

Causal models for mortality and longevity

The medical perspective

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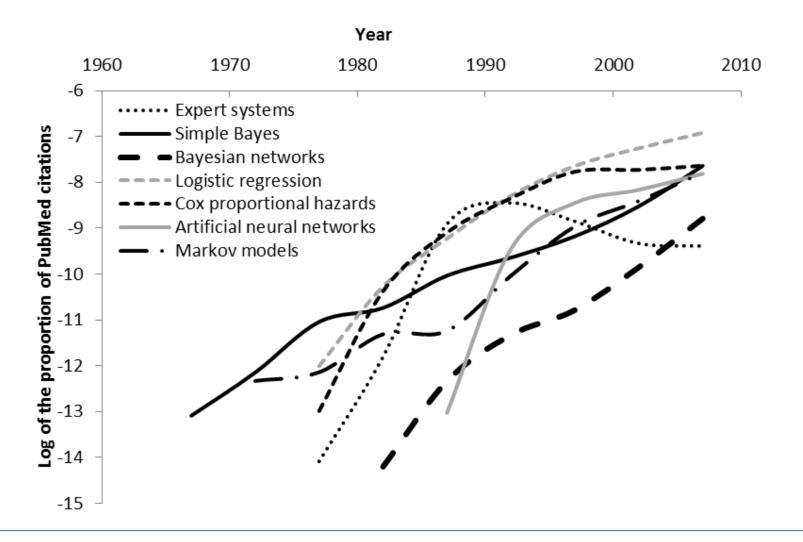
- Uses of medical modelling methods
- History of medical modelling (examples)
- What's hot (Discrete Event Simulation)
- Cannibalising models

Uses of causal medical modelling methods in retirement products

- Probabilistic mortality models.
- 'Classifiers' for underwriting.
- 'Cat' modelling of infectious disease.
- Modelling potential impacts of emerging medical technologies on longevity and mortality for improvement rate estimation. (e.g. impacts of 'polypill', cures for cancer, ageing-retardation)

History

Trends in medical modelling over time



Simple Bayes

- British models include:
- De Dombal's diagnostic system for abdominal pain ('Simple Bayes' with independence assumption). (1)
- Gammerman et al ('Proper Bayes' with no independence assumption). (2)

$$p(S_i|E) = \frac{p(E|S_i).p(S_i)}{p(E)} = \frac{p(E|S_i).p(S_i)}{\sum_{k=1}^{n} p(E|S_k).p(S_k)}$$

where:

S = a set of possible states for a variable = $\{S_1, S_2, ..., S_n\}$

 S_i = the state of interest

E = evidence

k = the index of the n possible states.

- 1. De Dombal FT, Leaper DJ, Staniland JR, McCann AP, Horrocks JC. Computer-aided diagnosis of acute abdominal pain. BrMedJ. 1972 Apr 1;2(5804):9–13.
- 2. Gammerman A, Thatcher AR. Bayesian diagnostic probabilities without assuming independence of symptoms. Methods Inf Med. 1991;30(1):15–22.

Regression models

Logistic regression

-
$$logit(p) = ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 \dots + \beta_n \cdot x_n$$

- where:
- p =the probability of the event
- l = a linear predictor
- b_i=the coefficient for the ith risk factor (In(odds ratio))
- b₀= the intercept for the linear predictor
- x_i = the value of the ith risk factor.

Cox proportional hazards

$$-h(t,X) = h_0(t).e^{\sum_{i=1}^n \beta_i x_i}$$

- where:
- h = hazard or force of mortality
- h_0 = hazard with optimal risk factors
- t = time
- X= a set of n risk factor values $\{x_1, x_2, ..., x_i, ..., x_n\}$
- b_i= the log-hazard ratio for a risk factor i.
- model.

Regression model examples

- Routinely used in analysis of epidemiological data in order to take account of dependence between variables.
- Risk stratification to target interventions.
 - support treatment decisions such as taking statins,
 - risk stratification for other reasons like fall prevention or reducing hospitalisation risk.

Examples

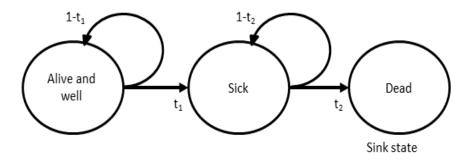
- 'Ubble' longevity risk calculator. (ubble.co.uk)
- QResearch. (<u>www.qresearch.org</u>) University of Nottingham and EMIS.
- QRisk 10 year risk of heart attack and stroke. (qrisk.org)
- QDiabetes 10 year risk of developing diabetes. (<u>www.qdscore.org</u>)
- Various (<u>www.mdcalc.com</u>)
 (http://reference.medscape.com/guide/medical-calculators)

Expert systems

- Computer systems that use a knowledge database and a set of logical rules to mimic the decision-making process of a human expert.
- For example, MYCIN rule based expert system for identifying bacterial infection and recommending treatment strategies. (Over 600 rules)
- Similar to underwriting rules systems where classes of risk are defined, and rules used to determine the class of risk.
- Evolving learning methods (Classification and Regression Trees - CART)

Markov model

- The Markov assumption
- The probability of transition from the current state depends only upon the present state and is unaffected by the history of state transitions prior to reaching the current state.
- Easily circumvented e.g. 'ex-smoker'.



Actuarial Markov model (state transition) – Chatterjee 2008

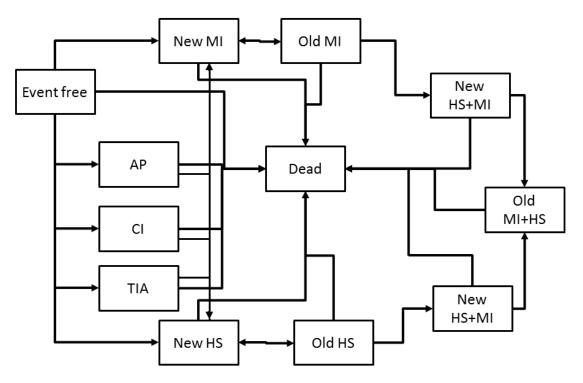


Figure 5-2 A diagram of the possible health states and transitions in Tushar Chatterjee's Markov state transition model. AP = angina pectoris, CI = coronary insufficiency, TIA = transient ischaemic attack, MI = myocardial infarction, HS = hard stroke.

 Chatterjee T. AN INDIVIDUAL LIFE HISTORY MODEL FOR HEART DISEASE, STROKE AND DEATH: STRUCTURE, PARAMETERISATION AND APPLICATIONS. Heriot-Watt University; 2008.

Bayesian networks (Influence diagrams)

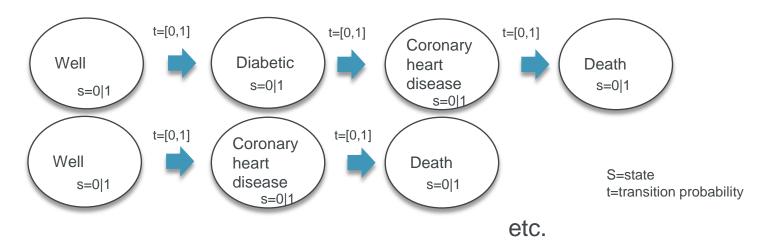
Differ from Markov models.

- Bayesian networks
- The focus is on the probabilistic influence of one state upon another.
 Directed acyclic graphs (no feedback loops). Nodes are state elements of the whole.
- Examples MUNIN for classifying ECGs. HUGIN was a generalised learning network based on work by Spiegelhalter and Lauritzen.
- Markov models
- The probability of transition from one state to another.

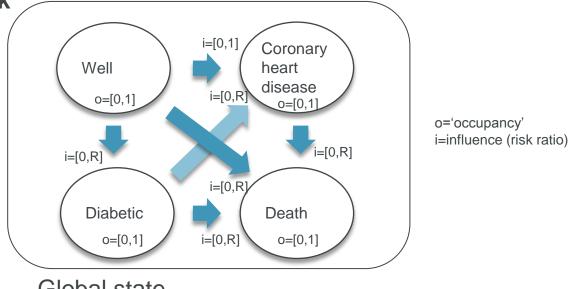
BUGS, WinBUGs and OpenBUGs software (http://www.mrc-bsu.cam.ac.uk/software/bugs/)Lauritzen

SS, Spiegelhalter DJ. Local computations with probabilities on graphical structures and their application to expert systems. Journal of the Royal Statistical Society. 1988;B 50:253–8.

Markov model

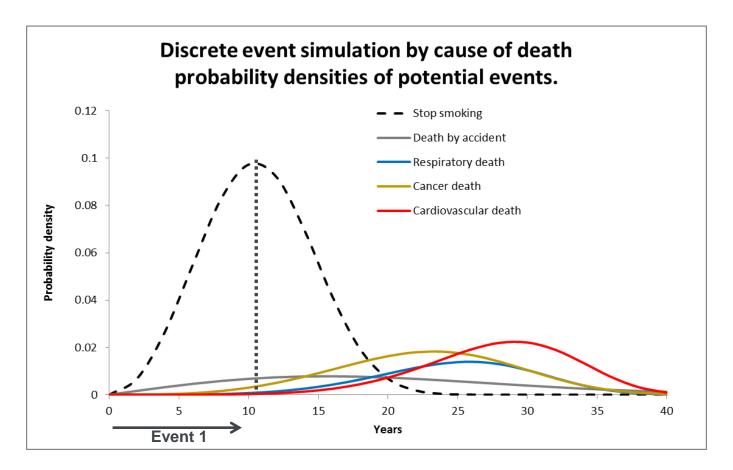






Global state

- Necessarily stochastic.
- Lends itself to causal models with intermediate driving states.
- In discrete event simulation (DES) the modelling process does not proceed in discrete time steps as in Markov models.
- Instead, a probability distribution for an event occurring over time is determined, and a random number, generated using this distribution, is used to select a time for an event.
- A number of parallel possible events are modelled and the random number generation is used to determine which event occurs first, in a particular simulation.
- Efficient.
- Can build quite complex models.

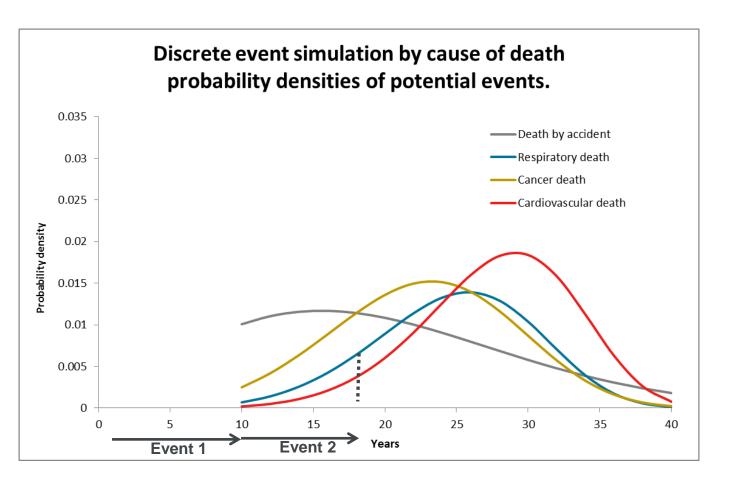


Event	Rand
Smoking	0.05
Accident	0.80
Respiratory	0.25
Cancer	0.33
CVD	0.62

First event

Quit smoking at 11 years.

^{*} Indicative figures only. *



Event	Rand
Accident	0.40
Respiratory	0.01
Cancer	0.91
CVD	0.49

Second event

Dies of respiratory disease at 18 years.

^{*} Indicative figures only. *

Cannibalising medical models - sources

- Pubmed (www.ncbi.nlm.nih.gov/pubmed)
- The Centre for Disease Control and Prevention. (www.cdc.gov)
- Secondary databases like TRIP. (<u>www.tripdatabase.com</u>)
- NICE Evidence Search (<u>https://www.evidence.nhs.uk/</u>)

Cannibalising medical models

- Independence a critical factor. Regression / Cox models ideal as independence taken account of.
- Selection of models according to the risk factors used, population characteristics, size and quality of data set.
 - Medical models often use variables not available in actuarial practice. (e.g. coronary calcification on CT scans).
- Know the source data, and your own. The data must be reliable and map reasonably from the evidence to your portfolio data.
- Take care to avoid double counting:
 - Non-independence
 - Age and gender may be included in regression models as independent variables, so should not be applied to an age/gender specific baseline.

Summary

- Logistic regression / Cox proportional hazards (CPH) models dominant.
 - Useful sources of independent hazard ratios to apply in actuarial models.
- Logical rules based methods (expert systems) in relative decline but machine learning methods (CART) may be applicable to underwriting rule generation.
- Discrete Event Simulation emerging as an efficient stochastic modelling method.

De-Dombal acute abdominal diagnosis

- Development began in the 1960s in Yorkshire. A European project by the 1990s.
- In the hands of a junior doctor as accurate at acute abdominal diagnosis as a consultant (~92%).
- Reduced number of bed-night occupancies.
- Reduced perforated appendix, morality and unnecessary laparotomy rates.

Leeds Computer Assisted Learning System

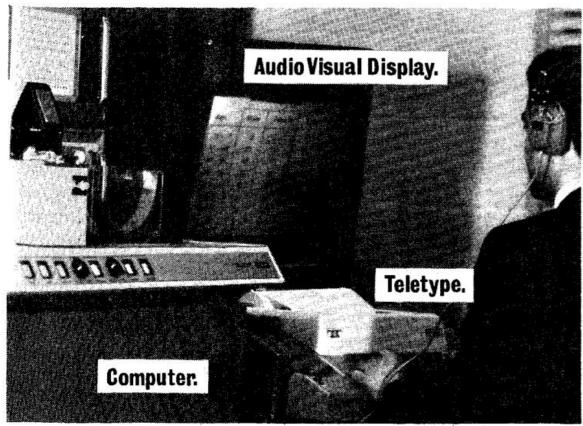


Fig. 1-Medical student using Leeds C.A.L. system.

De Dombal F., Hartley J., Sleeman D. A COMPUTER-ASSISTED SYSTEM FOR LEARNING CLINICAL DIAGNOSIS. The Lancet. 1969 Jan;293(7586):145–8.

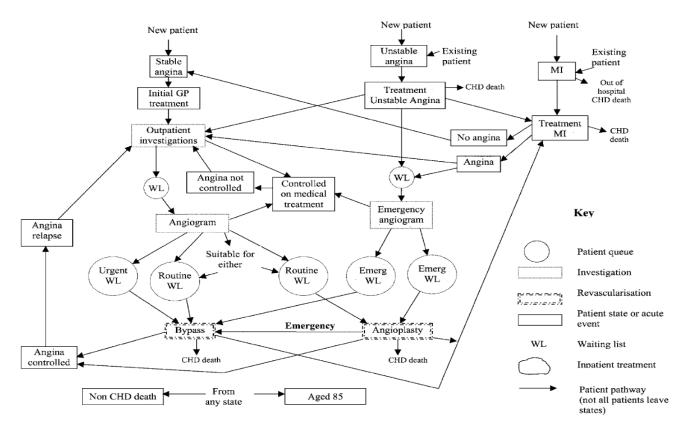
De Dombal

F. T. de Dombal

FEMALE AGE 20 TO 29 SITE ONSET ... RIGHT LOWER QUAD SITE PRESENT.LOWER HALF ONSET PAIN ... OVER 48 HRS AGO TYPE AT ONS . . COLICKY TYPE NOW....INTERMITTENT SEVERITY PAIN NOW MODERATE NAUSEA PRESENT UDMITING PRESENT APPETITE DECREASED BOWELS.....NORMAL-NO CHANGE MICTURITION . . NORMAL JAUNDICE NOT PRESENT PREV. PAIN. . . YES-SIMILAR PREV.SURG....NO PREV.ABD.OPRN DRUGS.....NO TREATMENT MOOD.....ANXIOUS COLOUR....FLUSHED ABD. MOVI...NORMAL ABD. SCAR...ABSENT DISTENSION . . . ABSENT TENDERNESS ... LOWER HALF ABOUT REBOUND ABSENT GUARDING PRESENT RIGIDITY ... ABSENT ABD.MASS....NOT FELT MURPHYS SIGN.NEGATIVE BOWEL SOUNDS . NORMAL RECTAL EXAM..NO ABNORMALITY

De Dombal FT. Surgical diagnosis assisted by a computer. Proc R Soc Lond, B, Biol Sci. 1973 Dec 21;184(77):433–40.

POSSIBLE DIAGNOSES
APPEND DIVERT PERFDU NONSAP CHOLEC SMBOBT PANCRE
PROBABILITIES ARE
25.44 0.13 0.00 73.74 0.00 0.69 0.00

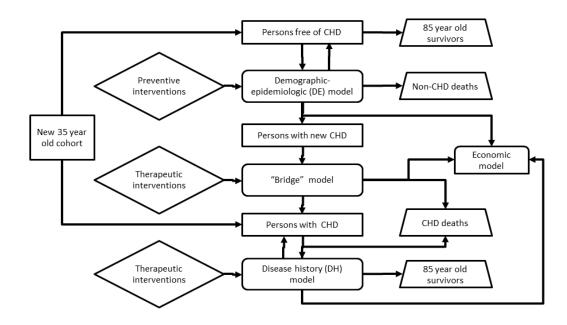


The flowchart for the pathways in the coronary heart disease treatment discrete event simulation model by Cooper et al.

Cooper K, Davies R, Roderick P, Chase D, Raftery J. The development of a simulation model of the treatment of coronary heart disease. Health Care Manag Sci. 2002 Nov;5(4):259–67.

Markov model (state transition) – Coronary Heart Disease Policy Model

- Emerged from Harvard in the 1980s.
- Used to formulate US coronary heart disease management policy. (1)



1. Cooper K, Davies R, Roderick P, Chase D, Raftery J. The development of a simulation model of the treatment of coronary heart disease. Health Care Manag Sci. 2002 Nov;5(4):259–67.

Others

Neural networks

- Classifier
- 'Black box' so of limited use in actuarial practice.
- Tendency to over-fit.
- Coronary heart disease events (PROCAM in Germany) (1)

Support vector machines

- Identifies the 'maximal hyperplane' that separates subjects in or out of a class.
- Finds the function using risk factors that describes the surface that optimally separates members of a class from non-members.
- Diagnosis od diabetes and prediabetes. (2)
- Computer Learning and Research Centre, Royal Holloway.

Other – logical trees, Dempster-Shafer Theory, fuzzy logic…

- 1. Voss R, Cullen P, Schulte H, Assmann G. Prediction of risk of coronary events in middle-aged men in the Prospective Cardiovascular Munster Study (PROCAM) using neural networks. IntJEpidemiol. 2002 Dec;31(6):1253–62.
- 2. Yu W, Liu T, Valdez R, Gwinn M, Khoury MJ. Application of support vector machine modeling for prediction of common diseases: the case of diabetes and pre-diabetes. BMC Medical Informatics and Decision Making. 2010;10(1):16.