CSCE 636 Neural Networks (Deep Learning)

Lecture 9: Deep Learning for Text and Sequences (continued)

Anxiao (Andrew) Jiang

Embedding layer and Recurrent layer

```
Say we have N = 100 movie reviews as a batch.
Each movie review has maxlen = 20 words.
We build a network with an embedding layer to classify the reviews.
```

```
model = Sequential()
model.add(Embedding(10000, 8, input_length=maxlen))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
```



```
Say we have N = 100 movie reviews as a batch.
Each movie review has maxlen = 20 words.
We build a network with an embedding layer to classify the reviews.
```

```
model = Sequential()
model.add(Embedding(10000, 8, input_length=maxlen))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
```











```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
```

```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
```







```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
Return the full sequence of outputs
```



```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Flatten())
```

```
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(SimpleRNN(32))
model.add(Dense(1, activation='sigmoid'))
```

```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(SimpleRNN(32))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(SimpleRNN(32))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(SimpleRNN(32)) The default is to return only the last output of RNN
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(SimpleRNN(32)) The default is to return only the last output of RNN
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Dense(1, activation='sigmoid'))
```

```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
```

```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(layers.Embedding(max_features, 32))
model.add(layers.Bidirectional(layers.LSTM(32)))
model.add(layers.Dense(1, activation='sigmoid'))
```

```
model = Sequential()
model.add(layers.Embedding(max_features, 32))
model.add(layers.Bidirectional(layers.LSTM(32)))
model.add(layers.Dense(1, activation='sigmoid'))
```



```
model = Sequential()
model.add(layers.Embedding(max_features, 32))
model.add(layers.Bidirectional(layers.LSTM(32)))
model.add(layers.Dense(1, activation='sigmoid'))
```



Quick Summary

- From the outside, a RNN layer looks just like an ordinary layer.
- Inside the RNN layer, data are processed sequentially.

Why do people prefer LSTM / GRU to SimpleRNN?

The following slides are based on the interesting lecture of Prof. Hung-yi Lee "Recurrent Neural Network" https://www.youtube.com/watch?v=xCGidAeyS4M&list=PLJV_el3uVTsPy9oCRY30oBPNLCo89yu49&index=30

How to Train an RNN

Expand the RNN to all N time steps. Define a loss function based on the output.



How to Train an RNN

Expand the RNN to all N time steps. Define a loss function based on the output.

Use Gradient Descent for Training: Back Propagation through time (BPTT)



Unfortunately

RNN-based network is not always easy to learn



Unfortunately

• RNN-based network is not always easy to learn





Unfortunately

RNN-based network is not always easy to learn

Real experiments on Language modeling





In commonly used gradient descent algorithms, The learning rate is dynamically adjusted: When the gradients are small, the algorithm makes the learning rate larger. When the gradients are large, the algorithm makes the learning rate smaller.

But when the gradients change abruptly, the algorithm does not know how to adjust the learning rate. Also, the loss function's value can change abruptly.

The error surface is rough.

Large Learning Rate x Large Gradient
very large change in weights



The error surface is rough.

Solution: Gradient Clipping (limit the maximum value for gradient)



Why does RNN have rough error surfaces (that is, very small and very large gradients)?

Why?

Consider a very simple RNN: just one neuron,

whose activation function is linear (namely, output = input), bias = 0, edge weight = 1 or w.



Why?



Why?

$$w = 1 \implies y^{1000} = 1$$

 $w = 1.01 \implies y^{1000} \approx 20000$



Why?

$$w = 1 \implies y^{1000} = 1$$

 $w = 1.01 \implies y^{1000} \approx 20000$
Large $\partial L/\partial w$
Learning rate?



Why?

$$w = 1 \longrightarrow y^{1000} = 1$$

 $w = 1.01 \longrightarrow y^{1000} \approx 20000$
 $w = 0.99 \longrightarrow y^{1000} \approx 0$
 $w = 0.01 \longrightarrow y^{1000} \approx 0$



Why?

$$w = 1 \longrightarrow y^{1000} = 1$$

 $w = 1.01 \longrightarrow y^{1000} \approx 20000$
 $w = 0.99 \longrightarrow y^{1000} \approx 0$
 $w = 0.01 \longrightarrow y^{1000} \approx 0$
Small
 $\partial L/\partial w$
 $dL/\partial w$
Large
 $\partial L/\partial w$
Large
Large
 $\partial L/\partial w$
Large
Large
 $\partial L/\partial w$





Helpful Techniques

- Long Short-term Memory (LSTM)
 - Can deal with gradient vanishing (not gradient explode)



Helpful Techniques

- Long Short-term Memory (LSTM)
 - Can deal with gradient vanishing (not gradient explode)





Helpful Techniques

Long Short-term Memory (LSTM)

 Can deal with gradient vanishing (not gradient explode)

Gated Recurrent Unit (GRU): simpler than LSTM.

LSTM: 3 gates. GRU: 2 gates.

Intuition of GRU: control input gate and forget gate together. When input gate is open, forget gate is closed and memory is erased. When input gate is closes, forget gate is open and memory is kept.

