#### RSACONFERENCE 2013

The Probability of Exploit

**Predictive Analytics & Security Management** 

**Doug Hubbard** 

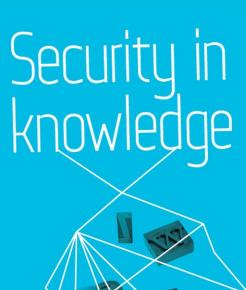
**Hubbard Decision Research, CEO** 

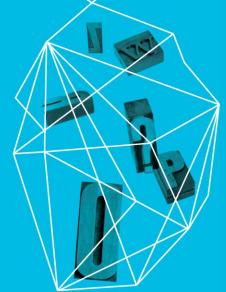
**Richard Seiersen** 

Kaiser Permanente, Director Information Security

Session ID: GRC-W21

Session Classification: General Interest





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Prelude:
The Truth About
Current Security Models

## Prelude: True, Not True or Irrational?





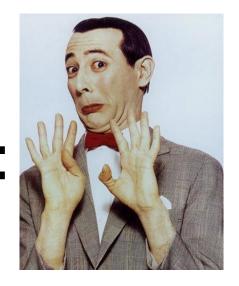
## Prelude: True, Not True or Irrational

OV	OWASP Inherent Risk Rating Worksheet  Threat Agent Vulnerability Business Impact																		
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			Fac	tors		Factors							Fac	tors					
ID	Risk Description	Skill level	Motive	Opportunity	Size	Ease of discovery	Ease of discovery  Ease of exploit  Awareness Intusion detection		Intusion detection	Likelihood	Likelihood Likelihood Rating		Patient safety Regulatory		Productivity	Impact	Impact Rating	Risk score (L * I)	Risk rating
1	Risk 1	4 9 4 5 9 9 6 3 <b>6.8 H</b> 2								2	0.5	2	0.1	1.2	Н	7.8	High		
									0.1	0.5	0.5	0.1	0.3	М	1.0	Low			
2	Risk 2	Q	1	U												0 - 0			
3	Risk 2 Risk 3	6	9	7	9	3	3	6	8	7.1	Н	10	0.5	0.1	0.1	2.7	E	18.9	Critical
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3	Risk 3	6		7	9	3	3	6	8	7.1		10	0.5	0.1	0.1	2.7	Е	18.9	
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Example Onl

## Prelude: We Believe (<u>ALL</u>) of These Are Equivalent!

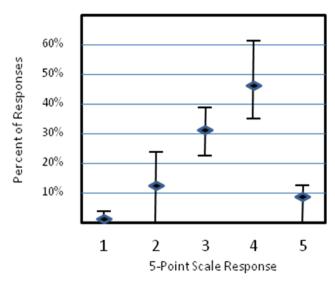
Inh	Inherent Risk Rating Worksheet Threat Agent Vulnerability Business Impact																		
		Th	reat	Age	nt	V	ulne	rabili	ty			Вι							
			Fac	tors			Fac	tors					Fac	tors					
ID	Risk Description	Skill level	Motive	Opportunity	Size	Ease of discovery			Intusion detection	Likelihood	Likelihood Rating	Patient safety	Regulatory	Revenue	Productivity	Impact	Impact Rating	Risk score (L * I)	Risk rating
1	Risk 1	4	9	4	5	9	9	6	3	6.8	Н	2	0.5	2	0.1	1.2	Н	7.8	High
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4	Risk 4	1	4	7	6	3	5	6	9	5.7	М	2	0.5	0.5	0.1	8.0	M	4.4	Moderate
													Ov	erall	Asses	sment	Risk	32.2	
	Extreme																		
	High																		
	Medium																		
L=	Low																		
N=	Negligible																		



## Prelude: & Why Should You Care?

#### .....Bad Models, Over Confidence & Placebos

Summary of response distributions of 5point scales



Hubbard D., Evans, D "Problems with scoring methods and ordinal scales in risk assessment" *IBM Systems Journal: Special Issue on Risk Management*, Oct 2009

- Scales obscure (rather than alleviate) the lack of information and create an illusion of communication (Budescu)
- The rounding effect of scales adds unexpected error (Cox).
- Arbitrary partitions have unexpected effects on scoring behavior (Fox)
- Scales introduce an error of "assumed ratios". (Hubbard, Evans)
- Clustering of responses amplifies all of the previously mentioned errors (Hubbard, Evans)



### Prelude: & Why Should You Care?

#### .....Bad Models, **Over Confidence** & **Placebos**

Gathering more information makes you feel more confident but, at some point, begins to reduce decision quality while confidence continues to increase.

- Collecting more than a few data points on horses makes expert handicappers worse at estimating outcomes (Tsai, Klayman, Hastie)
- Interaction with others only improves estimates up to a point, then they get worse (Heath, Gonzalez)
- Collecting more data about investments makes people worse at investing (Andreassen)
- Collecting more data about students makes counselors worse at predicting student performance.
   (Andreassen)
- An experiment with a popular method called "Analytic Hierarchy Process" shows confidence increased whether decisions are improved or degraded. (Williams, Dennis, Stam, Aronson)

We should assume increased confidence from analysis is a "placebo". Real benefits have to be measured.....we will show you how.



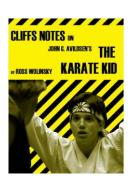
## What We Will Cover

- Current Model Problems & Solutions:
  - The Cliff Notes



- The first step in recovery is admitting you have <u>a problem</u>
- Calibrating the experts.....to be like bookies
- Streamlining Scores.....increasing consistency
- Speaking in probabilities.....real numbers, real math
  - Putting it all together......Monte Carlo Simulations to the rescue





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# Current Model Problems and Solutions (The

Cliff Notes)

#### Model Problems and Solutions: The Cliff Notes

Questions We **Should** Be Able To Answer

- Here are some risks plotted on a "typical heat map".
- Suppose mitigation costs were:

Risk 1: \$725K - High

Risk 2: \$95K - Low

Risk 3: \$2.5M - Critical

Risk 4: \$375K - Moderate

	lmp	act					
Low	Medium	Η̈́	gh	Extr	eme		
Moderate	High	Crit	ical	Crit	ical	Extreme	
Low	Moderate	H	gh	Crit	ical	High	_ik €
Low	Moderate	Hi	gh	Hi	gh	Medium	_ikelihood
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4 (	2	$\frac{1}{1}$			3)		

What mitigations should be funded and what is the priority among those?

#### Model Problems and Solutions: The Cliff Notes

**Decision Making Supported Quantitatively** 

- If risks and mitigation strategies were quantified in a meaningful way, decisions could be supported.
- In order to compute an ROI on mitigation decisions, we need to quantify likelihood, monetary impact, cost, and effectiveness

Risk	Likelihood / Yr	Impact / Yr	Mitigation Effectiveness	Mitigation Cost / Yr	Mitigation ROI	Action
Risk 1	37%	\$2M to \$40M	95%	\$725K	725%	Mitigate
Risk 2	11%	\$50K to \$400K	100%	\$95K	-80%	Track
Risk 3	34%	\$5M to \$80M	90%	\$2.5M	329%	Monitor
Risk 4	29%	\$500K to \$20M	98%	\$375K	437%	Mitigate

- •The optimal solution would be to mitigate Risks1 & 4 first.
- •If you have the resources, then mitigate Risk 3.
- •Risk 2 is not worth fixing.

**Example Only** 

#### Model Problems and Solutions: The Cliff Notes

Experts Vs. Quantitative Models

Paul Meehl assessed 150 studies comparing human experts to statistical models in many fields (predicting football games, the prognosis of liver disease, etc.).

"There is no controversy in social science which shows such a large body of qualitatively diverse studies coming out so uniformly in the same direction as this one. [With hardly] a half dozen studies showing even a weak tendency in favor of the [human expert], it is time to draw a practical conclusion."

Philip Tetlock tracked a total of over 82,000 forecasts from 284 political experts in a 20 year study covering elections, policy effects, wars, the economy and more.

"It is impossible to find any domain in which humans clearly outperformed crude extrapolation algorithms, less still sophisticated statistical ones."

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Fixing The Model...

Quantitatively

## Fixing The Model: The Problem

Inh	Inherent Risk Rating Worksheet Threat Agent Vulnerability Business Impact																		
		Th	reat	Age	ent	V	ulner	abili	ty			Bu	sines	s Impa	act				
			Fac	tors			Fac	tors					Fac	tors					
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4	Risk 4	1	4	7	6	3	5	6	9	5.7	M	2	0.5	0.5	0.1	0.8	M	4.4	Moderate
													٥v	erall	Asse s	sment	Risk	32.2	

E = Extreme
H = High
M = Medium
L = Low
N = Negligible

- The existing model starts with subjective scores for likelihood and impact
- Like most "popular" risk management models, scores are "added" to get ratings for likelihood and impact and a total "risk score".
- The scale used indicates relevant order, not actual units of measure (i.e. not real numbers), which introduces ambiguity; "adding" or "multiplying" adds further obscurity to the items being measured and compromises the risk assessment process.

**Example Only** 

# Fixing The Model: Subjectivity

<u>Human expertise is an important input</u> and it is hard to completely automate. But there are certain types of errors in human judgment we know how to measure and control for:

- Overconfidence Their chance of being right is much less than they believe
- Influence by irrelevant factors Factors like the order in which you consider projects, whether it is a 5-point scale or a 10-point scale, or how much other people in the room smile all affect your judgments
- Inconsistency When given the same sets of problems to evaluate, experts have a hard time giving the same answers; also, their memory is reconstructed so that they believe they always had one preference when in fact they didn't

"Experience is inevitable. Learning is not."

Decision science researcher Paul Schoemaker

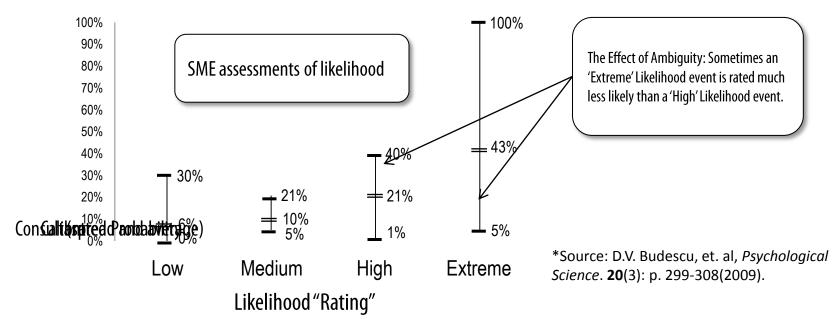


## Fixing The Model: Ambiguity Exercise

- What has a higher overall risk?
  - Two risks of "medium" impact and "high" likelihood
  - One risk of "high" impact and "medium" likelihood
  - Four risks of "low" impact and "medium" likelihood
- What is the probability of a low, medium, and high likelihood? Is this a probability per year, per month, ever, etc?
- On a 1 to 5 scale, what is more likely?
  - At least one of three events of a "2" likelihood
  - An event of "4" likelihood

### Fixing The Model: The Problem...ambiguity

- Using scores like 'Low,' Medium,' High,' etc., adds ambiguity, as people have wildly different interpretations
  of these labels for risk.\*
- When asked to estimate the likelihood of different risks, participants were consistent with other research on the use of these scales (see chart below).
  - For example, SME's may equate a Likelihood of 'Extreme' with a 5% chance of occurrence, while also equating a Likelihood of 'High' to a 40% chance of occurrence; this is inconsistent as higher probability should equate to a higher Likelihood rating.
- Using unambiguous quantitative estimates (e.g., chance of occurrence per year, 90% confidence interval for monetary impact) enables us to better assess and manage key Company risks.



## Fixing The Model: Calibration Exercise

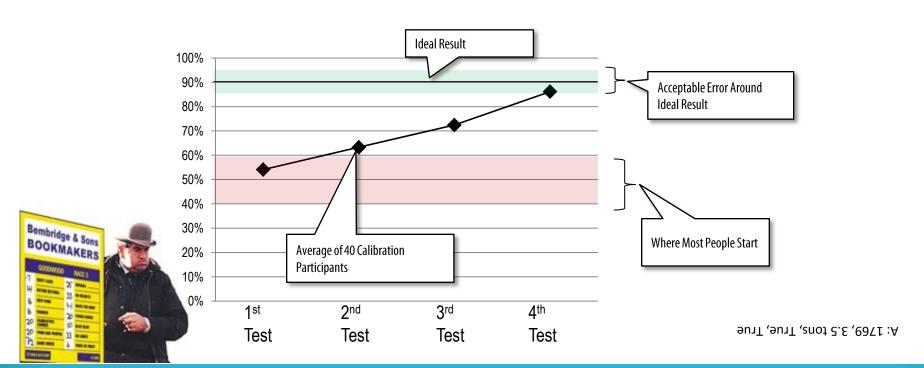
For the initial calibration test, you have two types of questions:

- For the questions that ask for a range, provide an upper and lower bound that you are 90% certain contains the correct answer
  - Napoleon Bonaparte was born what year? \_\_\_\_\_ to \_\_\_\_
  - What is the average weight of an adult male African elephant (tons)? \_\_\_\_\_to\_\_\_\_
- For the true/false questions, circle true or false and then circle the percentage that best represents your confidence in your response
  - Brazil has a larger population than Spain. True/False\_\_\_\_\_ Confidence:\_\_\_\_\_%
  - A hockey puck will fit in a golf hole. True/False\_\_\_\_\_ Confidence:\_\_\_\_\_%



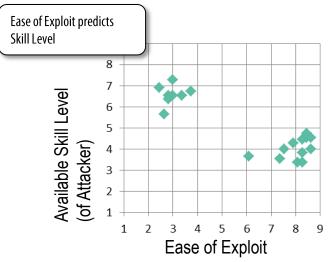
#### Fixing The Model: Calibrating Experts...to be like bookies

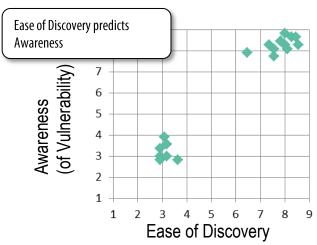
- Research shows that assessing subjective probabilities and ranges is a teachable skill.
- One of the calibration tasks for participants in training was estimating 90% Confidence Intervals.
- At first, they were like most people extremely overconfident.
- By fourth test, almost everyone could estimate 90% confidence intervals that contained the actual value about 90% of the time.



## Fixing The Model: Increasing Consistency

....getting rid of redundant scores



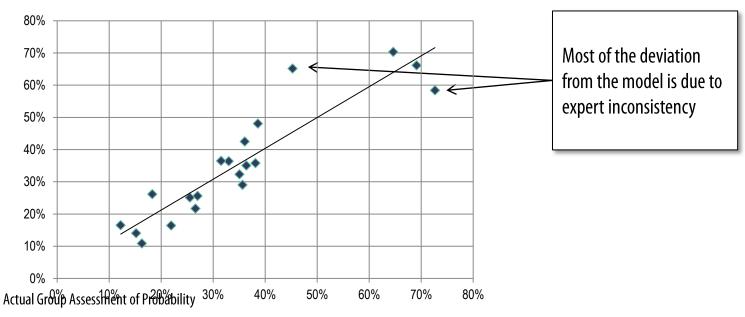


- Via independent tests, 11 SME's were asked to assign the 8 original factors and assess annual probability for 20 specific scenarios.
- We specified that likelihood mean chance per year of >1 occurrence.
- Irrelevant factors Motive and Intrusion Detection had almost no correlation to the estimated annual probability.
- Redundant factors Available Skill Level and Awareness were almost entirely predictable based on other scores (within +/- 1 point).
- The best model used only 4 of 8 factors.
- Scores are still used at this stage, but are minimized and converted directly to a meaningful probability.

## Fixing The Model: Speaking in Probabilities

....and further increasing consistency

- We developed a model that estimates the average probability scores of the security consultants.
- Comparing the new model we developed to actual security consultant group assessments shows that our model is more consistent than using security consultant probability assessments alone.
- Reducing inconsistency is an immediate benefit of the new model.



Group Assessment of Probability Predicted From New Model

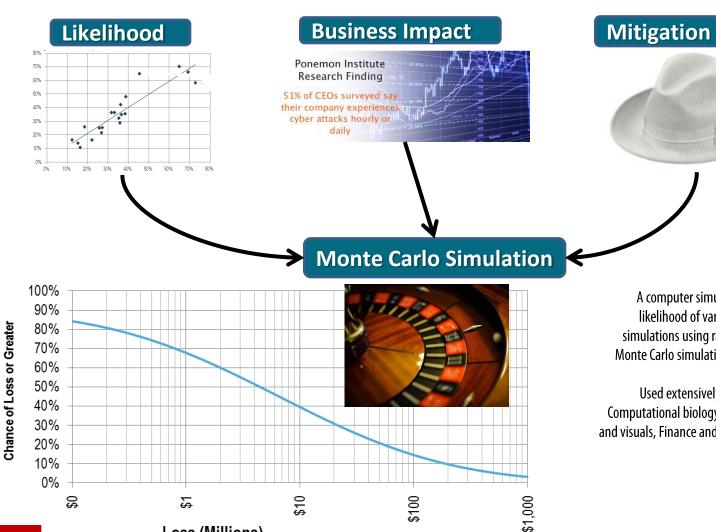
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# Putting It All Together... (Monte Carlos To The

Rescue)

#### Putting it All Together — Monte Carlo Simulations



**Mitigation Cost** 



**Monte Carlo Simulation** 

A computer simulation that seeks to determine the likelihood of various scenarios by running multiple simulations using random variables. The results of the Monte Carlo simulation show the most likely outcomes.

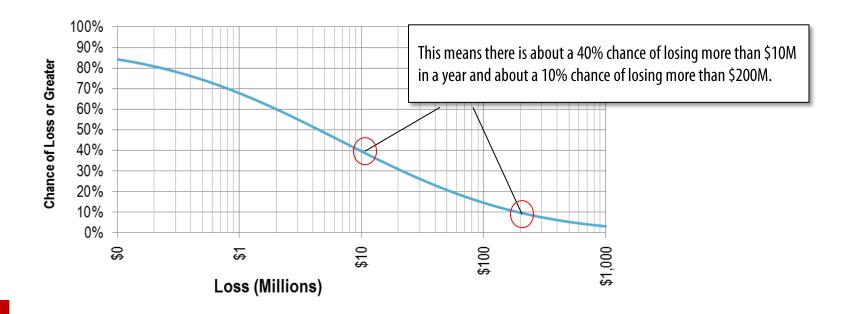
Used extensively in Physical sciences, Engineering, Computational biology, Applied statistics, Games, Design and visuals, Finance and business and Telecommunications

**Example Only** 

Loss (Millions)

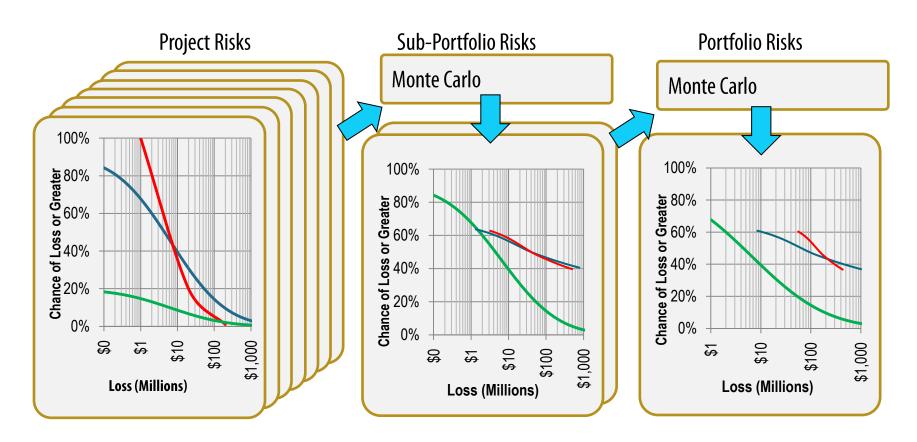
# Putting it All Together: Communicating Security Risks Quantitatively

- If we can express uncertainty of individual risk events quantitatively, we can answer quantitative risk questions like "What is the chance a given risk will result in more than \$5 million in losses in a given year?"
- The curve on this chart is based on calibrated estimates and the new model
- It represents the chance that a loss for a given a risk equal to or greater than some amount will occur in a given year.
- These can also be added up into Project and Portfolio risk in a meaningful way.



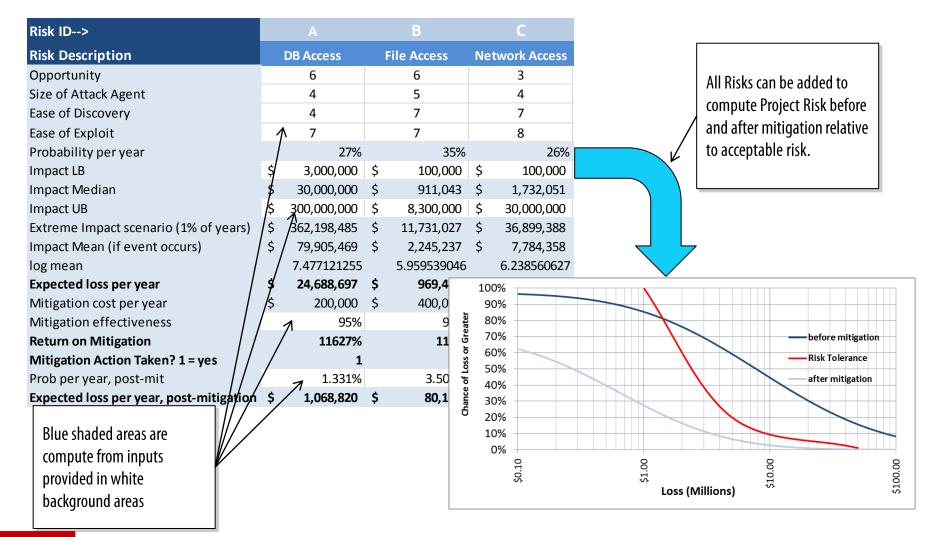
**Example Only** 

## Putting It All Together: Aggregating Security Risk



- A Monte Carlo simulation is used to roll Project Risks into Sub-Portfolio Risks into Portfolio Risks
- Each level can have an acceptable risk boundary defined by management

## Putting It All Together: Technical Details



**Example Only** 

#### -Putting It All Together: New Quantitative Model in Action

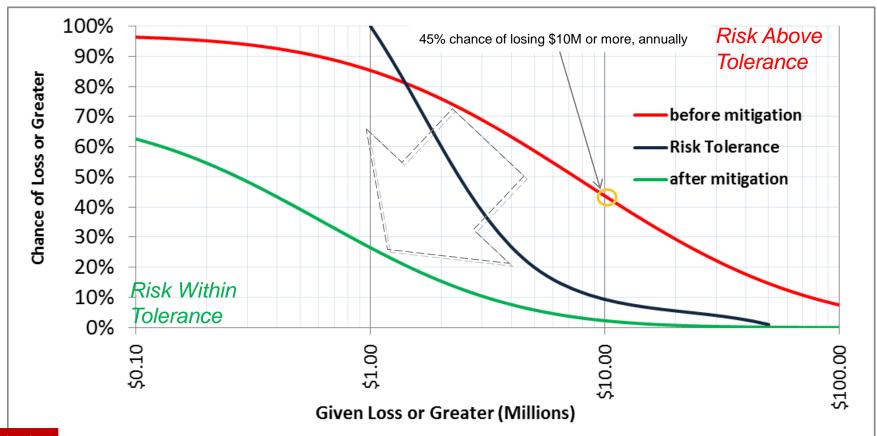
What action to take if only \$3.5M available for mitigation?

	Expected Loss / Yr	Mitigation Cost	Mitigation Effectiveness	Mitigation ROI	Action
DB Access	\$24.7M	\$800K	95%	2,832%	Mitigate
Physical Access	\$2.5M	\$300K	99%	727%	Mitigate
Application Authentication	\$4.4M	\$600K	95%	602%	Mitigate
Data in Transit	\$2.3M	\$600K	95%	267%	Mitigate
System Patch	\$2.8M	\$800K	95%	230%	Mitigate
Network Access Control	\$2.3M	\$400K	30% <b>3.5M</b>	74%	Mitigate
File Access	\$969K	\$600K	90%	45%	Monitor
Web Vulnerabilities	\$409K	\$800K	95%	-51%	Track
System Configuration	\$113K	\$500K	100%	-77%	Track

**Example Only** 

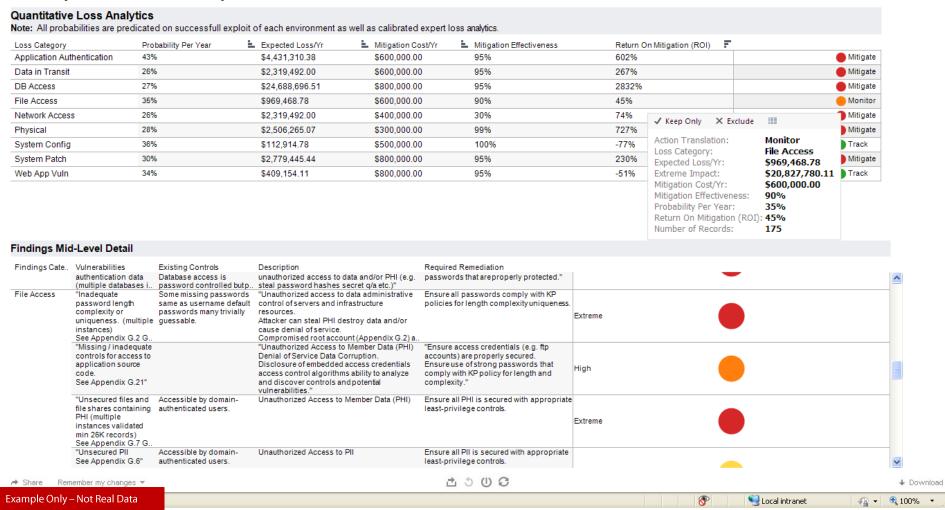
#### Putting It All Together: Project Loss Probability Curves

#### What is risk exposure after applying available mitigations?



# Putting It All Together: BI Applied

#### Security Assessment & Analytics Services



# **Calculation Detail**

Risk ID>	А		В		С		D		Е		F	G		Н		1	Project
Risk Description	DB Access	ı	File Access	Ne	twork Access	W	eb App Vuln	A	App Authen	S	ystem Patch	Physical	Da	ata in Transit	Sy	stem Config	
Opportunity	6		6		3		5		7		3	6		3		5	
Size of Attack Agent	4		5		4		5		5		5	7		4		5	
Ease of Discovery	4		7		7		8		8		8	3		8		8	
Ease of Exploit	7		7		8		7		8		8	4		7		8	
Probability per year	27%		35%		26%		34%		43%		30%	28%		26%		36%	97%
Impact LB	\$ 3,000,000	\$	100,000	\$	100,000	\$	100,000	\$	100,000	\$	100,000	\$ 100,000	\$	100,000	\$	100,000	\$ 341,724
Impact Median	\$ 30,000,000	\$	911,043	\$	1,732,051	\$	565,685	\$	1,732,051	\$	1,732,051	\$ 1,732,051	\$	1,732,051	\$	223,607	\$ 8,605,090
Impact UB	\$ 300,000,000	\$	8,300,000	\$	30,000,000	\$	3,200,000	\$	30,000,000	\$	30,000,000	\$ 30,000,000	\$	30,000,000	\$	500,000	\$ 133,349,880
Extreme Impact scenario (1% of years)	\$ 362,198,485	\$	11,731,027	\$	36,899,388	\$	4,137,352	\$	54,984,362	\$	41,634,906	\$ 38,890,679	\$	36,899,388	\$	570,736	\$ 503,298,821
Impact Mean (if event occurs)	\$ 79,905,469	\$	2,245,237	\$	7,784,358	\$	985,235	\$	7,784,358	\$	7,784,358	\$ 7,784,358	\$	7,784,358	\$	252,029	
log mean	7.477121255		5.959539046		6.238560627		5.752574989		6.238560627		6.238560627	6.238560627		6.238560627		5.349485002	6.934755394
Expected loss per year	\$ 24,688,697	\$	969,469	\$	2,319,492	\$	409,154	\$	4,431,310	\$	2,779,445	\$ 2,506,265	\$	2,319,492	\$	112,915	\$ 40,536,239
Mitigation cost per year	\$ 800,000	\$	600,000	\$	400,000	\$	800,000	\$	600,000	\$	800,000	\$ 300,000	\$	600,000	\$	500,000	\$5,400,001
Mitigation effectiveness	95%		90%		30%		95%		95%		95%	99%		95%		100%	
Return on Mitigation	2832%		45%		74%		-51%		602%		230%	727%		267%		-77%	6.86
Mitigation Action Taken? 1 = yes	1		1		1		0		1		1	1		1		0	
Prob per year, post-mit	1.331%		3.503%		18.026%		33.951%		2.169%		1.500%	0.275%		1.288%		36.081%	70%
Expected loss per year, post-mitigation	\$ 1,068,820	\$	80,162	\$	1,548,407	\$	409,154	\$	170,833	\$	117,769	\$ 21,460	\$	100,953	\$	112,915	\$ 3,630,473

#### **Selected Sources**

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- Andreassen, P." Judgmental extrapolation and market overreaction: On the use and disuse of news" *Journal of Behavioral Decision Making*, vol. 3 iss. 3, pp 153-174, Jul/Sep 1990
- Williams M. Dennis A., Stam A., Aronson J. "The impact of DSS use and information load on errors and decision quality" European Journal of Operational Research, Vol. 176, No. 1, 2007, pp 468-81
- Knutson et. al. "Nucleus accumbens activation mediates the influence of reward cues on financial risk taking" NeuroReport, 26 March 2008 - Volume 19 - Issue 5 - pp 509-513
- A small study presented at Cognitive Neuroscience Society meeting in 2009 by a grad student at U. of Michigan showed that simply being briefly exposed to smiling faces makes people more risk tolerant in betting games.
- Risk preferences show a strong correlation to testosterone levels which change daily (Sapienza Zingales, Maestripieri, 2009).
- Recalling past events that involved fear and anger change the perception of risk (Lerner, Keltner, 2001).