

## 1.검증용CNN기초.ipynb

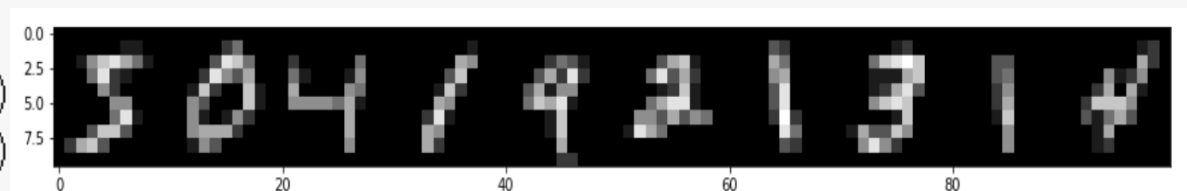
### 1. 텐서플로우 데이터셋의 흑백 28,28 손글씨 자료 50개를 갖고와서 CNN에 넣기 위하여 28,28,1로 변형

```
from tensorflow.keras import datasets, layers, models
(train_images, train_labels), (test_images, test_labels) = datasets.mnist.load_data()
```

```
train_images = train_images.reshape((60000, 28, 28, 1))[:50]
test_images = test_images.reshape((10000, 28, 28, 1))[:50]
train_labels=train_labels[:50]
test_labels=test_labels[:50]
```

### 2. 학습의 편의성을 위하여 50개 이미지를 높이, 너비를 10,10 으로 변경

```
from skimage.transform import resize
train_images = resize(train_images, (50,10, 10,1))
test_images = resize(train_images, (50,10, 10,1))
np.shape(train_images)
plt.imshow(np.hstack(train_images[:10]),cmap='gray')
```



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### 3. 계산검증의 편의성을 위하여 float를 int로 변경

```
pd.DataFrame(np.vstack(train_images[0]).reshape(10,10))
```

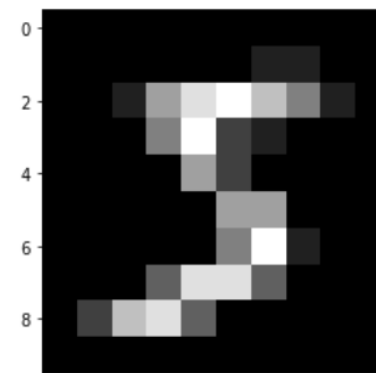
	0	1	2	3	4	5	6	7	8	9
0	0.000000	0.000000e+00	0.000000e+00	3.779813e-09	5.703982e-07	0.000004	1.042152e-05	0.000015	8.009369e-06	1.619335e-08
1	0.000000	3.493966e-07	7.807178e-04	7.999273e-03	2.619184e-02	0.059819	1.155171e-01	0.155306	7.679844e-02	1.519801e-04
2	0.000000	9.857660e-05	1.036307e-01	5.545328e-01	7.500384e-01	0.815209	6.413300e-01	0.491694	1.539254e-01	2.481732e-04
3	0.000000	2.617595e-05	5.656854e-02	4.300613e-01	8.046835e-01	0.233121	1.624373e-01	0.008346	1.218553e-03	5.837837e-07
4	0.000000	9.748591e-09	1.279662e-04	2.502775e-02	5.374982e-01	0.290856	3.380014e-02	0.000305	1.190274e-08	0.000000e+00
5	0.000000	0.000000e+00	6.266862e-09	2.610279e-04	6.696573e-02	0.564458	5.666593e-01	0.047100	1.411354e-05	0.000000e+00
6	0.000000	4.497760e-08	3.063738e-05	3.220381e-03	7.633813e-02	0.401042	8.656932e-01	0.157746	1.073702e-04	0.000000e+00
7	0.000008	5.200728e-03	7.889449e-02	3.434775e-01	7.748787e-01	0.739755	3.174749e-01	0.021589	2.289392e-06	0.000000e+00
8	0.000387	2.102920e-01	6.982965e-01	7.215174e-01	3.777502e-01	0.048582	1.853358e-03	0.000010	1.813034e-10	0.000000e+00
9	0.000029	1.430609e-02	3.384249e-02	1.997844e-02	1.852532e-03	0.000012	1.298005e-08	0.000000	0.000000e+00	0.000000e+00

```
train_images=(train_images*10).astype('int32')  
test_images=(test_images*10).astype('int32')  
pd.DataFrame(np.vstack(train_images[0]).reshape(10,10))
```

	0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	1	1	0	0
2	0	0	1	5	7	8	6	4	1	0
3	0	0	0	4	8	2	1	0	0	0
4	0	0	0	0	5	2	0	0	0	0
5	0	0	0	0	0	5	5	0	0	0
6	0	0	0	0	0	4	8	1	0	0
7	0	0	0	3	7	7	3	0	0	0
8	0	2	6	7	3	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0

	0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	1	1	0	0
2	0	0	1	5	7	8	6	4	1	0
3	0	0	0	4	8	2	1	0	0	0
4	0	0	0	0	5	2	0	0	0	0
5	0	0	0	0	0	5	5	0	0	0
6	0	0	0	0	0	4	8	1	0	0
7	0	0	0	3	7	7	3	0	0	0
8	0	2	6	7	3	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0

```
plt.imshow(train_images[0],  
           cmap='gray')
```



## 4. CNN 모델 제작

```
import tensorflow as tf
tf.random.set_seed(123)
model = models.Sequential()
model.add(layers.Conv2D(1, (3, 3), activation='relu', input_shape=(10, 10, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(2, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(2, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
```

.....> # output(10-3+1) → 8,8, 채널1  
 .....> # output( 4,4), 채널1  
 .....> # output( 4-3+1) → 2,2, 채널3  
 .....> # output( 2\*2\*3) --> 12  
 .....> # output( 2) , 총13\*2→26파라  
 .....> # output( 2) , 총13\*2→26파라

Model: "sequential\_11"

Layer (type)	Output Shape	Param #
conv2d_19 (Conv2D)	(None, 8, 8, 1)	10
max_pooling2d_8 (MaxPooling2D)	(None, 4, 4, 1)	0
conv2d_20 (Conv2D)	(None, 2, 2, 2)	20
flatten_10 (Flatten)	(None, 8)	0
dense_20 (Dense)	(None, 2)	18
dense_21 (Dense)	(None, 10)	30
Total params: 78		
Trainable params: 78		
Non-trainable params: 0		

1 import tensorflow as tf

2

3 get\_layer\_name = [layer.name for layer in model.layers]

4 get\_output = [layer.output for layer in model.layers]

5 get\_output

```
[<KerasTensor: shape=(None, 8, 8, 1) dtype=float32 (created by layer 'conv2d_19')>,
<KerasTensor: shape=(None, 4, 4, 1) dtype=float32 (created by layer 'max_pooling2d_8')>,
<KerasTensor: shape=(None, 2, 2, 2) dtype=float32 (created by layer 'conv2d_20')>,
<KerasTensor: shape=(None, 8) dtype=float32 (created by layer 'flatten_10')>,
<KerasTensor: shape=(None, 2) dtype=float32 (created by layer 'dense_20')>,
<KerasTensor: shape=(None, 10) dtype=float32 (created by layer 'dense_21')>]
```

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## 5. 모델 w값 setting

```
1 # 모델의 첫번째 레이어만 사용
2 visual_model = tf.keras.models.Model(inputs = model.input, outputs = get_output[0])
3 visual_model.summary()
4 test_img = np.expand_dims(test_images[0], axis = 0)
5 feature_maps = visual_model.predict(test_img)
```

0

Model: "model\_5"

Layer (type)	Output Shape	Param #
conv2d_6_input (InputLayer)	[(None, 10, 10, 1)]	0
conv2d_6 (Conv2D)	(None, 8, 8, 1)	10

Total params: 10  
Trainable params: 10  
Non-trainable params: 0

```
1 len(visual_model.get_weights()),w
2 visual_model.get_weights()[0],w
3 visual_model.get_weights()[1]
4
```

```
(2,
 array([[[[-0.4318703 ]],
          [[ 0.08380783]],
          [[-0.23193197]]],

        [[[ 0.05313462]],
          [[ 0.25442973]],
          [[ 0.33345792]]],

        [[[-0.22227043]],
          [[-0.02131751]],
          [[ 0.17737235]]], dtype=float32),
 array([0.00019932], dtype=float32))
```

```
import tensorflow as tf
tf.random.set_seed(123)
model = models.Sequential()
model.add(layers.Conv2D(1, (3, 3), activation='relu', input_shape=(10, 10, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(2, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(2, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
```

검증을 위하여 10,10,1을 input한 filter=1, kernel=3,3, stride=1,  
Padding 없음만 모델링하면  
10,10,1 => 8,8,1 로 출력됨

```
1 setW =np.array( [[-0.4318703, 0.08380783, -0.23193197],
2                  [0.05313462, 0.25442973, 0.33345792],
3                  [-0.22227043, -0.02131751, 0.17737235]])
4 setB= np.array([-0.00019932])
5
6
7 setW=setW.reshape(3,3,1,1)
8 weights =setW,setB
9 visual_model.set_weights(weights)
```

모델값 세팅

```
1 ### 검증을 위한 w,b값 출력
2 w=visual_model.get_weights()[0]
3 b=visual_model.get_weights()[1]
4 np.shape(w),np.vstack(w).reshape(3,3),b

((3, 3, 1, 1),
 array([[-0.4318703 ,  0.08380783, -0.23193197],
        [ 0.05313462,  0.25442973,  0.33345792],
        [-0.22227043, -0.02131751,  0.17737235]], dtype=float32),
 array([-0.00019932], dtype=float32))
```

레이어1개당 w,b 총2개

## 5. 모델 w값 setting

 $10 \times 10 \times 1$ 

```
1 ### 검증을 위한 w, b 값 출력
2 w=visual_model.get_weights()[0]
3 np.vstack(w).reshape(3,3)

array([[ -0.4318703 ,  0.08380783, -0.23193197],
       [ 0.05313462,  0.25442973,  0.33345792],
       [-0.22227043, -0.02131751,  0.17737235]], dtype=float32)
```

합성곱 최종 출력 괄호 빨간색은 음수값  
(relu함수에 의해서 0값으로 변경되어야함)

	0	1	2	3	4	5	6	7
0	0.1771730	0.8653449	0.9125492	0.1582048	(0.3289404)	(0.6088908)	(0.9341552)	(0.8574639)
1	0.3332586	2.6310094	4.9929982	4.0092682	2.5325703	2.6713052	1.0994523	0.0348986
2	(0.2321313)	0.2577803	2.9356898	(0.2653025)	(3.6310134)	(3.9638845)	(2.4349872)	(1.6438727)
3	(0.0001993)	(0.9279272)	0.1468658	1.3048444	(1.9646713)	(1.8918026)	(1.5434218)	(0.0001993)
4	(0.0001993)	(0.0001993)	(1.1598592)	2.3317549	2.2812119	(0.2083676)	(1.5340072)	(0.2224698)
5	(0.0001993)	0.5319177	1.1774546	0.5995451	1.7715637	(0.7789230)	(2.1468554)	0.0529353
6	1.0213998	1.6693350	2.1465672	1.7268447	0.9660892	(0.1539183)	(3.2119500)	(0.4320696)
7	2.5094077	3.2710578	1.7278900	(1.1974477)	(2.9730287)	(2.7718679)	(1.2958102)	(0.0001993)

[illegible][illegible][illegible][illegible][illegible][illegible][illegible][illegible]

## 6. 모델 결과 계산 (feature\_maps 계산)

test_images[0]									
0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0	0	0
0	0	1	0	8	6	4	1	0	0
0	0	0	4	8	2	1	0	0	0
0	0	0	0	5	2	0	0	0	0
0	0	0	0	0	5	5	0	0	0
0	0	0	0	0	4	8	1	0	0
0	0	0	3	7	7	3	0	0	0
0	2	6	7	3	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

1

w값 = 커널 3,3		
-0.4318703	0.0838078300	-0.2319319700
0.05313462	0.2544297300	0.33345792
-0.2222704	-0.0213175100	0.17737235

2

b값	
-0.00019932	

3

	0	1	2	3	4	5	6	7
0	0.1771730							
1								
2								
3								
4								
5								
6								
7								

```

1 # 파이썬에서 계산하여 봅니다.
2 wVal=np.vstack(w).reshape(3,3)
3 img=np.vstack(train_images[0]).reshape(10,10)
4 img[:3,:3]*wVal, np.sum(img[:3,:3]*wVal)+b

```

(array([[ -0. , 0. , -0. ],  
[ 0. , 0. , 0. ],  
[ -0. , -0. , 0.17737235]]),  
array([0.17717303], dtype=float32))

1번\*2번의합 + 3번

$0 \times -0.4318703 + 0 \times 0.08380783 + 0 \times -0.23193197 +$   
 $0 \times 0.05313462 + 0 \times 0.25442973 + 0 \times 0.33345792 +$   
 $0 \times -0.22227043 + 0 \times -0.02131751 + 1 \times 0.17737235 +$

+ -0.00019932

[0:3, 0:3] \* w값(커널3,3)

B값

## 6. 모델 결과 계산 (feature\_maps 계산)

	0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	1	1	0	0
2	0	0	1	5	7	8	6	4	1	0
3	0	0	0	4	8	2	1	0	0	0
4	0	0	0	0	5	2	0	0	0	0
5	0	0	0	0	0	5	5	0	0	0
6	0	0	0	0	0	4	8	1	0	0
7	0	0	0	3	7	7	3	0	0	0
8	0	2	6	7	3	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0

w값 = 커널 3,3		
-0.43187952	0.08381204	-0.23193252
0.05313142	0.2544299	0.3334544
-0.2222264	-0.02131628	0.1773645

b값
-0.00020013

## 빨간색 괄호는 - 값임

	0	1	2	3	4	5	6	7
0	0.1771730	0.8653449	0.9125492	0.1582048	(0.3289404)	(0.6088908)	(0.9341552)	(0.8574639)
1	0.3332586	2.6310094	4.9929982	4.0092682	2.5325703	2.6713052	1.0994523	0.0348986
2	(0.2321313)	0.2577803	2.9356898	(0.2653025)	(3.6310134)	(3.9638845)	(2.4349872)	(1.6438727)
3	(0.0001993)	(0.9279272)	0.1468658	1.3048444	(1.9646713)	(1.8918026)	(1.5434218)	(0.0001993)
4	(0.0001993)	(0.0001993)	(1.1598592)	2.3317549	2.2812119	(0.2083676)	(1.5340072)	(0.2224698)
5	(0.0001993)	0.5319177	1.1774546	0.5995451	1.7715637	(0.7789230)	(2.1468554)	0.0529353
6	1.0213998	1.6693350	2.1465672	1.7268447	0.9660892	(0.1539183)	(3.2119500)	(0.4320696)
7	2.5094077	3.2710578	1.7278900	(1.1974477)	(2.9730287)	(2.7718679)	(1.2958102)	(0.0001993)

```

1 # 파이썬에서 계산하여 봅니다.
2 wVal=np.vstack(w).reshape(3,3)
3 img=np.vstack(train_images[0]).reshape(10,10)
4 print('▶--- 0:3, 0:3 에서 스트라이드 1한 높이 0:3, 너비 1:4 인덱싱값 ')
5 print(img[0:3, 1:4])
6
7 print('\n▶-- img[0:3, 1:4] * w')
8 print(img[1:4,1:4]*wVal)
9
10 print('\n▶-- img[0:3, 1:4] * w의 합 + b')
11 np.sum(img[1:4,1:4]*wVal)+b

```

▶--- 0:3, 0:3 에서 스트라이드 1한 높이 0:3, 너비 1:4 인덱싱값

```

[[0 0 0]
 [0 0 0]
 [0 1 5]]

```

▶-- img[0:3, 1:4] \* w

```

[[-0.         0.         -0.         ]
 [ 0.         0.         0.         ]
 [-0.         -0.02131751  0.88686176]]

```

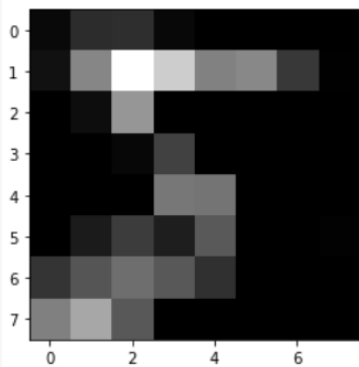
▶-- img[0:3, 1:4] \* w의 합 + b

```
array([0.86534494], dtype=float32)
```

## 7. 모델 최종값 계산- Relu 함수에 의해서 - 값은 0으로 변경됨

(10,10, 1) \* w 의 합 + b를  
스트라이드 1로한결과

	0	1	2	3	4	5	6	7
0	0.1771730	0.8653449	0.9125492	0.1582048	(0.3289404)	(0.6088908)	(0.9341552)	(0.8574639)
1	0.3332586	2.6310094	4.9929982	4.0092682	2.5325703	2.6713052	1.0994523	0.0348986
2	(0.2321313)	0.2577803	2.9356898	(0.2653025)	(3.6310134)	(3.9638845)	(2.4349872)	(1.6438727)
3	(0.0001993)	(0.9279272)	0.1468658	1.3048444	(1.9646713)	(1.8918026)	(1.5434218)	(0.0001993)
4	(0.0001993)	(0.0001993)	(1.1598592)	2.3317549	2.2812119	(0.2083676)	(1.5340072)	(0.2224698)
5	(0.0001993)	0.5319177	1.1774546	0.5995451	1.7715637	(0.7789230)	(2.1468554)	0.0529353
6	1.0213998	1.6693350	2.1465672	1.7268447	0.9660892	(0.1539183)	(3.2119500)	(0.4320696)
7	2.5094077	3.2710578	1.7278900	(1.1974477)	(2.9730287)	(2.7718679)	(1.2958102)	(0.0001993)



Relu 함수에 의해 <0 값은 0으로 치환한 결과  
pd.DataFrame(np.vstack(feature\_maps[0]).reshape(8,8))

```
1 ## 최종출력
2 len(feature_maps[0][0])
3 plt.imshow(feature_maps[0], cmap='gray')
4 pd.DataFrame(np.vstack(feature_maps[0]).reshape(8,8))
```

	0	1	2	3	4	5	6	7
0	0.177173	0.865345	0.912549	0.158205	0.000000	0.000000	0.000000	0.000000
1	0.333259	2.631009	4.992998	4.009268	2.532570	2.671305	1.099452	0.034899
2	0.000000	0.257780	2.935690	0.000000	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.146866	1.304844	0.000000	0.000000	0.000000	0.000000
4	0.000000	0.000000	0.000000	2.331755	2.281212	0.000000	0.000000	0.000000
5	0.000000	0.531918	1.177455	0.599545	1.771564	0.000000	0.000000	0.052935
6	1.021400	1.669335	2.146567	1.726845	0.966089	0.000000	0.000000	0.000000
7	2.509408	3.271058	1.727890	0.000000	0.000000	0.000000	0.000000	0.000000



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### 8. Pooling 값 확인: max pooling(2,2)는 2\*2의 4개의 자료중 가장 큰값을 꺼내는 값임 (stride는 pool값 2)

```
1 visual_model = tf.keras.models.Model(inputs = model.input, outputs = get_output[1])
2 visual_model.summary() # 28-3+1
3 test_img = np.expand_dims(test_images[0], axis = 0)
4 feature_maps = visual_model.predict(test_img)
```

Model: "model\_13"

Layer (type)	Output Shape	Param #
=====		
conv2d_17_input (InputLayer)	[(None, 10, 10, 1)]	0
=====		
conv2d_17 (Conv2D)	(None, 8, 8, 1)	10
=====		
max_pooling2d_7 (MaxPooling2)	(None, 4, 4, 1)	0
=====		

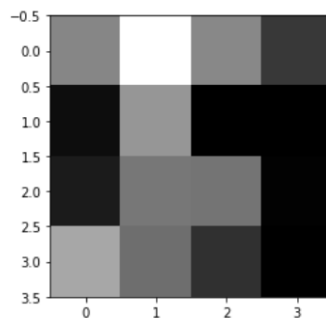
Total params: 10

Trainable params: 10

Non-trainable params: 0

	0	1	2	3	4	5	6	7
0	0.1771730	0.8653449	0.9125492	0.1582048	0.0000000	0.0000000	0.0000000	0.0000000
1	0.3332586	2.6310094	4.9929982	4.0092682	2.5325703	2.6713052	1.0994523	0.0348986
2	0.0000000	0.2577803	2.9356898	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000
3	0.0000000	0.0000000	0.1468658	1.3048444	0.0000000	0.0000000	0.0000000	0.0000000
4	0.0000000	0.0000000	0.0000000	2.3317549	2.2812119	0.0000000	0.0000000	0.0000000
5	0.0000000	0.5319177	1.1774546	0.5995451	1.7715637	0.0000000	0.0000000	0.0529353
6	1.0213998	1.6693350	2.1465672	1.7268447	0.9660892	0.0000000	0.0000000	0.0000000
7	2.5094077	3.2710578	1.7278900	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000

```
1 plt.imshow(feature_maps[0],cmap='gray')
2 plt.show()
3 pd.DataFrame(np.vstack(feature_maps[0]).reshape(4,4))
```



	0	1	2	3
0	2.631009	4.992998	2.671305	1.099452
1	0.257780	2.935690	0.000000	0.000000
2	0.531918	2.331755	2.281212	0.052935
3	3.271058	2.146567	0.966089	0.000000

## 9. Layer2번층 : 풀링층을 거친 자료를 다시 Conv2d할때

```

1 print(len(visual_model.get_weights()))
2 w=visual_model.get_weights()[0]
3 b=visual_model.get_weights()[1]
4 print(np.vstack(w).reshape(3,3),b)
5 print(np.shape(w), np.shape(b))
6 print('-'*100)
7 w=visual_model.get_weights()[2]
8 b=visual_model.get_weights()[3]
9 print(w,b)

```

```

4
[[-0.4318703  0.08380783 -0.23193197]
 [ 0.05313462  0.25442973  0.33345792]
 [-0.22227043 -0.02131751  0.17737235]] [-0.00019932]
(3, 3, 1, 1) (1,)

```

```

[[[[ 0.3674009 -0.35492098]]
  [[ 0.25632307  0.17448828]]
  [[ 0.13600942 -0.39838392]]]]

```

```

[[[ 0.2362543  0.11793062]]
 [[-0.46411705  0.05063149]]
 [[ 0.31956223 -0.05979198]]]

```

```

[[[ 0.43049613  0.24405327]]
 [[ 0.37376186 -0.05215767]]
 [[-0.1655781 -0.14671475]]] [0. 0.]

```

레이어의 일부  
분만 값을 세  
팅할수도 있음

```

1 setW =np.array( [[-0.4318703, 0.08380783, -0.23193197],
2                  [0.05313462, 0.25442973, 0.33345792],
3                  [-0.22227043, -0.02131751, 0.17737235]])
4 setB= np.array([-0.00019932])
5
6 w2=visual_model.get_weights()[2]
7 b2=visual_model.get_weights()[3]
8 setW=setW.reshape(3,3,1,1)
9
10 weights =[setW,setB,w2,b2]
11 visual_model.set_weights(weights)

```

```

1 len(visual_model.get_weights())
2 w=visual_model.get_weights()[2]
3 w, b

```

```

(array([[[[ 0.3674009 , -0.35492098]],
         [[ 0.25632307,  0.17448828]],
         [[ 0.13600942, -0.39838392]]]],

```

```

[[[ 0.2362543 ,  0.11793062]],
 [[-0.46411705,  0.05063149]],
 [[ 0.31956223, -0.05979198]]],

```

```

[[[ 0.43049613,  0.24405327]],
 [[ 0.37376186, -0.05215767]],

```

```

[[-0.1655781 , -0.14671475]]], dtype=float32),
array([0., 0.], dtype=float32))

```

## 1.검증용CNN기초.ipynb

### 9. Layer2번층 : 풀링층을 거친 자료를 다시 Conv2d할때

```
1 # maxpooling을 거쳐 나온값인 maxpoolResult값하고 3,3 씩 곱하기함
2 maxpoolResult
```

```
array([[2.6310093 , 4.992998 , 2.6713052 , 1.0994523 ],
       [0.2577803 , 2.93569 , 0. , 0. ],
       [0.53191775, 2.331755 , 2.2812119 , 0.0529353 ],
       [3.2710578 , 2.146567 , 0.9660892 , 0. ]], dtype=float32)
```

```
1 ### 전체 w,b값 확인
2 visual_model.get_weights()
```

```
[array([[[[-0.4318703 ],
          [[ 0.06380783]],
          [[-0.23193197]]],
        [[[-0.05313462]],
          [[ 0.25442973]],
          [[ 0.33345792]]],
        [[[-0.22227043]],
          [[-0.02131751]],
          [[ 0.17737235]]], dtype=float32),
 array([[-0.00019932], dtype=float32),
 array([[[[ 0.3674009 , -0.35492098]],
          [[ 0.25632307, 0.17448828]],
          [[ 0.11793062, -0.05979198]]],
        [[[-0.46411705, 0.05063149]],
          [[ 0.31956223, -0.05979198]]],
        [[[-0.43049613, 0.24405327]],
          [[ 0.37376186, -0.05215767]],
          [[-0.1655781 , -0.14671475]]], dtype=float32),
 array([0. , 0.], dtype=float32)]
```

Layer0  
3,(10,10,1)

Layer1  
2,(2,2,3)

```
1 f1=w[:, :, :, 0]
2 f2=w[:, :, :, 1]
3
4 print('maxpoolResult 값')
5 print(maxpoolResult[:3,:3])
6 print('\n▶피쳐1값', '-'*100, )
7 print(f1.reshape(3,3))
8 print('\n▶피쳐2값', '-'*100, )
9 print(f2.reshape(3,3))
10
11 print('\n▶[0:3,0:3]*피쳐1값+b[0]합', '-'*50)
12 np.sum(maxpoolResult[:3,:3]*f1.reshape(3,3))+b[0],#
13 np.sum(maxpoolResult[:3,:3]*f2.reshape(3,3))+b[0]
```

maxpoolResult 값  
[[2.6310093 4.992998 2.6713052 ]  
 [0.2577803 2.93569 0. ]  
 [0.53191775 2.331755 2.2812119 ]]

▶피쳐1값 -----  
[[ 0.3674009 0.25632307 0.13600942]  
 [ 0.2362543 -0.46411705 0.31956223]  
 [ 0.43049613 0.37376186 -0.1655781 ]]

▶피쳐2값 -----  
[[-0.35492098 0.17448828 -0.39838392]  
 [ 0.11793062 0.05063149 -0.05979198]  
 [ 0.24405327 -0.05215767 -0.14671475]]

▶[0:3,0:3]\*피쳐1값+b[0]합 -----  
(2.0309672, -1.2742374)

## 1.검증용CNN기초.ipynb

### 9. Layer2번층 : 풀링층을 거친 자료를 다시 Conv2d할때

```
1 f1=w[:, :, :, 0]
2 f2=w[:, :, :, 1]
3
4 print('maxpoolResult 값')
5 print(maxpoolResult[:, :, 3])
6 print('\n▶피쳐1값', '-'*100, )
7 print(f1.reshape(3,3))
8 print('\n▶피쳐2값', '-'*100, )
9 print(f2.reshape(3,3))
10
11 print('\n▶[0:3,0:3]*피쳐1값+b[0]합', '-'*50)
12 print(np.sum(maxpoolResult[:, :, 3]*f1.reshape(3,3))+b[0])
13
14 print('\n▶[0:3,0:3]*피쳐2값+b[1]합', '-'*50)
15 print(np.sum(maxpoolResult[:, :, 3]*f2.reshape(3,3))+b[1])
```

```
maxpoolResult 값
[[2.6310093  4.992998  2.6713052 ]
 [0.2577803  2.93569   0.          ]
 [0.53191775 2.331755  2.2812119 ]]
```

```
▶피쳐1값 -----
[[ 0.3674009  0.25632307  0.13600942]
 [ 0.2362543 -0.46411705  0.31956223]
 [ 0.43049613  0.37376186 -0.1655781 ]]
```

```
▶피쳐2값 -----
[[-0.35492098  0.17448828 -0.39838392]
 [ 0.11793062  0.05063149 -0.05979198]
 [ 0.24405327 -0.05215767 -0.14671475]]
```

```
▶[0:3,0:3]*피쳐1값+b[0]합 -----
2.0309672
```

```
▶[0:3,0:3]*피쳐2값+b[1]합 -----
-1.2742374
```

	0	1	2	3	필터1 커널사이즈 3*3			결과	
0	2.631009	4.992998	2.671305	.099452	0.3674009	0.256323	0.13600942	2.030967	5.209931
1	0.257780	2.935690	0.000000	0.000000	0.2362543	-0.46412	0.31956223	2.670163022	1.872805
2	0.531918	2.331755	2.281212	0.052935	0.43049613	0.373762	-0.1655781		
3	3.271058	2.146567	0.966089	0.000000	bias	0			

필터2 커널사이즈 3*3			결과	
-0.35492098	0.174488	-0.3983839	-1.274237336	-0.95548
0.11793062	0.050631	-0.059792	1.009756132	-0.18113
0.24405327	-0.05216	-0.1467148		
bias	0			

Relu함수 적용  
<0작아서 0으로 됨

```
1 feature_maps
array([[ 2.0309675,  0.          ],
       [ 5.2099314,  0.          ]],
      dtype=float32)
```

```
[[2.6701632, 1.0097562],
 [1.8728051, 0.          ]]]], dtype=float32)
```

## 1.검증용CNN기초.ipynb

### 9. Layer2번층 : 풀링층을 거친 자료를 다시 Conv2d할때

```
1 f1=w[:, :, :, 0]
2 f2=w[:, :, :, 1]
3
4 print('maxpoolResult 값')
5 print(maxpoolResult[0:3, 1:4])
6 print('\n▶ 피쳐1값', '-' * 100, )
7 print(f1.reshape(3,3))
8 print('\n▶ 피쳐2값', '-' * 100, )
9 print(f2.reshape(3,3))
10
11 print('\n▶ [0:3, 0:3] * 피쳐1값 + b[0] 합', '-' * 50)
12 print(np.sum(maxpoolResult[0:3, 1:4] * f1.reshape(3,3)) + b[0])
13
14 print('\n▶ [0:3, 0:3] * 피쳐2값 + b[1] 합', '-' * 50)
15 print(np.sum(maxpoolResult[0:3, 1:4] * f2.reshape(3,3)) + b[0])
```

```
maxpoolResult 값
[[4.992998  2.6713052 1.0994523]
 [2.93569   0.         0.         ]
 [2.331755  2.2812119 0.0529353]]
```

```
▶ 피쳐1값 -----
[[ 0.3674009  0.25632307 0.13600942]
 [ 0.2362543 -0.46411705 0.31956223]
 [ 0.43049613 0.37376186 -0.1655781 ]]
```

```
▶ 피쳐2값 -----
[[ 0.3674009  0.25632307 0.13600942]
 [ 0.2362543 -0.46411705 0.31956223]
 [ 0.43049613 0.37376186 -0.1655781 ]]
```

```
▶ [0:3, 0:3] * 피쳐1값 + b[0] 합 -----
5.2099314
```

```
▶ [0:3, 0:3] * 피쳐2값 + b[1] 합 -----
-0.9554814
```

	0	1	2	3	필터1 커널사이즈 3*3	결과
0	2.631009	4.992998	2.671305	1.099452	0.3674009 0.256323 0.13600942	2.030967392 <b>5.209931</b>
1	0.257780	2.935690	0.000000	0.000000	0.2362543 -0.46412 0.31956223	2.670163022 1.872805149
2	0.531918	2.331755	2.281212	0.052935	0.43049613 0.373762 -0.1655781	
3	3.271058	2.146567	0.966089	0.000000	bias 0	

필터2

커널사이즈 3*3		
-0.35492098	0.174488	-0.3983839
0.11793062	0.050631	-0.059792
0.24405327	-0.05216	-0.1467148
bias	0	

결과	
-1.27423734	-0.955481
1.009756132	-0.181128754

<0  
→ 0으로 됨

1 feature\_maps

```
array([[[[2.0309675, 0.         ],
          [5.2099314, 0.         ]],
```

```
        [[2.6701632, 1.0097562],
          [1.8728051, 0.         ]]]], dtype=float32)
```

## 1.검증용CNN기초.ipynb

### 9. Layer2번층 : 풀링층을 거친 자료를 다시 Conv2d할때

```
1 f1=w[:, :, :, 0]
2 f2=w[:, :, :, 1]
3
4 print('maxpoolResult 값')
5 print(maxpoolResult[1:4, 0:3])
6 print('\n▶ 피쳐1값', '-' * 100, )
7 print(f1.reshape(3, 3))
8 print('\n▶ 피쳐2값', '-' * 100, )
9 print(f2.reshape(3, 3))
10
11
12 print('\n▶ [0:3, 0:3]*피쳐1값+b[0] 합', '-' * 50)
13 print(np.sum(maxpoolResult[1:4, 0:3]*f1.reshape(3, 3))+b[0])
14
15 print('\n▶ [0:3, 0:3]*피쳐2값+b[1] 합', '-' * 50)
16 print(np.sum(maxpoolResult[1:4, 0:3]*f2.reshape(3, 3))+b[1])
```

```
maxpoolResult 값
[[0.2577803  2.93569  0.          ]
 [0.53191775 2.331755  2.2812119 ]
 [3.2710578  2.146567  0.9660892 ]]
```

```
▶ 피쳐1값 -----
[[ 0.3674009  0.25632307  0.13600942]
 [ 0.2362543 -0.46411705  0.31956223]
 [ 0.43049613  0.37376186 -0.1655781 ]]
```

```
▶ 피쳐2값 -----
[[-0.35492098  0.17448828 -0.39838392]
 [ 0.11793062  0.05063149 -0.05979198]
 [ 0.24405327 -0.05215767 -0.14671475]]
```

```
▶ [0:3, 0:3]*피쳐1값+b[0] 합 -----
2.6701632
```

```
▶ [0:3, 0:3]*피쳐2값+b[1] 합 -----
1.0097562
```

	0	1	2	3	필터1 커널사이즈 3*3			결과	
0	2.631009	4.992998	2.671305	1.099452	0.3674009	0.256323	0.13600942	2.030967392	5.209930882
1	0.257780	2.935690	0.000000	0.000000	0.2362543	-0.46412	0.31956223	2.670163	1.872805149
2	0.531918	2.331755	2.281212	0.052935	0.43049613	0.373762	-0.1655781		
3	3.271058	2.146567	0.966089	0.000000	bias	0			

	필터2 커널사이즈 3*3			결과	
	-0.35492098	0.174488	-0.3983839	-1.27423734	-0.955481445
	0.11793062	0.050631	-0.059792	1.009756	-0.181128754
	0.24405327	-0.05216	-0.1467148		
	bias	0			

```
1 feature_maps
array([[[[2.0309675, 0.          ],
         [5.2099314, 0.          ]],
       [[2.6701632, 1.0097562],
         [1.8728051, 0.          ]]]], dtype=float32)
```

# 1.검증용CNN기초.ipynb

## 9. Layer2번층 : 풀링층을 거친 자료를 다시 Conv2d할때

```

1 f1=w[:, :, :, 0]
2 f2=w[:, :, :, 1]
3
4 print('maxpoolResult 값')
5 print(maxpoolResult[1:4,1:4])
6 print('\n▶피쳐1값', '-'*100, )
7 print(f1.reshape(3,3))
8 print('\n▶피쳐2값', '-'*100, )
9 print(f1.reshape(3,3))
10
11 print('\n▶[0:3,0:3]*피쳐1값+b[0]할', '-'*50)
12 print(np.sum(maxpoolResult[1:4,1:4]*f1.reshape(3,3))+b[0])
13
14 print('\n▶[0:3,0:3]*피쳐2값+b[1]할', '-'*50)
15 np.sum(maxpoolResult[1:4,1:4]*f2.reshape(3,3))+b[0]

```

```

maxpoolResult 값
[[2.93569  0.         0.         ]
 [2.331755  2.2812119 0.0529353]
 [2.146567  0.9660892 0.         ]]

```

```

▶피쳐1값 -----
[[ 0.3674009  0.25632307 0.13600942]
 [ 0.2362543 -0.46411705 0.31956223]
 [ 0.43049613 0.37376186 -0.1655781 ]]

```

```

▶피쳐2값 -----
[[ 0.3674009  0.25632307 0.13600942]
 [ 0.2362543 -0.46411705 0.31956223]
 [ 0.43049613 0.37376186 -0.1655781 ]]

```

```

▶[0:3,0:3]*피쳐1값+b[0]할 -----
1.8728052

```

```

▶[0:3,0:3]*피쳐2값+b[1]할 -----
-0.1811288

```

	0	1	2	3	필터1		
					커널사이즈 3*3		결과
0	2.631009	4.992998	2.671305	1.099452	0.3674009	0.256323	0.13600942
1	0.257780	2.935690	0.000000	0.000000	0.2362543	-0.46412	0.31956223
2	0.531918	2.331755	2.281212	0.052935	0.43049613	0.373762	-0.1655781
3	3.271058	2.146567	0.966089	0.000000	bias	0	
							2.030967392
							5.209930882
							2.670163022
							1.872805

			필터2		
			커널사이즈 3*3		결과
			-0.35492098	0.174488	-0.3983839
			0.11793062	0.050631	-0.059792
			0.24405327	-0.05216	-0.1467148
			bias	0	
					-1.27423734
					-0.955481445
					1.009756132
					-0.181129

<0  
→ 0으로 됨

```

1 feature_maps
array([[[[2.0309675, 0.         ],
         [5.2099314, 0.         ]],
       [[2.6701632, 1.0097562],
         [1.8728051, 0.         ]]]], dtype=float32)

```

## 8. flatten()

1 feature\_maps

```
array([[[[2.0309675, 0.      ],
          [5.2099314, 0.      ]],

        [[2.6701632, 1.0097562],
          [1.8728051, 0.      ]]]], dtype=float32)
```

4]:

```
1 ###
2 visual_model = tf.keras.models.Model(inputs = model.input, outputs = get_output[3])
3 visual_model.summary()
4 test_img = np.expand_dims(test_images[0], axis = 0)
5 feature_maps = visual_model.predict(test_img)
6
```

Model: "model\_10"

Layer (type)	Output Shape	Param #
-----		
conv2d_6_input (InputLayer)	[(None, 10, 10, 1)]	0
conv2d_6 (Conv2D)	(None, 8, 8, 1)	10
max_pooling2d_3 (MaxPooling2)	(None, 4, 4, 1)	0
conv2d_7 (Conv2D)	(None, 2, 2, 2)	20
flatten_3 (Flatten)	(None, 8)	0
=====		

Total params: 30  
 Trainable params: 30  
 Non-trainable params: 0

5]: 1 len(visual\_model.get\_weights())

5]: 4

7]: 1 feature\_maps

```
7]: array([[2.0309675, 0.      , 5.2099314, 0.      , 2.6701632, 1.0097562,
           1.8728051, 0.      ]], dtype=float32)
```



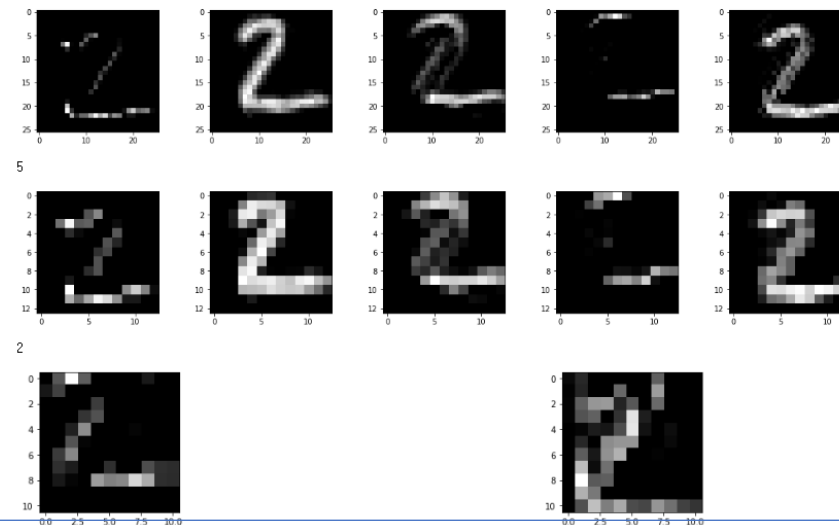
## 2. CNN 레이어별 출력물 확인.ipynb

### 활성화함수에 따른 결과 확인

```
1 model = models.Sequential()
2 model.add(layers.Conv2D(5, (3, 3), activation='relu', input_shape=(28, 28, 1)))
3 model.add(layers.MaxPooling2D((2, 2)))
4 model.add(layers.Conv2D(2, (3, 3), activation='relu'))
5
6 model.add(layers.Flatten())
7 model.add(layers.Dense(2, activation='relu'))
8 model.add(layers.Dense(10, activation='softmax'))
9
10
11 get_layer_name = [layer.name for layer in model.layers]
12 get_output = [layer.output for layer in model.layers]
13 get_output
```

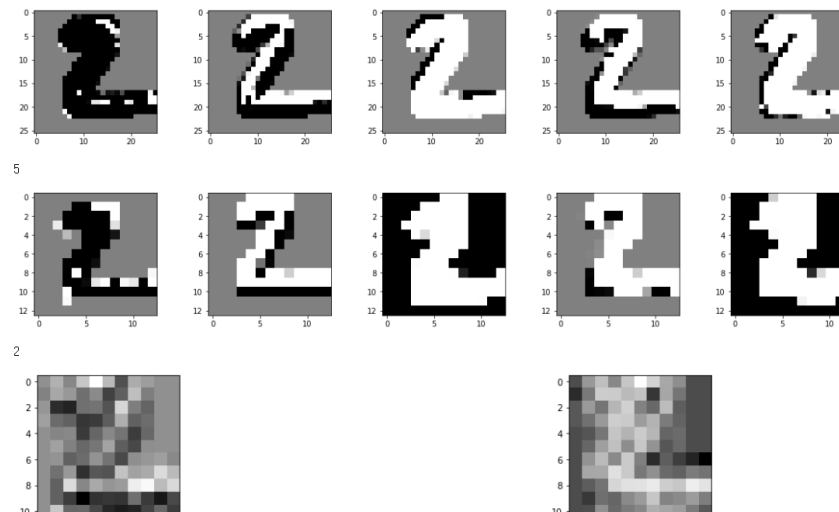
relu

<Figure size 1080x216 with 0 Axes>



```
1 model = models.Sequential()
2 model.add(layers.Conv2D(5, (3, 3), activation='sigmoid', input_shape=(28, 28, 1)))
3 model.add(layers.MaxPooling2D((2, 2)))
4 model.add(layers.Conv2D(2, (3, 3), activation='sigmoid'))
5
6 model.add(layers.Flatten())
7 model.add(layers.Dense(2, activation='sigmoid'))
8 model.add(layers.Dense(10, activation='softmax'))
9
10
11 get_layer_name = [layer.name for layer in model.layers]
12 get_output = [layer.output for layer in model.layers]
13 get_output
```

sigmoid



## 2. CNN 레이어별 출력물 확인.ipynb

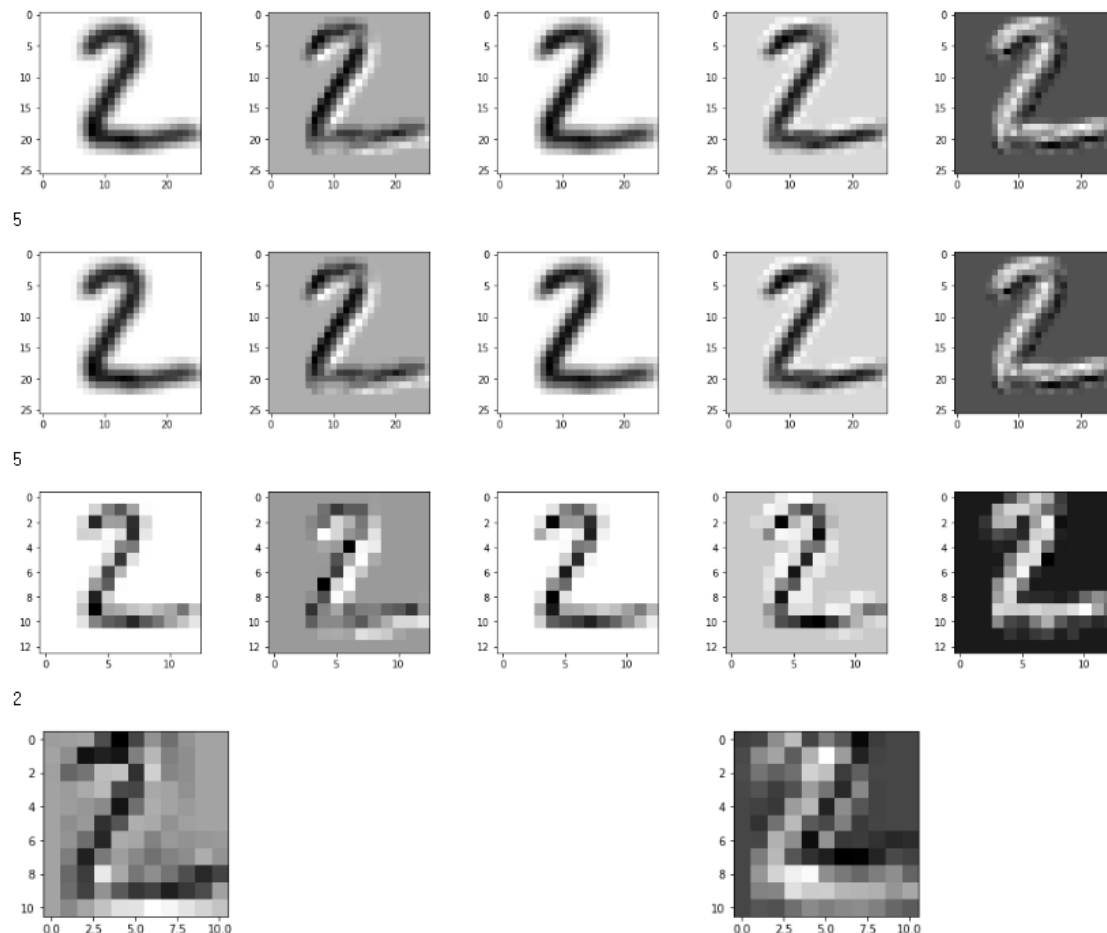
### 활성화함수에 따른 결과 확인

```
2 model = models.Sequential()
3 model.add(layers.Conv2D(5, (3, 3), input_shape=(28, 28, 1)))
4 model.add(layers.LeakyReLU(1))
5 model.add(layers.MaxPooling2D((2, 2)))
6 model.add(layers.Conv2D(2, (3, 3)))
7 model.add(layers.LeakyReLU())
8
9 model.add(layers.Flatten())
10 model.add(layers.Dense(2, activation='relu'))
11 #model.add(layers.LeakyReLU())
12 model.add(layers.Dense(10, activation='softmax'))
13
14 model.summary()
```

Model: "sequential\_48"

Layer (type)	Output Shape	Param #
conv2d_95 (Conv2D)	(None, 26, 26, 5)	50
leaky_re_lu_36 (LeakyReLU)	(None, 26, 26, 5)	0
max_pooling2d_47 (MaxPooling)	(None, 13, 13, 5)	0
conv2d_96 (Conv2D)	(None, 11, 11, 2)	92
leaky_re_lu_37 (LeakyReLU)	(None, 11, 11, 2)	0
flatten_47 (Flatten)	(None, 242)	0
dense_91 (Dense)	(None, 2)	486
dense_92 (Dense)	(None, 10)	30

Total params: 658  
Trainable params: 658  
Non-trainable params: 0



# 생성신경망에 필요한 기초지식

**확률분포 개념**    딥러닝 이야기를 꺼내기 전에 확률분포가 무엇인지를 알아보도록 하겠습니다! '확률분포(probability distribution)'는 확률 변수가 특정한 값을 가질 확률을 나타내는 함수를 의미함.  
가장 쉬운 예로는 주사위를 던지는 상황이 있습니다. 여기서 확률변수  $X$ 는 주사위를 던져 나올 수 있는 눈의 수로, 1부터 6까지의 자연수임. 그리고 각각의 확률변수 값이 나올 확률이 존재하는데, 이 경우에는 모두 1/6로 동일합니다.

주사위를 던졌을 때 6번 중에서 다음과 같은 횟수의 숫자가 나왔다고 하자.

X	1	2	3	4	5	6
P(X)	1/6	1/6	1/6	0/6	0/6	3/6

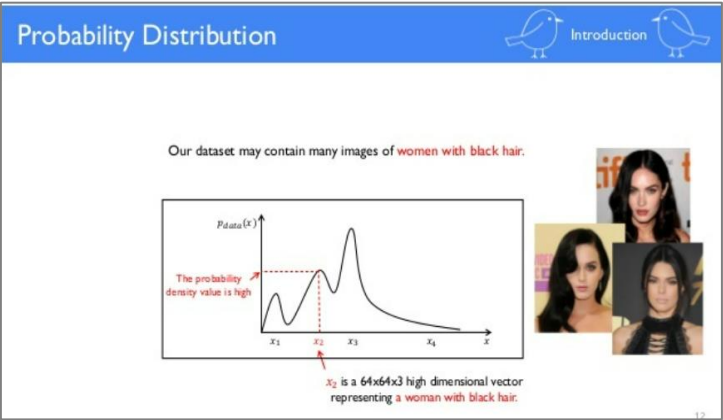
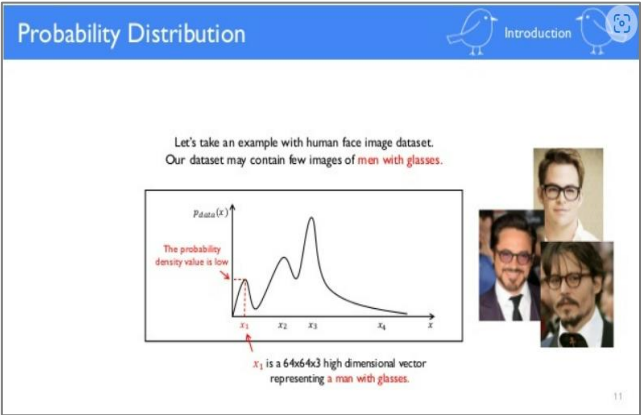
이를 그래프로 표현한다면, 이 비슷한 그림이 나올 것이다.

이산형확률분포

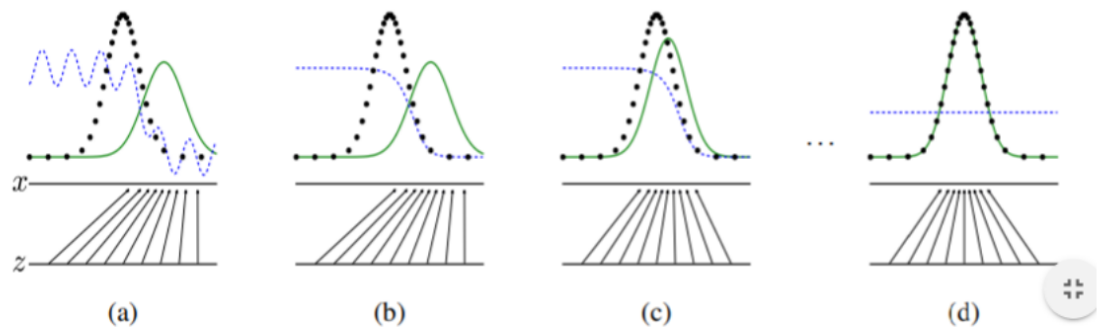
연속형확률분포

주사위의 눈과 같이 확률변수  $X$ 가 이산적으로 나타나는 확률분포를 우리는 이산형 확률분포, 또는 확률질량함수라고 함  
키, 몸무게와 같은 데이터는 이산형으로 나타내기가 어렵습니다. 이런 데이터를 나타내는 확률분포를 연속형 확률분포, 또는 '확률 밀도 함수 ' 라고 함.

GAN에는 기본적으로 Generator와 Discriminator, 2개의 네트워크가 존재하며 그 중 확률분포와 관련이 있는 모델은 바로 Generator(생성자) 임



# 생성신경망에 필요한 기초



검정 점선이 학습 데이터의 분포를, 초록 실선이 모델의 분포를 나타냅니다.

학습이 되지 않은 상태(a)의 generator는  $z$ 를  $x$ 와 같이 실제 데이터셋에 거의 존재하지 않는 사진으로 만들어냅니다. Discriminator의 피드백을 받으며 점차 generator는 실제 데이터 셋에 존재하는 사진들을 만들어냅니다.

$$\min_G \max_D V(D, G) = \underbrace{\mathbb{E}_{x \sim p_{data}(x)} [\log D(x)]}_{\text{생성자 (generator)}} + \underbrace{\mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]}_{\text{판별자 (Discriminator)}}$$

좋아! 이제 앞서 정의한 **minimax problem**을 잘 풀기만 하면 (즉, **global optimal**을 찾으면), generator가 만드는 **probability distribution( $p_g$ )**이 **data distribution( $p_{data}$ )**과 정확히 일치하도록 할 수 있다는 것을 알았습니다. 결국, Generator로 부터 뽑은 sample을 Discriminator가 실제와 구별할 수 없게 된다는 것이죠.

다만, "**어떤 모델**을 사용하고 **어떤 알고리즘**을 사용해야 이 문제를 **"잘"** 풀어줄 것이냐?"는 또 별개의 문제인데...