

How to Create a Machine Learning Model using Keras

CBIIT/FNL Workshop

Frederick National Laboratory for Cancer Research

Bioinformatics Analyst IV

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November 6, 2019

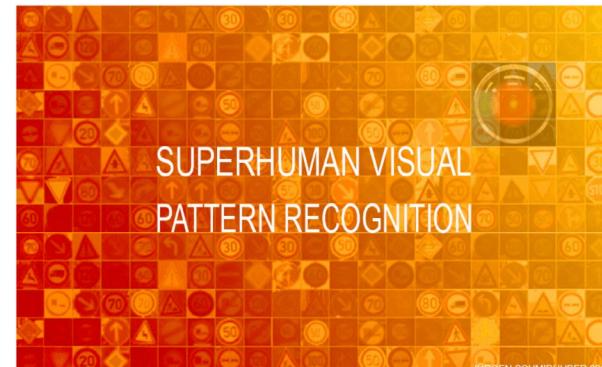
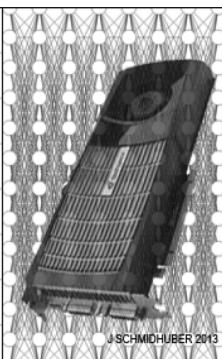
Outline

- Why Deep Learning?
- Why Keras?
- How does it work?
 - Convolution, ReLU, Max pooling, Fully-connected layer
 - Gradient Descent and Backpropagation
- Know your data
- Build/Train/Test your own network
- Glossary

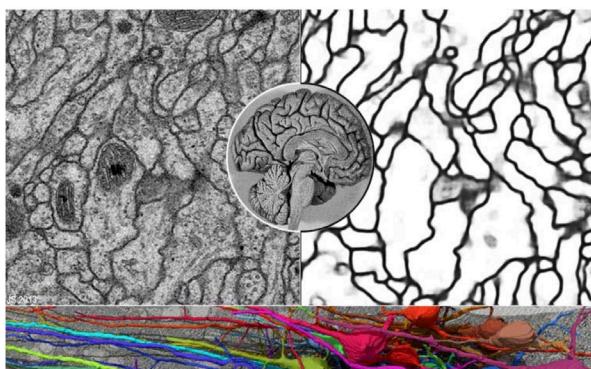
Why Deep Learning?



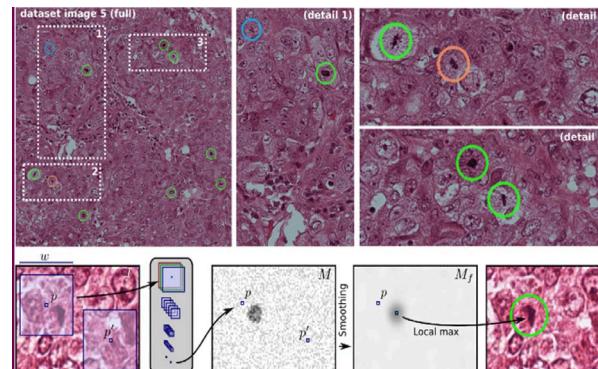
ICDAR 2011 Chinese handwriting



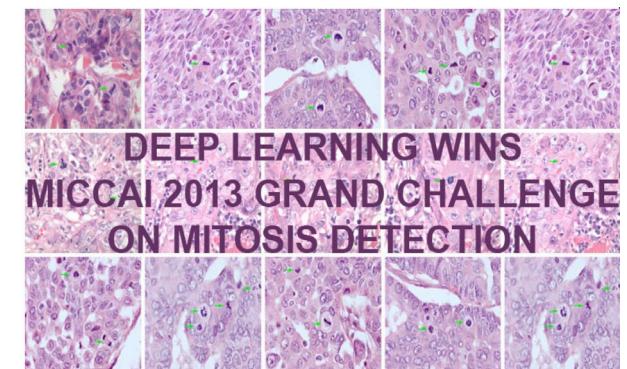
IJCNN 2011 traffic signs



ISBI 2012 brain segmentation



ICPR 2012 cancer detection



MICCAI 2013 Grand Challenge

Why Deep Learning?



Home

Dataset

Rules

Evaluation

Organizers

Download

Validation-Results

Test-Results

Workshop

Leaderboard

Join

Submit

Results

Welcome to the website of PAIP 2019 Challenge.
This competition is part of the [MICCAI 2019 Grand Challenge for Pathology](#).

Announcement

- Submission re-opened! (October 28, 2019)
- Challenge Results and leaderboard are announced (October 23, 2019)
- PAIP 2019 Program is now available. Check our details [Here](#)
- PAIP 2019 will be placed as a “Grand Pathology Challenge” at *Intercontinental Hotel Shenzhen, Barcelona Room*
- Test dataset released and submission start (September 02, 2019)
- Validation dataset released (August 12, 2019)
- Dataset, Rules, Evaluation page has been updated (July 25, 2019)
- Challenge schedule has been changed (July 17, 2019)
- Second training dataset released (May 20, 2019)
- First training dataset released (April 15, 2019)

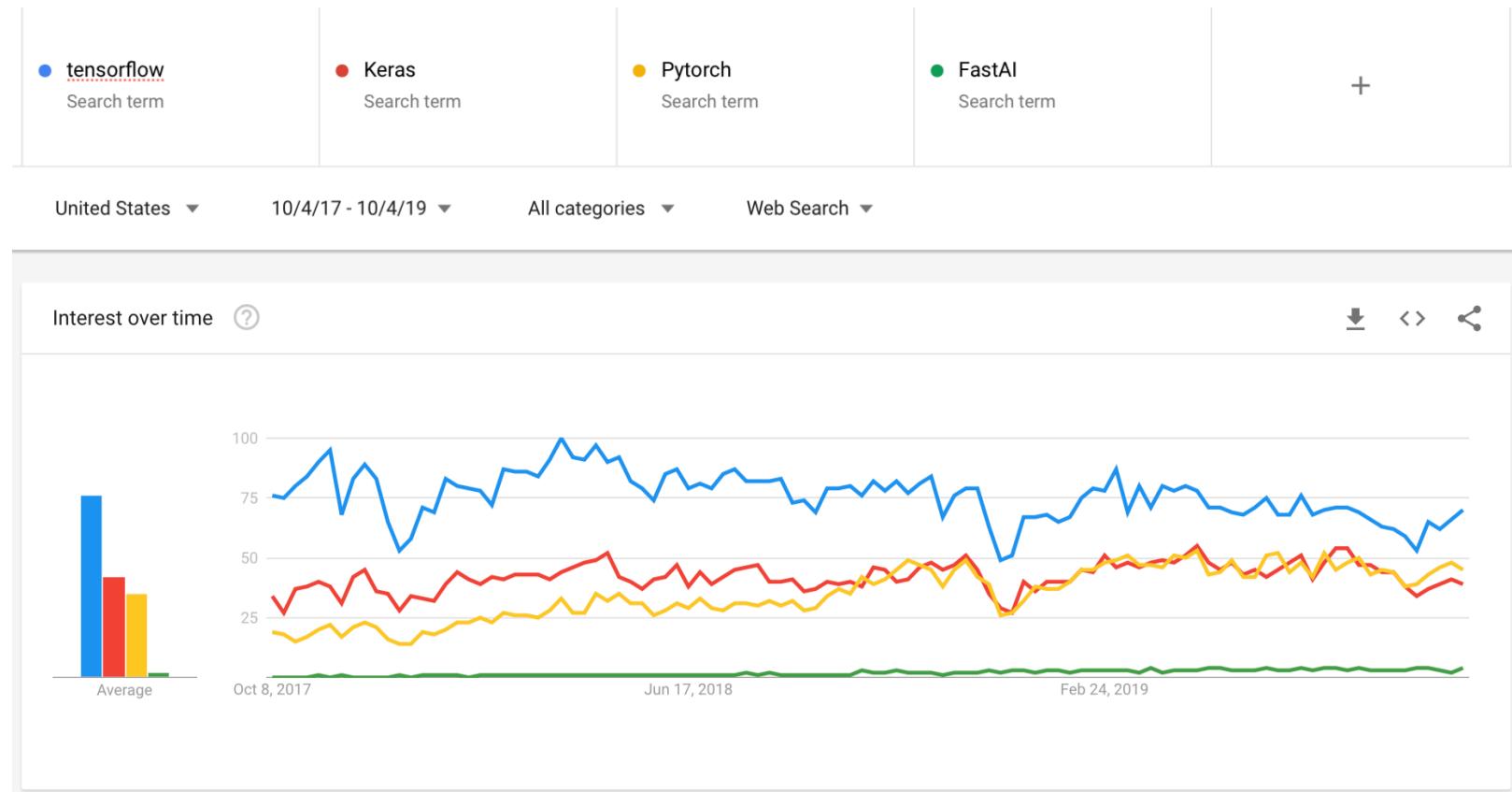
Overview

The goal of the challenge is to evaluate new and existing algorithms for automated detection of liver cancer in whole-slide images (WSIs). There are two tasks and therefore two leaderboards which evaluate the performance of the algorithms for each task. Participants can choose to join both tasks or the Task1 only according to their interests.

Task 1: Liver Cancer Segmentation
Task 2: Viable Tumor Burden Estimation

Rank	Username	Teamname	Final Score	model
1	newhyun00	indiv.	0.7889869765	EfficientNet-B4, UNet++
2	ys810137152	Sen	0.7772154253	SE-Resnext101, U-Net
3	mahendrakhened	MIRL-IITM	0.7503334877	DensNet-121, InceptionResNetV2, DeeplabV3plus
4	majianqiang	Damo AIC	0.6717777027	Resnet101, U-Net
5	gcggcg5	QuILL	0.6652272136	Densely connected convolutional block, U-net
6	ericzz	CUHK-Med	0.6624541354	DAU-Net, PFA-ScanNet
7	rschmitz	DAISYlab@UKE	0.6596204825	msYI-Net (ResNet18-U-Net)
8	bmarami	COSYPATH	0.6313201419	SegNet[2]
9	-	-	-	-
10	LRDE	Elodie Puybareau	0.5299381801	Custom VGG16(Segmentation)
11	12sigmayyx	Sig-IPPath	0.5214551375	Unet512, Unet2048

Why Keras?



Why Keras?

The screenshot shows the TensorFlow Core documentation page under the 'Learn' category. On the left, there's a sidebar with links like 'TensorFlow tutorials', 'Quickstart for beginners', and 'Quickstart for experts'. Below that is a 'BEGINNER' section with dropdown menus for 'ML basics with Keras', 'Load and preprocess data', 'Estimator', and 'ADVANCED' sections for 'Customization', 'Distributed training', 'Images', 'Text', 'Structured data', and 'Generative'. The main content area has a header 'Keras' with a star rating of 5 stars. It starts with a paragraph about tf.keras being TensorFlow's high-level API for building and training deep learning models. It lists three key advantages: 'User-friendly' (simple, consistent interface), 'Modular and composable' (models made by connecting configurable building blocks), and 'Easy to extend' (custom building blocks for research). It also mentions a guide for beginners and a set of starter tutorials. Further down, it suggests guides for power users and links to YouTube videos for a deep dive into Keras internals.

From: TensorFlow official website

How does it work?

```
If (circles):  
    if (brown-ish):  
        if (two triangles):  
            picture = dog  
        else:  
            picture = food
```

Traditional Programming



Dog

Image Source: guidedogs.org



Cookie

Image Source: foodnetwork.com

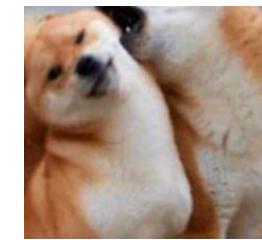
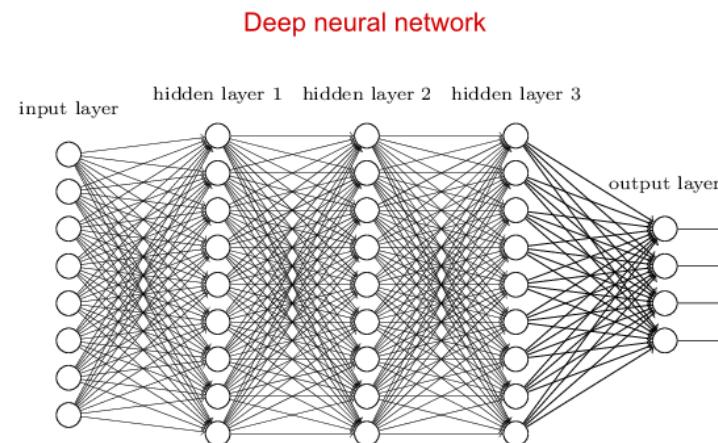
How does it work?



Dog vs. Food

Image source: boredpanda.com

How does it work?



Dog



Food

How does it work?

- Building Blocks of Convolutional Neural Network (CNN)
 - Convolution, ReLU, Pooling, and Fully-Connected (Dense) Layer

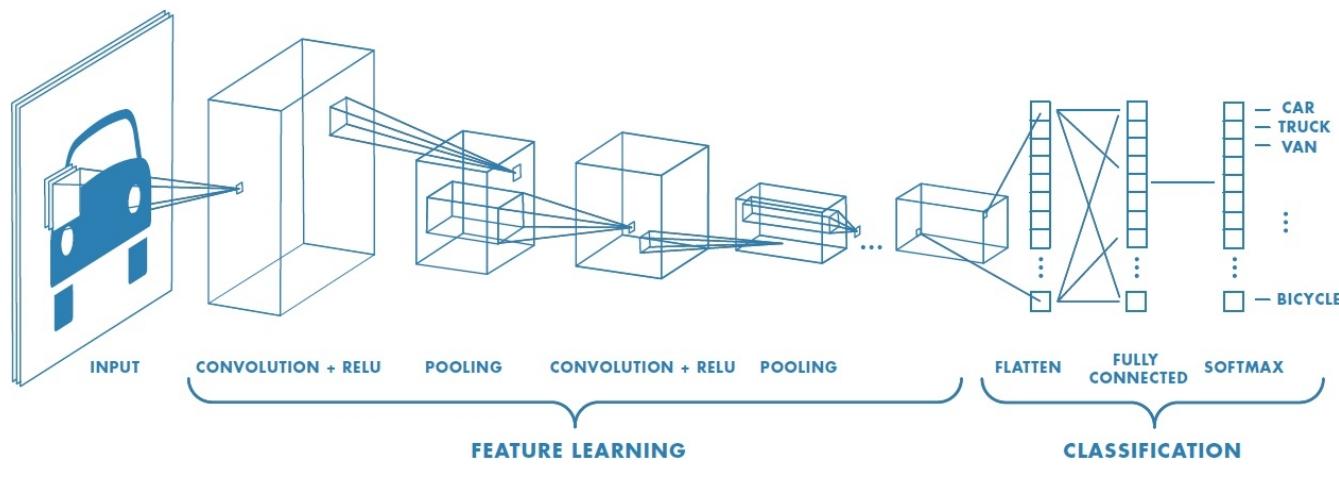
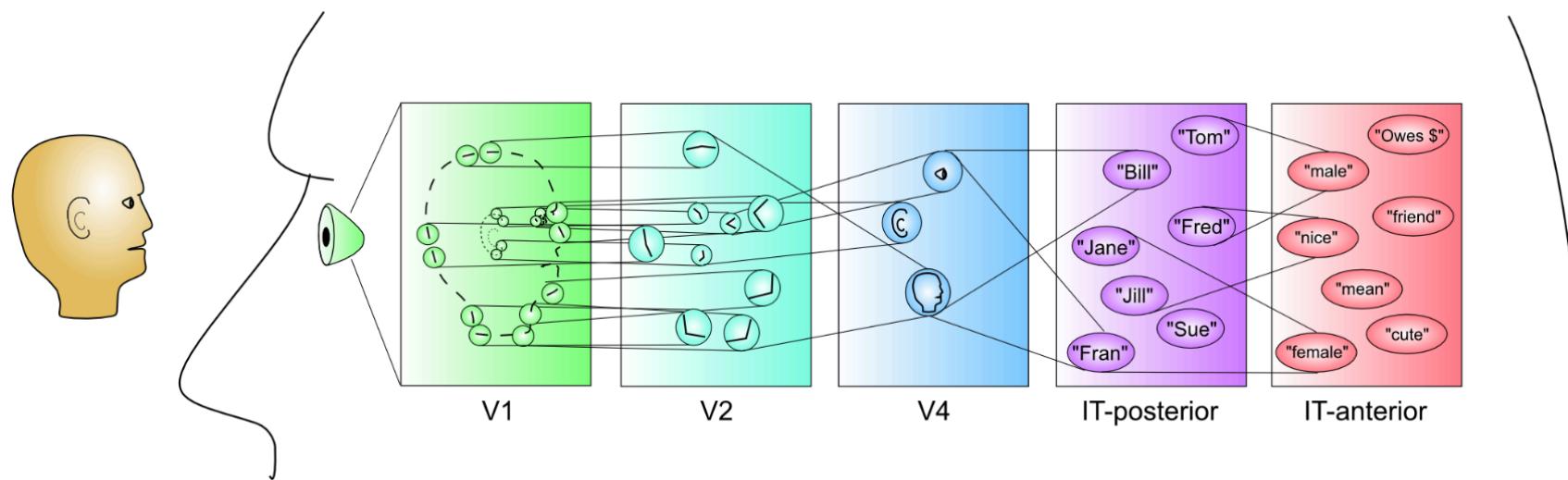


Image Source: MathWorks

How does it work?

- Why the CNN structured in such a way?

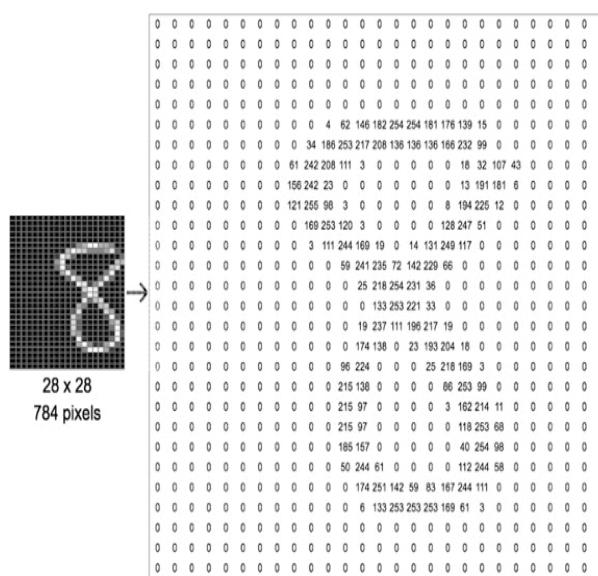


Hierarchy of visual detectors of increasing complexity achieves sophisticated perceptual categorization, with the higher levels being able to recognize 1000's of different objects, people, etc.

Image Source: Medicine Library

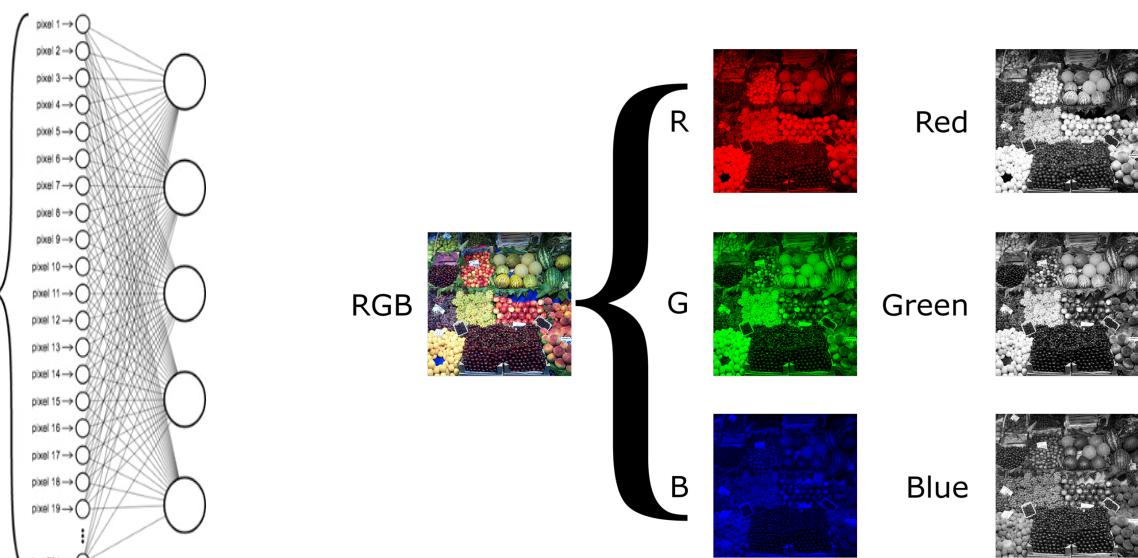
How does it work?

- Input



Matrix representation of a digit 8

Image credit: Deep Learning made easy with Deep Cognition from Medium

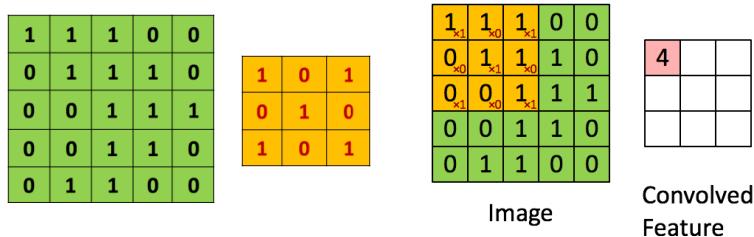


Composition of RGB from 3 Grayscale images

Image credit: Wikipedia

How does it work?

- Convolution



Convolution operation

Image credit: the data science blog



Convolution operation and its effect

Image credit: Deep Learning Methods for Vision (CVPR 12 tutorial)

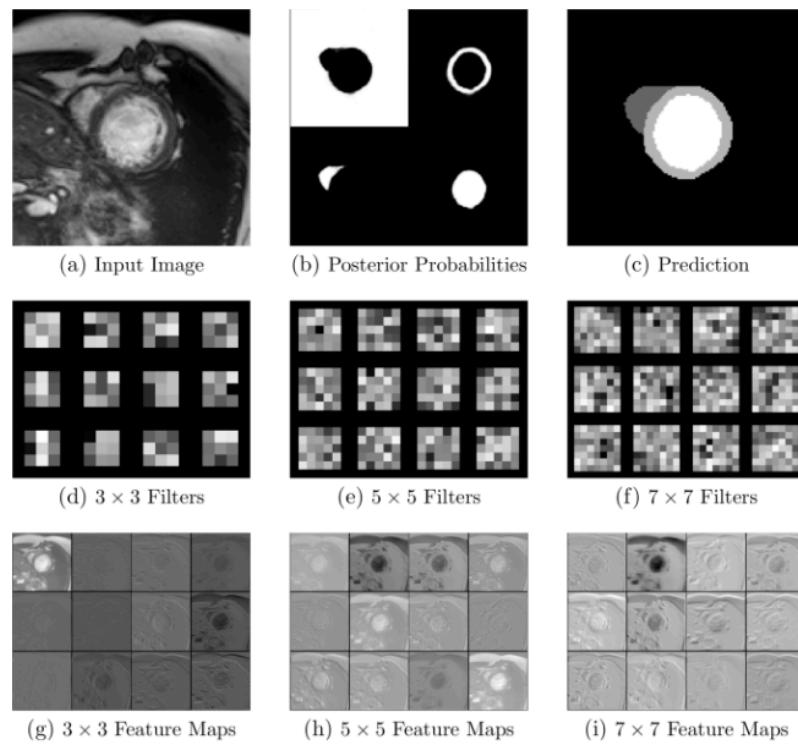
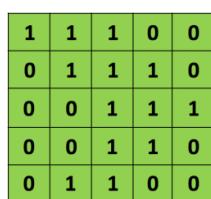
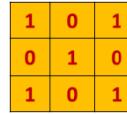
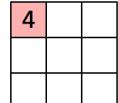


Figure 10: The figures compares illustrates the feature maps of trained model. (a) Input image fed to the network, (b) posterior probability maps after soft-max output, (c) The final prediction of labels, (d) - (f) visualization of the initial layers kernels- 3 × 3, 5 × 5 and 7 × 7, (g) - (i) Filter response to the input image (a).

Image credit: groundai.com

How does it work?

- Convolution

		
		Convolved Feature

Convolution operation

Image credit: the data science blog



Convolution operation and its effect

Image credit: Deep Learning Methods for Vision (CVPR 12 tutorial)

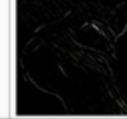
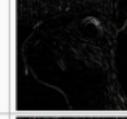
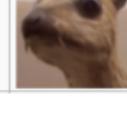
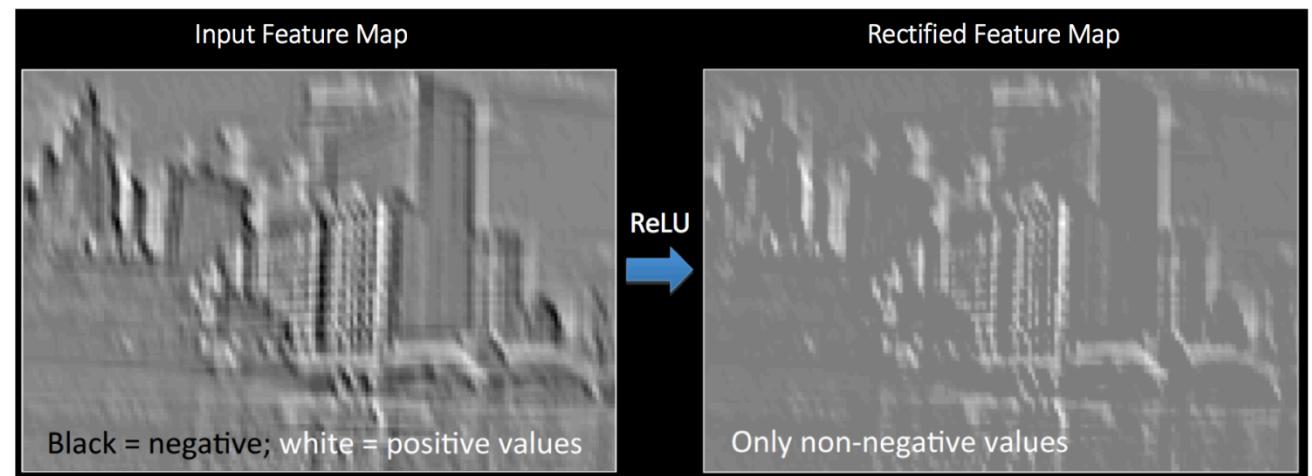
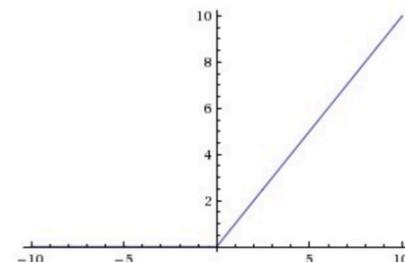
Operation	Filter	Convolved Image
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

Image credit: An Intuitive Explanation of Convolutional Neural Networks

How does it work?

- ReLU (Rectified Linear Unit)
 - Introducing non-linearity

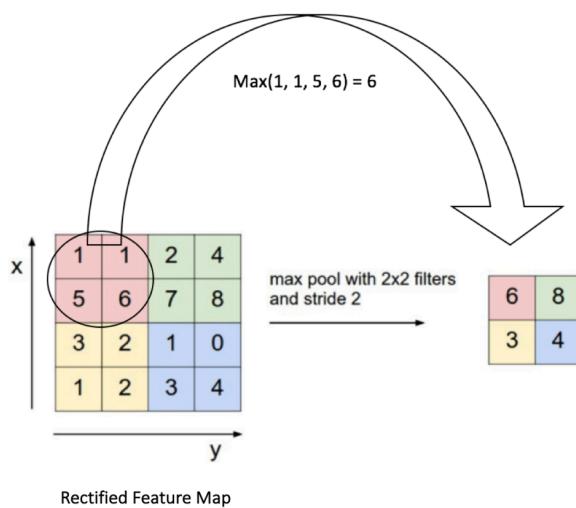
$$\text{Output} = \text{Max(zero, Input)}$$



*ReLU operation and its effect
Image credit: the data science blog*

How does it work?

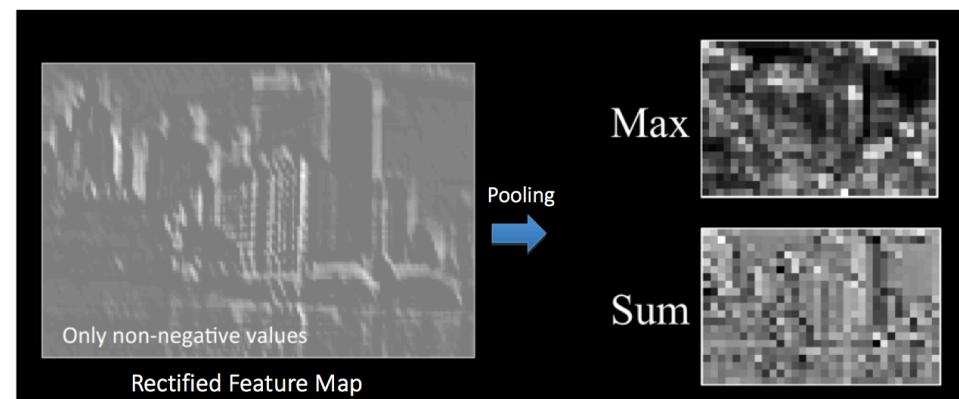
- Pooling (sub-sampling or down-sampling)
 - Reduce dimensionality and extract most import information



Rectified Feature Map

Max pooling operation

<http://cs231n.github.io/convolutional-networks/>

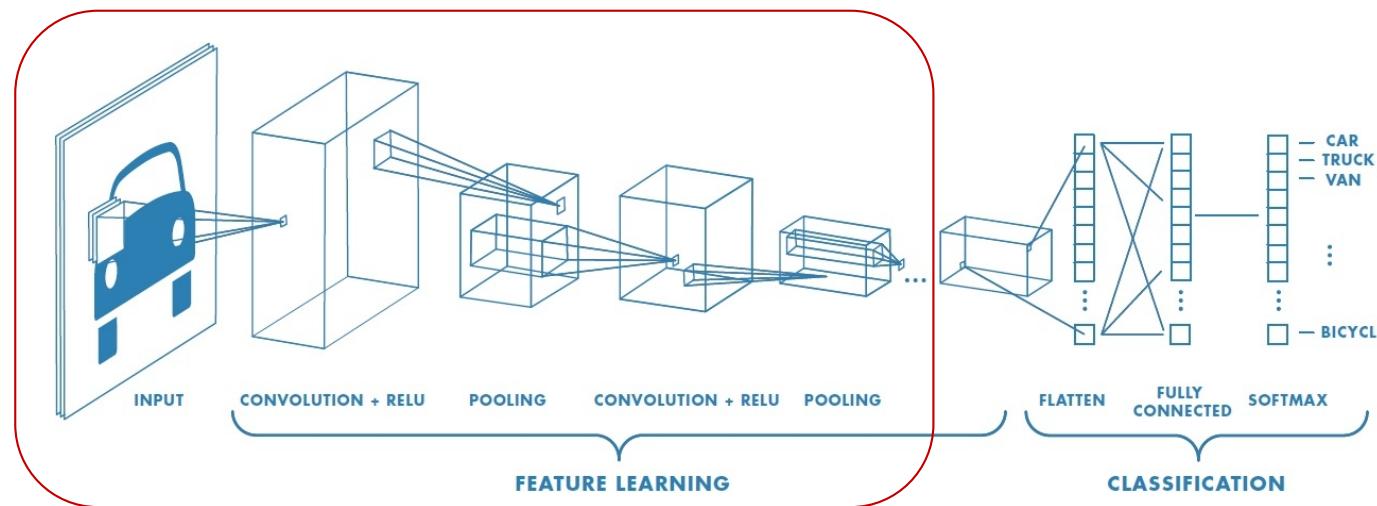


Max pooling effect

Neural Networks, MLSS2015 Summer School, Facebook AI Research,

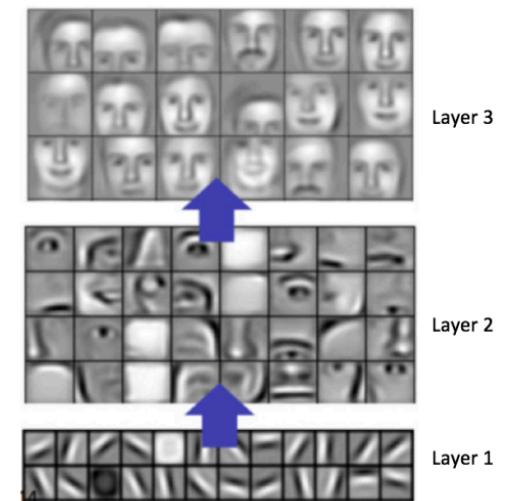
How does it work?

- Story so far



Simple convolutional neural network architecture

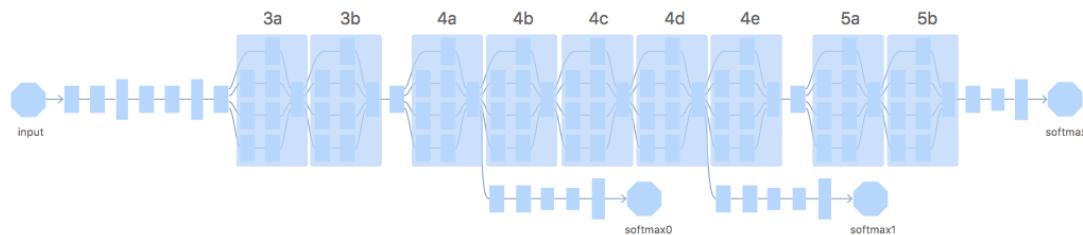
Image Source: MathWorks



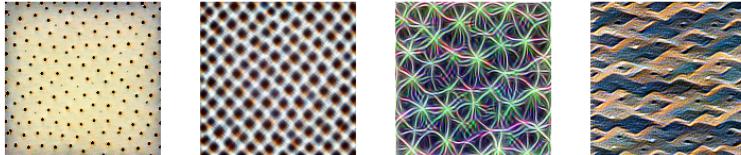
Learned features from a CNN

H. Lee, et al., PROC. OF THE 26th ICML, 2009

How does it work?



Layer 3a



This first inception layer already shows some quite interesting textures. Each neuron only looks at a small receptive field, so these channel visualizations show you a tiling of them.

Layer 3b



Textures become more complex, but are still very local.

Layer 4a



In this layer, which follows a pooling step, we see a significant increase in complexity. We begin to see more complex patterns, and even parts of objects.

Layer 4c



In this layer things get complex enough that it can often help to look at the neuron objective rather than the channel objective. You can find neurons responding to dogs on leashes only, many wheel detectors, and a lot of other fun neurons.

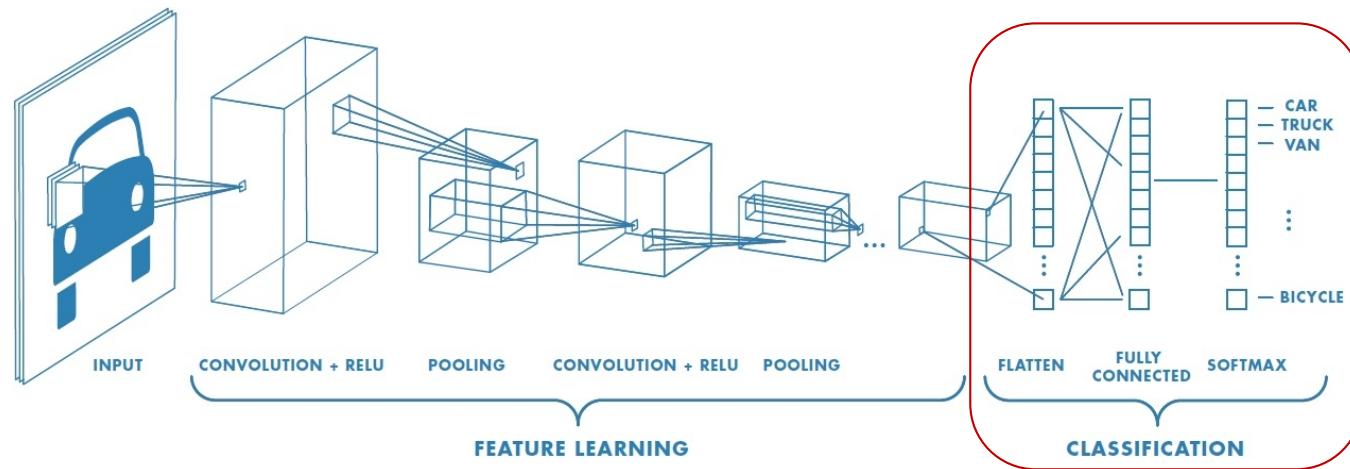
This is likely the most rewarding layer to start exploring!

GoogLeNet structure and visualization of its feature maps

Image Source: Feature Visualization from Distill

How does it work?

- Fully Connected Layer



Simple convolutional neural network architecture

Image Source: MathWorks

How does it work?

- Fully Connected Layer

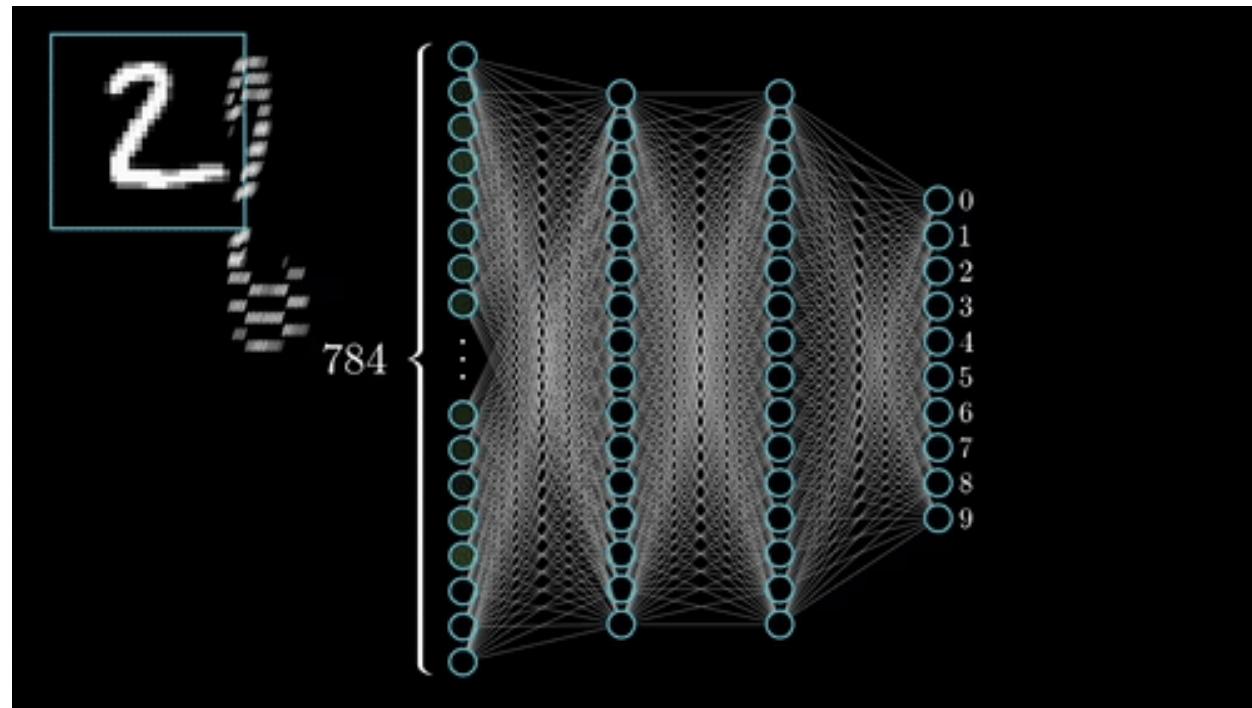


Image Source: Understanding Convolutional Neural Networks, Medium

How does it work?

- What are we training?
 - Weights and biases

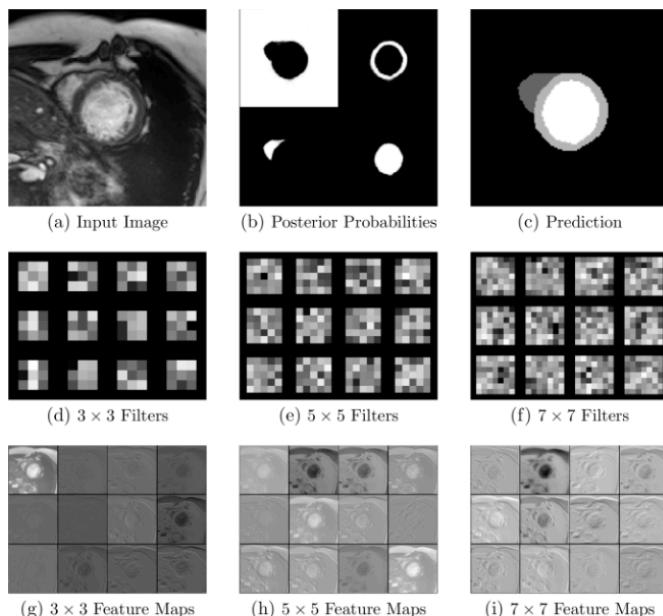
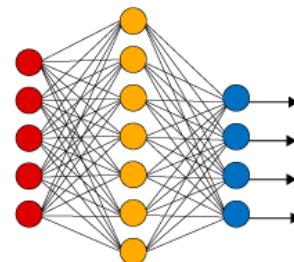


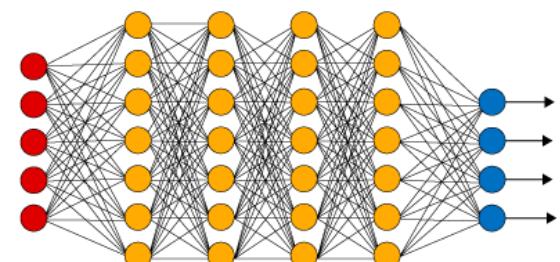
Figure 10: The figures compares illustrates the feature maps of trained model. (a) Input image fed to the network, (b) posterior probability maps after soft-max output, (c) The final prediction of labels, (d) ~ (f) visualization of the initial layers kernels- 3×3 , 5×5 and 7×7 , (g) - (i) Filter response to the input image (a).

Simple Neural Network



● Input Layer

Deep Learning Neural Network



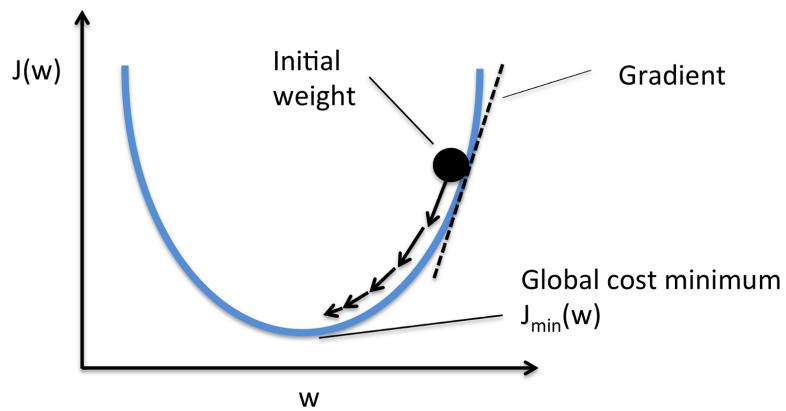
● Hidden Layer

● Output Layer

Image credit: Deep Learning made easy with Deep Cognition from Medium

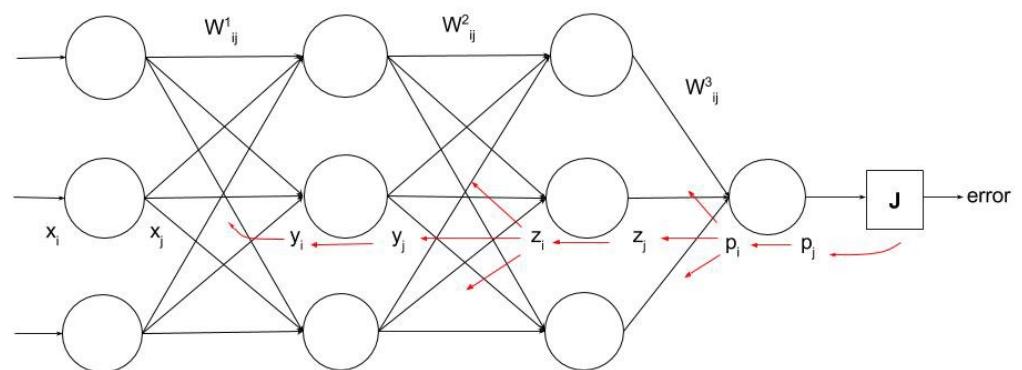
How does it work?

- How to train?
 - Gradient Descent and Backpropagation



Gradient descent mechanism

Image Source:
Gradient Descent: All You Need to Know from Medium

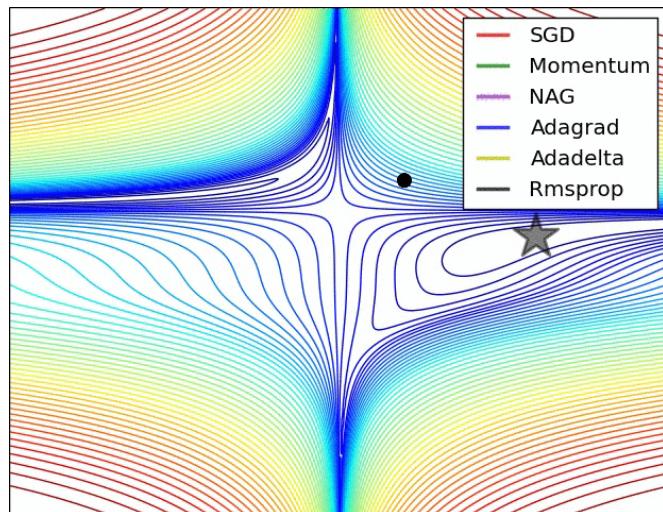


Backpropagating error to individual weights

Image Source:
Rohan & Lenny #1: Neural Networks & The Backpropagation Algorithm, Explained from Medium

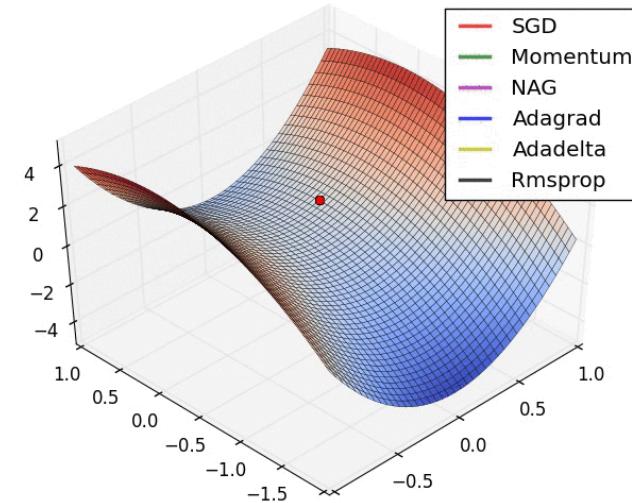
How does it work?

- How to train?
 - Gradient Descent is too slow



Different optimization methods on loss surface contours

Image Source: Sebastian Ruder webpage



Optimization methods on saddle point

Image Source: Sebastian Ruder webpage

Know Your Data

- Understanding your data is **CRUCIAL**
 - Kaggle: Breast Histopathology Images
 - URL: <https://www.kaggle.com/paultimothymooney/breast-histopathology-images>
 - Invasive Ductal Carcinoma Breast Cancer Images
 - Scanned at 40x optical magnification
 - Image Size: 50 x 50 x 3 (Height x Width x Channels)

Know Your Data

- Understanding your data is CRUCIAL
 - Kaggle: Breast Histopathology Images
 - Total number of patients: 279 (Train: 223, Valid: 28, Test: 28)
 - Total number of benign images: 198,783
 - Total number of malignant images: 78,786
 - Average number of benign images per patient: 712.32
 - Average number of malignant images per patient: 282.38
 - Maximum/Minimum number of benign images among patients: 223/14
 - Maximum/Minimum number of malignant images among patients: 1347/10

Build/Train/Test your own network

- Download/Analyze/Organize Data (Done, Organize_data.py)
- Setup a virtual environment (anaconda/mybinder) and install necessary packages
- Read/Explore data
- Create generators to feed images to your network
- Define your own network
- Compile and train your network
- Save and load trained model for testing
- Transfer learning (if time allows)

Glossary

- Batch size: Number of images that are trained simultaneously
- Step/Iteration: Training one batch
- One Epoch: Training entire image once
- Overfitting: Network is specifically optimized to solve training images
- Underfitting: Network performance is not fully utilized
- Dropout: Randomly discard information to avoid overfitting

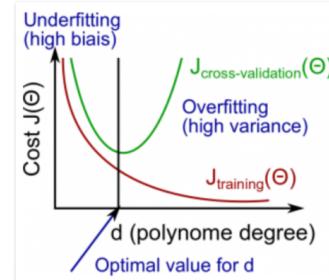
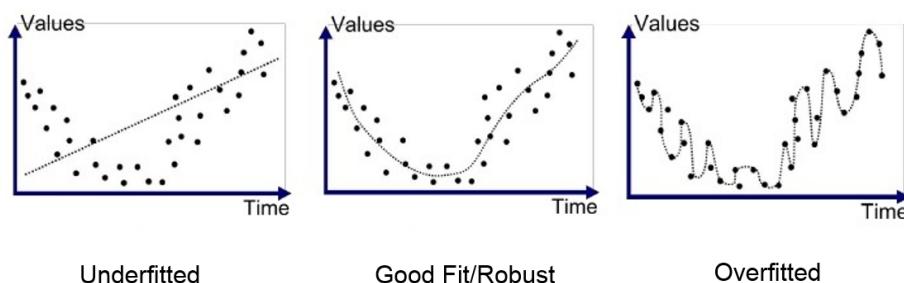
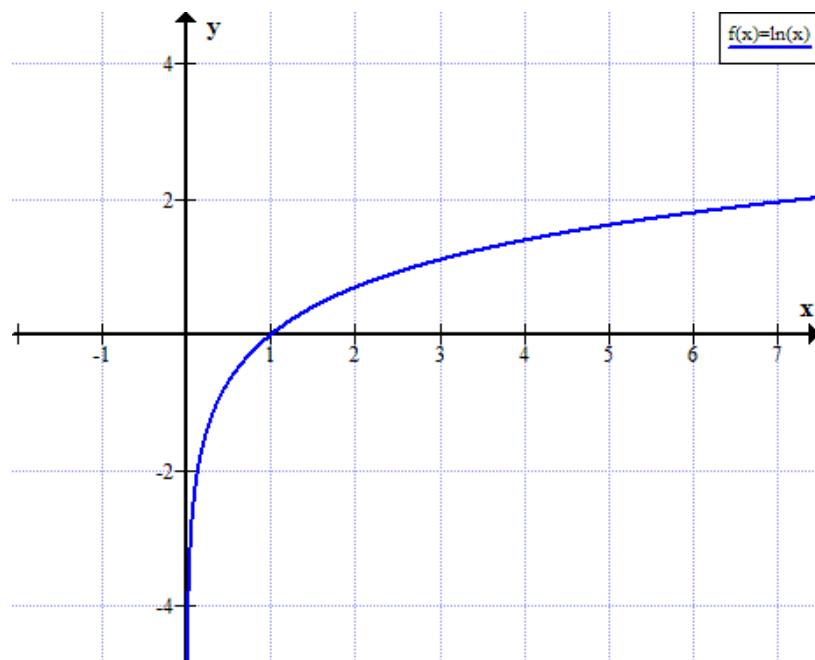


Image Source: *What is underfitting and overfitting in machine learning and how to deal with it.*, Medium

Glossary

- Loss/objective function: Binary cross entropy function

$$-(y * \log(p) + (1-y) * \log(1-p)) - (y*\log(p)+(1-y)*\log(1-p))$$



prediction/Label	y=0	y=1
p=0	0	
p=1		0

Environment Setup

- Anaconda (Your own laptop, can be faster)
 - conda create -n MyEnvName python=3
 - conda install pip
 - pip install --upgrade tensorflow **or** tensorflow-gpu
 - pip install Keras
 - conda install nb_conda
 - pip install scikit-learn
 - pip install matplotlib
 - pip install scikit-image
- Mybinder.org (Jupyter server)
 - <https://mybinder.org>
 - GitHub repository name or URL
 - https://github.com/newhyun00/DL_Workshop
 - Press launch