Instructor: Dennis Asamoah Owusu *Office*: Room 205E (Engineering Building) *Email*: dowusu@ashesi.edu.gh *Office hours:* Thursdays & Fridays 10:00– 11:00pm	**Faculty Intern (Teaching Assistant)** Maxwell Aladago Office: Faculty Intern's Office (Beside HR) Email: maxwell.aladago@ashesi.edu.gh *Office hours:* Mondays & Fridays 10:30am-1pm

Syllabus: Machine Learning (CS 452), Jan-May 2019

Meeting Times:
Monday & Wednesday: 8am – 9:30am (Location: Lab 222)
Friday 12:10pm to 1:40pm (Location: Lab 222)

Course Overview:

This course provides an introduction to machine learning. Topics include supervised and unsupervised machine learning, statistical inference and prediction. A wide variety of algorithms will be presented, including logistic regression, K-nearest neighbors, naive Bayes, decision trees, neural networks, K-means, mixtures of Gaussians, principal components analysis, Expectation Maximization. The course will also discuss modern applications of machine learning such as image segmentation and categorization, speech recognition, and text analysis.

Course Objectives:
1. To understand and be able to explain the foundational principles underlying the field of machine learning.
2. To be able to implement algorithms for regression, classification, clustering and dimensionality reduction.
3. To be able to design suitable machine learning models for a given real-world problem.
4. To be able to read and understand machine learning research papers.
5. To be able to give presentations on machine learning work to technical and non-technical audiences.

Ashesi Learning Goals Addressed in this Course:
1. **Critical Thinking and Quantitative Reasoning**: *An Ashesi student is able to apply critical thinking and quantitative reasoning to approach complex problems.* This course is all about problem-solving, design and implementation of algorithms. Students will develop the ability to analyze relevant problems, design algorithms to solve them, implement these algorithms and learn to optimize them for the given task.
2. **Communication**: *An Ashesi student is an excellent communicator in a variety of forms*. This course requires students to write project reports. At various points in the semester, they will need to present their work to technical and non-technical audiences.
3. **Curious and Skilled**: *An Ashesi student is inquisitive and confident, has breadth of knowledge, and has attained a high level of mastery in their chosen field.* This course aims to expose students to an advanced field of computer science, and encourage them to learn about the state-of the art in the field of machine learning.
4. **Technology Competence**: *An Ashesi student is an effective and flexible user of technology*. This course focuses on developing algorithms to train machine learning models.
5. **Leadership & Teamwork**: *An Ashesi student is adept at leading and functioning in teams*. Students are required to work in teams for their class project.

Textbook and other reference books:

Ian Goodfellow, Yoshua Bengio and Aaron Courville, *Deep Learning*, MIT Press 2016. *Note that this book is freely available in digital form at the link above.*
Christopher M. Bishop, *Pattern Recognition and Machine Learning*, Springer 2011.

Topics:

- Linear and non-linear regression
- Probability theory
- Maximum Likelihood and Maximum A Posteriori regression
- Model selection
- Locally weighted regression
- Logistic regression
- Gaussian Discriminant Analysis
- Naive Bayes
- k-NN
- Decision trees
- Multilayer Neural Networks
- Convolutional Neural Networks
- K-means
- Mixture of Gaussians
- Expectation Maximization
- Principal Component Analysis
- Multidimensional Scaling

Expectations:

The instructor is committed to helping you to be successful in this course. In return, there are some fundamental expectations of you.

Preparation and Participation

Your active participation enriches the course experience for everyone. This includes completing the class preparation assignments, participating in discussions, and even sharing interesting things about machine learning that you learn on your own. You are required to come to class, and to arrive on time. A record of poor or chronically late attendance could, at the end of the semester, result in a penalty against your course grade.

Academic honesty

You are expected to keep in mind at all times that *"An Ashesi student is an ethical, responsible and engaged member of his/her community"*. The work in this course is designed to help you develop skills essential to your future career success. You can only develop these skills if you do the work yourself.

All the work that you turn in *must* be your own. You may discuss homework assignments with other current CS 452 students, but your submission must be entirely your own work. That is, your code and any other solutions you submit must be created, written/typed, and documented by you alone. You may not copy anything directly from another student's work. For example, memorizing or copying onto paper a portion of someone else's solution would violate the honor code, even if you eventually turn in a different answer. Similarly, e-mailing a portion of your code to other students, or posting it on-line for them to see would violate the honor code. We do encourage discussion of assignments among students, subject to these rules.

You cannot make use of any code taken from outside references for your homework assignments, unless explicitly authorized to do so by the instructor. As a rule of thumb, you should treat any external code as software written by another CS 452 student: you are not allowed to copy it or to use it as a template to implement your solution.

You are allowed to use external software for your project. However, you should clearly report the use of external code and include pointers to such software in your project write-up. The project grade will be based on the novelty of your solution/application but also on the amount of new code written by you to implement the idea.
Keep this in mind when considering using software written by someone else.

Professionalism
You are expected to interact with your course colleagues, as well as the instructor and teaching assistant in a professional and polite manner at all times.

Evaluation Criteria

The course grade will be based on four homework assignments and a final project. The final project will involve three separate components: a proposal (counting for 15% of the project grade), a milestone (counting for 25% of the project grade) and a closing submission (counting for 60% of the project grade). A document titled "project guidelines" providing tips and suggestions for a successful final project will be made available.

Homework assignments (4):	60%
Final project:	40%

Late Policy

All assignments and submissions are due when stated. For the homework assignments, you have three "late days" which you may use at any time in the course. Once these late days are used, any homework turned in late will be penalized 25% per late day. *No exception!* Any portion of a late day is counted as one full day. Assignments are typically due at 11:59 pm of the due date. Both the code portion as well as the answers to technical questions must be submitted electronically via Courseware.

Schedule

Below is the tentative schedule for the course. Chapter references, when available, are to one of the recommended course textbooks, *Pattern Recognition and Machine Learning* by Christopher Bishop. Note also that the schedule is subject to change as needed.

Date	Topics	References	Out	Due
January 14	Course introduction			
January 16	Linear regression	Sec. 1.1		
January 18 (lab)	Probability theory (part 1)	Sec. 1.2		
January 21	Linear Regression	Sec 1.1	hw1	
January 23	ML Regression	Sec 3.1		
January 25 (lab)	Probability Theory 2			
January 28	MAP regression			
January 30	Model selection	Sec. 1.3		
February 4	*Locally weighted regression;* ***Project spotlight presentations***			project proposal write-up
February 6	Classification: logistic regression	Sec. 4.3		
February 11	Gaussian Discriminant Analysis	Sec. 4.2	hw2	hw1
February 13	Naive Bayes			
February 18	kNN	Sec. 2.5		
February 20	Decision trees	Sec. 14.4		
February 25	Support Vector Machines (part 1)	Sec. 7.1		
February 27	Support Vector Machines (part 2)			hw2

~~March 4~~	mid-semester break			
~~March 6~~	mid-semester break			
March 11	Kernels		hw3	
March 13	SMO			
March 18	Multi-layer neural networks (part 1); ***Project milestone presentations***			project milestone write-up
March 20	Multi-layer neural networks (part 2)			
March 25	k-means	Sec. 9.1		
March 23	Mixture of Gaussians	Sec. 9.2, 9.3		hw3
April 1	Expectation Maximization (part 1)	Sec. 12.2.2, 12.2.4	hw4	
April 3	Expectation Maximization (part 2)			
April 8	Principal Component Analysis (part 1)	Sec. 12.1		
April 10	Principal Component Analysis (part 2)			
April 15	Multidimensional Scaling			
April 17	Isomap			hw4
April 22	***Project closing presentations***			project closing write-up