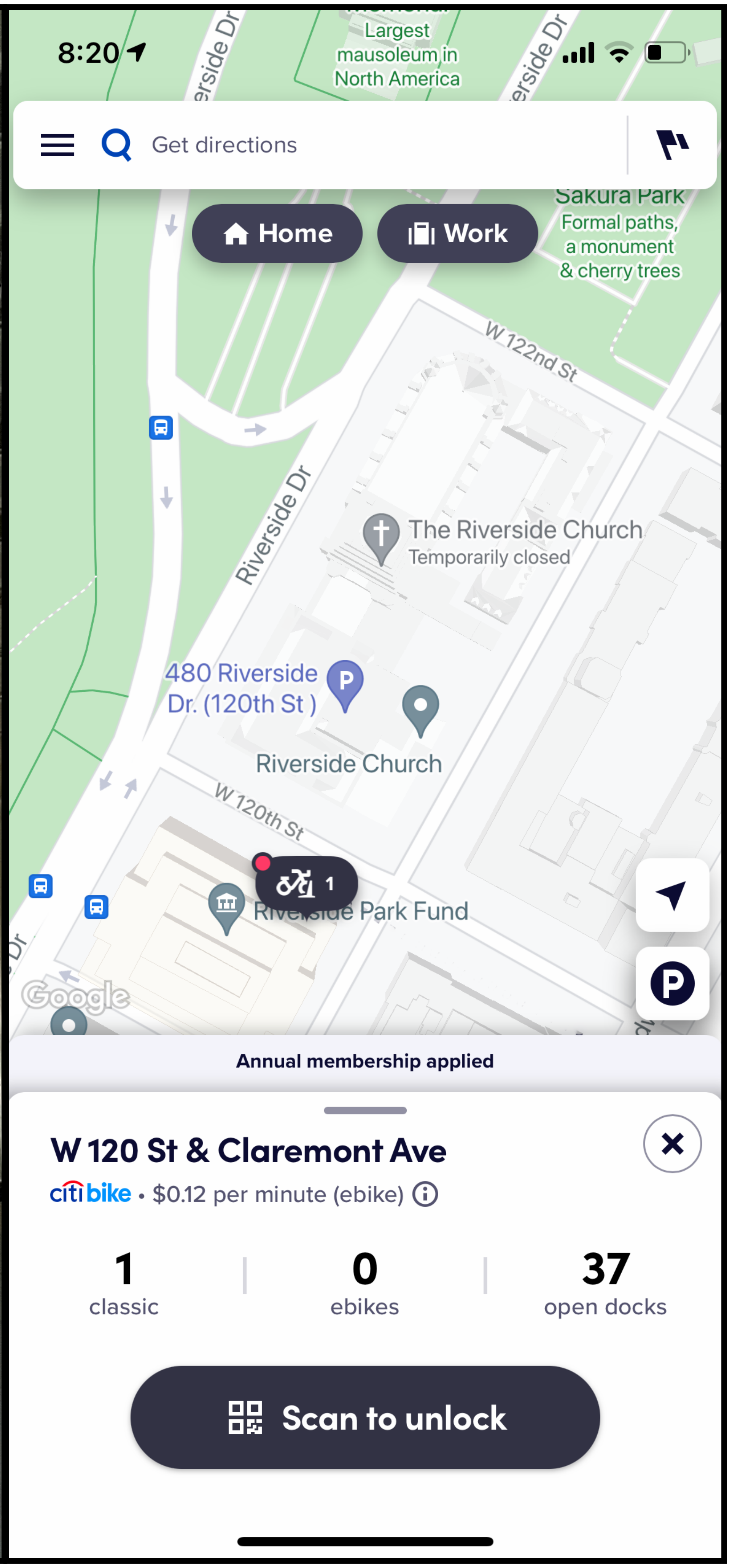
In what **contexts** may the data be generated?

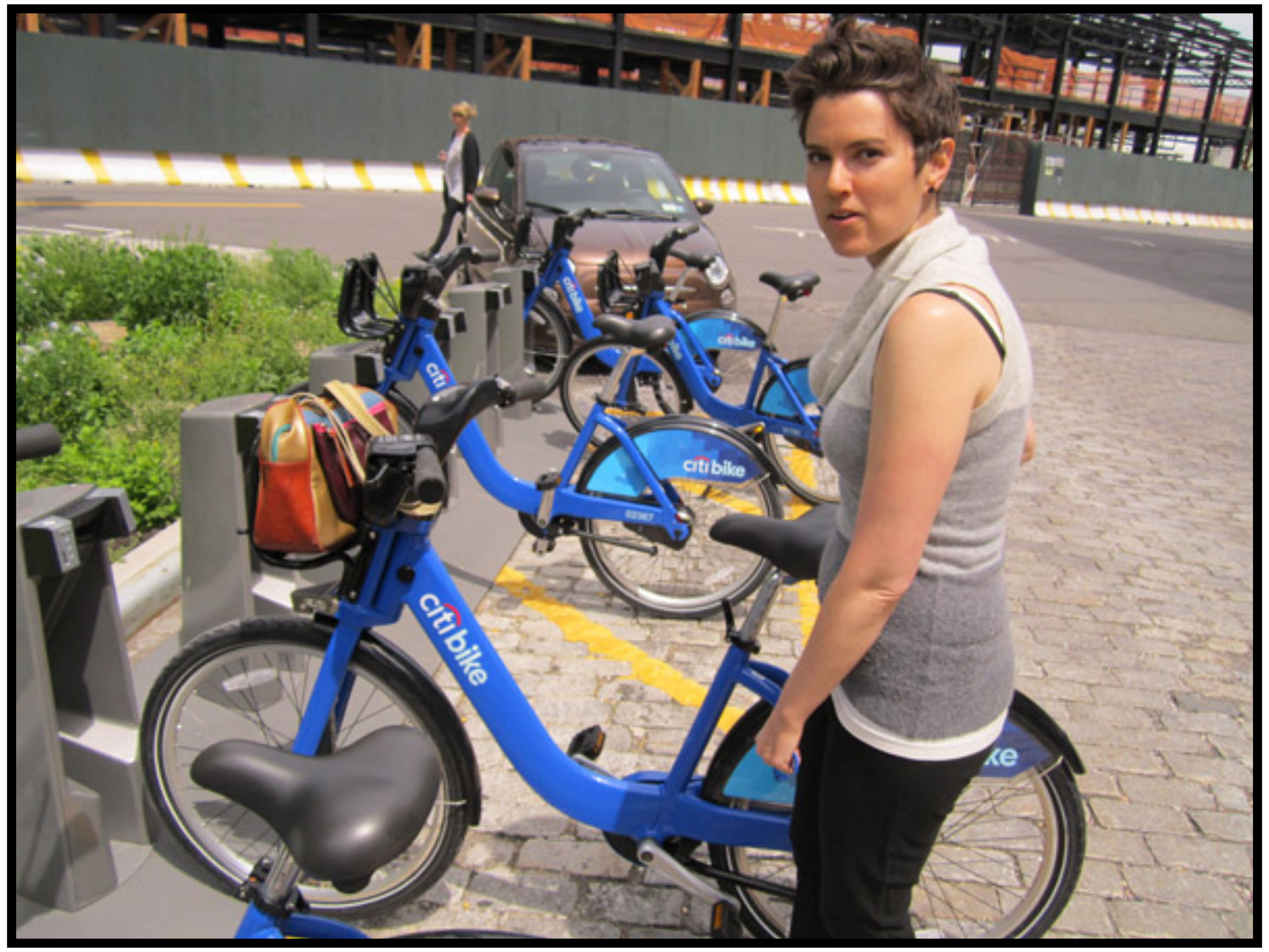
Is the **organization** ready to **tackle the problem** and **take actions from insights**?

 scott.spencer@columbia.edu

example case study, **exploring changes in usage of Citi Bike, a bike share in New York City**

example case study, **docking station outside our classroom and related information on iPhone app**

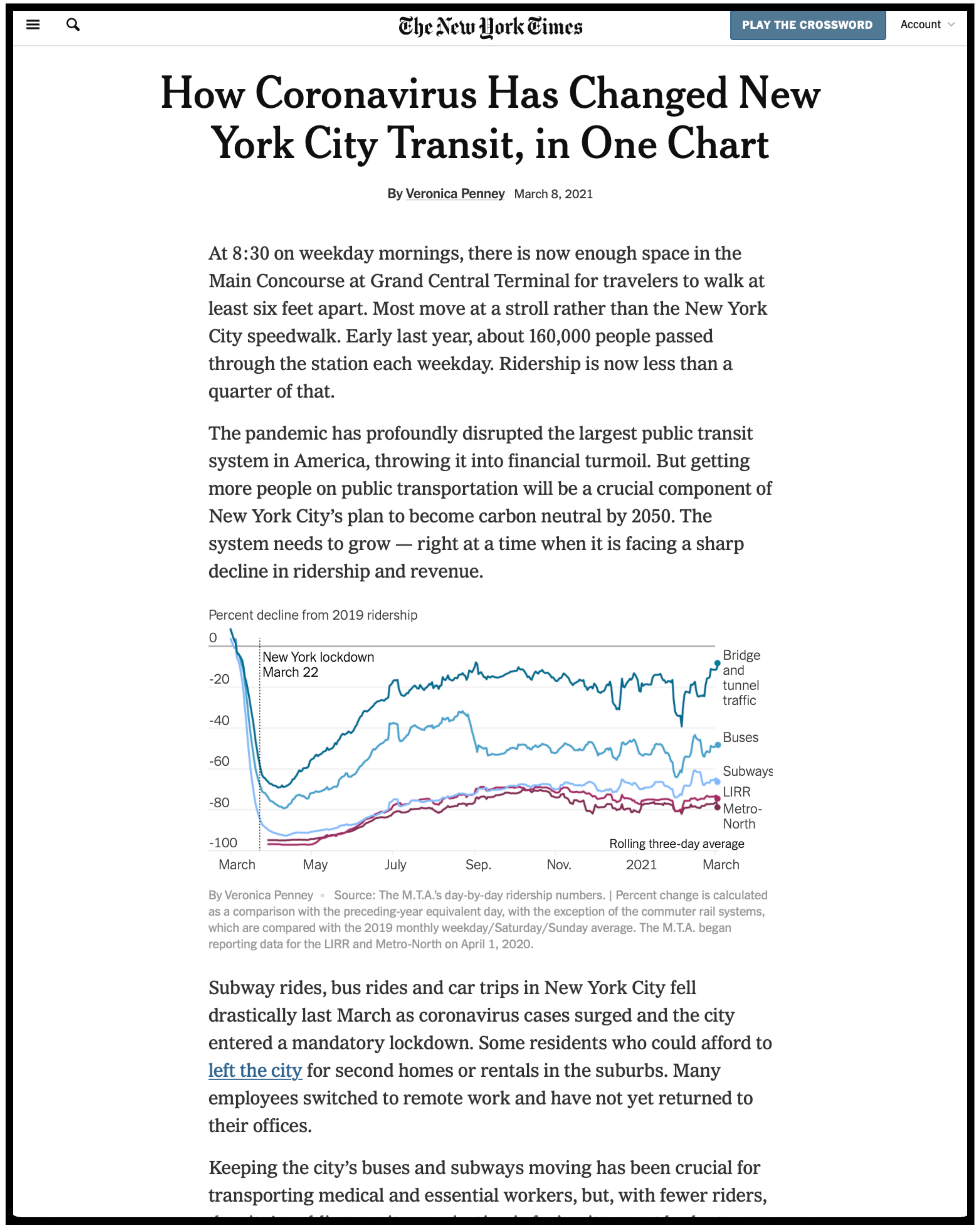




Rebalancing is one of the **biggest challenges** of any bike share system, especially in … New York where residents don't all work a traditional 9-5 schedule, and … people work in a variety of other neighborhoods.

— Simmons, Dani. Citi Bike spokeswoman. 2016

example case study, **changing conditions, how might the pandemic affect *current* rebalancing efforts?**


The New York Times PLAY THE CROSSWORD Account

How Coronavirus Has Changed New York City Transit, in One Chart

By Veronica Penney March 8, 2021

At 8:30 on weekday mornings, there is now enough space in the Main Concourse at Grand Central Terminal for travelers to walk at least six feet apart. Most move at a stroll rather than the New York City speedwalk. Early last year, about 160,000 people passed through the station each weekday. Ridership is now less than a quarter of that.

The pandemic has profoundly disrupted the largest public transit system in America, throwing it into financial turmoil. But getting more people on public transportation will be a crucial component of New York City's plan to become carbon neutral by 2050. The system needs to grow — right at a time when it is facing a sharp decline in ridership and revenue.

By Veronica Penney • Source: The M.T.A.'s day-by-day ridership numbers. | Percent change is calculated as a comparison with the preceding-year equivalent day, with the exception of the commuter rail systems, which are compared with the 2019 monthly weekday/Saturday/Sunday average. The M.T.A. began reporting data for the LIRR and Metro-North on April 1, 2020.

Subway rides, bus rides and car trips in New York City fell drastically last March as coronavirus cases surged and the city entered a mandatory lockdown. Some residents who could afford to left the city for second homes or rentals in the suburbs. Many employees switched to remote work and have not yet returned to their offices.

Keeping the city's buses and subways moving has been crucial for transporting medical and essential workers, but, with fewer riders,

For New York City to hit its climate goals, it **will be critical for more people to use** public transit, **bikes** or walking to commute **than before the pandemic.** When offices and businesses begin to reopen, more flexible remote options for workers could also be friendly for the planet.

Transit experts also say that existing tools and policies could encourage commuters to embrace low-emissions modes of transportation. **Bike shares and bike sales are experiencing a boom in the city**, which could help reduce transit emissions, but cycling advocates say continued investment in bike paths and protected lanes will be key for keeping people on their bikes as commuting returns to its post-pandemic normal.

— Penney, Veronica. New York Times. 2021

example case study, **Citi Bike's approaches to rebalancing**

Bike Angels

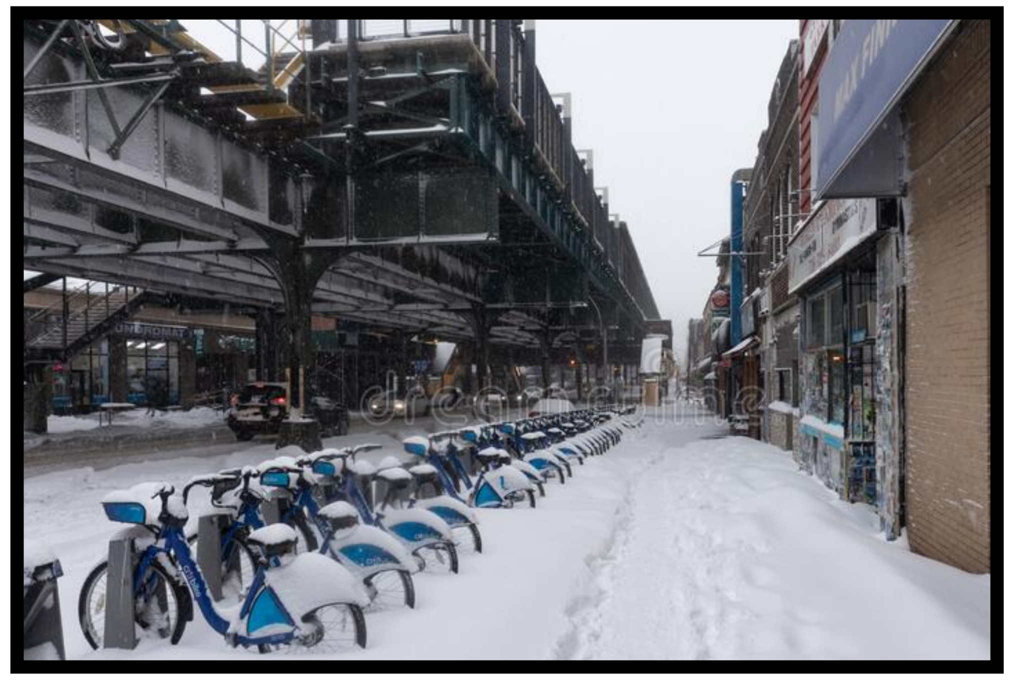
Valet schedule

Bike trains

Motorized vehicles

— Citi Bike. "How We're Rebalancing the Citi Bike System." *Citi Bike NYC* (blog), August 14, 2020. https://www.citibikenyc.com/blog/rebalancing-the-citi-bike-system.

 think about the tangible world, then how relevant events may be measured and recorded



Identifying events and user behavior

What **events** may be correlated with or cause empty or full bike docking stations?

What potential **user behaviors** or **preferences** may lead to these events?

From what **analogous** things could we draw **comparisons** to provide **context**?

Measurements of events and behaviors

How may these events and behaviors have been **measured and recorded**?

What **data are available**? Where? What form?

May these data be **sufficient to find insights** through analysis, useful for decisions and goals?

data, a basic taxonomy

DATUM | an abstraction of **a** real-world entity (person, object, or event). The terms *variable*, *feature*, and *attribute* are often used interchangeably to denote an individual abstraction. Data are the plural of datum.

DATA SET | consists of the data relating to a collection of entities, with each entity described in terms of a set of attributes. In its most basic form, a data set is organized in an $n \cdot m$ data matrix called the analytics record, where n is the number of entities (rows) and m is the number of attributes (columns).

Nominal types are *names* for categories, classes, or states of things.

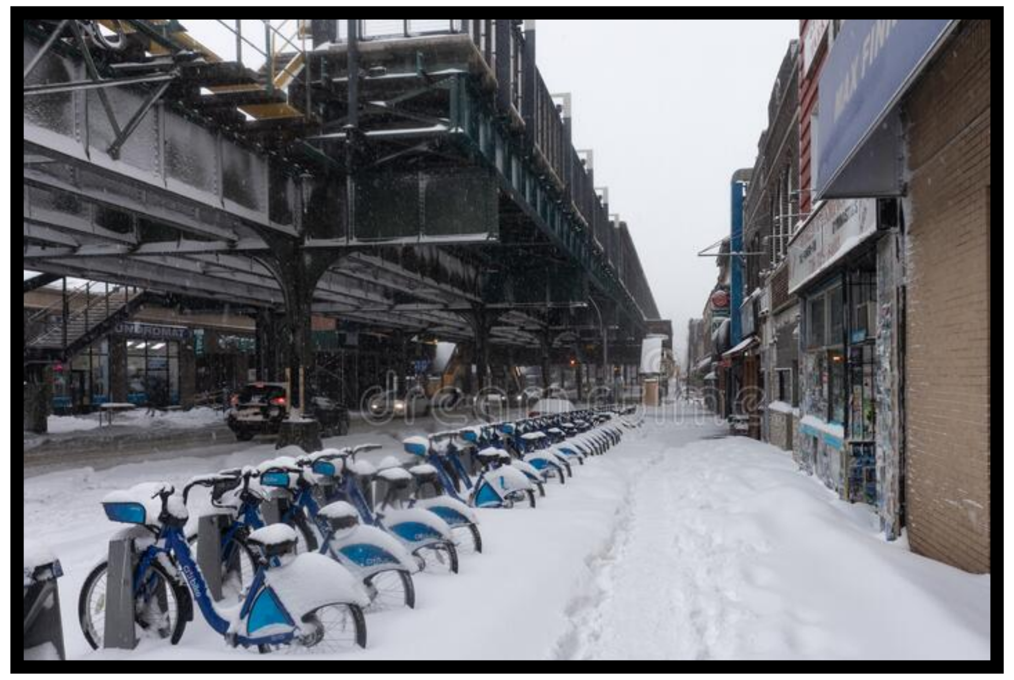
Ordinal types are similar to nominal types, except it is possible to *rank or order* categories of an ordinal type.

Numeric types are *measurable* quantities we can represent using integer or real values. Numeric types can be measured on an *interval* scale or a *ratio* scale.

Structured Data | data that can be stored in a table, and every instance in the table has the same structure (i.e., set of attributes).

Unstructured Data | data where each instance in the data set may have its own internal structure, and this structure is not necessarily the same in every instance.



Examples of publicly available data sources

Bike and **dock**: data are recorded of each bike unlocked and docked, along with remaining dock capacities at the locations, dates, and times of each event: https://www.citibikenyc.com/system-data

Taxi pickup and drop-off locations and times: https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page

Subway lines entrance/exit locations: https://data.cityofnewyork.us/Transportation/Subway-Stations/arq3-7z49

MTA usage data (and change since coronavirus): https://new.mta.info/coronavirus/ridership

Historical **weather**: National Weather Service. *API Web Service*. https://www.weather.gov/documentation/services-web-api; Yip, Stan. "Weatherr: Tools for Handling and Scraping Instant Weather Forecast Feeds." *Manual*, 2020. https://CRAN.R-project.org/package=weatherr.

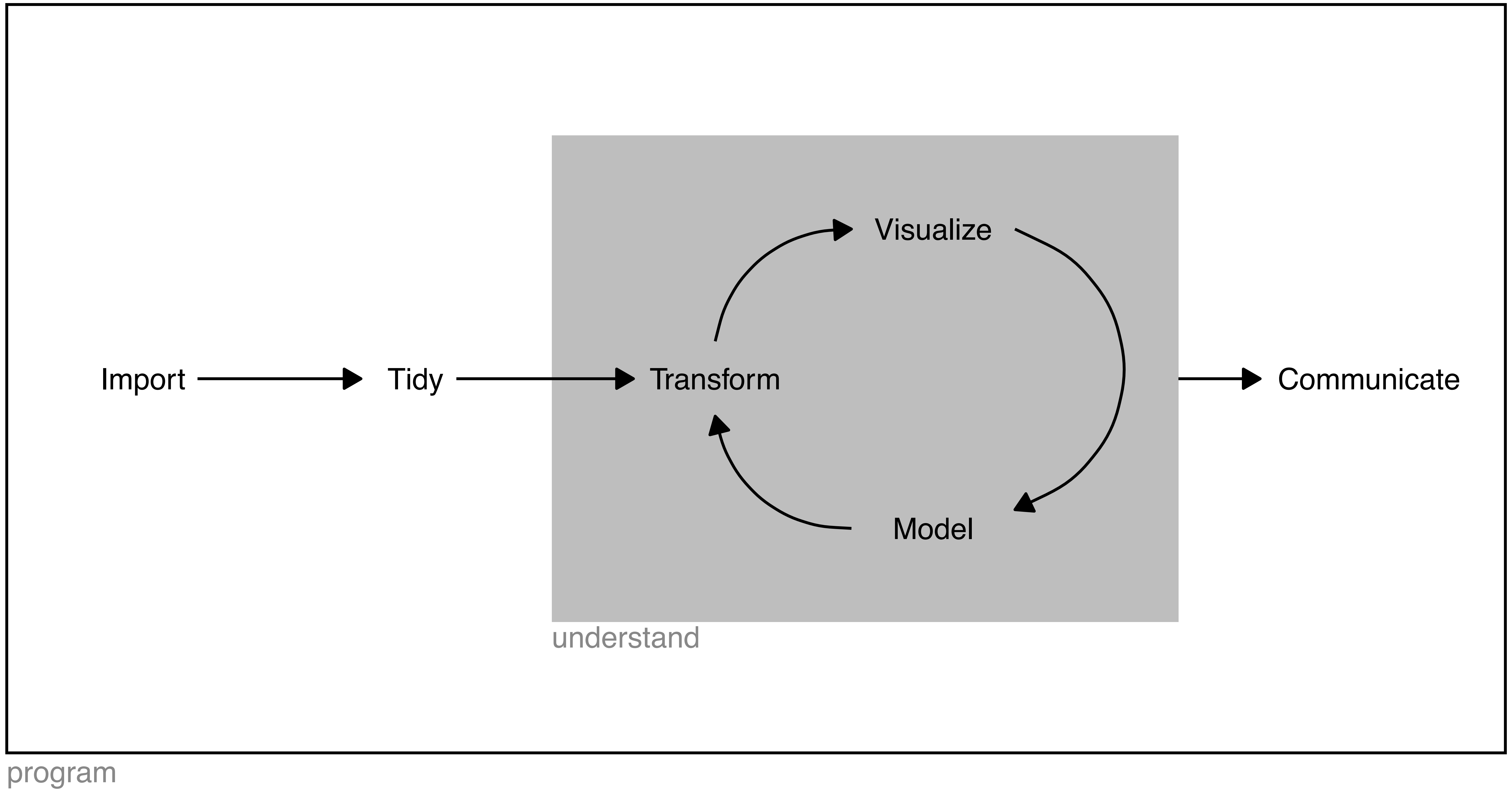
Geography (**elevation**): USGS. *Elevation Point Query Service*. https://ned.usgs.gov/epqs/; Hollister, Jeffrey, et al. "Elevatr: Access Elevation Data from Various APIs." Manual, 2021. https://doi.org/10.5281/zenodo.5119662.

Traffic data and more: http://www.nyc.gov/html/dot/html/about/datafeeds.shtml#realtime

Twitter: https://twitter.com/CitiBikeNYC; Gentry, Jeff. "TwitteR: R Based Twitter Client." Manual, 2015. https://CRAN.R-project.org/package=twitteR.

workflow, software tools for data exploration and analysis

explore & analyze, **a basic, general workflow**



— Adapted from **Wickham**, Hadley, and Garrett Grolemund. *R for Data Science*. https://r4ds.had.co.nz

R / tidyverse

Python / datar & plotnine

 demonstrations in R, can be mimicked in Python — loading libraries

R / tidyverse

```r
library(package_name)
```

Python / datar & plotnine

```python
from package_name import *
```

R / tidyverse

```
df_r <- read_csv("filename.csv")
```

Python / datar & plotnine

```
df_py = pd.read_csv("filename.csv")
```

 demonstrations in R, can be mimicked in Python — data structures

	R		Python
`1; 1L; TRUE; "foo"`	single-element vector	↔	scalar
`c(1.0, 2.0, 3.0); c(1L, 2L, 3L)`	multi-element vector	↔	list
`list(1L, TRUE, "foo")`	list of multiple types	↔	tuple
`list(a = 1L, b = TRUE, c = "foo")`	named list	↔	dict
`matrix(c(1, 2, 3, 4), nrow = 2, ncol = 2)`	matrix / array	↔	numpy ndarray
`data.frame(x = 1:3, y = c("a", "b", "c"))`	**data frame**	↔	**pandas DataFrame**
`function(x) x + 1`	function	↔	python function
`NULL; TRUE; FALSE`	NULL, TRUE, FALSE	↔	None, True, False

software tools, demonstrations in R, can be mimicked in Python — how functions work

R / tidyverse

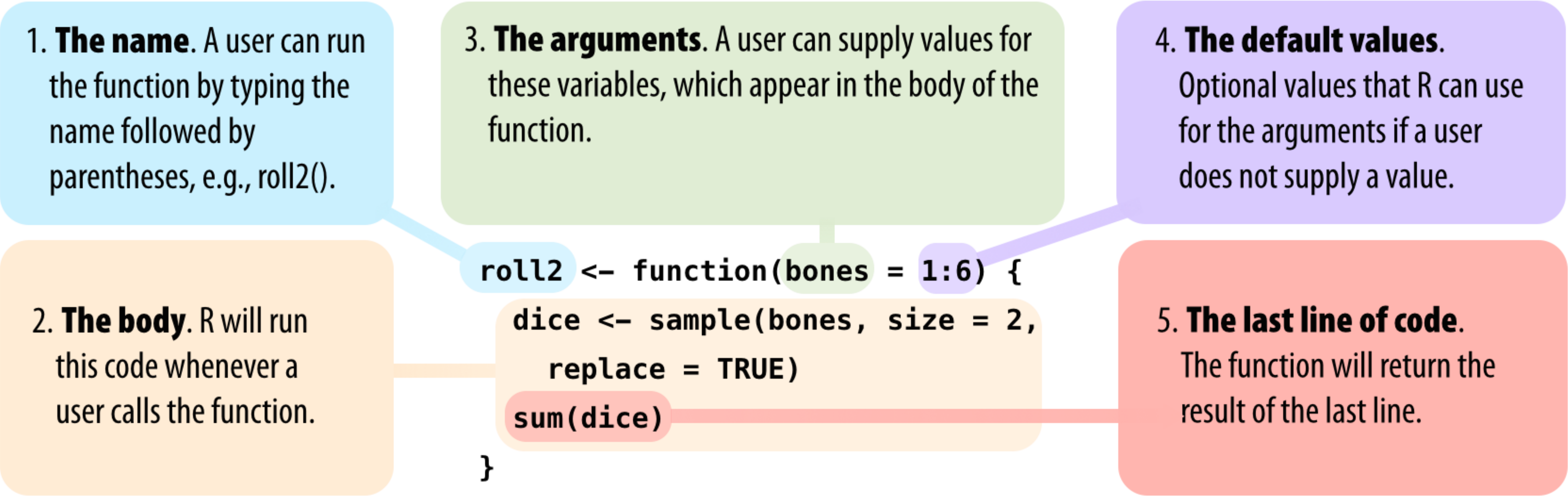
```
# basic function
returned_object <- function_name(parameter1, parameter2)

# object-oriented member function
final_object <- initial_object$member_function()
```

Python / datar & plotnine

```
#basic function
returned_object = function_name(parameter1, parameter2)

# object-oriented member function
final_object = initial_object.member_function()
```



Grolemund, Garrett. *Hands-On Programming with R.*
https://rstudio-education.github.io/hopr/

R / tidyverse

pipe operator %>%

```
final_object <- initial_object %>%
  f() %>%
  g() %>%
  h()
```

Python / datar & plotnine

pipe operator >>

```
final_object = initial_object >> \
  f() >> \
  g() >> \
  h()
```

	R / tidyverse	Python / datar & plotnine
shows data frame variables & types	`glimpse`	`info`
creates or modifies a variable	`mutate`	`mutate`
specifies variables (columns) to keep	`select`	`select`
renames variables	`rename`	`rename`
specifies observations (rows) to keep	`filter`	`filter`
specifies ordering of observations	`arrange`	`arrange`
specifies grouping of observations	`group_by`	`group_by`
specifies some summary of the data	`summarise`	`summarise`
convert form wide to long format	`pivot_longer`	`pivot_longer`
convert form long to wide format	`pivot_wider`	`pivot_wider`
map data to graphical elements	`ggplot`	`ggplot`

example case study, exploring data with software

R / tidyverse

```r
library(tidyverse)
```

Python / datar & plotnine

```python
import pandas as pd
from plotnine import *
from datar.all import *
from pipda import options
options.assume_all_piping = True
```

R / tidyverse

```r
df_r <- read_csv("data/201901-citibike-tripdata.csv")

df_r %>% glimpse()
```

```
Rows: 967,287
Columns: 15
$ tripduration              <dbl> 320, 316, 591, 2719, 303, 535, 280…
$ starttime                 <dttm> 2019-01-01 00:01:47, 2019-01-01 0…
$ stoptime                  <dttm> 2019-01-01 00:07:07, 2019-01-01 0…
$ `start station id`        <dbl> 3160, 519, 3171, 504, 229, 3630, 3…
$ `start station name`      <chr> "Central Park West & W 76 St", "Pe…
$ `start station latitude`  <dbl> 40.77897, 40.75187, 40.78525, 40.7…
$ `start station longitude` <dbl> -73.97375, -73.97771, -73.97667, -…
$ `end station id`          <dbl> 3283, 518, 3154, 3709, 503, 3529, …
$ `end station name`        <chr> "W 89 St & Columbus Ave", "E 39 St…
$ `end station latitude`    <dbl> 40.78822, 40.74780, 40.77314, 40.7…
$ `end station longitude`   <dbl> -73.97042, -73.97344, -73.95856, -…
$ bikeid                    <dbl> 15839, 32723, 27451, 21579, 35379,…
$ usertype                  <chr> "Subscriber", "Subscriber", "Subsc…
$ `birth year`              <dbl> 1971, 1964, 1987, 1990, 1979, 1989…
$ gender                    <dbl> 1, 1, 1, 1, 1, 2, 1, 1, 2, 1, 1, 2…
```

Python / datar & plotnine

```python
df_py = pd.read_csv("data/201901-citibike-tripdata.csv")

df_py.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 967287 entries, 0 to 967286
Data columns (total 15 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   tripduration             967287 non-null  int64
 1   starttime                967287 non-null  object
 2   stoptime                 967287 non-null  object
 3   start station id         967269 non-null  float64
 4   start station name       967269 non-null  object
 5   start station latitude   967287 non-null  float64
 6   start station longitude  967287 non-null  float64
 7   end station id           967269 non-null  float64
 8   end station name         967269 non-null  object
 9   end station latitude     967287 non-null  float64
 10  end station longitude    967287 non-null  float64
 11  bikeid                   967287 non-null  int64
 12  usertype                 967287 non-null  object
 13  birth year               967287 non-null  int64
 14  gender                   967287 non-null  int64
dtypes: float64(6), int64(4), object(5)
memory usage: 110.7+ MB
```

R / tidyverse

```r
df_r <- df_r %>% rename_all(function(x) gsub(" ", "_", x))


df_r <- df_r %>%
  filter(!is.na(start_station_id)) %>%
  arrange(starttime) %>%
  group_by(bikeid) %>%
  mutate(
    rebalanced =
      if_else(row_number() > 1 &
              start_station_id != lag(end_station_id),
              TRUE, FALSE)
  ) %>%
  ungroup()


df_r %>% pull(rebalanced) %>% table()
```

Python / datar & plotnine

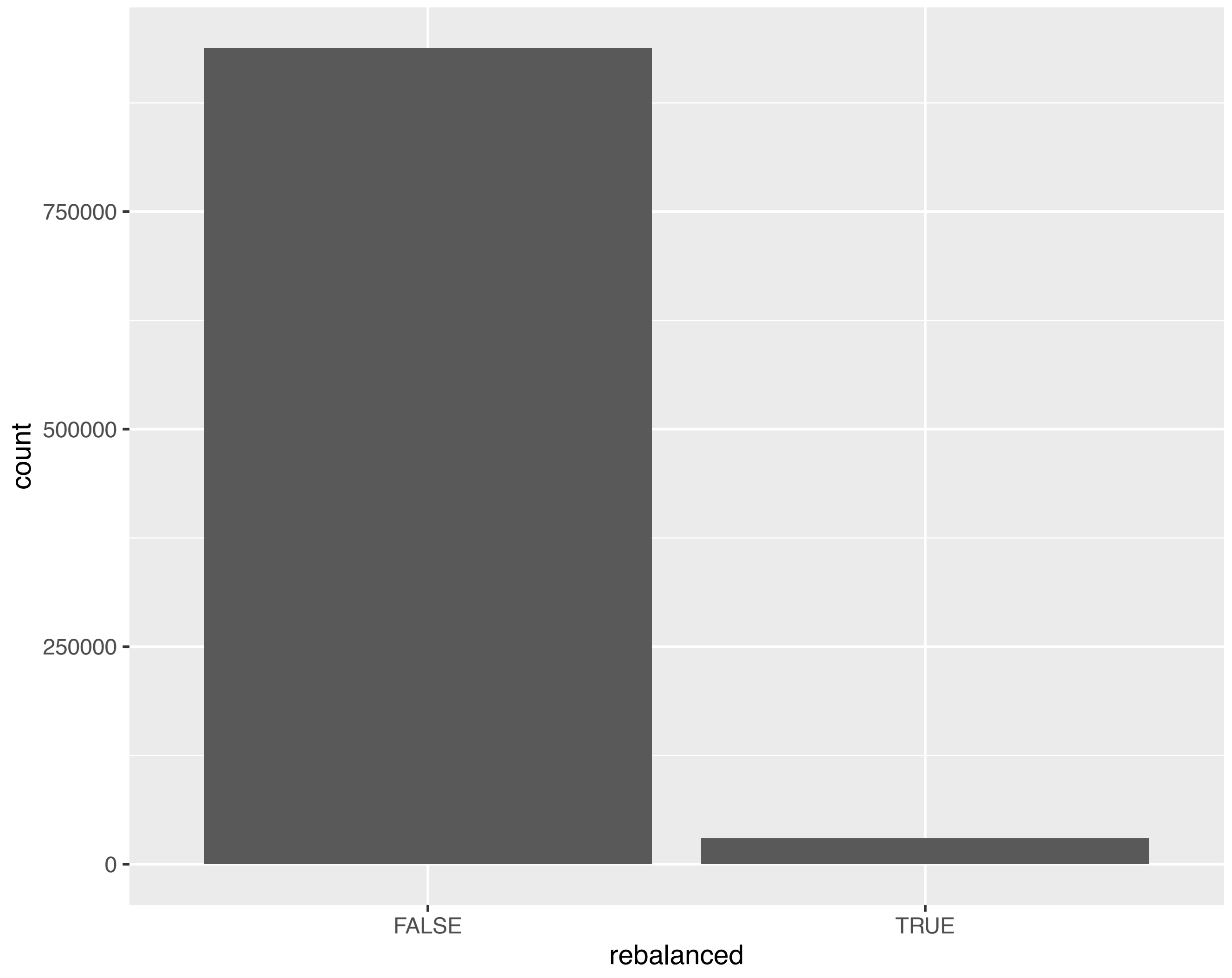
```python
df_py = df_py.rename(lambda x: x.replace(' ', '_'), axis = 1)


df_py = df_py >> \
  filter( f.start_station_id.notnull() ) >> \
  arrange(f.starttime) >> \
  group_by(f.bikeid) >> \
  mutate(
    rebalanced =
      if_else((row_number() > 1) &
              (f.start_station_id != lag(f.end_station_id)),
              True, False)
  ) >> \
  ungroup()


df_py.rebalanced.value_counts()
```

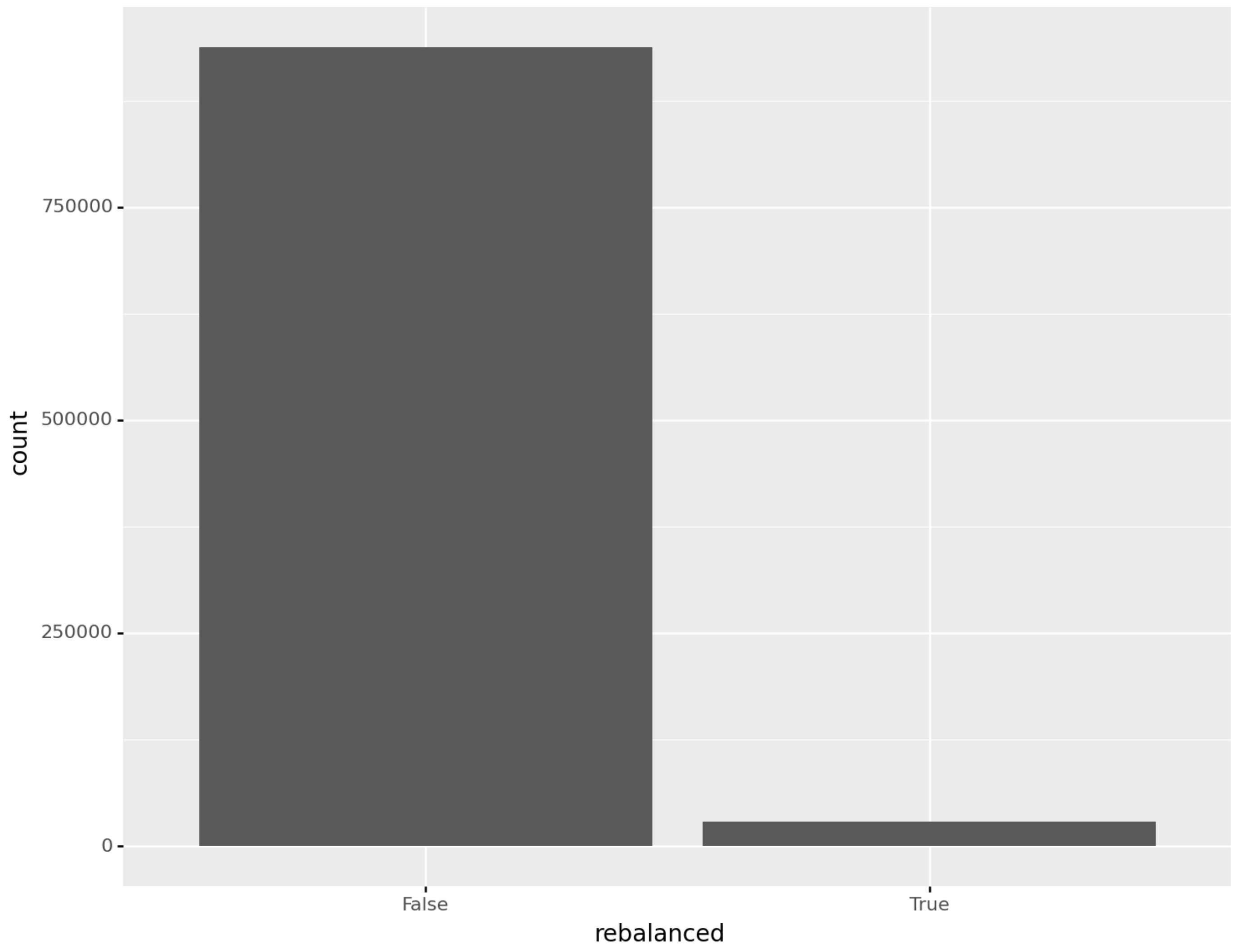
R / tidyverse

```
ggplot(data = df_r) +
  geom_bar(
    mapping = aes(x = rebalanced),
    stat = 'count'
  )
```

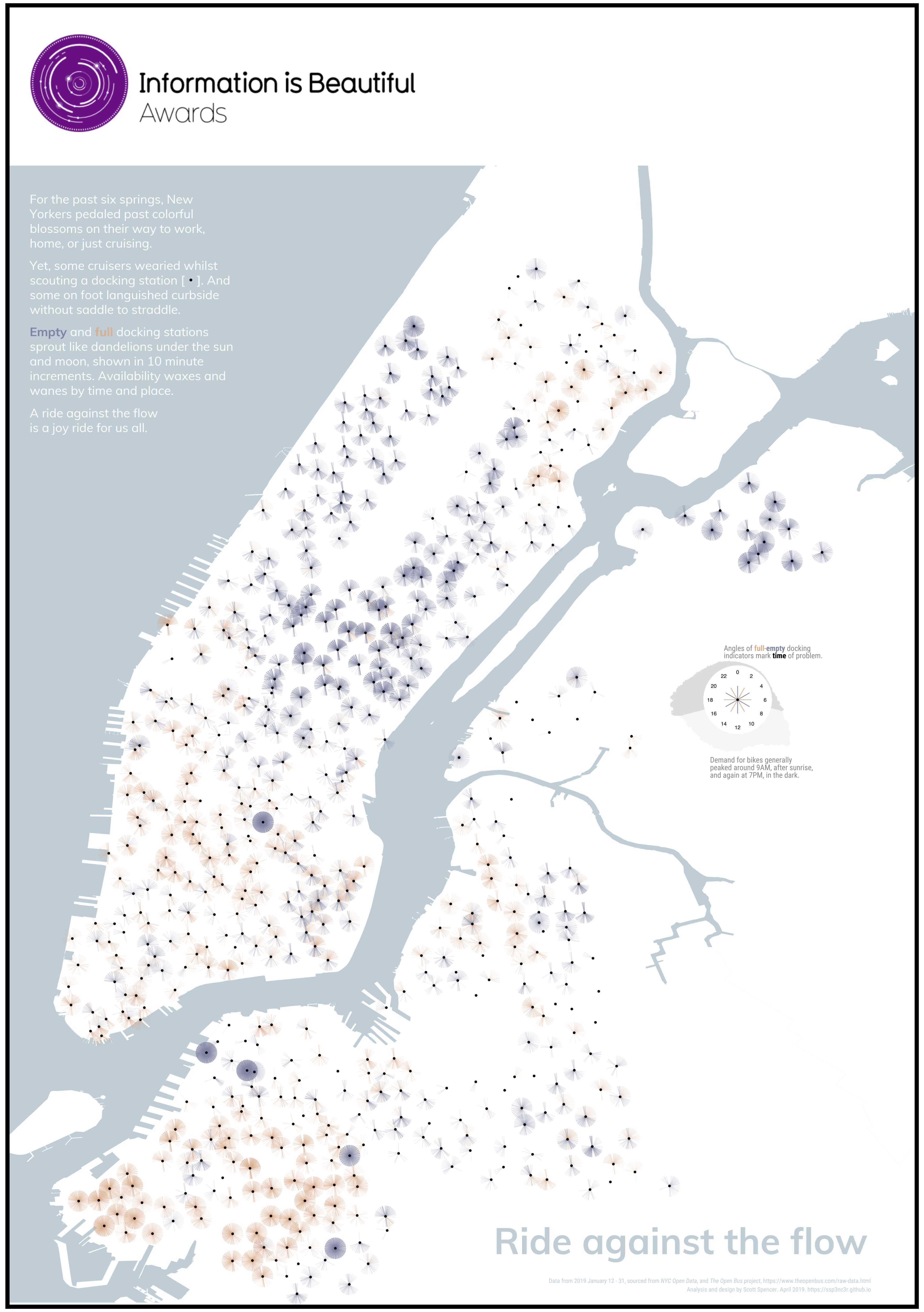


Python / datar & plotnine

```
ggplot(data = df_py) + \
geom_bar(
    mapping = aes(x = 'rebalanced'),
    stat = 'count'
  )
```

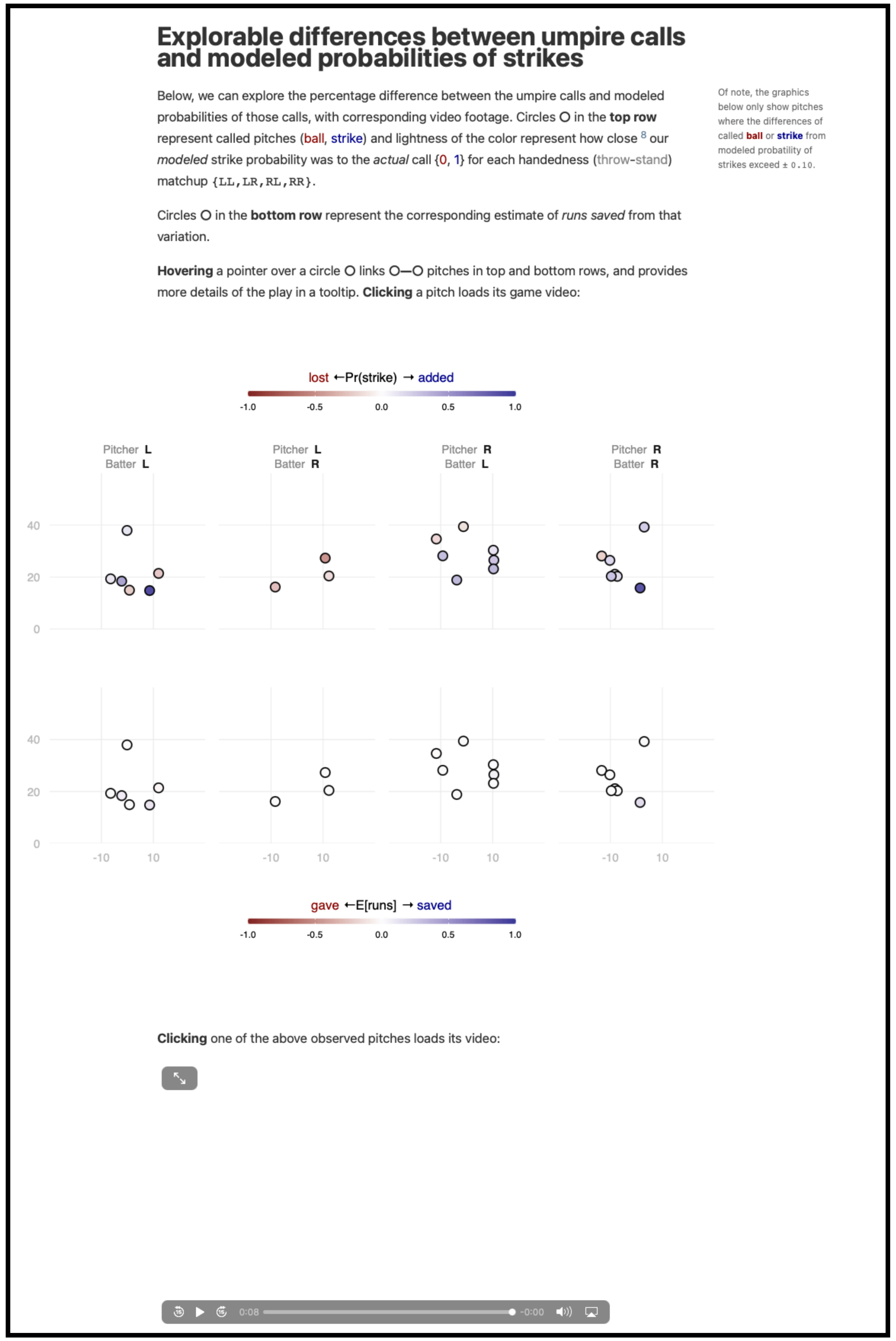


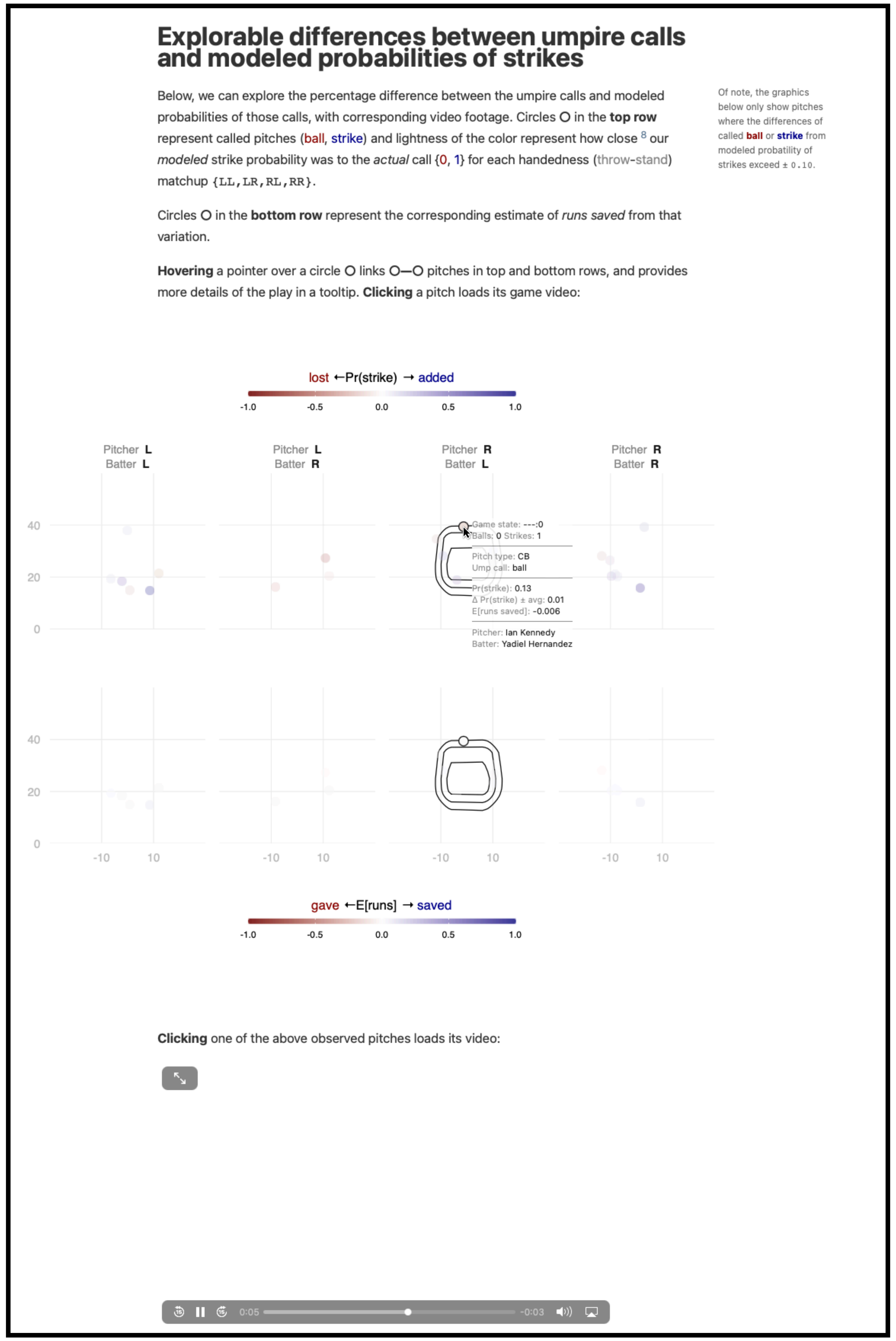
later in the course, example of an *interactive information graphic* with our Citi Bike case study

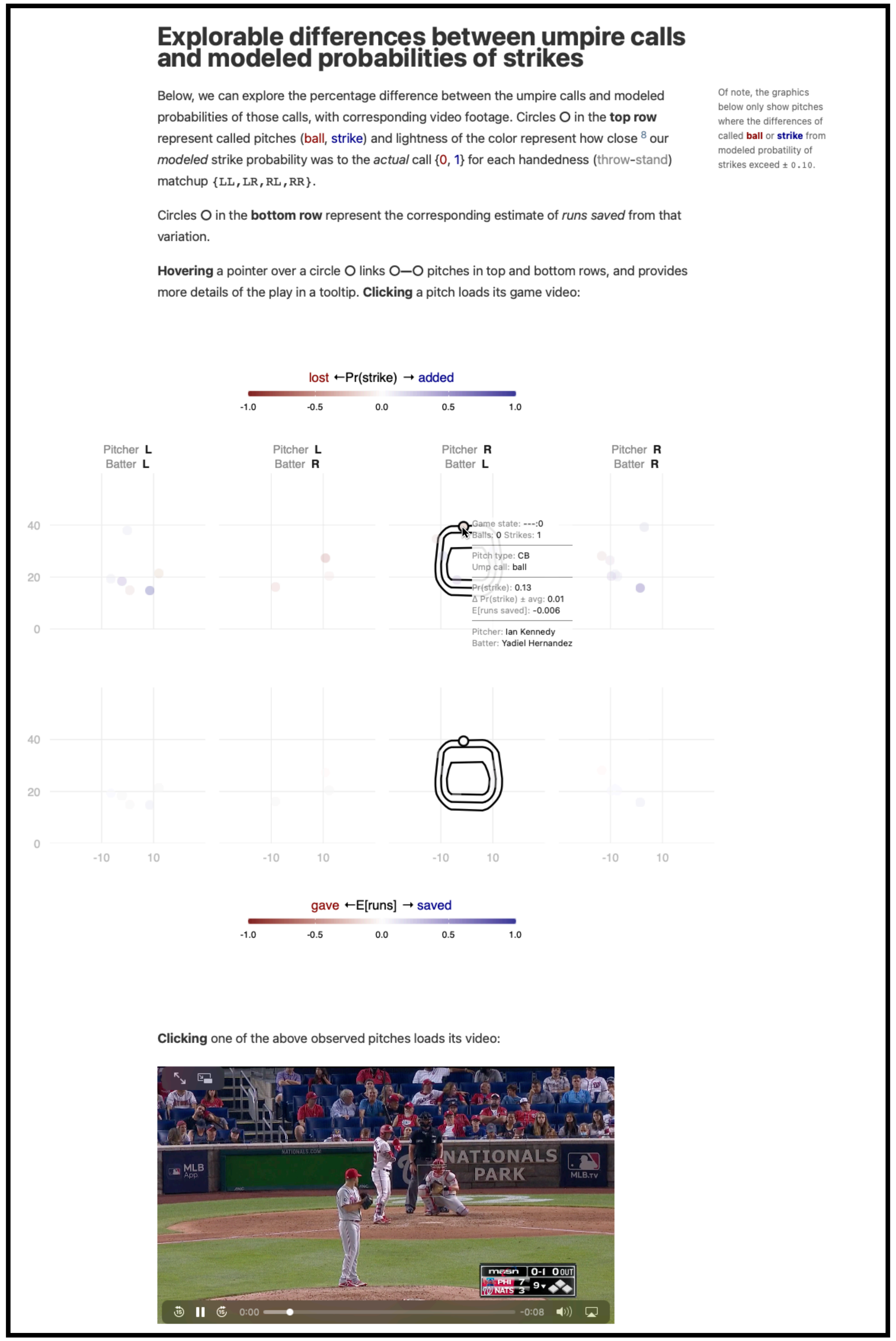


click for interactive version

later in the course, **example combining tools to create part of an *interactive communication* …**







Software: SQL, R (+ ggplot2 & other packages), Stan, HTML, CSS, javascript, D3.js, htmlwidgets

next deliverable, **homework one**

Individual Work

For learning data visualization
and written narrative techniques

Group work

For building graphics and narrative
into interactive communications

Sept 30	Oct 14	Oct 28	Nov 18	Nov 18	Dec 11	Dec 13
Homework 1 graphics	Homework 2 graphics	Homework 3 writing	Homework 4 graphics	Proposal	Interactive Communication	Multimodal communication
10%	10%	10%	10%	15%	20%	15%

Participation 10%

resources

References

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supplemental

R / tidyverse

saving *each* step

```
Temp1 <- f(initial_object)
Temp2 <- g(Temp1)
final_object <- h(Temp2)
```

pipe operator %>%

```
final_object <-
  initial_object %>%
  f() %>%
  g() %>%
  h()
```

Python / pandas

saving *each* step

```
Temp1 = initial_object.f()
Temp2 = Temp1.g()
final_object = Temp2.h()
```

method chaining

```
final_object = (
  initial_object
    .f()
    .g()
    .h()
)
```

pipe operator >> from pipda

```
final_object = initial_object >> \
  f() >> \
  g() >> \
  h()
```

 similarities between software languages — functions operating on data frames

	R / tidyverse	Python / pandas
shows data frame variables & types	`glimpse`	`info`
creates or modifies a variable	`mutate`	`assign`
specifies variables (columns) to keep	`select`	`filter`
renames variables	`rename`	`rename`
specifies observations (rows) to keep	`filter`	`query`
specifies ordering of observations	`arrange`	`sort_values`
specifies grouping of observations	`group_ by`	`groupby`
specifies some summary of the data	`summarise`	`agg`
convert form wide to long format	`pivot_longer`	`melt`
convert form long to wide format	`pivot_wider`	`pivot`

R / tidyverse

Python / pandas