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DECISION SUPPORT FOR TRAUMA SURGERY: CAUSAL MODELLING USING BAYESIAN NETWORKS

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1. SCORING SYSTEMS VS. CAUSAL MODELLING

Scoring systems abound in surgery; some (GCS, RTS) summarise relevant clinical conditions leaving decisions to a clinician. Others (MESS, MESI, TASH) aim to recommend the best treatment, often setting a threshold for a patient's score. However:

- This adds little to an experienced clinician's judgement especially when the score is close to the threshold.
- Its recommendations are mostly based on the previous decisions made in similar circumstances which may introduce historical bias
- The underlying clinical reasoning for making these predictions is unclear to the user.

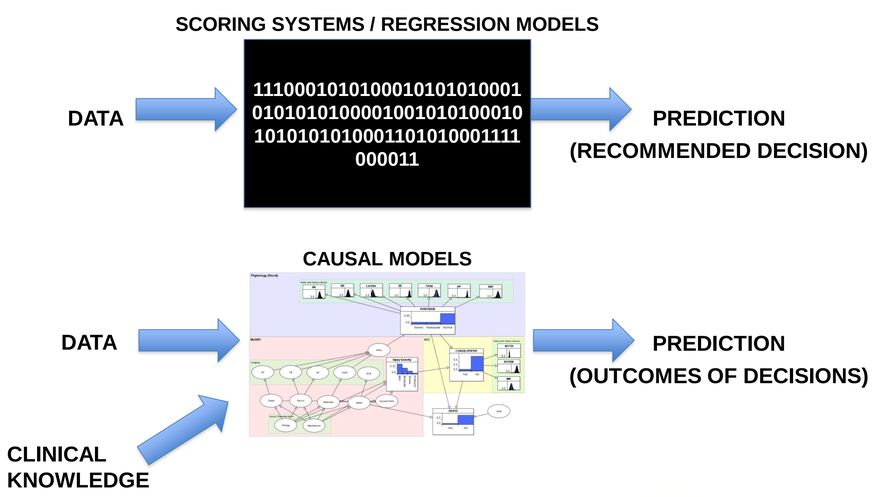

Figure 1. Differences of scoring systems and causal models

Our aim is to develop causal models that estimates the underlying clinical state of the patient and from that predicts the outcomes of treatment alternatives. These models represent the clinician's understanding of the underlying disease mechanism.

The data is used to learn the strength of these relations. However, several variables represents the underlying state of the patient and cannot be directly observed. Data of these variables is therefore not available. It is possible to infer these variables by a combination of clinical and knowledge and data of surrogate measurements.

Unlike, traditional statistical models, causal structure of BN can be locally modified. Parts of the model can be adapted to changing practices and circumstances in the light of clinician's knowledge.

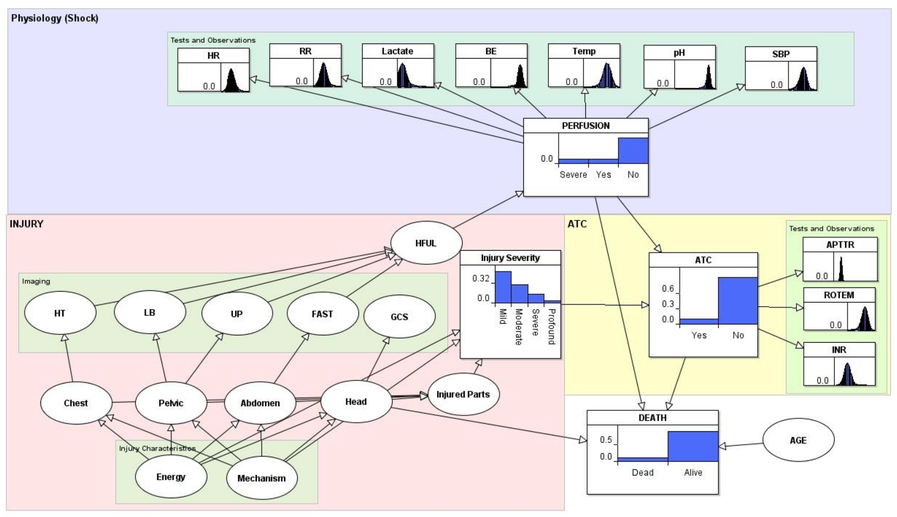

Figure 2. Causal Bayesian Network for Predicting ATC

2. BAYESIAN NETWORKS

Bayesian Networks (BN) are graphical probabilistic models that can be used to calculate the posterior probability of the unobserved variables in the model given any number of variables is observed. Each node in a BN represents a variable and each arc represents a dependency between the variables it connects. Every variable has a node probability table (NPT) which represents its probability distribution.

The graphical structure of BN is suitable for modelling causal relations by using a combination of medical knowledge and data.

3. CASE-STUDY: ATC in MANGLED EXTREMITY TREATMENT

Amputation of a mangled extremity is a critical decision with irreversible consequences for the patients. The initial steps of this decision is largely based on the physiological condition of the patient. We have developed a model capable of predicting acute traumatic coagulopathy (ATC) and risk of death, early in a trauma patient's course. This model is a part of a wider effort to provide decision-support for mangled extremities using causal Bayesian networks.

Figure 3. Mangled Extremity Decisions

4. LABELLING ATC STATUS

The true state of ATC for each patient is required to train the parameters of our model but blood tests like INR cannot perfectly estimate it. We used a systematic approach that automatically labels ATC status using all relevant measurements with a machine learning approach, and compares these labels with literature-based criteria about ATC. Discrepancies, plus a random subset of other cases, are reviewed by clinicians.

Table 1. Node Probability Table for ATC

	Perfusion		
ATC	Severe	Yes	No
Yes	0.65	0.26	0.01
No	0.35	0.74	0.99

5. RESULTS

A dataset of 600 patients were used to develop the model. Predictions of the model were generated by using measurements and observations available in the first 15 minutes after admission. The model were validated on:

1. The training dataset by using 10-fold cross validation
2. An external dataset consisting of 60 patients

At 0.90 sensitivity level, the model's specificity is over 0.80 on both cross-validation and test data.

Table 2. Results of ATC Model

	Cross-Validation Data	Test Data
AUROC for ATC	0.92	0.96
Specificity for ATC	0.81*	0.92**
AUROC for Death	0.89	0.93
Specificity for Death	0.75*	0.73**

*At 0.90 sensitivity, **At 1.00 sensitivity

The calibration of the model was tested by Hosmer-Lemeshow (HL) test. The ATC predictions has 4.4 (p-value 0.77) and 6.6 (p-value 0.68) HL statistics on cross-validation and test data respectively.

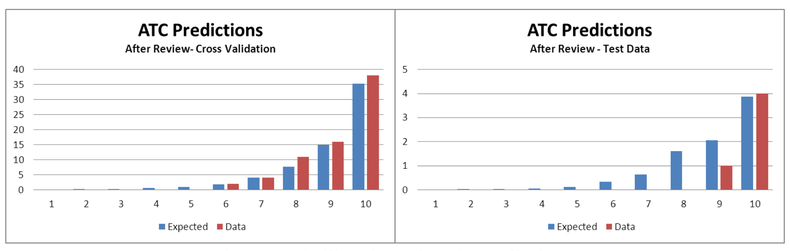

Figure 4. Calibration of ATC Predictions

6. CONCLUSION

A method of developing DSS that can assist the judgement of experienced clinicians has been demonstrated with a successful case study of ATC. The main benefits of causal modelling approach are:

- Making predictions based on the underlying clinical state which is clearly represented by a causal graph
- Using historical data in a more relevant way together with medical knowledge
- Predicting the outcomes of treatment alternatives

Our next step is to develop causal models to provide decision support in viability and functionality outcomes of mangled extremity treatment.

RADAR Risk Assessment and Decision Analysis Research Group

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