Case 3: IDSS based on Bayessian networks and Predictive models

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IDSS description

[Barbaros 2014]

Intelligent Decision Support System for Trauma Care

Decision supported:

Survival of traumatic patient

Partners:

- School of Electronic Engineering and Computer Science (Queen Mery University of London, UK)
- Center for Trauma Science (Queen Mery University of London, UK)
- The Royal London Hospital UK



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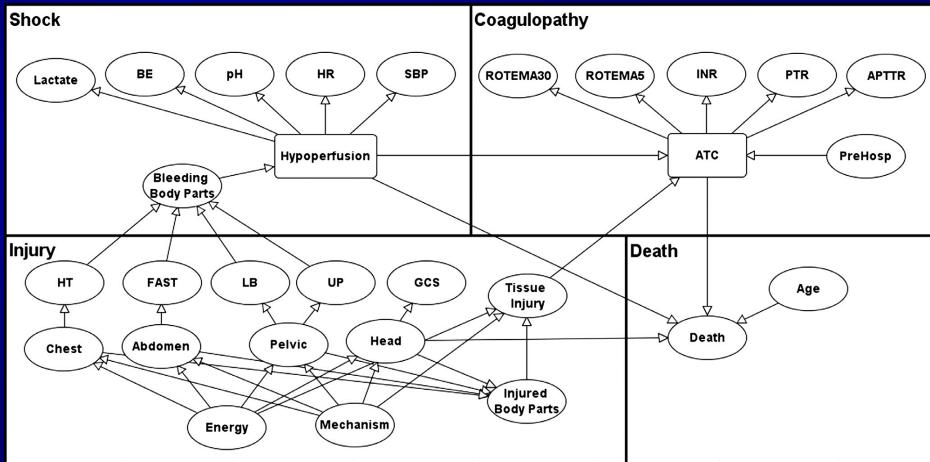


Expert-based structure of BYN:

- Consensus structure of common reasoning types
- Causal coherence guaranteed
- Combine expert knowledge and data when required



Bayessian network structure



Expert-based Bayessian network structure

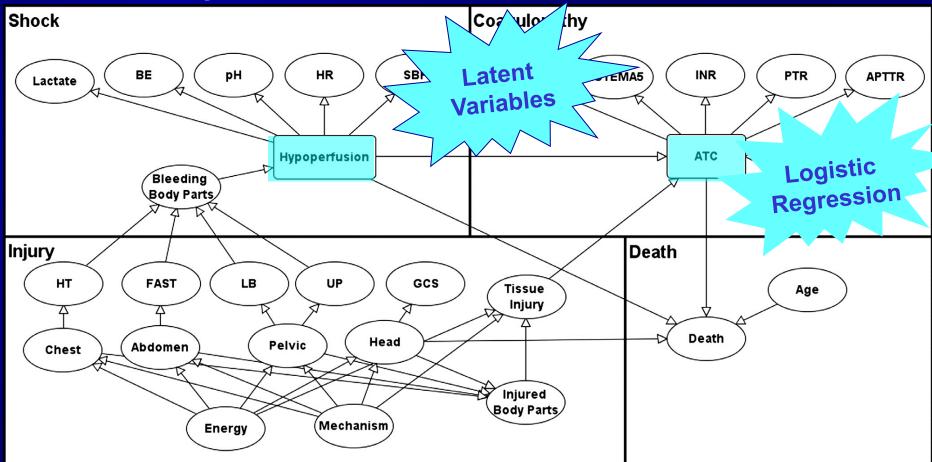
Domain knowledge is used to decide nodes and archs



- Expert-based structure of BYN:
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 - Exclude variables out of the scope of the model
- Identify latent variables and add to dataset
 Label latent variables in training set:



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BIC is considered outside of the scope of the current BYN because BIC effects coagulation by a mechanism different to ATC



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Predicting Coagulopathy

Usign BYN or a Predictive model

Predictive model [Mitra 2014]: COAST score:

entrapment, temperature <35 °C, systolic blood pressure <100 mm Hg, abdominal or pelvic content injury, chest decompression. Regressior

Learning: 1680 major trauma patients, 151 with coagulopathy Pre-hospital variables independently associated with ATC:

- were entrapment
- temperature
- systolic blood pressure
- abdominal or pelvic content injury
- pre-hospital chest decompression

(OR 1.85; 95% CI: 1.12-3.06) (OR 0.60; 95% CI: 0.60–0.72) (OR 0.99; 95% CI: 0.98-0.99) (OR 2.0; 95% CI: 1.27–3.12) (OR 4.99; 2.77–8.99).

Prospective Validation: 1225 major trauma patients, $COAST \ge 3$

- Specificity= 96.4%, sensitivity= 60.0%,
- area under the ROC curve: 0.83 (0.78–0.88).



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 - using clustering (EM)
 - Consensus of final label (expert review in case of inconsistency)

Measurements	After review		
	Yes	No	Unlabelled
ATC label review – m	easurements		
Yes	57	6	-
No	3	524	-
Unlabelled	1	5	4
			Total: 600



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- Learn BYN parameters with EM algorithm on extended dataset
 - Consider additional expert constraints on parameter orders if insufficient data is available

Cross validate the performance of the BYN: Specificity= 67%, sensitivity= 80.0%, AUROC: 0.81 (0.75–0.86)



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- Cross validate the performance of the BYN
- Expert-based model refinement



Expert based model refinement

Consider incipient coagulopathy

- Relabel patients with incipient coagulopathy as ATC=True
- Patients with initial measurements:
 Normal ATC values
 severe injury burden
 poor perfusion

(they will show significant ATC values soon after)

Retrain BYN and re-validate

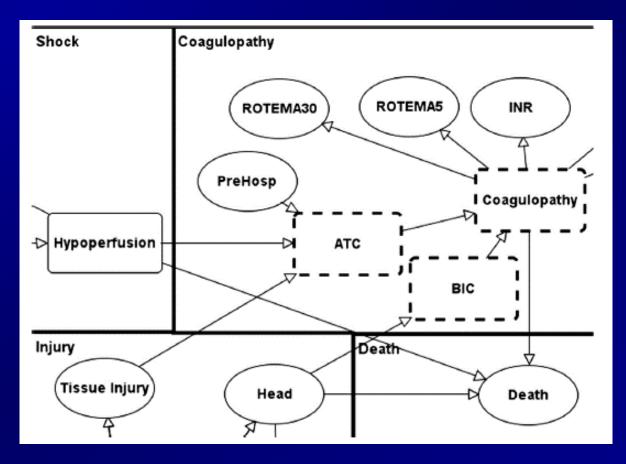
M0:

Specificity= 67%, sensitivity= 80.0%, AUROC: 0.81 (0.75–0.86) M1:

Specificity= 79%, sensitivity= 90.0%, AUROC: 0.92 (0.89-0.95)



Bayessian network structure



Expert-based refinement of Coagulopathy in BIC patients

