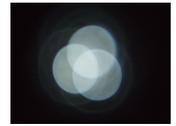


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Squaring the Circle: Where's the triangle

For me, this our 32nd newsletter is a matter of release. A sort of home coming—a renewal—the end of an era and a beginning of a new phase of life. Once a doctor always a doctor. Though the UK General Medical Council has seen fit to force retired doctors to loose all privileges, it does not imply that our dreams and passion for our profession diminishes, far from it.

There is an old medical adage: Physicians know everything, but do nothing. Surgeons know nothing, but do everything. Psychiatrists know nothing and do nothing. But Pathologists, they know everything and do everything, but they are always a day too late.

Hindsight is a grand thing. Better, for one's ego, that patients' recover on the day after one's visit, than the day before. And wise is the old doctor, who gives new medicines whilst they have power to work. Indeed, its strange but not untrue, that blue tablets make people sleep better, and red capsules help depression.

Indeed, it works for me, and might for you, but not for my wife, to tell yourself to stay awake when you can't sleep. Why then am I euphoric. Since the last newsletter, my golf has improved. I'm swinging the club, rather than trying to hit the ball. Furthermore, on a 16 day holiday cruising to Alaska, I realised how nice it was to live in a world without emails.

Far better, the time in Africa, 1963, when the banana boat brought in the papers and we sat by the pool reading two weeks daily newspapers—crisis in Cuba—World War Three to start. Read on "No were not" a storm in a tea cup. And the sun is shining.

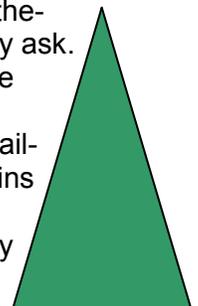
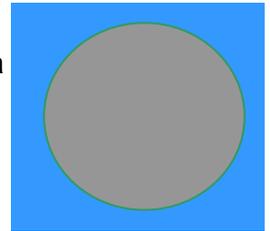
Moreover, and more to the point, I have just received my copy of our post 2008 Portrush Conference Springer Book 'Intelligent patient management'. Thanks to our 65 authors, many of whom were not at the conference, Elia's negotiating skills, Sally's final perseverance and Chris Nugent's involvement at University of Ulster in telemedicine we have a veritable feast, 19 papers giving a broad brush -insights into the strength and depth of clinically relevant mathematical models.

Seeing in print my contribution with the husband and wife New Zealand clinical team, I realised how their experience, trauma and joys, 1992-2007, matched our experience at St.George's 1968-1984. Changing staff leant behaviour causes conflict and takes time. Thereafter, further structural or organisational change, can and does, create once more the problem that had been solved.

Leading me to conclude that the one question that no public inquiry, or management change, considers is "WHY DID YOU DO WHAT YOU DID?" So there we are. Numerically and Mathematically, **we have squared the circle**, now we need to add the triangle. 'Why?' you may ask.

Well the grey circle is the data, the blue square is the model. So good, so far. But the green is the staff learnt behaviour. Why we do, what we do. Which depends on many things within and without the system under study: structure, purpose, past history, prevailing attitudes and knowledge, which taken together with countless other variables explains why one size never fits all.

So, whatever we do requires recognition that one size never fits all, and a philosophy of love. See DOUKABOR page 9



Forecasting for cancer services

Tracy Barber, Nicholas Brown, Rachael Hamilton-Keene, Philippa Hartney, Terry Mills¹

Editor's comment: Develops a hypothetical model which explains why the increasing incidence of cancer may reflect population ageing. Concludes, that geography is also a factor.

In December 2008, the Victorian Government in Australia released *Victoria's Cancer Action Plan 2008-2011*.¹ This provides a framework that outlines the Government's plans for dealing with cancer on a state-wide basis over the next few years.

It is noteworthy that "Victoria's cancer reform agenda is underpinned by the principle that patients should be treated as close to home as possible"¹. To this end, a network of integrated cancer services (ICS) across the State has been created. There are three ICS in the Melbourne metropolitan area, five regional ICS (each dealing with a non-metropolitan region of Victoria), and one state-wide ICS that specialises in paediatric cancer care. Each ICS plays a role in delivering cancer services in its part of Victoria, and together they seek to collaborate across the State. Palliative care services have been organised in a similar state-wide structure.

This article is written from the perspective of the Loddon Mallee Integrated Cancer Service which is one of the regional ICS.

The Loddon Mallee Region (LMR) covers about 60,000 square km (25% of the state of Victoria) and has a population of about 300,000 people. It also has a higher average age than populations in many other areas; therefore, because the probability of developing cancer increases with age, it has a higher incidence rate of cancer. Thus, LMR covers a large area, and has a modest size population in which there is a relatively high incidence rate of cancer. Furthermore, LMR has an acute shortage of health care professionals with expertise in cancer care.

These circumstances create major difficulties in providing cancer services to the region especially when one is endeavouring to support patients close to their homes.

For any given population, and in any given year, the *incidence* of cancer is the number of new cases diagnosed in that year and population. The *incidence rate* is the number of new cases per 100,000 head of population. An *age-specific incidence* is the incidence for a given age group, and the *age-specific incidence rate* is the incidence rate for the given age group. Since cancer is a notifiable disease in Australia, there are good data on the incidence of cancer across the nation.

In planning for cancer services, LMICS uses forecasts of the incidence of cancer in the region. For example, a business case for the introduction of a new cancer service in a particular city would be based, in part, on local forecasts of the incidence of cancer in the short-medium term. Forecasting is a necessary part of service planning.

The toy example in Table 1 illustrates key aspects of forecasting the incidence of cancer. By this we mean the incidence of all cancers covered by the cancer registry.

In this hypothetical population, there are only three age groups; nobody lives past the age of 89. The population is divided into three age groups and for each age group, we know the population size

Table 1: In this hypothetical population, during 1970-2000, the overall incidence of cancer has increased although the age-specific incidence in every age group is constant.						
	1970			2000		
Age	Population	P(Cancer)	Incidence	Population	P(Cancer)	Incidence
0-29	500	0.01	5	400	0.01	4
30-59	400	0.05	20	400	0.05	20
60-89	300	0.10	30	400	0.10	40
Total	1200	0.046	55	1200	0.053	64

and the incidence of cancer for each year. This is equivalent to knowing the proportion of people diagnosed with cancer in a particular age group and a particular year.

Notice that in 1970, 55 people out of 1200 were diagnosed with cancer and probability of being diagnosed with cancer is 0.046. Thirty years later, the probability of being diagnosed with cancer has risen to 0.053. Over the entire population, the probability of being diagnosed with cancer has increased. On the other hand, in each age group, the probability of being diagnosed with cancer is unchanged!

What has changed between 1970 and 2000 is the age distribution of the population. The population is ageing, there is a higher probability of being diagnosed with cancer when one is older, and hence, over the entire population, there is a higher probability of being diagnosed with cancer in 2000 than in 1970.

Although this example is hypothetical, it is consistent with our experience in LMR. The age-specific incidence rates for males and females have been steady over the last 10 years, and the overall incidence rate of cancer has been increasing for males and females. The situation may be different for a particular cancer such as prostate cancer.

Suppose that one wishes to forecast the incidence of cancer for the year 2020. Table 1 suggests that one approach is as follows. Use government population projections for the region to forecast the population for different age groups in 2020. The cancer registry will provide historical data on the probability of being diagnosed with cancer for each age group over many years. Apply some forecasting technique to this time series data, and forecast the probability of being diagnosed with cancer in each age group for 2020. Then the calculations in Table 1 can be performed for 2020. One can go further and calculate prediction intervals for the number of people who will be diagnosed with cancer in 2020.

Various approaches for forecasting the incidence of cancer have been proposed in the research literature. A promising approach based on functional data analysis² has been advanced recently by Erbas, Hyndman and Gertig (2007)³ and adopted by the Australian Institute of Health and Welfare.

However, the model used to develop a forecast for the incidence of cancer may vary with the geographic location. For example, in a study of the incidence of cancer in Nordic countries, the forecasting methods used for Iceland were different from those used in other countries⁴.

A key research question for LMICS is: Which forecasting method is most appropriate for the Loddon Mallee Region?

Notes and references

The authors are affiliated with the Loddon Mallee Integrated Cancer Service (<http://www.lmics.org.au/>).
Email: [tmills](mailto:tmills@bendigohealth.org.au) at [bendigohealth](http://bendigohealth.org.au) dot [org](http://bendigohealth.org.au) dot [au](http://bendigohealth.org.au).

1. Victoria Government Department of Human Services (2008). *Victoria's Cancer Action Plan 2008–2011*. Melbourne: Department of Human Services. Available at URL: <http://www.health.vic.gov.au/cancer/vcap.htm>.
2. Ramsay, J.O. and B.W. Silverman (2005). *Functional Data Analysis*. Second ed., New York: Springer.
3. Erbas, B., R. J. Hyndman, et al. (2007). Forecasting age-specific breast cancer mortality using functional data models. *Statistics in Medicine*, 26(2): 458–470.
4. Møller, B., H. Fekjær, et al. (2002). Prediction of cancer incidence in the Nordic countries up to the year 2020. *European Journal of Cancer Prevention*, 11(Supplement 1): S1-S96.

Submitted to *Nosokinetics News*, 18 May 2009

News from the Research Groups — University of Ulster

Sally McClean's Group, Lallit Garg (correspondent: garg-l@ulster.ac.uk)



Sequential pattern mining application for health care data

A new sequential pattern mining application to healthcare data, providing important information for health service managers and policy makers to help them to identify sequential patterns which require attention for efficiently managing scarce healthcare resources and developing effective healthcare management policies. Sequential patterns are identified as patient pathways using a non-homogeneous Markov model.

Probability, duration and cost of each sequential pattern are calculated and used to extract interesting patient pathways according to desired criteria of interestingness including most frequent pathways, least costly pathways, pathways having maximum average cost or other potentially interesting pathways.

This information can be helpful to healthcare professionals in resource planning and allocation, budgetary analysis and understanding the changing patterns of demand, inefficiencies and occasionally limiting steps in the care process as the effect of introducing new policies. The approach is illustrated using historical data on geriatric patients from an administrative database of a London hospital.

Garg L., McClean S. I., Meenan B. J. and Millard P. H. (2008). Non-homogeneous Markov Models for Sequential Pattern Mining of Healthcare Data. *IMA Journal of Management Mathematics*. doi:10.1093/imaman/dpn030.

Applying control theory to manage admission rates to meet scarce budgetary resource availability

An application of control theory to manage current admission rates to meet future scarce budgetary resource availability is described. This non-homogeneous Markov chain modelling based approach can also be used to predict the care resource requirements in the future and to estimate the effect of an admission policy in a care system.

An optimization technique is also presented to reduce the implementation complexity and time. The model presented in the paper is primarily developed for an elderly care system considering both hospital and community care and is illustrated using data on geriatric patients from a London hospital but it can be used for any care system with some modification.

Garg L., McClean, S. I., Meenan B. J., and Millard P. H. 2008. Optimal Control of Patient Admissions to Satisfy Resource Restrictions. In *Proceedings of the 21st IEEE International Symposium on Computer-Based Medical Systems 2008 (CBMS'08)*, Jyväskylä, Finland, June 17 - 19, 2008. pp. 512-517.

Bridging the gap: use and misuse of management science methods in management and planning

Reports an extensive scientific survey of different areas of management and planning in health care. Undertaken in an attempt to identify where there has :

- already been a substantial contribution from management science methods to healthcare problems, and where
- there is a clear potential for more work to be done and to gain an idea about the popularity of each method among the non-academic community (mainly industry, government and the user community).

The focus is on the read-across to the healthcare domain from such approaches applied generally to management and planning and how the methods can be used to improvement patient care.

The authors conclude that there are areas where healthcare practitioners and academic researchers are using management science approaches in a similar way to other service and manufacturing industries. However, there is still there is a gap which require urgent attention to help improve healthcare service management and planning decisions.

Academic researchers can hugely contribute to such developments by properly identifying the concepts and need for improvement and suitably adapting the management science methods for healthcare problems. And, conversely, practitioners can learn from academics that simple approaches may be adequate and complexity is not always necessary.

Also significant improvements may be made by academics focussing more on complex approaches with corresponding knowledge transfer to healthcare practitioners.

Garg L., and McClean S. I. (2008). Is management science doing enough to improve healthcare. *Proceedings of World Academy of Science, Engineering and Technology (WASET)*, Vol 30. July 2008, pp 76-80.

News from the Research Groups — University of Ulster (cont)

Patient pathways ending in death

A Markov chain model is used to extract patient pathways as a sequence of phases terminating in the absorbing state (death). Associated probability, duration and cost of each of these pathways is calculated and used to identify interesting pathways based on measures of interestingness for the various pathways such as high probability pathways, groups of patients who incur exceptional high costs or pathways that are very long lasting.

Such an approach might be used in association with healthcare process improvement technologies, such as Lean Thinking or Six Sigma where there is a focus on identifying value streams (pathways) that are particularly efficient or particularly inefficient. Waste, as characterised by inefficient pathways, might then be reduced by focusing on poorly performing pathways and trying to improve them.

High probability pathways provide a basis for choosing pathways suitable for such attention. On the other hand we can study high performing pathways to try to understand their salient features and how they lead to a good performance. The approach is illustrated using data on geriatric patients from an administrative database of a London hospital, and we identify interesting pathways for geriatric patients.

McClellan S. I., Garg L., Meenan B. J. and Millard P. H. (2007), Using Markov Models to Find Interesting Patient Pathways. In *Proceedings of the Twentieth IEEE International Symposium on Computer-Based Medical Systems 2007 (CBMS '07)*, Maribor, Slovenia. June 20-22, 2007. pp. 713-718.

Readers Write

Wisdom of Solomon: Samson's Riddle

Out of the lion's mouth came forth sweetness.

John Preater, Keele emailed:

Peter

Thank you for the work on the News. 'Out of the strong came forth sweetness' is Samson's Riddle not (Solomon's). See Judges Chapter 14 Verse 14

Regards

John

Judges 14, 14: on the internet:

A famous riddle was asked by the Sphinx: "What goes on four legs in the morning, on two at noon, on three at night?" [Oedipus](#) guessed the answer correctly: "Man—in infancy he crawls, at his prime he walks, in age he leans on a staff." Samson's riddle is also famous: "Out of the eater came forth meat, and out of the strong came forth sweetness" (Judges 14.14). It refers to a lion he had just killed, on which he saw bees and honey; he ate some of the lion and the honey. <http://www.encyclopedia.com/topic/riddle.aspx>

Arthur Alvarez, emailed

Peter

Two little understood points.

Firstly, Solomon was a dentist.

Second, the text has suffered from the Aramaic;

The scribe was struggling with the original which said 'bread and butter' (meaning 'fees')

Realising that bread and butter went into the mouth not out,

He suddenly felt very tired and called to his No. 4 Wife (his favourite)

"You finish it Sweetness". And she did

Arthur

So be it:

Intelligent Patient Management

Editors Sally McClean et, Peter Millard, Elia El-Darzi, Chris Nugent. Volume 189 In *Studies in Computational Intelligence*, Editor-in-Chief Prof J Kazprzyk. 2009 Springer-Verlag Berlin Heidelberg. ISBN 978-3-642-00178-9

(For Contents, see Appendix)

Part I: Intelligent Patient Management

Hands across the world

In 'Why Nosokinetics? *Measuring and Modelling the Process of Care*', Millard from London and Rae & Busby from Dunedin, New Zealand, using percentile distributions of length of stay at discharge, show how comprehensive change in the process of inpatient care establishes a new stable state of staff discharge behaviour. Thereafter, in geriatric medicine, because of the constrained nature of the bed allocation, admissions rise and fall dependent on how the balance of short and long stay inpatients changes. Whereas, bed borrowing in general medicine, reflects both the urgency of care and the unconstrained bed allocation.

To the best of our knowledge, this is the first time that the data analysis - leading to the Nosokinetics agenda has been repeated. In both services problems were solved: 1969 waiting lists for geriatrics in London, and 1994-2. 1994-1997 bed closure, bed crises in New Zealand. Only to return, when later decision making, based on no evidence of need, no waiting list (UK) and empty beds in Summer time (NZ) restructured the system.

Decision support: Operational, Strategic and Tactical

Next Belaidi *et al* focus our attention onto research leading 'Toward a Decision Support Tool for Emergency Networks in France'. Little attention has been paid in the literature onto the factors that precede emergency care. There is a rich literature for downstream management, follow up and co-ordination, but little research into the factors which influence arrival and requests.

In the French Emergency Supply Chain (ESC) arrangements are not explicit. One of the aims of their research is to fill this gap. Enterprise models and GRAI (Graphe à Résultats et Activités Interliés) conceptual models are described. Based on the theory of complex systems, the conceptual model enables understanding of organisations at three interrelated sub systems: physical, decision making and information. Four core actors are described, and classified by function: regulation, transport; treatment of emergencies, and follow-up care.

Clustering Lengths of Stay

Then El-Darzi's group at Harrow Campus, University of Westminster, and the Gorunescu's in Romania compare and contrast different methods of clustering length of stay data. In *Length of Stay-Based Clustering Methods for Patient Grouping*. Gaussian mixture models, *k*-means clustering and two-step clustering algorithms are described. A historic, 1994-1995 English Hospital Episode Statistics data is used; 103,846 first episode records: average stay 14 days, s.d. 52 days, median 7 days, range 0-4096 days.

Clearly the average misleads. The three clustering methods described five groups, however, the Gaussian mixture model was deemed to be more clinically meaningful and robust. 12%: 1day; 38%: 6 days; 37%: 15 days; 13%: 42 days; 1%:340 days.

Gait Analysis

Collaboration between McClean's group university of Ulster and Zeng's group in China underpins '*Machine Learning and Statistical Approaches to Support the Discrimination of Neuro-degenerative Diseases Based on Gait Analysis*'. Using a publicly available data set the results show that it is feasible to apply computational classification techniques to characterise gait cycles in three diseases.

Confidentiality

From Australia, Pang *et al*, describe collaborative research which tackles the problem of matching data from different data bases using a third party, where the actual data can not be disclosed. *Privacy-Preserving Fuzzy Matching Using a Public Reference Table* describes an algorithmic approach which can accommodate any distance metric used for comparing two strings (or values) and generating neighbourhood regions as long as they are symmetric.

Part II: Intelligent Healthcare Tools

Rostering and planning services

Chabrol *et al.* in '*Methodological Approach and Software Tools for the Hospital Systems*' which is now in practical use in the University Hospital of Clermont-Ferrand in France. The theory and methodology is describe and the use in surgical theatre rosters and in planning obstetric services is illustrated. The model takes into account strategic, tactical and operational factors at three levels - macroscopic (quantities), mesoscopic (activities by speciality)and microscopic (practical considerations).

Optimising resource use

Wang *et al.*, also from France, describe '*A Sizing Tool for Allocation Planning of Hospital Bed Resources*'. New funding methods and restrictions on working time, imply that resource allocation should be optimised. A linear-integer model is used, over three horizons, 4 week, 8 week and 12 week. Estimating bed usage in five specialities - cardiology, neurology, gastroenterology, haematology and pulmonology (respiratory). Results show that possibly two specialties, gastrology and haematology have spare capacity.

Modelling readmissions

Demir *et al.*, from the University of Westminster, London, describe "*A Grid Implementation for Profiling Hospitals Based on Patient Readmissions*". Develops a new statistically valid approach for comparing and contrasting emergency readmissions, based on the time series early and late readmissions. Two key questions are addressed, namely clustering clinical conditions that have similar length of stay distributions in the community before readmission, and profiling hospitals using Grid specific features. Performance measures were estimated for English National Hospitals and the differences between high and low performing hospitals are displayed.

Patient Journeys

Percival *et al.*, from Canada, report '*A Design for Modelling the Impact of Information and Communication Technologies on Patient Journeys in Neonatal Intensive Care Units*'. Measuring impact of technology depends on answering four key questions: When, Why, Who and How. Such models can be used to identify missing opportunities, defining gaps and duplication in information flow, in audit. The structured data model approach provides a rich source of data. Also the concept that patient journey models can be auto-generated foresees a new era in understanding of the use of technology in clinical care systems.

Patient Pathways

Adeyemi and Chausalet, from University of Westminster, present a random effects approach to '*Models for Extracting Information on Patient Pathways*'. Data used comes from a London tertiary referral unit. Operationally patient flow reflects the movement of patients through health care facilities. Two approaches, patient-specific reflects heterogeneity, and the population average in covariates, for which a random (mixed effect) satisfies. Individual patient differences, which are not explained solely by pathways, are explained by gestation age and birth weight. The model could be used in any situation where patient movements are physical.

Part III Intelligent Clinical Support

Bed borrowing

Bed-borrowing plagues modern hospitals. Why should this be? Tackling this problem, Keepers and Harrison from College of Charleston, SC, USA create a stochastic model to evaluate '*Internal Flows and Frequency of Internal Overflows in a Large Teaching Hospital*'. Bed censuses in 20 units of a teaching hospital, were used. Analysis shows that the ratio of steady state occupancy is an excellent predictor of internal overflows. If the steady state occupancy level to bed ratio is over 0.8 the internal overflow rate can be expected to be very high. In contrast the ratio of admissions to beds is very poor. The authors conclude that all hospitals could benefit from this simple analysis of their internal flows.

Continued in next newsletter. Full contents page 9

Summer School Madrid : July 6th—July 17th

Advanced Statistics and Data Mining

18 courses divided in 2 weeks. Attendees may register in each course independently.

Registration will be considered upon strict arrival order. For more information, please, visit

http://www.dia.fi.upm.es/index.php?page=presentation&hl=es_ES or

<http://biocomp.cnb.csic.es/~coss/Docencia/ADAM/ADAM.htm>

For your diary

IMA Health Care Modelling Conference

London, 29-31 March 2010

LAST WORDS

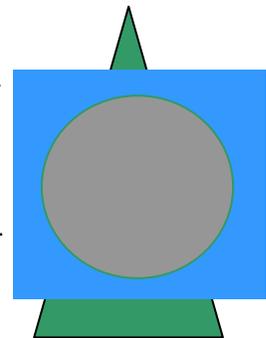
Two weeks ago, cruising to Alaska—no emails. What a relief - they are like a drug addiction. Easy to reject at 7.50 \$ dollars a minute internet access. Giving time to think and time to wonder why? What now? What next?

Then, at our dining table, as we chatted with Hazel and Don Gale, a retired teacher from Vancouver, he told us about his 1970's doctoral research into the Canadian Doukhobors. An 18th century religious sect, similar in some ways to the Quakers, but arising in the peasants, who rejected the pomp and ceremony of the Russian Orthodox church to wrestle with the spirit of the truth.

Persecuted in Russia, for their unorthodox ways, obeying the commandments, they created a community of love. Seeing that not one was greater than the other, in their village life, they bowed to each other at communal meetings showing their equivalence in the eyes of God.

Then the penny dropped. We've got the data and wonderful tools, which the computer revolution has given us, but to implement the tools, for good of all, we need an underlying philosophy of love. Recognising the interrelationship of all, in the pecking order of life.

http://www.spirit-wrestlers.com/excerpts/2006_Doukhobors_Overview.html



Nosokinetics News is the newsletter of the UK Nosokinetics Group

Nosokinetics is the science / subject of measuring and modelling the dynamic aspects of patient and client movement (flow) through health and social care systems. From the Greek, literally, *noso* (sickness) and *kinetics* (movement).

The group collaborates to organise conferences and disseminates news of our and others research and practical use of modelling to enhance decision making in health and social care systems.

Past issues in PDF at <http://www.nosokinetics.org/>

Thanks to IMS our web archive of full texts of submitted papers between 2006-2007 is at:

<http://www.iol.ie/~rjtechne/millard/index0.htm>

To receive a personal copy follow the instructions at

<http://www.jiscmail.ac.uk/lists/NOSOKINETICS-NEWSLETTER.html>

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Intelligent Patient Management

Series: *Studies in Computational Intelligence*, Vol. 189

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