

Machine Learning Foundations

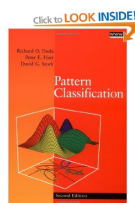
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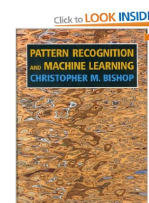
Summer School 2020

Good Books

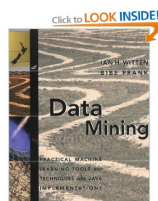
Well worth investing in books if you want to do more in this subject



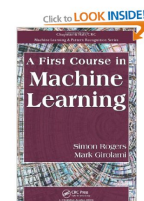
R.O.Duda, P.E.Hart & D.G.Stork
Pattern Classification



C.M. Bishop
Pattern Recognition and Machine Learning



I.H. Witten & E. Frank
Data Mining



S. Rogers & M. Girolami
A First Course in Machine Learning

"There is nothing to be learnt from a professor, which is not to be met with in books"
- David Hume (1711-1776)

(**Wikipedia:** "Hume had little respect for the professors of his time [...] He did not graduate")

Machine Learning as Data-driven Modelling

Single-slide overview of the subject and challenging questions

Data	$\{\mathbf{x}_n, \mathbf{y}_n\}_{n=1}^N$ $\{\mathbf{x}_n\}_{n=1}^N$
Function Approximator	$\mathbf{y} = f(\mathbf{x}, \boldsymbol{\theta}) + v$
Parameter Estimation	$E_0 = \sum_{n=1}^N \{\ \mathbf{y}_n - f(\mathbf{x}_n; \boldsymbol{\theta})\ \}^2$
Prediction	$\hat{\mathbf{y}}_{N+1} = f(\mathbf{x}_{N+1}, \hat{\boldsymbol{\theta}})$
Regularization	$E_1 = \sum_{n=1}^N \{\ \mathbf{y}_n - f(\mathbf{x}_n)\ \}^2 + g(\ \boldsymbol{\theta}\)$
Modelling Uncertainty	$p(\boldsymbol{\theta} \{\mathbf{x}_n, \mathbf{y}_n\}_{n=1}^N)$
Probabilistic Inference	$\mathbf{E}[g(\boldsymbol{\theta})] = \int g(\boldsymbol{\theta}) p(\boldsymbol{\theta}) d\boldsymbol{\theta} = \frac{1}{N_s} \sum_{n=1}^{N_s} g(\boldsymbol{\theta}^{(n)})$
Sequential Estimation	$\boldsymbol{\theta}(n-1 n-1) \longrightarrow \boldsymbol{\theta}(n n-1) \longrightarrow \boldsymbol{\theta}(n n)$ Kalman & Particle Filters; Reinforcement Learning