Lecture 1: Introduction

Instructor: Yuta TOYAMA (遠山 祐太)

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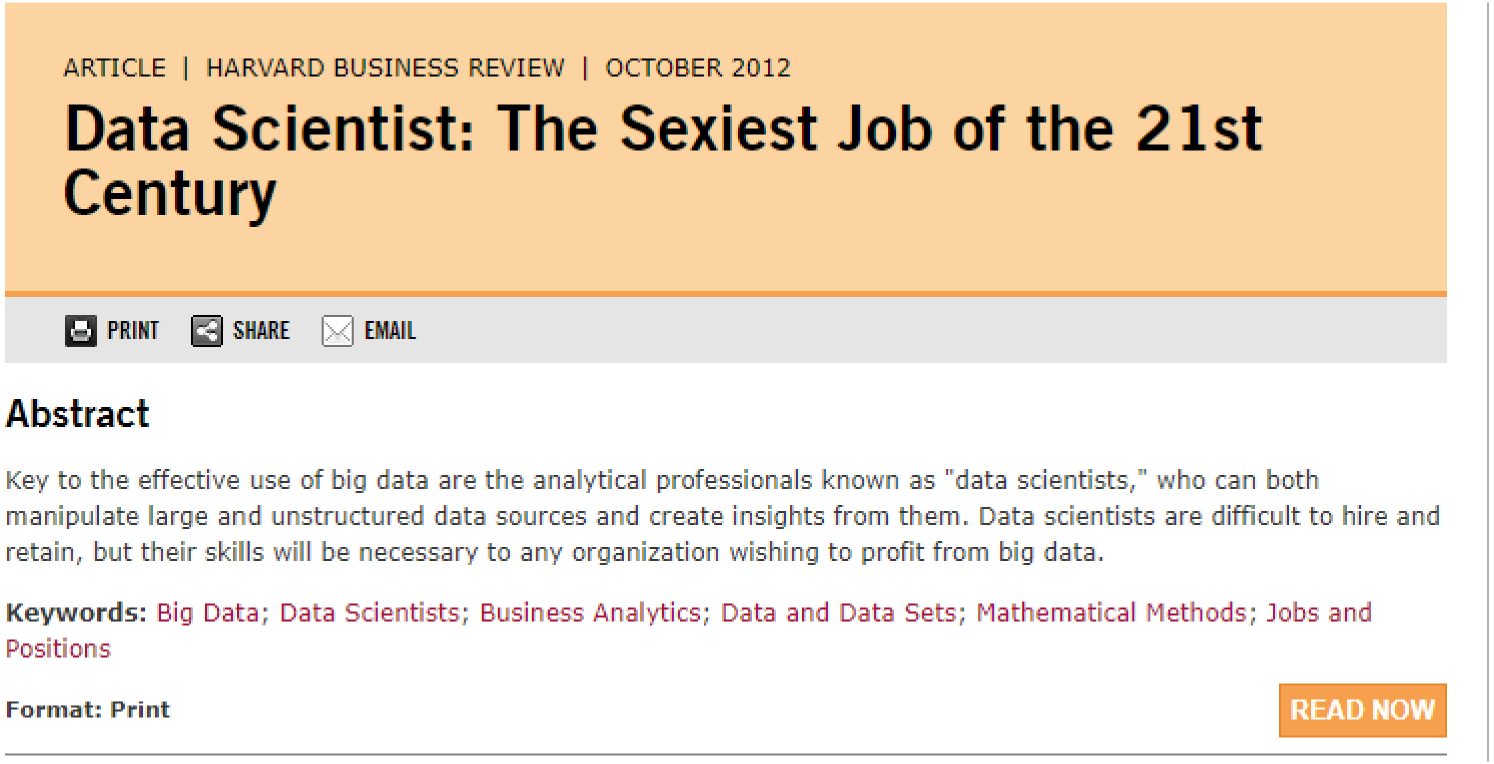
Welcome to the Course!!

About me

- Instructor: Yuta Toyama
- Research Field: Industrial Organization, Applied Econometrics, Energy and Environmental Economics

Data analysis is more important than ever



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Data Scientist: The Sexiest Job of the 21st Century

Abstract

Key to the effective use of big data are the analytical professionals known as "data scientists," who can both manipulate large and unstructured data sources and create insights from them. Data scientists are difficult to hire and retain, but their skills will be necessary to any organization wishing to profit from big data.

Keywords: Big Data; Data Scientists; Business Analytics; Data and Data Sets; Mathematical Methods; Jobs and Positions

Format: Print

Goal of the Course

- We will learn **causal inference (因果推論)** in economics.

- Goal 1: How to establish **causality** in data analysis.
  - Various tools: RCT, regression, IV, DID, RD, structural estimation
  - Implementation using R language.
  - **Students who took this course before won an award at the Data Science Competition and the thesis competition.**

- Goal 2: How to critically examine causal statements in research and journalism.
  - **Is my "causal" claim above really true?**

Contents today

1. What is causality?

2. Case: Data analysis during the Covid-19 crisis

3. Review of Probability: Conditional Expectation

What is Causality?

Causal Questions in Economics and Political Science

- Causality (因果): X causes/affects/impacts Y **holding other things fixed *(ceteris paribus)***

- Many questions are causal!
    - How much does an additional year of schooling increase your wage ?
    - How does online advertisement affect sales of products?
    - Do mergers between firms increase product prices?
    - Does democracy cause economic growth?
    - Does higher turnout benefit Democrats in presidential election?

Theoretical Models Implies Causal Relationship

- Consumers' Utility maximization:
  - Higher income leads to more consumption (all else being fixed)
  - Higher price (typically) implies less consumption (all else being fixed)
- Educational investment leads to higher income due to
  - higher human capital (人的資本)
  - signalling effect (シグナリング)
- Government spending stimulates GDP by multiplier effect (乗数効果)

Data Analysis to Establish Causality

- With data, we want to understand what is going on in reality.
- Ex 1: Test whether theoretical prediction is true.
- Ex 2: Determine the sign of ambiguous theoretical prediction.

Descriptive Analysis (記述統計)

- Describe the data (sample) as a first step.
    - College grads earn 98% more per hour than others
    - Income inequality higher now than 30 years ago
    - Health care costs growing more slowly after the Affordable Care Act (ACA)
    - Airline prices higher now than before merger wave
- Such analysis tells you the **correlation (相関)** between two variables

Does correlation imply causality?

- Example 1: Cities with many police officers have more crimes (positive correlation).
  - Does this really mean “X (police officers) causes Y (crimes)”?

- Example 2: Those who went to college earn more money by 10%.
  - Is this difference only due to college?

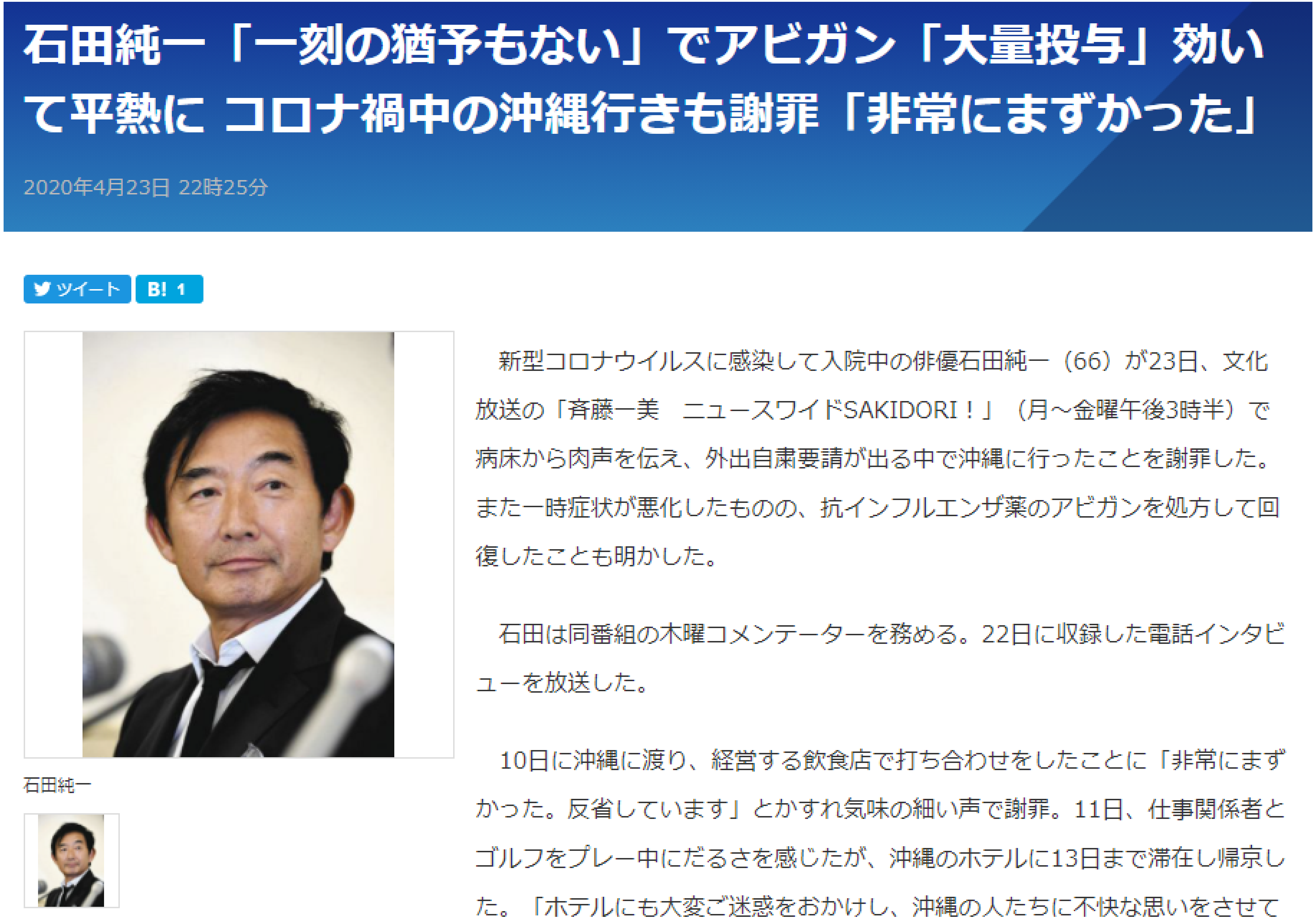
Three possible channels

1. Causality
2. Reverse causality
3. Third factor, or **confounder (交絡因子)**
    - often called **spurious correlation (見せかけの相関)**

Three Channels in Figure

Case: Is Avigan effective treatment for COVID-19?

- Some Japanese celebrities who caught COVID-19 report their own experience that Anti-flu drug Avigan was effective for recovery.
    - An episode from Junichi Ishida
- Does this mean Avigan is a silver bullet for COVID-19?
- Why do we care?
    - Side effects of Avigan, resource allocation of public funds, etc.



石田純一「一刻の猶予もない」でアビガン「大量投与」効いて平熱に コロナ禍中の沖縄行きも謝罪「非常にまずかった」

2020年4月23日 22時25分

石田純一

新型コロナウイルスに感染して入院中の俳優石田純一（66）が23日、文化放送の「斉藤一美　ニュースワイドSAKIDORI！」（月～金曜午後3時半）で病床から肉声を伝え、外出自粛要請が出る中で沖縄に行ったことを謝罪した。また一時症状が悪化したものの、抗インフルエンザ薬のアビガンを処方して回復したことも明かした。

石田は同番組の木曜コメンテーターを務める。22日に収録した電話インタビューを放送した。

10日に沖縄に渡り、経営する飲食店で打ち合わせをしたことに「非常にまずかった。反省しています」とかすれ気味の細い声で謝罪。11日、仕事関係者とゴルフをプレー中にだるさを感じたが、沖縄のホテルに13日まで滞在し帰京した。「ホテルにも大変ご迷惑をおかけし、沖縄の人たちに不快な思いをさせて

Difficulty 1: Counterfactual (反実仮想)

- **Counterfactual outcome** is never observed
- Even without Avigan, a patient might have gotten better.

Difficulty 2: Endogenous selection of treatment

- Suppose we have data on patients who got and did not get Avigan in their treatment.
- Does comparison of those people give you treatment effect of Avigan?
- Issue: Those who get Avigan and who do not get might be quite different in other aspects.

Solution: Clinical Trial

- Collect patients and **randomly** choose patients who are given the treatment.
    - Treatment group and control group.
- Compare the outcome of treatment and control group to see the effectiveness of treatment.
- Since 2020, various institutes have been conducting a clinical trial on Avigan for COVID-19. The results have been not assuring, though.

Case: Data Analysis during the COVID-19 Crisis

Data Analysis during the COVID-19 Crisis

- Perhaps, you might have started to see data analysis in the news more often than ever.
    - # of positive cases each day
    - flow of people (人流) based on mobile phone location (e.g., Agoop, NTT Docomo)
    - Effective reproduction number (実効再生算数)
    - Efficacy of COVID-19 vaccine from clinical trial
- Researchers in many fields have been conducting various analysis to tackle the crisis.
- Some examples in Economics
    - Macroeconomic analysis using SEIR (Susceptible-Exposed-Infectious-Recovered) model
    - Nowcasting (ナウキャスティング) using alternative data (オルタナティブデータ)
    - Evaluation of various policies towards the crisis. -> more on later

Reference: 経済セミナー別冊「新型コロナ危機に経済学で挑む」

Difficulties in Policy Analysis

- 1: **Observational study (観察研究)**:
  - Data is observation of what people actually do.
  - Unlike clinical trial, cannot randomize treatment of policy in general.
- 2: Data limitation
  - May not be able to observe what researchers need.
- With these obstacles, we still need to **draw the conclusion while clearly acknowledging its limitations**.

Case: Special Cash Payment

- Special Cash Payment (特別定額給付金): 100,000 JPY for everyone.
- Question: How much did people actually spend?
- Why we care?
  - Controversial policy (both supporters and)
  - Many countries have done a similar policy.
- Three empirical studies on this issue:
  - Kubota, Onishi, and Toyama (2021): Bank account data
  - Kaneda, Kubota, and Tanaka (2021): Financial app data
  - 宇南山・古村・服部 (2021): Official household survey (「家計調査」)
- I will explain Kubota, Onishi, and Toyama (2021) in detail.

Review of Conditional Expectation

Conditional Expectation (条件付き期待値)

- Overview
  - We are interested in the relationship between two different variables, say X and Y.
  - Conditional expectation is a way to characterize such relationship
  - Quick review of conditional expectation.
- Reference
  - Angrist and Pischke MHE Chapter 2 and 3.
  - 奥井ら

Conditional Distribution (条件付き分布)

- Let Y and X be the random variables (確率変数).
  - Let's say Y is the outcome variable and X is the explanatory variable.

- The probability distribution function (確率分布関数)
  - Discrete (離散):

    $$P(y, x) = Prob(X = x, Y = y)$$

    for $y \in \{y_1, \cdots, y_L\}$ and $x \in \{x_1, \cdots, x_L\}$
  - Continuous (連続): the density function (密度関数) $f(y, x)$ for $x \in \mathbb{R}$ and $y \in \mathbb{R}$.

- The conditional probability mass function for discrete case

$$P(y|x) = \frac{P(y,x)}{P(x)}$$

  where $P(x) = \sum_{i=1}^{N} P(y_i, x)$

- The conditional density function for continuous case $f(y|x) = \frac{f(y,x)}{f(x)}$

Conditional Expectation (条件付き期待値)

- The **conditional expectation** function

$$E[Y|X] = \sum_{l=1}^{L} y_l P(Y = y_l|X)$$

for a discrete case and

$$E[Y|X] = \int_{-\infty}^{\infty} y f(y|X) dy$$

for a continuous case.

Properties of Conditional Expectation Function

- Proposition CE1

  $$E[c(X)|X] = c(X)$$

  for a function $c(\cdot)$.

- Proposition CE2 (linearity)

  $$E[a(X)Y + b(X)|X] = a(X)E[Y|X] + b(X)$$

  for function $a(\cdot)$ and $b(\cdot)$.

- Proposition CE3. If X and Y are independent, then $E[Y|X] = E[Y]$

- Proof of CE3 (for a discrete case):

$$
\begin{aligned}
E[Y|X] &= \sum_{l=1}^{L} y_l P(Y = y_l|X) \\
&= \sum_{l=1}^{L} y_l \frac{P(Y = y_l, X)}{P(X)} = \sum_{l=1}^{L} y_l \frac{P(Y = y_l) \times P(X)}{P(X)} = E[Y].
\end{aligned}
$$

Note that we use $P(Y = y, X = x) = P(X = x)P(Y = y)$ by independence.

Law of iterated expectation (繰り返し期待値の法則)

- Proposition CE4 (**law of iterated expectation**)

$$E[Y] = E[E[Y|X]]$$

- Expectation of conditional expectation $E[Y|X]$ is unconditional expectation $E[Y]$

- Proof for a discrete case

$$
\begin{aligned}
E[Y] &= \sum_{l=1}^{L} y_l P(y_l) \\
&= \sum_{l=1}^{L} y_l \left[\sum_{l'=1}^{L} P(y_l, x_{l'}) \right] \\
&= \sum_{l=1}^{L} y_l \left[\sum_{l'=1}^{L} P(y_l|x_{l'}) P(x_{l'}) \right] \\
&= \sum_{l'=1}^{L} P(x_{l'}) \underbrace{\left[\sum_{l=1}^{L} P(y_l|x_{l'}) y_l \right]}_{E[Y|X]} = E[E[Y|X]]
\end{aligned}
$$

- Note: A similar proof for the continuous case, though it requires some technical conditions for the exchange of integrals (Fubini's theorem).

- Proposition CE4'

$$E[Y|X] = E\left[E[Y|X, Z]|X\right]$$

  - Conditional on X, can apply the law of iterated expectation.

- Proposition CE5: If $E[Y|X] = E[Y]$, then $Cov(X, Y) = 0$.
  - We often say $E[Y|X] = E[Y]$ is **mean independence**
  - Remember: The opposite is not true.

Another useful properties

- Law of iterated probability

$$P(Y) = \sum_{l=1}^{L} P(Y|x_l)P(x_l)$$

  for a discrete random variable X

- Law of total variance

$$Var(Y) = E[V(Y|X)] + V[E(Y|X)]$$