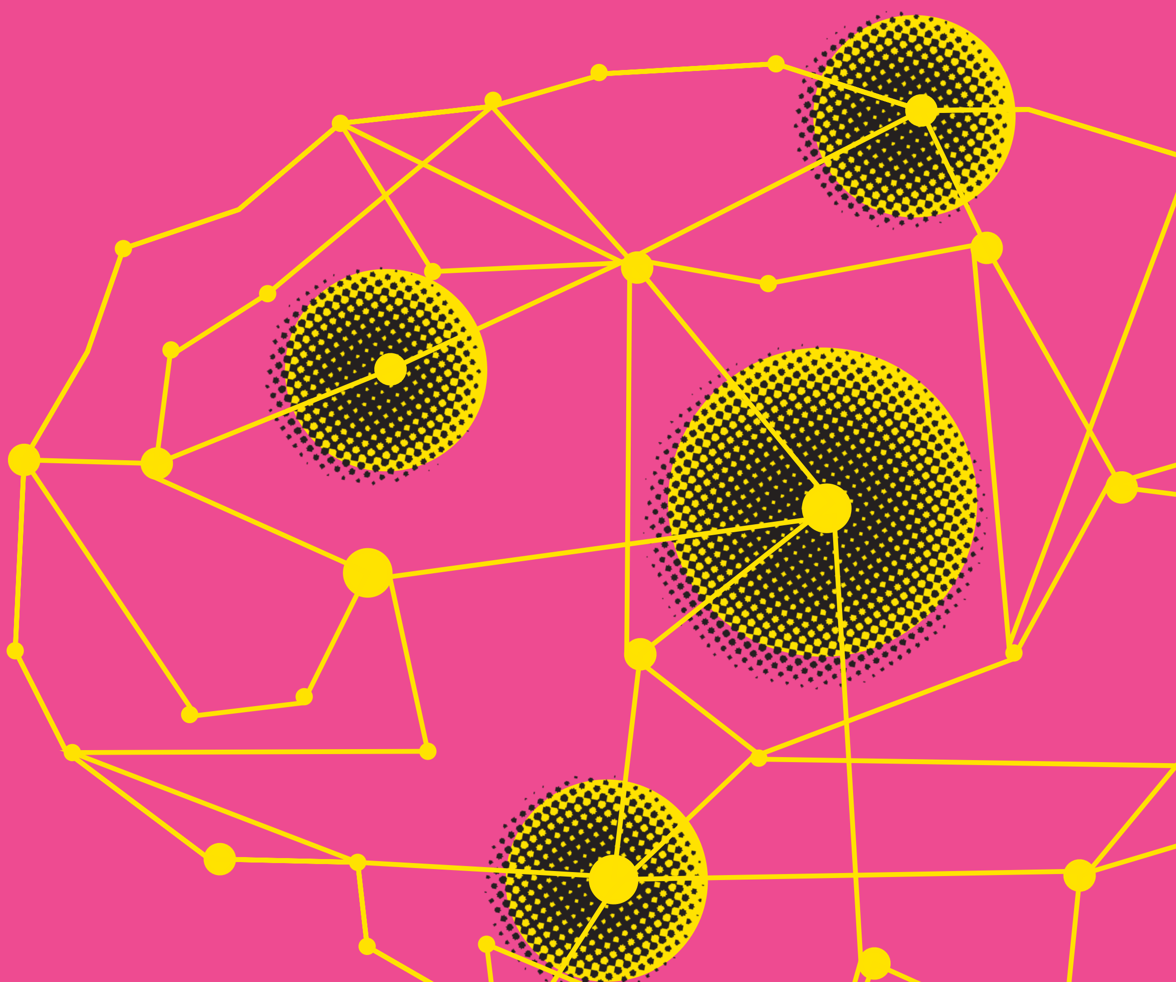
Predictive Analytics and AI in Governance: Data-driven government in a free society

ARTIFICIAL INTELLIGENCE, BIG DATA AND ALGORITHMIC DECISION-MAKING IN GOVERNMENT FROM A LIBERAL PERSPECTIVE



Design:
Andreas Pohancenik
(wirsindattraktiv.com)

Predictive Analytics and AI in Governance: Data-driven government in a free society – Artificial Intelligence, Big Data and Algorithmic Decision-Making in government from a liberal perspective

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ARTIFICIAL INTELLIGENCE, BIG DATA AND ALGORITHMIC DECISION-MAKING IN GOVERNMENT FROM A LIBERAL PERSPECTIVE

Author: Basanta E. P. Thapa

Editor: Dieter Feierabend

Executive Summary

Data-driven government, meaning the use of technologies like data analytics, Artificial Intelligence and algorithmic decision-making for policymaking and public administration, offers advantages as well as challenges for a free society. Possible benefits include more efficient and convenient delivery of public services as well as better-informed policymaking with predictive analytics, policy simulations, and real-time early warning systems. Challenges, specifically from a liberal perspective, encompass the autonomy of citizens and civil servants, the accountability of algorithmic systems and privacy.

Discussions of a regulatory framework for data-driven government revolve around algorithmic accountability and explainable AI, how to design a special right to appeal against algorithmic decisions, where and how to limit data-driven government, and oversight mechanisms.

Key recommendations for liberal policymakers to reap the benefits of data-driven government while avoiding its pitfalls are:

→ Build trust with transparent, accountable algorithmic systems, oversight mechanisms and collaboration with critics.

→ Member States should gather experience with data-driven government in regulatory sand boxes and try out different regulatory options.

→ Both Member States and the European Commission/Parliament should strengthen citizens, government employees and interest groups vis-à-vis algorithmic systems and data analytics with algorithmic literacy, suable rules, and a level playing field regarding the access to data and algorithms (i.e. a review of EU's General Data Protection Regulation).

Contents

1 Introduction

The powerful combination of algorithms and digital data, whether as Artificial Intelligence, Big Data Analytics or algorithmic decision-making systems, is supposed to revolutionise not only business, but how government works as well – turning it into a “data-driven government”. Efficiency gains from optimized resource allocation, effectiveness gains from policy simulations, fiscal gains from fraud detection, more responsiveness from sentiment analysis, more strategic policymaking from predictive analytics – there is a plethora of promises around the use of sophisticated digital data collection and analysis in government. As AI has become an inflated marketing buzzword, a critical examination of the different socio-technical approaches conflated in the term and a sober assessment of its opportunities for public administration is pertinent. Where does the “data deluge” come from? What can we generally do with it? What are possible applications in government?

However, data-driven government, AI and Big Data is surrounded by critical debates. Does Artificial incapacitate humans? Does Big Data discriminate? Does data-driven government relinquish democratic sovereignty? Such questions have to be examined to realize the potential benefits of data-driven government without walking into its pitfalls. This is particularly important from a perspective of political liberalism. Liberalism values progress, including technological advances and the gains in efficiency and knowledge that come along with it. However, a liberal stance also stresses free will, personal liberty and a strong position of citizens vis-à-vis government – values that could easily be affected by data-driven government.

Thus, this study strives to inform policymakers beyond salespeople’s’ promises and doomsayers’ worries to move forward towards a well-regulated data-driven government that supports rather than undermines a free society.

1.1 Scope and structure of the study

This study aims to provide a straightforward introduction to the political questions behind the use of technologies such as algorithmic decision-making, Big Data or Artificial Intelligence in government.

To this end, the second chapter disentangles and explains the technological buzzwords around data-driven government. The third chapter highlights the truly new qualities these technologies bring to government. Chapter 4 presents the general functions these technologies can fulfil in government, how these could be applied around the policy cycle and which promises are made on their basis. The fifth chapter exposes and assesses eight possible challenges of liberalism by data-driven government. Chapter 6 provides an overview over the most-debated policy options for the regulation of data-driven government. Finally, the summary includes policy recommendation for European liberals.

1.2 Examples of data-driven government in action

This study is interspersed with examples of data-driven government in action, to illustrate more abstract points and to give an idea of real-life applications. These examples are mostly drawn from cataloguing efforts by AlgorithmWatch, Bertelsmann Foundation, UN Global Pulse and the EU project Data4Policy. The geographic and thematic distribution of the examples is by no means representative but subject to selection biases of the catalogues and an author bias towards projects in Germany. As no further investigations of the examples were pursued, some projects might be misrepresented or since have failed.

2 Big Data, AI, ADM, ML – disentangling the buzzwords

Data-driven government refers to the use of new digital data technologies in public administration, such as “algorithmic decision-making”, “Artificial Intelligence”, “Big Data” or “Machine Learning” and the subsequent social and organisational transformation of government.

The four terms are often used as buzzwords, lack technical definitions and are colloquially frequently conflated. However, to assess their impact on government, a basic understanding of the technologies and their differences is necessary. For example, Artificial Intelligence may be trained with Big Data, but smaller data will often suffice. Machine Learning is a specific family of methods of Artificial Intelligence. On the other hand, Artificial Intelligence is always a form of algorithmic decision-making, even if that decision is just to categorize the content of an image. However, only a small share of algorithmic decision-making applications is based on Artificial Intelligence, as deterministic, rule-based ADM is more common and easier to handle.

2.1 Big Data

Big Data is a term that gained popularity in the early 2010s and refers to the "data deluge" that was unlocked by the increasing digitalisation of society. By definition, Big Data refers to very large amounts of data, especially unstructured data, from various sources and their analysis. While structured data consists of pre-set categories with defined values, e.g. height in centimetres or married/unmarried, unstructured data are typically sets of text, sound or images without any pre-defined data fields and values. In absence of a commonly agreed technical definition of Big Data, it is hard to say at which threshold data becomes Big.[1]

TABELLE 1: IDEAL-TYPICAL COMPARISON OF SMALL DATA AND BIG DATA[2]

	Small data	**Big data**
Volume	Limited to large	Very large
Exhaustivity (What share of the population is captured by the data?)	Samples	Entire populations
Resolution and identification (Can individual objects be identified and linked across data sets?)	Course & weak to tight & strong	Tight & strong
Relationality (Do different data sets share common data fields?)	Weak to strong	Strong
Velocity (How quickly/at what frequency is data available?)	Slow, freeze-framed/bundled	Fast, continuous
Variety (How structured is the data)	Limited to wide	Wide
Flexible and scalable (How easily can new data fields and new cases be added?)	Low to middling	High

The rise of Big Data as a buzzword sparked the development countless use cases for Big Data Analytics in business and government.[3] The unbridled believe in the power of Big-Data-based inductive analysis found its peak in the proclamation of the "End of Theory",[4] and was subsequently categorised as the ideology of "dataism".[5] However, Big Data has colloquially come to mean any kind of sophisticated data analytics as well as data collection, unfettered by technical definitions.

1 Ward & Barker 2013; De Mauro, Greco & Grimaldi 2015

2 Kitchin 2015, criteria questions added for clarification.

3 Mayer-Schönberger & Cukier 2013

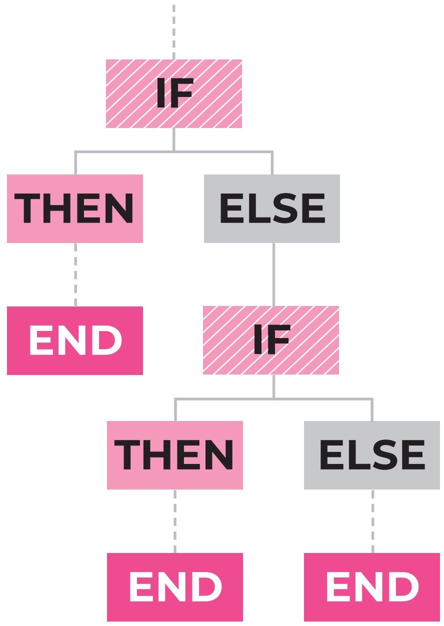
4 Anderson 2008

5 Van Dijck 2014

2.2 Algorithmic Decision-Making (ADM)

Generally, an algorithm is a set of rules or instructions to solve a specific problem, which can be executed by humans as well as computers machines. These rules can be handcrafted or machine-generated, e.g. by Artificial Intelligence. Classic examples for algorithms are if-then decision trees.

FIGURE 1: SIMPLE ALGORITHMS CAN BE DISPLAYED AS DECISION TREES



Algorithmic decision-making means the results of algorithms are put into action without a human in the loop, e.g. the circuits controlling traffic lights or the software-based granting of social benefits. Algorithms do not "think", but can be "smart" or "intelligent" in the sense that they can have complex decision models that can produce highly differentiated responses to external stimuli.

2.2.1 EXAMPLE: FACEBOOK NEWSFEED ALGORITHM

An everyday example for algorithmic decision-making is the curation of a user's Facebook newsfeed. To decide which content to present to the user in what order, the Facebook newsfeed algorithm scores all posts from the user's friends and followed Facebook pages based on a set of indicators. These indicators include engagement measures, e.g. how many likes and comments a posts receives, but also a predictive estimate whether the user will interact with the content, e.g. if the user always likes photos of cats but never reacts to photos of dogs, cat content is scored higher than dog content for this user.[6] These indicators are tallied to a compound score which determines individually for each user if and in what order content appears in the newsfeed.

6 Boyd 2019

2.2.2 EXAMPLE: ADM IN POLISH LABOUR SERVICES

ADM is used in governments across Europe, albeit often as pilot projects, as the report "Automating Society – Taking Stock of Automated Decision-Making in the EU"[7] highlights. For example, Polish labour offices determine the type of assistance an unemployed person can obtain with ADM since 2014. The algorithm aggregates the answers to a 24-item questionnaire to two main criteria, "distance from the labour market" and "readiness to enter or return to the labour market", and classifies the unemployed person according to these criteria.

2.3 Artificial Intelligence (AI)

Put simply, AI is a combination of ADM and Big Data, as it today mostly means self-optimizing algorithms that produce statistical decision models from large data sets. Artificial Intelligence is an old branch of computer science, around at least since the 1950s, which has experienced a third summer in recent years[8] and tries to answer the question: "How can computers learn to solve problems without being explicitly programmed?"[9]

Approaches to answer this question can be categorized as general/strong AI and narrow/weak AI. General AI tries to emulate and surpass the generalist problem-solving abilities of the human brain, autonomously solving every problem it is presented with. While very present in the public debate, general AI currently "remains in the realm of science fiction".[10] In contrast, narrow AI only strives to solve very particular problems while still applying intelligence in the sense of adapting to (relatively) new input and developing its own solutions. This report only refers to narrow AI.

Today, AI is mostly used synonymously with Machine Learning, neglecting its many other sub-fields. Machine Learning AIs are "trained" with existing (or synthesized) labelled data sets and try to find patterns which allow them to successfully categorise new input, e.g. to identify whether an image shows a muffin or a chihuahua.[11]

Another popular variety of AI is data mining or "knowledge discovery in databases" which open-endedly looks for patterns in existing data and thus produces classifications and correlations.

2.3.1 FRAUD DETECTION FOR HEALTH CARE BENEFITS OF BERLIN'S CIVIL SERVANTS

The government of Berlin uses AI to identify possibly fraudulent health bills of its civil servants.[12] The system looks for anomalies in the bills that are submitted for reimbursement, e.g. for bills that are significantly higher than for comparable cases and for cases that are similar to known fraudulent bills. Ten million cases from the past four years served as training data for the system. The system flags suspicious cases for further inquiry by human case workers.

7 AlgorithmWatch & Bertelsmann Stiftung 2019

8 Nilsson 2011

9 Koza et al. 1996

10 OECD Observatory of Public Sector Innovation 2019

11 Yao 2017

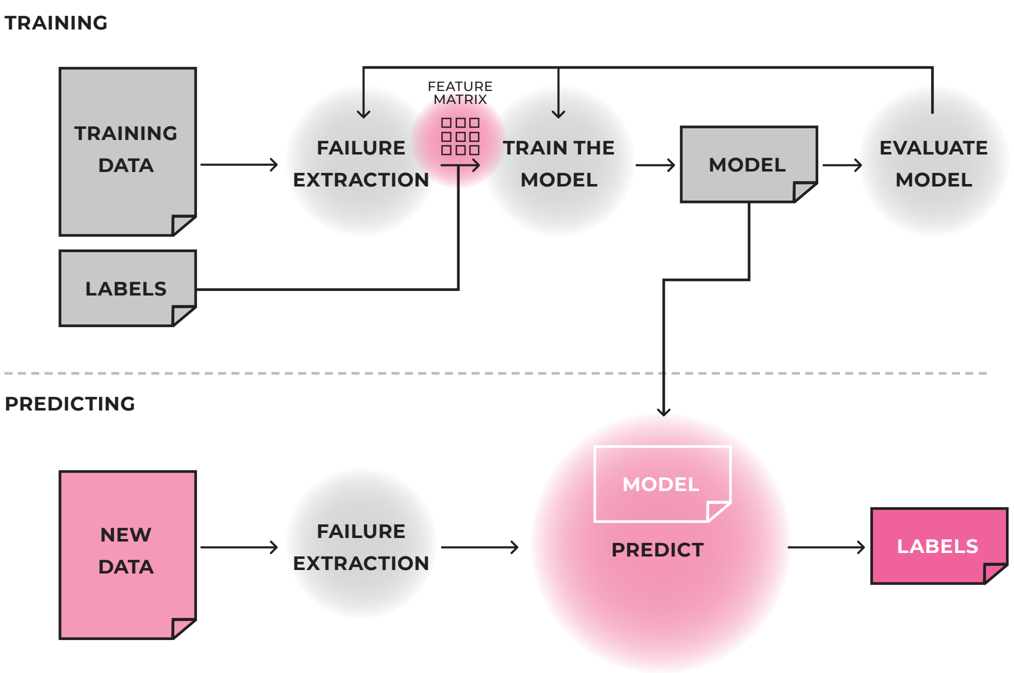
12 IBM 2017

2.4 Machine Learning (ML)

Machine Learning (ML) refers to a family of approaches to Artificial Intelligence. In a nutshell, ML – at least in its supervised variety – identifies patterns in categorised training data and translates these into statistical models that give informed estimates on the correct categories of newly input data. There are many alternative approaches, but supervised ML is the most relevant in the government sphere and provides a good basic understanding of the subject.

For example, many social services across Europe experiment with supervised ML as an early warning system for children in need. These projects all follow the same general principle: As training data serves a historic data set including children were in need and children that were not in need. Apart from the need for intervention, information such as performance at school, missed doctor's appointments and parents' police records may be included. The ML algorithm now tries to builds a statistical model that predicts the need for intervention for every case in the data set. While a missed doctor's appointment might have seemed like a perfect indicator for a child in need for the first ten examined cases, the statistical model grows more complex as cases of missed doctors' appointments appear where no intervention was necessary. This increasingly complicated model may for example take into account the frequency of missed doctors' appointments and its co-occurrence with other signals in the data. Once this statistical model is derived from the training data where the need for intervention was known, it can be applied to new cases to estimate whether they rather resemble cases that needed intervention in the past, or those cases that did not. ML algorithms can – but often do not – continue improving their statistical model while in action.

SUPERVISED LEARNING WORKFLOW



2.5 The new data technologies in a nutshell

Summing it up, Big Data refers to new digital possibilities of data collection and analysis. AI and Machine Learning are specific approaches to the analysis of large data sets. ADM are decision based either on the predictions of data-based technologies such as AI or on hand-crafted rules.

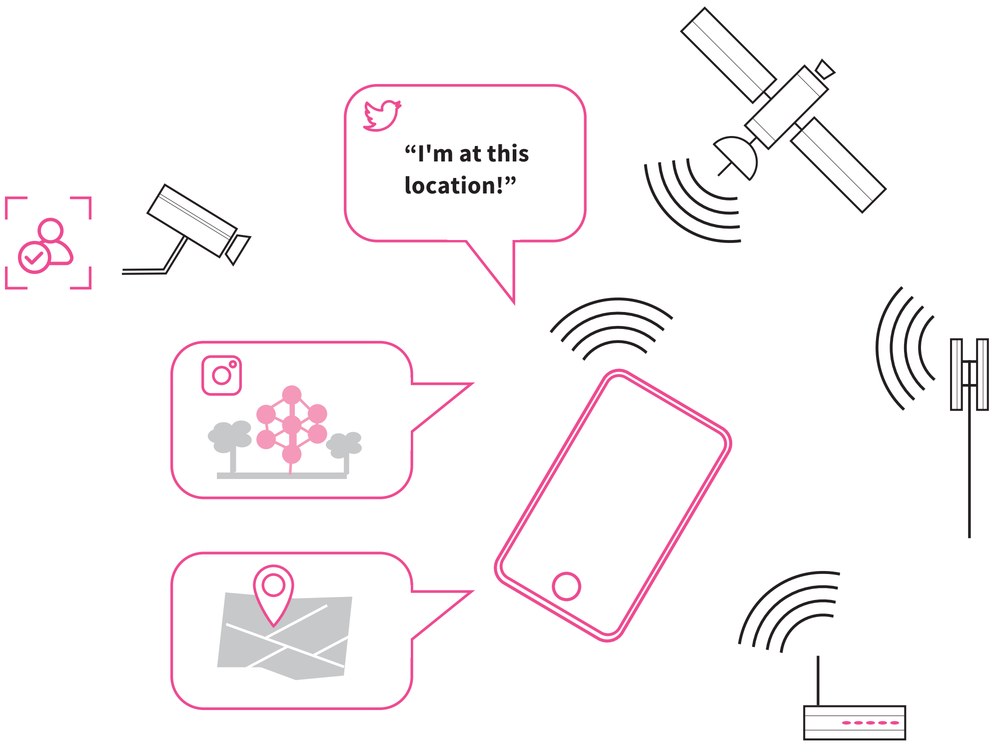
3 What is new about data-driven government?

What is new about the use of data technologies in government? After all, to govern has always meant to gather and process data, with the technology available at the time.[13] Mankind's earliest written records are cuneiform tax ledgers of the ancient city states of Mesopotamia.[14] In the 19th century, governments started using mechanical calculators, and in the 1960s and 1970s, government data processing increasingly shifted to the digital databases of mainframe computers. So, as data processing has always been essential to public administration, the current "data revolution" is not novel in principle but the new digital data technologies have enabled a leap in quality due to *data density, granularity, linked data and machine learning.* These new qualities enable more encompassing monitoring, more sophisticated analyses and predictions and thus more efficient and anticipatory government.

3.1 Data density

Data collection has become feasible and affordable in unprecedented density due to digital technologies. Whether it's electronic communication data off the Internet, transaction and process data from government and businesses or readings by networked sensors, more data on more objects in higher frequency has become available. In many cases, real-time monitoring ("nowcasting") from different data sources has become possible. This data density is the prerequisite for the new data analytics.

FIGURE 2: DENSE LOCATION DATA, E.G. FROM SIGNAL TRIANGULATION, SOCIAL MEDIA POSTS, MAP SEARCHES AND CCTV.

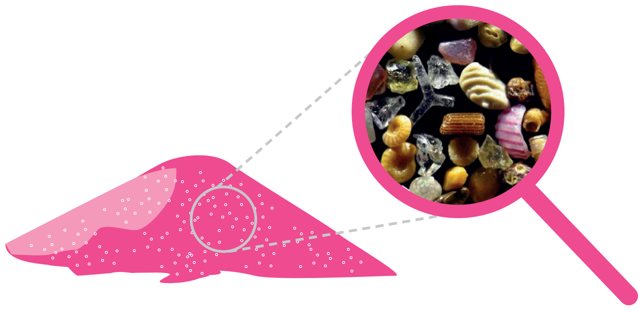


13 Scott 1998

14 Graeber 2015

3.2 Granularity

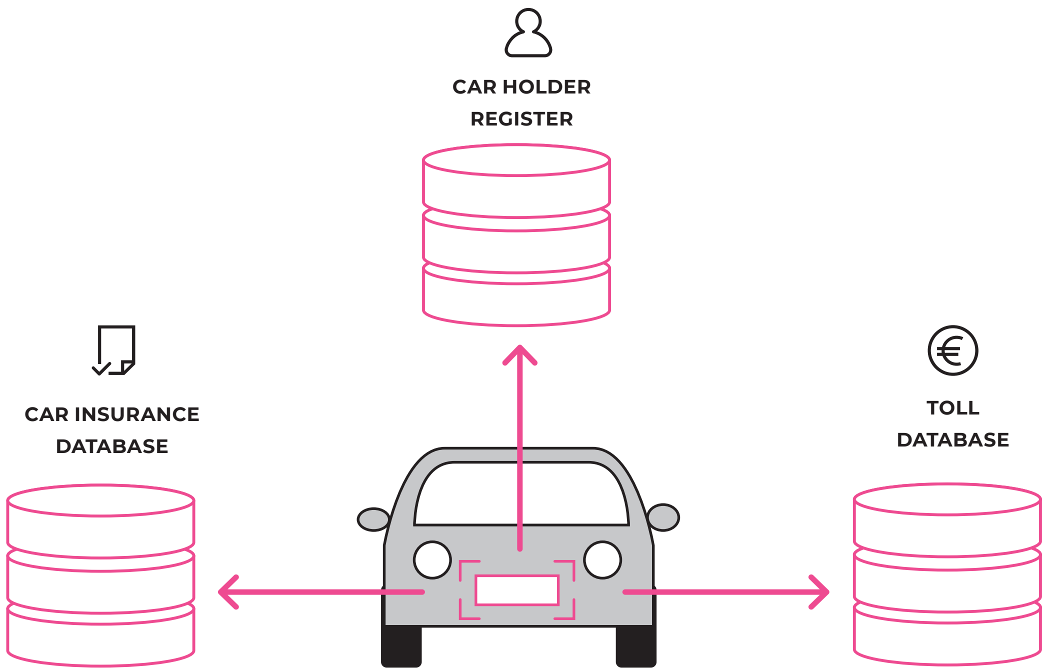
Granularity refers to the possibility of zooming in on the individual objects – e.g. citizens with their various attributes – constituting a data set, akin to examining single grains of sand in a desert. Thus, the categories and indicators used in statistical analyses can be rearranged and recombined at any time, to fit new questions or new angles of inquiry. The resulting simultaneity of a macro and micro perspective open up new possibilities for monitoring and data analytics.



3.3 Linked Data

Linked data refers to the combination of different data sets that describe the same objects. In a government context, these might for example be citizens, companies or cars. By linking data sets, additional information on the objects becomes available for analysis and data density increases. To maintain the granularity of data, objects must be uniquely identifiable across the data sets, for example using personal identification numbers.

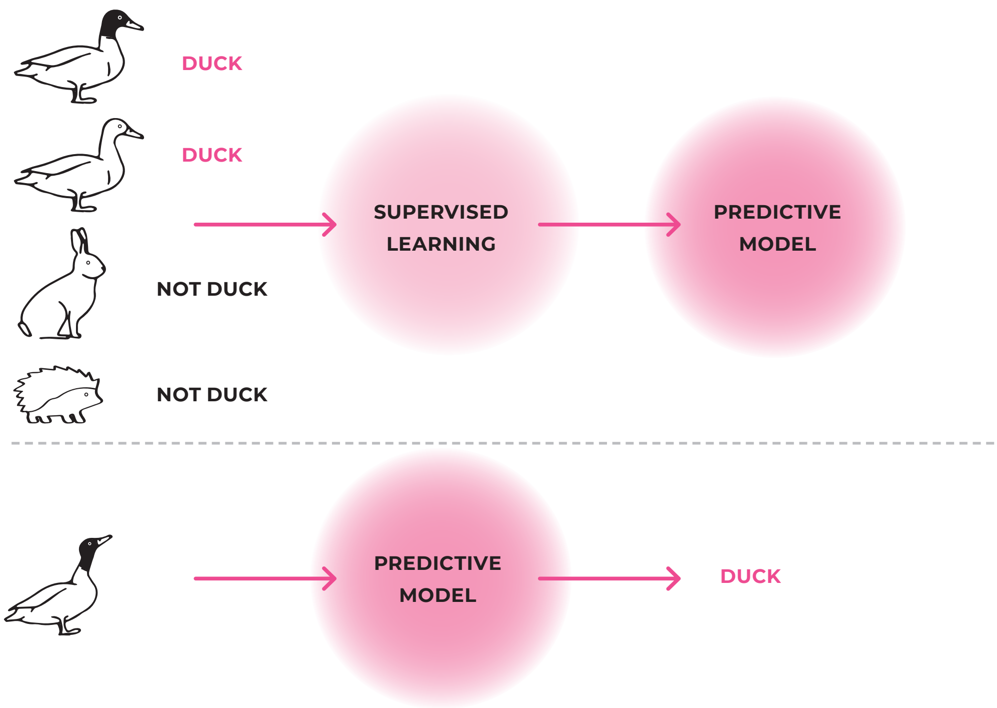
FIGURE 3: LINKING DATA SETS ABOUT CARS VIA THE PLATE NUMBER.



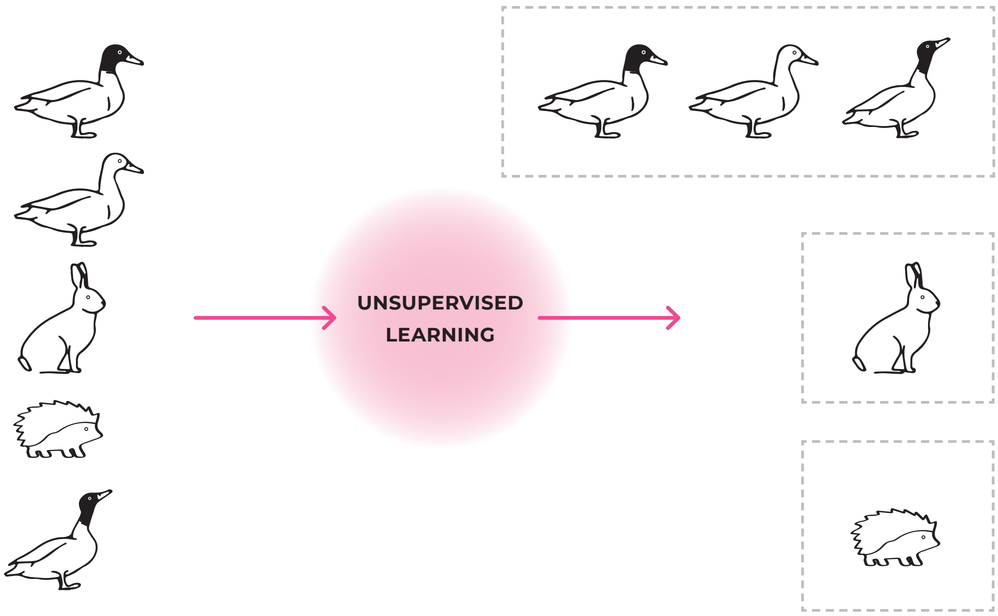
3.4 Machine Learning

Data density, granularity and linked data enable methods of analysis, such as Machine Learning, beyond traditional inferential statistics that are designed for situations of data poverty. The larger the analysed samples are in relation to the parent populations, the more robust statistically determined correlations are against random effects and other types of errors. Machine learning is a paradigm shift in data analysis, as categories and causal models are computer-generated from the data with self-optimizing algorithms. Thus, the search for correlations and causality is no longer limited to human creativity, but can be automated.

SUPERVISED LEARNING (CLASSIFICATION ALGORITHM)



UNSUPERVISED LEARNING (CLUSTERING ALGORITHM)



3.5 Data sources

The critical component for the use of data technologies is the availability of dense digital data. In the context of government, we can distinguish three general categories of data sources:

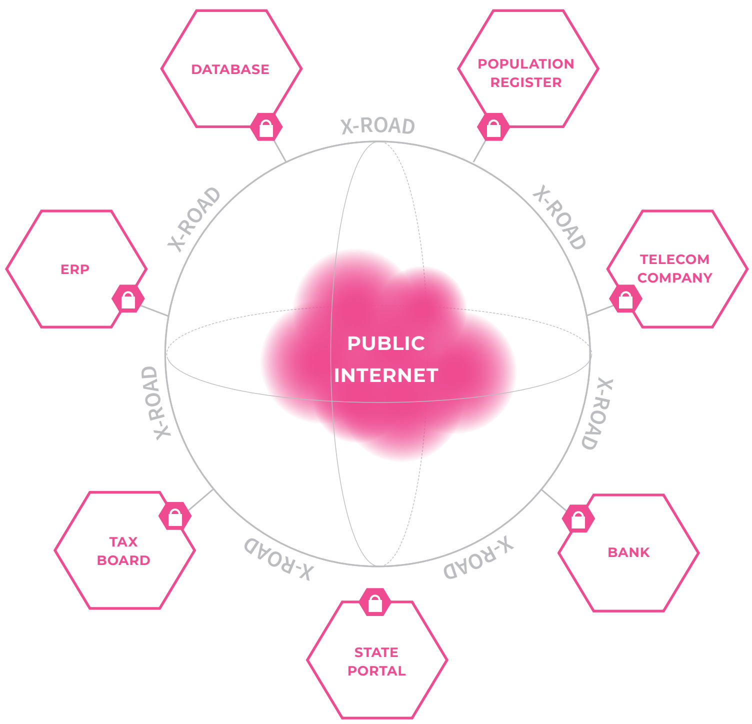
3.5.1 GOVERNMENTAL DATA SOURCES

Public administrations already hold a lot of data on the society and physical environment they govern in registers and files. Governments across Europe are increasingly modernising decentralised and paper-based registers into central databases with unique object identifies.[15] As government processes are increasingly digitalised, more governmental data sources are opened up, e.g. real-time data from administrative processes and transactions.

3.5.1.1 Example: Exchanging government data on the X-Road in Estonia

Since the 1990s, the Estonian government has constructed a connected information infrastructure for its administrative data, known as the X-Road. Via this protocol, government agencies can make inquiries to the country's various standardised central databases, such as the population register, business register, or medical prescription database. This digital data exchange can speed up and automate individual administrative processes and enable data analytics across the linked databases. A prominent example using this infrastructure stems from the business and finance sector. Based on this infrastructure, it is possible to establish a company in Estonia just in 3 hours.

FIGURE 4: SCHEMATIC OF THE ESTONIAN INFORMATION INFRASTRUCTURE X-ROAD
https://e-estonia.com/solutions/interoperability-services/x-road/



15 Gallo et al. 2014

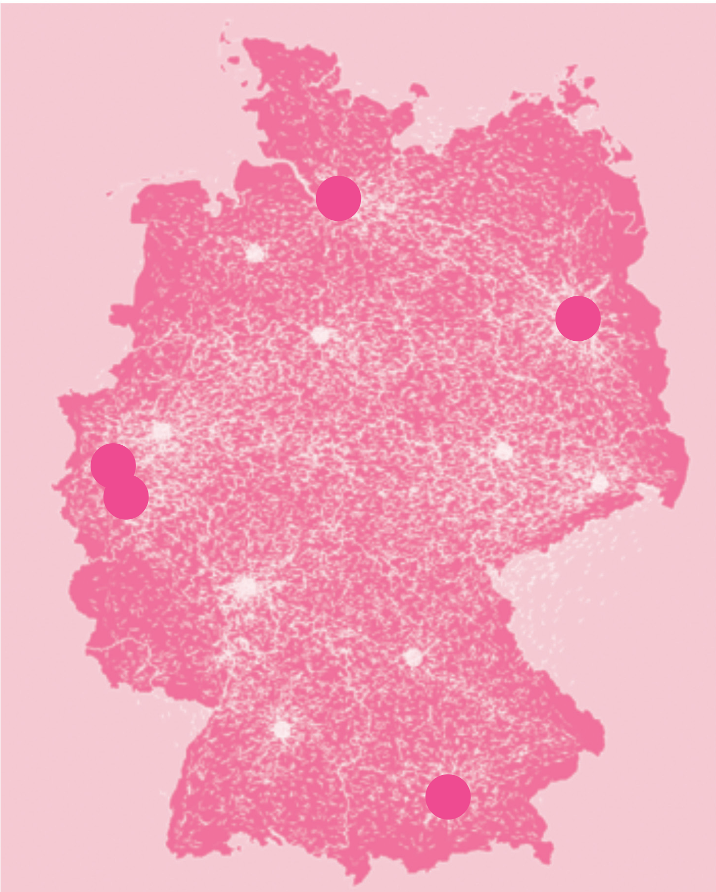
3.5.2 EXTERNAL DATA SOURCES

Within their legal boundaries, public administration can draw on data from private service providers such as digital platforms, transportation and telecommunication providers, or financial institutions. Publicly accessible electronic communication data, e.g. from social media, are another possible source. These external data sources can complement government records as linked data or provide insights more quickly than the official data collection process. However, public administration

3.5.2.1 External Big Data to complement Statistics Netherlands

Statistics Netherlands complements its statistics with external data for swifter insights.[16] For its consumer price index, prices are directly imported from supermarket scanners. Mobility data on when citizens move where is derived from mobile phone data with a data-sharing agreement with the telecommunication provider Vodafone. Consumer sentiment is measure in real time by sentiment analysis of social media, e.g. Twitter. As an evaluation report puts it: "When produced in a methodologically sound manner, official statistics based on Big Data can be cheaper, faster and more detailed than the official statistics known to date."[17]

FIGURE 5: SURFACE MOBILITY FLOWS ON A MONDAY MORNING IN GERMANY, BASED ON MOBILE PHONE DATA BY TELEFONICA
https://next.telefonica.de/so-bewegt-sich-deutschland



16 Poel et al. 2015

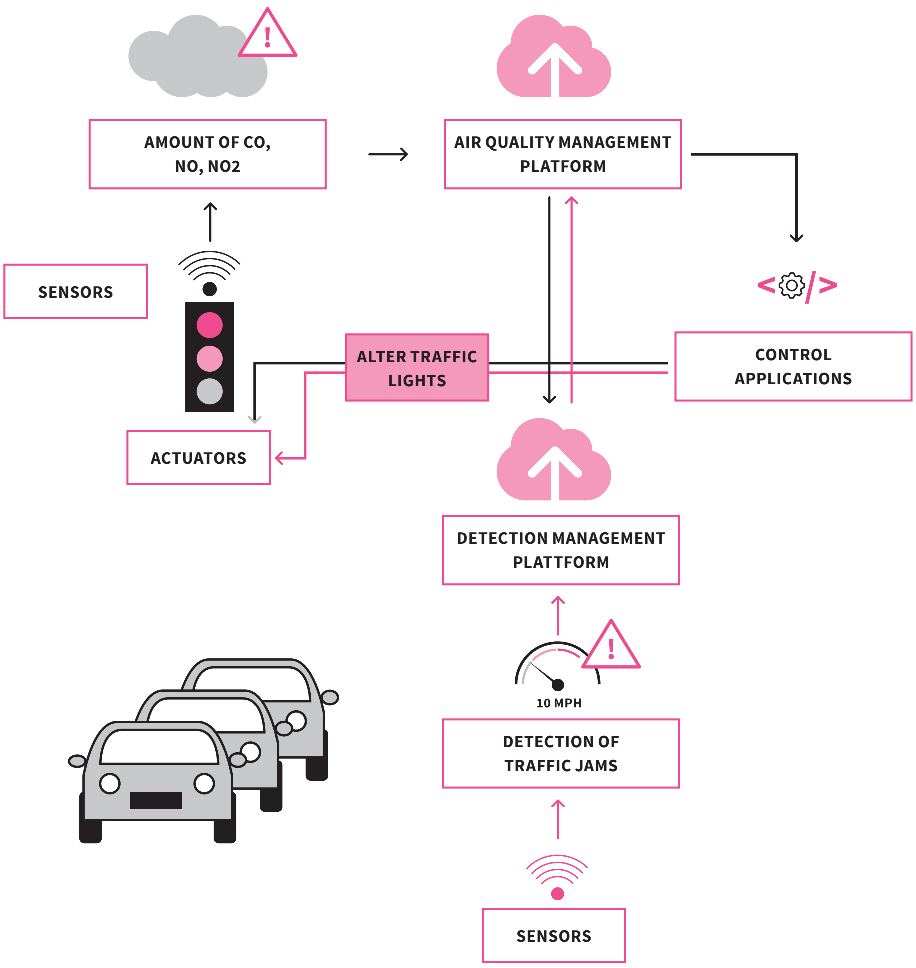
17 Daas et al. 2015

3.5.3 NETWORKED SENSORS AND THE INTERNET OF THINGS

Networked sensors and the Internet of Things in general are driving the collection of digital data on the physical environment. In a nutshell, physical objects are equipped with sensors and linked to the internet make their data accessible remotely. Such applications are most prominently discussed in the Smart City context, with sensors on temperature and air quality in city quarters, traffic surveillance or intelligent street lighting. Such cyberphysical systems produce dense data that might be used for data-driven government as well.

3.5.3.1 Example: Automated traffic management in Skopje

Skopje's UTOPIA (Urban Traffic Optimisation by Integrated Automation) project integrates data from inductive loop vehicle detectors in the roads, traffic monitoring cameras overhead, air quality sensors at selected intersections and vehicle location systems in public buses. Automated systems control traffic lights and variable message signs to optimise traffic flow, reduce air pollution and prioritise public transportation.[18] Project evaluations report a reduction in travel time of up to 20 percent.



18 Green Digital Charter 2015

3.6 Novel qualities of data-driven government

In conclusion, data-driven government is based on the dense observation of its social and physical environment by tapping digital databases of public administration and other actors as well as networked sensors. The fine-grained resolution of this data down to the individual case, even when linking different data sets, allow highly flexible analyses. Further, if large data sets are involved, methods of analysis beyond traditional inferential statistics can be applied.

4 Possible applications of data-driven government

Data analytics and ADM are highly flexible tools. So, what possible applications are there for data-driven government based on these new data technologies? Why and in what contexts are these technologies interesting? These questions are answered from two perspectives: One perspective from the generic functions that these technologies can fulfil or improve, and another from its field of application along the policy cycle.

4.1 Possible functions: From monitoring to decision-making

Data analytics can be used to improve almost every government process – at least in theory – if you think about it long enough. Generally, four basic applications of monitoring, analysis, prediction, and decision-making can be distinguished.

4.1.1 MONITORING

In public administration, monitoring and data acquisition are used for example to evaluate the uptake of new policies, to preserve public peace, or to determine the decision on applications for social benefits or building permits. Drawing on various digital sources and linking these allows more up to date and denser data than before.

4.1.1.1 Example: Gladsaxe risk assessment model for socially vulnerable children in Denmark

The Danish government is experimenting with a data-driven early warning system to identify socially vulnerable children. Drawing on different data sources, signals such as documented mental illness, missing dentist's and doctor's appointments or unemployment are taken into account in a point-based system. Once a certain threshold of points is reached, the child is automatically flagged and appropriate measures can be prompted.[19] The similar "Trouble Families" programme in the UK has been in effect since 2012.[20]

19 AlgorithmWatch & Bertelsmann Stiftung 2019

20 Bate & Bellis 2019

4.1.2 ANALYSIS

Analysis looks for causal relations between social phenomena. The increasing abundance of data and new digital methods such as Machine Learning render this task easier than ever before. Thus, data-driven government is also evidence-based government that can base its decisions on empirical insights.

4.1.2.1 Example: Analysing education monitoring data in Mannheim

The German city of Mannheim applies data analytics to its education monitoring data to disentangle effects on educational success of students, such as socioeconomic background, gender, geography, and policy design.[21] Insights from the analyses feed into municipal political debates and policymaking, and have initiated special education programmes for hot spot neighbourhoods.

4.1.3 PREDICTION

Predictive analytics can extrapolate probable paths of development from historical data. If certain combinations of characteristics led to a specific outcome in the past, the algorithm derives that similar combinations are likely to produce the same results in the future.

This has many applications in policymaking, from the simulation of the impact of different policy options to early warning systems that trigger individual government interventions.

4.1.3.1 Example: Predicting care needs of the elderly in Denmark and Spain

In Denmark and Spain, a few municipalities experiment with data analytics to predict when elderly citizens need assistance. While the Spanish cities of Bilbao and Barcelona rely on more indirect data, e.g. from social services, health, population, economic activity, and utility usage, the Danish pilot project in Copenhagen draws on the personal health and assistance history as well as semi-structured text by caretakers to predict when a new assistance level is needed.[22] The predictions of the Danish model are reported have an accuracy of 80 percent.

4.1.4 DECISION-MAKING

The largest potential for automated administrative decision-making lies with rule-based algorithms based on man-made decision-trees. However, in some cases it might also be sensible to employ self-learning predictive algorithms for decision-making or decision support. This refers to mass procedures such as applications for permits or traffic management, where large quantities of training data are available.

4.1.4.1 Example: Student placement in France

Study places at French public universities are allotted by an ADM system (formerly Admission Post-Bac, now Parcoursup). Applicants state a number of degree programmes and universities they would like to study at, and the ADM places students at universities based on their residence and a fit of their skillset to the degree's requirements. The ADM system was reformed in 2018 after the interest group "Droits des lycéens" successfully sued for the publication of the algorithm and it became apparent that the system produced a geographical bias, making it easier for Parisian graduates to enter the prestigious universities in Paris.[23]

21 IBM 2010

22 AlgorithmWatch & Bertelsmann Stiftung 2019

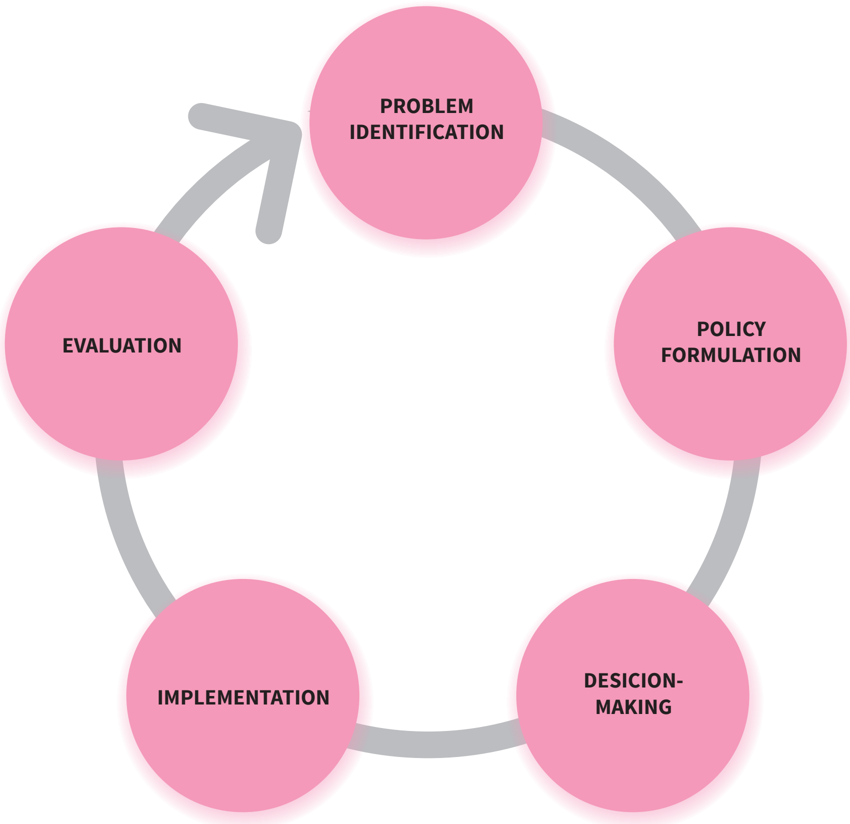
23 Lischka & Klingel 2017

4.2 Possible applications along the policy cycle

Data-driven practises can be employed in many different ways in the political-administrative system. A course around the policy cycle – from problem identification via policy implementation to evaluation – makes this plain.

The policy cycle is a heuristic model of the policy process from the point-of-view of the political-administrative system. It starts with a problem being set on the political agenda and continues with the formulation policy options, the decision for one of said policy options, its implementation and finally evaluation, which typically triggers yet another policy cycle.

TABELLE 2: SIMPLE VERSION OF THE POLICY CYCLE BY ANDERSON[24]



24 Anderson 1975

4.2.1 PROBLEM IDENTIFICATION

For an issue to become the subject of political discussion and eventually the target of policy interventions, it has to be identified as a problem first and put on the political agenda. The government's ability for such problem identification is greatly enhanced by the monitoring and analysis capabilities of data-driven technologies. By observing social and economic data, undesired developments can be detected early on. The automated analysis of media and social media can help identifying social discontent and its causes.

4.2.1.1 Example: UN Global Pulse nowcasting of food security in Indonesia and East Africa

Pilot projects by Global Pulse, the United Nations Big Data program, help to identify and locate food security issues early on. A proof-of-concept project in an undisclosed East African country showed that mobile phone airtime credit purchases and anonymised call detail records can serve as a proxy for various poverty dimensions, especially household expenditure on high-nutrient food items.[25] Thus, significant changes in the data indicates economic crises and particularly food security concerns. A pilot project in Indonesia has shown that Tweets mentioning the prices of basic food commodities (beef, chicken, onion and chili) can be used to track food prices in real time, allowing government to react to price spikes as they occur.[26]

4.2.2 POLICY FORMULATION

Once a problem is on the political agenda, political factions formulate different policy measures to tackle the problem. These policies are formed based on diverging policy goals as well as differing ideas of the chain of cause and effect underlying the problem. Data analytics can be of valuable assistance in uncovering complex causal systems behind policy problems and thus support evidence-based policy formulation.

4.2.2.1 Example: Predicting the need for child welfare services in Espoo

The Finnish city of Espoo experiments with predictive analytics in their child welfare and psychiatry services.[27] Examining 520,000 cases across 14 years, the AI system identified 280 factors that influence the need for child welfare services. Efforts to develop this into an early warning system are underway.

4.2.3 DECISION-MAKING

Government eventually chooses whether and which of the competing formulated policies to implement. Data-driven government can support these decision processes with demoscopic insights and with simulations based on predictive analytics to estimate the impacts of the different policy options.

4.2.3.1 Example: OpenFisca simulation of taxes and social benefit

Based on the rules on taxes and social benefits, the originally French OpenFisca platform can be used to simulate the impact of changes to these rules on the government budget and citizens' standard of living. For example, the French Movement for a Basic Income used OpenFisca to assess the effects of the introduction

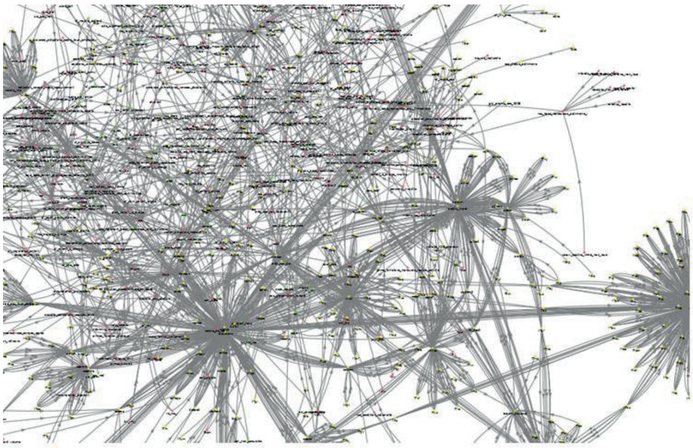
25 UN Global Pulse 2015b

26 UN Global Pulse 2014

27 AlgorithmWatch & Bertelsmann Stiftung 2019

of a basic income in France.[28] The Institut des politiques publiques has integrated OpenFisca in its microsimulation model of the French tax and benefit system which it uses for research and policy papers.[29]

FIGURE 6: GRAPH OF THE OVER 10,000 RULES ON TAXES AND SOCIAL BENEFITS IN FRANCE MODELLED IN THE OPENFISCA PLATFORM



4.2.4 IMPLEMENTATION

Usually, public administration is responsible for the implementation of new policies. Here, all possible functions of data-driven government can come into play: Data-driven monitoring, analysis, prediction and automated decision-making.

4.2.4.1 Example: Automation in the Finnish social insurance institution Kela

Kela, the Finnish government agency that handles most of the country's social benefits, has automated cross-checks and decisions on benefit applications, disbursing some 15 billion Euros.[30] To this end, the laws and regulations governing these benefits are translated into rule-based algorithms. Especially in the application phase, checking whether the information provided is sufficient, valid, and trustworthy speeds up the application process. However, the introduction of AI elements is planned for the next years.

28 Cauneau 2017

29 Mahdi et al. 2011

30 AlgorithmWatch & Bertelsmann Stiftung 2019

4.2.5 EVALUATION

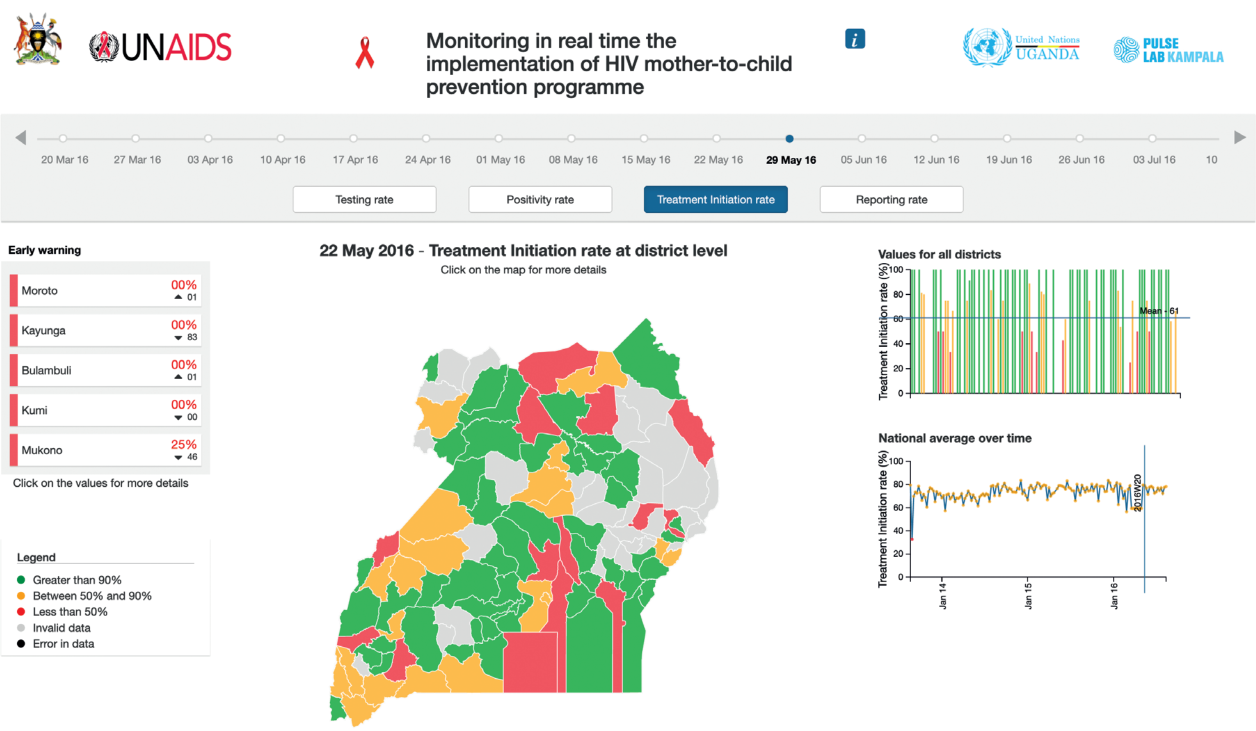
Optimally, every policy is evaluated after allowing for a sufficient time period for it to take effect. Not only do the enhanced data collection and analysis capabilities of data-driven technologies render policy evaluation much easier but policies can be evaluated and adjusted while they are implemented (see 3.3.4 Agile Government).[31]

4.2.5.1 Example: Real-time evaluation of a HIV prevention programme in Uganda

The UN Pulse Lab Kampala monitored and evaluated the rollout of a new prevention of mother-to-child HIV transmission programme to health centres across Uganda with data analytics.[32] Taking into account various data fields provided by the health centres, the analysis identified different factors effecting drop-out rates from the medication schedule, e.g. when centres are out of stock of the necessary medial supplies. Thus, crucial bottlenecks could be addressed already during the rollout.

FIGURE 7: DASHBOARD OF THE UGANDAN PREVENTION PROGRAMME

https://optionbplus.unglobalpulse.net//uganda/



4.3 Promises of data-driven government

Claims about the advantages of data-driven government typically fall into four categories: "faster, better, cheaper", holistic government, responsiveness, and agile government.

4.3.1 FASTER, BETTER, CHEAPER

Similar to most IT approaches in government, data-driven government is associated with efficiency gains.[33] Whether it is automated decisions-making for routine cases, the flagging of anomalous cases, optimised resource allocation, or preventive measures with predictive systems, all of these use cases promise to save time and money and increase service quality.

4.3.1.1 Example: ADM for social benefits in Trelleborg

The Swedish town of Trelleborg automatically issues social benefits with a system that cross-references incoming applications with related databases, e.g. tax data and social services and checks them for eligibility.[34] As a result, the number of case workers involved in the process was reduced from 11 to three.

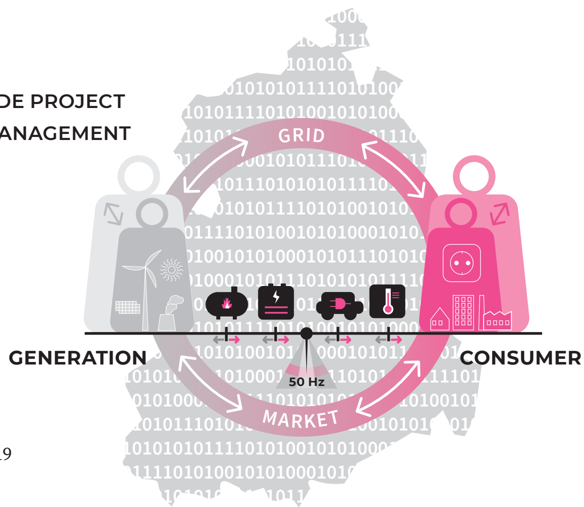
4.3.2 HOLISTIC GOVERNMENT

In this perspective, enhanced sensory system as well as analytics capabilities enable holistic government, i.e. anticipating complex interactions between social subsystems. How do new tax policies impact the policy field of education? What is the effect of altered traffic routing on economic growth? This perspective is particularly dominant in the Smart City discourse, e.g. linking urban and traffic planning with urban microclimates.[35]

4.3.2.1 Example: Smart management of energy production and consumption in north-eastern Germany

The German applied research project WindNODE uses data analytics to increase the overall efficiency of renewable energy production by managing energy consumption as well.[36] Weather forecasts to predict the electricity generation of solar panels and wind turbines are coordinated with flexible energy consumers such as production lines that can run at different times or commercial refrigerators that can be turned off for a few hours during times of low electricity production without significant temperature increases.

FIGURE 8: OVERVIEW OF THE WINDNODE PROJECT ON HOLISTIC ELECTRICITY MANAGEMENT
www.windnode.de



33 Mehr 2017
34 AlgorithmWatch & Bertelsmann Stiftung 2019
35 Manville et al. 2014
36 WindNODE 2018

4.3.3 RESPONSIVENESS

Data-driven government is regularly claimed to be more responsive to the needs and wishes of its citizens.[37] This typically refers to data on citizens' satisfaction with public services collected from social media or administrative process data. By monitoring and analysing these kinds of data, public administrations can address public complaints or adjust service delivery mechanisms with a low uptake.

4.3.3.1 Example: Analysing 311 calls in Houston

The US-American city of Houston runs data analytics on its 311 calls, the centralized hotline for non-emergency government services.[38] Such analytics provide an overview of issues bothering citizens, their hotspots and emerging trends. Further, responses to service calls can be coordinated more intelligently, e.g. sending the same truck to deal with a missed garbage pickup and a dead animal pickup in the same neighbourhood instead of two separate trucks (because different departments are involved). This not only increases efficiency of government services but also the responsiveness to citizen input.

4.3.4 AGILE GOVERNMENT

Does a policy measure reach the target group it was aimed at? Are incentives misdirected with unintended consequences? With dense and high frequency monitoring data on policy implementation, policy analysts can detect after a short time whether policy measures are on track or need to be readjusted. This enables "agile government"[39] modelled after agile software development,[40] with many iterations at short intervals – following the credo "Test early, test often" – evaluating and amending policies again and again.

This possibly entails a changed division of responsibilities between the political level of government and public administration. Agile government works best with clear policy goals and a set corridor of action, which would be the privilege of parliament and the political level of government, rather than enacting policy measures in detail. Within this corridor of action, public administration could then agilely look for the right configuration of policy measures to achieve the policy goals.

37 Goldsmith & Crawford 2014

38 Chatfield & Reddick 2017

39 Mergel, Gong & Bertot 2018

40 Beck et al. 2001

5 Challenges of data-driven government for liberal democracies

Data-driven government offers new possibilities for public administration to observe, regulate and intervene in society and individual citizens, often in unprecedented quality. As with any new technology, this poses the question: Which of these possibilities should we realize? Which should we limit?

These questions are crucial in the liberal democracies of Europe, with their emphasis on civil liberties, rule of law, citizen rights vis-à-vis the state, accountable and transparent government, and fair political discourse. Data-driven government is a powerful tool that can easily overturn carefully tended political equilibria and values if wielded imprudently.

The most salient of the challenges that data-driven government poses for liberal democracy are introduced here, touching especially questions of autonomy, accountability, and privacy. Further challenges are easily found in the countless publications by civil society organisations and researchers that critically examine data-driven government.

5.1 Data as supreme political argument

Data-driven government has the potential to create a skewed political playing field, as data-based evidence can be very convincing in political arguments but the resources to produce it are unevenly distributed.

5.1.1 THE SUPREMACY OF DATA-BASED EVIDENCE

Data-based evidence is particularly convincing in rational political debates, as it is culturally considered more valid than other types of knowledge.[41]

Since the age of enlightenment and the concurrent rise of scientific positivism, empirical evidence is regarded as the most substantial type of evidence. This applies even more to "calculative evidence",[42] i.e. empirical data refined with mathematical methods such as traditional statistics or artificial intelligence. In political debates, calculative evidence trumps other types of evidence, such as social evidence that is legitimised by a person's status or experiences or iconic-rhetoric evidence which gains weight from appeals to metaphors or well-known narratives.

Further, data-based political evidence resonates with the popular "rationalist model of politics",[43] which implicitly promises to supplant messy democratic deliberation with clean scientific decisions. Examples of the rationalist model in action were the

41 Van Dijck 2014

42 Rüb & Straßheim 2012

43 Wittrock 1991

planning euphoria of the 1960s, “management by numbers” as part of the New Public Management reform paradigm in the 1990s and 2000s as well as the ongoing interest in evidence-based policymaking.[44]

Thus, it is hard to counter a political position supported by data-based evidence with anything else than contrary data-based evidence in a rational discourse. However, sidestepping into irrationality and emotionalised rhetoric is a possible strategy, as the debates around climate policy or Brexit shown.

5.1.2 LIMITATIONS OF DATA-BASED EVIDENCE

While the new data technologies are able to collect impressive amounts of data and identify patterns within the data that are beyond the human brain, they are not infallible.[45] Even very large datasets can systematically underrepresent certain population groups, e.g. mobility data based on the movement of cell phones misses everyone without a cell phone.[46] The indicators selected for an analysis may cover only some aspects, and thus neglect important interests e.g. by focussing on efficiency and omitting social effects of a policy measure. Data quality is also an issue, as data is often gathered with a different purpose in mind than the analysis it is reused for. Thus, data-based evidence has to be critically assessed before it can be confidently used for decision-making.

5.1.3 DATA-BASED EVIDENCE IS HARD TO DENY

The new data technologies provide “evidence” that is hard to deny politically.

The core promise of data-driven government is to collect data at a density that is not feasibly for humans and to identify patterns within that data that humans cannot grasp. Hence, the results cannot be easily questioned as the analysis is hardly scrutable for humans. Paradoxically, this inscrutability adds to their power to convince.

The resources to produce equal data-based counter-evidence are unevenly distributed.[47] The data and algorithms necessary to critically assess the existing analysis and to generate counter-expertise may be openly available but often are not. Data may be exclusive to government and specific analyses only possible with expensive proprietary analytics software. Therefore, political arguments based on data analytics are likely to favour actors with more skills and resources, e.g. government or corporations rather than grassroots initiatives and NGOs.

5.1.4 ASSESSMENT FROM A LIBERAL PERSPECTIVE

Grounding policy in rational, empirical analysis is a traditional liberal value. Therefore, the enhanced possibilities for evidence-based policymaking with data analytics can generally welcomed. However, collective data should complement rather than drown out the voices of individuals. Further, for the sake of pluralism and a level political playing, data and algorithms have to be openly available to all citizens and interest groups.

44 Nowotny, Scott & Gibbons 2004

45 Boyd & Crawford 2012

46 Lerman 2013; Easton-Calabria & Allen 2015

47 Danaher 2016

5.2 Incapacitated humans in the loop

Keeping humans in the loop is a popular configuration to generate trust in ADM. However, these humans need to be empowered if they are to do more than just blindly confirm algorithmic recommendations.

5.2.1 HARD-TO-CONTRADICT ALGORITHMIC RECOMMENDATIONS

Data analytics and ADM systems are often implemented as decision support, providing assessments and recommendations to a human official who has the final say. Such human-in-the-loop solutions mollify worries about algorithmic errors and misassessments. However, it is a point of contention whether government employees actually dare to deviate from the algorithmic recommendation. In the case of the Polish algorithmic classification system for unemployed, official data show that the human case worker changed the algorithmic classification in less than one percent of the cases.[48]

In the risk-averse environment of public administration, the incentive structures are clear: If case workers follow the algorithmic recommendations and they turn out to be wrong, they can shift the blame to the ADM system. After all, how can humans be expected to notice what even an advanced computer system missed, unless it is blatantly obvious. However, if case workers deviate from the algorithmic recommendation and the decision is successfully challenged, the blame stays with them. Therefore, contradicting algorithmic recommendations is a hard decision.

A similar rationale applies to the struggle between data-based and policy recommendation and insights from the experience of seasoned government specialists.

5.2.2 EMPOWERING HUMANS

For humans in the loop to function as promised, they need to be empowered through qualification and a change in administrative culture.

To confidently assess the results of ADM systems and data analytics, the involved employees need basic data literacy, i.e. an understanding of underlying decision rules, statistical models and data.[49] Thus, they can complement their suspicion of an incorrect algorithmic recommendation based on their assessment of the case with a theory of why the algorithm might have failed here, e.g. due to the shaky quality of some data fields or signals in the case that could mislead the algorithm.

Further, a common understanding of the role of the human in the loop and a change in the allocation of blame is necessary in public administration. It is the job of the human in an algorithmic loop to second-guess, to question and to be sand in the gears. It is an important function of quality control and, if done properly, crucial to building trust in ADM systems and data analytics in government. Therefore, when humans in the loop slow down a process, it might reduce the promised time and efficiency gains through automation, but it is an integral part of the system.

48 AlgorithmWatch & Bertelsmann Stiftung 2019

49 Schield 2004

5.2.3 ASSESSMENT FROM A LIBERAL PERSPECTIVE

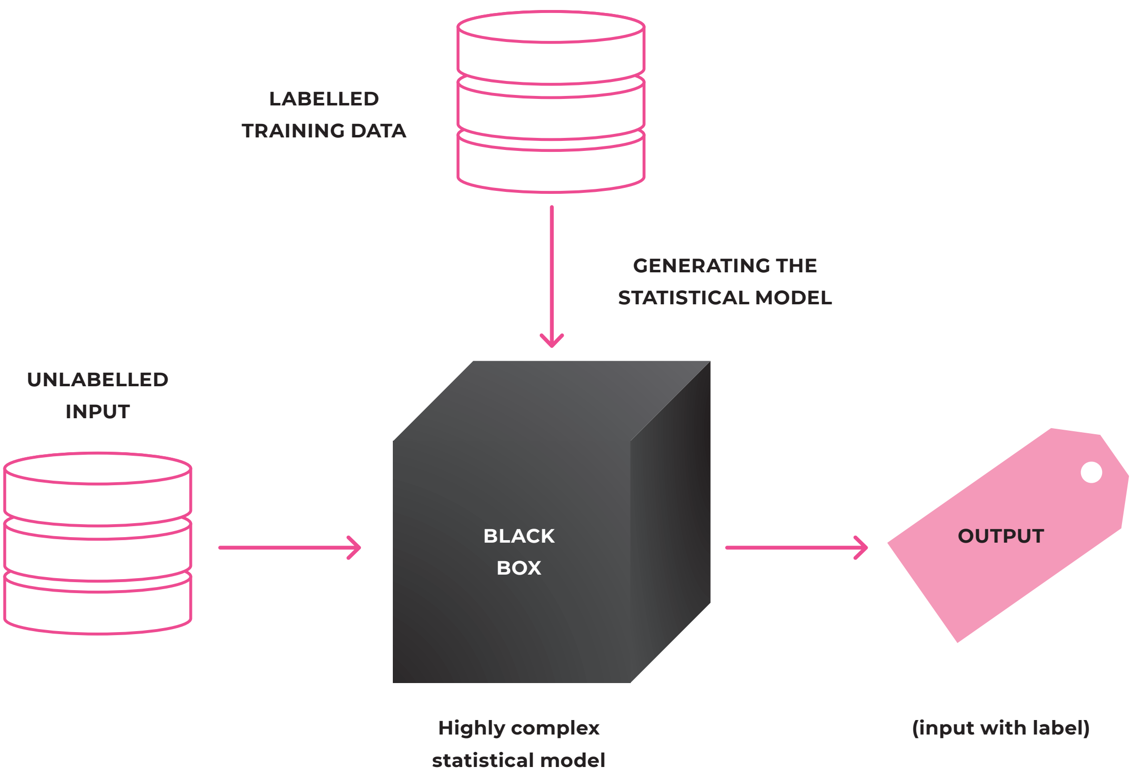
From a liberal perspective, human-in-the-loop configurations for data analytics and ADM systems are in most cases the preferred solution, especially in pilot projects, as they ensure a clear chain of responsibility and accountability for each citizen's case. However, if the humans in the loop are to be more than just tokens that blindly confirm algorithmic recommendations, they have to be empowered to act as true watchdogs.

5.3 Biased decisions from the Black Box

AI decisions can be opaque and reproduce biases present in the training data. However, data-driven decisions that directly affect citizens have to be transparent and/or accountable.

5.3.1 BLACK BOX AI

The statistical models produced by artificial intelligence (especially neural networks) are often so complex that they cannot be understood by humans.[50] Even written down, they are hardly intelligible due to the number of factors and their sophisticated mathematical relationships. Such systems are called "Black Boxes", as they will – once sufficiently trained – compute good predictions but what happens between input and output remains inscrutable to the user.



50 Bayamlıoğlu & Leenes 2018

5.3.2 BIASED AI

Artificial intelligence of the machine learning kind, which we today mostly refer to, is trained with existing data. Thus, looking at the attributes of each case it is provided with and the "decision" this has been labelled with, e.g. "cat" or "dog", "building permit granted" or "building permit denied", the algorithm optimizes a statistical model that is able to predict the "decision" from the case attributes. Therefore, any biases inherent to the training data become part of the statistical model and can reproduce social discrimination.[51]

5.3.2.1 Example: Predicting juvenile recidivism in Catalonia with humanity vs. machine intelligence

A research project in Catalonia compares the predictive power and fairness of a human-based expert assessment tool with machine learning to predict recidivism of juvenile offenders. The ML algorithm is trained based on some 5000 real life juvenile cases and then applied to about 900 cases for which predictions with the expert assessment tool were made. While the ML system slightly outperforms expert assessment in terms of predictive power, the researchers find that the "ML models tend to discriminate against male defendants, foreigners, or people of specific national groups. For instance, foreigners who did not recidivate are almost twice as likely to be wrongly classified as high risk by ML models than Spanish nationals."[52]

5.3.3 ALGORITHMIC ACCOUNTABILITY

Black Boxes and the possibility of biased AIs pose a problem of accountability.[53] If the algorithmic system produces a misprediction in a situation where it is used to support or make decisions, who is to blame? How can citizens assess whether they were treated fairly or if there is an inherent bias in the statistical model? How can a court rule on the lawfulness of an algorithm it does not understand?

For rule-based algorithms and simple AI-generated statistical models, algorithmic accountability can be ensured with transparency, i.e. publishing the decision models. However, enabling the accountability of highly complex algorithms has become an urgent socio-technical challenge, with algorithmic accountability flourishing as a field of research and expert debate.[54] [cite Special Issue on The Governance of Algorithms Philosophy & Technology] For example, the European Parliament Research Service published the 100-page report "A governance framework for algorithmic accountability and transparency" in April 2019. [See chapter 6]

5.3.4 ASSESSMENT FROM A LIBERAL PERSPECTIVE

Equal rights and equal treatment of all citizens are fundamental liberal values. At first glance, decision making by algorithms seem like a superior way to ensure equal treatment compared to humans.[55] However, AI-derived decision models can inadvertedly reproduce biases and result in discrimination. Thus, mechanisms of algorithmic accountability are needed to ensure equal treatment despite the Black Box. Further, for citizens to see eye to eye with the state, they have to be able to understand why public administration treats them in a certain way, e.g. if they are fined for a petty

51 Myers-West, Whittaker & Crawford 2019; Australian Human Rights Commission & World Economic Forum 2019

52 Tolan et al. 2019

53 Ananny & Crawford 2018

54 Donovan et al. 2018; Busch 2018

55 This holds true for rule-based algorithms.

offence or denied a permit. This principle is an important aspect of the rule of law. Additionally, rules that are hidden in a Black Box are not open to political discussion. Thus, in a liberal democracy, algorithmic decision affecting citizens in crucial ways have to be transparent or at least accountable in some way.

5.4 Panoptic monitoring

Surveillance can be an unintended side effect of efforts to improve public services with data. Data-driven government can become the infrastructure for a police state.

5.4.1 MONITORING FOR BETTER SERVICES

To apply data-driven government to all areas of life, society and environment would have to be pervasively monitored to produce the necessary dense data. This includes electronic communication, process data from public and private services and networked sensors. For example, the optimization of public transportation would benefit from granular data on passengers' daily travel routes.[56] CCTV observation of pedestrian movements can help to design better public spaces. Big-Data-based early warning systems in European social and youth services link data from education, law enforcement and health services to intervene before citizens spiral downwards.[57]

5.4.2 ACCIDENTAL BIG BROTHER

The quest for data-driven service improvement can inadvertedly enable structures for individual surveillance. Even anonymized granular data can often be deanonymized by meshing the with other datasets. For example, public transportation passenger data can be matched with residence, work place, gym, and children's kindergarten to identify individuals with a sufficient degree of certainty. CCTV recordings can be subject to facial and motion recognition to track individuals.

5.4.3 BUILDING THE INFRASTRUCTURE FOR A SURVEILLANCE SOCIETY

Security is an especially tempting field to apply technologies of data-driven government. The continuous observation of public spaces, convenient data collection on individuals and powerfully analytics to find suspicious patterns promise significant improvement in law enforcement and crime prevention. Concerns about the potential misuse of such systems are usually soothed with legal restrictions to their use and the democratic and constitutional values of the involved agencies. Nonetheless, implementing data-driven security systems means building the infrastructure for a surveillance society.

56 Economist Intelligence Unit 2017

57 Department for Communities and Local Government 2017

5.4.4 ASSESSMENT FROM A LIBERAL PERSPECTIVE

Championing the use of new technologies to improve public service quality and efficiency is a characteristic of progressive liberalism. However, data-driven government has to be limited when it starts to infringe citizens' liberty and privacy. Beyond the adherence to codified privacy regulations, this also entails the deliberate preservation and respect for spaces where citizens are free of government surveillance. Such spaces are not only important for the perceived freedom of citizens but are also safe areas where dissent to government can form. If a less pluralistically-minded government comes into power, existing data-driven security systems place a powerful surveillance system at its convenient disposal. Thus, a little potential improvement in public service quality and security may have to be sacrificed to avoid building the infrastructure for a surveillance society.

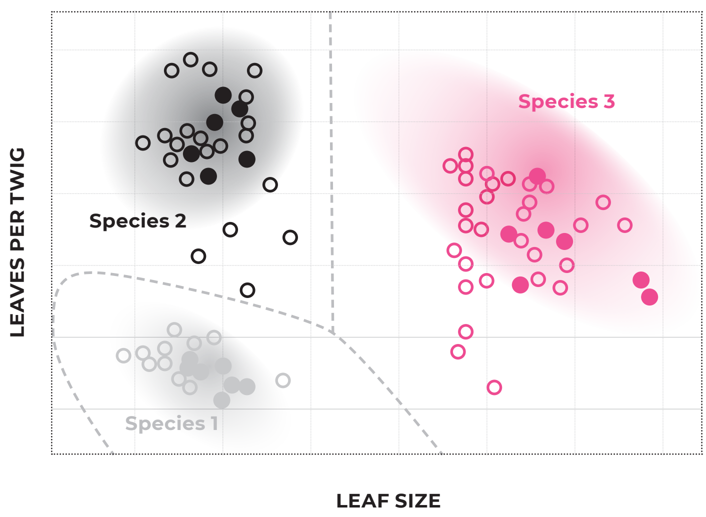
5.5 Social sorting and probabilistic regulation

Data analytics cluster citizens with similar characteristics and infer probable behaviour from this sorting. If applied thoughtlessly, this can lead to collective punishment and negate free will.

5.5.1 SOCIAL SORTING

Big Data Analytics segments datasets into clusters of similar attributes and outcomes. When dealing with citizens, people are thus grouped according to attributes such as socio-demographic characteristics. In other words: Citizens are socially sorted.

TABELLE 3: SORTING TREE SPECIES WITH MACHINE LEARNING



5.5.2 PROBABILISTIC REGULATION

Big Data Analytics and Machine Learning rely on statistical models that estimate the similarity of input cases to known cases. For example, the trained statistical model calculates a probability for people with a certain set of attributes to qualify for a social benefit. A newly input case is then assessed to resemble these people to a certain degree. The algorithm's "decision" in this case is consequently a product of both probabilities. Data-driven government is therefore regulation based on probabilities.

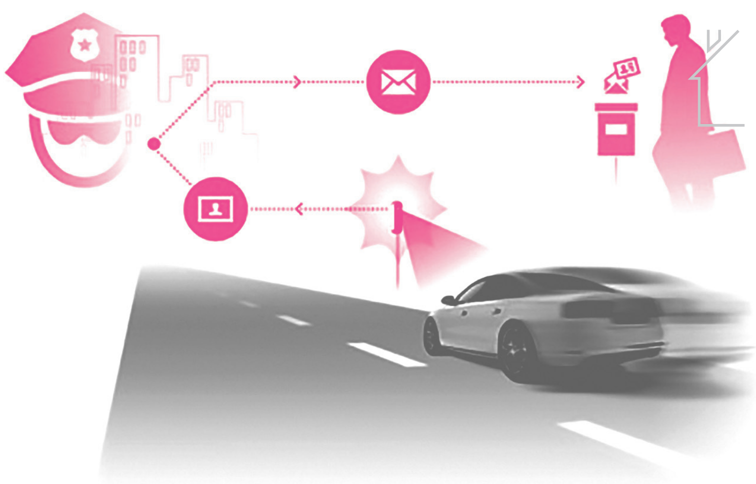
5.5.3 ASSESSMENT FROM A LIBERAL PERSPECTIVE

All statistical insights rely on probabilities, and if they regard people, social sorting. In a liberal democracy, social sorting and probabilistic regulation can become challenges if decision making is based on such insights without questioning them thoroughly. Akin to collective punishment, individual citizens gain advantages or disadvantages not on their own merit but based on their similarity to others, negating their individuality. On a more fundamental note, this also denies the free will of citizens, as it assumes that everyone who is alike behaves alike.

5.6 Automated "perfect enforcement"

5.6.1 FROM MONITORING TO PERFECT ENFORCEMENT

The close-knit monitoring networks of data-driven government enable an automated enforcement of rules in many contexts. Networked cars could me mandated to report their speeding drivers. CCTV cameras could automatically fine everyone who steps onto the lawn. Essentially, the "upload filters" to recognise and block copyright infringements discussed in the context of the 2018 EU Copyright Directive also constitute a form of automated enforcement.[58] As monitoring capabilities and pattern recognition improve, more and more transgressions could be automatically prosecuted as soon as they occur.[59]



58 International Federation of Library Associations and Institutions 2018

59 Yeung 2016

5.6.2 ASSESSMENT FROM A LIBERAL PERSPECTIVE

At first glance, perfect enforcement appears to be a good way to ensure equal treatment of citizens, as the detection of transgressions is no longer subject to random effects and biases, e.g. certain demographic groups being systematically checked more often for certain offences.

However, in a liberal democracy, citizens adhere voluntarily to laws because they consider them sensible and just, or at least respect the process through which they were passed. A society where citizens obey laws only because they are afraid of punishment is by definition authoritarian. Automated enforcement voids citizens' freedom to cooperate voluntarily, turning them into subjects who are forced into rule adherence. Thus, perfect enforcement should be employed judiciously in cases of very unfairly distributed law enforcement or temporarily to re-establish respect for rules and regulations, e.g. traffic violations. "It invites regulatory intervention that disrupts a wise equilibrium that depends upon regulators acting with a light touch, as they traditionally have done within liberal societies."[60]

5.7 The personalized state

Personalized government services can increase citizen satisfaction if trust in government is upheld but tread a fine line to becoming creepy in citizens' perception.

5.7.1 PERSONALIZED GOVERNMENT SERVICES

Data-driven government can be highly personalized. Public administration can pool information it already has and – if permitted – draw on external data sources to proactively provide services to citizens and companies. As a step in this direction, the Once Only Principle, which states that citizens should have to provide any information to government only once, is currently being implemented as a European standard across the EU.[61] Thus, government can pre-fill forms or check whether citizens or businesses qualify for certain services autonomously. Pre-filled tax declarations are implemented in varying degrees in many EU member states.[62] The Austrian "application-free" child benefit is an example for a proactive public service, as it is triggered by the child's birth and dispensed automatically if all necessary information is available.[63]

5.7.2 ASSESSMENT FROM A LIBERAL PERSPECTIVE

Personalized public services are an effective way to reduce the directly perceived administrative burden, resonating with the liberal ideal of a lean state. However, the perception of personalized services can easily turn from comfortable to invasive unless clear boundaries are respected. Central to this is trust in government, as personalized services make it evident how much data government holds on each

60 Zittrain 2008

61 Commission 2017

62 Brookes 2018

63 Waldecker 2018

citizen and also means relinquishing control, e.g. checking whether one has the right to certain public benefits. To preserve this trust, personalisation should be used for service provision rather than disciplinary measures. [Also see "perfect enforcement"]

5.8 Design-based regulation, nudging and governmentality

Design-based regulation, nudging and governmentality seem like elegant regulatory instruments and can be amplified by data-driven government. However, they can subvert citizen's freedom of will.

5.8.1 DESIGN-BASED REGULATION

Design-based regulation controls by limiting behavioural options. For examples, turnstiles that only turn one way effectively limit the alternatives for action to going through the turnstile or not. Unlike other forms of regulation that work as social rules, where citizens can freely choose their course of action if they accept the incentives or punishments that may be the consequences, design-based regulation eliminates such freedom of action. (Or at least significantly increases the effort for deviated from the offered options.) Design-based regulation is particularly easy to implement in digital and cyberphysical systems: Digital forms can be dynamically generated, including or excluding certain options in applications for services or permits. Cars could only unlock if presented with a valid driver's license, and shut down if sufficient signs of intoxication are detected from breath, blinking and steering patterns. Algorithms are an instrument well-suited to design-based regulation.[64]

5.8.2 NUDGING

Nudging is a more subtle variation of design-based regulation. Citizens are gently pushed in the preferred direction, e.g. by presenting options in a specific order. Options can also be framed with certain messages, such as emphasizing existing social norms. Indirect social pressure with messages like "95 percent of citizens in your neighbourhood pay their taxes on time" are also known to work well.[65] Setting default options in case of inaction is a successful nudging strategy that highlights its close relation to design-based regulation.

The tools of data-driven government allow to finely calibrate and possibly even personalize nudging strategies with the help of Big Data and Artificial Intelligence.

5.8.3 NEOLIBERAL GOVERNMENTALITY

In a nutshell, Foucault's concept of "neoliberal governmentality" refers to self-government in the sense of the internalisation of regulation.[66] Rather than as a response to explicit discipline and punishment, citizens display governmentally or socially desired behaviour by forcing themselves to adhere to internalized social norms, which can be reinforced by nudging. The quantification of citizens' behaviour, the possibility to compare with others and the knowledge of being measured, even if not actively observed, influences how they act. An everyday example for this is the use

64 Yeung 2018

65 Intra-European Organisation of Tax Administrations 2019

66 Bröckling, Krasmann & Lemke 2011

of fitness trackers. Data-driven government can become a powerful enabler amplifier of governmentality, depending on how it is designed.

5.8.4 ASSESSMENT FROM A LIBERAL PERSPECTIVE

At a first glance, design-based regulation, nudging, and governmentality seem to be policy instruments well-suited to a liberal government. They avoid disciplinary measures and citizens are in principle free to choose – with nudging more so than with design-based regulation. However, targeting citizens' subconsciousness can also be considered especially detrimental to freedom – more so than overt regulation with incentives and punishment – as it subtly undermines their free will.
Therefore, design-based regulation, nudging should be applied with care, preferably only in petty cases, such as nudging towards earlier tax payments, or where other instruments have failed to instigate behaviour beneficial to the common good, e.g. opt-in or opt-out mechanisms for organ donation. Governmentality is something to be aware of when designing data-driven policy instruments, as it subtly subverts individual freedom of will.

6 Regulatory Framework

Data-driven government offers many opportunities for smarter, more efficient and more responsive government. However, it also holds possible challenges for free societies. To reap the benefits while avoiding the challenges, a proper regulatory framework for data-driven government is needed. Unfortunately, there is no readymade recipe. However, there are different building blocks of such a framework in the discussion. These are regulations requiring explainable algorithmic decisions, ways to design a right to appeal against algorithmic decisions, deliberate limiting of data-driven government and oversight mechanisms.

This is a cursory overview, more detailed discussions on the governance of AI and similar technologies in government fill many pages.[67]

6.1 Explainable AI – Opening the Black Box

It is easy to agree that citizens should have a right to inspect and understand the algorithms that are used in governing them.[68] In fact, the EU's General Data Protection Regulation contains an, albeit legally disputed, "right to explanation" about algorithmic decisions for citizens.[69]

A harder question is how to achieve this transparency. Rule-based algorithms can usually be rendered comprehensible to humans when visualised as decision trees or something similar, even if these visualisations become very extensive for complex algorithms. For machine-generated algorithms, i.e. Artificial Intelligence, this is a technical challenge due to their immense complexity and dynamism. In simpler cases, experts could critically examine the algorithm if the training data and the applied statistical models are published. In many cases, even this is insufficient. So which strategies are in discussion to open the black box for Artificial Intelligence?

6.1.1 HIGHLIGHTING DECIDING FACTORS

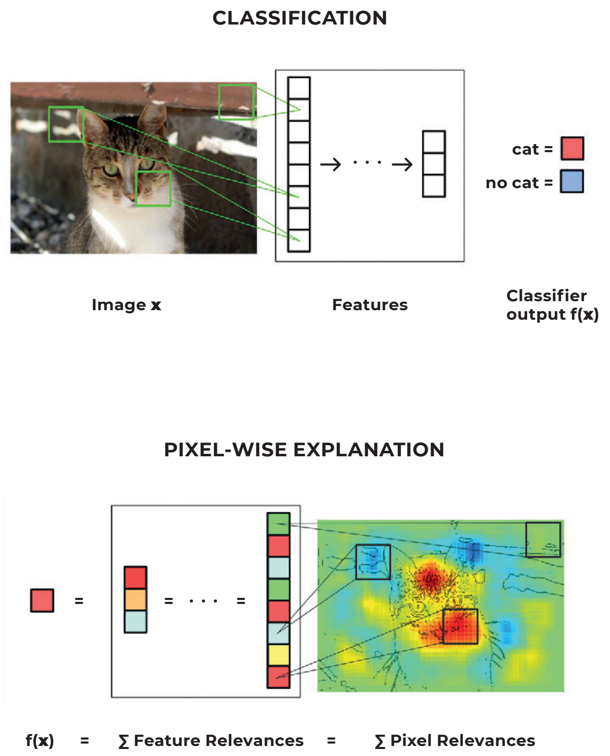
One school of approaches tries to single out the characteristics of a case which factored highest in its categorization. This is most obvious for image recognition algorithms, where the parts of the image that tipped the categorization are highlighted, e.g. with heat maps. While this approach is very intuitive and makes it easy to spot wrong classifications, it does not enable a thorough understanding and examination of the algorithm. Thus, it is currently only useful in specific cases.

67 Daly et al. 2019; AlgorithmWatch 2019; Kritikos 2019; European Parliamentary Research Service 2019

68 Brauneis & Goodman 2017

69 Wachter, Mittelstadt & Floridi 2017

FIGURE 9: EXAMPLE FOR THE HIGHLIGHTING OF CRITICAL FACTORS FOR THE DECISION TO CATEGORIZE THE IMAGE AS „CAT" [70]



6.1.2 COUNTERFACTUAL EXPLANATIONS

Counterfactual approaches try to explain algorithmic decisions by highlighting which parameters of a case would have to be altered to produce a different outcome.[71] For example, the automated denial of a building permit would be accompanied by a counterfactual explanation, which states that building permit would have been issued if the height of the roof was one meter lower and the façade designed more similarly to the neighbouring houses.

Counterfactual approaches are useful because they do not require any knowledge of algorithms and provide actionable insight on what to change to alter the outcome.

70 Bach et al. 2015

71 Wachter, Mittelstadt & Russell 2018

6.2 Right to appeal

If citizens feel unfairly treated by an algorithmic decision or as the result of a data-driven policy, they should have a right to appeal – as they should have against any decision by public administration they doubt. How can such a right to appeal against algorithmic decisions be realized beyond the traditional courts of appeal?

6.2.1 ALGORITHMIC COURT

Many ideas for a right to appeal against algorithmic decisions point towards an "algorithmic court", a court of justice or agency that specialises in examining algorithms and their results, as regular courts lack the necessary expertise. In such an institution, computer scientists, mathematicians and statisticians would assist lawyers in scrutinizing ADM systems against which complaints were raised.

6.2.2 ADM AS ZEROTH INSTANCE

Specifically for algorithmic decision-making in public administration, it has been suggested to treat such systems as a "zeroth instance". Thus, if citizens have doubts about a decision, they can escalate their case to a civil servant, who will re-examine it. Even if all citizens with negative algorithmic responses choose to escalate their cases, those who are satisfied with their initial responses still experience a time gain and lessen the workload for government employees.

In many European countries, e.g. France,[72] traffic offences such as speeding are handled fully automatedly, from capturing the transgression with networked sensors to registering the receipt of the fine. Only if citizens deny the accusations will a human official handle the case.

6.3 Limiting data-driven government

In a liberal society, data-driven government has to be limited with regards to what data it can use and what purposes it can pursue to preserve a balance of power between government and citizens.[73] Thus, a core question for the regulation of data-driven government is whether to render certain practices off-limits for government?

6.3.1 THE PROBLEM OF ANONYMISATION

Data-driven government has to be limited when it comes to personally identifying information in data sets, which could be used to reconstruct intimate details about a person's life. Here, anonymisation is an obvious recommendation. However, the capabilities of the new data technologies, e.g. through correlation attacks via linked data, make deanonymisation easy with just a few data fields. So, beyond a person's name, more and more data fields would have to be eliminated from the data set to guarantee anonymity, which at the same time renders the data set increasingly useless for meaningful analyses.

72 AlgorithmWatch & Bertelsmann Stiftung 2019

73 Goldzweig 2018

Beyond eliminating data fields, there are different anonymisation techniques, which the Personal Data Protection Commission of Singapore has evaluated in a very accessible report.[74] Effectively, a degree of granularity in the data has to be sacrificed to avoid identifiability of individual citizens. For example, a person's address would be generalized from the precise street and house to the town or precise age information would be generalized to age spans, e.g. 30–39 instead of 33.

Of course, what degree of generalisation is sufficient to ensure anonymity and how sensible the information has to be assessed for each dataset.

6.3.2 ETHICS GUIDELINES

The last years have seen a wave of ethics guidelines on AI and ADM in general and their use in government in particular.[75] These guidelines – or rather their production – drive an important debate about the risks and opportunities of these new technologies and what kinds of uses we as a society consider legitimate or reckless. Highlighting principles such as fairness or explicability again and again not only pushes the research agenda but also brings forward diverse policy options.

However, while ethics guidelines are important and can provide useful orientation, they cannot replace proper legal regulation. Ethics guidelines are not binding, do not entail sanctions and cannot be claimed. Particularly in the unequal relationship between government and citizens, codified rights and obligations to keep a data-driven government in check. Thus, ethics guidelines should be seen as steps towards regulation by law, not as a sufficient substitute.

TABELLE 4: PRINCIPLES FOR ACCOUNTABLE ALGORITHMS AND A SOCIAL IMPACT STATEMENT FOR ALGORITHMS BY FAT/ML[76]

RESPONSIBILITY

Make available externally visible avenues of redress for adverse individual or societal effects of an algorithmic decision system, and designate an internal role for the person who is responsible for the timely remedy of such issues.

EXPLAINABILITY

Ensure that algorithmic decisions as well as any data driving those decisions can be explained to end-users and other stakeholders in non-technical terms.

ACCURACY

Identify, log, and articulate sources of error and uncertainty throughout the algorithm and its data sources so that expected and worst-case implications can be understood and inform mitigation procedures.

AUDITABILITY

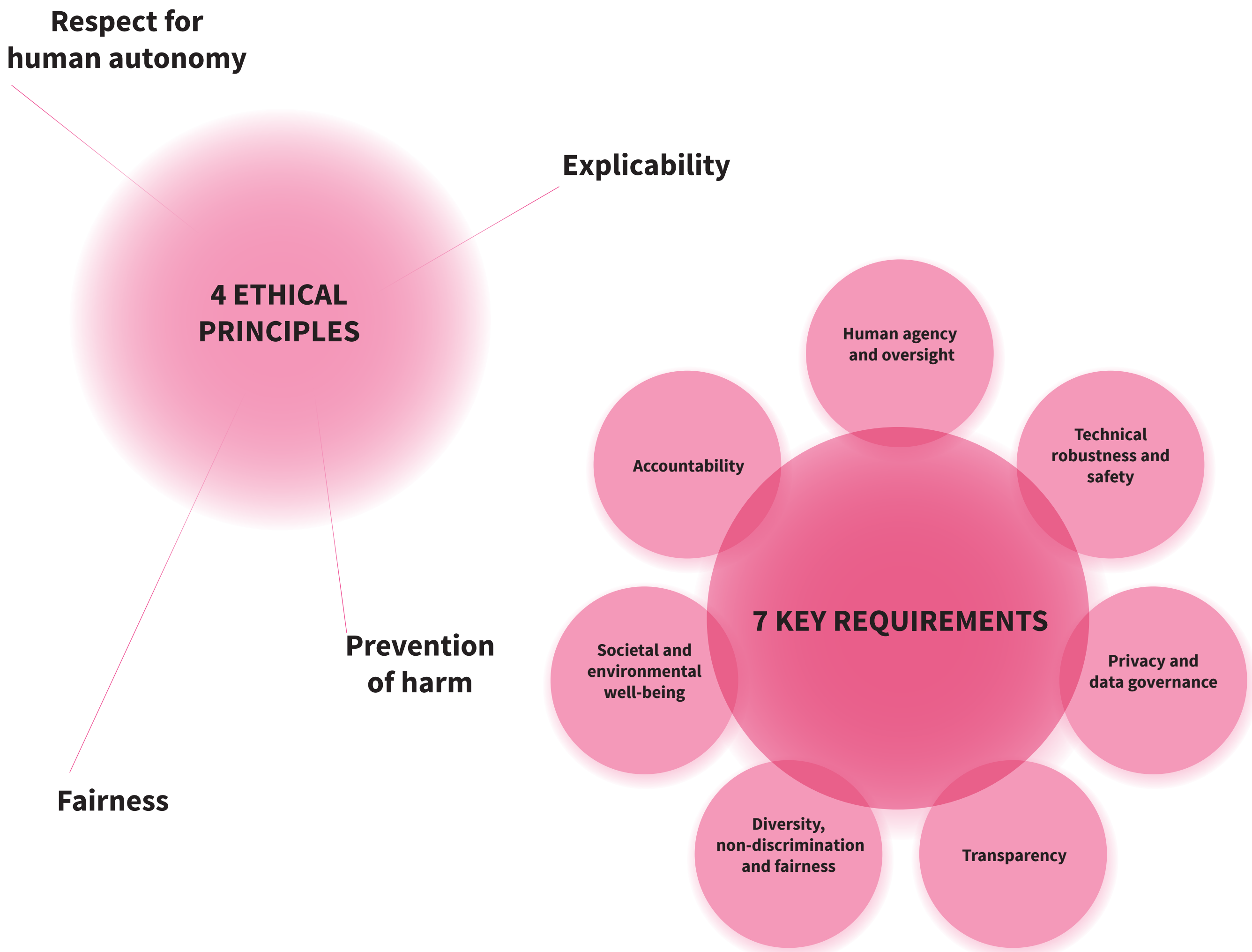
Enable interested third parties to probe, understand, and review the behaviour of the algorithm through disclosure of information that enables monitoring, checking, or criticism, including through provision of detailed documentation, technically suitable APIs, and permissive terms of use.

FAIRNESS

Ensure that algorithmic decisions do not create discriminatory or unjust impacts when comparing across different demographics (e.g. race, sex, etc).

74 Personal Data Protection Commission Singapore 2018
75 AlgorithmWatch 2019
76 FAT/ML 2018

FIGURE 10: KEY ELEMENTS OF THE ETHICS GUIDELINES FOR TRUSTWORTHY AI BY THE EU'S INDEPENDENT HIGH-LEVEL EXPERT GROUP ON ARTIFICIAL INTELLIGENCE[77]



6.3.3 REGULATORY SANDBOXES

In regulatory sandboxes, certain extant regulations are suspended or relaxed to test out innovative approaches for a limited area and time,[78] to answer questions such as: Which predicted risks did materialize? What unexpected effects did occur? How did benefits and problems balance? In Europe, regulatory sandboxes are predominantly used to evaluate innovations in financial and insurance services and autonomous driving. Experiences from regulatory sandboxes are then used to draft empirically-grounded rather than worry-driven regulation. This approach seems sensible for many sensitive areas of data-driven government, such as algorithmic decision-making or predictive analytics that directly affects citizens. Trying such technologies in a controlled environment while intensely examining the effects enables an informed public debate on their regulation.

77 European Commission 2019

78 UK Financial Conduct Authority 2015

79 Mulgan 2016; Tutt 2017

6.4 Oversight mechanisms

How to organise the institutions for the oversight of AI and ADM is a key question in the debate on the regulation of data-driven government. Given the complex nature of the technologies in question and their enormous potential harmful impact, it is argued that they cannot been overseen by the general public, but specialized institutions are necessary to control for algorithmic quality.

The three most distinct ideas in this discussion are all inspired by existing oversight arrangements: The certification approach draws on the mechanisms for the approval of new food and drug products. Ideas along the lines of in-house algorithm officers are inspired by similar roles in data protection. Finally, suggestions based on professional ethics borrow from the medical professions' self-regulation. These approaches are not exclusive and could be combined in practice.

6.4.1 CERTIFICATION APPROACH

The certification approach suggests that critical algorithms should be audited and approved by some kind of certification authority before deployment.[79] To this end, the authority would examine the algorithm or statistical model as far as it is intelligible for humans and run it with different datasets to assess its performance in action, especially with regards to biases and robustness to low data quality. There is also a number of tools and algorithms in development to computer-assist bias detection and other possible problems of Machine Learning systems.[80]

6.4.2 IN-HOUSE OFFICERS

In-house algorithm officers are independent watchdogs or ombudspeople within an organisation whose task is to ensure compliance of algorithms to ethical and legal standards.[81] Similar to today's data protection officers,[82] such officers would have to be called in for every complex algorithmic decision system developed or deployed by the organisation and provide advice and supervision. In fact, data protection officers are today often consulted on AI and Big Data projects of their organisation. However, proper algorithm officers would have their own specialised guidelines, training, and national support structures.

6.4.3 PROFESSIONAL ETHICS

Approaches based on professional ethics take inspiration from physicians' Hippocratic oaths and suggest self- and peer-regulation of those involved in training and programming algorithms.[83] Such ethics usually rely on a professional group identity the need for recognition by professional peers. While these ethics are usually not legally binding, they are socially enforced through the promise of acceptance and the threat of exclusion from the group. Thus, they less useful as sanctioning mechanism and better suited to institutionalise desired behaviour. The power of this approach therefore lies in embedding fundamental ethics guidelines in the professional identity, e.g. "Proper algorithmists always check for unfair biases in their algorithms and training data."

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80 Kleinman 2018

81 IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems 2019

82 Korff & Georges 2019

83 Simonite 2018; Filipović, Koska & Paganini 2018

7 Summary & policy recommendations

Data-driven government is a highly dynamic field, driven by advances in technology as well as innovative use cases. Most applications are still in a pilot stage, so there is scarce experience with the effects on government and society. However, the fundamental advantages and challenges of data-driven government can already be recognised and, based on the current evaluations and debates, general policy recommendations can be given.

7.1 Advantages of data-driven government

In a nutshell, data-driven government is able to observe its citizens and physical environment with unprecedented data density and analyse these observations. Specifically, the data sourced from administrative sources, third parties and networked sensors can be used for enhanced monitoring, analysis of social and environmental phenomena, prediction, and automated decisions.

These new capabilities are useful at all stages of the policy cycle and are said to improve efficiency, speed and quality of government services and policy implementation. Further, they enable a more holistic government that anticipates the complex interactions of social sub-systems and policy fields. The sharpened senses of government also enable more responsiveness to citizen input and satisfaction. Combined this could power an "agile government" that finetunes policies while they are implemented through iterations of trial-and-improvement.

7.2 Challenges of data-driven government

Data-driven government comes with a few disclaimers, as the lively debates around algorithms and data analytics in governments show. From a liberal perspective, autonomy, accountability, and privacy are the main concerns. If citizens are nudged, urged to confirm algorithmic recommendations, treated solely on statistical kinship, or automatically disciplined for every little transgression, their autonomy and free will stand to question. If administrative decisions are made in a Black Box and political arguments are supported by the results inscrutable data analytics, transparency and accountability are in danger. If government builds an encompassing surveillance system in the name of public service improvement and uses personalized government services for disciplinary measures, privacy – and in turn shelters for dissent – are at risk.

7.3 Policy recommendations

In light of the probable advantages and challenges of data-driven government, what are recommendations to liberal policymakers?

7.3.1 TREAT DATA-DRIVEN GOVERNMENT AS A POLITICAL QUESTION

Due to the technological solutions involved in data-driven government, it is tempting to dismiss this as a matter for computer scientists and engineers. However, as this study has shown, underneath the questions of technical implementation are deeply political questions about fairness, liberty, and accountability. Expose these questions and pull them into the political debate.

7.3.2 PRIORITIZE TRUST BUILDING

Public opinion about the new data technologies are ambivalent, given their potential for raising convenience and surveillance of public administration. Therefore, data-driven government needs citizens' trust to succeed. Thus, measures that build trust should be prioritized, e.g. data-driven approaches for government services rather than disciplinary purposes, transparency about the data and algorithms involved in ADM, and collaboration with critics.

7.3.3 BUILD REGULATORY SAND BOXES

There is not blueprint for how to regulate data-driven government to reap its benefits while avoiding all pitfalls yet. However, neither outright bans on AI in government nor total deregulation will serve this goal. Rather, regulatory sand boxes should be fostered, where applications of data-driven government can be tested – even those that contravene current rules – in a controlled environment. A key feature is the accompanying research and evaluation of these sand boxes to derive lessons learnt for the overall regulation of data-driven government.

7.3.4 SET OVERSIGHT MECHANISMS FOR EVERY INSTANCE OF DATA-DRIVEN GOVERNMENT

Although opinions about the right oversight mechanism for data-driven government are divided, every application of data-driven government should be overseen. This especially applies to ADM and data analytics that directly affect citizens and where biased or misdirected algorithms can cause substantial harm. Further, experience with different oversight solutions in action will provide insights of what works where.

7.3.5 DEMAND ACCOUNTABLE AND EXPLAINABLE DATA-DRIVEN GOVERNMENT

Citizens have to be able to understand how and why government makes decisions to hold it accountable. This also holds for ADM and AI, even if it is realized with incomplete and technically unsatisfying solutions. As algorithmic accountability becomes the norm, better solutions will be developed.

7.3.6 FOSTER ALGORITHMIC LITERACY

Sovereign citizens as well as responsible civil servants need algorithmic literacy, i.e. a basic understanding of how algorithmic and data-driven systems work, to confidently interact with and question data-driven government. Algorithmic literacy not only enables critical engagement but also boosts trust, as citizens can more easily reconstruct why an ADM system produces certain results. This concerns trainings for government employees as well as general education policy.

7.3.7 OPT FOR OPT-IN SOLUTIONS FOR ADM IN GOVERNMENT

As many citizens feel ambivalent or wary of data-driven government, it should not be imposed on them if possible. Rather, ADM – especially in pilot projects – should be offered as an opt-in solution. Often, faster processing and other inherent advantages are sufficient incentives for citizens to opt-in. In other cases, lower fees that mirror internal efficiency gains can increase the attractiveness of algorithmic solutions. If the ADM system works well, more and more citizens will opt in, and they will have done so willingly rather than being left no alternative.

7.3.8 SET UP SUABLE RULES AND LIABILITY FOR DATA-DRIVEN GOVERNMENT

Ethics guidelines are important step but citizens need a sharp sword they can wield against a data-driven government. Thus, enact rules addressing the specific challenges data-driven government that can be enforced and sanctioned. This includes clear provisions on liability, e.g. whether the agency using the algorithm or its developers are liable for errors.

7.3.9 EMPOWER DISSENT AGAINST DATA-DRIVEN GOVERNMENT

A data-driven government in a free society needs dissent. As the new data technologies can be persuasive, exclusive and overawing, it requires deliberate efforts to empower dissent. This includes government employees who act as humans in the loop of ADM systems, interest groups and watchdog that inspect ADM systems and data analytics for fairness, or political competitors who try to counter a Big-Data-supported argument. Empowerment might take the form of education for algorithmic literacy, requirements for algorithmic accountability and Open Data, or a political and administrative culture that welcomes rather than frowns upon the second-guessing and critical examination of its algorithmic systems.

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AUTHOR

Basanta E. P. Thapa explores the digitalisation of the public sector as a researcher at government think tank in Berlin and pursues his PhD on data-driven government at the DFG Research Training Group "Wicked Problems, Contested Administrations" at the University of Potsdam. He studied public administration, political science, and economics at the universities of Münster and Potsdam and worked as a researcher at Hertie School of Governance (Berlin), European Research Centre for Information Systems (Münster), and Tallinn University of Technology.

EDITOR

Dieter Feierabend works as scientific director at NEOS Lab. He holds a PhD in Social Sciences and a BSc in Statistics from the University of Vienna. In his studies, he focused on the relationship between policy issues and electoral behaviour. Furthermore, he is a graduate of the postgraduate program "Multi-Level Politics in Europe" at the Institute for Advanced Studies in Vienna. Before joining NEOS Lab, he worked as a freelance consultant i.e. for the Austrian Academy of Sciences (Institute for Technology Assessment).

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