lecture 11 of 14: april 7 2020

'AI reborn as ML'

chris wiggins + matt jones, Columbia

student reactions

```
...
  38 interpretability/interpretable/interpretive/interpreta
  32 black box
  36 rudin
  28 racial/race/racist
  27 propublica
  16 compas
  12 ethical/ethics
  12 pandemic/coronavirus
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themes for today (2015-2019)

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- role of money
- role of "tech" as differentiator

historical & social context: when we left AI (week 8, mar 10)....

Dartmouth 56 impact:

One vision was that AI means to "take symbolic information as input, manipulate it according to a set of formal rules, and in so doing can solve problems...

> *After the 1956 workshop, this became the dominant approach among academics*
>
> *most notably, human intelligence was the central exemplar around which early automation attempts were oriented.*

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> *most notably, human intelligence was the central exemplar around which early automation attempts were oriented.*

- SD
- Q: what might be the other approach?

Machine Learning as AI subaltern, the last half-century:

- 1950s: setting goals (but also: Sputnik, ARPA)

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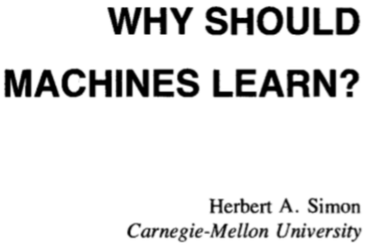
- 2010s shatter this via "deep nets", an echo of ANNs from 1943
  - "Overwhelmingly, machine learning systems are oriented towards one specific task: to make accurate predictions." – SD2019

example: Simon's "Why should machines learn?" (1983)

- attended Dartmouth '56



WHY SHOULD
MACHINES LEARN?

Herbert A. Simon
Carnegie-Mellon University

Figure 1: Simon

example: Simon's "Why should machines learn?" (1983)

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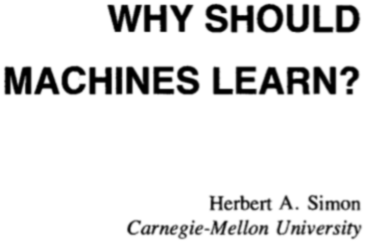
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Simon'83:

"skeptical challenge to learning as the road to the future in AI . . . (sometimes called cognitive simulation, or information processing psychology). . .

case against AI research in learning"

the most important kinds of learning research to carry out in AI are those that are oriented toward understanding human learning. Here as elsewhere, Man seems to be the measure of all things.

Simon'83: tension

- "Why Machine Learning? .... just program it"

vs.

> *"If we understand the domain ourselves, if we understand physics, why don't we just choose an internal representation and provide the problems to the system in that internal representation? What's all this learning and natural language understanding about?"*

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- "Why Machine Learning? .... just program it"
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> *"If we understand the domain ourselves, if we understand physics, why don't we just choose an internal representation and provide the problems to the system in that internal representation? What's all this learning and natural language understanding about?"*

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vs.

- Schema (13x) & representations (16x)

  "If we understand the domain ourselves, if we understand physics, why don't we just choose an internal representation and provide the problems to the system in that internal representation? What's all this learning and natural language understanding about?"

Simon: wrong

> *For those who were hoping that a small number of general rules could explain language, it is worth noting that language is inherently complex, with hundreds of thousands of vocabulary words and a vast variety of grammatical constructions. Every day, new words are coined and old usages are modified. This suggests that we can't reduce what we want to say to the free combination of a few abstract primitives.*

– A. Halevy, P. Norvig, and F. Pereira, "The Unreasonable Effectiveness of Data," (apologies to Wigner) readings: Jordan+Mitchell, Lewis-Kraus, Rudin, Angwin/Pro Publica

pre-Mitchell/Jordan: e.g., ML, 1959

Some Studies in Machine Learning Using the Game of Checkers

Arthur L. Samuel

Abstract: Two machine-learning procedures have been investigated in some detail using the game of checkers. Enough work has been done to verify the fact that a computer can be programmed so that it will learn to play a better game of checkers than can be played by the person who wrote the program. Furthermore, it can learn to do this in a remarkably short period of time (8 or 10 hours of machine-playing time) when given only the rules of the game, a sense of direction, and a redundant and incomplete list of parameters which are thought to have something to do with the game, but whose correct signs and relative weights are unknown and unspecified. The principles of machine learning verified by these experiments are, of course, applicable to many other situations.

Figure 2: Samuel, Arthur L. "Some studies in machine learning using the game of checkers." IBM Journal of research and development 3, no. 3 (1959): 210-229.

Mitchell/Jordan: defining ML, prior

prior to this collaboration

TM, 1997: Machine Learning is the study of computer algorithms that improve automatically through experience.

TM 2006: "How can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning processes? – Mitchell

MJ, 2009: "[Machine learning is just statistics]" –Jordan

Mitchell/Jordan: defining ML in 2015

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what even is machine learning?

"machine-learning algorithms can be viewed as searching through a large space of candidate programs, guided by training experience, to find a program that optimizes the performance metric." 255

1) "large space of candidate programs" (e.g. different decision trees for classifying)

Mitchell/Jordan: defining ML in 2015

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2) "training experience" (e.g. human classified data)

Mitchell/Jordan: defining ML in 2015

what even is machine learning?

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1) "large space of candidate programs" (e.g. different decision trees for classifying)
2) "training experience" (e.g. human classified data)
3) "metric" = what's most important to you (e.g. accuracy)

Mitchell/Jordan AI1.0 v AI2.0

> *Within artificial intelligence machine learning has emerged as the method of choice. . . it can be far easier to train a system. . . than to program it*

(A sentence that would not parse for most.. See Simon 83)

M/J: echoes of history

- Learning is "improving some measure of performance" (as in engineering $+$ optimization)

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- Learning is "improving some measure of performance" (as in engineering + optimization)
- "Conceptually... searching through... candidate programs"
- "causal modeling" (as in Yule 1898)

M/J: rise of .com

- "algorithms. . . customize their services"

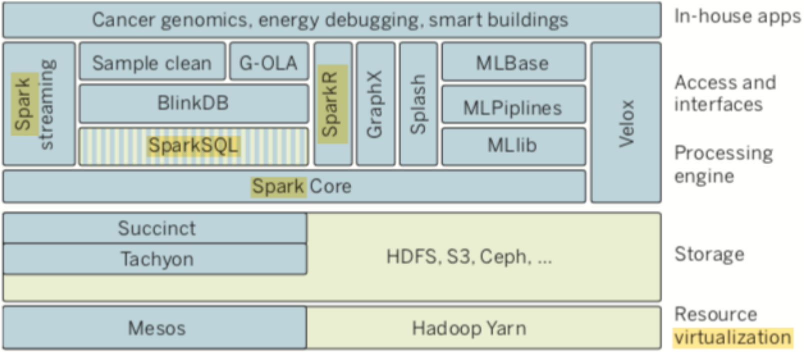

Figure 3: AMP stack

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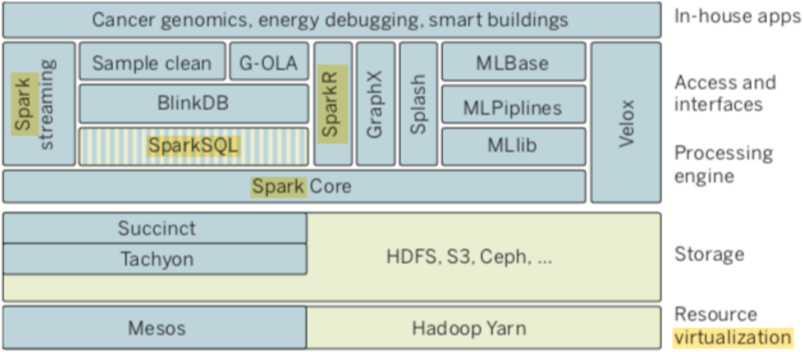

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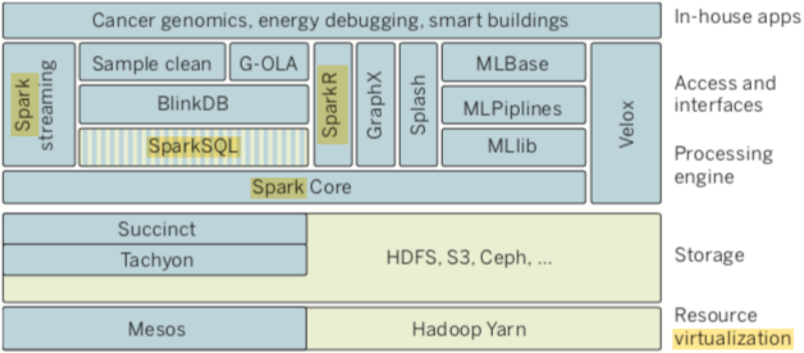

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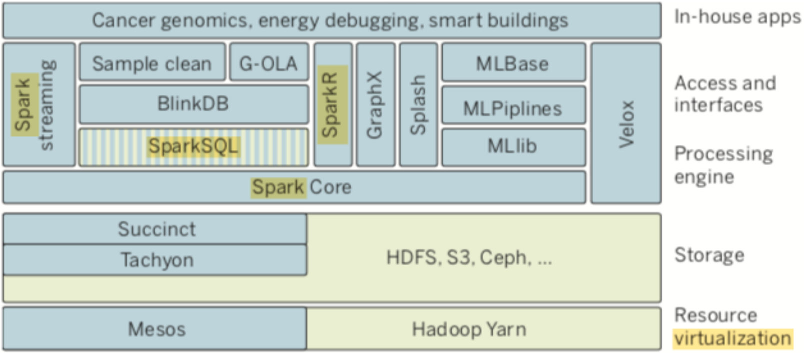

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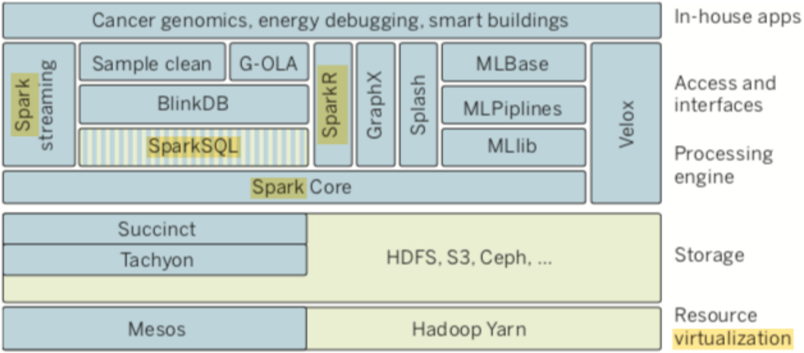
  - balance "time. . . space. . . accuracy"



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M/J: echoes of ethics

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- "differential privacy"

M/J: echoes of ethics

- “Granular, personalized... data”
- “minimize privacy effects”
- “differential privacy”
- “social, legal, political framework surrounding the deployment of a a system... cooperative or adversarial”"

M/J on ethics

As with any powerful technology, machine learning raises questions about which of its potential uses society should encourage and discourage. The push in recent years to collect new kinds of personal data, motivated by its economic value, leads to obvious privacy issues, as mentioned above. The increasing value of data also raises a second ethical issue: Who will have access to, and ownership of, online data, and who will reap its benefits? Currently, much data are collected by corporations for specific uses leading to improved profits, with little or no motive for data sharing. However, the potential benefits that society could realize, even from existing online data, would be considerable if those data were to be made available for public good.

M/J: 3 paradigms

- Supervised (main topic)

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- Unsupervised

M/J: 3 paradigms

- Supervised (main topic)
- Unsupervised
- Reinforcement

other thoughts on M/J?

Lewis-Kraus on Deep Neural Networks (DNN)

- Why great awakening?

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  - acutual "AI", i.e., recall the "N" of NLP

LK on DNN

Google's decision to reorganize itself around A.I. was the first major manifestation of what has become an industry wide machine-learning delirium. Over the past four years, six companies in particular — Google, Facebook, Apple, Amazon, Microsoft and the Chinese firm Baidu — have touched off an arms race for A.I. talent, particularly within universities. Corporate promises of resources and freedom have thinned out top academic departments. It has become widely known in Silicon Valley that Mark Zuckerberg, chief executive of Facebook, personally oversees, with phone calls and video-chat blandishments, his company's overtures to the most desirable graduate students. Starting salaries of seven figures are not unheard-of. Attendance at the field's most important academic conference has nearly quadrupled.

LK on history

- Turing 1950

LK on history

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- “brittle” “rules”

LK on history

- Turing 1950
- “brittle” “rules”
- GIGO + discrimination

LK on alchemy

> *Some of the stuff was not done in full consciousness.*
> *They didn't know themselves why they worked.*

cf., Ali Rahimi and Ben Recht, 2017

Other thoughts on Jones, MIJ/TM, LK?

Rudin

“High-Stakes” Explainable vs Interpretable

- “healthcare”, “justice”, “parole”,

“High-Stakes” Explainable vs Interpretable

- “healthcare”, “justice”, “parole”,
- what is difference between explainable and interpretable?

Interpretable

- no universal, but examples

Interpretable

- no universal, but examples
  - sparse

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- no universal, but examples
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  - additivity
- "can never be a single definition"

why black box?

- money

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    1. prediction-interpretability tradeoff

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    1. prediction-interpretability tradeoff
    2. explainable is “faithful”
    3. explanations are complete and make sense
    4. models contain information outside database

What does this look like as math?

- optimization

$$L = \frac{1}{n} \sum_{i} [i \text{ is misclassified}] + \lambda \text{size}(f)$$

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What does this look like as math?

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$$L = \frac{1}{n}\sum_i [i \text{ is misclassified}] + \lambda \text{size}(f)$$

- what sets λ?
- answer is about epistemic virtues as much as it is about optimization or statistics

Angwin et alia's "Machine Bias": context

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- huge impact on narrative
- contested! launches papers coming to different conclusions based on different definitions of fairness

Angwin et alia's "Machine Bias": content

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- functional, rhetorical, critical data capabilities

Table 1.1
The Conceptual Landscape of a Computer Multiliteracies Program

Category	Metaphor	Subject Position	Objective
Functional Literacy	computers as tools	students as users of technology	effective employment
Critical Literacy	computers as cultural artifacts	students as questioners of technology	informed critique
Rhetorical Literacy	computers as hypertextual media	students as producers of technology	reflective praxis

Figure 4: multi-capabilities

Angwin et alia's "Machine Bias": content

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  - cf Selber, Stuart A. Multiliteracies for a Digital Age. Carbondale: Southern Illinois UP, 2004. 240pp.

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- NB: data journalism done on GitHub with technical supplement

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power and principles

how did this capability rearrange power? who can now do what, from what, to whom?

role of rights, harms, justice?

foreshadowing data for Thursday

reminder of themes for today (2015-2019)

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up next

- ethics and impact

Appendix

- 2020-01-21 : 1 of 14 intro to course

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- 2020-01-28 : 2 of 14 setting the stakes

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- 2020-02-04 : 3 of 14 risk and social physics
- 2020-02-11 : 4 of 14 statecraft and quantitative racism
- 2020-02-18 : 5 of 14 intelligence, causality, and policy
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