On Machine Learning

Aggelos K. Katsaggelos

Joseph Cummings Professor Northwestern University Department of EECS Department of Linguistics Argonne National Laboratory NorthShore University Health System Evanston, IL 60208 http://ivpl.eecs.northwestern.edu



image & video processing lab

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What is Machine Learning

- A machine learning algorithm is an algorithm that is able to learn from data
- But what do we mean by learning?
- "A computer program is said to learn from <u>experience E</u> with respect to some class of <u>tasks T</u> and <u>performance measure P</u>, if its performance at tasks in T, as measured by P, improves with experience E." (Mitchell 1997)

Task

- ML allows us to tackle tasks that are too difficult to solve with fixed programs written and designed by human beings
 - From a scientific and philosophical point of view, ML is interesting because developing our understanding of ML entails developing our understanding of the principles that underlie intelligence
- ML tasks are usually described in terms of how the machine learning system should process an example

Common ML Task

- Classification $f: \mathbb{R}^n \to \{1, \cdots, k\}$
- Classification with missing inputs
- **Regression** $f: \mathbb{R}^n \to \mathbb{R}$
- Transcription (optical character recognition, speech processing)
- Structured outputs (any task where the output exhibits important <u>relationships</u> between the different elements, e.g. parsing a natural language segment, image segmentation, image captioning)

Common ML Task

- Anomaly detection (fraud detection; profile of user is build and used)
- Synthesis and Sampling (text to speech, video games: automatically generate textures for large objects)
- Imputation of missing values
- Denoising
- Density (or prob mass function) estimation

The Performance Measure

- Usually specific to the task T
- E.g. Classification
 - Accuracy (proportion of correct output)
 - Similarly: error rate (expected 0-1 loss)
- E.g. Density Estimation
 - Ave log probability the model assigns to some examples
- E.g. Transcription
 - Accuracy at transcribing entire sequences
 - Or more fine grained performance, e.g. partial credit for getting some words right
- E.g. Regression
 - should we penalize the system more if it frequently makes medium-sized mistakes or if it rarely makes very large mistakes?

The Experience E

- Machine learning algorithms can be broadly categorized as
- <u>unsupervised</u>
- <u>supervised</u>
- semi-supervised
- reinforcement learning algorithms

Is it a cat or a dog?



VS.



1. Gather data





2. Extract features

(what distinguishes a cat from a dog?)





- cats have **small** noses and **pointy** ears
- dogs have **big** noses and **round** ears

The *feature space*



3. Train the model (find best parameters via numerical optimization)



5. Test the model (on new data)





Meanwhile in the *feature space...*





conduct research, build products, tinker, and play. By prioritizing geometric intuition, algorithmic thinking, and practical real-world applications in disciplines including computer vision, natural language processing, economics, neuroscience, recommender systems, physics, and biology, this text provides readers with both a hucid understanding of foundational material as well as the practical tools needed to solve real-world problems. With in-depth Python and MATLAB/OCTAVE-based computational exercises and a complete treatment of cutting edge numerical optimization techniques, this is an essential resource for students and an ideal reference for researchers and practitioners working in machine learning, computer science, electrical engineering, signal processing, and numerical optimization

Providing a unique approach to machine learning, this text contains fresh and

intuitive, yet rigorous, descriptions of all fundamental concepts necessary to

KEY FEATURES

A presentation built on lucid geometric intuition
A unique treatment of state-of-the-art numerical optimization techniques
A fused introduction to logistic regression and support vector machines
Inclusion of feature design and learning as major topics
An unparalleled presentation of advanced topics through the lens of function

approximation • A refined description of deep neural networks and kernel methods

Jeremy Watt received his PhD in Computer Science and Electrical Engineering from Northwestern University. His research interests lie in machine learning and computer vision, as well as numerical optimization.

Reza Borhani received his PhD in Computer Science and Electrical Engineering from Northwestern University. His research interests lie in the design and analysis of algorithms for problems in machine learning and computer vision.

Aggelos K. Katsaggelos is a professor and holder of the Joseph Cummings chair in the Department of Electrical Engineering and Computer Science at Northwestern University, where he also heads the Image and Video Processing Laboratory.

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Watt, Borhani, and Katsaggelos

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Foundations, Algorithms, and Applications



Application Areas

- Regression, Classification, Dimensionality Reduction
- Financial modeling, weather forecasting, genetics
- Face/pedestrian/object detection, hand gesture recognition, speech recognition, optical character recognition, gender classification, sentiment analysis, spam detection
- Econometrics
- Neuroscience
- Driver-assisted and autonomous cars
- Recommendation systems

What is ML commonly used for today?

• Target advertising: recommend advertisements and products to users based on some understanding of their tastes, their consumption history, how they think, etc.,



ML a member of a bigger family

- Applied Statistics
- Operations Research
- Natural Language Processing
- Signal Processing
- Pattern Recognition
- Computer Vision
- Image Processing
- Speech Processing

Bigger Picture

- Big Data Analytics
 - Understanding the past: (*descriptive analytics* = what happened; *diagnostic analytics* = why did it happen)
 - Projecting the future: *predictive analytics* = what will happen
 - Seeing and improving future: *prescriptive analytics* = what will happen, when, why, and how to make the most out of this predicted future