

# 13강: 케라스와 신경망

인공지능 일반강좌 : 기계학습의 이해(L2-1)

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# 01. 텐서플로우 2.0 설치

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# 아나콘다를 이용한 설치(1)



Windows



macOS



Linux

## Anaconda 2019.10 for Windows Installer

### Python 3.7 version

[Download](#)

64-Bit Graphical Installer (462 MB)

32-Bit Graphical Installer (410 MB)

### Python 2.7 version

[Download](#)

64-Bit Graphical Installer (413 MB)

32-Bit Graphical Installer (356 MB)

# 아나콘다를 이용한 설치(2)

## 텐서플로우 설치 사양 확인

### System requirements

- Python 3.4–3.7
  - pip 19.0 or later (requires `manylinux2010` support)
  - Ubuntu 16.04 or later (64-bit)
  - macOS 10.12.6 (Sierra) or later (64-bit) (*no GPU support*)
  - Windows 7 or later (64-bit) (*Python 3 only*)
  - Raspbian 9.0 or later
  - [GPU support](#) requires a CUDA®-enabled card (*Ubuntu and Windows*)
-

# 아나콘다를 이용한 설치(3)

- 가상환경에 들어오기
  - ✓ 가상 환경 확인하기, base 만 있음.
  - ✓ 텐서플로우 2를 위한 가상환경 설정

```
(base) C:\Users\master>conda env list  
# conda environments:  
#  
base * C:\Users\master\Anaconda3
```

```
(base) C:\Users\master>conda create --name tf2 python=3.7 pip  
Collecting package metadata (current_repodata.json): done  
Solving environment: done  
  
## Package Plan ##  
  
environment location: C:\Users\master\Anaconda3\envs\tf2  
  
added / updated specs:  
  - pip  
  - python=3.7
```

# 아나콘다를 이용한 설치(4)

```
Downloading and Extracting Packages
python-3.7.6           | 14.8 MB    | #####
pip-20.0.2              | 1.7 MB     | #####
certifi-2019.11.28      | 154 KB     | #####
vs2015_runtime-14.16     | 1.1 MB     | #####
wheel-0.34.1             | 65 KB      | #####
openssl-1.1.1d            | 4.8 MB     | #####
setuptools-45.1.0          | 527 KB     | #####
ca-certificates-2020       | 125 KB     | #####
sqlite-3.30.1             | 627 KB     | #####
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
#
# To activate this environment, use
#
#     $ conda activate tf2
#
# To deactivate an active environment, use
#
#     $ conda deactivate
```

# 아나콘다를 이용한 설치(5)

```
(base) C:\Users\master>conda activate tf2

(tf2) C:\Users\master>conda list
# packages in environment at C:\Users\master\Anaconda3\envs\tf2:
#
# Name          Version   Build  Channel
ca-certificates    2020.1.1      0
certifi            2019.11.28  py37_0
openssl             1.1.1d    he774522_3
pip                  20.0.2    py37_1
python                3.7.6    h60c2a47_2
setuptools           45.1.0    py37_0
sqlite               3.30.1    he774522_0
vc                     14.1    h0510ff6_4
vs2015_runtime       14.16.27012  hf0eaf9b_1
wheel                 0.34.1    py37_0
wincertstore          0.2    py37_0

(tf2) C:\Users\master>
```

# 아나콘다를 이용한 설치(6)

- 자동으로 최신 텐서플로우 2.0 GPU 버전 설치

```
(base) C:\Users\master>conda activate tf2gpu  
(tf2gpu) C:\Users\master>pip install --ignore-installed --upgrade tensorflow-gpu==2.0  
Collecting tensorflow-gpu==2.0  
  Using cached tensorflow_gpu-2.0.0-cp37-cp37m-win_amd64.whl (285.3 MB)
```

```
Successfully built absl-py  
Installing collected packages: numpy, six, h5py, keras-applications, tensorflow-estimator, gast, keras-preprocessing, setuptools, markdown, pyasn1, rsa, cachetools, pyasn1-modules, google-auth, absl-py, chardet, idna, urllib3, certifi, requests, grpcio, oauthlib, requests-oauthlib, google-auth-oauthlib, werkzeug, protobuf, wheel, tensorboard, google-pasta, wrapt, termcolor, opt-einsum, scipy, astor, tensorflow  
Successfully installed absl-py-0.9.0 astor-0.8.1 cachetools-4.0.0 certifi-2019.11.28 chardet-3.0.4 gast-0.2.2 google-auth-1.11.0 google-auth-oauthlib-0.4.1 google-pasta-0.1.8 grpcio-1.26.0 h5py-2.10.0 idna-2.8 keras-applications-1.0.8 keras-preprocessing-1.1.0 markdown-3.1.1 numpy-1.18.1 oauthlib-3.1.0 opt-einsum-3.1.0 protobuf-3.11.2 pyasn1-0.4.8 pyasn1-modules-0.2.8 requests-2.22.0 requests-oauthlib-1.3.0 rsa-4.0 scipy-1.4.1 setuptools-45.1.0.post20200127 six-1.14.0 tensorboard-2.1.0 tensorflow-2.1.0 tensorflow-estimator-2.1.0 termcolor-1.1.0 urllib3-1.25.8 werkzeug-0.16.1 wheel-0.34.2 wrapt-1.11.2
```

# 아나콘다를 이용한 설치(7)

- 필수적인 라이브러리 설치

```
(tf2) C:\Users\master>
(tf2) C:\Users\master>pip install seaborn pandas matplotlib graphviz jupyter notebook
Collecting seaborn
  Downloading seaborn-0.10.0-py3-none-any.whl (215 kB)
    ||████████████████████████████████████████████████████████████████████████████████| 215 kB 211 kB/s
Collecting pandas
  Downloading pandas-1.0.0-cp37-cp37m-win_amd64.whl (9.0 MB)
    ||████████████████████████████████████████████████████████████████████████████████| 9.0 MB 819 kB/s
Collecting matplotlib
  Downloading matplotlib-3.1.3-cp37-cp37m-win_amd64.whl (104 kB)
    ||████████████████████████████████████████████████████████████████████████████████| 104 kB 1.1 kB/s
```

- 테스트하기
  - ✓ jupyter notebook

```
(tf2) C:\Users\master>jupyter notebook
```

# 아나콘다를 이용한 설치(8)

## 버전확인 1 : conda list

```
(tf2) C:\Users\user>
(tf2) C:\Users\user>conda list
# packages in environment at C:\Users\user\Anaconda3\envs\tf2:
#
# Name           Version      Build  Channel
ca-certificates 2019.11.28  hecc5488_0  conda-forge
certifi          2019.11.28  py38_0    conda-forge
openssl          1.1.1d      hfa6e2cd_0  conda-forge
pip              20.0.2       py38_0    conda-forge
python            3.8.1        he1f5543_1  conda-forge
setuptools       45.1.0       py38_0    conda-forge
sqlite            3.30.1      hfa6e2cd_0  conda-forge
vc                14.1         h0510ff6_4
vs2015_runtime   14.16.27012 hf0eaf9b_1
wheel             0.33.6       py38_0    conda-forge
wincertstore     0.2          py38_1003   conda-forge

(tf2) C:\Users\user>
```

# 아나콘다를 이용한 설치(9)

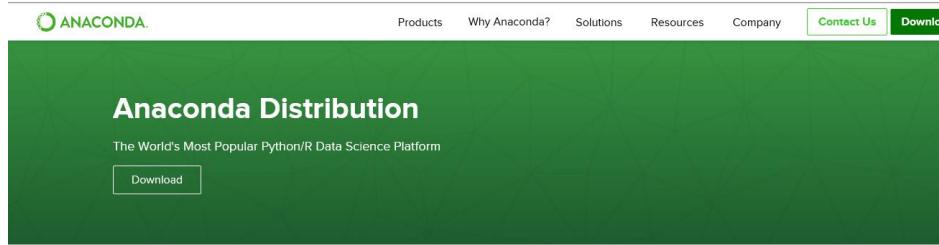
- GPU 버전 관련 에러 발생할 수도 있음
  - ✓ Tensorflow 2.0에서는 CUDA 툴킷 라이브러 버전 확인
    - 최신 CUDA는( 2019년 2월 이후) cudart64\_101.dll을 제공함
    - 하지만, Tensorflow 2.0은 cudart64\_100.dll을 요구함
    - 해결방법은 cudart64\_100.dll을 다운받아서 아래 위치에 저장함

C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v10.1\bin

```
[I 16:10:02.149 NotebookApp] Kernel started: 60c90c3f-7d12-46f6-8d5b-bd06315a1761
2020-01-31 16:10:14.970263: W tensorflow/stream_executor/platform/default/dso_loader.cc:55] Could not load dynamic library 'cudart64_100.dll'; dlsym error: cudart64_100.dll not found
```

```
(tf2gpu) C:\Users\master\work\ust-hands-on\ko>jupyter notebook
[I 16:18:39.890 NotebookApp] Serving notebooks from local directory: C:\Users\master\work\ust-hands-on\ko
[I 16:18:39.891 NotebookApp] The Jupyter Notebook is running at:
[I 16:18:39.893 NotebookApp] http://localhost:8888/?token=038352f53bd341d4b97dc857fb036ab8effb9bb8045d669e
[I 16:18:39.894 NotebookApp] or http://127.0.0.1:8888/?token=038352f53bd341d4b97dc857fb036ab8effb9bb8045d669e
[I 16:18:39.895 NotebookApp] Use Control-C to stop this server and shut down all kernels (twice to skip confirmation).
```

# Navigator를 이용한 설치(1)



The open-source Anaconda Distribution is the easiest way to perform Python/R data science and machine learning on Linux, Windows, and Mac OS X. With over 15 million users worldwide, it is the industry standard for developing, testing, and training on a single machine, enabling *individual data scientists* to:

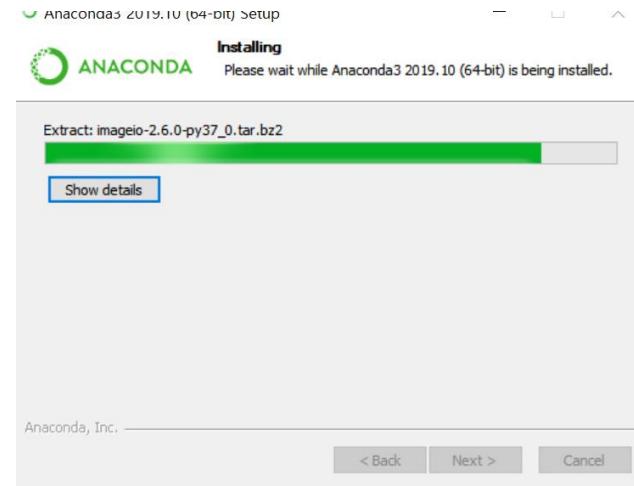
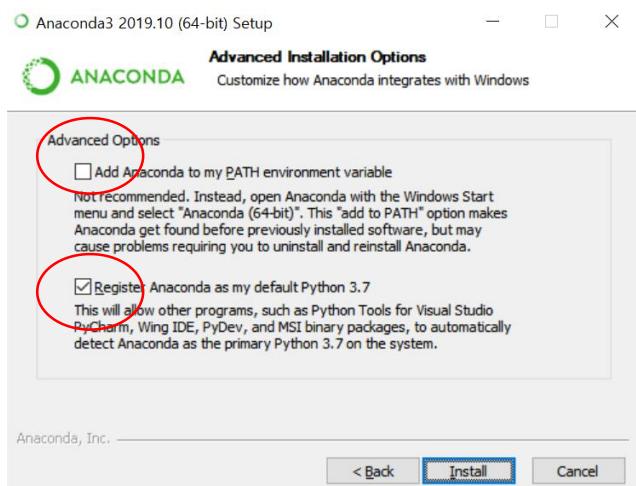
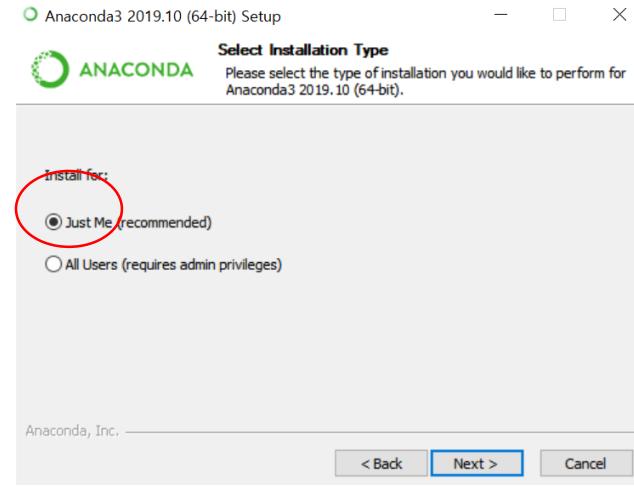
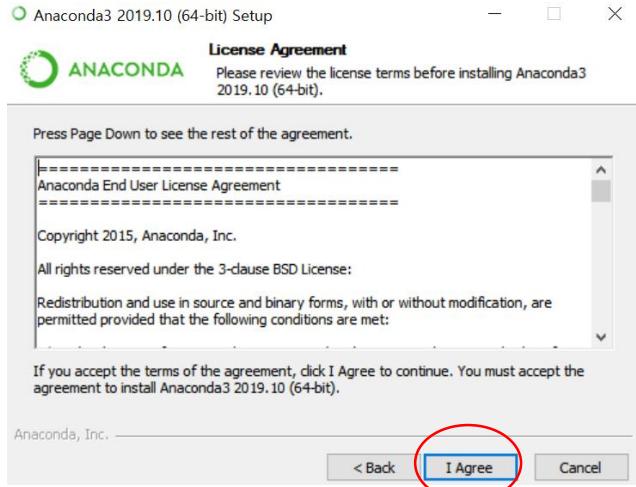
- Quickly download 1,500+ Python/R data science packages
- Manage libraries, dependencies, and environments with Conda
- Develop and train machine learning and deep learning models with scikit-learn, TensorFlow, and Theano
- Analyze data with scalability and performance with Dask, NumPy, pandas, and Numba
- Visualize results with Matplotlib, Bokeh, Datasader, and Holoviews



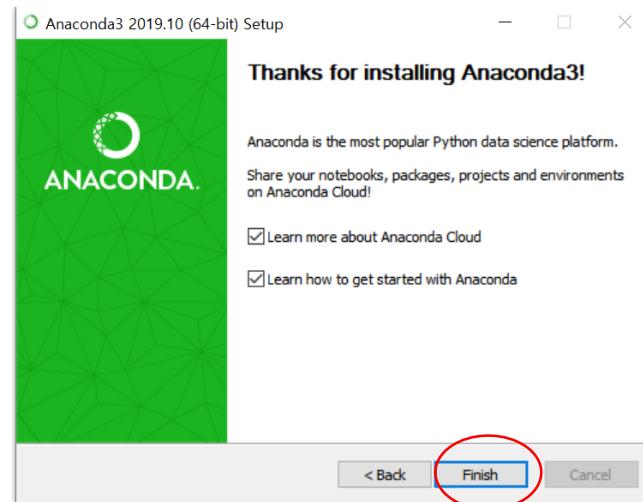
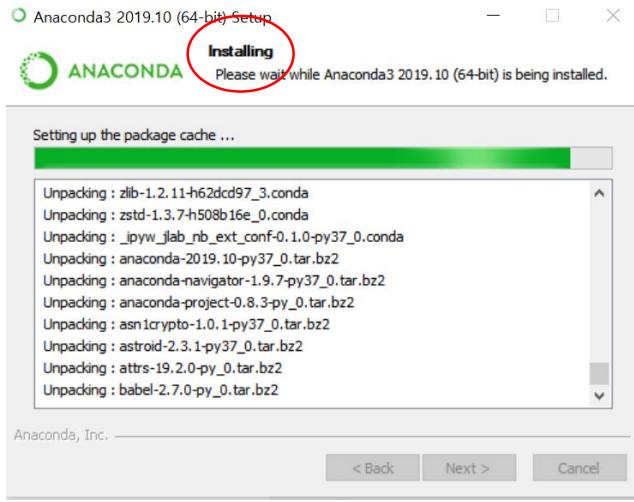
Windows | macOS | Linux

This screenshot shows the "Anaconda 2019.10 for Windows Installer" download page. It features two main sections: "Python 3.7 version" on the left and "Python 2.7 version" on the right. Each section includes a "Download" button and links for 64-Bit Graphical Installer and 32-Bit Graphical Installer. A red circle highlights the "Python 3.7 version" section. Both sections also have "Download" buttons.

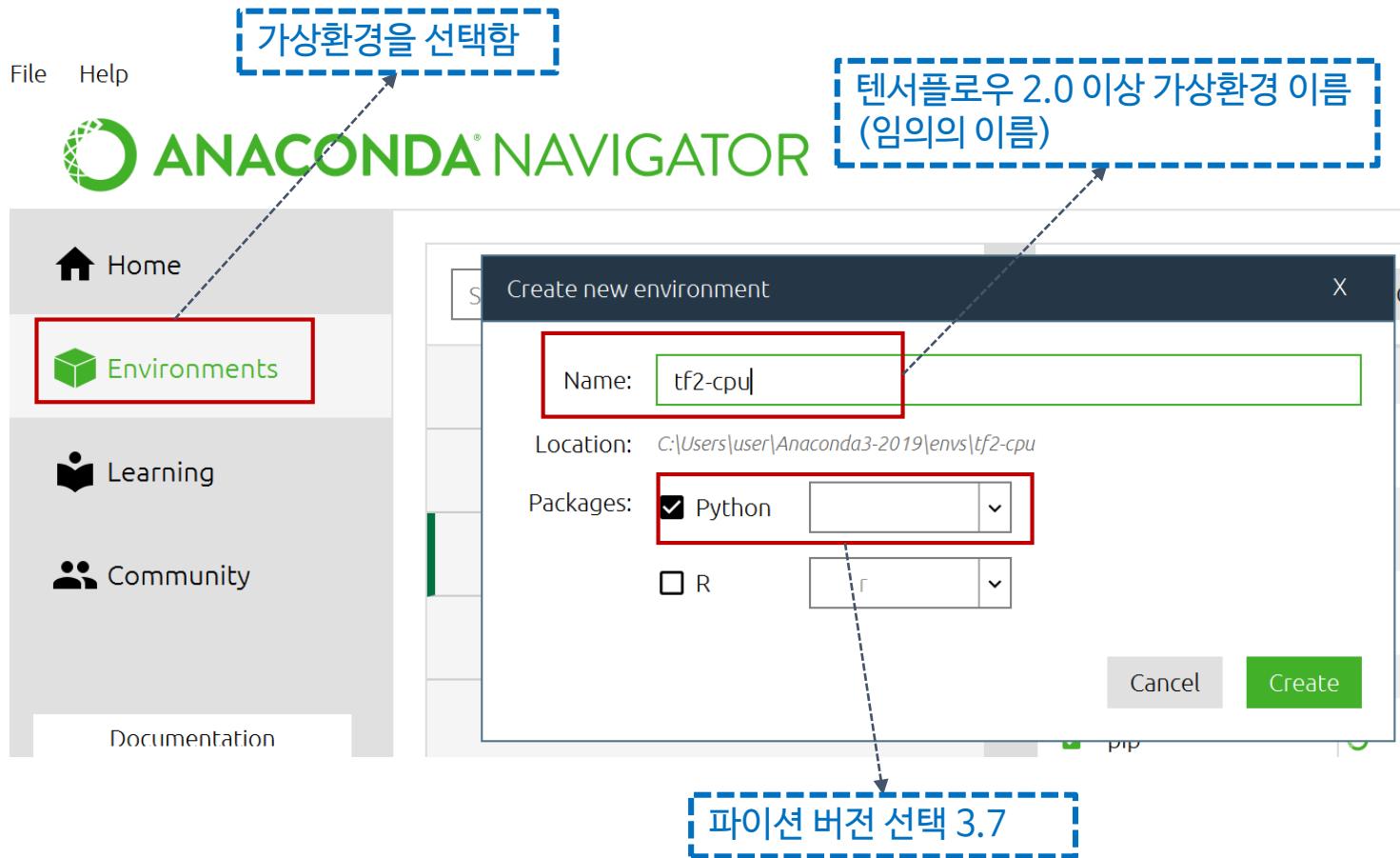
# Navigator를 이용한 설치(2)



# Navigator를 이용한 설치(3)



# Navigator를 이용한 설치(5)



# Navigator를 이용한 설치(6)



# Navigator를 이용한 설치(7)

가상환경을 만들자. 이름은 임의로 작성해도 됨



# Navigator를 이용한 설치(8)

새로운 가상환경 tf2에서,  
Not installed를 설정하고,  
Update index를 함

Not installed

Update index...

Name	T	Description	Version
alphalens	○		0.3.0
alphatwirl	○		0.25
alps	○		2.3.1
alsa-lib-cos6-i686	○		1.1.0
alsa-lib-cos6-x86_64	○		1.1.0
alsa-lib-cos7-ppc64le	○	(cdt) the advanced linux sound architecture (alsa) library	1.1.0
alsa-lib-devel-cos6...	○		1.1.0

12972 packages available

# Navigator를 이용한 설치(9)

The screenshot shows the Jupyter Notebook Navigator interface. At the top, there is a search bar labeled "Search Environments" with a magnifying glass icon. To the right of the search bar are dropdown menus for "Not installed" (selected), "Channels", "Update index...", and a search input field containing "tensorflow". A blue dashed box with the text "검색을 이용함." (Using search) is positioned above the search input.

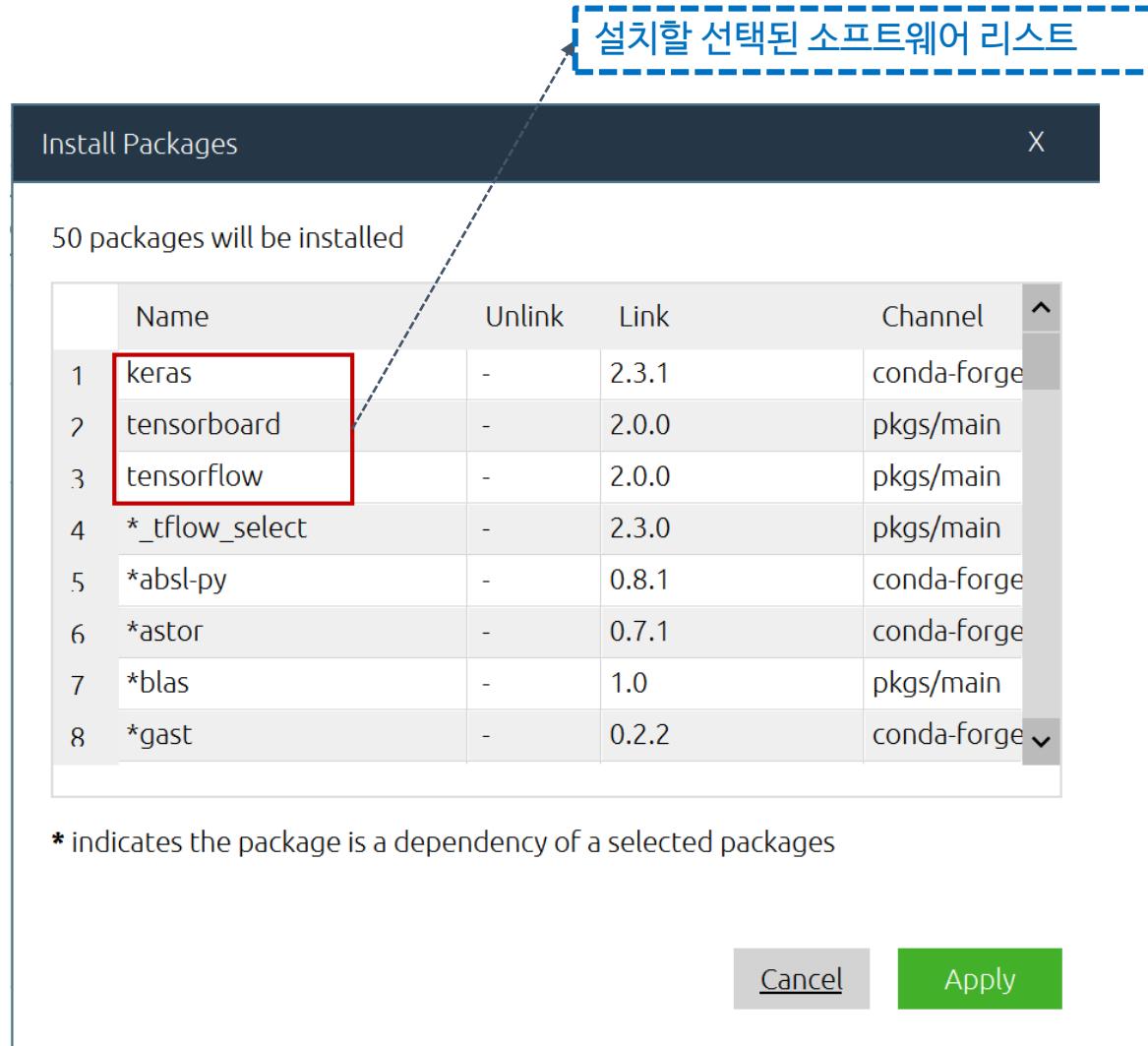
The main area displays a list of environments. On the left, there are two environment names: "base (root)" and "tf2". The "tf2" environment is highlighted with a green background and has a green arrow pointing to it from the left. Below the environments is a toolbar with icons for creating (+), cloning (copy), deleting (trash), and navigating (back/forward).

The central part of the interface is a table listing packages. The columns are "Name", "T", "Description", and "Version". The "Name" column includes checkboxes. The "Description" column contains brief descriptions of each package. The "Version" column shows the current version of each package. Two specific rows are highlighted with red boxes:

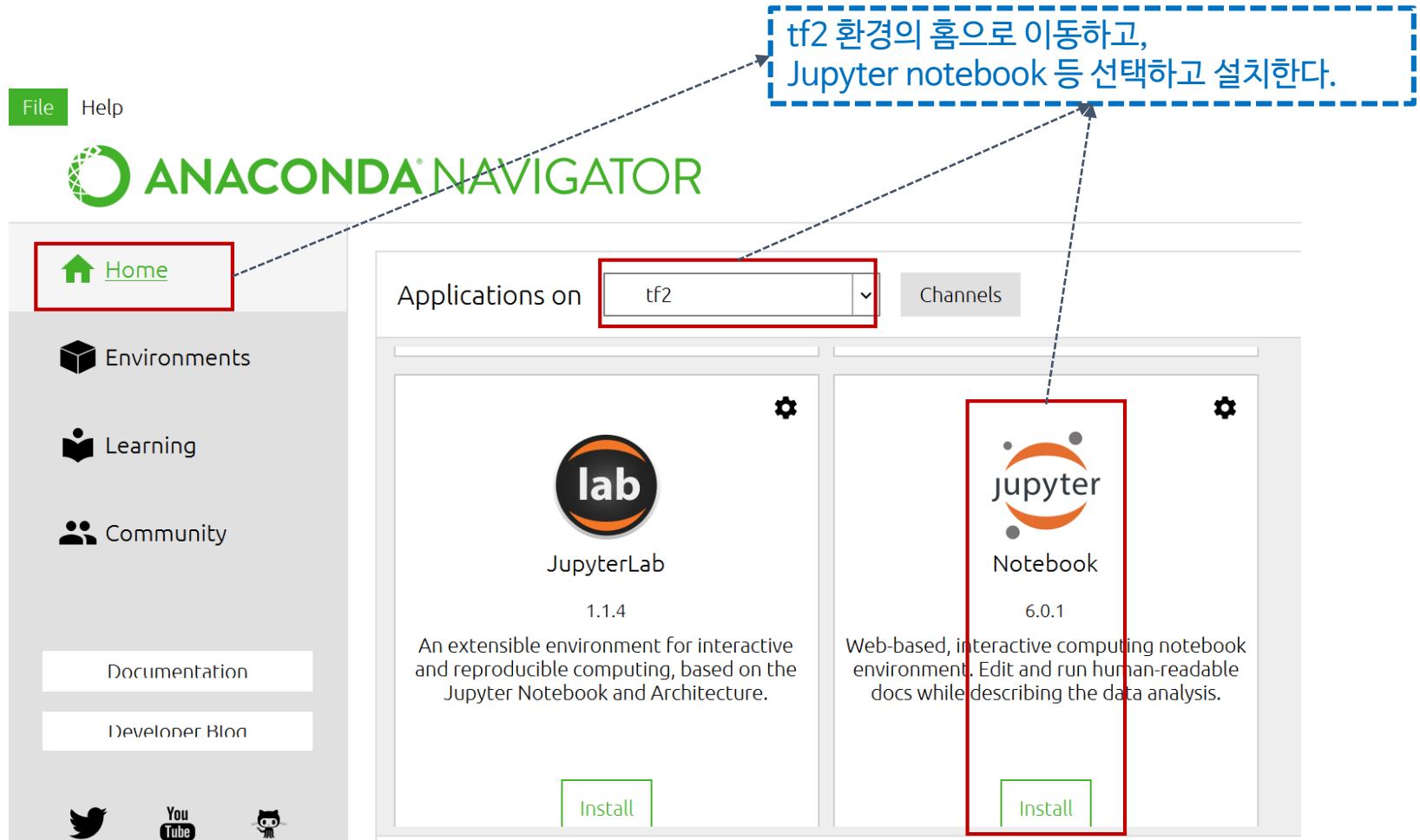
- keras**: Version 2.3.1. The row is highlighted with a red box, and a blue dashed box with the text "케라스와 텐서플로우 선택함. 버전을 확인할 것" (Select Keras and TensorFlow. Check the version) is positioned to the left of the table, pointing towards the keras row.
- tensorflow**: Version 2.0.0. This row is also highlighted with a red box.

Name	T	Description	Version
<input type="checkbox"/> dask-tensorflow			0.0.2
<input checked="" type="checkbox"/> keras		Deep learning library for theano and tensorflow	2.3.1
<input type="checkbox"/> keras-gpu		Deep learning library for theano and tensorflow	2.2.4
<input type="checkbox"/> opt_einsum		Optimizing einsum functions in numpy, tensorflow, dask, and more with contraction order optimization.	3.1.0
<input type="checkbox"/> r-tensorflow			2.0.0
<input type="checkbox"/> sagemaker-tensorflow-container			2.0.7
<input type="checkbox"/> tensorflow		Tensorflow is a machine learning library	2.0.0

# Navigator를 이용한 설치(10)



# Navigator를 이용한 설치(11)



## 02. Jupyter notebook 테마 변경

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# jupyter notebook 테마 변경(1)

- jupyterthemes 설치
  - ✓ \$pip install --upgrade jupyterthemes
  - ✓ \$pip install -upgrade notebook
  - ✓ jt -l( 알파벳 L)

```
Available Themes:  
chesterish  
grade3  
gruvboxd  
gruvboxl  
monokai  
oceans16  
onedork  
solarizedd  
solarizedl
```

## 02. 인공신경망 소개

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# 인공신경망 소개

- 인공신경망의 핵심은 딥러닝
- ANN은 다재다능하고 확장성이 좋다
  - ✓ 수 백 개의 이미지를 분류 (구글 이미지)
  - ✓ 음성 인식 서비스 성능을 높임(애플의 시리)
  - ✓ 매일 수억 명의 사용자에게 맞춤형 가장 좋은 비디오를 제공 (유튜브)
  - ✓ 수 백만 개 기보를 학습하고 스스로 학습하면서 성장 (알파고)

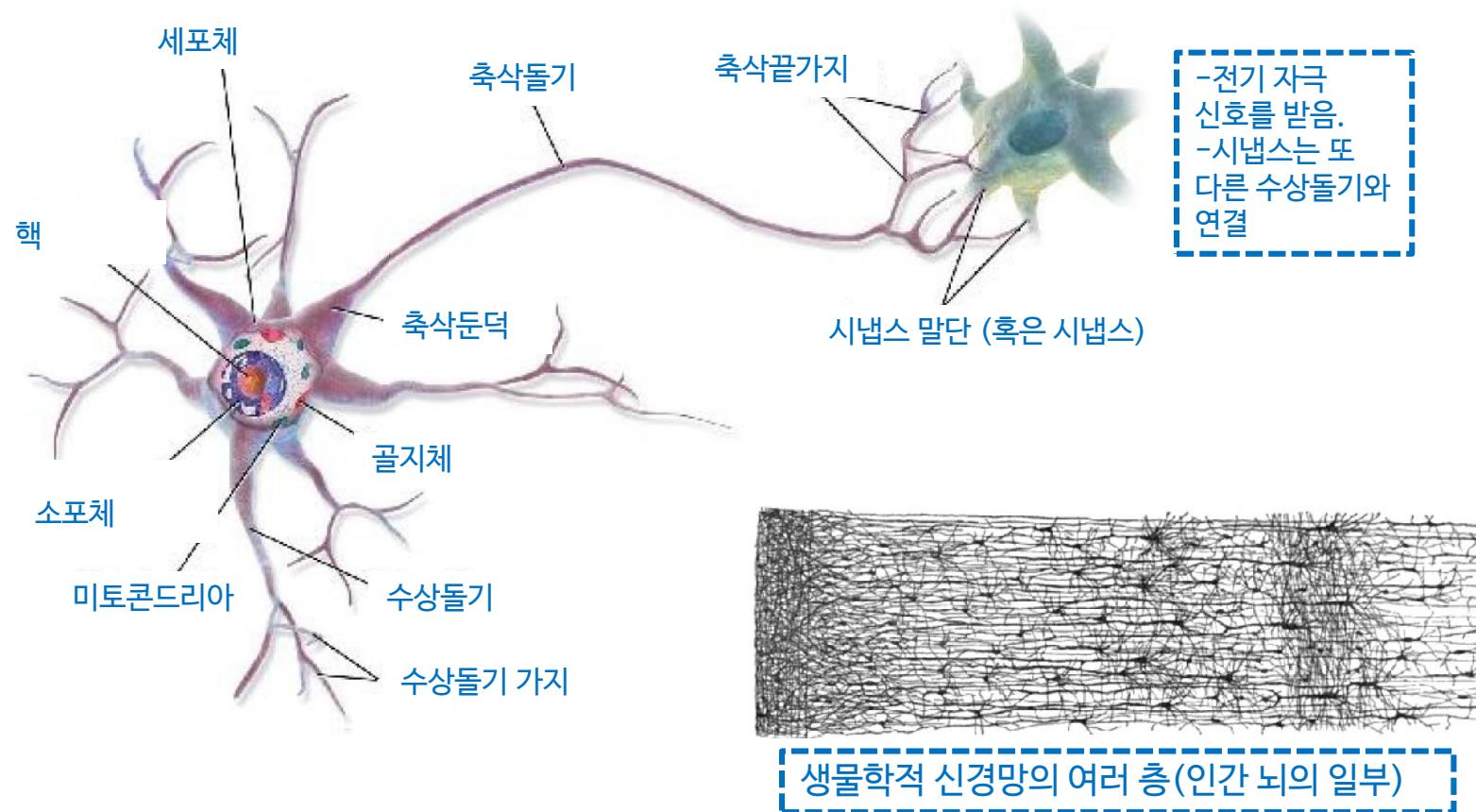
# 생물학적 뉴런에서 인공 뉴런까지

- **인공 신경망을 처음 소개 (1943년)**
  - ✓ 신경생리학자 워런 맥컬록(McCulloch)와 수학자 윌터 피츠(Pitts)가 처음 소개
    - 명제 논리를 사용해 동물 뇌의 생물학적 뉴런이 복잡한 계산을 위해 어떻게 상호작용하는지에 대한 간단한 계산 모델을 제시 함
- **인공 신경망의 초기 성과 (1960년대까지)**
  - ✓ 지능을 가진 기계와 대화를 기대. 하지만 긴 침체기가 옴
  - ✓ 1980년대 초에 새로운 네트워크 구조가 발견되고, ANN 관심을 다시 받음
  - ✓ 하지만 1990년대까지 SVM 처럼 머신러닝 기법을 선호함
    - 머신러닝이 더 나은 결과를 만들어 주었고, 이론적 기반이 탄탄함

# 인공 신경망이 부흥은 생활과 밀접

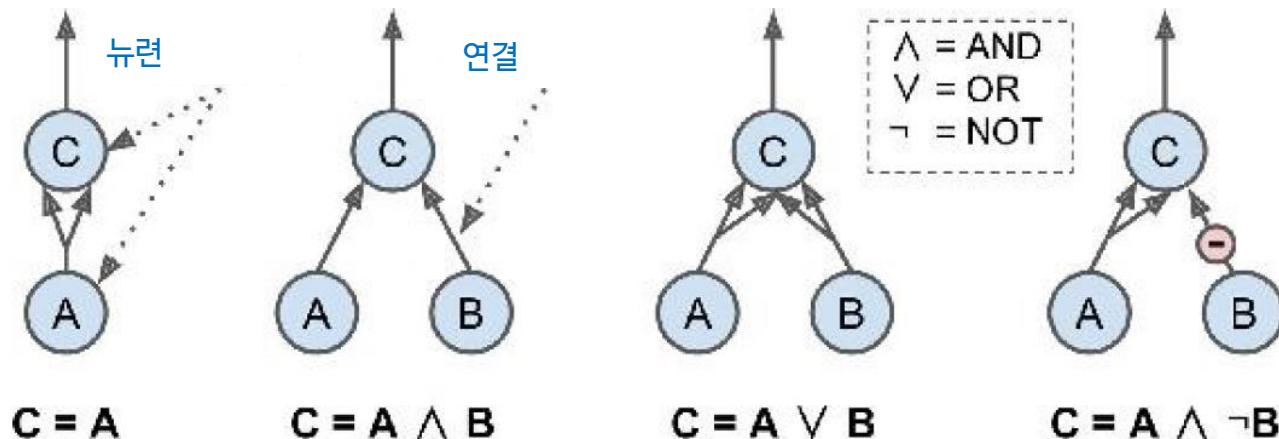
- 인공 신경망이 성공할 수 있는 요인들
  - ✓ 훈련을 위한 데이터가 엄청나게 많다.
  - ✓ 대규모 신경망 훈련이 가능할 정도의 계산 능력 기술이 발달함. (GPU 컴퓨팅 등)
  - ✓ 훈련 알고리즘이 향상되었다.
    - 1990년대와 비교하여 조금 변경된 것이지만 이 작은 변화는 커다란 영향을 끼침
- ✓ 일부 인공신경망의 이론상 제한이 실전에서는 문제가 되지 않는다고 밝혀짐
  - 국소최소점(local minima) 문제는 매우 드물고, 전역 최소점과 가까이 있음
- ✓ 인공신경망 분야에 투자와 진보의 선순환 시기이다.
  - 인공신경망 기반 제품들이 나오며, 더 많은 투자가 일어나서 기술이 향상됨

# 생물학적 뉴런



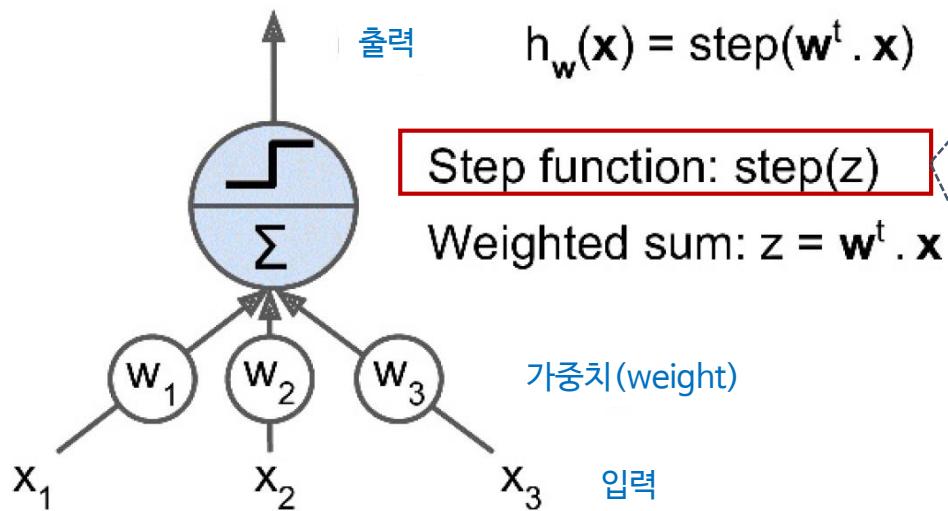
# 인공 뉴런을 사용한 논리 연산

- 워런 맥컬록과 워터 피츠가 제안한 인공 뉴런
  - 하나 이상의 이진(on/off) 입력과 하나의 출력으로 모델을 구성함

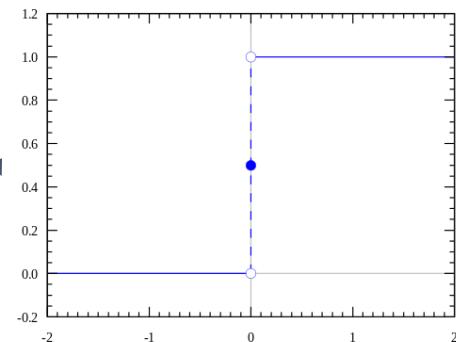


# 퍼셉트론 Perceptron

- 퍼셉트론(Perceptron)은 가장 간단한 인공 신경망 모델
  - ✓ 1957년 프랭크 로젠틀라트가 제안
  - ✓ 퍼셉트론은 TLU( Threshold logic unit) 형태의 인공 뉴런을 기반
    - 입력과 출력은 가중치(weight)와 관련이 있다.

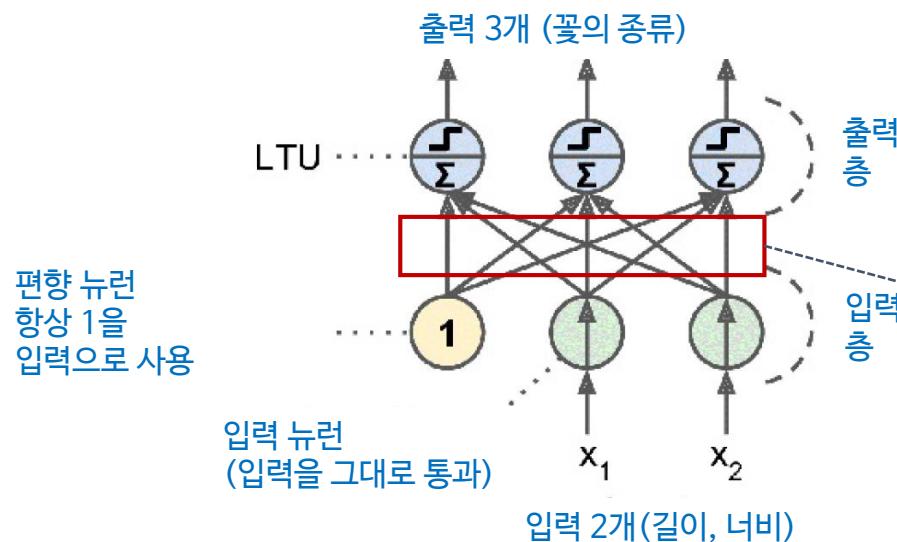


퍼셉트론에 일반적으로 사용하는 계단함수. 그래서 TLU는 간단한 선형 이진 분류 문제에 사용됨 (로지스틱 회귀 분류, SVM 처럼)



# 퍼셉트론 응용: 다중 출력 분류기

- 퍼셉트론 인공신경망을 붓꽃(iris)에 적용해보자
  - ✓ 붓꽃의 정보는 2개 (길이와 넓이)로, 3종류의 꽃을 맞추경우 정확도는?



가중치(weight)  
퍼셉트론 훈련은 어떻게?  
헤브학습(Hebbian Learning)  
- 서로 활성화되는 세포가 서로  
연결된다는 규칙을 따름  
- 즉, 가중치 업데이트

# 퍼셉트론 응용: 다중 출력 분류기

## 1.1 퍼셉트론

- 사이킷런 Perceptron()과 max\_iter 와 tol 의미

In [3]:

```
import numpy as np
from sklearn.datasets import load_iris
from sklearn.linear_model import Perceptron

iris = load_iris()
X = iris.data[:, (2, 3)] # 꽃잎(petal) 길이와 너비
y = (iris.target == 0).astype(np.int)

per_clf = Perceptron(max_iter=1000, tol=1e-3, random_state=42)
per_clf.fit(X, y)

y_pred = per_clf.predict([[2, 0.5]])
```

In [4]: y\_pred

Out [4]: array([1])

붓꽃 데이터

Perceptron

(2, 3) # 꽃잎(petal) 길이와 너비

perceptron는 sklearn 분류 알고리즘  
- max\_iter는 이포크 (epochs)  
- tol - stop criterion.

# 퍼셉트론 응용: 다중 출력 분류기

```
In [6]: a = -per_clf.coef_[0][0] / per_clf.coef_[0][1]
        b = -per_clf.intercept_ / per_clf.coef_[0][1]
```

```
In [7]: per_clf.coef_
```

```
Out[7]: array([-1.4, -2.2])
```

```
In [14]: per_clf.intercept_
```

```
Out[14]: array([4.])
```

```
In [15]: axes = [0, 5, 0, 3]
```

```
x0, x1 = np.meshgrid(
    np.linspace(axes[0], axes[1], 500).reshape(-1, 1),
    np.linspace(axes[2], axes[3], 200).reshape(-1, 1),
)
X_new = np.c_[x0.ravel(), x1.ravel()]
y_predict = per_clf.predict(X_new)
zz = y_predict.reshape(x0.shape)
```

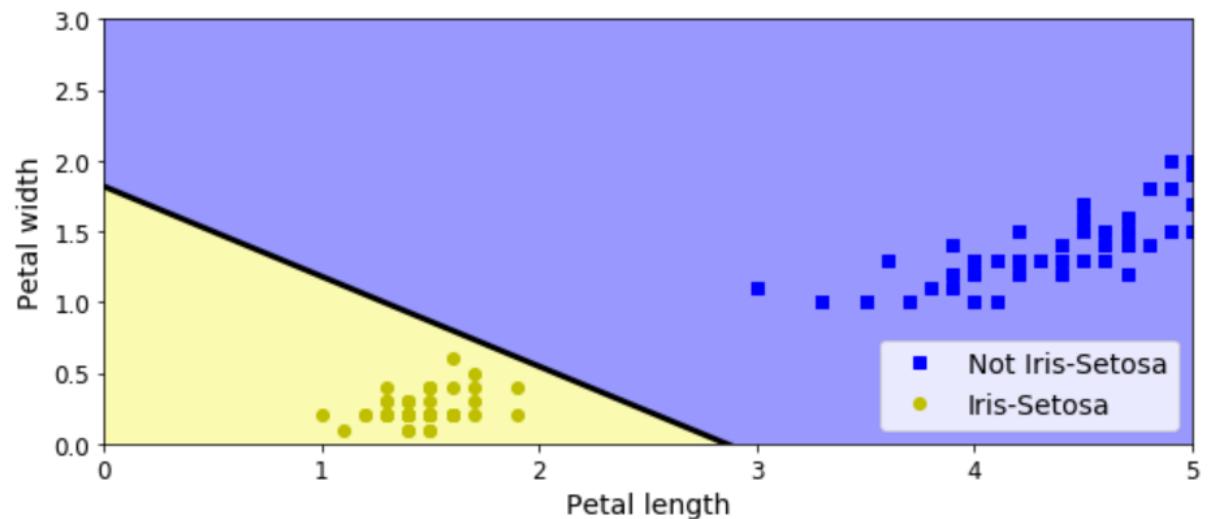
# 퍼셉트론 응용: 다중 출력 분류기

```
In [16]: plt.figure(figsize=(10, 4))
plt.plot(X[y==0, 0], X[y==0, 1], "bs", label="Not Iris-Setosa")
plt.plot(X[y==1, 0], X[y==1, 1], "yo", label="Iris-Setosa")

plt.plot([axes[0], axes[1]], [a * axes[0] + b, a * axes[1] + b], "k-", linewidth=3)
from matplotlib.colors import ListedColormap
custom_cmap = ListedColormap(['#9898ff', '#fafab0'])

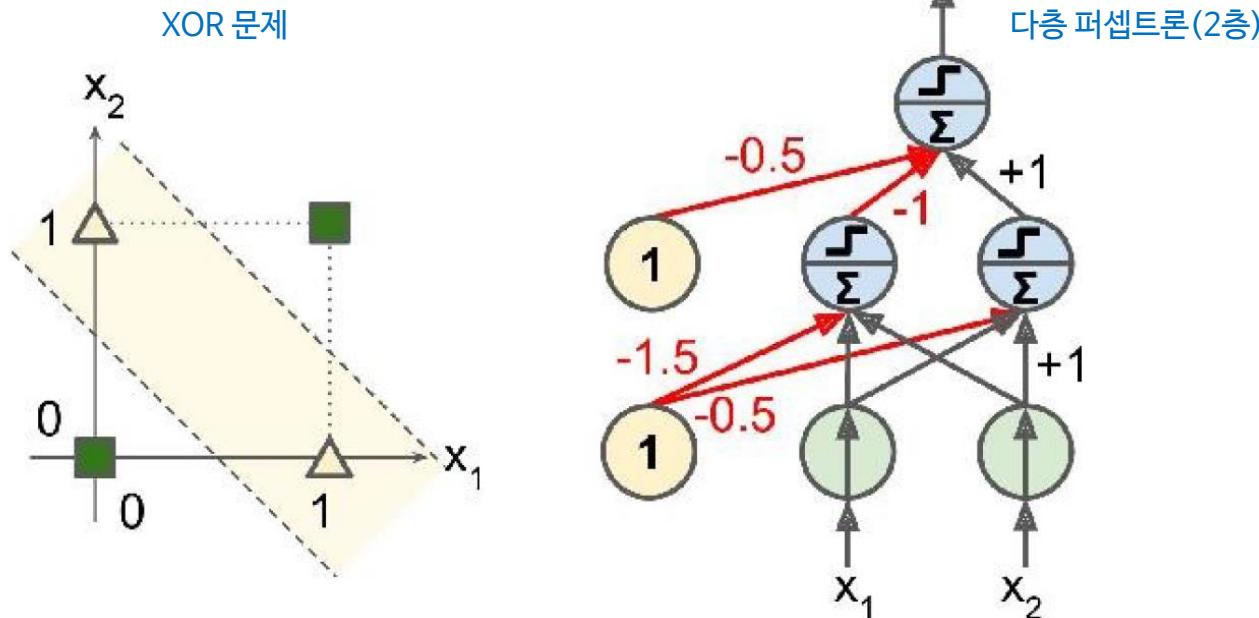
plt.contourf(x0, x1, zz, cmap=custom_cmap)
plt.xlabel("Petal length", fontsize=14)
plt.ylabel("Petal width", fontsize=14)
plt.legend(loc="lower right", fontsize=14)
plt.axis(axes)

plt.show()
```



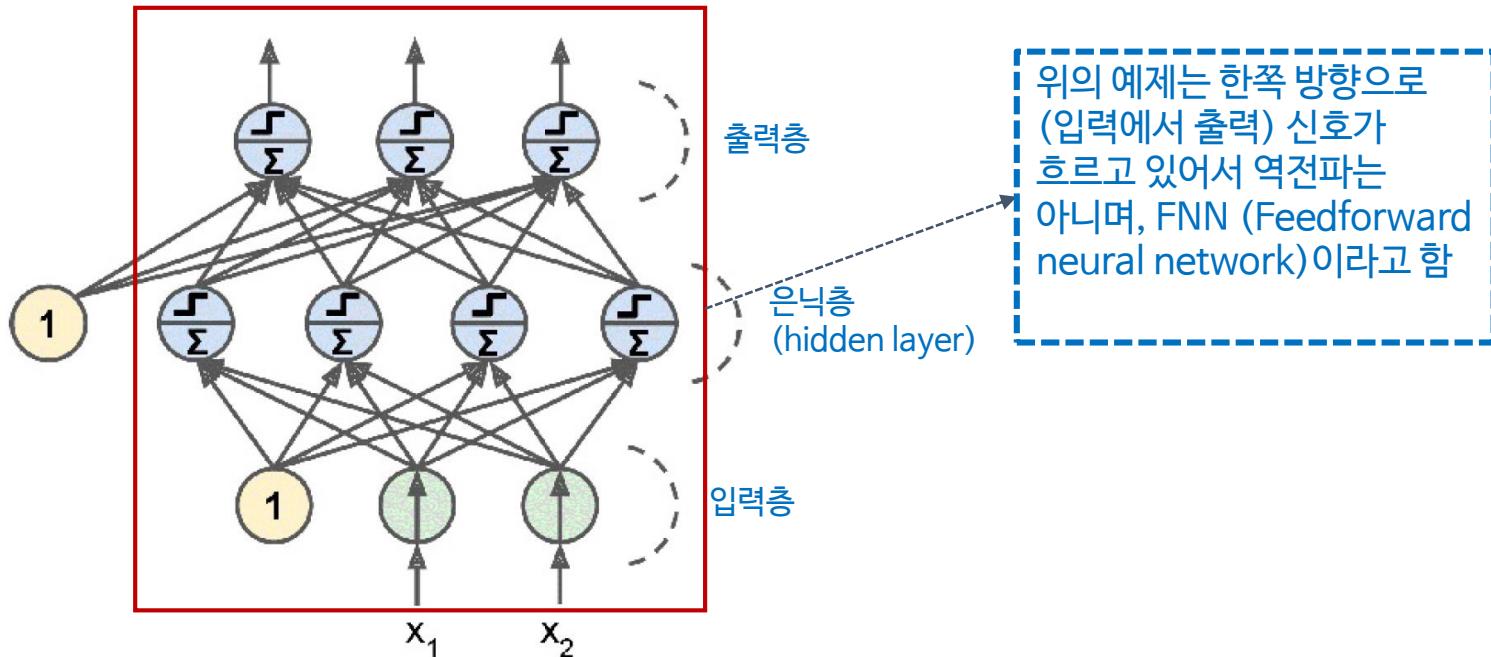
# MLP 다층 퍼셉트론의 등장

- XOR 문제는 퍼셉트론으로 풀수 없다. (1969년) 1차 암흑기
  - ✓ XOR(배타적 논리적 합) 분류 문제로 로지스틱 회귀도 이 문제는 풀 수 없다.
  - ✓ 마빈 민스키와 시모어 페퍼트는 퍼셉트론으로 XOR 문제를 풀 수 없다고 함
  - ✓ 하지만, 다층 퍼셉트론으로 XOR 문제를 해결함



# 다층 퍼셉트론과 역전파 (1)

- 심층신경망(DNN, Deep Neural Network)
  - 인공 신경망 은닉층이 2개 이상일 때 신경망임.
- 역전파(Backpropagation) (1986년, Hinton 교수)



## 다층 퍼셉트론과 역전파 (2)

- DNN (Deep Neural Network)
  - ✓ 여러 개의 은닉층을 포함한 ANN
  - ✓ 하지만 MLP의 훈련은 매우 어려웠고 잘 안되었음
- 역전파(Backpropagation) 1986년 by Hinton
  - ✓ 역전파 훈련 알고리즘 (1986, Rumelhart, Hinton), 경사 하강법을 사용함
  - ✓ 활성함수를 계단함수에서 시그모이드 혹은 로지스틱 함수로 변경함

$$\sigma(z) = \frac{1}{1+\exp(-z)}$$

# 역전파 알고리즘

- 역전파 알고리즘

- ✓ 각 훈련 샘플에 대해 먼저 예측을 만들고 (정방향 계산)
- ✓ 오차를 측정 하며
- ✓ 역방향으로 각 층을 거치면서 각 연결이 오차에 기인한 정도를 측정(역방향 계산)
- ✓ 마지막으로 이 오차가 감소하도록 가중치를 조금씩 조정함(경사 하강법 스텝)

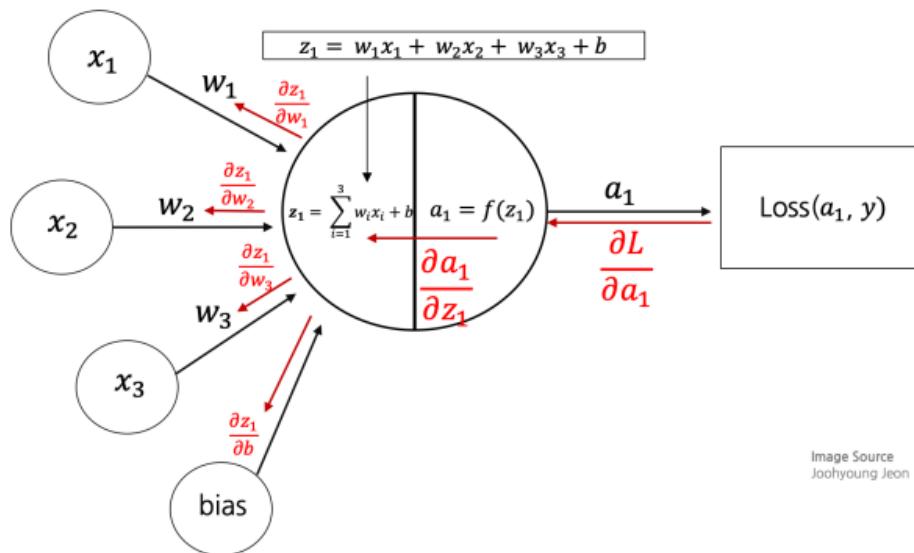
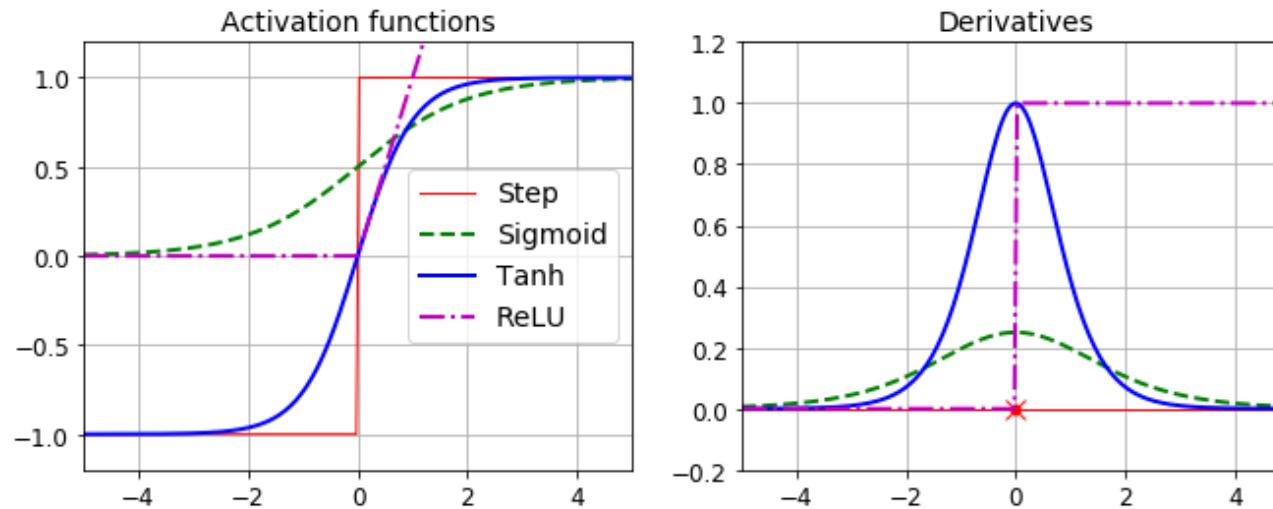


Image Source  
Joohyoung Jeon

# 활성함수

- 역전파 알고리즘에서는 중요한 변화는 활성함수의 도입
  - ✓ 다중 퍼셉트론의 계단 함수에서 미분 가능한 시그모이드 함수
- 최근 활성함수는 여러 종류가 있음
  - ✓ 하이퍼볼릭 탄젠트 함수, ReLU (Rectified Linear Unit)



## 03. MLP 회귀/분류

이홍석 (hsyi@kisti.re.kr)

[www.ust.ac.kr](http://www.ust.ac.kr)

# 회귀 MLP (1)

- 다층 퍼셉트론 회귀 예제로 주택 가격 예측을 보자
  - ✓ 출력은 1개의 값이됨
  - ✓ 회귀에서는 출력 값에 활성함수를 사용하지 않는다. 따라서 값은 이의의 수가 됨
  - ✓ 만일 주택 값이 항상 0보다 크면, ReLU 활성함수를 출력 값에 사용할 수 있음
  - ✓ 비용함수 (loss)는 일반적으로 평균제곱에러(MSE)를 사용하지만,
  - ✓ 이상치(outliers)가 많을 경우 평균절대값에러(MAE)를 사용을 권장함
    - 참고로, 후버(Huber) 비용함수는 위의 2개를 혼합한 것이다.
    - 후버 비용은 오차가 기준값(1) 보다 작으면 2차 모양을, 기준값보다 크면 선형이다.

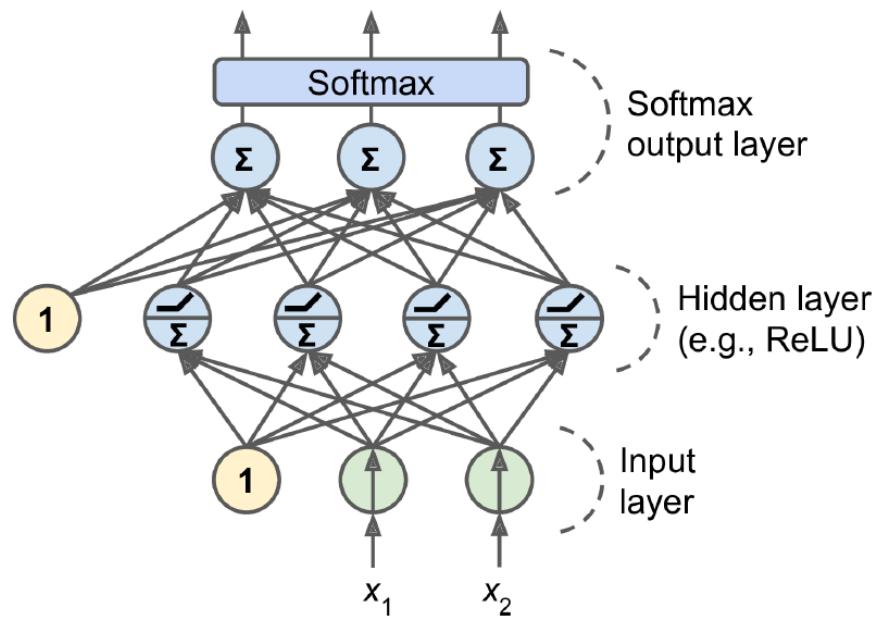
# 회귀 MLP (2)

Table 10-1. Typical Regression MLP Architecture

Hyperparameter	Typical Value
# input neurons	One per input feature (e.g., $28 \times 28 = 784$ for MNIST)
# hidden layers	Depends on the problem. Typically 1 to 5.
# neurons per hidden layer	Depends on the problem. Typically 10 to 100.
# output neurons	1 per prediction dimension
Hidden activation	ReLU (or SELU, see <a href="#">Chapter 11</a> )
Output activation	None or ReLU/Softplus (if positive outputs) or Logistic/Tanh (if bounded outputs)
Loss function	MSE or MAE/Huber (if outliers)

# 분류 MLP (1)

- 이진분류 문제
  - ✓ 1개의 출력값, 로지스틱 활성함수 이용함
- 멀티라벨 이진분류 문제 : 멀티클래스 분류
  - ✓ (예) 메일이 햄인지 스팸인지, 동시에 급한것인지 아닌지를 소프트 맥스로 처리함



# 분류 MLP (2)

- 분류 MLP에서 비용함수 종류
  - ✓ 비용함수는 확률분포를 예측하므로
  - ✓ 크로스-엔트로비 (cross-entropy) 혹은 로그 로스(log(loss))를 사용함

*Table 10-2. Typical Classification MLP Architecture*

Hyperparameter	Binary classification	Multilabel binary classification	Multiclass classification
Input and hidden layers	Same as regression	Same as regression	Same as regression
# output neurons	1	1 per label	1 per class
Output layer activation	Logistic	Logistic	Softmax
Loss function	Cross-Entropy	Cross-Entropy	Cross-Entropy

## 03. 이미지 분류 예제

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# tf.keras.losses 클래스 소개

`class BinaryCrossentropy`: Computes the cross-entropy loss between true labels and predicted labels.

`class CategoricalCrossentropy`: Computes the crossentropy loss between the labels and predictions.

`class CategoricalHinge`: Computes the categorical hinge loss between `y_true` and `y_pred`.

`class CosineSimilarity`: Computes the cosine similarity between `y_true` and `y_pred`.

`class Hinge`: Computes the hinge loss between `y_true` and `y_pred`.

`class Huber`: Computes the Huber loss between `y_true` and `y_pred`.

`class KLDivergence`: Computes Kullback-Leibler divergence loss between `y_true` and `y_pred`.

`class LogCosh`: Computes the logarithm of the hyperbolic cosine of the prediction error.

`class Loss`: Loss base class.

`class MeanAbsoluteError`: Computes the mean of absolute difference between labels and predictions.

`class MeanAbsolutePercentageError`: Computes the mean absolute percentage error between `y_true` and `y_pred`.

`class MeanSquaredError`: Computes the mean of squares of errors between labels and predictions.

`class MeanSquaredLogarithmicError`: Computes the mean squared logarithmic error between `y_true` and `y_pred`.

`class Poisson`: Computes the Poisson loss between `y_true` and `y_pred`.

`class Reduction`: Types of loss reduction.

`class SparseCategoricalCrossentropy`: Computes the crossentropy loss between the labels and predictions.

`class SquaredHinge`: Computes the squared hinge loss between `y_true` and `y_pred`.

# keras와 tensorflow 2 적용

- 이번 장의 목표
  - ✓ fashion NMIST dataset
  - ✓ keras.datasets에 있는 fashion NMIST 데이터 세트의 이미지 분류에 대하여 tensorflow2.+이상을 적용해 보자



```
fashion_mnist = keras.datasets.fashion_mnist  
(X_train_full, y_train_full), (X_test, y_test) = fashion_mnist.load_data()
```

```
In [21]: import tensorflow as tf  
from tensorflow import keras
```

```
In [22]: tf.__version__
```

```
Out[22]: '2.0.0'
```

```
In [23]: keras.__version__
```

```
Out[23]: '2.2.4-tf'
```

# 패션 NMINST 데이터(1)

- 패션 NMINST는 총 60,000개 훈련 데이터, 픽셀 크기는 28x28
- 테스트 데이터 개수는 10,000개

```
In [18]: X_train_full.shape
```

```
Out[18]: (60000, 28, 28)
```

```
In [29]: X_valid.shape
```

```
Out[29]: (5000, 28, 28)
```

```
In [21]: X_test.shape
```

```
Out[21]: (10000, 28, 28)
```

```
In [30]: X_test.shape
```

```
Out[30]: (10000, 28, 28)
```

```
In [19]: X_train_full.dtype
```

```
Out[19]: dtype('uint8')
```

- 검증 데이터 5000개 사용
- 훈련은 55,000개 모두 0~1로 스케일

```
In [20]: X_valid, X_train = X_train_full[:5000] / 255., X_train_full[5000:] / 255.  
y_valid, y_train = y_train_full[:5000], y_train_full[5000:]  
X_test = X_test / 255.
```

# 패션 MNIST 데이터(2)

```
plt.imshow(X_train[0], cmap="binary")
plt.axis('off')
plt.show()
```



```
plt.imshow(X_train[2], cmap="binary")
plt.axis('off')
plt.show()
```



In [23]: `y_train`

Out [23]: `array([4, 0, 7, ..., 3, 0, 5], dtype=uint8)`

In [24]: `class_names = ["T-shirt/top", "Trouser", "Pullover", "Dress", "Coat",
 "Sandal", "Shirt", "Sneaker", "Bag", "Ankle boot"]`

So the first image in the training set is a coat:

In [28]: `class_names[y_train[0]]`

Out [28]: 'Coat'

# 패션 MNIST 데이터(3)

```
for row in range(n_rows):
    for col in range(n_cols):
        index = n_cols * row + col
        plt.subplot(n_rows, n_cols, index + 1)
        plt.imshow(X_train[index], cmap="binary", interpolation="nearest")
        plt.axis('off')
        plt.title(class_names[y_train[index]], fontsize=12)
```



# 케라스 Sequential 모델 (1)

- 텐서플로 2.0의 권장 사항

- 1)작은 함수로 코드를 리팩토링 하자

- 텐서플로 1.x의 일반적인 사용패턴은 모든 연산을 결합하여 준비한 다음
- session.run()을 텐서를 평가 함
- 텐서플로 2.x에서는 필요할 때 호출할 수 있는 작은 함수로 코드를 리팩토링 함

- 2) 케라스 층과 모델을 사용해 변수를 관리하자

- 케라스 모델과 층은 재귀적으로 의존하는 모든 변수를 수집하여 variables와 trainable\_variables 속성으로 제공한다. 지역 범위로 변수 관리가 쉽다.

# 케라스 모델 (2)

- **케라스 사용**

```
import tensorflow as tf  
  
from tensorflow import keras
```

- **Sequential 모델 만들기**

✓ 케라스에서는 층(layer)을 조합하여 모델을 만듬. 모델은 층의 그래프이다.

- 가장 흔한 모델 구조는 층을 차례대로 쌓는 tf.keras.Sequential 모델이다.

# 케라스 모델 구성 및 층 설정 (3)

## 05. 케라스 사용하기

```
model = keras.models.Sequential()  
model.add(keras.layers.Flatten(input_shape=[28, 28]))  
model.add(keras.layers.Dense(300, activation="relu"))  
model.add(keras.layers.Dense(100, activation="relu"))  
model.add(keras.layers.Dense(10, activation="softmax"))
```

층을 차례로 쌓는 모델을 만들자

input을 일렬화 한다. 1개의 연속 메모리  
784개 1차원 배열로 변환. 학습되는  
가중치는 없고 데이터를 변환하기만 한다.

keras.layers.Dense 층이 연속적으로 연결되어 완전연결(fully-connected layer)  
층이라고 부름.

첫 번째 Dense 층은 300개 노드(뉴런)을 가진다.  
두 번째 층은 100개, 마지막 층은 10개의 뉴런이 소프트맥스 활성함수를 통해서  
확률적으로 반환함. 전체 확률합은 당연히 1이다.

# 케라스 모델 (4)

```
keras.backend.clear_session()  
np.random.seed(42)  
tf.random.set_seed(42)
```

케라는 고수준의 API를 모듈 방식으로 제공하며, 여러 다른 백엔드 엔진들을 연결함. clear 세션은 현재 케라스 그래프를 없애고, 새로운 그래프를 만들자

```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 300)	235500
dense_1 (Dense)	(None, 100)	30100
dense_2 (Dense)	(None, 10)	1010

Total params: 266,610

Trainable params: 266,610

Non-trainable params: 0

# 케라스 모델 summary (5)

```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 300)	235500
dense_1 (Dense)	(None, 100)	30100
dense_2 (Dense)	(None, 10)	1010

Total params: 266,610

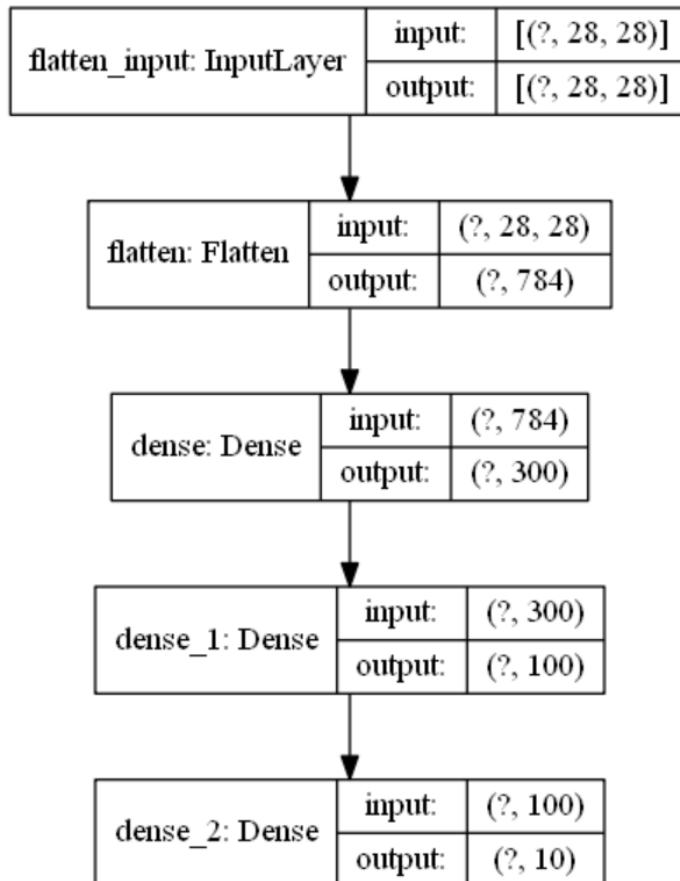
Trainable params: 266,610

Non-trainable params: 0

# 케라스 모델 구조 (6)

pydot과 graphviz가 설치가 안되어 있다면 !pip install pydot graphviz

```
keras.utils.plot_model(model, "my_mnist_model.png", show_shapes=True)
```



# 케라스 Sequential 모델 (7)

```
In [43]: hidden1 = model.layers[1]  
hidden1.name
```

```
Out[43]: 'dense'
```

```
In [44]: model.get_layer(hidden1.name) is hidden1
```

```
Out[44]: True
```

---

```
In [45]: weights, biases = hidden1.get_weights()
```

---

```
In [46]: weights
```

```
Out[46]: array([[ 0.02448617, -0.00877795, -0.02189048, ..., -0.02766046,  
    0.03859074, -0.06889391],  
   [ 0.00476504, -0.03105379, -0.0586676 , ...,  0.00602964,  
   -0.02763776, -0.04165364],  
   [-0.06189284, -0.06901957,  0.07102345, ..., -0.04238207,  
    0.07121518, -0.07331658],  
   ...,  
   [-0.03048757,  0.02155137, -0.05400612, ..., -0.00113463,  
    0.00228987,  0.05581069],  
   [ 0.07061854, -0.06960931,  0.07038955, ..., -0.00384101,  
    0.00034875,  0.02878492],  
   [-0.06022581,  0.01577859, -0.02585464, ..., -0.00527829,  
    0.00272203, -0.06793761]], dtype=float32)
```

## 케라스 Sequential 모델 (8)

`weights.shape`

(784, 300)

## biases

biases.shape

(300.)

# 케라스 Sequential 모델 (9)

```
model.compile(loss="sparse_categorical_crossentropy",
               optimizer="sgd",
               metrics=["accuracy"])
```

```
model.compile(loss=keras.losses.sparse_categorical_crossentropy,
               optimizer=keras.optimizers.SGD(),
               metrics=[keras.metrics.sparse_categorical_accuracy])
```

```
history = model.fit(X_train, y_train, epochs=30,
                      validation_data=(X_valid, y_valid))
```

Train on 55000 samples, validate on 5000 samples

Epoch 1/30

```
Epoch 27/30
55000/55000 [=====] - 3s 59us/sample - loss: 0.2362 - accuracy: 0.9145 - val_loss: 0.3002 - val_accuracy: 0.8890
Epoch 28/30
55000/55000 [=====] - 3s 59us/sample - loss: 0.2331 - accuracy: 0.9157 - val_loss: 0.3021 - val_accuracy: 0.8926
Epoch 29/30
55000/55000 [=====] - 3s 59us/sample - loss: 0.2289 - accuracy: 0.9182 - val_loss: 0.2985 - val_accuracy: 0.8924
Epoch 30/30
55000/55000 [=====] - 3s 59us/sample - loss: 0.2254 - accuracy: 0.9181 - val_loss: 0.3329 - val_accuracy: 0.8806
```

# 케라스 Sequential 모델 (10)

```
In [52]: history.params
```

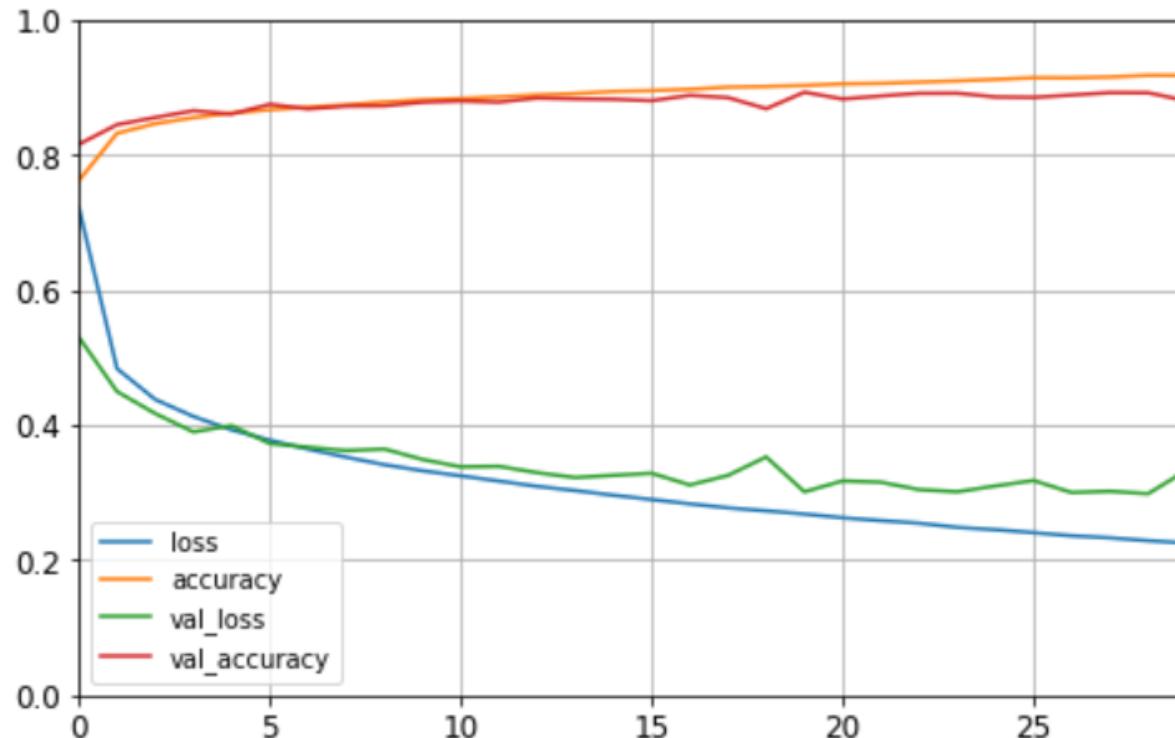
```
Out[52]: {'batch_size': 32,
          'epochs': 30,
          'steps': 1719,
          'samples': 55000,
          'verbose': 0,
          'do_validation': True,
          'metrics': ['loss', 'accuracy', 'val_loss', 'val_accuracy']}
```

```
In [53]: print(history.epoch)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,
 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29]
```

# 케라스 Sequential 모델 (11)

```
import pandas as pd
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1)
plt.show()
```



## 케라스 Sequential 모델 (12)

```
In [60]: model.evaluate(X_test, y_test)
```

39us/sample - loss: 0.3276 - accuracy: 0.8664

[0.3684497040987015, 0.8664]

```
In [61]: X_new = X_test[:3]
y_proba = model.predict(X_new)
y_proba.round(2)
```

# 케라스 Sequential 모델 (13)

```
In [69]: y_pred = model.predict_classes(X_new);y_pred
```

```
Out[69]: array([9, 2, 1], dtype=int64)
```

---

```
In [63]: np.array(class_names)[y_pred]
```

```
Out[63]: array(['Ankle boot', 'Pullover', 'Trouser'], dtype='<U11')
```

---

```
In [68]: y_new = y_test[:3];y_new
```

```
Out[68]: array([9, 2, 1], dtype=uint8)
```

# 케라스 Sequential 모델 (14)

```
In [66]: plt.figure(figsize=(7.2, 2.4))
for index, image in enumerate(X_new):
    plt.subplot(1, 3, index + 1)
    plt.imshow(image, cmap="binary", interpolation="nearest")
    plt.axis('off')
    plt.title(class_names[y_test[index]], fontsize=12)
plt.subplots_adjust(wspace=0.2, hspace=0.5)

plt.show()
```

Ankle boot



Pullover



Trouser



# 06. 다중 회귀 퍼셉트론 (1)

- California housing dataset

In [1]: ► `import numpy as np  
import tensorflow as tf  
from tensorflow import keras`

In [2]: ► `import pandas as pd`

In [3]: ► `keras.__version__`

Out[3]: '2.2.4-tf'

In [4]: ► `import matplotlib.pyplot as plt  
%matplotlib inline`

## 06. 다중 회귀 퍼셉트론 (2)

```
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

housing = fetch_california_housing()

X_train_full, X_test, y_train_full, y_test = train_test_split(housing.data,
    housing.target, random_state=42)

X_train, X_valid, y_train, y_valid = train_test_split(
    X_train_full, y_train_full, random_state=42)

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_valid = scaler.transform(X_valid)
X_test = scaler.transform(X_test)
```

## 06. 다중 회귀 퍼셉트론 (2)

```
model = keras.models.Sequential([
    keras.layers.Dense(30, activation="relu",
                       input_shape=X_train.shape[1:]),
    keras.layers.Dense(1)
])
```

```
model.compile(loss="mean_squared_error",
               optimizer=keras.optimizers.SGD(lr=1e-3))
```

```
history = model.fit(X_train, y_train,
                     epochs=30, validation_data=(X_valid, y_valid))
```

# 06. 다중 회귀 퍼셉트론 (2)

Train on 11610 samples, validate on 3870 samples

Epoch 1/30

11610/11610 [=====] - 3s 263us/sample - loss: 1.6321 - val\_loss: 1.5903

Epoch 2/30

11610/11610 [=====] - 1s 77us/sample - loss: 0.7124 - val\_loss: 0.6539

Epoch 3/30

11610/11610 [=====] - 1s 75us/sample - loss: 0.6348 - val\_loss: 0.6039

Epoch 4/30

11610/11610 [=====] - 1s 81us/sample - loss: 0.5983 - val\_loss: 0.5738

Epoch 5/30

11610/11610 [=====] - 1s 83us/sample - loss: 0.5713 - val\_loss: 0.5406

Epoch 6/30

11610/11610 [=====] - 1s 80us/sample - loss: 0.5482 - val\_loss: 0.5221

Epoch 7/30

11610/11610 [=====] - 1s 77us/sample - loss: 0.4122 - val\_loss: 0.3865

Epoch 8/30

11610/11610 [=====] - 1s 75us/sample - loss: 0.4102 - val\_loss: 0.3807

Epoch 9/30

11610/11610 [=====] - 1s 79us/sample - loss: 0.4083 - val\_loss: 0.3818

Epoch 10/30

11610/11610 [=====] - 1s 85us/sample - loss: 0.4065 - val\_loss: 0.3795

Epoch 11/30

11610/11610 [=====] - 1s 87us/sample - loss: 0.4050 - val\_loss: 0.3762

## 06. 다중 회귀 퍼셉트론 (2)

```
mse_test = model.evaluate(X_test, y_test)
```

```
5160/1 [=====
```

```
=====
```

```
=====
```

```
====] - 0s 30us/sample - loss: 0.3272
```

```
X_new = X_test[:3]
```

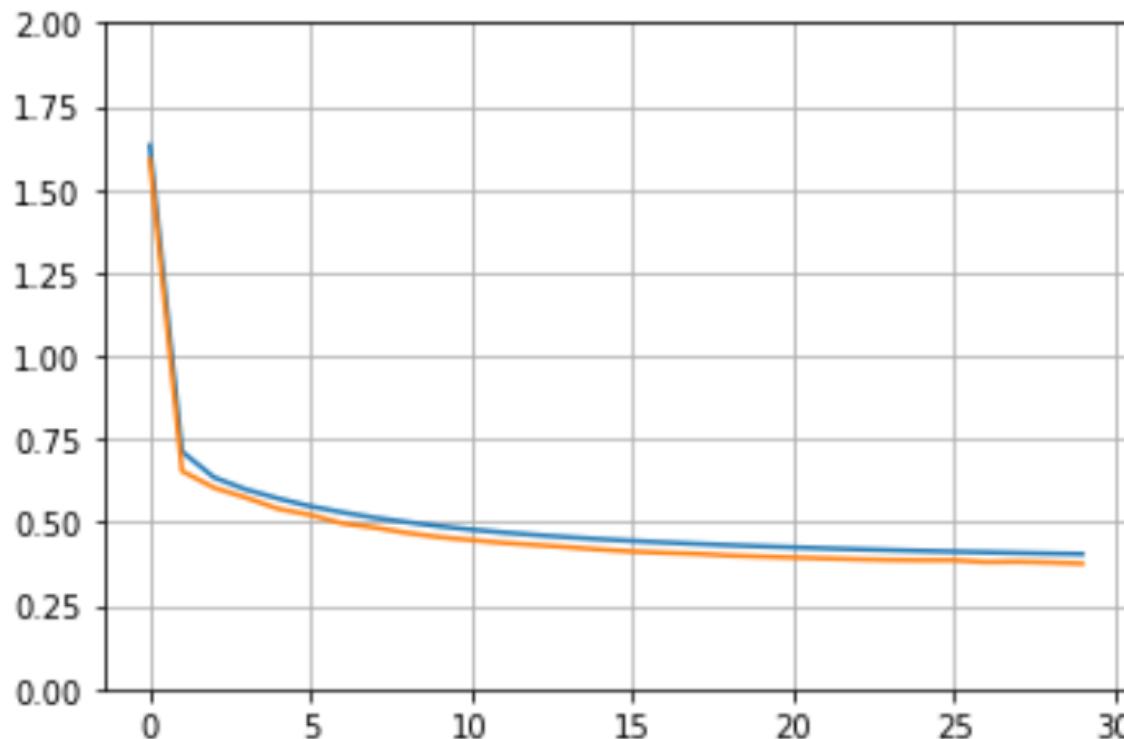
```
y_pred = model.predict(X_new)
```

```
y_pred
```

```
array([[0.39039648],  
       [1.7924039 ],  
       [3.2830522 ]], dtype=float32)
```

## 06. 다중 회귀 퍼셉트론 (2)

```
plt.plot(pd.DataFrame(history.history))
plt.grid(True)
plt.gca().set_ylim(0, 2)
plt.show()
```



## 07. Saving and Restoring

```
model = keras.models.Sequential([
    keras.layers.Dense(30, activation="relu", input_shape=[8]),
    keras.layers.Dense(30, activation="relu"),
    keras.layers.Dense(1)
])
```

```
model = keras.models.Sequential([
    keras.layers.Dense(30, activation="relu", input_shape=[8]),
    keras.layers.Dense(30, activation="relu"),
    keras.layers.Dense(1)
])
```

```
Train on 11610 samples, validate on 3870 samples
Epoch 1/10
11610/11610 [=====] - 3s 285us/sample - loss: 0.2769 - val_loss: 0.2770
Epoch 2/10
=====
===== ] - 0s 70us/sample - loss: 0.2228
```

# 07. Saving and Restoring

```
model.save("my_keras_model.h5")
```

```
model = keras.models.load_model("my_keras_model.h5")
```

```
model.predict(X_new)
```

```
array([[0.54909724],  
       [1.6584849 ],  
       [3.0271606 ]], dtype=float32)
```

```
model.save_weights("my_keras_weights.ckpt")
```

```
model.load_weights("my_keras_weights.ckpt")
```

```
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x203728f63c8>
```

# 08. 콜백

## 08. 훈련중 콜백 사용하기

▶ keras.backend.clear\_session()  
np.random.seed(42)  
tf.random.set\_seed(42)

▶ model = keras.models.Sequential([  
 keras.layers.Dense(30, activation="relu", input\_shape=[8]),  
 keras.layers.Dense(30, activation="relu"),  
 keras.layers.Dense(1)  
])

## 06. 다중 회귀 퍼셉트론 (2)

```
model.compile(loss="mse", optimizer=keras.optimizers.SGD(lr=1e-3))

checkpoint_cb = keras.callbacks.ModelCheckpoint("my_keras_model.h5",
                                                save_best_only=True)
history = model.fit(X_train, y_train, epochs=10,
                     validation_data=(X_valid, y_valid),
                     callbacks=[checkpoint_cb])

model = keras.models.load_model("my_keras_model.h5")
# rollback to best model

mse_test = model.evaluate(X_test, y_test)
```

---

```
=] - 0s 68us/sample - loss: 0.3719
```

## 06. 다중 회귀 퍼셉트론 (2)

```
model.compile(loss="mse", optimizer=keras.optimizers.SGD(lr=1e-3))

early_stopping_cb = keras.callbacks.EarlyStopping(patience=10,
                                                 restore_best_weights=True)

history = model.fit(X_train, y_train, epochs=100,
                     validation_data=(X_valid, y_valid),
                     callbacks=[checkpoint_cb, early_stopping_cb])

mse_test = model.evaluate(X_test, y_test)
|
```

```
Train on 11610 samples, validate on 3870 samples
Epoch 1/100
11610/11610 [=====] - 3s 219us/sample - loss: 0.4388 - val_loss: 0.4122
Epoch 2/100
11610/11610 [=====] - 1s 85us/sample - loss: 0.4319 - val_loss: 0.4046
```

# 08. 콜백

```
class PrintValTrainRatioCallback(keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs):
        print("val/train: {:.2f}".format(logs["val_loss"] / logs["loss"]))
```

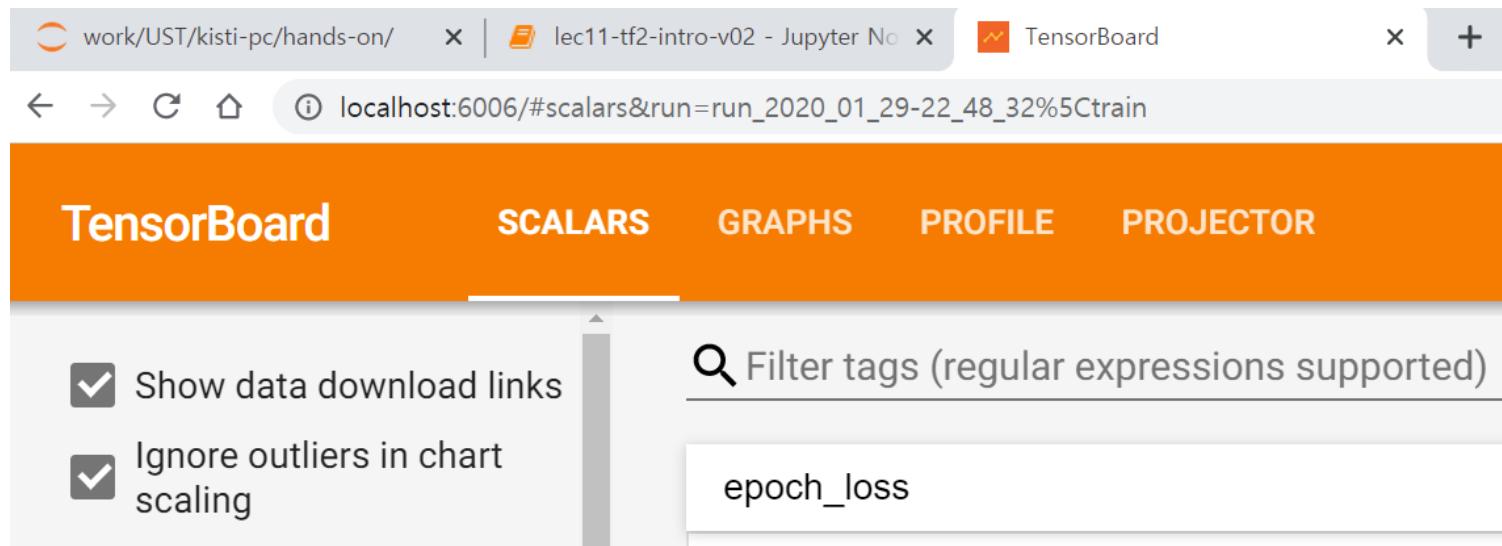
```
val_train_ratio_cb = PrintValTrainRatioCallback()
history = model.fit(X_train, y_train, epochs=1,
                     validation_data=(X_valid, y_valid),
                     callbacks=[val_train_ratio_cb])
```

---

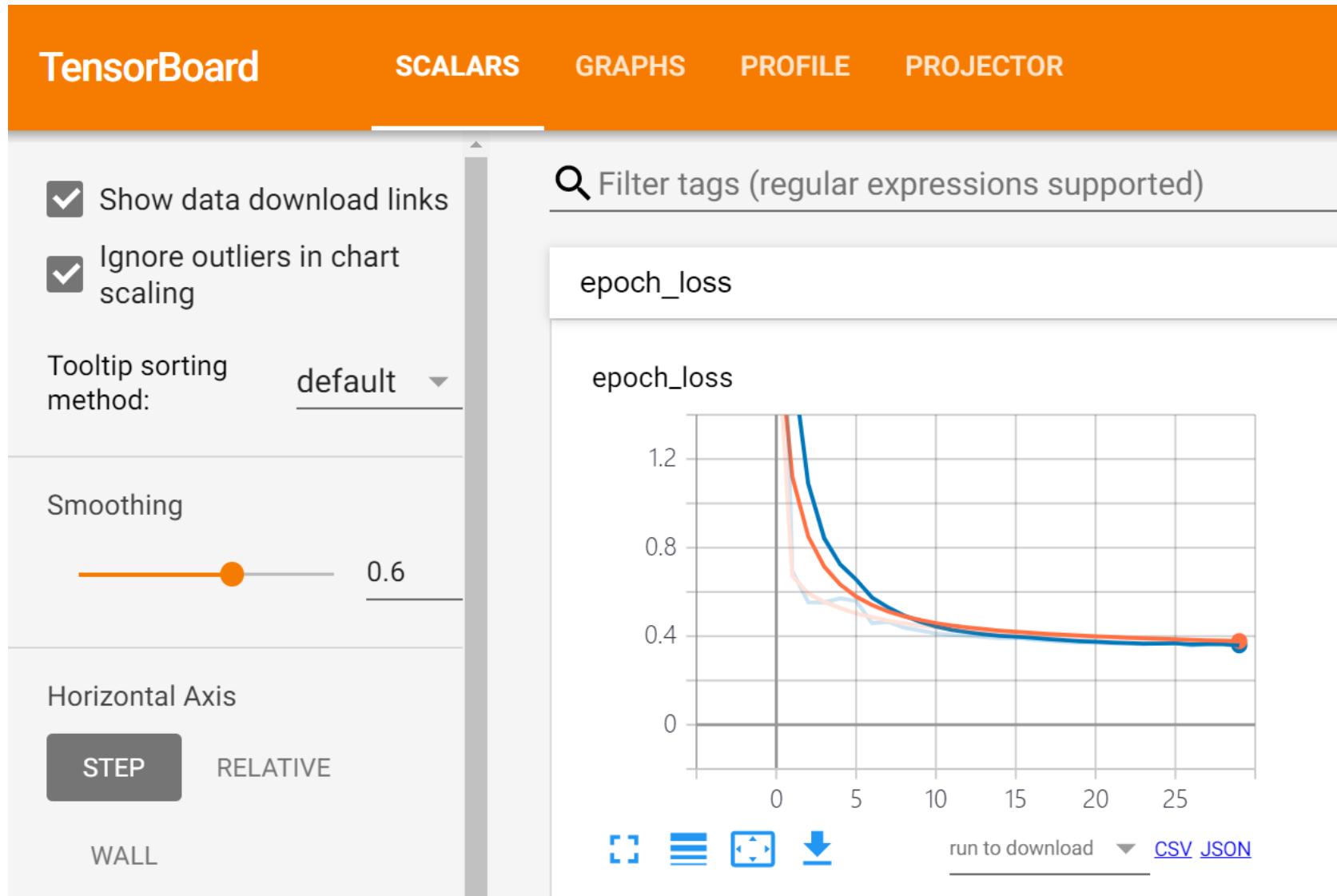
```
Train on 11610 samples, validate on 3870 samples
1168/11610 [=====>..] - ETA: 0s - loss: 0.3450
val/train: 1.10
11610/11610 [=====] - 1s 95us/sample - loss: 0.3465 - val_loss: 0.3825
```

# 09. tensorflow()

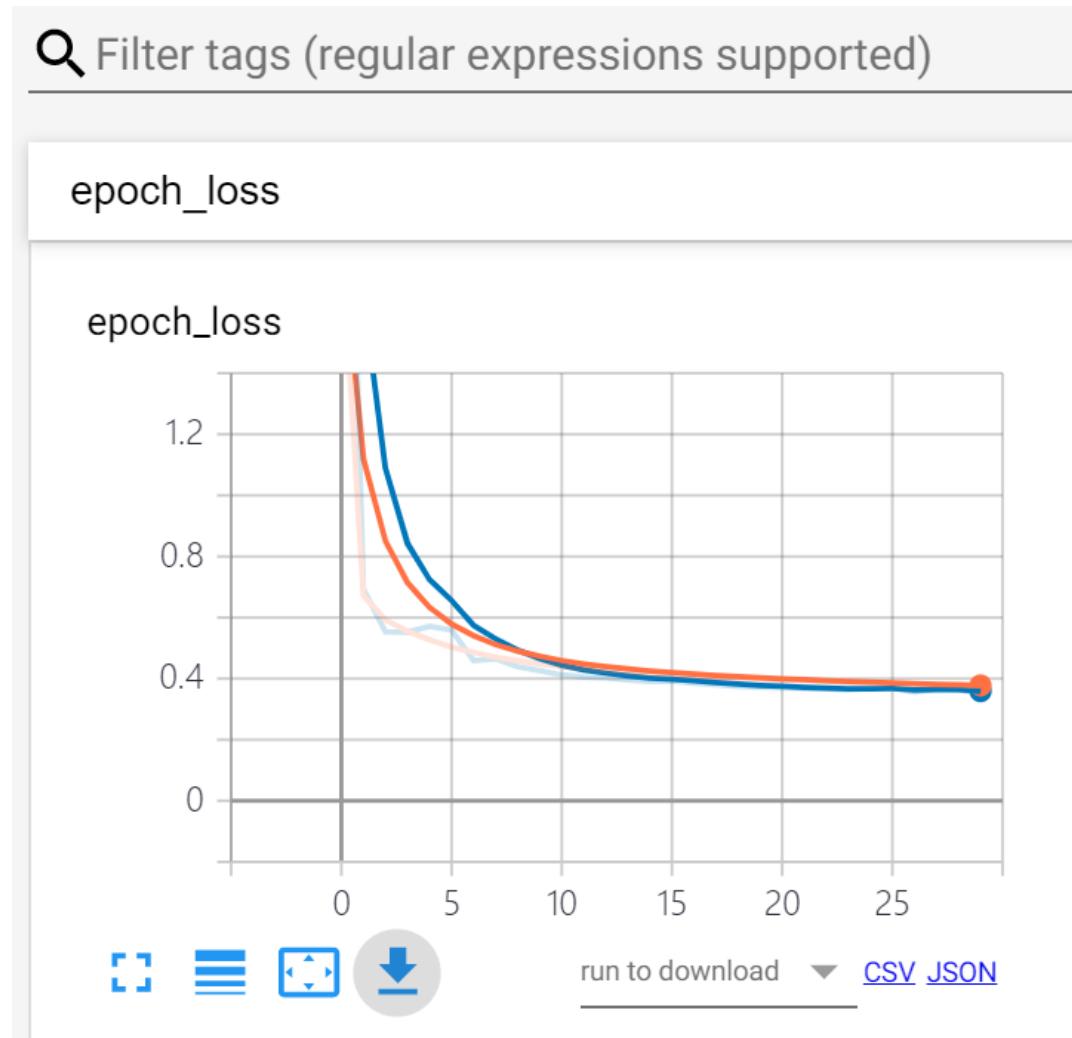
- 텐서보드 실행
  - ✓ \$ tensorboard --logdir=./my\_logs --port=6006
- 웹브라우저 (MS 엣지, 크롬) 주소 입력
  - ✓ [localhost:6006](http://localhost:6006)



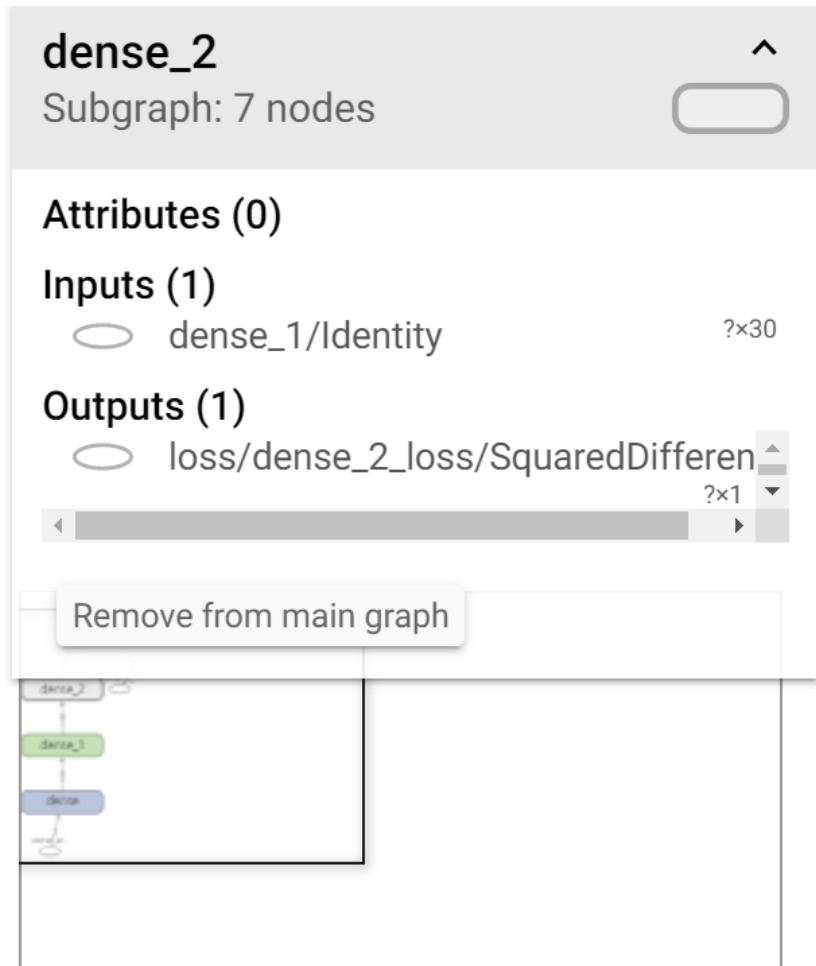
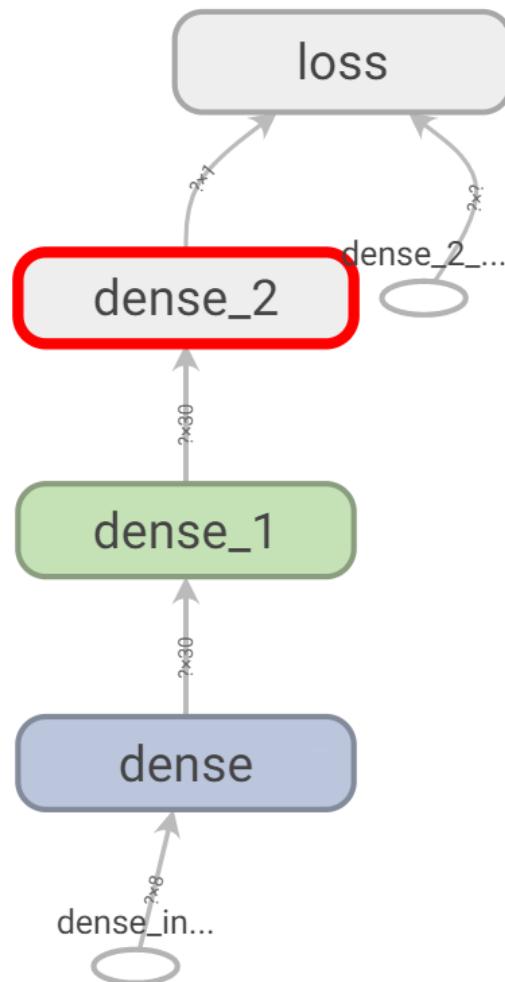
# tensorboard()



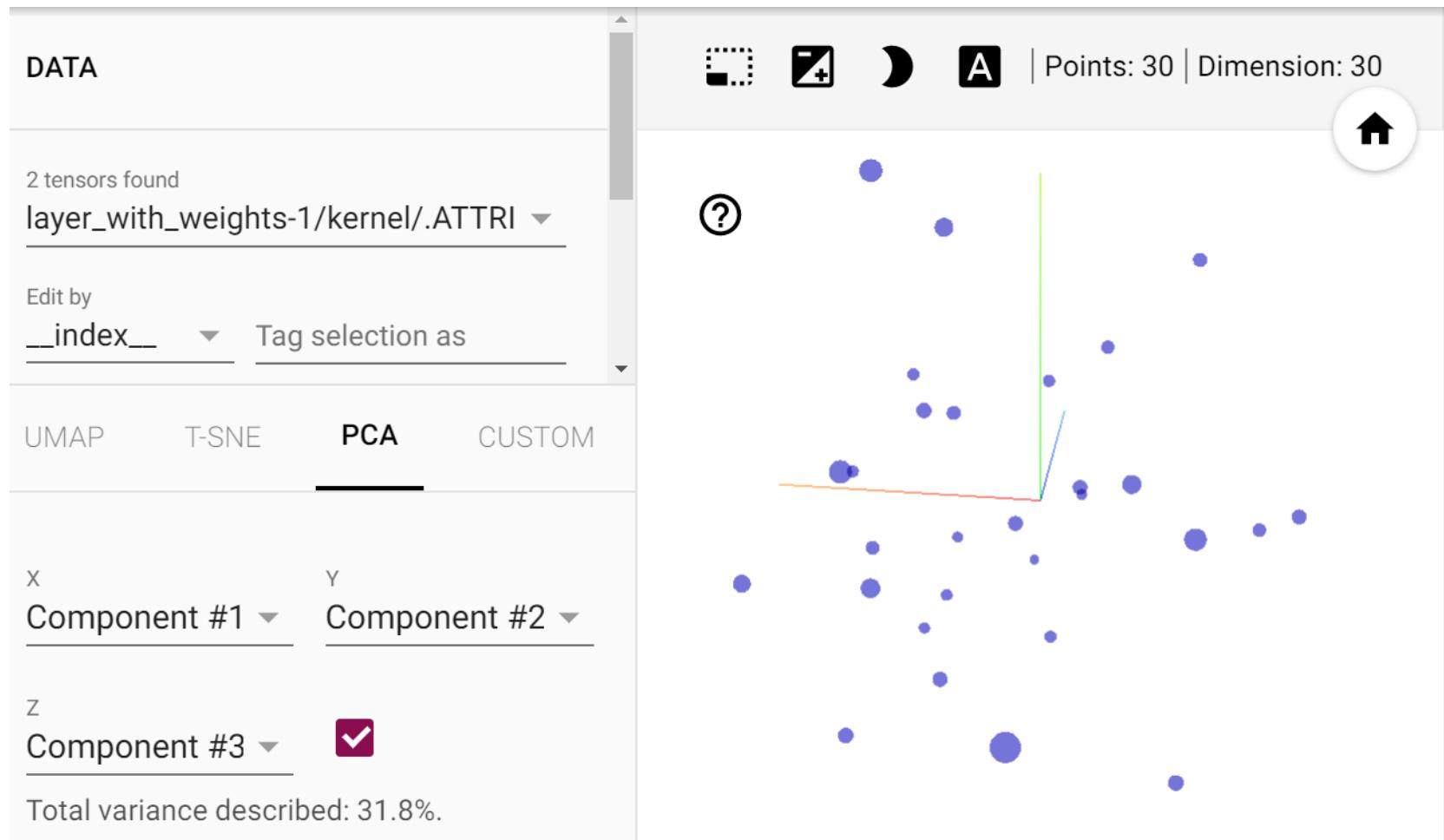
# tensorboard()



# tensorboard()



# tensorboard()



# 10. 하이퍼 파라미터 튜닝(1)

```
keras.backend.clear_session()  
np.random.seed(42)  
tf.random.set_seed(42)
```

---

```
def build_model(n_hidden=1, n_neurons=30,  
                learning_rate=3e-3, input_shape=[8]):  
  
    model = keras.models.Sequential()  
    model.add(keras.layers.InputLayer(input_shape=input_shape))  
  
    for layer in range(n_hidden):  
        model.add(keras.layers.Dense(n_neurons, activation="relu"))  
  
    model.add(keras.layers.Dense(1))|  
    optimizer = keras.optimizers.SGD(lr=learning_rate)  
    model.compile(loss="mse", optimizer=optimizer)  
    return model
```

# 10. 하이퍼 파라미터 튜닝(1)

```
keras_reg = keras.wrappers.scikit_learn.KerasRegressor(build_model)
```

```
keras_reg.fit(X_train, y_train, epochs=100,  
              validation_data=(X_valid, y_valid),  
              callbacks=[keras.callbacks.EarlyStopping(patience=10)])
```

Train on 11610 samples, validate on 3870 samples

Epoch 1/100

11610/11610 [=====] - 2s 150us/sample - loss: 1.1815 - val\_loss: 20.7837

Epoch 2/100

11610/11610 [=====] - 1s 80us/sample - loss: 0.7013 - val\_loss: 0.6646

Epoch 26/100

11610/11610 [=====] - 1s 94us/sample - loss: 0.3721 - val\_loss: 0.3986

<tensorflow.python.keras.callbacks.History at 0x203705a1d48>

# 10. 하이퍼 파라미터 튜닝(1)

```
mse_test = keras_reg.score(X_test, y_test)
```

---

```
=====] - 0s 35us/sample - loss: 0.2821
```

In [73]: ► y\_pred = keras\_reg.predict(X\_new)  
y\_pred

Out[73]: array([0.6270608, 1.7558155, 3.7607713], dtype=float32)

---

# 10. 하이퍼 파라미터 튜닝(1)

```
from scipy.stats import reciprocal
from sklearn.model_selection import RandomizedSearchCV

param_distributions = {
    "n_hidden": [0, 1, 2, 3],
    "n_neurons": np.arange(1, 100),
    "learning_rate": reciprocal(3e-4, 3e-2),
}
```

# 10. 하이퍼 파라미터 튜닝(1)

```
rnd_search_cv = RandomizedSearchCV(keras_reg,  
param_distributions, n_iter=10, cv=3, verbose=2)
```

```
rnd_search_cv.fit(X_train, y_train, epochs=20,  
validation_data=(X_valid, y_valid),  
callbacks=[keras.callbacks.EarlyStopping(patience=10)])
```

# Thank You!

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