



CIS 678 Machine Learning

Course Introduction

Course Introduction: CIS 678 (Machine Learning)

Communication Channels:

- **Blackboard messages (primary choice)**
- Email
- In person/Online

By appointment ([Booking Calendar](#)):
Mackinac Hall (MAK) D-2-216 (Allendale)

Course Faculty



Kamrul Hasan

INSTRUCTOR

Pronouns: he/him/his
Email: hasanka@gvsu.edu;
hasanka@mail.gvsu.edu

Week 1: CIS 678 Introduction

GVCIS678.02.202610.35111

CIS 678 02 - OL - Machine Learning (F25)

Content Calendar Announcements Discussions

Course Content

About this Course

Visible to students

Broad introduction to machine learning concepts. Topics include decision trees, neural networks, methods, explanation-based goal regression, applied machine learning component that processes programs.

Syllabus, Policy, and Regulations

Visible to students

Blackboard Introduction
&
Walkthrough!

Week 1 Plan

- **Get to know each other (networking)**
- Set up our course objective, guidelines, and evaluation procedure.
- Introduction to ML
- Set up our programming development environment(s), more specifically,
 - Google Colab(oratory) on your Google drive,
 - HPC cluster account (introduction)
- Basics of Math, Statistics, and Probability (Part 1)

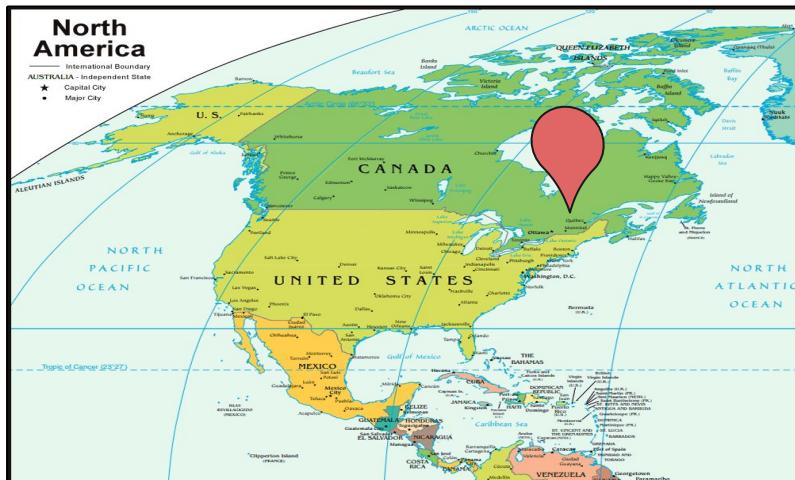
About myself

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- **Graduated from University of Montreal, 2014**
 - Multi-media data mining



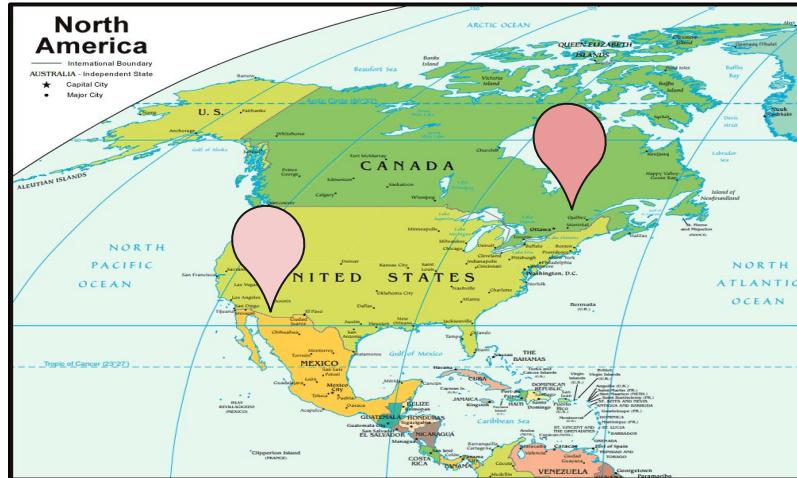
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- Born and raised in a tiny south Asian country, Bangladesh
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- **Probabilistic ML**
 - **Semi-supervised Learning**
 - **Generative AI** (example: LLMs ,ChatGPT)



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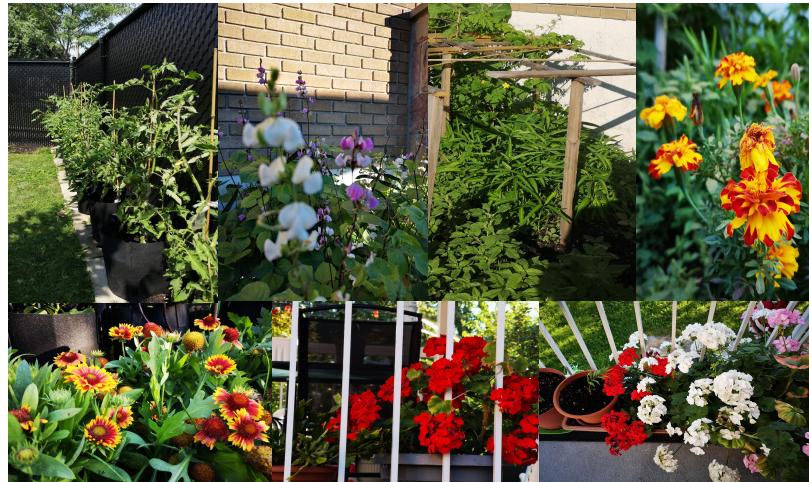
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- Travelling
- **Gardening**



About you!

- I hope I would get to know each of you as we progress
- We will meet in person and/or virtually as per our availability
- You will collaborate as groups
 - For discussion different topics: course specific and beyond
 - Final project
- I will seek your suggestions

Blackboard messages!

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General information (about the course)

Description: Broad introduction to

- Machine learning
- Topics include decision trees, neural networks, statistical methods, genetic algorithms, Bayesian learning methods, explanation-based goal regression, reinforcement learning, and learning frameworks.
- Includes an applied machine learning component that provides exposure to established algorithms and machine learning programs.

Prerequisite: Admission to graduate programs

Objective: Completing this course, you should be able to:

- Explain the general idea of Machine Learning and connect to some practical applications,
- Exercise and apply some standard supervised and unsupervised ML techniques,
- Identify and build models using appropriate ML techniques including Deep Learning and Reinforcement Learning,
- Evaluate models for their effectiveness and appropriateness,
- Utilize some latest ML development tools and techniques in their projects,
- Communicate findings using effective visualization and documentation.

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Textbook(s): There are no required textbooks for this course.

Some good options include:

- Bishop: [Pattern Recognition and Machine Learning](#).
- Murphy: [Machine Learning: a Probabilistic Perspective](#).
- Deisenroth, Faisal, and Ong: [Math for ML](#).
- Shalev-Shwartz and Ben-David: [Understanding Machine Learning: From Theory to Algorithms](#).
- [Deep Learning](#), Ian Good Fellow, Yoshua Bengio, and Aaron Courville
- Machine Learning with Python Cookbook: Practical Solutions from Preprocessing to Deep Learning Paperback – April 17 2018 by [Chris Albon](#)
- [Practical Deep Learning for Coders](#), Fastai, (Jeremy Howard & Sylvain Gugger)

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Requirements:

- Computer/workstation terminal
- Blackboard and Google Drive access,
- Google colaboratory setup
- Ability to run Python (and install any requisite Python packages).
- If you have any trouble, talk to the instructor, and we will work out a solution together.

Delivery Plan

General information:

- See **Blackboard** for detailed schedule
- Planning and **delivery per week**
- **Course materials** and **assignments** will be available on Blackboard **mostly** at the beginning of each week; sometimes as we progress.

Update your Blackboard settings so you receive your emails, messages, and notifications in time.

Delivery Plan

Introduction and networking (2W)

Week of	Topic (higher level)	Topic	Activity
January 12	Course introduction & Math and Probability Basics	Course introduction, regulations, and policies Math, Probability Basics (in brief; mainly directives)	Course introduction & networking
January 19	General idea of ML (connection to Math and Probability)	Polynomial curve fitting, connection between method of least squares and maximum likelihood learning.	
January 26	Supervised & unsupervised learning (general ML models)	Regression models	Assignment 1
February 02		Classification models; Model selection, HP optimization;	Assignment 1 (due)
February 09		Unsupervised learning (clustering)	Assignment 2, Quiz (1)
February 16		Curse of dimensionality, Linear Dimensionality Reduction, PCA	
February 23	Deep learning	Neural Networks (NNs): Feed Forward NNs	Assignment 2 (due)
March 02		NNs: Feed Forward NNs (cont.)	Assignment 3 Midterm exam Spring Break (March 08 - March 15)
March 09		NNs: Convolutional NNs	Spring Break (March 08 - March 15)
March 16		NNs: Convolutional NNs (cont.)	Assignment 3 (due)
March 23		Non linear dimensionality reduction (Auto encoders, RBMs)	Assignment 4, Quiz (2)
March 30	Time-series/sequence modeling	ARIMA, Recurrent NNs (RNNs)	
April 06	Special topics	Transformers, Generative AI	
April 13		Reinforcement learning	Assignment 4 (due)
April 20	Review and Exam	Course Review week	
April 27		Exam week	Final exam

Delivery Plan

General ML Models (4W)

Week of	Topic (higher level)	Topic	Activity
January 12	Course introduction & Math and Probability Basics	Course introduction, regulations, and policies Math, Probability Basics (in brief; mainly directives)	Course introduction & networking
January 19	General idea of ML (connection to Math and Probability)	Polynomial curve fitting, connection between method of least squares and maximum likelihood learning.	
January 26	Supervised & unsupervised learning (general ML models)	Regression models	Assignment 1
February 02		Classification models; Model selection, HP optimization;	Assignment 1 (due)
February 09		Unsupervised learning (clustering)	Assignment 2, Quiz (1)
February 16		Curse of dimensionality, Linear Dimensionality Reduction, PCA	
February 23	Deep learning	Neural Networks (NNs): Feed Forward NNs	Assignment 2 (due)
March 02		NNs: Feed Forward NNs (cont.)	Assignment 3 Midterm exam Spring Break (March 08 - March 15)
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Delivery Plan

Deep Learning
Models
&
Special Topics
(8W)

Week of	Topic (higher level)	Topic	Activity
January 12	Course introduction & Math and Probability Basics	Course introduction, regulations, and policies Math, Probability Basics (in brief; mainly directives)	Course introduction & networking
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Delivery Plan

Wrap Up (2W)

Week of	Topic (higher level)	Topic	Activity
January 12	Course introduction & Math and Probability Basics	Course introduction, regulations, and policies Math, Probability Basics (in brief; mainly directives)	Course introduction & networking
January 19	General idea of ML (connection to Math and Probability)	Polynomial curve fitting, connection between method of least squares and maximum likelihood learning.	
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Evaluation

Grading distribution:

- Weekly reflections: 5%
 - *Attendance & participation: 2%*
 - *Class engagement: 3%*
- Homework assignments: 40%
- Quizzes: 15%
- Midterm: 15%
- Final exam: 25%

Grade points:

A	93%	C	73%
A-	90%	C-	70%
B+	87%	D+	67%
B	83%	D	60%
B-	80%	F	Below 60%
C+	77%		

Note: Your final grade percentage will be rounded to the next integer percentage value. For example, an **89.1%** will round up to a **90%**.

Midterm, Quizzes, and Final Exam Policy

Written

- *Midterm exam,*
- *two quizzes,*
- *Final Exam*

will assess the concepts in machine learning covered up to that point. Additional details regarding the format and content of these assessments will be provided as the course progresses. There will be a final test. This is mainly to check student's critical, mathematical thinking, and problem solving ability as per this course is taught.

To help maintain the integrity of the course, all exams—including quizzes—will be conducted using the **Respondus LockDown Browser** with the webcam enabled. We will share detailed instructions before each exam or quiz to guide you through the process. Please take a moment to ensure that the LockDown Browser is installed and set up ahead of time. You can find helpful instructions in the guide below, and feel free to reach out to me if you have any questions or need assistance—I'm happy to help.

<https://services.qvsu.edu/TDClient/60/Portal/KB/ArticleDet?ID=9865>



Policy & expectation

Expectation: I expect the following to ensure your success in this course:

- check Blackboard on a regular basis for announcements, course material, and assignments
- stay up to date with required course materials.
- let me know how the class and my teaching can be improved
- adhere to the **GVSU policy of Academic Honesty** <http://www.gvsu.edu/coursepolicies/>

Course policy:

- Weekly reflections and homework assignments are to be completed **individually**.
- Due dates: All assignments will be due at 11:59pm Michigan time on the due date (unless otherwise stated).
- Late policy: You will lose 10% off of your maximum grade per day late, to a cap of 3 days (30% off), after which the assignment will not be accepted.

Policy & expectation

Academic Honesty:

- All students are expected to adhere to the academic honesty standards set forth by GVSU.
- In addition, students are expected to adhere to the academic guidelines as set forth by the CoC:
<https://www.gvsu.edu/computing/academic-honesty-30.htm>
- You can learn a lot from your peers, therefore, I encourage collaboration, but passing their work off as your own is prohibited.

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With respect to all individual assignments in this course:

- Document collaboration; **no electronic transfer of code** between students is permitted.
- You are encouraged to engage in conversations in **online forums**, but do not post solutions or solicit others to complete your work for you.
- You are encouraged to talk about problems with each other in **non-technical terms** (i.e., not code).
- Ultimately, **you are responsible** for all aspects of your submissions. You should be able to explain and defend if the work is entirely your own.

Policy & expectation

Use of Generative AI Tools for Learning

- Students are permitted to use generative AI tools (e.g., ChatGPT) to support their learning, such as clarifying concepts, generating test cases, or assisting with code debugging.
- However, AI must not be used to complete or generate any part of the final work submitted for credit.
- All AI use must be clearly documented, and students are responsible for verifying the accuracy of AI-generated content.
- Improper or undocumented use of AI may constitute an academic integrity violation.

For detailed usage guidelines, responsibilities, and documentation requirements, please refer to the full document: "**Guidelines for Using Generative AI Tools in Learning**", shared through **Blackboard**.



Useful resources

Blackboard: Course materials, assignments, grades, and announcements will be posted to Blackboard (<https://lms.gvsu.edu/>). It is your responsibility to stay informed.

Other academic resources: GVSU also provides opportunities for students to improve your **academic skills** through resources, such as:

- [The writing center](#)
- [Computing Success Center](#)
- [Speech lab](#)
- [Research consultants](#)
- [Library Resources](#)

Disability support : If you are in need of accommodations due to disability you must present a memo to me from Disability Support Resources (DSR), indicating the existence of a disability and the suggested reasonable accommodations. If you have not already done so, please contact the Disability Support Resources office (215 CON) by calling 331-2490 or email to dsrgvsu@gvsu.edu. Please note that I cannot provide accommodations based upon disability until I have received a copy of the DSR issued memo. All discussions will remain confidential. For more information, see <https://www.gvsu.edu/dsr/>

Computing Success Center: The Computing Success Center, located in MAK A-1-101, is a great place to get help or simply hang out. The Computing Success Center offers free drop-in tutoring for a variety of College of Computing courses throughout the week during the academic year.