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MML analysis of *all* data-sets and much more

(including theories of intelligence and automating database normalisation)

Statistical invariance, and
Statistical consistency

My papers (Dowe & Wallace, 1998; Comley & Dowe, 2003, 2005) first to show how to use both discrete (multi-state, categorical) and continuous valued variables in MML Bayesian nets.

Desiderata (in inference)

Statistical invariance

– Circle: $\hat{A} = \pi\ \hat{r}^2$

– Cube: $\hat{l}\ =\ \hat{A}^{1/2}\ =\ \hat{V}^{1/3}$

– Cartesian/Polar: $(\hat{x}, \hat{y}) = (\hat{r}\cos(\hat{\theta}), \hat{r}\sin(\hat{\theta}))$

Statistical consistency

As we get more and more data, we converge more and more closely to the true underlying model

(But what if data-generating source is outside our model space?)

Efficiency

Not only are we statistically consistent, but as we get more and more data we converge as rapidly as is possible to any underlying model.

Some methods of inference

Maximum Likelihood: Given data D, choose (probabilistic) hypothesis H to maximise $f(D|H)$ and minimise $-\log f(D|H)$.

- Statistically invariant — but tends to over-fit, "finding" non-existent patterns in random noise
- Also, how do we choose between models of increasing complexity and increasingly good fit e.g., constant, linear, quadratic, cubic, ...?
- Also, maximum likelihood chooses the hypothesis to make the already observed data as likely as possible.

  But, shouldn't we choose H so as to maximise $Pr(H|D)$?

Bayesianism, prior prob's, $Pr(H|D)$

Prior probability, $Pr(H)$

$Pr(H).Pr(D|H) = Pr(H\&D) =$
$Pr(D\&H) = Pr(D).Pr(H|D)$

So, $Pr(H|D) = \frac{Pr(H).Pr(D|H)}{Pr(D)} =$
$\frac{1}{Pr(D)}(Pr(H).Pr(D|H))$

$posterior(H|D) = \frac{prior(H)\ .\ likelihood(D|H)}{marginal(D)}$

Probability vs probability *density*

What is your (friend's) height? weight?
Measurement accuracy - used in MML in lower bound for some parameter estimates, but overlooked and ignored in classical approaches

Information Theory

$max_H\ Pr(H|D)\ =$

$max_H\ \frac{1}{Pr(D)}(Pr(H).Pr(D|H))\ =$

$max_H\ Pr(H).Pr(D|H)\ =$

$min_H\ -\log Pr(H)\ -\log Pr(D|H)$

Can do this if everything is a probability and not a density, whereupon $l_i = -\log_2 p_i$ is the binary code-length of an event of prob' p_i

$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{21}$
$\frac{1}{4}$	$\frac{1}{4}$	$\frac{2}{21}$
$\frac{1}{4}$	$\frac{1}{4}$	$\frac{3}{21}$
$\frac{1}{8}$	$\frac{1}{4}$	$\frac{6}{21}$
$\frac{1}{16}$		$\frac{4}{21}$
$\frac{1}{16}$		$\frac{5}{21}$

Uniqueness result [Dowe (2008a-b, 2011)] that logarithm-loss is unique invariant "*true*" scoring system.

Rankings - Probabilistic - Round 8 - All Tippers

- The values in in parentheses are the tip(s) you submitted.
- The number below this is your score for that game using those tips.
- Your total score for the round (and for the overall competition so far) are on the right hand side.
- The **[S]** denotes players who are primary or high school students.
- For the probabilistic competition, **T-W-D** denotes how many matches you've tipped, how many you tipped correctly, and how many 0.5's you tipped.

Jump to alias: Dave Find it Clear

		Geelong Collingwood	**Kangaroos** Melbourne	**Adelaide** Gold_Coast	**Sydney** P_Adelaide	Brisbane **Essendon**	**Hawthorn** St_Kilda	**W_Bulldogs** Richmond	**W_Coast** Fremantle	**This Round**	**TOTAL**	**T-W-D**	**Bol Calil**
		8.17.65 9.8.62	19.10.124 12.11.83	20.10.130 9.19.73	18.13.121 9.5.59	9.12.66 15.12.102	14.15.99 10.9.69	23.15.153 18.10.118	14.12.96 9.9.63	**(bits)**		**(no units**	
1	Wobbler Paul Davey	(0.400) -0.322	(0.550) 0.138	(0.800) 0.678	(0.800) 0.678	(0.150) 0.766	(0.700) 0.485	(0.420) -0.252	(0.500) 0.000	**2.171**	**15.895**	61-41-7	-7 0
2	Swanny Rick Swan	(0.530) 0.084	(0.460) -0.120	(0.530) 0.084	(0.850) 0.766	(0.150) 0.766	(0.580) 0.214	(0.530) 0.084	(0.470) -0.089	**1.788**	**15.141**	61-47-0	-5 0
3	Glenroi Glen Martin	(0.413) -0.276	(0.375) -0.415	(0.558) 0.158	(0.821) 0.715	(0.281) 0.524	(0.491) -0.026	(0.625) 0.322	(0.629) 0.331	**1.334**	**14.295**	60-45-0	-5 0
4	Facestompers Josh Tilla	(0.400) -0.322	(0.600) 0.263	(0.800) 0.678	(0.800) 0.678	(0.200) 0.678	(0.600) 0.263	(0.450) -0.152	(0.600) 0.263	**2.349**	**13.926**	52-34-1	-1 0
5	Bouncedown Evan Thompson	(*No Tip*) 0.000	(0.450) -0.152	(0.650) 0.379	(0.950) 0.926	(0.150) 0.766	(0.650) 0.379	(0.550) 0.138	(0.500) 0.000	**2.434**	**13.450**	60-41-1	-7 0
6	Noo Nick Orr	(0.300) -0.737	(0.520) 0.057	(0.700) 0.485	(0.800) 0.678	(0.300) 0.485	(0.530) 0.084	(0.550) 0.138	(0.510) 0.029	**1.219**	**13.268**	61-43-0	-4 0
7	Brebbles Paul Foerste	(0.460) -0.120	(0.640) 0.356	(0.830) 0.731	(0.780) 0.642	(0.450) 0.138	(0.600) 0.263	(0.610) 0.287	(0.540) 0.111	**2.407**	**13.057**	61-46-0	-2 0
8	Rourke Darren O'Shaughnessy	(0.430) -0.218	(0.510) 0.029	(0.850) 0.766	(0.850) 0.766	(0.320) 0.444	(0.470) -0.089	(0.600) 0.263	(0.450) -0.152	**1.807**	**12.980**	61-42-2	0 0
9	573v30 Stephen Bakic	(0.300) -0.737	(0.700) 0.485	(0.800) 0.678	(0.900) 0.848	(0.200) 0.678	(0.700) 0.485	(0.700) 0.485	(0.300) -0.737	**2.186**	**12.976**	60-43-0	0 0
10	Hoffy Tim Hof	(0.500) 0.000	(0.600) 0.263	(0.500) 0.000	(0.900) 0.848	(0.200) 0.678	(0.450) -0.152	(0.500) 0.000	(0.500) 0.000	**1.637**	**12.907**	61-39-8	-2 0
		Geelong Collingwood	**Kangaroos** Melbourne	**Adelaide** Gold_Coast	**Sydney** P_Adelaide	Brisbane **Essendon**	**Hawthorn** St_Kilda	**W_Bulldogs** Richmond	**W_Coast** Fremantle	**This Round**	**TOTAL**	**T-W-D**	**Bol Calil**
11	Rajah Christopher G Crawford	(0.450) -0.152	(0.450) -0.152	(0.750) 0.585	(0.750) 0.585	(0.400) 0.263	(0.650) 0.379	(0.450) -0.152	(0.550) 0.138	**1.493**	**12.887**	61-45-0	-6 0
12	Chandler09 Nick Chandler	(0.600) 0.263	(0.650) 0.379	(0.750) 0.585	(0.950) 0.926	(0.050) 0.926	(0.350) -0.515	(0.500) 0.000	(0.500) 0.000	**2.564**	**12.232**	61-36-11	4 0
13	Weighted Autotipper	(0.424) -0.237	(0.488) -0.036	(0.699) 0.484	(0.813) 0.701	(0.232) 0.618	(0.596) 0.254	(0.525) 0.069	(0.502) 0.007	**1.861**	**12.213**	61-43-0	-5 0
14	Mfcwow Andrew B	(*No Tip*) 0.000	(0.450) -0.152	(0.800) 0.678	(0.750) 0.585	(0.550) -0.152	(0.550) 0.138	(0.550) 0.138	(0.550) 0.138	**1.372**	**12.077**	60-43-0	-4 0
15	Prenda Luke Prendergast	(0.500) 0.000	(0.500) 0.000	(0.850) 0.766	(0.850) 0.766	(0.300) 0.485	(0.500) 0.000	(0.700) 0.485	(0.500) 0.000	**2.502**	**11.942**	61-30-19	-1 0
16	Tutankhgammon Philip Gammon	(0.350) -0.515	(0.500) 0.000	(0.870) 0.799	(0.860) 0.782	(0.160) 0.748	(0.710) 0.506	(0.570) 0.189	(0.480) -0.059	**2.451**	**11.807**	60-36-10	1 0
17	Marigoldman Mark Ulasowski	(0.500) 0.000	(0.500) 0.000	(0.800) 0.678	(0.880) 0.816	(0.120) 0.816	(0.700) 0.485	(0.340) -0.556	(0.500) 0.000	**2.238**	**11.688**	61-35-12	4 0
18	Micko52 Michael McEachen	(0.300) -0.737	(0.500) 0.000	(0.800) 0.678	(0.800) 0.678	(0.200) 0.678	(0.500) 0.000	(0.500) 0.000	(0.500) 0.000	**1.297**	**11.604**	61-34-16	-3 0
19	Roggercat Roger Walter	(0.500) 0.000	(0.400) -0.322	(0.700) 0.485	(0.800) 0.678	(0.200) 0.678	(0.600) 0.263	(0.600) 0.263	(0.350) -0.515	**1.531**	**11.580**	61-35-11	-0 0
20	Towmotar Ben Thompson	(0.300) -0.737	(0.300) -0.737	(0.700) 0.485	(0.800) 0.678	(0.200) 0.678	(0.700) 0.485	(0.400) -0.322	(0.600) 0.263	**0.794**	**11.550**	61-44-1	0 0
		Geelong Collingwood	**Kangaroos** Melbourne	**Adelaide** Gold_Coast	**Sydney** P_Adelaide	Brisbane **Essendon**	**Hawthorn** St_Kilda	**W_Bulldogs** Richmond	**W_Coast** Fremantle	**This Round**	**TOTAL**	**T-W-D**	**Bol Calil**
21	Toddytiger steve todorovic	(0.390) -0.358	(0.540) 0.111	(0.900) 0.848	(0.780) 0.642	(0.160) 0.748	(0.650) 0.379	(0.480) -0.059	(0.520) 0.057	**2.367**	**11.500**	61-41-2	2 0
22	Tandaman Ricky Walsh	(0.510) 0.029	(0.420) -0.252	(0.680) 0.444	(0.730) 0.546	(0.130) 0.799	(0.600) 0.263	(0.480) -0.059	(0.362) -0.466	**1.304**	**11.420**	61-42-0	1 0

Bayesian **Maximum A Posteriori** (MAP) maximises prior *density* multiplied by likelihood
This is not statistically invariant.
It also suffers the inconsistency and other problems of Max Likelihood.

Minimum Message Length (**MML**) is statistically invariant and has general statistical consistency properties (which Maximum Likelihood and Akaike's Information Criterion (AIC) don't have).

– MML is also far more efficient than Maximum Likelihood and AIC
– MML is always defined, whereas for some - or many - problems AIC is either undefined or poor

Conjecture (1998, ...) that only MML and very closely-related Bayesian methods are in general both statistically consistent and invariant.

Back-up Conjecture: If there are any such non-Bayesian methods, they will be far less efficient than MML.

Turing Machine
$f : States \times Symbols \rightarrow \{L, R\} \cup Symbols.$

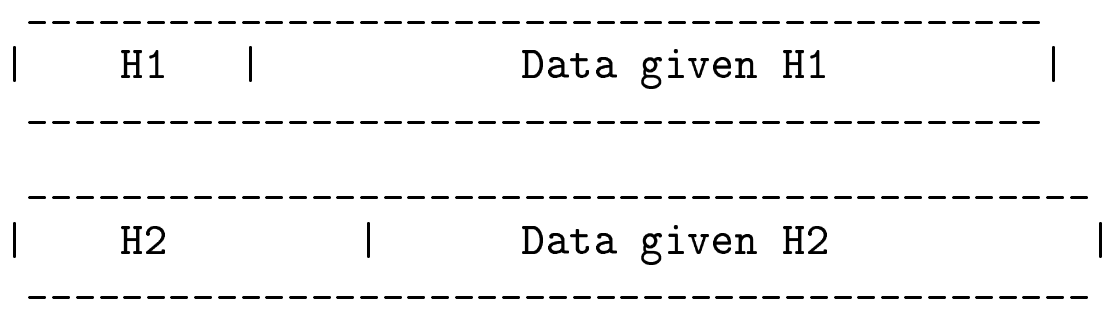
With binary alphabet,
$f : States \times \{0, 1\} \rightarrow \{L, R\} \cup \{0, 1\}.$

Any known computer program can be represented by a Turing Machine.

Universal Turing Machines (UTMs) are like a compiler and can be made to emulate *any* Turing Machine (TM).

Recalling from information theory that an event of probability p_i can be encoded by a binary code-word of length $l_i = \log_2 p_i$, and recalling from MML that choosing H to maximise $Pr(H|D)$ is equivalent to choosing H to minimise the length of a two-part message,

$$-\log Pr(H) \quad -\log Pr(D|H),$$



we can see the relationship between MML, (probabilistic) Turing machines and 2-part Kolmogorov complexity.

In principle, can infer *any* computable function. Relevant in *all* analysis domains - including bioinformatics and non-standard models of computing.

Solomonoff 85th Memorial Conference
Melbourne, Australia
30 Nov. - 2 Dec. 2011

3rd Call for Papers

Apologies for cross posting

Solomonoff 85th Memorial Conference

http://www.Solomonoff85thMemorial.monash.edu/

Proceedings of this multi-disciplinary conference will be published by Springer in the prestigious LNAI (LNCS) series
****
Dear Colleague

You are cordially invited to submit a paper and participate at Solomonoff 85th Memorial Conference which, will be held in Melbourne, Australia, between 30 November - 2 December 2011 with the possibility of a tutorial/workshop being organised on the 29th November 2011.

This multi-disciplinary Conference will be run back to back with the AI 2011 Conference in Perth, Australia.

This is a multi-disciplinary conference based on the wide range of applications of work related to or inspired by that of Ray Solomonoff. The contributions sought for this conference include, but are not restricted to, the following:-

Statistical inference and prediction, Econometrics *(including time series and panel data)*, in Principle proofs of financial market inefficiency, Theories of (quantifying) intelligence and new forms of *(universal)* intelligence test *(for robotic, terrestrial and extra-terrestrial life)*, the Singularity (or infinity point), when machine intelligence surpasses that of humans), the future of science, Philosophy of science, the Problem of induction, Evolutionary (tree) models in biology and linguistics, Geography, Climate modelling and bush-fire detection, Environmental science, Image processing, Spectral analysis, Engineering, Artificial intelligence, Machine learning, Statistics and Philosophy, Mathematics, Linguistics, Computer science, Data mining, Bioinformatics, Computational intelligence, Computational science, Life sciences, Physics, Knowledge discovery, Ethics, Computational biology, Computational linguistics, Collective intelligence, structure and computing connectivity of random nets, effect of Heisenberg's principle on channel capacity, Arguments that entropy is not the arrow of time, and etc. See also Ray Solomonoff's Publications (and his obituary).

(For more details, please see Extended Call for Papers.)

General and Program Chair
David Dowe, Monash University, Australia

Program Committee
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Co-ordinator
Dianne Nguyen, Monash University, Australia

You will find more information about the Conference at the following Website:

http://www.Solomonoff85thMemorial.monash.edu/

For more details on how to submit a paper(s), please refer to the Submission Page

Sponsors

Associated Events

- 24th Australasian Joint Conference on Artificial Intelligence (AI2011), 5-8 December, 2011
- 12th Asian Logic Conference, 15-20 December 2011

Important Dates

Extended Deadline of Paper Submission:	**16 June 2011** NEW
Notification of Acceptance of Paper:	**10 August 2011**
Receipt of Camera-Ready Copy:	**5 September 2011**
Conference Dates:	**30 Nov. - 2 Dec. 2011**

Ray Solomonoff's Publications

Contact Us

Solomonoff85thMemorial@monash.edu

This is the webpage of the project "Anytime Universal Intelligence" (ANYNT).

- **Funding Entity:** MEC (Ministerio de Educación y Ciencia), AYUDAS PARA LA REALIZACIÓN ACCIONES COMPLEMENTARIAS DENTRO DEL PROGRAMA NACIONAL DE PROYECTOS DE INVESTIGACIÓN FUNDAMENTAL, PLAN NACIONAL DE I+D+i 2008-2011
- **Type of Project:** EXPLORA
- **Acceptance rate:** 14 from 98 (14.2%)
- **Reference:** TIN2009-06078-E/TIN
- **Period:** September 2009 - December 2011

SUMMARY OF THE PROJECT:

Following ideas from the first intelligence definitions and tests based on Algorithmic Information Theory [Dowe and Hajek 1997] [Hernandez-Orallo 2000a] [Legg and Hutter 2007], we face the challenge of constructing the first universal, formal, but at the same time practical, intelligence test. The key issue is the notion of "anytime" test, which will allow a quick convergence of the test to the subject's level of intelligence and a progressively better assessment the more time we provide. If we succeed, science will be able to measure intelligence of higher animals (e.g. apes), humans and machines in a universal and practical way.

WORKING TEAM:

- José Hernández-Orallo, Associate Professor (T.U.), Departamento de Sistemas Informáticos y Computación, Universitat Politècnica de Valencia, Spain.
- David L. Dowe, Associate Professor, Clayton School of Information Technology, Monash University, Australia.
- María-Victoria Hernández-Lloreda, Associate Professor (T.U.), Departamento de Metodología de las Ciencias del Comportamiento Universidad Complutense de Madrid, Spain.
- Sergio España-Cubillo, Research Assistant, Departamento de Sistemas Informáticos y Computación, Universitat Politècnica de València, Spain.
- Javier Insa-Cabrera, Research Assistant, Departamento de Sistemas Informáticos y Computación, Universitat Politècnica de València, Spain.

Intelligence testing

Who are you calling bird-brained?

An attempt is being made to devise a universal intelligence test

Mar 3rd 2011 | from the print edition

WHAT is the IQ of a chimpanzee? Or a worm? Or a game-show-winning computer program? Or even an alien from the planet Zaarg who can learn any human language in a day, can beat chess grandmasters ten at a time and can instantly factor the products of large prime numbers? At the moment it is impossible to say. IQ tests depend on language, and even Watson, a computer program that beat two human contestants in a special edition of "Jeopardy!" (an American quiz show) on February 16th, does not have a perfect command of English. In any case there is, at the moment, no meaningful scale on which non-human intelligence can be compared with the human sort.

The most famous test for artificial intelligence is that devised by Alan Turing, a British computing pioneer. To pass the Turing test, and thus be considered intelligent, a program must fool a human being into believing that it is another human being. But the Turing test still requires the program to share a language with the tester and, because it is all or nothing, cannot be used to rank different forms of artificial intelligence against one another.

José Hernández-Orallo of the Polytechnic University of Valencia, in Spain, and David Dowe of Monash University, in Australia, think they can do better than this. They believe not only that a universal scale of intelligence can be devised, but also that it can be assessed without reference to language. If they are right, an insult like "bird-brained" will, in the future, be finely calibrated.

Dr Hernández-Orallo and Dr Dowe, both computer scientists, propose to make their measurement by borrowing a concept called Kolmogorov complexity from information theory, a branch of computer science. The Kolmogorov complexity of a computer's output is the shortest possible program (measured in the binary digits that lie at the bottom of all computer code) that could produce that output. On this measure, an entity's intelligence would be measured by the Kolmogorov complexity of the most complex tests it can solve—a clear, numerical value. In practice, calculating the true Kolmogorov complexity of a system is almost impossible. But an approximation can be made. And that, the researchers reckon, will be good enough.

Related topics

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Computer technology
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Technology

The well-honed methods of operant conditioning,

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Over the past five days

Latest blog posts - All times are GMT

What is the best hope for the underclass:

PhD scholarship: Statistics and Computer Science*Monash University*

Clayton School of Information Technology

Posted on: Wed Mar 30 2011

Rating and ranking sports players and teams using Minimum Message Length

Project: The project is on ``Rating and ranking sports players and teams using Minimum Message Length''. Rating systems go back at least as far as Harkness (1949) and the better-known Elo (1961) system for rating chess players. More recent attempts have been made to refine these systems in a variety of ways. We will refine the systems further - perhaps starting with chess but certainly going much further. This includes dealing with the challenging (Neyman-Scott-like) situation where, for some players and teams, there are few games per player or few games between different groups of players. Our enhanced modelling will be for a range of games and sports - including advantages such as, e.g., first move (as in chess), home ground and location, surface (as in tennis), etc. We will apply this to rating and ranking individuals and teams. We also refine how quickly ratings can change depending upon the strength of the player. All sorts of games and sports could use such better systems for rating and ranking teams.

Applicant background: Applicants should have a background - including completing at least the equivalent of an undergraduate degree - in at least one of mathematics, statistics, computer science and/or (information theory and) electrical engineering. Applicants should also be able to write computer programs - preferably in a variation of (e.g.) C or Java. If applicants consider themselves not to be strong at mathematics, then they should at least be fond of mathematics.

Salary: Standard PhD scholarship (Aus$26,667p.a.) [possibly tax-free] accompanied by additional top-up.

The scholarship is for the official Monash University standard duration of 3 years, although this might possibly be extended for a further 6 or possibly 12 months.

Starting date: February 2011 or as soon as possible thereafter.

Enquiries: Contact David dot Dowe at infotech dot monash.edu dot au with clear e-mail subject line and contents.

Some more of MML's *many* application areas

Scoring probabilistic predictions

My papers (Dowe & Wallace, 1998; Comley & Dowe, 2003, 2005) first to show how to use both discrete (multi-state, categorical) and continuous valued variables in MML Bayesian nets.

MML and Efficient Markets Hypothesis: markets *not* provably efficient

MML, Kolmogorov complexity and measures of "intelligence"

MML and Econometric Time Series

MML, Entropy and Time's Arrow

MML and Linguistics - inferring "dead" languages and human prehistory

MML, cosmological arguments and "Intelligent Design" (I.D.)

Philosophy of science, and N. Goodman's "grue" (paradox or) problem of induction, etc., etc.

see also *Solomonoff memorial conference* Call for Papers, etc.

etc.

Some of David Dowe's papers for further reading

* "MML, hybrid Bayesian network graphical models, statistical consistency, invariance & uniqueness", Handbook of Philos of Sci (Vol. 7: Handbook of Philosophy of Statistics), Elsevier, pp901-982, 2011

* "Measuring Universal Intelligence: Towards an Anytime Intelligence Test", Artificial Intelligence journal, Vol 174, Issue 18, December 2010, pp1508-1539, 2010
[Most downloaded from the *Artificial Intelligence* journal since early March 2011 and currently. Also discussed in "*The Economist*" magazine, 5/March/2011, page 82.]

* "Foreword re C. S. Wallace", Computer Journal, Vol. 51, No. 5 (Sept. 2008) [Christopher Stewart WALLACE (1933-2004) memorial special issue], pp523-560, 2008

* "Bayes Not Bust! Why Simplicity is no problem for Bayesians", British J. Philosophy of Science, Vol. 58, No. 4, December 2007, pp709 - 754, 2007

* "Minimum Message Length and Generalised Bayesian Networks with Asymmetric Languages", Chapter 11 in 'Advances in Minimum Description Length: Theory and Applications', MIT Press, April, 2005

* "General Bayesian Networks and Asymmetric Languages", Proc. 2nd Hawaii International Conference on Statistics and Related Fields, 5-8 June, 2003, 2003

* "MML clustering of multi-state, Poisson, von Mises circular and Gaussian distributions", Statistics and Computing, Vol. 10, No. 1, Jan. 2000, pp73-83, 2000

* "Minimum Message Length and Kolmogorov Complexity", Computer Journal, Vol. 42, No. 4, pp270-283, 1999 [Most downloaded from the *Computer Journal*.]

* "Kolmogorov complexity, minimum message length and inverse learning", 14th Australian Statistical Conf' (ASC-14), Broadbeach, Gold Coast, Qld, 6-10 July 1998, p144, 1998

www.csse.monash.edu.au/~dld/David.Dowe.publications.html