Machine Learning - Introduction & Overview

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A Few Quotes

- "A breakthrough in machine learning would be worth ten Microsofts" (Bill Gates, Microsoft)
- "Machine learning is the next Internet" (Tony Tether, Director, DARPA)
- "Machine learning is going to result in a real revolution" (Greg Papadopoulos, Ex CTO, Sun)

Machine Learning

- Automating automation
- Getting computers to program themselves
- Writing software is the bottleneck
- Let the data do the work instead!

Sample Applications

- Web search
- Computational biology
- Finance
- E-commerce
- Space exploration
- Robotics
- Information extraction
- Social networks

Growth of Machine Learning

- Improved machine learning algorithms
- Improved data capture, networking, faster computers, big data
- Software too complex to write by hand
- New sensors/IO devices
- Demand for self customization to user and environment

ML in a Nutshell

- Tens of thousands of machine learning algorithms
- Hundreds new every year
- Every machine learning algorithm has three components:
  1. Representation
  2. Evaluation
  3. Optimization

Representation

- Decision trees
- Sets of rules / Logic programs
- Instances
- Graphical models (Bayes/Markov nets)
- Neural networks
- Support vector machines
- Model ensembles
- Etc.

Evaluation

- Accuracy
- Precision and recall
- Squared error
- Likelihood
- Posterior probability
- Cost / Utility
- Margin
- Entropy
- K-L divergence
- Etc.

Optimization

- Combinatorial optimization E.g.: Greedy search
- Convex optimization E.g.: Gradient descent
- Constrained optimization E.g.: Linear programming

Types of Learning

- **Supervised (inductive) learning** - Training data includes desired outputs
- **Unsupervised learning** - Training data does not include desired outputs
- **Semi-supervised learning** - Training data includes a few desired outputs
- **Reinforcement learning** - Rewards from sequence of actions.

Supervised Learning

- Given examples of a function $(X, F(X))$
- Predict function $F(X)$ for new examples X
  1. Discrete $F(X)$: Classification
  2. Continuous $F(X)$: Regression
  3. $F(X) =$ Probability(X): Probability estimation

Classification

Assign object/event to one of a given finite set of categories (discrete or categorical values).

- Medical diagnosis
- Credit card applications or transactions
- Fraud detection in e-commerce
- Worm detection in network packets
- Spam filtering in email
- Recommended articles in a newspaper
- Recommended books, movies, music, or jokes
- Financial investments
- DNA sequences
- Spoken words
- Handwritten letters
- Astronomical images

Regression

Predicting a numeric value (continuous value)

- Predicting weather
- Predicting stock market
- Predicting monthly or yearly product sales

Example: Spam Filter

- Input: email
- Output: spam/ham
- Setup:
  - Get a large collection of example emails, each labeled “spam” or “ham”
  - Note: someone has to hand label all this data!
  - Want to learn to predict labels of new, future emails
- Features: The attributes used to make the ham / spam decision
  - Words: FREE!
  - Text Patterns: $dd, CAPS
  - Non-text: SenderInContacts
  - …

Dear Sir.

First, I must solicit your confidence in this transaction, this is by virture of its nature as being utterly confidencial and top secret. …

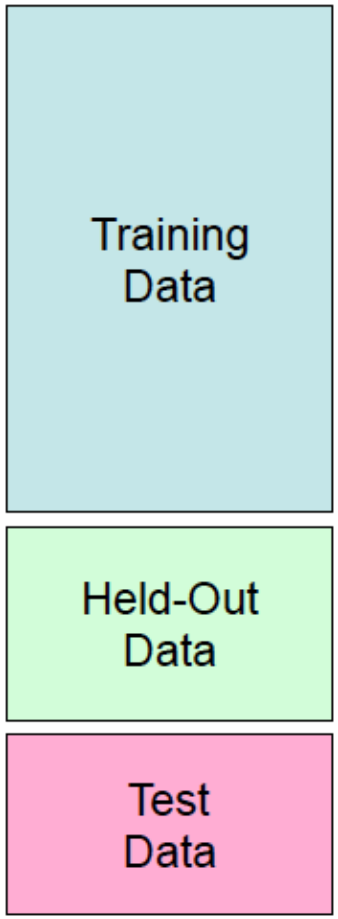
TO BE REMOVED FROM FUTURE MAILINGS, SIMPLY REPLY TO THIS MESSAGE AND PUT "REMOVE" IN THE SUBJECT.

99 MILLION EMAIL ADDRESSES FOR ONLY $99

Ok, Iknow this is blatantly OT but I'm beginning to go insane. Had an old Dell Dimension XPS sitting in the corner and decided to put it to use, I know it was working pre being stuck in the corner, but when I plugged it in, hit the power nothing happened.

Important Concepts

- Data: labeled instances, e.g. emails marked spam/ham
  - Training set
  - Held out set (sometimes call Validation set)
  - Test set
- Features: attribute-value pairs which characterize each x
- Experimentation cycle
  - Select a hypothesis f to best match training set
  - (Tune hyperparameters on held-out set)
  - Compute accuracy of test set
  - Very important: never "peek" at the test set!
- Evaluation
  - Accuracy: fraction of instances predicted correctly
- Overfitting and generalization
  - Want a classifier which does well on *test* data
  - Overfitting: fitting the training data very closely, but not generalizing well
  - We'll investigate overfitting and generalization formally in a few lectures



Supervised and Unsupervised Learning Algorithms

- Supervised learning
  1. Linear Regression
  2. Logistic Regresion
  3. Decision tree induction
  4. Bayesian learning
  5. Neural networks
  6. Support vector machines
  7. Model ensembles
- Unsupervised learning
  1. Clustering (Grouping similar things)
  2. Dimensionality reduction

Unsupervised Learning

Predict structure:

- Tree of life from DNA
- Find similar images
- Grouping similar things

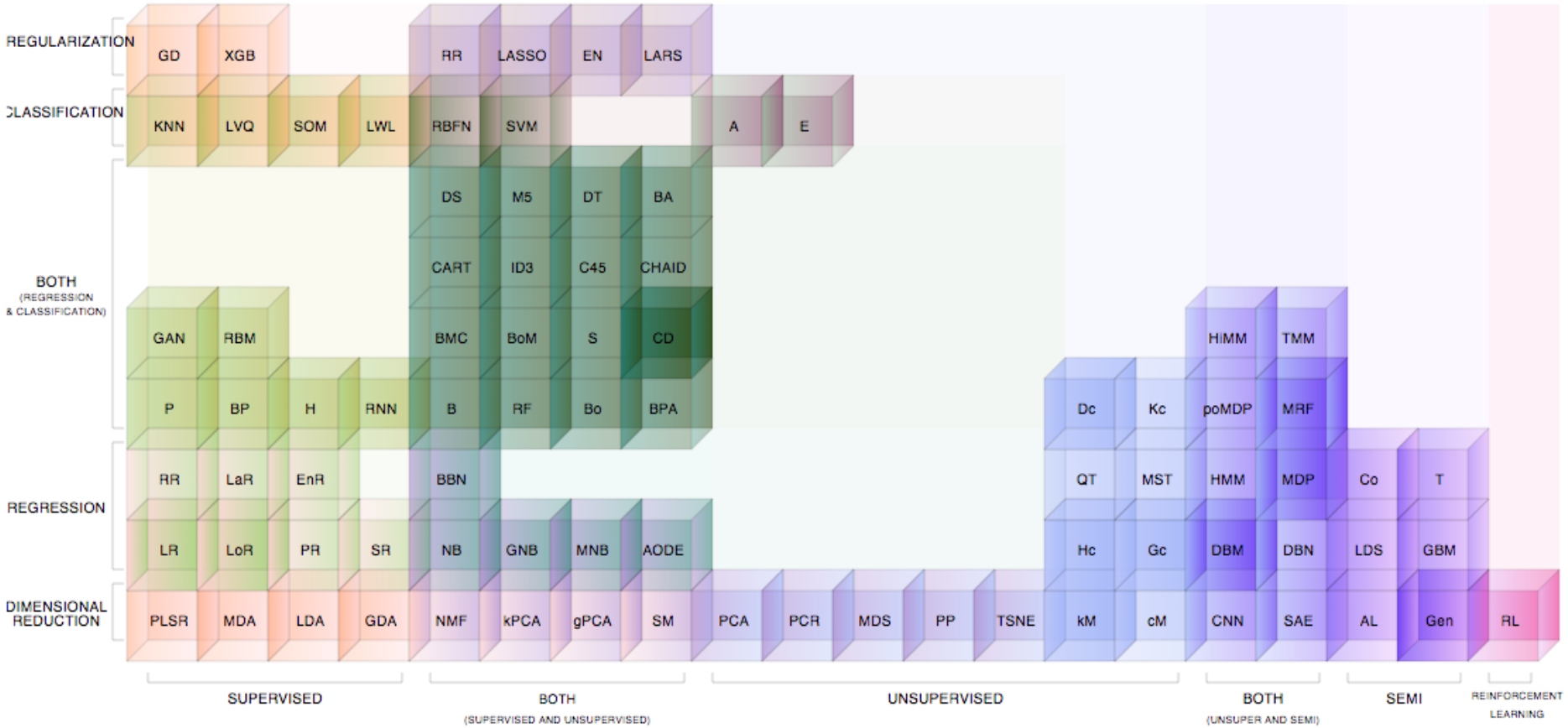
ML in Practice

- Understanding domain, prior knowledge, and goals
- Data integration, selection, cleaning
- Preprocessing
- Learning models
- Interpreting results
- Consolidating and deploying discovered knowledge
- Loop

Learning Problem

- Definition: "A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E." (Tom M. Mitchel)
- T: Recognizing hand-written words
  P: Percentage of words correctly classified
  E: Database of human-labeled images of handwritten words
- T: Driving on four-lane highways using vision sensors
  P: Average distance traveled before a human-judged error
  E: A sequence of images and steering commands recorded while observing a human driver.
- T: Categorize email messages as spam or legitimate.
  P: Percentage of email messages correctly classified.
  E: Database of emails, some with human-given labels

Periodic Table of ML Algorithms



ML Algorithms : Part I

- PLSR: Partial Least Squares Regression
- MDA: MixtureDiscriminant Analysis
- LDA: Linear discriminant analysis
- GDA: Generalized discriminant analysis
- LR: Linear Regression
- LoR: Logistic Regression
- PR: Polynomial Regression
- SR: Stepwise Regression
- LaR: Lasso Regression
- EnR: ElasticNet Regression
- EnR: ElasticNet Regression
- P: Perceptron
- BP: Back-Propagation

ML Algorithms : Part II

- H: Hopfield Network
- RBFN: Radial Basis Function Network
- KNN: K-Nearest Neighbour
- LVQ: Learning Vector Quantization
- SOM: Self-Organizing Map
- LWL: Locally Weighted Learning
- NMF: Non-negative Matrix Factorization
- kPCA: Kernel PCA
- gPCA: Graph-based kernel PCA
- SM: Sammon Mapping
- NB: Naive Bayes
- GNB: Gaussian Naive Bayes
- MNB: Multinomial Naive Bayes

ML Algorithms : Part III

- AODE: Averaged One-Dependence Estimators
- BBN: Bayesian Belief Network
- CART: Classification and Regression Tree
- ID3: Iterative Dichotomiser 3
- C45: C45
- CHAID: Chi-squared Automatic Interaction Detection
- DS: Decision Stump
- M5: M5
- CD: ConditionalDecision Trees
- B: Bayes optimal classifier
- RF: Random forests
- Bo: Boosting
- BPA: Bayesian parameter averaging

ML Algorithms : Part IV

- BMC: Bayesian model combination
- BoM: Bucket of models
- S: Stacking
- RR: Ridge Regression
- LASSO: Least Absolute Shrinkage and Selection Operator
- EN: Elastic Net
- LARS: Least-Angle Regression
- PCA: Principal component analysis
- PCR: Principal Component Regression
- MDS: Multidimensional Scaling
- PP: Projection Pursuit
- A: Apriori algorithm
- E: Eclat algorithm

ML Algorithms : Part V

- kM: K-means clustering algorithm
- cM: Fuzzy c-means clustering algorithm
- Hc: Hierarchical clustering algorithm
- Gc: Gaussian clustering algorithm
- QT: Quality Threshold clustering algorithm
- MST: MST based clustering algorithm
- Dc: Density based clustering algorithm
- Kc: Kernel k-means clustering algorithm
- HMM: Hidden Markov model
- MDP: Markov decision process
- poMDP: Partially observable Markov decision process
- MRF: Markov random field
- HiMM: Hierarchical Markov models

ML Algorithms : Part VI

- TMM: Tolerant Markov model
- DBM: Deep Boltzman Machine
- DBN: Deep Belief Networks
- CNN: Convolution neural networks
- SAE: Stacked Auto-Encoders
- AL: Active learning
- Gen: Generative models
- LDS: Low-density separation
- GBM: Graph-based methods
- Co: Co-training
- T: Transduction
- RNN: Recurring Neural Network
- GAN: Generative Adversarial Network

ML Algorithms : Part VII

- BA: Bootstrap Aggregating
- RBM: Restricted Boltzman Machine
- SVM: Support Vector Machines
- RL: Reinforcement Learning
- XGB: X-Gradient Boosting
- GD: Gradient Descent
- TSNE: t-Distributed Stochastic Neighbor Embedding
- DT: Decision Trees

References


Christopher M. Bishop, Pattern recognition and Machine learning. Springer, 2006.


Tom Mitchell, Machine learning. McGraw-Hill, 1997


https://refactored.ai/periodic-table