Social Data Science

Data and Big data

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In God we trust,
all others must bring data

W. Edwards Dewing

Today:

1. Empirical design
2. data generating process
3. modes of collection

    standard vs big data; examples

4. strategic data provision

roadmap

- Different data for different questions
- Theory and empirics, forecasting and hypothesis testing
- Effects of causes vs. Causes of effects
- Data generating process
- Modes of data collection – pros and cons
- Strategic data management and data production

Different data for different questions
or
Different questions for different data

Sometimes possible to separate **data collection process** from underlying **data generating process** – and sometimes not

Fundamental difference between what people do and what they say they do

'cheap talk' / 'put your money where your mouth is' / honest/costly signaling

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What is your question, again?

1. Research question from theory
2. Ideal empirical design
3. Feasible empirical design / collection
4. Results
5. Adjustment of theory/question/design
6. New results
7. …

A. What data do we have
B. What question can they answer
C. Research question
D. Results

All models are wrong – but some are useful

George Box

Two key goals

1. Forecasting: individual behavior, policy consequences, voting, Champions League, grades …
   Data science / machine learning (but also macroeconomics)
2. Hypothesis testing, derived from theory
   ´Traditional' social science

1. Forecasting

- Example: Bank wants to forecast non-payment on loans (P_d: probability of default)
- Couldn't care less about theory
- Rough "Data Science": try to predict from all available data
- Suppose we find that birth weight predicts default
  - Bank is happy, better fit (defer ethics etc)
  - Policy: does investing in pre-natal care reduce defaults?
- In practice: set of predictors typically taken from (some) theory, even if casual
- Complications: if customers know that P_d depends on birth weight, would/should they disclose it? What if loans only to disclosers? Would they tell the truth?

2. Hypothesis testing

- Theory (rational choice, sociology, biology, common sense, …) posits effect of X on Y
  A. Selection/type theory: People who are impatient cannot defer immediate pleasures -> smoke and drink while pregnant -> give birth sooner. If impatient parents -> impatient children (whether by nature or nurture), we have an explanation.
  B. Biological theory: low birth weight affects brain development and neurological wiring for patience.
- If (A), little role for policy; also, both can be true at same time
- How to distinguish: exogenous shock to birthweight, but ethically tricky ...

Goodhart's law

- Most popular: "When a measure becomes a target, it ceases to be a good measure."

- What he wrote: "Any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes."

Targets and Measures

- You cannot be told how your bank constructs your P_d. Why?
  - Goodhart's law: people will attempt to outmaneuver measure
  - (thought)example: spending on shoes good indicator of account overdraft -> shoe lovers will have others buy for them, ceases to be a good measure

Case of Google Flu

- Google Flu: web searches for Flu symptoms predicted actual flu cases
- By-product of Google's main service
- But from 2010, not so well: overestimated actual flu cases, partly as result of autosuggest feature, partly because model was overfitted (we'll return to that)
- Best predictor: number of cases past week

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Effects of causes
vs.
Causes of effects

Different questions

- Effects of causes: intervention, what is effect of policy X on outcome Y
- Causes of effects: Why does Z occur?

Effects of causes (forward causal questions)

- Narrow questions, sometimes (but not always) policy interventions
  - Effect of tax change on behavior
  - Effect of regulation on risk taking
  - Effect of schooling on earnings
  - Effect of smoking on lung cancer propensity
  - Effect of public health on schooling in Africa
  - …
- Often, but not always, amenable to treatments/ randomization/experimentation

Causes of effects (reverse causal inference)

- Much harder, but often more interesting
  - Why do some people smoke?
  - What are the causes of democratization?
  - Why do some people pursue a PhD why others drop out after primary school?
  - Why did Greece (almost) go bankrupt?
- Tensions with ”effects of causes” – search for causes sometimes derided as ‘party chatter’

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Data generating process

What is the **data generating process**?

Observational: endogenous decisions, researcher passive collector of data

Randomization: treatment-control

(Some) exogeneity: policy interventions, sometimes with comparisons, researchers sometimes involved

Important: more data does not give better result/more precision if estimator is biased

Randomized experiments

- Distinguish
  - **Lab experiments**: traditionally computer-based in econ, but also eye tracking/brain images (fMRI)/physiological
  - **Survey experiments**: assign survey respondents to different frames/treatments/primings, e.g. have SocDems and Liberals say same thing and look at support
  - **Field experiments**: experimental control in the real world, e.g. banks charging different rates to learn about mobility of customers; interventions against teacher absenteeism in India; …)

Randomized experiments

- Distinguish
  - Natural experiments
    (weather induced: effects of poverty on violence, randomization of names on election ballots, …)
  - Quasi-experiments
    (effects of change in policy; effect of tax reform on tax planning; effect of immigrant allocation on crime)
- Throughout: exogenous (outside of the individual) change

Randomized experiments

- Large, important current debate in (development) economics
- CofE: what are effects of penalties on teachers' absence in Indian village schools – evidence from randomized experiments
- **Randomly** selected teachers get harsh penalty for no-shows -> difference in absenteeism **causal effect** of penalty
- (Broader EofC Q: why is education sector in rural India so inefficient?)

Randomized experiments

- Strong on internal validity: from randomization **any** effect on absenteeism is from harsher penalties; good for testing theory
- Weak(er) on external validity – would effect be similar in Africa? Would effect from lab work outside lab? Why, why not?
- (compare: medicine works in similar ways across locations)

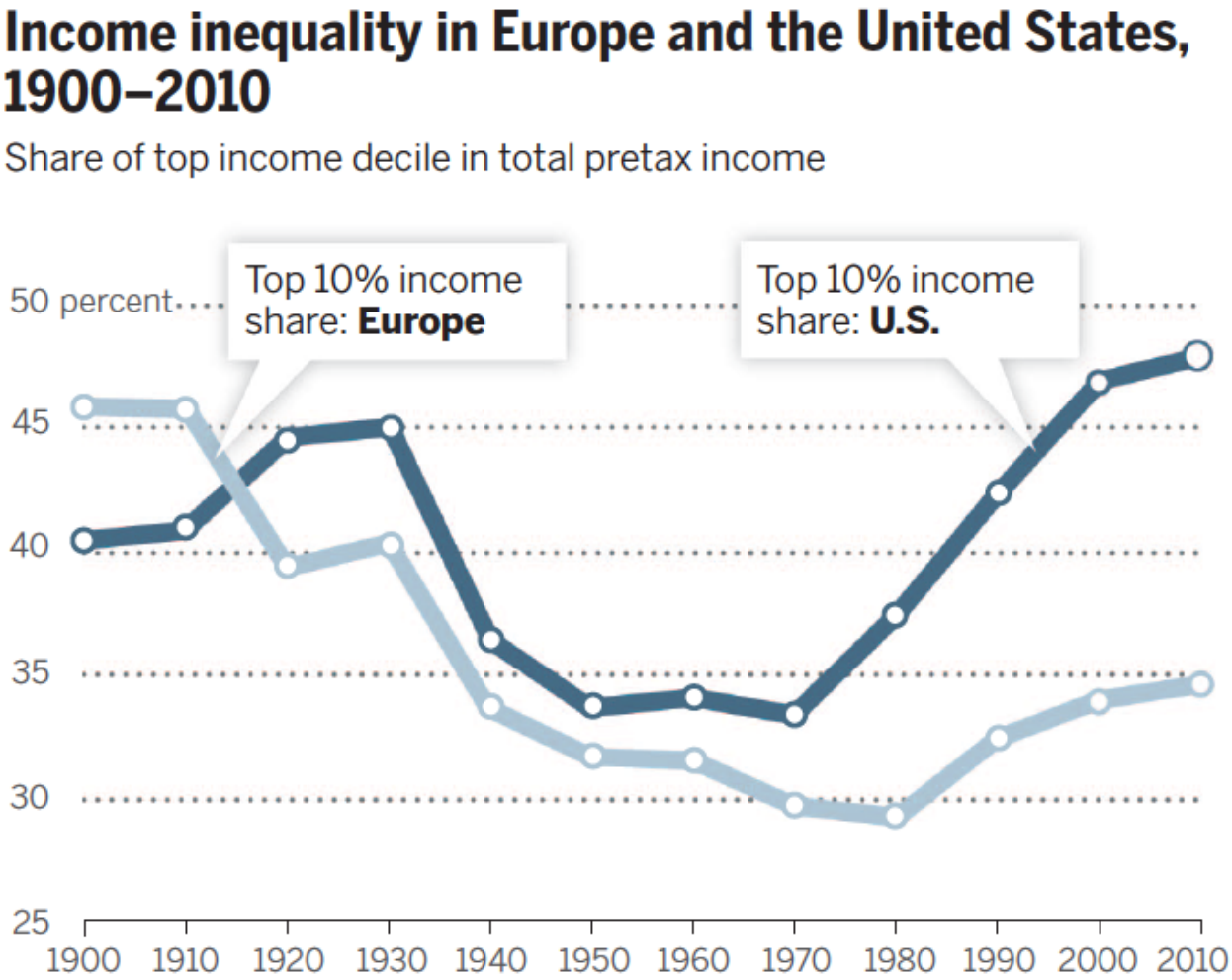
Randomized experiments

- Challenges
  - Limits to what can be studied by experimentation (ethics; law; feasibility)
  - Funding (field experiments expensive, survey exp less so)
  - Often **participation constraint** – voluntary participants' gain >= 0 or no incentive
  - Subjects leave for various (systematic) reasons
  - Large-scale randomization can be hard in field experiments

Observational data

- Generated without experimental or exogenous intervention
- Typically reveals correlations or descriptive patterns that can be interesting in themselves

Example: Inequality



Source: Piketty and Saez, Science 2014, tax return data

Observational data

- Generated without experimental or exogenous intervention
- Typically reveals correlations or descriptive patterns that can be interesting in themselves
  - Are in themselves silent about causality
  - Theory may be provide structure to learn about causal mechanism under strong assumptions
  - May conflate correlation and causality

Observational data

- Exple: Does being in private schools affect grades
  - Classic: Catholic schools and grades in US
  - Collect attendance and grades -> run regression
- But: suppose some parents are more focused on schooling than others
  - Send kids to private school more
  - More involved in school + homework
- What do higher grades measure?
  - Effect of private school OR effect of involved parents?

Observational data

- What to do?
  - Assign kids/parents randomly to private schools?
- More complicated
  - Waiting-list experiment design: people who sign up reveal themselves as school interested, compare grades between those in program and on waiting list -> much narrower design
  - Modeling (US case): use fact that Catholics are much more likely to choose Catholic schools

Big data is often observational

- Not always basis for causal claims
  - But interesting nonetheless: Description
- Can (potentially) be combined with natural/quasi-experiments.
  - Example: very detailed data on transportation/mobility and exogenous weather shocks-> effect of weather on mobility
  - Payday and consumption

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Modes of data collection

- (Ethnographic / participant observer)
- Survey
  - Interview survey (in person), phone survey, internet survey, …
- Administrative data
  - Used for administrative purposes
  - Some countries: census, tax return
  - DK: CPR-registry based
- (Primary collection: texts, counting)
- “Big data”: in social sciences typically a by-product of digital information

Modes of data collection

- Note: survey, admin data, big data can all have randomized / exogenous elements or be purely observational
- Often in Lab/field experiments: ask about income, education etc – but may be biased
- Sometimes: combine experimental data with admin or big data (but rare)

Ethnographic

- Pros
  - Attempt to understand situations from participants' perspective
  - Very detailed observations (e.g. dynamics at a meeting: who speaks when, who listens, who nods off and flirts etc)
- Cons
  - Very difficult to generalize (if even the goal)
  - Typically very small n, not for stats
  - Hard to reproduce / replicate

Surveys

- Pros
  - Can be cheap
  - Elicit info on attitudes, beliefs, expectations
  - Necessary when no other means exist
  - Combine with open-ended info
  - Easily anonymized (firms; China)
- Cons
  - Can be expensive
  - Non-random samples, sometimes very much so (paid surveys)
  - Cheap talk
  - Diverse interpretations (e.g. 1-10 scales, Maasai example)
  - Very different quality: interview vs. internet
  - Not full researcher control: Interviewer completions

Administrative data

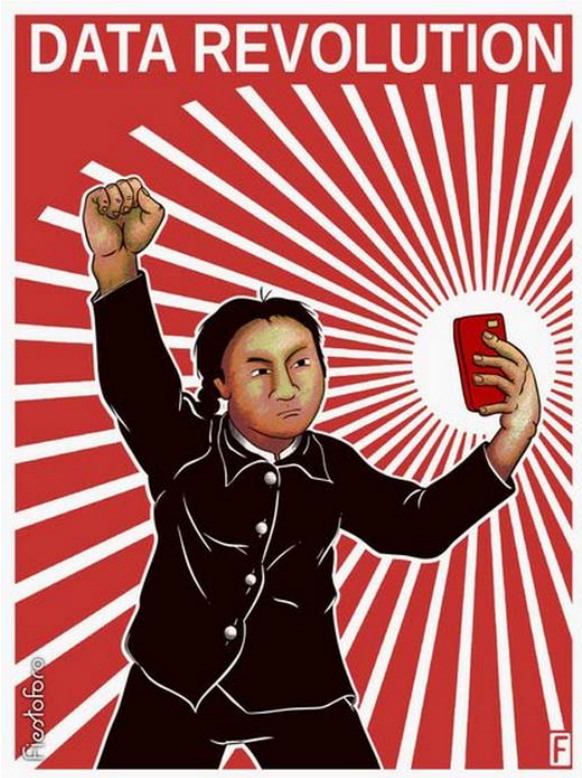
- Denmark, Norway, Sweden
  - Population-wide
  - Ex: Know population ‘by pressing Enter’
    - Most other countries: census (counting people), surveys, rough approximations
  - In DK, built on Central Person Registry number
  - System constructed for source taxation in 1960s, now used as ubiquitous identifier
- Why do some countries have CPR-like systems and some not?

Administrative data

- Pros
  - Often full population
  - In DK: third party reported -> no reporting bias, no survey bias
  - Very detailed, no survey fatigue
  - Often very precise, since used for admin purposes
- Cons
  - No soft data (attitudes, expectations); can be linked to surveys
  - Privacy concerns
  - Restricted to what is collected for admin reasons, both type and frequency (e.g. annual)

Administrative data

- Lots of work in Danish econ utilizes register data
  - Taxation
  - Education
  - Health
  - Financial decisions
  - Labor market
- Combined with
  - Personality measures
  - Attitudes/political prefs from surveys
  - Expectations from surveys
  - Biological data (neuro-measures, genetics)
  - Data from experiments



Viva la revolución?

Harnessing the Data Revolution for Good

Human Development Report Office

Big data

No agreed upon definition what Big Data is

- Large N?
- High frequency / much detail?
- Many different measurements?
- Based on what people do (‘honest signals’)
  - ctr surveys
  - Not always honest
- Different to different people/traditions
- To Americans, Danish admin/register data is big data

‘Big data’

- Pros
  - Often based on **real decisions** (as admin data), but more detail, e.g. auctions
  - **High frequency** (e.g. wifi), high granularity -> almost ‘large N ethnographic data’
  - Sometimes cheap/free
- Cons
  - No established protocol for collection
  - Sometimes dubious quality, selection issues (both known/unknown)
  - Start-up costs
  - Even more privacy concerns
  - Corporate gatekeepers -> bias in access (Facebook, Google)

Characteristics of ‘big data’

- Structured (row/column-style) vs. unstructured (images/sound)
- Temporally referenced (date, time, frequency)
- Geographically referenced (wifi, bluetooth, Google)
- Person identifiable (identify vs. distinguish individuals vs. not distinguish individuals)
  - Separate medium (e.g. phone) from owner

Example: Social Fabric

- Large-scale (N=1000) big data project
- Handed out smart phones to DTU freshmen
- Collected phone, SMS/text/email (not content), GPS, wifi, bluetooth data
- -> Where, when, with whom
- -> social networks

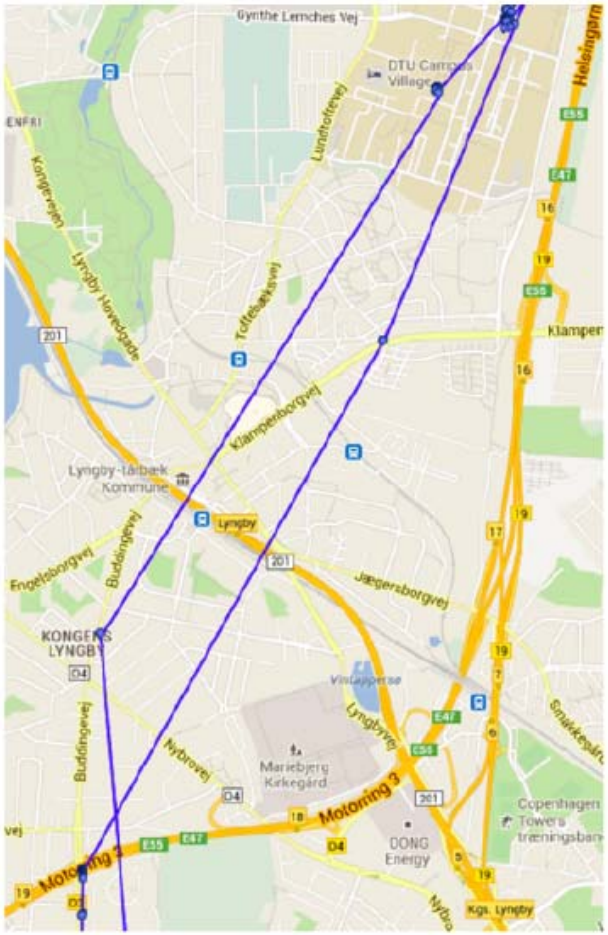
Why phone data

- Phones as **sociometers**
- Many/most people carry phone with them all the time
- Would be IMPOSSIBLE to have people report in detail for every 10 min every day for a year
- For this project: tailored software, but realized that many apps collect detailed wifi-data without telling
- Concern: take-up of phones

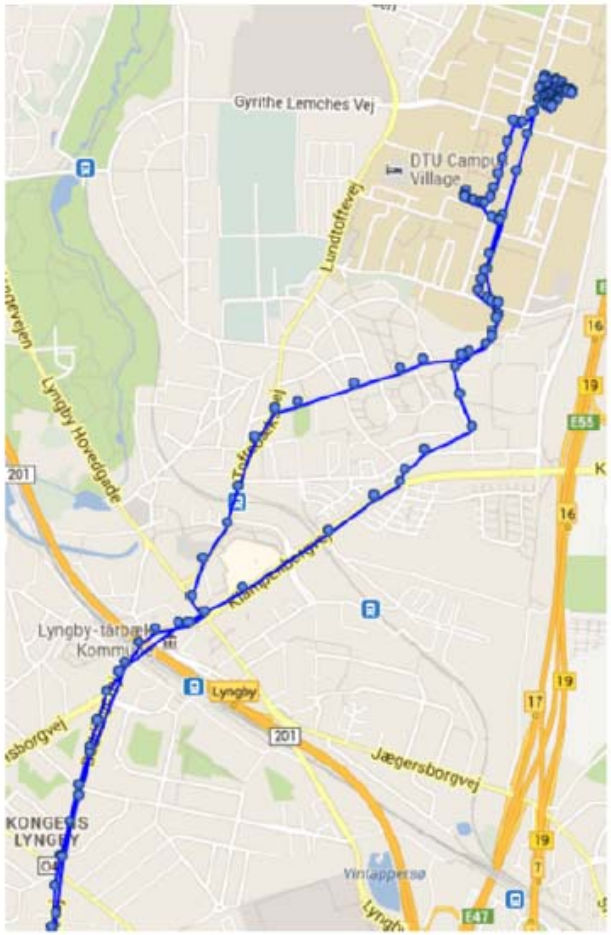
Example: Social Fabric

Phone locations 0500h Monday morning -> can predict where people at given time with 85% accuracy

Example: Social Fabric

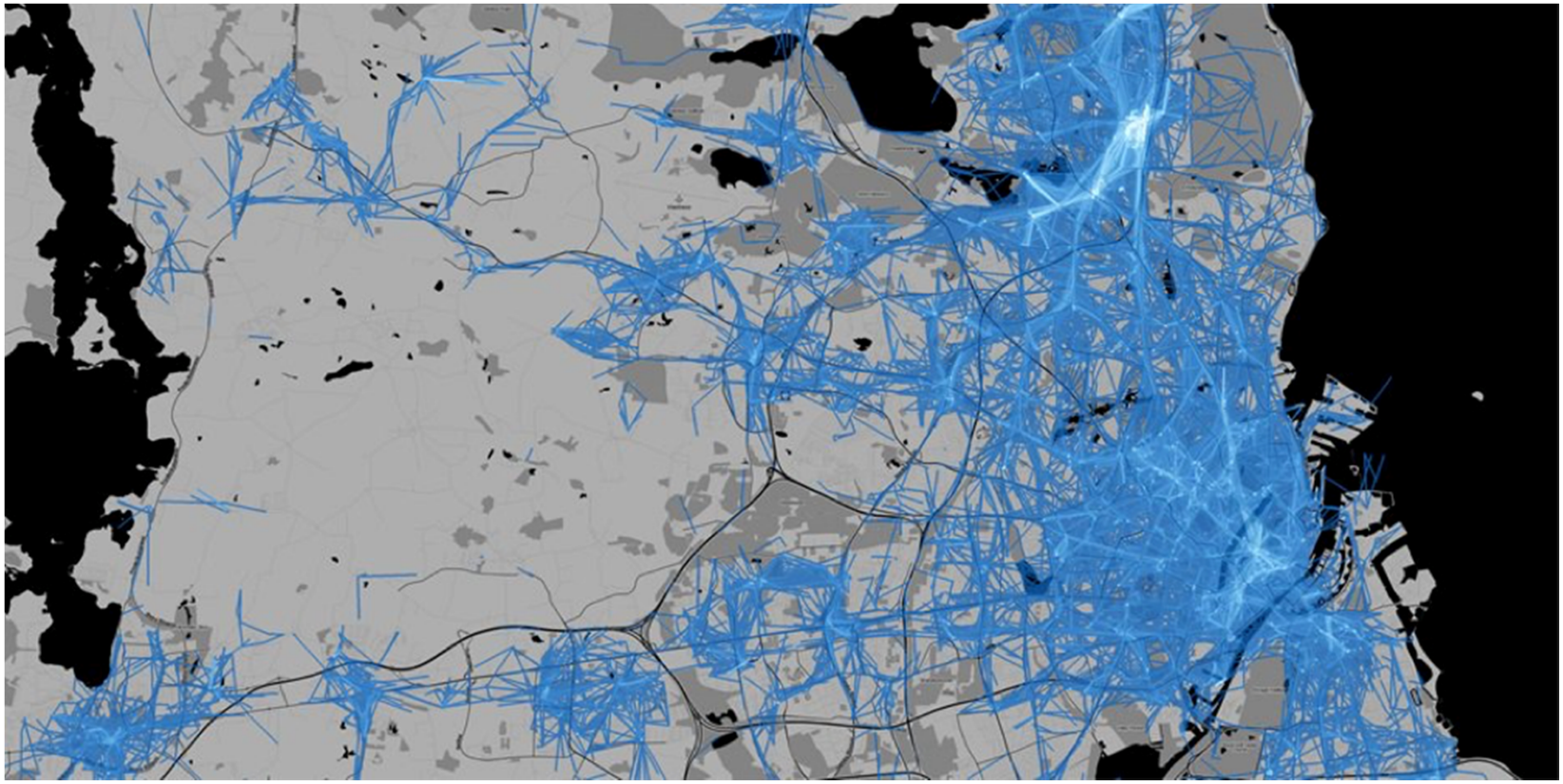


10 min GPS



wifi

Example: Social Fabric



Example: peer effects in education economics

- Students allocated to study and social groups, called vector groups (randomly)
- Are there peer effects, i.e. are students' grades/health behavior/study behavior affected by the group?
- Literature: sometimes yes, sometimes no; very heterogeneous
- Why? Perhaps being allocated to group is not = to actually meeting / using group

Example: peer effects

- Think of allocation to group as intention to treat (similar to offering treatment)
- Interesting example: Carrell et al, ECMA 2013. Small groups, yes peer effects; large groups: no/negative peer effects – WHY?
- Use phone to measure frequency of group members being together physically, measured by bluetooth
- Three parts: (i) yes they are more together; (ii) more together => work better together; (iii) peer effects?

Broader issue: Who meets, and how close are they?

- Again: use bluetooth signals to measure meetings (duration, participants)
- Analyzes 3.1 mio meetings over two months
- Some results:
  - Women/women pairs -> closer
  - Facebook friends -> closer
  - Same study -> closer
  - Difference in beauty -> further apart
  - One overweight, one not -> further apart
- People who stand very (too) close to others have fewer friends (!?)

Prediction vs causality

- Measure class attendance from phone data (wifi/GPS/bluetooth)
  - Either: construct clusters at slots known as teaching time; or: use admin info on class locations and construct GPS overlays
- Facebook activity

- Predict grades

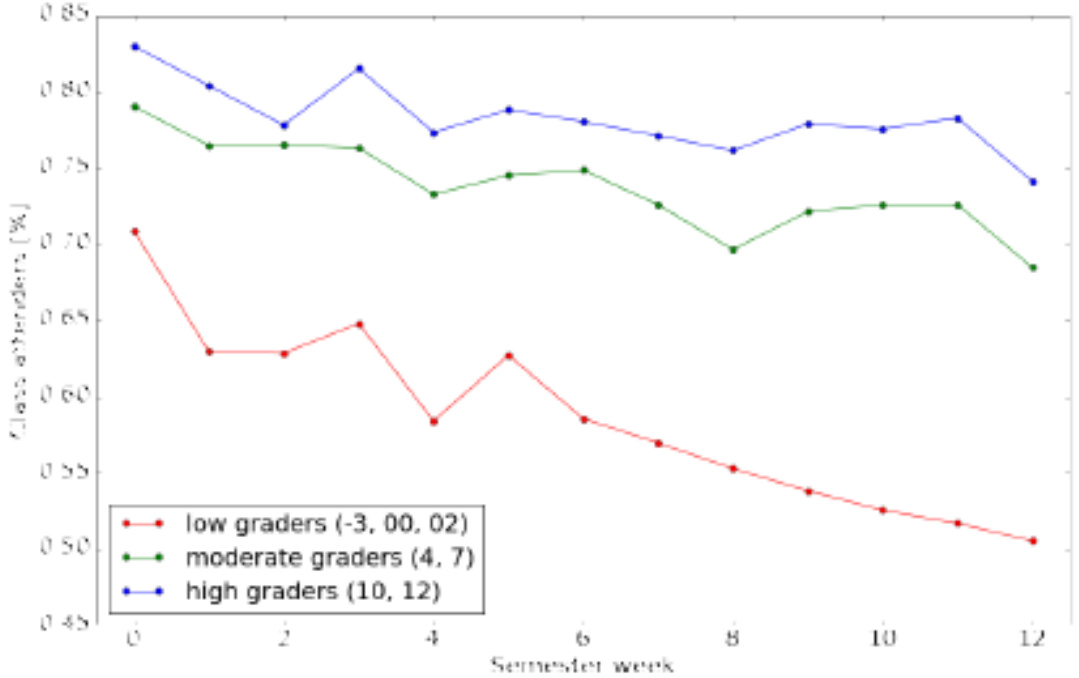
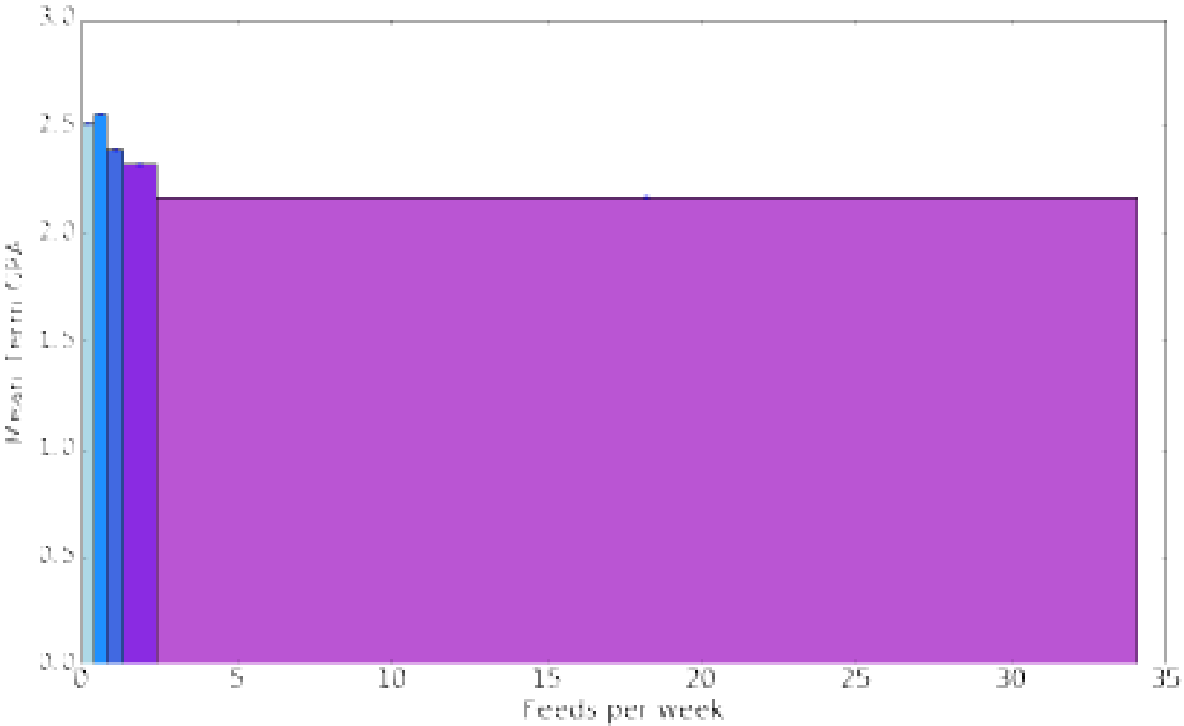
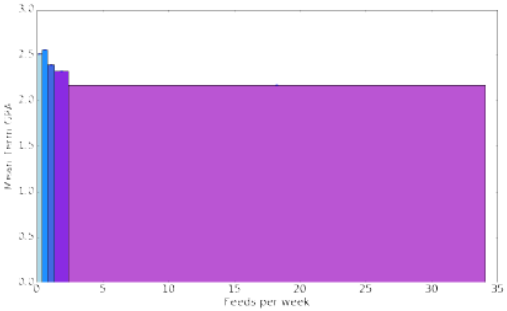
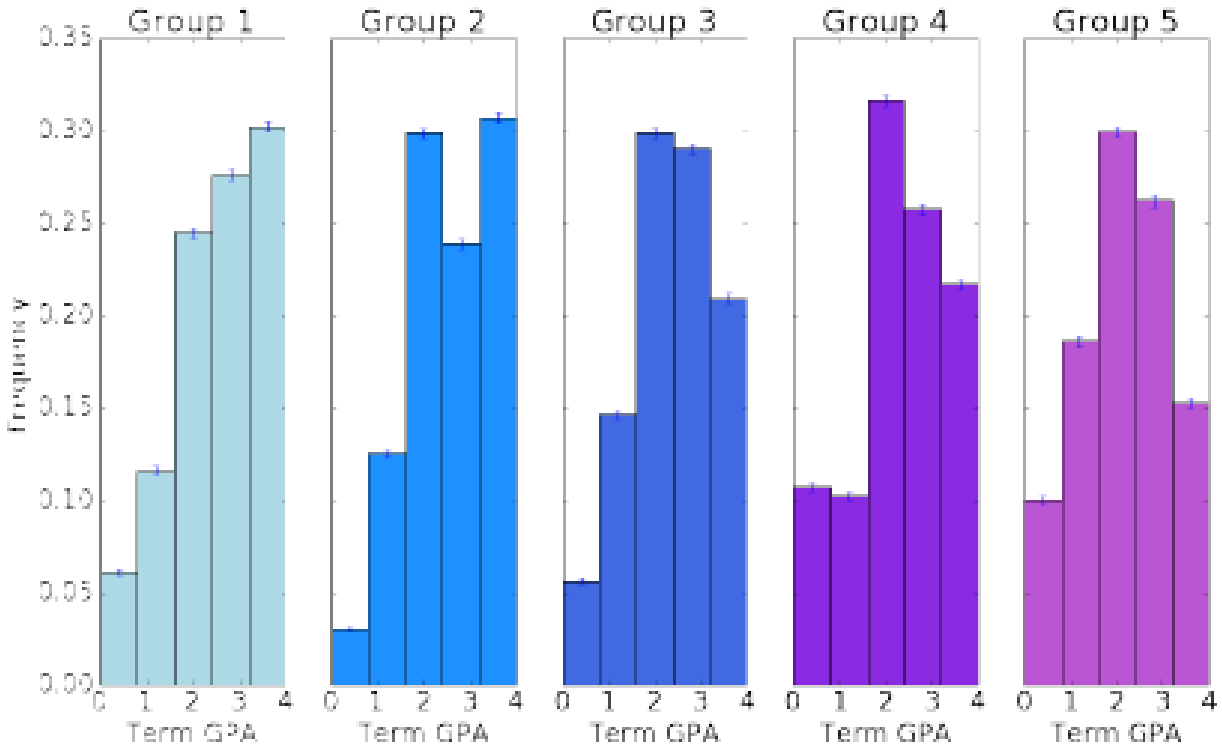


Figure 4: Change of class attendance over the 13-week semester. Students were grouped into high graders (12, 10; blue line), moderate graders (7, 4; green line), and low graders (02, 00, -3; red line). There is a significant decrease of class attenders for all three groups. At each point during the semester the ratio of class attenders of good graders is higher than that of low graders.


0
5
10
15
20
25
30
35
Feeds per week


Mean Term GPA
Feeds per week


Group 1
Group 2
Group 3
Group 4
Group 5
Frequency
Term GPA

Prediction vs causality

Attendance -> grades/comprehension

- People who attend more learn more
- People who spend less time on Facebook have more time for studying

AND/OR

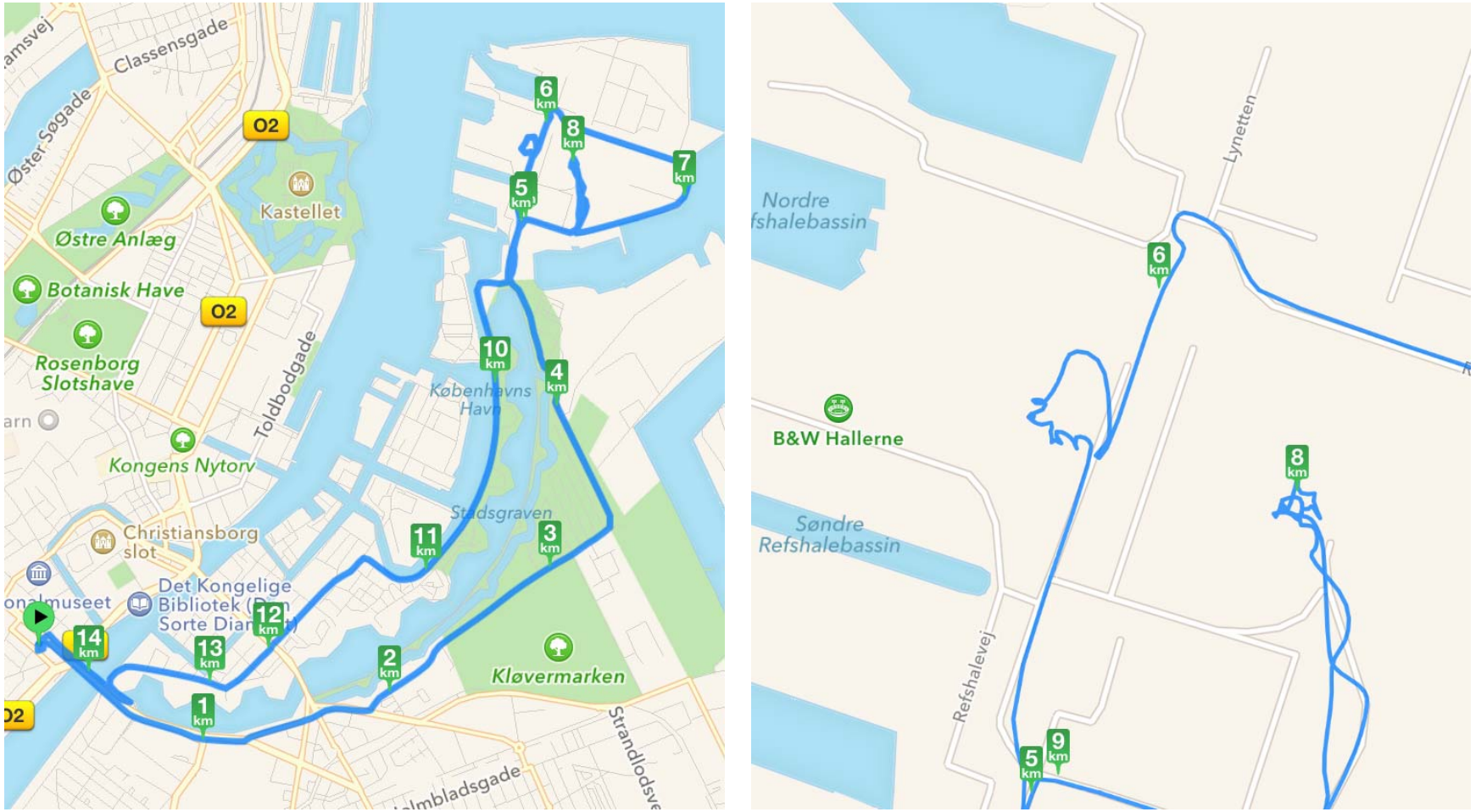
Grades/comprehension -> attendance

- Find courses hard -> stay at home, more tempted by Facebook

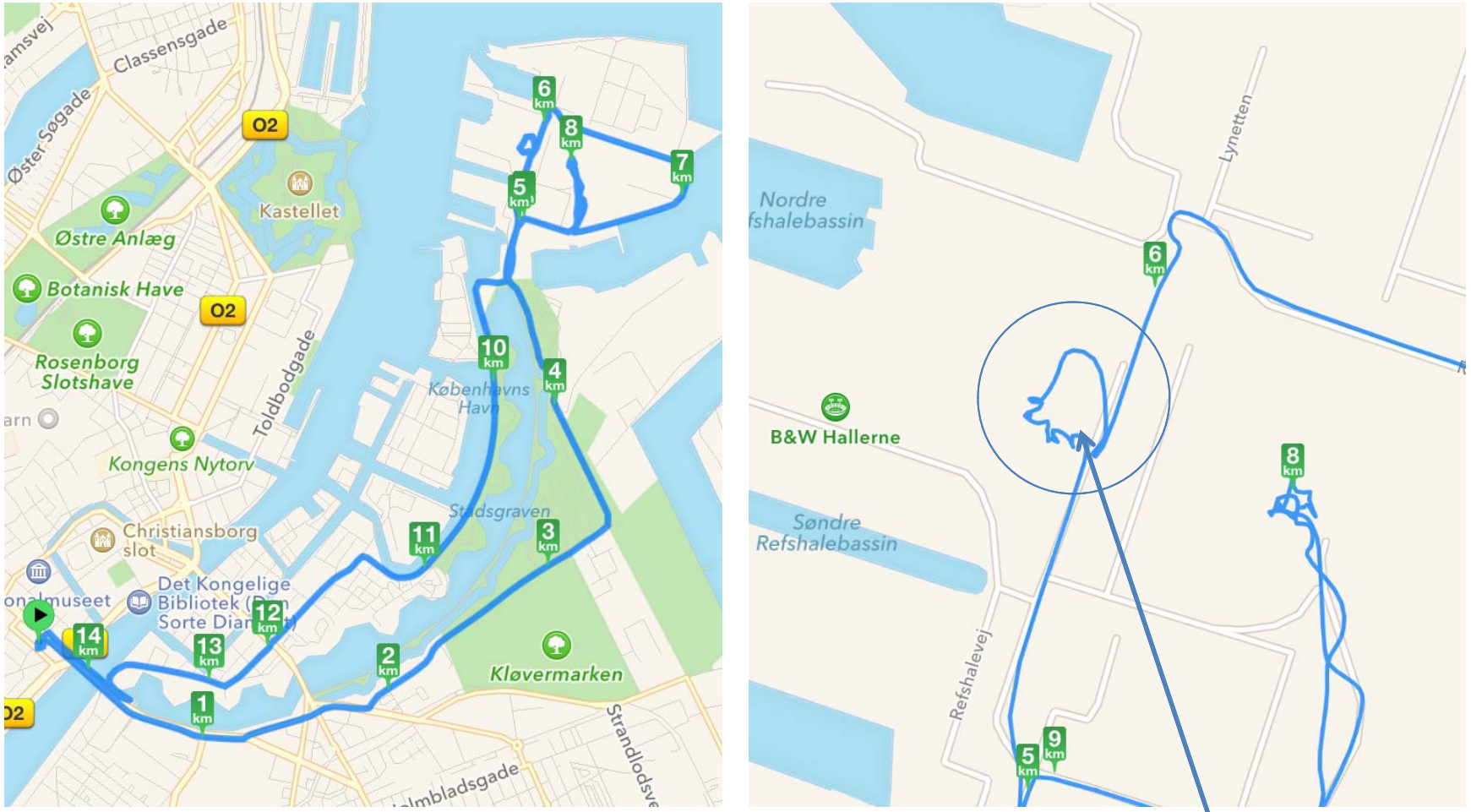
Example: CSS

Heat map of people with mobile devices on CSS (anonymous)

Example: David some Saturday



Example: David some Saturday



Example: how to measure consumer spending

- Economically important:
  - Indicator of health of economy
  - Important for understanding individual responses to policy
  - d.o. to economic shocks
  - Important for consumer prices -> inflation -> adjustments of wages and transfers
  - In developing countries: important for estimates of poverty, inequality

Example: consumer spending

- Traditional methods:
  - Consumer expenditure surveys (DK: forbrugsundersøgelsen)
  - Diary or scanner
  - Errors, selection
- Economists wanted access to individual spending data from Dankort for a long time
  - No luck
- Recently, Statistics Denmark got access to COOP-card data to measure inflation
  - To be made public soon, pretty good fit with existing measures (and much faster)
  - Nice idea, incentive compatible
  - Indep of payment type
  - But selection?

Example: consumer spending

- Attempts in developing economics
  - Use smart phones as scanner or means of payment
  - what can we infer about individuals from smart phone use (dedicated users)
  - Selection into who has smart phones
  - But should be seen against other ways of collecting data

- Qs:
  - How can we use smart phones to infer spending better?
  - What kinds of economically interesting data can we collect via smartphones?

Statistical analysis of Big Data

- Many observations: what does statistical significance mean?
  - And what is practical relevance? Size effects
- Multiple testing problems? If big data generates many variables, why not run through them all to see what is significant?
  - Correct standard errors
- In some cases, ‘eyeball econometrics’ can be difficult
  - Need systematic approach

Statistical/machine learning

- Suppose you have no or very little theory to guide you
- OLS is not only linear, but also presumes some idea of what actually goes in there and how
- Varian's Titanic example: who survived the Titanic
  - Two variables: Class and age
  - Researcher decide / guess vs. data analysis yield most likely (decision tree, but lots more complicated -> Snorre, later)
  - Einav, Levin: Econ should consider machine learning

Statistical analysis of Big Data

- But what if you have theory (or think you have) – e.g.combine econometrics and machine learning
- Goes back to old debate in economics
  - Milton Friedman (1953): judge a model by its predictions, not its assumptions
  - Machine learning made for prediction not for hypothesis testing and theory (in)validation

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Strategic data management and production

- People / firms / governments do not always provide truthful and/or complete data
- Example: No penalty for lying in surveys – but no reason not to either
- **Political reasons** for obscuring or inventing data: Greece in EU, Chinese economy
- Firms: Proprietary info, competition reasons, fooling customers and regulators (VW)

Strategic data management and production

- Individual demand for privacy (We return to this)
  - Could be **instrumental**:
    - lack of privacy decreases consumer surplus by better estimate of reservation price (e.g. Steering: Mac vs PC when ordering online)
    - Concerns about political issues
  - Or an **objective in itself**: Privacy as a political goal

Social desirability bias I

- Key concern in surveys, but more general problem:
  What if people answer so as to conform with general notions of what's desirable?
  - Examples: Won't admit to not voting or having sexually transmitted diseases, exaggerates income
  - Reports buying healthy food vs unhealthy food
  - Important for asking/assessing sensitive questions

Social desirability bias II

- Why?
- Distinguish
  a) self-deception
  b) impression management
- Example: What do you value most in a potential mate?
  - People say: "kind and understanding”
  - From dating data: physical attractiveness, status
  - Bias could be both (a) and (b)