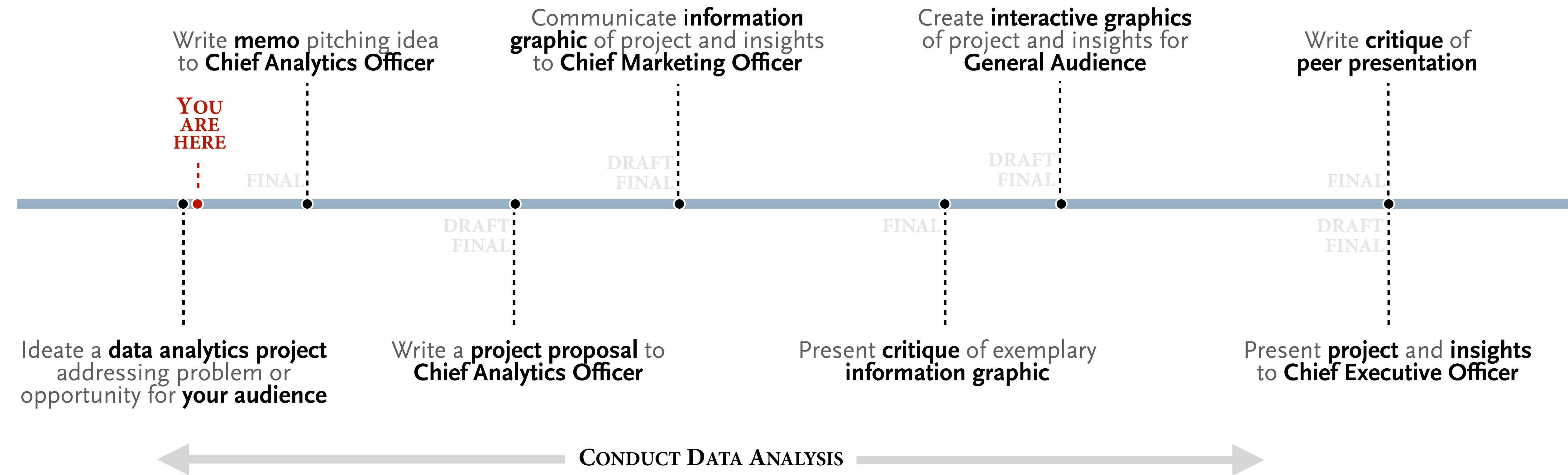


Storytelling with data

02 | *data* for analytics projects, and elements of *writing*

course overview | main course deliverables



data for analytics projects

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 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).

DATA MAY BE OF DIFFERENT TYPES, including nominal, ordinal, and numeric. These have subtypes as well.

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.

DATA HUMANISM

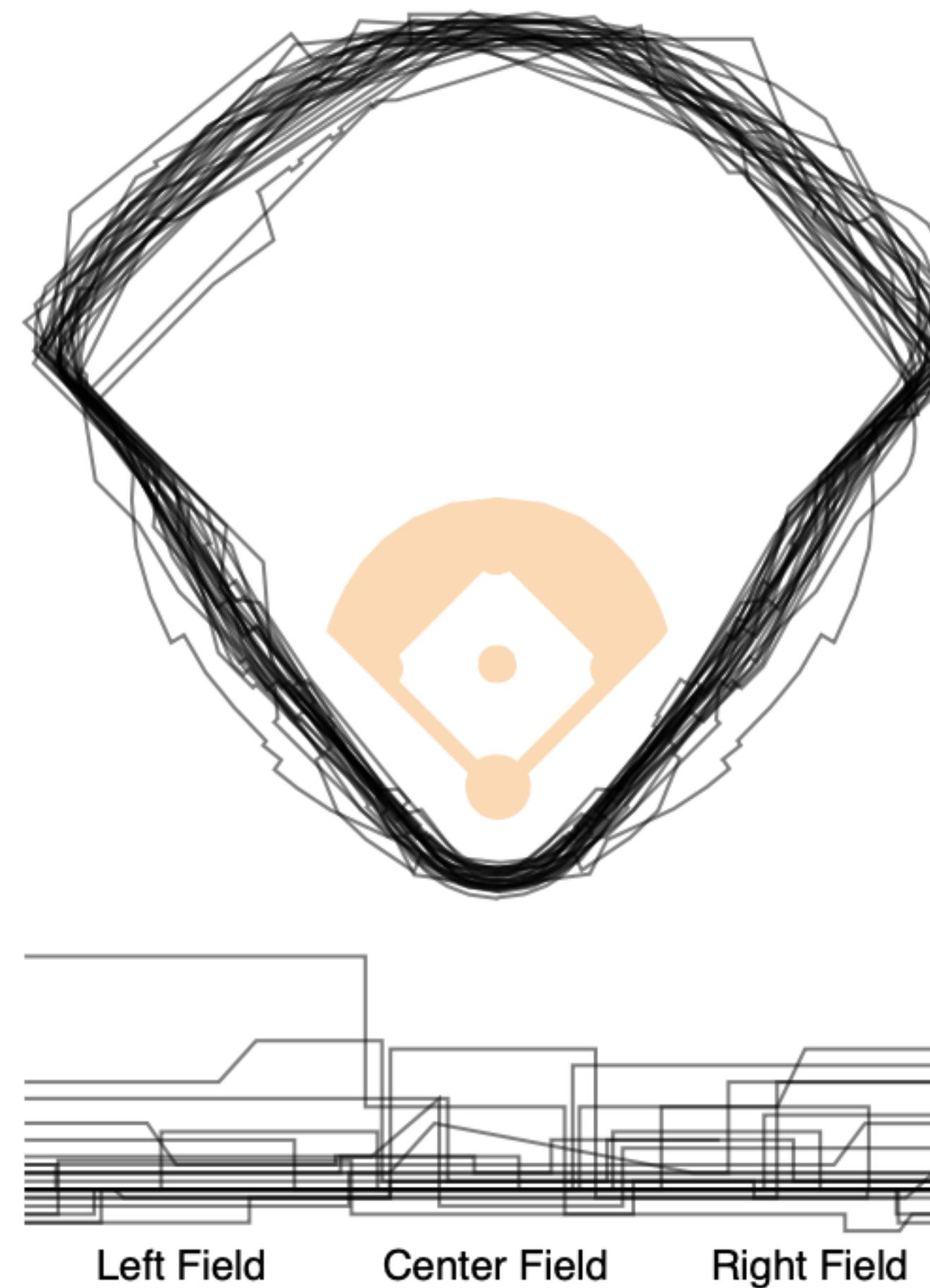
Data represents real life. It is a snapshot of the world in the same way that a picture catches a small moment in time. Numbers are always placeholders for something else, a way to capture a point of view—but sometimes this can get lost.

— Giorgia Lupi, *Information Designer*

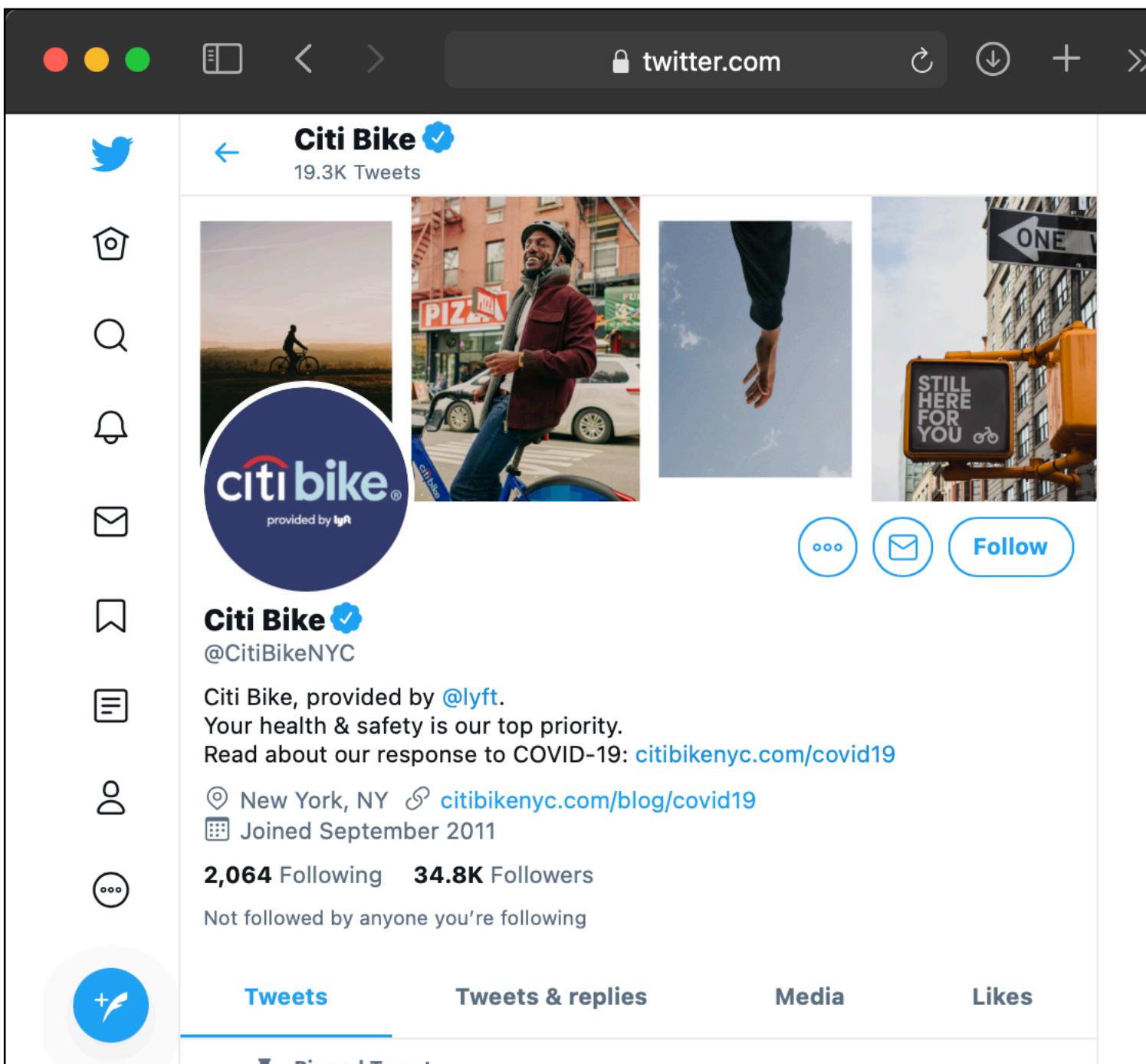
SMALL big data
imperfect infallible data bandwidth **QUALITY**
SUBJECTIVE impartial data
INSPIRING descriptive data
SERENDIPITOUS predictive data
data conventions **POSSIBILITIES**
data to simplify complexity / **DEPICT**
data processing **DRAWING**
data driven design
SPEND save time with data
data is numbers **PEOPLE**
data will make us more efficient **HUMAN.**

@giorgialupi

data for analytics projects | understanding data requires context



data for analytics projects | (un)structured data, more examples from the wild



```
# setup twitter developer account: https://developer.twitter.com for keys  
  
library(rtweet)  
  
TWITTER_KEY    <- "<enter your key from dev.twitter.com>"  
TWITTER_SECRET <- "<enter your key from dev.twitter.com>"  
ACCESS_TOKEN    <- "<enter your key from dev.twitter.com>"  
ACCESS_SECRET   <- "<enter your key from dev.twitter.com>"  
  
twitter_token <-  
  create_token(  
    app           = "apan_teaching",  
    consumer_key  = TWITTER_KEY,  
    consumer_secret = TWITTER_SECRET,  
    access_token   = ACCESS_TOKEN,  
    access_secret  = ACCESS_SECRET)  
  
cb <- get_timeline('CitiBikeNYC', n = 100, token = twitter_token)
```

importance of *comparison* and *change*

comparison | necessary for meaning

The idea of comparison is crucial. To make a point that is at all meaningful, statistical presentations must refer to differences between observation and expectation, or differences among observations.

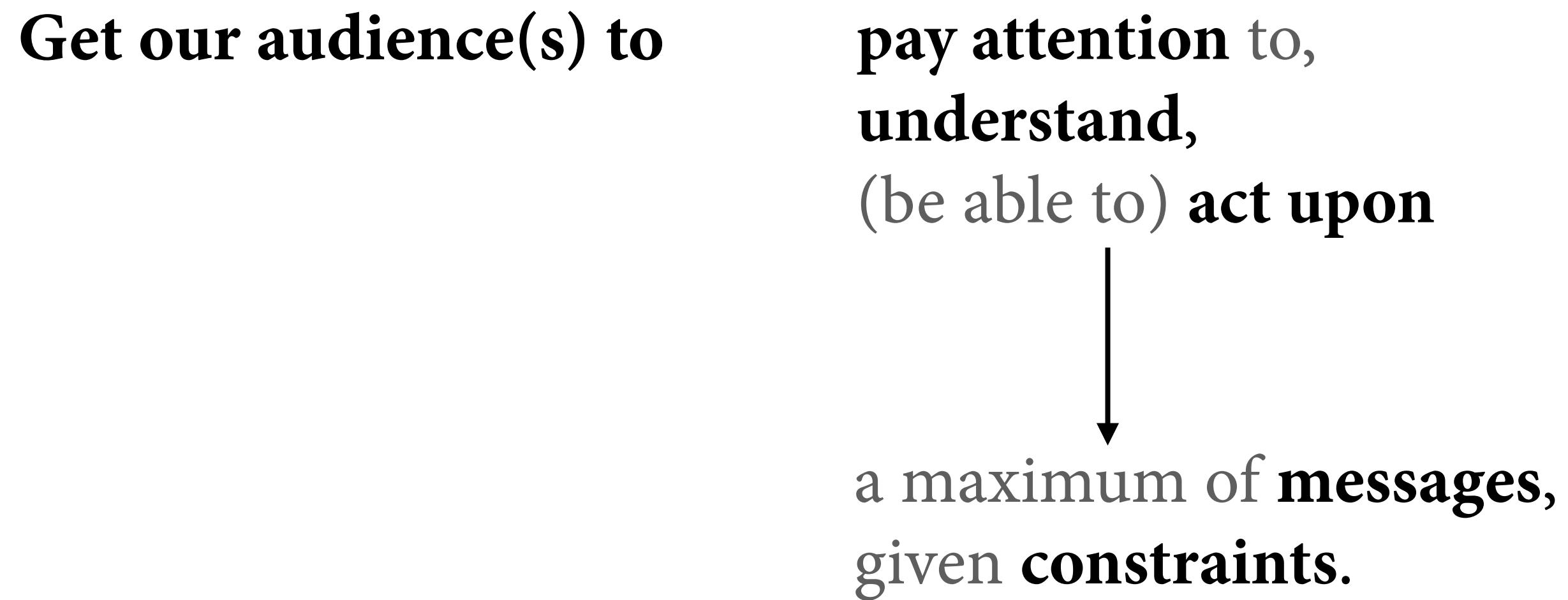
— Abelson, Robert, *Statistician, Professor*

The fundamental analytical act in statistical reasoning is to answer the question ‘Compared with what?’

— Tufte, Edward, *Statistician, Professor, Data Visualization Expert*

The average life expectancy of famous orchestral conductors is 73.4 years.

(business) communication, *fundamentals*



INFORMATION | A concentration of 175 μg per m^3 has been observed in urban areas.

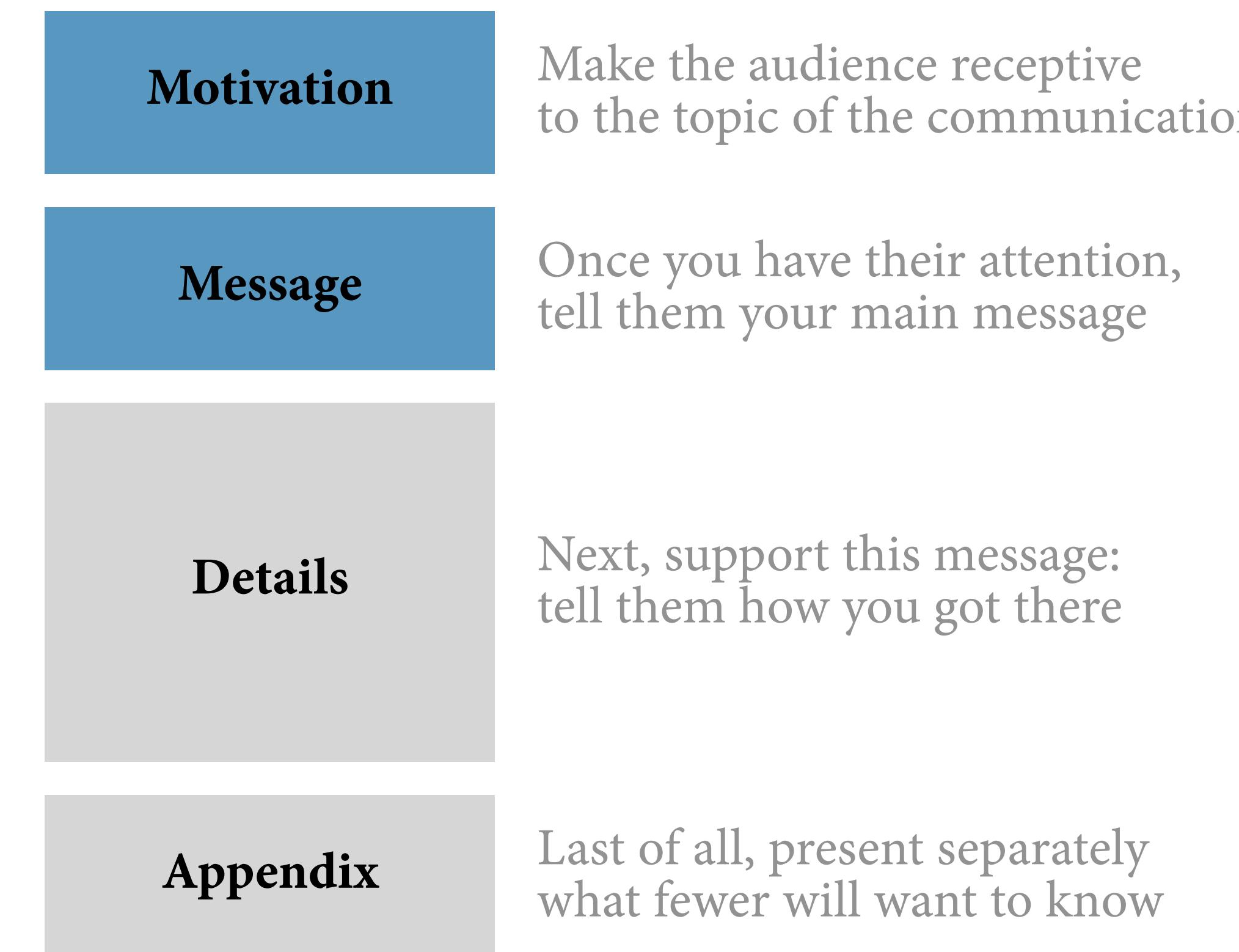
MESSAGE | A concentration in urban areas ($175 \mu\text{g}/\text{m}^3$) is unacceptably high.

Adapt to your audience

Maximize the signal-to-noise ratio

Use effective redundancy

(business) communication, *fundamentals* | first, motivation and message



examples for discussion and group exercise

CHIEF ANALYTICS OFFICER | heads up a company's data analytics operations, transforming data into business value, and drives data-related business change.

examples for discussion | (more) examples of analytics executives

Kelly Jin
Chief Analytics Officer
City of New York

B.A. Economics, Univ. Penn.
Post-Grad. Ed. in Data Science
Previous analytics appointments

Michael Frumin
Director of Product and Data Science
for Transit, Bikes, and Scooters at Lyft

B.S. Computer Science, Stanford
M.S. Operations Research, MIT
20 years experience with data

Scott Powers
Director of Quantitative Analysis
Los Angeles Dodgers

Ph.D. Statistics, Stanford Univ.
Fluent in R, Publications in
Machine Learning

Blair Borgia
Director of Data Intelligence
ERGO, a startup tech marketing firm

B.A. Math, Eastern. Mich. Univ.
Certifications in Python & SQL
20 years experience with data

examples for discussion | first example *draft memo*

motivation and message(s)?

details — specificity of analytics project components?

To Michael Frumin

Director of Product and Data Science
for Transit, Bikes, and Scooters at Lyft

2019 February 2

To inform the public on rebalancing, let's re-explore docking availability and bike usage with subway and weather

Let's re-explore station and ride data in the context of subway and weather information to gain insight for "rebalancing," broadening the factors we've told the public that "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 though there is a Central Business District, it's a huge one and people work in a variety of other neighborhoods as well" (Friedman 2017).

Recalling the previous, public study by Columbia University Center for Spatial Research (Saldarriaga 2013), it identified trends in bike usage using heatmaps. As those visualizations did not combine dimensions of space and time, which the public would find helpful to see trends in bike and station availability by neighborhood throughout a day, we can begin our analysis there.

We'll use published data from NYC OpenData and The Open Bus Project, including date, time, station ID, and ride instances for all our docking stations and bikes since we began service. To begin, we can visually explore the intersection of trends in both time and location with this data to understand problematic neighborhoods and, even, individual stations, using current data.

Then, we will build upon the initial work, exploring causal factors such as the availability of alternative transportation (e.g., subway stations near docking stations) and weather. Both of which, we have available data that can be joined using timestamps.

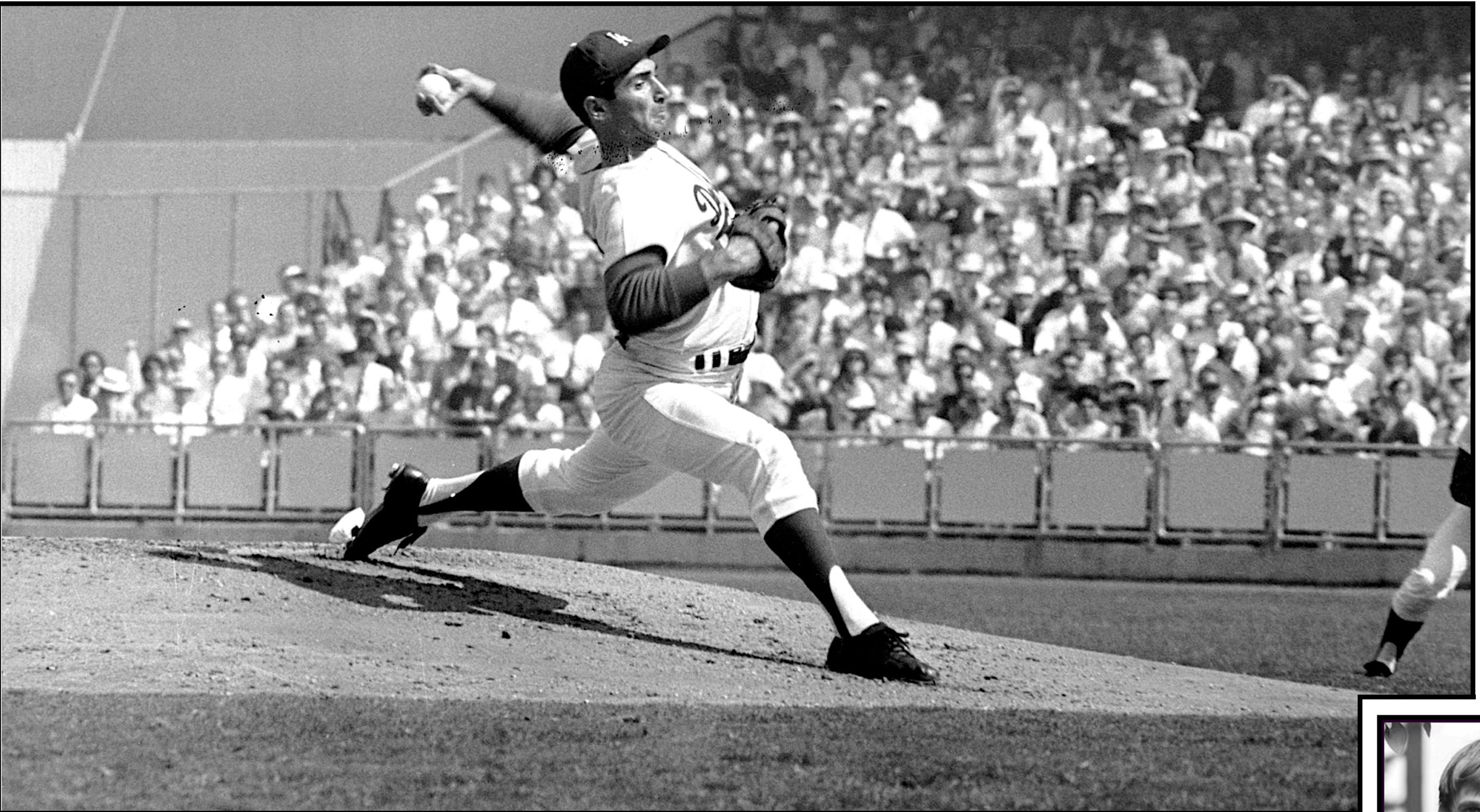
The project aligns with our goals and shows the public that we are, in Simmons's words, "innovative in how we meet this challenge." Let's draft a detailed proposal.

Sincerely,

Scott Spencer

Friedman, Matthew. "Citi Bike Racks Continue to Go Empty Just When Upper West Siders Need Them." News. West Side Rag (blog), August 19, 2017. <https://www.westsiderag.com/2017/08/19/citi-bike-racks-continue-to-go-empty-just-when-upper-west-siders-need-them>.

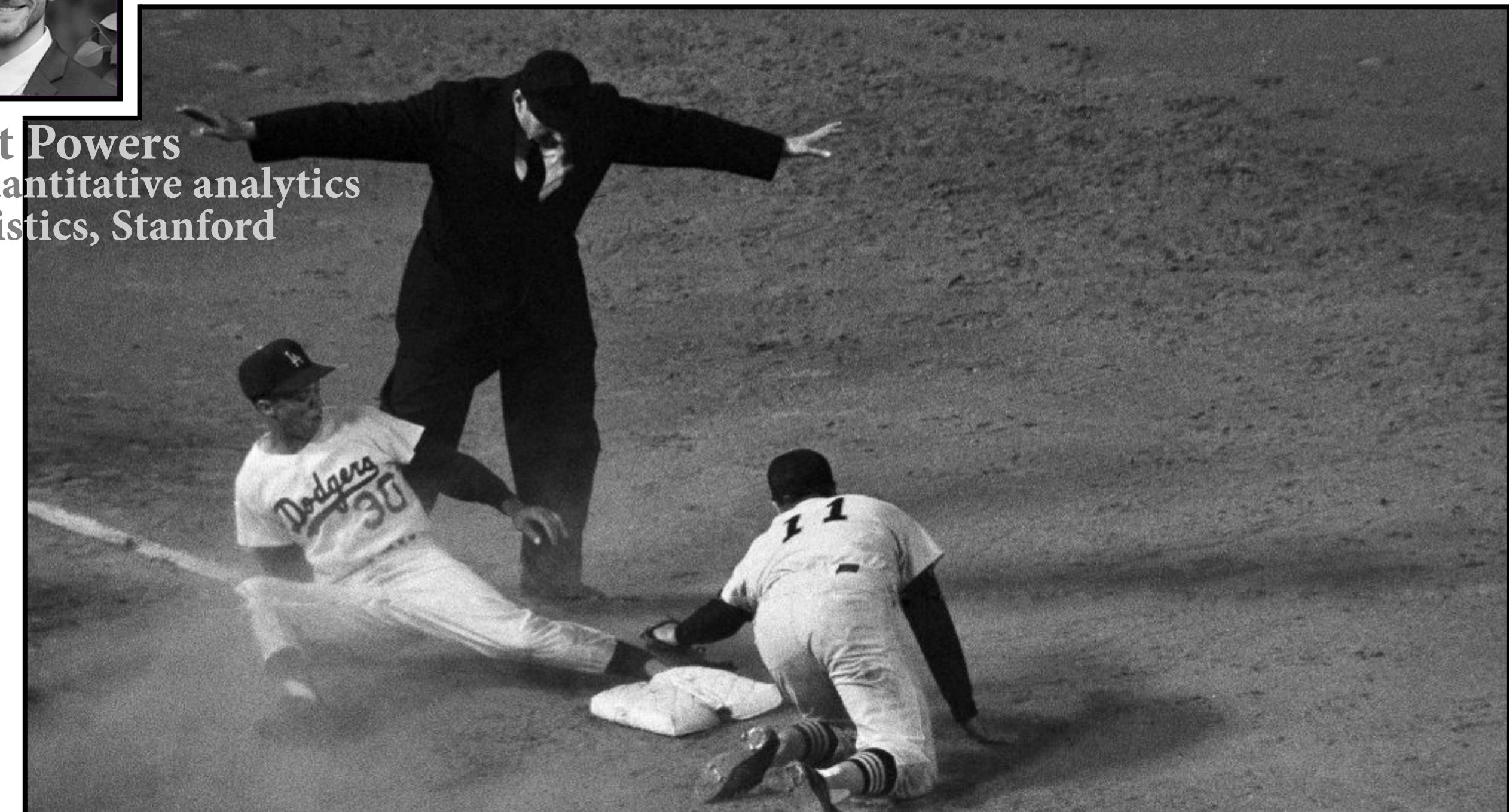
Saldarriaga, Juan Francisco. "CitiBike Rebalancing Study." Spatial Information Design Lab, Columbia University, 2013. <https://c4sr.columbia.edu/projects/citibike-rebalancing-study>.



baseball



Scott Powers
Director of quantitative analytics
PhD Statistics, Stanford



statistics, probability, computing

examples for discussion | second example *draft memo*

motivation and message(s)?

details — specificity of analytics project components?

To **Scott Powers**
Director, Quantitative Analytics

2019 February 2

Our game decisions should optimize expectations. Let's test the concept by modeling decisions to steal.

Our Sandy Koufax pitched a perfect game, the most likely event sequence, only once: those, we do not expect or plan. Since our decisions based on other most likely events don't align with expected outcomes, we leave wins unclaimed. To claim them, let's base decisions on expectations flowing from decision theory and probability models. A joint model of all events works best, but we can start small with, say, decisions to steal second base.

After defining our objective (e.g., optimize expected runs) we will, from Statcast data, weight everything that could happen by its probability and accumulate these probability distributions. Joint distributions of all events, an eventual goal, will allow us to ask counterfactuals — “what if we do *this*” or “what if our opponent does *that*” — and simulate games to learn how decisions change win probability. It enables optimal strategy.

Rational and optimal, this approach is more efficient for gaining wins. For perspective, each added win from the free-agent market costs 10 million, give or take, and the league salary cap prevents unlimited spend on talent. There is no cap, however, on investing in rational decision processes.

Computational issues are being addressed in Stan, a tool that enables inferences through advanced simulations. This open-source software is free but teaching its applications will require time. To shorten our learning curve, we can start with Stan interfaces that use familiar syntax (like lme4) but return joint probability distributions: R packages rthinking, brms, or rstanarm. Perfect games aside, we can test the concept with decisions to steal.

Sincerely,
Scott Spencer

A photograph showing a massive traffic jam in Jakarta. The scene is filled with bumper-to-bumper vehicles, primarily sedans and SUVs, interspersed with numerous motorbikes and their riders. Many of the motorcyclists are wearing colorful helmets. The traffic extends far into the background, creating a sense of gridlock.

Improving traffic safety
through video analysis in Jakarta

group exercise | revise write-up for new audience

“We want this project to provide a template for others who hope to successfully deploy machine learning and data driven systems in the developing world. . . . These lessons should be invaluable to the many researchers and data scientists who wish to partner with NGOs, governments, and other entities that are working to use machine learning in the developing world.”

In what ways are this audience and purpose similar to, and different from, the intended audience and purpose for the example memos?

Improving Traffic Safety Through Video Analysis in Jakarta, Indonesia

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Abstract

This project presents the results of a partnership with Jakarta Smart City (JSC) and United Nations Global Pulse Jakarta (PLJ) to create a video analysis pipeline for the purpose of improving traffic safety in Jakarta. The pipeline transforms raw traffic video footage into databases. By analyzing these patterns, the city of Jakarta will better understand how human behavior and built infrastructure contribute to traffic challenges and safety risks. The results of this work should also be broadly applicable to smart city initiatives around the globe as they improve urban planning and sustainability.

1 Introduction

The World Health Organization’s *Global status report on road safety 2015* estimates that over 1.2 million people die each year in traffic accidents [1]. Nearly 2000 such fatalities occur annually in the city of Jakarta, Indonesia. Many of these deaths are preventable through effective city planning. Jakarta has experienced rapid population growth over the last 50 years, from roughly two million people in 1970 to more than 10 million today. With this growth comes a rise in vehicle ownership and congestion, leading to an increase in the number of traffic incidents.

Improving Traffic Safety Through Video Analysis: Pulse Lab Jakarta.

Nearly 2,000 people die annually as a result of being involved in traffic-related accidents in Jakarta, Indonesia. The city government has invested resources in thousands of traffic cameras to help identify potential short-term (e.g. vendor carts in a hazardous location) and long-term (e.g. poorly engineered intersections) safety risks.

However, manually analysing the available footage is an overwhelming task for the city's Transportation Agency. In support of the Jakarta Smart City initiative, our team hopes to build a video-processing pipeline to extract structured information from raw traffic footage. This information can be integrated with collision, weather, and other data in order to build models which can help public officials quickly identify and assess traffic risks with the goal of reducing traffic-related fatalities and severe injuries.

resources

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