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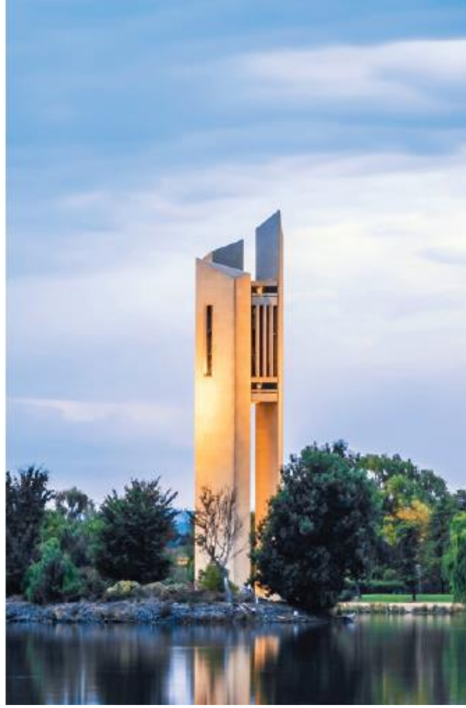

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The use of Bayesian Networks in Quantifying Evidence used to aid the Assurance Process

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Introduction

- Structured argumentation is often used for assurance and safety claims
- Goal Structuring Notation is a graphical method used to support argumentation of particular claims
- While argument claims need to be supported by evidence, strength of evidence supporting a claim is often not systematically considered
- Restructuring claims as a Bayesian Network supports quantifying the likelihood of the evidence supporting the claim
- An Object Oriented Bayesian Network model supports structuring a network model to consider the likelihood of relevant evidence for a system

Degrees of Belief and Uncertainty

- In engineering, beliefs about a system are based upon performing processes that investigate, prototype, design, build, measure and test
  - each step generating artefacts supporting conclusions reached, and that are reviewed to ensure accuracy and applicability
- Evidence generated supports the justifiable belief in the minds of stakeholders that the system is sound in design and function, i.e. it is fit for service
- We form mental representations that are depictive of reality, and that knowledge is the subset of beliefs that are both true and well justified (Smith, Benson & Curley 1991)
- Knowledge is rare and therefore people act in its absence – we qualify our beliefs with judgments that provide some gradings of likelihood (ibid)
  - e.g. it is cloudy outside, it is likely to rain

Known Unknowns, Unknown Unknowns

- We can express what is known to be unknown as opposed to what is not known to be unknown, or Known unknowns and Unknown unknowns
- This was somewhat famously put by former US Defense Secretary Donald Rumsfeld

  “...there are known knowns; there are things we know we know.

  We also know there are known unknowns; that is to say we know there are some things we do not know.

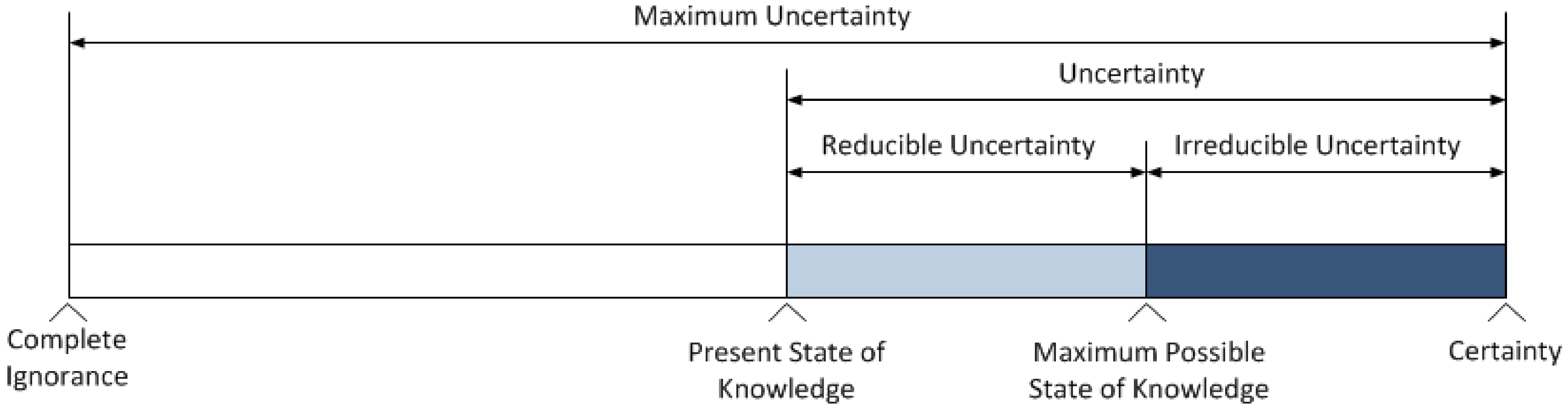
  But there are also unknown unknowns -- the ones we don't know we don't know” (Rumsfeld 2002)

Uncertainty

- Uncertainty can be defined in terms of knowledge, usually as a knowledge inadequacy
  - Uncertainty is the perceived lack of information, knowledge, beliefs, and feelings, whatever is necessary for accomplishing the task (Montagna 1980)
- Can also define uncertainty indirectly:
  - Define certainty as being the condition where everything is known
  - Therefore uncertainty is the gap between everything that can be known and what is actually known (Nikolaidis 2004)

Uncertainty

- Two components of uncertainty
  - reducible uncertainty –present state of knowledge can be increased by some means;
  - irreducible uncertainty – where (perhaps self evidently) it cannot



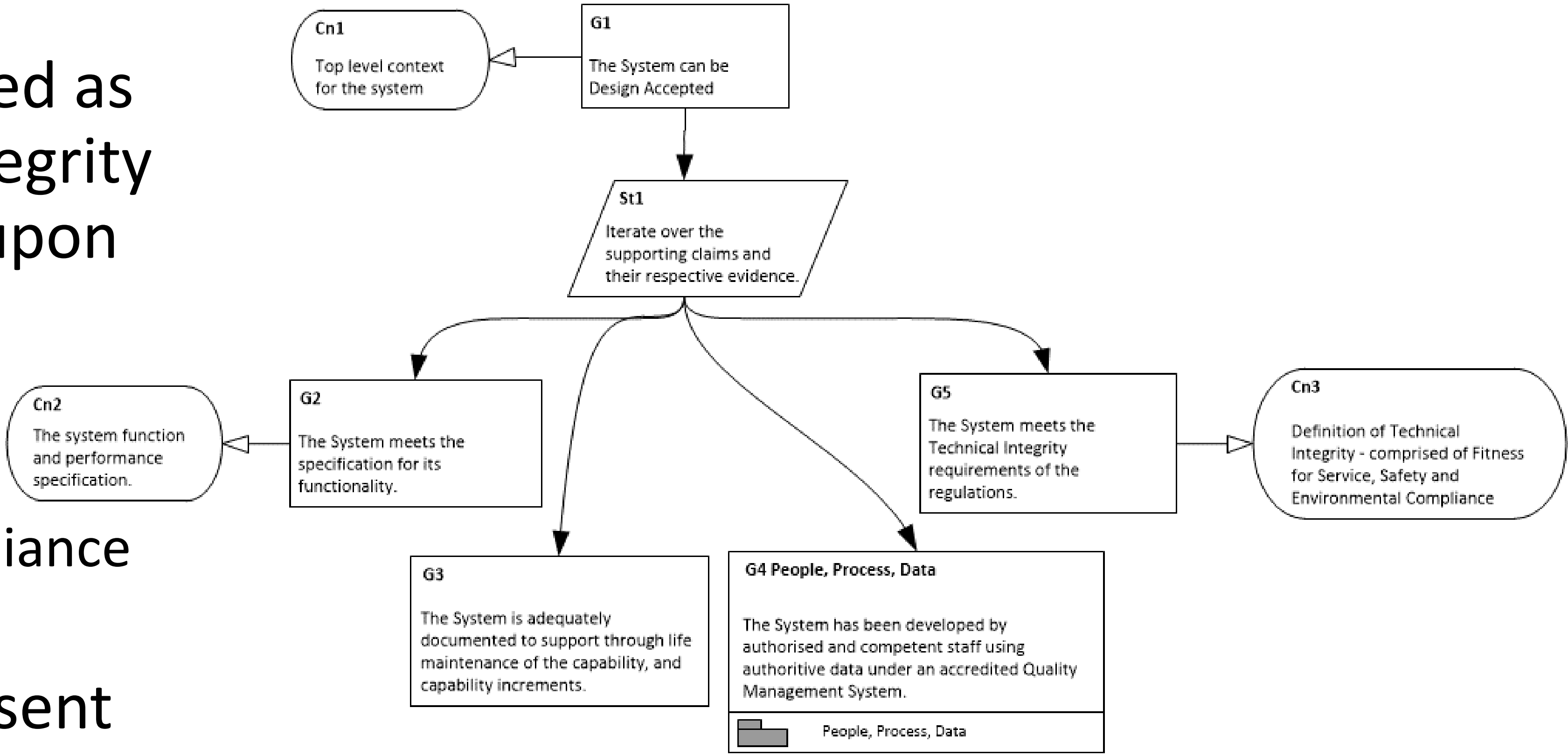
(adapted from (Nikolaidis 2004))

Technical Integrity

- Concept of Technical Integrity is used in Australian Defence Force (ADF) technical regulations as the foundation of a risk-based approach to materiel management
    - Technical regulation is to identify, analyse, assess, treat, monitor and communicate risk in the areas of **safety**, **performance** and **environmental compliance** (Department of Defence 2013)

GSN Based Design Acceptance Strategy

- A system can be argued as meeting Technical Integrity requirements based upon claims of satisfying
  - Safety,
  - Fitness for Service,
  - Environmental Compliance criteria
- Can use GSN to represent this argument



Evidence Quality

- Quality Evidence, as distinct from "the quality of evidence" is generally evidence provided by records of process activity

- Objective Quality Evidence (OQE), term often used but tough to find a formal definition
- Define from dictionary definition of the constituent parts:
  - Objective – not influenced by personal feelings or opinions in considering and representing facts;
  - Quality – the standard of something as measured against other things of a similar kind; and
  - Evidence – the available body of facts or information indicating whether a belief or proposition is true or valid (Sili 2017)

Quality Attributes of Evidence Representation

- A key element is a measure of the "value" and "strength" of the evidence that is supporting the claims that are made
- Note these measures are probabilities
  - An assessment on the balance of probabilities of the quality of evidence
  - Based upon the judgement of the evidence assessor is that it is likely to be of a particular quality that supports the claim
  - Many cases, judgement of the evidence assessor is not a repeatable process

Quality Attribute Dimensions

- Wang and Strong define four quality attribute dimensions:,
  - Intrinsic Data Quality, Contextual Data Quality, Representational Data Quality and Accessibility Data Quality (Wang & Strong 1996)
- We find that
  - Intrinsic and Contextual evidence elements in an argument structure most directly relate to claims about quality of evidence
  - Intrinsic – believable, accurate, objective
  - Contextual – relevant, timely, complete, traceable
- Note – An accurate piece of information comprising "evidence" with no relevance to a claim is of no value in supporting the claim

Probabilistic Models

- The issue is trying to predict or state the unknown
- Probabilistic models are used to account for uncertainty and imperfect knowledge of the world
- Our understanding of the world is limited by observation, and understanding of those observations
- In simple cases, we may have some intuition about uncertainty
- Where there are many events and possible outcomes, probability theory provides a calculus to extend the intuitive understanding of this uncertainty (Barber 2012)

Bayes Theorem

- Bayes Theorem summarises an intuitive world view where beliefs about the world view are revised based upon updated or new information
  - i.e. updating of estimates based upon new and updated information
- A modelling paradigm that allows incorporation of this information into the model as new information is obtained, which supports making more informed decisions
- Bayes Theorem is sometimes referred to as Common Sense Reasoning (Stone 2013)

Bayesian Networks

- (Pearl 1998) extended the concepts of Bayesian analysis to a causal network referred to as a Bayesian Network
- Extends to a network of causal variables represented by a directed acyclic graph
  - Sometimes referred to as Probabilistic Graphical Models (PGM) (Koller & Friedman 2009)
- Bayesian Network modelling has been applied to a multitude of problems in a wide variety of fields
  - including science, engineering, medicine, social science, safety science and others (Kruschke & Liddell 2017), (Downey 2012), (Etz et al. 2016), (Gelman et al. 2013) and many many more.

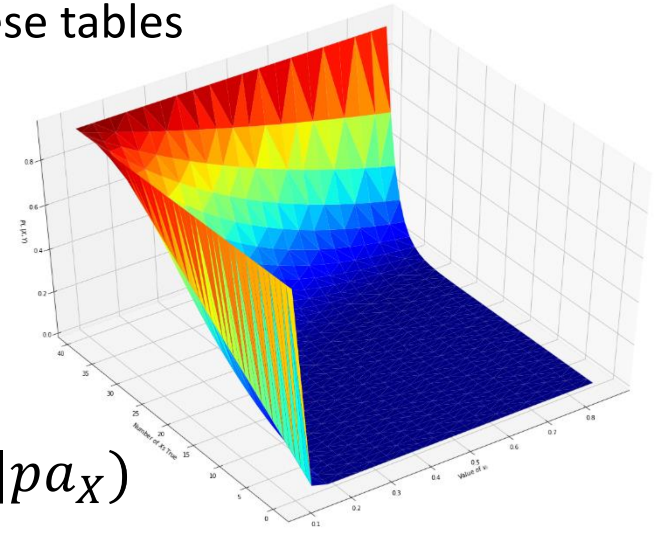
Bayesian Networks

- A Bayesian network represents a graphical model of inference – joint probability distribution over a set of variables X
- Joint probability density is described by a directed acyclic graph
  - Nodes of the graph represents a variable X_i in X, and
  - Arcs indicate parents of any variable, denoted by $pa(X_i)$.
- Each node is associated with a Conditional Probability Distribution (CPD), the probability $p(X_i)$ conditioned on its parents $pa(X_i)$
- As the graph is comprised of parent and child nodes, this factorises as:

$$p(X_1, \dots, X_n) = \prod_{i=1}^{n} p(X_i | pa(X_i))$$

Conditional Probability Distribution

- Development of the graph structure is only part of the network assembly problem
  - It is (of course) the "simple" part
- Other significant problem is development of the conditional probability distribution (CPD) for each node,
  - usually formulated in a table based representation known as a Conditional Probability Table (CPT) for each node
  - supports the propagation of probabilities through the network
  - In general, expert judgement is the most common method to develop these tables



- CPD specifies a conditional probability $P(x|pa_X)$ for every assignment of values of pa_X and x
- View as a function f that relates the inputs to the outputs

- i.e. for a given pa_X and x, f returns the conditional probability $P(x|pa_X)$

Object Oriented Bayesian Networks

- Can represent BN's in an Object Oriented way
  - Object Oriented Bayesian Networks (OOBN) are typically referred to as Probabilistic Relational Models (PRMs) (Koller and Freidman 1998)

- (Torti 2012) proposes a concrete implementation of OOBNs – Open Object Oriented Probabilistic Relational Model (O3PRM)
- Provides for abstract patterns of network structures as generic class entities
  - Encapsulates all relations between variables of the pattern
  - Combining classes and their relations allows rapid instantiation of large and complex network models

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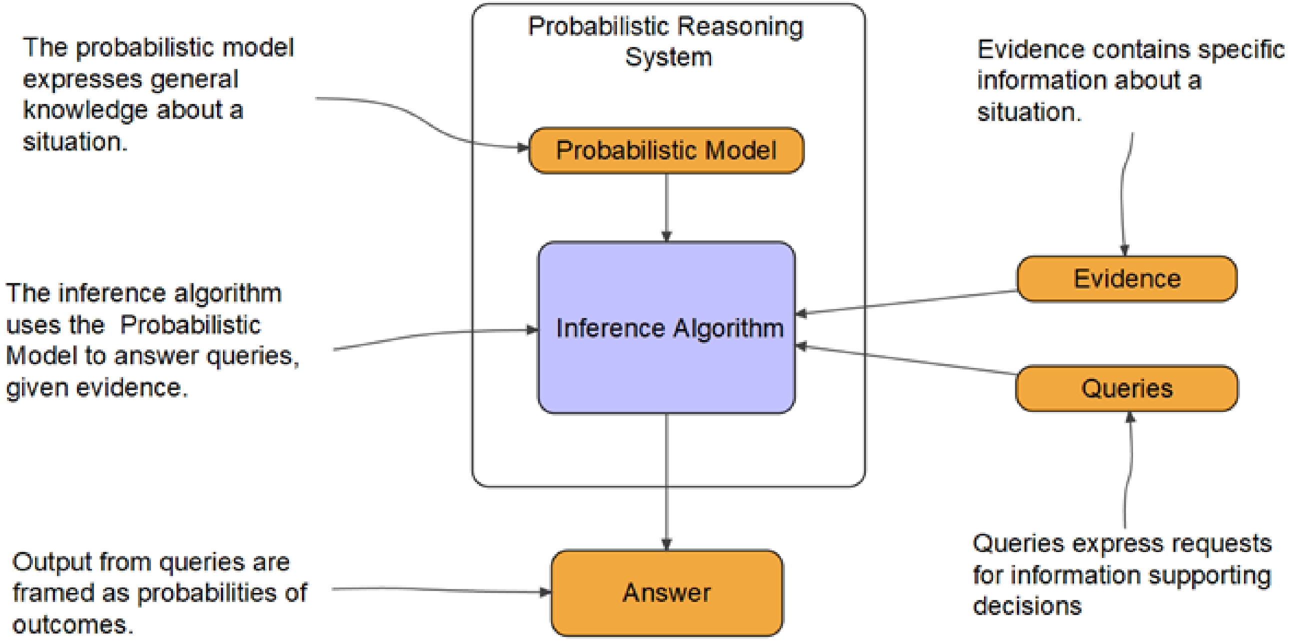
Probabilistic Reasoning

- A Probabilistic Reasoning System supports inference based upon
  - a Probabilistic Model and
  - associated evidence,
- Query the model to obtain information framed as probabilities of outcomes



(Pfeffer 2016)

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Revisiting the Technical Integrity Argument

- GSN can be used to formulate a structure for an acceptability claim, in particular a claim of Technical Integrity (Simmonds & Cook 2017)
- Lower level claim/argument structures can then be built up into an overall argument of acceptability of the system
- When constructed as a GSN based argument, we are building a directed graph that causally supports the claim or argument, dependent on the evidence that supports that claim
- There is a causality to this structure that can be represented as a Bayesian Network

An Assurance Network

- Consider the Top Level Claim as being the target "Latent" (unknown) variable of the network
- Parents nodes are Subclaims that support the Top Level Claim, and parent nodes of the Subclaims are the elements of Evidence that support the claims being made
  - Latent nodes are nodes about which we have no direct observation as to their value
- So the basic elements of GSN – Evidence and Claims are represented by nodes of the Bayesian Network
  - Aggregation of multiple pieces of evidence support a claim and
  - Aggregation of multiple claims support a top level claim

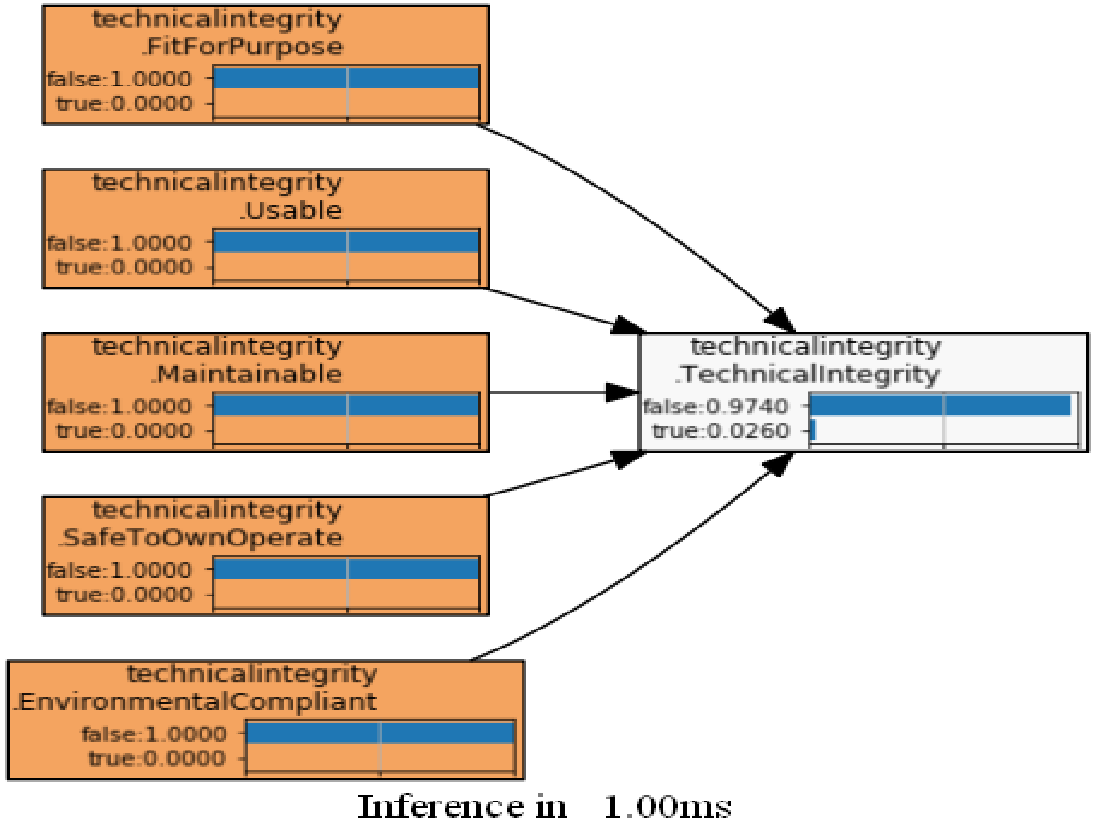
Simplified Technical Integrity Network

- A simplified technical Integrity argument can be defined in O3PRM as shown here
  - Default conditional probability tables are replaced during instantiation

```
class SimpleTechnicalIntegrity {
    boolean FitForPurpose {
        [ 0.50,   // False
          0.50 ] // True
    };
    boolean Usable {
        [ 0.50,   // False
          0.50 ] // True
    };
    boolean Maintainable {
        [ 0.50,   // False
          0.50 ] // True
    };
    boolean SafeToOwnOperate {
        [ 0.50,   // False
          0.50 ] // True
    };

    boolean EnvironmentalCompliant {
        // False | True =>
         [ 0.50,   // False
          0.50 ] // True
   };

 boolean TechnicalIntegrity dependson FitForPurpose, Usable,Maintainable,
     SafeToOwnOperate, EnvironmentalCompliant {
             //
             *,*,*,*,*: 1.00, 0.00;   // False
             *,*,*,*,*:  0.00, 1.00; // True
     };
}

system hasTechnicalIntegrity {
  SimpleTechnicalIntegrity technicalintegrity;
}
```

Simplified Technical Integrity Network

- This forms the network shown at right (shown with no evidence supporting the claim)
- The use of O3PRM makes it simple to instantiate multiple network instances
- Allows creation of large networks with relative ease



Weighted CPT Model – Noisy AND

- Some inputs of the model may be more important to reaching a conclusion about acceptability than others
- Use Noisy AND function – output is true as long as all inputs are true above a threshold probability
    - Provides a means of weighting the output of each parent node that aggregates relative weights of input nodes to reach a final acceptability likelihood
- Noisy AND function is defined as:

$$Y = NoisyAND(X_1, v_1, X_2, v_2, \dots, X_n, v_n, l)$$

$$P(Y = false | X_1, X_2, \dots, X_n) = 1 - (1 - l) \times \prod_{X_i \text{ is false}} (1 - v_i)$$

    - Where $l = leak\ value$ and $v_i = weights$.

- Leak value is the likelihood of the result not being true, even given all inputs as being true – probabilistic “Noise” (Fenton & Neil 2018)

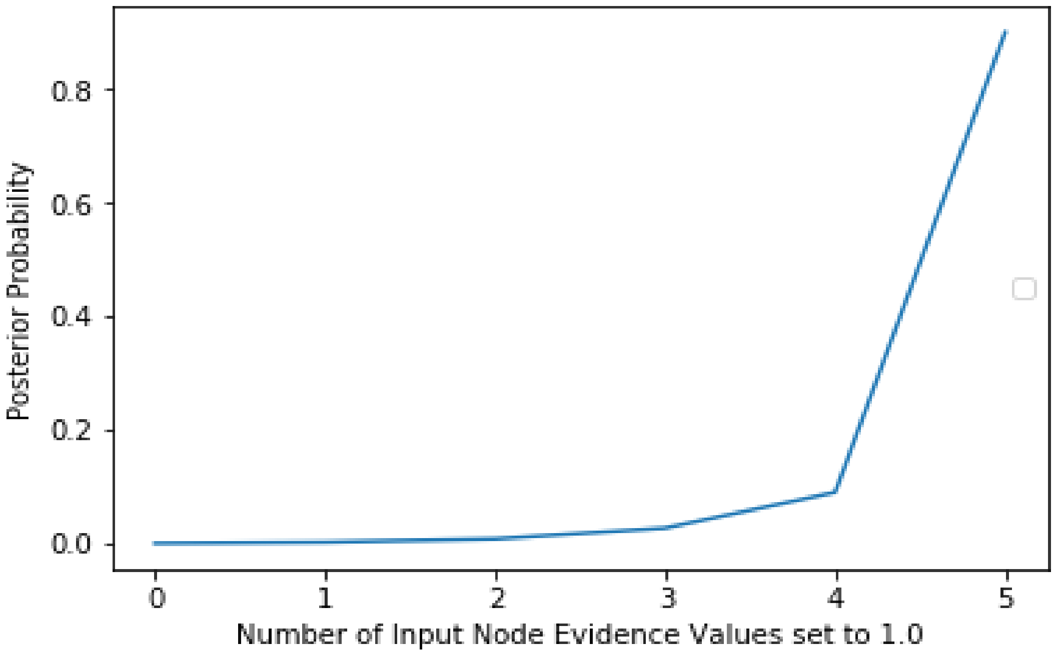
Model Querying

- Now straightforward to use this model to query the top level claim based upon the evidence known
  - Set the evidence node inputs based upon the evidence we have, then
  - Propagation of inputs through the combinatory node results in a posterior probability output indicative of the "Acceptability" of the system
- As evidence of appropriate quality to support the argument is built up, this propagation can be re-iterated and the value of the posterior probability output updated.

Noisy AND Thresholds

- If we plot the output of the network based upon these weights, the conditional output function resembles that shown at right
- This shows as input likelihoods approach true, the output is also approaching a probability that supports the acceptability conclusion

```
technicalintegrity_TechnicalIntegrity_noisyweights = [
                ['technicalintegrity.FitForPurpose',          0.8],
                ['technicalintegrity.Usable',                 0.7],
                ['technicalintegrity.Maintainable',           0.7],
                ['technicalintegrity.SafeToOwnOperate',       0.9],
                ['technicalintegrity.EnvironmentalCompliant', 0.7]
    ]
technicalintegrityleak = 0.1
```



Evidence

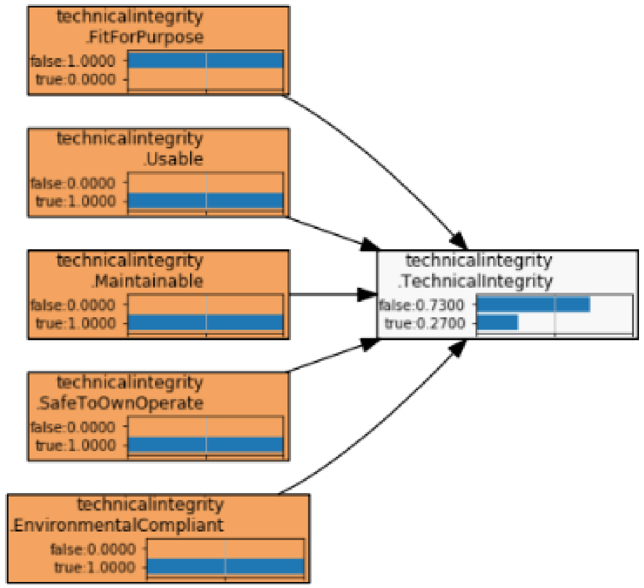
- Now set input evidence based upon assessment of available evidence against Contextual and Intrinsic criteria
  - Can input Hard Evidence – True/False
  - Soft Evidence – Captures uncertainty in our knowledge of the evidence

```
parent_evidence = {
    'technicalintegrity.EnvironmentalCompliant':  1,
     'technicalintegrity.FitForPurpose':          [0.5, 1.0],
     'technicalintegrity.Maintainable':           1,
     'technicalintegrity.SafeToOwnOperate':       1,
     'technicalintegrity.Usable':                 1
}
```

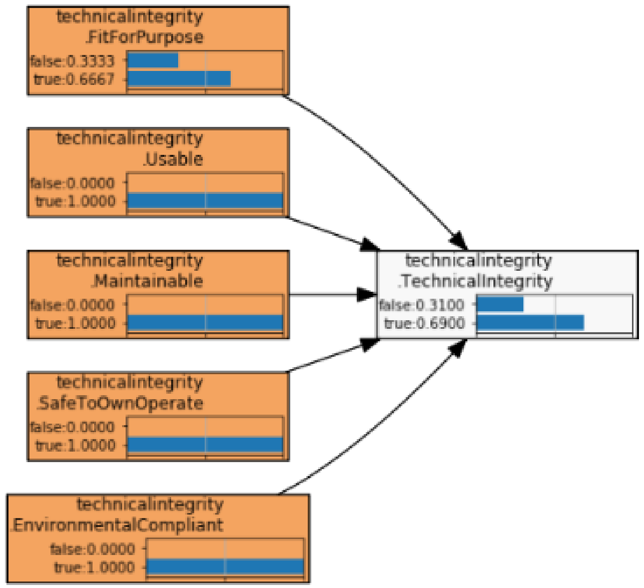
- E.g. Fitness for Purpose may be assessed on the basis of content of a Verification Cross Reference Matrix, assessing the completeness and applicability of verification evidence against requirements
- In this case we specify we are confident the requirements will be met (when verification is complete we believe the evidence to be true, however at this stage of the process, there is 50% uncertainty)

Technical Integrity Inference

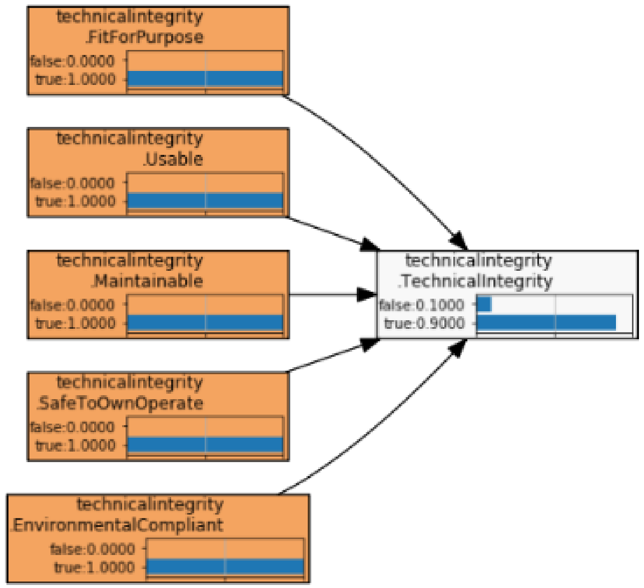
- Conduct three inferences with different evidence for the Fitness For Purpose



Inference in 1.00ms



Inference in 1.00ms



Inference in 1.00ms

Summary and Conclusions

- We have described a method for supporting an assurance argument using a situation specific Bayesian Network
- Assurance argument is formulated using Goal Structuring Notation
- This is used as basis to create a Probabilistic Relational Model (BN – O3PRM)
- Allows the combination of evidence assessed using Intrinsic and Contextual evidence attributes
- Using this model allows the build up of evidence to be assessed over time
- Noisy AND aggregation function is used to generate the conditional probability distribution that allows the setting of acceptability thresholds to appropriate values

Summary and Conclusions

- A simple Technical Integrity argument has been modelled to
  - demonstrate the method and results that can be achieved
- Provides a means to articulate relative acceptability of a system by assessing what we know about the evidence presented in support of an assurance argument
- While discrete numbers are produced in the resulting output, these are
  - a probability and
  - have arbitrary meaning – we assign the meaning ourselves based upon the criticality of the output for the system of analysis
- E.g. It may be perfectly acceptable for as much as 50% uncertainty early in the development of a system
- As the system matures and appropriate evidence produced, a smaller uncertainty figure (greater certainty figure) supports the assurance argument

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Questions ?