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Machine Learning Analysis
Feature Extraction

GyeongYeong, Kim

ML/DL Lab 2nd Day

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- Keras Model Analysis
  - Callback
  - History Confirmation
  - Wrong Sample Confirmation
  - Confusion Matrix
- Feature Extraction
  - CNN / Pooling Layer
  - Batch Normalization / DropOut
- Pytorch Feature Extraction
  - CNN / Pooling Layer
  - Batch Normalization / DropOut
  - Best Model Saving
  - History Confirmation
  - Confusion Matrix
  - Wrong Sample Confirmation
  - Early Stopping

Keras Callbacks

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- Keras Callbacks : 학습 이슈을 분석하거나 조정할 때 쓰이는 학습 보조기능

ModelCheckpoint : 학습 도중 모델 저장

TerminateOnNaN : NaN 손실이 발생했을 때 학습을 종료

RemoteMonitor : 이벤트를 서버에 스트림

LearningRateScheduler : 학습속도에 대해 스케쥴을 짬

EarlyStopping : 학습 양상을 보고 학습을 조기에 종료(Overfitting 방지)

Tensorboard : 텐서보드로 그래프를 확인할 수 있도록 학습 양상을 기록(동적 그래프나 활성화 히스토그램 시각화)

ReduceLROnPlateau : 측정 항목이 향상되지 않는 경우 학습속도를 줄임

구체적 내용 : https://keras.io/api/callbacks/

Model Checkpoint

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Model Checkpoint : 케라스의 모델(혹은 weight)를 규칙에 따라 저장하는 콜백

- file_path : 모델 저장 경로
- monitor(metric) /save_best_only(True/False) : 모니터할 metric 설정 및 이에 따른 높은 성능의 모델을 저장
- mode (auto/min/max) : 모니터할 metric의 최대나 최소 중 선택(acc는 max, loss는 min)
- Initial_value_threshold : 모니터할 최소/최대 기준값
- save_freq(int) : 저장할 주기(epoch 기준으로 설정)
- verbose(0/1/2) : 콜백이 적용될 시 표출할 모드
- (save_weight_only : full model의 저장 대신 weight만 저장)

```
checkpointer = ModelCheckpoint(filepath=model_name_path,
                               monitor='val_accuracy',
                               verbose=0,
                               save_best_only=True)
```

Early Stopping

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Keras Callbacks : 학습 이슈을 분석하거나 조정할 때 쓰이는 학습 보조기능

- monitor(metric) : 모니터할 기준
- patience(int) : 학습 개선이 없어 학습을 멈출 최소 epoch 기준
- verbose(0/1/2) : 콜백이 적용될 시 표출할 모드
- mode(auto/min/max) : monitor metric을 결정하는 기준
- baseline : 모니터하는 데에 있어서의 베이스라인 값
- restore_best_weights(True/False) : 가장 좋은 성능으로 저장할지 안할지 설정

```
earlystopper = EarlyStopping(monitor='val_accuracy',
                             patience=5,
                             verbose=0,
                             mode='auto')
```

TensorBoard

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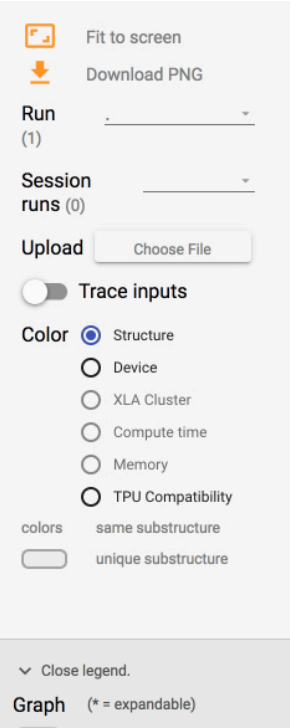
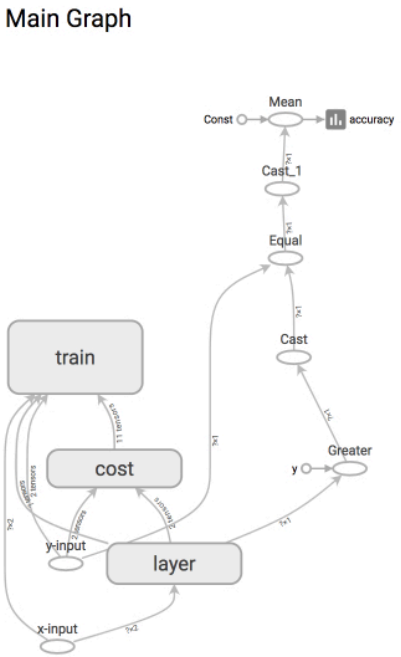
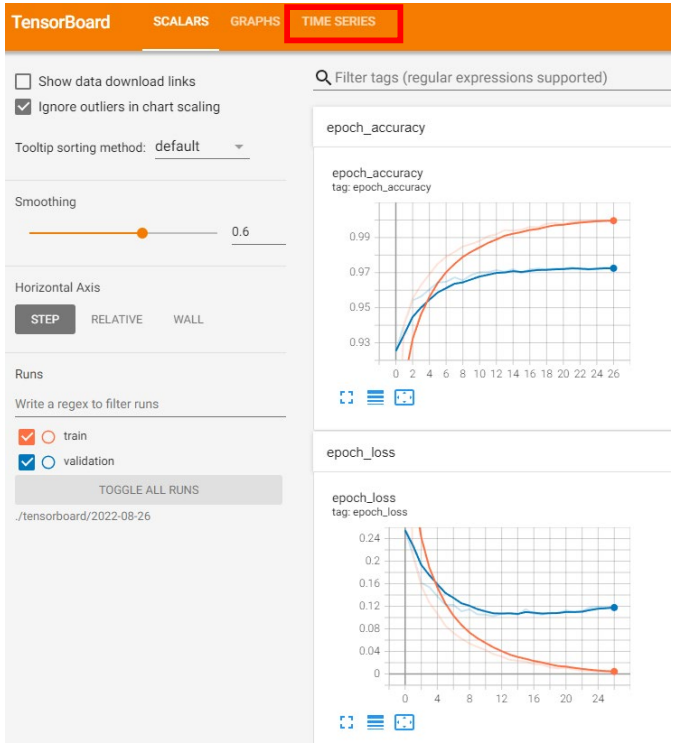
- Keras Callbacks 중 하나 : 시각화 도구로 활용됨

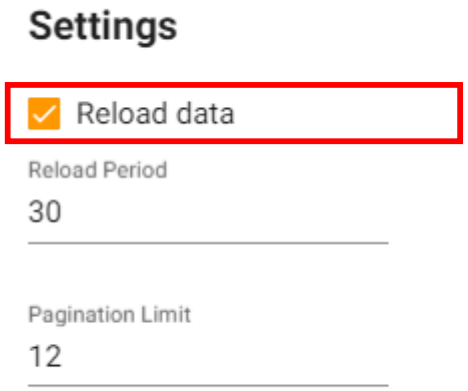
```
tb_saver = TensorBoard(log_dir=tensorboard_path,
                       write_graph=True)
```

- 실시간 업데이트 확인 가능 : Time Series 탭 내 Settings로 확인



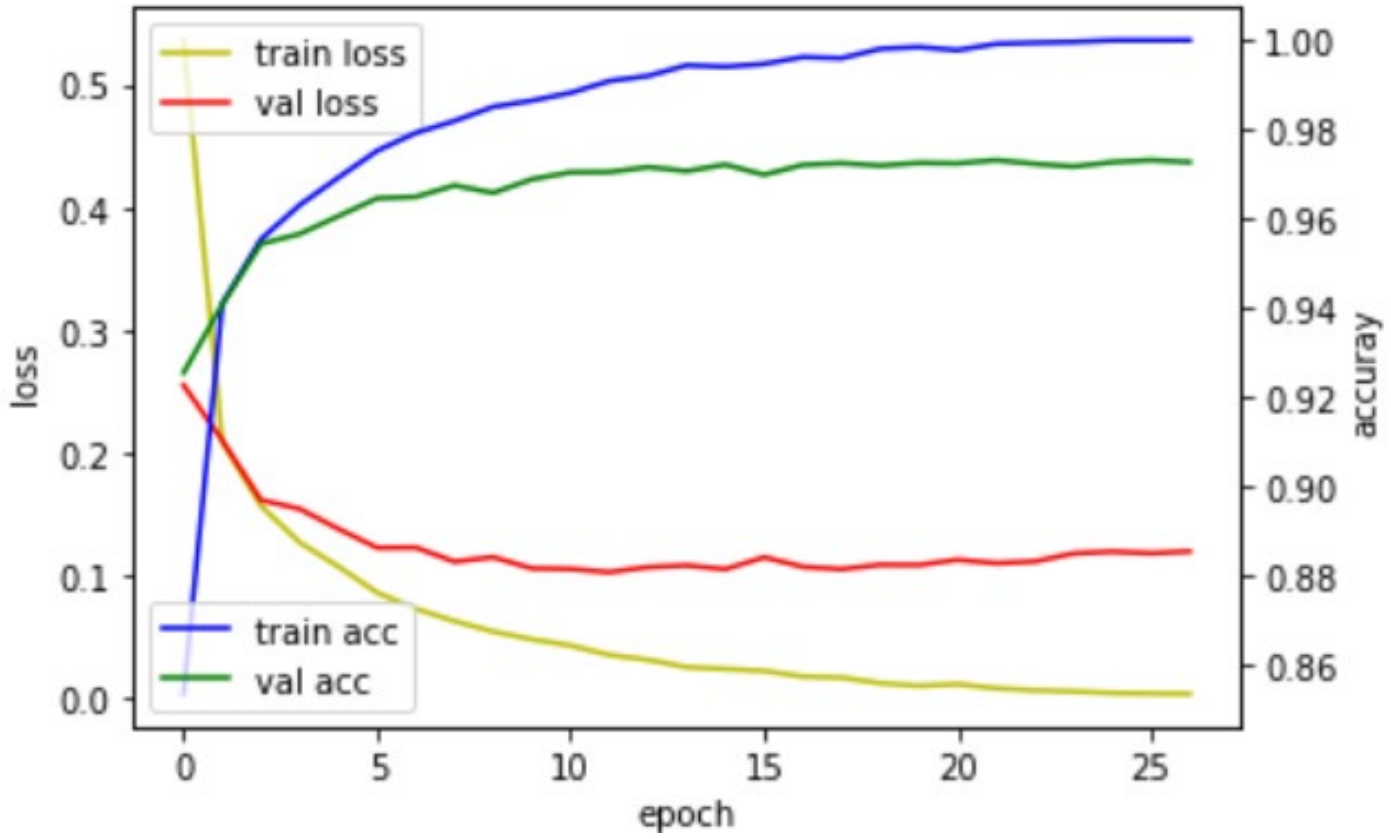






History 확인

- Epoch 마다의 학습 추이를 확인
- Loss나 Accuracy의 추이를 통해 추가 학습의 필요 여부, Underfitting/ Overfitting 확인



Confusion Matrix

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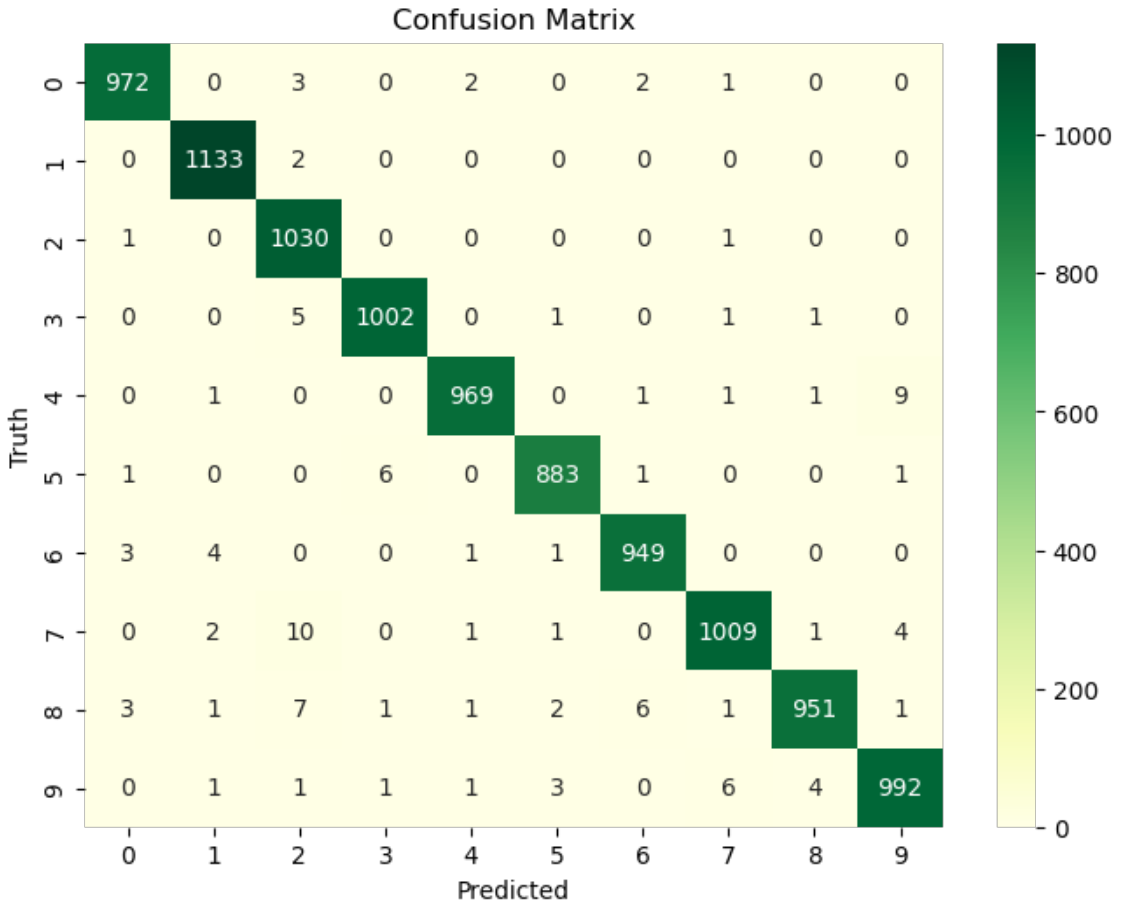
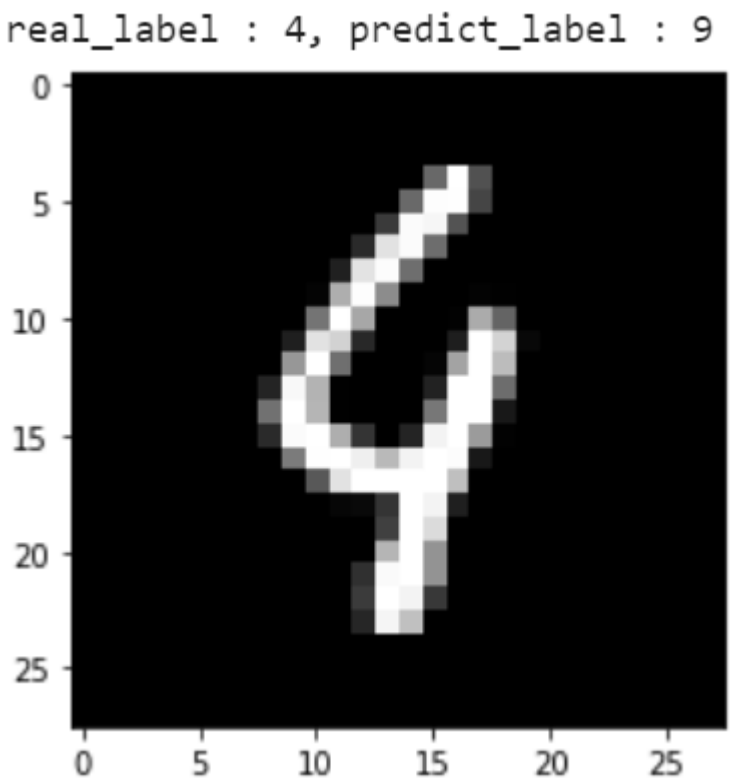
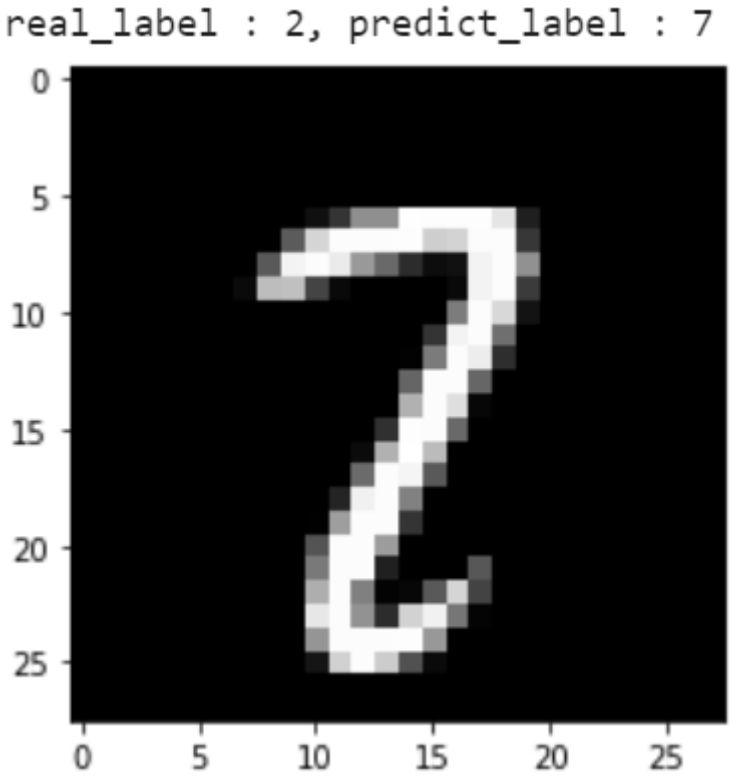
- 모델결과에 대한 분석이 용이함
- 클래스가 많으면 하기에 어려울 수 있음
- 모델의 구체적인 문제 사례를 확인하기엔 한계가 있음 → 특정 사례에 한해 직접 확인!



Wrong Sample 확인

- Confusion Matrix : 거시적 분석 / Wrong Sample : 미시적 분석
- 학습을 통한 개선이 가능한지의 여부를 확인 가능 (항상 네트워크 학습으로 해결할 수 있는 것은 아니다..!)





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Feature Extraction

Image classification

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```
def classify_image(image):
    # Some magic here?
    return class_label
```

Cat

어떻게 하면 컴퓨터가 '고양이'를 인식하도록 코딩할 수 있을까?

Traditional Image classification

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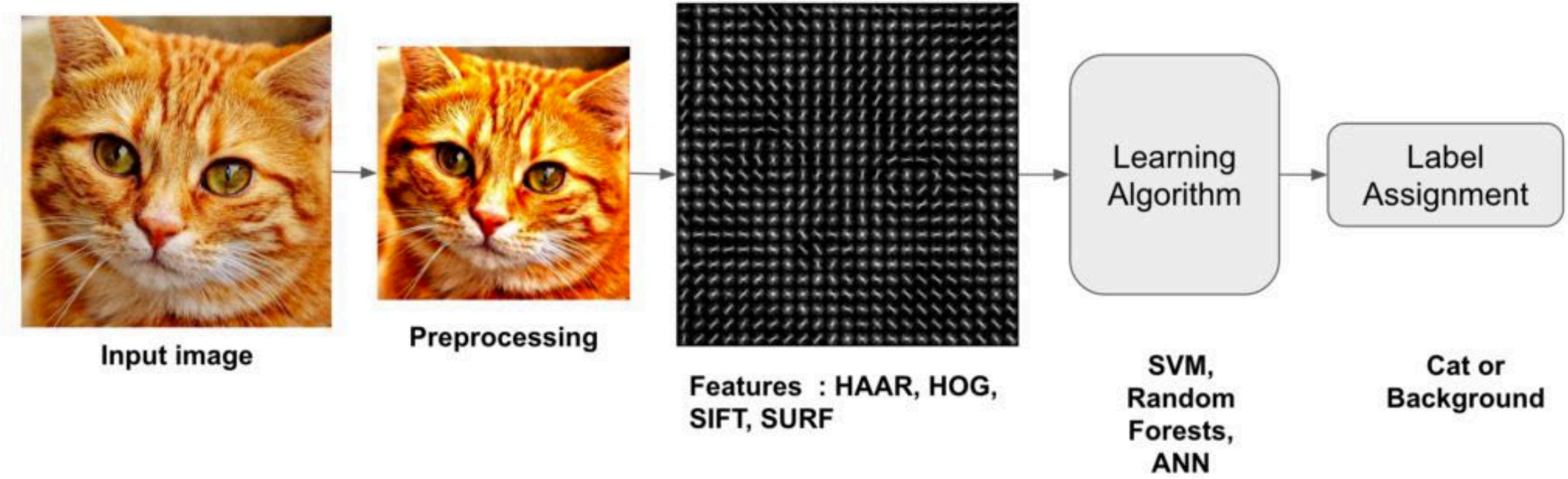
- Traditional Image Classification



Data → Feature extraction → Classification

Image classification

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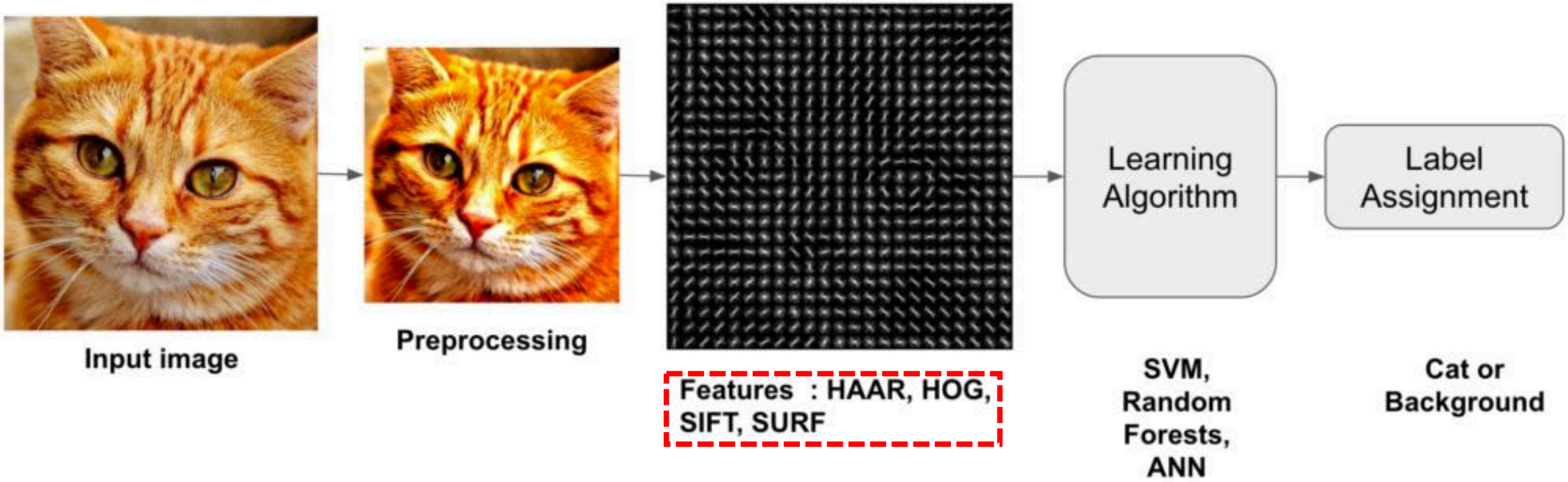

Data → Feature extraction → Classification

Convolution, max-pooling…

Overall Flow of Deep Learning

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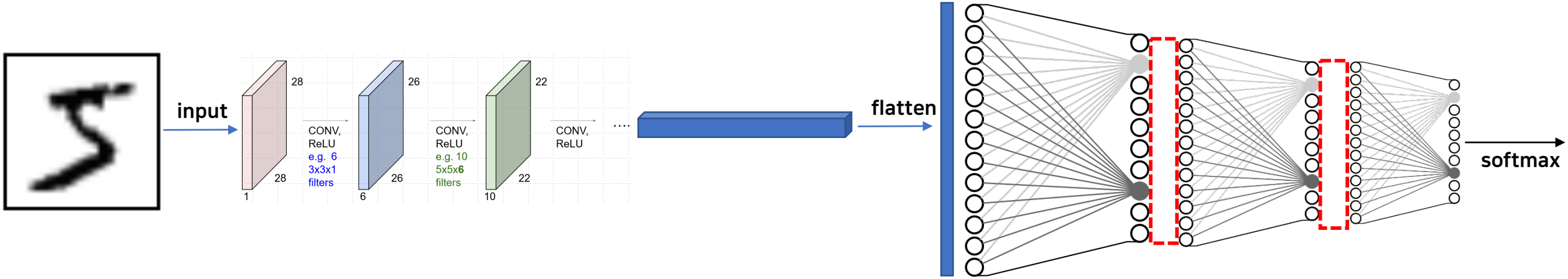
- CNN



Feature extraction
(Convolution, Pooling layer ….)

DNN
(Fully Connected, Activation layer …)

Fully Connected Layer

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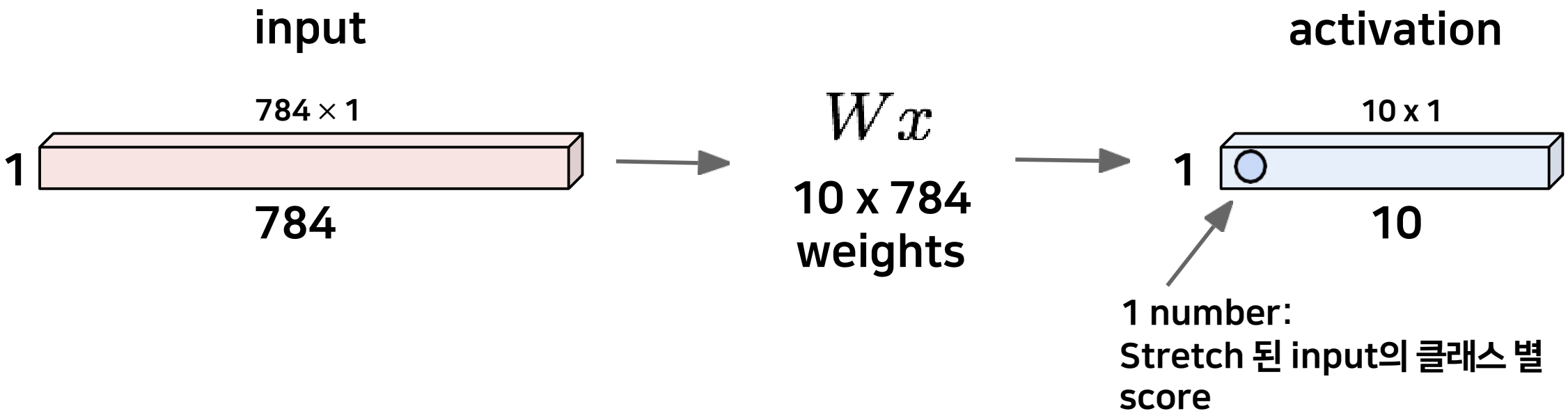

Convolution Layer

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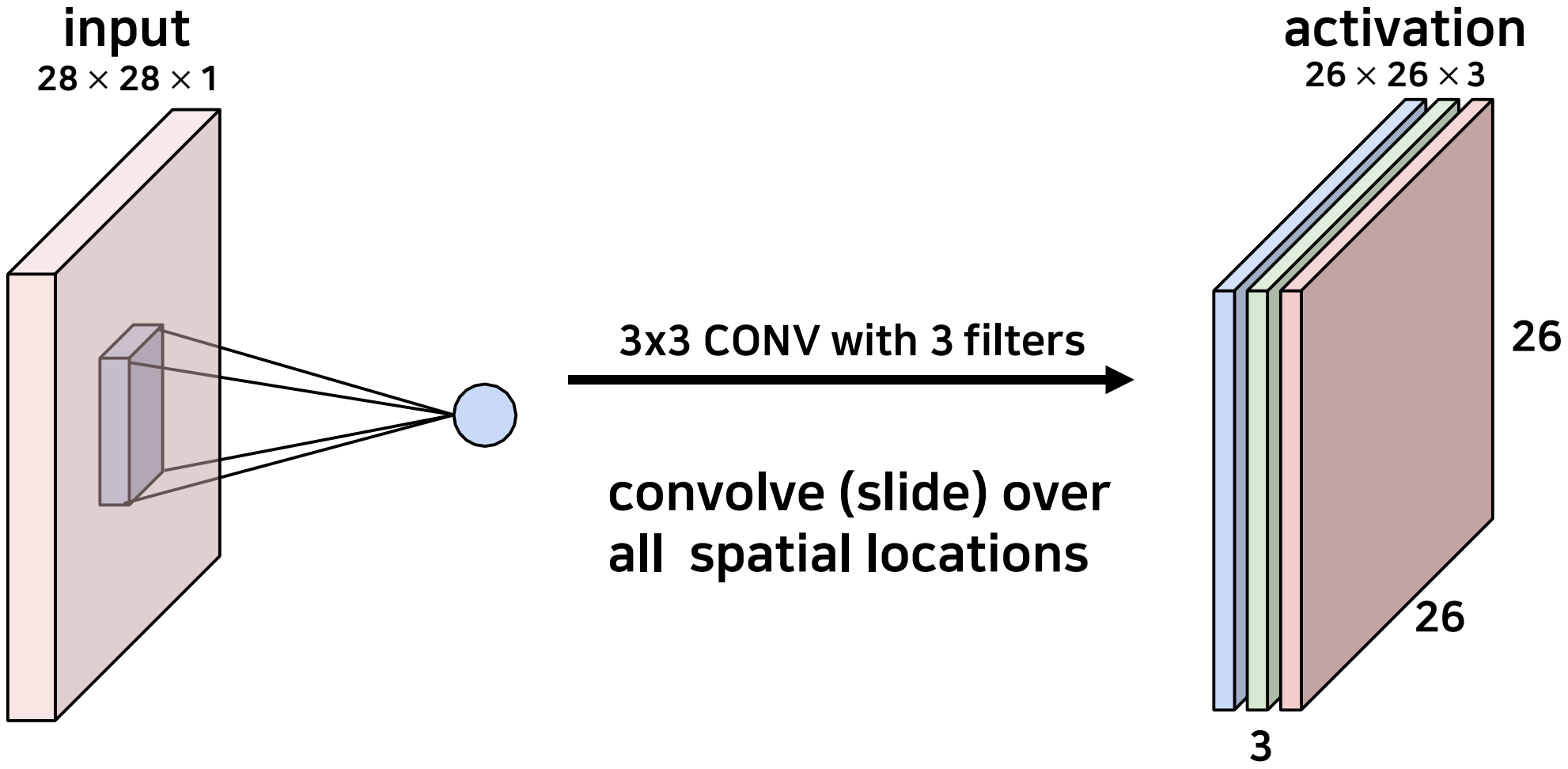

Convolution Layer

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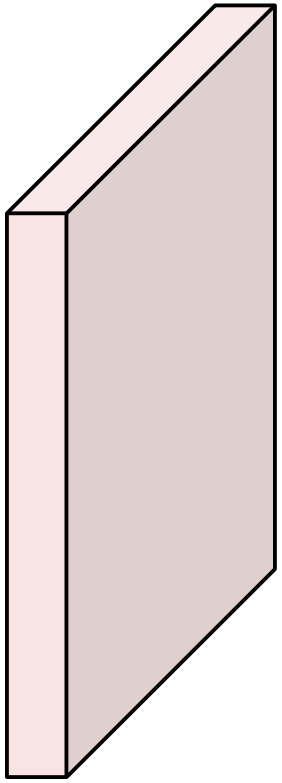
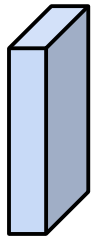
Filter는 input data와
같은 depth를 가짐

28x28x1 image



3x3x1 filter



Convolution Layer

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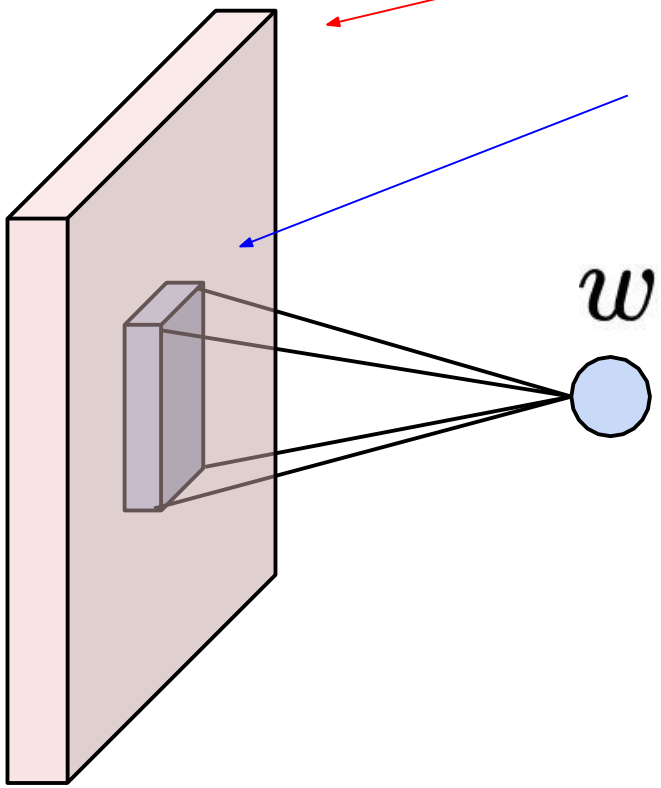

28x28x1 image
3x3x1 filter

1 number:
Image의 일부분과 filter를 element wise한 하나의 값이
activation map의 한 원소가 됨

$$w^T x + b$$

Convolution Layer

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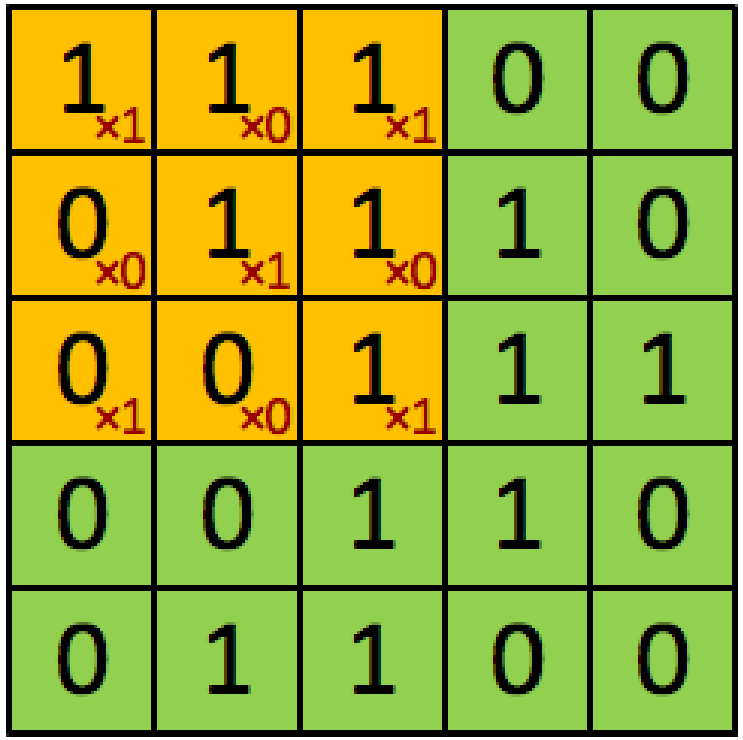

Convolution Layer

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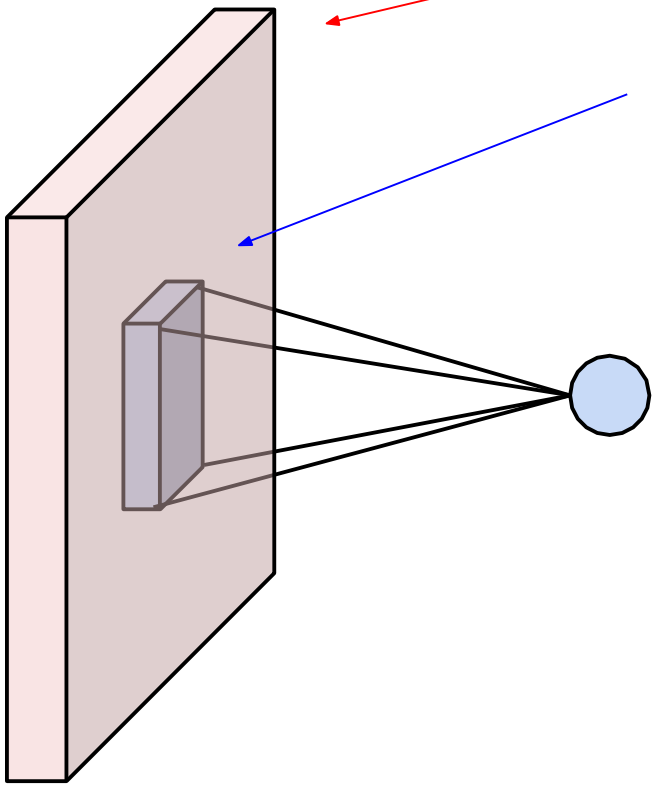

28x28x1 image
3x3x1 filter

convolve (slide) over
all spatial locations

activation map

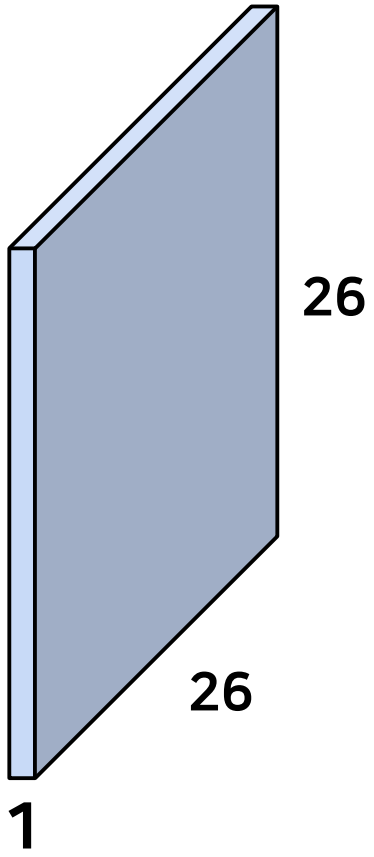

Image classification

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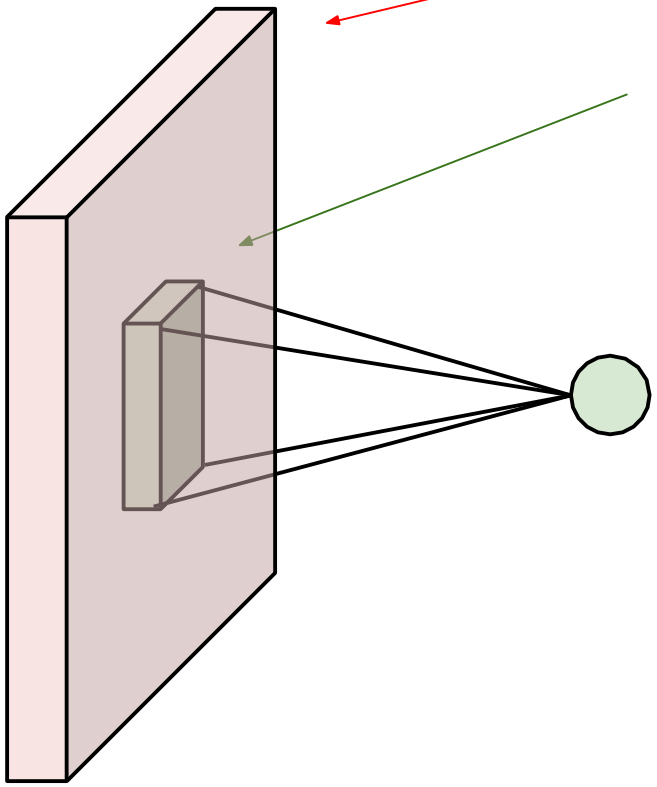
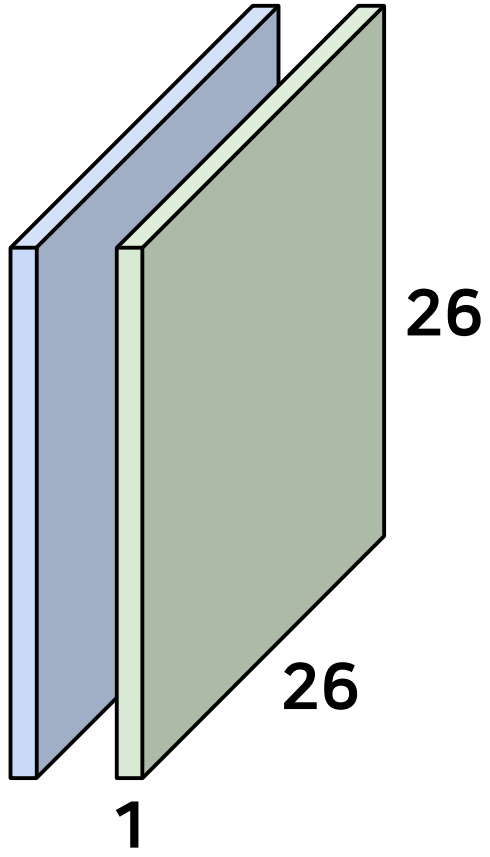


28x28x1 image

3x3x1 filter (second filter)

convolve (slide) over
all spatial locations

activation maps



Convolution Layer

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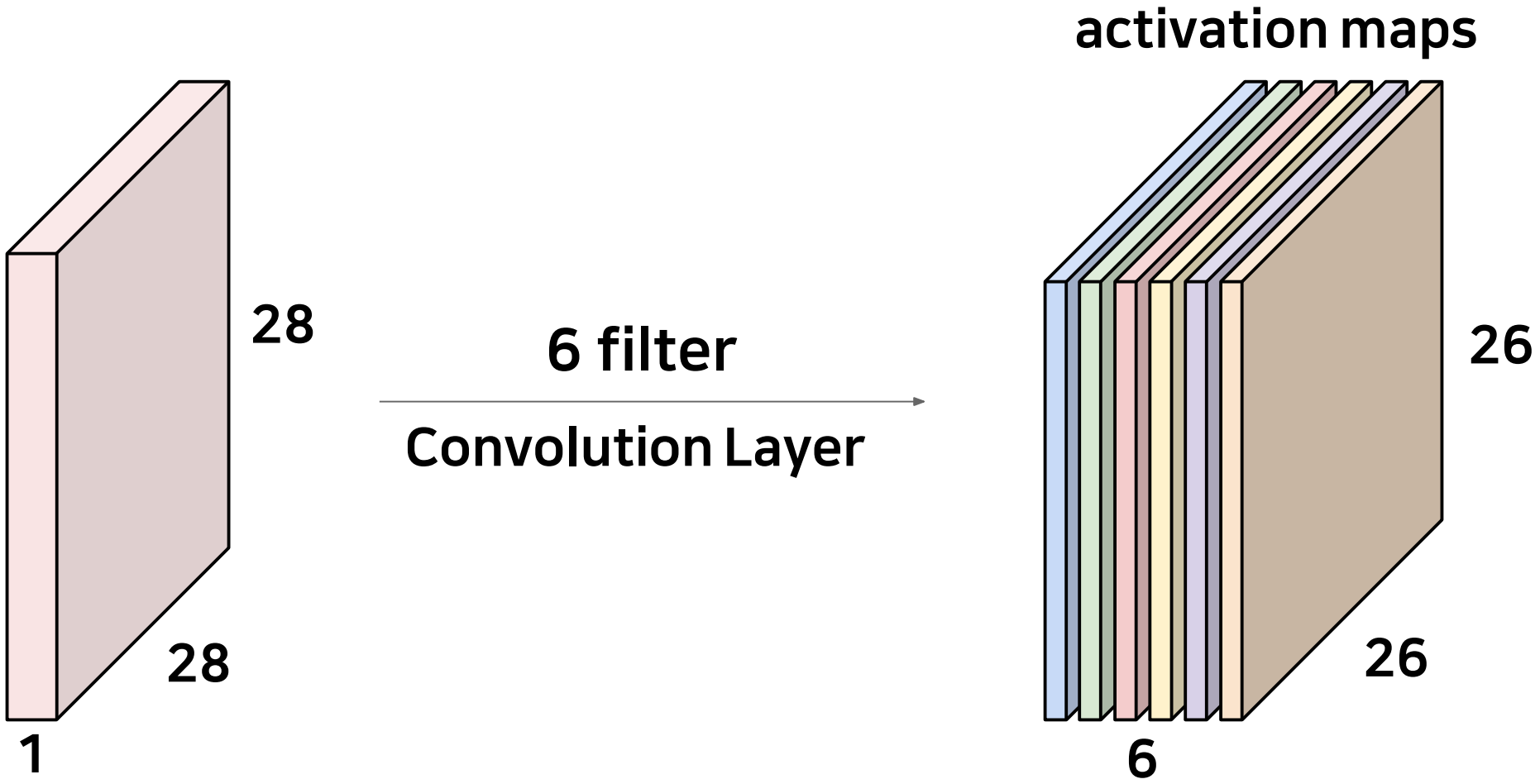

26x26x6의 새로운 이미지는 다음 layer로 전달

Convolution Layer

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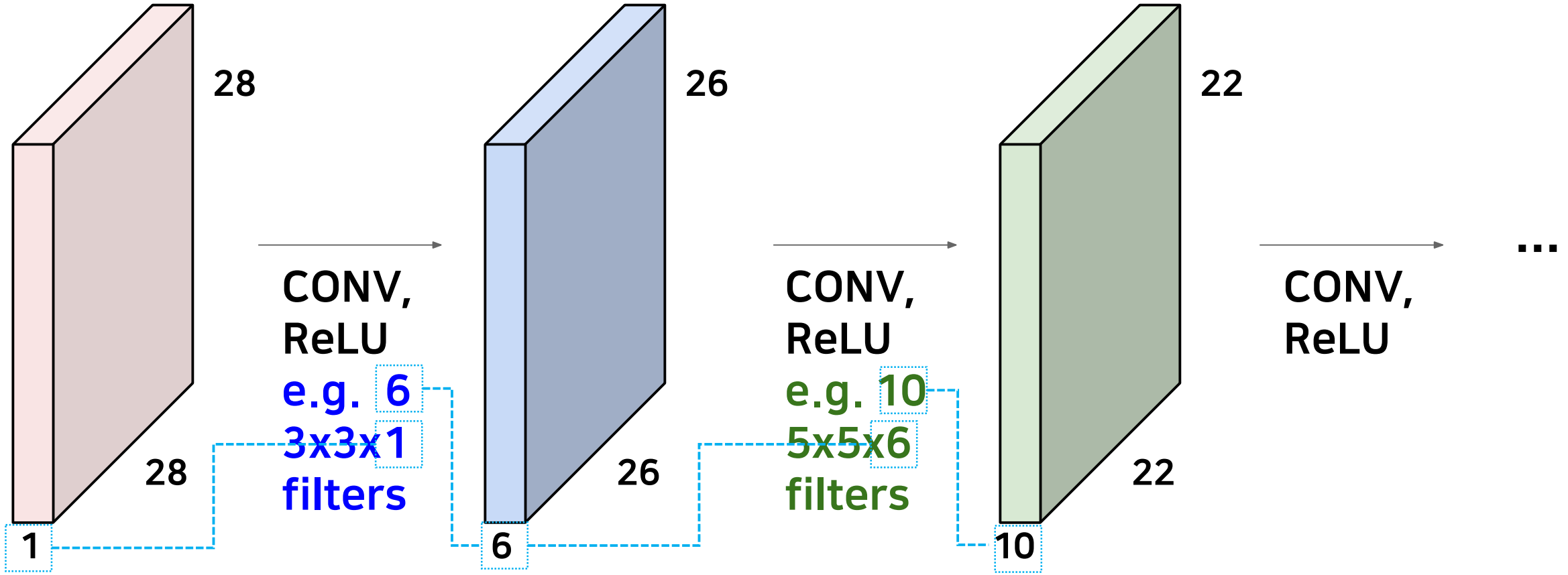

각각의 필터는 input image만큼의 depth를 가져야한다.
그리고 필터를 거친 activation map은 필터의 개수만큼 만들어 진다.
Padding을 적용하지 않으면 이미지의 크기가 점점 줄어들어 convolution을 진행할 수 없다. (28 -> 26 -> 22 ...)

1 ×1 Convolution Layer

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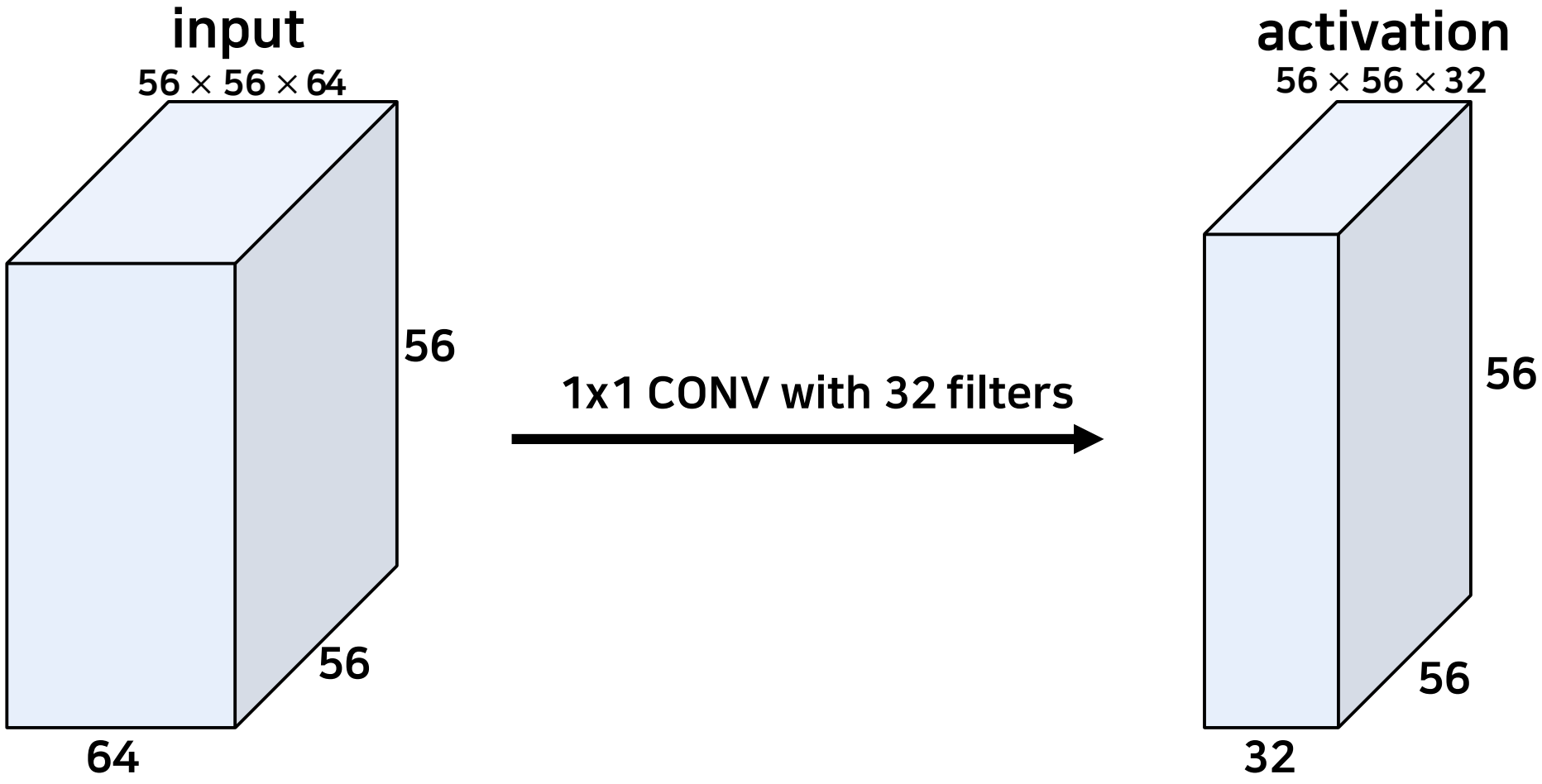

1x1 convolution layers : 이미지 크기는 유지, depth를 줄임

Pooling Layer

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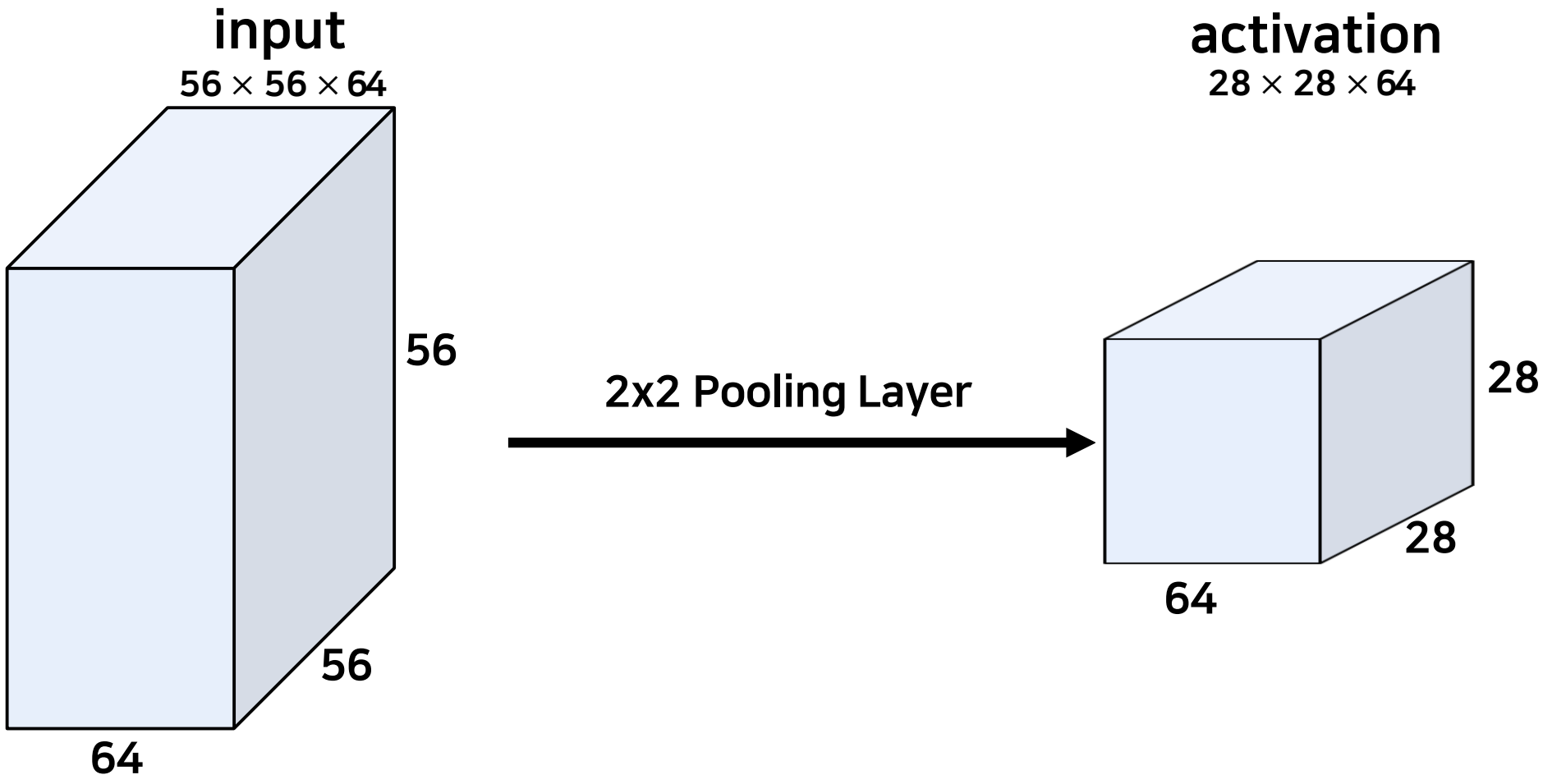

Pooling layers : 이미지 크기를 줄이고, depth를 유지

Pooling Layer

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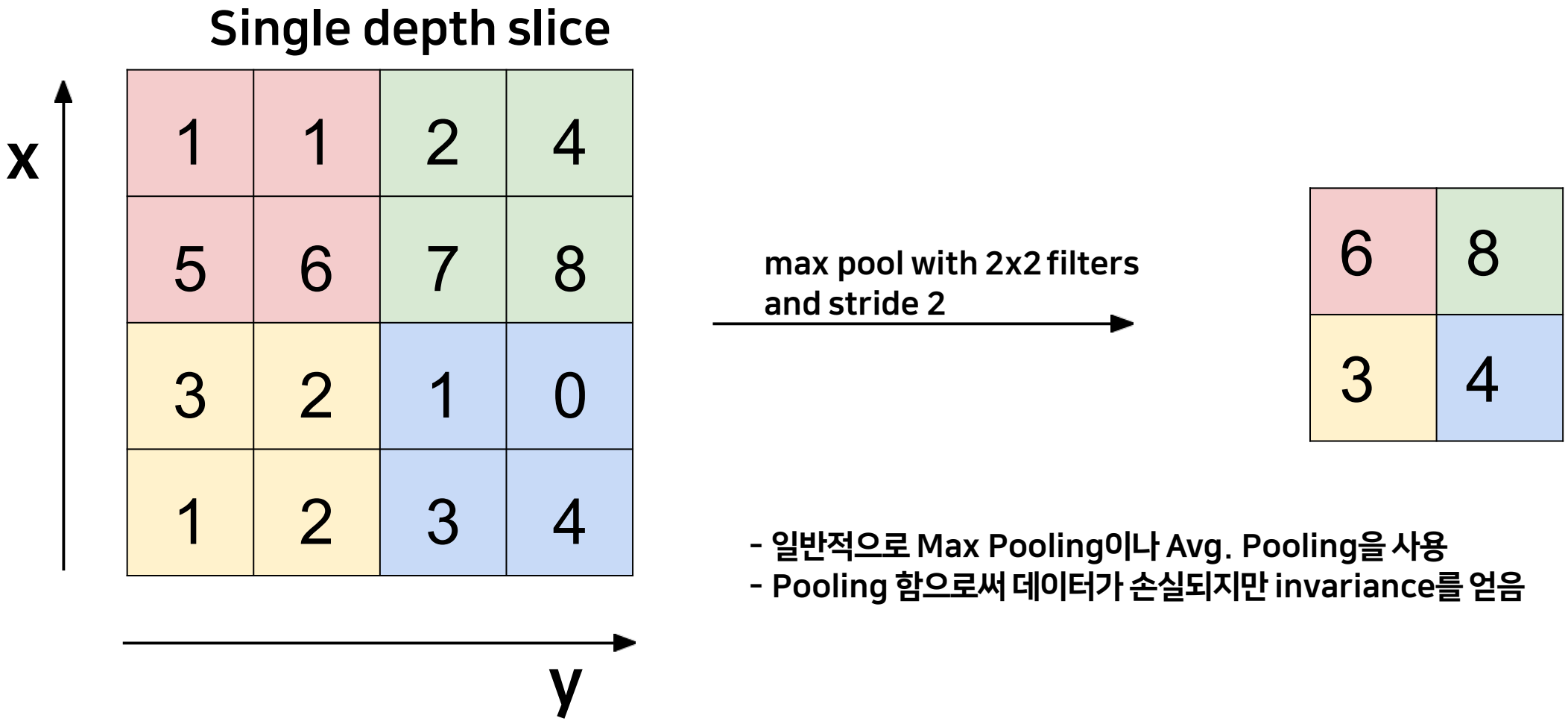

- 일반적으로 Max Pooling이나 Avg. Pooling을 사용
- Pooling 함으로써 데이터가 손실되지만 invariance를 얻음

Batch Normalization

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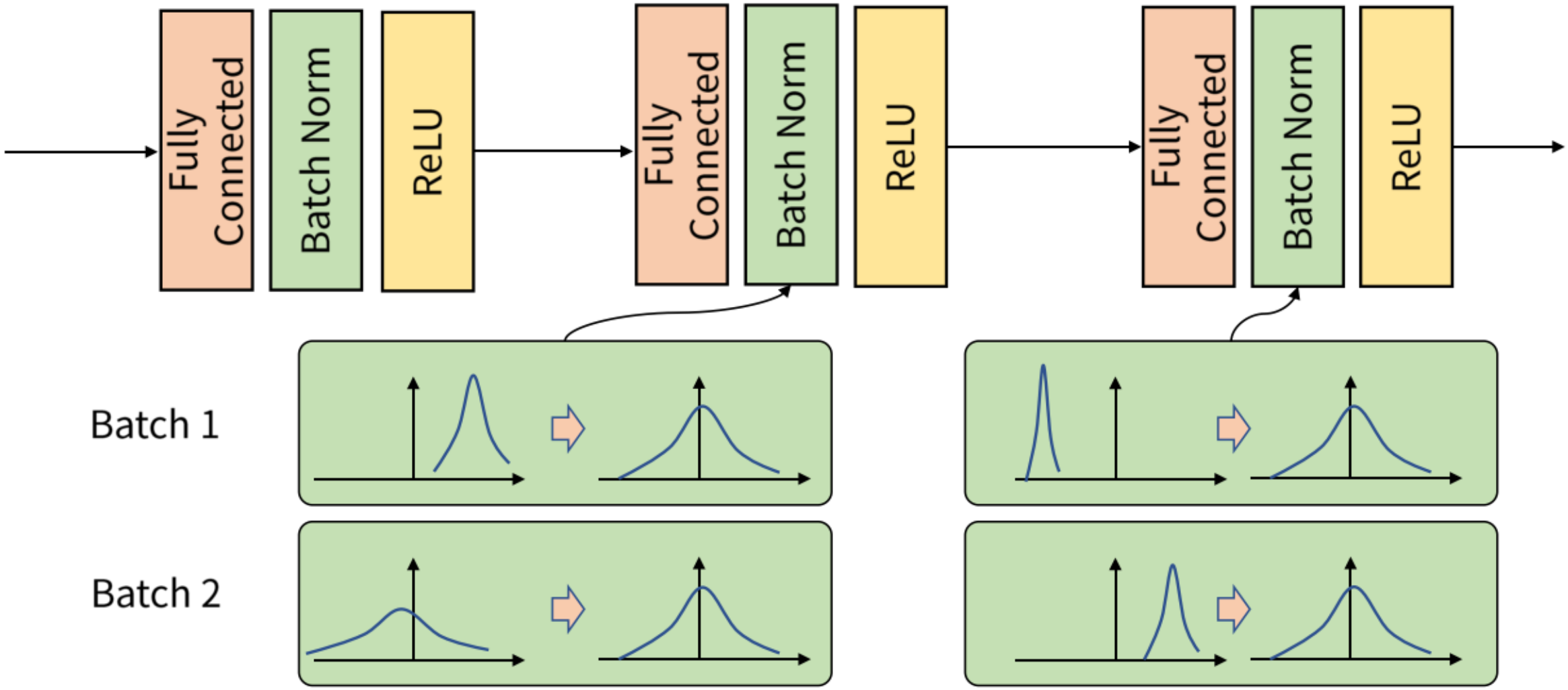

Dropout

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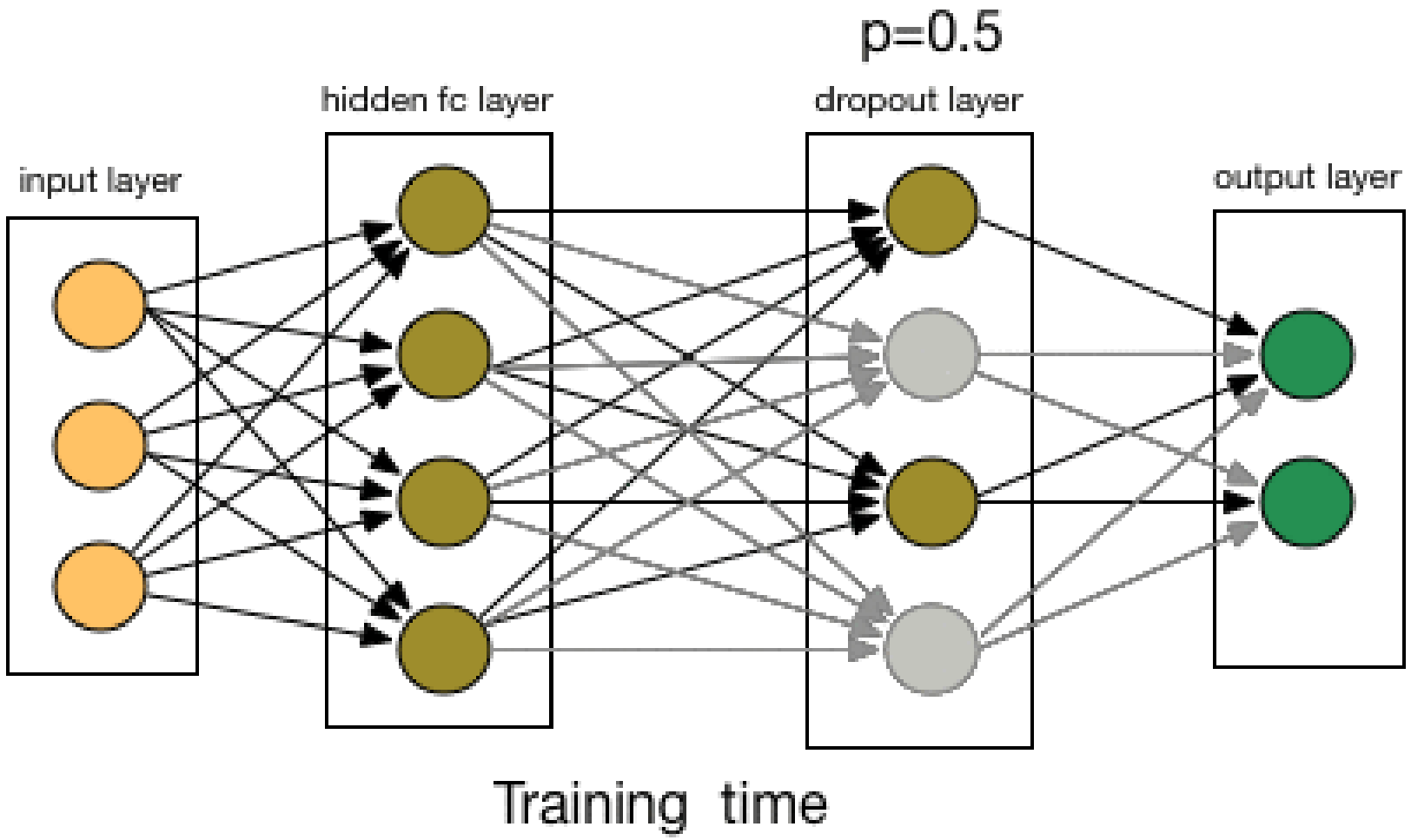

Dropout

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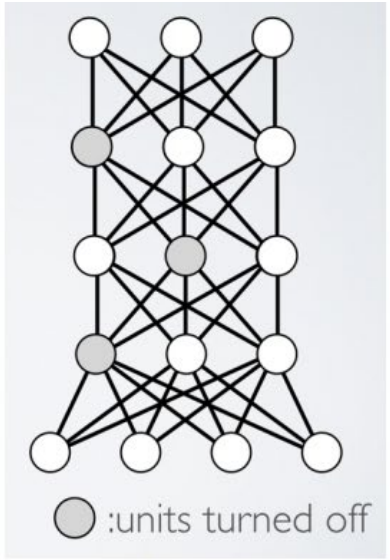
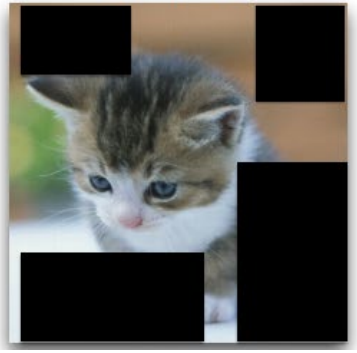
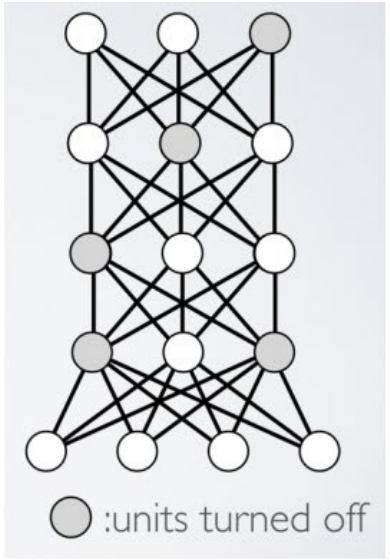
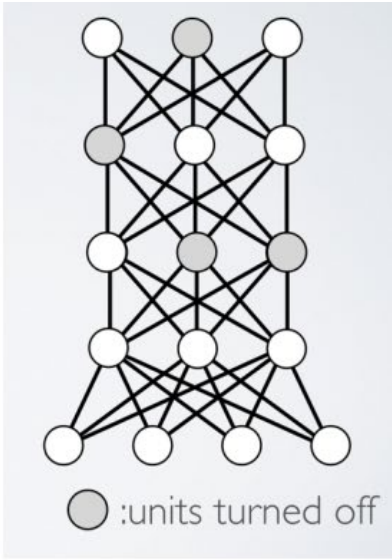


얼굴위주





색지우고



귀 빼고

Image classification

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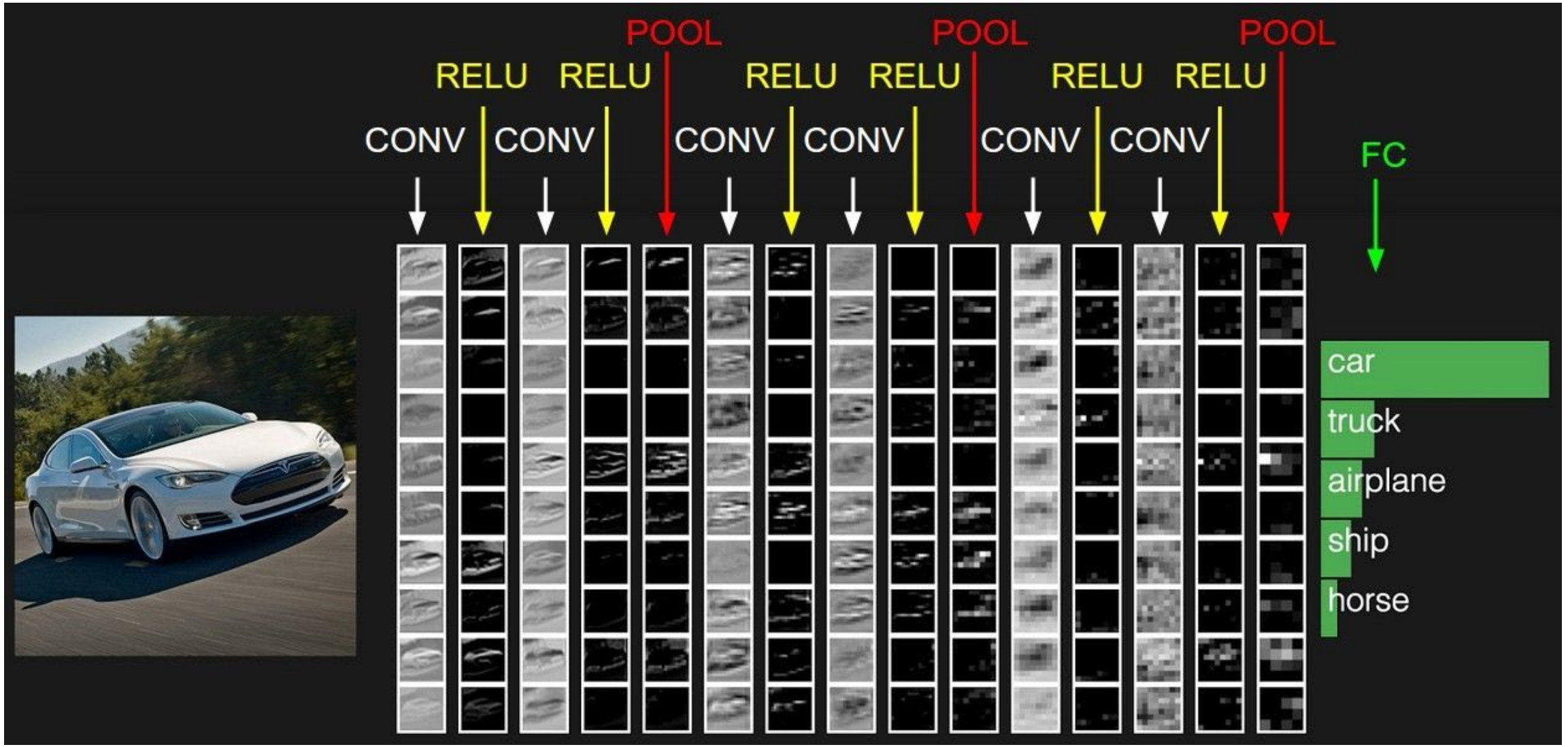

Code Running

2_KerasFeature Extraction.ipynb

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PyTorch Feature Extraction

I-Eon, Na

CNN Feature Extraction

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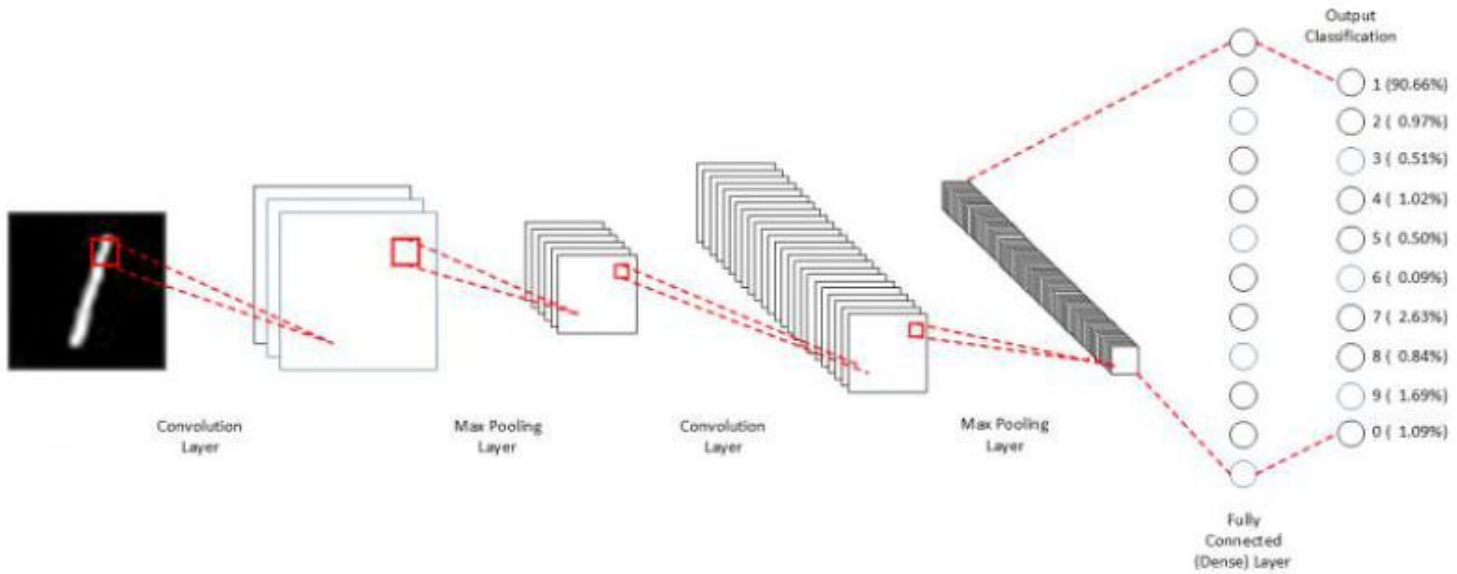
- **CNN – with MNIST**



- 특징을 추출하기 특화
- 기존 FC와 다르게 모든 뉴런들이 연결되어 있지 않음
- MLP에 비해 학습이 효율적이고, 모델의 성능도 더 좋음
- 여러가지 학습 기법 적용 예정 (Batch Nor., EarlySt., Dropout, Check Point Save 기법 등)

이미지 출처: https://minimin2.tistory.com/36

CNN – 데이터 전처리

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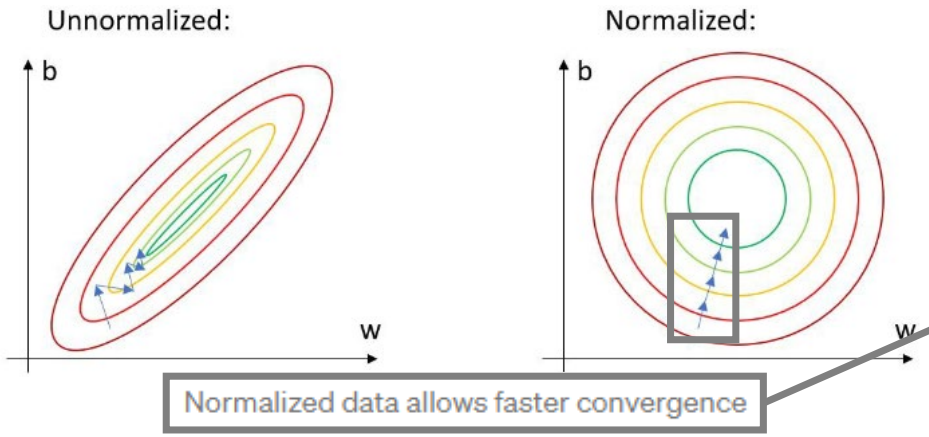
- **데이터 전처리 – Dataset Normalization**

```
transforms.Compose([ToTensor(),
                    Normalize(mean=(0.5,), std=(0.5, ))
```



데이터셋의 평균(mean)과 표준편차(std)를 계산하여 적용시

- 학습할 이미지 데이터셋이 일반적인 조도, 각도, 배경, 사물체가 아닌 경우는 직접 평균/표준편차를 계산하여 적용할 수 있습니다.

아래 함수는 이미지 데이터셋에 대하여 평균, 표준편차를 산출해 주는 함수 입니다.

```
def calculate_norm(dataset):
    # dataset의 axis=1, 2에 대한 평균 산출
    mean_ = np.array([np.mean(x.numpy(), axis=(1, 2)) for x, _ in dataset])
    # r, g, b 채널에 대한 각각의 평균 산출
    mean_r = mean_[:, 0].mean()
    mean_g = mean_[:, 1].mean()
    mean_b = mean_[:, 2].mean()
```

- MNIST 데이터 정규화 작업
(임의의 평균 & 표준편차 적용)
- 데이터 Normalize를 통하여
Global Minimum으로 빠르게 수렴
- 데이터의 평균과 표준편차를 직접 계산하여 적용 가능

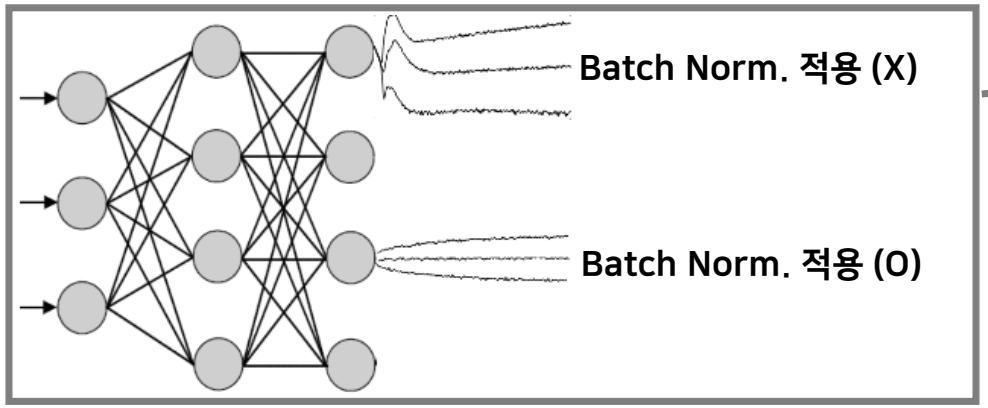
(링크: https://teddylee777.github.io/pytorch/torchvision-transform)

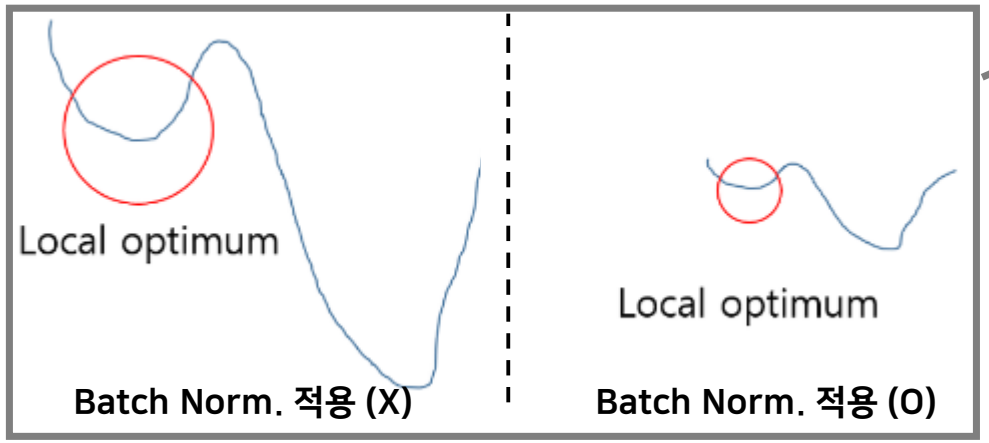
이미지 출처: https://towardsdatascience.com/how-to-calculate-the-mean-and-standard-deviation-normalizing-datasets-in-pytorch-704bd7d05f4c

CNN – 기능

- **기능 - Batch Normalization**

```
self.layer1 = torch.nn.Sequential(
    nn.Conv2d(in_channels=1, out_channels=32, kernel_
    nn.BatchNorm2d(32), #Batch Normalization을 수행
```





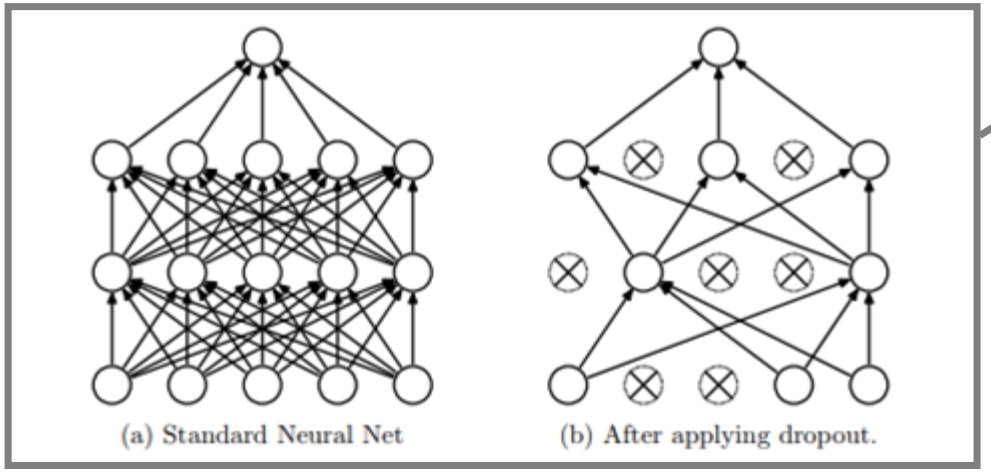
- 레이어 중간에 Batch Norm. 수행
- 이전 레이어의 파라미터 변화로 현재 레이어의 입력 분포가 바뀌는 현상 방지
- Local Minimum에 빠짐을 방지
- 수식 참조

(https://eehoeskrap.tistory.com/430#google_vignette)

CNN – 기능

- **기능 – Dropout**

```
self.layer1 = torch.nn.Sequential(
    nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3, st
    nn.BatchNorm2d(32),
    nn.ReLU(),
    nn.Dropout(0.4),
    nn.MaxPool2d(kernel_size = 2, stride = 2),
)
```



- Dropout 기법을 사용하여 과적합을 방지
- 랜덤한 확률로 Layer 내에 있는 뉴런들을 제거 후 학습하는 기법
- 매 학습 마다 새롭게 제거된 뉴런들의 조합으로 인하여 앙상블 러닝 효과 발생
- 일반적으로 0 ~ 0.5 사이로 사용

출처: https://m.blog.naver.com/PostView.naver?isHttpsRedirect=true&blogId=isu112600&logNo=221578533182

CNN – 기능

- **기능 - Early Stopping 기법**

```python
class EarlyStopping:
    """주어진 patience 이후로 validation loss가 개선되지 않으면 학습을 조기 중지"""
    def __init__(self, patience=7, verbose=False, delta=0, path='checkpoint.pt'):
        self.patience = patience
        self.verbose = verbose
# Training Iteration
while epoch_not_finished():
    start_time = time.time()
    tloss, tacc = epoch(train_loader_es)
    end_time = time.time()
    time_taken = end_time - start_time
    record_train_log(tloss, tacc, time_taken)
    with torch.no_grad():
        vloss, vacc = epoch(valid_loader_es)
        record_valid_log(vloss, vacc)
    print_log()

    # early_stopping는 validation loss가 감소하였는지 확인이 필요하며,
    # 만약 감소하였을경우 현제 모델을 checkpoint로 만든다.
    early_stopping(vloss, net)
    if early_stopping.early_stop:
        print("Early stopping")
        break
```

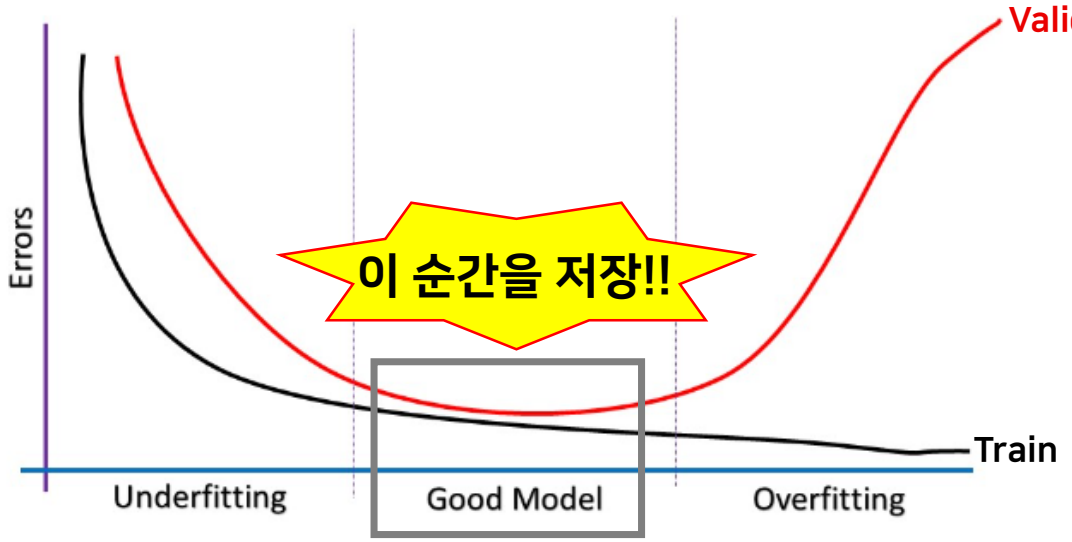
```
EarlyStopping counter: 10 out of 10
Early stopping

 Training completed!

====================== Test Result ======================

Test accuracy = 0.8904272151898734
Test loss = 0.4271463234496268
```

- 학습중 Over Fitting 판단시, 중간에 학습을 종료하는 기법
- [Patience]
  Validation Loss에 개선이 없으면 몇 번 기다렸다 학습을 중지 할지
- 학습 알고리즘에 Early Stopping 모듈을 추가하여 Over Fitting 감지 시, while문에서 break
- Early Stopping 작동 확인

CNN – 기능

- **기능 – Check Point Save 기법**

```
def __call__(self, val_loss, model):

    score = -val_loss

    if self.best_score is None:
        self.best_score = score
        self.save_checkpoint(val_loss, model)
def save_checkpoint(self, val_loss, model):
    # validation loss가 감소하면 모델을 저장한다.
    if self.verbose:
        print('Validation loss decresed ({:5} --> {:5}). Saving
    torch.save(model.state_dict(), self.path)
    self.val_loss_min = val_loss
```



- 학습 중 모델이 최고 점수를 기록하는 순간을 지속적으로 Epoch마다 저장
- EarlyStopping 이랑 비슷한 목적
- 학습 결과 Overfitting이 되었다고 하더라도, Best Model 보관 가능

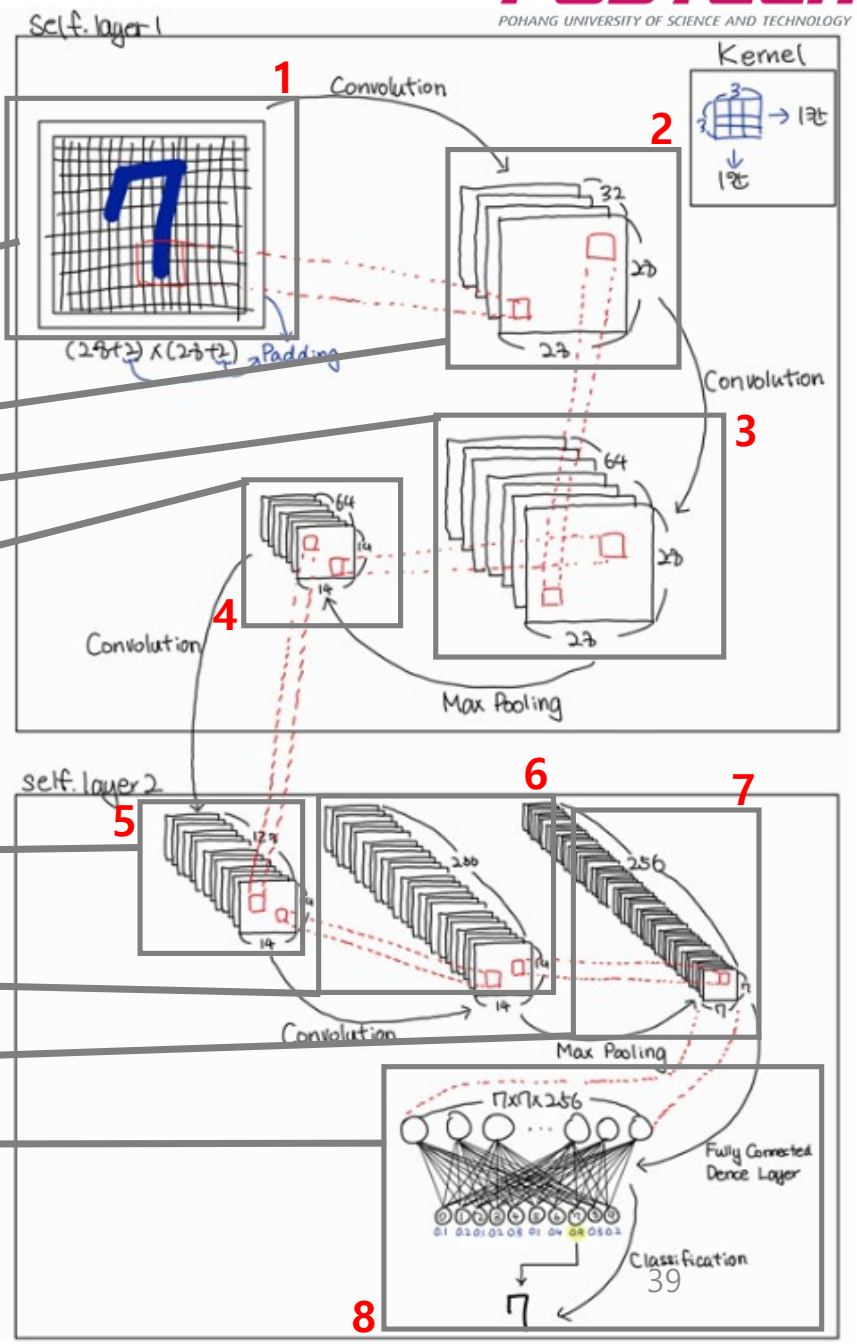
출처: https://meditationsonbianddatascience.com/2017/05/11/overfitting-underfitting-how-well-does-your-model-fit/

CNN – 모델 설계

PIAI Research Department

- **CNN(Convolutional Neural Network) 모델 설계**

```
class CNN_model(nn.Module):
    def __init__(self):
        super(CNN_model, self).__init__()

        # 1번 레이어 생성
        self.layer1 = torch.nn.Sequential(
            nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3, stride=1, padding=1),

            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.Dropout(0.1),
            nn.MaxPool2d(kernel_size = 2, stride = 2))

        # 2번 레이어 생성
        self.layer2 = torch.nn.Sequential(
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, stride=1, padding=1),

            nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size = 2, stride = 2))

        #마지막 0 ~ 9 classification을 위한 fully connected layer 생성
        self.fc1 = nn.Linear(7 * 7 * 256, 10, bias = True)

        #가중치 초기화
        nn.init.xavier_uniform_(self.fc1.weight)
```



CNN – 모델 설계

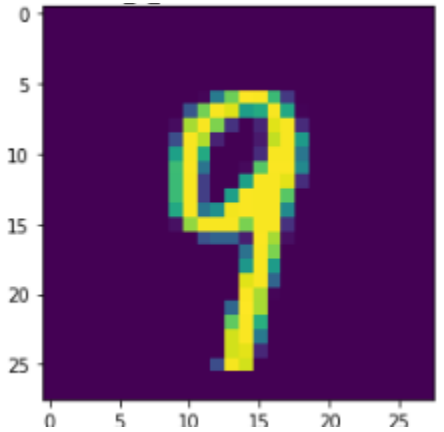
- **설계된 CNN 모델의 구조 확인**

```
43 # Model structure check
44 Summary(CNN_model().to(device), (1, 28, 28))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 32, 28, 28]             320
            Conv2d-2           [-1, 64, 28, 28]          18,496
       BatchNorm2d-3           [-1, 64, 28, 28]             128
              ReLU-4           [-1, 64, 28, 28]               0
           Dropout-5           [-1, 64, 28, 28]               0
         MaxPool2d-6           [-1, 64, 14, 14]               0
            Conv2d-7          [-1, 128, 14, 14]          73,856
            Conv2d-8          [-1, 256, 14, 14]         295,168
       BatchNorm2d-9          [-1, 256, 14, 14]             512
             ReLU-10          [-1, 256, 14, 14]               0
        MaxPool2d-11            [-1, 256, 7, 7]               0
           Linear-12                  [-1, 10]         125,450
================================================================
Total params: 513,930
Trainable params: 513,930
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 3.25
Params size (MB): 1.96
Estimated Total Size (MB): 5.22
----------------------------------------------------------------
```

- Summary 기능으로 설계된 모델의 구조 확인
- 입력 데이터 사이즈 확인
  (1, 28, 28)

  1: Gray Scale (1 channel 이미지)
  28 * 28: 사진의 화소



CNN – 모델 설계

- **CNN 모델 학습 알고리즘**

```python
# 학습 알고리즘
def epoch(data_loader, mode = 'train'):
    global epoch_cnt

    # 사용되는 변수 초기화
    iter_loss, iter_acc, last_grad_performed, last_out, last_label = [],

    for _data, _label in data_loader:
        data, label = _data.to(device), _label.to(device)

        # 1. Feed-forward
        if mode == 'train':
            net.train()
        else:
            net.eval()
        result, _ = net(data)
        _, out = torch.max(result, 1)
```

```python
        # 5. 컨퓨전 매트릭스 출력을 위해 기록
        last_out = out.cpu().detach()
        last_label = _label
```

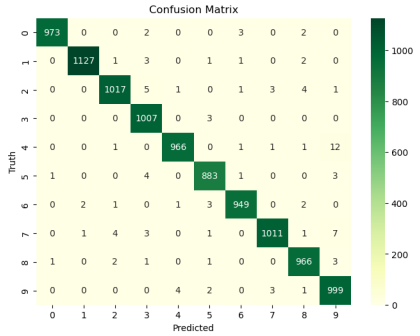
- Day1 알고리즘에서 **2개** 기능 추가

1) Train/Valid 모드에 따라 다르게 동작

- net.train() :
  dropout, batch nor. -> 사용

- net.eval() :
  dropout, batch nor. -> 미사용

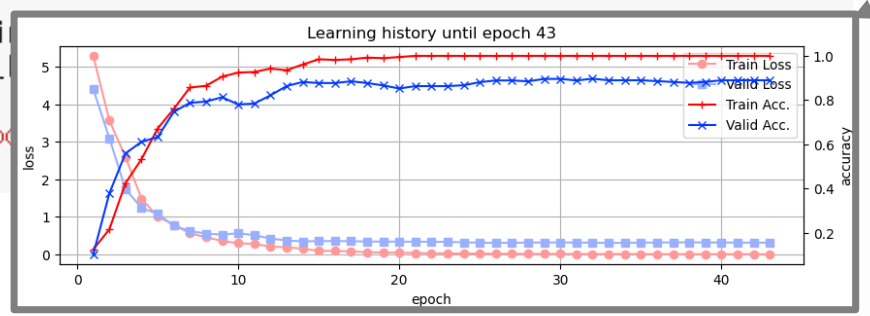
2) Confusion Matrix 기록 로직 추가



CNN – Verbose Setting(Graph)

- **Verbose – 실시간 학습 추이 그래프 출력**

```
# 학습 추이 그래프 출력
hist_fig, loss_axis = plt.subplots(figsize=(10, 3), dpi=99) # 그래프 사이즈 설정
hist_fig.patch.set_facecolor('white') # 그래프 배경색 설정

# Loss Line 구성
loss_t_line = plt.plot(iter_log, tloss_log, label='Train Loss', color='red', marker='o')
loss_v_line = plt.plot(iter_log, vloss_log, label='Valid Loss', color='blue', marker='s')
loss_axis.set_xlabel('epoch')
loss_axis.set_ylabel('loss')

# Acc. Line 구성
acc_axis = loss_axis.twinx()
acc_t_line = acc_axis.plot(iter_log, tacc_log, label='Train Acc.', color='red', marker='+')
acc_v_line = acc_axis.plot(iter_log, vacc_log, label='Valid Acc.', color='blue', marker='x')
acc_axis.set_ylabel('accuracy')

# 그래프 출력
hist_lines = loss_t_line + loss_v_li
loss_axis.legend(hist_lines, [l.get_l
loss_axis.grid() # 격자 설정
plt.title('Learning history until epo
plt.draw()
```



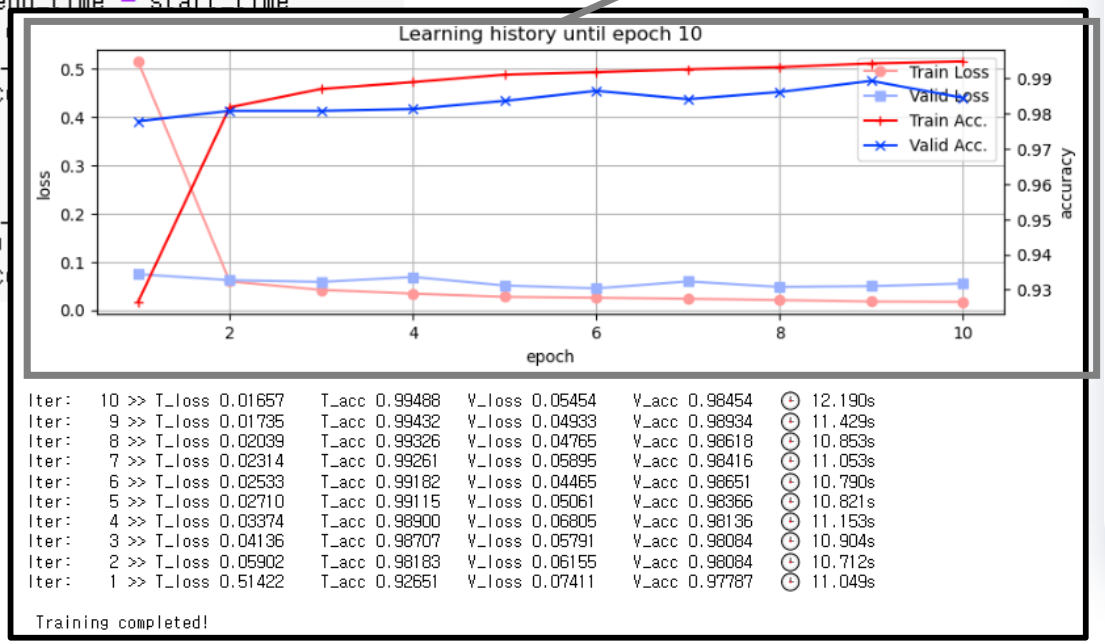
- 학습 추이를 그래프를 통하여 실시간으로 모니터링
- Train과 Validation에 대하여 Loss와 Acc.를 실시간으로 시각화

CNN – 모델 학습

PIAI Research Department

- **CNN 모델 학습**

```
# Training Initialization
init_model()
init_epoch()
init_log()
plt.rc('font', size = 10)

best_test_acc, best_epoch = 0, 0
# Training Iteration
while epoch_not_finished():
    start_time = time.time()
    tloss, tacc = epoch(train_loader)
    end_time = time.time()
    time_taken = end_time - start_time
    record_train_l
    with torch.no_
        vloss, vac
        record_val
    print_log()

    with torch.no_
        net.eval()
        _, test_ac
```




```
Iter:   10 >> T_loss 0.01657   T_acc 0.99488   V_loss 0.05454   V_acc 0.98454   12.190s
Iter:    9 >> T_loss 0.01735   T_acc 0.99432   V_loss 0.04933   V_acc 0.98934   11.429s
Iter:    8 >> T_loss 0.02039   T_acc 0.99326   V_loss 0.04765   V_acc 0.98618   10.853s
Iter:    7 >> T_loss 0.02314   T_acc 0.99261   V_loss 0.05895   V_acc 0.98416   11.053s
Iter:    6 >> T_loss 0.02533   T_acc 0.99182   V_loss 0.04465   V_acc 0.98651   10.790s
Iter:    5 >> T_loss 0.02710   T_acc 0.99115   V_loss 0.05061   V_acc 0.98366   10.821s
Iter:    4 >> T_loss 0.03374   T_acc 0.98900   V_loss 0.06805   V_acc 0.98136   11.153s
Iter:    3 >> T_loss 0.04136   T_acc 0.98707   V_loss 0.05791   V_acc 0.98084   10.904s
Iter:    2 >> T_loss 0.05902   T_acc 0.98183   V_loss 0.06155   V_acc 0.98084   10.712s
Iter:    1 >> T_loss 0.51422   T_acc 0.92651   V_loss 0.07411   V_acc 0.97787   11.049s

Training completed!
```

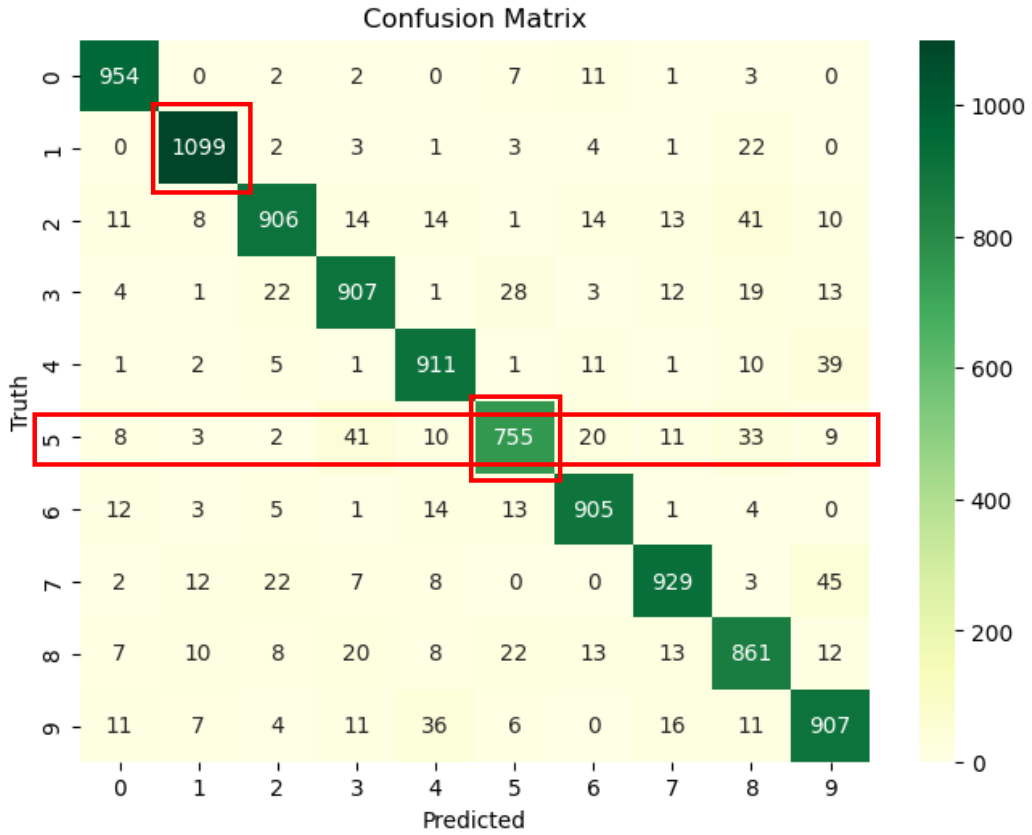
- CNN 모델 학습
- 실시간 그래프로 학습 추이 확인
- 모델의 정확도 확인

```
Test Acc.: 0.9898
Test Loss: 0.0321
```

CNN – 결과 분석

- **Confusion Matrix**

```
# Confusion matrix
our_cmatrix = confusion_matrix(test_label, test_out)
plt.figure(figsize=(8, 6), dpi=99)
sns.heatmap(our_cmatrix, annot=True, fmt='g', cmap='YlGn').set(xlabel='Predicted', ylabel='Truth')
plt.title('Confusion Matrix')
plt.show()
```



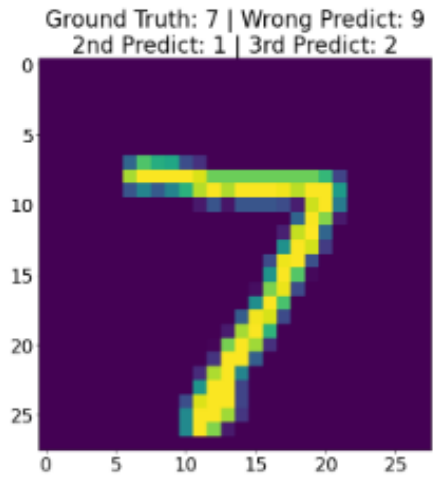
- 혼동 행렬을 통하여 모델이 예측하는 10개의 Class에 대한 성능을 한눈에 가시화
- 모든 Class에 대하여 모델이 분류한 결과 확인

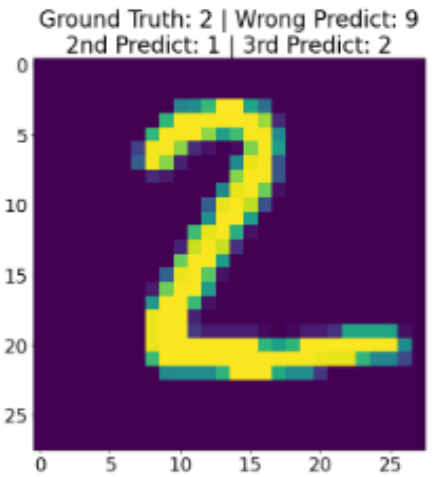
CNN – 결과 분석

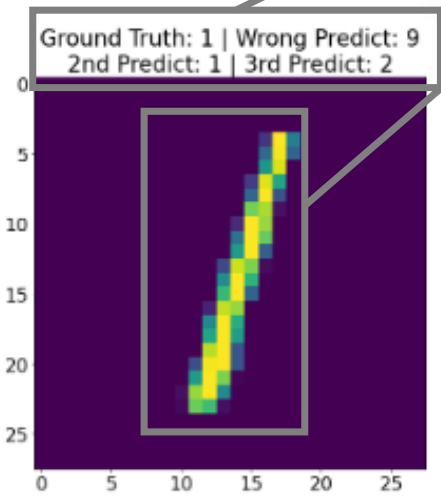
- **모델의 오 분류 사례 분석**

```
# 예측 결과 1, 2, 3순위를 만드는 과정
max_pred = max(pred_info)
second_pred = pred_info[1]
third_pred = pred_info[2]
pred_label = pred_info.index(max_pred)
second_label = pred_info.index(second_pred)
thirt_label = pred_info.index(third_pred)
```

```
# 정답과 예측 결과가 다른 경우(모델이 잘못 분류한 경우)
if gt_label != pred_label:
    # plt로 4개를 한번에 출력하기 때문에 4번동안 리스트에 누적시킨다
    show_cnt += 1
    wrong_pic, _ = test_data[cnt]
    plt_pic_list.append(wrong_pic)
    gt_label_list.append(gt_label)
    pred_label_list.append(pred_label)
    second_pred_label_list.append(second_label)
    third_pred_label_list.append(thirt_label)
    plt_cnt += 1
```







- 학습된 모델이 잘못 분류한 케이스 분석
- 모델의 Prediction 결과가 Ground Truth랑 다른 경우를 예측 확률 순위로 1, 2, 3위 출력
  (정답지가 1인 사진을 9로 잘못 예측했으며, 두번째 세번째 후보는 1과 2)
- 모델이 잘못했는지, 데이터가 잘못되었는지를 판단

Code Running

2. Pytorch CNN – Feature Extraction.ipynb