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MONTE CARLO ANALYSIS/SIMULATION

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Abstract: Monte Carlo methods, or Monte Carlo experiments, are a **broad class of computational algorithms that rely on repeated random sampling to obtain numerical results**. The Underlying concept is to use randomness to solve problems that might be deterministic in principle.
A Monte Carlo simulation can be used to tackle a range of problems in virtually every field such as finance, engineering, supply chain, and science. It is also referred to as a multiple probability simulation.

keywords: random, probability, simulation, statistics, distribution.

INTRODUCTION

- A Monte Carlo simulation is a model used to predict the probability of different outcomes when the intervention of random variables is present.
- Monte Carlo simulations help to explain the impact of risk and uncertainty in prediction and forecasting models.
- A variety of fields utilize Monte Carlo simulations, including finance, engineering, supply chain, and science.
- The basis of a Monte Carlo simulation involves assigning multiple values to an uncertain variable to achieve multiple results and then averaging the results to obtain an estimate.
- Monte Carlo simulations assume perfectly efficient markets.

Monte Carlo Simulation Method

The basis of a Monte Carlo simulation is that the probability of varying outcomes cannot be determined because of random variable interference. Therefore, a Monte Carlo simulation focuses on constantly repeating random samples to achieve certain results.
A Monte Carlo simulation takes the variable that has uncertainty and assigns it a random value. The model is then run and a result is provided. This process is repeated again and again while assigning the variable in question with many different values. Once the simulation is complete, the results are averaged together to provide an estimate.
One way to employ a Monte Carlo simulation is to model possible movements of asset prices using excel or a similar program. There are two components to an asset's price movement: drift, which is a constant directional movement, and a random input, which represents market vitality.

How Monte Carlo Simulation Works

Monte Carlo simulation performs risk analysis by building models of possible results by substituting a range of values—a probability distribution—for any factor that has inherent uncertainty. It then calculates results over and over, each time using a different set of random values from the probability functions. Depending upon the number of uncertainties and the ranges specified for them, a Monte Carlo simulation could involve thousands or tens of thousands of recalculations before it is complete. Monte Carlo simulation produces distributions of possible outcome values.
By using probability distributions, variables can have different probabilities of different outcomes occurring. Probability distributions are a much more realistic way of describing uncertainty in variables of a risk analysis.

- **Normal**

Or "bell curve." The user simply defines the mean or expected value and a standard deviation to describe the variation about the mean. Values in the middle near the mean are most likely to occur. It is symmetric and describes many natural phenomena such as people's heights. Examples of variables described by normal distributions include inflation rates and energy prices.

- **Lognormal**

Values are positively skewed, not symmetric like a normal distribution. It is used to represent values that don't go below zero but have unlimited positive potential. Examples of variables described by lognormal distributions include real estate property values, stock prices, and oil reserves.

- **Uniform**

All values have an equal chance of occurring, and the user simply defines the minimum and maximum. Examples of variables that could be uniformly distributed include manufacturing costs or future sales revenues for a new product.

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- **Triangular**

The user defines the minimum, most likely, and maximum values. Values around the most likely are more likely to occur. Variables that could be described by a triangular distribution include past sales history per unit of time and inventory levels.

- **PERT**

The user defines the minimum, most likely, and maximum values, just like the triangular distribution. Values around the most likely are more likely to occur. However values between the most likely and extremes are more likely to occur than the triangular; that is, the extremes are not as emphasized. An example of the use of a PERT distribution is to describe the duration of a task in a project management model.

- **Discrete**

The user defines specific values that may occur and the likelihood of each. An example might be the results of a lawsuit: 20% chance of positive verdict, 30% change of negative verdict, 40% chance of settlement, and 10% chance of mistrial.
During a Monte Carlo simulation, values are sampled at random from the input probability distributions. Each set of samples is called an iteration, and the resulting outcome from that sample is recorded. Monte Carlo simulation does this hundreds or thousands of times, and the result is a probability distribution of possible outcomes. In this way, Monte Carlo simulation provides a much more comprehensive view of what may happen. It tells you not only what could happen, but how likely it is to happen.

- Monte Carlo simulation provides a number of advantages over deterministic, or "single-point estimate" analysis:
  - Probabilistic Results. Results show not only what could happen, but how likely each outcome is.
  - Graphical Results. Because of the data a Monte Carlo simulation generates, it's easy to create graphs of different outcomes and their chances of occurrence. This is important for communicating findings to other stakeholders.
  - Sensitivity Analysis. With just a few cases, deterministic analysis makes it difficult to see which variables impact the outcome the most. In Monte Carlo simulation, it's easy to see which inputs had the biggest effect on bottom-line results.
  - Scenario Analysis: In deterministic models, it's very difficult to model different combinations of values for different inputs to see the effects of truly different scenarios. Using Monte Carlo simulation, analysts can see exactly which inputs had which values together when certain outcomes occurred. This is invaluable for pursuing further analysis.
  - Correlation of Inputs. In Monte Carlo simulation, it's possible to model interdependent relationships between input variables. It's important for accuracy to represent how, in reality, when some factors goesup, others go up or down accordingly.

An enhancement to Monte Carlo simulation is the use of Latin Hypercube sampling, which samples more accurately from the entire range of distribution functions.

Monte Carlo Methods in Statistics

Monte Carlo methods are experiments. Monte Carlo experimentation is the use of simulated random numbers to estimate some functions of a probability distribution. A problem that does not have a stochastic component sometimes may also be posed as a problem with a component that can be identified with an expectation of some function of a random variable. The problem is then solved by estimating the expected value by the use of a simulated sample from the distribution of the random variable.
Monte Carlo methods use random numbers, so to implement a Monte Carlo method, it is necessary to have a source of random numbers. As we mentioned above, there are a number of good methods for generating random numbers.
Monte Carlo methods are used in a variety of ways in statistics. They are widely used in the development of statistical methods, very often to compare methods or modifications of methods. Monte Carlo methods can also be used directly in statistical inference, for example, in Monte Carlo tests, and in parametric bootstrap methods.

Monte Carlo simulations are a useful way of evaluating both the accuracy and reproducibility of a particular pulse sequence and analysis method. They involve generating a simulated spectrum by combining simulated or experimental basis spectra together in approximately physiological concentrations and then adding noise to achieve SNR that is experimentally realistic. The simulated spectra can also be line broadened to simulate various shimming conditions. Finally, the simulated spectra are analyzed using the fitting method of choice, and the resulting estimated metabolite concentrations are compared with the known input concentrations (Hancu, 2009; Hancu & Port, 2011). By repeating this procedure many times, using different noise seeds, it is possible to generate an estimate of both the accuracy and the reproducibility of the analysis method. shows an example plot of the estimated versus actual metabolite concentration that can be generated using Monte Carlo simulations to assess both accuracy and reproducibility. One criticism of Monte Carlo simulations is that the simulated spectra often do not include any of the experimental imperfections that are observed in real data, and so the accuracy and reproducibility may be overestimated.

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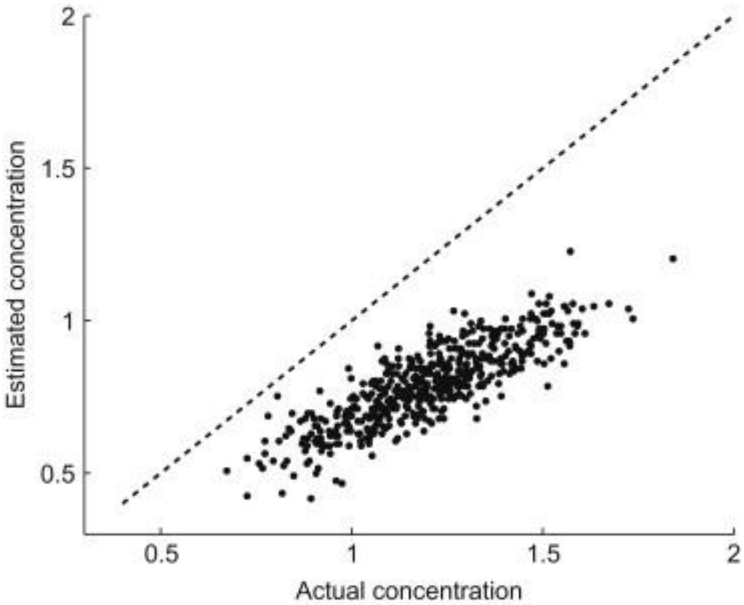

Numerical integration Most problems can be solved by integration Monte-Carlo integration is the most common application of Monte-Carlo methods Basic idea: Do not use a fixed grid, but random points, because: 1. Curse of dimensionality: a fixed grid in D dimensions requires N D points 2. The step size must be chosen first Monte Carlo Methods Stéphane Paltani What are Monte-Carlo methods? General concepts Applications Simple examples Generation of random variables Markov chains Monte-Carlo Error estimation Numerical integration Optimization Error estimation Given any arbitrary probability distribution and provided one is able to sample properly the distribution with a random variable (i.e., x ∼ f(x)), Monte-Carlo simulations can be used to: I determine the distribution properties (mean, variance,. . .) I determine confidence intervals, i.e. P(x > α) = R ∞ α f(x)dx I determine composition of distributions, i.e. given P(x), find P(h(x)), h(x) = x 2 ; cos(x) − sin(x); . . . Note that these are all integrals! Monte Carlo Methods Stéphane Paltani What are Monte-Carlo methods? General concepts Applications Simple examples Generation of random variables Markov chains Monte-Carlo Error estimation Numerical integration Optimization Optimization problems Numerical solutions to optimization.

SUMMARY AND CONCLUSION

This study chooses six main risk factors in system development area, which are widely mentioned by many researchers. Quantitative surveys are used to collect data on risk factors' potential effects and the level of project performance, then based on the data, we adopt SEM method and establish a multiple regression equation between project performance and six risk factors. At the beginning of the simulation, we use the existing data to fit a distribution for each risk factor, then through Monte-Carlo simulation, we get the probability distribution and frequency chart of project performance, on average, the project has a good performance with the mean value of 39.08. Also, the sensitivity chart shows that User Participation, Project Communication, Personnel Conflict have more greater impact on performance than other risk factors. In this study, we use questionnaires to collect data, but due to the limitation of time and space, we don't collect enough data across the whole country. Further research is expected to collect data in a wide range of system development projects. In addition, regarding the performance equation, we can also consider it from other perspectives, for example, performance can be expressed in revenue and cost function. Acknowledgements We would like to express our appreciate to the project managers in Dalian city for their support, and thank my roommates for their assistance in the process of giving out questionnaires. Also, I would like to thank Dr. Yang to give me such a chance to participate in this project.

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