Recurrent neural network

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Start from examples

- Slot filling

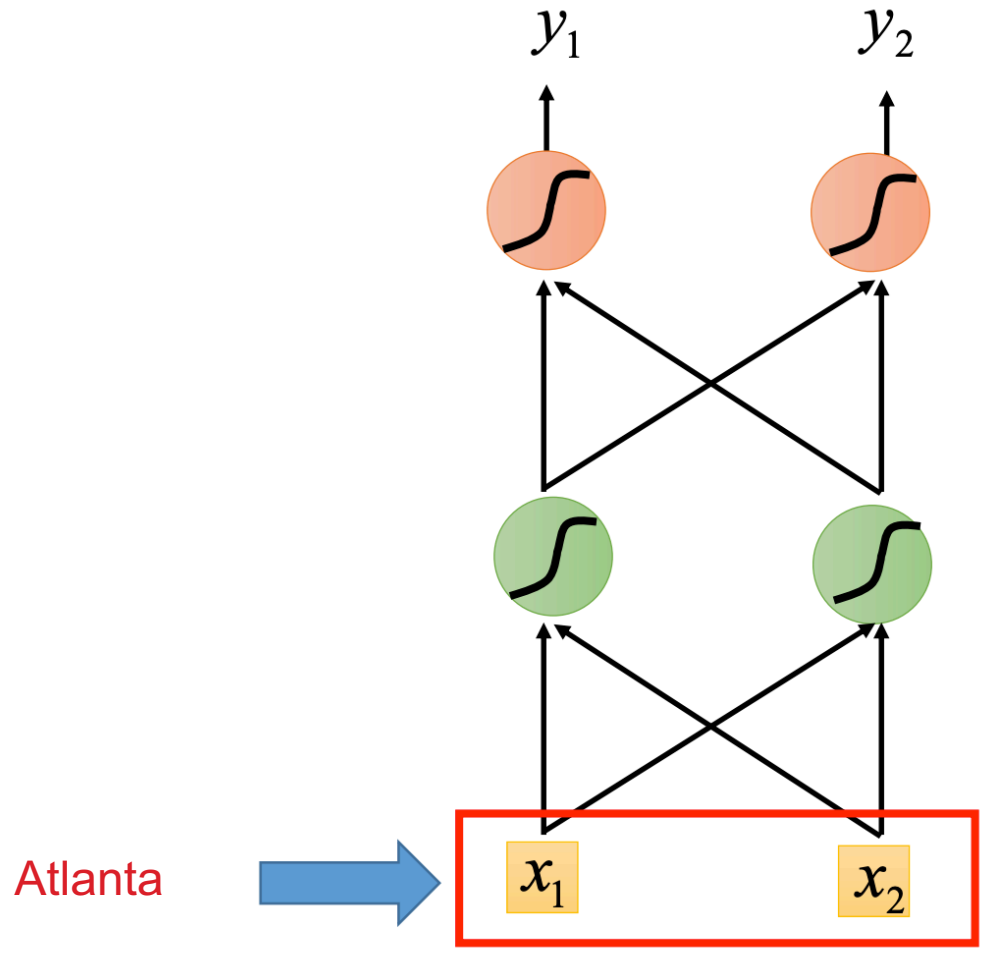
Start from examples

- Solving slot filling by Feedforward network?

- Input: a word

  (Each word is represented as a vector)

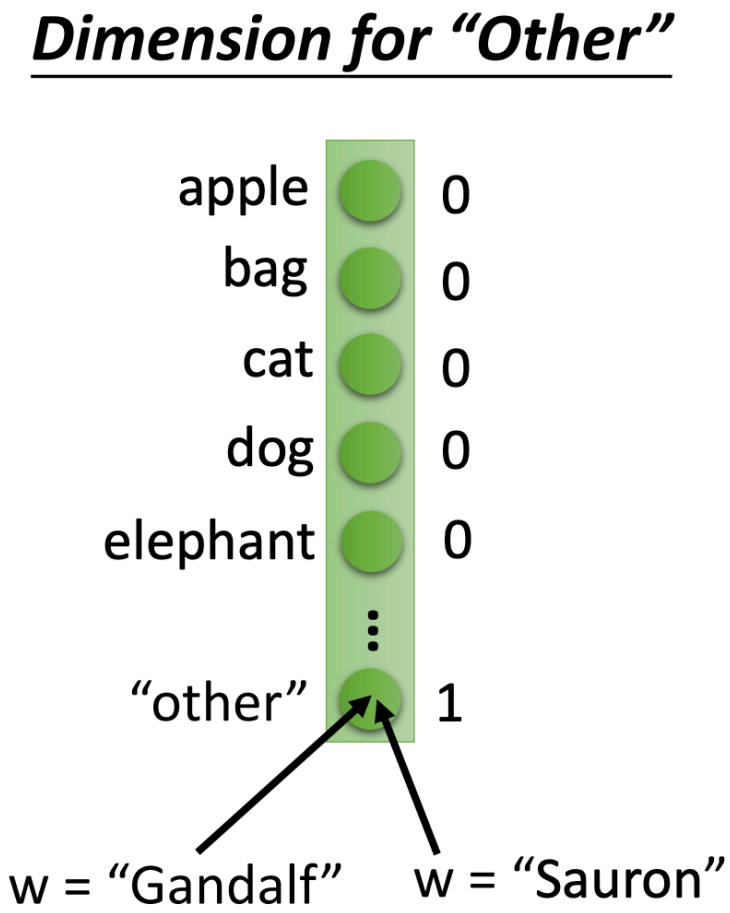
- How to represent each word as a vector?



How to represent each word as a vector?

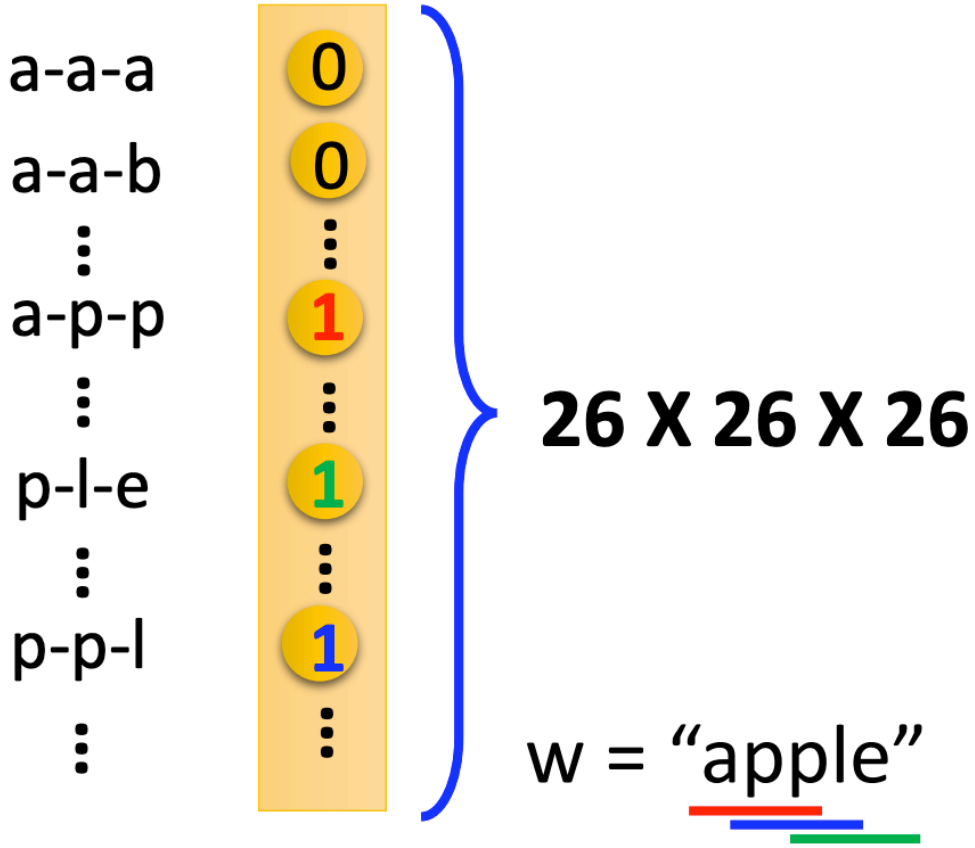
- 1-of-N Encoding
  - lexicon = {apple, bag, cat, dog, elephant}
  - The vector is lexicon size.
  - Each dimension corresponds to a word in the lexicon
  - The dimension for the word is 1, and others are 0

apple = [1 0 0 0 0]
bag = [0 1 0 0 0]
cat = [0 0 1 0 0]
dog = [0 0 0 1 0]
elephant = [0 0 0 0 1]



How to represent each word as a vector?

- Word hashing



Start from examples

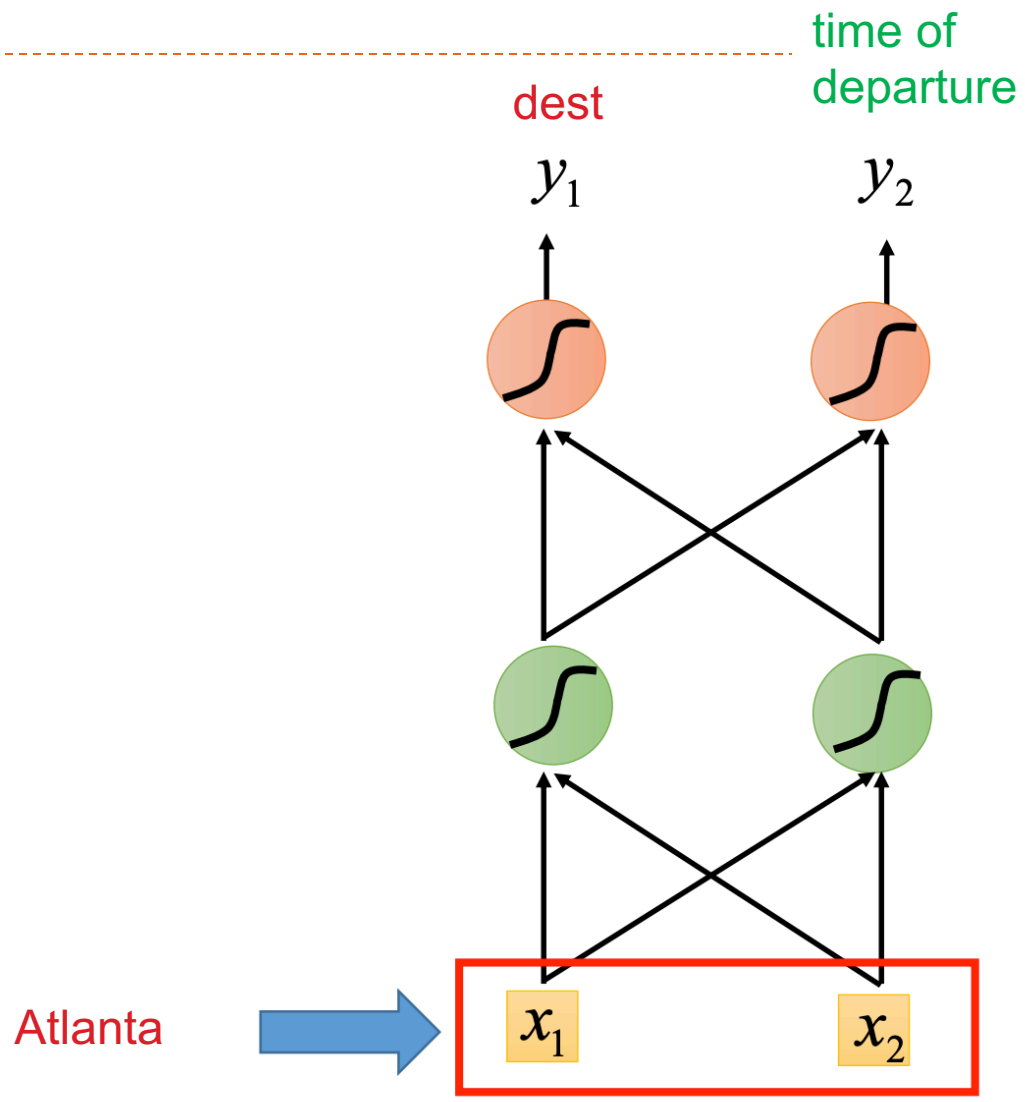
- Solving slot filling by Feedforward network?

- Input: a word

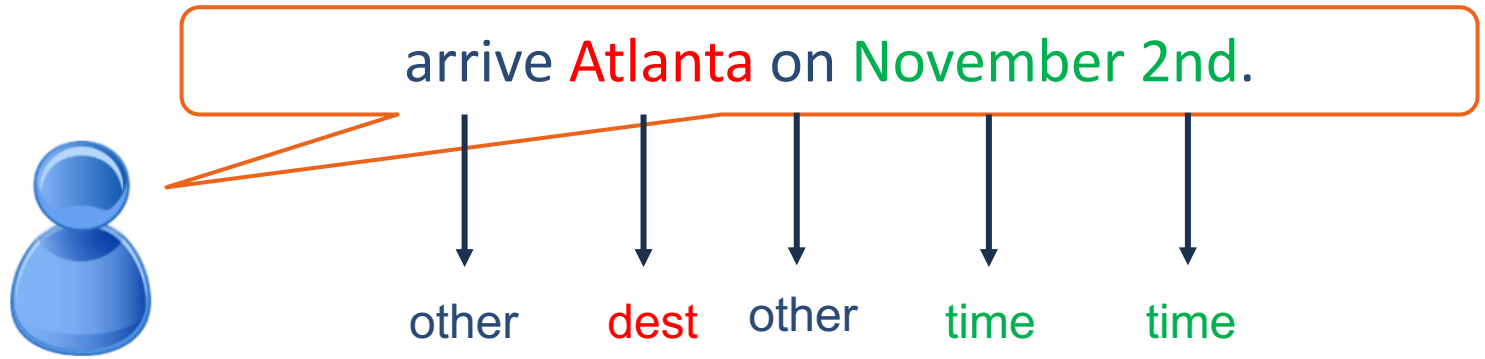
  (Each word is represented as a vector)

- Output:

  Probability distribution that the input word belonging to the slots

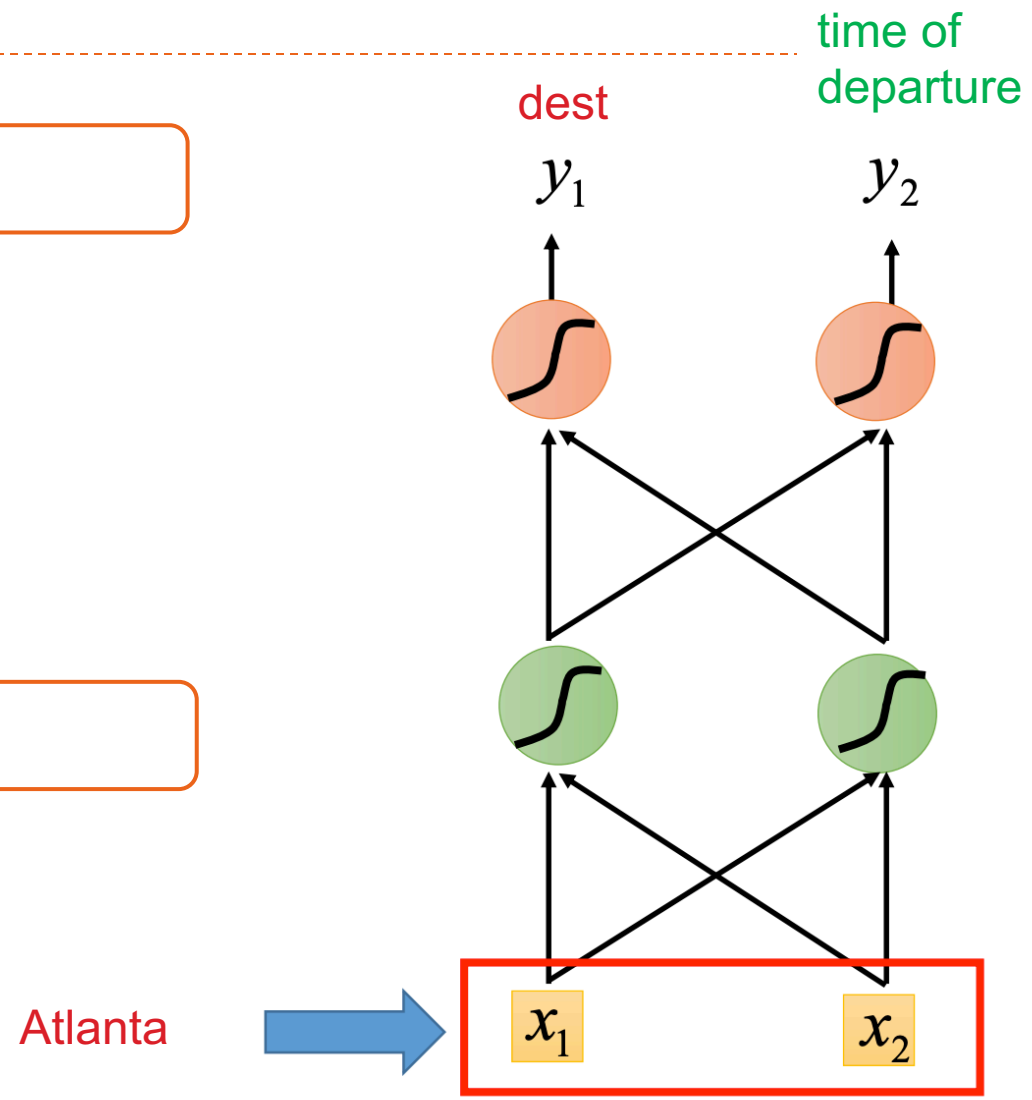


Start from examples



Problem?

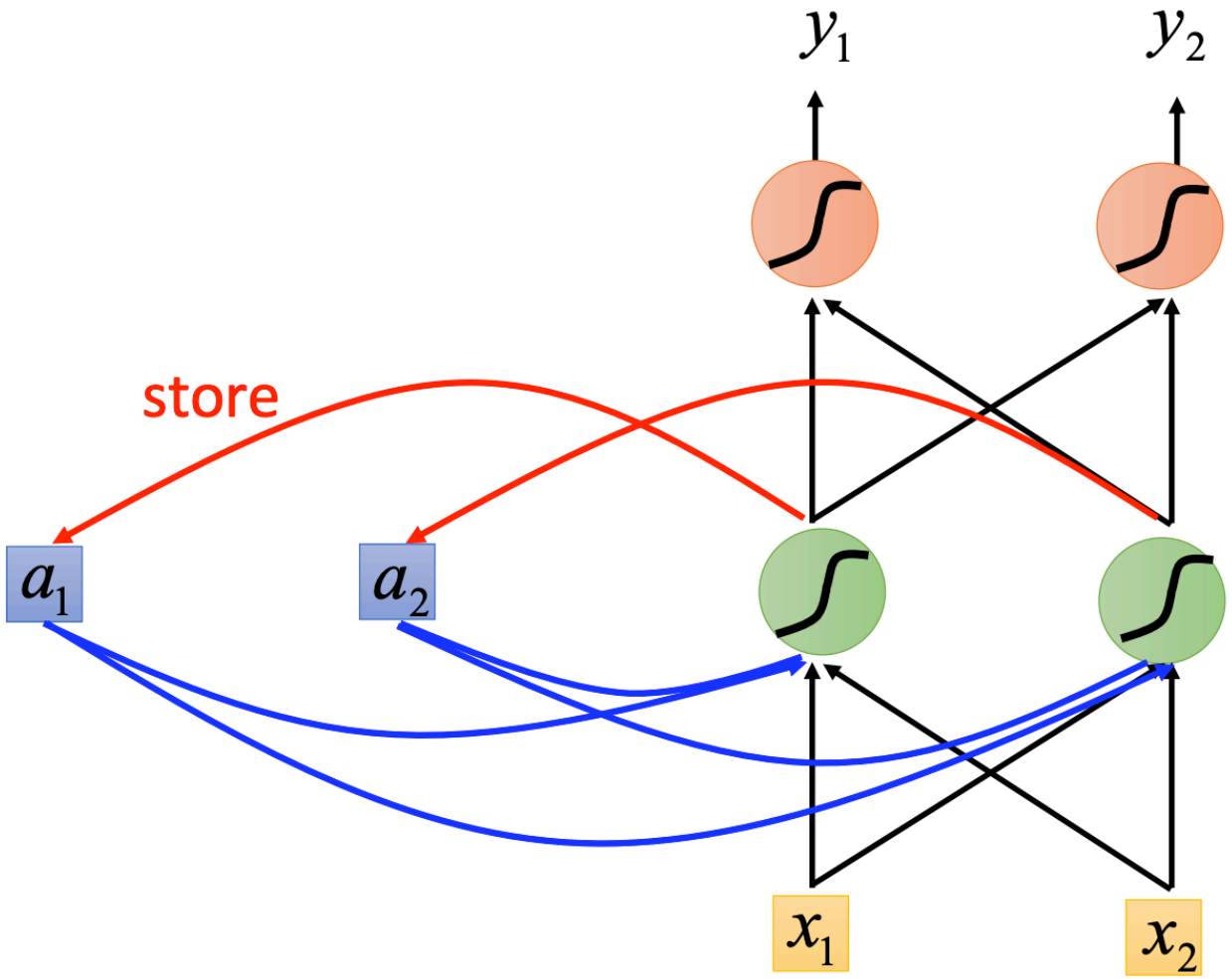
Neural network needs memory!



Start from examples: Recurrent Neural Network (RNN)

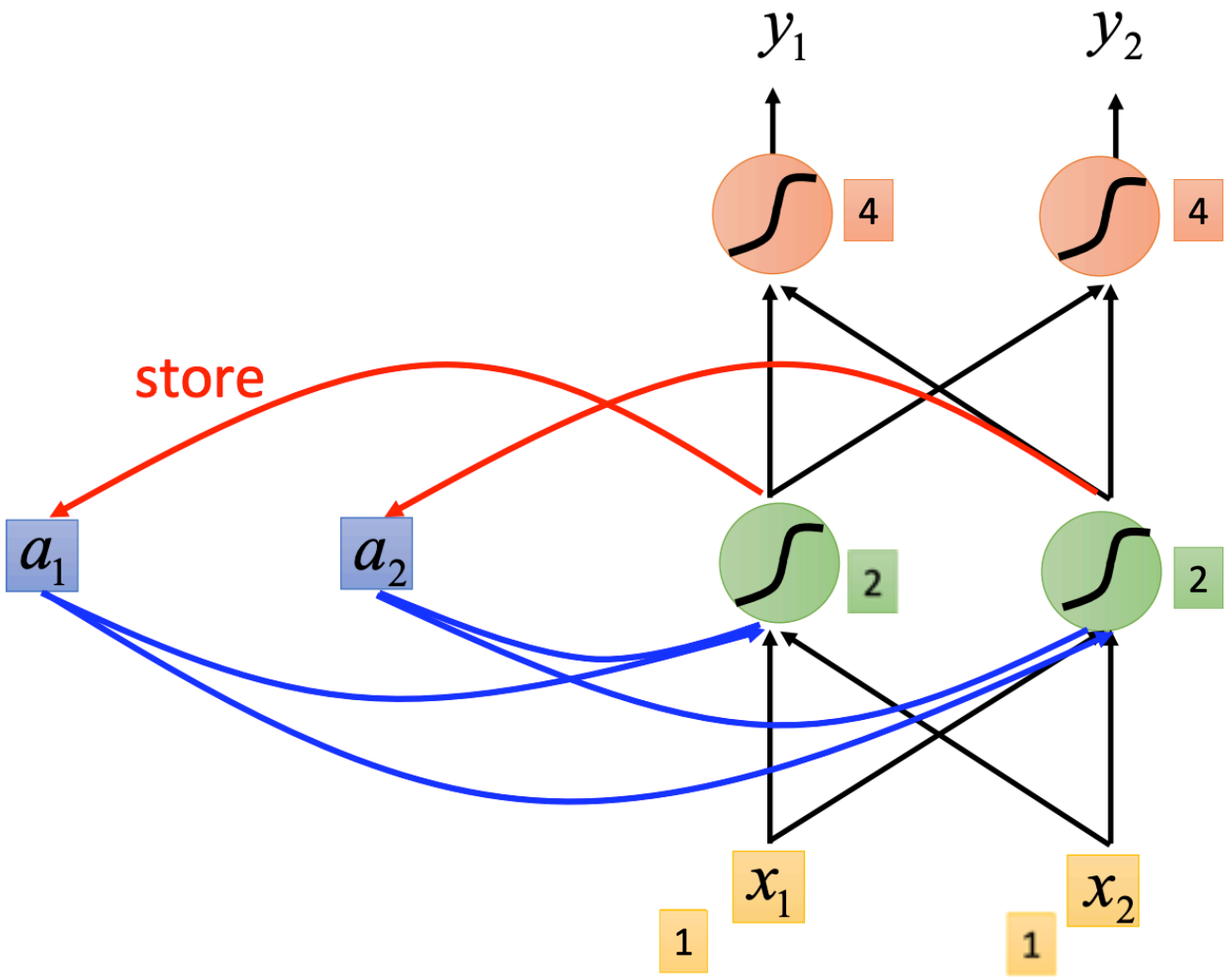
- The output of hidden layer are stored in the memory.

- Memory can be considered as another input.



Start from examples: Recurrent Neural Network (RNN)

- Suppose all the weights are “1”, no bias
- All activation functions are linear
- Input sequence: $\begin{bmatrix}1\\1\end{bmatrix}$

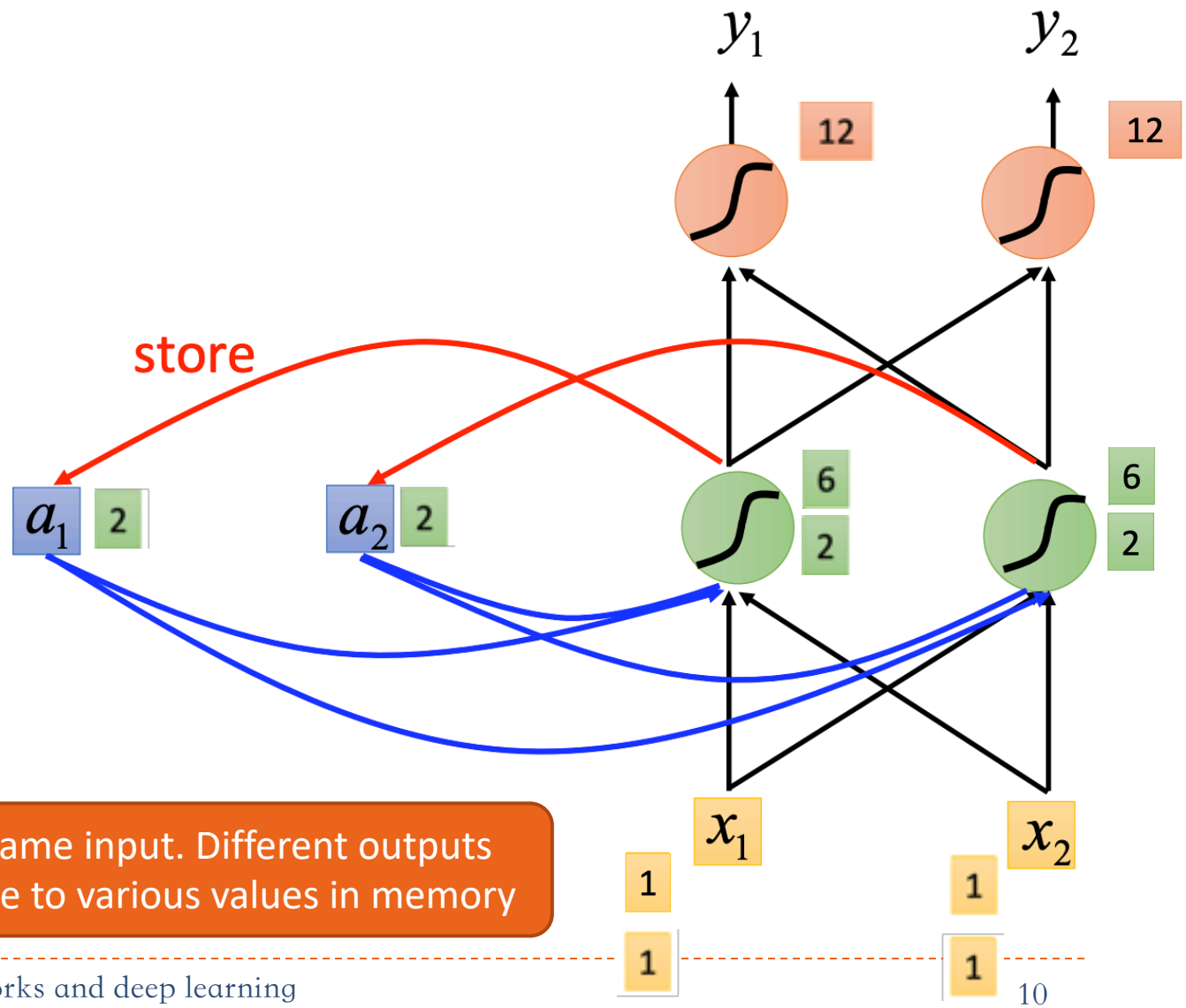


Start from examples: Recurrent Neural Network (RNN)

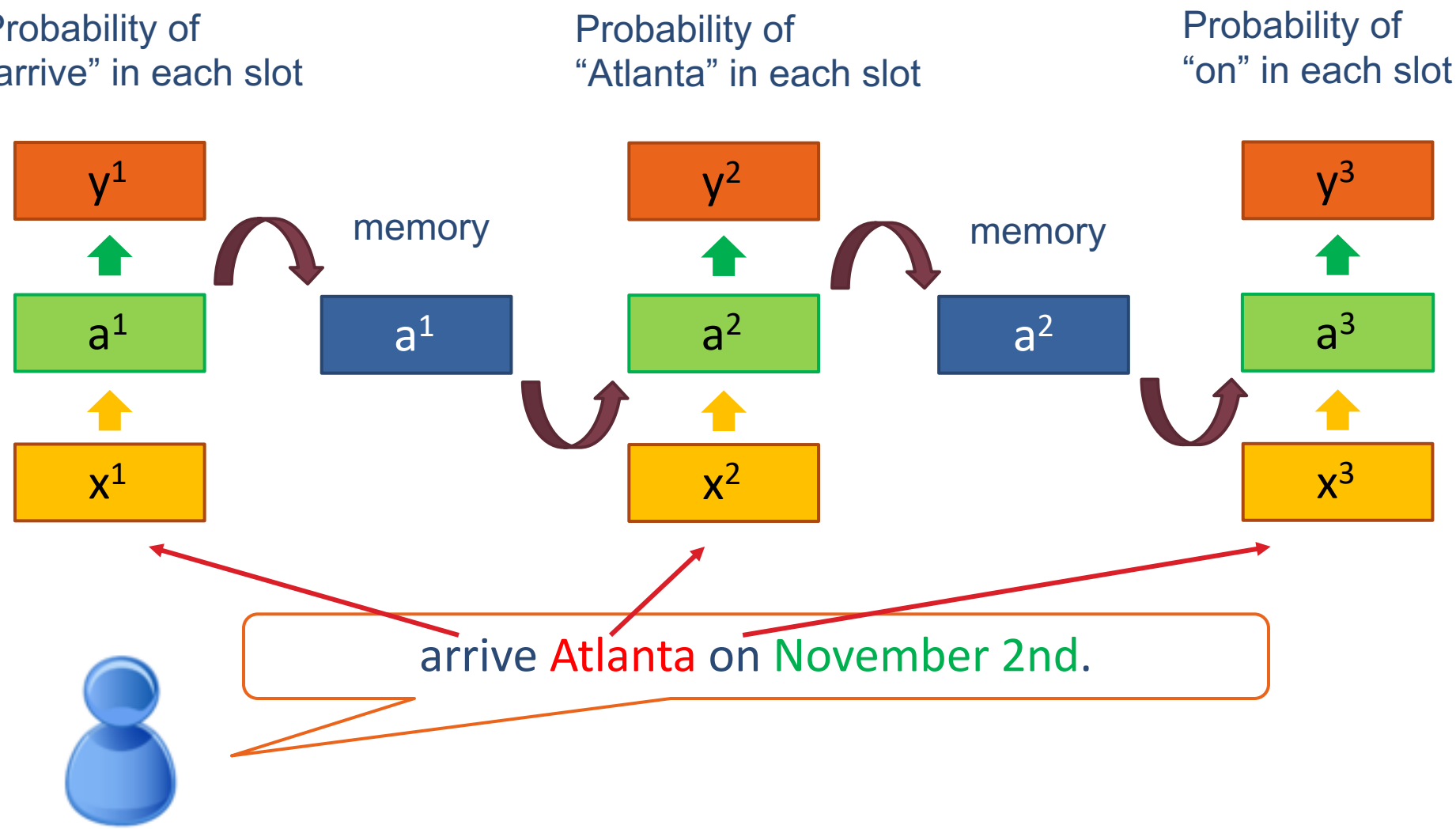
- Suppose all the weights are "1", no bias
- All activation functions are linear
- Input sequence: $\begin{bmatrix}1\\1\end{bmatrix}$ $\begin{bmatrix}1\\1\end{bmatrix}$
- Output sequence:

$\begin{bmatrix}4\\4\end{bmatrix}$ $\begin{bmatrix}12\\12\end{bmatrix}$

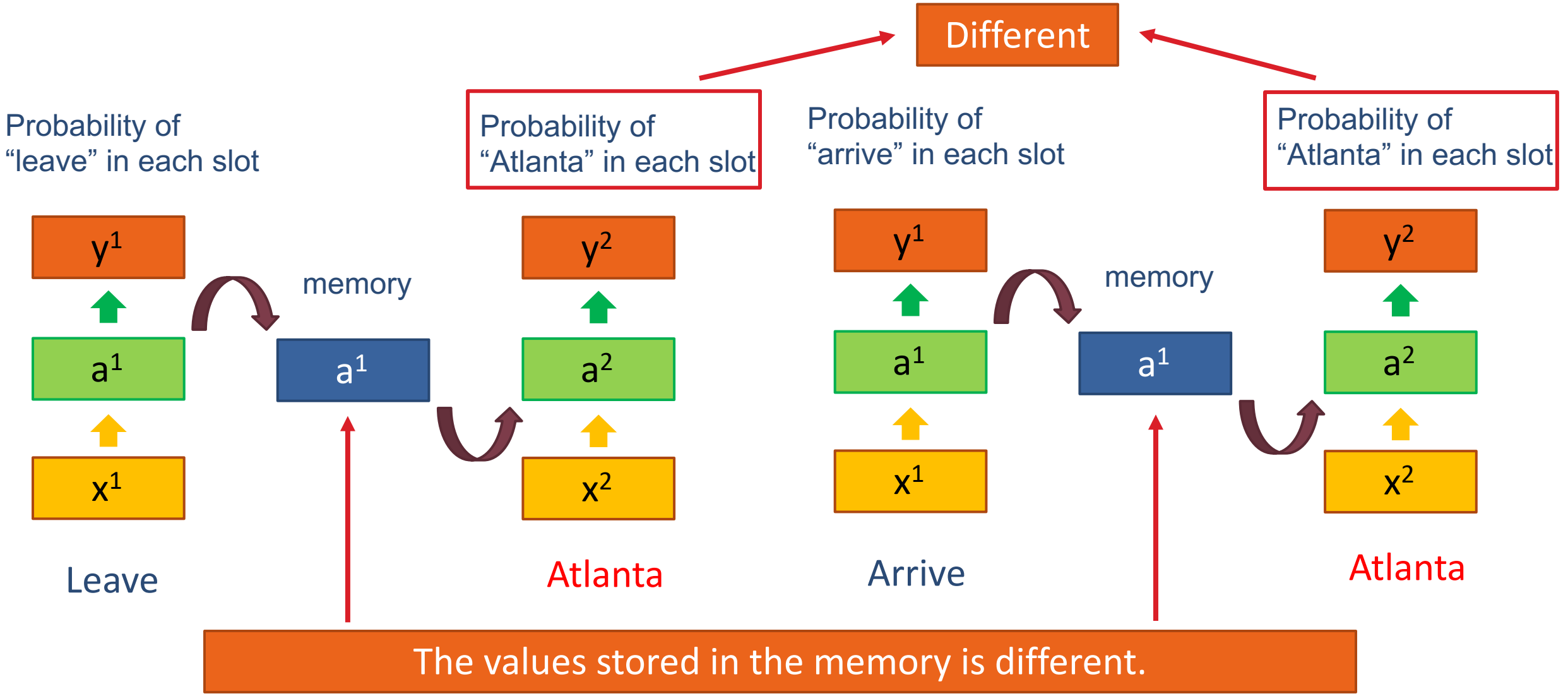
Same input. Different outputs due to various values in memory



Start from examples: Recurrent Neural Network (RNN)

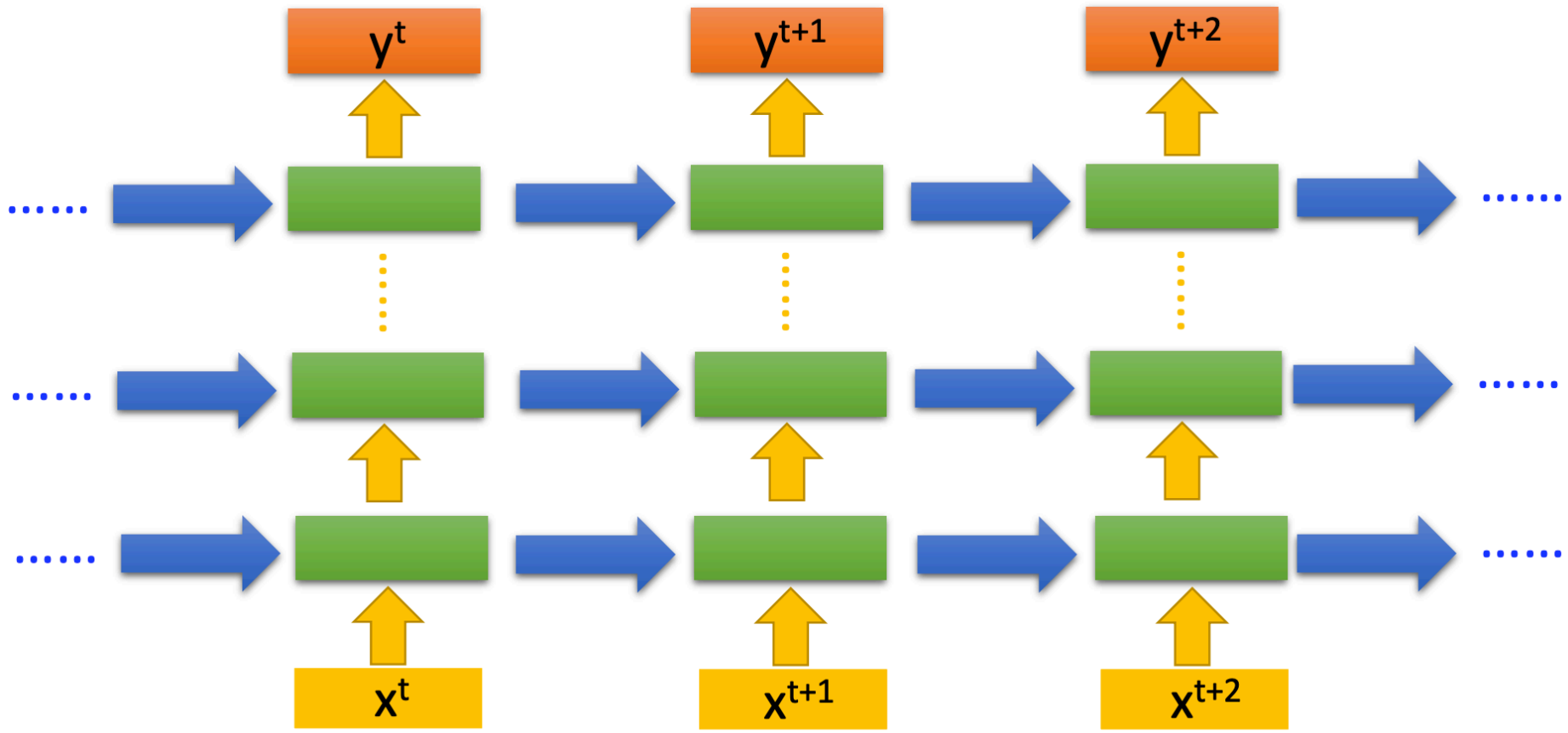


Start from examples: Recurrent Neural Network (RNN)



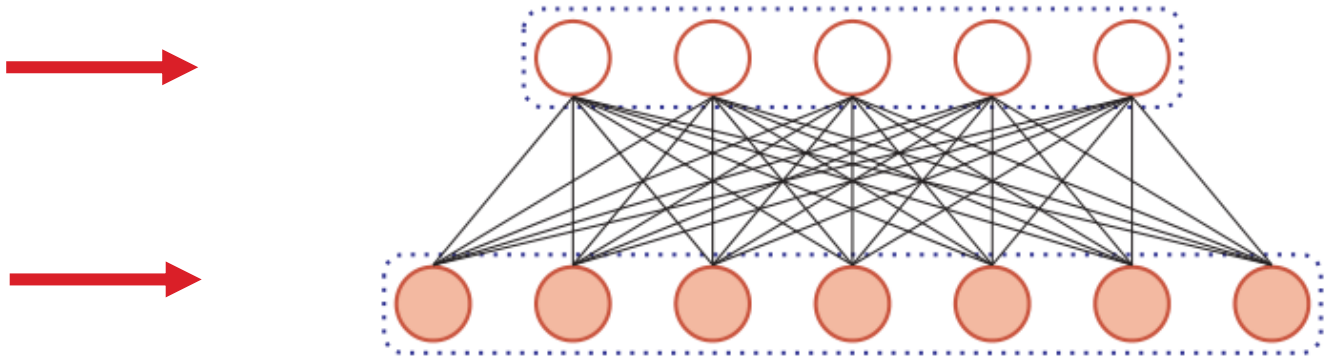
Start from examples: Recurrent Neural Network (RNN)

- Of course, it can be deep …

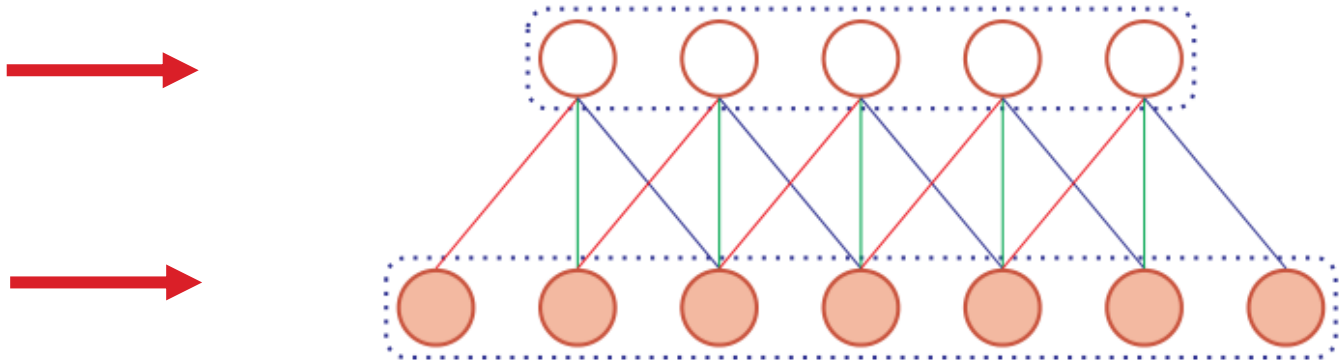


Feedforward network

- Connections exist between layers, and there is ***no connection*** between nodes in each layer. (No loop)



Feedforward neural network



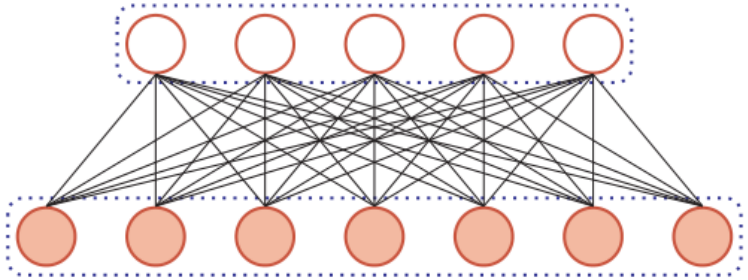
Convolutional neural network

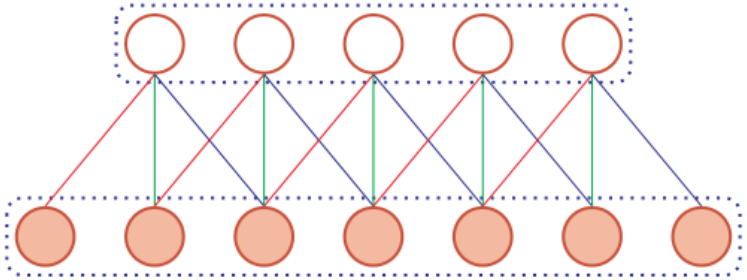
Feedforward network

- The dimensions of input and output are fixed and cannot be changed arbitrarily.

N

M

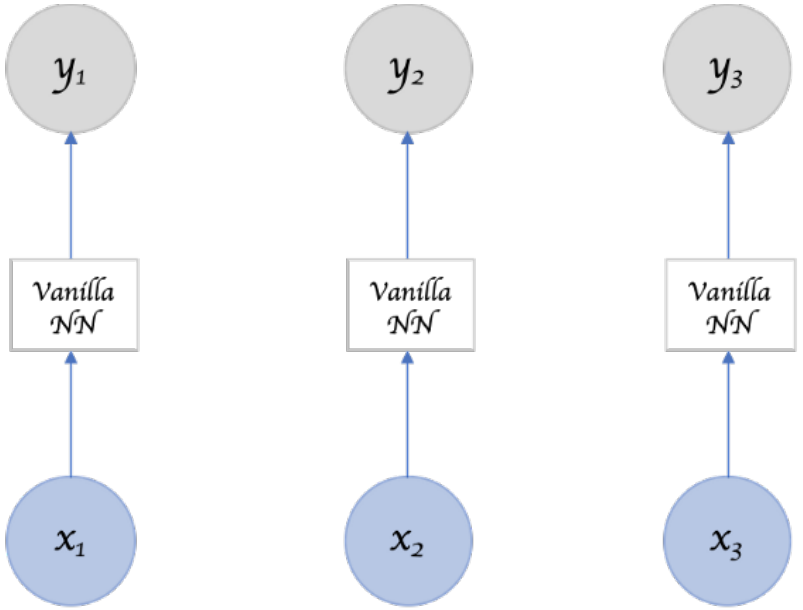




- Unable to process variable length sequence data (voice, video, text, etc.).

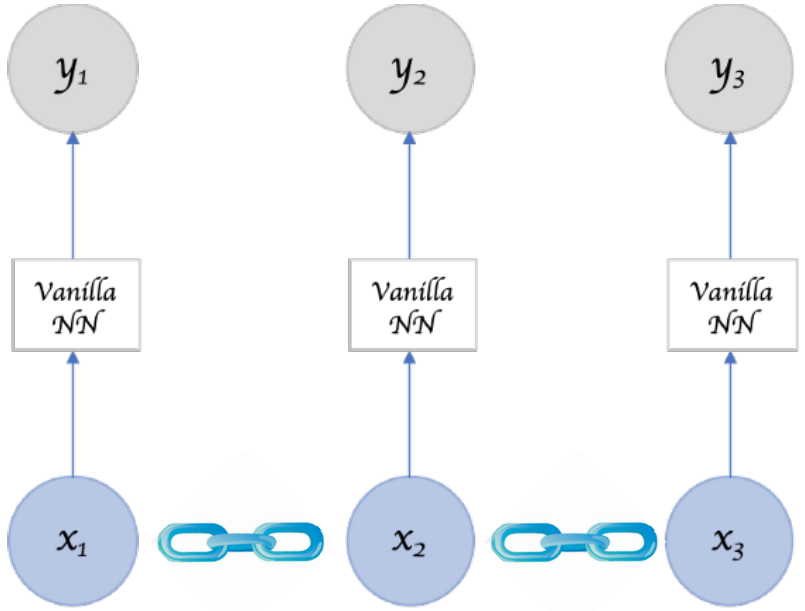
Feedforward network

- Assumed that each input is independent, it means that the output of each network only depends on the current input.



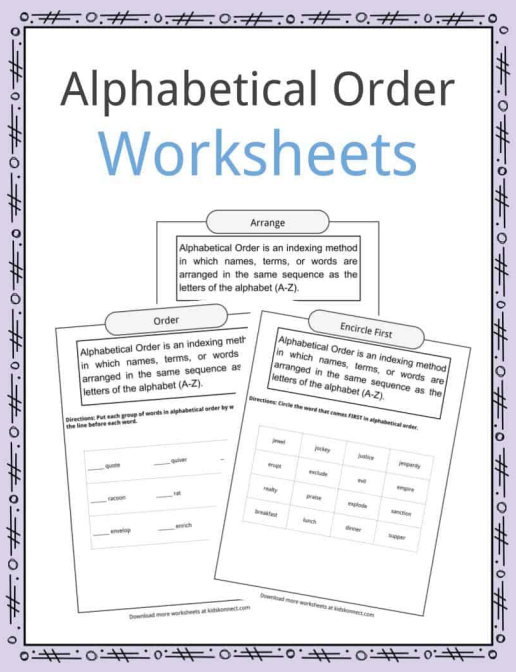
Feedforward network

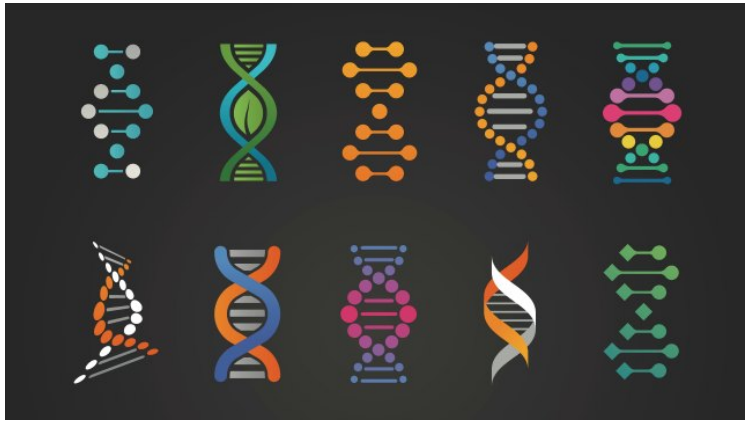
- Sequence data?



Example: cooking

Sequence data



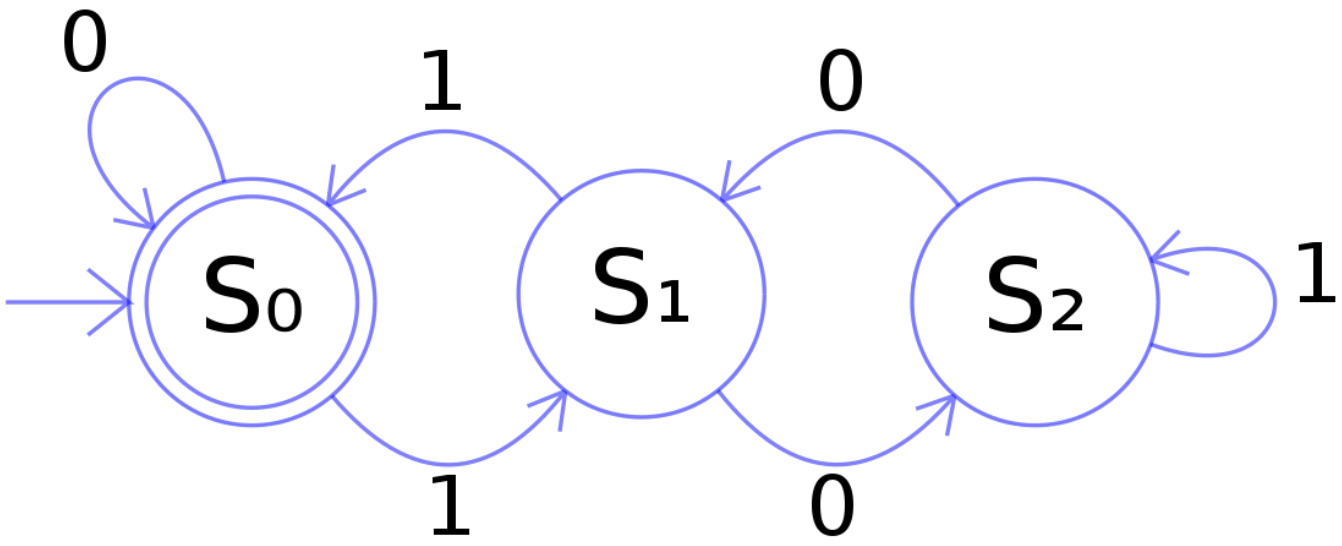


Language: the order of words defines their meaning

Time series data: time defines the occurrence of events

Genome sequence data: each sequence has a different meaning

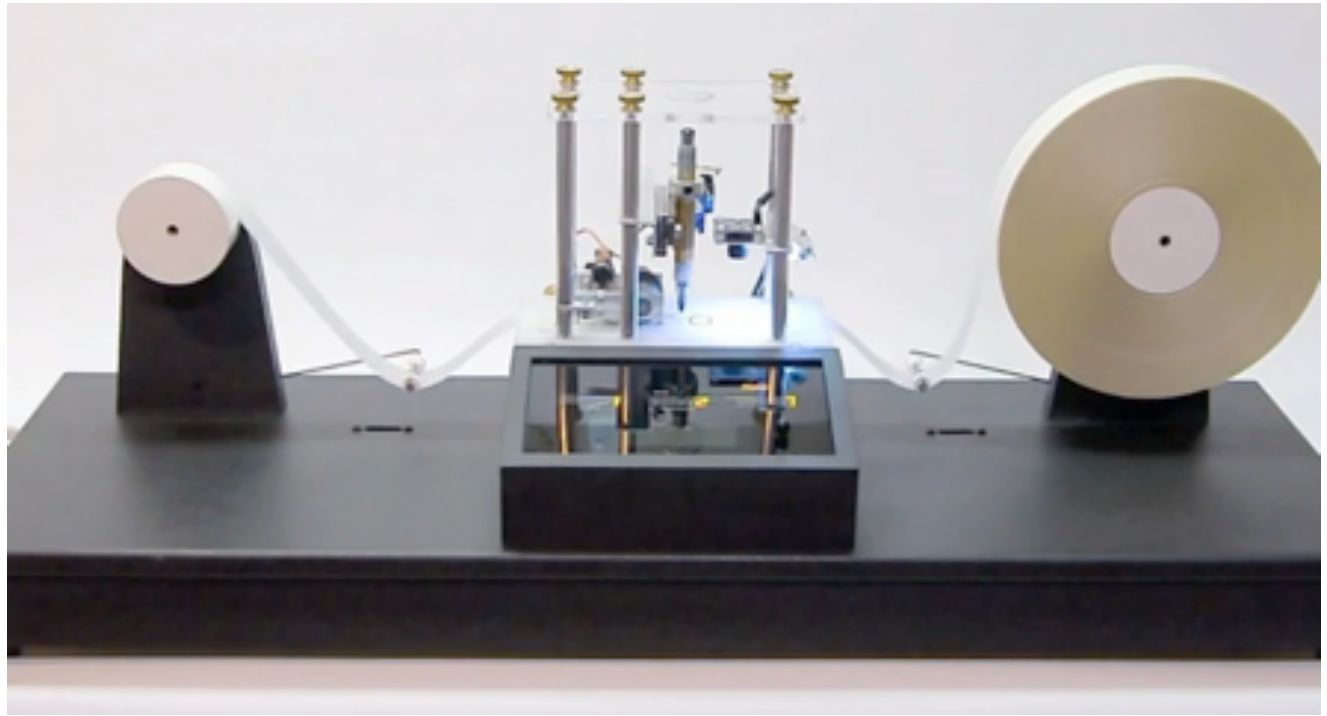
Finite Automata



How to use FNN to simulate a finite state automaton?

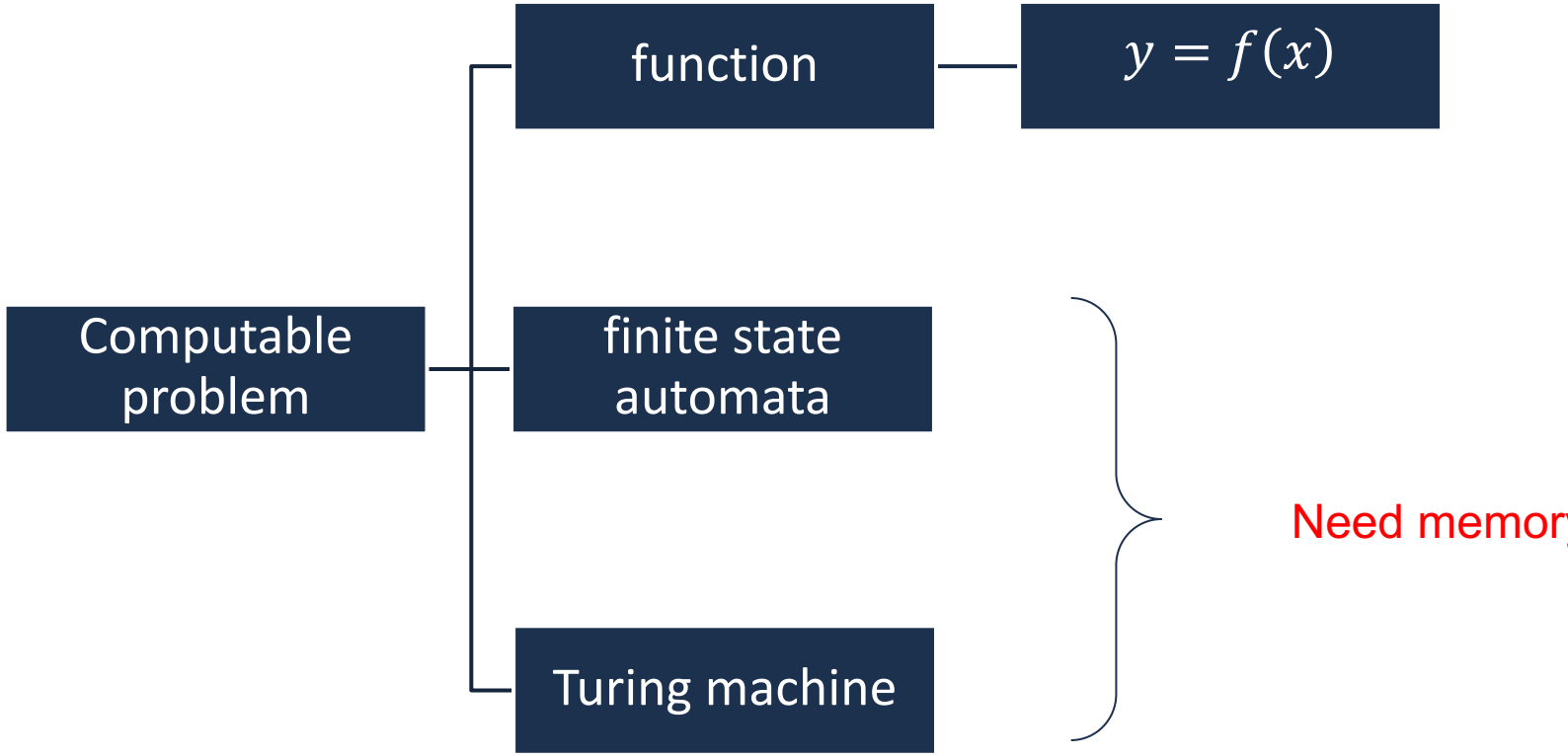
Turing Machine

- An abstract mathematical model that can be used to simulate any calculable problem.



How to use FNN to simulate a Turing machine?

Computable problem



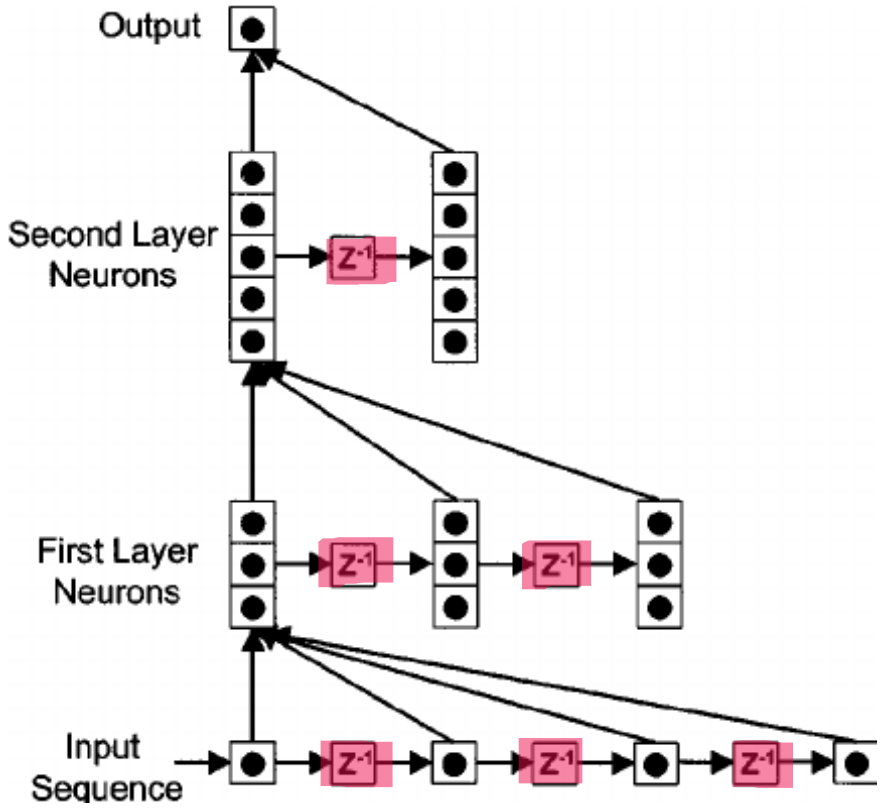
How to add memory to the network?

How to add memory to the network?

- Time Delay Neural Network (TDNN)
  - Establish an ***additional delay unit*** to store historical information of the network (can include input, output, hidden state, etc.)

$$\boldsymbol{h}_t^{(l)} = f\left(\boldsymbol{h}_t^{(l-1)}, \boldsymbol{h}_{t-1}^{(l-1)}, \cdots, \boldsymbol{h}_{t-K}^{(l-1)}\right)$$

  - In this way, the feedforward network has the ability of short-term memory.

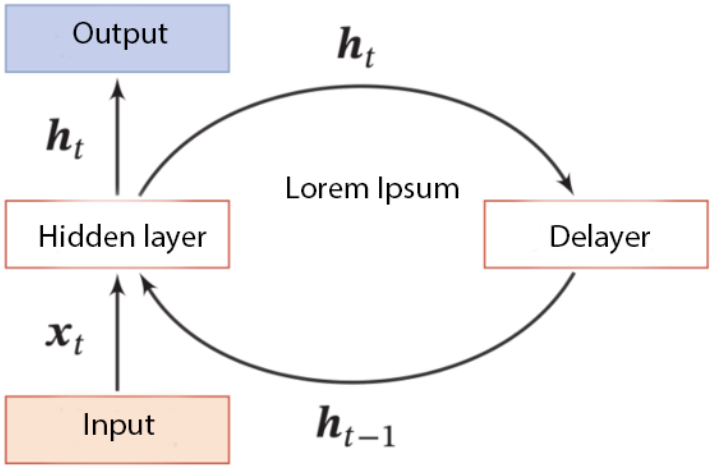


https://www.researchgate.net/publication/12314435_Neural_system_identification_model_of_human_sound_localization

Recurrent Neural Network (RNN)

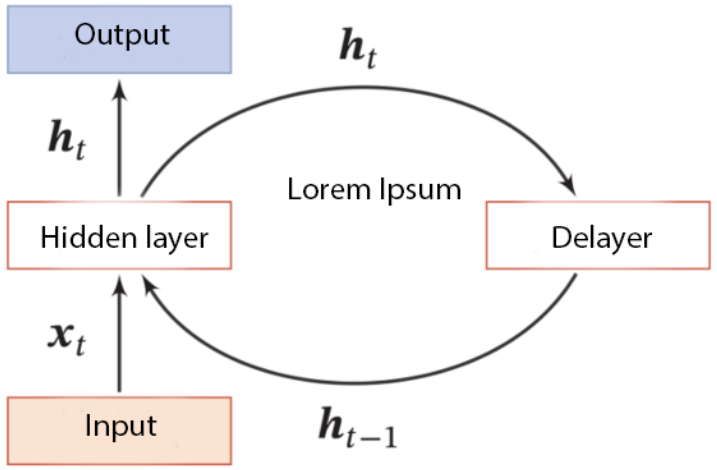
- RNN can process time series data of any length by using neurons with self-feedback.

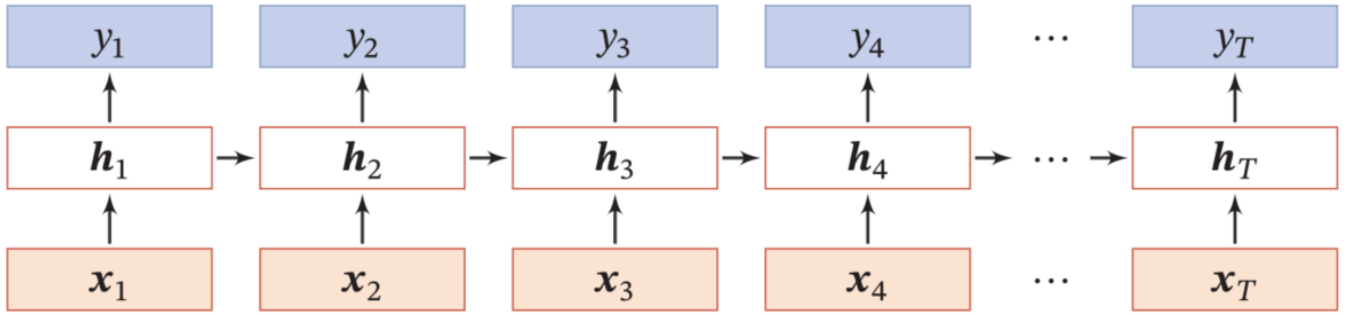
$$\boldsymbol{h}_t = f(\boldsymbol{h}_{t-1}, \boldsymbol{x}_t)$$



- RNNs are more in line with the structure of biological neural networks than feedforward neural networks 。
- RNNs have been widely used in tasks such as speech recognition, language modeling, and natural language generation

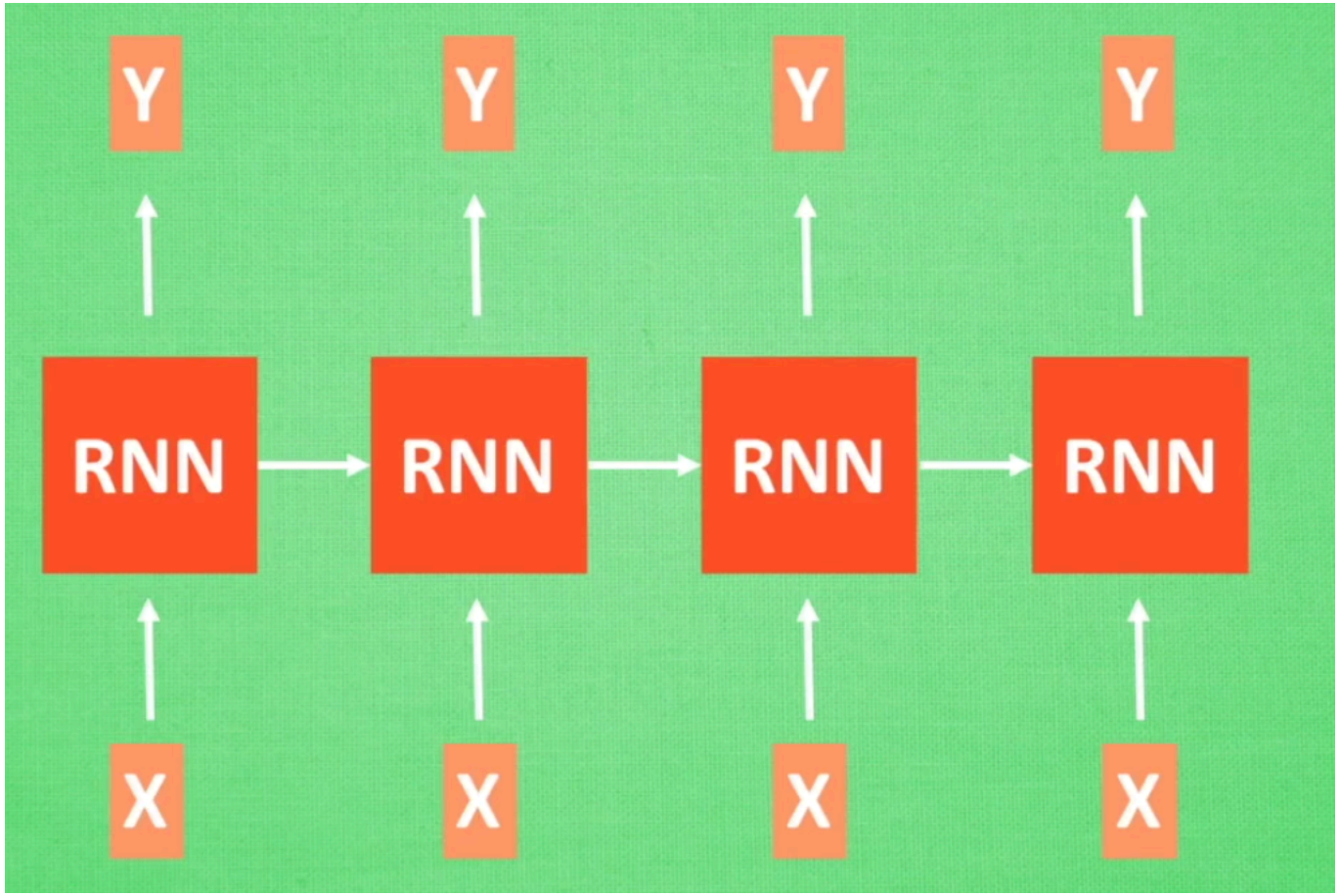
Expand by time





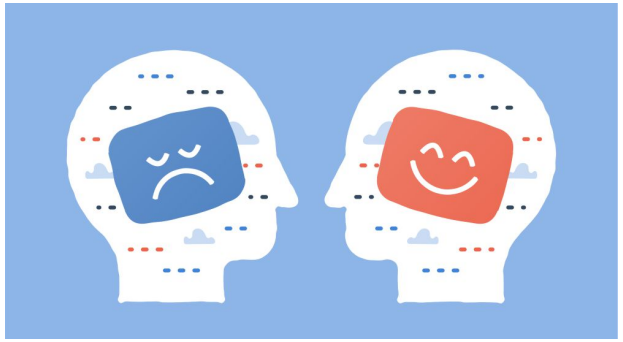
Application of Recurrent Neural Network

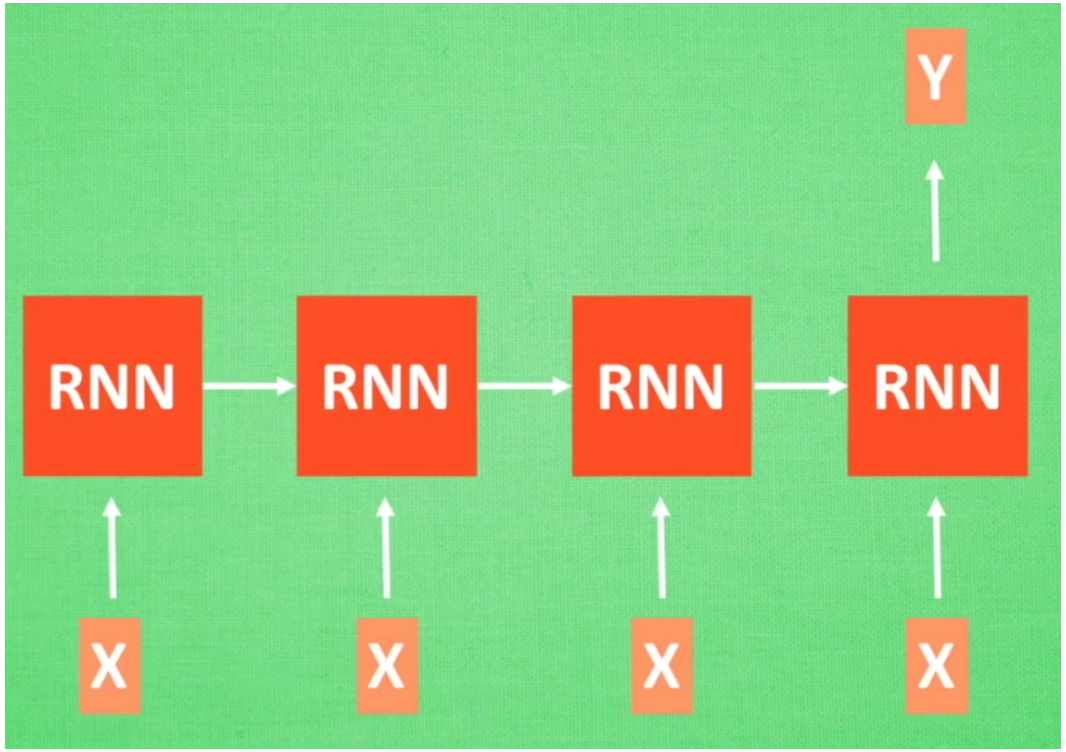
- The form of RNN is not only this one, but its structure is very flexible.



Application of Recurrent Neural Network

- To judge whether a person's words are positive or negative, we can use RNN that only outputs the judgment result at the last time point.

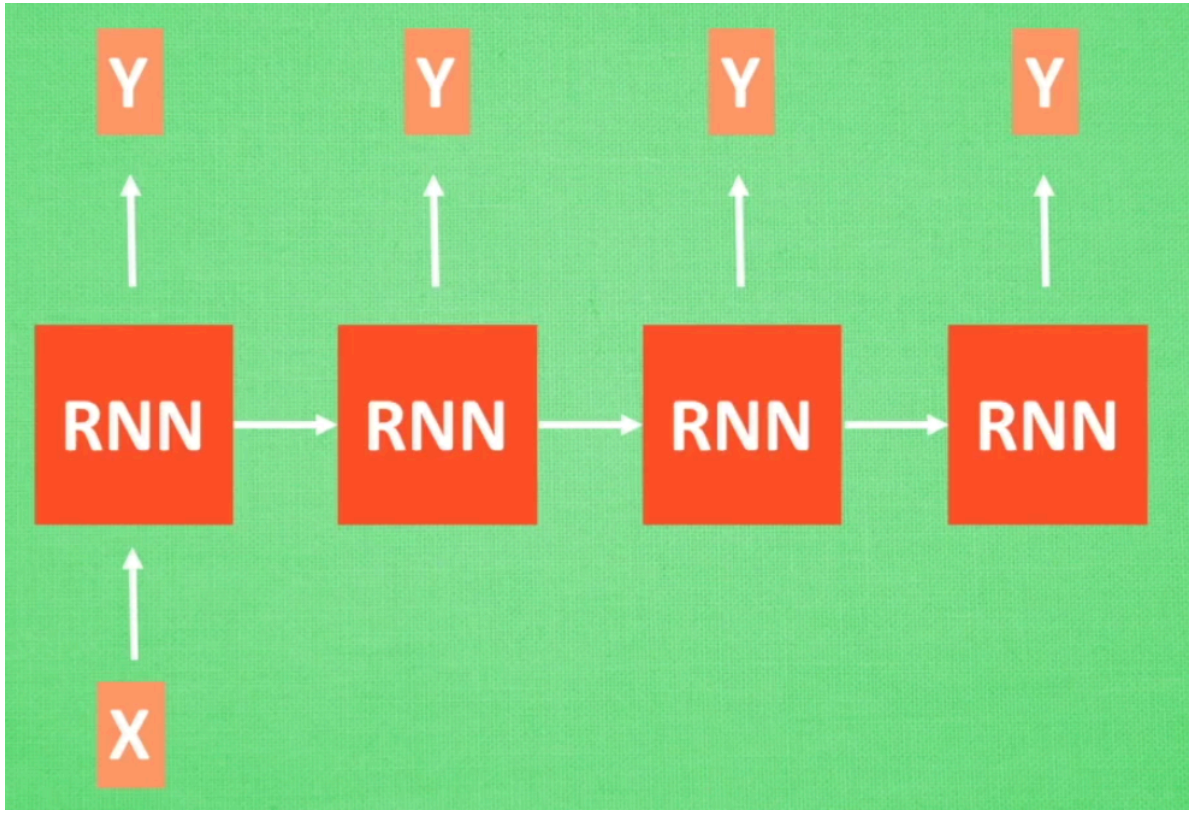




Many to one: Input is a vector sequence, but output is only one vector

Application of Recurrent Neural Network

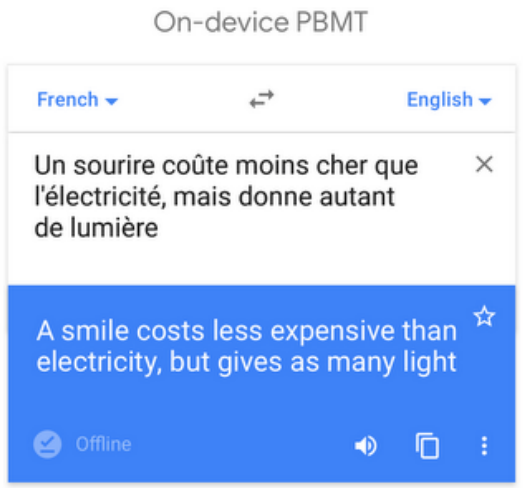
- Picture description RNN, we only need an X to replace the input picture, and then generate a paragraph describing the picture.

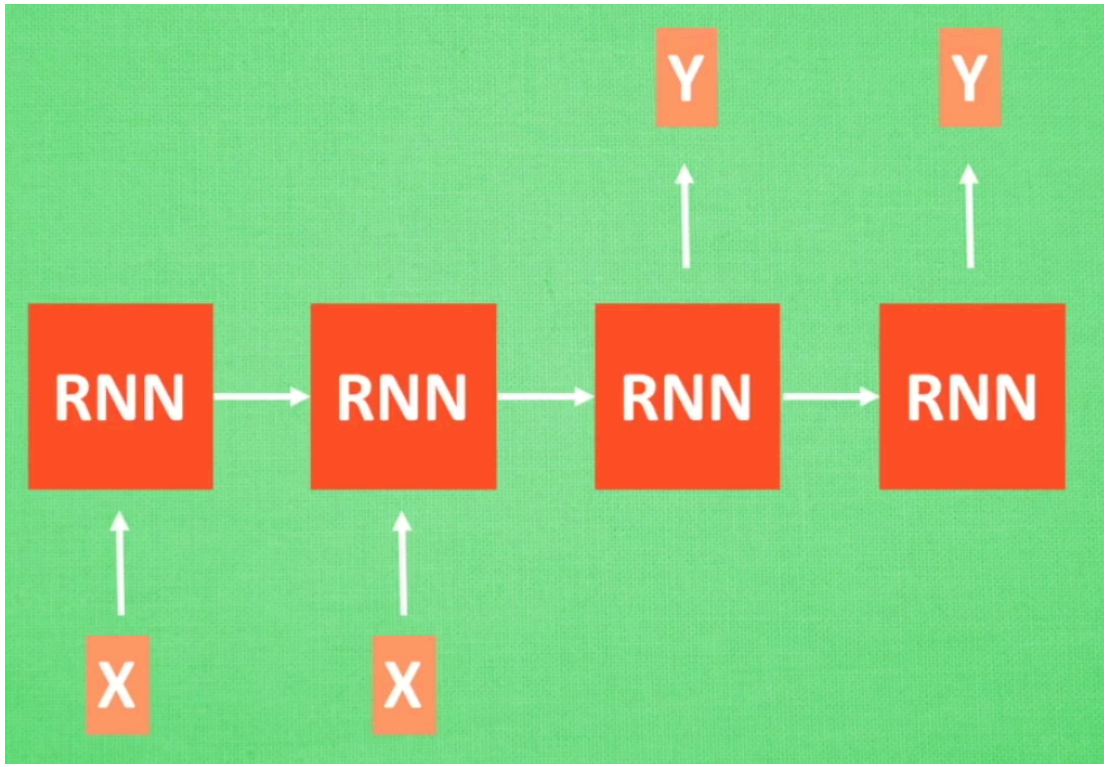


One to many: Input is only one vector, but output is a vector sequence

Application of Recurrent Neural Network

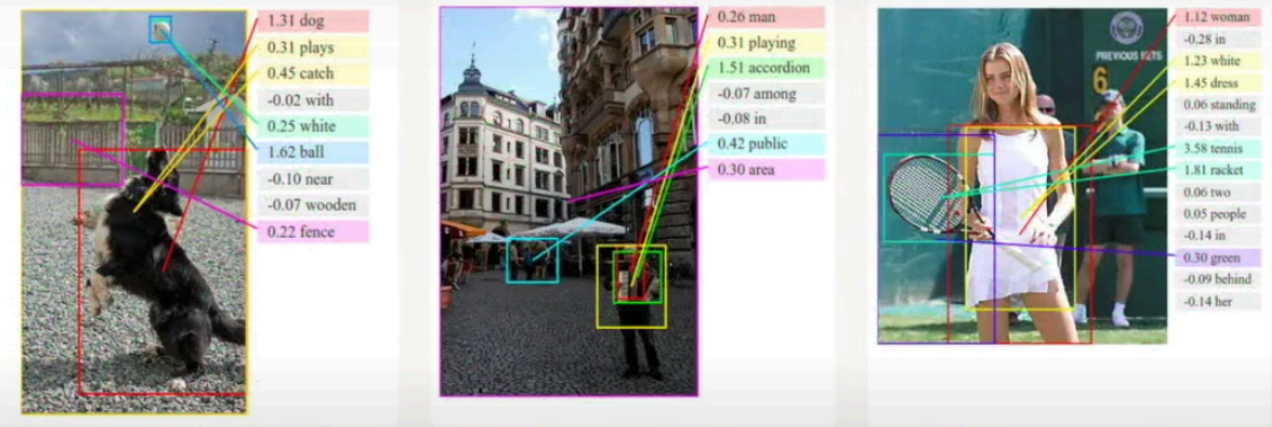
- The RNN of language translation gives a paragraph of English, and then translates into Japanese.





Many to Many: Both input and output are both sequences

More applications…

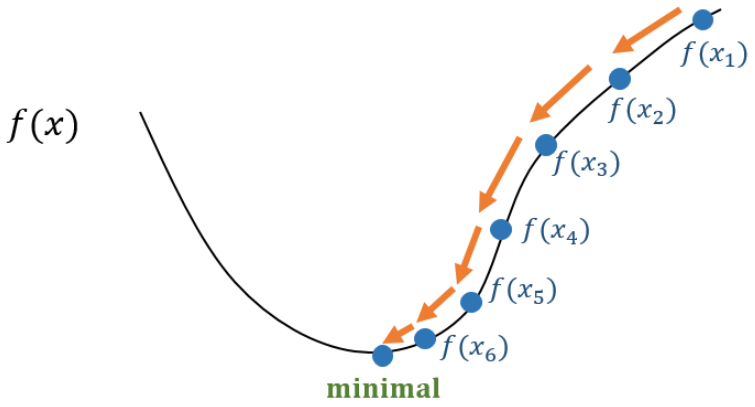


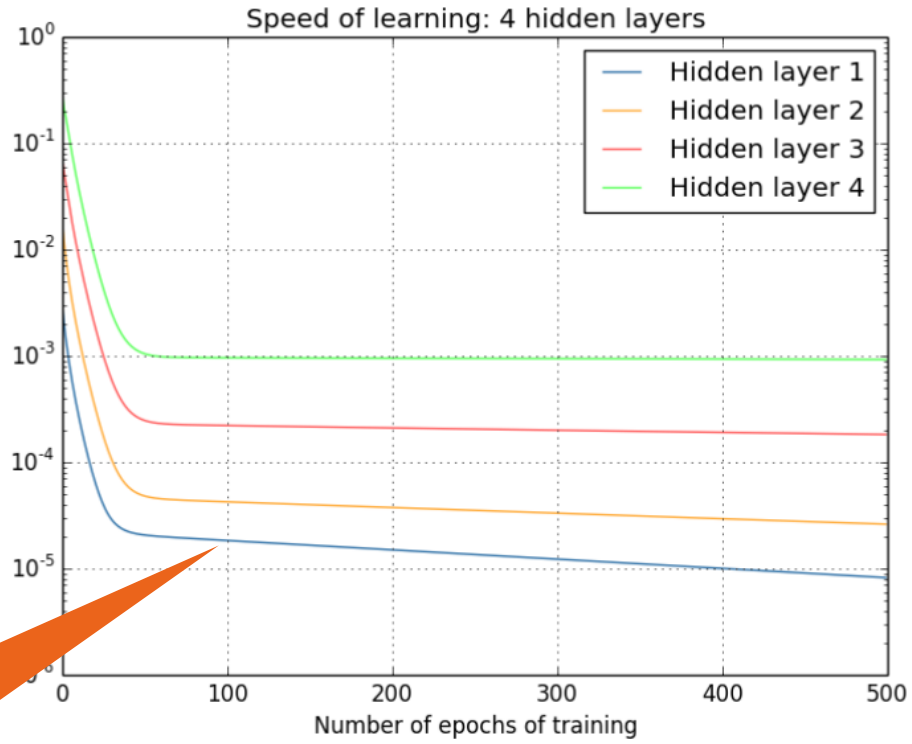

```
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
```

https://openai.com/blog/musenet/

Gradient vanishing problem (GVP)

- As the number of network layers increases, the gradient update will decrease toward exponential decay
- Our weights cannot be updated, which eventually leads to training failure

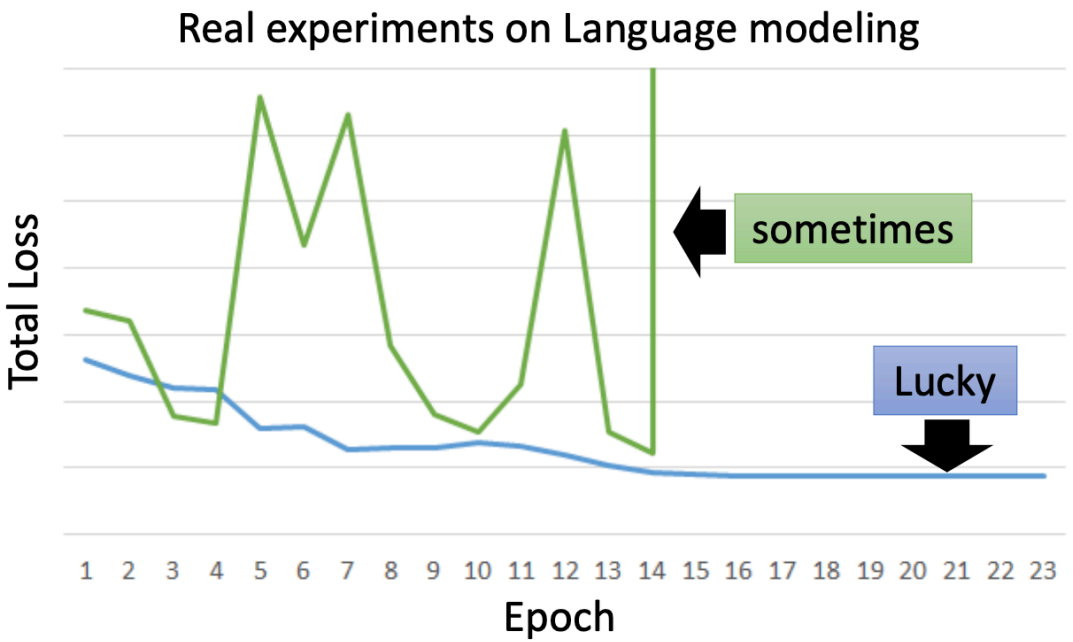




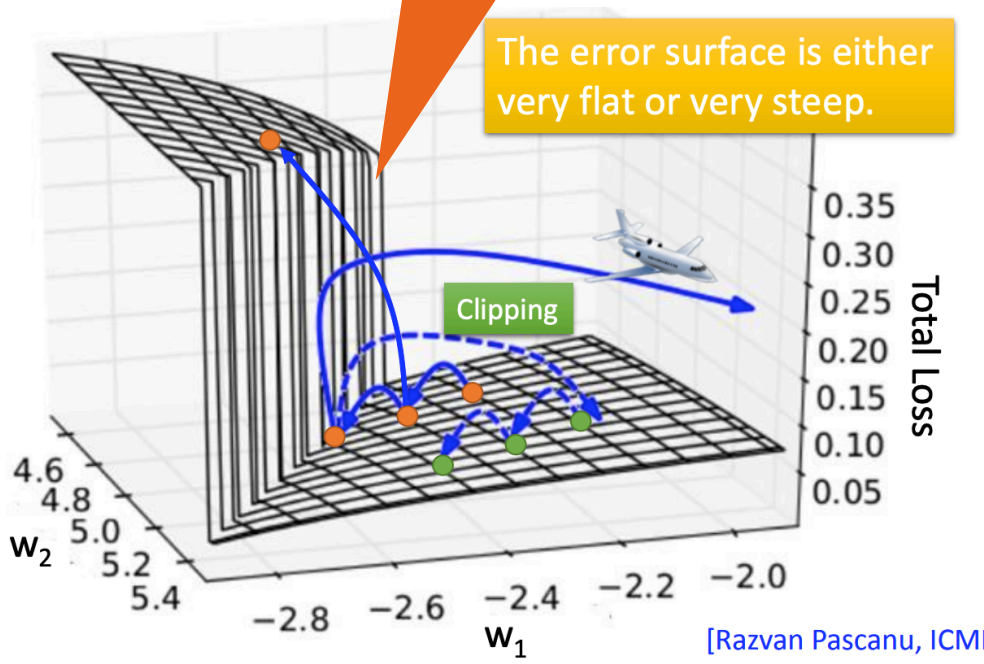
The update speed of the 4th hidden layer is two orders of magnitude slower than that of the 1st hidden layer

Gradient exploding problem (GEP)

- As the number of network layers increases, gradient updates will increase exponentially
- The gradient is too large, thereby greatly updating network parameters, causing network instability



When encountering gradient wall, calculate the gradient at a certain point on the wall, the gradient will increase instantly and point to an undesirable location



[Razvan Pascanu, ICML'13]

What is the consequence of GVP or GEP?

- The disappearance of the gradient will cause the network weights of the previous layer in our neural network to be unable to be updated, and thus stop learning

- Gradient explosion will make learning unstable, and parameter changes too large make it impossible to obtain optimal parameters

- Makes the network unable to learn well from the training data
  - E.g., recurrent neural networks(RNN) cannot learn on long input data sequences
  - E.g., the deep multi-layer perceptron network cannot update the weight because the weight value is NaN

What is the reason behind GVP or GEP?

$$f_{i+1} = f\left(f_i * w_{i+1}\right)$$

$f_i\ (x)$ ⇄ f_{i+1}

$$w \leftarrow w + \Delta w\ ,\ \Delta w = -\alpha \frac{\partial Loss}{w}$$

$$\Delta w_1 = \frac{\partial Loss}{\partial w_2} = \frac{\partial Loss}{\partial f_4} * \frac{\partial f_4}{\partial f_3} * \frac{\partial f_3}{\partial f_2} * \frac{\partial f_2}{\partial w_2}$$

$$= \frac{\partial Loss}{\partial f_n} * \frac{\partial f_n}{\partial f_{n-1}} * \cdots * \frac{\partial f_2}{\partial w_2}$$

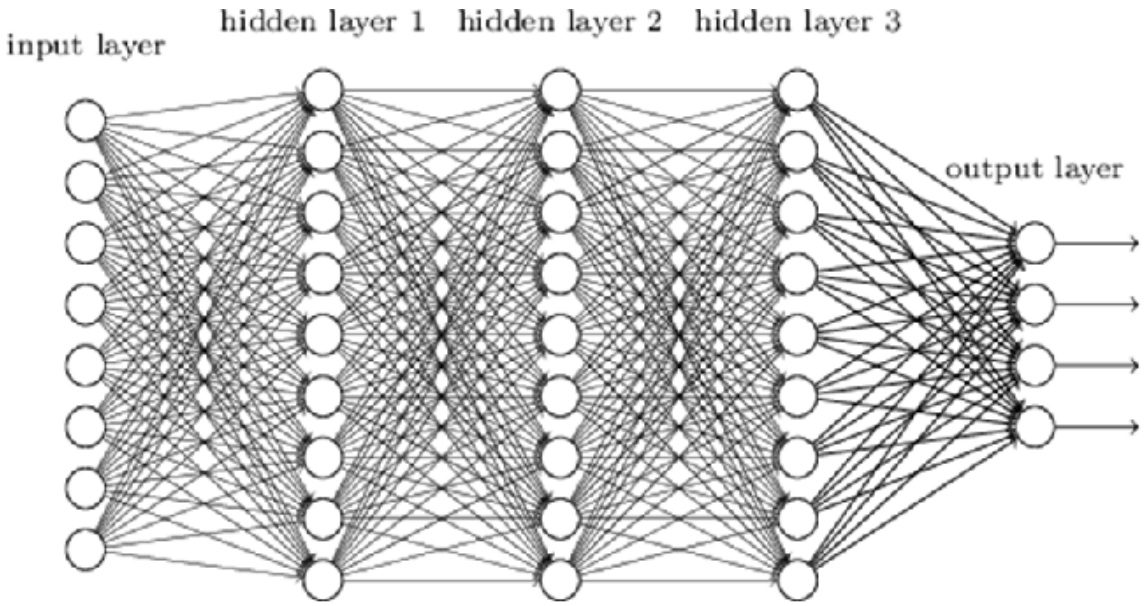
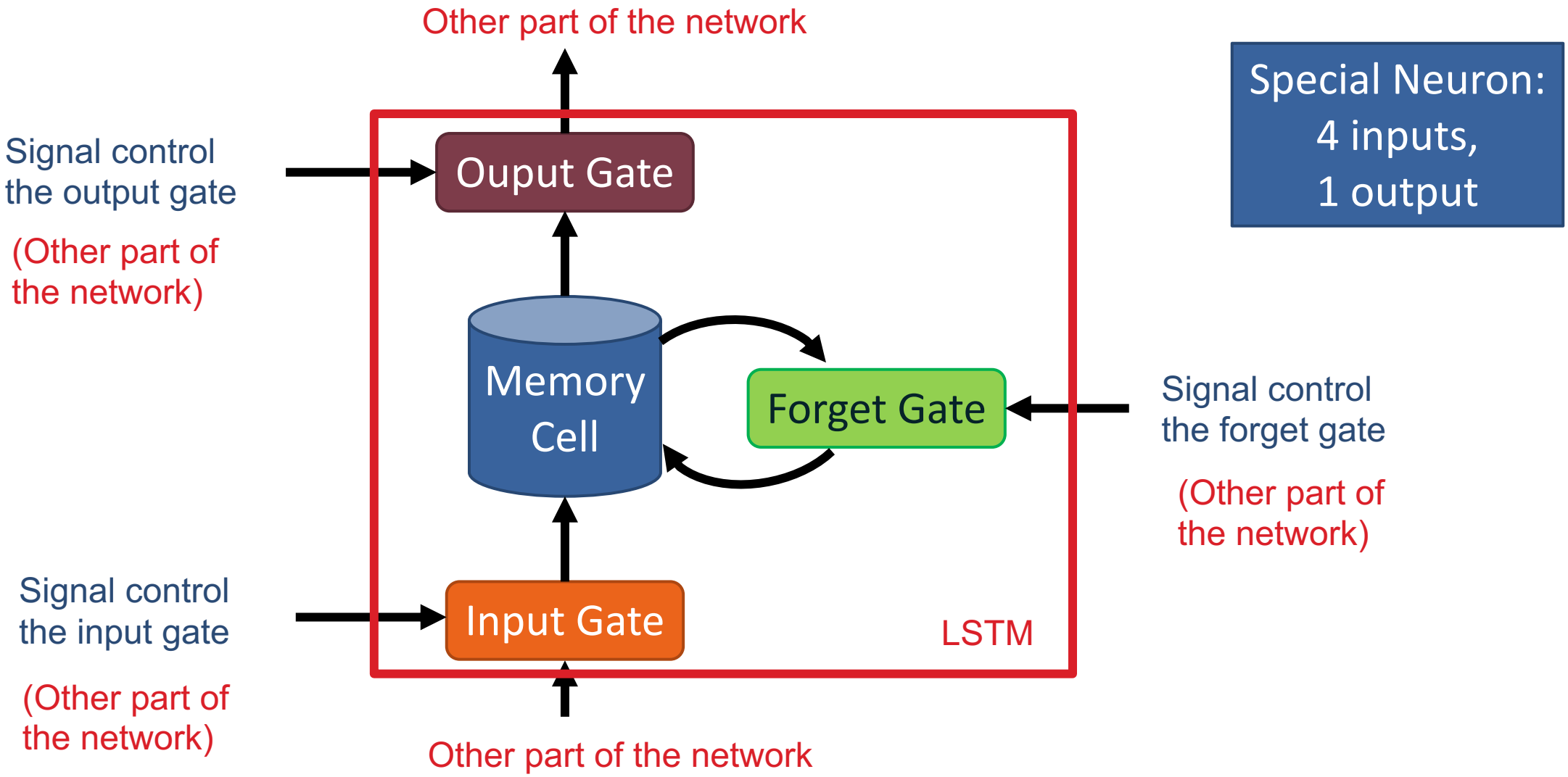


Fig. 2. An example of deep neural network with five layers

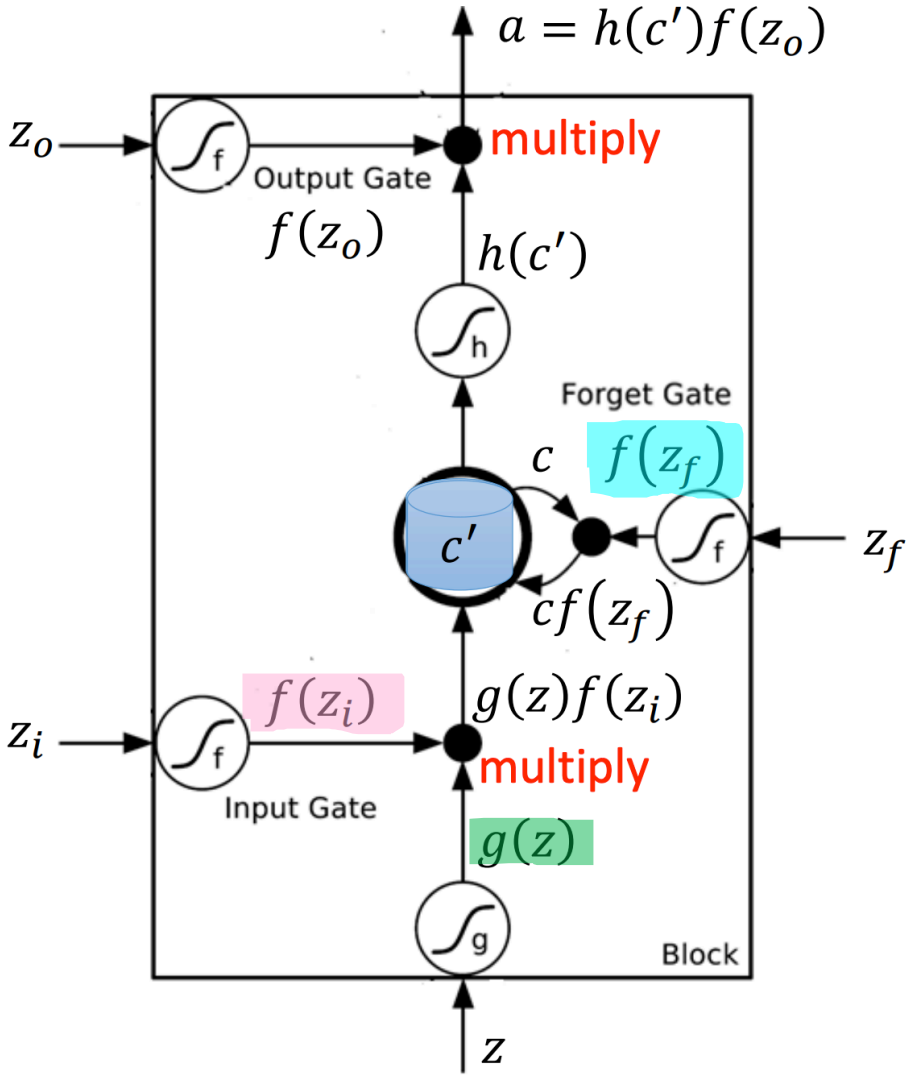
If this part is greater than 1, then when the number of layers increases, the final gradient update will increase exponentially, that is, gradient explosion occurs;

If this part is less than 1, then as the number of layers increases, the obtained gradient update information will decay exponentially, that is, the gradient disappears

Long Short-term Memory (LSTM)



Long Short-term Memory (LSTM)



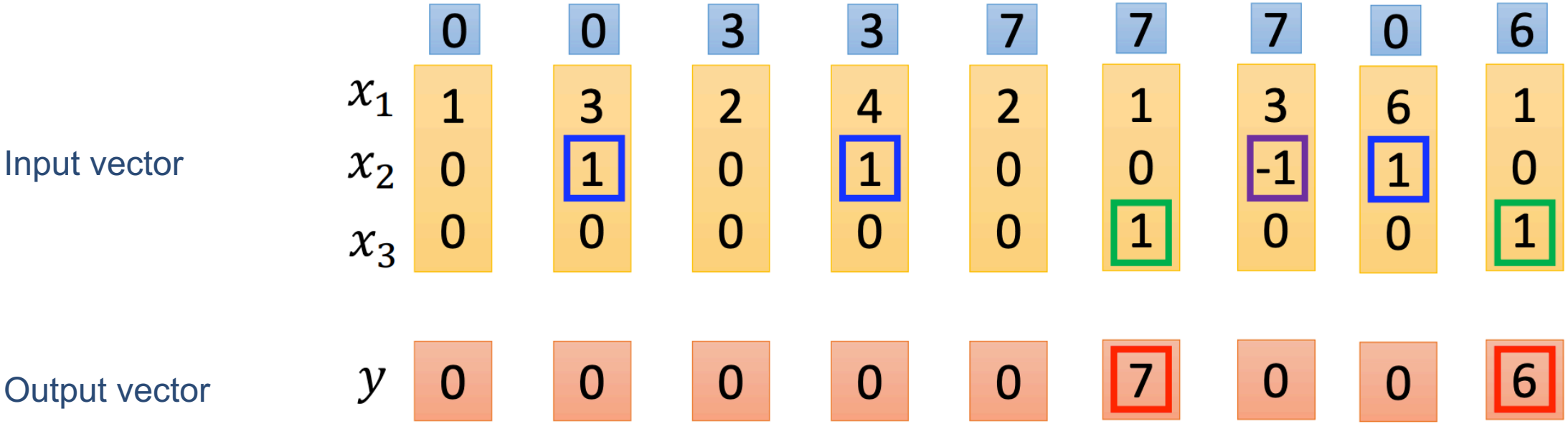
Activation function f is usually a sigmoid function

Between 0 and 1

Mimic open and close gate

$$c' = g(z)f(z_i) + cf(z_f)$$

LSTM - Example

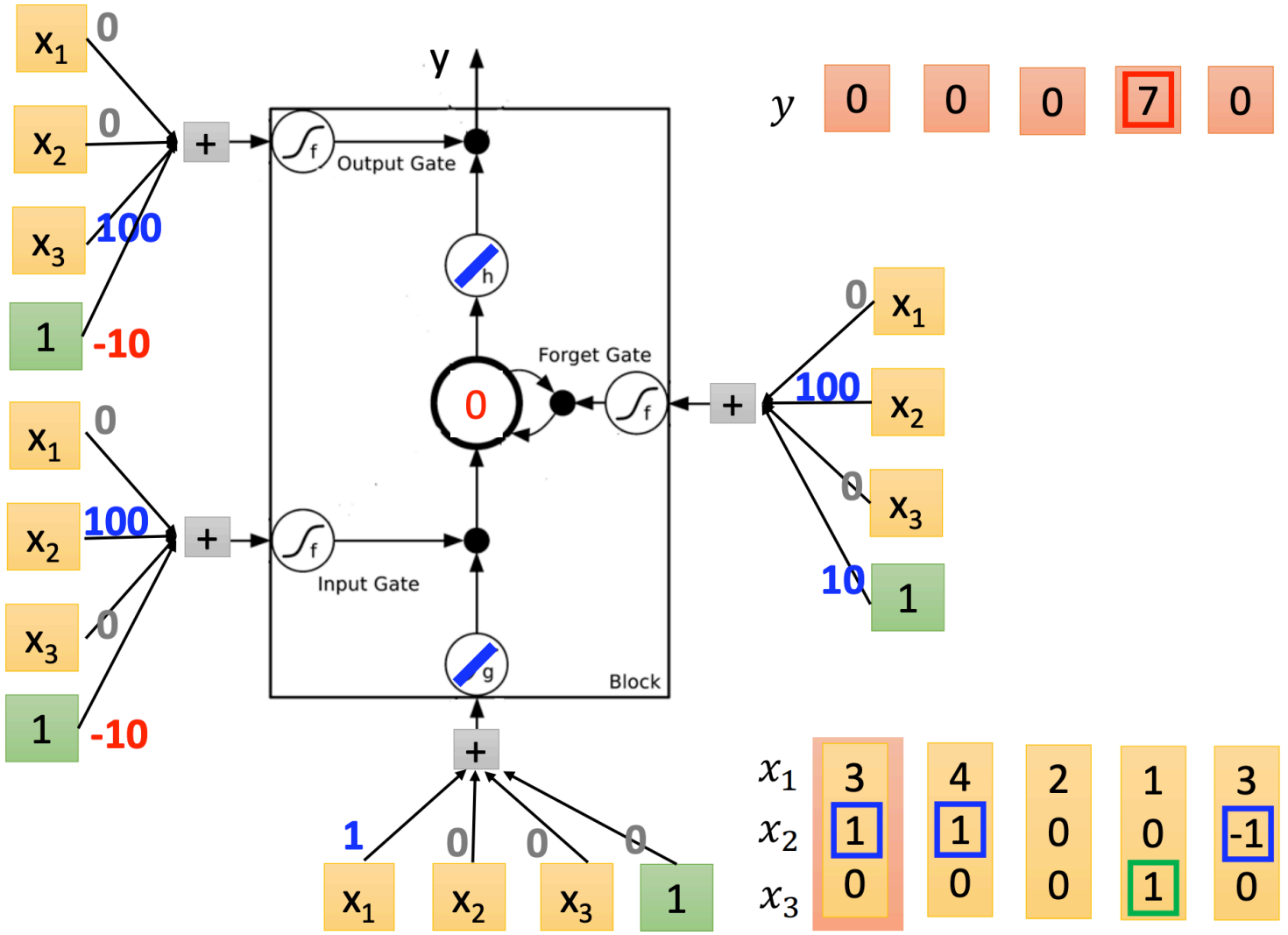


When x_2 = 1, add the numbers of x_1 into the memory

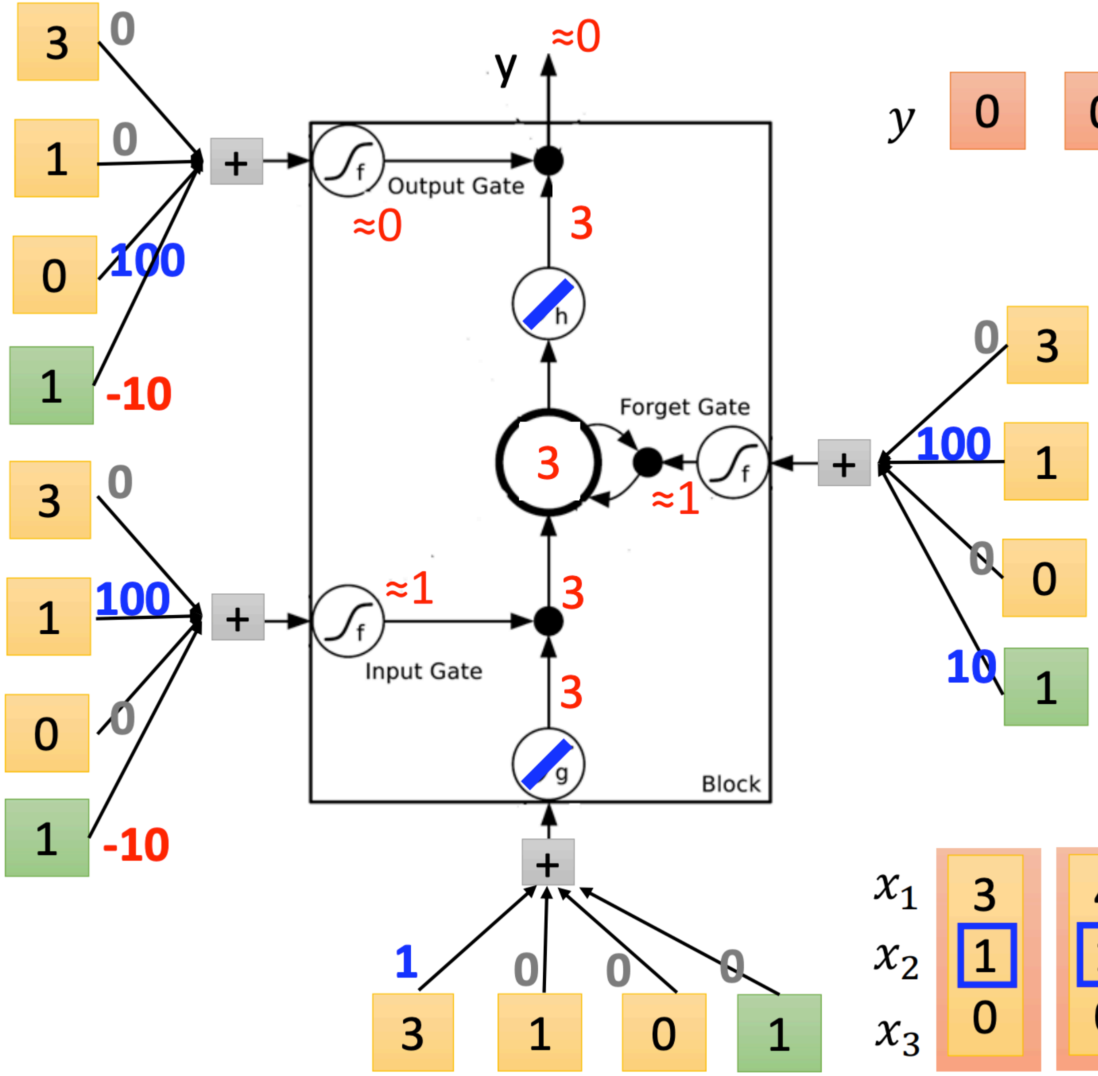
When x_2 = -1, reset the memory

When x_3 = 1, output the number in the memory

LSTM - Example

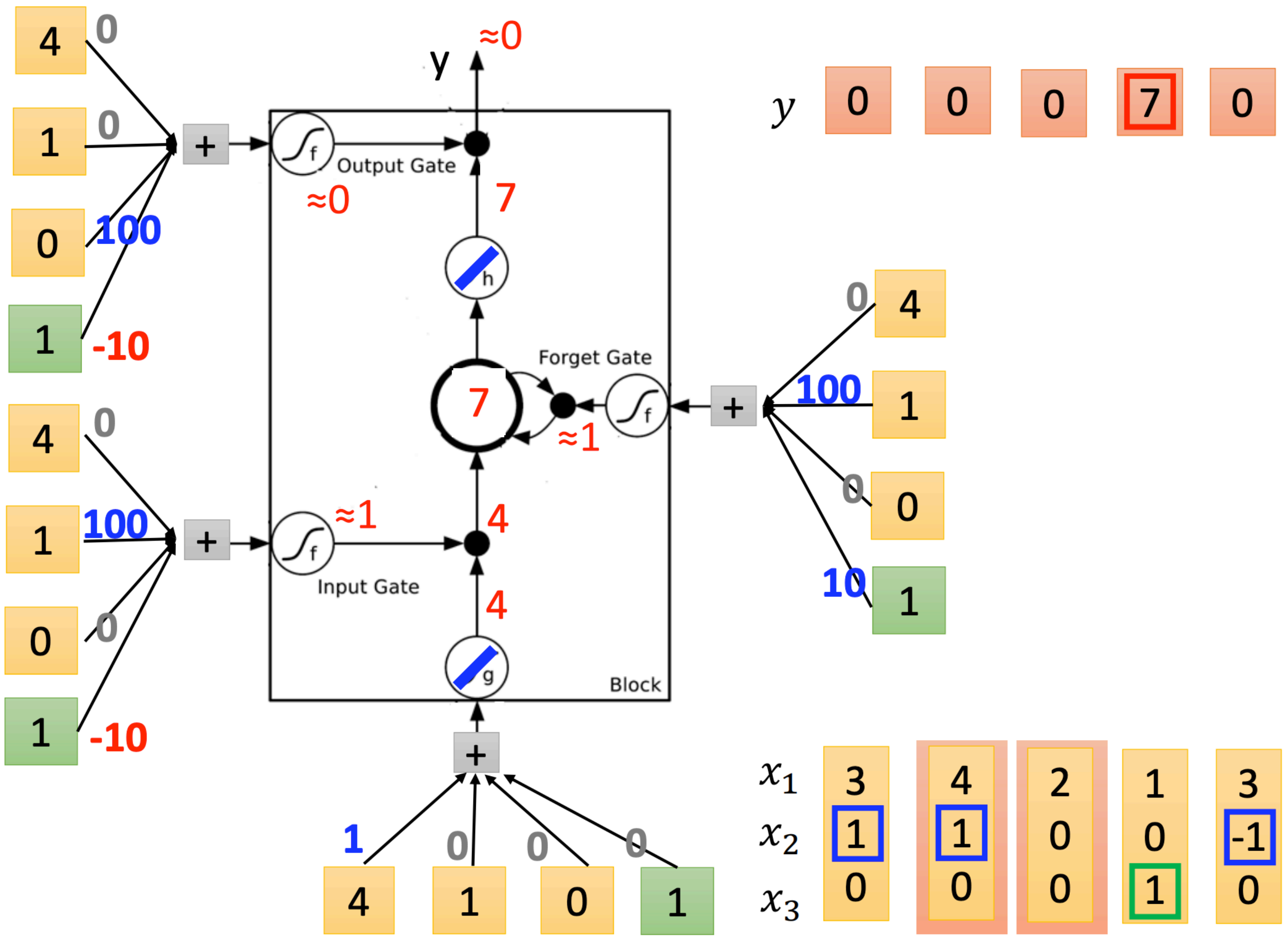


LSTM - Example

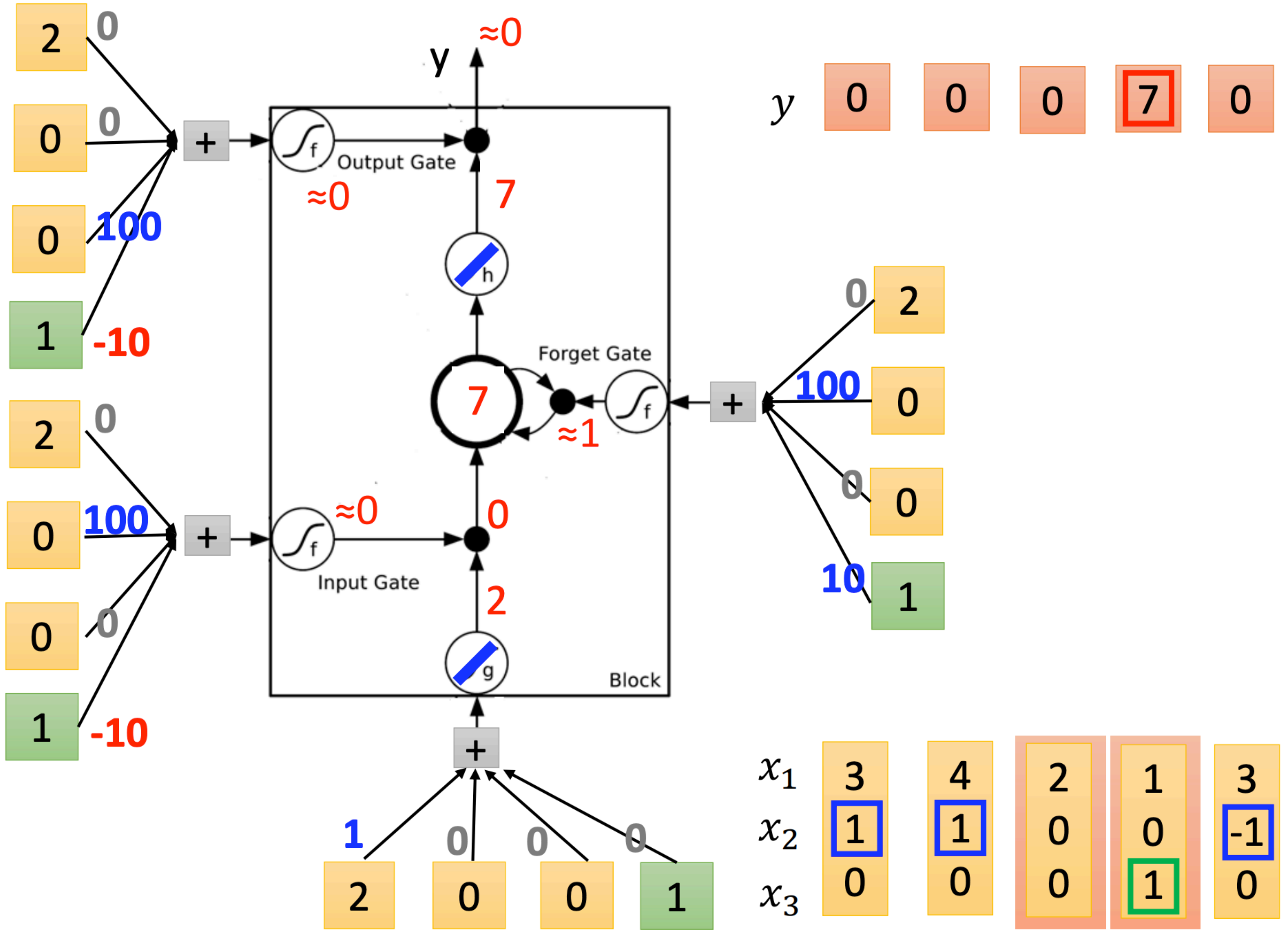


y	0	0	0	7	0
x_1	3	4	2	1	3
x_2	1	1	0	0	-1
x_3	0	0	0	1	0

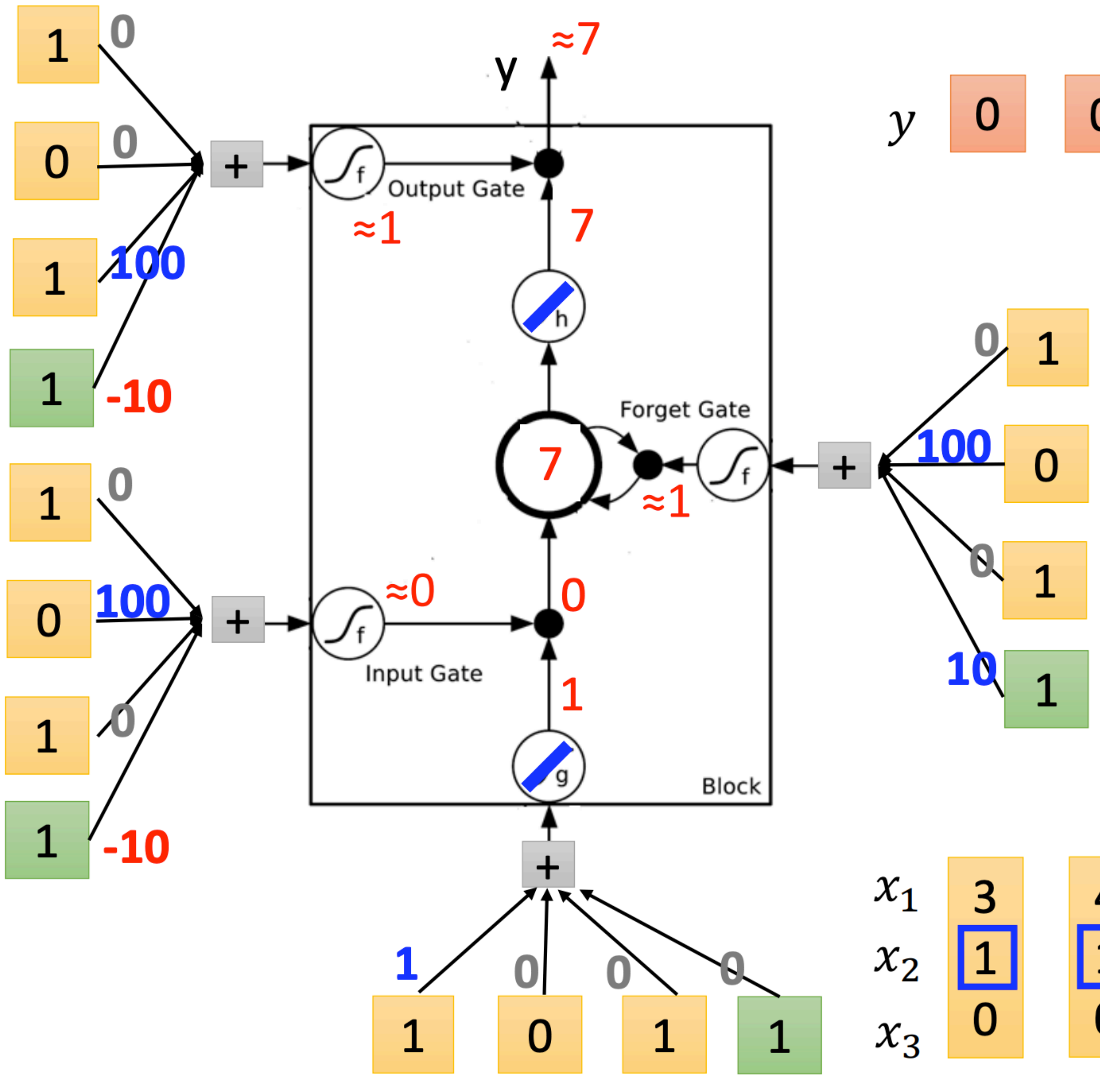
LSTM - Example



LSTM - Example



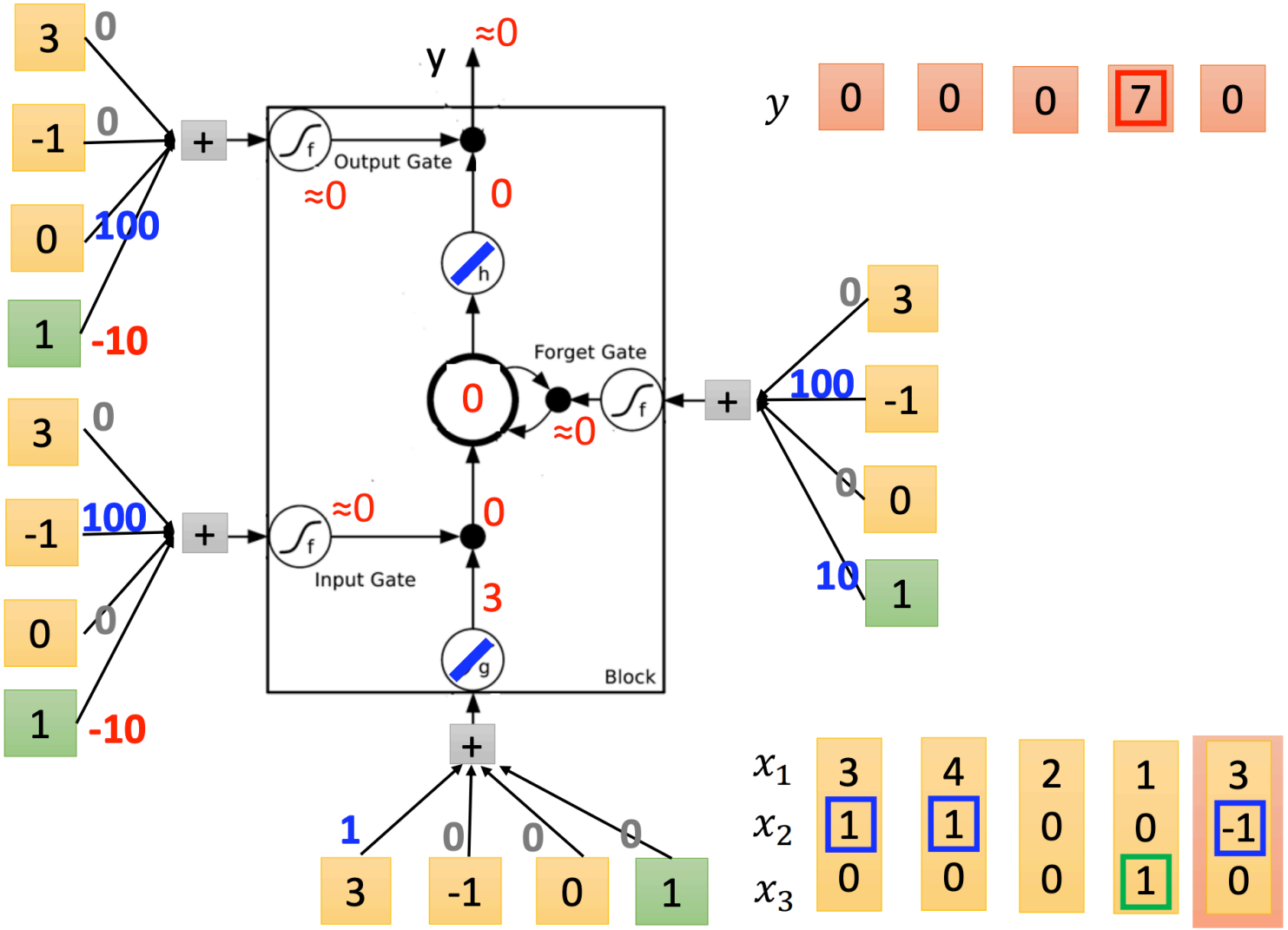
LSTM - Example



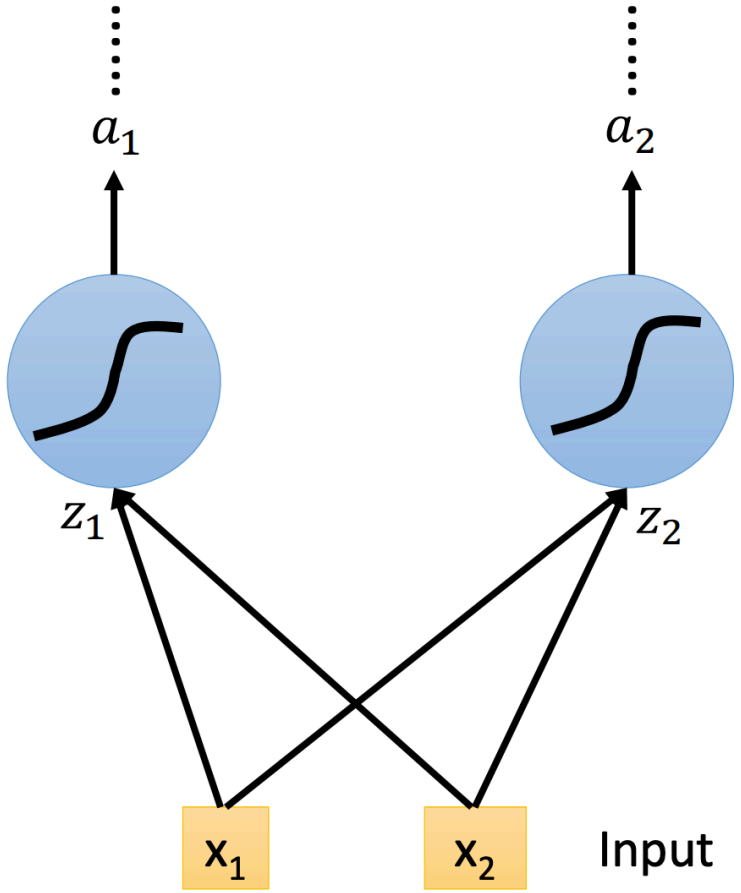
y	0	0	0	7	0

x_1	3	4	2	1	3
x_2	1	1	0	0	-1
x_3	0	0	0	1	0

LSTM - Example

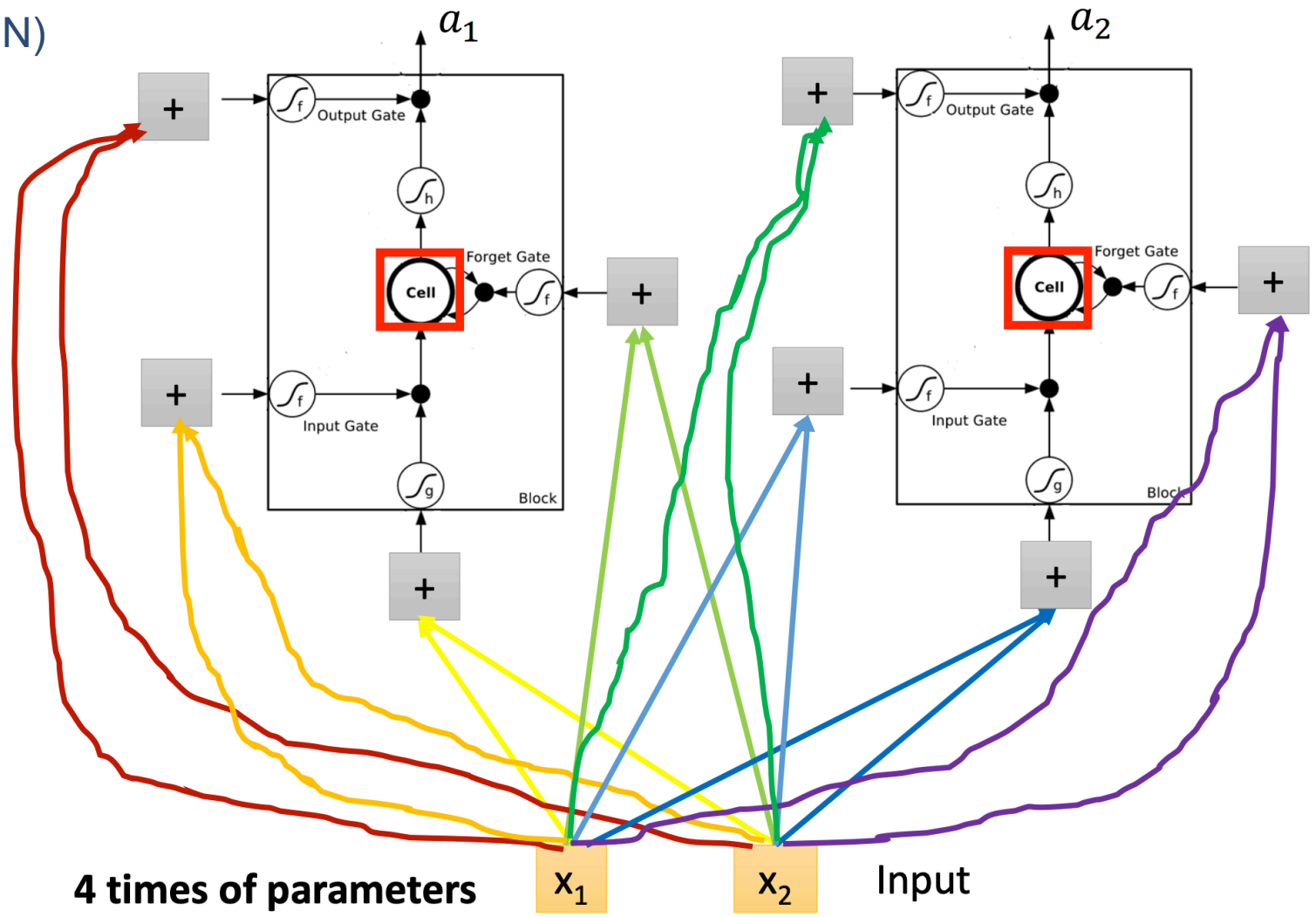


Original Network (Linear format)



Replace the neurons with LSTM to overcome GVP or GEP

(LSTM format RNN)

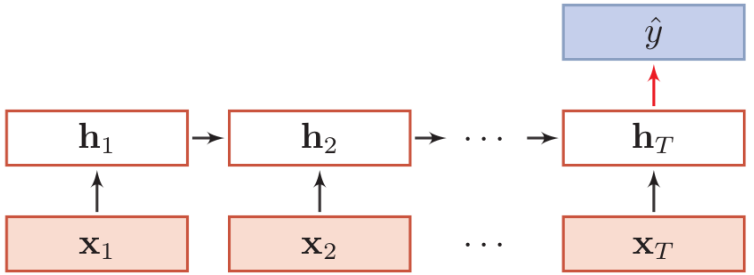


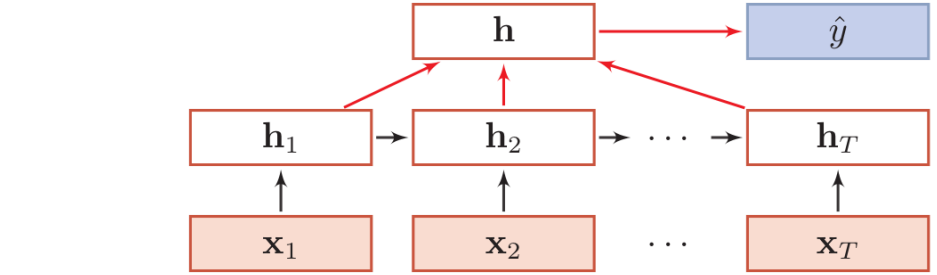
RNN applied to Machine Learning

Sequence

- From sequence to category

RNN





From sequence to category

- Sentiment classification

I watched this movie with a happy feeling

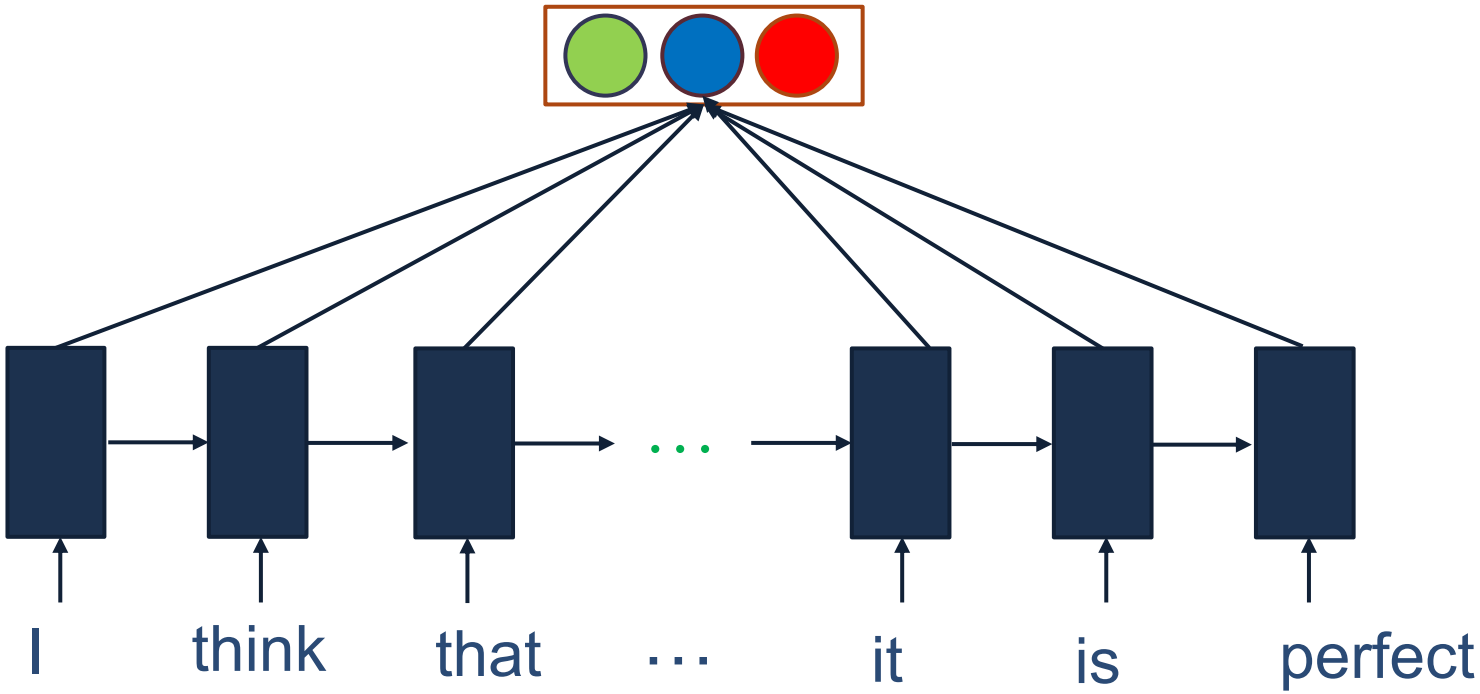
Positive

This movie is too bad

Negative

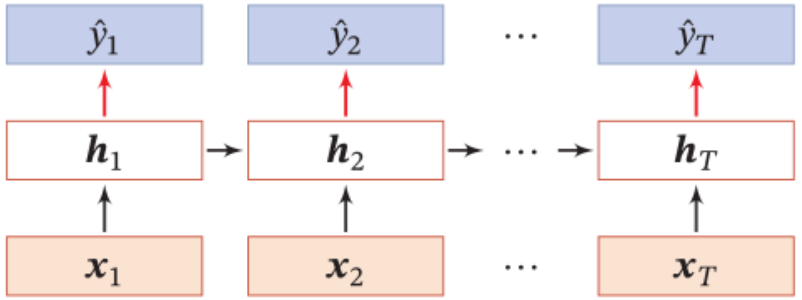
This movie is great

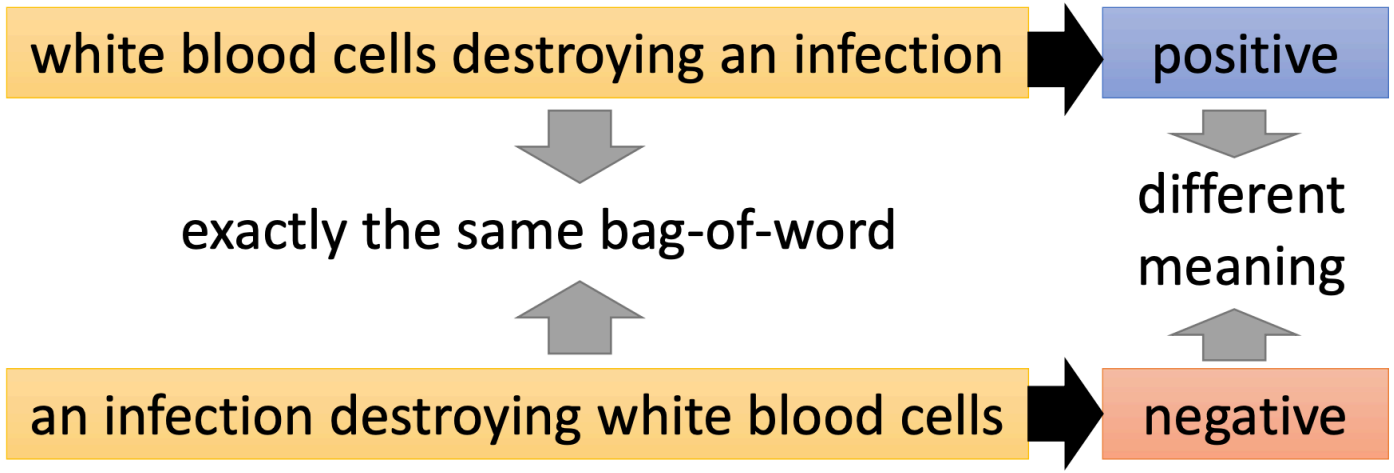
Positive



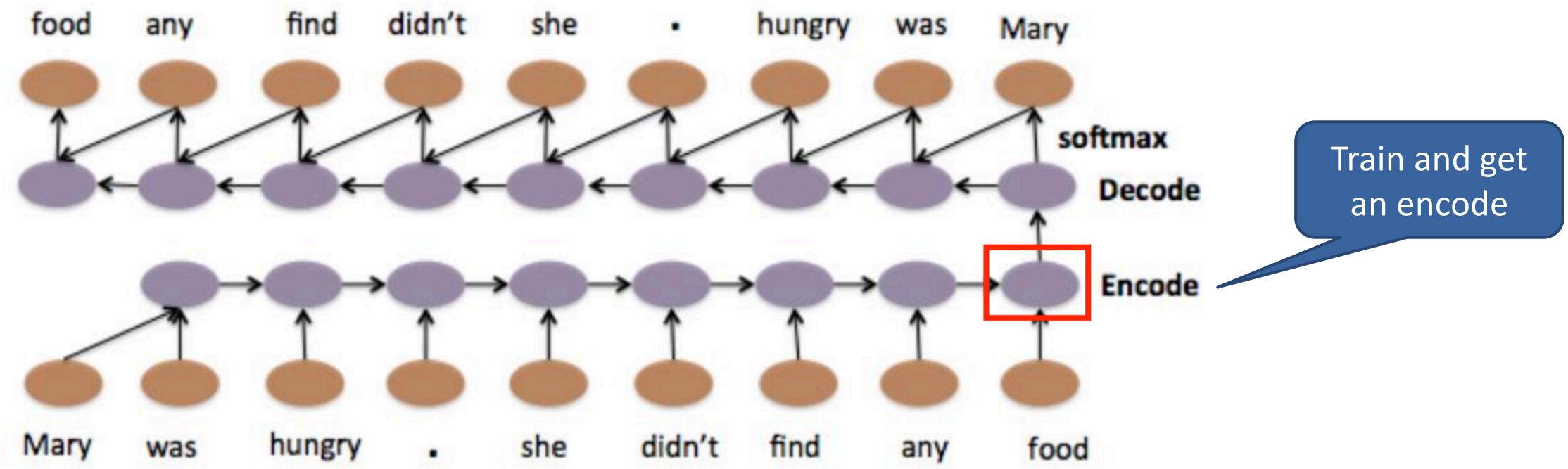
From sequence to sequence

- Auto-encoder - Text
  - To understand the meaning of a word sequence, the order of the words can not be ignored.





From sequence to sequence

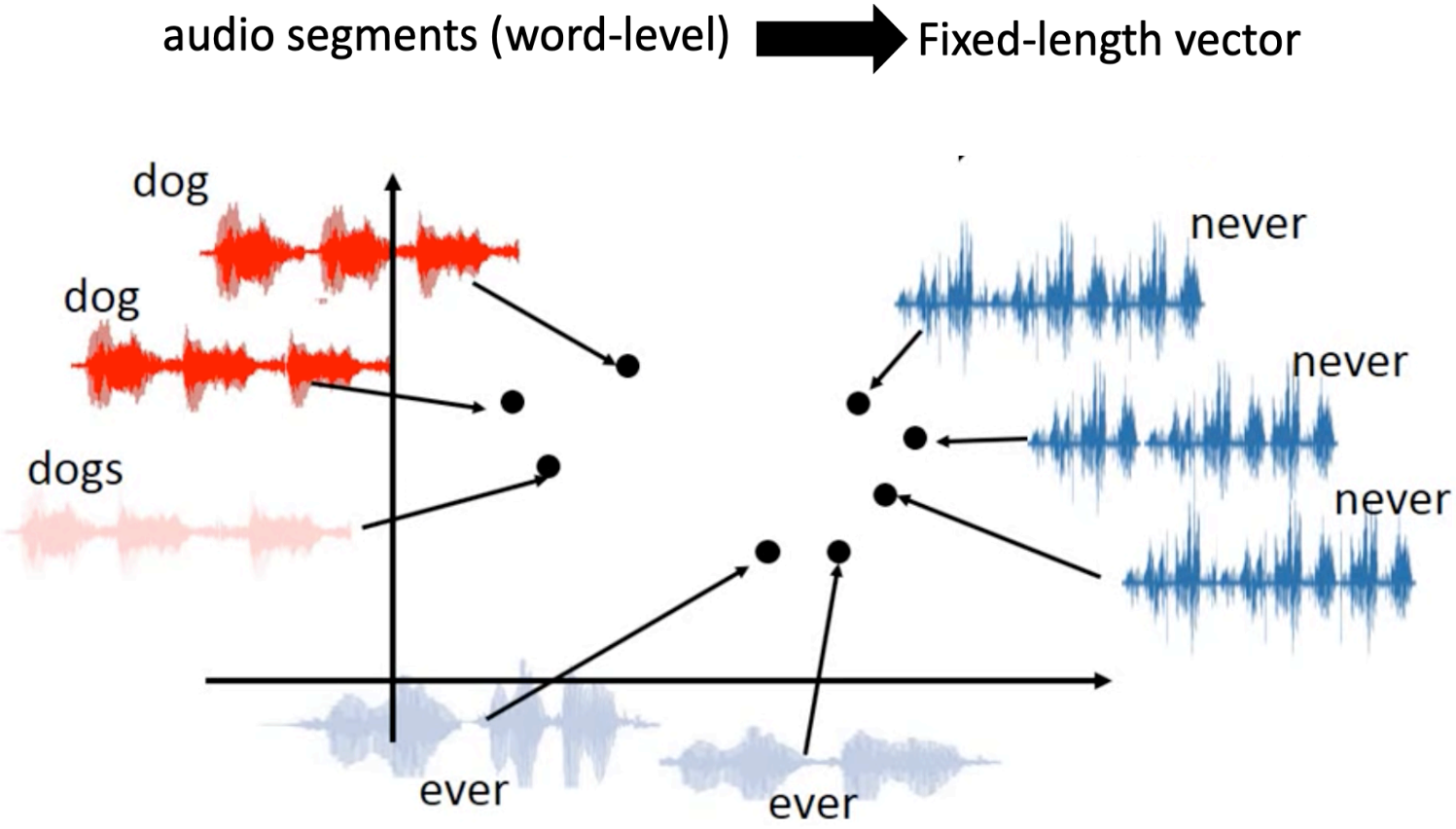


https://arxiv.org/pdf/1506.01057.pdf

From sequence to sequence

- Auto-encoder – Speech
  - Dimension reduction for a sequence with variable length

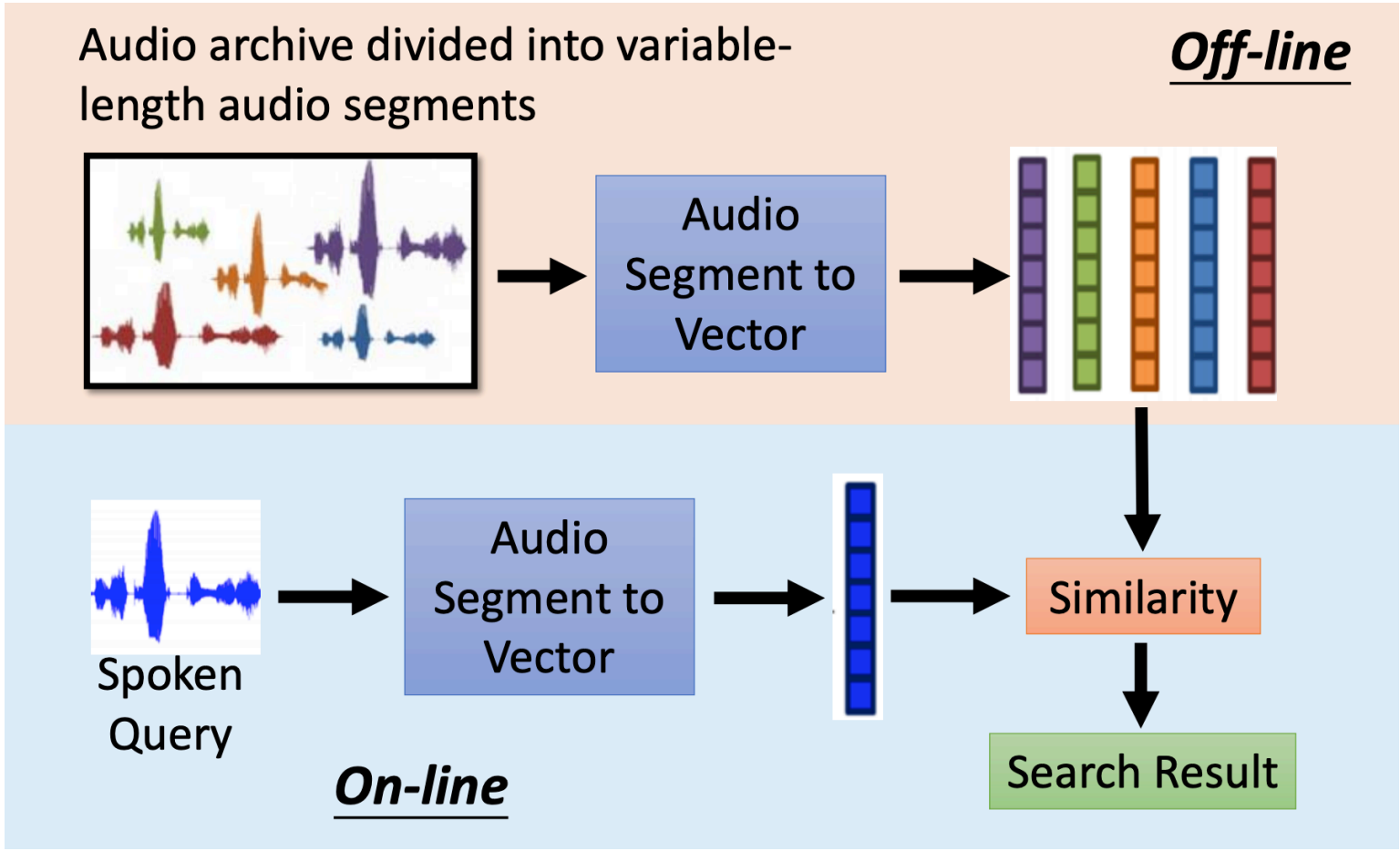
https://arxiv.org/pdf/1603.00982.pdf



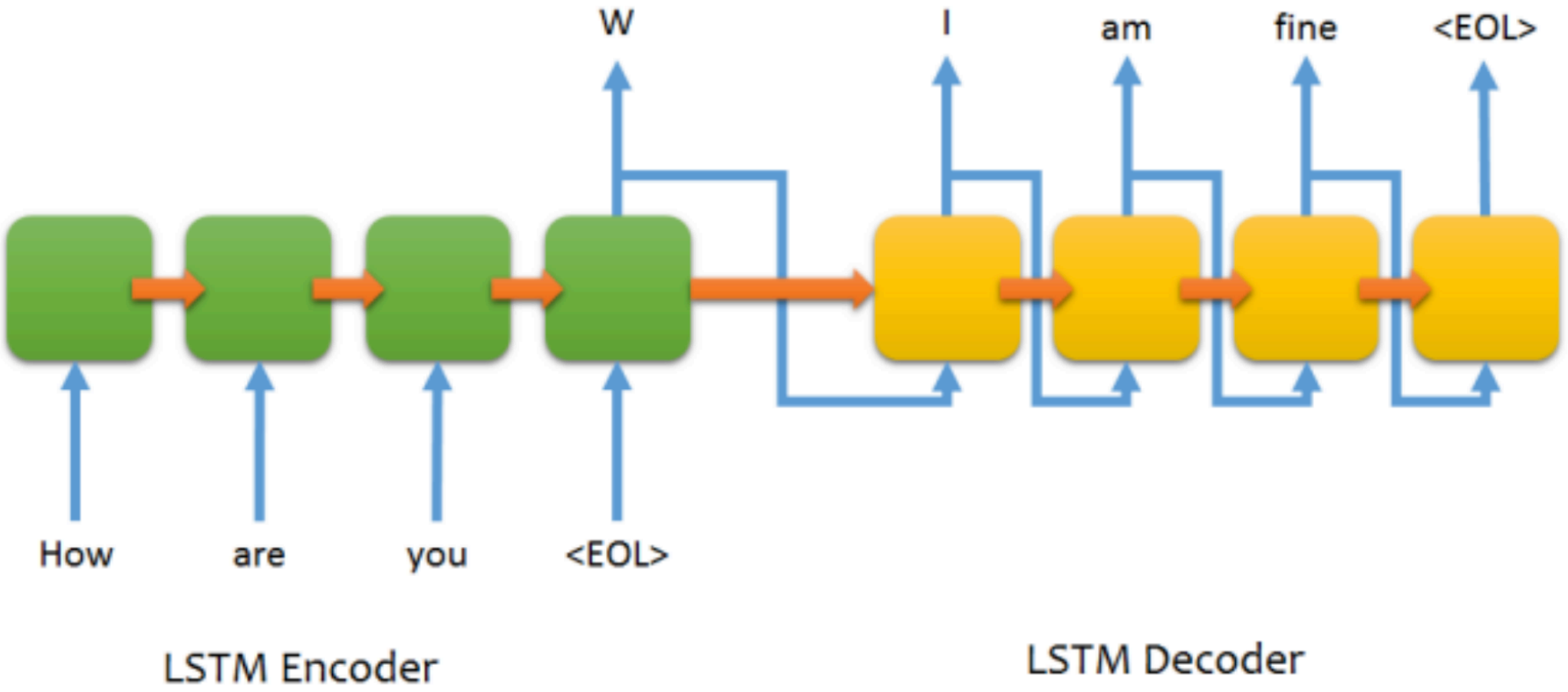
From sequence to sequence

https://arxiv.org/pdf/1603.00982.pdf

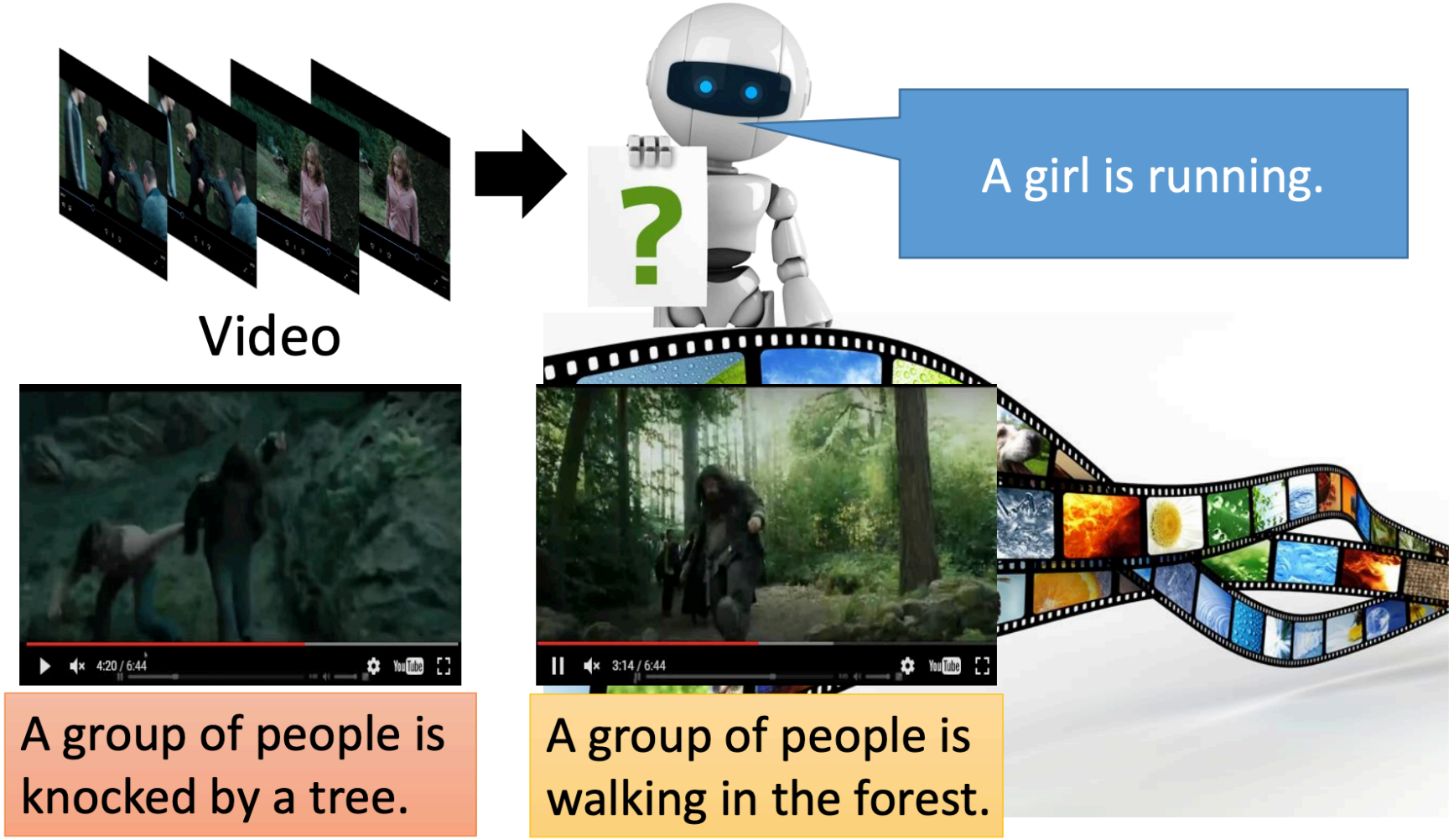
- Auto-encoder – Speech



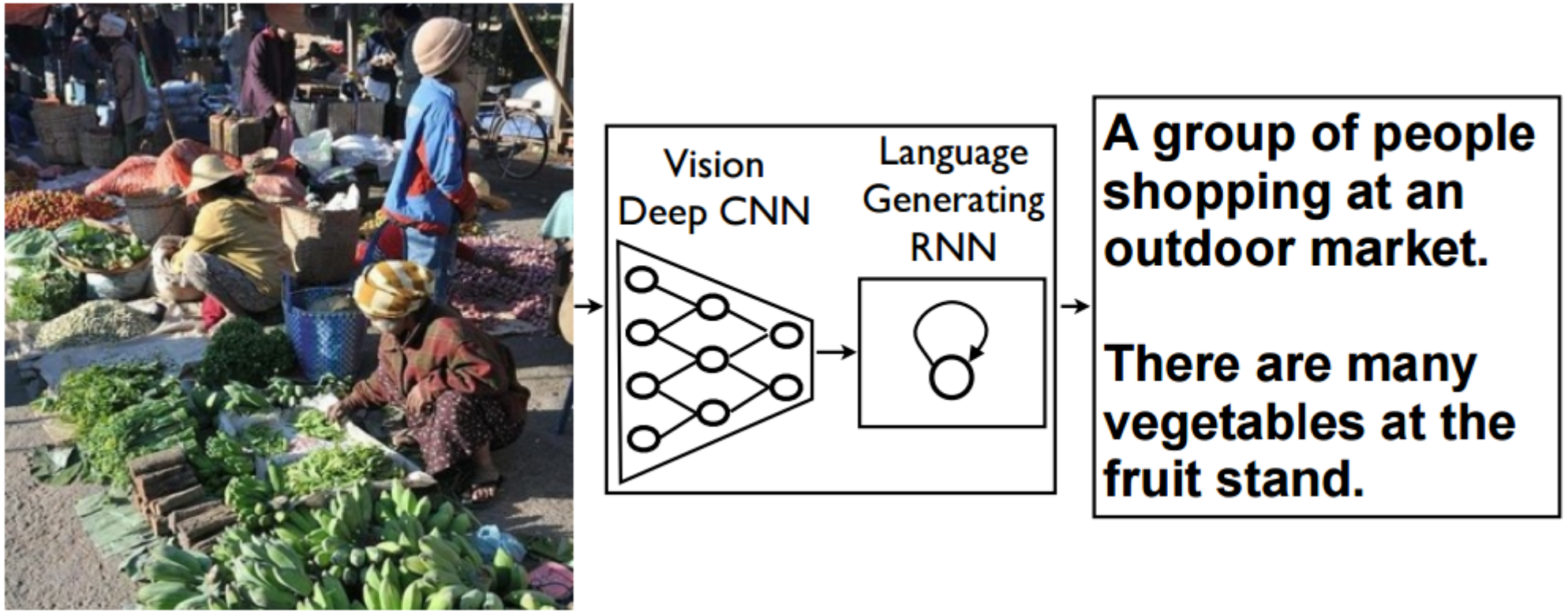
Application: Chat-bot



Application: Video Caption Generation



Add notes to pictures

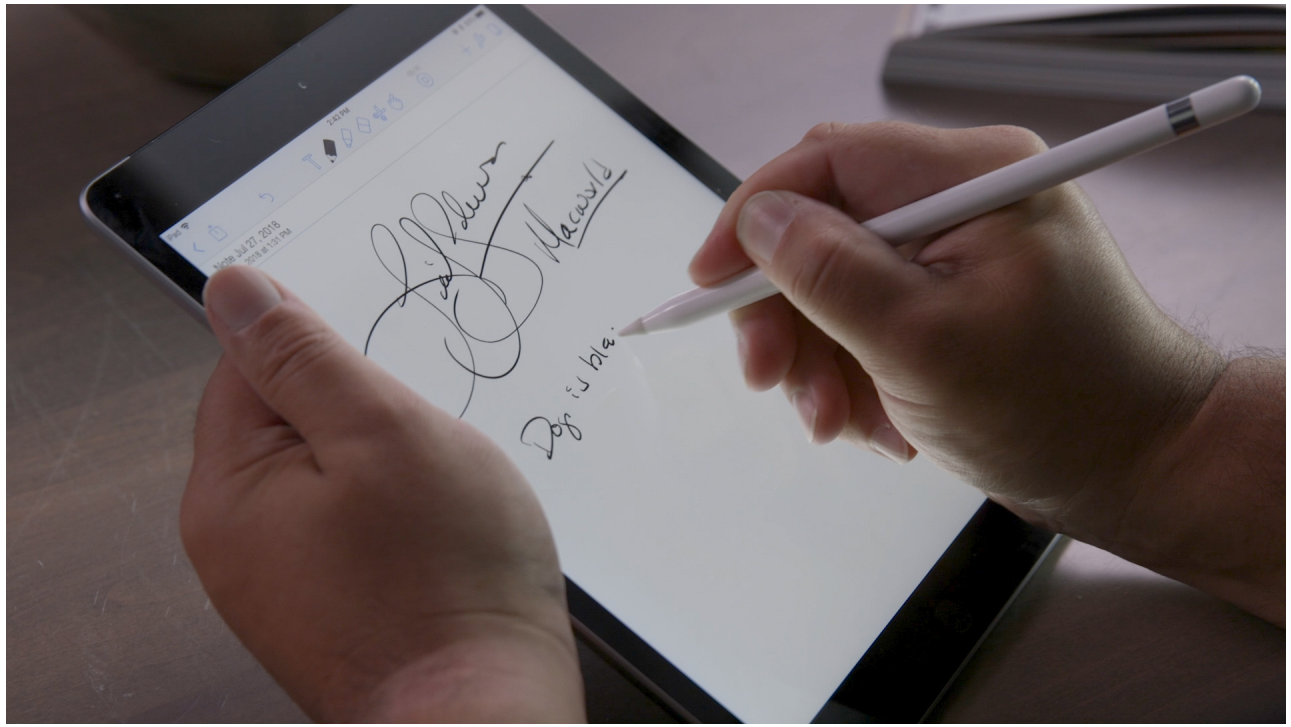


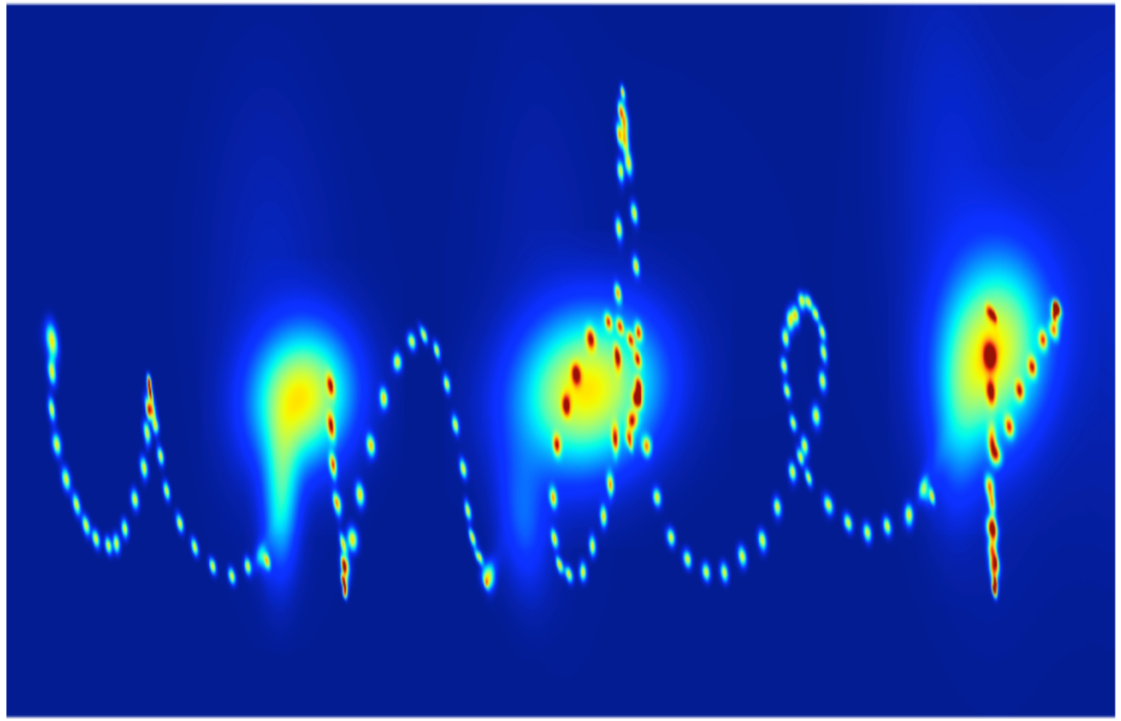
Add notes to pictures

Figure 5. A selection of evaluation results, grouped by human rating.

Handwriting prediction

- The writing track is regarded as a series of points
- Calculate the trajectory for the next second based on the previous input and offset





Recurrent neural network summary

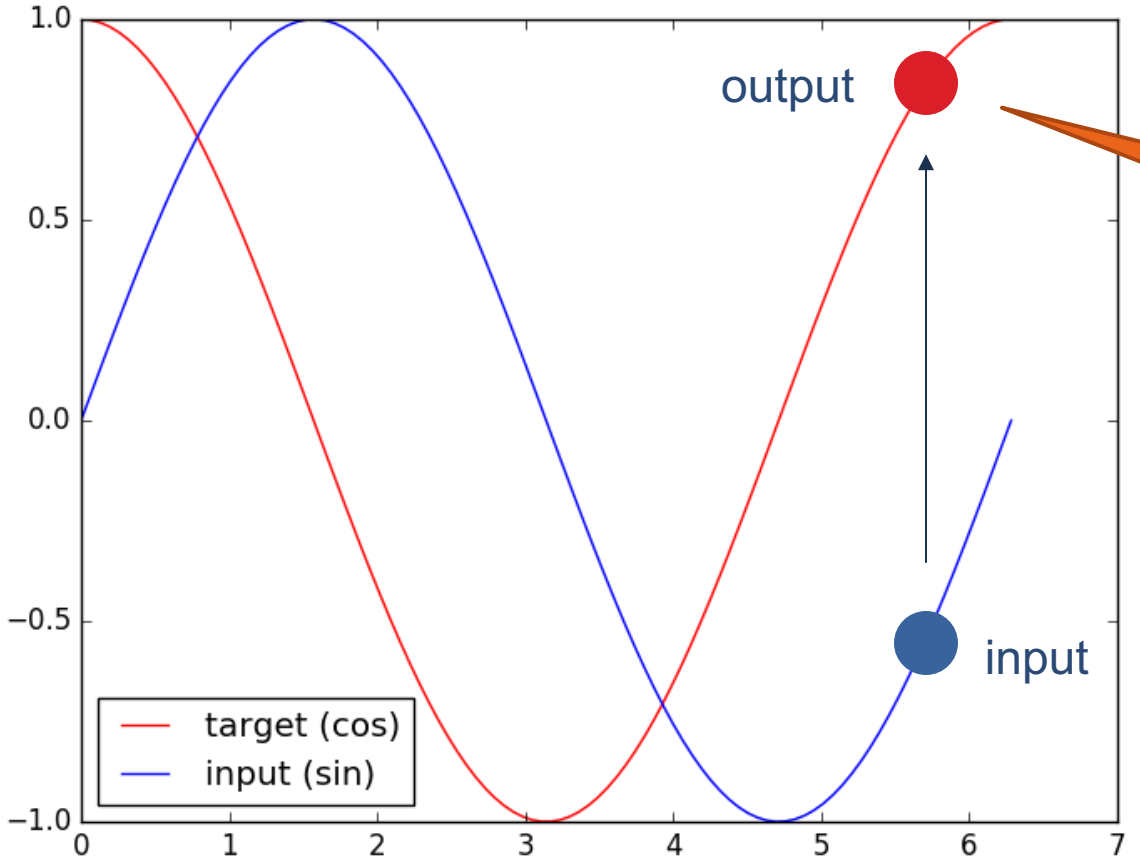
- Advantage:
  - Introduce memory

- Disadvantage:
  - Memory capacity problem
  - Parallel ability

https://github.com/kevinsuo/CS7357/blob/master/rnn/rnn2.py

Build an RNN

- Use RNN to predict time series



Use the sin curve to predict the cos curve

Build an RNN

- Torch
  - http://torch.ch/
  - Torch is an open-source machine learning library, a scientific computing framework, and a script language based on the Lua programming language.

- Hyper Parameters

```
1   import torch
2   from torch import nn
3   import numpy as np
4   import matplotlib.pyplot as plt
5
6   # Hyper Parameters
7   TIME_STEP = 10      # rnn time step
8   INPUT_SIZE = 1      # rnn input size
9   LR = 0.02           # learning rate
```

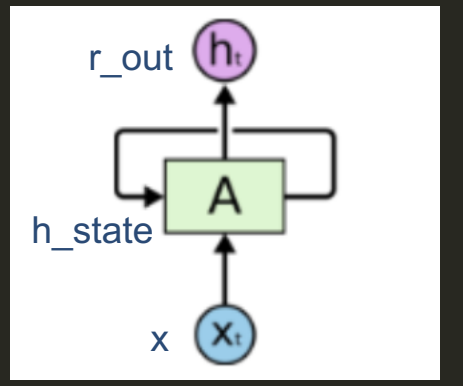
1 means every time step we give 1 point value of sin curve into RNN

Build an RNN

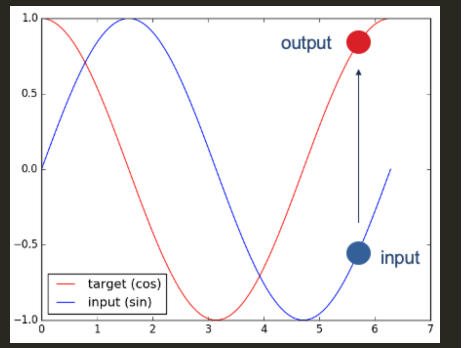
```python
class RNN(nn.Module):
    def __init__(self):
        super(RNN, self).__init__()

        self.rnn = nn.RNN(
            input_size=INPUT_SIZE,
            hidden_size=32,     # rnn hidden unit
            num_layers=1,       # number of rnn layer
            batch_first=True,   # input & output will has batch size as 1s dimension. e.g. (batch, time_step, input_size)
        )
        self.out = nn.Linear(32, 1)

    def forward(self, x, h_state):
        # x (batch, time_step, input_size)
        # h_state (n_layers, batch, hidden_size)
        # r_out (batch, time_step, hidden_size)
        r_out, h_state = self.rnn(x, h_state)

        outs = []    # save all predictions
        for time_step in range(r_out.size(1)):    # calculate output for each time step
            outs.append(self.out(r_out[:, time_step, :]))
        return torch.stack(outs, dim=1), h_state

        # instead, for simplicity, you can replace above codes by follows
        # r_out = r_out.view(-1, 32)
        # outs = self.out(r_out)
        # outs = outs.view(-1, TIME_STEP, 1)
        # return outs, h_state

        # or even simpler, since nn.Linear can accept inputs of any dimension
        # and returns outputs with same dimension except for the last
        # outs = self.out(r_out)
        # return outs

rnn = RNN()
print(rnn)
```

Larger number of layer could increase the accuracy but sacrifice the computation time by involving huge amount of computation

Here we use Linear format RNN. You can also use LSTM format as: self.out = nn.LSTM()



Save all predictions

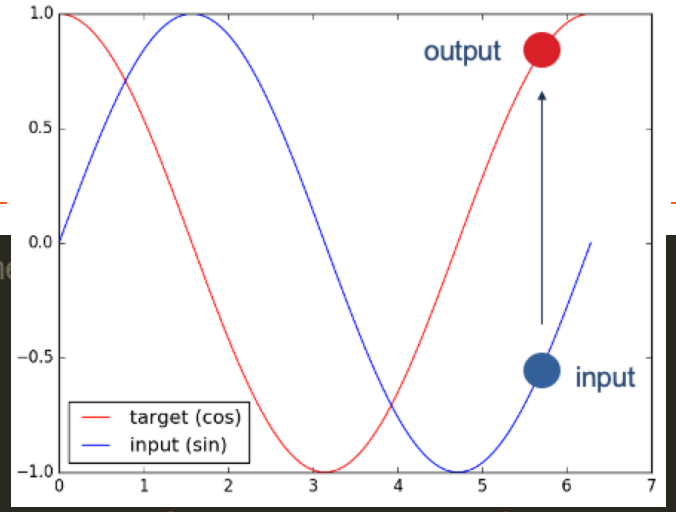


Build an RNN

- Train idea:
  - Use x as the input sin value, and then y as the output cos value you want to fit.
  - Because the two curves (sin, cos) have a certain relationship, we can use sin to predict cos
  - RNN will understand their relationship and use the parameters inside to analyze how the points on the sin curve at this moment correspond to the points on the cos curve.

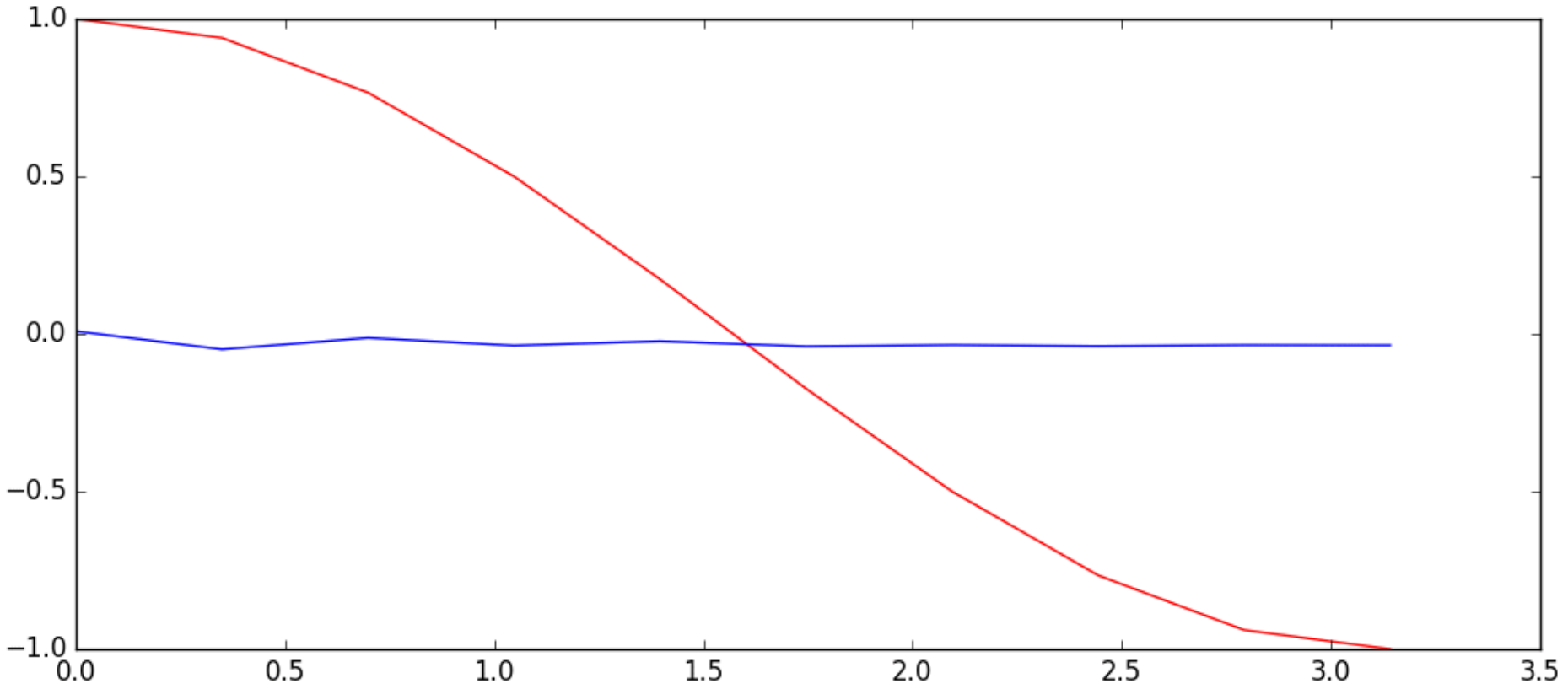
Build an RNN

```
58  optimizer = torch.optim.Adam(rnn.parameters(), lr=LR)   # optimize all cnn parame
59  loss_func = nn.MSELoss()
60
61  h_state = None      # for initial hidden state
62
63  plt.figure(1, figsize=(12, 5))
64  plt.ion()           # continuously plot
65
66  for step in range(100):
67      start, end = step * np.pi, (step+1)*np.pi   # time range
68      # use sin predicts cos
69      steps = np.linspace(start, end, TIME_STEP, dtype=np.float32, endpoint=False)  # float32 for converting torch FloatTensor
70      x_np = np.sin(steps)
71      y_np = np.cos(steps)
72
73      x = torch.from_numpy(x_np[np.newaxis, :, np.newaxis])    # shape (batch, time_step, input_size)
74      y = torch.from_numpy(y_np[np.newaxis, :, np.newaxis])
75
76      prediction, h_state = rnn(x, h_state)   # rnn output
77      # !! next step is important !!
78      h_state = h_state.data        # repack the hidden state, break the connection from last iteration
79
80      loss = loss_func(prediction, y)         # calculate loss
81      optimizer.zero_grad()                   # clear gradients for this training step
82      loss.backward()                         # backpropagation, compute gradients
83      optimizer.step()                        # apply gradients
```



Encapsulate x_np into a three-dimensional vector

Build an RNN



https://github.com/kevinsuo/CS7357/blob/master/rnn/rnn.py

Build an RNN

- Train a recurrent neural network on the IMDB large movie review dataset for sentiment analysis

- Large Movie Review Dataset
  - http://ai.stanford.edu/~amaas/data/sentiment/

  - This is a dataset for binary sentiment classification containing substantially more data than previous benchmark datasets. It provide a set of 25,000 highly polar movie reviews for training, and 25,000 for testing.

Build an RNN

- Step 1: Setup

```
import tensorflow_datasets as tfds
import tensorflow as tf
```

- Import matplotlib and create a helper function to plot graphs:

```
import matplotlib.pyplot as plt

def plot_graphs(history, metric):
  plt.plot(history.history[metric])
  plt.plot(history.history['val_'+metric], '')
  plt.xlabel("Epochs")
  plt.ylabel(metric)
  plt.legend([metric, 'val_'+metric])
```

Build an RNN

- Step 2: Setup input pipeline
  - The IMDB large movie review dataset is a binary classification dataset—all the reviews have either a positive or negative sentiment.
  - Download the dataset using TFDS. https://www.tensorflow.org/datasets

```
dataset, info = tfds.load('imdb_reviews/subwords8k', with_info=True,
                          as_supervised=True)
train_dataset, test_dataset = dataset['train'], dataset['test']
```

```
WARNING:absl:TFDS datasets with text encoding are deprecated and will be removed in a future version. Instead, you should use the plain text version and tokenize the text using `tensorflow_text` (See: https://www.tensorflow.org/tutorials/tensorflow_text/intro#tfdata_example)

Downloading and preparing dataset imdb_reviews/subwords8k/1.0.0 (download: 80.23 MiB, generated: Unknown size, total: 80.23 MiB) to /home/kbuilder/tensorflow_datasets/imdb_reviews/subwords8k/1.0.0... Shuffling and writing examples to /home/kbuilder/tensorflow_datasets/imdb_reviews/subwords8k/1.0.0.incomplete7GBYY4/imdb_reviews-train.tfrecord Shuffling and writing examples to /home/kbuilder/tensorflow_datasets/imdb_reviews/subwords8k/1.0.0.incomplete7GBYY4/imdb_reviews-test.tfrecord Shuffling and writing examples to /home/kbuilder/tensorflow_datasets/imdb_reviews/subwords8k/1.0.0.incomplete7GBYY4/imdb_reviews-unsupervised.tfrecord Dataset imdb_reviews downloaded and prepared to /home/kbuilder/tensorflow_datasets/imdb_reviews/subwords8k/1.0.0. Subsequent calls will reuse this data.
```

Build an RNN

- Step 2: Setup input pipeline
  - Data set info includes encoder (tfds.features.text.SubwordTextEncoder)

```
encoder = info.features['text'].encoder

print('Vocabulary size: {}'.format(encoder.vocab_size))
```

Vocabulary size: 8185

Build an RNN

- Step 2: Setup input pipeline
  - This text encoder will encode any string in a reversible manner and fall back to byte encoding if necessary

```
sample_string = 'Hello TensorFlow.'

encoded_string = encoder.encode(sample_string)
print('Encoded string is {}'.format(encoded_string))

original_string = encoder.decode(encoded_string)
print('The original string: "{}"'.format(original_string))
```

Encoded string is [4025, 222, 6307, 2327, 4043, 2120, 7975] The original string: "Hello TensorFlow."

Build an RNN

- Step 2: Setup input pipeline
  - This text encoder will encode any string in a reversible manner and fall back to byte encoding if necessary

```
assert original_string == sample_string

for index in encoded_string:
  print('{} ----&gt; {}'.format(index, encoder.decode([index])))
```

4025 ----> Hell
222 ----> o
6307 ----> Ten
2327 ----> sor
4043 ----> Fl
2120 ----> ow
7975 ----> .

Build an RNN

- Step 3: Prepare data for training
  - Create batches of these encoded strings. Use the padded_batch method to padded sequence zeros to the length of the longest string in the batch:

```
BUFFER_SIZE = 10000
BATCH_SIZE = 64


train_dataset = train_dataset.shuffle(BUFFER_SIZE)
train_dataset = train_dataset.padded_batch(BATCH_SIZE)

test_dataset = test_dataset.padded_batch(BATCH_SIZE)
```

Build an RNN

- Step 4: Create a model
  - Build a tf.keras.Sequential model and start with the embedding vector layer. The embedding vector layer stores a vector for each word. When called, it converts a sequence of word indexes into a sequence of vectors. These vectors are trainable. (On enough data) After training, words with similar meanings usually have similar vectors.
  - Compared with the equivalent operation of passing the one-hot encoding vector through the tf.keras.layers.Dense layer, this index search method is much more efficient.
  - Recurrent Neural Networks (RNN) process sequence input by traversing elements. RNN passes the output from one time step to its input, and then to the next step.
  - The tf.keras.layers.Bidirectional wrapper can also be used with RNN layers. This will propagate the input forward and backward through the RNN layer, and then connect the output. This helps RNN learn long-term dependencies.

Build an RNN

- Step 4: Create a model

```
model = tf.keras.Sequential([
    tf.keras.layers.Embedding(encoder.vocab_size, 64),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(64)),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1)
])
```

- Compile the Keras model to configure the training process:

```
model.compile(loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
              optimizer=tf.keras.optimizers.Adam(1e-4),
              metrics=['accuracy'])
```

Build an RNN

Step 5: Train a model

```
history = model.fit(train_dataset, epochs=10,
                    validation_data=test_dataset,
                    validation_steps=30)
```

```
Epoch 1/10 391/391 [==============================] - 41s 105ms/step - loss: 0.6363 - accuracy: 0.5736 - val_loss: 0.4592 -
val_accuracy: 0.8010
Epoch 2/10 391/391 [==============================] - 41s 105ms/step - loss: 0.3426 - accuracy: 0.8556 - val_loss: 0.3710 -
val_accuracy: 0.8417
Epoch 3/10 391/391 [==============================] - 42s 107ms/step - loss: 0.2520 - accuracy: 0.9047 - val_loss: 0.3444 -
val_accuracy: 0.8719
Epoch 4/10 391/391 [==============================] - 41s 105ms/step - loss: 0.2103 - accuracy: 0.9228 - val_loss: 0.3348 -
val_accuracy: 0.8625
Epoch 5/10 391/391 [==============================] - 42s 106ms/step - loss: 0.1803 - accuracy: 0.9360 - val_loss: 0.3591 -
val_accuracy: 0.8552
```

Build an RNN

Step 5: Train a model

```
test_loss, test_acc = model.evaluate(test_dataset)

print('Test Loss: {}'.format(test_loss))
print('Test Accuracy: {}'.format(test_acc))
```

391/391 [==============================] - 17s 43ms/step - loss: 0.4305 - accuracy: 0.8477

Test Loss: 0.430510908365249 63

Test Accuracy: 0.8476799726486206

Build an RNN

- Step 5: Train a model
  - If the forecast is >= 0.5, it is positive, otherwise it is negative.

```
def pad_to_size(vec, size):
  zeros = [0] * (size - len(vec))
  vec.extend(zeros)
  return vec


def sample_predict(sample_pred_text, pad):
  encoded_sample_pred_text = encoder.encode(sample_pred_text)

  if pad:
    encoded_sample_pred_text = pad_to_size(encoded_sample_pred_text, 64)
  encoded_sample_pred_text = tf.cast(encoded_sample_pred_text, tf.float32)
  predictions = model.predict(tf.expand_dims(encoded_sample_pred_text, 0))

  return (predictions)
```

Build an RNN

- Step 5: Train a model
  - If the forecast is >= 0.5, it is positive, otherwise it is negative.

```
# predict on a sample text without padding.

sample_pred_text = ('The movie was cool. The animation and the graphics '
                    'were out of this world. I would recommend this movie.')
predictions = sample_predict(sample_pred_text, pad=False)
print(predictions)
```

[[-0.11829309]]

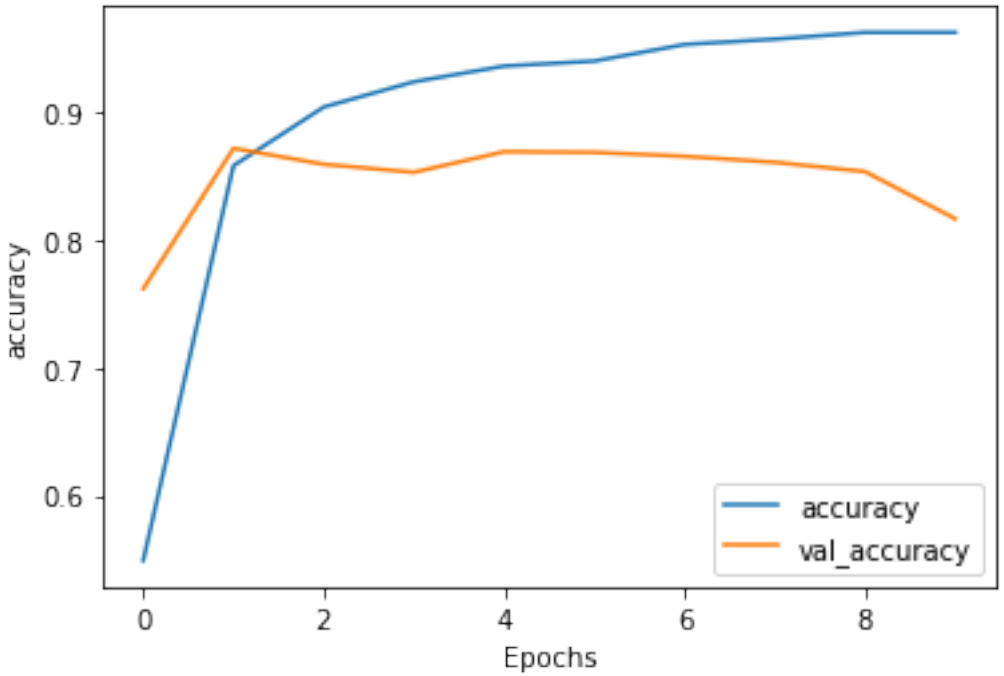
```
# predict on a sample text with padding

sample_pred_text = ('The movie was cool. The animation and the graphics '
                    'were out of this world. I would recommend this movie.')
predictions = sample_predict(sample_pred_text, pad=True)
print(predictions)
```

[[-1.162545]]

Build an RNN

- Step 5: Train a model

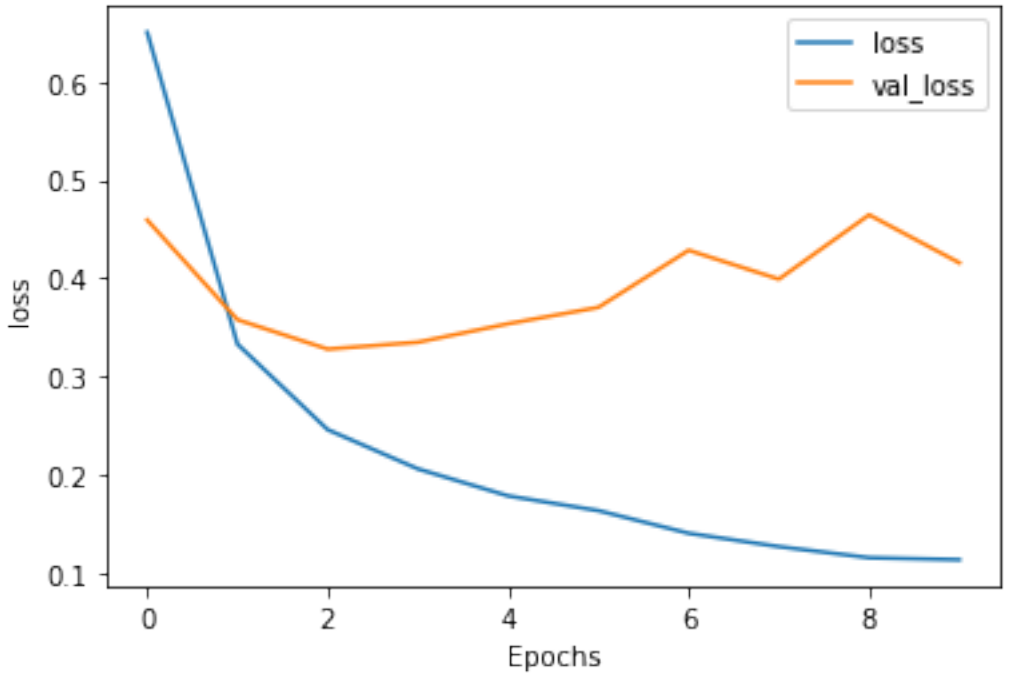
```
plot_graphs(history, 'accuracy')
```



Build an RNN

- Step 5: Train a model

```
plot_graphs(history, 'loss')
```



Build an RNN

- Step 6: add two or more LSTM layers
  - The Keras loop layer has two available modes, which are controlled by the return_sequences constructor parameter

```
model = tf.keras.Sequential([
    tf.keras.layers.Embedding(encoder.vocab_size, 64),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(64,  return_sequences=True)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32)),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(1)
])

model.compile(loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
              optimizer=tf.keras.optimizers.Adam(1e-4),
              metrics=['accuracy'])

history = model.fit(train_dataset, epochs=10,
                    validation_data=test_dataset,
                    validation_steps=30)
```

Build an RNN

- Step 6: add two or more LSTM layers

```
test_loss, test_acc = model.evaluate(test_dataset)

print('Test Loss: {}'.format(test_loss))
print('Test Accuracy: {}'.format(test_acc))
```

391/391 [==============================] - 30s 78ms/step - loss: 0.5205 - accuracy: 0.8572
Test Loss: 0.5204932689666748
Test Accuracy: 0.857200026512146

```
sample_pred_text = ('The movie was not good. The animation and the graphics
                    'were terrible. I would not recommend this movie.')
predictions = sample_predict(sample_pred_text, pad=False)
print(predictions)
```

[[-2.6377363]]

Build an RNN

- Step 6: add two or more LSTM layers

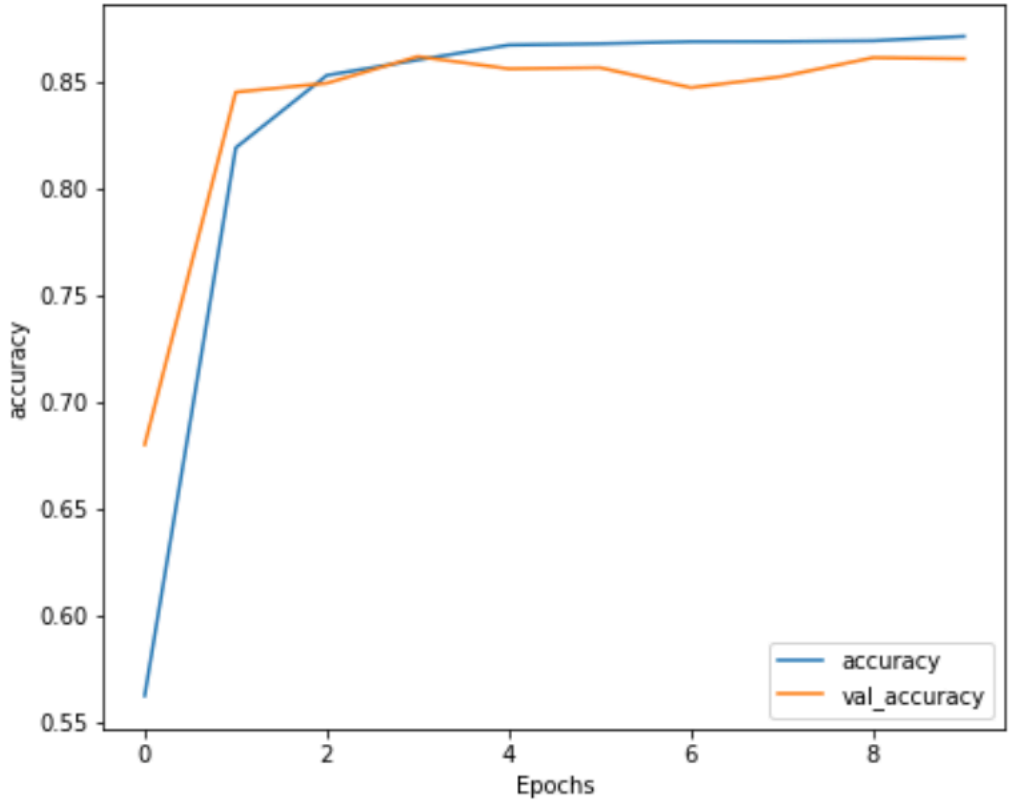
```
sample_pred_text = ('The movie was not good. The animation and the graphics '
                    'were terrible. I would not recommend this movie.')
predictions = sample_predict(sample_pred_text, pad=True)
print(predictions)
```

```
[[-3.0502243]]
```

Build an RNN

- Step 6: add two or more LSTM layers

```
plot_graphs(history, 'accuracy')
```

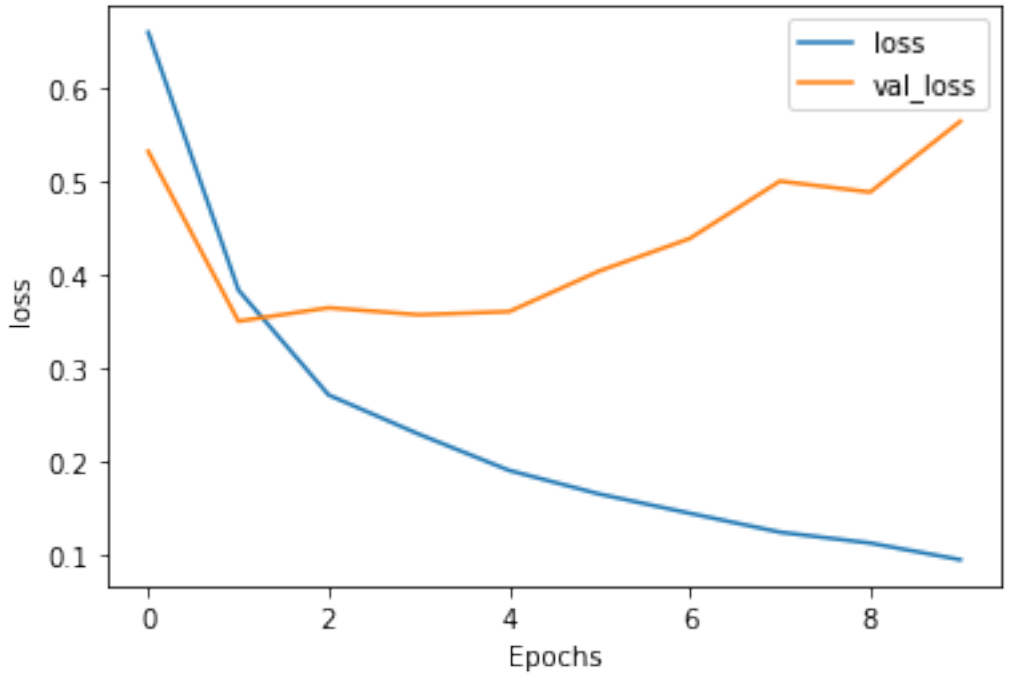


https://github.com/kevinsuo/CS7357/blob/master/rnn/rnn.py

Build an RNN

- Step 6: add two or more LSTM layers

```
plot_graphs(history, 'loss')
```



Build an RNN

```
python3 /Users/ksuo/Google Drive/github/CS7357/rnn
the MLIR optimization passes are enabled (registered 2)
391/391 [==============================] - 309s 784ms/step - loss: 0.6841 - accuracy: 0.5147 - val_l
oss: 0.4780 - val_accuracy: 0.7635
Epoch 2/10
391/391 [==============================] - 306s 782ms/step - loss: 0.3999 - accuracy: 0.8221 - val_l
oss: 0.3547 - val_accuracy: 0.8604
Epoch 3/10
391/391 [==============================] - 308s 789ms/step - loss: 0.2645 - accuracy: 0.8972 - val_l
oss: 0.3261 - val_accuracy: 0.8609
Epoch 4/10
391/391 [==============================] - 312s 798ms/step - loss: 0.2129 - accuracy: 0.9218 - val_l
oss: 0.3309 - val_accuracy: 0.8693
Epoch 5/10
391/391 [==============================] - 310s 793ms/step - loss: 0.1780 - accuracy: 0.9380 - val_l
oss: 0.3846 - val_accuracy: 0.8656
Epoch 6/10
391/391 [==============================] - 310s 792ms/step - loss: 0.1672 - accuracy: 0.9402 - val_l
oss: 0.3597 - val_accuracy: 0.8661
Epoch 7/10
391/391 [==============================] - 312s 798ms/step - loss: 0.1431 - accuracy: 0.9530 - val_l
oss: 0.3627 - val_accuracy: 0.8604
Epoch 8/10
391/391 [==============================] - 317s 812ms/step - loss: 0.1363 - accuracy: 0.9532 - val_l
oss: 0.4037 - val_accuracy: 0.8672
Epoch 9/10
391/391 [==============================] - 321s 821ms/step - loss: 0.1204 - accuracy: 0.9604 - val_l
oss: 0.4050 - val_accuracy: 0.8620
Epoch 10/10
391/391 [==============================] - 327s 837ms/step - loss: 0.1124 - accuracy: 0.9640 - val_l
oss: 0.4469 - val_accuracy: 0.8573
391/391 [==============================] - 83s 211ms/step - loss: 0.4457 - accuracy: 0.8553
Test Loss: 0.4457261264324188
Test Accuracy: 0.8553199768066406
[[0.07003495]]
[[-0.01062911]]
```