PIAI
인공지능연구원
POSTECH Institute of Artificial Intelligence

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Machine Learning
Deep Learning

GyeongYeong, Kim
I-Eon, Na

ML/DL Goal

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- Keras / Pytorch에 대한 전반적인 Framework에 이해한다.
- 이미지 데이터셋에 대한 분류를 딥러닝 네트워크로 학습할 수 있다.
- 자신이 학습한 모델에 대해 분석할 수 있다.
- 기존의 다른 모델을 가져와 적용할 수 있다.

ML/DL Lab

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- 1일차 : Framework / Classifier(~DNN)
- 2일차 : Analysis Tools / Feature Extraction(~CNN)
- 3일차 : Additional Func.(Data Augmentation / Fine Tuning)
  Customization
- 4일차 : Additional Func.(Data Augmentation / Fine Tuning)
  RNN / GAN

ML/DL Lab 1st Day

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- Keras Basic
  - Framework Introduction
  - Y=3X Regression
  - ANN/DNN with MNIST
  - Model 저장,로드
- Pytorch Basic
  - Framework Introduction
  - Y=3X Regression
  - ANN/DNN with MNIST
  - Model 저장,로드

ML/DL Lab 2nd Day

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- Keras Model Analysis
  - Callback
  - History 확인
  - 틀린샘플 확인
  - Confusion Matrix
- Feature Extraction
  - CNN / Pooling Layer
  - Batch Normalization / DropOut
- Pytorch Feature Extraction
  - CNN / Pooling Layer
  - Batch Normalization / DropOut
  - Best Model Saving
  - History 확인
  - Confusion Matrix
  - 틀린 샘플 확인
  - Early Stopping

ML/DL Lab 3rd Day

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- Keras Additional Functions
  - CIFAR10 Introduction
  - Model Summation
  - Data Augmentation
  - Transfer Learning
- Pytorch Additional Functions
  - Data Augmentation
  - Transfer Learning
  - Training Customized Dataset(Man/Monkey)

ML/DL Lab 4th Day

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- Keras Additional Functions
  - LSTM (with MNIST)
  - GAN (with MNIST)
- Pytorch Additional Functions
  - GAN (with MNIST)
  - Quiz

ML/DL Lab Recommendation

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- 인트로 – 코딩 – 직접 실습
- 이론과 다소 별개 : 구체적인 용어 특성이나 성질들은 이론 수업이나 검색으로 해결할 것
- Coding Time : 수업 시간 내 잘 집중해서 진행할 것(수업 이후 정답지 제공)
- 동작 관련 오류 : 각 반 보조에게 손들고 해결 요청
- 숙제 : 혼자 힘으로 다양하게 시도해보면서 배워볼 것
- 퀴즈 : 실습 수업 내용 잘 들으면서 공부할 것

ML/DL Homework

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- MNIST 데이터 셋의 학습 / 평가 / 분석 (Keras / Pytorch 중 택1)
- 제출 파일 : 해당 파일이 들어있는 zip 파일 : ex) HW_김경영.zip
  - Homework_(이름).ipynb (모두 Run한 상태로)
  - 보고서_(이름).docx

- 정확도(60%) - 진행 전략(20%) - 분석(20%)을 통합적으로 평가
  - 정확도 : 99.75% 넘으면 만점 (넘으면 굳이 더 학습해보려고 하진 않아도 됨)
  - 진행 전략 : Keras/Torch 라이브러리 내 적용할 수 있는 수준의 네트워크로 학습 (나름 시도해본 Trial들을 간단하게 정리해도 좋음!)
  - 학습 분석 : Under/Over fitting 여부 확인 / 학습 안정화 여부 확인
  - 성능 분석 : 잘못된 분류 케이스 확인 / 개선할 수 있는 방향 제안 / 현실적인 최대 정확도 제안

- 제출 시 최저점수가 40점이므로 늦더라도 제출 할 것 (미제출 : 0점)
- 표절 심증이 있을 시, 최저점수 반영

ML/DL Lab Quiz

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- True/False : 6문제 (30)
- 단답형 : 10문제 (30)
- 실습 코드 : 2문제 (20)
- 서술형 : 1문제 (20)

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Keras Basic

GyeongYeong, Kim

딥러닝 프레임워크 Timeline

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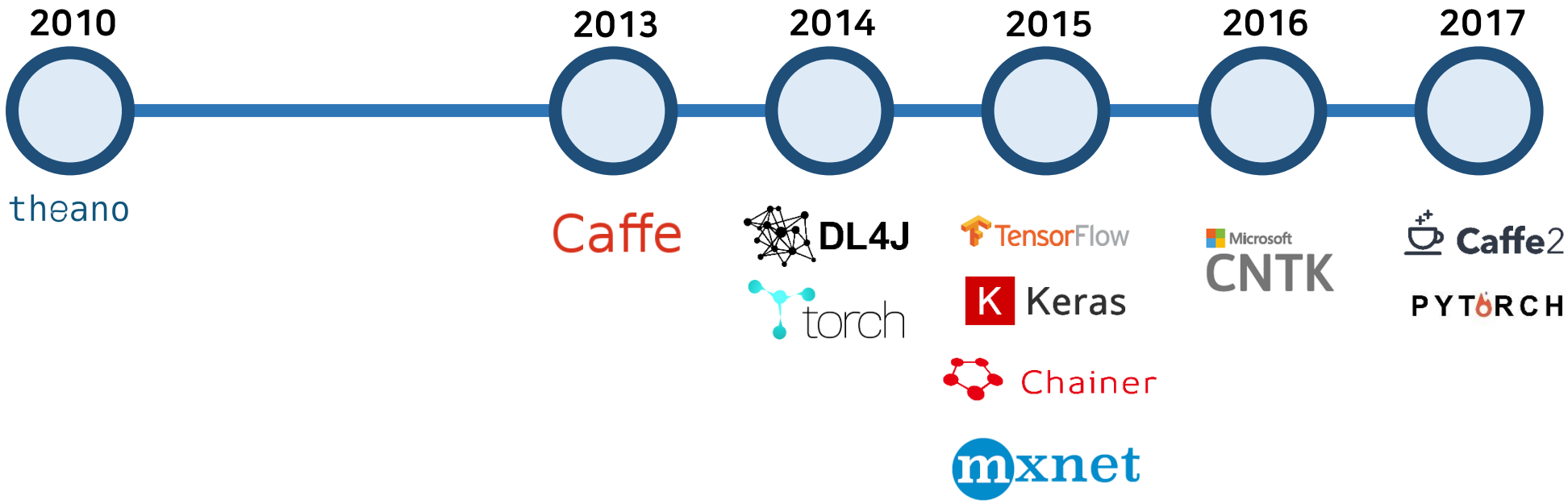

딥러닝 프레임워크 비교

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주체	플랫폼	모바일	언어	인터페이스	OpenMP	Cuda	OPenCL	멀티GPU	분산
SkyMind	Cross – platform	Android	Java	Java, Scala, Python	Y	Y	-	Y	Y (Spark)

장점

- 가장 많은 프로그래머를 보유하는 Java 기반 딥러닝 프레임워크
- 쉬운 이식성, 높은 안정성
- 문서화가 잘되어 있음
- 시각화 도구 제공

단점

- Java의 언어적 특성으로 인해 학습 및 테스트 과정이 번거로움
- 협소한 사용자 커뮤니티
- 부족한 예제

딥러닝 프레임워크 비교

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Caffe2

주체	플랫폼	모바일	언어	인터페이스	OpenMP	Cuda	OPenCL	멀티GPU	분산
BAIR, facebook	Linux, Mac	-	C++	Python, C++	Y	Y	-	Y	-

장점

- 이미지 처리에 특화
- Caffe Model Zoo를 통한 다양한 Pre-trained Model 제공

단점

- 이미지 이외의 데이터 처리에는 부적합(텍스트, 사운드 등)
- 유연하지 못한 API(C++/CUDA로 직접 구현 필요)
- 문서화가 잘 안되어 있음

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PYTORCH

주체	플랫폼	모바일	언어	인터페이스	OpenMP	Cuda	OPenCL	멀티GPU	분산
Facebook	Linux, Mac, Window	Android, iOS	Lua	python	Y	Y	Y	Y	Y

장점

- 알고리즘 모듈화가 잘되어 있어 사용이 용이
- 다양한 데이터 전처리 및 시각화 유틸리티 제공
- 직관적인 API
- 다양한 Pre-trained Model 제공

단점

- Lua 언어 자체가 Java/Python보다 폐쇄적
- 상용 어플리케이션이 아니라 연구용으로 적합

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theano

주체	플랫폼	모바일	언어	인터페이스	OpenMP	Cuda	OPenCL	멀티GPU	분산
Google	Linux, Mac, Window	-	Python	Python	Y	Y	-	Y	-

장점

- Low-level을 제어할 수 있는 API
- 빠르고 유연함
- Wrapper 프레임워크의 기반 프레임워크(Keras)

단점

- 매우 복잡함
- 2017년 이후 공식 지원 마감

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주체	플랫폼	모바일	언어	인터페이스	OpenMP	Cuda	OPenCL	멀티GPU	분산
Google	Linux, Mac, Window	Android, iOS	Python, C++	Python, C/C++, Java, Go	N	Y	-	Y	Y

장점

- Low-level / High level API 모두 제공
- 방대한 사용자 커뮤니티
- 문서화가 잘되어 있음
- 시각화 도구 제공(TensorBoard)

단점

- 런타임 중 그래프 변경 안됨
- 비교적 느림
- CUDA 연결 이슈에 민감함

딥러닝 프레임워크 비교

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Keras

주체	플랫폼	모바일	언어	인터페이스	OpenMP	Cuda	OPenCL	멀티GPU	분산
Francois Chollet	Linux, Mac, Window	-	Python	Python	Y(Theano) N(TF)	Y	-	Y	-

장점

- 직관적인 API 인터페이스
- Caffe, Torch, Tensorflow 등 다양한 딥러닝 프레임워크 모델 import 기능 제공
- 문서화가 잘되어 있음

단점

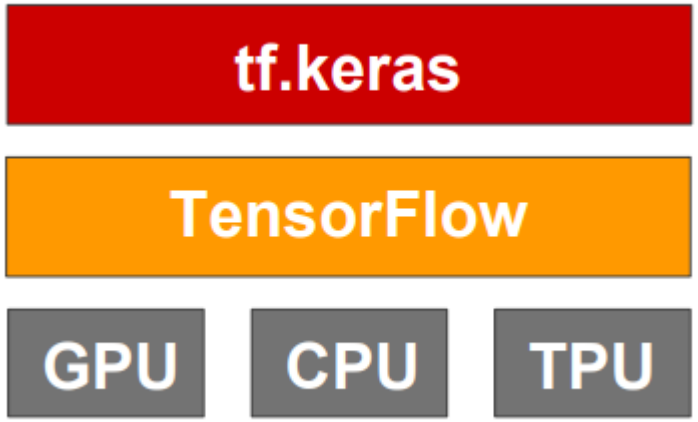
- 텐서플로우의 단점과 유사함

Keras

- tensorflow.keras (tf.keras) module
- Part of core TensorFlow since v1.14

- In-browser with GPU acceleration (WebKeras, Keras.js, WebDNN…)
- Android (TF, TF Lite), iPhone (native CoreML support), Raspberry Pi, JVm

- 쉬움!



Keras Framework Flow

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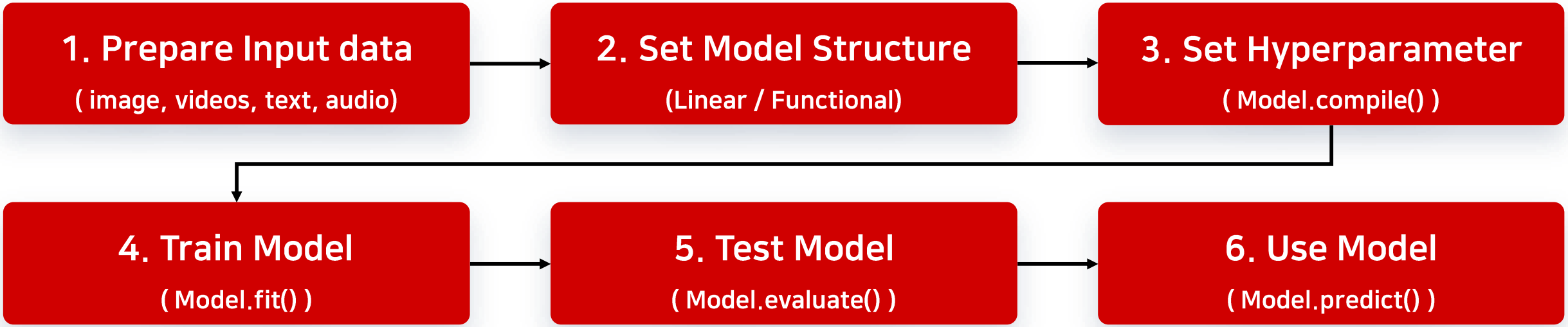
- Keras 주요 학습과정



Keras Framework Flow

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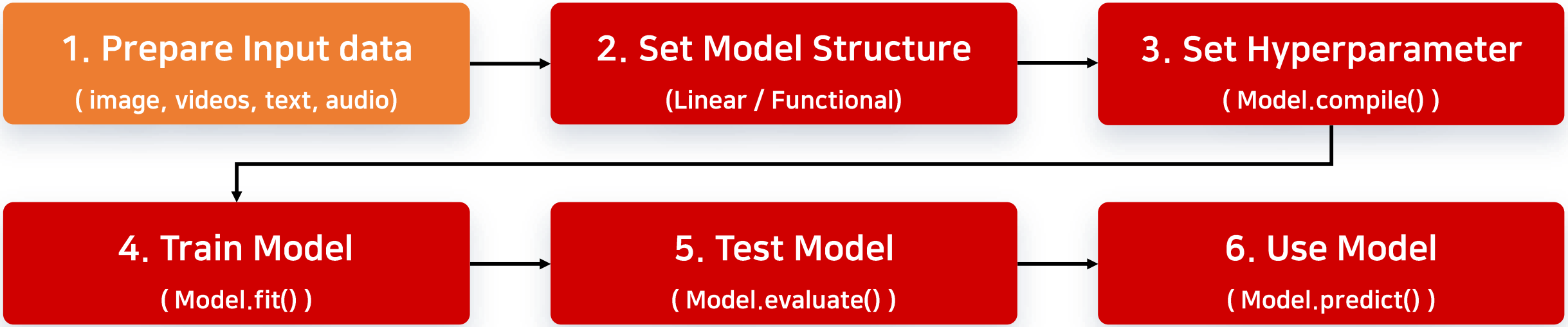

Input Data Preparation

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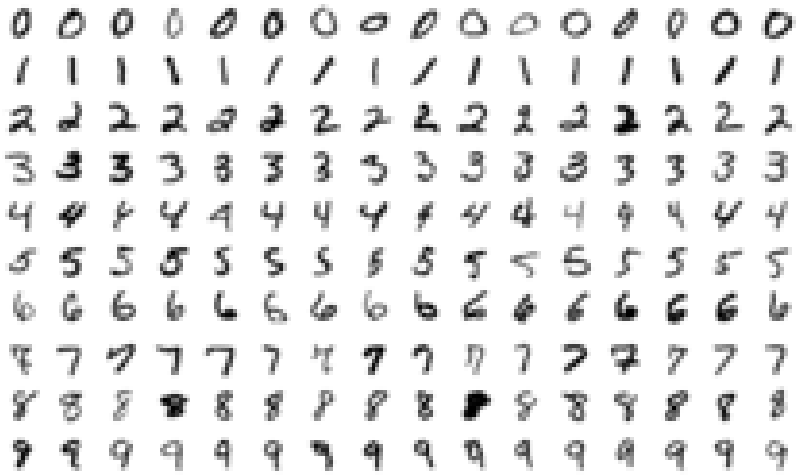
- MNIST Dataset



Label	5	0	4	1

- 손으로 쓴 숫자들로 이루어진 데이터셋
- 0~9의 10개 클래스로 구성
- 28X28크기의 grayscale 이미지와 라벨
- Training sample : 60,000개
- Test sample : 10,000개

Input Data Preparation

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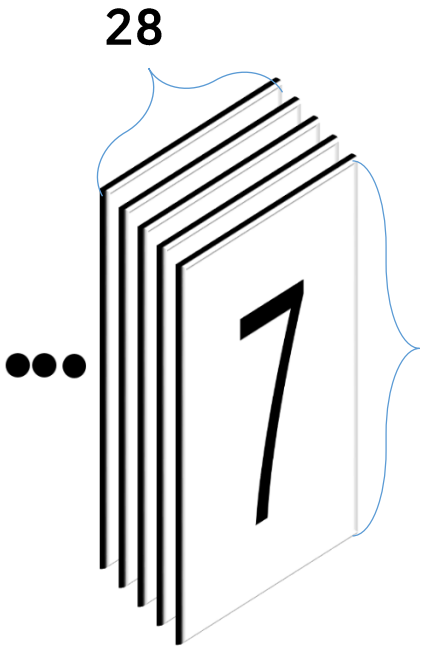
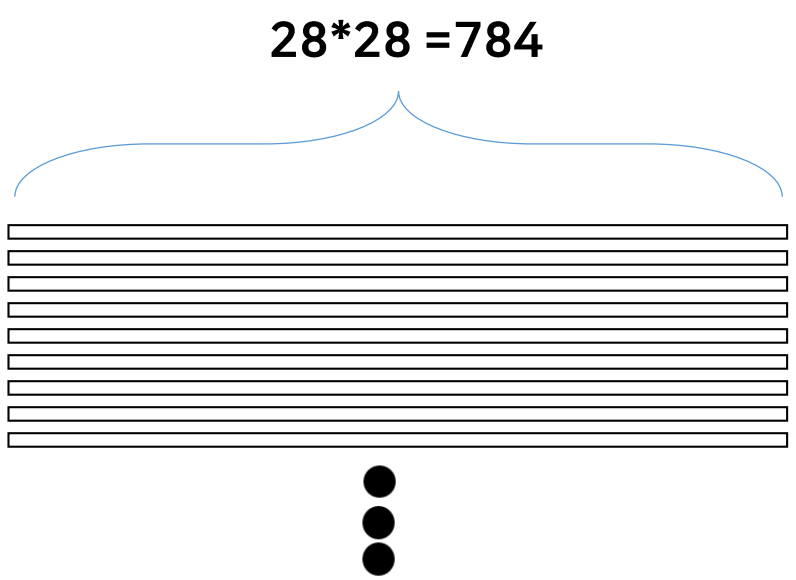
Image



flatten



Label

..... 4 5 7

one-hot encoding

0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	1	0	0

Keras Framework Flow

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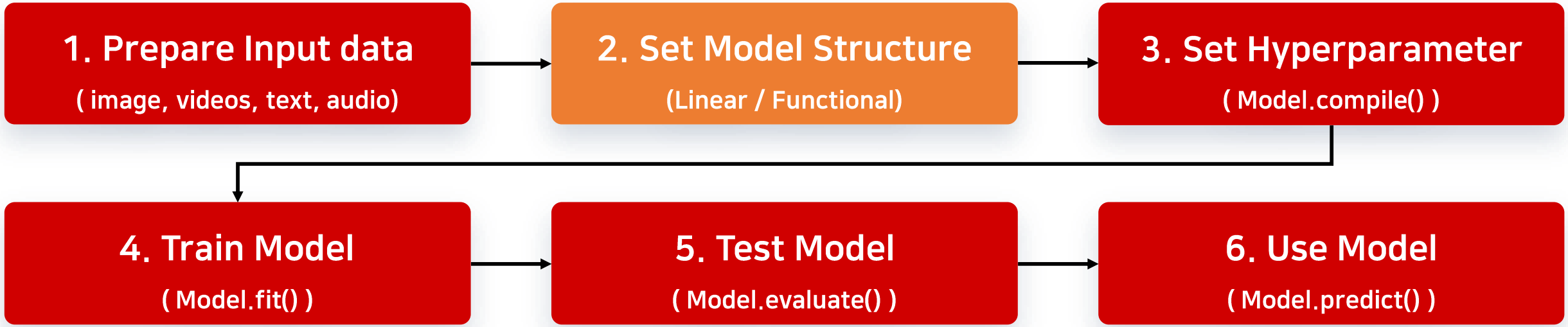

Overview of Image classification

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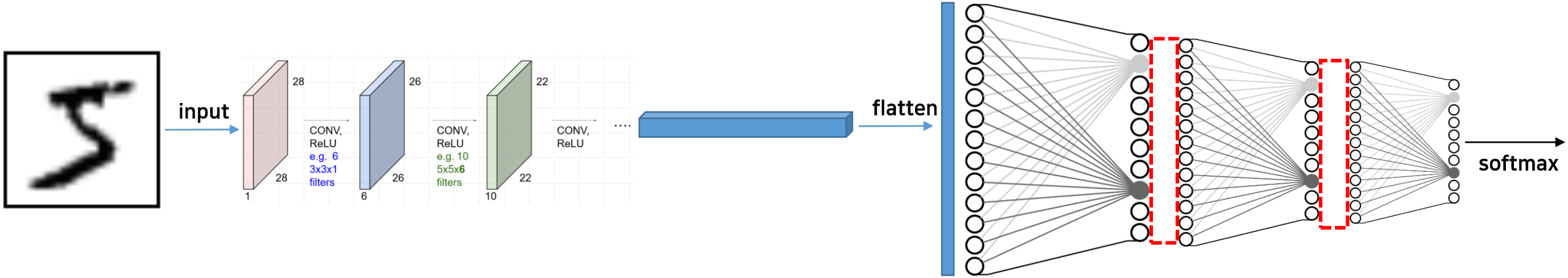

Feature extraction
(Convolution layer
Pooling layer)

Classifier
(Fully Connected layer
Activation layer)

Overview of Classifier

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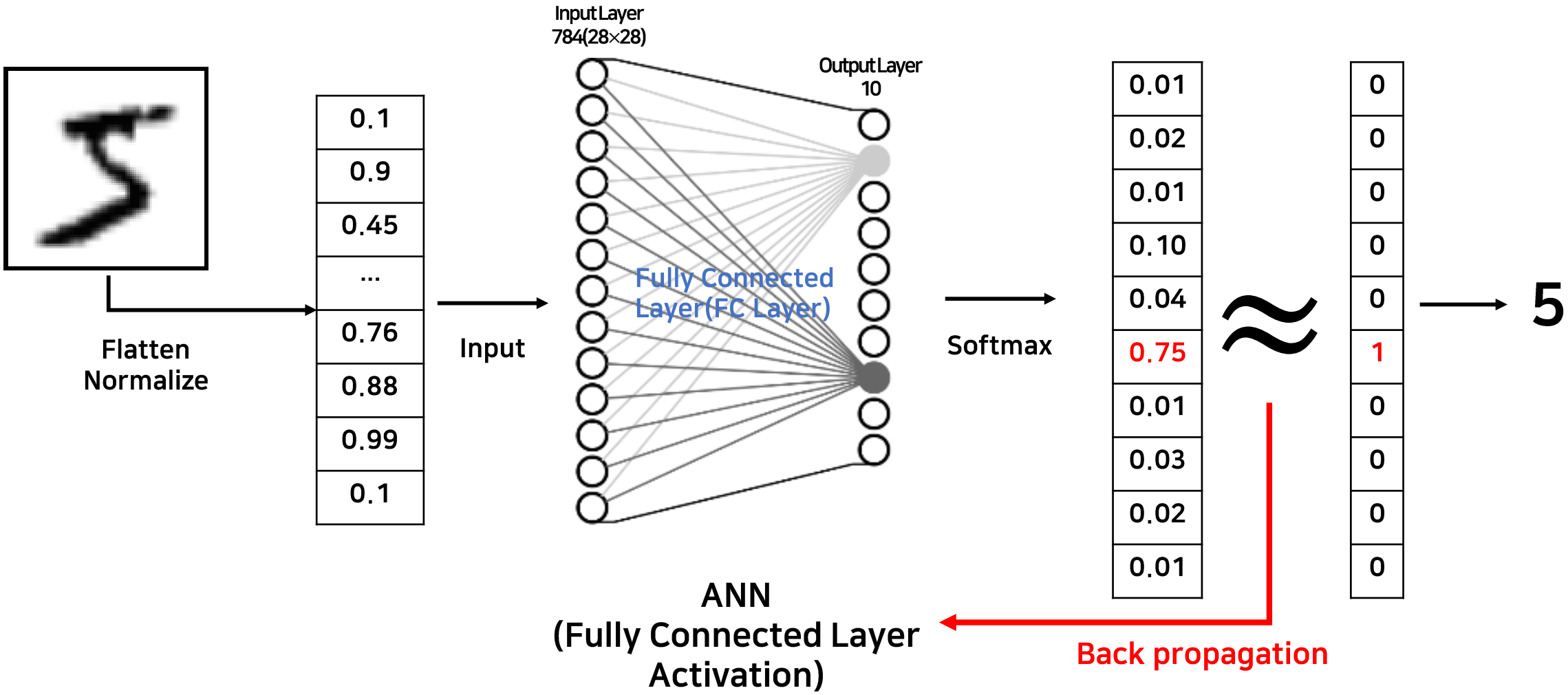

Linear Classifier

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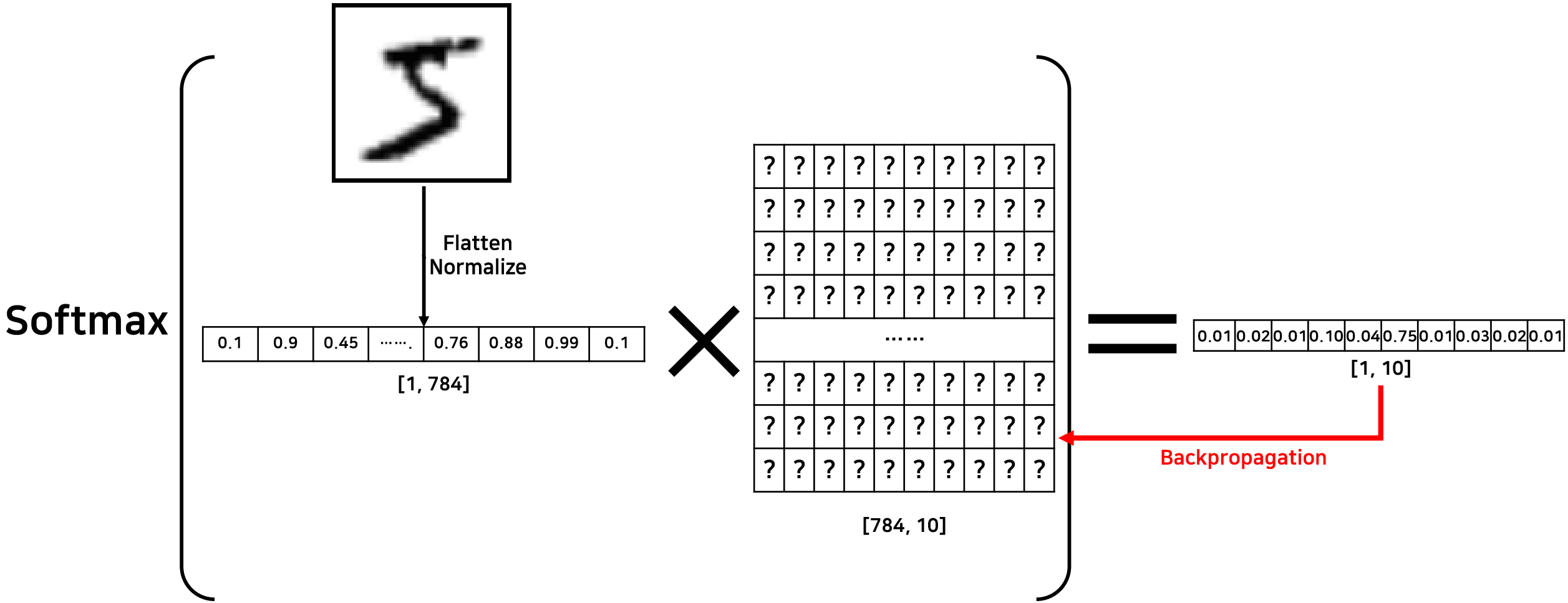

Linear Classifier

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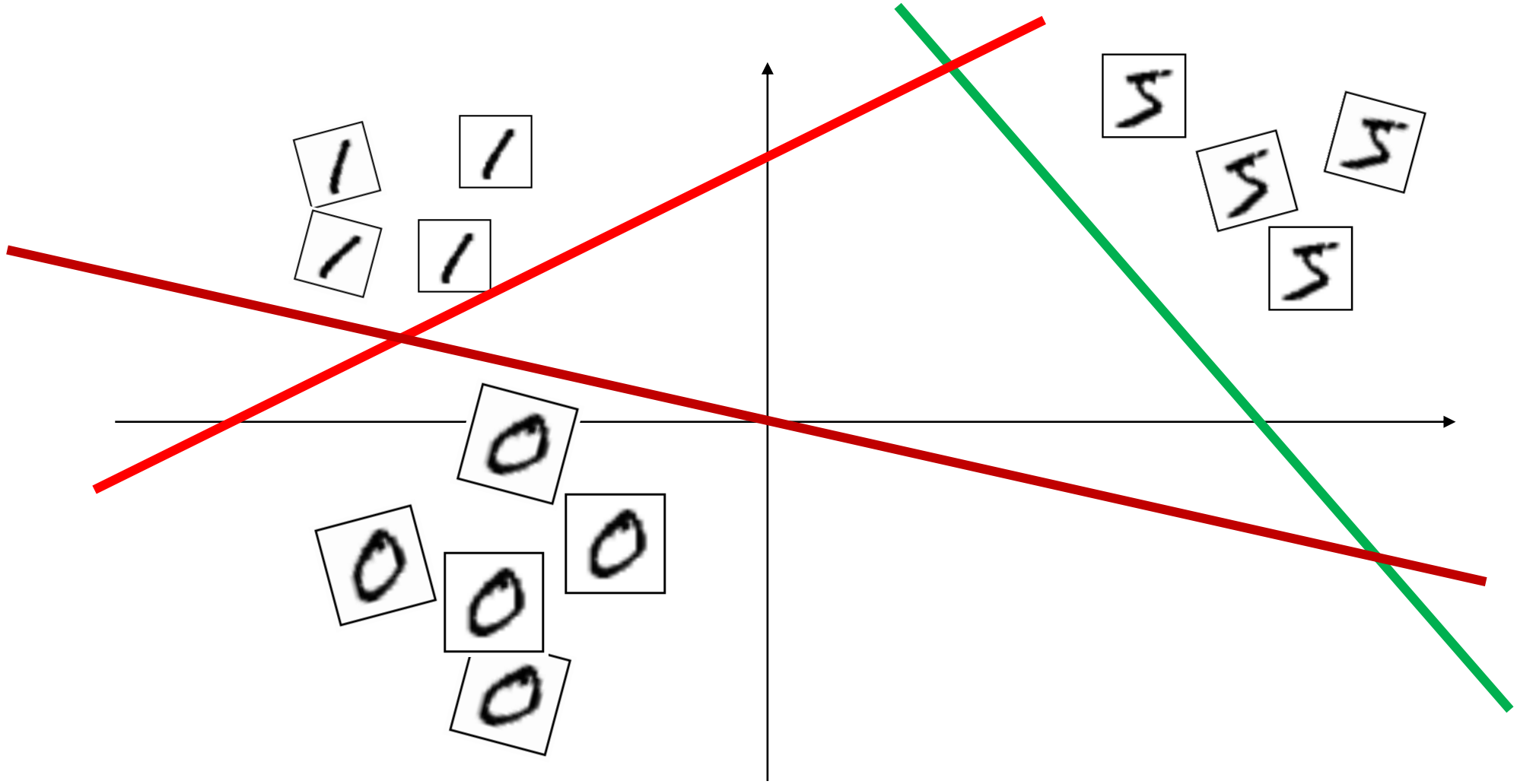

Overview of DNN

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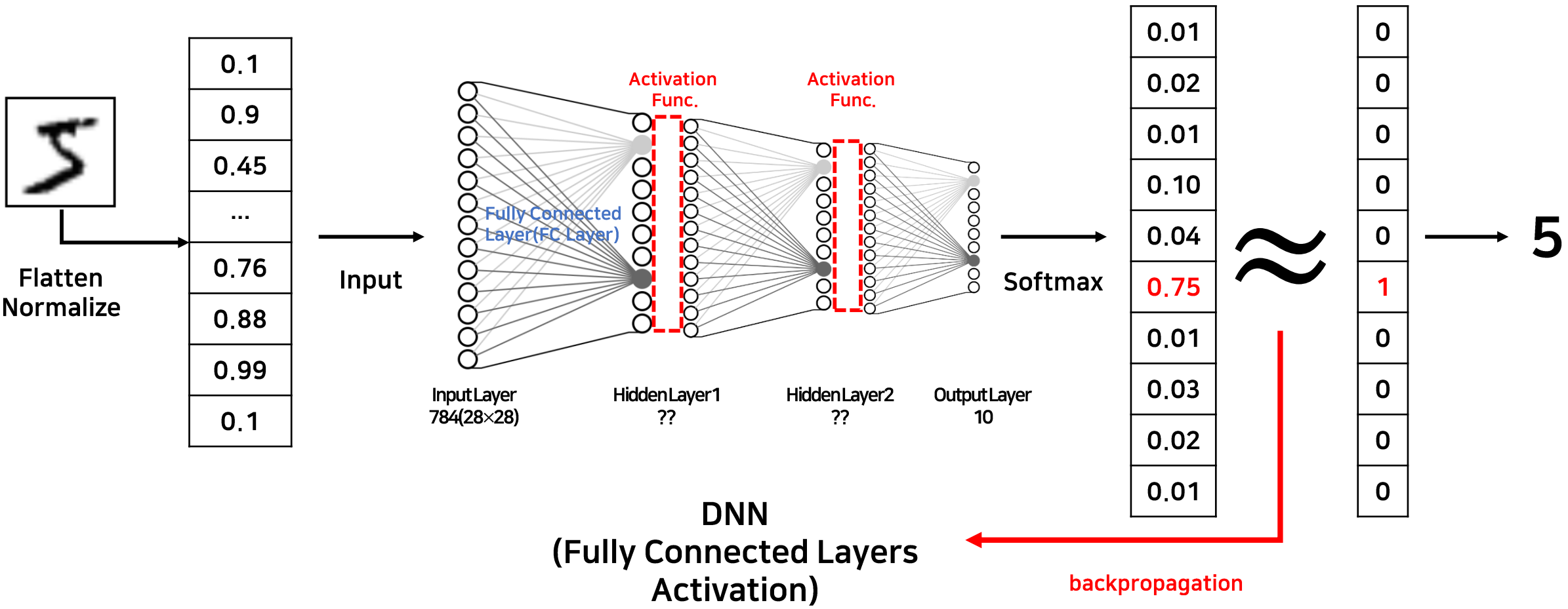

DNN Classifier

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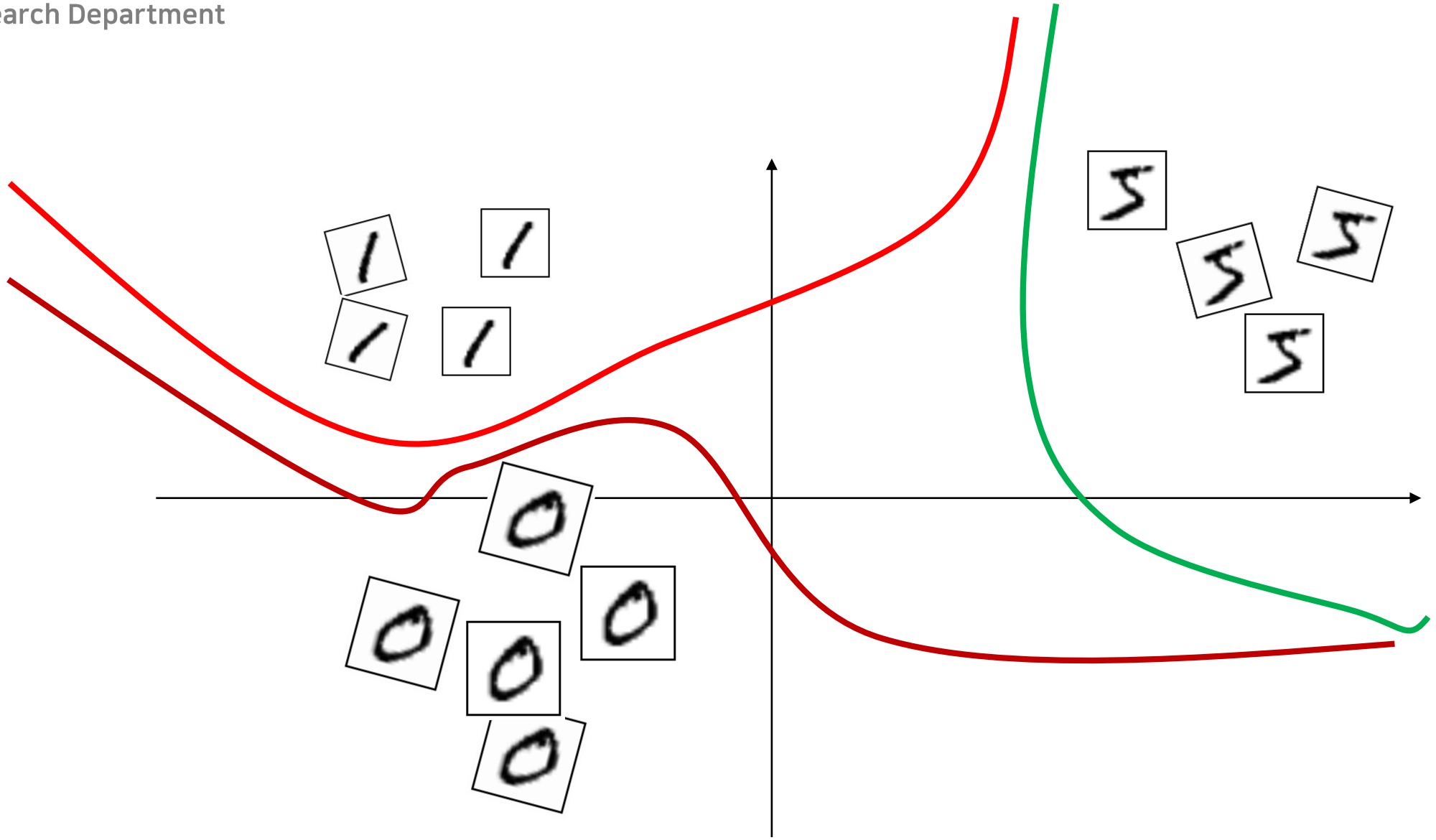

Classifier

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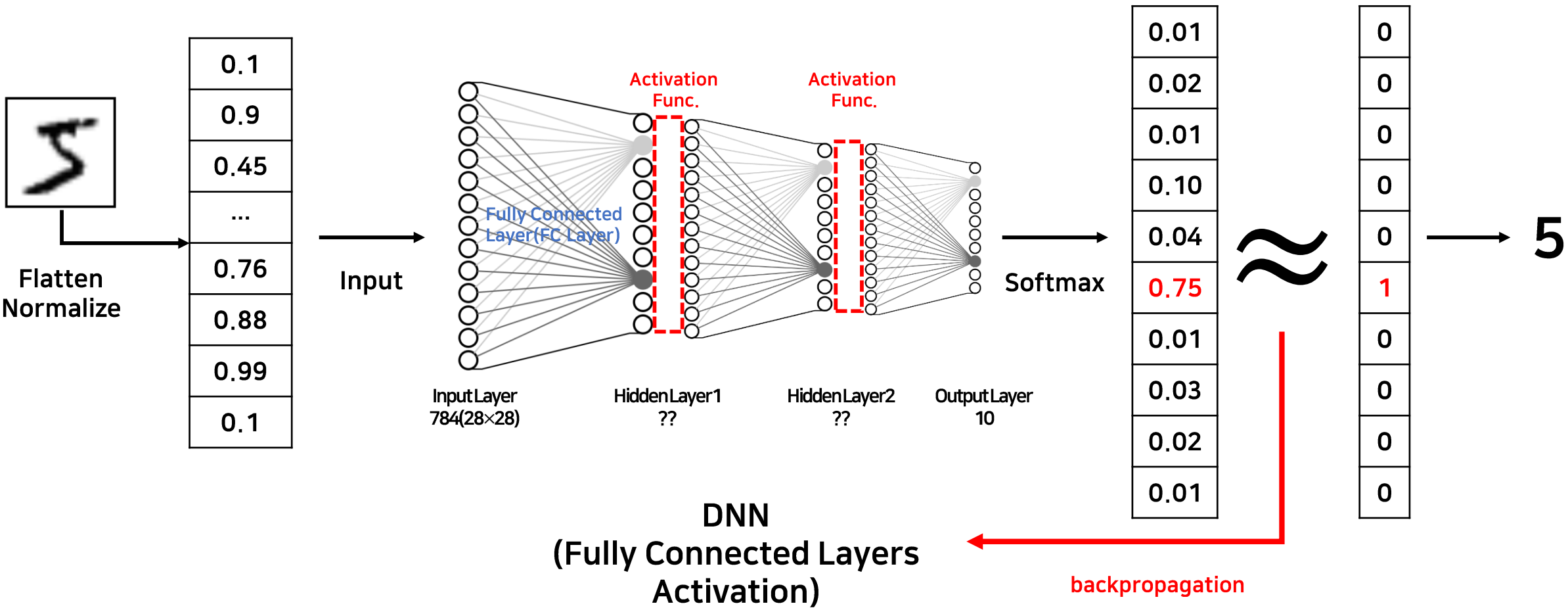

Network Definition

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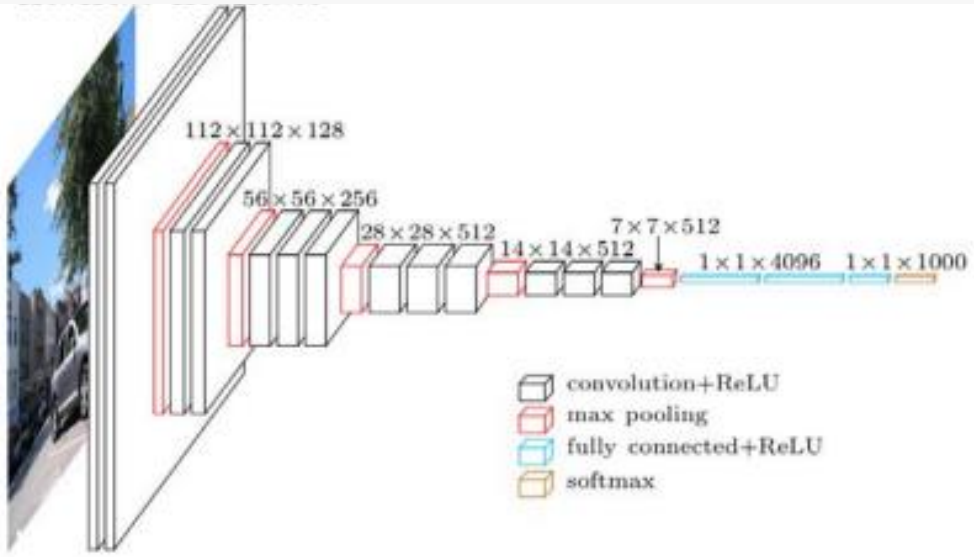
2. Define the model (Sequential style)

```
def DNN_seq(n_in, n_out):
    model = Sequential()
    model.add(Dense(units =256, input_shape=(n_in,), activation='relu'))
    model.add(Dense(units =128, input_shape=(256,), activation='relu'))
    model.add(Dense(units =64, input_shape=(128,), activation='relu'))
    model.add(Dense(units =32, input_shape=(64,), activation='relu'))
    model.add(Dense(units =n_out, input_shape=(32,), activation='softmax'))
    return model
```



- Linear stack of layers
- Useful for building simple models
- Simple classification network
- Encoder – Decoder models

Network Definition

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    model.add(Dense(units =32, input_shape=(64,), activation='relu'))
    model.add(Dense(units =n_out, input_shape=(32,), activation='softmax'))
    return model
```

- Sequential : Sequential 스타일로 진행하겠다고 설정
- Dense : Fully Connected Layer 종류
- Units : output 원소 개수
- Input_shape : input의 크기
- Activation : activation 함수 설정

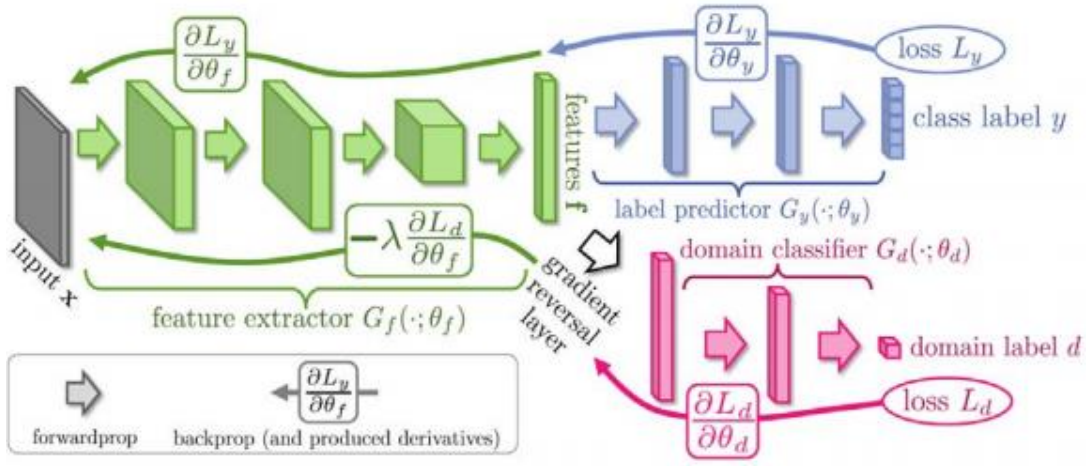
Network Definition

PIAI Research Department

2. Define the model (Functional style)

```
def DNN_func(n_in, n_out):
    x = Input(shape=(n_in,))
    x = Dense(256)(x)
    x = Activation('relu')(x)
    x = Dense(128)(x)
    x = Activation('relu')(x)
    x = Dense(64)(x)
    x = Activation('relu')(x)
    x = Dense(32)(x)
    x = Activation('relu')(x)
    x = Dense(n_out)(x)
    y = Activation('softmax')(x)
    model = Model(inputs = x, outputs = y)
    return model
```

- Multi-input and Multi-output models
- Complex models which forks into 2 or more branches
- Models with shared (Weights) layers



Network Definition

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    x = Activation('relu')(x)
    x = Dense(32)(x)
    x = Activation('relu')(x)
    x = Dense(n_out)(x)
    y = Activation('softmax')(x)
    model = Model(inputs = x, outputs = y)
    return model
```

- Input : Input Layer로 정의
- Dense(256)(x) : x layer를 input으로 256크기의 output이 나오도록 Fully Connected layer를 구성
- Activation('relu')(x) : x layer를 입력해 relu 활성화 함수를 적용
- Model(inputs = x, outputs = y) : x를 입력해서 y가 출력될 수 있도록 Model을 정의

Network Definition

PIAI Research Department

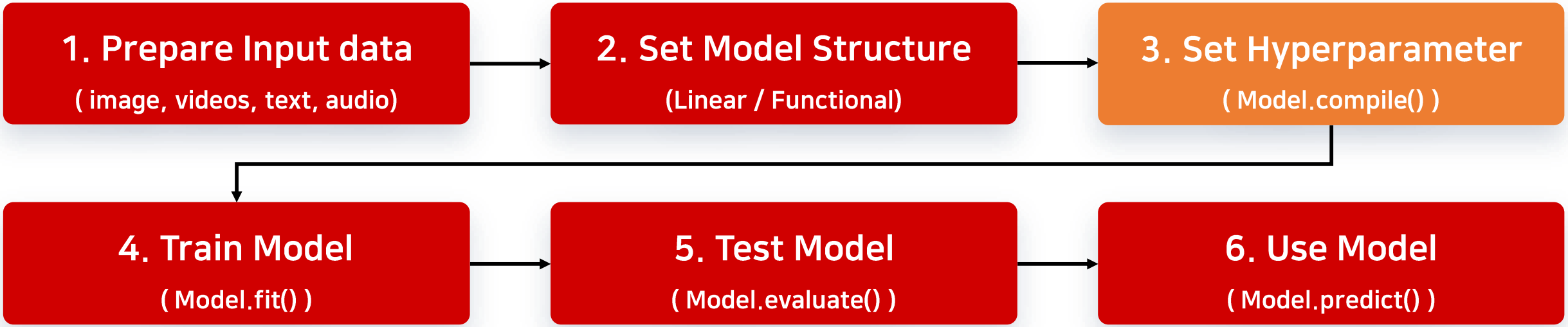
2. Define the model

```
model = DNN_seq(n_in, n_out)
model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_17 (Dense)            (None, 256)               200960

 dense_18 (Dense)            (None, 128)               32896

 dense_19 (Dense)            (None, 64)                8256

 dense_20 (Dense)            (None, 32)                2080

 dense_21 (Dense)            (None, 10)                330

=================================================================
Total params: 244,522
Trainable params: 244,522
Non-trainable params: 0
_________________________________________________________________
```

Keras Framework Flow

PIAI Research Department



Model Setting

PIAI Research Department

3. Model.compile() (Set Loss / Optimizer and Metrics)

```
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

Loss Functions: 알고리즘이 예측한 값과 실제 정답의 차이를 비교하기 위한 함수

종류

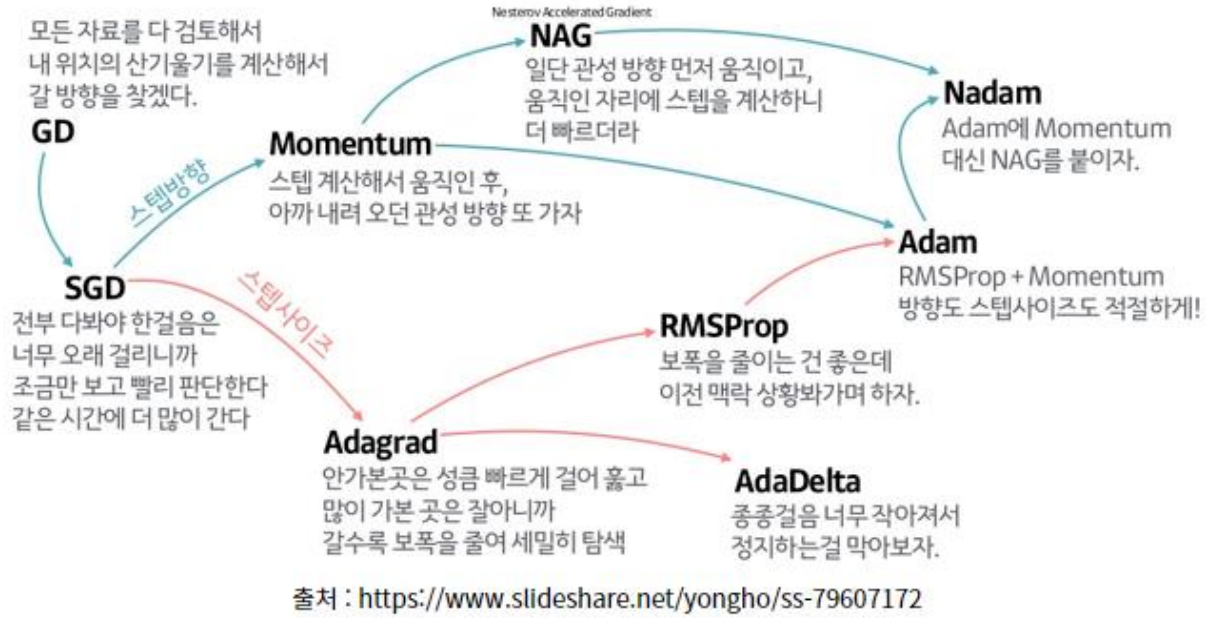
- Probablistic losses: binary_crossentropy, categorical_crossentropy, sparse_categorical_crossentory, poisson, kl_divergence
- Regression loss: rmse, mse, mae, mape, msle, cosine_similarity
- Hinge loss: hinge, squared_hinge, categorical_hinge,

Model Setting

PIAI Research Department

3. Model.compile() (Set optimizer and loss function)

```
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```



출처 : https://www.slideshare.net/yongho/ss-79607172

Optimizer Loss function의 최솟값을 찾아주고자 할 때 수행할 알고리즘

종류 : sgd, RMSprop, Adam, Adadelta, Adagrad, Adamax, Nadam, Ftrl

Model Setting

PIAI Research Department

3. Model.compile() (Set optimizer and loss function)

```
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

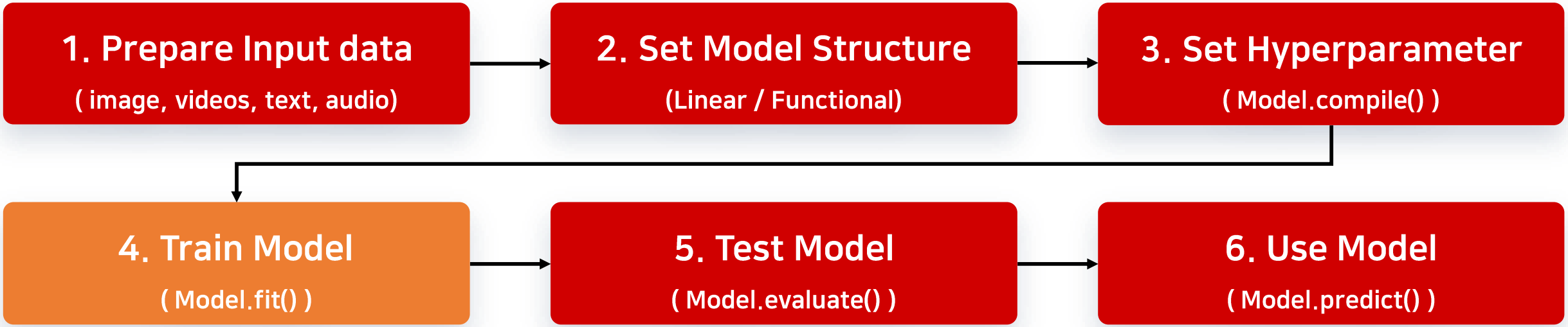
Metrics : 검증 데이터에서의 학습 모델의 성능에 대한 평가 지표 설정

종류:

- Loss
- accuracy, top_k_categorical_accuracy
- Recall, Precision, AUC
- MeanIoU

Keras Framework Flow

PIAI Research Department



Model Training

PIAI Research Department

4. Model.fit() (Train model)

```
model.fit(train_X, train_Y, epochs=epochs, batch_size=batch_size, validation_data=(vali_X, vali_Y), shuffle=False, callbacks=[checkpointer])

checkpointer=ModelCheckpoint(filepath=modelpath, monitor='val_acc', verbose=0, save_best_only=True)
```

- Train_X: Training data
- Train_Y: Target label
- validation_data: Tuple (vali_x, vali_y)
- validation_split:Fraction of the training data to be used as validation data (0~1 사이값)
- shuffle: whether to shuffle the training data before each epoch (Boolean)
- verbose: Verbosity mode(0, 1, or 2)

Model Training

PIAI Research Department

4. Model.fit() (Train model)

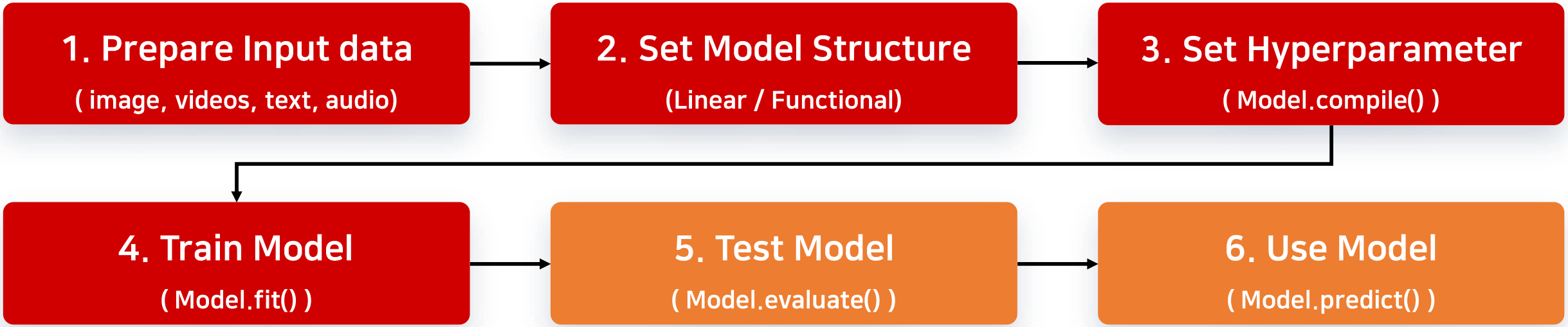
```
model.fit(train_X, train_Y, epochs=epochs, batch_size=batch_size, validation_data=(vali_X, vali_Y), shuffle=False, callbacks=[checkpointer])

checkpointer=ModelCheckpoint(filepath=modelpath, monitor='val_acc', verbose=0, save_best_only=True)
```

- epochs: Number of epochs to train the model
- batch_size: Number of samples per gradient update

- 1 Epoch : 전체 데이터 셋에 대해 한번 학습을 완료한 상태를 의미(보통 1 Epoch 후 validation 진행)
- Iteration : 1 Epoch을 완료하기 위해 필요한 Pass 회수(batch_size × Iteration ≈ Dataset Size)

Keras Framework Flow

PIAI Research Department



Model Application

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5. Model.evaluate() (Test model)

```
loss_and_accuracy = model.evaluate(X_test, Y_test, batch_size=128)
print('loss : %.4f, accruracy : %.4f'%(loss_and_accuracy[0],loss_and_accuracy[1]))
```

- x: test data
- y: target label
- batch_size: Number of samples per evaluation step
- verbose: Verbosity mode

6. Model.predict() (Use model)

```
model.predict(x, batch_size=128)
```

- x: input data
- batch_size: Number of samples per predict
- verbose: Verbosity mode

Code Running

(student) 1_Keras Basic & Classifier.ipynb

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PyTorch Basic

I-Eon Na

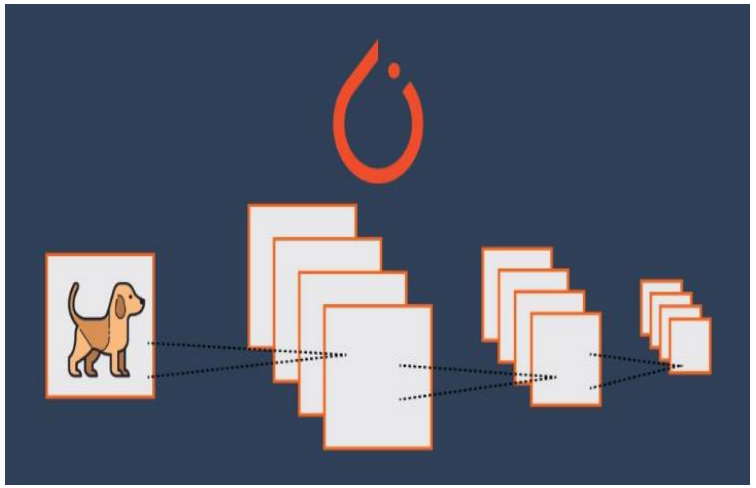
PyTorch Tutorial

PIAI Research Department

PYTORCH

- PyTorch (torch.nn) module
- Base on Torch and Caffe2
- similar Deep Learning library to TensorFlow

- Made by Facebook AI Research Team
- Simple to make and edit network and parameters on GPU



Keras VS PyTorch

Keras

간단..?

```
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='
model.add(MaxPool2D())
model.add(Conv2D(16, (3, 3), activation='
model.add(MaxPool2D())
model.add(Flatten())
model.add(Dense(10, activation='softmax')
```

동일 로직, 다른 코드

- 데이터 전처리 과정 간편
- 단일 코드로 간단한 모델 제작 가능
- Verbose 기능 제공(학습 추이 출력)

PyTorch

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

        self.conv1 = nn.Conv2d(3, 32
        self.conv2 = nn.Conv2d(32, 1
        self.fc1 = nn.Linear(16 * 6
        self.pool = nn.MaxPool2d(2,

    def forward(self, x):
        x = self.pool(F.relu(self.co
        x = self.pool(F.relu(self.co
        x = x.view(-1, 16 * 6 * 6)
        x = F.log_softmax(self.fc1(x

        return x
```

복잡..?

```
model = Net()
```

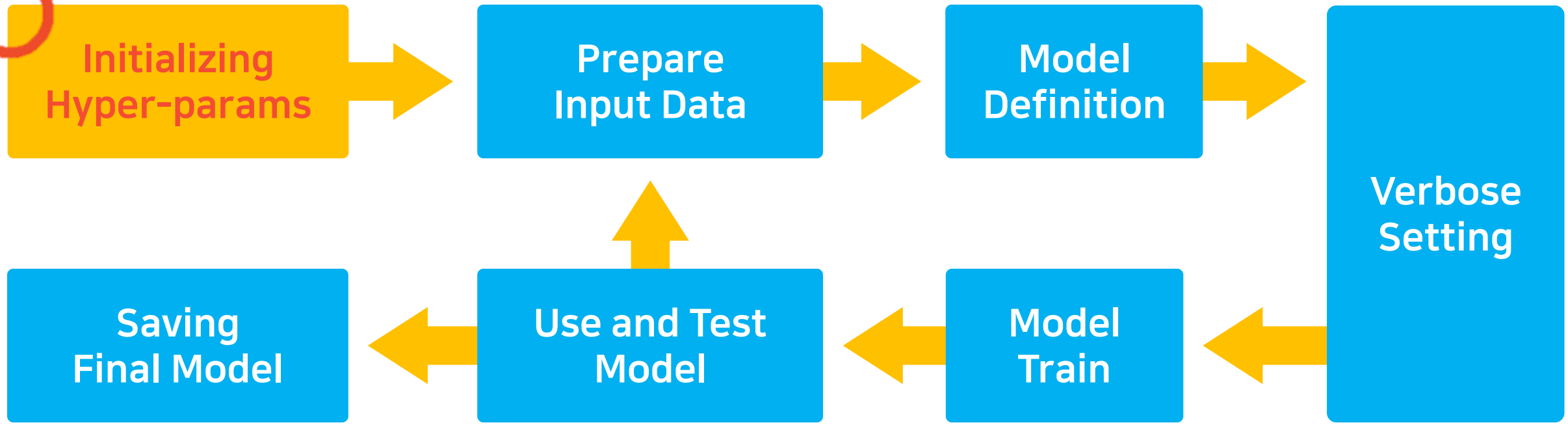
- 데이터 전처리 시 '데이터 로더' 개념 숙지 필요
- 코드가 비교적 복잡하지만 세부 파라미터 수정에 대한 자유도가 높음
- Verbose 기능 직접 코딩

출처: https://github.com/KerasKorea/KEKOxTutorial/blob/master/42_keras_or_pytorch_as_your_first_deep_learning_framework.md

PyTorch Framework Flow

PIAI Research Department

- Deep Learning 모델 구축 과정



HyperParameter Setting

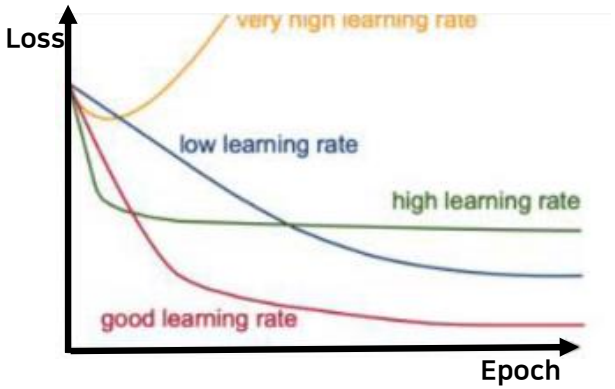
PIAI Research Department

- **하이퍼 파라미터 설정 - 1**

```
# 데이터 로더
batch_size = 32
```

```
# 하이퍼 파라미터
maximum_epoch = 10 # 최대 epoch
learning_rate = 0.01 # Learning Rate
```

- 데이터를 한번에 몇 개를 넣을지
- 전체 데이터셋을 몇 번 학습할지
- 학습하는 속도 조절



출처: https://bdtechtalks.com/2020/04/27/deep-learning-mode-connectivity-adversarial-attacks/gradient-descent-local-minima/
출처: https://m.blog.naver.com/qbxlvnf11/221449297033

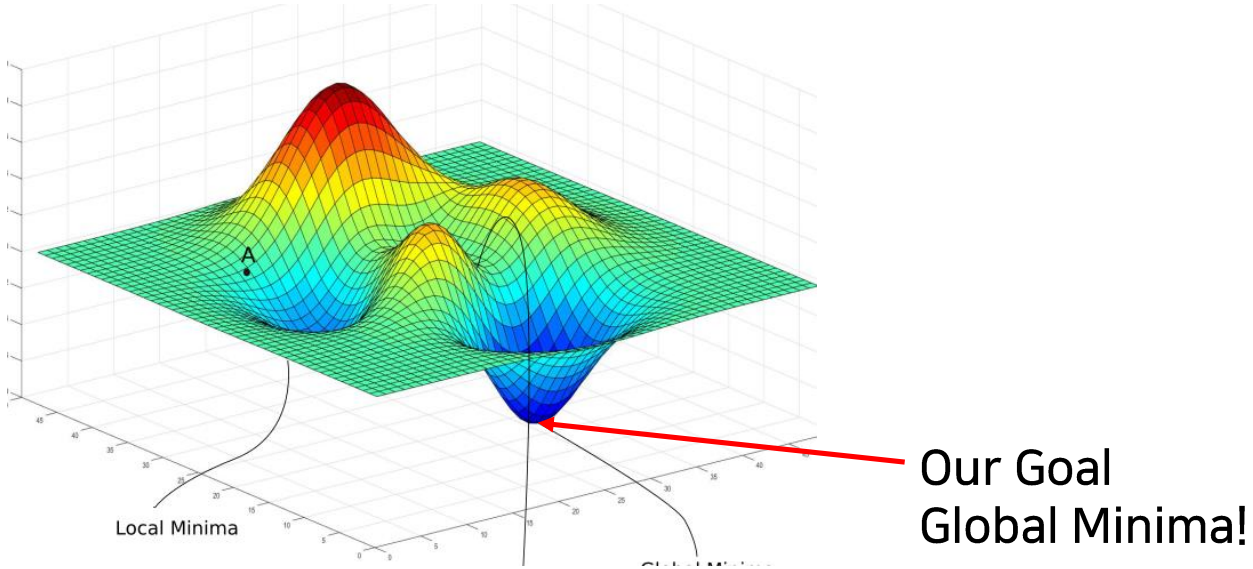
HyperParameter Setting

PIAI Research Department

- **하이퍼 파라미터 설정 - 2**

```
1  # Model
2  def init_model(_net):
3      global net, loss_fn, optim
4      net = _net.to(device)
5      loss_fn = nn.CrossEntropyLoss()
6  #     optim = Adam(net.parameters(), lr=learning_rate)
7      optim = SGD(net.parameters(), lr=learning_rate)
```

- 정답지와 예측값을 비교하여 '모델이 틀린 정도 ' 에 대해서 알아내는 Loss Function
- Gradient Descent를 어떻게 할지에 대해 Optimizer를 지정 (Stochastic Gradient Descent)



Our Goal
Global Minima!

출처: https://www.researchgate.net/figure/a-Graphical-depiction-of-training-loss-with-varying-learning-rates-The-optimal_fig7_346206645

HyperParameter Setting

PIAI Research Department

- **PyTorch에서 사용 가능한 Optimizer 종류**

`Adadelta`	Implements Adadelta algorithm.
`Adagrad`	Implements Adagrad algorithm.
`Adam`	Implements Adam algorithm.
`AdamW`	Implements AdamW algorithm.
`SparseAda`	Implements lazy version of Adam algorithm suitable for sparse tensors.
`Adamax`	Implements Adamax algorithm (a variant of Adam based on infinity norm).
`ASGD`	Implements Averaged Stochastic Gradient Descent.
`LBFGS`	Implements L-BFGS algorithm, heavily inspired by minFunc.
`NAdam`	Implements NAdam algorithm.
`RAdam`	Implements RAdam algorithm.
`RMSprop`	Implements RMSprop algorithm.
`Rprop`	Implements the resilient backpropagation algorithm.
`SGD`	Implements stochastic gradient descent (optionally with momentum).

출처: https://pytorch.org/docs/stable/optim.html

HyperParameter Setting

- PyTorch에서 사용 가능한 Loss Function 종류

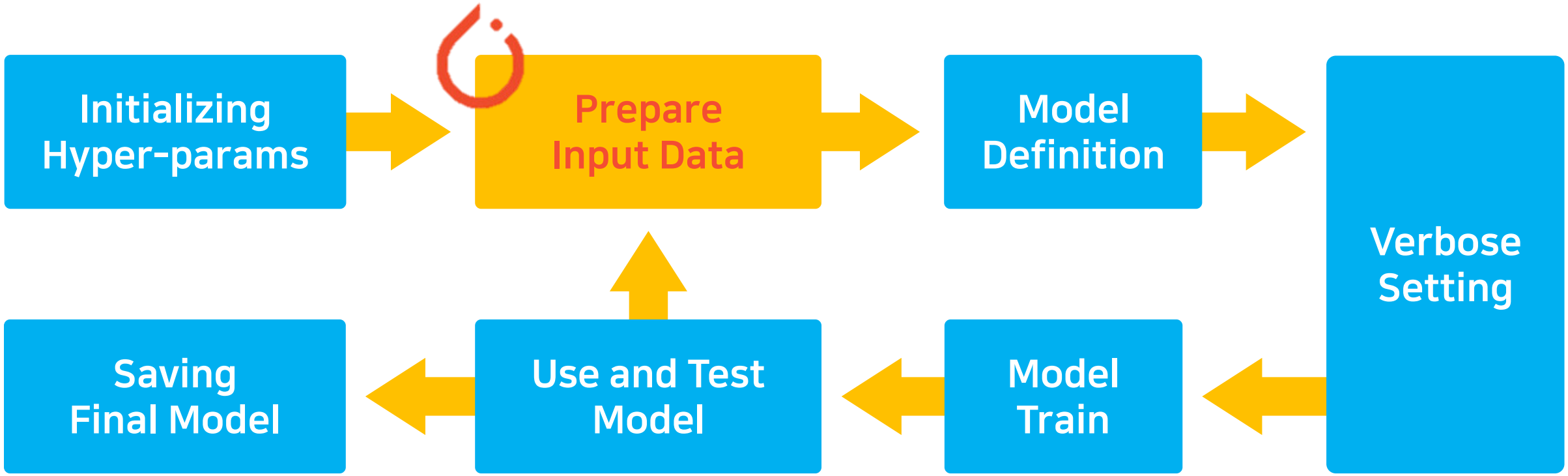
nn.L1Loss
nn.MSELoss
nn.CrossEntropyLoss
nn.CTCLoss
nn.NLLLoss
nn.PoissonNLLLoss
nn.GaussianNLLLoss
nn.KLDivLoss
nn.BCELoss
nn.BCEWithLogitsLoss
nn.MarginRankingLoss
nn.HingeEmbeddingLoss
nn.MultiLabelMarginLoss
nn.HuberLoss
nn.SmoothL1Loss
nn.SoftMarginLoss
nn.MultiLabelSoftMarginLoss
nn.CosineEmbeddingLoss
nn.MultiMarginLoss
nn.TripletMarginLoss
nn.TripletMarginWithDistanceLoss

출처: https://pytorch.org/docs/stable/nn.html#loss-functions

PyTorch Framework Flow

PIAI Research Department

- Deep Learning 모델 구축 과정



Dataset Preparation

- **데이터셋 Tensor 변환 & 전처리**

```
1 mnist_transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize(mean=(0.5,), std=(1.0,))])
2
```

텐서(Tensor)라고 하면 텐서플로우를 떠올리기 쉽지만, 사실 딥러닝에서는 데이터를 처리하기 위한 데이터의 형태라고 이해하면 된다.

```
In [355]:
1 a = [1, 2, 3], [4, 5, 6]

In [356]:
1 print(a)

([1, 2, 3], [4, 5, 6])

In [357]:
1 a = torch.tensor(a)
2 print(a)

tensor([[1, 2, 3],
        [4, 5, 6]])
```

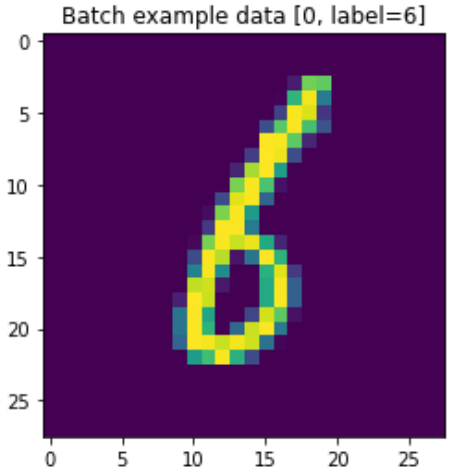
- Transform 옵션에서 텐서화, 정규화, 데이터 어그멘테이션 등 데이터 전처리에 대한 여러가지 옵션 제공
- 딥러닝 학습을 위해서는, Tensor 형식으로 변환해주어야 PyTorch에서 처리 가능

Dataset Preparation

- **전처리된 데이터셋을 DataLoader에 업로드**

```
# Train / Validation / Test 셋에 대한 데이터 로더 만들기
train_loader = DataLoader(train_data, batch_size=batch_size, shuffle=True, pin_memory=True, drop_last=True)
valid_loader = DataLoader(valid_data, batch_size=len(valid_data), pin_memory=True)
test_loader = DataLoader(test_data, batch_size=len(test_data), pin_memory=True)
```

```
Idx: 0 / X.shape = torch.Size([32, 1, 28, 28]) / Y.shape = torch.Size([32])

Y[0:32] = tensor([6, 0, 8, 5, 5, 2, 6, 3, 3, 7, 4, 6, 2, 4, 8, 1, 8, 6, 7, 8, 2, 6, 8, 9,
        9, 1, 8, 3, 7, 9, 5, 1])
```



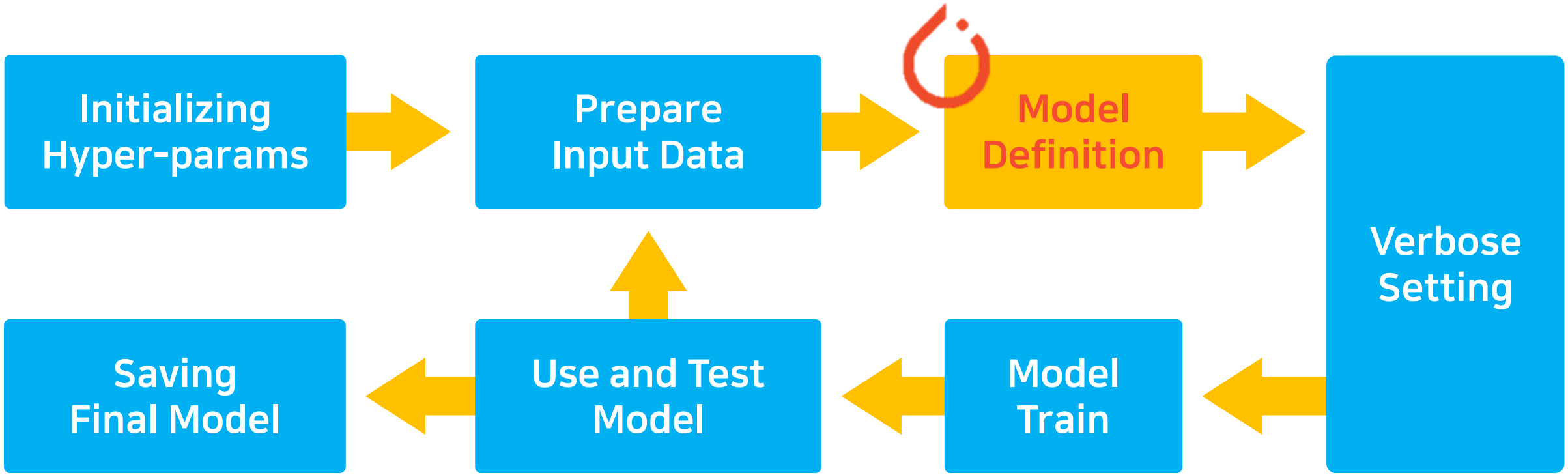

```
# 데이터 로더
batch_size = 32
```

- 전처리된 데이터를 DataLoader에 추가
- DataLoader 출력시, Batchsize에 맞게 구성되어 있음을 확인

PyTorch Framework Flow

PIAI Research Department

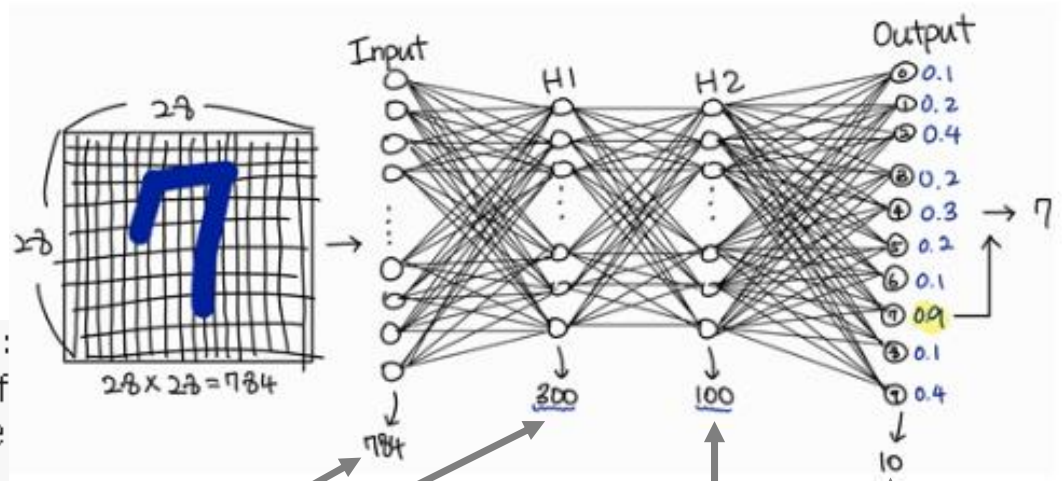
- Deep Learning 모델 구축 과정



Network Architecture Design

PIAI Research Department

- **딥러닝 모델 구조 설계**




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

        # 784 -> 300 -> 100 -> 10
        self.fc1 = nn.Linear(784, 300)
        self.act1 = nn.ReLU() # 활성함수 Relu 사용
        self.fc2 = nn.Linear(300, 100)
        self.act2 = nn.ReLU()
        self.fc3 = nn.Linear(100, 10)

    def forward(self, x):
        x = self.act1(self.fc1(x))
        x = self.act2(self.fc2(x))
        x = self.fc3(x)
        return x
```

- MLP(Multi Layer Perceptron) 모델 구조 설계

  1) 28 * 28의 pixel로 구성된 사진을 784개의 뉴런으로 입력

  2) 입력단과 출력단 사이에 HL 추가 (정확도 ↑ but 연산량 ↑)

  3) 히든 레이어에는 Activation Func.으로 ReLu 사용

  4) 입력을 0 ~ 9 中 하나로 분류하기 위하여 10개의 class로 결과 표출

Training Algorithm Setting

PIAI Research Department

```
def epoch(data_loader):
    global epoch_cnt
    iter_loss, iter_acc = [], []
    last_grad_performed = False

    # Mini-batch iterations
    for _data, _label in data_loader:
        data, label = _data.view([len(_data), -1]).tc


        # 1. Feed-forward
        result = net(data)
        _, out = torch.max(result, 1)

        # 2. Calculate loss
        loss = loss_fn(result, label)
        iter_loss.append(loss.item())

        # 3. Backward propagation(train mode 에서만)
        if result.requires_grad:
            optim.zero_grad()
            loss.backward()
            optim.step()
            last_grad_performed = True

        # 4. Calculate accuracy
        acc_partial = (out == label).float().sum()
        acc_partial = acc_partial / len(label)
        iter_acc.append(acc_partial.item())
```

Validation/Test 경우 torch.no_grad() 를 사용하여 if문을 만족 -> 학습 안함

```
with torch.no_grad():
    vloss, vacc = epoch(valid_loader)
```

- 모델이 Loss를 줄이는 방향으로 학습하도록 알고리즘 구축

1) 모델에 데이터 투입

2) 정답지와 결과를 비교하여 Loss 산정(Loss Function 사용)

3) Loss를 줄이기 위하여 Back Pro -pagation시행(Train 에서만)

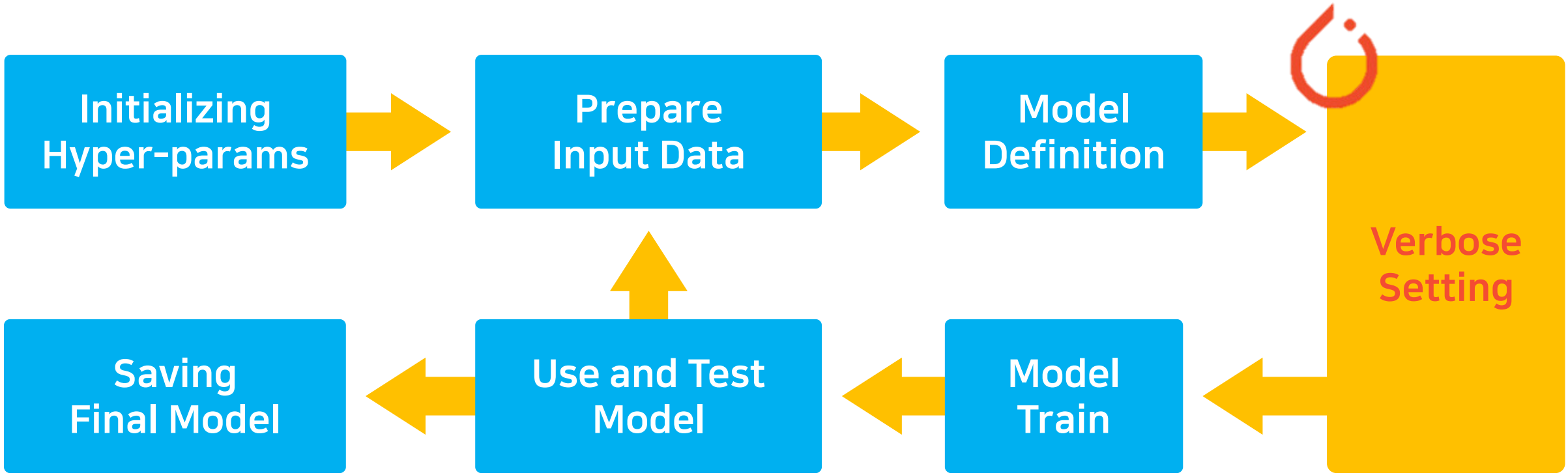
4) 1 Step 만큼 Gradient Decent 진행(Learning Rate만큼 Activ -ation Function으로 하강)

5) 1 ~ 4번을 Epochs 만큼 반복

PyTorch Framework Flow

PIAI Research Department

- Deep Learning 모델 구축 과정



Verbose Setting

- **Verbose(학습 Log 출력 여부) 설정**

```
def record_train_log(_tloss, _tacc, _time):
    # Train Log를 추가해준다
    time_log.append(_time)
    tloss_log.append(_tloss)
    tacc_log.append(_tacc)
    iter_log.append(epoch_cnt)

def record_valid_log(_vloss, _vacc):
    # Validation Log를 추가해준다
    vloss_log.append(_vloss)
    vacc_log.append(_vacc)
```

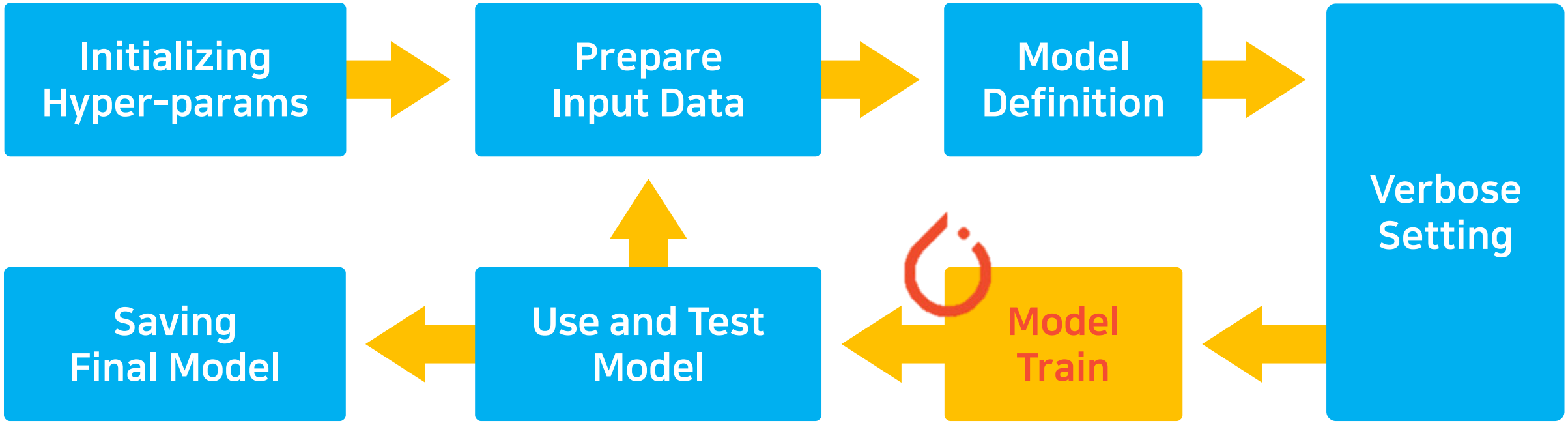
```
def print_log():
    # 로그 프린트

    # 소숫점 3자리 수까지 조절
    train_loss = round(last(tloss_log), 3)
    train_acc = round(last(tacc_log), 3)
    val_loss = round(last(vloss_log), 3)
    val_acc = round(last(vacc_log), 3)
    time_spent = round(last(time_log), 3)

    log_str = 'Epoch: {:3} | T_Loss {:5} | T_acc {:5} | V_Loss {:5} | V_acc. {:5} | W
    {:5}'.format(last(iter_log), train_loss, train_acc, val_loss, val_acc, time_spent)

    log_stack.append(log_str) # 프린트할 리스트에 추가
    clear_output(wait=True) # 출력물 모두 초기화

    for log_print in log_stack:
        print(log_print) # 매 에폭마다 추이를 출력
```

- 모델이 학습되는 동안의 실시간 추이를 볼 수 있도록 알고리즘 구축
- Train과 Validation의 Loss와 Acc.를 기록하는 기능
- 매 Epoch 마다 추이를 출력

PyTorch Framework Flow

PIAI Research Department

- Deep Learning 모델 구축 과정



Model Training

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- 딥러닝 모델 학습

```
1  # Training Initialization
2  init_model(ANN(784, 10))
3  init_epoch()
4  init_log()
5  losses_train, losses_val = [], []
6
7  # Training Iteration
8  while epoch_not_finished():
9      start_time = time.time()
10
11     tloss, tacc = epoch(train_loader)
12
13     losses_train.append(tloss)
14     end_time = time.time()
15     time_taken = end_time - start_time
16     record_train_log(tloss, tacc, time_taken)
17
18     with torch.no_grad():
19         vloss, vacc = epoch(valid_loader)
20
21     losses_val.append(vloss)
22     record_valid_log(vloss, vacc)
23     print_log()
24
25 print('\n Training completed!')
```

Verbose 함수

- 설계한 모델과 학습 알고리즘을 불러와 학습 진행
- 모델, Epoch 카운터, 로깅 관련 변수들 초기화
- 설정한 Epoch 수만큼 while(for)문을 돌면서 train 반복
- Train 파트
- Validation 파트
  torch.no_grad() = 역전파 학습을 하지 않는다
- Verbose(학습 추이) 출력

Model Training

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- **딥러닝 모델의 학습 추이 출력**

```
    print_log() # 로그를 프린트
print('₩n Training completed!')
```

```
Epoch:   1 | T_Loss 1.159 | T_acc 0.704 | V_Loss  0.47 | V_acc. 0.869 | 14.727
Epoch:   2 | T_Loss 0.393 | T_acc 0.887 | V_Loss 0.354 | V_acc. 0.897 | 15.019
Epoch:   3 | T_Loss 0.325 | T_acc 0.905 | V_Loss 0.313 | V_acc.  0.91 | 13.68
Epoch:   4 | T_Loss 0.289 | T_acc 0.915 | V_Loss 0.283 | V_acc. 0.915 | 14.157
Epoch:   5 | T_Loss  0.26 | T_acc 0.924 | V_Loss 0.272 | V_acc. 0.919 | 14.035
Epoch:   6 | T_Loss 0.236 | T_acc 0.931 | V_Loss 0.241 | V_acc.  0.93 | 14.326
Epoch:   7 | T_Loss 0.214 | T_acc 0.938 | V_Loss 0.223 | V_acc. 0.934 | 14.606
Epoch:   8 | T_Loss 0.194 | T_acc 0.943 | V_Loss 0.205 | V_acc. 0.938 | 15.849
Epoch:   9 | T_Loss 0.178 | T_acc 0.947 | V_Loss 0.191 | V_acc. 0.941 | 13.956
Epoch:  10 | T_Loss 0.163 | T_acc 0.953 | V_Loss  0.18 | V_acc. 0.944 | 13.761

Training completed!
```

- 각 epoch에 따라 로그를 출력
  1) Train Loss
  2) Train Acc.
  3) Validation Loss
  4) Validation Acc.
  5) 학습 소요 시간

PyTorch Framework Flow

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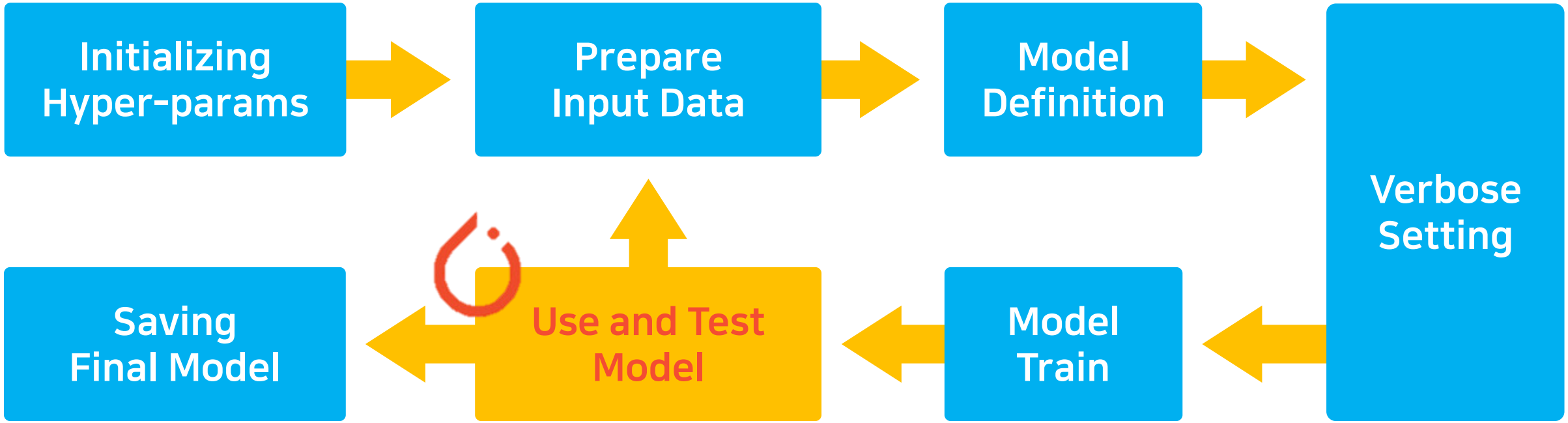
- Deep Learning 모델 구축 과정



Model Testing

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- **딥러닝 모델 정확도 산정**

```
24 # 정확도 검증
25 with torch.no_grad():
26     test_loss, test_acc = epoch(test_loader)
27     test_acc = round(test_acc, 4)
28     test_loss = round(test_loss, 4)
29     print('Test Acc.: {}'.format(test_acc))
30     print('Test Loss: {}'.format(test_loss))
```

```
 Training completed!
Test Acc.: 0.952
Test Loss: 0.1617
```

You can install TorchMetrics using pip or conda:

```
# Python Package Index (PyPI)
pip install torchmetrics
# Conda
conda install -c conda-forge torchmetrics
```

- 학습 완료 후 Test데이터 10,000장을 모델에 넣고 분류 (torch.no_grad() = 역전파 학습 off)
- 모델이 분류한 결과와 Ground Truth값을 비교하여 모델의 정확도 (Acc.) 산출
- PyTorch의 torchmetrics 기능을 통하여 다양한 평가 Metric 사용 가능

출처: https://torchmetrics.readthedocs.io/en/stable/pages/quickstart.html

Model Testing Visualization

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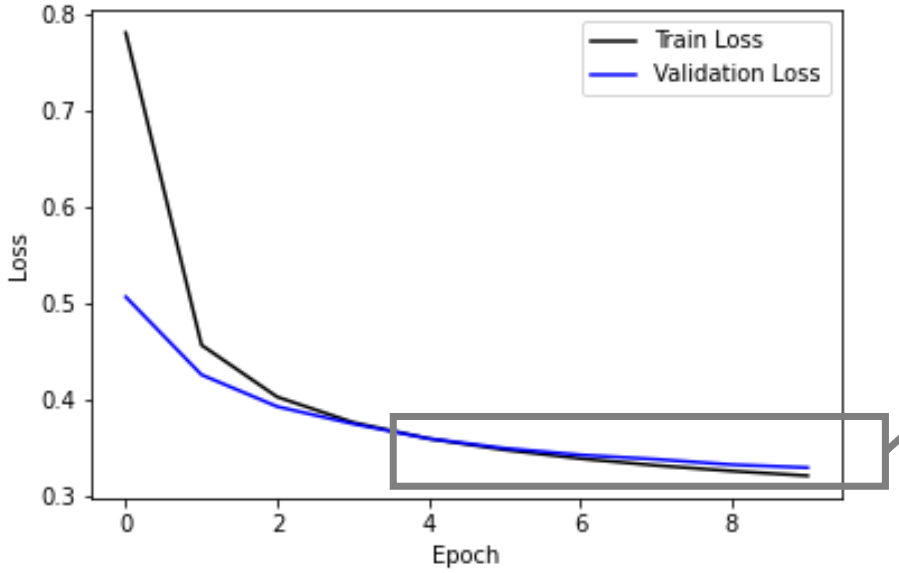
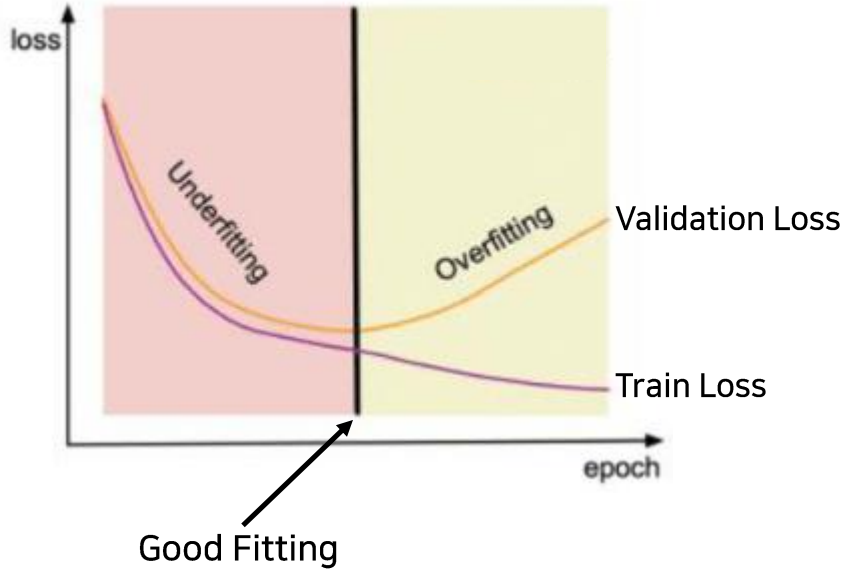
- **모델의 학습 추이를 그래프로 확인**

```
plt.plot(range(0, maximum_epoch, 1), losses_train, label = 'Train Lo
plt.plot(range(0, maximum_epoch, 1), losses_val, label = 'Validation
plt.legend(loc = 'upper right')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.show()
```



- 학습 중 진행된 epoch에 따라 감소되는 Loss의 추이를 시각화
- Loss가 계속 줄어들고 있는 그래프 추이로 보아, 추가 학습 가능



출처: https://www.researchgate.net/figure/a-Graphical-depiction-of-training-loss-with-varying-learning-rates-The-optimal_fig7_346206645

PyTorch Framework Flow

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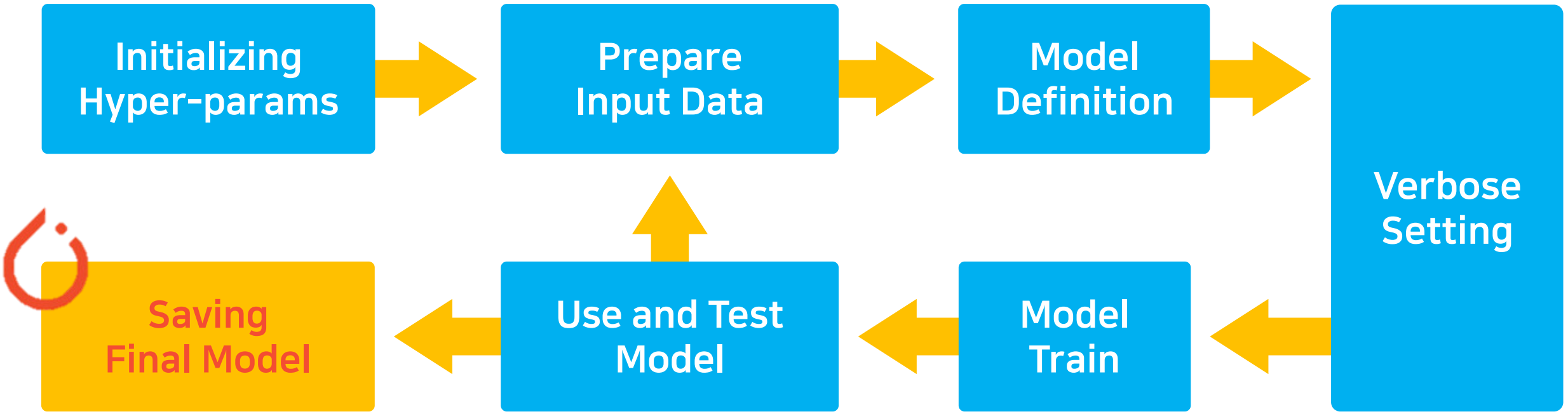
- Deep Learning 모델 구축 과정



Model Saving/Loading

- **모델 저장 / 로드**

```
1  torch.save(net.state_dict(), './model.pth')
2
3  net = MLP(in_features = 784, out_features = 10).to(device)
4
5  net.load_state_dict(torch.load('./model.pth'))
```

<All keys matched successfully>

- 학습된 모델을 저장하여, 필요시 로드하여 사용 가능
- 저장할 경로를 지정하여 모델을 .pth 포맷으로 저장
- 저장한 모델을 로드하기 위하여, 비어 있는 모델을 선언(입 출력 개수)
- 선언한 모델에, 저장되어 있는 모델의 경로를 입력하여 로드 후 사용

Code Running

(student) 1_Pytorch Basic & Classifier.ipynb