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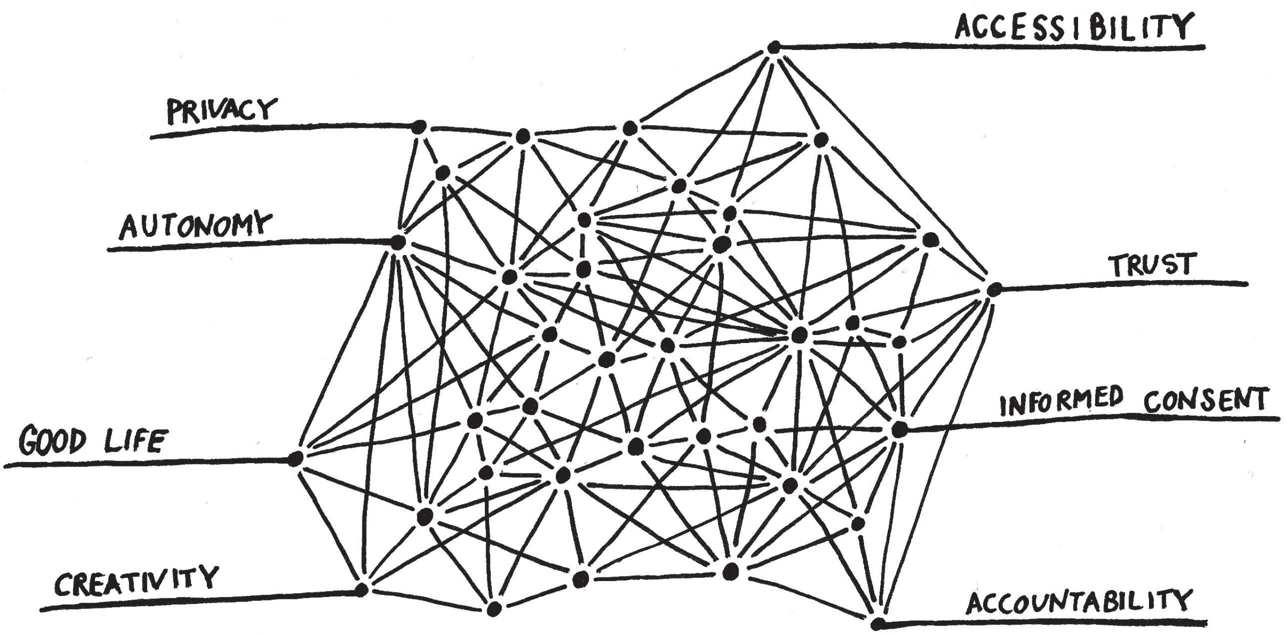

Handbook

Assessing ***ethical issues*** with regard to governmental ***data projects***

Disclaimer

The ‘Data Ethics Decision Aid’ is developed by the Utrecht Data School and Utrecht University on behalf of the Municipality of Utrecht.

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www.dataschool.nl/en/deda

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Utrecht, 2022.

As DEDA is used, we learn to improve it. These improvements will be implemented in future versions. If you are using DEDA and have any comments, please do not hesitate to share them with us. You can always mail to:

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Introduction

Why DEDA?

Big data, algorithms and new analytical methods promise great benefits for management and governance in the public sector, from facilitating smart cities to increasing economic prosperity. However, these opportunities also bring difficulties along with them. These difficulties are easy to ignore, but in the long run they can cause good intentions to lead to bad results. For example, there may be a liability case when something goes wrong - which can lead to a lawsuit - or a project may violate the guidelines of good governance. Companies and governments are increasingly under fire for the way they handle their use of data. In response, a number of laws and regulations have already been amended. Weighted fines for the invasion of privacy are an example of the EU's attempts to enforce a responsible use of personal information. Asides from privacy, there are a number of other problems that can arise from data projects. For example, data sets can have a questionable origin, or are taken out of context. There may also be a bias in the data sets, models and algorithms. In addition, there are sometimes questions about (possible) conflicts of interest between commercial companies and public institutions. There can also be a lack of critical evaluation of the social impact of data-driven policies. Such gray areas are often characterized by common values and social responsibility. Guidelines for ethical decision-making within a data project can help to make responsible decisions about the further course of the project.

The Data Ethics Decision Aid (DEDA) is a tool that helps to identify ethical issues and to develop a sense for value conflicts within a data project. DEDA can also help to create insight in the (public) values that are affected, or to document the ethical decision making process. DEDA is developed in close cooperation with data analysts of the municipality of Utrecht. DEDA helps to ensure a responsible handling of data, models, algorithms and more.

Purpose

The DEDA manual can be used together with the DEDA poster. The manual aims to provide further explanations about certain concepts and to go deeper into some of the questions. For some questions, examples are also given.

Use of the Handbook

1 You can use this Handbook as a support for the DEDA poster. The DEDA poster shows colored question clusters. The questions are structured in a manner so that they successively address data-related considerations (blue) and general considerations (green). For each cluster of questions, you will find explanations in the Handbook. You can use post-its to write down the answers to the questions, note down action points and collect responses to the poster.

2 In the section with data-related questions, you can skip any questions that are not (yet) relevant for the current project phase. However, we recommend that you revisit these questions as the project progresses.
The general considerations focus on questions surrounding responsibility, communication, transparency, privacy and bias.

Note: If you are unable to answer a question because you need additional details, we recommend you turn this into an action point as a way of answering the question. You can also write down specific points of interest for that question.

3 The last section of the DEDA poster requires extra attention to values. Based on the values that are important within your organization and for the project members, you can make decisions on the focus areas of the project and the possible obstacles that must be overcome. For this purpose, the conclusion offers some concluding questions.

DEDA globally maps everything surrounding your data project. When the conclusion from DEDA is that personal data is processed, which is also data with a high privacy risk for the persons concerned, then a DPIA (Data Protection Impact Assessment) must be completed. Filling in the DPIA is an obligation since 25 May 2018 on the basis of the GDPR (General Data Protection Regulation). The GDPR applies throughout Europe and has a direct effect in all Member States. More information on the DPIA can be found at the DEDA questions surrounding Privacy (p. 23).

Questions

DATA-RELATED CONSIDERATIONS

ALGORITHMS

Explanation

Algorithms can process data and develop insights based on that data. By using models, they can decide on which data will be given more importance. Some examples include: an algorithm that determines how many parking spaces are left in which garage; or an algorithm that estimates who does or does not qualify for social benefits. Algorithms make use of mathematical models. However, these models are rarely value-free. The values in models are expressed numerically and in calculations, giving an impression of neutrality.

However, algorithms are often constructed in such a way that a normative judgment is attached to a numerical value, such as “risk of fraud” or “unusual event”.

As an example, consider a neighborhood with smart lampposts that are equipped with sound sensors. If the sensors pick up a sound above 130 decibels, a warning signal is sent to the neighborhood policeman. The alert signal indicates the location of the lamppost and indicates that he may have to pass by it because, based on the noise, there may be an “unusual situation” taking place. Noise above 130 decibels may indeed be an unusual situation, such as a shooting, but can also represent everyday sounds such as a clapped balloon or renovation work.

Algorithms will increasingly inform decision-making. Therefore, it is important to understand how the output of algorithms comes about. Algorithms must be transparent, which means that they must be accessible for review by external experts and for verifications of the found results. Governments should be able to explain how the models and algorithms that they use work.

Models and algorithms are also subjects of accountability and good governance. Increasingly, government agencies are being asked to justify their models and algorithms. It may be unclear who the owner of an algorithm is. In addition, models and algorithms are sometimes not made public, which may make transparent communication about them difficult or impossible.

Explanation of false positives and false negatives

A false positive is a result that indicates a certain condition, while in reality this is not the case. This is the case, for example, when convicting an innocent person, or when reading a positive test result in case of illness or pregnancy while the person is not actually ill or pregnant.

A false negative is a result that incorrectly indicates that a certain condition is not the case. This is the case, for example, when acquitting a guilty person, or when reading a negative test result for illness or pregnancy while the person is indeed carrying the illness or is pregnant.

SOURCE

Explanation

It is important to consider where the data you want to use comes from. When datasets are bought, or the collection of data is outsourced, it is sometimes difficult to understand the context in which the data was initially collected.

Sometimes there is a “the more, the better” mentality when collecting data. This can be problematic when certain data is not relevant to the context of the project. It is important to properly reflect on this. A larger data set does not always lead to a better quality of research.

In addition, the shelf life of data is important. The GDPR contains regulations about the shelf life of data, but it is also necessary to become aware of the limited shelf life of some datasets. Ethical reflections on the origin of the dataset should for this reason begin with a reflection on what kind of data is actually needed for the project and how long this data will remain relevant.

ANONYMIZATION

Explanation

Anonymization is making personal data untraceable in the data set. This process is irreversible.

A possible technique that can be used here is **generalization**; for example, by reducing all personal identification data to age groups.

An example of anonymization is to change social security numbers within a data set to any other number, after which the original social security numbers are removed. Of course, it is important that the new random number is not linked to traceable personal data such as first name and surname.

Pseudonymization involves making a data set irreducible in a similar way, with the difference that the process can still be reversed. When we return to our previous example, in the case of pseudonymization the social security number is not completely removed. In that case, at least one person is necessary to reverse the pseudonymization. That person must have the key to reverse the process. When this happens, the random number will for example be replaced again by the original social security number, possibly even with personal data such as first name and surname.

VISUALIZATION

Explanation

Some projects require the visualization of data or the results of the data projects. This can be done in many different ways.

The main purpose of this question is to reflect on the way in which the data or the results are portrayed. Is this the best way, what are the reasons for choosing a (less) obvious way? Can a visualization be misinterpreted? What visualization style and techniques are used and do these express prejudices or bias? For example, the scale of a graph can influence the message conveyed, as can the chosen colors. Keep in mind that the same dataset visualized in different ways can also lead to different ‘readings’ of the data. In addition, it is important to note that not all results of a data project are suitable for visualization.

ACCESS

Explanation

Access can mean many different things, depending on the context. Here we are referring to the access to collected and archived data sets within your organization. Access is a relevant topic, because not every data set should be freely accessible. Some data sets contain confidential information and/or personal data. Thus, the confidentiality of this information must be ensured.

A second aspect that can be taken into account with this question is that commercial, third parties might be interested in the data or data sets. Access by third parties may raise ethical challenges that need to be carefully considered.

OPEN ACCESS AND THE REUSE OF DATA

Explanation

Sometimes data sets can not only be beneficial for one project, but can also be reused for other projects. However, it is quite possible that data collected for a specific project, loses validity for another project if it is reused.

Making data accessible within a company or municipality, or making data accessible to everyone (open access), involves various considerations. On the one hand, open access can increase transparency and trust, but on the other hand, trust can be damaged if the data turns out to be unsuitable to be shared with everyone.

In answering the questions on this topic, it may help to weigh up the advantages and disadvantages of reusing data.

GENERAL CONSIDERATIONS

RESPONSIBILITY

Explanation

Responsibility generally corresponds with the guidelines of your specific discipline, your organization and the rules that apply to your specific position. For civil servants in the Netherlands, this is the Gedragscode Ambtenaren. Basic values from this code of conduct inform responsible work with data:

- Good governance
- Confidential use of information (e.g. protecting data)
- Responsible use of public resources and infrastructures
- Conflict of interests

The general principle is to exercise fair and accountable governance, and keeping the interests of citizens in mind. Data projects often have an impact on the lives of citizens. Keep in mind that political parties, citizens, lawyers or activists can use their rights to inquire about your data projects.

COMMUNICATION

Explanation

It often happens that communication is only considered after things go wrong. In order to convey previous decisions about the project, it is important to think about how these decisions can be communicated. Perhaps an attending data scientist can explain certain technical decisions, but will they also inform the press? And what does the project manager want to communicate about the project? It is necessary to not only communicate unambiguously within the organization, but also to the outside world. This helps to express responsibility for the project and can help to create trust among parties who are not directly involved in the project, but who will be affected by it. Thinking about these questions can help when external experts have critical questions about the project.

TRANSPARENCY

Explanation

Governmental organizations are being held accountable by citizens, media and political parties. Because data projects can have an impact on public space, social interactions, personal livelihood and even civil rights, transparency is an important theme for those projects.

Transparency within data projects means that one is able to understand the data set and its origin, and can provide an explanation on the used data and its origin. It is also important that someone can explain the algorithms and models used to convert the data into usable information.

Transparency can also involve thinking about the necessary information you can, may or must provide to citizens and experts, so that they can make considerations regarding their own data or the project in question.

It is not always easy to be transparent. For example, models and algorithms can be very complex. Often, a high degree of knowledge, statistics and data science is required to understand these. In situations like this, transparency does not always mean that models and algorithms have to be translated into understandable language, but rather that they must be accessible for critical questioning.

Finally, within data projects, it is also possible to be too transparent, for example with regard to the data set. If this happens, a data breach may unintentionally occur, and too much information may be provided to people with bad intentions.

PRIVACY

Explanation

Everyone's privacy is protected by law (GDPR). By this law, the violation of privacy or leaks of personal information are punishable by high fines. Even if there is a general idea that people are careless with their right to privacy by being online on social media, or by being very open about intimate details about their personal life, this does not mean that the right to privacy loses its urgency. Privacy remains essential for democracy. After all, it is up to people themselves to decide what information they share.

About the Data Protection Impact Assessment (DPIA)

- *The DPIA is a tool to map out privacy risks in advance. Subsequently, measures can be taken to reduce these risks.*

- *Completion of the DPIA is not always mandatory. The DPIA is mandatory under the GDPR if there is a high privacy risk for the individuals whose data is being processed.*

- *Not every data project is a processing of personal data. Data from DEDA can be helpful in completing a (D)PIA.*

BIAS

Explanation

Bias is a major problem in data analytics. A biased data set, model or algorithm produces results that deviate from the reality it is trying to describe. In interpreting data sets, existing biases can be included in the data collection, analysis, storage, or in the choices based on the data.

If these prejudices are not recognized and prevented or resolved, discrimination can occur. This happens, for example, if certain population groups are over-represented in the data when compared to reality, or if, for example, an algorithm (unconsciously) learns an automatic preference for men while this is not relevant to the purpose.

Asides concrete signs of discrimination, it is also possible to have a gut feeling about your project. Gut feelings can be very useful in detecting possible bias, by recognizing early on that “something” in the project is not quite right. It is important to listen to these feelings and to investigate them. If these feelings are indeed based on an error in the data or in the project, valuable solutions can emerge early on and potential suffering can be prevented.

On this page you will find some examples of bias. Keep in mind that these are just a few examples of many. The list is therefore not exhaustive.

Types of bias

Confirmation bias
We all like to be surrounded by opinions and ideas that are similar to ours. This is why many people have friends with similar views and preferences as themselves. Confirmation bias is often reinforced by cognitive dissonance. Cognitive dissonance (described by psychologist B.F. Skinner) causes people to tend to ignore opinions that are not in line with one’s own point of view, even though these divergent opinions may be important and valid. This tendency can cause problems in the use of data, because important external views, or differing interpretations or concerns, are missed or not heard.

Ingroup biases
In line with the aforementioned bias is the tendency for people to agree with the dominant opinion in a group. If someone has a different opinion, for example by having a bad gut feeling or a viewpoint that differs from that of the group, they will not communicate this and tend to be quiet. They might be scared of getting it wrong or to say something stupid, for example. This kind of bias is very problematic in ethical considerations regarding data, as important insights from group members may go unmentioned, while they could prevent negative outcomes.

Selection bias
The results of your data collection, visualization, or interpretation may be affected, or even misleading, because of the information you collected in the first place. Certain groups of people may be missing, or may be disproportionately represented. What is presented as objective knowledge, may be influenced by the type of data used. Random sampling, control groups (when possible), and discussions with your team can minimize the risk of biased selection.

The cobra effect
The cobra effect occurs when the solution to the problem makes the problem bigger. The name comes from an anecdote from India during the time of the British colonization. The British government offered a bounty for every captured cobra. When people started to breed cobras to claim the bounty, the program was discontinued. The bred cobras, now worthless, were released into the wild. Thus, the apparent solution to the problem actually made the problem worse.

The feedback loop
A feedback loop ensures that in data projects the result of the project will in one way or the other be used in the project again and will be used as new data. This can be done intentionally, but when it happens unintentionally, it can have negative consequences.

FUTURE SCENARIOS

Explanation

Although some data projects are only relevant or in use for a short time, it is common for projects to have medium- to long-term effects. It is therefore important to think about these long-term effects now, and whether these would change the current state of affairs. It is then also necessary to have regular evaluations, to ensure that the data project still does what it is intended to do and does not have any (unintended) negative effects.

Explanation of function creep

Function creep means that information is used for a purpose that is not the original assigned purpose. For example: a security system is installed in the office, requiring employees to check in and out for the purpose of facilitating secure access. However, if this information is subsequently used to track or monitor individual employees, we speak of function creep. This is an invasion of privacy that goes beyond the established purpose of creating secure access.

FINISH

Finish

VALUES

Explanation

At the beginning of the workshop, you have written down a number of values. Take these out again and check for yourself whether these values are represented in the project, and if so, where.

One by one, take turns with the members of the project group and get them to say whether their values are represented in the project, and if so, where in the project this is the most apparent. The person whose turn it is may stick their values on the poster in a place where they think this is applicable. For example, the value “ownership” may be stuck to the questions about communication or to the questions about the source of the data. When it is your turn to stick your values on, explain to the rest of your group why you think the values belong in that place of the project. Discussing this as a group can lead to new insights.

It may also be the case that you find one of the values you have noted down fits everywhere in the project. In that case, you can stick that value in the middle of the poster.

Finally, it is also possible that one of the values you have written down is not represented in the project at all. In this case, discuss whether this value could be of interest to the project and whether it is necessary to change certain aspects of the project so that the value can be represented. It may happen that a value is less relevant for a project. For example, the value “loyalty” is less relevant for a data project that anonymously counts passers-by within a certain area.

Report of the project

You can use the DEDA Poster, including all answers and action points, as a basis for or in support of a report on the data project.

The answers and action points can serve as tools that make it easier to justify the project. For example, the answers can help to explain which choices were made, and, at least as important, why certain things were not done.

In support of that report, the following pages contain information on the most commonly used ethical theories. Some government organizations already use some of these theories in ethical decision-making. For other government organizations, these theories can help to make a decision on the moral problems that the workshop has brought to light.

Keep in mind that these ethical theories are not exhaustive and have been simplified for the sake of comprehensibility. Ethics is a very broad field with many sub-theories and (internal) conflicts. It is also not necessary for organizations to make these theories explicit in the organization, given the fact that hardly anyone makes use of just one moral theory in their actions. Nevertheless, the knowledge of these theories can help with making decisions and resolving possible conflicts.

Explanation for the ethical theories

Different ethical perspectives offer different outcomes.

The question of what is the “right” thing to do is difficult to answer, and different theories offer different answers. Moral theory tries to find a systemic way to provide answers on what one can or cannot do, is allowed to do or is required to do. In this section the most important theories within ethics will be discussed. Please note that within the different theories, sub-debates and competing debates take place.

Utilitarianism

“The greatest happiness for the greatest number.”

Utilitarianism looks mainly at the consequences of an action. An action is ethically justified if that action provides the greatest happiness for the greatest number of people. Within this theory, happiness is defined in different ways by different scholars. Bentham and Mill define happiness as the absence of pain and as having as much fun as possible.

Utilitarianism and data

Values such as “public safety” and “privacy” often come into conflict with each other. Dilemmas occur when more value is placed on one concept than the other. From a utilitarian perspective, more value will be placed on the welfare of the many (i.e. public safety) than on privacy. On the other hand, it can be argued that privacy is necessary for people’s well-being. In that case, the utilitarian perspective may bring about a different outcome. From the utilitarian perspective, one will try to weigh the argument for and the arguments against with a focus on people’s welfare. This is often called a “cost-benefit analysis”. It is important to note that within utilitarianism, every individual involved in a moral dilemma has equal value. This implies that “the self” or certain groups or individuals have no more value than others. That said, increasing the welfare of the many could cause the welfare of minorities to be ignored. This concept is called “the tyranny of the majority”. Similar examples can be found in the medical context, where it is said that a person could, for example, be sacrificed to become organ donors so that many other people can benefit from it.

Criticism of utilitarianism

A common criticism of utilitarianism is that the idea of utility or happiness is not really practical or useful for many people. In order to determine what is best for most people, one would have to know, consider and balance all possible positive and negative outcomes. One possibility for utilitarianism is to introduce rules that optimize the trade-off in most cases (so-called rule utilitarianism). But this argument leads us back to the aforementioned issue: balancing public safety against privacy. This problem is difficult to weigh and quantify. However, when such an issue is considered (for example, through the use of transparency or legitimate political institutions), utilitarianism can serve as a guiding moral theory in developing rules that can contribute to the ethical handling of data.

Deontology

"There are overarching principles that should guide our actions."

Deontology is often seen as the counterpart of utilitarianism. If focuses not on the consequences, but rather on the intentions of an action. This theory was developed by Immanuel Kant in particular. He called his theory the categorical imperative. The categorical imperative means that an action is right if it could be wished that everyone in the same situation would also choose that action. Because people are capable of rational thought, they are able to use the categorical imperative to guide their actions.

The above formulation is the best known variant of the categorical imperative. Another formulation of the categorical imperative states that we must never use other people merely as means, but always at the same time as ends. This formulation focuses on respect for the dignity and autonomy of other people. According to this formulation of the categorical imperative, it is therefore immoral to manipulate others or to hinder them in achieving their goals.

Deontology and data

Data projects promise to increase the quality of services provided by a company or municipality. At present, the way in which certain models are developed, tested and used is still relatively experimental. Practices that sometimes sound promising, such as improving public transport by using mobile data to monitor flows of people, would not be morally justifiable from the viewpoint of deontology. The reason for this is that the use of personal data without consent or knowledge of the persons concerned impairs the autonomy of the individual. However, there are ways in which the autonomy of these individuals could be respected. For example, when these individuals give their consent for the use of their data or by being transparent about how their data is used.

Criticism of deontology

Some critics argue that the categorical imperative is too abstract a principle and that it would therefore not help in specific decision-making. Moreover, deontology would not take into account any context relevant information that may be needed for decision-making in particular situations. Deontology may be too insensitive to particular features of certain practices, such as balancing privacy against security, or how personal data relates to a person's autonomy.

Virtue ethics

"How would a good person act in this situation?"

Virtue ethics differs from the previous two theories in that it focuses not on the question: "What is the right thing to do?", but rather on the question: "What kind of person do I have to be to do the right thing?". So the question asked has a unique focus on character, rather than the actions themselves.

This theory goes back to Plato and Aristotle who, among other things, wanted to answer the question as to what kind of qualities (virtues) of character are needed in order to be a good person. A virtue could be, for example, honesty: an honest person would tell the truth and refrain from telling lies. Other virtues may include courage, generosity, temperance, sincerity, wit and kindness. When these virtues are developed, practical wisdom will result in the person developing all the skills to come to the right decision themselves.

Virtue ethics and data

Professionals who work with technology, such as programmers, often have a solution-oriented focus. This focus often leads to a dominance of the utilitarian perspective. This perspective is often not explicitly expressed and therefore remains implicit. Some scholars argue that virtue ethics can be an alternative to the solution-oriented perspective. By this they mean that the focus should not so much be on concepts such as privacy or informed consent, but rather on the question of what kind of environment and data wisdom professionals need in order to make responsible choices. A virtuous data analyst would, for example, have virtues such as "respect for the sensitivity of personal data" and "caution and selectivity in communicating and sharing that data". People could be trained in such virtues or people could be selected based on these character traits.

Criticism of virtue ethics

One criticism of virtue ethics is that it does not really provide good guidance. Virtue ethics focuses on the question of what a good person would do in a given situation. This is not a complete roadmap to action. In addition, the imitation of the actions of a good person does not mean that the person imitating them actually possesses the virtues themselves.

Another criticism is that it is difficult to explain why certain character traits are virtuous and why others are not. Aristotle defined some virtues that were normal in his time, but would be controversial in today's world. It is thus difficult to measure and test virtues over time and across cultures.

Another argument against virtue ethics is that it has a blind spot or can be considered naive in the sense that companies and institutions often function with the help of an organizational hierarchy. Should every employee be virtuous? Or do we need virtuous managers to whom employees can conform? Such questions lead us away from virtue ethics itself and makes the application of virtue ethics more difficult.

Moral relativism

"The rightness of an action depends on the society you live in."

Within this theory, ethical decision-making is a social construct. We as a community have decided what is good and what is bad, but in theory we could also decide the opposite. Within moral relativism, personal moral codes are entirely dependent on the more code of a culture, which is understood as the sum of individual norms and values. An act that is seen as morally wrong in one part of the world may be seen as morally right in another part of the world. Eating pork, for example, is seen as morally wrong for Muslims, whereas for Christians it is not seen as problematic. This view stands in contrast to theories that assume there are absolute moral or ethical values valid for everyone.

Moral relativism and data

The concept of privacy has a long Western tradition. Western concepts of privacy focus mainly on the individual and what belongs to this individual as a person, for example intimacies with family and friends, secrets and hidden correspondence. Privacy can be experienced very differently within non-Western traditions. For example, the Chinese word for individual privacy, Yinsi, can be translated as "the hidden" or "the bad".

A culture is subject to change, and although privacy is woven into our traditions, a cultural relativist might argue that our modern culture has no need for a concept like privacy and that the relevance of the concept is already declining. "I don't have anything to hide" is a common argument from residents within the issue of government surveillance. Moreover, despite its controversial privacy policy, companies such as Facebook do not seem to have fewer users. The disappearance of the concept of privacy in such examples would be an argument for the existence of moral relativism.

From the point of view of moral relativism, determining whether something is an invasion of privacy will depend on the fundamental moral code of the culture in question.

Criticism of moral relativism

Criticism of moral relativism focuses on the difficulty of defining what a culture is. Can we, for example, speak of a Dutch culture? Or do we live in a Western culture? Or is culture more related to religious background? Another frequently mentioned point of criticism is that a person can have several cultural backgrounds. For example, what moral values apply to a person who grew up in the Netherlands, but whose parents come from China? A moral relativist would respond that the difficulty of defining a culture does not negate the premise that morality is cultural. Just because a culture is complex does not mean that it is not constitutive of our values.

Moral relativism could also be questioned philosophically. If moral relativism means that morality depends on culture, it ignores the possibility that some aspects can be traced back to human nature. Privacy is an example of this: it could be that the desire for privacy is an evolutionary or biological aspect of human nature and that therefore it should not be ignored. If moral relativism were to allow human nature to play a role, the position of moral relativism could be called into question, since facts relevant to moral theory can be found in common human nature, regardless of culture.

There are also arguments that there is no empirical evidence for moral relativism and that what we may see as morally irresponsible may in fact be experienced as morally responsible by other cultures. However, this is not because of a different moral framework, but because of a history of other culture and religion. The classic example is that of a tribe that kills elderly people when they turn fifty. In our eyes this is bad and in their eyes this is good. However, it is only morally justifiable according to the tribe because they believe that their bodies will remain in the afterlife. Thus, killing the elderly is justifiable to them from a belief and world view that is incomprehensible to us. Therefore, there is no hard moral relativity: differences in morality of different cultures can be explained on the basis of their faith and history, but not necessarily by reference to a different moral framework.

Moral particularism

“We can only decide what the right thing to do is in specific situations.”

This aspect of moral theory emphasizes that to judge whether an act is morally right or wrong, one must look at the facts in a given context. Such facts may be, for example, the availability of certain resources, a certain time or access to certain technology. Moral particularists therefore do not think that there are universal moral rules or principles that always apply in every situation. Moral particularists also do not think that morality is inherently cultural. They claim that the rightness and wrongness of an action depends in its entirety on the context. This means that an act is morally right if the situation and the context necessitate a certain action. However, some moral particularists believe that moral rules and principles in similar situations can provide a handle on what is right.

Moral particularism and data

This perspective does not look at general issues such as whether informed consent is necessary in data practices, but rather looks at what is necessary for a morally successful project per situation. The focus then changes from what the responsibilities of companies and governments are in general when it comes to data, to what the responsibilities are per project or case. In practice, this means that there should be much more respect for the diversity and differences of cases and more communication about what is needed per case.

Criticism of moral particularism

Broadly speaking, there are two forms of criticism of moral particularism. The first form of criticism states that without guidance from ultimate principles there would be nothing. People without ultimate principles of morality would have no reason to limit their choices and people would have no reason to make moral decisions. This criticism is mainly aimed at the motivation of people to act morally.

Secondly, it is argued that rationality should be consistent. There is a danger in focusing only on each situation individually and not having an overall consistency. For example, when we think of a specific situation in which someone hurts another person, it is difficult to explain why this is morally wrong. The argument here is that if there is no clear notion of why it is wrong to hurt others, we cannot make a clear argument for why it is wrong in this particular situation to hurt another.

Colophon

Concept:
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For updates see:

www.dataschool.nl/en/deda

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As DEDA is used, we learn to improve it. These improvements will be implemented in future versions. If you are using DEDA and have any comments, please do not hesitate to share them with us. You can always mail to:

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