



Next layer

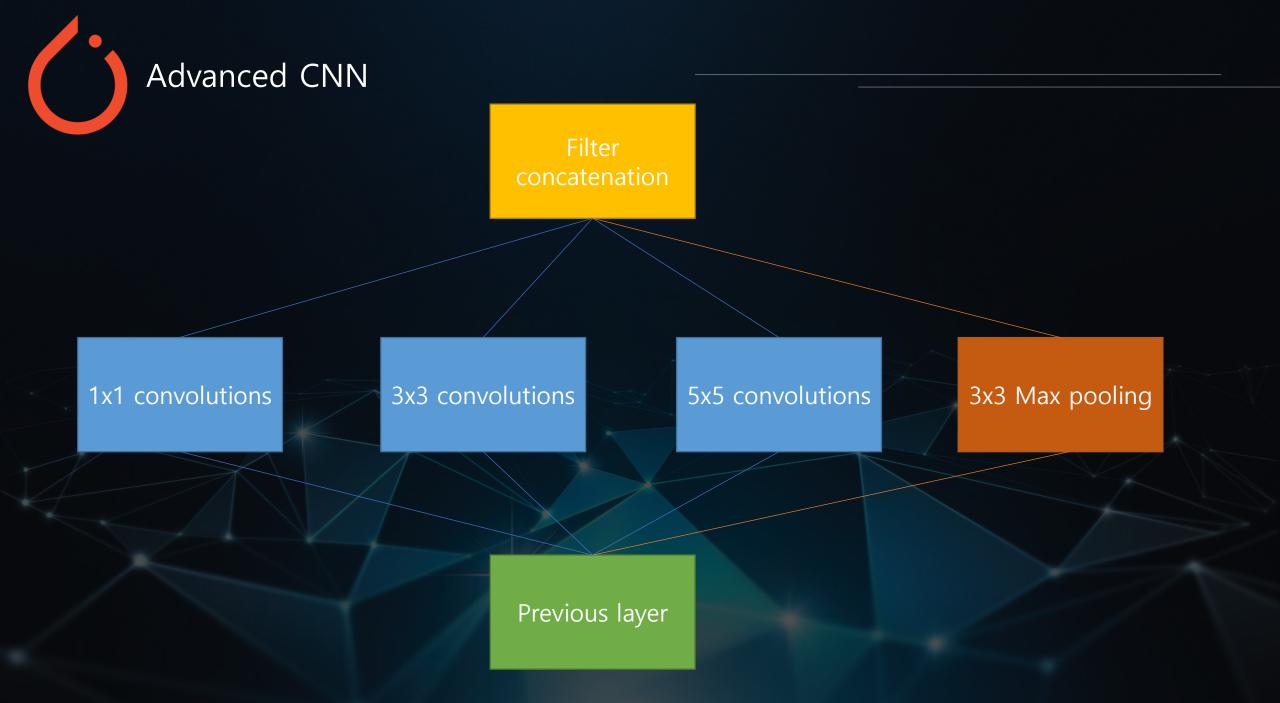
1x1 convolutions

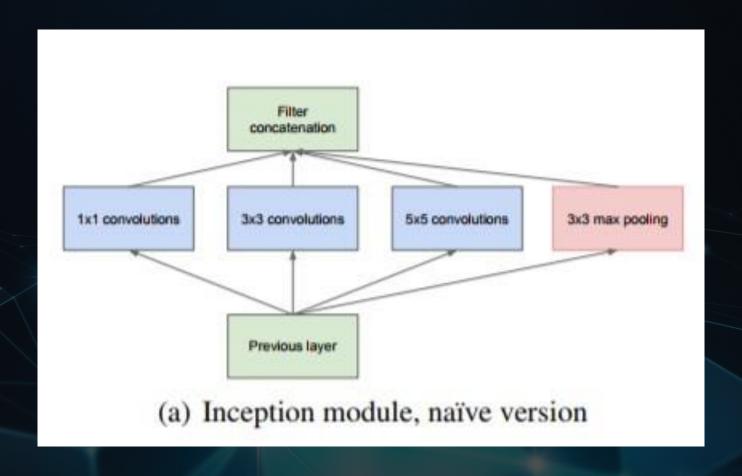
3x3 convolutions

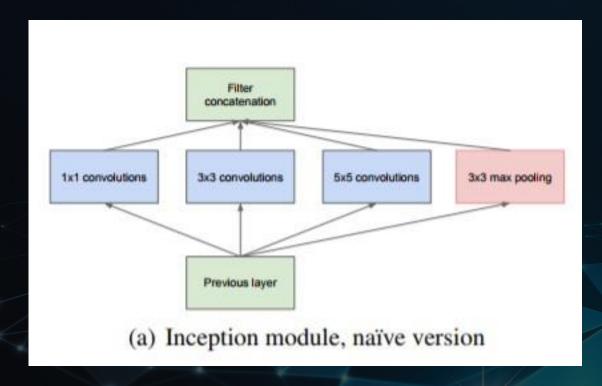
5x5 convolutions

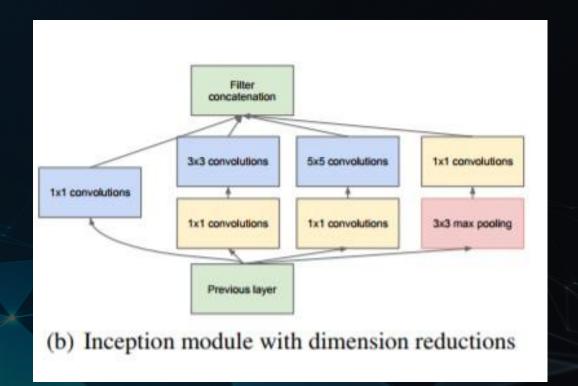
3x3 Max pooling

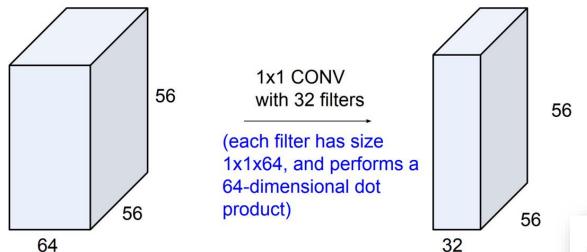
Previous layer











### Why 1x1 convolution

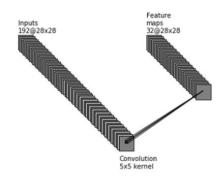


Figure 6. 5×5 convolutions inside the Inception module using the naive model

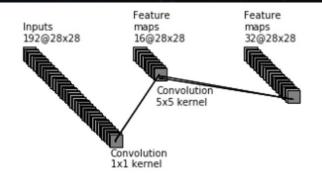


Figure 7. 1×1 convolutions serve as the dimensionalit reducers that limit the number of expensive 5×5 convolutions that follow



output

Linear + log\_softmax

Inception Module

Convolutions + Max Pool + relu

Inception Module

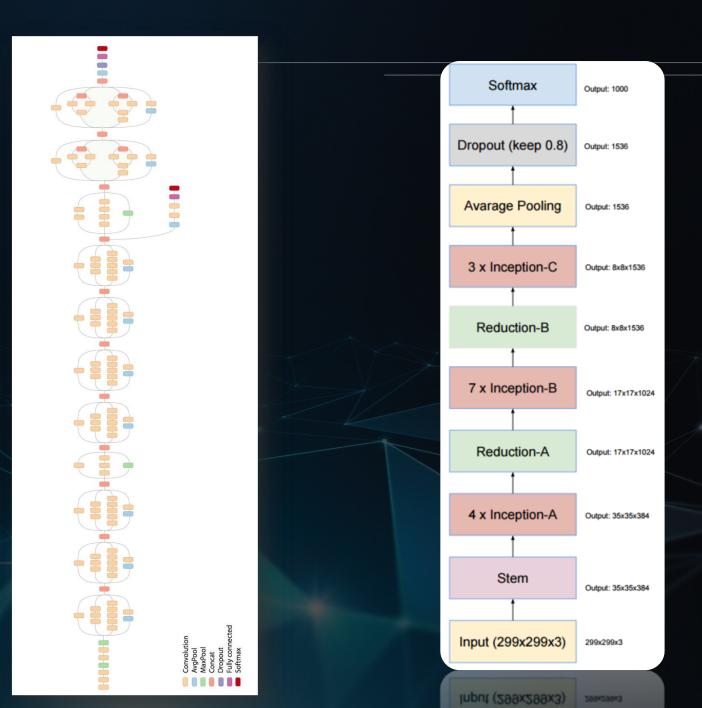
Convolutions + Max Pool + relu

Input

```
class Net(nn.Module):
    def init (self):
         super(Net, self). init ()
         self.conv1 = nn.Conv2d(1, 10, kernel size=5)
         self.conv2 = nn.Conv2d(88, 20, kernel size=5)
         self.incept1 = InceptionA(in channels=10)
         self.incept2 = InceptionA(in channels=20)
         self.mp = nn.MaxPool2d(2)
         self.fc = nn.Linear(1408, 10)
    def forward(self, x):
         in size = x.size(0)
        x = F.relu(self.mp(self.conv Train Epoch: 9 [48000/60000 (80%)]
                                                                               Loss: 0.049192
                                         Train Epoch: 9 [48640/60000 (81%)]
        x = self.incept1(x)
                                                                               Loss: 0.035681
                                         Train Epoch: 9 [49280/60000 (82%)]
                                                                               Loss: 0.006367
        x = F.relu(self.mp(self.conv)
                                         Train Epoch: 9 [49920/60000 (83%)]
                                                                               Loss: 0.035510
        x = self.incept2(x)
                                         Train Epoch: 9 [50560/60000 (84%)]
                                                                               Loss: 0.165726
        x = x.view(in size, -1) # f
                                         Train Epoch: 9 [51200/60000 (85%)]
                                                                               Loss: 0.050424
        x = self.fc(x)
                                         Train Epoch: 9 [51840/60000 (86%)]
                                                                               Loss: 0.164085
        return F.log softmax(x, -1)
                                         Train Epoch: 9 [52480/60000 (87%)]
                                                                               Loss: 0.008275
                                         Train Epoch: 9 [53120/60000 (88%)]
                                                                               Loss: 0.006872
                                         Train Epoch: 9 [53760/60000 (90%)]
                                                                               Loss: 0.048391
                                         Train Epoch: 9 [54400/60000 (91%)]
                                                                               Loss: 0.019315
                                         Train Epoch: 9 [55040/60000 (92%)]
                                                                               Loss: 0.027699
                                         Train Epoch: 9 [55680/60000 (93%)]
                                                                               Loss: 0.025706
                                         Train Epoch: 9 [56320/60000 (94%)]
                                                                               Loss: 0.042459
                                         Train Epoch: 9 [56960/60000 (95%)]
                                                                               Loss: 0.071335
                                         Train Epoch: 9 [57600/60000 (96%)]
                                                                               Loss: 0.040346
                                         Train Epoch: 9 [58240/60000 (97%)]
                                                                               Loss: 0.047501
                                         Train Epoch: 9 [58880/60000 (98%)]
                                                                               Loss: 0.089792
                                         Train Epoch: 9 [59520/60000 (99%)]
                                                                               Loss: 0.062169
                                         Test set: Average loss: 0.0446, Accuracy: 9864/10000 (99%)
```





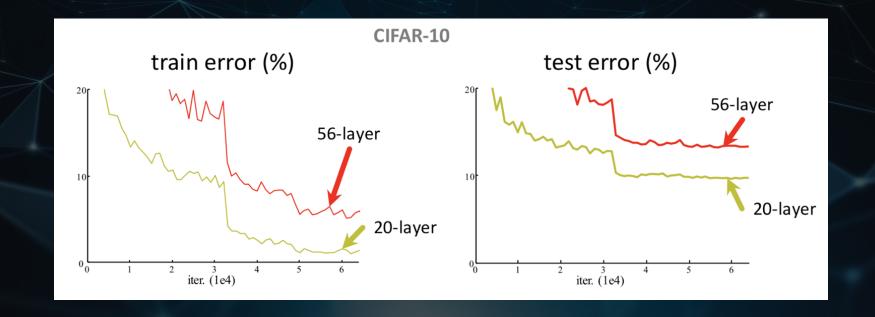


버전	특징
Inception. v1.	Inception module을 제시한 최초의 모델
Inception. v2	파라미터 수, 연산량, 복잡도를 줄이기 위해 convolution 필터를 3x3만으로 제한함.(VGG style 도입)
Inception. v3	v2에서 구조는 바뀌지 않고 일부 optimizer 종류와 convolution argument만 바뀜, 우리가 주로 사용하는 모델
Inception. v4	2015년에 Resnet을 추가하기 위해 발표, 세부적으로 달라진 inception layer 3개 사용(A, B, C)



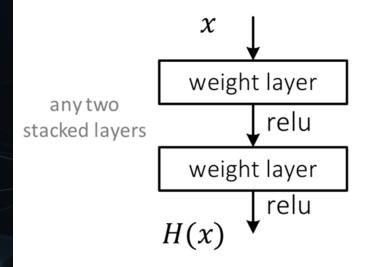
### Problems with stacking layers

- 1 Vanishing gradients problem
- 2 Back propagation kind of gives up...
- 3 Degradation problem
  - with increased network depth accuracy gets saturated and then rapidly degrades

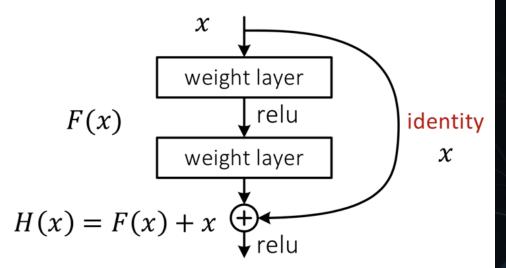


### Deep Residual Learning

• Plaint net



Residual net



```
self.conv1 = nn.Conv2d(1, 10, kernel size=5)
   self.conv2 = nn.Conv2d(88, 20, kernel size=5)
   self.conv3 = nn.Conv2d(88, 88, kernel size=9)
   self.incept1 = InceptionA(in channels=10)
   self.incept2 = InceptionA(in channels=20)
    self.mp = nn.MaxPool2d(2)
   self.fc = nn.Linear(1408, 10)
def forward(self, x):
   in size = x.size(0)
   x = F.relu(self.mp(self.conv1(x)))
   x = self.incept1(x)
   jump = self.conv3(x)
   x = F.relu(self.mp(self.conv2(x)))
   x = self.incept2(x)
   x = x + iump
    x = x.view(in size. -1) # flatten the tensor.
```

#### Inception

```
Train Epoch: 4 [50560/60000 (84%)]
                                         Loss: 0.066574
Train Epoch: 4 [51200/60000 (85%)]
                                         Loss: 0.069952
Train Epoch: 4 [51840/60000 (86%)]
                                         Loss: 0.156167
Train Epoch: 4 [52480/60000 (87%)]
                                         Loss: 0.276394
Train Epoch: 4 [53120/60000 (88%)]
                                         Loss: 0.126287
Train Epoch: 4 [53760/60000 (90%)]
                                         Loss: 0.046774
Train Epoch: 4 [54400/60000 (91%)]
                                         Loss: 0.061152
Train Epoch: 4 [55040/60000 (92%)]
                                         Loss: 0.068414
Train Epoch: 4 [55680/60000
                            (93%)]
                                         Loss: 0.038474
Train Epoch: 4 [56320/60000
                            (94%)1
                                         Loss: 0.017419
Train Epoch: 4 [56960/60000 (95%)]
                                         Loss: 0.128696
Train Epoch: 4 [57600/60000 (96%)]
                                         Loss: 0.036454
Train Epoch: 4 [58240/60000 (97%)]
                                         Loss: 0.053295
Train Epoch: 4 [58880/60000 (98%)]
                                         Loss: 0.032368
Train Epoch: 4 [59520/60000 (99%)]
                                         Loss: 0.092593
```

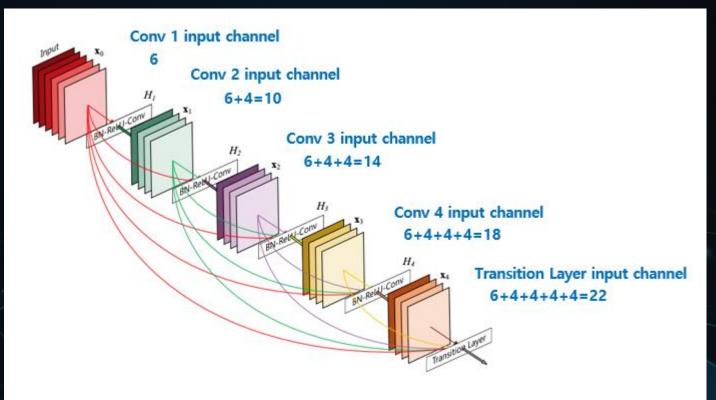
Test set: Average loss: 0.0682, Accuracy: 9771/10000 (98%)

### Inception Resnet

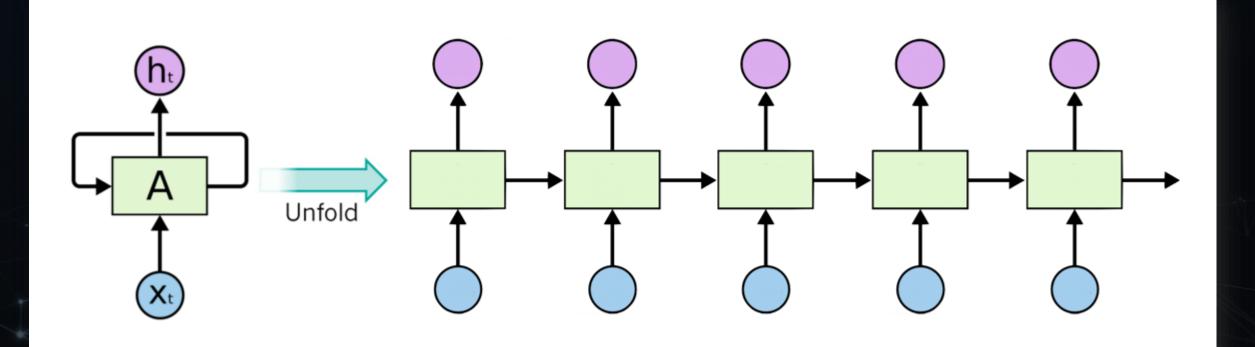
VS 4 epoch

```
Train Epoch: 4 [51840/60000 (86%)]
                                        Loss: 0.025530
Train Epoch: 4 [52480/60000 (87%)]
                                        Loss: 0.068905
Train Epoch: 4 [53120/60000 (88%)]
                                        Loss: 0.023693
Train Epoch: 4 [53760/60000 (90%)]
                                        Loss: 0.101106
Train Epoch: 4 [54400/60000 (91%)]
                                        Loss: 0.196795
Train Epoch: 4 [55040/60000 (92%)]
                                        Loss: 0.045218
Train Epoch: 4 [55680/60000 (93%)]
                                        Loss: 0.167126
Train Epoch: 4 [56320/60000 (94%)]
                                        Loss: 0.393767
Train Epoch: 4 [56960/60000 (95%)]
                                        Loss: 0.035607
Train Epoch: 4 [57600/60000 (96%)]
                                        Loss: 0.078126
Train Epoch: 4 [58240/60000 (97%)]
                                        Loss: 0.076608
Train Epoch: 4 [58880/60000 (98%)]
                                        Loss: 0.068349
Train Epoch: 4 [59520/60000 (99%)]
                                        Loss: 0.100903
```

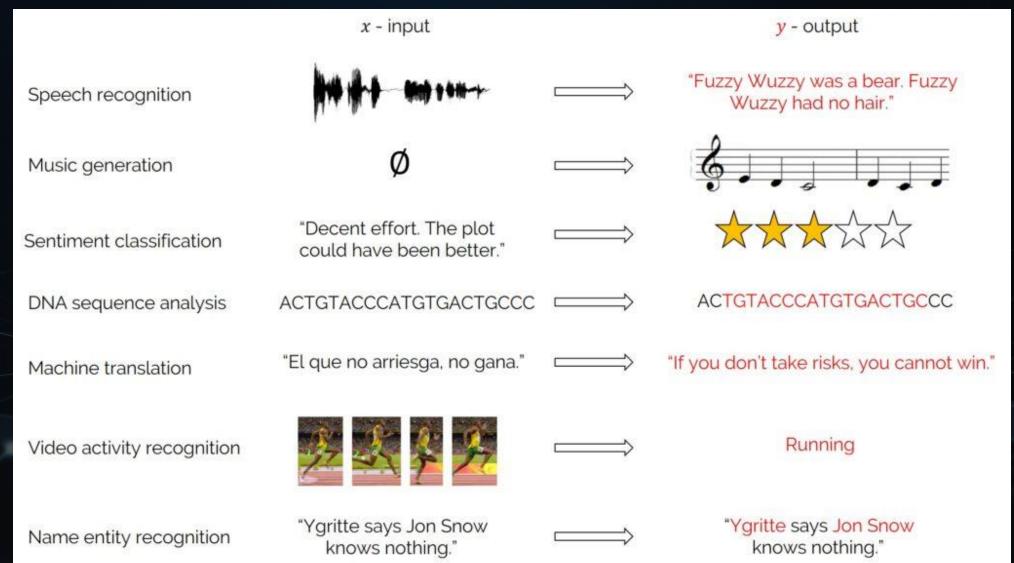
Test set: Average loss: 0.0712, Accuracy: 9760/10000 (98%)



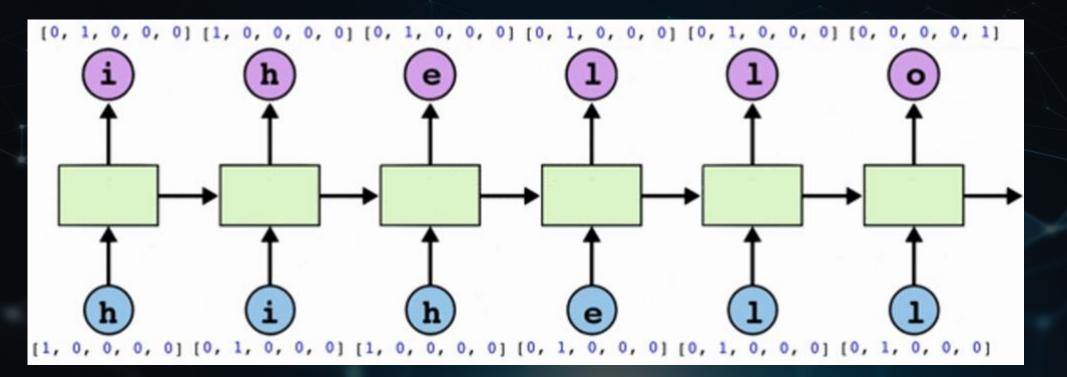
**Figure 1:** A 5-layer dense block with a growth rate of k=4. Each layer takes all preceding feature-maps as input.

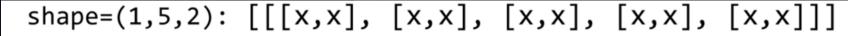


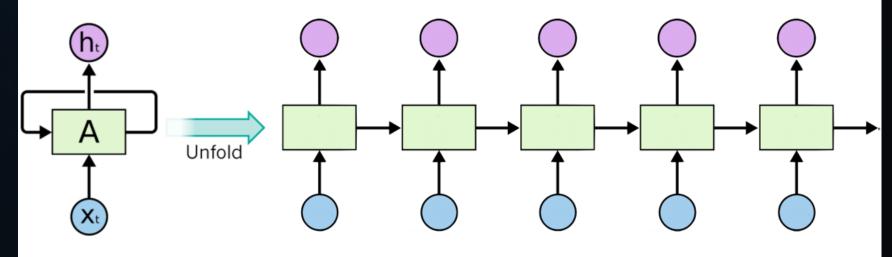




```
cell = nn.RNN(input size=4, hidden size=2, batch first=True)
Out
              cell = nn.GRU(input_size=4, hidden_size=2, batch_first=True)
              cell = nn.LSTM(input_size=4, hidden_size=2, batch_first=True)
               Hidden
                        # (num layers * num directions, batch, hidden size) whether batch first=True or False
                        hidden = Variable(torch.randn(1, 1, 2))
                        # Propagate input through RNN
                        # Input: (batch, seq len, input size) when batch first=True
        Input
                        inputs = Variable(torch.Tensor([h, e, 1, 1, o]))
                        for one in inputs:
                            one = one.view(1, 1, -1)
                            # Input: (batch, seq len, input size) when batch first=True
                            out, hidden = cell(one, hidden)
                            print("one input size", one.size(), "out size", out.size())
```

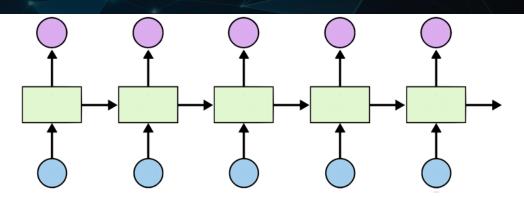






shape=(1,5,4): [[[1,0,0,0], [0,1,0,0], [0,0,1,0], [0,0,1,0], [0,0,0,1]]] h e l l o

Shape = (배치 수, 시퀀스 크기, input 크기)



shape=(3,5,4):  $[[[1,0,0,0], [0,1,0,0], [0,0,1,0], [0,0,1,0], [0,0,0,1]], \# hello \\ [[0,1,0,0], [0,0,0,1], [0,0,1,0], [0,0,1,0], [0,0,1,0]] \# eolll \\ [[0,0,1,0], [0,0,1,0], [0,1,0,0], [0,1,0,0], [0,0,1,0]]] \# lleel$ 

```
l before view: torch.Size([1, 1, 5])
after view: torch.Size([1, 5])
out = out.view(-1, num_classes)
```

# CrossEntropyLoss = LogSoftmax + NLLLoss
criterion = nn.CrossEntropyLoss()

```
model = Model()
# Set loss and optimizer function
# CrossEntropyLoss = LogSoftmax + NLLLoss
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.1)
# Train the model
for epoch in range(100):
   optimizer.zero grad()
   loss = 0
   hidden = model.init hidden()
    for input, label in zip(inputs, labels):
       hidden, output = model(hidden, input)
        loss += criterion(output, torch.LongTensor([label]))
   print(", epoch: %d, loss: %1.3f" % (epoch + 1, loss.item()))
    loss.backward()
   optimizer.step()
```

#### 시퀀스 사용 코드

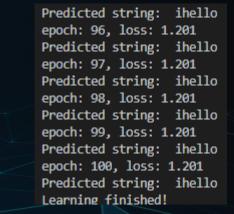
```
for epoch in range(100):
    outputs = rnn(inputs)
    optimizer.zero_grad()
    loss = criterion(outputs, labels)
    loss.backward()
    optimizer.step()
    _, idx = outputs.max(1)
    idx = idx.data.numpy()
    result_str = [idx2char[c] for c in idx.squeeze()]
    print("epoch: %d, loss: %1.3f" % (epoch + 1, loss.item()))
    print("Predicted string: ", ''.join(result_str))
```

Predicted string: ihello epoch: 96, loss: 0.458
Predicted string: ihello epoch: 97, loss: 0.458
Predicted string: ihello epoch: 98, loss: 0.458
Predicted string: ihello epoch: 99, loss: 0.458
Predicted string: ihello epoch: 100, loss: 0.458
Predicted string: ihello epoch: 100, loss: 0.458
Predicted string: ihello Learning finished!



### 소프트 맥스 적용

Predicted string: ihello epoch: 96, loss: 0.458
Predicted string: ihello epoch: 97, loss: 0.458
Predicted string: ihello epoch: 98, loss: 0.458
Predicted string: ihello epoch: 99, loss: 0.458
Predicted string: ihello epoch: 99, loss: 0.458
Predicted string: ihello epoch: 100, loss: 0.458
Predicted string: ihello Learning finished!



"e/(e+(k−1)/e)) = e^2/(e^2+k−1) = 0.71 이상의 값을 얻을 수 없다."



```
self.sm = nn.Softmax(dim=1)
self.rnn = nn.RNN(input_size=5, hidden_size=5, batch_first=True)
self.fc = nn.Linear(hidden_size, num_classes)

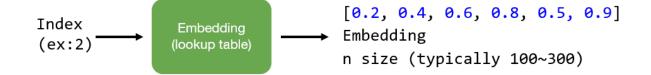
def forward(self, x):
    h_0 = Variable(torch.zeros(
        self.num_layers, x.size(0), self.hidden_size))
    x.view(x.size(0), self.sequence_length, self.input_size)
    out, _ = self.rnn(x, h_0)
# return self.sm(out.view(-1, num_classes))
return self.fc(out.view(-1, num_classes))
```

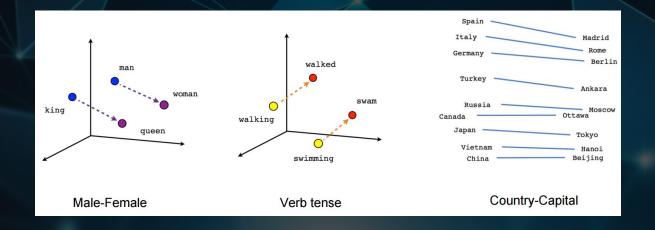
epoch: 96, loss: 0.001
Predicted string: ihello
epoch: 97, loss: 0.001
Predicted string: ihello
epoch: 98, loss: 0.001
Predicted string: ihello
epoch: 99, loss: 0.001
Predicted string: ihello
epoch: 100, loss: 0.001
Predicted string: ihello
epoch: 100, loss: 0.001
Predicted string: ihello
Learning finished!



### One hot VS embedding







```
batch size = 1
class Model(nn.Module):
                                                    sequence length = 6
                                                    num layers = 1
   def init (self, num layers, hidden size):
        super(Model, self). init ()
        self.num layers = num layers
        self.hidden size = hidden size
        self.embedding = nn.Embedding(input size, embedding size)
        self.rnn = nn.RNN(input size=embedding size,
                         hidden size=5, batch first=True)
        self.fc = nn.Linear(hidden size, num classes)
    def forward(self, x):
       h 0 = Variable(torch.zeros(
            self.num layers, x.size(0), self.hidden size))
        emb = self.embedding(x)
        emb = emb.view(batch size, sequence length, -1)
       out, = self.rnn(emb, h 0)
       return self.fc(out.view(-1, num classes))
```

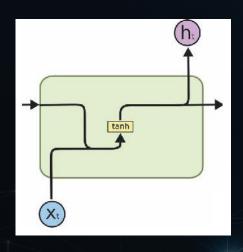
num\_classes = 5
input size = 5

hidden size = 5

embedding size = 10

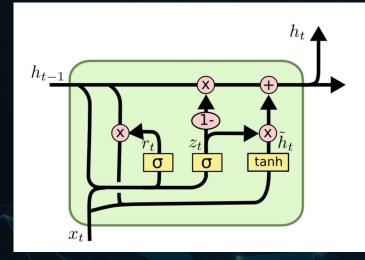
```
Predicted string: ihello
epoch: 93, loss: 0.007
Predicted string: ihello
epoch: 94, loss: 0.007
Predicted string: ihello
epoch: 95, loss: 0.007
Predicted string: ihello
epoch: 96, loss: 0.007
Predicted string: ihello
epoch: 97, loss: 0.007
Predicted string: ihello
epoch: 98, loss: 0.007
Predicted string: ihello
epoch: 99, loss: 0.007
Predicted string: ihello
epoch: 100, loss: 0.007
Predicted string: ihello
Learning finished!
```





#### **RNN**

$$egin{array}{lll} oldsymbol{a}^{(t)} &=& oldsymbol{b} + oldsymbol{W} oldsymbol{h}^{(t-1)} + oldsymbol{U} oldsymbol{x}^{(t)}, \ oldsymbol{h}^{(t)} &=& ext{tanh}(oldsymbol{a}^{(t)}), \ oldsymbol{o}^{(t)} &=& oldsymbol{c} + oldsymbol{V} oldsymbol{h}^{(t)}, \ oldsymbol{\hat{y}}^{(t)} &=& ext{softmax}(oldsymbol{o}^{(t)}), \end{array}$$



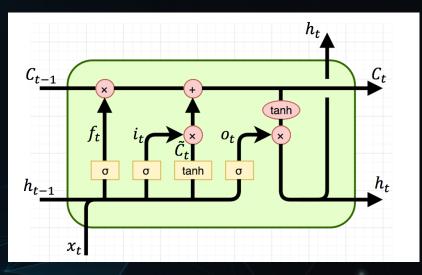
#### **GRU(Gated Recurrent Unit)**

$$z_{t} = \sigma(W_{z} \cdot [h_{t-1}, x_{t}])$$

$$r_{t} = \sigma(W_{r} \cdot [h_{t-1}, x_{t}])$$

$$\tilde{h}_{t} = \tanh(W \cdot [r_{t} * h_{t-1}, x_{t}])$$

$$h_{t} = (1 - z_{t}) * h_{t-1} + z_{t} * \tilde{h}_{t}$$



#### **LSTM(Long Short Term Memory Unit)**

$$f_{t} = \sigma (W_{f} \cdot [h_{t-1}, x_{t}] + b_{f})$$

$$i_{t} = \sigma (W_{i} \cdot [h_{t-1}, x_{t}] + b_{i})$$

$$\tilde{C}_{t} = \tanh(W_{C} \cdot [h_{t-1}, x_{t}] + b_{C})$$

$$C_{t} = f_{t} * C_{t-1} + i_{t} * \tilde{C}_{t}$$

$$o_{t} = \sigma (W_{o} [h_{t-1}, x_{t}] + b_{o})$$

$$h_{t} = o_{t} * \tanh(C_{t})$$



D-ai-ving

### 감사합니다!

https://excelsior-cjh.tistory.com/185

https://towardsdatascience.com/word-embeddings-and-the-chamber-of-secrets-lstm-gru-tf-keras-

de3f5c21bf16

https://hoya012.github.io/blog/DenseNet-Tutorial-1/

https://curaai00.tistory.com/1

https://arxiv.org/pdf/1512.03385v1.pdf

https://sotudy.tistory.com/13

https://blueskyvision.tistory.com/539

https://ikkison.tistory.com/86