The future of risk prediction

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In many healthcare settings, a patients' care is influenced by an assessment of their risk for an outcome or condition. Prognostic risk models determine this risk and are part of contemporary clinical practice. In some settings, these models are more accurate than clinician estimate of risk [1,2]. These risk models have historically been built using traditional statistical methods such as linear regression and calculated using small local datasets.

Often, these models make explicit assumptions of the data, such as linear relationships of risk factors to overall outcomes, and predefine factors in the model before model construction. This approach ignores underlying complex relationships between risk factors and actual outcomes while also preventing new unexpected relationships being found between patient factors and risk. Risk prediction approaches that can investigate more nuanced relationships, effectively explore larger datasets and also provide more accurate assessments should be explored and compared to current methods.

Data availability and volume is increasing exponentially in the healthcare industry. This is being driven by the automatic digitization of data in hospitals and the huge volumes of data captured from daily routines through sensors and smartphones [3, 4]. Currently the focus is on data capture but increasingly the focus is moving to data usage. Investigations are centred on how these huge data sets can be harnessed to provide insights in real time. People across sectors and skill specialties understand that data collection alone is not enough and we need interdisciplinary teams working to unlock the potential of the data we capture. New Zealand is uniquely positioned to make good use of this transformation with government mandated data collection existing for years and unique identifiers making data linking simple [5].

Machine learning (ML) is a set of techniques that has gained prominence in recent years for its ability to handle big data and deliver new insights [6]. ML developed from work looking into automatic pattern recognition and these techniques can overcome many common limits of traditional statistics. ML allows a machine to learn patterns through reinforcement and building complex relationships which minimise error between predictions and observed outcomes [7].

In this talk I will discuss what ML offers risk prediction, illustrate examples of where these techniques already permeate your life and also discuss successful examples of ML in risk prediction and an anaesthetic setting. I will also provide background on how these techniques work and help you to better grasp what some of the current buzzwords such as 'Artificial Intelligence' (AI) and 'deep learning' actually mean. These techniques are invariably going to be applied in health care for risk prediction and decision support. I hope to outline the strengths and weakness of these approaches.

References

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