

**ME470 – Uncertainty Quantification**  
**Spring 2011**  
**Syllabus**

**Synopsis:**

How much do you trust the predictive capabilities of your simulation? If you knew that a politician or executive was going to use the results of your computer model for some critical decision, how well would you sleep at night? How many footnotes and hand-waving caveats would you include in the README file of your code to adequately cover your tail in the event of a failed prediction?

To properly answer these questions, one must characterize and quantify the uncertainties inherent in the model and its predictions. The last decade has seen the emergence and growth of methods and procedures for *uncertainty quantification* for computer simulations. Techniques for calibrating models to available measurement data, propagating uncertainties from model inputs to model outputs, and accurately interpolating model predictions to untried input parameters are meant to instill confidence that a given simulation has some predictive capability.

This class will survey some of the methods used in the burgeoning field of uncertainty quantification. The goal is to introduce the student to the relevant paradigms so that she or he may assess the uncertainties in a given computational model for science and/or engineering.

**Instructor:**

Paul Constantine

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Office hours: Tue/Thu, 11am – Noon (after class) or by appointment

**TA:**

Gary Tang

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Office hours: Coming soon...

**Course info:**

Time: Tue/Thu 9:30 – 10:45

Room: 380-381T

Websites: [me470.stanford.edu](http://me470.stanford.edu), [www.piazzza.com/stanford](http://www.piazzza.com/stanford)

**Prerequisites:**

I will use loosely and freely use terms and notation from probability, approximation theory, functional analysis, linear algebra, optimization, differential equations, and numerical methods for differential equations. If you are unfamiliar with these subjects at a working level but really want to take this class, then see me after class.

**Course requirements:**

Four homeworks (drop the lowest grade) – 45%

Project (including a midterm proposal and a final write-up) – 45%

Class attendance/participation – 10%

If you want to audit, come see me.

**Homeworks:**

The content of the homeworks will correspond with the last four sections of the class. They will be assigned at the beginning of each section, and they will be due (electronically) one week after its section ends; no late homeworks accepted. I suggest you look over the homeworks before their corresponding lectures to keep them in mind.

Each homework will have three parts:

- Two or three conceptual questions – potentially requiring proofs or derivations.
- A short coding assignment implementing a variant of a method discussed and applying it to a simple test problem. I strongly prefer that you use Matlab, but if you even more strongly prefer something else, I'm open to discussing it.
- A reading assignment consisting of two or three papers. You must choose one of the papers and write a one-page summary/response.

I encourage you to work together and share ideas. However, each person must submit his/her own write-up.

**Projects:**

I prefer that you choose your own project. A one page project proposal will be due before the midterm, and I will return them shortly after with comments. If you are unable or uninterested in choosing a project, then I will put together two or three proposals you can choose from. (WARNING: A project that I devise will likely be related to my own harebrained curiosities.)

If your research is not in uncertainty quantification, then the projects should ideally be related to your existing research. In this case, you should seek to answer questions like: *What are the primary uncertainties in the models? How can we represent these uncertainties? What methods may then apply to these representations and models? How do I quantify uncertainties in this context? What insights does a quantification of uncertainty provide into the original problem?*

If your research is in some aspect of uncertainty quantification, then I expect a thorough review of a method or a thorough comparison of methods (in an apples-to-apples sense) on some relevant test problem. Or, you can take this opportunity to answer the questions above in the context of an interesting application.

The final project write-up should be six to ten pages long including figures and tables – roughly the length of a conference paper. I will provide a LaTeX template that I expect you to use.

**Books (recommended):**

*Numerical Methods for Stochastic Computations: A Spectral Methods Approach.*  
Dongbin Xiu

*Stochastic Simulation: Analysis and Algorithms.*

Soren Asmussen and Peter W. Glynn  
<http://www.springerlink.com/content/l24q63/>

*Spectral Methods for Uncertainty Quantification: With Applications to Computational Fluid Dynamics.*

Olivier P. Le Maître and Omar M. Knio  
<http://www.springerlink.com/content/978-90-481-3519-6>

*Large-Scale Inverse Problems and Quantification of Uncertainty.*

Lorenz Biegler, et al.  
<http://onlinelibrary.wiley.com/book/10.1002/9780470685853>

**Topics:**

*Introduction (Weeks 1 & 2)*

Background, motivation, relevant review of approximation theory and probability, verification and validation, aleatoric/epistemic uncertainty.

*Sampling methods (Weeks 3 & 4)*

Computing expectations/integrals, confidence intervals, Monte Carlo methods, importance sampling, variance reduction methods.

*Polynomial Spectral Methods (Weeks 5 & 6)*

Lagrange interpolation, orthogonal polynomials, Galerkin methods, Gaussian quadrature, Jacobi matrices, sparse grid methods, regression.

*Reduced Order/Surrogate Modeling (Weeks 7 & 8)*

Random field models, Kriging, reduced basis methods, proper orthogonal decomposition, residual minimizing methods.

*Parameter Estimation (Weeks 9 & 10)*

Inverse problems, Markov chain Monte Carlo methods, least squares methods, regularization, maximum entropy methods.

**Topics not covered (good ideas for projects!):**

Sensitivity analysis, particle filtering, dimension reduction, adjoint methods, coupled multi-physics systems, dimension-adaptive methods, anisotropic methods, etc.