Introduction to Machine Learning

CS 201R

Tyler Trogden

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- Grew up in Odessa, TX
- Went to BYU-Idaho and Montana State
- Fun Facts
  - Happily married 7 yrs.
  - Avid tennis players
  - Readers
  - Foodies
- Contact me:
  - trogdent@byu.edu
  - CS 201R Discord

The Syllabus

Grade Breakdown

- 5 Labs and a group project – 40%
- 14 Homework problems – 10%
  - Lowest 3 scores dropped
- Midterm and Final – 40%
- In class Quizzes – 10%
  - Every day
  - No makeup – I will drop the lowest 5 quizzes

- Everything is on Learning Suite
  - Content tab
  - Syllabus

Peer Instruction

- I pose a *challenge question* (often multiple choice), which will help solidify understanding of topics we have studied
  - Might not just be one correct answer
- You each get some time (1-2 minutes) to come up with your answer and vote
- Then you get some time to convince your group (neighbors) why you think you are right (2-3 minutes)
  - <u>Learn from and teach each other</u>!
- You vote again. May change your vote if you want.
- We discuss together the different responses, show the votes, give you opportunity to justify your thinking, and give you further insights

Peer Instruction (PI) Why

- Studies show this approach <u>improves learning</u>
- Learn by doing, discussing, and teaching each other
  - Curse of knowledge/expert blind-spot
  - Compared to talking with a peer who just figured it out and who can explain it in your own jargon
  - You never really know something until you can teach it to someone else – More improved learning!
- Learn to reason about your thinking and answers
- More enjoyable - You are involved and active in the learning

How Groups Interact

- Best if group members have different initial answers
- 3 is the “magic” group number
  - You can self-organize "on-the-fly" or sit together specifically to be a group
  - Can go 2-4 on a given day to make sure everyone is involved
- Teach and learn from each other: Discuss, reason, articulate
- If you know the answer, listen to where colleagues are coming from first, then be a great humble teacher, you will also learn by doing that, and you’ll be on the other side in the future
  - I can’t do that as well because every small group has different misunderstandings and you get to focus on your particular questions
- Be ready to justify to the class your vote and justifications!

Computation and Learning

- Programming - deterministic mappings
- We usually write programs that represent F
- Machine Learning: Learn F by sampling example (X, Y) pairs and learning to generalize Ys from Xs
- Is human decision making/intelligence the same?

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 model (neural network, etc.) on the training set until it solves it well
- The goal is to *generalize* on unseen data
- Test how well the model performs on unseen data: T*est set*
- Use the learning system on new examples

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

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

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?
- 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, Understanding and Creation
  - Surpassing Human Capacity with latest Deep Learning
- Language Translation
- Basic Research and Creativity
- Creating Art – Composing Music, etc.
- And on and on!

Example and Discussion

- Self-driving car – Imagine writing a program

Example and Discussion

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

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  - How to generalize better?

Example and Discussion

- Self-driving car
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  - Divide data into a Training Set and Test Set
  - Choose a learning model
  - Train model on Training set
  - Predict accuracy with the Test Set
  - How to generalize better?
    - More Data
    - Different Learning Models
    - Different Input Features

Standard Steps in Inductive Learning

1. Select Application
2. Gather and prepare data, label if necessary
3. Select Input features
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

Data

- To learn ML algorithms we will begin with simpler data
- But we will follow the same approach
  - Gather labeled data set. Which Input Features?
  - Divide data into a Training Set and Test Set
  - Choose a learning model
  - Train model on Training set
  - Predict accuracy with the Test Set

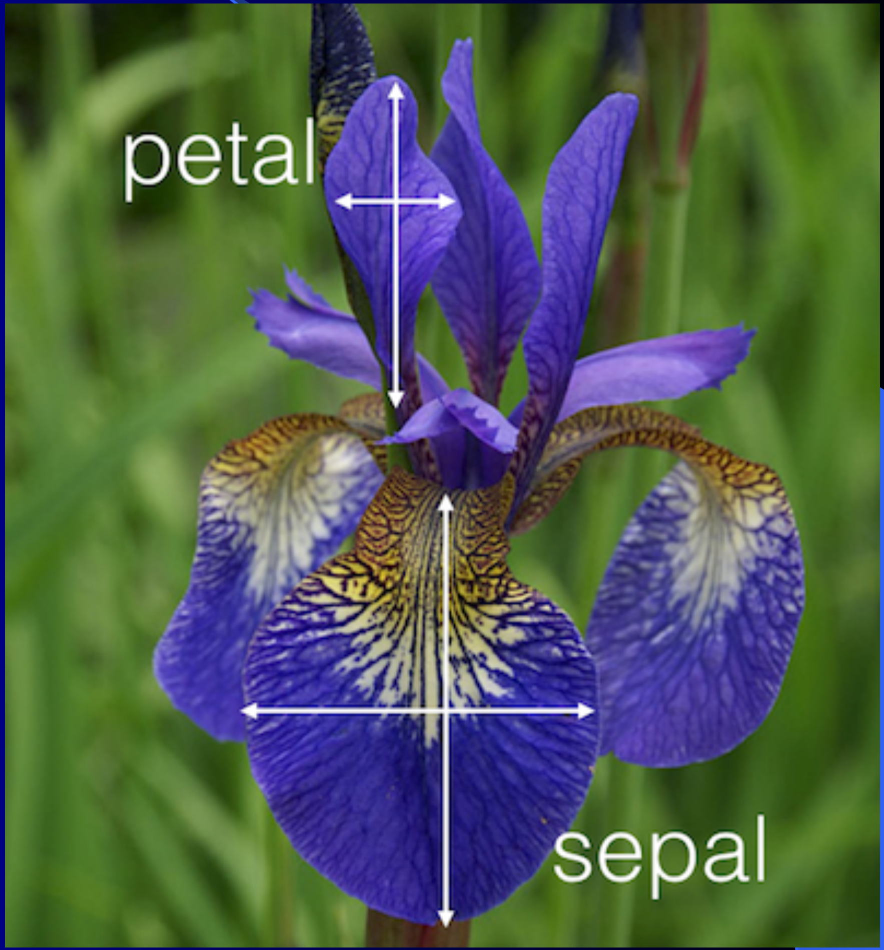
- Data is hosted by many servers
  - UC Irvine data repository - https://archive.ics.uci.edu/
  - Kaggle datasets - https://www.kaggle.com/datasets
  - Data.gov - https://data.gov/

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
  - Semi-Supervised Learning
  - Reinforcement Learning

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'