∨ 딥러닝1:회귀

∨ 1.환경준비

∨ (1) 라이브러리 로딩

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.metrics import *
from sklearn.preprocessing import MinMaxScaler

from keras.models import Sequential
from keras.layers import Dense
from keras.backend import clear_session
from keras.optimizers import Adam
```

• 학습곡선 그래프

∨ (2) 데이터로딩

```
path = 'https://raw.githubusercontent.com/DA4BAM/dataset/master/boston.csv'
data = pd.read_csv(path)
data.head()
```

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	lstat	medv	
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	4.98	24.0	ıl.
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	9.14	21.6	
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	4.03	34.7	
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	2.94	33.4	
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	5.33	36.2	

Next steps:

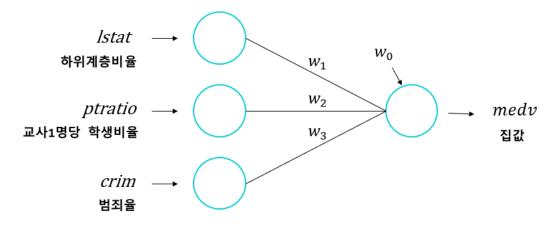
Generate code with data

View recommended plots

변수	설명
medv	타운별 집값(중위수)
crim	범죄율
zn	25,000 평방피트를 초과 거주지역 비율
indus	비소매상업지역 면적 비율
chas	찰스강변 위치(범주 : 강변1, 아니면 0)
nox	일산화질소 농도
rm	주택당 방 수
age	1940년 이전에 건축된 주택의 비율
dis	직업센터의 거리
rad	방사형 고속도로까지의 거리
tax	재산세율
ptratio	학생/교사 비율
Istat	인구 중 하위 계층 비율

∨ 2.데이터 준비

Istat, ptratio, crim 만 이용하여 medv를 예측하는 모델을 만들어 봅시다.



∨ (1) 데이터 준비

- x, y 나누기
 - o x: Istat, ptratio, crim
 - o y:medv

```
target = 'medv'
features = ['lstat', 'ptratio', 'crim']
x = data.loc[:, features]
y = data.loc[:, target]
```

- (2) NaN 조치
- (3) 가변수화
- ∨ (4) 데이터분할

```
x_train, x_val, y_train, y_val = train_test_split(x, y, test_size=.2, random_state = 20)
```

(5) Scaling

```
# 스케일러 선언
scaler = MinMaxScaler()

# train 셋으로 fitting & 적용
x_train = scaler.fit_transform(x_train)

# validation 셋은 적용만!
x_val = scaler.transform(x_val)
```

∨ 3.딥러닝1: 3개의 feature

∨ (1) 모델설계

```
# 분석단위의 shape
nfeatures = x_train.shape[1] #num of columns
nfeatures
```

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```
# 메모리 정리
clear_session()
```

Sequential 타입

모델요약 model.summarv()

Model: "sequential"

Layer (type)	Output Shape	Param #					
dense (Dense)	(None, 1)	13					
Total params: 13 (52.00 Byte) Trainable params: 13 (52.00 Byte) Non-trainable params: 0 (0.00 Byte)							

- · compile
 - optimizer = 'adam': 기본값으로 옵티마이저 사용(learning_rate = 0.001)
 - o optimizer = Adam(Ir = 0.1): 옵션 값 조정 가능
 - Ir과 learning_rate은 같지만, learning_rate 사용을 권장

model.compile(optimizer=Adam(0.1), loss='mse')

∨ (2) 학습

Epoch 1/20

validation_split=0.2: 학습시, 학습용 데이터에서 0.2 만큼 떼어 내서 검증셋으로 활용

history = model.fit(x_train , y_train, epochs = 20, validation_split=0.2).history # 20번 반복 # 20%를 검증셋 분리 # 가중치가 업데이트 되면서 그때그때마다의 성능을 측정하여 기록

```
11/11 [====
         Epoch 2/20
11/11 [====
            ========] - Os 7ms/step - loss: 342.1980 - val_loss: 315.6486
Epoch 3/20
11/11 [====
               ========] - 0s 8ms/step - loss: 236.4032 - val_loss: 238.3555
Epoch 4/20
           ========== ] - 0s 7ms/step - loss: 183.3738 - val_loss: 202.0274
11/11 [======
Epoch 5/20
11/11 [====
               ========] - 0s 6ms/step - loss: 160.7343 - val_loss: 181.8968
Epoch 6/20
11/11 [======
           Epoch 7/20
11/11 [=====
             Epoch 8/20
11/11 [=====
             Epoch 9/20
11/11 [======
           ========== ] - 0s 8ms/step - loss: 114.9785 - val_loss: 127.3080
Epoch 10/20
11/11 [=====
              ========] - 0s 7ms/step - loss: 106.3456 - val_loss: 116.1977
Epoch 11/20
           =========] - 0s 8ms/step - loss: 98.4367 - val_loss: 107.4543
11/11 [======
Epoch 12/20
11/11 [=====
              ========] - Os 8ms/step - loss: 92.3563 - val_loss: 99.5525
Epoch 13/20
Epoch 14/20
11/11 [=====
            ========== ] - 0s 7ms/step - loss: 82.4478 - val_loss: 86.1604
Epoch 15/20
            11/11 [=====
Epoch 16/20
           11/11 [=====
Epoch 17/20
11/11 [=====
               =======] - 0s 8ms/step - loss: 71.6463 - val_loss: 72.4373
Epoch 18/20
11/11 [=====
             =========] - 0s 8ms/step - loss: 69.0822 - val_loss: 68.6514
Epoch 19/20
11/11 [=====
                ========] - 0s 7ms/step - loss: 67.1005 - val_loss: 66.0043
Epoch 20/20
```

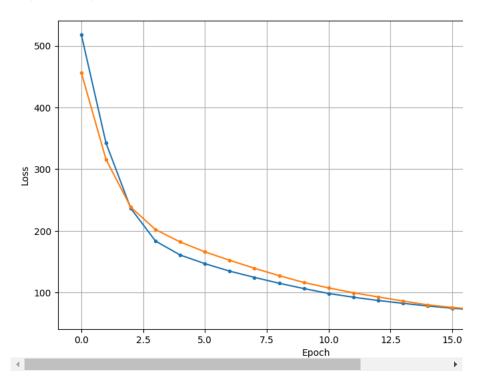
• 학습결과 그래프

```
# 함수로 만들어서 사용합시다.

def dl_history_plot(history):
    plt.figure(figsize=(10,6))
    plt.plot(history['loss'], label='train_err', marker = '.')
    plt.plot(history['val_loss'], label='val_err', marker = '.')

plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend()
    plt.grid()
    plt.show()
```

dl_history_plot(history)



∨ (3) 예측 및 검증

∨ 4.딥러닝2:전체 feature

• 이제 전체 데이터를 가지고 모델링을 시도해 보겠습니다.

∨ (1) 데이터 전처리

• 데이터 분할

```
target = 'medv'
x = data.drop(target, axis = 1)
y = data.loc[:, target]
x_train, x_val, y_train, y_val = train_test_split(x, y, test_size=.2, random_state = 20)

• 스케일링

scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
```

∨ (2) 모델링

x_val = scaler.transform(x_val)

• 모델설계

```
nfeatures = x_train.shape[1]
nfeatures

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# 메모리 정리
clear_session()

# Sequential 타입 모델 선언
model2 =Sequential(Dense(1, input_shape = (nfeatures,)))

# 모델요약
model2.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #					
dense (Dense)	(None, 1)	13					
Total params: 13 (52.00 Byte) Trainable params: 13 (52.00 Byte) Non-trainable params: 0 (0.00 Byte)							

• compile

model2.compile(optimizer=Adam(0.1), loss='mse')

• 학습

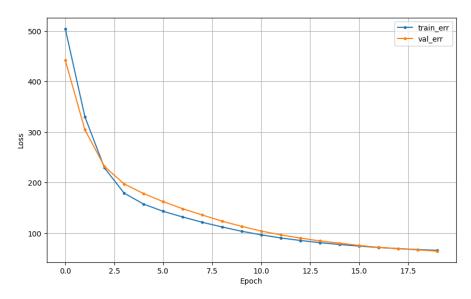
 $\label{eq:history} \textbf{history = model2.fit}(x_train \text{ , } y_train, \text{ epochs = 20, } validation_split=0.2). \textbf{history}$

```
Epoch 1/20
11/11 [====
        Epoch 2/20
11/11 [=====
        ========] - 0s 11ms/step - loss: 330.4849 - val_loss: 304.7272
Epoch 3/20
11/11 [=====
          =========] - 0s 10ms/step - loss: 229.2275 - val_loss: 231.9848
Epoch 4/20
Epoch 5/20
11/11 Γ====
          Epoch 6/20
11/11 [=====
         Epoch 7/20
11/11 Γ====
          ========] - 0s 9ms/step - loss: 131.9949 - val_loss: 148.3194
Epoch 8/20
11/11 [====
         ========] - 0s 8ms/step - loss: 121.5890 - val_loss: 136.0061
Epoch 9/20
         11/11 [=====
Epoch 10/20
11/11 [=====
       Epoch 11/20
```

```
11/11 [====
                        ========] - 0s 6ms/step - loss: 96.7510 - val_loss: 104.2314
Epoch 12/20
                        =======] - 0s 6ms/step - loss: 90.6481 - val_loss: 96.7122
11/11 [=====
Epoch 13/20
                                  ==] - 0s 6ms/step - loss: 85.6115 - val_loss: 90.3562
11/11 [====
Epoch 14/20
11/11 [=====
                                ====] - 0s 6ms/step - loss: 81.2935 - val_loss: 84.7137
Epoch 15/20
                       =======] - 0s 6ms/step - loss: 77.7168 - val_loss: 80.3703
11/11 [=====
Epoch 16/20
11/11 [=====
                        =======] - 0s 6ms/step - loss: 74.4987 - val_loss: 75.6778
Epoch 17/20
                         ========] - 0s 4ms/step - loss: 71.6750 - val_loss: 72.0910
11/11 [=====
Epoch 18/20
11/11 [====
                              =====] - 0s 6ms/step - loss: 69.5156 - val_loss: 69.4446
Epoch 19/20
                        =======] - 0s 6ms/step - loss: 67.6579 - val_loss: 67.0151
11/11 [=====
Epoch 20/20
                          =======] - 0s 8ms/step - loss: 66.0524 - val_loss: 64.4714
11/11 [=====
```

• 학습결과 그래프

dl_history_plot(history)



• 예측 및 평가

∨ 5.실습!

- 위 4번에 이어서, 여러분은 다음을 조절할 수 있습니다.
 - epochs(반복횟수), learning_rate(학습율)
- 4번 코드를 그대로 보면서 작성하고 위 두가지를 조절하며 성능을 높여봅시다!

(1) 데이터 전처리

nfeatures = x_train.shape[1]

• 데이터 분할

```
target = 'medv'
x = data.drop(target, axis = 1)
y = data.loc[:, target]
x_train, x_val, y_train, y_val = train_test_split(x, y, test_size=.2, random_state = 20)

• 스케일링

scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
x_val = scaler.transform(x_val)

• 모델 설계
```

```
nfeatures

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clear_session()
model = Sequential(Dense(1, input_shape = (nfeatures,)))
model.summary()

Model: "sequential"

Layer (type) Output Shape Param #

dense (Dense) (None, 1) 13

Total params: 13 (52.00 Byte)
```

• compile

 ${\tt model.compile} ({\tt optimizer=Adam} (0.2), \ {\tt loss='mse'})$

Trainable params: 13 (52.00 Byte)
Non-trainable params: 0 (0.00 Byte)

학습

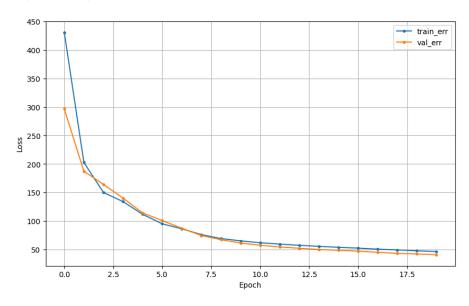
history = model.fit(x_train, y_train, epochs=20, validation_split=0.2).history

```
Epoch 1/20
           =========] - 1s 22ms/step - loss: 430.6400 - val_loss: 296.4463
11/11 Γ====
Epoch 2/20
11/11 [====
             ========] - 0s 7ms/step - loss: 202.8281 - val_loss: 187.4020
Epoch 3/20
Epoch 4/20
           11/11 [=====
Epoch 5/20
            ========] - 0s 6ms/step - loss: 111.8454 - val_loss: 114.3371
11/11 [=====
Epoch 6/20
              =======] - 0s 6ms/step - loss: 95.1658 - val_loss: 100.8489
11/11 [====
Epoch 7/20
11/11 [====
            =========] - 0s 8ms/step - loss: 86.4942 - val_loss: 87.4221
Epoch 8/20
11/11 [=====
            Epoch 9/20
11/11 [====
            ========] - Os 8ms/step - loss: 69.3516 - val_loss: 67.3232
Epoch 10/20
```

```
Epoch 11/20
Epoch 12/20
11/11 [=====
    Epoch 13/20
Epoch 14/20
Epoch 15/20
      11/11 [=====
Epoch 16/20
Epoch 17/20
11/11 [=====
     Epoch 18/20
11/11 [===========] - 0s 11ms/step - loss: 49.5388 - val_loss: 43.3967
Epoch 19/20
11/11 [=====
      Epoch 20/20
11/11 [==========] - 0s 10ms/step - loss: 46.6854 - val_loss: 41.1082
```

• 학습결과 그래프

dl_history_plot(history)



• 예측 및 평가

∨ 5.딥러닝3: hidden layer!

• 이제 레이어를 추가해 보겠습니다.

∨ (1) 데이터 전처리

• 데이터 분할

```
target = 'medv'
x = data.drop(target, axis = 1)
y = data.loc[:, target]
x_train, x_val, y_train, y_val = train_test_split(x, y, test_size=.2, random_state = 20)
```

• 스케일링

```
scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
x_val = scaler.transform(x_val)
```

nfeatures = x_train.shape[1] #num of columns

∨ (2) 모델링

• 모델설계

Model: "sequential"

Layer (type)	Output Shape	Param #				
dense (Dense)	(None, 2)	26				
dense_1 (Dense)	(None, 1)	3				
Total params: 29 (116.00 Byte) Trainable params: 29 (116.00 Byte) Non-trainable params: 0 (0.00 Byte)						

• compile

model3.compile(optimizer= Adam(learning_rate=0.1), loss = 'mse')

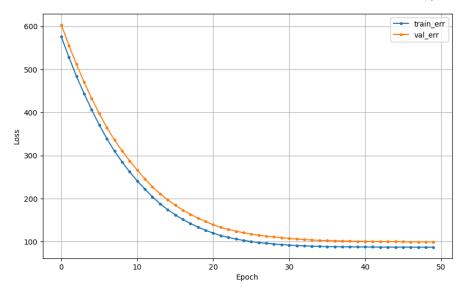
• 학습

hist = model3.fit(x_train, y_train, epochs = 50 , validation_split= .2).history

```
בטכנו 24/סט
11/11 [=====
              ========= ] - 0s 5ms/step - loss: 105.9005 - val_loss: 124.0245
Epoch 25/50
          11/11 [=====
Epoch 26/50
             11/11 [=====
Epoch 27/50
11/11 [=====
                 Epoch 28/50
               ========] - 0s 6ms/step - loss: 95.9381 - val_loss: 112.6250
11/11 [=====
Epoch 29/50
                 11/11 [=====
Epoch 30/50
11/11 [=====
               =======] - 0s 7ms/step - loss: 93.0090 - val_loss: 108.9917
Epoch 31/50
11/11 [====
                        ==] - 0s 7ms/step - loss: 91.8360 - val_loss: 107.3063
Epoch 32/50
11/11 [=====
               ========] - 0s 9ms/step - loss: 90.9151 - val_loss: 105.9331
Epoch 33/50
11/11 Γ=======
            Epoch 34/50
11/11 [=====
                   =======] - 0s 7ms/step - loss: 89.3106 - val_loss: 103.5834
Epoch 35/50
               11/11 [=====
Epoch 36/50
11/11 [=====
              Epoch 37/50
                 =======] - 0s 7ms/step - loss: 88.1299 - val_loss: 101.8126
11/11 [=====
Epoch 38/50
11/11 [=====
             Epoch 39/50
11/11 [====
                ========] - 0s 6ms/step - loss: 87.7131 - val_loss: 100.8942
Epoch 40/50
11/11 [======
             ========] - 0s 8ms/step - loss: 87.4897 - val_loss: 100.6448
Epoch 41/50
11/11 [=====
                 =======] - 0s 7ms/step - loss: 87.4230 - val_loss: 100.3058
Epoch 42/50
              ========= ] - 0s 6ms/step - loss: 87.2765 - val_loss: 100.1660
11/11 [=====
Epoch 43/50
11/11 [=====
                 Epoch 44/50
11/11 [=====
               ========] - 0s 5ms/step - loss: 87.1707 - val_loss: 99.8833
Epoch 45/50
11/11 [=====
              Epoch 46/50
11/11 [====
                   =======] - 0s 7ms/step - loss: 87.1190 - val_loss: 99.6054
Epoch 47/50
              ========] - 0s 5ms/step - loss: 87.0224 - val_loss: 99.4230
11/11 [=====
Epoch 48/50
                  =======] - 0s 7ms/step - loss: 86.9958 - val_loss: 99.3085
11/11 [=====
Epoch 49/50
11/11 Γ=====
               ========] - 0s 5ms/step - loss: 87.0096 - val_loss: 99.3382
Epoch 50/50
11/11 [=====
             =========] - 0s 6ms/step - loss: 87.0100 - val_loss: 99.3608
```

• 학습결과 그래프

dl_history_plot(hist)



• 예측 및 평가

∨ (3) 실습1

• 다음의 summary를 보고 모델을 설계하시오.

Layer (type)	Output Shape	Param #	
dense (Dense)	(None, 8)	104	
dense_1 (Dense)	(None, 1)	9	
clear_session() model = Sequenti model.summary()	al([Dense(8, Dense(1,		nape=(nfeatures,
Model: "se	quential"		

model. Sequential							
Layer (type)	Output	Shape	Param #				
dense (Dense)	(None,	8)	104				
dense_1 (Dense)	(None,	1)	9				
	======	.=========	:========				
Total params: 113 (452.00 Byte)							
Trainable params: 113 (452.00 Byte)							
Non-trainable params: 0 (0.0	0 Byte)						

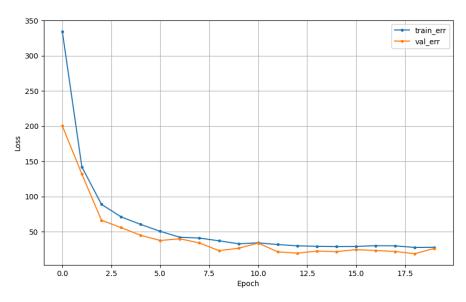
• 컴파일 + 학습

```
\label{eq:model.compile} $$ model.compile(optimizer=Adam(0.1), loss='mse')$    hist = model.fit(x_train, y_train, epochs=20, validation_split=0.2).history
```

```
Epoch 1/20
                 11/11 [====
Epoch 2/20
Epoch 3/20
11/11 [====
                  Epoch 4/20
Epoch 5/20
11/11 [=====
                ========] - Os 7ms/step - loss: 60.3257 - val_loss: 44.8203
Epoch 6/20
                ========= ] - 0s 7ms/step - loss: 50.4952 - val_loss: 37.4636
11/11 [====
Epoch 7/20
11/11 [=====
               ========] - 0s 7ms/step - loss: 42.0382 - val_loss: 39.8750
Epoch 8/20
                   =======] - 0s 8ms/step - loss: 40.8949 - val_loss: 33.9553
11/11 [====
Epoch 9/20
11/11 [======
             =========] - 0s 5ms/step - loss: 37.0261 - val_loss: 23.0622
Epoch 10/20
11/11 [=====
                    =======] - 0s 6ms/step - loss: 32.7690 - val_loss: 26.4188
Epoch 11/20
          11/11 [======
Epoch 12/20
11/11 [=====
                  =======] - Os 5ms/step - loss: 31.7085 - val_loss: 21.2967
Epoch 13/20
                  =======] - 0s 4ms/step - loss: 29.8812 - val_loss: 19.4856
11/11 [=====
Epoch 14/20
11/11 [=====
               ========] - 0s 5ms/step - loss: 29.1890 - val_loss: 22.4526
Epoch 15/20
                    ======] - 0s 6ms/step - loss: 28.7998 - val_loss: 21.6147
11/11 [=====
Epoch 16/20
              =========] - 0s 5ms/step - loss: 28.9595 - val_loss: 24.4729
11/11 [=====
Epoch 17/20
11/11 [=====
                  Epoch 18/20
11/11 [=====
               ========] - 0s 6ms/step - loss: 29.7795 - val_loss: 21.8541
Epoch 19/20
                    =======] - 0s 6ms/step - loss: 27.5816 - val_loss: 18.7020
11/11 [=====
Epoch 20/20
11/11 [=====
                  ========] - Os 7ms/step - loss: 27.7808 - val_loss: 26.2119
```

• 학습곡선

dl_history_plot(hist)



검증

∨ (4) 실습2

• 다음의 summary를 보고 모델을 설계하시오.

```
Output Shape Param #
    Laver (type)
  dense (Dense)
                  (None, 8)
                                         node, input_shape, activation
  dense_1 (Dense) (None, 4)
                                36
                                         node, activation
  dense_2 (Dense) (None, 1)
                                5
                                         node
clear_session()
model = Sequential([Dense(8, input_shape = (nfeatures,), activation = 'relu'),
                      Dense(4, activation = 'relu'),
                      Dense(1)])
model.summarv()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 8)	104
dense_1 (Dense)	(None, 4)	36
dense_2 (Dense)	(None, 1)	5
Total params: 145 (580.00 E Trainable params: 145 (580. Non-trainable params: 0 (0.	00 Byte)	

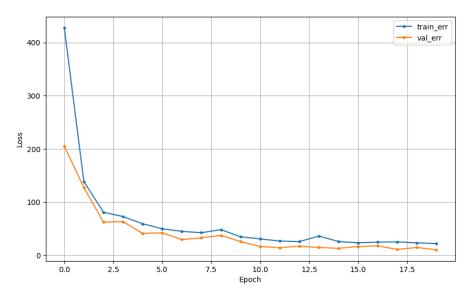
• 컴파일 + 학습

model.compile(optimizer=Adam(0.1), loss='mse')
hist = model.fit(x_train, y_train, epochs=20, validation_split=0.2).history

```
Epoch 1/20
11/11 [====
               Fnoch 2/20
11/11 [=====
              =========] - 0s 5ms/step - loss: 138.5264 - val_loss: 127.3764
Epoch 3/20
               11/11 [====
Epoch 4/20
11/11 [====
                  =======] - 0s 7ms/step - loss: 72.8263 - val_loss: 63.3644
Epoch 5/20
11/11 Γ====
                  =======] - 0s 7ms/step - loss: 59.3638 - val_loss: 41.2012
Epoch 6/20
                  ========] - 0s 7ms/step - loss: 49.9108 - val_loss: 42.3057
11/11 [====
Epoch 7/20
11/11 [====
                   =======] - 0s 7ms/step - loss: 45.0765 - val_loss: 29.6143
Epoch 8/20
11/11 [====
                 ========] - 0s 5ms/step - loss: 42.5264 - val_loss: 32.9538
Fnoch 9/20
11/11 [=====
             Epoch 10/20
                ======== ] - 0s 8ms/step - loss: 34.8551 - val loss: 25.9258
11/11 [=====
Epoch 11/20
11/11 [=====
                  ========] - 0s 8ms/step - loss: 30.8130 - val_loss: 16.6155
Epoch 12/20
                  =======] - 0s 7ms/step - loss: 26.9387 - val_loss: 14.3468
11/11 [===:
Epoch 13/20
11/11 [=====
                  =======] - 0s 10ms/step - loss: 25.7864 - val_loss: 17.2815
Epoch 14/20
11/11 [=====
                  ========] - 0s 7ms/step - loss: 36.1830 - val_loss: 14.7834
Epoch 15/20
```

• 학습곡선

dl_history_plot(hist)



검증

∨ (5) 실습3

• 이번에는 여러분이 원하는 대로 설계하고, 학습해 봅시다.

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 10)	130
dense_1 (Dense)	(None, 5)	55
dense_2 (Dense)	(None, 2)	12
dense_3 (Dense)	(None, 1)	3

Total params: 200 (800.00 Byte) Trainable params: 200 (800.00 Byte) Non-trainable params: 0 (0.00 Byte)

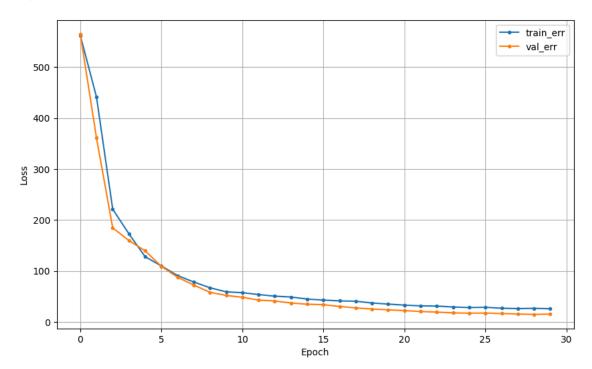
• 컴파일 + 학습

 $\label{eq:model_compile} $$ model.compile(optimizer=Adam(0.01), loss='mse')$ hist = model.fit(x_train, y_train, epochs=30, validation_split=0.2).history$

```
Epoch 2/30
11/11 [=====
                ================ ] - 0s 5ms/step - loss: 441.2220 - val loss: 360.9224
Epoch 3/30
11/11 [====
                     Epoch 4/30
11/11 [====
                      =======] - 0s 7ms/step - loss: 172.8001 - val_loss: 159.5147
Epoch 5/30
                     ========] - Os 5ms/step - loss: 127.9323 - val_loss: 139.5051
11/11 [====
Epoch 6/30
11/11 [====
                         ======] - 0s 6ms/step - loss: 109.7522 - val_loss: 108.9406
Epoch 7/30
                  ========] - 0s 6ms/step - loss: 90.8513 - val_loss: 87.5680
11/11 [=====
Epoch 8/30
11/11 [====
                        =======] - 0s 6ms/step - loss: 78.2152 - val_loss: 72.2928
Epoch 9/30
                    ========= ] - 0s 5ms/step - loss: 66.9805 - val loss: 57.9580
11/11 [=====
Epoch 10/30
11/11 [=====
                      ========] - 0s 7ms/step - loss: 58.9006 - val_loss: 51.8733
Epoch 11/30
                     ========] - 0s 6ms/step - loss: 57.2095 - val_loss: 48.2587
11/11 [=====
Epoch 12/30
                   ========] - Os 6ms/step - loss: 53.6062 - val_loss: 42.6373
11/11 [=====
Epoch 13/30
11/11 [====
                        =======] - 0s 6ms/step - loss: 50.3853 - val_loss: 40.9081
Epoch 14/30
11/11 [=====
                   ========] - Os 7ms/step - loss: 48.7626 - val_loss: 37.0658
Epoch 15/30
                               ==] - 0s 8ms/step - loss: 44.7278 - val_loss: 34.5931
11/11 [====
Epoch 16/30
11/11 [=====
                    ========] - 0s 8ms/step - loss: 42.8035 - val_loss: 33.7240
Epoch 17/30
11/11 [=====
                     ========] - 0s 8ms/step - loss: 41.0996 - val_loss: 30.1669
Epoch 18/30
                      -----] - 0s 6ms/step - loss: 40.4547 - val_loss: 27.4050
11/11 [=====
Epoch 19/30
11/11 [=====
                  ======== ] - 0s 8ms/step - loss: 37.0391 - val loss: 25.1136
Epoch 20/30
11/11 [====
                         =======] - 0s 6ms/step - loss: 34.8819 - val_loss: 23.6709
Epoch 21/30
                    ========] - 0s 7ms/step - loss: 32.8164 - val_loss: 22.0197
11/11 [=====
Epoch 22/30
11/11 [====
                         ======] - 0s 7ms/step - loss: 31.4117 - val_loss: 20.3374
Epoch 23/30
11/11 [======
                 Epoch 24/30
11/11 [=====
                   ========] - Os 8ms/step - loss: 29.1643 - val_loss: 17.5947
Epoch 25/30
11/11 [=====
                     ========] - 0s 8ms/step - loss: 28.0950 - val_loss: 16.9769
Epoch 26/30
11/11 [=====
                    ======== 1 - 0s 7ms/step - loss: 28.6024 - val loss: 17.2496
Epoch 27/30
11/11 [=====
                        =======] - 0s 8ms/step - loss: 26.7104 - val_loss: 16.3261
Epoch 28/30
11/11 [=====
                   ========] - 0s 7ms/step - loss: 25.9790 - val_loss: 15.4216
Epoch 29/30
11/11 [=====
                      =======] - Os 8ms/step - loss: 26.5143 - val_loss: 14.5859
Epoch 30/30
11/11 [======
```

• 학습곡선

dl_history_plot(hist)



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