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Chapter 1 : Predictive analytics - Wikipedia

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If you have any queries, please contact our administrators. The course description states that a familiarity with Excel is essential, exactly what constitutes familiarity? If you are concerned about your familiarity with Excel, then have a look at one of the early examples ahead of time. Are there any reading recommendations such as books and articles to make sure that my knowledge is sufficient for the course? All of the exercises we will cover in the course are included in this book, but there is no need to attempt the exercises ahead of time. The following article describes an introduction to Markov modelling: Briggs A, Sculpher M. Introducing Markov models for economic evaluation. PharmacoEconomics ; 13 4: An Excel version of the model can be downloaded from our website at http: Although I do not have direct modeling experience I am familiar with many of the basic concepts of economic modelling and have seen some of the models that have been developed by outside agencies for our company. I would be keen to participate in a course that challenges me, and I think that the course content of this course looks particularly interesting. Do you think that I would benefit from the course? Enthusiasm is probably the most important requirement. The key decision for you is whether to attend the Foundations course first or to go straight to the Advanced course. To help you decide, we suggest you review the article and model download listed under FAQ 2 above. If you find this challenging, consider starting with the Foundations course. Is the course the same as that held in York? Yes, the faculty and the material is the same as the York course, we run it twice, once at each of our institutions. The core faculty is the same, but the tutors will come from our respective research teams. Is the course ECTS-credit eligible? No, our courses are not credit eligible. Do you offer any discounts on the course fee? A discounted rate is available for applicants from the academic and public sector, and we can offer a further discount for multiple applicants. If a single company or institution books four places, we will offer a further place free of charge. Is the course fee including VAT? No, the course fee is VAT-exempt. How can I pay for the course? We are using Eventbrite for course fee payment. A variety of cards are accepted for payment. Alternatively, if you require one, we can issue an invoice which can be paid by bank transfer, Visa card, MasterCard or by cheque. If you need an invoice, please contact ihw-hehta glasgow. When is my payment of the course fee due? The course fee is payable in advance, and payment is due 30 days from the date of the invoice. What is included in the course fee? There is also a drinks reception on the Thursday evening for those attending the Advanced course. Is there accommodation available on the campus for students following this course? Unfortunately there is no accommodation available on the campus. However, when you book on the course we will send you a list of local establishments, with a variety of price ranges, which have been recommended by previous course participants. How often do you run the course? We run this course once a year in early autumn. The course also runs once a year in March at the University of York: Where can I find more information about your CPD courses? For details about our courses please visit our website at http: Downloads Supporting material for Decision Modelling for Health Economic Evaluation To support the exercises, we have developed a set of exercise templates and solutions. Files are labelled to correspond to the chapter numbering.

Chapter 2 : Sessions | iEMSs

â€¢ Resulting model is combination of two decision trees (T1 and T2) each with 2 leaves. â€¢ The value of is the mean MEDV, while P_MEDV is the predicted value â€¢ An observation with LSTAT = 6 and RM = 5 would have a P_MEDV value of +.

Coding standards or coding conventions Sustainable pace i. The core practices are derived from generally accepted best practices, and are taken to extremes: Interaction between developers and customers is good. Therefore, an XP team is supposed to have a customer on site, who specifies and prioritizes work for the team, and who can answer questions as soon as they arise. In practice, this role is sometimes fulfilled by a customer proxy. If learning is good, take it to extremes: Reduce the length of development and feedback cycles. Simple code is more likely to work. Therefore, extreme programmers only write code to meet actual needs at the present time in a project, and go to some lengths to reduce complexity and duplication in their code. If simple code is good, re-write code when it becomes complex. Code reviews are good. Therefore XP programmers work in pairs, sharing one screen and keyboard which also improves communication so that all code is reviewed as it is written. Testing code is good. Therefore, in XP, tests are written before the code is written. The code is considered complete when it passes the tests but then it needs refactoring to remove complexity. The system is periodically, or immediately tested using all pre-existing automated tests to assure that it works. It used to be thought that Extreme Programming could only work in small teams of fewer than 12 persons. However, XP has been used successfully on teams of over a hundred developers. Peter describes FDD as having just enough process to ensure scalability and repeatability while encouraging creativity and innovation. More specifically, Feature Driven Development asserts that: A system for building systems is necessary in order to scale to larger projects. A simple, but well-define process will work best. Process steps should be logical and their worth immediately obvious to each team member. Good processes move to the background so team members can focus on results. Short, iterative, feature-driven life cycles are best. FDD proceeds to address the items above with this simple process numbers in brackets indicate the project time spent: Develop an overall model 10 percent initial, 4 percent ongoing 2. Build a features list 4 percent initial, 1 percent ongoing 3. Plan by feature 2 percent initial, 2 percent ongoing 4. Design by feature 5. So the Joint Application Development JAD methodology aims to involve the client in the design and development of an application. This is accomplished through a series of collaborative workshops called JAD sessions. JAD focuses on the business problem rather than technical details. It is most applicable to the development of business systems, but it can be used successfully for systems software. Its success depends on effective leadership of the JAD sessions; on participation by key end-users, executives, and developers; and on achieving group synergy during JAD sessions. In contrast to the Waterfall approach, JAD is thought to lead to shorter development times and greater client satisfaction, both of which stem from the constant involvement of the client throughout the development process. On the other hand, with the traditional approach to systems development, the developer investigates the system requirements and develops an application, with client input consisting of a series of interviews. Rapid application development RAD , a variation on JAD, attempts to create an application more quickly through strategies that include fewer formal methodologies and reusing software components. This methodology embodies the notion of dynamic stability which can be thought of as similar to how Scrum embraces controlled chaos. Bob Charette, the originator, writes that the measurable goal of LD is to build software with one-third the human effort, one-third the development hours and one-third the investment as compared to what SEI Software Engineering Institute CMM Level 3 organization would achieve. There are 12 principles of Lean Development: Satisfying the customer is the highest priority. Always provide the best value for the money. Success depends on active customer participation. Every LD project is a team effort. Domain, not point, solutions. An 80 percent solution today instead of percent solution tomorrow. Product growth is feature growth, not size growth. Never push LD beyond its limits. Rapid-Development Languages RDLs produce their savings by reducing the amount of construction needed to build a product. Although the savings are realized during construction, the ability to shorten the construction cycle has projectwide implications: Because RDLs often lack first-rate performance, constrain flexibility, and are limited to specific kinds of problems, they are usually better suited to the development of in-house business software and limited-distribution custom software than systems software. RAD rapid application development proposes that products can be developed faster and of higher quality by: Using workshops or focus groups to gather requirements. Prototyping and user testing of designs. Following a schedule that defers design improvements to the next product version. Keeping review meetings and other team communication informal. There are commercial products that include requirements gathering tools, prototyping tools, software development environments such as those for the Java platform, groupware for communication among development members, and testing tools. RAD usually embraces object-oriented programming methodology, which inherently fosters software re-use. This process recognizes that the traditional waterfall approach can be inefficient because it idles key team members for extended periods of time. Many feel that the waterfall approach also introduces a lot of risk because it defers testing and integration until the end of the project lifecycle. Problems found at this stage are very expense to fix. By contrast, RUP represents an iterative approach that is superior for a number of reasons: It lets you take into account changing requirements which despite the best efforts of all project managers are still a reality on just about every project. Risks are usually discovered or addressed during integration. With the iterative approach, you can mitigate risks earlier. Iterative development provides management with a means of making tactical changes to the product. It allows you to release a product early with reduced functionality to counter a move by a competitor, or to adopt another vendor for a given technology. Iteration facilitates reuse; it is easier to identify common parts as they are partially designed or implemented than to recognize them during planning. When you can correct errors over several iterations, the result is a more robust architecture. Performance bottlenecks are discovered at a time when they can still be addressed, instead of creating panic on the eve of delivery. Developers can learn along the way, and their various abilities and specialties are more fully employed during the entire lifecycle. Testers start testing early, technical writers begin writing early, and so on. The development process itself can be improved and refined along the way. The assessment at the end of iteration not only looks at the status of the project from a product or schedule perspective, but also analyzes what should be changed in the organization and in the process to make it perform better in the next iteration. Scrum Methodology Scrum is an agile method for project management developed by Ken Schwaber. Its goal is to dramatically improve productivity in teams previously paralyzed by heavier, process-laden methodologies. Scrum is characterized by: A living backlog of prioritized work to be done. Completion of a largely fixed set of backlog items in a series of short iterations or sprints. A brief daily meeting called a scrum , at which progress is explained, upcoming work is described, and obstacles are raised. A brief planning session in which the backlog items for the sprint will be defined. A brief heartbeat retrospective, at which all team members reflect about the past sprint. Scrum is facilitated by a scrum master, whose primary job is to remove impediments to the ability of the team to deliver the sprint goal. The scrum master is not the leader of the team as they are self-organizing but acts as a productivity buffer between the team and any destabilizing influences. Scrum enables the creation of self-organizing teams by encouraging verbal communication across all team members and across all disciplines that are involved in the project. Spiral Methodology The Spiral Lifecycle Model is a sophisticated lifecycle model that focuses on early identification and reduction of project risks. A spiral project starts on a small scale, explores risks, makes a plan to handle the risks, and then decides whether to take the next step of the project - to do the next iteration of the spiral. It derives its rapiddevelopment benefit not from an increase in project speed, but from continuously reducing the projects risk level - which has an effect on the time required to deliver it. Success at using the Spiral Lifecycle Model depends on conscientious, attentive, and knowledgeable management. It can be used on most kinds of projects, and its risk-reduction focus is always beneficial. The spiral methodology extends the waterfall model by introducing prototyping. It is generally chosen over the waterfall approach for large, expensive, and complicated projects. At a high-level, the steps in the spiral model are as follows: The new system requirements are defined in as much detail as possible. This usually involves interviewing a number of users representing all the external or internal users and other aspects of the existing system. A preliminary design is created for the new system. A first prototype of the new system is constructed from the preliminary design. This is usually a scaled-down system, and represents an approximation of the characteristics of the final product.

Chapter 3 : Advanced Methods

High rate continuum modeling mesh reduction methodologies and advanced applications E. L. Baker, D. Pfau, J. M. Pincay, T. Vuong & K. W. Ng U.S. Army Armament.

Web-based systems development Reviews and Testimonials This book provides the latest research in topic areas ranging from spatio-temporal data modeling to software project management to user interface generation to empirical evaluation of web based system development methods. The chapters in this book represent the state of the art in several streams that are ongoing in SAND research is Europe and North America. While not exhaustive, these symposia represent on-going work in several different areas of SAND. As such, the papers here discuss work ranging from spatio-temporal data modeling to software project management to user interface generation to empirical evaluation of web based system development methods. It describes the implementation of the 3SST spatio-temporal data model on a relational platform. It describes a model that considers social and temporal aspects of identity within each group in order to address the varying nature of temporal success. It highlights the usefulness of cardinality constraints during schema integration, in query transformation for more efficient search strategies, and proposed avenues of future research in this area. This chapter proposes a formal representation of the information that intersects across different UML diagrams in order to form a cohesive view of the domain. It presents implicit assumptions made by software engineers during analysis and also describes suitable item sets in undergraduate SAND courses. It compares the curricula of information systems and computer science studies in Polish higher education institutions to the Association for Computing Machinery curricula recommendations and analyzes the prevalence of structured versus object-oriented approaches. The chapter explores the usage of UML specifications for interagency systems development, using a specific case study. The author explores the essential components of UML that need to be taught in a University curriculum, based on student surveys. It proposes a method to automatically infer a draft interface directly from an extended entity relationship EER model schema and lists the interactions that need to take place between the designer and the tool in order to generate the final user interface. The author attempts to determine the parameters, which should be taken into account in decisions relating to degrees of reusability that should be injected into code. This chapter encapsulates the main findings of an in-depth study of Web development practices in Ireland. The last four chapters are not from SIGSAND symposia; but were included because they represent topics that fit in well with the theme of this book. It motivates the need for conceptual expressiveness for enhancing the configurability of modeling languages. It utilizes game theory to design a trust based system so as to reduce false complaints filed by customers in high transaction environments. It illustrated how SAND principles can be used in the design of secure networks. It summarizes formal methods of system specification and illustrates how these can be used at the architecture stage to test complex software. Akhilesh Bajaj, University of Tulsa Dr. He received a B. He is on the editorial board of several journals in the MIS area. His research has been funded by the department of defense DOD. He teaches graduate courses on basic and advanced database systems, management of information systems, and enterprise wide systems. He teaches on a variety of subjects at the University of Gdansk, including information systems design, databases, e-business, and customer relationship management. He has authored more than publications in Polish and English. He is also the member of editorial boards of highly-ranked international professional journals.

Chapter 4 : Advanced Modeling Methods | PGIN | Course Catalog | The New School

Clarke, R. J. () Research Methodologies: 2 Agenda Definition of Research Research Paradigms (a.k.a research philosophy or research model) specifying concepts- phenomena of interest as defined in model, and.

HOME Advanced Methods This section presents an overview of advanced geospatial methods, which are used to estimate values at unsampled locations and model the spatial correlation of the data. These methods include varieties of kriging and conditional simulation. Kriging is a spatial interpolation method that allows estimation of values at unsampled locations and provides an estimate of the uncertainty in the interpolated values. Selection of a particular kriging method depends on the characteristics of the data set, such as trends present in the data or the degree of spatial correlation, which can be determined using variograms and other spatial correlation models. Information about using spatial correlation models, different kriging methods, and conditional simulation is also presented in this section. Spatial Correlation Models for Advanced Methods Kriging and simulation methods require a model of spatial correlation. Spatial autocorrelation can be modeled using the variogram or covariance function. Typically, the empirical variogram is plotted based on the data, and a variogram model is fit to the empirical variogram. These activities may be referred to as variography. In general, variography encompasses directional spatial autocorrelation, bivariate autocorrelation, and multivariate spatial autocorrelation. Most advanced geospatial methods rely on a search neighborhood to generate spatial predictions. The search neighborhood is selected based on the underlying spatial autocorrelation in the sampled population, and is simply the radius within which known values are used to predict unknown variables. Recognizing that correlation decreases with distance, the optimal search neighborhood is one which includes known values with a large influence and excludes the rest. The variogram expresses the variability of the data set as a function of space: The choice of the variogram parameters for example, lag, direction is a fundamental step for using advanced geospatial methods and should be done so as to be as representative as possible of the spatial characteristics of the data set. For example, if anisotropy is observed, which is common in environmental data, then an anisotropic variogram must be built that takes into account different spatial directions. Experimental variogram parameters are intrinsically linked to each particular data set; nevertheless, some recommendations can be made in order to create a suitable experimental curve. Lag When sampling is performed by following a regular grid, the regular distance between samples is taken as the value of the variogram lag. Distance between samples, however, is often irregular and the lag of the variogram then may be chosen by taking into account the different distances between the pairs of sampling locations. In this case, the value of the lag may be calculated by taking the average of distances between the sampling locations. As the distance between samples becomes larger, the reliability of the estimates of semivariance goes down. Consequently, a rough rule of thumb is that the maximum lag distance should not exceed half of the maximum distance between samples see Figure Angle Environmental data often has different levels of spatial correlation in different directions, which is referred to as anistropy. It is essential to account for anisotropy in variograms. Generally, the variogram map is used as a visualization tool for identifying anisotropic behaviors see Figure Anisotropy can be quantified by examining variograms constructed from data pairs along different directions. Then, four variograms are constructed: It is also possible to calculate the short-range variogram by taking shorter lags in order to specify the behavior at the origin. Therefore, a model must be created that is as representative as possible of the data and, by extension, of the experimental variogram previously constructed. The data set characteristics can guide the choice of the model to be used. In this case, an exponential or linear variogram may better represent this behavior. If a noncontinuous behavior is expected inorganic contamination, for instance or if analytical or sampling error is suspected, the nugget effect may represent such uncertainties. With the exception of the linear model, these theoretical models differ primarily in their behavior close to the origin. An illustration of the common theoretical variogram models is shown in Figure When fitting a variogram, whether to use a nugget effect, and the most suitable range or sill value must be determined. It is best to produce several variogram models that could match with the contaminant concentration behavior. Then, cross validation can be used to compare the accuracy of each model in order to identify the most appropriate. In the cross-validation process, several errors can be calculated such as mean standardized error or mean error. A robust model shows a standard error of the variance close to 1, a strong correlation between the true values and the estimated values and, finally, a standard error close to 0. Through the analysis of these parameters, the most suitable model the most accurate can be chosen. Figure 80 illustrates a cross-validation example and error analysis. Cross-validation example and error analysis using Isatis. The optimal search neighborhood is determined by the underlying spatial autocorrelation in the sampled population. The search neighborhood is optimized through evaluation of the semivariogram univariate case or cross-variogram multivariate case. Because kriging uses an optimized search neighborhood for generating spatial estimates the variogram is used to identify the distance over which properties are correlated , it is highly sensitive to the sample coverage, sample support, sample interval, and extent, which should be considered during the sampling design phases. The search neighborhood weights are chosen so that the estimator is unbiased difference between the predicted value and measured realization equals zero. Kriging solves a series of linear equations kriging system by minimizing the kriging variance. Different kriging methods are unique in their assumptions, constraints, limitations, and purpose. Popular kriging methods include ordinary kriging, indicator kriging, simple kriging see conditional simulation , factorial kriging, and universal kriging. Block kriging is a form of upscaling spatial information across a sampling domain. Point, or punctual, kriging is a means for downscaling spatial information across a sampling domain. The use of point or block kriging can be guided by the relationship of the sample design support and spacing to the interpolation grid cell size. Often, many different types of data are collected from a contaminated site to directly and indirectly assess factors controlling the fate and distribution of contaminants. In soil systems, for example, it is common to integrate environmental geophysics, LiDAR, and soil sample information to characterize a site in space over time. Measured parameters that exhibit shared structured spatial variation spatial autocorrelation or shared space-dependent variation can be used together for interpolation, which is the process of co-kriging. The search neighborhood is optimized through the cross variogram for co-kriging. Co-kriging is popular for integrating a high-resolution data set with a more sparsely sampled data set to generate spatial estimates with greater coverage. Co-kriging can be applied as block co-kriging or point co-kriging. In this case, the mean of the distribution is not representative of the data set. Ordinary kriging, also called the mean interpolator, performs the estimates of concentrations by using local means and the estimated values will be closely calculated around this mean. When an asymmetric distribution is observed, the kriged data histogram will not be consistent with the histogram of the original data. Performing logarithmic or Gaussian normalizing transformations of the raw distributions may remediate this effect. If they are being used, data transformation should be completed before proceeding with kriging methods. Moreover, Gaussian normal distributions are needed to perform the conditional simulation method. This type of distribution may minimize the influence of high values compared to the low ones, and reveal the best data distribution in order to obtain a more structured experimental variogram Below are general descriptions of point kriging and block kriging. These kriging approaches can be applied to all kriging methods discussed in this section. Point kriging generates a point-estimated value of a sampled property at an unsampled location, using optimally weighted, known sampled ambient values. Point kriging is useful for estimating or simulating a measured property at finer spatial resolutions than was used in sampling downscaling. Point kriging estimates are sensitive to local discontinuities and large nugget effects. Block kriging estimates a weighted average across a particular domain, in this case a grid cell or block. A predefined, regular-spaced interpolation grid is necessary to perform block kriging, which is ideal for studying regional patterns of variation, but not for local-scale variation. Block kriging inherently generates smoother maps than point kriging, helping to negate the effects of discontinuities in the data as well as other undesirable artifacts. The block kriging variance is lower in comparison to point kriging because the local scale variation, or within-block variation, is removedâ€”an advantage for data sets with a large nugget. Simple Kriging Simple kriging assumes that the mean of the data is constant and known, which is a restrictive assumption. Consequently, ordinary kriging is preferred because it assumes that the mean is unknown and must be estimated from the data. Simple kriging is not recommended to be used by itself, but is regularly applied in conditional simulation. Typical Applications Simple kriging is used for spatial interpolation when the mean and spatial correlation model are constant and known. Simple kriging is applied in conditional simulation. Data are second-order stationary if covariance function model is used or intrinsically stationary if variogram model is used. Spatial correlation is present among the data. No duplicate sites are present. The spatial correlation model for kriging can be based on either the covariance function or variogram. In general, it is easier to estimate a variogram model than a covariance function because no estimate of the mean is required. The pure nugget effect indicates the absence of spatial correlation. In this case, a deterministic geospatial method should be considered. Assumptions This method assumes the mean and variance are constant and known second-order stationarity. Strengths and Weaknesses This method is very restrictive due to the requirement that the mean is known. The quality of the kriging model fit to the data should be evaluated using cross validation or validation. In the context of optimization, see how to use the results of the geospatial methods to address specific optimization questions. Ordinary Kriging Ordinary kriging assumes that the overall mean is constant, though unknown, and the variance is finite the variogram has a sill value. The goal is to produce a set of estimates for which the variance of the errors is minimized. To accomplish this goal, ordinary kriging weights each sample based on its relative distance from the location of the data point to be predicted. Typical Applications Ordinary kriging is used to generate estimates of a sampled variable in unsampled locations. Using This Method This method is subject to the following constraints: Intrinsic stationarity â€"the variogram has a sill. No duplicate sites are used. The nugget is small relative to the sill. A pure nugget effect observed in the variogram indicates the absence of spatial correlation strict stationarity. A variogram with a large nugget relative to the sill indicates variability in the data that cannot be accurately predicted using kriging.

Chapter 5 : Software Development Methodologies

This dissertation, written by Shaghayegh Shabanian, and entitled Advanced Methodologies in Dynamic Traffic Assignment Modeling of Managed Lanes, having been approved in respect to style and intellectual content, is referred to you for judgment.

Advanced Methods and Approaches in Environmental Computing Advancements in computational methods and technology are always playing an important role for model development and application. Novel approaches that enable innovative software applications for environmental systems are requested; current and future computational challenges for modeling are among the proposed session topics. This session aims to serve as a forum for recent advances in the field of environmental software development that demonstrate experiences with big data, IoT, cloud, virtualisation or parallel computing and how these transform environmental modelling and software practice. Open Socio-environmental Modelling and Simulation Organizers: Min Chen, Jon Goodall, Albert Kettner, Alexey Voinov Applying socio-environmental modelling is a powerful strategy to better understand processes that interact with the earth surface. However, a single model alone has limited capacity for simulating complex socio-environmental phenomena, and it becomes a challenge for a single group with specific domain knowledge to address these comprehensive problems. In this respect, sharing models and therefore enabling their integration is a powerful approach, but at the same time a challenge to attract and engage dispersed multi-disciplinary experts. With collaborative research practices and the development of distributed, web-based architectures, an open socio-environmental modelling and simulation web-based architecture has now become within reach. Moreover, open refers to both the architecture and the research mode where ideas, data, knowledge, and models are freely shared. This session aims at exploring related theories, methods, and potential applications, facilitating communication between experts from multidisciplinary domains, encouraging extensive discussion regarding the potential directions of the field, and promoting further research for a bright future. Simulation, Optimization, and Metamodelling: Andre Dozier, Olaf David, John Labadie Managing environmental resources requires deep understanding of system responses to management solutions. Thus, for any given system, simulation of system responses is required while numerically optimizing management solutions. Often, as parallel efforts are being made to develop more accurate and integrated modelling infrastructure, environmental system models suffer from long computation times. Efforts to reduce computational complexities by parallelization or metamodelling have become important to better understand and optimize management solutions, but come with tradeoffs including increased resource utilization and decreased modelling accuracy. In this session, we will discuss the tradeoffs associated with metamodelling methodologies including linear regression, artificial neural networks, classification trees, and other forms of regression, and associated with parallelization of simulation, optimization, and metamodelling techniques. Andre Dozier, Olaf David Environmental resource assessment and management have long required improved technical modelling capacities because of the large breadth and variety of systems that influence environmental resources. Even with improved geophysical modelling capability, models struggle to predict impacts on social, environmental, and economic outcomes because of a lack of broader integration with socioeconomic or ecological feedbacks and methodologies. To enhance model integration capacities, the environmental modelling community has developed model integration frameworks. In this session, we will discuss a typology of problems these frameworks are designed to address, standards they implement to get there, languages they require, and platforms they sit on. We will also discuss ways of integrating across standards, languages, and platforms to identify techniques that span computing technologies to answer even larger integrated resource assessment and management problems. Wesley Lloyd, Olaf David Recent advances driven by the advent of cloud computing are enabling scientists to leverage increasingly accessible compute infrastructure for robust and cost effective environmental science. Innovations including the advent of software containers, by-the-second billing for compute resources, and serverless computing give modelers more options and flexibility than ever to deploy environmental science applications in the cloud while reducing infrastructure costs. Operating system containers such as Docker, support packaging all dependencies of environmental software into easy-to-build containers making software deployments easier while also improving the ability to reproduce scientific results. Scientists can disseminate preconfigured software and datasets easily through the convenient packaging offered by containers. Serverless computing platforms enable modelers to deploy code as microservices to the cloud providing always available, fault tolerant, and scalable software deployments for minimal cost. Additionally, cloud providers have improved infrastructure billing by now offering by-the-second, and even sub-second billing so that modelers will only pay for the resources they actually use. This session will provide a venue for the presentation and discussion on innovative uses of cloud computing, software services, virtualization, containerization, and serverless computing that enhance the development and deployment of Environmental Modelling Software. We will discuss how these new technologies are best leveraged to provide performance improvements and flexible software deployments while also providing cost effective infrastructure alternatives for hosting environment modelling software. These models provide a new avenue for improved water budget prediction, advancing hydrologic research, and opportunities for transformative experiences in graduate education. This session will cover a spectrum of topics including trade-offs between model resolution, accuracy, and computational requirements; near real-time flood forecasting and mapping applications; terrain and infrastructure feature description; model initialization and boundary condition specification; and new model performance evaluation methodologies. These advances in HPC have enable researchers to tackle ambitious and complex problems, e. This session focuses on but not limited to how recent evolution of HPC has enhanced research and discovery in environmental modelling. In particular submission are encouraged that introduce new ideas to the computational modelling field, modelling applications, and methodology to improve HPC performance. Big Data Solutions for Planning, Management, and Operation and Environmental Systems Processing data and environmental information using Big Data methods, identifying challenges, opportunities and solutions. Efficient environmental data management, storage, processing, and analytics at scale are topics for sessions in this stream. Andrea Cominola, Ashlynn Stillwell, Stefano Galelli, Andrea Castelletti Water and energy demands are changing worldwide due to population growth, urbanization, and land use and climate change. Understanding how these demands evolve at different spatial and temporal scales across heterogeneous scenarios is key to inform water and energy planning, management, and supply operations. Recent technological development and diffusion of advanced metering hardware, coupled with increasing data availability, emerging big data analytics, and data-learning techniques, are opening new opportunities to advance mathematical modelling of water and energy demands. This session aims to provide an active forum to discuss water and energy demand models emphasizing changing demand magnitude, peaks, spatial-temporal patterns, multi-sectoral interconnections, and multi-scale interrelations within the integrated urban water and energy systems. Hybrid modelling and innovative data analysis for integrated environmental decision support Organizers: Erechtchoukova Environmental resource assessment and management heavily rely on the results of observation data analysis, evaluation of related management scenarios via predicting their outcomes and developing mitigation measures, if such are necessary. The required analysis is interdisciplinary and complex since it is conducted on data collected by different agencies in various scales and forms based on data-driven, model-driven, or hybrid approaches. The latter are considered promising tool for solving multi-scale and interdisciplinary problems. The session invites original contributions on application of advanced analytical techniques to environmental resource assessment and management. The techniques include, but are not limited to, data-driven analysis and heterogeneous data integration and machining learning both supervised and unsupervised approaches, statistical data analysis and visualization, intelligent data analysis and its combination with process-based simulations, exploratory and confirmatory analysis. Hybrid frameworks and techniques, success stories of their application and lessons learned are also welcomed. According to the main focus of the iEMSs conference, we invite submissions of papers and presentations about applications of data science, data mining and related methodologies to sustainable food, energy and water systems, even if other environmental domains can be welcomed as well. New or improved techniques or methods are welcomed, as well as innovative applications, including heterogenous sources of information, like classical data, images, open text, semmantic data, georeferenced data, data streams among others. Integrated Social, Economic, Ecological, and Infrastructural Modeling Environmental models are increasingly used to assist planners and managers in the decision-making process. These processes often require integration of data and modeling tools from traditionally disparate disciplines. Moreover, interactions with stakeholders during model building may be vital for increased acceptance of modeling results. This session focuses on social, economic, ecological and infrastructural modeling efforts. Marcela Brugnach, Raffaele Giordano Participatory modelling expands modelling activity beyond prediction to include processes designed together with stakeholders bringing multiple forms of knowledge to the effort. However, doing so also brings the challenge of ambiguity, a type of uncertainty from the confusion among actors in the group over the concerning issues, problems and solutions; reflecting the many interpretations and meanings different actors bring to the modelling exercise. Ambiguity can be both a source of creativity and a source of conflict. While commonly overlooked during modelling, how ambiguity is resolved and embraced determines the quality of the participatory process supported by the modelling exercise, influencing what is being modeled and the outcomes generated. In this session we welcome contributions exploring methodological approaches or practical applications for coping with ambiguity in participatory modelling exercises. Decision-support tools have been developed to facilitate application of IWRM and prioritization of multiple goals and objectives by communities and watershed management organizations. This session will provide a series of case studies describing application of various decision support tools for IWRM, including both single and multiple-objective optimization approaches. Get Your Game On: Andre Dozier It has been said ten thousand hours or five years of full-time work generates an expert. Coincidently, by age 21, the average 21st-century young adult has accumulated 10, hours of game play! The benefits of serious games for scientific knowledge advancement and education have been shown clearly in several disciplines, but have yet to be thoroughly explored in managing natural resources. In this session, we will discuss contemporary and novel techniques that utilize games to enhance either current or future management of natural resources by i applying direct results of serious gameplay and associated scientific learning, ii training and educating a future generation on actions, consequences, and outcomes, and iii engaging the public to improve their awareness of problems and solutions. We will discuss learning opportunities that games present for both gamers and resource managers. Stakeholder groups use integrated models to explore the possible futures. Using these models can lead to improving social infrastructure institutional capacity and urban resilience. For this session we aim to bring together scholars who develop integrated models of urban systems and use them for policy support on topics like water governance, hurricane impacts, urban metabolism, urban heat effects, etc. Those models include both social dimensions actions of residents, political economy, evacuations, and land use change as well as biophysical dimensions urban climate, water runoff, subsidence, and pollution. Nagesh Kolagani, Alexey Voinov, Steven Gray, Miles McNall, Laura Schmitt-Olabisi The popularity of participatory modelling PM has grown considerably in recent years with the acknowledgement that the inclusion of stakeholders and a variety of perspectives are required to improve our understanding of social-ecological systems and current environmental problems. Yet a vast gap exists between what scientists know and what managers, policy-makers and other decision-makers do. The proposed session and the linked workshop will focus on interfaces, tools, methods and approaches that can be used in participatory modelling and stakeholder interaction, and effectively lead to action-oriented outcomes. The session and workshop will also consider ways of engaging decision-makers and stakeholders in a modelling process and methods for embedding modelling into decision making. We seek to attract action researchers and practitioners to explore recent developments in modelling with stakeholders, and invite papers on such efforts and on visualization, analytics, interaction, documentation, recording, and conceptualizing technologies that can help in these efforts. By bringing together diverse perspectives, we hope to assess current trends in the field and define new questions that characterize future directions in PM. We invite abstracts and proposals that represent a wide range of perspectives, including those from computer scientists, social and natural scientists, and cognitive scientists as well as those of decision-makers, managers or stakeholder experts. Some potential questions appropriate for this session include: How can computer models and mental models be better integrated to support decision-making? How computer interfaces can assist in linking mental models with systems models? How can they be improved for that purpose? How can model output be translated into terms meaningful for decision-makers? Ecosystem Services Values and Quantification: Audiences will be exposed to critical thinking on ecological flows of ecosystem services and their valuation methods. Our session welcomes three topics: Integrated Modelling of Urban Ecosystems Organizers: Green infrastructure in cities is heavily designed and managed, providing the opportunity to deliver multiple services. In order to identify the potential synergies or unintended consequences of interventions, integrated modelling approaches are needed, making use of inter- and trans-disciplinary collaborations. For example, modelling the contribution of vegetation to air pollution removal, urban cooling, and flood mitigation covers several scientific disciplines. Consideration of how people benefit from ES also requires input from psychology, economics, and social sciences. Interventions affecting the spatial configuration of green infrastructure involve engagement with stakeholders, civic society and planning authorities. However, many ES approaches fail to join these different components adequately. This session invites contributions covering the application of modelling approaches linking multiple services and beneficiaries, focusing on ES in urban environments. Ecosystem Services in a Context of Global Change: Quantification and Socio-economic Evaluation Organizers: In this context, it proposes to reconcile the water demand of society drinking water, agriculture, industry, cities, leisure, etc. In turn, ecosystem services are the many and varied benefits that humans freely gain from the natural environment. These natural benefits must be taken into account when studying the water management plans in a context of global change. For water resources, the related ecosystem services belong to provisioning, regulation, and cultural categories.

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Definition[edit] Predictive analytics is an area of statistics that deals with extracting information from data and using it to predict trends and behavior patterns. The enhancement of predictive web analytics calculates statistical probabilities of future events online. Predictive analytics statistical techniques include data modeling, machine learning, AI, deep learning algorithms and data mining. For example, identifying suspects after a crime has been committed, or credit card fraud as it occurs. It is important to note, however, that the accuracy and usability of results will depend greatly on the level of data analysis and the quality of assumptions. Predictive analytics is often defined as predicting at a more detailed level of granularity, i. This distinguishes it from forecasting. For example, "Predictive analyticsâ€"Technology that learns from experience data to predict the future behavior of individuals in order to drive better decisions. Define the project outcomes, deliverable, scope of the effort, business objectives, identify the data sets that are going to be used. Data mining for predictive analytics prepares data from multiple sources for analysis. This provides a complete view of customer interactions. Data Analysis is the process of inspecting, cleaning and modelling data with the objective of discovering useful information, arriving at conclusion Statistics: Statistical Analysis enables to validate the assumptions, hypothesis and test them using standard statistical models. Predictive modelling provides the ability to automatically create accurate predictive models about future. There are also options to choose the best solution with multi-modal evaluation. Predictive model deployment provides the option to deploy the analytical results into everyday decision making process to get results, reports and output by automating the decisions based on the modelling. Models are managed and monitored to review the model performance to ensure that it is providing the results expected. Types[edit] Generally, the term predictive analytics is used to mean predictive modeling , "scoring" data with predictive models, and forecasting. However, people are increasingly using the term to refer to related analytical disciplines, such as descriptive modeling and decision modeling or optimization. These disciplines also involve rigorous data analysis, and are widely used in business for segmentation and decision making, but have different purposes and the statistical techniques underlying them vary. Predictive models[edit] Predictive models are models of the relation between the specific performance of a unit in a sample and one or more known attributes or features of the unit. The objective of the model is to assess the likelihood that a similar unit in a different sample will exhibit the specific performance. This category encompasses models in many areas, such as marketing, where they seek out subtle data patterns to answer questions about customer performance, or fraud detection models. Predictive models often perform calculations during live transactions, for example, to evaluate the risk or opportunity of a given customer or transaction, in order to guide a decision. With advancements in computing speed, individual agent modeling systems have become capable of simulating human behaviour or reactions to given stimuli or scenarios. The available sample units with known attributes and known performances is referred to as the "training sample". The units in other samples, with known attributes but unknown performances, are referred to as "out of [training] sample" units. The out of sample units do not necessarily bear a chronological relation to the training sample units. For example, the training sample may consist of literary attributes of writings by Victorian authors, with known attribution, and the out-of sample unit may be newly found writing with unknown authorship; a predictive model may aid in attributing a work to a known author. Another example is given by analysis of blood splatter in simulated crime scenes in which the out of sample unit is the actual blood splatter pattern from a crime scene. The out of sample unit may be from the same time as the training units, from a previous time, or from a future time. Descriptive models[edit] Descriptive models quantify relationships in data in a way that is often used to classify customers or prospects into groups. Unlike predictive models that focus on predicting a single customer behavior such as credit risk , descriptive models identify many different relationships between customers or products. Descriptive models do not rank-order customers by their likelihood of taking a particular action the way predictive models do. Instead, descriptive models can be used, for example, to categorize customers by their product preferences and life stage. Descriptive modeling tools can be utilized to develop further models that can simulate large number of individualized agents and make predictions. Decision model Decision models describe the relationship between all the elements of a decisionâ€"the known data including results of predictive models , the decision, and the forecast results of the decisionâ€"in order to predict the results of decisions involving many variables. These models can be used in optimization, maximizing certain outcomes while minimizing others. Decision models are generally used to develop decision logic or a set of business rules that will produce the desired action for every customer or circumstance. Applications[edit] Although predictive analytics can be put to use in many applications, we outline a few examples where predictive analytics has shown positive impact in recent years. Analytical customer relationship management CRM [edit] Analytical customer relationship management CRM is a frequent commercial application of predictive analysis. Methods of predictive analysis are applied to customer data to pursue CRM objectives, which involve constructing a holistic view of the customer no matter where their information resides in the company or the department involved. CRM uses predictive analysis in applications for marketing campaigns, sales, and customer services to name a few. These tools are required in order for a company to posture and focus their efforts effectively across the breadth of their customer base. Several of the application areas described below direct marketing, cross-sell, customer retention are part of customer relationship management. Child protection[edit] Over the last 5 years, some child welfare agencies have started using predictive analytics to flag high risk cases. Additionally, sophisticated clinical decision support systems incorporate predictive analytics to support medical decision making at the point of care. A working definition has been proposed by Jerome A. It encompasses a variety of tools and interventions such as computerized alerts and reminders, clinical guidelines, order sets, patient data reports and dashboards, documentation templates, diagnostic support, and clinical workflow tools. They employed classical model-based and machine learning model-free methods to discriminate between different patient and control groups. Collection analytics[edit] Many portfolios have a set of delinquent customers who do not make their payments on time. The financial institution has to undertake collection activities on these customers to recover the amounts due. A lot of collection resources are wasted on customers who are difficult or impossible to recover. Predictive analytics can help optimize the allocation of collection resources by identifying the most effective collection agencies, contact strategies, legal actions and other strategies to each customer, thus significantly increasing recovery at the same time reducing collection costs. Cross-sell[edit] Often corporate organizations collect and maintain abundant data e. Customer retention[edit] With the number of competing services available, businesses need to focus efforts on maintaining continuous customer satisfaction , rewarding consumer loyalty and minimizing customer attrition. In addition, small increases in customer retention have been shown to increase profits disproportionately. Proper application of predictive analytics can lead to a more proactive retention strategy. Silent attrition, the behavior of a customer to slowly but steadily reduce usage, is another problem that many companies face. Predictive analytics can also predict this behavior, so that the company can take proper actions to increase customer activity. Direct marketing[edit] When marketing consumer products and services, there is the challenge of keeping up with competing products and consumer behavior. Apart from identifying prospects, predictive analytics can also help to identify the most effective combination of product versions, marketing material, communication channels and timing that should be used to target a given consumer. The goal of predictive analytics is typically to lower the cost per order or cost per action. Fraud detection[edit] Fraud is a big problem for many businesses and can be of various types: Some examples of likely victims are credit card issuers , insurance companies, [26] retail merchants, manufacturers, business-to-business suppliers and even services providers. Predictive modeling can also be used to identify high-risk fraud candidates in business or the public sector. Mark Nigrini developed a risk-scoring method to identify audit targets. He describes the use of this approach to detect fraud in the franchisee sales reports of an international fast-food chain. Each location is scored using 10 predictors. The 10 scores are then weighted to give one final overall risk score for each location. The same scoring approach was also used to identify high-risk check kiting accounts, potentially fraudulent travel agents, and questionable vendors. A reasonably complex model was used to identify fraudulent monthly reports submitted by divisional controllers. This type of solution utilizes heuristics in order to study normal web user behavior and detect anomalies indicating fraud attempts. Portfolio, product or economy-level prediction[edit] Often the focus of analysis is not the consumer but the product, portfolio, firm, industry or even the economy. For example, a retailer might be interested in predicting store-level demand for inventory management purposes. Or the Federal Reserve Board might be interested in predicting the unemployment rate for the next year. These types of problems can be addressed by predictive analytics using time series techniques see below. They can also be addressed via machine learning approaches which transform the original time series into a feature vector space, where the learning algorithm finds patterns that have predictive power. Project risk management When employing risk management techniques, the results are always to predict and benefit from a future scenario. The capital asset pricing model CAP-M "predicts" the best portfolio to maximize return. Probabilistic risk assessment PRA when combined with mini- Delphi techniques and statistical approaches yields accurate forecasts. These are examples of approaches that can extend from project to market, and from near to long term. Underwriting see below and other business approaches identify risk management as a predictive method. Underwriting[edit] Many businesses have to account for risk exposure due to their different services and determine the cost needed to cover the risk. For example, auto insurance providers need to accurately determine the amount of premium to charge to cover each automobile and driver. For a health insurance provider, predictive analytics can analyze a few years of past medical claims data, as well as lab, pharmacy and other records where available, to predict how expensive an enrollee is likely to be in the future. Predictive analytics can help underwrite these quantities by predicting the chances of illness, default , bankruptcy , etc. Predictive analytics can streamline the process of customer acquisition by predicting the future risk behavior of a customer using application level data. Proper predictive analytics can lead to proper pricing decisions, which can help mitigate future risk of default. Technology and big data influences[edit] Big data is a collection of data sets that are so large and complex that they become awkward to work with using traditional database management tools. The volume, variety and velocity of big data have introduced challenges across the board for capture, storage, search, sharing, analysis, and visualization. Examples of big data sources include web logs , RFID , sensor data, social networks , Internet search indexing, call detail records, military surveillance, and complex data in astronomic, biogeochemical, genomics, and atmospheric sciences. Big Data is the core of most predictive analytic services offered by IT organizations. Regression techniques[edit] Regression models are the mainstay of predictive analytics. The focus lies on establishing a mathematical equation as a model to represent the interactions between the different variables in consideration. Depending on the situation, there are a wide variety of models that can be applied while performing predictive analytics. Some of them are briefly discussed below. Linear regression model[edit] The linear regression model analyzes the relationship between the response or dependent variable and a set of independent or predictor variables. This relationship is expressed as an equation that predicts the response variable as a linear function of the parameters.

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Pricing methods for structured finance instruments can be essentially divided into two classes:1) bond models (single-scenario) and 2) stochastic methods. In addition, the Net Asset Value is a third approach commonly used to monitor these instruments.