Operational Risk

1. Understanding the IMA
2. Other Advanced Measurement Approaches
   Data Considerations
   Bayesian Estimation
   General Models of Loss and Frequency Distributions
3. Management of Operational Risks: Bayesian Belief Networks

1. Understanding the IMA

- A three stage approach aims to make capital charges progressively lower and more risk sensitive
  1. Basic Indicator
  2. Standardised Approach
  3. Advanced Measurement Approaches
    Internal measurement approach (IMA)
    Loss distribution approach (LDA)
    Scorecard approaches
- Aimed at flexibility, as opposed to 'one size fits all', but qualifying criteria become increasing stringent
- Floor for AMA is currently 75% of capital charge under standardised approach, but could be lowered.

Quantitative Requirements for AMA

- 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.
- The AMA requires historical internal loss data and exposure indicators in a form that is consistent with the business line/event type categories specified
- 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.

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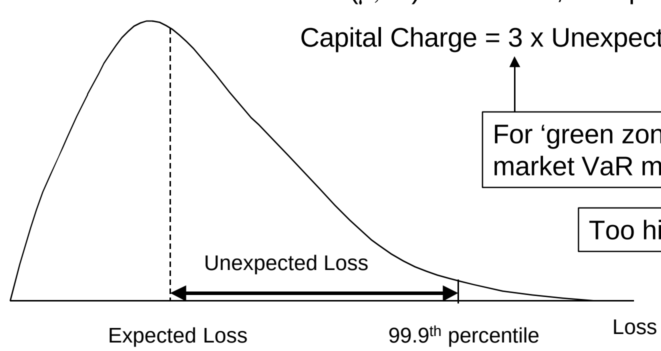
Unexpected Loss and Capital Charge

In $N(\mu, \sigma^2)$ distribution, unexpected loss = 3σ

Capital Charge = 3 x Unexpected Loss ≈ 9σ

For 'green zone' market VaR models

Too high for OpRisk?



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Calculating the Capital Charge

- For each business line/risk type

IMA ORR = gamma $\times$ 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
- The bank will be permitted to recognize empirical correlations in operational risk losses across business lines and event types, provided that it can demonstrate that its systems for measuring correlations are sound and implemented with integrity
- ?*!

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Gamma

"In determining the specific figure for gamma that will be applied across banks, the Committee plans to develop an industry wide operational loss distribution in consultation with the industry, and use the ratio of expected loss to a high percentile of the loss distribution (e.g. 99%)". **Basel Committee, CP2**

- The rules proposed in CP2.5, which allow banks to calibrate their own gammas, do not require that gamma should be independent of the size of their business.
- In fact we show that the method by which expected loss is calculated in CP2.5 implies that it is based on the binomial model, and the logical consequence of this is that gamma will be inversely proportional to the *square root* of the total number of loss events.
- This will vary over different LOBs and also over risk types

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Internal Measurement Approach

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				**N, p, L**			
Commercial Banking							
Payment and Settlements							
Asset Management							
Retail Brokerage							

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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).
- Then the expected total loss during the year is NpL

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Binomial Model

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

  $$\sigma = \{\sqrt{[N\ p\ (1 - p)]}\}\ L \approx L\ \sqrt{[N\ p]} \text{ if } p \text{ is small}$$

- Capital charge = expected loss x gamma $\approx$ kσ

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

  $$\textbf{Gamma} \approx \mathbf{k / \sqrt{[Np]}}$$

- **Note 1:** Np is the expected number of loss events during the time period: Banks do not need to obtain data for N and p separately
- **Note 2:** The formula shows that gamma should 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 ≈ 4 /√1000 ≈ 4/31.6 ≈ 0.13 and so, since expected loss is 1m$, the capital charge is only $130,000.
- **Example 2:** Gamma ≈ 4 /√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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Loss Variability

- Let μ_L be the expected loss, given that the event incurs a loss
- Let σ_L^2 be the variance of this loss.

$$Z \begin{cases} p & L : (\mu_L\ \sigma_L^2) \\ 1-p & 0 \end{cases}$$

$E(Z) = p\ \mu_L$

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

- Thus

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

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

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Effect of Loss Variability

- For high frequency, low impact loss events, the uncertainty about the severity of each loss is likely to be much smaller (compared to the expected loss) so the effect of uncertainty in loss severity is unlikely to increase capital charges significantly.
- But, returning to the corporate finance example, the operational loss may be highly variable; the standard deviation of the loss could be equal to its expected value.
- Consequently the gamma and the capital charge would increase by a factor of $\sqrt{(1 + (\sigma_L/\mu_L)^2)} = \sqrt{2}$. That is, the gamma will increase from 8 to about 11.3 (now about **100 times larger** than the transactions processing example) and the capital charge will reach $11.3 million.

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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.

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

and the capital charge will be given by the formula

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

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Alternative Loss Frequency Distributions

- A single parameter family probably offers insufficient scope to fit loss frequency distributions for all the different risk types and business lines encompassed by the bank's activities.
- In that case the bank may consider using a more flexible distribution such as the **gamma distribution**, which has two parameters α and β and the density function

$$f(x) = x^{\alpha-1}\exp(-x/\beta)/\beta^{\alpha}\Gamma(\alpha) \qquad x > 0.$$

- The mean and variance of the gamma distribution are $\beta\alpha$ and $\beta^2\alpha$ respectively. Therefore if the loss frequency is gamma distributed,

$$\textbf{gamma} = k \sqrt{\{1 + (\sigma_L/\mu_L)^2\}} / \sqrt{\alpha}$$

and the capital charge will be given by the formula

$$k\, \mu_L \sqrt{[(1 + (\sigma_L/\mu_L)^2)\, \beta^2\alpha\,]}$$

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Insurance

"It is currently of the view that if recognition of insurance is permitted, it should be limited to those banks that use AMA."

"If an explicit, formulaic treatment is developed, what standards should be in place for qualifying insurance companies and insurance products, and what is an appropriate formula for recognition of insurance that is risk-sensitive but not excessively complex?"

Basel Committee CP2.5

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Insurance

- 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] ≈ NpL since C ≈ pR
- The standard deviation is now (L – R) √[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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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 Freuqency

- 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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Dependence Between k and Expected Loss

- The calculation of k should take expected loss into account, as we did above.
- That is, unexpected loss is defined to be the difference between the upper percentile loss and the expected loss.
- Normally, accountants should make special provisions in the balance sheet to cover expected losses, so they do not need to be taken into risk capital charges.
- But some banks do not take unexpected loss to be the difference between the upper percentile and the expected loss, and this will increase capital charges for low impact high frequency risks in particular.

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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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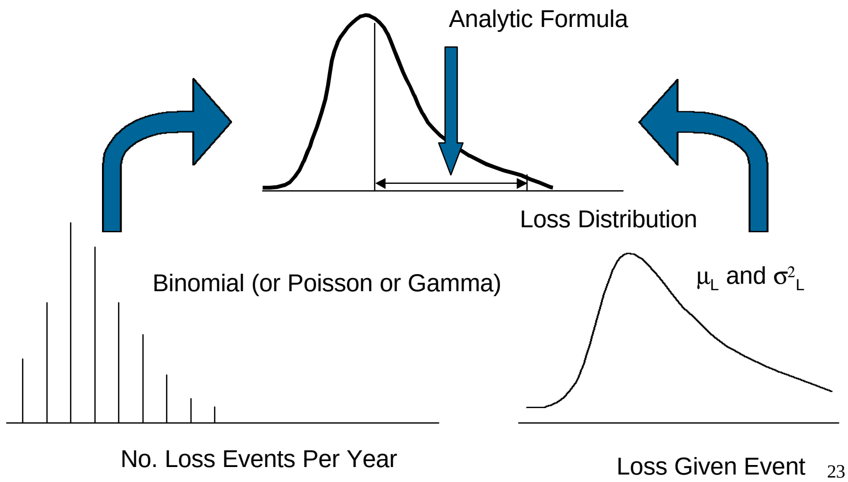
Summary of IMA



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Conclusions of the IMA Model

- For each line of business and risk type:

capital charge = **k** × **standard deviation** = **gamma** × **expected loss**

so

gamma = k × standard deviation / expected loss

- Capital charges should increase like the square root of the size of the business
- Capital charges should be inversely proportional to the frequency of events:
  - High frequency events should have relatively low gammas
  - Low frequency events should have relatively high gammas
- Minimum data requirements:
  - the expected number of loss events during the year
  - the expected loss given event

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2. Other Advanced Measurement Approaches

- 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 where there are normally plenty of data available there will be problems 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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Data Considerations

- When internal systems, processes and people are likely to have changed considerably the historic loss event data would no longer have the same relevance today
- The bank will have the option to use 'soft' data, in the form of opinions from industry experts.
- For low frequency risks, where internal data hardly exist, the bank may use 'soft' data from an external consortium, which is available, e.g. www.moreexchange.org.
- In both cases the 'soft' data are not necessarily as relevant as the bank would wish - there is trade-off between relevance and availability of data.
- To account for this, estimation of parameters should be based on Bayesian methods.

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CP2.5 on External Data

In CP2.5 there is no mention of the use of expert opinions, but it is recognized that banks may supplement their internal loss data with the external industry loss data

"….. the sharing of loss data, based on consistent definitions and metrics, is necessary to arrive at a comprehensive assessment of operational risk. For certain event types, banks may need to supplement their internal loss data with external, industry loss data"

"The bank must establish procedures for the use of external data as a supplement to its internal loss data."

Basel Committee CP2.5

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Bayesian Methods

- N may be the subject of an internal management target for the year, but how can p and L be forecast when there is very little 'hard' data?
- How can external ('soft') data be used in conjunction with internal ('hard') data?
- Classical methods (e.g. maximum likelihood estimation) would 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

Op Risk applications include EVT

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

Bayesian

Op Risk applications include BBNs

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

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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:

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

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

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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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Interpretation of Bayes' Rule

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

Posterior Density $\propto$ **Sample Likelihood** * **Prior Density**

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

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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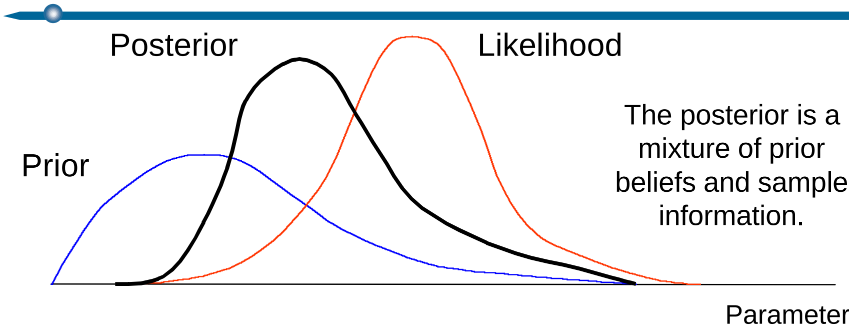
Posterior Density $\propto$ Sample Likelihood * Prior Density



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

No prior information
(uniform prior) $\Rightarrow$
posterior $\equiv$ likelihood

No sample information
(uniform likelihood) $\Rightarrow$
posterior $\equiv$ prior

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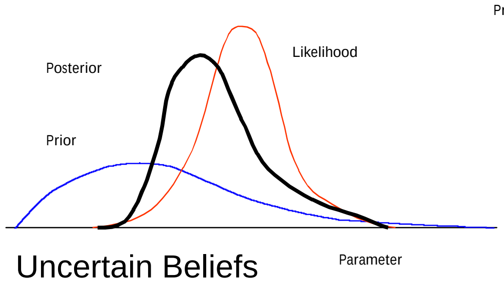
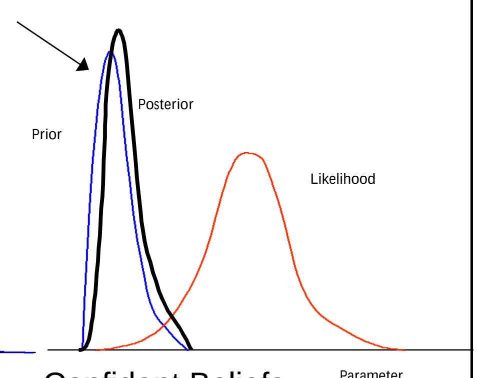
The Effect of Prior Beliefs

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*



Uncertain Beliefs



Confident Beliefs

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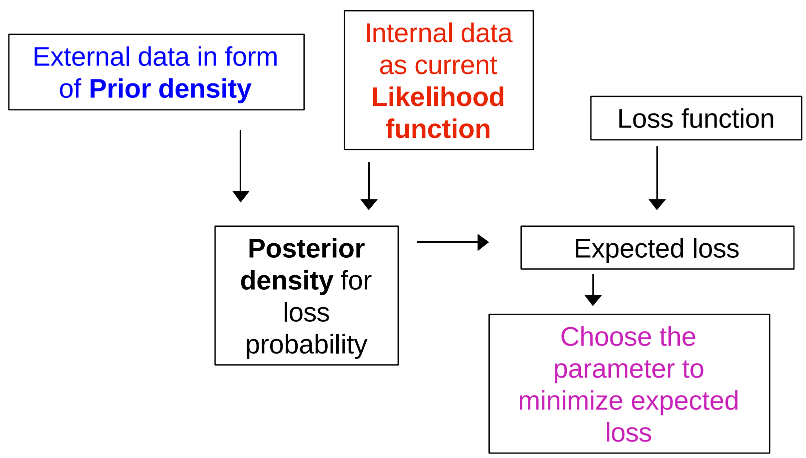
Bayesian Estimation



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Bayesian Estimators

Standard loss 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. It is particularly odd, when viewed from a Bayesian perspective, for estimating a probability

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Example: Using Bayesian Estimation with the IMA

Loss Given Event

- 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 given a loss event is 5m$ and the standard deviation of this loss is 2m$;
- Suppose that the 'soft' data, being obtained from an external consortium, shows an expected loss of 8m$ 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

  μ_L = **[(5/4) + (8/9)]/[(1/4) + (1/9)] = 5.92m$**
- The Bayesian estimate of the loss variance will be

  [4x9]/[(4 + 9)],
- Thus the standard deviation of the posterior is σ_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 – could be quite different from its historical value.
- Bayesian estimation of a probability are often based on beta densities of the form

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

- 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 $\Rightarrow$ posterior also a beta density
- Assume quadratic loss function $\Rightarrow$ 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.

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

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

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

- Thus

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

- With quadratic loss, Bayesian estimate of p = 13/1102 = 0.0118.
- **Note:** 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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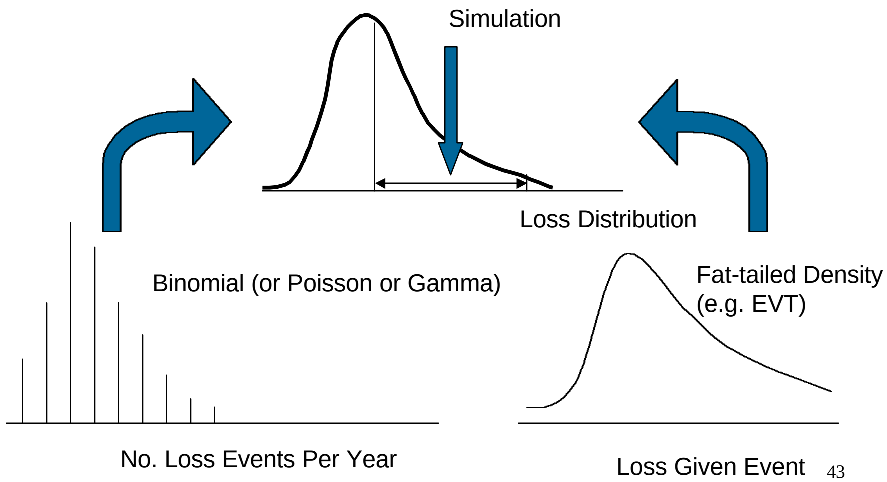
General Models of Loss and Frequency Distributions



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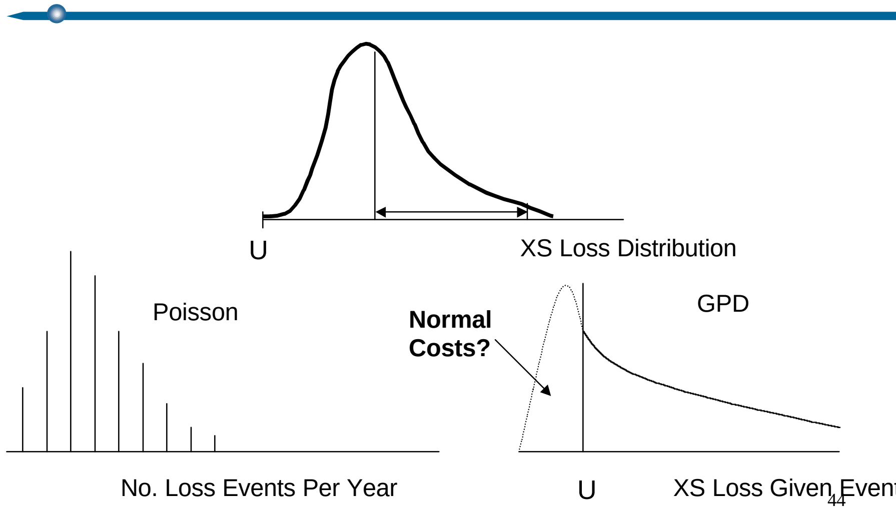
Low Frequency Risks



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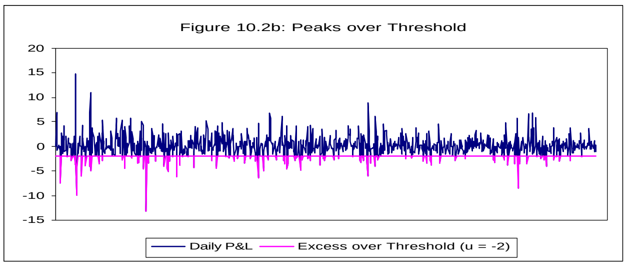
Example: POT Model

Peaks Over Threshold (POT) Model:

- Magnitude of excess loss over predefined threshold is modelled by a Generalized Pareto Distribution
- Frequency of excess loss over predefined threshold is modelled by a Poisson process



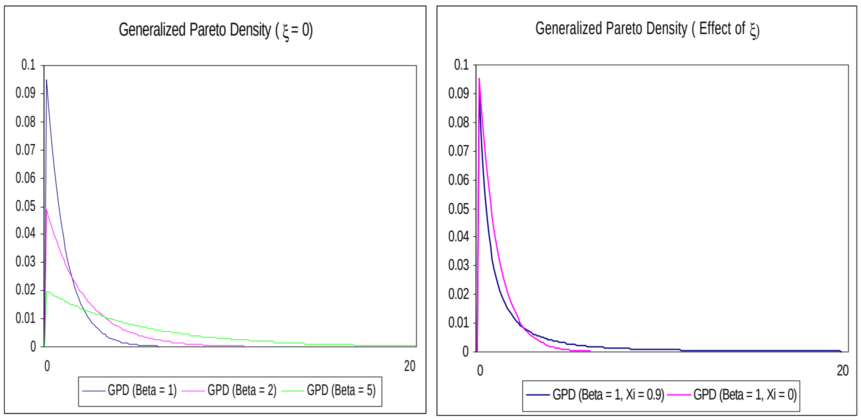
GPD

- The distribution function G_u of excess losses Y = max (X - U, 0) over a high and pre-defined threshold U has a simple relation to the distribution F(x) of X, the underlying loss.
- For most choices of underlying distribution F(x) the distribution G_u (y) will belong to the class of **generalized Pareto distributions (GPD):**

$$G_u(y) = \begin{cases} 1 - \exp(-y/\beta) & \text{if } \xi = 0 \\ 1 - (1 + \xi y/\beta)^{-1/\xi} & \text{if } \xi \neq 0 \end{cases}$$

O'Brien et al. (1999), Ceske and Hernandez (1999), Cruz (1999), Medova (2000), Dempster et al. (2001) and King (2001) have explored the use of EVT for the measurement of low frequency high impact operational risks.

Effect of β and ξ



The parameters parameters β and ξ determine the scale and shape of the GPD

Case Study

XS Loss (m$)	Year
7.14	1
8.79	2
18.62	5
22.52	6
54.53	6
331.75	7
232.96	7
43.36	7
66.49	8
24.36	8
2.39	8
1.50	8
9.52	8
2.92	8
190.74	8
68.81	8
288.87	8
83.61	9
49.78	9

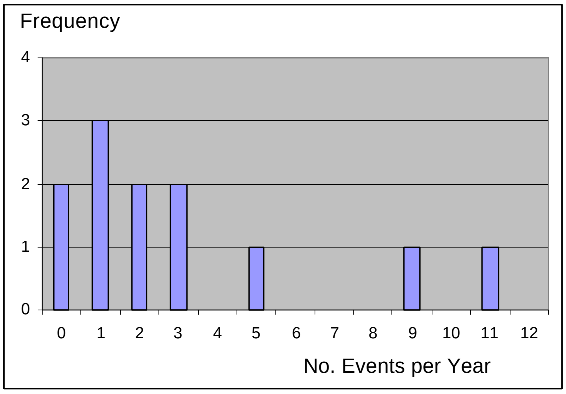
XS Loss (m$)	Year
22.30	9
2.00	9
1.28	9
8.73	9
2.31	9
9.94	9
22.21	9
17.36	9
81.37	9
13.41	10
19.23	10
18.83	10
60.99	10
6.07	10
8.06	11
1.94	11
10.77	11
2.49	12
8.81	12

Historical data on loss (over 1m$) due to external events.

Recorded over a period of 12 years

Total capitalization of banks reporting losses was 50bn$

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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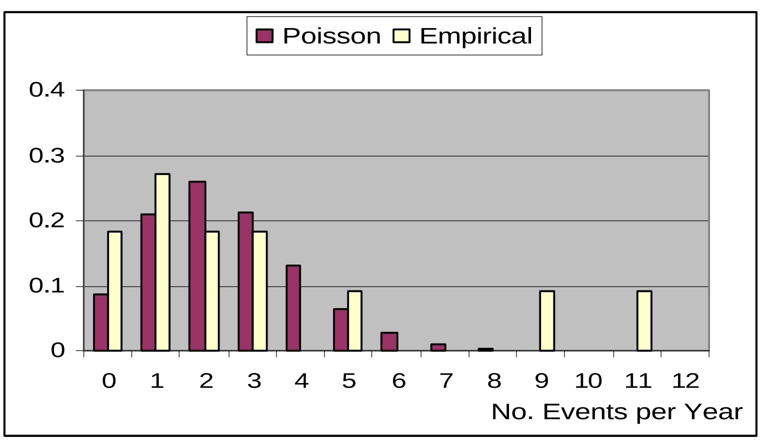
Poisson Loss Frequency



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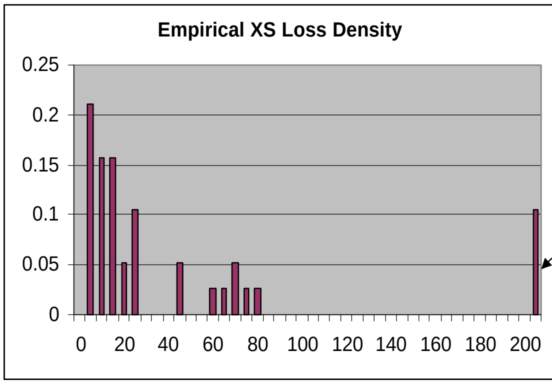
Excess Loss Distribution



Three events in excess of 200m$

Take these actual amounts into account for the calculation of

Expected XS Loss

and

Stdev of XS Loss

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Results: IMA

- With gamma loss frequency, the IMA capital charge is:

$$\mathbf{k}\,\mu_\Lambda \sqrt{\left[\left(1 + (\sigma_\Lambda/\mu_\Lambda)^2\right)\lambda\right]}$$

- Very approximately:

$$\mu_\Lambda = \mathbf{50m\$},\ \sigma_\Lambda = \mathbf{100m\$},\ \lambda = \mathbf{2.45}$$

- That is:

$$\mathbf{100\ k\ \sqrt{2.45} \approx 150\ k\ m\$}$$

- Or, with k ≈ 4 [???], IMA capital charge ≈ 600m$
- This charge corresponds to a total capitalization of 50bn$
- Suppose your bank has a capitalization of 5bn$
- Then the IMA charge will be approximately 60m$

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Results: Simulation

Rand	Poisson Draw	Expected Loss	99.9 Percentile	Capital Charge
0.682462	2.889923962	142.82	1193.351366	1050.53
0.654338	2.755214155	136.16	1137.724943	1001.57
0.46074	1.99166152	98.43	822.4271733	724.00
0.143747	0.945063903	46.70	390.2501636	343.55
0.946555	5.378788046	265.81	2221.090986	1955.28
0.331269	1.562953003	77.24	645.3983305	568.16
0.601285	2.522015166	124.64	1041.428869	916.79
0.4299	1.886232894	93.22	778.8919813	685.68
0.26015	1.335120032	65.98	551.3180744	485.34
0.14729	0.957772954	47.33	395.4981785	348.17
0.749638	3.254813237	160.85	1344.026996	1183.18
0.406855	1.80910547	89.40	747.0433519	657.64
0.932794	5.080855772	251.09	2098.064258	1846.97

Results: Simulation

Rand	Poisson Draw	Expected Loss	99.9 Percentile	Capital Charge
0.148154	0.960856141	56.47	415.1144261	358.64
0.622101	2.610640877	153.44	1127.863624	974.42
0.863338	4.126004569	242.51	1782.539493	1540.03
0.058524	0.59543936	35.00	257.2450314	222.25
0.977436	6.468399079	380.18	2794.513826	2414.33
0.609995	2.558685992	150.39	1105.417785	955.03
0.96898	6.071277312	356.84	2622.947066	2266.11
0.559519	2.353494892	138.33	1016.769982	878.44
0.246314	1.290529781	75.85	557.5418695	481.69
0.258837	1.330897703	78.22	574.9818443	496.76
0.254341	1.316423095	77.37	568.7284434	491.36
0.093173	0.751292646	44.16	324.5776367	280.42
0.265299	1.351662604	79.44	583.9528126	504.51

Comparison of Results

- AMA capital charge ≈ 400m$
- This charge corresponds to a total capitalization of 50bn$
- Suppose your bank has a capitalization of 5bn$
- Then the IMA charge will be approximately 40m$
- Source of error …… k?

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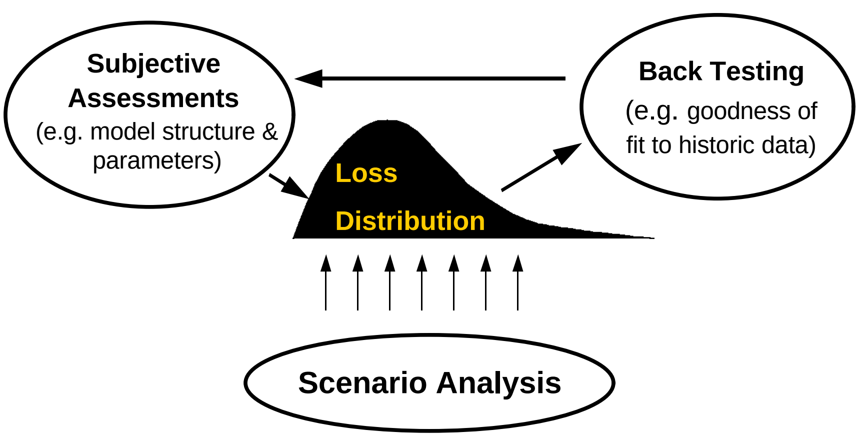
Where do we go from here?



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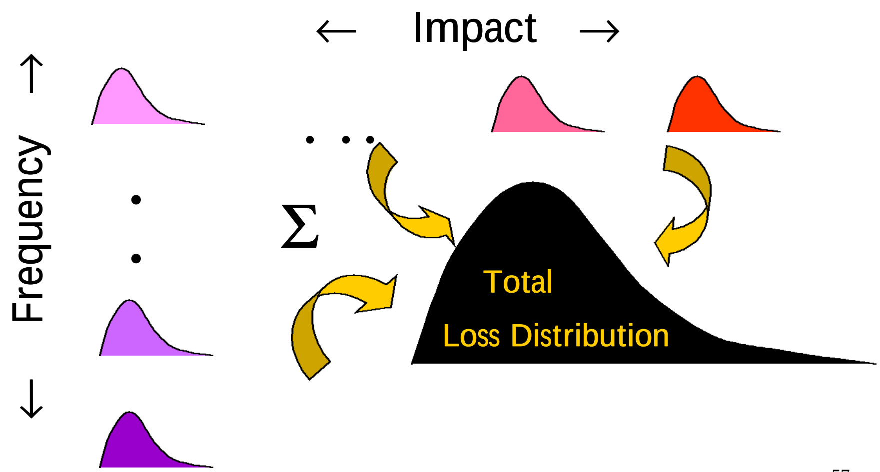
Aggregation



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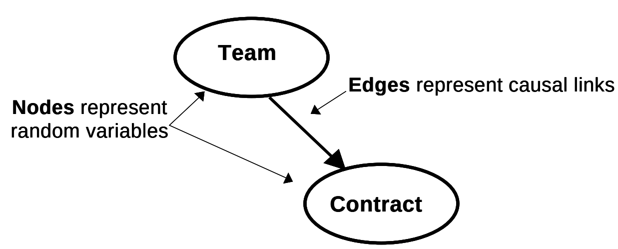
3. Management of Operational Risks

- 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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Bayesian Belief Networks (BBNs)

Advantages:

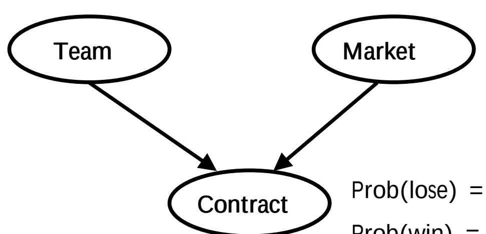
- BBNs describe the factors that are thought to influence operational risk, thus providing explicit incentives for behavioural modifications;
- They provide a framework for scenario analysis: to measure maximum operational loss, and to integrate operational risk with market and credit risk;
- Augmenting 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

Node Probabilities

Prob(good) = 0.75
Prob(bad) = 0.25

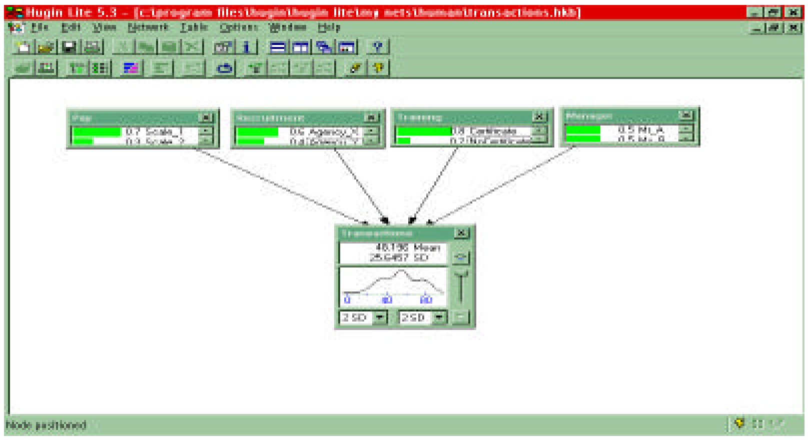


Prob(good) = 0.5
Prob(bad) = 0.5

Prob(lose) = 0.3125
Prob(win) = 0.6875

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)

Discrete and Continuous Nodes



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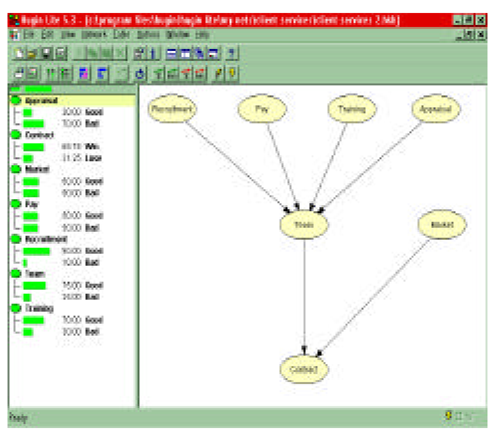
Describing the Network

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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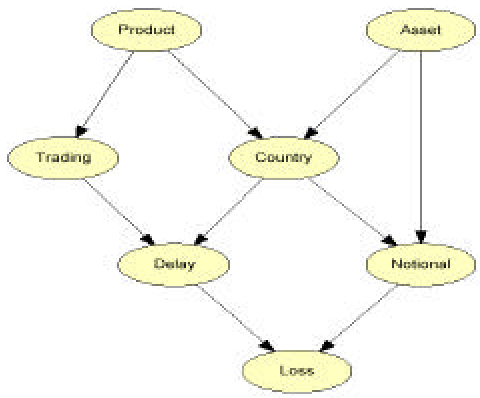
Example: Settlement Loss

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



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
17.64	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)

Scenario Analysis:
Maximum Operational Loss

Asset	
* 100.00	FX
-	Security

Country	
-	Europe
* 100.00	Asia

Product	
-	Underlying
* 100.00	Derivative

Trading	
* 100.00	OTC
-	Exchange

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

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

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

Expected Loss = 957.7$

99% Tail Loss = 8,400$

(per transaction)

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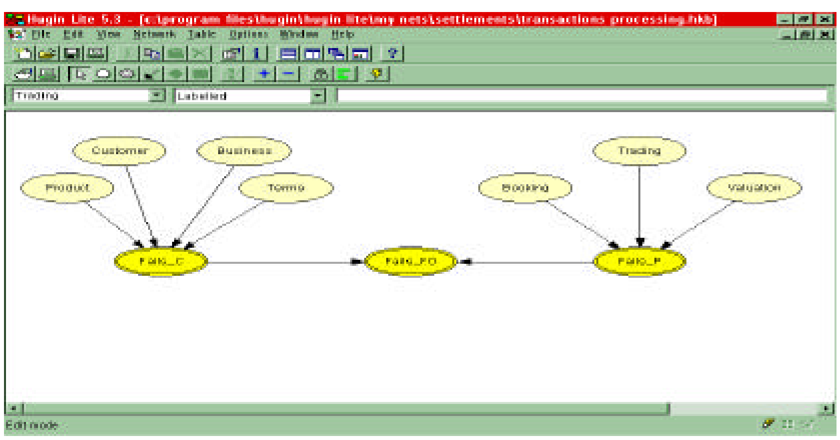
Example: Number of Fails



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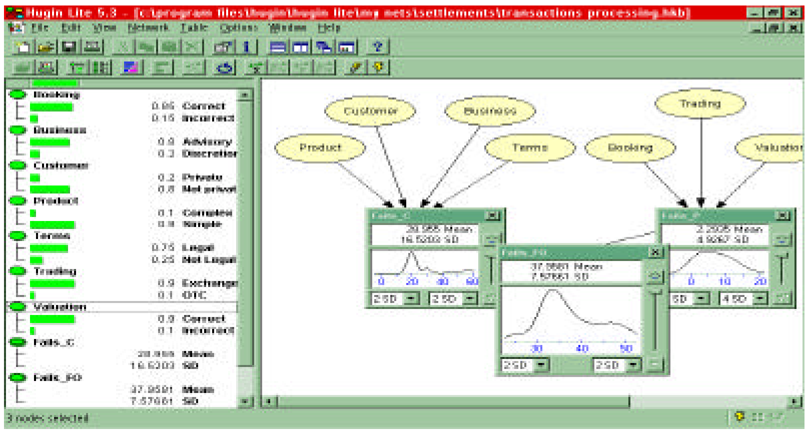
Multivariate Distributon



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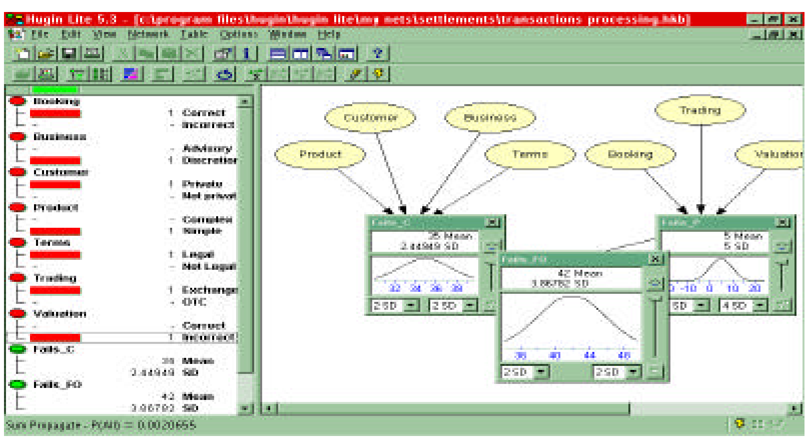
Marginal Distributions



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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

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BSC Performance Indicators

- **Financial**
  - % income paid in fines or interest penalties
- **Customer**
  - % customers satisfied with quality and timeliness
- **Internal processes**
  - % employees satisfied with work environment, professionalism, culture, empowerment and values
- **Learning and growth**
  - % employees meeting a qualification standard

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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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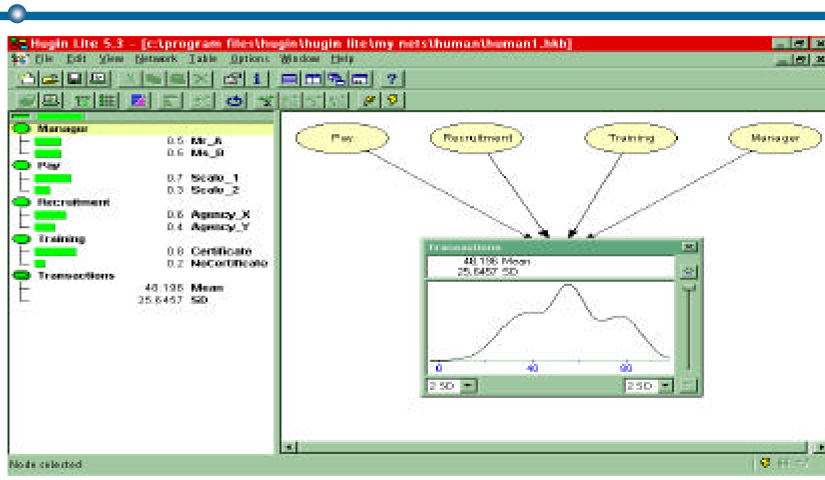
Example:
Number of Transactions Processed



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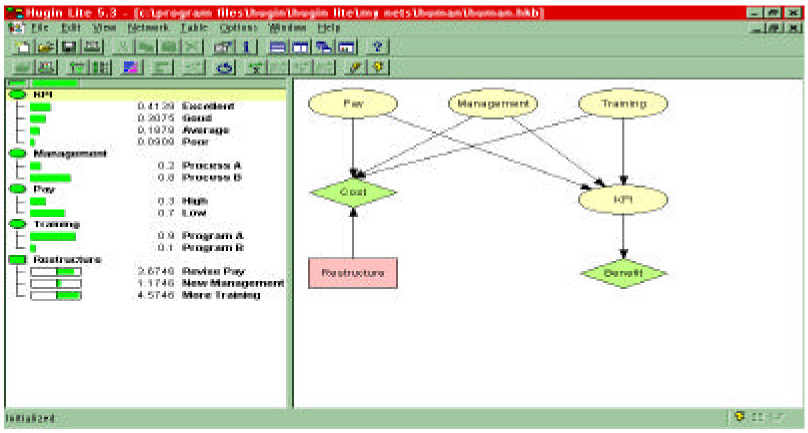
ISMA CENTRE

Bayesian Decision Networks



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ISMA CENTRE

Summary and Conclusions

- Bayesian networks are useful in **scenario analysis** over the attributes of operational risks:
  - 'maximum operational loss' scenarios can be identified to help the operational risk manager focus on the important factors that influence operational risk.
  - Scenario analysis over market and credit risk factors is useful for the integration of operational risk measures with market and credit risk measures
- Management of operational risks may be facilitated by the use of a **Bayesian decision network**, to increase transparency of senior management decisions: they allow the decision maker to base choices on 'what if?' scenarios.

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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Hüsler, J. and R.-D. Reiss (eds.) (1989) *Extreme Value Theory* Lect. Notes in Statistics *51*, Springer, New York.

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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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Wilson, D. (1999) 'Is your operational risk capital adequate?' *Operational Risk Special Report, Risk Magazine, July 1999.*

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)
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