ML Overview

GeoComput & ML

2021-05-04 Tue

Course Structure

GeoComputation

- Linux environment
- Geo computational tools : gdal/ogr, pktools, grass, etc.

$\Uparrow$

*Geo***Coding**

$\Downarrow$

GeoModelling

- GeoMath
- GeoStats

Class Survey

Topics	Speakers
Python	web
R	web
TensorFlow	guest ?
unSupervised Learning	LS
Image processing ?	LS ?
ML Optimisation	LS
rivernetwork delinearation	GA + LS
from project discussions	GA + LS

Course Outlook

Dates	Contents	Speaker
0504	projects + ML overview	LS
0506	projects + ML opt.	LS
0511	unsupervised learning	LS
0518	specific topics	LS + GA
0520	ANN	guest
0525	ANN	guest
0527	LSTM	guest
0601	presentation day	
0604	presentation day	

Project Workflow

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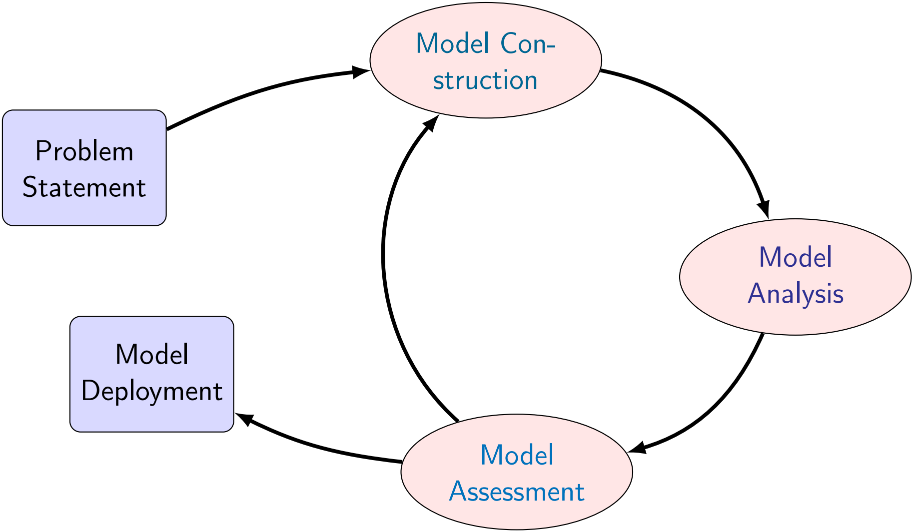
- Model Deployment
  presentation : map output

Iterative Process



Project Guidance

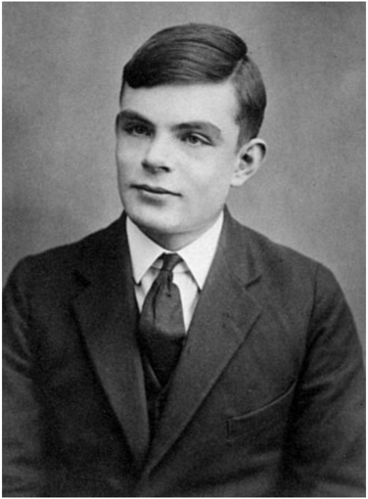
Broad Sense

- Prediction and/or Analytics
- Coding languages

Evaluation

- Clear concepts
- Logic reasoning
- Numerical ability
- Presentability

Machine Thinking



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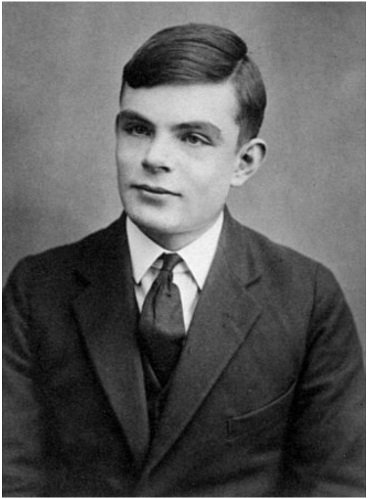
Machine Thinking



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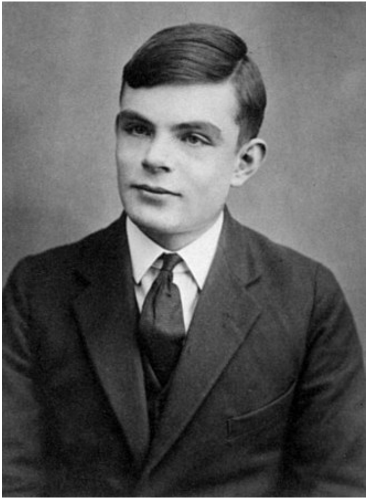

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- Turing test : indistinguishable from human reactions

AI Foundation

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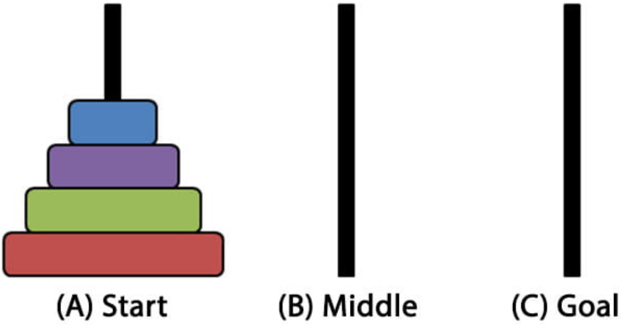
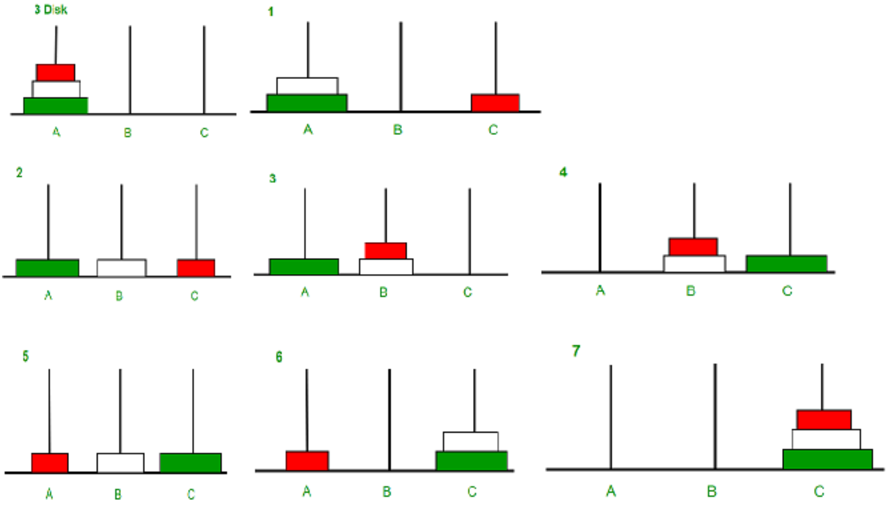


Optimal Solution



Combinatorial explosion

- average 200 possible moves
- anticipating next four moves
- more than 320 billion combinations

Expert System

- 1970s : capturing human knowledge
- logic-based
- deduction
- logic knots

Agent-based AI

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$$
\begin{aligned}
P(C|+) &= \frac{P(+|C)P(C)}{P(+|C)P(C) + P(+|C^c)P(C^c)} \\
&= \frac{0.8 \times 0.1}{0.8 \times 0.1 + 0.96 \times 0.9} = 48\%
\end{aligned}
$$

Deep Learning

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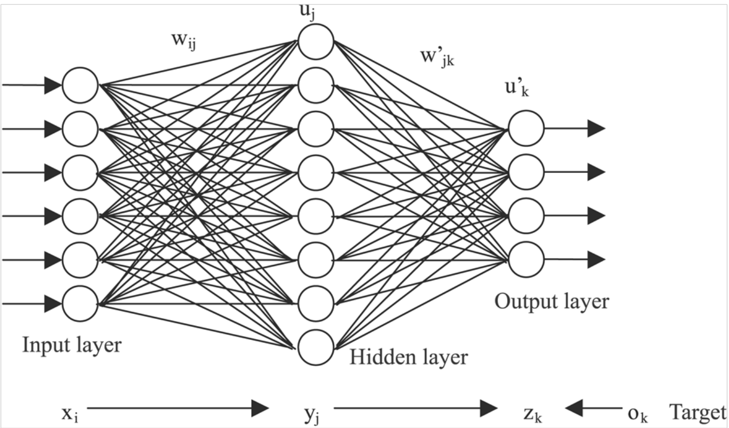

Well-posed Problem

Definition

A computer program is said to learn from experience E w.r.t. some tasks T and performance measure P, if its performance at tasks T as measured by P improves with experience E.

`For example, a computer programs learns to play Go game might improves its performance as measured by its ability to win, through the experience of playing against itself.`

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- hyperparameters tuning

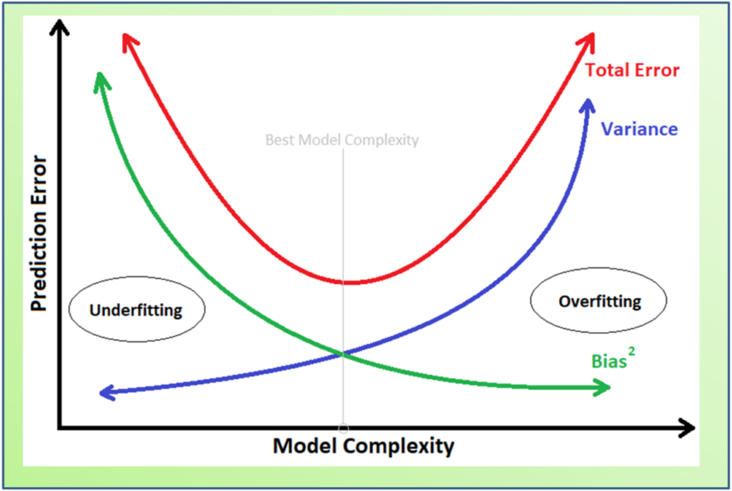
Bias vs. Variance

Given $y = f(x) + \epsilon$

$$E[y] = E[f + \epsilon] = E[f] = f$$

$$\begin{aligned}
E[(y - \hat{f})^2] &= E[(f + \epsilon - \hat{f})^2] \\
&= E[(f - E[\hat{f}] + \epsilon - \hat{f} + E[\hat{f}])^2] \\
&= E[(f - E[\hat{f}])^2] + E[\epsilon]^2 + E[(E[\hat{f}] - \hat{f})^2] - 2E[(E[\hat{f}] - \hat{f})(f - E[\hat{f}])] \\
&= E[(f - E[\hat{f}])^2] + E[\epsilon]^2 + E[(E[\hat{f}] - \hat{f})^2] - 2(E[\hat{f}]f - E[\hat{f}]f + E[\hat{f}]E[\hat{f}] - E[\hat{f}]E[\hat{f}]) \\
&= Bias(\hat{f}^2) + Var[\hat{f}] + \sigma^2
\end{aligned}$$

Bias vs. Variance



MLE

Let $p_{MDL}(\boldsymbol{x};\boldsymbol{\theta})$ be a parametric family of probability distribution over the same space indexed by $\boldsymbol{\theta}$.

$$\boldsymbol{\theta}_{ML} = arg\,\underset{\boldsymbol{\theta}}{max} \sum log(p_{MDL}(\boldsymbol{x};\boldsymbol{\theta}))$$

$$\boldsymbol{\theta}_{ML} = arg\,\underset{\boldsymbol{\theta}}{max}\, \mathbb{E}[x \sim \hat{p}_{DAT}] log(p_{MDL}(\boldsymbol{x};\boldsymbol{\theta}))$$

Bayes Statistics

$\boldsymbol{\theta}$ as a prior distribution : $p(\boldsymbol{\theta})$

$$p(\boldsymbol{\theta}|x^{(1)} \dots x^{(m)}) = \frac{p(x^{(1)}, \dots, x^{(m)}|\boldsymbol{\theta})p(\boldsymbol{\theta})}{p(x^{(1)}, \dots, x^{(m)})}$$

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