UVA CS 4774: Machine Learning

S3: Lecture 19: Recent Deep Neural Networks: A Quick Overview

Dr. Yanjun Qi

University of Virginia
Department of Computer Science

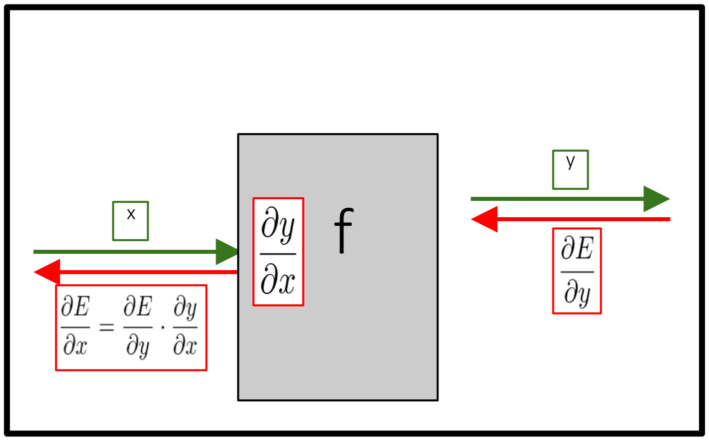
Module I

Recent Deep Neural Networks : A Quick Overview on 10 Trends

Dr. Yanjun Qi
yanjun@virginia.edu

University of Virginia
Department of Computer Science

Recap: Building Deep Neural Nets



http://cs231n.stanford.edu/slides/winter1516_lecture5.pdf

Deep Learning in a Nutshell

Data

↓

Representation
(DNN Topology)

↓

Task

↓

Score Function

↓

Search/Optimization

↓

Models, Parameters

Hyperparameter, Metrics

↓

Hardware

Disclaimer: it is quite hard to make important topics of machine learning fit on a one-semester schedule.

Disclaimer: it is quite hard to make important topics of deep learning fit on a one-session schedule.

We aim to make the content reasonably digestible in an introductory manner. We try to focus on a modularity view by introducing important variables to digest machine learning into chunks regarding data/ representation / loss-functions / optimizations / model characteristics. That said, our goals here are to highlight the most foundational design choices in machine learning about algorithm designs, workflows, what to learn and how to learn it, and to expose the trade-offs in those choices. We think this teaching style provides students with context concerning those choices and helps them build a much deeper understanding.

Data

Representation
(DNN Topology)

Task

Score Function

Search/Optimization

Models, Parameters

Hyperparameter, Metrics

Hardware

2D Grid / 1D Grid / 3D Grid /
Graph / Set / Codes / …

Different network topology

Prediction / Generation /
Reinforce / Reasoning / …

New Loss / New Learning
formulation

New optimization / Search for
optimizer / distributed e.g.
Asynchronous SGD

weights, bias / Accuracy / F1
/ robustness / interpretability
/ safety / trust / software 2.0

GPU / TPU / many Edge devices

Selected Trends

https://qdata.github.io/deep2Read/

- **Module I**
  - Data
  - Representation f()
- **Module II**
  - Task
- **Module III: Training Workflow**
  - Score Function
  - Search/Optimization
- **Module IV: On Deployment**
  - Models, Parameters
  - Hyperparameter, Metrics
  - Hardware

Data:
1. DNN on graphs / trees / sets
2. NTM 4program induction

Representation f():
1. CNN / Residual / Memory
2. RNN / Attention / Seq2Seq / Transformer …

Task:
1. Deep Generative models/ DeepFake
2. Deep reinforcement learning
3. Few-shots / Meta learning / AGI?

Search/Optimization:
1. Autoencoder / self supervised training
2. Generative Adversarial Networks (GAN)
3. Learning to optimize /Learning to search architecture (AutoML)

Models, Parameters / Hyperparameter, Metrics:
1. Validate / Evade / Test / Verify
2. Understand DNNs

Hardware:
1. Model Compression / Efficient Net

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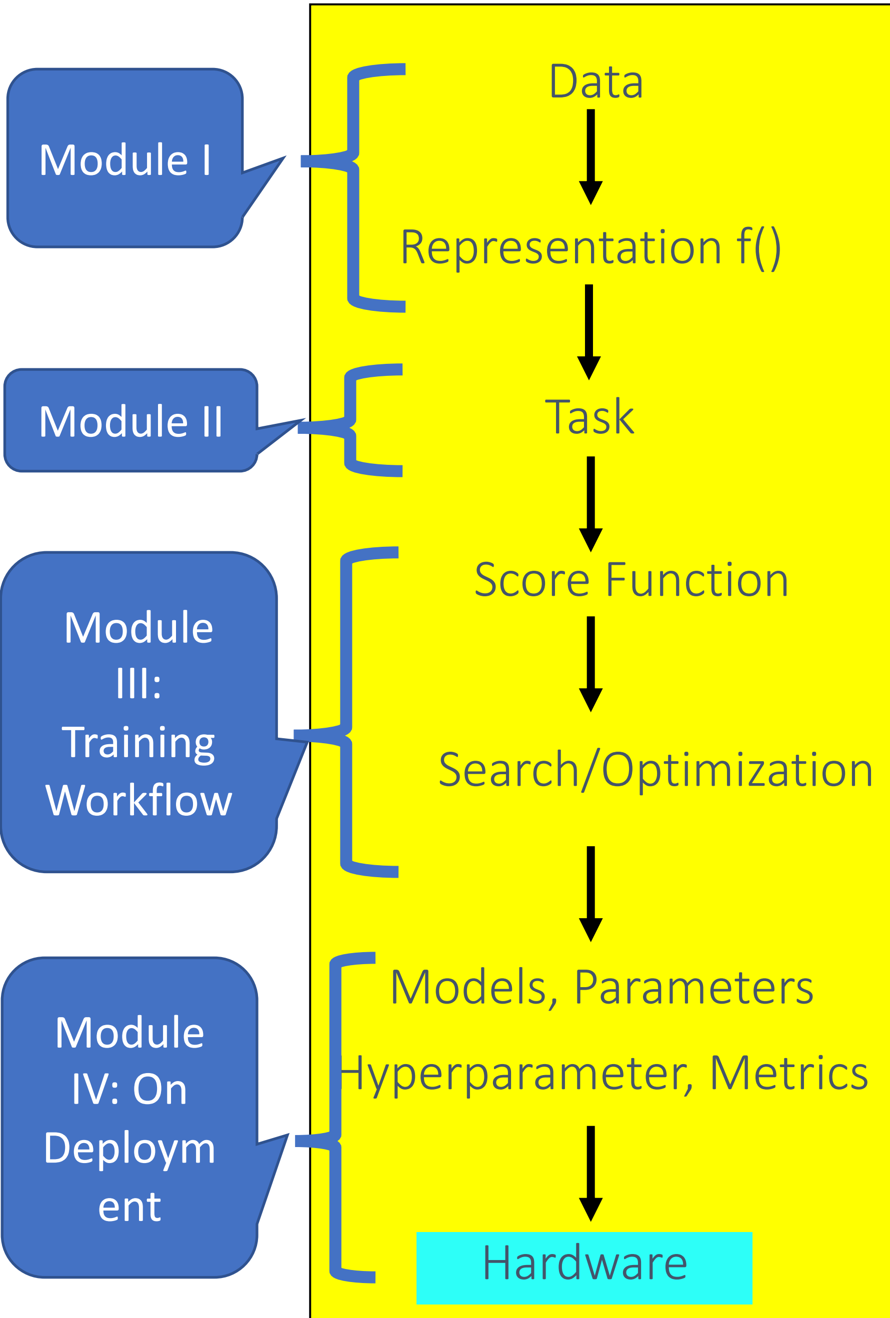


1. DNN on graphs / trees / sets
2. NTM 4program induction

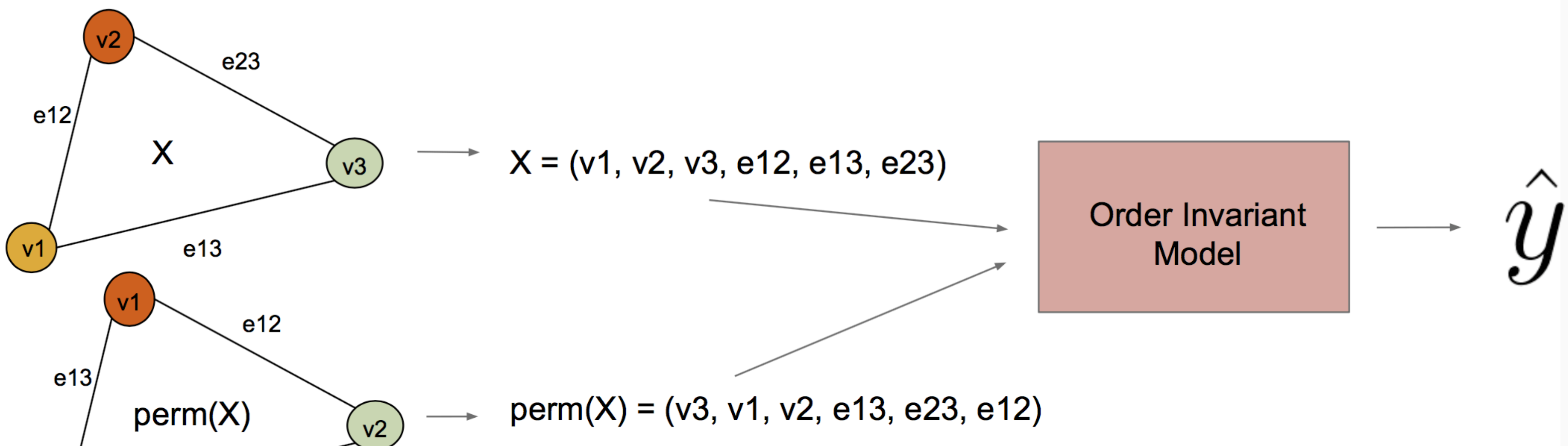
Recent Trend (1): Variants of Input, e.g., Graphs, Trees, Sets

Inputs and Outputs

Inductive Bias for Graphs

Arch

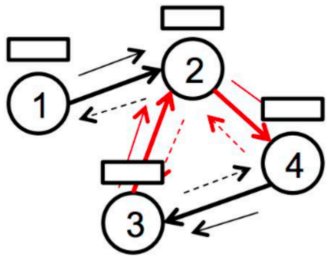
- If we have a graph on N nodes, there are N! possible orderings of the nodes.
- Ideally want a model invariant to the order of nodes.



Slides credits: Justin Gilmer

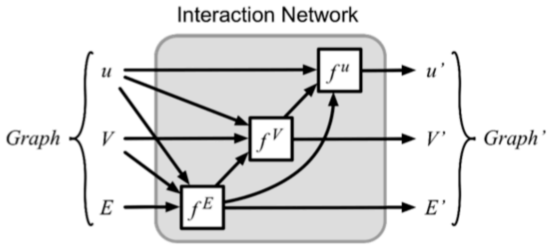
Adapt from From NIPS 2017 DL Trend Tutorial

Geometric Deep Learning on Graphs and Manifolds, NIPS 2017 Tutorial



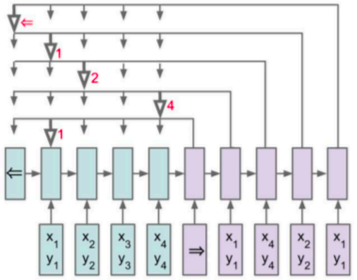
Graph Nets (GNs) are a class of models that:

- Use graphs as inputs and/or outputs and/or latent representation
- Manipulate graph-structured representations
- Reflect relational structure
- Share model components across entities and relations



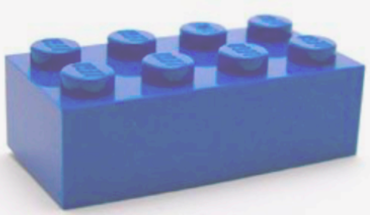
Examples include:

- Graph Neural Networks *(Scarselli et al 07; 08)*
- Recursive Neural Networks *(Goller et al 96)*
- Pointer Networks *(Vinyals et al 2015)*
- Graph Convolutional Networks *(Bruna et al 2013; Duvenaud et al 15; Henaff et al 15; Kipf & Welling 16; Defferrard et al 17)*
- Gated Graph Neural Networks *(Li et al 15)*
- Interaction Networks *(Battaglia et al 2016; Raposo et al 2017;)*
- **Message Passing Networks** *(Gilmer et al. 2017)*



Adapt from From NIPS 2017 DL Trend Tutorial

Recent Trend (2):
Reasoning Tasks in the form of Symbolic input/ outputs / e.g., Program Induction



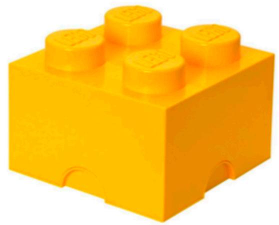
Inputs and Outputs:

- Discrete symbols, (e.g. the program itself)
- Program execution traces
- Program I/O pairs

These can also be mixed with perceptual data.

Architectures:

- (Mostly) recurrent
- Sometimes including ConvNets as a visual front-end.



Losses:

- Differentiable, predicting discrete program outputs or code itself: softmax cross entropy.
- Not differentiable: RL

Adapt from From NIPS 2017 DL Trend Tutorial

Neural Program Induction - Research Landscape

- Neural network is the program:
  - Learning to Execute, Neural Turing Machine, Neural GPU, Neural RAM, Neural Programmer-Interpreter, Neural Task Programmer, Differentiable Forth Interpreter

2+3
⇩ Network
5

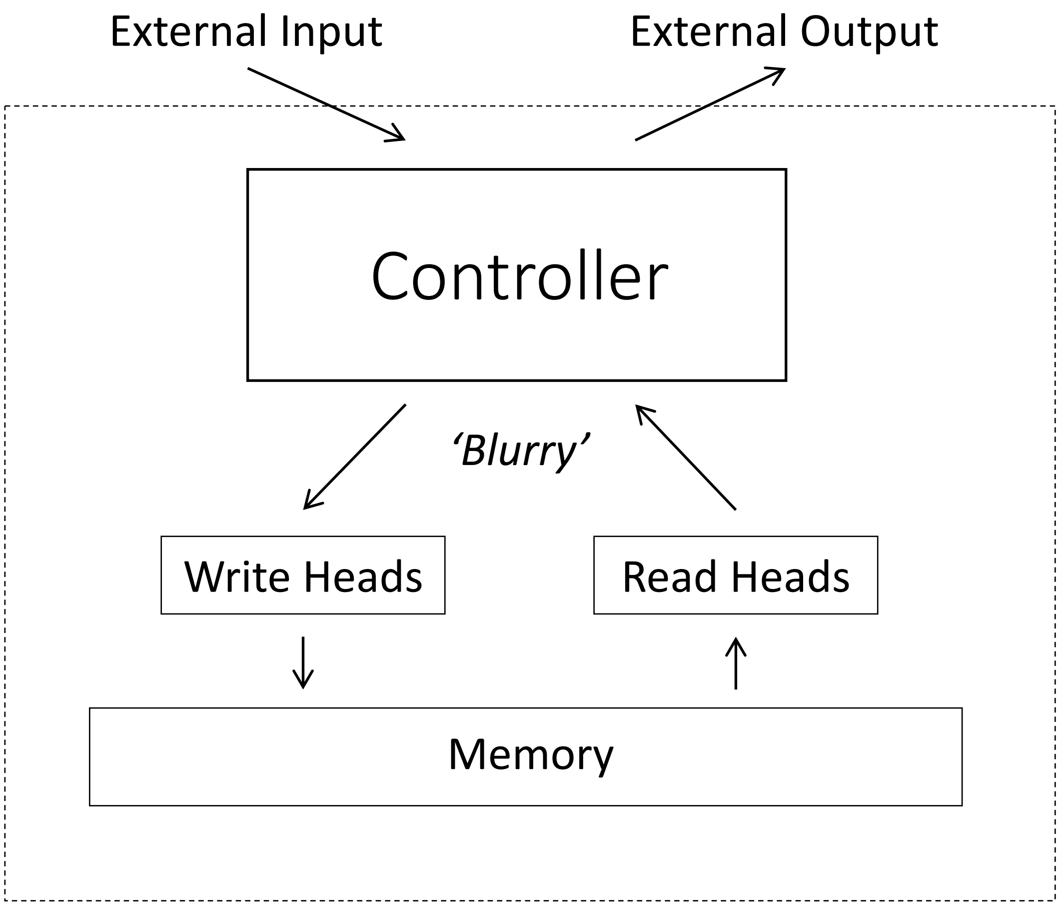
- Neural network generates source code :
  - DeepCoder, RobustFill, Neural Inductive Logic Programming

2,3⇒5
⇩ Network
`sum(a,b)`

- Probabilistic programming with neural networks:
  - TerpreT, Edward, Picture

Adapt from From NIPS 2017 DL Trend Tutorial

Neural Turing Machines



Neural Turing Machines, Graves et. al., arXiv:1410.5401

Task with Sequential Symbolic Form

- Computer Programs , …
- Sequence decision making, e.g., games with symbolic

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Models, Parameters

Hyperparameter, Metrics

↓

Hardware

- Grid: ConvNet
- Language: Self-attention
- Graph: GNN
- SymbolicSeq: NTM

Selected Trends

https://qdata.github.io/deep2Read/

Module I

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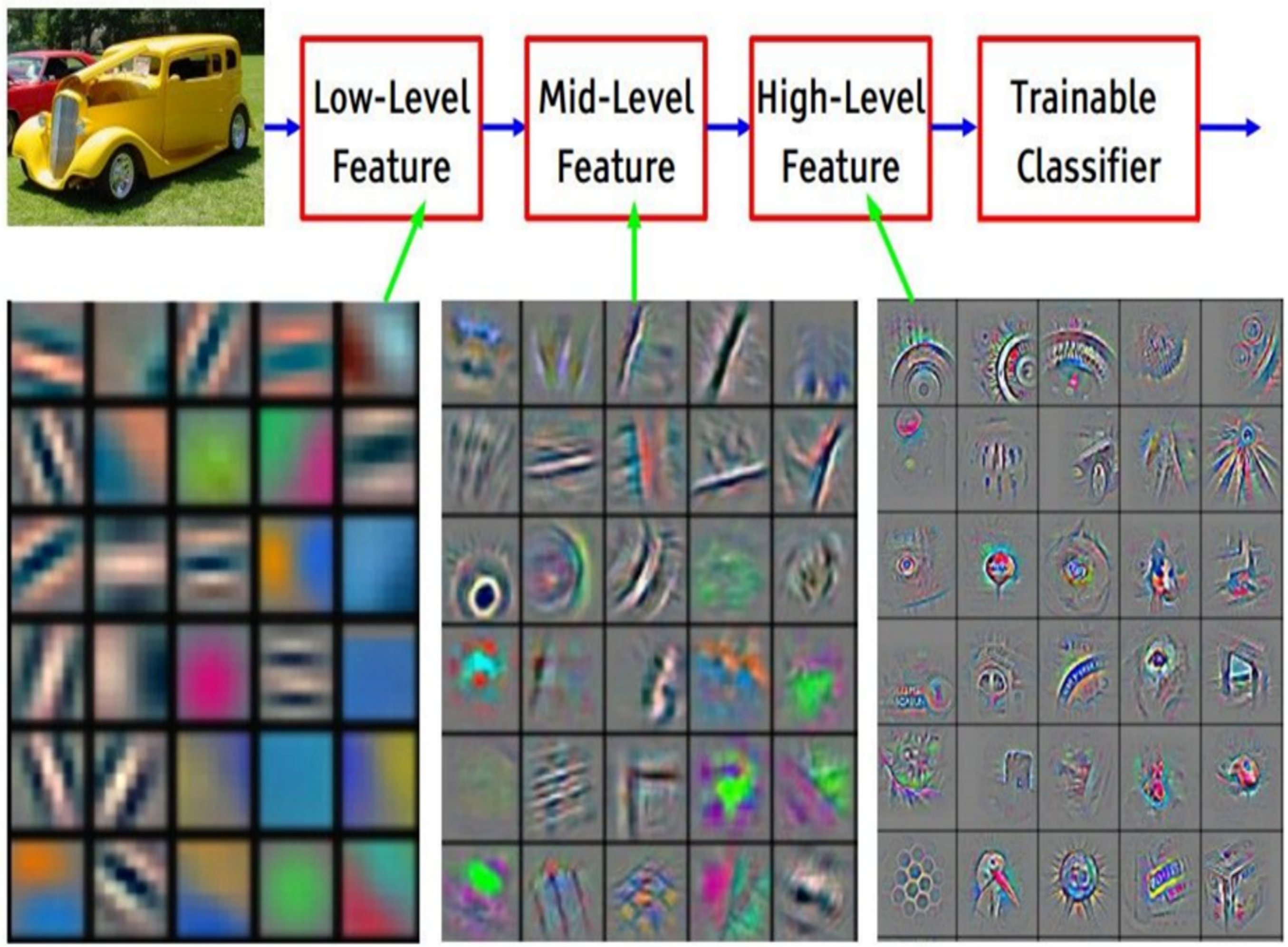
Convolutional Neural Networks

F

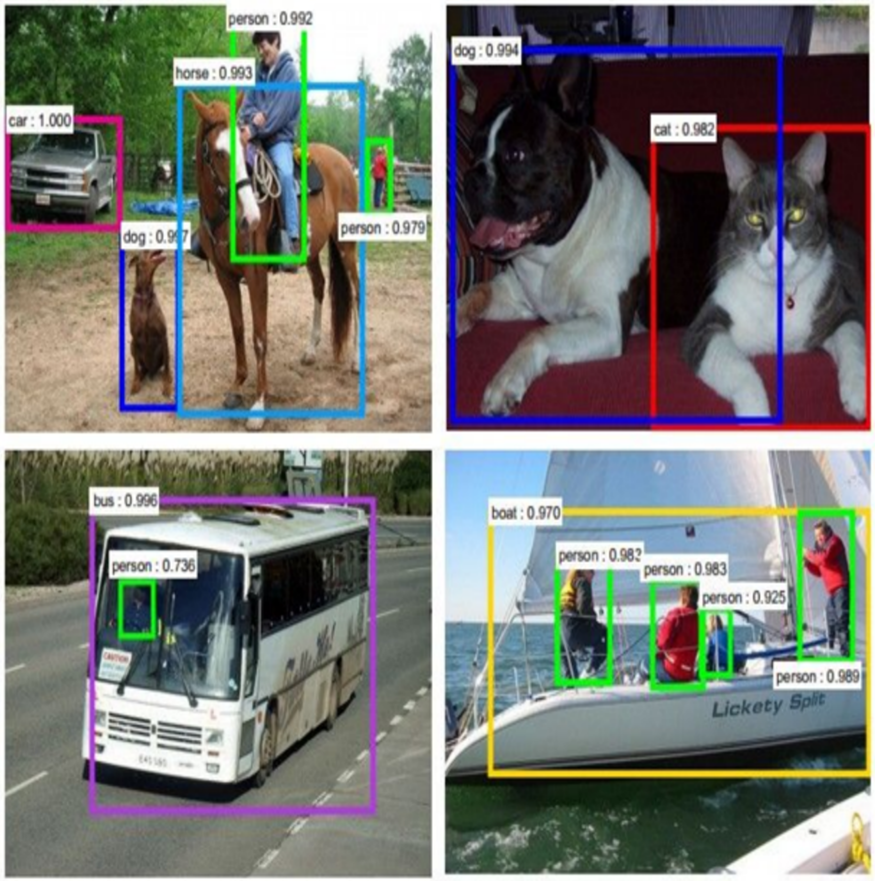
[From recent Yann LeCun slides]



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

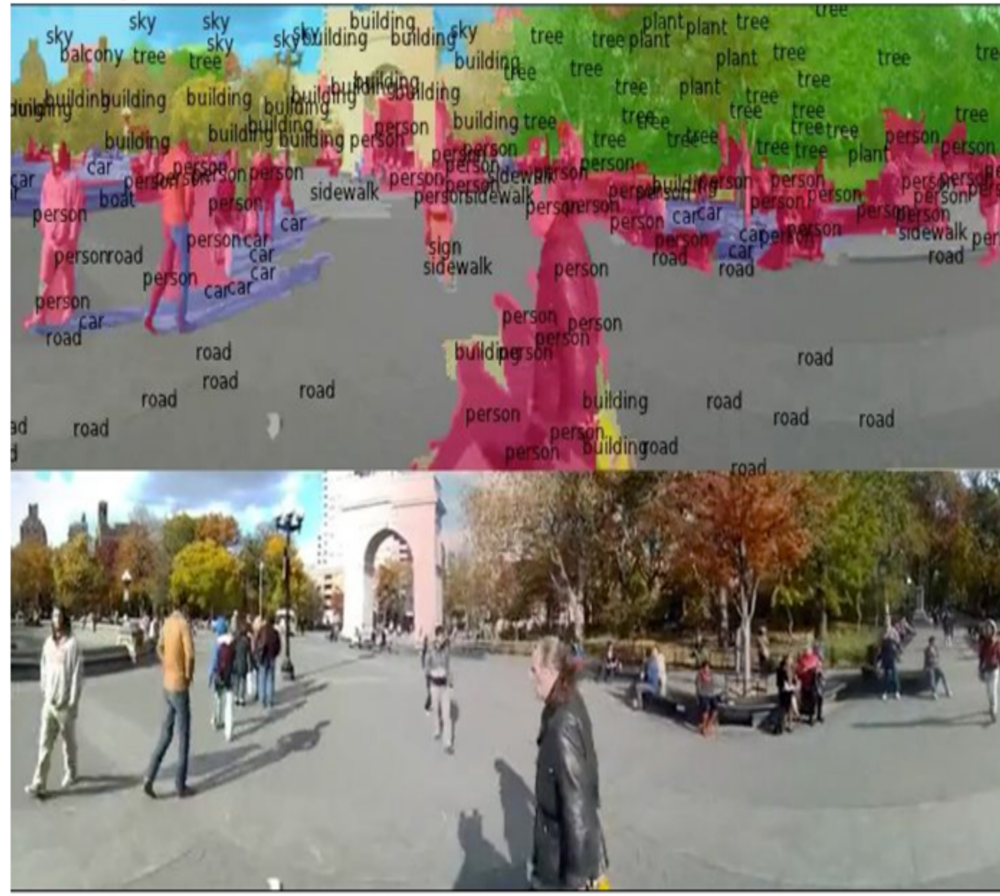
ConvNets are everywhere

Detection



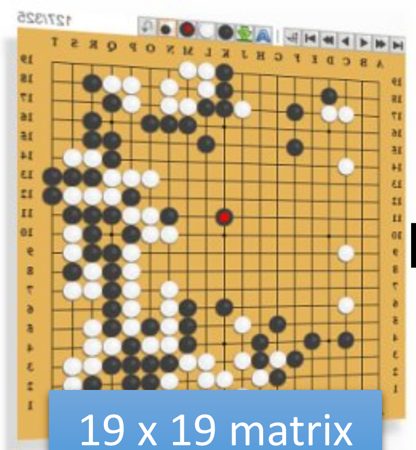
[Faster R-CNN: Ren, He, Girshick, Sun 2015]

Segmentation



[Farabet et al., 2012]

More Application: Playing Go



19 x 19 vector

19 x 19 matrix (image)

Black: 1

white: -1

none: 0

Network

Next move (19 x 19 positions)

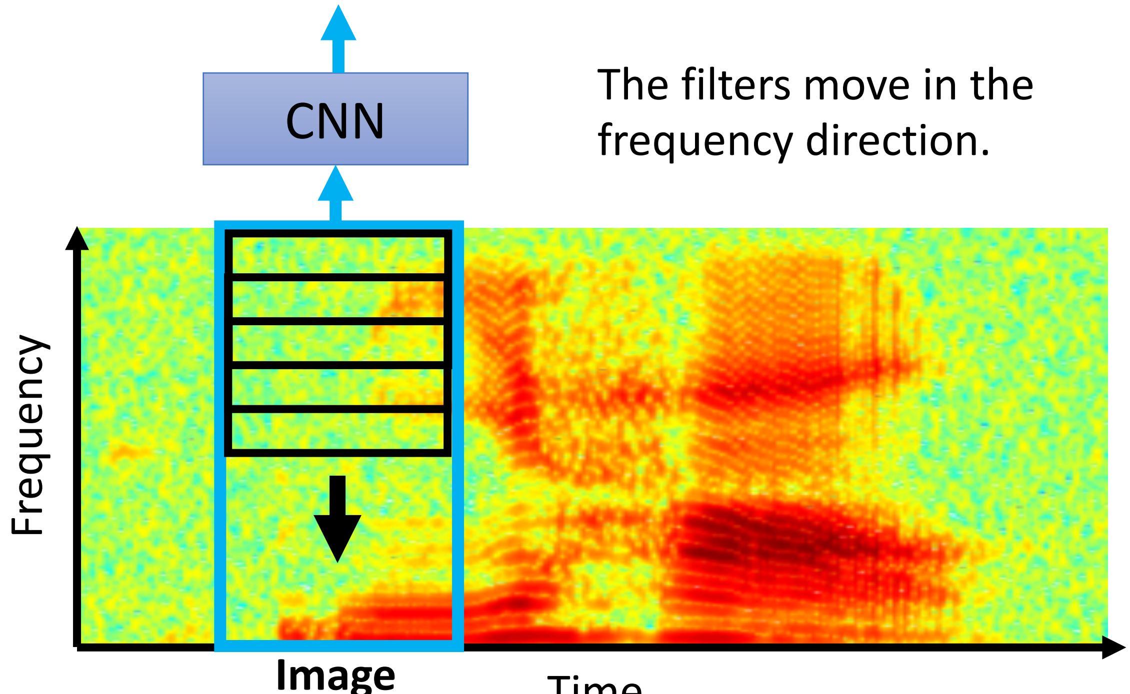
19 x 19 vector

Fully-connected feedforward network can be used

But CNN performs much better.

Dr. Hung-yi Lee’s CNN slides

More Application: Speech

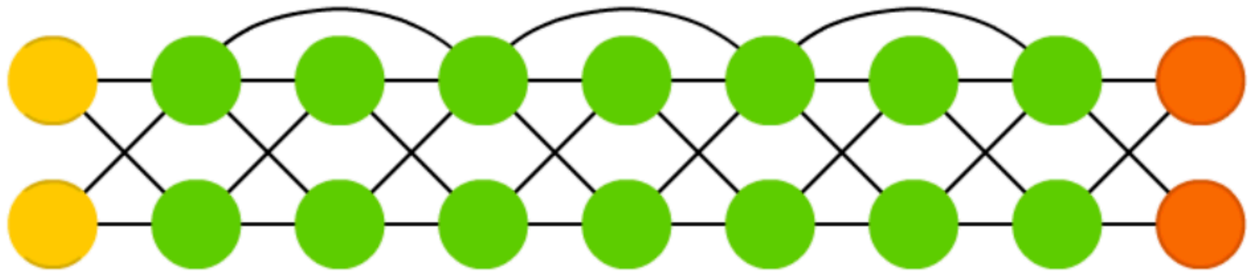


The filters move in the frequency direction.

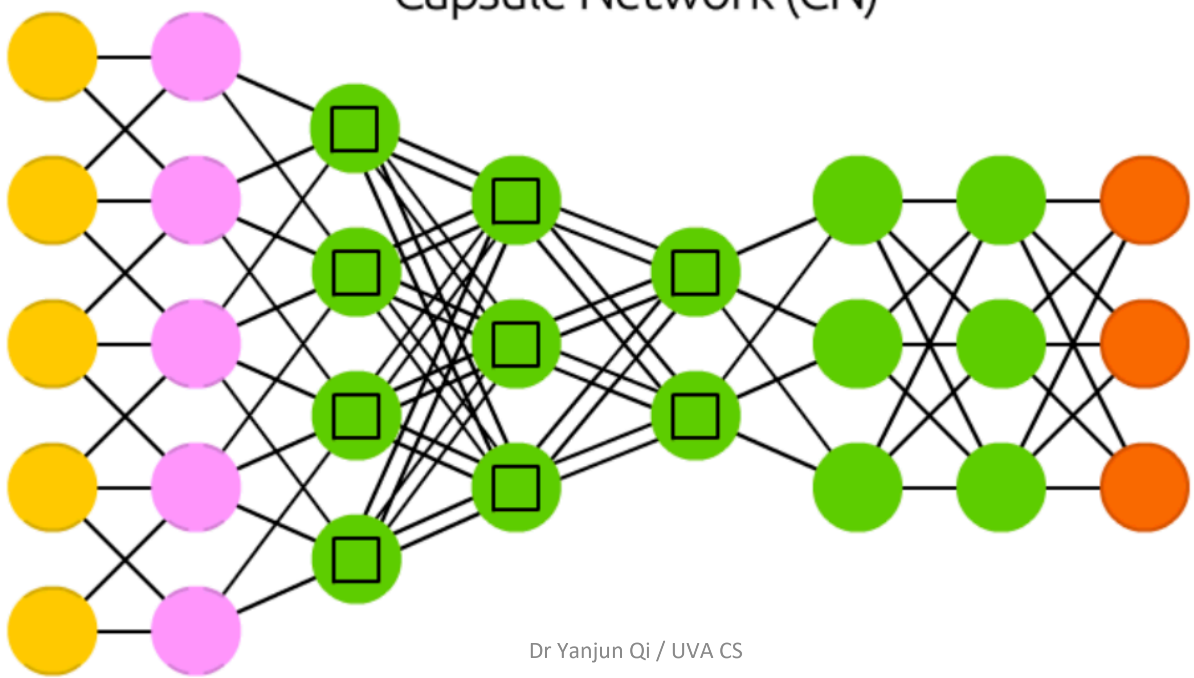
Spectrogram

Dr. Hung-yi Lee's CNN slides

Deep Residual Network (DRN)



Capsule Network (CN)

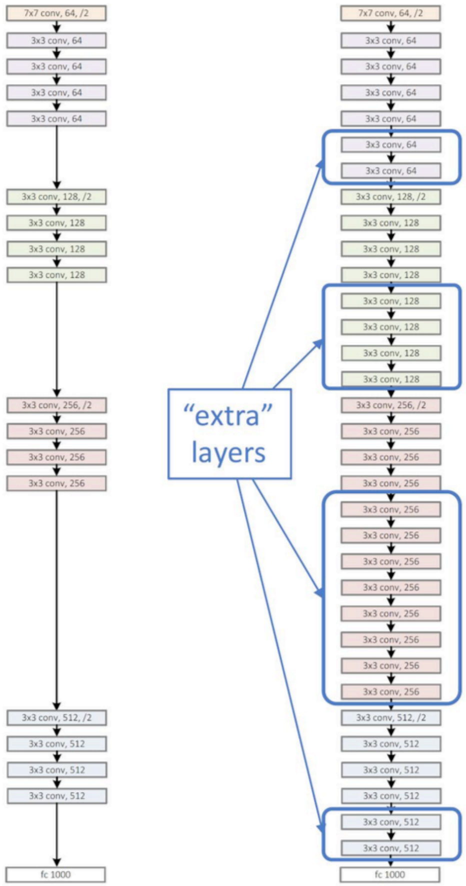


Residual Trick:

Arch

Residual/Skip Connections

a shallower model (18 layers)



a deeper counterpart (34 layers)

- Richer solution space
- A deeper model should not have **higher training error**
- A solution *by construction*:
  - original layers: copied from a learned shallower model
  - extra layers: set as identity
  - at least the same training error
- Optimization difficulties: solvers cannot find the solution when going deeper…

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Selected Trends

https://qdata.github.io/deep2Read/

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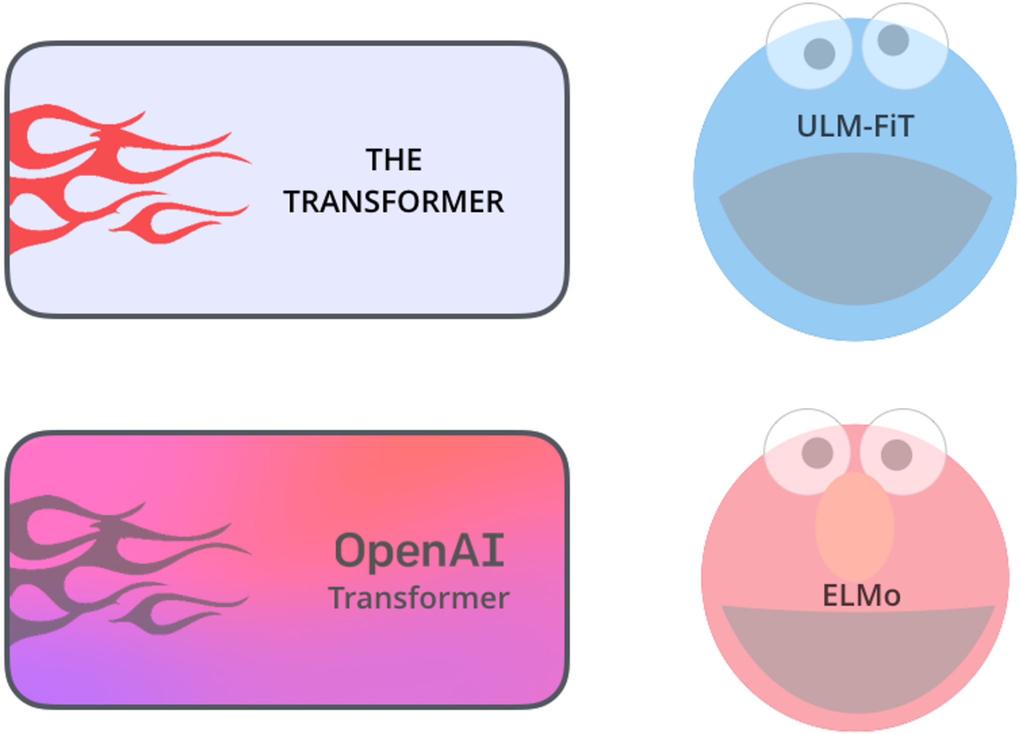
Notable pre-trained NLP models

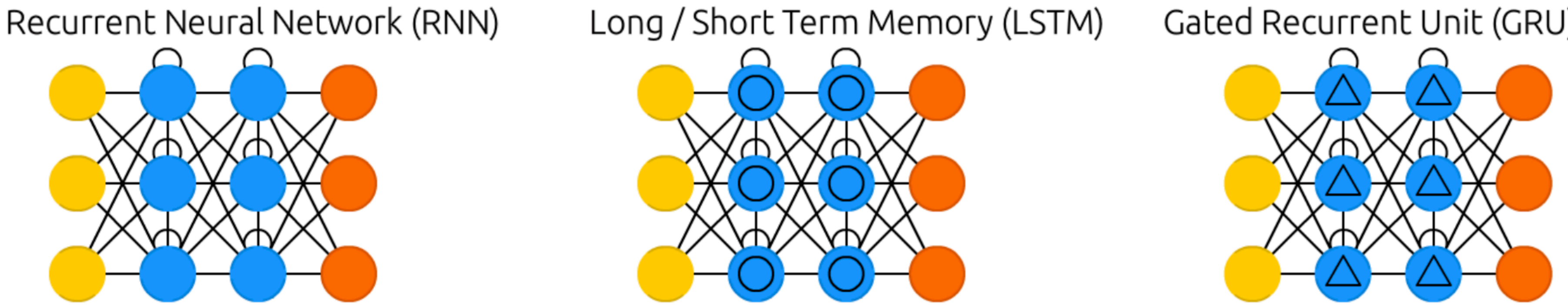


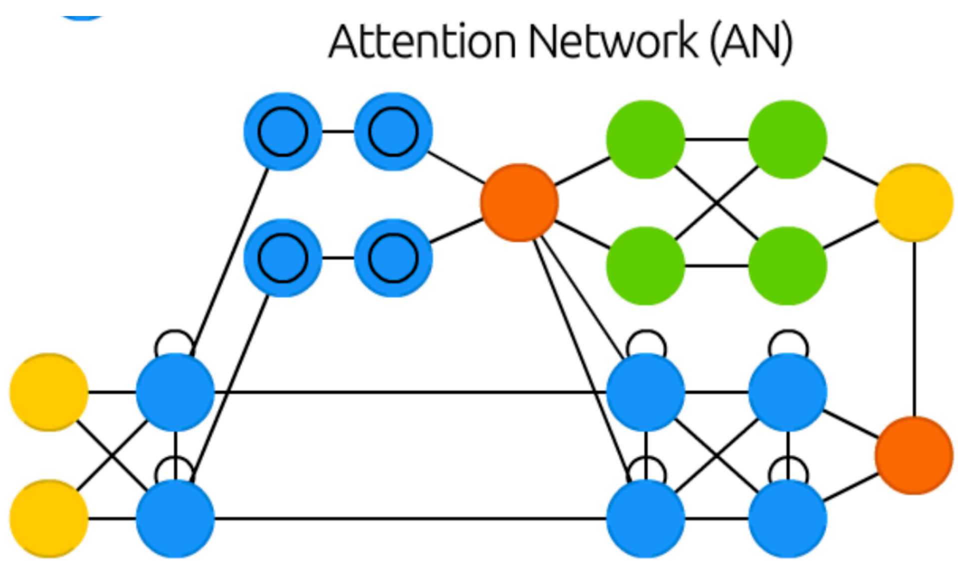
- BERT (Google)
- XLNet (Google/CMU)
- RoBERTa (Facebook)
- DistilBERT (HuggingFace)
- CTRL (Salesforce)
- GPT-2 (OpenAI)
- ALBERT (Google)
- Megatron (NVIDIA)

ELMo: Embeddings from Language Models
Pre-trained biLSTM for contextual embedding

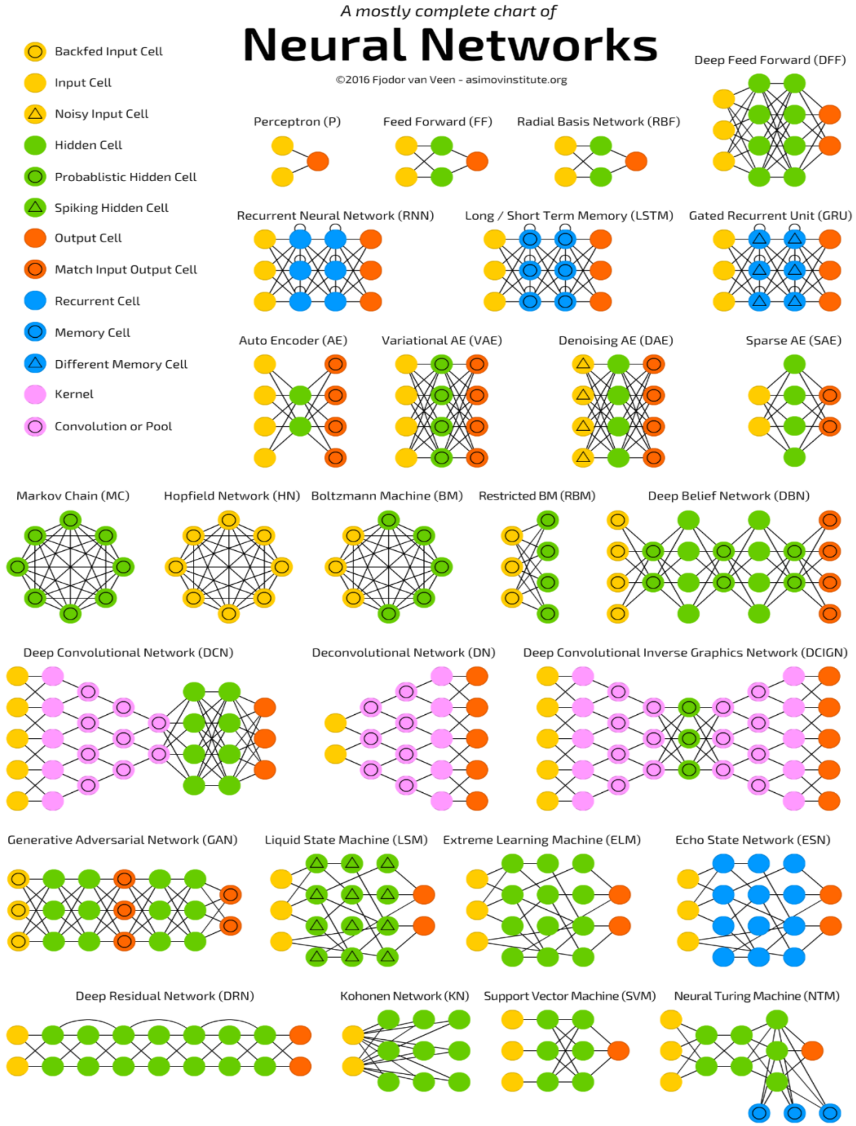
BERT: Bidirectional Encoder Representations from Transformers
Pre-trained transformer encoder for sentence embedding

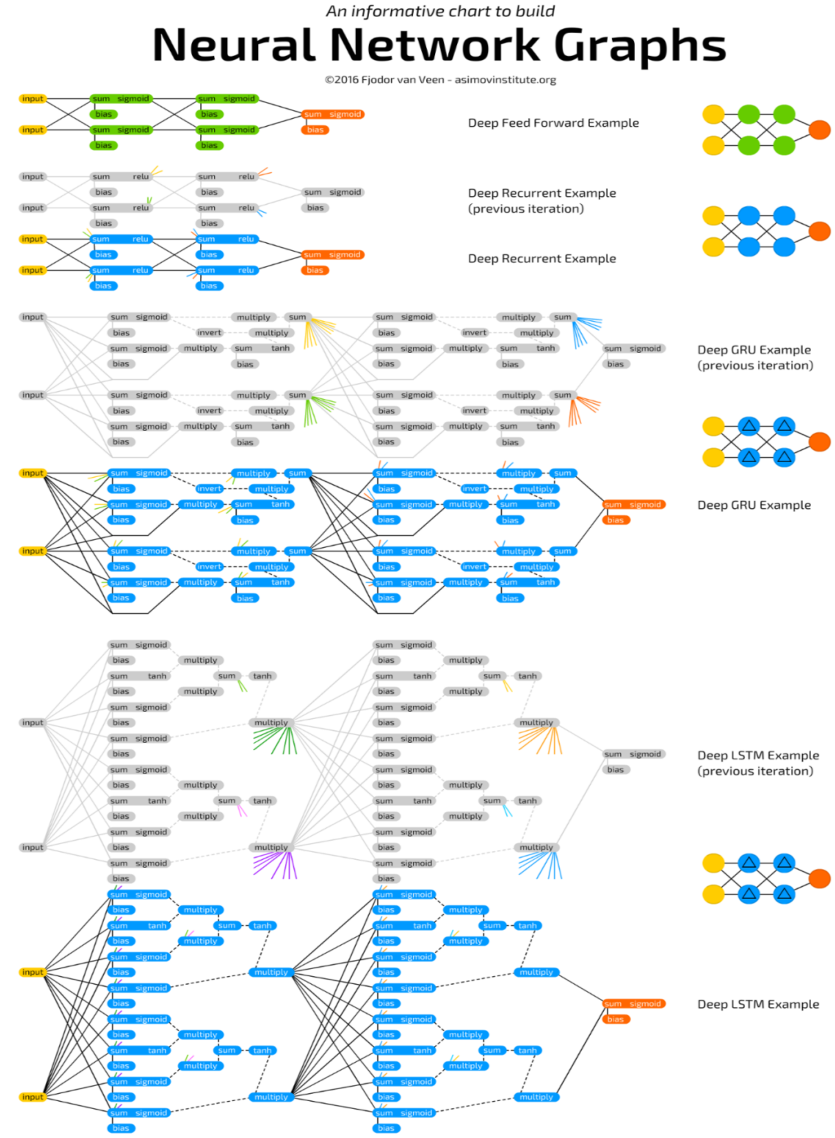
Based: Dr. Yangqiu Song's slides


Recurrent Neural Network (RNN)
Long / Short Term Memory (LSTM)
Gated Recurrent Unit (GRU)


Attention Network (AN)

https://www.asimovinstitute.org/neural-network-zoo/





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Module II

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https://qdata.github.io/deep2Read/

Module I

Module II

Module III: Training Workflow

Module IV: On Deployment

Data

Representation f()

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Hardware

1. Deep Generative models/ DeepFake
2. Deep reinforcement learning
3. Few-shots / Meta learning / AGI?

Recent Trend (3): Deep Generative Models

Generative models - Research Landscape

- Latent variable models (VAE, DRAW)
- Implicit (GAN, GMMN, Progressive GAN)
- Transform (NICE, IAF, Real NVP)
- **Autoregressive** (NADE, MADE, RIDE, PixelCNN, WaveNet)

UAI 2017 Tutorial on Deep Generative Models.

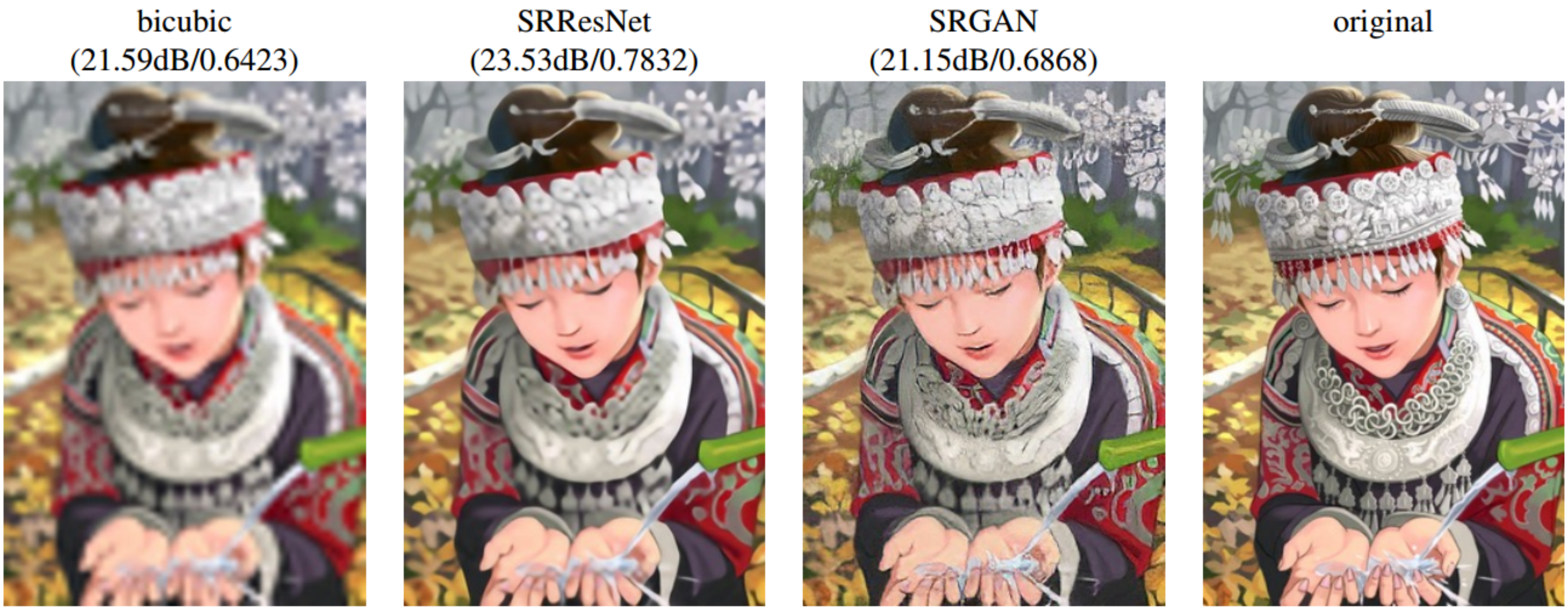
NIPS 2016 Tutorial on Generative Adversarial Networks

Why Generative Models?

- Excellent test of ability to use high-dimensional, complicated probability distributions
- Simulate possible futures for planning or simulated RL
- Missing data
  - Semi-supervised learning
- Multi-modal outputs
- Realistic generation tasks

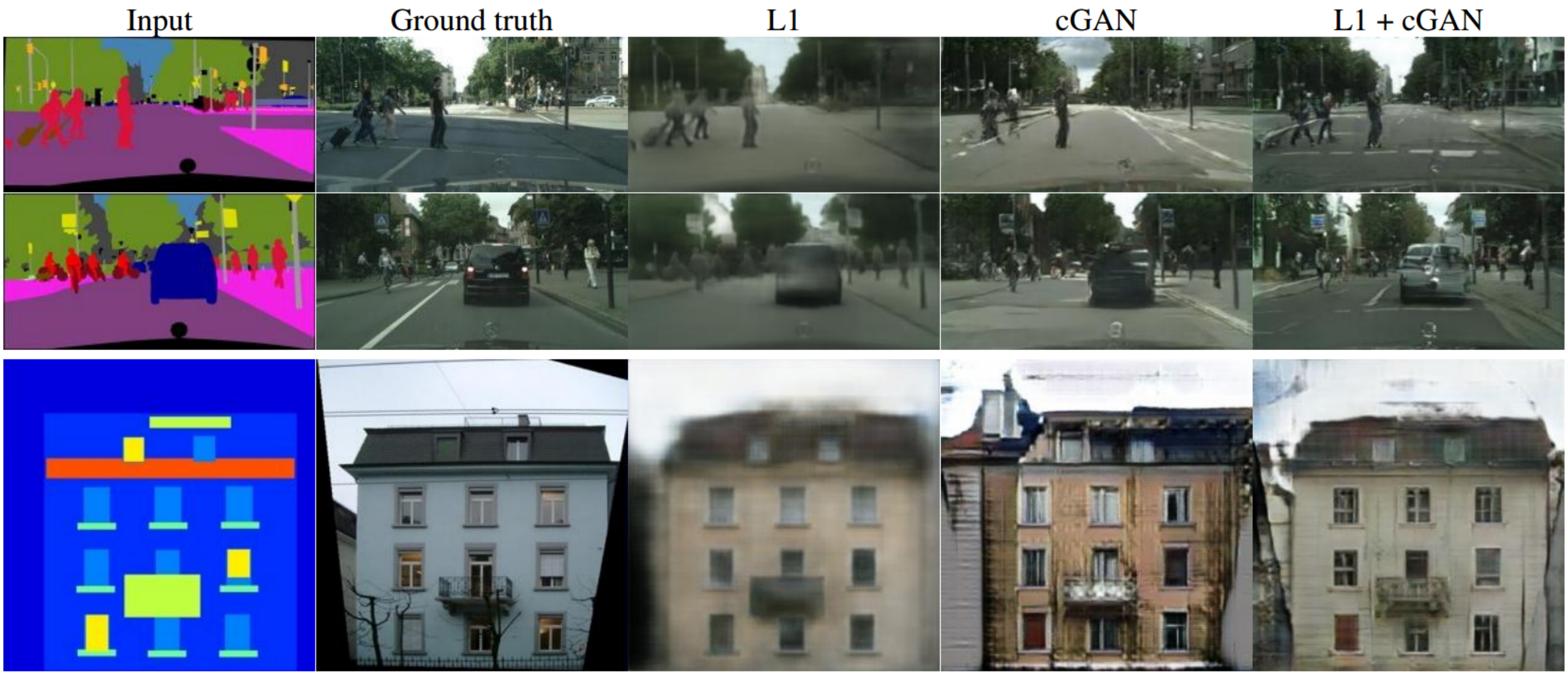
(Goodfellow 2016)

Image Super-Resolution



[Ledig et al. CVPR 2017]

Label2Image



[Isola et al. CVPR 2017]

Edges2Image

[Isola et al. CVPR 2017]

Text2Image

this small bird has a pink breast and crown, and black primaries and secondaries.

this magnificent fellow is almost all black with a red crest, and white cheek patch.

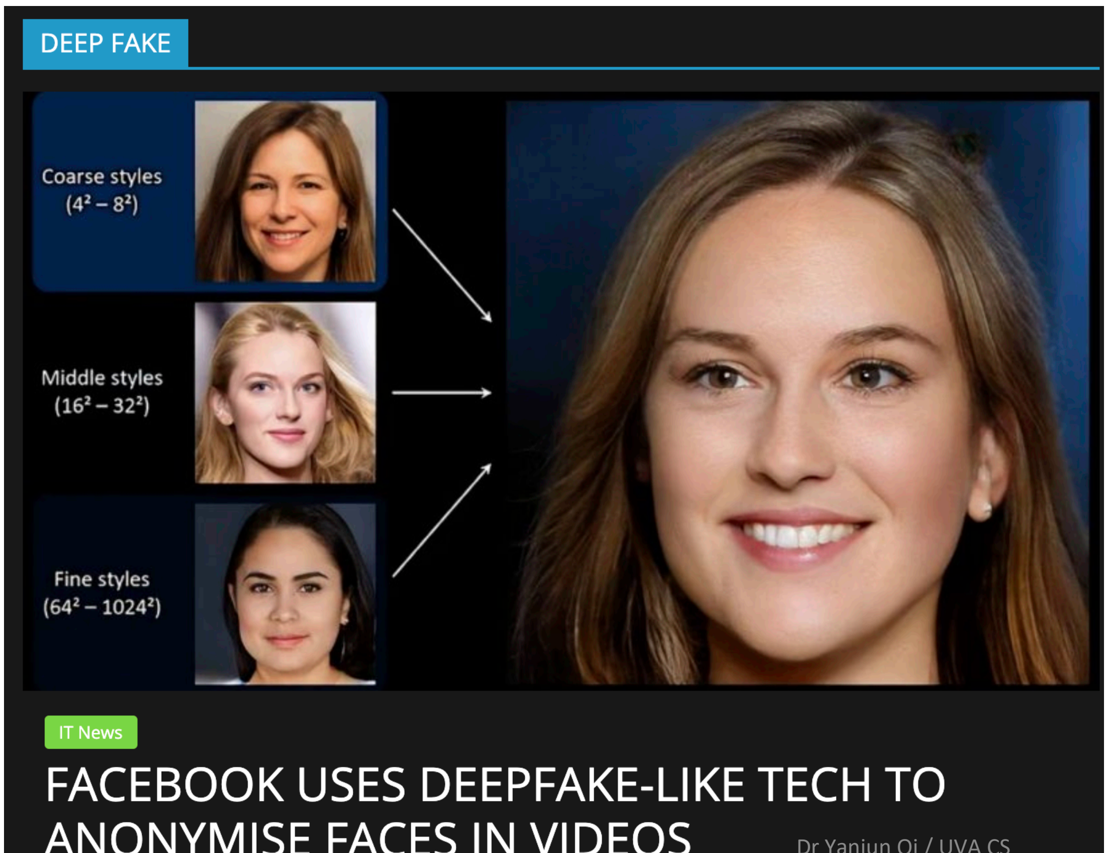
the flower has petals that are bright pinkish purple with white stigma

this white and yellow flower have thin white petals and a round yellow stamen

[Reed et al. ICML 2016]

DeepFake (Generation and Detection)

- A deepfake is generally understood to be a video in which the face of one person has been swapped with the face of another person
- Many variations on this (face swap, puppet-master, lip-sync)



https://github.com/iperov/DeepFaceLab

De-Aged the face

Deepfake history

June 2016
Face2Face paper released

July 2017
Synthesizing Obama paper released (audio lip syncing)

Winter 2017
r/deepfakes subreddit created

Feb 2018
r/deepfakes subreddit banned

April 2018
Jordan Peele Obama PSA deepfake released

June 2018
In Ictu Oculi: Exposing AI Generated Fake Face Videos by Detecting Eye Blinking paper released

Sept 2018
MesoNet: a Compact Facial Video Forgery Detection Network paper released

April 2019
FaceForensics++ paper and dataset released

May 2019
Few Shot Adversarial Learning of Realistic Neural Talking Heads Model paper released

June 2019
Text-Based Editing of Talking-head Video paper released

June 2019
Mark Zuckerberg deepfake released

https://i.blackhat.com/USA-19/Thursday/us-19-Price-Playing-Offense-And-Defense-With-Deepfakes.pdf

Recent Trend (4): Deep Reinforcement Learning

10 Breakthrough Technologies

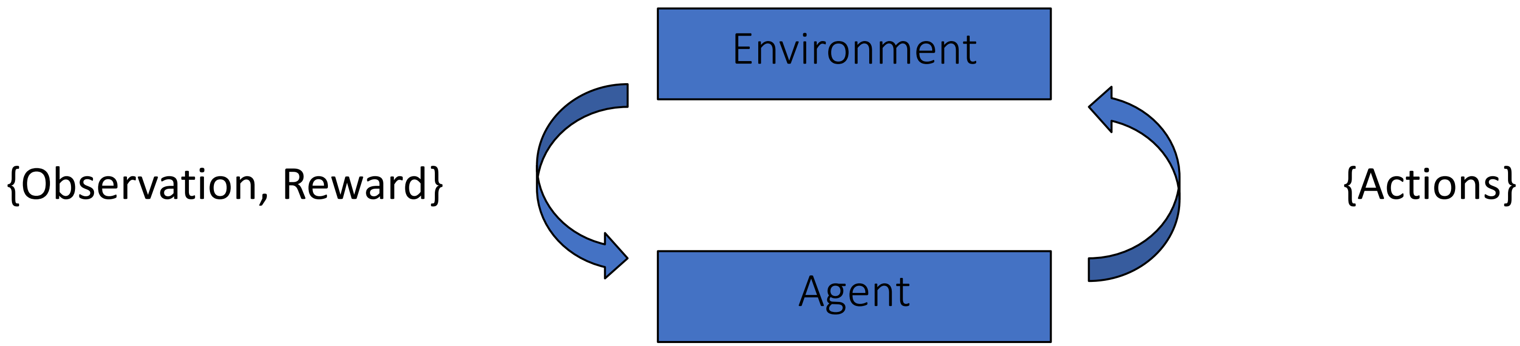
2017

These technologies all have staying power. They will affect the economy and our politics, improve medicine, or influence our culture. Some are unfolding now; others will take a decade or more to develop. But you should know about all of them right now.

MIT Technology Review

Reinforcement Learning (RL)

- What's Reinforcement Learning?

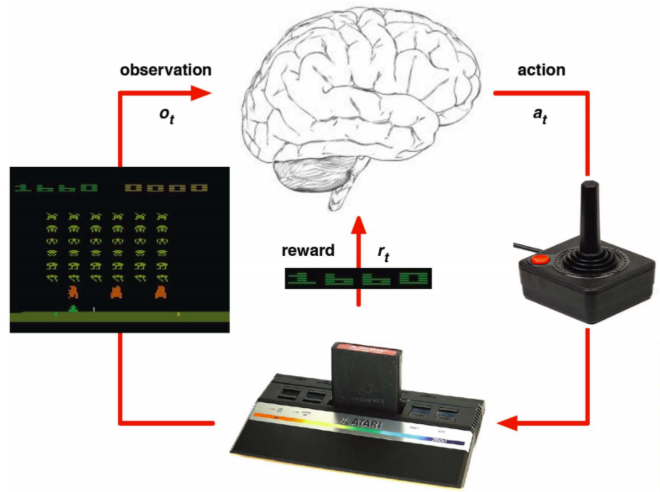


- Agent interacts with an environment and learns by maximizing a scalar reward signal
- No labels or any other supervision signal.
- Previously suffering from hand-craft states or representation.

Adapt from Professor Qiang Yang of HK UST

Deep Reinforcement Learning

- Human

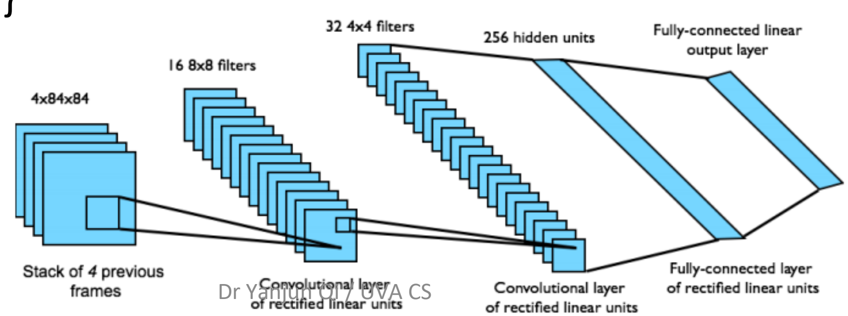


- So what's **DEEP** RL?

Environment

{Raw Observation, Reward}

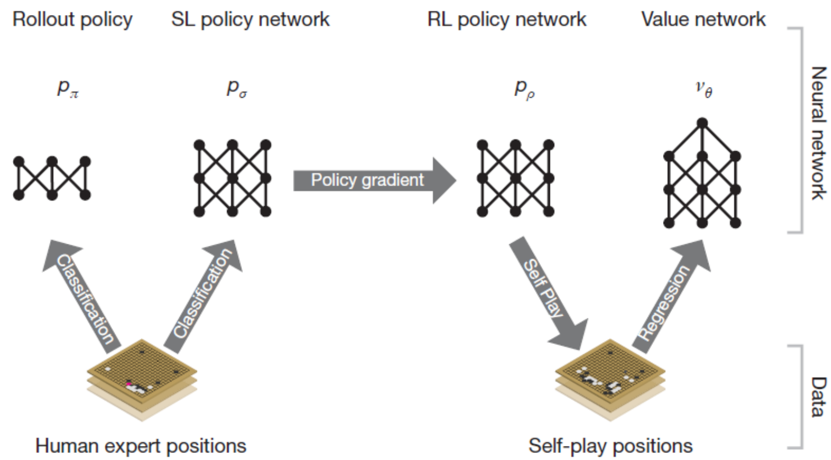
{Actions}



Adapt from Professor Qiang Yang of HK UST

AlphaGO: Learning Pipeline

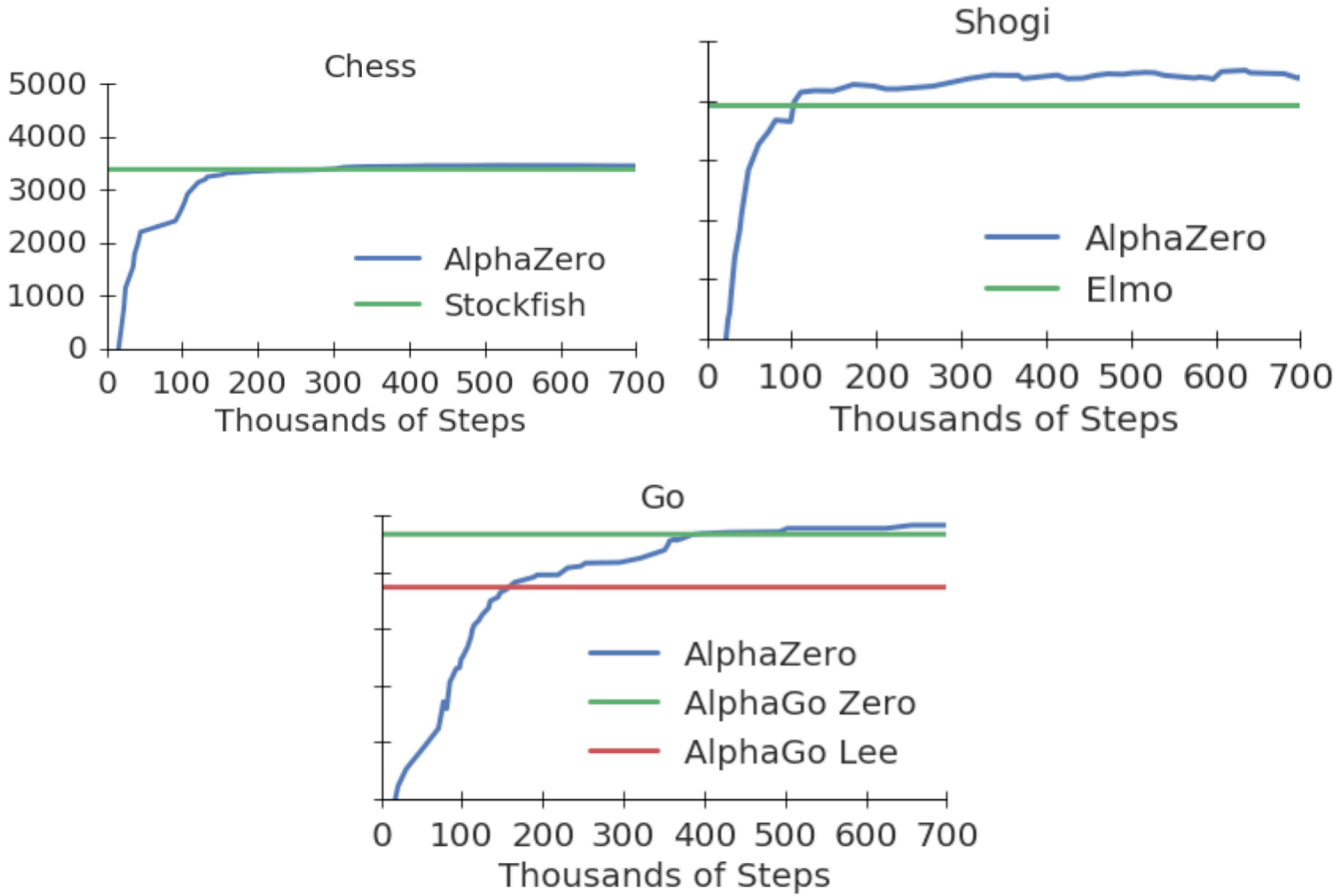
- Combine Supervised Learning (SL) and RL to learn the search direction in Monte Carlo Tree Search



Silver, David, et al. 2016.

- SL policy Network
  - Prior search probability or potential
- Rollout:
  - combine with MCTS for quick simulation on leaf node
- Value Network:
  - Build the Global feeling on the leaf node situation

Silver, David, et al. "Mastering the game of Go with deep neural networks and tree search." *Nature* 529.7587 (2016): 484-489.



Silver, David et al. (2017b). “Mastering the Game of Go without Human Knowledge”. In: Nature 550.7676, pp. 354–359.

OpenAI
Spinning Up

latest

Search docs

USER DOCUMENTATION

- Introduction
- Installation
- Algorithms
- Running Experiments
- Experiment Outputs
- Plotting Results

INTRODUCTION TO RL

- Part 1: Key Concepts in RL
- Part 2: Kinds of RL Algorithms
- Part 3: Intro to Policy Optimization

RESOURCES

- Spinning Up as a Deep RL Researcher
- Key Papers in Deep RL

Benchmarks for Spinning Up Implementations

Table of Contents

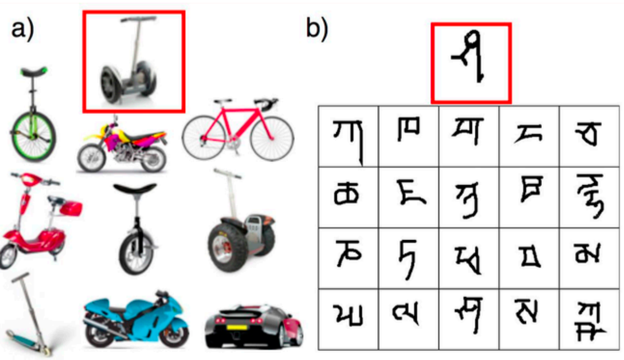
We benchmarked the Spinning Up algorithm implementations in five environments from the MuJoCo Gym task suite: HalfCheetah, Hopper, Walker2d, Swimmer, and Ant.

Performance in Each Environment

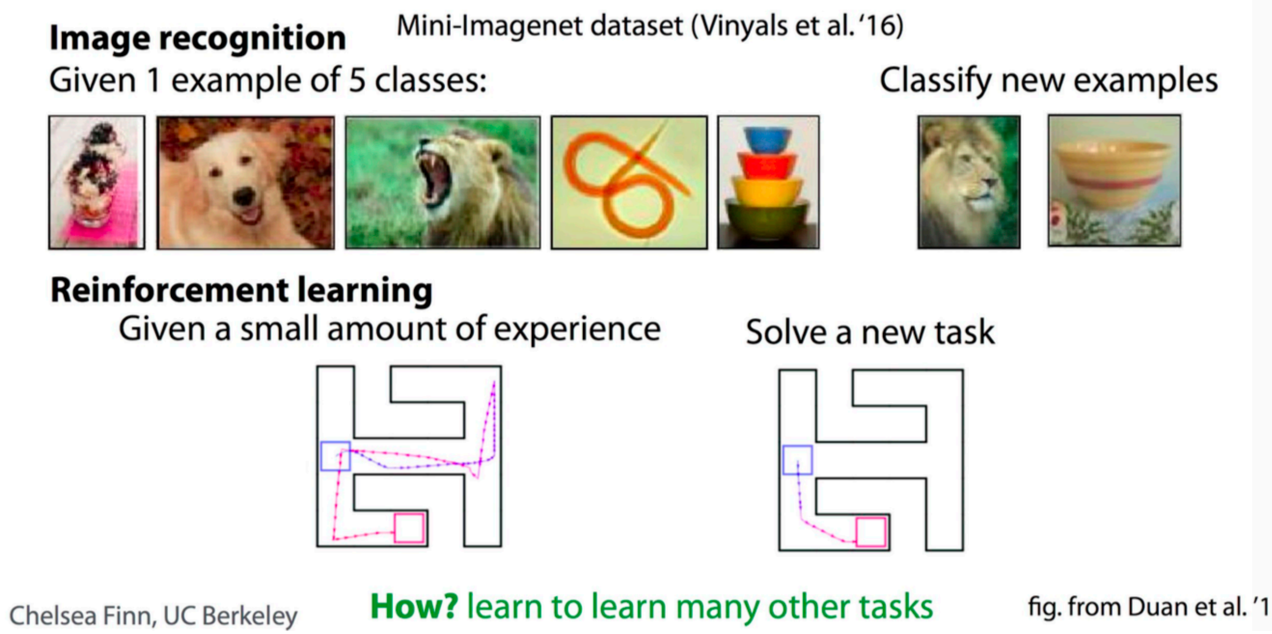
Recent Trend (5): Meta Learning: Learning to Learn

Learning to Learn

- What is Meta Learning / Learning to Learn?
  - Go beyond train/test from same distribution.
  - Task between train/test changes, so model has to "learn to learn"
- Datasets



Lake et al, 2013, 2015



Adapt from From NIPS 2017 DL Trend Tutorial

AGI (Artificial General Intelligence) versus Narrow AI

Intelligence…

AGI:

- "The ability to achieve complex goals in complex environments using limited computational resources"
- Autonomy
- Practical understanding of self and others
- Understanding "what the problem is" as opposed to just solving problems posed explicitly by programmers
- Solving problems that were not known to the programmers

Narrow AI: game -playing, medical diagnosis, car-driving, etc.

Credit: Ben Goertzel, PhD

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Module III

Deep Learnin in a Nutshe

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Representation (DNN Topology)

Task

Score Function

Search/Optimization

Models, Parameters

Hyperparameter, Metrics

Hardware

- Training / Searching / Learning
  - With new losses
  - With new training workflow
  - Scaling up with GPU
  - Hyperparameter Search

Selected Trends

https://qdata.github.io/deep2Read/

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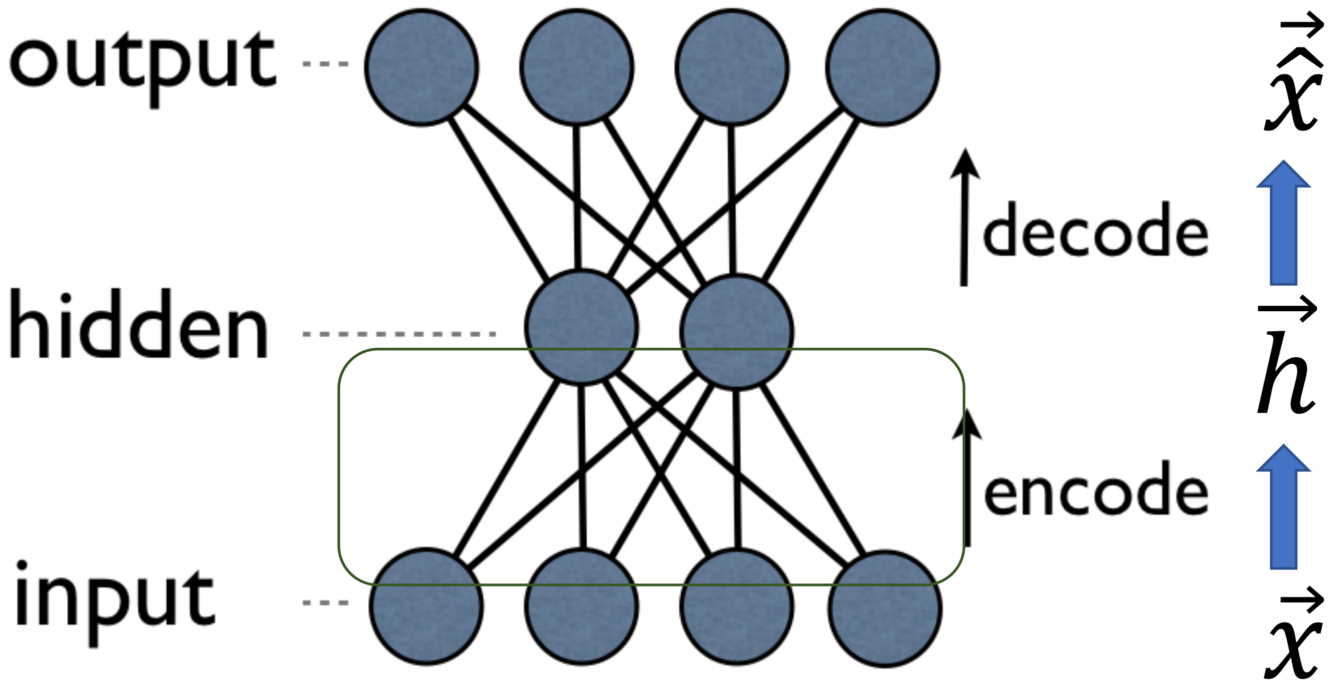
1. Autoencoder / self supervised training
2. Generative Adversarial Networks (GAN)
3. Learning to optimize /Learning to search architecture (AutoML)

Module IV: On Deployment
- ↓
- Models, Parameters
- Hyperparameter, Metrics
- ↓
- Hardware

Recent Trend (6): Layer-wise pretraining workflow/ Auto-Encoder / Self-supervised

Losses

an auto-encoder-decoder is trained to reproduce the input



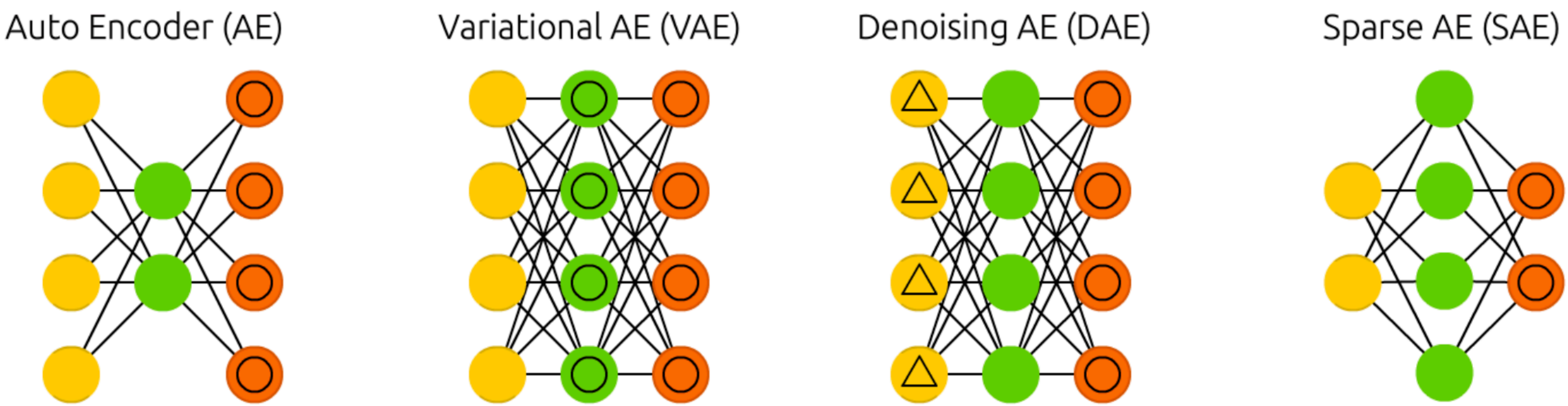
Minimize diff

$$|\vec{\hat{x}} - \vec{x}|$$

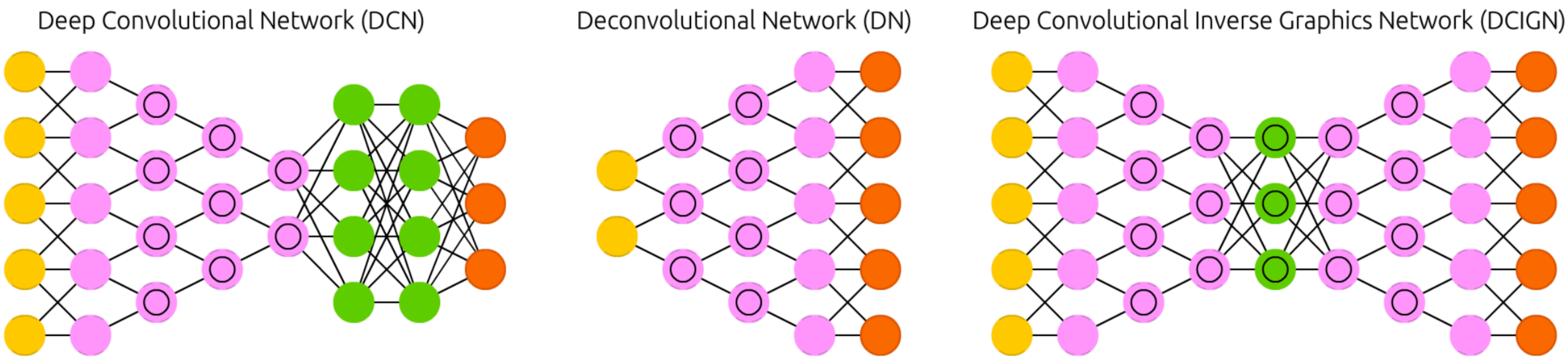
Reconstruction Loss: force the 'hidden layer' units to become good / reliable feature detectors

https://www.macs.hw.ac.uk/~dwcorne/Teaching/introdl.ppt

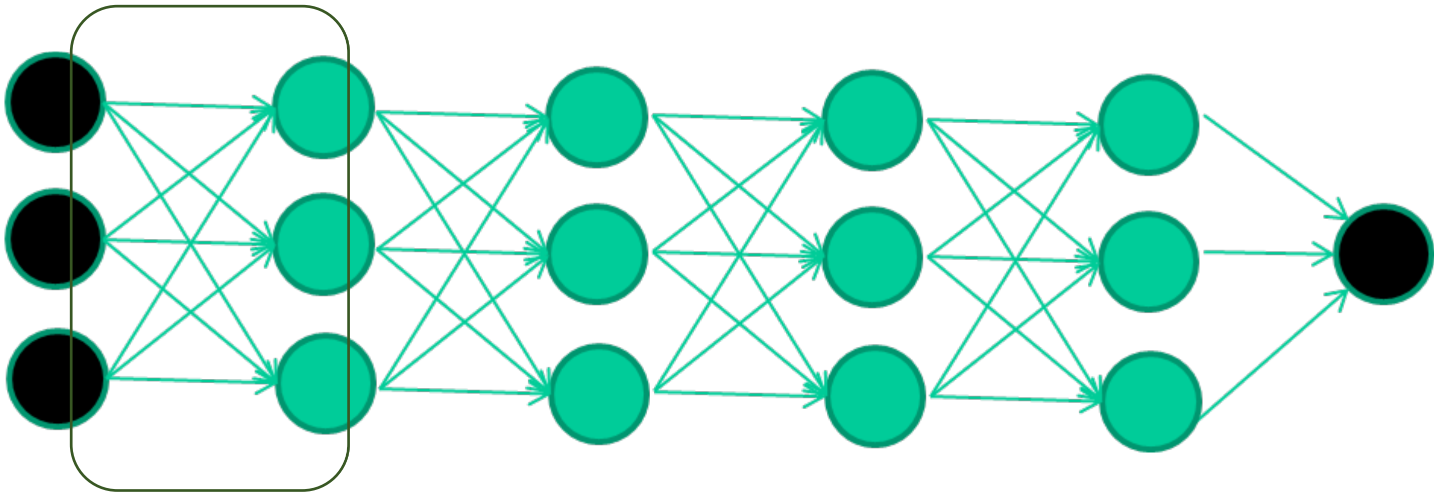
Many Variations



DCIGN


Deep Convolutional Network (DCN)
Deconvolutional Network (DN)
Deep Convolutional Inverse Graphics Network (DCIGN)

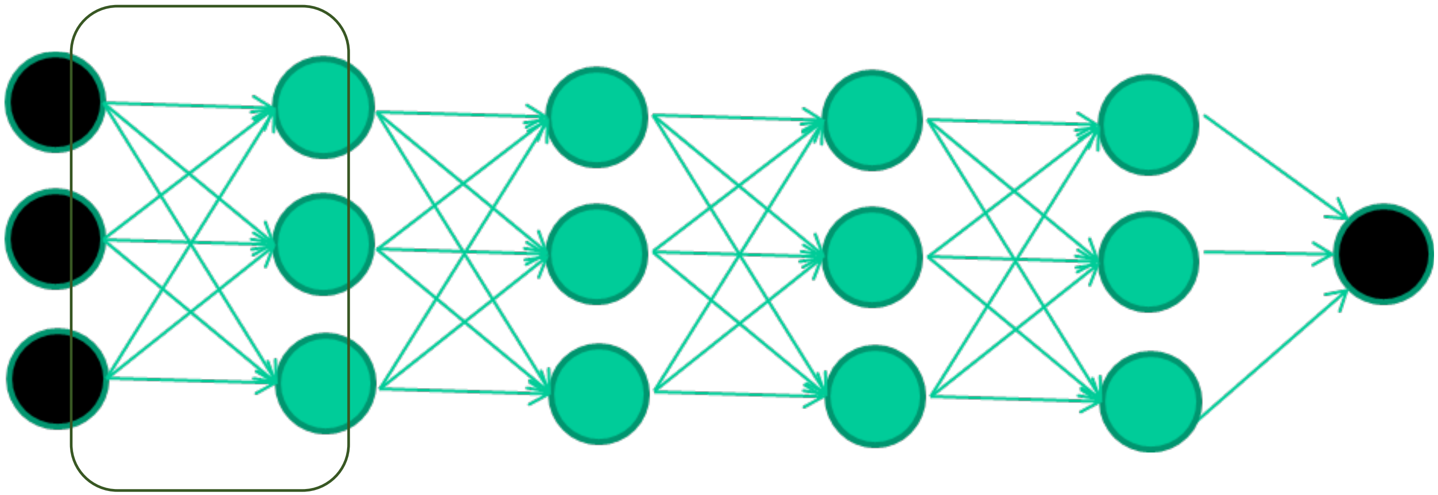
The new way to train multi-layer NNs…



Train **this** layer first

https://www.macs.hw.ac.uk/~dwcorne/Teaching/introdl.ppt

The new way to train multi-layer NNs…



Each layer can be trained well first with some types of self-supervised loss (e.g. reconstruction loss)

Basically, it is forced to learn good features that describe what comes from the previous layer

https://www.macs.hw.ac.uk/~dwcorne/Teaching/introdl.ppt

Unsupervised Pre-training

- Use our original idea, but **pick a better starting point**
- **Train each level** of the model in a **greedy** way

1. Unsupervised Pre-training
   - Use **unlabeled** data
   - Work bottom-up
     - Train hidden layer 1. Then fix its parameters.
     - Train hidden layer 2. Then fix its parameters.
     - …
     - Train hidden layer n. Then fix its parameters.
2. Supervised Fine-tuning
   - Use **labeled** data to train following “Idea #1”
   - Refine the features by backpropagation so that they become tuned to the end-task

Pre-Training of DNN layer-layer

- DNN Model Training can be tricky due to…
  - Nonconvexity
  - Vanishing gradients
- Layer-wise pre-training can help with both!
  - Unsupervised
  - Supervised
  - learn features at different levels of abstraction

Recent Trend (7): Generative Adversarial Networks (GAN): One Sample Generation workflow

Optimization

Losses

10 BREAKTHROUGH TECHNOLOGIES 2018

MIT Technology Review

Dueling Neural Networks

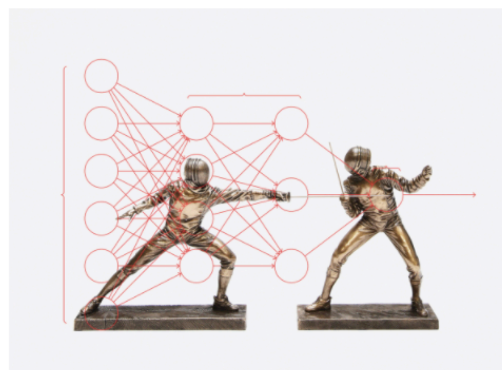
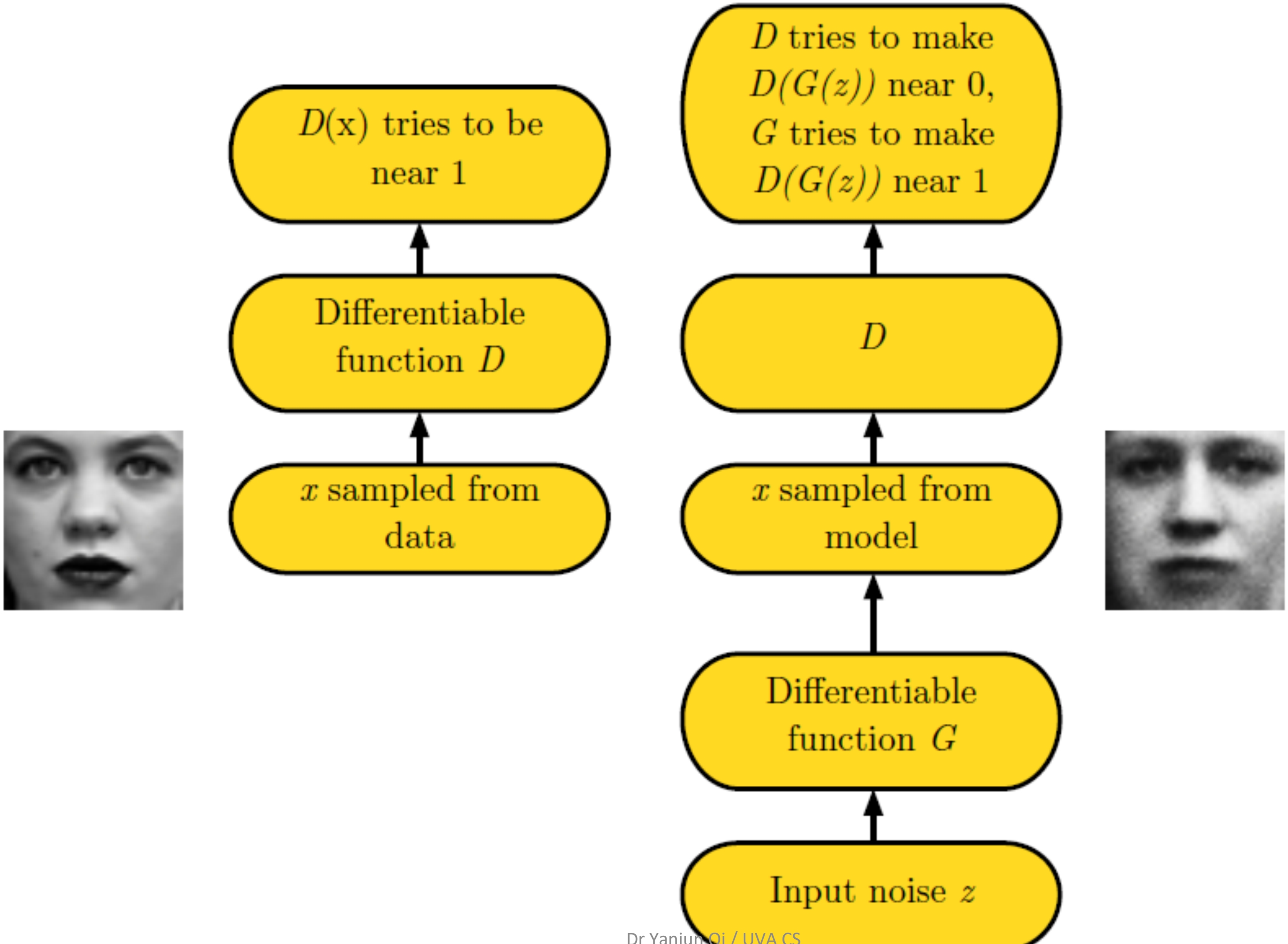


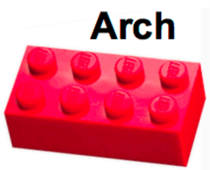
ILLUSTRATION BY DEREK BRAHNEY | DIAGRAM COURTESY OF MICHAEL NIELSEN, "NEURAL NETWORKS AND DEEP LEARNING", DETERMINATION PRESS, 2015

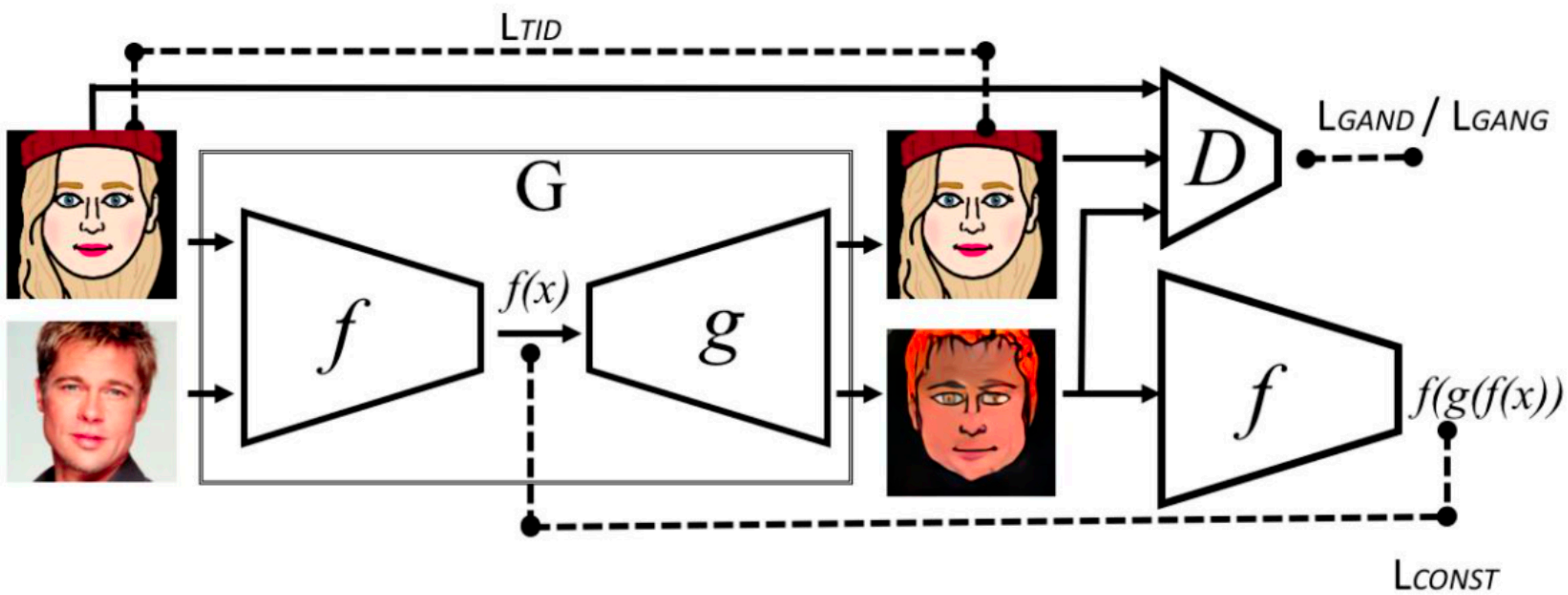
Adversarial Nets Framework



(Goodfellow 2016)

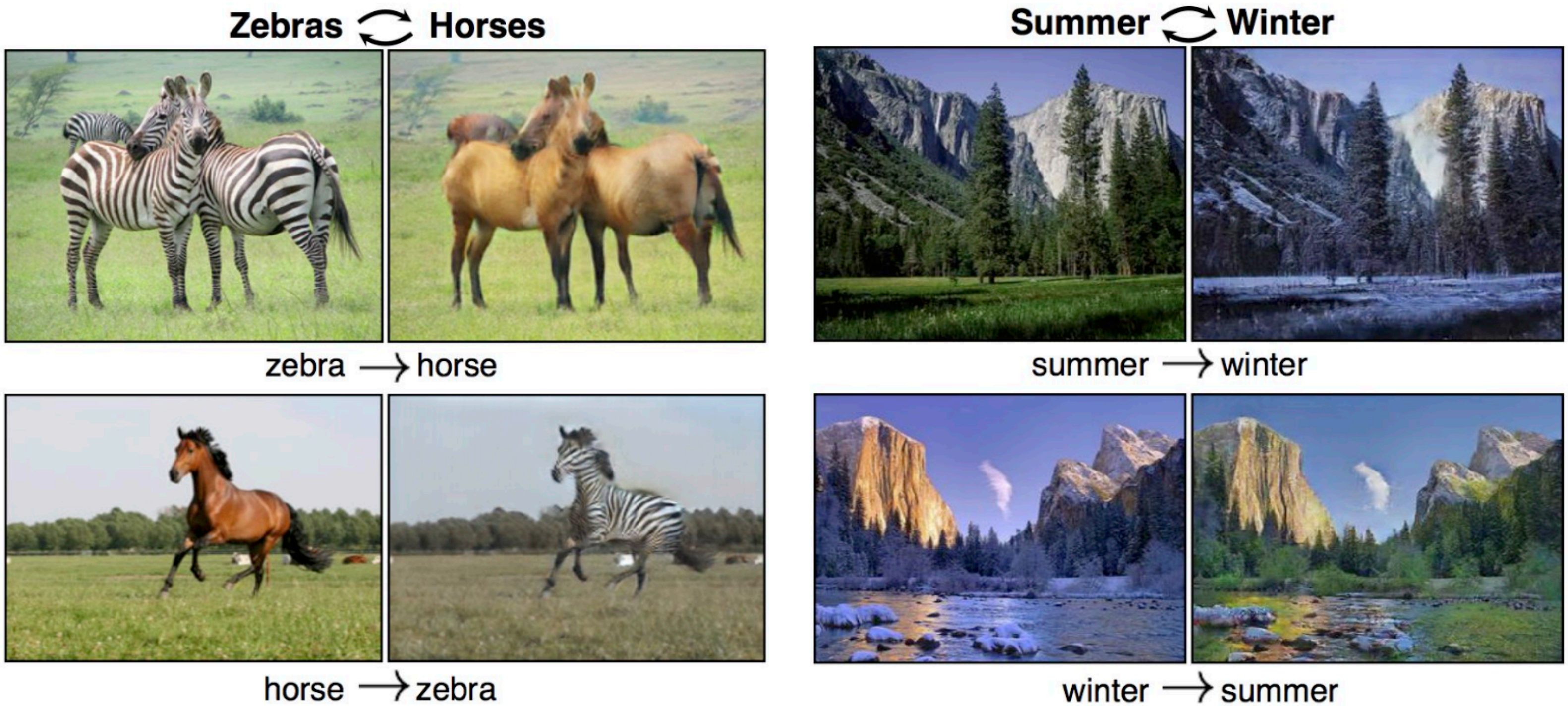
Unsupervised cross-domain image generation





1. Taigmen et al. *"Unsupervised Cross-domain image generation"*. In *ICLR 2017*.

CycleGAN



1. Zhu et al. “Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks”. In ICCV, 2017.

This paper captures special characteristics of one image collection and figures out how these characteristics could be translated into the other image collection, all in the absence of any paired training examples. CycleGANs method can also be applied in variety of applications such as Collection Style Transfer, Object Transfiguration, season transfer and photo enhancement.

Progressive GAN

PROGRESSIVE GROWING OF GANS FOR IMPROVED QUALITY, STABILITY, AND VARIATION, ICLR 2018

A Style-Based Generator Archi
Generative Adversarial Ne

Tero Karras
NVIDIA
tkarras@nvidia.com

Samuli Laine
NVIDIA
slaine@nvidia.com

CVPR 2019

StyleGAN

- propose a new generator architecture for GAN which can generate high quality images (called StyleGAN)
- leads to an automatically learned, unsupervised separation of high-level attributes (latent space disentangled)
- propose two new automated metrics for quantifying disentanglement
- propose a high quality dataset of human faces (FFHQ)

Recent Trend (8): AutoML workflow: Learning to Optimize / Learning to Search DNN architecture

Optimization

Neural Architecture Search with Reinforcement Learning, ICLR17

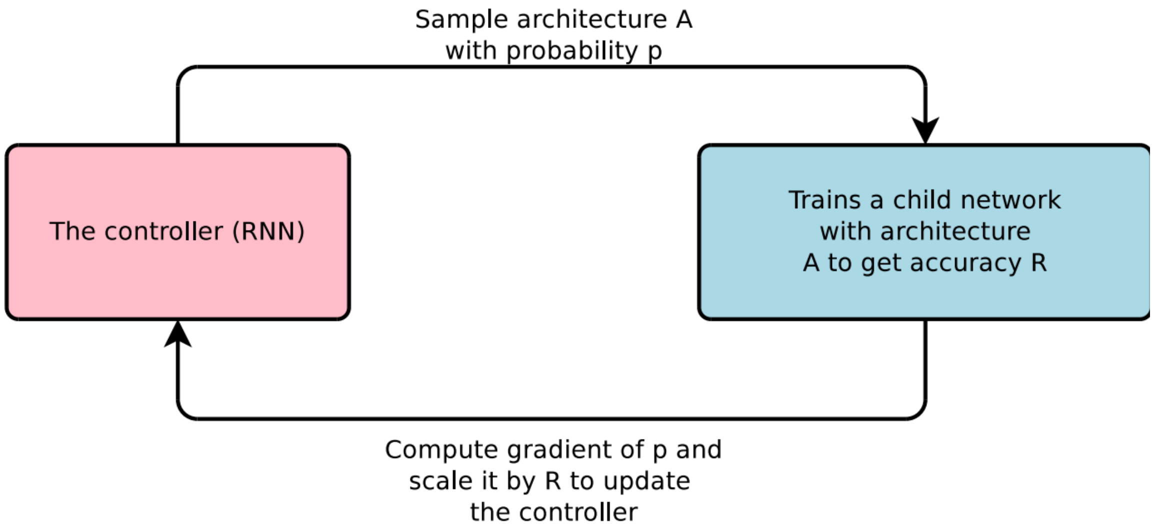
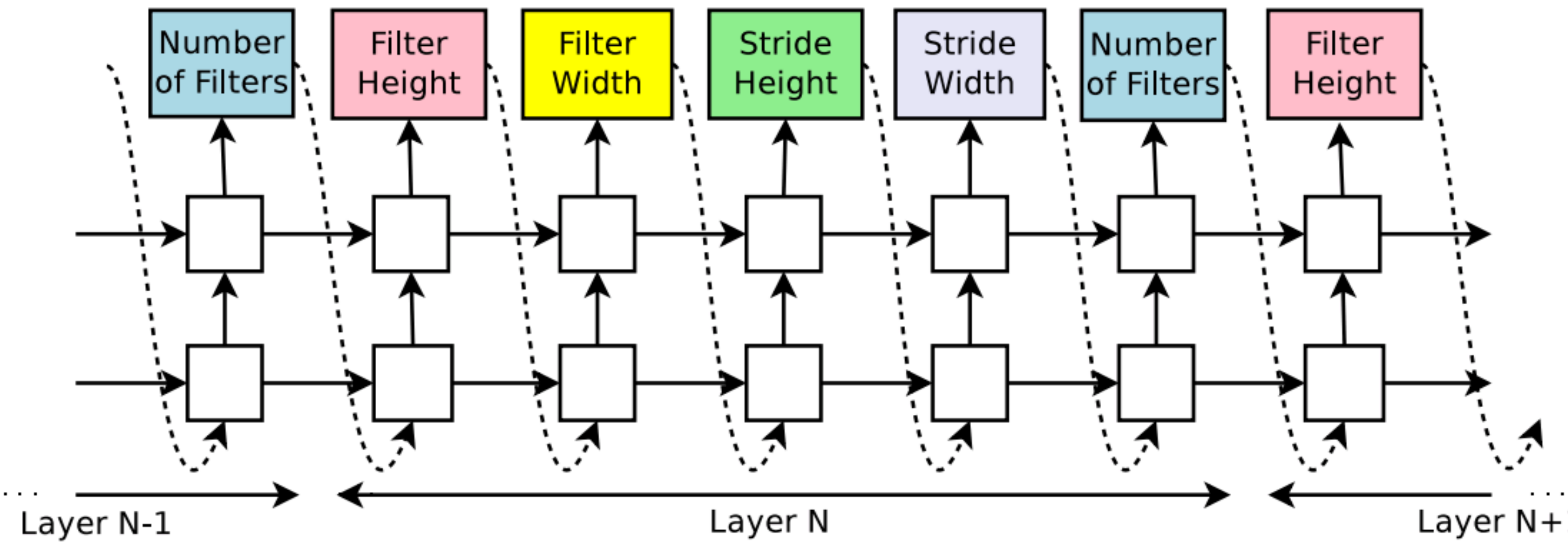


Figure 1: An overview of Neural Architecture Search.



Neural Optimizer Search with Reinforcement Learning, ICML17

- e.g. hyperpara search

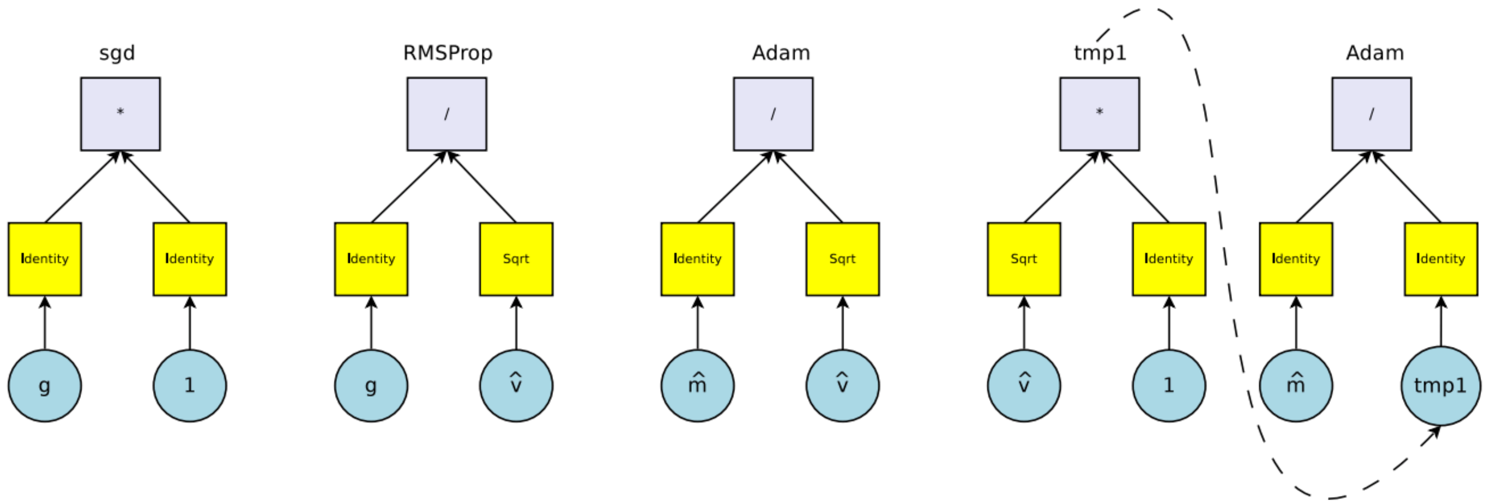


Figure 2. Computation graph of some commonly used optimizers: SGD, RMSProp, Adam. Here, we show the computation of Adam in 1 step and 2 steps. Blue boxes correspond to input primitives or temporary outputs, yellow boxes are unary functions and gray boxes represent binary functions. g is the gradient, $\hat{m}$ is the bias-corrected running estimate of the gradient, and $\hat{v}$ is the bias-corrected running estimate of the squared gradient.

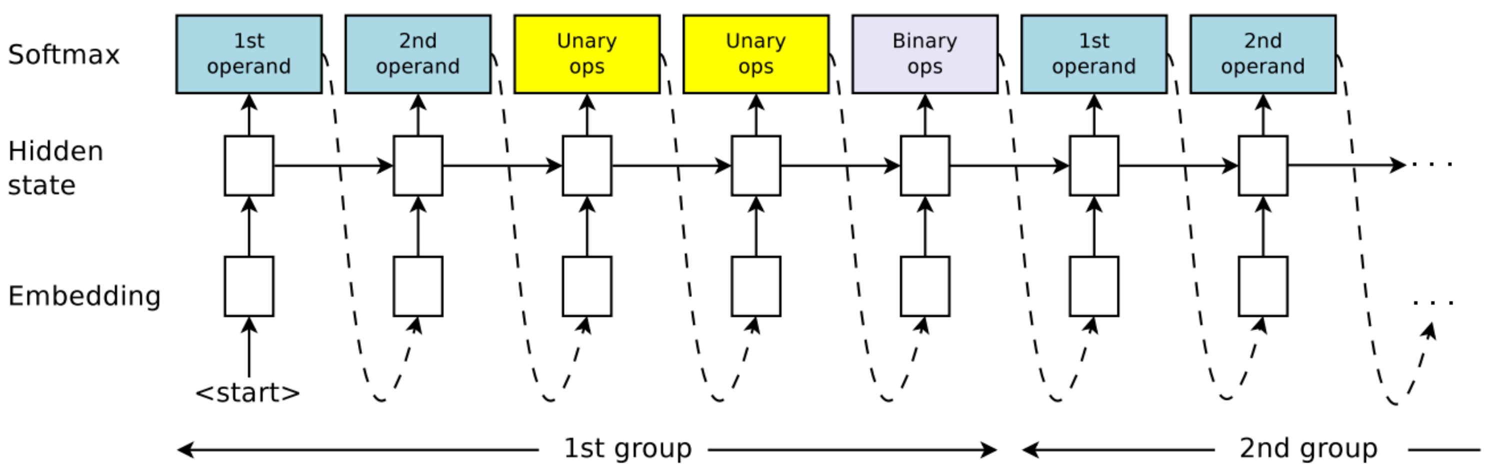


Figure 3. Overview of the controller RNN. The controller iteratively selects subsequences of length 5. It first selects the 1st and 2nd operands op_1 and op_2, then 2 unary functions u_1 and u_2 to apply to the operands and finally a binary function b that combines the outputs of the unary functions. The resulting $b(u_1(op_1), u_2(op_2))$ then becomes an operand that can be selected in the subsequent group of predictions or becomes the update rule. Every prediction is carried out by a softmax classifier and then fed into the next time step as input.

UVA CS 4774: Machine Learning

S3: Lecture 19: Recent Deep Neural Networks: A Quick Overview

Dr. Yanjun Qi

University of Virginia
Department of Computer Science

Module IV

Deep Learning in a Nutshell

Data

↓

Representation (DNN Topology)

↓

Task

↓

Score Function

↓

Search/Optimization

↓

Models, Parameters

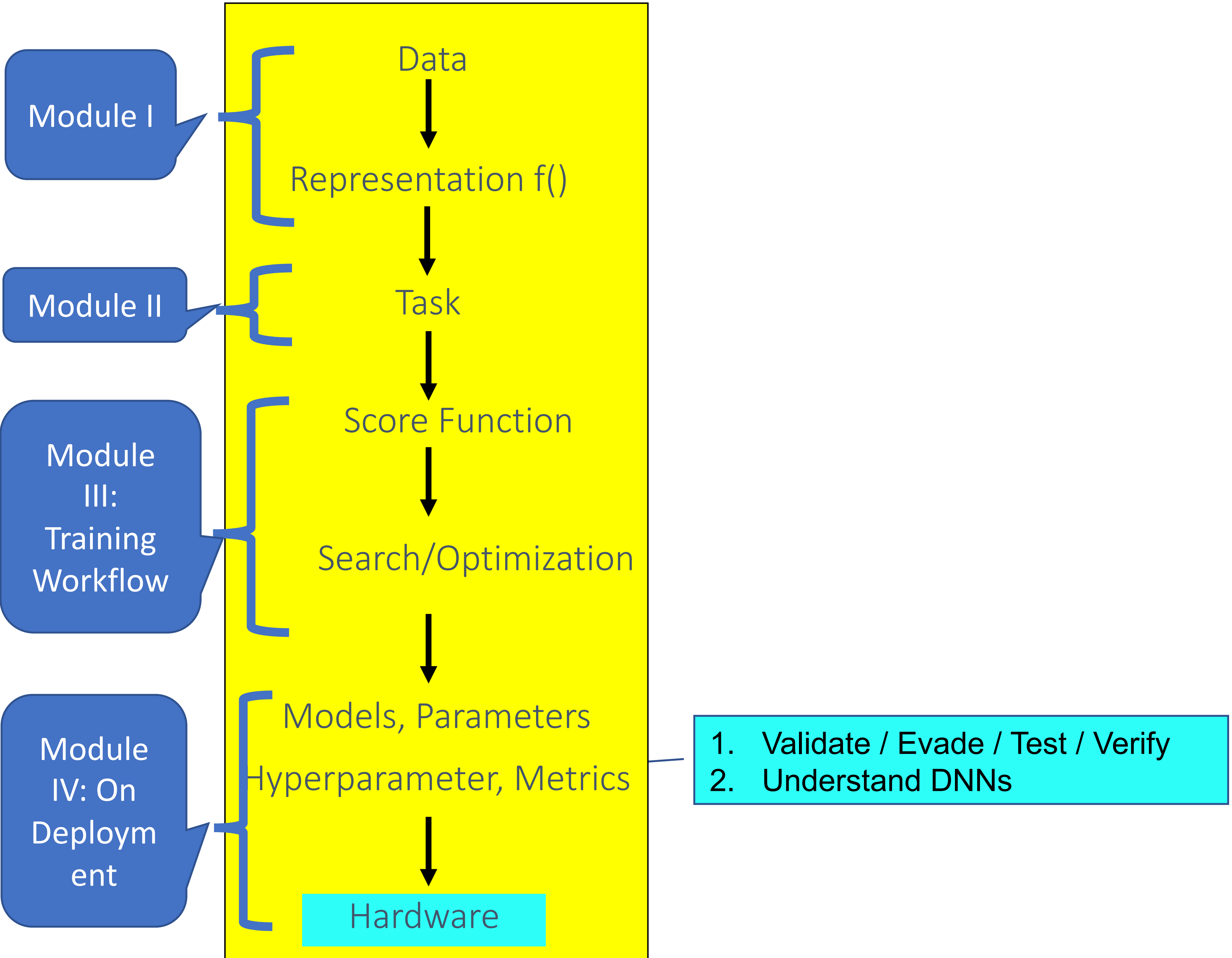
Hyperparameter, Metrics

↓

Hardware

Selected Trends

https://qdata.github.io/deep2Read/



Recent Trend (9):
Robustness / Trustworthiness / Understand / Verify / Test / Evade / Detect Bias / Protect / Manage DNN Models

Validation

Understand DNN

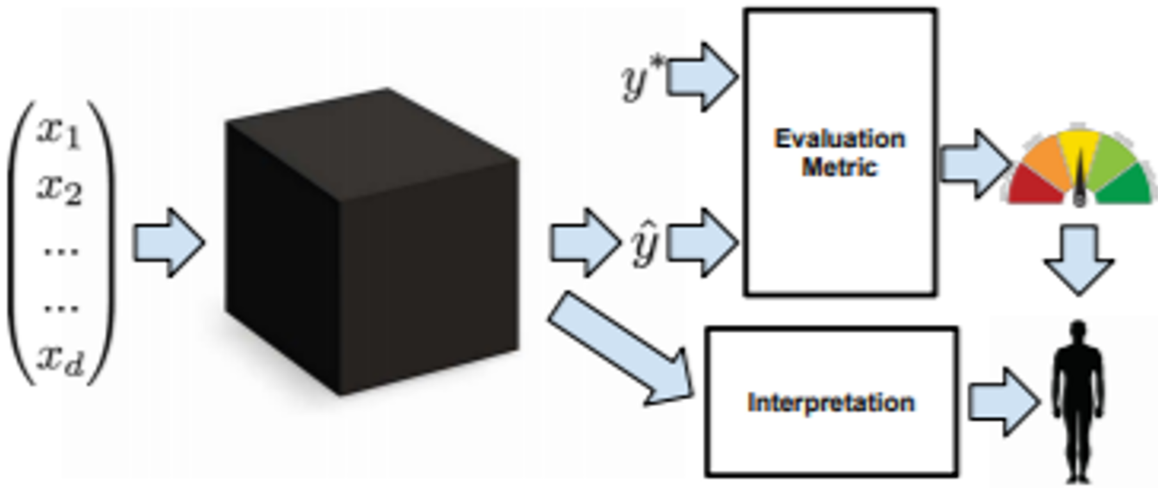


Figure 1. Typically, evaluation metrics require only predictions and *ground truth* labels. When stakeholders additionally demand *interpretability*, we might infer the existence of desiderata that cannot be captured in this fashion.

Interpretation Methods: Overview

- Post-hoc explanations
  - Feature visualization
  - Feature attribution
    - Instance-wise vs. model-wide
  - Feature visualization + attribution
  - Training example attribution
- Inherently interpretable models

Dataset Examples show us what neurons respond to in practice

Optimization isolates the causes of behavior from mere correlations. A neuron may not be detecting what you initially thought.

Baseball—or stripes? *mixed4a, Unit 6*

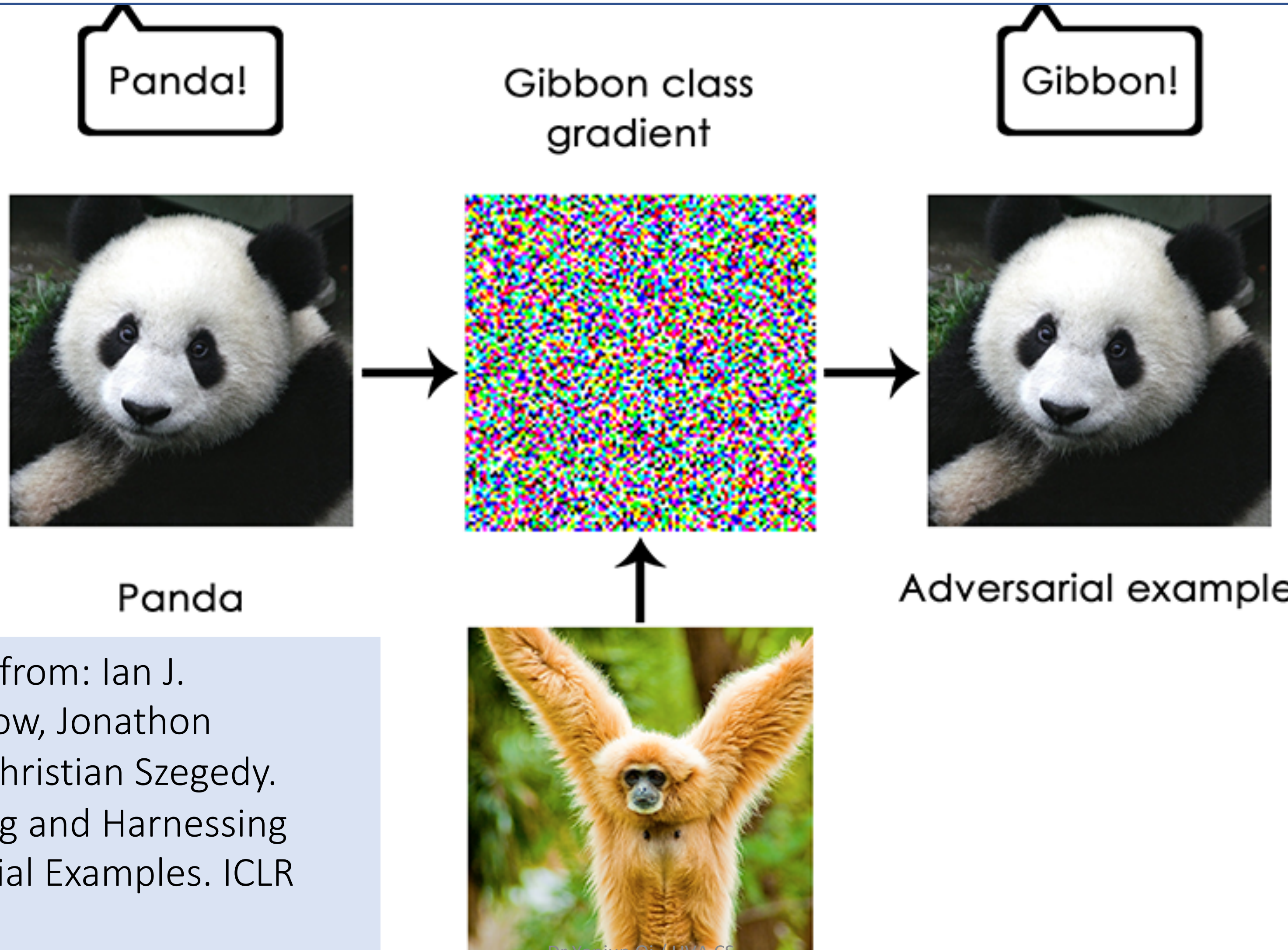
Animal faces—or snouts? *mixed4a, Unit 240*

Clouds—or fluffiness? *mixed4a, Unit 453*

Buildings—or sky? *mixed4a, Unit 492*

To Fool DNN, e.g. Adversarial Examples (AE)

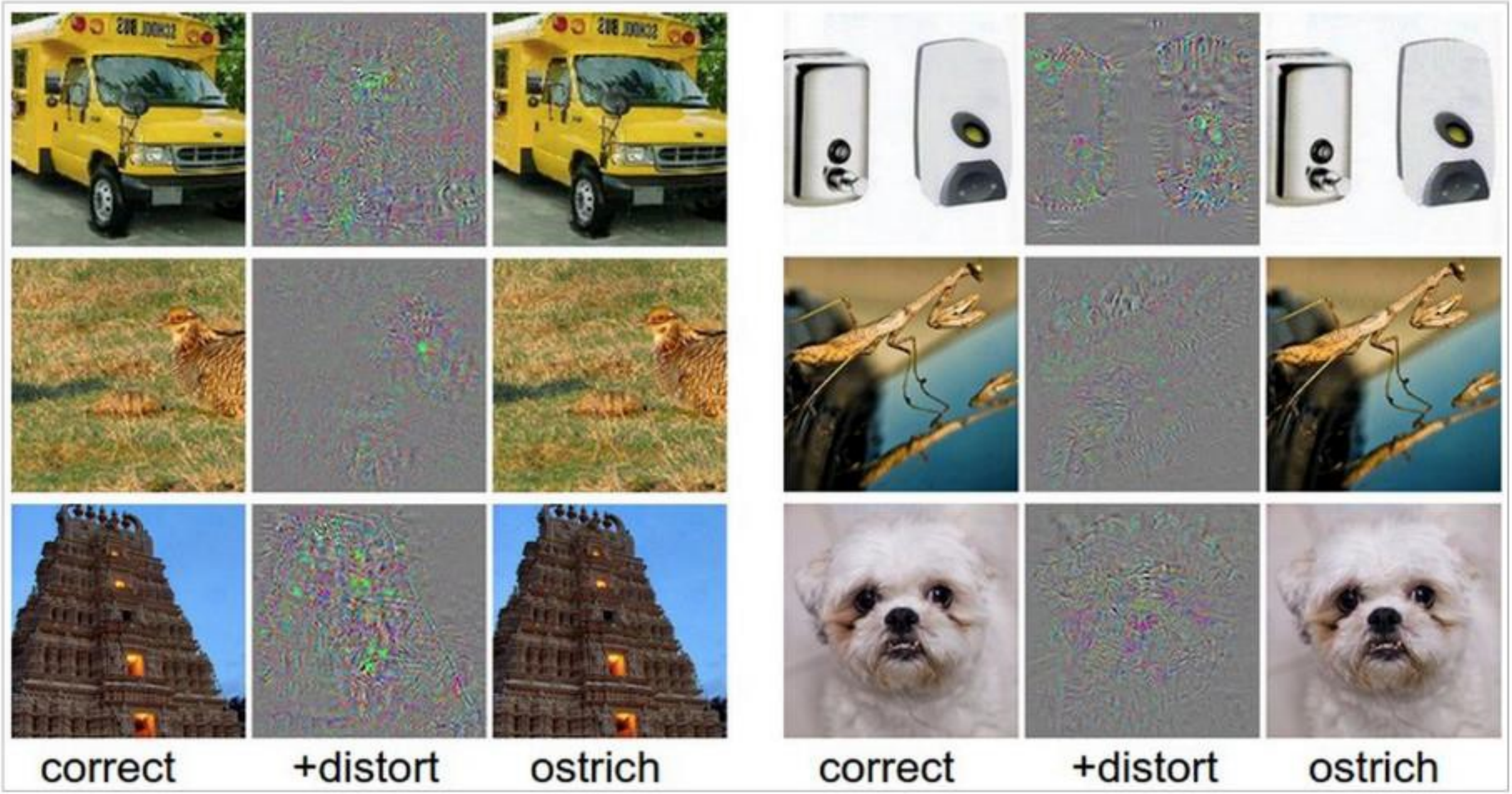
"panda" + $0.007 \times [noise]$ "gibbon"



Example from: Ian J. Goodfellow, Jonathon Shlens, Christian Szegedy. Explaining and Harnessing Adversarial Examples. ICLR 2015.

[Francois Chollet]() - https://blog.keras.io/the-limitations-of-deep-learning.html

Breaking CNNs



Take a correctly classified image (left image in both columns), and add a tiny distortion (middle) to fool the ConvNet with the resulting image (right).

Intriguing properties of neural networks [Szegedy ICLR 2014]

Andrej Karpathy

Verify DNN, e.g. "Reluplex: An efficient SMT solver for verifying deep neural networks." International Conference on Computer Aided Verification. 2017.

Provably robust?

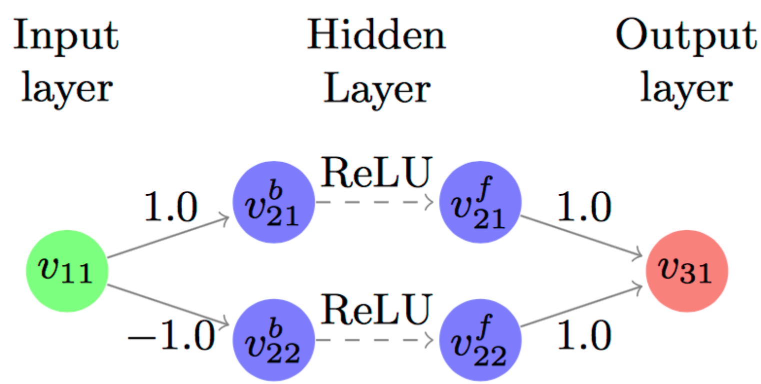


Table 3: Local adversarial robustness tests. All times are in seconds.

	$\delta = 0.1$		$\delta = 0.075$		$\delta = 0.05$		$\delta = 0.025$		$\delta = 0.01$		Total
	Result	Time	Result	Time	Result	Time	Result	Time	Result	Time	Time
Point 1	SAT	135	SAT	239	SAT	24	UNSAT	609	UNSAT	57	1064
Point 2	UNSAT	5880	UNSAT	1167	UNSAT	285	UNSAT	57	UNSAT	5	7394
Point 3	UNSAT	863	UNSAT	436	UNSAT	99	UNSAT	53	UNSAT	1	1452
Point 4	SAT	2	SAT	977	SAT	1168	UNSAT	656	UNSAT	7	2810
Point 5	UNSAT	14560	UNSAT	4344	UNSAT	1331	UNSAT	221	UNSAT	6	20462

Deep Learning in a Nutshell

Data

Representation (DNN Topology)

Task

Score Function

Search/Optimization

Models, Parameters

Hyperparameter, Metrics

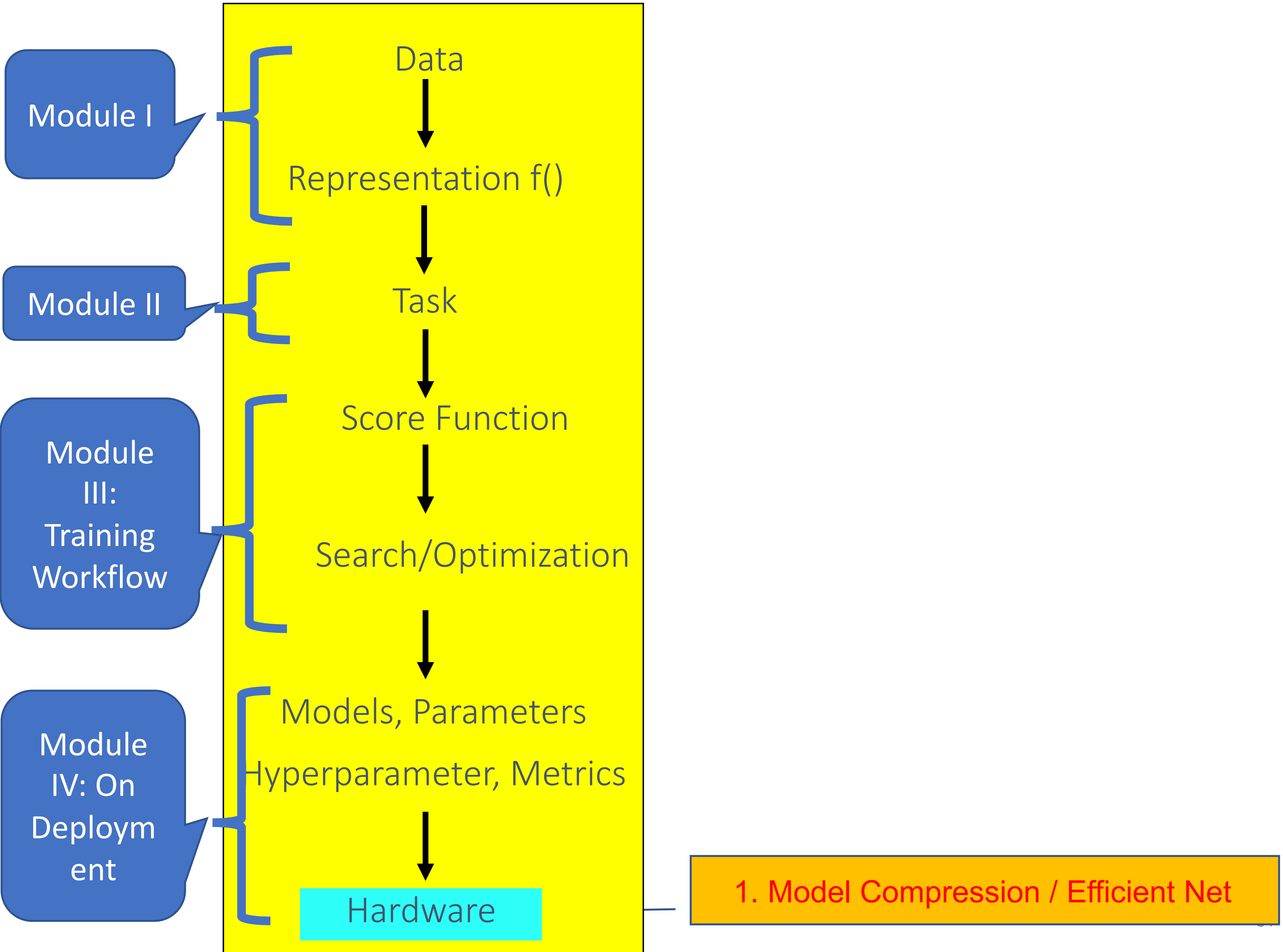
Hardware

Recent Trend (10): Hardware and DNN

Hardware Adaption

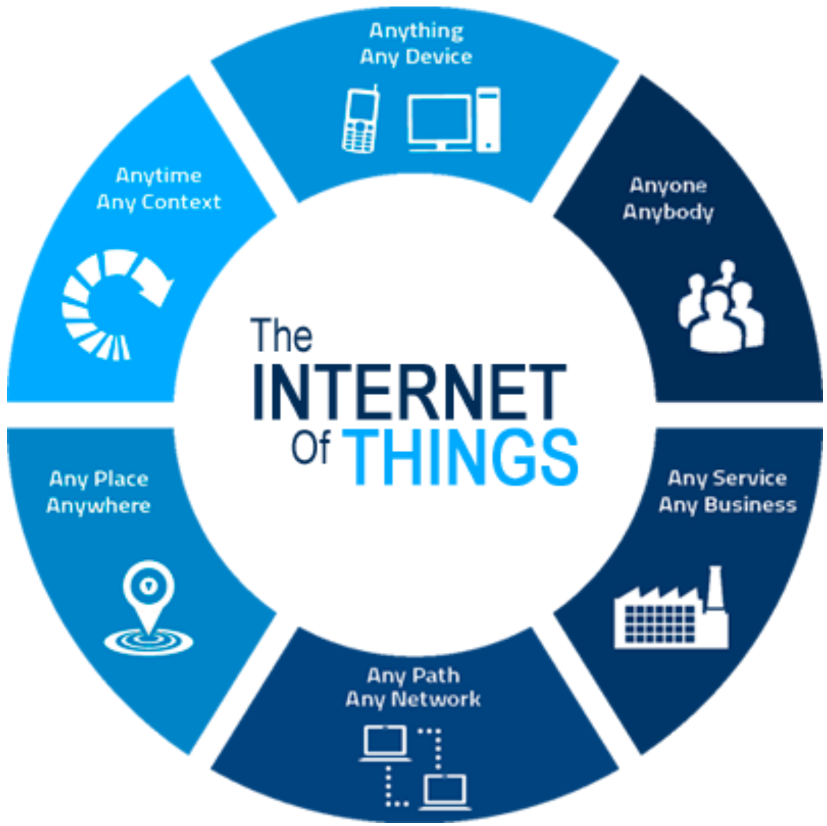
Selected Trends

https://qdata.github.io/deep2Read/



Applications – efficient edge inference on IoT/ mobile devices

Global IoT spend in manufacturing to reach $70 billion by 2020

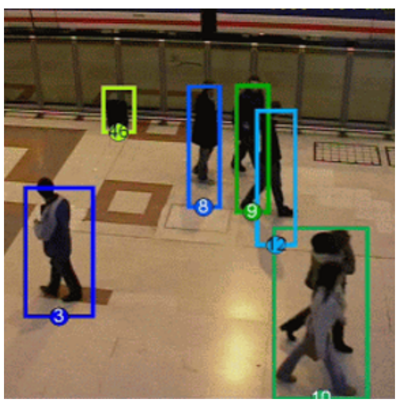


20 billion connected devices by 2020

From GTNEXUS

Applications –
efficient edge inference on mobile devices

Object detection



Speech recognition

Language translation

Autonomous decision making

DNN Model Compression Methods: Overview

(a) Model pruning (neurons, filters, kernels, layer)

- Magnitude-based method
  - Iterative pruning + Retraining
  - Pruning with rehabilitation
- Hessian-based method
  - Diagonal Hessian-based method
  - Full Hessian-based method

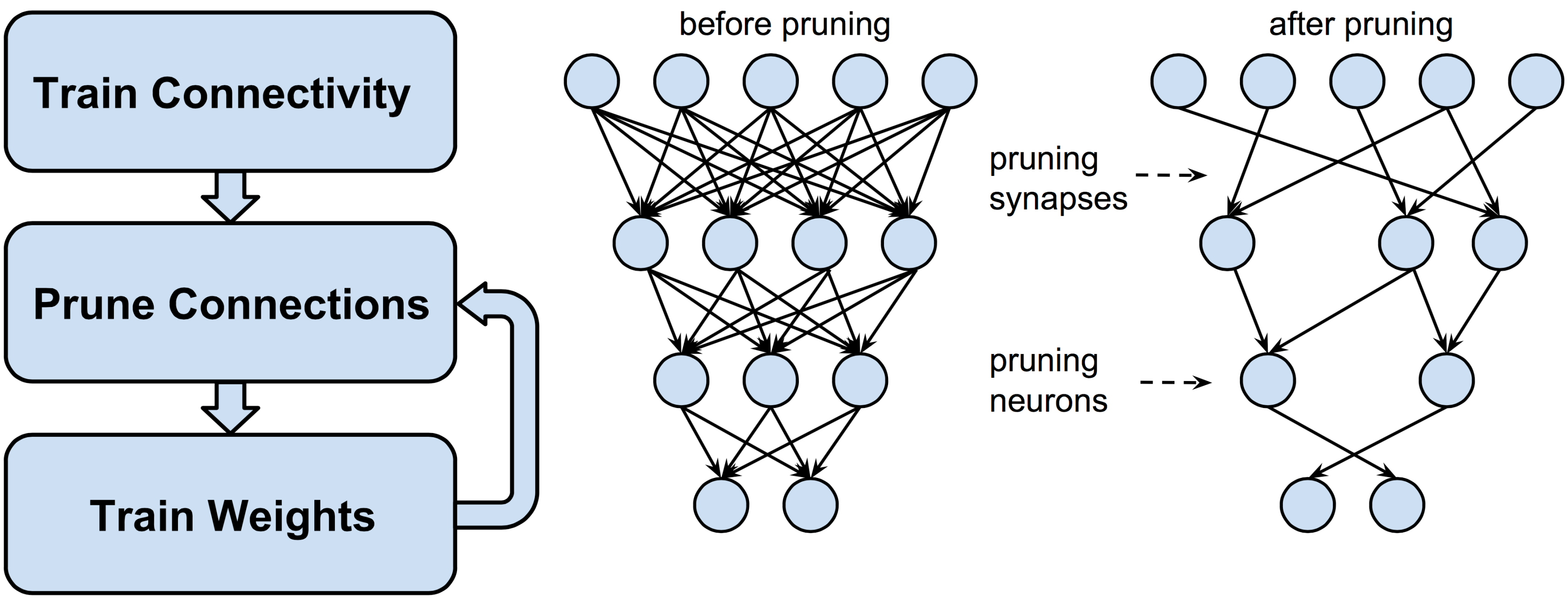
(b) Construct simpler filters / e.g.

- Decomposition, Matrix Factorization , Singular Value Decomposition (SVD)
- Flattened Convolutions

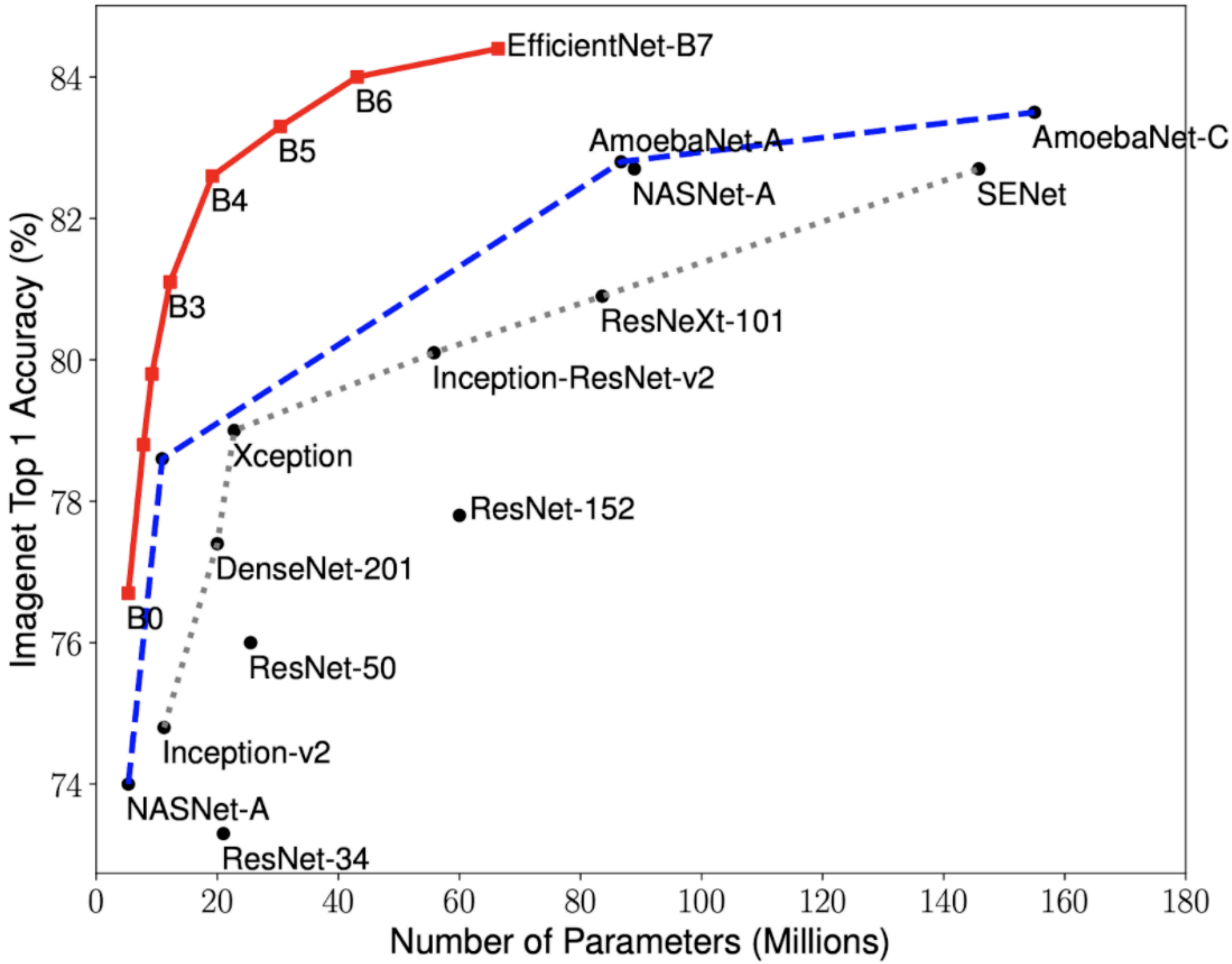
(c) Quantization of activations, weights, and even gradients.

- Full Quantization
  - Fixed-point format
  - Code book
- Quantization with full-precision copy

For example: Magnitude-based method: Iterative Pruning + Retraining



Han, Song, et al. "Learning both weights and connections for efficient neural network." NIPS. 2015.



https://ai.googleblog.com/2019/05/efficientnet-improving-accuracy-and.html

Recap: Selected Trends https://qdata.github.io/deep2Read/

Module I
- Data
- Representation f()

Module II
- Task

Module III: Training Workflow
- Score Function
- Search/Optimization

Module IV: On Deployment
- Models, Parameters
- Hyperparameter, Metrics
- Hardware

Data:
1. DNN on graphs / trees / sets
2. NTM 4program induction

Representation f():
1. CNN / Residual / Memory
2. RNN / Attention / Seq2Seq / Transformer …

Task:
1. Deep Generative models/ DeepFake
2. Deep reinforcement learning
3. Few-shots / Meta learning / AGI?

Search/Optimization:
1. Autoencoder / self supervised training
2. Generative Adversarial Networks (GAN)
3. Learning to optimize /Learning to search architecture (AutoML)

Models, Parameters / Hyperparameter, Metrics:
1. Validate / Evade / Test / Verify
2. Understand DNNs

Hardware:
1. Model Compression / Efficient Net

References

- Dr. Yann Lecun's deep learning tutorials
- Dr. Li Deng's ICML 2014 Deep Learning Tutorial
- Dr. Kai Yu's deep learning tutorial
- Dr. Rob Fergus' deep learning tutorial
- Prof. Nando de Freitas' slides
- Olivier Grisel's talk at Paris Data Geeks / Open World Forum
- Hastie, Trevor, et al. *The elements of statistical learning*. Vol. 2. No. 1. New York: Springer, 2009.
- Dr. Hung-yi Lee's CNN slides
- NIPS 2017 DL Trend Tutorial

Recap: Basic MLP Neural Network Models

Data: X	X: Tabular
Task: y	Classification / Regression
Representation: : x, f()	Multilayer Network topology
Score Function: L()	neg Log-likelihood , Cross-Entropy / MSE / Many more
Search/Optimization : argmin()	SGD / Backprop
Models, Parameters, metrics	Weights and biases in NN Layers / Accuracy / F1

Recap: Convolutional Network Models on 2D Grid / Image

Data: X

Task: y

Representation: : x, f()

Score Function: L()

Search/Optimization : argmin()

Models, Parameters, metrics

X: 2D Grid Imaging

Classification

Convolutional Neural Networks

Cross Entropy Loss

SGD / Backprop

weights, bias / architecture /

/ Accuracy / F1

Recap: Auto Encoder

Data: X

Task: y

Representation: : x, f()

Score Function: L()

Search/Optimization : argmin()

Models, Parameters, metrics

X: Tabular / 2D / 1D / 3D / Graph /…

Dimension Reduction / Representations Learning

e.g., Gaussian assumption

e.g., Reconstruction Error / Variational MLE

SGD / Backprop

e.g., Disentangled Representations