Fundamentals of Stochastic Approximation Theory

CMPUT 659

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Goals for this course

- **Primary goal**: Complete a research paper in machine learning or reinforcement learning, intended for a specific venue
  - workshop, conference or journal
  - does not have to be theoretical paper, can be any machine learning or reinforcement learning topic (even a project you've already started)
- Secondary goal: Become a bit more comfortable with mathematical tools in theory in RL
  - the fundamentals of stochastic approximation theory

Primary goal

- Write a complete research paper
  - this is **much harder** than a project
  - a **polished paper**, with a precise question, is much harder than just reporting an idea and/or a bunch of results for a project
- Be part of a larger research group, pushing ideas and understanding forward together, in a collaborative way
- Finish the course with a paper that is almost ready to be submitted

Why is this harder than a project?

- The last 10% can be the most difficult

- Once you write the paper to be a concise paper with a clear message, it can significantly change what you thought you set out to do
    - For other research projects in your past, it was likely not a strong requirement that the paper would have to pass peer review
    - When you know its going to be reviewed, you have to ask yourself: “What is the scientific community getting from this paper? What am I trying to show? Is it meaningful and did I actually show it?”

- You need to polish the paper, in the right format for a venue, of the right length, communicated to the right audience
    - You have to craft the motivation (the pitch) and the sentences
    - You likely need to become a latex experts. vspace is your friend

Working as a team is good

- Projects can be done in pairs
- There will be related topics across projects; you should draw on the insights from your peers to make progress on your project
- You will be reporting weekly progress on your project

Secondary goal: Theory

- Becoming comfortable with stochastic approximation theory is extremely useful in both machine learning and reinforcement learning

- Ajin is an expert in this theory, and luckily he is going to teach us all about it
  - starting from the beginning with background material

- To encourage this goal, there will be
  - two assignments
  - a final paper discussion applying your knowledge to read a more advanced theory paper in ML or RL

Stochastic approximation

- You already know many algorithms based on stochastic approximation
  - stochastic gradient descent
  - temporal difference learning
- This course (stochastic approximation theory) will help you understand convergence results for these algorithms
- The theory involves understanding stochastic processes, and dynamical systems that describe changing parameters/functions over time (as learning progresses)

Topics in the course

Lecture 1	Introduction
Lecture 2	Real analysis: properties of real numbers, sequences, series, topology
Lecture 3	Real analysis: compact sets, continuous functions
Lecture 4	Real analysis: differentiation and integration
Lecture 5	Probability theory: probability and expectation
Lecture 6	Probability theory: convergence theorems
Lecture 7	Probability theory: conditional expectation
Lecture 8	Martingales
Lecture 9	Martingales
Lecture 10	Martingales
Lecture 11	Dynamical systems: existence and uniqueness of solutions
Lecture 12	Dynamical systems: stability, linear autonomous systems, gradient flow
Lecture 13	Stochastic approximation algorithms: chapter 2 of Borkar's text
Lecture 14	Stochastic approximation algorithms: chapter 2 of Borkar's text (cont)
Lecture 15	Stochastic approximation algorithms: chapter 3 of Borkar's text
Lecture 16	Stochastic approximation algorithms: chapter 6 of Borkar's text
Lecture 17	Stochastic approximation algorithms: chapter 4 of Borkar's text

Grading

- Assignments (2): 20%
- Weekly progress reporting: 10%
- Initial draft: 20%
- Final paper: 50%
- Everything submitted on eClass; schedule maintained on github pages

Criteria for selecting a project

- Pick a concrete, feasible topic
  - Too broad: “I am going to investigate exploration”
  - More specific: “I am going to investigate a simple idea I have for estimating counts for a state, under function approximation, for use in count-based exploration approaches”
- Err on the side of small —> the goal of this course is to get you to do a simple (small) idea well, not a big idea poorly
  - In the beginning, many projects start smaller as you become more knowledgeable in the topic
  - Once you have a good background, you can more easily know if your ideas are novel and/or write that bigger journal paper
- Can relate to an on-going research project outside of this course

Potential concerns

- What if the idea does not work out?
  - Insight gained from a concrete project almost always leads to a reasonable direction, that can be at least published in a workshop
  - For this course, I will allow negative results, if you try an idea that many would agree should be effective

- What if I do not complete the final draft on time?
  - For example, I specified a broad topic and didn't end up completing it in time
  - This is a project course (not an easy course); you have to complete the project
  - You will hopefully learn an important skill: scaling back a project to be the right size, even it seems to be getting out-of-hand
  - I recommend ensuring that progress is being made regularly, and that the scope of the project remains feasible; if not, talk to me early

Sharing code and getting access to computation

- My group has some code for evaluating policy evaluation algorithms (i.e., algorithm learning value functions), written in c
  - both on and off-policy
- There are frameworks available out there for experiments
  - RLToolkit and OpenAI Gym
  - Tensorflow
- Computation: many of you have access to computational resources. If you do not, and your project will need it, talk to me
  - Cybera
  - Google provides some free compute
  - If you have an advisor, you can use Compute Canada

Project Ideas

- If you know what you might want to work on, email me
- I can provide some suggested project ideas on eclass and we can discuss them in class
- What are some topics you are interested in?
  - Time series prediction?
  - Control with RL?
  - Model-based RL?
  - Sample efficient policy evaluation in RL
  - Step-size selection?
  - Auxiliary tasks?

Office hours

- Ajin will set his office hours for the material on the syllabus
- I will come to this lecture room every MW at 9, so you can ask some questions before lecture
- Ajin and I can both meet about projects to provide some guidance by appointment
  - The amount of time we spend on this depends a bit on how many projects there are