Lecture 1:

Introduction to Machine Learning

Winter 2018

Kai-Wei Chang

CS @ UCLA

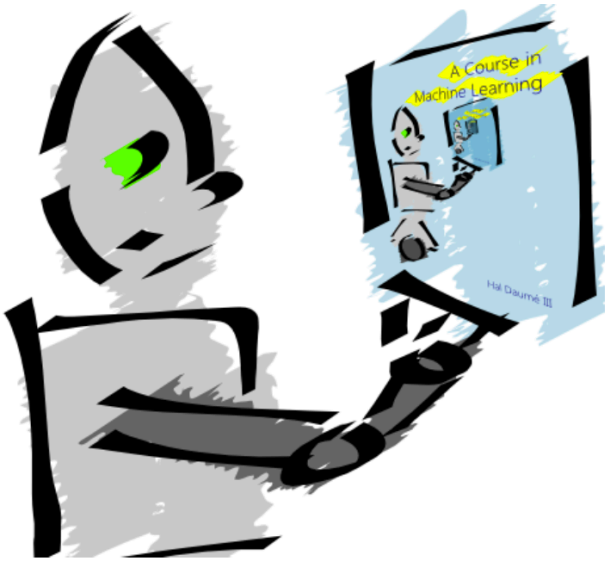
kw+cm146@kwchang.net

The instructor gratefully acknowledges Eric Eaton (UPenn), who assembled the original slides, Jessica Wu (Harvey Mudd), David Kauchak (Pomona), Dan Roth (Upenn), Sriram Sankararaman (UCLA), whose slides are also heavily used, and the many others who made their course materials freely available online.

What is machine learning?

Machine learning is about predicting the future based on the past.

-- Hal Daume III



Slide credit: David Kauchak

What is machine learning?

Machine Learning is the study of algorithms that

- improve their performance P
- at some task T
- with experience E.

A well-defined learning task is given by <P, T, E>.

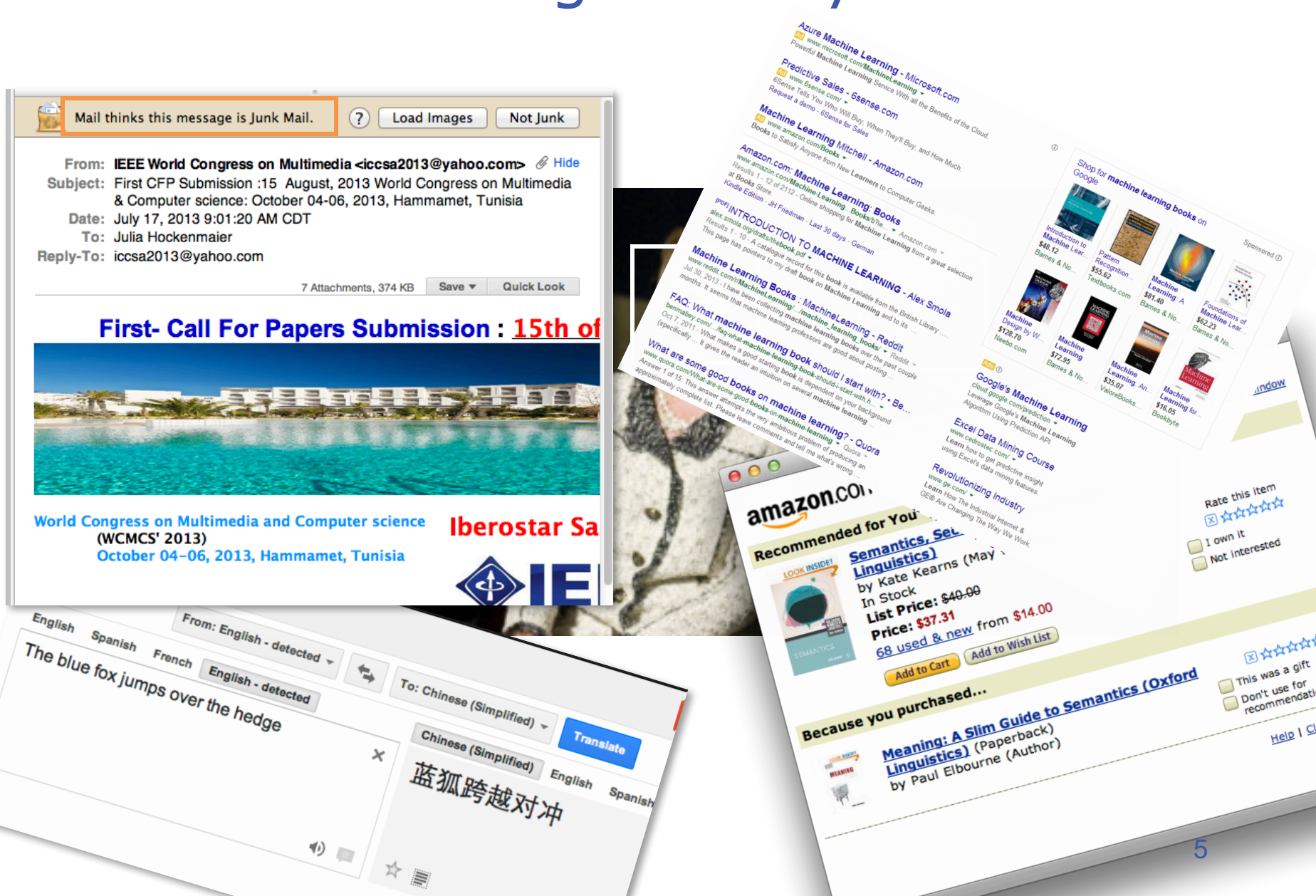
[Definition by Tom Mitchell (1998)]

Based on slide by Eric Eaton

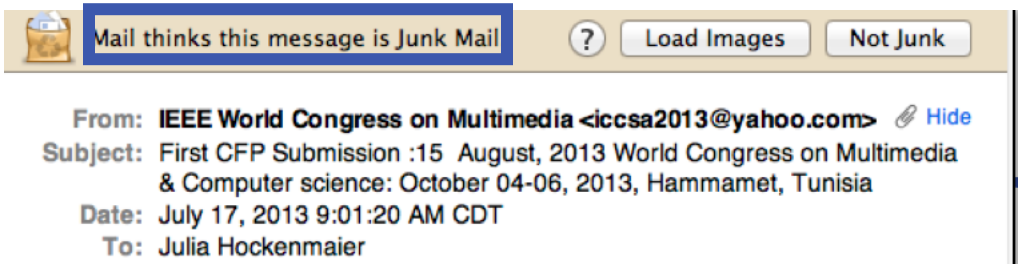
Goals of this course: Learn about

- Fundamental concepts and algorithms
- Common techniques/tools used
  - theoretical understanding
  - practical implementation
  - best practices

Machine learning is everywhere



Applications: Spam Detection



- This is a binary classification task: Assign one of two labels (i.e. yes/no) to the input (here, an email message)
- Classification requires a model (a classifier) to determine which label to assign to items.
- In this class, we study algorithms and techniques to learn such models from data.

Administrivia

CM146 Team

- Kai-Wei Chang (Eng XI 374)
  - Tuesday, 4:00 PM – 5:00 PM (or: appointment)
- TAs

Wasi Ahmad

Sajad Darabi

Xinzhu Bei

Seungbae Kim

Varun Saboo

Registration

- Course is currently full
  - Students on the waiting list will be enrolled in case some one drops. -- No guarantees though
  - Expect several students will drop the course

- Won't be giving PTEs til the first math quiz

Prerequisites

- The pillars of machine learning
  - Probability and statistics
  - Linear algebra
  - Calculus/Optimization

Prerequisites

- The pillars of machine learning
  - Probability and statistics
  - Linear algebra
  - Calculus/Optimization

- Computer science background
  - Algorithms
  - Programming experience: we will use Python, numpy and scikit-learn

Math background

- Mini quiz on math background (1/16)
  - In class, closed-book and closed-notes mini quiz that will help you evaluate your background.
  - Does not count towards your final grade

- Problem set 0 posted to self evaluate if you have the background and to help you recall concepts that you might have learned.

Course format

- Problem Sets
  - Six problem sets (0 -- 5) & Review Quizzes (every week)
  - Due at 11:59pm on the due date
  - 24hr late credits, that's it.
  - Will be using gradescope to manage submissions (will send out submission instruction)
- All solutions must be clearly written or typed.
  - Unreadable answers will not be graded. We encourage using LaTeX to type answers.
  - Solutions will be graded on both correctness and clarity

Exams

- Scheduled for 2/13, 3/22
  - Exams are in class, closed-book and closed-notes and will cover material from the lectures and the problem sets.
- No alternate or make-up exams
  - Except for disability/medical/emergency reasons documented and communicated to the instructor prior to the exam date.
  - Exam dates and times cannot be changed to accommodate scheduling conflicts with other classes or job fair/interview.

Policies

- Attendance and class participation
  - Although not a formal component of the grade, Attendance is important
  - We look forward to your active participation.
  - If you are absent without a documented excuse, the instructor and TA will not be able to go over missed lecture material
- Video recordings
  - we aim to make it available.
  - You should not rely on these recordings as a substitute for lectures.

Policies

- Regrading request
  - Must be made within one week after the grade is released regardless of any reason
  - We reserve the right to regrade problems for a given regrade request.

Final grade

- Default cut-off for letter grade is:

> 96	93	90	86	83	80	76	73	70	< 70
A +	A	A-	B+	B	B-	C+	C	C-	D

- We will not make adjustments for individuals
  - E.g., no round up (i.e., 89.99 = B+)
- We reserve the right to curve the final grades
  - The cut-off score will only get lower (i.e., you may get a better letter grade)
- This is a heavy course

Academic integrity policy

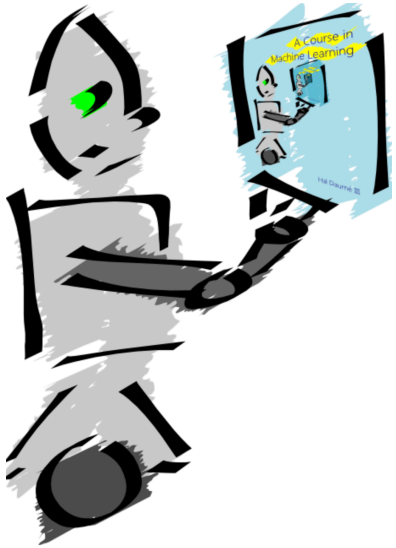
- No cheating
  - Homework and Exam
  - In particular, you are free to discuss homework problems. However, you must write up your own solutions (solution/program). You must also acknowledge all collaborators. Please don't use any old solution you found.
  - All incidents will report to the student office

CM146 on Web

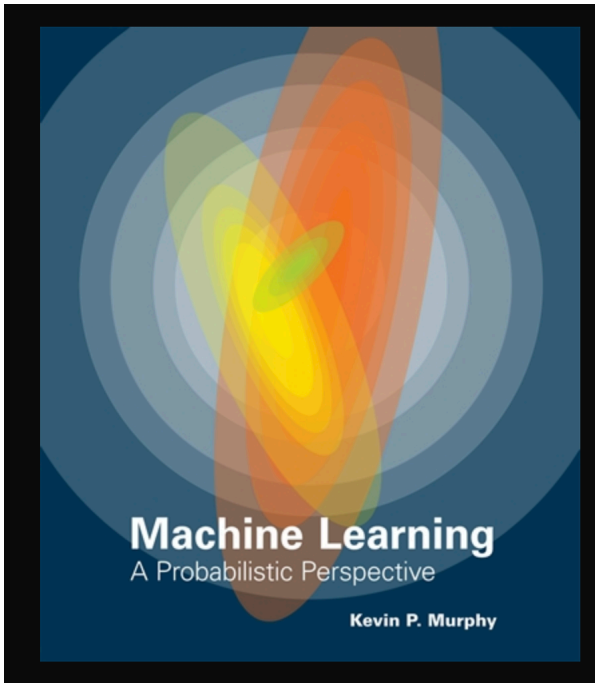
- Course website:
- Piazza:
  - Strongly encourage students to post here (publicly or privately) rather than email staff directly (you will get a faster response this way)
- Gradescope:
  - Maintain homwork/grade

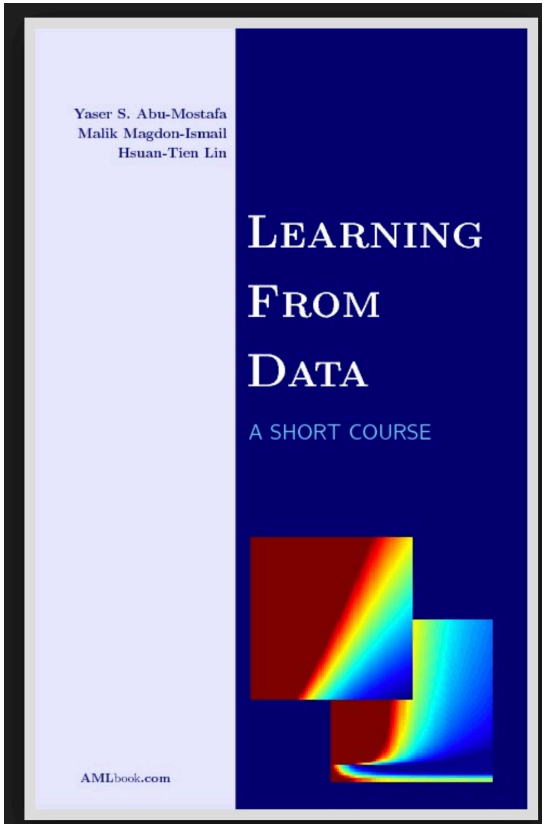
Textbook

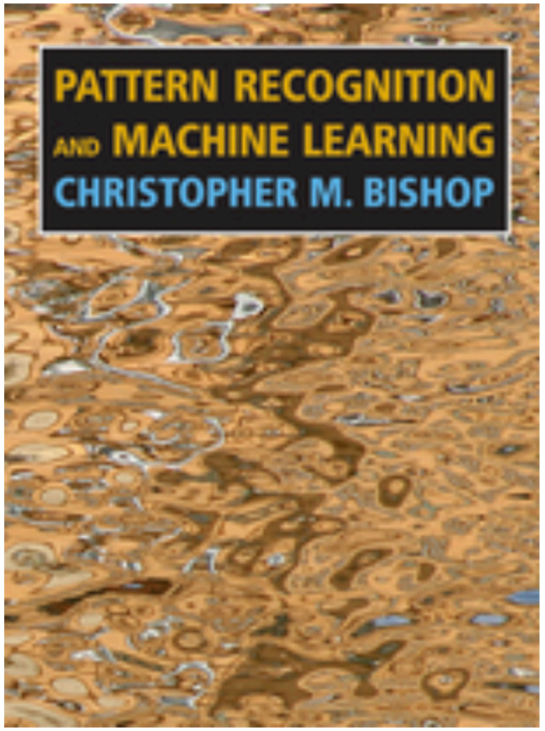
- No textbook
  - Primary reference:
    A course in machine learning by Hal Daume III (CIML). Freely available online http://ciml.info/



Other references



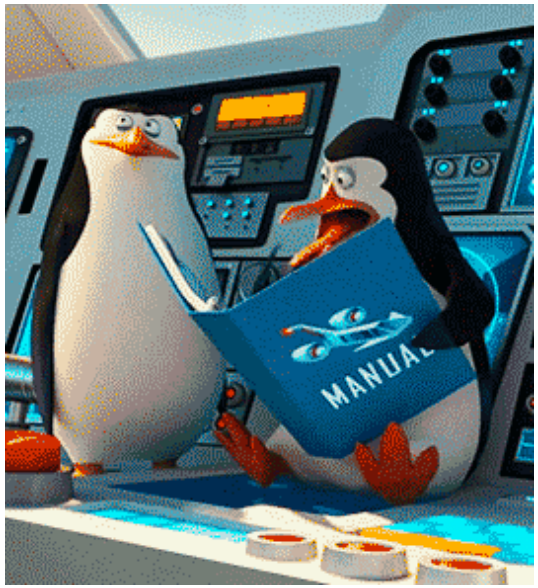




What is machine learning?

Learning

- **Learning is at the core of**
  - Understanding high level cognition
  - Performing knowledge intensive inferences
  - Building adaptive, intelligent systems
  - Dealing with messy, real world data



Learning

- **Learning has multiple purposes**
  - Knowledge acquisition
  - Integration of various knowledge sources to ensure robust behavior
  - Adaptation (human, systems)
  - Decision Making (Predictions)

Learning = Generalization

H. Simon -

"Learning denotes changes in the system that are adaptive in the sense that they enable the system to do the task or tasks drawn from the same population more efficiently and more effectively the next time."

The ability to perform a task in a situation which has never been encountered before

Learning = Generalization

Mail thinks this message is junk mail.

Not junk

- The learner has to be able to classify items it has never seen before.

Define the learning task

Improve on task T, with respect to
performance metric P, based on experience E

T: Playing checkers
P: Percentage of games won against an arbitrary opponent
E: Playing practice games against itself

T: Recognizing hand-written words
P: Percentage of words correctly classified
E: Database of human-labeled images of handwritten words

T: Driving on four-lane highways using vision sensors
P: Average distance traveled before a human-judged error
E: A sequence of images and steering commands recorded while observing a human driver

T: Categorize email messages as spam or legitimate
P: Percentage of email messages correctly classified
E: Database of emails, some with human-given labels

Slide credit: Ray Mooney

Learning = Generalization

The ability to perform a task in a situation which has never been encountered before

- Classification
  - Medical diagnosis; credit card applications; hand-written letters; ad selection; sentiment assignment,…
- Planning and acting
  - Navigation; game playing (chess, backgammon, go); driving a car
- Skills
  - Balancing a pole; playing tennis
- Common sense reasoning
  - Natural language interactions

Why Machine Learning?

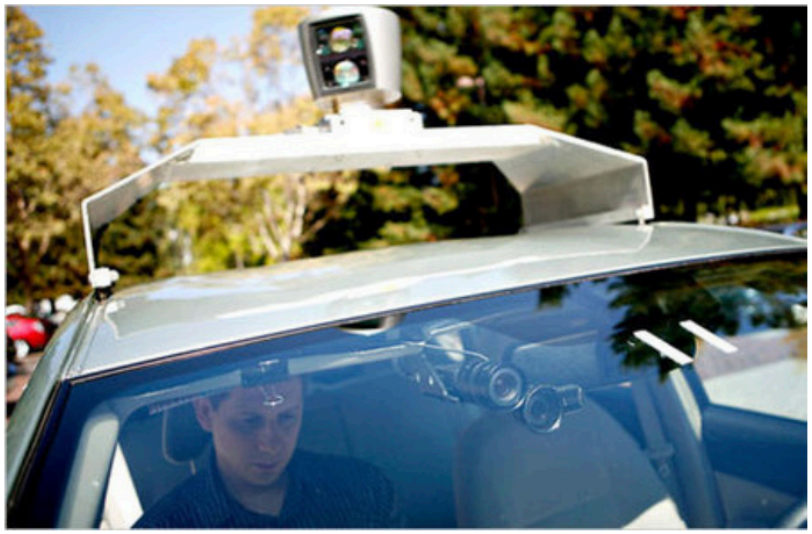
- Computer systems with new capabilities.
  - Develop systems that are too difficult or impossible to construct manually .
  - Develop systems that can automatically adapt and customize themselves to the needs of the individual user through experience.
  - Discover knowledge and patterns in databases, e.g. discovering purchasing patterns
  - Solve the kinds of problems now reserved for humans.

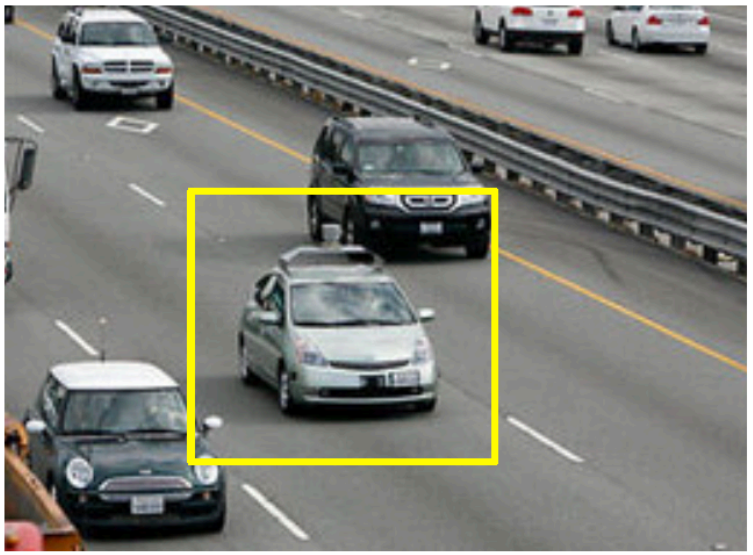
Why Study Learning?

- Computer systems with new capabilities
- Understand human and biological learning
- Exciting moments for ML:
  - Initial algorithms and theory in place.
  - Growing amounts of on-line data
  - Computational power available.

State of the art applications of ML

Autonomous Cars





- Nevada made it legal for autonomous cars to drive on roads in June 2011
- As of 2013, four states (Nevada, Florida, California, and Michigan) have legalized autonomous cars

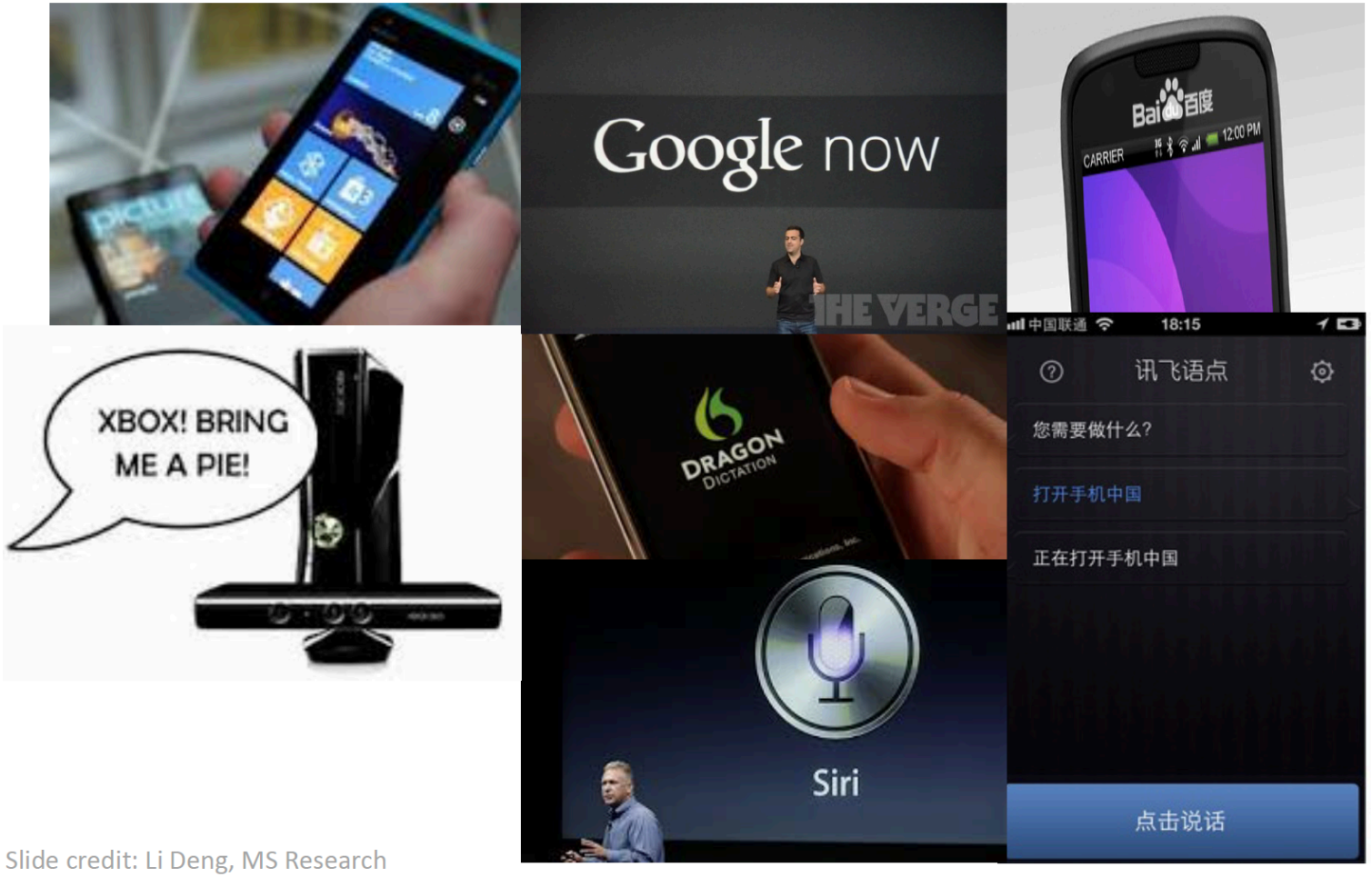
Slide credit: Eric Eaton

State of the art applications of ML

Computer Vision

State of the art applications of ML

Speech Recognition

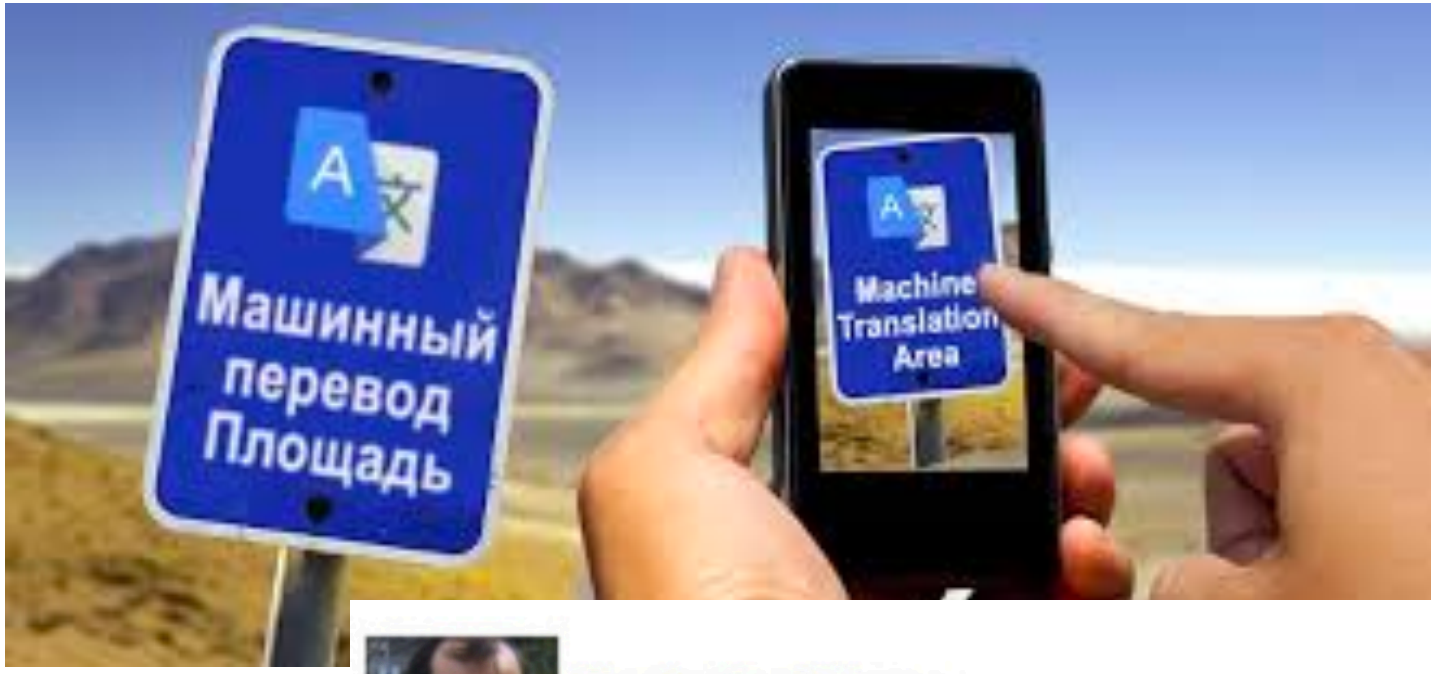


Slide credit: Li Deng, MS Research

State of the art applications of ML

- Reinforcement Learning

Machine translation



Necip Fazil Ayan

1 hr •

Onların, İzmir'in neden hayır dediğini anlamalarını beklemiyoruz.

We don't expect them to understand why Izmir said no.

• Rate this translation

Learning in the future

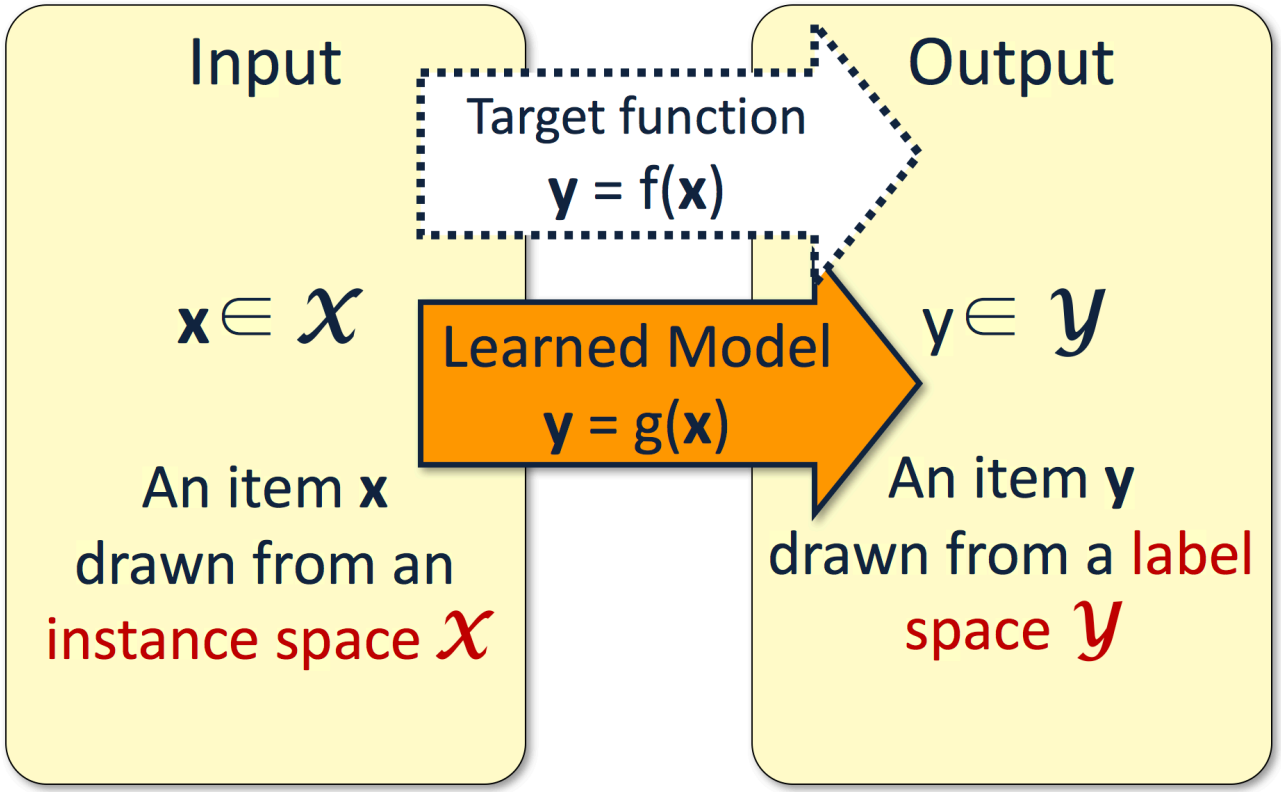
- Learning techniques will be a basis for application that involves a connection to the messy real world
- Prospects for broader future applications make for fundamental research and development opportunities
- Many unresolved issues – Theory and Systems
  - While it's hot, there are many things we don't know how to do

Work in Machine Learning

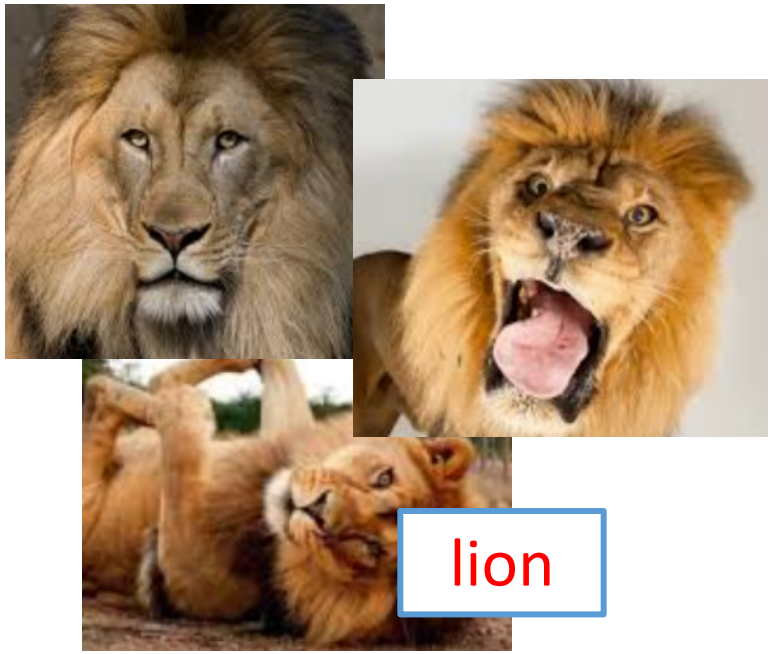
- Makes Use of:
  - Probability and Statistics; Linear Algebra; Calculus; Theory of Computation;
- Related to:
  - Philosophy, Psychology ,Neurobiology, Linguistics, Vision, Robotics,….
- Has applications in:
  - AI (Natural Language; Vision; Planning; HCI)
  - Engineering (Agriculture; Civil; …)
  - Computer Science (Compilers; Architecture; Systems; data bases…)

Types of learning (protocols)

- Supervised learning
  - Given: labeled training instances (or examples)
  - Goal: learn mapping that predicts label for test instance



Training phase:



lion

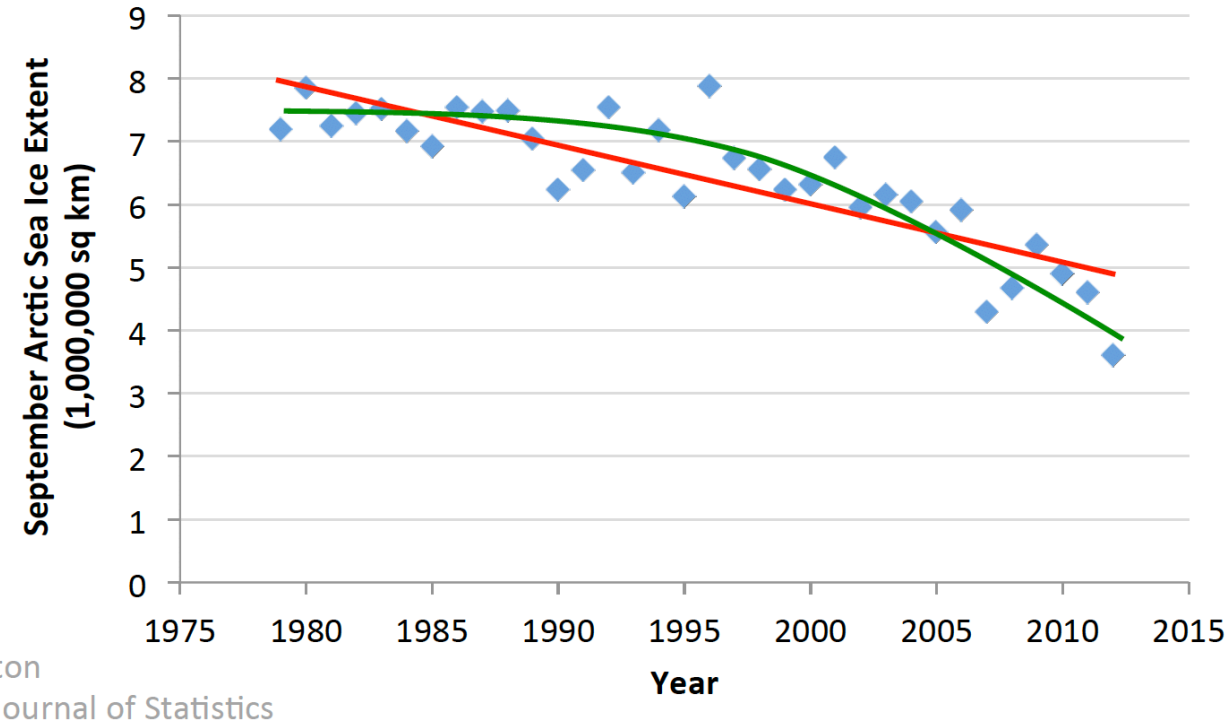
Not lion

Test phase:

??

Supervised Learning (Regression)

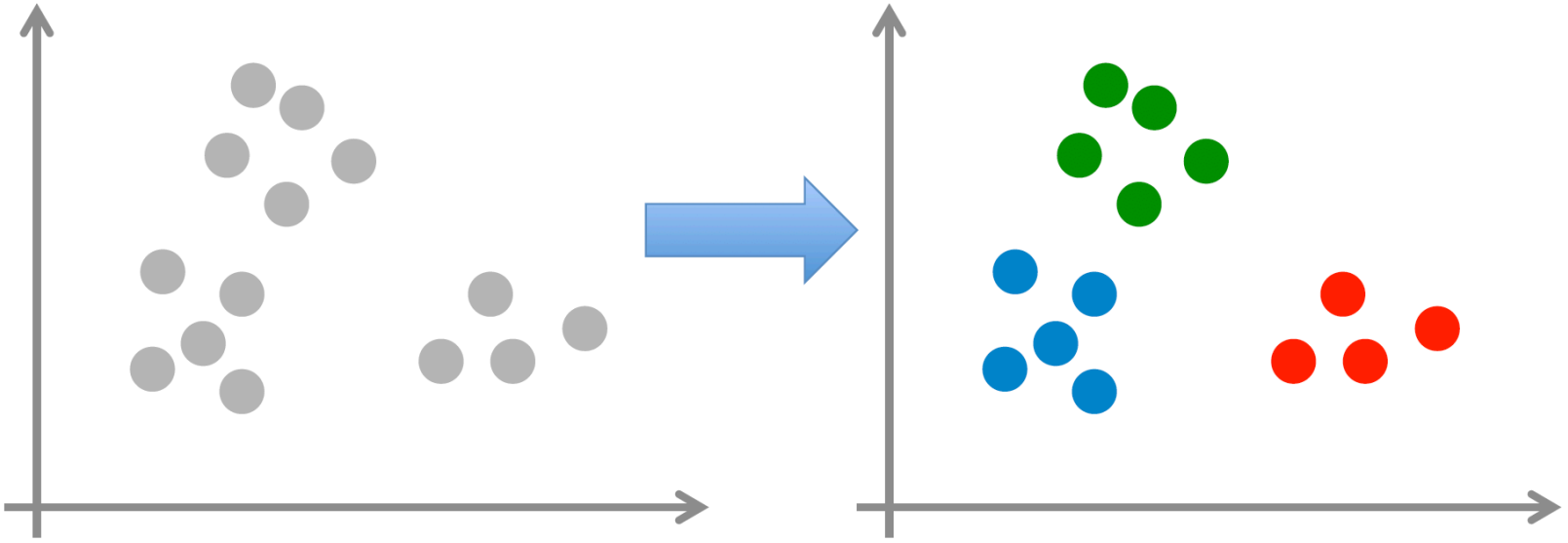
- Given $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$
- Learn a function $f(x)$ to predict y given x
  - y is real-valued == regression



Slide credit: Eric Eaton
Data from G. Witt. Journal of Statistics Education, Volume 21, Number 1 (2013)

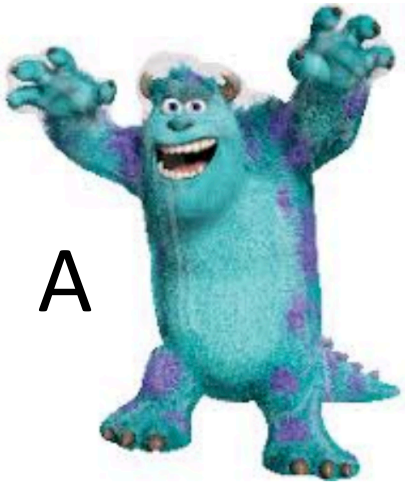
Unsupervised learning

- Given: unlabeled inputs
- Goal: learn some intrinsic structure in inputs



How many "kinds of monsters" are there?

A

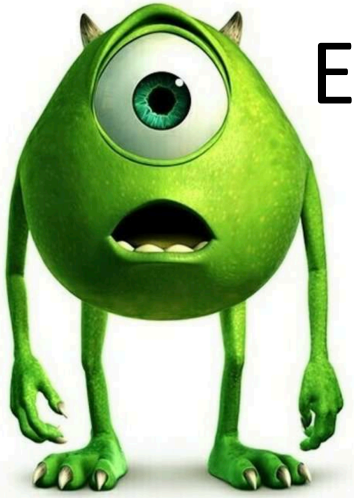


B

C

D

E



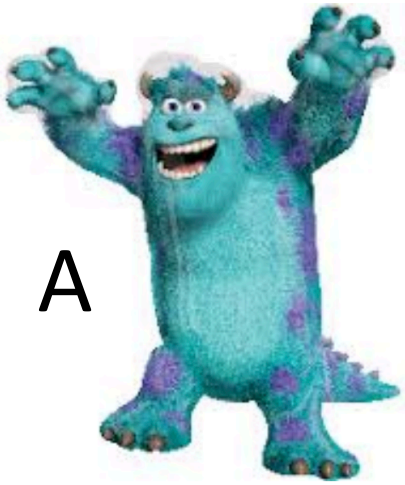
F

G

H

How many "kinds of monsters" are there?

A



B

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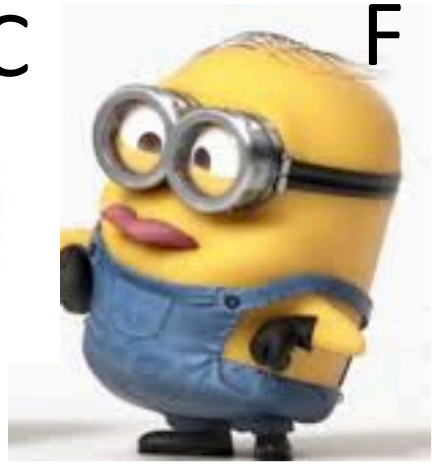
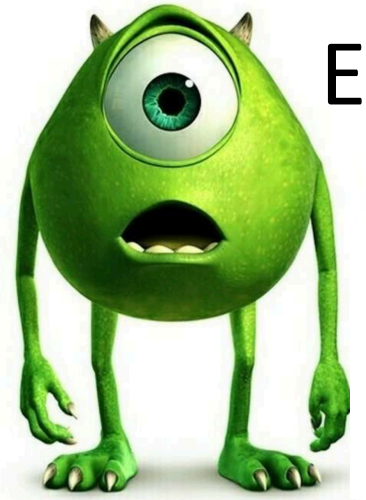


E



G

D

H

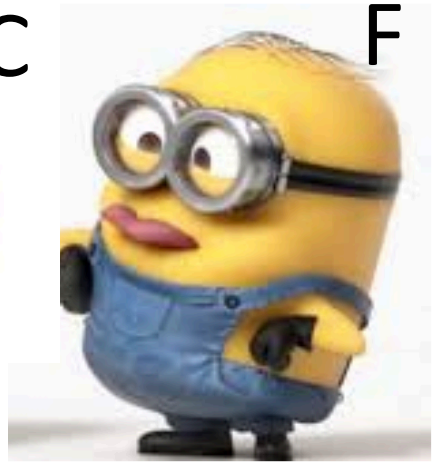
How many "kinds of monsters" are there?

H

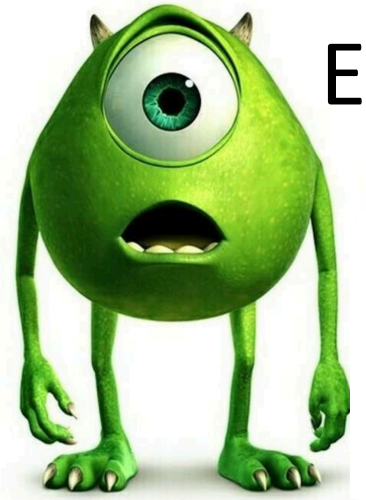
B

C

F



E

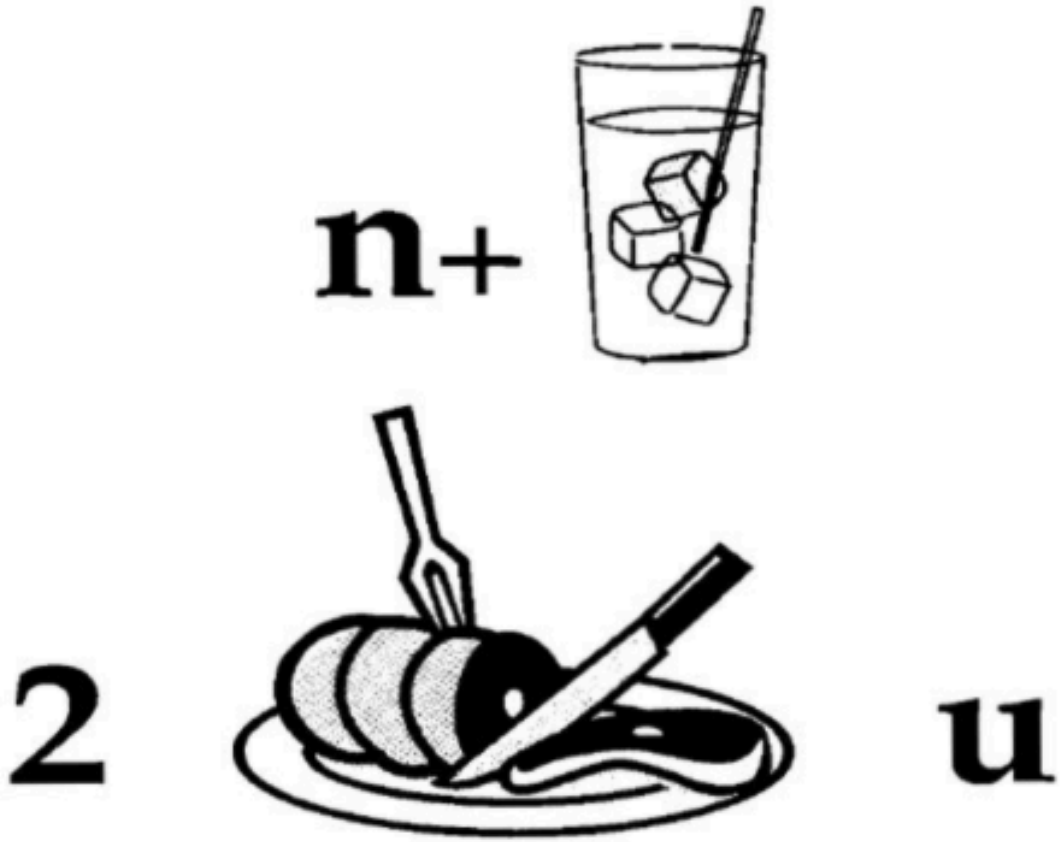


G

D

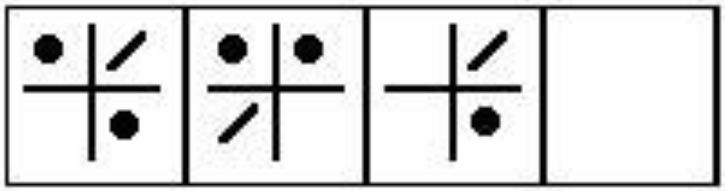
A

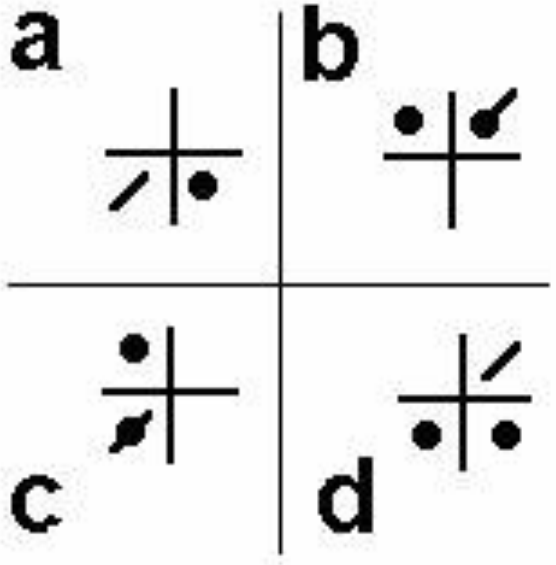
Decipher



Credit: Dan Roth

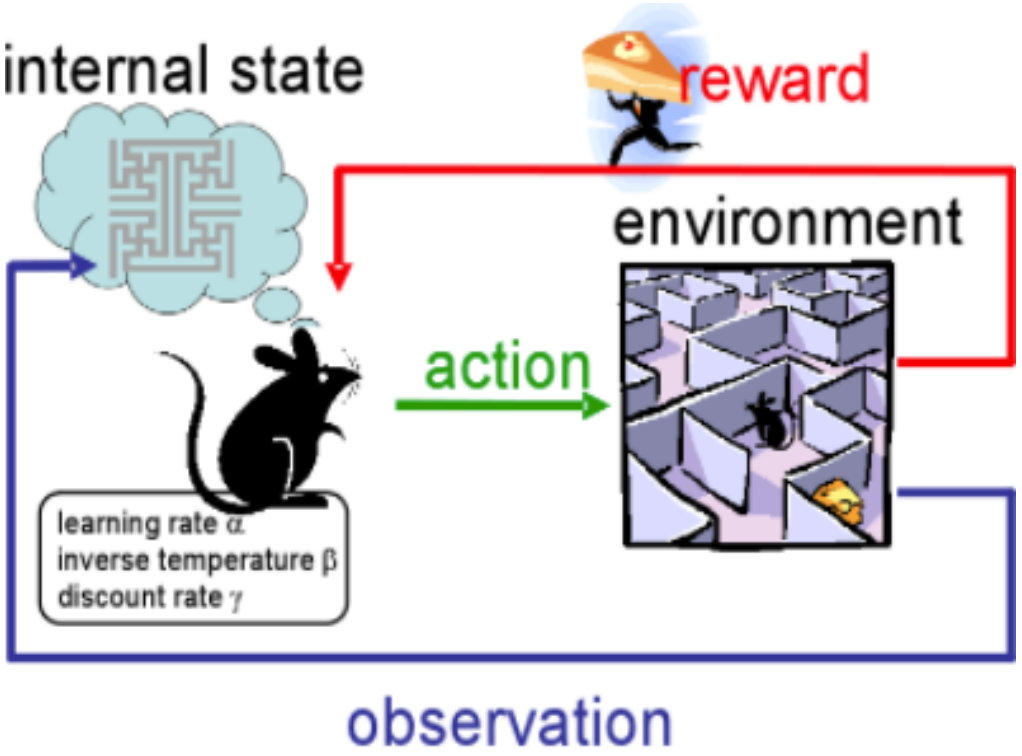
IQ test





Reinforcement Learning

- Given sequence of states and actions with rewards
- Learn policy that maximizes agent's reward



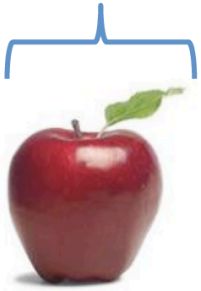
(image taken from Cyber Rodent Project)

Framing a Learning Problem

Representing instances/examples

What is an instance?
How is it represented?

instances



features

$feat_1$, $feat_2$, $feat_3$, $feat_4$,…
red, round, leaf, 3oz, …

$feat_1$, $feat_2$, $feat_3$, $feat_4$,…
green, round, no leaf, 4oz, …

$feat_1$, $feat_2$, $feat_3$, $feat_4$,…
yellow, curved, no leaf, 4oz, …

$feat_1$, $feat_2$, $feat_3$, $feat_4$,…
green, curved, no leaf, 5oz, …

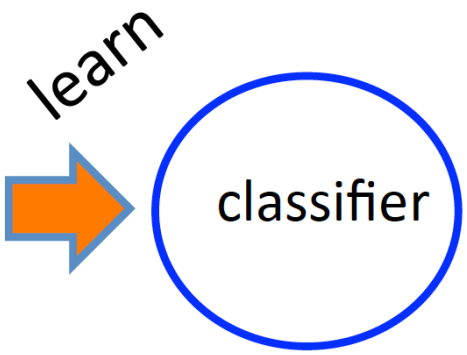
How our algorithms actually "view" the data

Features are the questions we can ask about the instances

Based on slide by David Kauchak

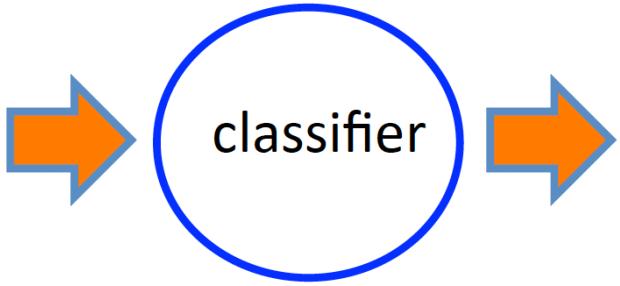
Learning Algorithm

instances	label
red, round, leaf, 3oz, …	apple
green, round, no leaf, 4oz, …	apple
yellow, curved, no leaf, 4oz, …	banana
green, curved, no leaf, 5oz, …	banana



During learning/training/induction, learn a model of what distinguishes apples and bananas *based on the features*

red, round, no leaf, 4oz, …



apple or banana?

apple Why?

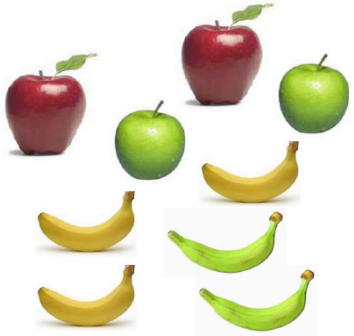
The classifier classifies a new instance *based on the features*

Based on slide by David Kauchak

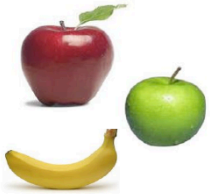
Learning = generalization

- Learning is about ***generalizing*** from training data
- What does this ***assume*** about training and test set?

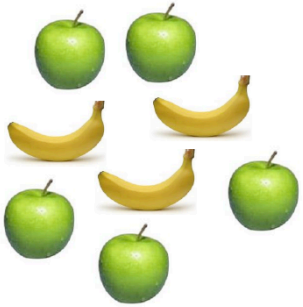
Training data



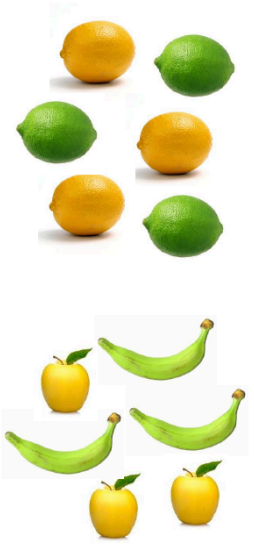
Test set



Training data



Test set

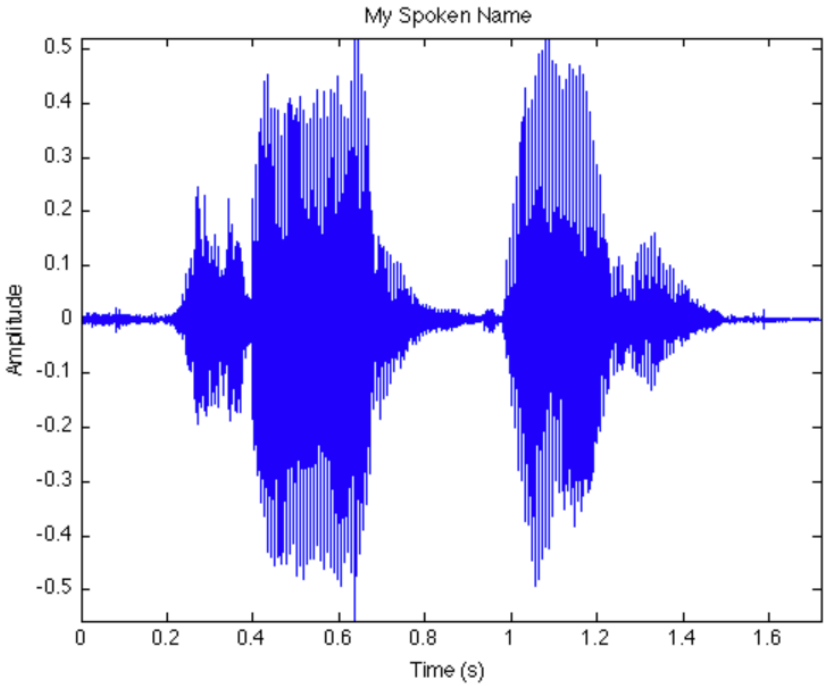


Not always the case, but we'll often assume it is!

Challenges

Challenges: Representation

- Representation:
  How to represent input/output?



Challenges: What is the right model?

- Usually depends on size of data, type of problem, prior knowledge, annotation quality …
- Also depends on the goal: model size / test-time budget / accuracy v.s. speed

Challenges: Debugging

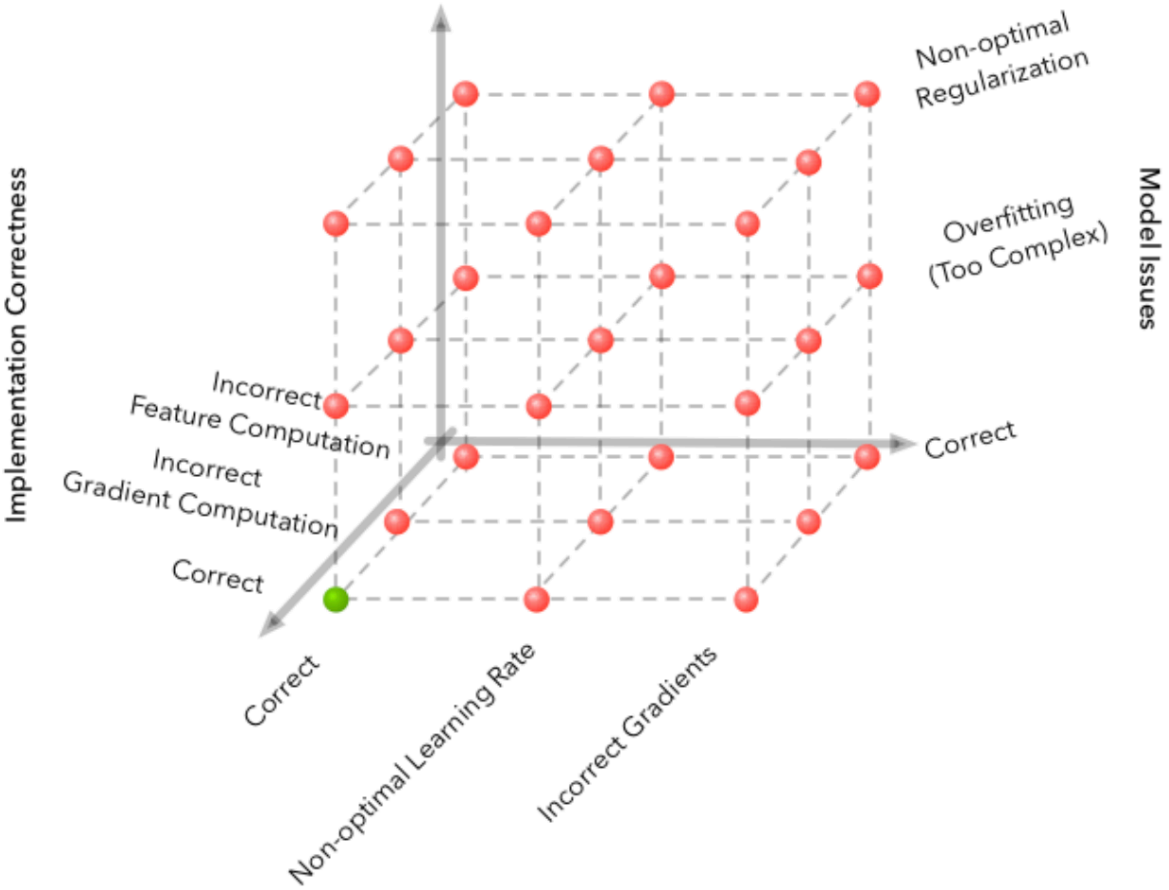
Debugging a program

Credit: S. Zayd Enam

http://ai.stanford.edu/~zayd/why-is-machine-learning-hard.html

Challenges: Debugging

Debugging a ML model

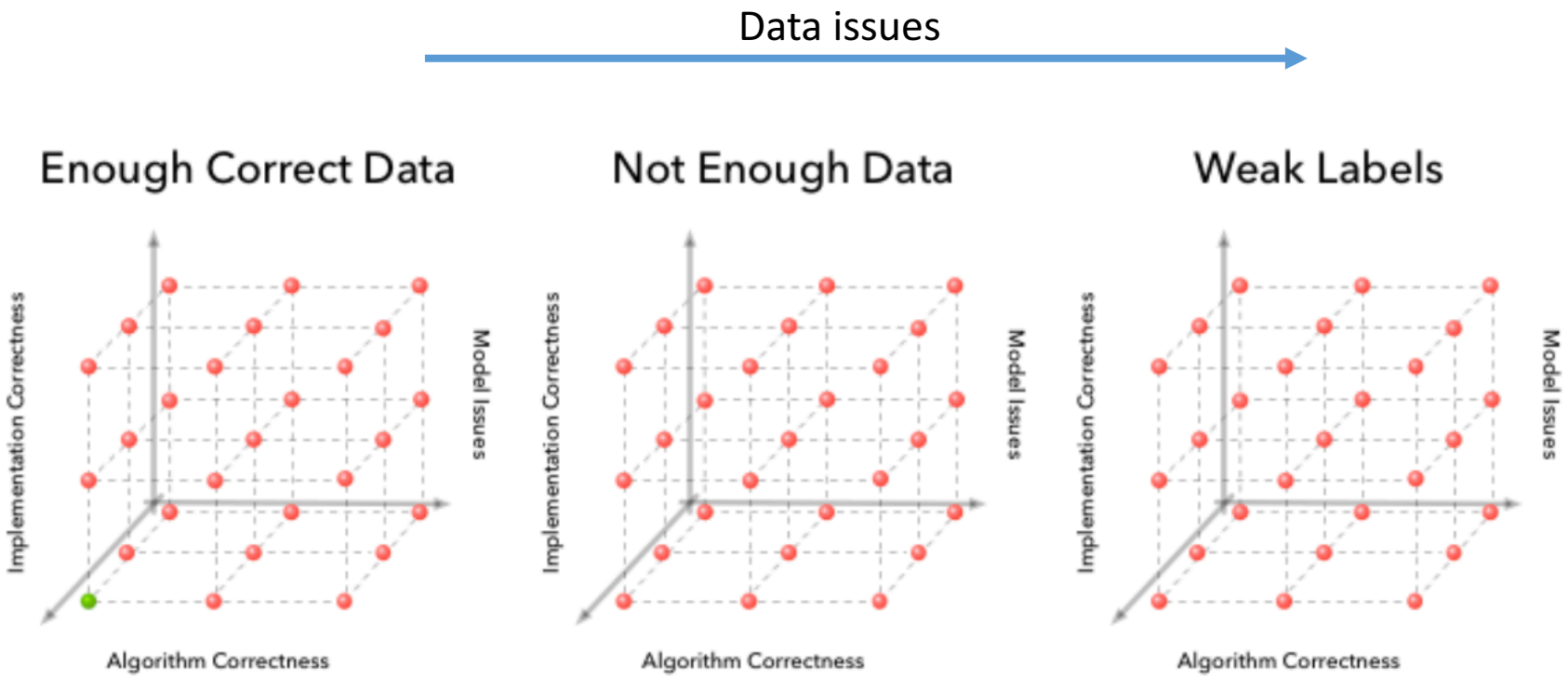


Credit: S. Zayd Enam

http://ai.stanford.edu/~zayd/why-is-machine-learning-hard.html

Challenges: Debugging

Debugging a ML model



Credit: S. Zayd Enam

http://ai.stanford.edu/~zayd/why-is-machine-learning-hard.html

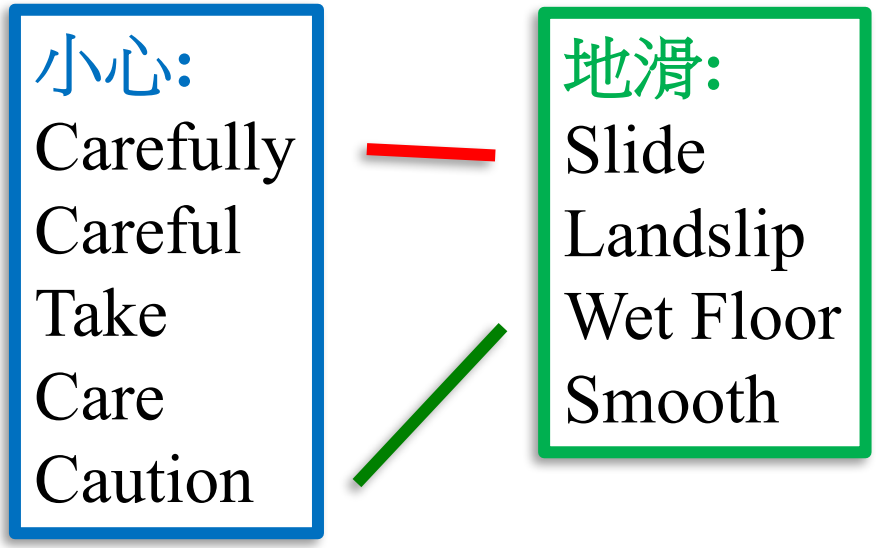
Challenges: Structured Inference

- Many predictions are compositional
  - Require an inference process

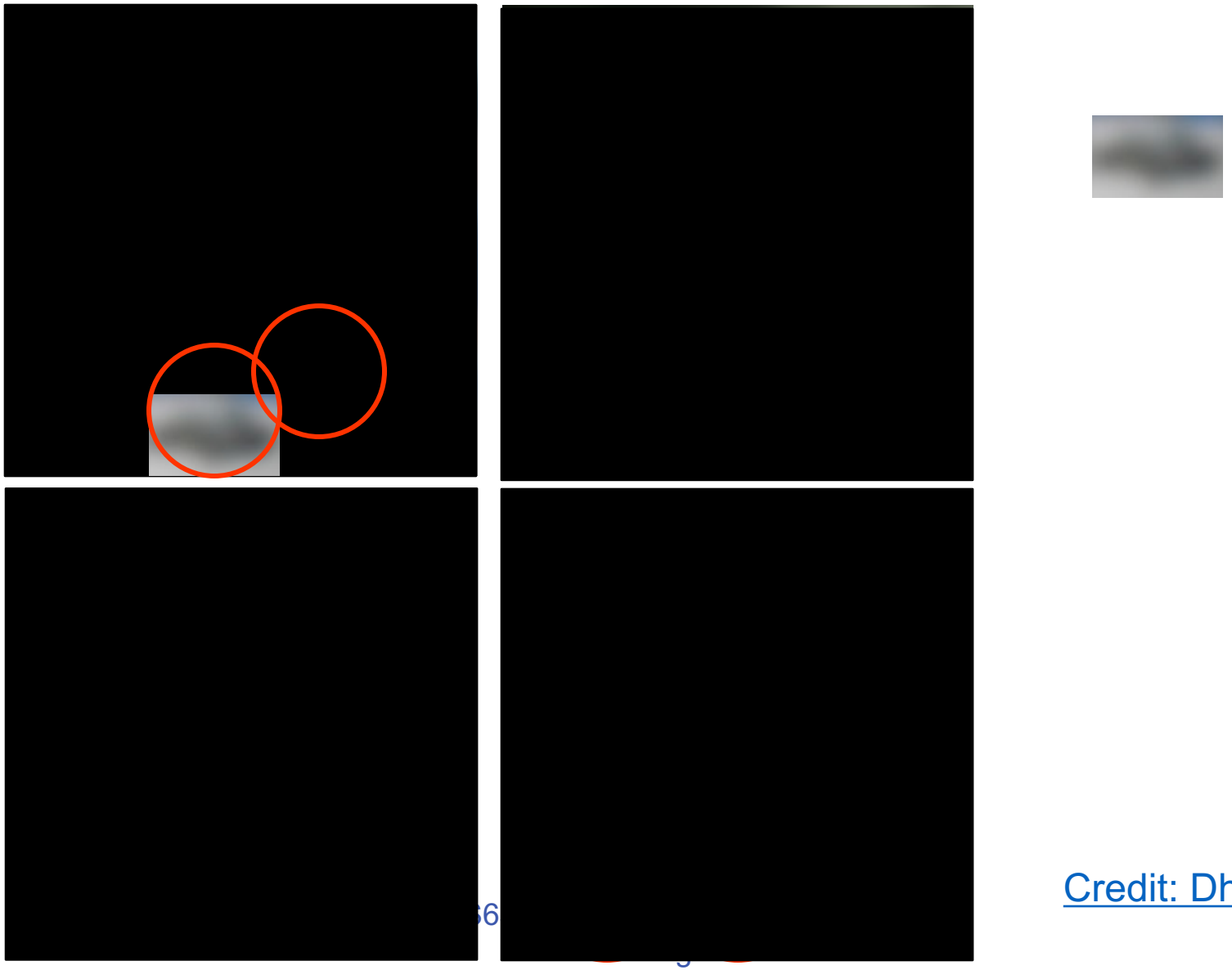
Challenges: Structured Inference

Carefully Slide

Challenges: Structured Inference



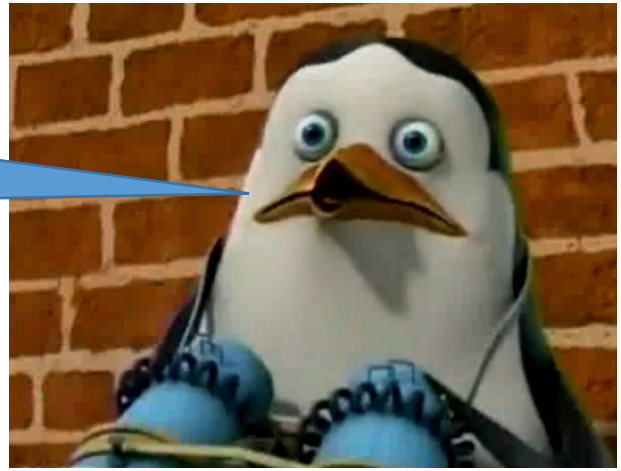
Challenges: Structured Inference



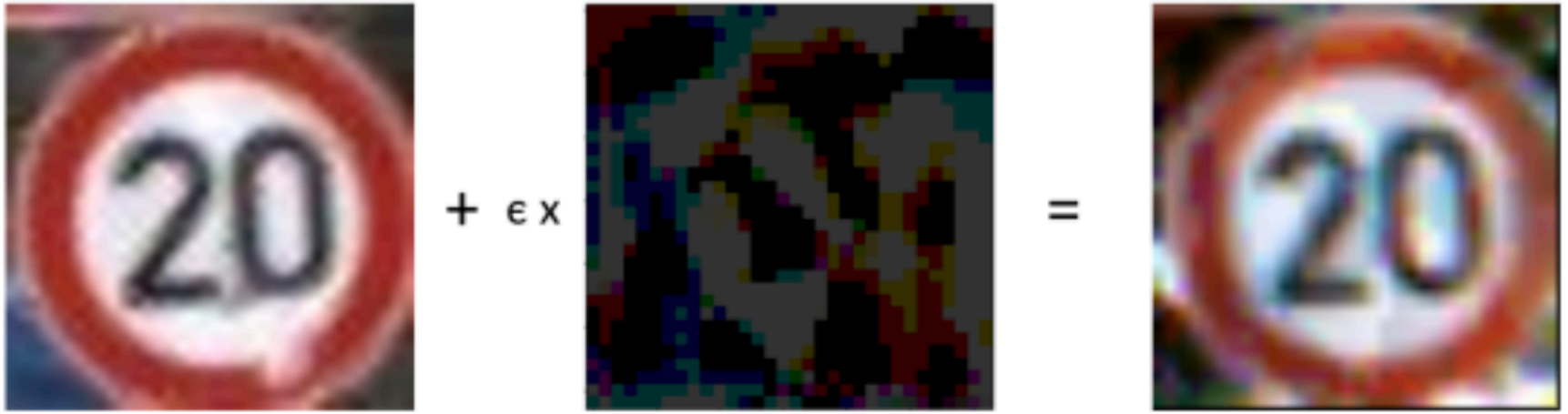
Credit: Dhruv Batra

Challenges: Structured Inference

Challenges: Robustness



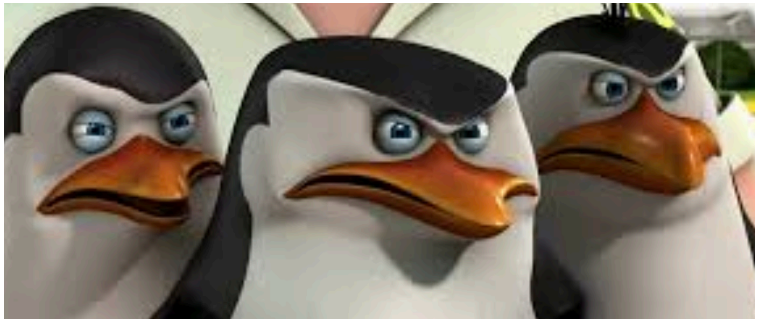
Challenges: Adversarial Attack



93%, 20 Km/h Sign

$sign(\nabla * J(\theta, x, y))$

90%, 80 Km/h Sign



https://arxiv.org/abs/1712.09327v1

Fairness in ML

Select photo

✕ The photo you want to upload does not meet our criteria because:

- Subject eyes are closed

Please refer to the technical requirements.
You have 9 attempts left.

Check the photo requirements.

Read more about common photo problems and

start again and re-enter the CAPTCHA security check.

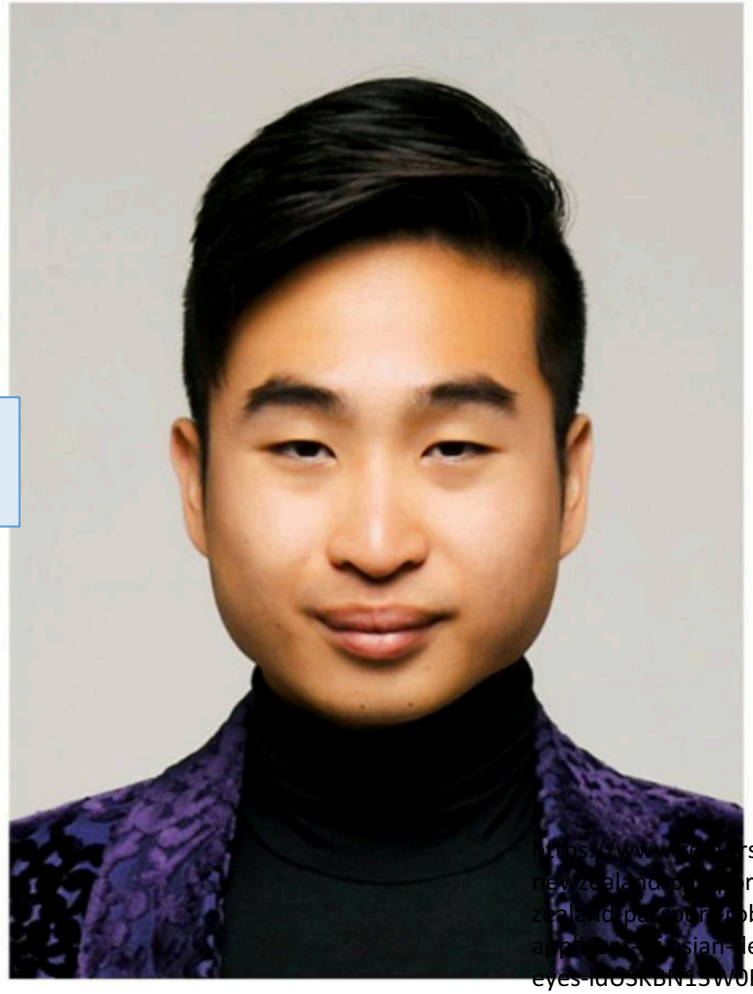
Reference number: 20161206-81

Filename: Untitled.jpg

If you wish to contact us about the photo, you must provide us with the reference number given above.

Please print this information for your records.

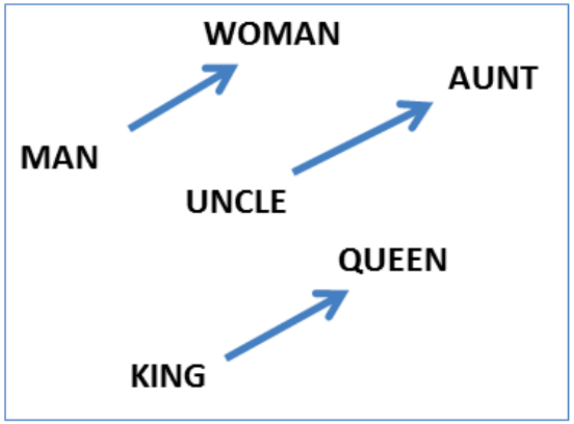
Subject eyes are closed



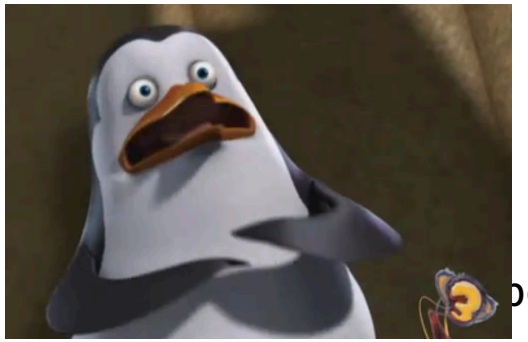
https://www.reuters.com/article/us-newzealand-passport-error/new-zealand-passport-robot-tells-applicant-of-asian-descent-to-open-eyes-idUSKBN13W0RL

Fairness in ML-– Word embedding bias

- $v_{man} - v_{woman} + v_{uncle} \sim v_{aunt}$



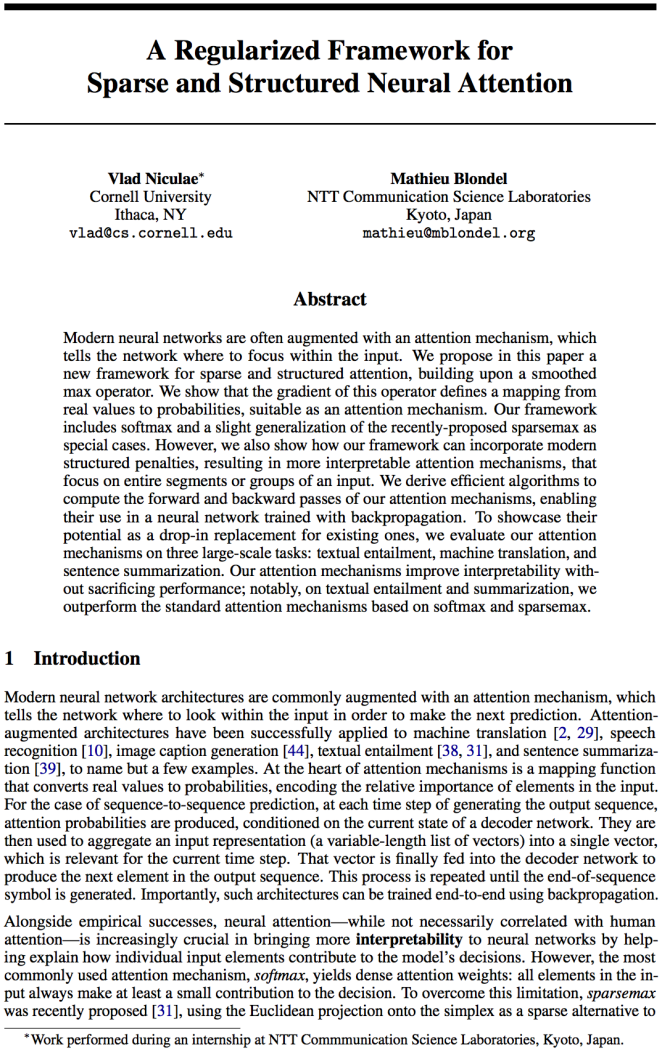
he: ___	she: __
uncle	aunt
lion	
surgeon	
architect	
beer	
professor	



bedding trained from the news

Why taking this course?

Building fundamental knowledge



A Regularized Framework for Sparse and Structured Neural Attention

Vlad Niculae* Cornell University Ithaca, NY vlad@cs.cornell.edu

Mathieu Blondel NTT Communication Science Laboratories Kyoto, Japan mathieu@mblondel.org

Abstract

Modern neural networks are often augmented with an attention mechanism, which tells the network where to focus within the input. We propose in this paper a new framework for sparse and structured attention, building upon a smoothed max operator. We show that the gradient of this operator defines a mapping from real values to probabilities, suitable as an attention mechanism. Our framework includes softmax and a slight generalization of the recently-proposed sparsemax as special cases. However, we also show how our framework can incorporate modern structured penalties, resulting in more interpretable attention mechanisms, that focus on entire segments or groups of an input. We derive efficient algorithms to compute the forward and backward passes of our attention mechanisms, enabling their use in a neural network trained with backpropagation. To showcase their potential as a drop-in replacement for existing ones, we evaluate our attention mechanisms on three large-scale tasks: textual entailment, machine translation, and sentence summarization. Our attention mechanisms improve interpretability without sacrificing performance; notably, on textual entailment and summarization, we outperform the standard attention mechanisms based on softmax and sparsemax.

1 Introduction

Modern neural network architectures are commonly augmented with an attention mechanism, which tells the network where to look within the input in order to make the next prediction. Attention-augmented architectures have been successfully applied to machine translation [2, 29], speech recognition [10], image caption generation [44], textual entailment [38, 31], and sentence summarization [39], to name but a few examples. At the heart of attention mechanisms is a mapping function that converts real values to probabilities, encoding the relative importance of elements in the input. For the case of sequence-to-sequence prediction, at each time step of generating the output sequence, attention probabilities are produced, conditioned on the current state of a decoder network. They are then used to aggregate an input representation (a variable-length list of vectors) into a single vector, which is relevant for the current time step. That vector is finally fed into the decoder network to produce the next element in the output sequence. This process is repeated until the end-of-sequence symbol is generated. Importantly, such architectures can be trained end-to-end using backpropagation.

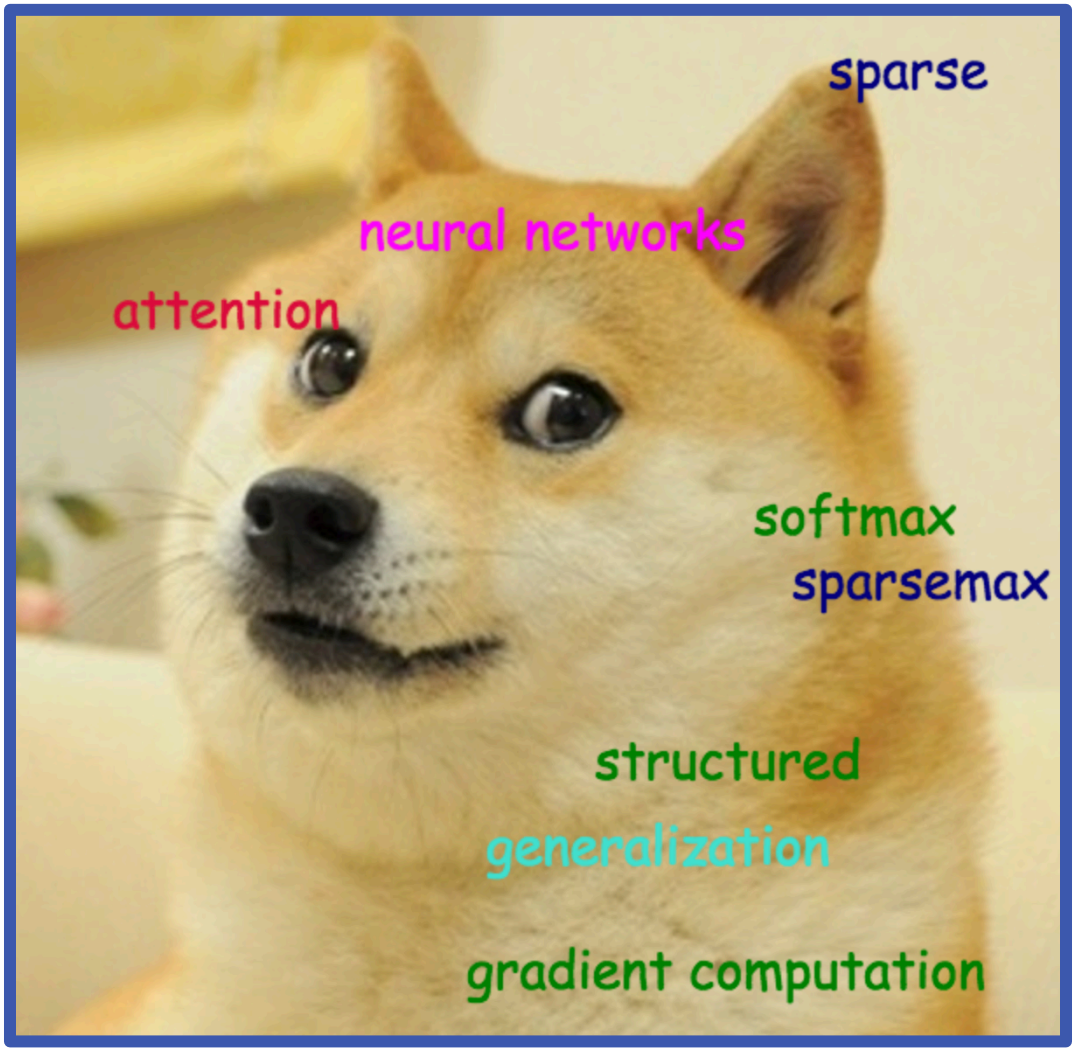
Alongside empirical successes, neural attention—while not necessarily correlated with human attention—is increasingly crucial in bringing more **interpretability** to neural networks by helping explain how individual input elements contribute to the model's decisions. However, the most commonly used attention mechanism, *softmax*, yields dense attention weights: all elements in the input always make at least a small contribution to the decision. To overcome this limitation, *sparsemax* was recently proposed [31], using the Euclidean projection onto the simplex as a sparse alternative to

*Work performed during an internship at NTT Commmunication Science Laboratories, Kyoto, Japan.

31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

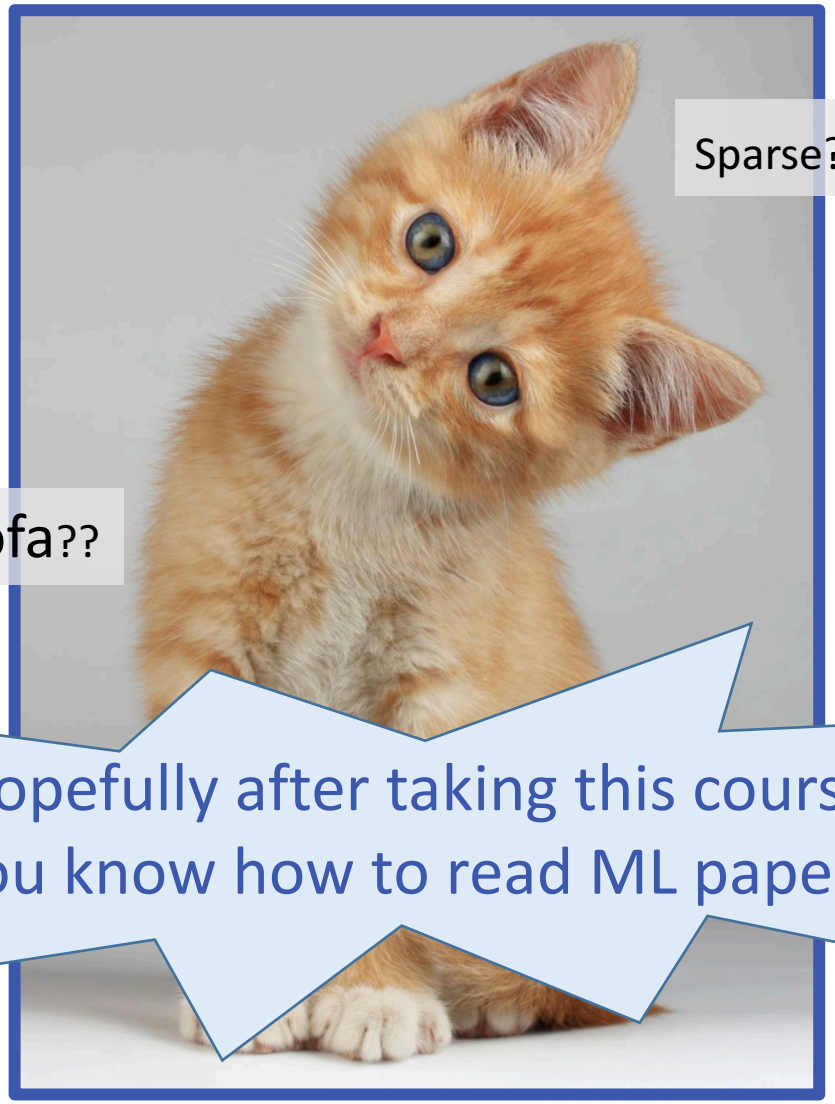
Modern neural networks ….. attention mechanism, … We propose in this paper a new framework for sparse and structured attention, building upon a smoothed max operator. We show that the gradient of this operator defines a mapping from real values to probabilities, suitable as an attention mechanism. Our framework includes softmax and a slight generalization of the recently-proposed sparsemax as special cases. ……

What it looks like to ML researchers



What it looks like to normal people

What it looks like to normal people



Sparse?? Spaghetti??

softmax?? Sofa??

Hopefully after taking this course
you know how to read ML papers

What does ML beginners may do

How to train an image classifier?

Deep Learning!

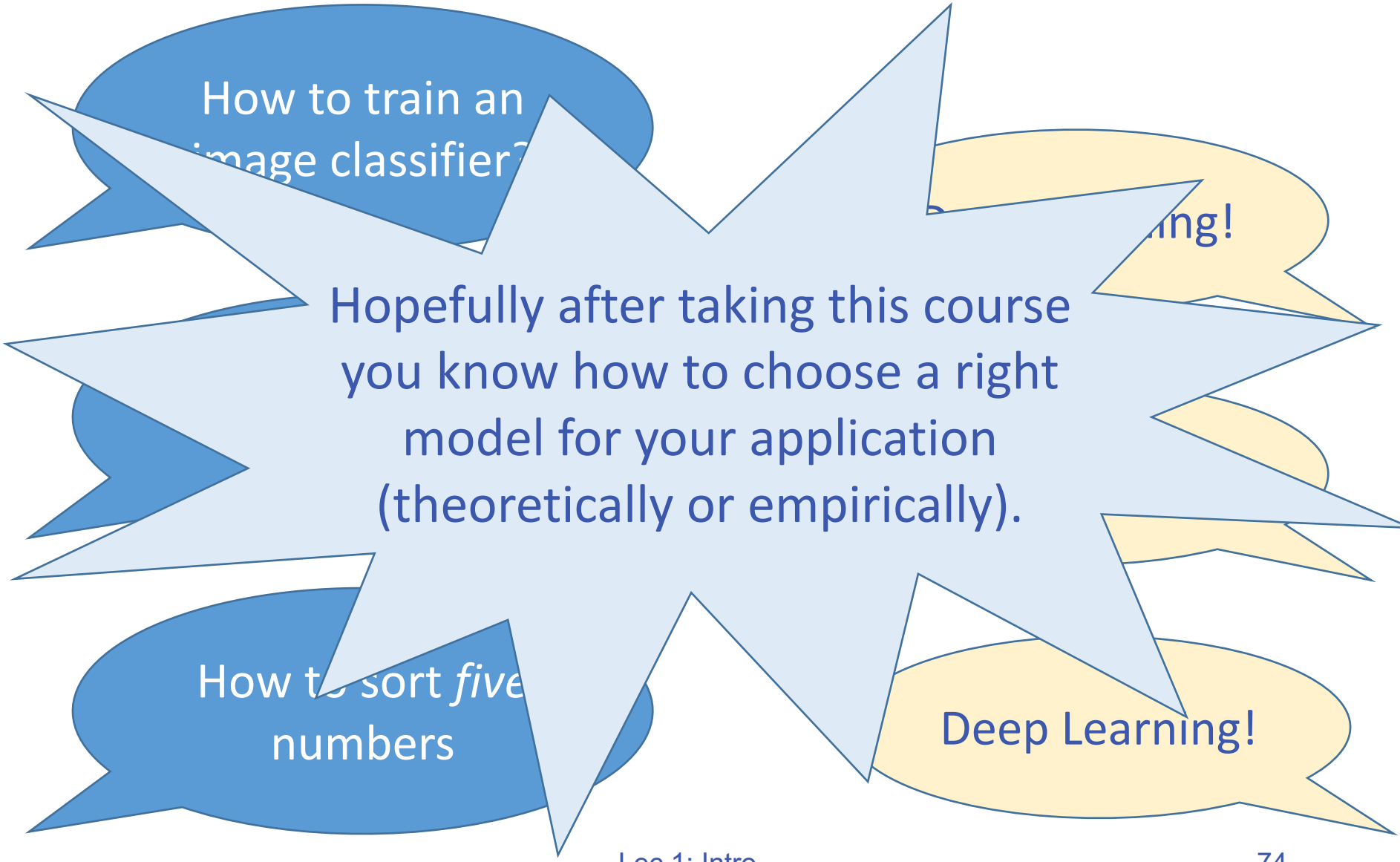
How to train a model on a small dataset

Deep Learning!

How to sort *five* numbers

Deep Learning!

What does ML beginners may do



What will we learn?

- Supervised learning
  - Decision tree, Perceptron, Linear models, support vector machines, kernel methods
  - Learning theory
- Unsupervised learning
  - Clustering, Hidden Markov Models
  - EM algorithms
- Practical Issues
  - Experimental evaluation; Implementing ML models