Deep Learning Tutorial #4

Ref.

- Collado, Julian, et al. "Learning to identify electrons." Physical Review D 103.11 (2021): 116028.
- Collado, Julian, et al. "Learning to isolate muons." Journal of High Energy Physics 2021.10 (2021): 1-17.

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Day.4 (execrcise) `Learning to Identify Electrons`

> `Learning to Identify Electrons` 논문을 재현해 보자.

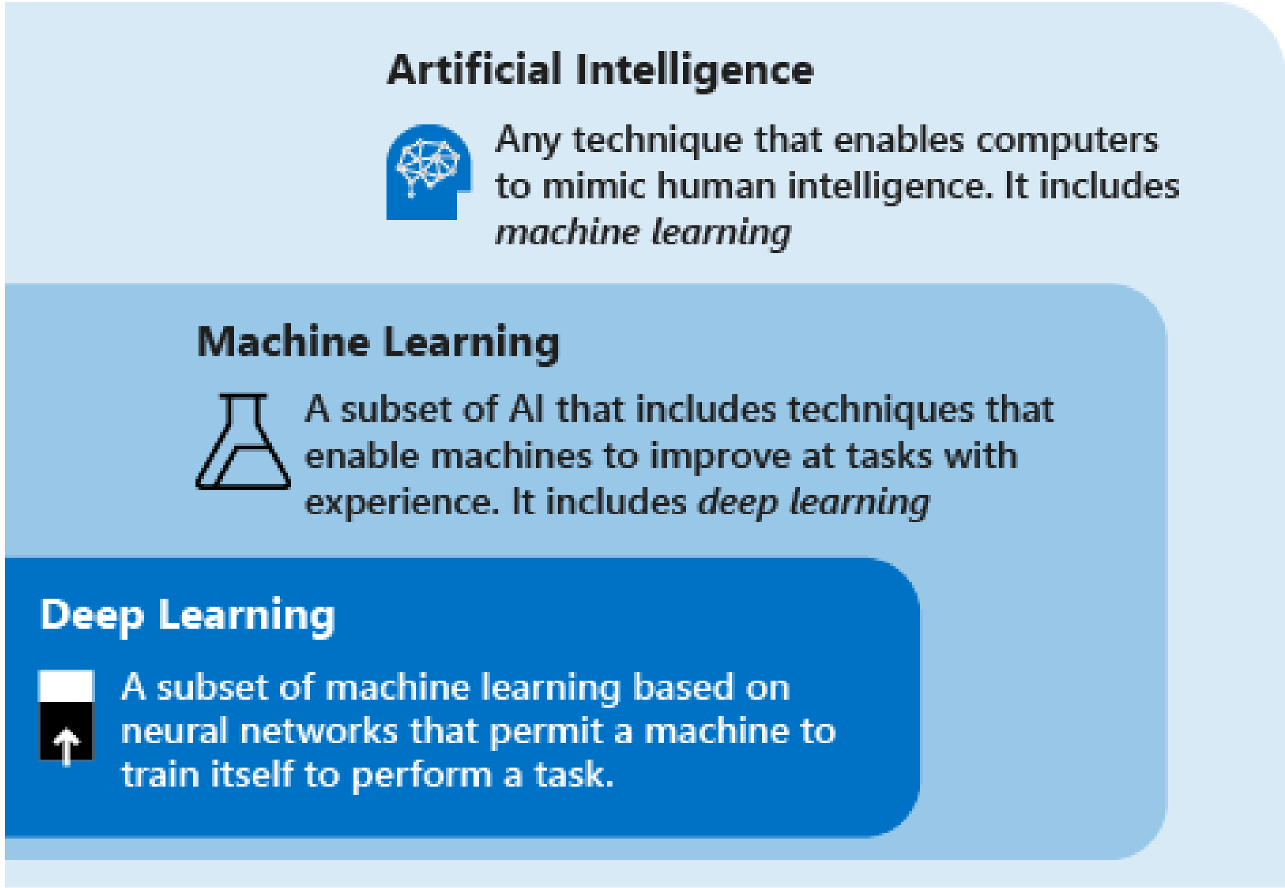
Index

- ~~Day.1 : (Intro) - Hands-On~~
- ~~Day.2 : (Example) - `LeNet-5` 구현해보기~~
- ~~Day.3 : (execrcise) - `Learning to Identify Electrons` 재현 준비~~
- Day.4 : (execrcise) - `Learning to Identify Electrons` 재현
- Day.5 : (practice) - `Learning to Isolate Muons` 재현

Review. Again CNN

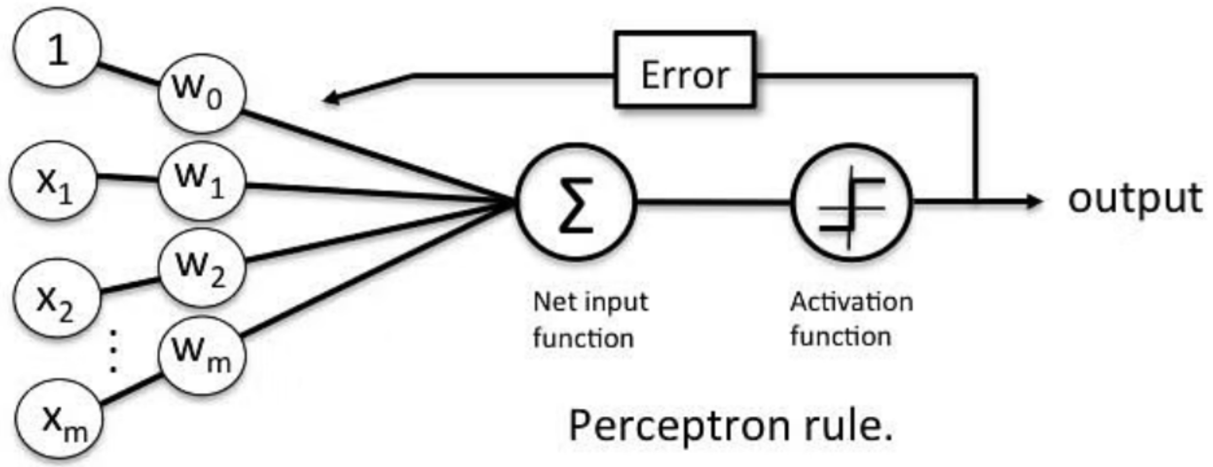
1.a previous story

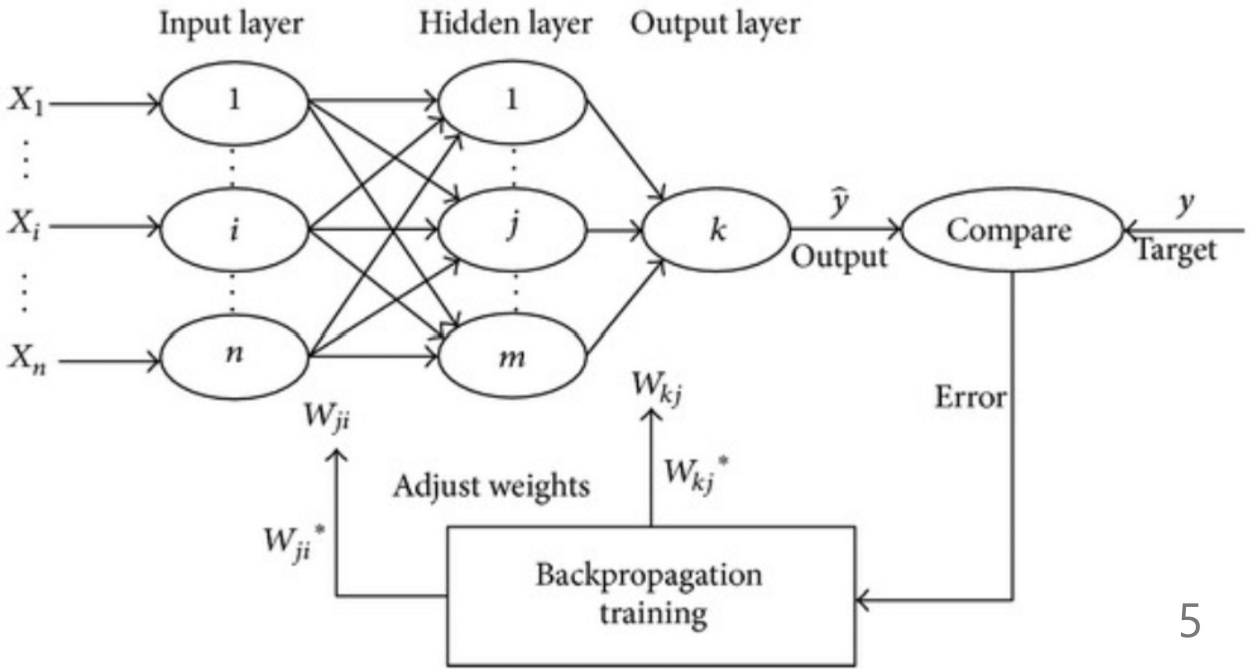
- 실험 환경 설정에 관한 안내
- AI, 머신러닝, 딥러닝에 대한 짧은 소개



1.b previous story

- Perceptron(퍼셉트론), 다수의 값을 입력받아 하나의 값으로 출력하는 알고리즘($y = ax + b$)
- MultiLayer Perceptron(다층 퍼셉트론 혹은 MLP),
- 은닉층이 2개 이상인 신경망을 심층 신경망이라 하는데, 이 때 심층 신경망을 학습시키는 과정을 '딥러닝'이라 함.

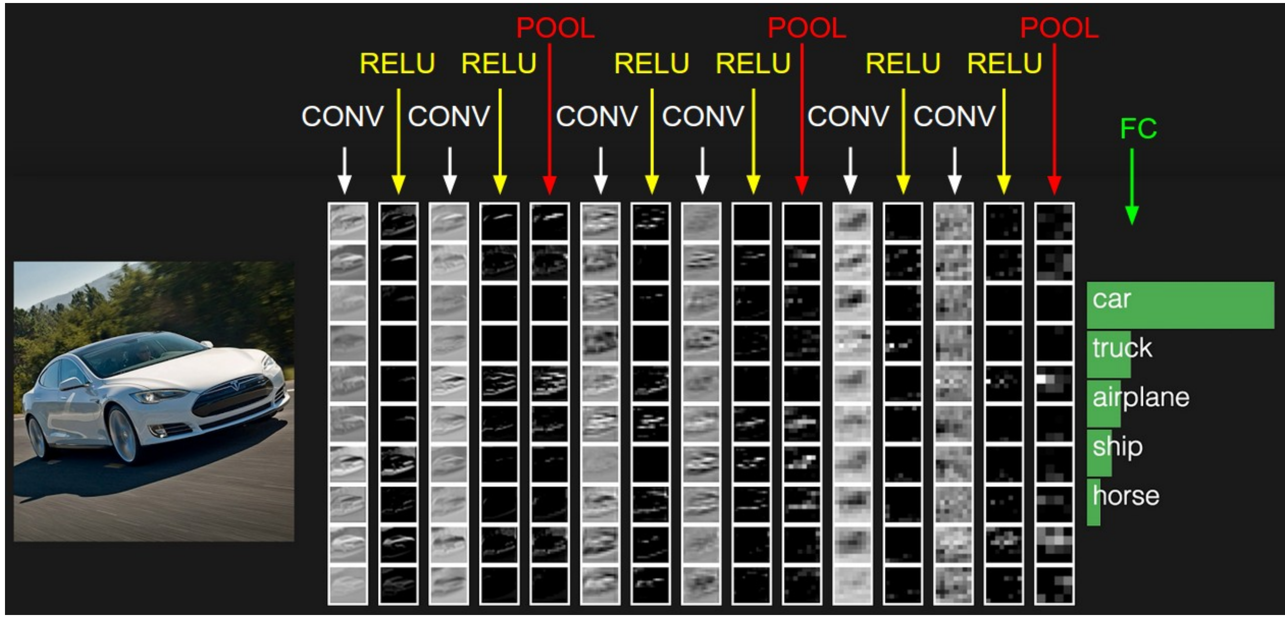




1.c CNN

- Convolutional Layer
  - filter(or image)
  - kernel
  - stride
  - padding
- Pooling Layer
  - avg
  - max

> https://sigmadream.github.io/cnn-vis/



1.d Check Python Syntax

> https://docs.python.org/3/tutorial/index.html

- Data Structures
- Function
- Classes

2. 구현 시작

X. NEURAL NETWORK HYPERPARAMETERS AND ARCHITECTURE

TABLE III. Hyperparameter ranges for bayesian optimization of convolutional networks

Parameter	Range
Num. of conv. blocks	[1, 4]
Num. of filters	[8, 128]
Num. of dense layers	[1, 3]
Num. of hidden units	[1, 200]
Learning rate	[0.0001, 0.01]
Dropout	[0.0, 0.5]

TABLE IV. Hyperparameter ranges for bayesian optimization of fully connected networks

Parameter	Range
Num. of dense layers	[1, 8]
Num. of hidden units	[1, 200]
Learning rate	[0.0001, 0.01]
Dropout	[0.0, 0.5]

TABLE V. Best hyperparameters found per model.

features	conv.	filters	dense	hidden	LR	DP
ECal	3	117	2	160	0.0001	0.0
Hcal	2	27	2	84	0.01	0.5
Ecal+HCal	3	47	2	146	0.0001	0.0
HL	-	-	5	149	0.001	0.0019

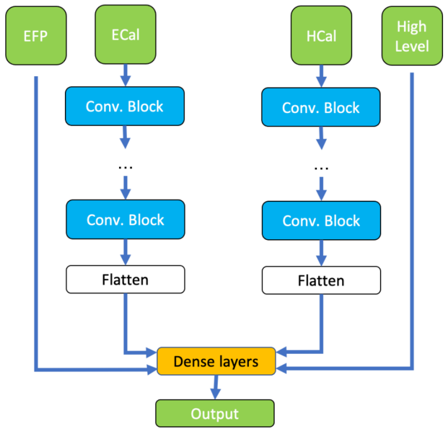


FIG. 8. Diagram of the architecture of the convolutional neural network.

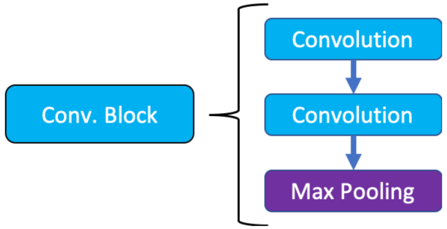


FIG. 9. Diagram of convolutional block appearing in network architecture, see Fig 8.

2.1.a 우리가 알고 있는 것

```
et_and_ht 2 <class 'list'>
(42977, 31, 31, 1)
(42977, 32, 32, 1)
et_and_ht_and_hl 3 <class 'list'>
(42977, 31, 31, 1)
(42977, 32, 32, 1)
(42977, 7)
hl_and_mass 2 <class 'list'>
(42977, 7)
(42977, 1)
```

2.1.b 우리가 알고 있는 것

```
{'feature': 'hl', 'filters': 16, 'numConvBlocks': 1, 'p': 0, 'optimizer': 'adam', 'epochs': 100, 'batchSize': 128, 'iso_positions': (), 'efp_positions': (), 'numLayers': 5, 'units': 149, 'lr': 0.001, 'dp': 0.0019}
{'feature': 'et_and_ht', 'filters': 47, 'numConvBlocks': 3, 'p': 0, 'optimizer': 'adam', 'epochs': 100, 'batchSize': 128, 'iso_positions': (), 'efp_positions': (), 'numLayers': 2, 'units': 146, 'lr': 0.0001, 'dp': 0.0}
{'feature': 'et', 'filters': 117, 'numConvBlocks': 3, 'p': 0, 'optimizer': 'adam', 'epochs': 100, 'batchSize': 128, 'iso_positions': (), 'efp_positions': (), 'numLayers': 2, 'units': 160, 'lr': 0.0001, 'dp': 0.0}
{'feature': 'ht', 'filters': 27, 'numConvBlocks': 2, 'p': 0, 'optimizer': 'adam', 'epochs': 100, 'batchSize': 128, 'iso_positions': (), 'efp_positions': (), 'numLayers': 2, 'units': 84, 'lr': 0.01, 'dp': 0.5}
{'feature': 'et_and_ht_and_hl', 'filters': 34, 'numConvBlocks': 3, 'p': 0, 'optimizer': 'adam', 'epochs': 100, 'batchSize': 128, 'iso_positions': (), 'efp_positions': (), 'numLayers': 2, 'units': 154, 'lr': 0.0001, 'dp': 0.0}
{'feature': 'mass', 'filters': 16, 'numConvBlocks': 1, 'p': 0, 'optimizer': 'adam', 'epochs': 100, 'batchSize': 128, 'iso_positions': (), 'efp_positions': (), 'numLayers': 3, 'units': 10, 'lr': 0.01, 'dp': 0.0}
{'feature': 'hl_and_mass', 'filters': 16, 'numConvBlocks': 1, 'p': 0, 'optimizer': 'adam', 'epochs': 100, 'batchSize': 128, 'iso_positions': (), 'efp_positions': (), 'numLayers': 3, 'units': 109, 'lr': 0.0013, 'dp': 0.0}
```

2.2 가장 작은 것 부터 구현

```python
def conv_block(layer, filters, activation='relu'):
    layer=Conv2D(filters, kernel_size=(3, 3),activation=activation,padding='same')(layer)
    layer=Conv2D(filters, kernel_size=(3, 3), activation=activation,padding='same')(layer)
    layer=MaxPooling2D(pool_size=(2, 2),padding='same')(layer)
    return layer
```

> q1. 그런데 이 함수는 어떻게 동작하는 건가요?
> q2. 이거 실행은 어떻게?

2.3.a TF에서 모델을 작성하는 3가지 기본 구조

- Sequential

```
# build a model (5 layers)
model = tf.keras.Sequential([
    # 1. filter(kernel channel) = 32, kernel = 3, relu, conv2d layer
    tf.keras.layers.Conv2D(32, 3, activation='relu'),
    # 2. filter = 64, kernel = 3, relu, conv2d layer
    tf.keras.layers.Conv2D(64, 3, activation='relu'),
    # 3. flatten layer
    tf.keras.layers.Flatten(),
    # 4. output = 128 nodes, relu, fully-connected dense layer
    tf.keras.layers.Dense(128, activation='relu'),
    # 5. ouput = class (data), relu, fully-connected dense layer
    tf.keras.layers.Dense(10, activation='softmax')
])
```

2.3.b TF에서 모델을 작성하는 3가지 기본 구조

- Functional

```
# build a model (5 layers)
model = tf.keras.Sequential([
    # 1. filter(kernel channel) = 32, kernel = 3, relu, conv2d layer
    tf.keras.layers.Conv2D(32, 3, activation='relu'),
    # 2. filter = 64, kernel = 3, relu, conv2d layer
    tf.keras.layers.Conv2D(64, 3, activation='relu'),
    # 3. flatten layer
    tf.keras.layers.Flatten(),
    # 4. output = 128 nodes, relu, fully-connected dense layer
    tf.keras.layers.Dense(128, activation='relu'),
    # 5. ouput = class (data), relu, fully-connected dense layer
    tf.keras.layers.Dense(10, activation='softmax')
])
```

2.3.c TF에서 모델을 작성하는 3가지 기본 구조

- Subclassing

```
class MNISTModel(tf.keras.Model):
    def __init__(self):
        super(MNISTModel, self).__init__()
        # 1. filter(kernel channel) = 32, kernel = 3, relu, conv2d layer
        self.Conv2D1 = tf.keras.layers.Conv2D(32, 3, activation = 'relu')
        # 2. filter = 64, kernel = 3, relu, conv2d layer
        self.Conv2D2 = tf.keras.layers.Conv2D(64, 3, activation = 'relu')
        # 3. flatten layer
        self.Flatten = tf.keras.layers.Flatten()
        # 4. output = 128 nodes, relu, fully-connected dense layer
        self.Dense1 = tf.keras.layers.Dense(128, activation = 'relu')
        # 5. ouput = class (data), relu, fully-connected dense layer
        self.Dense2 = tf.keras.layers.Dense(10, activation = 'softmax')

    def call(self, x):
        x = self.Conv2D1(x)
        x = self.Conv2D2(x)
        x = self.Flatten(x)
        x = self.Dense1(x)
        x = self.Dense2(x)
        return x
```

2.4 가장 작은 것 부터 이해

```
def conv_block(layer, filters, activation='relu'):
    layer=Conv2D(filters, kernel_size=(3, 3),activation=activation,padding='same')(layer)
    layer=Conv2D(filters, kernel_size=(3, 3), activation=activation,padding='same')(layer)
    layer=MaxPooling2D(pool_size=(2, 2),padding='same')(layer)
    return layer
```

> ~~q1. 그런데 이 함수는 어떻게 동작하는 건가요?~~ => Functional
> q2. 이거 실행은 어떻게?

2.5 가장 작은 것 부터 실행

```
def conv_block(layer, filters, activation='relu'):
    layer=Conv2D(filters, kernel_size=(3, 3),activation=activation,padding='same')(layer)
    layer=Conv2D(filters, kernel_size=(3, 3), activation=activation,padding='same')(layer)
    layer=MaxPooling2D(pool_size=(2, 2),padding='same')(layer)
    return layer
```

> ~~q1. 그런데 이 함수는 어떻게 동작하는 건가요?~~ => Functional
>
> q2. 이거 실행은 어떻게? 예상되는 결과값은?

```
input=Input(shape=(31, 31, 1))
layer=conv_block(input, filters=117)
KerasTensor(type_spec=TensorSpec(shape=(None, 31, 31, 117), dtype=tf.float32, name=None), name='conv2d_7/Relu:0', description="created by layer 'conv2d_7'")
```

2.6.a 작은 구성요소가 반복적으로 사용

- 언제나 Input과 Output 부터

```python
# 초기값
feature = params['feature']
input_img = []
flat_layers = []
towers = []

for pos, input_i in enumerate(params['input_shapes']):
    if len(input_i) == 3:
        input_img.append(Input(shape=input_i, name='image_%i'%pos))
    else:
        flat_layers.append(Input(shape=input_i, name='flat_%i'%pos))
all_inputs = input_img+flat_layers
```

2.6.a 작은 구성요소가 반복적으로 사용

- 언제나 Input과 Output 부터

```
...
if params['optimizer'] == 'adam':
    optimizer = keras.optimizers.Adam(lr=params['lr'])
model.compile(loss=keras.losses.binary_crossentropy, optimizer=optimizer)
my_model = model
return my_model
```

2.7. 그렇다면 가장 간단한 예제를 선택

- 간단한 예제를 하나 선택(42977 x 7, hl)
- Input: Flatten(7)
- Dense + Dropout
- Dense + Dropout
- Dense + Dropout
- Dense + Dropout
- Dense
- Output: Dense(1)

> 전형적인 MLP

2.8 연결

```
x1   x2   x3
 \   /    /
   y1    /
     \  /
      y2

from keras.models import Model
from keras.layers import Dense, Input, concatenate

first_input = Input(shape=(2, ))
first_dense = Dense(1, )(first_input)

second_input = Input(shape=(2, ))
second_dense = Dense(1, )(second_input)

merge_one = concatenate([first_dense, second_dense])

third_input = Input(shape=(1, ))
merge_two = concatenate([merge_one, third_input])

model = Model(inputs=[first_input, second_input, third_input], outputs=merge_two)
```

2.9 레이어를 연결

```
if len(flat_layers) > 1:
    layer = keras.layers.concatenate(flat_layers, axis=-1)
else:
    layer = flat_layers[0]
```