Course Overview
WHAT IS MACHINE LEARNING?
Artificial Intelligence

The basic goal of AI is to develop intelligent machines.

This consists of many sub-goals:

• Perception
• Reasoning
• Control / Motion / Manipulation
• Planning
• Communication
• Creativity
• Learning
Artificial Intelligence

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• Learning

“Deep Style” from https://deepdreamgenerator.com/#gallery
Artificial Intelligence

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- Learning
What is Machine Learning?

The goal of this course is to provide you with a toolbox:

- Machine Learning
- Statistics
- Probability
- Computer Science
- Optimization
What is ML?

- Computer Science
- Optimization
- Statistics
- Probability
- Calculus
- Measure Theory
- Linear Algebra
- Domain of Interest
What is ML?

**Speech Recognition**
1. Learning to recognize spoken words

   **THEN**
   "...the SPHINX system (e.g. Lee 1989) learns speaker-specific strategies for recognizing the prosodic sounds (phonemes) and words from the observed speech signal... neural network methods... Hidden Markov models..."

   **NOW**
   (Mitchell, 1997)

   Source: https://www.statetemplate.com/great-knowledge-base/showdown/AI/1999/06/28

   ![Speech Recognition](https://via.placeholder.com/150)

**Robotics**
2. Learning to drive an autonomous vehicle

   **THEN**
   "...the ALVINN system (Pomerleau 1989) has used its learned strategies to drive unassisted at 70 miles per hour for 50 miles on public highways among other cars..."

   **NOW**
   (Mitchell, 1997)

   Waymo.com

   ![Robotics](https://via.placeholder.com/150)

**Games / Reasoning**
3. Learning to beat the masters at board games

   **THEN**
   "...the world's top computer program for backgammon, TD-GAMMON (Tesauro, 1992, 1995), learned its strategy by playing over one million practice games against each...

   **NOW**
   (Mitchell, 1997)

   ![Games](https://via.placeholder.com/150)

**Computer Vision**
4. Learning to recognize images

   **THEN**
   "...the recognizer is a convolution network that can be spatially replicated. From the network output, a hidden Markov model produces word scores. The entire system is globally trained to minimize word level errors..."

   **NOW**
   (LeCun et al., 1995)

   ![Computer Vision](https://via.placeholder.com/150)

**Learning Theory**
5. In what cases and how well can we learn?

   - How many examples do we need to learn?
   - How do we quantify our ability to generalize to unseen data?
   - Which algorithms are better suited to specific learning settings?
Speech Recognition

1. Learning to recognize spoken words

“…the SPHINX system (e.g. Lee 1989) learns speaker-specific strategies for recognizing the primitive sounds (phonemes) and words from the observed speech signal…neural network methods…hidden Markov models…”

(Mitchell, 1997)

Source: https://www.stonetemple.com/great-knowledge-box-showdown/#VoiceStudyResults
2. Learning to drive an autonomous vehicle

“...the ALVINN system (Pomerleau 1989) has used its learned strategies to drive unassisted at 70 miles per hour for 90 miles on public highways among other cars...”

(Mitchell, 1997)

waymo.com
## Robotics

### 2. Learning to drive an autonomous vehicle

<table>
<thead>
<tr>
<th>THEN</th>
<th>NOW</th>
</tr>
</thead>
<tbody>
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<td>“...the ALVINN system (Pomerleau 1989) has used its learned strategies to drive unassisted at 70 miles per hour for 90 miles on public highways among other cars...”</td>
<td><img src="https://www.geek.com/wp-content/uploads/2016/03/uber.jpg" alt="Image of an autonomous vehicle" /></td>
</tr>
</tbody>
</table>

(Mitchell, 1997)

Roboticics

2. Learning to drive an autonomous vehicle

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<td>(Mitchell, 1997)</td>
</tr>
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</table>

https://www.argo.ai/
3. Learning to beat the masters at board games

THEN

“...the world’s top computer program for backgammon, TD-GAMMON (Tesauro, 1992, 1995), learned its strategy by playing over one million practice games against itself...”

(Mitchell, 1997)

NOW
4. Learning to recognize images

“…The recognizer is a convolution network that can be spatially replicated. From the network output, a hidden Markov model produces word scores. The entire system is globally trained to minimize word-level errors.…”

(LeCun et al., 1995)
Learning Theory

• 5. In what cases and how well can we learn?

Sample Complexity Results

**Definition 0.1.** The **sample complexity** of a learning algorithm is the number of examples required to achieve arbitrarily small error (with respect to the optimal hypothesis) with high probability (i.e., close to 1).

**Four Cases we care about…**

<table>
<thead>
<tr>
<th></th>
<th>Realizable</th>
<th>Agnostic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finite $</td>
<td>\mathcal{H}</td>
<td>$</td>
</tr>
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<td>$</td>
</tr>
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1. How many examples do we need to learn?
2. How do we quantify our ability to generalize to unseen data?
3. Which algorithms are better suited to specific learning settings?
What is ML?

Speech Recognition
1. Learning to recognize spoken words
   THEN
   "...the SPINEC system (e.g. Luce, 1989) learns speaker-specific strategies for recognizing the sparse sounds (phonemes) and words from the observed speech signal... neural network methods... hidden Markov models..." 
   (Mitchell, 1997)
   NOW

   ![Speech Recognition Example]

   Source: https://www.statemate.com/greatknowledge-base/showdown/WhichSpeechRec

Robotics
2. Learning to drive an autonomous vehicle
   THEN
   "...the ALVINN system (Pomerleau, 1989) has used its learned strategies to drive unassisted at 70 miles per hour for 90 miles on public highways among other cars..." 
   (Mitchell, 1997)
   NOW

   ![Robotics Example]

   Waymo.com

Games / Reasoning
3. Learning to beat the masters at board games
   THEN
   "...the world's top computer program for backgammon, TD-GAMMON (Tennenholt, 1992, 1995), learned its strategy by playing over one million practice games against itself..." 
   (Mitchell, 1997)
   NOW

   ![Games Example]

Computer Vision
4. Learning to recognize images
   THEN
   "...The recogniser is a convolution network that can be spatially replicated. From the network output, a hidden Markov model produces word scores. The entire system is globally trained to minimize word error..." 
   (Li-Cun et al., 1995)
   NOW

   ![Computer Vision Example]

   Images from https://blog.teamco.com/generative-models/

Learning Theory
5. In what cases and how well can we learn?
   - Sample Complexity Results
   - Revolution of Death
   - Hidden Markov Model

   1. How many examples do we need to learn?
   2. How do we quantitify our ability to generalize to unseen data?
   3. Which algorithms are better suited to specific learning settings?
What is Machine Learning?

The goal of this course is to provide you with a toolbox:

- Machine Learning
- Statistics
- Probability
- Computer Science
- Optimization

To solve all the problems above and more
Societal Impacts of ML
What ethical responsibilities do we have as machine learning experts?

Question: What are the possible societal impacts of machine learning for each case below?

Answer:

1) Search results for news are optimized for ad revenue.

http://bing.com/

2) An autonomous vehicle is permitted to drive unassisted on the road.

http://arstechnica.com/

3) A doctor is prompted by an intelligent system with a plausible diagnosis for her patient.

https://flic.kr/p/HNJUzV
Topics

• Foundations
  – Probability
  – MLE, MAP
  – Optimization

• Classifiers
  – KNN
  – Naïve Bayes
  – Logistic Regression
  – Perceptron
  – SVM

• Regression
  – Linear Regression

• Important Concepts
  – Kernels
  – Regularization and Overfitting
  – Experimental Design

• Unsupervised Learning
  – K-means / Lloyd’s method
  – PCA
  – EM / GMMs

• Neural Networks
  – Feedforward Neural Nets
  – Basic architectures
  – Backpropagation
  – CNNs, LSTMs

• Graphical Models
  – Bayesian Networks
  – HMMs
  – Learning and Inference

• Learning Theory
  – Statistical Estimation (covered right before midterm)
  – PAC Learning

• Other Learning Paradigms
  – Matrix Factorization
  – Reinforcement Learning
  – Information Theory
Learning Paradigms:
What data is available and when? What form of prediction?
- supervised learning
- unsupervised learning
- semi-supervised learning
- reinforcement learning
- active learning
- imitation learning
- domain adaptation
- online learning
- density estimation
- recommender systems
- feature learning
- manifold learning
- dimensionality reduction
- ensemble learning
- distant supervision
- hyperparameter optimization

Problem Formulation:
What is the structure of our output prediction?
- boolean: Binary Classification
- categorical: Multiclass Classification
- ordinal: Ordinal Classification
- real: Regression
- ordering: Ranking
- multiple discrete: Structured Prediction
- multiple continuous: (e.g. dynamical systems)
- both discrete & cont.: (e.g. mixed graphical models)

Facets of Building ML Systems:
How to build systems that are robust, efficient, adaptive, effective?
1. Data prep
2. Model selection
3. Training (optimization / search)
4. Hyperparameter tuning on validation data
5. (Blind) Assessment on test data

Theoretical Foundations:
What principles guide learning?
- probabilistic
- information theoretic
- evolutionary search
- ML as optimization

Big Ideas in ML:
Which are the ideas driving development of the field?
- inductive bias
- generalization / overfitting
- bias-variance decomposition
- generative vs. discriminative
- deep nets, graphical models
- PAC learning
- distant rewards

Application Areas:
Key challenges?
- NLP, Speech, Computer Vision, Robotics, Medicine, Search

Big Picture
DEFINING LEARNING PROBLEMS
Well-Posed Learning Problems

Three components \(<T,P,E>:\):

1. Task, \(T\)
2. Performance measure, \(P\)
3. Experience, \(E\)

Definition of learning:
A computer program learns if its performance at task \(T\), as measured by \(P\), improves with experience \(E\).

Definition from (Mitchell, 1997)
Example Learning Problems

Learning to beat the masters at **chess**

1. **Task, T:**

2. **Performance measure, P:**

3. **Experience, E:**
Example Learning Problems

Learning to respond to voice commands (Siri)

1. Task, $T$:

2. Performance measure, $P$:

3. Experience, $E$:
Solution #1: Expert Systems

- Over 20 years ago, we had rule-based systems:
  1. Put a bunch of linguists in a room
  2. Have them think about the structure of their native language and write down the rules they devise

<table>
<thead>
<tr>
<th>Question</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Give me directions to Starbucks</td>
<td>If: “give me directions to X” Then: directions(here, nearest(X))</td>
</tr>
<tr>
<td>How do I get to Starbucks?</td>
<td>If: “how do i get to X” Then: directions(here, nearest(X))</td>
</tr>
<tr>
<td>Where is the nearest Starbucks?</td>
<td>If: “where is the nearest X” Then: directions(here, nearest(X))</td>
</tr>
</tbody>
</table>
Capturing the Knowledge of Experts

Solution #1: Expert Systems

Over 20 years ago, we had rule-based systems:

1. Put a bunch of linguists in a room
2. Have them think about the structure of their native language and write down the rules they devise

<table>
<thead>
<tr>
<th>If: “I need directions to X”</th>
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<tr>
<td>Then: directions(here, nearest(X))</td>
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<th>If: “X directions”</th>
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<td>Then: directions(here, nearest(X))</td>
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<table>
<thead>
<tr>
<th>If: “Is there an X nearby”</th>
</tr>
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<tr>
<td>Then: directions(here, nearest(X))</td>
</tr>
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</table>
Solution #2: Annotate Data and Learn

• Experts:
  – **Very good at** answering questions about specific cases
  – **Not very good at** telling **HOW** they do it

• 1990s: So why not just have them tell you what they do on **SPECIFIC CASES** and then let **MACHINE LEARNING** tell you how to come to the same decisions that they did
Solution #2: Annotate Data and Learn

1. Collect raw sentences \( \{x^{(1)}, \ldots, x^{(n)}\} \)
2. Experts annotate their meaning \( \{y^{(1)}, \ldots, y^{(n)}\} \)

<table>
<thead>
<tr>
<th>(x^{(1)}): How do I get to Starbucks?</th>
<th>(x^{(3)}): Send a text to John that I’ll be late</th>
</tr>
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<tbody>
<tr>
<td>(y^{(1)}): directions(here, nearest(Starbucks))</td>
<td>(y^{(3)}): txtmsg(John, I’ll be late)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(x^{(2)}): Show me the closest Starbucks</th>
<th>(x^{(4)}): Set an alarm for seven in the morning</th>
</tr>
</thead>
<tbody>
<tr>
<td>(y^{(2)}): map(nearest(Starbucks))</td>
<td>(y^{(4)}): setalarm(7:00AM)</td>
</tr>
</tbody>
</table>
Example Learning Problems

Learning to respond to voice commands (Siri)

1. Task, $T$: predicting action from speech
2. Performance measure, $P$: percent of correct actions taken in user pilot study
3. Experience, $E$: examples of (speech, action) pairs
Problem Formulation

• Often, the same task can be formulated in more than one way:
• Ex: Loan applications
  – creditworthiness/score (regression)
  – probability of default (density estimation)
  – loan decision (classification)

Problem Formulation:
What is the structure of our output prediction?

<table>
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<td>Ranking</td>
</tr>
<tr>
<td>multiple discrete</td>
<td>Structured Prediction</td>
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<tr>
<td>multiple continuous</td>
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<tr>
<td>both discrete &amp; cont.</td>
<td>(e.g. mixed graphical models)</td>
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Well-posed Learning Problems

In-Class Exercise
1. Select a task, T
2. Identify performance measure, P
3. Identify experience, E
4. Report ideas back to rest of class

Example Tasks
- Identify objects in an image
- Translate from one human language to another
- Recognize speech
- Assess risk (e.g. in loan application)
- Make decisions (e.g. in loan application)
- Assess potential (e.g. in admission decisions)
- Categorize a complex situation (e.g. medical diagnosis)
- Predict outcome (e.g. medical prognosis, stock prices, inflation, temperature)
- Predict events (default on loans, quitting school, war)
- Plan ahead under perfect knowledge (chess)
- Plan ahead under partial knowledge (poker, bridge)

Examples from Roni Rosenfeld
SYLLABUS HIGHLIGHTS
Syllabus Highlights

The syllabus is located on the course webpage:

http://www.cs.cmu.edu/~mgormley/courses/10601

or

http://mlcourse.org

The course policies are required reading.
Syllabus Highlights

• **Grading**: 50% homework, 15% exam 1, 15% exam 2, 15% exam 3, 5% participation
• **Exam 1**: evening exam, Thu, Sep. 30
• **Exam 2**: evening exam, Tue, Nov. 02
• **Exam 3**: final exam week, date TBD by registrar
• **Homework**: ~3 written and ~6 written + programming
  – 6 grace days for homework assignments
  – Late submissions: 75% day 1, 50% day 2, 25% day 3
  – No submissions accepted after 3 days w/o extension
  – Extension requests: see syllabus
• **Recitations**: Fridays, same time/place as lecture (optional, interactive sessions)
• **Readings**: required, online PDFs, recommended for after lecture
• **Technologies**: Piazza (discussion), Gradescope (homework), Google Forms (polls)
• **Academic Integrity**:
  – Collaboration encouraged, but must be documented
  – Solutions must always be written independently
  – No re-use of found code / past assignments
  – Severe penalties (i.e.. failure)
• **Office Hours**: posted on Google Calendar on “Office Hours” page
Lectures

• You should ask lots of questions
  – Interrupting (by raising a hand) to ask your question is strongly encouraged
  – Asking questions later (or in real time) on Piazza is also great

• When I ask a question…
  – I want you to answer
  – Even if you don’t answer, think it through as though I’m about to call on you

• Interaction improves learning (both in-class and at my office hours)
You are not *required* to read a textbook, but it will help immensely!
### Where can I find...?

<table>
<thead>
<tr>
<th>Date</th>
<th>Lecture</th>
<th>Readings</th>
<th>Announcements</th>
</tr>
</thead>
</table>
- Command Line and File I/O Tutorial, 10601 Course Staff (2020).  
|            |                                                                        | ![Image](image12x18to780x492) 10601 Notation Crib Sheet, Matt Gormley (2018).  
Command Line and File I/O Tutorial, 10601 Course Staff (2020).  
Visual Information Theory, Christopher Olah (2015). blog. | HW1 out                  |
| Fri, 5-Feb | Recitation: HW1  [Handout] [Solutions]                                | ![Image](image12x18to780x492) 10601 Notation Crib Sheet, Matt Gormley (2018).  
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Command Line and File I/O Tutorial, 10601 Course Staff (2020).  
Visual Information Theory, Christopher Olah (2015). blog. | HW1 out                  |
| Mon, 8-Feb | Lecture 3: Generalizing from examples - the Big Picture  [Slides] [Poll] | - Limits of Learning, Hal Daumé III (2017). CIML, Chapter 2.                            | HW1 due                  |
| Fri, 12-Feb| Recitation: HW2  [Handout] [Solutions]                                | ![Image](image12x18to780x492) 10601 Notation Crib Sheet, Matt Gormley (2018).  
Command Line and File I/O Tutorial, 10601 Course Staff (2020).  
Visual Information Theory, Christopher Olah (2015). blog. | ![Image](image12x18to780x492) 10601 Notation Crib Sheet, Matt Gormley (2018).  
Command Line and File I/O Tutorial, 10601 Course Staff (2020).  
Visual Information Theory, Christopher Olah (2015). blog. | HW2 out                  |
| Mon, 15-Feb| Lecture 5: Model Selection  [Slides] [Whiteboard] [Poll]              | - The Perceptron, Hal Daumé III (2017). CIML, Chapter 4.                                | HW1 solution session  (Thursday) |
Where can I find...?
Where can I find…?

Introduction to Machine Learning

Assignments

There will be 8 homework assignments during the semester in addition to the exams. The assignments will consist of both theoretical and practical assignments will be released via a Piazza announcement explaining where to find the handout, starter code, LaTeX template, etc.

- Homework 1: Background Material (written / programming)
  Handout
- Homework 2: Decision Trees (written / programming)
  Handout
- Homework 3: KNN, Perceptron, and Linear Regression (written)
  Handout
- Mock Exam 1:
  Handout and Solution
- Homework 4: Logistic Regression (written / programming)
  Handout
- Homework 5: Neural Networks (written / programming)
  Handout
- Homework 6: Neural Networks and Reinforcement Learning (written / programming)
  Handout
- Homework 7: Graphical Models (written / programming)
In-Class Polls

Q: How do these In-Class Polls work?

A: Don’t worry about it for today. We won’t use them until the second week of class, i.e. the third lecture.

Details are on the syllabus.
PREREQUISITES
Prerequisites

What they are:

• Significant programming experience (15-122)
  – Written programs of 100s of lines of code
  – Comfortable learning a new language

• Probability and statistics (36-217, 36-225, etc.)

• Mathematical maturity: discrete mathematics (21-127, 15-151), linear algebra, and calculus
Prerequisites

What if you need additional review?
• Consider first taking 10-606/607: Mathematical/Computational Foundations for Machine Learning
• More details here: https://www.cs.cmu.edu/~pvirtue/10606/

How to describe 606/607 to a friend

606/607 is...

- a formal presentation of mathematics and computer science...
- motivated by (carefully chosen) real-world problems that arise in machine learning...
- where the broader picture of how those problems arise is treated somewhat informally.
Prerequisites

What if you need additional review?
• Consider first taking 10-606/607: Mathematical/Computational Foundations for Machine Learning
• More details here: https://www.cs.cmu.edu/~pvirtue/10606/
Oh, the Places You'll Use Probability!

By Dr. Seuss
Oh, the Places You’ll Use Probability!

Supervised Classification

• Naïve Bayes

\[ p(y|x_1, x_2, \ldots, x_n) = \frac{1}{Z} p(y) \prod_{i=1}^{n} p(x_i|y) \]

• Logistic regression

\[ P(Y = y|X = x; \theta) = p(y|x; \theta) = \frac{\exp(\theta_y \cdot f(x))}{\sum_{y'} \exp(\theta_{y'} \cdot f(x))} \]

Note: This is just motivation – we’ll cover these topics later!
Oh, the Places You’ll Use Probability!

ML Theory
(Example: Sample Complexity)

- **Goal:** $h$ has small error over $D$.

  True error: $err_D(h) = \Pr_{x \sim D} (h(x) \neq c^*(x))$

  How often $h(x) \neq c^*(x)$ over future instances drawn at random from $D$

- **But, can only measure:**

  Training error: $err_S(h) = \frac{1}{m} \sum_i I(h(x_i) \neq c^*(x_i))$

  How often $h(x) \neq c^*(x)$ over training instances

**Sample complexity:** bound $err_D(h)$ in terms of $err_S(h)$

Note: This is just motivation – we’ll cover these topics later!
Oh, the Places You’ll Use Probability!

Deep Learning
(Example: Deep Bi-directional RNN)

Note: This is just motivation – we’ll cover these topics later!
Oh, the Places You’ll Use Probability!

Graphical Models

• Hidden Markov Model (HMM)

• Conditional Random Field (CRF)

Note: This is just motivation – we’ll cover these topics later!
Prerequisites

What if I’m not sure whether I meet them?
• Don’t worry: we’re not sure either
• However, we’ve designed a way to assess your background knowledge so that you know what to study!

(see instructions of written portion of HW1)
Reminders

• Homework 1: Background
  – Out: Wed, Sep 1 (2nd lecture)
  – Due: Wed, Sep 8 at 11:59pm
  – Two parts:
    1. written part to Gradescope
    2. programming part to Gradescope
  – unique policy for this assignment:
    1. two submissions for written (see writeup for details)
    2. unlimited submissions for programming (i.e. keep submitting until you get 100%)
Learning Objectives

You should be able to...

1. Formulate a well-posed learning problem for a real-world task by identifying the task, performance measure, and training experience

2. Describe common learning paradigms in terms of the type of data available, when it’s available, the form of prediction, and the structure of the output prediction

3. Implement Decision Tree training and prediction (w/simple scoring function)

4. Explain the difference between memorization and generalization [CIML]

5. Identify examples of the ethical responsibilities of an ML expert