

Risk & Investment Conference
Leeds, June 2012

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Operational Risk **Business friendly** **models**

Agenda

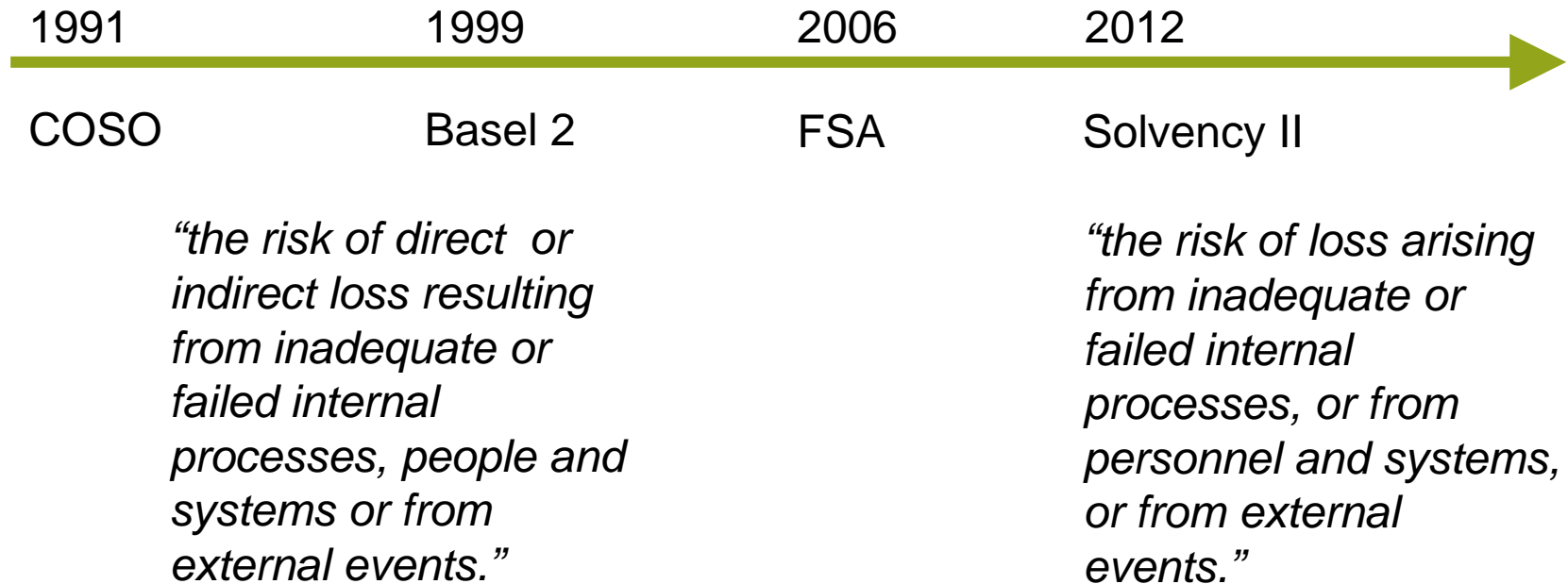
- Quick overview of operational risk challenge
- Reminder of typical modelling approaches
- Case study of Bayesian Network approach



Background

What's the problem?

Definitions



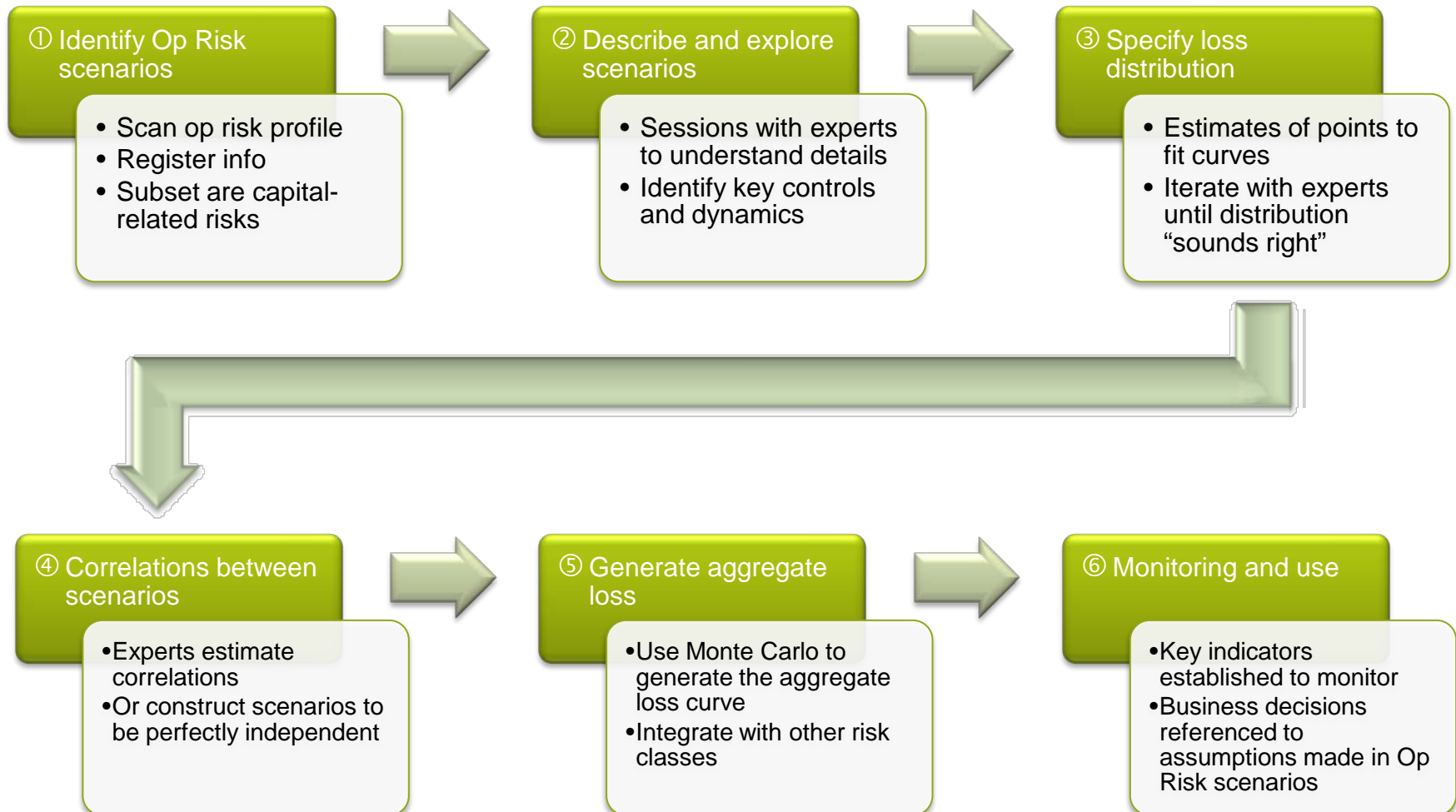
Regulatory Definitions

- Conflict/discomfort between capital and control
- Basel I and Solvency II essentially define op risk capital as a contingency against mistakes
- Internal models used to “justify” lower capital than regulatory buffer
- So far fail to link model and management...
- Analysis of crisis shows importance of op risk

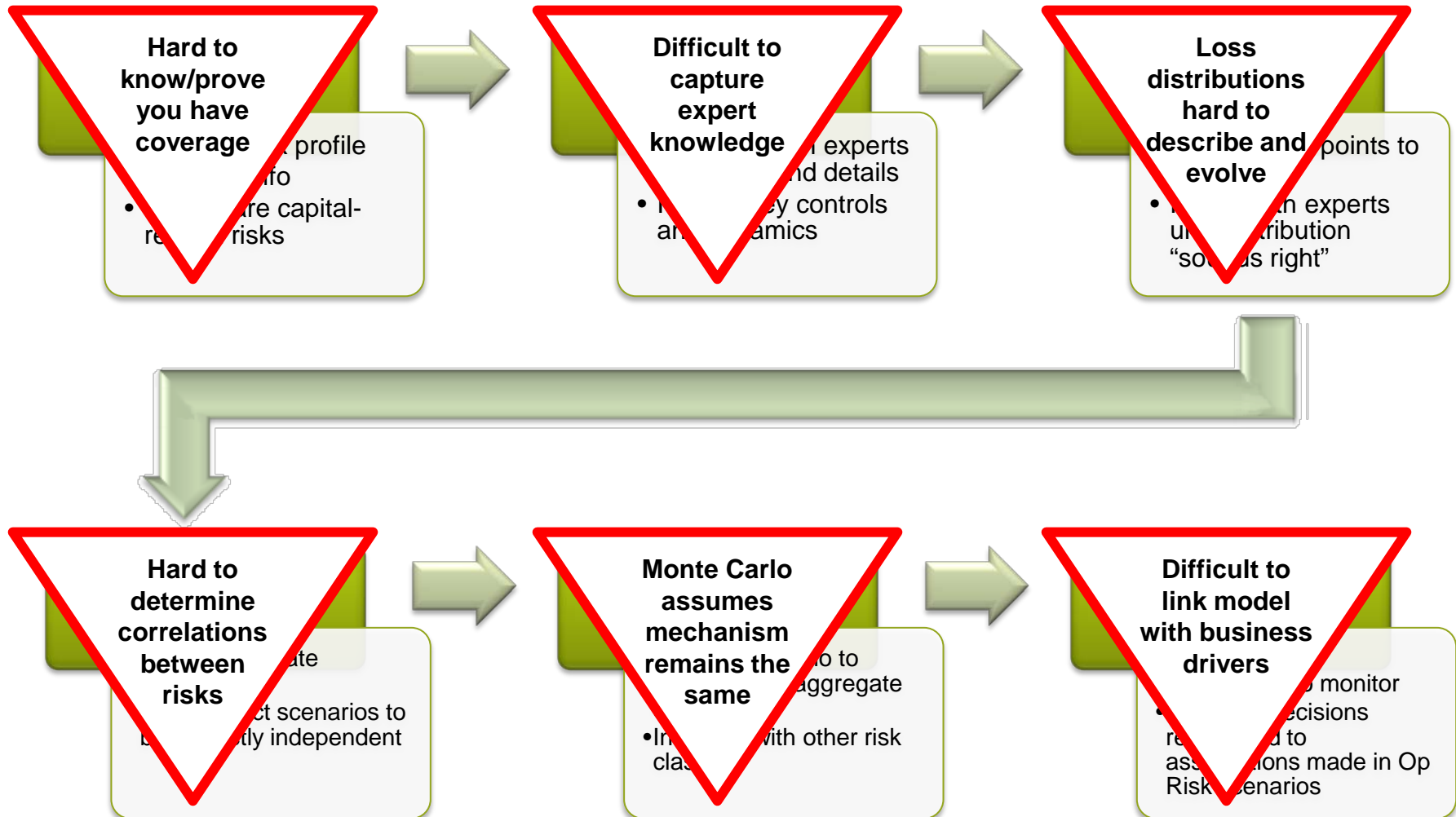
Op Risk vs. The Rest

- Financial risks
 - Lots of data
 - Outcome easy to spot
 - Similar for everyone...share data
 - Exogenous drivers
- Operational risks
 - No data for most of distribution
 - Heterogeneous
 - Endogenous drivers...which interact

Typical Process



Typical Process



So, Why is it Hard to Quantify?

- It feels complicated
- Too many possibilities
- Too many unknowns



It depends...



What if



But then....

- It is actually “complex” and people often use the wrong tools

Reaction To Complexity

- Break it down
 - Make simplifying assumptions
 - Solve the simpler problems
 - Add them up again
 - Job done!
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- Complexity sciences show that complicated systems are reducible ... complex ones aren't

Understanding Uncertainty

Symptoms



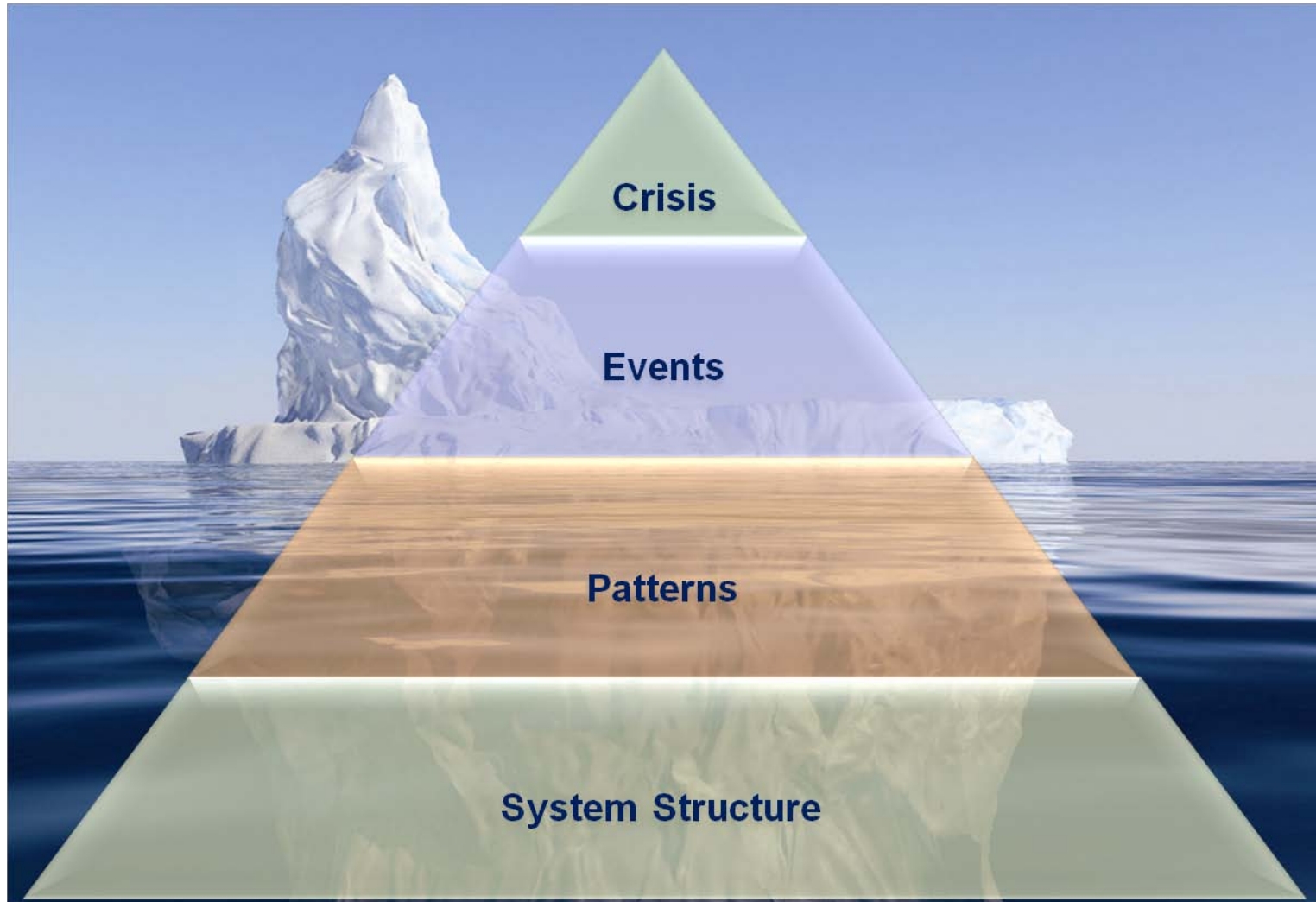
Causes



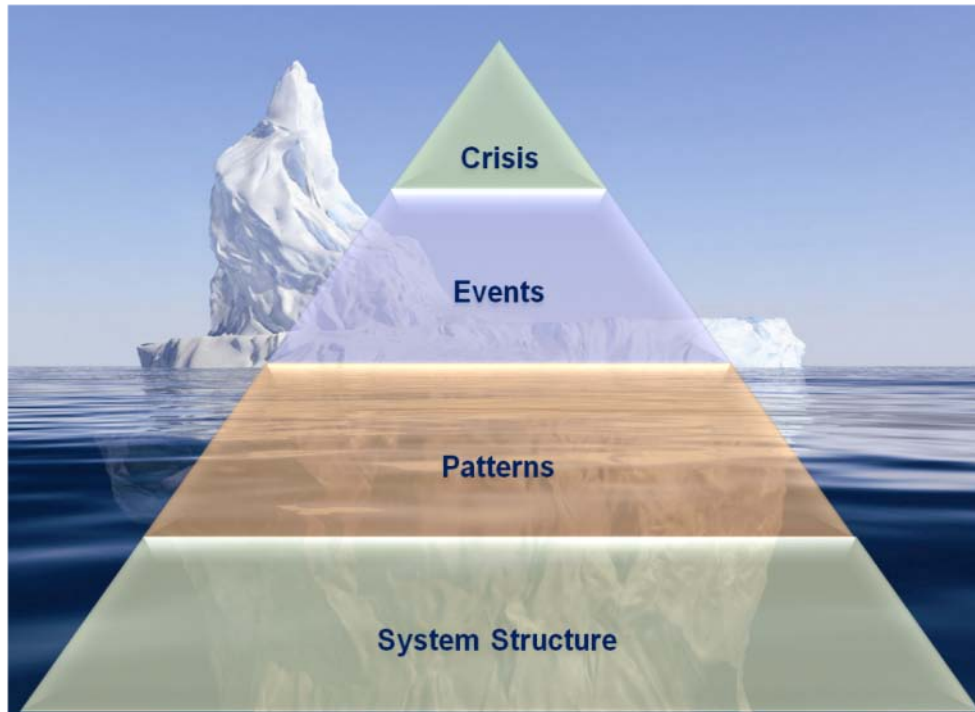
Sense-making



Understanding



Different Approach for Complex Situations



Statistical models, assuming constant drivers
Registers assuming single characteristics
Scenarios “imagined”
Emerging risks by spotting events

Models based on system drivers
Descriptions of risk profile taken holistically
Scenarios derived from risk profile
Emerging risks spotted early from system

So operational risk is hard (mostly) because people look at it through the wrong lens

What do the right tools need?

- Join outcomes to underlying mechanism (not just proximate causes)
 - Need to be adaptive
 - Should be able to spot patterns
 - Should not pre-judge the outcome
 - Beware implicit assumptions
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- Must be understandable by business, modellers and risk managers (as well as their stakeholders)



Quantification – Act 1

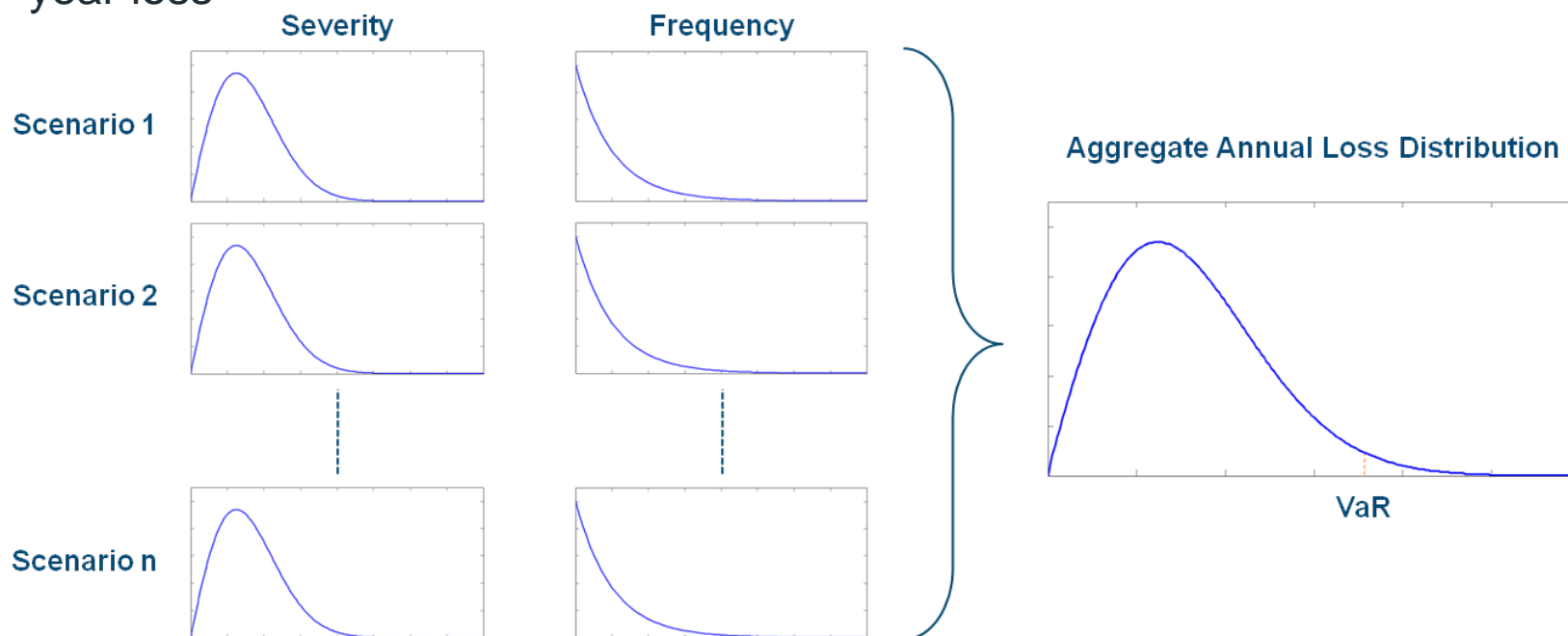
Quick review of common approaches

What Are You Modelling?

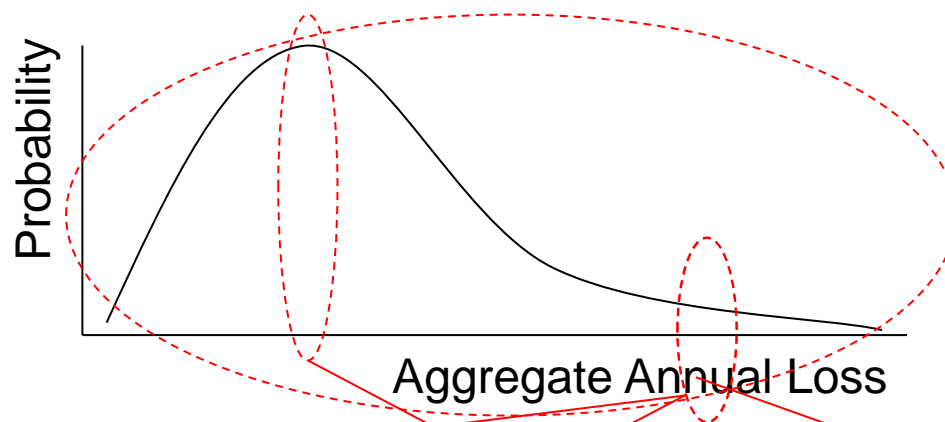
- Key decision...what is the modelling exercise for?
 - Regulatory capital
 - Economic capital
 - Business understanding...?
- For some purposes you need to include new business
- ...for others you don't
- Not all scenarios have capital consequences
- Many business objectives conflict...how to resolve

Loss Models

- Objective (of modelling) is to “quantify” the annual aggregate loss from operational risk events
- Consider the loss at the risk tolerance level required e.g. 99.5% point for one year loss



Loss Models – Approaches



① Scenario

Estimate an “extreme” outcome

② Fit Curve

Make an assumption about the shape of the loss curve and fit by estimating points on the curve (e.g. mode/tail)

③ Whole Curve

Produce an estimate of the whole curve

Loss Models

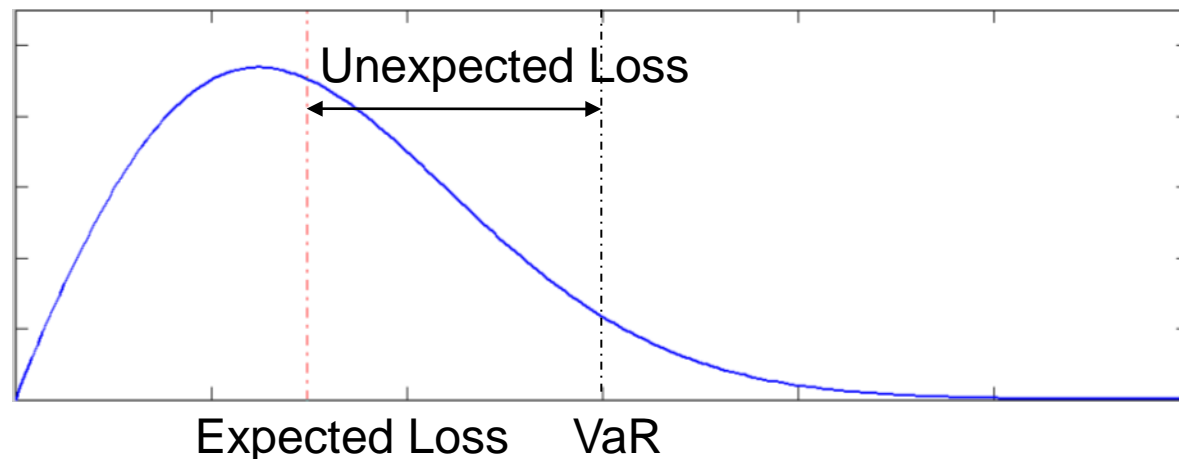
- Traditional approaches all fundamentally based around estimating the aggregate annual loss curve
- Scenarios can be independent or connected
- “Connections” can be achieved through correlation or simple/complex cause
- Modelling can be tail estimate or distribution estimate
- Loss distribution generated discretely or by Monte Carlo (analytical nearly always impossible)

Choosing Scenarios

- Need a set of scenarios which cover op risk profile
 - What is it?
 - Consider strategy, business plan, risk strategy, etc.
 - Workshops
 - Brainstorming
 - Past failures
 - Market scanning
-
- Are you sure you have got everything?

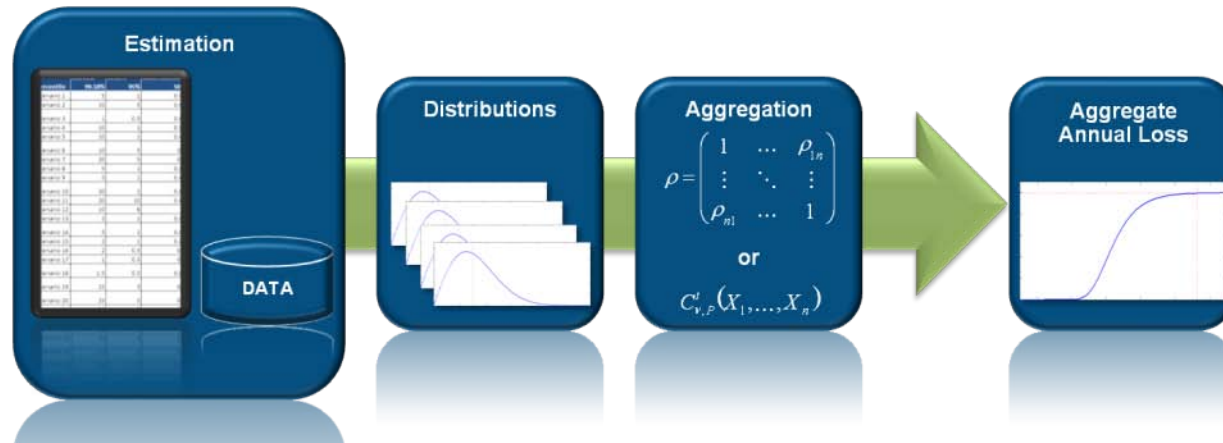
Fitted Distributions

- Often break down risk scenarios by type:
 - High frequency / Low impact
 - Moderate frequency / moderate impact
 - Low frequency / high impact
- Each behave differently and broadly independently of each other (why?)
- Model separately and add up



Fitted Distributions

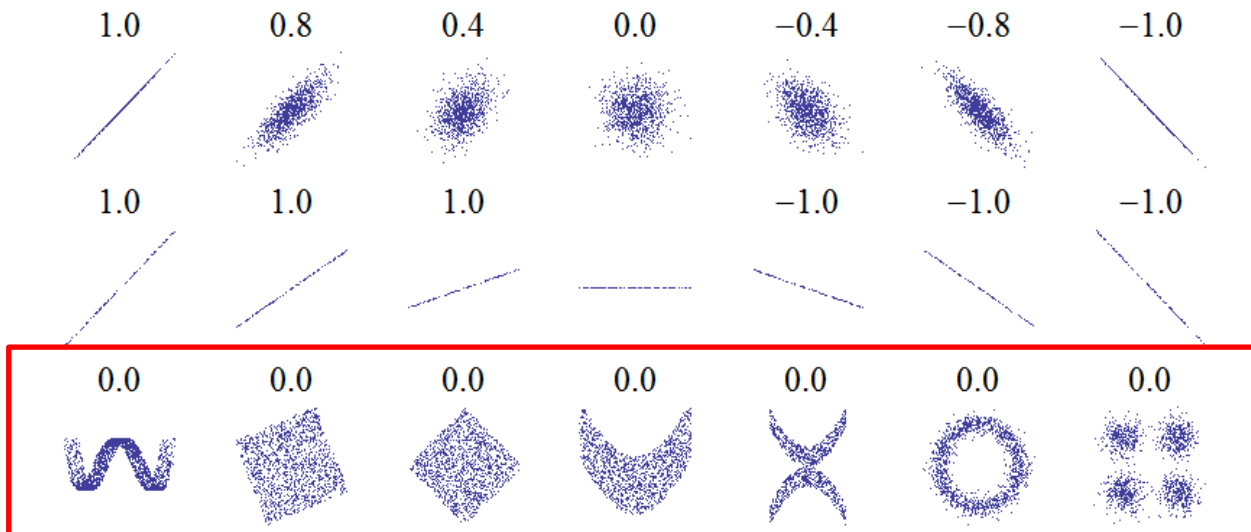
- Could use data or expert opinion, or combination
- Fit a distribution
 - parametric if using expert opinion
 - may be non-parametric if enough data
- Aggregate using “correlation” or “copula”
- Identify required tolerance level for capital



Aggregation – Caution

- Correlation not very good at non-linear dependence
- Op Risks often (nearly always?) non-linear so be careful

Different levels of correlation



Correlation will not spot non-linear relationships

Aggregation

- Copula approach
 - Correlation effects tend not to be linear – things which are generally unconnected may tend to move in the same way under extreme conditions
 - A Copula can be used as a way of modelling non-linear dependence
 - Function mapping marginal distributions to multivariate distribution
 - Still need to estimate rank correlations though
 - (also need to be aware that dependencies can change over time)



Quantification – Act 2

Merging Models and Management

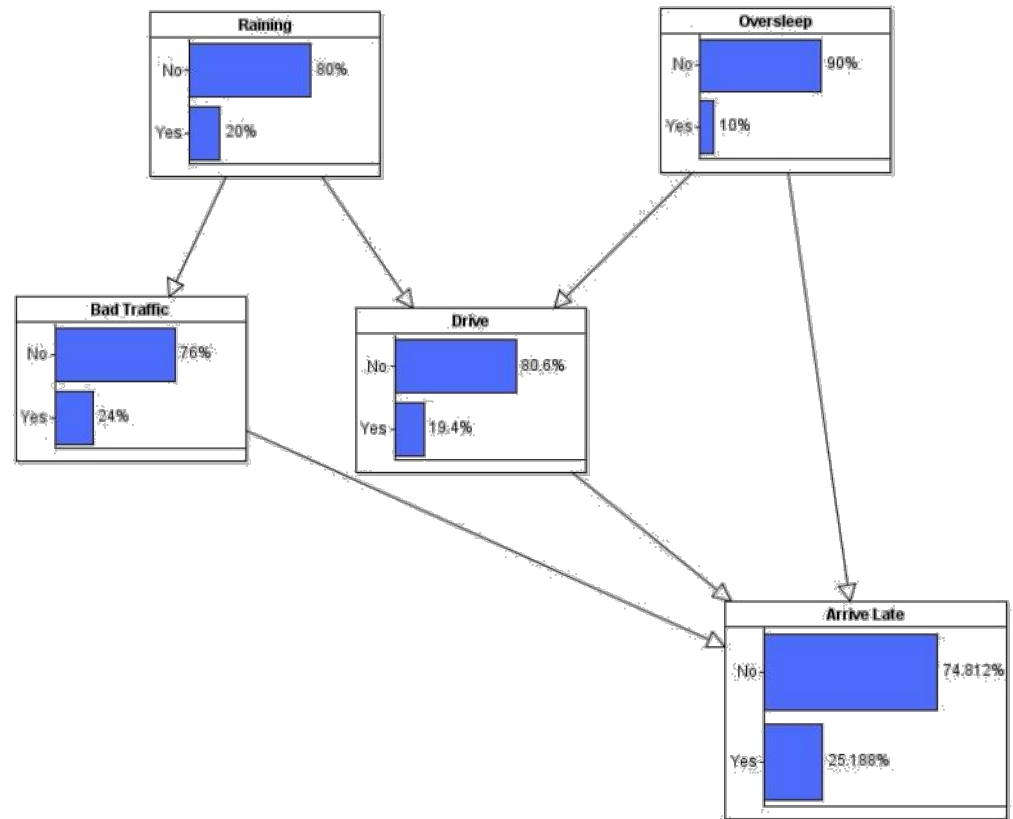
Another Approach

- Alternative modelling approaches combine judgement and data
- Model built in terms of real business dynamics
- More useful as a risk management tool (outcomes and drivers)
- Can simultaneously assess capital and non-capital outcomes
- Model can learn as observations made
- Thank you to Rev Thomas Bayes

$$\begin{aligned}p(A, B) &= p(A|B)p(B) \\p(B, A) &= p(B|A)p(A) \\ \Rightarrow p(A|B) &= \frac{p(B|A)p(A)}{p(B)}\end{aligned}$$

Bayesian Networks – Introduction

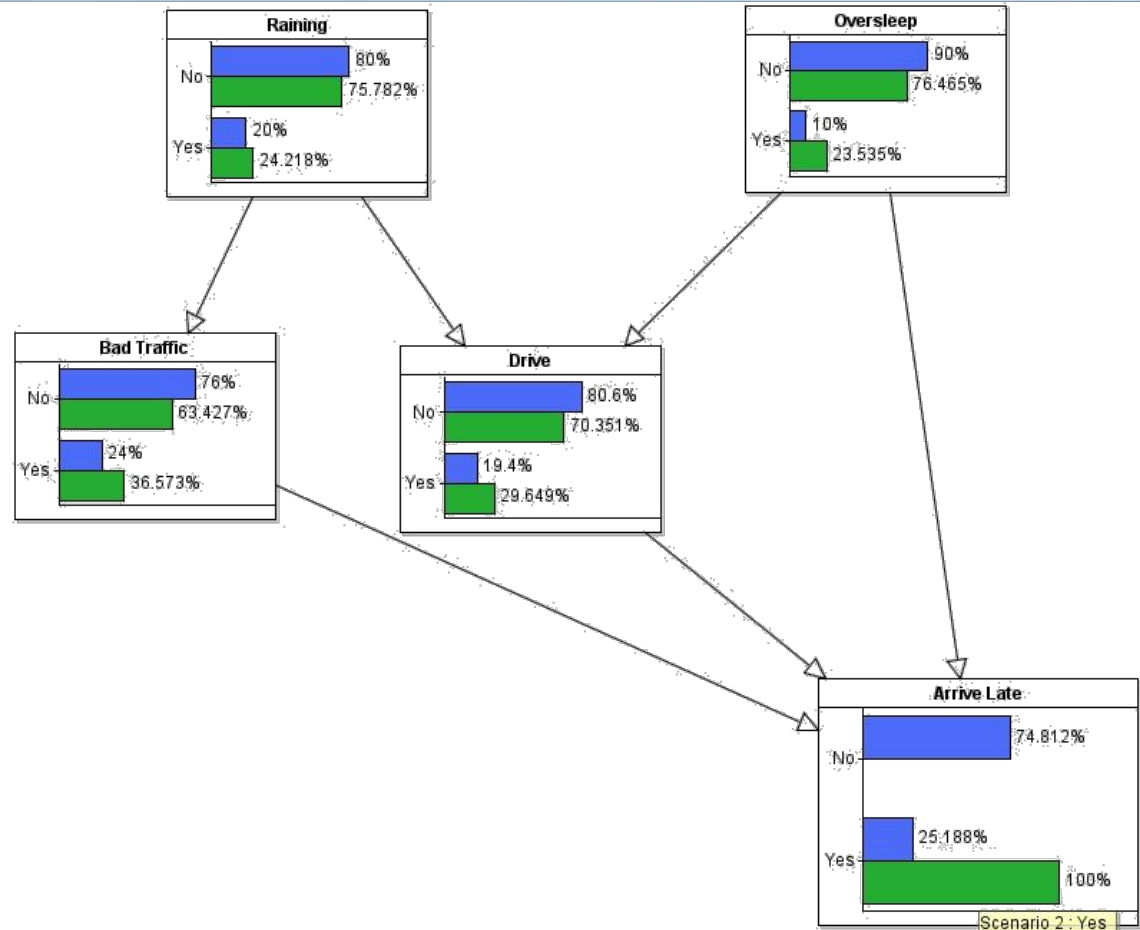
- Simple model of arrival time
- Depends upon
 - Getting up on time
 - Weather
 - Mode of transport
- Estimate of late arrival is “conditional upon” states of these factors



Source: Milliman, using AgenaRisk™

Bayesian Networks – Introduction

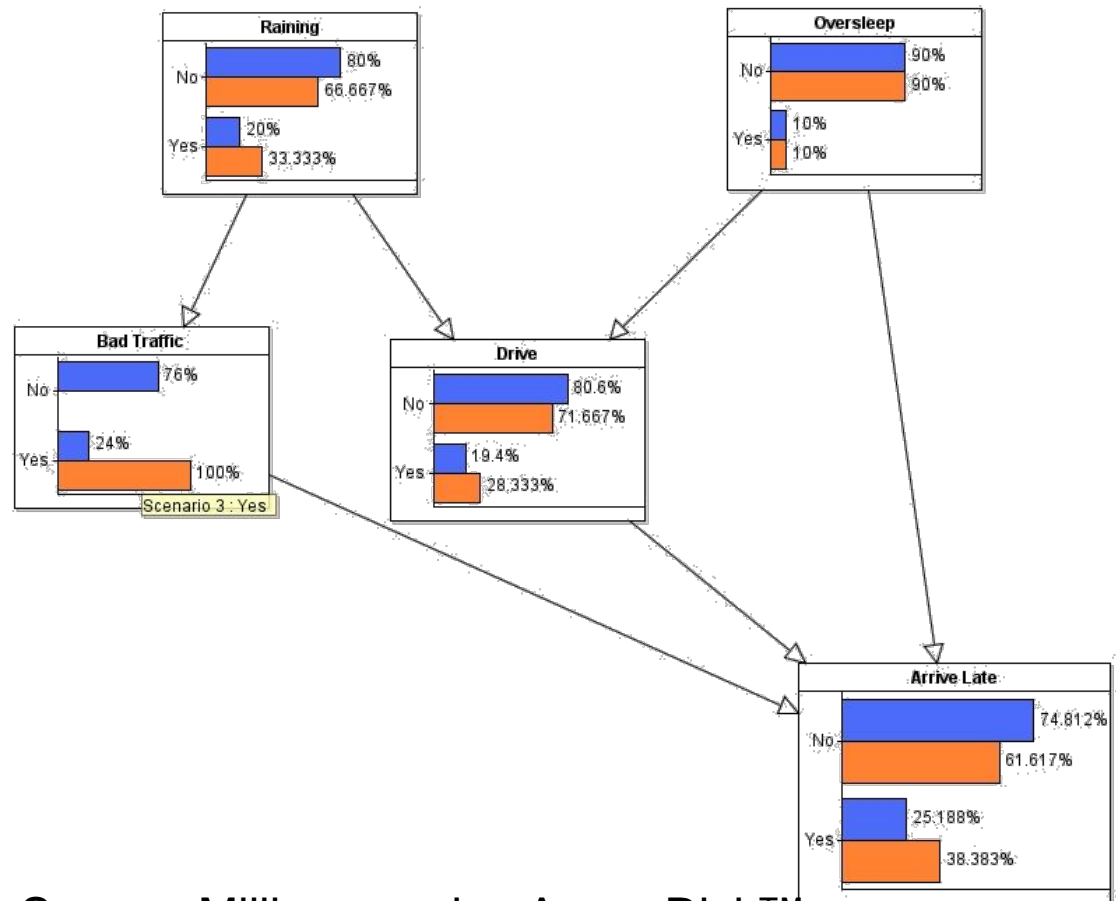
- If we know they arrive late, how does that change our view of the other factors?



Source: Milliman, using AgenaRisk™

Bayesian Networks – Introduction

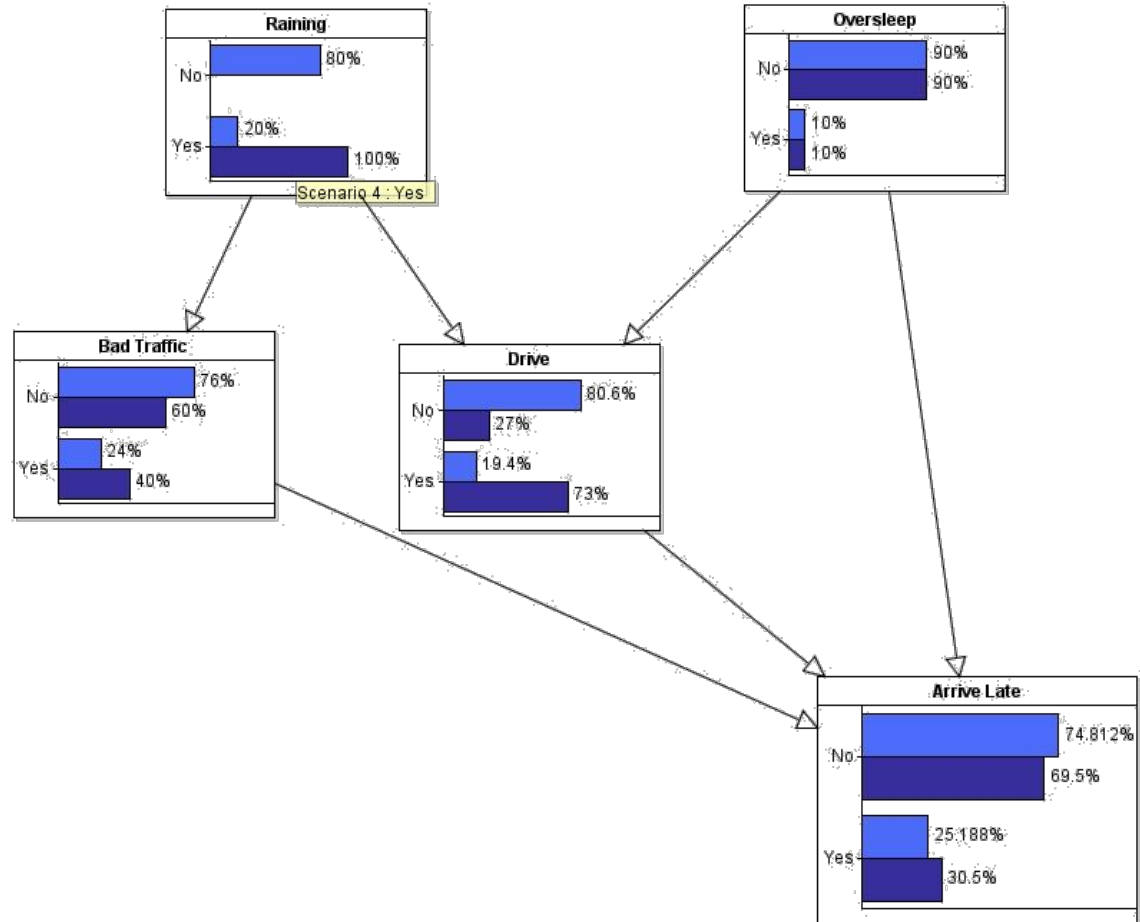
- If we know traffic is bad how does that change our view of other parameters?



Source: Milliman, using AgenaRisk™

Bayesian Networks – Introduction

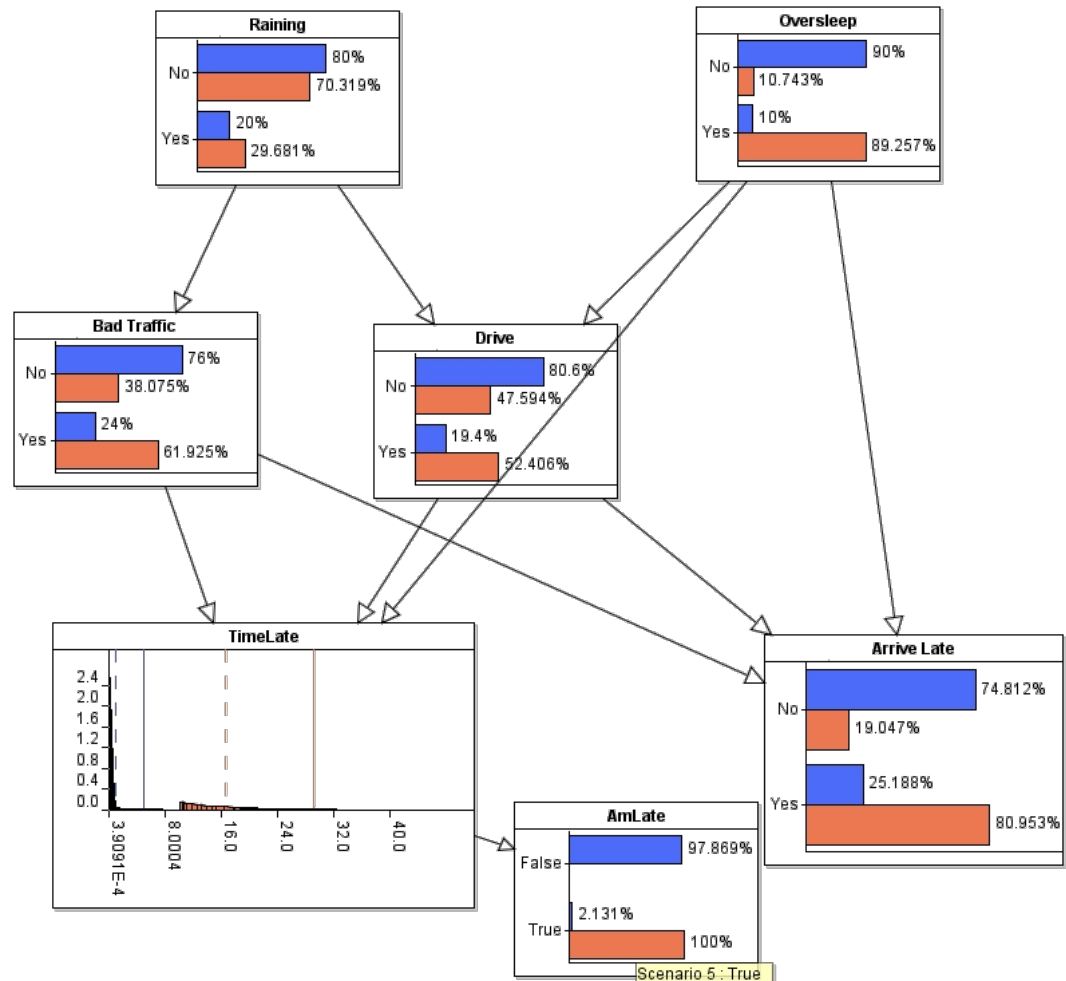
- If we know it is raining how does that change our view of the other factors?



Source: Milliman, using AgenaRisk™

Bayesian Networks – Introduction

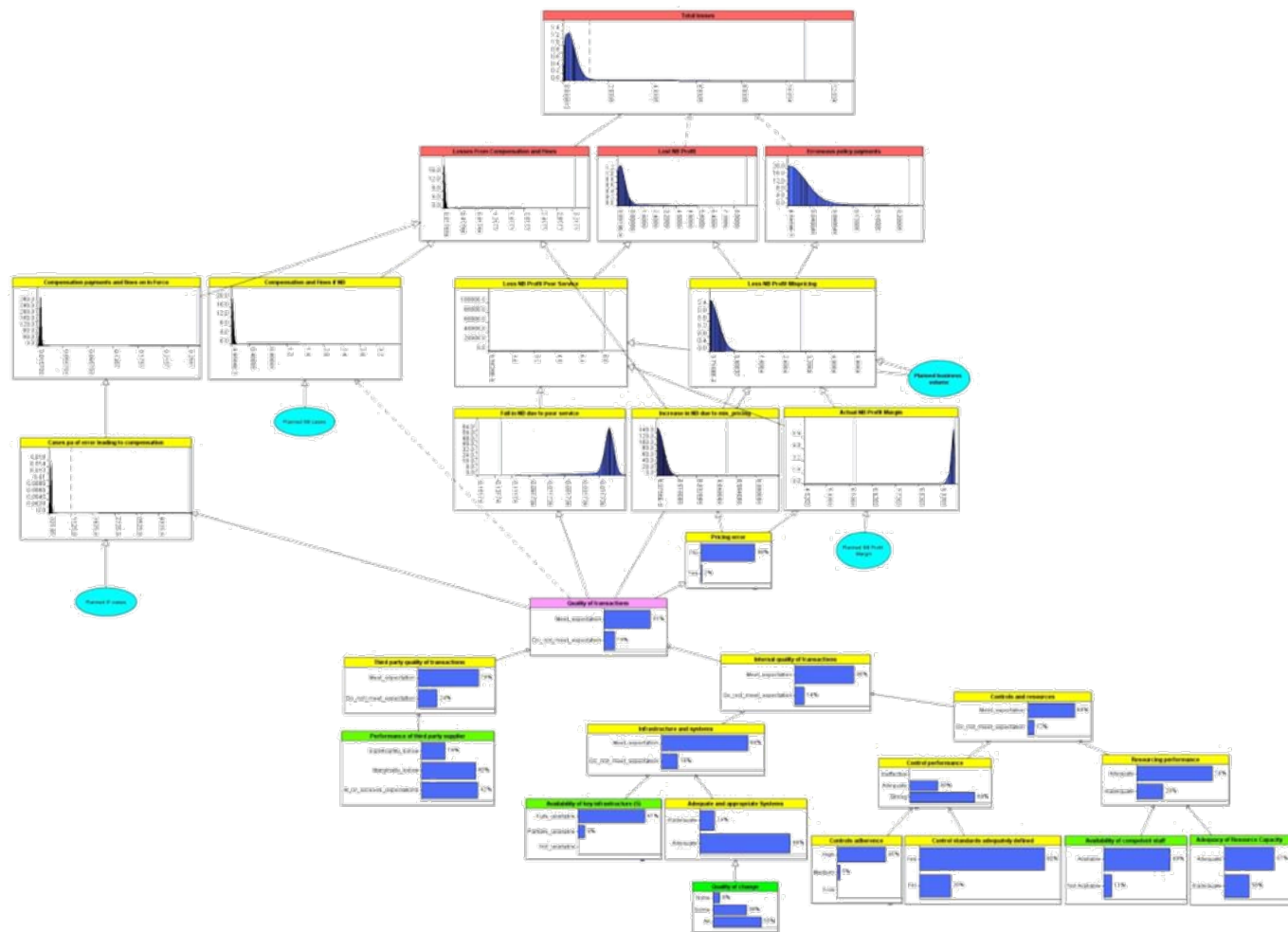
- If they arrive more than 10 minutes late, what state are the other factors in?



Source: Milliman, using AgenaRisk™

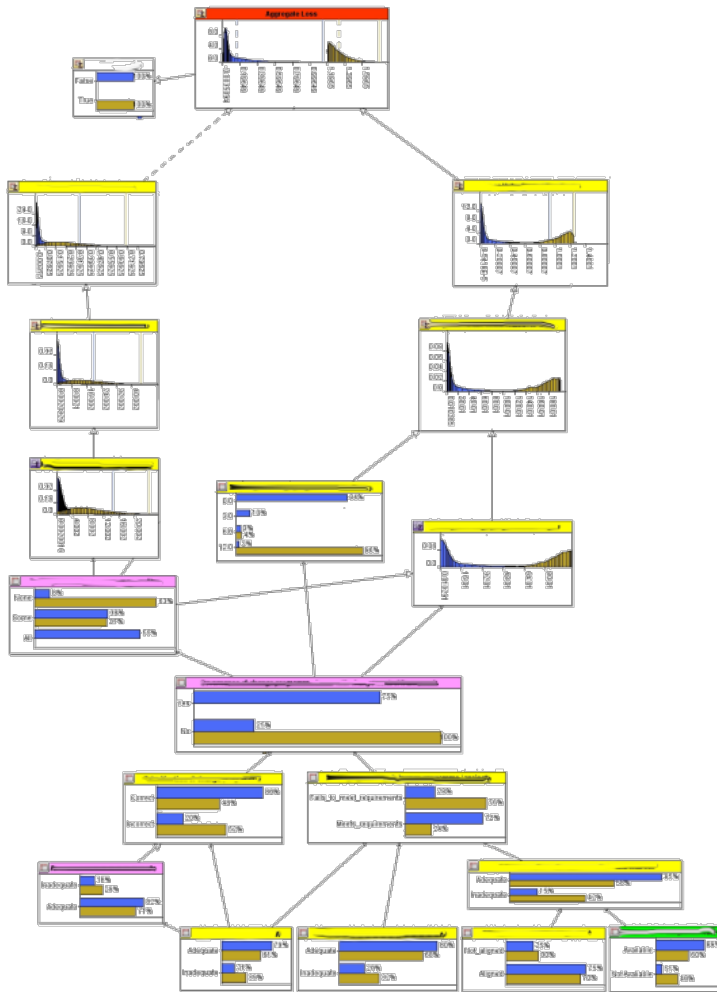
Bayesian Networks – Operational Risk

- Describing outcomes (e.g. capital) in terms of drivers means you can “explain” different outcomes in a real way



Source: Milliman, using AgenaRisk™

Bayesian Networks – Operational Risk



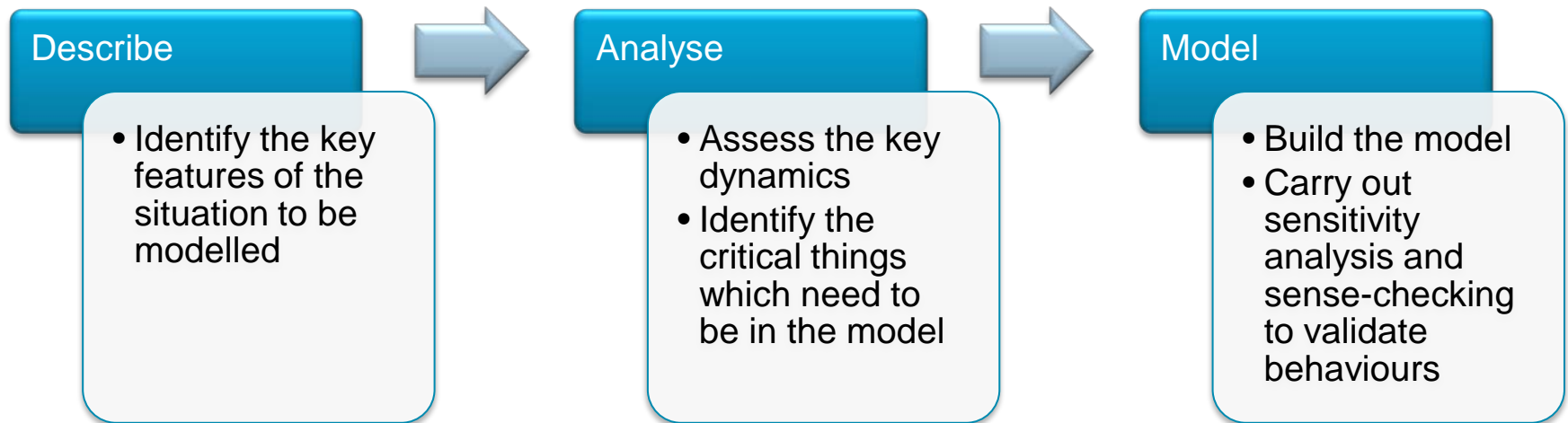
Aggregate outcome depends upon complex array of possible world states

Final outcome comprises a variety of individual outcomes all of which depend upon a complex array of possible world states

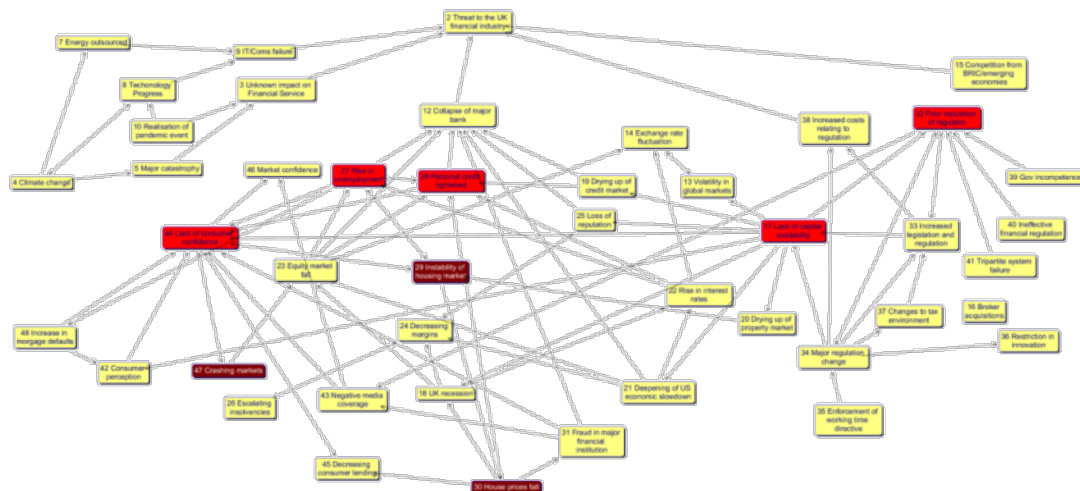
The world states can be described contingent upon the interactions and states of a variety of key factors

Source: Milliman, using AgenaRisk™

How To Build The Network



Cognitive Mapping – It's all in your head!

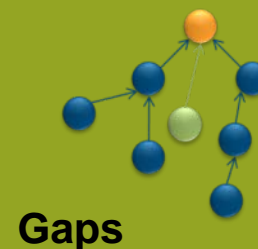
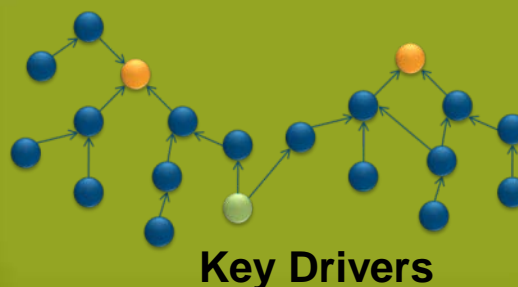
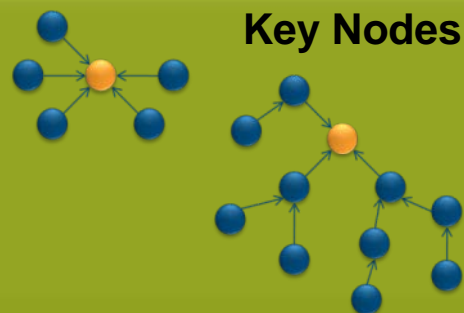


People form complex models in their head of what they see/think. It is possible to use cognitive mapping techniques to reconstruct the highly complex risk profiles in a robust, repeatable way.

You can evidence areas where narrative is too brief or where there are conflicting views.

It is a natural way for experts to engage but helps them combine their thoughts with others and identify the really important facts.

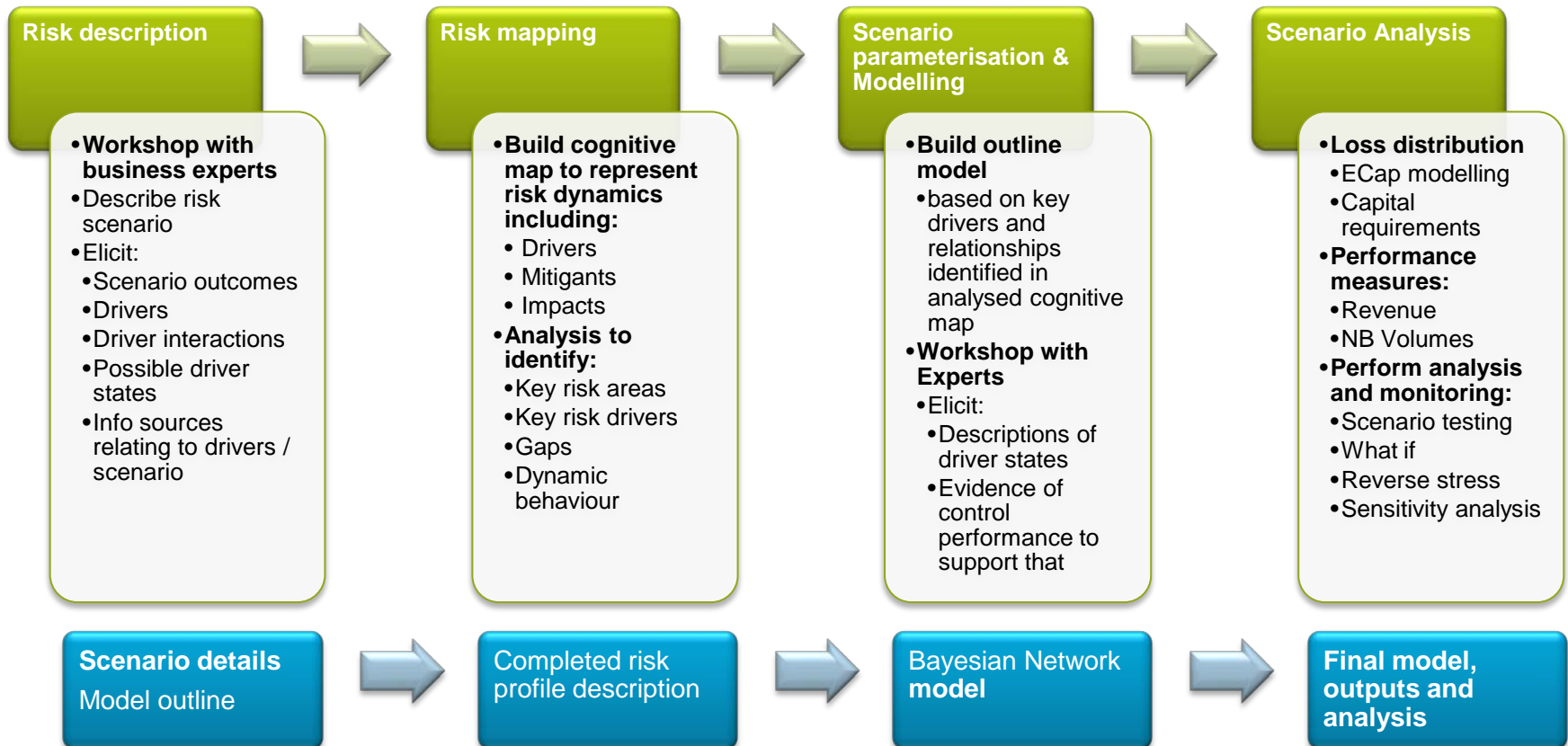
Source: Milliman



First Step

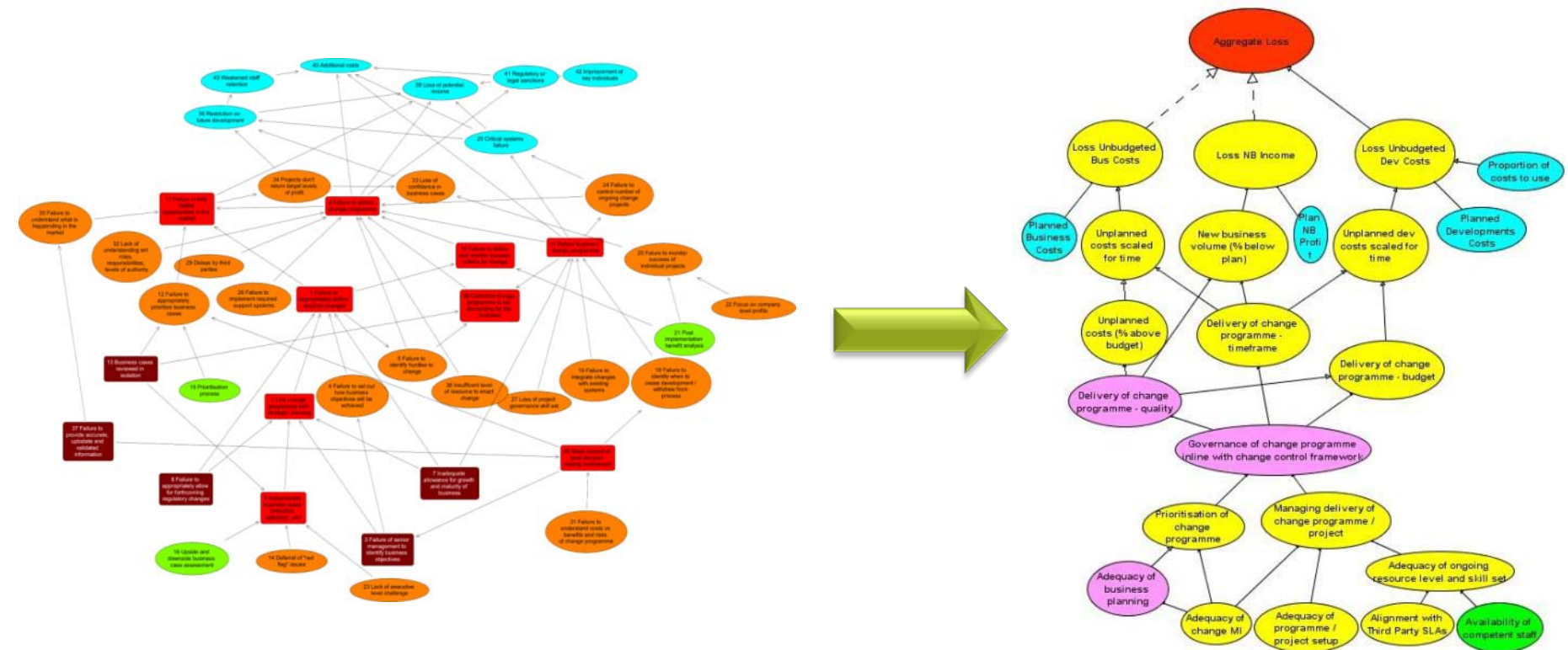
- What to model?
- Analyse business strategy and plan to understand operational risk profile
- Workshop with experts to describe dynamics and interesting features of business
- Discussion converted to cognitive map and analysed
- Operational risk profile determined
- Key scenarios identified and validated with experts
- Cross reference to loss data, external data, etc.

Process – Building the Model



Modelling the scenarios

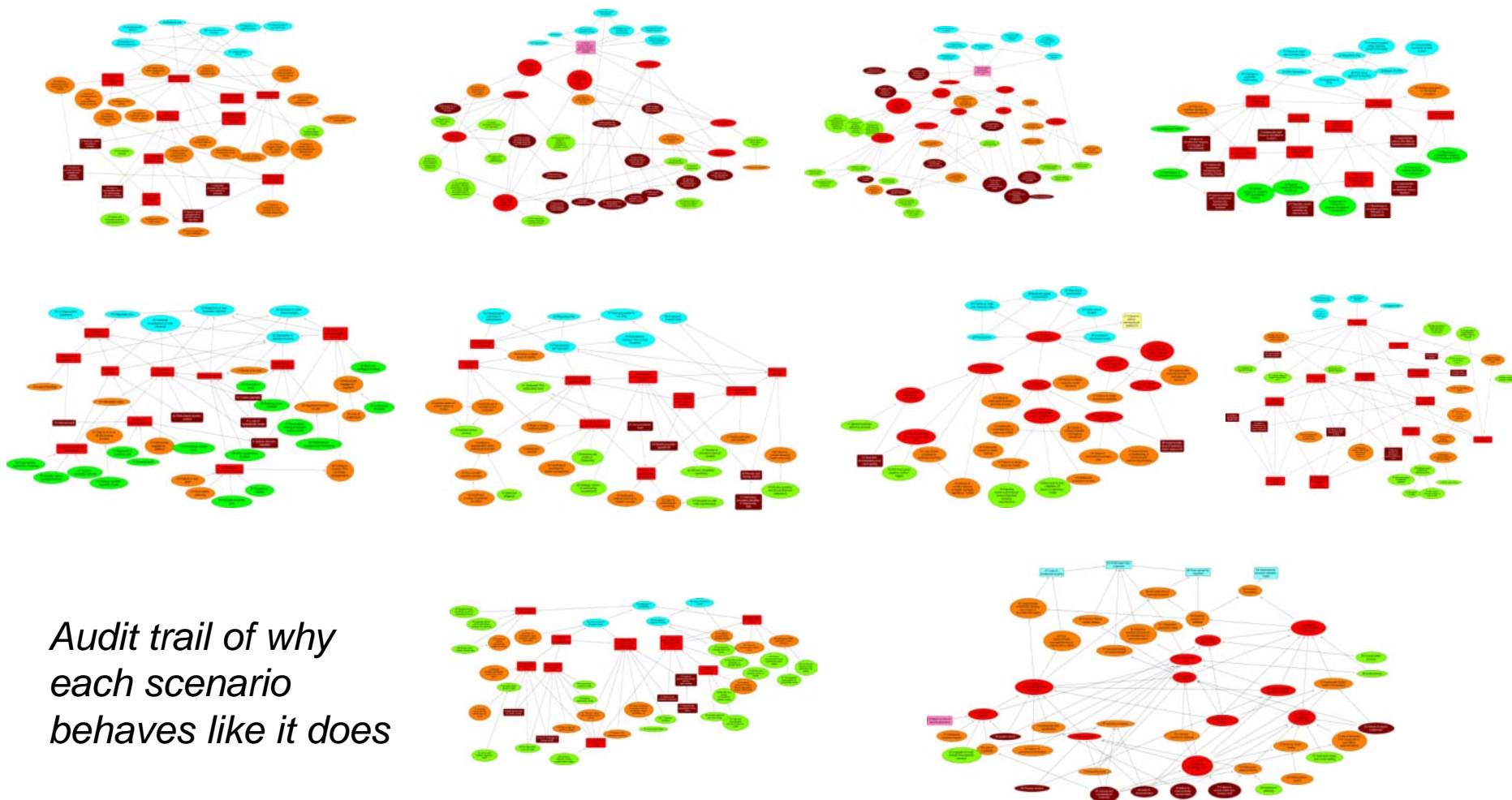
- Convert what you “know” into a “model”



Modelling Considerations

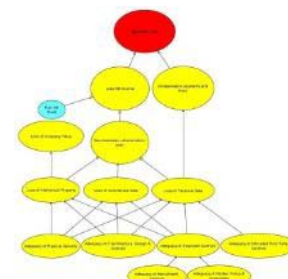
- Minimally complex
- Choose states which reflection transitions in the model
- Granularity must reflect what you can measure
- Loop of sensitivity analysis to challenge and validate
- Plan ahead
 - Which variables scale with growth
 - Which variables only apply for some uses

Describing Scenarios

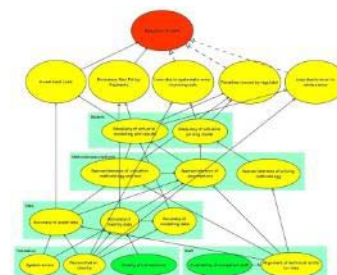


*Audit trail of why
each scenario
behaves like it does*

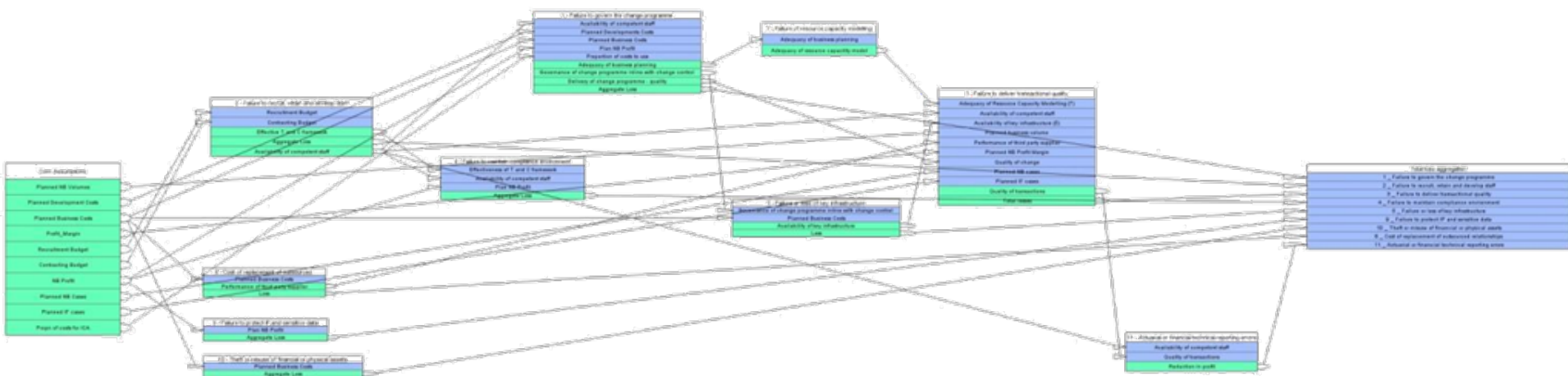
Building the models



*Clear linkage
between
“explanation” and
model*



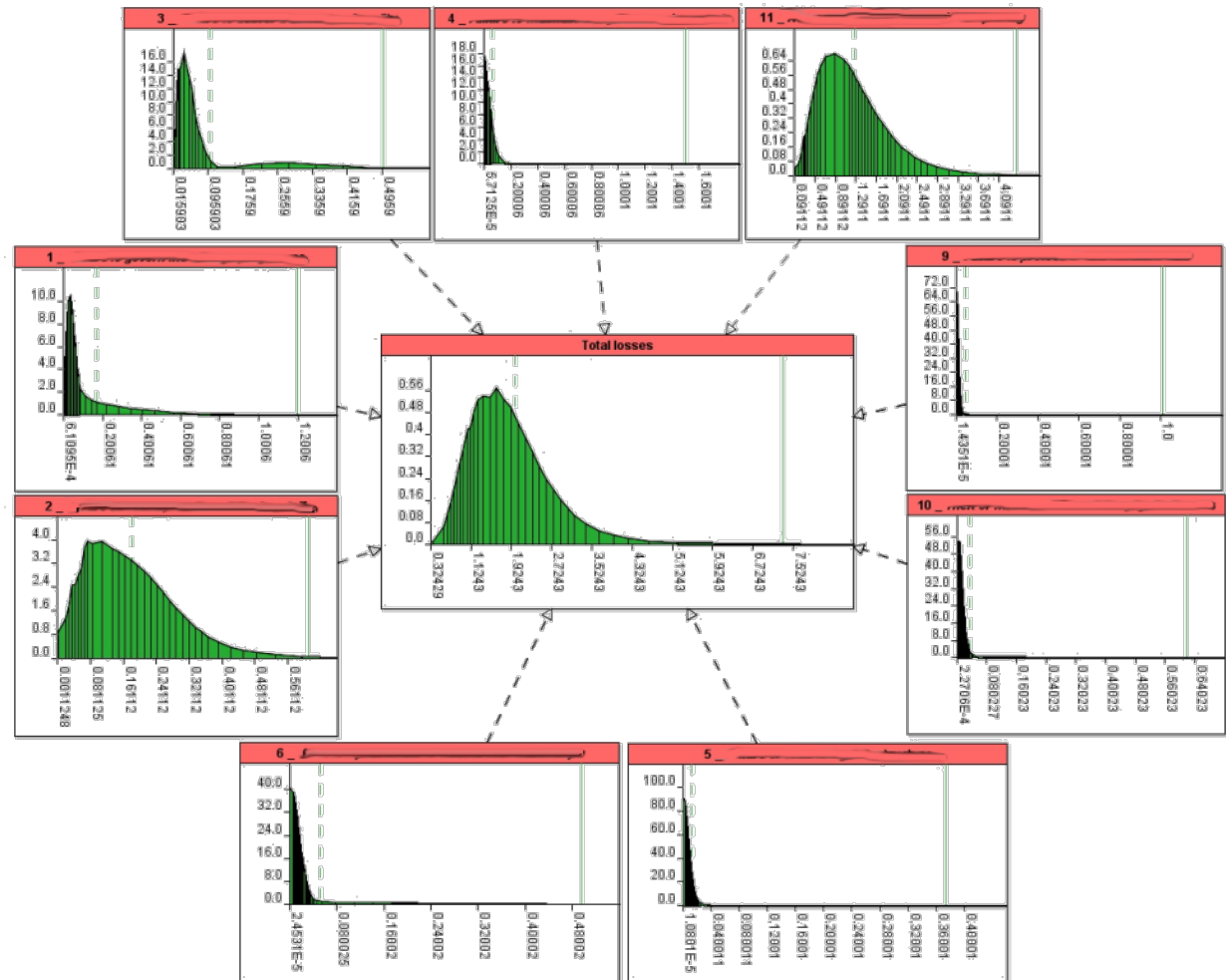
Common factors



No need for correlations. Underlying dynamics captured directly. End results for each scenario already partially diversified

Bayesian Networks

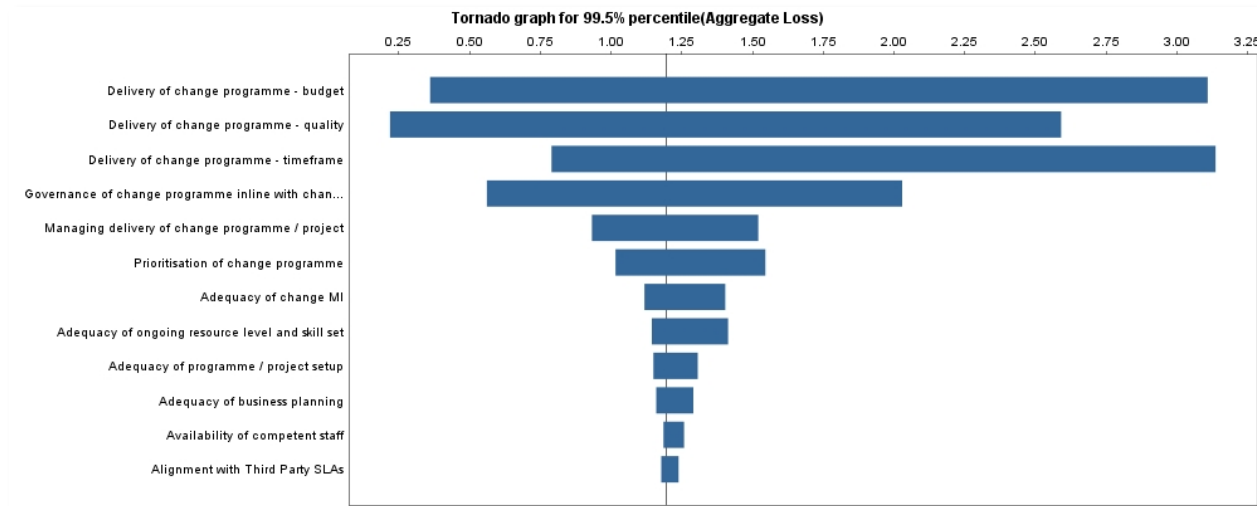
- Aggregate is a convolution of scenario results
- Create more realistic loss curves
- Build in non-linear effects and sudden transitions



Source: Milliman, using AgenaRisk™

Asking Questions

- Stress / scenarios
- Sensitivity
- What if
- Best improvement...worst deterioration

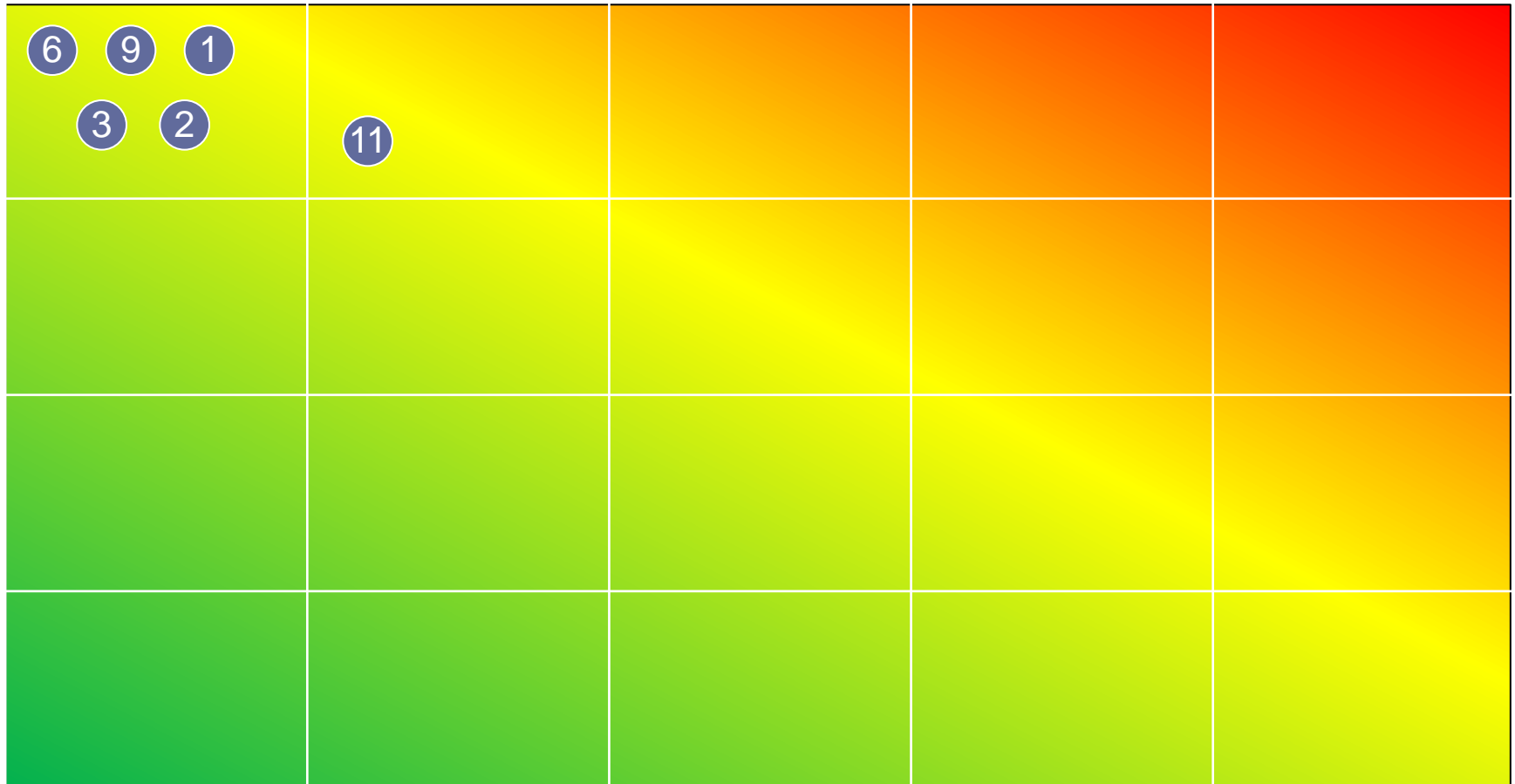


Reporting

- Linkage between each point of distribution and underlying drivers
- Can look at different frequencies to understand drivers
 - Which factors influence the “mode”?
 - Which things are “probable”?
 - What drives potential risk outcomes?
 - What drives rare risk outcomes (on the boundary of risk appetite)?
- Explore what could force a transition from one frequency to another

Heat Map 1 – Frequent Outcomes (Mode)

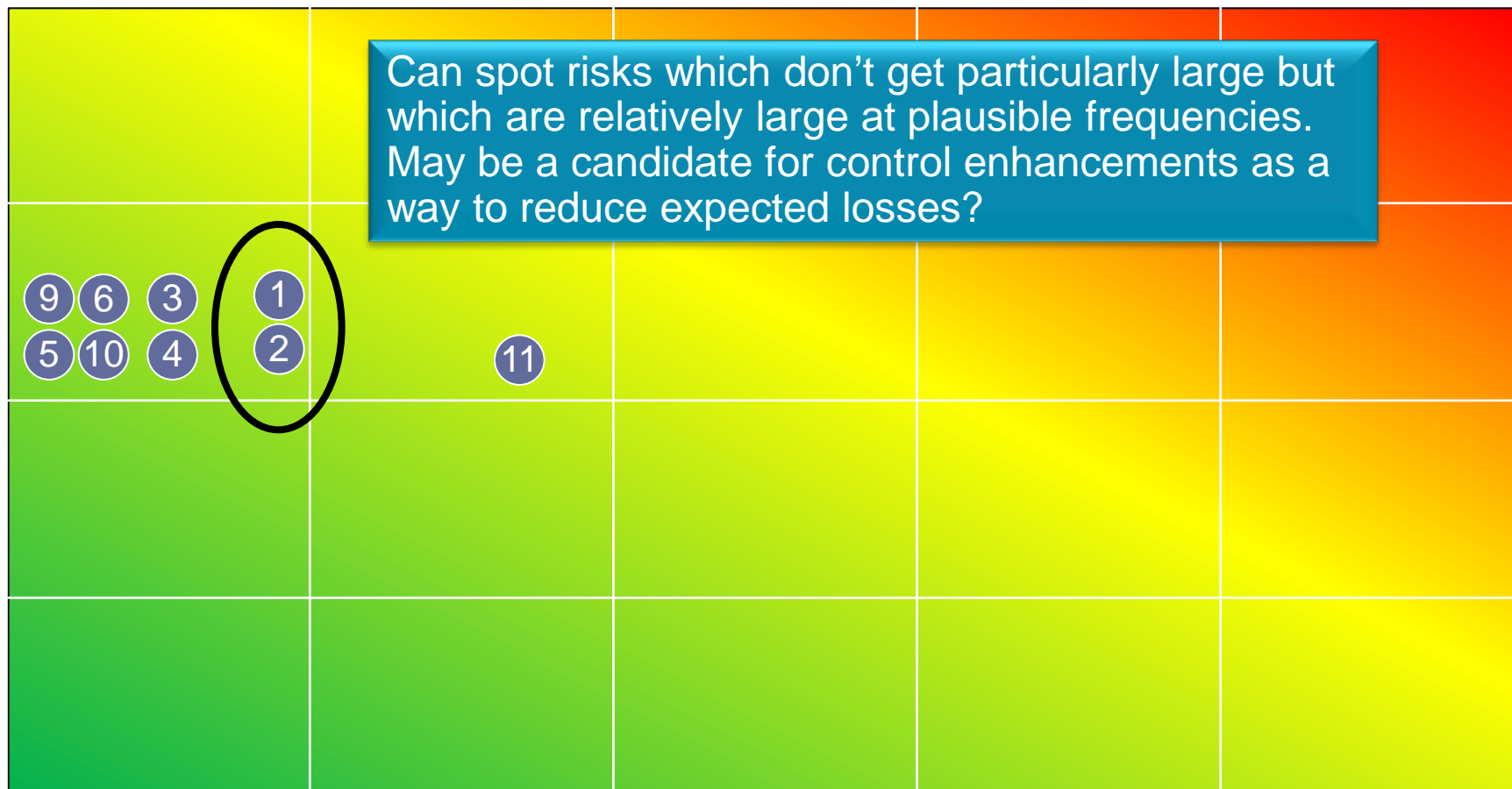
Likelihood



Impact

Heat Map 2 – Probable Outcomes (75%)

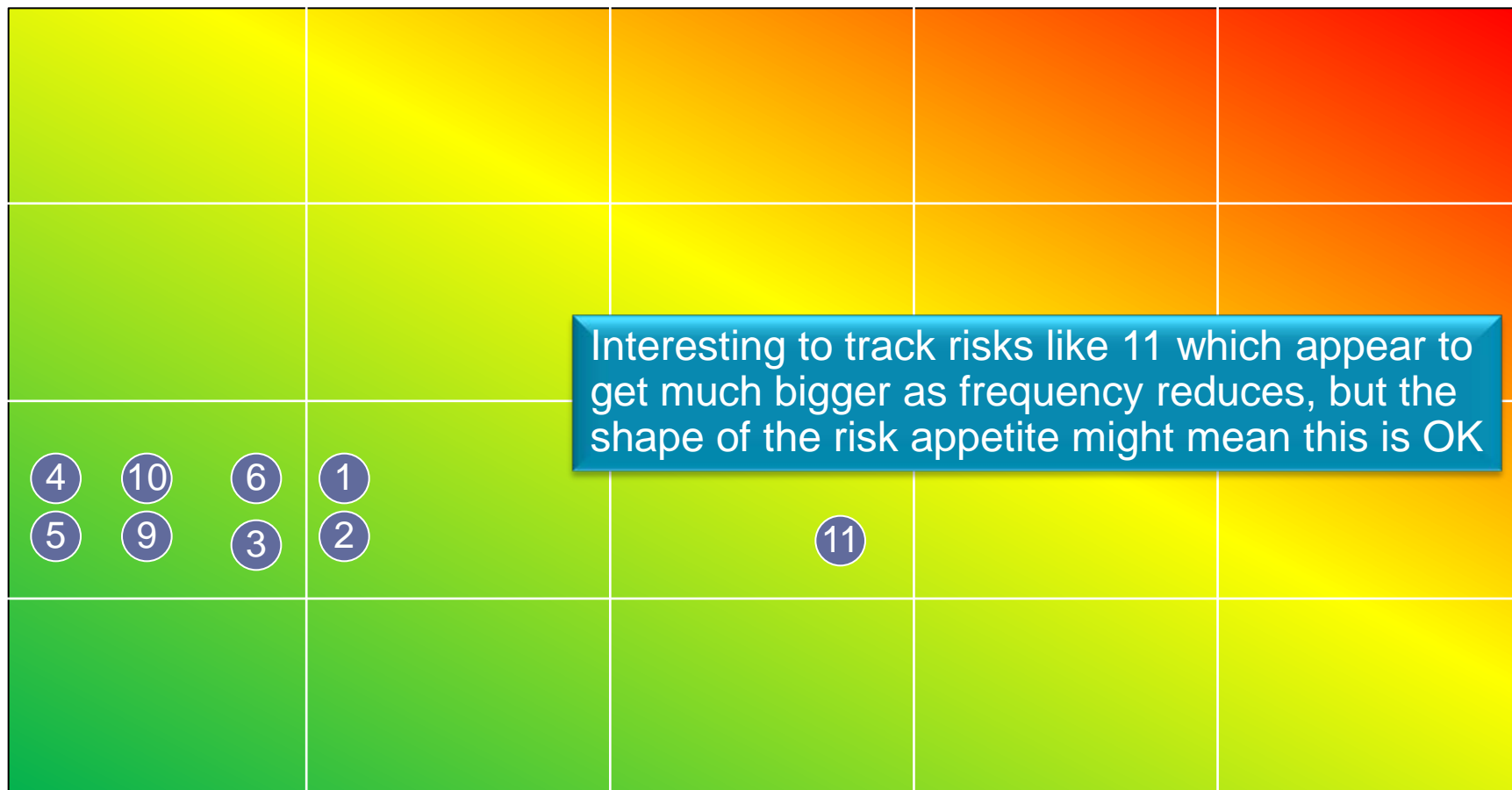
Likelihood



Impact

Heat Map 3 – Possible Outcomes (90%)

Likelihood

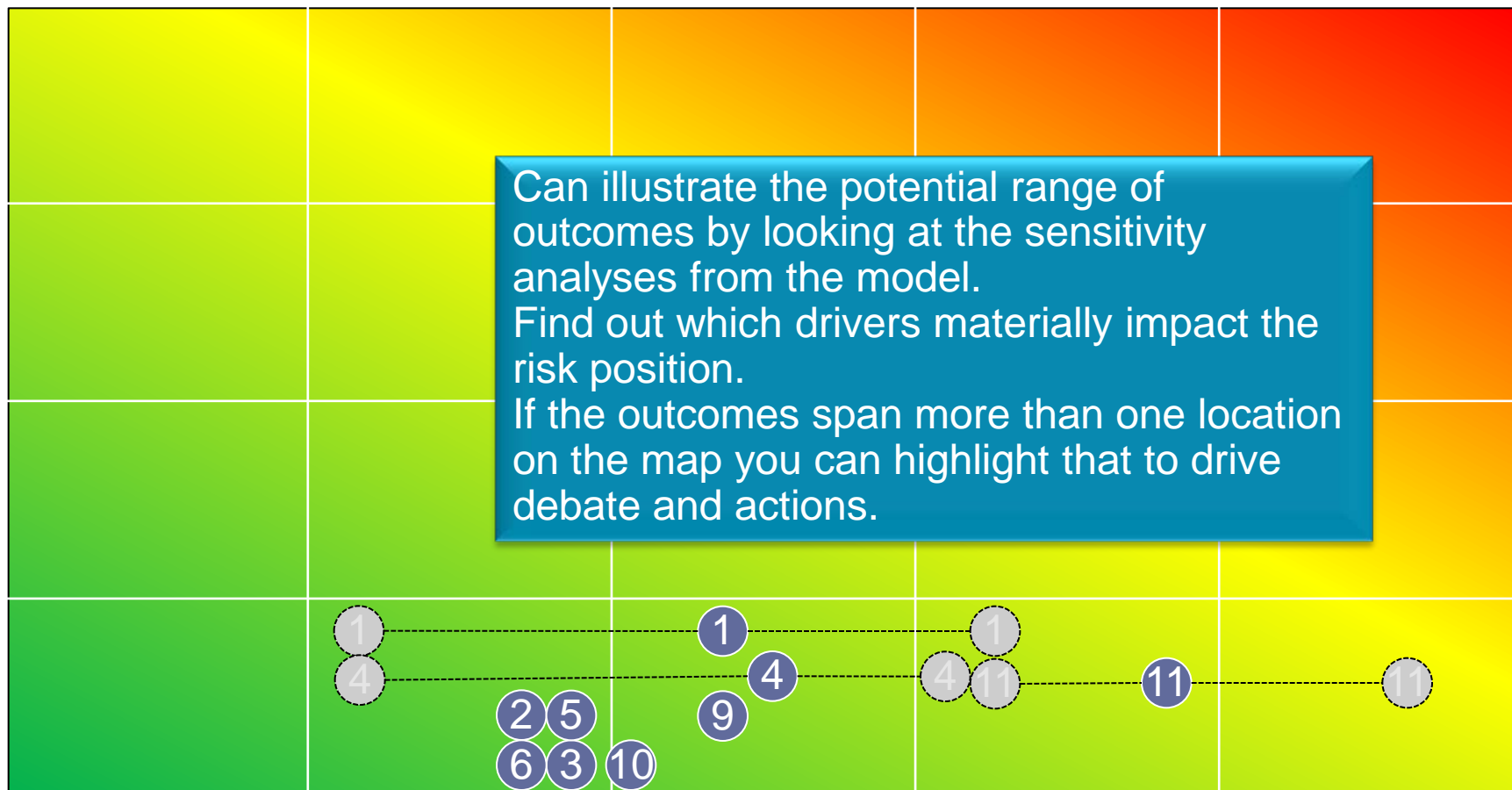


Interesting to track risks like 11 which appear to get much bigger as frequency reduces, but the shape of the risk appetite might mean this is OK

Impact

Heat Map 4 – Rare Outcomes (99.5%)

Likelihood



Impact



Reflection

Was it worth it?

What happened next

- Business felt listened to
- Business felt strong “ownership” of model
- Improved communication between finance teams and business about risk drivers
- Dialogue about op risk was framed in business terms but had clear capital consequences
- Subsequently able to challenge beliefs about sources of extreme outcomes
- Increased engagement at Board/Senior Management level



Summary

Op Risk can be modelled

Summary

- Reasons why op risk is hard:
 - It is pervasive...boundary issues
 - It is adaptive...challenges typical frequentist approach
 - There is only data to support the modal behaviour
 - Causes tend to be mostly endogenous...industry data an issue
- Systems theory provides a suitable lens to make sense of it
- Expert insight can be harnessed
- Op risk is about “management”...engagement can be achieved between business, risk and modellers

Questions or comments?

Expressions of individual views by members of The Actuarial Profession and its staff are encouraged.

The views expressed in this presentation are those of the presenter.

