10-301/10-601 Introducción al Aprendizaje Automático

Departamento de Aprendizaje Automático
Escuela de Ciencias de la Computación
Universidad Carnegie Mellon

Descripción del Curso

Matt Gormley & Henry Chai

Lección 1
1 de agosto de 2024

Course Overview

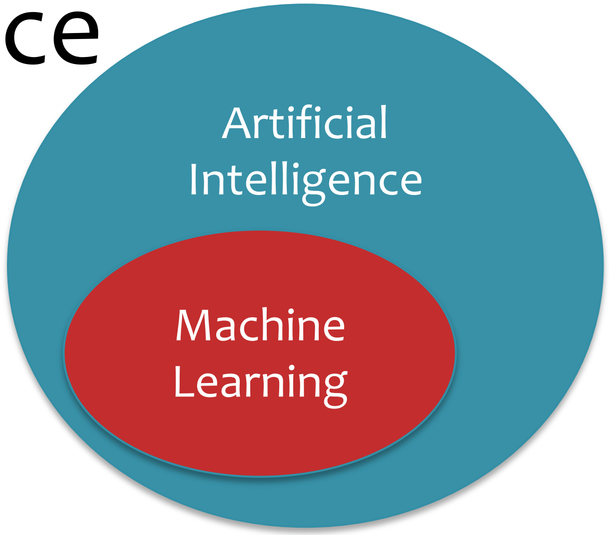
Matt Gormley & Henry Chai

Lecture 1

Aug. 26, 2024

WHAT IS MACHINE LEARNING?

Artificial Intelligence

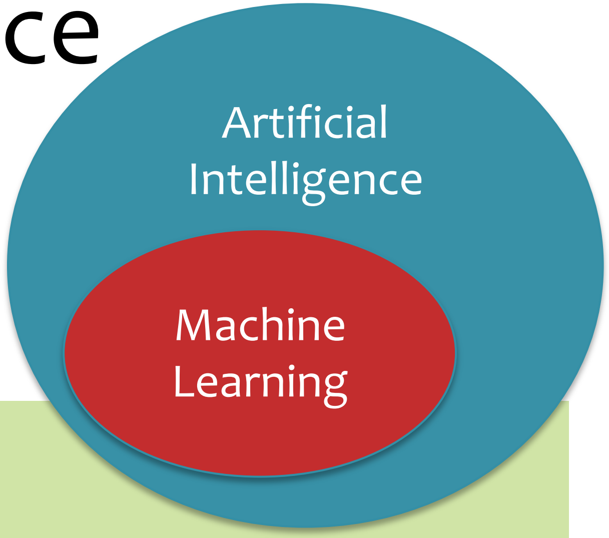


The basic goal of AI is to develop intelligent machines.

This consists of many sub-goals:

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

Artificial Intelligence



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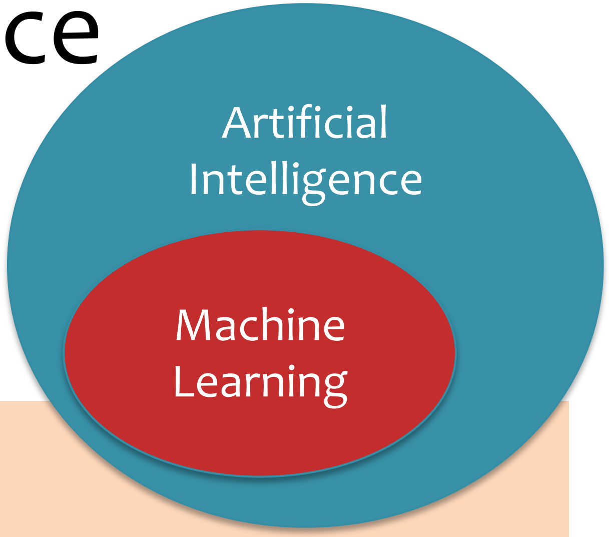

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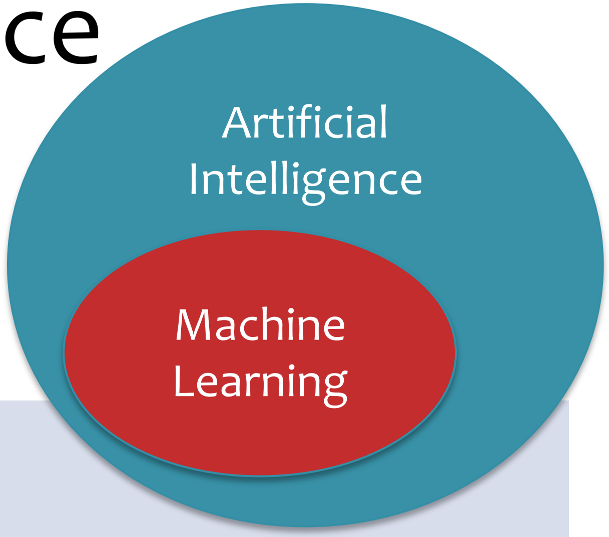

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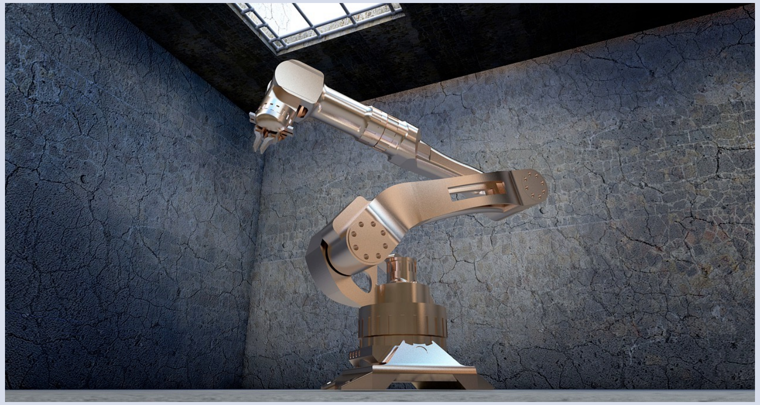

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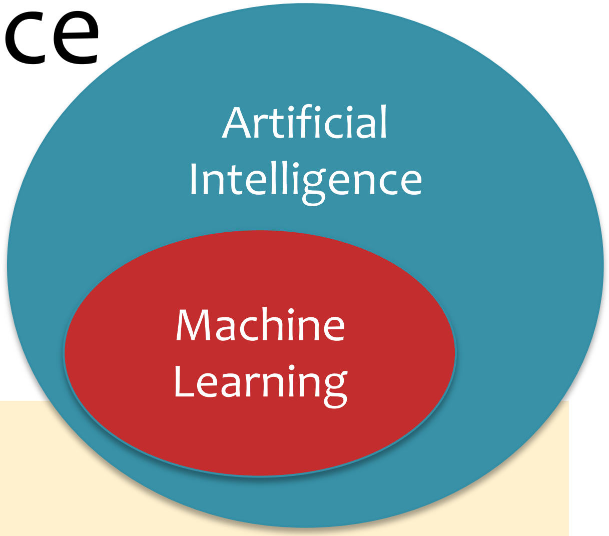

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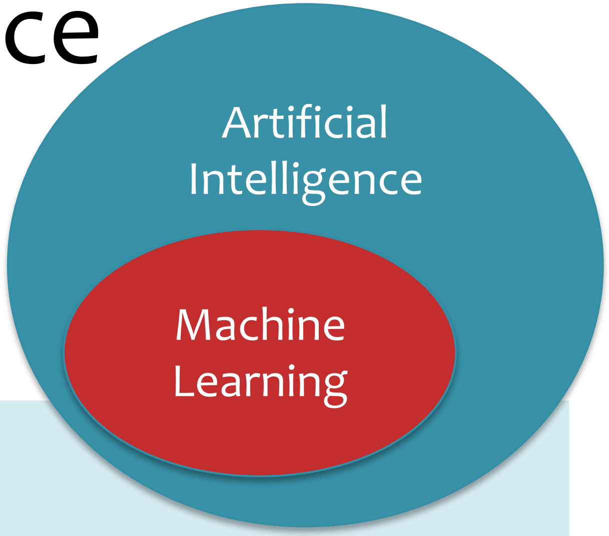

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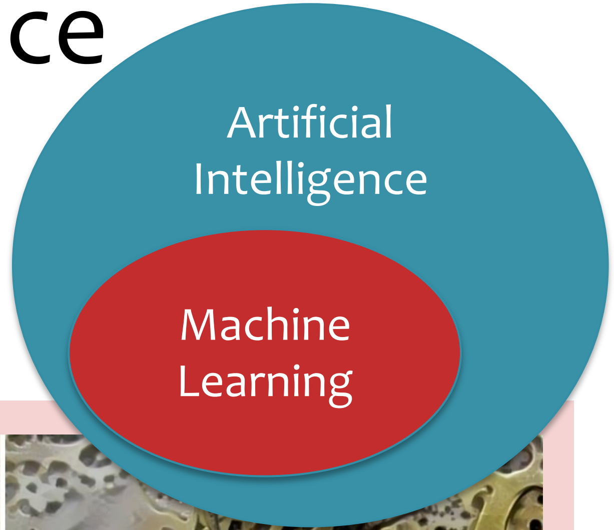

“Deep Style” from https://deepdreamgenerator.com/#gallery

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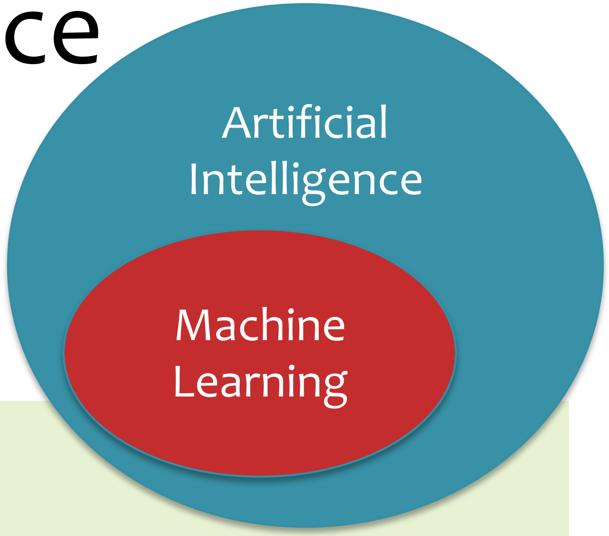
Artificial Intelligence

Machine Learning

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What is Machine Learning?

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

Machine Learning

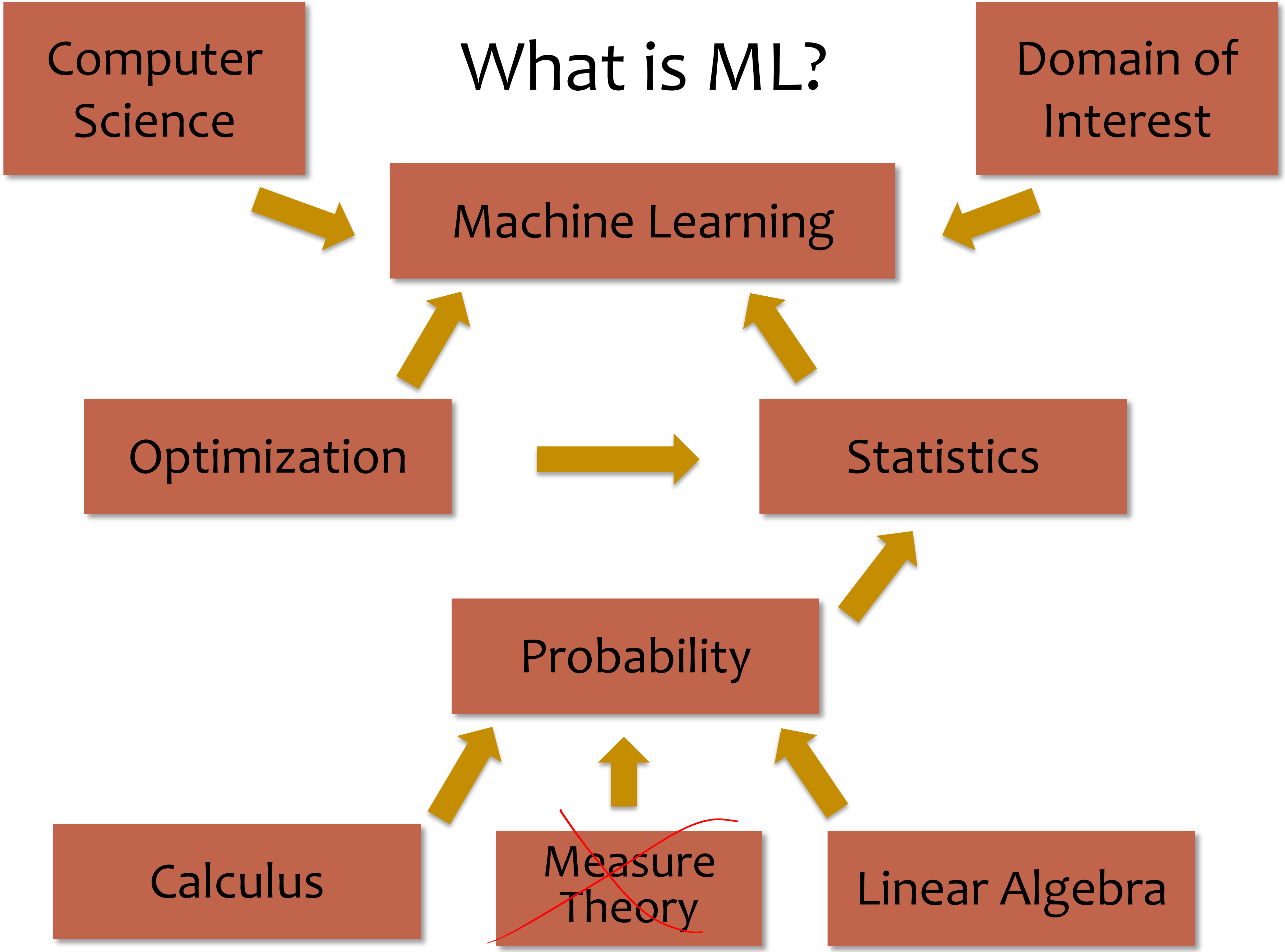
Statistics

Probability

Computer Science

Optimization

What is ML?



Computer Science

Domain of Interest

Machine Learning

Optimization

Statistics

Probability

Calculus

~~Measure Theory~~

Linear Algebra

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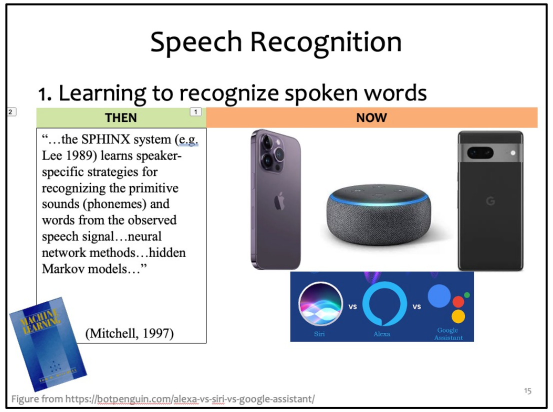

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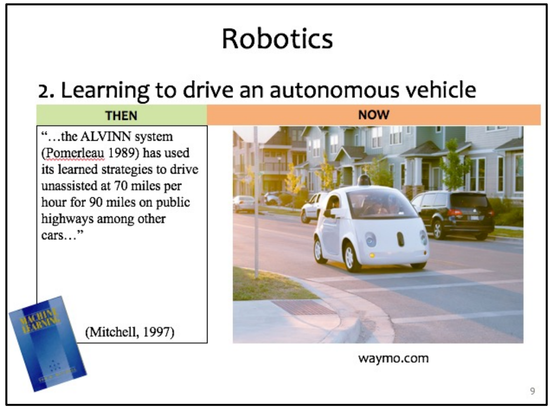

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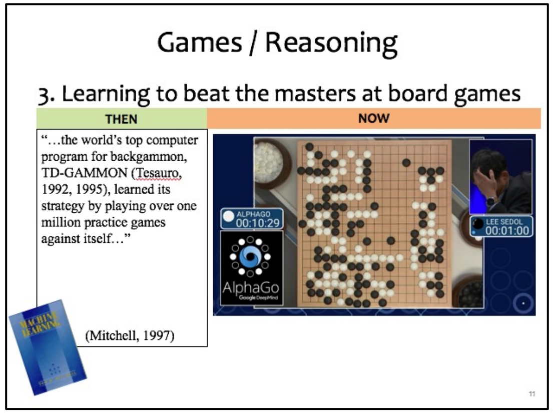

Games / Reasoning

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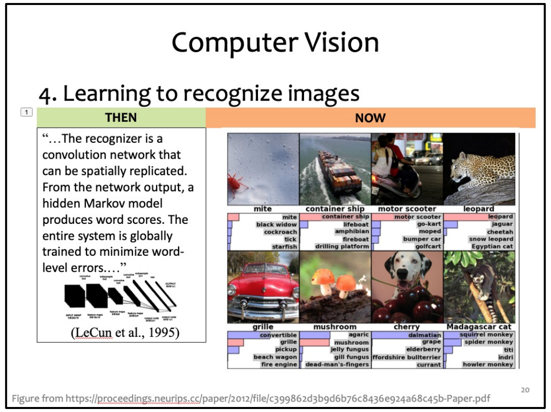

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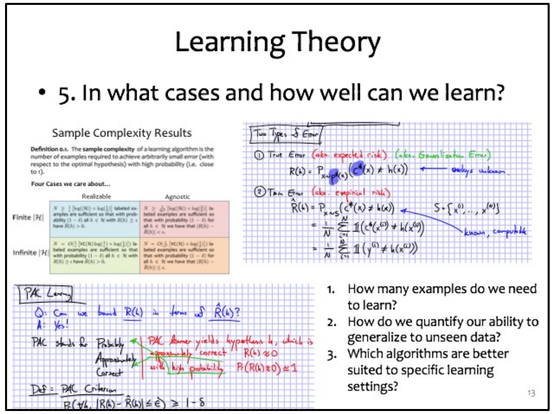

Learning Theory

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

Sample Complexity Results

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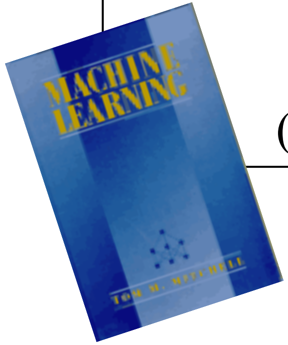

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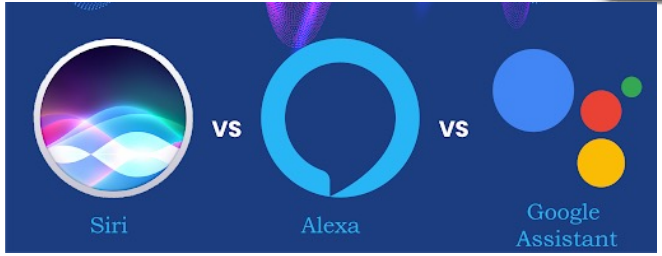

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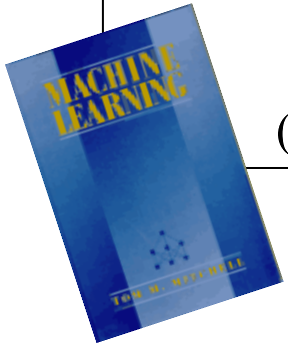

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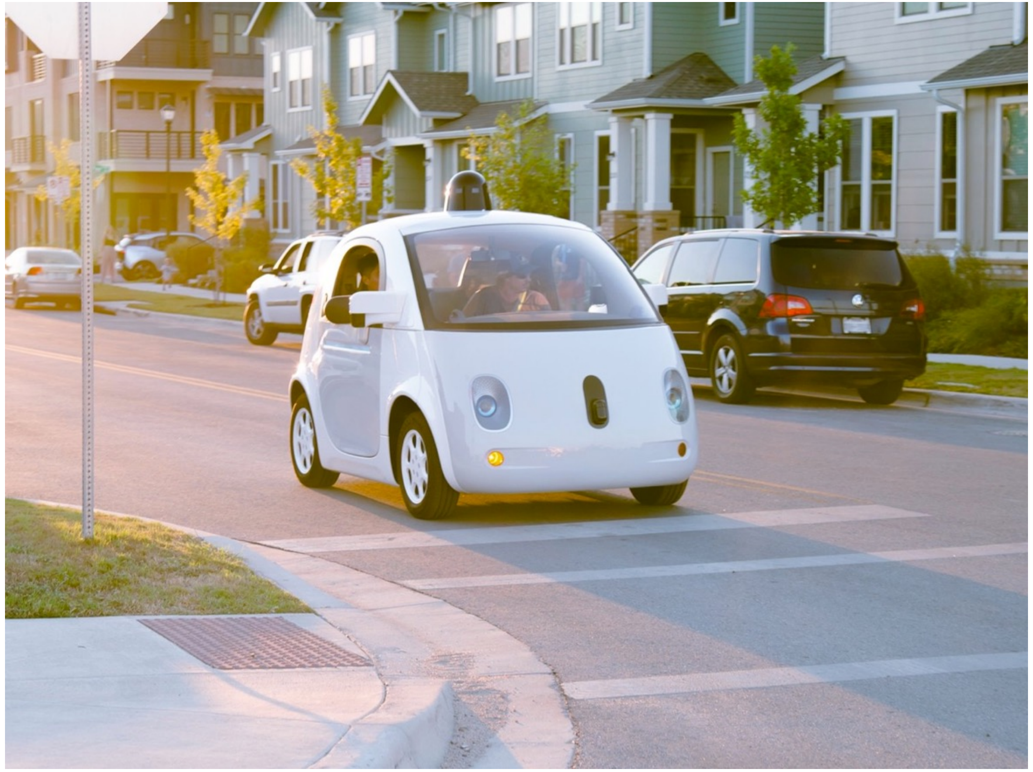

waymo.com

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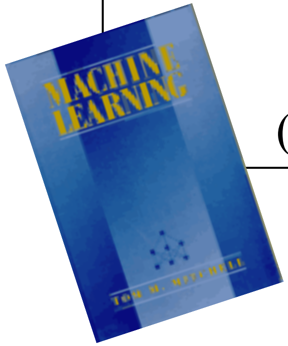

aurora.tech

Figure from https://www.bloomberg.com/news/articles/2019-02-07/aurora-self-driving-startup-gets-funding-from-sequoia-amazon

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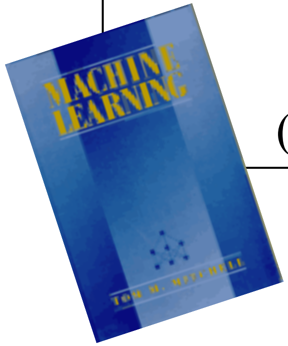

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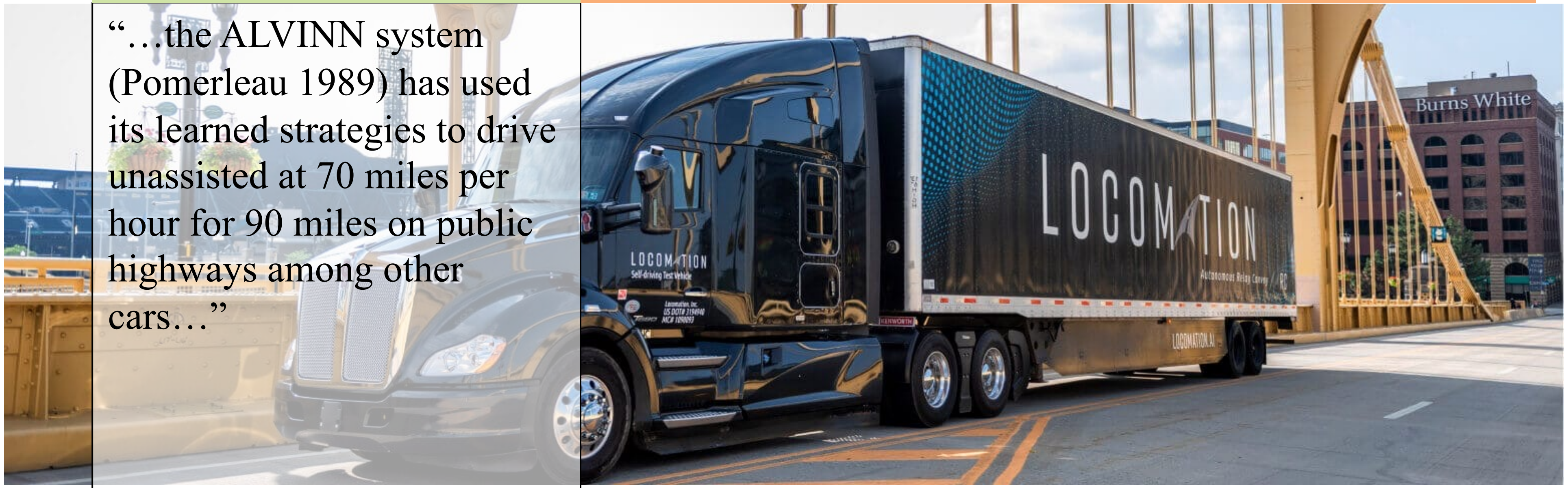

locomation.ai

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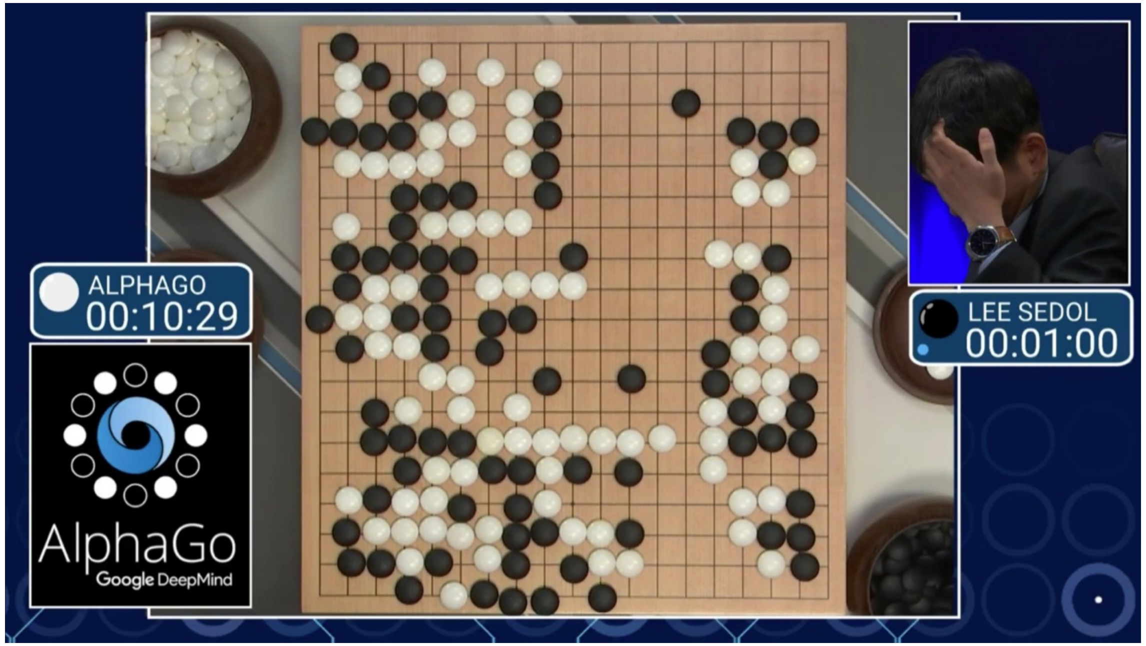
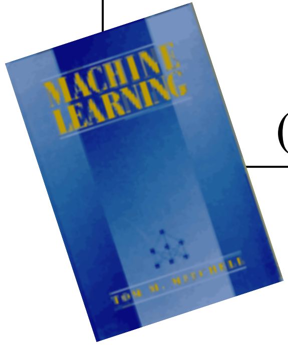
"…the world's top computer program for backgammon, TD-GAMMON (Tesauro, 1992, 1995), learned its strategy by playing over one million practice games against itself…" (Mitchell, 1997)	 ALPHAGO 00:10:29 LEE SEDOL 00:01:00 AlphaGo Google DeepMind



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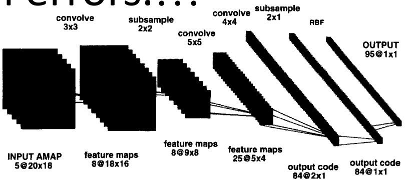

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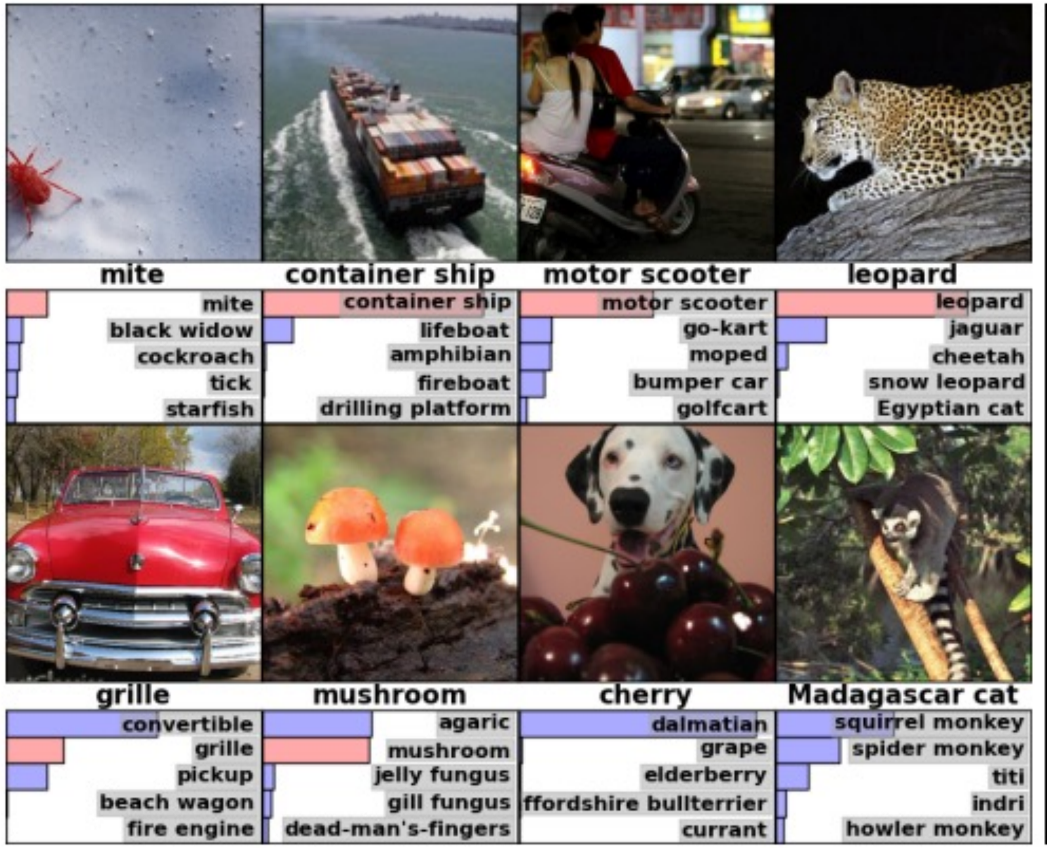

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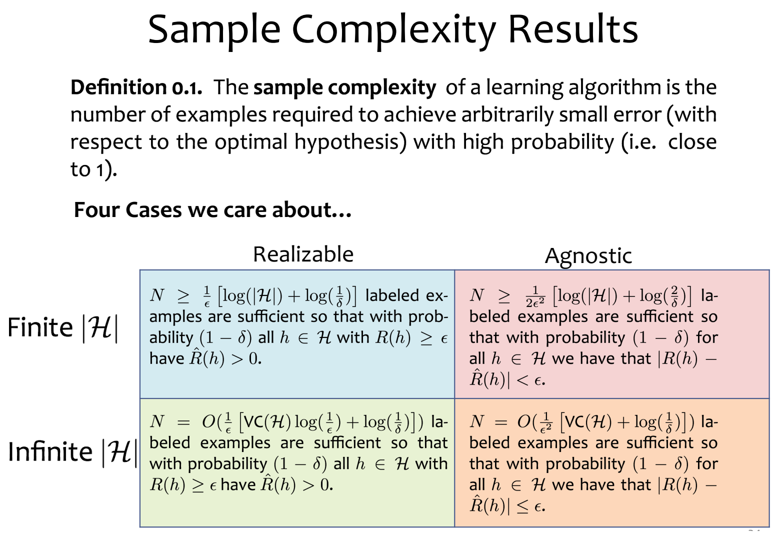

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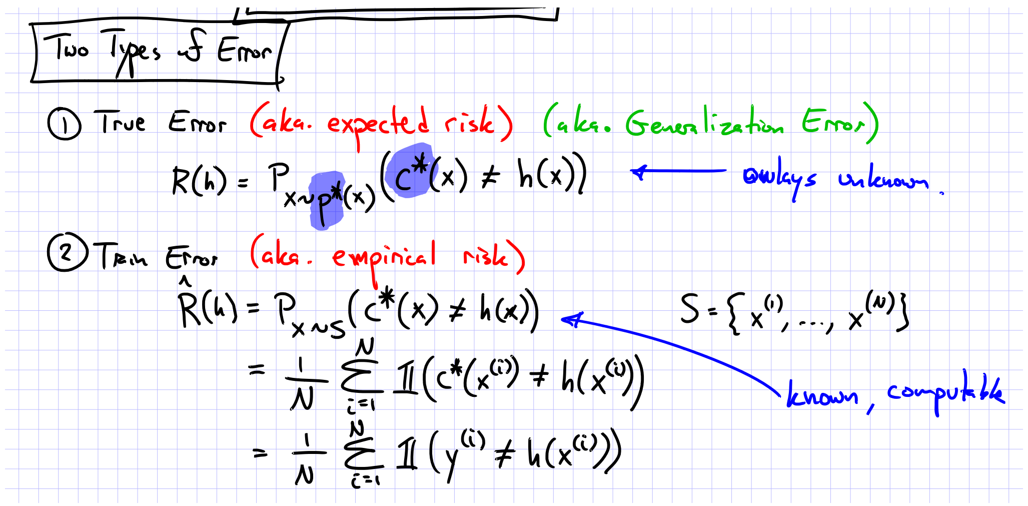

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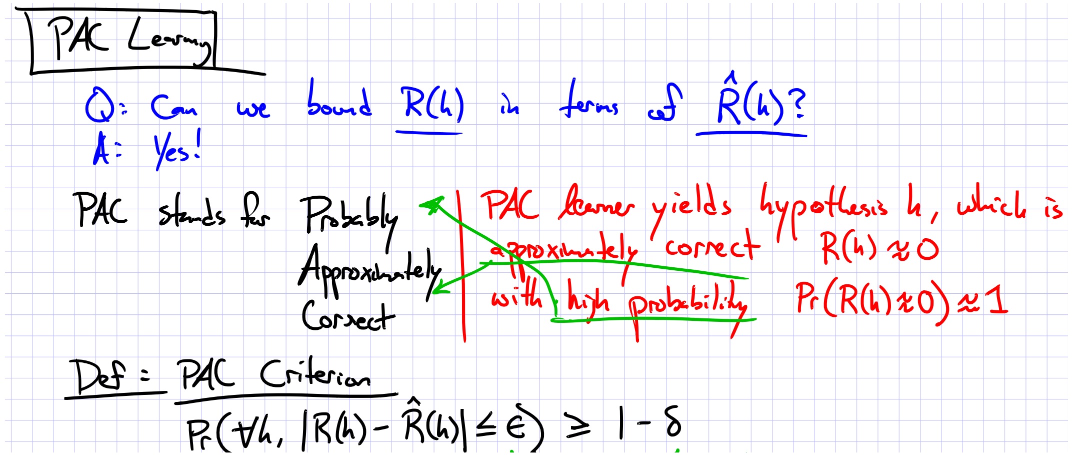

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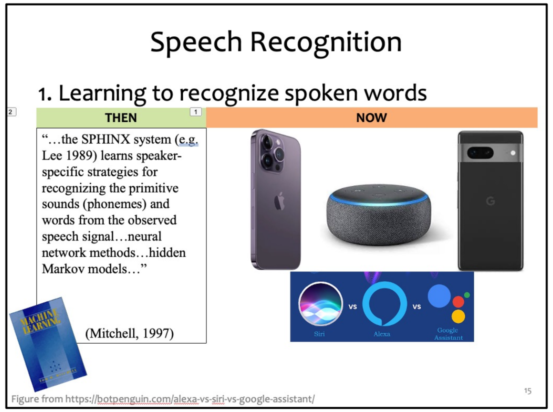

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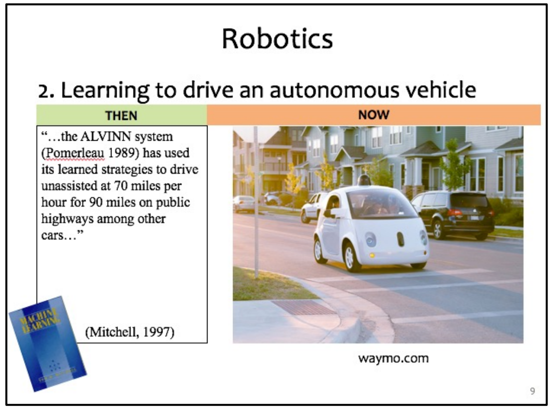

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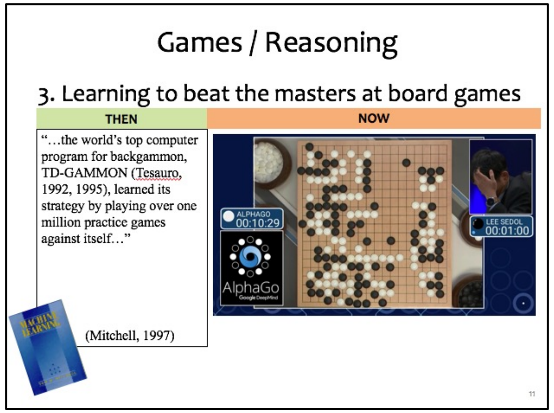

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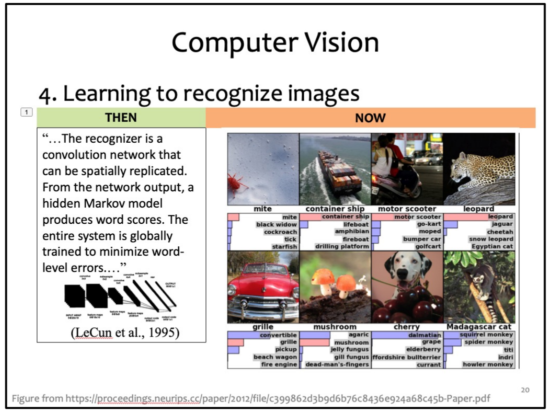

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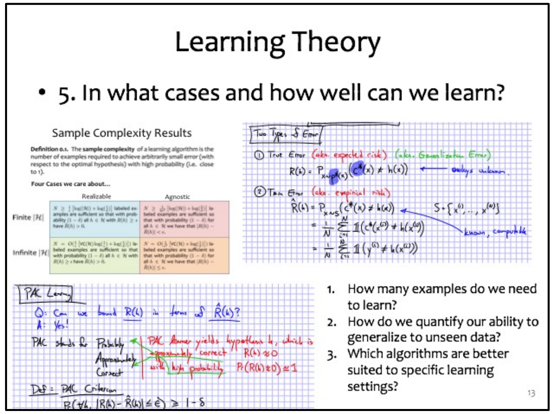

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Computer Science

Optimization

To solve all the problems above and more

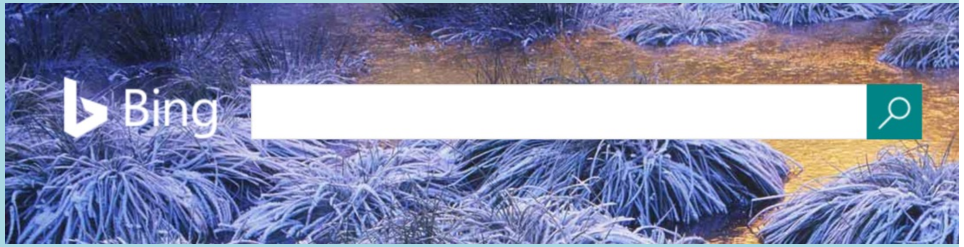
Societal Impacts of ML

What ethical responsibilities do we have as machine learning experts?

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

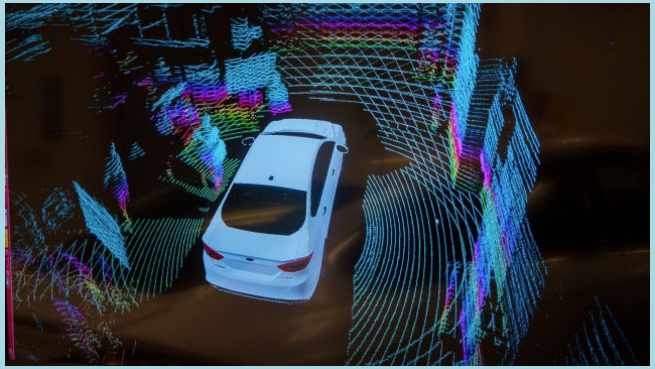
Answer:

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



http://bing.com/

http://arstechnica.com/

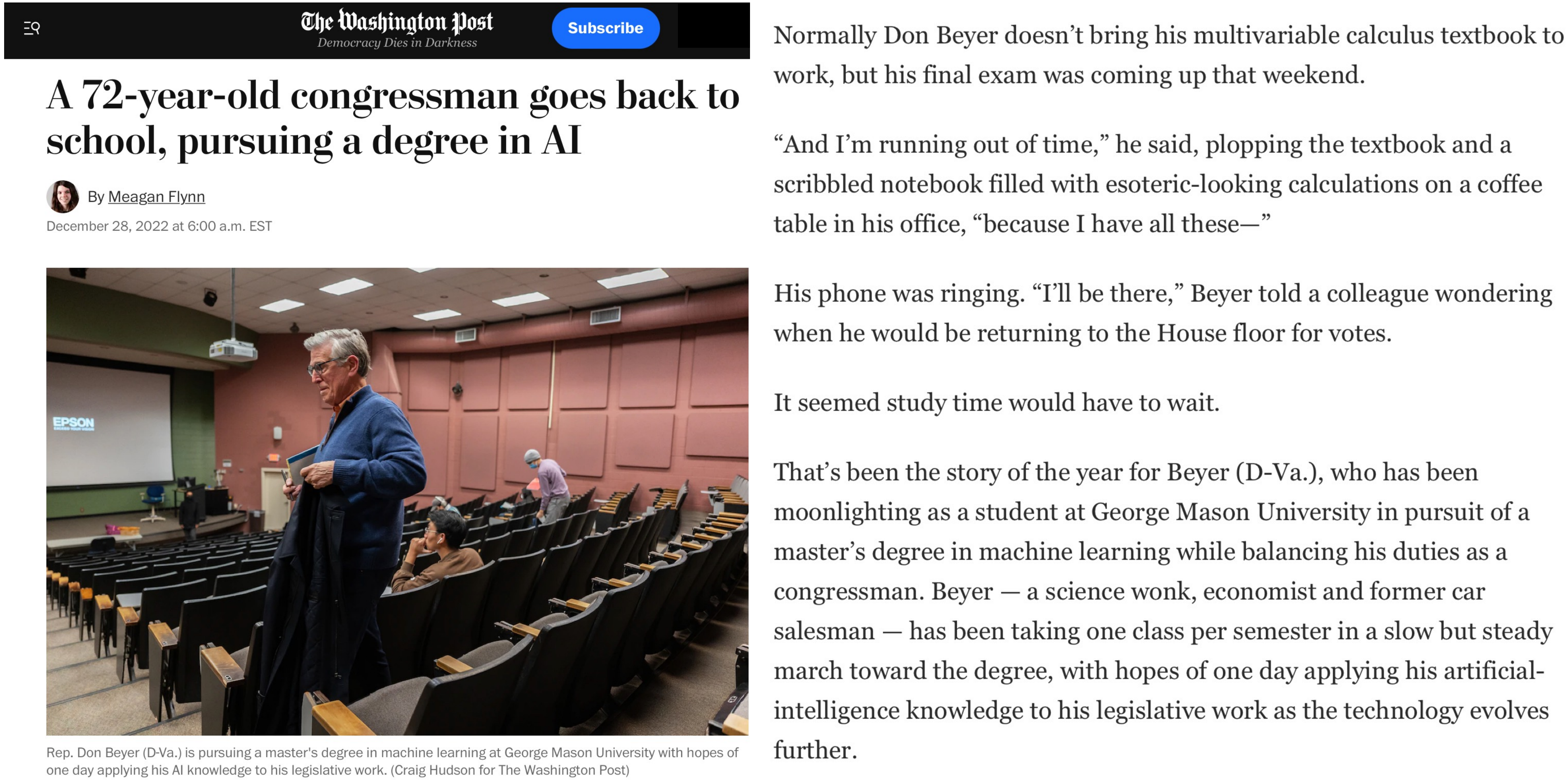


2) An autonomous vehicle is permitted to drive unassisted on the road.

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



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

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

- 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

Deep Learning
GenAI

- Learning Theory
  - Statistical Estimation (covered right before midterm)
  - PAC Learning
- Other Learning Paradigms
  - Matrix Factorization
  - Reinforcement Learning
  - Information Theory

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*: play chess very well
2. Performance measure, *P*:
   - score based on pieces/state
   - proportion of games won
   - # moves to win
   - time taken per move
   - chess ranking
3. Experience, *E*:
   - past games (tournaments)
   - strategies
   - current games played by the system

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)**

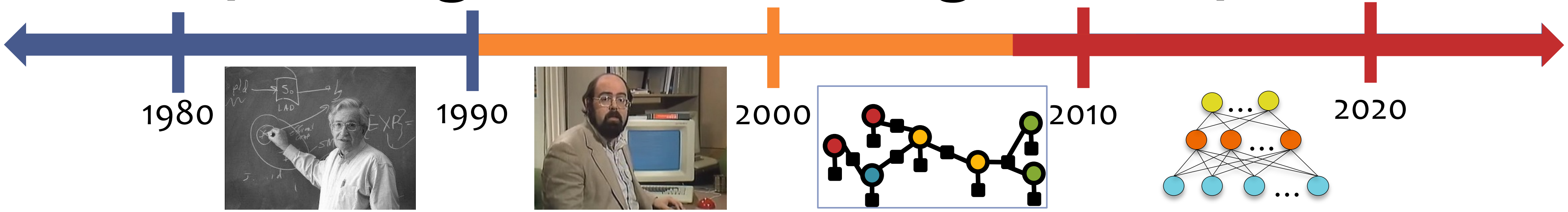
1. Task, *T*:

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



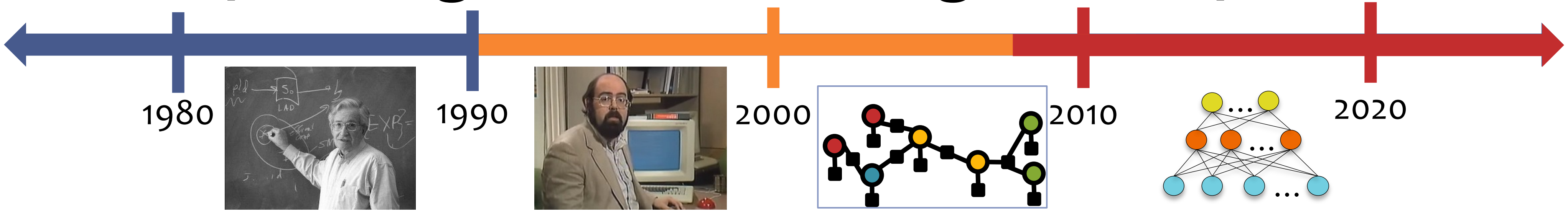
Solution #1: Expert Systems

- 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



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 = "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!"

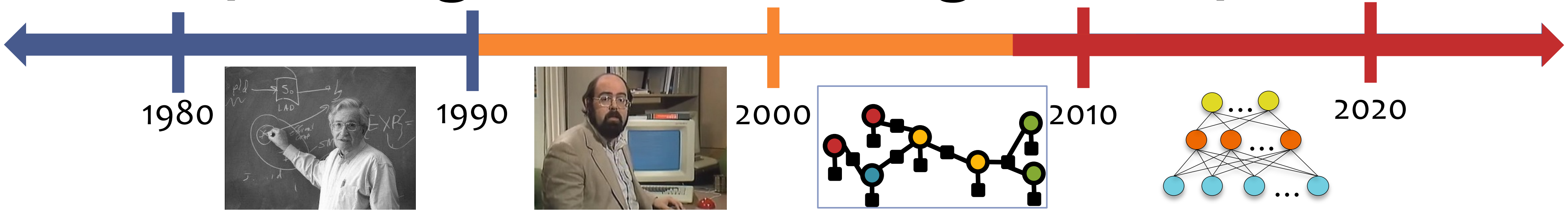
Rules…
if x matches "give me directions to Z":   cmd = DIRECTIONS(here, nearest(Z))
if x matches "how do i get to Z":   cmd = DIRECTIONS(here, nearest(Z))
if x matches "where is the nearest Z":   cmd = DIRECTIONS(here, nearest(Z))

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))

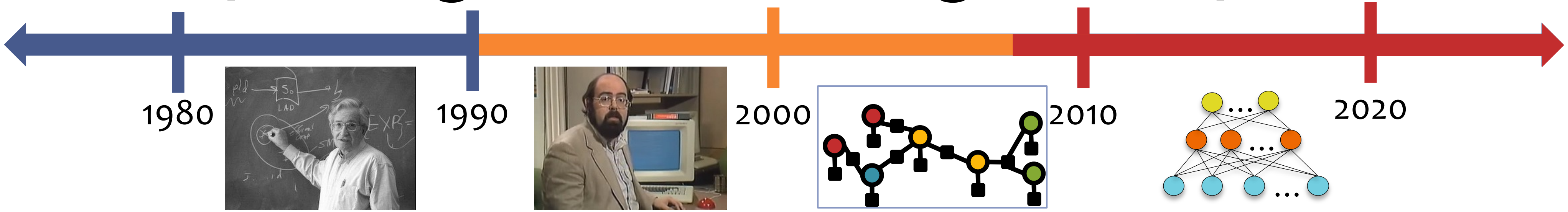
Capturing the Knowledge of Experts



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



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?`

$y^{(1)}$: `DIRECTIONS(here, nearest(Starbucks))`

$x^{(2)}$: `Show me the closest Starbucks`

$y^{(2)}$: `MAP(nearest(Starbucks))`

$x^{(3)}$: `Send a text to John that I'll be late`

$y^{(3)}$: `TXTNSG(John, I'll be late)`

$x^{(4)}$: `Set an alarm for seven in the morning`

$y^{(4)}$: `SETALARM(7:00AM)`

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.

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

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
4. Report ideas back to rest of class

Well-posed Learning Problems

task, T	performance measure, P	experience, E
- sports commenter	- human expert comments on the quality of the output - A/B testing w/ viewers	- past streams of [insert sport here] -

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

Well-posed Learning Problems

task, T	performance measure, P	experience, E
- automatically respond to text messages	- closeness to user's message - quality of response - readability - semantic similarity - Turing test	- logs of text messages, varying recipients - emoji usage - language of interaction - history of chats - priority - human-in-the-loop

(without any math!)

SUPERVISED LEARNING

Building a Trash Classifier

- Suppose the friends OF THE RIVERFRONT ask CMU 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

- *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

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3	-	brown	none	low

Unlabeled Dataset:

	features		
index	**color**	**sound**	**weight**
1	brown	none	high
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3	brown	none	low

Supervised Binary Classification

- *Def*: an **example** contains a label (aka. class) and features (aka. point or attributes)
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Classifier

features →label

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

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 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
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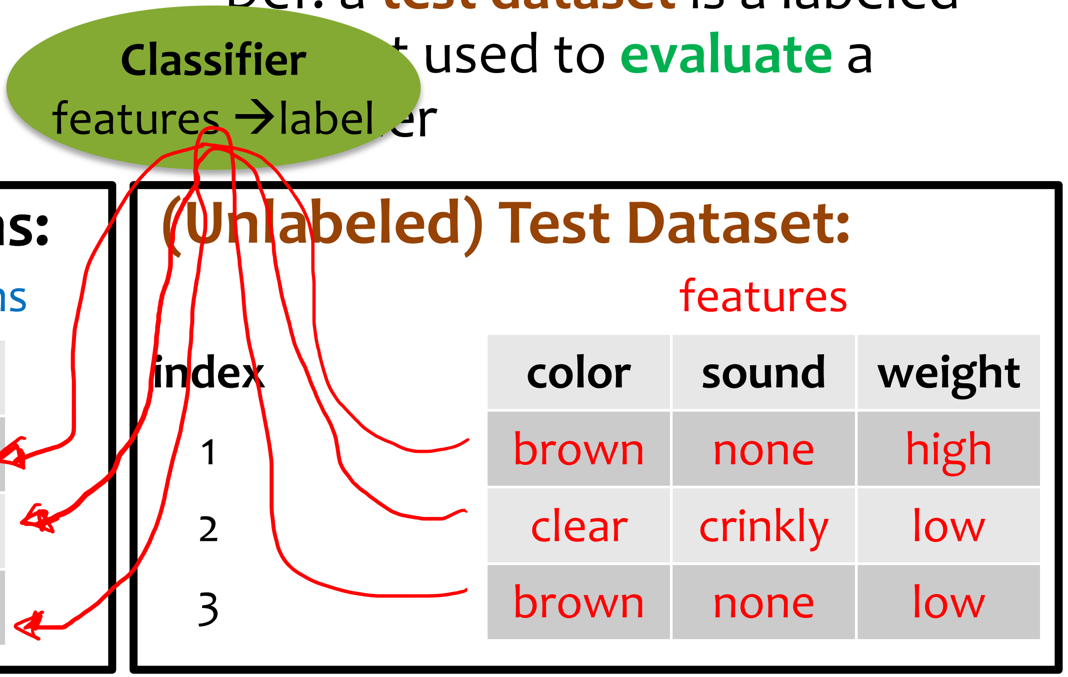

Classifier

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*: **predictions** are the output of a trained classifier
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- *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

error rate = 1/3

Test Predictions:

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

(Labeled) Test Dataset:

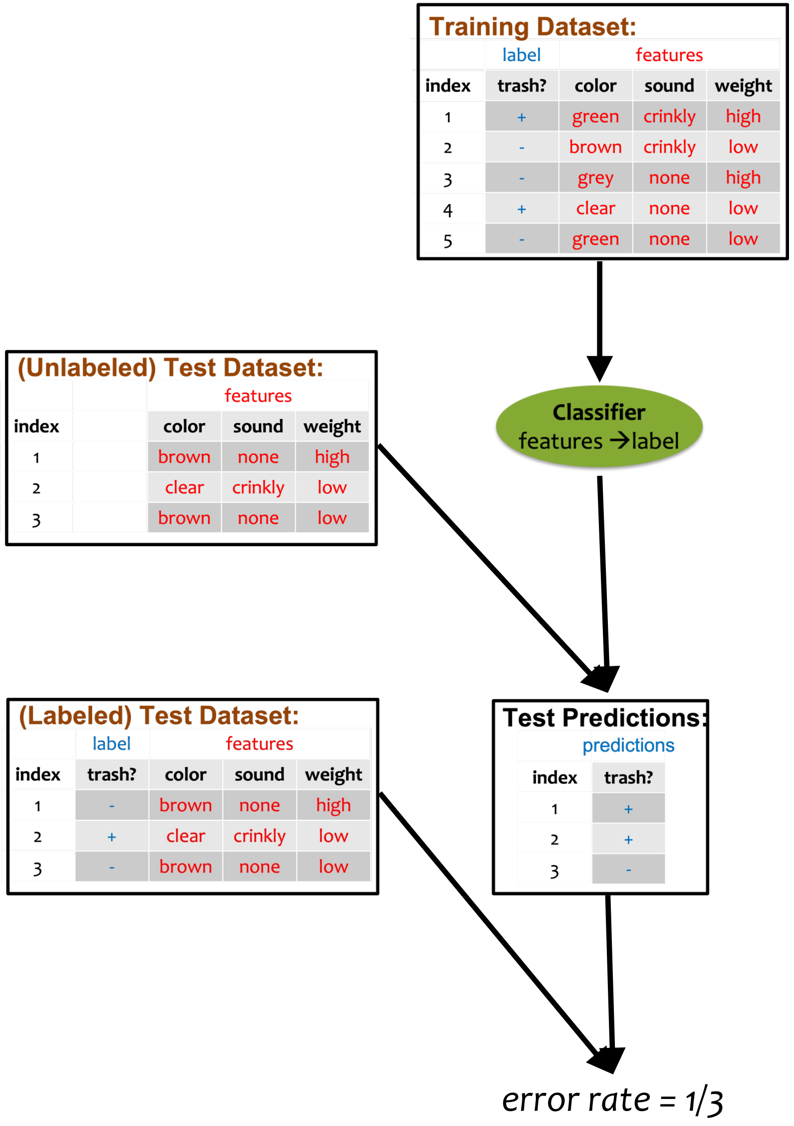
	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

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)



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

Classifier
features →label

(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	-

error rate = 1/3

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**
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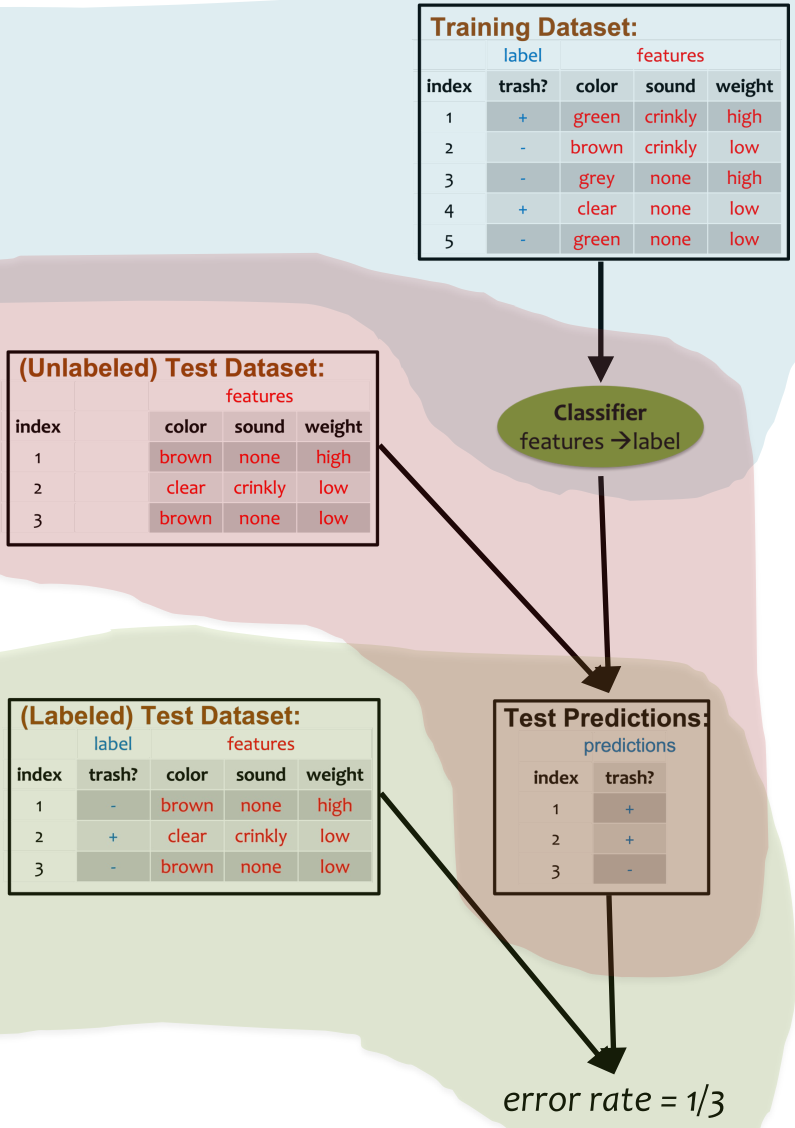

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1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
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(Unlabeled) Test Dataset:

		features		
index		color	sound	weight
1		brown	none	high
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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	-

error rate = 1/3

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
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- Step 3: evaluation
  - *Given*: **predictions** from Phase II
    : labeled **test dataset**
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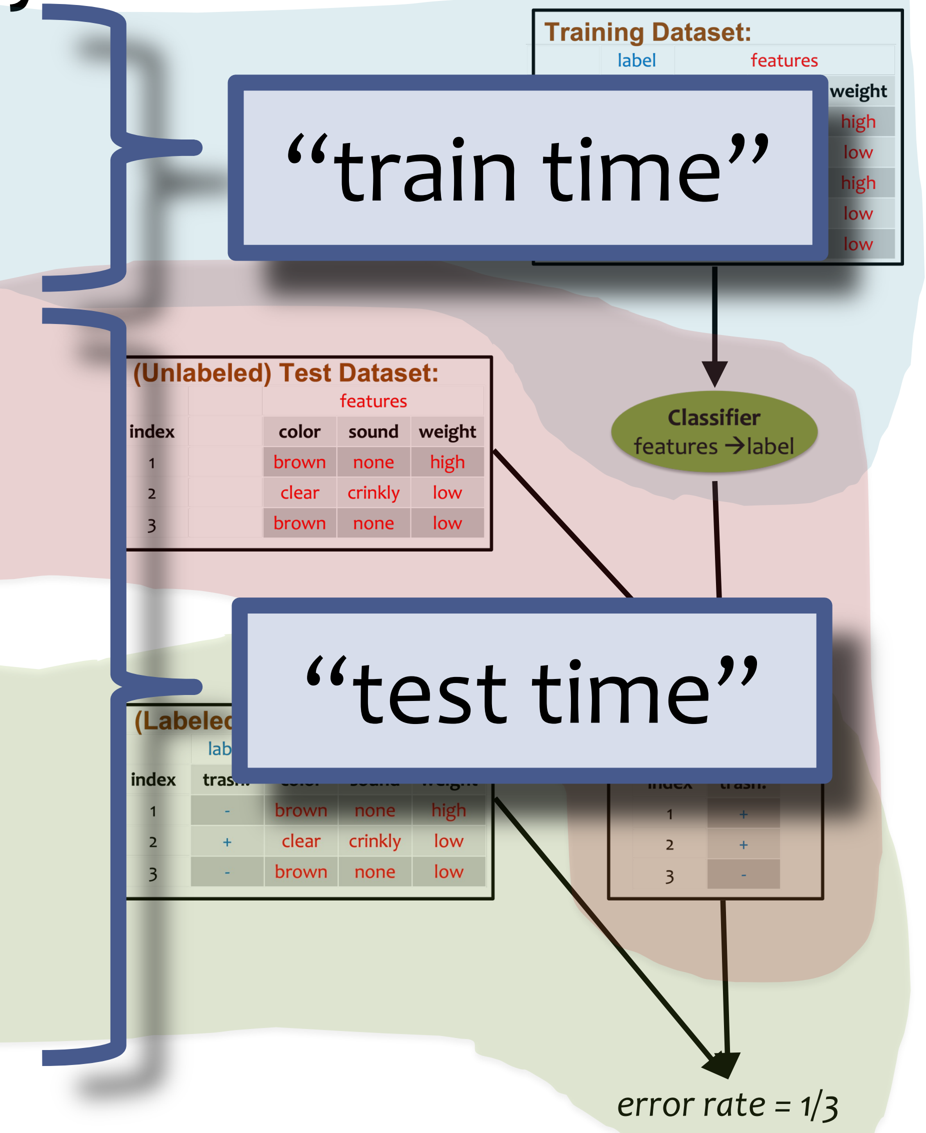

weight
high
low
high
low
low

(Unlabeled) Test Dataset:

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

index	tras			
1	-	brown	none	high
2	+	clear	crinkly	low
3	-	brown	none	low

1	+
2	+
3	-

Supervised Binary Classification

- Step 1: training
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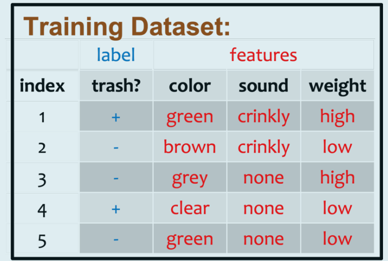

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	label	features		
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1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

(Unlabeled) Test Dataset:

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:

	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 = 2/3

Test Dataset:

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

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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
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Random Classifier

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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 = 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:

	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

Majority Vote Classifier

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!

error rate = 2/5

Train Predictions:

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

Training Dataset:

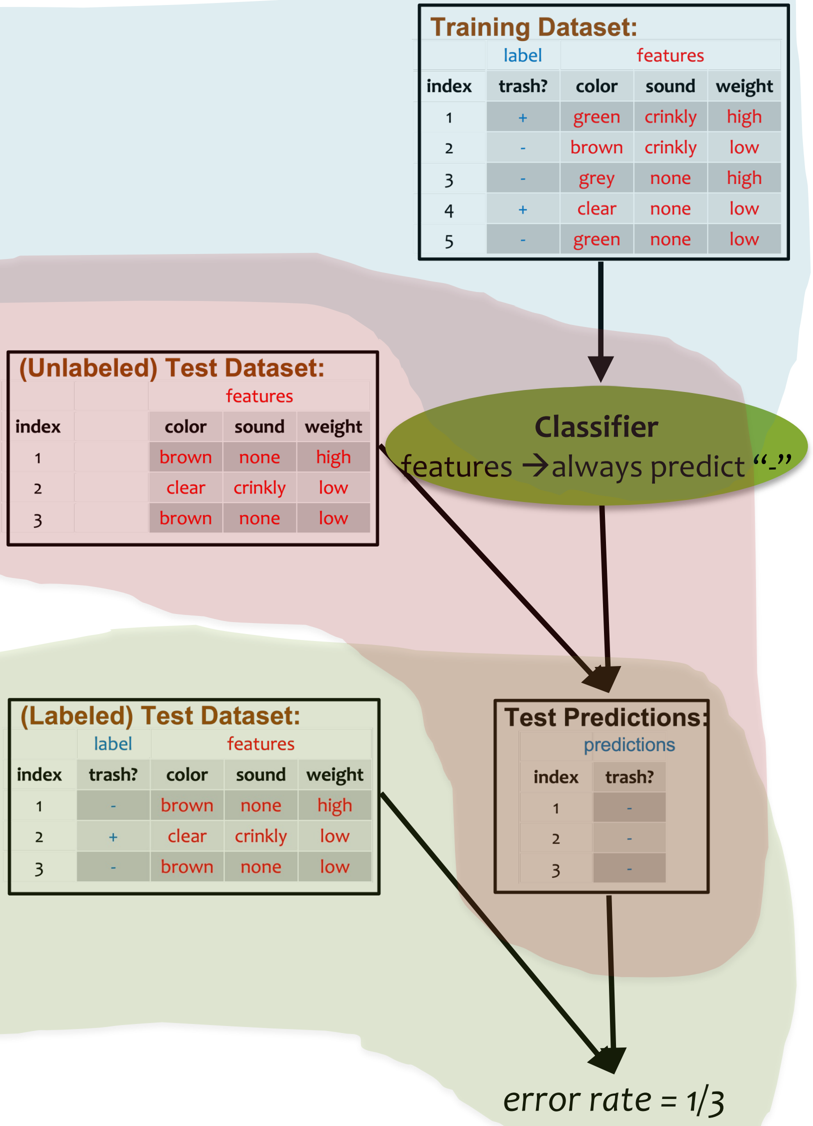
	label	features		
index	**trash?**	**color**	**sound**	**weight**
1	+	green	crinkly	high
2	-	brown	crinkly	low
3	-	grey	none	high
4	+	clear	none	low
5	-	green	none	low

Majority Vote Classifier

- 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)



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

Classifier

features →always predict "-"

(Unlabeled) Test Dataset:

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

Test Predictions:

	predictions
index	trash?
1	-
2	-
3	-

(Labeled) Test Dataset:

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

error rate = 1/3

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

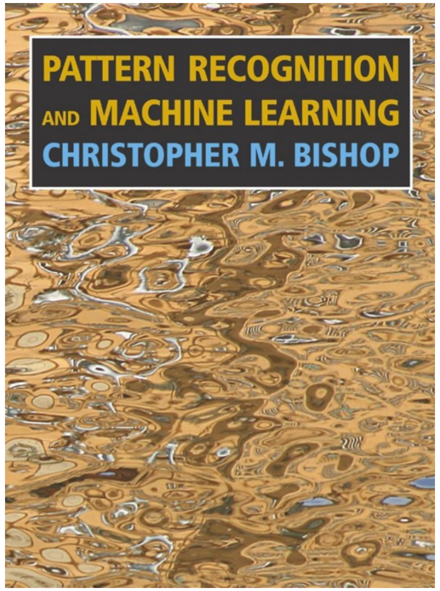
- **Grading**: 50% homework, 15% exam 1, 15% exam 2, 15% exam 3, 5% participation
- **Exam 1**: evening, Mon, Sep. 30
- **Exam 2**: evening, Thu, Nov. 7
- **Exam 3**: final exam week, date TBD by registrar
- **Homework**: 3 written and 6 written + programming (Python)
  - 6 grace days for homework assignments
  - Late submissions: 75% day 1, 50% day 2, 25% day 3
  - No submissions accepted after 3 days w/o extension; HW3, HW6, HW9 only 2 days
  - Extension requests: for emergencies, 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 (e.g. -100%)
- **Office Hours**: posted on Google Calendar on "Office Hours" page

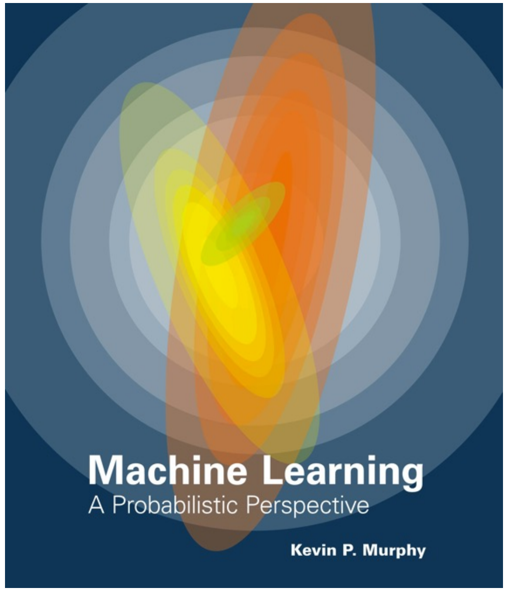
Lectures

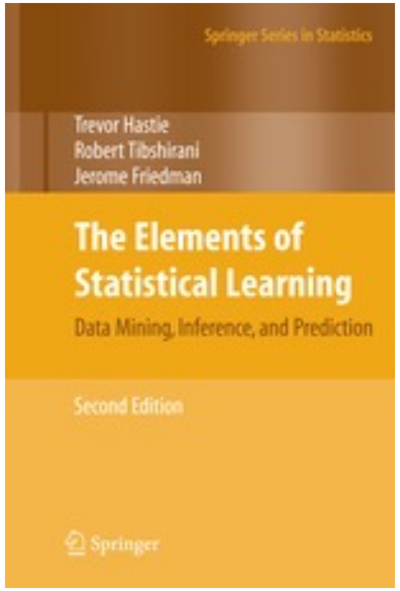
- You should ask lots of questions
  - Interrupting (by raising a hand) to ask your question is strongly encouraged
  - Asking questions later (or in real time) on Piazza is also great
- When I ask a question…
  - I want you to answer
  - Even if you don't answer, think it through as though I'm about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

Textbooks

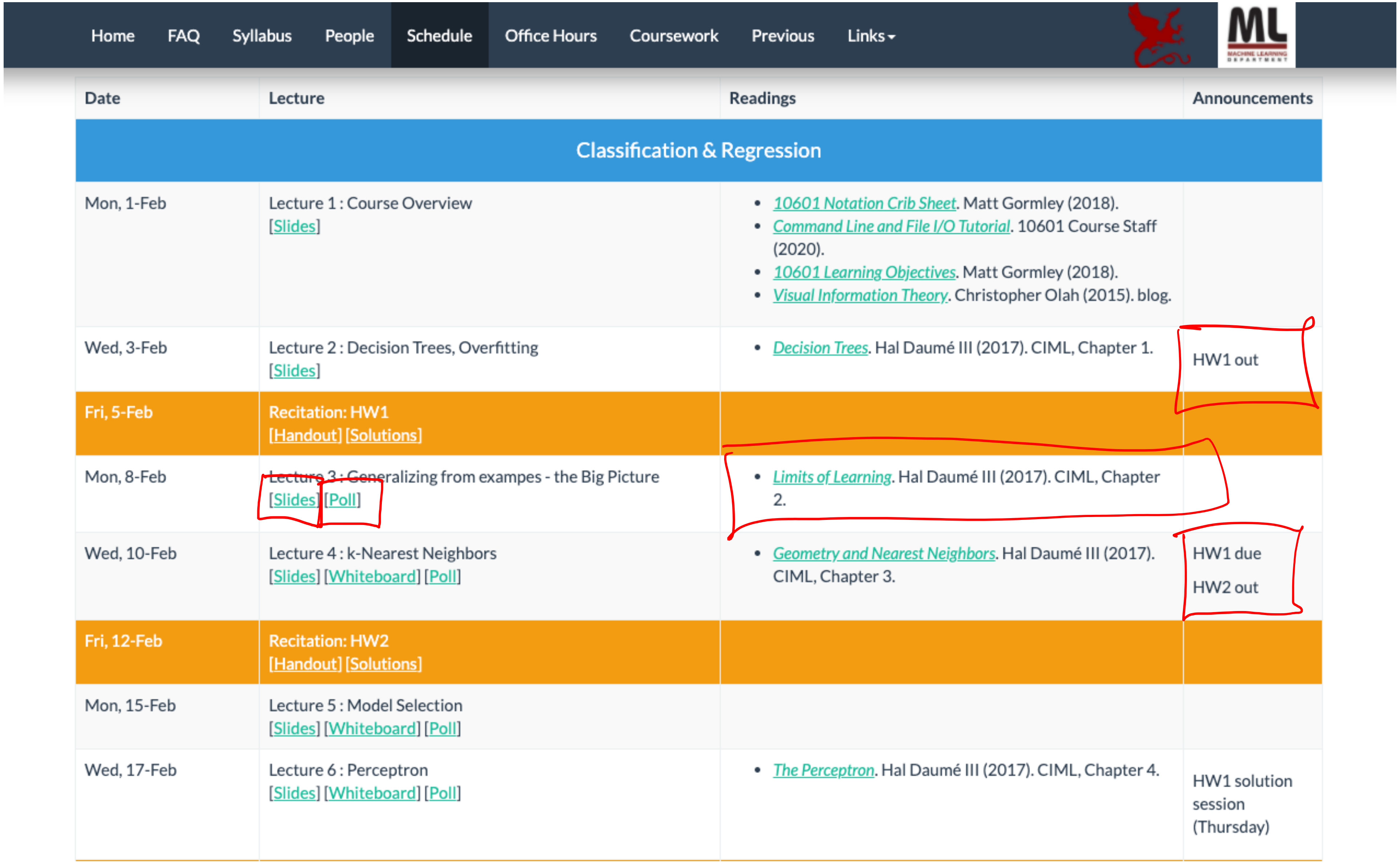
You are not *required* to read a textbook, but it will help immensely!





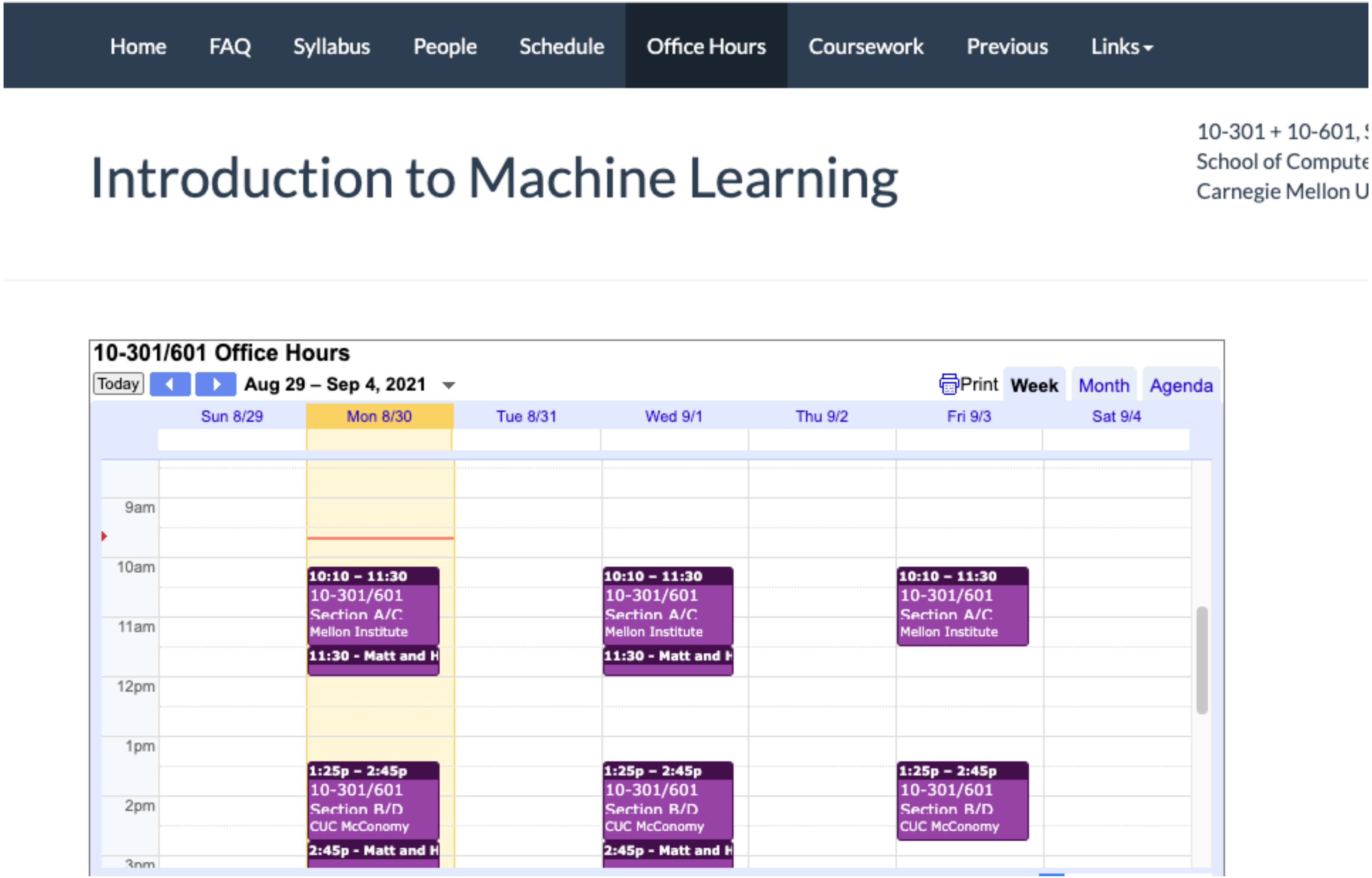

Springer Series in Statistics
Trevor Hastie
Robert Tibshirani
Jerome Friedman
The Elements of Statistical Learning
Data Mining, Inference, and Prediction
Second Edition
Springer

Where can I find…?



Date	Lecture	Readings	Announcements
	Classification & Regression		
Mon, 1-Feb	Lecture 1 : Course Overview [Slides]	• *10601 Notation Crib Sheet*. Matt Gormley (2018). • *Command Line and File I/O Tutorial*. 10601 Course Staff (2020). • *10601 Learning Objectives*. Matt Gormley (2018). • *Visual Information Theory*. Christopher Olah (2015). blog.	
Wed, 3-Feb	Lecture 2 : Decision Trees, Overfitting [Slides]	• *Decision Trees*. Hal Daumé III (2017). CIML, Chapter 1.	HW1 out
Fri, 5-Feb	Recitation: HW1 [Handout] [Solutions]		
Mon, 8-Feb	Lecture 3 : Generalizing from exampes - the Big Picture [Slides] [Poll]	• *Limits of Learning*. Hal Daumé III (2017). CIML, Chapter 2.	
Wed, 10-Feb	Lecture 4 : k-Nearest Neighbors [Slides] [Whiteboard] [Poll]	• *Geometry and Nearest Neighbors*. Hal Daumé III (2017). CIML, Chapter 3.	HW1 due HW2 out
Fri, 12-Feb	Recitation: HW2 [Handout] [Solutions]		
Mon, 15-Feb	Lecture 5 : Model Selection [Slides] [Whiteboard] [Poll]		
Wed, 17-Feb	Lecture 6 : Perceptron [Slides] [Whiteboard] [Poll]	• *The Perceptron*. Hal Daumé III (2017). CIML, Chapter 4.	HW1 solution session (Thursday)

Where can I find…?



Introduction to Machine Learning

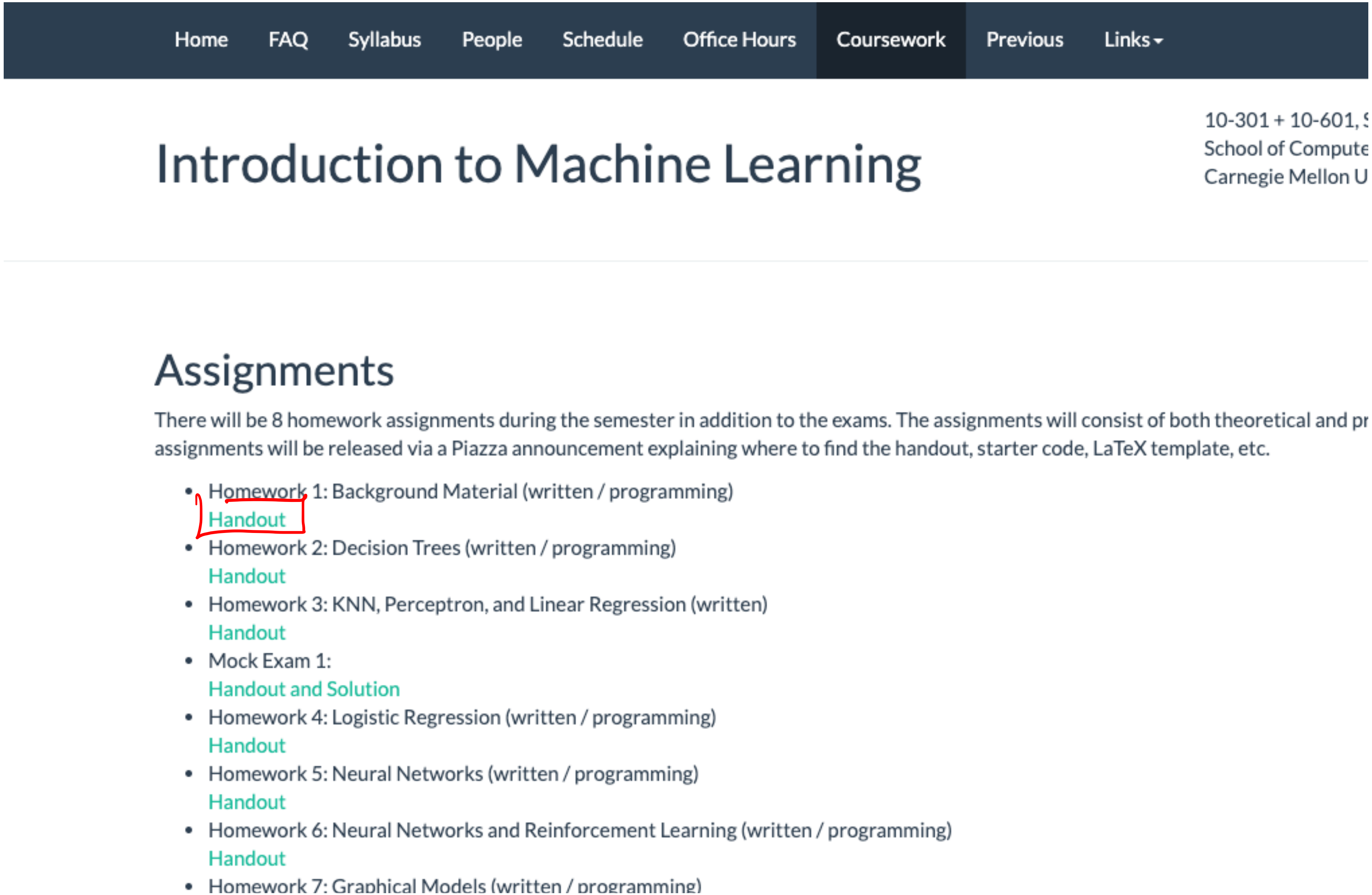
10-301 + 10-601,
School of Compute
Carnegie Mellon U

10-301/601 Office Hours

Aug 29 – Sep 4, 2021

	Sun 8/29	Mon 8/30	Tue 8/31	Wed 9/1	Thu 9/2	Fri 9/3	Sat 9/4
9am							
10am		10:10 – 11:30 10-301/601 Section A/C Mellon Institute		10:10 – 11:30 10-301/601 Section A/C Mellon Institute		10:10 – 11:30 10-301/601 Section A/C Mellon Institute	
11am		11:30 - Matt and H		11:30 - Matt and H			
12pm							
1pm		1:25p – 2:45p 10-301/601 Section B/D CUC McConomy		1:25p – 2:45p 10-301/601 Section B/D CUC McConomy		1:25p – 2:45p 10-301/601 Section B/D CUC McConomy	
2pm		2:45p - Matt and H		2:45p - Matt and H			
3pm							

Where can I find…?



10-301 + 10-601,
School of Compute
Carnegie Mellon U

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 pr
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

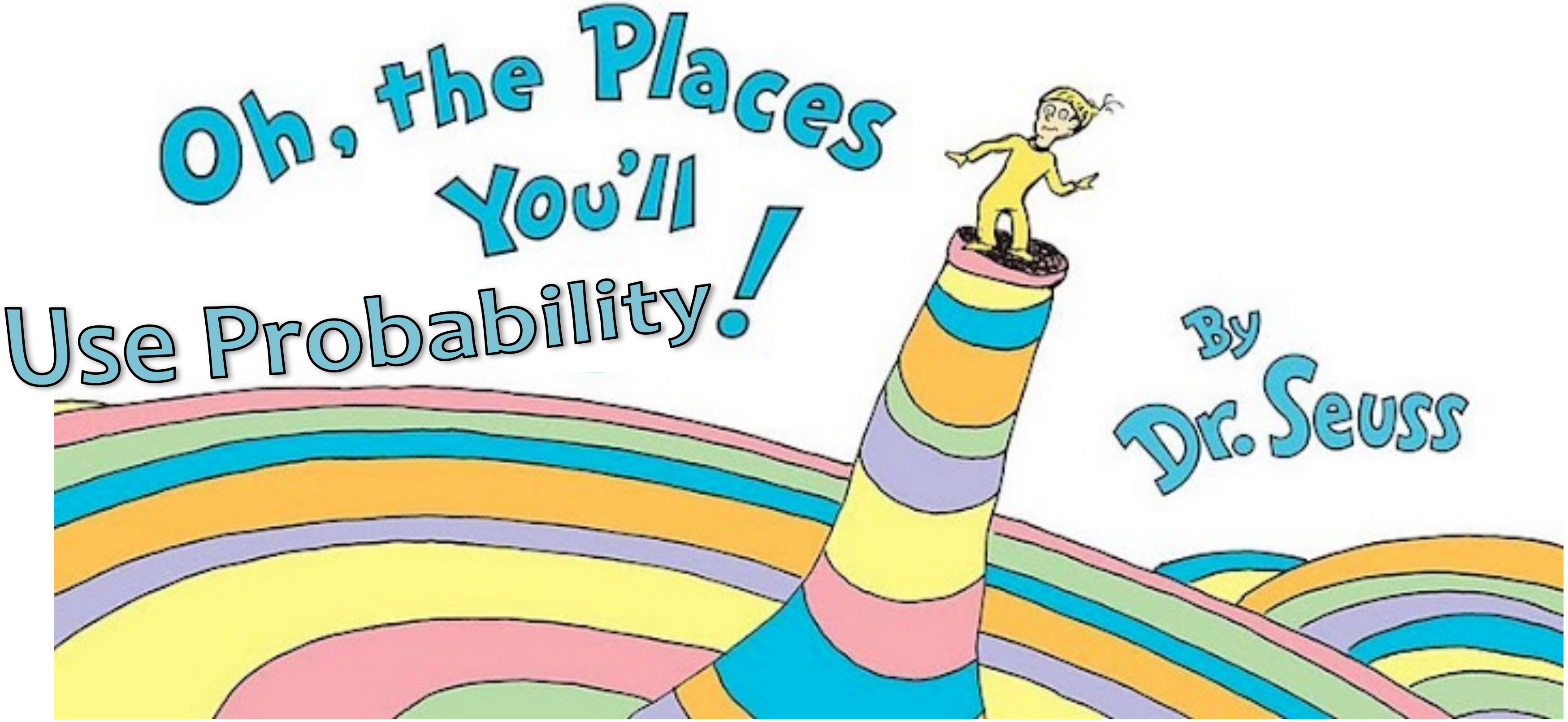
How to describe 606/607 to a friend

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**.



Use Probability

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

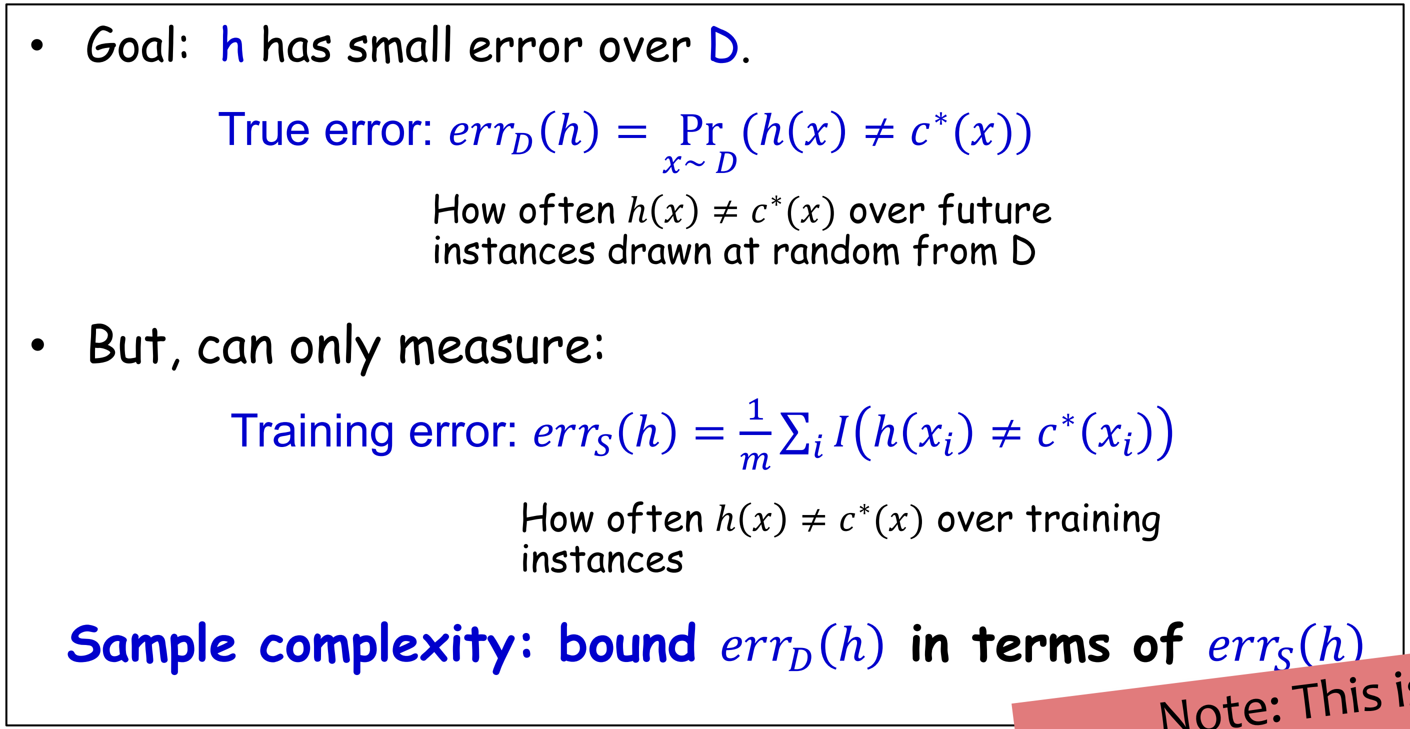
$$\begin{aligned} P(Y = y|X = x; \boldsymbol{\theta}) &= p(y|x; \boldsymbol{\theta}) \\ &= \frac{\exp(\boldsymbol{\theta}_y \cdot \mathbf{f}(x))}{\sum_{y'} \exp(\boldsymbol{\theta}_{y'} \cdot \mathbf{f}(x))} \end{aligned}$$

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

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

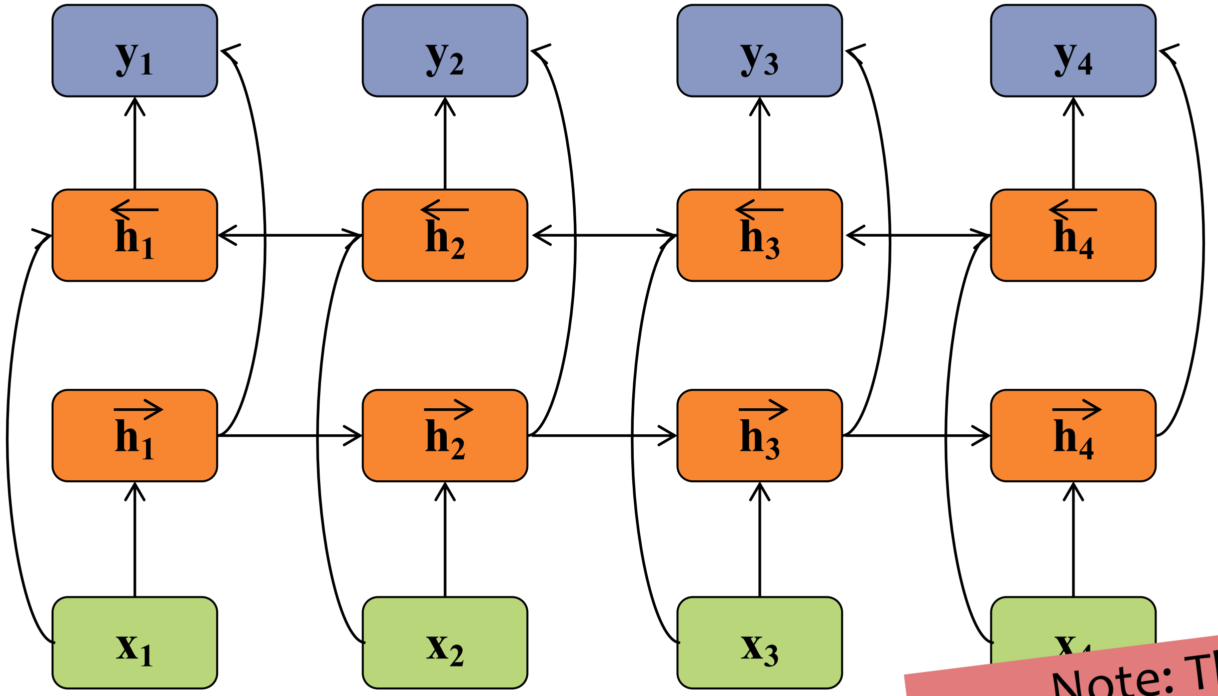
Sample complexity: bound $err_D(h)$ in terms of $err_S(h)$

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)

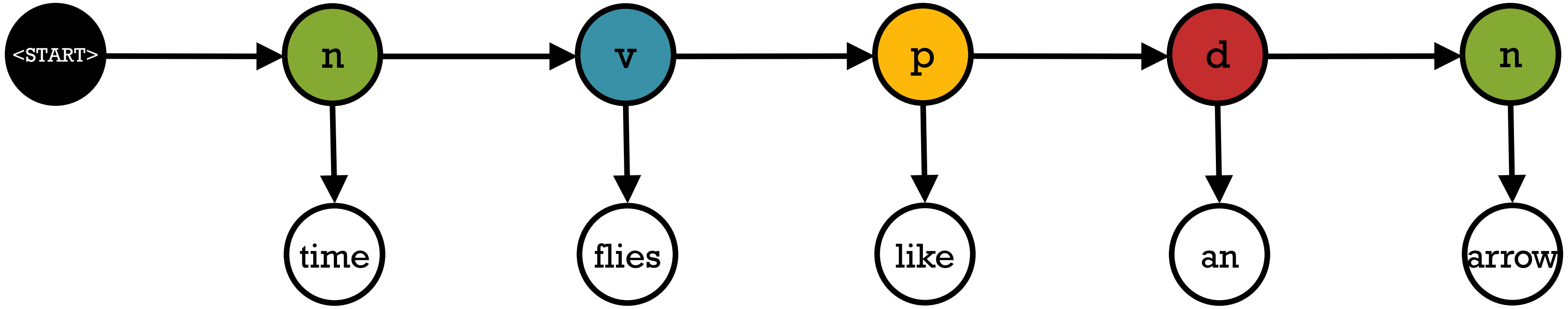


Note: This is just motivation – we'll cover these topics later!

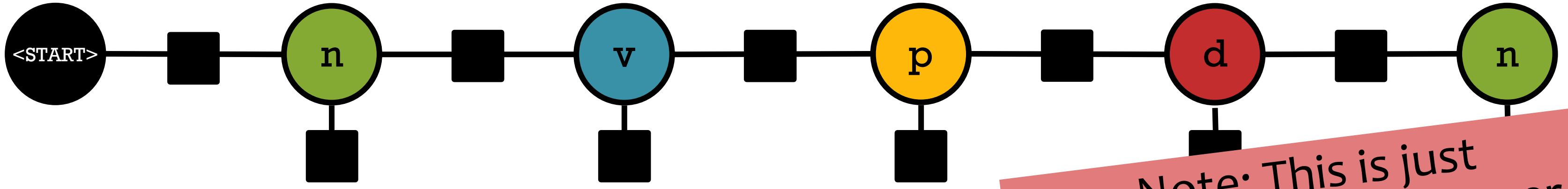
Oh, the Places You'll Use Probability!

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!

Reminders

- **Homework 1: Background**
  - **Out: Mon, Aug 26**
  - **Due: Wed, Sep 4 at 11:59pm**
  - Two parts:
    1. written part to Gradescope
    2. programming part to Gradescope

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

Q&A