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MODEL RISK MANAGEMENT: A STRESS TESTING APPROACH TO EFFECTIVE MODEL VERIFICATION AND VALIDATION

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Model Risk Analytics
Quantifying Model Risk for Financial Institutions

Agenda

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Quantifying Model Risk for Financial Institutions

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COMPREHENSIVE MODEL RISK MANAGEMENT FOR FINANCIAL INSTITUTIONS
- ADVISORY SERVICES
- PLATFORM TO MANAGE MODEL RISK
- TRAINING AND AUDITS

MODEL RISK – A BRIEF INTRODUCTION

Knight Has 'All Hands on Deck' After $440 Million Bug

By Whitney Kisling | Aug 2, 2012 3:17 PM ET | **26 Comments** **Email** **Print**

Knight Capital Group Inc. (KCG) has "all hands on deck" and is in close contact with creditors, clients and counterparties as it tries to weather trading errors that cost it $440 million, Chief Executive Officer Thomas Joyce said.

Joyce said it's "hard to comment" on discussions with creditors as Knight stock extended a two-day plunge to 77 percent and the firm explored strategic and financial alternatives following a loss almost four times its annual profit. The problems were triggered by what Joyce called "a large bug" in software as the company, one of the largest U.S. market makers, prepared to trade with a **New York** Stock Exchange

Photographer: Andrew Harrer/Bloomberg

Thomas Joyce, chairman and chief executive officer of Knight Capita

The SEC's Knight Capital Fine Adds Insult to Injury

By Matthew Philips | October 17, 2013

SEND TO Kindle

Photograph by Jin Lee/Bloomberg

Knight Capital Group's trading booth at the New York Stock Exchange

As financial institutions depend on models for decision making, Model Risk Management is critical

Financial accidents have cost companies millions of dollars and was blamed for the financial crisis of 2008

Goldman Sachs technical error causes erroneous U.S. option trades

Tue, Aug 20 2013

By Caroline Valetkevitch and Doris Frankel

NEW YORK/CHICAGO (Reuters) - A flood of erroneous trades hit U.S. equity options markets on Tuesday as they opened for business when Goldman Sachs Group (GS because of a technical error, the latest trading problem to hit the options market this year.

Major options exchanges including platforms run by CBOE Holdings (CBOE.O: Quote, Profile, Research, Stock Buzz), Nasdaq OMX Group Inc (NDAQ.O: Quote, Profile, R reviewing the trades, sent in roughly the first quarter hour of trading and affecting options on shares with listing symbols beginning with the letters H through L.

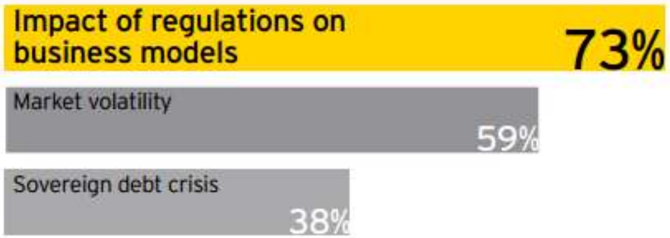
Exchanges have the option to adjust prices or nullify, or "bust," the trades if they are determined to have been made in error. NYSE Euronext's NYSE Amex Options mark

Goldman Sachs said in a statement the firm does not face material loss or risk from the issue. The firm declined to comment further.

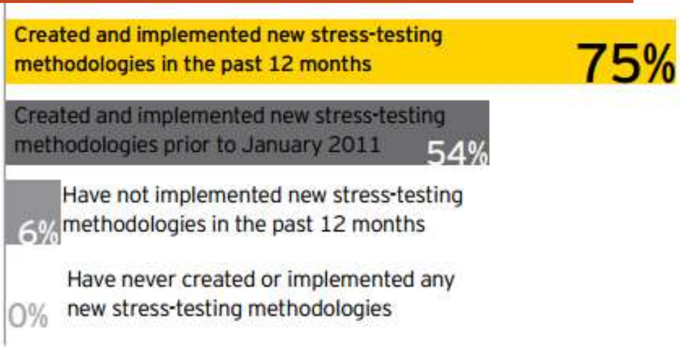
A person familiar with the problem, who declined to be identified, said the cause was a computer glitch in which indications of interest in equity options were sent as act others were not.

Concerned about systemic risk, regulators have stepped up regulations to setup model risk programs

All Banks, Insurance Companies and Credit Rating agencies in the US and EU are affected by these regulations



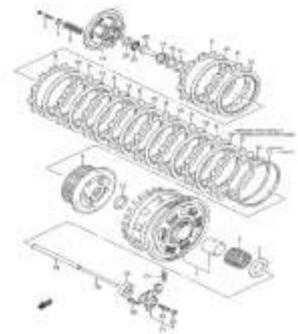
Source: E&Y Survey 69 banks & 6 insurance companies



Financial institutions face challenges implementing Model Risk Programs

1

Quantitative models are complex: Measuring model risk is not easy



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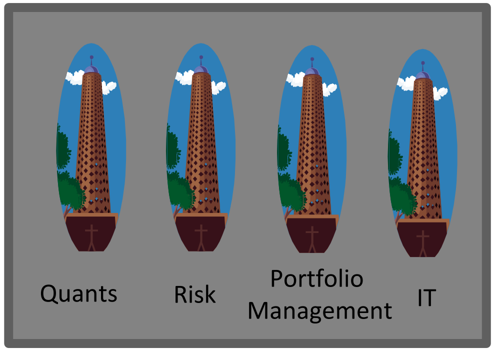
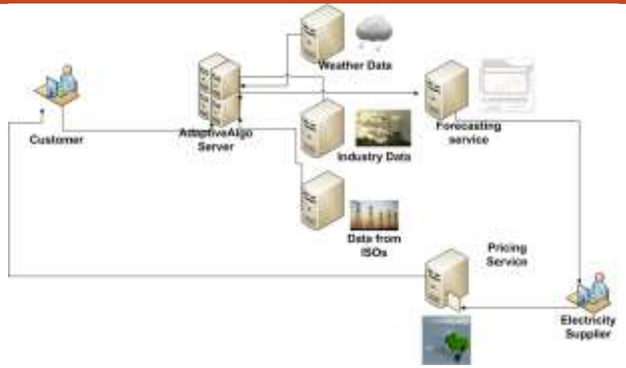
Quantitative systems are complex : Many stakeholders





3

Novelty: Lack of guidance and ambiguity on regulations

?

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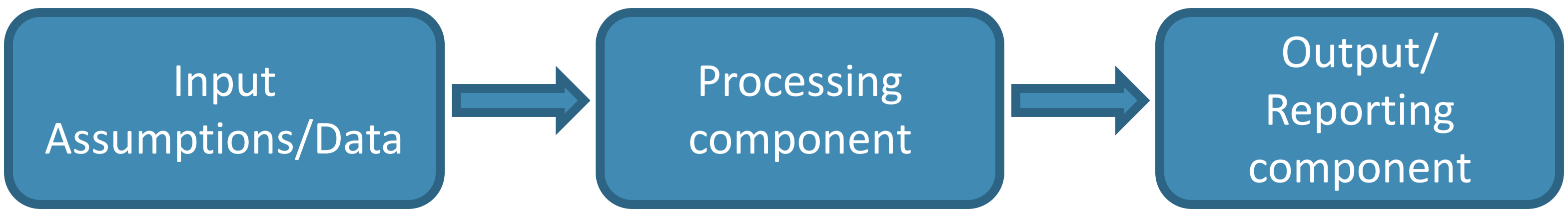
Model Defined

"Model refers to a quantitative method, system, or approach that applies statistical, economic, financial, or mathematical theories, techniques, and assumptions to process input data into quantitative estimates" [1]



Ref:

[1] . Supervisory Letter SR 11-7 on guidance on Model Risk

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Model Risk and Validation Defined

"Model risk is the potential for adverse consequences from decisions based on incorrect or misused model outputs and reports. " [1]

"Model validation is the set of processes and activities intended to verify that models are performing as expected, in line with their design objectives and business uses. " [1]

Ref:

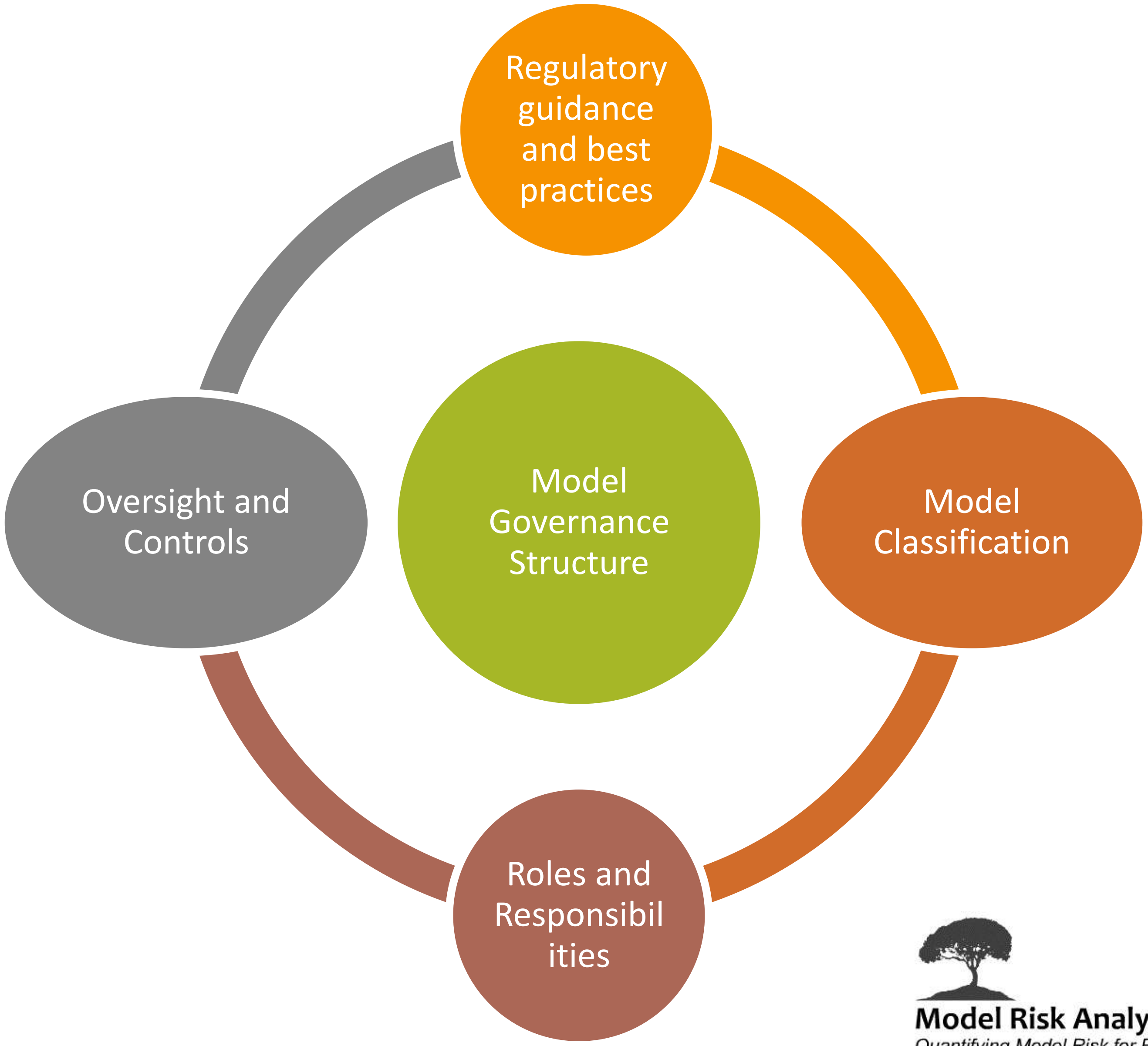
[1] . Supervisory Letter SR 11-7 on guidance on Model Risk

A FRAMEWORK DRIVEN APPROACH TO MODEL RISK MANAGEMENT

Elements of a Model Risk Management framework

1. **Model Governance structure**: Addresses regulatory requirements, roles, responsibilities, oversight, control and escalation procedures
2. **Model Lifecycle management**: Addresses the processes involved in the design, development, testing, deployment and use of models. Also addresses testing and documentation plans and change management.
3. **Model Review and Validation Process**: Addresses internal and external model review, verification, validation and ongoing monitoring of models (both qualitative and quantitative)

Model Governance Structure



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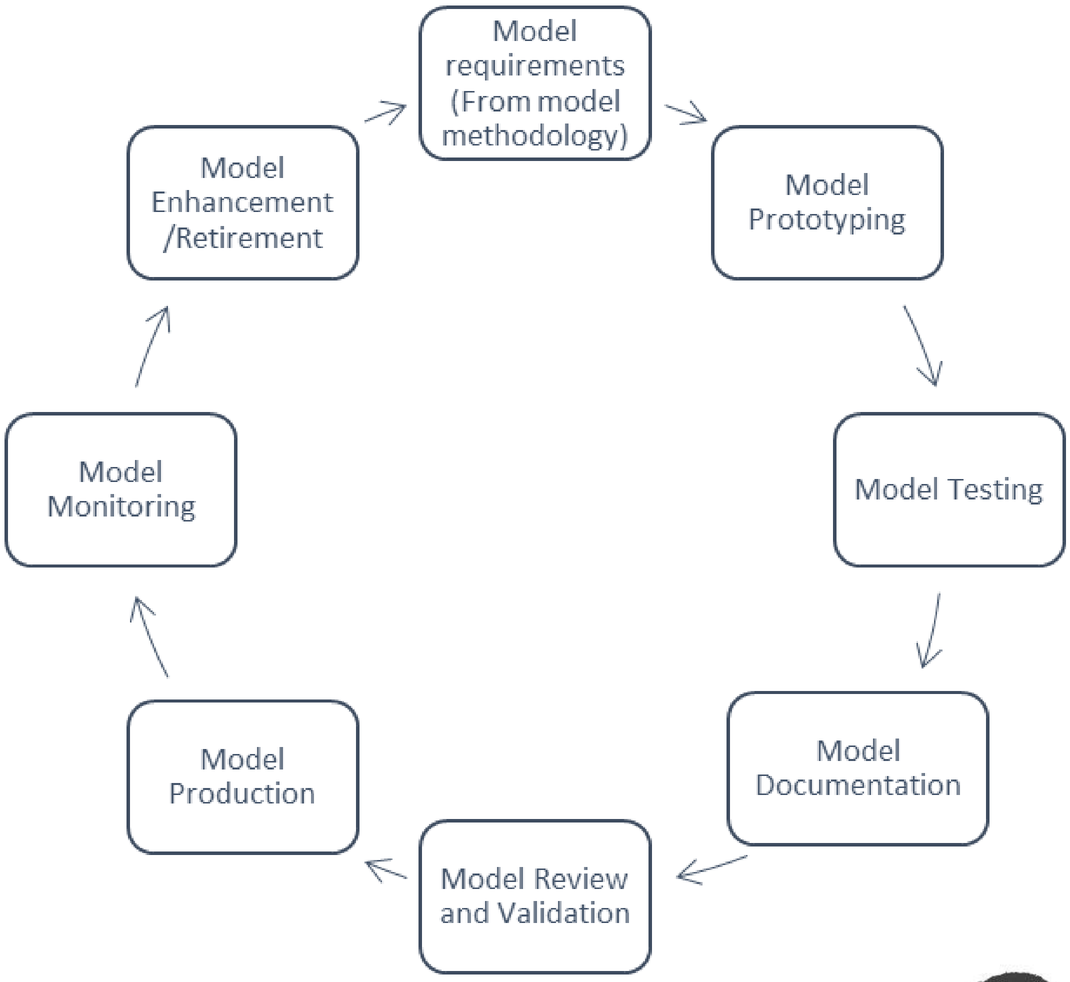
Model Lifecycle Management



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Policy:

Model Policy Review

Structure:

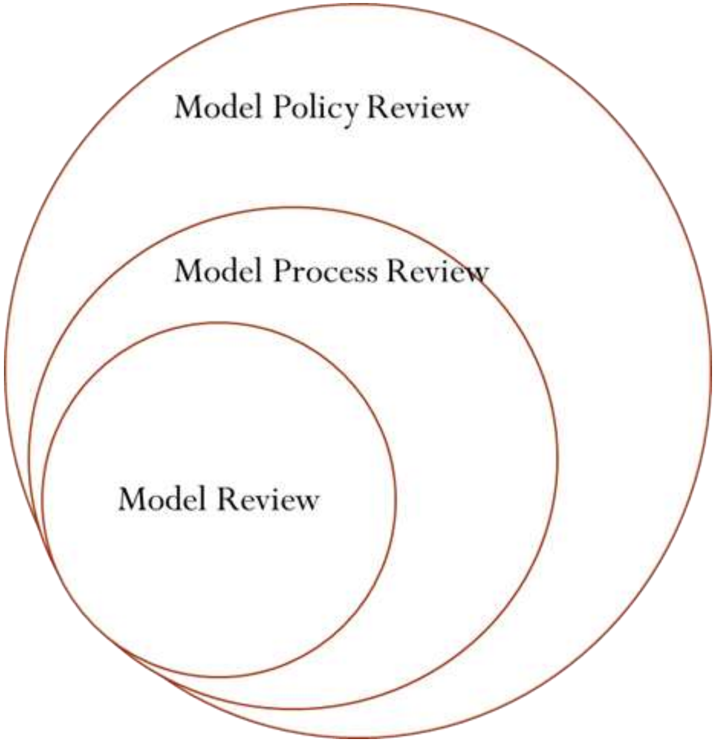
Model Process Review

Content:

Model Review

Model Verification

Model Validation



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1. Quantifying Model Risk:
   - Classification and Measurement of Model Risk

2. Role of Model Verification for Model Risk Management

3. Leveraging technology to scale stress and scenario testing

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QUANTIFYING MODEL RISK

Organizational Structure

How to engage all departments strategically to have a comprehensive view of Model Risk ?

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Theory to Practice : How to cross the chasm ?

- Theory
- Regulations
- Local Laws

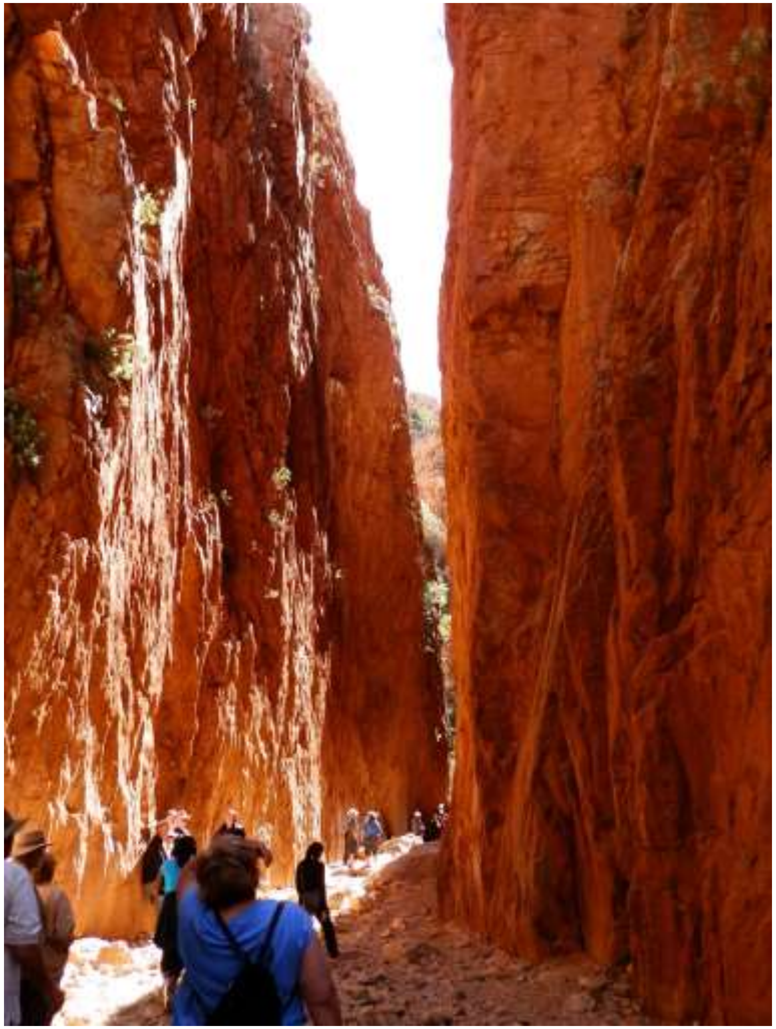

Image Courtesy: http://rednomadoz.blogspot.com.au/

- Practical IT systems
- Company policies
- Company culture and Best practices

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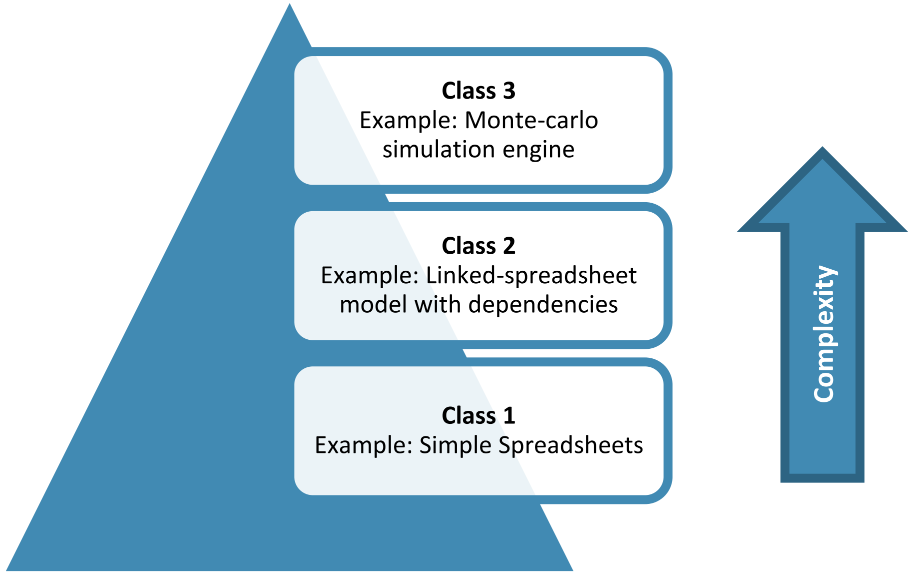
Classifying Model Risk



1. **Class 1 Models:** Simple Models typically involving less complex atomic calculations
2. **Class 2 Models:** Models more complicated than Class 1 models
3. **Class 3 Models:** Typically involves sophisticated mathematical/statistical techniques

Model Risk Assessment Framework

- **Aspects :**
  - Risk issues identified during model review
- **Impact :**
  - What are the consequences of these issues ?
- **Probability of Occurrence:**
  - Chances of the aspect occurring.
- **Risk Score:**
  - Impact * Probability of Occurrence
- **Model Risk Controls :**
  - What actions are taken to alleviate/eliminate the impact ?
- **Residual Risk Score:**
  - Risk Scores – Risk Scores considering model risk controls
  - Indicates exposures still not addressed
- **Ranking :**
  - Aspects sorted by Residual Risk scores to identify issues that needs to be prioritized

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Scoring Guidelines

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	QuantModel				Risk Scores due to potential impacts				Risk Scores after considering model risk controls				Unaddressed Risk
2	Model	File	Version	Aspects	Impacts	Impact score	Probability of Occurrence	Risk Score	Model Risk Controls	New Impact Score	New Probability of Occurrence	New Risk Score	Residual Risk
3	Stress Model		v1.0										
4	1	ReadData.m		Input < 0	Code Failure								
5	2	ReadData.m		No input checking	Erroneous results								

Sample Risk grading considering impact and likelihood of occurrence

		Risk Scores				
Impact	5	5	10	15	20	25
	4	4	8	12	16	20
	3	3	6	9	12	15
	2	2	4	6	8	10
	1	1	2	3	4	5
		1	2	3	4	5
		Likelihood of occurrence				

	Red	High Risk
	Yellow	Moderate Risk
	Green	Low Risk

High Impact- High likelihood of occurrence : Needs adequate model risk control measures to mitigate risk

High Impact – Low likelihood of occurrence: Address through model risk control measures and contingency plans

Low Impact – High likelihood of occurrence : Lower priority model risk control measures

Low Impact – Low likelihood of occurrence: Least priority model risk control measures

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1. **Clustering to bucket "similar" risks**
   - Identifying training opportunities and best practices for model development
2. **K-Nearest Neighbor (k-NN) to automatically derive risk scores**
   - Leveraging expert scoring to help prioritize issues
3. **Conjoint analysis**
   - Identifying what combination of a limited number of attributes is most influential on respondent choice or decision making

ROLE OF MODEL VERIFICATION IN MODEL RISK MANAGEMENT

Verification is defined as:

"The process of determining that a model or simulation implementation and its associated data accurately represent the developer's conceptual description and specifications".

Validation is defined as:

"The process of determining the degree to which a model or simulation and its associated data are an accurate representation of the real world from the perspective of the intended uses of the model".

Ref: DoD Modeling and Simulation (M&S) Verification, Validation, and Accreditation (VV&A), DoD Instruction 5000.61, December 9, 2009.

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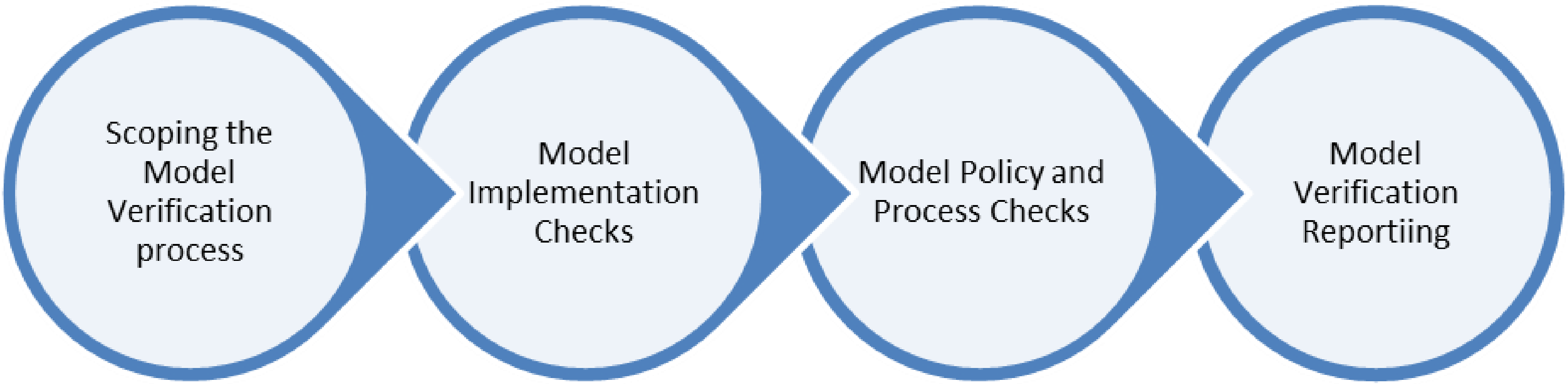
Elements of Model Verification



The Model Verification process

1. Scoping the Model Verification Process

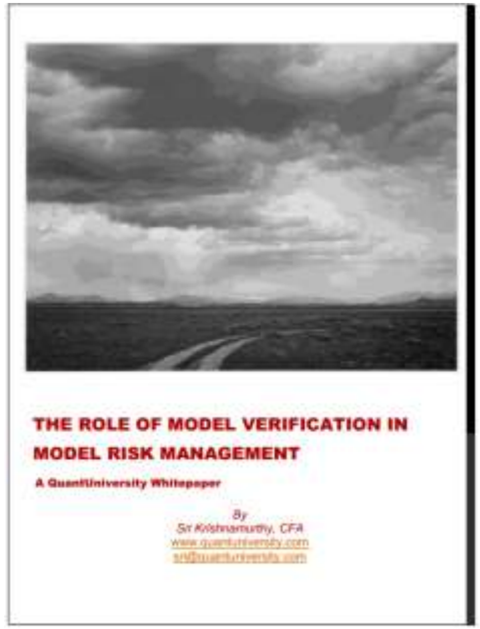
- **Model Scope**
- **Model Specification -> Model Design -> Model Implementation**
- **Acceptance criteria**

2. Model Implementation Checks

- **The Levers for the model: Input /Output Analysis**
- **Failure modes**
- **Determining the degree of correctness**

3. Model Policy and Process Checks

4. Model Verification Reporting


THE ROLE OF MODEL VERIFICATION IN MODEL RISK MANAGEMENT

A QuantUniversity Whitepaper

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The Role of Model Verification in Model Risk Management
Oct 2014

http://quantuniversity.com/ModelVerificationForMRM.pdf

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STRESS TESTING AND SCENARIO TESTING TO EVALUATE MODEL RISK

Stress Tests and Scenario Tests

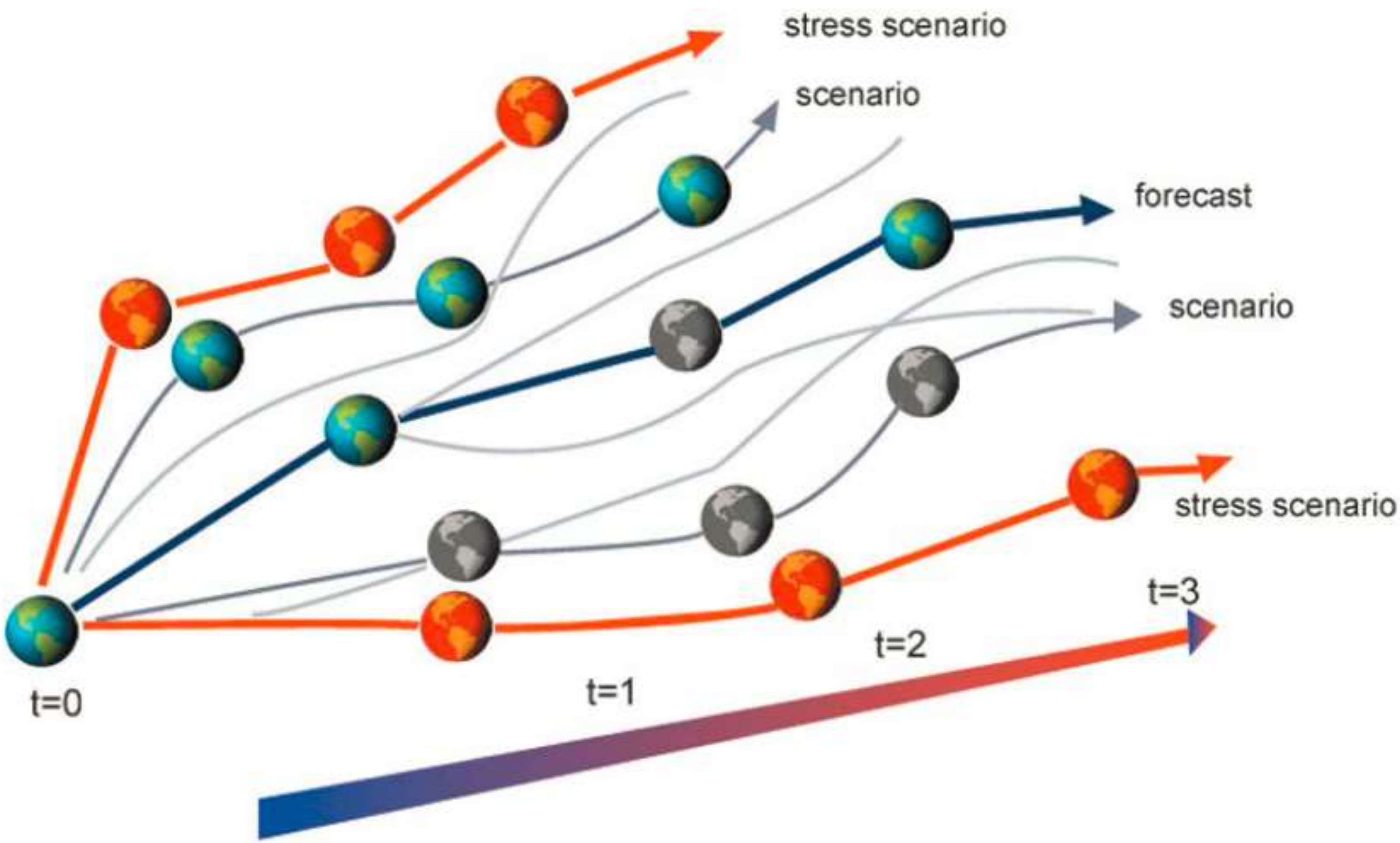

Figure courtesy: http://www.actuaries.org/CTTEES_SOLV/Documents/StressTestingPaper.pdf

1. Scenarios :

"A scenario is a possible future environment, either at a point in time or over a period of time."

"Considers the impact of a combination of events"

2. Sensitivity Analysis:

"A sensitivity is the effect of a set of alternative assumptions regarding a future environment. "

3. Stress Testing:

Analysis of the impact of single extreme events (or risk factors)

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Ref: http://www.actuaries.org/CTTEES_SOLV/Documents/StressTestingPaper.pdf

Regulatory efforts

SR 11-7 says "Banks benefit from conducting model stress testing to check performance over a wide range of inputs and parameter values, including extreme values, to verify that the model is robust"

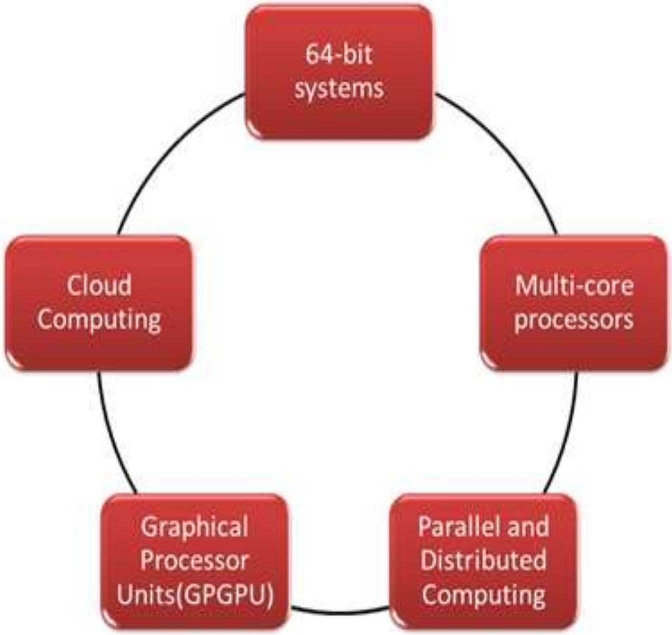
In fact, **SR14-03** explicitly calls for all models used for Dodd-Frank Act Company-Run Stress Tests must fall under the purview of Model Risk Management.

In addition **SR12-07** calls for incorporating validation or other type of independent review of the stress testing framework to ensure the integrity of stress testing processes and results.

1. **Difficult to build parametric models – Simulation driven approach necessary**
2. **Parameter space can explode easily**
3. **Tests independent of each other (Embarrassingly parallel)**
4. **Complete test-coverage – Useless**
5. **Human intervention required**
6. **Tests to be designed and customized for the companies needs considering portfolios, organization structure and regulatory obligations**

Ref: http://www.actuaries.org/CTTEES_SOLV/Documents/StressTestingPaper.pdf

- Advances in technology in the last two decades have significantly enhanced the toolsets quants have to develop, test and scale innovative quantitative applications
- Simulation and stress testing in risk management are vastly scalable due to innovations in parallel and distributed computing
- Restricting the number of tests due to lack of technological resources not an excuse



Ref: Gaining the Technology Edge: http://www.quantuniversity.com/w5.html

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Leverage technology to scale analytics

1. 64 bit systems : Addressable space ~ 8TB
2. Multi-core processors : Explicit and Implicit Multi-threading
3. Parallel and Distributed Computing : Leverage commodity/Specialized hardware to scale problems
4. General-purpose computing on graphics processing units : Use graphics cards to scale your algorithms
5. Cloud Computing

Ref: Gaining the Technology Edge: http://www.quantuniversity.com/w5.html

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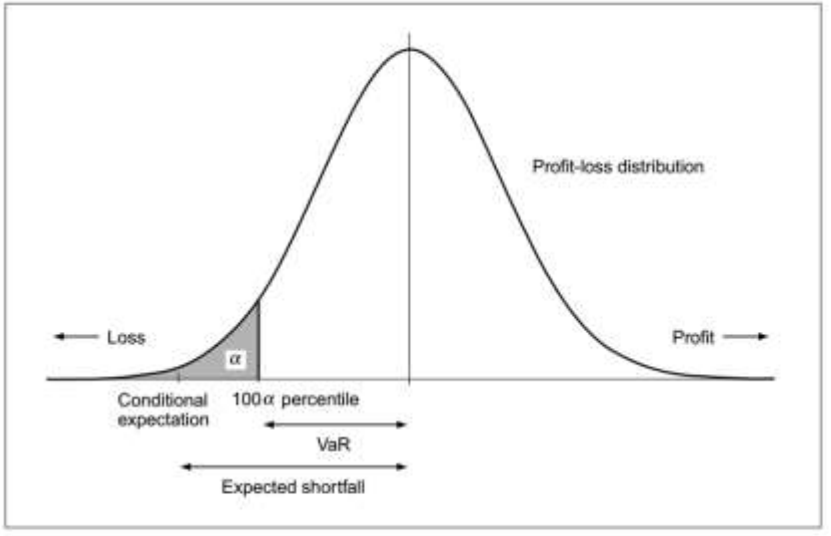
1. Model Implementation
    - Does it actually work for all intended use cases?
2. Model parameter testing
    - Number of parameters
    - How many Scenarios
3. Model Applicability
4. Model Benchmarking against Reference Implementation
    - Python vs MATLAB
5. Model Migration (version)
    - Regression Testing v1.0 to v2.0
6. Model Use case validation
    - Can we use the results to make decisions?

DEMO

Value-at-Risk & Conditional Value-at-Risk

- **VaR :** The predicted maximum loss of a portfolio with a specified probability level (e,g., 95%) over a certain period of time (e.g. one day)
- **CVaR (Expected Shortfall) :** The expected value of the loss given that the loss exceeds VaR



Ref: Optimization Methods in Finance by Gerard Cornuejols, Reha Tutuncu, Cambridge University Press
Image courtesy: http://www.imes.boj.or.jp/english/publication/mes/2002/me20-1-3.pdf)

How to Implement VaR and CVaR?

Methodology:

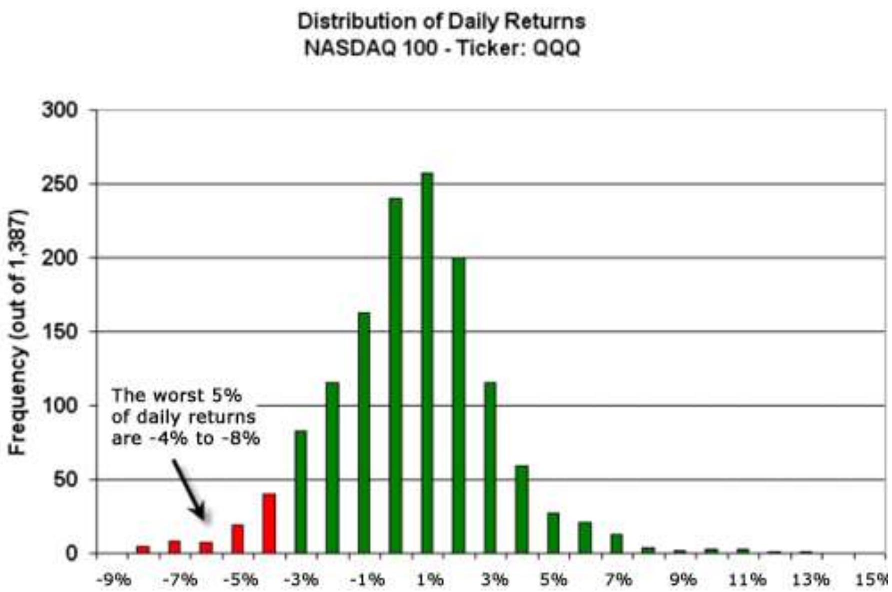
- Historical
- Variance-Covariance method
- Monte-Carlo simulations

All 3 models are implemented in:

- MATLAB
- Python
- R

Methods to compute VaR and CVaR

- Historical method



1. Compute Daily Returns and sort them in ascending order
2. For a given confidence level (α, e.g. 95%) , find $VaR_{\alpha}(X)$ such that:

$$P(X <= VaR_{\alpha}(X)) = \alpha$$

3. Compute CVaR by taking the average loss of the tail

Image Courtesy: http://www.investopedia.com/articles/04/092904.asp

Methods to compute VaR and CVaR

- Variance-Covariance Method

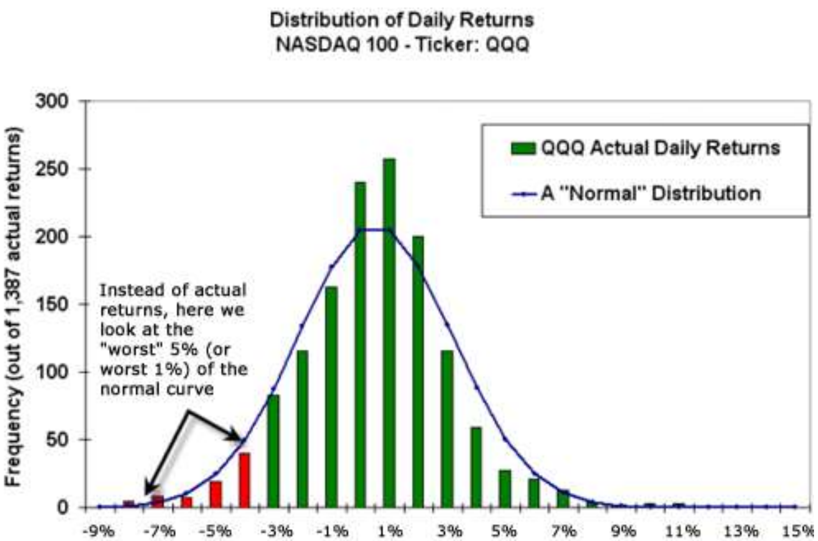


Image Courtesy: http://www.investopedia.com/articles/04/092904.asp

1. Compute Daily Returns and fit a Normal distribution to obtain mean and Standard Deviation (μ & σ)
2. For a given confidence level (α, e.g. 95%) , find $VaR_{\alpha}(X)$ such that:

$$P(X <= VaR_{\alpha}(X)) = \alpha$$

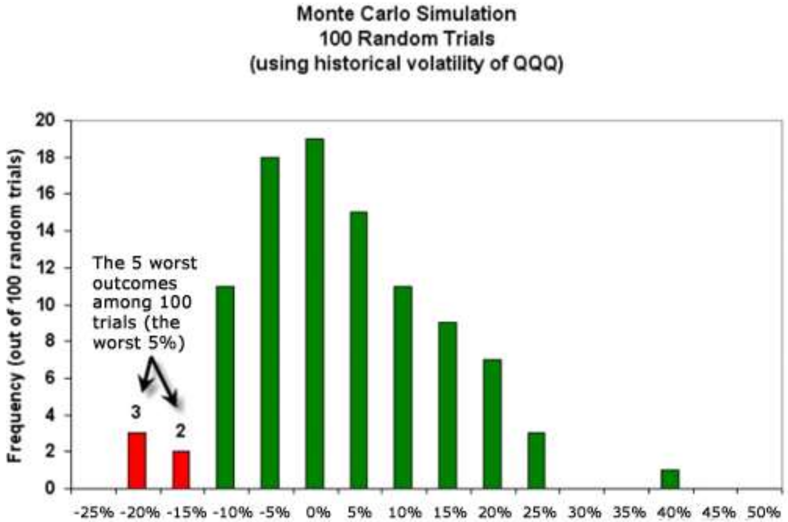
Example 95% => -1.65* σ

3. Compute CVaR by taking the average loss of the tail

(See Yamai and Yoshiba http://www.imes.boj.or.jp/english/publication/mes/2002/me20-1-3.pdf)

Methods to compute VaR and CVaR

- Monte-Carlo Simulations



1. Compute Daily Returns and fit a Normal distribution to obtain mean and Standard Deviation (μ & σ)
2. Run n Monte-Carlo simulations with random numbers drawn from a normal distribution described by (μ & σ)
3. For a given confidence level (α, e.g. 95%) , find VaR_{α} (X) such that:

$$P(X <= VaR_{\alpha}(X)) = \alpha$$

4. Compute CVaR by taking the average loss of the tail

Image Courtesy: http://www.investopedia.com/articles/04/092904.asp

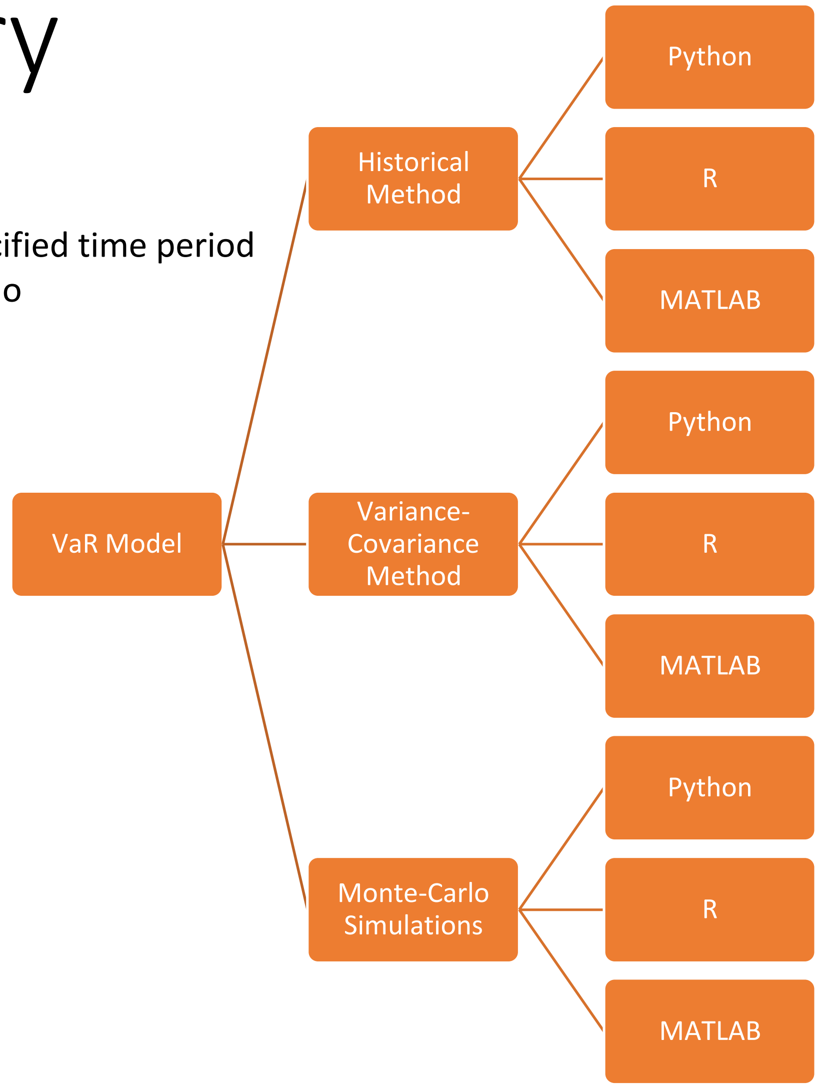
Model Summary

Given:

1. Historical Daily price time series for a specified time period
2. Constituents of a 3-asset long-only portfolio

Compute:

VaR and CVaR



Model Verification criteria

1. Model Benchmarking
   - MATLAB vs Python vs R
2. Parameter sweeps
   - Different Confidence Intervals (90, 95, 99)
3. Model Convergence
   - How many simulations needed ? (100, 500, 1000)
4. How do different methods compare?
   - Historical vs Variance-Covariance vs Monte-Carlo methods

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Value at Risk Demo

Search...

Asset 1

Asset 1

Allocation 1

Allocation 1

Asset 2

Asset 2

Allocation 2

Allocation 2

Asset 3

Asset 3

Allocation 3

Allocation 3

Enter Start Date

mm/dd/yyyy

Enter End Date

mm/dd/yyyy

METHOD	CONTROLLER	CONFIDENCE	SIMULATIONS
HIST	Matlab	80	100
NORM	Python	90	500
GARCH	R	99	1000
ALL			

Submit

Model Risk Analytics

Var Calculation Results

Search...

- All Jobs
- Method
- Controller
- Confidence
- Simulations
- Clean Up and New Test

Job ID	Asset 1	Allocation 1	Asset 2	Allocation 2	Asset 3	Allocation 3	Start Date	End Date	Platform	Iterations	Method	Confidence	VaR	CVaR	Status	Note
1	AAPL	10	AMZN	10	YHOO	80	10/10/2010	10/10/2011	Python	100	Historical	90	0.0000	0.0000	Submitted	
1	AAPL	10	AMZN	10	YHOO	80	10/10/2010	10/10/2011	Python	100	Historical	90	-0.0206	-0.0338	Completed	Job Com withc error
2	AAPL	10	AMZN	10	YHOO	80	10/10/2010	10/10/2011	R	100	Historical	90	-0.0204	-0.0321	Completed	Job Com withc error
2	AAPL	10	AMZN	10	YHOO	80	10/10/2010	10/10/2011	R	100	Historical	90	0.0000	0.0000	Submitted	
3	AAPL	10	AMZN	10	YHOO	80	10/10/2010	10/10/2011	Python	100	Distributed	90	0.0000	0.0000	Submitted	
3	AAPL	10	AMZN	10	YHOO	80	10/10/2010	10/10/2011	Python	100	Distributed	90	-0.0243	-0.0329	Completed	Job Com withc error
4	AAPL	10	AMZN	10	YHOO	80	10/10/2010	10/10/2011	R	100	Distributed	90	-0.0223	-0.0311	Completed	Job Com withc error
4	AAPL	10	AMZN	10	YHOO	80	10/10/2010	10/10/2011	R	100	Distributed	90	0.0000	0.0000	Submitted	

Where have we used this approach?

Example 1: External Model Verification

- Large bank, no formal model validation team
- Model to estimate future cash flows factoring defaults and many other parameters
- 20+ parameters, 100+ assets
- Impossible to manually stress test the model thoroughly

Solution :

- Identified important parameters and ran more than 10000 tests automatically
- Identified multiple issues where model failed especially when handling edge cases

Where have we used this approach?

Example 2: Energy Forecasting and Risk Management

- Energy company with more than 100,000 customers
- Model to estimate future energy usage based on historical usage, temperature forecasts etc.
- 5+ parameters, 100K+ assets
- Data-Driven model to help source wholesale energy and to hedge exposures

Solution :

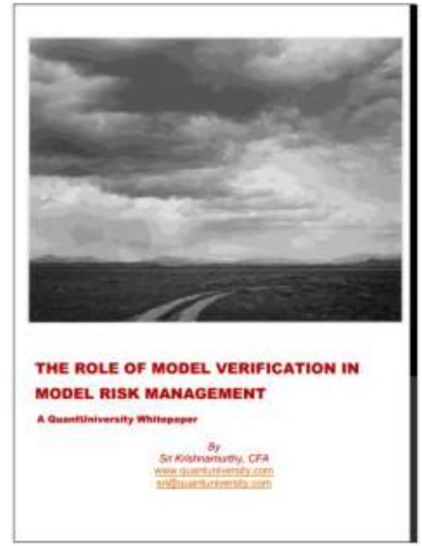
- Working on building 100K+ models that will be clustered later
- Need to run the model monthly factoring changing portfolio characteristics and new market information

Features

- Asynchronous
- Language-agnostic model parameter specification
- Can support massive scale of tests
- Systematic and Test results archivable and reproducible

Additional Features in the Works

- Model Definition Language
  - To specify model parameters
- ModelRisk Engine Optimization
  - Leverage infrastructure in the cloud
    - Resource constraints:
      - Budget
      - Time constraints
    - Priority queues and jobs
    - Dynamic scaling and load balancing



Quantifying Model Risk
Wilmott Magazine
January 2014

The Decalogue
Wilmott Magazine
July 2014

The Role of Model Verification in Model Risk Management
Oct 2014

Copies can be downloaded at :

http://www.quantuniversity.com/w6.html

http://www.quantuniversity.com/w9.html

http://quantuniversity.com/ModelVerificationForMRM.pdf

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Thank you!

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