Machine Learning



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About Me

- Founded a computer consulting business in high school
- PhD from University of Michigan (Go Blue!)
- Imagineer with Disney Research, Boston







What is Machine Learning (ML)?

The study/construction of algorithms that can learn from data

The study of algorithms that improve their performance **P** at some task **T** with experience **E** – Tom Mitchell (CMU)

Fusion of algorithms, artificial intelligence, statistics, optimization theory, visualization, ...



Natural Language Processing (NLP)







Modern NLP algorithms are typically based on statistical ML

Applications

- - -

- Summarization
- Machine Translation
- Speech Processing
- Sentiment Analysis



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Computer Vision

Methods for acquiring, processing, analyzing, and understanding images

Applications

- Image search
- Facial recognition
- Object tracking
- Image restoration











Games, Robotics, Medicine, Ads, ...













Different Motivations

Position	Salary [*]
Data Scientist	\$118,709
Machine Learning Engineer	\$112,500
Software Engineer	\$90,374

"A data scientist is someone who knows more statistics than a computer scientist and more computer science than a statistician."

– Josh Blumenstock (UW)

"Data Scientist = statistician + programmer + coach + storyteller + artist" - Shlomo Aragmon (III. Inst. of Tech)

*glassdoor.com, National Avg



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Types of Problems

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning



Supervised Learning

Training



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Testing



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MNIST



Supervised Tasks

Classification

Binary vs. multi-class





Regression

M = 1M = 00 x1 x M = 9M = 30 0 1 \boldsymbol{x}

Issues

- Feature selection
- Overfitting \bullet
 - Regularization, cross validation



Machine Learning

Common Algorithms

- Nearest Neighbor (kNN)
- Decision Tree learning (e.g. ID3, C4.5, RF)
- Support Vector Machine (SVM)
- Neural Networks
 - Backpropagation
 - Deep learning



kNN

Training

• Store all examples

Testing

- Find the nearest *k* neighbors to target
 - Via distance function
- Vote on class



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2D Multiclass Classification

Boundary Tree



1-NN via Linear Scan





MATH 650 - Machine Learning, Wentworth Institute of Technology

24 October 2014

Decision Trees/Forests



Support Vector Machine (SVM)





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Artificial Neural Networks (ANN)



Gradient descent



21 January 2015



Backpropagation



Feedforward vs. Recurrant



Deep Architectures Vanishing Gradient

Unsupervised Learning

No right answer, find "interesting structure"

<u>Tasks</u>

- Clustering
- Dimensionality reduction
- Density estimation
- Discovering graph structure
- Matrix completion



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Common Algorithms

k-Means Clustering

http://web.stanford.edu/~kvmohan/kmeansvoronoi/kmeans.html

- Collaborative Filtering
- Principle Component Analysis (PCA)
- Expectation Maximization (EM)
- Neural Networks (e.g. RBM)



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Reinforcement Learning (RL) Choose actions to maximize future reward







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The RL Cycle

Issues. credit assignment, exploration vs. exploitation, reward function, ...





Temporal Difference (TD) Learning

 $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$

- Evidence that some neurons (dopamine) operate similarly
- Lead to world-class play via TD-Gammon (neural network trained via TD-learning)



Challenges

- Big Data
 - Parametric vs. Nonparametric
- Curse of Dimensionality
- No Free Lunch



Big Data – The Four V's



Parametric algorithm: model does not grow with data size



The Curse of Dimensionality

"Various phenomena that arise when analyzing and organizing data in high-dimensional spaces (often with hundreds or thousands of dimensions) that do not occur in low-dimensional settings such as the three-dimensional physical space of everyday experience." – Wikipedia

- Memory requirement increases
- Required sampling increases
- Distance functions become less useful



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No Free Lunch

- There is no universally best model a set of assumptions that works well in one domain may work poorly in another
- We need many different models, and algorithms that have different speedaccuracy-complexity tradeoffs



Some Nice Starting Points

<u>Books</u>

- "Machine Learning in Action"
- "Data Mining: Practical Machine Learning Tools and Techniques"
- "Pattern Recognition and Machine Learning"
- "Machine Learning: A Probabilistic Perspective"

<u>Courses</u>

- Fall 2015 @ WIT (MATH+COMP)!
- Coursera: <u>https://www.coursera.org/course/ml</u>
- CMU: <u>http://www.cs.cmu.edu/~tom/10701_sp11/</u>
- UW: <u>https://class.coursera.org/datasci-002/lecture</u>

<u>Sites</u>

- DataTau/Kaggle
- MNIST/UCI Machine Learning Repository
- DataQuest.io
- deeplearning.net
- neuralnetworksanddeeplearning.com

Academia

- E/ICML
- NIPS
- AAAI
- UAI



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Thank You :) Questions?

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