1. **Instructors.**
   Murat A. Erdogdu  
   Email: csc2532prof@cs.toronto.edu  
   Office: Pratt # 286b  
   Office Hours: Th 16:15-17:15

2. **Lectures.** Th 14:00-16:00, SS 2108

3. **Teaching Assistants.**  
   Rozhina Ghanavi, Calum MacRury  
   Email: csc2532ta@cs.toronto.edu

4. **Course webpages.** Course webpage contains all course information, additional readings, assignments, announcements, office hours, etc. Please check regularly!
   - [https://erdogdu.github.io/csc2532/](https://erdogdu.github.io/csc2532/)  
   - [q.utoronto.ca](http://q.utoronto.ca)

5. **Course Evaluation.**
   - 3 assignments: 30%  
   - Midterm exam: 40%  
   - Project: 30%

6. **Course Outline.** This course covers several topics in classical machine learning theory. In this course, we will try to answer questions like
   - How fast will your algorithm converge?  
   - How much data do you need to get good prediction results?  
   - What is the performance of your algorithm on test data?

Topics may include:
1/09: Introduction & Stein Paradox  
1/16: Exponential Families  
1/23: Asymptotic statistics (hw1 out)  
1/30: Uniform convergence & Generalization (project proposal due)  
2/06: Epsilon-nets and covering technique (hw1 due & hw2 out)  
2/13: Rademacher complexity I  
2/20: Rademacher complexity II (hw2 due & hw3 out)  
2/27: VC dimension (project progress report due)
3/05: PAC-Bayes bounds & Stability (hw 3 due)
3/12: Midterm (in class)
3/19: Kernel Methods I
3/26: Kernel Methods II
4/02: Topic based on class vote (project final report due)
   - Sampling/Online Learning/Optimization/Double descent/...

7. Prerequisites. CSC2515 is a prerequisite. This class requires a good informal knowledge of probability theory, linear algebra, real analysis. Homework 0 is a good way to check your background.

8. Textbooks. There is no required course textbook. The following materials can be helpful.
   - Understanding Machine Learning by Shai Shalev-Shwartz and Shai Ben-David
   - High Dimensional Probability by Roman Vershynin
   - Information Theory, Inference, and Learning Algorithms by David MacKay
   - Elements of Statistical Learning by Jerome Friedman, Trevor Hastie, and Robert Tibshirani

9. Assignments. There will be 3 assignments in this course.

   9.1. Collaboration policy. After attempting the problems on an individual basis, you may discuss and work together on the homework assignments with up to two classmates. However, you must write your own code and write up your own solutions individually. Groups should bundle their solutions and submit together by explicitly stating the name of any collaborators at the top of their homework.

10. Exam. There will be a in-class midterm exam (tentatively) on Mar 12. Details will be announced on the course webpage. You can bring an optional A4 cheat sheet - double-sided.

11. Project. Final project should give you experience carrying out theoretical research.

   11.1. Objectives. Your project goal is to make a significant contribution to understanding a machine learning related observation. An ideal project will begin with an interesting observation, later explained through theory, and end with a thorough empirical analysis.

   Several research directions will be posted on the course webpage, but the list is by no means comprehensive, and your project topic need not be drawn from it. You will review relevant literature, find interesting research directions, and either develop novel methodology, or explain an observed behavior related to a learning algorithm.

   11.2. Collaboration policy. You may work on the project alone or in a group of two; the standards for a group project will be higher. We strongly encourage you to come to office hours to discuss your project ideas, progress, and difficulties with the course staff.

   11.3. Evaluation. Evaluation will be based on two reports:

   1. Proposal 2%: 1/2 page, to be submitted on 1/30
   2. Progress report 8%: 1 page, to be submitted on 2/27
   3. Final report 20%: 3 pages, to be submitted on 4/02
12. Late policy. If you are traveling, you may email your submission to one of the course staff in advance of the deadline. Ten percent of the value will be deducted for each late day. No credit will be given for assignments submitted after the solutions have been posted. Exceptions will be made for documented emergencies.

13. Grading concerns. Any requests to have graded work re-evaluated must be made within one week of the date the grade is released. Re-evaluation may result in a decrease in the grade.

14. Computing. In the assignments and project, you may need to write your own programs, debug them, and use them to conduct various experiments, plot curves, etc. You may use any programming language, but Python, and R might be preferable.

15. Missed exam/test.

- If a test is missed for a valid reason, you must submit documentation to the course instructor.
- If a test is missed for a valid medical reason, you must submit the University of Toronto Verification of Student Illness or Injury form to your instructor within one week of the test.
- The form will only be accepted as valid if the form is filled out according to the instructions on the form.
- Important: The form must indicate that the degree of incapacitation on academic functioning is moderate, serious, or severe in order to be considered a valid medical reason for missing the term test. If the form indicates that the degree of incapacitation on academic functioning is negligible or mild then this will not be considered a valid medical reason.
- If the midterm test is missed for a valid reason then the final project will be submitted separately from the group and will be evaluated on individual basis. Final project will be worth 70% of your final grade.
- Other reasons for missing a test will require prior approval by your instructor. If prior approval is not received for non-medical reasons then you will receive a term test grade of zero.