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PANEL: ARE WE EFFECTIVELY PREPARING OUR STUDENTS TO BE CERTIFIED ANALYTICS PROFESSIONALS?

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ABSTRACT

An increase in media and business attention has raised the visibility of Operations Research and "Analytics." In 2012, INFORMS announced its Certified Analytics Professional (CAP) program to provide practitioners a standardized qualification in the field. Are we doing an adequate job of preparing our students to be analytics professionals in simulation? Our simulation courses tend to be heavily focused on methodology and analysis. Can and should we make room for the less technical skills tested during the certification process?

1 INTRODUCTION

In 2012, INFORMS announced its Certified Analytics Professional (CAP) program to provide practitioners a standardized qualification in the field. According to the CAP examination materials, a certified analytics professional should be able to handle the following tasks: (1) Framing the business problem; (2) Re-framing the business problem as an analytics problem; (3) Managing data (identification, acquisition, cleaning, analysis); (4) Selecting a methodology; (5) Building a model; (6) Deploying the model; (7) Managing the model over its life cycle; (8) Other soft skills such as partnering, communication, and teamwork.

This panel examines whether we are or should be preparing our students to be analytics professionals, as defined by CAP. The first four authors draw from many years of experience as professionals, academ ics, and consultants to provide a variety of viewpoints on the topic. The fifth author serves as the panel organizer and moderator.

2 RUSSELL CHENG: PREPARING STUDENTS TO BE ANALYTICS PROFESSIONALS

First, some comments on the eligibility requirements for taking the Certified Analytics Professional CAP exam (2013).

The eligibility requirements for taking the exam are demanding, particularly the length of time requirement of analytics work related experience. It is not clear if the nature of this experience is to be assessed for its quality, diversity and comprehensiveness and if there are criteria to be met if such experience is to be deemed satisfactory. Analytic work that is elementary, repetitive and narrow is a far cry from work that is advanced, varied and broadly based. A new taught course is judged on its syllabus, content and learning outcomes which all need to be set out. There needs to be equivalent aspects set out when defining what constitutes adequate analytic work related experience. Also just as one can become expert in specific academic subject areas, for example stochastic processes or combinatorial optimization, achieving comparable reputation and status irrespective of the actual area, so it should be recognized that work experience can be just as specific and still be equally well regarded.

In terms of my own background, my initial education was very mathematically focused involving mainly highly theoretical courses where, for example, matrices were regarded as simple applications of linear transformations. There was little regard for presentational skills. Elegance and incisive analysis was all that counted. Homework exercises were challenging problems requiring insightful non-standard application of what might otherwise have been elementary techniques. For my BS degree, my experience of even such basic communication skills as report writing and making presentations was almost non-existent.

However I am in many ways grateful for having received such an academic education. It has allowed me to tackle practical problems, at least technical problems, knowing that I have the background and knowledge to deploy powerful, well-founded methods for formulating and solving such problems with efficient, sometimes even elegant, methods. I would not want to see strong degree programmes watered down in trying to make them more 'practical'.

However I am very aware of the importance of being able to operate and work in the practical world. The three universities that I taught at were very different, but in all the degree programmes that I was involved with we placed great emphasis on exposure to the practicalities of the problems that our students studied. In particular we placed great emphasis on project work, in the majority of cases initiated and involving the collaboration and/or sponsorship of non-academic institutions including companies large and small ranging over a truly great diversity of different areas.

In my first institution, the University of Wales Institute of Science and Technology, now absorbed in Cardiff University, we offered the so-called sandwich course degree, a four year BS programme comprising two academic years, then a year out 'on placement' in industry followed by a final academic year. In the placement year the student was typically enrolled as an employee of a sponsoring company or organisation. The student would have an on-site industrial supervisor who was in touch on an essentially daily basis, and an academic supervisor in less regular contact but who would formally visit the student on-site three times in the year on placement. The year was graded and there were formal reports from the industrial and academic supervisors, with the industrial supervisor having to enter a grade for each of a number of criteria.

Even though the year out was carefully prepared, there was still significant variation experienced by different students. The nature of the work, the suitability of the project, the degree of care and supervision offered by the sponsoring organisation could all be rather variable. However despite this, I never had a student say it had not been a worthwhile year. A worry of some students was that they might have difficulty in returning to academic work in their final year. However it was always the case that they came back to university much clearer in what they wanted from their taught courses, they would be much better motivated and a year more mature in their studies.

In my second institution, the University of Kent at Canterbury, we ran four-year Management Science with a Foreign Language (usually French or German) BS programmes. A year was spent abroad, where students took technical courses delivered in the foreign language, but there was usually no industrial experience as such. It was impressive how confident, and multi-lingual such students became. These students would have to undertake a double unit project in their final year. I started to find sponsors for these projects in my time there and some were excellent ones in offering really good manufacturing experience.

In my last institution, Southampton University, we ran a well regarded MS programme in OR, later this was done in parallel with an MS in Management Science. These are one year programmes, including a three month summer project sponsored by an outside organisation. In my time there, we were able to guarantee every enrolled student such a project. At its high point some 60 odd projects had to be found each year. We asked for a financial contribution from each sponsor. This contribution was useful in ensuring that the sponsor provided only projects they were seriously interested in. The projects were discussed and had content and objectives agreed well before hand – a hugely time consuming task. We appointed first one then a second Industrial Liaison Officer whose overriding task was to find and set up such projects. These were part-time but senior posts, reflecting the importance attached. We were fortunate in finding excellent people for this who annually obtained a splendid variety of interesting and challenging projects. My own experience included projects done for high profile organisations like the World Health Organisation, McLaren Formula 1 Racing and British Airways. Allocating the projects was a challenging OR exercise using a bespoke computer programme which usually ensured every student was allocated one of their top three choices!

The MS degrees were well supported by an Industrial Committee, made up of members from organisations who regularly recruited OR graduates, who reviewed our courses and gave advice on their content and objectives.

The above arrangements provide three possible templates for how an OR department can include genuine industrial/business experience in their programmes without watering down their academic content; experience that students find really useful and important.

3 PETER HAAS: CAP-FRIENDLY SIMULATION INSTRUCTION

3.1 The Challenge

In my dual role as an industrial researcher and a consulting professor, I have conflicting feelings about the central question of this panel. In my industrial work, I have seen projects come to grief precisely due to a lack of the softer problem-framing, data management, teamwork, and communication skills required for CAP certification ("CAP skills", for short). So it seems clear that teaching such skills is essential, regardless of one's opinion of the CAP certification process itself. On the other hand, as an instructor of a ten-week graduate simulation course for students with widely varying skills and backgrounds, the prospect of cramming more material into an already intense course seems daunting at best. I believe, however, that the CAP challenge can, and should, spur innovation in the teaching of simulation. The following sections provide some suggestions and strategies for teaching CAP skills as part of an analytics curriculum in general, and a simulation class in particular.

3.2 Strategies for a CAP-Friendly Analytics Curriculum

Clearly, promoting CAP skills is a task that extends beyond an individual simulation class and encompasses the entire course of study. Two key issues here are real-world exposure and learning to deal with data.

3.2.1 Get Real

I would argue that tasks (1), (2), (3), (6), and (7) are almost impossible to teach in a classroom. Most textbook examples and case studies that can be consumed in an academic quarter are unrealistically well posed, small-scale, and simple compared to most of what I have encountered in industry. As a result, many students are shell-shocked by the ambiguities and complexities of their first post-graduation job. I would argue that the only real way to learn these skills is by doing, through project classes with real clients, summer internships, practicums, and the like. Such problem-focused experiences expose the student to the entire analytics toolkit and promote understanding of the relationship of simulation to other methodologies. Such experiences should be included as a mandatory requirement for any analytics degree program.

3.2.2 Teach Data-Wrangling Skills

Data is the locus of some significant tension between the simulation and broader analytics communities. The latter community typically obsesses about purely data-driven analysis techniques such as time-series analysis, data and text mining, and machine learning, while often scanting the role of first-principles models such as those used in simulation. The extreme version of this position was enunciated by Chris Anderson in his 2008 article in Wired Magazine, "The end of theory: The data deluge makes the scientific method obsolete" (Anderson 2008). The simulation community, on the other hand, traditionally has been a bit wary of data. One reason is that data has been traditionally hard to come by (think of stop-watches on factory floors). A deeper reason is that the purpose of a simulation study is to predict behavior of systems that do not now exist. Thus spending a lot of effort gathering data to validate a model offers no actual guarantees on the quality of the resulting analysis, and can result in unnatural torqueing of the model to match the data. (See Conway and McClain (2003) for a nice exposition of these ideas.)

There are compelling reasons why simulation practitioners need to become more data friendly. First, stop-watches have been replaced by ubiquitous sensors and web logs, and it is easy to obtain massive amounts of potentially useful data. Second, such data is being used not merely for model calibration and validation, but also to discover and quantify entities and relationships, such as in social network models, that can in turn be incorporated into the structure of simulation models. Indeed, the ability to exploit data is becoming increasingly important as simulation is used to attack ever-broader problems that often involve complex systems-of-systems, especially those involving human social interactions and behaviors. Overall, an analytics professional needs to master the interplay of data and models, becoming adept at explaining to the dataphiles the role of simulation as "deep predictive analytics", while also understanding the tools for obtaining, cleaning, transforming, storing, and analyzing data. It may make sense to require that analytics students take a course in information management prior to taking a simulation course. Then at least some of the simulation assignments could involve the retrieval and processing of data to build or parameterize a simulation model. Of course, real-world project experience, as discussed previously, is invaluable for learning data-management skills.

3.3 A More CAP-Friendly Simulation Class

In addition to curriculum-wide changes, what can be done within the scope of a simulation course to better promote CAP skills? Some suggestions are given below.

3.3.1 Provide Good War Stories

Although it is typically not possible to expose students to full-blown industrial problems, one can at least try to enrich the student experience with success stories and cautionary tales from the real world. For example, I try to attend interesting applied talks at the INFORMS National Meeting, WSC, and so on, and convince the speakers to give me copies of their slide decks, which I then post in a "practitioners gallery" on the class website. The hope is to entice the students to look at this material outside of class, so that they can be exposed to interesting CAP issues without a further hit on classroom time.

3.3.2 Encourage a Stochastic-Process Mindset

Carefully distinguish between a stochastic model, one or more stochastic processes associated with the stochastic model, and simulation as a tool for estimating or optimizing various functionals of the stochastic process. This viewpoint encourages clear thinking that separates the modeling and solution components of a project, and encourages thoughtful decisions about the most appropriate solution method for a given model. Forcing students to specify a stochastic model via a formalism such as networks of queues, event graphs, stochastic Petri nets, or generalized semi-Markov processes actively encourages parsimonious modeling, promotes precise model specification, and encourages flexibility in thinking about models.

3.3.3 Encourage Skepticism

Although activities around critiquing and sensitivity analysis of simulation models have traditionally been a part of any good simulation course, these activities are more important than ever in developing the critical-thinking skills central to analytics professionals. *Every* stochastic model presented in class should be critiqued, at least briefly. When dealing with a model that has been simplified for pedagogical purposes, try to give a glimpse of what the real-world analogues look like. Similarly, give students multiple opportunities to explore the effects of mis-specification with respect to statistical dependence, variability, skewness, non-stationarity, and so on, in a hands-on manner.

3.3.4 Reinforce the Basics

Many of the questions currently on the CAP exam are concerned with basic understanding of uncertainty and risk. So in addition to the usual technical material on simulation, try to occasionally give students some basic problems aimed at sharpening their probabilistic intuition. Sam Savage's book "The Flaw of Averages" is an excellent source of material for such exercises (Savage 2012). The sample CAP problems also make good examples. (Some of them are derived from Savage's book.) One interesting exercise is to have students analyze the differences in expected performance between a small number of alternative systems and explain their results; the twist is that, unknown to the students, the expected performance is actually identical for all systems. This exercise is a great way to drive home the importance of confidence intervals.

3.3.5 Teach More Effectively

A broad array of methods for improving engineering education have been proposed over the past few decades, and many of these align well with the goals of CAP education. An excellent discussion of such methods can be found in Felder et al. (2000). (Felder's website at NCSU contains many more teaching resources.) Many of these ideas involve teamwork, such as breaking up a lecture with idea-generating and problem-solving discussions in groups of two or three, or assigning cooperative learning exercises as homework. The latter activity involves forming mixed-ability teams, having the teams rotate specified roles, having the teams self-assess their performance, and so on. All of these activities map to CAP skills. Other ideas include methods for balancing concrete and abstract ideas in each class; this leads to more effective learning and helps prepare students to apply their skills in real-world situations. Finally, many techniques address improvement of communication skills, which are increasingly important when dealing with non-traditional consumers of simulation results.

3.4 Conclusion

Attempting to teach CAP skills over and above simulation methodology is difficult, but crucial. The responsibility for teaching CAP skills will need to be spread across the entire curriculum; in general, more attention needs to be paid to information-management skills, and students need guaranteed exposure to industrial-strength projects. That said, the CAP challenge can spur improvements in the teaching of simulation, such as modernizing the selection and balance of course topics, leveraging the experiences of practicing professionals, and adopting teaching methods that better promote the critical thinking, communication, and teamwork skills that are central to real-world effectiveness and professional success.

4 STEWART ROBINSON: EDUCATION FOR SIMULATION IN ANALYTICS AND THE ROLE OF SOFT SKILLS

4.1 Simulation in Analytics

I start this discussion by considering the positioning of simulation within analytics through a comparison of their respective definitions. I offer here my own definition of simulation: 'experimentation with a simplified imitation (on a computer) of an operations system as it progresses through time, for the purpose of better understanding and/or improving that system' (Robinson 2004). I could, of course, enter into a debate about the efficacy of this definition and I think it would be useful to test a range of simulation definitions for their match with the field of analytics. For now I highlight the key elements of this definition: a model that represents a system progressing through time, experimentation with that model, and the desire to understand and improve the system under study.

Unsurprisingly, there are a range of definitions for analytics. One of the best known is from Davenport and Harris (2007), who define analytics as the 'extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions. The analytics may be input for human decisions or may drive fully automated decisions.' Meanwhile, INFORMS define analytics as 'the scientific process of transforming data into insight for making better decisions' (www.informs.org/About-INFORMS/What-is-Analytics accessed May 2013).

Both analytics definitions identify the role of models in analytics, assuming we accept that models are the transformation process in the INFORMS definition. It can be assumed that simulation models are one of the model types referred to (Lustig et al. 2010). Both analytics definitions also highlight the aim of improving decision-making and in the latter case, for generating insight; this is similar to 'understanding and/or improving' in the simulation definition. Experimentation is not directly referred to in the definitions of analytics, but it seems safe to assume that this is covered by the 'extensive use of ... models'. As such, there seems to be a clear correspondence between the two and the simulation field is at least linked with analytics.

One possible divergence between analytics and simulation is that a simulation does not necessarily consume large volumes of data. Some simulations rely on very little data and at an extreme are purely theoretical models; see, for instance, Schelling's agent-based model of segregation (Schelling 1971). On the other hand, simulations can generate large volumes of data to which 'analytics' needs to be applied. This divergence might suggest that the simulation field intersects with analytics, but that it is not completely subsumed within it.

Lustig et al. (2010) describe three categories of analytics: descriptive, predictive and prescriptive. They place Monte Carlo simulation in the predictive analytics category. It is probably correct to assume that simulation (more generally than just Monte Carlo) is largely used in a predictive mode to determine the outcome (model outputs) of a set of actions (model inputs). Simulation is not, however, exclusively used for this purpose. Simulations are used in descriptive mode for understanding a system; it is often stated that much of the benefit of simulation comes from building the model. Simulations are also used prescriptively when optimising a model output (Basu 2013); although simulation optimisation does not seem to be extensively used.

My own work on analytics and operational research (www.whatisanalytics.co.uk accessed May 2013) identifies three strands in the analytics movement: technology, quantitative methods and decision-making. We can see elements of all these in the simulation field:

- Technology = modeling methodology
- Quantitative = analysis methodology
- Decision-making = simulation in practice

From this discussion I conclude that the simulation field intersects with analytic, but that it is not completely subsumed within it. Simulation is, of course, much smaller than the whole field of analytics. So given that simulation has a role within analytics, are we providing an adequate education in simulation for our students to be effective at using simulation as an analytics professional?

4.2 Preparing Students to be Analytics Professionals in Simulation

What does a typical simulation course look like? I suspect that simulation courses vary widely in content, and this will depend in part on the background of the staff teaching the course and the school from which the course is being taught. We know that simulation is taught from many perspectives e.g., business, engineering, computing and mathematics/statistics. As such, it is not possible to talk of a typical course.

Robinson and Davis (2010) discuss their undergraduate simulation course which they ran at the University of Warwick in the UK. The content of the eight week course is shown in Table 1. Whether this is anything like typical for a simulation course I will leave the reader to determine from their own experience.

Table 1: Content of the Warwick Simulation Course (Robinson and Davis 2010)

Week	Lecture	Workshop
1	What is simulation? Types, when to use it, an example case study.	
2	The discrete-event simulation method: activity cycle diagrams and the 3-phase method.	
3	Software for simulation: SIMUL8 and Visual Logic	
4	Conceptual modeling	Basics of Simul8
5	Input data: collection and analysis, Stat::Fit	More Simul8- Visual Logic
6	Verification and validation: concepts and methods	Stat::Fit software
7	Experimentation 1: obtaining results from a single run and comparing pairs of runs	Modeling exercise
8	Experimentation 2: running and comparing multiple scenarios	Experimentation

The Robinson and Davies (RD) course focuses on a range of skills covering computing, statistics, problem structuring/framing and project management. This is in line with Robinson's view that the practice of simulation requires skills in 'problem solving, computing, statistics, project management, people management and communication' (Robinson 2004 p. xviii). The students' learning was assessed across five criteria, as outlined in Table 2.

So does a course of this nature prepare a student for a career of using simulation as an analytics professional? To help answer this, I consider the skills required for someone working in analytics. In setting up their certified analytics program INFORMS carried out a job task analysis to identify the duties and responsibilities of an analytics professional (Nestler, Levis, and Klimack 2012). The 36 tasks identified were grouped into seven domains. The tasks and domains were then weighted with respect to their importance. Table 3 shows the domains and their respective weights.

Table 2: Simulation Module Assessment (Robinson and Davies 2010)

Element	Weight
Problem Specification and Conceptual Model	15%
Data Collection and Analysis	10%
Simulation Model in SIMUL8	25%
Verification and Validation	10%
Experimentation and Analysis	40%
Total	**100%**

There is not a direct correspondence between the headings in Table 2 and Table 3, which in itself suggest a mismatch between the RD course and the needs of an analytics professional. Broadly speaking RD place much less emphasis on problem and model framing (15% against 32%), data (10% against 22%), and model building including method selection (25% against 31%). RD place much greater emphasis on using the model (40% against 9%), whilst they do not directly assess life cycle management. RD directly address model validation which does not appear as its own domain in Table 3, although it is included in specific job tasks as a sub-set of model building and deployment.

Table 3: Analytics Professionals Job Task Domains (Nestler, Levis, and Klimack 2012)

Domain	Weight
Business problem (Question) framing	15%
Analytics problem framing	17%
Data	22%
Methodology (approach) selection	15%
Model building	16%
Deployment	9%
Life cycle management	6%

If we assume that the INFORMS job task domains are correct for simulation modelers, then I might conclude that there is a mismatch between the RD course and the needs of analytics professionals. However, we are only comparing at a surface level. This discrepancy might have arisen because the analytics job tasks are measuring what people actually do, while the RD course is teaching what should be done. Further, we are not considering the wider context of the degree programs within which the RD course sits. It is likely that students are gaining simulation/analytics relevant skills from other parts of their education.

We would expect some differences between simulation training and generic training for analytics. For instance, use of simulation models requires extensive knowledge of experimentation and analysis, which is not required for many of the other analytic modeling approaches (e.g. linear programming). This could explain the emphasis on experimentation in the RD course.

4.3 The Role of Soft Skills in Simulation Education

Should there be more emphasis on soft skills in simulation education? Almost certainly yes. A particular need is to develop skills in conceptual modeling (Robinson 2012). A key shortcoming in many simulation studies is developing over-elaborate models, or even incorrect models – a type III error (Balci 1994). Conceptual modeling is not easy to teach, but we should be attempting to develop our simulation curricula around this topic.

Problem framing is another vital soft skill for simulation modelers. Educating students in problem structuring methods (Rosenhead and Mingers 2001) could be highly beneficial in helping to develop these skills. Kotiadis (2007), for instance, demonstrates how one such problem structuring method (soft systems methodology) was used for determining objectives in a simulation study.

A third soft skill is the selection of the appropriate simulation method. More and more courses seem to be covering multiple simulation methods e.g. Monte Carlo, discrete event, system dynamics and agent based. Students need to learn how to select the appropriate method. The problem is that there is little established theory to help guide method selection.

Broader skills in communication, presentation and project management should also be developed. However, these are less simulation specific and probably belong in other parts of the university curriculum.

5 LEE SCHRUBEN: CAP COMMENTS

While I have reservations about the CAP written exam, I believe that developing the soft skills identified by the CAP program is vital to our students' success. We can help them do this without lowering the technical depth of our simulation courses by simply changing two letters in our course descriptions.

5.1 Projects to Products

A few years ago, I made a revolutionary change to my undergraduate simulation course without fully realizing it at the time. I changed two letters in my syllabus: instead of requiring the usual simulation group project, I required a term pro<u>du</u>ct. This introduced my students, some for the first time, to the soft skills essential to their becoming successful engineers.

A simulation term product is distinct from a conventional term project in that students create a tool to solve a class of problems, not just a solution to a specific problem. Product creation includes designing an interface and tutorials so others can use the product independently. The resulting simulation term product is typically a web site or spreadsheet that asks users for input, automatically runs some simulation experiments, and presents the results.

At the end of the course, all student teams present their products in a mini-conference for peer evaluation. They then post a video product sales pitch and demonstration on the internet (search YouTube: *IEOR 131, Berkeley, Simulation* for some examples). Finally, they are required to write confidential evaluations of their classmates' efforts. These activities give students the feedback they care about most, their friends' opinions. A successful term product involves market research and sales strategy development typically outside the scope of simulation education (but in the analytics job tasks identified by the CAP program). Students have featured links to their product videos on their résumés and credited these with successfully landing their first-choice jobs.

5.2 Teaching to pass the CAP written exam

Judging from the published sample questions, I think it is a mistake to teach too much toward passing the CAP written test. This written exam constitutes only part of the entire INFORMS Certified Analytics Professional (CAP) Program. There are educational and experience qualifications to be eligible to take the exam and an "attestation from an employer confirming adequate mastery of soft skills in analytics". I am concerned that some of these are recommended instead of required. Many questions are qualitative with subjective answers, much like a state driving license exam without a road test. (Full disclosure: I took the practice exam on the web and was told I missed a question. I believe the answer given is incorrect, but objecting would probably be like arguing about a question on my driver's exam (which didn't work.)

5.3 The Dastardly D's of Data

The CAP written exam puts too much emphasis on data analysis. Data is overrated. I try to put data into perspective for my students by telling them about the Dastardly D's of Data. (I know, that sounds silly, but I want them to remember it and they do (see the movie *Dodgeball*)). Data can be

1. Dated – data is old when it is recorded… (it's called *dā'tə* for a reason).
2. Dependent – people tend to be less eager to join longer lines.
3. Dynamic – Saturday nights in an hospital emergency room are not like Tuesday mornings.
4. Distorted – people can call different things the same name (sales ≠ demand), observer effect.
5. Deleted – data can be censored (e.g. in clinical trials), accidentally erased, or not transcribed.
6. Damaged – by errors in recording, collection, or communication, etc.
7. Doctored – well-intentioned people might try to "clean" a data set.
8. Dangerous – racial or personality profiling (I added this after seeing a data-driven automobile).
9. Deceptive – some of the above might be intentional.

I would feel better if the CAP program focused more on modeling than data analysis. Data analysis can tell us what happened, and we can hope the past will repeat itself. Modeling is how humans think about the future. Simulation modeling enables us to examine the consequences of possible futures.

5.4 Simulation in the CAP

Last year, several of us volunteered to submit possible questions on simulation for the CAP exam. I received thoughtful feedback on these questions from the CAP exam review committee. Perhaps up to six questions on simulation fundamentals might be included on the exam; however, this has not been confirmed by the committee. Our least technical question, or a very similar one, was included in the posted practice questions. We submitted simulation methodology questions hoping to include some technical rigor on the written exam. There is no evidence that happened. Several practice questions asked candidates to select the name of the most appropriate tool to use for a brief problem description. Knowing the name of a methodology does not mean the candidate necessarily understands how or when to use it, or is aware of the risks in violating the underlying assumptions. The hazards are increased by the proliferation of black-box software packages. The professional needs to know when <u>not</u> to use these. These aspects of analytics methodology do not appear to be rigorously tested, but should be central to all university courses.

My main concern is that CAP might become yet another among the many revenue-generating professional certification programs that have no legal standing and are of questionable merit. These can require expensive training by the sponsoring organizations or private contractors. (INFORMS is soliciting CAP training programs presumably with profit sharing.)

My limited interactions with the CAP exam review committee were positive and I believe the INFORMS Certification Task Force members are trying to make this a legitimate professional certification. The CAP program has a long way to go before it achieves the status of credentials like Professional Engineers, Certified Public Accountants, Law Bar Members, Board Certified Physicians, etc. with legal practice rights. I hope this is the future for the CAP™ program, but I am worried it could devolve into a money-making gimmick.

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