שנה"ל תשפ"א

שם הקורס:	מבוא ללמידת מכונה / Introduction to Machine Learning
שם המרצה:	ד"ר אייל קולמן

מטרות הקורס: Course Goals

Hovering over the vast world of Machine Learning. By the end of this course, you'll be familiar with many ML techniques, have some experience in some of them, and hopefully you would acquire a desire to dive deeper into the Machine Learning domain.

נושאי הלימוד: Course Program

Probability theory, Bayesian classifiers, Models estimation, Proximity measures, Dimensionality reduction and feature selection, Artificial Neural Networks, Support Vector Machines, Decision trees, Unsupervised Learning (clustering, association rules, and anomaly detection), Evaluation approaches, and a taste of NLP (Natural Language Processing) and Deep Learning

הרכב הציון:Course Grade

60% פרוייקט
30% מבחן סיום
10% תרגילי בית

תוצרי למידה : Learning Outcomes

By the end of the course the students will be familiar with several Machine Learning techniques. They will have the ability to design data-driven algorithms, choose the most suitable Machine Learning technique for a specific problem, apply the selected model, analyze the results, and understand the advantages and drawbacks of their solution. This will allow them to solve real-life problems without any known analytic solution.

ביבליוגרפיה: Bibliography

Pattern Classification, 2nd Edition, Duda, Hart and Stock, 2001

Introduction to Machine Learning with Python: A Guide for Data Scientists, Andreas C. Müller, Sarah Guido, 2016

שנה"ל תשפ"א

סילבוס מפורט:

1. Probability theory – basic concepts and introduction
2. Naïve Bayes:
    a. Likelihood, log-likelihood
    b. Risk Minimization
3. Model estimation:
    a. GMMs and AGMMs
    b. EM (expectation-minimization)
    c. Example for Normal distributions
    d. Conjugate Priors
    e. Laplace's Rule of succession
    f. Non-parametric models:
        1. Histogram based
        2. K Nearest Neighbor Density Estimation
    g. K-Nearest Neighbor Classifier
4. Distance measures
    a. Distance/Metric definitions
    b. Distance in Euclidean / Non-Euclidean spaces, KL-divergence, L norms, Bhattacharyya distance, Earth moving, Mahalanobis distance, Information distance, Kolmogorov–Smirnov distance
5. Dimensionality reduction, feature engineering and data preprocessing
    a. Correlation, mutual information, MRMR
    b. Scatter Matrices
    c. PCA
    d. LDA
6. Evaluation Techniques:
    a. Bias-Variance Dilemma
    b. Hold-out sets
    c. Cross-validation

d. Adjusted R^2

e. Likelihood-based theoretical approaches (AIC, BIC)

f. Confusion matrix and its measures: Accuracy, Precision, Recall, F_1 score, etc.

g. ROC curve, AUC and partial-AUC

h. Lift Charts and Gain Charts

i. Loss functions

7. Supervised Learning:

    a. Linear and Logistic regression

    b. Training methods:

        i. (Stochastic) Gradient Descent

        ii. Batch and stochastic training

        iii. Momentum

        iv. Learning rate

        v. Regularization

        vi. Bootstrapping

8. Decision trees: C45, CART, CHAID, J4.8, Information Gain, Ratio Gain, Gini Index

9. Ensemble Methods – Random Forest, Boosting, AdaBoost, Bagging

10. Support Vector Machines:

    a. Maximal margin principle

    b. Non-linear separation

    c. Kernels: Linear, Gaussian, Polynomial, Hyperbolic

    d. Non-separable cases

11. Unsupervised Learning:

    a. Clustering: Hierarchical, Centroid-based, Distribution-based, Density-based (DBSCAN, OPTICS)

    b. Association Rules:

        i. Support, Confidence and Lift

        ii. Association rules detection

c. Outlier detection: Extreme Value Analysis, Probabilistic models, Linear models, Proximity-based models