2019 Summer School of Biomedical Engineering

Deep Learning based Biosignal Processing:

Autoencoders & Recurrent Neural Networks

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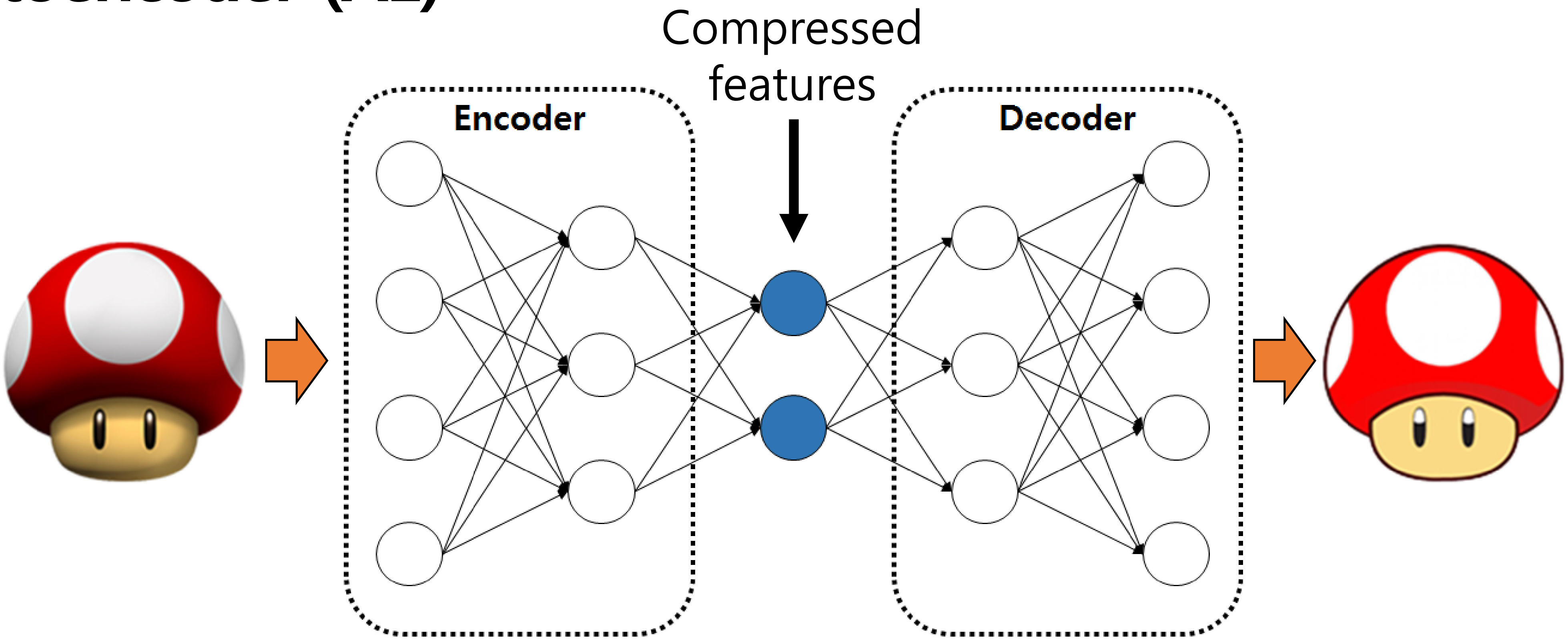
Autoencoder (AE)



- Autoencoders are neural networks trained to output the input
- The input is reduced/compressed, and the key features are learned
  - Any spurious noise/data are eliminated during feature reduction

Autoencoder (AE) 실습

① Validation mini-batch loop을 만드세요 (line 205)

② Optimizer를 변경하고 학습 시간을 비교하세요 (line 158)

③ Loss function을 L1으로 변경하고 학습 결과 (loss)를 비교하세요 (line 154)

④ Output layer에 activation function을 추가하고 결과를 비교하세요 (line 136)

⑤ Hidden layer에 노드수와 activation function을 변경하고 결과를 비교하세요 (line 127)

⑥ Autoencoder을 hidden layer 수를 3으로 변경하고 결과를 비교하세요 (line 124)

⑦ 학습된 autoencoder에 0으로 된 데이터를 넣어서 나오는 결과를 확인하세요 (line 239)

1) Validation mini-batch loop

Training

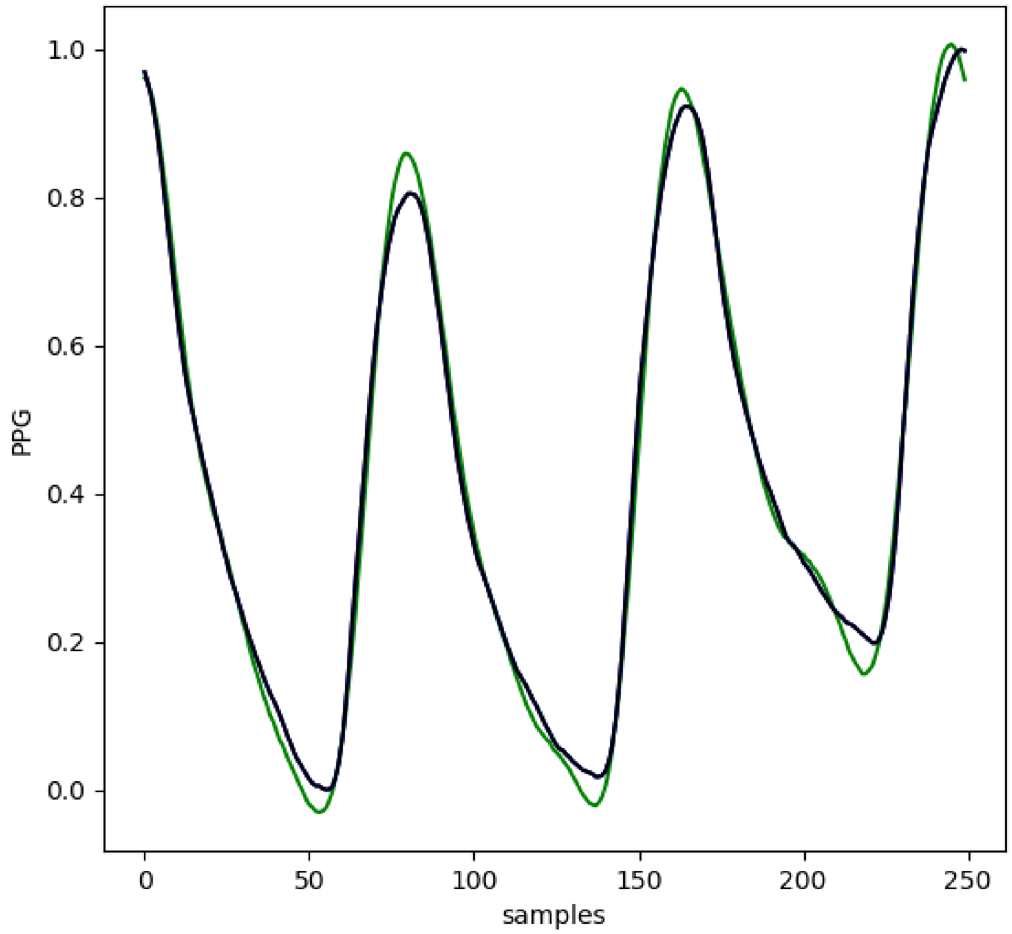
```
# create a variable to hold training loss value after each epoch
train_loss = 0
# set a for-loop to go through the training set
for i in range(total_batch):

    # set index for training data batch
    batch_index = i * batch_size

    # extract training data batch
    batch = train_input[batch_index:batch_index + batch_size]
    label = train_output[batch_index:batch_index + batch_size]

    # run optimizer and calculate loss
    _, loss1 = sess.run([optimizer, loss], feed_dict={X: batch, Y: label, prob: 0.5})

    # add loss at end of batch to the total training loss for this epoch
    train_loss += loss1/total_batch

train_loss_epochs.append(train_loss)
```

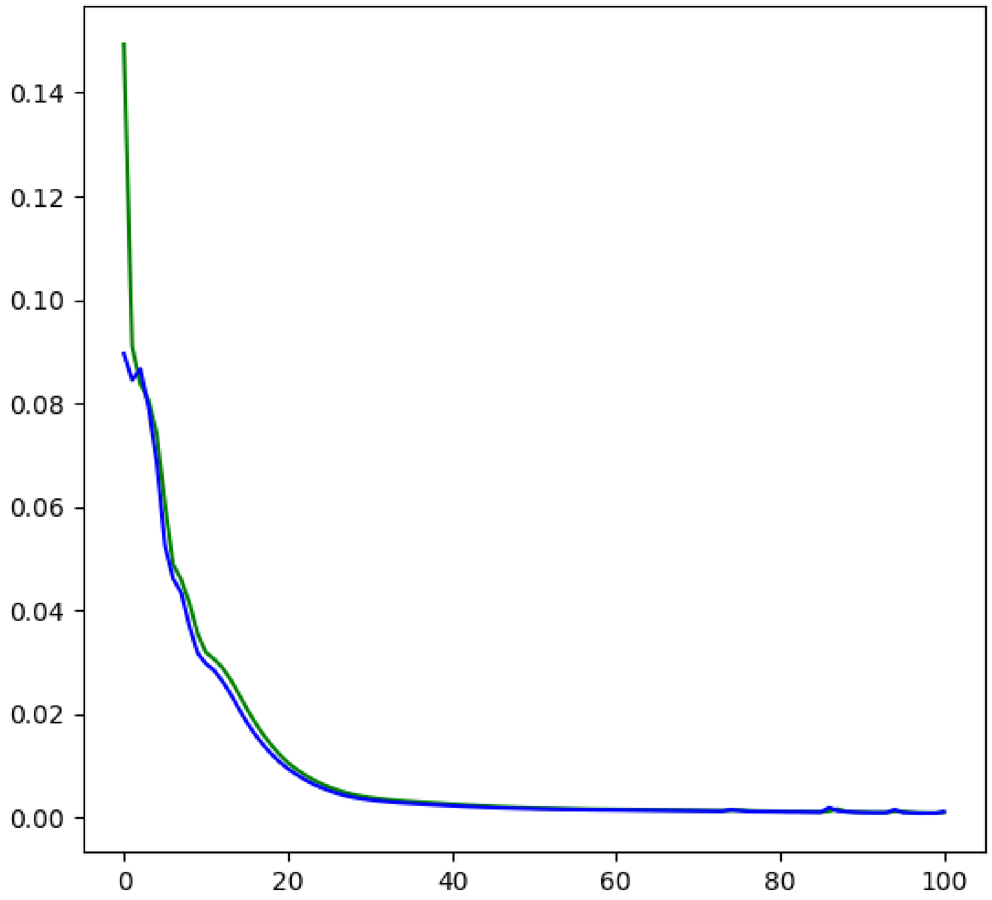
Validation

2) Optimizer 변경

Adam

```
optimizer = tf.train.AdamOptimizer(learning_rate=0.01).minimize(loss)
```

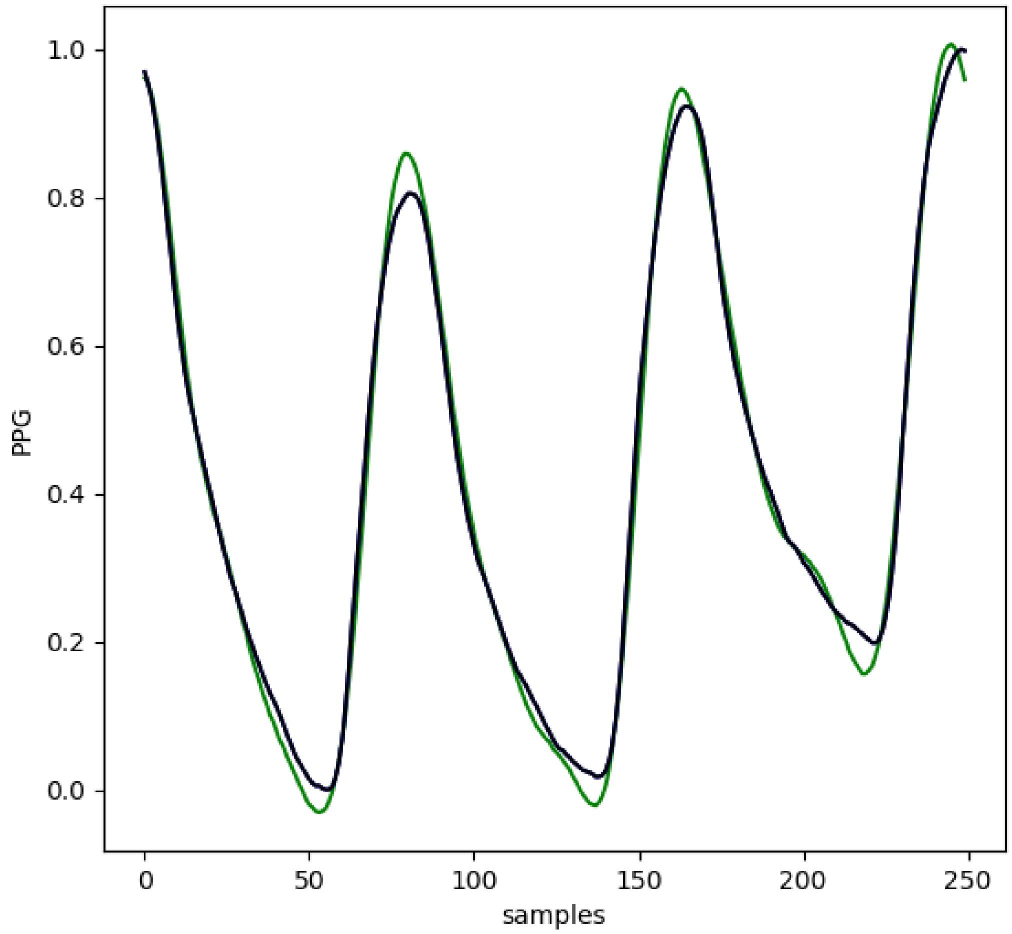


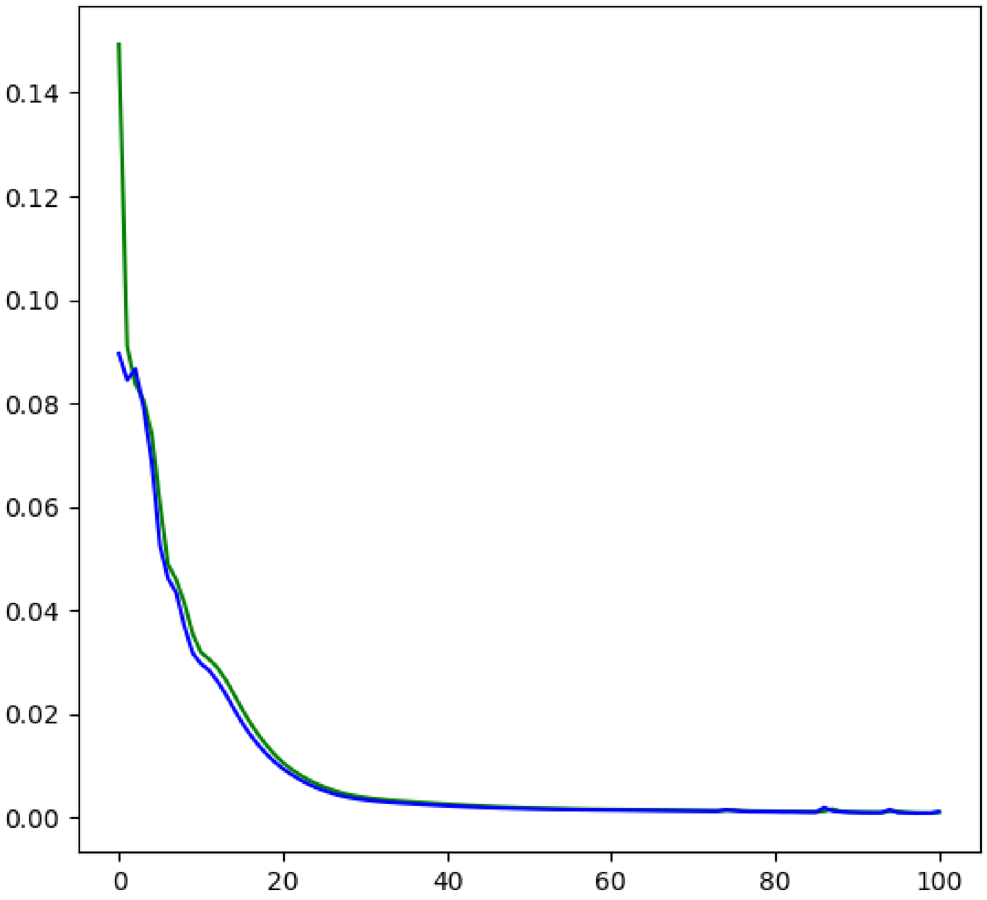


3) Loss Function 변경

L2 loss

```
loss = tf.losses.mean_squared_error(Y, prediction)
```

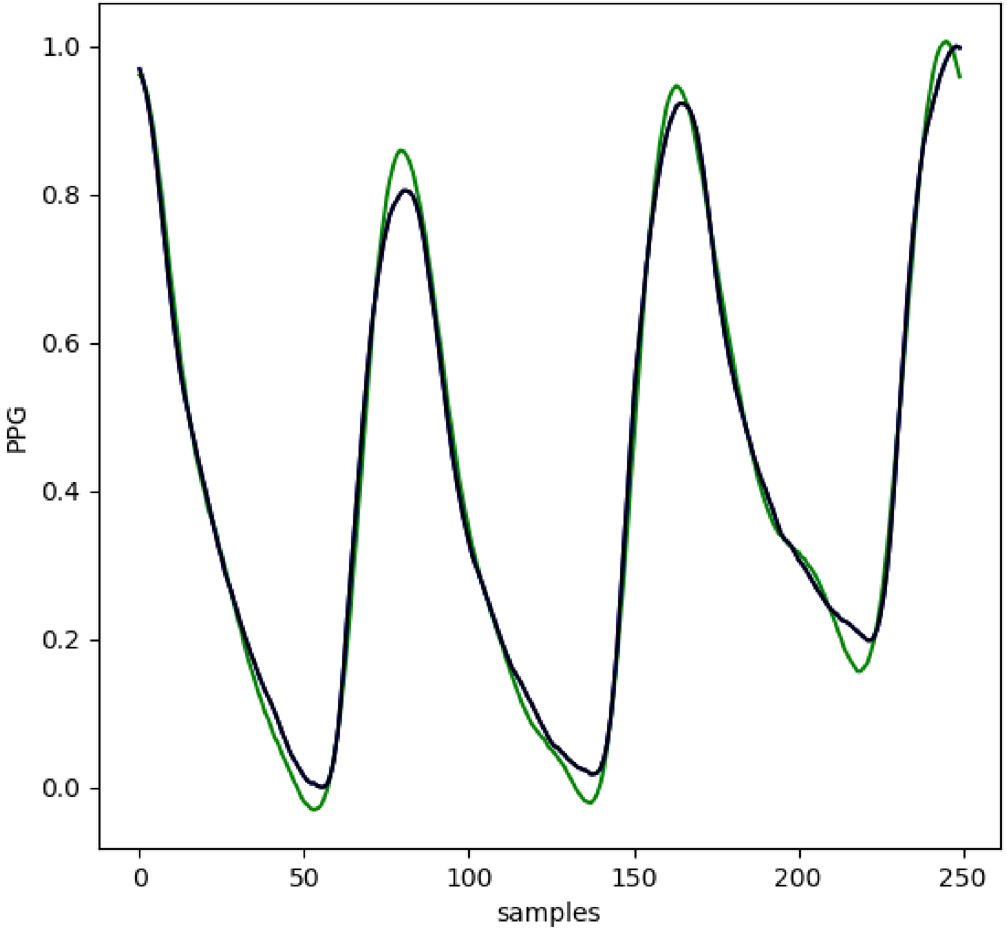


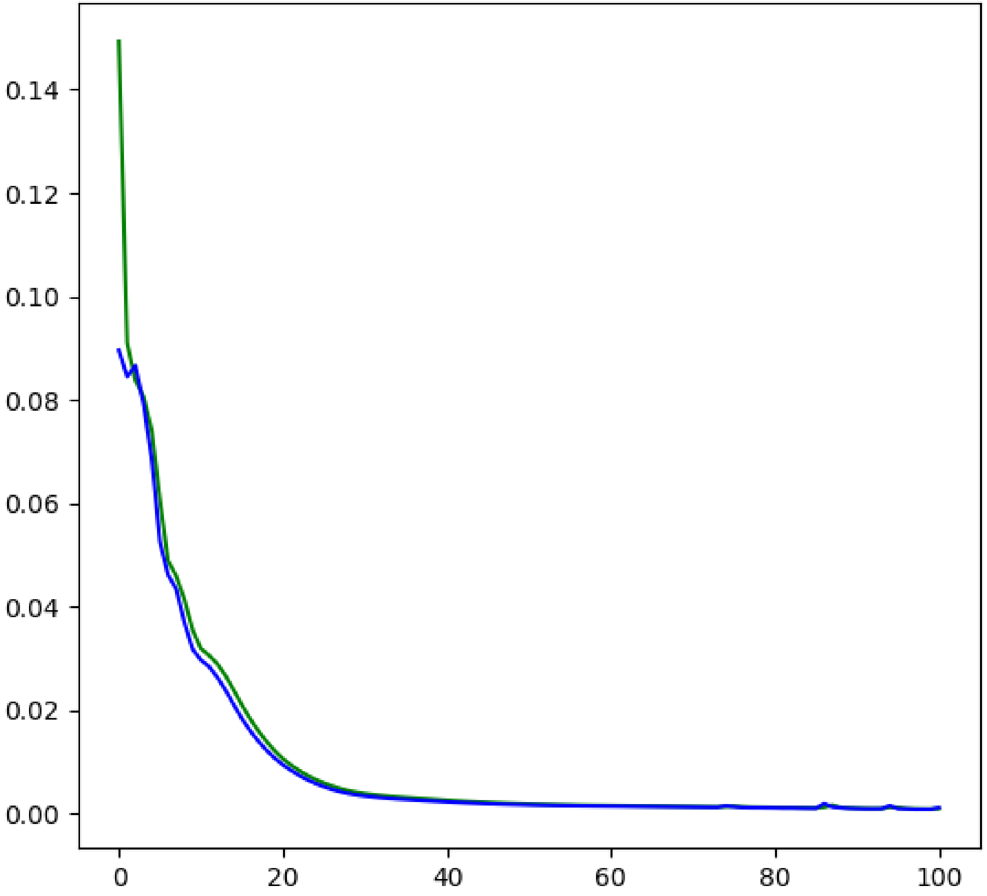


4) Output Activation 추가

No Activation

```
logit = tf.layers.dense(encode, signal_length, activation=None,
```

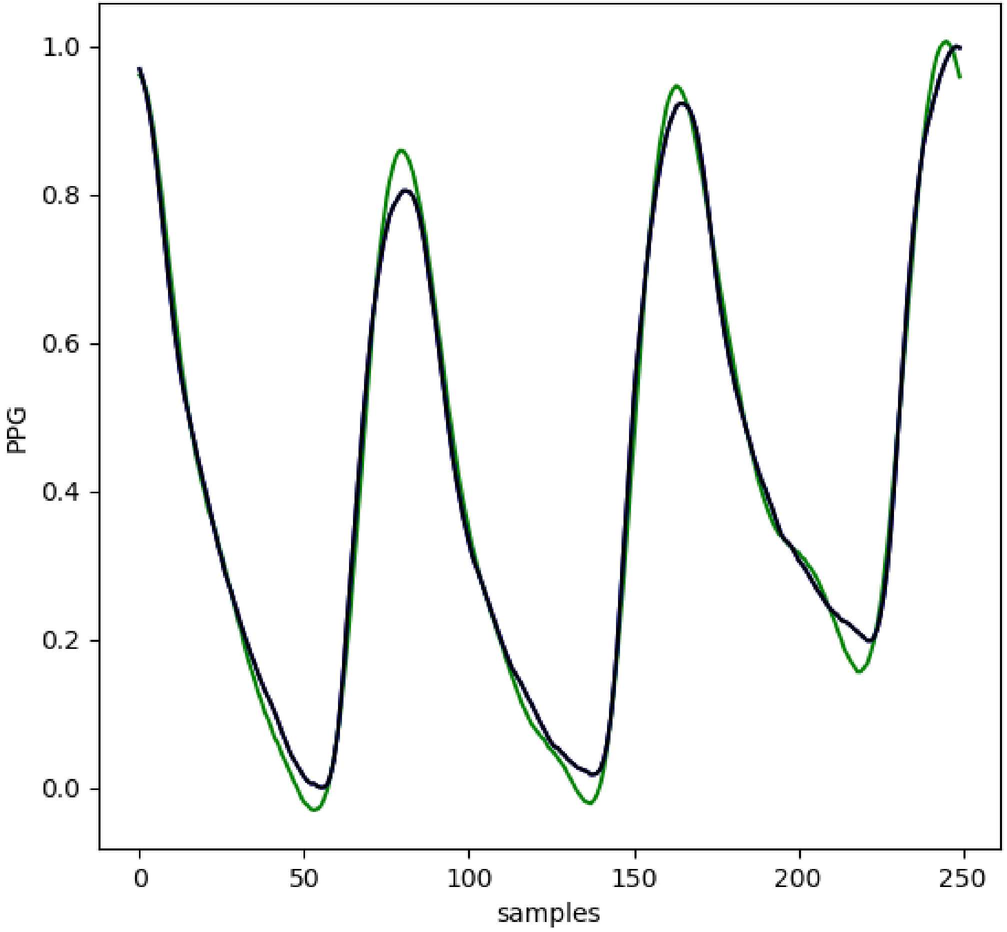


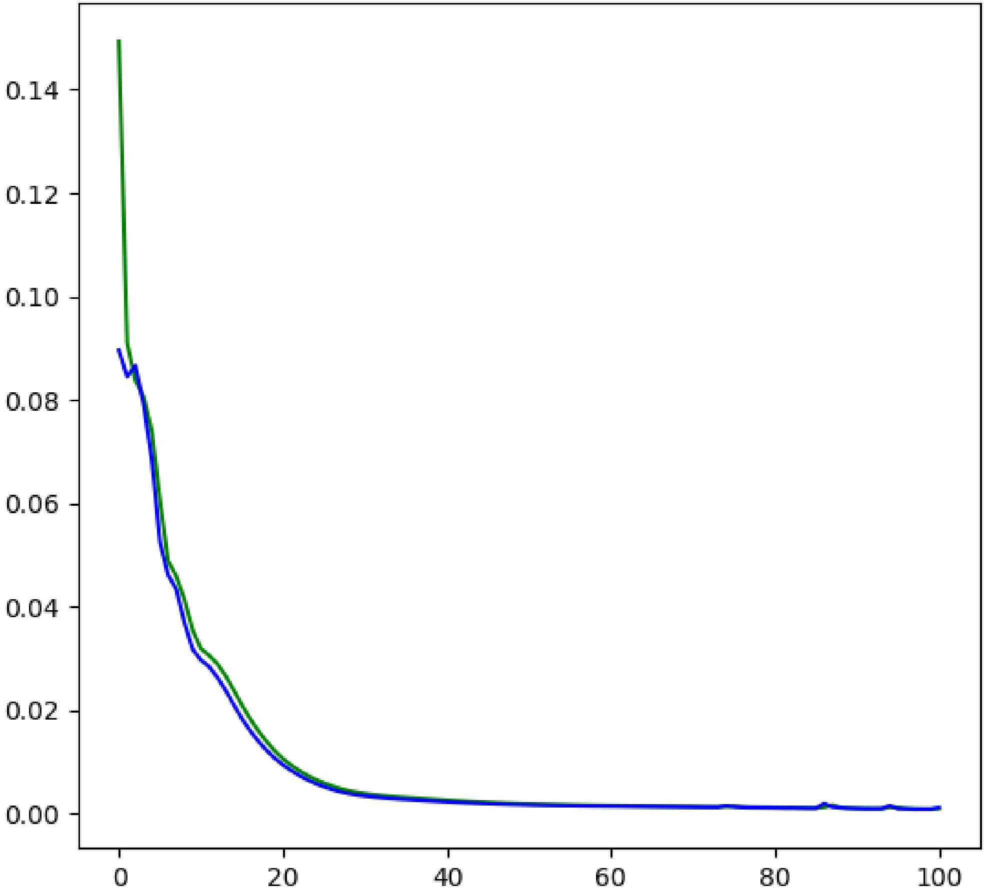


5) Hidden Layer 변경

기존 hidden layer

```
encode = tf.layers.dense(x, num_hidden_nodes, activation=tf.nn.sigmoid,
```

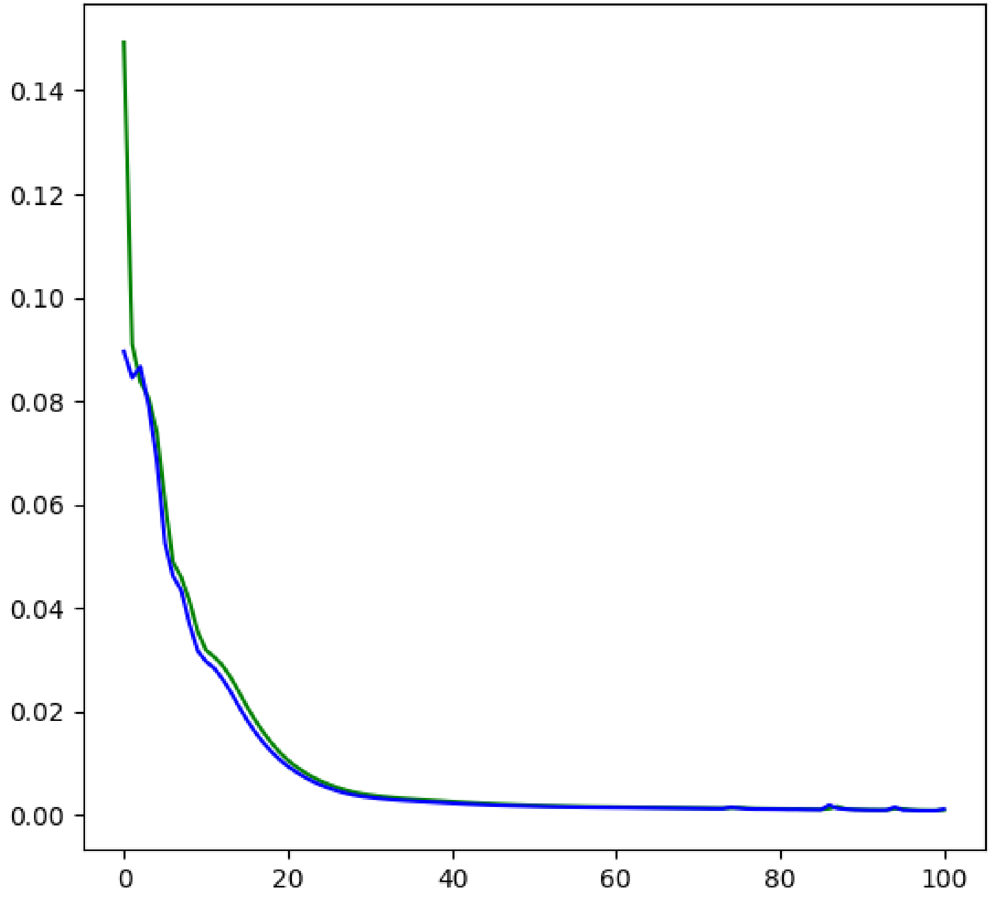




6) Hidden Layer 구조 변경

기존 hidden layer

```
encode = tf.layers.dense(x, num_hidden_nodes, activation=tf.nn.sigmoid,
                         use_bias=True, name='encoding_layer',
                         kernel_initializer=tf.truncated_normal_initializer(stddev=0.01),
                         bias_initializer=tf.ones_initializer())
encode = tf.layers.dropout(encode, rate=probability)
```



7) 정수 데이터 autoencoding 결과 확인

np.ones 함수 사용:

np.ones((size), datatype)

예) np.ones((1,5), float) → [1.0 1.0 1.0 1.0 1.0]

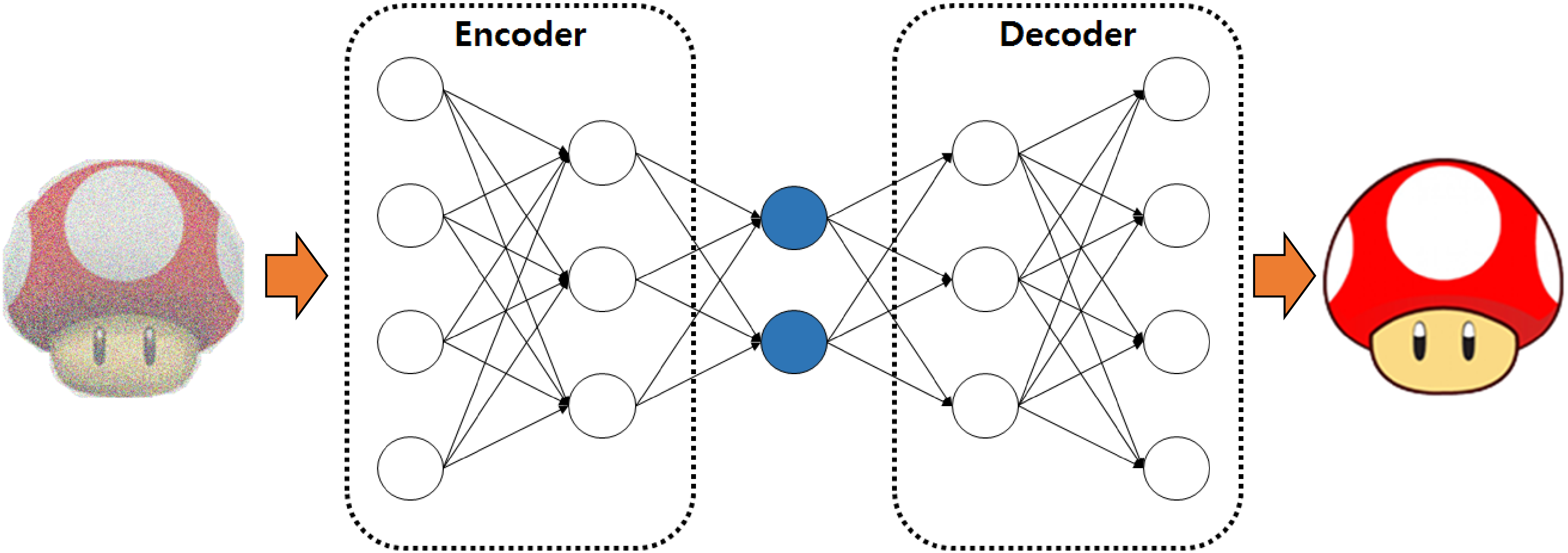
예) np.ones((2,5), float) → [[1.0 1.0 1.0 1.0 1.0] , [1.0 1.0 1.0 1.0 1.0]]

예) 0.5*np.ones((2,5), float) → [[0.5 0.5 0.5 0.5 0.5] , [0.5 0.5 0.5 0.5 0.5]]

가공된 데이터로 출력 보기:

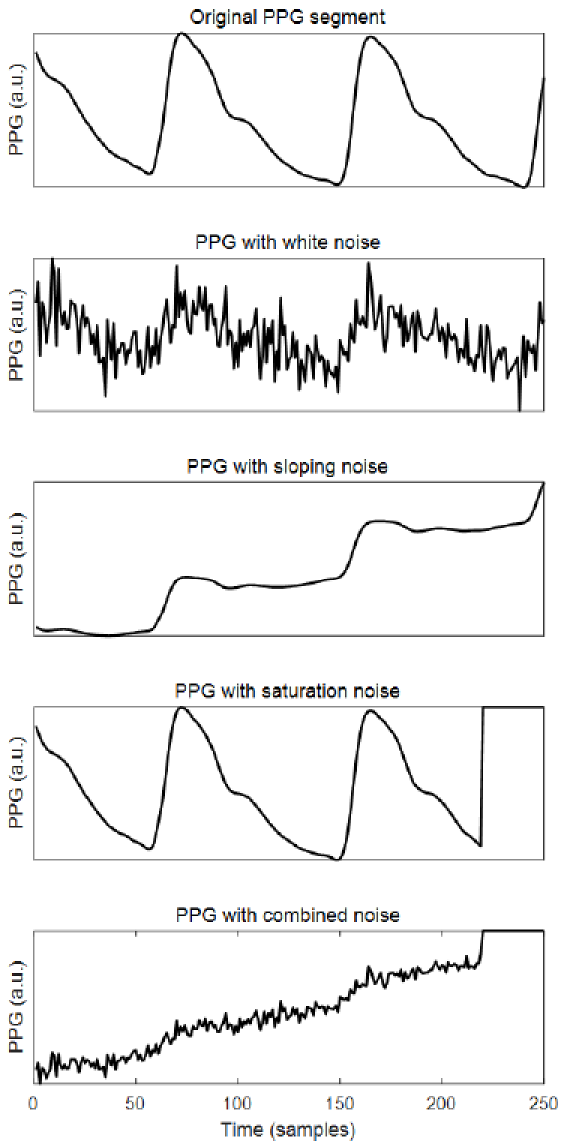
output = sess.run(prediction, feed_dict={X: 가공데이터}

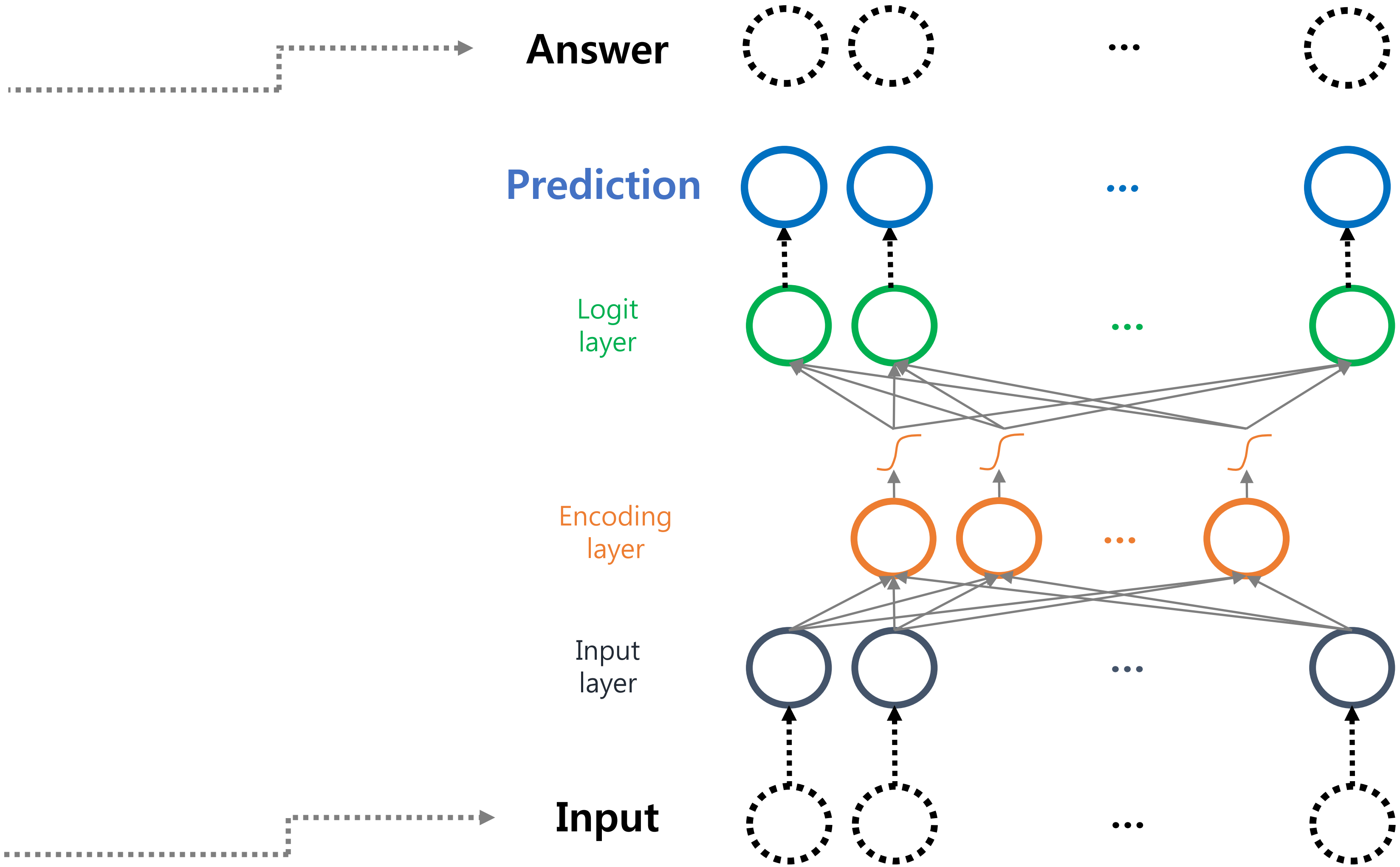
Denoising Autoencoder (DAE)



- Inputs have added noise
- The compression of features in the input eliminates any spurious noise that does not belong to reconstruction of the noise-free input

Training AE for PPG Denoising

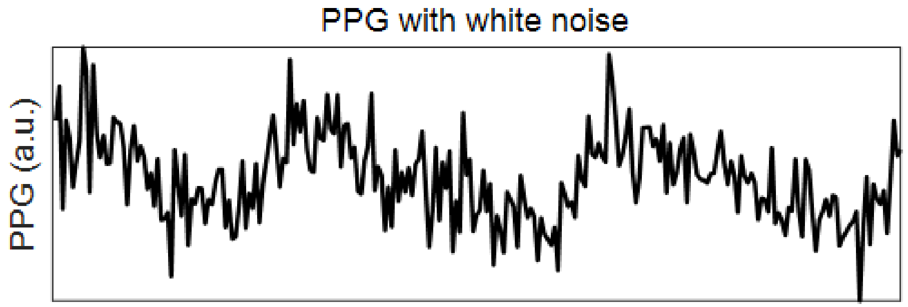




Noise Generation

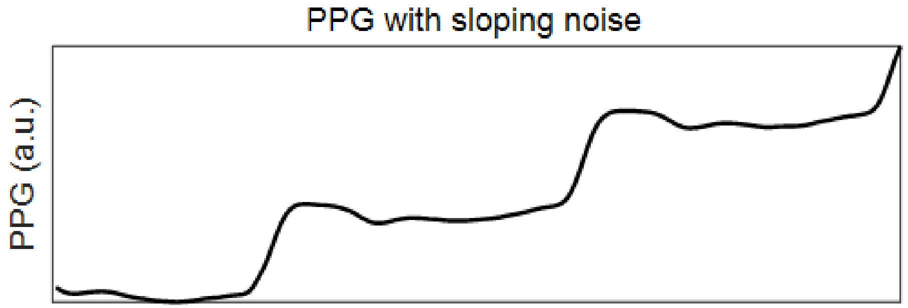
White noise:
(high frequency)

$$c_i^1 = s_i + \frac{1}{3} \cdot N(0,1)$$



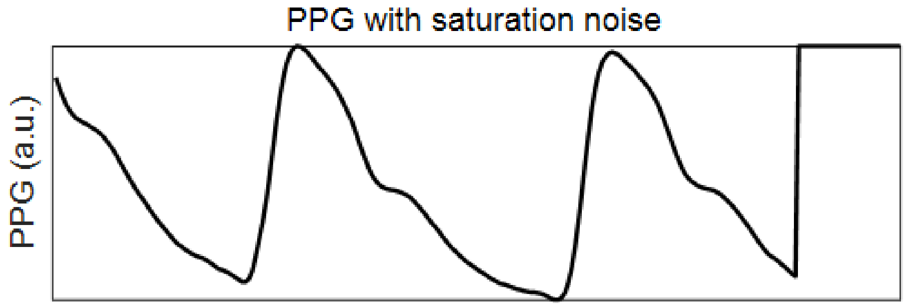
Sloping noise:
(low frequency)

$$c_i^2 = s_i + \frac{2}{250} \cdot i \cdot U(-1,1)$$



Saturation noise:

$$c_i^3 = 0 \text{ or } 1 \text{ if } x_1 < i \le x_2$$
$$c_i^3 = s_i \text{ otherwise}$$

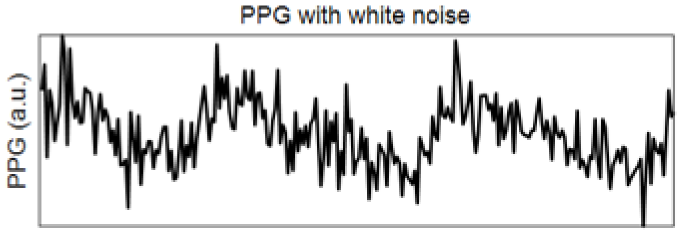


Denoising autoencoder (DAE) 실습

① 각각 노이즈 모델을 numpy를 사용해서 만들어보세요

White noise:
(high frequency)

$$c_i^1 = s_i + \frac{1}{3} \cdot N(0,1)$$



Random normal 함수

- **np.random.randn 함수 사용**
- **np.random.randn(size)**

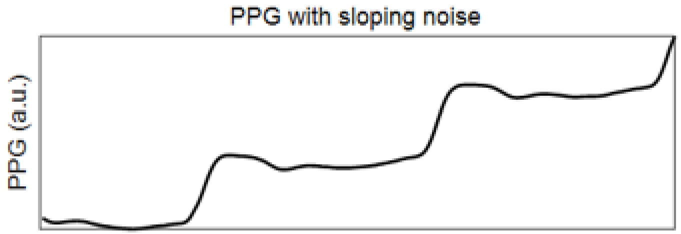
- 예) np.random.randn(5) → [1.42976 -0.89163182 0.47766052 -0.30909519 0.07349453]

Denoising autoencoder (DAE) 실습

① 각각 노이즈 모델을 numpy를 사용해서 만들어보세요

Sloping noise:
(low frequency)

$$c_i^2 = s_i + \frac{2}{250} \cdot i \cdot U(-1,1)$$



Random uniform함수

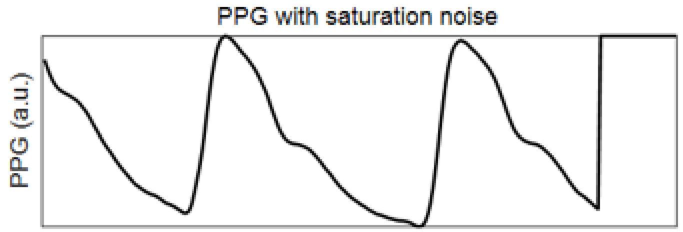
- **np.random.rand 함수 사용해서 랜덤한 slope 생성**
- **for loop 활용해서 각 셈플의 데이터 포인트에 slope 더하기**
- **np.random.rand(size): 0~1사이 uniform distribution**

- 예) np.random.rand(1) → [0.90283792]

Denoising autoencoder (DAE) 실습

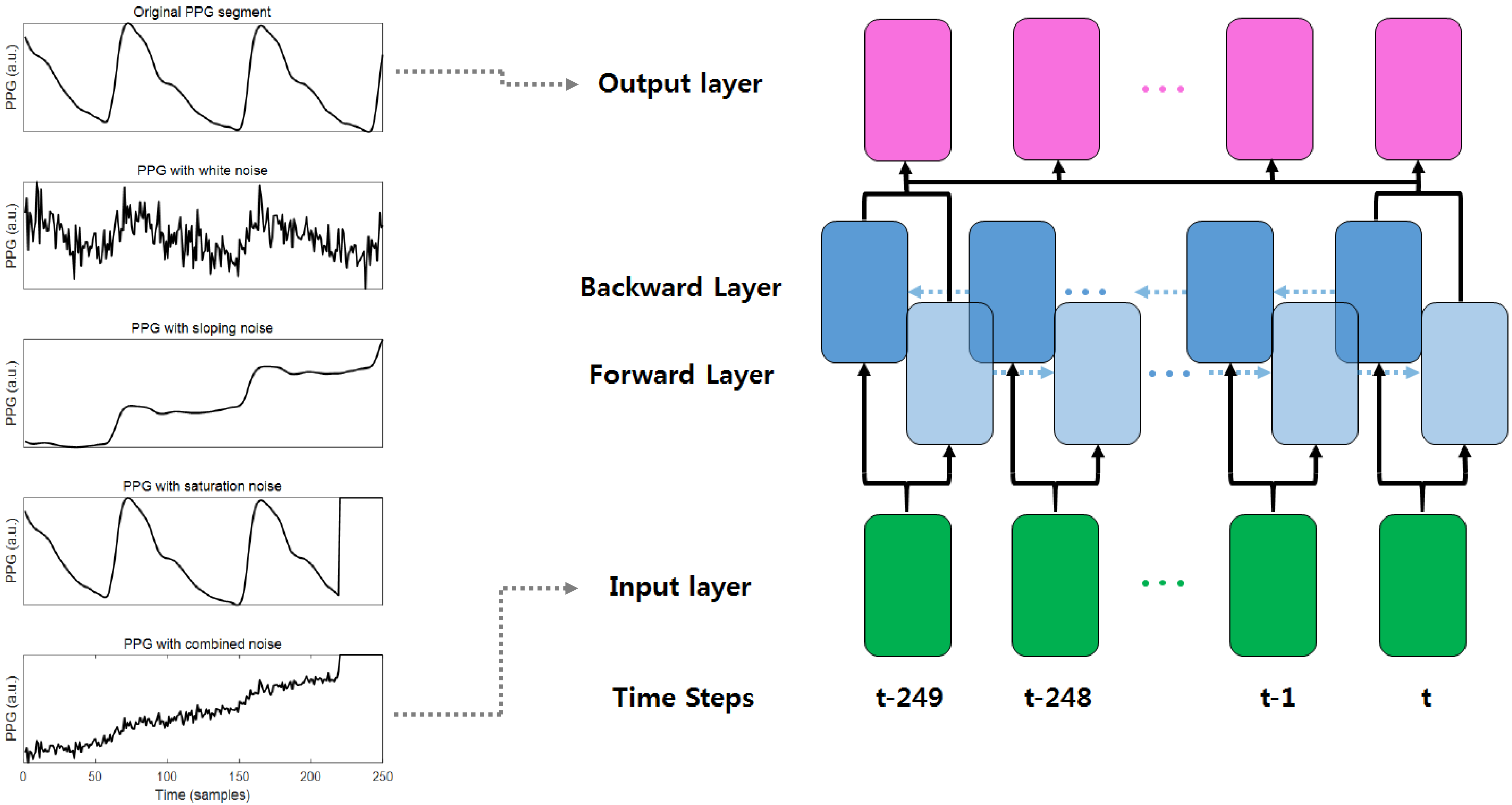
① 각각 노이즈 모델을 numpy를 사용해서 만들어보세요

Saturation noise: $c_i^3 = 0 \text{ or } 1 \text{ if } x_1 < i \le x_2$
$c_i^3 = s_i \text{ otherwise}$



- **np.random.rand 함수 사용해서 saturation 시작점 설정**
  - 시작점이 float인 경우 indexin을 위해 int으로 변경
  - 예) int(102.723433) → 102
- **np.random.rand 함수 사용해서 saturation 종료점 설정**
- **np.random.rand 함수 사용해서 saturation 값 0,1 설정**
- **np.ones 사용해서 saturation 구간의 정수 벡터 생성**

Training BRAE for PPG Denoising



Tensorflow Recurrent AE

데이터와 placeholder의 dimension에 number of inputs dimension을 추가함

unstack 함수를 사용하여 time step 을 첫 dimension으로 설정해줌

LSTM cell의 구조를 설정함

Many-to-one 구조를 사용하여 맨 마지막 timestep에 output만 사용하고, 그 후에 fully connected layer로 원 데이터의 사이즈 구축

```
print(train_input[0])
train_input = np.reshape(train_input, [len(train_input), signal_length, 1])
print(train_input[0])
val_input = np.reshape(val_input, [len(val_input), signal_length, 1])
X = tf.placeholder("float", [None, signal_length, 1])

def RAE(x, probability, num_hidden_nodes):
    # Unstack to get a list of 'timesteps' tensors of shape (batch_size, n_input)
    # before unstacking shape = batch_size, timesteps, num_input
    x = tf.unstack(tf.transpose(x, perm=[1, 0, 2]))
    # x = tf.unstack(x, signal_length, 1)
    # after unstacking shape = timesteps, batch_size, num_input

    lstm_fw_cell = rnn.LSTMCell(num_hidden_nodes, forget_bias=1.0)
    lstm_fw_cell = rnn.DropoutWrapper(cell=lstm_fw_cell, output_keep_prob=probability)

    outputs, _ = rnn.static_rnn(lstm_fw_cell, x, dtype=tf.float32)
    print(outputs.get_shape())

    # Linear activation, using rnn inner loop last output
    logit = tf.layers.dense(outputs[-1], signal_length, activation=None,
                            use_bias=True, name='output_layer',
                            kernel_initializer=tf.truncated_normal_initializer(stddev=0.01),
                            bias_initializer=tf.ones_initializer())
    print(logit.get_shape())

    return logit
```

Tensorflow Bidirectional Recurrent AE

Recurrent AE와 똑같지만 forward cell과 backward cell을 둘 다 설정해주고 rnn.static_bidirectional_rnn 함수로 bidirectional 구조 설정

```
def BRAE(x, probability, num_hidden_nodes):
    # Unstack to get a list of 'timesteps' tensors of shape (batch_size, n_input)
    # before unstacking shape = batch_size, timesteps, num_input
    x = tf.unstack(tf.transpose(x, perm=[1, 0, 2]))
    # x = tf.unstack(x, signal_length, 1)
    # after unstacking shape = timesteps, batch_size, num_input

    lstm_fw_cell = rnn.LSTMCell(num_hidden_nodes, forget_bias=1.0)
    lstm_fw_cell = rnn.DropoutWrapper(cell=lstm_fw_cell, output_keep_prob=probability)
    lstm_bw_cell = rnn.LSTMCell(num_hidden_nodes, forget_bias=1.0)
    lstm_bw_cell = rnn.DropoutWrapper(cell=lstm_bw_cell, output_keep_prob=probability)

    outputs, _, _ = rnn.static_bidirectional_rnn(lstm_fw_cell, lstm_bw_cell, x, dtype=tf.float32)
    print(outputs.get_shape())

    # Linear activation, using rnn inner loop last output
    logit = tf.layers.dense(outputs[-1], signal_length, activation=None,
                            use_bias=True, name='output_layer',
                            kernel_initializer=tf.truncated_normal_initializer(stddev=0.01),
                            bias_initializer=tf.ones_initializer())
    print(logit.get_shape())

    return logit
```

① RAE_practice_solution.py 파일을 변경해서 bidirectional RAE (BRAE)를 만들어 보세요

② RAE와 BRAE의 outputs.get_shape() 차이를 확인해보세요

실습: 학습된 RAE 모델을 활용한 PPG Denoising

기존
(without restoring checkpoint)

```python
with tf.Session() as sess:
    # run the initializer
    sess.run(init)
    # Writer
    writer = tf.summary.FileWriter(FILEWRITER_PATH)
    # Saver
    saver = tf.train.Saver(max_to_keep=200)

    # pick a goal for the loss value
    old_loss = 0.001
```

학습된 모델 checkpoint 설정

```python
    os.makedirs(FILEWRITER_PATH)
CHECKPOINT_PATH = './RAE_tensorboard/checkpoints'
if not os.path.isdir(CHECKPOINT_PATH):
    os.makedirs(CHECKPOINT_PATH)
```

학습된 모델 복원
(with restoring checkpoint)

```python
with tf.Session() as sess:
    # run the initializer
    sess.run(init)
    # Writer
    writer = tf.summary.FileWriter(FILEWRITER_PATH)
    # Saver
    saver = tf.train.Saver(max_to_keep=200)
    # restore checkpoint ================================================================================================
    latest_ckpt = tf.train.latest_checkpoint(CHECKPOINT_PATH)
    print("loading the lastest checkpoint: " + latest_ckpt)
    saver.restore(sess, latest_ckpt)

    # pick a goal for the loss value
```

실습: 학습된 모델을 활용한 PPG Denoising

① 학습된 RAE 모델을 복구해서 결과를 출력해보세요 (RAE_apply.py 파일 사용)

② 학습된 BRAE 모델을 복구하고 연장으로 학습하는 코드를 작성해보세요

- 학습된 BRAE 모델 checkpoint 설정 필요
- RAE 구조를 BRAE 구조로 변경 필요

③ 다른 데이터 (external_val1.txt, … external_val10.txt)를 로딩해서 학습된 BRAE에 적용하는 코드를 작성해보세요

- 데이터 로딩 구현 필요 (1 x N 신호를 $\frac{N}{250}$ x 250로 변환 필요, for loop 활용)