2. CNN

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Contents

Today's Goal

- We will compare the performance of the imbalanced and balanced image data to the neural network model.
- Especially, the "Convolutional Neural Networks(CNN)" models are known for their high performance in image classification.
- Put imbalanced and balanced data aside, in this time, we will look at the various CNN models and their details.

MLP

- Before understanding the CNN models, you should be familiar with the basic Neural Network model. It is called the "Multilayer Perceptron(MLP)", as one case of "Deep Neural Network(DNN)".

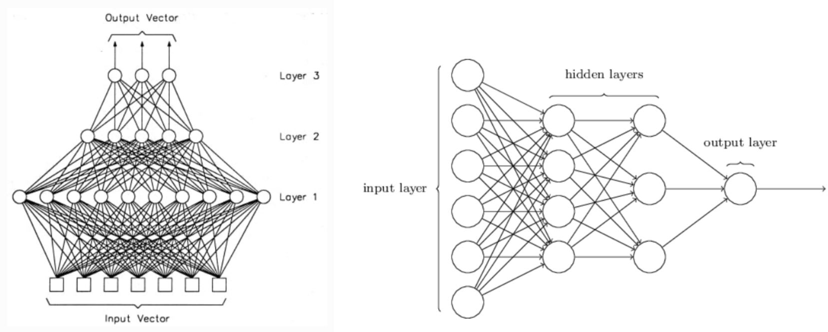
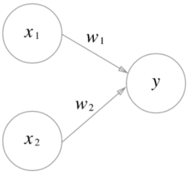


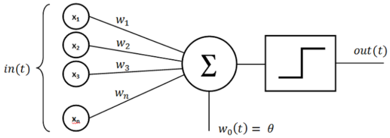
Figure 1: The MLP Sturctures

MLP

- The Perceptron proposed by Frank Rosenblatt in 1957 has the following structure:



(a) Perceptron1



(b) Perceptron2

Figure 2: Perceptron

- This can be considered as a matter of simply drawing a straight line and classifying it. And stacking them together(MLP) can solve problems like "XOR".

MLP

- The MLP model is also called "Feed-forward Deep Neural Network".
- Besides, the MLP structure's one layer in Figure 1 is called a "Fully Connected Layer" or "Dense Layer".
- Basically, the layers are consists of three parts : Input Layer, Hidden Layer, Output Layer.
- The circle shape is called the Node and the lines mean the Weights. And all of the weights are parameters for learning.
- Therefore, in the MLP structure, these lines(weights) are considered a model.
- The one thing to note is that the model complexity increases exponentially with the depth of the model.[3]

CNN: LeNet5

- The CNN model was contrived by "Yann Lecun" who was inspired by "Cat Thought Experiment" conducted by "David H. Hubel" and "Torsten Wiesel" in 1958.
- In 1998, professor Yann. invented LeNet5 which was the ancestor of CNN and used for mail classification.

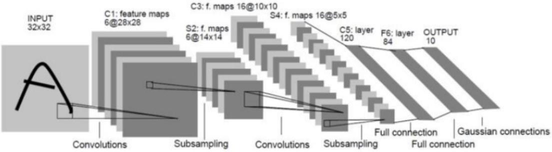


Figure 3: LeNet5

CNN: Model

- The following Figure 4 is the basic form of the CNN model.

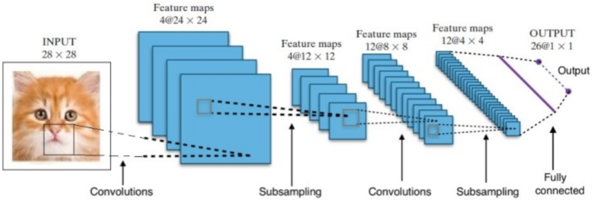


Figure 4: The CNN Model

- To understanding the CNN well, you acquaint the following terms : **Convolution, Filter, Feature Map, Stride, Padding, Pooling, Activation Function, etc.**

CNN: 1. Convolution, Filter, Feature Map

- The convolution is the act of multplying and adding numbers easily.
- Let's think of the green square as an image and the yellow square as a Filter. Then, the convolution operation proceeds like Figure 4 and the output is called Feature Map.

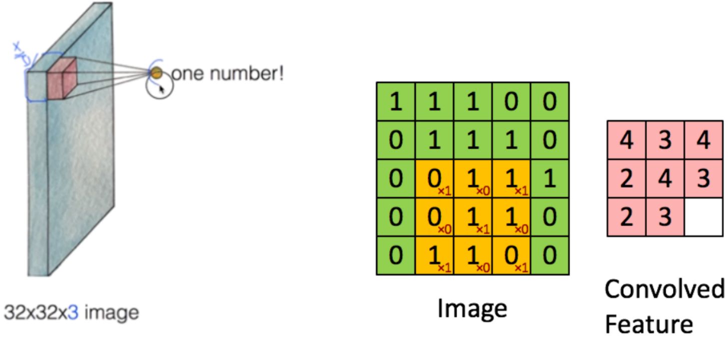
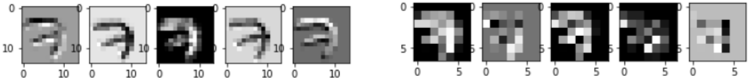


Figure 5: Convoluton operation

- The following Figure 5 shows the change of the image data(MNIST data) when the Convolution operation is performed one time.



(a) Before (b) After

Figure 6: Image Change

- In the following figure, you can see the Filter, Feature Map, and Stride: Filter $= 3 \times 3$ ($\times 3$ if RGB), Stride $= 2$, Feature Map $= 3 \times 3$ ($\times 3$ if RGB)

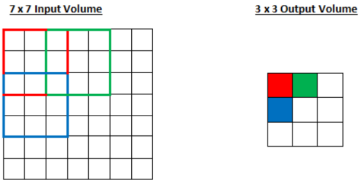


Figure 7: Stride with size 2

- Remeber we are working on the one image.

CNN: 3. Padding

- Also, sometimes we want to make the same size feature map as the input or adjust it arbitrarily.
- In this case, we use the Padding(or Zero Padding) method.

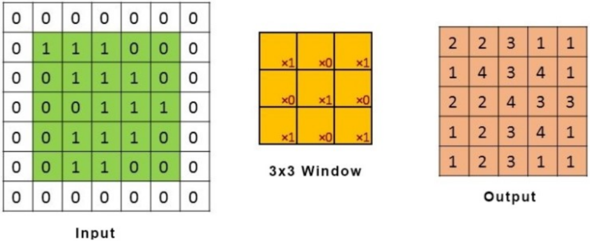


Figure 8: Zero Padding with size 1

- In the above, the Padding Size is 1

CNN: 4. Equation

- There is a relationship between Input(image), Output(Feature Map), Stride, Padding :

$$O = \frac{(I - F + 2P)}{S} + 1$$

$$O = Output,\ I = Input,\ F = Filter,\ P = Padding$$

- Also if you want to make the same size Feature Map as the input, use the following equation.

$$P = \frac{(F - 1)}{2}$$

$$P = Padding,\ F = Filter$$

- The above formulas are calculated for the horizontal and vertical directions respectively

CNN: 5. Pooling

- The Pooling is used to compress the information.
- This results in preventing the model from overfitting and avoiding the use of many parameters.
- There are Max Pooling, Mean Pooling methods and so on.

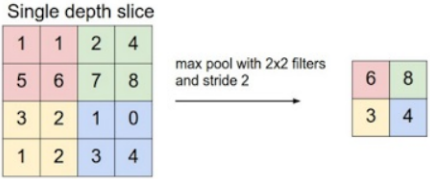
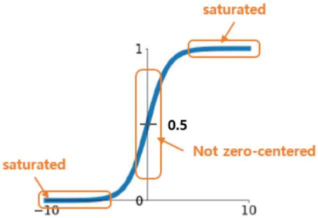


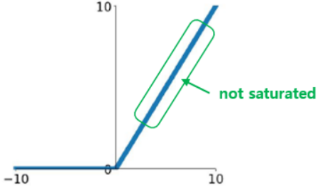
Figure 9: Max Pooling

CNN: 6. Activation Function

- The activation function makes the data nonlinear.
- The CNN model usually uses Rectified Linear Unit(ReLU) as an activation function for avoiding gradient vanishing.
- Of course, there are many other activation functions : Tanh, Maxout, LeakyReLU, ELU, and so forth.



(a) Sigmoid



(b) ReLU

Figure 10: Activation Functions

CNN: 7. More

Let's take a look at the following terms simply.

- Cost Function
  1. This is a function related to our goal. It is important to update this value low.
  2. According to purpose, use the loss function appropriately and variously.
- Gradient Descent Algorithm
  1. It is algorithm for updating parameters.
  2. The basic form of Gradient Descent updating equation is $w_{k+1} = w_k - \lambda_k \nabla f(w_k)$ for each parameters. w is a parameter and f is a Cost Function(Convex, Differentiable).
- Backpropagation
  1. This method is used to calculate the gradient values for which nodes affect the Cost Function.
  2. Basically, it is calculated through the Chain Rule.

CNN: Summary

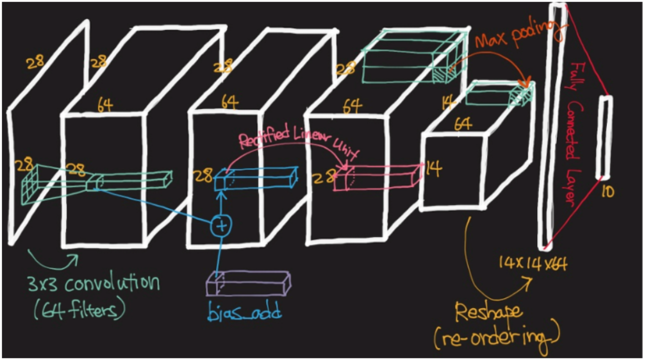


Figure 11: CNN Layer Structure

CNN: Summary

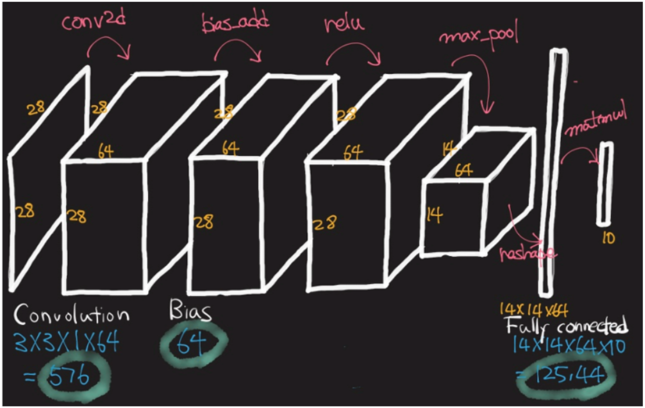


Figure 12: Parameters Calculation

CNN: Summary

Machine can do it!

Figure 13: Dogs and Cats

- ImageNet Large Scale Visual Recognition Challenge(ILSVRC), launched in 2010 first, is a contest to evaluate the performance of image classification algorithms using large amounts of image data (1000 categories, 1.4 million data).

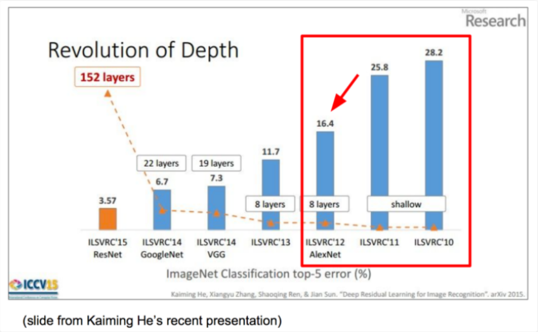
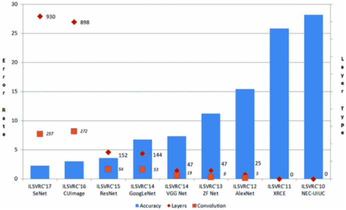


Figure 14: ILSVRC Models

Advanced CNN: ILSVRC Contest

- You should know the AlexNet, VGG19, GoogLeNet, and ResNet CNN models.
- We will focus on the AlexNet and VGG19 this time.



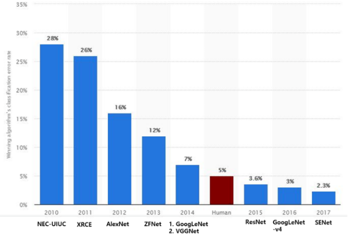


Figure 15: Error Rate until 2017

Advanced CNN: AlexNet

- The Alexnet[2] accelerated the development of the CNN model for image classification problems by using **ReLU, LRN, Data Augmentation, Dropout and so on.**
- Because the Alexnet used more deeper Network than other models at that time, people began to be increasingly interested in the depth of the overall Neural Network.

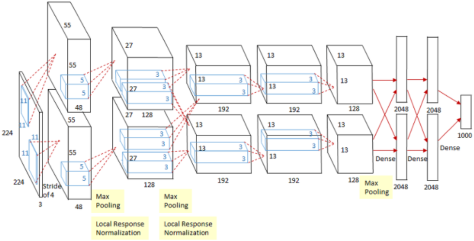


Figure 16: AlexNet Structure

Advanced CNN: AlexNet

- There are many Activation Functions. And we will focus on the ReLU.

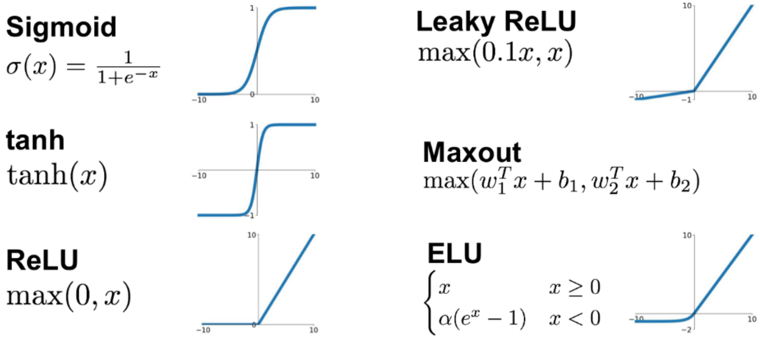


Figure 17: Activation Functions

Advanced CNN: AlexNet

Let's take a look at the following terms.

- Local Response Normalization(LRN)
  1. The LRN is a kind of normalization method based on ideas from neurobiology. It makes a node more stronger when the node is relatively strong to be compared with its surroundings.
  2. This method isn't used nowadays.
- Data Augmentation
  1. Data Augmentation means an expansion of the number of data.
  2. Cut the image appropriately and perform "Crop" or "Flip".
  3. The Color Variation(Jittering) is performed by fitting PCA.
- Dropout
  1. Dropout is the act of randomly turning off a node during the training.
  2. It is often used for prevent models from overfitting.

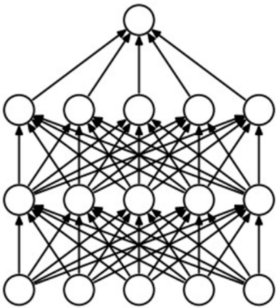
- LRN

$$b^i_{x,y} = a^i_{x,y} / \left(k + \alpha \sum_{j=max(0,i-n/2)}^{min(N-1,i+n/2)} (a^j_{x,y})^2 \right)^{\beta}$$

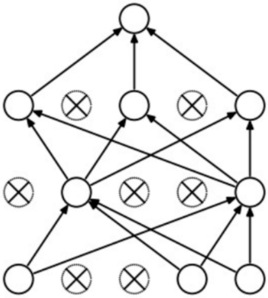
1. $a^i_{x,y}$: The activity of a neuron computed by applying kernel i at position (x, y).
2. $b^i_{x,y}$: The response-normalized activity.
3. n : 'Adjacent' kernel maps at the same spatial position.
4. N : The total number of kernels in the layer.
5. k, n, α, β : Hyper parameters.
6. AlexNet used $k = 2$, $n = 5$, $\alpha = 10^{-4}$, and $\beta = 0.75$.

Advanced CNN: AlexNet

- Dropout



(a) Standard Neural Network



(b) Applying Dropout

Figure 18: Dropout: A Simple Way to Prevent Neural Networks from Overfitting

- The AlexNet consists of 5 Convolution layers and 3 Fully-connected layers.
- It has almost 63,000,000 parameters.

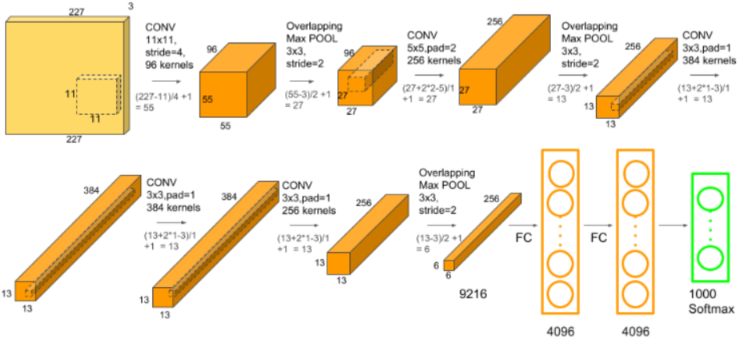


Figure 19: Specific AlexNet

Advanced CNN: VGG19

- Since the emergence of the Alexnet, people have begun to be concerned about how the depth of Neural Network models affects performance.
- the VGG19, which was runner-up at ILSVRC in 2014, is simpler than GoogLeNet.
- For this reason, properly modified VGG model [4] has been widely used.

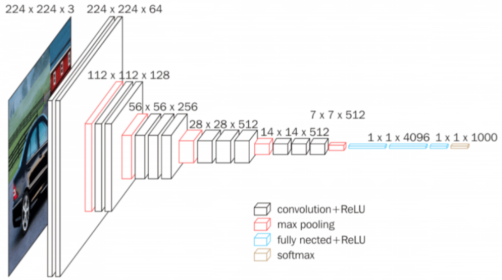


Figure 20: VGG19 Structure

Advanced CNN: VGG19

- VGG models are characterized by using only 3×3 Filters.
- That's because of 2 reasons : more nonlinearity and fewer parameters.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure 21: VGG models

Advanced CNN: VGG19

- As VGG models becomes deeper, Gradient Vanishing and Overfitting problems become greater
- In the VGG models article, team VGG corrected this problem using the results obtained with prior-learning through the VGG11.

- Moreover, there is relatively new models GoogLeNet and ResNet.

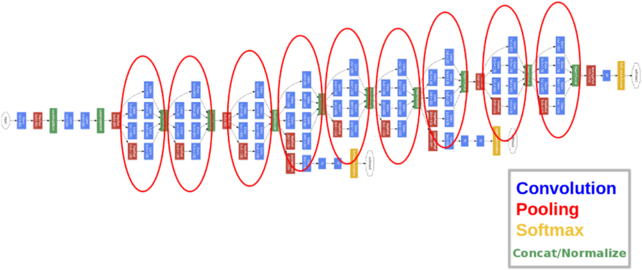


Figure 22: GoogLeNet

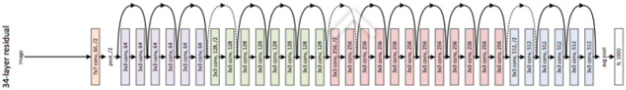
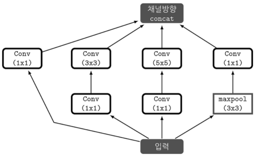


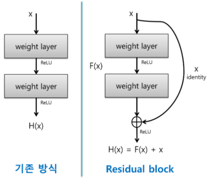
Figure 23: ResNet

Advanced CNN: And..

- Although not covered in this ppt, you can check each model through the following : GoogLeNet[5] , ResNet[1]



(a) Inception Module



(b) Residual Learning

Figure 24: Key concepts in each model

Next

- In preprocessing, data augumentation can be expressed in various ways :
  1. ~~Flip all data left and right for small number of labels.~~
  2. ~~Make an object(data) through the rotation or translation invariance (Crop).~~
  3. Use the ADASYN, SMOTE, GAN , etc.
  4. Balance the label with other data.
- ~~Also we will cover the various model such as the Alexnet, VGG19, ResNet18 etc.~~
- And last, we will talk about the various ensembles like voting system, through the combination of above models.

Reference

[1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[2] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

[3] Maithra Raghu, Ben Poole, Jon Kleinberg, Surya Ganguli, and Jascha Sohl Dickstein. On the expressive power of deep neural networks. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 2847–2854. JMLR. org, 2017.

[4] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

[5] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1–9, 2015.