



GETTING *DATA PROTECTION* RIGHT

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Tweets

Media

Vind-ik-leuks



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Data Pseudo Science thrives on data
obesitas and pattern obesitas. This is
what you get:

James Breakwell @XplodingUnicorn

I registered for a running club

My bank immediately sent me a
fraud alert

Apparently the only reason I'd
exercise is if my card was stolen

what's next?



1. From online to onlife
2. Machine Learning
3. Data Protection

what's next?

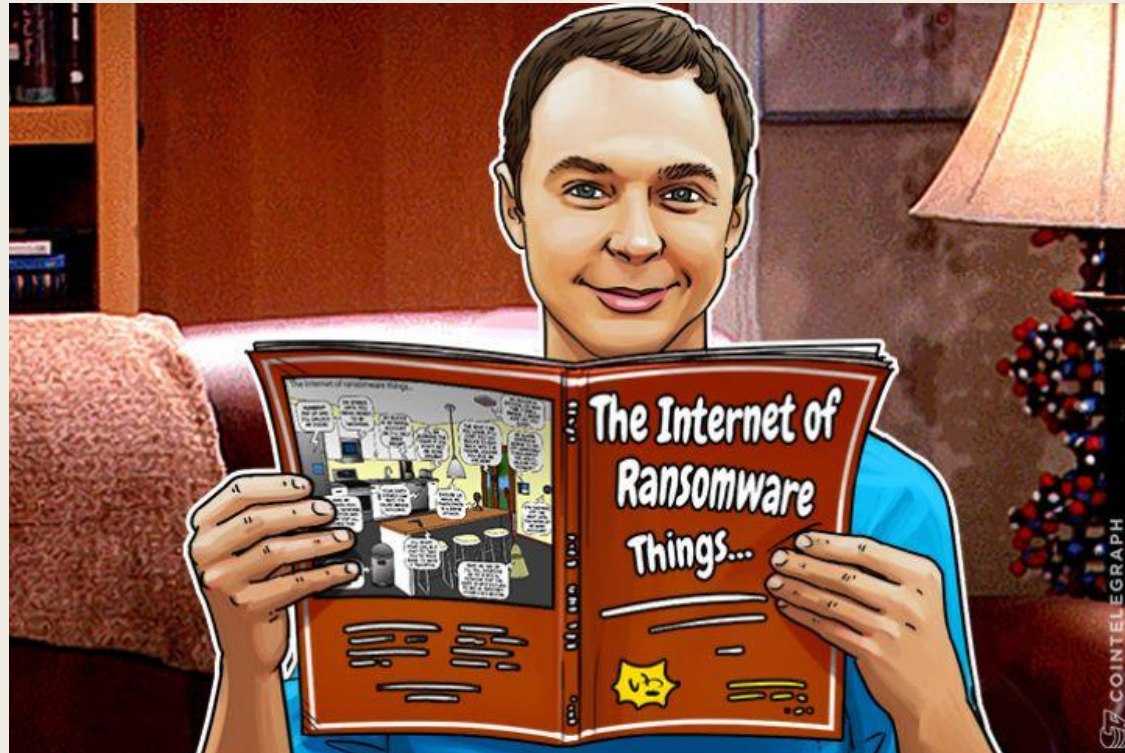


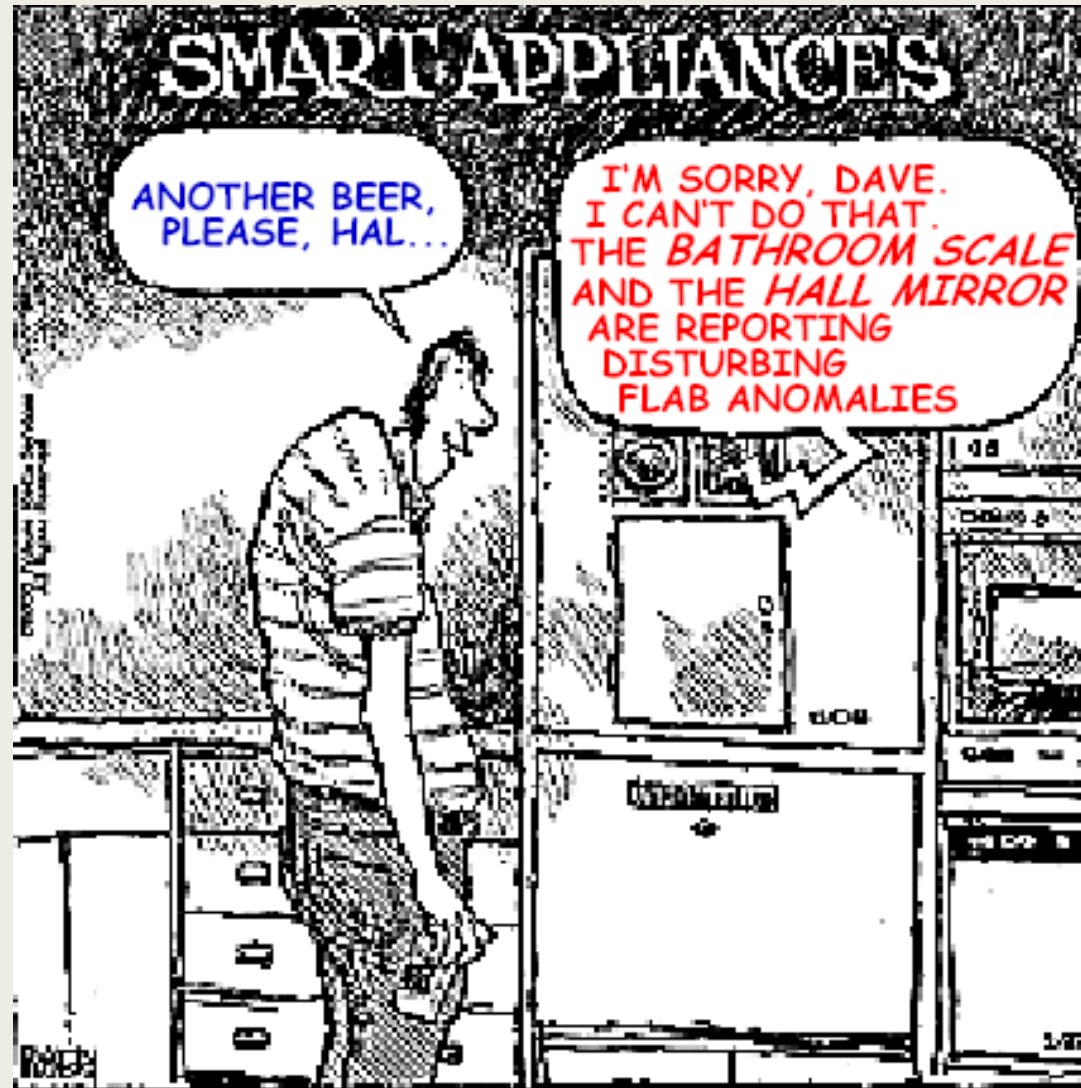
1. From online to onlife

online → onlife

- internet: packet switching & routing, network structure,
- world wide web: hyperlinking
- search engines, blogs, social media, web portals
- web platforms [network effects & filter bubbles; reputation & fake news]
- mobile applications [moving towards IoT, wearables]
- IoT: cyberphysical infrastructures [connected cars, smart energy grids]
- cloud computing, fog computing & edge computing







onlife: data driven agency


- creating added value from big data or small data
- predicting behaviours
- pre-empting behaviours

- interplay of backend & frontend of computing systems
- interfaces *enable* but they also *hide*, nudge and force [AB testing, 'by design' paradigms]

onlife: digital unconscious

Big Data Space:

- accumulation of behavioural and other data
- mobile and polymorphous data & hypothesis spaces
- distributed storage [once data has been shared, control becomes a challenge]
- distributed access [access to data or to the inferences, to training set & algos]



“The future is already here – it's just not
evenly distributed.”

– William Gibson

onlife: digital unconscious

Big Data Space:

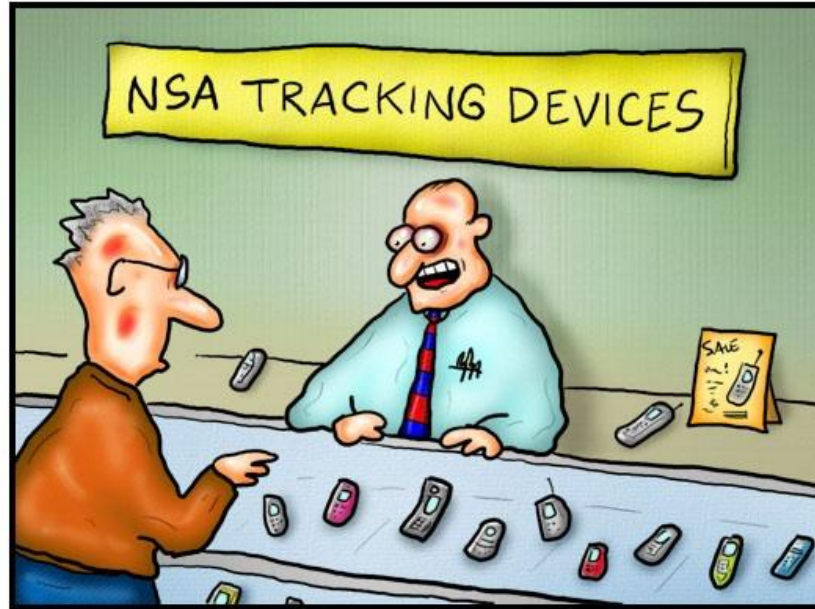
the envelop of big data space drives human agency, providing convenience & resilience

Weiser's *calm computing*, IBM's *autonomic computing*:

- increasing dependence on the dynamics of interacting data driven cyberphysical systems

DOCTOR FUN

17 May 2006

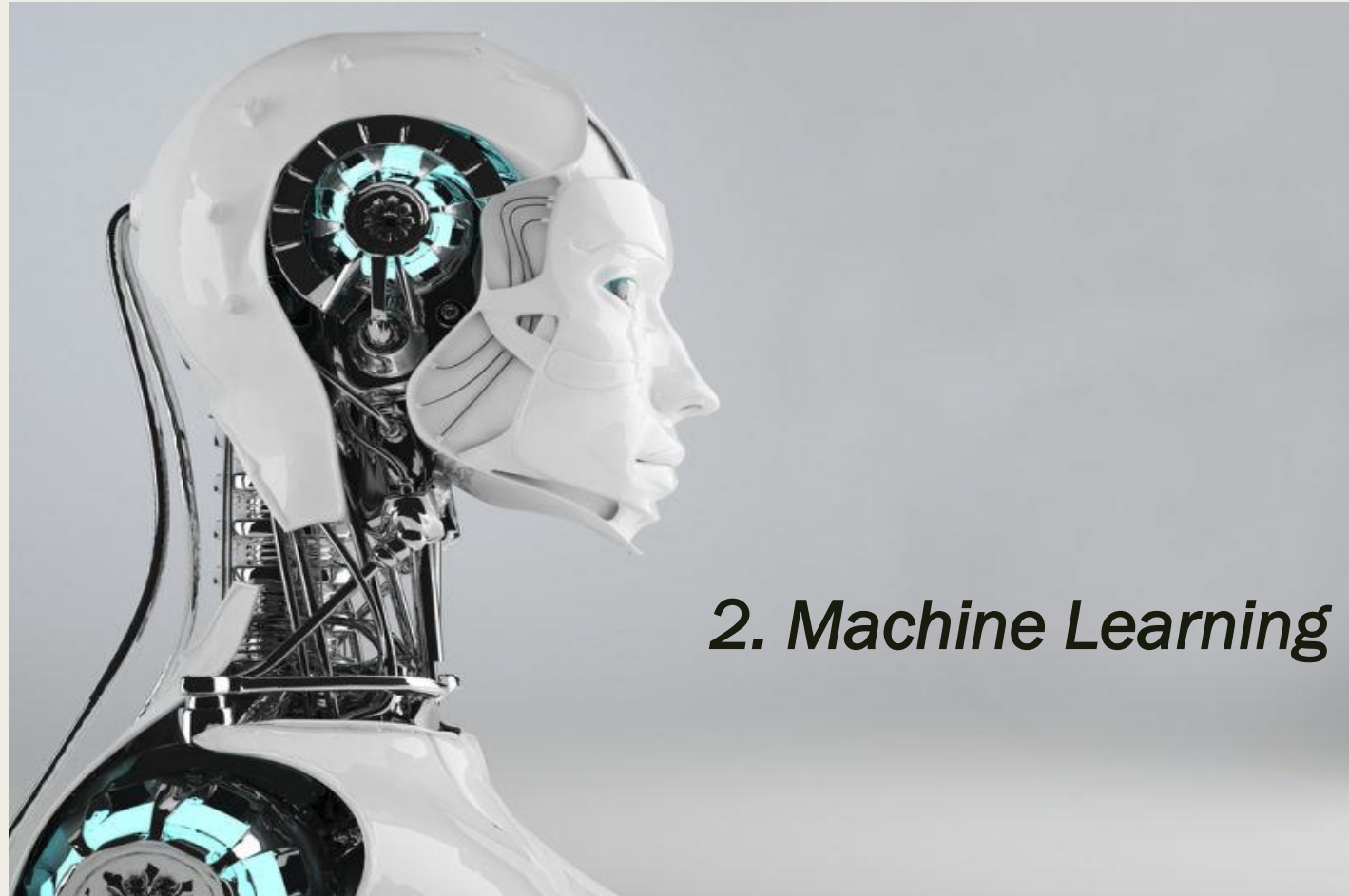


Copyright © 2006 David Farley, d-farley@ibiblio.org
<http://ibiblio.org/Dave/drfun.html>

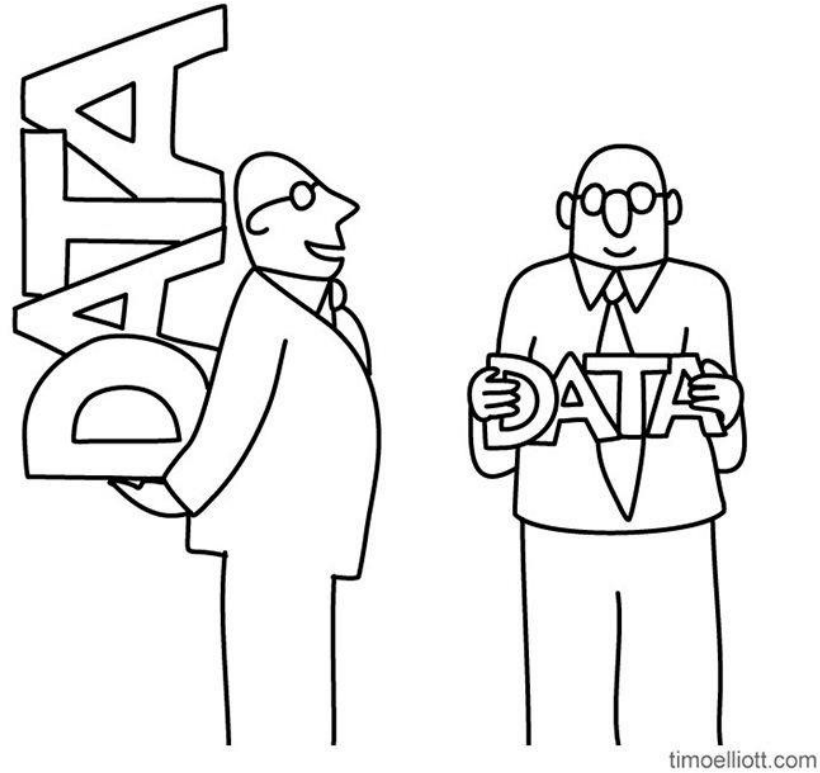
This cartoon is made available on the Internet for personal viewing only. Opinions expressed herein are solely those of the author.

"Yeah - we used to call them cell phones."

what's next?



2. Machine Learning



“I think you’ll find that mine is bigger...”

big data, open data, personal data

■ BIG

- volume (*but, $n=all$ is nonsense*)
- variety (*unstructured in sense of different formats*)
- velocity (*real time, streaming*)

■ OPEN as opposed to proprietary? reuse? repurposing? public-private?

- *creating added value is hard work, not evident, no guarantees for return on investment*

■ PERSONAL data: IoT will contribute to a further explosion of personal data

- *high risk high gain (think DPIA)? anonymisation will mostly be pseudonymisation!*

machine learning (ML)

“we say that a machine learns:

- with respect to a particular task **T**,
- performance metric **P**, and
- type of experience **E**,

if

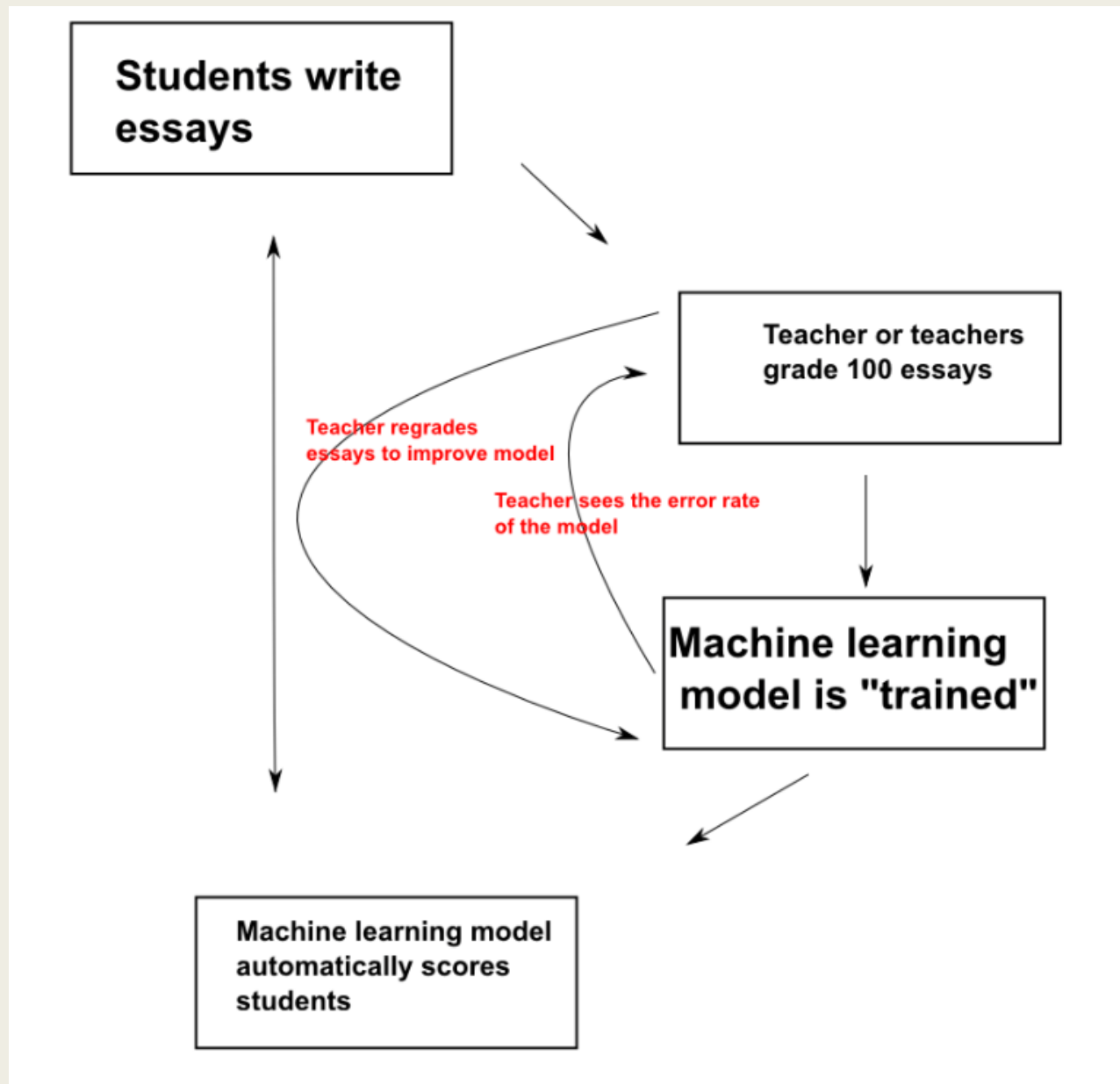
- the system reliably improves its performance **P**
- at task **T**,
- following experience **E**.”

(Tom Mitchell)

<http://www.cs.cmu.edu/~tom/mlbook.html>

types of machine learning

- *supervised* (learning from examples – requires labelling, domain expertise)
- *reinforcement* (learning by correction - requires prior domain expertise)
- *unsupervised* (bottom up, inductive – danger of overfitting)



bias optimisation spurious correlations

- 2. have a network trained to recognize animal faces
- 1. present it with a picture of a flower
- 2. run the algorithms
- 3. check the output (see what it sees)

<http://www.nature.com/news/can-we-open-the-black-box-of-ai-1.20731>

DO AIs DREAM OF ELECTRIC SHEEP?

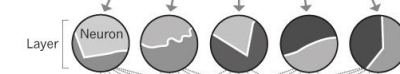
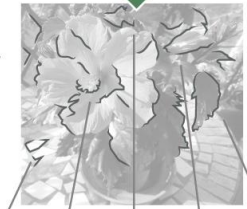
In an effort to understand how artificial neural networks encode information, researchers invented the Deep Dream technique.

Starting with a network (below) that has been trained to recognize shapes such as animal faces, Deep Dream gives it an image of, say, a flower. Then it repeatedly modifies the flower image to maximize the network's animal-face response.



HIDDEN LAYERS

The network comprises millions of computational units that are stacked in dozens of layers and linked by digital connections. It has been trained by feeding in a vast library of animal reference images, then adjusting the connections until the final response is correct.



Synapse



After training, units in the first layers generally respond to simple features, such as edges, while intermediate layers respond to complex shapes and the final layers respond to complete faces.



After a few iterations, the Deep Dream image begins to resemble a hallucination in which animal faces are everywhere. Other networks will produce images sprouting eyes, buildings or even fruit.

Wolpert: no free lunch theorem

Where

d = training set;

f = 'target' input-output relationships;

h = hypothesis (the algorithm's guess for f made in response to d); and

C = off-training-set 'loss' associated with f and h ('generalization error')

How well you do

is determined by how 'aligned' your learning algorithm $P(h | d)$ is with the actual posterior, $P(f | d)$.

Check <http://www.no-free-lunch.org>

Wolpert: no free lunch theorem

Summary:

- The bias that is necessary to mine the data will co-determine the results*
- This relates to the fact that the data used to train an algorithm is finite*
- 'Reality', whatever that is, escapes the inherent reduction*
- Data is not the same as what it refers to or what it is a trace of*





trade-offs

- **NFL theorem**
 - *overfitting, overgeneralization*
- **training set, domain knowledge, hypotheses space, test set**
 - *accuracy, precision, speed, iteration*
- **low hanging fruit**
 - *may be cheap and/or available but not very helpfull*
- **data nor algorithms are objective**
 - *bias in the data, bias of the algos, guess what: bias in the output*
- **the more data, the larger the hypotheses space, the more patterns**
 - *spurious correlations, computational artefacts*

data hoarding & obesity

- **data obesity:** lots of data, but often incorrect, incomplete, irrelevant (low hanging fruit)
 - *any personal data stored presents security and other **risks** (need for DPIA, DPbD)*
 - ***purpose limitation is crucial: select before you collect** (and while, and after)*
- **pattern obesity:** trained algorithms can see patterns anywhere, added value?
 - *training set and algorithms **necessarily** contain bias, this **may** be problematic (need for DPIA, DPbD)*
 - ***purpose limitation is crucial: to prevent spurious correlations, to **test relevance*****

agile and lean computing

■ agile software development:

- *iteration instead of waterfall*
- *collaboration domain experts, data scientists, whoever invests*
- *initial purpose (prediction of behaviour, example: tax office, car insurance)*
- *granular purposing (testing specific patterns, AB testing to nudge specific behaviour)*

■ lean computing:

- *less data = more effective & more efficient*

■ methodological integrity:

- *make your software testable and contestable: mathematical & empirical software verification*
- *secure logging, open source*

what's next?



4. Data Protection Law

privacy and autonomy

- ***the implications of pre-emptive computing:***
 - *AB testing & nudging*
 - *pre-emption of our intent, playing with our autonomy*
 - *we become subject to decisions of data-driven agents*
 - *this choice architecture may generate manipulability*

non-discrimination

■ three types of *bias*:

- *bias inherent in any action-perception-system (APS)*
- *bias that some would qualify as unfair*
- *bias that discriminates on the basis of prohibited legal grounds*

the opacity argument in ML:

1. intentional concealment

- trade secrets, IP rights, public security

2. we have learned to read and write, not to code or do machine learning

- monopoly of the new ‘clerks’, the end of democracy

3. mismatch between mathematical optimization and human semantics

- when it comes to law and justice we cannot settle for ‘computer says no’

- inspired by: Jenna Burrell, *How the machine ‘thinks’: Understanding opacity in machine learning algorithms*, in *Big Data & Society*, January-June 2016, 1-12

due process

- in the case of automated decisions taken by AI systems we need:
 1. to know **that** ML or other algorithms determined the decision
 2. to know **which data points** inform the decision and how they are weighted
 3. which are the **envisaged consequences** of the employment of the algorithms

Admiral to price car insurance based on Facebook posts

Insurer's algorithm analyses social media usage to identify safe drivers in unprecedented use of customer data

next?
in data

The insurer will examine posts and likes by the Facebook user, [although not photos](#), looking for habits that research shows are linked to these traits. These include writing in short concrete sentences, using lists, and arranging to meet friends at a set time and place, rather than just “tonight”.

In contrast, evidence that the [Facebook](#) user might be overconfident - such as the use of exclamation marks and the frequent use of “always” or “never” rather than “maybe” - will count against them.

Facebook forces Admiral to pull plan to price car insurance based on posts

Insurer withdraws initiative with hours to go as privacy campaigners criticise 'intrusive' attempt to analyse users' data



Nature editorial 22 september 2016

- “To avoid bias and improve transparency, algorithm designers **must make data sources and profiles public.**”
- “People should have the right to see their own data, **how profiles are derived and have the right to challenge them.**”
- “Some proposed remedies are technical, such as developing new computational techniques that better address and correct discrimination both in training data sets and in the algorithms — a sort of **affirmative algorithmic action.**”

the Onlife's Choice Architecture

- nudge theory, cognitive psychology, behavioural economics
 - what options does an environment give its inhabitants?
- what options does a data-driven environment give its 'users'?
- which are the defaults? e.g. withdrawal of consent in GDPR
- architecture is politics

Data Protection law's Choice Architecture

■ how does DP law constrain and reconfigure the Onlife's choice architectures?

1. what choice architecture does DP law provide data subjects?
2. what choice architecture does DP law provide data controllers?

data minimisation

= a choice architecture for data controllers:

- think 'training sets': select before you collect
- think of how to avoid 'low hanging fruit'
- think of how to ensure accuracy, relevance, pertinence
- data minimisation, if done well, should avoid both data and pattern obesity
 - *detect productive bias, while also detecting unfair or prohibited bias*
 - *make data sets available for inspection and contestation*

purpose limitation

= a choice architecture for data controllers

- think ‘training sets’: select before you collect (*and while you collect and after*)
- think of how to avoid ‘low hanging fruit’ (*GIGA*)
- think of how to ensure accuracy, relevance, pertinence (*depending on purpose*)
 - *purpose specification, if done well, should avoid both data and pattern obesitas*
 - *purpose should direct the development and employment of data-driven applications*
 - *experimentation can be a purpose, but not in itself*
- the choice of algorithms should be informed by the purpose

automated decision rights

■ current choice architecture of AI:

- ML, IoT is meant to pre-empt our intent
- to run smoothly under the radar of everyday life
- it is all about continuous surreptitious automated decisions

automated decision rights

= choice architecture for data subjects (EU legislation)

1. the right not to be subject to automated decisions that have a significant impact
2. the right to a notification, an explanation and anticipation if exception applies

automated decision rights

= choice architecture for data subjects:

1. the right not to be subject to automated decisions that have a significant impact, unless
 - a. *necessary for contract*
 - b. *authorised by EU or MS law*
 - c. *explicit consent*

under a and c: right to human intervention, possibility to contest

prohibition to make such decisions based on sensitive data

automated decision rights

= choice architecture for data subjects:

2. the right to a notification, an explanation and anticipation if exception applies
 - *existence of decisions based on profiling*
 - *meaningful information about the logic involved (= explanation?)*
 - *significance and envisaged consequences of such processing*

legal protection by design

■ Data Protection by Design:

- *JASP (open source) v SPSS (proprietary)*
- *can give you output based on Bayesian and classical statistics*
- *on same data set*
- *imagine training same algorithms on different data sets*

■ science and open society fit well together:

- *make systems testable (science), make systems contestable (Rule of Law)*
- *if you can't test it you can't contest it*

DP & Privacy law: Choice Architecture

■ individual citizens need:

- *the capability to reinvent themselves,*
- *to segregate their data-driven audiences,*
- *have their human dignity respected by the data-driven infrastructures*
- *make sure their robotic social companions don't tell on them beyond necessary*
- *the capability to detect and contest bias in their data-driven environments*

DP & Privacy law: Choice Architecture

- **the architects of our new data-driven world need:**
 - *integrity of method: rigorously sound and contestable methodologies (bias)*
 - *accountability: (con)testability of both data sets and algorithms*
 - *fairness: testing bias in the training set, testing bias in the learning algorithm*
 - *privacy & data protection: reduce manipulability, go for participation and respect*

‘by design’ paradigm

- *architecture is politics*
- *translate fairness, methodological integrity, fundamental rights into the architecture*
- *Data Protection by Default: engineer data minimisation as a requirement*
- *Data Protection by Design: engineer state of the art DP tools as a requirement*

'by design' paradigm

■ *architecture is politics*

- *we cannot always be saved by design*
- *resilience will depend on: testability & contestability*
- *ultimately this is in the interest of data subjects and controllers*

■ *ML as a utility*



