

Deep Learning Application: Medical Image Segmentation using Convolutional Neural Networks





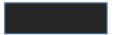
Dennys Mallqui

MSc Computer Science degree student

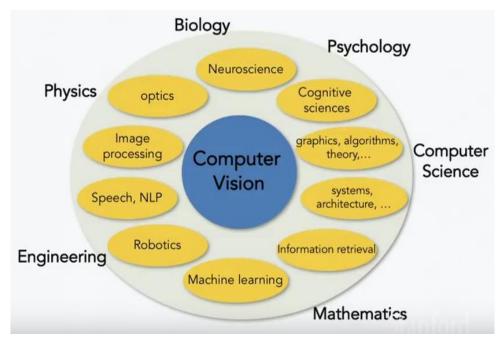
Federal University of São Carlos – Brazil

Computer Vision – Definition

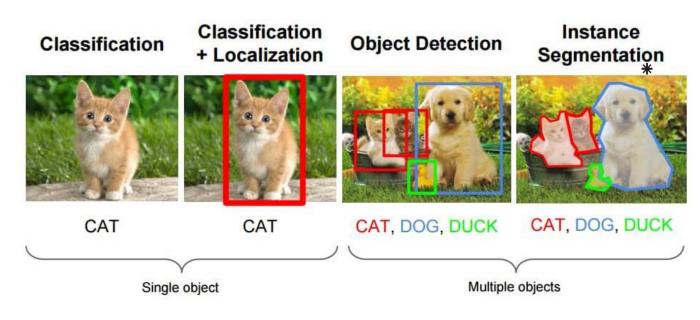
Is an interdisciplinary field that has as the goal extract knowledge from visual data.



Relation with other fields



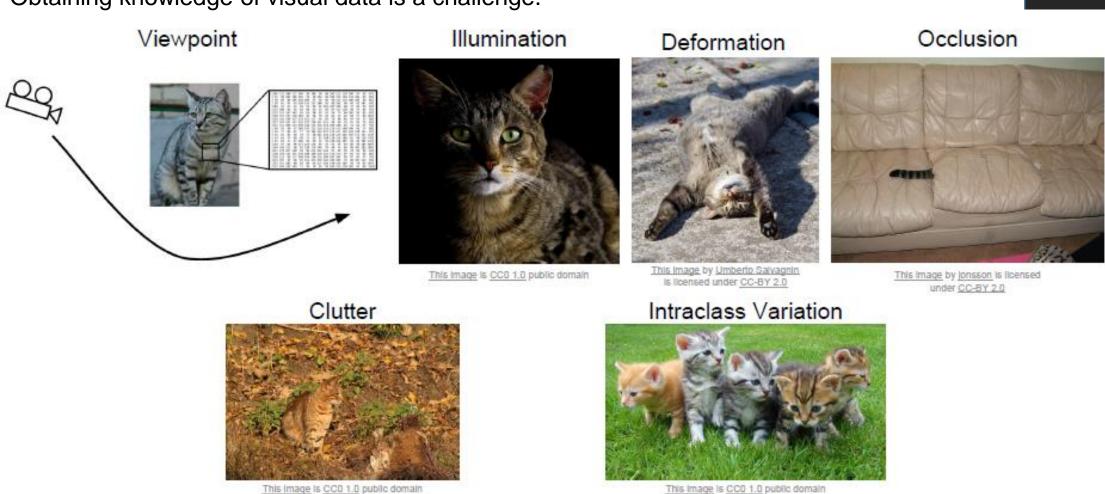
Computer vision tasks



Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017

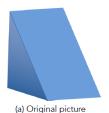
Computer Vision – Challenge

Obtaining knowledge of visual data is a challenge.

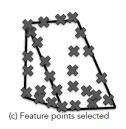


Computer Vision – Evolution

Block World (Larry Roberts, 1963)





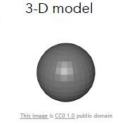


Stage of Visual Representation (David Marr, 1970s)



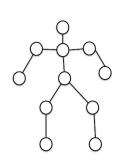






Generalized Cylinder (Brook & Binford, 1979)

Pictoral Structure (Fischler & Elschlager, 1973)



Simplification (David Lowe, 1987)



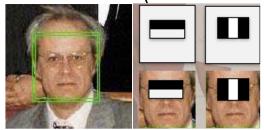
Normalized Cut (Shi & Malik, 1997)



"SIFT" (David Lowe, 1999)



Face detection (Viola & Jones, 2001)



PASCAL Visual Object Challenge (Everingham et al. 2006 – 2012)



20 Classes or categories

Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017

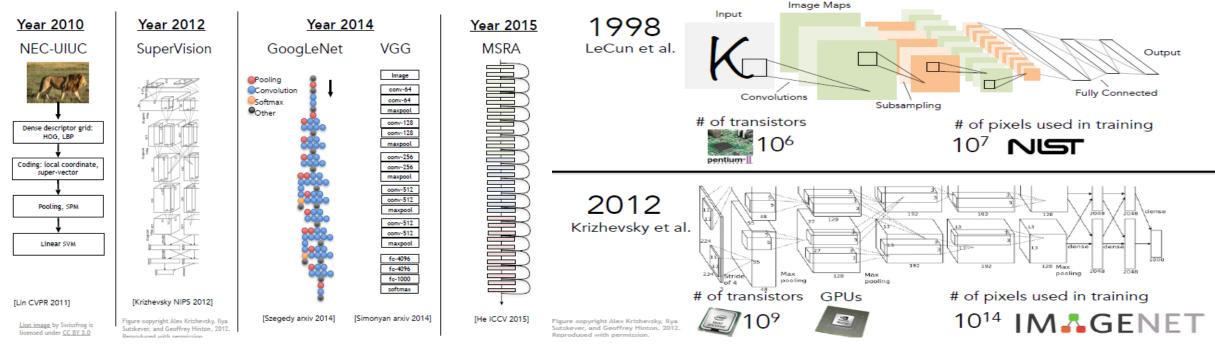
Computer Vision – Why Deep Learning?

Deng, Dong, Socher, Li, Li, & Fei-Fei, 2009



Average Error (2010 – 2017)

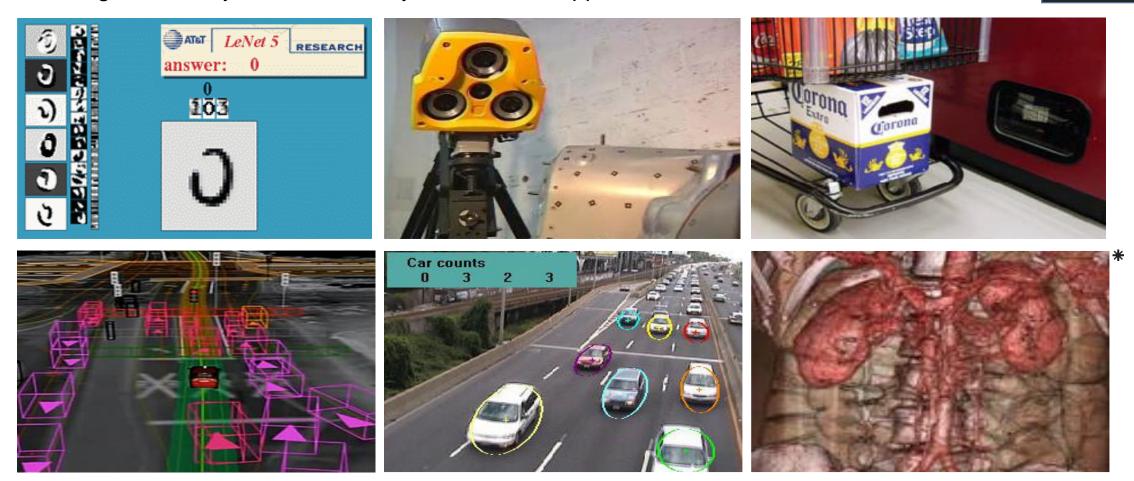




Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017

Computer Vision – Industrial Applications

Is being used today in a wide variety of real-world applications, which include:

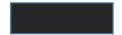


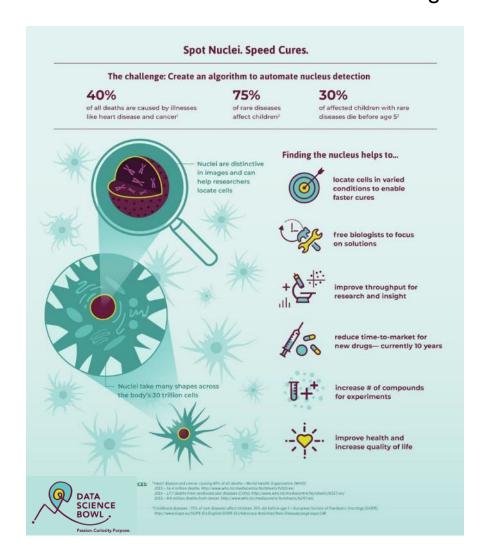
Richard Szeliski, Computer vision application and algorithms, September 2014 (adapted 2017)

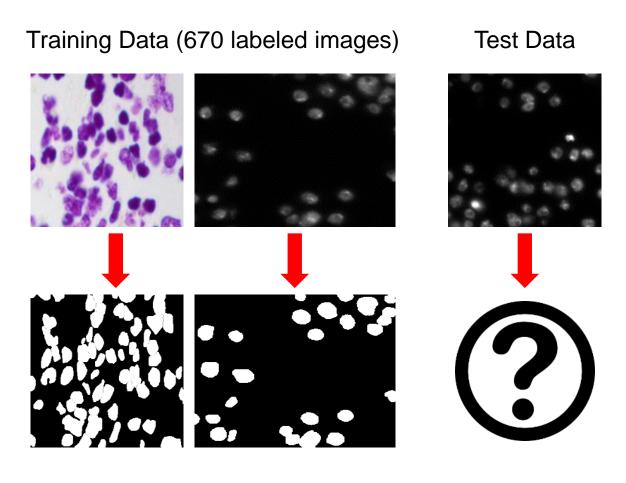
^{*} Inner the present scope

Biomedical Image Segmentation – Overview

The 2018 Data Science Bowl challenge: Create a solution to automate nucleus detection.







2018 Data Science Bowl (<u>link</u>)

Deep Learning - Neural Network Model

Biological Inspiration (... but just is a model) More of 1 hidden layer => "Deep" Learning Impulses carried toward cell body dendrite output layer output laver hidden layer hidden layer 1 hidden layer 2 axon "3-layer Neural Net", or cell body "2-layer Neural Net", or "2-hidden-layer Neural Net" "1-hidden-layer Neural Net" "Fully-connected" layers Impulses carried away from cell body x_0 This image by Felipe Perucho synapse axon from a neuron w_0x_0 Leaky ReLU **Sigmoid** $\max(0.1x,x)$ dendrite $\sigma(x) = \frac{1}{1 + e^{-x}}$ cell body w_1x_1 tanh Maxout tanh(x) $\max(w_1^T x + b_1, w_2^T x + b_2)$ activation function $w_{2}x_{2}$ **ReLU** $\max(0,x)$

Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017

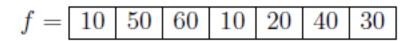
Deep Learning – Approach Comparison

Feature Extraction vs Deep Learning Feature Extraction 10 numbers giving scores for classes training Krizhevsky, Sutskever, and Hinton, "Imagenet classification Figure copyright Krizhevsky, Sutskever, and Hinton, 2012. Reproduced with permission 10 numbers giving scores for classes training

Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017

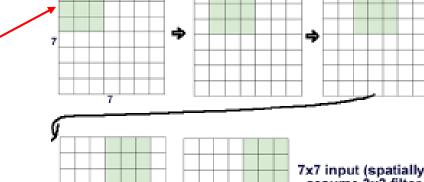
Deep Learning – Convolution Operator

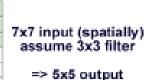
Convolution 1D Convolution 2D



$$g = \boxed{1/3 \ | \ 1/3 \ | \ 1/3 \ |}$$

Kernel (K)





0 0 0 0

0

| 10 | 50 | 60 | 10 | 20 | 30 | 40 |
|----|-----|-----|-----|----|----|----|
| 0 | 1/3 | 1/3 | 1/3 | 0 | 0 | 0 |

$$\frac{1}{3}50 + \frac{1}{3}60 + \frac{1}{3}10 = \frac{50}{3} + \frac{60}{3} + \frac{10}{3} = \frac{120}{3} = 40$$

In practice: Common to zero pad the border

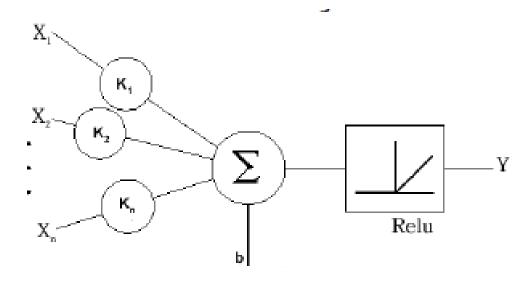
Cornell University, CS1114: Introduction to Computing using Matlab and Robotics, Spring 2013.

Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017

Deep Learning – Convolution Neuron

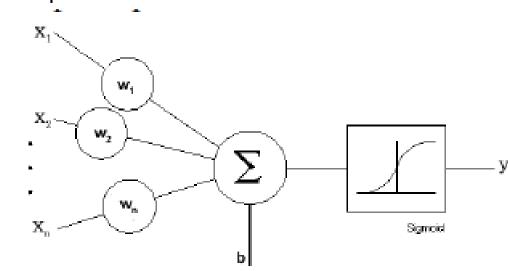
Kernel (K) vs Weights (W)

Convolution neuron



$$Y = g(b + \sum K_i * X_i)$$

Perceptron

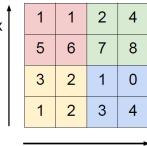


$$y = g(b + \sum w_i x_i)$$

Deep Learning – Other Functions

Max Pooling

Single depth slice

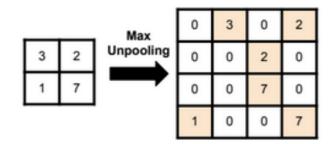


max pool with 2x2 filters and stride 2

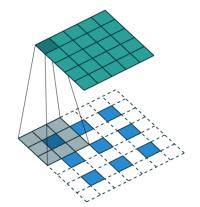
| 6 | 8 |
|---|---|
| 3 | 4 |

Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017

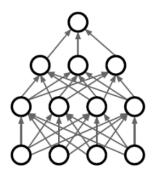
Un Max Pooling

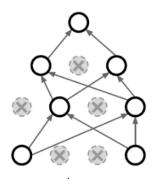


Convolution Transpose



Dropout



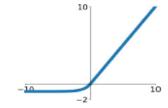


Srivastava et al, "Dropout: A simple way to prevent neural networks from overfitting", JMLR 2014

Transfer Functions

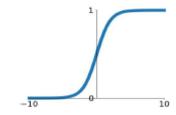
ELU

$$\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



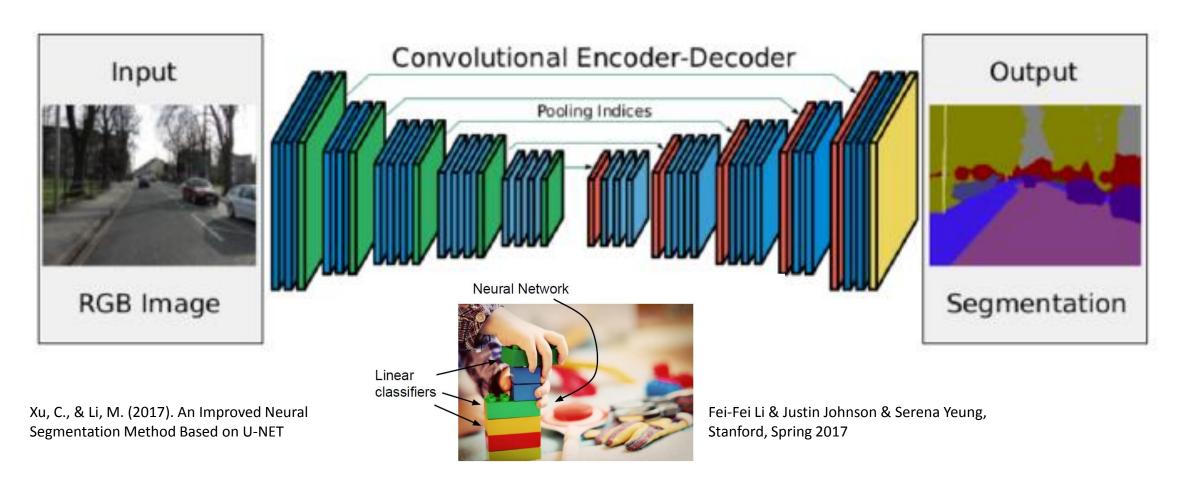
Sigmoid

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$



Deep Learning – Image Segmentation

Each linear function represents a building block



Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention* (pp. 234-241). Springer, Cham.

Deep Learning – Put All Together (example)

For biomedical image segmentation challenge will be use U-net architecture.

Image RGB (256x256) Image Gray Scale Convolution (256x256) (3x3) (Padding: 1) 16 Dropout Max Pooling (2x2)Convolution Transpose 128 Copy (2x2)Concatenate Convolution 128 ELU (1x1) Sigmoid

Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention* (pp. 234-241). Springer, Cham.

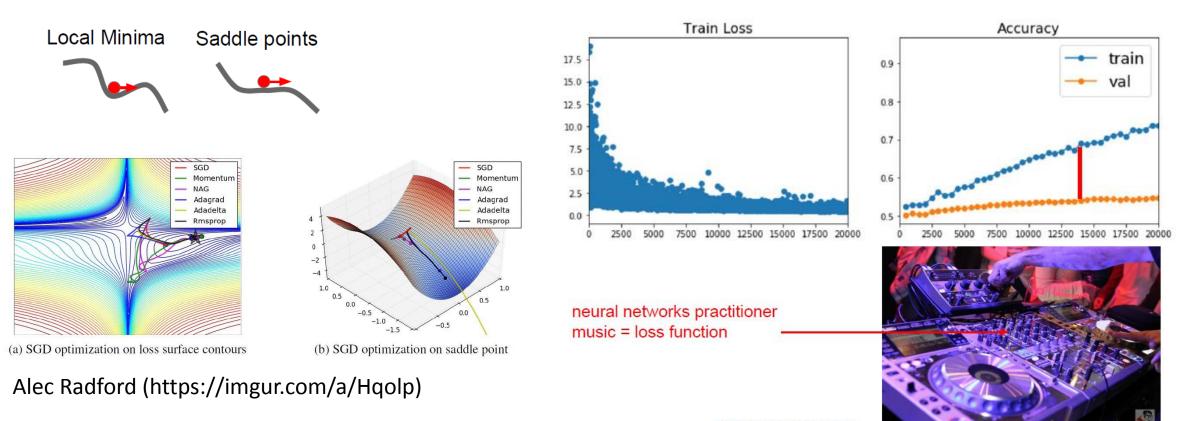
Deep Learning – Weight/Bias calculation

For this model (U-net example) we need to calculate 1,941,105 parameters!



How to obtain best solution?

How to improve single-model performance?



Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017 Ludwin Lope, Computer Vision, Master Dissertation, USP Brazil, 2018

Deep Learning – Why GPU?

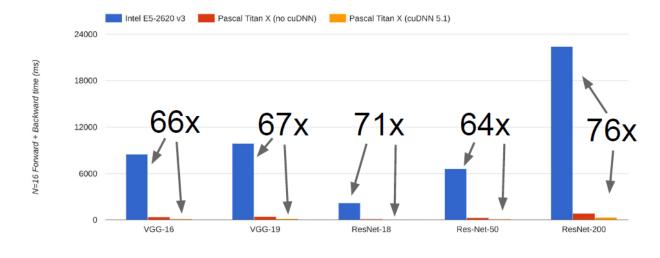
The massive amount of calculations require the use of hardware that helps accelerate processes.



CPU vs GPU

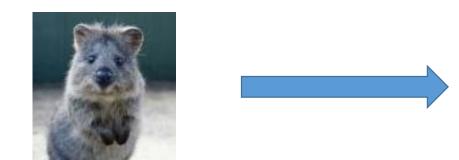
| | # Cores | Clock Speed | Memory | Price |
|---------------------------------|--|-------------|--------------------|--------|
| CPU (Intel Core i7-7700k) | 4 (8 threads with hyperthreading) | 4.4 GHz | Shared with system | \$339 |
| CPU (Intel Core i7-6950X) | 10 (20 threads with hyperthreading) | 3.5 GHz | Shared with system | \$1723 |
| GPU (NVIDIA Titan Xp) | 3840 | 1.6 GHz | 12 GB GDDR5X | \$1200 |
| GPU (NVIDIA GTX 1070) | 1920 | 1.68 GHz | 8 GB GDDR5 | \$399 |

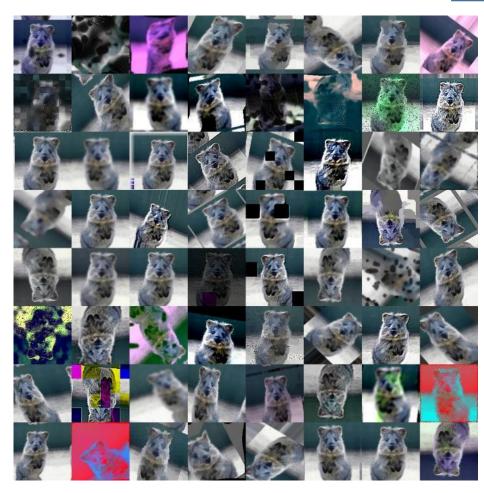
CPU vs GPU in practice



Deep Learning – Data Augmentation

Is possible apply data augmentation techniques for increment training data.

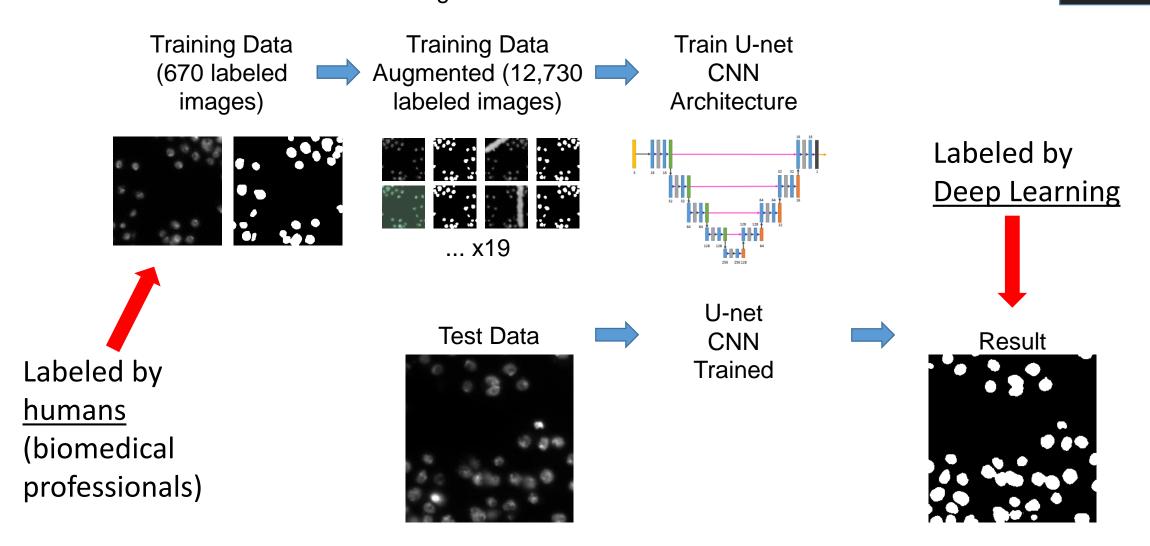




https://github.com/aleju/imgaug

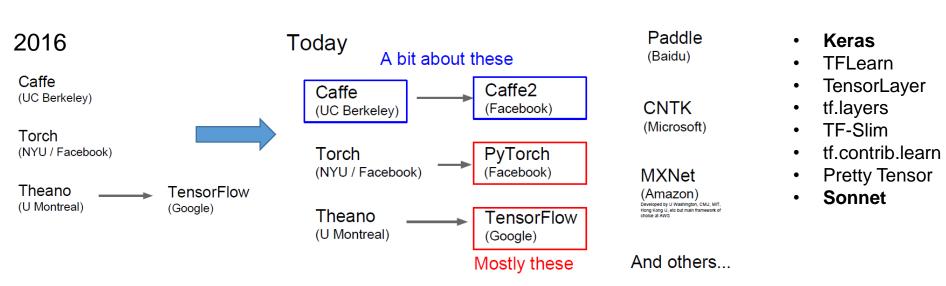
Biomedical Image Segmentation – Application

The 2018 Data Science Bowl challenge: Create a solution to automate nucleus detection.



Deep Learning – Implementation

Frameworks: Wrappers:



"TensorFlow is a safe bet for most projects. Not perfect but has huge community, wide usage. Maybe pair with high-level wrapper (Keras, Sonnet, etc)

I think **PyTorch** is best for research. However still new, there can be rough patches.

Use **TensorFlow** for one graph over many machines

Consider Caffe, Caffe2, or TensorFlow for production deployment

Consider **TensorFlow** or **Caffe2** for mobile"

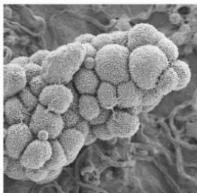
Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017

Deep Learning – Applications

From Medicine to Cybersecurity (your imagination is the limit!).

DEEP LEARNING EVERYWHERE











INTERNET & CLOUD

Image Classification Speech Recognition Language Translation Language Processing Sentiment Analysis Recommendation

MEDICINE & BIOLOGY

Cancer Cell Detection Diabetic Grading Drug Discovery

MEDIA & ENTERTAINMENT

Video Captioning Video Search Real Time Translation

SECURITY & DEFENSE

Face Detection Video Surveillance Satellite Imagery

AUTONOMOUS MACHINES

Pedestrian Detection Lane Tracking Recognize Traffic Sign

Deep Learning – Applications

Recommender Systems Everywhere







Deep Learning – Applications

Image Descriptors



"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."



'two young girls are playing with lego toy."



"girl in pink dress is jumping in air."



"black and white dog jumps over bar."



"young girl in pink shirt is swinging on swing.*

... and so on

Karpathy, A., & Fei-Fei, L. (2015). Deep visual-semantic alignments for generating image descriptions. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 3128-3137).

Deep Learning – Cloud Platforms

The battle for machine learning











Amazon Machine Learning

aws.amazon.com/machine-learning



Machine Learning in the Cloud

Building a better Forecast with H2O and Salesforce

Mark Masterson Application Engineer mark masterson@kenandy.c @MarkMastersonSF

Government Use Cases and Opportunities

Al opens great opportunities for governments

Case Study: Philippines - Department of Science and Technology - Intelligent Operations Center

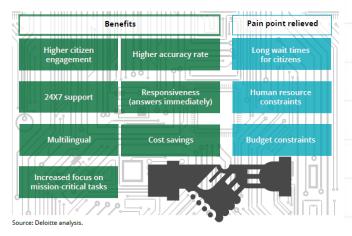


Case Study: Dutch Government - Using Text Mining and Machine Learning for Detection of Child Abuse











Indra, Best Government Emerging Technologies, 2017 Deloite, Al-augmented government, 2017

References

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- Deloite, Al-augmented government, 2017.
- Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n Course, Stanford, Spring 2017.
- Forbes, McKinsey's State Of Machine Learning And Al, 2017.
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- Karpathy, A., & Fei-Fei, L. Deep visual-semantic alignments for generating image descriptions. In *Proceedings* of the IEEE conference on computer vision and pattern recognition (pp. 3128-3137), 2015.
- Ludwin Lope, Deep Learning Presentation, USP, Brazil, 2018.
- Mingxuan Sun, Introduction to Deep Learning and Its Applications, Louisiana State University, USA, 2016.
- Richard Szeliski, Computer vision application and algorithms, September 2014.
- Ronneberger, O., Fischer, P., & Brox, T. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention* (pp. 234-241). Springer, Cham, 2015.

Thank you!

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LIAA-UFSCar