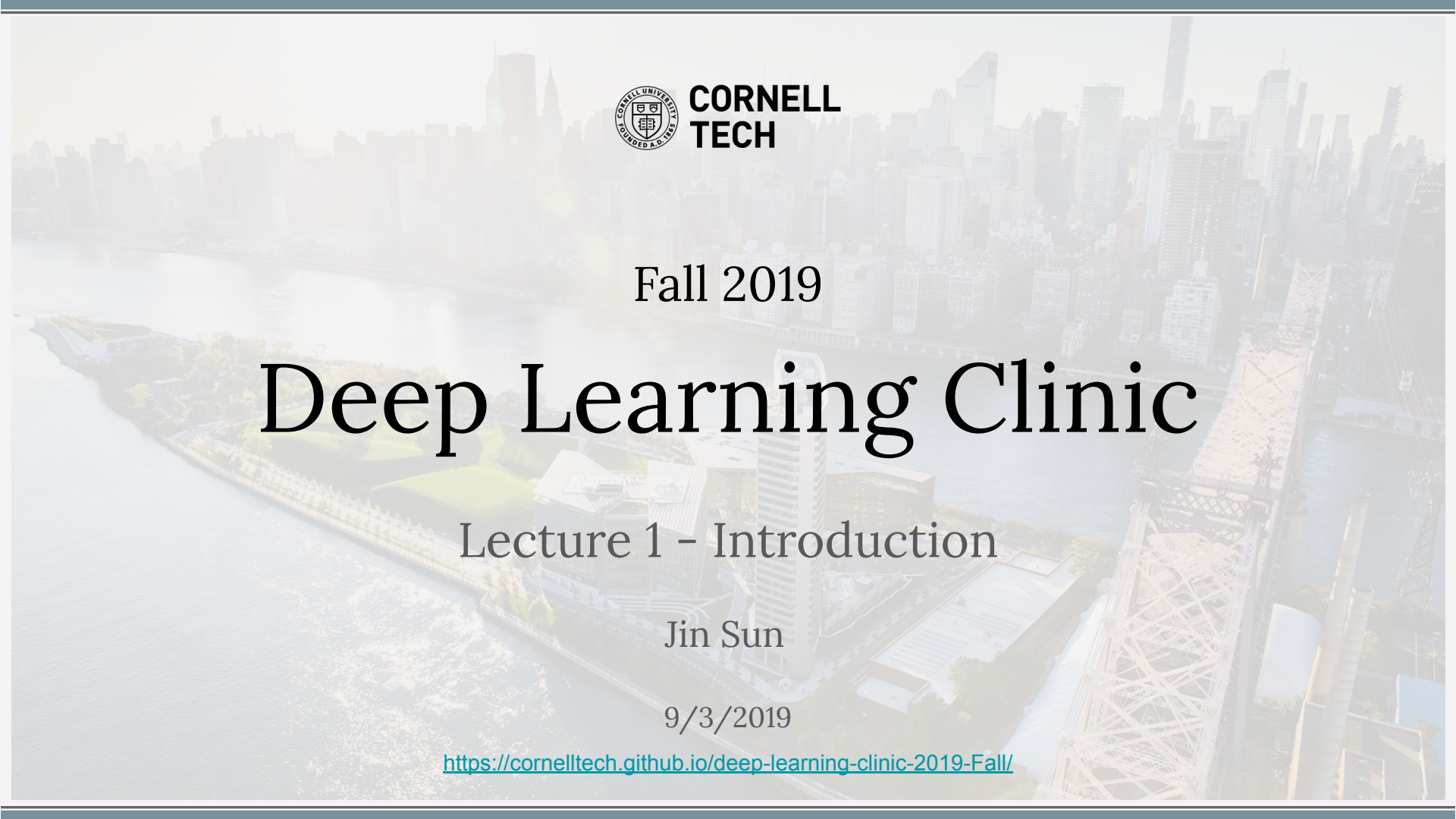


CORNELL TECH

Fall 2019

Deep Learning Clinic

Lecture 1 - Introduction

Jin Sun

9/3/2019

https://cornelltech.github.io/deep-learning-clinic-2019-Fall/

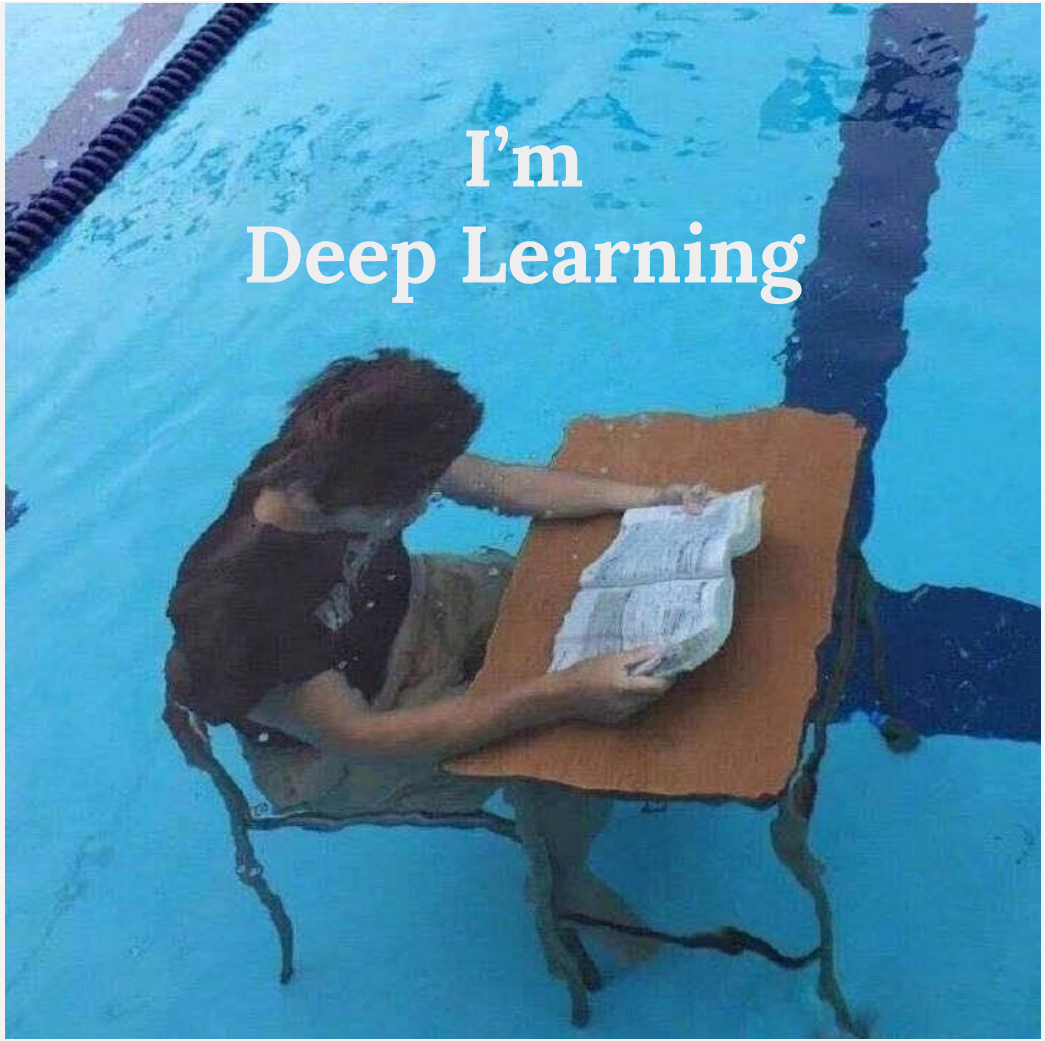
Today

- **Overview of the class**
  - Background
  - Logistics
- Lectures preview
- Office hours preview
- FAQ

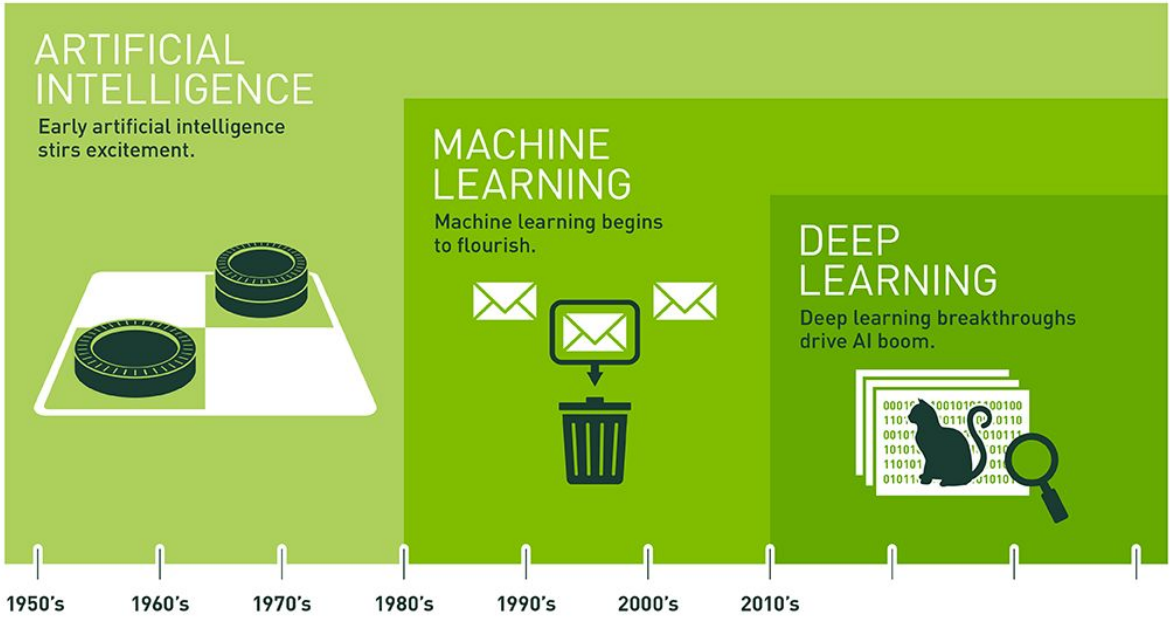
Course page:
https://cornelltech.github.io/deep-learning-clinic-2019-Fall/

Slack channel:
https://cornelltechdlc.slack.com/

What is Deep Learning


I'm
Deep Learning

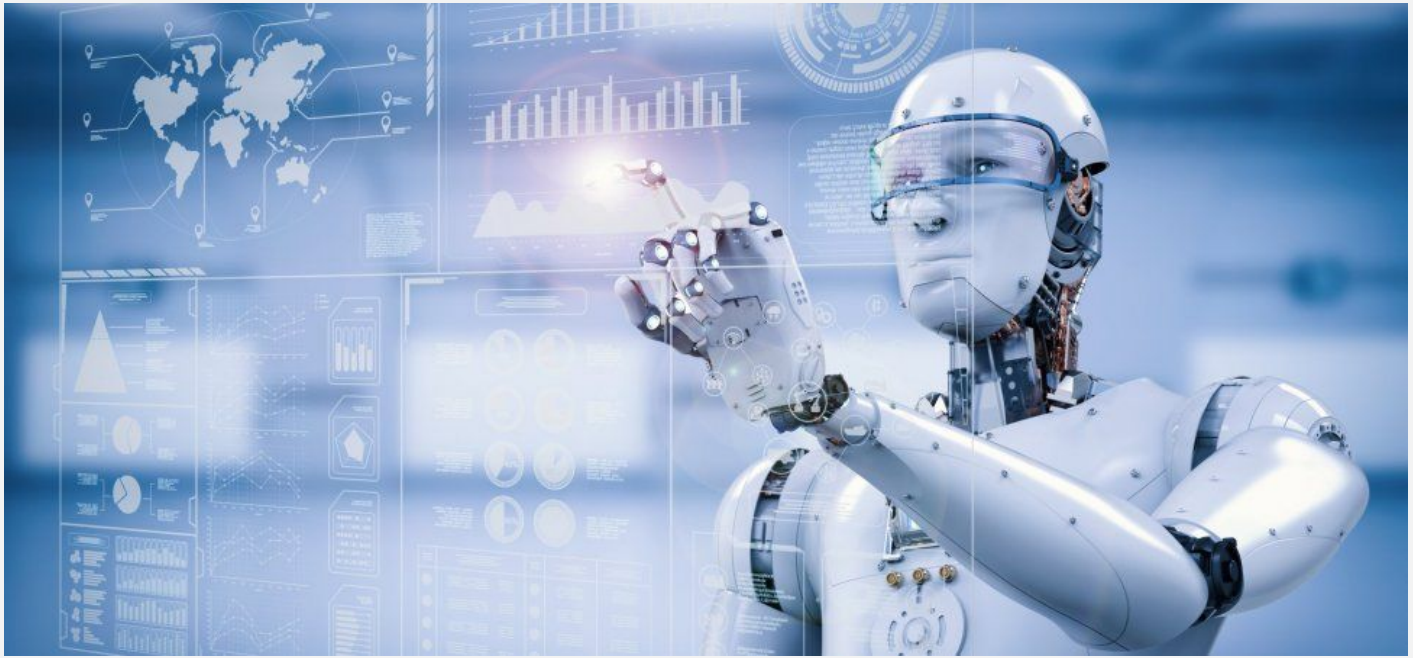
What is Deep Learning



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

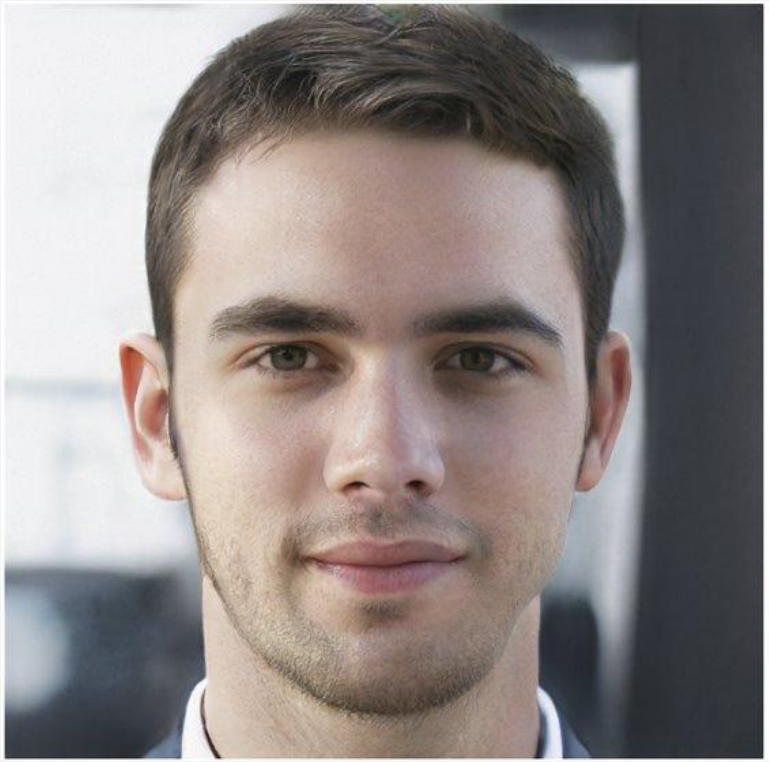
What can DL do

Artificial Intelligence (AI) to the general public:



What can DL do

We are not there yet but ML/DL can do many cool things:



Which face is real?

Everybody Dance Now

Overview of DLC - Background

“The true challenge to artificial intelligence proved to be solving the tasks that are easy for people to perform but hard for people to describe formally.
...
This solution is to allow computers to **learn from experience** and understand the world in terms of **a hierarchy of concepts**... enables the computer to **learn complicated concepts by building them out of simpler ones**.

If we draw a graph showing how these concepts are built on top of each other, **the graph is deep**...

For this reason, we call this approach to AI ***deep learning***.”

-- *Deep Learning* by Ian Goodfellow and Yoshua Bengio and Aaron Courville

Overview of DLC - Background

What DL is good for

Problems with massive data

Classification problems

Regression problems

Correlation relationship

What DL is not good at

Limited amount data

Partial labels

Structure output

Long term relationship

Causal relationship

Overview of DLC

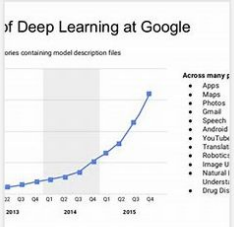
deep learning tutorial

Deep Learning Tutorial **PDF**

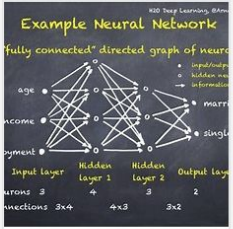
Open Source Deep Learning Tutorial

Deep Learning **Examples**

Deep Learning **Explained**

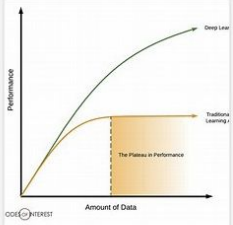


Deep Learning Google

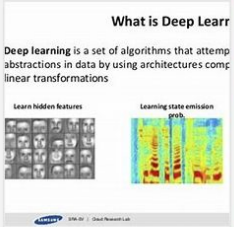


Deep Learning Example

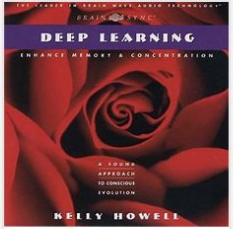
Deep Learning Tools



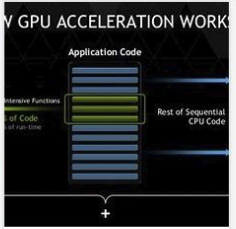
Deep Learning Plateau



Deep Learning Algorithms

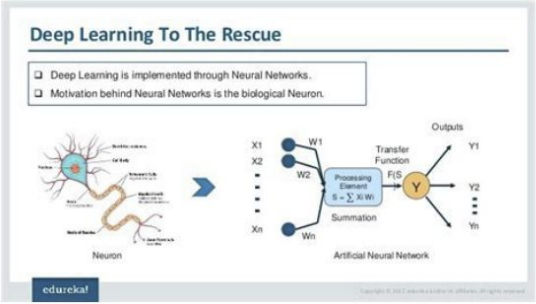


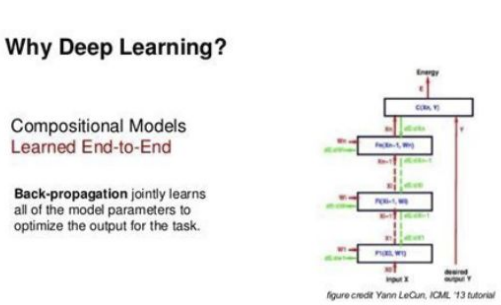
Deep Learning Kelly Howell



Deep Learning GPU

Deep Processing a





DL/ML Basic Concepts

Real World Application

Hands On

Step-by-step

Deep Learning Clinic

Practical Guidance

One-on-one

Get Started

For You

Technical Background

What tools to use

How to use existing tools

Eager to solve complex real world problems

How to train a DL model

Overview of DLC - Logistics

Lecture Session

Tue 9:30-10:45am, Bloomberg 061

- Introduction to:
  - Techniques
  - Tools
  - Tricks
  - How to solve a real-world problem

Office Hour Session

Wed 2:00-3:00pm, Bloomberg 316

- One-on-one advice
- Problem solving:
  - Feasibility evaluation
  - Modeling and task formulation
  - Network design
  - Practical guidance on training

Zero-credit, no assignments or evaluations.

Jin Sun

jinsun@cornell.edu - *Please include the tag ‘DLC’ in the subject

Research Interest:
Computer Vision (object detection, scene understanding)

Office Hour:
Wed 2-3pm Bloomberg 316

http://www.cs.cornell.edu/~jinsun/

Slack channel: https://cornelltechdlc.slack.com/, open to cornell.edu address

Reference

Online Courses

MIT 6.S191: Introduction to Deep Learning link

Stanford CS231n: Convolutional Neural Networks for Visual Recognition link

Free Textbooks

A Course in Machine Learning by Hal Daume III link

Deep Learning by Ian Goodfellow and Yoshua Bengio and Aaron Courville link

Today

- Overview of the class
  - Background
  - Logistics
- **Lectures preview** - Whole semesters lectures in a day
- Office hours preview
- FAQ

Lec 1: Deep Learning Frameworks

How to set up a basic deep learning development environment:

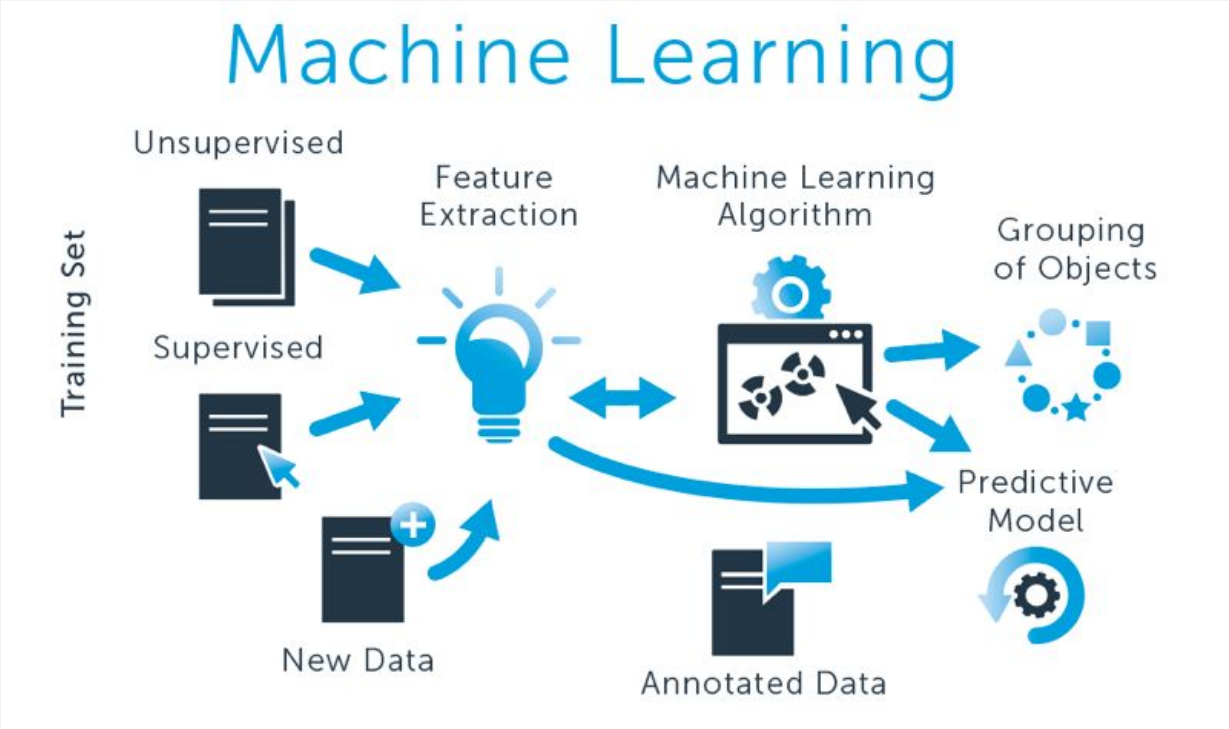
- Python virtualenv
- Anaconda
- Docker
- Jupyter Notebook

Lec 1: Deep Learning Frameworks

How to set up a basic deep learning development environment:

By the end of this lecture, you'll have a working DL environment to play with!

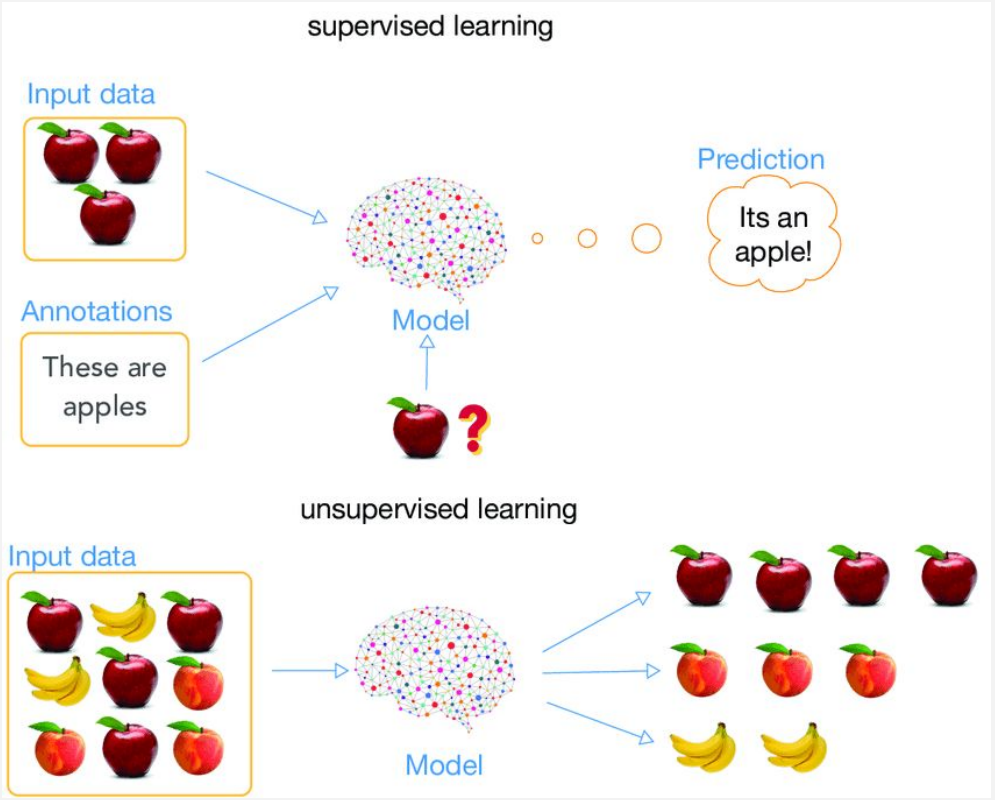
Lec 2: Brief Introduction to Machine Learning



Lec 2: Brief Introduction to Machine Learning

Core ML concepts:

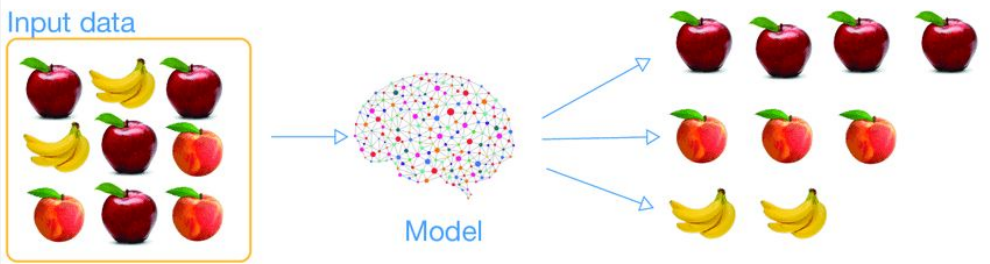
- Supervised learning
- Unsupervised learning



Lec 2: Brief Introduction to Machine Learning

Core ML concepts:

Classification

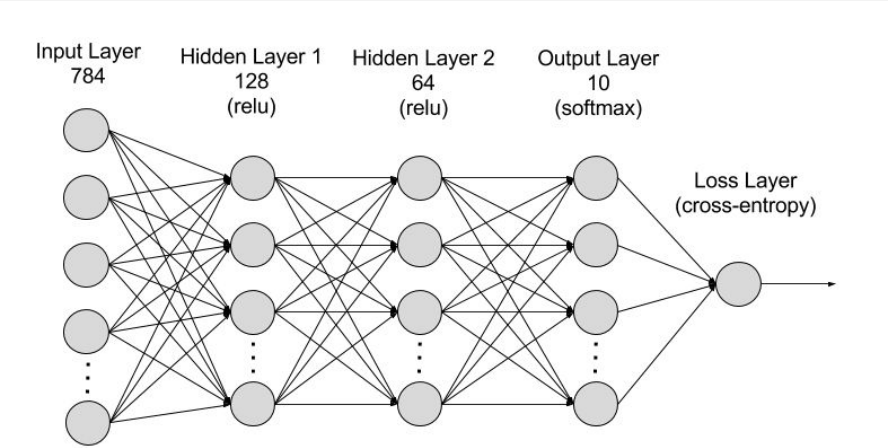


Regression

Lec 3: Brief Introduction to Deep Learning

Core DL topics:

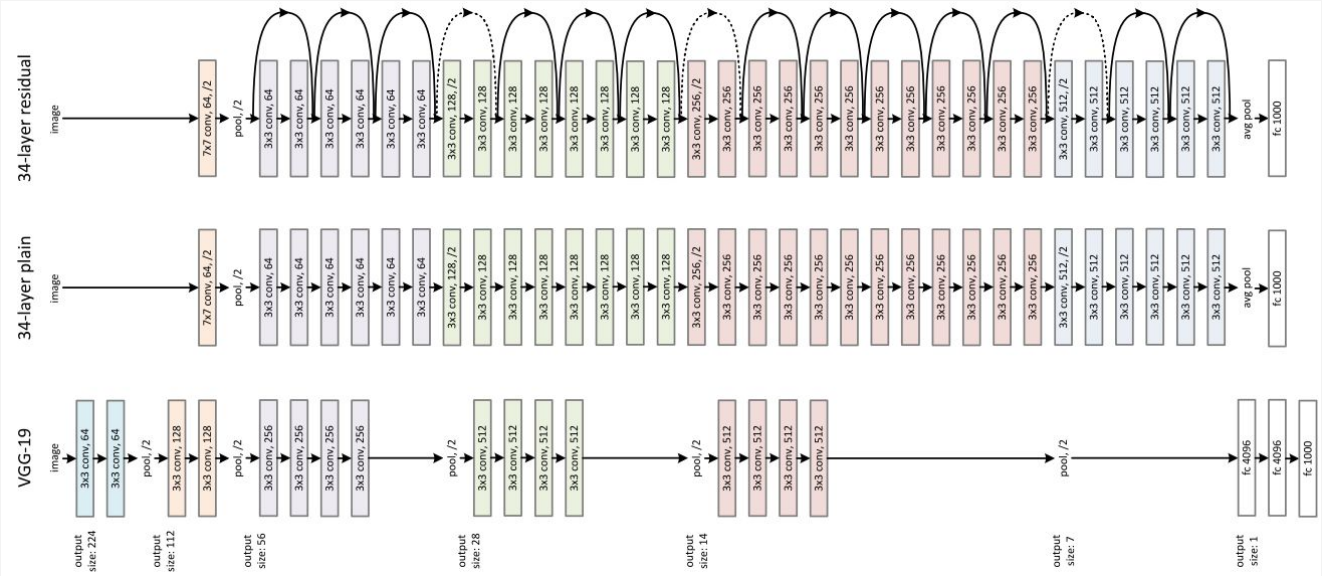
Network structures



Lec 3: Brief Introduction to Deep Learning

Core DL topics:

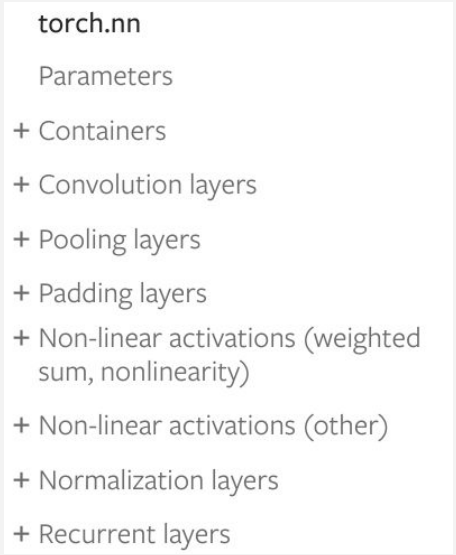
Network structures



Lec 3: Brief Introduction to Deep Learning

Core DL topics:

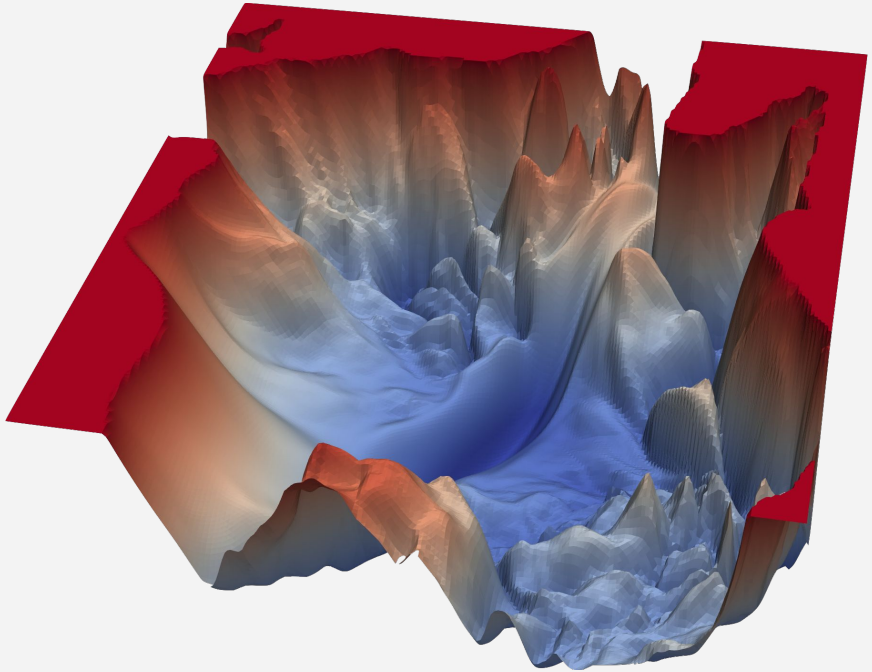
Common neural network building blocks



Lec 3: Brief Introduction to Deep Learning

Core DL topics:

- Backpropagation
- Optimization

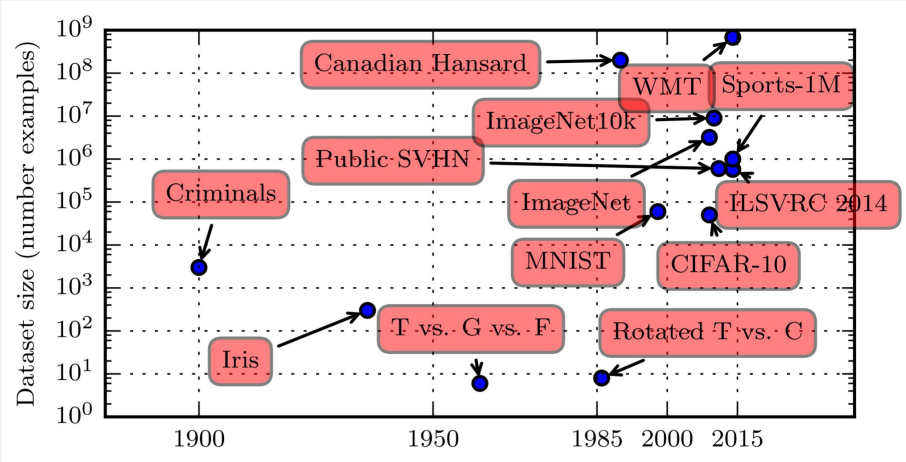


https://www.cs.umd.edu/~tomg/projects/landscapes/

Lec 4: Data

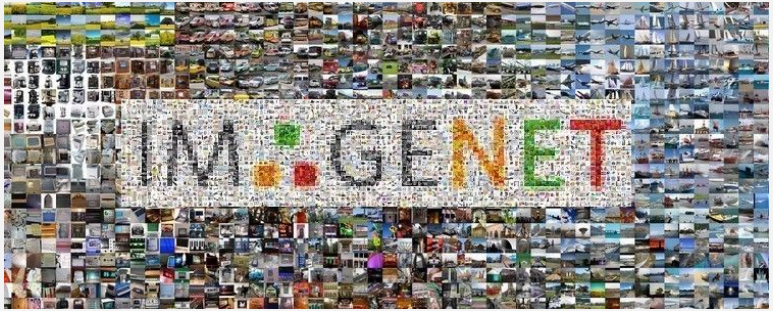
Main Reasons Behind the Success of DL

Hardware

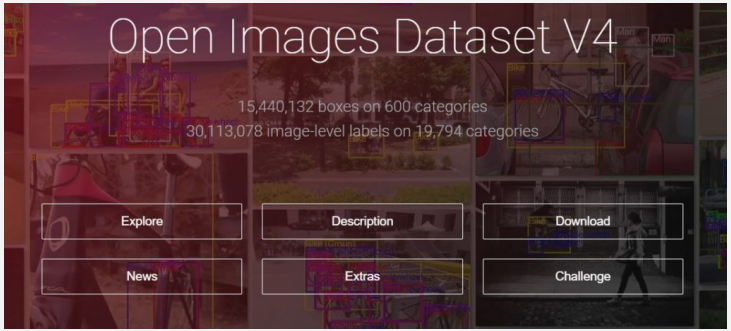


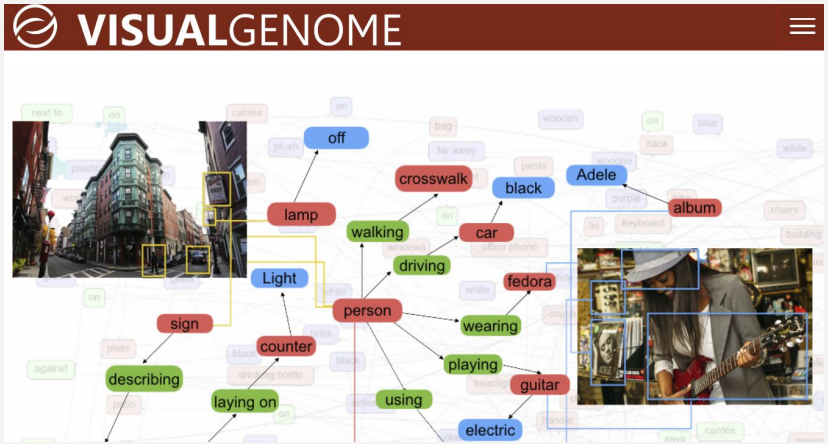
Data

Lec 4: Data


IMAGENET

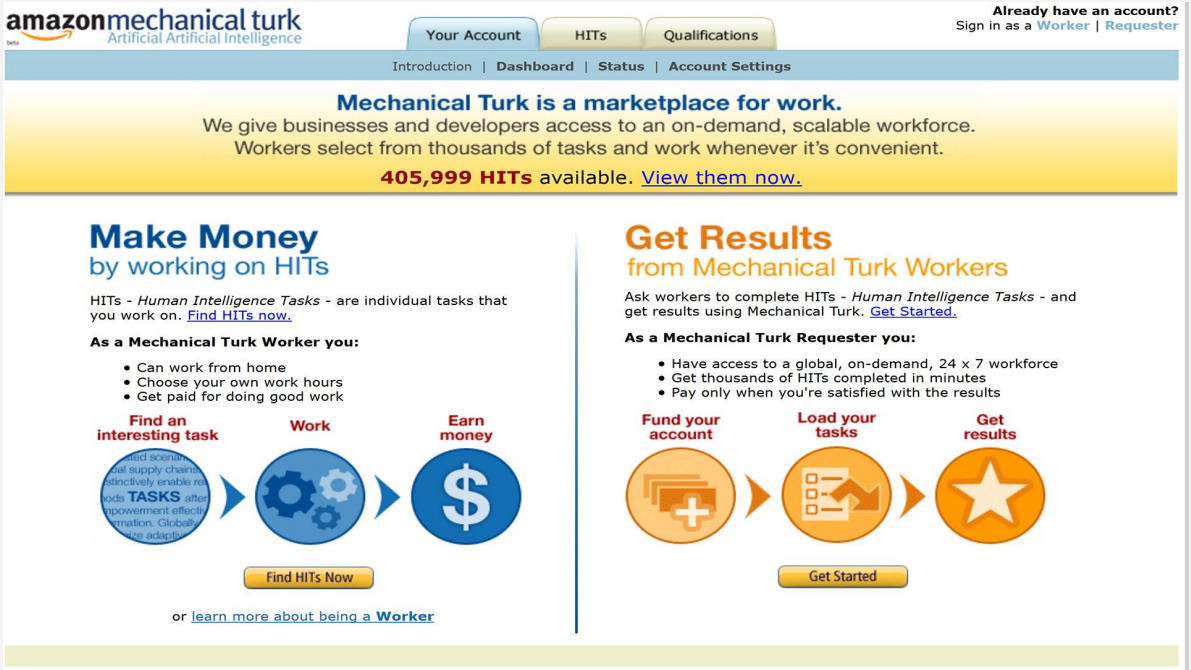

COCO
Common Objects in Context


Open Images Dataset V4
15,440,132 boxes on 600 categories
30,113,078 image-level labels on 19,794 categories
Explore
Description
Download
News
Extras
Challenge


VISUALGENOME
off
crosswalk
black
Adele
album
lamp
walking
car
driving
Light
fedora
person
wearing
sign
counter
playing
describing
guitar
laying on
using
electric

Lec 4: Data

Data Collection, Annotation, and Verification



Lec 5: Neural Network Architectures

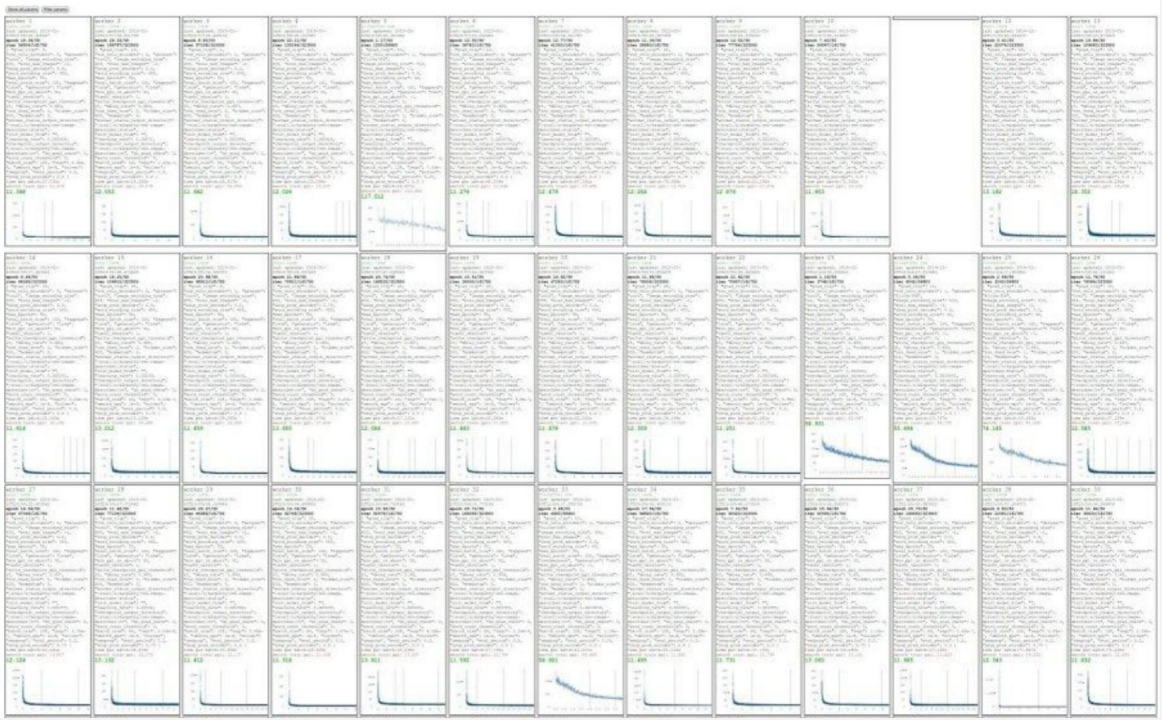
Model search: How to find the best structure for your problem

There are a lot of design choices:

Number of layers, which non-linear layer to use, number of filters and etc.

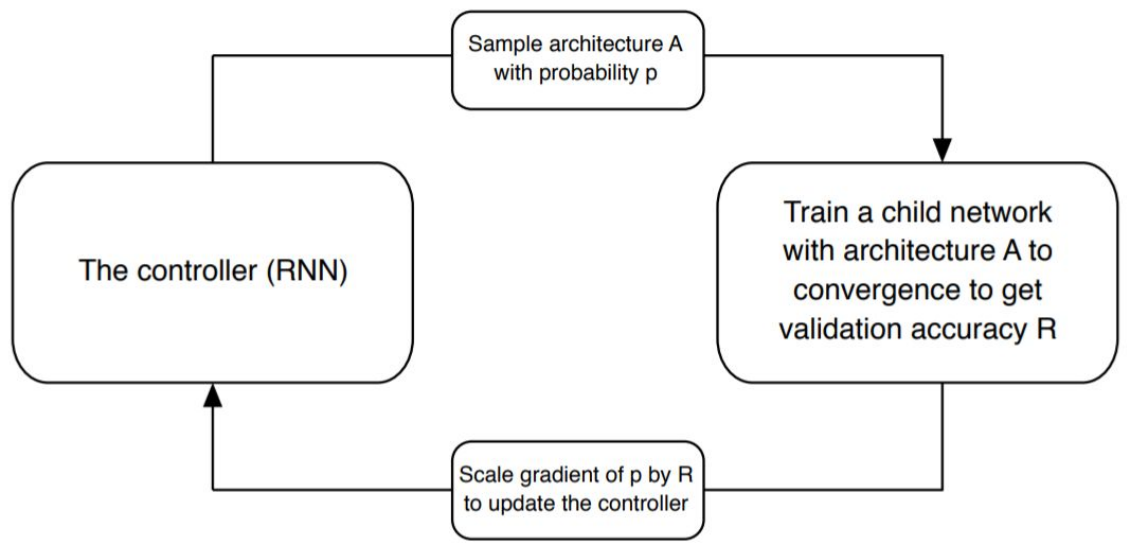
Lec 5: Neural Network Architectures

Model search: How to find the best structure for your problem



Lec 5: Neural Network Architectures

Model search: Google AutoML



https://arxiv.org/abs/1611.01578
https://arxiv.org/pdf/1707.07012.pdf

Lec 6: Tricks on Training Neural Networks

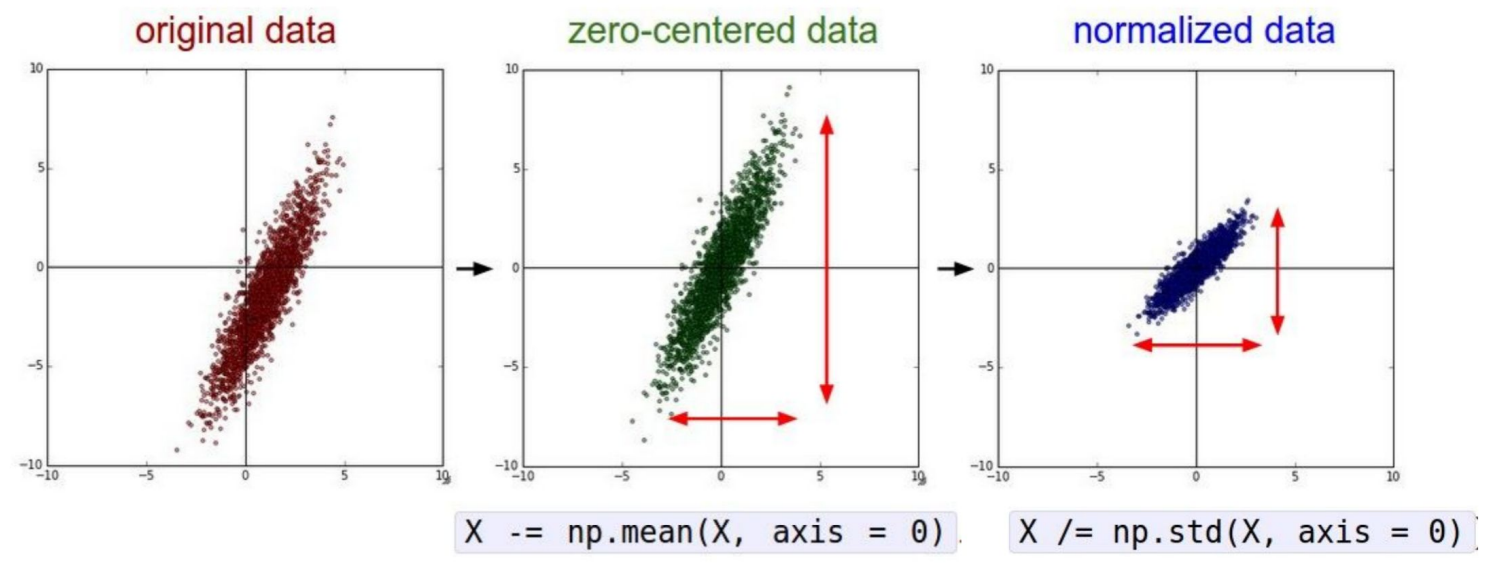
Training a (good) neural network is an art.

There is no principal approach that ‘guarantee to work’.

But there are tricks people found useful.

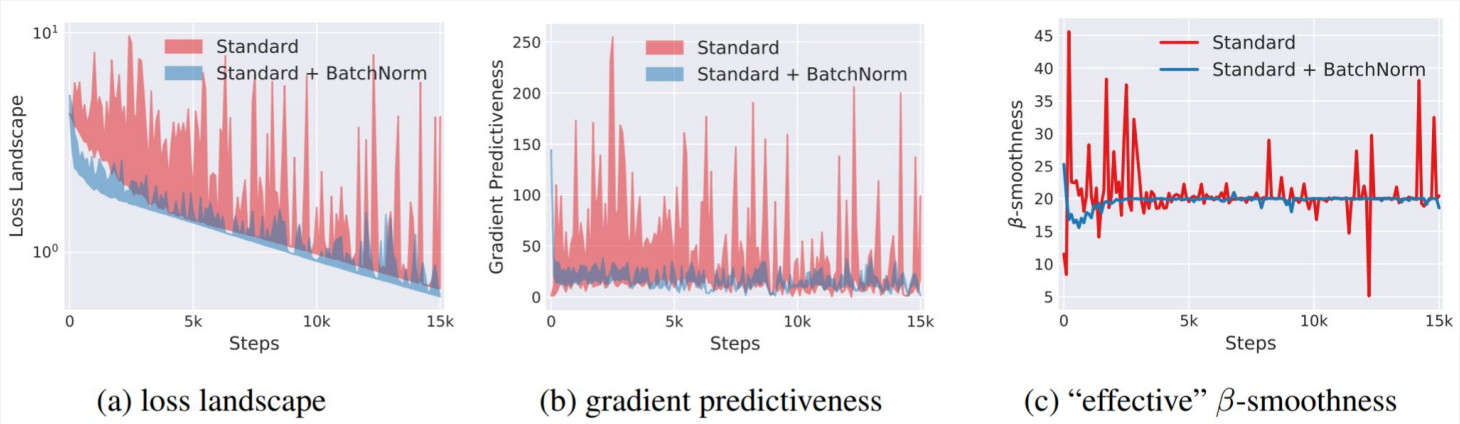
Lec 6: Tricks on Training Neural Networks

Data Pre-processing



Lec 6: Tricks on Training Neural Networks

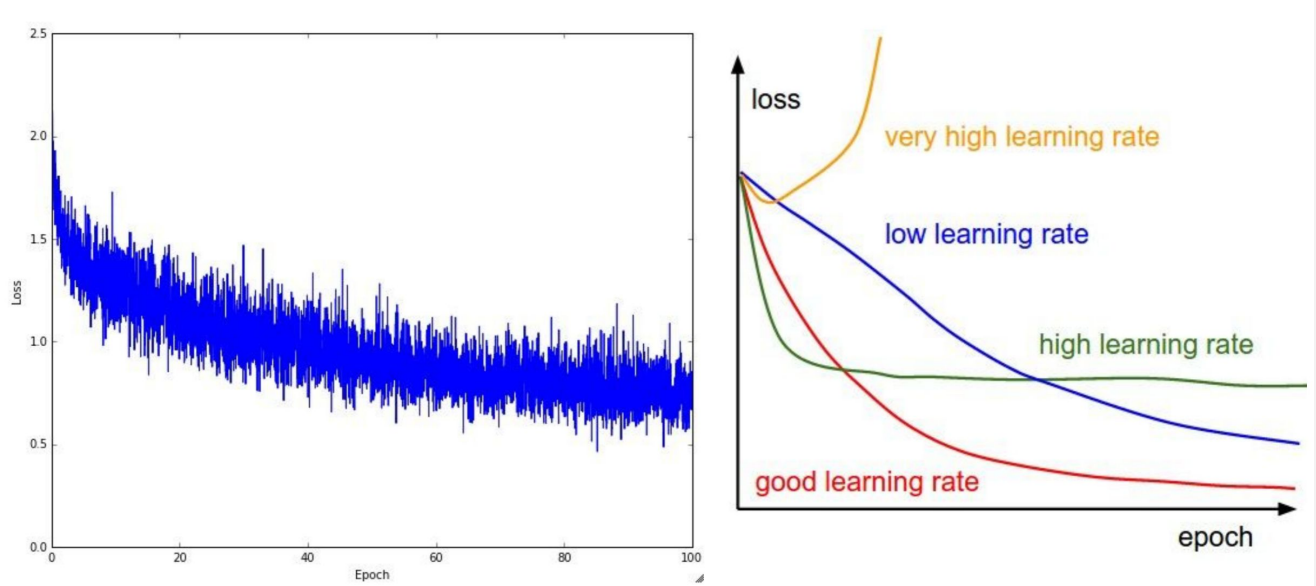
Adding special layers such as BatchNorm



(a) loss landscape (b) gradient predictiveness (c) "effective" β-smoothness

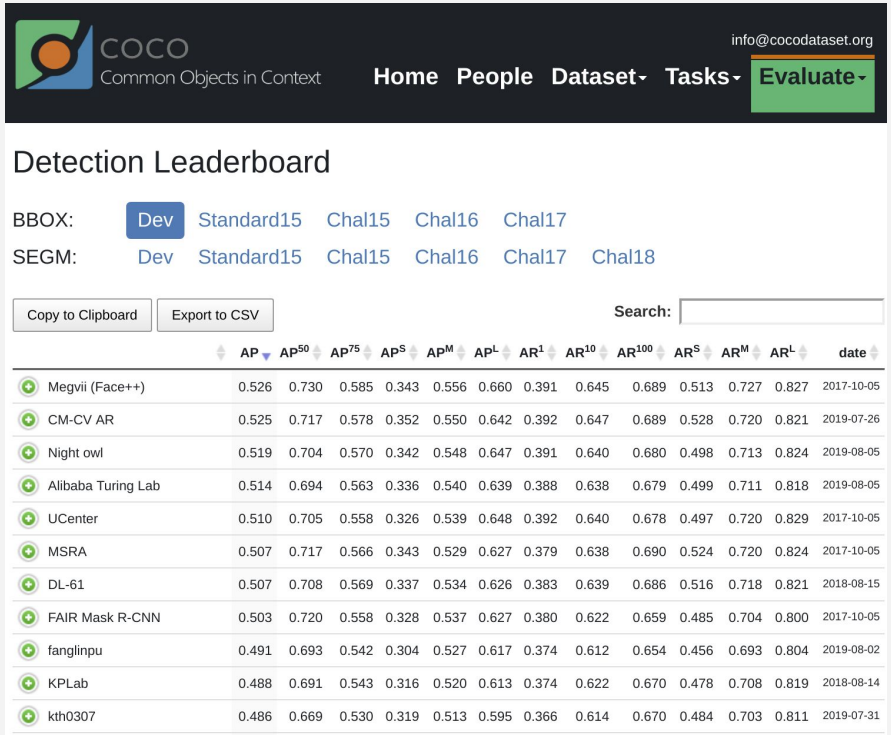
Lec 6: Tricks on Training Neural Networks

How to diagnose training curves



Lec 7: Machine Learning Model Evaluation

How do I know which model is the best?



COCO Common Objects in Context

info@cocodataset.org

Home People Dataset Tasks Evaluate

Detection Leaderboard

BBOX: Dev Standard15 Chal15 Chal16 Chal17

SEGM: Dev Standard15 Chal15 Chal16 Chal17 Chal18

Copy to Clipboard Export to CSV Search:

	AP	AP^{50}	AP^{75}	AP^{S}	AP^{M}	AP^{L}	AR^{1}	AR^{10}	AR^{100}	AR^{S}	AR^{M}	AR^{L}	date
Megvii (Face++)	0.526	0.730	0.585	0.343	0.556	0.660	0.391	0.645	0.689	0.513	0.727	0.827	2017-10-05
CM-CV AR	0.525	0.717	0.578	0.352	0.550	0.642	0.392	0.647	0.689	0.528	0.720	0.821	2019-07-26
Night owl	0.519	0.704	0.570	0.342	0.548	0.647	0.391	0.640	0.680	0.498	0.713	0.824	2019-08-05
Alibaba Turing Lab	0.514	0.694	0.563	0.336	0.540	0.639	0.388	0.638	0.679	0.499	0.711	0.818	2019-08-05
UCenter	0.510	0.705	0.558	0.326	0.539	0.648	0.392	0.640	0.678	0.497	0.720	0.829	2017-10-05
MSRA	0.507	0.717	0.566	0.343	0.529	0.627	0.379	0.638	0.690	0.524	0.720	0.824	2017-10-05
DL-61	0.507	0.708	0.569	0.337	0.534	0.626	0.383	0.639	0.686	0.516	0.718	0.821	2018-08-15
FAIR Mask R-CNN	0.503	0.720	0.558	0.328	0.537	0.627	0.380	0.622	0.659	0.485	0.704	0.800	2017-10-05
fanglinpu	0.491	0.693	0.542	0.304	0.527	0.617	0.374	0.612	0.654	0.456	0.693	0.804	2019-08-02
KPLab	0.488	0.691	0.543	0.316	0.520	0.613	0.374	0.622	0.670	0.478	0.708	0.819	2018-08-14
kth0307	0.486	0.669	0.530	0.319	0.513	0.595	0.366	0.614	0.670	0.484	0.703	0.811	2019-07-31

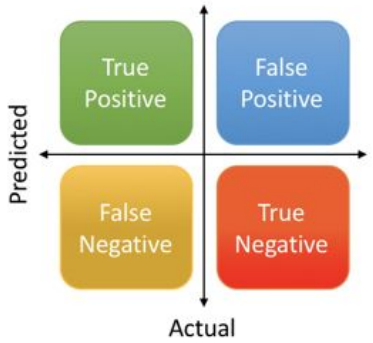
Lec 7: Machine Learning Model Evaluation

Classification metric

$$\textbf{Precision} = \frac{\text{True Positive}}{\text{Actual Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

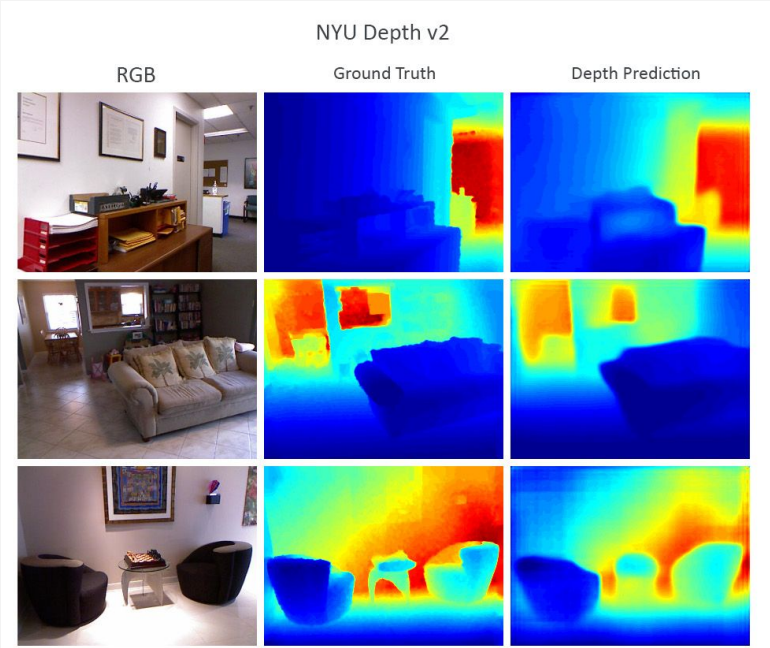
$$\textbf{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

$$\textbf{Accuracy} = \frac{\text{True Positive + True Negative}}{\text{Total}}$$



Lec 7: Machine Learning Model Evaluation

Regression metric



Threshold: % of y_i s.t. $\max(\frac{y_i}{y_i^*}, \frac{y_i^*}{y_i}) = \delta < thr$

Abs Relative difference: $\frac{1}{|T|}\sum_{y \in T} |y - y^*|/y^*$

Squared Relative difference: $\frac{1}{|T|}\sum_{y \in T} ||y - y^*||^2/y^*$

RMSE (linear): $\sqrt{\frac{1}{|T|}\sum_{y \in T} ||y_i - y_i^*||^2}$

RMSE (log): $\sqrt{\frac{1}{|T|}\sum_{y \in T} ||\log y_i - \log y_i^*||^2}$

RMSE (log, scale-invariant): The error Eqn. 1

Lec 7: Machine Learning Model Evaluation

Task-dependent metric

SYSTEM A: Israeli officials (2-GRAM MATCH) responsibility of airport (1-GRAM MATCH) safety

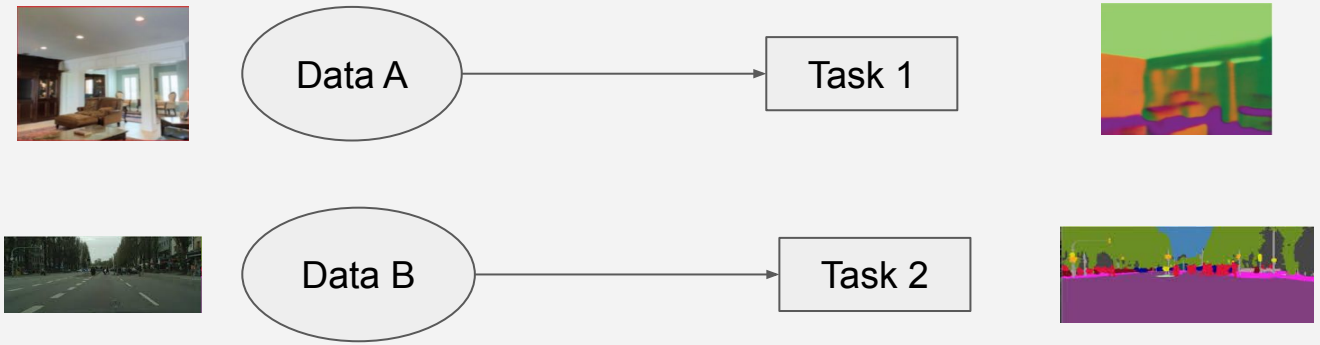
REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: airport security (2-GRAM MATCH) Israeli officials are responsible (4-GRAM MATCH)

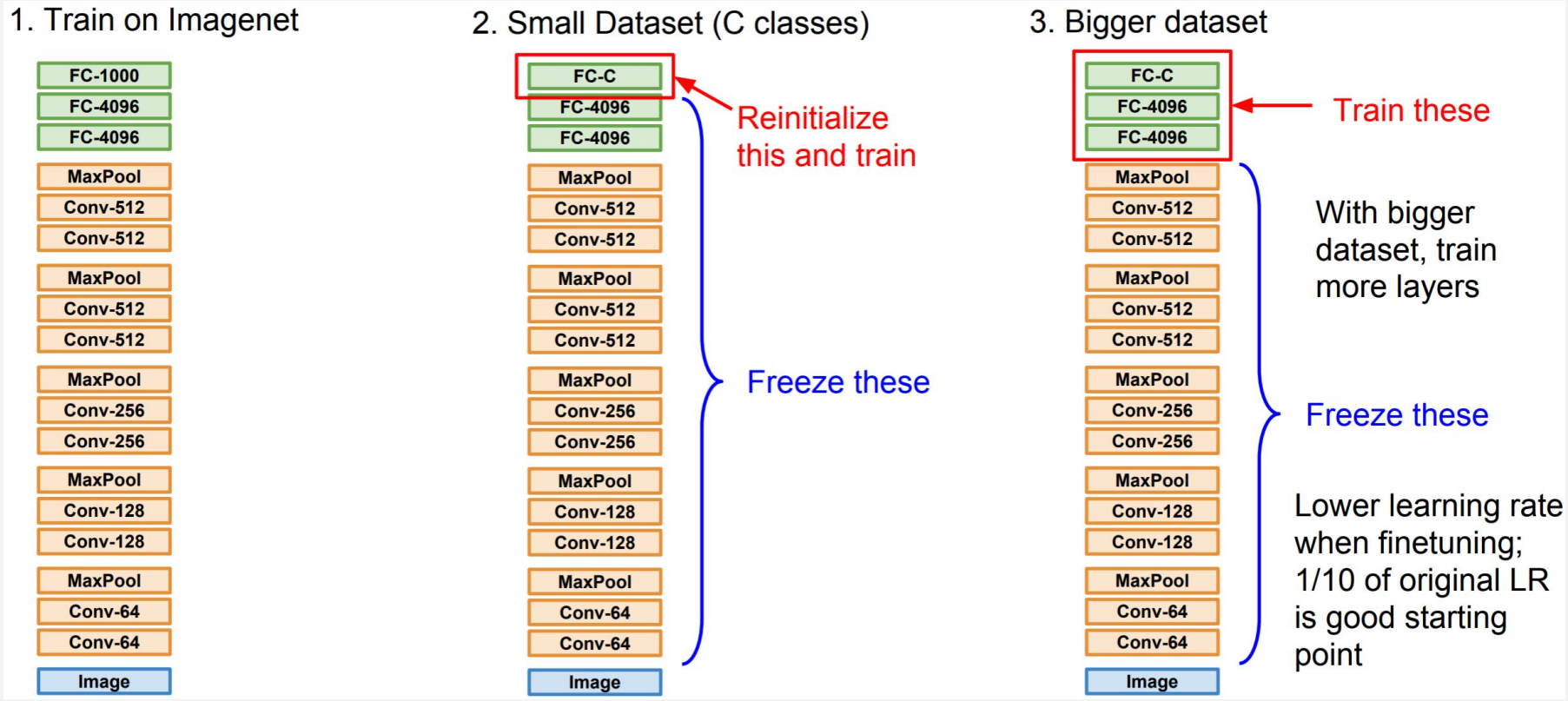
Metric	System A	System B
precision (1gram)	3/6	6/6
precision (2gram)	1/5	4/5
precision (3gram)	0/4	2/4
precision (4gram)	0/3	1/3
brevity penalty	6/7	6/7
BLEU	0%	52%

Lec 8: Case Study: Transfer Learning

- Fine-tuning
- Domain Transfer / Adaptation
- Multi-Task Learning
- Lifelong Learning



Lec 8: Case Study: Transfer Learning

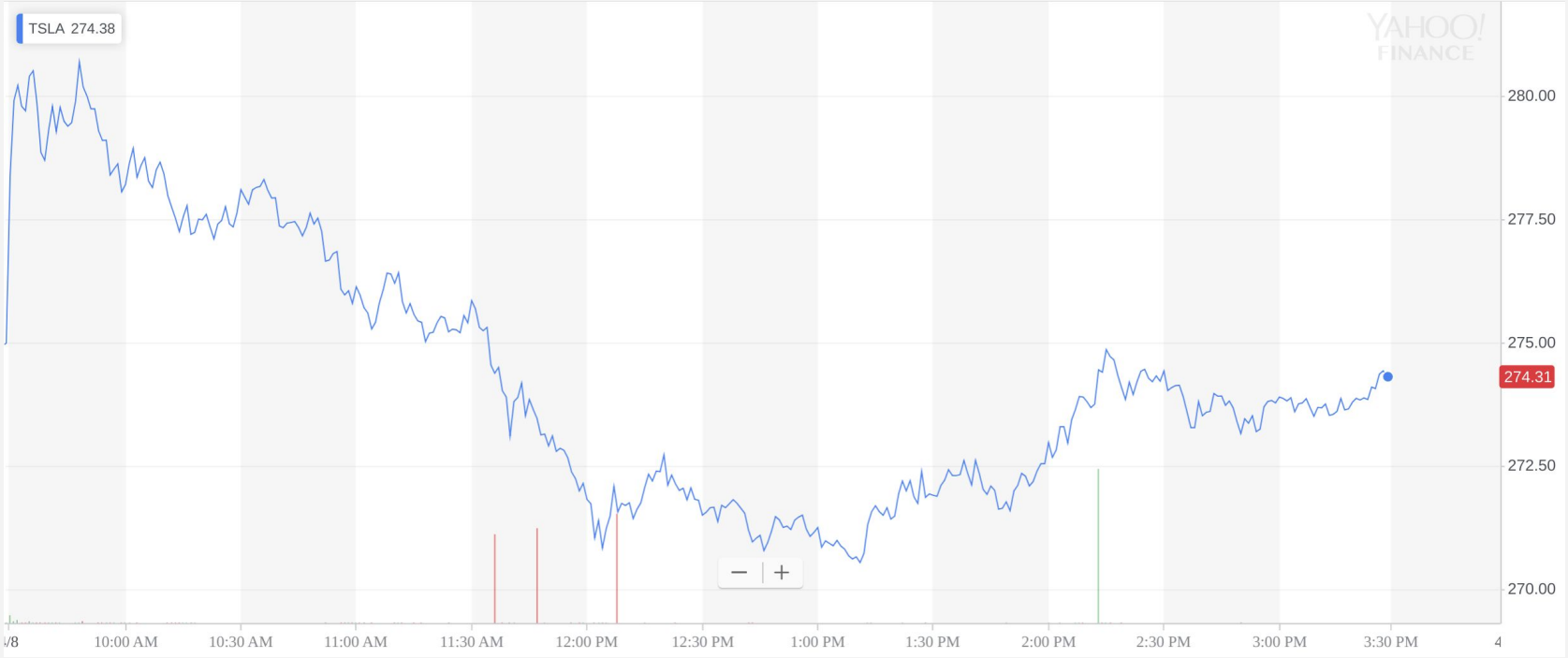


Lec 8: Case Study: Transfer Learning

Slides from “What you saw is not what you get” Domain adaptation for deep learning, Kate Saenko

Lec 8: Case Study: Transfer Learning

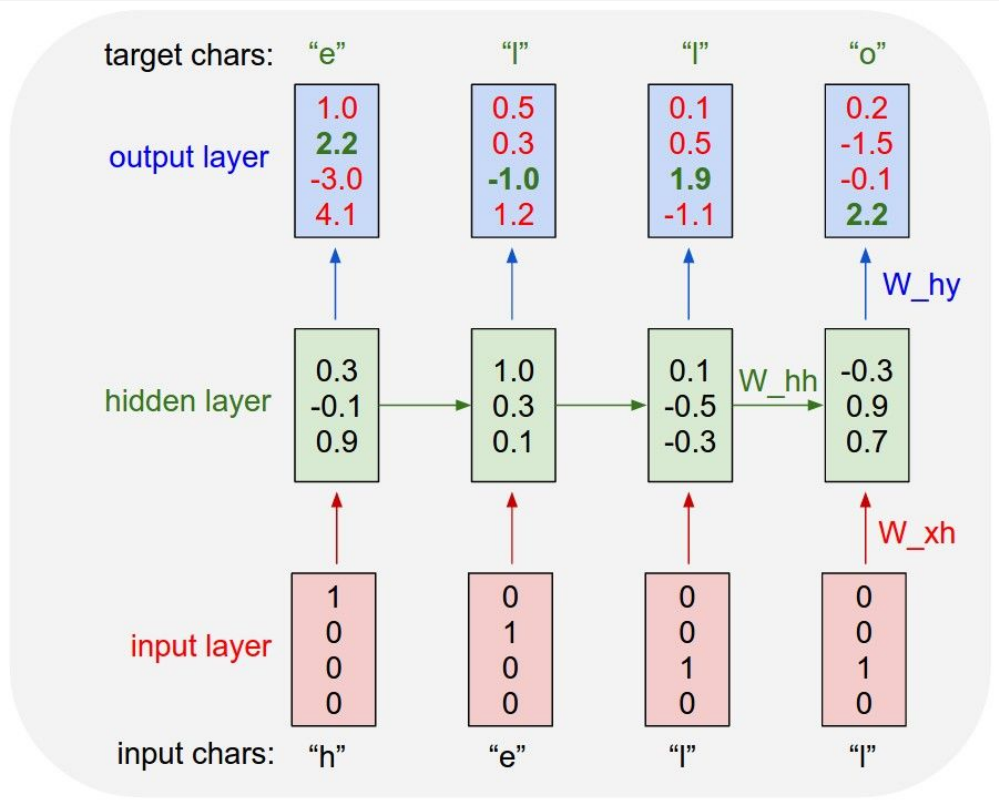
Lec 9: Case Study: Sequential Data Modeling



Lec 9: Case Study: Sequential Data Modeling

Simple RNNs

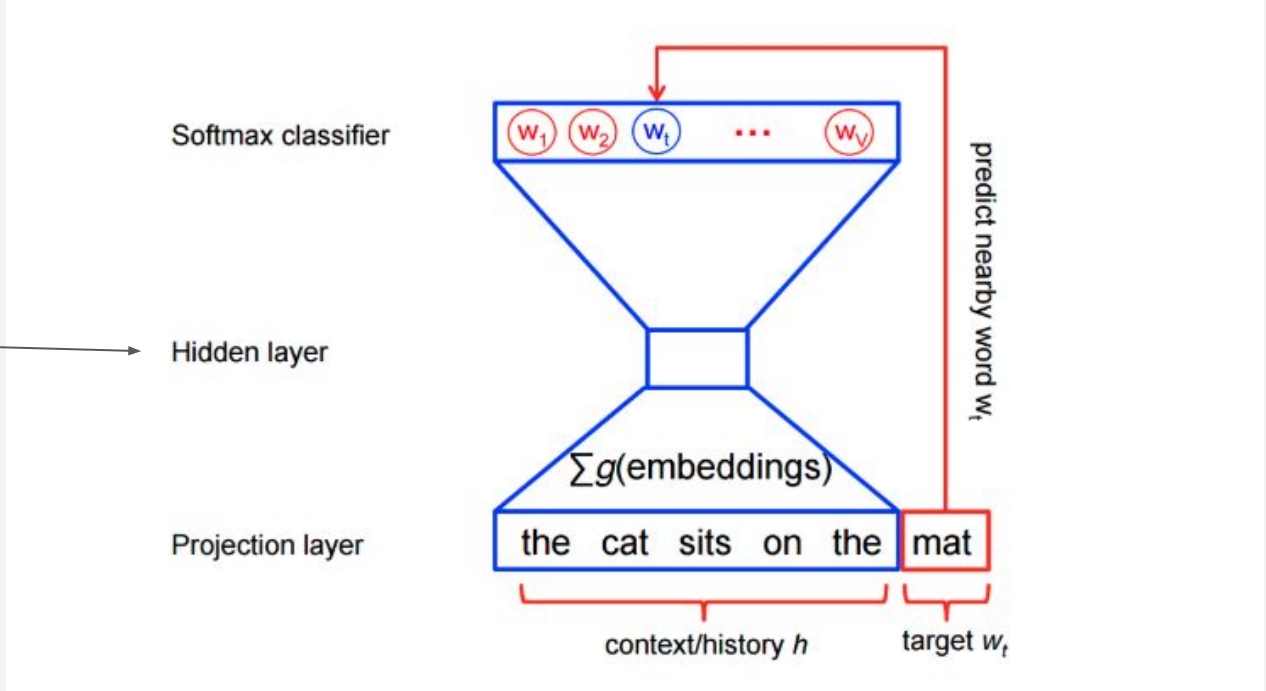
LSTM, GRU



Lec 9: Case Study: Sequential Data Modeling

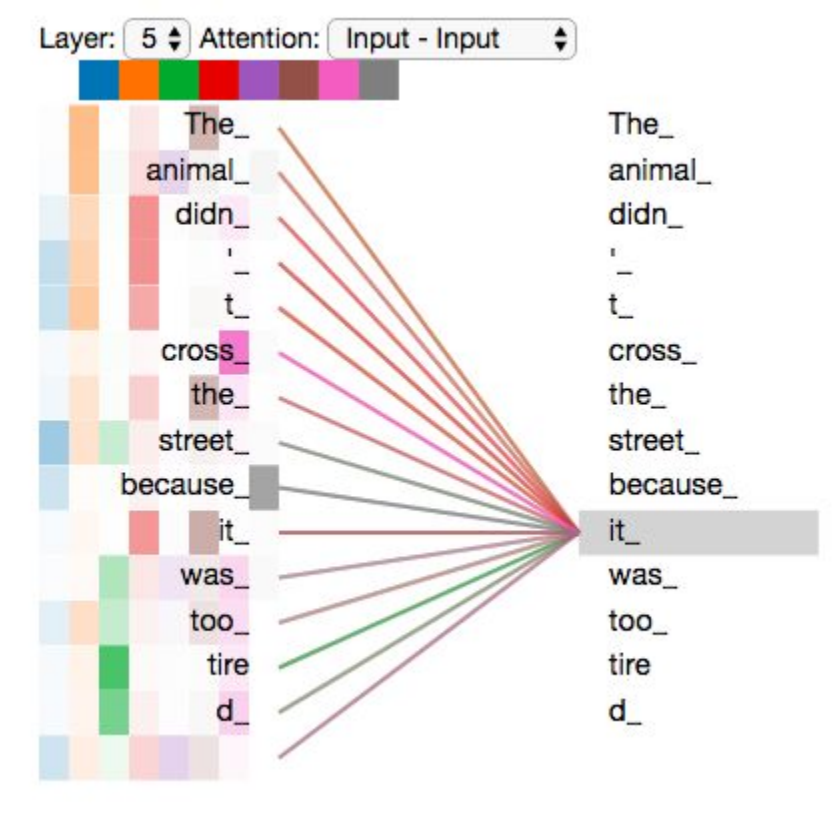
NLP Word2Vec Model

Learned embedding



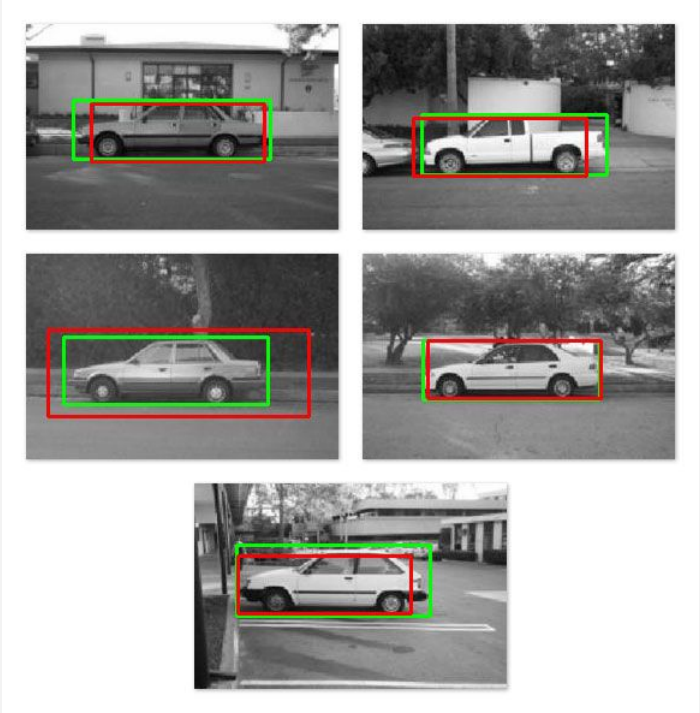
Lec 9: Case Study: Sequential Data Modeling

Attention Models

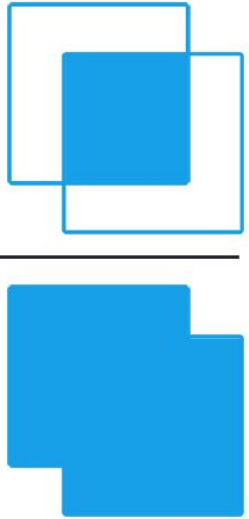


Lec 10: Case Study: Object Detection and Segmentation

Object Detection



$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



Lec 10: Case Study: Object Detection and Segmentation

Semantic Segmentation

Input

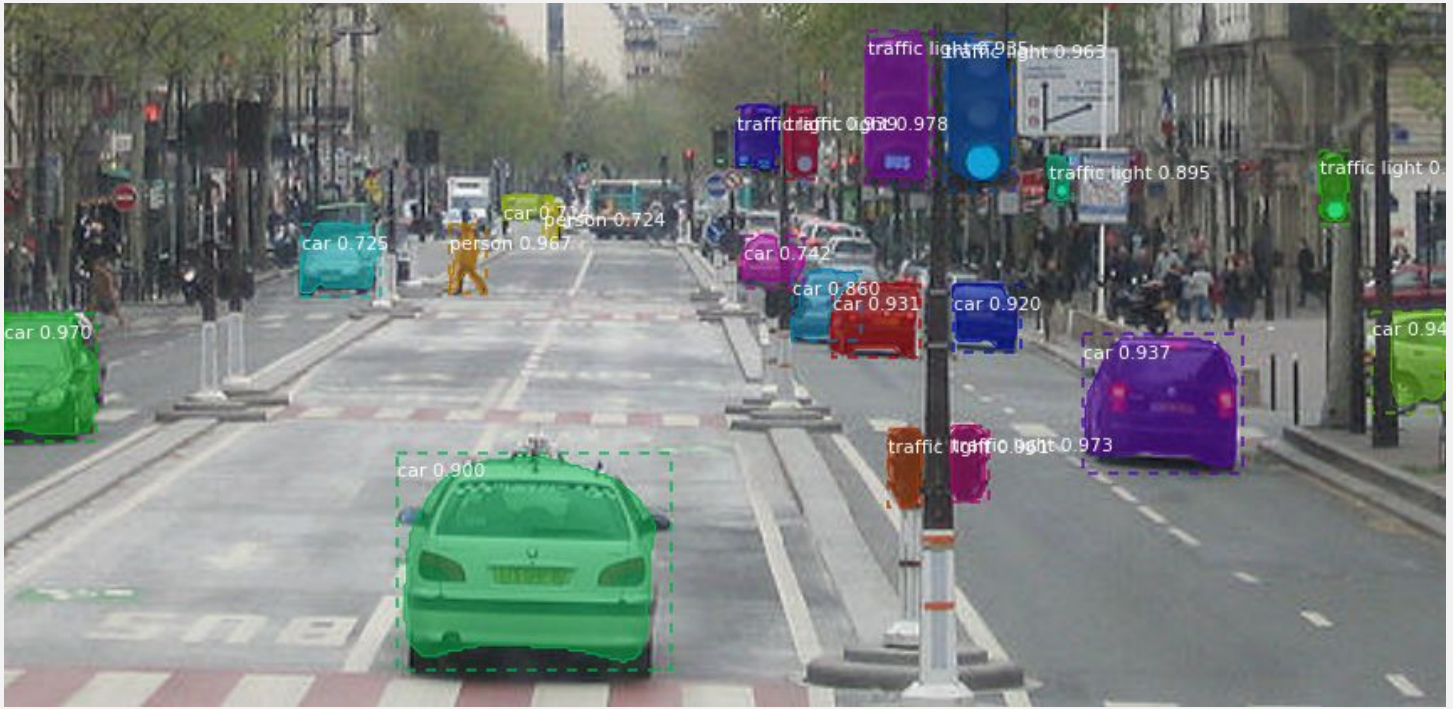
Ground truth

Prediction

Green: road
Orange: car
Purple: person

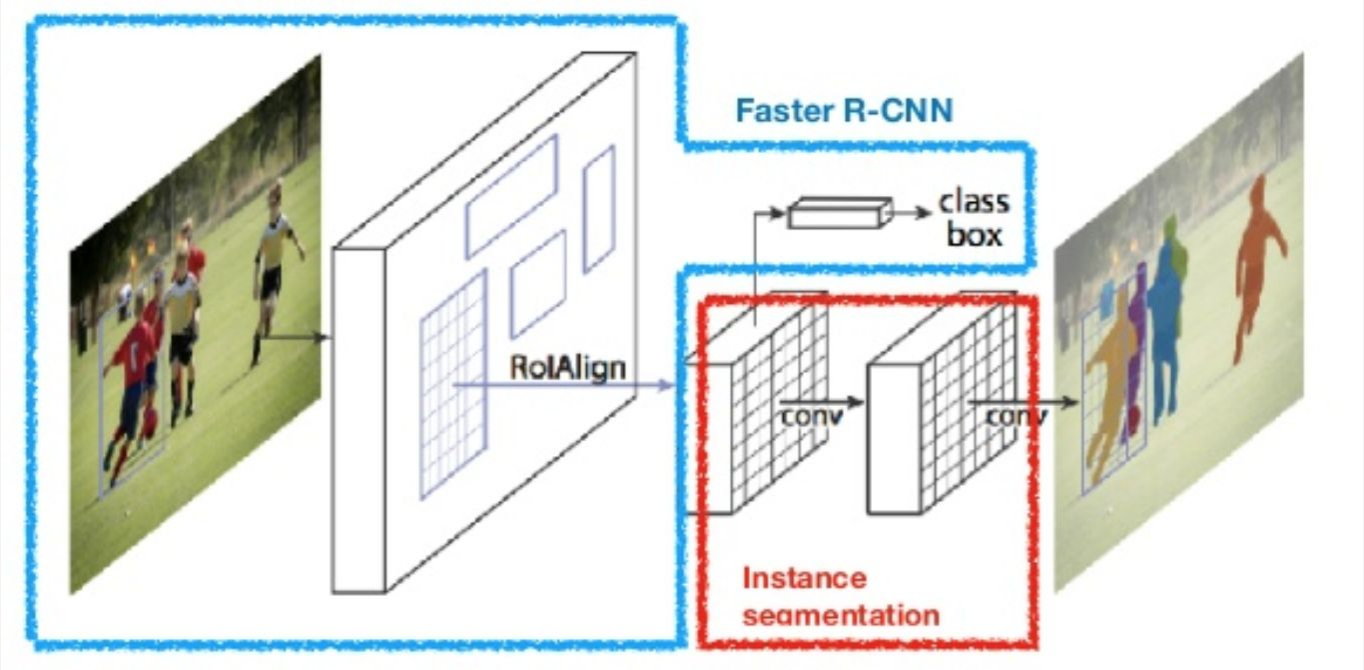
Lec 10: Case Study: Object Detection and Segmentation

Instance Segmentation

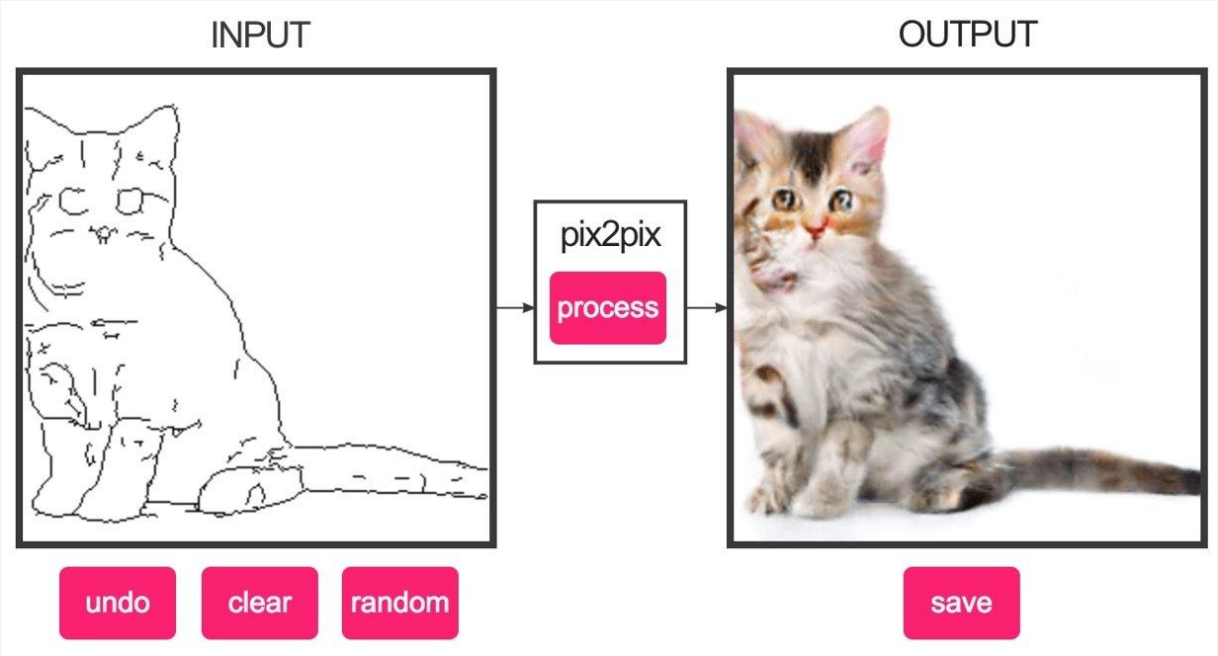


Lec 10: Case Study: Object Detection and Segmentation

Mask RCNN

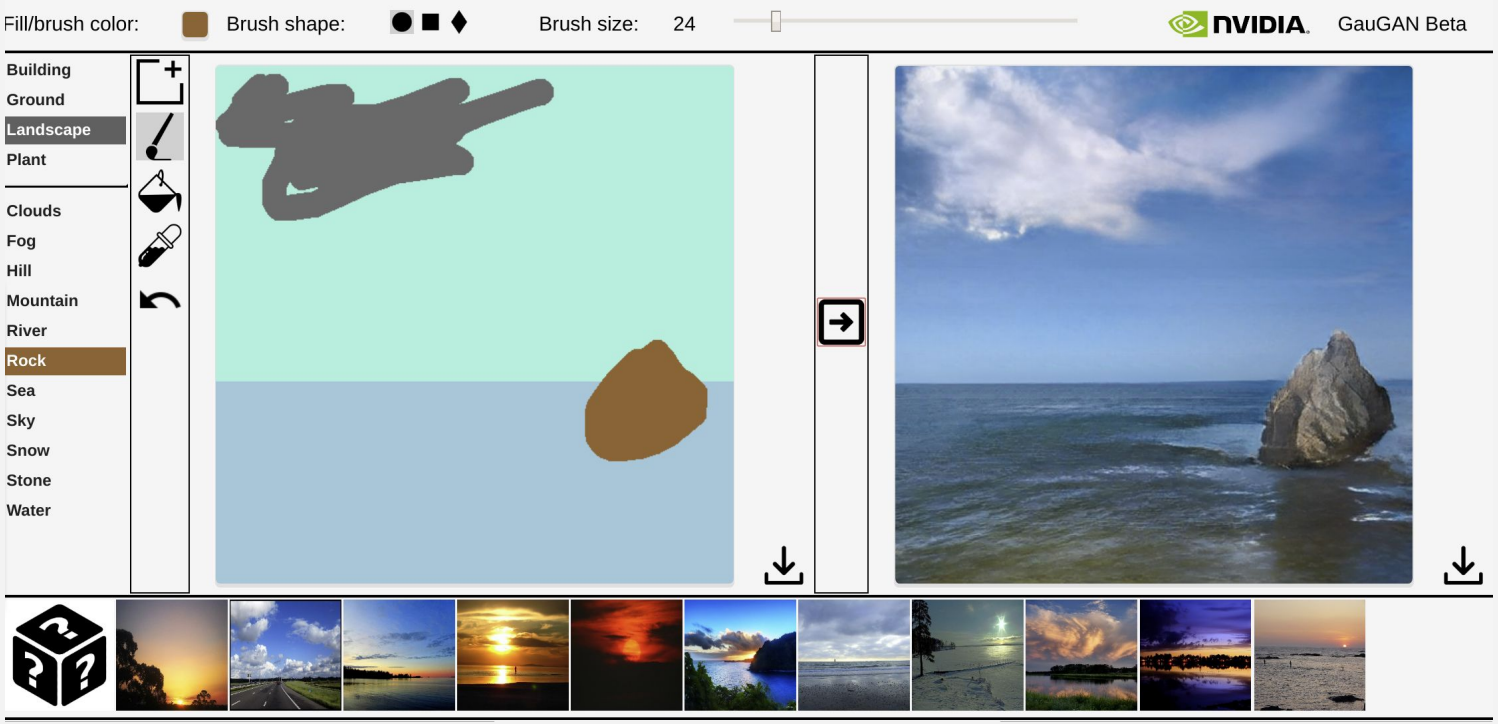


Lec 11: Case Study: Generative Adversarial Networks



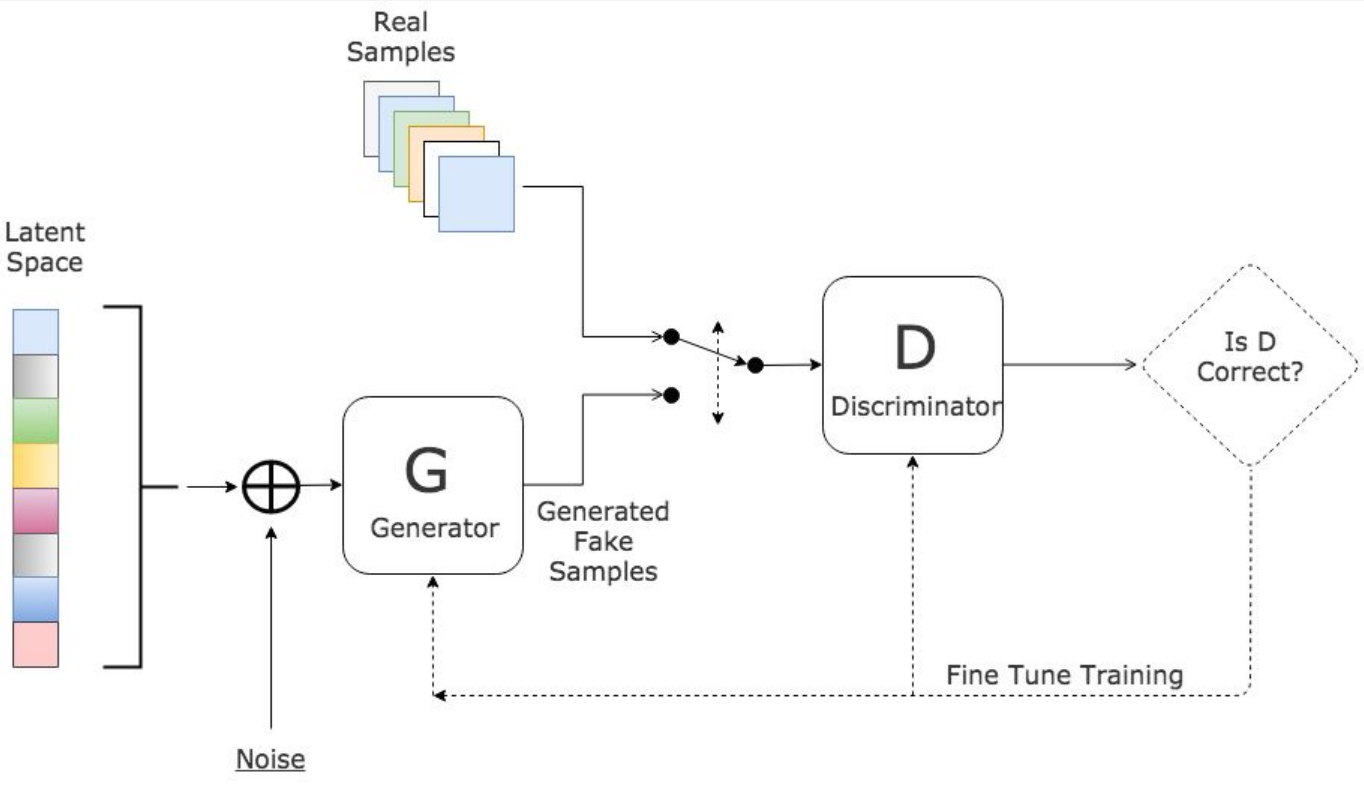
https://affinelayer.com/pixsrv/

Lec 11: Case Study: Generative Adversarial Networks



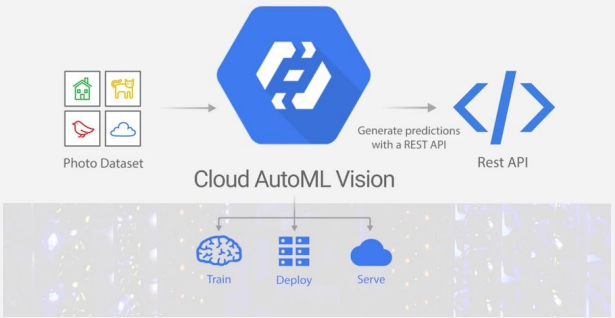
http://nvidia-research-mingyuliu.com/gaugan

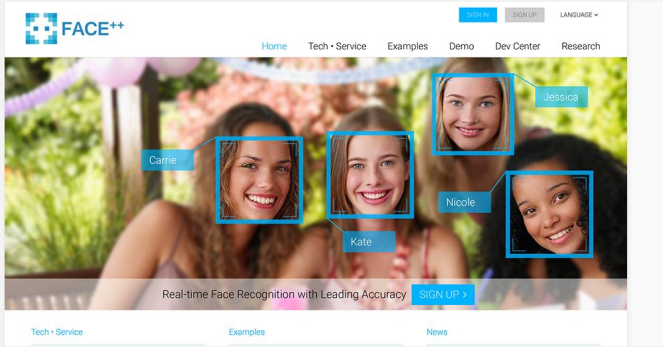
Lec 11: Case Study: Generative Adversarial Networks

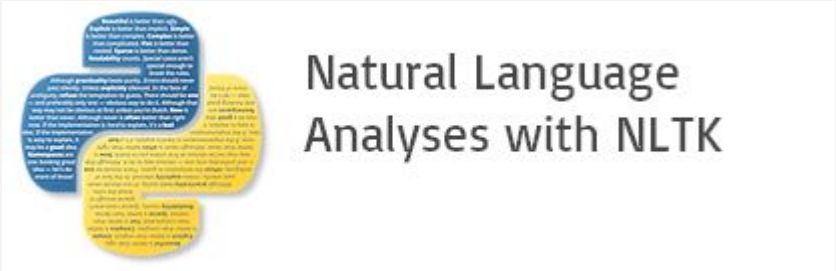


Lec 12: Real-World Ready Machine Learning Tools

Tools that are widely used and proven to be effective in real-world problems



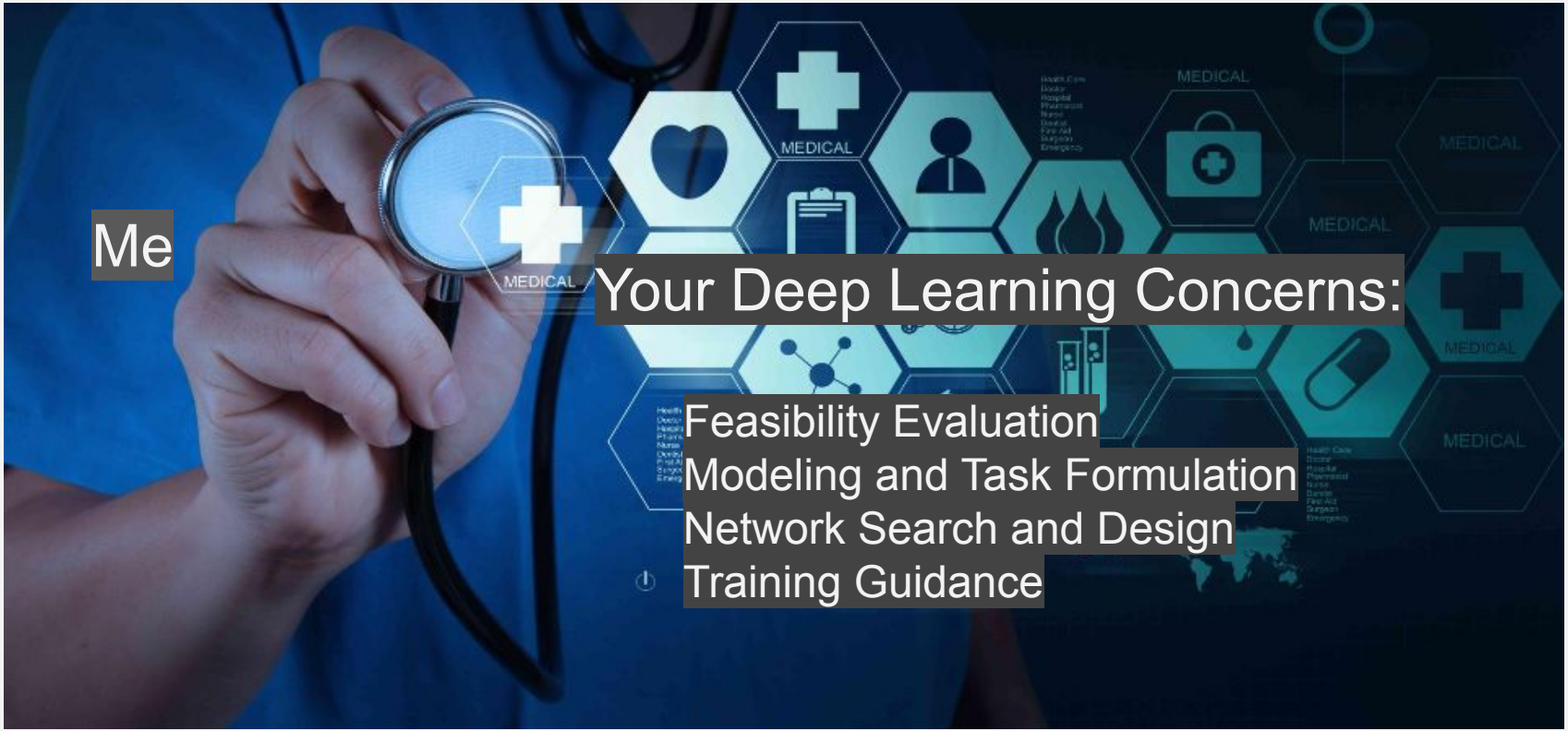




Today

- Overview of the class
  - Background
  - Logistics
- Lectures preview
- **Office hours preview**
- FAQ

Office Hours Preview



Case I

You have some idea about starting a research project or product studio project.

You'd like to know:

1) Is my problem too hard?
2) How to formulate my problem into a learning problem?
3) How to collect my data? How much data is needed?

Case II

You are working on your project involving in training some neural networks.

You were wondering:

1) How can I improve my network's performance?
2) What other models I can try?
3) My network is not training well, what's wrong?
4) Should I collect more data?

Today

- Overview of the class
  - Background
  - Logistics
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- Office hours preview
- **FAQ**

FAQ

Can I attend only selected sessions?

Sure! But I recommend to you to attend the first few introduction lectures to grasp some basic understanding about DL/ML.

I don't have a strong technical background, can I still attend?

Of course! Come for the lectures that provide high level idea and how to use existing tools for quick prototyping.

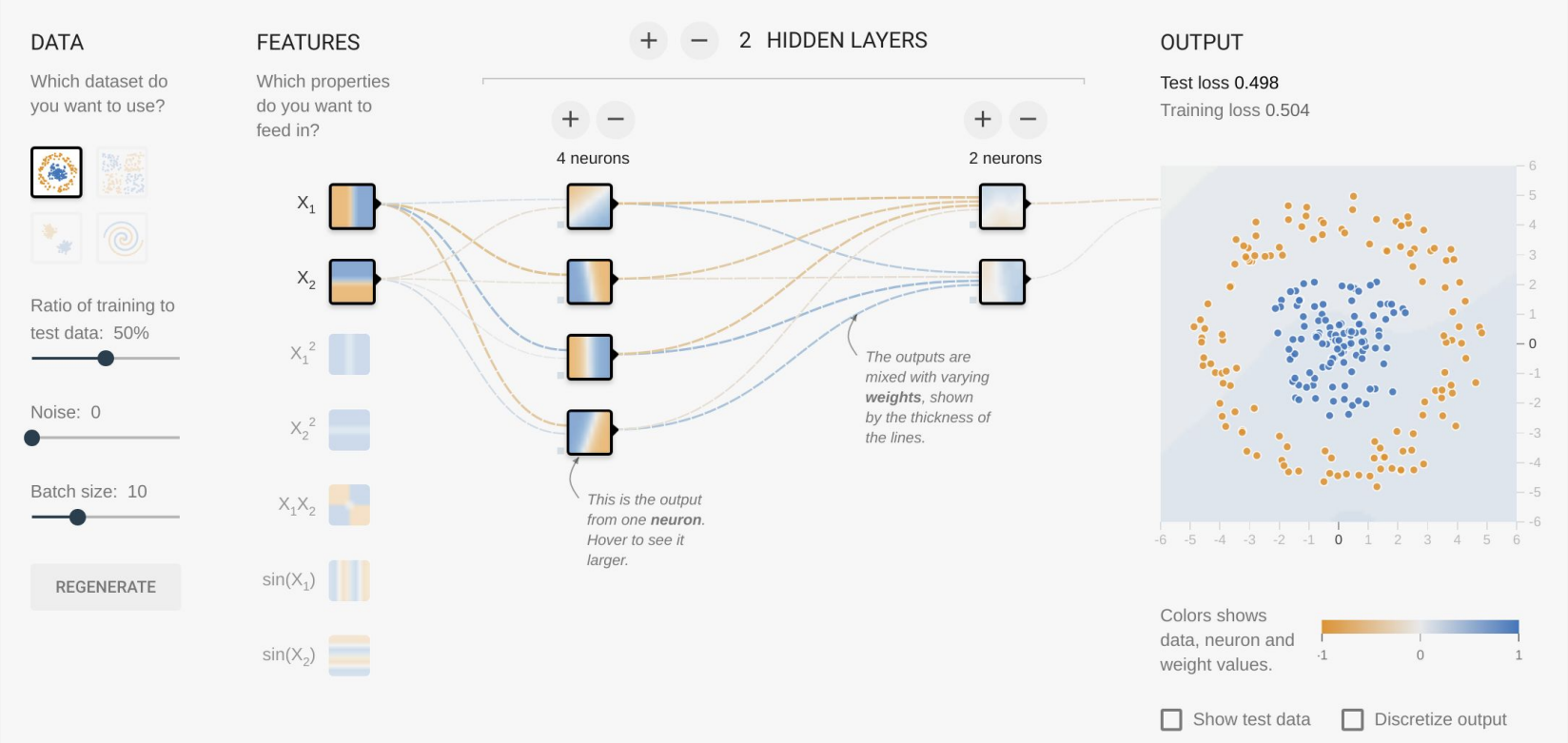
Next Week:

Deep Learning Frameworks

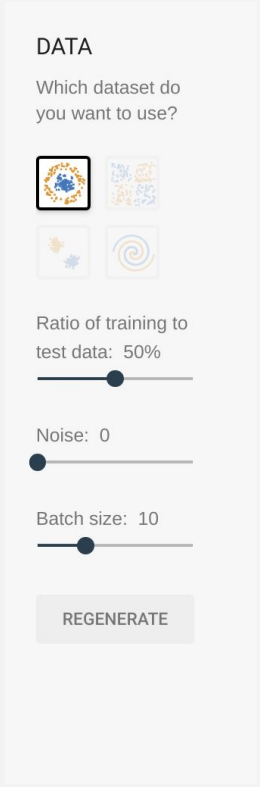
Extra

- Overview of the class
  - Background
  - Logistics
- Lectures preview
- Office hours preview
- **A simple interactive machine learning example**

A Simple Interactive Machine Learning Example



A Neural Network Playground [Link]



Data:

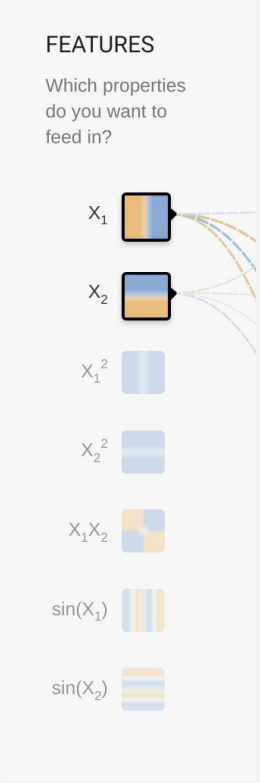
(x,y) 2D Points

Binary Label

Train/Test Split

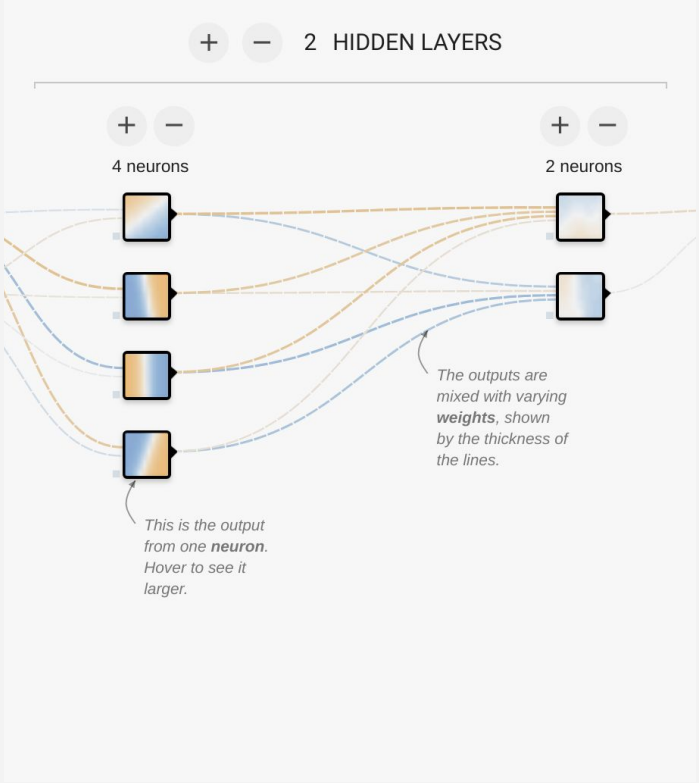
Noise Level

Batch Size



Feature Representation:

Learning problem becomes easier/harder with different feature representations, even with the same data!



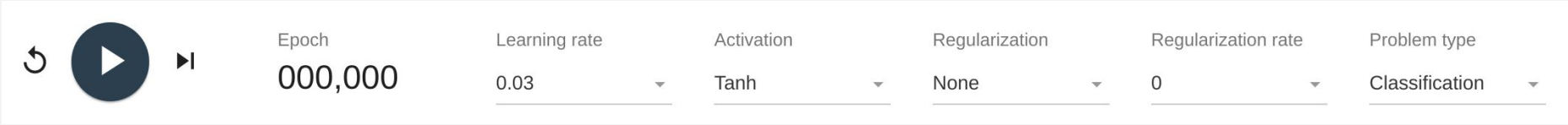
A Learning Model:

Network Structure

Layers

Connectivity

No network works for all the problems!



Training:

Train/Test Loss

Epochs

Optimization Algorithm

Evaluation:

Metric (accuracy, distance, …)

Cross-validation