STA3020-01
딥러닝입문
SPRING 2019

INSTRUCTOR: 박종선 (Chongsun Park)
MEETING TIMES: M. 16:30-17:45 & W. 15:00-16:15
PLACE: 다산경제관 5 층 32530
OFFICE: Room 32404, 다산경제관 (Tel: 02-760-0468)
EMAIL: cspark@skku.edu
OFFICE HOURS: W. 2:00~3:00pm, Th. 2:00~3:00 pm (or by appointment)

TEXT: Deep Learning with R, Chollet and Allaire, Manning, 2017
Course Materials: iCAMPUS course bulletin board
REFERENCES: Deep Learning, Goodfellow et al., MIT press, 2016

PREREQUISITE: 통계학개론, 수리통계학, 회귀분석입문, 통계프로그래밍입문(또는 통계계산입문)

[TOPICS]

1. Introduction to Deep Learning
2. Mathematical blocks of neural networks
3. Getting started with Neural Networks
4. Fundamentals of Machine Learning
5. Deep Learning for Computer Vision
6. Deep Learning for Text and Sequences

[GRADING]

How will I be evaluated in this course?

1. Attendance:	**5%**
2. Homeworks:	**5%**
3. Project:	**40%**
4. Final:	**50%**

Total:	**100%**

[Lecture notes and additional materials]

Lecture notes and materials like data sets will be updated every Sunday on the iCAMPUS course bulletin.

[Statistical Package]

1. We will use R (Rstudio with Keras) for numerical illustrations.
2. R: http://cran.r-project.org/ -> R precompiled binary for Windows (95 and later)
3. Rstudio: https://www.rstudio.com/
4. Tensorflow for R: https://tensorflow.rstudio.com/

[Text Website]

https://www.manning.com/books/deep-learning-with-r

[Reference Website]

https://mitpress.mit.edu/books/deep-learning

1. ***Inventors have long dreamed of creating machines that think.***
2. ***When proprogrammable computers were first conceived, people wondered whether they might become intelligent, over a hundred years before one was built (Lovelace, 1842).***
3. ***In the early days of artificial intelligence, the field rapidly tackled and solved problems that are intellectually difficult for human beings but relatively straightforward for computers—problems that can be described by a list of formal, mathematical rules.***
4. ***This book is about a solution to these more intuitive problems. This solution is to allow computers to learn from experience and understand the world in terms of a hierarchy of concepts, with each concept defined in terms of its relation to simpler concepts. (deep learning)***
5. ***Deep Blue chess-playing system***
6. ***Chess can be completely described by a very brief list of completely formal rules, easily provided ahead of time by the programmer.***
7. ***Differences between formal and informal (subjective and intuitive) knowledge.***
8. ***Knowledge base approach to artificial intelligence fails. Why?***
9. ***The difficulties faced by systems relying on hard-coded knowledge suggest that AI systems need the ability to acquire their own knowledge, by extracting patterns from raw data. This capability is known as machine learning. (Eg. logistic regression)***
10. ***What is features?***
11. ***Importance of proper representation.***

CHAPTER 1 What is deep learning?

1.1 Artificial intelligence, machine learning, and deep learning

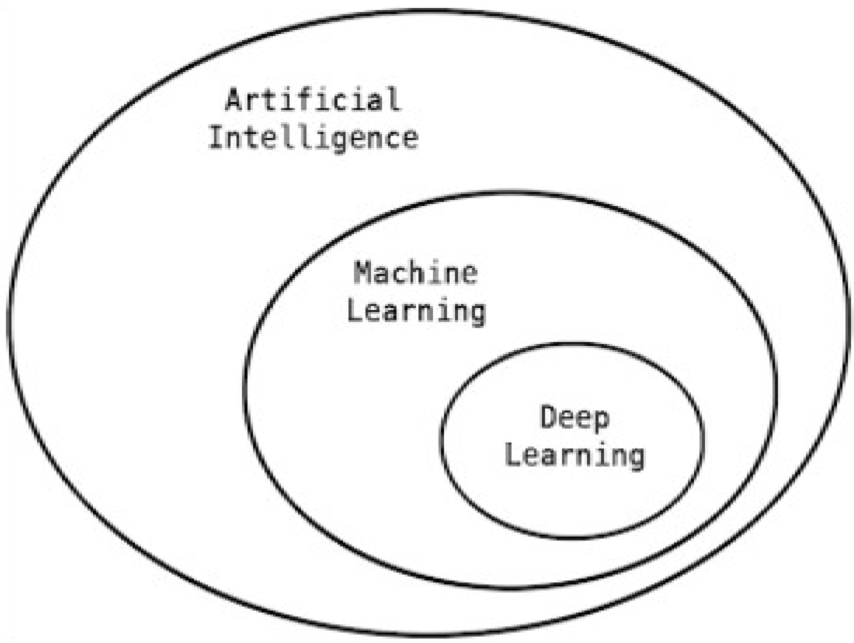

Figure 1.1 Artificial intelligence, machine learning, and deep learning

1.1.1 Artificial intelligence

A concise definition of the field would be as follows: *the effort to automate intellectual tasks normally performed by humans.*

1.1.2 Machine learning

Machine learning arises from this question: could a computer go beyond "what we know how to order it to perform" and learn on its own how to perform a specified task? Could a computer surprise us? Rather than programmers crafting data-processing rules by hand, could a computer automatically learn these rules by looking at data?

This question opens the door to a new programming paradigm. In classical programming, the paradigm of symbolic AI, humans input rules (a program) and data to be processed according to these rules, and out come answers (see figure 1.2). With machine learning, humans input data as well as the answers expected from the data, and outcome the rules. These rules can then be applied to new data to produce original answers.

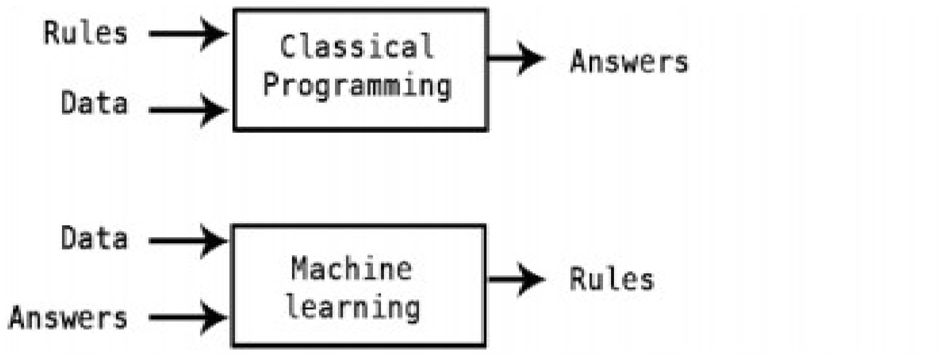

Figure 1.2 Machine learning: a new programming paradigm

A machine-learning system is rather than explicitly programmed. It's trained presented with many examples relevant to a task, and it finds statistical structure in these examples that eventually allows the system to come up with rules for automating the task.

1.1.3 Learning representations from data

- *Input data points*—For instance, if the task is speech recognition, these data points could be sound files of people speaking. If the task is image tagging, they could be picture files.
- *Examples of the expected output*—In a speech-recognition task, these could be human-generated transcripts of sound files. In an image task, expected outputs could tags such as "dog", "cat", and so on.
- *A way to measure whether the algorithm is doing a good job*—This is necessary in order to determine the distance between the algorithm's current output and its expected output. The measurement is used as a feedback signal to adjust the way the algorithm works. This adjustment step is what we call *learning*.

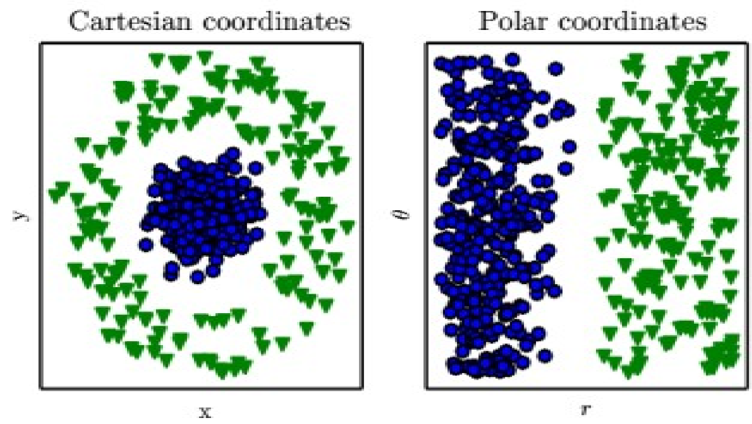

Figure 1.1: Example of different representations: suppose we want to separate two categories of data by drawing a line between them in a scatterplot. In the plot on the left, we represent some data using Cartesian coordinates, and the task is impossible. In the plot on the right, we represent the data with polar coordinates and the task becomes simple to solve with a vertical line. (Figure produced in collaboration with David Warde-Farley)

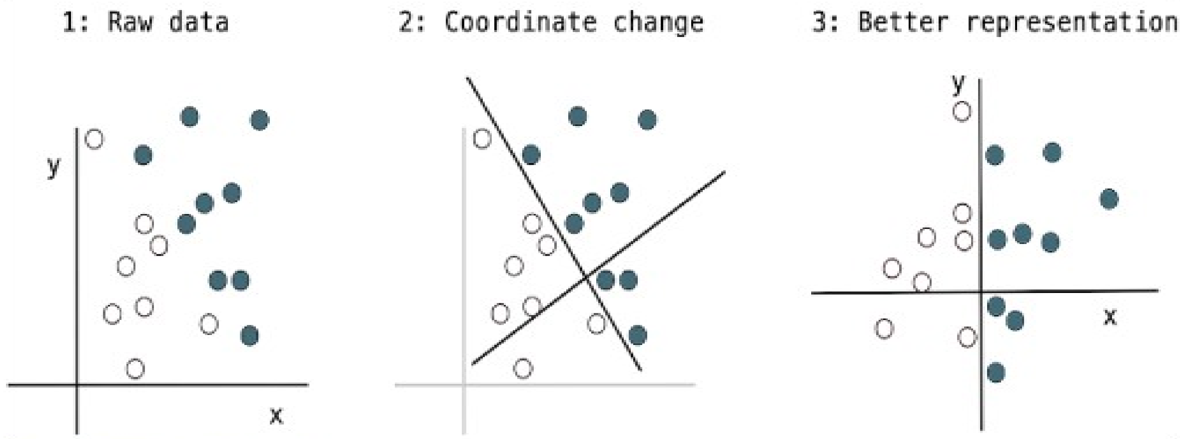

Figure 1.4 Coordinate change

1.1.4 The “deep” in deep learning

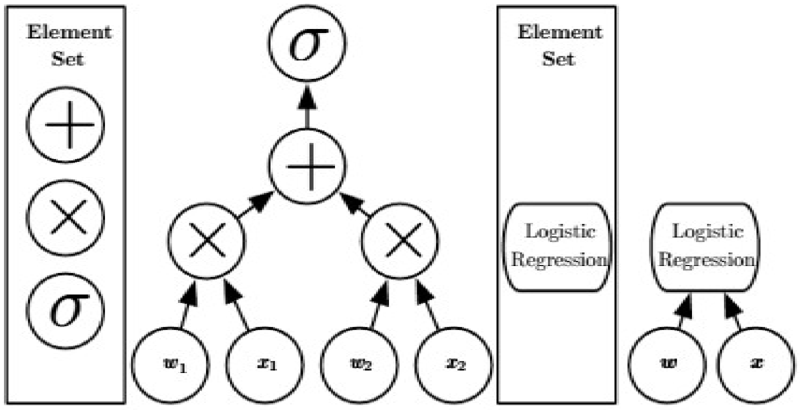

Figure 1.3: Illustration of computational graphs mapping an input to an output where each node performs an operation. Depth is the length of the longest path from input to output but depends on the definition of what constitutes a possible computational step. The computation depicted in these graphs is the output of a logistic regression model, $\sigma(\boldsymbol{w}^T\boldsymbol{x})$, where σ is the logistic sigmoid function. If we use addition, multiplication and logistic sigmoids as the elements of our computer language, then this model has depth three. If we view logistic regression as an element itself, then this model has depth one.

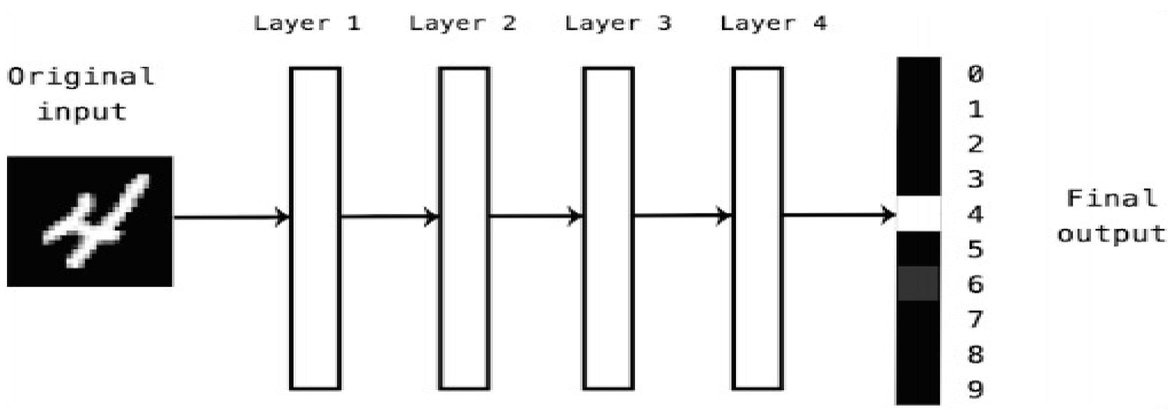

Figure 1.5 A deep neural network for digit classification

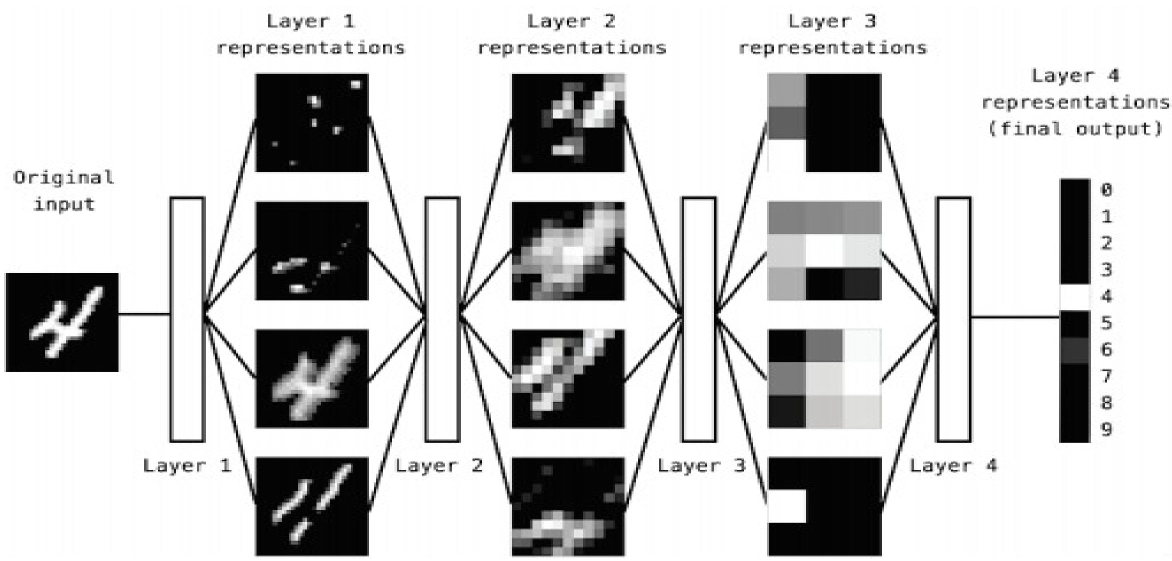

Figure 1.6 Deep representations learned by a digit-classification model

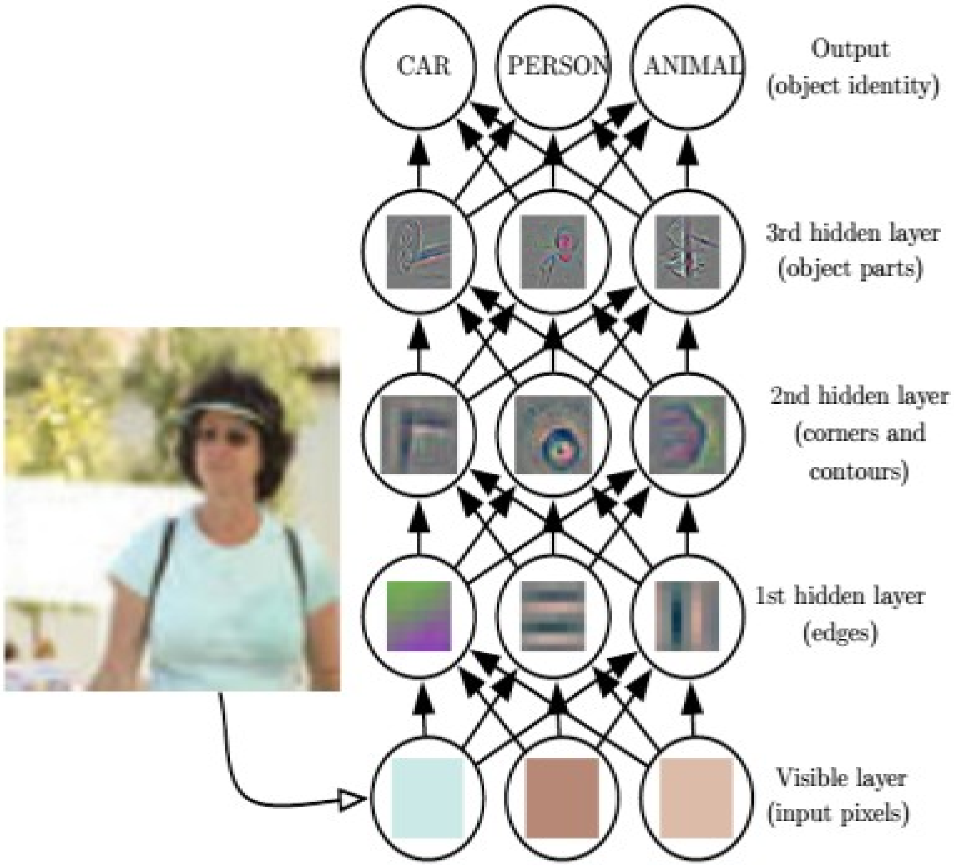

Figure 1.2: Illustration of a deep learning model. It is difficult for a computer to understand the meaning of raw sensory input data, such as this image represented as a collection of pixel values. The function mapping from a set of pixels to an object identity is very complicated. Learning or evaluating this mapping seems insurmountable if tackled directly. Deep learning resolves this difficulty by breaking the desired complicated mapping into a series of nested simple mappings, each described by a different layer of the model. The input is presented at the *visible layer*, so named because it contains the variables that we are able to observe. Then a series of *hidden layers* extracts increasingly abstract features from the image. These layers are called "hidden" because their values are not given in the data; instead the model must determine which concepts are useful for explaining the relationships in the observed data. The images here are visualizations of the kind of feature represented by each hidden unit. Given the pixels, the first layer can easily identify edges, by comparing the brightness of neighboring pixels. Given the first hidden layer's description of the edges, the second hidden layer can easily search for corners and extended contours, which are recognizable as collections of edges. Given the second hidden layer's description of the image in terms of corners and contours, the third hidden layer can detect entire parts of specific objects, by finding specific collections of contours and corners. Finally, this description of the image in terms of the object parts it contains can be used to recognize the objects present in the image. Images reproduced with permission from Zeiler and Fergus (2014).

1.1.5 Understanding how deep learning works, in three figures

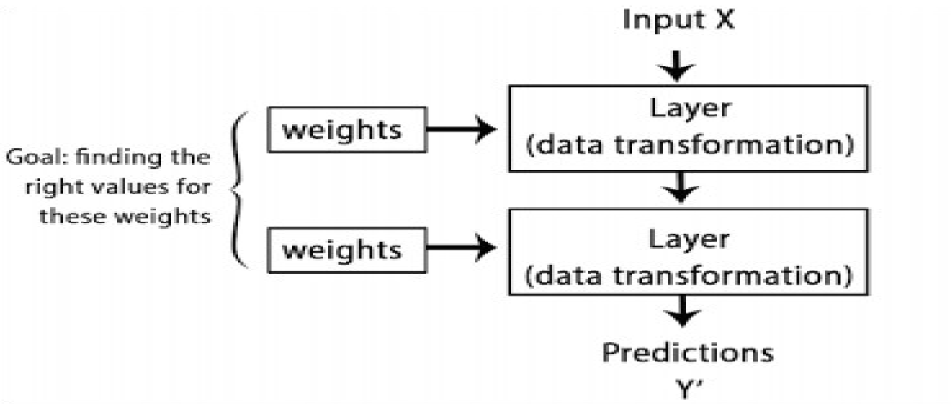

Figure 1.7 A neural network is parametrized by its weights.

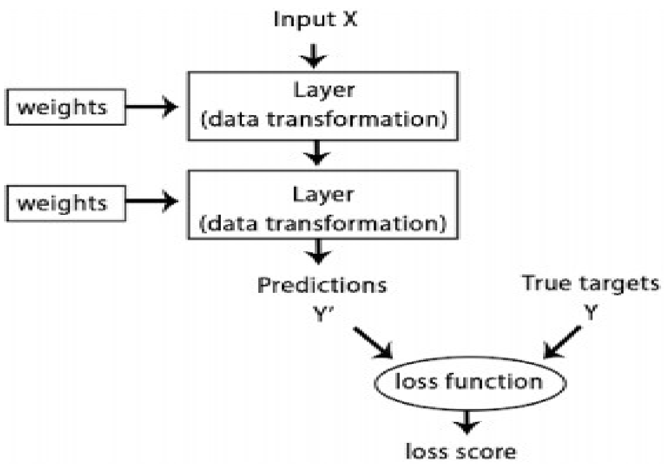

Figure 1.8 A loss function measures the quality of the network's output.

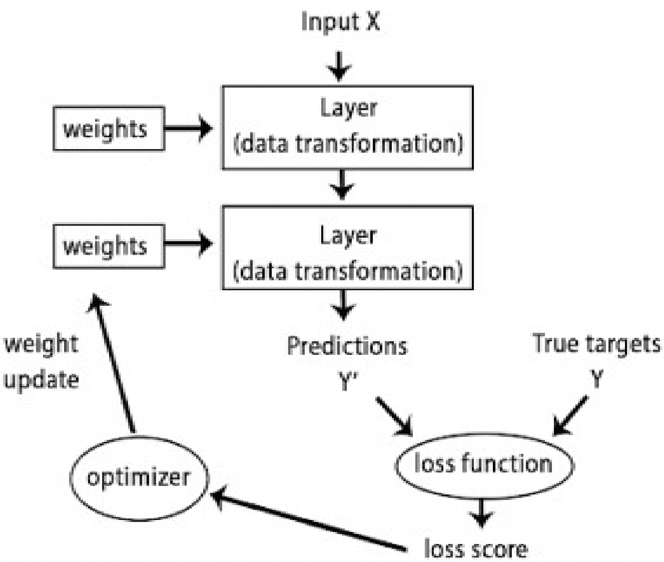

Figure 1.9 The loss score is used as a feedback signal to adjust the weights.

1.1.6 What deep learning has achieved so far

- Near-human-level image classification
- Near-human-level speech recognition
- Near-human-level handwriting transcription
- Improved machine translation
- Improved text-to-speech conversion
- Digital assistants such as Google Now and Amazon Alexa
- Near-human-level autonomous driving
- Improved ad targeting, as used by Google, Baidu, and Bing
- Improved search results on the Web
- Ability to answer natural-language questions
- Superhuman Go playing