CS 4803 / 7643: Deep Learning

Website: https://www.cc.gatech.edu/classes/AY2020/cs7643_fall/

Piazza: https://piazza.com/gatech/fall2019/cs48037643

Canvas: https://gatech.instructure.com/courses/60374 (4803)
https://gatech.instructure.com/courses/60364 (7643)

Gradescope: https://www.gradescope.com/courses/56799 (4803)
https://www.gradescope.com/courses/53817 (7643)

Dhruv Batra

School of Interactive Computing
Georgia Tech

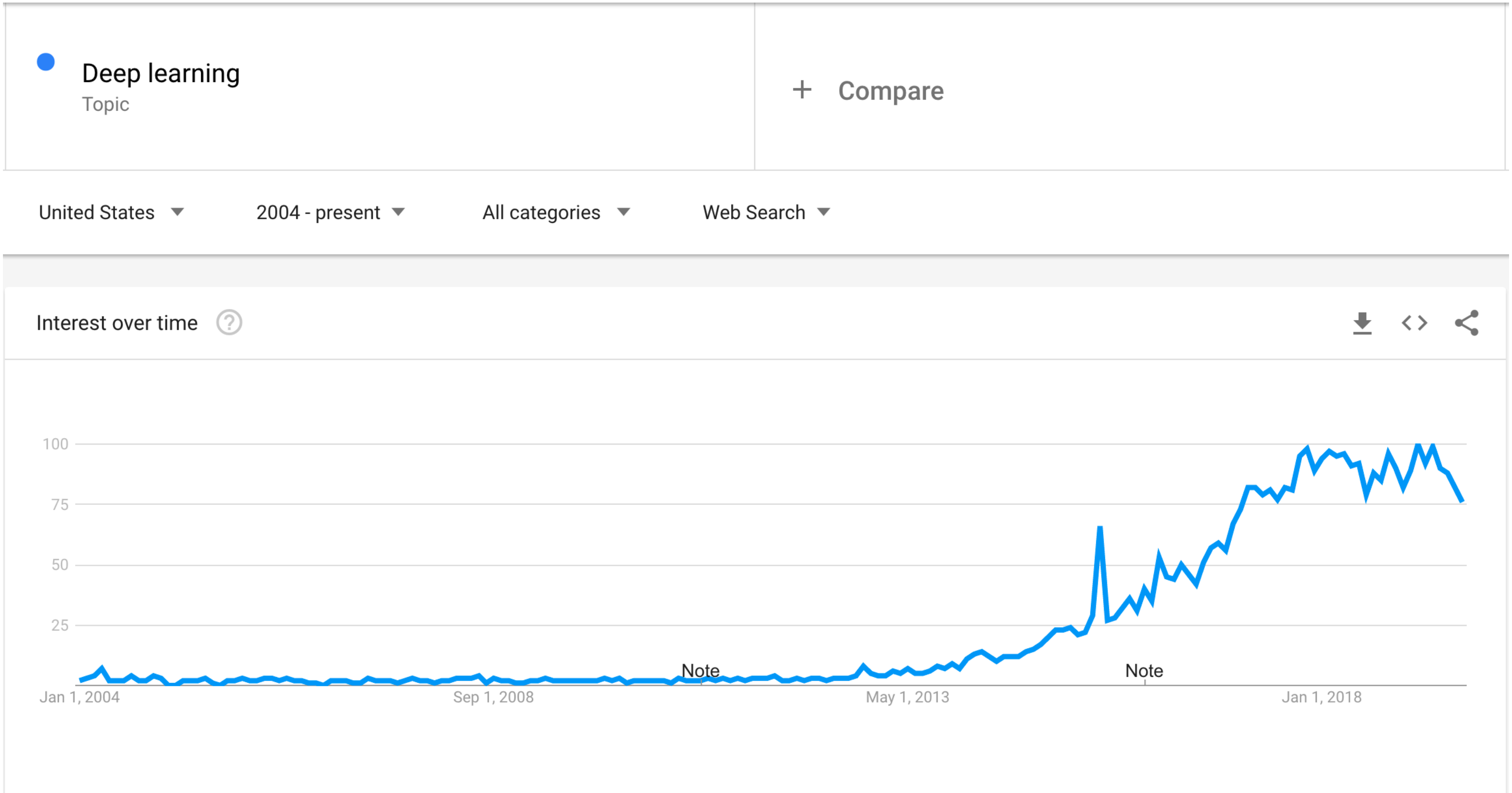
What are we here to discuss?

Some of the most exciting developments in

Machine Learning, Vision, NLP, Speech, Robotics & AI in general

in the last decade!

Proxy for public interest



AlphaGo seals 4-1 victory over Go grandmaster Lee Sedol

DeepMind's artificial intelligence astonishes fans to defeat human opponent and offers evidence computer software has mastered a major challenge

The world's top Go player, Lee Sedol, lost the final game of the Google DeepMind challenge match. Photograph: Yonhap/Reuters

Google DeepMind's AlphaGo program triumphed in its final game against South Korean Go grandmaster Lee Sedol to win the series 4-1, providing further evidence of the landmark achievement for an artificial intelligence program.

Outline

- What is Deep Learning, the field, about?
  - Highlight of some recent projects from my lab

- What is this class about?
  - What to expect?
  - Logistics

- FAQ

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Demo time

vqa.cloudcv.org.

demo.visualdialog.org

Concepts

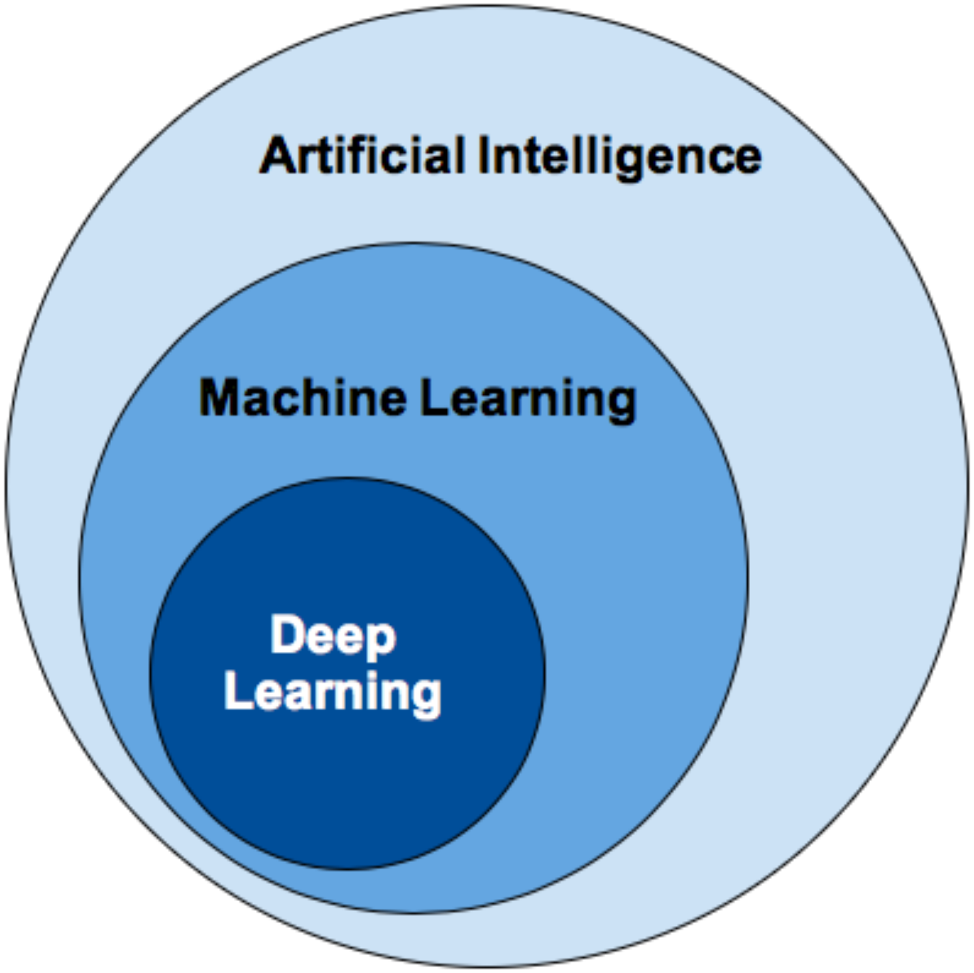


Image Credit: https://www.sumologic.com/blog/machine-learning-deep-learning/

What is (general) intelligence?

- Boring textbook answer

  The ability to acquire and apply knowledge and skills
  - Dictionary

- My favorite

  The ability to navigate in problem space
  - Siddhartha Mukherjee, Columbia

What is artificial intelligence?

- Boring textbook answer

Intelligence demonstrated by machines

  – Wikipedia

- My favorite

The science and engineering of making computers behave in ways that, until recently, we thought required human intelligence.

  – Andrew Moore, CMU

What is machine learning?

- My favorite

  Study of algorithms that

  improve their performance (P)

  at some task (T)

  with experience (E)

  - Tom Mitchell, CMU

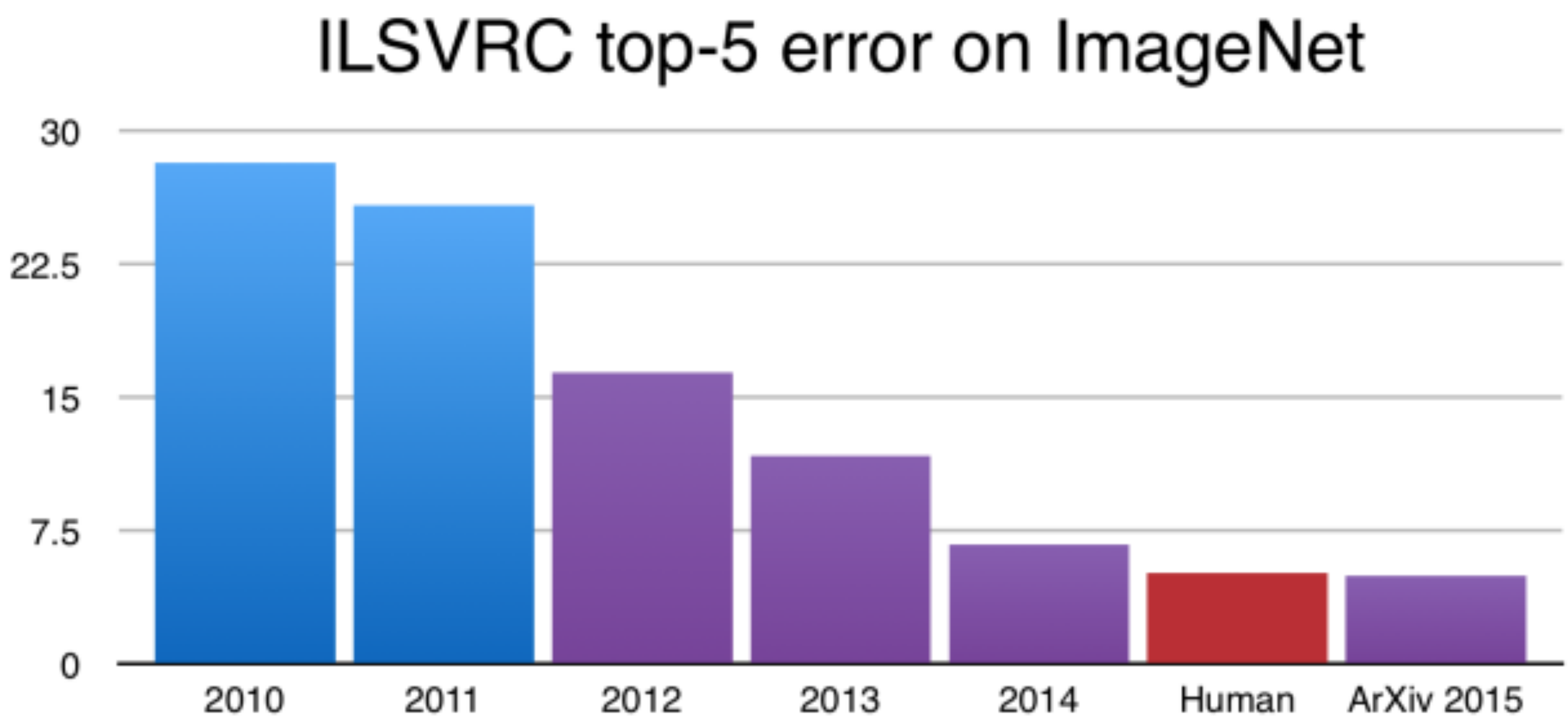
Image Classification

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

1000 object classes **1.4M/50k/100k images**

http://image-net.org/challenges/LSVRC/{2010,…,2015}

Image Classification

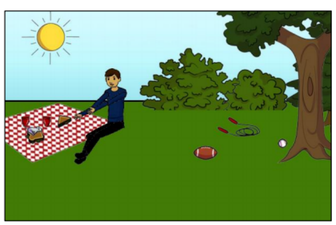


Tasks are getting bolder

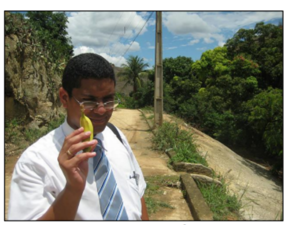
A group of young people playing a game of Frisbee
Vinyals et al., 2015

What color are her eyes?
What is the mustache made of?

How many slices of pizza are there?
Is this a vegetarian pizza?



Is this person expecting company?
What is just under the tree?



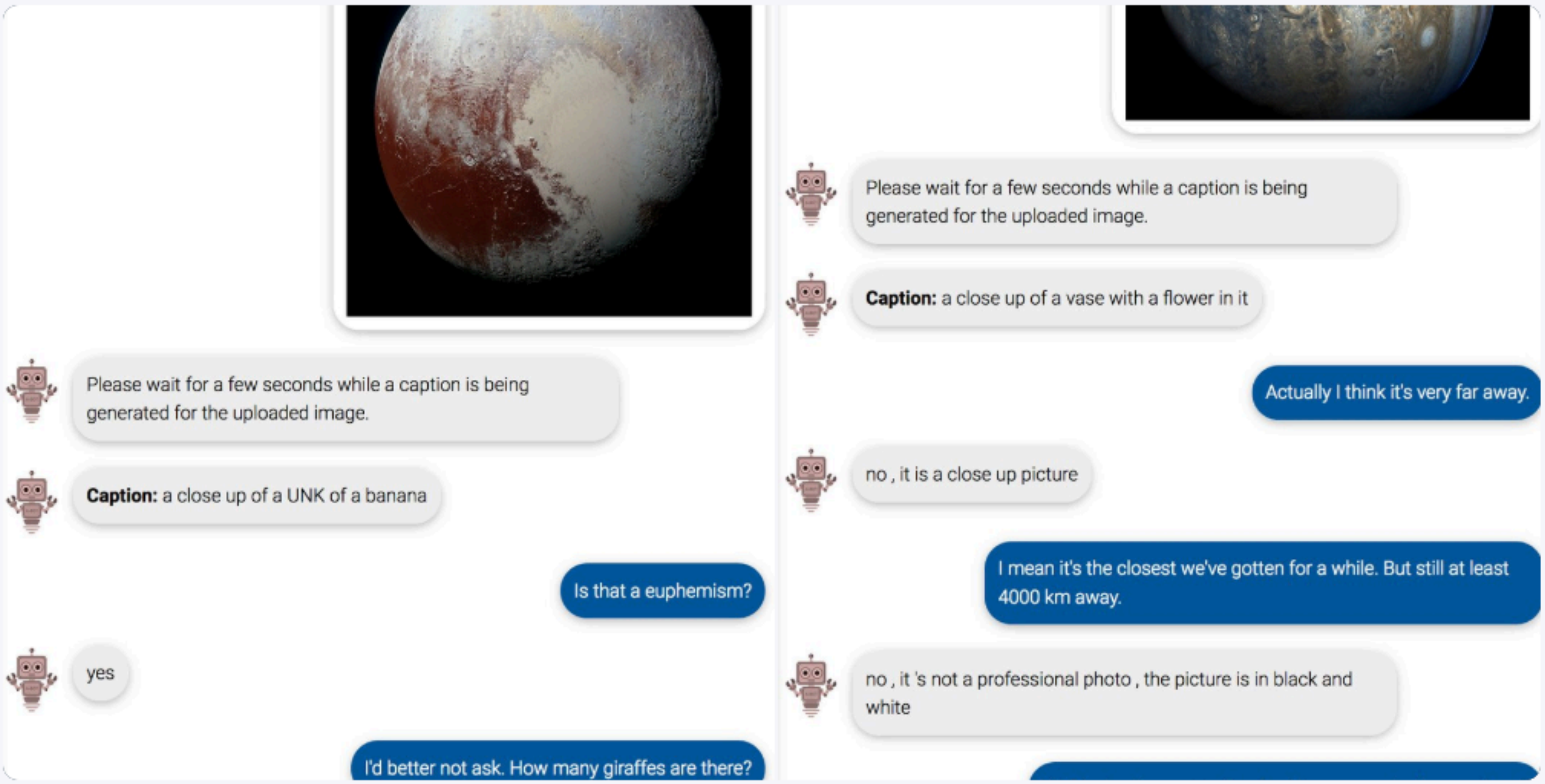
Does it appear to be rainy?
Does this person have 20/20 vision?

Antol et al., 2015

Das et al., 2017

Janelle Shane @JanelleCShane · Jun 24

One fun thing I discovered about Visual Chatbot.
It learned from answers that humans gave, and apparently nobody ever asked "how many giraffes are there?" when the answer was zero.
demo.visualdialog.org



24 159 515

Embodied Question Answering

[CVPR ’18]

Abhishek Das
(Georgia Tech)

Samyak Datta
(Georgia Tech)

Georgia Gkioxari
(FAIR)

Stefan Lee
(Georgia Tech)

Devi Parikh
(Georgia Tech / FAIR)

Dhruv Batra
(Georgia Tech / FAIR)


What is to the left of the shower?
Cabinet
M
M-BOT

PACMAN-RL

PACMAN-RL

So what *is* Deep (Machine) Learning?

- Representation Learning
- Neural Networks
- Deep Unsupervised/Reinforcement/Structured/
  <insert-qualifier-here>
  Learning
- Simply: Deep Learning

So what *is* Deep (Machine) Learning?

- A few different ideas:

- (Hierarchical) Compositionality
  - Cascade of non-linear transformations
  - Multiple layers of representations

- End-to-End Learning
  - Learning (goal-driven) representations
  - Learning to feature extraction

- Distributed Representations
  - No single neuron "encodes" everything
  - Groups of neurons work together

Traditional Machine Learning

VISION

hand-crafted features
SIFT/HOG

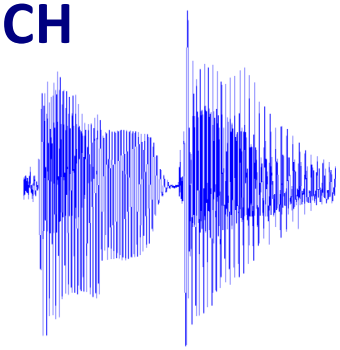
fixed

your favorite classifier

learned

"car"

SPEECH



hand-crafted features
MFCC

fixed

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learned

\ˈd ē p\

NLP

This burrito place
is yummy and fun!

hand-crafted features
Bag-of-words

fixed

your favorite classifier

learned

"+"

Slide Credit: Marc'Aurelio Ranzato, Yann LeCun

Hierarchical Compositionality

VISION

pixels → edge → texton → motif → part → object

SPEECH

sample → spectral band → formant → motif → phone → word

NLP

character → word → NP/VP/.. → clause → sentence → story

Building A Complicated Function

Given a library of simple functions

$\sin(x)$

$\log(x)$

$\cos(x)$

x^3

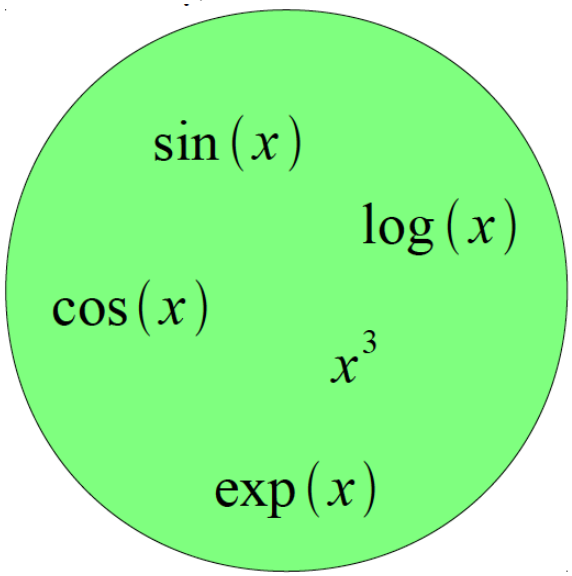
$\exp(x)$

Compose into a

complicate function

Building A Complicated Function

Given a library of simple functions



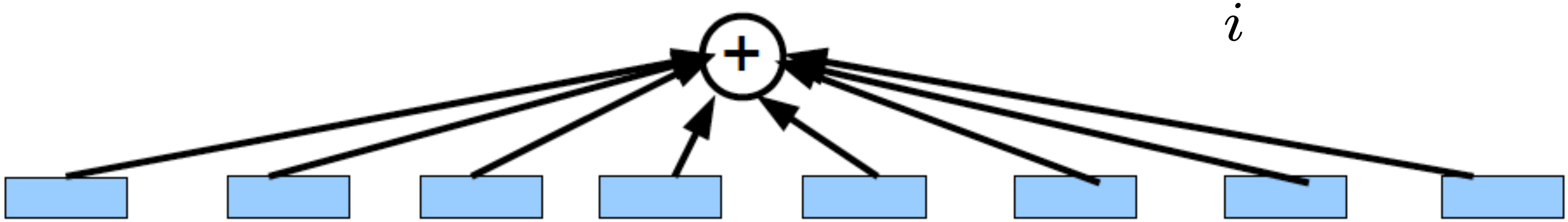
Compose into a

complicate function

Idea 1: Linear Combinations

- Boosting
- Kernels
- …

$$f(x) = \sum_i \alpha_i g_i(x)$$



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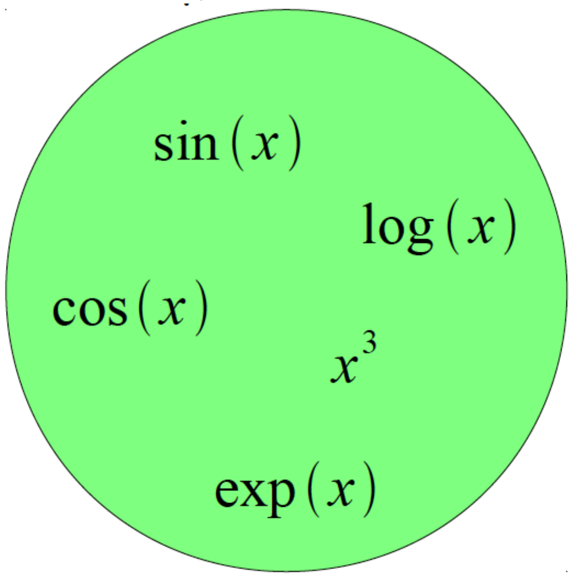


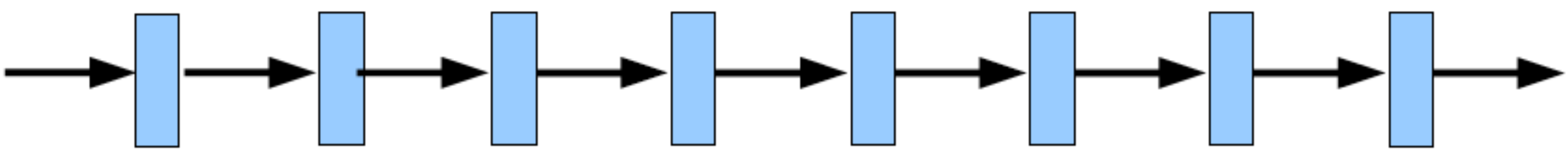
Compose into a

complicate function

Idea 2: Compositions

- Deep Learning
- Grammar models
- Scattering transforms…

$$f(x) = g_1(g_2(\ldots(g_n(x)\ldots))$$



Slide Credit: Marc'Aurelio Ranzato, Yann LeCun

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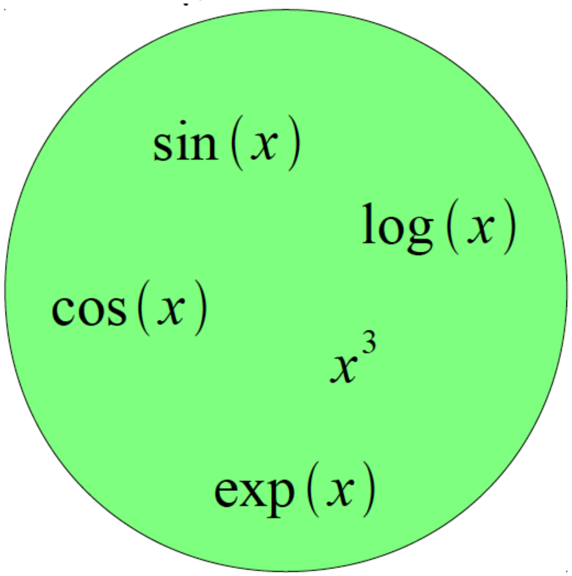

Compose into a

complicate function

Idea 2: Compositions

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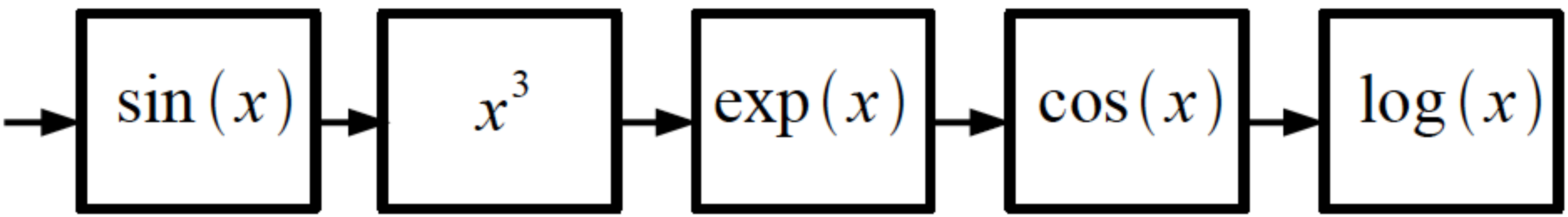
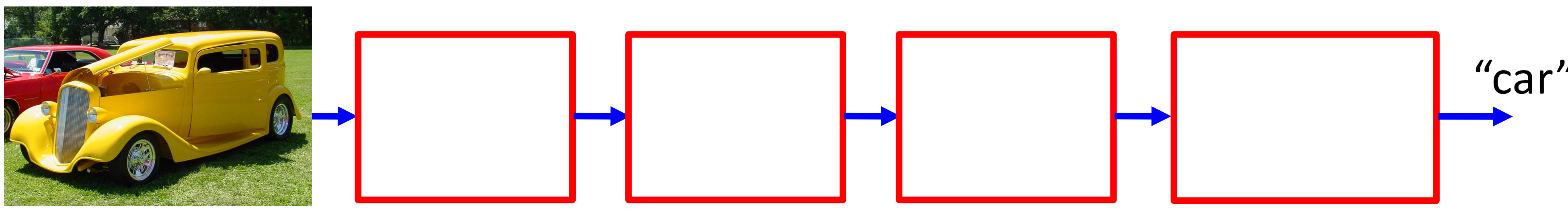
- Scattering transforms…

$$f(x) = \log(\cos(\exp(\sin^3(x))))$$



Deep Learning = Hierarchical Compositionality



Slide Credit: Marc'Aurelio Ranzato, Yann LeCun

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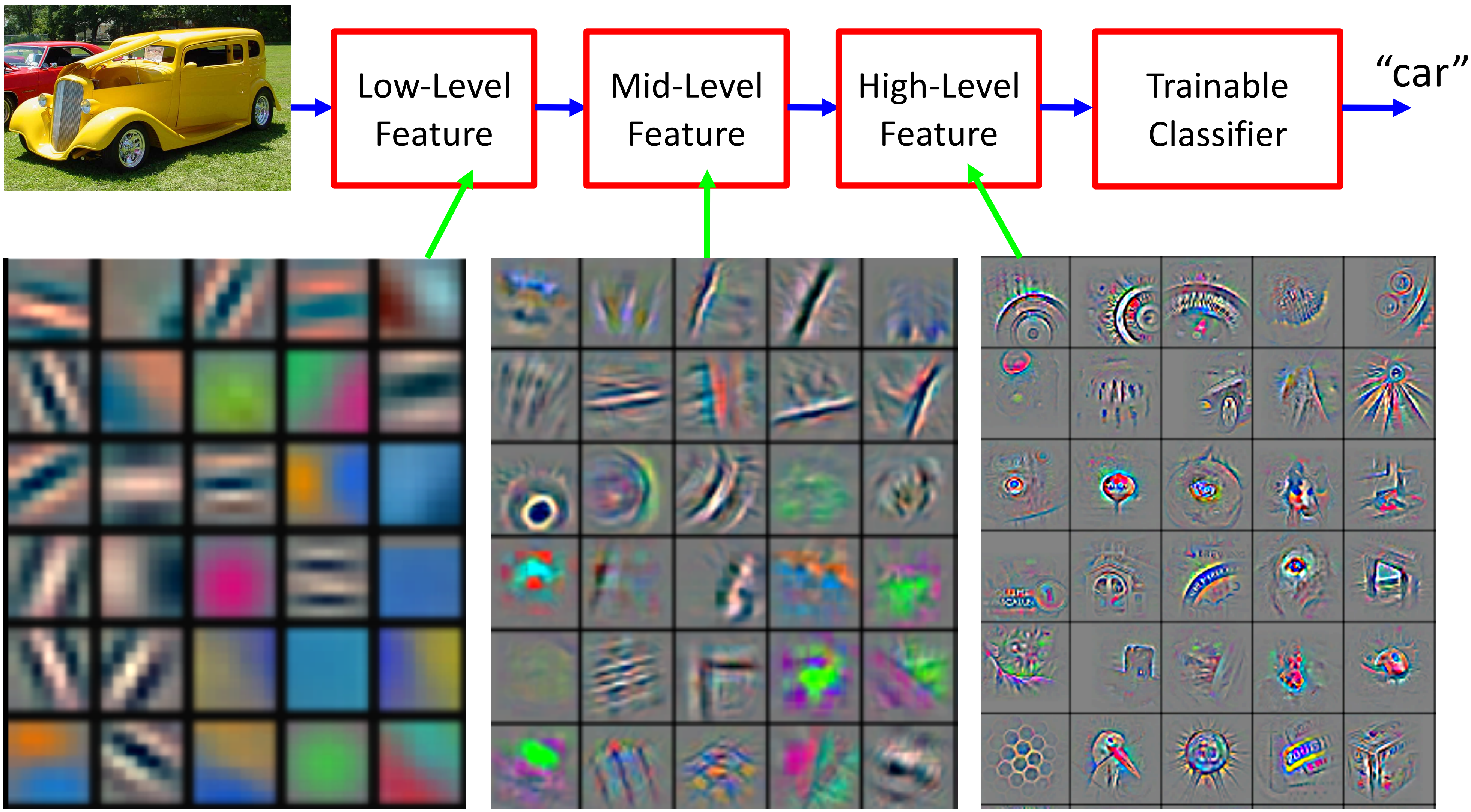

Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Slide Credit: Marc'Aurelio Ranzato, Yann LeCun

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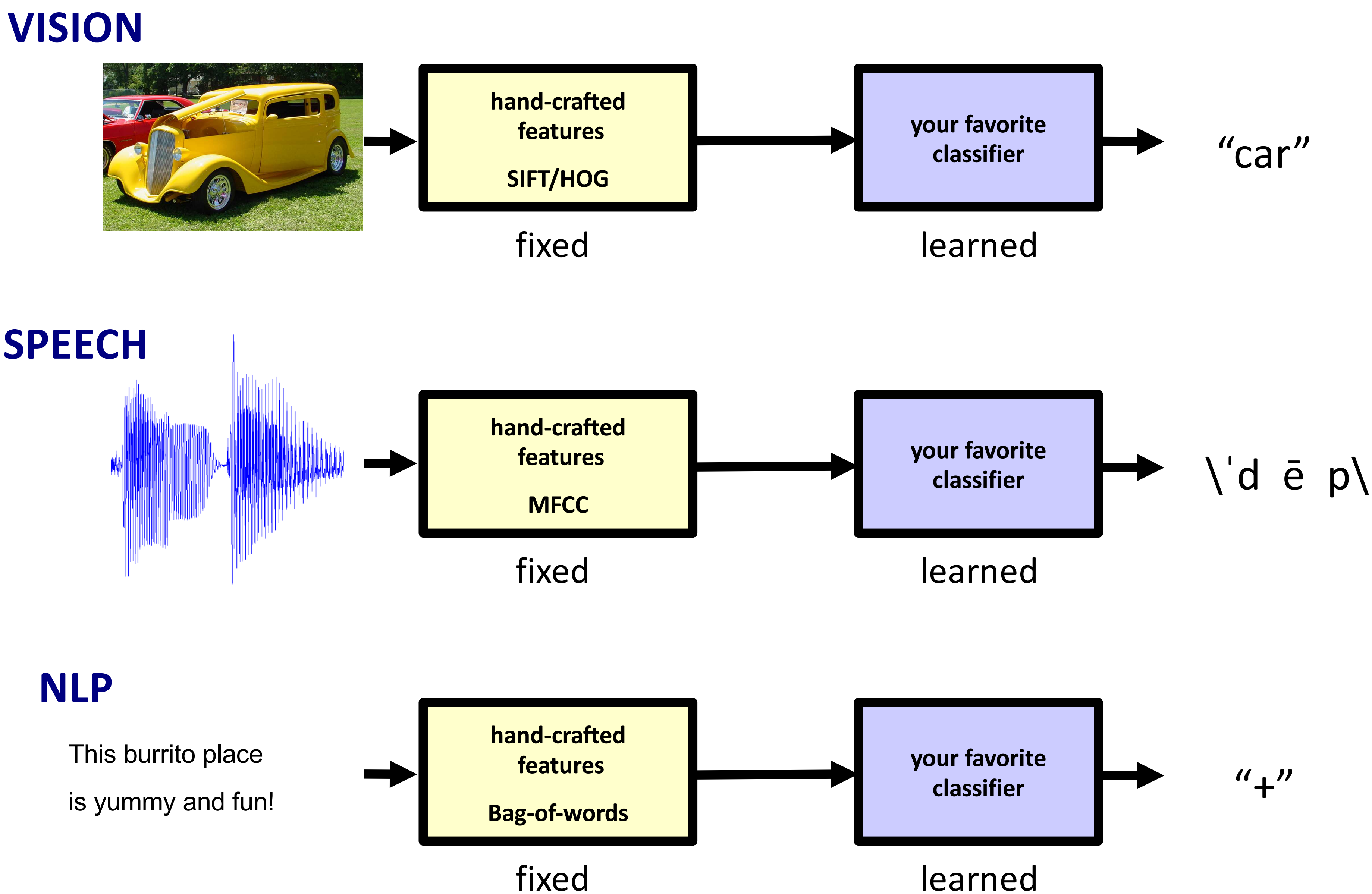
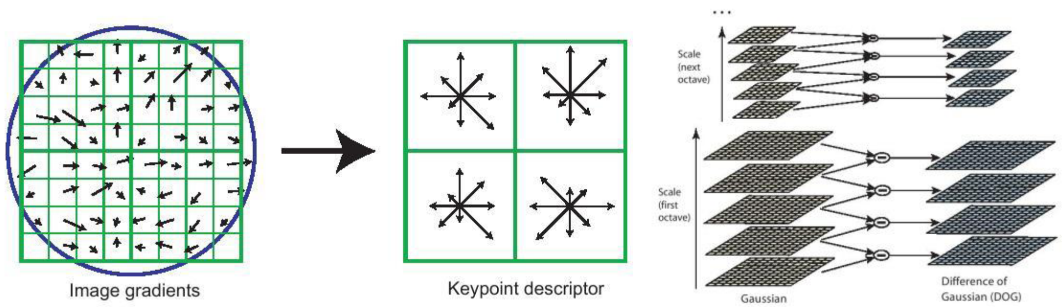
Traditional Machine Learning

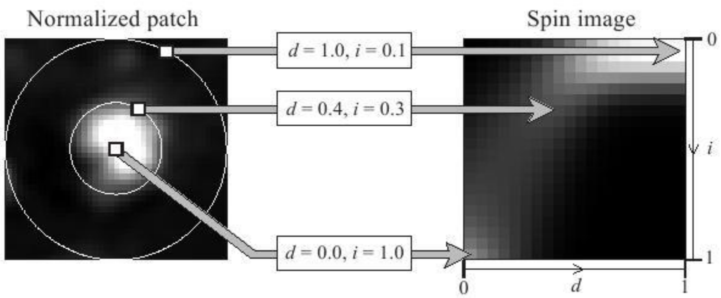


Slide Credit: Marc'Aurelio Ranzato, Yann LeCun

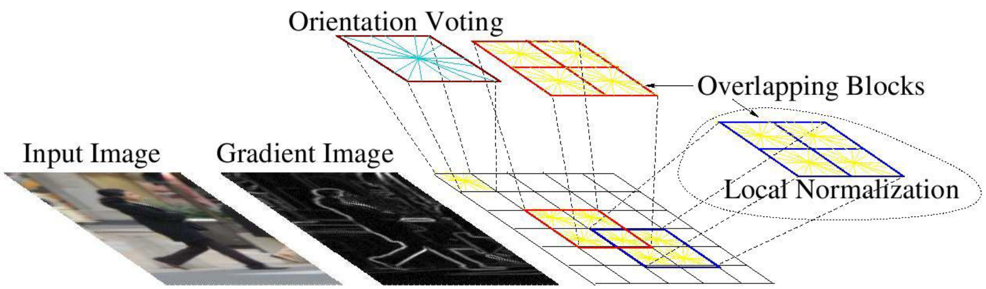
Feature Engineering



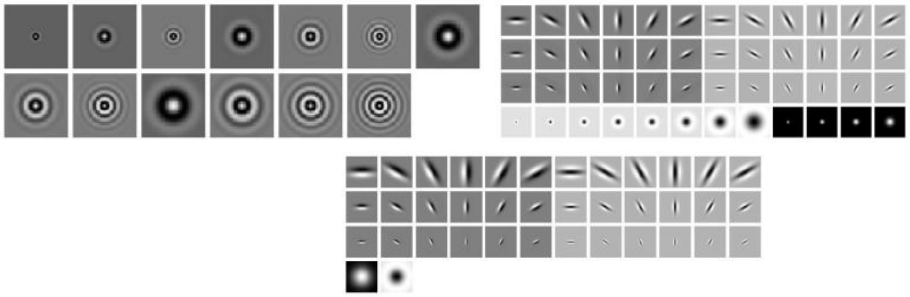
SIFT



Spin Images



HoG



Textons

and many many more….

Traditional Machine Learning (more accurately)

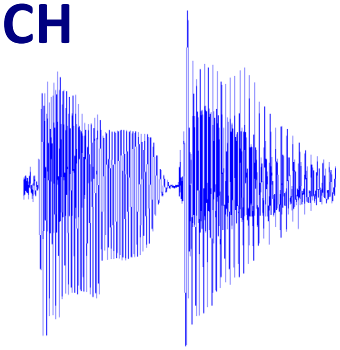
"Learned"

VISION

SIFT/HOG → K-Means/ pooling → classifier → "car"

fixed | unsupervised | supervised

SPEECH



MFCC → Mixture of Gaussians → classifier → \ˈd ē p\

fixed | unsupervised | supervised

NLP

This burrito place is yummy and fun!

Parse Tree Syntactic → n-grams → classifier → "+"

fixed | unsupervised | supervised

Deep Learning = End-to-End Learning

"Learned"

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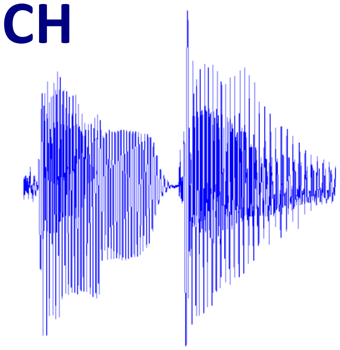
SPEECH



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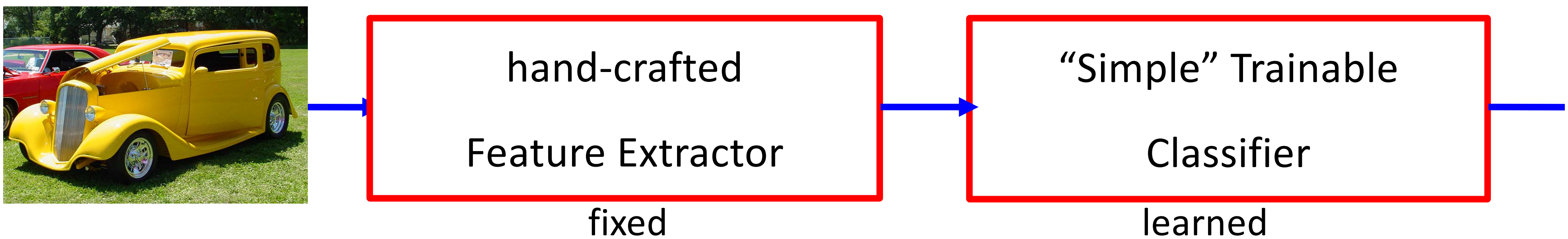
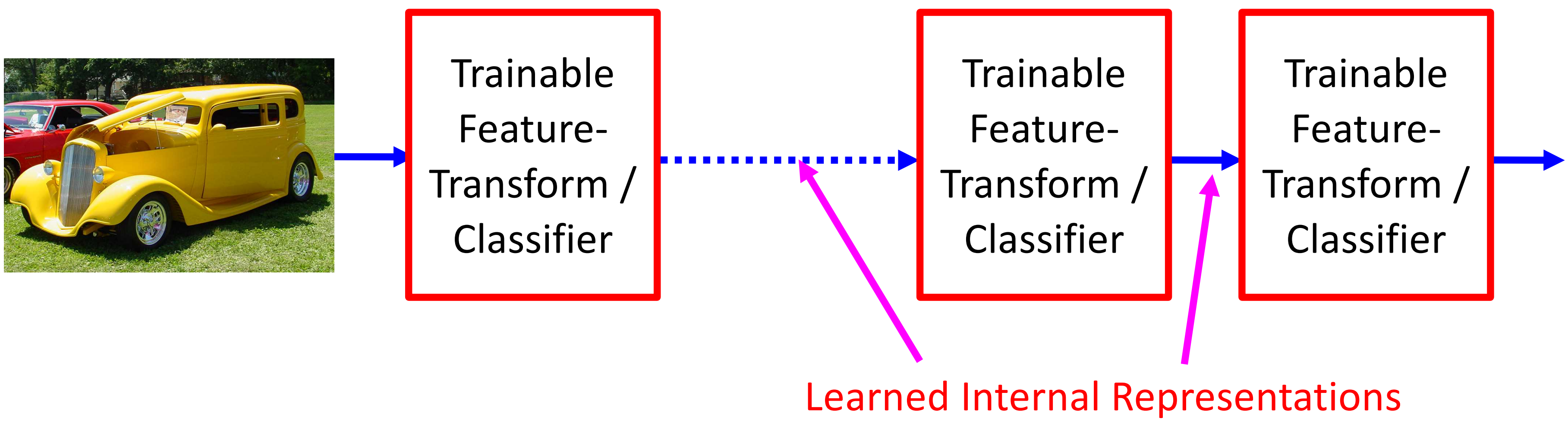
“Shallow” vs Deep Learning

- “Shallow” models



- Deep models



Slide Credit: Marc'Aurelio Ranzato, Yann LeCun

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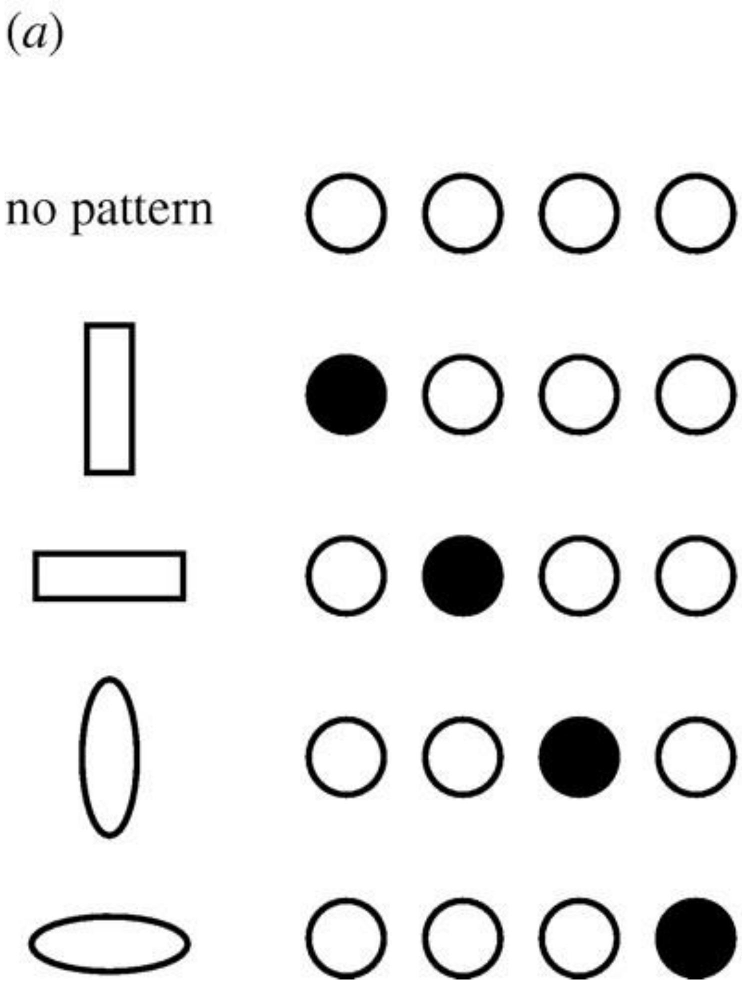
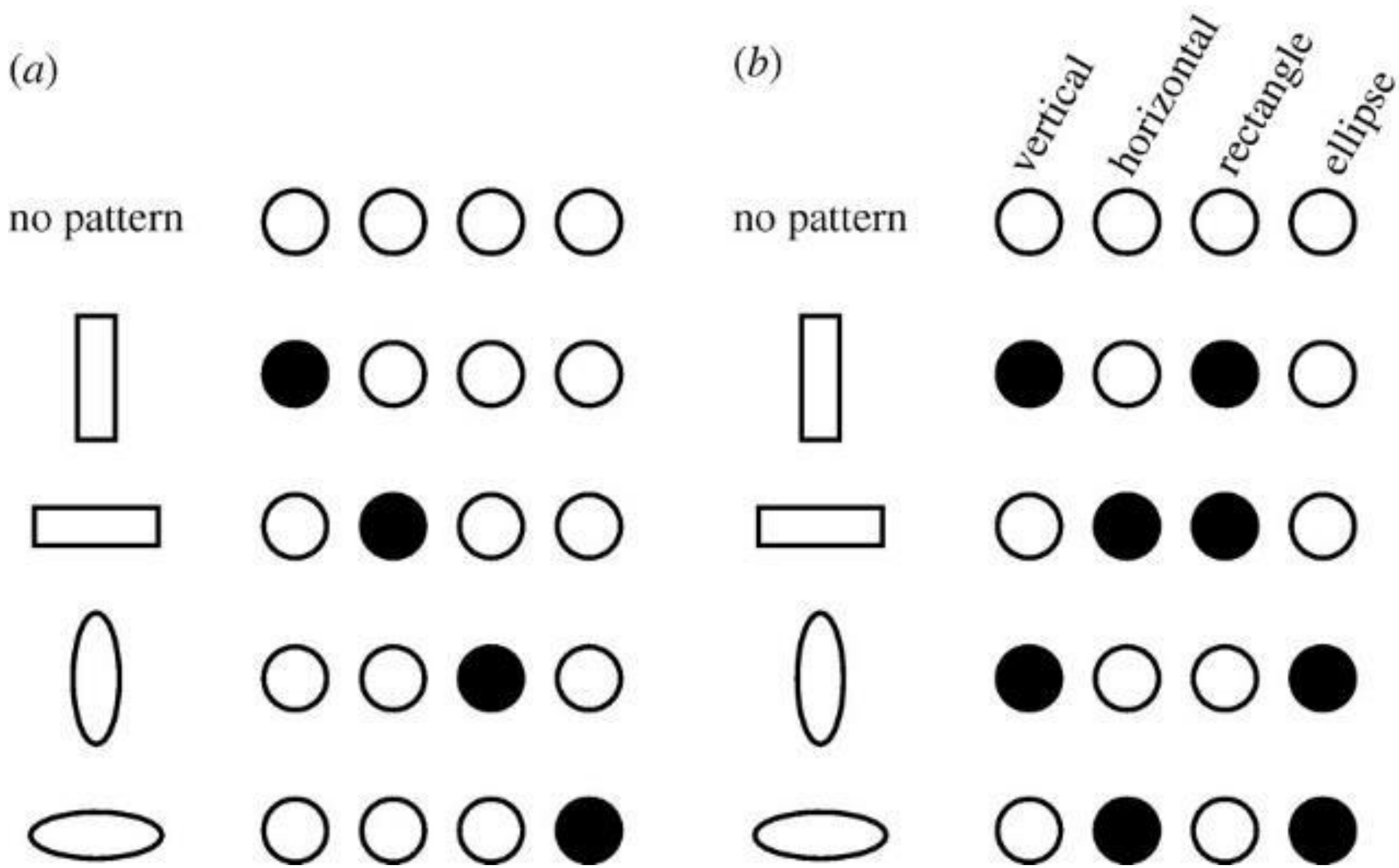
Distributed Representations Toy Example

- Local vs Distributed



Distributed Representations Toy Example

- Can we interpret each dimension?



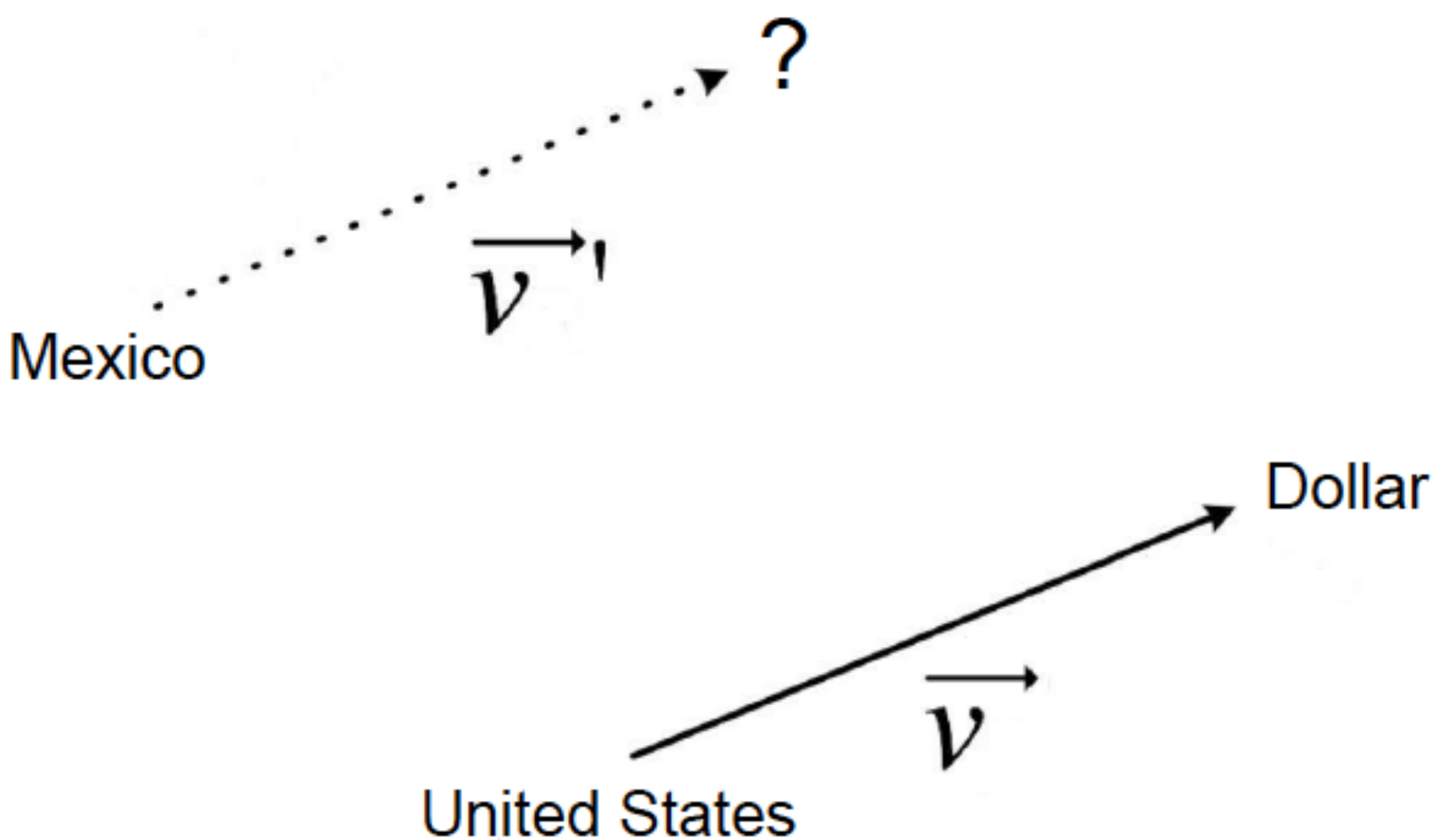
Power of distributed representations!

Local ● ● ○ ● = VR + HR + HE = ?

Distributed ● ● ○ ● = V + H + E ≈ ○

Power of distributed representations!

- United States:Dollar :: Mexico:?



ThisPlusThat.me

Image Credit: http://insightdatascience.com/blog/thisplusthat_a_search_engine_that_lets_you_add_words_as_vectors.html

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Benefits of Deep/Representation Learning

- (Usually) Better Performance
  - *"Because gradient descent is better than you"*
    Yann LeCun

- New domains without "experts"
  - RGBD/Lidar
  - Multi-spectral data
  - Gene-expression data
  - Unclear how to hand-engineer

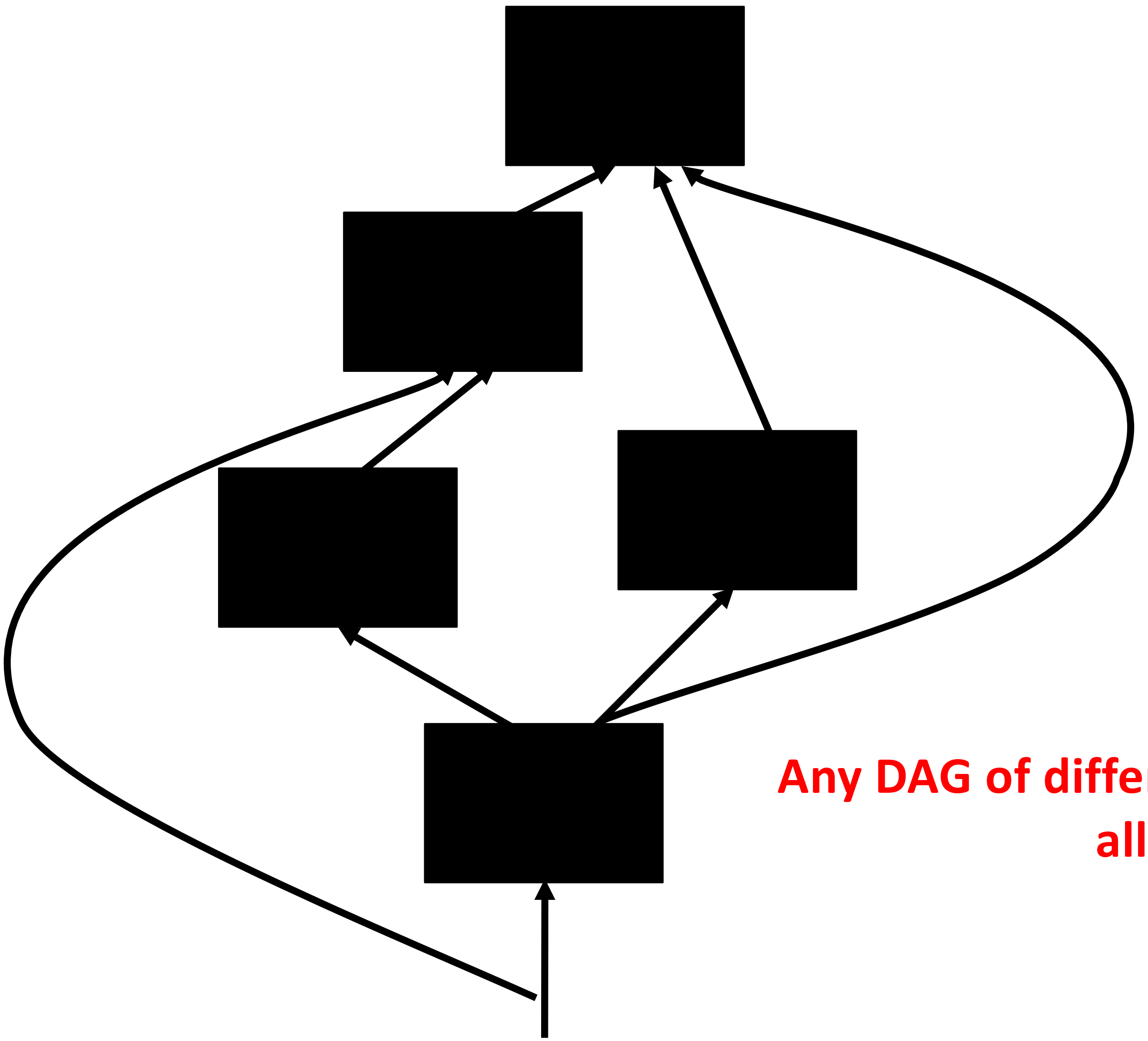
“Expert” intuitions can be misleading

- *“Every time I fire a linguist, the performance of our speech recognition system goes up”*
  – Fred Jelinik, IBM ’98

Benefits of Deep/Representation Learning

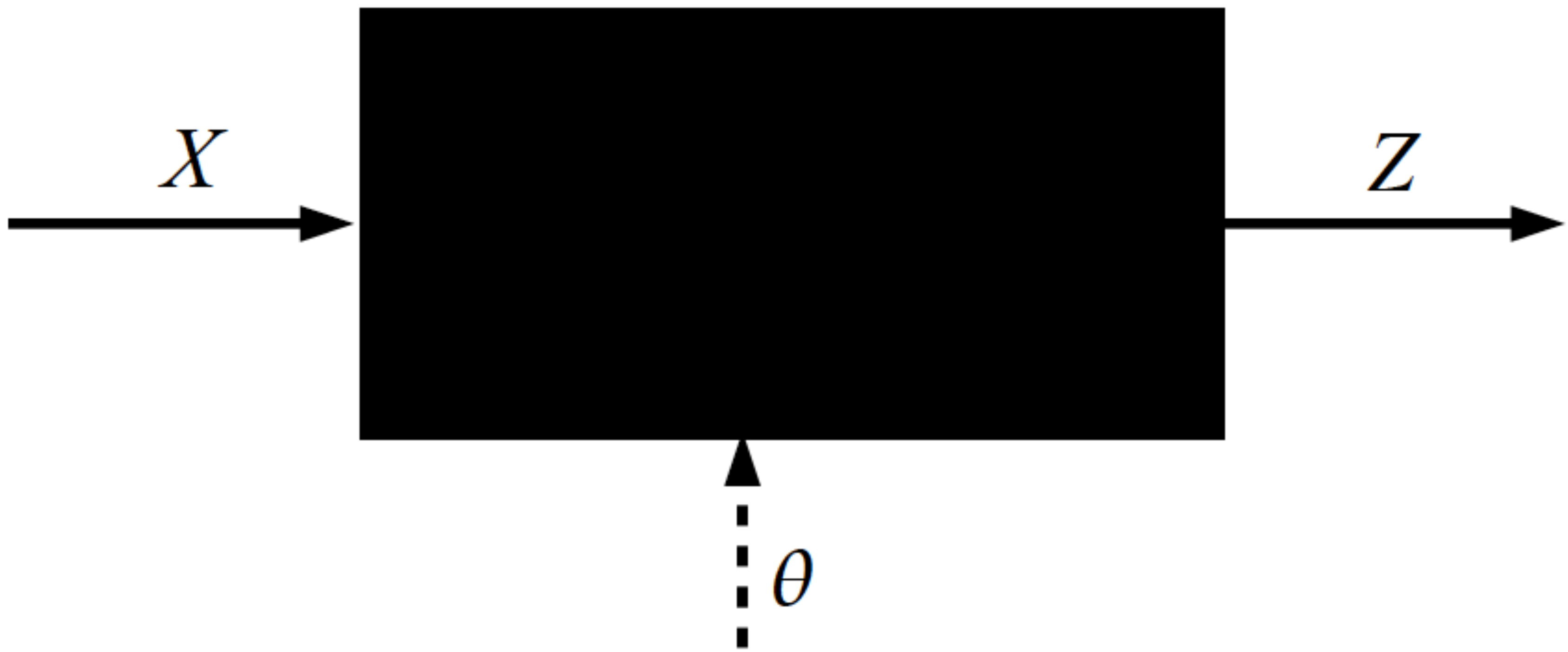
- Modularity!
- Plug and play architectures!

Differentiable Computation Graph

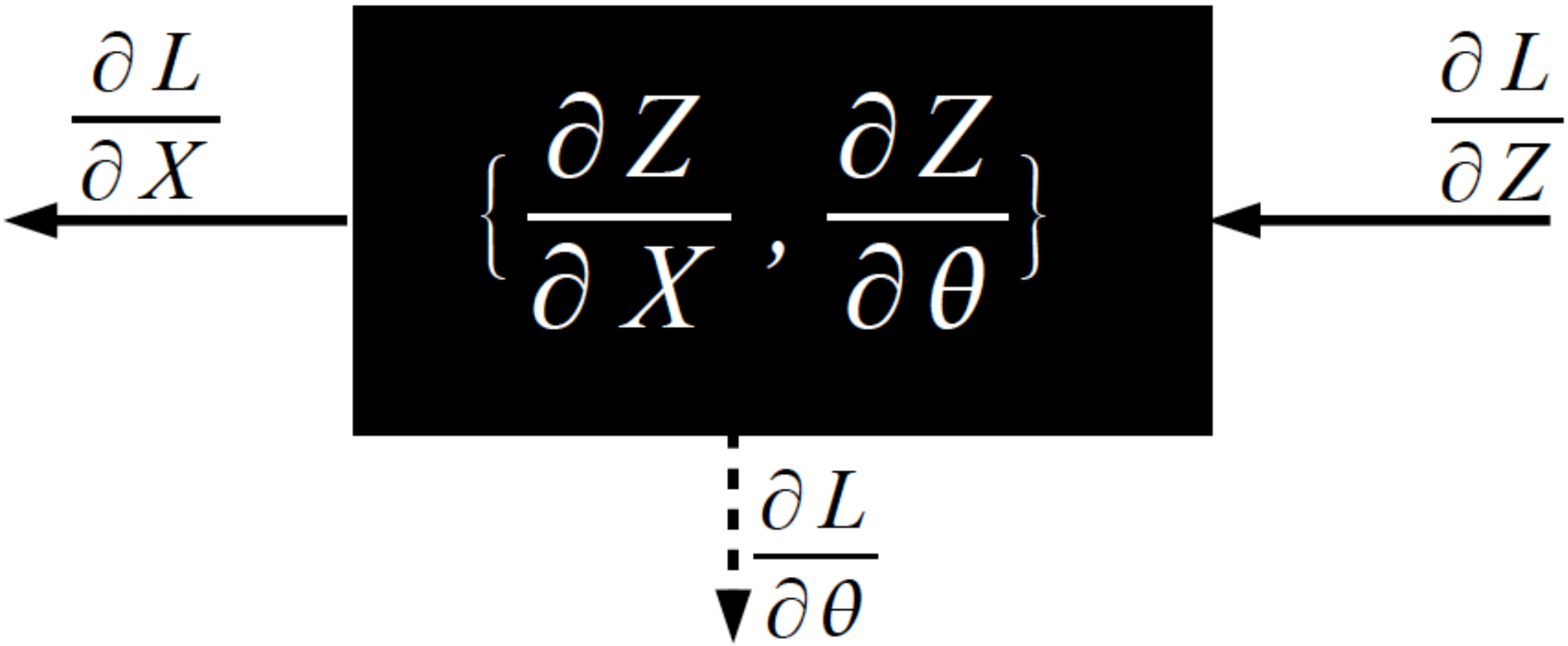


Any DAG of differentialble modules is allowed!

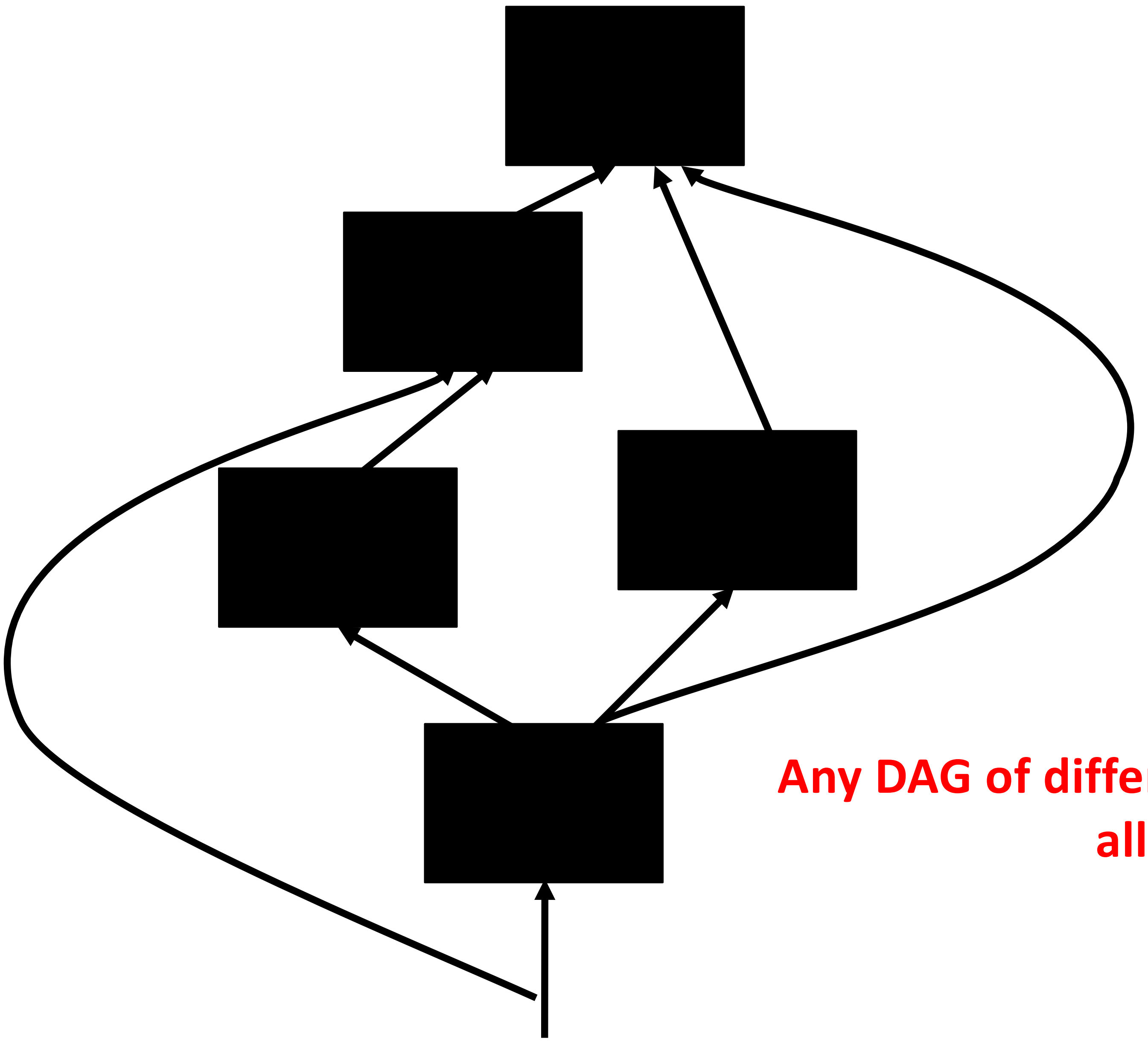
Key Computation: Forward-Prop



Key Computation: Back-Prop



Differentiable Computation Graph



Any DAG of differentialble modules is allowed!

Slide Credit: Marc'Aurelio Ranzato

Problems with Deep Learning

- Problem#1: Non-Convex! Non-Convex! Non-Convex!
  - Depth>=3: most losses non-convex in parameters
  - Theoretically, all bets are off
  - Leads to stochasticity
    - different initializations → different local minima

- Standard response #1
  - "Yes, but all interesting learning problems are non-convex"
  - For example, human learning
    - Order matters → wave hands → non-convexity

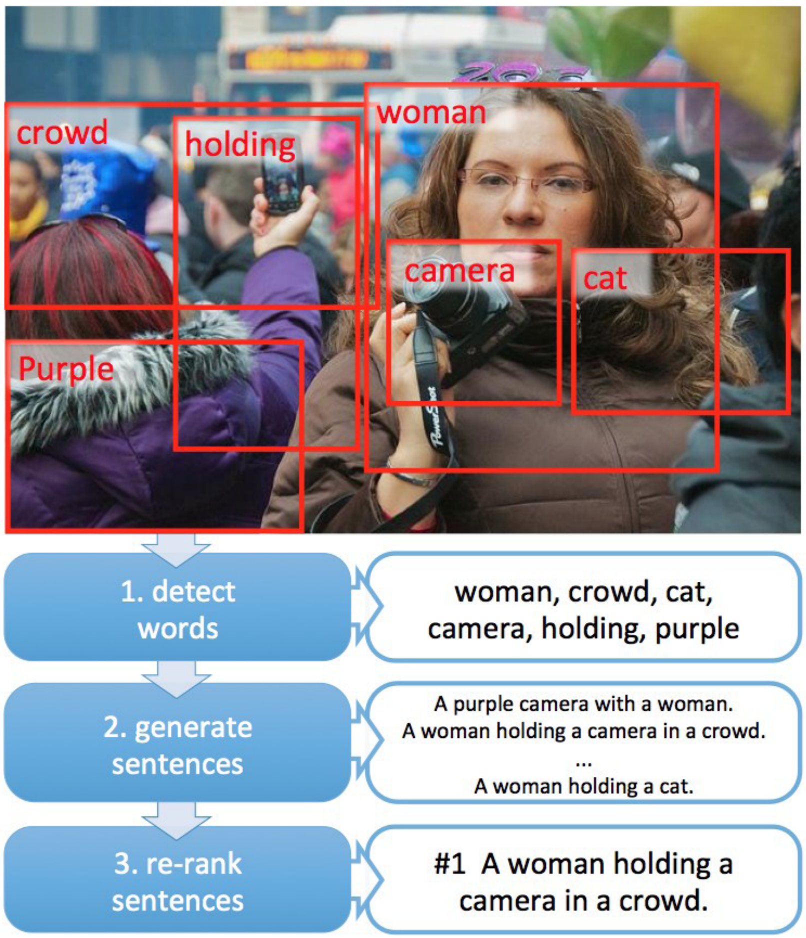
- Standard response #2
  - "Yes, but it often works!"

Problems with Deep Learning

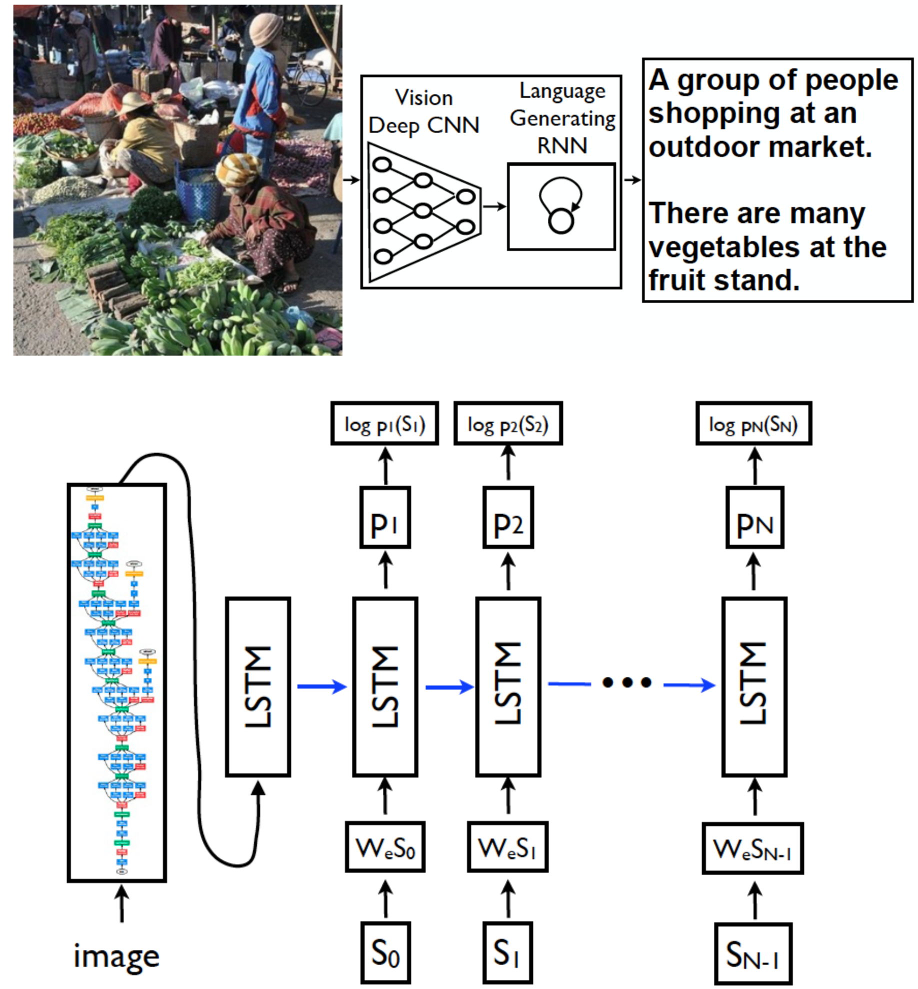
- Problem#2: Lack of interpretability
  - Hard to track down what's failing
  - Pipeline systems have "oracle" performances at each step
  - In end-to-end systems, it's hard to know why things are not working

Problems with Deep Learning

- Problem#2: Lack of interpretability



[Fang et al. CVPR15]



[Vinyals et al. CVPR15]

Pipeline

End-to-End

Problems with Deep Learning

- Problem#2: Lack of interpretability
  - Hard to track down what's failing
  - Pipeline systems have "oracle" performances at each step
  - In end-to-end systems, it's hard to know why things are not working

- Standard response #1
  - Tricks of the trade: visualize features, add losses at different layers, pre-train to avoid degenerate initializations…
  - "We're working on it"

- Standard response #2
  - "Yes, but it often works!"

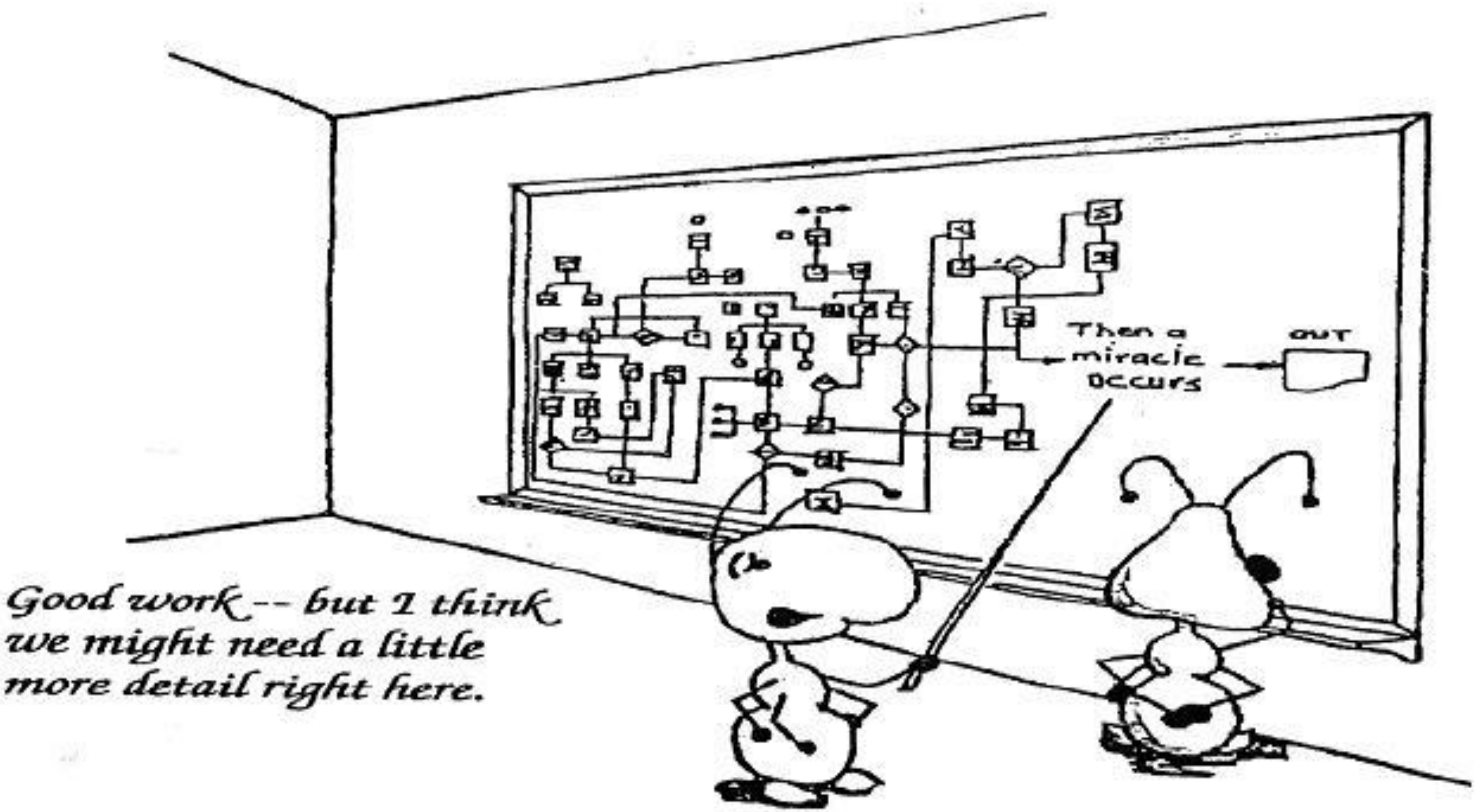
Problems with Deep Learning

- Problem#3: Lack of easy reproducibility
  – Direct consequence of stochasticity & non-convexity

- Standard response #1
  – It's getting much better
  – Standard toolkits/libraries/frameworks now available
  – PyTorch, TensorFlow, MxNet…

- Standard response #2
  – "Yes, but it often works!"

Yes it works, but how?



Outline

- What is Deep Learning, the field, about?
  - Highlight of some recent projects from my lab
- What is this class about?
  - What to expect?
  - Logistics
- FAQ

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What is this class about?

What was F17 DL class about?

- Firehose of arxiv

Arxiv Fire Hose

PhD Student

Deep Learning papers

Cornell University Library
arXiv.org

What was F17 DL class about?

- Goal:
  - After taking this class, you should be able to pick up the latest Arxiv paper, easily understand it, & implement it.

- Target Audience:
  - Junior/Senior PhD students who want to *conduct research and publish in Deep Learning.*

    (think ICLR/CVPR papers as outcomes)

What is the F19 DL class about?

- Introduction to Deep Learning

- Goal:
  - After finishing this class, you should be ready to get started on your first DL research project.
    - CNNs
    - RNNs
    - Deep Reinforcement Learning
    - Generative Models (VAEs, GANs)

- Target Audience:
  - Senior undergrads, MS-ML, and new PhD students

What this class is NOT

- NOT the target audience:
  - Advanced grad-students already working in ML/DL areas
  - People looking to understand latest and greatest cutting-edge research (e.g. GANs, AlphaGo, etc)
  - Undergraduate/Masters students looking to graduate with a DL class on their resume.
- NOT the goal:
  - Teaching a toolkit. “Intro to TensorFlow/PyTorch”
  - Intro to Machine Learning

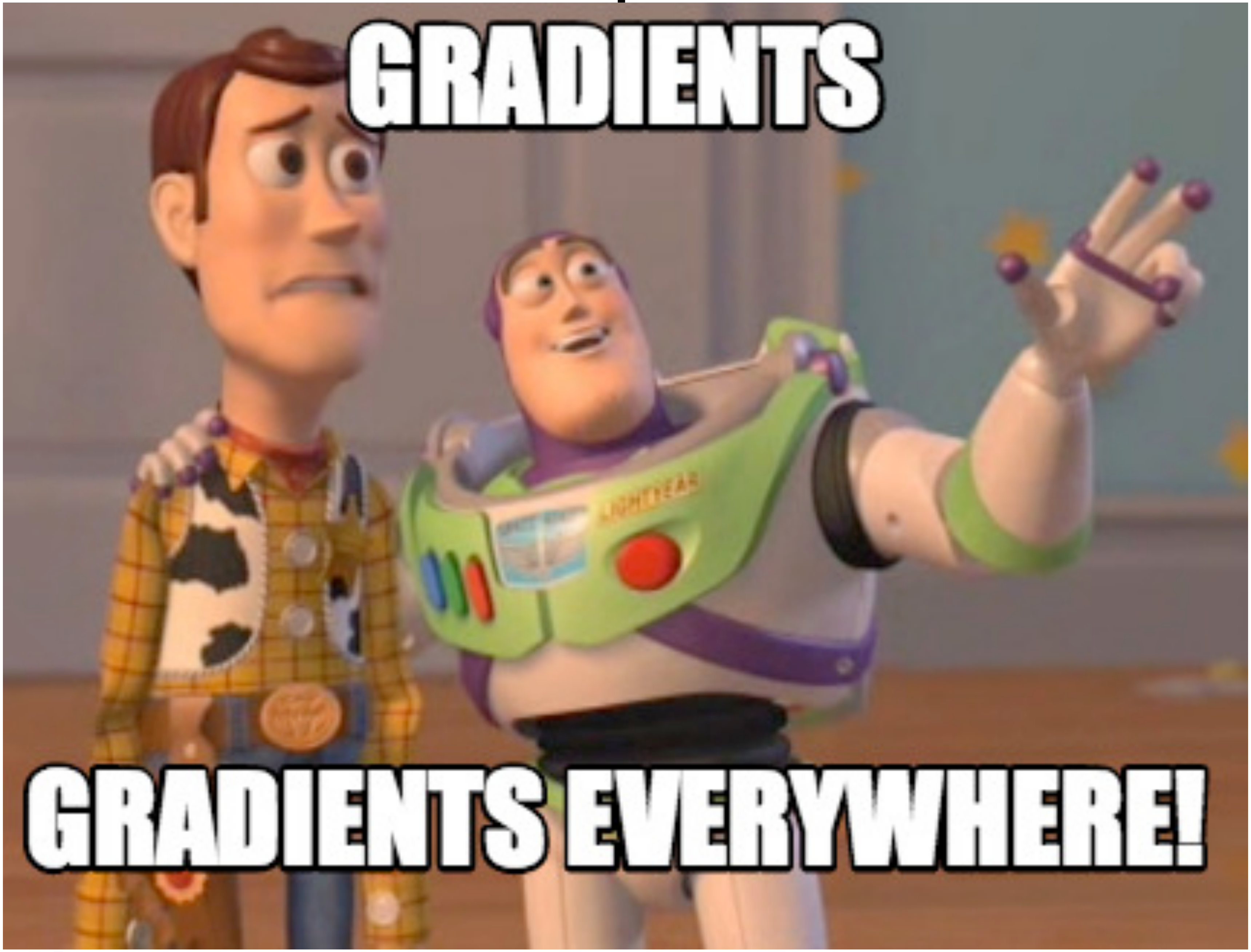
Caveat

- This is an ADVANCED Machine Learning class
  - This should NOT be your first introduction to ML
  - You will need a formal class; not just self-reading/coursera
  - If you took CS 7641/ISYE 6740/CSE 6740 @GT, you're in the right place
  - If you took an equivalent class elsewhere, see list of topics taught in CS 7641 to be sure.

Prerequisites

- Intro Machine Learning
  - Classifiers, regressors, loss functions, MLE, MAP
- Linear Algebra
  - Matrix multiplication, eigenvalues, positive semi-definiteness…
- Calculus
  - Multi-variate gradients, hessians, jacobians…

Prerequisites



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- Linear Algebra
  - Matrix multiplication, eigenvalues, positive semi-definiteness…
- Calculus
  - Multi-variate gradients, hessians, jacobians…
- Programming!
  - Homeworks will require Python!
  - Libraries/Frameworks: PyTorch
  - HW0+4 (pure python), HW1 (python + PyTorch), HW2+3 (PyTorch)
  - Your language of choice for project

Course Information

- Instructor: Dhruv Batra
  - dbatra@gatech
  - Location: 219 CCB

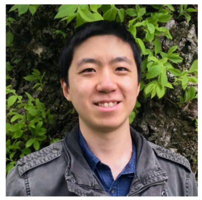
My Research Group + Collaborators

Research Scientists

Stefan Lee

Peter Anderson

Postdoc

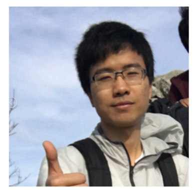


Zhile Ren

Ramakrishna Vedantam
Ph.D. Student

Arjun Chandrasekaran
Ph.D. Student

Jiasen Lu
Ph.D. Student



Jianwei Yang
Ph.D. Student

Samyak Datta
Ph.D. Student

Prithvijit Chattopadhyay
M.S. Student

Viraj Prabhu
M.S. Student

Ramprasaath Selvaraju
Ph.D. Student

PhD Students

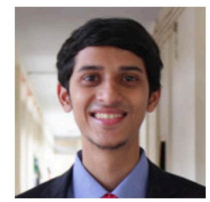
Aishwarya Agrawal
(2014 — Present)

Yash Goyal
(2014 — Present)

Michael Cogswell
(2015 — Present)

Abhishek Das
(2016 — Present)

Ashwin Kalyan
(2016 — Present)



Nirbhay Modhe
(2017 — Present)

Erik Wijmans
(2017 — Present)

Harsh Agrawal
(2018 — Present)

Deshraj Yadav
(2017 — Present) MS

TAs

[Harsh Agrawal]

Neha Jain

Ashwin Kalyan

Harish Kamath

Anishi Mehta

Nirbhay Modhe

Michael Piseno

Viraj Prabhu

Sarah Wiegreffe

Organization & Deliverables

- 4 problem-sets+homeworks (80%)
  - Mix of theory (PS) and implementation (HW)
  - First one goes out next week
    - Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early
- Final project (20%)
  - Projects done in groups of 3-4
- (Bonus) Class Participation (5%)
  - Contribute to class discussions on Piazza
  - Ask questions, answer questions

Late Days

- "Free" Late Days
  - 7 late days for the semester
    - Use for HWs
    - Cannot use for project related deadlines
  - After free late days are used up:
    - 25% penalty for each late day

PS0

- Out today; due Aug 22
  - Available on class webpage + Canvas

- Grading
  - Not counted towards your final grade, but required
  - <=50% means that you might not be prepared for the class

- Topics
  - PS: probability, calculus, convexity, proving things

Project

- Goal
  - Chance to try Deep Learning
  - Encouraged to apply to your research (computer vision, NLP, robotics,…)
  - Must be done this semester.
  - Can combine with other classes
    - get permission from both instructors; delineate different parts
  - Extra credit for shooting for a publication

- Main categories
  - Application/Survey
    - Compare a bunch of existing algorithms on a new application domain of your interest
  - Formulation/Development
    - Formulate a new model or algorithm for a new or old problem
  - Theory
    - Theoretically analyze an existing algorithm

Computing

- Major bottleneck
  - GPUs

- Options
  - Your own / group / advisor's resources
  - Google Cloud Credits
    - $50 credits to every registered student courtesy Google
  - Google Colab
    - jupyter-notebook + free GPU instance

4803 vs 7643

- Level differentiation
- HWs
  – Extra credit questions for 4803 students, necessary for 7643
- Project
  – Higher expectations from 7643

Outline

- What is Deep Learning, the field, about?
  - Highlight of some recent projects from my lab
- What is this class about?
  - What to expect?
  - Logistics
- FAQ

Waitlist / Audit / Sit in

- Waitlist
  - Class is full. Size will not increase further.
  - Do PS0. Come to first few classes.
  - Hope people drop.
- "I need this class to graduate"
  - Talk to your degree program advisor. They control the process of making sure you have options to graduate on time.
- Audit or Pass/Fail
  - We will give preference to people taking class for credit.
- Sitting in
  - Talk to instructor.

Research

- “Can I work with your group for funding/credits/neither?”
  - I am not taking new advising duties.
  - If you can find one of my students to supervise you,
    I am happy to sign off on the paperwork.
  - Your responsibility to approach them and ask.
    It will help if you know what they are working on.

What is the re-grading policy?

- Homework assignments
  - **Within 1 week** of receiving grades: see the TAs

- This is an advanced grad class.
  - The goal is understanding the material and making progress towards our research.

What is the collaboration policy?

- Collaboration
  - Only on HWs and project (not allowed in HW0).
  - You may discuss the questions
  - Each student writes their own answers
  - Write on your homework anyone with whom you collaborate
  - Each student must write their own code for the programming part

- Zero tolerance on plagiarism
  - Neither ethical nor in your best interest
  - Always credit your sources
  - Don’t cheat. We will find out.

How do I get in touch?

- Primary means of communication -- Piazza
  - No direct emails to Instructor unless private information
  - Instructor/TAs can provide answers to everyone on forum
  - Class participation credit for answering questions!
  - No posting answers. We will monitor.

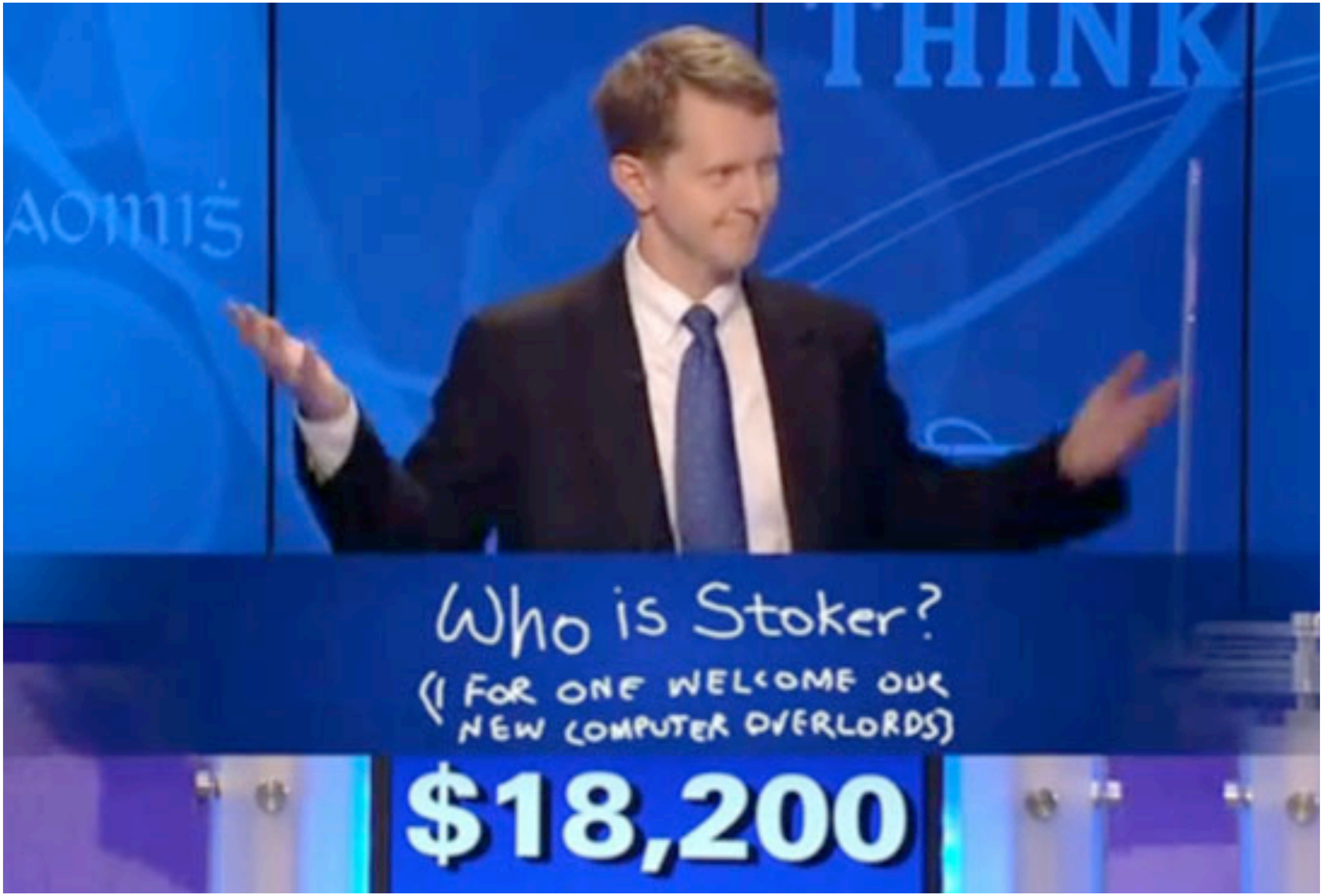
- Staff Mailing List
  - f19-cs4803-cs7643-staff@googlegroups.com

- Links:
  - Website: https://www.cc.gatech.edu/classes/AY2020/cs7643_fall/
  - Piazza: https://piazza.com/gatech/fall2019/cs48037643
  - Canvas: https://gatech.instructure.com/courses/60374 (4803)
    https://gatech.instructure.com/courses/60364 (7643)
  - Gradescope: https://www.gradescope.com/courses/56799 (4803)
    https://www.gradescope.com/courses/53817 (7643)

Todo

- PS0
  - Due: Aug 22 11:00am

Welcome



THINK
Who is Stoker?
(I FOR ONE WELCOME OUR NEW COMPUTER OVERLORDS)
$18,200