Risk assessment using Bayesian decision networks

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Forecasting fog for Melbourne airport

- important task
- done by the forecasters; information used by airlines
- prior knowledge enables airlines:
    - carry more fuel on aircrafts
    - prepare for diversions (fly crews and planes)
        - ➢ avoid crash, save time and money
- false alarms are expensive and should be minimised

Problems

- uncertainty in observations
- incomplete knowledge
- forecasts are subjective

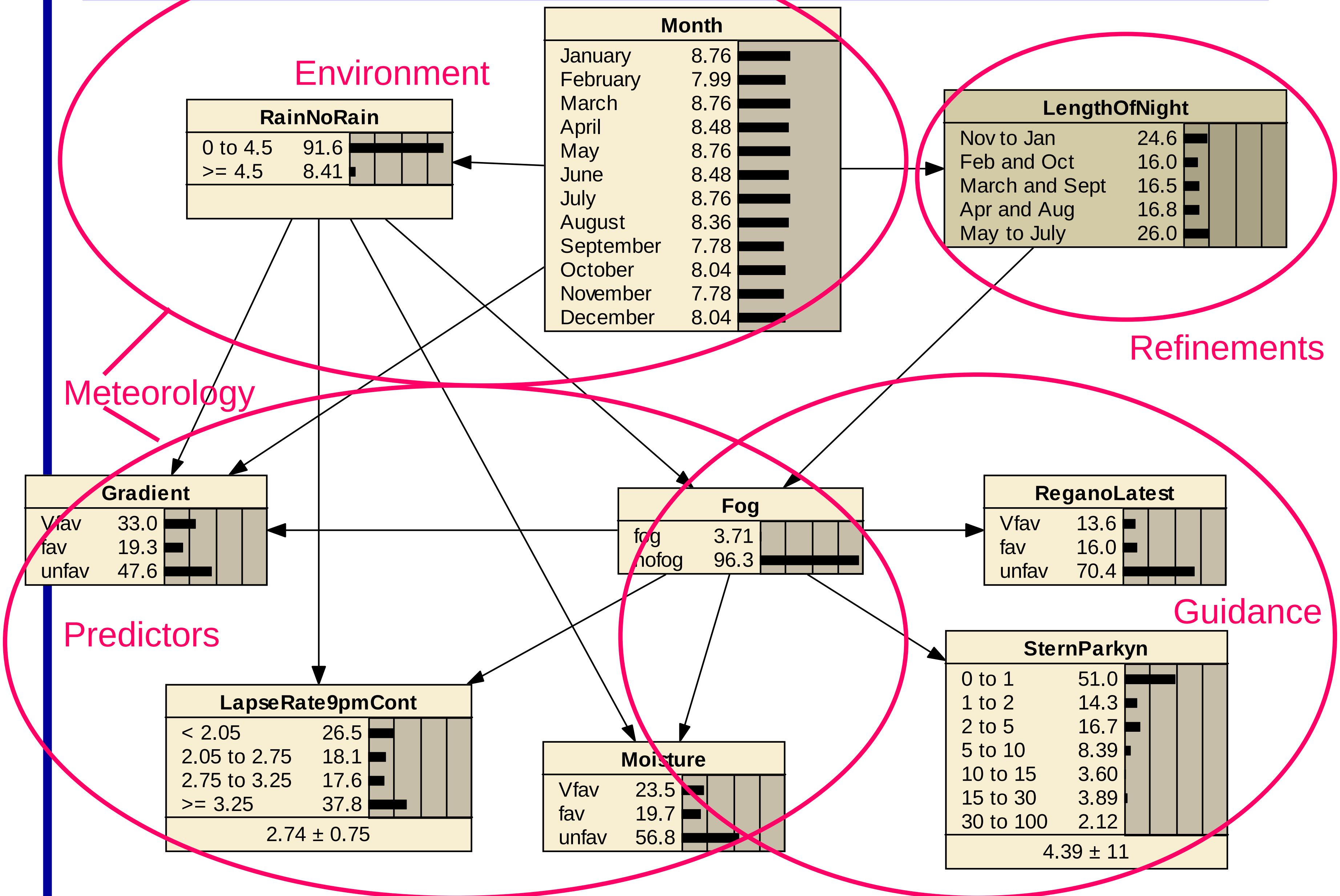
Aim of project

creating an <u>objective</u> guidance to support the prediction of Fog at Melbourne Airport

Reasoning under uncertainty: probability theory

- probability theory is one of the scientific ways of dealing with reasoning under uncertainty
  - applying formal statistics can yield better results, compared with subjective judgment
  - the final output of the process is objective and is based on a solid mathematical basis
- for applying probability theory we have used Bayesian Networks technology

Bayesian Network for forecasting fog



Evaluation: using a ROC curve

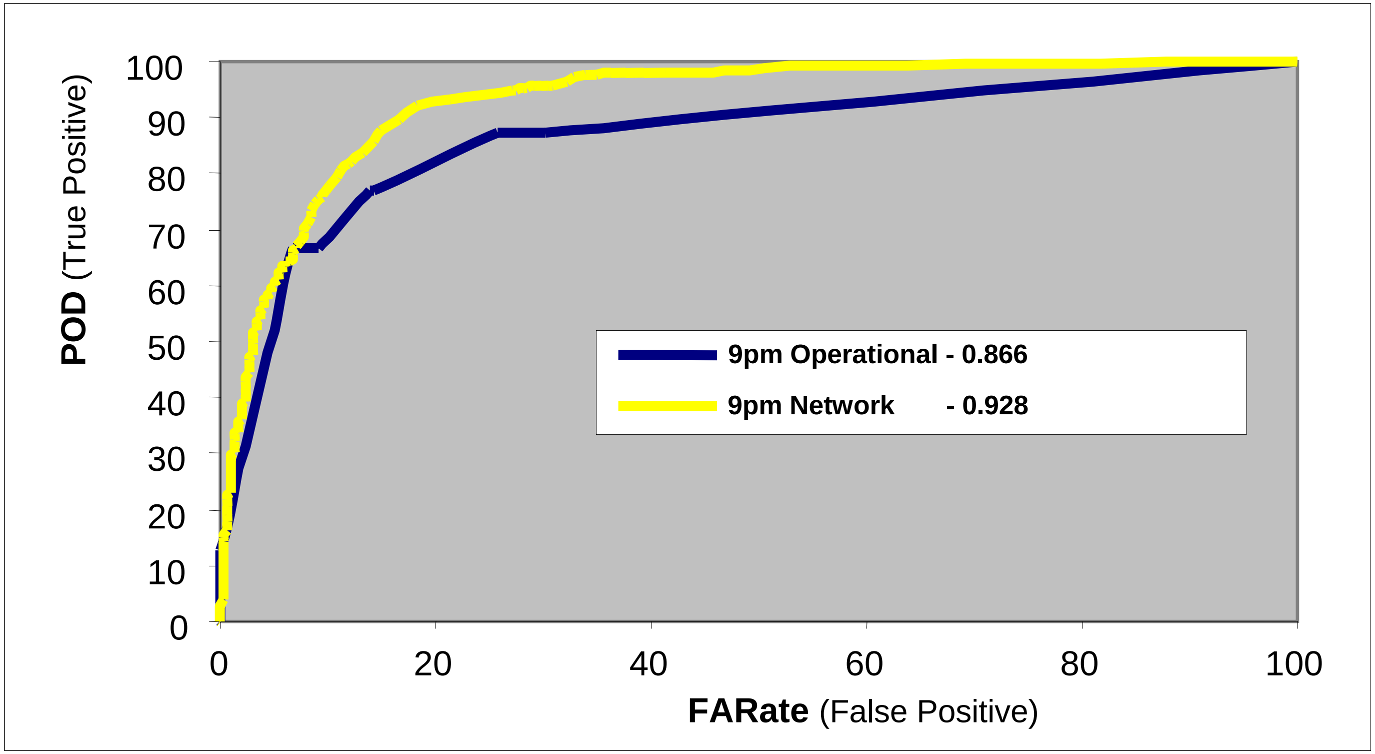
- Receiver Operating Characteristic (ROC) curves
- P(actual event predicted as event)

  vs.

  P(actual no-event predicted as event)
- Area Under Curve (AUC) can be used as a measurement of the accuracy of the model (perfect model: AUC = 1)
- ROC curve can be used to find cutoff values

ROC evaluation of the Melbourne network

- Bayesian Networks yield probabilities
- evaluation by ROC curves



Forecasters' evaluation measures

- POD (True Positive Rate)

$$\frac{\text{True Positive}}{(\text{True Positive} + \text{False Negative})} = \#\text{fog events}$$

- False Positive Rate

$$\frac{\text{False Positive}}{(\text{False Positive} + \text{True Negative})} = \#\text{no-fog events}$$

- False Positive Ratio (FAR)

$$\frac{\text{False Positive}}{(\text{False Positive} + \text{True Positive})} = \#\text{fog was forecasted}$$

POD & FAR – operational (current) *vs.* network

we take Bayesian Network output and apply cut-offs to make fog forecasting decisions

- 1% cutoff was used for Code Grey (low probabilities of fog)
- 20% cutoff was used for TAF (high probabilities of fog)

Forecast	**Operational**		**Network**	
	POD (%)	**FAR (%)**	**POD (%)**	**FAR (%)**
3pm TAF	**56**	**73**	**67**	**76**
3pm TAF and Code Grey	**87**	**90**	**94**	**89**
9pm TAF	**67**	**73**	**69**	**78**
9pm TAF and Code Grey	**87**	**90**	**95**	**89**

TAF - **T**erminal **A**erodrome **F**orecasts (high prob of fog >= 30%), **Code Grey** – (low prob of Fog < 30%)

POD – Power Of Prediction = True Positive Rate, FAR – False Alarm Ratio

Refining decision using forecasters cut-offs

Forecast Decision	CUT-OFF
No fog	0-1
<5% Code Grey	1-5
5% Code Grey	5-10
10% Code Grey	10-15
20% Code Grey	15-20
Fog on TAF	20-100

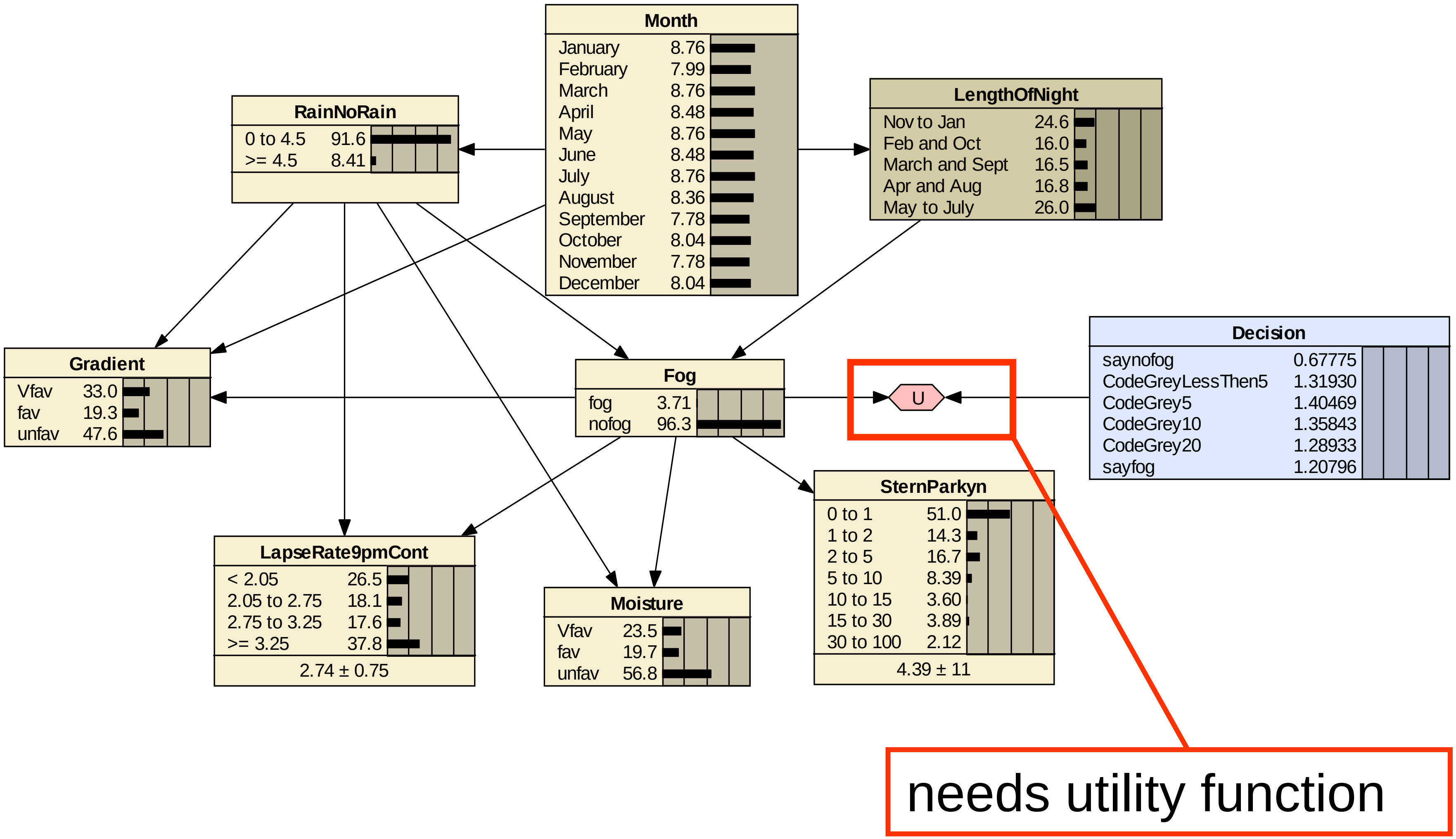
TAF - **T**erminal **A**erodrome **F**orecasts (high prob of fog >= 30%), **Code Grey** – (low prob of Fog < 30%)

POD – Power Of Prediction = True Positive Rate, FAR – False Alarm Ratio

Turning probability to decision: decision theory

- the calculation of the probability distribution of Fog, given observations, is based on Probability Theory
- Instead of using cut-offs on probabilities we apply Decision Theory
- we use Decision Theory to calculate the expected utility of a situation
- a utility function assigns a single number (preference) to a situation to express its desirability
- given new evidence, the decision network calculates the expected utility of the possible decisions
- a rational 'agent' chooses an action that maximises its expected utility

decision network for Fog



Different situations and forecasters' preferences

decision	actual	preferences
Say No Fog	Fog	1
Say Code Grey - less than 5% chance of fog	Fog	3
Say Code Grey - 5% chance of fog	Fog	36
Say Code Grey - 10% chance of fog	Fog	38
Say Code Grey - 20% chance of fog	Fog	39
Say TAF – Prob Fog	Fog	40
Say No Fog	No Fog	20
Say Code Grey - less than 5% chance of fog	No Fog	19
Say Code Grey - 5% chance of fog	No Fog	18
Say Code Grey - 10% chance of fog	No Fog	17
Say Code Grey - 20% chance of fog	No Fog	16
Say TAF – Prob Fog	No Fog	15

BUT, what are the aviation decision makers preferences?

TAF - **T**erminal **A**erodrome **F**orecasts (high prob of fog >= 30%), **Code Grey** – (low prob of Fog < 30%)

Preferences elicitation

- direct preferences elicitation is not possible because we do not know actual risk-analysis models used in aviation industry
- instead, we need to find preferences using the information we have
- we know that
  - aviation industry would like POD = 100%, FAR = 0%
  - current operational forecast POD = 56, FAR = 73
  - situations can be ranked according to significance
    - missing fog may be catastrophic
    - false alarm is un-desirable

find utility function that improves POD and FAR

POD – Power Of Prediction = True Positive Rate, FAR – False Alarm Ratio

Expected utility function

- given the network structure, the Expected Utility (EU) of a particular decision is defined to be the sum of the possible outcomes of the decision weighted by their probabilities:

EU(decisionA)=

P(Fog)*u(Fog,decisionA)+P(noFog)*u(NoFog,decisionA)

(a simplified definition)

Finding utility function by solving constraints

Instead of direct preferences elicitation from experts the next steps are:

- make a set of constraints
- feed it to constraint solver
- use the new constraint solver-produced utilities

Set of constraints for preferences

order

- X1<X2<X12<X11<X10<X9<X8<X7<X3<X4<X5<X6

use cut-off probabilities + utility function definition to form constraints

(1<i<7 and 7<j<13)

- for 0<=P(fog)<1 =>
  P(fog)*X1 + P(nofog)*X7 > P(fog)*Xi + P(fog)*xj
  (for i<>1 and j<>7)
- for 1<=P(fog)<5 =>
  P(fog)*X2 + P(nofog)*X8 > P(fog)*Xi + P(fog)*xj
  (for i<>2 and j<>8)
- etc.

more constraints

- X2 < 9*X1 (X2 is not that great)
- X12 > 16*X1 (Worst false alarm is 16 times better than a complete miss)
- X3 < 80*X1 . . .

decision	actual	pref
Say No Fog	Fog	X1
Say Code Grey - less than 5% chance of fog	Fog	X2
Say Code Grey - 5% chance of fog	Fog	X3
Say Code Grey - 10% chance of fog	Fog	X4
Say Code Grey - 20% chance of fog	Fog	X5
Say TAF – Prob Fog	Fog	X6
Say No Fog	No Fog	X7
Say Code Grey - less than 5% chance of fog	No Fog	X8
Say Code Grey - 5% chance of fog	No Fog	X9
Say Code Grey - 10% chance of fog	No Fog	X10
Say Code Grey - 20% chance of fog	No Fog	X11
Say TAF – Prob Fog	No Fog	X12

Different situations and constraints preferences

decision	actual	forecasters	output of constraints solver
Say No Fog	Fog	1	1
Say Code Grey - less than 5% chance of fog	Fog	3	11
Say Code Grey - 5% chance of fog	Fog	36	62
Say Code Grey - 10% chance of fog	Fog	38	84.16
Say Code Grey - 20% chance of fog	Fog	39	96.75
Say TAF – Prob Fog	Fog	40	106.42
Say No Fog	No Fog	20	29.65
Say Code Grey - less than 5% chance of fog	No Fog	19	29.55
Say Code Grey - 5% chance of fog	No Fog	18	26.87
Say Code Grey - 10% chance of fog	No Fog	17	24.42
Say Code Grey - 20% chance of fog	No Fog	16	22.21
Say TAF – Prob Fog	No Fog	15	19.8

yields utility function for a decision network

relative importance of missing fog larger then forecaster estimate

Conclusions

- it is important to distinguish between the user of the Bayesian Network (forecasters) and the user of the information the network provides (aviation industry)

- inferring the utility function using available information enables the use of decision theory even if direct elicitation of preferences from experts is impossible

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