Operational Risk Measurement: Advanced Approaches

Prof. Carol Alexander
ISMA Centre, University of Reading, UK
c.alexander@ismacentre.rdg.ac.uk
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1. Introducing the Advanced Measurement Approaches (AMA)

These include:

- Internal Measurement Approach (**IMA**)
- Loss Distribution Approach (**LDA**)
- Scorecard Approaches (for risks with no loss data)

Carrots:

- **Insurance** (mitigation of charges when events are insured is only permitted under AMA)
- **Reduction in capital charge** (but a floor is currently set at 75% of the total charge under the standardized approach)

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Quantitative Requirements for AMA

- The AMA requires **historical loss data** in a form that is consistent with the business line/event type categories specified on the next slide.
- The model must be based on a minimum historical observation period of **five years**. However, during an initial transition period, a three-year historical data window might be accepted for all business lines and event types.
- The bank must be able to demonstrate that the risk measure used for regulatory capital purposes reflects a holding period of **one-year** and a confidence level of **99.9 percent**.

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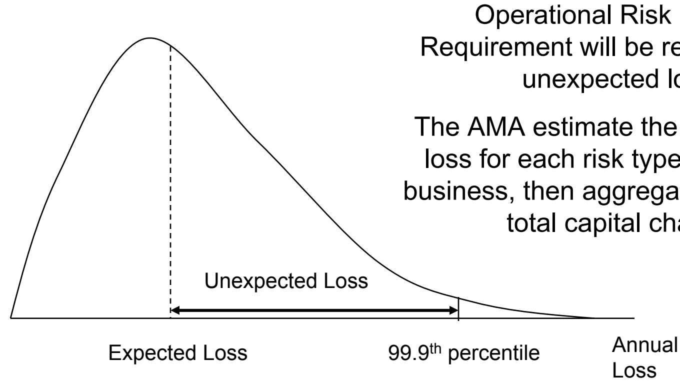
Unexpected Loss and Capital Charge



Operational Risk Capital Requirement will be related to the unexpected loss

The AMA estimate the unexpected loss for each risk type and line of business, then aggregate to obtain a total capital charge

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Data: Loss Severity and Frequency

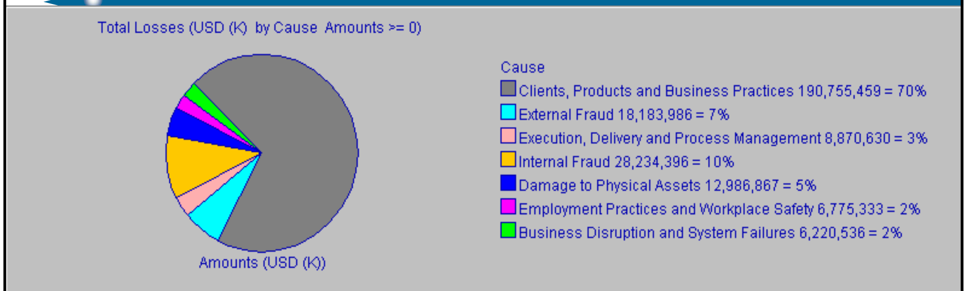
Line of Business ↓	Risk Types						
	Internal Fraud	External Fraud	Damage to Physical Assets	Employment Practices	Business Practices	Business Disruption	Process Management
Corporate Finance							
Trading and Sales							
Retail Banking							
Commercial Banking							
Payment and Settlements							
Asset Management							
Retail Brokerage							
Agency & Custody							

ISMA CENTRE

OP-Vantage

- Historical data points from past 10+ years
- More than 7,000 loss events greater than US$1 million, totalling US$272 Billion of losses
- Events mapped to multiple hierarchies, including Basel's recent QIS risk categories
- Semi-annual updates (average 500+ events above US$1 million per update)
- Strict standards for inclusion and categorization. Excludes events such as rumours, estimates of lost income, pending litigations and unsettled disputes
- Summary descriptions of loss events
- Loss data gathered from a multitude of global sources
- Available as a standalone database or within the OpVar® software suite

Losses by Risk Type



Clients, Products and Business Practices: Failure to meet obligations to clients; faulty design or nature of product

EG. Bankers Trust incurred huge legal losses (several hundreds of million dollars) by selling inappropriate exotic products

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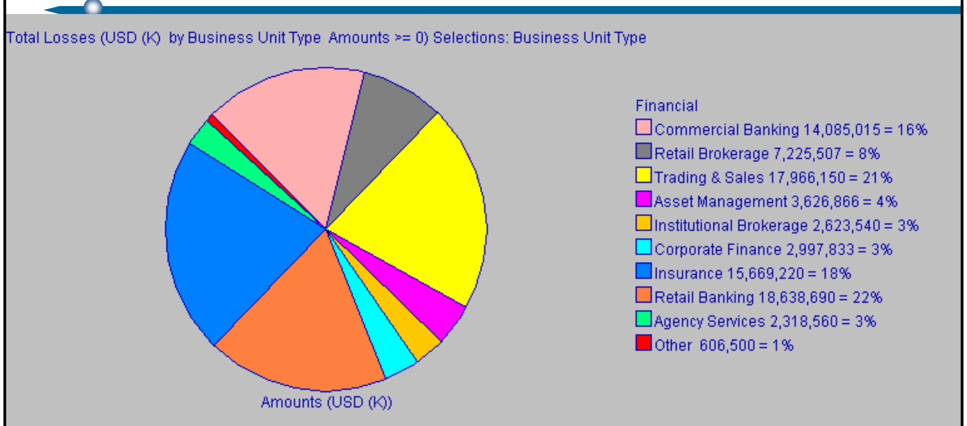
Losses by Line of Business



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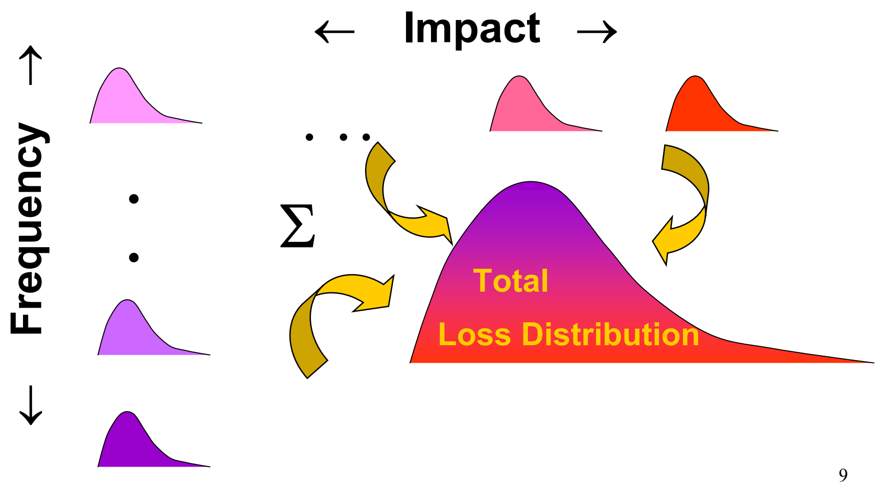
Aggregation



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2. The Internal Measurement Approach (IMA)

- A simple form of LDA, based on some strong distributional assumptions
- For each business line/risk type

  IMA ORR = gamma × expected loss
- Assumes unexpected loss is a multiple of expected loss
- The total operational risk capital charge is the sum of all charges over business lines and risk types
- This assumes the worst possible case, of perfect correlation between individual risks

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Binomial Model

- For a particular LOB and a particular type of risk, denote the probability of a loss event by p and the expected loss given event by L
- Assume the exposure indicator N = the total number of events that are susceptible to operational losses during one year
- Assume independence between loss events. Then, the parameters N and p and the random variable L correspond to those of a binomial distribution B(N, p) on the states (0, L).
- The total loss is the result of N independent 'Bernoulli' trials where in each trial the probability of losing an amount L is p and the probability of losing 0 is (1 – p).

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What is Gamma?

- In the binomial model the expected loss is μ = N p L and the standard deviation of loss is

  $\sigma = \{\sqrt{[N\, p\, (1 - p)]}\}\, L \approx L\, \sqrt{[N\, p]}$ if p is small
- Capital charge = unexpected loss = gamma x expected loss
- Assume unexpected loss $\approx k\sigma$ where k is a constant.. Then

  Gamma $\approx k\sigma / \mu = k\, L\, \sqrt{[N\, p]} / NpL$

  Gamma $\approx$ k / $\sqrt{[Np]}$
- **Note 1:** Gamma is NOT a constant, independent of risk type.
- **Note 2:** Np is the expected number of loss events in one year: Banks do NOT need to obtain data for N and p separately
- **Note 3:** Gamma will be low for high frequency risks and high for low frequency risks

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Examples

- **Example 1:** If 25,000 transactions are processed in a year by a back office, the probability of a failed transaction is 0.04 and the expected loss given that a transaction has failed is $1000, the expected total loss over a year is $1 million.

- **Example 2:** If 50 investment banking deals have been done in one year, the probability of an unauthorized or illegal deal is 0.005 and the expected loss if a deal is unauthorized or illegal is $4 million, then the expected total loss will also be $1 million.

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Examples

- However the distribution of the losses will be very different, so also will the gamma factors: **assume k = 4 for both risk types**

- **Example 1:** Gamma $\approx 4/\sqrt{1000} \approx 4/31.6 \approx 0.13$ and so, since expected loss is 1m$, the capital charge is only $130,000.

- **Example 2:** Gamma $\approx 4/\sqrt{0.25} = 8$, leading to a capital requirement of $8m.

- Note that the gamma (and capital charge) is **63 times larger** for the corporate finance example than for the back office transactions processing example.

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Extending the Binomial IMA Model

- The binomial IMA model can be extended to deal with random loss amounts (*Binomial Gammas,* Operational Risk, April 2001).
- It may also be extended to the use of alternative loss frequency distributions (*Rules and Models,* Risk Magazine, January 2002).
- …and it provides a simple formula for mitigation by insurance (*Rules and Models,* Risk Magazine, January 2002).
- Finally, the parameter estimates may be based on Bayesian estimation (*Taking Control of Operational Risk,* Futures and Options World, December 2001)

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Including Insurance in the IMA

- Insurance reduces the loss amount when the event occurs (an amount R is recovered) but introduces a premium C to be paid even if the event does not occur
- In the binomial model with N Bernoulli trials, an amount L – R is lost with probability p and C is lost with probability 1.
- The expected loss is now $N[p(L – R) + C] \approx NpL$ since $C \approx pR$
- The standard deviation is now $(L – R) \sqrt{[Np]}$ if p is small, so

$$\textbf{gamma} \approx \mathbf{k}\ [1 - r]/\ \sqrt{[Np]}$$

  where r = R/L is the recovery rate
- Thus insurance will decrease gamma by an amount which depends on recovery rate.

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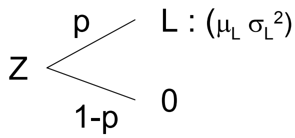
Loss Variability

- Let μ_L be the expected loss severity
- Let σ_L^2 be the variance of the loss severity.



$E(Z) = p\ \mu_L$

$Var(Z) = p(1-p)\ \mu_L^2 + p\ \sigma_L^2 \approx p(\mu_L^2 + \sigma_L^2)$

- Thus

$$\textbf{gamma} \approx k\ \sqrt{[1 + (\sigma_L/\mu_L)^2]}/\sqrt{[Np]}$$

- This shows that loss variability will increase the gamma factors: but much more so for low frequency high impact risks……

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Alternative Loss Frequency Distributions

Poisson Model for Gamma

- Another loss frequency distribution that can be used with the IMA is the Poisson, with parameter λ which corresponds to the expected number of loss events in the time horizon.

$$\textbf{Gamma} = k\ [1 - r]\ \sqrt{[1 + (\sigma_L/\mu_L)^2]}\ /\ \sqrt{\lambda}$$

- The IMA ORR (i.e. the capital charge) will be given by the formula

$$k\ \mu_L\ [1 - r]\ \sqrt{[(1 + (\sigma_L/\mu_L)^2)\ \lambda\ ]}$$

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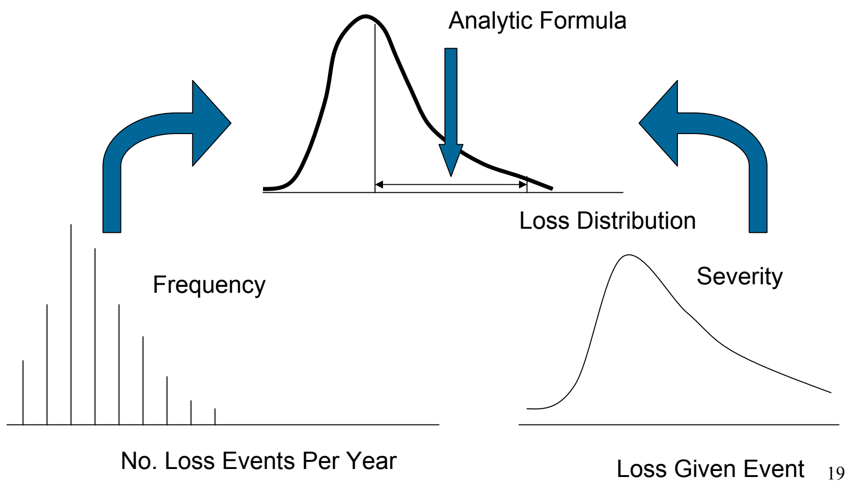
Summary of IMA



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Example

XS Loss (m$)	Year	XS Loss (m$)	Year
7.14	1	22.30	9
8.79	2	2.00	9
18.62	5	1.28	9
22.52	6	8.73	9
54.53	6	2.31	9
331.75	7	9.94	9
232.96	7	22.21	9
43.36	7	17.36	9
66.49	8	81.37	9
24.36	8	13.41	10
2.39	8	19.23	10
1.50	8	18.83	10
9.52	8	60.99	10
2.92	8	6.07	10
190.74	8	8.06	11
68.81	8	1.94	11
288.87	8	10.77	11
83.61	9	2.49	12
49.78	9	8.81	12

Historical data on loss (over 1m$) due to Internal Fraud.

Recorded over a period of 12 years

Total capitalization of banks reporting losses was 250bn$

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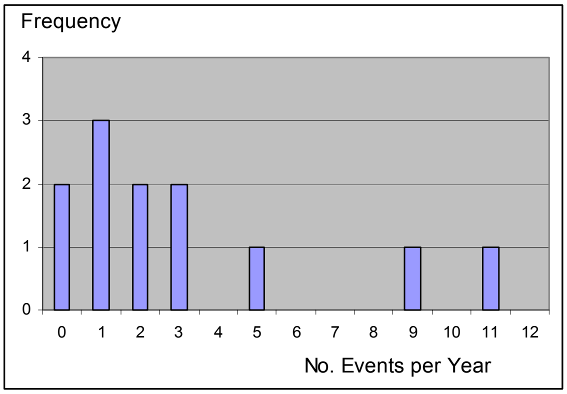
Empirical Loss Frequency



Expected no. loss events per year = 2.4545

$\Rightarrow$ Model loss frequency with Poisson density with $\lambda \approx 2.45$

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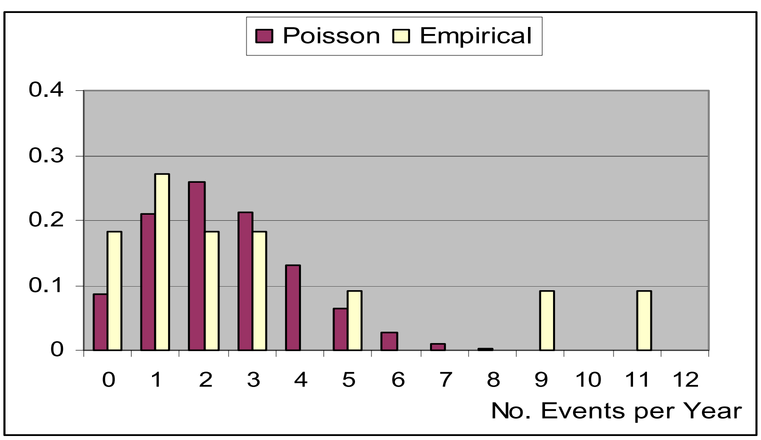
Poisson Loss Frequency



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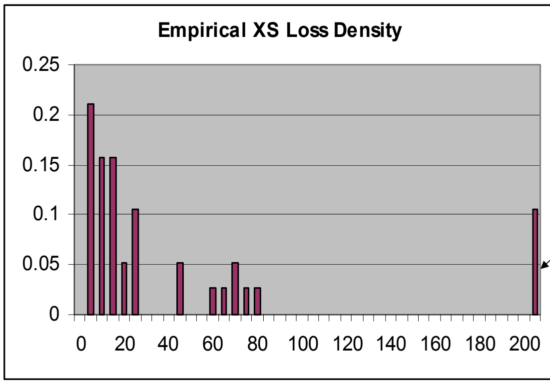
Loss Severity Distribution



Three events in excess of 200m$

Expected Loss = 50m$

and

Stdev = 100m$

IMA Capital Charge

- The IMA capital charge is:

  $$\mathbf{k}\ \mu_L \sqrt{[(1 + (\sigma_L/\mu_L)^2)\ \lambda\ ]}$$

- We have:

  μ_L **= 50m$,** σ_L **= 100m$,** λ = **2.45**

- That is, capital charge is:

  50 k √(5x2.45) = 175 k m$

- Or, with k = 3 [???], IMA capital charge = 525m$
- This charge corresponds to a total capitalization of 250bn$
- Suppose your bank has a capitalization of 10bn$
- Then the IMA charge will be 525/sqrt(25) = 105m$

Comments on the IMA: What is k?

- k is the ratio of the unexpected loss to the standard deviation.
- For example, in the standard normal distribution and for the 99.9% confidence level that is recommended in CP2.5 for the LDA, k = 3.10, as can be found from standard normal tables.
- For the binomial distribution with N = 20 and p = 0.05 (so the expected number of loss events is 1) the standard deviation is 0.9747 and the 99.9% percentile is 5.6818, so

$$k = (5.6818 – 1)/0.9747 = 4.80.$$

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Dependence Between k and Frequency

- In general, the value of the multiplier k depends more on the type of risk than the type of distribution that is assumed for loss frequency.
- High frequency risks, such as those associated with transactions processing, should have lower multipliers than low frequency risks, such a fraud.
- For example, using the Poisson distribution with expected number of loss events equal to 1, the standard deviation is 1 and the 99.9% percentile is 5.84, so

$$k = (5.84 – 1)/1 = 4.84;$$

- But for higher frequency risks where the expected number of loss events is, say, 20, the Poisson distribution has standard deviation $\sqrt{20}$ and 99.9% percentile 35.714, so

$$k = (35.714 – 20)/ \sqrt{20} = 3.51.$$

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Regulators Approach to k

- Regulators might use their approval process to introduce a 'fudge factor' to the multiplier, as they have done with internal models for market risk.
- They may wish to set the multiplier by calibrating the operational risk capital obtained from this "bottom-up" IMA approach to that determined from their "top-down" approach.
- This is what they are attempting to do with the multipliers (alpha and beta) for the Basic Indicator method and the Standardized Approach to operational risk capital measurement.

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Conclusions of the IMA Model

- For each line of business and risk type:

$$\textbf{capital charge} = k\, \mu_L\, [1 - r] \sqrt{[(1 + (\sigma_L/\mu_L)^2)\, \lambda\,]}$$

- Minimum data requirements:
  - the expected loss frequency λ
  - the expected loss severity μ_L
- Capital charges should increase as the square root of the expected loss frequency but linearly with expected loss severity
- Capital charges will be
  - high for low frequency high impact risks, and
  - low for high frequency low impact risks.

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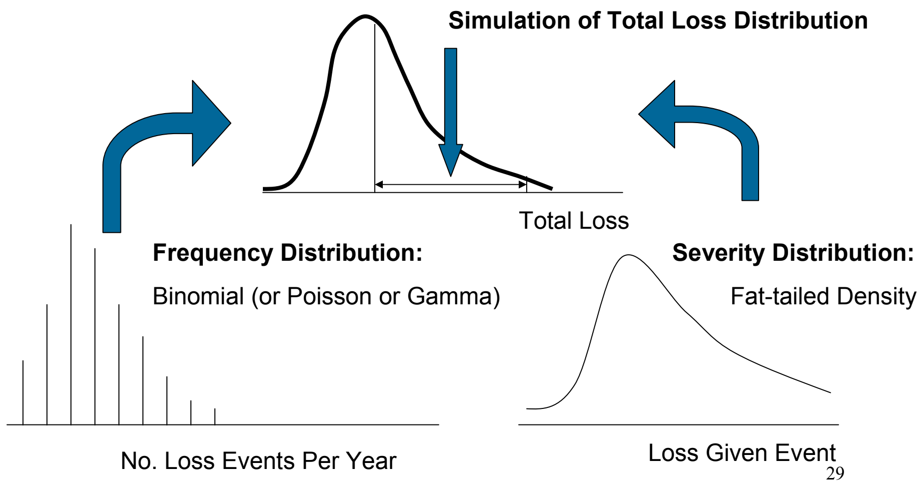
3. Loss Distribution Approach (LDA)



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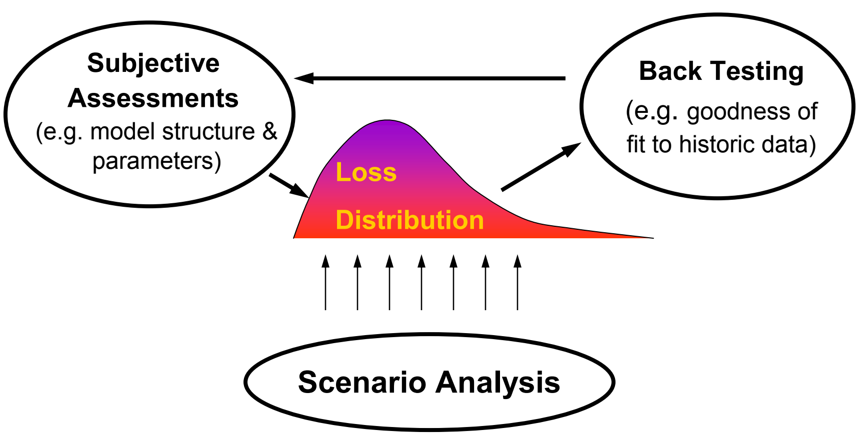
Advantages of the LDA



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Case Study

Year	Loss (m$)
1	38.19
1	10.01
1	21.09
1	2.39
1	1.86
1	26.86
1	34.84
1	37.30
1	4.29
1	43.52
1	1.87
1	5.24
1	22.32
1	19.19
1	20.37
1	12.44
1	21.97
1	4.36
1	28.66
1	6.30

Historical data on loss (over 1m$) due to all types of operational risks.

Recorded over a period of 10 years

Loss stated in current value

Total capitalization of banks reporting losses was 150bn$

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Loss Frequency Distribution

Year	No. Events	Probability
1	75	0.1
2	70	0.1
3	76	0.1
4	71	0.1
5	98	0.1
6	76	0.1
7	100	0.1
8	137	0.1
9	136	0.1
10	97	0.1

Expected no. loss events per year λ = 93.6

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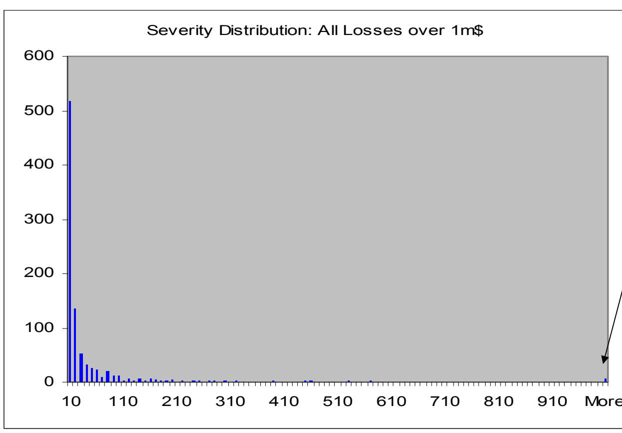
Loss Severity Distribution

Loss	Frequency
10	518
20	135
30	54
40	32
50	26
60	24
70	10
80	21
90	12
100	11
110	3
120	6
130	3
140	8
150	3
160	6
170	4
180	2
⋮	⋮

Average Loss μ_L = 50m$

Standard Deviation σ_L = 159m$

Loss Severity Distribution



8 out of 950 loss events were losses over 1bn$. Exclude these?

IMA Model

IMA Model: k =	2
E[No. Loss Events/Year]	93.60
Mean Loss Severity:	50
StDev Loss Severity:	159
Total OpVaR (m$):	**3237**
Per Bank OpVaR (m$)	**836**
Total Cap (bn$)	150
Unit Cap (bn$)	10

= 3237/sqrt(15)

Capital charge (with k = 2) is 8.36% of the banks capitalization

LDA Model

Simulation:

- Take a random draw on the frequency distribution for the number of loss events
- For the ith simulation, suppose this number is n_i
- Then take n_i random draws from the loss severity distribution and sum them to get a total loss for the year
- Repeat for i = 1000 simulations
- This gives a simulated total loss distribution based on Σn_i different loss amounts
- Calculate the capital charge as the difference between the 99.9^{th} percentile and the expected loss of this distribution
- Investigate robustness of the model by repeating this several times

Empirical Simulation

Without the 8 large losses:

LDA Model:		Sim 1	Sim 2	Sim 3	Sim 4	Sim 5
Expected Total Loss:		3721	3685	3774	3552	3653
99.9 Percentile Loss:		6195	7323	7642	6898	7690
Total OpVaR (m$):		**2473**	**3638**	**3868**	**3346**	**4037**
Per Bank OpVaR (m$)		**639**	**939**	**999**	**864**	**1042**
Total Cap (bn$)	150					
Unit Cap (bn$)	10					

With the 8 large losses:

LDA Model:		Sim 1	Sim 2	Sim 3	Sim 4	Sim 5
Expected Total Loss:		5559	5801	5345	5738	5752
99.9 Percentile Loss:		14411	12981	12215	12247	13606
Total OpVaR (m$):		**8852**	**7180**	**6870**	**6509**	**7853**
Per Bank OpVaR (m$)		**2286**	**1854**	**1774**	**1681**	**2028**
Total Cap (bn$)	150					
Unit Cap (bn$)	10					

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4. Data Considerations

- We have seen that low frequency high impact risks will have the largest effect on the bank's total capital charge, but for these risks, data are very difficult to obtain: by definition, internal data are likely to be sparse and unreliable
- Even for high frequency risks there are data problems: Using historical loss data over a 5 year period will be problematic following a merger, acquisition or sale of assets: operational processes would change.
- Therefore, when a bank's operations undergo a significant change in size, it is *not* sufficient to simply re-scale the capital charge by the square root of the size of its current operations.

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‘Hard’ and ‘Soft’ Data

- When historic loss event data is either not relevant or not available the bank may consider using 'soft' data, in the form of
  - opinions from industry experts.
  - data from an external consortium
- How can this type of data be used in conjunction with current internal (‘hard’) data?
- Classical methods (e.g. maximum likelihood estimation) treat all data as the same
- Bayesian methods may be used to combine the two data sources in the proper fashion

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Bayes Rule

The **Reverend Thomas Bayes** was born in London (1702) and died in Kent (1761).

His **Essay Towards Solving a Problem in the Doctrine of Chances,** published posthumously in 1763, laid the foundations for modern statistical inference.

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Classical vs Bayesian Methods

Classical

Assume that at any point in time there is a 'true' value for a model parameter.

Bayesian

What is the probability of the model parameter given the data?

Bayes' Rule

- For two events X and Y, their joint probability is the product of the conditional probability and the unconditional probability:

$$\text{Prob}(X \text{ and } Y) = \text{prob}(X|Y)\ \text{prob}(Y)$$

- Or, by symmetry:

$$\text{Prob}(X \text{ and } Y) = \text{prob}(Y|X)\ \text{prob}(X)$$

$$\text{prob}(X|Y) = [\ \text{prob}(Y|X) / \text{prob}(Y)]\ \text{prob}(X)$$

Interpretation of Bayes' Rule

prob(parameters | data) = prob(data | parameters)*prob(parameters) / prob(data)

Posterior Density ∝ **Sample Likelihood** * **Prior Density**

$$f_{\theta|\mathbf{X}}(\theta|X) \propto f_{\mathbf{X}|\theta}(X|\theta) * f_{\theta}(\theta)$$

This is how Bayesian models allow prior beliefs about the value of a parameter, which may be very subjective, to influence parameter estimates.

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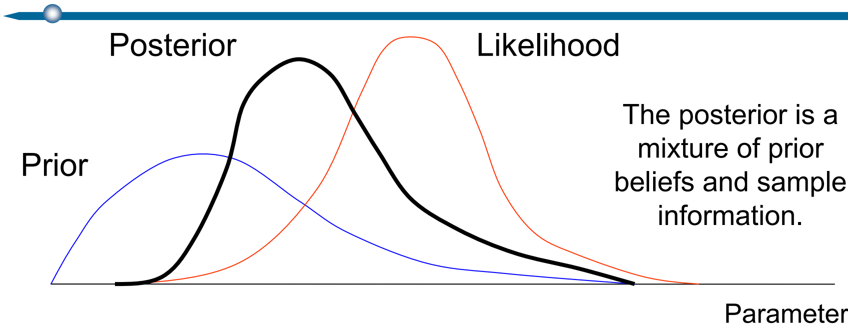
Posterior Density ∝ Sample Likelihood * Prior Density



The posterior is a mixture of prior beliefs and sample information.

No prior information
(uniform prior) ⇒
posterior ≡ likelihood

No sample information
(uniform likelihood) ⇒
posterior ≡ prior

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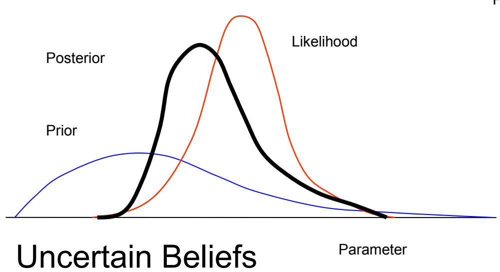
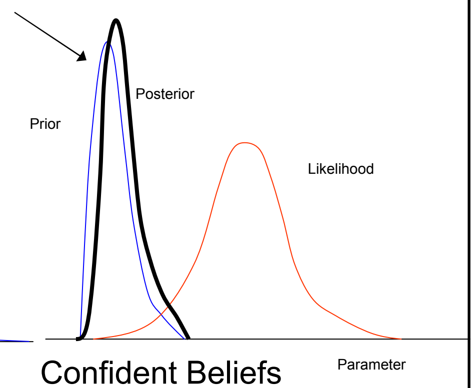
The Effect of Prior Beliefs

If prior beliefs are expressed with a great deal of certainty, Bayesian estimates will be close to prior expectations *and they will have small standard errors*





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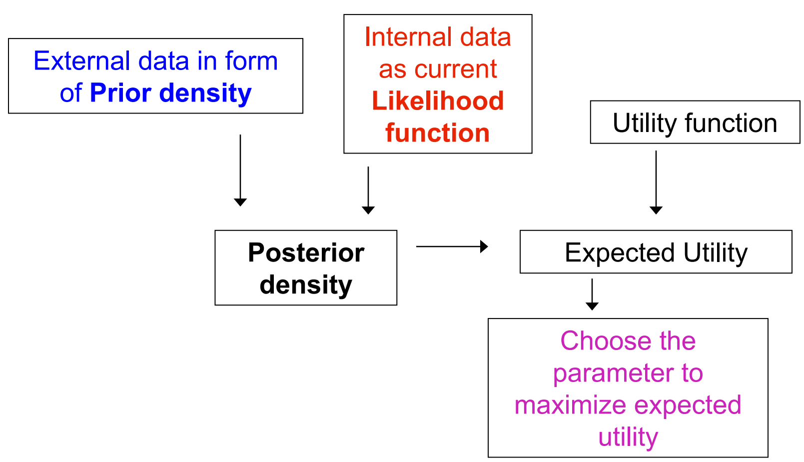
Bayesian Estimation



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Bayesian Estimators

Standard Utility functions:		Optimal estimator:
Zero One	→	**Mode** of posterior
Absolute	→	**Median** of posterior
Quadratic	→	**Mean** of posterior

Maximum likelihood estimation (MLE) is a crude form of Bayesian estimation.

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Example: Using Bayesian Estimation with the IMA

Loss Severity

- If both 'hard' internal data and 'soft' data are available on the distribution of losses, then Bayesian methods can be used to estimate μ_L and σ_L.
- Suppose that in the 'hard' internal data the expected loss severity is 5m$ and the standard deviation is 2m$;
- Suppose that the 'soft' data, being obtained from an external consortium, shows an expected loss severity of 8m$ and a loss standard deviation of 3m$.
- Assuming normality of loss amounts, the prior density that is based on external data is N(8, 9) and the sample likelihood that is based on internal data is N(5, 4).

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Example: Using Bayesian Estimation with the IMA

- The posterior density for L will also be normal, with mean μ_L that is a weighted average of the prior expectation and the internal sample mean.
- The weights will be the reciprocals of the variances of the respective distributions.
- In fact the Bayesian estimate for the expected loss will be

$$\mu_L = [(5/4) + (8/9)]/[(1/4) + (1/9)] = 5.92\text{m\$}$$

- The Bayesian estimate of the loss variance will be

$$[4\text{x}9]/[(4 + 9)],$$

giving the standard deviation of the posterior: $\sigma_L =$ **1.66m$.**

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Example: Using Bayesian Estimation with the IMA

Loss Frequency

- Consider using a target or projected value for N – this could be quite different from its historical value.
- Bayesian estimation of a probability are often based on beta densities of the form

$$f(p) \propto p^a(1 - p)^b \qquad 0 < p < 1.$$

- Bayesian estimates for p can use beta prior densities that are based on external data, or subjective opinions from industry experts, or 'soft' internal data.
- Sample likelihood: beta density based on 'hard' data ⇒ posterior also a beta density
- Assume quadratic loss function ⇒ Bayesian estimate of p = mean of the posterior density = (a + 1)/(a + b + 2) with a and b being the parameters of the posterior density.

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Example: Using Bayesian Estimation with the IMA

- **Example:** internal data indicate that 2 out of 100 new deals have incurred a loss due to unauthorized or fraudulent activity.

sample likelihood $\propto p^2(1-p)^{98}$

- In an external database there were 10 unauthorized or fraudulent deals in the 1000 deals recorded

prior density $\propto p^{10}(1-p)^{990}$

- Thus

posterior $\propto p^{12}(1-p)^{1088}$

- With quadratic loss, Bayesian estimate of p = 13/1102 = 0.0118.

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Example: Summary

k=2	Internal	External	Combined (Bayesian)
Number Events	100	1000	1100
Probability of Event	0.02	0.01	0.0118
Expected Loss	5	8	5.92
Std Dev Loss	2	3	1.66
Capital Charge	15.23	17.09	13.36

Remark: There is great potential to massage operational risk capital charge calculations using targets for N and Bayesian estimates for p, μ_L and σ_L.

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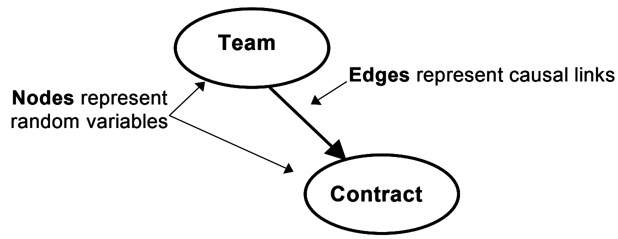
5. Management of Operational Risks

- Bayesian belief networks have many applications to modelling high frequency low impact operational risks such as the human risks where our focus should be on improved risk management and control procedures, rather than capital charges.

The basic structure of a Bayesian network is a directed acyclic graph



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Example of Bayes' Rule

- You are in charge of client services, and your team in the UK has not been very reliable.
- You believe that one quarter of the time they provide an unsatisfactory service, and that when this occurs the probability of losing the client rises from 20% to 65%.
- If a client in the UK is lost, what is the probability that they have received unsatisfactory service from the UK team?

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Example of Bayes' Rule

- Let X be the event 'unsatisfactory service' and Y be the event 'lose the client'.
- Your prior belief is that prob(X) = 0.25.
- You also know that prob(Y|X) = 0.65.
- Now Bayes' Rule can be used to find prob(X|Y) as follows:
- First calculate the unconditional probability of losing the client:

  prob(Y) = prob(Y and X) + prob(Y and not X)
  = prob(Y|X) prob(X) + prob (Y|not X) prob (not X)
  = 0.65 * 0.25 + 0.2 * 0.75 = 0.3125.
- Bayes' Rule gives the posterior probability of unsatisfactory service given that a client has been lost as:

  prob(X|Y) = prob(Y|X) prob(X)/prob(Y)
  = 0.65 * 0.25 / 0.3125 = 0.52

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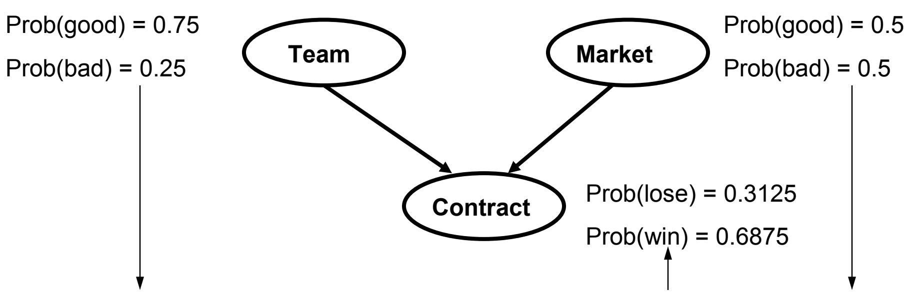
Node Probabilities



Prob(lose) = prob(lose | T=good and M=good) prob(T=good and M=good)
+ prob(lose | T=good and M=bad) prob(T=good and M=bad)
+ prob(lose | T=bad and M=good) prob(T=bad and M=good)
+ prob(lose | T=bad and M=bad) prob(T=bad and M=bad)

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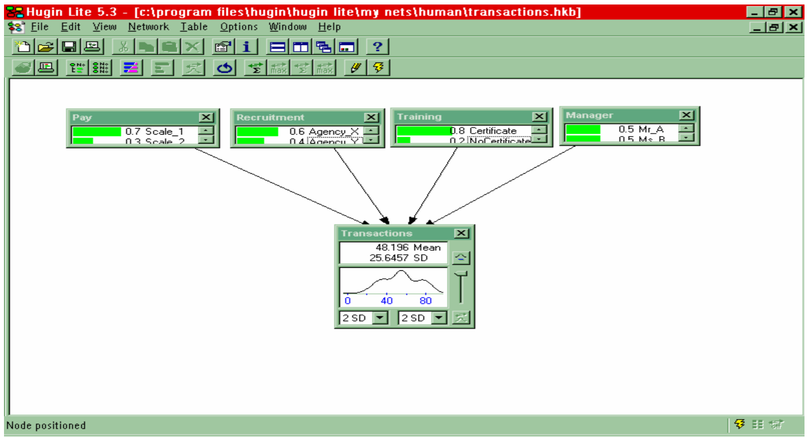
Discrete and Continuous Nodes



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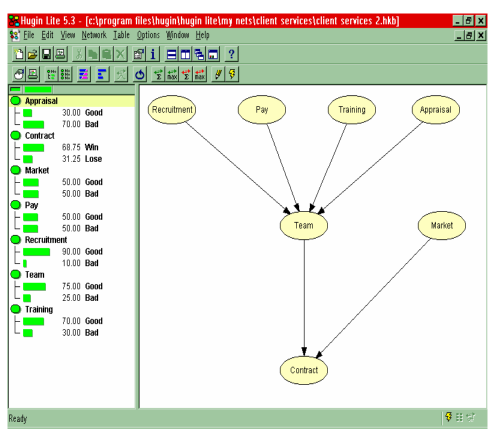
Describing the Network

Nodes, edges, and probabilities are added to model the influence of causal factors for each node

The Bayesian network is completed when all initial nodes can be assigned probabilities



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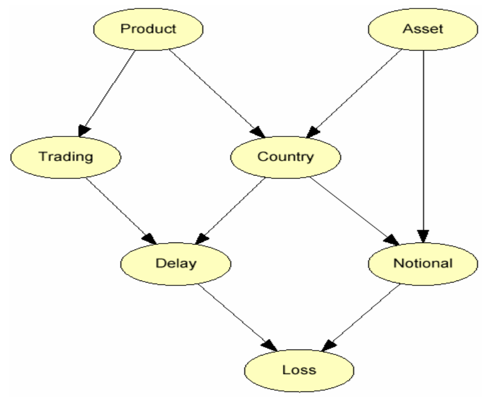
Example: Settlement Loss

Operational (as opposed to credit) settlement loss is **"the interest lost and the fines imposed as a result of incorrect settlement"**



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Initial Probabilities

Asset	
80.00	FX
20.00	Security

Country	
47.20	Europe
52.80	Asia

Product	
30.00	Underlying
70.00	Derivative

Trading	
17.00	OTC
83.00	Exchange

Delay	
85.65	None
6.18	1 day
3.63	2 days
1.94	3 days
0.88	4 days
1.72	> 4 days

Notional	
13.96	<10
10.00	10-20
10.36	20-30
17.84	30-40
26.36	40-50
21.68	>50

Loss	
90.22	0
3.11	0-1,000
1.77	1,000-2,000
1.50	2,000-3,000
1.40	3,000-4,000
1.31	4,000-5,000
0.69	5,000-10,000

Expected Loss = 239.3$

99% Tail Loss = 6,750$

(per transaction)

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Scenario Analysis:
Maximum Operational Loss

Asset	
* 100.00	FX
-	Security

Country	
-	Europe
* 100.00	Asia

Delay	
50.00	None
30.00	1 day
10.00	2 days
1.00	3 days
1.00	4 days
8.00	> 4 days

Loss	
64.70	0
9.50	0-1,000
6.02	1,000-2,000
5.61	2,000-3,000
5.39	3,000-4,000
5.66	4,000-5,000
3.12	5,000-10,000

Product	
-	Underlying
* 100.00	Derivative

Trading	
* 100.00	OTC
-	Exchange

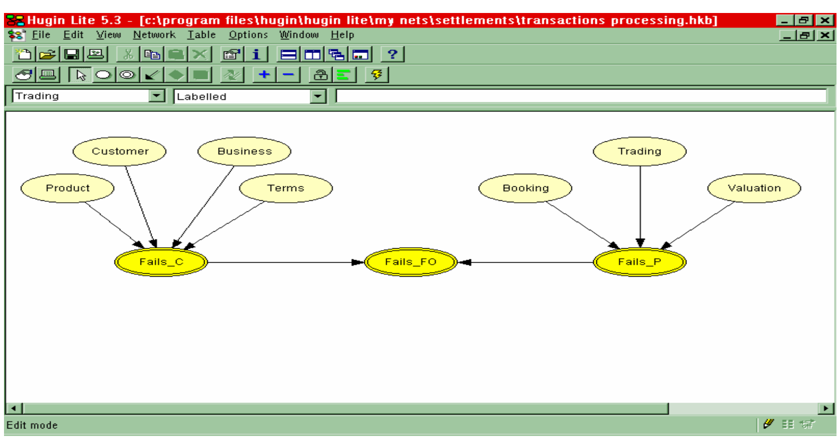
Notional	
10.00	<10
5.00	10-20
5.00	20-30
25.00	30-40
30.00	40-50
25.00	>50

Expected Loss = 957.7$

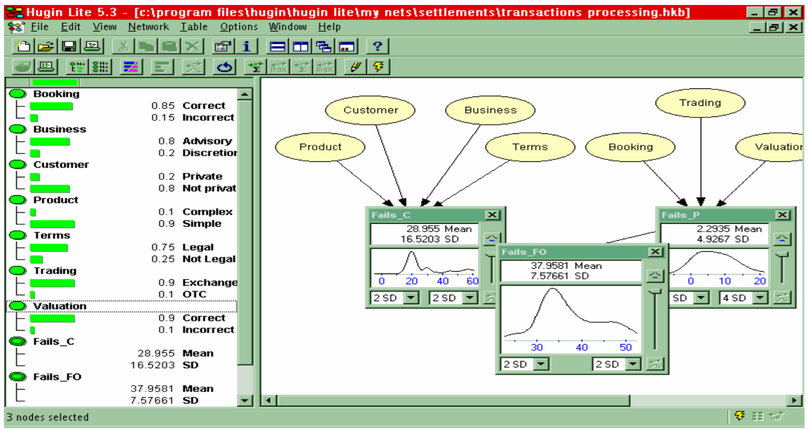
99% Tail Loss = 8,400$

(per transaction)

Example: Number of Fails



Multivariate Distributon



BBNs for Human Risks

Human risk has been defined as the risk of **inadequate** staffing for required activities

- **Measures of human adequacy:**
  - Balanced Scorecard (Kaplan & Norton)
  - Key Performance Indicators
- **'Causal' factors or 'Attributes':**
  - Lack of training
  - Poor recruitment processes
  - Loss of key employees
  - Poor management
  - Working culture

Key Performance Indicators

Function	Quantity	Quality
Back Office	Number of transactions processed per day	Proportion of internal errors in transactions processing
Middle Office	Timeliness of reports Delay in systems implementation; IT response time	Proportion of errors in reports Systems downtime
Front Office	Propriety traders: 'Information ratio' Sales: Number of contacts	Proportion of ticketing errors; Time stamp delays Credit quality of contacts; Customer complaints

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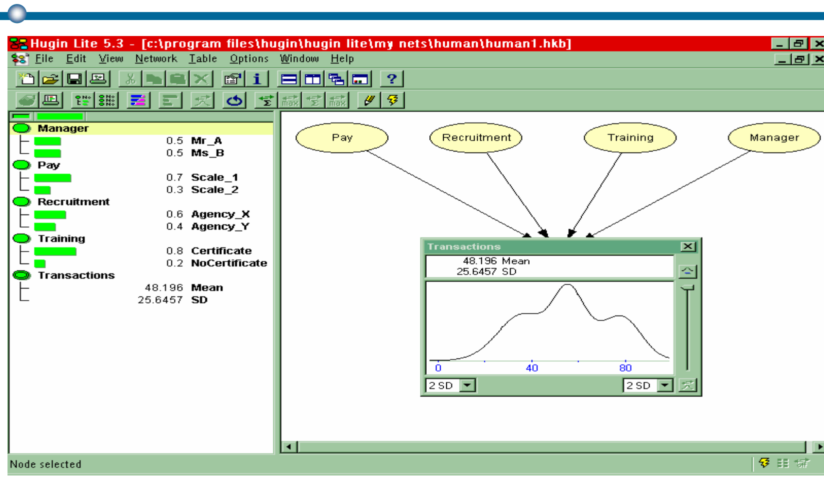
Example: Number of Transactions Processed



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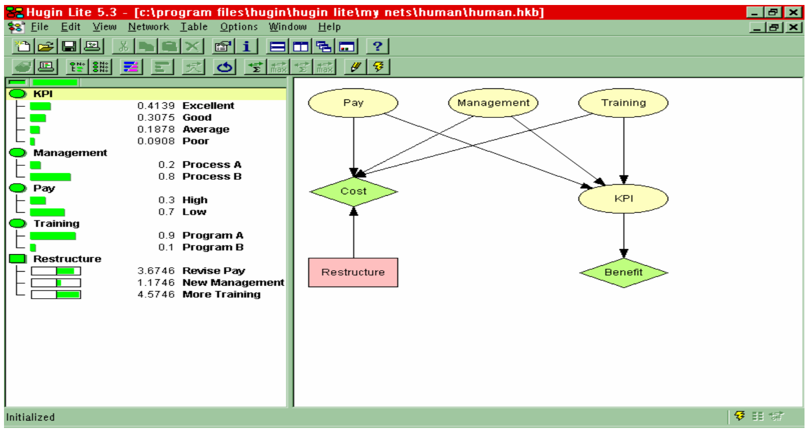
Bayesian Decision Networks



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Summary of BBNs

Advantages:

- BBNs describe the factors that are thought to influence operational risk, thus providing explicit incentives for behavioural modifications;
- They provide a framework for scenario analysis: to measure maximum operational loss, and to integrate operational risk with market and credit risk;
- Augmenting a BBN with decision nodes and utilities improves transparency for management decisions. Thus decisions may be based on 'what if?' scenarios

Limitations:

- No unique structure; a BBN is a picture of the mind of the modeller
- Therefore BBNs require much clarity in their construction and rigorous back testing

Note: Amongst others, Wilson (1999), Alexander (2000, 2001) and King (2001) have advocated the use of BBNs for modelling high frequency low impact operational risks

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Useful Links: Performance Measures

- hrba.org (Human Resources Benchmarking Association) and fsbba.org (Financial Services and Banking Benchmarking Association)
- afit.af.mil and pr.doe.gov/bsc001.htm (Balance Scorecard meta-resource pages)
- bscol.com (Balance Scorecard Collaborative - Kaplan and Norton) and pr.doe.gov/pmmfinal.pdf (Guide to Balance Scorecard Methodology)
- mentorme.com/html/D-Keyperfind.html and totalmetrics.com/tr-kpa.htm (Monitoring KPIs)
- kpisystems.com/case_studies/banking/bi_kpi_ops_values.htm (some KPIs for banking operations)

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Useful Links: Bayesian Networks

- http.cs.berkeley.edu/~murphyk/Bayes/bnsoft.html (list of free Bayesian network software)
- dia.uned.es/~fjdiez/bayes (meta-resource page for Bayesian networks)
- research.microsoft.com/research/dtg/msbn/default.htm (*MSBN* a free non-commercial Excel compatible BBN)
- hugin.dk (leading commercial BBN with free demo version *Hugin Light*)
- lumina.com (makers of *Analytica*, leading software package for quantitative business models)
- dcs.qmw.ac.uk/research/radar (Risk Assessment and Decision Analysis Research, QMW College London and their consultancy agena.co.uk specializing in risk management of computer-based systems)
- genoauk.com (Operational risk consultancy firm)
- algorithmics.com (Watchdog Bayesian network product)
- eoy.co.uk (Ermst and Young Bayesian network product)

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Medova, E. (2000) 'Measuring Risk by Extreme Values' *RISK Magazine,* 13:11 pp s20-s26.

Morgan, M.G. and M. Henrion (1990) *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis* Cambridge University Press. (Reprinted in 1998).

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Olve, N-G., Roy, J. and M. Wetter *Performance Drivers: A Guide to Using the Balanced Scorecard* John Wiley, New York.

Pearl, J. (1988) *Probabilistic Reasoning in Intelligent Systems* (Morgan Kaufmann)

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Reiss, R.-D. and Thomas, M. (1997) *Statistical Analysis of Extreme Values*, Birkhäuser, Basel.

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Useful Links: Bayesian Networks

- http.cs.berkeley.edu/~murphyk/Bayes/bnsoft.html (list of free Bayesian network software)
- dia.uned.es/~fjdiez/bayes (meta-resource page for Bayesian networks)
- research.microsoft.com/research/dtg/msbn/default.htm (*MSBN* a free non-commercial Excel compatible BBN)
- hugin.dk (leading commercial BBN with free demo version *Hugin Light*)
- lumina.com (makers of *Analytica*, leading software package for quantitative business models)
- dcs.qmw.ac.uk/research/radar (Risk Assessment and Decision Analysis Research, QMW College London and their consultancy agena.co.uk specializing in risk management of computer-based systems)
- genoauk.com (Operational risk consultancy firm)
- algorithmics.com (Watchdog Bayesian network product)
- eoy.co.uk (Ermst and Young Bayesian network product)