DA 513 – Machine Learning I

Spring 2019

Description: Machine learning aims to develop computer programs that improve their performance through experience by capturing relevant abstractions of past training input. This course will cover fundamental approaches in machine learning (k-NN, decision trees, Bayesian approaches, neural networks, support vector machines, ensemble learning), as well as getting a solid foundation on theoretical concepts such as overfitting, curse of dimensionality, bias-variance dilemma.

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Reference Book(s): No required textbooks, but below you can find a list of reference books. Lecture readings will be posted on SUCourse.

- Ethem Alpaydın, Introduction to Machine Learning, 2e. The MIT Press, 2010. (online available at the IC)
- Tom Mitchell, Machine Learning, McGraw Hill, 1997.
- Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani. An Introduction to Statistical Learning: with Applications in R (online version available).
- Kevin P. Murphy, Machine Learning: a Probabilistic Perspective, The MIT Press, 2012.
- Introduction to Machine Learning with Python, Andreas C. Müller & Sarah Guido, 2016.
- Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques for Building Intelligent Systems, Aurélien Geron, 2017.
- Christopher M. Bishop, Pattern Recognition and Machine Learning, Springer, 2011 (most comprehensive)

Course Web site: SUCourse

Grading

- **% 50 in-class exam** The exam will test your knowledge of the fundamentals (what you must know after this course), rather than challenging you with difficult problems.
- **% 20 homework** Tentative 4 homework assignments. We recommend using Python for the homework assignments.
- **% 30 project** The purpose of the project is to get hands on practical experience. You will work groups of three people. The course project will be 3-4 alternative projects to choose from. The projects will be assigned by the 4th Lecture. By the end of the semester you will be
- Must have a min. of **25/100** from the final and **50/100** overall to pass the course
- In addition to the homework we will have in class work and 3-4 study questions after each class.

Tentative Outline

Lecture 1
- Course Information
- Intro to machine learning: Supervised learning paradigms with examples; performance evaluation…

Lecture 2
- Simple linear regression, polynomial regression, multiple linear regression
- Gradient descent
- Regularization

Lecture 3
- Decision trees for classification and regression
- Overfitting
- K-NN, distance measures, scale normalization, curse of dimensionality
- ➢ **HW1 is assigned**

Lecture 4

- Feedforward Neural Networks

Lecture 5

- Deep Learning Overview
- Convolutional Neural Networks
- **HW2 is assigned**

Lecture 6

- Probability review (PDFs; Joint, conditional, prior, independence, conditional independence)
- Bayes theorem
- **Projects are announced**

Lecture 7

- Multivariate Normal distribution
- Gaussian Bayes Classifier

Lecture 8

- Naïve Bayes
- MLE + MAP Estimate, Laplace smoothing
- **HW3 is assigned**

Lecture 9

- Linear Classifiers, Multiclass classification, Logistic Regression

Lecture 10

- Data processing and Representation Issues for Different Classifiers: Issues with missing features, feature selection, imbalanced data

Lecture 11

- SVM Classification and Regression
- **HW4 is assigned**

Lecture 12

- Ensemble methods; Bagging, Boosting, Random Forests

Lecture 13

- **Final exam**

Lecture 14

- **Project presentations**