Course Logistics and Introduction to Machine Learning

Piyush Rai

Introduction to Machine Learning (CS771A)

July 31, 2018

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- **Course name:** Introduction to Machine Learning or "ML" (CS771A)
- **Timing and Venue:** Tue/Thur 6:00-7:30pm, L-16

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The TA Team


Shivam Bansal


Dhanajit Brahma


Sunabha Chatterjee


Prerit Garg


Gopichand Kotana


Neeraj Kumar


Pawan Kumar


Kranti Parida


Kawal Preet


Prem Raj

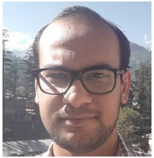

Utsav Singh


Samik Some


Vinay Verma

Project Mentors


Homanga Bhardwaj


Aadil Hayat


Ankit Jalan


Varun Khare


Sarthak Mittal


Gurpreet Singh

.. and some more..

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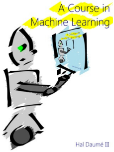

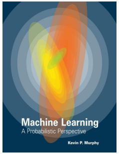

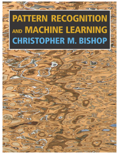

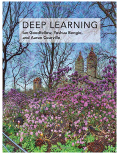

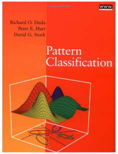

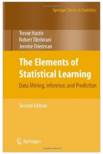

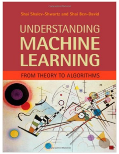

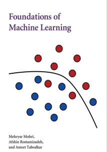

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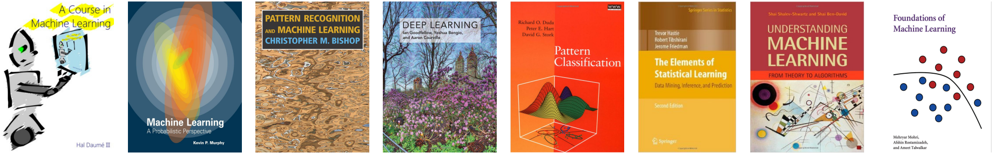

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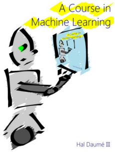

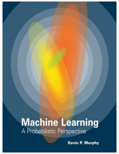

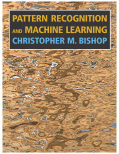

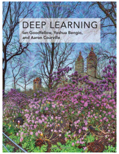

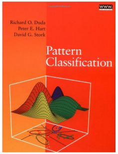

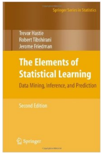

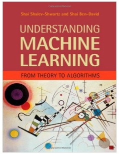

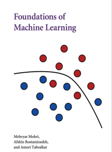

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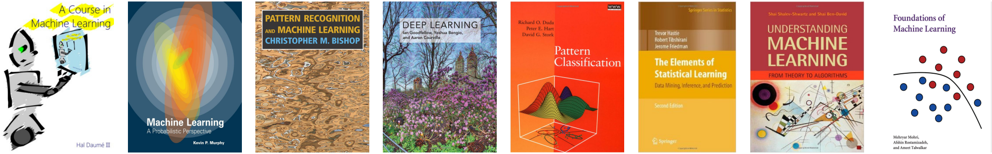

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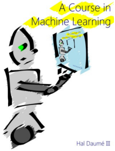

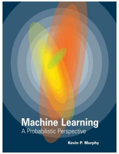

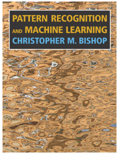

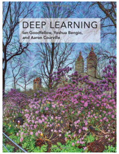

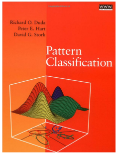

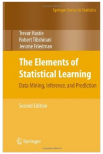

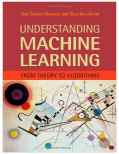

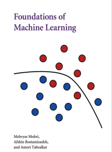

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Intro to Machine Learning

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- The learned model can be used to
  - Detect patterns/structures/themes/trends etc. in the data
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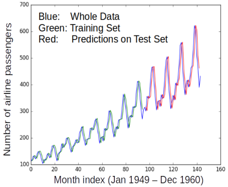

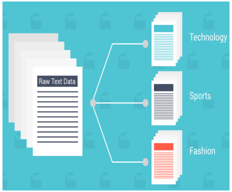

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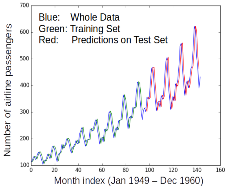

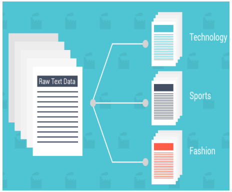

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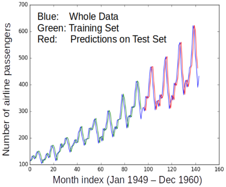

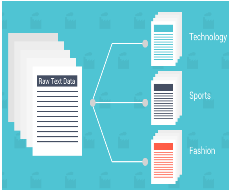

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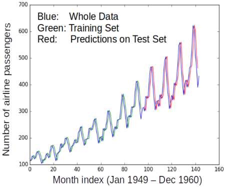
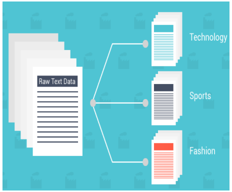
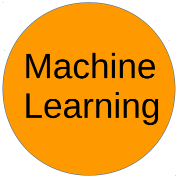




- Modern ML algorithms are heavily "data-driven"
  - No need to pre-define and hard-code all the rules (usually infeasible/impossible anyway)
  - The rules are not "static"; can adapt as the ML algo ingests more and more data

A Loose Taxonomy for ML



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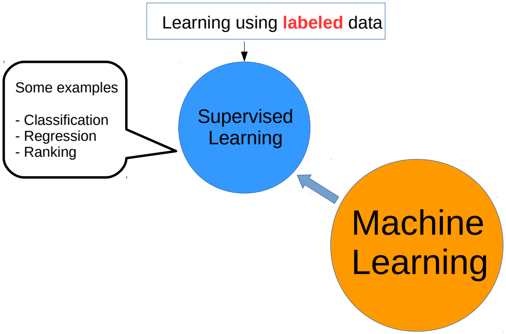

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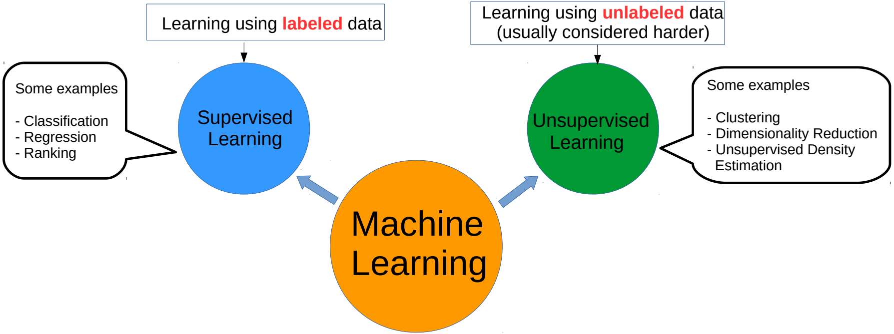

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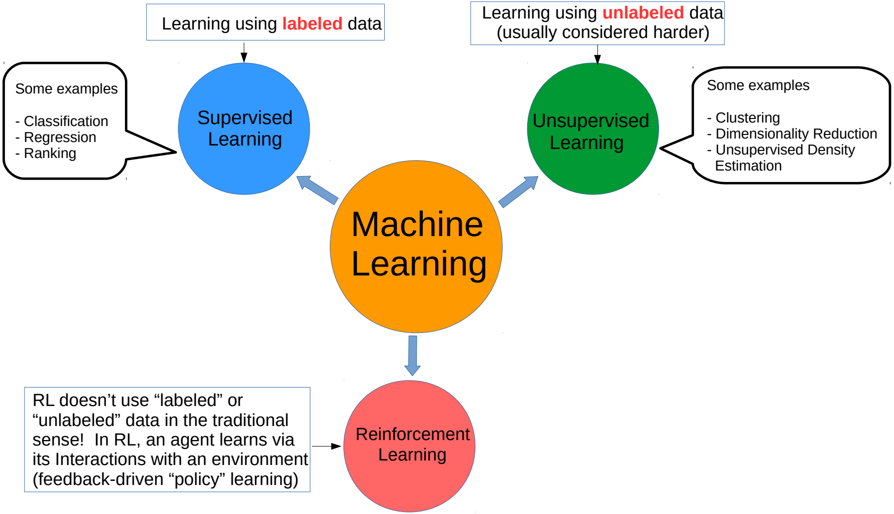

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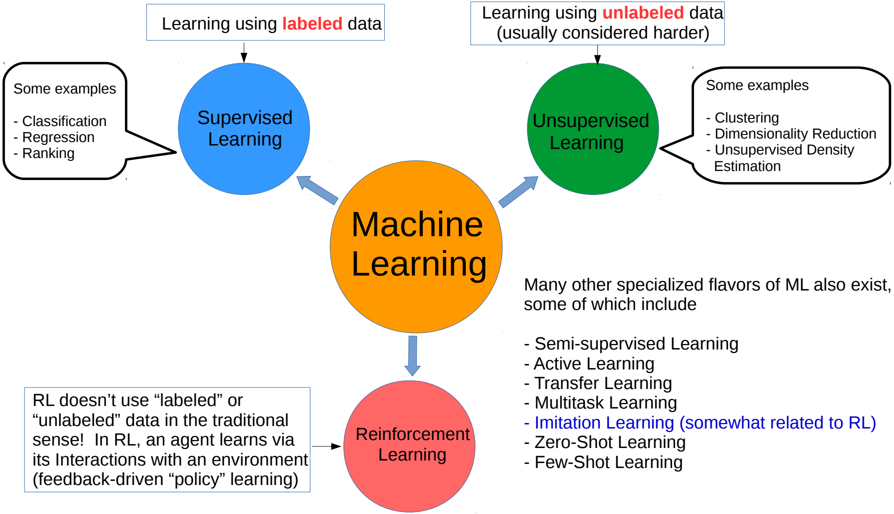
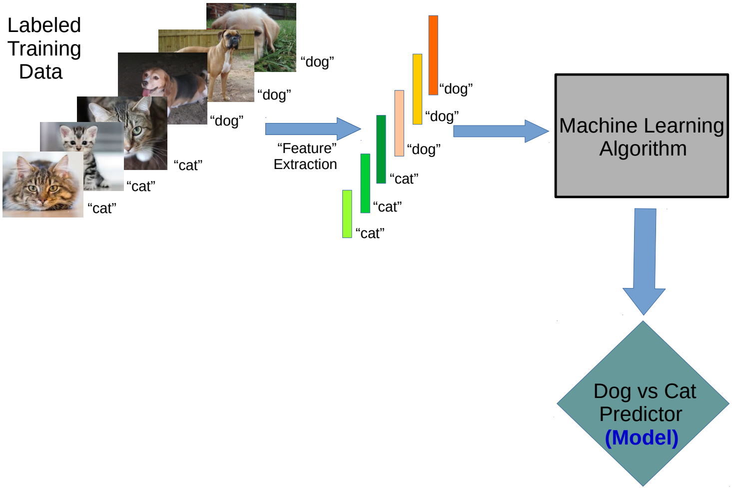


Many other specialized flavors of ML also exist, some of which include

- Semi-supervised Learning
- Active Learning
- Transfer Learning
- Multitask Learning
- Imitation Learning (somewhat related to RL)
- Zero-Shot Learning
- Few-Shot Learning

A Typical Supervised Learning Workflow (for Classification)



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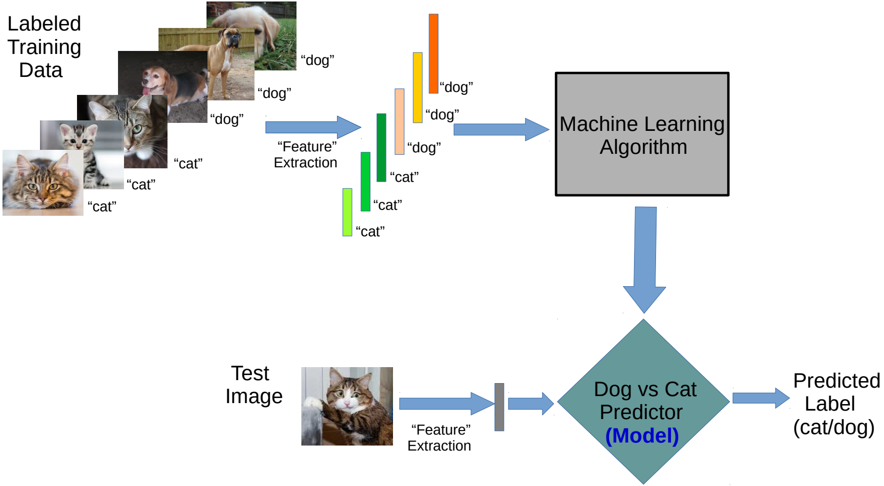

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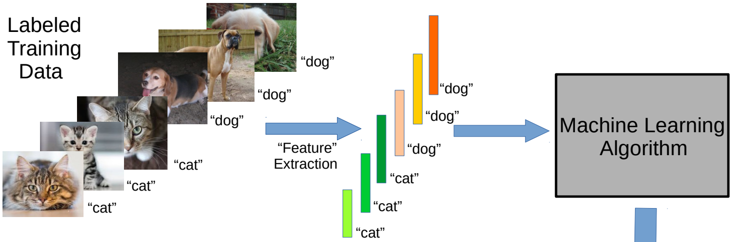
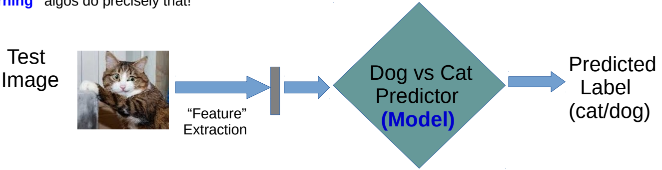
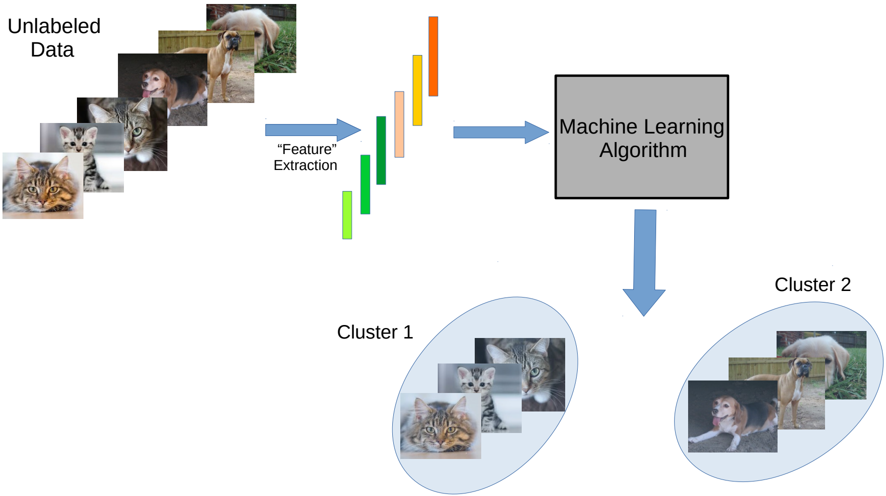


Note: The feature extraction phase may be part of the machine learning algorithm itself
(referred to "feature learning" or "representation learning")
Modern **"deep learning"** algos do precisely that!



A Typical Unupervised Learning Workflow (for Clustering)



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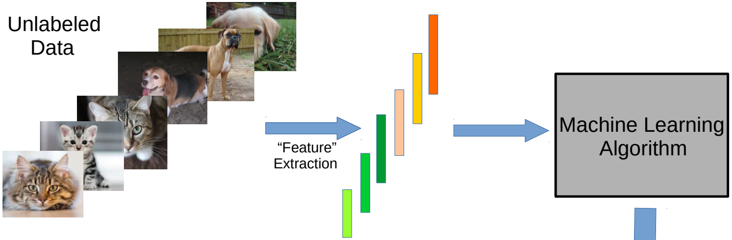
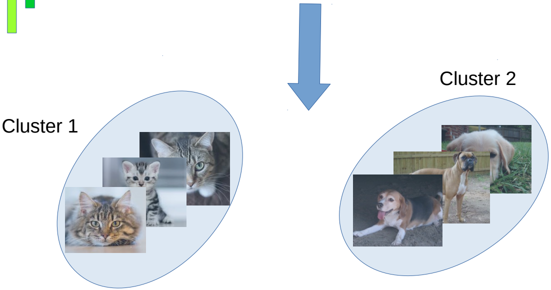
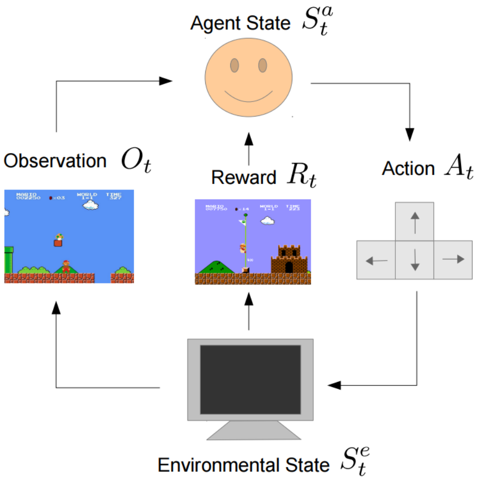




Note: Unsupervised Learning too can have (and often has) a "test" phase. E.g., in this case, given a new cat/dog image, predict which of the two clusters it belongs to.

Can do it by assigning the image to the cluster with closer centroid

A Typical Reinforcement Learning Workflow



Agent's goal is to learn a policy for some task

Agent does the following repeatedly

- Senses/observes the environment
- Takes an action based on its current policy
- Receives a reward for that action
- Updates its policy

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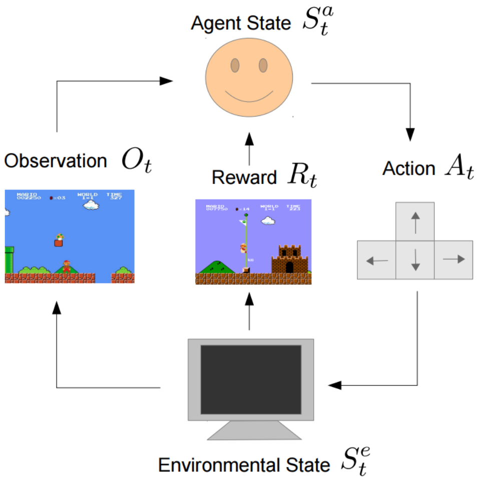

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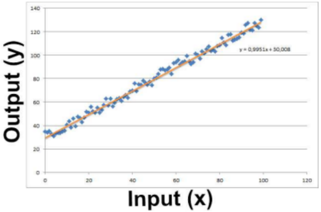
There IS supervision, not explicit (as in Supervised Learning) but rather implicit (feedback based)

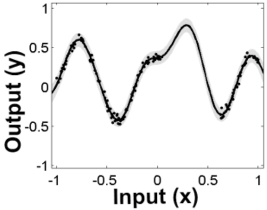
Geometric View of Some Basic ML Problems

Regression

Supervised Learning: Learn a line/curve (the "model") using training data consisting of Input-output pairs (each output is a real-valued number)

Use it to predict the outputs for new "test" inputs

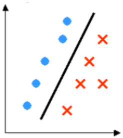




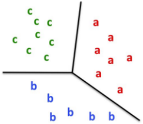
Classification

Supervised Learning: Learn a linear/nonlinear separator (the "model") using training data consisting of input-output pairs (each output is discrete-valued "label" of the corresponding input)

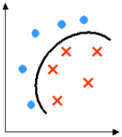
Use it to predict the labels for new "test" inputs



Two-Class (binary)
Linear Classification



Multi-Class
Linear Classification



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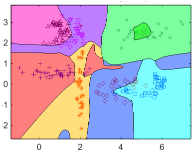

Multi-Class
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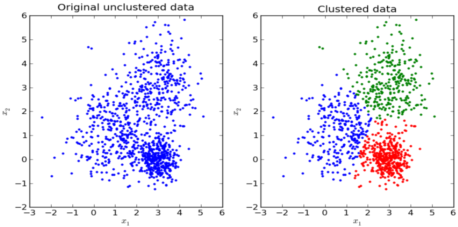
Geometric View of Some Basic ML Problems

Clustering

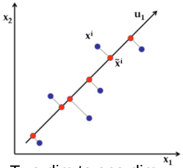
Unsupervised Learning: Learn the grouping structure for a given set of unlabeled inputs



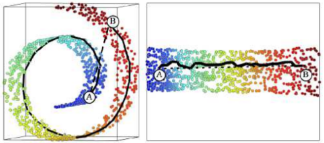
Dimensionality Reduction

Unsupervised Learning: Learn a Low-dimensional representation for a given set of high-dimensional inputs

Note: DR also comes in supervised flavors (supervised DR)

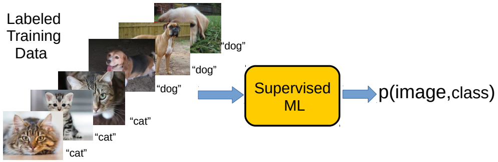


Two-dim to one-dim linear projection



Three-dim to two-dim nonlinear projection (a.k.a. manifold learning)

- Supervised Learning ("predict y given $\boldsymbol{x}$") can be thought of as estimating $p(y|\boldsymbol{x})$



Machine Learning = Probability Density Estimation

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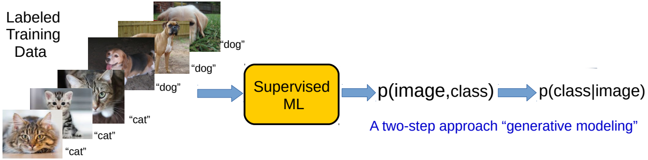

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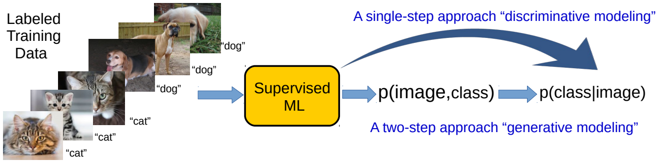

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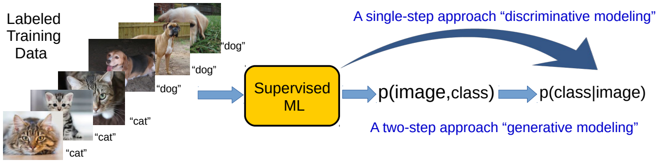

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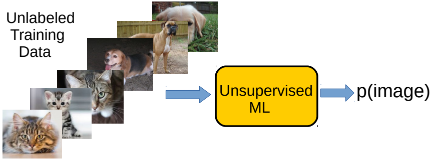

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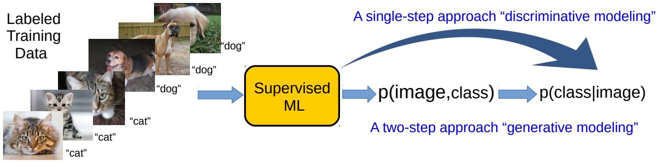

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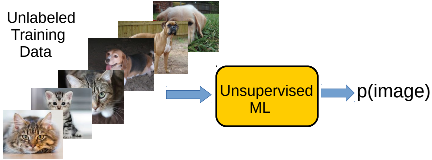

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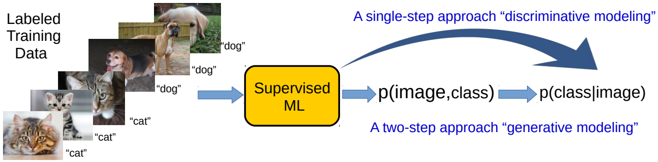

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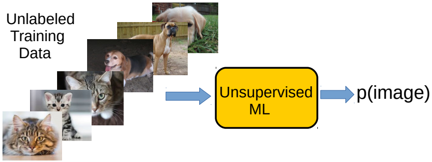

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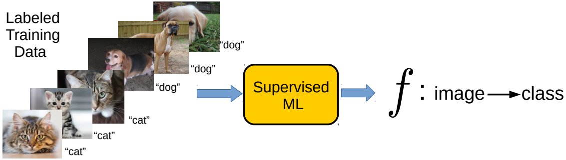
- Other ML paradigms (e.g., Reinforcement Learning) can be thought of as learning prob. density

Machine Learning = Function Approximation

- Supervised Learning ("predict y given $\boldsymbol{x}$") can be thought learning a function that maps $\boldsymbol{x}$ to y



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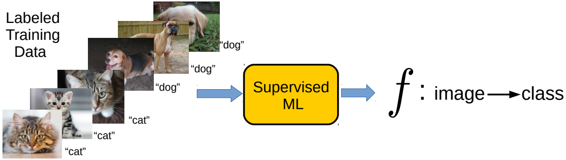

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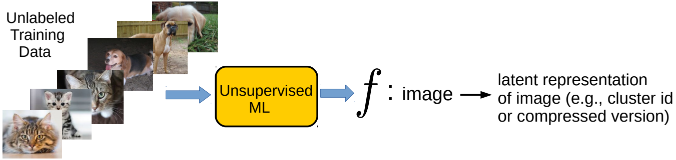

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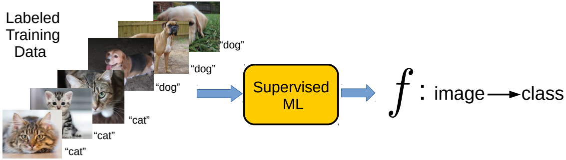

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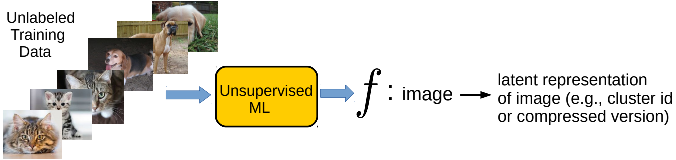

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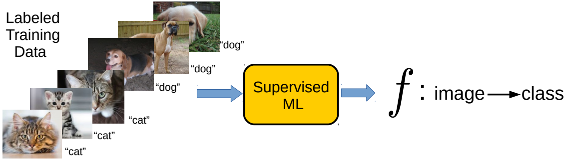

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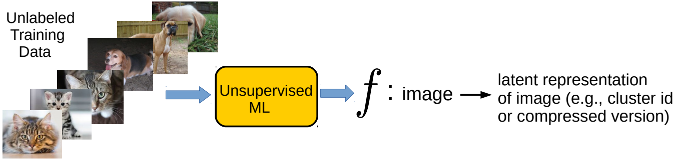

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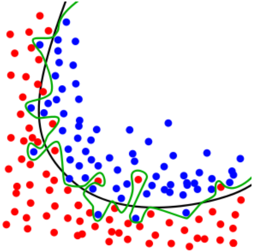
Overfitting and Generalization

- Doing well on the training data is not enough for an ML algorithm



- Trying to do too well (or perfectly) on training data may lead to bad "generalization"

Picture courtesy: Wikipedia

Overfitting and Generalization

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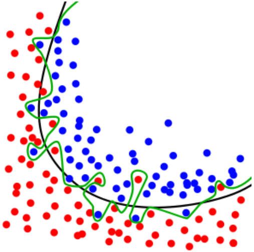

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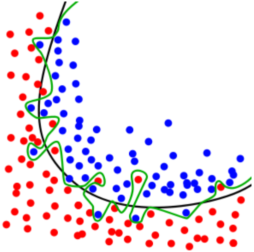
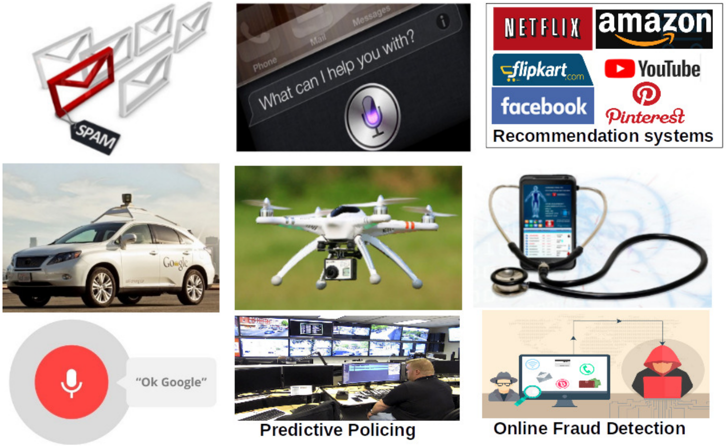


- Trying to do too well (or perfectly) on training data may lead to bad "generalization"
- Generalization: Ability of an ML algorithm to do well on future "test" data
- Simple models/functions tend to prevent overfiting and generalize well: A key principle in designing ML algorithms (called "regularization"; more on this later)

Picture courtesy: Wikipedia

Machine Learning in the real-world

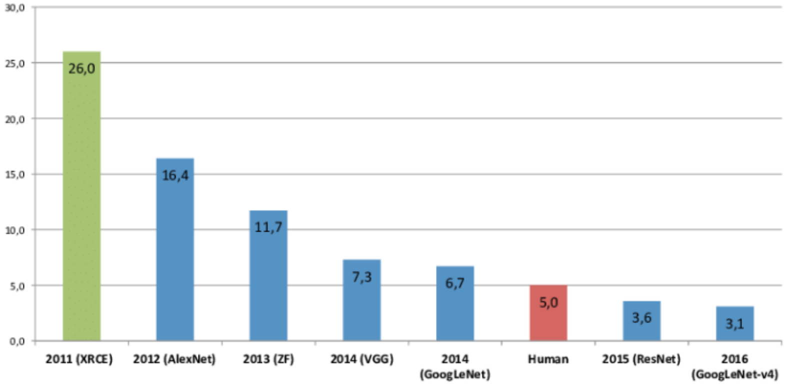
Broadly applicable in many domains (e.g., internet, robotics, healthcare and biology, computer vision, NLP, databases, computer systems, finance, etc.).



Picture courtesy: gizmodo.com,rcdronearena.com,www.wiseyak.com,www.charlesdong.com

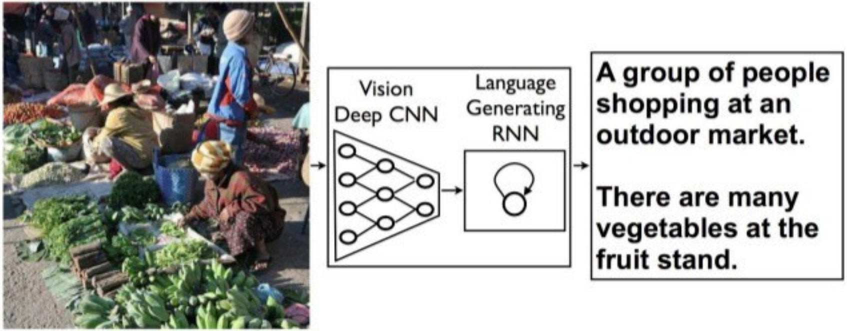
Machine Learning helps Computer Vision

ML algorithms can learn to recognize images better than humans!



Machine Learning helps Computer Vision

ML algorithms can learn to generate captions for images



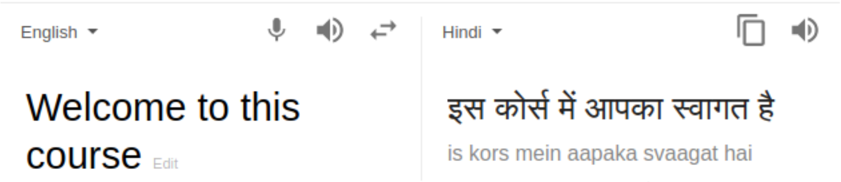
http://arxiv.org/abs/1411.4555 "Show and Tell: A Neural Image Caption Generator"

Machine Learning helps Computer Vision

ML algorithms can learn to answer questions about images (Visual QA)

Machine Learning helps NLP

ML algorithms can learn to translate text



(even “transliterate”)

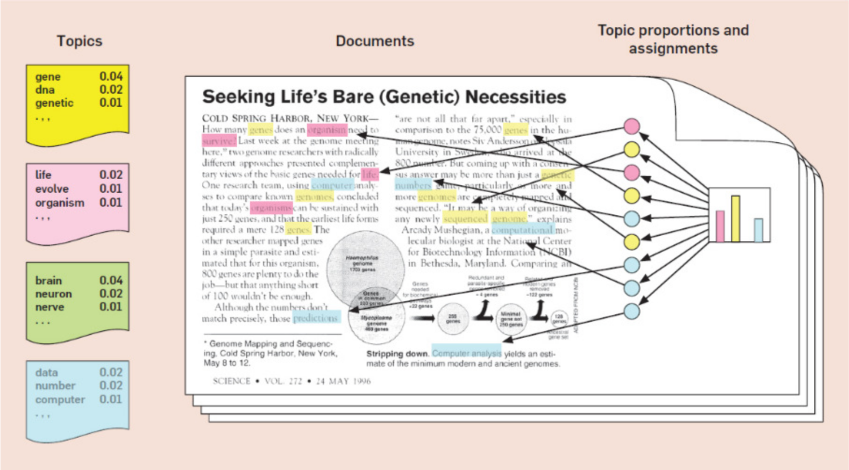
Machine Learning helps NLP

ML algorithms can learn to summarize text

Input: Article 1st sentence	Model-written headline
metro-goldwyn-mayer reported a third-quarter net loss of dlrs 16 million due mainly to the effect of accounting rules adopted this year	mgm reports 16 million net loss on higher revenue
starting from july 1, the island province of hainan in southern china will implement strict market access control on all incoming livestock and animal products to prevent the possible spread of epidemic diseases	hainan to curb spread of diseases
australian wine exports hit a record 52.1 million liters worth 260 million dollars (143 million us) in september, the government statistics office reported on monday	australian wine exports hit record high in september

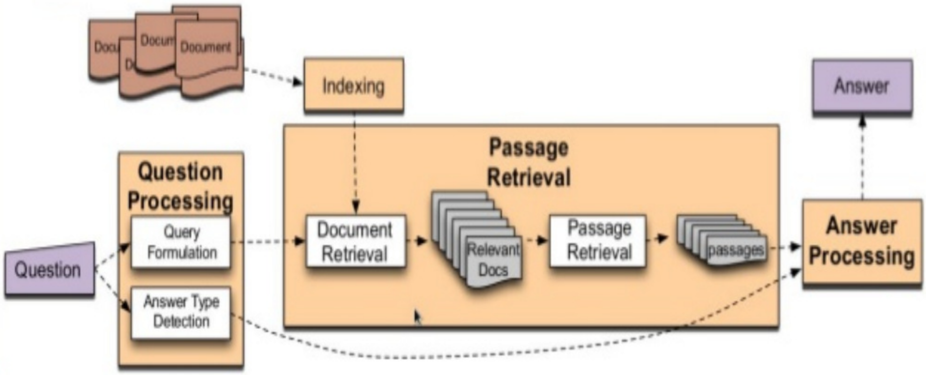
Machine Learning helps NLP

ML algorithms can learn the topics in a text corpus ("Topic Modeling")



Machine Learning helps Search and Info Retrieval

ML algorithms can learn to search for the answer to a given question from a large database of documents



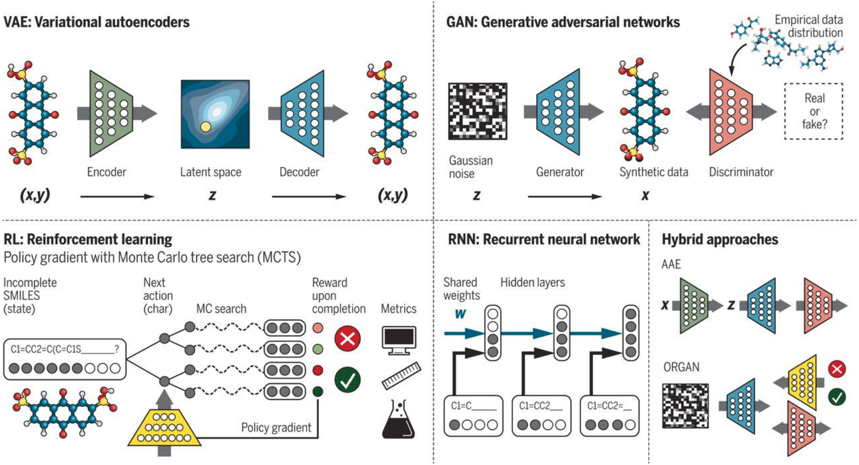
Machine Learning meets Speech Processing

ML algorithms can learn to translate speech in **real time**

Picture courtesy: https://news.microsoft.com/

Machine Learning helps Chemistry

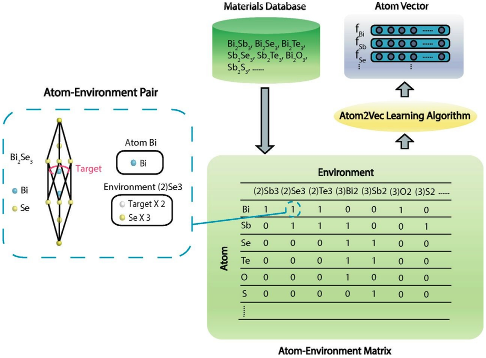
ML algorithms can understand properties of molecules and learn to synthesize new molecules



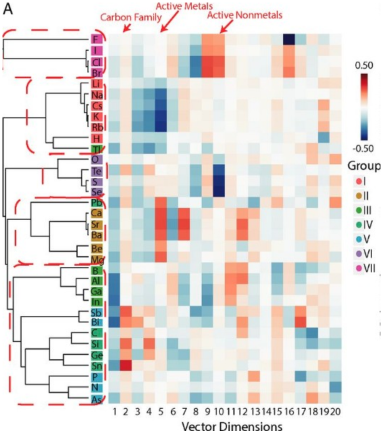
Picture courtesy: Inverse molecular design using machine learning: Generative models for matter engineering (Science, 2018)

Machine Learning helps Chemistry

ML algorithms can "read" databases of matetials and recreate the Periodic Table within hours



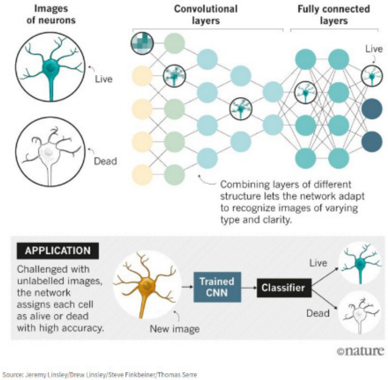
"Recreated" Periodic Table



Picture courtesy: Learning atoms for materials discovery (PNAS, 2018)

Machine Learning helps Many Other Areas..

Biology



Finance

Picture courtesy: (1) https://www.nature.com/articles/d41586-018-02174-z (2) https://responsiblefinanceforum.org

Machine Learning: A Brief Timeline and Some Milestones

1750-1900

- Origins of Bayes Theorem: Thomas Bayes and Pierre-Simon Laplace (~1800)
- Least Squares method: Legendre (1805)

1900-1950

- Early works on PCA (Peason), Factor Analysis (Spearman), CCA (by Hotelling), for exploratory data analysis
- Early works on Discriminant Analysis methods (Fisher) for classification
- McCulloch-Pitts model of the artificial neuron (1943)
- Turing predicted that Machine Learning is possible (1947)
- Design of the "Turing Test" (1950)

1950-1960

- Minsky & Edmonds' neural net machine (SNARC)
- Arthur Samuels' Checkers Player based on Machine Learning
- Rosenblatt's Perceptron algo
- Widrow-Hoff's ADALINE algo
- K-means clustering algo (Lloyd)
- Early origins of Reinforcement Learning (Bellman and others)

1960-1970

- Multi-layer ADALINE (called MADALINE)
- Nearest Neighbors algorithm
- Early works on Genetic Algorithms inspired by natural evolution (John Holland)

1970-1980

- Minsky-Papert showed that Perceptron can't learn XOR function (and nonlinear functions in general). Led to the so-called "AI Winter"
- Automatic Differentiation (later rediscovered as Backprop)

1980-1990

- Fukushima's Neurocognitron model for visual recognition
- Multi-layer Perceptrons (can learn nonlinear functions). Sunny days of AI are back!
- The Backpropagation algorithm to train deep neural nets
- Decision Trees, ID3 (Quinlan)
- NetTalk: Neural nets that can learn to pronounce English words
- Modern Reinforcement Learning

1990-2000

- Neural nets slumber due to lack of compute power
- Support Vector Machines (SVM), Kernel methods, Bayesian methods
- Random Forests, Boosting
- Continued work on neural nets for images, sequences (CNN, LSTM, etc)
- Deep Blue beats Kasparov

2000-2010

- Continued focus on classical statistical and probabilistic models, connections b/w learning & cognition
- Areas like vision, NLP, speech embrace data-driven ML methods as opposed to rule-based methods
- ML based algorithm wins the Netflix Challenge
- Neural nets re-emerged and rebranded as Deep Learning (Hinton, Bengio, LeCun, Ng, and others), thanks to improved training, GPUs

2010-2020

- Watson beats Humans in Jeopardy!
- Advances in ML/deep learning result in breakthroughs in areas like vision, NLP, speech, etc.
- Software frameworks (e.g., Tensorflow, PyTorch, ease implementing ML algos)
- Drones, self-driving cars, etc.
- A lot of industry/media focus, excitement, and hype
- Focus on Fairness, Accountability, and Transparency in ML algorithms

Road Ahead

Another AI Winter ?

(Tentative) List of topics

- Supervised Learning
  - nearest-neighbors methods, decision trees
  - linear/non-linear regression and classification
- Unsupervised Learning
  - Clustering and density estimation
  - Dimensionality reduction and manifold learning
  - Latent factor models and matrix factorization
- Probabilistic Modeling
- Deep Learning
- Ensemble Methods
- Learning from sequential data
- Recent advances in ML

Course Goals

By the end of the semester, you should be able to:

- Understand how various machine learning algorithms work
- Implement them (and, hopefully, their variants/improvements) on your own
- Look at a real-world problem and identify if ML is an appropriate solution
- If so, identify what types of algorithms might be applicable
- Feel inspired to work on and learn more about Machine Learning :-)

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- If so, identify what types of algorithms might be applicable
- Feel inspired to work on and learn more about Machine Learning :-)

Caution: There will be quite a bit of maths in this course (can't be avoided!). You are expected to be (or to make yourself) comfortable with multivariate calculus, linear algebra, probability and statistics. Please use the provided reference materials to brush up these concepts.