Brief Introduction to Machine Learning

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Why Machine Learning?

- Abundance of data: the data deluge.
 - Scientific instruments.
 - Data acquisition devices.
 - Internet and the web.
 - All sectors of human society producing and digitizing data (e.g., your cell phone).
- Not enough human expertise or human power to make sense of such huge amounts of data.

What Is Machine Learning?

- A subfield of Al that is rapidly growing in importance.
- Performance of a system is improved based on learning experience.
- Learning from data.

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Machine Learning in the News



IBM's Watson Google DeepMind's AlphaGo

- IBM's Watson beats human champions: Jeopardy (game show)
- Google detects cats from YouTube videos.
- Google Glass app recognizes people it sees.
- Legal, medical, financial applications.
- Google DeepMind: Atari 2600 game playing, AlphaGo, AlphaStar

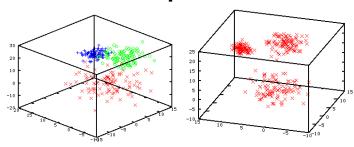
What Does It Take to do ML?

A lot of math (but not too deep):

- Linear algebra
- Calculus
- Probability and statistics
- Differential geometry
- Numerical methods

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Example Data



- Left: supervised
- Right: unsupervised
- Typically very high dimensional (10,000, 1 million [or more]).

Types of Machine Learning

- 1. Supervised learning
 - Input-Target pairs
 - $\{\langle \vec{x}_i, \vec{t}_i \rangle | i = 1, 2, ..., n\}$
- 2. Unsupervised learning
 - A bunch of inputs (unlabeled)
 - $\{\vec{x}_i|i=1,2,...,n\}$
- 3. Reinforcement learning
 - $\bullet \ \ \mathsf{state}_1 \xrightarrow{} \ \ \mathsf{state}_2 \xrightarrow{} \ \ \mathsf{state}_3, \dots \ , \mathsf{reward}$
 - $s_{t+1} = \delta(s_t, a_t), r_{t+1} = \rho(s_t, a_t)$

High-dimensional Data





- Images: these are 2D images, but ...
- These are $50 \times 50 = 2,500$ -dimensional vectors.
 - Each such image is a single point in 2,500-dimensional space.

Supervised Learning

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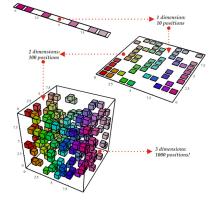
Supervised Learning Issues

- How well will it do on training inputs?
- How well will it do on novel inputs?
 - Generalization.
- How many samples needed for sufficient performance and generalization?
 - Sample complexity
 - Curse of dimensionality
 - Computational learning theory
- Catastrophic forgetting (online learning hard).

Supervised Learning

- Regression: approximating y = f(x)
- Classification: face recognition, hand-written character recognition, credit risk assessment, etc.
- Techniques:
 - Neural networks
 - Decision tree learning
 - Support vector machines
 - Radial basis functions
 - Naive Bayes learning
 - k-nearest neighbor 10

Addendum: Curse of Dimensionality



From: Yoshua Bengio's page

 Exponentially many points needed to achieve same density of training samples.

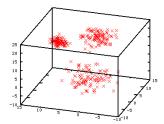
Unsupervised Learning

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Unsupervised Learning Issues

- Discovering structure.
- Discovering features.
- Removing redundancy.
- How many clusters?
- What distance measures to use?

Unsupervised Learning



Clustering, feature extraction, blind source separation, dimensionality reduction, etc.

- Principal Component Analysis (PCA)
- Self-Organizing Maps (SOM)
- Independent Component Analysis (ICA)
- Multi-Dimensional Scaling (MDS)
- ISOMAP, Locally Linear Embedding (LLE)
- t-distr. Stochastic Neighbor Embedding (t-SNE)

Reinforcement Learning

Reinforcement Learning

- Very different from supervised and unsupervised learning.
- Multi agent control, robot control, game playing, scheduling, etc.
- Techniques:
 - Value function-based: Q-learning, Temporal difference (TD) learning
 - Direct policy search: Neuroevolution, genetic algorithms.

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Wrap Up

Reinforcement Learning Issues

- Discrete states and actions was a norm.
- Scalability an issue.
- Certain assumptions: state-action pair visited infinitely often.
- Online learning, safety, transfer, imitation, etc.
- Deep reinforcement learning disrupted a lot of the traditional assumptions.

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Summary

- Machine learning is a rapidly developing field with great promise:
 - Big data
 - Deep neural networks
 - Fast computing: GPGPU, cloud, etc.
- Three types of ML:
 - Supervised learning
 - Unsupervised learning
 - Reinforcement learning
- Need to look beyond ML:
 - ML good at solving problems, but not posing problems (Choe and Mann 2012).