Models of active learning in perception and cognition

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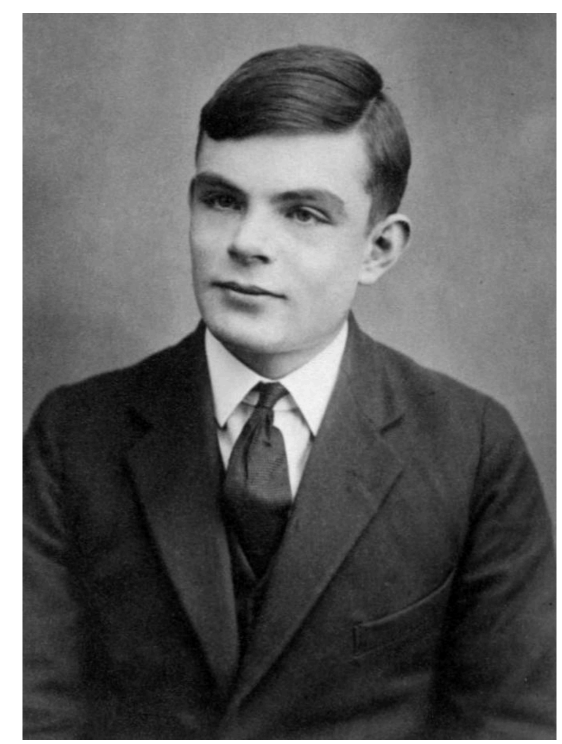
DTU summer school—Machine Learning and Human Cognition

Artificial intelligence inspired by human learning

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulates the child's? If this were then subjected to an appropriate course of education one would obtain the adult brain. Presumably the child-brain is something like a note-book as



Turing, 1950

Active learning: a dominant mode of learning

Fig. 1 **Child's play is science.**
["Playing Doctors" by Frederick Daniel Hardy (1827–1911)]

Gopnik, 2012

"People are intuitive scientists; their information-seeking actions are **optimal experiments**."

Coenen, Nelson & Gureckis, 2019

Pioneering work on active machine learning

- **Why active learning?**
  - Measurements are expensive and/or slow, and we want to know where to look next so as to learn as much as possible (often the case for applied active machine learning).
  - There is an immense amount of data, and we wish to select a subset of data points that is most useful for our purposes (often the case for human learning).

- **Objective function used:**
  - **Expected information gain**, where information gain is the reduction in the Shannon entropy of the model parameters after the measurement
  - Distribution of model parameters inferred via Bayes' rule

- **Demonstrations of active learning:**
  - find a good interpolation model
  - predict the value of the interpolant accurately in a limited region

    (the first two are the prefigure of Bayesian optimization)
  - discriminate between two or more models (optimal experiments)

MacKay, 1992

Pioneering work on active learning in cognition

Rational analysis of Wason's selection task using expected information gain

entropy on hypotheses after receiving data

entropy on hypotheses before receiving data

expectation

$$E(I_g) = \left[\sum_{k=1}^{m} P(D_k) I(H_i \mid D) \right] - I(H_i), \qquad (6)$$

where

$$P(D_k) = \sum_{j=1}^{n} P(H_j) P(D_k \mid H_j).$$

predictive distribution

Oaksford & Chater, 1994
Anderson, 1990

Can try a version of Wason's task at: https://www.philosophyexperiments.com/wason/

Modeling approach: rational / ideal-observer analysis

- Identifying task-relevant stimulus properties
  - define the hypothesis space, the model parameter space, the likelihood function, etc
- Describing how to use those properties to perform the task
  - Bayesian inference + action selection based on an objective such as the expected information gain
- Providing a benchmark against which to compare the performance of real or model systems
  - design and conduct human experiments
  - compare human performance to simulated ideal observer / rational agent exposed to the same stimuli
- Suggesting principled hypotheses and models for real performance
  - degrade ideal observer / rational agent by incorporating realistic noise, approximate inference, etc.
- I like this approach because:
  - makes the modeling assumptions very explicit
  - gives quantitative and detailed predictions
  - shows what optimal behavior looks like
  - shows how different factors affect optimality
  - sets up a framework for using machine learning models as models of human behavior

Geisler, 2011

Schedule

- **Active sensing talk** (~20 minutes + Q&A)
  - A model of active learning in perception (Yang, 2016)
  - How efficient are humans at gathering information for pattern categorization with eye movement?
  - Talk uploaded to https://www.youtube.com/watch?v=A5MiqFkEHQE&t=7s

- **Self-teaching talk** (~15 minutes + Q&A)
  - A model of active learning in cognition (Yang, 2019)
  - Can we unify pedagogical learning and active learning, the two most dominant modes of learning?
  - Talk uploaded to https://www.youtube.com/watch?v=G6P-y1Esh70

- **A short break?** (~5 minutes)

- **Active learning tutorial** (~2 hours)
  - Code the most common active learning model—expected information gain—in the simplest scenario—finding decision boundary in 1d discrete space.
  - Please access the tutorial at: https://github.com/firekg/AL-tutorial

References (alphabetical order)

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My papers, slides, and talks can be found on my website:
http://scottchenghsinyang.com/

Levels of analysis

TABLE 1-1
Levels of Cognitive Theory According to Various Cognitive Scientists

Marr	*Chomsky*	*Pylyshyn*	*Rumelhart and McClelland*	*Newell*	*Anderson*
	Competence				
Computational Theory		Semantic Level		Knowledge Level	Rational Level
Representation and Algorithm	Performance	Algorithm	Macrotheory/ Rules	Program Symbol Level	Algorithm
		Functional Architecture	Microtheory PDP models	Register Transfer Level	Implementation
Hardware Implementation		Biological Level		Device	Biological

Anderson, 1990