Introduction to Machine Learning

CS 270

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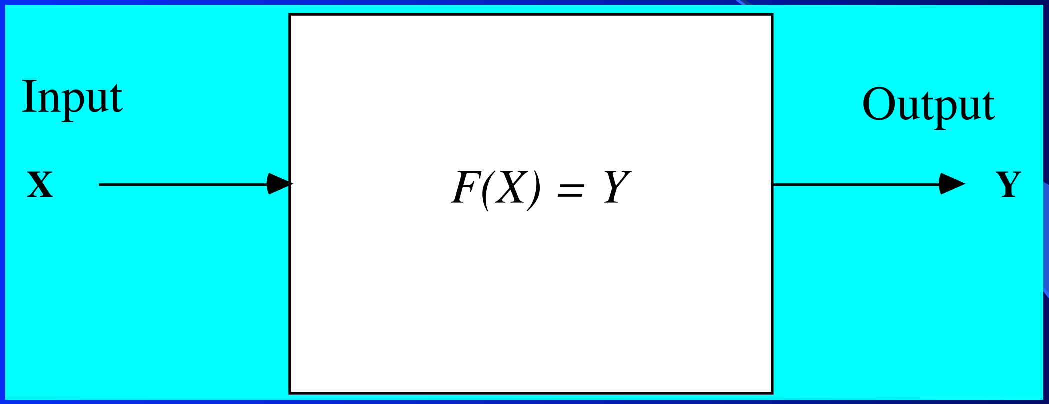
Computation and Learning



- Deterministic mappings
- We usually program *F*
- Machine Learning: Learn *F* by sampling example *X*/*Y* pairs and learning to generalize *Y*'s for *X*'s not sampled
- Is human decision making/intelligence the same?

Intelligence and Agency

"All truth is independent in that sphere in which God has placed it, to act for itself, as all intelligence also; otherwise there is no existence. Behold, here is the agency of man…" Doctrine and Covenants 93:30,31

What is Inductive Machine Learning

- Gather a *data set* of labeled examples from some task and divide them into a *training set* and a *test set*
- Speech recognition, medical diagnosis, financial forecasting, document classification, etc.
- Train a learning model (neural network, etc.) on the training set until it solves it well
- The goal is to *generalize* on novel data not yet seen
- Test how well the model performs on novel data: *Test Set*
- Use the learning system on new examples

Example Application - Heart Attack Diagnosis

- The patient has a set of symptoms - Age, type of pain, heart rate, blood pressure, temperature, etc.
- Given these symptoms in an Emergency Room setting, a doctor must diagnose whether a heart attack has occurred.
- How do you train a machine learning model to solve this problem using the inductive learning model?
- Consistent approach
- Knowledge of ML approach not always critical
- Need to select a reasonable set of input features

Machine Learning Applications

- Self Driving Cars
- Speech Recognition
- Image, Video and Text Recognition and Creation
  - Surpassing Human Capacity with latest Deep Learning
- Language Translation
- Basic Research and Creativity
- Creating Art – Composing Music, etc.
- Generative AI
- And on and on!

Motivation

- Costs and Errors in Programming
- Our inability to program complex and "subjective" tasks
- General, easy-to use mechanism for a large set of applications
- Improvement in application accuracy - Empirical

Example and Discussion

- Self-driving car – Imagine writing a program


TikTok
@londonlaz

Example and Discussion

- Self-driving car
  - Gather labeled data set. Which Input Features?

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  - How to generalize better?

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  - How to generalize better?
    - More Data
    - Different Learning Models
    - Different Input Features

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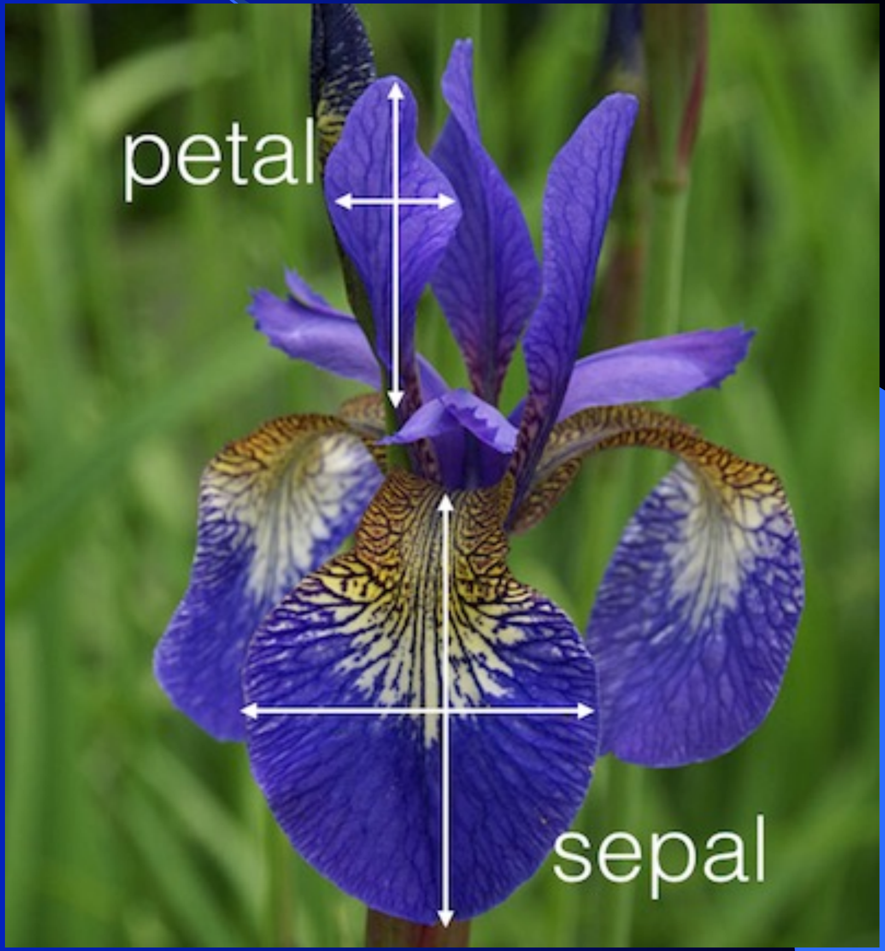
  - How to generalize better?
    - More Data
    - Different Learning Models
    - Different Input Features
  - Issues
    - Social Response
    - Super-Human driving?
- Stock Forecasting, Medical Diagnosis, etc. – Same steps!

UC Irvine Machine Learning Data Base
Iris Data Set

4.8,3.0,1.4,0.3,	Iris-setosa
5.1,3.8,1.6,0.2,	Iris-setosa
4.6,3.2,1.4,0.2,	Iris-setosa
5.3,3.7,1.5,0.2,	Iris-setosa
5.0,3.3,1.4,0.2,	Iris-setosa
7.0,3.2,4.7,1.4,	Iris-versicolor
6.4,3.2,4.5,1.5,	Iris-versicolor
6.9,3.1,4.9,1.5,	Iris-versicolor
5.5,2.3,4.0,1.3,	Iris-versicolor
6.5,2.8,4.6,1.5,	Iris-versicolor
6.0,2.2,5.0,1.5,	Iris-viginica
6.9,3.2,5.7,2.3,	Iris-viginica
5.6,2.8,4.9,2.0,	Iris-viginica
7.7,2.8,6.7,2.0,	Iris-viginica
6.3,2.7,4.9,1.8,	Iris-viginica



Glass Data Set

1.51793,12.79,3.5,1.12,73.03,0.64,8.77,0,0,	'build wind float'
1.51643,12.16,3.52,1.35,72.89,0.57,8.53,0,0,	'vehic wind float'
1.51793,13.21,3.48,1.41,72.64,0.59,8.43,0,0,	'build wind float'
1.51299,14.4,1.74,1.54,74.55,0,7.59,0,0,	tableware
1.53393,12.3,0,1,70.16,0.12,16.19,0,0.24,	'build wind non-float'
1.51779,13.64,3.65,0.65,73,0.06,8.93,0,0,	'vehic wind float'
1.51837,13.14,2.84,1.28,72.85,0.55,9.07,0,0,	'build wind float'
1.51545,14.14,0,2.68,73.39,0.08,9.07,0.61,0.05,	'headlamps'
1.51789,13.19,3.9,1.3,72.33,0.55,8.44,0,0.28,	'build wind non-float'
1.51625,13.36,3.58,1.49,72.72,0.45,8.21,0,0,	'build wind non-float'
1.51743,12.2,3.25,1.16,73.55,0.62,8.9,0,0.24,	'build wind non-float'
1.52223,13.21,3.77,0.79,71.99,0.13,10.02,0,0,	'build wind float'
1.52121,14.03,3.76,0.58,71.79,0.11,9.65,0,0,	'vehic wind float'

Machine Learning Sketch History

- Neural Networks - Connectionist - Biological Plausibility
  - Late 50's, early 60's, Rosenblatt, Perceptron
  - Minsky & Papert 1969 - The Lull, symbolic expansion
  - Late 80's - Backpropagation, Hopfield, etc. - The explosion
- Machine Learning - Artificial Intelligence – Symbolic - Psychological Plausibility
  - Samuel (1959) - Checkers evaluation strategies
  - 1970's and on - ID3, Instance Based Learning, Rule induction, …
- Currently – Symbolic and connectionist lumped under ML
- Recent explosion with deep learning
  - ChatGPT, etc.
  - Many people currently use (incorrectly?) the terms AI and ML/Deep Learning as synonyms

Inductive Learning

- Input is a vector of features where the features can be an arbitrary mix of nominal (discrete) and real values
- Output can be a scalar or vector and can be nominal (classification) or real (regression)
  - Structured input/output is also possible
- Spectrum of Inductive Learning Algorithms
  - Standard Supervised Learning with Labeled Examples
  - Unsupervised Learning – Clustering
  - Semi-Supervised Learning
  - Reinforcement Learning

Other Machine Learning Areas

- Case Based Reasoning
- Analogical Reasoning
- Speed-up Learning
- Data Mining
- COLT – Computational Learning Theory
- Inductive Learning (including data mining) is the most studied and successful to date

Standard Steps in Inductive Learning

1. Select Application
2. Select Input features for the application
3. Gather and prepare data, label if necessary
4. Train with learning model(s) – training set
5. Test learned hypothesis on novel data – test set
6. Iterate through steps 2-5 to gain further improvements
7. Use on actual data

Our Approach in this Course

- Objectively study important learning models and issues in machine learning
- Understand at a depth sufficient to walk through learning algorithms
- Simulate in most cases with real data
- Analyze strengths and weaknesses of the models
- Learn sufficiently so that you can use machine learning to solve real world problems in your future careers
  - Also potential to propose research directions for improving the art of machine learning

Goals of the BYU Neural Networks and Machine Learning Laboratory http://axon.cs.byu.edu/home.html

- Active PhD and MS students
- Proposal, Extension and Demonstration of improved Learning Models
- Generalization Accuracy
- Speed of Learning, Fault Tolerance
- Models combining the best aspects of Neural Network and Machine Learning Paradigms
- Various Approaches
- Use applications to drive the research direction