



# Ethics in Data Science

*By Dr. Salimah Mokhtar*



# Learning Objectives:

1. To define ethics
2. To illustrate the importance of ethics in Data Science
3. To examine ethics checklist for data scientist
4. To explain the digital footprint
5. To present concepts related to ethical behavior
6. To discuss matters related to ethics in Data Science.



# What are Ethics?

Webster defines ethics as:

“the discipline dealing with what is good and bad and with moral duty and obligation; a set of moral principles or values; a theory or system of moral values; the principles of conduct governing an individual or a group”

**Ethics** describe a code of behavior (what is right and wrong).

- They are shared universal value / societal rule
- Ethic is not law
- Branch of philosophy that "involves systematizing, defending, and recommending concepts of right and wrong behavior".





# What is Data Ethics?

Data ethics is a **branch of academic ethics** as well as a business-strategy data-driven companies develop to deal with the societal impact of their products and services.

*“Data ethics is a new branch of ethics that studies and evaluates **moral problems** related to data (including generation, recording, curation, processing, dissemination, sharing and use), algorithms (including artificial intelligence, artificial agents, machine learning and robots) and corresponding practices (including responsible innovation, programming, hacking and professional codes), in order to formulate and support morally good solutions (e.g., right conducts or right values)” (Floridi and Taddeo 2016, 1).*

Floridi L, Taddeo M. 2016 What is data ethics? Phil. Trans. R. Soc. A 374: 20160360.  
<http://dx.doi.org/10.1098/rsta.2016.0360>

Data ethics should be addressed at all stages:

- 1. Stewarding data** – collecting it, maintaining it and sharing it.
- 2. Creating information from that data** – in the form of products and services, analysis and insights, or stories and visualisations.
- 3. Deciding what to do** – informed by information from multiple sources along with experience and understanding.

# Ethics and Data Science



Mike Loukides,  
Hilary Mason  
& DJ Patil

Learn how to think through the ethics surrounding privacy, data sharing, and algorithmic decision-making.

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- Who owns data?
- How we value different aspects of privacy?
- How we get informed consent?
- What it means to be fair?

How do we put ethical principles into practice?



# Why Data Science Ethics Matters?

<https://www.youtube.com/watch?v=mA4gypAiRYU&t=159s>



# Why Ethics in Data Science is Important?

## Making decisions about consumer credit

In financial institution - To determine if people qualify for credit – use demographic data → traditional machine learning algorithm.

One of variables was immigration status and immigration class (refugee, family reunification, business, etc).

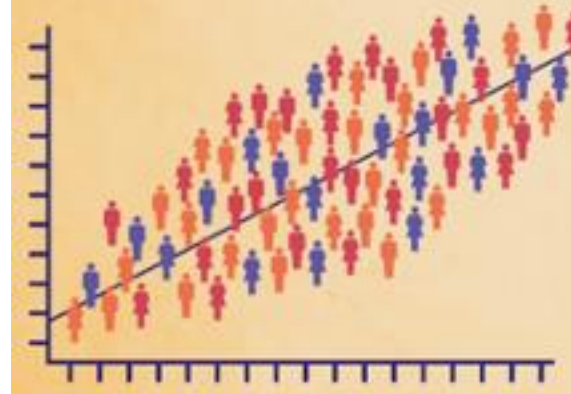
This variable was associated with a negative coefficient.



Based on data of previous generation.

Entirely different set of social and international circumstances.

**Unfairly and mistakenly losing large potential customer base.**



Data used incorrectly can also cause unintended harm.  
This was an unethical decision.

**Instances of high-impact and high-profile data science research that has resulted in flawed or inaccurate findings, as well as ethical and legal quandaries.**

**A few examples are listed here:**

**(1) Inaccurate predictions of flu trends.**

In 2013, Google Flu Trends over-predicted true influenza-related doctors' visits as determined by the Centers for Disease Control and Prevention. This has been primarily attributed to overreliance on outdated models (Butler, 2013).

**Bad Data and Bad Models lead to bad decisions**

**(2) Release of personally identifiable data.**

The abundance of data available on individuals from companies and social media can present ethical dilemmas to researchers in terms of privacy, scalability of results, and subject participation agreement. For instance, a 2013 study linking numerous Twitter users to sensitive information from their financial institutions prompted discussions of when researchers should be required to obtain written consent when using nominally publicly accessible information (Danyllo et al., 2013).

### **(3) Biases in predictive policing.**

There is much debate over the use and appropriateness of predictive policing—the use of data science by law enforcement to predict crime before it occurs. There is no consensus yet on the effectiveness of this methodology, and civil liberties groups argue that the data used to develop (i.e., train) the models are inherently biased (Hvistendahl, 2016).

### **(4) Surveillance of citizens.**

China is deploying facial recognition technologies as well as other data science approaches to track individuals and influence behavior. The national goal is to link these surveillance systems by 2020 to “implement a national ‘social credit’ system that would assign every citizen a rating based on how they behave at work, in public venues, and in their financial dealings” (Chin and Lin, 2017).

# Why develop a data science code of ethics?

**Data for  
Good  
Exchange  
2018**  
Bloomberg

<https://www.youtube.com/watch?v=s8qjmImu1LQ>



# Existing Ethical Code Addressing Data

ACM <http://ethics.acm.org/code-of-ethics/>

IEEE <https://www.ieee.org/about/compliance.html>

ASA <https://www.amstat.org/ASA/Your-Career/Ethical-Guidelines-for-Statistical-Practice.aspx>

Need a **consensus** that ethical standards need to come from within data science itself, as well as from legislators, grassroots movements and other stakeholders.

*"We need to have that ethical understanding, we need to have that training, and we need to have something akin to a Hippocratic Oath."*

Github Senior Machine Learning Data Scientist Omoju Miller

## Should Data Scientists Adhere to a Hippocratic Oath?

As concerns mount over the uses of data, some in the field are trying to forge ethical guidelines.

<https://www.wired.com/story/should-data-scientists-adhere-to-a-hippocratic-oath/>

# Of oaths and checklists

Oaths have their value, but checklists will help put principles into practice.

By Mike Loukides, Hilary Mason, and DJ Patil. July 17, 2018

## An ethics checklist for data scientists

**deon** is a command line tool that allows you to easily add an ethics checklist to your data science projects. We support creating a new, standalone checklist file or appending a checklist to an existing analysis in [many common formats](#).

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**δέον** • (déon) [n.] (*Ancient Greek*) wikitionary

Duty; that which is binding, needful, right, proper.

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*Deon adds an ethics checklist to your data science projects.*

<https://deon.drivendata.org/>

## A. Data Collection

- ☐ **A.1 Informed consent:** If there are human subjects, have they given informed consent, where subjects affirmatively opt-in and have a clear understanding of the data uses to which they consent?
- ☐ **A.2 Collection bias:** Have we considered sources of bias that could be introduced during data collection and survey design and taken steps to mitigate those?
- ☐ **A.3 Limit PII exposure:** Have we considered ways to minimize exposure of personally identifiable information (PII) for example through anonymization or not collecting information that isn't relevant for analysis?
- ☐ **A.4 Downstream bias mitigation:** Have we considered ways to enable testing downstream results for biased outcomes (e.g., collecting data on protected group status like race or gender)?

## B. Data Storage

- ☐ **B.1 Data security:** Do we have a plan to protect and secure data (e.g., encryption at rest and in transit, access controls on internal users and third parties, access logs, and up-to-date software)?
- ☐ **B.2 Right to be forgotten:** Do we have a mechanism through which an individual can request their personal information be removed?
- ☐ **B.3 Data retention plan:** Is there a schedule or plan to delete the data after it is no longer needed?

## C. Analysis

- ☐ **C.1 Missing perspectives:** Have we sought to address blindspots in the analysis through engagement with relevant stakeholders (e.g., checking assumptions and discussing implications with affected communities and subject matter experts)?
- ☐ **C.2 Dataset bias:** Have we examined the data for possible sources of bias and taken steps to mitigate or address these biases (e.g., stereotype perpetuation, confirmation bias, imbalanced classes, or omitted confounding variables)?
- ☐ **C.3 Honest representation:** Are our visualizations, summary statistics, and reports designed to honestly represent the underlying data?
- ☐ **C.4 Privacy in analysis:** Have we ensured that data with PII are not used or displayed unless necessary for the analysis?
- ☐ **C.5 Auditability:** Is the process of generating the analysis well documented and reproducible if we discover issues in the future?



## D. Modeling

- ☐ **D.1 Proxy discrimination:** Have we ensured that the model does not rely on variables or proxies for variables that are unfairly discriminatory?
- ☐ **D.2 Fairness across groups:** Have we tested model results for fairness with respect to different affected groups (e.g., tested for disparate error rates)?
- ☐ **D.3 Metric selection:** Have we considered the effects of optimizing for our defined metrics and considered additional metrics?
- ☐ **D.4 Explainability:** Can we explain in understandable terms a decision the model made in cases where a justification is needed?
- ☐ **D.5 Communicate bias:** Have we communicated the shortcomings, limitations, and biases of the model to relevant stakeholders in ways that can be generally understood?

## E. Deployment

- ☐ **E.1 Redress:** Have we discussed with our organization a plan for response if users are harmed by the results (e.g., how does the data science team evaluate these cases and update analysis and models to prevent future harm)?
- ☐ **E.2 Roll back:** Is there a way to turn off or roll back the model in production if necessary?
- ☐ **E.3 Concept drift:** Do we test and monitor for concept drift to ensure the model remains fair over time?
- ☐ **E.4 Unintended use:** Have we taken steps to identify and prevent unintended uses and abuse of the model and do we have a plan to monitor these once the model is deployed?



- Perhaps no area of ethics in data science has received more attention today than the **protection of personal data**.
- The digital transformation of our interactions with social and economics communities defined us by **what we search for on the internet, what we eat, where we travel to, where we hold membership accounts, etc.**
- Organizations and individuals can leverage this data to uncover powerful findings.

# Digital Footprint

**Digital footprint** or **digital shadow** or **digital dossier** refers to one's unique set of traceable digital activities, actions, contributions and communications manifested on the Internet or on digital devices. (Wikipedia)





# Examples of Digital Footprints

- Your search history.
- Text messages, including deleted messages.
- Photos and videos, including deleted ones.
- Tagged photos, even those you never wanted online.
- Likes/loves on sites like Facebook and Instagram.
- Browsing history, even when you are on 'Incognito' mode.



# The Explicit and Implicit Digital You



Your **explicit footprint** is easier to get a hold of. It relates to data you can find, and in some cases, you can control. Explicit footprint data typically relates to profile pages, likes, comments, purchase histories etc.

A simple test to check your explicit footprint is to search for your name in a search engine. The higher up the page is the more explicit your footprint on the given page or application is.

Your **implicit footprint** relates to data points that you are not fully aware of. This includes data coming from almost any digital application or device you are engaging with. Examples range from tracking technology (e.g., online tracking or mobile location tracking) and engagement data for content filter algorithms (e.g., using page views to understand what topics you are interested in) to engagement data for advertisement and purchase data for item recommendations (e.g., Amazon's Product recommendation).

- \* A digital footprint can affect...
- \* Job applications
- \* School admission
- \* What people think about you



Be careful about

- \* What you put online
- \* The websites you join
- \* Forms you fill out
- \* Who you give information to
- \* Photos you post

To reduce digital footprint



DuckDuckGo

The search  
engine that  
**doesn't track  
you**

DDG is an internet [search engine](#) that emphasizes protecting searchers' [privacy](#) and avoiding the [filter bubble](#) of [personalized search](#) results.

# Managing Own Digital Footprints

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How do I permanently delete my digital footprint?

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How do I delete all traces of me on the Internet?

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Do digital footprints ever go away?

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How do I wipe myself off the Internet?

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Is digital footprint permanent?

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<https://myfuture.edu.au/career-articles/details/5-ways-to-clean-up-your-digital-footprint>

<https://www.cmu.edu/iso/aware/protect-your-privacy/digital-footprint.html>

# Ethics Matters

Data Science has great power---to **harm** and to **help**.

Data Scientists must care about how this power is used!

- Cannot hide behind a claim of “neutral technology”.

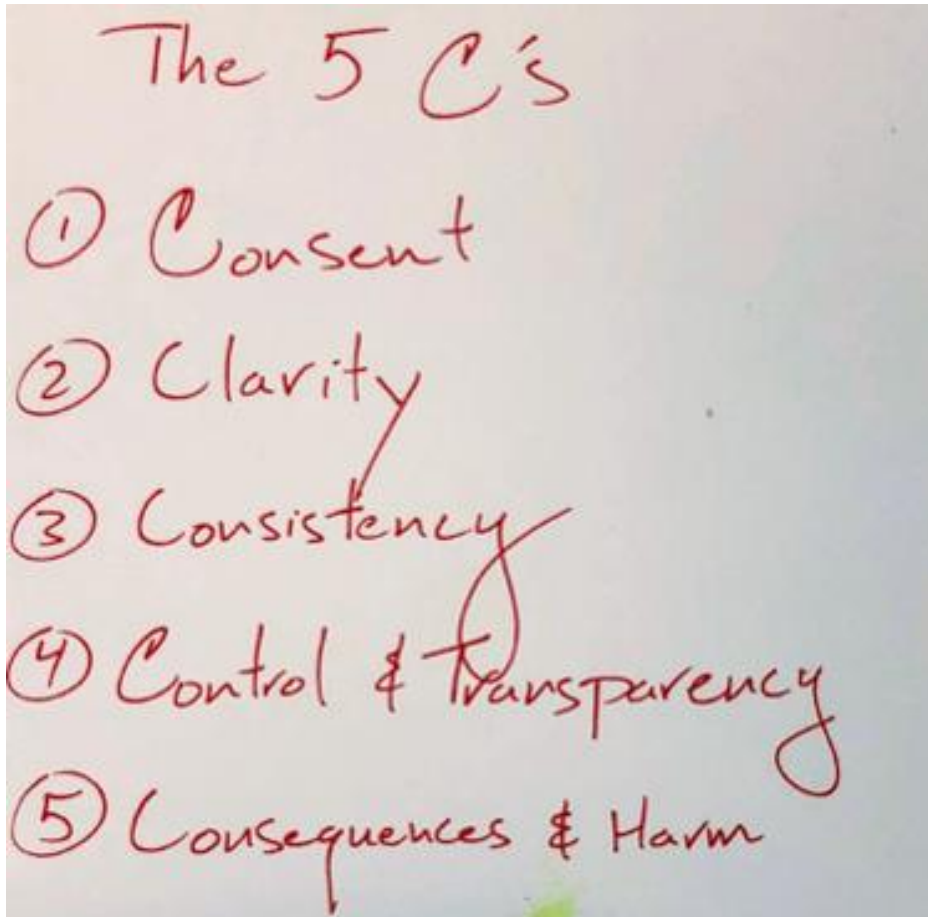
We are all better off if we voluntarily limit how this power is used.

**Ethical Analysis Is Difficult** - In a complex world, with many actors, it is often not easy to see where the problem lies and how to define limits to the use of Data Science.





# Five (5) Framing Guidelines - About Building Data Products



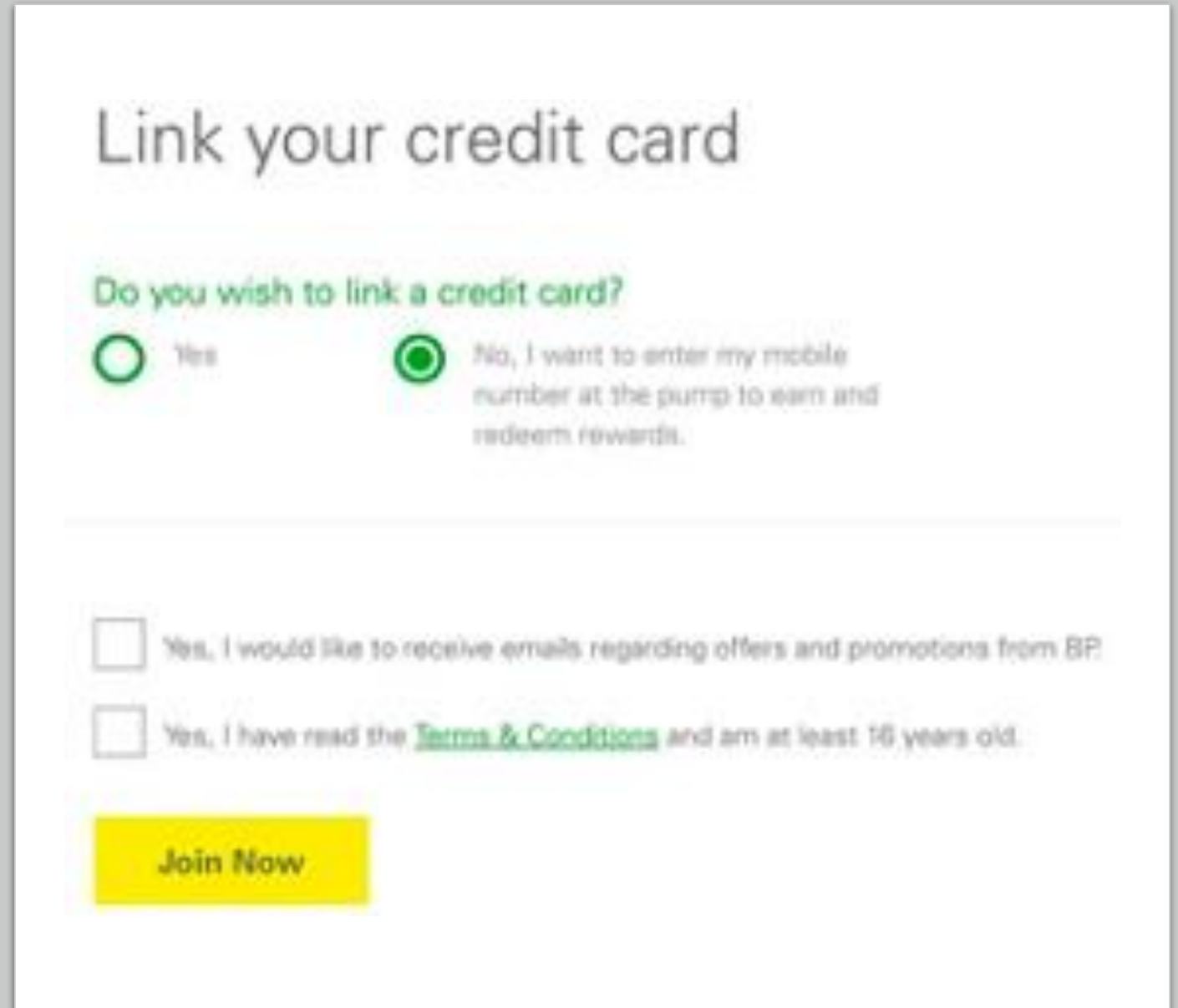
1. Agreement starts with obtaining **consent** to collect and use data.
2. Users must have **clarity** about what data they are providing, what is going to be done with the data, and any downstream consequences of how their data is used.
3. Trust requires **consistency** over time. Restoring trust requires a prolonged period of consistent behavior.
4. Once you have given your data to a service, you must be able to understand what is happening to your data.
5. Essential to ask whether the data that is being collected could cause harm to an individual or a group.

<https://www.oreilly.com/radar/the-five-cs/>

# Informed Consent

Data / Human subjects must be

- Informed about the experiment / intended use & purpose of data collected.
- Consent to the experiment / use of data.
  - Voluntarily
- Must have the right to withdraw consent at any time.



The screenshot shows a mobile app registration screen with the title "Link your credit card". Below the title is a question: "Do you wish to link a credit card?". There are two radio button options: "Yes" (which is unselected) and "No, I want to enter my mobile number at the pump to earn and redeem rewards." (which is selected). Below this, there are two checkboxes: "Yes, I would like to receive emails regarding offers and promotions from BP?" (unselected) and "Yes, I have read the [Terms & Conditions](#) and am at least 16 years old." (unselected). At the bottom of the form is a yellow button labeled "Join Now".

# Data Ownership

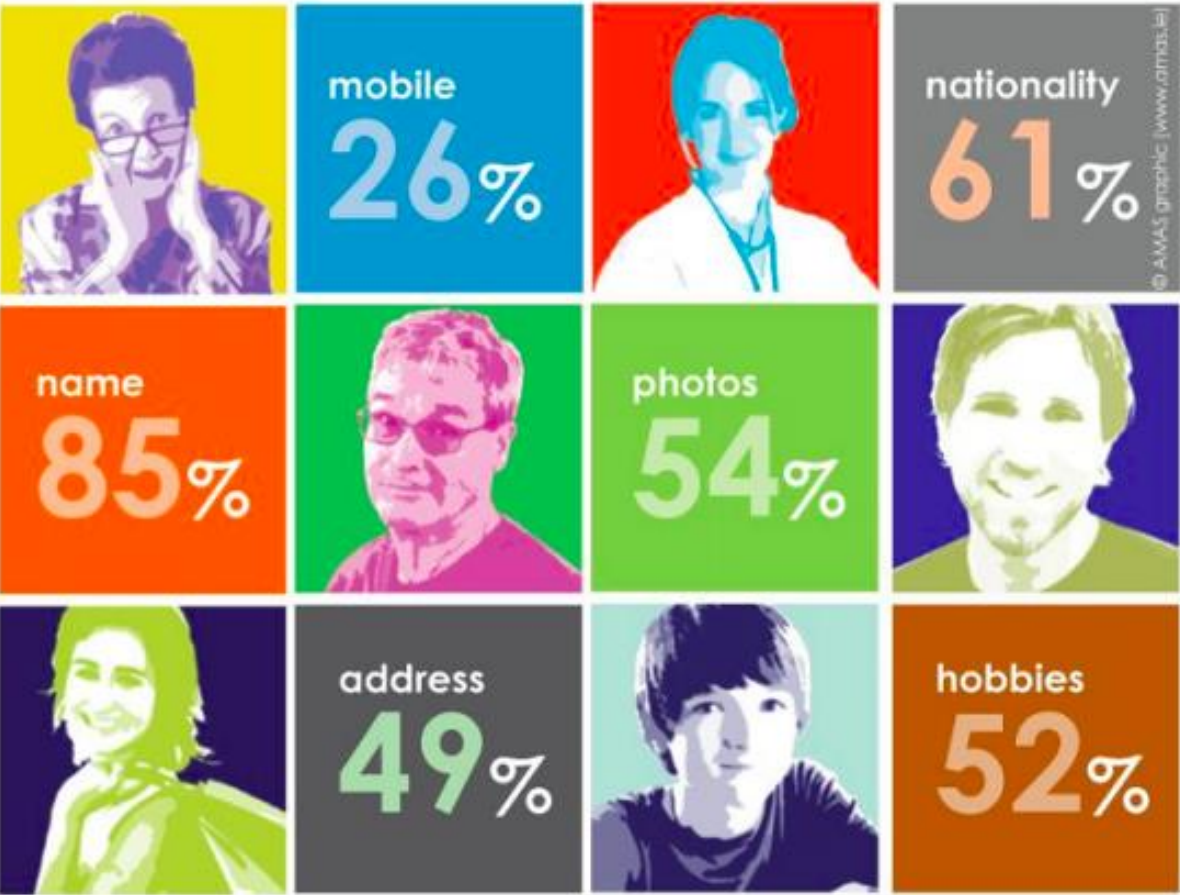
- Most of the time you don't own the data about you. The data belongs to the company who collected it.
- Nevertheless, we might have some control over these data that aren't ours because they are about us.
- We need to create the principle to reason about this control and that's the main concern of a discussion about the right to privacy.
- If the company goes bankrupt, the company buying it should keep the same privacy.

# Privacy

- **Privacy** is a basic human need.
- Even for people who have nothing to hide!
- Privacy is the first concern that comes to so many minds when we talk about Big Data.
- How do we get the value we would like by collecting, linking, and analyzing data, while at the same time avoiding the harms that can occur due to data about us being collected, linked, analyzed, and propagated?
- In the past, one could get a fresh start by:
  - moving to a new place
  - waiting till the past fades (reputation can rebuild over time)
- Big Data is universal and never forgets.
- Data Science results in major asymmetries in knowledge.



What we share on social media



<https://www.intechopen.com/chapters/70973>

# Collection vs Use

- Privacy is usually harmed only upon use of data.
- Collection is a necessary first step before use
- Existence of collection can quickly lead to use
- But collection without use may sometimes be right
- e.g., surveillance
  - By the time you know what you need, it is too late to go back and get it.

# Loss of Privacy

Due to loss of control over personal data.

*I am ok with you having certain data about me that I have chosen to share with you or that is public, but I really do not want you to share my data in ways that I do not approve.*

## **Do not Underestimate Analysis!**

A smart meter at your house can recognize “signatures” of water use every time you flush the toilet, take a shower, or wash clothes.

# “Waste” Data Collection

Your ID is taken at the club (Name, address, age)

- How this data is being used ? Is it stored ?

## Meta Data

E.g phone call, metadata includes

- Caller
- Callee
- Time of Date of Call
- Duration & Location

# Anonymity

Anonymity has, and always will be, at the heart of the Internet.

When we talk about anonymity online, we refer to the fact that messages posted anonymously cannot be linked back to the offline identity of the sender.

A key identifier that follows us as we navigate online is our **IP address**.

Only a few platforms, such as [Tor](#), cannot be tracked.

As the famous 1993 New Yorker cartoon illustrates:

- ✓ You can say whoever you are
- ✓ You can say whatever you are
- ✓ You can make up a persona





## **ID for Transactions**

- **Anonymity** is quite impossible!
- You must provide an address to receive goods.
- You must give your name for travel booking.
- You must reveal your location to get cellular service.
- You must disclose intimate details of your health care and lifestyle to get effective medical care.
- Anonymity is virtually impossible, with enough other data.
- Face can be recognised in image data.

# Wayback Machine

The Wayback Machine is a digital archive of the World Wide Web and other information on the Internet. It was launched in 2001 by the Internet Archive, a nonprofit organization based in San Francisco.

Archives pages on the web (<https://archive.org/web/> - 300 billion pages saved over time)

- ✓ almost everything that is accessible
- ✓ should be retain forever.

If you have an unflattering page written about you, it will survive forever in the archive (even if the original is removed).

# Anonymizing Datasets

A lot of the data we collect today can easily be linked to an individual, household or entity.

However, using data without taking care to protect the identity of the data owner can lead to lots of problems and potential lawsuits.

**Data anonymization** easily put, is ensuring that we can't tell the actual data owner by looking at the data.



## Data Anonymization Techniques

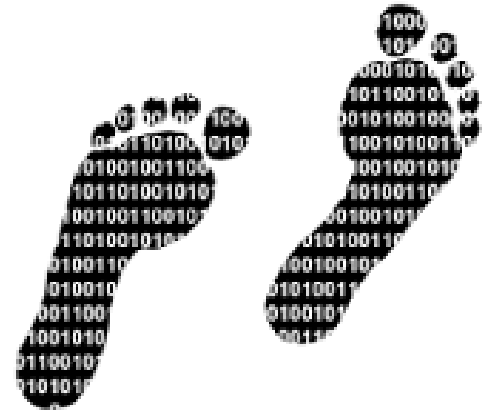
Data masking—hiding data with altered values. You can create a **mirror version of a database** and apply modification techniques such as character shuffling, encryption, and word or character substitution.

For example, you can replace a value character with a symbol such as “\*” or “x”.

# Right to be Forgotten

Laws are often written to clear a person's record after some years.

What you leave behind when you are online / use apps?



Viktor Mayer Schönberger on  
*The Right to be Forgotten*

The right to silence on past events in life that are no longer occurring. The right to be forgotten leads to allowing individuals to have information, videos, or photographs about themselves deleted from certain internet records so that they cannot be found by search engines.

<https://www.youtube.com/watch?v=9Xpk26bJ7FU>



A pair of black-rimmed glasses with round lenses is resting on an open notebook. The notebook has a red ribbon bookmark. The background is blurred, showing a wooden surface and some papers.

# Main Reference

- <https://www.slideshare.net/HJvanVeen/ethics-in-data-science-and-machine-learning>

# Soft Skills

## From Course Overview



### ✓ Certification

- Data Science Ethics – edX
- Data Science Ethics – Coursera, online.umich.edu

### ✓ Data Science ethics pledge (your personal commitment statement on this matter)



Catalog > Computer Science Courses

### Data Science Ethics

Learn how to think through the ethics surrounding privacy, data sharing, and algorithmic decision-making.

 UNIVERSITY OF MICHIGAN

13,878 already enrolled!

[View Course](#)





### Data Science Ethics

★★★★★ 4.8 610 ratings



H.V. Jagadish



# The ethics of collecting data (10:17 mins)

[https://www.ted.com/talks/marie\\_wallace\\_the\\_ethics\\_of\\_collecting\\_data](https://www.ted.com/talks/marie_wallace_the_ethics_of_collecting_data)



A high-speed photograph of a water droplet hitting a surface, creating a crown-shaped splash. The water is clear and the background is a soft, out-of-focus blue and purple gradient. The splash is centered in the frame, with several thin, pointed droplets rising from the rim.

**Thank You for Your Attention**