Manhattan College

Department of Mathematics

MATG 557 Section 61 ***Machine Learning*** Spring 2022

Class Time: Monday, Thursday 6:30-7:45 P.M. *Class Room*: RLC 104

Instructor: Angel R. Pineda, Ph.D. *Office*: RLC 201H
Email: angel.pineda@manhattan.edu *Phone*: 718-862-7730
Website: https://angel-r-pineda.github.io/

Office Hours: Monday 5:50-6:20 pm, Thursday 5:50-6:20 pm, or by appointment.

Required Textbook:
Pattern Recognition and Machine Learning (2006)
Author: Christopher M. Bishop, Publisher: Springer
This text is available for free online:
https://www.microsoft.com/en-us/research/publication/pattern-recognition-machine-learning/

Recommended Textbooks:
(For Python Implementation of Machine Learning)
Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow, 2nd Edition (2019)
Author: Aurelien Geron, Publisher: O'Reilly
Python Notebooks available on Github:
https://github.com/ageron/handson-ml2

(For an undergraduate version of the material with a statistical bent)
Introduction to Statistical Learning, 2nd. Ed.
Authors: Gareth James, Daniella Witten, Trevor Hastie and Robert Tibshirani, Publisher: Springer
This text is available for free online:
https://www.statlearning.com/

Required Course Software:
Anaconda Distribution of Python
(Including Spyder & Jupyter Notebooks)
This software is available for free online:
https://www.anaconda.com/products/individual

Catalog Course Description:
An introduction to the field of machine learning and its real-world applications, emphasizing the coding of machine learning algorithms to iteratively learn from data and to automate analytical model building. Topics include supervised & unsupervised learning, Bayesian decision theory, non-parametric methods, linear discriminant functions, multi-layer neural networks, stochastic methods and cluster analysis. Programming experience will be useful. A project is required. Not open to students with credit for MATH 457.

Prerequisites: (MATH 372 or MATH 351) and MATH 285 and (MATH 331 or MATH 336*).*

Learning Outcomes: Upon successful completion of this course, the student will be able to:

- Understand the general field of machine learning and its associated algorithms.
- Write code for algorithms in machine learning.
- Apply machine learning algorithms to concrete problems.

Course Homepage (Moodle):
Here you will find four features that will be used in this course:

- *Email:* make sure that your email on Moodle is one that you check regularly. Homework assignments, announcements and other class related information will be sent via email.
- *Course Information and Documents:* material covered each week, assignments and solution keys.
- *Student Discussion Board:* this online forum allows for students and faculty to communicate about the course.
- *Grades:* students will be able to keep track of their grades online.

Assessment of Student Learning:

Homework (50 %)
There will be weekly assignments. A large part of the learning will be in these weekly assignments.

Take Home Midterm Exam (25 %): Thursday March 24

Final Project (25 %)
In the course project, the student will write a paper and give a presentation on a topic of their choice with the instructor's approval. The project will use Python programming to solve a machine learning problem. Details for the course project will be given after the Midterm Exam. The final project will be presented on Monday May 9 from 6:30-8:30 pm.

Tentative Grading Scale

Percent	90-100	85-89	80-84	75-79	70-74	65-69	60-64	50-59	0-49
Grade	A	A-	B+	B	B-	C+	C	D	F

The exact grading scale will be determined after the final exam. The numerical scores in the tentative grading scale guarantee the associated letter grade but the instructor may change the scale to the student's benefit.

Dates to Remember:

January 19: First day of classes
January 28: Late Registration & Add/Drop Ends
March 10: Midterm Grades Due
March 14-18: Spring Break
April 14-18: Easter Holiday (No Classes)
April 10: Last Day to Withdraw from Courses
April 20: (Wednesday) Monday Schedule
May 6: Last Day of Classes

Class Policies

- Late homework will not be accepted after the solutions are distributed. In case the homework is handed in before the solutions are posted it will be marked 20% off for every day (or part thereof) it is late.
- No make-up exams will be given, unless you have a medical or family emergency. These emergencies require valid documentation. The grade for a missed exam is zero.
- You should acknowledge all collaborators and external sources for HW and code.

- Attendance is expected. In the case of an absence, you should notify the instructor of the reason.
- Cell phones (or other technology not related to the class) in the classroom is only allowed with express permission of the instructor for special circumstances. In general cell phone or other potentially disruptive technology use is not allowed in class.

Suggestions for Success

- The course requires a time commitment of about 6 hours outside of class time per week (about 3 per class hour). The material builds on itself, so it is very important not to fall behind. Make sure to make enough space in your schedule to spend the time needed.
- I suggest you work in groups on your homework but hand in individual solutions, not copied from each other. Doing the homework is when most of the learning occurs.
- Treat your homework as a study guide for exams. Write solutions to problems in a neat and organized fashion.
- Review your notes from the previous lecture before each class.
- Read the textbook. It will complement the presentation in lecture and help give you the big picture of the material.
- I encourage you to come to office hours regularly. I will do my best to help you.

Academic Integrity:
As students of Manhattan College, you have each signed The Manhattan College Honor Pledge:

As a Manhattan College student, I will not lie, cheat, or steal in my academic endeavors, nor will I accept the actions of those who do. I will conduct myself responsibly and honorably in all my activities as a Manhattan College student. I am accountable to the Manhattan College community and dedicate myself to a life of honor.

Whenever you put your name on work to be handed in for grading in this class, you are reaffirming the above pledge. Violations of the Honor Code include, but are not limited to, cheating, plagiarism, fabrication, and other forms of academic misconduct. Students should familiarize themselves with the Manhattan College Student Code of Conduct and Academic Policies found at:
https://inside.manhattan.edu/student-life/dean-of-students/code-conduct.php#academicintegrity

Special Accommodations:

- Students with special needs should bring appropriate documentation to the Specialized Resource Center, Thomas Hall 3.15, https://inside.manhattan.edu/academic-resources/specialized-resource-center/, to obtain an Academic Adjustment/Auxiliary Aid form. Bring the completed form to me as soon as possible, and together we will decide on how best to fulfill the adjustments and/or aids listed on the form.
- Student athletes should bring their event schedules to me as soon as possible.

Copyright Materials: Copyright in educational materials prepared by the College faculty member is owned by the faculty member, and may not be shared without his or her permission.

The material in this syllabus may be changed at the instructor's discretion. Any changes will be communicated to the students. During these challenging times, we need to be particularly flexible.

Tentative Course Outline:

Week	**Topic**
Week 1 (01/17-01/23)	Introduction to each other and machine learning
Week 2 (01/24-01/30)	Introduction to machine learning (Bishop Chapter 1)
Week 3 (01/31-02/06)	Parametric density estimation (Bishop Chapter 2)
Week 4 (02/07-02/13)	Nonparametric density estimation (Bishop Chapter 2)
Week 5 (02/14 – 02/20)	Linear models for regression (Bishop Chapter 3)
Week 6 (02/21 – 02/27)	Linear models for regression (Bishop Chapter 3)
Week 7 (02/28 – 03/06)	Linear models for classification (Bishop Chapter 4)
Week 8 (03/07 – 03/13)	Linear models for classification (Bishop Chapter 4)
Week 9 (03/14 – 03/20)	**Spring break**
Week 10 (03/21 – 03/27)	Review and **midterm exam**
Week 11 (03/28 – 04/03)	Neural networks (Bishop Chapter 5), **final project discussion**
Week 12 (04/04 – 04/10)	Neural networks (Bishop Chapter 5 and other sources)
Week 13 (04/11 – 04/17)	Model validation and resampling (ISLR Chapter 5), **Easter break**
Week 14 (04/18 -04/24)	Clustering (Bishop Chapter 9)
Week 15 (04/25 – 05/01)	Dimension reduction (Bishop Chapter 12)
Week 16 (05/02 – 05/08)	**Final project** (initial presentations, paper and code)
Week 17 (05/09 – 05/15)	**Final project** (final presentations, paper and code)