Syllabus
ECSE – 4410 / 6410: Pattern Recognition

-- 3hrs Credit --

Fall 2022 (Final 8.15.22)

University of Georgia

Instructor and Office Hours

- Name: Thirimachos Bourlai
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- Office: 115 Boyd

Offering

- Every year

Office Hours

- **ZOOM hours:** Every Wednesday 8:30 a.m. – 9:30 a.m.
- In person hours: Every Wednesday 8:30 a.m. – 9:30 a.m.
- If students need to see the instructor at any other time, they are kindly requested to make an appointment by telephone or e-mail.
- E-mail is the preferred means of communication.

Textbook

- **Main Book:** Pattern Classification by Duda, Hart and Stork, Second Edition, ISBN: 9-780471056690
- **Suggested Material that will help you**:
    - C. M. Bishop, "Pattern Recognition and Machine Learning", 2006
    - Computational Statistics Handbook with MATLAB (3rd Edition or later) - Book by Angel R. Martinez and Wendy L. Martinez

Prerequisites

The primary prerequisite is a strong commitment to learning and hard work. Competence in programming in some high-level language (C++; C#; Python etc.) and *ideally in MATLAB*, at the level of basic data structures and algorithms (CSCI 2720 or equivalent) will be assumed. Prior exposure to programming computer vision, image processing, and statistics is a strong plus. The course will be mathematically involved in certain parts. A definite advantage is strong analytical and mathematical skills.

Others: An undergraduate level understanding of probability, statistics and linear algebra is assumed. Basic knowledge on Signal and Image Processing is essential. Intermediate knowledge of MATLAB is essential.

Required prerequisites:

- CSCI 1301 or ELEE 2040
- ENGR 2090 Probability & Statistics for Engineers

Preferred Prerequisites:

- NA

Course Description

The course will discuss the pattern recognition stages and topics including Bayesian Decision Theory, Estimation Theory, Linear Discrimination Functions, Nonparametric Techniques, Support Vector Machines, Neural Networks, and Clustering Algorithms. The course is focused on applying engineering problems and solutions (for example: object detection, recognition and tracking).

Additional Requirements for Graduate students

Graduate students are required to propose their own pattern recognition engineering project based on a literature survey of selected course topics. They are expected to design and develop their own code, share it for assessment, present their work and submit a final project report.

Course Objectives or Expected Learning Outcomes

Student learning outcomes are designed to specify what both undergraduate and graduate students will be able to perform after completion of the course:

- Ability to select and implement pattern recognition techniques, on a computing environment, which are suitable for engineering applications.
- Ability to prototype, model, and test various pattern recognition algorithms.
- Ability to identify the characteristics of datasets, pre-process them, and compare the impact of using different datasets on pattern recognition system performance.
- Ability to integrate pattern recognition libraries and mathematical and statistical tools with modern technologies (MATLAB, Python).
- Ability to understand different types of metrics available to evaluate the performance of pattern recognition engineering solutions.

- Ability to select a prototyped model and make it work on a practical scenario, first at small and, then, at larger scale.

Additional course objectives or expected learning outcomes for Graduate Students

- Ability to solve problems associated with *batch learning, and large-scale data characteristics*, including high dimensionality, dynamically growing data and scalability issues.
- Ability to understand and apply *scaling up pattern recognition approaches* and associated computing techniques and technologies (e.g. data augmentation).
- Ability to recognize and implement various ways of *selecting suitable model* parameters for different machine learning techniques.
- Graduate students will also perform a relevant literature study and project related to course topics listed.

Topical Outline

This course will introduce a graduate audience to salient topics in Machine Learning, and Pattern Recognition - (Supervised and Unsupervised Learning):

- Supportive Material to Linear Algebra and Probability Theory
- Introduction to pattern recognition
- Linear Regression
- Logistic Regression
- Gradient Descent
- Neural Networks
- Support Vector Machines (SVMs)
- Bayesian decision theory
- Linear Discriminant functions
- Clustering
- Dimensionality Reduction
    - Principal Component Analysis and Multidimensional Scaling
- Density estimation schemes
- Nearest-neighbor rule
- Feature Extraction
- Pattern Recognition Case Studies (Invited Speakers / Experts)

The topics will be taught not necessarily in the above order.

- The **project component** of this course will test the student's ability to design and evaluate classifiers on appropriate datasets

Course Outcomes

- A good knowledge of Bayesian decision theory and Bayesian learning.
- Fundamental understanding of feature extraction (selected topics), and of classifiers such as nearest-neighbor rule, linear discriminant function, neural networks and SVMs.
- Ability to evaluate the performance of various classifiers on real-world datasets.

Weight/Distribution of Course Points:

The tentative weight associated with each grading component is as follows:

• Homework and Quizzes	-	10%
• Project: Meeting Milestones & Reports	-	15%
• Midterm exam	-	25%
• Project*	-	50%, including (i) Final Project Report, (ii) Presentation / DEMO that the code is working (iii) Code submitted – Instructor will check (code and readme file / how to run) **Expected: via a Google Drive or equivalent, all 3 items above.**

Note on Grade Assessment: the project counts 50% and the students will be assessed, evenly, on each of the tasks above, namely, Final Progress Report; Presentation/Demo; and Code.

Additional Requirements for Grad students (6000 vs. 4000 Section)

- **Graduate students** are **required** to have completed a full project related to machine learning, run existing and/or, preferably, generate new code. They are **required** to make modifications to code/programs found online, not just run it as is, and design and run their own experiments. They are **expected** to explain the project, processes and generated outcomes and what they did different in case their starting point is a project/code found online. *The recommendation will be to design and develop their own code and as a starting point find a paper with associate code.* They are **required** to share the code for assessment, present their work and submit a final report.
- **Undergraduate students:**
  - *The recommendation will be to find a paper with associate code to start working with. They* are **required** to run the code they found *as is – no*

alterations will be expected although encouraged. Testing with new data and find flaws and potential issues and challenges is expected.
    - In their final report, they are **expected** to briefly explain the project, processes and generated outcomes. They are **required** to share the code for assessment, present the paper their found online and submit a final report.

Project Presentations - Due to COV19 challenges

- Students are expected to present their Presentation/DEMO via ZOOM on the same dates as originally planned – a plan will be present and shared with the students.
- The students need to be able to share their screen and present.
- If they cannot connect and present for ANY reason (due to bandwidth etc.) → they are expected to send a recorded presentation, namely one presentation for each student, independent on the group they are at (if they are part of a group project).
- *Note*: Instructor will send one ZOOM invite to all students that are expected to attend, i.e., one invited for Days 1 and 2 during the last week before the finals.
- *Time the presentations start and end*: during regular course hour or longer if necessary since we will be in Zoom.
- *Duration of presentations*: no less than 10 min per person.
- *Structure of presentations:*
    - **Slide 1:** **Title etc.**
    - **Slide 2:** **Problem you are solving**
    - **Slides 3-6:** **Tools you are using to solve the problem**
        - Datasets; Methodology; Approach; Algorithmic Steps; How do you establish a baseline; How do you assess performance (e.g. on detection to see at IOU 50%; for X proposals; Precision and Recall etc.)
    - **Slides 7:** **Experiments you performed**
    - **Slide 8-9:** **Results**
    - **Slide 10:** **Conclusions**
    - **Slide 11:** **Thank you; Q&A**

* NOTE: *Regarding the Project*: It is not acceptable that the students propose to work on a class project that is the same as the one they work in their own research, i.e. funded work in their labs.

Final Grading Scale:

The grading scheme (%) will be as follows:

A	>= 90
B	>= 80, <90
C	>= 70, <80
D	>= 60, <70
F	<60

Grading Policy:

- A hard copy of the **homework** and **project reports** must be turned in before lecture begins on the due date.
- No make-up for midterm and finals, including demo presentations for individuals or a group of students.
- Make-up for exams will be issued only under exceptional circumstances provided prior arrangements are made with the instructor.
- Instructor reserves the right to deny requests for make-up exams.

Course Outcomes:

- A good knowledge of Bayesian decision theory and Bayesian learning.
- Fundamental understanding of feature extraction (selected topics), and of classifiers such as nearest-neighbor rule, linear discriminant function, neural networks and SVMs.
- Ability to evaluate the performance of various classifiers on real-world datasets.

Course and Institutional Policies

Attendance Policy:

https://provost.uga.edu/policies/academic-affairs-policy-manual/4-06-class-attendance/

- Missing or late submission of presentations and reports receive zero credit.
- Makeup exams and quizzes for university-excused reasons only (illness, family emergency, etc.).
- Notice must be given prior to missed exam/quiz via university email.
- Unexpected missing exams and quizzes will result in zero credit.
- Attendance is not mandatory but highly recommended.

Participation Policy:
Participation in in-class examples and discussion is strongly encouraged but it will not be assessed

Late Assignment and Missed Exam Policy:
Excused exam/quiz absence must be retaken as soon as the student is able to return to campus and should be scheduled prior to original exam date if possible.

University Honor Code and Academic Honesty Policy

- UGA Student Honor Code: "I will be academically honest in all of my academic work and will not tolerate academic dishonesty of others." *A Culture of Honesty*, the University's policy and procedures for handling cases of suspected dishonesty, can be found at http://ovpi.uga.edu/academic-honesty. Every course syllabus should include the instructor's expectations related to academic integrity.
- All academic work must meet the standards contained in *A Culture of Honesty*. Students are responsible for informing themselves about those standards before performing any academic work.