Course Overview

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SIST, ShanghaiTech

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Slides Courtesy of Matt Gormley & Henry Chai, CMU

WHAT IS MACHINE LEARNING?

Artificial Intelligence

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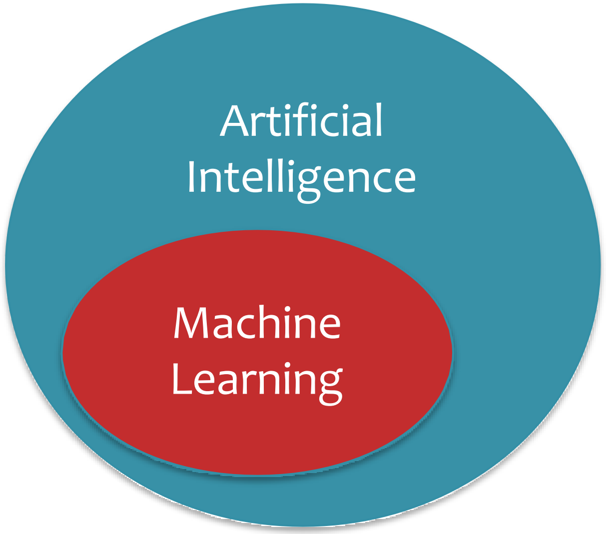
The basic goal of AI is to develop intelligent machines.

This consists of many sub-goals:

- Perception
- Reasoning
- Control / Motion / Manipulation
- Planning
- Communication
- Creativity
- Learning



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"Deep Style" from https://deepdreamgenerator.com/#gallery

Artificial Intelligence

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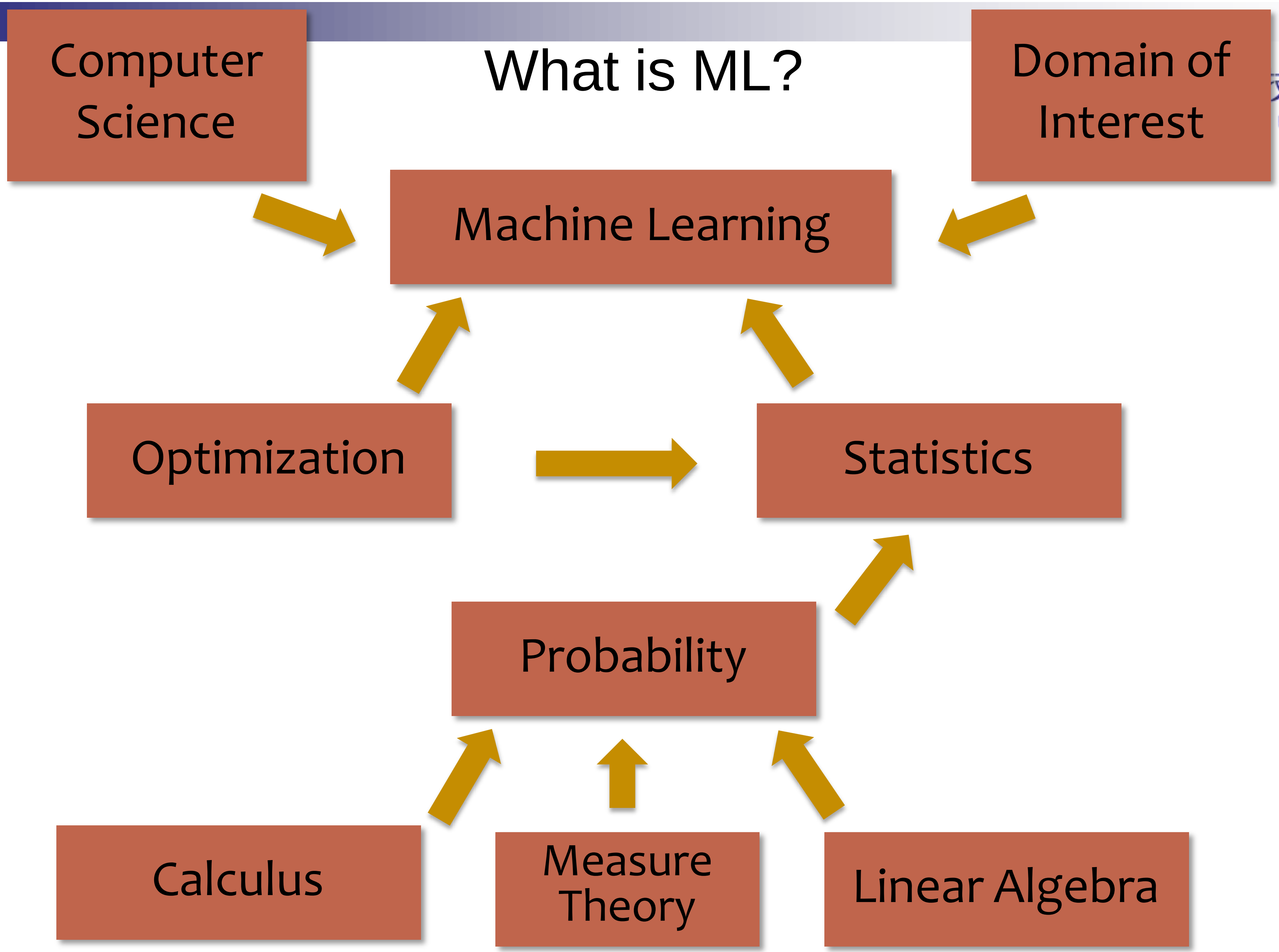
What is Machine Learning?

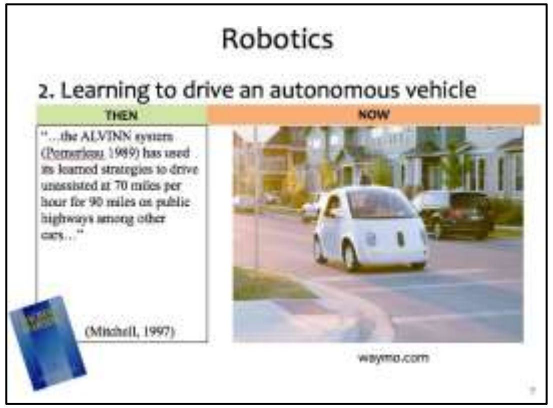
The goal of this course is to provide you with a toolbox:

What is ML?

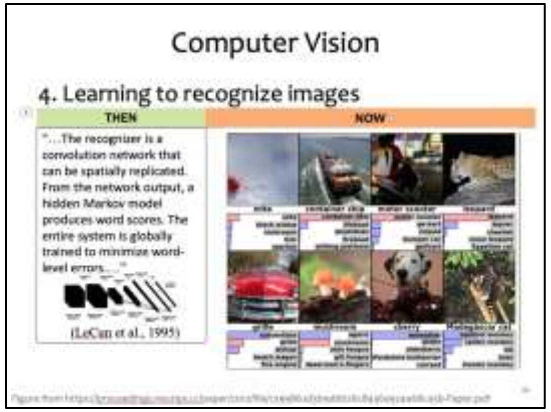

Computer Science
Domain of Interest
Machine Learning
Optimization
Statistics
Probability
Calculus
Measure Theory
Linear Algebra

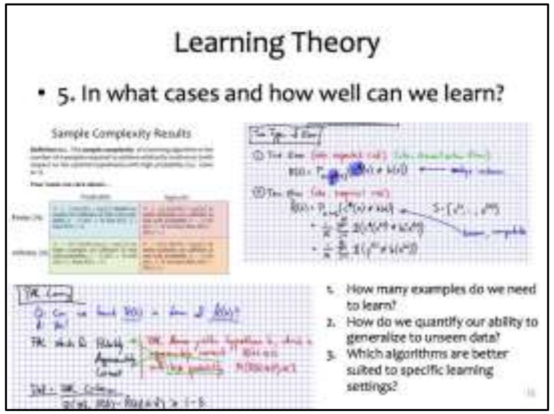
What is ML?


Speech Recognition
1. Learning to recognize spoken words
THEN
NOW
"…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)


Robotics
2. Learning to drive an autonomous vehicle
THEN
NOW
"…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


Games / Reasoning
3. Learning to beat the masters at board games
THEN
NOW
"…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)
AlphaGo


Computer Vision
4. Learning to recognize images
THEN
NOW
"…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
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?

1. Learning to recognize spoken words

THEN	NOW
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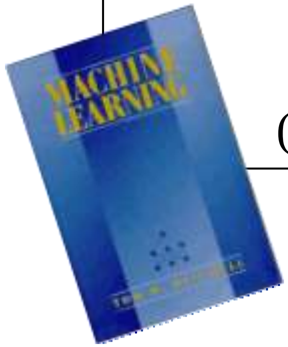
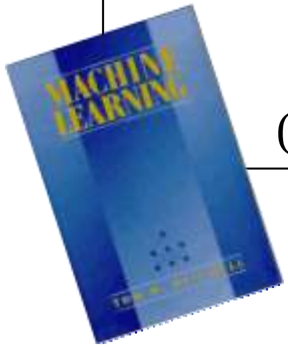


Figure from https://botpenguin.com/alexa-vs-siri-vs-google-assistant/

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

waymo.com

3. Learning to beat the masters at board games

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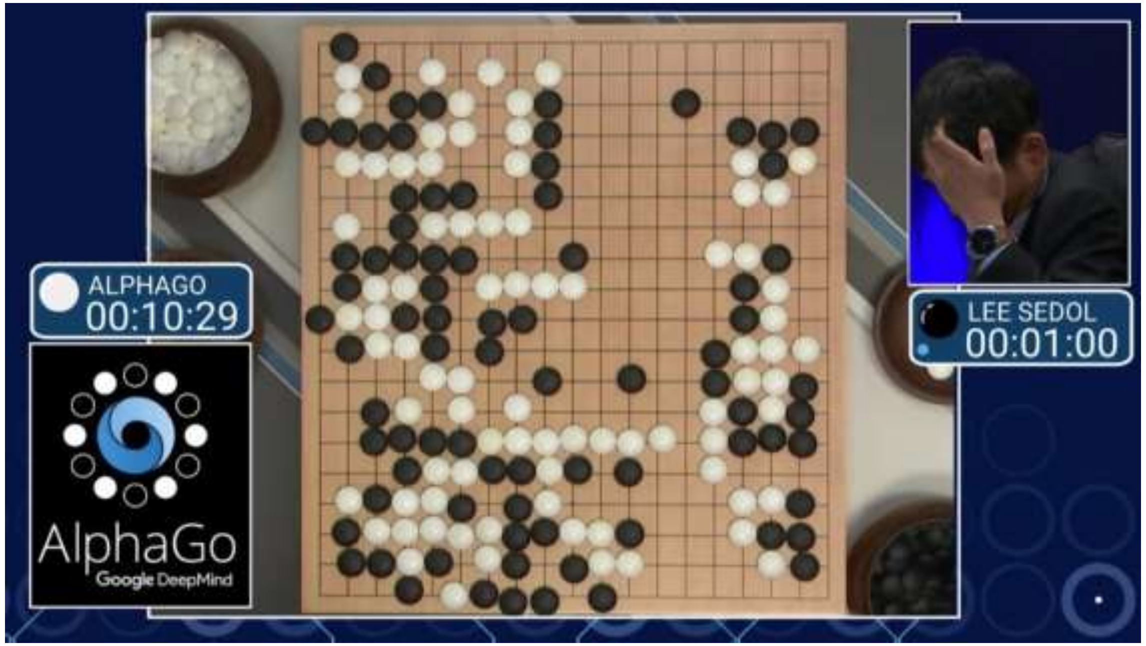
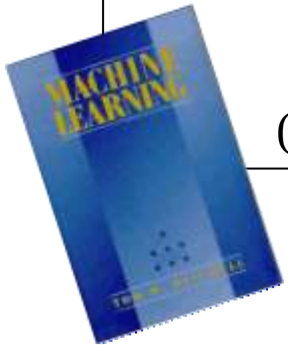
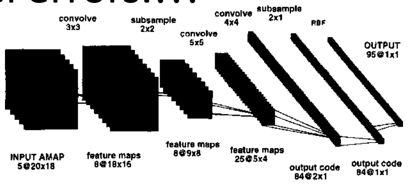
"…the world's top computer program for backgammon, TD-GAMMON (Tesauro, 1992, 1995), learned its strategy by playing over one million practice games against itself…" (Mitchell, 1997)	



4. Learning to recognize images

THEN	NOW
"…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)

Figure from https://proceedings.neurips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

- 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...

	Realizable	Agnostic
Finite $\lvert\mathcal{H}\rvert$	$N \geq \frac{1}{\epsilon}\left[\log(\lvert\mathcal{H}\rvert) + \log(\frac{1}{\delta})\right]$ labeled examples are sufficient so that with probability $(1-\delta)$ all $h \in \mathcal{H}$ with $R(h) \geq \epsilon$ have $\hat{R}(h) > 0$.	$N \geq \frac{1}{2\epsilon^2}\left[\log(\lvert\mathcal{H}\rvert) + \log(\frac{2}{\delta})\right]$ labeled examples are sufficient so that with probability $(1-\delta)$ for all $h \in \mathcal{H}$ we have that $\lvert R(h) - \hat{R}(h)\rvert < \epsilon$.
Infinite $\lvert\mathcal{H}\rvert$	$N = O(\frac{1}{\epsilon}\left[\text{VC}(\mathcal{H})\log(\frac{1}{\epsilon}) + \log(\frac{1}{\delta})\right])$ labeled examples are sufficient so that with probability $(1-\delta)$ all $h \in \mathcal{H}$ with $R(h) \geq \epsilon$ have $\hat{R}(h) > 0$.	$N = O(\frac{1}{\epsilon^2}\left[\text{VC}(\mathcal{H}) + \log(\frac{1}{\delta})\right])$ labeled examples are sufficient so that with probability $(1-\delta)$ for all $h \in \mathcal{H}$ we have that $\lvert R(h) - \hat{R}(h)\rvert \leq \epsilon$.

Two Types of Error

① True Error (aka. expected risk) (aka. Generalization Error)

$$R(h) = P_{x \sim p^*(x)}(c^*(x) \neq h(x)) \leftarrow \text{always unknown}$$

② Train Error (aka. empirical risk)

$$\hat{R}(h) = P_{x \sim S}(c^*(x) \neq h(x)) \qquad S = \{x^{(1)}, \ldots, x^{(N)}\}$$

$$= \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}(c^*(x^{(i)}) \neq h(x^{(i)})) \qquad \text{known, computable}$$

$$= \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}(y^{(i)} \neq h(x^{(i)}))$$

PAC Learning

Q: Can we bound $R(h)$ in terms of $\hat{R}(h)$?

A: Yes!

PAC stands for Probably Approximately Correct

PAC learner yields hypothesis h, which is approximately correct $R(h) \approx 0$ with high probability $\Pr(R(h) \approx 0) \approx 1$

Def: PAC Criterion

$$\Pr(\forall h, \lvert R(h) - \hat{R}(h)\rvert \leq \epsilon) \geq 1 - \delta$$

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 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

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What ethical responsibilities do we have as machine learning experts?

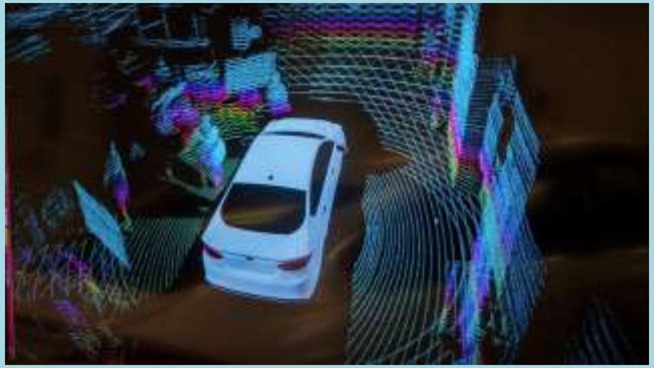
Question: What are the possible societal impacts of machine learning for each case below?

Answer:

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

http://bing.com/

http://arstechnica.com/



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

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

https://flic.kr/p/HNJUzV

Societal Impacts of ML

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The Washington Post
Democracy Dies in Darkness
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A 72-year-old congressman goes back to school, pursuing a degree in AI

By Meagan Flynn
December 28, 2022 at 6:00 a.m. EST

Rep. Don Beyer (D-Va.) is pursuing a master's degree in machine learning at George Mason University with hopes of one day applying his AI knowledge to his legislative work. (Craig Hudson for The Washington Post)

Normally Don Beyer doesn't bring his multivariable calculus textbook to work, but his final exam was coming up that weekend.

"And I'm running out of time," he said, plopping the textbook and a scribbled notebook filled with esoteric-looking calculations on a coffee table in his office, "because I have all these—"

His phone was ringing. "I'll be there," Beyer told a colleague wondering when he would be returning to the House floor for votes.

It seemed study time would have to wait.

That's been the story of the year for Beyer (D-Va.), who has been moonlighting as a student at George Mason University in pursuit of a master's degree in machine learning while balancing his duties as a congressman. Beyer — a science wonk, economist and former car salesman — has been taking one class per semester in a slow but steady march toward the degree, with hopes of one day applying his artificial-intelligence knowledge to his legislative work as the technology evolves further.

Figure from https://www.washingtonpost.com/dc-md-va/2022/12/28/beyer-student-artificial-intelligence-degree/

ML Big Picture

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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)

Application Areas

Key challenges?

NLP, Speech, Computer Vision, Robotics, Medicine, Search

Theoretical Foundations:

What principles guide learning?

- ❑ probabilistic
- ❑ information theoretic
- ❑ evolutionary search
- ❑ ML as optimization

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*

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*

Topics

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- Foundations
  - Probability
  - Optimization
- Classification
  - KNN
  - Logistic Regression
  - Perceptron
- Regression
  - Linear Regression
- Important Concepts
  - Kernels
  - Regularization and Overfitting
  - Experimental Design
- Unsupervised Learning
  - K-means
  - PCA
- Neural Networks
  - Feedforward Neural Nets
  - Basic architectures
  - Backpropagation
- Deep Learning
  - CNNs
  - RNNs
  - Transformers
- Reinforcement Learning
  - Value Iteration / Policy Iteration
  - Q-Learning
  - Deep Q-Learning
- Learning Theory
  - PAC Learning
- Societal Impacts of ML
- Other Learning Paradigms
  - Matrix Factorization
  - Ensemble Methods

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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*:

Example Learning Problems

Learning to **respond to voice commands (Siri)**

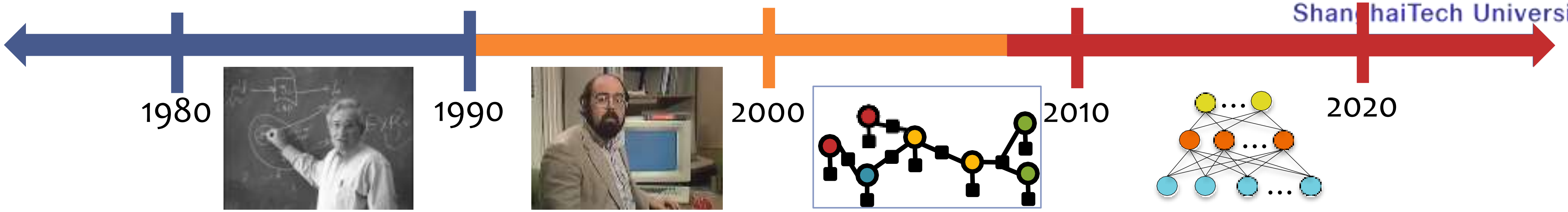
1. Task, *T*:

Given a transcribed sentence `x` predict the command `y`

Example:

```
x = "Give me directions to Starbucks"
y = DIRECTIONS(here, nearest(Starbucks))
```

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

Introspection…
x = "Give me directions to Starbucks"
x = "Send Jill a txt asking for directions"
x = "Play the best hit music by TXT"
x = "How do I get to Pitt's Department of Music"

Rules…
~~if "directions" in x:~~ ~~type = DIRECTIONS()~~
~~if "txt" in x:~~ ~~type = TXTMSG()~~ ~~elif "directions" in x:~~ ~~type = DIRECTIONS()~~
~~if "music" in x:~~ ~~type = MUSIC()~~ ~~elif "txt" in x:~~ ~~type = TXTMSG()~~ ~~elif "directions" in x:~~ ~~type = DIRECTIONS()~~

Capturing the Knowledge of Experts

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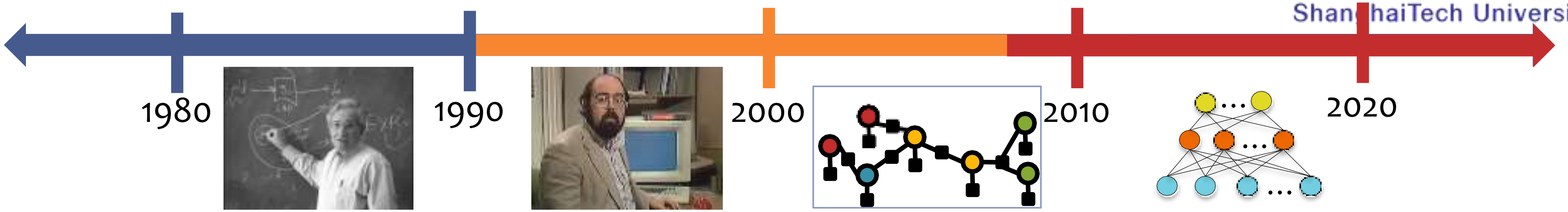

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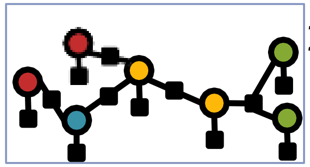
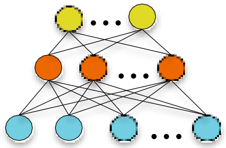
Introspection…
x = "Give me directions to Starbucks"
x = "How do I get to Starbucks?"
x = "Where is the nearest Starbucks?"
x = "I need directions to Starbucks"
x = "Is there a Starbucks nearby?
x = "Starbucks now!"

Rules…
if x matches "give me directions to Z": cmd = DIRECTIONS(here, nearest(Z))
if x matches "how do i get to Z": cmd = DIRECTIONS(here, nearest(Z))
if x matches "where is the nearest Z": cmd = DIRECTIONS(here, nearest(Z))
if x matches "I need directions to Z": cmd = DIRECTIONS(here, nearest(Z))
if x matches "Is there a Z nearby": cmd = DIRECTIONS(here, nearest(Z))
if x matches "Z now!": cmd = DIRECTIONS(here, nearest(Z))

Capturing the Knowledge of Experts

1980  1990  2000  2010  2020

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

Capturing the Knowledge of Experts

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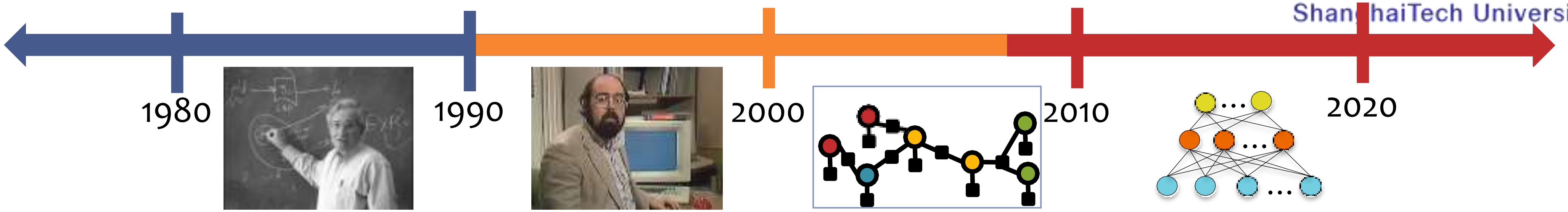

Solution #2: Annotate Data and Learn

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

$x^{(1)}$: `How do I get to Starbucks?`	$x^{(3)}$: `Send a text to John that I'll be late`
$y^{(1)}$: `DIRECTIONS(here, nearest(Starbucks))`	$y^{(3)}$: `TXTNSG(John, I'll be late)`
$x^{(2)}$: `Show me the closest Starbucks`	$x^{(4)}$: `Set an alarm for seven in the morning`
$y^{(2)}$: `MAP(nearest(Starbucks))`	$y^{(4)}$: `SETALARM(7:00AM)`

Example Learning Problems

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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

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Often, the same task can be formulated in more than one way.

Example: Loan applications

- creditworthiness/score (regression)
- probability of default (density estimation)
- loan decision (classification)

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)

Well-posed Learning Problems

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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

In-Class Exercise

1. Select a **task**, T
2. Identify **performance measure**, P
3. Identify **experience**, E
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Well-posed Learning Problems

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task, T	**performance measure, P**	**experience, E**

In-Class Exercise

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Well-posed Learning Problems

task, T	performance measure, P	experience, E

(without any math!)

SUPERVISED LEARNING

Building a Trash Classifier

- Suppose the friends OF THE RIVERFRONT ask ShanghaiTech to build a robot for collecting trash along Pittsburgh's rivers
- You are tasked with building a classifier that detects whether an object is a piece of trash (+) or not a piece of trash (-)
- The robot can detect an object's *color*, *sound*, and *weight*
- You manually annotate the following dataset based on objects you find

trash?	color	sound	weight
+	green	crinkly	high
-	brown	crinkly	low
-	grey	none	high
+	clear	none	low
-	green	none	low

WARNING!

Like many fields, Machine Learning is riddled with copious amounts of technical jargon!

For many terms we'll define in this class, you'll find four or five different terms in the literature that refer to the same thing.

Supervised Binary Classification

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- *Def:* an **example** contains a label (aka. class) and features (aka. point or attributes)
- *Def:* a **labeled dataset** consists of rows, where each row is an example
- *Def:* an **unlabeled dataset** only has features

One example:

label	features		
trash?	color	sound	weight
-	brown	none	high

Labeled Dataset:

	label	features		
index	trash?	color	sound	weight
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

Unlabeled Dataset:

	features		
index	color	sound	weight
1	brown	none	high
2	clear	crinkly	low
3	brown	none	low

Supervised Binary Classification

- *Def:* an **example** contains a label (aka. class) and features (aka. point or attributes)
- *Def:* a **labeled dataset** consists of rows, where each row is an example
- *Def:* an **unlabeled dataset** only has features

Classifier
features → label

Training Dataset:

	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

- *Def:* a **classifier** is a function that takes in features and predicts a label
- *Def:* a **training dataset** is a labeled dataset used to **learn** a classifier
- Def: a **test dataset** is a labeled dataset used to **evaluate** a classifier

Test Dataset:

	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

Supervised Binary Classification

- *Def*: **predictions** are the output of a trained classifier
- *Def*: **error rate** is the proportion of examples on which we predicted the wrong label

- *Def*: a **classifier** is a function that takes in features and predicts a label
- *Def*: a **training dataset** is a labeled dataset used to **learn** a classifier
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Classifier
features → label

Test Predictions:

	predictions
index	trash?
1	+
2	+
3	-

(Unlabeled) Test Dataset:

	features		
index	color	sound	weight
1	brown	none	high
2	clear	crinkly	low
3	brown	none	low

Supervised Binary Classification

- *Def*: a **classifier** is a function that takes in features and predicts a label
- *Def*: a **training dataset** is a labeled dataset used to **learn** a classifier
- Def: a **test dataset** is a labeled dataset used to **evaluate** a classifier

- *Def*: **predictions** are the output of a trained classifier
- *Def*: **error rate** is the proportion of examples on which we predicted the wrong label

error rate = 1/3

Test Predictions:

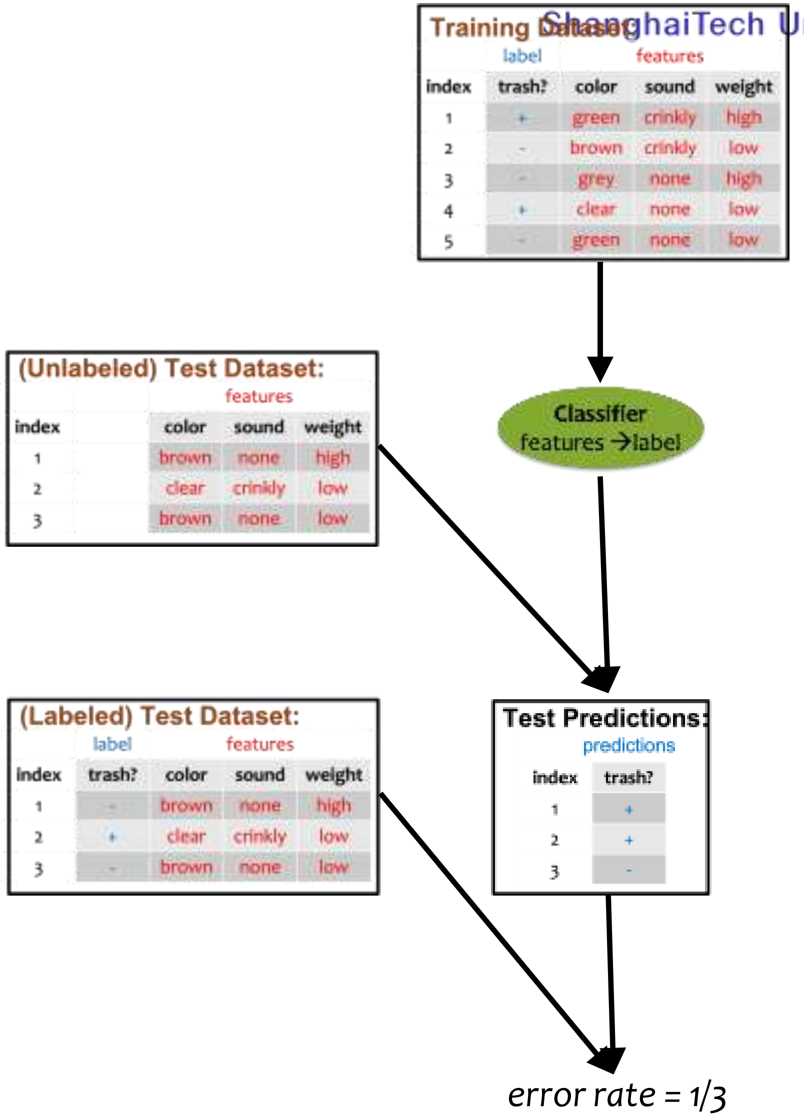
index	trash? (predictions)
1	+
2	+
3	-

(Labeled) Test Dataset:

index	trash? (label)	color (features)	sound (features)	weight (features)
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

Supervised Binary Classification

- Step 1: training
  - *Given*: labeled **training dataset**
  - *Goal*: learn a **classifier** from the training dataset
- Step 2: prediction
  - *Given*: unlabeled **test dataset**
    : learned classifier
  - *Goal:* **predict** a label for each instance
- Step 3: evaluation
  - *Given*: **predictions** from Step II
    : labeled **test dataset**
  - *Goal:* compute the **test error rate** (i.e. error rate on the test dataset)



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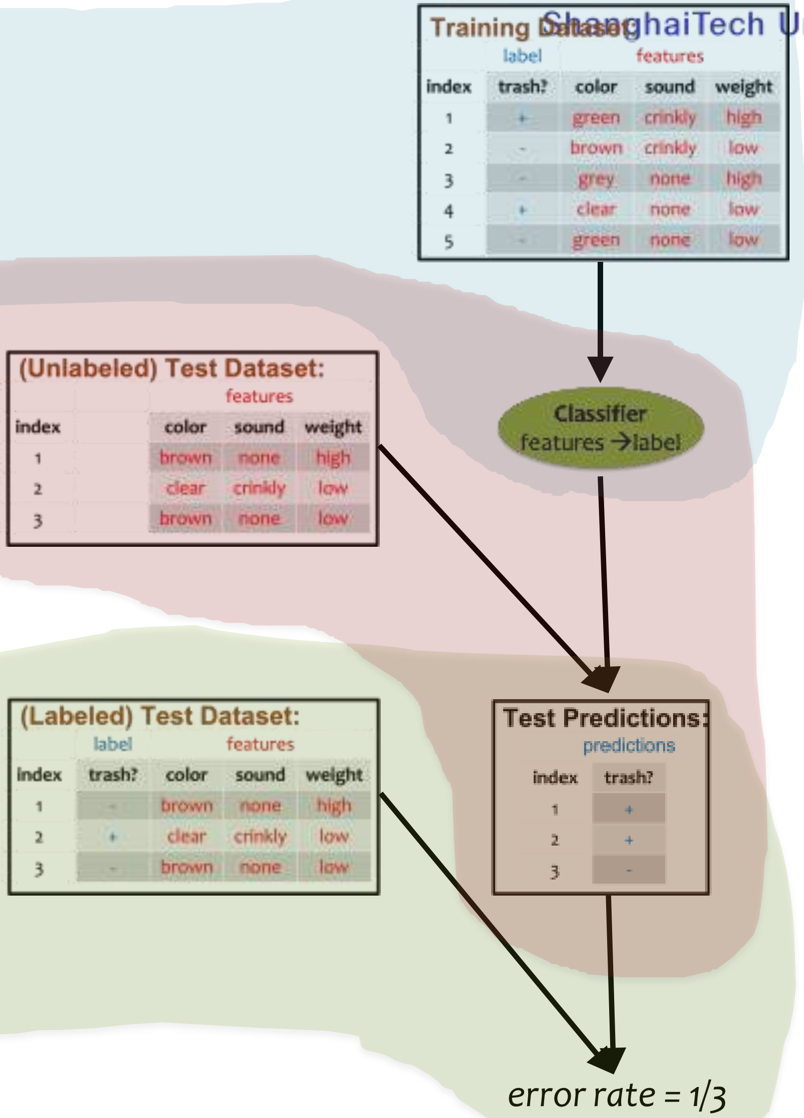

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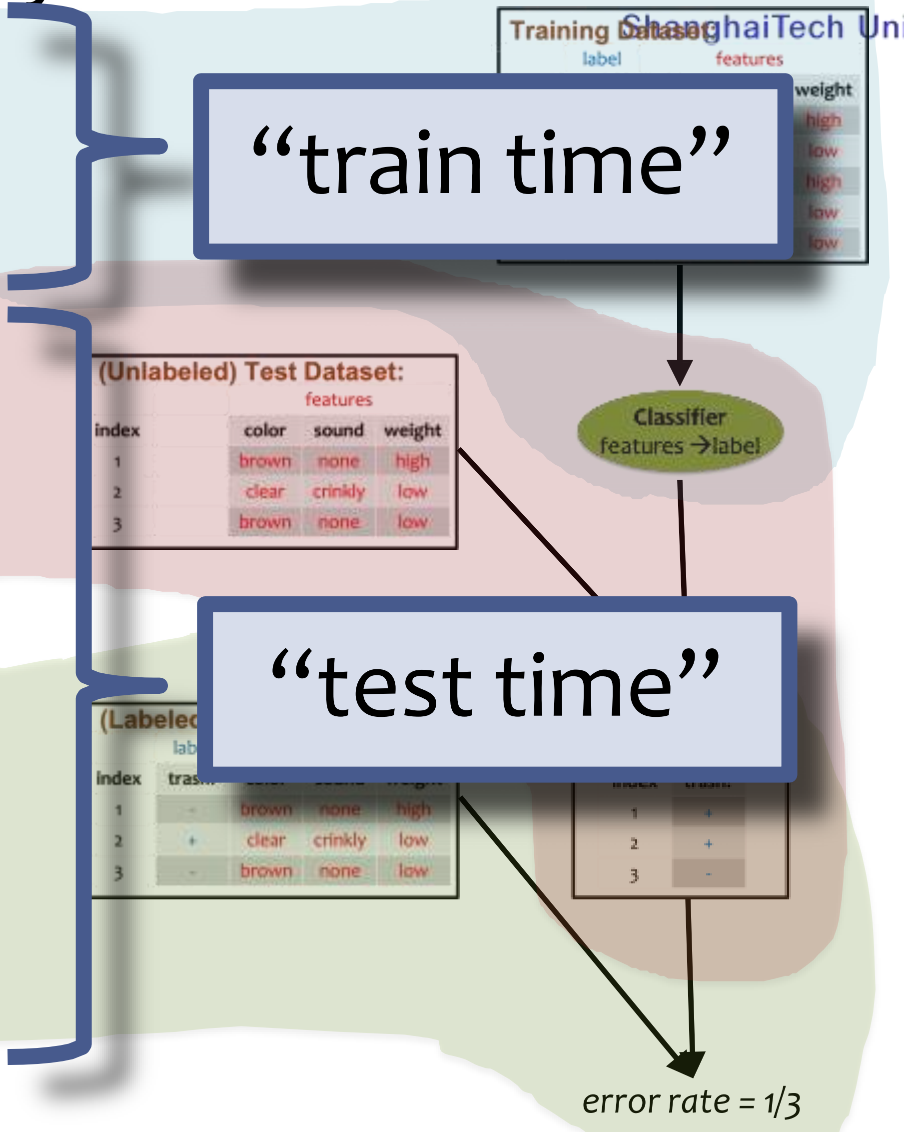

Supervised Binary Classification

- Step 1: training
  - *Given*: labeled **training dataset**
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  - *Goal:* **predict** a label for e instance
- Step 3: evaluation
  - *Given*: **predictions** from
  - : labeled **test datas**
  - *Goal:* compute the **test e** **rate** (i.e. error rate on th dataset)

Training Dataset

	label	features		
index	trash?	color	sound	weight
1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

Key question in Machine Learning:

How do we learn the classifier from data?

Random Classifier

The **random classifier** takes in the features and always predicts a random label.

…this is a terrible idea. It completely **ignores the training data!**

Classifier
features →random!

Training Dataset:

index	trash? (label)	color (features)	sound (features)	weight (features)
1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

Test Predictions:

index	trash? (pr edictions)
1	-
2	-
3	+

error rate = 2/3

Test Dataset:

index	trash? (label)	color (features)	sound (features)	weight (features)
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

Random Classifier

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The **random classifier** takes in the features and always predicts a random label.

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Classifier
features →random!

Training Dataset:

	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

Test Predictions:

	predictions
index	**trash?**
1	+
2	+
3	-

error rate = 1/3

Test Dataset:

	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

Random Classifier

上海科技大学 ShanghaiTech University

The **random classifier** takes in the features and always predicts a random label.

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Classifier
features →random!

Training Dataset:

	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

Test Predictions:

	pr edictions
index	**trash?**
1	+
2	-
3	+

error rate = 3/3

Test Dataset:

	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

Majority Vote Classifier

The **majority vote classifier** takes in the features and always predicts the **most common label** in the training dataset.

… this is still a pretty bad idea. It completely **ignores the features**!

Classifier
features → always predict "-"

Training Dataset:

	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

Test Predictions:

	pr edictions
index	**trash?**
1	-
2	-
3	-

error rate = 1/3

Test Dataset:

	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

Majority Vote Classifier

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The **majority vote classifier** takes in the features and always predicts the **most common label** in the training dataset.

Classifier
features →always predict "-"

…this is still a pretty bad idea. It completely **ignores the features**!

The majority vote classifier even ignores the features if it's making predictions on the training dataset!

Train Predictions:

pr edictions

index	trash?
1	-
2	-
3	-
4	-
5	-

error rate = 2/5

Training Dataset:

	label	features		
index	trash?	color	sound	weight
1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

Majority Vote Classifier

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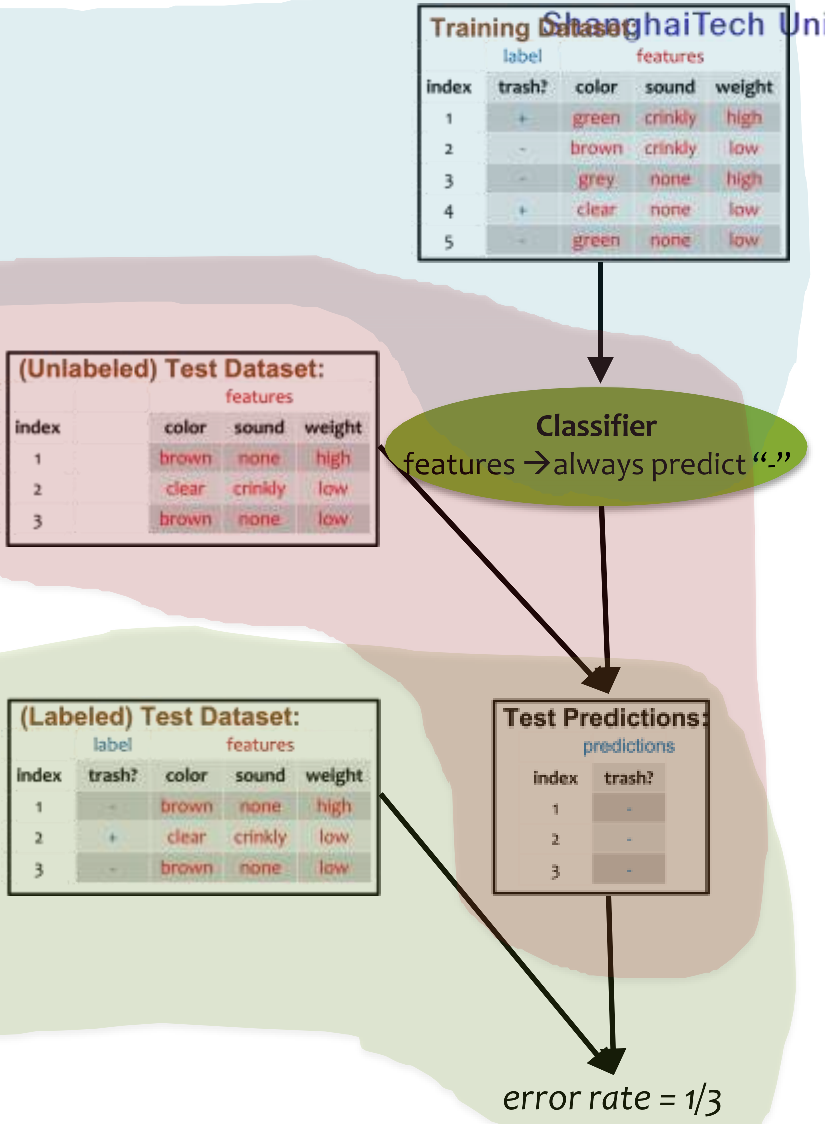

Training Dataset:

	label	features		
index	trash?	color	sound	weight
1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

(Unlabeled) Test Dataset:

	features		
index	color	sound	weight
1	brown	none	high
2	clear	crinkly	low
3	brown	none	low

(Labeled) Test Dataset:

	label	features		
index	trash?	color	sound	weight
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

Test Predictions:

	predictions
index	trash?
1	-
2	-
3	-

SYLLABUS HIGHLIGHTS

Introduction to Machine Learning CS182

上海科技大学
ShanghaiTech University

General information

- Course Time: Tue. & Thu., 13:00-14:40
- Online: Piazza & Gradescope
- 16 weeks (64 credit hours)
- HW Recitation Time:

  Plz vote via https://tp.wjx.top/vm/wFcJ3Jz.aspx#

All class communication via Piazza

- https://piazza.com/shanghaitech.edu.cn/spring2025/cs182

  Access Code: x7i6kvzq4ym
- Announcements and discussion
- Read it regularly
- Post all questions/comments there
- Direct email is not a good idea

Grading

- Homework: 30%
- Course project: 30%
- Final exam: 40%

Highlights

- Please write your HW, project, and exam in English
- Submitted to GradeScope: www.gradescope.com Entry Code: **NYKBDZ**
- For HW:
  - 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.
- Once any plagiarism or cheating is confirmed, relevant assignments or exams will receive 0 points

Instructor and TAs

上海科技大学
ShanghaiTech University

- Instructor: Prof Yujiao Shi
  - shiyj2@shanghaitech.edu.cn
  - Office hours: 10:00 am – 11:00 am Wed
  - Location: SIST 1C-303C

- TAs:
  - Shouchen Zhou zhoushch@shanghaitech.edu.cn
  - Chuyang Xiao xiaochy@shanghaitech.edu.cn
  - Hui Ren renhui@shanghaitech.edu.cn
  - Yichao Zhu zhuych12022@shanghaitech.edu.cn
  - Office hours: same as HW Recitation time

Lectures

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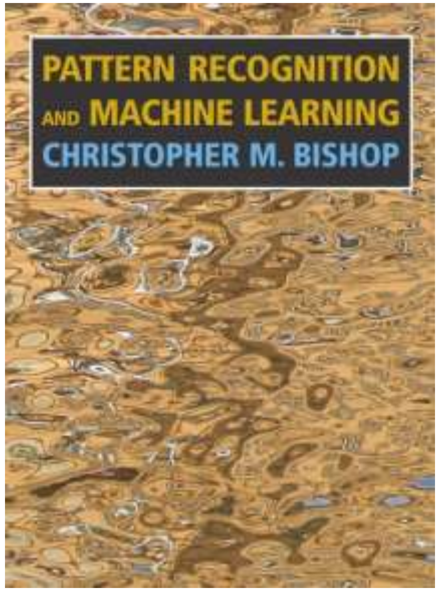
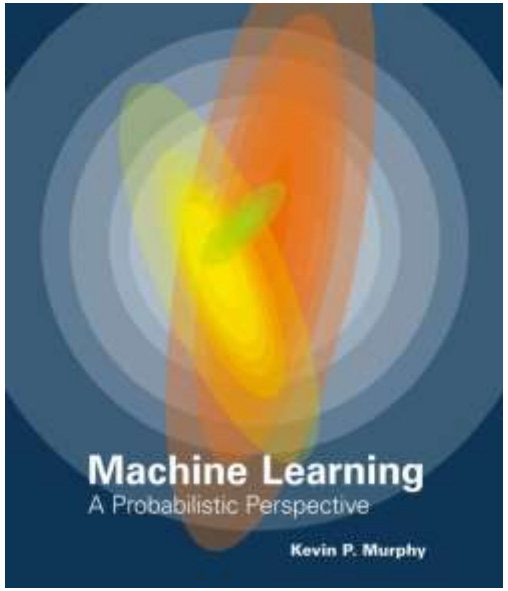
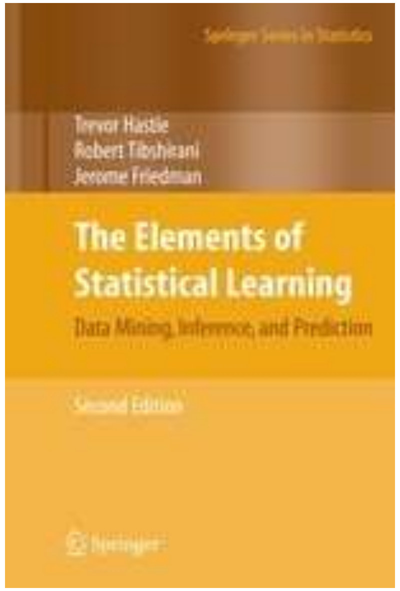
- You should ask lots of questions
  - Interrupting (by raising a hand) to ask your question is strongly encouraged
  - Asking questions later (or in real time) on Piazza is also great
- When I ask a question…
  - I want you to answer
  - Even if you don’t answer, think it through as though I’m about to call on you
- Interaction improves learning (both in-class and at my office hours)

Textbooks

You are not *required* to read a textbook, but it will help immensely!







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.

PREREQUISITES

Prerequisites

What they are:

- Significant programming experience
  - Written programs of 100s of lines of code
  - Comfortable learning a new language
- Probability and statistics
- Mathematical maturity: discrete mathematics, linear algebra, and calculus

Learning Objectives

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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