SYLLABUS 2018

Course Title: Autonomous Decision Making in the Real World
Course Number: ABE 598
Semester: Spring 2018
Classroom: 106B1 Engineering Hall
Class Time: Tuesday-Thursday 11:00AM - 12:20PM

1 Instructor

Asst. Prof. Girish Chowdhary
ABE Office: 376 Agricultural Sciences and Engineering Building (AESB)
CSL Office: 150 CSL (I will be in CSL office on Wed-Fridays most weeks)
Office Hours: One hour before and after the class, come to my office or we hang out after the class
Phone: (217) 300-3952
Email: girishc@illinois.edu

2 Course Description

The objective of this course is to cover theory and techniques essential for building cyber-physical systems capable of autonomous decision making in the real-world.
This course will lay a foundation for theory and techniques in autonomous planning, machine learning, and adaptive sequential decision making. Topics covered include Planning under uncertainty, Bayesian Nonparametric machine learning, Deep learning and Neural Networks, Markov Decision Processes, and Reinforcement Learning. Student chosen applied projects, involving real aerial and ground robots, are a key element of this course.

3 Texts

This course will draw from a number of texts and papers, being an integrative graduate level course. I do not expect that you will be purchasing all of these texts, but if you are interested in building a Machine Learning and Autonomy library, these texts will be the right ones to invest in. I will provide scans and summaries where appropriate on Piazza. In addition, a number of papers are included in the required reading.

The primary texts utilized are:

Classical AI (Module 1)

1. Russel and Norvig, Artificial Intelligence, a Modern Approach (http://aima.cs.berkeley.edu/)

2. Lavalle, Planning Algorithms, available online: http://planning.cs.uiuc.edu/

Machine Learning and Deep Learning (Module 2)

3. Murphy, Machine Learning, A probabilistic Perspective
4. Goodfellow et al., Deep Learning
5. Bishop, Machine Learning and Pattern Recognition

Sequential Decision Making and Reinforcement Learning (Module 3)

6. Kochendefer et al., Decision Making Under Uncertainty: Theory and Application
7. Busoniou, Reinforcement Learning and Markov Decision Processes
8. Bertsakes, Neurodynamic Programming

4 Course Motivation

This section of the syllabus explains the motivation behind the creation of this course and what you can expect to get out of it.

Summary:
The purpose of this course is to prepare students in learning and applying leading techniques from machine learning, artificial intelligence, sequential decision making, and control for creating autonomous decision making systems that operate in the real world. These autonomous systems will enable robots, or a team of robots, to do useful things. The real-world is full of uncertainties, dynamically changing, and only partially observed. We do not yet have fully autonomous systems that can deal with these challenges. It is the purpose of this course to survey the literature and acquaint students with the state-of-the-art.

More in depth motivation:
Autonomy, artificial intelligence, machine learning are some of the most rapidly growing areas in the applied sciences. The early advances in these areas have been fueled by the impact AI and machine learning software has made on social media and internet data management. In this course however, we are interested in advances motivated by engineering applications.

Indeed, some of the most exciting developments in engineering next decade will be a result of innovations in these areas. They include: Autonomous cars and vehicles, agricultural robotics, Unmanned Aerial Systems (UAS), smart-grids, smart and connected traffic networks, smart cities, and internet of things.

In all of these and other emerging applications, the enabling technology is seamless integration of Cyber and Physical components. Cyber components include software, embedded computers, sensors, and other electronic and computational artifacts; while physical components include hardware (cars, airplanes, power lines) that is subject to the rules of physics (dynamics, kinematics, elctromechanics, fluid flows).

Autonomous cyber-physical systems (CPS) are expected to achieve the following:

- Understand, perceive, and model the environment in which they operate
- Make real-time decisions to meet higher level objectives
- Ensure the safety of the system and its stake-holders
- Operate robustly in a wide variety of environments
- Collaborate with other systems

This course was created to provide a wide as well as deep introduction to principles of autonomous decision making.

5 Learning Outcomes

This graduate level course is an integrative course, our focus during this semester will be to understand and synthesize the various techniques utilized in autonomous decision making and planning.

This course will provide a wide introduction to the field of autonomous decision making, and a deep introduction to machine learning and reinforcement learning. Our focus will be on adaptive decision making in uncertain environments, and we will accomplish this by studying the the interplay between machine learning, reinforcement learning, and adaptive control.

All of our development will be theoretically motivated, but in this course I will place a particular emphasis on fundamental understanding of principles and their interrelations, development of practical algorithms, and development of high-quality software.

The specific learning outcomes are:

1. Develop algorithms and architectures for autonomous decision making in the real world
2. Understand fundamental principles of machine learning
    a. Regression, with specific emphasis on linear models, Kernel based models, Neural Networks, and Gaussian Processes
    b. Classification: with specific emphasis on Support Vector Machines, Neural Networks, and Gaussian processes
    c. Clustering: beginning with K-means clustering and culminating with specific emphasis on Bayesian nonparametric clustering
3. Understand fundamental principles of reinforcement learning:
    a. Markov Decision Process formulation of reinforcement learning: MDP algorithms: Value/Policy iteration and trajectory based methods
    b. Model free RL algorithms: SARSA, Q-learning and variants

    c. Model based RL algorithms: GP-RL
4. Understand what is Deep-learning and its principles
    a. Deep Neural Networks
    b. Deep Reinforcement Learning
    c. Where to from here?
5. Understand the connections between adaptive-optimal control and RL
    a. Model Reference Adaptive control and its relationship with policy gradient methods
    b. Adaptive model predictive control and its relationship with model based RL
6. Survey a selection of papers in relevant areas of autonomous decision making
7. Demonstrate the ability to develop software to achieve machine learning, reinforcement learning, and control tasks through a set of problem sets
8. Demonstrate integrative knowledge of the topics covered in a final project relating to autonomous decision making for engineering applications

At the end of this course, you should be able to generate algorithms and architectures for autonomous decision making in real-world environments.

6 Course Prerequisites

There are no specific prerequisites to this course. However, students are expected to have graduate standing (or permission from instructor), and introductory or undergraduate level linear algebra, linear control, introduction to probability, and software programming.

Programming: An introductory knowledge of programming is essential for this course. You may choose any programming language that you are comfortable with for the problem sets and the project. However, most of the templates provided by the instructor will be in MATLAB. Furthermore, we might sometimes use code from online repositories, which may be in Python or C++. Both are easy languages to learn for what we want to do, and I think you will be fine if you haven't used these languages before but know about programming in general. If you are not comfortable programming however, we should have a conversation.

7 Course Outline

1. **Module 1 Introduction to Autonomous Decision Making**
    a. What is autonomy
    b. Autonomous Agents
2. **Module 2 Some preliminaries**
    i. Probability Theory, with an emphasis on Bayesian formulations
    ii. Information Theory
    iii. Bayesian information fusion: Kalman Filters
3. **Module 3 Classical Artificial Intelligence**

a. Search:
    i. Solving decision making problems through search
    ii. Search techniques
b. Motion planning
    i. Configuration spaces, groups, and SO(3)
    ii. Sampling based motion planning
c. Logistic Planning (non-sequential decision making)
    i. Linear Programming
    ii. Chance constrained optimization and the notion of Risk

4. **Module 4 Machine Learning for autonomy**
    a. Principles of machine learning for knowledge representation: regression, clustering, classification, and association
    b. Regression
        i. Linear regression
        ii. Kernel models
        iii. Gaussian Process Regression
    c. Classification (Supervised learning)
        i. Logistic regression
        ii. Support vector machines
        iii. Neural Networks (Deep and non-deep)
    d. Clustering (Unsupervised learning)
        i. K-means clustering
        ii. Dirichlet process clustering and Bayesian nonparametrics
    e. Deep Neural Networks
    f. Spatiotemporal modeling
        i. Modeling of spatiotemporal systems, Evolving Gaussian Processes
    g. Hidden Markov Models
5. **Module 5 Sequential decision making under Uncertainty**
    a. Markov decision processes
        i. The Markovian assumption in sequential decision making problem formulation
        ii. State, Action, and Transition spaces
        iii. Dynamic programming, value iteration, policy iteration, Trajectory-based algorithms
        iv. POMDPs (with SARSOP), DEC-POMDPs
    b. Approximate Dynamic Programming
        i. State-Action space parameterization and approximate representations
        ii. Linearly parameterized representations: kernel models, mixed-resolution tables, iFDD
        iii. Convergence results
    c. Reinforcement learning
        i. The MDP formulation for RL
        ii. The Exploration vs Exploitation tradeoff
        iii. Temporal difference methods
            1. On-Policy: SARSA, LSPI and variants

        2. Off-Policy: Q-learning, Q-iteration and variants
    iv. Approximate Reinforcement Learning
        1. Linearly parameterized representations: kernel models, mixed-resolution tables, iFDD
        2. Neural Network approximations
        3. Convergence results, performance results
    v. Model based RL
        1. GP based RL
        2. The POMDP formulation of Model Based RL
    vi. Deep Reinforcement learning
        1. Deep Q (Google Deepmind's version)
        2. Value iteration networks

6. **Module 6: Where to from here? (If time permits)**
    a. Integrating RL, ML, and control for robotics
    b. Games, simulations, and virtual worlds
    c. The future of machine learning in a connected world
    d. Autonomous decision making and internet of things

8 Grading

Grades will be determined based on demonstrated proficiency on problem sets, weekly readings and presentations, a project, and a final examination. Problem sets involve mathematical problem formulation, analysis, and software development in MATLAB or programming language of student's choice. The points associated with each graded event are shown below along with the associated letter grade.

Point Breakout:

Problem Sets	= 450 points
Weekly readings	= 50 points
Project	= 500 points
Total	**= 1000 points**

Grading Scale:

A+	= 950-1000 Total Points
A	= 900-960 Total Points
A-	= 880-900 Total Points
B+	= 850-880 Total Points
B	= 800-850 Total Points
B-	= 780-800 Total Points
C, C-, C+	= 700-780 Total Points
D, D-, D+	= 600-699 Total Points
F	= 0-599 Total Points

Occasionally, students will be offered the opportunity to obtain extra credit points. These points are added to the student's total while the total points for the course remains at 1000.

One and only one deliverable can be turned in late by 2 days. For every other deliverable, and past the 2 days for the first late deliverable, you will be penalized 20% per day of grade earned for that deliverable.

50 points will be allocated to weekly readings. We may execute in-class presentations, depending on the number of students enrolled. If in-class presentations are executed, each student will present one paper in a 10 minute talk, utilizing power-point or other tools. The expectation will be a concise overview of the paper demonstrating your understanding and helping others understand.

Project accounts for half the grade of this class. Projects shall be evaluated on an individual basis. Furthermore, each student shall submit an individual report focusing on his or her contributions to the project.

Projects will be selected early (within first 4 weeks of class), instructor will provide help and guidance in identifying appropriate projects. Projects may be chosen from student's graduate research.

The final report of the paper will be in the form of a conference style paper.

Students have the opportunity to pursue publication options with me if their projects are well-executed and lead to meaningful contribution.

Project deliverables:

1. Problem formulation: 50 points
2. Iteration 1: 100 points
3. Final report: 300 points

9 Policies and Ethics

Academic Integrity

Please review and reflect on the academic integrity policy of the University of Illinois, http://studentcode.illinois.edu/article1_part4_1-401.html, to which we subscribe. By turning in materials for review, you certify that all work presented is your own and has been done by you independently, or as a member of a designated group for group assignments.
If, in the course of your writing, you use the words or ideas of another writer, proper acknowledgement must be given (using IEEE or other appropriate citation style of your preference). Not to do so is to commit plagiarism, a form of academic dishonesty. If you are not absolutely clear on what constitutes plagiarism and how to cite sources appropriately, now is the time to learn. Please ask me!

Please be aware that the consequences for plagiarism or other forms of academic dishonesty will be severe. Students who violate university standards of academic integrity are subject to disciplinary action, including a reduced grade, failure in the course, and suspension or dismissal from the University.

Criteria for grading homework assignments include (but are not limited to) creativity and the amount of original work demonstrated in the assignment. However, students are permitted to use and adapt the work of others, provided that the following guidelines are followed:

- Use of other people's material must not infringe the copyright of the original author, nor violate the terms of any licensing agreement. Know and respect the principles of fair use with respect to copyrighted material.
- Students must scrupulously attribute the original source and author of whatever material has been adapted for the assignment. Summarize the changes or adaptations that have been made. Make plain how much of the assignment represents original work.

Statement of Inclusion http://www.inclusiveillinois.illinois.edu/mission.html As the state's premier public university, the University of Illinois at Urbana-Champaign's core mission is to serve the interests of the diverse people of the state of Illinois and beyond. The institution thus values inclusion and a pluralistic learning and research environment, one which we respect the varied perspectives and lived experiences of a diverse community and global workforce. We support diversity of worldviews, histories, and cultural knowledge across a range of social groups including race, ethnicity, gender identity, sexual orientation, abilities, economic class, religion, and their intersections.

Accessibly Statement *Text from Graduate College website* To obtain accessibility-related academic adjustments and/or auxiliary aids, students with disabilities must contact the course instructor and the Disability Resources and Educational Services (DRES) as soon as possible. To contact DRES you may visit 1207 S. Oak St., Champaign, call 333-4603 (V/TTY), or e-mail a message to disability@uiuc.edu.

Per guidelines from the Chancellor's Committee on Access and Accomodations (http://ccaa.dres.illinois.edu/guidelines.php), this statement must be included: This syllabus may be obtained in alternative formats upon request. Please contact the instructor.

10 Organization and Course Calendar

The following calendar is tentative and subject to change

Class no	Date		Topic in class	Suggested Reading	Problem Set	Projects
1	1/16/18	M1	Welcome	Russell and Norvig CH 1, 2		
2	1/18/18		Autonomous decision making	Russell and Norvig CH 1, 2		
3	1/23/18		Why study autonomous decision making		P1 Out	
4	1/25/18	M2	Overview of some mathematical preliminaries	Bishop Ch 2		
5	1/30/18		Overview of some mathematical preliminaries	Murphy Ch 2-3		
6	2/1/18		Kalman Filters: Bayesian inference	Murphy Ch 2-3		Project IT 0
7	2/6/18	M3	Classical Artificial Intelligence	Russell and Norvig CH 3, 4, 5		
8	2/8/18		Classical Artificial Intelligence	Lavalle Ch 4, 5		
9	2/13/18	M4	Machine learning introduction	Murhphy Ch 1	P1 In, P2 out	
10	2/15/18		ML: Regression	Murphy Ch 7		
11	2/20/18		ML: Regression, Kernel Models and GPs	Murphy Ch 14, 15		
12	2/22/18		ML: Regression spatiotemporal systems	Murphy Ch 14, 15		
13	2/27/18		ML: Classification: SVMs and Kernel methods	Bishop Ch 4, 7		
14	3/1/18		ML: Neural Network classifiers	Bishop Ch 5		
15	3/6/18		ML: Deep Learning	Murphy 28		
16	3/8/18		ML : Deep Learning	Goodfellow Ch 9, 10		
17	3/13/18		ML: Unsupervised Clustering	Murphy 25		
18	3/15/18		ML: Clustering, Bayesian Nonparametrics		P2 In	Project IT 1
	3/20/18		Spring Break			

	3/22/18		Spring Break			
19	3/27/18	M5	Sequential Decision Making under Uncertainty	Kochendefer Ch 3	P 3 Out	
20	3/29/18		RL: MDPs	Kochendefer Ch 4		
21	4/3/18		RL: Dynamic Programming, Value iteration..	Kochendefer Ch 4		
22	4/5/18		RL: POMDPs, DEC-POMDPS, NEXP complete problems	Kochendefer Ch 6		
23	4/10/18		RL: Reinorcement Learning SARSA, Q-learning and variants	Kochendefer Ch 5, Kaebling 1996		
24	4/12/18		RL: Approximate dynamic programming	Busoniu Ch 3		
25	4/17/18		RL: Approximate RL, multi-resolution and kernel based	Geramifard et al. 2013		
26	4/19/18		RL: Deep RL			
27	4/24/18		RL: Deep RL			
28	4/26/18	M6	Where to from here? Final project presentations		P3 In	
29	5/1/18	M7	Final projcet presentation			Final Project

Per-class required readings are shown below. These papers have been uploaded in Piazza.

Class no	**Date**	Paper for reading
1	1/17/18	
2	1/19/18	
3	1/24/18	R1 DOD Autonomy roadmap
4	1/26/18	
5	1/31/18	R2 Tennenbaum et al. 2011
6	2/2/18	R3 Yamauchi 1997
7	2/7/18	R4 Karaman and Frazzoli 2011

8	2/9/18	R5 Frazzoli et al. 2002
9	2/14/18	R6 Julier 1997
10	2/16/18	R7 Csato and Opper 2002
11	2/21/18	R8 Le at al 2013
12	2/23/18	R9 Kingravi et al. 2016
13	2/28/18	R10 Scholkofp 98
14	3/2/18	R11 Krizhevsky et al. 2012
15	3/7/18	R12 Tsung-Yi 15
16	3/9/18	R13 Goodfellow et al. 2014
17	3/14/18	R14 Kulis et al. 2012
18	3/16/18	R15 Blei et al. 2003
	3/21/18	R16 Zhang17
	3/23/18	R17 Lee09
19	3/28/18	R18 Ure 2012 GNC
20	3/30/18	R19 Tamar 2016
21	4/4/18	R20 Mnih 2015
22	4/6/18	R21 Kurniawati 2008

23	4/11/18	R22 Tsitsikilis 1997
24	4/13/18	R23 Atkeson 97
25	4/18/18	R24 Mnih2015b-DQN
26	4/20/18	R25 Lillicrap DDPG
27	4/25/18	R26 Pattanaik 17
28	4/27/18	R27 Sutton 99
29	5/2/18	