The first goal is to learn how to formulate models for the purposes of control, in applications ranging from finance to power systems to medicine. Linear and Markov models are chosen to capture essential dynamics and uncertainty. The course will provide several approaches to design control laws based on these models, and methods to approximate the performance of the controlled system. In parallel with these algorithmic objectives, students will be provided with an introduction to basic dynamic programming theory, closely related stability theory for Markovian\(^1\) and linear systems, and simulation and stochastic approximation concepts underlying reinforcement learning.

It is intended for graduate students who have some background in control and stochastic processes. Experience with Matlab is essential.

*Why do we need noisy models?* When you introduce the word “stochastic” to control, this just means that you are bringing in a larger range of tools for understanding how to control systems, and evaluate their performance. Name a tool from probability, and you have something useful for control synthesis. In particular, there is the question of *information*. This may mean the data available for control, or information about the system to be controlled. There may be variables of interest that are not directly observed, so we will want to estimate. Tools to be applied include nonlinear filtering and *stochastic approximation*, which is the foundation of reinforcement learning.

“Noisy models” provide insight for constructing approximately optimal policies for control, and architectures for control based on partial information.

*Office hours* Held Wednesdays from 4:00-5:00 p.m. (often extended) in 455 NEB. I can be reached for questions by electronic mail at meyn@ece.ufl.edu (not via e-learning).

*Exams, homework, and grading* Homework problems will be assigned on a ∼bi-weekly basis, to be handed in at the beginning of class on the date due. They will be graded and returned the following week. *Late homework cannot be accepted.*

There will be two evening midterm exams, February 26 and April 23, from 7:20 - 8:50 p.m. You will be allowed one sheet of notes (8\(\frac{1}{2}\) × 11; both sides) in the first exam, and two in the second. Otherwise, the exams are closed-book and closed-notes.

*Grading scheme:* Homework problems will count 15\(\%\)^2, the midterm exams 60\(\%\), and the final project will count 25\(\%\) towards the final grade in the course.

In addition to the University-wide holidays, class is cancelled on days of overlap with, *Second Workshop on Cognition & Control*, January 15-16, 2014.

See the ccc website for other local events

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1 A *Markov process* is nothing more than a nonlinear state space model subject to noise.

2 I encourage collaboration on homework!
References: The following are available free on-line (send your thanks to CUP):

www.meyn.ece.ufl.edu/archive/spm_pubs.html
⊙ S. P. Meyn, *Control Techniques for Complex networks*.  
www.meyn.ece.ufl.edu/archive/spm_pubs.html

The following are valuable background (send your thanks to Profs. Hajek and van Handel):

⊙ B. Hajek, *Exploration of Random Processes for Engineers*.  
www.ifp.illinois.edu/~hajek/Papers/randomprocesses.html
www.princeton.edu/~rvan/orf557/hmm080728.pdf

The following textbooks are of value, but not needed to follow the course.

⊙ D. Bertsekas and S. Shreve, *Stochastic Optimal Control: The Discrete-Time Case*  
web.mit.edu/dimitrib/www/soc.html
⊙ P. R. Kumar, *Stochastic systems: Estimation, identification, and adaptive control.*
⊙ Torsten Soderstrom, *Discrete-time stochastic systems: estimation and control.*

Course Outline:

I. Nonlinear State Space Models

1) Overview & examples. Review of concepts from optimal control
2) Markov models and more examples
3) Lyapunov theory for stability and performance
4) Numerical techniques and Monte-Carlo for performance estimation

II. Optimal Control

1) Controlled Markov models and examples
2) Approximate dynamic programming
3) Numerical techniques: Policy and value iteration, LP methods.
4) Partial information. Multi-armed bandits First Midterm Exam

III. Linear Theory

1) Linear systems: Controllability, observability. Optimal control.
2) Partial information and the Kalman filter.

IV. Adaptation and Learning

1) Simulation and stochastic approximation: overview of theory and applications
2) TD Learning and examples Second Midterm Exam
3) TD Learning ctd (and Thanksgiving break)
4) Q Learning
5) Review and thoughts for the future