ML/DL for Everyone with PYTORCH

Lecture 12: RNN

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Code: https://github.com/hunkim/PyTorchZeroToAll
Slides: http://bit.ly/PyTorchZeroAll

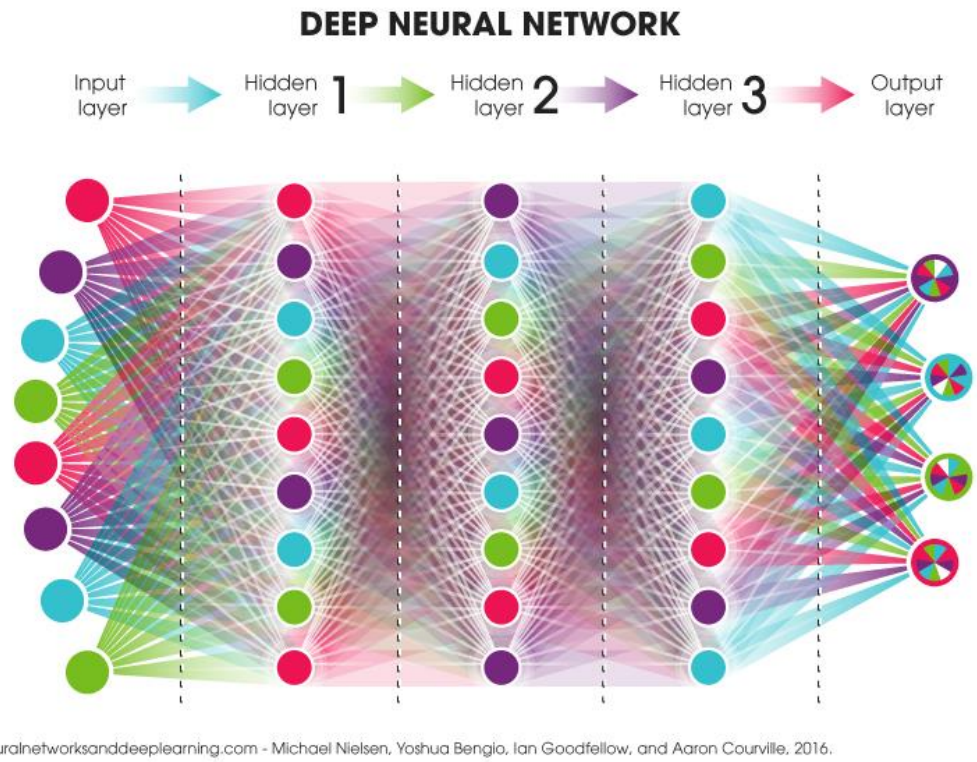
Call for Comments

Please feel free to add comments directly on these slides.

Other slides: http://bit.ly/PyTorchZeroAll

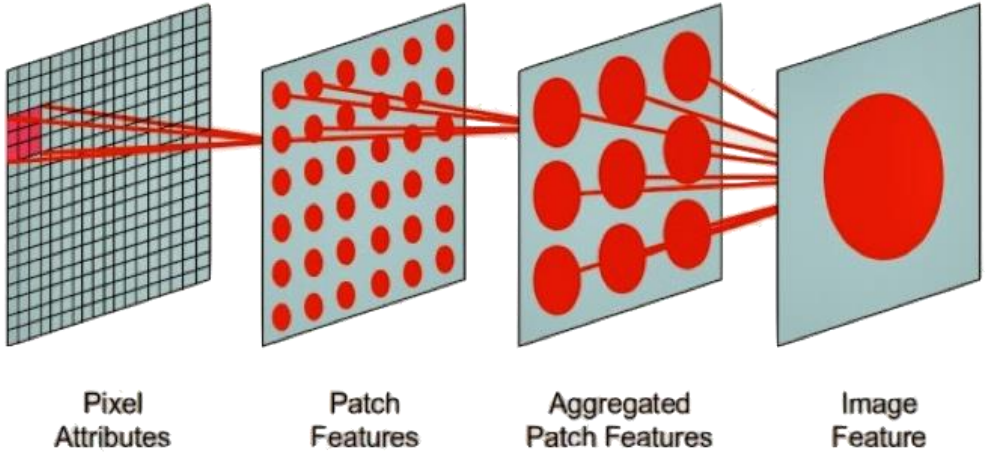
Picture from http://www.tssablog.org/archives/3280

DNN, CNN, RNN



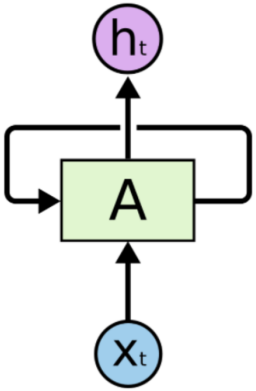
https://blog.ttro.com/artificial-intelligence-will-shape-e-learning-for-good/

DNN, CNN, RNN



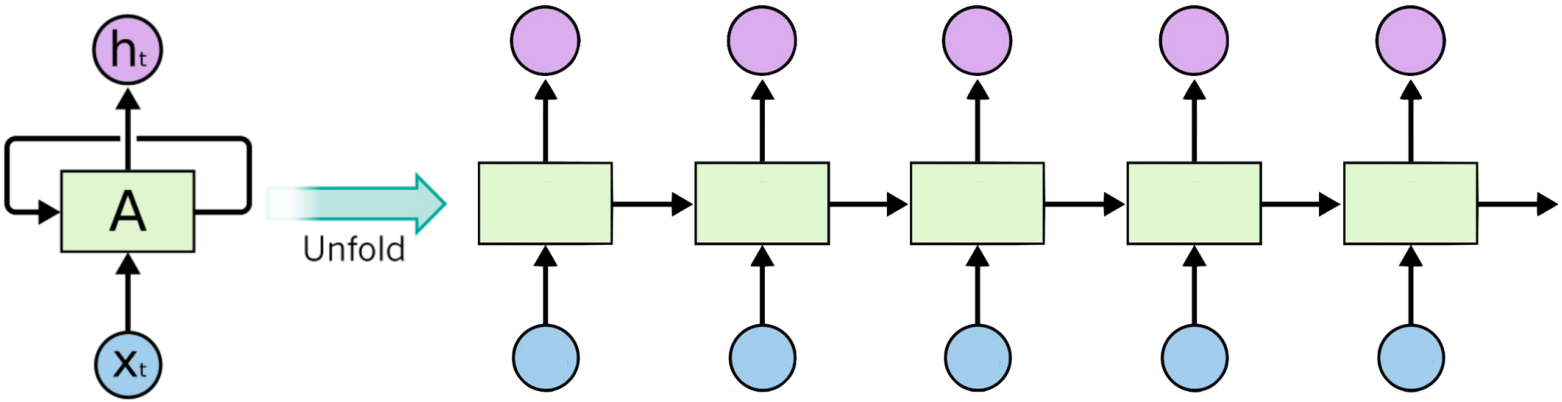
http://practicalquant.blogspot.hk/2013/10/deep-learning-oral-traditions.html

DNN, CNN, RNN



http://practicalquant.blogspot.hk/2013/10/deep-learning-oral-traditions.html

DNN, CNN, RNN



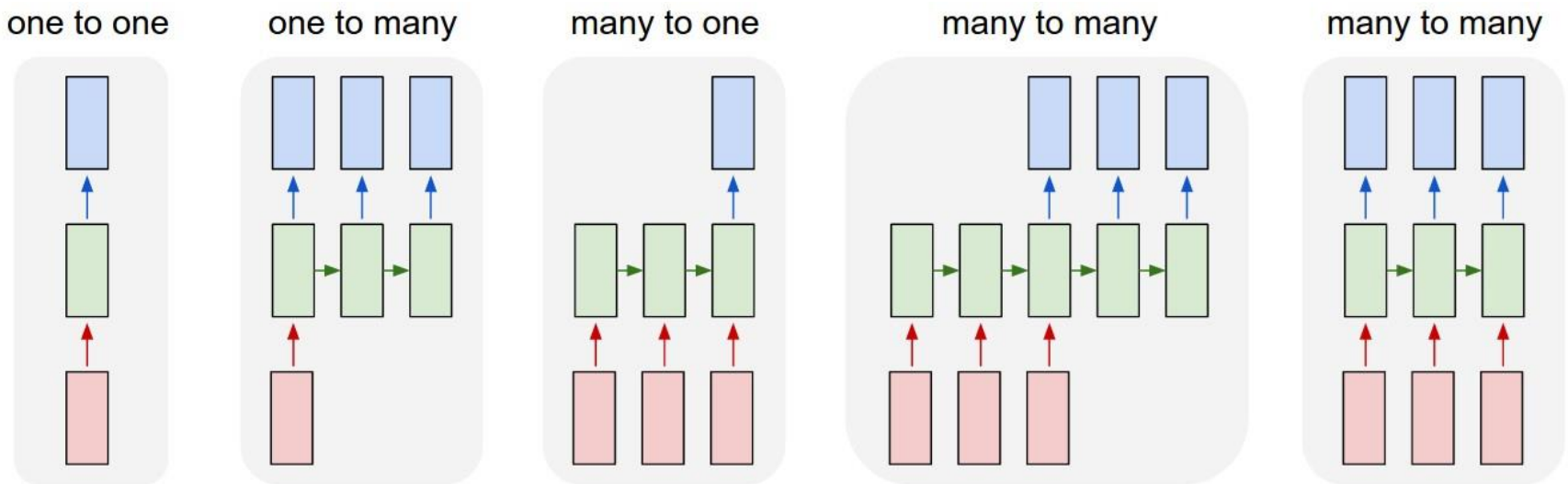
http://practicalquant.blogspot.hk/2013/10/deep-learning-oral-traditions.html

RNN Applications: series of data

- Time series prediction
- Language modeling (text generation)
- Text sentiment analysis
- Named entity recognition
- Translation
- Speech recognition
- Anomaly detection in time series
- Music composition
- ...

https://stats.stackexchange.com/questions/304431/practical-applications-or-rnn

RNN Models

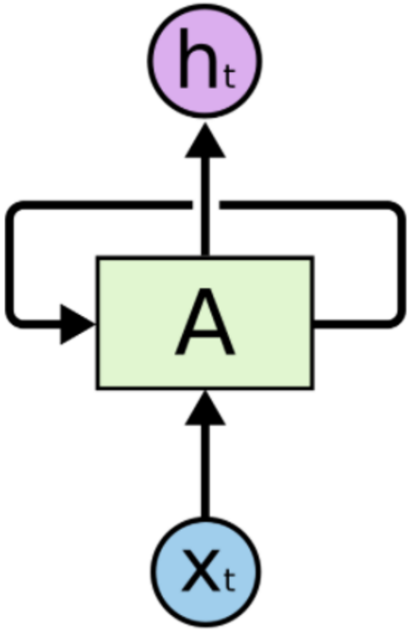


http://karpathy.github.io/2015/05/21/rnn-effectiveness/

RNN topics

- RNN Basics
- Teach RNN to say ‘hello’
  - One-hot VS embedding
- RNN classification (name)
  - RNN on GPU
- RNN language modeling
  - Teacher forcing
- Sequence to sequence

RNN in PyTorch

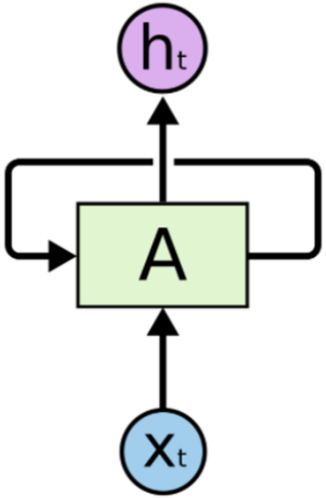



```
cell = nn.LSTM(input_size=4, hidden_size=2, batch_first=True)

...

inputs = ... # (batch_size, seq_len, input_size) with batch_first=True
hidden = (... , ...) # (num_layers, batch_size, hidden_size)

# Bidirectional RNN*
hidden = (... , ...) # (num_layers*2, batch_size, hidden_size)
...

out, hidden = cell(inputs, hidden)
```

One hot encoding for letters, h, e, l, l, o

```
# One hot encoding
h = [1, 0, 0, 0]
e = [0, 1, 0, 0]
l = [0, 0, 1, 0]
o = [0, 0, 0, 1]
```

One node: 4 (*input-dim*) in 2 (*hidden_size*)

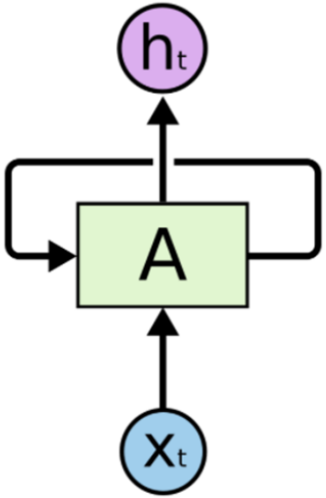



```
h [[[1,0,0,0]]]
  shape=(1,1,4)
```

```
# One hot encoding
h = [1, 0, 0, 0]
e = [0, 1, 0, 0]
l = [0, 0, 1, 0]
o = [0, 0, 0, 1]
```

One node: 4 (*input-dim*) in 2 (*hidden_size*)

```
[[[x,x]]]
shape=(1,1,2)
```



hidden_size=2

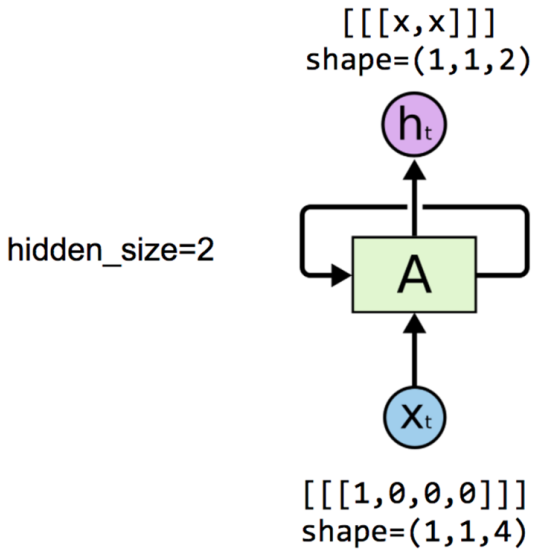
```
# One hot encoding
h = [1, 0, 0, 0]
e = [0, 1, 0, 0]
l = [0, 0, 1, 0]
o = [0, 0, 0, 1]
```

```
h [[[1,0,0,0]]]
  shape=(1,1,4)
```

One node: 4 (*input_dim*) in 2 (*hidden_size*)

```
# One cell RNN input_dim (4) -> output_dim (2)
cell = nn.LSTM(input_size=4, hidden_size=2, batch_first=True)

# One letter input
inputs = autograd.Variable(torch.Tensor([[h]])) # rank = (1, 1, 4)

# initialize the hidden state.
# (num_layers * num_directions, batch, hidden_size)
hidden = (autograd.Variable(torch.randn(1, 1, 2)),
          autograd.Variable(torch.randn((1, 1, 2))))

# Feed to one element at a time.
# after each step, hidden contains the hidden state.
out, hidden = cell(inputs, hidden)
print("out", out.data)
```

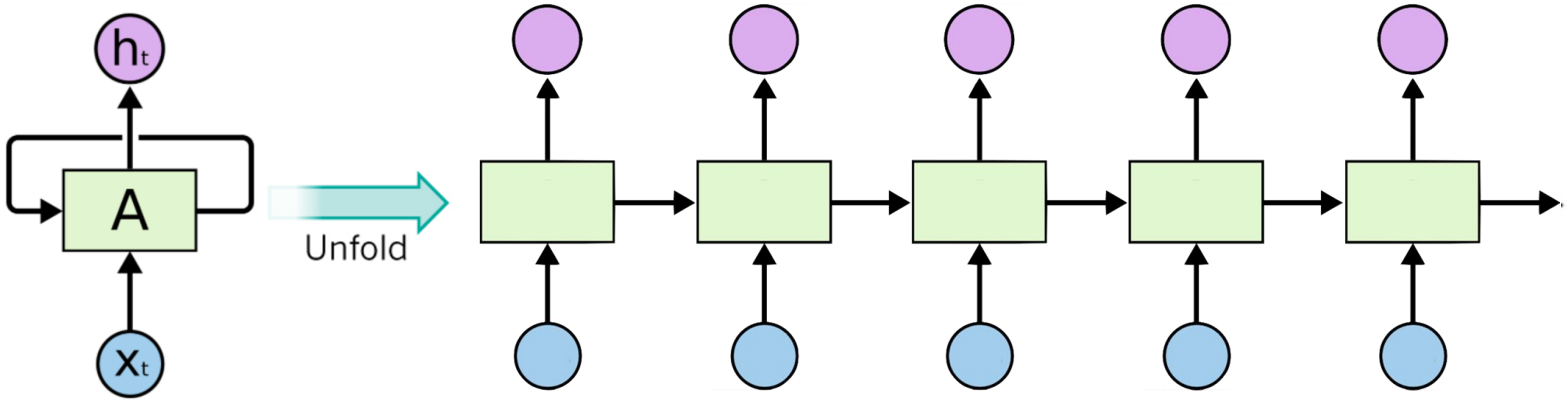
```
-0.1243  0.0738
[torch.FloatTensor of size 1x1x2]
```



Unfolding to n sequences

```
hidden_size=2
seq_len=5
```

shape=(1,5,2): [[[x,x], [x,x], [x,x], [x,x], [x,x]]]



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

https://github.com/hunkim/DeepLearningZeroToAll/blob/master/lab-12-0-rnn_basics.ipynb

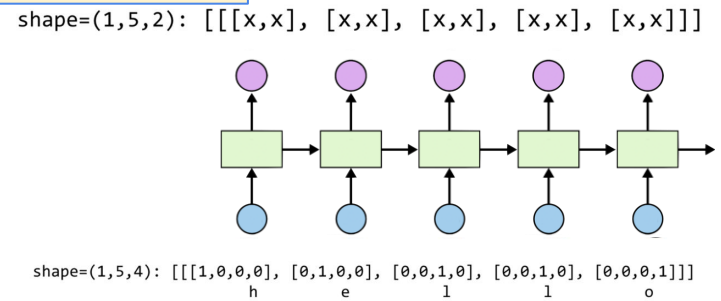
Unfolding to n sequences

```
# One cell RNN input_dim (4) -> output_dim (2). sequence: 5
cell = nn.LSTM(input_size=4, hidden_size=2, batch_first=True)

inputs = autograd.Variable(torch.Tensor([[h, e, l, l, o]]))
print("input size", inputs.size())

hidden = (autograd.Variable(torch.randn(1, 1, 2)), autograd.Variable(
    torch.randn((1, 1, 2))))  # clean out hidden state

out, hidden = cell(inputs, hidden)
print(out.data)
```

```
# One hot encoding
h = [1, 0, 0, 0]
e = [0, 1, 0, 0]
l = [0, 0, 1, 0]
o = [0, 0, 0, 1]
```

```
input size torch.Size([1, 5, 4])

(0 ,.,.) =
 -0.1825  0.0737
 -0.1981  0.1164
 -0.3367  0.2095
 -0.3625  0.2503
 -0.2038  0.3626
[torch.FloatTensor of size 1x5x2]
```

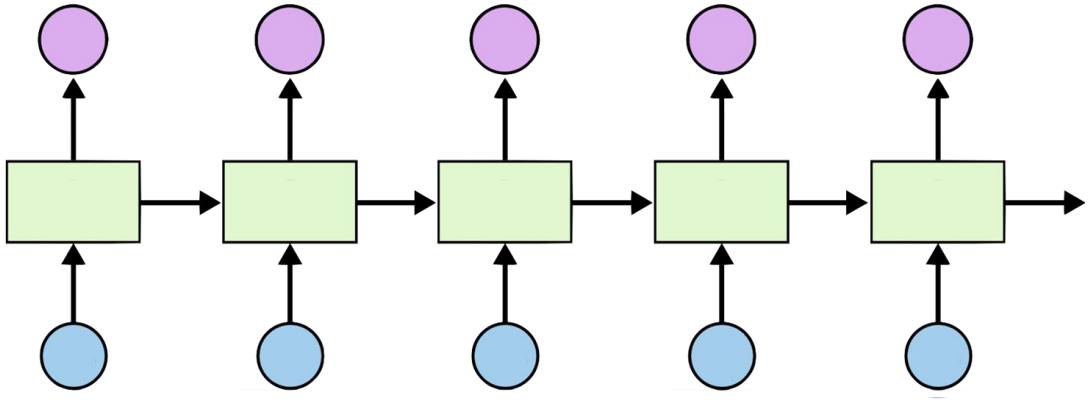
hidden_size=2
seq_len=5



Batching input

```
Hidden_size=2
sequence_length=5
batch_size=3
```

```
shape=(3,5,2): [[[x,x], [x,x], [x,x], [x,x], [x,x]],
                [[x,x], [x,x], [x,x], [x,x], [x,x]],
                [[x,x], [x,x], [x,x], [x,x], [x,x]]]
```

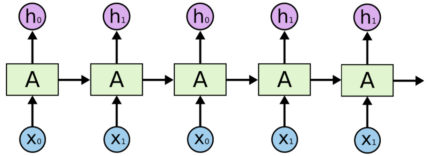


```
shape=(3,5,4): [[[1,0,0,0], [0,1,0,0], [0,0,1,0], [0,0,1,0], [0,0,0,1]], # hello
                [[0,1,0,0], [0,0,0,1], [0,0,1,0], [0,0,1,0], [0,0,1,0]]  # eolll
                [[0,0,1,0], [0,0,1,0], [0,1,0,0], [0,1,0,0], [0,0,1,0]]] # lleel
```

Batching input

```
# One cell RNN input_dim (4) -> output_dim (2). sequence: 5, batch 3
# 3 batches 'hello', 'eolll', 'lleel'
# rank = (3, 5, 4)
inputs = autograd.Variable(torch.Tensor([[h, e, l, l, o],
                                         [e, o, l, l, l],
                                         [l, l, e, e, l]]))
print("input size", inputs.size()) # input size torch.Size([3, 5, 4])

# (num_layers * num_directions, batch, hidden_size)
hidden = (autograd.Variable(torch.randn(1, 3, 2)), autograd.Variable(
   torch.randn((1, 3, 2))))

out, hidden = cell(inputs, hidden)
print("out size", out.size()) # out size torch.Size([3, 5, 2])
```

```
shape=(3,5,2): [[[x,x], [x,x], [x,x], [x,x], [x,x]],
                [[x,x], [x,x], [x,x], [x,x], [x,x]],
                [[x,x], [x,x], [x,x], [x,x], [x,x]]]
```

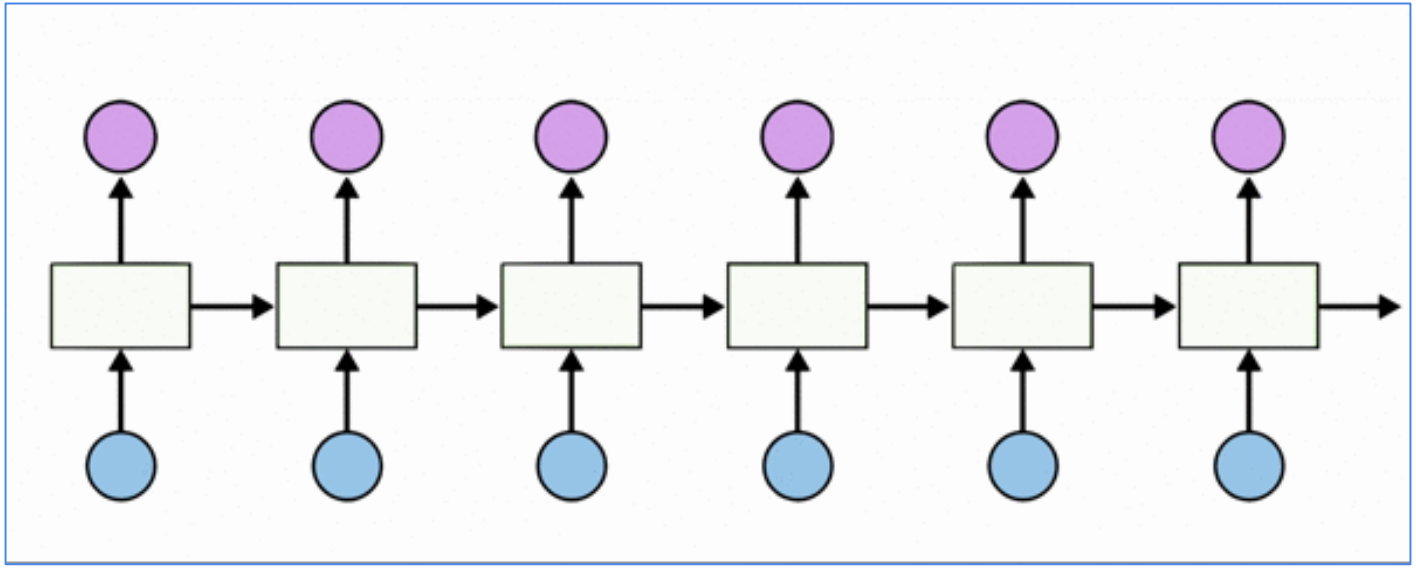


Hidden_size=2
sequence_length=5
batch_size=3

```
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
```

Teach RNN ‘hihell’ to ‘ihello’

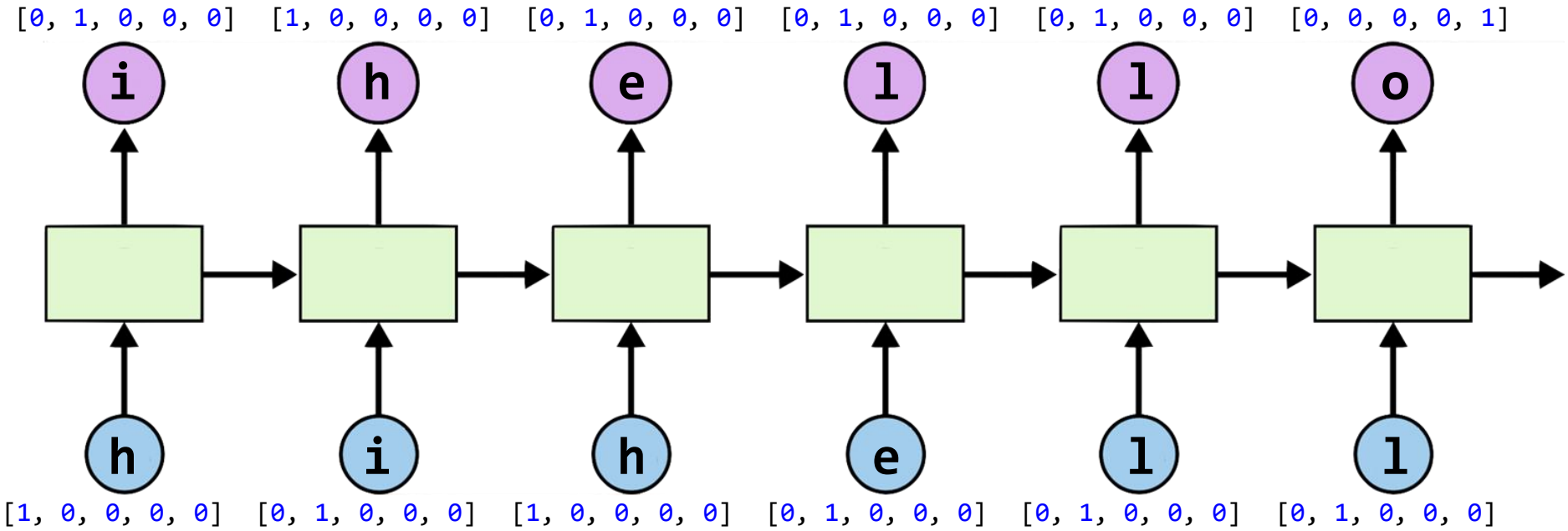
```
[1, 0, 0, 0, 0],   # h 0
[0, 1, 0, 0, 0],   # i 1
[0, 0, 1, 0, 0],   # e 2
[0, 0, 0, 1, 0],   # l 3
[0, 0, 0, 0, 1],   # o 4
```



Teach RNN ‘hihell’ to ‘ihello’

```
[1, 0, 0, 0, 0],   # h 0
[0, 1, 0, 0, 0],   # i 1
[0, 0, 1, 0, 0],   # e 2
[0, 0, 0, 1, 0],   # l 3
[0, 0, 0, 0, 1],   # o 4
```

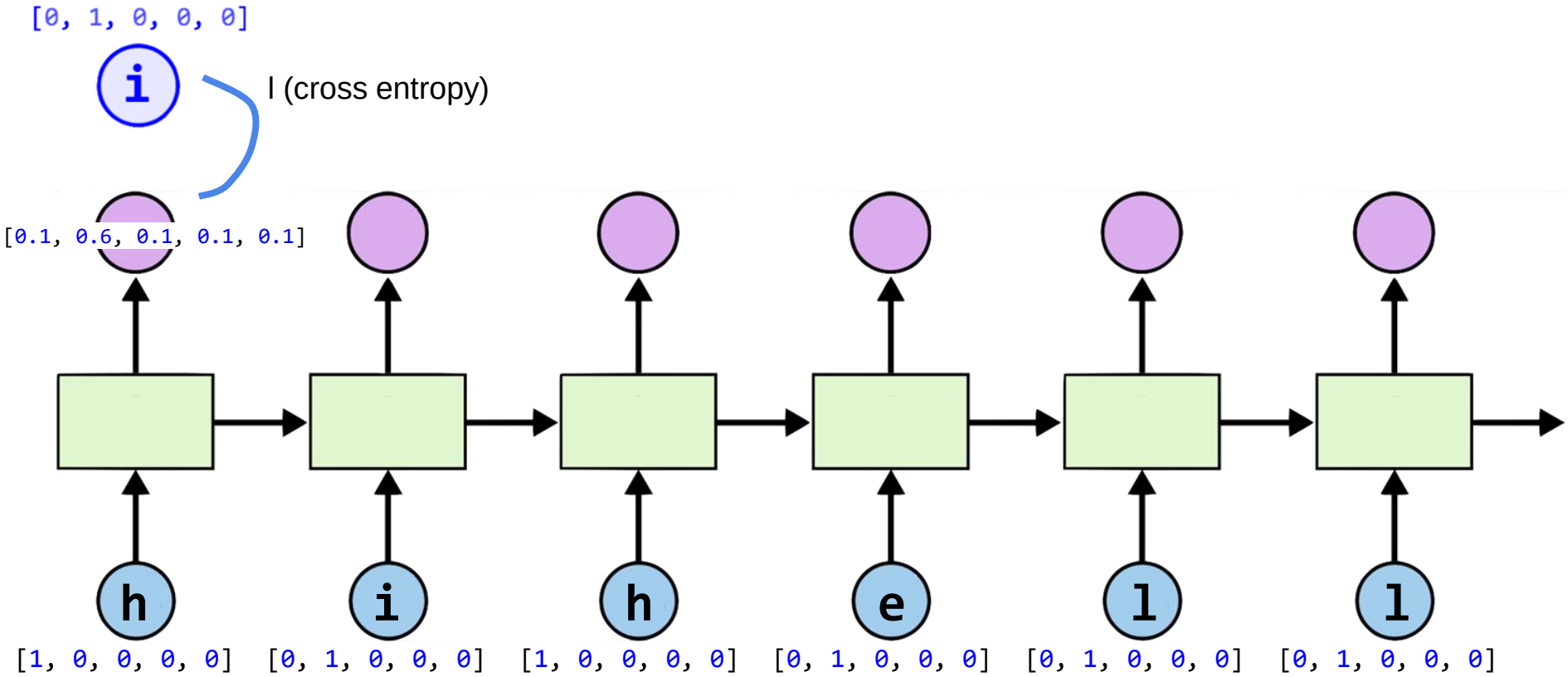
output_dim = 5



Input_dim = 5

Loss and training

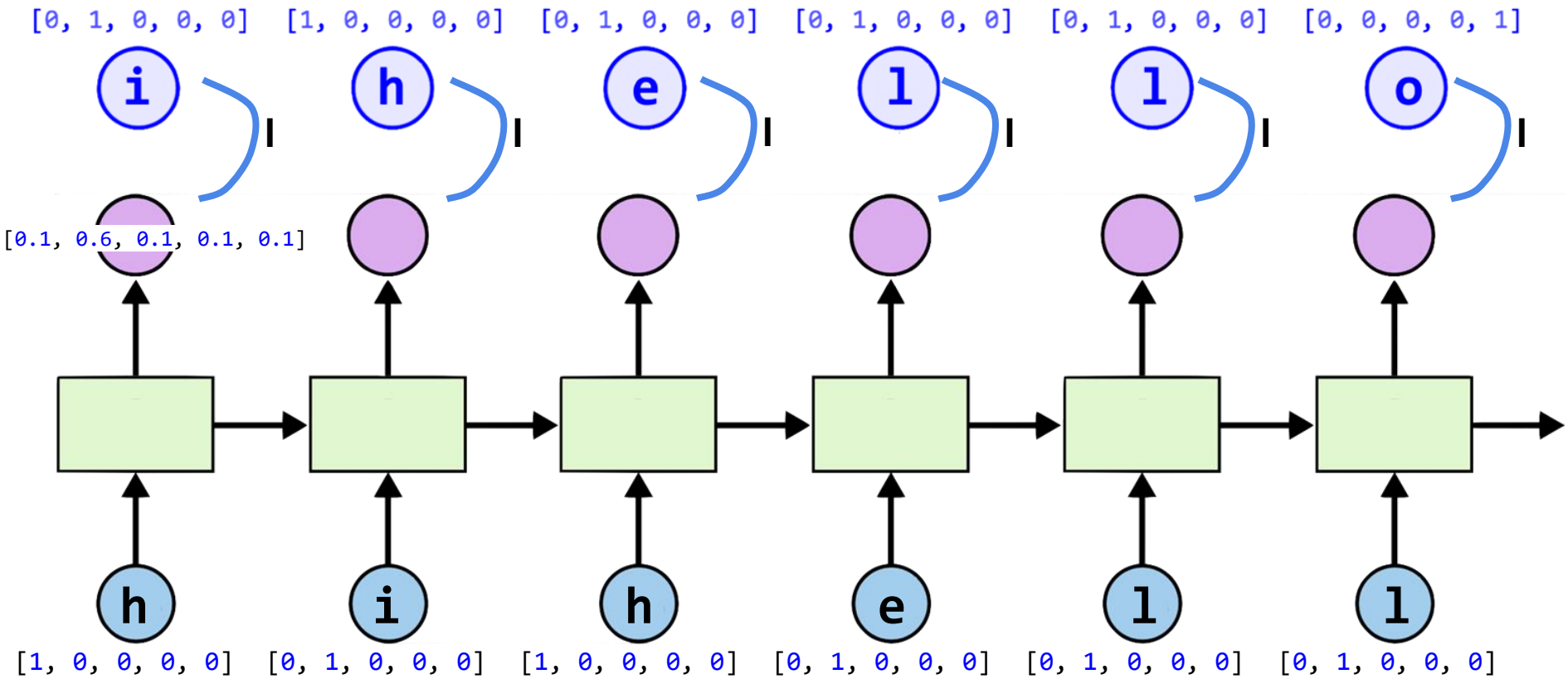
`output_dim = 5`



`Input_dim = 5`

Loss and training

`output_dim = 5`



`Input_dim = 5`

(1)Data preparation 1

```
idx2char = ['h', 'i', 'e', 'l', 'o']

# Teach hihell -> ihello
x_data = [[0, 1, 0, 2, 3, 3]]   # hihell
x_one_hot = [[[1, 0, 0, 0, 0],   # h 0
              [0, 1, 0, 0, 0],    # i 1
              [1, 0, 0, 0, 0],    # h 0
              [0, 0, 1, 0, 0],    # e 2
              [0, 0, 0, 1, 0],    # l 3
              [0, 0, 0, 1, 0]]]   # l 3

y_data = [1, 0, 2, 3, 3, 4]    # ihello

# As we have one batch of samples, we will change them to variables only once
inputs = Variable(torch.Tensor(x_one_hot))
labels = Variable(torch.LongTensor(y_data))
```

(1)Data preparation 2

```
idx2char = ['h', 'i', 'e', 'l', 'o']

# Teach hihell -> ihello
x_data = [0, 1, 0, 2, 3, 3]   # hihell
one_hot_lookup =[[1, 0, 0, 0, 0],  # 0
                 [0, 1, 0, 0, 0],  # 1
                 [0, 0, 1, 0, 0],  # 2
                 [0, 0, 0, 1, 0],  # 3
                 [0, 0, 0, 0, 1]]  # 4

y_data = [1, 0, 2, 3, 3, 4]    # ihello
x_one_hot = [one_hot_lookup[x] for x in x_data]

# As we have one batch of samples, we will change them to variables only once
inputs = Variable(torch.Tensor(x_one_hot))
labels = Variable(torch.LongTensor(y_data))
```

(2) Parameters

```
num_classes = 5
input_size = 5  # one-hot size
hidden_size = 5  # output from the LSTM. 5 to directly predict one-hot
batch_size = 1   # one sentence
sequence_length = 1  # Let's do one by one
num_layers = 1  # one-layer rnn
```

(3) Our model

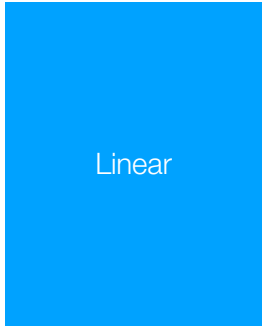
```
class Model(nn.Module):

    def __init__(self):
        super(Model, self).__init__()
        self.rnn = nn.RNN(input_size=input_size,
                          hidden_size=hidden_size, batch_first=True)

    def forward(self, hidden, x):
        # Reshape input in (batch_size, sequence_length, input_size)
        x = x.view(batch_size, sequence_length, input_size)

        # Propagate input through RNN
        # Input: (batch, seq_len, input_size)
        # hidden: (batch, num_layers * num_directions, hidden_size)
        out, hidden = self.rnn(x, hidden)
        out = out.view(-1, num_classes)
        return hidden, out

    def init_hidden(self):
        # Initialize hidden and cell states
        # (batch, num_layers * num_directions, hidden_size) for batch_first=True
        return Variable(torch.zeros(batch_size, num_layers, hidden_size))
```

```
num_classes = 5
input_size = 5  # one-hot size
hidden_size = 5  # output from the LSTM.
batch_size = 1   # one sentence
sequence_length = 1
num_layers = 1  # one-layer rnn
```

Designing Loss

Predict Y, one of five {h, i, e, l, o} $Y \in R^{N \times ?}$

o `[0, 0, 0, 0, 1]`



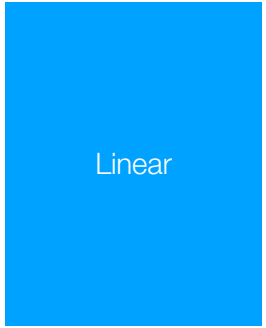
Some input: X 1 `[0, 0, 0, 1, 0]`

Designing Loss

```
out = rnn_out.view(-1, 5)
```

Predict Y, one of five {h, i, e, l, o} $Y \in R^{N \times 5}$

o [0, 0, 0, 0, 1]



Some input: X 1 [0, 0, 0, 1, 0]

(3) Our model

```
class Model(nn.Module):

    def __init__(self):
        super(Model, self).__init__()
        self.rnn = nn.RNN(input_size=input_size,
                          hidden_size=hidden_size, batch_first=True)

    def forward(self, hidden, x):
        # Reshape input in (batch_size, sequence_length, input_size)
        x = x.view(batch_size, sequence_length, input_size)

        # Propagate input through RNN
        # Input: (batch, seq_len, input_size)
        # hidden: (batch, num_layers * num_directions, hidden_size)
        out, hidden = self.rnn(x, hidden)
        out = out.view(-1, num_classes)
        return hidden, out

    def init_hidden(self):
        # Initialize hidden and cell states
        # (batch, num_layers * num_directions, hidden_size) for batch_first=True
        return Variable(torch.zeros(batch_size, num_layers, hidden_size))
```

$$Y \in R^{N \times 5}$$

```
num_classes = 5
input_size = 5  # one-hot size
hidden_size = 5  # output from the LSTM.
batch_size = 1   # one sentence
sequence_length = 1
num_layers = 1  # one-layer rnn
```

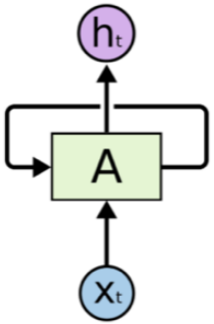
Designing Loss

```
out = rnn_out.view(-1, 5)
```

Predict Y, one of five {h, i, e, l, o} $Y \in R^{N \times 5}$

o `[0, 0, 0, 0, 1]`

f(h,i,h,e,l)

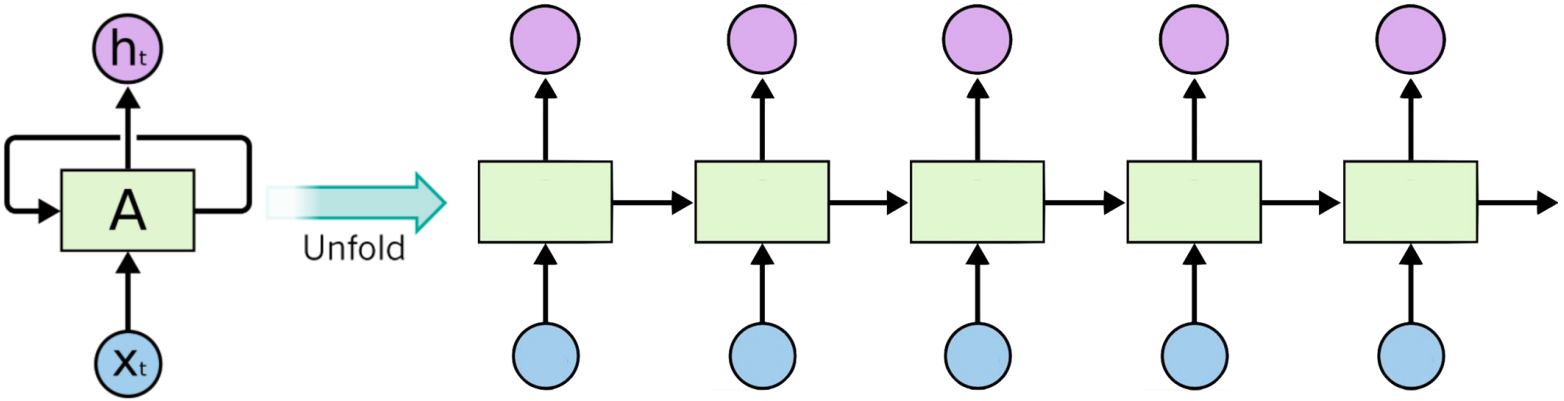


CrossEntropy

```
criterion = nn.CrossEntropyLoss()
```

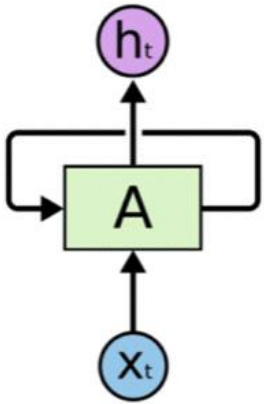
Some input: X 1 `[0, 0, 0, 1, 0]`

Unfolding one to n sequences

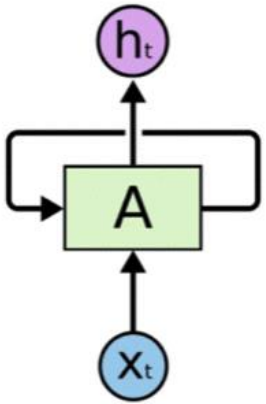


Teach RNN ‘hihell’ to ‘ihello’

```
[1, 0, 0, 0, 0],   # h 0
[0, 1, 0, 0, 0],   # i 1
[0, 0, 1, 0, 0],   # e 2
[0, 0, 0, 1, 0],   # l 3
[0, 0, 0, 0, 1],   # o 4
```



Teach RNN ‘hihell’ to ‘ihello’




```
loss = 0
hidden = model.init_hidden()

sys.stdout.write("predicted string: ")
for input, label in zip(inputs, labels):
   hidden, output = model(hidden, input)
   loss += criterion(output, label)

print(", epoch: %d, loss: %1.3f" %
                (epoch + 1, loss.data[0]))

loss.backward()
optimizer.step()
```

(4) Loss & Training

```
# Instantiate RNN model
model = Model()

# Set loss and optimizer function
# CrossEntropyLoss = LogSoftmax + NLLLoss
criterion = torch.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()
    sys.stdout.write("predicted string: ")
    for input, label in zip(inputs, labels):
        # print(input.size(), label.size())
        hidden, output = model(hidden, input)
        val, idx = output.max(1)
        sys.stdout.write(idx2char[idx.data[0]])
        loss += criterion(output, label)

    print(", epoch: %d, loss: %1.3f" % (epoch + 1, loss.data[0]))

    loss.backward()
    optimizer.step()
```

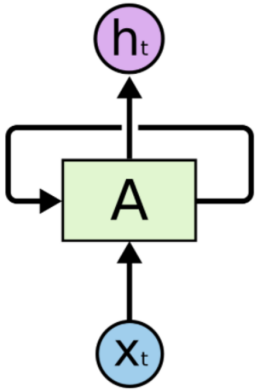
```python
# Instantiate RNN model
model = Model()

# Set loss and optimizer function
# CrossEntropyLoss = LogSoftmax + NLLLoss
criterion = torch.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()
    sys.stdout.write("predicted string: ")
    for input, label in zip(inputs, labels):
        # print(input.size(), label.size())
        hidden, output = model(hidden, input)
        val, idx = output.max(1)
        sys.stdout.write(idx2char[idx.data[0]])
        loss += criterion(output, label)

    print(", epoch: %d, loss: %1.3f" % (epoch + 1, loss.data[0]))

    loss.backward()
    optimizer.step()
```

(5) the results


```
epoch: 1, loss: 1.673
Predicted string:  ehehee
epoch: 2, loss: 1.403
Predicted string:  ehehel
epoch: 3, loss: 1.240
Predicted string:  ehelll
...
epoch: 95, loss: 0.458
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
```

RNN with a sequence

```
self.rnn = nn.RNN(input_size=5, hidden_size=5, batch_first=True)
```




```
[1, 0, 0, 0, 0],   # h 0
[0, 1, 0, 0, 0],   # i 1
[0, 0, 1, 0, 0],   # e 2
[0, 0, 0, 1, 0],   # l 3
[0, 0, 0, 0, 1],   # o 4
```

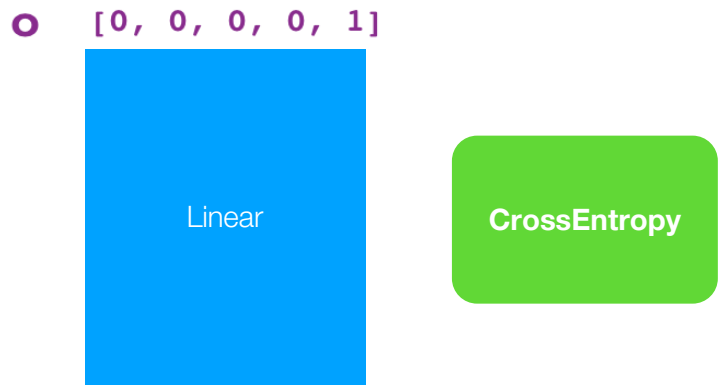
(5) ENJOY the results

```python
# Instantiate RNN model
rnn = RNN(num_classes, input_size, hidden_size, num_layers)
print(rnn)

# Set loss and optimizer function
# CrossEntropyLoss = LogSoftmax + NLLLoss
criterion = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(rnn.parameters(), lr=0.1)

# Train the model
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.data[0]))
    print("Predicted string: ", ''.join(result_str))

print("Learning finished!")
```

```python
for input, label in zip(inputs, labels):
        # print(input.size(), label.size())
        hidden, output = model(hidden, input)
        val, idx = output.max(1)
        sys.stdout.write(idx2char[idx.data[0]])
        loss += criterion(output, label)
```

Exercise 12-1:
Implement using a softmax classifier for 'hihell' to 'ihello'

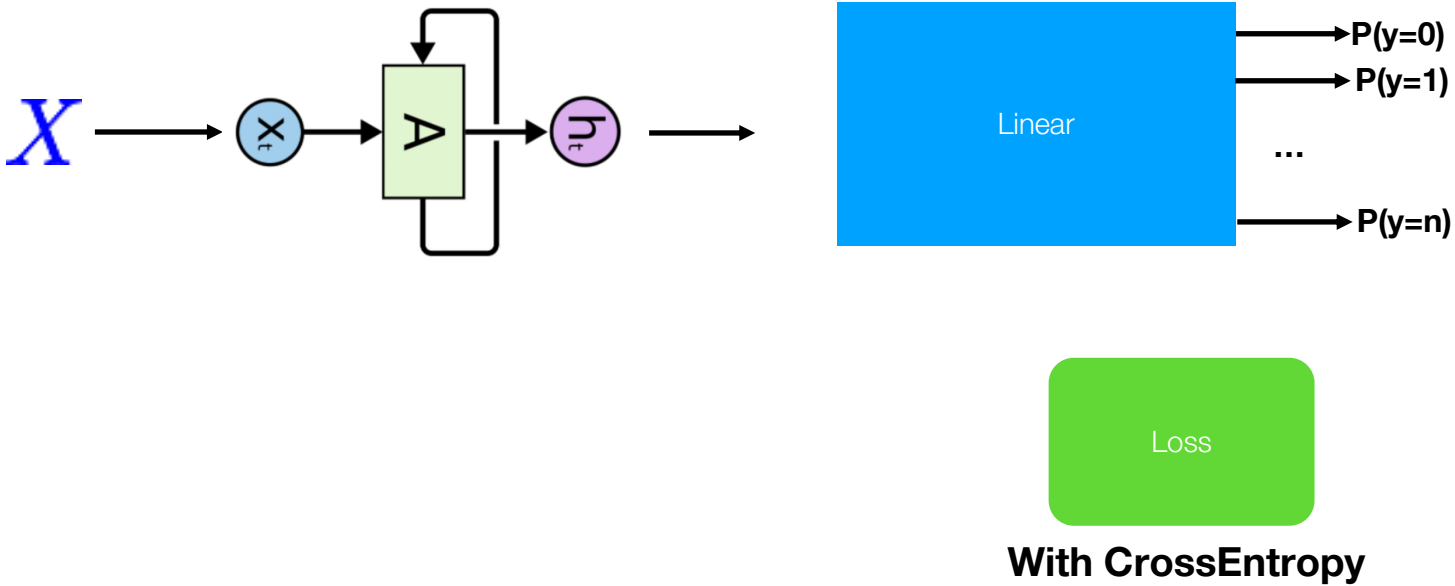
Predict Y, one of five {h, i, e, l, o} $Y \in R^{N \times 5}$



Some input: X 1 [0, 0, 0, 1, 0]

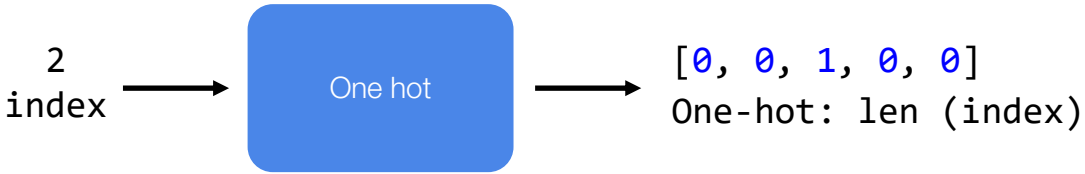
Why does it not work?

Exercise 12-2: Combine RNN+Linear



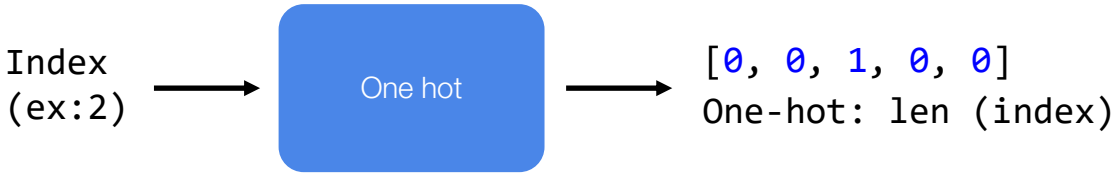
Why does it train faster (more stable)?

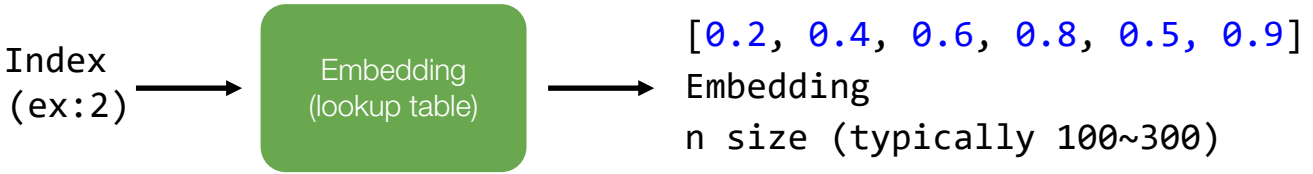
One hot VS embedding




```
x_one_hot = [[[1, 0, 0, 0, 0],   # h 0
              [0, 1, 0, 0, 0],   # i 1
              [1, 0, 0, 0, 0],   # h 0
              [0, 0, 1, 0, 0],   # e 2
              [0, 0, 0, 1, 0],   # l 3
              [0, 0, 0, 1, 0]]]  # l 3
```

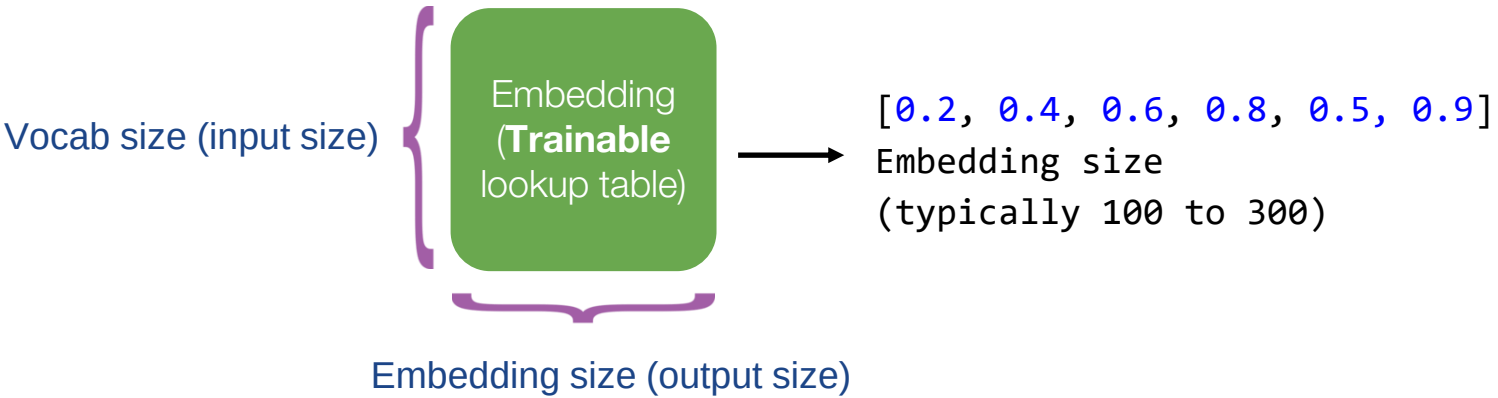
One hot VS embedding



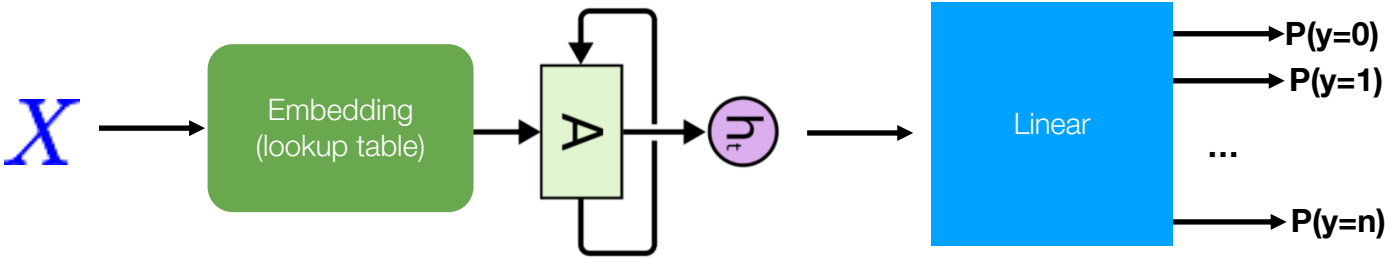


One hot VS embedding

```
self.embeddings = nn.Embedding(vocab_size, output_size)
...
emb = self.embeddings(x)
```



Exercise 12-3: Combine RNN+Linear using embedding



Loss

With CrossEntropy

Under the hood: RNN

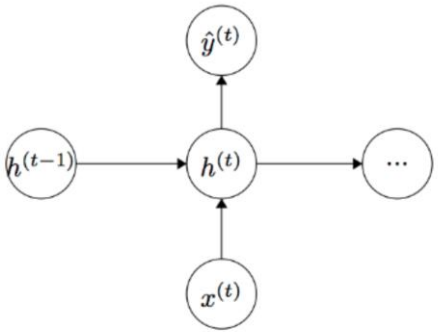


Figure 3: The inputs and outputs to a neuron of a RNN

https://cs224d.stanford.edu/lecture_notes/LectureNotes4.pdf

Under the hood: RNN

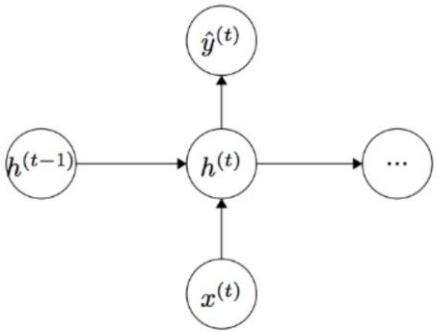


Figure 3: The inputs and outputs to a neuron of a RNN

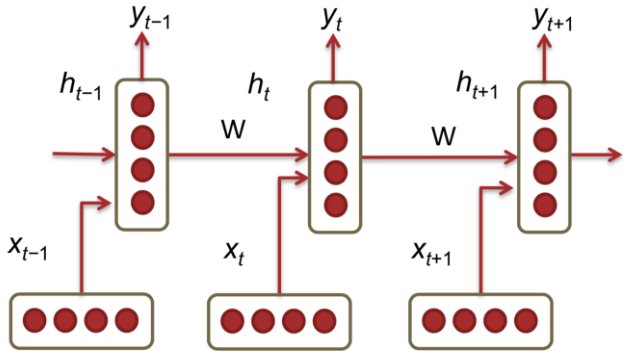


Figure 2: A Recurrent Neural Network (RNN). Three time-steps are shown.

https://cs224d.stanford.edu/lecture_notes/LectureNotes4.pdf

Under the hood: RNN

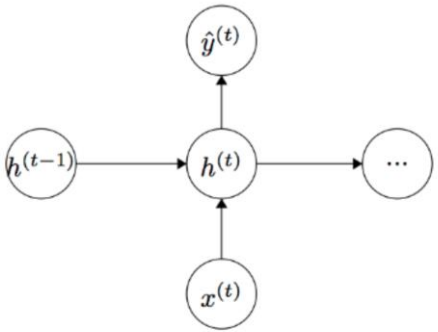


Figure 3: The inputs and outputs to a neuron of a RNN

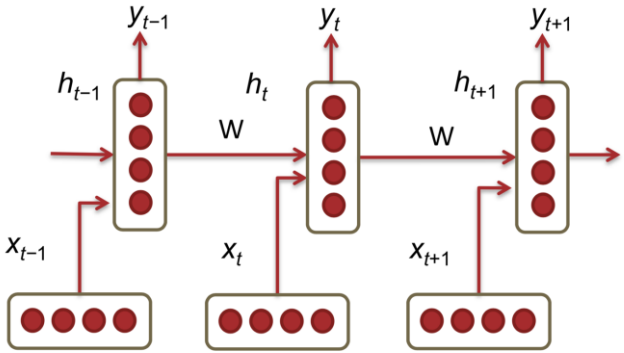
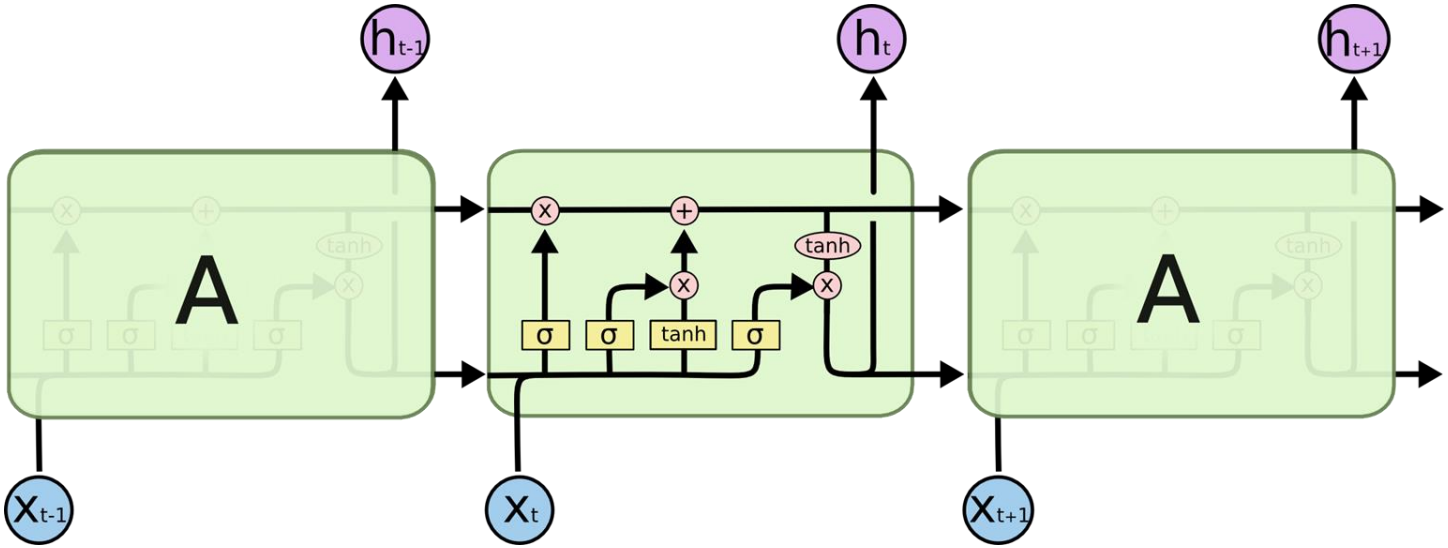


Figure 2: A Recurrent Neural Network (RNN). Three time-steps are shown.

$$
\begin{aligned}
\boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}, \\
\boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}), \\
\boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)}, \\
\hat{\boldsymbol{y}}^{(t)} &= \operatorname{softmax}(\boldsymbol{o}^{(t)}),
\end{aligned}
$$

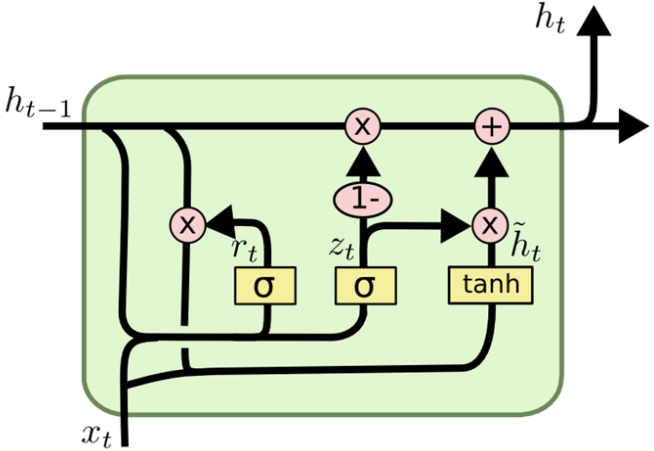
https://cs224d.stanford.edu/lecture_notes/LectureNotes4.pdf

Under the hood: LSTM



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Under the hood: GRU

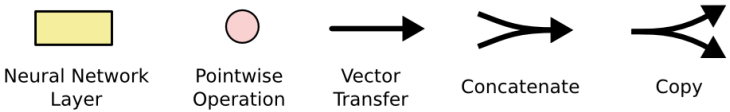


$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Exercise 12-5: Implement RNN

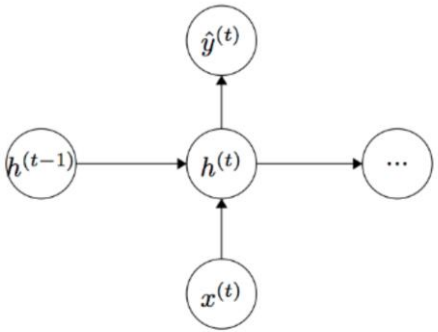


Figure 3: The inputs and outputs to a neuron of a RNN

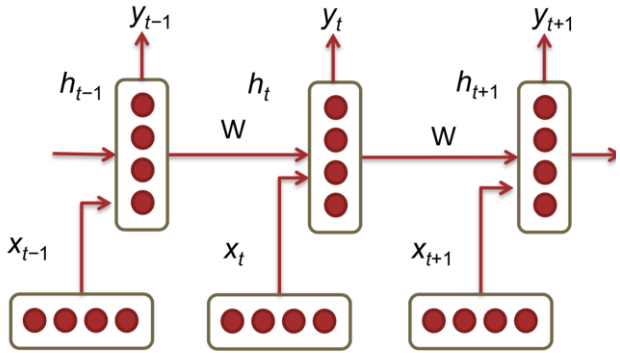


Figure 2: A Recurrent Neural Network (RNN). Three time-steps are shown.

$$
\begin{aligned}
\boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}, \\
\boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}), \\
\boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)}, \\
\hat{\boldsymbol{y}}^{(t)} &= \operatorname{softmax}(\boldsymbol{o}^{(t)}),
\end{aligned}
$$

Hint: http://blog.varunajayasiri.com/numpy_lstm.html

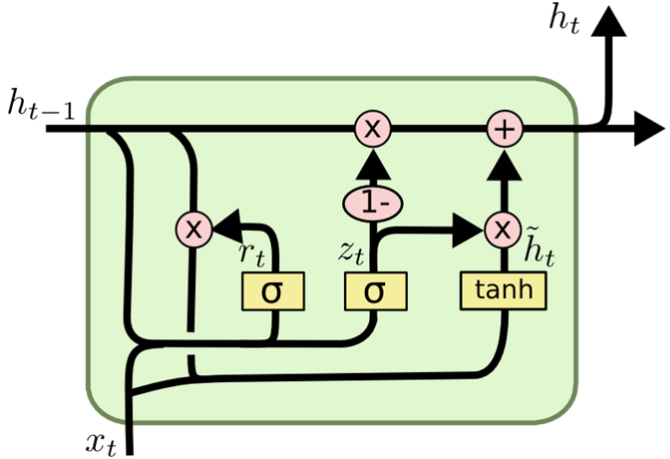
https://cs224d.stanford.edu/lecture_notes/LectureNotes4.pdf

Exercise 12-5: Implement RNN

```
class RNN(nn.Module):
    def __init__(self, input_size, hidden_size):
        super(RNN, self).__init__()

        self.input_size = input_size
        self.hidden_size = hidden_size

         ...
    def forward(self, input, hidden):
        hidden = ...
        output = ...
        return output, hidden


rnn = RNN(...)
```

$$
\begin{aligned}
\boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}, \\
\boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}), \\
\boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)}, \\
\hat{\boldsymbol{y}}^{(t)} &= \operatorname{softmax}(\boldsymbol{o}^{(t)}),
\end{aligned}
$$

Exercise 12-6: Implement GRU



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

- http://blog.varunajayasiri.com/numpy_lstm.html
- http://www.wildml.com/2015/10/recurrent-neural-network-tutorial-part-4-implementing-a-grulstm-rnn-with-python-and-theano/

Lecture 13: RNN II