HUMANS VS ROBOTS!

(CAN A MACHINE DO AN ACTUARY'S JOB?)

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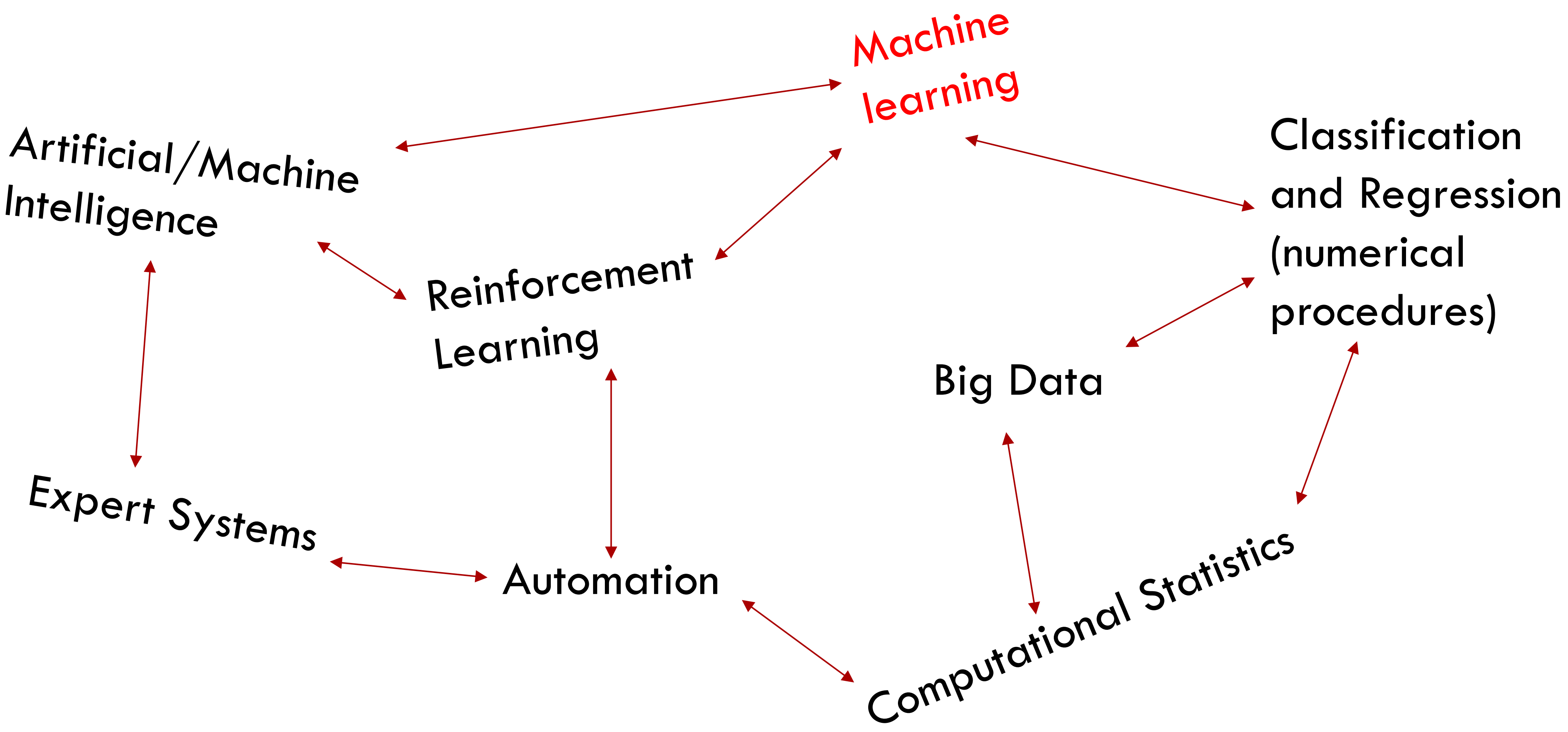
THE HILL
Artificial intelligence — the arms race we may not be able to control
BY FORMER REP. MIKE ROGERS (R-MICH.), OPINION CONTRIBUTOR — 09/21/17 11:00 AM EDT
THE VIEWS EXPRESSED BY CONTRIBUTORS ARE THEIR OWN AND NOT THE VIEW OF THE HILL

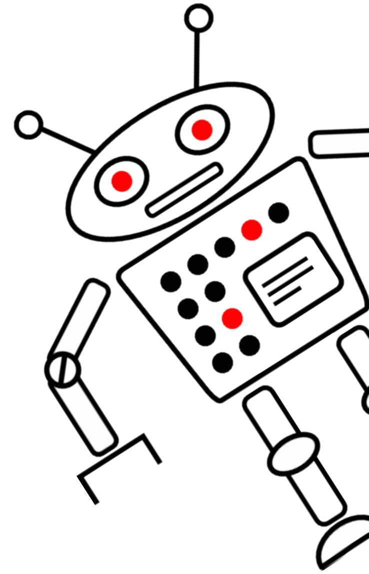
TheActuary
The magazine of the Institute & Faculty of Actuaries

Financial jobs most at risk from robots

Almost a quarter of UK business leaders in the finance and accounting sector believe a high level of jobs in their organisation will be automatable in the next decade.

JARGON BUSTING





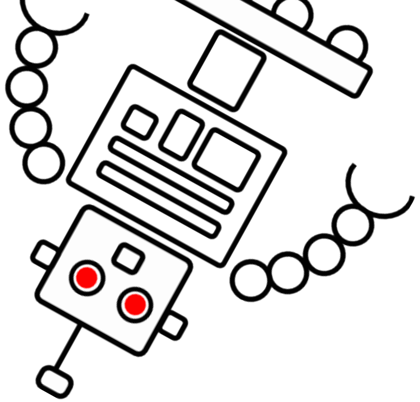
"MACHINE LEARNING"

- Large overlap with "computational statistics"
- Machine learning is a label for a class of general purpose algorithms:
  1. Classification algorithms, for e.g. image/ handwriting / voice recognition
  2. Regression algorithms, for model fitting and prediction
  3. "Reinforcement learning" algorithms which navigate a physical or data space by a trial-and-error process
- (ML may also be taken to include the "expert systems" – the decision making and actioning algorithms that take the classification / regression output and action a system of rules)

CLASSICAL VS COMPUTATIONAL STATISTICS

Classical	Computational ("machine learning")
Restricted to data that conforms to known mathematical distributions	Adaptable to arbitrarily distributed data
Choice of model requires expert judgement	Models more flexible and generally applicable (although still a large choice of approach)
Few model parameters	Many model parameters
Fast fitting (well defined analytical and numerical processes)	Slow fitting (complex numerical procedures that cannot be done by hand)
Can fit to small amounts of underlying data	Requires very large amounts of data for both model fitting and testing

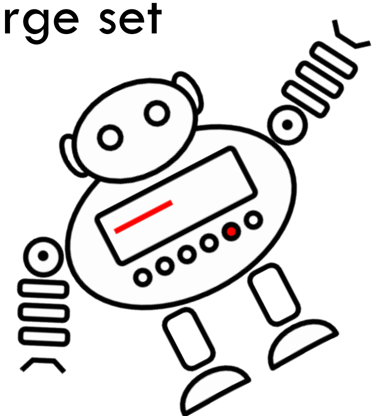
“BIG DATA”



- ML algorithms can be useful in situations where traditional statistical analysis struggles. They can be more general-purpose and require fewer initial assumptions (e.g. prior assessment of likely statistical distributions)
- However - they have *many* more model parameters and so require vast amounts of pre-categorised data for training (and more for testing) – hence “big data”
- **Most** actuarial problems **are not** Big Data problems (but some are)

MOST ACTUARIAL PROBLEMS ARE NOT BIG DATA PROBLEMS?

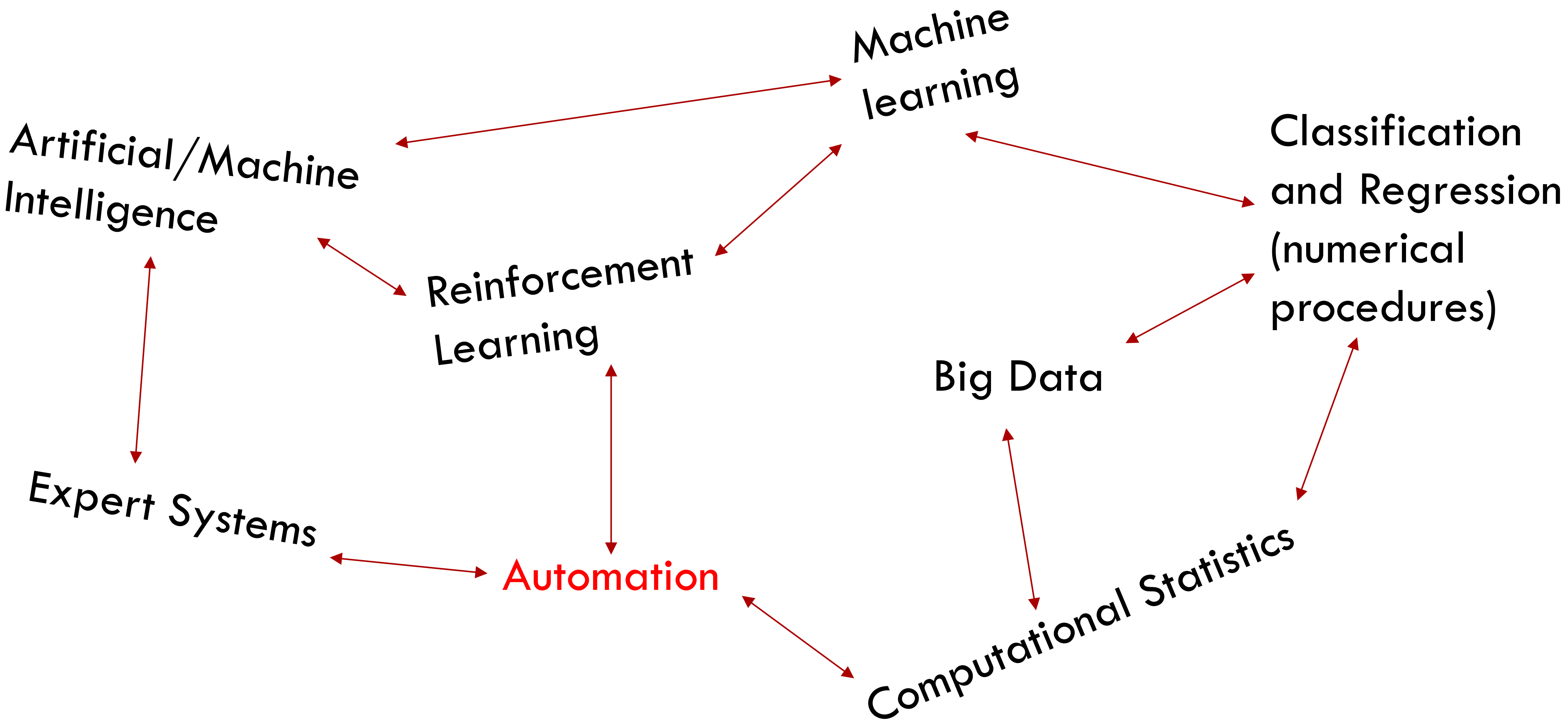
- Scale – most (but not all) actuarial data sets are not large enough for ML techniques to work (e.g. mortality problems). Exception - telematics
- Quality – most actuarial data sets are not high quality data. Possible exception – large insurer claims data
- Direction of travel – ML problems reduce large datasets to a small set of summary statistics or classifications but most actuarial science generally works in the opposite direction, turning a small/medium set of data (policy or admin data) into a large set of data (financial projections /cashflows / contingency forecasts etc)



MACHINE LEARNING CONCLUSIONS:

- Most of the recent innovations in the field of “Machine Learning” augment and improve on existing methods in classical statistics for new applications
- ML techniques do not replace the expert – ML algorithms require a great deal of expertise and knowledge to use and implement successfully
- If your job involves a high degree of data analysis, model fitting, and statistical work then you may already be incorporating ML techniques into your skillset
- This field represents an **opportunity** for actuaries – not a threat

JARGON BUSTING



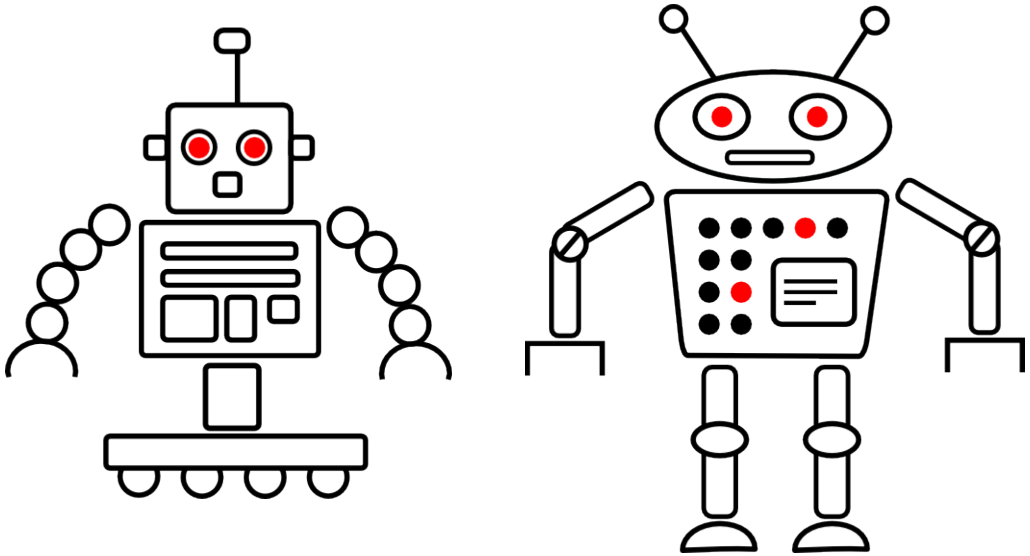
"AUTOMATION"

Dictionary definition:

"…the technique of making an apparatus, a process, or a system operate automatically (by itself, without conscious human thought or attention)"

Popular definition:

"Robots taking jobs"



THIS IS NOT A NEW DISCUSSION

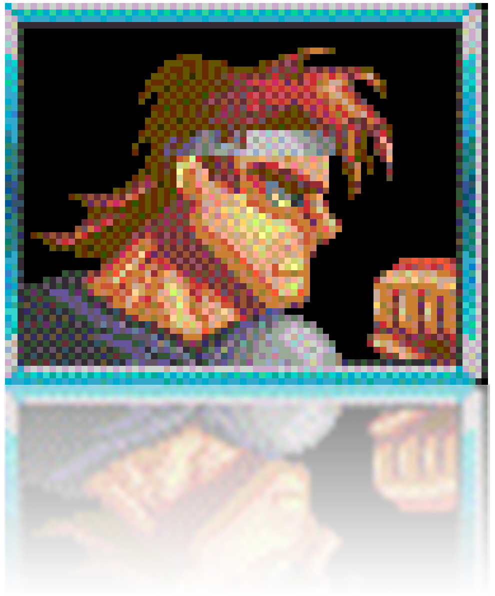
"It is unworthy of excellent men to lose hours like slaves in the labour of calculation which could safely be relegated to anyone else if machines were used."

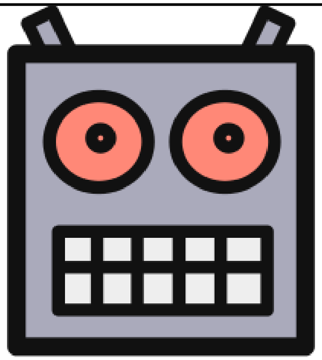
- Gottfried Wilhelm von Leibniz (1 July 1646 – 14 November 1716)

(Describing, in 1685, the value to astronomers of the hand-cranked calculating machine he had invented in 1673.)

THE MORE THINGS CHANGE…

When (roughly)	Innovation	Impact on actuaries
40 years ago	Handheld electronic calculators	Fewer pre-calculated factor tables
35 years ago	Mainframe computers commonly used in business	Computerised bulk calculations replace "squared paper" hand-calcs
25 years ago	Desktop computers on all desks	Spreadsheets replace mainframe computer systems
Now…?	Automation	Artisan workflows replaced by automated workflows



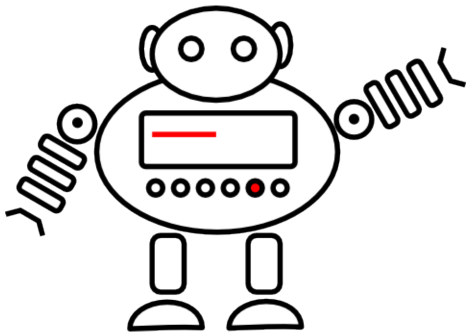


Curriculum Vitae

Name:	Robbie
Occupation:	Robot
Key Skills:	• I am **consistent** – given the same task and inputs, I will produce the same results each time • I am (almost) free from bias and prior expectations • I do not get bored or tired and I am happy to do tedious, repetitive manual tasks at high speed
Weaknesses:	• However, I am a bit **stupid** – I will carry out their instructions exactly, no matter how nonsensical this might be • My thought processes are often **opaque** and difficult to audit

CAN A MACHINE DO YOUR JOB?

- Automation works best on tasks which are **predictable** and **repetitive**
- How predictable is your daily workflow? How repetitive?
- Most may conclude that there may be aspects to your job that a machine can do more efficiently than you and to a higher quality standard, but machines would be hard pressed to replace you entirely



Q. WHAT ARE THE SQUISHY HUMANS GOOD FOR?

A. Everything else, including:

- Project specification – desired outcomes and deliverables
- Process design and testing (assisted by checking and testing procedures)
- Review, investigation and fault-checking
- Tailoring and Communication
- Applying "common sense" (experience, context and real world values and judgement)

AUTOMATION IN THE WORKPLACE

"Redesigning a business workflow to allow machines to do the things that machines do best, and humans to do the things that humans do best"

- *Giles Duffin*

(when asked)

- **Not** relying on untested or unchecked software
- **Not** removing the human expert from the overall workflow
- **Not giving the machine free rein**

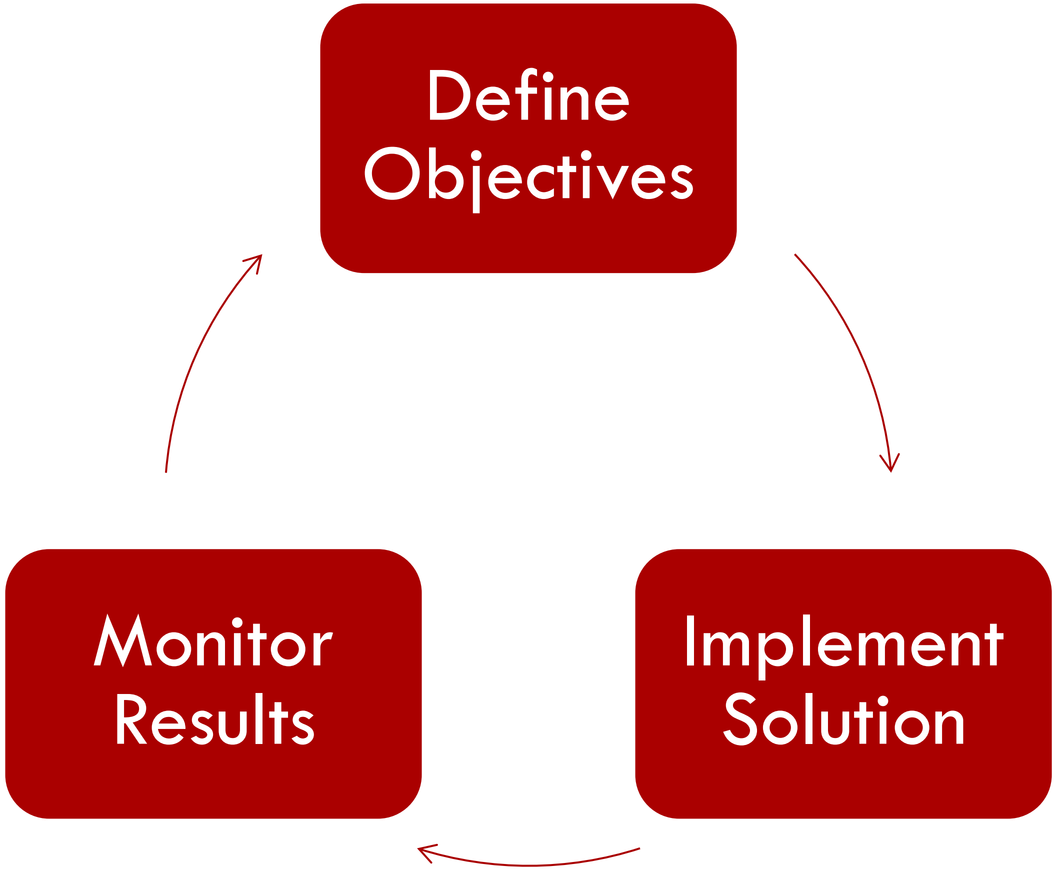
TOOLS NOT ROBOTS

"…many tasks involve goals that are complex, poorly-defined, or hard to specify. Overcoming this limitation … could increase the reach of machine learning more broadly"

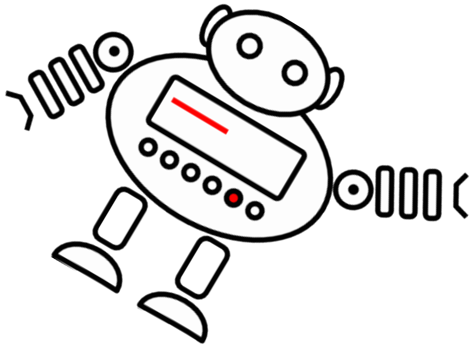
"An alternative approach is to allow a human to provide feedback on our system's current behaviour and to use this feedback to define the task."

"Deep reinforcement learning from human preferences"
- arXiv:1706.03741 [stat.ML] 13 Jul 2017

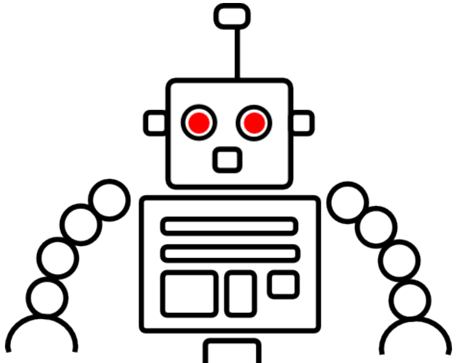
IN OTHER WORDS… THE ACTUARIAL CONTROL CYCLE



AUTOMATION – CONCLUSIONS: GIVE THE TEDIOUS JOBS TO THE MACHINE



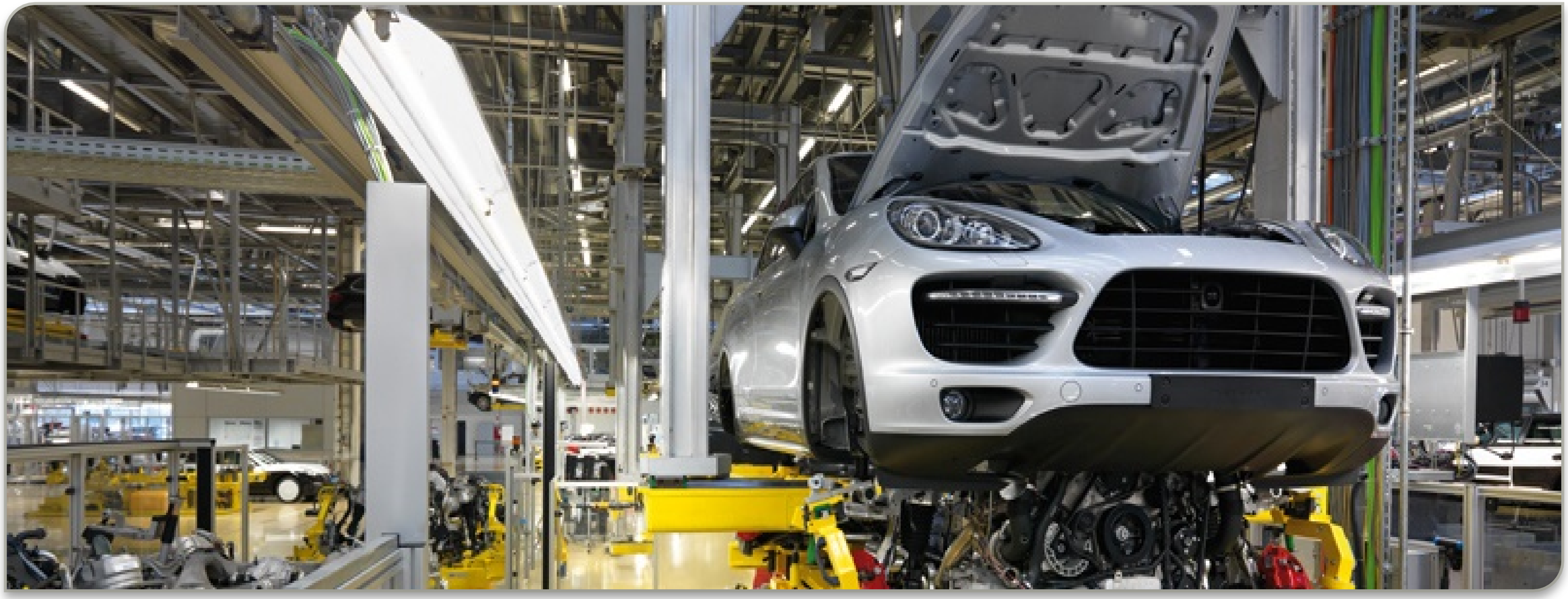
- Importing data into models
- Recalculating
- Moving data and results between models or systems or into reports (e.g. “mail merge” or “copy & paste”)
- Producing documentation, test cases and (most of) the audit trail
- Testing (running test data through processes and checking “nothing is broken”)
- Producing first draft advice from templates



A PREDICTION

PACKARD AUTO PLANT – DETROIT 1910

(before Henry Ford introduced the moving assembly line in 1913 for the Ford Model T)



PORSCHE (LEIPZIG)

SOME CONCLUSIONS

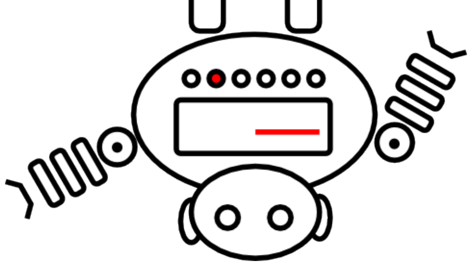
WHERE DO ACTUARIES FIT?

1. Using core actuarial skills to define machine objectives:
   - I.e. translating natural language problem into a mathematical objective / reward function description that can be followed by a machine
2. Using the actuarial control cycle approach ("define problem, implement solution, monitor results") for model training (see later)
3. Using actuarial "numerical and probabilistic intuition" to apply common sense / reasonableness checks to ML results and behaviour

ALSO…

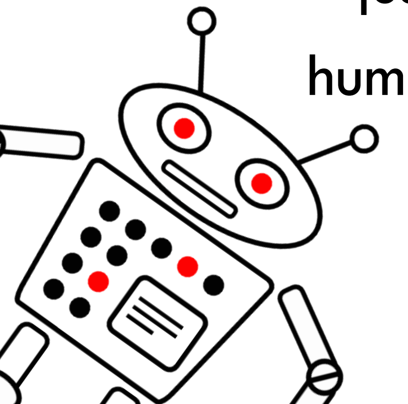
Machine Learning models are only as good as their training data.

Actuaries can apply objective rigour and technical skill in the collection, aggregation, cleaning, and correct interpretation of the huge datasets needed to train ML models



THERE IS NO REASON TO FEAR

- Machine Learning is a specialised and limited discipline. Jobs involving the analysis of past data to predict future outcomes will evolve to embrace new ways to model data and new statistical techniques, but these new methods still need a great deal of expert knowledge
- Automation does not involve cutting the expert out from the workflow entirely – just moving the tedious and manual tasks into safer hands and freeing up human time for more value-added work



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