Computer Science
Regularization Methods for Machine Learning
Syllabus

Catalog listing:	CMSC 510
Course Level:	Graduate
Prerequisites:	graduate standing in computer science or acceptance into five-year accelerated program in computer science
Instructor:	Tomasz Arodz
Office:	E4252
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Classroom:	W105
Class website:	Canvas
Class time:	TR 3:30-4:45pm
Office Hours:	T 1:30pm-3:30pm

1.0– Overview (Catalog Course Description):

3 lecture hours. 3 credits. Enrollment restricted to students with graduate standing in computer science or related discipline such as bioinformatics or acceptance into five-year accelerated program in computer science. The course will assume undergraduate-level background in algorithms, linear algebra, calculus, statistics and probability. Upon successful completion of this course, the student will be able to understand recent advances in machine learning and apply machine-learning tools that go beyond learning from data, as well as have the ability to incorporate additional knowledge about the learning problem. Topics covered will include optimization-based view of supervised machine learning; classical regularization approaches including weight decay and Lasso; regularization terms incorporating additional knowledge about structures in the feature space, including group lasso and graph-based regularization terms; semi-supervised learning using graphs linking unlabeled and labeled samples.

2.0– Course Structure:

Lecture hours/week – 3
Lab hours/week – 0

3.0– Course Goals

Upon successful completion of this course, the student will be able to understand recent advances in machine learning and apply machine learning tools that go beyond learning from data, and can include additional knowledge about the domain. The course will assume undergraduate-level background in algorithms, linear algebra, multivariate calculus, statistics, and probability.

4.0– Major Topics Covered:

- Introduction to machine learning and the need for regularization
  - Loss, risk, empirical risk minimization
  - L1 and L2 regularization
- Regularization using group of features and graph of features
  - Group lasso
  - Submodular regularization
- Semi-supervised learning using graph of samples
  - Spectral graph theory
  - Semi-supervised Support Vector Machines
- Regularization in large models
  - Weight decay
  - Weight sharing
  - Dropout
  - Transfer learning
  - Spectral methods

5.0– Textbook(s):

None. Slides will be shared after each class.

6.0– Evaluation:

General Instructions:

For grading, the course will use four projects to be completed by each student in Python (numpy, tensorflow, pytorch) and a test.

Grading:

Category	% weight
4 Programming Projects	60 (15 each)
Test	40

Grading Scale:

A [90% - 100%], B [80% - 90%), C [70% - 80%), D [60%-70%), F [0% - 60%)

Students should visit *http://go.vcu.edu/syllabus* and review all syllabus statement information. The full university syllabus statement includes information on safety, registration, the VCU Honor Code, student conduct, withdrawal and more.