MACHINE LEARNING (ML) Basics: CS5200

The goal of learning is prediction. Learning falls into many categories, including:

- **Supervised learning,**
- **Unsupervised learning,**
- **Semi-supervised learning**
- **Transfer Learning**
- **Online learning, and**
- **Reinforcement learning**
- **Incremental Learning**
- **Deep Learning.**

Supervised learning is best understood and studied.

Machine Learning is ...

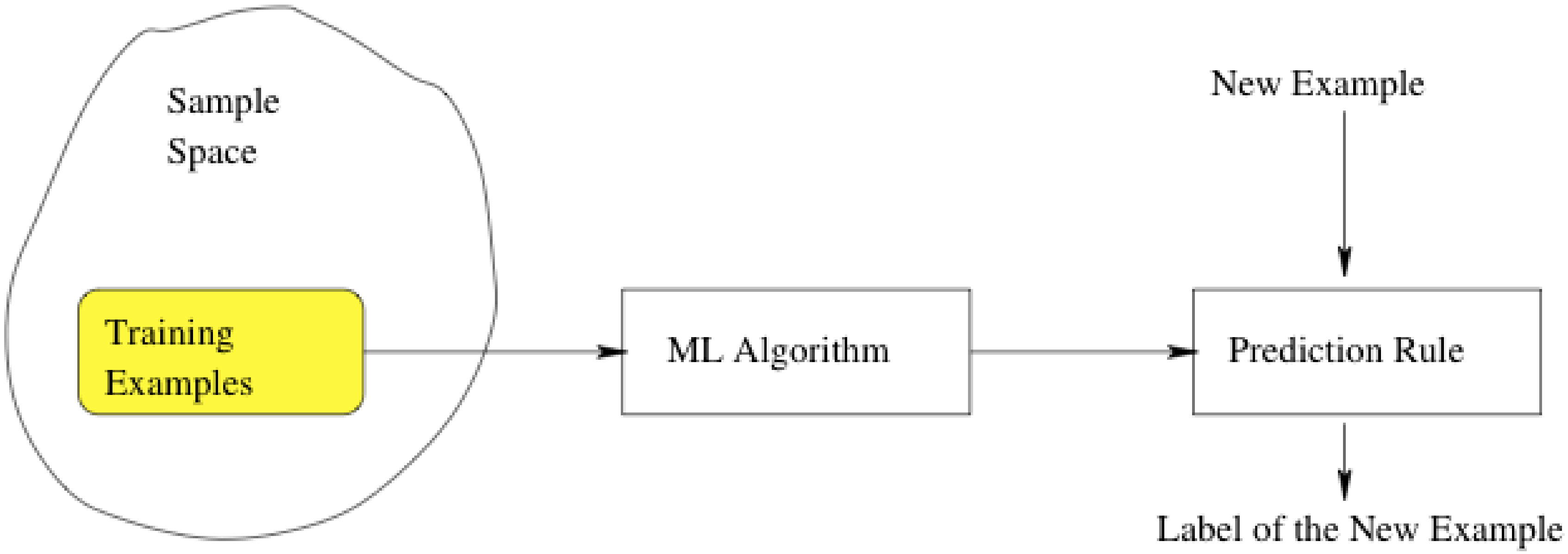
an algorithm that can learn from data without relying on rules-based programming.

In supervised learning, an algorithm is given samples that are labeled in some useful way. For example, the samples might be descriptions of apples, and the labels could be whether or not the apples are edible.

Supervised learning involves learning from a training set of data. Every point in the training is an input-output pair, where the input maps to an output. The learning problem consists of inferring the function that maps between the input and the output in a predictive fashion, such that the learned function can be used to predict output from future input.

The algorithm takes these previously labeled samples and uses them to induce a classifier. This classifier is a function that assigns labels to samples including the samples that have never been previously seen by the algorithm.

The goal of the supervised learning algorithm is to optimize some measure of performance such as minimizing the number of mistakes made on new samples.



Machine Learning is …

a subfield of computer science and artificial intelligence which deals with building systems that can learn from data, instead of explicitly programmed instructions.

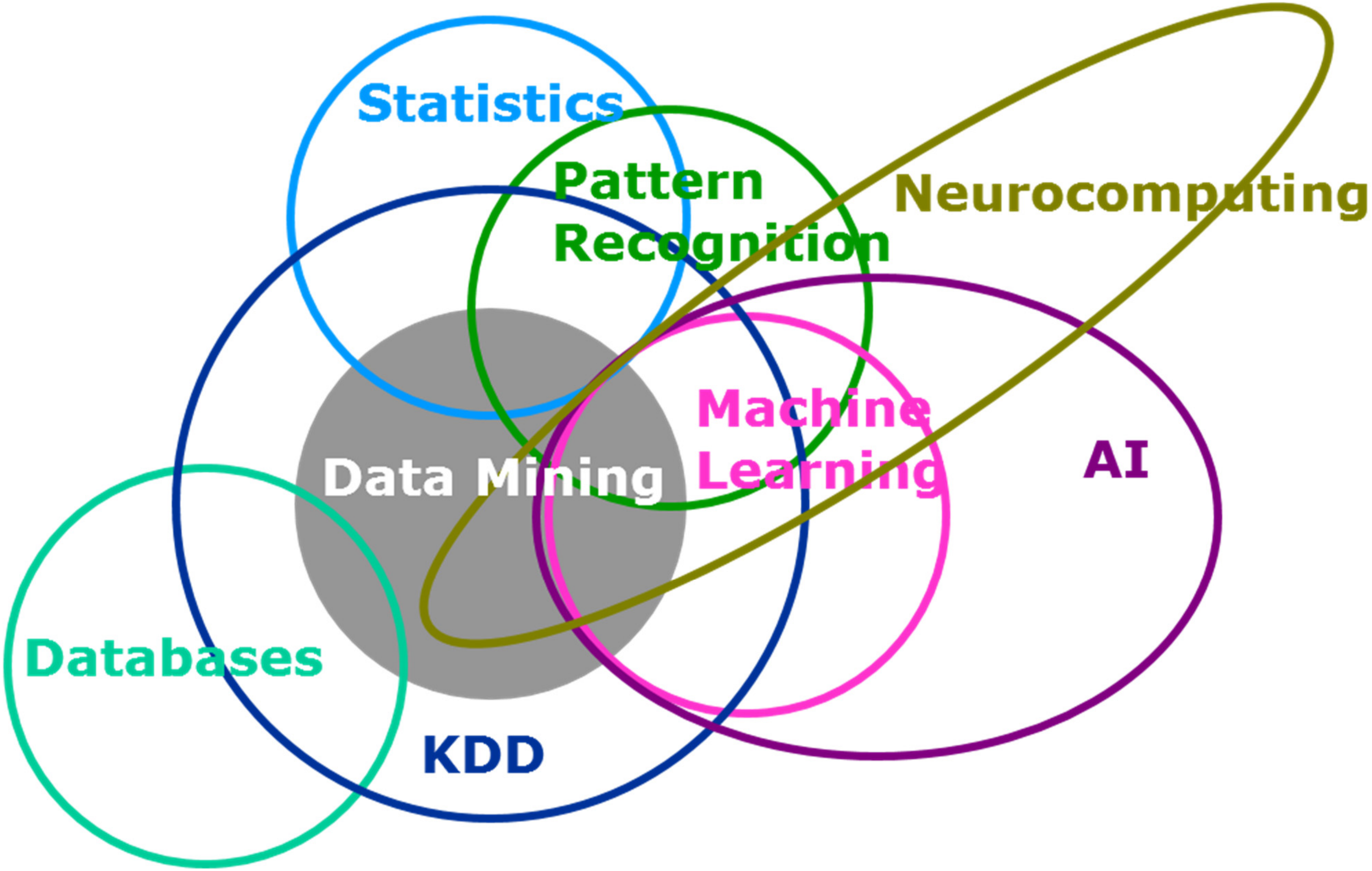
Computational learning theory studies the time complexity and feasibility of learning. In computational learning theory, a computation is considered feasible if it can be done in polynomial time.

Classification problems are those for which the output will be an element from a discrete set of labels. Classification is very common for machine learning applications. The input would be represented by a large multidimensional vector whose elements represent pixels in the picture, say CV applications.

After learning a function based on the training set data, that function is validated on a test set of data, data that did not appear in the training set.

Computational learning theory
(Wikipedia)

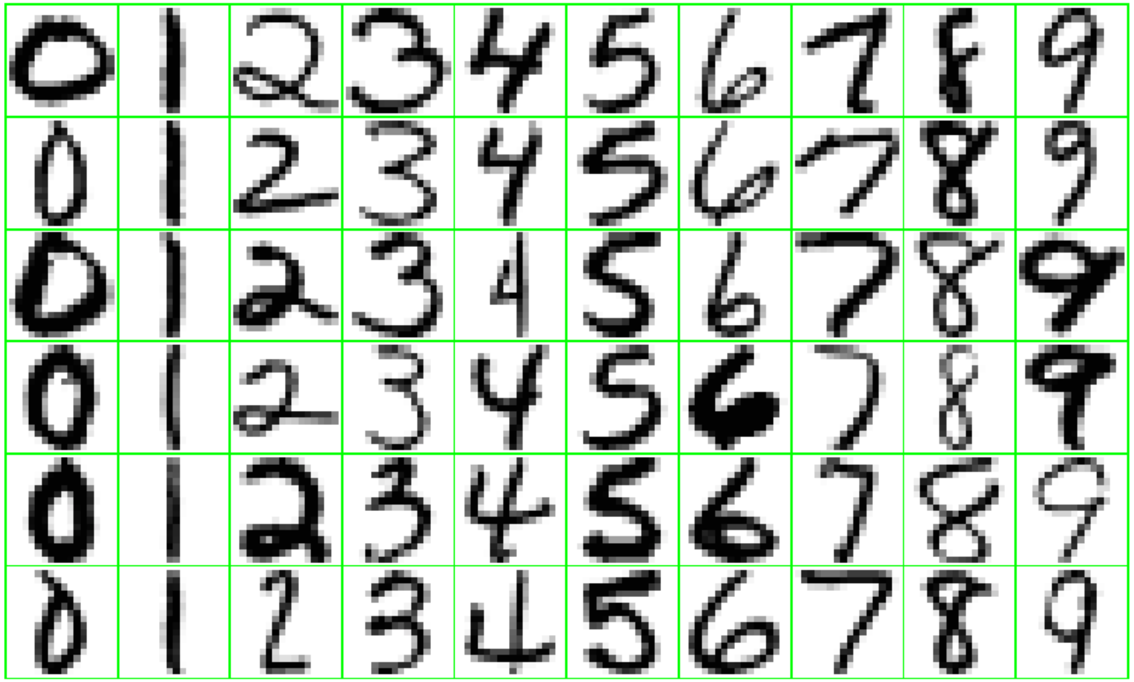
- **Probably approximately correct learning** (PAC learning) --Leslie Valiant
  - inspired boosting
- **VC theory** --Vladimir Vapnik
  - led to SVMs
- **Bayesian inference** --Thomas Bayes
- **Algorithmic learning theory** --E. M. Gold
- **Online machine learning** --Nick Littlestone
- SRM (**Structural risk minimization)**
  - model estimation


Statistics
Pattern Recognition
Neurocomputing
Machine Learning
AI
Data Mining
Databases
KDD

Example: Recognition of Handwritten Digits

- Data: images are single digits 16x16 8-bit gray-scale, normalized for size and orientation
- Classify: newly written digits

- Non-binary classification problem
- Low tolerance to misclassifications



Categories of <u>Supervised Learning</u>:

- Linear Regression – Prediction using Least Squares
- Function Approximation – Linear basis expansion, cross entropy
- Bayes
- Regularization
- Kernel methods & SVM;
- Basis and Dictionary methods;
- Model selection
- Perceptron, ANN
- Bagging, Boosting, Additive Trees
- Logistic Regression, LDA
- Inductive Learning
- Decision Trees
- Deep Learning

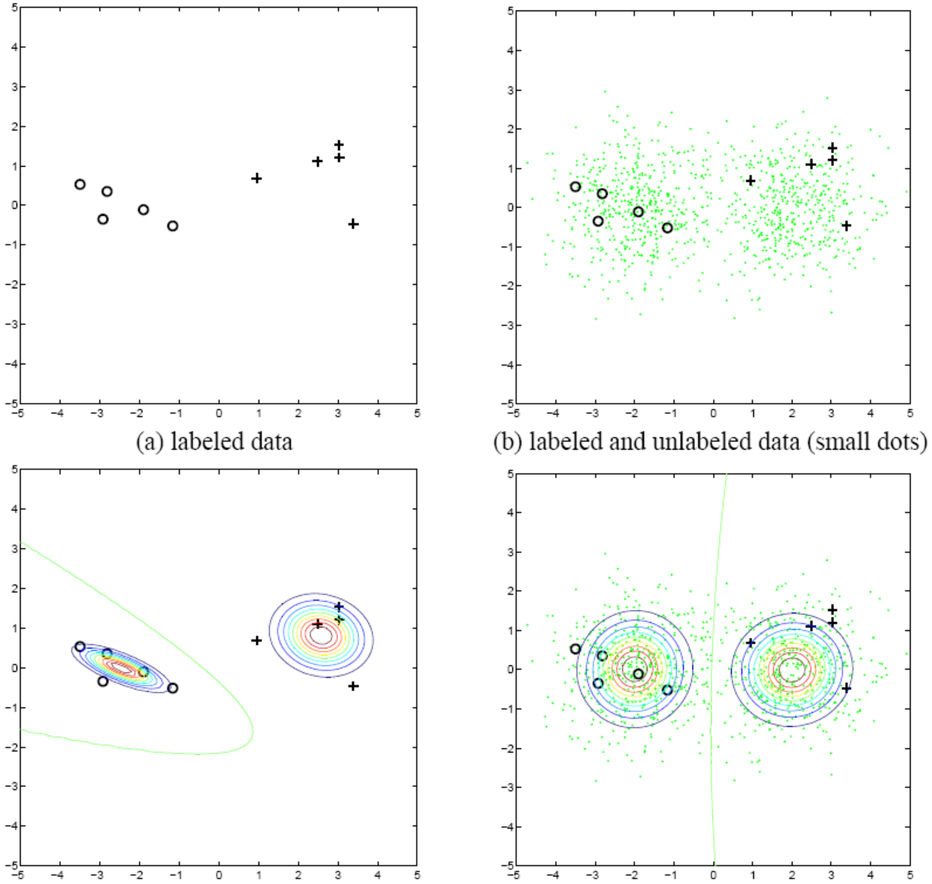
Unsupervised Learning

- No training data in the form of (input, output) pair is available
- Applications:
  - Dimensionality reduction
  - Data compression
  - Outlier detection
  - Classification
  - Segmentation/clustering
  - Probability density estimation
  - …

Semi-supervised Learning

- Uses both labeled data (in the form (input, output) pairs) and unlabelled data for learning
- When labeling of data is a costly affair semi-supervised techniques could be very useful
- Examples: Generative models, self-training, co-training

Example: Semi-supervised Learning



(a) labeled data

(b) labeled and unlabeled data (small dots)

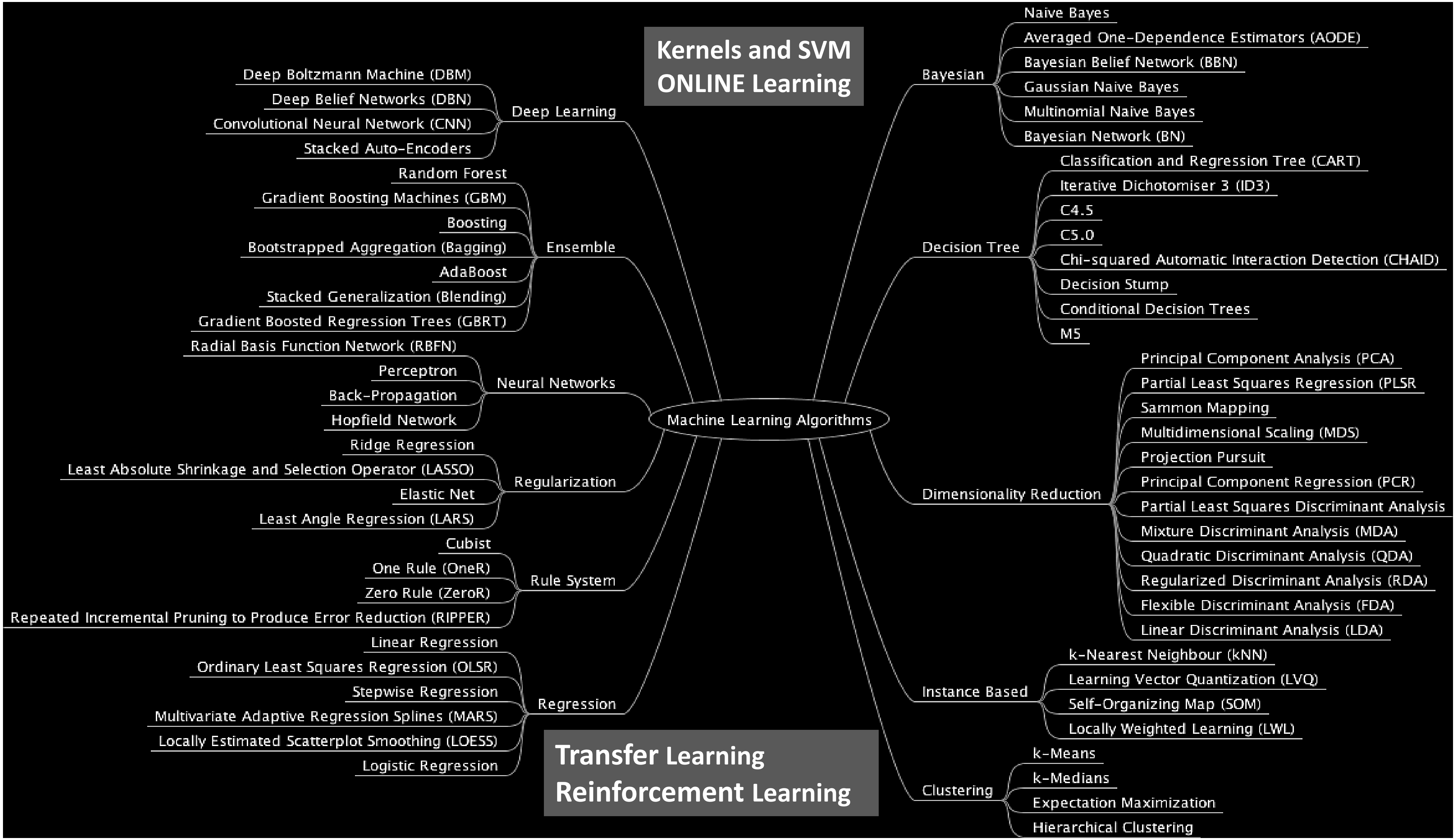
(c) model learned from labeled data

(d) model learned from labeled and unlabeled data

Source: Semi-supervised literature survey by X. Zhu, Technical Report

Reinforcement Learning

- Reinforcement learning is the problem faced by an agent that must learn behavior through trial-and-error interactions with a dynamic environment.
- There is no teacher telling the agent wrong or right
- There is critic that gives a reward / penalty for the agent’s action
- Applications:
  - Robotics
  - Combinatorial search problems, such as games
  - Industrial manufacturing
  - Many others!



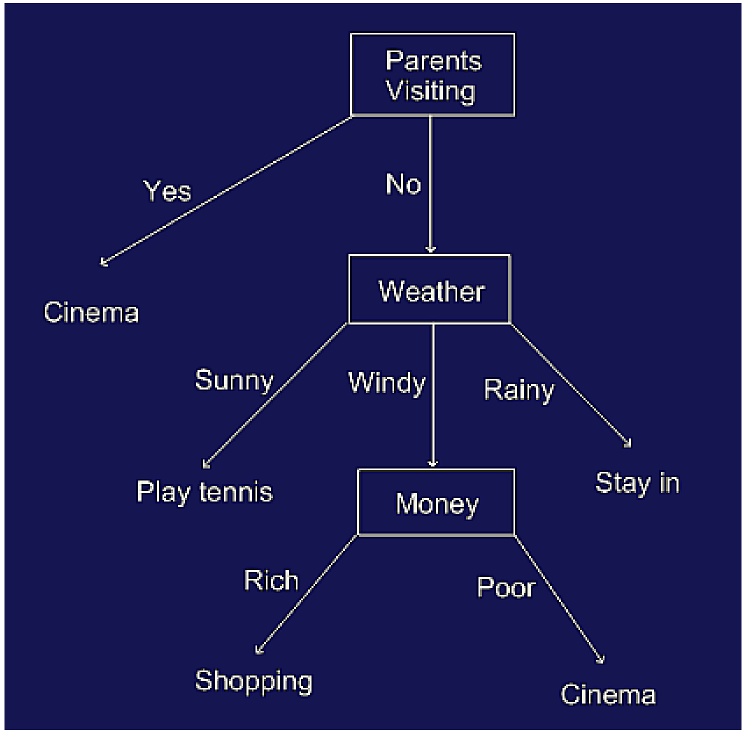
Kernels and SVM
ONLINE Learning

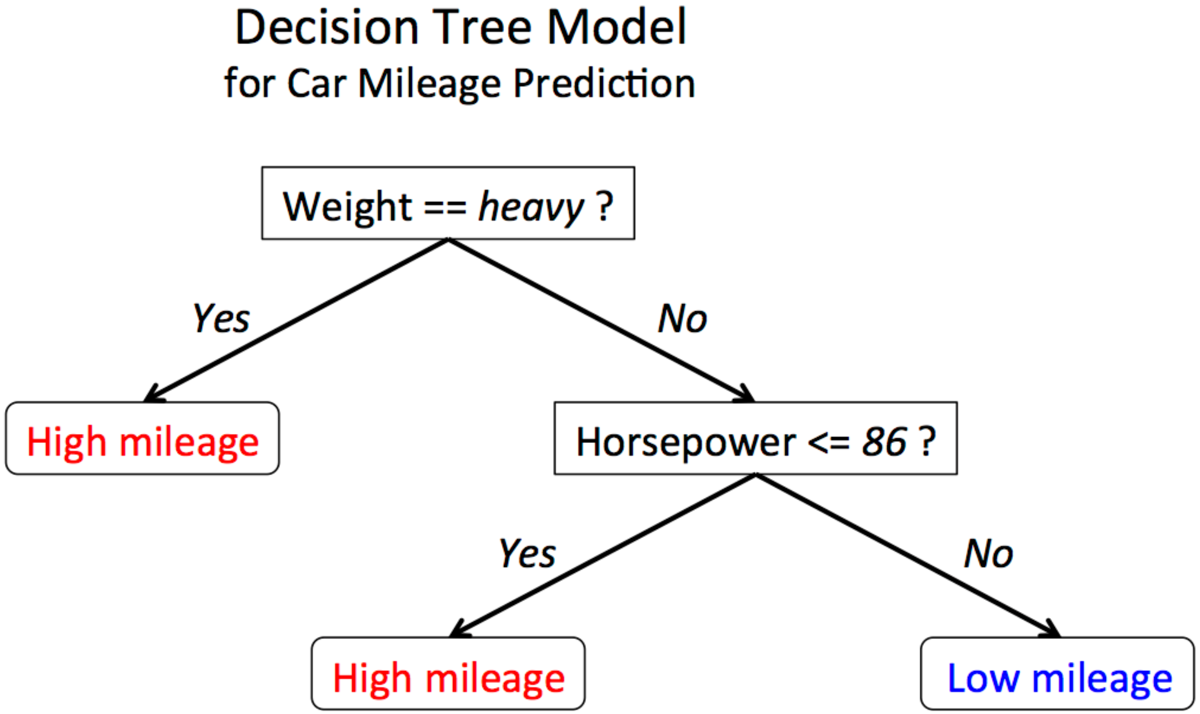
Transfer Learning
Reinforcement Learning

- Machine Learning Algorithms
  - Deep Learning
    - Deep Boltzmann Machine (DBM)
    - Deep Belief Networks (DBN)
    - Convolutional Neural Network (CNN)
    - Stacked Auto-Encoders
  - Ensemble
    - Random Forest
    - Gradient Boosting Machines (GBM)
    - Boosting
    - Bootstrapped Aggregation (Bagging)
    - AdaBoost
    - Stacked Generalization (Blending)
    - Gradient Boosted Regression Trees (GBRT)
  - Neural Networks
    - Radial Basis Function Network (RBFN)
    - Perceptron
    - Back-Propagation
    - Hopfield Network
  - Regularization
    - Ridge Regression
    - Least Absolute Shrinkage and Selection Operator (LASSO)
    - Elastic Net
    - Least Angle Regression (LARS)
  - Rule System
    - Cubist
    - One Rule (OneR)
    - Zero Rule (ZeroR)
    - Repeated Incremental Pruning to Produce Error Reduction (RIPPER)
  - Regression
    - Linear Regression
    - Ordinary Least Squares Regression (OLSR)
    - Stepwise Regression
    - Multivariate Adaptive Regression Splines (MARS)
    - Locally Estimated Scatterplot Smoothing (LOESS)
    - Logistic Regression
  - Bayesian
    - Naive Bayes
    - Averaged One-Dependence Estimators (AODE)
    - Bayesian Belief Network (BBN)
    - Gaussian Naive Bayes
    - Multinomial Naive Bayes
    - Bayesian Network (BN)
  - Decision Tree
    - Classification and Regression Tree (CART)
    - Iterative Dichotomiser 3 (ID3)
    - C4.5
    - C5.0
    - Chi-squared Automatic Interaction Detection (CHAID)
    - Decision Stump
    - Conditional Decision Trees
    - M5
  - Dimensionality Reduction
    - Principal Component Analysis (PCA)
    - Partial Least Squares Regression (PLSR
    - Sammon Mapping
    - Multidimensional Scaling (MDS)
    - Projection Pursuit
    - Principal Component Regression (PCR)
    - Partial Least Squares Discriminant Analysis
    - Mixture Discriminant Analysis (MDA)
    - Quadratic Discriminant Analysis (QDA)
    - Regularized Discriminant Analysis (RDA)
    - Flexible Discriminant Analysis (FDA)
    - Linear Discriminant Analysis (LDA)
  - Instance Based
    - k-Nearest Neighbour (kNN)
    - Learning Vector Quantization (LVQ)
    - Self-Organizing Map (SOM)
    - Locally Weighted Learning (LWL)
  - Clustering
    - k-Means
    - k-Medians
    - Expectation Maximization
    - Hierarchical Clustering

Decision trees

- One possible representation for hypotheses
- E.g., here is the “true” tree for deciding whether to wait:





https://www.crondose.com/2016/07/easy-way-understand-decision-trees/

http://www.doc.ic.ac.uk/~sgc/teaching/pre2012/v231/lecture11.html

ONLINE LEARNING (src: Wiki)

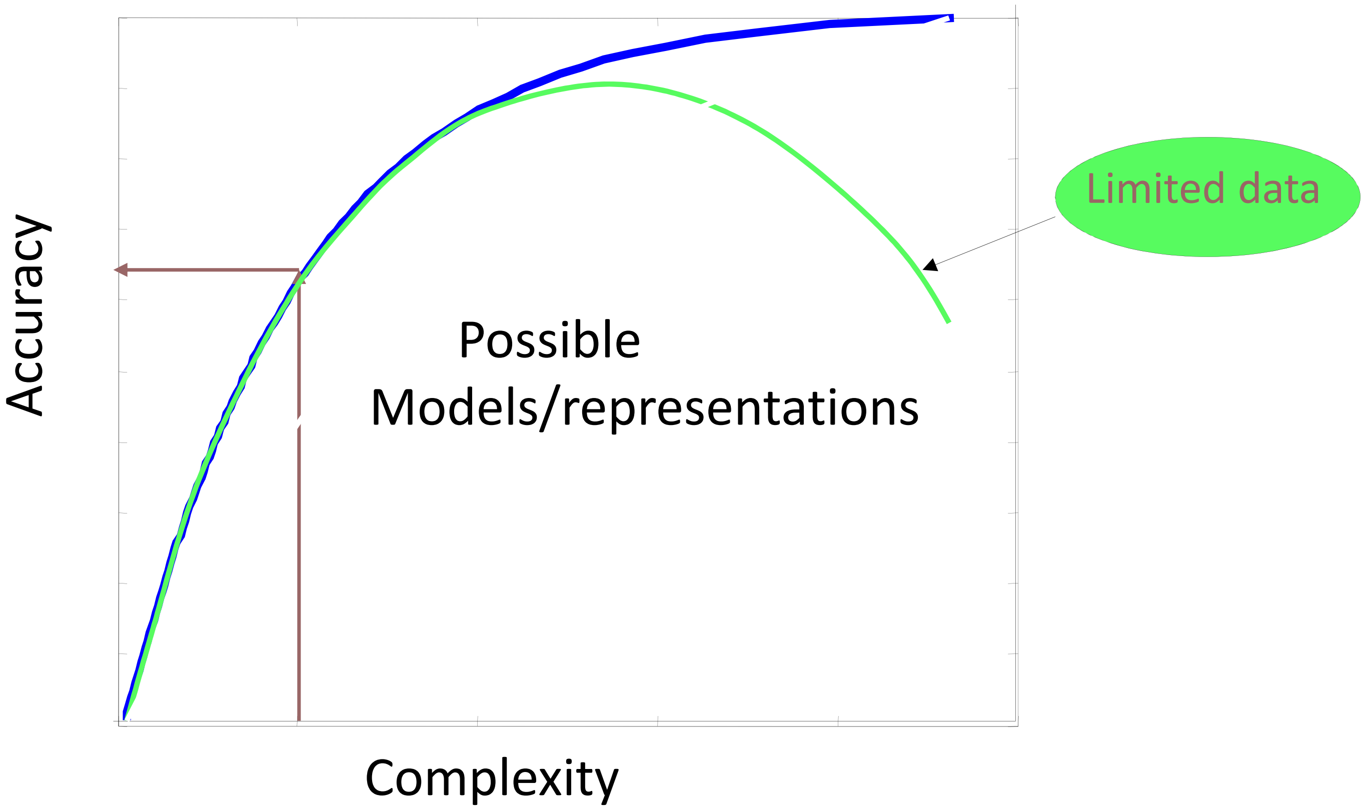
In Online machine learning data becomes available in a sequential order and is used to update our best predictor for future data at each step, as opposed to batch learning techniques which generate the best predictor by learning on the entire training data set at once.

In this case, it is necessary for the algorithm to dynamically adapt to new patterns in the data, or when the data itself is generated as a function of time, e.g. stock price prediction. Online learning algorithms may be prone to catastrophic interference. This problem is tackled by incremental learning approaches.

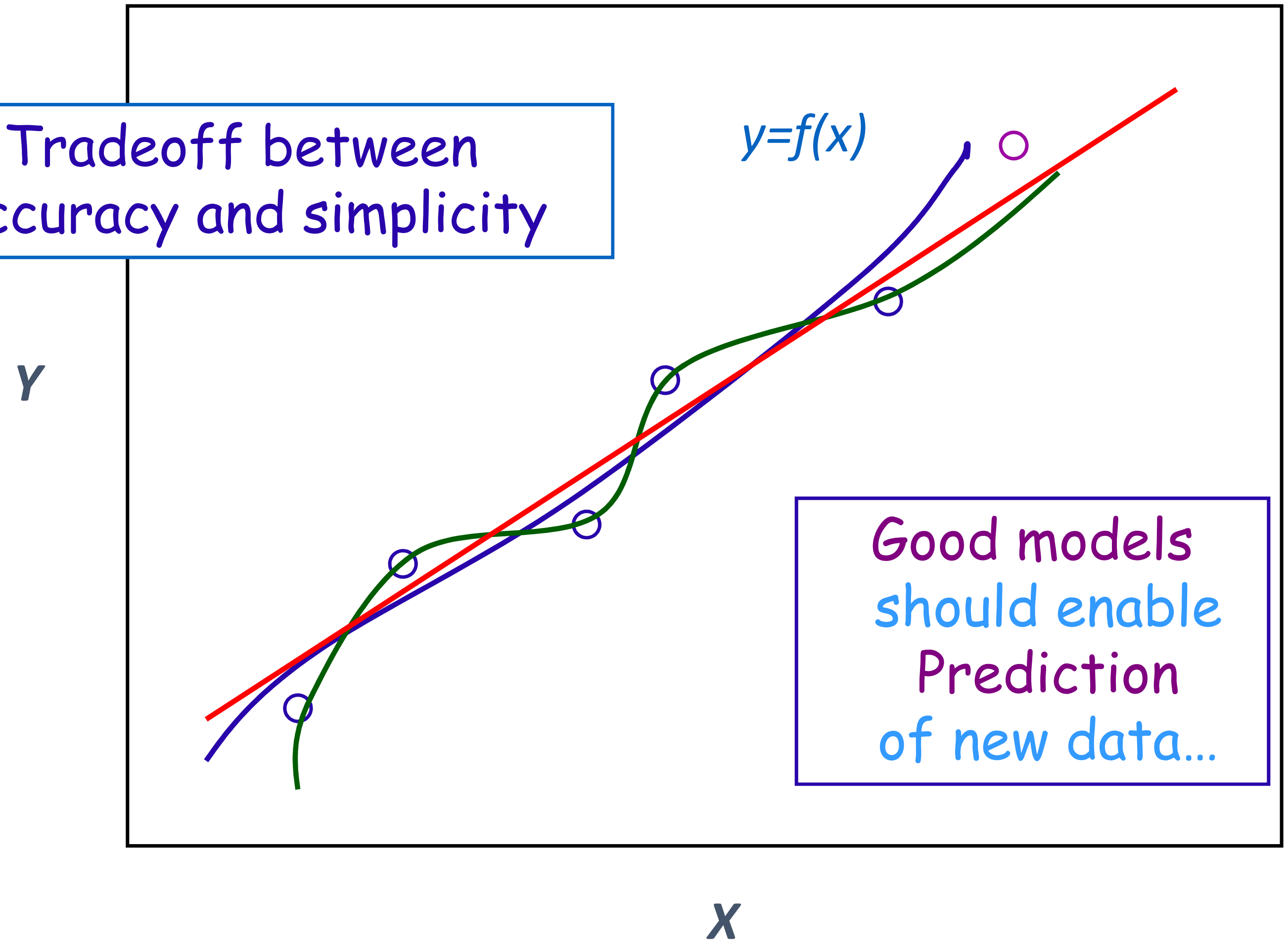
A purely online model would learn based on just the new input , the current best predictor and some extra stored information (which is usually expected to have storage requirements independent of training data size).

A common strategy to overcome the issue of storage, is to learn using mini-batches, which process a small batch of data points at a time, this can be considered as pseudo-online learning for much smaller than the total number of training points.

A Fundamental Dilemma of Science: Model Complexity vs Prediction Accuracy

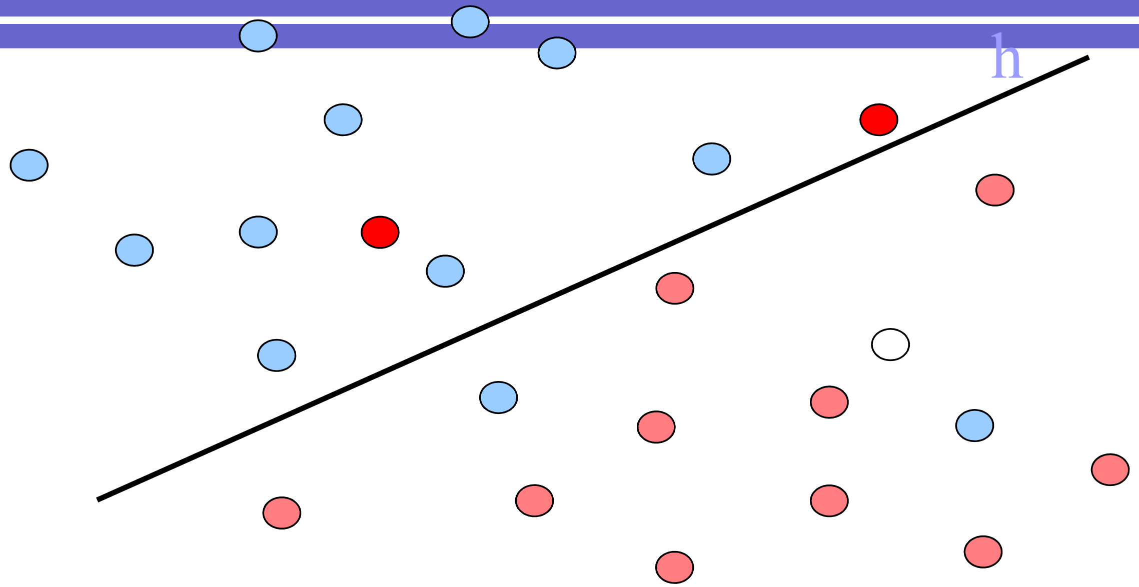


Tradeoff between accuracy and simplicity



Good models should enable Prediction of new data...

Concrete learning paradigm- linear separators

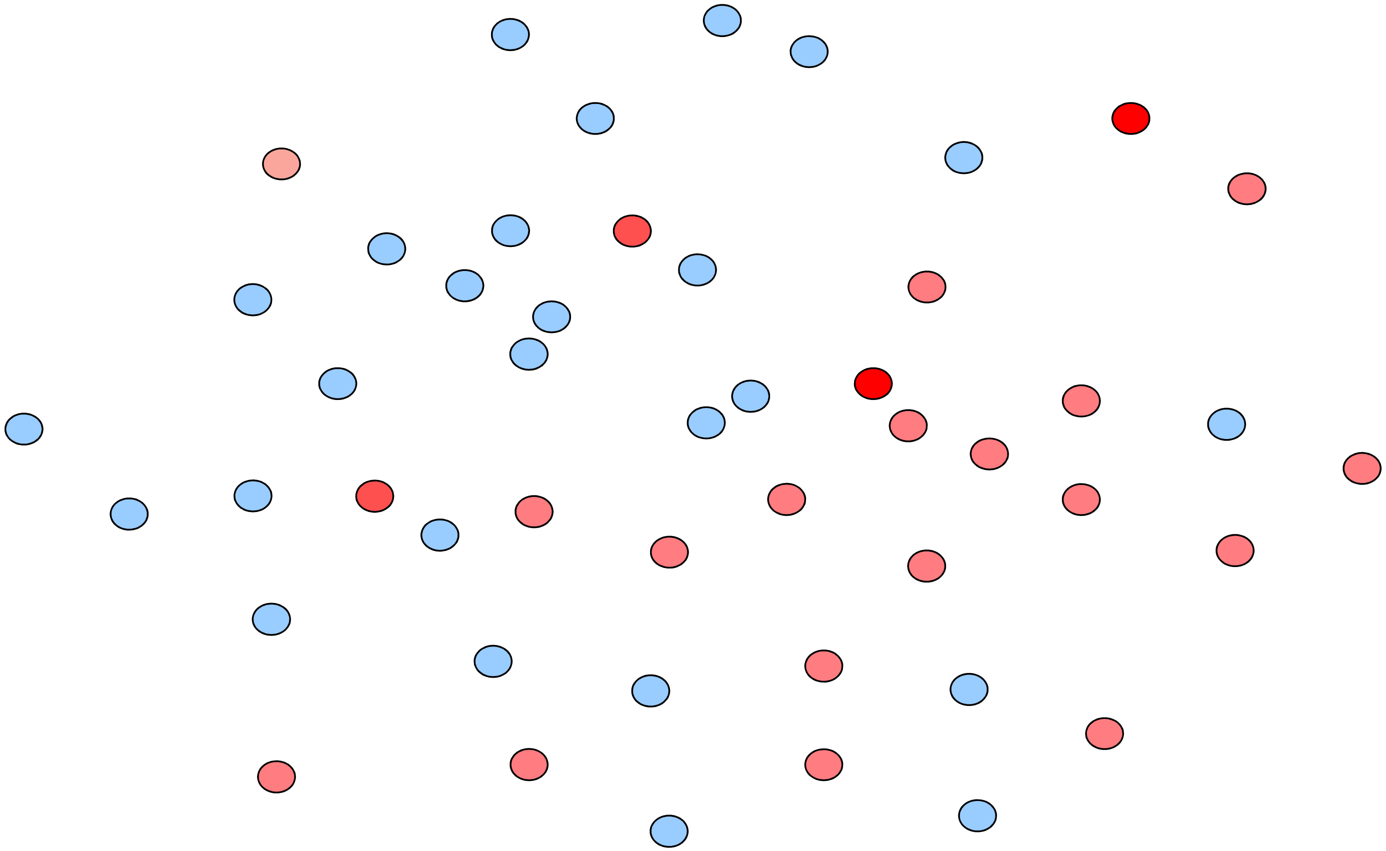


The predictor h: Sign ($\sum w_i\ x_i$+b)

(where **w** is the weight vector of the hyperplane **h**,

and **x=(x_1, …x_i,…x_n)** is the example to classify)

Potential problem –
data may not be *linearly separable*

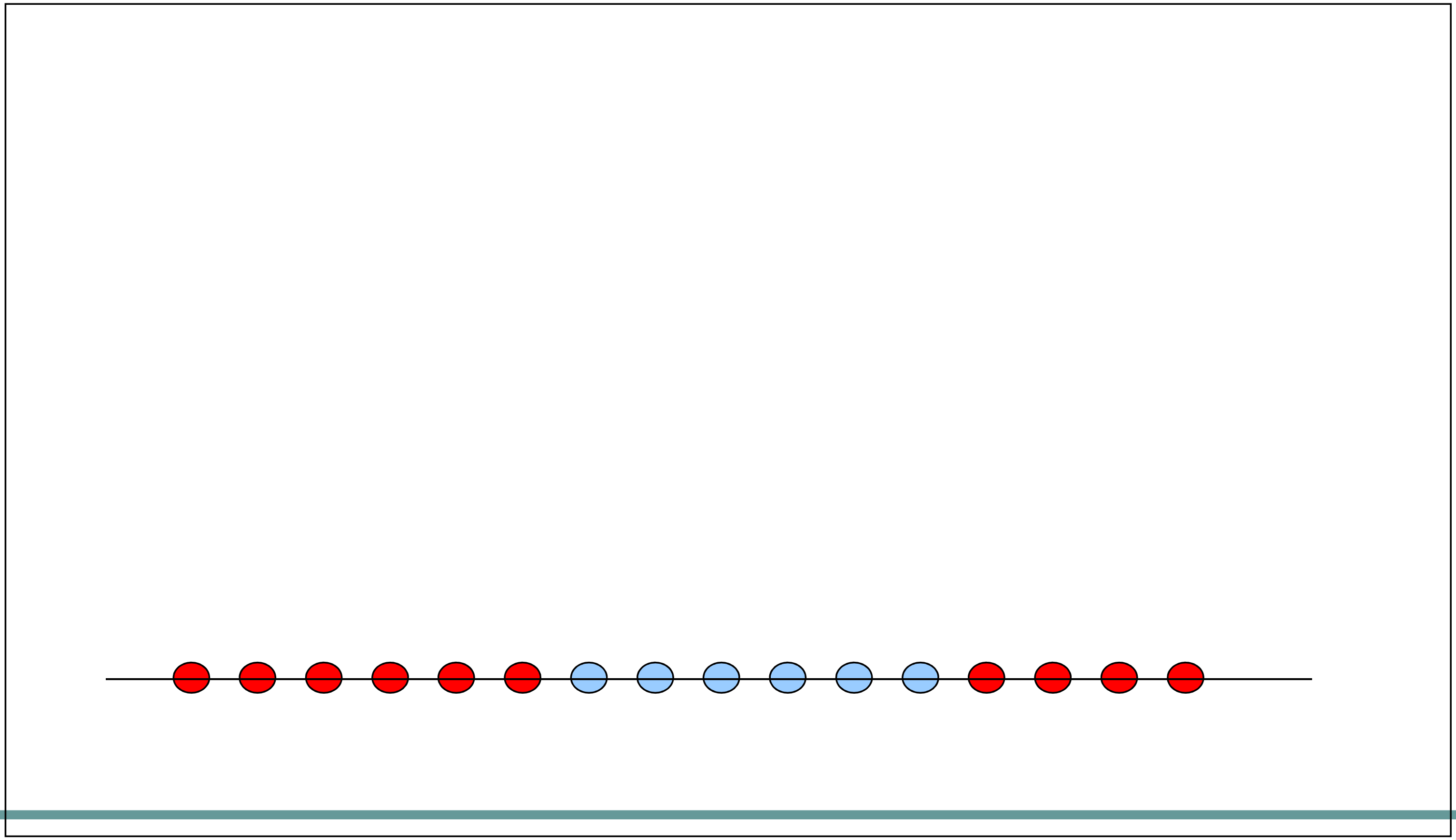


The SVM Paradigm

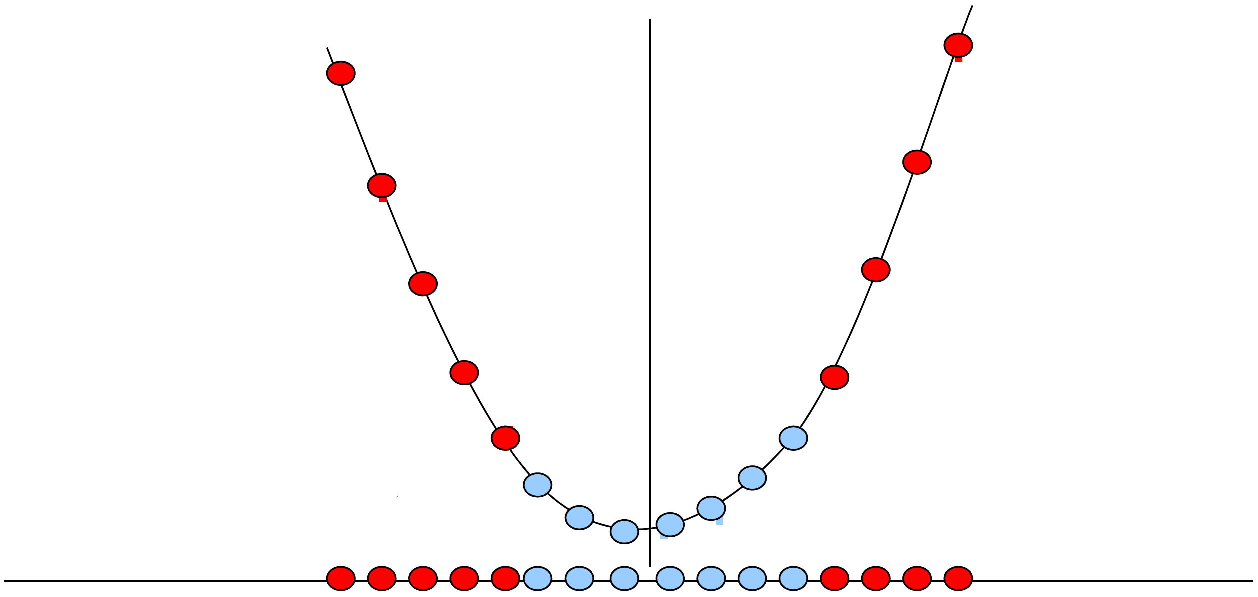
- Choose an *Embedding* of the domain *X* into some high dimensional Euclidean space, so that the data sample becomes (almost) linearly separable.
- Find a large-margin data-separating hyperplane in this image space, and use it for prediction.

⇨ **Important gain:** *When the data is separable, finding such a hyperplane is computationally feasible.*

The SVM Idea: an Example

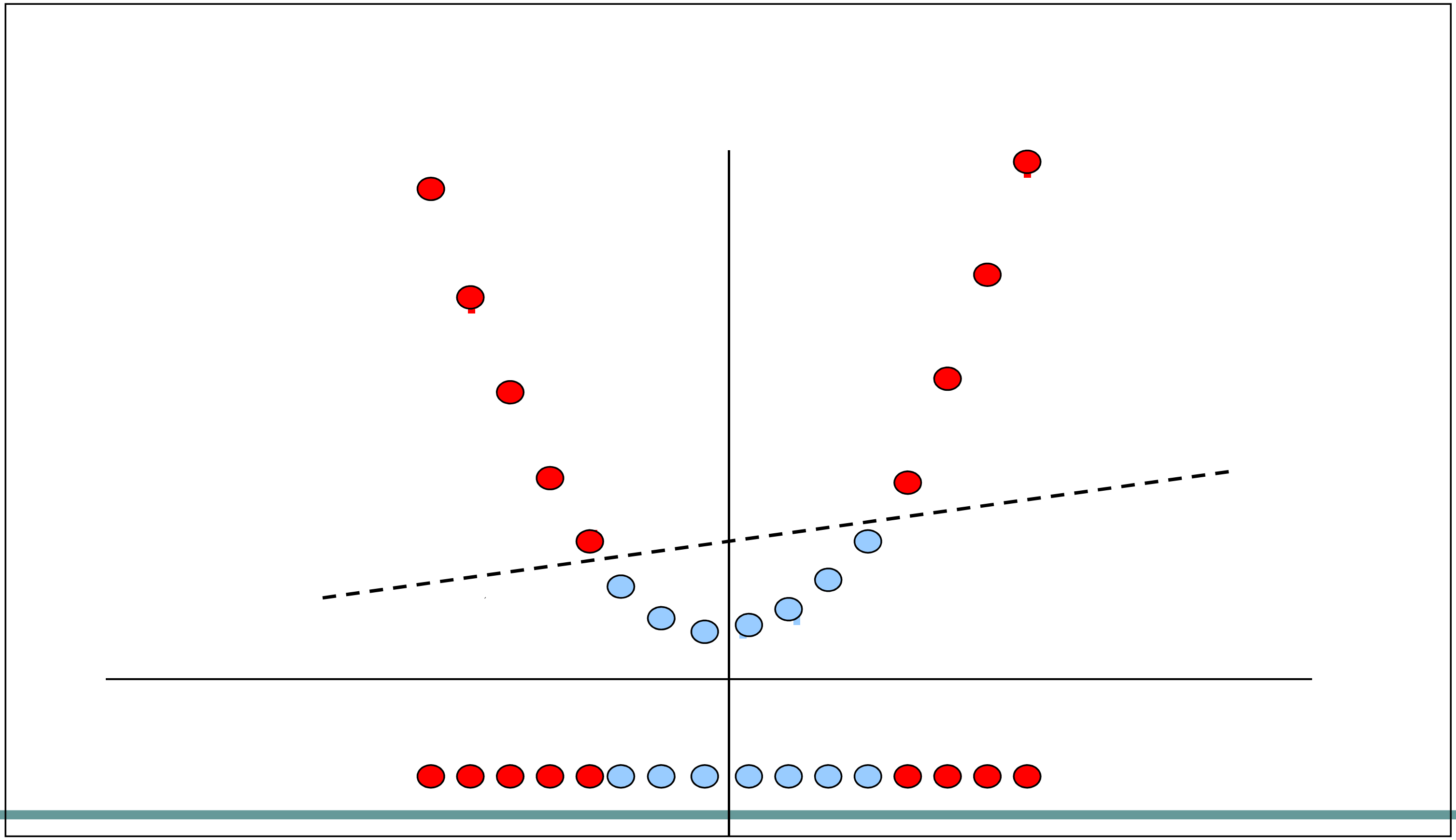


The SVM Idea: an Example



$x \mapsto (x, x^2)$

The SVM Idea: an Example



Controlling Computational Complexity

Potentially the embeddings may require very high Euclidean dimension.

How can we search for hyperplanes efficiently?

The Kernel Trick: Use algorithms that depend only on the inner product of sample points.

Kernel-Based Algorithms

Rather than define the embedding explicitly, define just the matrix of the inner products in the range space.

$$\begin{pmatrix} K(x_1x_1) & K(x_1x_2) & \cdots\cdots & K(x_1x_m) \\ \vdots & & & \vdots \\ & & K(x_ix_j) & \\ \vdots & & & \vdots \\ K(x_mx_1) & & \cdots\cdots\cdots & K(x_mx_m) \end{pmatrix}$$

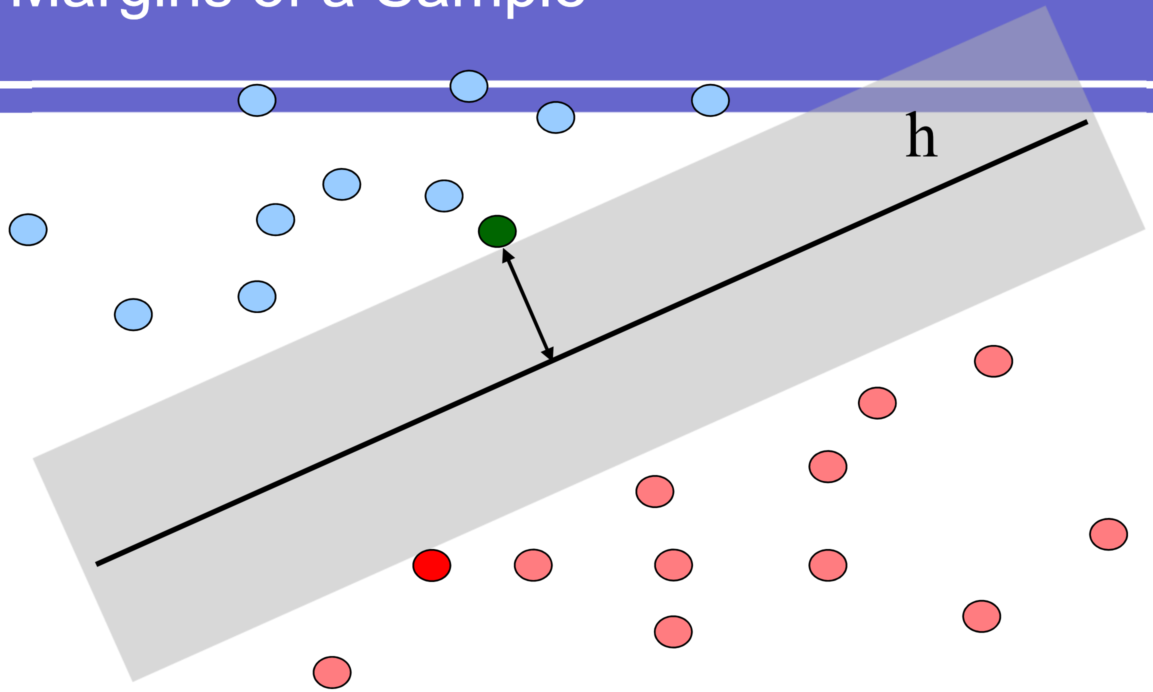
Mercer Theorem: If the matrix is symmetric and positive semi-definite, then it is the inner product matrix with respect to some embedding

Support Vector Machines (SVMs)

On input: Sample $(x_1\ y_1)\ \ldots\ (x_m y_m)$ and a kernel matrix K

Output: A “good” separating hyperplane

The Margins of a Sample



$$\max_{\text{separating } h} \; \min_{x_i} \; w_n \cdot x_i$$

(where w_n is the weight vector of the hyperplane h)

Summary of SVM learning

1. The user chooses a “Kernel Matrix”

   - a measure of similarity between input points.

2. Upon viewing the training data, the algorithm finds a linear separator the maximizes the margins (in the high dimensional “Feature Space”).

- **- Model Selection;**
- **- Online Learning**
- **- Curse of Dimensionality**
- **- Bias-Variance Tradeoff**
- **- Transfer Learning – Domain Adaptation**
- **- BOW, Sparse Coding**
- **- Incremental Learning**

References and Journals

- Text: *The Elements of Statistical Learning* by Hastie, Tibshirani, and Friedman (book website: http://www-stat.stanford.edu/~tibs/ElemStatLearn/)
- Reference books:
  - *Pattern Classification* by Duda, Hart and Stork
  - ***Pattern Recognition and Machine Learning* by C.M. Bishop**
  - *Machine Learning* by T. Mitchell
  - *Introduction to Machine Learning* by E. Alpaydin
- Some related journals / associations:
  - Machine Learning (Kluwer).
  - Journal of Machine Learning Research.
  - Journal of AI Research (JAIR).
  - Data Mining and Knowledge Discovery - An International Journal.
  - Journal of Experimental and Theoretical Artificial Intelligence (JETAI).
  - Evolutionary Computation.
  - Artificial Life.
  - Fuzzy Sets and Systems
  - IEEE Intelligent Systems (Formerly IEEE Expert)
  - **IEEE Transactions on Knowledge and Data Engineering**
  - **IEEE Transactions on Pattern Analysis and Machine Intelligence**
  - **IEEE Transactions on Systems, Man and Cybernetics**
  - Journal of AI Research
  - Journal of Intelligent Information Systems
  - Journal of the American Statistical Association
  - Journal of the Royal Statistical Society

References and Journals…

- **Pattern Recognition**
- Pattern Recognition Letters
- Pattern Analysis and Applications.
- Computational Intelligence .
- Journal of Intelligent Systems .
- Annals of Mathematics and Artificial Intelligence.
- IDEAL, the online scientific journal library by Academic Press.
-
- ACM (Association for Computing Machinery).
- Association for Uncertainty in Artificial Intelligence.
- ACM SIGAR
- **ACM SIGMOD**
- American Statistical Association.
- Artificial Intelligence
- Artificial Intelligence in Engineering
- Artificial Intelligence in Medicine
- Artificial Intelligence Review
- Bioinformatics
- Data and Knowledge Engineering
- Evolutionary Computation

Some Conferences & Workshops

- Congress on Evolutionary Computation
- European Conference on Machine Learning and Principles and Practice of Knowledge Discovery
- **The ACM SIGKDD International Conference on Knowledge Discovery and Data Mining**
- National Conference on Artificial Intelligence
- Genetic and Evolutionary Computation Conference
- **International Conference on Machine Learning (ICML, ECML, ICLR**)
- Conference on Autonomous Agents and Multiagent Systems
- European Symposium on Artificial Neural Networks Advances in Computational Intelligence and Learning
- Artificial and Ambient Intelligence
- Computational Intelligence in Biomedical Engineering
- IEEE International Symposium on Approximate Dynamic Programming and Reinforcement Learning
- International Joint Conference on Artificial Intelligence (**IJCAI**)

ECCAI (European Coordinating Committee on Artificial Intelligence).

AAAI (American Association for Artificial Intelligence).

NIPS, CVPR

EXAM PATTERN (tentative range, to be finalized before ES):

END SEM (3 Hrs) -	**40-50;**
Quiz 2 (1 Hr. each) –	**20-30;**
Software Assignments –	**20-25**

Quiz 1 - 16-02-2019 (Duration: 60 mins)

Quiz 2 - 16-03-2019 (Duration: 60 mins)

End Semester - 20-04-2019 (Duration: 150-180 mins)

Software Assignment 1:

Announcement:	**25-01-2019**
Deadline:	**25-02-2019**

Software Assignment 2:

Announcement:	**21-02-2019**
Deadline:	**05-04-2019**