Data Science Process and Objectives

CSE481DS Data Science Capstone

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Presentation of Project Plans

Groups	Project Topic
Group 1	IPO feasibility
Group 2	Influence of Research Papers
Group 3	Restaurants and Decision Making
Group 4	TBD

Today's order: 2,3,4,1

Please make this interactive and share your feedback.

5 Minute Break

What is
Data Science?

What is science?

- From the Latin word scientia, meaning **knowledge**
- A **systematic** enterprise that builds and organizes knowledge in the form of **testable explanations and predictions** about the universe

So what is data science?

- Data Science seeks to discover new knowledge by answering questions through data

What data science is **not**

https://xkcd.com/1838/

How to turn observational, biased, **scientifically "weak" data** into strong scientific results?

Fundamental Data Science Challenges

Scientific method in data science

1. Ask a **question**.
2. State a **hypothesis** about the answer to the question.
3. Make a **testable prediction** that would provide evidence in favor of the hypothesis if correct.
4. Test the prediction via an **experiment involving data.**
5. Draw the **appropriate conclusions** through analyses of experimental results.

[e.g. Roger Bacon, 1265]

Associated Challenges

Domain Knowledge & Theory

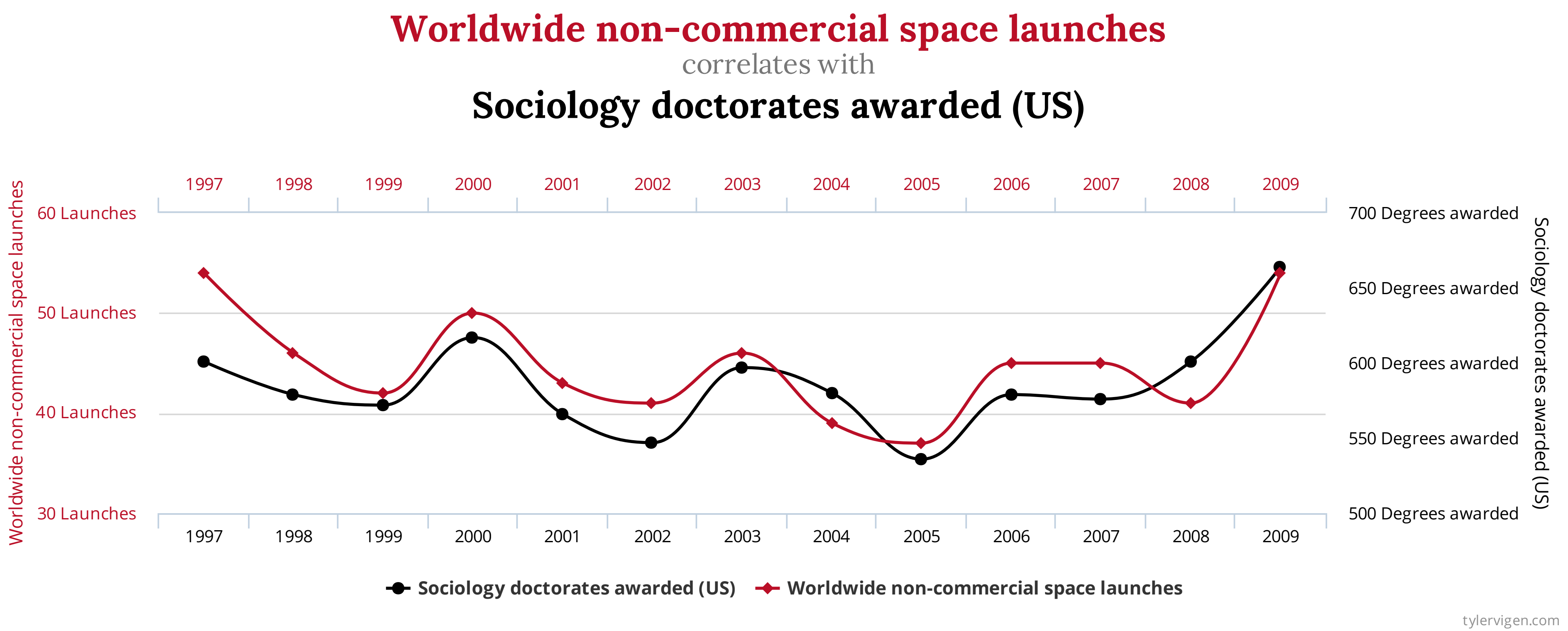
Construct Validity
Are you measuring what you think you are measuring?

Internal Validity
Confounding & Causal Inference
Robustness of findings

Model Intelligibility

External Validity
Incomplete picture of external world

Goal: Valid inferences from data



http://www.tylervigen.com/spurious-correlations

Prediction is not enough!

Causality

- We are typically interested in cause and effect
  - T causes Y if changing T leads to a change in Y *keeping everything else constant*
- Intervention: *What if we do X?*
- Counterfactual: *Was it X that caused Y? What if I had acted differently?*

We will learn about causality later in the course!

Interventionist definition (https://plato.stanford.edu/entries/causation-mani/)

Importance for Decision Making

- Which treatment should doctor recommend for kidney stones?
- **Simpson's paradox:** After accounting for the confounder (stone size) the best choice reverses.

	Treatment A	Treatment B
	78% (273/350)	**83%** (289/350)

Charig et al., BMJ 1986

Why Observational (Data) Science is still critical

In many cases, we cannot randomize / intervene / A-B test (cf. offline evaluation).

- **Practicality:** Exposure to treatment may be hard to manipulate
  - Ex: Environmental effects (air pollution)
- **Ethical concerns:** Known negative effects
  - Ex: Is suicide contagious?
- **Efficiency:** Experimental science is expensive and takes time
  - Ex: Studying impact on mortality 10 years later
- ...

What if I have a ton of data?

Big data to the rescue?

- “Look at how much data I had…”
- ”How could I be wrong? I used 3 billion data points!”
- “This is just noise. All the problems will cancel out…”

- Beware! You need to worry about bias and variance!
- **More data does not help you reduce bias!**
- **This course: Sources of bias, how to model it, & what to do about it**

The Reasonable Uneffectiveness of Big Data

- "The Unreasonable Effectiveness of Data"
  - By Alon Halevy, Peter Norvig, and Fernando Pereira at Google
  - Simple models + Lots of data work very well

- Now consider context of causal inference
  - Measurement error, confounding, and selection bias common threats to causal inference, are independent of sample size
  - When we can't observe counterfactuals, observing more data will not help us!

We will learn about causality later in the course!

Challenge 1: Construct Validity

- Def: Are you measuring what you think you are measuring?
  - Especially important operationalization of theoretical construct / new "sensor"
    (e.g. social media, linguistic proxy)
- How to demonstrate?
  - Convergent validity: Simultaneous measures of same construct correlate
  - Discriminant validity: Doesn't measure what it shouldn't

Big Data typically means little control over how anything was measured

Challenge 2: Internal Validity

- Def: Soundness of research design
- What potential selection effects / confounding are there?
  - Is data missing non-randomly?
  - Could measurement be biased across key groups?
  - Does population change across multiple analyses (complicating comparisons)?

Internal Validity (cont.)

- How robust are findings across different choices along the way?
  - How robust are results with respect to inclusion/exclusion of outliers?
- How many hypotheses are being tested?
  - May need to control false discovery rate
- Are distributional / parametric assumptions valid?
  - Consider non-parametric models and bootstrapping

Big Data typically means observational data, convenience samples, and no pre-registration

Challenge 3: External Validity

- Def: Can findings be generalized to other situations and to other people?
- How biased is the study population?
  - Ex: “Internet Explorer users”
  - Ex: “Chrome latest beta users”
  - Ex: “Smartphone owner + health app installed”
  - Convenience samples can be WEIRD, especially motivated, lack key groups of interest, …

Big Data typically means more data, but more of the same!

Big Data does not address…

...common threats to causal inference, including:

1. Construct validity
   - E.g. measurement error
2. Internal Validity
   - E.g. confounding
3. External Validity
   - E.g. selection effects

Summary: Data Science Objectives

1. Formulate a research question
2. Identify a dataset with which to answer the question
3. Design an analysis process (next)
4. Consider construct, internal and external validity
   - Remember that more data doesn't necessarily help

What is the Data Science Process?

Data Science as a Process

- Separate iterative process into a sequence of activities with different points of failure
- **What does it take to get data science right?**

Data | Analysis Process | Decision

- Framework for your group projects and evaluating data science projects

Process Steps Explained

Define

- *Define the goal and type of the analysis.* Failure modes: Goal of analysis does not match scientific or business need.

Collect

- *Measure / collect data to analyze.* Failure modes: Selection bias (e.g., population mismatch, selective labeling…).

Process Steps Explained (2)

Annotate

- *Augment data with labels or other metadata.* Failure modes: Annotator disagreement; erroneous codes or labels.

Wrangle

- *Clean, filter, summarize, and/or integrate data.* Failure modes: Incorrect filtering, e.g., high-leverage outliers. Incorrect joins with other datasets.

Process Steps Explained (3)

Profile

- *Inspect shape and structure of data.* Failure modes: Overlook data quality issues or violations of distributional assumptions.

Operationalize

- *Define and validate central measures, which may be proxies.* Failure modes: Lack of construct validity (i.e., not measuring what you think you are measuring).

Process Steps Explained (4)

Explore

- *Interactively explore data and variable relationships.* Failure mode: Confirmation bias; unclean split between train/test data.

Model

- *Define and fit models of relationships in data.* Failure modes: Lack of internal validity. Failure to identify effect, e.g., due to confounding or violated assumptions.

Process Steps Explained (5)

Evaluate

- *Measure explanatory power or predictive accuracy of model using appropriate statistical techniques.* Failure modes: p-hacking, overuse of test set data.

Report

- *Report results and potential generalizations.* Failure modes: Misinterpretation (e.g., generalization, uncertainty), miscommunication via errors or omissions. Lack of focus on most important findings.

Process Steps Explained (6)

Deploy

- *Deploy model or enact decision.* Failure modes: Distribution drift, e.g., changes in data pipeline upstream, changing assumptions, adversarial input.

What does this mean for you?

- **Plan** your own project along these stages
- When learning about other projects **pay attention to potential pitfalls** across all phases
- When working on your own project, **explicitly address each step and failure modes**

Teaser for next week: Example Study

Brief Overview of Study Context & Main Results

How Physically Active Are We?

Physical activity is extremely important for health [Lee et al., 2012]. But we do not know how much physical activity people get!

According to WHO:

- 5-54% of Germans don't get enough activity
- No data for Switzerland and Israel

Health research limitations today:

- High cost, short-term, limited scale
- Biases from self-reporting

Wearable and Mobile Devices

69% adults own smartphones in developed countries
46% in developing economies (rapidly growing)

Wearable and mobile devices generate massive digital traces of real-world behavior and health

Activity Tracking

azumio

Tracking actions

- Steps (automatic)
- Runs
- Walks
- Workouts
- Biking
- Weight
- Heart rate
- Food
- Drinks
- And many, many others

Dataset Statistics

- Data from 2011
- 717,527 anonymized users
- Users from 111 countries
- 68 million days of steps tracking
  - **100 billion** data points (2TB), Minute-by-minute
- Focus on 46 countries with >=1,000 users
  - 32 high-income, 14 middle-income countries

Today: 6M users, 160M days of activity, 800M actions tracked

Data in Context

- Our data: 68 million days of activity from over 700,000 individuals in 111 countries

1400x larger than largest existing gold-standard datasets:

- NHANES [Troiano et al., MSSE 2008]
- IPEN [Van Dyck et al., Int. J. Obes. 2015]

Size of NHANES relative to full slide (Azumio)

Population data available at:
http://activityinequality.stanford.edu/

Worldwide Activity

nature International weekly journal of science

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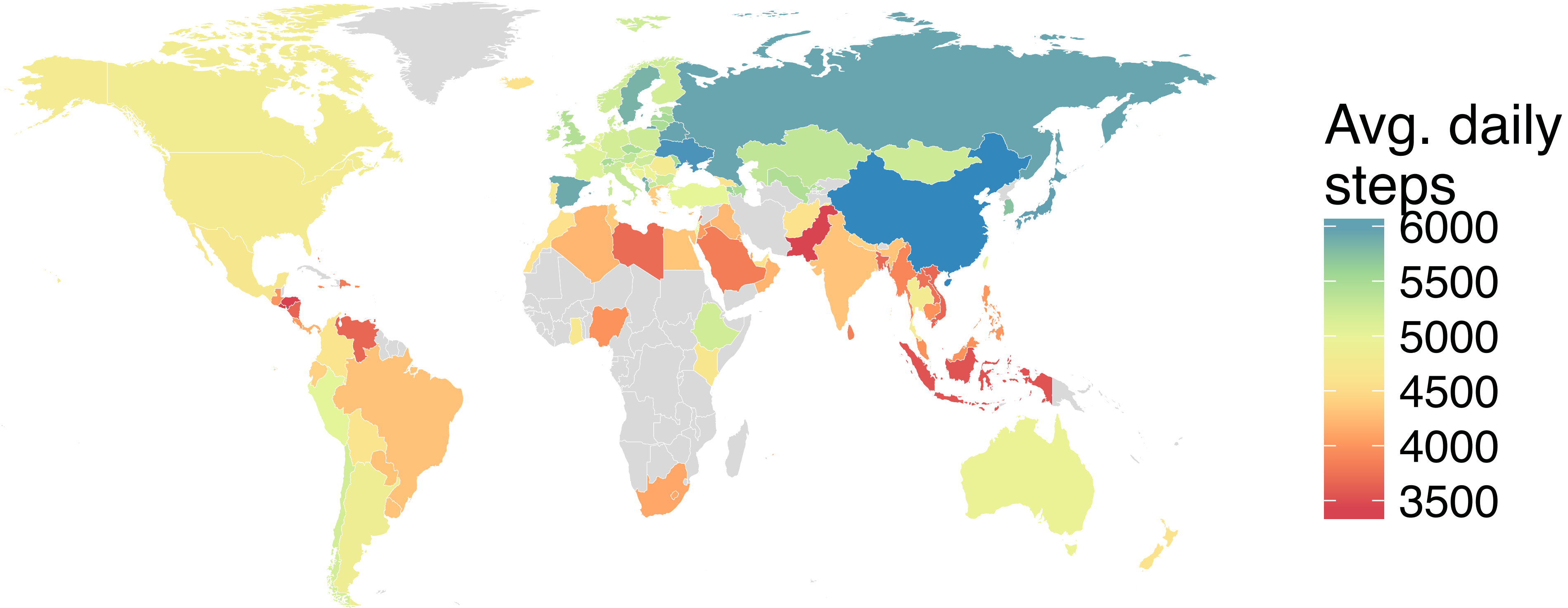
Archive > Volume 547 > Issue 7663 > Letters > Article

Large-scale physical activity data reveal worldwide activity inequality

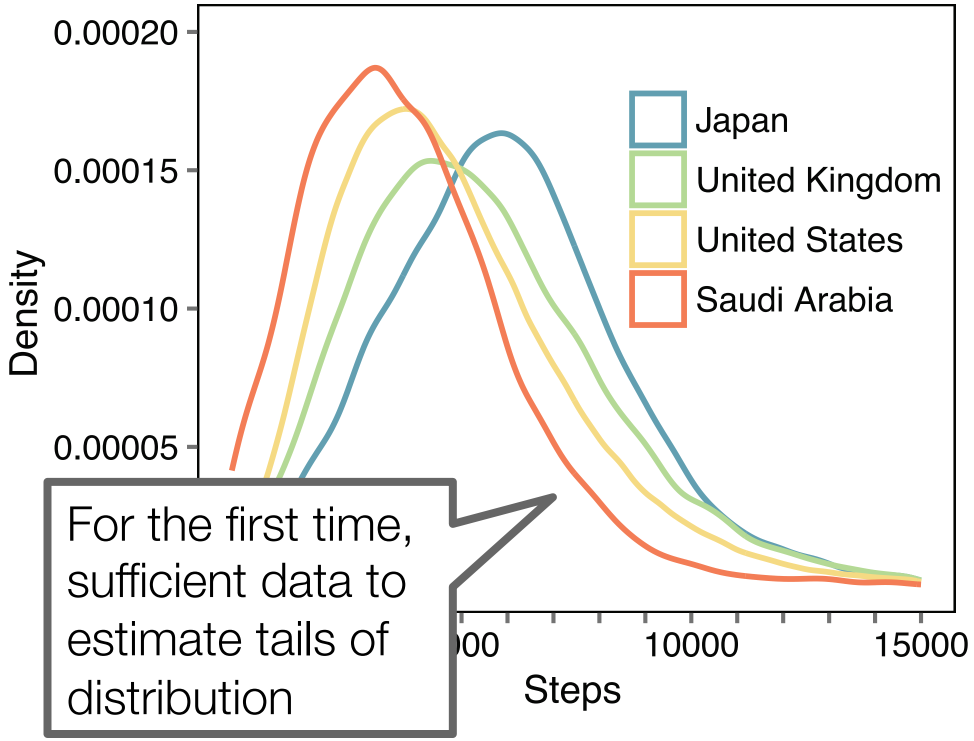
Tim Althoff, Rok Sosič, Jennifer L. Hicks, Abby C. King, Scott L. Delp & Jure Leskovec



But, how is activity distributed within the population?

Result 1: Inequality of Physical Activity

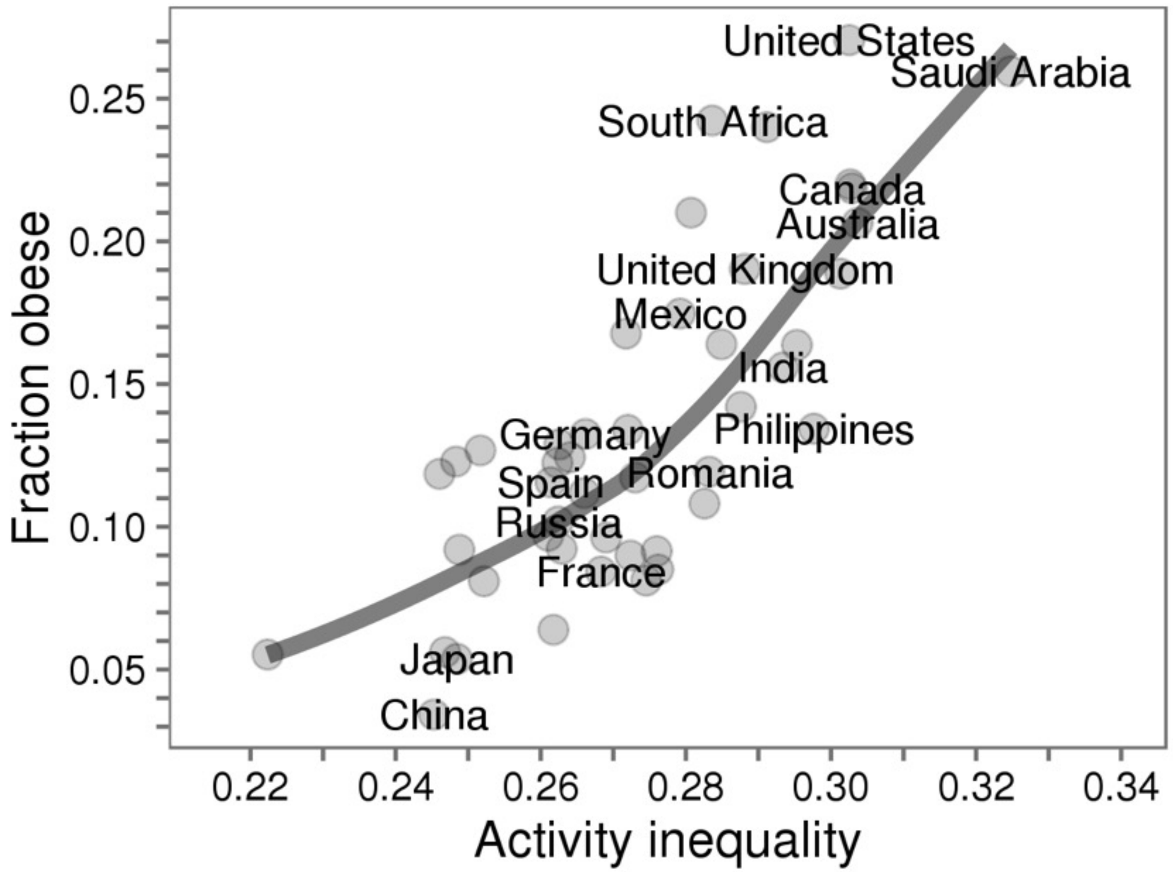
Difference in means



- **How (un)evenly is activity distributed?**
- Gini index of the activity distribution:
  - Activity rich vs. activity poor people

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2\sum_{i=1}^{n}\sum_{j=1}^{n} x_j}$$

Result 2: Activity Inequality Predicts Obesity

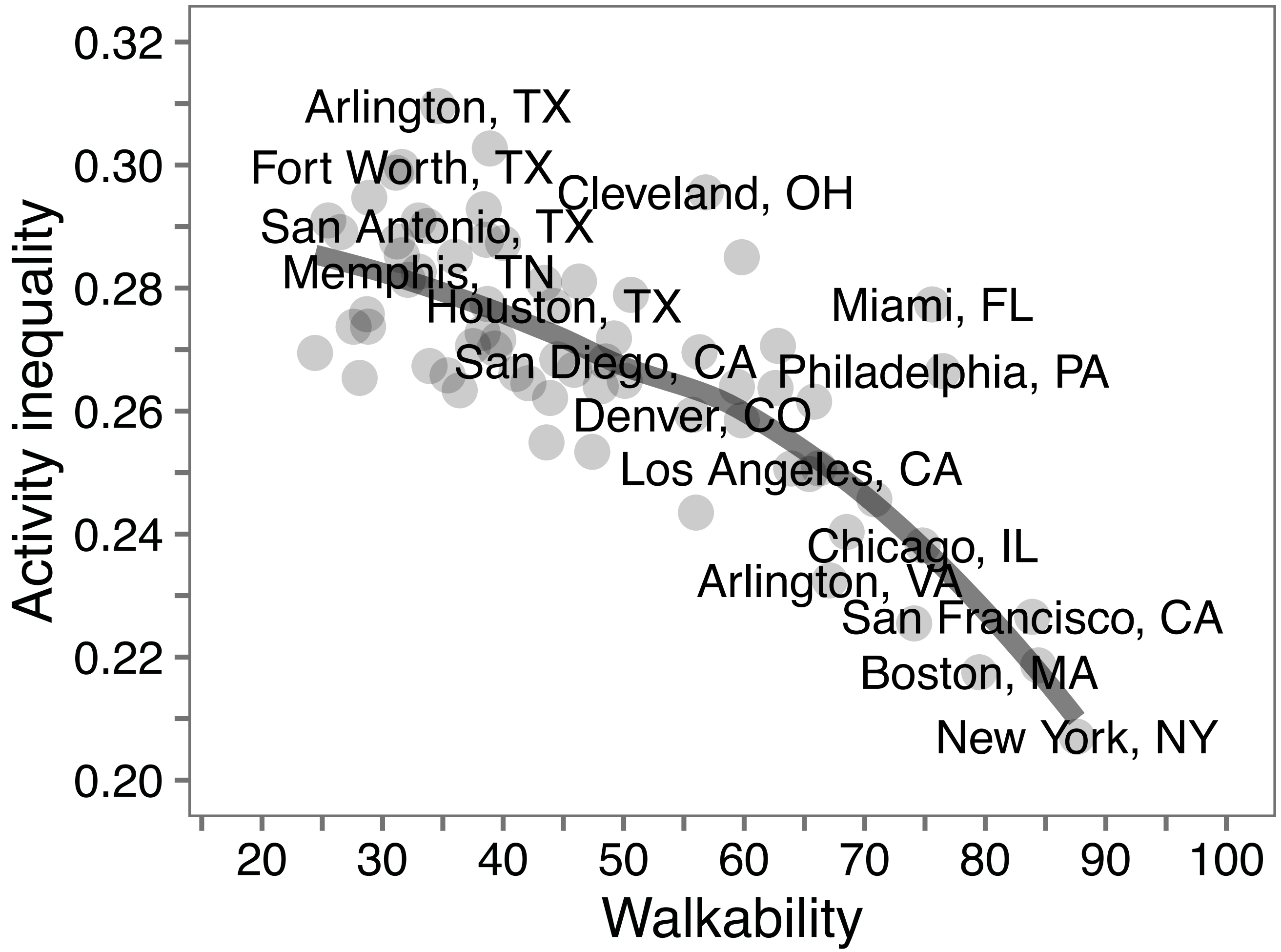


Tails/extremes matter more than the mean

R^2=0.64 (vs. 0.47 for avg. activity)

Massive digital traces uniquely enable studying tails!

Result 3: Walkability Reduces Inequality



Open Q&A

Thank you for sharing your feedback with us!

https://bit.ly/cse481ds-feedback